Project 2

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```
# Clean the env. variables and plots
rm(list = ls())
```

```
library(MASS)
library(glmnet)
```

```
## Loading required package: Matrix

## Loaded glmnet 4.1-2
```

```
library(pls)
```

```
##
## Attaching package: 'pls'

## The following object is masked from 'package:stats':
##
##     loadings
```

```
library(mgcv)
```

```
## Loading required package: nlme

## This is mgcv 1.8-36. For overview type 'help("mgcv-package")'.
```

```
library(rpart)
library(caret)
```

```
## Loading required package: lattice

## Loading required package: ggplot2

##
## Attaching package: 'caret'

## The following object is masked from 'package:pls':
##
##     R2
```

```r
library(olsrr)
```

```
##
## Attaching package: 'olsrr'

## The following object is masked from 'package:MASS':
##
##     cement

## The following object is masked from 'package:datasets':
##
##     rivers
```

```r
library(boot)
```

```
##
## Attaching package: 'boot'

## The following object is masked from 'package:lattice':
##
##     melanoma
```

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following object is masked from 'package:nlme':
##
##     collapse

## The following object is masked from 'package:MASS':
##
##     select

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(e1071)
library(ipred)
library(performance)
library(h2o)
```

```
##
## ----------------------------------------------------------------------
##
## Your next step is to start H2O:
##     > h2o.init()
##
## For H2O package documentation, ask for help:
##     > ??h2o
##
## After starting H2O, you can use the Web UI at http://localhost:54321
## For more information visit https://docs.h2o.ai
##
## ----------------------------------------------------------------------
```

```
##
## Attaching package: 'h2o'
```

```
## The following objects are masked from 'package:stats':
##
##     cor, sd, var
```

```
## The following objects are masked from 'package:base':
##
##     &&, %*%, %in%, ||, apply, as.factor, as.numeric, colnames,
##     colnames<-, ifelse, is.character, is.factor, is.numeric, log,
##     log10, log1p, log2, round, signif, trunc
```

```
rsq <- function(formula, data, indices) {
  d <- data[indices,] # allows boot to select sample
  fit <- lm(formula, data=d)
  return(summary(fit)$r.square)
}

# Helper Functions
get.MSPE = function(Y, Y.hat) {
  residuals = Y - Y.hat
  resid.sq = residuals ^ 2
  SSPE = sum(resid.sq)
  MSPE = SSPE / length(Y)
  return(MSPE)
}
```

```
data = read.csv('/Users/dhruv/Desktop/Docs/STAT_652/Project2/Data2021_final.csv',header=TRUE)
summary(data)
```

```
##        Y                X1               X2                X3
##  Min.   : 7.855   Min.   :-49.00   Min.   :-48.000   Min.   :-35.40
##  1st Qu.:12.000   1st Qu.:  8.25   1st Qu.:  4.000   1st Qu.: 15.30
##  Median :12.830   Median : 14.00   Median :  7.000   Median : 15.80
##  Mean   :12.921   Mean   : 13.61   Mean   :  7.601   Mean   : 15.49
##  3rd Qu.:13.775   3rd Qu.: 19.00   3rd Qu.: 13.000   3rd Qu.: 16.30
##  Max.   :17.744   Max.   : 71.00   Max.   : 64.000   Max.   : 67.00
```

```
##        X4                X5               X6               X7
##  Min.   :-50.000   Min.   :-42.20   Min.   :-41.00   Min.   :-46.700
##  1st Qu.:  1.000   1st Qu.: 10.80   1st Qu.: 18.00   1st Qu.:  3.600
##  Median :  2.000   Median : 12.50   Median : 21.00   Median :  3.800
##  Mean   :  2.348   Mean   : 12.39   Mean   : 21.02   Mean   :  3.757
##  3rd Qu.:  3.000   3rd Qu.: 14.20   3rd Qu.: 24.00   3rd Qu.:  3.900
##  Max.   : 57.000   Max.   : 66.10   Max.   : 76.00   Max.   : 54.000
##        X8               X9               X10               X11
##  Min.   :-25.40   Min.   :-50.00   Min.   :-48.000   Min.   : 159.0
##  1st Qu.: 30.30   1st Qu.:  0.00   1st Qu.:  2.000   1st Qu.: 512.0
##  Median : 35.40   Median :  1.00   Median :  3.000   Median : 669.0
##  Mean   : 35.95   Mean   : 10.39   Mean   :  3.012   Mean   : 711.0
##  3rd Qu.: 41.40   3rd Qu.:  5.00   3rd Qu.:  3.000   3rd Qu.: 888.8
##  Max.   : 97.50   Max.   :149.00   Max.   : 54.000   Max.   :1802.0
##       X12               X13                X14               X15
##  Min.   :-44.000   Min.   :-49.8600   Min.   : -23.20   Min.   :-49.000
##  1st Qu.:  7.000   1st Qu.:  0.8825   1st Qu.:  83.67   1st Qu.:  5.000
##  Median :  9.000   Median :  2.0000   Median : 189.88   Median :  9.000
##  Mean   :  9.311   Mean   :  3.0388   Mean   : 252.98   Mean   :  8.749
##  3rd Qu.: 10.000   3rd Qu.:  3.9375   3rd Qu.: 346.64   3rd Qu.: 12.000
##  Max.   : 61.000   Max.   : 58.3900   Max.   :1545.88   Max.   : 65.000
```

```r
# Randomly selecting 10 rows as test data from training data.
set.seed(301471961)
ind = sample(nrow(data), 10, replace = TRUE)
model_test_data = data[ind, ]
data = data[-ind, ]

test_data = read.csv('/Users/dhruv/Desktop/Docs/STAT_652/Project2/Data2021test_final_noY.csv',header=TRU
summary(test_data)
```

```
##        X1               X2                X3               X4
##  Min.   :-48.00   Min.   :-49.000   Min.   :-35.50   Min.   :-50.000
##  1st Qu.: 11.00   1st Qu.:  4.000   1st Qu.: 15.30   1st Qu.:  1.000
##  Median : 16.00   Median :  7.000   Median : 15.80   Median :  2.000
##  Mean   : 14.23   Mean   :  8.007   Mean   : 15.98   Mean   :  1.937
##  3rd Qu.: 21.00   3rd Qu.: 13.000   3rd Qu.: 16.30   3rd Qu.:  3.000
##  Max.   : 74.00   Max.   : 64.000   Max.   : 68.50   Max.   : 57.000
##        X5               X6               X7                X8
##  Min.   :-43.00   Min.   :-40.00   Min.   :-46.800   Min.   :-41.40
##  1st Qu.: 10.70   1st Qu.: 19.00   1st Qu.:  3.600   1st Qu.: 29.98
##  Median : 12.40   Median : 22.00   Median :  3.800   Median : 35.80
##  Mean   : 12.30   Mean   : 21.45   Mean   :  3.631   Mean   : 35.88
##  3rd Qu.: 13.93   3rd Qu.: 24.00   3rd Qu.:  3.900   3rd Qu.: 41.40
##  Max.   : 68.60   Max.   : 79.00   Max.   : 54.200   Max.   :101.00
##        X9                X10               X11               X12
##  Min.   :-50.000   Min.   :-48.000   Min.   :  23.0   Min.   :-44.000
##  1st Qu.:  0.000   1st Qu.:  2.000   1st Qu.: 515.0   1st Qu.:  7.000
##  Median :  1.000   Median :  3.000   Median : 695.0   Median :  9.000
##  Mean   :  9.049   Mean   :  2.902   Mean   : 719.0   Mean   :  8.822
##  3rd Qu.:  4.000   3rd Qu.:  3.000   3rd Qu.: 891.2   3rd Qu.: 10.000
##  Max.   :155.000   Max.   : 54.000   Max.   :2334.0   Max.   : 61.000
##       X13                X14              X15
##  Min.   :-49.9600   Min.   : -40.08   Min.   :-49.000
```

```
##  1st Qu.:  0.8275   1st Qu.:  75.11   1st Qu.:  5.000
##  Median :  1.9400   Median : 168.76   Median :  9.000
##  Mean   :  2.4918   Mean   : 236.08   Mean   :  8.669
##  3rd Qu.:  3.6700   3rd Qu.: 331.84   3rd Qu.: 12.000
##  Max.   : 61.2000   Max.   :1954.01   Max.   : 65.000
```

```r
# Finding if any column has null values
sapply(data, function(x) sum(is.na(x)))
```

```
##   Y  X1  X2  X3  X4  X5  X6  X7  X8  X9 X10 X11 X12 X13 X14 X15
##   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
```

```r
# Linear Regression Model
lm_model = lm(Y~.,data)

# For the summary we can find the X1 is the most important variable.
summary(lm_model)
```

```
##
## Call:
## lm(formula = Y ~ ., data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8772 -0.9091 -0.0877  0.8404  4.7129
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 12.7248945  0.2680924  47.465  < 2e-16 ***
## X1           0.0180254  0.0040810   4.417 1.15e-05 ***
## X2          -0.0085127  0.0043564  -1.954   0.0511 .
## X3           0.0017829  0.0046490   0.384   0.7015
## X4          -0.0046188  0.0045707  -1.011   0.3126
## X5          -0.0010330  0.0045180  -0.229   0.8192
## X6          -0.0087683  0.0044878  -1.954   0.0511 .
## X7          -0.0054892  0.0047281  -1.161   0.2460
## X8           0.0017366  0.0039744   0.437   0.6623
## X9          -0.0032074  0.0021119  -1.519   0.1293
## X10          0.0075678  0.0046479   1.628   0.1039
## X11          0.0002991  0.0001903   1.571   0.1166
## X12         -0.0044165  0.0046605  -0.948   0.3436
## X13          0.0070873  0.0045852   1.546   0.1226
## X14         -0.0003014  0.0002442  -1.234   0.2175
## X15          0.0058114  0.0043543   1.335   0.1824
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.4 on 724 degrees of freedom
## Multiple R-squared:  0.05642,    Adjusted R-squared:  0.03687
## F-statistic: 2.886 on 15 and 724 DF,  p-value: 0.0001935
```

```r
### Trying different variable selection methods to choose the important variables

# 1. Forward Selection
# Using P value
fwd_sel_model_p = ols_step_forward_p(lm_model,penter = 0.05)

# Selection Summary: X1 most important
fwd_sel_model_p
```

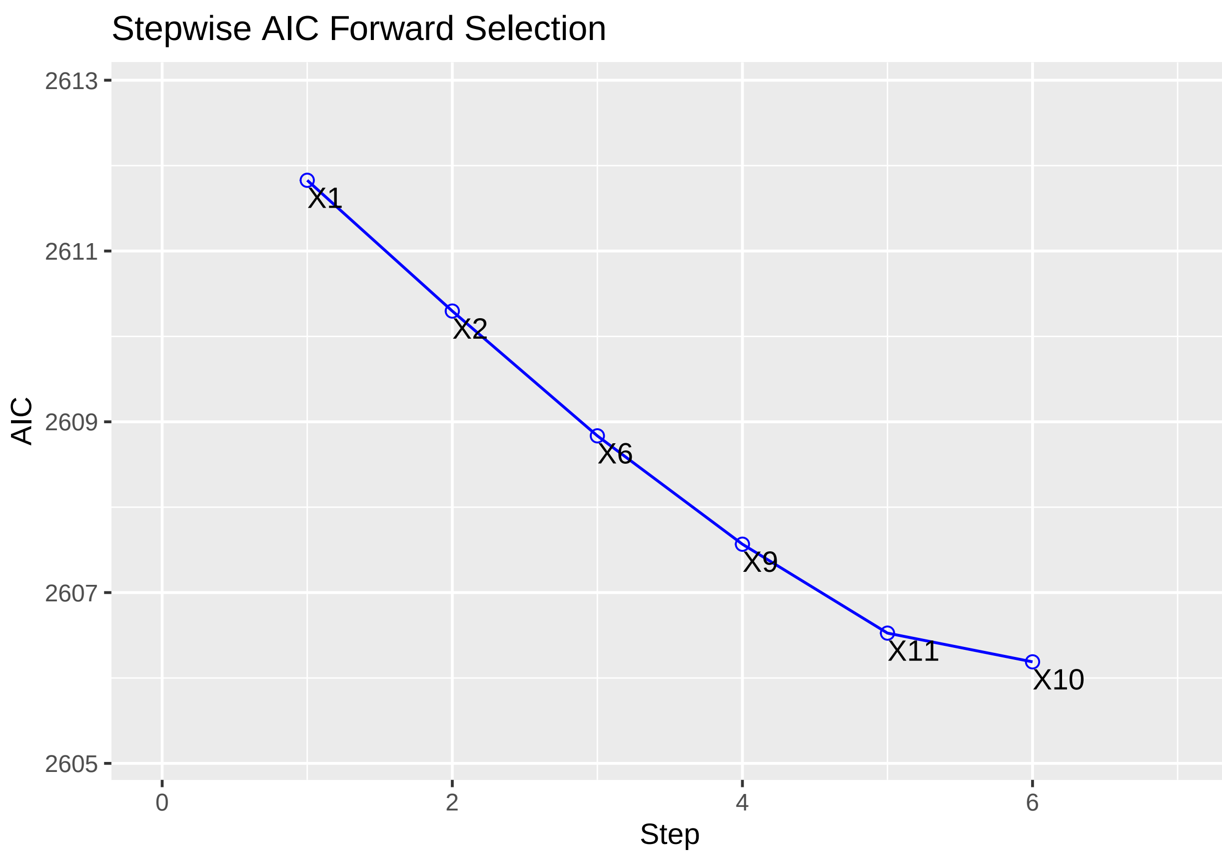
```
##
##                              Selection Summary
## ------------------------------------------------------------------------------
##         Variable                  Adj.
## Step    Entered     R-Square    R-Square     C(p)         AIC        RMSE
## ------------------------------------------------------------------------------
##    1    X1            0.0250      0.0237    12.0856    2611.8281    1.4093
## ------------------------------------------------------------------------------
```

```r
# 2. Forward Regression
# Using AIC:
fwd_sel_model_aic = ols_step_forward_aic(lm_model)

# Selection Summary: X1, X11, X9, X6, X2 are important variables
fwd_sel_model_aic
```

```
##
##                           Selection Summary
## -----------------------------------------------------------------------
## Variable       AIC       Sum Sq      RSS        R-Sq      Adj. R-Sq
## -----------------------------------------------------------------------
## X1          2611.828    37.634    1465.809    0.02503      0.02371
## X2          2610.297    44.613    1458.830    0.02967      0.02704
## X6          2608.836    51.420    1452.023    0.03420      0.03026
## X9          2607.567    57.820    1445.623    0.03846      0.03323
## X11         2606.525    63.749    1439.694    0.04240      0.03588
## X10         2606.189    68.288    1435.156    0.04542      0.03761
## -----------------------------------------------------------------------
```

```r
# Plotting how much each variable contributes: We can see relative contribution amongst the selected va
plot(fwd_sel_model_aic)
```




```r
# 3. #Backward Elimination Method
# Using p value
back_sel_model_p = ols_step_backward_p(lm_model, prem = 0.05)

# Elimination Summary: ["X3"  "X5"  "X8"  "X12" "X4"  "X10" "X14" "X7"  "X13" "X15" "X2"  "X6"  "X9"  "
back_sel_model_p
```

```
##
##
##                           Elimination Summary
## -------------------------------------------------------------------------
##         Variable                  Adj.
## Step    Removed     R-Square    R-Square     C(p)         AIC        RMSE
## -------------------------------------------------------------------------
##    1    X5            0.0564      0.0381    14.0523    2613.6643    1.3989
##    2    X3            0.0562      0.0393    12.2055    2611.8210    1.3981
##    3    X8            0.0559      0.0403    10.3857    2610.0050    1.3973
##    4    X4            0.0548      0.0405     9.2505    2608.8879    1.3971
##    5    X12           0.0535      0.0406     8.2040    2607.8602    1.3971
##    6    X7            0.0519      0.0402     7.4950    2607.1745    1.3974
##    7    X14           0.0495      0.0391     7.2738    2606.9818    1.3981
##    8    X13           0.0476      0.0385     6.7462    2606.4743    1.3986
##    9    X15           0.0454      0.0376     6.4414    2606.1890    1.3993
##   10    X10           0.0424      0.0359     6.7576    2606.5254    1.4005
##   11    X11           0.0385      0.0332     7.7836    2607.5667    1.4024
##   12    X9            0.0342      0.0303     9.0499    2608.8356    1.4046
```

```
##    13    X6            0.0297       0.027    10.5241    2610.2967    1.4069
##    14    X2             0.025      0.0237    12.0856    2611.8281    1.4093
## ---------------------------------------------------------------------------
```

```r
# Backward Elimination Method
# Using AIC value
back_sel_model_aic = ols_step_backward_aic(lm_model)

# Elimination Summary: ["X3"  "X5"  "X8"  "X12" "X4"  "X10" "X14" "X7"  "X13" "X15"] can be removed.
back_sel_model_aic
```

```
##
##
##                       Backward Elimination Summary
## ---------------------------------------------------------------------
## Variable        AIC         RSS       Sum Sq      R-Sq      Adj. R-Sq
## ---------------------------------------------------------------------
## Full Model    2615.611    1418.615    84.828    0.05642      0.03687
## X5            2613.664    1418.718    84.725    0.05635      0.03813
## X3            2611.821    1419.018    84.425    0.05615      0.03925
## X8            2610.005    1419.371    84.072    0.05592      0.04034
## X4            2608.888    1421.066    82.378    0.05479      0.04051
## X12           2607.860    1422.934    80.509    0.05355      0.04057
## X7            2607.175    1425.463    77.980    0.05187      0.04018
## X14           2606.982    1428.949    74.494    0.04955      0.03915
## X13           2606.474    1431.834    71.609    0.04763      0.03852
## X15           2606.189    1435.156    68.288    0.04542      0.03761
## ---------------------------------------------------------------------
```

```r
# Step-wise using P value
stepwise_model_p = ols_step_both_p(lm_model,prem = 0.05, pent = 0.05)

# Step-wise
# Selection Summary: Only variable X1 was added
stepwise_model_p
```

```
##
##                              Stepwise Selection Summary
## --------------------------------------------------------------------------------------
##                     Added/                 Adj.
## Step    Variable    Removed     R-Square    R-Square     C(p)        AIC        RMSE
## --------------------------------------------------------------------------------------
##    1       X1       addition       0.025       0.024    12.0860    2611.8281    1.4093
## --------------------------------------------------------------------------------------
```

```r
# Step-wise selection using AIC
stepwise_model_aic = ols_step_both_aic(lm_model)

# Step-wise Summary: ["X1"  "X11"  "X9"  "X6"  "X2"] were added to get best AIC value
stepwise_model_aic
```

```
##
```

```
##
##                               Stepwise Summary
## -----------------------------------------------------------------------------
## Variable     Method       AIC         RSS        Sum Sq     R-Sq      Adj. R-Sq
## -----------------------------------------------------------------------------
## X1          addition    2611.828    1465.809    37.634    0.02503      0.02371
## X2          addition    2610.297    1458.830    44.613    0.02967      0.02704
## X6          addition    2608.836    1452.023    51.420    0.03420      0.03026
## X9          addition    2607.567    1445.623    57.820    0.03846      0.03323
## X11         addition    2606.525    1439.694    63.749    0.04240      0.03588
## X10         addition    2606.189    1435.156    68.288    0.04542      0.03761
## -----------------------------------------------------------------------------
```

```r
set.seed(301471961)

# Fitting best model using K-fold CV method
n = nrow(data)
K = 10
all.models = c("LS", "Step", "Ridge", "LAS-Min", "LAS-1se", "PLS", "GAM","Full-Tree", "Min-Tree", "1SE-
CV.MSPEs = array(0, dim = c(length(all.models), K))
rownames(CV.MSPEs) = all.models
colnames(CV.MSPEs) = 1:K

lambda.vals = seq(from = 0, to = 100, by = 0.05)

n = nrow(data)

for(i in 1:K){

  # Random Index
  new.order = sample.int(n)
  ind.train = which(new.order <= n * 0.75)
  ind.valid = which(new.order > n * 0.75)

  # Splitting the Data-set
  data.train = data[ind.train, ]
  data.valid = data[ind.valid, ]

  Y.train = data.train$Y
  Y.valid = data.valid$Y

  mat.train.int = model.matrix(Y ~ ., data = data.train)
  mat.train = mat.train.int[,-1]
  mat.valid.int = model.matrix(Y ~ ., data = data.valid)
  mat.valid = mat.valid.int[,-1]

  ##########
  ### LS ###
  ##########
  fit.ls = lm(Y ~ ., data = data.train)
  pred.ls = predict(fit.ls, data.valid)
  MSPE.ls = get.MSPE(Y.valid, pred.ls)
  CV.MSPEs["LS", i] = MSPE.ls
```

```
############
### Step ###
############
fit.start = lm(Y ~ 1, data = data.train)
fit.step = step(fit.start, list(upper = fit.ls), trace = 0)
pred.step = predict(fit.step, data.valid)
MSPE.step = get.MSPE(Y.valid, pred.step)
CV.MSPEs["Step", i] = MSPE.step

#############
### Ridge ###
#############

### Fit ridge regression
### We already definite lambda.vals. No need to re-invent the wheel
fit.ridge = lm.ridge(Y ~ ., lambda = lambda.vals, data = data.train)

### Get optimal lambda value
ind.min.GCV = which.min(fit.ridge$GCV)
lambda.min = lambda.vals[ind.min.GCV]

### Get coefficients for optimal model
all.coefs.ridge = coef(fit.ridge)
coef.min.ridge = all.coefs.ridge[ind.min.GCV,]

### Get predictions and MSPE on validation set
pred.ridge = mat.valid.int %*% coef.min.ridge
pred.ridge = as.numeric(pred.ridge)
MSPE.ridge = get.MSPE(Y.valid, pred.ridge)
CV.MSPEs["Ridge", i] = MSPE.ridge


#############
### LASSO ###
#############

### Fit model
fit.LASSO = cv.glmnet(mat.train, Y.train)

### Get optimal lambda values
lambda.min = fit.LASSO$lambda.min
lambda.1se = fit.LASSO$lambda.1se

### Get predictions
pred.min_lasso = predict(fit.LASSO, mat.valid, lambda.min)
pred.1se = predict(fit.LASSO, mat.valid, lambda.1se)

### Get and store MSPEs
MSPE.min = get.MSPE(Y.valid, pred.min_lasso)
MSPE.1se = get.MSPE(Y.valid, pred.1se)
CV.MSPEs["LAS-Min", i] = MSPE.min
CV.MSPEs["LAS-1se", i] = MSPE.1se
```

```r
#############################
### Partial Least Squares ###
#############################

### Fit PLS
fit.pls = plsr(Y ~ ., data = data.train, validation = "CV", segments = 10)


### Get optimal number of folds
CV.pls = fit.pls$validation
PRESS.pls = CV.pls$PRESS
n.comps = which.min(PRESS.pls)

### Get predictions and MSPE
pred.pls = predict(fit.pls, data.valid, ncomp = n.comps)
MSPE.pls = get.MSPE(Y.valid, pred.pls)
CV.MSPEs["PLS", i] = MSPE.pls

###########
### GAM ###
###########

### Fit model
fit.gam = gam(Y ~ s(X1) + s(X11) + s(X9) + s(X6) + s(X2) + s(X10) + s(X15), data = data.train)

### Get predictions and MSPE
pred.gam = predict(fit.gam, data.valid)
MSPE.gam = get.MSPE(Y.valid, pred.gam)
CV.MSPEs["GAM", i] = MSPE.gam

#################
### Full Tree ###
#################

fit.tree = rpart(Y ~ ., data = data.train, cp = 0)

### Get the CP table
info.tree = fit.tree$cptable

### Get predictions
pred.full = predict(fit.tree, data.valid)
MSPE.full = get.MSPE(Y.valid, pred.full)
CV.MSPEs["Full-Tree", i] = MSPE.full

###################
### Min CV Tree ###
###################

### Get minimum CV error and corresponding CP value
ind.best = which.min(info.tree[, "xerror"])
CV.best = info.tree[ind.best, "xerror"]
CP.best = info.tree[ind.best, "CP"]
```

```
  ### Get the geometric mean of best CP with one above it
  if (ind.best == 1) {
    CP.GM = CP.best
  }
  else{
    CP.above = info.tree[ind.best - 1, "CP"]
    CP.GM = sqrt(CP.best * CP.above)
  }

  ### Fit minimum CV error tree
  fit.tree.min = prune(fit.tree, cp = CP.best)

  ### Get predictions and MSPE
  pred.min = predict(fit.tree.min, data.valid)
  MSPE.min = get.MSPE(Y.valid, pred.min)
  CV.MSPEs["Min-Tree", i] = MSPE.min

  ########################
  ### 1SE Rule CV Tree ###
  ########################

  ### Get 1se rule CP value
  err.min = info.tree[ind.best, "xerror"]
  se.min = info.tree[ind.best, "xstd"]

  threshold = err.min + se.min
  ind.1se = min(which(info.tree[1:ind.best, "xerror"] < threshold))

  ### Take geometric mean with superior row
  CP.1se.raw = info.tree[ind.1se, "CP"]

  if (ind.1se == 1) {
    ### If best CP is in row 1, store this value
    CP.1se = CP.1se.raw
  }
  else{
    ### If best CP is not in row 1, average this with the value from the ### row above it.
    ### Value from row above
    CP.above = info.tree[ind.1se - 1, "CP"]

    ### (Geometric) average
    CP.1se = sqrt(CP.1se.raw * CP.above)
  }

  ### Prune the tree
  fit.tree.1se = prune(fit.tree, cp = CP.1se)

  ### Get predictions and MSPE
  pred.1se = predict(fit.tree.1se, data.valid)
  MSPE.1se = get.MSPE(Y.valid, pred.1se)
  CV.MSPEs["1SE-Tree", i] = MSPE.1se
}
```

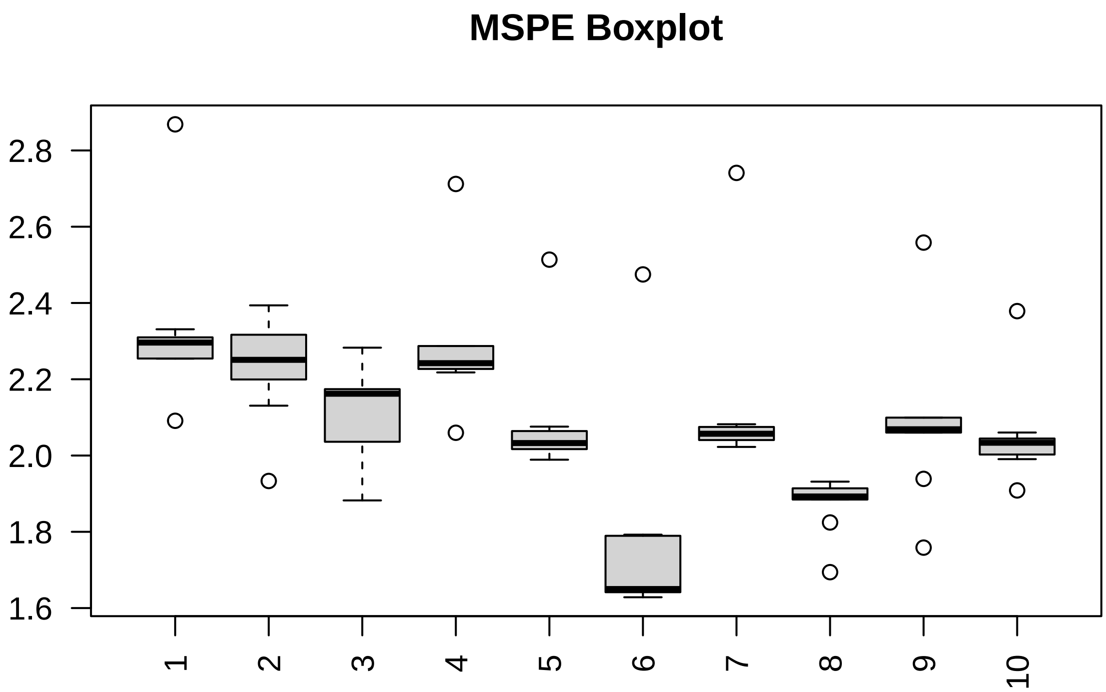
```r
CV.MSPEs
```

```
##                  1        2        3        4        5        6        7
## LS        2.262826 2.199506 2.174115 2.239086 2.026980 1.644678 2.041498
## Step      2.287486 2.239805 2.189244 2.258342 2.064131 1.699231 2.065840
## Ridge     2.254373 2.203214 2.151474 2.227014 1.997511 1.628392 2.027461
## LAS-Min   2.254025 2.262128 2.144635 2.245310 2.016814 1.641607 2.048312
## LAS-1se   2.309883 2.316721 2.172645 2.287196 1.989073 1.652671 2.074964
## PLS       2.331110 2.285897 2.173540 2.217923 2.038460 1.647188 2.040617
## GAM       2.091092 1.933269 1.882283 2.059659 2.022764 1.631334 2.022538
## Full-Tree 2.868454 2.343721 2.282801 2.712111 2.513663 2.474951 2.741155
## Min-Tree  2.304910 2.393777 2.036022 2.235144 2.075740 1.789475 2.082046
## 1SE-Tree  2.309883 2.130736 1.932816 2.287196 2.056348 1.792475 2.074964
##                  8        9       10
## LS        1.892345 2.086754 2.002616
## Step      1.914008 2.063151 2.038700
## Ridge     1.886477 2.069589 1.990547
## LAS-Min   1.892848 2.068131 2.013093
## LAS-1se   1.931517 2.099387 2.044572
## PLS       1.884597 2.060205 2.060292
## GAM       1.694160 1.758533 1.908523
## Full-Tree 1.909727 2.558427 2.378676
## Min-Tree  1.824420 1.938802 2.028302
## 1SE-Tree  1.931517 2.099387 2.044572
```

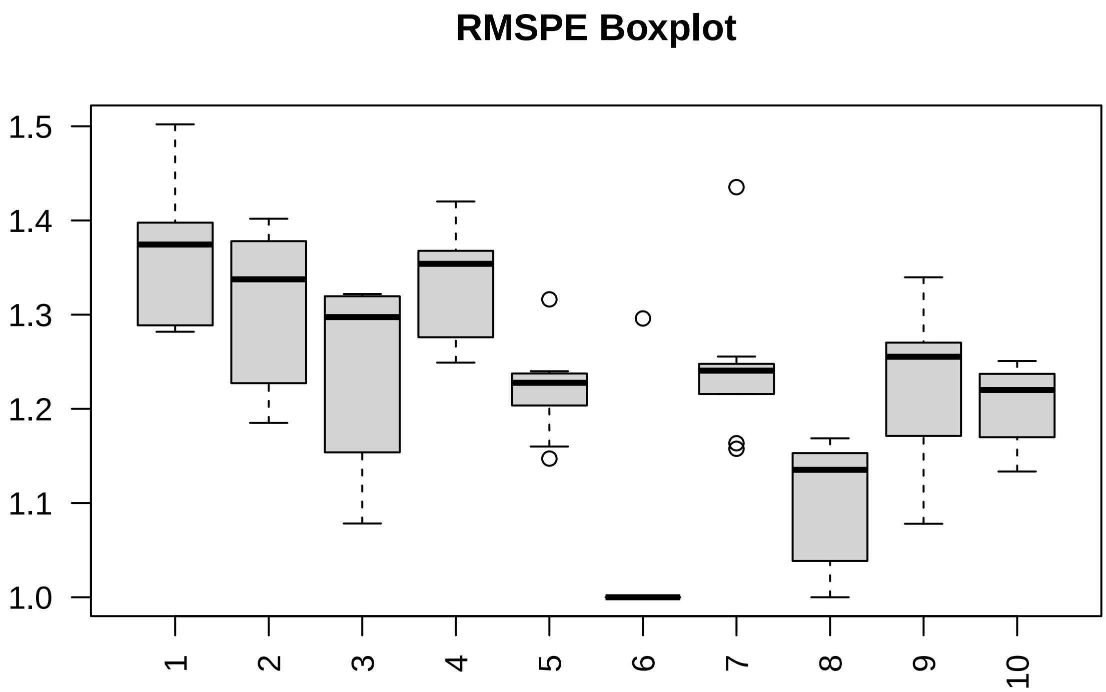
```r
# Average MSPE
rowMeans(CV.MSPEs)
```

```
##        LS      Step     Ridge   LAS-Min   LAS-1se       PLS       GAM Full-Tree
##  2.057040  2.081994  2.043605  2.058690  2.087863  2.073983  1.900415  2.478369
##  Min-Tree  1SE-Tree
##  2.070864  2.065989
```

```r
### Make boxplot
boxplot(CV.MSPEs, las = 2, main = "MSPE Boxplot")
```




```r
### Get relative MSPEs and make boxplot
CV.RMSPEs = apply(CV.MSPEs, 1, function(W) W/min(W))
CV.RMSPEs = t(CV.RMSPEs)
boxplot(CV.RMSPEs, las = 2, main = "RMSPE Boxplot")
```




```r
# Code for best model

# Initializing environment
h2o.init(nthreads = -1)
```

```
##  Connection successful!
##
## R is connected to the H2O cluster:
##     H2O cluster uptime:         2 hours 4 minutes
##     H2O cluster timezone:       America/Vancouver
##     H2O data parsing timezone:  UTC
##     H2O cluster version:        3.34.0.3
##     H2O cluster version age:    1 month and 21 days
##     H2O cluster name:           H2O_started_from_R_dhruv_ygi863
##     H2O cluster total nodes:    1
##     H2O cluster total memory:   0.70 GB
##     H2O cluster total cores:    4
##     H2O cluster allowed cores:  4
##     H2O cluster healthy:        TRUE
##     H2O Connection ip:          localhost
##     H2O Connection port:        54321
##     H2O Connection proxy:       NA
##     H2O Internal Security:      FALSE
##     H2O API Extensions:         Amazon S3, XGBoost, Algos, AutoML, Core V3, TargetEncoder, Core V4
##     R Version:                  R version 4.1.1 (2021-08-10)
```

```r
y = "Y"
x = setdiff(names(data), y)

train.h2o = as.h2o(data)
```

```
##   |                                                                              |
```

```r
h2o.fit1 <- h2o.gbm(
  x = x,
  y = y,
  training_frame = train.h2o,
  nfolds = 5,
  ntrees = 5000,
  stopping_rounds = 10,
  stopping_tolerance = 0,
  seed = 301471961
)
```

```
## Warning in .h2o.processResponseWarnings(res): early stopping is enabled but neither score_tree_inter

##   |                                                                              |
```

```r
h2o.fit1@parameters$ntrees # 41
```

```
## [1] 39
```

```r
h2o.rmse(h2o.fit1, xval = TRUE) # 1.278083
```

```
## [1] 1.278757
```

```r
split = h2o.splitFrame(train.h2o, ratios = 0.75)
train = split[[1]]
valid = split[[2]]

h2o.final <- h2o.gbm(
  x = x,
  y = y,
  training_frame = train.h2o,
  nfolds = 5,
  ntrees = 5000,
  learn_rate = 0.01,
  learn_rate_annealing = 1,
  max_depth = 1,
  min_rows = 1,
  sample_rate = 0.75,
  col_sample_rate = 1,
  stopping_rounds = 10,
  stopping_tolerance = 0,
  seed = 301471961
)
```

```
## Warning in .h2o.processResponseWarnings(res): early stopping is enabled but neither score_tree_inter
```

```
##   |                                                                              |
```

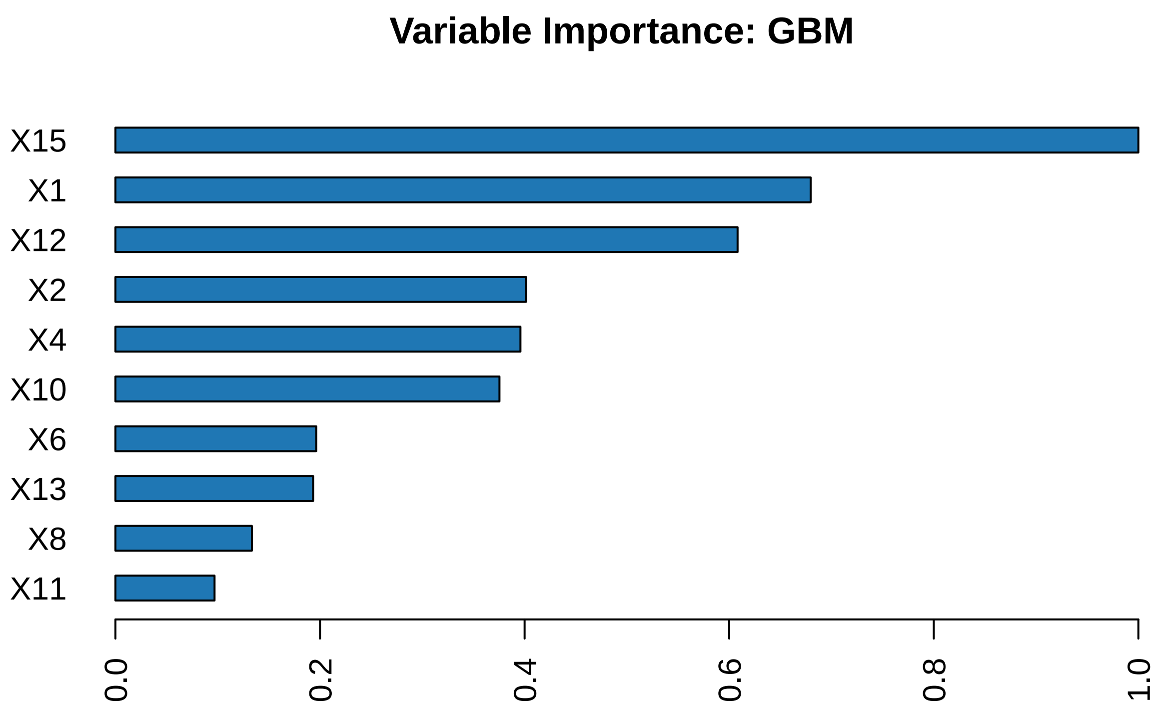
```
h2o.final@parameters$ntrees
```

```
## [1] 5000
```

```
h2o.rmse(h2o.final, xval = TRUE)
```

```
## [1] 1.294353
```

```
h2o.varimp_plot(h2o.final, num_of_features = 10)
```




```
# Validating model
test.h2o <- as.h2o(model_test_data)
```

```
##   |                                                                              |
```

```
h2o.performance(model = h2o.final, newdata = test.h2o)
```

```
## H2ORegressionMetrics: gbm
##
## MSE:  3.20338
## RMSE:  1.789799
## MAE:  1.506297
## RMSLE:  0.1345529
## Mean Residual Deviance :  3.20338
```

```
h2o.predict(h2o.final, newdata = test.h2o)
```

```
##   |                                                                              |

##    predict
## 1 12.71176
## 2 10.61467
## 3 12.84556
## 4 13.57291
## 5 13.08423
## 6 12.92769
##
## [10 rows x 1 column]
```

```
pred.h2o = predict(h2o.final, test.h2o)
```

```
##   |                                                                              |
```

```
test_acc = get.MSPE(model_test_data$Y,pred.h2o) # 1.10928


# Getting prediction for test_data
test.h2o <- as.h2o(test_data)
```

```
##   |                                                                              |
```

```
h2o.performance(model = h2o.final, newdata = test.h2o)
```

```
## [1] "WARNING: Model metrics cannot be calculated and metric_json is empty due to the absence of the 

## NULL
```

```
h2o.predict(h2o.final, newdata = test.h2o)
```

```
##   |                                                                              |

##    predict
## 1 12.11686
## 2 13.00003
## 3 13.12212
## 4 13.75701
## 5 12.61131
## 6 12.81275
##
## [3000 rows x 1 column]
```

```r
predictions = predict(h2o.final, test.h2o)
```

```
##   |                                                                              |
```

```r
h2o.exportFile(predictions, path = "test.csv")
```

```
##   |                                                                              |
```