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HW7 Stat 4315
7.1
(1) df = 1
(2) df=1
(3) df = 2
(4) df = 3
7.3
Using R, we can obtain the following code and result:
data<-read.table("http://www.stat.ufl.edu/~rrandles/sta4210/Rclassnotes/data/te
names(data)<-c("Y","X1","X2")
attach(data)
fit1<-lm(Y~X1)
fit2<-lm(Y~X2)
fit3<-lm(Y~X1+X2)
anova(fit1)
anova(fit2)
anova(fit3)
 > anova(fit3)
 Analysis of Variance Table
 Response: Y
            Df Sum Sq Mean Sq F value Pr(>F)
 X1
             1 1566.45 1566.45 215.947 1.778e-09 ***
            1 306.25 306.25 42.219 2.011e-05 ***
 Residuals 13 94.30
                            7.25
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
SSR (X_1, X_2) = 1566.45 + 306.25 = 1872.7
SSR(X1) = 1566.45 SSR(X_2 | X_1) = 306.25
b.
\text{H0: } \beta_2 = 0
Ha: \beta_2 \neq 0
F^* = \frac{SSR(X_2|X_1)/(3-2)}{SSE(X_1,X_2)/(16-3)} = \frac{306.25/1}{94.30/13} = 42.22
F^* = 42.219 F_{1.13}^{-1}(0.99) = 9.073806
Since F^* > F_{1,13}^{-1}(0.99), we can conclude H_{\alpha}: \beta_2 \neq 0.
```

The p-value is 2.011×10^{-5} , close to 0

```
7.7
> data=read.table("618.txt")
> attach(data)
> X1=data[,2]
 > X2=data[,3]
 > X3=data[,4]
 > X4=data[,5]
 > Y=data[,1]
 > fitA=lm(Y~X4+X1+X2+X3)
 > anova(fitA)
 Analysis of Variance Table
 Response: Y
             Df Sum Sq Mean Sq F value Pr(>F)
 X4
             1 67.775 67.775 52.4369 3.073e-10 ***
              1 42.275 42.275 32.7074 2.004e-07 ***
 Х1
              1 27.857 27.857 21.5531 1.412e-05 ***
 X2
             1 0.420 0.420 0.3248
 Residuals 76 98.231
                         1.293
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1
SSR(X_4) = 67.775, SSR(X_1|X_4) = 168.782-126.508 = 42.274,
SSR(X_2|X_1,X_4) = 126.508-98.650 = 27.858,
SSR(X_3|X_1, X_2, X_4) = 98.650-98.231 = 0.419
b.
> fitB=lm(Y~X4+X1+X2)
> anova(fitB, fitA)
Analysis of Variance Table
Model 1: Y \sim X4 + X1 + X2
Model 2: Y \sim X4 + X1 + X2 + X3
  Res.Df RSS Df Sum of Sq F Pr(>F)
1 77 98.650
       76 98.231 1 0.41975 0.3248 0.5704
> qf(0.99,1,76)
[1] 6.980578
                      Ha: \beta_3 \neq 0
H0: \beta_3 = 0
F^* = \frac{SSR(X_3 \mid X_1, X_2, X_4) / 1}{SSE(X_1, X_2, X_3, X_4) / 13} = \frac{0.419 / 1}{98.231 / 76} = 0.324
F_{1.76}^{-1}(0.99) = 6.980578
Since F^* < F_{1.76}^{-1}(0.99), we can conclude H_0: \beta_3 = 0.
The P-value is 0.570
```

7.10 > anova(fit1) Analysis of Variance Table Response: Y + 0.1 * X1 - 0.4 * X2 Df Sum Sq Mean Sq F value 9.205 9.205 6.5187 0.01263 * 1 31.872 31.872 22.5713 9.058e-06 *** X4 Residuals 78 110.141 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 > anova(fit2) Analysis of Variance Table Response: Y Df Sum Sq Mean Sq F value Pr(>F) 1 14.819 14.819 11.4649 0.001125 ** X1 1 72.802 72.802 56.3262 9.699e-11 *** X2 1 8.381 8.381 6.4846 0.012904 * 1 42.325 42.325 32.7464 1.976e-07 *** Residuals 76 98.231 1.293 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 H_0 : β_1 =-0.1, β_2 =0.4; H_a : $\beta_1\neq$ -0.1 or $\beta_2\neq$ 0.4

Full model:
$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

Reduced model:
$$Y = \beta_0 - 0.1X_1 + 0.4X_2 + \beta_3 X_3 + \beta_4 X_4$$

$$F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \div \frac{SSE(F)}{df_F} = \frac{110.141 - 98.231}{2} \div \frac{98.231}{76} = 4.6073$$

Since $F^* < F_{2.76}^{-1}(0.99) = 4.89584$, we can conclude $H_0: \beta_1 = -0.1, \beta_2 = 0.4$.

According to executions in R, we can get the following results

```
> cor(X1,Y)^2
 [1] 0.796365
 > cor(X2,Y)^2
 [1] 0.155694
 > cor(X1,X2)^2
 [1] 0
> summary(fit1)
Call:
lm(formula = Y \sim X1)
Residuals:
  Min 1Q Median 3Q Max
-7.475 -4.688 -0.100 4.638 7.525
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 5.349 on 14 degrees of freedom
Multiple R-squared: 0.7964, Adjusted R-squared: 0.7818
F-statistic: 54.75 on 1 and 14 DF, p-value: 3.356e-06
> summary(fit2)
 Call:
 lm(formula = Y \sim X2)
 Residuals:
                              3Q
               1Q Median
     Min
                                       Max
  -16.375 -7.312 -0.125 8.688 16.625
 Coefficients:
             Estimate Std. Error t value Pr(>|t|)
 (Intercept) 68.625 8.610 7.970 1.43e-06 ***
X2 4.375 2.723 1.607 0.13
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
 Residual standard error: 10.89 on 14 degrees of freedom
 Multiple R-squared: 0.1557, Adjusted R-squared: 0.09539
 F-statistic: 2.582 on 1 and 14 DF, p-value: 0.1304
> summary(fit3)
 Call:
 lm(formula = Y \sim X1 + X2)
 Residuals:
           1Q Median
                       3Q
  -4.400 -1.762 0.025 1.587 4.200
 Coefficients:
            Estimate Std. Error t value Pr(>|t|)
 (Intercept) 37.6500 2.9961 12.566 1.20e-08 ***
X1 4.4250 0.3011 14.695 1.78e-09 ***
X2 4.3750 0.6733 6.498 2.01e-05 ***
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 2.693 on 13 degrees of freedom
Multiple R-squared: 0.9521, Adjusted R-squared: 0.9447
F-statistic: 129.1 on 2 and 13 DF, p-value: 2.658e-09
```

```
> anova(fit1)
Analysis of Variance Table
Response: Y
          Df Sum Sq Mean Sq F value
                                        Pr(>F)
          1 1566.45 1566.45 54.751 3.356e-06 ***
Residuals 14 400.55
                       28.61
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> anova(fit2)
Analysis of Variance Table
Response: Y
          Df Sum Sq Mean Sq F value Pr(>F)
          1 306.25 306.25 2.5817 0.1304
X2
Residuals 14 1660.75 118.62
> anova(fit3)
Analysis of Variance Table
Response: Y
          Df Sum Sq Mean Sq F value
X1
          1 1566.45 1566.45 215.947 1.778e-09 ***
X2
           1 306.25 306.25 42.219 2.011e-05 ***
Residuals 13 94.30
                        7.25
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
R_{\rm Y1}^2 = 0.7964
```

Interpretation: It means the proportion of variance of Y explained by X1, when X1 is the only covariate in the linear regression model. It also equals to the square of cor(X1,Y). X2 explains a high variation of Y.

$$R_{y_2}^2 = 0.1557$$

Interpretation: It means the proportion of variance of Y explained by X2, when X1 is the only covariate in the linear regression model. It also equals to the square of cor(X2,Y). Compared to X1, X2 explains a significant less variation of Y.

$$R_{12}^2 = 0$$

Interpretation: It equals to the square of cor(X2,Y) = 0, which indicates that X1 and X2 are not correlated with each other.

$$R_{Y||2}^2 = \frac{SSR(X_1 \mid X_2)}{SSE(X_2)} = 0.9432$$

Interpretation: It measures the proportion reduction in the variation in Y remaining after X2 is included in the model that is gained by also including X1 in the model. When X1 is added into the regression model containing X2, thee rror sum of squares SSE(X2) is reduced by 94.32%.

$$R_{Y2|1}^2 = \frac{SSR(X_2 \mid X_1)}{SSE(X_1)} = 0.7645$$

Interpretation: It measures the proportion reduction in the variation in Y remaining after X1 is included in the model that is gained by also including X2 in the model. When X2 is added into the regression model containing X1, the error sum of squares SSE(X2) is reduced by 94.32%.

$$R^2 = 0.9521$$

Interpretation: It measures the proportion reduction in the variation in Y remaining when X1 and X2 are included in the model. X1 and X2 explain 95.21% of the variation of Y.

```
7.24
a.
> summary(fit1)
Call:
lm(formula = Y \sim X1)
Residuals:
  Min 10 Median
                    30
                           Max
-7.475 -4.688 -0.100 4.638 7.525
Coefficients:
          Estimate Std. Error t value Pr(>|t|)
(Intercept) 50.775 4.395 11.554 1.52e-08 ***
                      0.598 7.399 3.36e-06 ***
             4.425
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 5.349 on 14 degrees of freedom
Multiple R-squared: 0.7964, Adjusted R-squared: 0.7818
F-statistic: 54.75 on 1 and 14 DF, p-value: 3.356e-06
Therefore, the fitted regression function is Y = 4.425X_1 + 50.775.
```

b.

```
> summary(fit2)
 Call:
 lm(formula = Y \sim X2)
 Residuals:
   Min 1Q Median 3Q
                                  Max
 -16.375 -7.312 -0.125 8.688 16.625
 Coefficients:
           Estimate Std. Error t value Pr(>|t|)
 (Intercept) 68.625
                       8.610 7.970 1.43e-06 ***
              4.375
                         2.723 1.607
                                          0.13
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
 Residual standard error: 10.89 on 14 degrees of freedom
 Multiple R-squared: 0.1557, Adjusted R-squared:
 F-statistic: 2.582 on 1 and 14 DF, p-value: 0.1304
```

When relating Y to X_1 and X_2 , the regression function is $Y = 37.65 + 4.425X_1 + 4.375X_2$. The coefficient of X_1 here is equivalent to that in part (a). And it indicates that X_1 and X_2 is uncorrelated.

```
> fit4<-lm(Y~X2+X1)
> anova(fit4)
Analysis of Variance Table
Response: Y
          Df Sum Sq Mean Sq F value Pr(>F)
          1 306.25 306.25 42.219 2.011e-05 ***
X2
         1 1566.45 1566.45 215.947 1.778e-09 ***
Residuals 13 94.30 7.25
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Yes, it is equal. SSR(X_1 | X_2) = SSR(X_1) = 1566.45.
d.
> data<-read.table("6.txt")</pre>
> attach(data)
> cor(data)
                     V2
           V1
V1 1.0000000 0.8923929 0.3945807
V2 0.8923929 1.0000000 0.0000000
V3 0.3945807 0.0000000 1.0000000
```

According to the output of R, X_1 and X_2 are uncorrelated.

Proof:

$$r_{Y1}^2 = 1 - \frac{SSE(X_1)}{SSTO} \implies SSE(X_1) = (1 - r_{Y1}^2)SSTO$$
 (1)

$$SSR(X_1) = r_{Y_1}^2 SSTO$$
 (2)

Since
$$SSR(X_1, X_2) = b_1 \sum (X_{i1} - \bar{X}_1)(Y_i - \bar{Y}) + b_2 \sum (X_{i2} - \bar{X}_2)(Y_i - \bar{Y})$$

While
$$b_1 = \frac{\sum (X_{i1} - \bar{X}_1)(Y_i - \bar{Y})}{\sum (X_{i1} - \bar{X}_1)^2} - \left[\frac{\sum (Y_i - \bar{Y})^2}{\sum (X_{i1} - \bar{X}_1)^2}\right]^{1/2} r_{Y2} r_{12}}{1 - r_{12}^2}$$
,

$$b_{2} = \frac{\sum (X_{i2} - \bar{X}_{2})(Y_{i} - \bar{Y})}{\sum (X_{i2} - \bar{X}_{2})^{2}} - \left[\frac{\sum (Y_{i} - \bar{Y})^{2}}{\sum (X_{i2} - \bar{X}_{2})^{2}}\right]^{1/2} r_{Y1} r_{12}}{1 - r_{12}^{2}}$$

Substituting b_1 , b_2 into the above expression of $SSR(X_1, X_2)$ yields

$$SSR(X_1, X_2) = \frac{1}{1 - r_{12}^2} \left[\sum (Y_i - \overline{Y})^2 r_{Y1}^2 + \sum (Y_i - \overline{Y})^2 r_{Y2}^2 - 2 \sum (Y_i - \overline{Y})^2 r_{Y1} r_{Y2} r_{12} \right]$$
(3)

Since
$$r_{Y2|1}^2 = \frac{SSR(X_2 | X_1)}{SSE(X_1)} = \frac{SSR(X_1, X_2) - SSR(X_1)}{SSE(X_1)}$$
 (4)

Substituting (1), (2), (3) into (4) and simplifying yields:

$$r_{Y2|1}^2 = \frac{\left(r_{Y2} - r_{12}r_{Y1}\right)^2}{\left(1 - r_{Y1}^2\right)\left(1 - r_{12}^2\right)}$$