**Question 1**

**a.)**

> model1 <- lm(LOSS ~ CLMINSUR1 + SEATBELT1 + ATTORNEY1 + CLMSEX1 + factor(MARITAL) + CLMAGE)

> summary(model1)

Call:

lm(formula = LOSS ~ CLMINSUR1 + SEATBELT1 + ATTORNEY1 + CLMSEX1 +

factor(MARITAL) + CLMAGE)

Residuals:

Min 1Q Median 3Q Max

-19.903 -4.518 -1.846 0.466 264.106

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 15.78429 3.88372 4.064 5.17e-05 \*\*\*

CLMINSUR1TRUE -2.00846 1.62472 -1.236 0.217

SEATBELT1TRUE -14.59133 3.55391 -4.106 4.33e-05 \*\*\*

ATTORNEY1TRUE 6.39352 0.96216 6.645 4.80e-11 \*\*\*

CLMSEX1TRUE 0.38066 0.96940 0.393 0.695

factor(MARITAL)2 -1.66404 1.14918 -1.448 0.148

factor(MARITAL)3 -2.81182 4.72568 -0.595 0.552

factor(MARITAL)4 0.69435 3.00151 0.231 0.817

CLMAGE 0.04156 0.03410 1.219 0.223

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 15.7 on 1082 degrees of freedom

(249 observations deleted due to missingness)

Multiple R-squared: 0.06457, Adjusted R-squared: 0.05765

F-statistic: 9.336 on 8 and 1082 DF, p-value: 1.619e-12

CLMINSUR has a p-value of 0.217 which is greater than alpha=0.05. Therefore, CLMINSUR is not a significant variable.

SEATBELT has a p-value of 4.33e-05 which is less than alpha=0.05. Therefore, SEATBELT is a significant variable.

**b.)**

s = 15.7 (It seems high but hard to tell since there is no other model to compare with)

R2 = 0.06457 (very low which is bad)

Adjusted R2 = 0.05765 (very low which is bad)

p-value = 1.619e-12 (low which is good)

Since s is high, R2 is bad, and adjusted R2 is bad, the goodness of fit of the model is not good.

**c.)**

The coefficient of CLMSEX is 0.38066.

When the person is male, the LOSS claim increases by 0.38066\*1,000 dollars ($380.66) as compared to females, holding all other explanatory variables constant.

**d.)**

The coefficient when MARITAL=3 is -2.81182.

When the person is a widow, the LOSS claim decreases by 2.81182\*1,000 dollars ($2,811.82) as compared to a married person, holding all other explanatory variables constant.

**e.)**

> model2 <- lm(LOSS ~ CLMINSUR1 + SEATBELT1 + ATTORNEY1 + CLMSEX1 + factor(MARITAL) + CLMAGE + CLMSEX1\*CLMAGE)

> summary(model2)

Call:

lm(formula = LOSS ~ CLMINSUR1 + SEATBELT1 + ATTORNEY1 + CLMSEX1 +

factor(MARITAL) + CLMAGE + CLMSEX1 \* CLMAGE)

Residuals:

Min 1Q Median 3Q Max

-20.270 -4.550 -1.799 0.569 263.778

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 15.09286 3.96662 3.805 0.00015 \*\*\*

CLMINSUR1TRUE -2.02749 1.62507 -1.248 0.21244

SEATBELT1TRUE -14.67013 3.55552 -4.126 3.97e-05 \*\*\*

ATTORNEY1TRUE 6.39779 0.96229 6.649 4.69e-11 \*\*\*

CLMSEX1TRUE 1.95728 2.07474 0.943 0.34569

factor(MARITAL)2 -1.63862 1.14970 -1.425 0.15437

factor(MARITAL)3 -3.56132 4.80602 -0.741 0.45885

factor(MARITAL)4 0.60335 3.00373 0.201 0.84084

CLMAGE 0.06533 0.04390 1.488 0.13703

CLMSEX1TRUE:CLMAGE -0.04868 0.05664 -0.860 0.39024

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 15.7 on 1081 degrees of freedom

(249 observations deleted due to missingness)

Multiple R-squared: 0.06521, Adjusted R-squared: 0.05742

F-statistic: 8.378 on 9 and 1081 DF, p-value: 3.701e-12

Hypothesis Test

H0 : βCLMSEX1\*CLMAGE = 0

Ha : βCLMSEX1\*CLMAGE ≠ 0

t-statistic = -0.860

t-critical = > qt(0.975, 1081) = [1] 1.962161

Since l t-statistic l is less than t-critical, we accept H0 and reject Ha.

p-value = 0.39024

Since CLMSEX\*1\*CLMAGE has p-value of 0.39024 which is greater than alpha=0.05, we accept H0 and reject Ha.

This also shows that the interaction term is not a significant variable in predicting LOSS.

**f.)**

> NewData <- data.frame(ATTORNEY1=TRUE, CLMSEX1=TRUE, MARITAL=2, CLMINSUR1=FALSE, SEATBELT1=FALSE, CLMAGE=35)

> predict(model2, NewData, interval="confidence", level=0.95)

fit lwr upr

1 22.39197 15.32221 29.46173

LOSS prediction = 22.39197\*$1,000 = $22,391.97

**g.)**

> predict(model2, NewData, interval="confidence", level=0.95)

fit lwr upr

1 22.39197 15.32221 29.46173

95% CI = (15.32221, 29.46173)

Given someone who does have an attorney, is male, single, their vehicle was insured, they were not wearing a seatbelt and they are 35, they will have predicted losses ranging from $15,322.21 to $29,461.73.

**Question 2**

**a.)**

> model1 <- lm(Test3 ~ Gender + GPA + GradSchl + ClassRow + siblings + countries + jobs + tattoos + pets + HW3)

> summary(model1)

Call:

lm(formula = Test3 ~ Gender + GPA + GradSchl + ClassRow + siblings +

countries + jobs + tattoos + pets + HW3)

Residuals:

Min 1Q Median 3Q Max

-52.378 -3.718 -0.539 5.518 20.361

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 27.56042 12.27242 2.246 0.0283 \*

GenderMale -3.47887 2.79421 -1.245 0.2178

GPA 8.85384 3.43812 2.575 0.0124 \*

GradSchlyes 2.13222 2.75278 0.775 0.4415

ClassRow 0.54910 1.03831 0.529 0.5988

siblings -0.12145 1.28396 -0.095 0.9249

countries 0.08731 0.25797 0.338 0.7362

jobs 2.77797 1.65169 1.682 0.0976 .

tattoos -2.34708 2.02892 -1.157 0.2518

pets 0.09825 1.04416 0.094 0.9253

HW3 0.64052 0.11199 5.719 3.3e-07 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.68 on 62 degrees of freedom

Multiple R-squared: 0.5373, Adjusted R-squared: 0.4627

F-statistic: 7.2 on 10 and 62 DF, p-value: 2.05e-07

> step(model1)

Start: AIC=355.84

Test3 ~ Gender + GPA + GradSchl + ClassRow + siblings + countries +

jobs + tattoos + pets + HW3

Df Sum of Sq RSS AIC

- pets 1 1.0 7071.1 353.85

- siblings 1 1.0 7071.1 353.85

- countries 1 13.1 7083.2 353.98

- ClassRow 1 31.9 7102.0 354.17

- GradSchl 1 68.4 7138.5 354.54

- tattoos 1 152.6 7222.7 355.40

- Gender 1 176.8 7246.9 355.64

<none> 7070.1 355.84

- jobs 1 322.6 7392.7 357.10

- GPA 1 756.2 7826.3 361.26

- HW3 1 3730.1 10800.2 384.77

Step: AIC=353.85

Test3 ~ Gender + GPA + GradSchl + ClassRow + siblings + countries +

jobs + tattoos + HW3

Df Sum of Sq RSS AIC

- siblings 1 0.7 7071.8 351.86

- countries 1 12.7 7083.8 351.98

- ClassRow 1 31.1 7102.2 352.17

- GradSchl 1 67.9 7139.0 352.55

- tattoos 1 169.6 7240.7 353.58

- Gender 1 175.8 7246.9 353.64

<none> 7071.1 353.85

- jobs 1 321.9 7393.0 355.10

- GPA 1 757.5 7828.6 359.28

- HW3 1 3730.0 10801.1 382.78

Step: AIC=351.86

Test3 ~ Gender + GPA + GradSchl + ClassRow + countries + jobs +

tattoos + HW3

Df Sum of Sq RSS AIC

- countries 1 12.2 7084.0 349.98

- ClassRow 1 32.1 7103.9 350.19

- GradSchl 1 67.9 7139.7 350.56

- tattoos 1 168.9 7240.7 351.58

- Gender 1 176.6 7248.4 351.66

<none> 7071.8 351.86

- jobs 1 346.0 7417.8 353.35

- GPA 1 758.6 7830.4 357.30

- HW3 1 3733.6 10805.4 380.81

Step: AIC=349.98

Test3 ~ Gender + GPA + GradSchl + ClassRow + jobs + tattoos +

HW3

Df Sum of Sq RSS AIC

- ClassRow 1 27.3 7111.3 348.27

- GradSchl 1 60.2 7144.2 348.60

- tattoos 1 159.8 7243.9 349.61

- Gender 1 164.6 7248.6 349.66

<none> 7084.0 349.98

- jobs 1 334.3 7418.3 351.35

- GPA 1 766.4 7850.4 355.48

- HW3 1 3778.3 10862.3 379.19

Step: AIC=348.27

Test3 ~ Gender + GPA + GradSchl + jobs + tattoos + HW3

Df Sum of Sq RSS AIC

- GradSchl 1 71.0 7182.3 346.99

- Gender 1 147.5 7258.8 347.76

- tattoos 1 170.0 7281.3 347.99

<none> 7111.3 348.27

- jobs 1 318.6 7429.9 349.47

- GPA 1 800.3 7911.6 354.05

- HW3 1 3765.0 10876.3 377.28

Step: AIC=346.99

Test3 ~ Gender + GPA + jobs + tattoos + HW3

Df Sum of Sq RSS AIC

- Gender 1 147.0 7329.4 346.47

- tattoos 1 191.5 7373.9 346.91

<none> 7182.3 346.99

- jobs 1 363.6 7546.0 348.60

- GPA 1 894.8 8077.1 353.56

- HW3 1 3965.7 11148.0 377.08

Step: AIC=346.47

Test3 ~ GPA + jobs + tattoos + HW3

Df Sum of Sq RSS AIC

- tattoos 1 165.0 7494.4 346.10

<none> 7329.4 346.47

- jobs 1 364.4 7693.8 348.01

- GPA 1 1068.3 8397.6 354.40

- HW3 1 4253.8 11583.2 377.88

Step: AIC=346.1

Test3 ~ GPA + jobs + HW3

Df Sum of Sq RSS AIC

<none> 7494.4 346.10

- jobs 1 384.6 7879.0 347.75

- GPA 1 1054.1 8548.5 353.70

- HW3 1 4400.5 11894.9 377.82

Call:

lm(formula = Test3 ~ GPA + jobs + HW3)

Coefficients:

(Intercept) GPA jobs HW3

22.4196 10.0621 2.7695 0.6722

> modelB <- lm(Test3 ~ GPA + jobs + HW3)

> summary(modelB)

Call:

lm(formula = Test3 ~ GPA + jobs + HW3)

Residuals:

Min 1Q Median 3Q Max

-52.357 -4.106 -0.814 4.985 21.834

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 22.4196 10.4328 2.149 0.03515 \*

GPA 10.0621 3.2299 3.115 0.00268 \*\*

jobs 2.7695 1.4718 1.882 0.06409 .

HW3 0.6722 0.1056 6.365 1.84e-08 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.42 on 69 degrees of freedom

Multiple R-squared: 0.5095, Adjusted R-squared: 0.4882

F-statistic: 23.89 on 3 and 69 DF, p-value: 1.026e-10

Stepwise model only choose GPA, jobs and HW3 variables.

S in the stepwise model is better since it is lower than s in model 1.

R2 in model 1 is better since it is greater than R2 in the stepwise model.

Adjusted R2 in stepwise model is better since it is greater than adjusted R2 in model 1.

AIC in stepwise model is better since it is lower than AIC in model 1.

**b.)**

> modelB2 <- lm(Test3 ~ GPA + jobs + HW3 + GPA2 + jobs2 + HW32)

> summary(modelB2)

Call:

lm(formula = Test3 ~ GPA + jobs + HW3 + GPA2 + jobs2 + HW32)

Residuals:

Min 1Q Median 3Q Max

-33.263 -6.295 -0.503 6.247 25.428

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) -66.41896 54.92054 -1.209 0.230837

GPA 56.19789 34.36654 1.635 0.106757

jobs -3.40416 3.94668 -0.863 0.391515

HW3 2.16773 0.37726 5.746 2.53e-07 \*\*\*

GPA2 -6.96113 5.28367 -1.317 0.192233

jobs2 2.09880 1.14720 1.829 0.071842 .

HW32 -0.02542 0.00635 -4.003 0.000161 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.325 on 66 degrees of freedom

Multiple R-squared: 0.6244, Adjusted R-squared: 0.5903

F-statistic: 18.29 on 6 and 66 DF, p-value: 2.218e-12

> anova(modelB)

Analysis of Variance Table

Response: Test3

Df Sum Sq Mean Sq F value Pr(>F)

GPA 1 3384.4 3384.4 31.1593 4.348e-07 \*\*\*

jobs 1 1.1 1.1 0.0097 0.9218

HW3 1 4400.5 4400.5 40.5143 1.843e-08 \*\*\*

Residuals 69 7494.4 108.6

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(modelB2)

Analysis of Variance Table

Response: Test3

Df Sum Sq Mean Sq F value Pr(>F)

GPA 1 3384.4 3384.4 38.9215 3.565e-08 \*\*\*

jobs 1 1.1 1.1 0.0121 0.9126104

HW3 1 4400.5 4400.5 50.6070 1.016e-09 \*\*\*

GPA2 1 302.1 302.1 3.4742 0.0667819 .

jobs2 1 59.9 59.9 0.6885 0.4096614

HW32 1 1393.5 1393.5 16.0261 0.0001608 \*\*\*

Residuals 66 5738.9 87.0

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

H0 : βGPA2 = βjobs2 = βHW32 = 0

Ha : Betas ≠ 0

F-ratio = ((Error SS) reduced – (Error SS) full ) / p(sfull)2

= (7494.4 – 5738.9) / (3\*9.3252)

= 6.7295

F-critical = > qf(.95, 3, 66) = [1] 2.743711

Since F-ratio is greater than F-critical, reject H0 and accept Ha. Therefore, the three squared terms are jointly statistically significant predictor of Test3.

**c.)**

From modelB,

> NewData <- data.frame(Gender='Female', GPA=3.23, GradSchl='no', ClassRow=2, siblings=1, countries=2, jobs=2, tattoos=0, pets=3, HW3=85)

> predict(modelB, NewData, interval="prediction", level=0.95)

fit lwr upr

1 117.5976 93.91676 141.2784

95% PI = (93.91676, 141.2784)

From modelB2

> NewData1 <- data.frame(Gender='Female', GPA=3.23, GPA2=3.23^2, GradSchl='no', ClassRow=2, siblings=1, countries=2, jobs=2, jobs2= 2^2, tattoos=0, pets=3, HW3=85, HW32=85^2)

> predict(modelB2, NewData1, interval="prediction", level=0.95)

fit lwr upr

1 44.65612 1.348856 87.96338

95% PI = (1.348856, 87.96338)

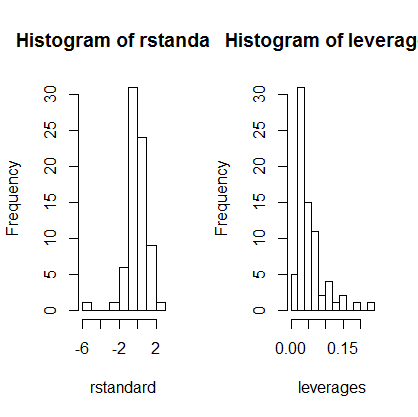
Since modelB2 has lower s, higher R2 and higher adjusted R2 than modelB, it has a better goodness of fit. Therefore, 95% prediction interval is (1.348856, 87.96338).

**d.)**

> par(mfrow=c(1,2))

> hist(rstandard)

> hist(leverages)



Since most of the points is within (-2, 2) in rstandard histogram, we can consider points outside the range to be the outliers.

For leverages histogram, there are a few points on the right side of the graph that can be considered to have high leverage.

**e.)**

> rstandard

1 2 3 4 5 6

0.184445415 -0.900221853 -1.002258318 1.273804198 1.639357945 -0.467150276

7 8 9 10 11 12

-1.365640029 -0.335829299 -0.366628186 0.391470323 1.079248228 0.064428262

13 14 15 16 17 18

0.051673775 1.351193014 0.263032931 0.197963082 0.418408648 -0.120325169

19 20 21 22 23 24

0.215672485 -5.459639961 -0.328723956 0.470884110 0.622655825 0.459984760

25 26 27 28 29 30

1.942063621 -2.076408742 -0.094228807 1.379230688 0.648960245 -0.332696114

31 32 33 34 35 36

-0.391780824 -1.217361067 -0.096242457 -0.082518179 0.377602458 -0.293028287

37 38 39 40 41 42

0.163454992 -0.171999760 0.810977323 2.214607367 0.959603144 0.029386472

43 44 45 46 47 48

-0.007304653 1.401690655 -1.121496035 -0.770637288 -0.424633487 -0.654408516

49 50 51 52 53 54

-0.401505440 0.485086599 0.802425628 0.727227410 -0.078857149 -0.704858976

55 56 57 58 59 60

-0.111019777 -0.036326242 -0.117143601 -0.516590375 -0.219668107 0.628409275

61 62 63 64 65 66

-0.772876310 0.189693416 -0.301073435 0.186856589 -0.086392106 1.441777449

67 68 69 70 71 72

-0.843304694 0.636736438 -1.162624663 -0.646141775 -0.259220749 -1.014844446

73

1.259554168

As mentioned in part (d), points outside interval (-2, 2) are the outliers. Therefore, points 20, 26 and 40 are the outliers in this model.

**f.)**

> leverages

1 2 3 4 5 6 7

0.03560401 0.04694945 0.23467485 0.06174554 0.03302745 0.07794129 0.06523023

8 9 10 11 12 13 14

0.09428187 0.05636996 0.01693314 0.03022274 0.02407692 0.04079783 0.03725421

15 16 17 18 19 20 21

0.02412596 0.03996510 0.06423654 0.04931441 0.03125417 0.15330251 0.02365432

22 23 24 25 26 27 28

0.04904300 0.03730173 0.04559938 0.12506752 0.15206487 0.03365521 0.18368021

29 30 31 32 33 34 35

0.03326937 0.04164270 0.03506044 0.06812659 0.02138901 0.07427886 0.05939035

36 37 38 39 40 41 42

0.04539765 0.02268594 0.04099498 0.01664025 0.10507456 0.05794213 0.03872138

43 44 45 46 47 48 49

0.02863423 0.02240438 0.02240438 0.11723627 0.02649136 0.02967551 0.03719424

50 51 52 53 54 55 56

0.02773101 0.07274532 0.06051273 0.01942656 0.03393889 0.02681245 0.04574337

57 58 59 60 61 62 63

0.04747990 0.02093215 0.10636189 0.07558515 0.02922293 0.07199147 0.05622692

64 65 66 67 68 69 70

0.03132546 0.01725154 0.03547798 0.11858821 0.06329673 0.08507101 0.03874676

71 72 73

0.01894487 0.02987764 0.05468004

To be considered high leverage, the leverage must be greater than 3(3+1)/73 = 0.164383562.

Observations 3 with leverage of 0.23467485 and 28 with leverage of 0.18368021 exceed the cutoff point of 0.164383562 and can be said to have high leverage values.

**g.)**

> modelB3 <- lm(Test3 ~ GPA + jobs + HW3, subset=-c(20,26,40))

> summary(modelB3)

Call:

lm(formula = Test3 ~ GPA + jobs + HW3, subset = -c(20, 26, 40))

Residuals:

Min 1Q Median 3Q Max

-21.0116 -4.2779 0.2742 4.2326 12.5264

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 38.84004 7.21026 5.387 1.03e-06 \*\*\*

GPA 8.42561 2.21737 3.800 0.000318 \*\*\*

jobs 2.36145 1.01193 2.334 0.022671 \*

HW3 0.41870 0.08345 5.017 4.21e-06 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.975 on 66 degrees of freedom

Multiple R-squared: 0.4776, Adjusted R-squared: 0.4539

F-statistic: 20.11 on 3 and 66 DF, p-value: 2.273e-09

In modelB,

Residual standard error: 10.42 on 69 degrees of freedom

Multiple R-squared: 0.5095, Adjusted R-squared: 0.4882

F-statistic: 23.89 on 3 and 69 DF, p-value: 1.026e-10

S in this model is better since it is lower than s in model B.

R2 in model B is better since it is greater than R2 in this model.

Adjusted R2 in model B is better since it is greater than adjusted R2 in this model.

**h.)**

> cor(cbind(GPA, jobs, HW3))

GPA jobs HW3

GPA 1.00000000 -0.01097167 0.3270477

jobs -0.01097167 1.00000000 -0.2689029

HW3 0.32704769 -0.26890287 1.0000000

> vif(modelB)

GPA jobs HW3

1.130695 1.082733 1.214608

GPA and HW3 have the strongest correlation. But all correlations are quite low which is not too strong. Collinearity does not seem to be an issue in this model. Since all VIFs are less than 10, we can say severe collinearity does not exist.

**i.)**

> model2 <- lm(Test3 ~ factor(Laptop))

> summary(model2)

Call:

lm(formula = Test3 ~ factor(Laptop))

Residuals:

Min 1Q Median 3Q Max

-60.500 -2.259 1.241 6.833 25.500

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 72.00 13.83 5.207 2.31e-06 \*\*\*

factor(Laptop)Apple 10.50 16.93 0.620 0.537

factor(Laptop)Asus 21.50 16.93 1.270 0.209

factor(Laptop)Compaq 24.00 19.55 1.227 0.224

factor(Laptop)Dell 16.68 14.31 1.165 0.248

factor(Laptop)HP 10.17 14.21 0.716 0.477

factor(Laptop)Mac 15.26 14.08 1.084 0.283

factor(Laptop)PC 14.00 19.55 0.716 0.477

factor(Laptop)Sony 2.00 19.55 0.102 0.919

factor(Laptop)Toshiba -11.50 15.46 -0.744 0.460

factor(Laptop)Vaio 11.00 16.93 0.650 0.518

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 13.83 on 62 degrees of freedom

Multiple R-squared: 0.2243, Adjusted R-squared: 0.09918

F-statistic: 1.793 on 10 and 62 DF, p-value: 0.08065

All p-values for each type of laptops are greater than alpha=0.05. Therefore, Laptop is not a significant variable in predicting Test3.

**j.)**

s = 13.83 (It is high which is bad)

R2 = 0.2243 (It is low which is bad)

Adjusted R2 = 0.09918 (very low which is bad)

p-value = 0.08065 (low which is good)

Since s is high, R2 is bad, and adjusted R2 is bad, the goodness of fit of the model is not good.

**k.)**

The coefficient of Dell = 16.68

When the student use Dell laptop, the Test 3 score increase by 16.68 as compared to Apple laptop, holding all other explanatory variables constant.

**l.)**

> model3 <- lm(Test3 ~ factor(Laptop) + HW3 + GPA)

> summary(model3)

Call:

lm(formula = Test3 ~ factor(Laptop) + HW3 + GPA)

Residuals:

Min 1Q Median 3Q Max

-37.265 -4.375 -0.138 4.975 20.994

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 34.2635 13.7568 2.491 0.0155 \*

factor(Laptop)Apple -4.8586 12.5497 -0.387 0.7000

factor(Laptop)Asus -0.5628 12.8542 -0.044 0.9652

factor(Laptop)Compaq 7.7373 14.4616 0.535 0.5946

factor(Laptop)Dell -5.6505 10.9009 -0.518 0.6061

factor(Laptop)HP -4.1200 10.5492 -0.391 0.6975

factor(Laptop)Mac -5.1077 10.6420 -0.480 0.6330

factor(Laptop)PC 3.3811 14.5359 0.233 0.8169

factor(Laptop)Sony -5.5068 14.3190 -0.385 0.7019

factor(Laptop)Toshiba -23.9980 11.4258 -2.100 0.0399 \*

factor(Laptop)Vaio -9.3053 12.7588 -0.729 0.4686

HW3 0.6102 0.1097 5.562 6.52e-07 \*\*\*

GPA 9.9997 3.2890 3.040 0.0035 \*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.1 on 60 degrees of freedom

Multiple R-squared: 0.5998, Adjusted R-squared: 0.5198

F-statistic: 7.494 on 12 and 60 DF, p-value: 3.295e-08

The coefficients of Compaq and PC changed from positive to negative. Other type of laptops’ coefficients sign remain the same. This might be because the changes in GPA and HW3 could be affected by Laptop variable.