

# Problem Sheet 3

Theory of Inference

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## Question 1

Part a)

$$\begin{aligned}
 \|\tilde{\mathbf{y}} - \tilde{\mathbf{X}}\beta\|^2 &= \sum_i (\tilde{y}_i - \sum_j \tilde{X}_{ij}\beta_j)^2 \\
 &= \sum_i (W_{ii}y_i - \sum_j W_{ij}X_{ij}\beta_j)^2 \\
 &= \sum_i W_{ii}^2 (y_i - \sum_j X_{ij}\beta_j)^2 \\
 \text{Define } W_{ij} &:= \begin{cases} \frac{1}{\sqrt{n_{se(i)}}} & i \equiv j \\ 0 & \text{otherwise} \end{cases} \\
 \Rightarrow \|\tilde{\mathbf{y}} - \tilde{\mathbf{X}}\beta\|^2 &= \sum_i \frac{1}{\sqrt{n_{se(i)}}} (y_i - \sum_j X_{ij}\beta_j)^2
 \end{aligned}$$

Part b)

$$\begin{aligned}
 \text{We have } \|\tilde{\mathbf{y}} - \tilde{\mathbf{X}}\beta\|^2 &= (\tilde{\mathbf{y}} - \tilde{\mathbf{X}}\beta)^T (\tilde{\mathbf{y}} - \tilde{\mathbf{X}}\beta) \\
 &= (\mathbf{y} - \mathbf{X}\beta)^T \mathbf{W}^2 (\mathbf{y} - \mathbf{X}\beta) \\
 &= \mathbf{y}^T \mathbf{W}^2 \mathbf{y} - \mathbf{y}^T \mathbf{W}^2 \mathbf{X}\beta - \beta^T \mathbf{X}^T \mathbf{W}^2 \mathbf{y} + \beta^T \mathbf{X}^T \mathbf{W}^2 \mathbf{X}\beta \\
 \Rightarrow \frac{\partial}{\partial \beta} \|\tilde{\mathbf{y}} - \tilde{\mathbf{X}}\beta\| &= -\mathbf{X}^T \mathbf{W}^2 \mathbf{y} - \mathbf{X}^T \mathbf{W}^2 \mathbf{y} + 2\mathbf{X}^T \mathbf{W}^2 \mathbf{X}\beta \\
 \text{Setting } 0 &= \frac{\partial}{\partial \beta} \|\tilde{\mathbf{y}} - \tilde{\mathbf{X}}\beta\| \\
 \Rightarrow 0 &= 2(\mathbf{X}^T \mathbf{W}^2 \mathbf{X}\hat{\beta}_{\text{WLS}} + \mathbf{X}^T \mathbf{W}^2 \mathbf{X}\hat{\beta}_{\text{WLS}}) \\
 \Rightarrow \hat{\beta}_{\text{WLS}} &= (\mathbf{X}^T \mathbf{W}^2 \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}^2 \mathbf{y} \\
 \Rightarrow \mathbb{E}[\hat{\beta}_{\text{WLS}}] &= \mathbb{E}((\mathbf{X}^T \mathbf{W}^2 \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}^2 \mathbf{y}) \\
 &= (\mathbf{X}^T \mathbf{W}^2 \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}^2 \mathbb{E}(\mathbf{y}) \\
 &= (\mathbf{X}^T \mathbf{W}^2 \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}^2 \mathbf{X}\beta \\
 &= \beta
 \end{aligned}$$

Since  $\mathbb{E}(\hat{\beta}_{\text{WLS}}) = \beta$  then  $\hat{\beta}_{\text{WLS}}$  is an unbiased estimator of  $\beta$ .

Part c)

Since this estimator is unbiased and fulfils all the residual assumptions I would recommend the weighted least squares estimator here as it takes into account more information than a standard least squares estimator.

## Question 2

Model doesn't account for the fact that the markets close at night. There are likely to be sizable changes in the price of a share between closing and opening of the markets. This could be seen by regular spikes in model residual values at the start of each day.

## Question 3

Part a)

If we know that an observation is not in group one or two, then it must be in group three. Thus the groups are not independent & the model matrix is rank deficient. This means we cannot invert the matrix.

**Part b)**

```
m1<-lm(weight ~ group,data=PlantGrowth)
```

In this interpretation value which is the expected value for observations in `ctrl` group. There are then two binary variables which state whether the observation was made from `grouptrt1` or `grouptrt2` (these are not independent). The parameters associated with each of these variables is the expected difference in `weight` for observations in that group, compared to `ctrl`.

**Part c)**

$$H_0 : \beta = \begin{pmatrix} \mu \\ 0 \\ 0 \end{pmatrix} \text{ against } H_1 : \beta \neq \begin{pmatrix} \mu \\ 0 \\ 0 \end{pmatrix}.$$

```
anova(m1)
```

```
## Analysis of Variance Table
##
## Response: weight
##           Df Sum Sq Mean Sq F value Pr(>F)
## group      2  3.7663  1.8832  4.8461 0.01591 *
## Residuals 27 10.4921  0.3886
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We reject null hypothesis at the 5% level. Thus concluding that `group` is needed in the model. It uses the results in second 3.4.4 of the notes, in particular

$$F = \frac{(RSS_0 - RSS_1)/q}{RSS_1/(n-p)}$$

where  $n = 30$ ,  $p = 3$ ,  $q = 3$ . \$TODO check this

**Part d)**

```
m0<-lm(weight~1,data=PlantGrowth)
anova(m0,m1)
```

```
## Analysis of Variance Table
##
## Model 1: weight ~ 1
## Model 2: weight ~ group
##   Res.Df    RSS Df Sum of Sq    F Pr(>F)
## 1      29 14.258
## 2      27 10.492  2    3.7663 4.8461 0.01591 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Same result as in part c).

**Part e)**

```
summary(m1)
```

```
##
## Call:
```

```
## lm(formula = weight ~ group, data = PlantGrowth)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.0710 -0.4180 -0.0060  0.2627  1.3690
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   5.0320     0.1971  25.527  <2e-16 ***
## grouptrt1    -0.3710     0.2788  -1.331   0.1944
## grouptrt2     0.4940     0.2788   1.772   0.0877 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6234 on 27 degrees of freedom
## Multiple R-squared:  0.2641, Adjusted R-squared:  0.2096
## F-statistic: 4.846 on 2 and 27 DF,  p-value: 0.01591
```

$H_0 : \beta = \mathbf{0}$  against  $H_1 : \beta \neq \mathbf{0}$ . The  $p$ -Value is unchanged.

## Part f)

We have that

$$\frac{\hat{\beta}_2 - \beta_i}{\hat{\sigma}_{\hat{\beta}_2}} \sim t_{27}$$

Thus

$$\begin{aligned} 1 - 2\alpha &= \mathbb{P}\left(-t_{27}(\alpha) < \frac{\hat{\beta}_2 - \beta_i}{\hat{\sigma}_{\hat{\beta}_2}} < t_{27}(\alpha)\right) \\ &= \mathbb{P}(\hat{\beta}_2 - t_{27}(\alpha)\hat{\sigma}_{\hat{\beta}_2} < \beta_2 < \hat{\beta}_2 + t_{27}(\alpha)\hat{\sigma}_{\hat{\beta}_2}) \end{aligned}$$

In this scenario we have that

$$\begin{aligned} \hat{\beta}_2 &= \bar{x}_{\text{trt2}} - \bar{x}_{\text{ctrl}} \\ &= 5.525 - 5.032 \\ &= 0.4940 \\ \hat{\sigma}_{\hat{\beta}_2}^2 &= \frac{1}{10-1} \sum_{i=1}^{10} (y_i - \hat{y}_i)^2 \\ &= \frac{1}{9} 1.76284 \\ &= 0.1959 \\ \implies \hat{\sigma}_{\hat{\beta}_2} &= 0.4425733 \end{aligned}$$

Giving us the following 90% confidence interval for difference between treatment 2 and the control

$$\begin{aligned} [0.4940 - 1.703 \cdot 0.4425733, 0.4940 + 1.703 \cdot 0.4425733] \\ = [-0.272, 4.342] \end{aligned}$$