CS498 AML, AMO HW6

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TOTAL POINTS

95 / 100

QUESTION 1

1 code for regression and resulting model. 0/0

√ - 0 pts Correct

QUESTION 2

2 a screenshot of your diagnostic plot and a few sentences of your explanation. **45** / **50**

- + 10 pts Correct
- + 45 Point adjustment
 - remove too many outliers

QUESTION 3

3 a screenshot of your new diagnostic plot.

- + 0 pts Correct
- + 20 Point adjustment

QUESTION 4

4 a screenshot of your code for subproblem 2. 10 / 10

- + 0 pts Correct
- + 10 Point adjustment

QUESTION 5

5 a screenshot of Box-Cox transformation plot and the best value you chose. 10 / 10

- √ 0 pts Correct
 - 10 pts Click here to replace this description.

QUESTION 6

6 result of the standardized residuals of the regression after Box-Cox transformation and a plot of fitted house price against true house price. 10 / 10

√ - 0 pts Correct

QUESTION 7

7 code for subproblems 3 and 4. 0/0

- √ 0 pts Correct
 - 5 pts Click here to replace this description.

QUESTION 8

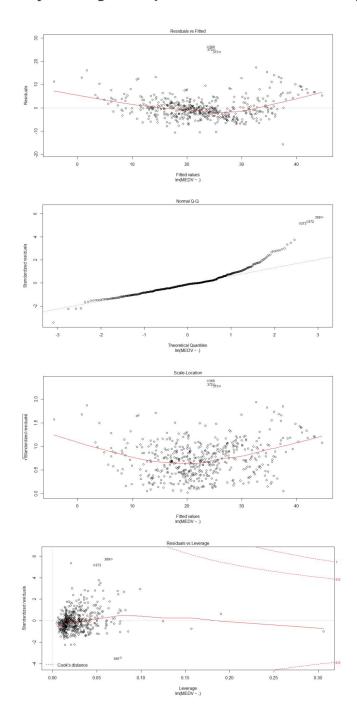
8 late penalty o / o

- √ 0 pts Correct
 - **5 pts** 1 day
 - 10 pts 2 days
 - 15 pts 3 days
 - 20 pts 4 days
 - 30 pts max

1) Code for regression and resulting model

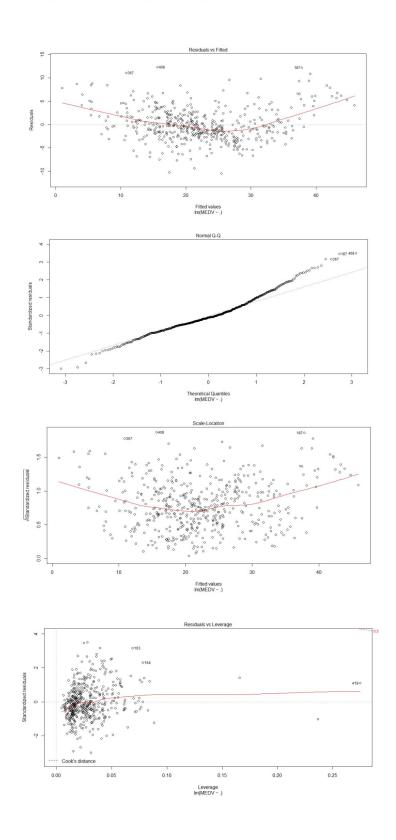
```
# Load Data
getwd()
setwd("C:/Users/asinghal/Downloads/aml hw6-master/aml hw6-master")
housing_data = read.table("housing.data.txt", header=FALSE, col.names = c("CRIM", "ZN",
"INDUS", "CHAS", "NOX", "RM", "AGE", "DIS", "RAD", "TAX", "PTRATIO", "B", "LSTAT",
"MEDV"))
# Generate regression model
model = Im(MEDV ~ ., data = housing data)
summary(model)
plot(model)
call:
lm(formula = MEDV \sim ., data = housing_data)
Residuals:
    Min
             1Q Median
                              3Q
                                      мах
         -2.730
-15.595
                 -0.518
                           1.777
                                   26.199
Coefficients:
               Estimate Std. Error t value Pr(>|t|)
                                    7.144 3.28e-12 ***
(Intercept)
             3.646e+01
                        5.103e+00
                                    -3.287 0.001087 **
CRIM
            -1.080e-01
                         3.286e-02
                                    3.382 0.000778 ***
             4.642e-02 1.373e-02
ZΝ
INDUS
             2.056e-02
                         6.150e-02
                                     0.334 0.738288
             2.687e+00 8.616e-01
                                     3.118 0.001925 **
CHAS
            -1.777e+01
                         3.820e+00
                                    -4.651 4.25e-06 ***
NOX
             3.810e+00 4.179e-01
                                     9.116 < 2e-16 ***
RM
             6.922e-04 1.321e-02
                                     0.052 0.958229
AGE
            -1.476e+00 1.995e-01
                                    -7.398 6.01e-13 ***
DIS
             3.060e-01
                         6.635e-02
                                     4.613 5.07e-06 ***
RAD
            -1.233e-02 3.760e-03
                                    -3.280 0.001112 **
TAX
PTRATIO
            -9.527e-01 1.308e-01
                                    -7.283 1.31e-12 ***
             9.312e-03 2.686e-03
                                    3.467 0.000573 ***
            -5.248e-01 5.072e-02 -10.347 < 2e-16 ***
LSTAT
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 4.745 on 492 degrees of freedom
Multiple R-squared: 0.7406.
                               Adjusted R-squared: 0.7338
F-statistic: 108.1 on 13 and 492 DF, p-value: < 2.2e-16
```

2) Screenshot of your diagnostic plot and a few sentences of your explanation:



Following are the outliers were removed as we choose removed all points with a cook distance 4. 65,142,149,162,163,164,167,187,196,205,215,226,229,234,254,263,268,365,366,368,369,370,371,372,373,375,376,381,413,415.

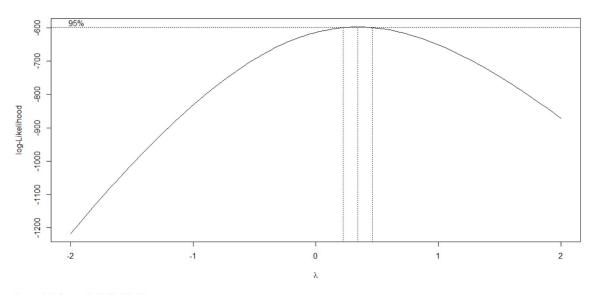
3) Screenshot of your new diagnostic plot:



4) Screenshot of your code for subproblem 2.

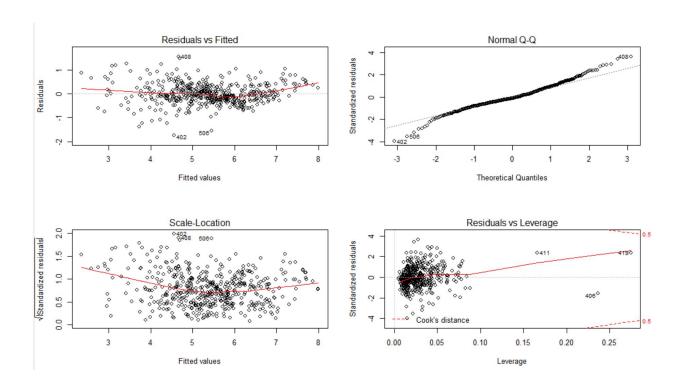
```
fitted_resid = function(model, pointcol = "blue", linecol = "black") {
 plot(fitted(model), rstandard(model),
    col = pointcol, pch = 20, cex = 1.5,
    xlab = "Fitted", ylab = "Residuals")
 abline(h = 0, col = linecol, lwd = 2)
}
par(mfrow=c(1,1))
fitted_resid (model)
possible_outliers= as.numeric(names(resid(model)[cooks.distance(model) > 10 /
length(cooks.distance(model))]))
cat("Removing", length(possible_outliers), "outliers")
cleaned_data = housing_data[-possible_outliers, ]
new_model = Im(MEDV ~ ., data = cleaned_data)
summary(model)
plot(new_model)
par(mfrow=c(1,1))
fitted_resid (new_model)
```

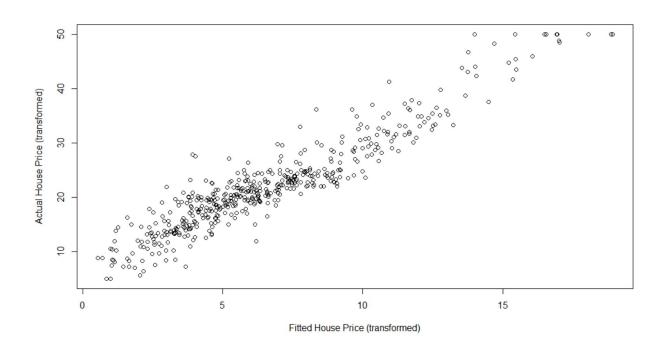
5) Screenshot of Box-Cox transformation plot and the best value you chose.



Best Value: 0.3434343

6) Result of the standardized residuals of the regression after Box-Cox transformation and a plot of fitted house price against true house price.





7) Code for subproblems 3 and 4.

```
# boxcox
library(MASS)
bc = boxcox(new_model)
lambda = bc$x[which.max(bc$y)]
lambda

transformed_model = lm(((MEDV ^ lambda - 1)/lambda) ~ ., data = cleaned_data)
summary(transformed_model)
plot(transformed_model)
plot((((transformed_model$fitted.values)*lambda)^(1/lambda),
cleaned_housing_data$MEDV, xlab="Fitted House Price (transformed)",
ylab="Actual House Price (transformed)")
```