

# STAT5703 HW3 Exercise 4

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## Exercise 4.

### Question 1.

$$\begin{aligned} \text{var}(\hat{\epsilon}_i) &= \text{var}[Y_i - \hat{Y}_i] = E[(Y_i - \hat{Y}_i)^2] - E[(Y_i - \hat{Y}_i)]^2 \\ \text{var}(\delta_i) &= \text{var}[\hat{Y}_i - E[Y_i]] = E[(\hat{Y}_i - E[Y_i])^2] - E[(\hat{Y}_i - E[Y_i])]^2 \\ \text{var}(\delta_i) - \text{var}(\hat{\epsilon}_i) &= E[(\hat{Y}_i - (E[Y_i]))^2] - E[(Y_i - \hat{Y}_i)^2] = E[(\hat{Y}_i - E[Y_i])^2] - E[RSS(\hat{Y}_i)] \\ E[RSS(\hat{Y}_i)] + \sum \text{var}(\delta_i) - \sum \text{var}(\hat{\epsilon}_i) &= \sum E[(\hat{Y}_i - (E[Y_i]))^2] = E[\sum (\hat{Y}_i - E[Y_i])^2] = \sigma^2 \Gamma \end{aligned}$$

### Question 2.

to prove  $E[\frac{1}{\sigma^2}RSS(\hat{Y}) + 2tr(S) - n] = \Gamma$ , we only need to prove  $\sigma^2 E[RSS(\hat{Y}) + 2tr(S) - n] = \sigma^2 \Gamma$ ,  
 $\sigma^2(2tr(S) - n) = \sum \text{var}(\delta_i) - \sum \text{var}(\hat{\epsilon}_i)$   
 $= E[(\delta - \delta_\mu)^T(\delta - \delta_\mu)] - E[(\hat{\epsilon} - \hat{\epsilon}_\mu)^T(\hat{\epsilon} - \hat{\epsilon}_\mu)]$

$$\begin{aligned} \hat{\epsilon} &= Y - \hat{Y} = (I - S)Y \\ \hat{\epsilon}_\mu &= (I - S)E[Y] = (I - S)\mu \\ \delta &= \hat{Y} - E[Y] = \hat{Y} - \mu = SY - \mu \\ \delta_\mu &= SEY - \mu = (S - I)\mu \end{aligned}$$

Therefore,

$$\begin{aligned} \hat{\epsilon} - \hat{\epsilon}_\mu &= (I - S)Y - (I - S)\mu = (I - S)(Y - \mu) \\ \delta - \delta_\mu &= S(Y - \mu) \end{aligned}$$

Now, we can go back to  $E[(\delta - \delta_\mu)^T(\delta - \delta_\mu)] - E[(\hat{\epsilon} - \hat{\epsilon}_\mu)^T(\hat{\epsilon} - \hat{\epsilon}_\mu)]$   
 $= E[(Y - \mu)^T S^T S(Y - \mu)] - E[(Y - \mu)^T (I - S)^T (I - S)(Y - \mu)]$   
 $= E[(Y - \mu)^T (-I + S + S^T)(Y - \mu)]$   
 $= tr[(-I + S + S^T)cov(Y - \mu)] + (E[Y - \mu])^T (-I + S + S^T)E[Y - \mu]$   
 $= \sigma^2 tr[-I + S + S^T] = \sigma^2(-n + 2tr[s])$  proved.

### Question 3.

$re(S) = tr(X^T X(X^T X)^{-1}) = tr(I_P) = p$  therefore  $C_p = \frac{1}{\sigma^2}RSS(\hat{Y}) + 2p - n$  Note that  $AIC = 2p - 2l$  and  $l = -\frac{1}{2}(n \log \sigma^2 + \frac{1}{\sigma^2}RSS(\hat{Y}) + C)$  So  $AIC = \frac{1}{\sigma^2}RSS(\hat{Y}) + 2p - n \log \sigma^2 + C$  is similar to  $C_P$  if we treat  $\sigma^2$ ,  $n$  to constant.

### Question 4.

We have  $AIC(\hat{\beta}_{q+1}) - AIC(\hat{\beta}) = 2 - 2(l_{q+1} - l_q)$  where  $l_q = -\frac{1}{2}(n \log(RSS(\hat{\beta}_q) + n - n \log n)$  Therefore  $P(AIC(\hat{\beta}_{q+1}) - AIC(\hat{\beta})) < 0$   
 $= P(2 + n \log \frac{RSS(\hat{\beta}_{q+1})}{RSS(\hat{\beta}_q)} < 0)$   
 $= P(n \log(1 - X_1^2/n) < -2)$  where  $n \rightarrow \infty$   $P(n \log(1 - X_1^2/n) < -2) = P(X_1^2 > 2) > 0$

**Question 5.**

$BIC = -2l(\hat{\theta}) + p \log n$ , So  $P(BIC(\hat{\beta}_{q+1}) - BIC(\hat{\beta}_q) < 0) =$   
 $P(\log n + n \log \frac{RSS(\hat{\beta}_{q+1})}{RSS(\hat{\beta}_q)} < 0)$  where  $n \rightarrow \infty$   $P(\log n + n \log \frac{RSS(\hat{\beta}_{q+1})}{RSS(\hat{\beta}_q)} < 0) = P(\log n - X_1^2 < 0)$   
 $P(X_1^2 > \log n) = 0$