

STAT 511 Solution to HW2 Spring 2008

1. (a) The matrix A is

$$\begin{pmatrix} 0.5 & 0.5 & -0.5 & -0.5 & -0.5 & -0.5 & 0.5 & 0.5 \\ 0.25 & 0.25 & 0.25 & 0.25 & -0.25 & -0.25 & -0.25 & -0.25 \end{pmatrix}$$

- (b) Since we know that $H_0 : C\beta = 0$ is equivalent to $H_0 : EY \in C(X) \cap C(A')^\perp$, it is enough to show that $C(X_0) = C(X) \cap C(A')^\perp$. It can be verified that $P_{A'}X_0 = 0$, so $C(X_0) \subset C(A')^\perp$ and clearly $C(X_0) \subset C(X)$. This means $C(X_0) \subset C(X) \cap C(A')^\perp$. To prove $(C(X) \cap C(A')^\perp) \subset C(X_0)$, it is enough to show that the 1st, 4th, 5th columns belong to $C(A')^\perp$, but the other columns of X do not belong to $C(A')^\perp$. We know 1st, 4th, 5th columns belong to $C(A')^\perp$ from the fact that $P_{A'}X_0 = 0$ and we can verify that $P_{A'}x_i \neq 0$ for $i = 2, 3, 6, 7, 8$, where x_i is the i th column of X . Then $C(X_0) = C(X) \cap C(A')^\perp$.

- (c) $H_0 : C\beta = 0$ tests the hypothesis of "B main effects only".

2. (a) Under Gauss-Markov assumption, we know $EY = X\beta$ and $\text{Var}(Y) = \sigma^2 I$. Then $E(Y - \hat{Y}) = E(I - P_X)Y = E(I - P_X)X\beta = 0$ and $\text{Var}(Y - \hat{Y}) = (I - P_X)\text{Var}(Y)(I - P_X) = \sigma^2(I - P_X)$.

$$\begin{aligned} \text{Cov}(\hat{Y}, Y - \hat{Y}) &= \text{Cov}(P_X Y, (I - P_X)Y) = P_X \text{Var}(Y)(I - P_X)' \\ &= \sigma^2 P_X (I - P_X)' = 0. \end{aligned}$$

Thus, there is no correlation between \hat{Y} and $Y - \hat{Y}$.

- (b) $E(Y - \hat{Y})'(Y - \hat{Y}) = E(Y'(I - P_X)Y) = \text{tr}((I - P_X)\sigma^2 I) + (X\beta)'(I - P_X)(X\beta) = \sigma^2 \text{tr}(I - P_X) = \sigma^2(n - \text{rank}(X))$.

3. (a) An appropriate estimate of EY is $\hat{Y} = X(X^T V_i^{-1} X)^{-1} (X^T V_i^{-1} Y)$, $i = 1, 2$. The estimate of $C\beta$ is $\hat{C}\beta = C(X^T V_i^{-1} X)^{-1} (X^T V_i^{-1} Y)$.

For V_1 , the two estimates are $\hat{Y} = (1.8, 1.8, 4, 6, 3.5, 3.5, 3.5)$ and $\hat{C}\beta = (1.8, 4, 6, 3.5)$.

For V_2 , the two estimates are $\hat{Y} = (2, 2, 4, 6, 3.6129, 3.6129, 3.6129)$ and $\hat{C}\beta = (2, 4, 6, 3.6129)$.

- (b) The covariance matrix for GLS estimate of EY is

$$\text{Var}(\hat{Y}_{GLS}) = X(X^T V_i^{-1} X)^{-1} X^T V_i^{-1} X(X^T V_i^{-1} X)^{-1} X^T = X(X^T V_i^{-1} X)^{-1} X^T.$$

For OLS estimate of EY is $\text{Var}(\hat{Y}_{OLS}) = X(X^T X)^{-1} X^T V_i X(X^T X)^{-1} X^T$.

For V_1 we can get the variance for \hat{Y}_{GLS} and \hat{Y}_{OLS} , respectively, as

$$\begin{pmatrix} 0.8 & 0.8 & 0 & 0 & 0 & 0 & 0 \\ 0.8 & 0.8 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2/3 & 2/3 & 2/3 \\ 0 & 0 & 0 & 0 & 2/3 & 2/3 & 2/3 \\ 0 & 0 & 0 & 0 & 2/3 & 2/3 & 2/3 \end{pmatrix} \quad \begin{pmatrix} 1.25 & 1.25 & 0 & 0 & 0 & 0 & 0 \\ 1.25 & 1.25 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{pmatrix}.$$

For V_2 we can get the variance for \hat{Y}_{GLS} and \hat{Y}_{OLS} , respectively, as

$$\begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.387 & 0.387 & 0.387 \\ 0 & 0 & 0 & 0 & 0.387 & 0.387 & 0.387 \\ 0 & 0 & 0 & 0 & 0.387 & 0.387 & 0.387 \end{pmatrix} \begin{pmatrix} 1.75 & 1.75 & 0 & 0 & 0 & 0 & 0 \\ 1.75 & 1.75 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.778 & 0.778 & 0.778 \\ 0 & 0 & 0 & 0 & 0.778 & 0.778 & 0.778 \\ 0 & 0 & 0 & 0 & 0.778 & 0.778 & 0.778 \end{pmatrix}.$$

Similarly, for $C\beta$ we can get the similar formula for the variance of the estimates.

For V_1 , we have the variance of $\hat{C}\beta_{GLS}$ and $\hat{C}\beta_{OLS}$, respectively, as

$$\begin{pmatrix} 0.8 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2/3 \end{pmatrix} \begin{pmatrix} 1.25 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

For V_2 , we get the variance of $\hat{C}\beta_{GLS}$ and $\hat{C}\beta_{OLS}$, respectively, as

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 4 & -1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0.387 \end{pmatrix} \begin{pmatrix} 1.75 & 0 & 0 & 0 \\ 0 & 4 & -1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0.778 \end{pmatrix}.$$

4. (a) Use `lm` in R, we get

```
> X <- matrix(c(1,1,rep(c(rep(0,7),1),3),1,1),7,4)
> Y<-c(2,1,4,6,3,5,4)
> V1<-c(1,4,4,1,1,4,4)
> fit<-lm(Y~X-1,weights=1/V1)
> fit$coefficients
  X1  X2  X3  X4
1.8 4.0 6.0 3.5
```

Then the estimate for 4 cell means are (1.8, 4, 6, 3.5).

(b) Use `lm.gls()` in R, we get

```
> V2<-diag(c(1,4,4,1,1,4,4))
> V2[1,2]<-V2[2,1]<-1
> V2[3,4]<-V2[4,3]<-V2[5,6]<-V2[6,5]<--1
> fit<-lm.gls(Y~X-1, W=solve(V2))
> fit$coefficient
      X1      X2      X3      X4
2.000000 4.000000 6.000000 3.612903
```

Then the estimate for 4 cell means as (2, 4, 6, 3.6129).