Homework 6

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3.14

(a)

$$H_0: Y_{i,i} = \beta_0 + \beta_1 X_i + \epsilon_{i,i}$$
 reduced model

$$H_0$$
: $Y_{i,i} = \mu_{i,i} + \epsilon_{i,i}$, full model

$$SSR(R) = \sum_{i=1}^{4} \sum_{i} (\beta_0 + \beta_1 X_j - Y_{ij})^2$$

$$SSR(F) = \sum_{j=1}^{4} \sum_{i} (Y_{ij} - \overline{Y}_{j})^{2}$$

$$F^* = \frac{SSE(R) - SSE(F)}{df_r - df_F} \div \frac{SSE(F)}{df_F}$$

$$= \frac{SSE - SSPE}{c - 2} \div \frac{SSPE}{n - c}$$

$$=\frac{146.425-128.75}{4-2}\div\frac{128.75}{16-4}$$

$$= 0.8237$$

Since $F^* \le F(0.99, 3,11) = 6.9266$, so the conclusion is H_0 .

```
miu <- tapply(data$v1, data$v2, mean)
se <- 0
for (i in as.numeric(names(miu))){
    se <- se + sum((data[data$v2 == i, 1] - miu[which(names(miu) == i)])^2)
}
df <- nrow(data1) - length(miu)
yfit <- lm(v1 ~ v2, data = data)$fitted.values
sse <- sum((data1[, 1] - yfit) ^ 2)
sslf <- sse - se
Fstat <- (sslf/(length(miu)-2))/(se/df)</pre>
```

F-stat 0.82369

6.926608

(b)

There is no substantial advantage or disadvantage.

(c)

The test indicate that the linear regression line is invalid and transformation to data may generate better results.

(a)

[1] 0.5704773

```
y.mean <- mean(data$Y)
 SST \leftarrow sum((Y-y.mean)^2)
 L <- lm(Y \sim X1 + X2 + X3 + X4)
 SSE <- sum((L$residuals)^2)
 SSR <- SST-SSE
 SSR4 <- SST-sum(((lm(Y~X4)$residuals))^2)</pre>
 SSE4 <- sum(((lm(Y~X4))$residuals)^2)
 SSE14 <- sum(((lm(Y\sim X1+X4))\$residuals)^2)
 SSR1_4 <- SSE4-SSE14
  \begin{array}{lll} SSE14 & <- \ sum(((lm(Y\sim X1+X4))\ residuals)^2) \\ SSE142 & <- \ sum(((lm(Y\sim X1+X4+X2))\ residuals)^2) \\ \end{array} 
 SSR2_14 <- SSE14-SSE142
 SSR3_142 <- SSE142-SSE1423
 SS <- c(SSR,SSR4,SSR1_4,SSR2_14,SSR3_142,SSE,SST)
 df < c(4,1,1,1,1,76,80)
 MS <- SS/df
 df <- data.frame(SS=SS,df=df,MS=MS)
rownames(df) <- c("Regression","X4","X1|X4","X2|X1,X4","X3|X1,X2,X4","Error","Total")
                            SS df
 ##
 ## Regression 138.3269061 4 34.5817265
 ## X4
            67.7750980 1 67.7750980
42.2745683 1 42.2745683
 ## X1|X4
 ## X2|X1,X4 27.8574935 1 27.8574935 ## X3|X1,X2,X4 0.4197463 1 0.4197463 ## Error 98.2305939 76 1.2925078 ## Total 236.5578000 20
(b)
H_0: \beta_3 = 0
H_A: \beta_3 \neq 0
F^* = \frac{SSE(R) - SSE(F)}{df_r - df_F} \div \frac{SSE(F)}{df_F}
=\frac{SSR(X_3|X_1,X_2,X_4)}{(n-4)-(n-5)}\div\frac{SSE(X_1,X_2,X_3,X_4)}{n-5}
=\frac{0.4197}{1} \div \frac{98.2306}{76}
= 0.3247
Since F^* \le F(0.99, 1.76) = 6.9806, so the conclusion is H_0.
  > p_value <- 1 - pf(0.3247,1,76)
  > p_value
```

```
sser <- sum((data$v1 + 0.1*data$v2 - 0.4*data$v3 - lm(v1+0.1*v2-0.4*v3 ~ v4 + v5, data = data)$fitted.values)^2)  
Fstat <- ((sser - sse)/2)/(sse/76)  
cat(Fstat)  
cat(qf(0.99, 2, 76))  
F^* = 4.6076 \le F(0.99; 2, 76) = 4.8958 
H_0: \beta_1 = -0.1 \text{ and } \beta_2 = 0.4 
H_A: \beta_1 \ne -0.1 \text{ or } \beta_2 \ne 0.4
```

Based on the calculation result, we can conclude H_0

7.16

(a)

```
data16 <- read.table("http://users.stat.ufl.edu/~rrandles/sta4210/Rclassnote
n <- nrow(data16)
y <- (data16$V1 - mean(data16$V1))/sd(data16$V1)/(n-1)^.5
coef(lm(y \sim x1 + x2))
beta1s < coef(lm(y \sim x1 + x2))[2]
beta1s
beta1 <- beta1s*sd(data16$v1)/sd(data16$v2)</pre>
beta1
coef(lm(v1\sim v2+v3, data = data16))[2]
> coef(1m(y
                    x1
 (Intercept)
                      x1
-1.238444e-17 8.923929e-01 3.945807e-01
> beta1s <-
              coef(lm(y \sim x1 + x2))[2]
> beta1s
0.8923929
> beta1 <- beta1s*sd(data16$v1)/sd(data16$v2)</pre>
> beta1
4.425
> coef(lm(v1\sim v2+v3, data = data16))[2]
4.425
                    Y^* = -1.238 \times 10^{-17} + 0.892X_1^* + 0.395X_2^*
```

(b)

When X_1^* increase 1-unit, Y^* will increase 0.892 if X_2^* is constant.

(c)

Yes, they are the same.

7.24

The fitted line is:

```
Y = 50.775 + 4.425X_1
```

The coefficient of first order regression function with Y is the same as the coefficient obtained before. So, they are the same.

```
Yes, SSR(X_1) = SSR(X_1|X_2)
```

It shows that X_1 and X_2 are independent.

7.37

(a)

```
data737 <- read.table("http://users.stat.ufl.edu/~rrandles/sta4210/Rclassnotes/</pre>
lm1 <- lm(v8~v5+v16, data=data737)</pre>
lm2 <- lm(v8~v5+v16+v4, data=data737)
lm5 <- lm(v8~v5+v16+v10, data=data737)
sse1 <- sum((data737$v8 - lm1$fitted.values)^2)
sse2 <- sum((data737$V8 - lm2$fitted.values)^2)
sse3 <- sum((data737$v8 - lm3$fitted.values)^2)
sse4 <- sum((data737$v8 - lm4$fitted.values)^2)
sse5 <- sum((data737$v8 - lm5$fitted.values)^2)
Rsquare12 <- (sse1 - sse2)/sse1; Rsquare12
Rsquare13 <- (sse1 - sse3)/sse1; Rsquare13</pre>
Rsquare14 <- (sse1 - sse4)/sse1; Rsquare14
Rsquare15 <- (sse1 - sse5)/sse1; Rsquare15
> Rsquare12 <- (sse1 - sse2)/sse1;</pre>
                                                 Rsquare12
[1] 0.02882495
> Rsquare13 <- (sse1 - sse3)/sse1;</pre>
                                                 Rsquare13
[1] 0.003842367
                   <- (sse1 - sse4)/sse1;
> Rsquare14
                                                 Rsquare14
[1] 0.5538182
                   <- (sse1 - sse5)/sse1; Rsquare15
> Rsquare15
[1] 0.007323408
```

(b)

Number of hospital beds is the best one, It has the largest coefficients of partial determination.

(c)

```
Fstat <- (sse1 - sse4)/(sse4/(nrow(data737)-4)); Fstat
qf(0.99,1,436)
(sse1-sse2)/(sse2/(nrow(data737)-4))
(sse1-sse3)/(sse3/(nrow(data737)-4))
(sse1-sse4)/(sse4/(nrow(data737)-4))
(sse1-sse5)/(sse5/(nrow(data737)-4))
 > Fstat <- (sse1 - sse4)/(sse4/(nrow(data737)-4));</pre>
                                                                         Fstat
 [1] 541.1801
 > qf(0.99,1,436)
 [1] 6.693358
 > (sse1-sse2)/(sse2/(nrow(data737)-4))
 [1] 12.94069
 > (sse1-sse3)/(sse3/(nrow(data737)-4))
 [1] 1.681734
 > (sse1-sse4)/(sse4/(nrow(data737)-4))
 [1] 541.1801
 > (sse1-sse5)/(sse5/(nrow(data737)-4))
 [1] 3.216562
F^* = 541.1801 \le F(0.99; 1,437) = 6.693358
```

So, we conclude H_A , X_5 is helpful to the model.

No, F-statistics for other three variables are not as large as it for number of hospita beds since their coefficients of partial determination are smaller.