## BACS HW16 Student ID: 110065508

Due: 2022/06/05Special thanks to 108071001

Question 1. First, split the data into train and test sets (70:30).

# Question 1

	Estimate	Std. Error	t value	$\Pr(> t )$
(Intercept)	7.68571305514322	0.381446482860176	20.1488633412318	1.34317494264466e-55
log.weight.	-0.892922806578692	0.0353182162549613	-25.282216976438	6.32840618595712e-73
log.acceleration.	0.0742013254761747	0.0446141749715566	1.66317825048835	0.0974457001142396
model_year	0.0303228848528229	0.00208984158869215	14.5096571036274	1.33646119837473e-35
factor(origin)2	0.0477657895161414	0.021722121774988	2.19894677006836	0.0287362555776429
factor(origin)3	0.0182650327019749	0.0226373246965084	0.806854738660532	0.420465631824332

(b) By the following codes,

```
# Question 1 (b)

mpg_actual_train <- train_set$log.mpg. # true label of train set

mpg_actual_test <- test_set$log.mpg. # true label of test set

mpg_predicted_train <- predict(lm_trained, train_set) # predict on train set

mpg_predicted_test <- predict(lm_trained, test_set) # predict on test set

pred_err_train <- mpg_actual_train - mpg_predicted_train # error on training set

pred_err_test <- mpg_actual_test - mpg_predicted_test # error on testing set

mse_is <- mean((mpg_predicted_train - mpg_actual_train)^2) # MSE_IS

mse_oos <- mean((mpg_predicted_test - mpg_actual_test)^2) # MSE_OOS
```

we have  $MSE_{IS} \approx 0.01316246$ , and  $MSE_{OOS} \approx 0.01401028$ .

(c) I save the dataframe to a .csv file, then convert into LATEX table by online tools.

```
# Question 1 (c)
result_dataframe <- cbind(mpg_actual_test, mpg_predicted_test, pred_err_test)
names(result_dataframe) <- c("Actual log.mpg.", "Predict log.mpg.", "error")
write.table(result_dataframe[1:5, 1:3], file="1c.csv", sep = ",", col.names=NA)
```

	mpg_actual_test	$mpg\_predicted\_test$	pred_err_test
1	2.83321334405622	2.72063665910161	0.112576684954602
3	3.67376581630389	3.46832859503583	0.205437221268057
4	2.77258872223978	2.79377976849132	-0.0211910462515355
9	2.70805020110221	2.98543919467625	-0.277388993574044
11	3.19867311755068	3.36255680850516	-0.163883690954478

```
# Question 2 (a)
   MSE <- function(model, dataset, actual) {</pre>
     predicted <- predict(model, dataset) # predict</pre>
     pred_err <- actual - predicted # error</pre>
     mse <- mean((predicted - actual)^2) # MSE</pre>
     return(mse)
   }
7
   # Split the origin dataset without log-transformed
   train_set_org <- cars[train_indices,]</pre>
10
11
   # Compute the MSE_IS'
12
   MSE_cars_lm <- MSE(cars_lm, train_set_org, train_set_org$mpg)</pre>
   MSE_cars_log_lm <- MSE(cars_log_lm, train_set, train_set$log.mpg.)
   MSE_cars_log_full_lm <- MSE(cars_log_full_lm, train_set, train_set$log.mpg.)
   We have that
     • cars_lm: MSE_{IS} \approx 11.5206
     • cars_log_lm: MSE_{IS} \approx 0.01325627
     • cars_log_full_lm: MSE_{IS} \approx 0.01255269
   (b) The implementation of k-fold is in the following codes:
   # Question 2 (b)
   # Calculates mse_oos across all folds
   k_fold_mse <- function(model, dataset, k=10) { # model should be a string
     fold_pred_errors <- sapply(1:k, \(i) {</pre>
        fold_i_pe(model, i, k, dataset)
     pred_errors <- unlist(fold_pred_errors)</pre>
     mean(pred_errors^2)
   }
10
   # Calculates prediction error for fold i out of k
   fold_i_pe <- function(model, i, k, dataset) {</pre>
12
     folds <- cut(1:nrow(dataset), k, labels = FALSE) # cut into 10 folds
14
     # Split the dataset
15
     test_indices <- which(folds == i)
16
     train_indices <- setdiff(1:nrow(dataset), train_indices)</pre>
     train_set <- dataset[train_indices,]</pre>
18
     test_set <- dataset[test_indices,]</pre>
20
     # train
21
     if (model == "cars_lm") {
22
        trained_model <- lm(mpg ~ weight + acceleration +
23
                                model_year + factor(origin), data=train_set)
24
        actual <- test_set$mpg</pre>
25
     }
26
     else if (model == "cars_log_lm") {
27
        trained_model <- lm(log.mpg. ~ log.weight. + log.acceleration. +</pre>
28
                                model_year + factor(origin), data=train_set)
29
```

```
actual <- test_set$log.mpg.</pre>
30
         }
         else if (model == "cars_log_full_lm") {
             trained_model \leftarrow lm(log.mpg. \sim log.cylinders. + log.displacement. + log.displacement.
                                                       log.horsepower. + log.weight. + log.acceleration. +
                                                       model_year + factor(origin), data=train_set)
             actual <- test_set$log.mpg.</pre>
         }
38
         # predict
39
         predictions <- predict(trained_model, test_set)</pre>
40
         return(actual - predictions)
      }
42
      cars_lm_mse <- k_fold_mse("cars_lm", cars, 10)</pre>
44
      cars_log_lm_mse <- k_fold_mse("cars_log_lm", cars_log, 10)
      cars_log_full_lm_mse <- k_fold_mse("cars_log_full_lm", cars_log, 10)</pre>
46
```

We have that

- cars\_lm:  $MSE_{OOS} \approx 11.20695$
- cars\_log\_lm:  $MSE_{OOS} \approx 0.01382051$
- cars\_log\_full\_lm:  $MSE_{OOS} \approx 0.01361829$
- (ii) Since MSE<sub>OOS</sub> drops from 11 to 0.01, so the non-linearity seem to harm the predictions.
- (iii) As (ii), the multicollinearity seem to harm the predictions as well.
- (c) Use the function I write in (b),

```
# Question 2 (c)
cars_log_lm_392folds_mse <- k_fold_mse("cars_log_lm", cars_log, 392)
```

In this case,  $MSE_{OOS} \approx 0.01382051$ .