Applied Statistical Methods - Solution 10

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Problem 1: Sire Model

Use the following dataset to predict breeding values using a sire model. The dataset is available from ## https://charlotte-ngs.github.io/asmss2022/data/asm_ped_sim_data.csv

Hints

- The variance component σ_s^2 of the sire effect can be assumed to be 2.25. The variance component σ_e^2 of the random resiudals is 36.
- Sex is modelled as a fixed effect.
- The sire pedigree relationship can be computed using the pedigreemm package.

Solution

• Read the data

2 0 1.3333333 -0.6666667 ## 8 0 -0.6666667 1.3333333

```
s_ex10_p01_data_path <- "https://charlotte-ngs.github.io/asmss2022/data/asm_ped_sim_data.csv"
tbl_ex10_p01 <- readr::read_csv(s_ex10_p01_data_path)
## Rows: 8 Columns: 5
## -- Column specification -----
## Delimiter: ","
## chr (1): SEX
## dbl (4): ID, SIRE, DAM, P
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
  • Compute the inverse sire relationship matrix
vec_sire <- unique(tbl_ex10_p01$SIRE)</pre>
vec_sire <- vec_sire[!is.na(vec_sire)]</pre>
n_nr_sire <- length(vec_sire)</pre>
ped_sire <- pedigreemm::pedigree(sire = c(NA, NA, 2),</pre>
                                 dam = rep(NA, n_nr_sire),
                                 label = as.character(vec_sire))
mat_A_inv_sire <- as.matrix(pedigreemm::getAInv(ped = ped_sire))</pre>
mat_A_inv_sire
## 1 1 0.0000000 0.0000000
```

• Setup the mixed model equations. The mixed model equations are

$$\left[\begin{array}{cc} X^TX & X^TZ \\ Z^TX & Z^TZ + \lambda_s * A_s^{-1} \end{array}\right] \left[\begin{array}{c} \hat{b} \\ \hat{s} \end{array}\right] = \left[\begin{array}{c} X^Ty \\ Z^Ty \end{array}\right]$$

where $\lambda_s = \sigma_e^2/\sigma_s^2$.

The components of the mixed model equations are shown in the following table

Component	Description
\overline{X}	Given in the data
Z	Given in the data
y	Given in the data
λ_s	Given by variance components
$\stackrel{\lambda_s}{A_s^{-1}}$	Computed above

The matrix X

```
mat_X <- model.matrix(lm(P ~ 0 + SEX, data = tbl_ex10_p01))
attr(mat_X, "assign") <- NULL
attr(mat_X, "contrasts") <- NULL
colnames(mat_X) <- NULL
mat_X</pre>
```

```
##
     [,1] [,2]
## 1
## 2
         1
              0
## 3
        0
              1
## 4
        0
## 5
## 6
        0
## 7
        0
## 8
         1
              0
```

The matrix Z

```
mat_Z <- model.matrix(lm(P ~ 0 + as.factor(SIRE), data = tbl_ex10_p01))
attr(mat_Z, "assign") <- NULL
attr(mat_Z, "contrasts") <- NULL
colnames(mat_Z) <- NULL
mat_Z</pre>
```

```
##
     [,1] [,2] [,3]
## 1
              0
                   0
        1
## 2
        0
                   0
              1
## 3
        1
              0
                   0
## 4
        0
              1
                   0
## 5
        1
                   0
## 6
        0
              0
                   1
## 7
              0
                   0
        1
## 8
                   1
```

The vector y

```
vec_y <- tbl_ex10_p01$P
vec_y</pre>
```

```
## [1] 16.7 13.9 26.0 4.3 18.8 5.2 6.6 27.5
```

The mixed model equations are

```
mat_xtx <- crossprod(mat_X)</pre>
mat_xtz <- crossprod(mat_X, mat_Z)</pre>
mat_ztx <- t(mat_xtz)</pre>
lambda_s <- sigma_e2 / sigma_s2</pre>
mat_ztz_a_inv_lambda <- crossprod(mat_Z) + lambda_s * mat_A_inv_sire</pre>
mat_coef <- rbind(cbind(mat_xtx, mat_xtz), cbind(mat_ztx, mat_ztz_a_inv_lambda))</pre>
mat_xty <- crossprod(mat_X, vec_y)</pre>
mat_zty <- crossprod(mat_Z, vec_y)</pre>
mat_rhs <- rbind(mat_xty, mat_zty)</pre>
```

• Solve mixed model equations. The solution is obtained by

```
mat_sol_sire <- solve(mat_coef, mat_rhs)</pre>
mat_sol_sire
##
            [,1]
##
     19.4721453
##
     11.9901384
## 1 0.6328720
## 2 -0.6878893
## 8 -0.2614187
The solution for the fixed effects are
mat_sol_sire[1:2,]
##
## 19.47215 11.99014
The predicted breeding values are
mat_sol_sire[3:nrow(mat_sol_sire),]
##
                                     8
   0.6328720 -0.6878893 -0.2614187
```

Problem 2: Animal Model

Use the same dataset as in Problem 1 to predict breeding values, but use an animal model instead of a sire model. The dataset is available from

https://charlotte-ngs.github.io/asmss2022/data/asm_ped_sim_data.csv

Hints

- The variance component σ_u^2 of the breeding value can be assumed to be 9. The variance component σ_e^2 of the random resiudals is 36.
- Sex is modelled as a fixed effect.
- The numerator relationship matrix can be computed using the pedigreemm package.

Solution

• Read the data

```
s_ex10_p02_data_path <- "https://charlotte-ngs.github.io/asmss2022/data/asm_ped_sim_data.csv"
tbl_ex10_p02 <- readr::read_csv(s_ex10_p02_data_path)</pre>
```

```
## Rows: 8 Columns: 5

## -- Column specification ------
## Delimiter: ","

## chr (1): SEX

## dbl (4): ID, SIRE, DAM, P

##

## i Use `spec()` to retrieve the full column specification for this data.

## i Specify the column types or set `show_col_types = FALSE` to quiet this message.

• Compute the inverse sire relationship matrix

ped <- pedigreemm::pedigree(sire = c(rep(NA, 4), tbl ex10 p02$SIRE).</pre>
```

```
##
                3
                    4 5 6 7 8 9 10 11 12
         0.0 0.5 0.5 -1 1 -1 0 -1
## 1
     3.0
     0.0 2.0 0.5 0.5 0 -1
                          0 -1
     0.5 0.5 2.0 0.0 0 0 -1 -1 0 0
     0.5 0.5 0.0 2.0 -1 -1
                              0 0 0 0
## 4
    -1.0 0.0 0.0 -1.0
                      3
                         0
                           0
                              1 0 -1
                              0 -1 0 -1
     1.0 -1.0 0.0 -1.0
                      0
                         3
                           0
## 7 -1.0 0.0 -1.0 0.0
                         0
                           2
                              0 0 0 0 0
                      0
     0.0 -1.0 -1.0 0.0
                      1
                        0
                           0
                              3 0 -1
## 9 -1.0 0.0 0.0 0.0 0 -1
                           0 0 2 0 0 0
## 10 0.0 0.0 0.0 0.0 -1
                           0 -1 0 2 0 0
## 11 -1.0 0.0 0.0 0.0 0 -1 0 0 0 2 0
## 12 0.0 0.0 0.0 0.0 -1 0 0 -1 0 0
```

• Setup the mixed model equations. The mixed model equations are

$$\left[\begin{array}{cc} X^TX & X^TZ \\ Z^TX & Z^TZ + \lambda*A^{-1} \end{array}\right] \left[\begin{array}{c} \hat{b} \\ \hat{u} \end{array}\right] = \left[\begin{array}{c} X^Ty \\ Z^Ty \end{array}\right]$$

where $\lambda = \sigma_e^2/\sigma_u^2$.

The components of the mixed model equations are shown in the following table

Component	Description
\overline{X}	Given in the data
Z	Given in the data
y	Given in the data
λ	Given by variance components
A^{-1}	Computed above

The matrix X

```
mat_X <- model.matrix(lm(P ~ 0 + SEX, data = tbl_ex10_p02))
attr(mat_X, "assign") <- NULL
attr(mat_X, "contrasts") <- NULL
colnames(mat_X) <- NULL
mat_X</pre>
```

```
##
     [,1] [,2]
## 1
              0
        1
## 2
         1
              0
## 3
        0
              1
## 4
        0
              1
## 5
        0
              1
## 6
        0
              1
## 7
        0
              1
## 8
        1
              0
```

The matrix Z

```
# model matrix from data
mat_Z <- model.matrix(lm(P ~ 0 + as.factor(ID), data = tbl_ex10_p02))
attr(mat_Z, "assign") <- NULL
attr(mat_Z, "contrasts") <- NULL
colnames(mat_Z) <- NULL
# add founders
mat_Z <- cbind(matrix(0, nrow = nrow(mat_Z), ncol = 4), mat_Z)
mat_Z</pre>
```

```
[,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12]
##
## 1
             0
                   0
                        0
                                   0
                                        0
                                              0
                                                   0
                              1
                              0
## 2
        0
             0
                   0
                        0
                                   1
                                        0
                                              0
                                                   0
                                                         0
                                                                0
                                                                      0
## 3
        0
             0
                   0
                        0
                              0
                                   0
                                              0
                                                   0
                                                         0
                                                                0
                                                                      0
                                        1
## 4
        0
             0
                   0
                        0
                              0
                                   0
                                             1
                                                         0
                                                                      0
                   0
## 5
        0
             0
                        0
                              0
                                   0
                                        0
                                             0
                                                   1
                                                         0
                                                                0
                                                                      0
## 6
        0
             0
                   0
                        0
                              0
                                   0
                                        0
                                             0
                                                   0
                                                         1
                                                                      0
## 7
        0
             0
                   0
                        0
                              0
                                   0
                                        0
                                              0
                                                  0
                                                         0
                                                                      0
                                                                1
## 8
                   0
                        0
                                   0
                                              0
                                                                      1
```

The vector y

```
vec_y <- tbl_ex10_p02$P
vec_y</pre>
```

```
## [1] 16.7 13.9 26.0 4.3 18.8 5.2 6.6 27.5
```

The mixed model equations are

```
mat_xtx <- crossprod(mat_X)
mat_xtz <- crossprod(mat_X, mat_Z)
mat_ztx <- t(mat_xtz)
lambda <- sigma_e2 / sigma_u2
mat_ztz_a_inv_lambda <- crossprod(mat_Z) + lambda * mat_A_inv
mat_coef <- rbind(cbind(mat_xtx, mat_xtz), cbind(mat_ztx, mat_ztz_a_inv_lambda))
mat_xty <- crossprod(mat_X, vec_y)
mat_zty <- crossprod(mat_Z, vec_y)
mat_rhs <- rbind(mat_xty, mat_zty)</pre>
```

• Solve mixed model equations. The solution is obtained by

```
mat_sol <- solve(mat_coef, mat_rhs)
mat_sol</pre>
```

```
## [,1]
## 19.7175571343
## 12.1523850711
```

```
## 1
       1.2950766779
## 2
     -1.2250000000
       0.6784481962
## 3
      -0.7485248741
## 4
## 5
      -0.0007843862
## 6
     -1.4612270230
       2.4157460473
     -1.0238113159
## 8
## 9
       0.6647792832
## 10 -1.2278630978
## 11 -0.6907762724
## 12 0.4093400063
The solution for the fixed effects are
mat_sol[1:2,]
##
## 19.71756 12.15239
The predicted breeding values are
mat_sol[3:nrow(mat_sol),]
##
                                             3
                                                                           5
    1.2950766779 -1.2250000000
                                 0.6784481962 -0.7485248741 -0.0007843862 -1.4612270230
##
                                                                                             2.4157460473 -1
##
                             10
                                            11
```

Problem 3: Model Comparison

0.6647792832 -1.2278630978 -0.6907762724

Compare the order of the predicted breeding values for the sires from the sire model and from the animal model.

0.4093400063

Solution

• Sire model

[1] 7 1 3 9 12 5 11 4 8 2 10 6

The order of the sires is the same under both models