

ASReml workshop

3.1 Variance structures

Arthur Gilmour



NSW DEPARTMENT OF
PRIMARY INDUSTRIES



Overview

- Traditional variance models assume independent effects: $\sigma^2 \mathbf{I}$
- General variance structures
 - Unstructured - every variance and covariance is a separate parameter
 - Structured - variances and covariances are functions of parameters
- Spatial models
 - correlation based on distance
 - parameterized in terms of correlation and variance



Overview

- Traditional variance models
- General variance structures
 - Unstructured- Structured
- Spatial models
 - correlation based on distance
 - parameterized in terms of correlation and variance
- Compound variance structures
 - formed as a direct product



General Variance structures

- Unstructured (US) is parameterised directly as variances and covariances
- Symmetric Lower triangle rowwise

$$V_{11}$$

$$V_{21} \quad V_{22}$$

$$V_{31} \quad V_{32} \quad V_{33}$$

Reduced parameterization

- Diagonal (DIAG) has zero covariances
Factor Analytic (FACV, XFA): $\Sigma = \Lambda\Lambda' + \Psi$
Cholesky (CHOLn, CHOLnC): $\Sigma = LDL'$
where L is unit lower triangle
Antedependence (ANTE n): $\Sigma^{-1} = UDU'$
where U is unit lower triangle



Reduced parameterization

- Aim in using alternate forms is
 - to accommodate the variance heterogeneity adequately while minimising the number of parameters
 - force a positive definite structure.
- ANTE (a generalization of AR) is suited to ordered levels (e.g. times)
- CHOL, XFA, FACV are suited to unordered levels (e.g. sites, traits)



General variance structures

- DIAG - off diagonal is zero
- CHOL_{*i*} - $\Sigma = LDL'$
 - L is lower triangle unit matrix with i off-diagonal bands
 - D is diagonal matrix of conditional variances.

CHOL1 of order 4

■ e.g. in CHOL1 $L = \begin{pmatrix} 1 & 0 & 0 & 0 \\ a & 1 & 0 & 0 \\ 0 & b & 1 & 0 \\ 0 & 0 & c & 1 \end{pmatrix}$

$D = \text{diag}(A \ B \ C \ D)$ so that

$$\Sigma = \begin{pmatrix} A & aA & 0 & 0 \\ aA & aAa + B & bB & 0 \\ 0 & bB & bBb + C & cC \\ 0 & 0 & cC & cCc + D \end{pmatrix}$$

CHOL1C of order 4

■ e.g. in CHOL1C $L = \begin{pmatrix} 1 & 0 & 0 & 0 \\ a & 1 & 0 & 0 \\ b & 0 & 1 & 0 \\ c & 0 & 0 & 1 \end{pmatrix}$

$D = \text{diag}(A \ B \ C \ D)$ so that

$$\Sigma = \begin{pmatrix} A & aA & bA & cA \\ aA & aAa + B & bAa & cAa \\ bA & bAa & bAb + C & bAc \\ cA & aAc & cAb & cAc + D \end{pmatrix}$$

Antedependence

- is a generalized form of Autoregressive
- $\text{ANTE}_i - \Sigma^{-1} = \mathbf{U}\mathbf{D}\mathbf{U}'$
 - \mathbf{U} is upper triangle unit matrix with i off-diagonal bands
 - \mathbf{D} is diagonal matrix of conditional inverse variances.
- Since parameterization is obtuse for CHOL and ANTE, you may supply an unstructured matrix as starting values and ASReml will factorize it.

Factor Analytic

- Correlation Form: FA_i

$$\Sigma = D(LL' + E)D'$$

Parameters are elements of $p \times i$ matrix L and $\text{diag}(\Sigma) = DD$; E is defined such that $\text{diag}(LL' + E)$ is Identity.

- Variance Form: FACV_i

$$\Sigma = \Lambda\Lambda' + \Psi$$

Parameters are $\Lambda = DL$ and $\Psi = DED$

Extended Factor Analytic

- Same parameterization as FACV but in order $(\Psi) \text{vec}(\Lambda)$
- Elements of Ψ may be zero (making Σ singular)
- Requires use of $\text{xfa}(T, i)$ model term which inserts i columns of zeros into the design matrix corresponding to the i factors.
- Much faster than FA_i and FACV_i when more than 10 levels in term.

Extended Factor Analytic

```
■ ... xfa(Trait,1).dam ...  
   xfa(Trait,1).dam 2  
   xfa(Trait,1) 0 XFA1
```

```
2*0
```

```
1.1 0.9
```

```
dam
```

```
Covariance/Variance/Correlation Mat
```

```
1.550      1.000      1.000
```

```
1.437      1.332      1.000
```

```
1.245      1.154      1.000
```



Other structures

- US - unstructured
- OWN_i - user supplies program to calculate G and the derivatives of G
- AINV - Use fixed relationship matrix
- GIV_i - Use user defined fixed relationship matrix (see .giv, .grm)



Spatial structures

- ID - Identity

CORU - uniform correlation

AR1 $1 \ \rho \ \rho^2 \ \rho^3 \ \rho^4 \ \rho^5 \dots$

AR2, MA1, MA2, ARMA, SAR1, SAR2,

CORU, CORB, CORH

EXP, GAU

IEXP, AEXP, IGAU, AGAU, IEUC, LVR, ISP,

SPH, MAT

one or two dimensional distance



Variances

- Equal variance correlation
append V to code e.g. AR1V, CORUV
- Unequal (Heterogeneous) variance
correlation
append H to code e.g. AR1H, CORUH
- If D is the diagonal matrix of variances, and
 C is a correlation matrix, $\Sigma = D^{0.5} C D^{0.5}$

ASReml workshop

3.2 Spatial Analysis

Arthur Gilmour



NSW DEPARTMENT OF
PRIMARY INDUSTRIES



Two basic kinds

- Regular grid e.g. field trial
 - interest is in adjusting for other effects



Two basic kinds

- Regular grid e.g. field trial
 - interest is in adjusting for other effects
- Irregular grid e.g. survey
 - interest is in modelling the spatial pattern
 - kriging



Two basic kinds

- Regular grid e.g. field trial
 - interest is in adjusting for other effects
- Irregular grid e.g. survey
 - interest is in modelling the spatial pattern
 - kriging
- ASReml is regularly used for former
 - developing capability for latter



Single field trial

- Slate Hall Farm - Barley 1976
 - Balanced Incomplete block design
 - 25 varieties, 6 replicates
 - layout 10 rows by 15 columns
- BIB Model
 - fixed: treatments
 - random: rep block
- Spatial Model
 - Autoregressive error model $R = \Sigma_R \otimes \Sigma_C$

Slate Hall base

- Slate Hall 1976 Cereal trial
rep 6 latrow 30 latcol 30
fldrow 10 fldcol 15
variety 25
yield !/100
shf.dat !DOPART \$1
!DISPLAY 15 !SPATIAL !TWOWAY



Slate Hall - Design based

- !PART 1 RCB Analysis
yield ~ mu var !r rep

- !PART 2 # BIB analysis
yield ~ mu var !r rep latrow latcol

Slate Hall - Model based

```
■ !PART 3 #      Fitting AR1.AR1
yield ~ mu var
predict var
1 2
fldrow fldrow AR .1
fldcol fldcol AR .1
```


Slate Hall - + Design

Model

```
■ !PART 4 #      Fitting AR1.AR1
yield ~ mu var !r rep latrow latcol
predict var
1 2
fldrow fldrow AR .1
fldcol fldcol AR .1
```

Slate Hall - summary

Model	LogL(l)	$-2\Delta(l)$
RCB	-167.694	2
■ BIB design	-132.134	4
Spatial model	-124.676	3
BIB+Spatial	-124.312	6

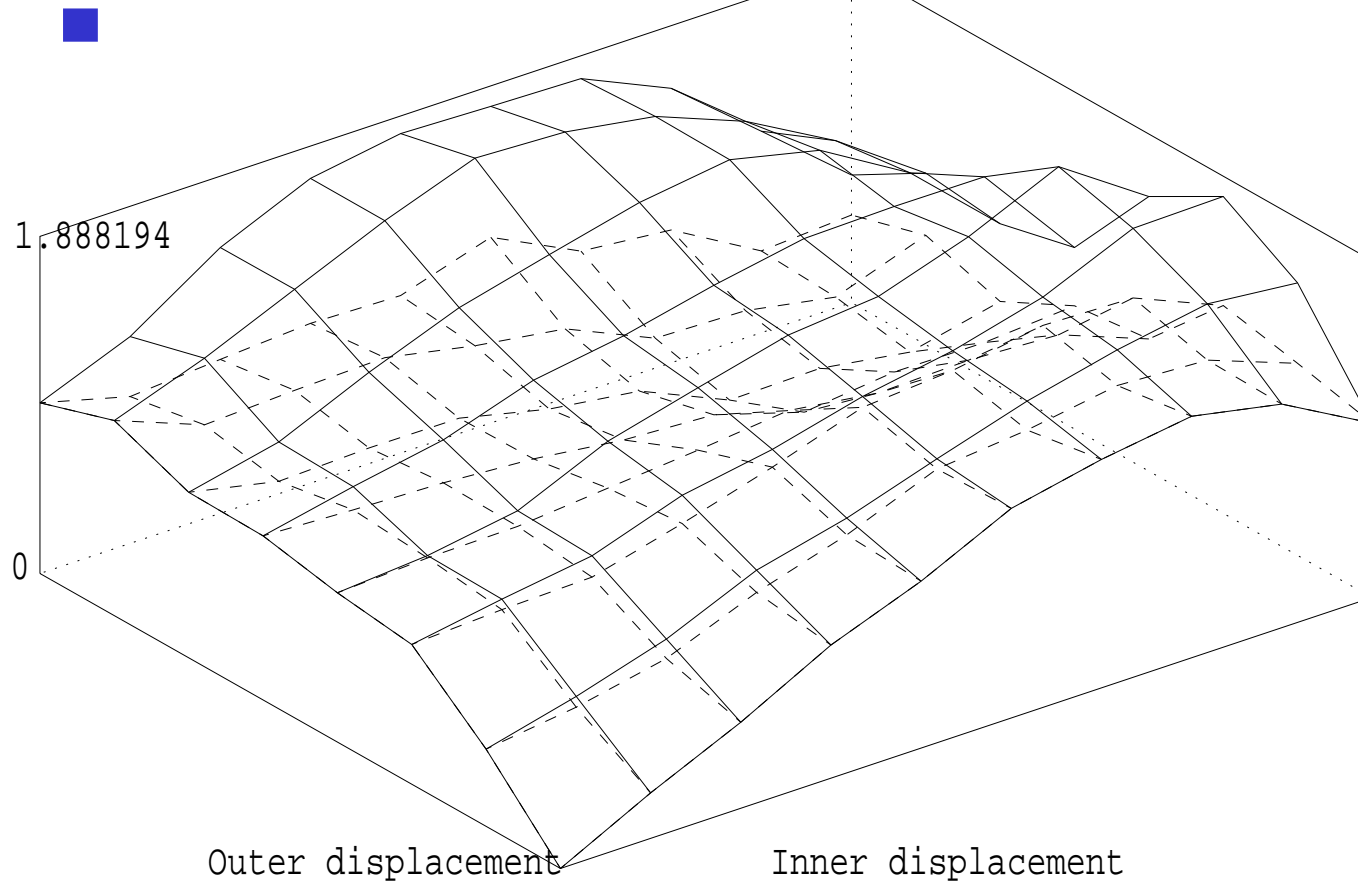
- Spatial correlation model fits better than the BIB model

Spatial components

■ Source	terms	Gamma	Component	Comp/SE	%
rep	6	6	.2003E-05	.724166E-05	0.00
latrow	30	30	.6327E-01	.228684	0.71
latcol	30	30	.1608E-03	.581362E-03	0.00
Variance	150	125	1.000	3.61464	4.28
Residual AutoR	10	.4652	.465209	4.85	
Residual AutoR	15	.6741	.674095	8.76	

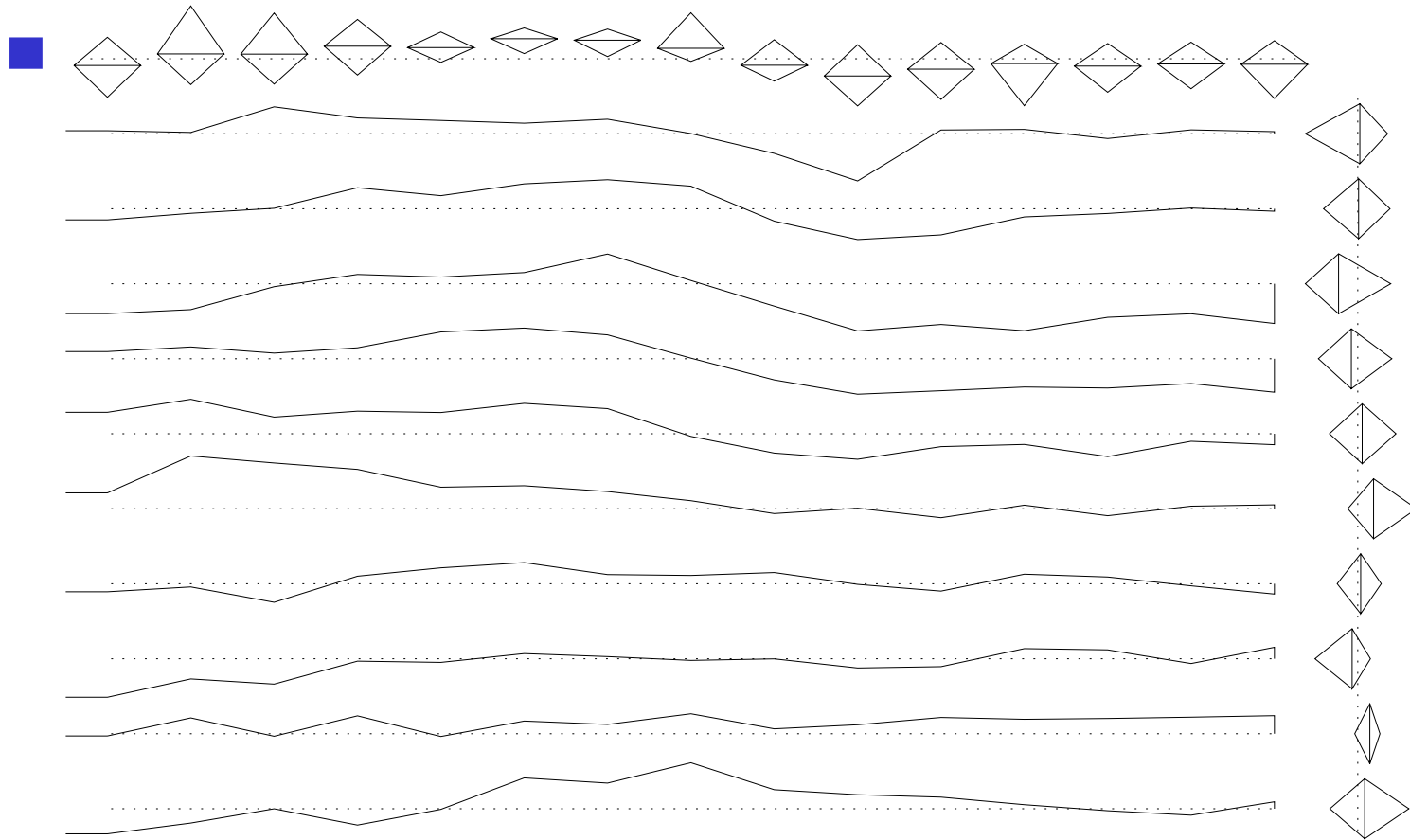
Variogram

Slate Hall 1976 Cereal trial F3.1
Variogram of residuals 31 Jan 2005 16:15:30



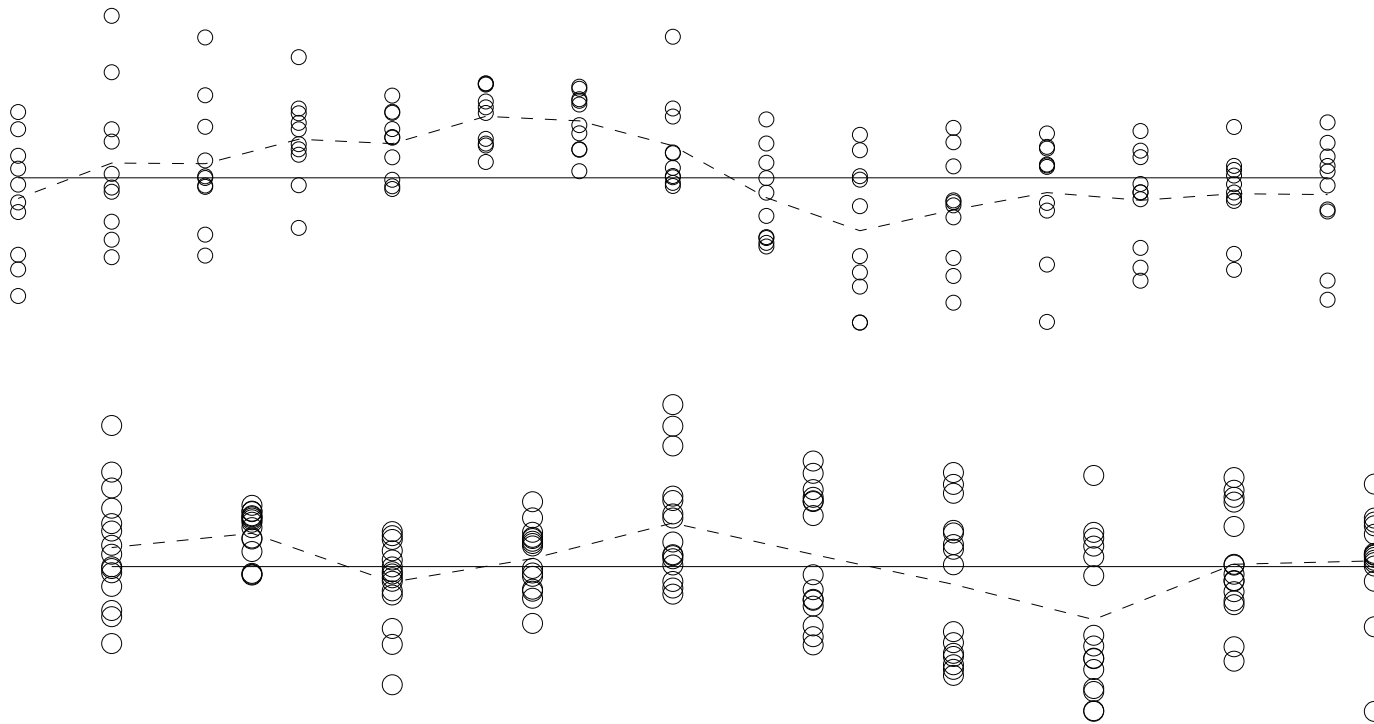
Residual to plan

Slate Hall 1976 Cereal trial F3 1
Field plot of residuals 31 Jan 2005 16:15:30
Range: -4.80 5.37



row/column

Residuals V Row and Column position: 31 Jan 2005 16:15:30
Slate Hall 1976 Cereal trial F3 1
Range: -4.80 5.37





Multi environment trial

- In early generational cereal breeding, run several trials with 1 or two replicates of test lines, 20 percent check lines for error estimation.
- More power from fitting as correlated effects across sites.

MET in ASReml

- Three Multi Environment Trial

```
seq
col 15      # Actually 12 12 and 15 respectively
row 34      # Actually 34 34 and 28 respectively
chks 7      # Check 7 is the test lines
test 336    # coded 0 for check lines
geno 337
yld    !*.01
site 3
met.dat    !section site
```


Spatial models

```
■ yld ~ site chk.site !r at(site,3).row .02,  
    at(site).col .90 .40 .036 site.test
```

```
site 2 1
```

```
12 col AR .1271 !S2=2.19
```

```
34 row AR .751
```

```
12 col AR .25 !S2=0.84
```

```
34 row AR .56
```

```
15 col ID !S2=0.19
```

```
28 row AR .38
```

Model genetic variation

```
■ site.test 2
  site 0 FA1
    .5 .5 .5
    .1 .1 .1
  test
```

Components

Source	Model	terms	Component	Comp/SE	%
Residual	1236	1213			
at(site,01).col	15	15	0.323302E-05	0.00	0
at(site,02).col	15	15	0.142114	1.32	0
at(site,03).col	15	15	0.446791E-01	1.77	0
at(site,3).row	34	34	0.241380E-01	2.80	0
Variance[1]	408	0	2.60271	5.18	0
Residual	AR=AutoR	12	0.407051	4.45	0
Residual	AR=AutoR	34	0.882580	33.50	0
Variance[2]	408	0	1.00339	8.29	0
Residual	AR=AutoR	12	0.282407	4.84	0
Residual	AR=AutoR	34	0.580701	11.37	0
Variance[3]	420	0	0.105411	5.59	0
Residual	AR=AutoR	28	0.687455	10.14	0

Factor Analytic

■ site.test	FA D(L	1	1	0.518516	5.35	0
site.test	FA D(L	1	2	1.13028	2.18	0
site.test	FA D(L	1	3	0.735010	6.04	0
site.test	FA D(L	0	1	0.991585	7.99	0
site.test	FA D(L	0	2	0.731805E-01	1.07	0
site.test	FA D(L	0	3	0.121810	7.17	0

Covariance/Variance/Correlation FA D(LL'+E)D

0.9916 0.5865 0.3811

0.1579 0.7308E-01 0.8313

0.1325 0.7844E-01 0.1218



Spatial analysis in Forest Genetic trials.

- Typically not a complete rectangle
 - add missing values to complete the pattern
 - use map points (if < 5000 trees)
- With Tree model, must include Nugget variance
 - either Nugget is residual, spatial is in G or spatial is residual and Nugget is G,
- spatial model typically superior to 'design' model for growth/production traits
 - less so for disease and conformation traits



MicroArray

- spatial pattern

ASReml workshop

3.3 Repeated Measures

Arthur Gilmour



NSW DEPARTMENT OF
PRIMARY INDUSTRIES



Main approaches

- General variance structure
(Multivariate approach)
UnStructured, Autoregressive, EXPponential
- Repeated measures
Longitudinal model
Repeated measures.



Multivariate approach

- Suited when most animals have most measures
- Repeats are at significant standard times
Say WWT, 200dayWT, 400dayWT, 600dayWT
- Discuss



Multivariate

- WWT WT200 WT400 WT600 ~ Trait Tr.sex
!r Tr.animal !f Tr.cohort

1 2 1

0

Trait 0 US

10*0

Tr.animal 2

Tr 0 US

10*0

animal 0 AINV

Multivariate

```
■ WWT WT200 WT400 WT600 ~ Trait Tr.sex,  
  !r Tr.animal !f Tr.cohort
```

```
1 2 1
```

```
0
```

```
Trait 0 US
```

```
10*0
```

```
Tr.animal 2
```

```
Tr 0 US
```

```
10*0
```

```
animal 0 AINV
```

Multivariate

```
■ WWT WT200 WT400 WT600 ~ Trait Tr.sex,  
  !r Tr.animal !f Tr.cohort  
  
1 2 1  
0  
Trait 0 US  
10*0  
  
Tr.animal 2  
Tr 0 US  
10*0  
animal 0 AINV
```



Random Regression

- Appropriate when
 - there is considerable unbalance in times of measurement
 - there are varying numbers of measurements
 - all animals have multiple measures
- Concept: Regression for each individual consisting of an overall response pattern (fixed) plus an individual (random) adjustment.



RR principles

- This is a reduced parameterization model which must be well formulated
 - mean profile of higher order than random profile - random profile generally low order
- Usually formulated as polynomial but could be low order spline

RR Example

- !WORK 150

This is random regression analysis of

```
animal !P sire 89 !I dam 1052
```

```
year 2 !I !V21=V4 !==2 !*-365
```

```
flock 5 sex 2 !A aod
```

```
tobr 3 !I dob !-14800 !+V21
```

```
age wt fat emd
```

```
sdf01a.ped !SKIP 1
```

```
sdfwfm1.csv !SKIP 1 !MVremove !DOPA
```

```
!DDF !TYPEIISS !MAXIT 20
```

RR Model

```
■ !PART 1 # Linear RR
emd ~ mu age year wt sex sex.wt flock,
    tobr aod dob year.dob year.age,
    year.sex year.flock year.tobr,
    sex.dob tobr.dob,
!r animal animal.age,
    ide(animal) ide(animal).age,
    at(year,1,2).spl(age,20)
```


RR G structure

```
■ 0 0 2
  animal 2
  2 0 US !GP # Intercept and slope
  1.3 0.01 0.01
  animal 0 AINV
  ide(animal) 2# Intercept and slope
  2 0 US !GP
  1.6 0.01 0.03
  ide(animal)
```



Fitting PART 1

- Fixed terms year.age, year.sex year.tobr are NS
- variance of ide(animal).age is at boundary
- LogL after dropping 3 interactions was -726.867

Quadratic RR

```
■ !PART 2 # Quadratic RR using pol
emd ~ mu age year wt sex sex.wt flo
dob year.dob year.flock sex.dob
!r pol(age,2).animal pol(age,1).
at(year,1,2).spl(age,20)
0 0 2
pol(age,2).animal 2
3 0 US
1.6 .6 .6 .3 .3 .3
animal 0 AINV
pol(age,1).ide(animal)
2 0 US
```

PART 2 G structures

```
■ 0 0 2
  pol(age,2).animal 2
  3 0 US
  1.6 .6 .6 .3 .3 .3
  animal 0 AINV
  pol(age,1).ide(animal)
  2 0 US
  2.1 .6 1.3
  ide(animal)
```



PART 2

- LogL -643.67 so significant quadratic curvature
- Obtained initial values by ignoring G structure in initial run.

Spline curvature

```
■ !PART 3
  !SPLINE spl(age,3) 4 0 6
emd ~ mu age year wt sex sex.wt flo
      year.dob year.age year.sex year.
  !r animal animal.age animal.spl(age
      ide(animal) ide(animal).age,
      ide(animal).spl(age,3),
      at(year,1,2).spl(age,20)
0 0 2
animal 2
3 0 US !GU # Icept,slope,spl
1.3 0.1 0.01
```

Simpler

- !PART 4

```
emd ~ mu age year wt sex sex.wt flock tobr  
year.dob year.age -year.sex year.flock ye  
!r pol(age,2).animal ide(animal) ,  
at(year,1).spl(age,20) at(year,2).spl(age
```

```
0 0 1  
pol(age,2).animal 2  
3 0 US  
1.6  
.6 .6  
3 3 3
```



Interpretation

- .res file has `pol()` coefficients. say T Form TGT' to get full matrix of variances (all times).