

Giang Vu - 4445745
STAT 2131
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Homework 7

1) a) • $(v - Hv)^T(Hv) = 0$

We have $(v - Hv)^T(Hv)$

$$= v^T Hv - v^T H^T H v$$

$$= v^T Hv - v^T HHv \quad (\text{as } H^T = H)$$

$$= v^T Hv - v^T Hv \quad (\text{as } HH = H^2 = I)$$

$$= 0$$

• Prove $Hv = \operatorname{argmin} \|v - u\|_2^2$

• $u \in \operatorname{Im}(H)$

$$\begin{aligned}
 \text{ii) } \|v - u\|_2^2 &= \|v - Hv + Hv - u\|_2^2 \\
 &= \|(v - Hv) + (Hv - u)\|_2^2 \\
 &= [(v - Hv) + (Hv - u)]^T [(v - Hv) + (Hv - u)] \\
 &= \overset{(1)}{(v - Hv)^T (v - Hv)} + \overset{(2)}{(v - Hv)^T (Hv - u)} \\
 &\quad + \overset{(3)}{(Hv - u)^T (v - Hv)} + \overset{(4)}{(Hv - u)^T (Hv - u)}
 \end{aligned}$$

Let's look at $(1) = (v - Hv)^T (v - Hv) = \|v - Hv\|_2^2$

$(4) = (Hv - u)^T (Hv - u) = \|Hv - u\|_2^2$

$(2) = (v - Hv)^T (Hv - u)$

$$= v^T Hv - v^T u - v^T H^T Hv + v^T H^T u$$

$$= v^T Hv - v^T u - v^T H v + v^T u$$

(because $H^T H = H H = H$
and $H^T u = Hu = u$)

$\Rightarrow (2) = (v^T Hv - v^T Hv) + (v^T u - v^T u) = 0$

$(3) = (Hv - u)^T (v - Hv)$

$$= v^T H^T v - v^T H H v - u^T v + u^T H v$$

$$= v^T H v - v^T H v - u^T v + u^T v$$

(because $H = H^T = H H$)

and $u^T H = (Hu)^T = u^T$)

$$= 0$$

$\Rightarrow \|v - u\|_2^2 = (1) + (2) + (3) + (4)$

$$= \|v - Hv\|_2^2 + 0 + 0 + \|Hv - u\|_2^2$$

$$= \|v - Hv\|_2^2 + \|Hv - u\|_2^2$$

which is $\geq \|v - Hv\|_2^2$

Therefore, $u = Hv = \arg \min_{u \in \text{Im}(x)} \|v - u\|_2^2$

b) We have H & P are both orthogonal projection matrices onto $X_{n \times p}$

Suppose we have $u \in \text{Im}(X)$

$$\Rightarrow Hu = u \text{ and } Pu = u$$

$$\Rightarrow Hu = Pu \Rightarrow H = P$$

$\Rightarrow H$ is unique

c) 4 properties :

$$(1) XX^+X = X$$

$$(3) (XX^+)^T = XX^+$$

$$(2) X^+XX^+ = X^+$$

$$(4) (X^+X)^T = X^+X$$

We have $H = XX^+$

- Symmetry

$$H^T = (XX^+)^T = XX^+ = H \quad (\text{using property (3)})$$

- Idempotence

$$HH = XX^+XX^+ = (XX^+X)X^+ = XX^+ = H \quad (\text{using property (1)})$$

$$\Rightarrow H^2 = H$$

- $\text{im}(H) = \text{im}(X)$

Let $a \in \text{Im}(H)$, $a \in \mathbb{R}^n$

$$\Rightarrow a = \underset{n \times n \times 1}{H} \underset{n \times 1}{v_1} = \underset{n \times p}{X} \underset{p \times 1}{X^+} \underset{n \times 1}{v_1} = \underset{p \times n}{X} \underbrace{\underset{n \times 1}{X^+ v_1}}_{\text{a } p \times 1 \text{ vector}}$$

$$\Rightarrow a \in \text{Im}(X)$$

$$\Rightarrow \text{Im}(H) \subset \text{Im}(X)$$

$$\begin{aligned} \text{Let } b \in \text{Im}(X) \Rightarrow b &= \underset{n \times 1}{X} \underset{p \times 1}{v_2} = \underset{n \times p}{X} \underset{p \times n}{X^+} \underset{n \times p}{X} \underset{p \times 1}{v_2} \\ b \in \mathbb{R}^n &= \underset{n \times p}{X} \underset{p \times 1}{X^+ (X v_2)} \end{aligned}$$

$$= \underset{n \times p}{H} \underbrace{\underset{p \times 1}{X v_2}}_{\text{a } n \times 1 \text{ vector}}$$

$$\Rightarrow b \in \text{Im}(H)$$

$$\Rightarrow \text{Im}(X) \subset \text{Im}(H)$$

$$\hookrightarrow \text{Im}(H) = \text{Im}(X)$$

$$2a) \hat{\beta}_{ols} = (X^T X)^{-1} X^T y$$

$$\text{Var}(\hat{\beta}_{ols}) = \text{Var}((X^T X)^{-1} X^T y)$$

$$= (X^T X)^{-1} X^T \text{Var}(y) X (X^T X)^{-1}$$

$$= (X^T X)^{-1} X^T \sigma^2 I X (X^T X)^{-1}$$

$$= \sigma^2 (X^T X)^{-1} X^T X (X^T X)^{-1}$$

$$= \sigma^2 (X^T X)^{-1}$$

$$H = X (X^T X)^{-1} X^T$$

b) • Prove $A^T X = I_p$

Because $\tilde{\beta}$ is a linear unbiased estimator for $\beta \Rightarrow E(\tilde{\beta}) = \beta$

$$\Rightarrow E(A^T Y) = \beta \Rightarrow E(A^T X \beta) = \beta \Rightarrow A^T X \beta = \beta$$

$$\Rightarrow A^T X = I_p$$

$$\begin{aligned}
 \bullet \text{ Var}(\tilde{\beta}) &= \text{Var}(A^T y) \\
 &= A^T \text{Var}(y) A \\
 &= A^T \sigma^2 I A = \sigma^2 A^T A
 \end{aligned}$$

$$\begin{aligned}
c) \text{Var}(\tilde{\beta}) &= \sigma^2 A^T A \quad (\text{from part b}) \\
&= \sigma^2 A^T I A = \sigma^2 A^T (H + I - H) A \\
&= \sigma^2 A^T H A + \sigma^2 A^T (I - H) A \\
&= \sigma^2 A^T X (X^T X)^{-1} X^T A + \sigma^2 A^T (I - H) A \\
&= \sigma^2 \cdot I \cdot (X^T X)^{-1} \cdot I + \sigma^2 A^T (I - H) A \\
&= \sigma^2 (X^T X)^{-1} + \sigma^2 A^T (I - H) A \\
&= \text{Var}(\hat{\beta}_{OLS}) + \sigma^2 A^T (I - H) A
\end{aligned}$$

We can see that $A^T (I - H) A$ is a quadratic form, and $I - H = Q$ is an orthogonal projection, hence it is symmetric.

From HW5, we showed that all the eigenvalues of Q (or $I - H$) are either 0 or 1, so the eigenvalues of $(I - H)$ are all ≥ 0 .

$\Rightarrow \sigma^2 A^T (I - H) A$ is a positive semi-definite matrix, we call this M .

$$\Rightarrow \text{Var}(\tilde{\beta}) = \text{Var}(\hat{\beta}_{OLS}) + M$$

$$\begin{aligned}
d) \text{Var}(q^T \tilde{\beta}) &= q^T \text{Var}(\tilde{\beta}) (q^T)^T \\
&= q^T (\text{Var}(\hat{\beta}_{OLS}) + M) q \\
&= q^T \text{Var}(\hat{\beta}_{OLS}) q + q^T M q \\
&= \text{Var}(q^T \hat{\beta}_{OLS}) + \underbrace{q^T M q}_{\geq 0} \quad (\text{from part c}) \\
\Rightarrow \text{Var}(q^T \tilde{\beta}) &\geq \text{Var}(q^T \hat{\beta}_{OLS})
\end{aligned}$$

$$e) i) E(\tilde{Y}) = E(\tilde{X}\beta + \tilde{E})$$

$$\text{We have } \tilde{Y} = \tilde{X}\beta + \tilde{E}$$

$$\Rightarrow R^{-1}Y = R^{-1}X\beta + \tilde{E} = R^{-1}(X\beta + \frac{1}{R^{-1}}\tilde{E})$$

$$\Rightarrow Y = X\beta + \frac{1}{R^{-1}}\tilde{E}$$

$$\text{But } Y = X\beta + E \Rightarrow \tilde{E} = R^{-1}E$$

$$\begin{aligned} \Rightarrow E(\tilde{Y}) &= E(R^{-1}X\beta + R^{-1}E) \\ &= R^{-1}E(X\beta) + R^{-1}E(\tilde{E}) \\ &= R^{-1}X\beta \end{aligned}$$

$$\begin{aligned} \text{Var}(\tilde{Y}) &= \text{Var}(R^{-1}Y) \\ &= R^{-1} \text{Var}(Y) (R^{-1})^T \\ &= R^{-1} \sigma^2 \Sigma (R^T)^{-1} \\ &= \sigma^2 (R^{-1}R) (R^T (R^T)^{-1}) \quad (\text{as } \Sigma = RR^T) \\ &= \sigma^2 \end{aligned}$$

$$ii) \Sigma = RR^T \Rightarrow \Sigma^{-1} = (R^T)^{-1} R^{-1}$$

$$\Sigma^T = (R^T)^T R^T = RR^T \Rightarrow (\Sigma^T)^{-1} = (\Sigma^{-1})^T = (R^T)^T R^{-1}$$

$\hat{\beta}_{GLS}$ minimizes the function $f(\beta) = (\tilde{Y} - \tilde{X}\beta)^T (\tilde{Y} - \tilde{X}\beta)$

Set $\nabla_{\beta} f(\beta) = 0$ and solve for $\hat{\beta}_{GLS}$

$$\begin{aligned} \text{We have } f(\beta) &= (R^{-1}(Y - X\beta))^T (R^{-1}(Y - X\beta)) \\ &= (Y - X\beta)^T (R^T)^{-1} R^{-1} (Y - X\beta) \\ &= (Y - X\beta)^T \Sigma^{-1} (Y - X\beta) \end{aligned}$$

$$\begin{aligned} \Rightarrow f(\beta) &= Y^T \Sigma^{-1} Y - Y^T \Sigma^{-1} X\beta - \beta^T X^T \Sigma^{-1} Y + \beta^T X^T \Sigma^{-1} X\beta \\ (Y^T \Sigma^{-1} X\beta &= (Y^T \Sigma^{-1} X\beta)^T = \beta^T X^T \Sigma^{-1} Y \text{ is a scalar}) \end{aligned}$$

$$\Rightarrow f(\beta) = Y^T \Sigma^{-1} Y - 2\beta^T X^T \Sigma^{-1} Y + \beta^T X^T \Sigma^{-1} X\beta$$

$$\Rightarrow \nabla_{\beta} f(\beta) = 0 = -2X^T \Sigma^{-1} Y + 2X^T \Sigma^{-1} X\beta$$

$$\text{Set } \nabla_{\beta} f(\beta) = 0$$

$$\Rightarrow -2X^T \Sigma^{-1} Y + 2X^T \Sigma^{-1} X\hat{\beta}_{GLS} = 0$$

$$\Rightarrow X^T \Sigma^{-1} X\hat{\beta}_{GLS} = X^T \Sigma^{-1} Y$$

$$\Rightarrow \hat{\beta}_{GLS} = (X^T \Sigma^{-1} X)^{-1} X^T \Sigma^{-1} Y$$

HW7

Giang Vu

10/6/2020

Problem 3 (6.10 & 7.4)

6.10 - a

```
#read data
hw7 <- read.csv("/Users/giangvu/Desktop/STAT 2131 - Applied Stat Methods 1/HW/hw7/hw7.3data.csv", sep = ",")
mod73 <- lm(Y ~ X1 + X2 + X3, data = hw7)
sum73 <- summary(mod73)
sum73
```

```
##
## Call:
## lm(formula = Y ~ X1 + X2 + X3, data = hw7)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -264.05 -110.73  -22.52   79.29  295.75
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.150e+03  1.956e+02  21.220  < 2e-16 ***
## X1           7.871e-04  3.646e-04   2.159   0.0359 *
## X2          -1.317e+01  2.309e+01  -0.570   0.5712
## X3           6.236e+02  6.264e+01   9.954  2.94e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 143.3 on 48 degrees of freedom
## Multiple R-squared:  0.6883, Adjusted R-squared:  0.6689
## F-statistic: 35.34 on 3 and 48 DF,  p-value: 3.316e-12
```

The estimated regression function is

$$\hat{Y} = 4150 + 0.0007871X_1 - 13.17X_2 + 623.6X_3$$

Interpretation of coefficients:

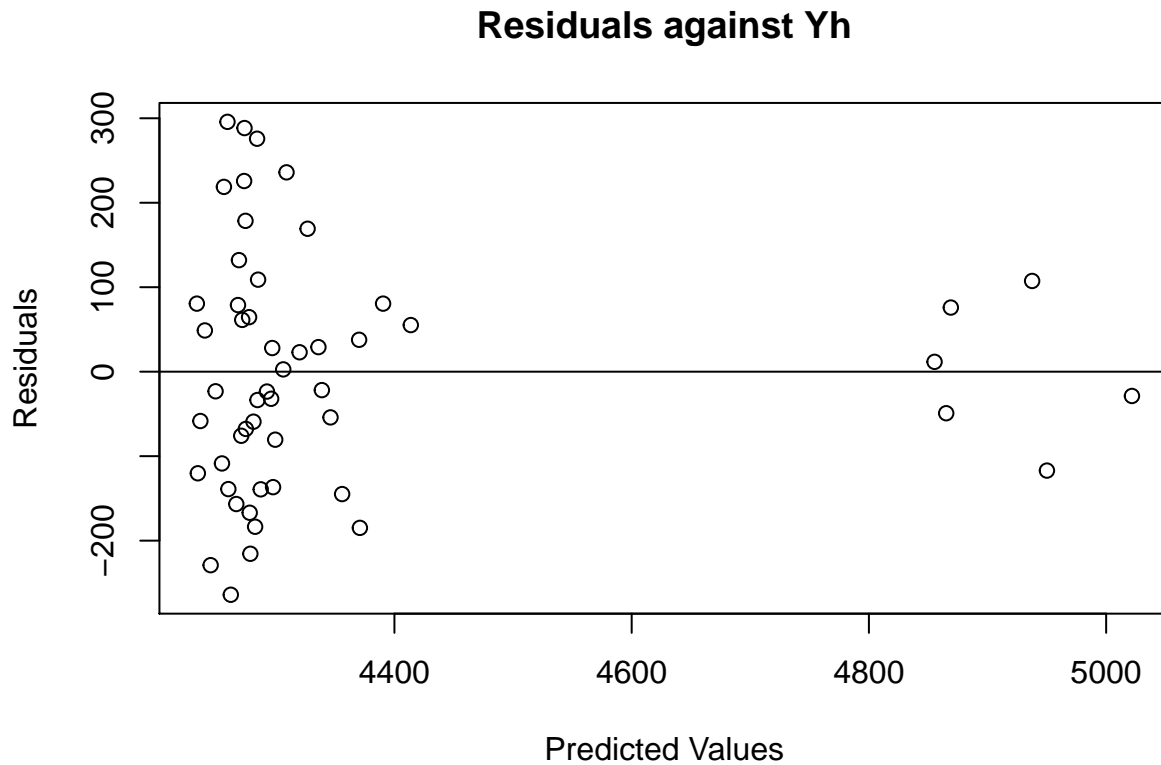
When number of cases shipped increases by 1 case, the total labor hours is expected to increase by 0.0007871 hour.

When indirect costs of total labor hours increases by 1 percentage point, the total labor hours is expected to decrease by 13.17 hours.

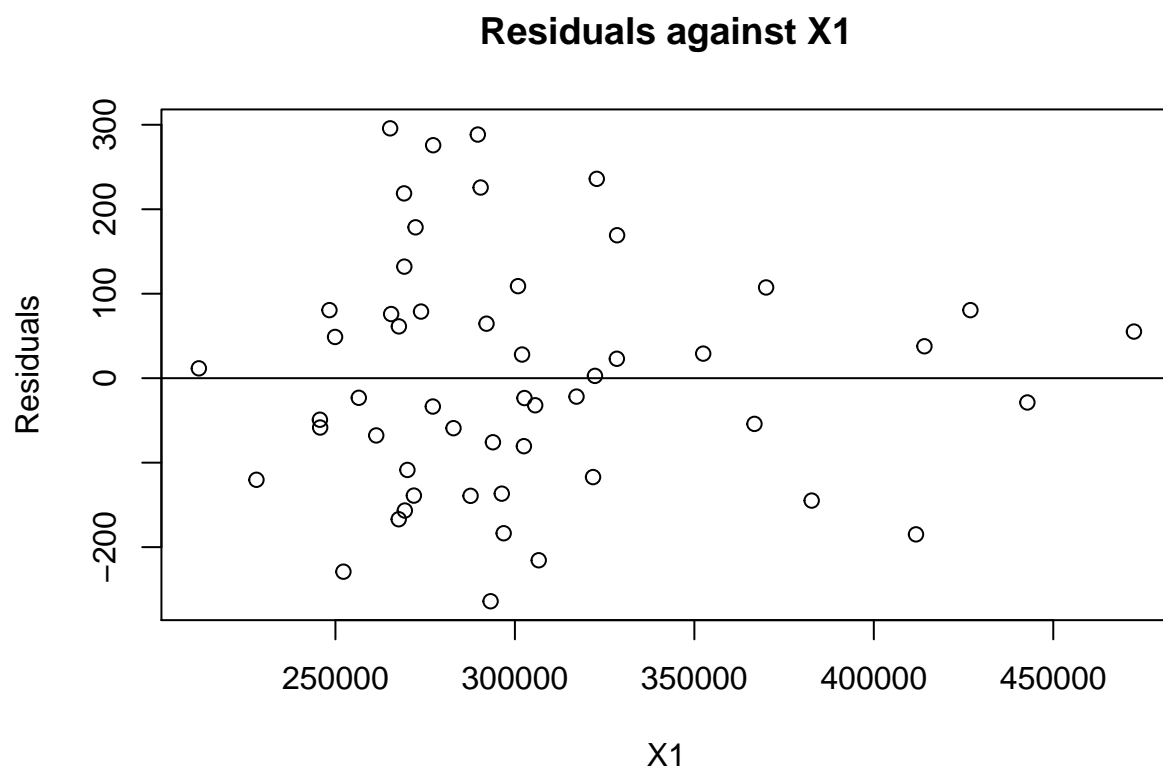
When the week has a holiday, the total labor hours is expected to increase by 623.6 hours, and there's no change expected with total labor hours when the week has no holiday.

6.10 - c

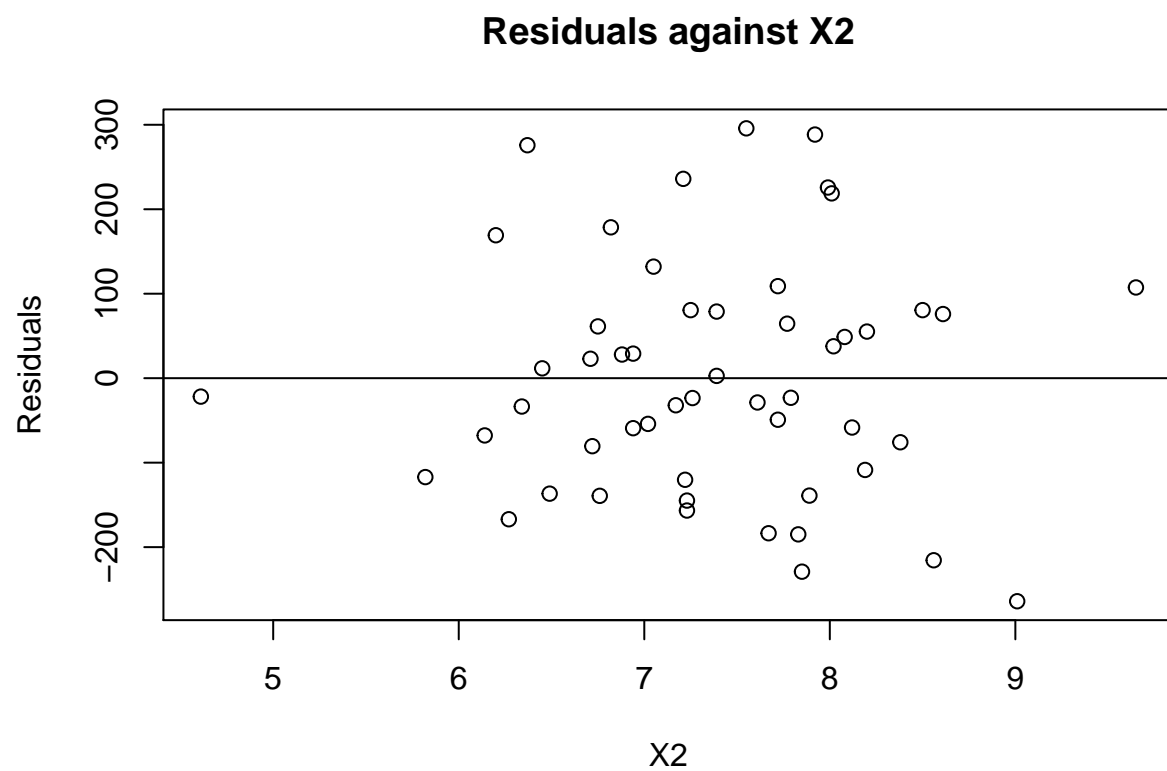
```
#residuals against Yh  
plot(predict(mod73), resid(mod73),  
      ylab = "Residuals", xlab = "Predicted Values", main = "Residuals against Yh")  
abline(0,0)
```



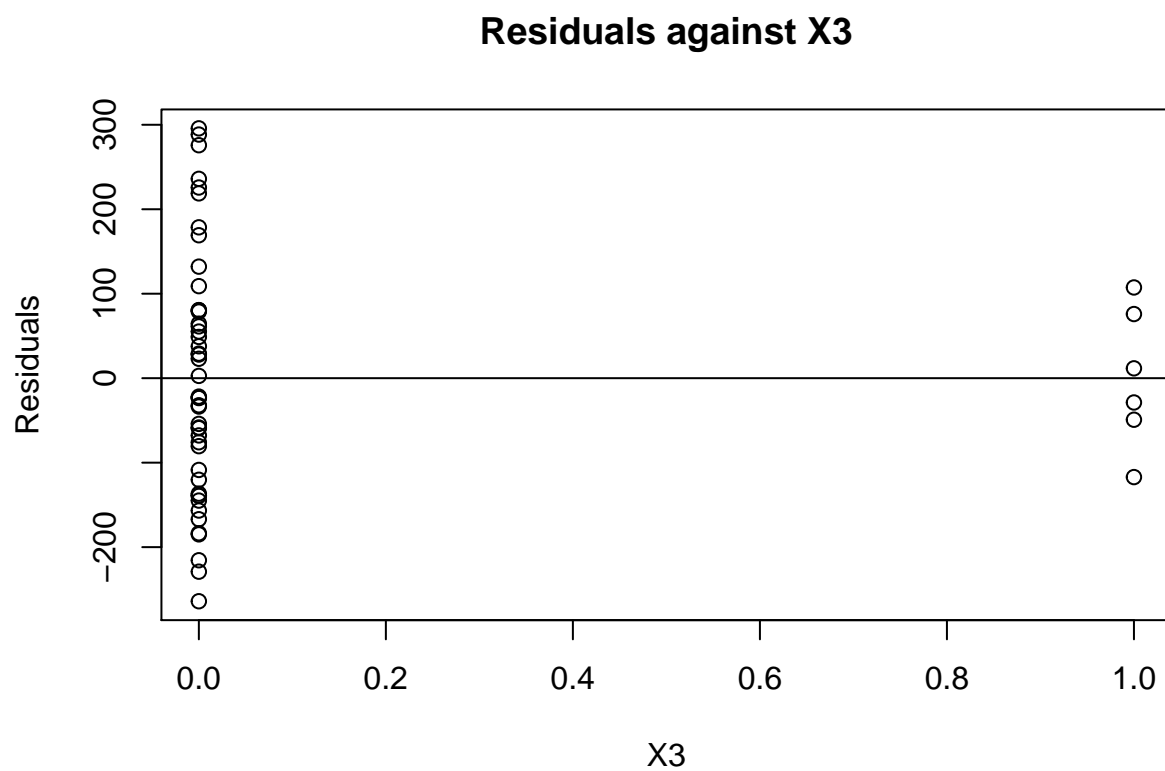
```
#residuals against X1  
plot(hw7$X1, resid(mod73),  
      ylab = "Residuals", xlab = "X1", main = "Residuals against X1")  
abline(0,0)
```

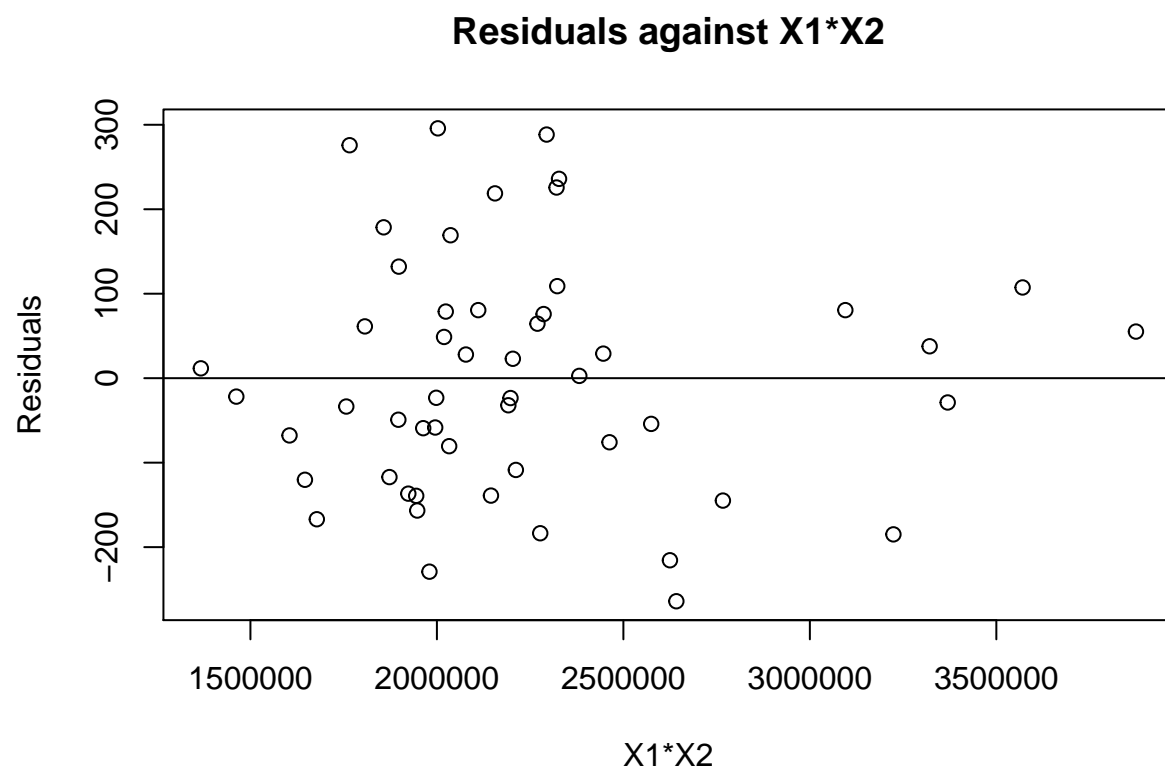
```
#residuals against X2  
plot(hw7$X2, resid(mod73),  
      ylab = "Residuals", xlab = "X2", main = "Residuals against X2")  
abline(0,0)
```



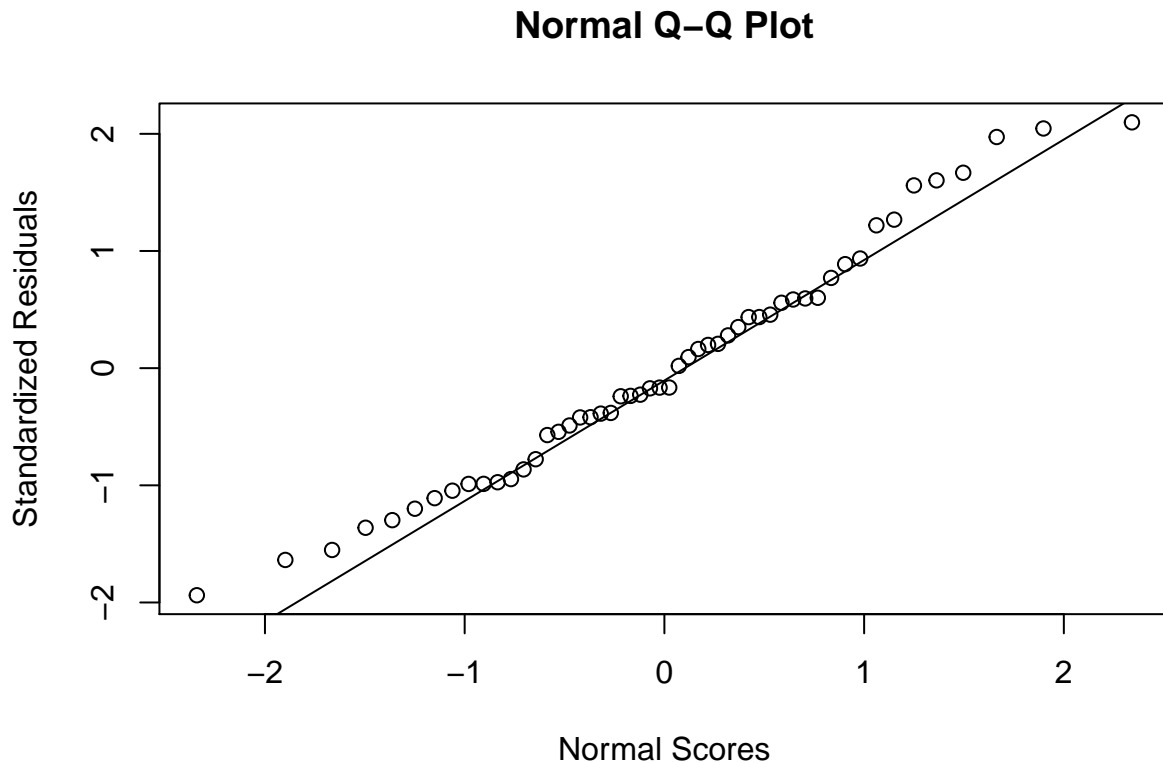
```
#Residuals against X3  
plot(hw7$X3, resid(mod73),  
      ylab = "Residuals", xlab = "X3", main = "Residuals against X3")  
abline(0,0)
```



```
#Residuals against X1*X2
plot(hw7$X1*hw7$X2, resid(mod73),
      ylab = "Residuals", xlab = "X1*X2", main = "Residuals against X1*X2")
abline(0,0)
```

```
#normal prob plot  
qqnorm(rstandard(mod73),  
       ylab="Standardized Residuals",  
       xlab="Normal Scores")  
qqline(rstandard(mod73))
```



From the residual plots, we can see that there are no relationships between the residuals and X_1 , X_2 , and $X_1 \cdot X_2$. There's some pattern between residuals and predicted values of Y , and between residuals and X_3 as well. From the normal probability plot, we can see that the residuals have a relatively normal distribution.

7.4 - b

```
linearHypothesis(mod73,c("X2=0"))
```

```
## Linear hypothesis test
##
## Hypothesis:
## X2 = 0
##
## Model 1: restricted model
## Model 2: Y ~ X1 + X2 + X3
##
##   Res.Df    RSS Df Sum of Sq    F Pr(>F)
## 1      49 992204
## 2      48 985530   1   6674.6 0.3251 0.5712
```

We test the following hypotheses

$$H_0 : \beta_2 = 0$$

$$H_a : \beta_2 \neq 0$$

$$SSR(X_2|X_1, X_3) = 6674.6$$

$$SSE(X_1, X_2, X_3) = 985530$$

$$F^* = \frac{6674.6/(2-1)}{985530/(52-4)} = 0.325 < F(0.95, 1, 48) = 4.04$$

If F^* is smaller than or equal to $F(0.95, 1, 48)$, we fail to reject H_0 , otherwise we reject H_0 .
 In this situation, we fail to reject H_0 and conclude that we can drop X_2 from our regression.
 From the test, we get p-value = 0.5712, which is greater than $\alpha = 0.05$.

Problem 4 (6.16)

#6.16 - a

```
#read data
hw7.4 <- read.csv("/Users/giangvu/Desktop/STAT 2131 - Applied Stat Methods 1/HW/hw7/hw7.4data.csv", sep=
#fit model
mod74 <- lm(Y ~ X1 + X2 + X3, data = hw7.4)
sum74 <- summary(mod74)
sum74
```

```
##
## Call:
## lm(formula = Y ~ X1 + X2 + X3, data = hw7.4)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.3524  -6.4230   0.5196   8.3715  17.1601
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  158.4913    18.1259   8.744 5.26e-11 ***
## X1           -1.1416     0.2148  -5.315 3.81e-06 ***
## X2           -0.4420     0.4920  -0.898  0.3741
## X3          -13.4702     7.0997  -1.897  0.0647 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.06 on 42 degrees of freedom
## Multiple R-squared:  0.6822, Adjusted R-squared:  0.6595
## F-statistic: 30.05 on 3 and 42 DF,  p-value: 1.542e-10
```

```
#hypothesis testing
linearHypothesis(mod74, c("X1=0", "X2=0", "X3=0"))
```

```
## Linear hypothesis test
```



```
##
## Hypothesis:
## X1 = 0
## X2 = 0
## X3 = 0
##
## Model 1: restricted model
## Model 2: Y ~ X1 + X2 + X3
##
##   Res.Df    RSS Df Sum of Sq    F    Pr(>F)
## 1      45 13369.3
## 2      42  4248.8   3    9120.5 30.052 1.542e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We test the following hypotheses

$$H_0 : \beta_1 = \beta_2 = \beta_3 = 0$$

$$H_a : \text{not all } \beta_i = 0$$

$$SSR = 9120.5$$

$$SSE = 4248.8$$

$$F^* = \frac{9120.5/(4-1)}{4248.8/(46-4)} = 30.05 > F(0.9, 3, 42) = 2.23$$

If F^* is smaller than or equal to $F(0.9, 3, 42)$, we fail to reject H_0 , otherwise we reject H_0 .

In this situation, we reject H_0 and conclude that there is a regression relation between Y and the 3 X 's.

From the test, we get p-value = 1.542e-10, which is smaller than $\alpha = 0.1$.

#6.16 - b

The interval estimates of B_1 , B_2 , B_3 using a 90% family confidence coefficient is calculated below

```
confint(mod74, level=1-0.10/(2*3))
```

```
##           0.833 %    99.167 %
## (Intercept) 113.291314 203.6911891
## X1          -1.677249 -0.6059751
## X2          -1.668803  0.7847947
## X3          -31.174356  4.2340294
```

From the result, we could see that only the interval for variable X_1 (patient's age) doesn't contain 0, while X_2 (illness severity) and X_3 (anxiety level) do. Therefore, we could say that X_1 might be the only significant predictor here.

#6.16 - c

$$SSR = 9120.5$$

$$SSTO = 13369.3$$

The coefficient of multiple determination is

$$R^2 = \frac{9120.5}{13369.3} = 0.68$$

This coefficient of multiple determination tells us that about 68% of the variability in patient satisfaction can be explained by patient's age, severity of illness and anxiety level together.

5) a) X has n rows and there are r rows that are identical to the i th row
The i th diagonal entry of H is h_i or h_{ii}

We have $H_{ii} = (H^2)_{ii} = \sum_{j=1}^n H_{ij} H_{ji}$ (because $H^2 = H$)

Because H is also symmetric $\Rightarrow H_{ij} = H_{ji}$

$$\Rightarrow h_i = H_{ii} = \sum_{j=1}^n (H_{ij})^2 \geq \sum_{\text{only identical rows}} (H_{ij})^2$$

But we only have r identical rows

$$\Rightarrow h_i \geq r (H_{ij})^2 = r h_{ij}^2$$

$$\Rightarrow h_{ij} \leq \frac{1}{r}$$

Now define a matrix $A = H - \frac{1}{n} I_n I_n^T$
 A is an orthogonal projection matrix, A is symmetric, idempotent, and positive semidefinite

We have $H_{ii} = A_{ii} + \left(\frac{1}{n} I_n I_n^T\right)_{ii}$
 $(\geq 0) \quad (= \frac{1}{n})$

$$\Rightarrow H_{ii} \geq \frac{1}{n}$$

$$\Rightarrow h_i \geq \frac{1}{n}$$

So we have $\frac{1}{n} \leq h_i \leq \frac{1}{r}$

b) The equalities exist when the number of identical rows in X are exactly n

\Rightarrow All rows of X are identical $\Rightarrow n = r$

$$\Rightarrow \frac{1}{n} = \frac{1}{r} = h_i$$