ASReml User Guide

Release 1.0

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Preface

ASReml is a statistical package that fits linear mixed models using Residual Maximum Likelihood (REML). It has been under development since 1993 and is a joint venture between the Biometrics Program of NSW Agriculture and the Biomathematics Unit previously the Statistics Department of Rothamsted Experiment Station. This guide relates to the August 2002 version of ASReml.

Linear mixed effects models provide a rich and flexible tool for the analysis of many data sets commonly arising in the agricultural, biological, medical and environmental sciences. Typical applications include the analysis of (un)balanced longitudinal data, repeated measures analysis, the analysis of (un)balanced designed experiments, the analysis of multi-environment trials, the analysis of both univariate and multivariate animal breeding and genetics data and the analysis of regular or irregular spatial data.

One of the strengths of ASReml is the wide range of possible variance models for the random effects in the linear mixed model. There is a potential cost for this wide choice. Users should be aware of the dangers of either overfitting or attempting to fit inappropriate variance models to small or highly unbalanced data sets. We stress the importance of the use of data-driven diagnostics and encourage the user to read the examples chapter, in which we have attempted to not only present the syntax of ASReml in the context of real analyses but also to indicate some of the modelling approaches we have found useful.

Another strength of ASReml is the use of the Average Information (AI) algorithm and sparse matrix methods for fitting the linear mixed model. This enables ASReml to analyse large and complex data sets quite efficiently. We have concentrated on expanding the range of variance models and improving the speed and reliability of the *engine* rather than providing comprehensive reporting facilities. However, the facilities are adequate for most situations. The *engine* of ASReml is used by the REML directive in GENSTAT and by the samm class of functions in S-PLUS. Both of these have good data manipulation and graphical facilities. The guide has 15 chapters. Chapter 1 introduces ASReml and describes the conventions used in this guide. Chapter 2 outlines some basic theory while Chapter 3 presents an overview of the syntax of ASReml through a simple example. Data file preparation is described in Chapter 4 and Chapter 5 describes how to input data into ASReml. Chapters 6 and 7 are key chapters which present the syntax for specifying the linear model and the variance models for the random effects in the linear mixed model. Chapters 8 and 9 describe special commands for multivariate and genetic analyses respectively. Chapter 10 deals with prediction of linear functions of fixed and random effects in the linear mixed model and Chapter 11 presents the syntax for forming functions of variance components. Chapter 12 demonstrates running an ASReml job and explains the interactive menu features available and Chapter 13 gives a detailed explanation of the output files. Chapter 14 gives an overview of the error messages generated in ASReml and some guidance as to their probable cause. The guide concludes with the most extensive chapter which presents the examples.

The data sets and ASReml input files used in this guide are available for electronic distribution from http://vsn-intl.com/asreml. They remain the property of the authors or of the original source but may be freely distributed provided the source is acknowledged. The authors would appreciate feedback and suggestions for improvements to the program and this guide.

Upgrades

ASRemI is being continually upgraded to implement new developments in the application of linear mixed models. The release version will be distributed by VSN on CD to licensed users. A developmental version is available to licensees of the current release version via the ASRemI website. This User Guide and a Reference Manual are also available on that site. Most users will not need to access the developmental version unless they are actively involved in testing a new development.

Acknowledgements

We gratefully acknowledge the Grains Research and Development Corporation of Australia for their financial support for our research since 1988. Brian Cullis and Arthur Gilmour wish to thank NSW Agriculture, and in particular Alan Gleeson for having faith in the project and for providing a stimulating and exciting environment for applied biometrical research and consulting. Rothamsted Research receives grant-aided support from the Biotechnology and Biological Sciences Research Council of the United Kingdom. We sincerely thank Ari Verbyla, Dave Butler and Alison Smith, the other members of the ASReml 'team'. Ari is thanked for his contribution to the cubic smoothing splines technology, on-going testing of the software and numerous helpful discussions and insight. Dave is thanked for his support of the project and in the latter years the development of the samm class of functions. Alison is thanked for her contribution to Chapter 15, the development of many of the approaches for the analysis of multi-section trials, and constant and undeterred commitment to ASReml. We also thank Ian White for his contribution to the spline methodology and Simon Harding and Megan Cherry for licensing and installation software.

ASRemI was available free of charge for a number of years and we acknowledge our users who have supported the package through its early development. We look forward to their continued support and interaction. ASRemI is now distributed by VSN-International on behalf of NSW Agriculture and Rothamsted Research. Proceeds are used to support continued development. Please visit http://www.VSN-Intl.com or email info@VSN-Intl.com for further information.

Arthur Gilmour acknowledges the grace of God through Jesus Christ who enables this research to proceed. *Be exalted O God, above the heavens: and Thy glory above all the earth. Psalm 108:5.*

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Introduction

What ASReml can do

Installation

How to use the guide

Help and discussion list

Typographic conventions

1.1 What ASReml can do

ASRemI (pronounced A S Remel) is used to fit linear mixed models to quite large data sets with complex variance models. It extends the range of variance models available for the analysis of experimental data. ASRemI has application in the analysis of

- (un)balanced longitudinal data,
- repeated measures data (multivariate analysis of variance and spline type models),
- (un)balanced designed experiments,
- multi-environment trials and meta analysis,
- univariate and multivariate animal breeding and genetics data (involving a relationship matrix for correlated effects),
- regular or irregular spatial data.

The engine of ASRemI forms the basis of the REML procedure in GENSTAT. An interface for SPLUS called samm has also been developed. While these interfaces will be adequate for many analyses, some large problems will need to use ASRemI. The ASRemI user interface is concise. Most effort has been directed towards efficiency of the engine. It normally operates in a batch mode.

Problem size depends on the sparsity of the mixed model equations and the size of your computer. However, models with 100,000 effects have been fitted successfully. The computational efficiency of ASReml arises from using the Average Information REML procedure (giving quadratic convergence) and sparse matrix operations. ASReml has been operational since March 1996 and is updated periodically.

1.2 Installation

Installation instructions vary for the various platforms and are distributed with the program. If you find the instructions inadequate for some reason, please email asreml@VSN-Intl.com.

1.3 How to use this guide

Theory	The guide consists of 15 chapters. Chapter 1 introduces ASReml and describes the conventions used in the guide. Chapter 2 outlines some basic theory which you may need to come back to.				
Getting started	New ASRemI users are advised to read Chapter 3 before attempting to code their first job. It presents an overview of basic ASRemI coding demonstrated on a real				
Examples	data example. Chapter 15 presents a range of examples to assist users further. When coding you first job, look for an example to use as a template.				
Data file	Data file preparation is described in Chapter 4, while Chapter 5 describes how to input data into ASReml. Chapters 6 and 7 are key chapters which present the syntax for specifying the linear model and the variance models for the random				
Linear model Variance model	effects in the linear mixed model. Variance modelling is a complex aspect of analysis. We introduce variance modelling in ASRemI by example in Chapter 7.				
Prediction	Chapters 8 and 9 describe special commands for multivariate and genetic analyses respectively. Chapter 10 deals with prediction of fixed and random effects from the linear mixed model and Chapter 11 presents the syntax for forming functions of variance components.				
Output	Chapter 12 discusses running an ASReml job and explains the interactive menu features available. Chapter 13 gives a detailed explanation of the output files. Chapter 14 gives an overview of the error messages generated in ASReml and some guidance as to their probable cause.				

1.4 Help and discussion list

Supported users of ASRemI may email asreml@VSN-Intl.com for assistence. When requesting help for a job that is not working as you expect, please send the input command file, the data file and the corresponding primary output file along with a description of the problem.

There is also an ASRemI discussion list. To join (leave) the list, send an email to ASReml-request@chiswick.anprod.csiro.au with the word subscribe (unsubscribe) in the body of the message.

The address for messages to the list is ASReml@chiswick.anprod.csiro.au.

1 Introduction

1.5 Typographic conventions

A hands on approach is the best way to develop a working understanding of a new computing package. We therefore begin by presenting a guided tour of ASReml using a sample data set for demonstration (see Chapter 3). Throughout the guide new concepts are demonstrated by example wherever possible.

In this guide you will often find framed sample boxes to the right of the page as shown here. These contain ASRemI command file (sample) code. Note that

- the code under discussion is highlighted in bold type for easy identification,
- the continuation symbol (:) is used to indicate that some of the original code is omitted.

```
An example ASReml code box
bold type highlights sections
of code currently under
discussion
remaining code is not
highlighted
: indicates that some of the
original code is omitted from
the display
```

Data examples are displayed in larger boxes in the body of the text, see, for example, page 34. Other conventions are as follows:

- keyboard key names appear in SMALLCAPS, for example, TAB and ESC,
- example code within the body of the text is in this size and font and is highlighted in bold type, see pages 27 and 40,
- in the presentation of general ASRemI syntax, for example

[path] asreml basename[.as] [arguments]

- typewriter font is used for text that must be typed verbatim, for example, asreml and .as after *basename* in the example,
- *italic font* is used to name information to be supplied by the user, for example, *basename* stands for the name of a file with an **.as** filename extension,
- square brackets indicate that the enclosed text and/or arguments are not always required.
- ASReml output is in this size and font, see page 28,
- this font is used for all other code.

Some theory

The linear mixed model

Introduction Direct product structures Variance structures for the errors: R structures Variance structures for the random effects: G structures

Estimation

Estimation of the variance parameters Estimation/prediction of fixed and random effects

What are BLUPs?

Combining variance models

Inference

Tests of hypotheses: variance parameters Tests of hypotheses: fixed effects

2.1 The linear mixed model

Introduction

If \boldsymbol{y} denotes the $n \times 1$ vector of observations, the linear mixed model can be written as

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{u} + \boldsymbol{e} \tag{2.1}$$

where $\boldsymbol{\tau}$ is the $p \times 1$ vector of fixed effects, \boldsymbol{X} is an $n \times p$ design matrix of full column rank which associates observations with the appropriate combination of fixed effects, \boldsymbol{u} is the $q \times 1$ vector of random effects, \boldsymbol{Z} is the $n \times q$ design matrix which associates observations with the appropriate combination of random effects, and \boldsymbol{e} is the $n \times 1$ vector of residual errors.

The model (2.1) is called a linear mixed model or linear mixed effects model. It is assumed

$$\begin{bmatrix} \boldsymbol{u} \\ \boldsymbol{e} \end{bmatrix} \sim N\left(\begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{0} \end{bmatrix}, \ \theta \begin{bmatrix} \boldsymbol{G}(\boldsymbol{\gamma}) & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{R}(\boldsymbol{\phi}) \end{bmatrix} \right)$$
(2.2)

where the matrices \boldsymbol{G} and \boldsymbol{R} are functions of parameters $\boldsymbol{\gamma}$ and $\boldsymbol{\phi}$, respectively. The parameter $\boldsymbol{\theta}$ is a variance parameter which we will refer to as the scale parameter. In mixed effects models with more than one residual variance, arising for example in the analysis of data with more than one section (see below) or variate, the parameter $\boldsymbol{\theta}$ is fixed to one. In mixed effects models with a single residual variance then $\boldsymbol{\theta}$ is equal to the residual variance (σ^2). In this case \boldsymbol{R} must be a correlation matrix (see Table 2.1 for a discussion).

Direct product structures

To undertake variance modelling in ASReml you need to understand the formation of variance structures via direct products (\otimes). The direct product of two matrices $A^{(m \times p)}$ and $B^{(n \times q)}$ is

$$\left[\begin{array}{cccc} a_{11}\boldsymbol{B} & \dots & a_{1p}\boldsymbol{B} \\ \vdots & \ddots & \vdots \\ a_{m1}\boldsymbol{B} & \ddots & a_{mp}\boldsymbol{B} \end{array}\right]$$

Direct products in R structures

Consider a vector of common errors associated with an experiment. The usual least squares assumption (and the default in ASRemI) is that these are independently and identically distributed (IID). However, if e was from a field experiment

laid out in a rectangular array of r rows by c columns, we could arrange the residuals as a matrix and might consider that they were autocorrelated within rows and columns. Writing the residuals as a vector in field order, that is, by sorting the residuals rows within columns (plots within blocks) the variance of the residuals might then be

$$\sigma_e^2 \ \mathbf{\Sigma}_c(
ho_c) \otimes \mathbf{\Sigma}_r(
ho_r)$$

where $\Sigma_c(\rho_c)$ and $\Sigma_r(\rho_r)$ are correlation matrices for the row model (order r, autocorrelation parameter ρ_r) and column model (order c, autocorrelation parameter ρ_c) respectively. More specifically, a two-dimensional separable autoregressive spatial structure (AR1 \otimes AR1) is sometimes assumed for the common errors in a field trial analysis (see Gogel (1997) and Cullis *et al.* (1998) for examples). In this case

$$\boldsymbol{\Sigma}_{r} = \begin{bmatrix} 1 & & & & \\ \rho_{r} & 1 & & & \\ \rho_{r}^{2} & \rho_{r} & 1 & & \\ \vdots & \vdots & \vdots & \ddots & \\ \rho_{r}^{r-1} & \rho_{r}^{r-2} & \rho_{r}^{r-3} & \dots & 1 \end{bmatrix} \text{ and } \boldsymbol{\Sigma}_{c} = \begin{bmatrix} 1 & & & & \\ \rho_{c} & 1 & & & \\ \rho_{c}^{2} & \rho_{c} & 1 & & \\ \vdots & \vdots & \vdots & \ddots & \\ \rho_{c}^{c-1} & \rho_{c}^{c-2} & \rho_{c}^{c-3} & \dots & 1 \end{bmatrix}.$$

See Chapter 8 Alternatively, the residuals might relate to a multivariate analysis with n_t traits for further de- and n units and be ordered traits within units. In this case an appropriate tails variance structure might be

 $oldsymbol{I}_n\otimes oldsymbol{\Sigma}$

where $\Sigma^{(n_t \times n_t)}$ is a general or *unstructured* variance matrix.

Direct products in G structures

Likewise, the random terms in u in the model may have a direct product structure. For example, for a field trial with s sites, g varieties and the effects ordered varieties within sites, the model term site.variety may have the variance structure

$$oldsymbol{\Sigma}\otimesoldsymbol{I}_q$$

where Σ is the variance matrix for sites. This would imply that the varieties are independent random effects within each site, have different variances at each site, and are correlated across sites. **Important** Whenever a random term is formed as the interaction of two factors you should consider whether the IID assumption is sufficient or if a direct product structure might be more appropriate.

Variance structures for the errors: R structures

The vector e will in some situations be a series of vectors indexed by a factor or factors. The convention we adopt is to refer to these as *sections*. Thus $e = [e'_1, e'_2, \ldots, e'_s]'$ and the e_j represent the errors of *sections* of the data. For example, these sections may represent different experiments in a multi-environment trial (MET), or different trials in a meta analysis. It is assumed that \mathbf{R} is the direct sum of s matrices \mathbf{R}_j , $j = 1 \ldots s$, that is,

$$\boldsymbol{R} = \bigoplus_{j=1}^{s} \boldsymbol{R}_{j} = \begin{bmatrix} \boldsymbol{R}_{1} & 0 & \dots & 0 & 0 \\ 0 & \boldsymbol{R}_{2} & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & \boldsymbol{R}_{s-1} & 0 \\ 0 & 0 & \dots & 0 & \boldsymbol{R}_{s} \end{bmatrix}$$

so that each section has its own variance structure which is assumed to be independent of the structures in other sections.

A structure for the residual variance for the spatial analysis of multi-environment trials (Cullis *et al.*, 1998) is given by

$$egin{array}{rcl} m{R}_j &=& m{R}_j(m{\phi}_j) \ &=& \sigma_j^2(m{\Sigma}_j(m{
ho}_j)), \end{array}$$

Each section represents a trial and we note that this model accounts for between trial error variance heterogeneity (σ_j^2) and possibly a different spatial variance model for each trial.

In the simplest case the matrix \mathbf{R} could be known and proportional to an identity matrix. Each component matrix, \mathbf{R}_j (or \mathbf{R} itself for one section) is assumed to be the direct product (see Searle, 1982) of one, two or three component matrices. The component matrices are related to the underlying structure of the data. If the structure is defined by factors, for example, replicates, rows and columns, then the matrix \mathbf{R} can be constructed as a direct product of three matrices describing the nature of the correlation across replicates, rows and columns. These factors must completely describe the structure of the data, which means that

- 1. the number of combined levels of the factors must equal the number of data points,
- 2. each factor combination must uniquely specify a single data point.

These conditions are necessary to ensure the expression $var(e) = \theta R$ is valid. The assumption that the overall variance structure can be constructed as a direct product of matrices corresponding to underlying factors is called the assumption of separability and assumes that any correlation process across levels of a factor is independent of any other factors in the term. Multivariate data and repeated measures data usually satisfy the assumption of separability. In particular, if the data are indexed by factors units and traits (for multivariate data) or times (for repeated measures data), then the R structure may be written as units \otimes traits or units \otimes times. This assumption is sometimes required to make the estimation process computationally feasible, though it can be relaxed, for certain applications, for example fitting isotropic covariance models to irregularly spaced spatial data.

Variance structures for the random effects: G structures

The $q \times 1$ vector of random effects is often composed of b subvectors $\boldsymbol{u} = [\boldsymbol{u}_1' \ \boldsymbol{u}_2' \ \dots \ \boldsymbol{u}_b']'$ where the subvectors \boldsymbol{u}_i are of length q_i and these subvectors are usually assumed independent normally distributed with variance matrices $\theta \boldsymbol{G}_i$. Thus just like \boldsymbol{R} we have

$$\boldsymbol{G} = \oplus_{i=1}^{b} \boldsymbol{G}_{i} = \begin{bmatrix} \boldsymbol{G}_{1} & 0 & \dots & 0 & 0 \\ 0 & \boldsymbol{G}_{2} & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & \boldsymbol{G}_{b-1} & 0 \\ 0 & 0 & \dots & 0 & \boldsymbol{G}_{b} \end{bmatrix}$$

There is a corresponding partition in $Z, Z = [Z_1 \ Z_2 \ \dots \ Z_b]$. As before each submatrix, G_i , is assumed to be the direct product of one, two or three component matrices. These matrices are indexed for each of the factors constituting the term in the linear model. For example, the term *site.genotype* has two factors and so the matrix G_i is comprised of two component matrices defining the variance structure for each factor in the term.

Models for the component matrices G_i include the standard model for which $G_i = \gamma_i I_{q_i}$ and direct product models for correlated random factors given by

$$oldsymbol{G}_i = oldsymbol{G}_{i1} \otimes oldsymbol{G}_{i2} \otimes oldsymbol{G}_{i3}$$

for three component factors. The vector u_i is therefore assumed to be the vector representation of a 3-way array. For two factors the vector u_i is simply the vec of a matrix with rows and columns indexed by the component factors in the term, where vec of a matrix is a function which stacks the columns of its matrix argument below each other.

A range of models are available for the components of both R and G. They include correlation (C) models (that is, where the diagonals are 1), or covariance

(V) models and are discussed in detail in Chapter 7. Some correlation models include

- autoregressive (order 1 or 2)
- moving average (order 1 or 2)
- $\mathsf{ARMA}(1,1)$
- uniform
- banded
- general correlation.

Some of the covariance models include

- diagonal (that is, independent with heterogeneous variances)
- antedependence
- unstructured
- factor analytic.

There is the facility within ASRemI to allow for a nonzero covariance between the subvectors of \boldsymbol{u} , for example in random regression models. In this setting the intercept and say the slope for each unit are assumed to be correlated and it is more natural to consider the the two component terms as a single term, which gives rise to a single G structure. This concept is discussed later.

2.2 Estimation

Estimation involves two processes that are closely linked. They are performed within the 'engine' of ASRemI. One process involves estimation of τ and prediction of u (although the latter may not always be of interest) for given θ , ϕ and γ . The other process involves estimation of these variance parameters. Note that in the following sections we have set $\theta = 1$ to simplify the presentation of results.

Estimation of the variance parameters

Estimation of the variance parameters is carried out using residual or restricted maximum likelihood (REML), developed by Patterson and Thompson (1971). An historical development of the theory can be found in Searle *et al.* (1992). Note firstly that

$$\boldsymbol{y} \sim N(\boldsymbol{X}\boldsymbol{\tau}, \ \boldsymbol{H}).$$
 (2.3)

where H = R + ZGZ'. REML does not use (2.3) for estimation of variance parameters, but rather uses a distribution free of τ , essentially based on error contrasts or *residuals*. The derivation given below is presented in Verbyla (1990).

We transform \boldsymbol{y} using a non-singular matrix $\boldsymbol{L} = [\boldsymbol{L}_1 \ \boldsymbol{L}_2]$ such that

$$L'_1 X = I_p, \quad L'_2 X = 0.$$

If $y_j = L'_j y, j = 1, 2,$

$$\begin{bmatrix} \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \end{bmatrix} \sim N\left(\begin{bmatrix} \boldsymbol{\tau} \\ \boldsymbol{0} \end{bmatrix}, \begin{bmatrix} \boldsymbol{L}_1' \boldsymbol{H} \boldsymbol{L}_1 & \boldsymbol{L}_1' \boldsymbol{H} \boldsymbol{L}_2 \\ \boldsymbol{L}_2' \boldsymbol{H} \boldsymbol{L}_1 & \boldsymbol{L}_2' \boldsymbol{H} \boldsymbol{L}_2 \end{bmatrix}\right).$$

The full distribution of L'y can be partitioned into a conditional distribution, namely $y_1|y_2$, for estimation of τ , and a marginal distribution based on y_2 for estimation of γ and ϕ ; the latter is the basis of the **residual likelihood**.

The estimate of τ is found by equating y_1 to its conditional expectation, and after some algebra we find,

$$\hat{\tau} = (X'H^{-1}X)^{-1}X'H^{-1}y$$

Estimation of $\kappa = [\gamma' \phi']'$ is based on the log residual likelihood,

$$\ell_{R} = -\frac{1}{2} (\log \det L'_{2} H^{-1} L_{2} + y'_{2} (L'_{2} H L_{2})^{-1} y_{2}) = -\frac{1}{2} (\log \det X' H^{-1} X + \log \det H + y' P y_{2})$$
(2.4)

where

$$P = H^{-1} - H^{-1}X(X'H^{-1}X)^{-1}X'H^{-1}$$

Note that $\mathbf{y}' \mathbf{P} \mathbf{y} = (\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\tau}})' \mathbf{H}^{-1} (\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\tau}})$. The log-likelihood (2.4) depends on \mathbf{X} and not on the particular non-unique transformation defined by \mathbf{L} .

The log residual likelihood (ignoring constants) can be written as

$$\ell_R = -\frac{1}{2} (\log \det \boldsymbol{C} + \log \det \boldsymbol{R} + \log \det \boldsymbol{G} + \boldsymbol{y'} \boldsymbol{P} \boldsymbol{y}).$$
(2.5)

We can also write

$$P = R^{-1} - R^{-1}WC^{-1}W'R^{-1}$$

with $W = [X \ Z]$. Letting $\kappa = (\gamma, \phi)$, the REML estimates of κ_i are found by calculating the score

$$U(\kappa_i) = \partial \ell_R / \partial \kappa_i = -\frac{1}{2} [\operatorname{tr} (\boldsymbol{P} \boldsymbol{H}_i) - \boldsymbol{y}' \boldsymbol{P} \boldsymbol{H}_i \boldsymbol{P} \boldsymbol{y}]$$
(2.6)

and equating to zero. Note that $H_i = \partial H / \partial \kappa_i$.

The elements of the observed information matrix are

$$-\frac{\partial^{2}\ell_{R}}{\partial\kappa_{i}\partial\kappa_{j}} = \frac{1}{2}\operatorname{tr}\left(\boldsymbol{P}\boldsymbol{H}_{ij}\right) - \frac{1}{2}\operatorname{tr}\left(\boldsymbol{P}\boldsymbol{H}_{i}\boldsymbol{P}\boldsymbol{H}_{j}\right) + \boldsymbol{y}'\boldsymbol{P}\boldsymbol{H}_{i}\boldsymbol{P}\boldsymbol{H}_{j}\boldsymbol{P}\boldsymbol{y} - \frac{1}{2}\boldsymbol{y}'\boldsymbol{P}\boldsymbol{H}_{ij}\boldsymbol{P}\boldsymbol{y} \qquad (2.7)$$

where $\boldsymbol{H}_{ij} = \partial^2 \boldsymbol{H} / \partial \kappa_i \partial \kappa_j$.

The elements of the expected information matrix are

$$E\left(-\frac{\partial^2 \ell_R}{\partial \kappa_i \partial \kappa_j}\right) = \frac{1}{2} \operatorname{tr}\left(\boldsymbol{P}\boldsymbol{H}_i \boldsymbol{P}\boldsymbol{H}_j\right).$$
(2.8)

Given an initial estimate $\kappa^{(0)}$, an update of κ , $\kappa^{(1)}$ using the Fisher-scoring (FS) algorithm is

$$\boldsymbol{\kappa}^{(1)} = \boldsymbol{\kappa}^{(0)} + \boldsymbol{I}(\boldsymbol{\kappa}^{(0)}, \boldsymbol{\kappa}^{(0)})^{-1} \boldsymbol{U}(\boldsymbol{\kappa}^{(0)})$$
(2.9)

where $U(\kappa^{(0)})$ is the score vector (2.6) and $I(\kappa^{(0)}, \kappa^{(0)})$ is the expected information matrix (2.8) of κ evaluated at $\kappa^{(0)}$.

For large models or large data sets, the evaluation of the trace terms in either (2.7) or (2.8) is either not feasible or is very computer intensive. To overcome this problem ASRemI uses the AI algorithm (Gilmour, Thompson and Cullis, 1995). The matrix denoted by \mathcal{I}_A is obtained by averaging (2.7) and (2.8) and approximating $\mathbf{y'PH}_{ij}\mathbf{Py}$ by its expectation, tr (\mathbf{PH}_{ij}) in those cases when $\mathbf{H}_{ij} \neq 0$. For variance components models (that is those linear with respect to variances in \mathbf{H}), the terms in \mathcal{I}_A are exact averages of those in (2.7) and (2.8). The basic idea is to use $\mathcal{I}_A(\kappa_i, \kappa_j)$ in place of the expected information matrix in (2.9) to update $\boldsymbol{\kappa}$.

The elements of \mathcal{I}_A are

$$\mathcal{I}_{\mathcal{A}}(\kappa_i,\kappa_j) = \frac{1}{2} \boldsymbol{y}' \boldsymbol{P} \boldsymbol{H}_i \boldsymbol{P} \boldsymbol{H}_j \boldsymbol{P} \boldsymbol{y}.$$
(2.10)

The \mathcal{I}_A matrix is the (scaled) residual sums of squares and products matrix of

$$oldsymbol{y} = [oldsymbol{y}_1, \dots, oldsymbol{y}_k]$$

where \boldsymbol{y}_i is the 'working' variate for $\boldsymbol{\kappa}_i$ and is given by

$$egin{array}{rcl} m{y}_i &=& m{H}_i m{P} m{y} \ &=& m{H}_i m{R}^{-1} m{ ilde{e}} \ &=& m{R}_i m{R}^{-1} m{ ilde{e}}, & \kappa_i \in m{\phi} \ &=& m{Z} m{G}_i m{G}^{-1} m{ ilde{u}}, & \kappa_i \in m{\gamma} \end{array}$$

where $\tilde{\boldsymbol{e}} = \boldsymbol{y} - \boldsymbol{X}\hat{\boldsymbol{\tau}} - \boldsymbol{Z}\tilde{\boldsymbol{u}}$, $\hat{\boldsymbol{\tau}}$ and $\tilde{\boldsymbol{u}}$ are solutions to (2.11). In this form the AI matrix is relatively straightforward to calculate.

The combination of the AI algorithm with sparse matrix methods, in which only non-zero values are stored, gives an efficient algorithm in terms of both computing time and workspace.

Estimation/prediction of the fixed and random effects

To estimate $\boldsymbol{\tau}$ and predict \boldsymbol{u} the objective function

$$\log f_{\boldsymbol{Y}}(\boldsymbol{y} \mid \boldsymbol{u} ; \boldsymbol{\tau}, \boldsymbol{R}) + \log f_{\boldsymbol{U}}(\boldsymbol{u} ; \boldsymbol{G})$$

is used. The is the log-joint distribution of (Y, u).

Differentiating with respect to τ and u leads to the mixed model equations (Robinson, 1991) which are given by

$$\begin{bmatrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{X}'\mathbf{R}^{-1}\mathbf{Z} \\ \mathbf{Z}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{Z}'\mathbf{R}^{-1}\mathbf{Z} + \mathbf{G}^{-1} \end{bmatrix} \begin{bmatrix} \hat{\boldsymbol{\tau}} \\ \tilde{\boldsymbol{u}} \end{bmatrix} = \begin{bmatrix} \mathbf{X}'\mathbf{R}^{-1}\boldsymbol{y} \\ \mathbf{Z}'\mathbf{R}^{-1}\boldsymbol{y} \end{bmatrix}.$$
 (2.11)

These can be written as

$$C\tilde{oldsymbol{eta}} = WR^{-1}y$$

where $\boldsymbol{C} = \boldsymbol{W}' \boldsymbol{R}^{-1} \boldsymbol{W} + \boldsymbol{G}^*, \ \boldsymbol{\beta} = [\boldsymbol{\tau}' \ \boldsymbol{u}']'$ and

$$oldsymbol{G}^* = \left[egin{array}{cc} oldsymbol{0} & oldsymbol{0} \\ oldsymbol{0} & oldsymbol{G}^{-1} \end{array}
ight].$$

The solution of (2.11) requires values for γ and ϕ . In practice we replace γ and ϕ by their REML estimates $\hat{\gamma}$ and $\hat{\phi}$.

Note that $\hat{\tau}$ is the best linear unbiased estimator (BLUE) of τ , while \tilde{u} is the best linear unbiased predictor (BLUP) of u for known γ and ϕ . We also note that

$$\tilde{\boldsymbol{\beta}} - \boldsymbol{\beta} = \begin{bmatrix} \hat{\boldsymbol{\tau}} - \boldsymbol{\tau} \\ \tilde{\boldsymbol{u}} - \boldsymbol{u} \end{bmatrix} \sim N\left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \ \boldsymbol{C}^{-1} \right).$$

2.3 What are BLUPs?

Consider a balanced one-way classification. For data records ordered r repeats within b treatments, the linear mixed model is $\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{u} + \boldsymbol{e}$ where $\boldsymbol{X} =$ $\mathbf{1}_b \otimes \mathbf{1}_r$ is the design matrix for $\boldsymbol{\tau}, \boldsymbol{Z} = \boldsymbol{I}_b \otimes \mathbf{1}_r$ is the design matrix for the btreatment effects u_i and \boldsymbol{e} is the error vector. In the following we assume, that the treatment effects are random. That is, $\boldsymbol{u} \sim N(\boldsymbol{A}\boldsymbol{\psi}, \sigma_b^2 \boldsymbol{I}_b)$, for some design matrix \boldsymbol{A} and parameter vector $\boldsymbol{\psi}$. It can be shown that

$$\tilde{\boldsymbol{u}} = \frac{b\sigma_b^2}{b\sigma_b^2 + \sigma^2} (\bar{\boldsymbol{y}} - \boldsymbol{1}\bar{\boldsymbol{y}}_{..}) + \frac{\sigma^2}{b\sigma_b^2 + \sigma^2} \boldsymbol{A}\boldsymbol{\psi}$$
(2.12)

where \bar{y} is the vector of treatment means, \bar{y} . is the grand mean. The differences of the treatment means and the grand mean are the estimates of treatment effects if treatment effects are fixed. The BLUP is therefore a weighted mean of the data based estimate and the 'prior' mean $A\psi$. If $\psi = 0$, the BLUP in (2.12) becomes

$$\tilde{\boldsymbol{u}} = \frac{b\sigma_b^2}{b\sigma_b^2 + \sigma^2} (\bar{\boldsymbol{y}} - \mathbf{1}\bar{\boldsymbol{y}}_{..})$$
(2.13)

and the BLUP is a so-called shrinkage estimate. As σ_b^2 becomes large relative to σ^2 , the BLUP tends to the fixed effect solution, while for small σ_b^2 relative to σ^2 the BLUP tends towards zero, the assumed initial mean. Thus (2.13) represents a weighted mean which involves the prior assumption that the u_i have zero mean.

Note also that the BLUPs in this simple case are constrained to sum to zero. This is essentially because the unit vector defining X can be found by summing the columns of the Z matrix. This linear dependence of the matrices translates to dependence of the BLUPs and hence constraints. This aspect occurs whenever the column space of X is contained in the column space of Z. The dependence is slightly more complex with correlated random effects.

2.4 Combining variance models

The combination of variance models within G structures and R structures and between G structures and R structures is a difficult and important concept. The underlying principle is that each \mathbf{R}_i and \mathbf{G}_i variance model can only have a single scaling variance parameter associated with it. If there is more than one scaling variance parameter for any \mathbf{R}_i or \mathbf{G}_i then this results in the variance model being overspecified, or *nonidentifiable*. Some variance models are presented in Table 2.1 to illustrate this principle.

While all 9 forms of model in Table 2.1 can be specified within ASRemI only models of forms 1 and 2 are recommended. Models 4-6 have too few variance parameters and are likely to cause serious estimation problems. For model 3, where the scale parameter θ has been fitted (univariate single site analysis), it becomes the scale for G. This parameterisation is bizarre and is not recommended. Models 7-9 have too many variance parameters and ASRemI will arbitrarily fix one of the variance parameters leading to possible confusion for the user. If you fix the variance parameter to a particular value then it does not count for the purposes of applying the principle that there be only one scaling variance parameter. That is, models 7-9 can be made identifiable by fixing all but one of the nonidentifiable scaling parameters in each of G and R to a particular value.

model	G_1	G_2	R_1	R_2	θ	comment
1. 2. 3. 4. 5. 6. 7. 8. 9.	V V C * C C V V *	C C * C V C *	C V C C V * V V	C C C C C C * C V	y n y n y n * y	valid valid valid, but not recommended inappropriate as R is a correlation model inappropriate, same scale for R and G inappropriate, no scaling parameter for G nonidentifiable, 2 scaling parameters for G nonidentifiable, scale for R and overall scale nonidentifiable, 2 scaling parameters for R

Table 2.1 Combination of models for G and R structures

* indicates the entry is not relevant in this case

Note that G_1 and G_2 are interchangeable in this table, as are R_1 and R_2

2.5 Inference

Tests of hypotheses: variance parameters

Inference concerning variance parameters of a linear mixed effects model usually relies on approximate distributions for the (RE)ML estimates derived from asymptotic results.

It can be shown that the approximate variance matrix for the REML estimates is given by the inverse of the expected information matrix (Cox and Hinkley, 1974, section 4.8). Since this matrix is not available in ASRemI we replace the expected information matrix by the AI matrix. Furthermore the REML estimates are consistent and asymptotically normal, though in small samples this approximation appears to be unreliable (see later).

A general method for comparing the fit of nested models fitted by REML is the REML likelihood ratio test, or REMLRT. The REMLRT is only valid if the fixed effects are the same for both models. In ASRemI this requires not only the same fixed effects model, but also the same parameterisation.

If ℓ_{R2} is the REML log-likelihood of the more general model and ℓ_{R1} is the REML log-likelihood of the restricted model (that is, the REML log-likelihood under the null hypothesis), then the REMLRT is given by

$$D = 2\log(\ell_{R2}/\ell_{R1}) = 2\left[\log(\ell_{R2}) - \log(\ell_{R1})\right]$$
(2.14)

which is strictly positive. If r_i is the number of parameters estimated in model i, then the asymptotic distribution of the REMLRT, under the restricted model is $\chi^2_{r_2-r_1}$.

The REMLRT is implicitly two-sided, and must be adjusted when the test involves an hypothesis with the parameter on the boundary of the parameter space. In fact, theoretically it can be shown that for a single variance component, say, the asymptotic distribution of the REMLRT is a mixture of χ^2 variates, where the mixing probabilities are 0.5, one with 0 degrees of freedom (spike at 0) and the other with 1 degree of freedom. The distribution of the REMLRT for the test that k variance components are zero, or tests involved in random regressions, which involve both variance and covariance components, involves a mixture of χ^2 variates from 0 to k degrees of freedom. See Self and Liang (1987) for details.

Tests concerning variance components in generally balanced designs, such as the balanced one-way classification, can be derived from the usual analysis of variance. It can be shown that the REMLRT for a variance component being zero is
a monotone function of the F-statistic for the associated term.

To compare two (or more) non-nested models we can evaluate the Akaike Information Criteria (AIC) or the Bayesian Information Criteria (BIC) for each model. These are given by

$$AIC = -2\ell_{Ri} + 2t_i$$

$$BIC = -2\ell_{Ri} + t_i \log \nu$$
(2.15)

where t_i is the number of variance parameters in model *i* and $\nu = n - p$ is the residual degrees of freedom. AIC and BIC are calculated for each model and the model with the smallest value is chosen as the preferred model.

Diagnostics

In this section we will briefly review some of the diagnostics that have been implemented in ASReml for examining the adequacy of the assumed variance matrix for either R or G structures, or for examining the distributional assumptions regarding e or u. Firstly we note that the BLUP of the residual vector is given by

$$\tilde{\boldsymbol{e}} = \boldsymbol{y} - \boldsymbol{W}\tilde{\boldsymbol{\beta}}$$
$$= \boldsymbol{R}\boldsymbol{P}\boldsymbol{y}$$
(2.16)

It follows that

$$E(\tilde{\boldsymbol{e}}) = \boldsymbol{0}$$

var $(\tilde{\boldsymbol{e}}) = \boldsymbol{R} - \boldsymbol{W}\boldsymbol{C}^{-1}\boldsymbol{W}'$

The matrix $WC^{-1}W'$ is the so-called 'extended hat' matrix. It is the linear mixed effects model analogue of $X(X'X)^{-1}X'$ for ordinary linear models. The diagonal elements are returned in the .yht file by ASReml.

The variogram has been suggested as a useful diagnostic for assisting with the identification of appropriate variance models for spatial data (Cressie, 1991). Gilmour *et al.* (1997) demonstrate its usefulness for the identification of the sources of variation in the analysis of field experiments. If the elements of the data vector (and hence the residual vector) are indexed by a vector of spatial coordinates, $s_i, i = 1, \ldots, n$, then the ordinates of the sample variogram are given by

$$v_{ij} = \frac{1}{2} \left[\tilde{e}_i(\boldsymbol{s}_i) - \tilde{e}_j(\boldsymbol{s}_j) \right], \quad i, j = 1, \dots, n; \quad i \neq j$$

The sample variogram is the triple $(l_{ij1}, l_{ij2}, v_{ij})$ where $l_{ij1} = |s_{i1} - s_{j1}|$ and $l_{ij2} = |s_{i2} - s_{j2}|$ are the absolute displacements. If the data arise from a regular

array there will be many v_{ij} with the same absolute displacements, in which case ASRemI displays the vector $(l_{ij1}, l_{ij2}, \bar{v}_{ij})$ as a perspective plot and returns it in the .res file.

Tests of hypotheses: fixed effects

Testing the significance of fixed effects under REML does introduce a difficulty. The standard approach is to use likelihood ratio methods. Unfortunately, if the fixed effects part of the model is changed, the residual likelihood changes. Thus the maximized residual likelihood under the null and alternative hypotheses are not comparable. Alternative methods are required.

An obvious approach is to use the Wald statistic. To test the hypothesis H_0 : $L\tau = l$ for given $L, r \times p$, and $l, r \times 1$, the Wald statistic is given by

$$W = (L\hat{\tau} - l)' \{ L(X'H^{-1}X)^{-1}L' \}^{-1} (L\hat{\tau} - l)$$
(2.17)

and asymptotically, this statistic has a chi-square distribution on r degrees of freedom. These are marginal tests, so that there is an adjustment for all other terms in the fixed part of the model.

It is also possible to carry out a sequential test so that higher order terms, for example interactions, are adjusted for lower order terms in the model. The latter tests conform more to the analysis of variance philosophy. The test statistic implicit in this sequential approach is the change in residual sum of squares between the model not containing the term and that containing the term.

ASRemI produces an F-statistic by dividing the Wald test by r. In this form it is possible to perform an approximate F test. The numerator degrees of freedom for this test is r. The denominator degrees of freedom is generally not known exactly. It is possible, though anti-conservative for most situations to use the residual degrees of freedom for the denominator. For balanced designs the F statistics produced by ASRemI are numerically identical to the F-tests obtained from the standard analysis of variance.

A guided tour

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Nebraska Intrastate Nursery (NIN) field experiment

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The ASReml command file

The title line Reading the data The data file line Specifying the terms in the mixed model Tabulation Prediction Variance structures

Running the job

Description of output files

The .asr file The .sln file The .yht file

Tabulation, predicted values and functions of the variance components

3.1 Introduction

This chapter presents a guided tour of ASReml, from data file preparation and basic aspects of the ASReml command file, to running an ASReml job and interpreting the output files. You are encouraged to read this chapter before moving to the later chapters;

- a real data example is used in this chapter for demonstration, see below,
- the same data are also used in later chapters,
- links to the formal discussion of topics are clearly signposted by margin notes.

Note that some aspects of ASReml, in particular, pedigree files (see Chapter 9) and multivariate analysis (see Chapter 8) are only covered in later chapters.

ASRemI is usually run in batch mode from a command prompt. You will need a file editor to create the command file and to view the various output files. On unix systems, vi and emacs are commonly used. Under Windows, there are several program editors available such as Brief and Winedt. You can use NOTEPAD or WORDPAD. ASRemI has a built in editor which is accessed through menu mode (page).

3.2 Nebraska Intrastate Nursery (NIN) field experiment

The yield data from an advanced Nebraska Intrastate Nursery (NIN) breeding trial conducted at Alliance in 1988/89 will be used for demonstration, see Stroup *et al.* (1994) for details. Four replicates of 19 released cultivars, 35 experimental wheat lines and 2 additional triticale lines were laid out in a 22 row by 11 column rectangular array of plots; the varieties were allocated to the plots using a randomised complete block (RCB) design. In field trials, complete replicates are typically allocated to consecutive groups of *whole* columns, but rather, overlapped columns. Table 3.1 gives the allocation of varieties to plots in field plan order with replicates 1 and 3 in *ITALICS* and replicates 2 and 4 in **BOLD**.

					column					
1	2	3	4	Q	6	7	8	9	10	11
	NE83407	BUCKSKIN	NE87612	VONA	NE87512	NE87408	CODY	BUCKSKIN	NE87612	KS831374
	CENTURA	NE86527	NE87613	NE87463	NE83407	NE83407	NE87612	NE83406	BUCKSKIN	NE86482
ı	SCOUT66	NE86582	NE87615	NE86507	NE87403	NORKAN	NE87457	NE87409	NE85556	NE85623
	COLT	NE86606	NE87619	BUCKSKIN	NE87457	REDLAND	NE84557	NE87499	BRULE	NE86527
	NE83498	NE86607	NE87627	ROUGHRIDER	NE83406	KS831374	NE83T12	CENTURA	NE86507	NE87451
ı	NE84557	ROUGHRIDER		NE86527	COLT	COLT	NE86507	NE83432	ROUGHRIDER	NE87409
ı	NE83432	VONA	CENTURA	SCOUT66	NE87522	NE86527	TAM200	NE87512	VONA	GAGE
	NE85556	SIOUXLAND	NE85623	NE86509	NORKAN	VONA	NE87613	ROUGHRIDER	NE83404	NE83407
1	NE85623	GAGE	CODY	NE86606	NE87615	TAM107	ARAPAHOE	NE83498	CODY	NE87615
1	CENTURAK78	NE83T12	NE86582	NE84557	NE85556	CENTURAK78	SCOUT66		NE87463	ARAPAHOE
	NORKAN	NE86T666	NE87408	KS831374	TAM200	NE87627	NE87403	NE86T666	NE86582	CHEYENNE
	KS831374	NE87403	NE87451	GAGE	LANCOTA	NE86T666	NE85623	NE87403	NE87499	REDLAND
ı	TAM200	NE87408	NE83432	NE87619	NE86503	NE87615	NE86509	NE87512	NORKAN	NE83432
	NE86482	NE87409	CENTURAK78	NE87499	NE86482	NE86501	NE85556	NE87446	SCOUT66	NE87619
	HOMESTEAD	NE87446	NE83T12	CHEYENNE	BRULE	NE87522	HOMESTEAD	CENTURA	NE87513	NE83498
LANCER	LANCOTA	NE87451	NE87409	NE86607	NE87612	CHEYENNE	NE83404	NE86503	NE83T12	NE87613
BRULE	NE86501	NE87457	NE87513	NE83498	NE87613	SIOUXLAND	NE86503	NE87408	CENTURAK78	NE86501
REDLAND	NE86503	NE87463	NE87627	NE83404	NE86T666	NE87451	NE86582	COLT	NE87627	TAM200
CODY	NE86507	NE87499	ARAPAHOE	NE87446	I	GAGE	NE87619	LANCER	NE86606	NE87522
ARAPAHOE	NE86509	NE87512	LANCER	SIOUXLAND	NE86607	LANCER	NE87463	NE83406	NE87457	NE84557
NE83404	TAM107	NE87513	TAM107	HOMESTEAD	LANCOTA	NE87446	NE86606	NE86607	NE86509	TAM107
NE83406	CHEYENNE	NE87522	REDLAND	NE86501	NE87513	NE86482	BRULE	SIOUXLAND	LANCOTA	HOMESTEAD

3.1: Trial layout and allocation of varieties to plots in the NIN field trial

3.3 The ASReml data file

for details

See Chapter 4 The standard format of an ASRemI data file is to have the data arranged in space, TAB or comma separated columns/fields with a line for each sampling unit. The columns contain covariates, factors, response variates (traits) and weight variables in any convenient order. This is the first 30 lines of the file nin89.asd containing the data for the NIN variety trial. The data are in field order (rows within columns) and an optional row of field labels (first row) has been included. In this case there are 11 space separated data fields (variety...column) and the complete file has 224 data rows, one for each variety in each replicate.

optional field labels data line sampling unit 1 data line sampling unit 2

.

Note that in Chapter 7 these data are analysed using spatial methods of analysis, see model **3a** in Section 7.3. For spatial analysis using a separable error structure (see Chapter 2) the data file must first be augmented to specify the complete 22

```
variety id pid raw repl nloc yield lat long row column
                                                              optional field labels
LANCER 1 NA NA 1 4 NA 4.3 1.2 1 1
                                                              file
                                                                   augmented
LANCER 1 NA NA 1 4 NA 4.3 2.4 2 1
                                                              missing values for first
LANCER 1 NA NA 1 4 NA 4.3 3.6 3 1
                                                              15 plots and 3 buffer
LANCER 1 NA NA 1 4 NA 4.3 4.8 4 1
                                                              plots and variety coded
LANCER 1 NA NA 1 4 NA 4.3 6 5 1
                                                              LANCER to complete
LANCER 1 NA NA 1 4 NA 4.3 7.2 6 1
                                                              22 \times 11 array
LANCER 1 NA NA 1 4 NA 4.3 8.4 7 1
LANCER 1 NA NA 1 4 NA 4.3 9.6 8 1
LANCER 1 NA NA 1 4 NA 4.3 10.8 9 1
LANCER 1 NA NA 1 4 NA 4.3 12 10 1
LANCER 1 NA NA 1 4 NA 4.3 13.2 11 1
LANCER 1 NA NA 1 4 NA 4.3 14.4 12 1
LANCER 1 NA NA 1 4 NA 4.3 15.6 13 1
LANCER 1 NA NA 1 4 NA 4.3 16.8 14 1
LANCER 1 NA NA 1 4 NA 4.3 18 15 1
LANCER 1 NA NA 2 4 NA 17.2 7.2 6 4
                                                              buffer plots
LANCER 1 NA NA 3 4 NA 25.8 22.8 19 6
                                                              between reps
LANCER 1 NA NA 4 4 NA 38.7 12.0 10 9
LANCER 1 1101 585 1 4 29.25 4.3 19.2 16 1
                                                              original data
BRULE 2 1102 631 1 4 31.55 4.3 20.4 17 1
REDLAND 3 1103 701 1 4 35.05 4.3 21.6 18 1
CODY 4 1104 602 1 4 30.1 4.3 22.8 19 1
```

row \times 11 column array of plots. These are the first 20 lines of the augmented data file nin89aug.asd with 242 data rows.

Note that

- the pid, raw, repl and yield data for the missing plots have all been made NA (one of the three missing value indicators in ASReml, see Section 4.2),
- variety is coded LANCER for all missing plots; one of the variety names must be used but the particular choice is arbitrary.

3.4 The ASReml command file

See Chapters 5, By convention an ASReml command file has a .as extension. The file defines 6 and 7 for de-

- tails
- a title line to describe the job,
- labels for the data fields in the data file and the name of the data file,
- the linear mixed model and the variance model(s) if required,
- output options including directives for tabulation and prediction. •

by

Below is the ASRemI command file for an RCB analysis of the NIN field trial data highlighting the main sections. Notice the order of the main sections.



The title line

The first non-blank line in an ASRemI command file is taken as the title for the job and is used to identify the analysis for future reference.

NIN	Alliance	trial	1989	
var	iety !A			
id				
:				

Reading the data

The data fields are defined prior to the data file name to tell ASRemI how many fields to expect in the data file and what the fields are. Field definitions must be given for all fields in the data file and in the order in which they appear in the data file. **Data field defini**tions must be indented. In this case there are 11 data fields in the data file nin89.asd, see Section 3.3. They are specified in the command file in the order they appear in the data file, that is, variety ... column. The !A after variety tells ASRemI that the first field is al-

NIN Alliance trial 1989
variety !A
id
pid
raw
repl 4
nloc
yield
lat
long
row 22
column 11
nin89.asd !skip 1
:
•

phanumeric and the 4 after repl tells ASReml that the field called repl (the fifth field read) is a numeric factor with 4 levels. Similarly for row and column. The other data fields include variates (yield) and various other variables.

The data file line

The data file name is specified immediately after the last data field definition. Data file qualifiers that relate to data input and output are also placed on this line if they are required.

- See Section 5.7 In this example, !skip 1 tells ASRem! to read the data from nin89.asd but to ignore the first line in this file, the line containing the field labels.
- See Section 5.8 The data file line can also contain qualifiers that control other aspects of the analysis. These qualifiers are presented in Section 5.8.

```
NIN Alliance trial 1989
variety !A
id
pid
:
row 22
column 11
nin89.asd !skip 1
yield ~ mu variety !r repl
tabulate yield ~ variety
predict variety
0 0 1
repl 1
repl 0 IDV 0.1
```

Specifying the terms in the mixed model

See Chapter 6 The linear mixed model is specified as a list of model terms and qualifiers. All elements must be space separated. ASRemI accommodates a wide range of analyses. See Section 2.1 for a brief discussion and general algebraic formulation of the linear mixed model. The model specified here for the NIN data is a simple random effects RCB model including fixed variety effects and random replicate effects. The reserved word mu fits a constant term (inter-

```
NIN Alliance trial 1989
variety !A

column 11
nin89.asd !skip 1
yield ~ mu variety !r repl
tabulate yield ~ variety
predict variety
0 0 1
repl 1
repl 0 IDV 0.1
```

cept), variety fits a fixed variety effect and repl fits a random replicate effect. The !r qualifier tells ASReml to fit the terms that appear after this qualifier as random effects.

Tabulation

See Chapter 10 Tabulate statements provide a simple way of exploring the structure of a data file. They appear after the model line and before any variance structure definition lines. In this case the 56 simple variety means for yield are formed and written to a .tab output file. See Chapter 10 for a discussion of tabulation.

```
NIN Alliance trial 1989
variety !A
column 11
nin89.asd !skip 1
yield ~ mu variety !r repl
tabulate yield ~ variety
predict variety
0 0 1
repl 1
repl 0 IDV 0.1
```

Prediction

See Chapter 10 Prediction statements also appear after the model statement and before any variance structure lines. In this case the 56 variety means for yield would be formed and returned in the .pvs output file. See Chapter 10 for a detailed discussion of prediction in ASReml.

NIN Alliance trial 1989 variety !A
:
column 11
nin89.asd !skip 1
yield \sim mu variety !r repl
tabulate yield \sim variety
predict variety
001
repl 1
repl 0 IDV 0.1

Variance structures

See Chapter 7 An extensive range of variance structures can be fitted in ASReml. See Chapter 7 for a lengthy discussion of variance modelling in ASReml. In this case independent and identically distributed random replicate effects are specified using the identifier IDV in a *G structure*. G structures are described in Section 2.1 and the list of available variance structures/models is presented in Table 7.3. Note that IDV is the default variance structure for

```
NIN Alliance trial 1989
variety !A
:
column 11
nin89.asd !skip 1
yield ~ mu variety !r repl
tabulate yield ~ variety
predict variety
0 0 1
repl 1
repl 0 IDV 0.1
```

random effects so that the last 3 lines presented here are purely for example: the same analysis would be performed if these lines were omitted.

3.5 Running the job

An ASReml job is often run from a command line. The basic command to run See Chapter 12 an ASReml job is normally

asreml *basename*[.as]

where *basename*[.as] is the name of the command file. For example, the command to run nin89.as is

asreml nin89.as

However, if the path to program asreml.exe is not specified in your system's PATH environment variable, a *path* to this program must also be given. In this case the command to run the ASReml job in a $\mathsf{PC}/\mathsf{Windows}$ environment is

```
[path] asreml basename[.as]
```

tension

where *path* might be c:\asreml\ pointing to the location of the ASReml program. Make a habit of ASReml is always run using an ASCII text command file. In this guide we assume giving command the command file has a filename extension .as. ASReml also recognises the files the .as ex- filename extension .asc as an ASRemI command file. When these are used, the extension (.as or .asc) may be omitted from *basename*.as in the command line if there is no file in the same sub-directory with the name basename. There are options and arguments that can be supplied on the command line to modify a job at run time. These are described in Chapter 12.

3.6 **Description of output files**

A series of output files are produced with each ASReml run. Running the example as above, the primary output is written to **nin89.asr**. This file contains a summary of the data, the iteration sequence, estimates of the variance parameters, an analysis of variance (ANOVA) table and estimates of the fixed effects. The estimates of all the fixed and random effects are written to nin89.sln. The residuals, predicted values of the observations and the diagonal elements of the hat matrix (see Chapter 2) are returned in nin89.yht, see Section 13.3. Other files include the .res, .asl, .asp, .pin, .pvc, .pvs, .tab, .vvp and .vrb files, see Section 13.4.

The .asr file

Below is nin89.asr with pointers to the main sections. The title line gives the version of ASReml used (in square brackets) and the title of the job. The second

line gives the date and time that the job was run. The following output presents a data summary, the iteration sequence, the estimated variance parameters, an ANOVA and estimates of the fixed effects. The second to last line notifies the user of possible outliers as recorded in the **.res** file and the final line gives the date and time that the job was completed and a statement about convergence. The general announcements box (outlined in asterisks) at the top of the file notifies the user of current release features.

title line	ASReml 1.0 [31 Aug	7 2002] ni	in all	iance t	rial					
date and time	13 Sep 2002 12:55:1	7.777 8.	.00 МЪ	vte Wi	ndows	nin89				
release features	* ASRem1 2002 *****	**********	*****	******	******	*******	***			
	* Contact asreml@vs	sn-intl con	for	licensi	ng and	support	*			
	* Use !{ and !} when fitting covariance across terms *									

	OUALTETERS: ISKTP 1						u .			
data summary	Reading nin89 asd	- FRFE FORM	AT ski	nning	1 line	i c				
data Summary	Folder: C:\asr\ex\r	anov	II DRI	PPING	1 1110					
	Inivariate analysis	anex a of wield								
	Univariate analysis Using 224 roce	ords of	224	road						
	Model term St	ize Type	COI	Minim	יוו 🕅	loan	Mavimum	#zero	#mic.	-
	1 variety	56 Factor	1	1	28 5	000	56	0	"IIIIOC	n n
	2 id	00 140001	2	1 000	20.0	50	56 00	0		, n
	2 ru 3 nid		2	1101	20	20	4156	0		, n
	4 ray		4	21 00	51	0.5	840 0	0		Ś
	5 repl	4 Factor	5	1	2 5	000	4	0	Č	Ś
	6 nloc	1 1 40001	6	4 000	4	000	4 000	0		Ś
	7 vield	1 Variate	ں ح	1 050	25	53	42 00	0	Č	Ś
	8 lat	i variav	 8	4 300	27	22	47 30	0	Č	Ś
	9 long		9	1,200	14	. 08	26.40	0	(5
	10 row	22 Factor	10	1	11 7	321	22	0	(n n
	11 column	11 Factor	11	1	6.3	304	11	0	(5
	12 mii	1 Constar	nt Ter					, in the second s		·
	Forming 61 equations: 57 dense									
	Initial updates will be shrunk by factor 0.316									
	NOTICE: 1 (more	e) singular	rities							
iteration	1 LogL=-454.807	S2= 50	0.329	·	168 df	0.1000	1.000)		
sequence	2 LogL=-454.663	S2= 50	0.120		168 df	0.1173	1.000)		
	3 LogL=-454.532	S2= 49	9.868		168 df	0.1463	1.000)		
	4 LogL=-454.472	S2= 49	9.637		168 df	0.1866	1.000)		
	5 LogL=-454.469	S2= 49	9.585		168 df	0.1986	1.000)		
	6 LogL=-454.469	S2= 49	9.582		168 df	0.1993	1.000)		
	Final parameter val	lues			0.1	9932	1.0000			
estimated	Source	Model	terms	Ga	mma	Compone	nt Comp/	SE 7	6 C	
variance	repl	4	4	0.199	323	9.882	91 1.	12 () P	
parameters	Variance	224	168	1.00	000	49.58	24 9.	08 (P	

ANOVA	Analysis of Varia	nce DF	F-incr		
	1 variety	55	0.88		
	NOTICE: ASREML ca	nnot yet determi	ne the correct den	ominator DF	s for
	these F s	tatistics. They	will not exceed t	he Residual	DF
	which app	lies only if all	components are KN	IOWN.	
estimated effects		Estimate	Standard Error	T-value	T-prev
	1 variety				
	BRULE	-2.48750	4.97908	-0.50	
	REDLAND	1.93750	4.97908	0.39	0.89
	CODY	-7.35000	4.97908	-1.48	-1.87
	ARAPAHOE	0.875000	4.97908	0.18	1.65
	NE83404	-1.17500	4.97908	-0.24	-0.41
	: NE87619	2.70000	4.97908	0.54	1.12
	NE87627	-5.33750	4.97908	-1.07	-1.61
	12 mu				
		57 28.5625	3.85568	7.41	
	5 repl	4 ef	fects fitted		
outlier info	1 possible outli	ers: see .res fi	le		
completion info	Finished: 13 Sep	2002 12:55:22.13	3 LogL Converged	L	

The .sln file

The following is an extract from nin89.sln containing the estimated variety effects, intercept and random replicate effects in this order (column 3) with standard errors (column 4). Note that the variety effects are returned in the order of their first appearance in the data file, see replicate 1 in Table 3.1. Note also that LANCER did not appear in the list in the .asr file because it was aliased with mu (see 6.9) but it does appear here.

variety	LANCER	0.000	0.000
variety	BRULE	-2.487	4.979
variety	REDLAND	1.938	4.979
variety	CODY	-7.350	4.979
variety	ARAPAHOE	0.8750	4.979
variety	NE83404	-1.175	4.979
variety	NE83406	-4.287	4.979
variety	NE83407	-5.875	4.979

variety	CENTURA		-6.912	4.979
variety	SCOUT66		-1.037	4.979
variety	COLT		-1.562	4.979
variety	NE83498		1.563	4.979
variety	NE84557		-8.037	4.979
variety	NE83432		-8.837	4.979
variety	NE87615		-2.875	4.979
variety	NE87619		2.700	4.979
variety	NE87627		-5.337	4.979
mu		1	28.56	3.856
repl		1	1.880	1.755
repl		2	2.843	1.755
repl		3	-0.8713	1.755
repl		4	-3.852	1.755

The .yht file

The following is an extract from nin89.yht containing the predicted values of the observations (column 2), the residuals (column 3) and the diagonal elements of the hat matrix. This final column can be used in tests involving the residuals, see Section 2.5 under Diagnostics.

Record	Yhat	Residual	Hat
1	30.442	-1.192	13.01
2	27.955	3.595	13.01
3	32.380	2.670	13.01
4	23.092	7.008	13.01
5	31.317	1.733	13.01
6	29.267	0.9829	13.01
7	26.155	9.045	13.01
8	24.567	-5.167	13.01
9	23.530	0.8204	13.01
:			
222	16.673	9.877	13.01
223	24.548	1.052	13.01
224	23.786	3.114	13.01

3.7 Tabulation, predicted values and functions of the variance components

It may take several runs of ASRemI to determine an appropriate model for the data, that is, the fixed and random effects that are important. During this process you may wish to explore the data by simple tabulation. Having identified an appropriate model, you may then wish to form predicted values or functions of the variance components. The facilities available in ASRemI to determine predicted values and functions of the variance components are described in Chapters 10 and 11 respectively. Our example only includes tabulation and prediction.

The statement

```
tabulate yield \sim variety
```

in nin89.as results in nin89.tab as follows:

nin alliance trial

13 Sep 2002 12:35:40

	variety	
	LANCER	28.56
	BRULE	26.07
	REDLAND	30.50
	CODY	21.21
	ARAPAHOE	29.44
	NE83404	27.39
	NE83406	24.28
	NE83407	22.69
	CENTURA	21.65
	SCOUT66	27.52
	COLT	27.00
÷		
	NE87522	25.00
	NE87612	21.80
	NE87613	29.40
	NE87615	25.69
	NE87619	31.26
	NE87627	23.23

Simple tabulation of yield

The

predict variety

statement after the model statement in nin89.as results in the nin89.pvs file displayed below (some output omitted) containing the 56 predicted variety means, also in the order in which they first appear in the data file (column 2), together with standard errors (column 3). An average standard error of difference among the predicted variety means is displayed immediately after the list of predicted values. As in the .asr file, date, time and trial information are given the title line. The Ecode for each prediction (column 4) is usually E indicating the prediction is of an estimable function. Predictions of non-estimable functions are usually not printed, see Chapter 10.

title line	nin alliance tri	al			13 Sep 2002 12:35:40 nin893			
	Ecode is E for	Ecode is E for Estimable, * for Not Estimable						
	 Predicted valu	es of yield	1					
	repl	is ignored in	n the prediction	(except where	e specifically included			
	variety	Predict	ed_Value Standard	d_Error Ecode				
predicted variety effects	LANCER		28.5625	3.8557 E				
	BRULE		26.0750	3.8557 E				
	REDLAND		30.5000	3.8557 E				
	CODY		21.2125	3.8557 E				
	ARAPAHOE		29.4375	3.8557 E				
	NE83404		27.3875	3.8557 E				
	NE83406		24.2750	3.8557 E				
	NE83407		22.6875	3.8557 E				
	CENTURA		21.6500	3.8557 E				
	SCOUT66		27.5250	3.8557 E				
	COLT		27.0000	3.8557 E				
	NE87613		29.4000	3.8557 E				
	NE87615		25.6875	3.8557 E				
	NE87619		31.2625	3.8557 E				
	NE87627		23.2250	3.8557 E				
	SED: Overall S	Standard Error	of Difference	4.979				

Data file preparation

Introduction

The data file

Free format data files Binary format data files

4.1 Introduction

The first step in an ASReml analysis is to prepare the data file. Data file preparation is described in this chapter using the NIN example of Chapter 3 for demonstration. The first 25 lines of the data file are as follows:

```
variety id pid raw repl nloc yield lat long row column
BRULE 2 1102 631 1 4 31.55 4.3 20.4 17 1
REDLAND 3 1103 701 1 4 35.05 4.3 21.6 18 1
CODY 4 1104 602 1 4 30.1 4.3 22.8 19 1
ARAPAHOE 5 1105 661 1 4 33.05 4.3 24 20 1
NE83404 6 1106 605 1 4 30.25 4.3 25.2 21 1
NE83406 7 1107 704 1 4 35.2 4.3 26.4 22 1
NE83407 8 1108 388 1 4 19.4 8.6 1.2 1 2
CENTURA 9 1109 487 1 4 24.35 8.6 2.4 2 2
SCOUT66 10 1110 511 1 4 25.55 8.6 3.6 3 2
COLT 11 1111 502 1 4 25.1 8.6 4.8 4 2
NE83498 12 1112 492 1 4 24.6 8.6 6 5 2
NE84557 13 1113 509 1 4 25.45 8.6 7.2 6 2
NE83432 14 1114 268 1 4 13.4 8.6 8.4 7 2
NE85556 15 1115 633 1 4 31.65 8.6 9.6 8 2
NE85623 16 1116 513 1 4 25.65 8.6 10.8 9 2
CENTURK78 17 1117 632 1 4 31.6 8.6 12 10 2
NORKAN 18 1118 446 1 4 22.3 8.6 13.2 11 2
KS831374 19 1119 684 1 4 34.2 8.6 14.4 12 2
TAM200 20 1120 422 1 4 21.1 8.6 15.6 13 2
NE86482 21 1121 560 1 4 28 8.6 16.8 14 2
HOMESTEAD 22 1122 566 1 4 28.3 8.6 18 15 2
LANCOTA 23 1123 514 1 4 25.7 8.6 19.2 16 2
NE86501 24 1124 635 1 4 31.75 8.6 20.4 17 2
NE86503 25 1125 840 1 4 42 8.6 21.6 18 2
```

4.2 The data file

The standard format of an ASRemI data file is to have the data arranged in columns/fields with a single line for each sampling unit. The columns contain variates and covariates (numeric), factors (alphanumeric), traits (response variables) and weight variables in any order that is convenient to the user. The data file may be free format, fixed format or a binary file.

Free format data files

The data are read free format (SPACE, comma or TAB separated) unless the file name has extension .bin for real binary, or .dbl for double precision binary (see

below). Important points to note are as follows:

- blank lines are ignored,
- column headings, field labels or comments may be present at the top of the file provided that the !skip qualifier (Table 5.2) is used to skip over them,
- NA,* and . are accepted as coding for *missing values* in free format data files;
 - missing values can also be coded with a unique value (for example, 0 or -9) and then using the !M or !D qualifiers to declare them as missing values (see Table 5.1),
- comma delimited files whose file name ends in .csv or for which the !CSV qualifier is set recognise empty fields as missing values,
 - a line beginning with a comma implies a preceding missing value,
 - consecutive commas imply a missing value,
 - a line ending with a comma implies a trailing missing value,
 - if the filename does not end in .csv or the !CSV qualifier is not set, commas are treated as white space,
- characters following # on a line are ignored so this character may not be used in alphanumeric fields,
- blank spaces, tabs and commas must not be used (embedded) in alphanumeric fields unless the label is enclosed in quotes, for example, the name Willow Creek would need to be appear in the data file as 'Willow Creek' to avoid error,
- the \$ symbol must not be used in the data file,
- alphanumeric fields are truncated to 20 characters in length,
- extra data fields on a line are ignored,
- if there are fewer data items on a line than ASRemI expects the remainder are taken from the following line(s) except in .csv files were they are taken as missing. If you end up with half the number of records you expected, this is probably the reason,
- all lines beginning with ! followed by a blank are copied to the .asr file as comments for the output; their contents are ignored,
- a data file line may not exceed 418 characters; if the data fields will not fit in 418 characters, put some on the next line.

Fixed format data files

The format must be supplied with the **!FORMAT** qualifier which is described in (Table 5.5). However, if all fields are present and are separated, the file can be read free format.

Binary format data files

Conventions for binary files are as follows:

- binary files are read as unformatted Fortran binary in single precision if the filename has a .bin or .BIN extension,
- fortran binary data files are read in double precision if the filename has a .dbl or .DBL extension,
- ASReml recognises the value -1e37 as a missing value in binary files,
- fortran binary in the above means all real (.bin) or all double precision (.dbl) variables; mixed types, that is, integer and alphabetic binary representation of variables is not allowed in binary files,
- binary files can only be used in conjunction with a pedigree file if the pedigree fields are coded in the binary file so that they correspond with the pedigree file (this can be done using the **!SAVE** option in ASRemI to form the binary file, see Table 5.5), or the identifiers are whole numbers less than 9,999,999 and the **!RECODE** qualifier is specified (see Table 5.5).

5 Command file: Reading the data

Introduction

Important rules

Title line

Specifying and reading the data

Data field definition syntax

Transforming the data

Transformation syntax Other rules and examples Special note on covariates Other examples

Data file line

 $\mathsf{Data}\ \mathsf{line}\ \mathsf{syntax}$

Data file qualifiers

Job control qualifiers

5.1 Introduction

In the code box to the right is the ASReml command file nin89.as for the Nebraska Intrastate Nursery (NIN) field experiment introduced Chapter 3. The lines that are highlighted in bold/blue type relate to reading in the data. In this chapter we use this example to discuss reading in the data in detail.

5.2 Important rules

In the ASRemI command file

- all characters following a # symbol on a line are ignored,
- all blank lines are ignored,
- lines beginning with ! followed by a blank are copied to the .asr file as comments for the output,
- a blank is the usual separator; TAB is also a separator,
- maximum line length is 418 characters but it is usually best to limit lines to 80 characters for ease of editing,
- a comma as the last character on the line is used to indicate that the current list is continued on the next line; a comma is not needed when ASRemI knows how many values to read,
- reserved words used in specifying the linear model (Table 6.1) are case sensitive; they need to be typed exactly as defined: they may not be abbreviated.
- a qualifier is a particular letter sequence beginning with an ! which sets an option or changes some aspect of ASReml;
 - some qualifiers require arguments,
 - qualifiers must appear on the correct line,
 - qualifier identifiers are not case sensitive,
 - qualifier identifiers may be truncated to 3 characters.

```
NIN Alliance Trial 1989
 variety !A
 id
pid
 raw
 repl 4
 nloc
 yield
 lat
 long
row 22
column 11
alliance89.asd !skip 1
yield \sim mu variety
1 2
11 column AR1 .424
22 row AR1 .904
```

5.3 Title line

The first 40 characters of the first nonblank line in an ASReml command file are taken as a title for the job. Use this to identify the analysis for future reference.

5.4 Specifying and reading the data

The data fields are defined immediately after the job title. They tell ASRemI how many fields to expect in the data file and what they are. Data field definitions

- should be given for all fields in the data file; data fields on the end of a data line that do not have a corresponding field definition will be ignored,
- must be presented in the order in which they appear in the data file,

Important

• can appear with other definitions on the

• must be indented one or more spaces,

- data fields can be transformed as they are defined (see below),
- additional data fields can be created by transformation; these should be listed after the data fields read from the data file.

Data field definition syntax

Data field definitions appear in the ASReml command file in the form

SPACE label [field_type] [transformations]

• SPACE

same line,

- is a required space
- label
 - is an alphanumeric string to identify the field,

```
NIN Alliance Trial 1989

variety !A

id

pid

raw

repl 4

nloc

yield

lat

long

row 22

column 11

alliance89.asd !skip 1

yield ~ mu variety

:
```

NIN Alliance Trial 1989

variety !A

id

pid

39

- has a maximum of 31 characters of which only 20 are printed; the remaining characters are not displayed,
- must begin with a letter,
- must not contain the special characters ., *, :, /, !, #, or (,
- reserved words (Table 6.1 and Table 7.3) must not be used,
- *field_type* defines how a variable is interpreted if specified in the linear model,
 - for a variate, leave *field_type* blank or specify 1,
 - for a model factor, various qualifiers are required depending on the form of the factor coding where n is the number of levels of the factor and s is a list of labels to be assigned to the levels:
 - * or n is used when the data field has values $1 \dots n$ directly coding for the factor unless the levels are to be labelled (see !L),
 - !A[n] is required if the data field is alphanumeric,
 - !I[n] is required if the data is numeric but not 1...n; !I must be followed by n if more than 1000 codes are present,
 - !L s is used when the data field is numeric with values 1...n and labels are to be assigned to the n levels, for example
 Sex !L Male Female
 If there are many labels, they may be written over several lines by using a trailing comma to indicate continuation of the list.
 !P indicates the special case of a pedigree factor; ASReml will determine the levels from the pedigree file, see Section 9.3,

A warning is printed if the nominated value for n does not agree with the actual number of levels found in the data and if the nominated value is too small the correct value is used.

- for a group of m variates

is used when m	contiguous data fields	are to be
treated as a factor	or group of variates.	For example
longhand	shorthand	
÷	:	
X1 X2 X3 X4 X5 y	X !G 5 y	
data.dat	data.dat	
y \sim mu X1 X2 X3 X4	X5 y \sim mu X	
	is used when m treated as a factor longhand : X1 X2 X3 X4 X5 y data.dat y ~ mu X1 X2 X3 X4	is used when m contiguous data fields treated as a factor or group of variates. longhand shorthand \vdots \vdots \vdots X1 X2 X3 X4 X5 y X !G 5 y data.dat data.dat y ~ mu X1 X2 X3 X4 X5 y ~ mu X

so that the 5 variates can be referred to in the model as X by using $X \ !G \ 5$

- $\bullet \ transformations$
 - see below

5.5 Transforming the data

Transformation is the process of modifying the data (for example, dividing all of the data values in a field by 10) or deriving new data for analysis (for example, summing the data in two fields). Sometimes it will be easier to use a spreadsheet to calculate derived variables than to modify variables using ASRemI transformations.

Note that in ASReml

- alpha and integer fields are converted to numbers before transformations are applied,
- transformations may be applied to any data field since all data fields are stored as real numbers, but it may not be sensible to change factor level codes,
- all fields in a record are read before transformations are performed,
- transformations are performed in the order of appearance.

Transformation syntax

Transformations have one of six forms, namely

! operator	to perform an operation on the current field, for example, !ABS to take absolute values,
! operator value	to perform an operation involving an argument on the current field, for example, !+3 to add 3 to all elements in the field,
! operator V field	to perform an operation on the current field using the data in another field, for example, !-V2 to subtract field 2 from the current field
!V target	to change the field modified by subsequent transformations,
!V target = value	to change all of the data in a target field to a given value,
!V target = V field	to overwrite the data in a target field by the data values of another field; a special case is when <i>field</i> is 0 instructing ASRemI to put the record number into the target field.

• ! flags the presence of the transformation

- operator is one of the symbols outlined in Table 5.1,
- *value* is the argument required by the transformation,
- V is a literal character and is followed by the number (*target* or *field*) of a data field; the data field is used or modified depending on the context,
- V*field* may be replaced by the name of the field if the field is already named.
- in the first three forms the operation is performed on the *current* field; this will be the field associated with the label unless this field has been reset by specifying a new *target* in a preceding transformation,
- the fourth form changes the focus for subsequent transformations to the field *target*,
- in the last two forms the operation is performed on the *target* field which is modified as a consequence, for example, to create a copy of field 11, which is an existing data field, we would use !V22=V11 which copies field 11 into field 22; if field 22 does not exist in the data it is created; note that subsequent transformations on the line will also apply to the *target*,
- ASReml expects to read values for each variable from the data file unless the variable and all subsequent ones are created using !=. The number of variables read can be explicitly set using the !READ qualifier described in Table 5.5.

qualifier	argument	action	examples
!=, !+, !-, !*, !/	υ	usual arithmetic meaning; note that, 0/0 gives 0 but $v/0$ gives a missing value where v is any number other than 0.	yield !/10
!^	v	raises the data (which must be pos- itive) to the power v .	yield SQRyld !=yield !^0.5
!^	0	takes natural logarithms of the data (which must be positive).	yield LNyield !=yield !^0
!^	-1	takes reciprocal of data (data must be positive).	yield INVyield !=yield !^-1
!>, !<, !<>, !==, !<=, !>=	v	logical operators forming 1 if true, 0 if false.	yield high !=yield !>10
! ABS		takes absolute values - no argument required.	yield ABSyield !=yield !ABS
! ARCSIN	υ	forms an ArcSin transformation us- ing the sample size specified in the argument which may be a number or another field. In the side exam- ple, for two existing fields Germ and Total containing counts, we form the ArcSin for their ratio (ASG) by copying the Germ field and applying the ArcSin transformation using the Total field as sample size.	Germ Total ASG !=Germ !ARCSIN Total
!COS, !SIN	8	takes cosine and sine of the data variable with period s having default 2π ; omit s if data is in radians, set s to 360 if data is in degrees.	Day CosDay !=Day !COS 365
!D	υ	!Dv removes records with v or 'miss- ing value' in the field; if $!D$ is used after $!A$ or $!I$, v should refer to the encoded factor level rather than the value in the data file (see also Sec- tion 4.2).	yield !D-9
!EXP		takes antilog base e - no argument required.	Rate !EXP

Table 5.1: List of	^t transformation	qualifiers	and thei	r actions	with	examples

qualifier	argument	action	examples
!Jddm, !Jmmd !Jyyd		!Jddm converts a date in the form $ddmmccyy$, $ddmmyy$ or $ddmm$ into days. !Jmmd converts a date in the form $ccyymmdd$, $yymmdd$ or $mmdd$ into days. !Jyyd converts a date in the form $ccyyddd$ or $yyddd$ into days. These calculate the number of days since December 31 1900 and are valid for dates from January 1 1900 to December 31 2099; note that if cc is omitted it is taken as 19 if $yy > 50$ and 20 if $yy < 50$, the date string must be entirely numeric: characters such as / may not be present.	
!M	υ	!Mv converts data values of v to missing; if !M is used after !A or !I, v should refer to the encoded fac- tor level rather than the value in the data file (see also Section 4.2).	yield !M-9
!MAX, !MIN, !MOD	v	the maximum, minimum and modulus of the field values and the value v .	yield !MAX 9
!NA	υ	replaces any missing values in the variate with the value v .	Rate !NA O
!SET	vlist	for $vlist$, a list of n values, the data values $1 \dots n$ are replaced by the cor- responding element from $vlist$; data values that are < 1 or $> n$ are re- placed by zero. $vlist$ may run over	treat !L C A B CvR !=treat !SET 1 -1 -1
		several lines provided each incom- plete line ends with a comma, i.e., a comma is used as a continuation symbol (see Other examples below).	group !=treat !SET 1, 2 2 3 3 4

List of transformation qualifiers and their actions with examples

qualifier	argument	action	examples
! SUB	vlist	replaces data values = v_i with their index <i>i</i> where <i>vlist</i> is a vector of <i>n</i> values. Data values not found in <i>vlist</i> are set to 0. <i>vlist</i> may run over several lines if necessary pro- vided each incomplete line ends with a comma. ASReml allows for a small rounding error when matching. It may not distinguish properly if val- ues in <i>vlist</i> only differ in the sixth decimal place (see Other examples below).	year 3 !SUB 66 67 68
! SEQ		replaces the data values with a se- quential number starting at 1 which increments whenever the data value changes between successive records; the current field is presumed to de- fine a factor and the number of levels in the new factor is set to the num- ber of levels identified in this sequen- tial process (see Other examples be- low). Missing values remain miss- ing.	plot !=V3 !SEQ
!Vtarget=	value	assigns value to data field tar- get overwriting previous contents; subsequent transformation qualifiers will operate on data field target.	!V3=2.5
	Vfield	assigns the contents of data field field to data field target overwriting previous contents; subsequent trans- formation qualifiers will operate on data field target. If field is 0 the number of the data record is in- serted.	!V10=V3 !V11=block !V12=V0

List of transformation qualifiers and their actions with examples

Other rules and examples

Other rules include the following

- missing values are unaffected by arithmetic operations, that is, missing values in the current or target column remain missing after the transformation has been performed except in assignment
 - !+3 will leave missing values (NA, * and .) as missing,
 - !=3 will change missing values to 3,
- multiple arithmetic operations cannot be expressed in a complex expression but must be given as separate operations that are performed in sequence as they appear, for example, yield !-120 !*0.0333 would calculate 0.0333 * (yield - 120).

ASReml code	action
yield !MO	changes the zero entries in yield to missing values
yield !^O	takes natural logarithms of the yield data
score !-5	subtracts 5 from all values in $\verb score $
score !SET -0.5 1.5 2.5	replaces data values of 1, 2 and 3 with -0.5, 1.5 and 2.5 respectively
score !SUB -0.5 1.5 2.5	replaces data values of -0.5, 1.5 and 2.5 with 1, 2 and 3 respectively; a data value of 1.51 would be replaced by 0 since it is not in the list or very close to a number in the list
block 8 variety 20 yield plot * !=variety !SEQ	 in the case where there are multiple units per plot, contiguous plots have different treatments, and the records are sorted units within plots within blocks,
	this code generates a plot factor assuming a new plot whenever the code in V2 (variety) changes; no field would be read unless there were later definitions which are not created by transformation,
Var 3 Nit 4 VxN 12 !=Var !-1 !*4 !+Nit	assuming Var is coded 1:3 and Nit is coded 1:4, this syntax could be used to create a new factor VxN with the 12 levels of the composite Var by Nit factor.

Special note on covariates

Covariates are variates that appear as independent variables in the model. It is recommended that covariates be centred and scaled to have a mean of zero and a variance of approximately one to avoid failure to detect singularities. This can be achieved either

- externally to ASReml in data file preparation,
- using !- mean !/ scale where mean and scale are user supplied values, for example, age !-200 !/10.

5.6 Data file line

The purpose of the data file line is to

- nominate the data file,
- specify qualifiers to modify
 - the reading of the data,
 - the output produced,
 - the operation of ASRemI , see Table 5.2.

Data line syntax

The data file line appears in the ASRemI command file in the form

datafile [qualifiers]

- *datafile* is the path name of the file that contains the variates, factors, covariates, traits (response variates) and weight variables represented as data fields, see Chapter 4; the path name may not include embedded blanks,
- the qualifiers tell ASRemI to modify either
 - the reading of the data and/or the output produced, see Table 5.2 below for a list of data file related qualifiers,
 - the operation of ASReml, see Tables 5.3 to 5.6 for a list of job control qualifiers
- the data file related qualifiers must appear on the data file line,
- the job control qualifiers may appear on the data file line or on the following line,

variety !A
...
row 22
column 11
alliance89.asd !skip 1
yield ~ mu variety
...

NIN Alliance Trial 1989

- the arguments to qualifiers are represented by the following symbols
 - f a filename,
 - n an integer number, typically a count,
 - p a vector of real numbers, typically in increasing order,
 - r a real number,
 - s a character string,
 - t a model term label,
 - v the number or label of a data variable,
 - vlist a list of variable labels.

5.7 Data file qualifiers

Table 5.2 lists the qualifiers relating to data input and output. These include !SKIP, !CSV, !FILTER, !SELECT and !PRINT. These must occur on the data file name line. Use the Index to check for examples or further discussion of these qualifiers.

qualifier	action
Frequently used data file qual	ifier
!SKIP n	causes the first n records of the (non-binary) data file to be ignored. Typically these lines contain column headings for the data fields.
Other data file qualifiers	
!CSV	used to make consecutive commas imply a missing value; this, is automatically set if the file name ends with $.\tt csv$ or $.\tt CSV$ (see also Section 4.2)
!FILTER υ !SELECT n	enables a subset of the data to be analysed; v is the number or name of a data field. When reading data, the value in field v is checked <i>after</i> any transformations are performed. If !select is omitted, records with zero in field v are omitted from the analysis. Otherwise, records with n in field v are retained and all other records are omitted. Warning If the filter column contains a missing value, the value from the previous non-missing record is assumed in that position.

Table 5.2: Qualifiers relating to data input and output

5.8 Job control qualifiers

The following table provides a comprehensive list of the job control qualifiers. These change or control various aspects of the analysis. Job control qualifiers may be placed on the data file line and the following line. Use the **Index** to check for examples or further discussion of these qualifiers.

Important Many of these are only required in very special circumstances and new users should not attempt to understand all of them. You do need to understand that all general qualifiers are specified here. Many of these qualifiers are referenced in other chapters where their purpose will be more evident.

qualifier	action
!MAXIT n	sets the maximum number of iterations; the default is 10 iter- ations. ASReml iterates for n iterations unless convergence is achieved first. Convergence is presumed when the REML log- likelihood changes less than 0.002^* current iteration number and the individual variance parameter estimates change less than 1%.
	To abort the job at the end of the current iteration, create a file named ABORTASR.NOW in the directory in which the job is running. At the end of each iteration, ASReml checks for this file and if present, stops the job, writing out the normal results. On case sensitive operating systems (eg. Unix), the filename must be upper case. Note that the ABORTASR.NOW file is deleted so nothing of importance should be placed in it.
	If the job has not converged in n iterations, use the !CONTINUE qualifier to resume iterating from the current point.
	If you perform a system level abort (CTRL C or close the program window) output files other than the .rsv file will be incomplete. The .rsv file should still be functional for resuming iteration at the most recent parameter estimates (see !CONTINUE).
	Use !MAXIT 1 where you want estimates of fixed effects and predictions of random effects for the particular set of variance parameters supplied as initial values. Otherwise the estimates and predictions will be for the updated variance parameters (see also the !BLUP qualifier below).

Table 5.3: List of frequently used job control qualifiers

qualifier	action
!ASMV n	indicates a multivariate analysis is required although the data is presented in a univariate form. 'Multivariate Analysis' is used in the narrow sense where an unstructured error variance matrix is fitted across traits, records are independent, and observations may be missing for particular traits, see Chapter 8 for a complete discussion.
	The data is presumed arranged in lots of n records where n is the number of <i>traits</i> . It may be necessary to expand the data file to achieve this structure, inserting a missing value NA on the additional records. This option is sometimes relevant for some forms of repeated measures analysis. There will need to be a factor in the data to code for trait as the intrinsic Trait factor is undefined when the data is presented in a univariate manner.
! ASUV	indicates that a <i>univariate</i> analysis is required although the data is presented in a multivariate form. Specifically, it allows you to have an error variance other than $I \otimes \Sigma$ where Σ is the unstructured variance structure (with the US variance model in ASReml, see Table 7.3). If there are <i>missing values</i> in the data, you must include $!f mv$ on the end of the linear model. The intrinsic Trait factor is defined and may be used in the model, see Chapter 8 for a complete discussion.
	This option is used for repeated measures analysis when the variance structure required is not the standard multivariate unstructured matrix.
!COLFAC v	is used with !SECTION v and !ROWFAC v to instruct ASReml to set up R structures for analysing a multi-environment trial with a separable first order autoregressive model for each site (environment). v is the name of a factor or variate containing column numbers $(1 \dots n_c \text{ where } n_c \text{ is the number of columns})$ on which the data is to be sorted. See !SECTION for more detail.

Table 5.4: List of occasionally used job control qualifiers

qualifier	action
! CONTINUE	is used to restart/resume iterations from the point reached in a previous iteration. This qualifier can alternately be set from the command line using the option letters C (continue) or F (final) (see Section 12.3 on job control command line options). After each iteration, ASReml writes the current values of the variance parameters to a file with extension .rsv (re-start values). The .rsv file contains information to identify individual variance parameters.
	The !CONTINUE qualifier causes ASReml to scan the .rsv file for parameter values related to the current model replacing the values obtained from the .as file before iteration resumes. If the model has changed, ASReml will pick up the values it recognises as being for the same terms. Furthermore, AS- Reml will use estimates in the .rsv file for certain models to provide starting values for certain more general models, in- serting reasonable defaults where necessary. The transitions recognised are listed and discussed in 7.10.
	DIAG to FA1 DIAG to CORUH (uniform heterogeneous) CORUH to FA1 FAi to FA $i+1$ FAi to CORGH (full heterogeneous) FAi to US (full heterogeneous) CORGH (heterogeneous) to US See the !DOPART qualifier for how this may be exploited.
!DISPLAY n	 is used to select particular graphic displays. In spatial analysis, four graphic displays are possible. Coding these 1=variogram 2=histogram 4=row and column trends 8=perspective plot of residuals set n to the sum of the codes for the desired graphics. The default is 9. Note that the graphics are only displayed in compiled versions of ASReml linked with Interacter (that is, SUN and PC) versions. However, line printer versions of these graphics are written to the .res file. See the G command line option (Section 12.3 on graphics) for how to save the graphs in a file for printing. Use !NODISPLAY to suppress graphic displays.

List of occasionally used job control qualifiers

qualifier	action
!DOPART n	is provided so that several analyses can be coded and run sequentially without having to edit the .as file between runs. Sections of the .as file can be delineated by !PART n lines. These lines begin with the word !PART followed by a number. The lines after the !PART line are ignored unless n on the !DOPART qualifier matches n on the pre- ceding !PART statement or there is no n on the !PART line which means always include. By setting the !DOPART argument to \$1, the part processed can be specified at run time from the command line (see Section 12.4). See Sec- tions 15.7 and 15.10 for examples. The default value of n is 1.
	One situation where this might be useful is where it is neces- sary to run simpler models to get reasonable starting values for more complex variance models. The more complex mod- els are specified in later parts and the !CONTINUE command is used to pick up the previous estimates.
!MVINCLUDE	when ASRemI detects missing values in the design it will report this fact and abort the job unless !MVINCLUDE is specified. Otherwise, use the !D transformation to drop the records with the missing values.
! MVREMOVE	instructs ASReml to discard records which have missing values in the design matrix.
!NODISPLAY	used to suppress the graphic display of the variogram and residuals which is otherwise produced for spatial analyses in the PC and SUN versions. This option is usually set on the command line using the option letter \mathbb{N} (see Section 12.3 on graphics). The display is dependent on the program being compiled with the Interacter library. The text version of the graphics is still written to the .res file.
!PVAL υ p	provides a mechanism for nominating the particular points to be predicted for covariates including $fac(), leg(), spl()$ and pol(). The points are specified here so that they can be included in the appropriate design matrices. v is the name of a data field. p is the list of values at which prediction is required.
!PVAL f vlist	is used to read <i>predict_points</i> for several variables from a file. <i>vlist</i> is the names of the variables having values defined. If the file contains unwanted fields, put the pseudo variate label skip in the appropriate position in <i>vlist</i> to ignore them. The file should only have numeric values. <i>predict_points</i> cannot be specified for design factors.

List of occasionally used job control qualifiers
qualifier	action
!ROWFAC υ	is used with !SECTION v and !COLFAC v to instruct ASRemI to setup the R structures for multi-environment spatial analysis. n is the name of a factor or variate containing row numbers $(1 \dots n_r)$ where n_r is the number of rows) on which the data is to be sorted. See !SECTION for more detail.
!SECTION v	specifies the factor in the data that defines the data sections. This qualifier enables ASRemI to check that sections have been correctly dimensioned but does not cause ASRemI to sort the data unless !ROWFAC and !COLFAC are also specified. Data is assumed to be sorted by section. The following is a basic example assuming 5 sites (sections).
	When !ROWFAC v and !COLFAC v are both specified ASReml generates the R structures for a standard AR \otimes AR spatial analysis. The R structure lines that a user would normally be required to work out and type into the .as file (see the example of Section 15.6) are written to the .res file. The user may then cut and paste them into the .as file for a later run if the structures need to be modified.
	<pre>Basic multi-environment trial analysis site 5 # sites coded 1 5 column * # columns coded 1 row * # rows coded 1 variety !A # variety names yield met.dat !SECTION site !ROWFAC row !COLFAC col yield ~ site !r variety site.variety !f mv site 2 0 # variance header line</pre>
	# asreml inserts the 10 lines required to define # the R structure lines for the five sites here

List of occasionally used job control qualifiers

qualifier	action
!SPLINE t p	defines a spline model term with an explicit set of knot points. The basic form of the spline model term, $spl(v)$, is defined in Table 6.1 where v is the underlying variate. The basic form uses the unique data values as the knot points. The extended form is $spl(v,n)$ which uses n knot points. Use this !SPLINE qualifier where t is $spl(v,n)$ to supply an explicit set of n knot points (p) for the model term t . Using the extended form without using this qualifier results in n equally spaced knot points being used. The !SPLINE qualifier may only be used on a line by itself after the data file line and before the model line.
	When knot points are explicitly supplied they should be in increasing order and adequately cover the range of the data or ASRemI will modify them before they are applied. If you choose to spread them over several lines use a comma at the end of incomplete lines so that ASRemI will to continue read- ing values from the next line of input. If the explicit points do not adequately cover the range, a message is printed and the values are rescaled unless !NOCHECK is also specified. In- adequate coverage is when the explicit range does not cover the midpoint of the actual range. See also !KNOTS, !PVAL and !SCALE.
!STEP r	reduces the update step sizes of the variance parameters. The default value is the reciprocal of the square root of !MAXIT . It may be set between 0.01 and 1.0. The step size is increased towards 1 each iteration. Starting at 0.1, the sequence would be 0.1, 0.32, 0.56, 1. This option is useful when you do not have good starting values, especially in multivariate analyses.

List of occasionally used job control qualifiers

qualifier	action
!BLUP n	restricts ASReml to performing only part of the first iteration. The estimation routine is aborted after n = 1: forming the estimates of the vector of fixed and random effects, n = 2: forming the estimates of the vector of fixed and random effects, REML log-likelihood and residuals (this is the default), n = 3: forming the estimates of the vector of fixed and random effects, REML log-likelihood, residuals and inverse coefficient matrix.
	ASRemI prints its standard reports as if it had completed the iteration normally, but since it has not completed it, some of the information printed will be incorrect. In particular, variance information on the variance parameters will always be wrong. Standard errors on the estimates will be wrong unless $n=3$. Residuals are not available if $n=1$. Use of $n=3$ or $n=2$ will halve the processing time when compared to the alternative of using !MAXIT 1. However, !MAXIT 1 does result in a complete and correct output report.
!DATAFILE f	specifies the datafile name replacing the one obtained from the datafile name line. It is required when different !PARTS (see !DOPART in Table 5.4) of a job must read different files. The !SKIP qualifier, if specified, will be applied when read- ing the file.
!DENSE n	reduces the number of equations solved densely. By default, sparse matrix methods are applied to the random effects and any fixed effects listed after random factors. Use !DENSE n to apply sparse methods to effects listed before !r . This qualifier will not increase the number of dense equations (maximum of 800) and individual model terms will not be split so that only part is in the dense section. n should be kept small (<100) for faster processing.
!DF n	alters the error degrees of freedom from ν to $\nu - n$. This qualifier might be used when analysing pre-adjusted data to reduce the degrees of freedom (<i>n</i> negative) or when weights are used in lieu of actual data records to supply error infor- mation (<i>n</i> positive). The degrees of freedom is only used in the calculation of the residual variance in a univariate single site analysis. The option will have no effect in analyses with multiple error variances (for sites or traits) other than in the reported degrees of freedom. Use !ADJUST <i>r</i> rather than !DF <i>n</i> if <i>r</i> is not a whole number.

Table 5.5: List of rarely used job control qualifiers

qualifier	action
!FORMAT s	supplies a FORTRAN like FORMAT statement for reading fixed format files. A simple example is !FORMAT(3I4,5F6.2) which reads 3 integer fields and 5 floating point fields from the first 42 characters of each data line. A format statement is en- closed in parentheses and may include 1 level of nested paren- theses, for example, e.g. !FORMAT(4x,3(I4,f8.2)). Field descriptors are
	• $r\mathbf{X}$ to skip r character positions,
	 rAw to define r consecutive fields of w characters width, rIw to define r consecutive fields of w characters width, and
	 <i>rFw.d</i> to define <i>r</i> consecutive fields of <i>w</i> characters width; <i>d</i> indicates where to insert the decimal point if it is not explicitly present in the field,
	where r is an optional repeat count.
	In ASReml, the A and I field descriptors are treated identi- cally and simply set the field width. Whether the field is interpreted alphabetically or as a number is controlled by the !A qualifier.
	Other legal components of a format statement are
	• the , character; required to separate fields - blanks are not permitted in the format.
	• the / character; indicates the next field is to be read from the next line. However a / on the end of a format to skip a line is not honoured.
	• BZ; the default action is to read blank fields as missing values. * and NA are also honoured as missing values. If you wish to read blank fields as zeros, include the string BZ.
	 the string BM; switches back to 'blank missing' mode. the string Tc; moves the 'last character read' pointer to line position c so that the next field starts at position c + 1. For example TO goes back to the beginning of the line. the string D; invokes debug mode.
	A format showing these components is !FORMAT(D,3I4,8X,A6,3(2x,F5.2)/4x,BZ,20I1) and is suitable for reading 27 fields from 2 data records such as 111122223333xxxxxxALPHAFxx 4.12xx 5.32xx 6.32 xxxx123 567 901 345 7890

List of rarely used job control qualifiers

is used to set a grouping variable for plotting, see $!\tt X.$

qualifier	action
!JOIN	is used to join lines in plots, see $!X$.
PRINT n	causes ASRemI to print the transformed data file to base- name.asp. If $n < 0$, data fields 1mod(n) are written to the file, n = 0, nothing is written, n = 1, all data fields are written to the file if it does not exist, n = 2, all data fields are written to the file overwriting any previous contents, $n > 2$, data fields $n \dots t$ are written to the file where t is the last defined column.
!READ n	formally instructs ASReml to read n data fields from the data file. It is needed when there are extra columns in the data file that are only required for combination into earlier fields in transformations.
!RECODE	required when reading a binary data file with pedigree iden- tifiers that have not been recoded according to the pedigree file. It is not needed when the file was formed using the !SAVE option but will be needed if formed in some other way (see also Section 4.2).
!REPORT	forces ASRemI to attempt to produce the standard output re- port when there is a failure of the iteration algorithm. Usu- ally no report is produced unless the algorithm has at least produced estimates for the fixed and random effects in the model. Note that residuals are not included in the output forced by this qualifier. This option is primarily intended to help debugging a job that is not converging properly.
!RESIDUALS [2]	on the data file line or following lines instructs ASRemI to write the transformed data and the residuals to a binary file. The residual is the last field. The file <i>basename.srs</i> is written in single precision unless the argument is 2 in which case <i>base- name.drs</i> is written in double precision. The file will not be written from a spatial analysis (two-dimensional error) when the data records have been sorted into field order because the residuals are not in the same order that the data is stored. The residual from a spatial analysis will have the units part added to it when units is also fitted. The .drs file could be renamed (with extension .dbl) and used for input in a subsequent run.

List of rarely used job control qualifiers

action
on the data file line or following lines instructs ASRemI to write the data to a binary file. The file asrdata.bin is written in single precision if the argument n is 1 or 3; asrdata.dbl is written in double precision if the argument n is 2 or 4; the data values are written before transformation if the argument is 1 or 2 and after transformation if the argument is 3 or 4. The default is single precision after transformation (see also Section 4.2).
specifies that n constraints are to be applied to the variance parameters. The constraint lines occur after the G structures are defined. The constraints are described in Section 7.9. The variance header line (Section 7.4) must be present, even if only 0 0 0 indicating there are no explicit R or G structures (see also Section 7.9).
is used to plot the (transformed) data. Use $!X$ to specify the <i>x</i> variable, $!Y$ to specify the <i>y</i> variable and $!G$ to specify a grouping variable. $!JOIN$ joins the points when the <i>x</i> value increases between consecutive records. The grouping variable may be omitted for a simple scatter plot. Omit $!Y$ <i>y</i> produce a histogram of the <i>x</i> variable.
For example,
!X age !Y height !G sex
Note that the graphs are only produced in the graphics versions of ASRemI (Section 12.3).
For multivariate repeated measures data, ASRemI can plot the response profiles if the first response is nominated with the !Y qualifier and the following analysis is of the multi- variate data. ASRemI assumes the response variables are in contiguous fields and are equally spaced. For example Response profiles Treatment !A Y1 Y2 Y3 Y4 Y5 rm.asd !Y Y1 !G Treatment !JOIN

List of rarely used job control qualifiers

qualifier	action
!CINV n	prints the portion of the inverse of the coefficient matrix per- taining to the n^{th} term in the linear model. Because the model has not been defined when ASRemI reads this line, it is up to the user to count the terms in the model to iden- tify the portion of the inverse of the coefficient matrix to be printed. The option is ignored if the portion is not wholly in the SPARSE stored equations. The portion of the inverse is printed to a file with extension .cii The sparse form of the matrix only is printed in the form $i j C^{ij}$, that is, elements of C^{ij} that were not needed in the estimation process are not included in the file.
!EXTRA n	forces another $mod(n, 10)$ rounds of iteration after apparent convergence. The default for n is 1. This qualifier has lower priority than !MAXIT and ABORTASR.NOW (see !MAXIT for de- tails). Convergence is judged by changes in the REML log-likelihood value and variance parameters. However, sometimes the vari- ance parameter convergence criteria has not been satisfied.
!FACPOINTS n	affects the number of distinct points recognised by the fac() model function (Table 6.1). The default value of n is 1000 so that points closer than 0.1% of the range are regarded as the same point.
!KNOTS n	changes the default knot points used when fitting a spline to data with more than n different values of the spline variable. When there are more than n (default 50) points, ASRemI will default to using n equally spaced knot points.
! NOCHECK	forces ASReml to use any explicitly set spline knot points (see !SPLINE) even if they do not appear to adequately cover the data values.
!NOREORDER	prevents the automatic reversal of the order of the fixed terms (in the dense equations) and possible reordering of terms in the sparse equations.
!NOSCRATCH	forces ASRemI to hold the data in memory. ASRemI will usually hold the data on a scratch file rather than in memory. In large jobs, the system area where scratch files are held may not be large enough. A Unix system may put this file in the /tmp directory which may not have enough space to hold it.
POLPOINTS n	affects the number of distinct points recognised by the $pol()$ model function (Table 6.1). The default value of n is 1000 so that points closer than 0.1% of the range are regarded as the same point.

Table 5.6: List of very rarely used job control qualifiers

qualifier	action
!PPOINTS n	influences the number of points used when predicting splines and polynomials. The design matrix generated by the leg(), pol() and spl() functions are modified to include extra rows that are accessed by the PREDICT directive. The default value of n is 21 if there is no !PPOINTS qualifier. The range of the data is divided by $n-1$ to give a step size i . For each point p in the list, a predict point is inserted at $p + i$ if there is no data value in the interval $[p,p+1.1\times i]$. !PPOINTS is ignored if !PVAL is specified for the variable. This process also effects the number of levels identified by the fac() model term.
!SCALE 1	When forming a design matrix for the spl() model term, ASRemI uses a standardized scale (independent of the actual scale of the variable). The qualifier !SCALE 1 forces ASRemI to use the scale of the variable. The default standardised scale is appropriate in most circumstances.
!SLOW n	reduces the update step sizes of the variance parameters more persistently than the !STEP r qualifier. If specified, ASRem looks at the potential size of the updates and if any are large, it reduces the size of r . If n is greater than 10 ASRem also modifies the Information matrix by multiplying the diagonal elements by n . This has the effect of further reducing the updates. This option may help when you do not have good starting values, especially in multivariate analyses.

List of very rarely used job control qualifiers

_

Command file: Specifying the terms in the mixed model

6

Introduction

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6.1 Introduction

The linear mixed model is specified in ASRemI as a series of model terms and qualifiers. In this chapter the model formula syntax is described.

6.2 Specifying model formulae in ASReml

The linear mixed model is specified in AS-Reml as a series of model terms and qualifiers. Model terms include factor and variate labels (Section 5.4), functions of labels, special terms and interactions of these. The model is specified immediately after the data file and any job control qualifier lines. The syntax for specifying the model is

```
NIN Alliance Trial 1989
variety
column 11
alliance89.asd !skip 1
yield ~ mu variety !r repl,
!f mv
1 2
11 column AR1 .3
22 row AR1 .3
```

response [!wt weight] \sim fixed [!r random] [!f sparse_fixed]

- *response* is the label for the response variable(s) to be analysed; multivariate analysis is discussed in Chapter 8,
- *weight* is a label of a variable containing weights; weighted analysis is discussed in Section 6.7,
- \sim separates *response* from the list of fixed and random terms,
- *fixed* represents the list of primary fixed explanatory terms, that is, variates, factors, interactions and special terms for which analysis of variance (ANOVA) type tests are required. See Table 6.1 for a brief definition of model terms, allowable operators and commonly used functions. The full definition is in Section 6.6,
- *random* represents the list of explanatory terms to be fitted as random effects, see Table 6.1,
- *sparse_fixed* are additional fixed terms not included in the ANOVA table.

General rules

The following general rules apply in specifying the linear mixed model

- all elements in the model must be space separated,
- the character ~ separates the response variables(s) from the explanatory variables in the model,

Choose
that will avoid
confusionlabels- labels are case sensitive,
- labels may be abbreviated (truncated) when used in

- labels may be abbreviated (truncated) when used in the model line but care must be taken that the truncated form is not ambiguous. If the truncated form matches more than one label, the term associated with the first match is assumed,
- model terms may only appear once in the model line; repeated occurrences are ignored,
- model terms other than the original data fields are defined the first time they appear on the model line. They may be abbreviated (truncated) if they are referred to again provided no ambiguity is introduced.

Important It is often clearer if labels are not abbreviated. If abbreviations are used then they need to be chosen to avoid confusion.

• if the model is written over several lines, all but the final line must end with a comma to indicate that the list is continued.

In Tables 6.1 and 6.2, the arguments in model term functions are represented by the following symbols

- f the label of a data variable defined as a model factor,
- k, n an integer number,
- r a real number,
- t a model term label (includes data variables),
- v, y the label of a data variable,

Parsing of model terms in ASRemI is not very sophisticated. Where a model term takes another model term as an argument, the argument must be predefined. If necessary, include the argument in the model line with a leading '-' which will cause the term to be defined but not fitted.

	model term	brief description		common usage	
			lixed	random	
reserved words	mu	the constant term or intercept	\checkmark		
	mv	a term to estimate missing values	\checkmark		
	Trait	multivariate counterpart to mu	\checkmark		
	units	forms a factor with a level for each experimental unit		\checkmark	
operators	. or :	placed between labels to specify an interaction	\checkmark	\checkmark	
	/	placed between labels to create con- ditional terms (Section 6.5)	\checkmark	\checkmark	
	-	placed before model terms to exclude them from the model	\checkmark	\checkmark	
	,	placed at the end of a line to in- dicate that the model specification continues on the next line			
	+	treated as a space	\checkmark	\checkmark	
	!{ !}	placed around some model terms when it is important the terms not be reordered (Section 6.4)		\checkmark	
commonly used functions	at(<i>f</i> , <i>n</i>)	condition on level n of factor f	\checkmark	\checkmark	
	fac(v)	forms a factor from v with a level for each unique value in v		\checkmark	
	fac(v,y)	forms a factor with a level for each combination of values in v and y			
	lin(f)	forms a variable from the factor f with values equal to $1n$ corresponding to $level(1)level(n)$ of the factor	\checkmark		
	<pre>spl(v[,k])</pre>	forms the design matrix for the ran- dom component of a cubic spline for variable v		\checkmark	
other functions	and(<i>t</i> [, <i>r</i>])	adds r times the design matrix for model term t to the previous design matrix; r has a default value of 1. If t is complex if may be necessary to predefine it by saying -t and(t,r)			

Table 6.1: Summary of reserved words, allowable operators and functions

model term	brief description	commo fixed	on usage random
$\cos(v,r)$	forms cosine from v with period r	\checkmark	
giv(f,n)	associates the $n{\rm th}$.giv G-inverse with the factor f		\checkmark
ide(f)	fits pedigree factor f without relationship matrix		\checkmark
inv(v[,r])	forms reciprocal of $v + r$	\checkmark	
leg(v,[-]n)	forms $n+1$ legendre polynomials of order 0 (intercept), 1 (linear) n from the values in v ; the intercept polynomial is omitted if v is pre- ceded by the negative sign.	\checkmark	
$\log(v[,r])$	forms natural logarithm of $v + r$	\checkmark	
ma1(f)	constructs MA1 design matrix for factor \boldsymbol{f}		\checkmark
ma1	forms an $\texttt{MA1}$ design matrix from plot numbers		\checkmark
pol(v,[-]n)	forms $n+1$ orthogonal polynomials of order 0 (intercept), 1 (linear) n from the values in v ; the intercept polynomial is omitted if n is pre- ceded by the negative sign.	\checkmark	
sin(v,r)	forms sine from v with period r	\checkmark	
sqrt(v[,r])	forms square root of $v + r$	\checkmark	
uni(f)	forms a factor with a level for each record where factor f is non-zero		\checkmark
uni(f , n)	forms a factor with a level for each record where factor f has level n		\checkmark
xfa(f,k)	is formally a copy of factor f with k extra levels. This is used when fitting extended factor analytic models (XFA, Table 7.3) of order k in a sparser form.		\checkmark

Summary of reserved words, allowable operators and functions

ASRemI code	action
yield \sim mu variety	fits a model with a constant and fixed variety effects
yield \sim mu variety !r block	fits a model with a constant term, fixed variety effects and random block effects
yield \sim mu time variety time.variety	fits a saturated model with fixed time and variety main effects and time by variety interaction effects
livewt \sim mu breed sex breed.sex !r sire	fits a model with fixed breed, sex and breed by sex interaction effects and random sire effects

Examples

6.3 Fixed terms in the model

Primary fixed terms

The *fixed* list in the model formula

- describes the fixed covariates, factors and interactions including special functions to be included in the ANOVA table,
- generally begins with the reserved word mu which fits a constant term, mean or intercept, see Table 6.1.

```
NIN Alliance Trial 1989
variety
:
row 22
column 11
alliance89.asd !skip 1
!mvinclude
yield ~ mu variety !r repl,
!f mv
1 2
11 column AR1 .3
22 row AR1 .3
```

Table 6.1 includes the reserved words and special functions used in the *fixed* list.

Sparse fixed terms

The !f sparse_fixed terms in model formula

- are the fixed covariates (for example, the fixed lin(row) covariate now included in the model formula), factors and interactions including special functions and reserved words (for example mv, see Table 6.1) for which ANOVA type tests are not required,
- include large (>100 levels) terms.

6.4 Random terms in the model

The !r random terms in the model formula

- comprise random covariates, factors and interactions including special functions and reserved words, see Table 6.1,
- involve an initial non-zero variance component or ratio (relative to the residual variance) default 0.1; the initial value can be specified after the model term or if the variance structure is not scaled identity, by syntax described in detail in Chapter 7,

```
NIN Alliance Trial 1989
variety
:
row 22
column 11
alliance89.asd !skip 1
yield ~ mu variety !r repl,
!f mv lin(row)
1 2
11 column AR1 .424
22 row AR1 .904
```

```
NIN Alliance Trial 1989
variety
...
row 22
column 11
alliance89.asd !skip 1
yield ~ mu variety !r repl,
!f mv 1 2
11 column AR1 .424
22 row AR1 .904
```

- an initial value of its variance (ratio) may be followed by a !GP (restricted to be positive, the default), !GU (unrestricted) or !GF (fixed) qualifier, see Table 7.4,
- use !{ and !} to group model terms that may not be reordered. Normally ASRemI will reorder the model terms in the sparse equations putting smaller terms first to speed up calculations. However, the order must be preserved if the user defines a structure for a term which also covers the following term(s) (a way of defining a covariance structure across model terms). Grouping is specifically required if the model terms are of differing sizes (number of effects). For example, for traits weaning_weight and yearling_weight, an animal model with maternal weaning weight should specify model terms

```
!{ Trait.animal at(Trait,1).dam !}
```

when fitting a genetic covariance between the direct and maternal effects.

6.5 Interactions and conditional factors

Interactions

- interactions are formed by joining two or more terms with a '.' or a ':', for example, **a.b** is the interaction of factors **a** and **b**,
- interaction levels are arranged with the levels of the second factor nested within the levels of the first,
- labels of factors including interactions are restricted to 31 characters of which only the first 20 are ever displayed. Thus for interaction terms it is often necessary to shorten the names of the component factors in a systematic way, for example, if Time and Treatment are defined in this order, the interaction between Time and Treatment could be specified in the model as Time.Treat; remember that the first match is taken so that if the label of each field begins with a different letter, the first letter is sufficient to identify the term,
- interactions can involve model functions,
- a*b is expanded to a b a.b
- a*b*c*d is expanded to a b c d a.b a.c a.d b.c b.d c.d a.b.c a.b.d a.c.d b.c.d a.b.c.d
- a. (b c d) e is expanded to a.b a.c a.d e. This syntax is detected by the string '.(' and the closing parenthesis must occur on the same line and before any comma indicating continuation. Any number of terms may be enclosed. Each may have '-' prepended to suppress it from the model but insert an extra space before the first term if this facility is required. Each enclosed term may have initial values and qualifiers following. For example,

```
yield~site site.(lin(row) !r variety) at(site,1).(row .3 col .2)
```

expands to

```
yield~site site.lin(row) !r site.variety at(site,1).row .3,
at(site,1).col .2
```

Conditional factors

A conditional factor is a factor that is present only when another factor has a particular level.

- individual components can be specified using the at(f,n) function (see Table 6.2), for example, at(site,1).row will fit row as a factor only for site 1,
- a complete set of conditional terms are specified by joining two terms with a /

- a/b creates a series of factors representing b nested within a. b may be any previously defined model term. A factor is created for each level of a; each has the size of b. For example, if site and geno are factors with 3 and 10 levels respectively, then for site/geno ASReml constructs 3 new factors site_1.geno, site_2.geno and site_3.geno, each with 10 levels,
- the first term must be a factor,
- this is similar to forming an interaction except that a separate model term is created for each level of the first factor; this is useful for random terms when each component can have a different variance. The same effect is achieved by using an interaction and associating a DIAG variance structure with the first component (see Section 7.5).

6.6 Alphabetic list of model functions

Table 6.2 presents detailed descriptions of the model functions discussed above. Note that some three letter function names may be abbreviated to the first letter.

model function	action
and(t, r) a(t, r)	overlays (adds) r times the design matrix for model term t to the existing design matrix. Specifically, if the model up to this point has p effects and t has a effects, the a columns of the design matrix for t are multiplied by r and added to the last a of the p columns already defined. This can be used to force a correlation of 1 between two terms with different variances as in a diallel analysis male and(female) Note that if the overlaid term is complex, it must be predefined.
at(f,n)	defines a binary variable which is 1 if the factor f has level n for the record. For example, to fit a row factor only for site 3, use the expression $at(site,3).row$.
$\cos(v,r)$	forms cosine from v with period r
fac(v) fac(v,y)	fac(v) forms a factor with a level for each value of x and any additional points inserted as discussed with the qualifiers !PPOINTS and !PVAL . fac(v, y) forms a factor with a level for each combination of values from v and y . The values are reported in the .res file.
giv(f,n) g(f,n)	associates the <i>n</i> th .giv G-inverse with the factor. This is used when there is a known (except for scale) G-structure other than the additive inverse genetic relationship matrix. The G-inverse is supplied in a file whose name has the file extension .giv described in Section 9.6

Table 6.2: Alphabetic list of model functions and descriptions

model function	action
ide(f) i(f)	is used to take a copy of a pedigree factor f and fit it without the genetic relationship covariance. This facilitates fitting a <i>second animal effect</i> . Thus, to form a direct, maternal genetic and maternal environment model, the maternal environment is defined as a second animal effect coded the same as dams.
inv(v[,r])	forms the reciprocal of $v+r.$ This may also be used to transform the response variable.
leg(<i>v</i> ,[-] <i>n</i>)	forms $n+1$ legendre polynomials of order 0 (intercept), 1 (linear) n from the values in v ; the intercept polynomial is omitted if n is preceded by the negative sign.
lin(f) l(f)	takes the coding of factor f as a covariate. The function is defined for f being a simple factor, Trait and units. The $lin(f)$ function does not centre or scale the variable. Motivation: Sometimes you may wish to fit a covariate as a random factor as well. If the coding is say $1n$, then you should define the field as a factor in the field definition and use the $lin()$ function to include it as a covariate in the model. Do not centre the field as a covariate values are irregular, you would leave the field as a covariate and use the fac() function to derive a factor version.
log(<i>v</i> [, <i>r</i>])	forms the natural log of $v + r$. This may also be used to transform the response variable.
ma1 ma1(<i>f</i>)	creates a first-differenced (by rows) design matrix which, when defining a random effect, is equivalent to fitting a moving average variance structure in one dimension. In the mal form, the first-difference operator is coded across all data points (assuming they are in time/space order). Otherwise the coding is based on the codes in the field indicated.
mu	is used to fit the intercept/constant term. It is normally present and listed first in the model. It should be present in the model if there are no other fixed factors or if all fixed terms are covariates or contrasts except in the special case of regression through the origin.

Alphabetic list of model functions and descriptions

model function	action
mv	is used to estimate missing values in the response variable. Formally this creates a model term with a column for each missing value. Each column contains zeros except for a solitary -1 in the record containing the corresponding missing value. This is used in spatial analyses so that computing advantages arising from a balanced spatial layout can be exploited. The equations for mv and any terms that follow are always included in the sparse set of equations.
	Missing values are handled in three possible ways during analysis. In the simplest case, records containing missing values in the response vari- able are deleted. For multivariate (including some repeated measures) analysis, records with missing values are not deleted but ASReml drops the missing observation and uses the appropriate unstructured R-inverse matrix. For regular spatial analysis, we prefer to retain separability and therefore estimate the missing value(s) by including the special term mv in the model.
pol(<i>v</i> , <i>n</i>) p(<i>v</i> , <i>n</i>)	forms a set of orthogonal polynomials of order $ n $ based on the unique values in variate (or factor) v and any additional interpolated points, see !PPOINTS and !PVAL in Table 5.4. It includes the intercept if n is positive, omits it if n is negative. For example, pol(time,2) forms a design matrix with three columns of the orthogonal polynomial of degree 2 from the variable time. Alternatively, pol(time,-2) is a term with two columns having centred and scaled linear coefficients in the first column and centred and scaled quadratic coefficients in the second column. The actual values of the coefficients are written to the .res file. This factor could be interacted with a design factor to fit random regression models.
sin(v,r)	forms sine from v with period r
spl(v[,k]) s(v[,k])	In order to fit spline models associated with a variate v and k knot points in ASReml, v is included as a covariate in the model and $spl(v, k)$ as a random term. The knot points can be explicitly specified using the !SPLINE qualifier (Table 5.4). If k is specified but !SPLINE is not specified, equally spaced points are used. If k is not specified and there are less than 50 unique data values, they are used as knot points. If there are more than 50 unique points then 50 equally spaced points will be used. The spline design matrix formed is written to the .res file. An example of the use of $spl()$ is
	price \sim mu week !r spl(week)
sqrt(v[,r])	forms the square root of $v + r$. This may also be used to transform the response variable.

Alphabetic list of model functions and descriptions

model function	action
Trait	is used with multivariate data to fit the individual trait means. It is formally equivalent to mu but Trait is a more natural label for use with multivariate data. It is interacted with other factors to estimate their effects for all traits.
units	creates a factor with a level for every record in the data file. This is used to fit the 'nugget' variance when a correlation structure is applied to the residual.
uni(f[,0[,n]])	creates a factor with a new level whenever there is a level present for the factor f . Levels (effects) are not created if the level of factor f is 0, missing or negative. The size may be set in the third argument by setting the second argument to zero.
uni(f,k[,n])	creates a factor with a level for every record subject to the factor level of f equalling k , i.e. a new level is created for the factor whenever a new record is encountered whose integer truncated data value from data field f is k . Thus uni(site,2) would be used to create an independent error term for site 2 in a multi-environment trial and is equivalent to at(site,2).units. The default size of this model term is the number of data records. The user may specify a lower number as the third argument. There is little computational penalty from the default but the .sln file may be substantially larger than needed.
xfa(f,k)	Factor analytic models are discussed in Chapter 7. There are three forms, FAk, FACVk and XFAk where k is the number of factors. The XFAk form is a sparse formulation that requires an extra k levels to be inserted into the mixed model equations for the k factors. This is achieved by the $xfa(f, k)$ model function which defines a design matrix based on the design matrix for f augmented with k columns of zeros for the k factors.

Alphabelic list of model functions and descriptio	Alphabetic	list of	model	functions	and	description
---	------------	---------	-------	-----------	-----	-------------

6.7 Weights

Weighted analyses are achieved by using !WT weight as a qualifier to the response variable. An example of this is y !WT wt ~ mu A X where y is the name of the response variable and wt is the name of a variate in the data containing weights. If these are relative weights (to be scaled by the units variance) then this is all that is required. If they are absolute weights, that is, the reciprocal of known variances, use the !S2==1 qualifier described in Table 7.4 to fix the unit variance. When a structure is present in the residuals the weights are applied as a matrix

product. If Σ is the structure and W is the diagonal matrix constructed from the square root of the values of the variate weight, then $\mathbf{R}^{-1} = \mathbf{W} \boldsymbol{\Sigma}^{-1} \mathbf{W}$. Negative weights are treated as zeros.

6.8 Missing values

Missing values in the response

mv controls the estimation of missing values. It is sometimes computationally convenient to estimate missing values, for example, in spatial analysis of regular arrays, see example **3a** in Section 7.3. The default action is to exclude units with missing values, and in multivariate analyses, the R matrix is modified to reflect the missing value pattern.

Formally, mv creates a factor with a covariate for each missing value. The covariates are coded 0 except in the record where the particular missing value occurs, where it is coded -1.

```
NIN Alliance Trial 1989
variety
row 22
column 11
alliance89.asd !skip 1
yield \sim mu variety !r repl,
!f mv
1 2
11 column AR1 .424
22 row AR1 .904
```

Missing values in the explanatory variables

ASRemI will abort the analysis if it finds missing values in the design matrix unless !MVINCLUDE or !MVREMOVE is specified, see Section 5.8. !MVINCLUDE causes the missing value to be treated as a zero. !MVREMOVE causes ASRemI to discard the whole record. Records with missing values in particular fields can be explicitly dropped using the !D transformation, Table 5.1.

Covariates: Treating missing values as zero in covariates is usually only sensible if the covariate is centred (has mean of zero).

Design factors: Where the factor level is zero (or missing and the !MVINCLUDE qualifier is specified), no level is assigned to the factor for that record.

6.9 Some technical details about model fitting in ASReml

Sparse versus dense

ASReml partitions the terms in the linear model into two parts: a *dense* set and a *sparse* set. The partition is at the $!\mathbf{r}$ point unless explicitly set with the !DENSE data line qualifier or \mathbf{mv} is included before $!\mathbf{r}$, see Table 5.5. The special term \mathbf{mv} is always included in sparse. Thus *random* and *sparse* terms are estimated using sparse matrix methods which result in faster processing. The inverse coefficient matrix is fully formed for the terms in the dense set. The inverse coefficient matrix is only partially formed for terms in the sparse set. Typically, the sparse set is large resulting in savings in memory and computing. A consequence is that the variance matrix for estimates is only available for equations in the dense portion.

Ordering of terms in ASReml

The order in which estimates for the fixed and random effects in linear mixed model are reported will usually differ from the order the model terms are specified. Estimates are obtained by solving the corresponding mixed model equations (Gilmour *et al.*, 1995). ASReml partitions the equations into a *dense* set which typically includes the *primary fixed* factors, and a *sparse* set which includes the rest including any missing value (mv) covariates. ASReml first orders the equations in the sparse part to maintain as much sparcity as it can during the estimation. After absorbing them, it absorbs the model terms associated with the dense equations in the order specified. Within each term it absorbs the terms starting with the highest level. In the dense equations so that the ANOVA table has correct marginalization.

Aliasing and singularities

A singularity is reported in ASReml when there is either

- a linear dependence in the design matrix and therefore no information left to estimate the corresponding effect, or
- no data for that fixed effect.

ASRemI handles singularities by setting to zero and ignoring equations detected as aliasses. Since ASRemI solves from the bottom up, the first level (and hence the last level processed) of a factor is the one that will be declared singular and dropped from the model. The number of singularities is reported in the .asr file immediately prior to the REML log-likelihood (LogL) line for that iteration (see Section 13.3). The singular effects can be identified in the .sln file (see also Section 13.3). Estimates that are zero and have zero for their standard error are the effects reported as singular.

Warning Singularities in the *sparse_fixed* terms of the model may change with changes in the random terms included in the model. If this happens it will mean that changes in the REML log-likelihood are not valid for testing the changes made to the random model. This situation is not easily detected as the only evidence will be in the .sln file where different fixed effects are singular. A likelihood ratio test is not valid if the fixed model has changed.

Examples of aliasing

The sequence of models in Table 6.3 are presented to facilitate an understanding of over-parameterised models. It is assumed that var is a factor with 4 levels, trt with 3 levels and rep with 3 levels and that all var.trt combinations are present in the data.

model	number of sin- gularities	order of fitting
yield \sim var !r rep	0	rep var
yield \sim mu var !r rep	1	rep mu var first level of var is aliassed and set to zero
yield \sim var trt !r rep	1	rep var trt var fully fitted, first level of trt is aliassed and set to zero
yield \sim mu var trt, var.trt !r rep	8	rep mu var trt var.trt first levels of both var and trt are aliassed and set to zero, together with subsequent interactions
yield \sim mu var trt !r rep, !f var.trt	8	[var.trt rep] mu var trt var.trt fitted before mu, var and trt, var.trt fully fitted; mu, var and trt are completely singular and set to zero. The order within [var.trt rep] is de- termined internally.

6.10 Testing of terms

An analysis of variance table of F ratio statistics labelled F-incr is displayed. It allows approximate testing of the term adjusted for terms not in the table or higher in the table as portrayed in Table 6.4.

No denominator degrees of freedom is supplied since the denominator degrees of freedom is not easy to deduce in a mixed model. The *Error degrees of freedom* is a maximum value for the denominator but sometimes a much smaller value is appropriate (Kenward and Roger, 1997).

Table 6.4: Schematic analysis of variance table from fitting the model yield \sim mu A B X A.B A.X B.X A.B.X !r rep

source	F-incremental
mu	mu rep
A	A mu rep
В	B A mu rep
X	X B A mu rep
A.B	A.B X B A mu rep
A.X	A.X A.B X B A mu rep
B.X	B.X A.X A.B X B A mu rep
A.B.X	A.B.X B.X A.X A.B X B A mu rep

Command file: Specifying the variance structures

7

Introduction

Non-singular variance matrices

Variance model specification in ASReml

A sequence of structures for the NIN data

Variance structures

General syntax Variance header line R structure definition G structure header and definition lines

Variance model description

Forming the variance models from correlation models Additional notes of variance models

Variance structure qualifiers

Rules for combining variance models

G structures involving more than one random term

Constraining variance parameters

Parameter constraint within a variance model Constraints between and within variance models

Model building using the !CONTINUE qualifier

7.1 Introduction

The subject of this chapter is variance model specification in ASRemI. ASRemI allows a wide range of models to be fitted. The key concepts you need to understand are

- the mixed linear model $\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{u} + \boldsymbol{e}$ has a residual term $\boldsymbol{e} \sim N(\boldsymbol{0}, \boldsymbol{R})$ and random effects $\boldsymbol{u} \sim N(\boldsymbol{0}, \boldsymbol{G})$,
- we use the terms R structure and G structure to refer to the independent blocks of R and G respectively,
- R and G structures are typically formed as a direct product of particular variance models,
- variance models may be correlation matrices or variance matrices with equal or unequal variances on the diagonal. A model for a correlation matrix (eg. AR1) can be converted to an equal variance form (eg. AR1V) and to a heterogeneous variance form (eg. AR1H),
- variances are sometimes estimated as variance ratios (relative to the residual variance).

These issues are fully discussed in Chapter 2. In this chapter we begin by considering an ordered sequence of variance structures for the NIN variety trial (see Section 7.3). This is to introduce variance modelling in practice. We then present the topics in detail.

Non singular variance matrices

When undertaking the REML estimation, ASRemI needs to invert each variance matrix. For this it requires that the matrices be negative definite or positive definite. They must not be singular. Negative definite matrices will have negative diagonal elements on the diagonal of the matrix and/or its inverse. The exception is the XFA model which has been specifically designed to fit singular matrices (Thompson *et al.* 2003).

Let $\mathbf{x}' \mathbf{A} \mathbf{x}$ represent an arbitrary quadratic form for $\mathbf{x} = (x_1, \ldots, x_n)'$. The quadratic form is said to be nonnegative definite if $\mathbf{x}' \mathbf{A} \mathbf{x} \ge \mathbf{0}$ for all $\mathbf{x} \in \mathbf{R}^n$. If $\mathbf{x}' \mathbf{A} \mathbf{x}$ is nonnegative definite and in addition the null vector $\mathbf{0}$ is the only value of \mathbf{x} for which $\mathbf{x}' \mathbf{A} \mathbf{x} = \mathbf{0}$, then the quadratic form is said to be positive definite. Hence the matrix \mathbf{A} is said to be positive definite if $\mathbf{x}' \mathbf{A} \mathbf{x}$ is positive definite, see Harville (1997), pp 211.

7.2 Variance model specification in ASReml

The variance models are specified in the AS-Reml command file after the model line, as shown in the code box. In this case just one variance model is specified (for replicates, see model **2b** below for details). predict and tabulate lines may appear after the model line and before the first variance structure line. These are described in Chapter 10.

```
NIN Alliance Trial 1989
variety !A
:
column 11
nin89.asd !skip 1
yield ~ mu variety !r repl
0 0 1
repl 1
repl 0 IDV 0.1
```

Table 7.3 presents the full range of variance models available in ASRemI. The identifiers for specifying the individual variance models in the command file are described in Section 7.5 under Specifying the variance models in ASRemI. Many of the models are correlation models. However, these are generalised to homogeneous variance models by appending V to the base identifier. They are generalised to heterogeneous variance models by appending H to the base identifier.

7.3 A sequence of structures for the NIN data

Eight variance structures of increasing complexity are now considered for the NIN field trial data (see Chapter 3 for an introduction to these data). This is to give you a feel for variance modelling in ASReml and some of the models that are possible. Table 7.3 lists the variance models that are available in ASReml.

See Section 2.1 Before proceeding, it is useful to link this section to the algebra of Chapter 2. In this case the mixed linear model is

$$oldsymbol{y} = oldsymbol{X} oldsymbol{ au} + oldsymbol{Z} oldsymbol{u} + oldsymbol{e}$$

where \boldsymbol{y} is the vector of yield data, $\boldsymbol{\tau}$ is a vector of fixed variety effects but would also include fixed replicate effects in a simple RCB analysis and might also include fixed missing value effects when spatial models are considered, $\boldsymbol{u} \sim N(\boldsymbol{0}, \boldsymbol{G})$ is a vector of random effects (for example, random replicate effects) and the errors are in $\boldsymbol{e} \sim N(\boldsymbol{0}, \boldsymbol{R})$. The focus of this discussion is on

- changes to \boldsymbol{u} and \boldsymbol{e} and the assumptions about these terms,
- the impact this has on the specification of the G structures for u and the R structures for e.

1 Traditional randomised complete block (RCB) analysis

The only random term in a traditional RCB analysis of these data is the (residual) error term $\boldsymbol{e} \sim N(\boldsymbol{0}, \sigma_e^2 \boldsymbol{I}_{224})$. The model therefore involves just one R structure and no G structures ($\boldsymbol{u} = \boldsymbol{0}$). In ASReml

- the error term is implicit in the model and is not formally specified on the model line,
- the IID variance structure $(\mathbf{R} = \sigma_e^2 \mathbf{I}_{224})$ is the default for error.

Important The error term is *always* present in the model but does not need to be formally declared when it has the default IID structure.

2a Random effects RCB analysis

The random effects RCB model has 2 random terms to indicate that the total variation in the data is comprised of 2 components, a random replicate effect $\boldsymbol{u}_r \sim N(\boldsymbol{0}, \gamma_r \sigma_e^2 \boldsymbol{I}_4)$ where $\gamma_r = \sigma_r^2 / \sigma_e^2$, and error as in **1**. This model involves both the original implicit IID R structure and an implicit IID G structure for the random replicates. In ASRemI

• IID variance structure is the default for the extra random terms in the model.

For this reason the only change to the original command file is the !r before See Section 6.4 repl. Important All random terms (other than error which is implicit) must be written after !r in the model specification line(s).

```
NIN Alliance Trial 1989
variety !A
id
pid
raw
repl 4
:
row 22
column 11
nin89.asd !skip 1
yield ~ mu variety !r repl
```

```
NIN Alliance Trial 1989
variety !A
id
pid
raw
repl 4
:
row 22
column 11
nin89.asd !skip 1
yield ~ mu variety repl
```

2b Random effects RCB analysis with a G structure specified

This model is equivalent to 2a but we explicitly specify the G structure for repl, that is, $u_r \sim N(0, \gamma_r \sigma_e^2 I_4)$, to introduce the syntax. See Section 7.4 The 0 0 1 line is called the *variance header* line. In general, the first two elements of this line refer to the R structures and the third element is the number of G structures. In this case 0 0 tells ASReml that there are no explicit R structures but there is one G structure See page 92 (1). The next two lines define the G structure. The first line, a G structure header line, links the structure that follows to a term in the lin-

ear model (repl) and indicates that it involves

```
NIN Alliance Trial 1989

variety !A

id

pid

raw

repl 4

:

row 22

column 11

nin89.asd !skip 1

yield ~ mu variety !r repl

0 0 1

repl 1

4 0 IDV 0.1
```

one variance model (1) (a 2 would mean that the structure was the direct product of two variance models). The second line tells ASRemI that the variance model for replicates is IDV of order 4 ($\sigma_r^2 I_4$). The 0.1 is a starting value for $\gamma_r = \sigma_r^2 / \sigma_e^2$; a starting value must be specified. Finally, the second element (0) on the last line of the file indicates that the effects are in standard order. There is almost always a 0 (no sorting) in this position for G structures. The following points should be noted:

• the 4 on the final line could have been written as repl to give

repl 0 IDV 0.1

This would tell ASRemI that the order or dimension of the IDV variance model is equal to the number of levels in repl (4 in this case),

- when specifying G structures, the user should ensure that one scale parameter is present. ASRemI does not automatically include and estimate a scale parameter for a G structure when the explicit G structure does not include one. For this reason
 - the model supplied when the G structure involves just one variance model must *not* be a correlation model (all diagonal elements equal 1),
 - all but one of the models supplied when the G structure involves more than one variance model must be correlation models; the other must be either an homogeneous or a heterogeneous variance model (see Section 7.5 for the distinction between these models; see also 5 for an example),
- an initial value must be supplied for all parameters in G structure definitions. ASRemI expects initial values immediately after the variance model identifier

See Sections 2.1 and 7.5

or on the next line (0.1 directly after IDV in this case),

- 0 is ignored as an initial value on the model line,
- if ASRemI does not find an initial value after the identifier, it will look on the next line,

See Chapter 14

See page 90

- if ASRemI does not find an initial value it will stop and give an error message in the .asr file,
- in this case $\mathbf{V} = \sigma_r^2 \mathbf{Z}_r \mathbf{Z}'_r + \sigma_e^2 \mathbf{I}_{224}$ which is fitted as $\sigma_e^2 (\gamma_r \mathbf{Z}_r \mathbf{Z}'_r + \mathbf{I}_{224})$ where γ_r is a variance ratio $(\gamma_r = \sigma_r^2 / \sigma_e^2)$ and σ_e^2 is the scale parameter. Thus 0.1 is a reasonable initial value for γ_r regardless of the scale of the data.

3a Two-dimensional spatial model with spatial correlation in one direction

This syntax specifies a two-dimensional spatial structure for error but with spatial correlation in the row direction only, that is, $\boldsymbol{e} \sim N(\boldsymbol{0}, \sigma_e^2 \boldsymbol{I}_{11} \otimes \boldsymbol{\Sigma}_r(\rho_r))$. The variance header line tells ASRemI that there is one R structure (1) which is a direct product of two variance models (2); there are no G structures (0). The next two lines define the two models that form the R structure. A structure definition line must be specified for *each* model. For $\boldsymbol{V} = \sigma_e^2 \boldsymbol{I}_{11} \otimes \boldsymbol{\Sigma}(\rho_r)$, the first matrix is an identity matrix of order 11 for columns (ID), the second matrix is a first order autoregres-



sive correlation matrix of order 22 for rows (AR1) and the variance scale parameter σ_e^2 is implicit. Note the following:

- placing column and row in the second position on lines 1 and 2 respectively tells ASRemI to internally sort the data *rows within columns* before processing the job. This is to ensure that the data matches the direct product structure specified. If column and row were replaced with 0 in these two lines, ASRemI would assume that the data were already sorted in this order (which is not true in this case),
- the 0.3 on line 2 specifies a starting autoregressive row correlation of 0.3. Note that for spatial analysis in two dimensions using a separable model, a complete matrix or array of plots must be present. To achieve this we augmented the data with the 18 records for the missing yields as shown on page 23. In the

See Chapter 13 See Sections 6.3

and 6.9

and 7.5

augmented data file the yield data for the missing plots have all been made NA (one of the missing value indicators in ASRemI) and variety has been arbitrarily coded LANCER for all of the missing plots (any of the variety names could have been used),

!f mv is now included in the model specification. This tells ASRemI to estimate the missing values. The !f before mv indicates that the missing values are fixed effects in the *sparse* set of terms,

• unlike the case with G structures, ASReml automatically includes and estimates a scale parameter for R structures (σ_e^2 for $V = \sigma_e^2(I_{11} \otimes \Sigma(\rho_r))$) in this case). This is why the variance models specified for row (AR1) and column (ID) are correlation models. The user could specify a non-correlation model (diagonal See Sections 2.1 elements $\neq 1$) in the R structure definition, for example, ID could be replaced by IDV to represent $V = \sigma_e^2(\sigma_c^2 I_{11}) \otimes \Sigma(\rho_r)$. However, IDV would then need to be followed by !S2=1 to fix σ_e^2 at 1 and prevent ASReml trying (unsuccessfully) to estimate two confounded parameters: the scale parameter associated with See Section 7.7 IDV and the implicit error variance parameter, see Section 2.1 under Combining variance models. Specifically, the code

11 column IDV 48 !S2==1

would be required in this case, where 48 is the starting value for the variances. This complexity allows for heterogeneous error variance.

3b Two-dimensional separable autoregressive spatial model

This model extends **3a** by specifying a first order autoregressive correlation model of order 11 for columns (AR1). The R structure in this case is therefore the direct product of two autoregressive correlation matrices that is, $\mathbf{V} = \sigma_e^2 \boldsymbol{\Sigma}_c(\rho_c) \otimes \boldsymbol{\Sigma}_r(\rho_r)$, giving a twodimensional first order separable autoregressive spatial structure for error. The starting column correlation in this case is also 0.3. Again note that σ_e^2 is implicit.

NIN Alliance Trial 1989
variety !A
id
÷
row 22
column 11
nin89aug.asd !skip 1
yield \sim mu variety !f mv
1 2 0
11 column AR1 0.3
22 row AR1 0.3

3c Two-dimensional separable autoregressive spatial model with measurement error

This model extends **3b** by adding a random units term. Thus

 $V = \sigma_e^2 (\gamma_\eta I_{242} + \Sigma_c(\rho_c) \otimes \Sigma_r(\rho_r))$. The reserved word units tells ASRemI to construct an additional random term with one level for each experimental unit so that a second (independent) error term can be fitted. A units term is fitted in the model in cases like this, where a variance structure is applied to the errors. Because a G structure is not explicitly specified here for units, the default IDV

```
NIN Alliance Trial 1989

variety !A

id

:

row 22

column 11

nin89aug.asd !skip 1

yield ~ mu variety !r units,

!f mv

1 2 0

11 column AR1 0.3

22 row AR1 0.3
```

structure is assumed. The units term is often fitted in spatial models for field trial data to allow for a nugget effect.

4 Two-dimensional separable autoregressive spatial model with random replicate effects

See Section 7.4

This is essentially a combination of **2b** and **3c** to demonstrate specifying an R structure and a G structure in the same model. The variance header line **1 2 1** indicates that there is one R structure (1) that involves two variance models (2) and is therefore the direct product of two matrices, and there is one G structure (1). The R structures are defined first so the next two lines are the R structure definition lines for e, as in **3b**. The last two lines are the G structure definition lines for repl, as in **2b**. In this case $\mathbf{V} = \sigma_e^2 (\gamma_r I_{242} + \Sigma_c(\rho_c) \otimes \Sigma_r(\rho_r))$.

5 Two-dimensional separable autoregressive spatial model defined as a G structure

This model is equivalent to **3c** but with the spatial model defined as a G structure rather than an R structure. As discussed in **2b**,

- See Section 7.7 *all but one* of the models supplied when the G structure involves more than one variance model must be correlation models,
 - the other model must not be a correlation model, that is, the other model must be either an homogeneous or a heterogeneous variance model, and an initial value for the scale parameter must be supplied.

```
NIN Alliance Trial 1989

variety !A

id

:

row 22

column 11

nin89.asd !skip 1

yield ~ mu variety,

!r row.column

0 0 1

row.column 2

row 0 AR1V 0.3 0.1

column 0 AR1 0.3
```

For this reason, the model for rows is now

AR1V and an initial value of 0.1 has been supplied for the scale parameter. In this case $\mathbf{V} = \sigma_e^2 (\gamma_{rc} \boldsymbol{\Sigma}_c(\rho_c) \otimes \boldsymbol{\Sigma}_r(\rho_r) + I_{224})$. Use of row.column as a G structure is a useful approach for analysing incomplete spatial arrays. This approach will often run faster for large trials but requires more memory.

Important Note that we have used the original version of the data and !f mv is omitted from this analysis since row.column is fitted as a G structure. If we had used the augmented data nin89aug.asd we would still omit !f mv and ASRemI would discard the records with missing yield.

	ASRemI syntax	extra random	terms		residual error	term	
		term	G stru	cture	term	R strue	cture
			models	3		models	
			1	2		1	2
1	yield \sim mu variety repl	-	-		error	ID	-
2a	yield \sim mu variety, !r repl	repl	IDV		error	ID	-
2b	<pre>yield ~ mu variety, !r repl 0 0 1 repl 1 4 0 IDV 0.1</pre>	repl	IDV		error	ID	-
3a	yield ~ mu variety, !f mv 1 2 0 11 column ID 22 row AR1 0.3	-	-		column.row	ID	AR1
3b	<pre>yield ~ mu variety, !f mv 1 2 0 11 column AR1 0.3 22 row AR1 0.3</pre>	-	-		column.row	AR1	AR1
3с	yield ~ mu variety, !r units !f mv 1 2 0 11 column AR1 0.3 22 row AR1 0.3	units	IDV		column.row	AR1	AR1
4	<pre>yield ~ mu variety, !r repl !f mv 1 2 1 11 column AR1 0.3 22 row AR1 0.3 repl 1 4 0 IDV 0.1</pre>	repl	IDV		column.row	AR1	AR1
5	<pre>yield ~ mu variety, !r column.row 0 0 1 column.row 2 column 0 AR1 .3 row 0 AR1V 0.3 0.1</pre>	column.row	AR1	AR1V	error	ID	-

Table 7.1: Sequence of variance structures for the NIN field trial data

7.4 Variance structures

The previous sections have introduced variance modelling in ASRemI using the NIN data for demonstration. In this and the remaining sections the syntax is described formally. However, where appropriate we continue to reference the example.

General syntax

Variance model specification in ASRemI has the following general form [variance header line [R structure definition lines] [G structure header and definition lines] [variance parameter constraints]]

- variance header line specifies the number of R and G structures,
- *R structure definition lines* define the R structures (variance models for error) as specified in the variance header line,
- *G structure header and definition lines* define the G structures (variance models for the additional random terms in the model) as specified in the variance header line; these lines are always placed after any R structure definition lines,
- variance parameter constraints are included if parameter constraints are to be imposed, see the !VCC c qualifier in Table 5.5 and Section 7.9 on constraints between and within variance structures.

A schematic outline of the variance model specification lines (variance header line, and R and G structure definition lines) is presented in Table 7.2 using the variance model of $\bf{4}$ for demonstration.

general syntax			model 4
variance header line	$[s \ [c \ [g]$]]	1 2 1
R structure definition lines	S_1	C_1 C_2 : C_c	11 column AR1 0.3 22 row AR1 0.3
	S_2	C_1 : C_c	- : -
	÷	÷	÷
	S_s	C_1 : C_c	-
G structure definition lines	G_1		repl 1 4 0 IDV 0.1
	G_2		-
	:		÷
	Gg		-

	Table 7.2:	Schematic	outline of	of	variance	model	specification	in	ASReml
--	------------	-----------	------------	----	----------	-------	---------------	----	--------
Variance header line

See Table 7.3 See Section 7.7 The variance header line is of the form $[s \ [c \ [g]]]$

- *s* and *c* relate to the R structures, *g* is the number of G structures,
- the variance header line may be omitted if the default IID R structure is required, no G structures are being explicitly defined and there are no parameter constraints (see !VCC and examples 1 and 2a),
- *s* is used to code the number of independent sections in the error term
 - if s = 0, the default IID R structure is assumed and no R structure definition lines are required (as in examples **2b** and **5**),

```
NIN Alliance Trial 1989
variety !A
id
:
row 22
column 11
nin89aug.asd !skip 1
yield ~ mu variety !r repl,
!f mv
1 2 1
22 row AR1 0.3
11 column AR1 0.3
repl 1
repl 0 IDV 0.1
```

- if s > 0, s R structure definitions are required, one for each of the s sections (as in examples 3a, 3b, 3c and 4),
- for the analysis of multi-section data s can be replaced by the name of a factor with the appropriate number of levels, one for each section,
- c is the number of component variance models involved in the variance structure for the error term for each section; for example, **3a**, **3b** and **3c** have column.row as the error term and the variance structure for column.row involves 2 variance models, the first for column and the second for row,
 - c has a default value of 2 when s is not specified as zero,
- g is the number of variance structures (G structures) that will be explicitly specified for the random terms in the model.

R and G structures are now discussed with reference to s, c and g. As already noted, each variance structure may involve several variance models which relate to the individual terms involved in the random effect or error. For example, a two factor interaction may have a variance model for each of the two factors involved in the interaction. Variance models are listed in Table 7.3. As indicated in the discussion of **2b**, care must be taken with respect to scale parameters when combining variance models (see also Section 7.7).

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R structure definition

For each of the s sections there must be $c \ R$ structure definitions. Each definition may take several lines. Each R structure definition specifies a variance model and has the form

order [field model [initial_values] [qualifiers] [additional_initial_values]]

• *order* is either the number of levels in the corresponding term or the name of a factor that has the same number of levels as the term, for example,

11 column AR1 0.5

is equivalent to

column column AR1 0.5

when column is a factor with 11 levels,

• *field* is the name of the data field (variate or factor) that corresponds to the term and therefore indexes the levels of the term;



- ASReml uses this field to sort the units so they match the R structure,
- in the example the data will be sorted internally rows within columns for the analysis but the residuals will be printed in the .yht file in the original order (which is actually rows within columns in this case).

Important It is assumed that the joint indexing of the components uniquely defines the experimental units,

- if *field* is a variable, it can be plot coordinates provided the plots are in a regular grid. Thus in this example

11 lat AR1 0.3 22 long AR1 0.3

is valid because lat gives column position and long gives row position, and the positions are on a regular grid. The autoregressive correlation values will still be on an plot index basis (1, 2, 3, ...), not on a distance basis (10m, 20m, 30m, ...),

- if the data is sorted appropriately for the order the models are specified, set field to 0,
- *model* specifies the variance model for the term, for example,

22 row AR1 0.3

chooses a first order autoregressive model for the row error process,

- all the variance models available in ASReml are listed in Table 7.3,
- these models have associated variance parameters,
- a error variance component (σ_e^2 for the example, see Section 7.3) is automatically estimated for each section,
- the default *model* is ID,
- *initial_values* are initial or starting values for the variance parameters and must be supplied, for example,

22 row AR1 0.3

chooses an autoregressive model for the row error process (see Table 7.1) with a starting value of 0.3 for the row correlation,

- *qualifiers* tell ASRemI to modify the variance model in some way; the qualifiers are described in Table 7.4,
- *additional_initial_values* are read from the following lines if there are not enough initial values on the model line. Each variance model has a certain number of parameters. If insufficient non zero values are found on the model line ASReml expects to find them on the following line(s),
 - initial values of 0.0 will be ignored if they are on the model line but are accepted on subsequent lines,
 - the notation n * v (for example, 5 * 0.1) is permitted on subsequent lines (but not the model line) when there are n repeats of a particular initial value v,
 - only in a few specified cases is 0 permitted as an initial value of a non-zero parameter.

G structure header and definition lines

There are g sets of G structure definition lines and each set is of the form

model_term d
order [key model [initial_values] [qualifier]
[additional_initial_values]]
order [key model [initial_values] [qualifier]
[additional_initial_values]]

order [key model [initial_values] [qualifier] [additional_initial_values]]

- *model_term* is the term from the linear model to which the variance structure applies; the variance structure may cover additional terms in the linear model, see Section 7.8
- *d* is the number of variance models and hence direct product matrices involved in the G structure; the following lines define the *d* variance models,
- *order* is either the number of levels in the term or the name of a factor that has the same number of levels as the component,

```
NIN Alliance Trial 1989
variety !A
id
.
row 22
column 11
nin89aug.asd !skip 1
yield ~ mu variety !r repl,
!f mv
1 2 1
22 row AR1 0.3
11 column AR1 0.3
repl 1
repl 0 IDV 0.1
```

- *key* is usually zero but for power models (EXP, GAU,...) provides the distance data needed to construct the model,
- model is the ASReml variance model identifier/acronym selected for the term,
 - variance models are listed in Table 7.3,
 - these models have associated variance parameters,
- *initial_values* are initial or starting values for the variance parameters, the values for initial values are as described above for R structure definition lines,
- *qualifier* tells ASReml to modify the variance model in some way; the qualifiers are described in Table 7.4.

7.5 Variance model description

Table 7.3 presents the full range of variance models, that is, correlation, homogeneous variance and heterogeneous variance models available in ASRemI. The table contains the model identifier, a brief description, its algebraic form and the number of parameters. The first section defines (BASE) correlation models and in the next section we show how to extend them to form variance models. The second section defines some models parameterized as variance/covariance matrices rather than as correlation matrices. The third section covers some special cases where the covariance structure is known except for the scale.

Forming variance models from correlation models

The base identifiers presented in the first part of Table 7.3 are used to specify the correlation models. The corresponding homogeneous and heterogeneous variance models are specified by appending V and H to the base identifiers respectively. This convention holds for most models. However, no V or H should be appended to the base identifiers for the heterogeneous variance models at the end of the table (from DIAG on).

In summary, to specify

• a correlation model, provide the base identifier given in Table 7.3, for example

EXP .1

is an exponential correlation model,

• an homogeneous variance model, append a V to the base identifier and provide an additional initial value for the variance, for example,

EXPV .1 .3

is an exponential variance model,

• a heterogeneous variance model, append an H to the base identifier and provide additional initial values for the diagonal variances, for example,

CORUH .1 .3 .4 .2

is a 3-dimensional uniform correlation variance model, heterogeneous form.

Important See Section 7.7 for rules on combining variance models and important notes regarding initial values.

The algebraic forms of the homogeneous and heterogeneous variance models are determined as follows. Let $C^{(\omega \times \omega)} = [C_{ij}]$ denote the correlation matrix for a particular correlation model. If $\Sigma^{(\omega \times \omega)}$ is the corresponding homogeneous variance matrix then

$$\Sigma = \sigma^2 C.$$

It has just one more parameter than the correlation model. For example, the homogeneous variance model corresponding to the ID correlation model has variance matrix $\Sigma = \sigma^2 I_{\omega}$ (specified IDV in the ASReml command file, see below) and one parameter. The initial values for the variance parameters are listed after the initial values for the correlation parameters. For example, in

AR1V 0.3 0.5

0.3 is the initial spatial correlation parameter and 0.5 is the initial variance parameter value.

Similarly, if $\Sigma_h^{(\omega \times \omega)}$ is the heterogeneous variance matrix corresponding to C, then

$$\Sigma_h = DCD$$

where $D^{(\omega \times \omega)} = \text{diag}(\sigma_i)$. In this case there are an additional ω parameters. For example, the heterogeneous variance model corresponding to ID has variance matrix

$$\Sigma_h = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{\omega}^2 \end{bmatrix}$$

(specified IDH in the ASReml command file, see below) and involves the ω parameters $\sigma_1^2 \dots \sigma_{\omega}^2$.

Additional notes on variance models

These additional notes are to assist in interpreting Table 7.3.

- the IDH and DIAG models fit the same diagonal variance structure,
- the CORGH and US models fit the same completely general variance structure parameterized differently,
- in CHOLk models $\Sigma = LDL'$ where L is lower triangular with ones on the diagonal, D is diagonal and k is the number of non-zero off diagonals in L,
- in ANTE k models $\Sigma^{-1} = UDU'$ where U is upper triangular with ones on the diagonal, D is diagonal and k is the number of non-zero off diagonals in U,
- the CHOLk and ANTEk models are equivalent to the US structure, that is, the full variance structure, when k is $\omega 1$,

• initial values for US, CHOL and ANTE structures are given in the form of a US matrix which is specified lower triangle row-wise, viz

```
\begin{bmatrix} \sigma_{_{11}} & & \\ \sigma_{_{21}} & \sigma_{_{22}} & \\ \sigma_{_{31}} & \sigma_{_{32}} & \sigma_{_{33}} \end{bmatrix},
```

that is, initial values are given in the order, $1 = \sigma_{11}$, $2 = \sigma_{21}$, $3 = \sigma_{22}$,...

- the US model is associated with several special features of ASReml. When used in the R structure for multivariate data, ASReml automatically recognises patterns of missing values in the responses (see Chapter 8). Also, there is an option to update its values by EM rather than AI when its AI updates make the matrix non positive definite.
- power models rely on the definition of distance for the associated term, for example,
 - the distance between time points in a one-dimensional longitudinal analysis,
 - the spatial distance between plot coordinates in a two-dimensional field trial analysis.

Information for determining distances is supplied by the key argument on the structure line.

- For one dimensional cases, *key* may be
 - * the name of a data field containing the coordinate values
 - * 0 in which case a vector of coordinates of length *order* must be supplied after all R and G structure lines.
- In two directions (IEXP, IGAU, IEUC, AEXP, AGAU) the key argument in the G structure definition has either
 - * the form rrcc where rr is the number of a data field containing the coordinates for the first dimension and cc is the number of a data field containing the coordinates for the second direction. For example, in the analysis of spatial data, if the x coordinate was in field 3 and the y coordinate was in field 4, the second argument would be 304.
 - * or when used with a factor created by the fac() model term, the syntax would be as demonstrated in the following example

```
:
y ~ mu ...!r fac(x,y) ...
:
fac(x,y) 1
fac(x,y) fac(x,y) EUCV .7 1.3
```

- FAk, FACVk and XFAk are different parameterizations of the factor analytic model in which Σ is modelled as $\Sigma = \Gamma \Gamma' + \Psi$ where $\Gamma^{(\omega \times k)}$ is a matrix of loadings on the covariance scale and Ψ is a diagonal vector of specific variances. See Smith *et al.* (2001) and Thompson *et al.* (2003) for examples of factor analytic models in multi-environment trials. The general limitations are
 - that Ψ may not include zeros except in the XFAk formulation
 - constraints are required in Γ for k > 1 for identifiability. Typically, one zero is placed in the second column, two zeros in the third column, etc.
 - The total number of parameters fitted $(k\omega + \omega k(k-1)/2)$ may not exceed $\omega(\omega + 1)/2$.
- in FAk models the variance-covariance matrix $\Sigma^{(\omega \times \omega)}$ is modelled on the correlation scale as $\Sigma = DCD$, where
 - $D^{(\omega \times \omega)}$ is diagonal,
 - $DD = \operatorname{diag}(\Sigma)$,
 - $C^{(\omega \times \omega)}$ is a correlation matrix of the form FF' + E where $F^{(\omega \times k)}$ is a matrix of loadings on the correlation scale and E is diagonal and is defined by difference so that (FF' + E) is a correlation matrix (diagonal elements equal 1),
 - the parameters are specified in the order loadings for each factor (\mathbf{F}) followed by the variances (diag (Σ)); when k is greater than 1, constraints on the elements of \mathbf{F} are required, see Table 7.5,
- FACVk models (CV for *covariance*) are an alternative formulation of FA models in which Σ is modelled as $\Sigma = \Gamma \Gamma' + \Psi$ where $\Gamma^{(\omega \times k)}$ is a matrix of loadings on the covariance scale and Ψ is diagonal
 - the parameters are specified in the order loadings (Γ) followed by variances (Ψ); when k is greater than 1, constraints on the elements of Γ are required, see Table 7.5,
 - the parameters in FACV are related to those in FA by $\Gamma = DF$ and $\Psi = DED$,
- XFAk (X for *extended*) is the third form of the factor analytic model and has the same parameterisation as for FACV, that is, $\Sigma = \Gamma \Gamma' + \Psi$. However, XFA models
 - the parameters are specified in the order diag (Ψ) and vec (Γ) ; when k is greater than 1, constraints on the elements of Γ are required, see Table 7.5,
 - can only be used in G structures in combination with the xfa(f,k) model term,

- return the factors as well as the effects.
- permit some elements of Ψ to be fixed to zero,
- may not be used in R structures,
- are computationally faster than the FACV formulation for large problems when k is much smaller than ω ,

Special consideration is required when using the XFAk model. The SSP must be expanded to have room to hold the k factors. This is achieved by using the xfa(f, k) model term in place of f in the model. For example,

```
y ~ site !r geno.xfa(site,2)
0 0 1
geno.xfa(site,2) 2
geno
xfa(site,2) 0 XFA2
```

• the OWN variance structure is a facility whereby users may specify their own variance structure. This facility requires the user to supply a program MYOWNGDG that reads the current set of parameters, forms the G matrix and a full set of derivative matrices, and writes these to disk. Before each iteration, ASRemI writes the OWN parameters to a file, runs MYOWNGDG (which it presumes forms the G and derivative matrix) and then reads the matrices back in. An example of MYOWNGDG.f90 is distributed with ASRemI. It duplicates the AR1 and AR2 structures. The following job fits an AR2 structure using this program.

Example of using the OWN structure
 rep
 blcol
 blrow
 variety 25
 yield
shf.asd !skip 1
y ~ va
1 2
10 0 AR1 .1
15 0 OWN2 .2 .1 !TRR

The file written by ASReml has extension .own and looks like

15 2 1 0.6025860D+000.1164403D+00 This file was written by asreml for reading by your program MYOWNGDG asreml writes this file, runs your program and then reads shfown.gdg which it presumes has the following format: The first lines should agree with the top of this file specifying the order of the matrices (15) the number of variance parameters (2) and a control parameter you can specify (1). These are written in (315) format. They are followed by the list of variance parameters written in (6D13.7) format. Follow this with 3 matrices written in (6D13.7) format. 120 elements being lower triangle These are to be each of row-wise of the G matrix and its derivatives with respect to the parameters in turn.

This file contains details about what is expected in the file written by your program. The filename used has the same basename as the job you are running with extension .own for the file written by ASRemI and .gdg for the file your program writes. The type of the parameters is set with the !T qualifier described below. The control parameter is set using the !F qualifier.

- !F2 applies to OWN models. With OWN, the argument of !F is passed to the MYOWNGDG program as an argument the program can access. This is the mechanism that allows several OWN models to be fitted in a single run.
- !Ts is used to set the type of the parameters. It is primarily used in conjunction with the OWN structure as ASReml knows the type in other cases. The valid type codes are as follows:

code	description	action if $!GP$ is set
V	variance	forced positive
G	variance ratio	forced positive
R	correlation	-1 < r < 1
С	covariance	
Р	positive correlation	0 < r < 1
L	loading	

This coding also affects whether the parameter is scaled by σ^2 in the output report.

base	description	algebraic	number of parameters †			
identifier		form	corr	homo's variance	hetero's variance	
Correlatio	on models					
ID	identity	$C_{ii}=1,\;C_{ij}=0,\;\;i\neq j$	0	1	ω	
AR[1]	1 st order autoregressive	$\begin{split} C_{ii} &= 1, \; C_{i+1,i} = \phi_1 \\ C_{ij} &= \phi_1 C_{i-1,j}, \; i > j+1 \\ \phi_1 < 1 \end{split}$	1	2	$1 + \omega$	
SAR	symmetric autoregressive	$\begin{split} &C_{ii} = 1, \\ &C_{i+1,i} = \phi_1/(1+\phi_1^2/4) \\ &C_{ij} = \phi_1 C_{i-1,j} - \phi_1^2/4 \; C_{i-2,j}, \\ &i > j+1 \\ & \phi_1 < 1 \end{split}$	1	2	$1 + \omega$	
AR2	2 nd order autoregressive	$\begin{split} &C_{ii} = 1, \\ &C_{i+1,i} = \phi_1/(1-\phi_2) \\ &C_{ij} = \phi_1 C_{i-1,j} + \phi_2 C_{i-2,j}, \; i > j+1 \\ & \phi_1 < (1-\phi_2), \phi_2 < 1 \end{split}$	2	3	$2 + \omega$	
MA[1]	1 st order moving average	$\begin{split} &C_{ii} = 1, \\ &C_{i+1,i} = -\theta_1/(1+\theta_1^2) \\ &C_{ji} = 0, \; j > i+2 \\ & \theta_1 < 1 \end{split}$	1	2	$1 + \omega$	
MA2	2 ^{<i>nd</i>} order moving average	$\begin{split} &C_{ii} = 1, \\ &C_{i+1,i} = -\theta_1(1-\theta_2)/(1+\theta_1^2+\theta_2^2) \\ &C_{i+2,i} = -\theta_2/(1+\theta_1^2+\theta_2^2) \\ &C_{ji} = 0, \; j > i+2 \\ &\theta_2 \pm \theta_1 < 1 \\ & \theta_1 < 1, \; \theta_2 < 1 \end{split}$	2	3	$2 + \omega$	
ARMA	autoregressive moving average	$\begin{split} &C_{ii} = 1, \\ &C_{i+1,i} = (\theta - \phi)(1 - \theta \phi)/(1 + \\ &\theta^2 - 2\theta \phi) \\ &C_{ji} = \phi C_{j-1,i}, \ j > i+1 \\ & \theta < 1, \ \phi < 1 \end{split}$	2	3	$2 + \omega$	
CORU	uniform correlation	$C_{ii}=1,\;C_{ij}=\phi,\;i\neq j$	1	2	$1 + \omega$	

Table 7.3: Details of the variance models available in ASRemI

base	description	algebraic	nu	number of parameters †			
identifier		form	corr	homo's variance	hetero's variance		
CORB	banded correlation	$\begin{split} C_{ii} &= 1 \\ C_{i+j,i} &= \phi_j, \ 1 \leq j \leq \omega - 1 \\ \phi_j < 1 \end{split}$	$\omega - 1$	ω	$2\omega - 1$		
CORG	general correlation $CORGH = US$	$\begin{split} C_{ii} &= 1 \\ C_{ij} &= \phi_{ij}, \; i \neq j \\ \phi_{ij} < 1 \end{split}$	$\frac{\omega(\omega-1)}{2}$	$\frac{\omega(\omega-1)}{2}$ +1	$\frac{\frac{\omega(\omega-1)}{2}}{+\omega}$		
One-dimen	sional power models						
EXP	exponential	$\begin{split} C_{ii} &= 1 \\ C_{ij} &= \phi^{ x_i - x_j }, \; i \neq j \\ x_i \; \text{are coordinates} \\ 0 &< \phi < 1 \end{split}$	1	2	$1 + \omega$		
GAU	gaussian	$\begin{split} C_{ii} &= 1 \\ C_{ij} &= \phi^{(x_i - x_j)^2} \\ x_i \text{ are coordinates} \\ 0 &< \phi < 1 \end{split}$	1	2	$1 + \omega$		
Two-dimer	isional power models						
IEXP	isotropic expo- nential	$\begin{split} &C_{ii} = 1 \\ &C_{ij} = \phi^{ x_i - x_j + y_i - y_j } \\ & \boldsymbol{x} \text{ and } \boldsymbol{y} \text{ vectors of coordinates} \\ &0 < \phi < 1 \end{split}$	1	2	$1 + \omega$		
IGAU	isotropic gaus- sian	$\begin{split} &C_{ii} = 1 \\ &C_{ij} = \phi^{(x_i - x_j)^2 + (y_i - y_j)^2} \\ & \boldsymbol{x} \text{ and } \boldsymbol{y} \text{ vectors of coordinates} \\ &0 < \phi < 1 \end{split}$	1	2	$1 + \omega$		
IEUC	isotropic eu- clidean	$\begin{split} &C_{ii} = 1 \\ &C_{ij} = \phi \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \\ & \textbf{\textit{x}} \text{ and } \textbf{\textit{y}} \text{ vectors of coordinates} \\ &0 < \phi < 1 \end{split}$	1	2	$1 + \omega$		

Details of the variance models available in ASRemI

base	description	algebraic	number of parameters †				
identifier		form	corr	homo's variance	hetero's variance		
AEXP	anisotropic ex- ponential	$\begin{split} &C_{ii} = 1 \\ &C_{ij} = \phi_1^{ x_i - x_j } \phi_2^{ y_i - y_j } \\ & \textbf{x} \text{ and } \textbf{y} \text{ vectors of coordinates} \\ &0 < \phi_1 < 1, 0 < \phi_2 < 1 \end{split}$	2	3	$^{2+\omega}$		
AGAU	anisotropic gaussian	$\begin{split} &C_{ii} = 1\\ &C_{ij} = \phi_1^{\left(x_i - x_j\right)^2} \phi_2^{\left(y_i - y_j\right)^2}\\ &\textbf{x} \text{ and } \textbf{y} \text{ vectors of coordinates}\\ &0 < \phi_1 < 1, 0 < \phi_2 < 1 \end{split}$	2	3	$2 + \omega$		
Additional heterogeneous variance models							
DIAG	diagonal = IDH	$\pmb{\Sigma}_{ii}=\phi_i~\pmb{\Sigma}_{ij}=0,~i\neq j$	-	-	ω		
US	unstructured general covari- ance matrix	${oldsymbol{\Sigma}}_{ij}=\phi_{ij}$	-	-	$\frac{\omega(\omega+1)}{2}$		
OWNk	$\begin{array}{llllllllllllllllllllllllllllllllllll$		-	-	k		
ANTE[1] ANTEk	$ \begin{array}{cccc} 1_{th}^{st} & k & \text{order} \\ k^{th} & \text{antede-} \\ & \text{pendence} \\ 1 \leq k \leq \omega - 1 \end{array} $	$\begin{split} \boldsymbol{\Sigma}^{-1} &= \boldsymbol{U} \boldsymbol{D} \boldsymbol{U}' \\ D_{ii} &= d_i, \ D_{ij} = 0, \ i \neq j \\ U_{ii} &= 1, \ U_{ij} = u_{ij}, \ 1 \leq j - i \leq k \\ \boldsymbol{U}_{ij} &= 0, \ i > j \end{split}$	-	-	$\frac{\omega(\omega+1)}{2}$		
CHOL[1] CHOL k	$ \begin{array}{ll} 1_{th}^{st} & k \text{order} \\ k^{th} & \text{cholesky} \\ 1 \leq k \leq \omega - 1 \end{array} $	$\begin{split} \boldsymbol{\Sigma} &= L \boldsymbol{D} L' \\ D_{ii} &= d_i, \ D_{ij} = 0, \ i \neq j \\ L_{ii} &= 1, \ L_{ij} = l_{ij}, \ 1 \leq i-j \leq k \end{split}$	-	-	$\frac{\omega(\omega+1)}{2}$		
FA[1] FA <i>k</i>	$egin{array}{ccc} 1^{st} & k ext{ order} \ k^{th} & ext{factor} \ analytic \end{array}$	$egin{aligned} m{\Sigma} &= m{D}m{C}m{D}, \ m{C} &= m{F}m{F}' + m{E}, \ m{F} \ contains \ k \ correlation \ factors \ m{E} \ diagonal \ m{D}m{D} &= ext{diag}\left(m{\Sigma} ight) \end{aligned}$	-	-	$\begin{aligned} &\omega+\omega\\ &k\omega+\omega\end{aligned}$		

Details of the variance models available in ASRemI

base	description		algebraic	number of parameters †			
identifier			form	corr	homo's variance	hetero's variance	
	st						
FACV[1] FACVk	$\frac{1}{k^{th}}$	k order factor	$\Sigma = \Gamma \Gamma' + \Psi,$ Γ contains covariance factors	-	-	$\omega + \omega$ $k\omega + \omega$	
TROVIN	10	analytic	Ψ contains specific variance				
		covariance form					
XFA[1]	1^{st}	k order	$oldsymbol{\Sigma} = oldsymbol{\Gamma} oldsymbol{\Gamma}' + oldsymbol{\Psi},$	-	-	$\omega + \omega$	
$\mathtt{XFA}k$	$k^{^{th}}$	k^{th} extended	Γ contains covariance factors			$k\omega+\omega$	
		factor analytic	Ψ contains specific variance				
		covariance					
		form					
Inverse r	elatio	nship matric	es [‡]				
AINV	invers	se relationship ma	atrix derived from pedigree	0	1	-	
GIV1	gener	alised inverse nur	nber 1	0	1	-	
:	:		:	:	:		
				•			
GTAP	gener	ansed inverse nur	nder o	U	1	-	

Details of the variance models available in ASRemI

[†] This is the number of values the user must supply as initial values where ω is the dimension of the matrix. The homogeneous variance form is specified by appending V to the correlation basename; the heterogeneous variance form is specified by appending H to the correlation basename

 ‡ These must be associated with 1 variance parameter unless used in direct product with another structure which provides the variance.

7.6 Variance structure qualifiers

Table 7.4 describes the R and G structure line qualifiers.

Table 7.4: List of R and G structure qualifiers

qualifier	action
!= <i>s</i> !GP, !GU, !GF, !GZ	used to constrain parameters within variance structures, see Section 7.9. modify the updating of the variance parameters. The exact action of these codes in setting bounds for parameters depends on the particular model.
	!GP (the default in most cases) attempts to keep the parameter in the theoretical parameter space and is activated when the update of a parameter would take it outside its space. For example, if an update would make a variance negative, the negative value is replaced by a small positive value. Under the !GP condition, repeated attempts to make a variance negative are detected and the value is then <i>fixed</i> at a small positive value. This is shown in the output in that the parameter will have the code B rather than P appended to the value in the variance component table.
	$!GU$ (unrestricted) does not limit the updates to the parameter. This allows variance parameters to go negative and correlation parameters to exceed ± 1 . Negative variance components may lead to problems; the mixed model coefficient matrix may become non-positive definite. In this case the sequence of REML log-likelihoods may be erratic and you may need to experiment with starting values.
	!GF fixes the parameter at its starting value
	$! {\tt GZ}$ only applies to ${\tt FA}$ and ${\tt FACV}$ models and fixes the parameter in an ${\tt FA}$ factor to ${\tt ZERO}$
	For multiple parameters, the form $!GXXXX$ can be used to specify F, P, U or Z for the parameters individually. A shorthand notation allows a repeat count before a code letter. Thus $!GPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPPP$
	For a US model, !GP forces ASRemI to attempt to keep the matrix positive definite. After each AI update, it extracts the eigenvalues of the updated matrix. If any are negative or zero, the AI update is discarded and an EM update is performed. Notice that the EM update is applied to all of the variance parameters in the particular US model and cannot be applied to only a subset of them.

qualifier	action
!S2=value	sets the value of the error variance within the section: the $!S2=$ qualifier may be used in R structure definitions to represent the residual vari- ance associated with the particular section. There is always an error variance parameter associated with a section R structure. In multiple section analyses the $!S2=$ qualifier is used on the first of the <i>c</i> lines for each section to set the initial error variance for that section. If this is not supplied, ASRemI calculates an initial value that is half the simple variance of the data in the site. To fix the variance $!S2==v$ is used.
!S2==value	is used in a similar manner to $!{\tt S2=}$ except that the variance is fixed at the value.
!S2==1	is often used in the analysis of multiple section data and in multivariate analyses and when variance parameters are included in the R structure models.

7.7 Rules for combining variance models

As noted in Section 2.1 under Combining variance models, variance structures are sometimes formed by combining variance models. For example, a two factor interaction may involve two variance models, one for each of the two factors in the interaction. Some of the rules for combining variance models differ for R structures and G structures. A summary of the rules is as follows:

- when combining variance models in both R and G structures, the resulting direct product structure must match the ordered effects with the outer factor first, for example, the G structure in the example opposite is for column.row which tells ASRemI that the direct product structure matches the effects ordered rows *within* columns. This is why the G structure definition line for column is specified first,
- ASRemI automatically includes and estimates an error variance parameter for each

NIN Alliance Trial 1989 variety !A id : row 22 column 11 nin89.asd !skip 1 yield ~ mu variety !r repl, !f mv 0 0 1 column.row 2 column 0 AR1 0.4 row 0 ARV1 0.3 0.1

section of an R structure. The variance structures defined by the user should therefore normally be correlation matrices. A variance model can be specified See Sections 2.1

and 7.5

but the !S2==1 qualifier would then be required to fix the error variance at 1 and prevent ASReml trying to estimate two confounded parameters (error variance and the parameter corresponding to the variance model specified, see **3a** on page 83),

- ASReml does not have an implicit scale parameter for G structures that are defined explicitly. For this reason the model supplied when the G structure involves just one variance model must be a variance model; an initial value must be supplied for this associated scale parameter; this is discussed under *additional_initial_values* on page 91,
- when the G structure involves more than one variance model, one must be either a homogeneous or a heterogeneous variance model and the rest should be correlation models; if more than one are non-correlation models then the **!GF** qualifier should be used to avoid identifiability problems, that is, ASRemI trying to estimate confounded parameters.

7.8 G structures involving more than one random term

The usual case is that a variance structure applies to a particular term in the linear model and that there is no covariance between model terms. Sometimes it is appropriate to include a covariance. Then, it is essential that the model terms be listed together and that the variance structure defined for the first term be the structure required for both terms. When the terms are of different size, the terms should be linked together with the ! { and ! } qualifiers (Table 6.1). While ASRemI will check the overall size, it does not check that the order of effects matches the structure definition so the user must be careful to get this right. Check that the terms are conformable by considering the order of the fitted effects and ensuring the first term of the direct product corresponds to the outer factor in the nesting of the effects. Two examples are

• random regressions where we want a covariance between intercept and slope

```
:
!r animal animal.time
:
animal 2
2 0 US 3 -.5 2
animal
```

is equivalent (though not identical because of the scaling changes) to

÷

```
!r pol(time,1).animal
  ÷
 pol(time,1).animal 2
 pol(time,1) 0 US 1 -.1 .2
 animal
• maternal/direct genetic covariance
  lambid !P
  sireid !P
  damid !P
  :
 wwt ywt ~ Trait Trait.sex !r !{ Trait.lambid at(Trait,2).damid !}
 Trait.lambid 2
 3 0 US
 1.3
                 # Var(wwt_D)
 1.0 2.2
                 # Cov(wwt_D,ywt_D) Var(ywt_D)
 -.1 -.2 0.8
                 # Cov(wwt_D,wwt_M) Cov(ywt_D,wwt_M) Var(wwt_M)
 lambid O AINV # AINV explicitly requests to use A inverse
```

7.9 Constraining variance parameters

Parameter constraints within a variance model

Equality of parameters in a variance model can be specified using the !=s qualifier where s is a string of letters and/or zeros (see Table 7.4). Positions in the string correspond to the parameters of the variance model:

- all parameters with the same letter in the structure are treated as the same parameter,
- A to Z matches a to z, so that 26 equalities at most can be formed,
- all parameters corresponding to 0 in the string are unconstrained.

Examples are presented in Table 7.5.

ASReml code	action
!=ABACBAOCBA	constrain all parameters corresponding to A to be equal, similarly for B and C. The 7th parameter would be left uncon- strained. This sequence applied to an unstructured 4×4 matrix would make it banded, that is A B A C B A 0 C B A
<pre>site.gen 2 # G header line site 0 US .3 !=0A0AA0 !GPUPUUP .1 .4 .1 .1 .3 gen</pre>	this example defines a structure for the genotype by site interaction effects in a MET in which the genotypes are independent random effects within sites but are correlated across sites with equal covariance.
<pre>site 0 FA2 !G4PZ3P4P !=00000000VVVV 4*.9 # initial values for 1st factor 0 3*.1 # initial values for 2nd factor # first fixed at 0 4*.2 # init values for site variances</pre>	a 2 factor Factor Analytic model for 4 sites with equal variance is specified us- ing this syntax. The first loading in the second factor is constrained equal to 0 for identifiability. P places restrictions on the magnitude of the loadings and the variances to be positive.
<pre>xfa(site,2) 0 XFA2 !=VVVV0 !4P4PZ3P 4*.2 # initial specific variances 4*1.2 # initial loadings for 1st factor 0 3*.3 # initial loadings for 2nd factor</pre>	a 2 factor Factor analytic model in which the specific variances are all equal.

T-1-1-7 F.	E	- f				•	
Table (.5)	Examples	OT	constraining	variance	parameters	In	ASRemi

Constraints between and within variance models

More general relationships between variance parameters can be defined using the !VCCc qualifier placed on the data file definition line.

- !VCC c specifies that there are c constraint lines defining constraints to be applied,
- the constraint lines occur after the variance header line and any R and G structure lines, that is, there must be a variance header line,
- each constraint is specified in a separate line in the form

 $P_1 \ast V_1 \quad P_2 \ast V_2 \quad \dots \quad$

- P_i is the number of a parameter and V_i is a coefficient,
- P_1 is the primary parameter number,
- * indicates that the next values (V_i) is a weighting coefficient,
- if the coefficient is 1 you may omit the * 1,
- if the coefficient is -1 you may write $-P_i$ instead of $P_i * -1$,
- the meaning of the coefficients is as follows $P_2 = V_2 * P_1/V_1$,
- typically $V_1 = 1$,
- a variance parameter may only be included in constraints once,
- the P_i terms refer to positions in the full variance parameter vector. This may change if the model is changed. The full vector includes a term for each factor in the model and then a term for each parameter defined in the R and G structures. A list of P_i numbers and their initial values is returned in the .asl file to help you to check the numbers. Alternatively, examine the .asr file from an initial run with !VCC included but no arguments supplied. The job will terminate but ASRemI will provide the P_i values associated with each variance component. Otherwise the numbers are given in the .res file.

The following are examples:

ASRemI code	action
57*.1	parameter 7 is a tenth of parameter 5
5 -7	parameter 7 is the negative of parameter 5 $$
32 34 35 37 38 39	for a (4×4) US matrix given by parameters $31 \dots 40$, the covariances are forced to be equal.

7.10 Model building using the **!**CONTINUE qualifier

In complex models, the Average Information algorithm can have difficulty maximising the REML log-likelihood when starting values are not reasonably close. ASReml has several internal strategies to cope with this problem but these are not always successful.

When the user needs to provide better starting values, one method is to fit a simpler variance model. For example, it can be difficult to guess reasonable starting values for an unstructured variance matrix. A first step might be to assume independence and just estimate the variances. If all the variances are not positive, there is little point proceeding to try and estimate the covariances.

The **!CONTINUE** qualifier instructs **ASRemI** to retrieve variance parameters from the .rsv file if it exists rather than using the values in the .asr file. When reading the .rsv file, it will take results from some matrices as supplying starting values for other matrices. The transitions recognised are

DIAG to CORUH DIAG to FA1 CORUH to FA1 FA*i* to FA*i+1* FA*i* to CORGH FA*i* to US CORGH to US

The use of the .rsv file with !CONTINUE in this way reduces the need for the user to type in the updated starting values.

The various models may be written in various $!PART \ s$ of the job and controlled by the !DOPART qualifier. When used with the -r qualifier on the command line (see Chapter 12), the output from the various parts has the partnumber appended to the filename. In this case it would be necessary to copy the .rsv files with the new part number before running the next part to take advantage of this facility.

Command file: Multivariate analysis

8

Introduction

Wether trial data

Model specification

Variance structures

Specifying multivariate variance structures in ASRemI

The output for a multivariate analysis

More than two response variates

8.1 Introduction

Multivariate analysis is used here in the narrow sense of a multivariate mixed model. There are many other multivariate analysis techniques which are not covered by ASRemI. Multivariate analysis is used when we are interested in estimating the correlations between distinct traits (for example, fleece weight and fibre diameter in sheep) and for repeated measures of a single trait.

Wether trial data

Three important traits for the Australian wool industry are the weight of wool grown per year, the cleanness and the diameter of that wool. Much of the wool is produced from wethers and most major producers have traditionally used a particular strain or bloodline. In an effort to assess the importance of bloodline differences, many wether trials have now been conducted. The trial analysed here was conducted from 1984 to 1988. It involves 35 teams of wethers representing 27 bloodlines. The teams were run together for three years at Borenore near Orange. The file contains greasy fleece weight (kg), yield (percentage of clean fleece weight to greasy fleece weight) and fibre diameter (microns).

The command file wether.as for a basic bivariate analysis of this data is presented to the right. Below is an extract of the first few lines of the data file wether.dat.

Orange Wether Trial 1984-8 SheepID !I TRIAL BloodLine !I TEAM * YEAR * GFW YLD FDIAM wether.dat !skip 1 GFW FDIAM \sim Trait Trait.YEAR, !r Trait.TEAM Trait.SheepID 1 2 2 1485 0 ID Trait 0 US .2 .2 .4 Trait.TEAM 2 Trait 0 US 0.4 0.3 1.3 TEAM O ID Trait.SheepID 2 Trait 0 US 0.2 0.2 2 SheepID 0 ID predict YEAR Trait

```
SheepID Site Bloodline Team Year GFW Yield FD
0101 3 21 1 1 5.6 74.3 18.5
0101 3 21 1 2 6.0 71.2 19.6
0101 3 21 1 3 8.0 75.7 21.5
0102 3 21 1 1 5.3 70.9 20.8
0102 3 21 1 2 5.7 66.1 20.9
0102 3 21 1 3 6.8 70.3 22.1
0103 3 21 1 1 5.0 80.7 18.9
0103 3 21 1 2 5.5 75.5 19.9
0103 3 21 1 3 7.0 76.6 21.9
4013 3 43 35 1 7.9 75.9 22.6
4013 3 43 35 2 7.8 70.3 23.9
4013 3 43 35 3 9.0 76.2 25.4
4014 3 43 35 1 8.3 66.5 22.2
4014 3 43 35 2 7.8 63.9 23.3
4014 3 43 35 3 9.9 69.8 25.5
4015 3 43 35 1 6.9 75.1 20.0
4015 3 43 35 2 7.6 71.2 20.3
4015 3 43 35 3 8.5 78.1 21.7
```

8.2 Model specification

The syntax for specifying a multivariate linear model in ASReml is

Y-variates ~ fixed [!r random] [!f sparse_fixed]

- *Y-variates* is a list of traits,
- *fixed*, *random* and *sparse_fixed* are as in the univariate case (see Chapter 6) but involve the special term **Trait** and interactions with **Trait**.

The design matrix for Trait is has a level (column) for each trait.

- Trait by itself fits the mean for each variate,
- In an interaction Trait.Fac fits the factor Fac for each variate and Trait.Cov fits the covariate Cov for each variate.

ASReml internally rearranges the data so that n data records containing t traits each becomes n sets of t analysis records indexed by the internal factor Trait *i.e.* nt analysis records ordered Trait within data record. If the data is already in this long form, use the **!ASMV** t qualifier to indicate that a multivariate analysis is required.

8.3 Variance structures

Using the notation of Chapter 7, consider a multivariate analysis with t traits and n units in which the data are ordered *traits* within *units*. An algebraic expression for the variance matrix in this case is

 $oldsymbol{I}_n\otimes oldsymbol{\Sigma}$

where $\Sigma^{(t \times t)}$ is an unstructured variance matrix.

Specifying multivariate variance structures in ASReml

A more sophisticated error structure is required for multivariate analysis. For a standard multivariate analysis

- the error structure for the residual must be specified as two-dimensional with independent records and an unstructured variance matrix across traits; records may have observations missing in different patterns and these are handled internally during analysis,
- the R structure *must* be ordered traits within units, that is, the R structure definition line for units must be specified before the line for Trait,
- variance parameters are variances not variance ratios,
- the R structure definition line for units, that is, 1485 0 ID, could be replaced by 0 or 0 0 ID; this tells ASRemI to fill in the

TRIAL BloodLine !I TEAM * YEAR * GFW YLD FDIAM wether.dat !skip 1 GFW FDIAM \sim Trait Trait.YEAR, !r Trait.TEAM Trait.SheepID 1 2 2 1485 0 ID Trait 0 US 3*0 Trait.TEAM 2 Trait 0 US 3*0 TEAM 0 ID Trait.SheepID 2 Trait 0 US 3*0 SheepID 0 ID

predict YEAR Trait

Orange Wether Trial 1984-8

SheepID !I

- number of units and is a useful option when the exact number of units in the data is not known to the user,
- the error variance matrix is specified by the model Trait 0 US
 - the initial values are for the lower triangle of the (symmetric) matrix specified row-wise,
 - finding reasonable initial values can be a problem. If initial values are written on the next line in the form q * 0 where q is t(t+1)/2 and t is the number of traits, ASReml will take half of the phenotypic variance matrix of the data as an initial value, see .as file in code box for example,

- the special qualifiers relating to multivariate analysis are $!\,\texttt{ASUV}$ and $!\,\texttt{ASMV}$ t, see Table 5.4 for detail
 - to use an error structure other than US for the residual stratum you must also specify !ASUV (see Table 5.4) and include mv in the model if there are missing values,
 - to perform a multivariate analysis when the data have already been expanded use !ASMV t (see Table 5.4)
 - *t* is the number of traits that ASReml should expect,
 - the data file must have t records for each multivariate record although some may be coded missing.

8.4 The output for a multivariate analysis

Below is the output returned in the .asr file for this analysis.

ASReml 1.0 [31 Aug 2002] Orange Wether Trial 1984-88 16 Sep 2002 16:32:50.370 64.00 Mbyte MSWindow wether * Contact asreml@vsn-intl.com for licensing and support * Use !{ and !} when fitting covariance across terms Folder: C:\asr\ex\manex BloodLine !I QUALIFIERS: !SKIP 1 Reading wether.dat FREE FORMAT skipping 1 lines traits Bivariate analysis of GFW and FDIAM 1485 records of 1485 read Using Model term Size Type COL #zero #miss Minimum Mean Maximum 261.0956 0 1 SheepID 521 Factor 1 1 521 0 2 TRIAL 2 3.000 3.000 3.000 0 0 3 BloodLine 27 Factor 3 1 13.4323 27 0 0 4 TEAM 35 Factor 4 1 18.0067 35 0 0 0 5 YEAR 3 Factor 5 1 2.0391 3 0 6 GFW 6 4.100 11.20 0 0 1 Variate 7.478 7 YLD 7 60.30 75.11 88.60 0 0 22.29 0 0 8 FDIAM 1 Variate 8 15.90 30.60 9 Trait 2 Traits/Variat 10 Trait.YEAR 6 Interaction 9 Trait 2 5 YEAR 3 : : 11 Trait.TEAM 70 Interaction 9 Trait 2 4 TEAM 35 • •

	12 Trait.SheepID	1042 Interactio	on 9	Trait	: 2 1 She	epID	: 521
	1485 identity						
	2 UnStructu	re 0.2000	0.2	000 0	. 4000		
	2970 records a	ssumed sorted	2	within	1485		
	2 UnStructu	re 0.4000	0.3	1	. 3000		
	35 identity						
	Structure for Tra	it.TEAM	has	70	levels defined		
	2 UnStructu	re 0.2000	0.2	2000 2	. 0000		
	521 identity						
	Structure for Tra	it.SheepID	has	1042	levels defined		
	Forming 1120 e	quations: 8 d	lense	i.			
	Initial updates w	ill be shrunk b	oy fa	ctor (0.316		
	NOTICE: 2 (mo	re) singulariti	les,				
convergence	1 LogL=-886.521	S2= 1.000)0	2964	df		
	2 LogL=-818.508	S2= 1.000)0	2964	df		
	3 LogL=-755.911	S2= 1.000)0	2964	df		
	4 LogL=-725.374	S2= 1.000)0	2964	df		
	5 LogL=-723.475	S2= 1.000)0	2964	df		
	6 LogL=-723.462	S2= 1.000)0	2964	df		
	7 LogL=-723.462	S2= 1.000)0	2964	df		
	8 LogL=-723.462	S2= 1.000)0	2964	df		
	Source	Model ter	ms	Gamma	Component	Comp/SE	% C
final	Residual	UnStruct	1	0.198351	0.198351	21.94	0 U
components	Residual	UnStruct	1	0.128890	0.128890	12.40	0 U
	Residual	UnStruct	2	0.440601	0.440601	21.93	0 U
	Trait.TEAM	UnStruct	1	0.374493	0.374493	3.89	0 U
	Trait.TEAM	UnStruct	1	0.388740	0.388740	2.60	0 U
	Trait.TEAM	UnStruct	2	1.36533	1.36533	3.74	0 U
	Trait.SheepID	UnStruct	1	0.257159	0.257159	12.09	0 U
	Trait.SheepID	UnStruct	1	0.219557	0.219557	5.55	0 U
	Trait.SheepID	UnStruct	2	1.92082	1.92082	14.35	0 U
Residual	Covariance/Varian	ce/Correlation	Matr	ix UnStru	ictured		
0.4360 is the	0.1984 0.4360						
correlation	0.1289 0.4406						
Trait.TEAM	Covariance/Varian	ce/Correlation	Matr	ix UnStru	ictured		
	0.3745 0.5436						
	0.3887 1.365						
Trait.SheepID	Covariance/Varian	ce/Correlation	Matr	ix UnStru	ictured		
	0.2572 0.3124						
	0.2196 1.921						

Analysis	of Variance	DF	F-incr		
9 Trait	5	2	5936.27		
10 Trait	.YEAR	4	1096.41		
NOTICE:	ASReml cannot yet determine	the cor	rrect denominator DFs for		
	these F statistics. They wi	ill not	exceed the Residual DF		
	which applies only if all components are KNOWN.				

Estimate		Standard Error	T-value	T-prev	
10 Trait.YEAR					
	2	-0.102262	0.290190E-01	-3.52	
	3	1.06636	0.290831E-01	36.67	42.07
	5	1.17407	0.433905E-01	27.06	
	6	2.53439	0.434880E-01	58.28	32.85
9 Trait					
	7	7.13717	0.107933	66.13	
	8	21.0569	0.209095	100.71	78.16
11 Trait.TEAM			70 effects f:	itted	
12 Trait.SheepII)		1042 effects f:	itted	
SLOPES FOR LOG(AE	S (RE	S)) on LOG(P	V) for Section 1		
1.00 1.54					
17 possible outl	iers	: see .res f	ile		
Finished: 16 Sep	2002	16:32:54.71	0 LogL Converged		

8.5 More than two response variates

Wolfinger (1996) summarises a range of variance structures that can be fitted to repeated measures data and demonstrates the models using five weights taken weekly on 27 rats subjected to 3 treatments. The command file for this analysis is presented to demonstrate a multivariate analysis involving more than two response variables (five in this case). Note that the two dimensional structure for com-

```
Wolfinger rat data
treat !A
wt0 wt1 wt2 wt3 wt4
rat.dat
wt0 wt1 wt2 wt3 wt4 ~ Trait,
treat Trait.treat
1 2 0
27 0 ID #error variance
Trait 0 US
15 * 0
```

mon error meets the requirement of independent units and is correctly ordered traits with units. Note also the use of 15 * 0 for the error variance matrix (15 = 5(5+1)/2, see Section 8.3).

9 Command file: Genetic analysis

Introduction

The command file

The pedigree file

Reading in the pedigree file

Genetic groups

GIV files

The example

Multivariate genetic analysis

9.1 Introduction

In an 'animal model' or 'sire model' genetic analysis we have data on a set of animals that are genetically linked via a pedigree. The genetic effects are therefore correlated and, assuming normal modes of inheritance, the correlation expected from additive genetic effects can be derived from the pedigree provided all the genetic links are in the pedigree. The additive genetic relationship matrix (sometimes called the numerator relationship matrix) can be calculated from the pedigree. It is actually the *inverse* relationship matrix that is formed by ASRemI for analysis.

For the more general situation where the pedigree based inverse relationship matrix is not the appropriate/required matrix, the user can provide a particular general inverse variance (GIV) matrix explicitly in a .giv file.

In this chapter we consider data presented in Harvey (1977) using the command file harvey.as.

9.2 The command file

In ASReml the !P data field qualifier indicates that the corresponding data field has an associated pedigree. The file containing the pedigree (harvey.ped in the example) for animal is specified immediately prior to the data file definition. See below for the first 20 lines of harvey.ped together with the corresponding lines of the data file harvey.dat. All individuals appearing in the data file must appear in the pedigree file. When all the pedigree infor-

```
Pedigree file example
animal !P
sire !A
dam
lines 2
damage
adailygain
harvey.ped !ALPHA
harvey.dat
adailygain mu lines, !r
animal 0.25
```

mation (individual, male_parent, female_parent) appears as the first three fields of the data file, the data file can double as the pedigree file. In this example the line harvey.ped !ALPHA could be replaced with harvey.dat !ALPHA. Typically additional individuals providing additional genetic links are present in the pedigree file.

9.3 The pedigree file

The pedigree file is used to define the genetic relationships for fitting a genetic animal model and is required if the !P qualifier is associated with a data field. The pedigree file

- has three fields; the identity of an individual (name or tag), its sire and its dam (or maternal grand sire, defined with the !MGS qualifier, Table 9.1); the identity for the individual *must* come first in the file,
- is sorted so that the line giving the pedigree of an individual appears before any line where that individual appears as a parent,
- is read free format; it may be the same file as the data file if the data file is free format and has the necessary identities in the first three fields, see below,
- is specified on the line immediately preceding the data file line in the command file,
- use identity 0 or * for unknown parents.

harvey.ped

harvey.dat

	_										
101 SIRE_1 0		101	$SIRE_1$	0	1	3	192	390	2241		
102 SIRE_1 0		102	$SIRE_1$	0	1	3	154	403	2651		
103 SIRE_1 0		103	$SIRE_1$	0	1	4	185	432	2411		
104 SIRE_1 0		104	$SIRE_1$	0	1	4	183	457	2251		
105 SIRE_1 0		105	$SIRE_1$	0	1	5	186	483	2581		
106 SIRE_1 0		106	$SIRE_1$	0	1	5	177	469	2671		
107 SIRE_1 0		107	SIRE_1	0	1	5	177	428	2711		
108 SIRE_1 0		108	SIRE_1	0	1	5	163	439	2471		
109 SIRE_2 0		109	SIRE_2	0	1	4	188	439	2292		
110 SIRE_2 0		110	SIRE_2	0	1	4	178	407	2262		
111 SIRE_2 0		111	SIRE_2	0	1	5	198	498	1972		
112 SIRE_2 0		112	SIRE_2	0	1	5	193	459	2142		
113 SIRE_2 0		113	SIRE_2	0	1	5	186	459	2442		
114 SIRE_2 0		114	SIRE_2	0	1	5	175	375	2522		
115 SIRE_2 0		115	SIRE_2	0	1	5	171	382	1722		
116 SIRE_2 0		116	SIRE_2	0	1	5	168	417	2752		
117 SIRE_3 0		117	SIRE_3	0	1	3	154	389	2383		
118 SIRE_3 0		118	SIRE_3	0	1	4	184	414	2463		
119 SIRE_3 0		119	$SIRE_3$	0	1	5	174	483	2293		
120 SIRE_3 0		120	SIRE_3	0	1	5	170	430	2303		
:		:									
•		•									

9.4 Reading in the pedigree file

The syntax for specifying a pedigree file in the ASRemI command file is *pedigree_file* [qualifiers]

- the qualifiers are listed in Table 9.1,
- the identities (individual, male_parent, female_parent) are merged into a single list and the inverse relationship is formed before the data file is read,
- when the data file is read, data fields with the **!P** qualifier are recoded according to the combined identity list,
- the inverse relationship matrix is automatically associated with factors coded from the pedigree file unless some other covariance structure is specified. The inverse relationship matrix is specified with the variance model name AINV,
- the inverse relationship matrix is written to ainverse.bin,
 - if ainverse.bin already exists ASRemI assumes it was formed in a previous run and has the correct inverse
 - ainverse.bin is read, rather than the inverse being reformed (unless !MAKE is specified); this saves time when performing repeated analyses based on a particular pedigree,
 - delete ainverse.bin or specify !MAKE if the pedigree is changed between runs,
- identities are printed in the .sln file,
 - identities should be whole numbers less than 200,000,000 unless ALPHA is specified,
 - pedigree lines for parents must precede their progeny,
 - unknown parents should be given the identity number 0,
 - if an individual appearing as a parent does not appear in the first column, it is assumed to have unknown parents, that is, parents with unknown parentage do not need their own line in the file,
 - identities may appear as both male and female parents, for example, in forestry.

9.5 Genetic groups

If all individuals belong to one genetic group, then use 0 as the identity of the parents of base individuals. However, if base individuals belong to various genetic groups this is indicated by the !GROUP qualifier and the pedigree file must begin by identifying these groups. All base individuals should have group identifiers as parents. In this case the identity 0 will only appear on the group identity lines, as in the following genetic group example.

Genetic group example
animal !P
sire 9 !A
dam
lines 2
damage
adailygain
harveyg.ped !ALPHA !MAKE !GROUP 3
harvey.dat
adailygain \sim mu
!r animal 02.5 !GU

G1 0 0
G2 0 0
G3 0 0
SIRE_1 G1 G1
SIRE_2 G1 G1
SIRE_3 G1 G1
SIRE_4 G2 G2
SIRE_5 G2 G2
SIRE_6 G3 G3
SIRE_7 G3 G3
SIRE_8 G3 G3
SIRE_9 G3 G3
101 SIRE_1 G1
102 SIRE_1 G1
103 SIRE_1 G1
:
163 STRF 9 G3
164 STRE 9 G3
165 STRF 9 C3
100 01101-0 00

Note that the sires in this example were from three lines. The same model can be fitted treating these as genetic groups, see Chapter 15.

Important It is usually appropriate to allocate a genetic group identifier where the parent is unknown.

Table 9.1: List of pedigree file qualifiers

qualifier	description
! ALPHA	indicates that the identities are alphanumeric with up to 20 characters; otherwise by default they are numeric whole numbers $< 200,000,000$.
!GIV	instructs ASReml to write out the A-inverse in the format of $\verb".giv"$ files.

qualifier	description
!GROUPS g	includes genetic groups in the pedigree. The first g lines of the pedigree identify genetic groups (with zero in both the sire and dam fields). All other lines must specify one of the genetic groups as sire or dam if the actual parent is unknown.
! MAKE	tells ASReml to make the A-inverse (rather than trying to retrieve it from the ainverse.bin file).
!MGS	<pre>indicates that the third identity is the sire of the dam rather than the dam; a dam identity is created and interposed into the pedigree so that a pedigree line animal sire mgs is interpreted as dam mgs 0 animal sire dam with a new dam being constructed for each such animal.</pre>
!REPEAT	tells ASReml to ignore repeat occurrences of lines in the pedigree file. Warning Use of this option will avoid the check that animals occur in chronological order, but chronological order is still required.
!SKIP n	allows you to skip n header lines at the top of the file.

List of pedigree file qualifiers

9.6 Reading a user defined inverse relationship matrix

Sometimes an inverse relationship matrix is required other than the one ASReml can produce from the pedigree file. We call this a GIV (G inverse) matrix. The user can prepare a .giv file containing this matrix and use it in the analysis. The syntax for specifying a G inverse file named *name.giv* is

name.giv [!SKIP n]

- the named file must have a .giv extension,
- the G inverse files must be specified on the line(s) immediately prior to the data file line after any pedigree file,
- up to 6 G inverse matrices may be defined,
- the file must be free format with three numbers per line, namely

row column value

defining the lower triangle row-wise of the matrix,

- 1 1 1 2 2 1 3 3 1 4 4 1 5 5 1.0666667 6 5 -0.2666667 6 6 1.0666667 7 1.0666667 8 7 -0.2666667 8 8 1.0666667 9 9 1.0666667 10 9 -0.2666667 10 10 1.0666667 11 11 1.0666667 12 11 -0.2666667 12 12 1.0666667
- the file must be sorted *column* within *row*,
- every diagonal element must be represented; missing off-diagonal elements are assumed to be zero cells,
- the file is used by associating it with a factor in the model. The number and order of the rows must agree with the size and order of the associated factor,
- the !SKIP n qualifier tells ASReml to skip n header lines in the file.

The .giv file presented in the code box gives the following G inverse matrix

$$\left[\begin{array}{ccc} I_4 & \mathbf{0} \\ \mathbf{0} & I_4 \otimes \left[\begin{array}{cc} 1.067 & -0.267 \\ -0.267 & 1.067 \end{array}\right] \right]$$

The .giv file can be associated with a factor in two ways:

• the first is to declare a G structure for the model term and to refer to the .giv file with the corresponding identifier GIV1, GIV2, GIV3, GIV4, GIV5, GIV6; for example,

```
animal 1for a one-dimensional structure put the scale pa-<br/>rameter (0.12 in this case) after the GIVg identifier,site.variety 2for a two-dimensional structure.site 0 CORUH 0.58*1.5variety 0 GIV1Variety 0 GIV1
```

• the second is for one-dimensional structures; in this case the .giv structure can be directly associated with the term using the giv(f, i) model function which associates the *i*th .giv file with factor f, for example,

```
giv(animal,1) 0.12
```

is equivalent to the first of the preceding examples.

The example continued

Below is an extension of harvey.as to include a .giv file. A portion of harvey.giv is presented to the right. In this case the G inverse matrix is simply an identity matrix of order 74 scaled by 0.5, that is, $0.5I_{74}$. This model is simply an example which is easy to verify. Note that harvey.giv is specified on the line immediately preceding harvey.dat.

Model term specification associating the harvey.giv structure to the coding of sire takes precedence over the relationship matrix structure implied by the !P qualifier for sire. In this case, the !P is being used to amalgamate animals and sires into a single list.

command file

.giv file

GIV file example	01 01 .5
animal !P	02 02 .5
sire !P	03 03 .5
dam	04 04 .5
lines 2	05 05 .5
damage	
adailygain	
harvey.ped !ALPHA	
harvey.giv # giv structure file	72 72 .5
harvey.dat	73 73 .5
adailygain \sim mu line, !r giv(sire,1) .25	74 74 .5
Tabulation of the data and prediction from the model

10

Introduction

Tabulation

Prediction

Examples

10.1 Introduction

Tabulation is the process of forming simple tables of averages and counts from the data. Such tables are useful for looking at the structure of the data and numbers of observations associated with factor combinations. Multiple tabulate directives may be specified in a job.

Prediction is the process of forming a linear function of the vector of fixed and random effects in the linear model to obtain an estimated or predicted value for a quantity of interest. It is primarily used for predicting tables of adjusted means. If a table is based on a subset of the explanatory variables then the other variables need to be accounted for. It is usual to form a predicted value either at specified values of the remaining variables, or averaging over them in some way.

This chapter describes the tabulate directive and the predict directive introduced in Section 3.4 under Prediction. However, we first describe the process and explain some of the concepts.

Our approach to prediction is a generalisation of that of Lane and Nelder (1982) who consider fixed effects models. They form fitted values for all combinations of the explanatory variables in the model, then take marginal means across the explanatory variables not relevent to the current prediction. Our case is more general in that random effects can be fitted in our (mixed) models. A full description can be found in Gilmour *et al.* (2002) and Welham *et al.* (2003).

Random factor terms may contribute to predictions in several ways. They may be evaluated at a values specified by the user, they may be averaged over, or they may be omitted from the fitted values used to form the prediction. Averaging over the set of random effects gives a prediction specific to the random effects observed. We describe this as a 'conditional' prediction. Omitting the term from the model produces a prediction at the population average (zero), that is, substituting the assumed population mean for an unknown random effect. We call this a 'marginal' prediction. Note that in any prediction, some terms may be evaluated as conditional and others at marginal values, depending on the aim of prediction.

For fixed factors there is no pre-defined population average, so there is no natural interpretation for a prediction derived by omitting a fixed term from the fitted values. Averages must therefore be taken over all the levels present to give a sample specific average, or value(s) must be specified by the user. For covariate terms (fixed or random) the associated effect represents the coefficient of a linear trend in the data with respect to the covariate values. These terms should be evaluated at a given value of the covariate, or averaged over several given values. Omission of a covariate from the predictive model is equivalent to predicting at a zero covariate value, which is often inappropriate.

Interaction terms constructed from factors generate an effect for each combination of the factor levels, and behave like single factor terms in prediction. Interactions constructed from covariates fit a linear trend for the product of the covariate values and behave like a single covariate term. An interaction of a factor and a covariate fits a linear trend for the covariate for each level of the factor. For both fixed and random terms, a value for the covariate must be given, but the factor levels may be evaluated at a given level, averaged over or (for random terms only) omitted.

Before considering some examples in detail, it is useful to consider the conceptual steps involved in the prediction process. Given the explanatory variables used to define the linear (mixed) model, the four main steps are

(a) Choose the explanatory variable(s) and their respective value(s) for which predictions are required; the variables involved will be referred to as the *classify* set and together define the multiway table to be predicted.

(b) Determine which variables should be averaged over to form predictions. The values to be averaged over must also be defined for each variable; the variables involved will be referred to as the *averaging* set. The combination of the classify set with these averaging variables defines a multiway hyper-table. Note that variables evaluated at only one value, for example, a covariate at its mean value, can be formally introduced as part of the classifying or averaging set.

(c) Determine which terms from the linear mixed model are to be used in forming predictions for each cell in the multiway hyper-table in order to give appropriate conditional or marginal prediction.

(d) Choose the weights to be used when averaging cells in the hyper-table to produce the multiway table to be reported.

Note that after steps (a) and (b) there may be some explanatory variables in the fitted model that do not classify the hyper-table. These variables occur in terms that are ignored when forming the predicted values. It was deduced above that

fixed terms could not sensibly be ignored in forming predictions, so that variables should only be omitted from the hyper-table when they only appear in random terms. Whether terms derived from these variables should be used when forming predictions depends on the application and aim of prediction.

The main difference in this prediction process compared to that described by Lane and Nelder (1982) is the choice of whether to include or exclude model terms when forming predictions. In linear models, since all terms are fixed, terms not in the classify set must be in the averaging set.

10.2 Tabulation

A tabulate directive is provided to enable simple summaries of the data to be formed for the purpose of checking the structure of the data. Multiple tabulate statements are permitted and they must appear immediately after the linear model. The tabulate statement has the form

tabulate $response_variables$ [!Wt weight !count !filter filter !select value] ~ factors

- tabulate is the directive name and must begin in column 1,
- response_variables is a list of variates for which means are required,
- !Wt weight nominates a variable containing weights,
- !count requests counts as well as means to be reported,
- !filter filter nominates a factor for selecting a portion of the data,
- !select value indicates that only records with value in the filter column are to be included,
- \sim factors identifies the factors to be used for classifying the data. Only factors (not covariates) may be nominated and no more than six may be nominated.

ASRemI prints the multiway table of means omitting empty cells to a file with extension .tab.

10.3 Prediction

The first step is to specify the classify set of explanatory variables after the **predict** directive. The predict statement(s) may appear immediately after the model line (before or after any **tabulate** statements) or after the R and G structure lines. The syntax is

predict *factors* [qualifiers]

```
variety !A
:
column 11
nin89.asd !skip 1
yield ~ mu variety !r repl
predict variety
0 0 1
repl 1
repl 0 IDV 0.1
```

NIN Alliance trial 1989

- predict must be the first element of the predict statement, commencing in column 1 in upper or lower case,
- *factors* is a list of the variables defining a multiway table to be predicted; each variable may be followed by a list of specific values at which the prediction is to occur
- the *qualifiers* instruct ASReml to modify the predictions in some way, see Table 10.1 for a list of the prediction qualifiers,
- several predict statements may be specified.

ASRemI parses the predict statement before fitting the model. If any syntax problems are encountered, these are reported in the .pvs file after which the statement is ignored: the job is completed as if the erroneous prediction statement did not exist. The predictions are formed as an extra process in the final iteration and are reported to the .pvs file. Consequently, aborting a run by creating the ABORTASR.NOW file will cause any predict statements to be ignored.

By default, factors are predicted at each level, simple covariates are predicted at their overall mean and covariates used as a basis for splines or orthogonal polynomials are predicted at their design points. Model terms **mv** and **units** are always ignored.

Prediction at particular values of a covariate or particular levels of a factor is achieved by listing the values after the variate/factor name. Where there is a sequence of values, use the notation $a \ b \ \ldots \ n$ to represent the sequence of values from $a \ to \ n$ with step size b - a. The default stepsize is 1 (in which case b may be omitted). A colon (:) may replace the ellipsis (...). An increasing sequence is assumed. When giving particular values for factors, use the coded level (1:n) rather than the label (alphabetical or integer).

The second step is to specify the averaging set. The default averaging set is those explanatory variables involved in fixed effect model terms that are not in the classifying set. By default variables that only define random model terms are ignored. The qualifier **!AVERAGE** allows these variables to be added to the default averaging set.

The third step is to determine the linear model terms to use in prediction. The default rule is that all model terms based entirely on the classifying and averaging set are used. Two qualifiers allow this default set of model terms to be modified by adding (!USE) or removing (!IGNORE) terms. The qualifier !ONLYUSE explicitly specifies the model terms to use, ignoring all others. The qualifier !EXCEPT explicitly specifies the model terms not to use, including all others. These qualifiers may implicitly modify the averaging set by including variables defining terms in the predicted model not in the classify set. It is sometimes easier to specify the classify set and the prediction linear model and allow ASRemI to construct the averaging set.

The fourth step is to choose the weighting for forming means over dimensions in the hyper-table. The default is to average over the specified levels but the qualifier !AVERAGE *factor weights* can be used to specify weights to be used in averaging over a factor.

There are often situations in which the fixed effects design matrix X is not of full column rank. These can be classified according to the cause of aliasing.

1. linear dependencies among the model terms due to over-parameterisation of the model,

2. no data present for some factor combinations so that the corresponding effects cannot be estimated,

3. linear dependencies due to other, usually unexpected, structure in the data.

The first type of aliasing is imposed by the parameterisation chosen and can be determined from the model. The second type of aliasing can be detected when setting up the design matrix for parameter estimation (which may require revision of imposed constraints). The third type can then be detected during the absorption of the mixed model equations. Dependencies (aliasing) can be dealt with in several ways and ASReml checks that predictions are of estimable functions in the sense defined by Searle (1971, p160) and are invariant to the constraint method used.

Normally ASRemI does not print predictions of non-estimable functions but the **!PRINTALL** qualifier instructs ASRemI to print them.

If the data has missing combinations of factors there is the possibility that the corresponding cells of the hyper-table are not estimable and hence margins of the table are not estimable. In some cases it is useful to construct margins of tables based only on those cells that have data present. The qualifier **!PRESENT** does this.

The **predict** statement may be continued on subsequent lines by terminating the current line with a comma.

Table 10.1 is a list of the prediction qualifiers with the following syntax:

- *f* is an explanatory variable which is a factor,
- *t* is a list of terms in the fitted model,
- v is a list of explanatory variables.

Table 10.1: List of prediction qualifiers

qualifier	action
Controlling formation of	tables
!AVERAGE f [weights]	is used to formally include a variable in the averaging set and to explicitly set the weights for averaging. Variables that only appear in random model terms are not included in the averaging set unless included with this qualifier. The default for <i>weights</i> is equal weights. The list <i>weights</i> can have syntax like $\{3*1 \ 0 \ 2*1\}/5$ to represent the sequence $0.2 \ 0.2 \ 0.2 \ 0.2 \ 0.2$. The string inside the curly brace is expanded first and the expression n*v means n occurrences of v. A separate !AVERAGE qualifier is required for each variable requiring explicit weights or to be added to the default averaging set.
!PARALLEL [v]	without arguments means all classify variables are expanded in parallel. Otherwise up to four variables from the classify set may be specified.

qualifier	action
PRESENT v	is used when averaging is to be based only on cells with data. v is a list of variables and may include variables in the classify set. v may not include variables with an explicit !AVERAGE qualifier. ASReml works out what combinations are present from the design matrix W . At present, the model must contain the factor as a simple main effect.
Controlling inclusion of m	nodel terms
!EXCEPT t	causes the prediction to include all fitted model terms not in t .
!IGNORE t	causes ASRemI to set up a prediction model based on the default rules and then removes the terms in t . This might be used to omit the spline Lack of fit term (!IGNORE fac(x)) from predictions as in
	yield \sim mu x variety !r spl(x) fac(x) predict x !IGNORE fac(x)
	which would predict points on the spline curve averaging over variety.
!ONLYUSE t	causes the prediction to include only model terms in t . It can be used for example to form a table of slopes as in
	HI \sim mu X variety X.variety predict variety X 1 !onlyuse X X.variety
!USE t	causes $ASRemI$ to set up a prediction model based on the default rules and then adds the terms listed in t .
Printing	
PLOT [x]	instructs ASRemI to attempt a plot of the predicted values. This qualifier is only applicable in versions of ASRemI linked with the Interacter Graphics library. If there is no argument, ASRemI uses the variable with the largest number of discrete values as the x variable in the graph. It draws a line for each combination of the other variables.
!PRINTALL	instructs ASRemI to print the predicted value, even if it is not of an estimable function. By default, ASRemI only prints predic- tions that are of estimable functions.
! SED	is specified to request all <i>standard errors of difference</i> be printed. Normally only an average value is printed.
! VPV	is specified to request that the variance matrix of predicted values be printed to the $.{\tt pvs}$ file.

List of prediction qualifiers

Examples

Examples are as follows:

```
yield \sim mu variety !r repl predict variety
```

is used to predict variety means in the NIN field trial analysis. Random **repl** is ignored in the prediction.

```
yield \sim mu x variety !r repl predict variety
```

predicts variety means at the average of x ignoring random repl.

```
yield \sim mu x variety repl
predict variety x 2
```

forms the hyper-table based on variety and repl at the covariate value of 2 and then averages across repl to produce variety predictions.

```
GFW Fdiam \sim Trait Trait.Year !r Trait.Team predict Trait Team
```

forms the hyper-table for each trait based on Year and Team with each linear combination in each cell of the hyper-table for each trait using Team and Year effects. Team predictions are produced by averaging over years.

```
yield \sim variety !r site.variety predict variety
```

will ignore the site.variety term in forming the predictions while

```
predict variety !AVERAGE site
```

forms the hyper-table based on site and variety with each linear combination in each cell using variety and site.variety effects and then forms averages across sites to produce variety predictions.

Functions of variance components

Introduction

Syntax

Linear combinations of components Heritability Correlation A more detailed example

11

11.1 Introduction

ASReml includes a post-analysis procedure to calculate functions of variance components. Its intended use is when the variance components are either simple variances or are vari-

F phenvar 1 + 2 # pheno var F genvar 1 * 4 # geno var H herit 4 3 # heritability

ances and covariances in an unstructured matrix. The functions covered are linear combinations of the variance components (for example, phenotypic variance), a ratio of two components (for example, heritabilities) and the correlation based on three components (for example, genetic correlation). The user must prepare a .pin file. A simple sample .pin file is shown in the ASReml code box above. The .pin file specifies the functions to be calculated. The user re-runs ASReml with the -P command line option specifying the .pin file as the input file. AS-Reml reads the model information from the .asr and .vvp files and calculates the requested functions. These are reported in the .pvc file.

11.2 Syntax

Functions of the variance components are specified in the .pin file in lines of the form

letter label coefficients

- *letter* is either F, H or R as follows
 - F is for linear combinations of variance components,
 - H is for forming the ratio of two components,
 - R is for forming the correlation based on three components,
- *label* names the result,
- *coefficients* is the list of coefficients for the linear function.

Linear combinations of components

First ASRemI extracts the variance components from the .asr file and their variance matrix from the .vvp file. Each linear function formed by an F line is added to the list of

```
F phenvar 1 + 2 # pheno var
F genvar 1 * 4 # geno var
H herit 4 3 # heritability
```

components. Thus, the number of coefficients increases by one each line. We seek to calculate k + c'v, cov (c'v, v) and var(c'v) where v is the vector of existing variance components, c is the vector of coefficients for the linear function and k is an optional offset which is usually omitted but would be 1 to represent the

residual variance in a probit analysis and 3.289 to represent the residual variance in a logit analysis. The general form of the directive is

F label $a + b * c_b + c + d + m * k$

where a, b, c and d are subscripts to existing components v_a, v_b, v_c and v_d and c_b is a multiplier for v_b . m is a number bigger than the current length of v to flag the special case of adding the offset k. Where matrices are to be combined the form

F label a:b *k + c:d

can be used, as in the Coopworth data example, see page 252.

Assuming that the .pin file in the ASRemI code box corresponds to a simple sire model and that variance component 1 is the sire variance and variance component 2 is the residual variance, then

```
F phenvar 1+2
```

gives a third component which is the sum of the variance components, that is, the phenotypic variance, and

F genvar 1 * 4

gives a fourth component which is the sire variance component multiplied by 4, that is, the genotypic variance.

Heritability

Heritabilities are requested by lines in the .pin file beginning with an H. The specific form of the directive in this case is

```
F phenvar 1 + 2 # pheno var
F genvar 1 * 4 # geno var
H herit 4 3 # heritability
```

H label n d

This calculates σ_n^2/σ_d^2 and $se[\sigma_n^2/\sigma_d^2]$ where *n* and *d* are integers pointing to components v_n and v_d that are to be used as the numerator and denominator respectively in the heritability calculation.

$$\operatorname{Var}\left(\frac{\sigma_n^2}{\sigma_d^2}\right) = \left(\frac{\sigma_n^2}{\sigma_d^2}\right)^2 \left(\frac{\operatorname{Var}(\sigma_n^2)}{\sigma_n^4} + \frac{\operatorname{Var}(\sigma_d^2)}{\sigma_d^4} - \frac{2\operatorname{Cov}(\sigma_n^2, \sigma_d^2)}{\sigma_n^2 \sigma_d^2}\right)$$

In the example

H herit 4 3

calculates the heritability by calculating component 4 (from second line of .pin)

/ component 3 (from first line of .pin), that is, genetic variance / phenotypic variance.

Correlation

Correlations are requested by lines in the .pin file beginning with an R. The specific form of the directive is

F phenvar 1:3 + 4:6 R phencorr 7 8 9 R gencorr 4:6

R label a ab b

This calculates the correlation $r = \sigma_{ab}/\sqrt{\sigma_a^2 \sigma_b^2}$ and the associated standard error. *a*, *b* and *ab* are integers indicating the position of the components to be used. Alternatively,

R label aa:nn

calculates the correlation $r = \sigma_{ab}/\sqrt{\sigma_a^2 \sigma_b^2}$ for all correlations in the lower triangular row-wise matrix represented by components *aa* to *nn* and the associated standard errors.

$$\operatorname{var}(r) = r^{2} \left[\frac{\operatorname{var}\left(\sigma_{a}^{2}\right)}{4\sigma_{a}^{2}} + \frac{\operatorname{var}\left(\sigma_{b}^{2}\right)}{4\sigma_{b}^{2}} + \frac{\operatorname{var}\left(\sigma_{ab}\right)}{\sigma_{ab}^{2}} \right]$$
$$+ \frac{2\operatorname{cov}\left(\sigma_{a}^{2}\right)\sigma_{b}^{2}}{4\sigma_{a}^{2}\sigma_{b}^{2}} - \frac{2\operatorname{cov}\left(\sigma_{a}^{2}\right)\sigma_{ab}}{2\sigma_{a}^{2}\sigma_{ab}} - \frac{2\operatorname{cov}\left(\sigma_{ab}\right)\sigma_{b}^{2}}{2\sigma_{ab}\sigma_{b}^{2}}$$

In the example

R phencorr 7 8 9

calculates the phenotypic covariance by calculating component 8 / $\sqrt{\text{component 7} \times \text{component 9}}$ where components 7, 8 and 9 are created with the first line of the .pin file, and

R gencorr 4:6

calculates the genotypic covariance by calculating component 5 / $\sqrt{\text{component 4} \times \text{component 6}}$ where components 4, 5 and 6 are variance components from the analysis.

÷

A more detailed example

The example .pin file in this code box is a little more complicated. It relates to the **bivariate sire model** in **bsiremod.as** shown below.

F phenvar 1:3 + 4:6
F addvar $4:6 * 4$
H heritA 10 7
H heritB 12 9
R phencorr 7 8 9
R gencorr 4:6

.asr file

Source	Model ter	rms	Gamma	Component	Comp/SE	%
Residual	UnStruct	1	26.2197	26.2197	18.01	0
Residual	UnStruct	1	2.85090	2.85090	9.55	0
Residual	UnStruct	2	1.71556	1.71556	18.00	0
Tr.sire	UnStruct	1	16.5262	16.5262	2.69	0
Tr.sire	UnStruct	1	1.14422	1.14422	1.94	0
Tr.sire	UnStruct	2	0.132847	0.132847	1.88	0

The ASReml file bsiremod.as is presented in the code box to the right. Above is the section of the .asr file that displays the variance component table on which the .pin file is based.

```
Bivariate sire model
sire !I
ywt fat
bsiremod.asd
ywt fat ~ Trait !r Trait.sire
1 2 1
0 # ASReml will count units
Trait 0 US
3*0
Trait.sire 2
Trait 0 US
3*0
sire
```

Numbering the parameters reported in bsiremod.asr (and bsiremod.vvp)

- **1** error variance for ywt
- 2 error covariance for ywt and fat
- **3** error variance for fat
- 4 sire variance component for ywt
- 5 sire covariance for ywt and fat
- **6** sire covariance for **fat**

then

```
F phenvar 1:3 + 4:6
```

creates new components 7 = 1+4, 8 = 2+5and 9 = 3+6,

```
F addvar 4:6 * 4
```

creates new components $\mathbf{10} = \mathbf{4} \times 4$, $\mathbf{11} = \mathbf{5} \times 4$ and $\mathbf{12} = \mathbf{3} \times 4$,

H heritA 10 7

forms 10 / 7 to give the heritability for ywt,

H heritB 12 9

forms 12 / 9 to give the heritability for fat,

R phencorr 7 8 9

forms $8/\sqrt{7 \times 9}$, that is, the phenotypic correlation between ywt and fat,

R gencorr 4:6

forms $5 / \sqrt{4:6}$, that is, the genetic correlation between ywt and fat.

The result is:

7 phenvar	1	42.75	6.297				
8 phenvar	2	3.995	0.6761				
9 phenvar	3	1.848	0.1183				
10 addvar 4	4	66.10	24.58				
11 addvar 5	5	4.577	2.354				
12 addvar 6	6	0.5314	0.2831				
h2ywt		= addvar	10/phenvar	7=		1.5465	0.3574
h2fat		= addvar	12/phenvar	9=		0.2875	0.1430
phencorr		= phenvar	r /SQR[phenvar	*phenvai	r]=	0.4495	0.0483
gencor 2	2 1	= Tr.si	5/SQR[Tr.si	4*Tr.si	6]=	0.7722	0.1537

.pvc file

12 Command file: Running the job

Introduction

The command line

Command line options

Debug command line options Graphics command line options Job control command line options Memory command line options Menu command line options Non-graphics command line options Post-processing calculation of variance components Examples

Advanced processing arguments

Standard use of arguments Entering command line arguments interactively

12.1 Introduction

The command line is discussed in this chapter. Command line options enable more memory to be accessed to run the job, control some graphics output, enable use of a simple menu and control advanced processing options.

12.2 The command line

The basic command to run ASReml is

```
[path] ASReml basename[.as[c]]
```

- path provides the path to the ASRemI program which is usually called asrem1.exe in a PC environment. In a UNIX environment, ASRemI is usually run trough a shell script called ASRem1.
 - if the ASReml program is in the search path then *path* is not required and the word ASReml will suffice; for example

```
ASReml nin89.as
```

will run the NIN analysis,

- if asreml.exe(ASReml) is not in the search path then *path* is required, for example, if asreml.exe is in the subdirectory c:\Asreml then

c:\Asreml\asreml nin89.as

will run nin89.as,

- ASReml invokes the ASReml program,
- *basename* is the name of the .as[c] command file.

The basic command line can be extended with options and arguments to

```
[path] ASRem1 [options] basename[.as[c]] [arguments]
```

• *options* is a string preceded by a – (minus) sign. Its components control several operations (batch, graphic, memory, ...) at run time; for example, the command line

ASReml -s4 rat.as

tells ASRemI to run the job rat.as with memory allocation increased to 128mb,

• *arguments* provide a mechanism (mostly for advanced users) to modify a job at run time; for example, the command line

ASReml rat.as alpha beta

tells ASRemI to process the job in rat.as as if it read alpha wherever \$1 appears in the file rat.as, beta wherever \$2 appears and 0 wherever \$3 appears (see below).

12.3 Command line options

Table 12.1 presents the command line options available in ASRemI with brief descriptions. Detailed descriptions follow. Command line options are not case sensitive.

option	type	action
Frequently used con	nmand line options	
C	job control	continue iterations using previous estimates as initial values
F	job control	continue for one more iteration using previous estimates as initial values
L	non-graphics output	direct screen output to file <i>basename.asl</i>
N	graphics	suppress interactive graphics
Ss	memory	control available memory
Other command lin	e options	
D	debug	invoke debug mode
E	debug	invoke extended debug mode
Gg	graphics	set interactive graphics device
I	graphics	permit interactive graphics to be displayed
М	menu	request menu mode
Р	post-processing	calculation of function of variance components
R	job control	repeat run for each argument

Table 12.1:	Command	line	options
-------------	---------	------	---------

Command line options should be combined in a single string preceded by a -

(minus) sign. For example -LNS3

could be used for this combination of options.

Debug command line options (D, E)

D and E invoke debug mode and increase the information written to the screen or .asl file. This information is not useful to most users. On Unix systems, if ASRemI is crashing use the system script command to capture the screen output rather than using the L option, as the .asl file is not properly closed after a crash.

Graphics command line options (G, I, N)

The I option permits the variogram and residual graphics to be displayed. This is the default unless the L option is specified.

The \mathbb{N} option prevents any graphics from being displayed. This is also the default when the L option is specified.

The Gg option sets the file type for hard copy versions of the variogram and residual graphics. Hard copy is only formed if the graphics are displayed.

Graphics are produced in the PC and SUN versions of ASRemI using the Interacter graphics library. ASRemI writes the graphics to file aspi.e where p indicates the part of the job, i indicates the contents of the figure (as given in the following table) and e indicates the file type, for example ps for postscript:

i	file contents
_1_R	marginal means of residuals from spatial analysis for section
_2_V	1 variogram of residuals from spatial analysis for section 2
_1_S	residuals in field plan
_A_H	histogram of residuals
Rv_E	residuals plotted against expected values
XY_G	figure produced by $!X$, $!Y$ and $!G$ qualifiers
_PVa	Predicted values plotted

The file type can be specified by following the G option by a number g, as follows:

description
HP-GL
Postscript (default for Unix)
BMP
Windows Print Manager
WinMetaFile (default for Windows)
HP-GL2
EncapsulatedPostScript

Not all of these file types are available on all systems but 2, 12 and 22 should all be available. The file type may also be set from the user menu by selecting Opt Form from the menu.

Job control command line options (C, F, R)

C indicates that the job is to continue iterating from the values in the .rsv file. This is equivalent to setting the !CONTINUE data file line qualifier, see Table 5.4 for details.

F indicates that the job is to continue for one more iteration from the values in the .rsv file. This is useful when using predict, see Chapter 10.

R runs ASReml once for each argument on the command line (see page 148) and includes the argument in the output file name, see the multivariate animal genetics example of Section 15.10 at page 250.

Memory command line options (S)

 S_s is used to increase memory allocation to the program. The base memory allocated is approximately 8mb (1 million double precision words). s is a digit. The memory allocated is 2^s times the base amount. The sequence is 8, 32, 64, 128, 256, 512, 1024,...

If your system cannot provide the requested memory, the request will be diminished until it can be satisfied. On multi-user systems, do not make s larger than necessary or other users may complain.

The memory requirements depend on problem size and may be quite large. If Ss is not active (it is compiler dependent) you will need to request a version of ASRemI compiled with a larger workspace.

Menu command line options (M)

M runs ASReml in menu mode. This mode is only available for the Microsoft Windows, Intel Linux and Sun Solaris versions of ASReml as these are linked with the Interacter graphics library. Menu mode is particularly intended to make ASReml easier to use under Windows. The menu enables you to edit the command file, run the job and view the output from within ASReml. Otherwise these are separate operations from the command line. Menu mode is suitable for regular analyses but large/long runs are better run from the command line as information reporting the progress of the job is not readily visible when running in menu mode. The primary menu options are

- File
 - when menu mode is invoked without a filename argument, the File option is invoked to input a file name,
 - normally you will open an existing .as command file but you may nominate a .dat, .asd or .csv file in which case ASRemI will create a .as template file for you to edit
 - this is helpful if the data file contains field names on the first line,
 - the .as file is displayed in an edit window,
- Edit
 - invokes a primitive editor for you to edit the .as file and then run the job; you must explicitly save the file before running it,
- Run
 - this runs the current job and returns the .asl (if L option is active) or .asr file to a scroll screen for the user to scan or print,
- View
 - this invokes a submenu which allows you to browse the .asr, .asl, .sln, .res or .pvs files,
 - the browse menu allows you to search for particular text strings,
- Opt
 - displays the current state of the C, D, E, G, L and R command line options and allows you to toggle their state,
 - the graphics line shows the current hard copy graphics file type,
- Help
 - displays a syntax summary in a browse window,

- Exit
 - closes ASRemI down,
- Quit
 - returns to the previous menu,
- Info
 - describes the main menu.

Log file (L)

L causes most of the screen output to be directed to a file with the file extension .asl. This is desirable for batch processing. It also suppresses the interactive graphics (available for spatial analyses) unless the I option is also specified.

Post-processing calculation of variance components (P)

P invokes the post-processing sub-program, see Chapter 11; this sub-program is used to calculate functions of variance components from the information in the .asr and .vvp files and it is run after the model has been fitted.

Examples

ASRemI code	action
asreml -L rat.as	send screen output to rat.asl and suppress interactive graphics
asreml -LS3 rat.as	increase memory to 8 $(=2^3)$ times the base amount
asreml -IL rat.as	send screen output to rat.asl but display interactive graphics
asreml -N rat.as	allow screen output but suppress interactive graphics
asreml -ILS2 rat.as	increase memory to 4 times the base amount, send screen output to rat.asl but display interactive graphics
asreml -MS2 rat.as	invoke Menu model to edit and run the $\texttt{rat.as}$ job using 32Mb workspace

12.4 Advanced processing arguments

Standard use of arguments

Command line arguments are intended to facilitate the running of a sequence of jobs that require small changes to the command file between runs. The output file name is modified by the use of this feature if the -R option is specified. This use is demonstrated in the Coopworth example of Section 15.10, see page 250.

Command line arguments are strings listed on the command line after *basename*, the command file name. These strings are inserted into the command file at run time. When the input routine finds a n in the command file it substitutes the *n*th argument string from the command line. *n* may take the values 1...9 to indicate up to 9 strings after the command file name. If the argument has 1 character a trailing blank is attached to the character and inserted into the command file. If no argument exists, a zero is inserted. For example,

asreml rat.as alpha beta

tells ASRemI to process the job in rat.as as if it read alpha wherever \$1 appears in the command file, beta wherever \$2 appears and 0 wherever \$3 appears.

in command file	on command line	becomes in ASRemI run
abc\$1def	no argument	abc0 def
abc\$1def	with argument X	abcX def
abc\$1def	with argument XY	abcXYdef
abc\$1def	with argument XYZ	abcXYZdef
abc\$1 def	with argument $\boldsymbol{X}\boldsymbol{X}$	abcXX def
abc\$1 def	with argument XXX	abcXXX def
abc\$1 def (multiple spaces)	with argument XXX	abcXXX def

Table 12.2: The use of arguments in ASReml

Recycle

Recycle mode is invoked with the R option. Assuming there are say 4 arguments 11 22 33 44, the job is run 4 times: in the first run the arguments are 11 22 33 44; in the second run the arguments are 22 33 44; in the third run the arguments are 33 44; in the fourth run the argument is 44. Usually this mode is used with \$1 in the command file so that only the first of the arguments is honoured in a particular run. This is mainly used in conjunction with the !DOPART qualifier. Note that the names of the output files will be formed using a root based on *basename* and the current first argument so that they are not overwritten.

Entering command line arguments interactively

Another way to gain some interactive control of a job in the PC environment is to insert !?{*text*} in the .as file where you want to specify the rest of the line at run time. ASReml prompts with *text* and waits for a response which is used to compete the line. The !? qualifier may be used anywhere in the job and the line is modified from that point.

Warning Unfortunately the prompt may not appear on the top screen under some windows operating systems in which case it may not be obvious that ASReml is waiting for a keyboard response.

Description of output files

Introduction

An example

Key output files

The .asr file The .sln file The .yht file

Other ASReml output files

The .res file The .vrb file The .vvp file The .rsv file The .dpr file The .pvc file The .pvs file The .tab file

ASReml output objects and where to find them

13.1 Introduction

With each ASReml run a number of output files are produced. ASReml generates the output files by appending various filename extensions to *basename*. A brief description of the filename extensions is presented in Table 13.1. The .sln and .yht files, in particular, are often quite large and could fill up your disk space. You should therefore regularly tidy your working directories.

file	description
Key output files	
.asr	contains a summary of the data and analysis results.
.sln	contains the estimates of the fixed and random effects and their corresponding standard errors.
.yht	contains the predicted values, residuals and diagonal elements of the hat matrix for each data point.
Other output files	
.asl	contains a progress log and error messages if the L command line options is specified.
.asp	contains transformed data, see !PRINT in Table 5.2.
.dbr/.dpr/.spr	contains the data and residuals in a binary form for further analysis (see !RESIDUALS , Table 5.5).
.pvc	contains the report produced with the P option.
.pvs	contains predictions formed by the predict directive.
.res	contains information from using the pol(), spl() and fac() functions, the iteration sequence for the variance components and some statistics derived from the residuals to assist with model selection.
.rsv	contains the final parameter values for reading back if the !CONTINUE qualifier is invoked, see Table 5.4.
.tab	contains tables formed by the tabulate directive.
.veo	holds the equation order to speed up re-running big jobs when the model is unchanged. This is a binary file of no use to the user.
.vrb	contains the estimates of the fixed effects and their variance.
.vvp	contains the approximate variances of the variance parameters. It is designed to be read back with the P option for calculating functions of the variance parameters.

Table 13.1: Summary of ASReml output files

Summary of ASReml output files

file

description

13.2 An example

In this chapter the ASReml output files are discussed with reference to a two-dimensional separable autoregressive spatial analysis of the NIN field trial data, see model **3b** on page 83 of Chapter 7 for details. The ASReml command file for this analysis is presented to the right. Recall that this model specifies a separable autoregressive correlation structure for residual or plot errors that is the direct product of an autoregressive correlation matrix of order 22 for rows and an autoregressive correlation matrix of order 11 for columns. In this case 0.3 is the starting correlation for both columns and rows.

```
NIN Alliance Trial 1989
variety !A
id
raw
repl 4
nloc
yield
lat
long
row 22
column 11
nin89.asd !skip 1
yield \sim mu variety !f mv
predict variety
1 2 0
22 row AR1 0.3
11 column AR1 0.3
```

13.3 Key output files

The key ASReml output files are the .asr, .sln and .yht files.

The .asr file

This file contains

- a general announcements box (outlined in asterisks) containing current messages,
- a summary of the data to validate the specification of the model,
- a summary of the fitting process to check convergence,
- a summary of the variance parameters:
 - The Gamma column reports the actual parameter fitted,

- the **Component** column reports the gamma converted to a variance scale if appropriate,
- Comp/SE is the ratio of the component relative to the square root of the diagonal element of the inverse of the average information matrix Warning Comp/SE should not be used for formal testing,
- The % shows the percentage change in the parameter at the last iteration,
- use the .pin file described Chapter 11 to calculate meaningful functions of the variance components,
- an analysis of variance (ANOVA) table (Section 6.10). The table contains the numerator degrees of freedom for the term and F-tests for approximate testing of effects. This is incremental test adjusted for *preceding terms only*.
- estimated effects, their standard errors and t values for equations in the DENSE portion of the SSP matrix; the T-prev column tests difference between successive coefficients in the same factor.

The following is a truncated version of nin89.asr.

version & title	ASReml 1.0 [3]	1 Aug 2002] ni:	n all	iance tria	al						
date & time	10 Sep 2002 04	:20:15.350 8	.00 M	byte Wind	dows nin89)					
license	Licensed to: A:	rthur Gilmour									
announcements	* ASReml 2002 *********************************										
box	* Contact asre	nl@vsn-intl.com	for	licensing	and suppor	rt *					
	* Use !{ and !]	} when fitting	covar	iance acr	oss terms	*					
version & title AS date & time 10 license Lic announcements * A box * C * U *** Fol QUA Rea Uni data summary Usi 4 5 6 7	**********	**************************************									
	Folder: C:\asr\ex\manex										
	QUALIFIERS: !SKIP 1										
	Reading nin.asd FREE FORMAT skipping 1 lines										
	Univariate ana	lysis of yield		Ŭ							
data summary	Using 242 records of 242 read										
	Model term	Size Type	COL	Minimum	Mean	Maximum	#zero	#miss			
	1 variety	56 Factor	1	1	26.4545	56	0	0			
	2 id		2	1.000	26.45	56.00	0	0			
	3 pid		3	1101.	2628.	4156.	0	18			
	4 raw		4	21.00	510.5	840.0	0	18			
	5 repl	4 Factor	5	1	2.4132	4	0	0			
	6 nloc		6	4.000	4.000	4.000	0	0			
	7 yield	1 Variate	7	1.050	25.53	42.00	0	18			
	8 lat		8	4.300	25.80	47.30	0	0			

	9 long	9	1.200 13	3.80 26.	40	0 0				
	10 row	22 Factor 10	1 11.5	000	22	0 0				
	11 column	11 Factor 11	1 6.0	000	11	0 0				
	12 mu	1 Constant Ter	m							
	13 mv_estimates	18 Missing valu	le							
	22 AR=AutoReg	0.3000								
	11 AR=AutoReg	0.3000								
	Forming 75 eq	uations: 57 dem	ise.							
	Initial updates wi	ll be shrunk by	factor 0.31	.6						
	NOTICE: 1 (mor	e) singularities	δ,							
iterations	1 LogL=-419.949	S2= 39.387	168 df	1.000	0.3000	0.3000				
sequence	2 LogL=-410.420	S2= 38.350	168 df	1.000	0.4030	0.3461				
	3 LogL=-402.549	S2= 40.253	168 df	1.000	0.5202	0.3999				
	4 LogL=-399.465	S2= 46.228	168 df	1.000	0.6233	0.4423				
	5 LogL=-399.331	S2= 48.139	168 df	1.000	0.6475	0.4414				
	6 LogL=-399.324	S2= 48.580	168 df	1.000	0.6535	0.4389				
	7 LogL = -399.324	S2= 48.680	168 df	1.000	0.6550	0.4379				
	8 LogL=-399.324	S2= 48,705	168 df	1.000	0.6554	0.4376				
	Final parameter va	lues	100 41	0000 0.65	549 0 4	3750				
	rindi paramotor ta									
	Source	Model terms	. Gamma	Component	Comp/SE	% C				
variance	Variance	242 168	3 1 00000	48 7045	6 81	0 P				
parameters	Besidual	AB=AutoB 22	0 655488	0 655488	11 63	0 11				
parameter	Residual	AR=AutoR 11	0.437497	0.437497	5.43	0 U				
ANOVA	Analvsis of Varian	ce	DF F-	incr						
	12 mu		1 33	31.90						
	1 variety		55	2.23						
	NOTICE: ASReml cannot yet determine the correct denominator DFs for									
	these F statistics. They will not exceed the Residual DF									
	which app	lies only if all	components ar	e KNOWN.						
		Estimate	Standard Erro	or T-value	T-pre	₽V				
	1 variety									
estimated	BRULE	2.98387	2.84137	1.05						
effects	REDLAND	4.70621	2.97738	1.58	0.62	2				
	CODY	-0.316046	2.96066	-0.11	-1.76	3				
	ARAPAHOE	2.95377	2.72658	1.08	1.16	3				
	NE83404	1.63070	2.89322	0.56	-0.48	3				
	NE83406	1.29029	2.77143	0.47	-0.12	2				
	NE83407	0.308992	3.13838	0.10	-0.31					
	CENTURA	2.26393	3.00167	0.75	0.66	5				
		1 02051	0 02270	0.25	-0.40	`				
	ME0/010 ME07610	1.03201	2.90019	0.35	-0.40	/)				
	ME01013	0.9308/ -4.97949	2.84941	2.08	1.82	2				
	10 mm	-4.3/848	2.99740	-1.46	-3.72	:				
	12 mu	F7 04 0000	0 40400							
	10	DI 24.0892	2.46480	9.//						
aution in fa	13 mv_estimates		18 effect	s litted						
outlier into	6 possi	Die Outliers: se	e .res 111e							
completion info	rinisnea: 10 Sep 2	002 04:20:34.508	b LogL Conver	gea						

The .sln file

The .sln file contains estimates of the fixed and random effects with their standard errors in an array with four columns ordered as

factor_name level estimate standard_error

Note that the error presented for the estimate of a random effect is the square root of the prediction error variance. The .sln file can easily be read into a GENSTAT spreadsheet or an S-PLUS data frame. This is a reduced version of nin89.sln. Note that

- the order of some terms may differ from the order in which those terms were specified in the model statement,
- the missing value estimates appear at the end of the file in this example.

variety estimates	variety	LANCER	0.000	0.000
	variety	BRULE	2.987	2.842
	variety	REDLAND	4.707	2.978
	variety	CODY	-0.3131	2.961
	variety	ARAPAHOE	2.954	2.727
	variety	NE87615	1.035	2.934
	variety	NE87619	5.939	2.850
	variety	NE87627	-4.376	2.998
intercept	mu	1	24.09	2.465
missing value	mv_estimates	1	21.91	6.729
estimates	mv_estimates	2	23.22	6.721
	mv_estimates	3	22.52	6.708
	mv_estimates	4	23.49	6.676
	mv_estimates	5	22.26	6.698
	mv_estimates	6	24.47	6.707
	mv_estimates	7	20.14	6.697
	mv_estimates	8	25.01	6.691
	mv_estimates	9	24.29	6.676
	mv_estimates	10	26.30	6.658
	mv_estimates	11	24.99	6.590
	mv_estimates	12	27.78	6.492
	•			

÷

The .yht file

The .yht file contains the predicted values of the data in the original order (this is not changed by supplying row/column order in spatial analyses), the residuals and the diagonal elements of the hat matrix. Where an observation is missing, the residual, missing values predicted value and Hat value are also declared missing. The missing value estimates with standard errors are reported in the .sln file.

This is the first 20 lines of nin89.yht. Note that the values corresponding to the missing data (first 15 records) are all -0.1000E-36 which is the internal value used for missing values.

		nat
-0.10000E-36	-0.1000E-36	-0.1000E-36
24.088	5.162	6.074
27.074	4.476	6.222
28.795	6.255	6.282
23.775	6.325	6.235
27.042	6.008	5.962
24.695	1.855	6.114
25.452	0.1475	6.158
22.465	4.435	6.604
	-0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 24.088 27.074 28.795 23.775 27.042 24.695 25.452 22.465	-0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.1000E-36 -0.10000E-36 -0.1000E-36 -0.10000E-36

13.4 Other ASReml output files

The .res file

The .res file contains miscellaneous supplementary information including

- a list of unique values of x formed by using the fac() model term,
- a list of unique (x, y) combinations formed by using the fac(x, y) model term,
- orthogonal polynomials produced by pol() model term,
- the design matrix formed for the spl() model term,
- predicted values of the curvature component of cubic smoothing splines,
- the empirical variance-covariance matrix based on the BLUPs when a $\Sigma \otimes I$ or $I \otimes \Sigma$ structure is used; this may be used to obtain starting values for another run of ASReml,
- a table showing the variance components for each iteration,
- some statistics derived from the residuals from two-dimensional data (multivariate, repeated measures or spatial)
 - the residuals from a spatial analysis will have the units part added to them (defined as the combined residual) unless the data records were sorted (within ASRemI) in which case the units and the correlated residuals are in different orders (data file order and field order respectively),
 - the residuals are printed in the .yht file but the statistics in the .res file are calculated from the combined residual,
 - the Covariance/Variance/Correlation (C/V/C) matrix calculated directly from the residuals; it contains the covariance below the diagonals, the variances on the diagonal and the correlations above the diagonal - these may help with finding starting values,
 - relevant portions of the estimated variance matrix for each term for which an R structure or a G structure has been associated,
- a variogram and spatial correlations for spatial analysis; the spatial correlations are based on distance between data points (see Gilmour *et al.*, 1997),
- the slope of the *log(absolute residual)* on *log(predicted value)* for assessing possible mean-variance relationships and the location of large residuals. For example,

SLOPES FOR LOG(ABS(RES)) ON LOG(PV) for section 1

0.99 2.01 4.34

produced from a trivariate analysis reports the slopes. A slope of b suggests

that y^{1-b} might have less mean variance relationship. If there is no mean variance relation, a slope of zero is expected. A slope of $\frac{1}{2}$ suggests a SQRT transformation might resolve the dependence; a slope of 1 means a LOG transformation might be appropriate. So, for the 3 traits, $log(y_1)$, y_2^{-1} and y_3^{-3} are indicated. This diagnostic strategy works better when based on grouped data regressing log(standard deviation) on log(mean).

Also,

STND RES 16 -2.35 6.58 5.64

indicates that for the 16th data record, the residuals are -2.35, 6.58 and 5.64 times the respective standard deviations. The standard deviation used in this test is calculated directly from the residuals rather than from the analysis. They are intended to flag the records with large residuals rather than to precisely quantify their relative size. They are not studentised residuals and are generally not relevant when the user has fitted heterogeneous variances.

This is nin89.res.

	Covariance	/Variance	/Correlat	ion matrix	c of Resi	duals	Section	1
C/V/C matrix	18.261	0.522	0.688	0.684	0.819	0.496	0.445	0.499
	0.053	0.083	0.180					
	14.887	44.523	0.710	0.550	0.517	0.215	0.568	0.550
	0.439	0.263	0.318					
	14.934	24.080	25.811	0.626	0.727	0.494	0.534	0.587
	0.332	0.185	0.329					
	14.193	17.818	15.433	23.546	0.735	0.479	0.587	0.303
	0.055	-0.059	0.059					
	21.332	21.041	22.519	21.751	37.185	0.345	0.501	0.540
	0.212	0.236	0.279					
	14.092	9.539	16.664	15.431	13.984	44.158	0.614	0.033
	-0.314	-0.482	-0.417					
	13.350	26.637	19.067	20.022	21.461	28.647	49.371	0.435
	0.173	-0.037	-0.053					
	22.425	38.622	31.364	15.478	34.628	2.300	32.134	110.587
	0.762	0.721	0.778					
	3.040	39.560	22.759	3.613	17.429	-28.133	16.449	108.223
	182.312	0.887	0.885					
	4.373	21.628	11.579	-3.524	17.764	-39.584	-3.237	93.638
	147.844	152.427	0.921					
	10.074	27.827	21.927	3.767	22.284	-36.277	-4.919	107.276
	156.540	148.997	171.732					
	Fitted Cov	ariance/V	ariance m	atrix of H	Residuals	is Al	R=AutoReg	
	1.000	0.438	0.192	0.084	0.037	0.016	0.007	0.003
	0.001	0.001	0.000					

plot in



Figures 13.1 to 13.4 show the graphics derived from the residuals when the !DISPLAY 15 qualifier is specified and which are written to .eps files by running

ASReml -g22 nin89.as

The graphs are a variogram of the residuals from the spatial analysis for site 1 (Figure 13.1), a plot of the residuals in field plan order (Figure 13.2), plots of the marginal means of the residuals (Figure 13.3) and a histogram of the residuals (Figure 13.4). The selection of which plots are displayed is controlled by the **!DISPLAY** qualifier (Table 5.4). By default, the variogram and field plan are displayed.



Figure 13.1 Variogram of residuals

The sample variogram is a plot of the semi-variances of differences of residuals at particular distances. The (0,0) position is zero because the difference is identically zero. ASReml displays the plot for distances 0, 1, 2, ..., 8, 9-10, 11-14, 15-20,

The plot of residuals in field plan order (Figure 13.2) contains in its top and right margins a diamond showing the minimum, mean and maximum residual for that row or column. Note that a gap identifies where the missing values occur.

The plot of marginal means of residuals shows residuals for each row/column as well as the trend in their means.



Figure 13.2 Plot of residuals in field plan order

The .vrb file

The .vrb file contains the estimates of the effects together with their approximate prediction variance matrix corresponding to the dense portion. The file is formatted for reading back for post processing. The number of equations in the dense portion can be increased (to a maximum of 800) using the !DENSE option (Table 5.5) but not to include random effects. The matrix is lower triangular row-wise in the order that the parameters are printed in the .sln file. It can be thought of as a partitioned lower triangular matrix,

$$\left[\begin{array}{cc} \sigma^2 & . \\ \\ \tilde{\boldsymbol{\beta}}_D & \sigma^2 \boldsymbol{C}^{DD} \end{array} \right]$$



Figure 13.3 Plot of the marginal means of the residuals



Figure 13.4 Histogram of residuals
where $\tilde{\boldsymbol{\beta}}_{D}$ is the dense portion of $\boldsymbol{\beta}$ and C^{DD} is the dense portion of C^{-1} . This is the first 20 rows of nin89.vrb. Note that the first element is the estimated error variance, that is, 48.6802, see the variance component estimates in the .asr output.

```
0.486802E + 02
                 0.00000E + 00
                                 0.00000E + 00
                                                 0.298660E + 01
                                                                 0.000000E + 00
0.807551E + 01
                 0.470711E + 01
                                 0.00000E + 00
                                                 0.456648E + 01
                                                                 0.886687E + 01
-0.313123E + 00
                 0.000000E + 00
                                 0.410031E + 01
                                                 0.476546E + 01
                                                                 0.876708E + 01
                 0.00000E + 00
0.295404E + 01
                                 0.343331E + 01
                                                 0.389620E + 01
                                                                 0.416124E + 01
0.743616E + 01
                 0.163302E + 01
                                 0.00000E + 00
                                                 0.377176E + 01
                                                                 0.428109E + 01
0.472519E + 01
                 0.402696E + 01
                                 0.837281E + 01
                                                 0.129013E + 01
                                                                 0.000000E + 00
0.330076E + 01
                 0.347471E + 01
                                 0.357605E + 01 0.316915E + 01
                                                                 0.412130E + 01
0.768275E + 01
                 0.310018E + 00
                                 0.00000E + 00 0.376637E + 01
                                                                 0.419780E + 01
0.395693E + 01
                 0.383429E + 01
                                 0.458492E + 01 0.378585E + 01
                                                                 0.985202E + 01
0.226478E + 01
                 0.000000E + 00 0.379286E + 01 0.442457E + 01
                                                                 0.439485E + 01
0.402503E + 01
                 0.440539E + 01 0.362391E + 01
                                                 0.502071E + 01
                                                                 0.901191E + 01
0.508553E + 01
                 0.000000E + 00 0.393626E + 01
                                                 0.430512E + 01
                                                                 0.423753E + 01
0.428826E + 01
                 0.417864E + 01 0.363341E + 01
                                                 0.444776E + 01
                                                                 0.527289E + 01
                                 0.00000E + 00
0.855241E + 01
                 0.243687E + 01
                                                 0.351386E + 01
                                                                 0.369983E + 01
                                 0.362019E + 01
0.384055E + 01
                 0.330171E + 01
                                                0.352370E + 01
                                                                 0.359516E + 01
0.392097E + 01
                 0.406762E + 01 0.801579E + 01 0.475935E + 01
                                                                 0.000000E + 00
....
```

The first 5 rows of the lower triangular matrix in this case are

48.6802					-
0	0				
2.98660	0	8.07551			
4.70711	0	4.56648	8.86687		
-0.313123	0	4.10031	4.76546	8.76708	
:	:	:	:	:	·

The .vvp file

The .vvp file contains the inverse of the average information matrix on the components scale. The file is formatted for reading back under the control of the .pin file described in Chapter 11. The matrix is lower triangular row-wise in the order the parameters are printed in the .asr file. This is nin89.vvp with the parameter estimates in the order error variance, spatial row correlation, spatial column correlation.

```
Variance of Variance components 3
51.0852
0.217089 0.318058E-02
0.677748E-01 -0.201181E-02 0.649355E-02
```

The .rsv file

The .rsv file contains the variance parameters from the most recent iteration of a model. The primary use of the .rsv file is to supply the values for the !CONTINUE qualifier (see Table 5.4) and the C command line option (see Table 12.1). It contains sufficient information to match terms so that it can be used when the variance model has been changed. This is nin89.rsv.

76 6						
0.000000	0.00000		0.00000	1.000000	0.6553855	0.4375849
RSTRUCTURE	1	2				
VARIANCE	1	1	0 1.00000			
STRUCTURE	22	1	10.655385			
STRUCTURE	11	1	10.437585			

The .dpr file

The .dpr file contains the data and residuals from the analysis in double precision binary form. The file is produced when the !RES qualifier (Table 4.3) is invoked. The file could be renamed with filename extension .dbl and used for input to another run of ASRemI. Alternatively, it could be used by another Fortran program or package. Factors will have level codes if they were coded using !A or !I. All the data from the run plus an extra column of residuals is in the file. Records omitted from the analysis are omitted from the file.

The .pvc file

The .pvc file contains functions of the variance components produced by running a .pin file on the results of an ASReml run as described in Chapter 11. The .pin and .pvc files for a half-sib analysis of the Coopworth data are presented in Section 15.10.

The .pvs file

The .pvs file contains the predicted values formed when a predict statement is included in the job. Below is an edited version of nin89.pvs. See Section 3.6 for the .pvs file for the simple RCB analysis of the NIN data considered in that chapter.

title line nin alliance trial

10 Sep 2002 04:20:15 nin89

Ecode is E for Estimable, * for Not Estimable

	Warning: mv_estimates	is ignored for	or prediction	
	Prodicted values of v	:	1	
	riedicted values of y	TETU		
	variety P	redicted_Value Standa	rd_Error Ecode	
predicted variety	LANCER	24.0875	2.4645 E	
means	BRULE	27.0749	2.4944 E	
	REDLAND	28.7949	2.5064 E	
	CODY	23.7752	2.4970 E	
	ARAPAHOE	27.0416	2.4417 E	
	NE83404	25.7212	2.4424 E	
	NE83406	25.3776	2.5028 E	
	NE83407	24.3978	2.6882 E	
	CENTURA	26.3525	2.4763 E	
	SCOUT66	29.1732	2.4361 E	
:				
	NE87615	25.1238	2.4434 E	
	NE87619	30.0267	2.4666 E	
	NE87627	19.7126	2.4833 E	
SED summary	SED: Overall Standard	Error of Difference	2.925	

The .tab file

The .tab file contains the simple variety means and cell frequencies. Below is an edited version of nin89.tab.

nin alliance trial

10 Sep 2002 04:20:15

	variety		
	LANCER	28.56	4
	BRULE	26.07	4
	REDLAND	30.50	4
	CODY	21.21	4
	ARAPAHOE	29.44	4
	NE83404	27.39	4
	NE83406	24.28	4
	NE83407	22.69	4
	CENTURA	21.65	4
	SCOUT66	27.52	4
	COLT	27.00	4
÷			
	NE87615	25.69	4
	NE87619	31.26	4
	NE87627	23.23	4

Simple tabulation of yield

13.5 ASReml output objects and where to find them

Table 13.2 presents a list of objects produced with each ASReml run and where to find them in the output files.

output object	found in	comment
analysis of variance table	. asr file	the analysis of variance table contains F-statistics for each term in the <i>fixed</i> part of the model. These provide for an incremental test of significance (see Section 6.10).
data summary	.asr file	includes the number of records read and retained for analysis, the minimum, mean, maximum, number of zeros, number of missing values per data field, factor/variate field distinction
elapsed time	.asr file	this can be determined by comparing the start time with the finishing time.
fixed and random effects	.sln file	the effects that were included in the dense portion of the solution are also printed in the .asr file with their standard error, a t-statistic for testing that effect and a t-statistic for testing it against the preceding effect in that factor.
heritability	.pvc file	placed in the $.{\tt pvc}$ file when postprocessing with a .pin file
histogram of residu- als	.res file	and graphics file
intermediate results	.asl file	given if the $\neg \mathtt{DL}$ command line option is used.
mean/variance rela- tionship	.res file	for non-spatial analyses ASReml prints the slope of the regression of $log(abs(residual))$ against log(predicted value). This regression is ex- pected to be near zero if the variance is inde- pendent of the mean. A power of the mean data transformation might be indicated otherwise. The suggested power is approximately $(1-b)$ where b is the slope. A slope of 1 suggests a log transfor-

mation. This is indicative only and should not be blindly applied. Weighted analysis or identifying the cause of the heterogeneity should also be considered. This statistic is not reliable in genetic animal models or when **units** is included in the linear model because then the predicted value

includes some of the residual.

Table 13.2: ASReml output objects and where to find them

output object	found in	comment
observed variance/ covariance matrix formed from BLUPs and residuals	. res file	for an interaction fitted as random effects, when the first [outer] dimension is smaller than the in- ner dimension less 10, ASRemI prints an observed variance matrix calculated from the BLUPs. The observed correlations are printed in the upper tri- angle. Since this matrix is not well scaled as an es- timate of the underlying variance component ma- trix, a rescaled version is also printed, scaled ac- cording to the fitted variance parameters. The primary purpose for this output is to provide rea- sonable starting values for fitting more complex variance structure. The correlations may also be of interest. After a multivariate analysis, a sim- ilar matrix is also provided, calculated from the residuals.
phenotypic variance	.pvc file	placed in the $\tt.pvc$ file when postprocessing with a <code>.pin</code> file
plot of residuals against field position	graphics file	
possible outliers	.res file	these are residuals that are more than 3.5 stan- dard deviations in magnitude
predicted (fitted) values at the data points	.yht file	these in the are printed in the second column
predicted values	.pvs file	given if a $\verb"predict"$ statement is supplied in the <code>.as</code> file.
REML log-likelihood	.asr file	the REML log-likelihood is given for each iteration. The REML log-likelihood should have converged
residuals	.yht file	and in binary form in .dpr file; these are printed in column 3. Furthermore, for multivariate analyses the residuals will be in data order (traits within records). However, in a univariate analysis with missing values that are not fitted, there will be fewer residuals than data records - there will be no residual where the data was missing so this can make it difficult to line up the values unless you can manipulate them in another program (spread- sheet).
score	.asl file	given if the $-DL$ command line option is used.

Table of output objects and where to find them ASRemI

output object	found in	comment
tables of means	.tab file .pvs file	simple averages of cross classified data are pro- duced by the tabulate directive to the .tab file. Adjusted means predicted from the fitted model are written to the .pvs file by the predict direc- tive.
variance of variance parameters	.vvp file	based on the inverse of the average information matrix
variance parameters	.asr file .res file	the values at each iteration are printed in the .res file. The final values are arranged in a table, printed with labels and converted if necessary to variances.
variogram	graphics file	

Table of output objects and where to find them ASRemI

Error messages

Introduction

Common problems

Things to check in the ${\tt.asr}$ file

An example

Error messages

Warning messages

14.1 Introduction

When ASRemI finds an inconsistency it prints an error message to the screen (or the .asl file) and dumps the current information to the .asr file. Below is the screen output for a job that has been terminated due to an error. If a job has an error you should

- try and identify the problem from the error message in the Fault: line and the text of the Last line read: (this appears twice in the file to make it easier to find),
- check that all labels have been defined and are in the correct case,
- some errors arise from conflicting information; the error may point to something that appears valid but is inconsistent with something that is wrong earlier in the file,
- reduce to a simpler model and gradually build up to the desired analysis this should help to identify the exact location of the problem.

If the problem is not resolved from the above list, you may need to email the Help Desk at asreml@vsn-intl.com. Please send the .as file, (a sample of) the data, the .asr file and the .asl file produced by running

asreml -dl basename.as

See Chapter 12 The -dl command line option invokes debug mode and sends all non-graphics screen output to the .asl file.

In this chapter we show some of the common typographical problems. Errors arising from attempts to fit an inappropriate model are often harder to resolve. Following is an example of output when the data file is not correctly named or is not present (ASReml tries to interpret the filename as a variable name when the file is not found).

	Warning: FIELD DEFINITION line	s should	be IND	ENTED					
messages	There is no file called nine.asd								
	Invalid label for data field: '	nine.asd'	conta	ins a 1	reserve	ed chai	racter		
	or may get confused w	ith a pre	vious 1	label d	or rese	erved w	vord		
	Fault 12 FORMAT error readin	g data st	ructure	es					
	Last line read was: nine.asd	!slip 1							
	Currently defined structures,	COLS and	LEVELS						
	1 variety	-1	56	0	0	0	0		
	2 id	-2	1	0	0	0	0		
	3 pid	-3	1	0	0	0	0		
	4 raw	-4	1	0	0	0	0		
	5 repl	-5	4	0	0	0	0		
	6 nloc	-6	1	0	0	0	0		
	7 yield	-7	1	0	0	0	0		
	8 lat	-8	1	0	0	0	0		
	9 long	-9	1	0	0	0	0		
	10 row	-10	22	0	0	0	0		
	11 column	-11	11	0	0	0	0		
filename!	12 nine.asd	0	0	0	0	0	0		
	ninerr1 C:\asr\ex\manex								
	12 factors defined [max 500].								
	0 variance parameters [max 9	00]. 2	specia	l stru	ctures				
last line read	Last line read was: nine.asd	!slip 1							
	12 12 -1 0 1000								
fault message	Finished: 10 Sep 2002 05:13:16.	745 FOR	MAT er	ror rea	ading o	lata st	ructure	3	

14.2 Common problems

Common problems in coding ASReml are as follows:

- a variable name has been misspelt; variable names are case sensitive,
- a model term has been misspelt; model term funcions and reserved words (mu, Trait, mv, units) are case sensitive,
- the data file name is misspelt or the wrong path has been given the pathname may not include embedded blanks,
- a qualifier has been misspelt or is in the wrong place,
- there is an inconsistency between the variance header line and the structure definition lines presented,

:

- failure to use commas appropriately in model definition lines,
- there is an error in the R structure definition lines,
- there is an error in the G structure definition lines,
 - there is a factor name error,
 - there is a missing parameter,
- there is an error in the predict statement,
- model term mv not included in the model when there are missing values in the • data when the user wishes to retain their records in the analysis.

The most common problem in running ASReml is that a variable label is misspelt.

14.3 Things to check in the .asr file

The information that ASRemI dumps in the .asr file when an error is encountered is intended to give you some idea of the particular error:

- if there is no data summary ASRemI has failed before or while reading the model line,
- if ASReml has completed one iteration the problem is probably associated with starting values of the variance parameters or the logic of the model rather than the syntax per se.

Part of the file nin89.asr presented in Chapter 13 is displayed below to indicate the lines of the .asr file that should be checked. You should check that

- sufficient workspace has been obtained,
- the records read/lines read/records used are correct,
- mean min max information is correct for each variable,
- ANOVA table has the expected degrees of freedom.

	ASReml 1.0 [31 Aug 2002] nin alliance trial
workspace	10 Sep 2002 04:20:15.350 \textcolor{blue} 8.00 Mbyte \textcolor{black} Windows nin89
	Licensed to: Arthur Gilmour
	* ASReml 2002 *********************************
	* Contact asreml@vsn-intl.com for licensing and support *
	* Use !{ and !} when fitting covariance across terms *

working direc-Folder: C:\asr\ex\manex tory QUALIFIERS: !SKIP 1 Reading nin.asd FREE FORMAT skipping 1 lines Univariate analysis of yield 242 records of records read Using 242 read Model term Size Type COL Minimum Mean Maximum #zero #miss 26.4545 0 data summary 1 variety 56 Factor 1 1 56 0 2 id 2 1.000 26.45 56.00 0 0 3 pid 3 1101. 2628. 4156. 0 18 4 raw 4 21.00 510.5 840.0 0 18 5 1 2.4132 4 5 repl 4 Factor 0 0 6 nloc 6 4.000 0 4.000 4.000 0 7 yield 1 Variate 7 1.050 25.53 42.00 0 18 8 lat 8 4.300 25.80 47.30 0 0 9 long 9 1.200 13.80 26.40 0 0 10 row 22 Factor 10 1 0 0 11.5000 22 11 column 11 Factor 11 1 6.0000 11 0 0 12 mu 1 Constant Term 13 mv_estimates 18 Missing value 22 AR=AutoReg 0.3000 11 AR=AutoReg 0.3000 Forming 75 equations: 57 dense. Initial updates will be shrunk by factor 0.316 NOTICE: 1 (more) singularities, 168 df iteration 1 LogL=-419.949 S2= 39.387 1.000 0.3000 0.3000 2 LogL=-410.420 S2= 38.350 0.3461 sequence 168 df 1.000 0.4030 3 LogL=-402.549 0.5202 0.3999 S2= 40.253 168 df 1.000 4 LogL=-399.465 S2= 46.228 168 df 1.000 0.6233 0.4423 5 LogL=-399.331 S2= 48.139 168 df 1.000 0.6475 0.4414 6 LogL=-399.324 S2= 48.580 168 df 1.000 0.6535 0.4389 7 LogL=-399.324 S2= 48.680 168 df 1.000 0.6550 0.4379 8 LogL=-399.324 S2= 48.705 168 df 1.000 0.6554 0.4376 Final parameter values 1.0000 0.65549 0.43750 Source Model terms Gamma Component Comp/SE % C Variance 48.7045 6.81 0 P 242 168 1.00000 Residual 0.655488 0.655488 11.63 0 U AR=AutoR 22 Residual AR=AutoR 11 0.437497 0.437497 5.43 0 U

ANOVA	Analysis of V	Variance	DF F-inc	r						
	12 mu		1 331.9	0						
	1 variety		55 2.2	3						
	NOTICE: ASRe	NOTICE: ASReml cannot yet determine the correct denominator DFs for								
	thes	e F statistics. The	y will not exceed	the Residua	l DF					
	whic	h applies only if al	l components are K	NOWN.						
		Estimate	Standard Error	T-value	T-prev					
	1 variety									
	BRULE	2.98387	2.84137	1.05						
	REDLAND	4.70621	2.97738	1.58	0.62					
	CODY	-0.316046	2.96066	-0.11	-1.76					
	:	:	:	:	:					
	NE87615	1.03251	2.93379	0.35	-0.40					
	NE87619	5.93687	2.84941	2.08	1.82					
	NE87627	-4.37848	2.99740	-1.46	-3.72					
	12 mu									
		57 24.0892	2.46480	9.77						
	13 mv_estima	ites	18 effects f	itted						
outliers?	6	possible outliers: s	see .res file							
	Einiched, 10	Finished, 10 Sep 2002 04:20:24 E08 Lost Converged								

Finished: 10 Sep 2002 04:20:34.508 LogL Converged

14.4 An example

tion 7.3

See 2a in Sec- This is the command file for a simple RCB analysis of the NIN variety trial data in the first part. However, this file contains eight common mistakes in coding ASReml. We also show two common mistakes associated with spatial analyses in the second part. The errors are highlighted and the numbers indicate the order in which they are detected. Each error is discussed with reference to the output written to the .asr file. A summary of the errors is as follows:

- 1. data file not found,
- 2. unrecognised qualifier,
- 3. incorrectly defined alphanumeric factor,

```
nin alliance trial
variety 56 # 3.
id
pid
raw
repl 4
nloc
yield
lat
long
row 22
column 11
nin.asd !slip 1 !dopart $1
# 1. & 2.
!part 1
yield~mu variety # 4.
!r Repl # 5.
0 0 1
Repl 1 # 6.
2 0 IDV 0.1 # 7.
!part 2
yield~mu variety # 9.
1 2
11 row AR1 .1 #10.
22 col AR1 .1
!part
predict voriety # 8.
```

- 4. comma missing from first line of model,
- 5. misspelt variable label in linear model,
- 6. misspelt variable label in G structure header line,
- wrong levels declared in G structure model line,
- 8. misspelt variable label in predict statement.
- 9. mv omitted from spatial model
- 10. wrong levels declared in R structure model lines

1. Data file not found

Running this job produces the .asr file in Section 14.1. The first problem is that ASReml cannot find the data file nine.asd as indicated in the error message above the Fault line. ASReml reports the last line read before the job was terminated, an error message nin alliance trial : nine.asd !slip 1 yield \sim mu variety .

FORMAT error reading data structures

and other information obtained to that point. In this case the program only made it to the data file definition line in the command file. Since nine.asd commences in column 1, ASReml checks for a file of this name (in the working directory since no path is supplied). Since ASReml did not find the data file it tried to interpret the line as a variable definition but . is not permitted in a variable label. The problem is either that the filename is misspelt or a pathname is required. In this case the data file was given as nine.asd rather than nin.asd.

2. An unrecognised qualifier and 3. An incorrectly defined factor

After supplying the correct pathname and re-running the job, ASRemI produces the warning message

WARNING: Unrecognised qualifier at character 22 !slip 1

followed by the fault message

ERROR Reading the data.

The warning does not cause the job to terminate immediately but arises because

error

hint

!slip is not a recognised data file line qualifier; the correct qualifier is !skip. The job terminates when reading the header line of the nin.asd file which is alphabetic when it is expecting numeric values. The following output displays the error message produced.

```
ASReml 1.0 [31 Aug 2002] nin alliance trial
10 Sep 2002 05:13:58.815
                         8.00 Mbyte Windows ninerr2
Licensed to: Arthur Gilmour
* Contact asreml@vsn-intl.com for licensing and support
* Use !{ and !} when fitting covariance across terms
Folder: C:\asr\ex\manex
QUALIFIERS: !SLIP 1
Warning: Unrecognised qualifier at character
                                          9 !SLIP 1
Reading nin.asd FREE FORMAT skipping
                                      0 lines
Univariate analysis of yield
Field 1 [variety] of record
                               1 [line
                                            1] is not valid.
Increase the number of levels in factor variety
         0 ERROR Reading the data
Fault
Last line read was: variety id pid raw rep nloc yield lat long row column
Currently defined structures, COLS and LEVELS
 1 variety
                                      56
                                           56
                                                             0
                                  1
                                                  0
                                                       0
 :
12 mu
                                 0
                                       1
                                           -8
                                                  0
                                                      -1
                                                             0
ninerr2 nin.asd
Model specification: TERM LEVELS GAMMAS
mu
                                  0
                                        0.000
variety
                                  0
                                        0.000
 12 factors defined [max 500].
  0 variance parameters [max 900].
                                  2 special structures
Last line read was: variety id pid raw rep nloc yield lat long row column
  12
         0
               0
                        1000
                    0
Finished: 10 Sep 2002 05:14:00.348
                                  ERROR Reading the data
```

Fixing the error by changing !slip to !skip however still produces the fault message

```
ERROR Reading the data.
```

The portion of output given below shows that ASReml has baulked at the name

LANCER in the first field on the first data line. This alphabetic data field is not declared as alphabetic. The correct data field definition for variety is

```
variety !A
```

to indicate that variety is a character field.

```
ASReml 1.0 [31 Aug 2002] nin alliance trial
10 Sep 2002 05:14:00.818
                          8.00 Mbyte Windows ninerr3
Licensed to: Arthur Gilmour
* ASReml 2002 ***************
* Contact asreml@vsn-intl.com for licensing and support
* Use !{ and !} when fitting covariance across terms
Folder: C:\asr\ex\manex
QUALIFIERS: !SKIP 1
Reading nin.asd FREE FORMAT skipping
                                       1 lines
Univariate analysis of yield
Field 1 [LANCER] of record
                                1 [line
                                             1] is not valid.
Increase the number of levels in factor variety
Fault
         0 ERROR Reading the data
Last line read was: LANCER 1 NA NA 1 4 NA 4.3 1.2 1 1
Currently defined structures, COLS and LEVELS
 1 variety
                                   1
                                        56
                                             56
                                                    0
                                                          0
                                                               0
 :
                                        1
                                             -8
 12 mu
                                   0
                                                    0
                                                         -1
                                                               0
ninerr3 variety id
                       pid
                                      rep
                                              nloc
                                                     yield
                                                             lat
                               raw
Model specification: TERM LEVELS GAMMAS
                                    0
                                         0.000
mu
variety
                                    0
                                         0.000
 12 factors defined [max 500].
                                    2 special structures
  0 variance parameters [max 900].
Last line read was: LANCER 1 NA NA 1 4 NA 4.3 1.2 1 1
   12
         0
                0
                     0
                         1000
Finished: 10 Sep 2002 05:14:02.000
                                    ERROR Reading the data
```

4. A missing comma and 5. A misspelt factor name in linear model

The model has been written over two lines but ASRemI does not realise this because the first line does not end with a comma.

```
nin alliance trial
variety !A
...
repl 4
...
nin.asd !skip 1
yield ~ mu variety
!r Repl
...
```

The missing comma causes the error message

Variance header: SECTIONS DIMNS GSTRUCT

as ASRemI tries to interpret the second line of the model (see Last line read) as the variance header line. The .asr file is displayed below. Note that the data has now been successfully read as indicated by the data summary. You should always check the data summary to ensure that the correct number of records have been detected and the data values match the names appropriately.

```
ASReml 1.0 [31 Aug 2002] nin alliance trial
10 Sep 2002 05:14:02.310
                         8.00 Mbyte Windows ninerr4
Licensed to: Arthur Gilmour
* Contact asreml@vsn-intl.com for licensing and support
* Use !{ and !} when fitting covariance across terms
Folder: C:\asr\ex\manex
QUALIFIERS: !SKIP 1
Reading nin.asd FREE FORMAT skipping
                                      1 lines
Univariate analysis of yield
          224 records of
Using
                           242 read
Model term
                                                              #zero #miss
               Size Type
                           COL
                                 Minimum
                                           Mean
                                                    Maximum
 1 variety
                 56 Factor
                             1
                                   1
                                        28.5000
                                                       56
                                                                 0
                                                                       0
 2 id
                               1.000
                             2
                                          28.50
                                                    56.00
                                                                 0
                                                                       0
 3 pid
                             3
                               1101.
                                          2628.
                                                    4156.
                                                                 0
                                                                       0
 4 raw
                             4
                                21.00
                                          510.5
                                                    840.0
                                                                 0
                                                                       0
 5 repl
                  4 Factor
                             5
                                   1
                                         2.5000
                                                        4
                                                                 0
                                                                       0
 6 nloc
                               4.000
                                                                 0
                             6
                                          4.000
                                                    4.000
                                                                       0
 7 vield
                             7 1.050
                                                    42.00
                                                                 0
                                                                       0
                  1 Variate
                                          25.53
 8 lat
                             8
                               4.300
                                          27.22
                                                    47.30
                                                                 0
                                                                       0
 9 long
                             9
                               1.200
                                          14.08
                                                    26.40
                                                                 0
                                                                       0
10 row
                 22 Factor
                            10
                                   1
                                        11.7321
                                                       22
                                                                 0
                                                                       0
                                                                 0
11 column
                 11 Factor
                            11
                                   1
                                         6.3304
                                                       11
                                                                       0
12 mu
                  1 Constant Term
         0 Variance header: SECTIONS DIMNS GSTRUCT
Fault
                      !r Repl 0 0 0 0
Last line read was:
ninerr4 variety id
                      pid
                                             nloc
                                                    yield lat
                              raw
                                     rep
Model specification: TERM LEVELS GAMMAS
```

```
variety
                                     56
                                            0.000
                                            0.000
mu
                                      1
 12 factors defined [max 500].
   0 variance parameters [max 900].
                                      2 special structures
Final parameter values
Last line read was:
                        !r Repl 0 0 0 0
   12
         0
              242
                    224
                           1000
Finished: 10 Sep 2002 05:14:03.552 Variance header: SECTIONS DIMNS GSTRUCT
```

Inserting a comma on the end of the first line of the model to give

```
yield \sim mu variety,
!r Repl
```

solves that problem but produces the error message

```
Error reading model factor list
```

because **Repl** should have been spelt **repl**. Portion of the output is displayed. Since the model line is parsed before the data is read, this run failed before reading the data.

```
ASReml 1.0 [31 Aug 2002] nin alliance trial
10 Sep 2002 05:14:03.863
                       8.00 Mbyte Windows ninerr5
Licensed to: Arthur Gilmour
* Contact asreml@vsn-intl.com for licensing and support
* Use !{ and !} when fitting covariance across terms
Folder: C:\asr\ex\manex
QUALIFIERS: !SKIP 1
Reading nin.asd FREE FORMAT skipping
                                   1 lines
        0 Error reading model factor list
Fault
Last line read was:
                      Repl
Currently defined structures, COLS and LEVELS
 1 variety
                               1
                                    2
                                         2
                                              0
                                                   0
                                                        0
 :
12 mu
                               0
                                    1
                                        -8
                                              0
                                                   -1
                                                        0
ninerr5 variety id
                     pid
                                  rep
                                         nloc
                                                yield
                                                       lat
                           raw
 12 factors defined [max 500].
  0 variance parameters [max 900].
                                2 special structures
Last line read was:
                      Repl
```

12 0 -1 0 1000 Finished: 10 Sep 2002 05:14:05.034 Error reading model factor list

6. Misspelt factor name and 7. Wrong levels declaration in the G structure definition lines

The next error message that ASRemI presents is

G structure header: Factor, order

indicating that there is something wrong in the G structure definition lines. In this case the replicate term in the first G structure definition line has been spelt incorrectly. To correct this error replace Repl with repl.

```
nin alliance trial
÷
nin.asd !skip 1
yield \sim mu variety
!r Repl
001
Repl 1
2 0 IDV 0.1
```

```
ASReml 1.0 [31 Aug 2002] nin alliance trial
10 Sep 2002 05:14:05.355
                        8.00 Mbyte Windows ninerr6
Licensed to: Arthur Gilmour
* Contact asreml@vsn-intl.com for licensing and support
* Use !{ and !} when fitting covariance across terms
Folder: C:\asr\ex\manex
QUALIFIERS: !SKIP 1
Reading nin.asd FREE FORMAT skipping
                                     1 lines
Univariate analysis of yield
         224 records of
Using
                          242 read
Model term
               Size Type
                          COL
                                                            #zero #miss
                                Minimum
                                         Mean
                                                  Maximum
                56 Factor
                                  1
                                       28.5000
                                                     56
                                                               0
 1 variety
                            1
 2 id
                            2
                              1.000
                                         28.50
                                                  56.00
                                                               0
 3 pid
                            3 1101.
                                         2628.
                                                  4156.
                                                               0
                               21.00
                                                               0
 4 raw
                            4
                                         510.5
                                                   840.0
 5 repl
                 4 Factor
                            5
                                  1
                                        2.5000
                                                      4
                                                               0
                            6 4.000
 6 nloc
                                        4.000
                                                  4.000
                                                               0
 7 yield
                 1 Variate
                            7 1.050
                                         25.53
                                                  42.00
                                                               0
 8 lat
                              4.300
                                         27.22
                                                  47.30
                                                               0
                            8
 9 long
                            9
                              1.200
                                         14.08
                                                   26.40
                                                               0
                                                     22
                                                               0
10 row
                22 Factor
                           10
                                  1
                                       11.7321
11 column
                11 Factor
                           11
                                  1
                                        6.3304
                                                     11
                                                               0
```

0

0

0

0

0

0

0

0

0

0

0

```
12 mu
                     1 Constant Term
Fault
           1 G structure header: Factor, order
 Last line read was: Repl 1 0 0 0 0
ninerr6 variety id
                          pid
                                  raw
                                          rep
                                                  nloc
                                                           yield lat
 Model specification: TERM LEVELS GAMMAS
variety
                                             0.000
                                      56
mu
                                       1
                                             0.000
                                       4
                                              0.100
repl
SECTIONS
             224
                       4
                               1
   TYPE
               0
                       0
                               0
 STRUCT
             224
                       0
                               0
                                       0
                                                0
                                                        0
                                                                0
  12 factors defined [max 500].
   4 variance parameters [max 900].
                                       2 special structures
Final parameter values
                                               0.10000
                                                           1.0000
 Last line read was: Repl 1 0 0 0 0
                242
                      224
   12
          1
                            1000
Finished: 10 Sep 2002 05:14:06.556
                                      G structure header: Factor, order
```

```
Fixing the header line, we then get the error message

Structure / Factor mismatch

This arose because repl has 4 levels but we have only declared 2 in the G structure

model line. The G structure should read

repl 1

4 0 IDV 0.1
```

The last lines of the output with this error are displayed below.

```
6.3304
 11 column
                    11 Factor
                                11
                                        1
                                                             11
                                                                         0
                                                                               0
 12 mu
                     1 Constant Term
      2 identity
                        0.1000
Structure for repl
                                  has
                                            2 levels defined
Fault
           1 Structure / Factor mismatch
 Last line read was: 2 0 IDV 0.1 0 0 0 0
ninerr7 variety id
                          pid
                                  raw
                                          rep
                                                  nloc
                                                          yield
                                                                 lat
 Model specification: TERM LEVELS GAMMAS
variety
                                      56
                                             0.000
                                             0.000
mu
                                       1
                                             0.100
repl
                                       4
SECTIONS
             224
                       4
                               1
                            1002
   TYPE
              0
                       0
```

STRUCT 224 0 0 0 0 0 0 2 5 0 0 1 0 1 12 factors defined [max 500]. 5 variance parameters [max 900]. 2 special structures 0.10000 0.10000 Final parameter values 1.0000 Last line read was: 2 0 IDV 0.1 0 0 0 0 12 242 224 1 1000 Finished: 10 Sep 2002 05:14:08.069 Structure / Factor mismatch

8. A misspelt factor name in the predict statement

The final error in the job is that a factor name is misspelt in the predict statement. This is a non-fatal error. The faulty statement is simply ignored by ASReml and no .pvs file is produced. To rectify this statement correct voriety to variety.

see Chapter 13

9. Forgetting mv in a spatial analysis

The first error message from running part 2 of the job is

```
R structures imply 0 + 242 records: only 224 exist
```

Checking the seventh line of the output below, we see that there were 242 records read but only 224 were retained for analysis. There are three reasons records are dropped.

- 1. the **!FILTER** qualifier has been specified,
- 2. the !D transformation qualifier has been specified and

3. there are missing values in the response variable and the user has not specified that they be estimated.

The last applies here so we must change the model line to read yield \sim mu variety mv.

```
:
Reading nin.asd FREE FORMAT skipping
                                           1 lines
Univariate analysis of yield
           224 records of
Using
                              242 read
Model term
                 Size Type
                              COL
                                     Minimum
                                                Mean
                                                           Maximum
                                                                     #zero #miss
 1 variety
                   56 Factor
                                 1
                                        1
                                             28.5000
                                                              56
                                                                         0
                                                                               0
:
12 mu
                    1 Constant Term
                       0.1000
    11 AR=AutoReg
```

```
22 AR=AutoReg
                         0.1000
 Maybe you need to include 'mv' in the model
 Fault
           1 R structures imply
                                         0 242 records: only 224 e+
                       22 column AR1 0.1 0 0 0 0 0
 Last line read was:
 ninerr9 variety id
                           pid
                                   raw
                                            rep
                                                    nloc
                                                             yield
                                                                     lat
 Model specification: TERM LEVELS GAMMAS
 variety
                                        56
                                               0.000
                                               0.000
 mu
                                         1
SECTIONS
             242
                        3
                                1
 STRUCT
                        1
                                1
              11
                                         4
                                                 0
                                                          1
                                                                 10
              22
                        1
                                1
                                         5
                                                 0
                                                          1
                                                                 11
   12 factors defined [max 500].
    5 variance parameters [max 900].
                                         2 special structures
 Final parameter values
                                                 0.0000
                                                            -.10000E-360.10000
 0.10000
 Last line read was: 22 column AR1 0.1 0 0 0 0 0
    12
           1
                242
                       224
                             1000
 Finished: 10 Sep 2002 05:14:11.143
                                        R structures imply
                                                                   0 242 records: only
224 \text{ exist} +
```

10. Field layout error in a spatial analysis

The final common error we highlight is the misspecification of the field layout. In this case we have 'accidently' switched the levels in rows and columns. However, ASRemI can detect this error because we have also asked it to sort the data into field order. Had sorting not been requested, ASRemI would not have been able to detect that the lines of the data file were not sorted into the appropriate field order and spatial analysis would be wrong.

```
:
Reading nin.asd FREE FORMAT skipping
                                            1 lines
Univariate analysis of yield
Using
           242 records of
                               242 read
                               COL
Model term
                 Size Type
                                      Minimum
                                                 Mean
                                                            Maximum
                                                                       #zero #miss
                    56 Factor
                                                                           0
                                                                                 0
 1 variety
                                 1
                                         1
                                              26.4545
                                                               56
 10 row
                    22 Factor
                                 10
                                         1
                                              11.5000
                                                                22
                                                                           0
                                                                                  0
 11 column
                    11 Factor
                                 11
                                         1
                                               6.0000
                                                               11
                                                                           0
                                                                                 0
 12 mu
                    1 Constant Term
 13 mv_estimates
                   18 Missing value
```

```
11 AR=AutoReg
                       0.1000
    22 AR=AutoReg
                       0.1000
 Warning: Spatial mapping information for side 1 of order 11
         ranges from
                           1.0 to
                                      22.0
 Warning: Spatial mapping information for side 2 of order 22
         ranges from
                           1.0 to
                                      11.0
Fault
          2 Sorting data into field order
 Last line read was: 22 column AR1 0.1 0 0 0 0 0
                         pid
ninerr10 variety id
                                                       yield lat
                                raw
                                        rep
                                                nloc
 Model specification: TERM LEVELS GAMMAS
                                           0.000
variety
                                     56
                                           0.000
                                     1
mu
                                     18
                                           0.000
mv_estimates
SECTIONS
            242
                      4
                              1
 STRUCT
             11
                      1
                              1
                                     5
                                             0
                                                            10
                                                     1
             22
                      1
                              1
                                      6
                                             0
                                                     1
                                                            11
  13 factors defined [max 500].
   6 variance parameters [max 900].
                                     2 special structures
Final parameter values
                                             0.0000
                                                       -.10000E-360.10000
 0.10000
 Last line read was: 22 column AR1 0.1 0 0 0 0 0
   13
          2
               242
                     242
                          1000
Finished: 10 Sep 2002 05:14:12.655 Sorting data into field order
```

14.5 Information, Warning and Error messages

ASReml prints information, warning and error messages in the .asr file. The major information messages are in Table 14.2. A list of warning messages together with the likely meaning(s) is presented in Table 14.1. Error messages with their probable cause(s) is presented in Table 14.3.

information message	comment
Logl converged	the REML log-likelihood changes between iter- ations were less than 0.002 * iteration number.
Logl converged, parameters not converged	the change in REML log-likelihood was small and convergence was assumed but the param- eters are, in fact, still changing.
Logl not converged	the maximum number of iterations was reached before the REML log-likelihood con- verged. Examine the sequence of estimates. You may need more iterations in which case restart with C command line option (see Sec- tion 12.3 on job control). Otherwise restart with more appropriate initial variances. It may be necessary to simplify the model and estimate the dominant components before es- timating other terms.

Table 14.1: Some information messages and comments

_

warning message	likely meaning
Warning: e missing values generated by !^ transformation	data values should be positive.
Warning: i singularities in AI matrix	usually means variance model is overparame- terized.
Warning: m variance structures were modified	the structures are probably at the boundary of the parameter space.
Warning: n missing values were detected in the design	either use $\texttt{!MVINCLUDE}$ or delete the records.
Warning: n negative weights	it is better to avoid negative weights unless you can check ASRemI is doing the correct thing with them.
Warning: r records were read from multiple lines	check you have the intended number of fields per line.
WARNING <i>term</i> has more levels [##] than expected [##]:	You have probably mis-specified the number of levels in the factor or omitted the !I qual- ifier (see Section 5.4 on data field definition syntax). ASRemI corrects the number of lev- els.
Warning: $term$ in the predict !IGNORE list	the term did not appear in the model.
Warning: $term$ in the predict !USE list	the term did not appear in the model.
Warning: $term$ is ignored for prediction	terms like units and mv cannot be included in prediction.
Warning: Check if you need the !RECODE qualifier	!RECODE may be needed if the binary file was not prepared with $ASRemI$.
Warning: Code B - fixed at a boundary (!GP)	suggest drop the term and refit the model.
Warning: Eigen analysis check of US matrix skipped	matrix is probably OK.
WARNING: Extra lines on the end of the input file:	this indicates that there are some lines on the end of the .as file that were not used. The first "extra" line is displayed. This is only a problem if you intended ASRemI to read these lines.
Warning: Fewer levels found in $term$	ASReml increases to the correct value.
Warning: FIELD DEFINITION lines should be INDENTED	indent them to avert this message.

Table 14.2: List of warning messages and likely meaning(s)

warning message	likely meaning			
Warning: Fixed levels for factor	user nominated more levels than are permit- ted.			
Warning: Initial gamma value is zero	constraint parameter is probably wrongly as- signed.			
Warning: Invalid argument.	fix the argument.			
Warning: It is usual to include Trait	in multivariate analysis model.			
Warning: LogL Converged; Parameters Not Converged	you may need more iterations.			
Warning: LogL not converged	restart to do more iterations (see $\texttt{!CONTINUE}$).			
Warning: Missing cells in table	missing cells are normally not reported.			
Warning: More levels found in $term$	consider setting levels correctly.			
Warning: PREDICT LINE IGNORED - TOO MANY	limit is 100.			
Warning: PREDICT statement is being ignored	because it contains errors.			
Warning: Second occurrence of term dropped	if you really want to fit this term twice, create a copy with another name.			
Warning: Spatial mapping information for side	gives details so you can check ASRemI is doing what you intend.			
Warning: Standard errors	that is, these standard errors are approximate.			
Warning: SYNTAX CHANGE: $text$ may be invalid	use the correct syntax.			
Warning: The !A qualifier ignored when reading BINARY data	the $! \texttt{A}$ fields will be treated as factors but are not encoded.			
Warning: The !SPLINE qualifier has been redefined.	use correct syntax.			
Warning: The !X !Y !G qualifiers are ignored. There is no data to plot	revise the qualifier arguments.			
Warning: The estimation was ABORTED	do not accept the estimates printed.			
Warning: The labels for predictions are erroneous	the labels for predicted terms are probably out of kilter. Try a simpler predict statement. If the problem persists, send for help.			

List of warning messages and likely meaning(s)

warning message	likely meaning			
Warning: This US structure is not positive definite	check the initial values.			
Warning: Unrecognised qualifier at character	the qualifier either is misspelt or is in the wrong place.			
Warning: US matrix was not positive definite: MODIFIED	the initial values were modified.			
Warning: User specified spline points	the points have been rescaled to suit the data values.			
Warning: Variance parameters were modified by BENDing	ASRemI may not have converged to the best estimate.			
WARNING Likelihood decreased. Check gammas and singularities.:	a common reason is that some constraints have restricted the gammas. Add the !GU qualifier to any factor definition whose gamma value is approaching zero (or the correlation is ap- proaching (-)1. Alternatively, more singular- ities may have been detected. You should identify where the singularities are expected and modify the data so that they are omitted or consistently detected. One possibility is to centre and scale covariates involved in interac- tions so that their standard deviation is close to 1.			

List of warning messages and likely meaning(s)

error message	probable cause		
Convergence failure:	the program did not proceed to convergence because the REML log-likelihood was fluctuat- ing wildly. One possible reason is that some singular terms in the model are not being de- tected consistently. Otherwise, the updated G structures are not positive definite. There are some things to try:		
	 define US structures as positive definite by using !GP, supply better starting values, fix parameters that you are confident of while getting better estimates for others (that is, fix variances when estimating covariances), fit a simpler model, 		
	 reorganise the model to reduce covariance terms (for example, use CORUH instead of US.) 		
Error reading the model factor list:	the model specification line is in error: a vari- able is probably misnamed.		
Error reading the data:	the data file could not be interpreted: alphanumeric fields need the $!A$ qualifier.		
Error reading the data file name:	data file name may be wrong		
Error opening the file:	the named file did not exist or was of the wrong file type (binary = unformatted, sequential).		
Error structures are wrong size:	the declared size of the error structures does not match the actual number of data records.		
Error in R structure:	the error model is not correctly specified.		
FORMAT error reading factor	Likely causes are		
Definitions:	 bad syntax or invalid characters in the variable labels; variable labels must not include any of these symbols; ! -+(:#\$ and ., the data file name is misspelt, there are too many variables declared or there is no valid <i>value</i> supplied with an arithmetic transformation option. 		
Getting Pedigree:	an error occurred processing the pedigree. The pedigree file must be ascii, free format with ANIMAL, SIRE and DAM as the first three fields.		

error message	probable cause
G-structure header: Factor order:	there is a problem reading G structure header line. The line must contain the name of a term in the linear model spelt exactly as it appears in the model
G structure: ORDER O MODEL GAMMAS:	a G structure line cannot be interpreted.
Insufficient knots for :	there must be at least 3 distinct data values
Invalid factor in model:	a term in the <i>model specification</i> is not among the terms that have been defined. Check the spelling.
Invalid model factor :	there is a problem with the named variable.
Invalid definition of a factor:	there is a problem with forming one of the <i>generated</i> factors. The most probable cause is that an interaction cannot be formed.
Invalid weight/filter column number:	the weight and filter columns must be data fields. Check the data summary.
Invalid factor definition:	a term in the model has no levels
Missing values not allowed here:	missing observations have been dropped so that multivariate structure is messed up.
Maximum number of special structures exceeded	special structures are weights, the Ainverse and GIV structures. The limit is 8 and so no more than 6 GIV structures can be defined.
Negative Sum of Squares:	This is typically caused by negative variance parameters; try changing the starting values or using the !STEP option. If the problem oc- curs after several iterations it is likely that the variance components are very small. Try sim- plifying the model. In multivariate analyses it arises if the error variance is (becomes) nega- tive definite. Try specifying !GP on the struc- ture line for the error variance.
NFACT out of range:	too many terms are being defined.
Increase workspace with -Ss command line option:	on some systems the command line option -S3 may help. If the data set is not extremely big, check the data summary.
Out of memory absorbing:	use -S option to increase the memory alloca- tion. It may be possible to revise the models to increase sparsity.

error message	probable cause
Out of memory: forming design:	factors are probably not declared properly. Check the number of levels. Possibly use the -S command line option.
Overflow structure table:	occurs when space allocated for the structure table is exceeded. There is room for three structures for each model term for wich G structures are explicitly declared. The error might occur when ASReml needs to construct rows of the table for structured terms when the user has not formally declared the struc- tures. Increasing g on the variance header line for the number of G structures (see page 89) will increase the space allocated for the table. You will need to add extra explicit declara- tions also.
No residual variation:	after fitting the model, the residual variation is essentially zero, that is, the model fully ex- plains the data. If this is intended, use the !BLUP 1 qualifier so that you can see the es- timates. Otherwise check that the dependent values are what you intend and then identify which variables explain it. Again, the !BLUP 1 qualifier might help.
PROGRAM failed in AIABS:	increase memory.
Pedigree coding errors:	check the pedigree file and see any messages in the output. Check that identifiers and pedi- grees are in chronological order.
Pedigree factor has wrong size:	the A-inverse factors are not the same size as the A-inverse. Delete the ainverse bin file and rerun the job.
Pedigree too big:	program will need to be recompiled if file is correct.
Reading factor names:	something is wrong in the terms definitions. It could also be that the data file is misnamed.
Reading the data:	if you read less data than you expect, there are two likely explanations. First, the data file has less fields than implied by the data structure definitions (you will probably read half the expected number). Second, there is an alphanumeric field where a numeric field is expected.

error message	probable cause
Reading Update step size:	check the !STEP qualifier argument.
Variance header: SEC DIM GSTRUCT:	error with the variance header line. Often, some other error has meant that the wrong line is being interpreted as the variance header line. Commonly, the model is written over sev- eral lines but the incomplete lines do not all end with a comma.
R structure error ORDER SORTCOL MODEL GAMMAS:	an error reading the error model.
Segmentation fault:	this is a Unix memory error. The first thing to try is to increase the memory workspace using the $-S$ (see Section 12.3 on memory) command line option. Otherwise you may need to send your data and the .as files to the Help Desk for debugging.
Sorting the data into field order:	the field order coding in the spatial error model does not generate a complete grid with one observation in each cell; missing values may be deleted: they should be fitted. Also may be due to incorrect specification of num- ber of rows or columns.
STOP SCRATCH FILE DATA STORAGE ERROR:	ASReml attempts to hold the data on a scratch file. Check that the disk partition where the scratch files might be written is not too full; use the !NOSCRATCH qualifier to avoid these scratch files.
Structure/ Factor mismatch:	the declared size of a variance structure does not match the size of the model term that it is associated with.
Too BIG! Use -S option:	memory overflow. Simplify the model, check factor definitions and increase memory using the $-\mathbf{S}$ command line option (see Section 12.3 on memory).
Too many alphanumeric factor level labels:	if the factor level labels are actually all inte- gers, use the !I option instead. Otherwise, you will have to convert a factor with alphanu- meric labels to numeric sequential codes ex- ternal to ASRemI so that an !A option can be avoided.

error message	probable cause
Unable to invert R or G [US?] matrix:	this message occurs when there is an error forming the inverse of a variance structure. The probable cause is a non positive definite (initial) variance structure (US, CHOL and ANTE models). It may also occur if an <i>identity by un-</i> <i>structured</i> ($ID \otimes US$) error variance model is not specified in a multivariate analysis (including !ASMV), see Chapter 8. If the failure is on the first iteration, the problem is with the starting values. If on a subsequent iteration, the up- dates have caused the problem. You could try reducing the updates by using the !STEP qual- ifier. Otherwise, you could try fitting an al- ternative parameterisation. The CORCH model
Unable to invert R or G [CORR?] matrix:	generally refers to a problem setting up the mixed model equations. Most commonly, it is caused by a non positive definite matrix.

Examples

Introduction

Split plot design - Oats

Unbalanced nested design - Rats

Source of variability in unbalanced data - Volts

Balanced repeated measures - Height

Spatial analysis of a field experiment - Barley

Unreplicated early generation variety trial - Wheat

Paired Case-Control study - Rice

Standard analysis A multivariate approach Interpretation of results

Balanced longitudinal data - Oranges

Initial analyses Random coefficients and cubic smoothing splines

Multivariate animal genetics data - Sheep

Half-sib analysis Animal model

15.1 Introduction

In this chapter we present the analysis of a variety of examples. The primary aim is to illustrate the capabilities of ASReml in the context of analysing real data sets. We also discuss the output produced by ASReml and indicate when problems may occur. Statistical concepts and issues are discussed as necessary but we stress that the analyses are illustrative, not prescriptive.

15.2 Split plot design - Oats

The first example involves the analysis of a split plot design originally presented by Yates (1935). The experiment was conducted to assess the effects on yield of three oat varieties (Golden Rain, Marvellous and Victory) with four levels of nitrogen application (0, 0.2, 0.4 and 0.6 cwt/acre). The field layout consisted of six blocks (labelled I, II, III, IV, V and VI) with three whole-plots per block each split into four sub-plots. The three varieties were randomly allocated to the three whole-plots while the four levels of nitrogen application were randomly assigned to the four sub-plots within each whole-plot. The data is presented in Table 15.1.

		nitrogen				
block	variety	0.0cwt	0.2cwt	0.4cwt	0.6cwt	
	GR	111	130	157	174	
1	Μ	117	114	161	141	
	V	105	140	118	156	
	GR	61	91	97	100	
11	Μ	70	108	126	149	
	V	96	124	121	144	
	GR	68	64	112	86	
111	Μ	60	102	89	96	
	V	89	129	132	124	
	GR	74	89	81	122	
IV	Μ	64	103	132	133	
	V	70	89	104	117	
	GR	62	90	100	116	
V	Μ	80	82	94	126	
	V	63	70	109	99	
	GR	53	74	118	113	
VI	Μ	89	82	86	104	
	V	97	99	119	121	

Table 15.1 A split-plot field trial of oat varieties and nitrogen application

A standard analysis of these data recognises the two basic elements inherent in the experiment. These two aspects are firstly the stratification of the experiment units, that is the blocks, whole-plots and sub-plots, and secondly, the treatment structure that is superimposed on the experimental material. The latter is of prime interest, in the presence of stratification. Thus the aim of the analysis is to examine the importance of the treatment effects while accounting for the stratification and restricted randomisation of the treatments to the experimental units. The ASRemI input file is presented below.

```
split plot example
 blocks 6
               # Coded 1...6 in first data field of oats.asd
 nitrogen !A 4 # Coded alphabetically
               # Coded 1...4
 subplots *
 variety !A 3 # Coded alphabetically
 wplots
               # Coded 1...3
          *
vield
oats.asd !SKIP 2
yield ~ mu variety nitrogen variety.nitrogen !r blocks blocks.wplots
predict nitrogen # Print table of predicted nitrogen means
predict variety
predict variety nitrogen !SED
```

The data fields were blocks, wplots, subplots, variety, nitrogen and yield. The first five variables are factors that describe the stratification or experiment design and treatments. The standard split plot analysis is achieved by fitting the model terms blocks and blocks.wplots as random effects. The blocks.wplots.subplots term is not listed in the model because this interaction corresponds to the experimental units and is automatically included as the residual term. The fixed effects include the main effects of both variety and nitrogen and their interaction. The tables of predicted means and associated standard errors of differences (SEDs) have been requested. These are reported in the .pvs file. Abbreviated output is shown below.

Source	Model	terms		Gamma	Component	Comp/SE	% C
blocks	6	6	1.	21116	214.477	1.27	0 P
blocks.wplots	18	18	0.5	98937	106.062	1.56	0 P
Variance	72	60	1.	00000	177.083	4.74	0 P
Analysis of Va	ariance		DF	F-incr			
4 variety			2	1.49			
2 nitrogen			3	37.69			
8 variety.ni	itrogen		6	0.30			

For simple variance component models such as the above, the default parameterisation for the variance component parameters is as the ratio to the residual variance. Thus ASRemI prints the variance component ratio and variance component for each term in the random model in the columns labelled Gamma and Component respectively.

The analysis of variance (ANOVA) is printed below this summary. The usual decomposition has three strata, with treatment effects separating into different strata as a consequence of the balanced design and the allocation of variety to whole-plots. In this balanced case, it is straightforward to derive the ANOVA estimates of the stratum variances from the above REML estimates of the variance components. That is

 $\begin{array}{lll} blocks &=& 12\tilde{\sigma}_b^2+4\tilde{\sigma}_w^2+\tilde{\sigma}^2=3175.1\\ blocks.wplots &=& 4\tilde{\sigma}_w^2+\tilde{\sigma}^2=601.3\\ residual &=& \tilde{\sigma}^2=177.1 \end{array}$

The default output for testing fixed effects used by ASRemI is a table of socalled incremental F-tests. These F-tests are described in Section 6.10. The statistics are simply the appropriate Wald test statistics divided by the number of estimable effects for that term. In this example there are three terms included in the summary. The overall mean (denoted by mu) is of no interest for these data. The tests are sequential, that is the effect of each term is assessed by the change in sums of squares achieved by adding the term to the current model, defined by the model which includes those terms appearing above the current term given the variance parameters. For example, the test of nitrogen is calculated from the change in sums of squares for the two models mu variety nitrogen and mu variety. No refitting occurs, that is the variance parameters are held constant at the REML estimates obtained from the currently specified fixed model.

The incremental Wald statistics have an asymptotic χ^2 distribution, with degrees of freedom (df) given by the number of estimable effects (the number in the DF column). In this example, the incremental F-tests are numerically the same as the ANOVA F-tests, however ASRemI currently has no facility for automatically determining the appropriate denominator df for testing fixed effects. This is a simple problem for balanced designs, such as the split plot design, but it is not straightforward to determine the relevant denominator df in unbalanced designs, such as the rat data set described in the next section.

Tables of predicted means are presented for the nitrogen, variety, and variety by nitrogen tables in the .pvs file. The qualifier !SED has been used on the third predict statement and so the matrix of SEDs for the variety by nitrogen table
is printed. For the first two predictions, the average SED is calculated from the average variance of differences. Note also that the order of the predictions (e.g. 0.6_cwt, 0.4_cwt 0.2_cwt 0_cwt for nitrogen) is simply the order those treatment labels were discovered in the data file.

```
Split plot analysis - oat Variety.Nitrogen
                                                  26 Aug 2002 00:26:33
                                                  oats
Ecode is E for Estimable, * for Not Estimable
---- --- ---- ---- 1 ---- ---- ---- ---- ---- ----
variety is averaged over fixed levels
Predicted values of yield
blocks is ignored in the prediction (except where specifically included
           is ignored in the prediction (except where specifically included
wplots
nitrogen
               Predicted_Value Standard_Error Ecode
0.6 cwt
                     123.3889 7.1747 E
                     114.2222
                                    7.1747 E
0.4_cwt
                       98.8889
                                    7.1747 E
0.2_cwt
                       79.3889
0_cwt
                                    7.1747 E
SED: Overall Standard Error of Difference 4.436
---- --- ---- ---- 2 ---- ---- ---- ---- ---- ----
nitrogen is averaged over fixed levels
Predicted values of yield
blocks is ignored in the prediction (except where specifically included
           is ignored in the prediction (except where specifically included
wplots
               Predicted_Value Standard_Error Ecode
variety
Marvellous
                      109.7917 7.7975 E
                                    7.7975 E
Victory
                      97.6250
                      104.5000 7.7975 E
Golden rain
SED: Overall Standard Error of Difference 7.079
---- ---- ---- ---- 3 ---- ---- ---- ---- ---- ----
Predicted values of yield
blocks is ignored in the prediction (except where specifically included
           is ignored in the prediction (except where specifically included
wplots
                                Predicted_Value Standard_Error Ecode
variety
               nitrogen
                                       126.8333 9.1070 E
Marvellous
                0.6_cwt
                                                     9.1070 E
                0.6_cwt
                                       118.5000
Victory
                                       124.8333
                                                     9.1070 E
Golden_rain
                0.6_cwt
              0.6_cwt
0.4_cwt
                                                     9.1070 E
Marvellous
                                      117.1667
                                      110.8333
                                                     9.1070 E
Victory
               0.4_cwt
Golden_rain
              0.4_cwt
                                                     9.1070 E
                                      114.6667
                                      108.5000
                                                     9.1070 E
Marvellous
               0.2_cwt
                                       89.6667
Victory
               0.2_cwt
                                                    9.1070 E
```

Golden_rain	0.2_cwt		98.5000	9.1070 E
Marvellous	0_cwt		86.6667	9.1070 E
Victory	0_cwt		71.5000	9.1070 E
Golden_rain	0_cwt		80.0000	9.1070 E
Predicted va	alues with SED(PV)			
126.833				
118.500	9.71503			
124.833	9.71503	9.71503		
117.167	7.68295	9.71503	9.71503	
110.833	9.71503	7.68295	9.71503	9.71503
114.667	9.71503	9.71503	7.68295	9.71503
9.71503				
108.500	7.68295	9.71503	9.71503	7.68295
9.71503	9.71503			
89.6667	9.71503	7.68295	9.71503	9.71503
7.68295	9.71503	9.71503		
98.5000	9.71503	9.71503	7.68295	9.71503
9.71503	7.68295	9.71503	9.71503	
86.6667	7.68295	9.71503	9.71503	7.68295
9.71503	9.71503	7.68295	9.71503	9.71503
71.5000	9.71503	7.68295	9.71503	9.71503
7.68295	9.71503	9.71503	7.68295	9.71503
9.71503				
80.0000	9.71503	9.71503	7.68295	9.71503
9.71503	7.68295	9.71503	9.71503	7.68295
9.71503	9.71503			
SED: Min	7.6830 Mean	9.1608 Max	9.7150	

15.3 Unbalanced nested design - Rats

The second example we consider is a data set which illustrates some further aspects of testing fixed effects in linear mixed models. This example differs from the split plot example, as it is unbalanced and so more care is required in assessing the significance of fixed effects.

The experiment was reported by Dempster *et al.* (1984) and was designed to compare the effect of three doses of an experimental compound (control, low and high) on the maternal performance of rats. Thirty female rats (dams) were randomly split into three groups of 10 and each group randomly assigned to the three different doses. All pups in each litter were weighed. The litters differed in total size and in the numbers of males and females. Thus the additional covariate, littersize was included in the analysis. The differential effect of the compound on male and female pups was also of interest. Three litters had to be dropped from experiment, which meant that one dose had only 7 dams. The analysis

must account for the presence of between dam variation, but must also recognise the stratification of the experimental units (pups within litters) and that doses and littersize belong to the dam stratum. Table 15.2 presents an indicative AOV decomposition for this experiment.

stratum	decomposition	type	df or ne
constant dams	1	F	1
	dose	F	2
	littersize	\mathbf{F}	1
	dam	R	27
dams.pup	s		
	sex	\mathbf{F}	1
	dose.sex	\mathbf{F}	2
error		R	

Table 15.2 Rat data: AOV decomposition

The dose and littersize effects are tested against the residual dam variation, while the remaining effects are tested against the residual within litter variation. The ASRemI input to achieve this analysis is presented below.

```
Rats example
dose 3 !A
sex 2 !A
littersize
dam 27
pup 18
weight
                     # Change DOPART argument to select each PART
rats.asd !DOPART 1
!PART 1
weight ~ mu littersize dose sex dose.sex !r dam
!PART 2
weight ~ mu littersize sex dose !r dam
!PART 3
weight ~ mu sex dose littersize !r dam
!PART 4
weight ~ mu littersize dose sex !r dam
```

The input file contains an example of the use of the **!DOPART** qualifier. Its argument specifies which part to execute. We will discuss the models in the four parts. The full model is fitted in part 1. Abbreviated output from this analysis is presented below.

```
S2= 0.19670
                                               0.1000
LogL= 74.2174
                                      315 df
                                                           1.000
LogL= 79.1577
                  S2= 0.18751
                                      315 df
                                               0.1488
                                                           1.000
LogL= 83.9407
                  S2= 0.17755
                                      315 df
                                               0.2446
                                                           1.000
LogL= 86.8093
                  S2= 0.16903
                                      315 df
                                               0.4254
                                                           1.000
LogL= 87.2249
                  S2= 0.16594
                                      315 df
                                               0.5521
                                                           1.000
LogL= 87.2398
                  S2= 0.16532
                                      315 df
                                               0.5854
                                                           1.000
LogL= 87.2398
                  S2= 0.16530
                                               0.5867
                                      315 df
                                                           1.000
Final parameter values
                                              0.58667
                                                          1.0000
Source
             Model terms
                                                      Comp/SE
                                                                % C
                              Gamma
                                         Component
                27
                       27
                           0.586674
                                          0.969769E-01
                                                         2.92
                                                                0 P
dam
Variance
               322
                      315
                            1.00000
                                          0.165299
                                                        12.09
                                                                0 P
Analysis of Variance
                           DF
                                  F-incr
 3 littersize
                            1
                                    27.99
                            2
 1 dose
                                    12.15
 2 sex
                            1
                                    57.96
                            2
                                     0.40
 8 dose.sex
```

The iterative sequence has converged and the variance component parameter for dam hasn't changed for the last two iterations. The incremental Wald tests indicate that the interaction between dose and sex is not significant. Since these tests are sequential, the test for the dose.sex term is appropriate as it respects marginality with both the main effects of dose and sex fitted before the interaction.

Before proceeding we note the .res file reports several possible outliers, in particular unit 66 has a standardised residual of -8.80 (see Figure 15.1). The weight of this female rat, within litter 9 is only 3.68, compared to weights of 7.26 and 6.58 for two other female sibling pups. This weight appears erroneous, but without knowledge of the actual experiment we retain the observation in the following.



Figure 15.1 Residual plot for the rat data

We refit the model without the dose.sex term. Note that the variance parameters are re-estimated, though there is little change from the previous analysis. The output below presents the incremental Wald tests for this analysis.

Source	Model	terms	Ga	mma	Component	Comp/SE	% C	2
dam	27	27	0.595	157	0.979179E-	01 2.93	0 F	•
Variance	322	317	1.00	000	0.164524	12.13	0 F	>
Analysis of	Varian	ce	DF	F-in	ıcr			
7 mu			1	8981.	48			
3 litters	ize		1	27.	85			
2 sex			1	59.	54			
1 dose			2	11.	42			

The three remaining fixed effects appear significant, though an additional two models (part 3 and part 4) must be fitted to properly test the fixed effects in the model. Table 15.3 presents the summary of these analyses.

The second column of F-tests pertains to a model which (wrongly) excludes the dam term. The impact of deleting the dam term on the F-tests for the fixed effects is substantial and not surprising. This example reinforces the importance of preserving the strata of the design when assessing the significance of fixed effects.

		F-test					
term	df	with \mathtt{dam}	without dam				
littersize	1	46.43	146.50				
dose	1	11.42	58.43				
sex	1	58.27	24.52				

Table 15.3: Summary of F-tests of fixed effects adjusted for the other factors for the rat data

15.4 Source of variability in unbalanced data - Volts

In this example we illustrate an analysis of unbalanced data in which the main aim is to determine the sources of variation rather than assess the significance of imposed treatments. The data are taken from Cox and Snell (1981) and involve an experiment to examine the variability in the production of car voltage regulators. Standard production of regulators involves two steps. Regulators are taken from the production line and passed to a setting station which adjusts the regulator to operate within a specified range of voltage. From the setting station the regulator is then passed to a testing station where it is tested and returned if outside the required range.

A total of 64 regulators were tested at four testing stations (teststat). The voltage for individual regulators was set at a total of 10 setting stations (setstat). A variable number of regulators (between 4 to 8) were set at each station, however each regulator was tested at every testing station. The ASRemI input file is presented below

```
Voltage data
teststat 4  # 4 testing stations tested each regulator
setstat !A  # 10 setting stations each set 4-8 regulators
regulatr 8  # regulators numbered within setting stations
voltage
5-3-6.asd !skip 1
voltage ~ mu !r setstat setstat.regulatr teststat setstat.teststat
0 0 0
```

The factor **regulatr** numbers the regulators within each setting station. Thus the term **setstat.regulatr** allows for differential effects of each regulator, while the other terms examine the effects of the setting and testing stations and possible interaction. The abbreviated output is given below

```
LogL= 188.604
                  S2= 0.67074E-01
                                     255 df
LogL= 199.530
                  S2= 0.59303E-01
                                     255 df
LogL= 203.007
                  S2= 0.52814E-01
                                     255 df
                  S2= 0.51278E-01
LogL= 203.240
                                     255 df
LogL= 203.242
                  S2= 0.51141E-01
                                     255 df
LogL= 203.242
                                     255 df
                  S2= 0.51140E-01
                                                                    % C
Source
                 Model
                        terms
                                  Gamma
                                            Component
                                                         Comp/SE
setstat
                    10
                           10 0.233418
                                             0.119371E-01
                                                             1.35
                                                                    0 P
                    80
                           64
                               0.601817
                                             0.307771E-01
                                                             3.64
                                                                    0 P
setstat.regulatr
teststat
                    4
                           4
                              0.642752E-01 0.328706E-02
                                                             0.98
                                                                    0 P
                    40
                           40 0.100000E-08 0.511404E-10
                                                             0.00
                                                                    0 B
setstat.teststat
Variance
                   256
                          255
                               1.00000
                                             0.511404E-01
                                                             9.72
                                                                    0 P
Warning: Code B - fixed at a boundary (!GP)
                                                  F - fixed by user
              ? - liable to change from P to B
                                                  P - positive definite
                                                  U - unbounded
              C - Constrained by user (!VCC)
              S - Singular Information matrix
```

The convergence criteria has been satisfied after six iterations. A warning message in printed below the summary of the variance components because the variance component for the setstat.teststat term has been fixed near the boundary. The default constraint for variance components (!GP) is to ensure that the REML estimate remains positive. Under this constraint, if an update for any variance component results in a negative value then ASRemI sets that variance component to a small positive value. If this occurs in subsequent iterations the parameter is fixed to a small positive value and the code B replaces P in the C column of the summary table. The default constraint can be overridden using the !GU qualifier, but it is not generally recommended for standard analyses.

Figure 15.2 presents the residual plot which indicates two unusual data values. These values are successive observations, namely observation 210 and 211, being testing stations 2 and 3 for setting station 9(J), regulator 2. These observations will not be dropped from the following analyses for consistency with other analyses conducted by Cox and Snell (1981) and in the GENSTAT manual.

The REML log-likelihood from the model without the setstat.teststat term was 203.242, the same as the REML log-likelihood for the previous model. Table 15.4 presents a summary of the REML log-likelihood ratio for the remaining terms in the model. The summary of the ASReml output for the current model is given below. The column labelled Comp/SE is printed by ASReml to give a guide



ltage example 5-3-6 from the GENSTAT REML manual

Figure 15.2 Residual plot for the voltage data

as to the significance of the variance component for each term in the model. The statistic is simply the REML estimate of the variance component divided by the square root of the diagonal element (for each component) of the inverse of the average information matrix. The diagonal elements of the expected (not the average) information matrix are the asymptotic variances of the REML estimates of the variance parameters. These Comp/SE statistics cannot be used to test the null hypothesis that the variance component is zero. If we had used this crude measure then the conclusions would have been inconsistent with the conclusions obtained from the REML log-likelihood ratio (see Table 15.4).

Source	Model	terms	Gamma	Component	Comp/SE	% C
setstat	10	10	0.233417	0.119370E-01	1.35	0 P
setstat.regulati	r 80	64	0.601817	0.307771E-01	1 3.64	0 P
teststat	4	4	0.642752E-01	0.328705E-02	2 0.98	0 P
Variance	256	255	1.00000	0.511402E-01	1 9.72	0 P

15.5 Balanced repeated measures - Height

The data for this example is taken from the GENSTAT manual. It consists of a total of 5 measurements of height (cm) taken on 14 plants. The 14 plants were either diseased or healthy and were arranged in a glasshouse in a completely

Residuals vs Fitted valu

terms	REML log-likelihood	$-2\times$ difference	P-value
— setstat	200.31	5.864	.0077
— setstat.regulatr	184.15	38.19	.0000
— teststat	199.71	7.064	.0039

Table 15.4: REML log-likelihood ratio for the variance components in the voltage data

random design. The heights were measured 1, 3, 5, 7 and 10 weeks after the plants were placed in the glasshouse. There were 7 plants in each treatment. The data are depicted in Figure 15.3 obtained by qualifier line

!Y y1 !G tmt !JOIN

in the following multivariate ASReml job.



Figure 15.3 Trellis plot of the height for each of 14 plants

In the following we illustrate how various repeated measures analyses can be conducted in ASReml. For these analyses it is convenient to arrange the data in a multivariate form, with 7 fields representing the plant number, treatment identification and the 5 heights. The ASReml input file, up to the specification of the R structure is given by

```
This is plant data multivariate

tmt !A # Diseased Healthy

plant 14

y1 y3 y5 y7 y10

plantmult.asd !skip 1 !ASUV
```

The focus is modelling of the error variance for the data. Specifically we fit the multivariate regression model given by

$$Y = DT + E \tag{15.1}$$

where $\boldsymbol{Y}^{14\times 5}$ is the matrix of heights, $\boldsymbol{D}^{14\times 2}$ is the design matrix, $\boldsymbol{T}^{2\times 5}$ is the matrix of fixed effects and $\boldsymbol{E}^{14\times 5}$ is the matrix of errors. The heights taken on the same plants will be correlated and so we assume that

$$\operatorname{var}\left(\operatorname{vec}(\boldsymbol{E})\right) = \boldsymbol{I}_{14} \otimes \boldsymbol{\Sigma} \tag{15.2}$$

where $\Sigma^{5 \times 5}$ is a symmetric positive definite matrix.

The variance models used for Σ are given in Table 15.5. These represent some commonly used models for the analysis of repeated measures data (see Wolfinger, 1986). The variance models are fitted by changing the last four lines of the input file. The sequence of commands for the first model fitted is given below

```
y1 y3 y5 y7 y10 ~ Trait tmt Tr.tmt !r units
1 2 0
14
Tr
```

model	number of parameters	REML log-likelihood	BIC
Uniform Power Heterogeneous Power Antedependence (order 1) Unstructured	$2 \\ 2 \\ 6 \\ 9 \\ 15$	-196.88 -182.98 -171.50 -160.37 -158.04	$\begin{array}{r} 401.95\\ 374.15\\ 367.57\\ 357.51\\ 377.50\end{array}$

Table 15.5 Summary of variance models fitted to the plant data

The split plot in time model can be fitted in two ways, either by fitting a units term plus an independent residual as above, or by specifying a CORU variance model for the R-structure as follows

y1 y3 y5 y7 y10 ~ Trait tmt Tr.tmt 1 2 0 14 Tr 0 CORU .5

The two forms for Σ are given by

$$\begin{split} \boldsymbol{\Sigma} &= \sigma_1^2 \boldsymbol{J} + \sigma_2^2 \boldsymbol{I}, & \text{units} \\ \boldsymbol{\Sigma} &= \sigma_e^2 \boldsymbol{I} + \sigma_e^2 \rho (\boldsymbol{J} - \boldsymbol{I}), & \text{CORU} \end{split} \tag{15.3}$$

It follows that

$$\begin{aligned}
\sigma_e^2 &= \sigma_1^2 + \sigma_2^2 \\
\rho &= \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}
\end{aligned} \tag{15.4}$$

Portions of the two outputs are given below. The REML log-likelihoods for the two models are the same and it is easy to verify that the REML estimates of the variance parameters satisfy (15.4), viz. $\sigma_e^2 = 286.310 \approx 159.858 + 126.528 = 286.386$; 159.858/286.386 = 0.558191.

#								
#								
# !r units								
#								
LogL=-204.593	S2=	224.61		60	df	0.1000	1.000	
LogL=-201.233	S2=	186.52		60	df	0.2339	1.000	
LogL=-198.453	S2=	155.09		60	df	0.4870	1.000	
LogL=-197.041	S2=	133.85		60	df	0.9339	1.000	
LogL=-196.881	S2=	127.56		60	df	1.204	1.000	
LogL=-196.877	S2=	126.53		60	df	1.261	1.000	
Final parameter	r values	3				1.2634	1.0000	
Source	Model	terms	Gamma		C	omponent	Comp/SE	% C
units	14	14	1.26342			159.858	2.11	0 P
Variance	70	60	1.00000			126.528	4.90	0 P
#								
# CORU								
#								
LogL=-196.975	S2=	264.10		60	df	1.000	0.5000	
LogL=-196.924	S2=	270.14		60	df	1.000	0.5178	
LogL=-196.886	S2=	278.58		60	df	1.000	0.5400	

LogL=-196.8	77 S2⁼	= 286.	23	60	df	1.000	0.5580		
LogL=-196.8	77 S2=	= 286.	31	60	df	1.000	0.5582		
Final param	eter value	es				1.0000	0.55819		
Source	Model	terms	Gamma		Com	ponent	Comp/SE	%	с
Variance	70	60	1.00000		2	86.310	3.65	0	Ρ
Residual	CORRelat	5	0.558191		0.	558191	4.28	0	U

A more realistic model for repeated measures data would allow the correlations to decrease as the lag increases such as occurs with the first order autoregressive model. However, since the heights are not measured at equally spaced time points we use the EXP model. The correlation function is given by

$$\rho(u) = \phi^u$$

where u is the time lag is weeks. The coding for this is

A portion of the output is given below

LogL=-183	.734	S2= 43	35.58	60	df	1.000	0.	9500	
LogL=-183	.255	S2= 37	70.40	60	df	1.000	0.	9388	
LogL=-183	.010	S2= 32	21.50	60	df	1.000	0.	9260	
LogL=-182	.980	S2= 29	98.84	60	df	1.000	0.	9179	
LogL=-182	.979	S2= 30	02.02	60	df	1.000	0.	9192	
Final par	ameter va	lues				1.0000	0.9	1897	
Source	Model	terms	Gamma	C	ompor	nent	Comp/SE	% (С
Variance	70	60	1.00000		302	.021	3.11	0 1	P
Residual	POW-EXP	5	0.918971	(0.918	3971	29.53	0 0	Ü

When fitting power models be careful to ensure the scale of the defining variate, here time, does not result in an estimate of ϕ too close to 1. For example, use of days in this example would result in an estimate for ϕ of about .993.

The residual plot from this analysis is presented in Figure 15.4. This suggests increasing variance over time. This can be modelled by using the EXPH model,



Figure 15.4 Residual plots for the EXP variance model for the plant data

which models Σ by

$$\boldsymbol{\Sigma} = \boldsymbol{D}^{0.5} \boldsymbol{C} \boldsymbol{D}^{0.5}$$

where D is a diagonal matrix of variances and C is a correlation matrix with elements given by $c_{ij} = \phi^{|t_i - t_j|}$. The coding for this is

y1 y3 y5 y7 y10 ~ Trait tmt Tr.tmt 1 2 0 14 !S2==1 Tr 0 EXPH .5 100 200 300 300 300 1 3 5 7 10

Note that it is necessary to fix the scale parameter to 1 (!S2==1) to ensure that the elements of D are identifiable. Abbreviated output from this analysis is given below.

1	LogL=-195.598	S2=	1.0000	60	df	:	1	components	constrained
2	LogL=-179.036	S2=	1.0000	60	df				
3	LogL=-175.483	S2=	1.0000	60	df				
4	LogL=-173.128	S2=	1.0000	60	df				
5	LogL=-171.980	S2=	1.0000	60	df				
6	LogL=-171.615	S2=	1.0000	60	df				
7	LogL=-171.527	S2=	1.0000	60	df				

8 LogL=-171.504	S2= 1.	.0000	60	df		
9 LogL=-171.498	S2= 1.	0000	60	df		
10 LogL=-171.496	S2= 1.	.0000	60	df		
Source	Model	terms	Gamma	Component	Comp/SE	% C
Residual	POW-EXP	5	0.906917	0.906917	21.89	0 U
Residual	POW-EXP	5	60.9599	60,9599	2.12	0 U
Residual	POW-EXP	5	72,9904	72,9904	1.99	0 U
Residual	POW-EXP	5	309.259	309.259	2.22	ΟU
Residual	POW-EXP	5	436.380	436.380	2.52	0 U
Residual	POW-EXP	5	382.369	382.369	2.74	0 U
Covariance/Variance,	/Correlati	ion Mat	rix POWER			
61.11 0.8227	0.6769	0.	5569	0.4156		
54.88 72.80	0.8227	0.	6769	0.5051		
93.12 123.5	309.7	0.	8227	0.6140		
91.02 120.7	302.7	4	37.1	0.7462		
63.57 84.34	211.4	3	05.3	382.9		
Analysis of Variance	9		DF	F-incr		
8 Trait	-		5	127.95		
1 tmt			1	0.00		
9 Tr.tmt			4	4.75		

The last two models we fit are the antedependence model of order 1 and the unstructured model. These require, as starting values the lower triangle of the full variance matrix. We use the REML estimate of Σ from the heterogeneous power model shown in the previous output. The antedependence model models Σ by the inverse cholesky decomposition

$$\Sigma^{-1} = UDU'$$

where D is a diagonal matrix and U is a unit upper triangular matrix. For an antedependence model of order q, then $u_{ij} = 0$ for j > i + q - 1. The antedependence model of order 1 has 9 parameters for these data, 5 in D and 4 in U. The input is given by

```
y1 y3 y5 y7 y10 ~ Trait tmt Tr.tmt
1 2 0
14 !S2==1
Tr O ANTE
  60.16
  54.65
             73.65
  91.50
             123.3
                        306.4
             120.2
                        298.6
                                    431.8
  89.17
  62.21
             83.85
                         208.3
                                    301.2
                                               379.8
```

The abbreviated output file is given below

1 LogL=-17	71.501	S2=	1.0000		60	df		
2 LogL=-17	70.097	S2=	1.0000		60	df		
3 LogL=-16	6.085	S2=	1.0000		60	df		
4 LogL=-16	31.335	S2=	1.0000		60	df		
5 LogL=-16	60.407	S2=	1.0000		60	df		
6 LogL=-16	50.370	S2=	1.0000		60	df		
7 LogL=-16	30.369	S2=	1.0000		60	df		
Source	Model	terms	Gam	ma	Comp	ponent	Comp/SE	% C
Residual	ANTE=UDU	1	0.2686	57E-01	0.2	268657E-01	2.44	0 U
Residual	ANTE=UDU	1	-0.6284	13	-0.6	528413	-2.55	0 U
Residual	ANTE=UDU	2	0.3728	01E-01	0.3	372801E-01	2.41	0 U
Residual	ANTE=UDU	2	-1.491	.08	-1	49108	-2.54	0 U
Residual	ANTE=UDU	3	0.5996	32E-02	0.5	5 <mark>99632E-</mark> 02	2.43	0 U
Residual	ANTE=UDU	3	-1.280	41	-1	. 28041	-6.19	0 U
Residual	ANTE=UDU	4	0.7897	13E-02	0.7	789713E-02	2.44	0 U
Residual	ANTE=UDU	4	-0.9678	15	-0.9	967815	-15.40	0 U
Residual	ANTE=UDU	5	0.3906	35E-01	0.3	390635E-01	2.45	0 U
Covariance	e/Variance	e/Corre	elation	Matrix	ANTE	E=UDU'		
37.20	0.5946	0.3	3549	0.3114	1	0.3040		
23.38	41.55	0.5	5968	0.5237	7	0.5112		
34.83	61.89	25	58.9	0.8775	5	0.8565		
44.58	79.22	33	31.4	550.8	3	0.9761		
43.14	76.67	32	20.7	533.0)	541.4		
Analysis o	of Variand	ce			DF	F-incr		
8 Trait					5	188.84		
1 tmt					1	4.14		
9 Tr.tm	t				4	3.91		

The iterative sequence converged and the antedependence parameter estimates are printed successively for each time, the element of D and then the row of U. I.e.

$$\boldsymbol{D} = \operatorname{diag} \begin{bmatrix} 0.0269\\ 0.0373\\ 0.0060\\ 0.0079\\ 0.0391 \end{bmatrix}, \boldsymbol{U} = \begin{bmatrix} 1 & -0.6284 & 0 & 0 & 0\\ 0 & 1 & -1.4911 & 0 & 0\\ 0 & 0 & 1 & -1.2804 & 0\\ 0 & 0 & 0 & 1 & -0.9678\\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

Finally the input and output files for the unstructured model are presented below. The REML estimate of Σ from the ANTE model is used to provide starting values.

```
###########
#input
###########
y1 y3 y5 y7 y10 ~ Trait tmt Tr.tmt
1 2 0
14 !S2==1
Tr 0 US
  37.20
  23.38
             41.55
  34.83
             61.89
                         258.9
  44.58
             79.22
                         331.4
                                     550.8
  43.14
             76.67
                         320.7
                                     533.0
                                                541.4
############
# output
############
1 LogL=-160.368
                                          60 df
                     S2=
                         1.0000
2 LogL=-159.027
                     S2=
                                          60 df
                          1.0000
3 LogL=-158.247
                     S2=
                         1.0000
                                          60 df
4 LogL=-158.040
                     S2= 1.0000
                                          60 df
5 LogL=-158.036
                     S2= 1.0000
                                          60 df
                                                                  % C
 Source
                               Gamma
                                          Component
                                                        Comp/SE
             Model
                    terms
 Residual US=UnStr
                            37.2262
                                           37.2262
                                                          2.45
                                                                 0 U
                       1
 Residual US=UnStr
                        1
                            23.3935
                                           23.3935
                                                          1.77
                                                                 0 U
 Residual US=UnStr
                        2
                            41.5195
                                           41.5195
                                                          2.45
                                                                 0 U
 Residual US=UnStr
                            51.6524
                                           51.6524
                                                          1.61
                                                                 0 U
                        1
 Residual US=UnStr
                        2
                            61.9169
                                           61.9169
                                                          1.78
                                                                 0 U
 Residual US=UnStr
                            259.121
                                           259.121
                                                          2.45
                                                                 0 U
                        3
 Residual US=UnStr
                            70.8113
                                                          1.54
                                                                 0 U
                        1
                                           70.8113
                                                                 0 U
 Residual US=UnStr
                        2
                                                          1.23
                            57.6146
                                           57.6146
 Residual US=UnStr
                        3
                            331.807
                                           331.807
                                                          2.29
                                                                 0 U
 Residual US=UnStr
                            551.507
                                           551.507
                                                          2.45
                                                                 0 U
                        4
 Residual US=UnStr
                                                          1.60
                                                                 0 U
                        1
                            73.7857
                                           73.7857
 Residual US=UnStr
                        2
                            62.5691
                                           62.5691
                                                          1.33
                                                                 0 U
 Residual US=UnStr
                            330.851
                                           330.851
                                                          2.29
                                                                 0 U
                        3
 Residual US=UnStr
                        4
                            533.756
                                           533.756
                                                          2.42
                                                                 0 U
 Residual US=UnStr
                        5
                            542.175
                                           542.175
                                                          2.45
                                                                 0 U
 Covariance/Variance/Correlation Matrix US=UnStructu
  37.23
            0.5950
                        0.5259
                                   0.4942
                                               0.5194
  23.39
             41.52
                        0.5969
                                   0.3807
                                               0.4170
                         259.1
  51.65
             61.92
                                   0.8777
                                               0.8827
  70.81
                         331.8
                                    551.5
                                               0.9761
             57.61
                         330.9
  73.79
             62.57
                                     533.8
                                                542.2
```

The antedependence model of order 1 is clearly more parsimonious than the unstructured model. Table 15.6 presents the incremental Wald tests for each of the variance models. There is a surprising level of discrepancy between models for the Wald tests. The main effect of treatment is significant for the uniform, power and antedependence models.

model	treatment (df=1)	treatment.time (df=4)
Uniform Power Heterogeneous power Antedependence (order 1)	9.41 6.86 0.00 4.14 1.71	5.10 6.13 4.81 3.96 4.46
Unstructured	1.(1	4.40

Table 15.6: Summary of Wald test for fixed effects for variance models fitted to the plant data

15.6 Spatial analysis of a field experiment - Barley

In this section we illustrate the ASReml syntax for performing spatial and incomplete block analysis of a field experiment. There has been a large amount of interest in developing techniques for the analysis of spatial data both in the context of field experiments and geostatistical data (see for example, Cullis and Gleeson, 1991; Cressie, 1991; Gilmour *et al.*, 1997). This example illustrates the analysis of 'so-called' regular spatial data, in which the data is observed on a lattice or regular grid. This is typical of most small plot designed field experiments. Spatial data is often irregularly spaced, either by design or because of the observational nature of the study. The techniques we present in the following can be extended for the analysis of irregularly spaced spatial data, though, larger spatial data sets may be computationally challenging, depending on the degree of irregularity or models fitted.

The data we consider is taken from Gilmour *et al.* (1995) and involves a field experiment designed to compare the performance of 25 varieties of barley. The experiment was conducted at Slate Hall Farm, UK in 1976, and was designed as a balanced lattice square with replicates laid out as shown in Table 15.7. The data fields were Rep, RowBlk, ColBlk, row, column and yield. Lattice row and column numbering is typically within replicates and so the terms specified in the linear model to account for the lattice row and lattice column effects would be Rep.latticerow Rep.latticecolumn. However, in this example lattice rows and columns are both numbered from 1 to 30 across replicates (see Table 15.7). The terms in the linear model are therefore simply RowBlk ColBlk. Additional fields row and column indicate the spatial layout of the plots. The ASReml input file is presented below. Three models have been fitted to these data. The lattice analysis is included for comparison in PART 3. In PART 1 we use the separable first order autoregressive model to model the variance structure of the plot errors. Gilmour *et al.* (1997) suggest this is often a useful model to commence the spatial modelling process. The form of the variance matrix for the plot errors (R structure) is given by

$$\sigma^2 \mathbf{\Sigma} = \sigma^2 (\mathbf{\Sigma}_c \otimes \mathbf{\Sigma}_r) \tag{15.5}$$

where Σ_c and Σ_r are 15×15 and 10×10 matrix functions of the column (ϕ_c) and row (ϕ_r) autoregressive parameters respectively.

						COIU		nepn	cate 1	evers					
Row	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3
2	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3
3	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3
4	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3
5	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3
6	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6
7	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6
8	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6
9	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6
10	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6
						Col	umn ·	- Row	blk le	evels					
Row	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	1	1	1	1	11	11	11	11	11	21	21	21	21	21
2	2	2	2	2	2	12	12	12	12	12	22	22	22	22	22
3	3	3	3	3	3	13	13	13	13	13	23	23	23	23	23
4	4	4	4	4	4	14	14	14	14	14	24	24	24	24	24
5	5	5	5	5	5	15	15	15	15	15	25	25	25	25	25
6	6	6	6	6	6	16	16	16	16	16	26	26	26	26	26
7	7	7	7	7	7	17	17	17	17	17	27	27	27	27	27
8	8	8	8	8	8	18	18	18	18	18	28	28	28	28	28
9	9	9	9	9	9	19	19	19	19	19	29	29	29	29	29
10	10	10	10	10	10	20	20	20	20	20	30	30	30	30	30
						Co	lumn	- Col	blk le	vels					
Row	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
3	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
4	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
5	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
6	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
7	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
8	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
9	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
10	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30

Table 15.7 Field layout of Slate Hall Farm experiment

Column Poplicate levels

Gilmour *et al.* (1997) recommend revision of the current spatial model based on the use of diagnostics such as the sample variogram of the residuals (from the current model). This diagnostic and a summary of row and column residual trends are produced by default with graphical versions of ASRemI when a spatial model has been fitted to the errors. It can be suppressed, by the use of the -noption on the command line. We have produced the following plots by use of the -g22 option.

```
Slate Hall example
             # Six replicates of 5x5 plots in 2x3 arrangement
  Rep 6
  RowBlk 30 # Rows within replicates numbered across replicates
  ColBlk 30 # Columns within replicates numbered across replicates
  row 10
             # Field row
  column 15 # Field column
  variety 25
  yield
shf.asd !skip 1 !DOPART 1
!PART 1 # AR1 x AR1
y ~ mu var
predict var
1 2
15 column AR1 0.1 # Second field is specified so ASReml can sort
10 row AR1 0.1
                    # records properly into field order
!PART 2 # AR1 x AR1 + units
y ~ mu var !r units
predict var
1 2
15 column AR1 0.1
10 row AR1 0.1
!PART 3 # incomplete blocks
y ~ mu var !r Rep Rowblk Colblk
predict var
```

Abbreviated ASReml output file is presented below. The iterative sequence has converged to column and row correlation parameters of (.68377,.45859) respectively. The plot size and orientation is not known and so it is not possible to ascertain whether these values are spatially sensible. It is generally found that the closer the plot centroids, the higher the spatial correlation. This is not always the case and if the highest between plot correlation relates to the larger spatial distance then this may suggest the presence of extraneous variation (see Gilmour *et al.*, 1997), for example. Figure 15.5 presents a plot of the sample variogram of the residuals from this model. The plot appears in reasonable agreement with the model.

Residual

The next model includes a measurement error or nugget effect component. That is the variance model for the plot errors is now given by

$$\sigma^2 \Sigma = \sigma^2 (\Sigma_c \otimes \Sigma_r) + \psi \boldsymbol{I}_{150}$$
(15.6)

where ψ is the ratio of nugget variance to error variance (σ^2). The abbreviated output for this model is given below. There is a significant improvement in the REML log-likelihood with the inclusion of the nugget effect (see Table 15.8).



Figure 15.5 Sample variogram of the AR1×AR1 model for the Slate Hall data

# AR1 x AR1						
# 1 LogL=-739.681	S2= 3603	34. 125	df 1.	000 0.1	.000 (0.1000
2 LogL=-714.340	S2= 2810	9. 125	df 1.	000 0.4	049 (0.1870
3 LogL=-703.338	S2= 2991	.4. 125	df 1.	000 0.5	5737 (0.3122
4 LogL=-700.371	S2= 3746	54 . 125	df 1.	000 0.6	5789 (0.4320
5 LogL=-700.324	S2= 3860	. 125	df 1.	000 0.6	838 (0.4542
6 LogL=-700.322	S2= 3873	35. 125	df 1.	000 0.6	838 (0.4579
7 LogL=-700.322	S2= 3875	i4. 125	df 1.	000 0.6	838 (0.4585
8 LogL=-700.322	S2= 3875	57. 125	df 1.	000 0.6	838 (0.4586
Final parameter val	ues		1.0000	0.68377	0.4586	51
Source	Model te	erms Gamma	Comp	onent Co	mp/SE 2	6 C
Variance	150	125 1.00000	38	756.6	5.00 (D P
Residual	AR=AutoR	15 0.683767	0.6	83767	10.80 (ט ט

10 0.458607

AR=AutoR

0.458607

5.55

0 U

Analysis of Variance	Э		DF	F-	incr				
8 mu			1	85	0.71				
6 variety			24	1	3.04				
# AR1 x AR1 + units									
1 LogL=-740.735	S2= 3	33225.	125	df	:	2 co	mponents	const	trained
2 LogL=-723.595	S2= 1	L1661.	125	df	:	1 co	mponents	const	trained
3 LogL=-698.498	S2= 4	16239.	125	df					
4 LogL=-696.847	S2= 4	4725.	125	df					
5 LogL=-696.823	S2= 4	15563.	125	df					
6 LogL=-696.823	S2= 4	15753.	125	df					
7 LogL=-696.823	S2= 4	15796.	125	df					
Source	Model	terms	Gamma		Compo	nent	Comp/S	E ?	% C
units	150	150	0.106154		486	31.48	2.7	2 (0 P
Variance	150	125	1.00000		457	96.3	2.7	'4 (0 P
Residual	AR=AutoF	R 15	0.843795		0.84	3795	12.3	3 (υc
Residual	AR=AutoF	R 10	0.682686		0.68	82686	6.6	68 (υC
Analysis of Variance	Э		DF	F-	incr				
8 mu			1	25	9.82				
6 variety			24	1	0.22				

The lattice analysis (with recovery of between block information) is presented below. This variance model is not competitive with the preceding spatial models. The models can be formally compared using the BIC values for example.

# IB analysis						
1 LogL=-734.184	S2= 2	6778.	125	df		
2 LogL=-720.060	S2= 1	6591.	125	df		
3 LogL=-711.119	S2= 1	1173.	125	df		
4 LogL=-707.937	S2= 8	562.4	125	df		
5 LogL=-707.786	S2= 8	8091.2	125	df		
6 LogL=-707.786	S2= 8	8061.8	125	df		
7 LogL=-707.786	S2= 8	8061.8	125	df		
Source	Model	terms	Gamma	Component	Comp/SE	% C
Rep	6	6	0.528714	4262.39	0.62	0 P
Rep RowBlk	6 30	6 30	0.528714 1.93444	4262.39 15595.1	0.62 3.06	0 P 0 P
Rep RowBlk ColBlk	6 30 30	6 30 30	0.528714 1.93444 1.83725	4262.39 15595.1 14811.6	0.62 3.06 3.04	0 P 0 P 0 P
Rep RowBlk ColBlk Variance	6 30 30 150	6 30 30 125	0.528714 1.93444 1.83725 1.00000	4262.39 15595.1 14811.6 8061.81	0.62 3.06 3.04 6.01	0 P 0 P 0 P 0 P
Rep RowBlk ColBlk Variance	6 30 30 150	6 30 30 125	0.528714 1.93444 1.83725 1.00000	4262.39 15595.1 14811.6 8061.81	0.62 3.06 3.04 6.01	0 P 0 P 0 P 0 P
Rep RowBlk ColBlk Variance Analysis of Variance	6 30 30 150	6 30 30 125	0.528714 1.93444 1.83725 1.00000 DF	4262.39 15595.1 14811.6 8061.81 F-incr	0.62 3.06 3.04 6.01	0 P 0 P 0 P 0 P
Rep RowBlk ColBlk Variance Analysis of Variance 8 mu	6 30 30 150	6 30 30 125	0.528714 1.93444 1.83725 1.00000 DF 1	4262.39 15595.1 14811.6 8061.81 F-incr 1216.29	0.62 3.06 3.04 6.01	0 P 0 P 0 P 0 P

Finally, we present portions of the .pvs files to illustrate the prediction facility of ASRemI . The first five and last three variety means are presented for illustration. The overall SED printed is the square root of the average variance of difference between the variety means. The two spatial analyses have a range of SEDs which are available if the !SED qualifier is used. All variety comparisons have the same SED from the third analysis as the design is a balanced lattice square. The F-test statistics for the spatial models are greater than for the lattice analysis. We note the F-test for the AR1×AR1 + units model is smaller than the F-test for the AR1×AR1.

```
Predicted values of yield
#AR1 x AR1
variety
                     Predicted_Value Standard_Error Ecode
       1.0000
                           1257.9763
                                             64.6146 E
       2.0000
                           1501.4483
                                             64.9783 E
       3.0000
                           1404.9874
                                             64.6260 E
       4.0000
                           1412.5674
                                             64.9027 E
                                             65.5889 E
       5.0000
                            1514.4764
      23.0000
                            1311.4888
                                             64.0767 E
      24.0000
                            1586.7840
                                             64.7043 E
      25.0000
                           1592.0204
                                             63.5939 E
SED: Overall Standard Error of Difference
                                              59.05
#AR1 x AR1 + units
variety
                     Predicted_Value Standard_Error Ecode
       1.0000
                           1245.5843
                                             97.8591 E
       2.0000
                           1516.2331
                                             97.8473 E
       3.0000
                           1403.9863
                                             98.2398 E
       4.0000
                           1404.9202
                                             97.9875 E
                                             98.3607 E
       5.0000
                           1471.6197
      23.0000
                                             98.0402 E
                            1316.8726
      24.0000
                           1557.5278
                                             98.1272 E
      25.0000
                           1573.8920
                                             97.9803 E
SED: Overall Standard Error of Difference
                                              60.51
# IB
Rep
                      is ignored in the prediction
RowBlk
                      is ignored in the prediction
ColBlk
                      is ignored in the prediction
variety
                     Predicted_Value Standard_Error Ecode
                                             60.1994 E
       1.0000
                            1283.5870
                                             60.1994 E
       2.0000
                            1549.0133
       3.0000
                            1420.9307
                                             60.1994 E
       4.0000
                            1451.8554
                                             60.1994 E
       5.0000
                            1533.2749
                                             60.1994 E
```

	23.0000		13	29	. 1088	60.	1994	E
	24.0000		15	46	. 4699	60.	1994	E
	25.0000		16	30	. 6285	60.	1994	E
SED:	Overall	Standard	Error	of	Difference	62	2.02	

Notice the differences in SE and SED associated with the various models. Choosing a model on the basis of smallest SE or SED is not recommended because the model is not necessarily fitting the variability present in the data.

model	REML log-likelihood	number of parameters	F-test	SED
AR1×AR1 AR1×AR1 + units IB	-700.32 -696.82 -707.79	3 4 4	$13.04 \\ 10.22 \\ 8.84$	$59.0 \\ 60.5 \\ 62.0$

Table 15.8 Summary of models for the Slate Hall data

15.7 Unreplicated early generation variety trial - Wheat

To further illustrate the approaches presented in the previous section, we consider an unreplicated field experiment conducted at Tullibigeal situated in southwestern NSW. The trial was an S1 (early stage) wheat variety evaluation trial and consisted of 525 test lines which were randomly assigned to plots in a 67 by 10 array. There was a check plot variety every 6 plots within each column. That is the check variety was sown on rows $1, 7, 13, \ldots, 67$ of each column. This variety was numbered 526. A further 6 replicated commercially available varieties (numbered 527 to 532) were also randomly assigned to plots with between 3 to 5 plots of each. The aim of these trials is to identify and retain the top, say 20%of lines for further testing. Cullis et al. (1989) considered the analysis of early generation variety trials, and presented a one-dimensional spatial analysis which was an extension of the approach developed by Gleeson and Cullis (1987). The test line effects are assumed random, while the check variety effects are considered fixed. This may not be sensible or justifiable for most trials and can lead to inconsistent comparisons between check varieties and test lines. Given the large amount of replication afforded to check varieties there will be very little shrinkage irrespective of the realised heritability.

In the following we assume that the variety effects (including both check, replicated and unreplicated lines) is random. We consider an initial analysis with spatial correlation in one direction and present three further spatial models for comparison. The ASReml input file is presented below.

```
Tullibigeal trial
  linenum
  yield
  weed
  column 10
  row 67
  variety 532 # testlines 1:525, check lines 526:532
tulli.asd !skip 1 !DOPART 1
!PART 1
                              # AR1 x I
y ~ mu weed mv !r variety
1 2
67 row AR1 0.1
10 column I 0
!PART 2
                               # AR1 x AR1
y ~ mu weed mv !r variety
1 2
67 row AR1 0.1
10 column AR1 0.1
!PART 3
                               # AR1 x AR1 + column trend
y ~ mu weed pol(column,-1) mv !r variety
1 2
67 row AR1 0.1
10 column AR1 0.1
!PART 4
                              # AR1 x AR1 + Nugget + column trend
y ~ mu weed pol(column,-1) mv !r variety units
1 2
67 row AR1 0.1
10 column AR1 0.1
predict var
```

The data fields represent the factors variety, row and column, a covariate weed and the plot yield (yield). There are three parts in the ASRemI file. We begin with the one-dimensional spatial model, which assumes the variance model for the plot effects within columns is described by a first order autoregressive process. The abbreviated output file is presented below.

1 LogL=-4280.75	S2= 0.12850E+06	666 df	0.1000	1.000	0.1000
2 LogL=-4268.57	S2= 0.12138E+06	666 df	0.1516	1.000	0.1798

3 LogL=-4255.89	S2= 0.	10968E+0	666	df 0.	2977	1.000	0.2980
4 LogL=-4243.76	S2= 8	8033.	666	df 0.	7398	1.000	0.4939
5 LogL=-4240.59	S2= 8	4420.	666	df 0.	9125	1.000	0.6016
6 LogL=-4240.01	S2= 8	5617.	666	df 0.	9344	1.000	0.6428
7 LogL=-4239.91	S2= 8	6032.	666	df 0.	9474	1.000	0.6596
8 LogL=-4239.88	S2= 8	6189.	666	df 0.	9540	1.000	0.6668
9 LogL=-4239.88	S2= 8	6253.	666	df 0.	9571	1.000	0.6700
10 LogL=-4239.88	S2= 8	6280.	666	df 0.	9585	1.000	0.6714
Final parameter valu	ies			0.95918	1.0	000 0.6	7205
Source	Model	terms	Gamma	Com	ponent	Comp/SE	% C
variety	532	532	0.959184	8	2758.6	8.98	0 P
Variance	670	666	1.00000	8	6280.2	9.12	0 P
Residual	AR=AutoR	. 67	0.672052	0.	672052	16.04	1 U
Analysis of Variance	Э		DF	F-incr	F-	adj	
7 mu			1	9799.18	9336	.79	
3 weed			1	109.33	109	.33	

The iterative sequence converged, the REML estimate of the autoregressive parameter indicating substantial within column heterogeneity.

The abbreviated output from the two-dimensional AR1 \times AR1 spatial model is now presented.

1 LogL=-4277.99	S2= 0.	12850E+0	666	df			
2 LogL=-4266.13	S2= 0.	12097E+0	666	df			
3 LogL=-4253.05	S2= 0.	10777E+0	666	df			
4 LogL=-4238.72	S2= 8	33156.	666	df			
5 LogL=-4234.53	S2= 7	79868.	666	df			
6 LogL=-4233.78	S2= 8	32024.	666	df			
7 LogL=-4233.67	S2= 8	32725.	666	df			
8 LogL=-4233.65	S2= 8	32975.	666	df			
9 LogL=-4233.65	S2= 8	33065.	666	df			
10 LogL=-4233.65	S2= 8	33100.	666	df			
Source	Model	terms	Gamma	Comp	onent	Comp/SE	% C
variety	532	532	1.06038	88	117.5	9.92	0 P
Variance	670	666	1.00000	83	100.1	8.90	0 P
Residual	AR=AutoR	R 67	0.685387	0.6	85387	16.65	0 U
Residual	AR=AutoR	R 10	0.285909	0.2	85909	3.87	0 U
Analysis of Variance	Э		DF	F-incr	F-a	łj	
7 mu			1	6248.65	6117.3	37	
3 weed			1	85.84	85.8	34	

The change in REML log-likelihood is significant ($\chi^2_1 = 12.46, p < .001$) with

the inclusion of the autoregressive parameter for columns. Figure 15.6 presents the sample variogram of the residuals for the AR1×AR1 model. There is an indication that a linear drift from column 1 to column 10 is present. We include a linear regression coefficient pol(column,-1) in the model to account for this. Note we use the '-1' option in the pol term to exclude the overall constant in the regression, as it is already fitted. The linear regression of column number on yield is significant (t = -2.96). The sample variogram (15.7) is more satisfactory, though interpretation of variograms is often difficult, particularly for unreplicated trials. This is an issue for further research.



Figure 15.6 Sample variogram of the AR1×AR1 model for the Tullibigeal data

The abbreviated output for this model and the final model in which a nugget effect has been included is presented below.

#AR1xAR1 + pol(column,	-1)				
1 LogL=-4270.99	S2= 0.12730E+06	665 df			
2 LogL=-4258.95	S2= 0.11961E+06	665 df			
3 LogL=-4245.27	S2= 0.10545E+06	665 df			
4 LogL=-4229.50	S2= 78387.	665 df			
5 LogL=-4226.02	S2= 75375.	665 df			
6 LogL=-4225.64	S2= 77373.	665 df			
7 LogL=-4225.60	S2= 77710.	665 df			
8 LogL=-4225.60	S2= 77786.	665 df			
9 LogL=-4225.60	S2= 77806.	665 df			
Source	Model terms	Gamma	Component	Comp/SE	% C

variety	532	532	1.14370	88	986.3	9.9	1 O P
Variance	670	665	1.00000	77	806.0	8.79	9 O P
Residual	AR=AutoR	ι 67	0.671436	0.6	71436	15.60	5 O U
Residual	AR=AutoR	a 10	0.266088	0.2	66088	3.53	30U
Analysis of Varianc	e		DF	F-incr	F-adj		
7 mu			1	7082.49	6726.77		
3 weed			1	91.96	70.00		
8 pol(column,-1)			1	8.74	8.74		
#							
<pre>#AR1xAR1 + units + p</pre>	ol(column	1,-1)					
# 1 LogI = 4070 74	80- 0	1160251	06 665	af .	1	onta	constrained
1 LogL = -4272.74	S2- 0.	11003E+	665	df ·		onte d	constrained
2 LogL = 4200.07 3 LogL = -4228.96	S2- C S2= 7	6724	665	df .	I Compone	ents	Constrained
4 Log = -4220.50	S2- 7 S2- 5	5858	665	df			
4 LogL = 4220.03	S2- 0 S2- 5		665	df			
6 LogL = -4220.13	S2- C S2= 5	4732	665	df			
7 LogL = -4220.10	S2= 5	4717	665	df			
8 $L_{og}L = -4220.18$	S2= 5	4715	665	df			
0 1081 1220.10	52 0	, 11 10.	000	ui			
Source	Model	terms	Gamma	Comp	onent Co	omp/SI	E%C
variety	532	532	1.34824	73	769.0	7.08	3 O P
units	670	670	0.556400	30	443.6	3.7	7 O P
Variance	670	665	1.00000	54	715.2	5.1	5 O P
Residual	AR=AutoR	ι 67	0.837503	0.8	37503	18.6	7 O U
Residual	AR=AutoR	a 10	0.375382	0.3	75382	3.20	5 O U
Analysis of Varianc	e		DF	F-incr	F-adj		
7 mu			1	4241.39	4259.90		
3 weed			1	86.39	72.73		
8 pol(column,-1)			1	4.84	4.84		

The increase in REML log-likelihood is significant. The predicted means for the varieties can be produced and printed in the <code>.pvs</code> file as shown below

Warning: mv_estim	ates is ignore	d for prediction	
Warning: units	is ignore	d for prediction	
	1		
column	evaluated at	5.5000	
weed	is evaluated at av	erage value of 0.45	97
Predicted values	of yield	-	
variety	Predicted_Value Sta	ndard_Error Ecode	
1.0000	2917.1782	179.2881 E	
2.0000	2957.7405	178.7688 E	
3.0000	2872.7615	176.9880 E	



Figure 15.7: Sample variogram of the AR1 \times AR1 + pol(column,-1) model for the Tullibigeal data

4.0000		29	86.4725		178.7424	Ε
			•			
522.0000		27	84.7683		179.1541	Е
523.0000		29	04.9421		179.5383	Е
524.0000		27	40.0330		178.8465	Е
525.0000		26	69.9565		179.2444	Е
526.0000		23	85.9806		44.2159	Е
527.0000		26	97.0670		133.4406	Е
528.0000		27	27.0324		112.2650	Е
529.0000		26	99.8243		103.9062	Е
530.0000		30	10.3907		112.3080	Е
531.0000		30	20.0720		112.2553	Е
532.0000		30	67.4479		112.6645	Е
SED: Overall	Standard	Error	of Diffe	rence	245.8	

Note that the (replicated) check lines have lower SE than the (unreplicated) test lines. There will also be large diffeneces in SEDs. Rather than obtaining the large table of all SEDs, you could do the prediction in parts predict var 1:525 column 5.5 predict var 526:532 column 5.5 !SED to examine the matrix of pairwise prediction errors of variety differences.

15.8 Paired Case-Control study - Rice

This data is concerned with an experiment conducted to investigate the tolerance of rice varieties to attack by the larvae of bloodworms. The data have been kindly provided by Dr. Mark Stevens, Yanco Agricultural Institute. A full description of the experiment is given by Stevens *et al.* (1999). Bloodworms are a significant pest of rice in the Murray and Murrumbidgee irrigation areas where they can cause poor establishment and substantial yield loss.

The experiment commenced with the transplanting of rice seedlings into trays. Each tray contained 32 seedlings and the trays were paired so that a control tray (no bloodworms) and a treated tray (bloodworms added) were grown in a controlled environment room for the duration of the experiment. At the end of this time rice plants were carefully extracted, the root system washed and root area determined for the tray using an image analysis system described by Stevens *et al.* (1999). Two pairs of trays, each pair corresponding to a different variety, were included in each run. A new batch of bloodworm larvae was used for each run. A total of 44 varieties was investigated with three replicates of each. Unfortunately the variety concurrence within runs was less than optimal. Eight varieties occurred with only one other variety, 22 with two other varieties and the remaining 14 with three different varieties.

In the next three sections we present an exhaustive analysis of these data using equivalent univariate and multivariate techniques. It is convenient to use two data files one for each approach. The univariate data file consists of factors pair, run, variety, tmt, unit and variate rootwt. The factor unit labels the individual trays, pair labels pairs of trays (to which varieties are allocated) and tmt is the two level bloodworm treatment factor (control/treated). The multivariate data file consists of factors variety and run and variates for root weight of both the control and exposed treatments (labelled yc and ye respectively).

Figure 15.8 presents a plot of the treated and the control root area (on the square root scale) for each variety. There is a strong dependence between the treated and control root area, which is not surprising. The aim of the experiment was to determine the tolerance of varieties to bloodworms thence identify the most tolerant varieties. The definition of tolerance should allow for the fact that varieties differ in their inherent seedling vigour (Figure 15.8). The original approach of the scientist was to regress the treated root area against the control root area and define the index of vigour as the residual from this regression. This approach is clearly inefficient since there is error in both variables. We seek to



determine an index of tolerance from the joint analysis of treated and control root area.

Figure 15.8: Rice bloodworm data: Plot of square root of root weight for treated versus control

Standard analysis

Preliminary analyses indicated variance heterogeneity so that subsequent analyses were conducted on the square root scale. The allocation of bloodworm treatments within varieties and varieties within runs defines a nested block structure of the form

```
run/variety/tmt = run + run.variety + run.variety.tmt
    ( = run + pair + pair.tmt )
    ( = run + run.variety + units )
```

There is an additional blocking term, however, due to the fact that the bloodworms within a run are derived from the same batch of larvae whereas between runs the bloodworms come from different sources. This defines a block structure of the form

Combining the two provides the full block structure for the design, namely

```
run + run.variety + run.tmt + run.tmt.variety
= run + run.variety + run.tmt + units
= run + pair + run.tmt + pair.tmt
```

In line with the aims of the experiment the treatment structure comprises variety and treatment main effects and treatment by variety interactions. In the traditional approach the terms in the block structure are regarded as random and the treatment terms as fixed. The choice of treatment terms as fixed or random depends largely on the aims of the experiment. The aim of this example is to select the "best" varieties. The definition of best is somewhat more complex since it does not involve the single trait sqrt(rootwt) but rather two traits, namely sqrt(rootwt) in the presence/absence of bloodworms. Thus to minimise selection bias the variety main effects and thence the tmt.variety interactions are taken as random. The main effect of treatment is fitted as fixed to allow for the likely scenario that rather than a single population of treatment by variety effects there are in fact two populations (control and treated) with a different mean for each. There is evidence of this prior to analysis with the large difference in mean sqrt(rootwt) for the two groups (14.93 and 8.23 for control and treated respectively). The inclusion of tmt as a fixed effect ensures that BLUPs of tmt.variety effects are shrunk to the correct mean (treatment means rather than an overall mean).

The model for the data is given by

$$y = X\tau + Z_1u_1 + Z_2u_2 + Z_3u_3 + Z_4u_4 + Z_5u_5 + e$$
(15.7)

where \boldsymbol{y} is a vector of length n = 264 containing the sqrt(rootwt) values, $\boldsymbol{\tau}$ corresponds to a constant term and the fixed treatment contrast and $\boldsymbol{u}_1 \dots \boldsymbol{u}_5$ correspond to random variety, treatment by variety, run, treatment by run and variety by run effects. The random effects and error are assumed to be independent Gaussian variables with zero means and variance structures var $(\boldsymbol{u}_i) = \sigma_i^2 \boldsymbol{I}_{b_i}$ (where b_i is the length of \boldsymbol{u}_i , $i = 1 \dots 5$) and var $(\boldsymbol{e}) = \sigma^2 \boldsymbol{I}_n$.

The ASReml code for this analysis is given by

Bloodworm data Dr M Stevens pair 132 rootwt

```
run 66
tmt 2 !A
id
variety 44 !A
worm.txt !skip 1 !DOPART 1
!PART 1
sqrt(rootwt) ~ mu tmt !r variety variety.tmt run pair run.tmt
0 0 0
!PART 2
sqrt(rootwt) ~ mu tmt !r variety tmt.variety run pair tmt.run,
uni(tmt,2)
0 0 2
tmt.variety 2
2 0 DIAG .1 .1 !GU
44 0 0
tmt.run 2
2 0 DIAG .1 .1 !GU
66 0 0
```

The two parts in the input file define the two univariate analyses we will conduct. We consider the results from the analysis defined in PART 1 first. A portion of the output file is presented below.

1 LogL=-369.089	S2= 4	4.1533	262	df		
2 LogL=-357.871	S2= 2	2.6834	262	df		
3 LogL=-349.520	S2= 3	1.7986	262	df		
4 LogL=-345.739	S2=	1.3719	262	df		
5 LogL=-345.306	S2=	1.3216	262	df		
6 LogL=-345.267	S2= 3	1.3155	262	df		
7 LogL=-345.264	S2= 3	1.3149	262	df		
8 LogL=-345.263	S2=	1.3149	262	df		
Source	Model	terms	Gamma	Component	Comp/SE	% C
variety	44	44	1.80947	2.37920	3.01	0 P
run	66	66	0.244243	0.321144	0.59	0 P
variety.tmt	88	88	0.374220	0.492047	1.78	0 P
pair	132	132	0.742328	0.976057	2.51	0 P
run.tmt	132	132	1.32973	1.74841	3.65	0 P
Variance	264	262	1.00000	1.31486	4.42	0 P
Analysis of Variance			DF	F-incr		
7 mu			1	1484.96		
4 tmt			1	469.35		

The estimated variance components from this analysis are given in column (a) of table 15.9. The variance component for the variety main effects is large. There

	(a)	(b)	
source		$\operatorname{control}$	treated
variety	2.378	2.	334
tmt.variety	0.492	1.505	-0.372
run	0.321	0.	319
tmt.run	1.748	1.388	2.223
variety.run (pair)	0.976	0.9	987
tmt.pair	1.315	1.156	1.359
REML log-likelihood	-345.256	-34	3.22

Table 15.9: Estimated variance components from univariate analyses of bloodworm data. (a) Model with homogeneous variance for all terms and (b) Model with heterogeneous variance for interactions involving tmt

is evidence of tmt.variety interactions so we may expect some discrimination between varieties in terms of tolerance to bloodworms.

Given the large difference (p < 0.001) between tmt means we may wish to allow for heterogeneity of variance associated with tmt. Thus we fit a separate variety variance for each level of tmt so that instead of assuming var $(u_2) = \sigma_2^2 I_{88}$ we assume

$$\operatorname{var}\left(\boldsymbol{u}_{2}\right) = \left[\begin{array}{cc} \sigma_{2c}^{2} & 0\\ 0 & \sigma_{2t}^{2} \end{array}\right] \otimes \boldsymbol{I}_{44}$$

where σ_{2c}^2 and σ_{2t}^2 are the tmt.variety interaction variances for control and treated respectively. This model can be achieved using a diagonal variance structure for the treatment part of the interaction. We also fit a separate **run** variance for each level of tmt and heterogeneity at the residual level, by including the uni(tmt,2) term. We have chosen level 2 of tmt as we expect more variation for the exposed treatment and thus the extra variance component for this term should be positive. Had we mistakenly specified level 1 then ASRemI would have estimated a negative component by setting the !GU option for this term. The portion of the ASRemI output for this analysis is given below.

1	LogL=-369.991	S2=	4.0377	262 df				
2	LogL=-357.468	S2=	2.5831	262 df				
3	LogL=-348.310	S2=	1.6917	262 df	:	1	components	constrained

4 LogL=-344.027	S2= 1.	.2176	262	df :	1 componen	ts cor	nstrain	led
5 LogL=-343.573	S2= 1.	. 1605	262	df :	1 componen	ts cor	nstrain	led
6 LogL=-343.428	S2= 1.	. 1498	262	df :	1 componen	ts cor	nstrain	led
7 LogL=-343.234	S2= 1.	. 1531	262	df				
8 LogL=-343.228	S2= 1.	. 1572	262	df				
9 LogL=-343.228	S2= 1.	. 1563	262	df				
Source	Model	terms	Gamma	Compon	nent Com	p/SE	% C	
variety	44	44	2.01903	2.33	3451	3.01	0 P	
run	66	66	0.276045	0.319	9178	0.59	0 P	
pair	132	132	0.853941	0.987	7372	2.59	0 P	
uni(tmt,2)	264	264	0.176158	0.203	3684	0.32	0 P	
Variance	264	262	1.00000	1.15	625	2.77	0 P	
tmt.variety	DIAGonal	1	1.30142	1.50)477	2.26	0 U	
tmt.variety	DIAGonal	2	-0.321901	-0.372	- 2199	0.82	0 U	
tmt.run	DIAGonal	1	1.20098	1.38	3864	2.18	0 U	
tmt.run	DIAGonal	2	1.92457	2.22	2530	3.07	0 U	
Analysis of Variand	ce		DF	F-incr				
7 mu			1	1276.91				
4 tmt			1	448.86				

The estimated variance components from this analysis are given in column (b) of table 15.9. There is no significant variance heterogeneity at the residual or tmt.run level. This indicates that the square root transformation of the data has successfully stabilised the error variance. There is, however, significant variance heterogeneity for tmt.variety interactions with the variance being much greater for the control group. This reflects the fact that in the absence of bloodworms the potential maximum root area is greater. Note that the tmt.variety interaction variance for the treated group is negative. The negative component is meaningful (and in fact necessary and obtained by use of the !GU option) in this context since it should be considered as part of the variance structure for the combined variety main effects and treatment by variety interactions. That is,

$$\operatorname{var}\left(\mathbf{1}_{2}\otimes\mathbf{u}_{1}+\mathbf{u}_{2}\right)=\left[\begin{array}{cc}\sigma_{1}^{2}+\sigma_{2c}^{2}&\sigma_{1}^{2}\\\sigma_{1}^{2}&\sigma_{1}^{2}+\sigma_{2t}^{2}\end{array}\right]\otimes\mathbf{I}_{44}$$
(15.8)

Using the estimates from table 15.9 this structure is estimated as

$$\left[\begin{array}{rrr} 3.84 & 2.33 \\ 2.33 & 1.96 \end{array}\right] \otimes \boldsymbol{I}_{44}$$

Thus the variance of the variety effects in the control group (also known as the genetic variance for this group) is 3.84. The genetic variance for the treated group is much lower (1.96). The genetic correlation is $2.33/\sqrt{3.84 * 1.96} = 0.85$ which is strong, supporting earlier indications of the dependence between the treated and control root area (Figure 15.8).

effects	bivariate (model 15.10)	univariate (model 15.7)
trait.variety trait.run trait.pair	$egin{array}{c} oldsymbol{u}_v\ oldsymbol{u}_r\ oldsymbol{e}^*\end{array}$	$egin{aligned} & 1_2\otimes oldsymbol{u}_1+oldsymbol{u}_2\ & 1_2\otimes oldsymbol{u}_3+oldsymbol{u}_4\ & 1_2\otimes oldsymbol{u}_5+oldsymbol{e} \end{aligned}$

T.I.I. 1F 10	E				•	The second second	- · · · ·	and the state of a	
Table 15.10	Equivalence	ΟΤ	random	errects	In	bivariate	and	univariate	analyses

A multivariate approach

In this simple case in which the variance heterogeneity is associated with the two level factor tmt, the analysis is equivalent to a bivariate analysis in which the two traits correspond to the two levels of tmt, namely sqrt(rootwt) for control and treated. The model for each trait is given by

$$\boldsymbol{y}_j = \boldsymbol{X}\boldsymbol{\tau}_j + \boldsymbol{Z}_v \boldsymbol{u}_{v_j} + \boldsymbol{Z}_r \boldsymbol{u}_{r_j} + \boldsymbol{e}_j \quad (j = c, t)$$
(15.9)

where \boldsymbol{y}_j is a vector of length n = 132 containing the sqrtroot values for variate j (j = c for control and j = t for treated), $\boldsymbol{\tau}_j$ corresponds to a constant term and \boldsymbol{u}_{v_j} and \boldsymbol{u}_{r_j} correspond to random variety and run effects. The design matrices are the same for both traits. The random effects and error are assumed to be independent Gaussian variables with zero means and variance structures $\operatorname{var}(\boldsymbol{u}_{v_j}) = \sigma_{v_j}^2 \boldsymbol{I}_{44}$, $\operatorname{var}(\boldsymbol{u}_{r_j}) = \sigma_{r_j}^2 \boldsymbol{I}_{66}$ and $\operatorname{var}(\boldsymbol{e}_j) = \sigma_j^2 \boldsymbol{I}_{132}$. The bivariate model can be written as a direct extension of (15.9), namely

$$\boldsymbol{y} = (\boldsymbol{I}_2 \otimes \boldsymbol{X}) \boldsymbol{\tau} + (\boldsymbol{I}_2 \otimes \boldsymbol{Z}_v) \boldsymbol{u}_v + (\boldsymbol{I}_2 \otimes \boldsymbol{Z}_r) \boldsymbol{u}_r + \boldsymbol{e}^*$$
(15.10)

where $\boldsymbol{y} = (\boldsymbol{y}_c', \boldsymbol{y}_t')', \ \boldsymbol{u}_v = (\boldsymbol{u}_{v_c}', \boldsymbol{u}_{v_t}')', \ \boldsymbol{u}_r = (\boldsymbol{u}_{r_c}', \boldsymbol{u}_{r_t}')' \ \text{and} \ \boldsymbol{e}^* = (\boldsymbol{e}_c', \boldsymbol{e}_t')'.$

There is an equivalence between the effects in this bivariate model and the univariate model of (15.7). The variety effects for each trait (u_v in the bivariate model) are partitioned in (15.7) into variety main effects and tmt.variety interactions so that $u_v = \mathbf{1}_2 \otimes u_1 + u_2$. There is a similar partitioning for the run effects and the errors (see table 15.10).

In addition to the assumptions in the models for individual traits (15.9) the bivariate analysis involves the assumptions $\operatorname{cov}(\boldsymbol{u}_{v_c}) \boldsymbol{u}'_{v_t} = \sigma_{v_{ct}} \boldsymbol{I}_{44}$, $\operatorname{cov}(\boldsymbol{u}_{r_c}) \boldsymbol{u}'_{r_t} = \sigma_{r_{ct}} \boldsymbol{I}_{66}$ and $\operatorname{cov}(\boldsymbol{e}_c) \boldsymbol{e}'_t = \sigma_{ct} \boldsymbol{I}_{132}$. Thus random effects and errors are correlated between traits. So, for example, the variance matrix for the variety effects for each trait is given by

$$\operatorname{var}\left(\boldsymbol{u}_{v}\right) = \left[\begin{array}{cc} \sigma_{v_{c}}^{2} & \sigma_{v_{ct}} \\ \sigma_{v_{ct}} & \sigma_{v_{t}}^{2} \end{array}\right] \otimes \boldsymbol{I}_{44}$$

This unstructured form for trait.variety in the bivariate analysis is equivalent to the variety main effect plus heterogeneous tmt.variety interaction variance structure (15.8) in the univariate analysis. Similarly the unstructured form for trait.run is equivalent to the run main effect plus heterogeneous tmt.run interaction variance structure. The unstructured form for the errors (trait.pair) in the bivariate analysis is equivalent to the pair plus heterogeneous error (tmt.pair) variance in the univariate analysis.

This bivariate analysis is achieved in ASRemI as follows, noting that the tmt factor here is equivalent to traits

```
this is for the paired data
 id
 pair 132
 run 66
 variety 44 !A
ус уе
wormm.asd !skip 1 !X syc !Y sye
sqrt(yc) sqrt(ye) ~ Trait !r Tr.variety Tr.run
1 2 2
132 !S2==1
Tr 0 US 2.21 1.1 2.427
Tr.variety 2
2 0 US 1.401 1 1.477
44 0 0
Tr.run 2
2 0 US .79 .5 2.887
66 0 0
predict variety
```

A portion of the output from this analysis is presented below.

1	LogL=-354.998	S2=	1.0000	262	df		
2	LogL=-350.056	S2=	1.0000	262	df		
3	LogL=-345.557	S2=	1.0000	262	df		
4	LogL=-343.386	S2=	1.0000	262	df		
5	LogL=-343.226	S2=	1.0000	262	df		
6	LogL=-343.220	S2=	1.0000	262	df		
7	LogL=-343.220	S2=	1.0000	262	df		
8	LogL=-343.220	S2=	1.0000	262	df		
Source		Model	terms	Gamma	Component	Comp/SE	% C
------------	-----------	-------------	---------	-------------	-----------	---------	-----
Residual		UnStruct	1	2.14373	2.14373	4.44	0 U
Residual		UnStruct	1	0.987401	0.987401	2.59	0 U
Residual		UnStruct	2	2.34751	2.34751	4.62	0 U
Tr.variety		UnStruct	1	3.83959	3.83959	3.47	0 U
Tr.variety		UnStruct	1	2.33394	2.33394	3.01	0 U
Tr.variety		UnStruct	2	1.96173	1.96173	2.69	0 U
Tr.run		UnStruct	1	1.70788	1.70788	2.62	0 U
Tr.run		UnStruct	1	0.319145	0.319145	0.59	0 U
Tr.run		UnStruct	2	2.54326	2.54326	3.20	0 U
Covariance	/Variance	e/Correlat:	ion Mat	rix UnStrue	ctured		
2.144	0.4402						
0.9874	2.348						
Covariance	/Variance	e/Correlat:	ion Mat	rix UnStrue	ctured		
3.840	0.8504						
2.334	1.962						
Covariance	/Variance	e/Correlat:	ion Mat	rix UnStrue	ctured		
1.708	0.1531						
0.3191	2.543						

The resultant REML log-likelihood is identical to that of the heterogeneous univariate analysis (column (b) of table 15.9). The estimated variance parameters are given in Table 15.11.

Predicted variety means are produced in the .pvs. These are used in the following section on interpretation of results. A portion of the file is presented below. There is a wide range in SED reflecting the imbalance of the variety concurrence within runs.

```
Assuming Power transformation was (Y+ 0.000)<sup>^</sup> 0.500
```

Table 15.11: Estimated variance parameters from bivariate analysis of bloodworm data

source	control variance	treated variance	covariance
us(trait).variety us(trait).run us(trait).pair	$3.84 \\ 1.71 \\ 2.14$	$1.96 \\ 2.54 \\ 2.35$	$2.33 \\ 0.32 \\ 0.99$

run	is ignored	in the predict	tion (except	where	specifically	included
Trait	variety	Power_value	Stand_Error	Ecode	Retransformed	approx_SE
sqrt(yc)	AliCombo	14.9532	0.9181	Е	223.5982	27.4571
<pre>sqrt(ye)</pre>	AliCombo	7.9941	0.7993	Е	63.9054	12.7790
<pre>sqrt(yc)</pre>	Bluebelle	13.1033	0.9310	Е	171.6969	24.3980
sqrt(ye)	Bluebelle	6.6299	0.8062	Е	43.9559	10.6901
<pre>sqrt(yc)</pre>	C22	16.6679	0.9181	Е	277.8192	30.6057
sqrt(ye)	C22	8.9543	0.7993	Е	80.1798	14.3140
sqrt(yc)	Chiyohikari	17.3393	0.9301	Е	300.6510	32.2538
sqrt(ye)	Chiyohikari	9.6433	0.8057	Е	92.9927	15.5393
<pre>sqrt(yc)</pre>	YRK1	15.1859	0.9549	Е	230.6103	29.0012
sqrt(ye)	YRK1	8.3356	0.8190	Е	69.4817	13.6534
sqrt(yc)	YRK3	13.3057	0.9549	Е	177.0428	25.4106
sqrt(ye)	YRK3	8.1133	0.8190	Е	65.8264	13.2894
SED: Overa	11 Standard Erro	or of Differen	ce 1 215			



Figure 15.9 BLUPs for treated for each variety plotted against BLUPs for control

Interpretation of results

Recall that the researcher is interested in varietal tolerance to bloodworms. This could be defined in various ways. One option is to consider the regression implicit in the variance structure for the trait by variety effects. The variance structure can arise from a regression of treated variety effects on control effects, namely

$$u_{v_t} = \beta u_{v_c} + \epsilon$$

where the slope $\beta = \sigma_{v_{ct}}/\sigma_{v_c}^2$. Tolerance can be defined in terms of the deviations from regression, ϵ . Varieties with large positive deviations have greatest tolerance to bloodworms. Note that this is similar to the researcher's original intentions except that the regression has been conducted at the genotypic rather than the phenotypic level. In Figure 15.9 the BLUPs for treated have been plotted against the BLUPs for control for each variety and the fitted regression line (slope = 0.61) has been drawn. Varieties with large positive deviations from the regression line include YRK3, Calrose, HR19 and WC1403.



Figure 15.10: Estimated deviations from regression of treated on control for each variety plotted against estimate for control

An alternative definition of tolerance is the simple difference between treated and control BLUPs for each variety, namely $\boldsymbol{\delta} = \boldsymbol{u}_{v_c} - \boldsymbol{u}_{v_t}$. Unless $\beta = 1$ the two measures $\boldsymbol{\epsilon}$ and $\boldsymbol{\delta}$ have very different interpretations. The key difference is that $\boldsymbol{\epsilon}$ is a measure which is *independent* of inherent vigour whereas $\boldsymbol{\delta}$ is not. To see this consider

$$\begin{aligned} \cos\left(\boldsymbol{\epsilon}\right)\boldsymbol{u}_{v_{c}}^{\prime} &= \cos\left(\boldsymbol{u}_{v_{t}} - \beta\boldsymbol{u}_{v_{c}}\right)\boldsymbol{u}_{v_{c}}^{\prime} \\ &= \left(\sigma_{v_{ct}} - \frac{\sigma_{v_{ct}}}{\sigma_{v_{c}}^{2}}\sigma_{v_{c}}^{2}\right)\boldsymbol{I}_{44} \\ &= \boldsymbol{0}\end{aligned}$$

whereas

$$\begin{array}{lll} \cos\left(\boldsymbol{\delta}\right)\boldsymbol{u}_{v_c}' &=& \cos\left(\boldsymbol{u}_{v_c}-\boldsymbol{u}_{v_t}\right)\boldsymbol{u}_{v_c}' \\ &=& \left(\sigma_{v_c}^2-\sigma_{v_{ct}}\right)\boldsymbol{I}_{44} \end{array}$$



Figure 15.11: Estimated difference between control and treated for each variety plotted against estimate for control

The independence of $\boldsymbol{\epsilon}$ and \boldsymbol{u}_{v_c} and dependence between $\boldsymbol{\delta}$ and \boldsymbol{u}_{v_c} is clearly illustrated in Figures 15.10 and 15.11. In this example the two measures have provided very different rankings of the varieties. The choice of tolerance measure depends on the aim of the experiment. In this experiment the aim was to identify tolerance which is independent of inherent vigour so the deviations from regression measure is preferred.

15.9 Balanced longitudinal data - Random coefficients and cubic smoothing splines - Oranges

We now illustrate the use of random coefficients and cubic smoothing splines for the analysis of balanced longitudinal data. The implementation of cubic smoothing splines in ASRemI was originally based on the mixed model formulation presented by Verbyla *et al.* (1999). More recently the technology has been enhanced so that the user can specify knot points; in the original approach the knot points were taken to be the ordered set of unique values of the explanatory variable. The specification of knot points is particularly useful if the number of unique values in the explanatory variable is large, or if units are measured at different times.

The data we use was originally reported by Draper and Smith (1998, ex24N, p559) and has recently been reanalysed by Pinheiro and Bates (2000, p338). The data are displayed in Figure 15.12 and are the trunk circumferences (in millimetres) of each of 5 trees taken at 7 times. All trees were measured at the same time so that the data are balanced. The aim of the study is unclear, though, both previous analyses involved modelling the overall 'growth' curve, accounting for the obvious variation in both level and shape between trees. Pinheiro and Bates (2000) used a nonlinear mixed effects modelling approach, in which they modelled the growth curves by a three parameter logistic function of age, given by

$$y = \frac{\phi_1}{1 + \exp\left[-(x - \phi_2)/\phi_3\right]} \tag{15.11}$$

where y is the trunk circumference, x is the tree age in days since December 31 1968, ϕ_1 is the asymptotic height, ϕ_2 is the inflection point or the time at which the tree reaches $0.5\phi_1$, ϕ_3 is the time elapsed between trees reaching half and about 3/4 of ϕ_1 .

The datafile consists of 5 columns viz, **Tree**, a factor with 5 levels, **x**, tree age in days since 31st December 1968, **circ** the trunk circumference and **season**. The last column **season** was added after noting that tree age spans several years and if



Figure 15.12 Trellis plot of trunk circumference for each tree

converted to day of year, measurements were taken in either Spring (April/May) or Autumn (September/October).

First we demonstrate the fitting of a cubic spline in ASRemI by restricting the dataset to tree 1 only. The model includes the intercept and linear regression of trunk circumference on x and an additional random term spl(x,7) which instructs ASRemI to include a random term with a special design matrix with 7-2 = 5 columns which relate to the vector, $\boldsymbol{\delta}$ whose elements $\delta_i, i = 2, \ldots, 6$ are the second differentials of the cubic spline at the knot points. The second differentials of a natural cubic spline are zero at the first and last knot points (Green and Silverman, 1994). The ASRemI job is

Note that the data for tree 1 has been selected by use of the !filter and !select qualifiers. Also note the use of !PVAL so that the spline curve is properly predicted at the additional nominated points. These additional data points are required for ASRemI to form the design matrix to properly interpolate the cubic smoothing spline between knot points in the prediction process. Since the spline knot points are specifically nominated in the !SPLINE line, these extra points have no effect on the analysis run time. The !SPLINE line does not modify the analysis in this example since it simply nominates the 7 ages in the data file. The same analysis would result if the !SPLINE line was omitted and spl(x,7) in the model was replaced with spl(x).

An extract of the output file is presented below

1 LogL=-20.9043	S2=	48.470	5	df	0.1000	1.000	
2 LogL=-20.9017	S2=	49.022	5	df	0.9266E-01	1.000	
3 LogL=-20.8999	S2=	49.774	5	df	0.8356E-01	1.000	
4 LogL=-20.8996	S2=	50.148	5	df	0.7937E-01	1.000	
5 LogL=-20.8996	S2=	50.213	5	df	0.7866E-01	1.000	
Final parameter valu	es			0.7	8798E-01 1.00	000	
Source	Model	terms	Gamma		Component	Comp/SE	% C
<pre>spl(x,7)</pre>	5	5 5	0.787982	E-01	3.95671	0.40	0 P
Variance	7	5	1.00000		50.2133	1.32	0 P
Analysis of Variance			DF	F-	incr F-a	ıdj	
7 mu			1	138	2.13 18.	03	
3 x			1	21	7.50 217.	50	
NOTICE: ASReml cann	ot yet	determi	ne the cor	rect	denominator	DFs for	
these F sta	tistics	s. They	will not o	exce	ed the Residu	al DF	
which appli	es only	v if all	component	s ar	e KNOWN.		
	Estimat	e	Standard 1	Erro	r T-value	T-prev	
3 x							
1	-0.12	26873	0.5524	71E-	02 -22.96		
7 mu							
2	-0.39	7376	5.755	69	-0.07		
6 spl(x,7)			5 ef:	fect	s fitted		
Finished: 30 Sep 200	2 20:24	1:53.752	LogL Co	nver	ged		

The REML estimate of the smoothing constant indicates that there is some nonlinearity. The fitted cubic smoothing spline is presented in Figure 15.13. The fitted values were obtained from the .pvs file. The four points below the line were the spring measurements.



Figure 15.13 Fitted cubic smoothing spline for tree 1

We now consider the analysis of the full dataset. Following Verbyla *et al.* (1999) we consider the analysis of variance decomposition (see Table 15.12) which models the overall and individual curves.

An overall spline is fitted as well as tree deviation splines. We note however, that the intercept and slope for the tree deviation splines are assumed to be random effects. This is consistent with Verbyla *et al.* (1999). In this sense the tree deviation splines play a role in modelling the conditional curves for each tree and variance modelling. The intercept and slope for each tree are included as random coefficients (denoted by RC in Table 15.12). Thus, if $U^{5\times 2}$ is the matrix of intercepts (column 1) and slopes (column 2) for each tree, then we assume that

$$\operatorname{var}\left(\operatorname{vec}(\boldsymbol{U})\right) = \boldsymbol{\Sigma} \otimes \boldsymbol{I}_5$$

where Σ is a 2 × 2 symmetric positive definite matrix. Non smooth variation can be modelled at the overall mean (across trees) level and this is achieved in ASRemI by inclusion of fac(x) as a random term.

stratum	decomposition	type	df or ne
constant	1	F	1
age	x spl(x,7) for a(x)	F R P	$\begin{array}{c} 1 \\ 5 \\ 7 \end{array}$
tree	tree	RC	5
age.tree error	x.tree spl(x,7).tree	RC R R	$5\\25$

Table 15.12 Orange data: AOV decomposition

An extract of the ASReml input file is presented below.

```
circ ~ mu x !r Tree 4.6 Tree.x .000094 spl(x,7) .1,
spl(x,7).Tree 2.3 fac(x) 13.9
0 0 1
Tree 2
2 0 US 4.6 .00001 .000094
5 0 0
predict x Tree !IGNORE fac(x)
```

We stress the importance of model building in these settings, where we generally commence with relatively simple variance models and update to more complex variance models if appropriate. Table 15.13 presents the sequence of fitted models we have used. Note that the REML log-likelihoods for models 1 and 2 are comparable and likewise for models 3 to 6. The REML log-likelihoods are not comparable between these groups due to the inclusion of the fixed **season** term in the second set of models.

We begin by modelling the variance matrix for the intercept and slope for each tree, Σ , as a diagonal matrix as there is no point including a covariance component between the intercept and slope if the variance component(s) for one (or

		model							
term	1	2	3	4	5	6			
tree	У	У	У	у	У	У			
x.tree	У	У	У	У	У	У			
(covariance)	n	n	n	n	n	У			
spl(x,7)	У	У	У	У	n	У			
tree.spl(x,7)	У	У	У	n	У	У			
fac(x)	n	У	У	n	n	n			
season	n	n	У	У	У	У			
REML log-likelihood	-97.78	-94.07	-87.95	-91.22	-90.18	-87.43			
REML log-likelihood	-97.78	-94.07	-87.95	-91.22	-90.18	-87			

Table 15.13 Sequence of models fitted to the Orange data

both) is zero. Model 1 also does not include a non-smooth component at the overall level (that is, fac(x)). Abbreviated output is shown below.

11 LogL=-97.7788	S2= 6.3702 33 df					
Source	Model	terms	Gamma	Component	Comp/SE	% C
Tree	5	5	4.78452	30.4782	1.24	0 P
Tree.x	5	5	0.938442E-04	0.597805E-0	3 1.41	0 P
<pre>spl(x,7)</pre>	5	5	100.403	639.587	1.55	0 P
<pre>spl(x,7).Tree</pre>	25	25	1.11475	7.10114	1.44	0 P
Variance	35	33	1.00000	6.37018	1.74	0 P
Analysis of Variance			DF F-	incr F-a	dj	
8 mu			1 4	7.06 43.	77	
5 x			1 9	5.00 95.	00	

A quick look suggests this is fine until we look at the predicted curves in Figure 15.14. The fit is unacceptable because the spline has picked up too much curvature, and suggests that there may be systematic non-smooth variation at the overall level. This can be formally examined by including the fac(x) term as a random effect. This increased the log-likelihood 3.71 (P < 0.05) with the spl(x,7) smoothing constants heading to the boundary. There is a possible explanation in the season factor. When this is added (Model 3) it has an F ratio



Figure 15.14 Plot of fitted cubic smoothing spline for model 1

of 107.5 (P < 0.01) while the fac(x) term goes to the boundry. Notice that the inclusion of the fixed term season in models 3 to 6 means that comparisons with models 1 and 2 on the basis of the log-likelihood are not valid. The spring measurements are lower than the autumn measurements so growth is slower in winter. Models 4 and 5 successively examined each term, indicating that both smoothing constants are significant (P < 0.05). Lastly we add the covariance parameter between the intercept and slope for each tree in model 6. This ensures that the covariance model will be translation invariant. A portion of the output file for model 6 is presented below.

11 LogL=-87.4291	S2= 5	. 6329	32 df			
Source	Model	terms	Gamma	Component	Comp/SE	% C
<pre>spl(x,7)</pre>	5	5	2.17207	12.2350	1.09	0 P
<pre>spl(x,7).Tree</pre>	25	25	1.38506	7.80187	1.47	0 P
Variance	35	32	1.00000	5.63286	1.72	0 P
Tree	UnStruct	1	5.62102	31.6624	1.26	0 U
Tree	UnStruct	1	-0.124177E-01	-0.699474E-01	-0.85	0 U
Tree	UnStruct	2	0.108357E-03	0.610357E-03	3 1.40	0 U
Covariance/Variance	/Correlat	ion Mat	trix UnStructu	ired		
5.621 -0.5032						
-0.1242E-01 0.1084E-	03					
Analysis of Varianc	e		DF F-	incr		
8 mu			1 16	69.87		

5 x

6 Season



92.78

1



justed for season effects), with fitted profiles across time and confidence intervals

Figure 15.15 presents the predicted growth over time for individual trees and a marginal prediction for trees with approximate confidence intervals $(2\pm\times$ standard error of prediction). Within this figure, the data is adjusted to remove the estimated seasonal effect. The conclusions from this analysis are quite different from those obtained by the nonlinear mixed effects analysis. The individual curves for each tree are not convincingly modelled by a logistic function. Figure 15.16 presents a plot of the residuals from the nonlinear model fitted on p340 of Pinheiro and Bates (2000). The distinct pattern in the residuals, which is the same for all trees is taken up in our analysis by the season term.



Figure 15.16 Plot of the residuals from the nonlinear model of Pinheiro and Bates

15.10 Multivariate animal genetics data - Sheep

The analysis of incomplete or unbalanced multivariate data often presents computational difficulties. These difficulties are exacerbated by either the number of random effects in the linear mixed model, the number of traits, the complexity of the variance models being fitted to the random effects or the size of the problem. In this section we illustrate two approaches to the analysis of a complex set of incomplete multivariate data.

Much of the difficulty in conducting these types of analyses in ASReml is centred on obtaining good starting values. Derivative based algorithms such as the AI algorithm can be unreliable when fitting complex variance structures unless good starting values are available. Poor starting values may result in divergence of the algorithm or slow convergence. A particular problem with fitting unstructured variance models is keeping the estimated variance matrix positive definite. These are not simple issues and in the following we present a pragmatic approach which attempts to overcome some of these problems.

The data are taken from a large genetic study on Coopworth lambs. A total of 5 traits, namely weaning weight (wwt), yearling weight (ywt), greasy fleece weight (gfw), fibre diameter (fdm) and ultrasound fat depth at the C site (fat) were measured on 7043 lambs. The lambs were the progeny of 92 sires and 3561 dams, produced from 4871 litters over 49 flock-year combinations. Not all traits were measured on each group. No pedigree data was available for either sires or dams.

The aim of the analysis is to estimate heritability (h^2) of each trait and to estimate the genetic correlations between the five traits. We will present two approaches, a half-sib analysis and an analysis based on the use of an animal model, which directly defines the genetic covariance between the progeny and sires and dams.

The data fields included factors defining sire, dam and lamb (tag), covariates such as age, the age of the lamb at a set time, brr the birth rearing rank (1 = born single raised single, 2 = born twin raised single, 3 = born twin raised twin and 4 = other), sex (M, F) and grp a factor indicating the flock-year combination.

Half-sib analysis

In the half-sib analysis we include terms for the random effects of sires, dams and litters. In univariate analyses the variance component for sires is denoted by $\sigma_s^2 = \frac{1}{4}\sigma_A^2$ where σ_A^2 is the additive genetic variance, the variance component for dams is denoted by $\sigma_d^2 = \frac{1}{4}\sigma_A^2 + \sigma_m^2$ where σ_m^2 is the maternal variance component and the variance component for litters is denoted by σ_l^2 and represents variation attributable to the particular mating.

For a multivariate analysis these variance components for sires, dams and litters are, in theory replaced by unstructured matrices, one for each term. Additionally we assume the residuals for each trait may be correlated. Thus for this example we would like to fit a total of 4 unstructured variance models. For such a situation, it is sensible to commence the modelling process with a series of univariate analyses. These give starting values for the diagonals of the variance matrices, but also indicate what variance components are estimable. The ASRemI job for the univariate analyses is given below

```
Multivariate Sire & Dam model
tag
sire 92 !I
dam 3561 !I
```

term	wwt	ywt	gfw	fdm	fat
sire	3.68	3.57	3.95	1.92	$\begin{array}{c} 1.92 \\ 0.05 \\ 0.00 \\ 1.74 \\ 1.83 \end{array}$
dam	6.25	4.93	2.78	0.37	
litter	8.79	0.99	2.23	1.91	
age.grp	2.29	1.39	0.31	1.15	
sex.grp	2.90	3.43	3.70	-	

Table 15.14: REML estimates of a subset of the variance parameters for each trait for the genetic example, expressed as a ratio to their asymptotic s.e.

Table 15.15 Wald tests of the fixed effects for each trait for the genetic example

	term	wwt	ywt	gfw	fdm	fat
	age brr sex	331.3 554.6 196.1	67.1 73.4 123.3	52.4 14.9 0.2	$2.6 \\ 0.3 \\ 2.9$	7.5 13.9 0.6 5.0
		10.0	1.1	1.3		
grp 49 sex						
brr 4 litter 4871						
age wwt gfw !MO fdm ./wwt/coop.bin	!MO ywt !MO fat	! MO # ! MO	!MO reco	odes ze	ros as	missin
wwt ~ mu age brr	sex age.sex	!r sire	dam lit	age.gr	p sex.	grp !f

Tables 15.14 and 15.15 present the summary of these analyses. Fibre diameter was measured on only 2 female lambs and so interactions with **sex** were not fitted. The dam variance component was quite small for both fibre diameter and fat. The REML estimate of the variance component associated with litters was

effectively zero for fat.

Thus in the multivariate analysis we consider fitting the following models to the sire, dam and litter effects,

$$\begin{array}{lll} \operatorname{var}\left(\boldsymbol{u}_{s}\right) &=& \boldsymbol{\Sigma}_{s}\otimes\boldsymbol{I}_{92} \\ \operatorname{var}\left(\boldsymbol{u}_{d}\right) &=& \boldsymbol{\Sigma}_{d}\otimes\boldsymbol{I}_{3561} \\ \operatorname{var}\left(\boldsymbol{u}_{l}\right) &=& \boldsymbol{\Sigma}_{l}\otimes\boldsymbol{I}_{4891} \end{array}$$

where $\Sigma_s^{5\times 5}$, $\Sigma_d^{3\times 3}$ and $\Sigma_l^{4\times 4}$ are positive definite symmetric matrices corresponding to the between traits variance matrices for sires, dams and litters respectively. The variance matrix for dams does not involve fibre diameter and fat depth, while the variance matrix for litters does not involve fat depth. The effects in each of the above vectors are ordered levels within traits. Lastly we assume that the residual variance matrix is given by

$$oldsymbol{\Sigma}_{e}\otimesoldsymbol{I}_{7043}$$

Table 15.16 presents the sequence variance models fitted to each of the four random terms sire, dam, litter and error in the ASRemI job presented below.

```
Multivariate Sire & Dam model
 tag
 sire
        92 !I
 dam 3561 !I
         49
 grp
 sex
          4
 brr
 litter 4871
                                    # !MO identifies missing values
 age
            wwt
                  !mO ywt
                            !m0
 gfw
        !mO fdm
                  !mO fat
                            !m0
./wwt/coop.bin
                 !DOPART $1 !CONTINUE !MAXIT 20
!PART 3
!EXTRA 4
!PART
wwt ywt gfw fdm fat ~ Trait Tr.age Tr.brr Tr.sex Tr.age.sex,
          !r Tr.sire,
         at(Tr,1).dam at(Tr,2).dam at(Tr,3).dam,
         at(Tr,1).lit at(Tr,2).lit at(Tr,3).lit at(Tr,4).lit,
         at(Trait,1).age.grp .0024,
         at(Trait,2).age.grp .0019,
         at(Trait,4).age.grp .0020,
         at(Trait,5).age.grp .00026,
         at(Trait,1).sex.grp .93,
         at(Trait,2).sex.grp 16.0,
```

```
at(Trait,3).sex.grp .28,
         at(Trait,5).sex.grp 1.18,
 !f Tr.grp
1 2 3
                         \#1\ R structure with 2 dimensions and 3 G structures
0 0 0
                         #Independent across animals
Tr 0 US
                         #General structure across traits
15*0.
                         #Asreml will estimate some starting values
Tr.sire 2
                         #Sire effects.
!PART 1
                         #Initial analysis ignoring genetic correlations
Tr 0 DIAG
                         #Specified diagonal variance structure
0.608 1.298 0.015 0.197 0.035
                                   #Initial sire variances
!PART 2
                         #Factor Analytic model
Tr O FA1 !GP
   0.5 0.5 -.01 -.01 0.1
                                   #Correlation factors
0.608 1.298 0.015 0.197 0.035
                                   #Variances
!PART 3
                         #Unstructured variance model
Tr 0 US
0.6199
                         #Lower triangle row-wise
0.6939
            1.602
0.003219 0.007424 0.01509
-0.02532 -0.05840 -0.0002709 0.1807
0.06013 0.1387
                   0.0006433 -0.005061 0.03487
!PART
sire
#Maternal structure covers the 3 model terms
#
                at(Tr,1).dam at(Tr,2).dam at(Tr,3).dam
at(Tr,1).dam 2
                                # Maternal effects.
!PART 1
3 O CORGH !GU
                                # Equivalent to Unstructured
.9
.1 .1
2.2 4.14 0.018
!PART 2
3 O CORGH !GU
.9
.1 .1
2.2 4.14 0.018
!PART 3
3 0 US !GU
.9
.1 .1
2.2 4.14 0.018
```

```
!PART
dam
#Litter structure covers the 4 model terms at(Tr,1).lit at(Tr,2).lit
#at(Tr,3).lit at(Tr,4).lit
at(Tr,1).lit 2
                                # Litter effects.
!PART 1
4 O DIAG
                                # Diagonal structure
3.74 0.97 0.019 0.941
!PART 2
4 0 FA1 !GP
                                # Factor Analytic 1
.5 .5 .01 .1
4.95 4.63 0.037 0.941
!PART 3
4 0 US
                                # Unstructured
5.073
 3.545
            3.914
0.1274
           0.08909 0.02865
0.07277 0.05090 0.001829 1.019
!PART
lit
```

Table 15.16: Variance models fitted for each part of the ASReml job in the analysis of the genetic example

term	matrix	!Part 1	!Part 2	!Part 3
sire	$egin{array}{lll} \mathbf{\Sigma}_s \ \mathbf{\Sigma}_d \ \mathbf{\Sigma}_l \ \mathbf{\Sigma}_e \end{array}$	DIAG	FA1	US
dam		CORGH	CORGH	US
litter		DIAG	FA1	US
error		US	US	US

In **!PART 1**, the error variance model is taken to be unstructured, but the starting values are set to zero. This instructs **ASRemI** to obtain starting values from the sample covariance matrix of the data. For incomplete data the matrix so obtained may not, in general be positive definite. Care should be taken when using this option for incomplete multivariate data. The command to run this file for **!PART 1** is

asreml -nrs3 mt 1

The results from this analysis can be automatically used by ASRemI for the next part, if the .rsv is copied prior to running the next part. That is, we add the **!PART 2** coding to the job, copy mt1.rsv to mt2.rsv so that when we run **!PART 2** it starts from where **!PART 1** finished, and run the job using

asreml -cnrs3 mt 2

Finally, we use the **!PART 3** coding to obtain the final analysis, copy mt2.rsv to mt3.rsv and run the final stage starting from the stage 2 results. Note that we are using the automatic updating associated with **!CONTINUE**.

A portion of the final output file is presented below.

NOTICE:	165 (ma	ore)	sin	gularit	ies,					
LogL=-21425	5.9	S2=	= 1	.0000	3500	06 df				
LogL=-21423	3.7	S2=	- 1	.0000	3500	06 df				
LogL=-21420).9	S2=	= 1	.0000	3500	06 df				
LogL=-21420).1	S2=	= 1	.0000	3500	06 df				
LogL=-21419	9.9	S2=	- 1	.0000	3500	06 df				
LogL=-21419	9.9	S2=	= 1	.0000	3500	06 df				
LogL=-21419	9.9	S2=	= 1	.0000	3500	06 df				
LogL=-21419	9.9	S2=	= 1	.0000	3500)6 df				
LogL=-21419	9.9	S2=	= 1	.0000	3500)6 df				
LogL=-21419	9.9	S2=	- 1	.0000	3500	06 df				
Source	Мос	iel t	term	s G	amma	Comp	onent	Comp/SE	% C	3
at(Tr,1).ag	ge.grp	49	49	0.1353	58E-02	0.135	358E-02	2.03	0 F	2
at(Tr,2).ag	ge.grp	49	46	0.1015	60E-02	0.101	560E-02	1.24	0 F	כ
at(Tr,4).ag	ge.grp	49	11	0.1765	13E-02	0.176	513E-02	1.13	0 F	2
at(Tr,5).ag	ge.grp	49	28	0.2092	78E-03	0.209	278E-03	1.68	0 F	2
at(Tr,1).se	ex.grp	49	49	0.9196	10	0.919	610	2.89	0 F	כ
at(Tr,2).se	ex.grp	49	46	15.39	12	15.3	912	3.50	0 F	כ
at(Tr,3).se	ex.grp	49	46	0.2794	96	0.279	496	3.71	0 F	כ
at(Tr,5).se	ex.grp	49	28	1.440	32	1.44	032	1.80	0 F	כ
	•									
Covariance	/Varian	ice/(Corr	elation	Matrix	US=Un	Structu			
9.462	0.5691	1	0.3	2356	0.1640)	0.2183			
7.332	17.54	1	0.4	4241	0.2494	Ł	0.4639			
0.2728	0.6686	3	0.	1417	0.3994	Ł	0.1679			
0.9625	1.994	1	0.1	2870	3.642	2	0.4875E	-01		
0.8336	2.412	2	0.	7846E-0	1 0.1155	5	1.541			
Covariance	/Varia	1ce/0	Corr	elation	Matrix	US=Un	Structu			
0.5941	0.7044	1	0.3	2966	0.2028	3	0.2703			
0.6745	1.544	1	0.	1364E-0	1-0.1227	7	0.5726			
0.2800E-01	0.2076	3E-02	2 0.	1500E-0	1 0.1114	1 –	0.4818E	-02		

```
0.6224E-01-0.6072E-01 0.5433E-02 0.1586
                                    -0.6334
0.3789E-01 0.1294 -0.1073E-03-0.4588E-01 0.3308E-01
Covariance/Variance/Correlation Matrix US=UnStructu
 2.161 1.010 0.7663
 2.196
         2.186 0.8301
0.1577 0.1718 0.1959E-01
Covariance/Variance/Correlation Matrix US=UnStructu
 3.547 0.5065 -0.1099 -0.4097E-01
                0.1740
 1.555
         2.657
                         -0.5150
-0.2787E-01 0.3822E-01 0.1815E-01-0.3281
-0.7313E-01-0.7957 -0.4190E-01 0.8984
Analysis of Variance DF
                            F-incr
 15 Tr.age
                      5
                             98.95
                     15
 17 Tr.sex
 16 Tr.brr
                            116.72
                      5 59.78
                      4
                              4.90
 19 Tr.age.sex
```

The REML estimates of all the variance matrices are positive definite. Heritabilities for each trait can be calculated using the .pin file facility of ASRemI. The heritability is given by

$$h^2 = \frac{\sigma_A^2}{\sigma_P^2}$$

where σ_P^2 is the phenotypic variance and is given by

$$\sigma_P^2 = \sigma_s^2 + \sigma_d^2 + \sigma_l^2 + \sigma_e^2$$

recalling that

$$\sigma_s^2 = \frac{1}{4}\sigma_A^2$$

$$\sigma_d^2 = \frac{1}{4}\sigma_A^2 + \sigma_m^2$$

In the half-sib analysis we only use the estimate of additive genetic variance from the sire variance component. The ASReml .pin file is presented below along with the output from the following command

```
asreml -p mt3
```

```
      F phenWYG 9:14 + 24:29 + 39:44 + 45:50
      # defines 55:60

      F phenD 15:18 + 30:33 +
      51:54
      # defines 61:64

      F phenF 19:23 + 34:38
      # defines 65:69
```

F Direct 24:38 * 4.	# defines 70:84	4
F Maternal 39:44 - 24:29	# defines 85:9	0
H WWTh2 70 55		
H YWTh2 72 57		
H GFWh2 75 60		
H FDMh2 79 64		
H FATh2 84 69		
R GenCor 24:38		
R MatCor 85:90		
55 phenWYG 9 15.76 0.3130		
56 phenWYG 10 11.76 0.3749		
57 phenWYG 11 23.92 0.6313		
· · · · · · · ·		
70 Direct 24 2.376 0.6458		
71 Direct 25 2.698 0.8487		
72 Direct 26 6.174 1.585		
73 Direct 27 0.1120 0.7330E-01		
85 Maternal 39 1.567 0.3788		
86 Maternal 40 1.521 0.4368		
87 Maternal 41 0.6419 0.7797		
WWTh2 = Direct 2 70/phenWYG 55=	0.1507	0.0396
YWTh2 = Direct 2 72/phenWYG 57=	0.2581	0.0624
GFWh2 = Direct 2 75/phenWYG 60=	0.3084	0.0716
FDMh2 = Direct 3 79/phenD 18 64=	0.1350	0.0717
FATh2 = Direct 3 84/phenF 23 69=	0.0841	0.0402
GenCor 2 1 = Tr.si 25/SQR[Tr.si 24*Tr.si	26]= 0.7044	0.1025
GenCor 3 1 = Tr.si 27/SQR[Tr.si 24*Tr.si	29]= 0.2966	0.1720
GenCor 3 2 = Tr.si 28/SQR[Tr.si 26*Tr.si	29]= 0.0136	0.1810
GenCor 4 1 = Tr.si 30/SQR[Tr.si 24*Tr.si	33]= 0.2028	0.3513
GenCor 4 2 = Tr.si 31/SQR[Tr.si 26*Tr.si	33]= -0.1227	0.3247
GenCor 4 3 = Tr.si 32/SQR[Tr.si 29*Tr.si	33]= 0.1115	0.3868
GenCor 5 1 = Tr.si 34/SQR[Tr.si 24*Tr.si	38]= 0.2703	0.2724
GenCor 5 2 = Tr.si 35/SQR[Tr.si 26*Tr.si	38]= 0.5726	0.2022
GenCor 5 3 = Tr.si 36/SQR[Tr.si 29*Tr.si	38]= -0.0048	0.2653
GenCor 5 4 = Tr.si 37/SQR[Tr.si 33*Tr.si	38]= -0.6333	0.3775
MatCor 2 1 = Mater 86/SQR[Mater 85*Mater	87]= 1.5168	0.7131
MatCor 3 1 = Mater 88/SQR[Mater 85*Mater	90]= 1.5285	1.1561
MatCor 3 2 = Mater 89/SQR[Mater 87*Mater	90]= 3.1251	2.7985

Animal model

In this section we will illustrate the use of .ped files to define the genetic pedigree structure between animals. This is an alternate method of estimating additive genetic variance for these data. The variance matrix of the animals (sires, dams

and lambs) for which we only have data on lambs is given by

$$\operatorname{var}\left(\boldsymbol{u}_{A}\right)=\boldsymbol{\Sigma}_{A}\otimes\boldsymbol{A}^{-1}$$

where A^{-1} is the inverse of the genetic relationship matrix. There are a total of 10696 = 92 + 3561 + 7043 animals in the pedigree. The ASReml input file is presented below. Note that this model is not equivalent to the sire/dam/litter model with respect to the animal/litter components for gfw, fd and fat.

```
Multivariate Animal model
  tag !P
  sire
  dam !P
  grp
         49
  sex
  brr
          4
  litter 4871
                                   # !MO identifies missing values
  age
            wwt
                  !mO ywt
                            1m0
       !mO fdm
  gfw
                  !mO fat
                            !mO
./wwt/coop.ped
                 !DOPART $1 !CONTINUE !MAXIT 20 !RECODE !STEP 0.01
./wwt/coop.bin
  # $1 allows selection of PART as a command line argument
!PART 3
 !EXTRA 4
              # Force 4 more iterations after convergence criterion met
!PART
wwt ywt gfw fdm fat ~ Trait Tr.age Tr.brr Tr.sex Tr.age.sex,
          !r Tr.tag ,
         at(Tr,1).dam, at(Tr,2).dam, -at(Tr,3).dam .003,
         at(Tr,1).lit, at(Tr,2).lit, at(Tr,3).lit, at(Tr,4).lit,
         at(Trait,1).age.grp .0024,
         at(Trait,2).age.grp .0019,
         at(Trait,4).age.grp .0020,
         at(Trait,5).age.grp .00026,
         at(Trait,1).sex.grp .93,
         at(Trait,2).sex.grp 16.0,
         at(Trait,3).sex.grp .28,
         at(Trait,5).sex.grp 1.18,
 !f Tr.grp
1 2 3
         # One multivariate R structure, 3 G structures
0 0 0
         # No structure across lamb records
         # First zero lets ASReml count te number of records
Tr 0 US
                         #General structure across traits
7.66
5.33 13
.18 .66 .10
.78 2.1 .27 3.2
.73 2.02 .08 .20 1.44
```

Tr.tag 2 # Direct animal effects. **!PART 2** Tr O FA1 !GP 0.5 0.5 -.01 -.01 0.1 2.4 5.2 0.06 .8 .14 **!PART 3** Tr 0 US 2.4800 2.8 6.4 0.0128 0.03 0.06 -.1 -.22 -.0011 0.72 0.24 0.55 0.0026 -0.0202 0.14 **!PART** tag at(Tr,1).dam 2 # Maternal effects. **!PART 2** 2 O CORGH !GFU .99 1.6 2.54 **!PART 3** 2 0 US !GU 1.1 .58 .31 **!PART** dam # Litter effects. at(Tr,1).lit 2 **!PART 2** 4 0 FA1 !GP # Factor Analytic .5 .5 .01 .1 .01 4.95 4.63 0.037 0.941 0.102 **!PART 3** 4 0 US # Unstructured 5.073 3.545 3.914 0.1274 0.08909 0.02865 0.07277 0.05090 0.001829 1.019 **!PART** lit

The term Tr.tag now replaces the sire (and part of dam) terms in the half-sib analysis. This analysis uses information from both sires and dams to estimate additive genetic variance. The dam variance component is this analysis only estimates the maternal variance component. It is only significant for the weaning and yearling weights. The litter variation remains unchanged. The ASReml input file again consists of several parts, which progressively build up to fitting unstructured variance models to Tr.tag, Tr.dam, Tr.litter and error. A portion of the output file is presented below.

dam !P !mO ywt wwt. !m0 age gfw !mO fdm !m0 fat 1m0 A-inverse retrieved from ainverse.bin PEDIGREE [../wwt/coop.ped] has 10696 identities, 29474 Non zero elements QUALIFIERS: !DOPART 3 !CONTINUE !MAXIT 20 !RECODE !STEP 0.01 Reading ../wwt/coop.bin as BINARY SINGLE PRECISION Model term Size Type COL Minimum Mean Maximum #zero #miss 10696 Direct 1 tag 1 3.000 5380. 0.1070E+05 0 0 2 sire 1 Covariat 2 1.000 48.06 92.00 0 0 3 dam 10696 Direct 3 1.000 5197. 0.1070E+05 0 0 . . Forming 95033 equations: 40 dense Initial updates will be shrunk by factor 0.010 NOTICE: 165 (more) singularities, LogL=-21432.6 S2= 1.0000 35006 df LogL=-21432.3 S2= 1.0000 35006 df LogL=-21429.6 S2= 1.0000 35006 df LogL=-21423.2 S2= 1.0000 35006 df 35006 df LogL=-21420.1 S2= 1.0000 LogL=-21420.1 S2= 1.0000 35006 df LogL=-21417.6 S2= 1.0000 35006 df LogL=-21417.2 S2= 1.0000 35006 df LogL=-21417.2 S2= 1.0000 35006 df LogL=-21417.2 S2= 1.0000 35006 df S2= 1.0000 LogL=-21417.2 35006 df LogL=-21417.2 S2= 1.0000 35006 df S2= 1.0000 LogL=-21417.2 35006 df S2= 1.0000 LogL=-21417.2 35006 df LogL=-21417.2 S2= 1.0000 35006 df Source Model terms Gamma Component Comp/SE % C at(Tr,1).age.grp 49 49 0.132682E-02 0.132682E-02 2.02 0 P at(Tr,2).age.grp 49 46 0.908219E-03 0.908219E-03 0 P 1.15 at(Tr,4).age.grp 49 11 0.175614E-02 0.175614E-02 1.13 0 P 0 P at(Tr,5).age.grp 49 28 0.223617E-03 0.223617E-03 1.73 at(Tr,1).sex.grp 49 49 0.902586 0.902586 2.88 0 P at(Tr,2).sex.grp 49 46 15.3623 15.3623 3.50 0 P at(Tr,3).sex.grp 49 46 0.280673 0.280673 3.71 0 P at(Tr,5).sex.grp 49 28 1.42136 1.42136 1.80 0 P . Covariance/Variance/Correlation Matrix US=UnStructu 0.4918 0.1339 0.1875 7.476 0.1333 4.768 12.57 0.4381 0.3425 0.3938

0.1189	0.5049	0.1056	0.4864	0.1298	
0.9377	2.221	0.2891	3.345	0.1171	
0.4208	1.612	0.4869E-0	1 0.2473	1.333	
Covariance/Variance/Correlation Matrix US=UnStructu					
3.898	0.8164	0.5763	0.3898E-	01 0.6148	
4.877	9.154	0.3689	-0.1849	0.7217	
0.3029	0.2971	0.7085E-0	1-0.2416E-	01 0.3041	
0.6019E-0	01-0.4375	-0.5030E-02	2 0.6117	-0.4672	
0.6154	1.107	0.4104E-0	1-0.1853	0.2570	
Covariance/Variance/Correlation Matrix US=UnStructu					
0.9988	0.7024				
0.5881	-0.7018				
Covariance/Variance/Correlation Matrix US=UnStructu					
3.714	0.5511	0.1635	-0.6157E-	01	
2.019	3.614	0.5176	-0.4380		
0.4506E-0	01 0.1407	0.2045E-0	1-0.3338		
-0.1021	-0.7166	-0.4108E-0	1 0.7407		
Analysis	of Variance	DF	F-incr		
15 Tr.ag	ge	5	99.16		
16 Tr.b	rr	15	116.52		
17 Tr.se	ex	5	59.94		
19 Tr.age.sex		4	5.10		

There is no guarantee that variance component matrices will be positive definite and this example highlights this issue. We used the **!GU** qualifier on the maternal component to obtain the matrix

$$\left[\begin{array}{cc} 0.9988 & 0.5881 \\ 0.5881 & -0.7018 \end{array}\right].$$

ASReml reports the correlation as 0.7024 which it obtains by ignoring the sign in -0.7018. This is the maternal component for ywt. Since it is entirely reasonable to expect maternal influences on growth to have dissipated at 12 months of age, it would be reasonable to refit the model omitting at(Tr,2).dam and changing the dimension of the G structure.

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