hw5.R

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```
# import packages
library(GGally)

## Loading required package: ggplot2

## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2

library(caret)

## Loading required package: lattice

library(rpart.plot)

## Loading required package: rpart

library(gridExtra)
library(labelVector)
library(tidyverse)

## ── Attaching packages ──────────────────────────────────────────────── tidyverse 1.3.0 ──

## ✓ tibble  3.0.3     ✓ dplyr   1.0.2
## ✓ tidyr   1.1.0     ✓ stringr 1.4.0
## ✓ readr   1.3.1     ✓ forcats 0.5.0
## ✓ purrr   0.3.4

## ── Conflicts ─────────────────────────────────────────────────── tidyverse_conflicts() ──
## x dplyr::combine() masks gridExtra::combine()
## x dplyr::filter()  masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## x purrr::lift()    masks caret::lift()

# Analysis
# Processing and Visualizing data
# a) Load the data. Get a summary of the data, report it. Use ggplot to plot
a histogram for the distribution of the number of bike-rides.
```

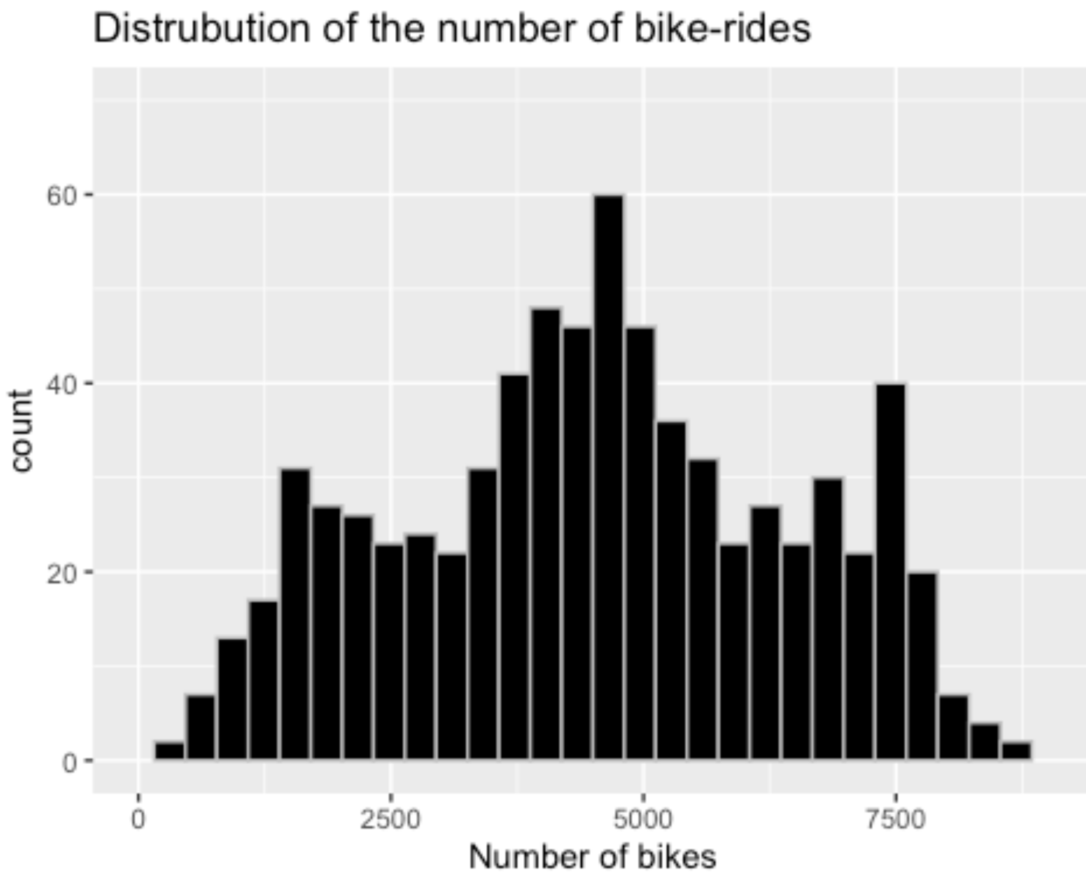
```r
df <- read.csv("bike_day.csv")
summary(df)
```

```
##     cnt_bike        atemp             hum          windspeed          temp
##  Min.   :  22   Min.   : 3.95   Min.   : 0.00   Min.   : 1.50   Min.   :
2.42
##  1st Qu.:3152   1st Qu.:16.89   1st Qu.:52.00   1st Qu.: 9.04   1st
Qu.:13.82
##  Median :4548   Median :24.34   Median :62.67   Median :12.13   Median
:20.43
##  Mean   :4504   Mean   :23.72   Mean   :62.79   Mean   :12.76   Mean
:20.31
##  3rd Qu.:5956   3rd Qu.:30.43   3rd Qu.:73.02   3rd Qu.:15.62   3rd
Qu.:26.88
##  Max.   :8714   Max.   :42.04   Max.   :97.25   Max.   :34.00   Max.
:35.33
##     holiday          workingday
##  Min.   :0.00000   Min.   :0.000
##  1st Qu.:0.00000   1st Qu.:0.000
##  Median :0.00000   Median :1.000
##  Mean   :0.02873   Mean   :0.684
##  3rd Qu.:0.00000   3rd Qu.:1.000
##  Max.   :1.00000   Max.   :1.000
```

```r
# histogram
ggplot(data = df, aes(cnt_bike)) +
  xlim(0, 9000) +
  ylim(0, 70) +
  geom_histogram(colour = "grey", fill = "black") +
  ggtitle("Distrubution of the number of bike-rides") +
  labs(x = "Number of bikes")
```

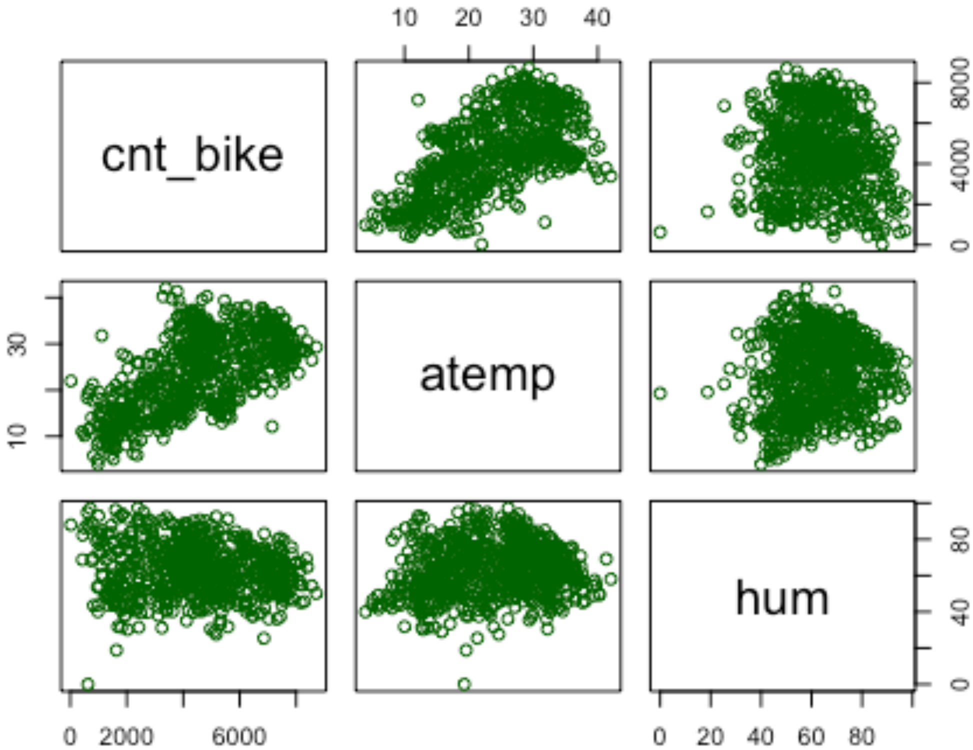
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
# The highest cnt is 8714 and the lowest is 22. It has the most count
# around the center of the graph (3750 - 6000). Also the highest count
# is around 60 and most counts are less than 40.

# b) Use the function pairs() to produce a plot of the relationships among
count, atemp and hum.
pairs(df[,1:3], col = "darkgreen")
```




```
# bike count (cnt_bike) and atemp seems to have a positive relationship,
while atemp and hum, and cnt_bike and hum do not have relationship


# c) (0.2) Split the data into 80% training and 20% testing.
trainRows <- createDataPartition(y = df$cnt_bike, p = 0.8, list = FALSE)
train_set <- df[trainRows,]
test_set <- df[-trainRows,]

# Train a K-NN model
# a) Decide whether you need to standardize the data or not
# A. Yes. We need to standardize the data in K-NN.
# We will standardize all the attributes besides cnt_bike because that is our
y-value.

train_set_stand <- train_set
test_set_stand <- test_set
library(standardize)

##
##  ***********************************************************
##             Loading standardize package version 0.2.2
```

```
##      Call standardize.news() to see new features/changes
##  ***********************************************************

#Apply the standardization
train_set_stand[,2:7] <- apply(train_set_stand[,2:7], MARGIN = 2, FUN =
scale)
test_set_stand[,2:7]<- apply(test_set_stand[,2:7], MARGIN = 2, FUN = scale)


# b) Train a k-NN model on the appropriate attributes.

knn_model <- train(cnt_bike~., train_set_stand, method = "knn")
knn_model

## k-Nearest Neighbors
##
## 587 samples
##   6 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 587, 587, 587, 587, 587, 587, ...
## Resampling results across tuning parameters:
##
##   k  RMSE      Rsquared   MAE
##   5  1415.673  0.4864054  1155.578
##   7  1385.400  0.5029210  1141.224
##   9  1365.367  0.5158304  1135.913
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 9.

# The algorithm used k = 5, 7, 9

# c) Get the predictions from k-NN model
knnPred <- predict(knn_model, test_set_stand)
# create a histogram of the distribution of bike rides
h_pred_knn <- ggplot(data= test_set_stand, aes(x = knnPred)) +
  xlim(0, 9000) +
  ylim(0, 18) +
  geom_histogram(colour = "lightblue", fill = "darkblue") +
  ggtitle("KNN, Distribution of Predicted bike rides") +
  labs(x = "Predicted bike rides")

bike_dist<- ggplot(data=test_set_stand, aes(x = cnt_bike)) +
  geom_histogram(colour = "grey", fill = "black") +
  xlim (0,9000) +
  ylim (0,18) +
  ggtitle("Original Bike Distribution") +
  labs(x = "Bike rides")
```

```r
grid.arrange(bike_dist, h_pred_knn, nrow=1)

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 2 rows containing missing values (geom_bar).

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

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```
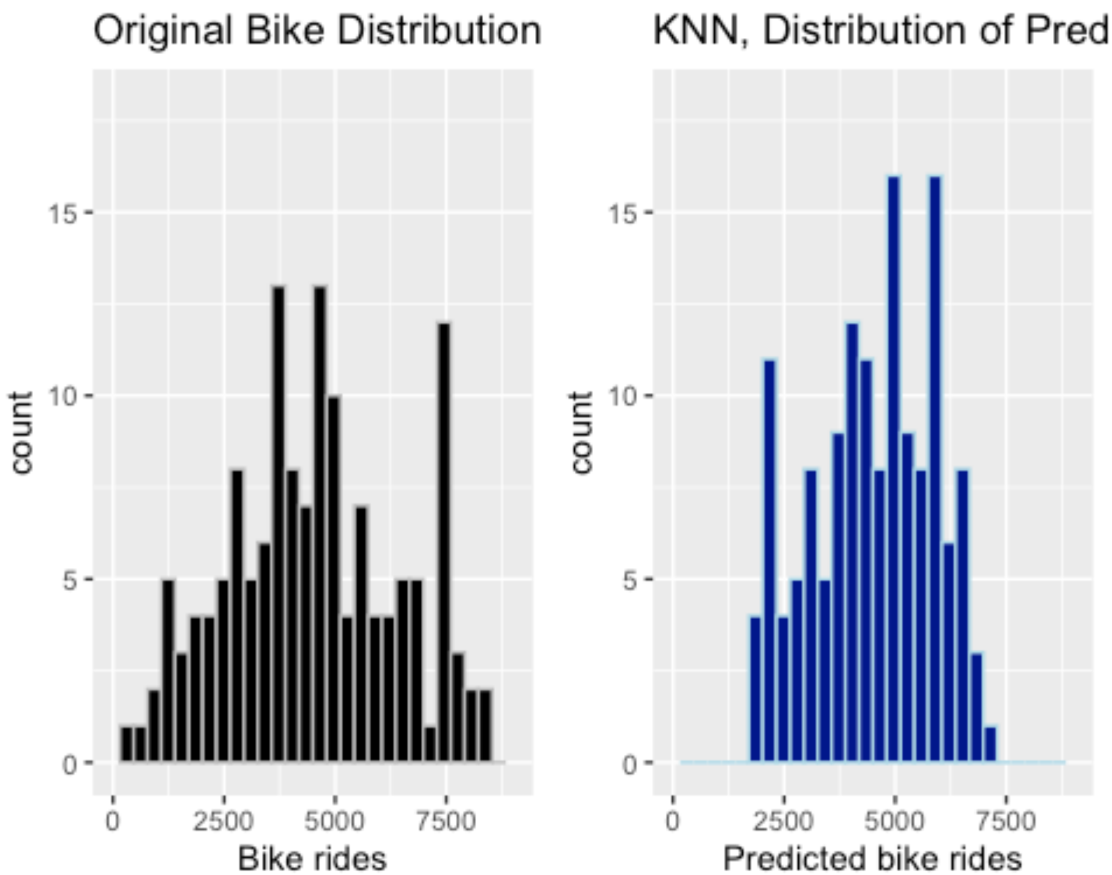
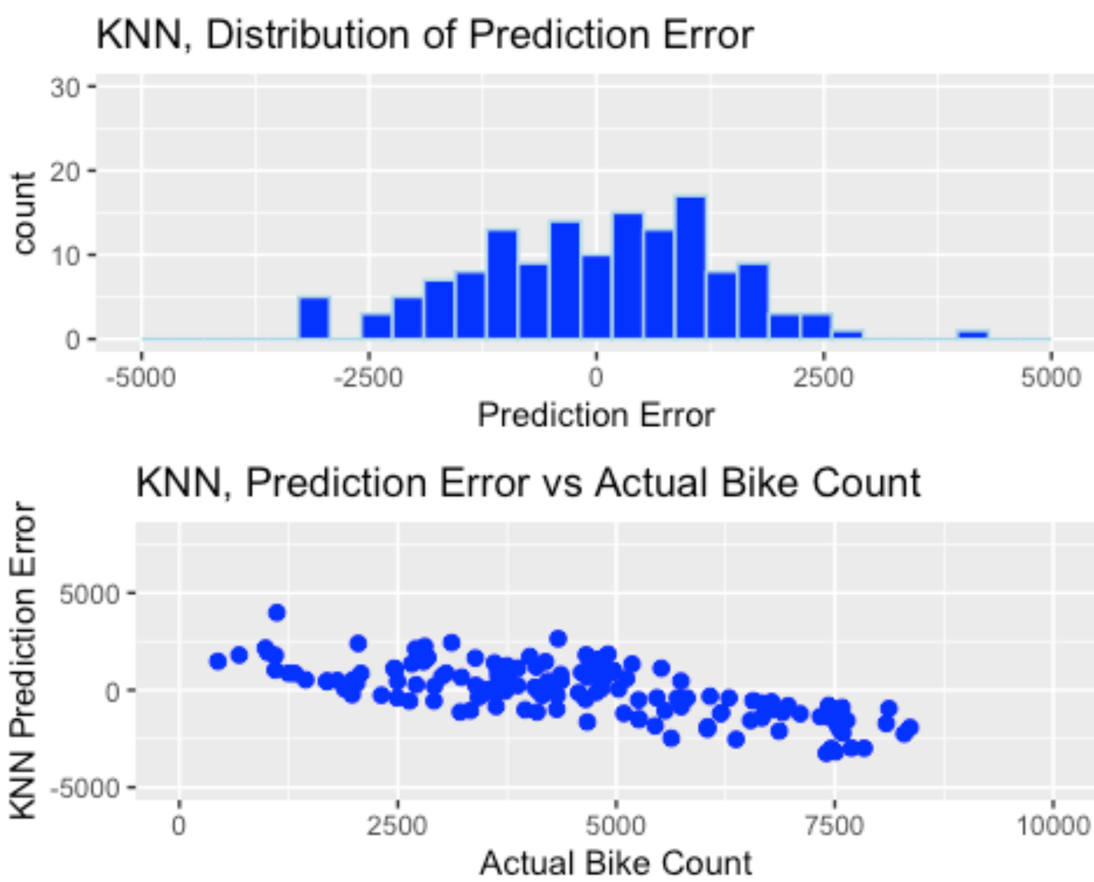



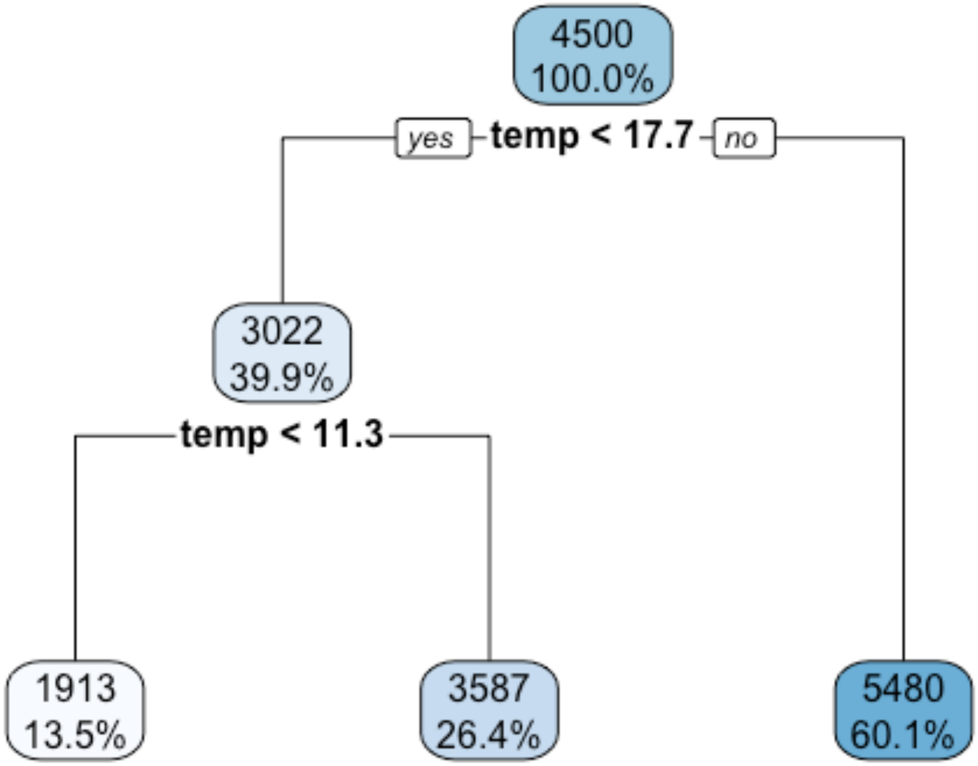

```r
# I think the performance of K-NN is OK. Even though each counts are not
# the same, the shape of overall graph looks kind of similar.

#d) Computer the prediction error for the k-NN model
# create ggolit histrogram for the error
knn_error <-knnPred - test_set_stand$cnt_bike

#Visualize the prediction error
#Histogram of the distribution of the prediction error
h_error_knn = ggplot(data= test_set_stand, aes(x = knn_error)) +
  geom_histogram(colour = "lightblue", fill = "blue") +
  xlim (-5000, 5000) +
  ylim (0, 30) +
```

```
  ggtitle("KNN, Distribution of Prediction Error") +
  labs(x = "Prediction Error")


#Plot prediction error vs actual price
p_error_knn<- ggplot(data = test_set_stand, aes(x=cnt_bike, y=knn_error)) +
  geom_point(size=2, color = "blue") +
  ylim (-5000, 8000) +
  xlim (0, 10000) +
  ggtitle("KNN, Prediction Error vs Actual Bike Count") +
  labs(x = "Actual Bike Count", y = "KNN Prediction Error")

grid.arrange(h_error_knn, p_error_knn)

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

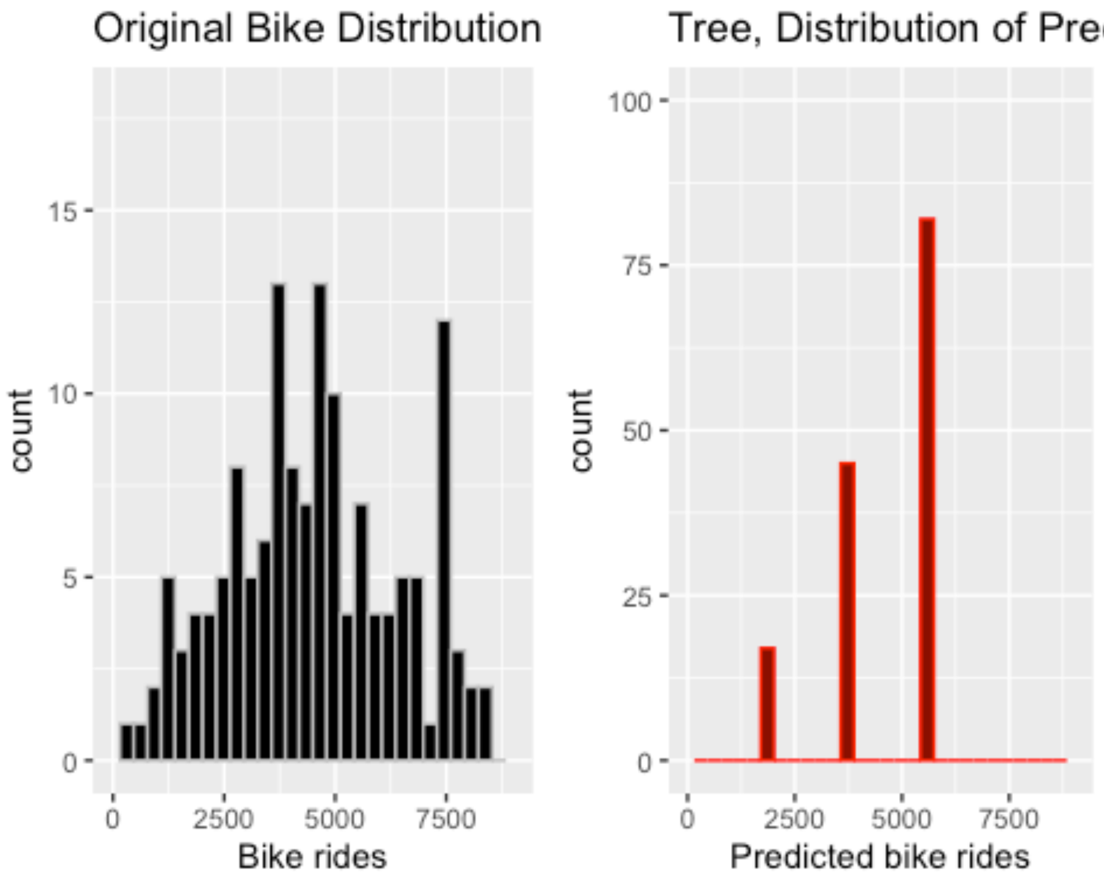



```
# It seems like there are more negative errors by looking at
# the distribution of Prediction Error. Also, KNN have more positive
# error when the actual bike count is < 5000 and negative error when
# actual bike count is > 5000
# We could say K-NN is under-predicting.

#e)
```

```r
knnME <- mean(knn_error)
knnME

## [1] -20.2392

knnRMSE<- RMSE(pred = knnPred, obs = test_set_stand$cnt_bike)
knnRMSE

## [1] 1359.406

# ME of -20 tells us that on average we are under-predicting by about 20.
# RMSE of 1359 tells us that on average our prediction is off by 1359 bike
counts

# Train a Regression Tree
#f) Decide whether to standardize.
# No. We do not have to standarize the data in regression tree.

#g) Train a regression tree
rtree <- train(cnt_bike~., train_set, method = "rpart")

## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
trainInfo, :
## There were missing values in resampled performance measures.

rtree

## CART
##
## 587 samples
##   6 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 587, 587, 587, 587, 587, 587, ...
## Resampling results across tuning parameters:
##
##   cp          RMSE      Rsquared   MAE
##   0.05290532  1480.938  0.4183129  1233.859
##   0.06659281  1512.564  0.3928347  1267.285
##   0.38629891  1703.105  0.3450741  1419.709
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was cp = 0.05290532.

# Plot the final tree
rpart.plot(rtree$finalModel, digits=-3)
```

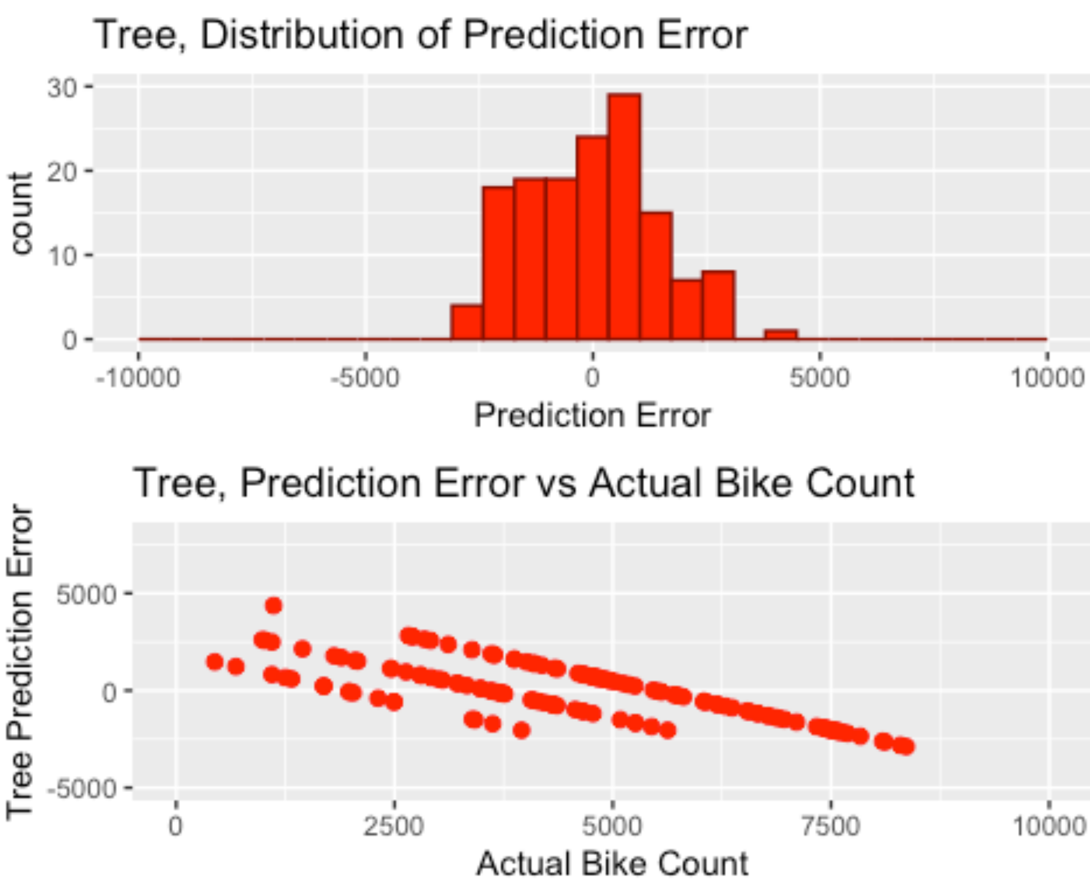



```
# The algorithm picked temp < 17.7, temp < 11.3 for the attributes.

# h) Get the predictions from the regression tree and use ggplot
# to create a histogram of the distribution of the predicted bike rides
# compare it to the histogram of the true count
treePred <- predict(rtree, test_set)
h_pred_tree<- ggplot(data= test_set, aes(x = treePred)) +
  geom_histogram(colour = "red", fill = "darkred") +
  xlim (0,9000) +
  ylim (0, 100) +
  ggtitle("Tree, Distribution of Predictions") +
  labs(x = "Predicted bike rides")

#compare to the actual price distribution we created above
grid.arrange(bike_dist,h_pred_tree, nrow=1)

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 2 rows containing missing values (geom_bar).

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
# Regression tree only produced three bars in the graph.
# Just by looking at the graph, regression tree does not seem to be
performing well because it only has three bars while the original one has a
lot. It does not capture all the details.

# i) Compute the prediction error for the regression tree and
# create a ggplot histogram for the prediction error

# Prediction error
tree_error <-treePred - test_set$cnt_bike
h_error_tree<- ggplot(data= test_set, aes(x = tree_error)) +
  geom_histogram(colour = "darkred", fill = "red") +
  xlim (-10000, 10000) +
  ylim (0, 30) +
  ggtitle("Tree, Distribution of Prediction Error") +
  labs(x = "Prediction Error")

#Plot prediction error vs actual price
p_error_tree<- ggplot(data = test_set, aes(x=cnt_bike, y=tree_error)) +
  geom_point(size=2, color = "red") +
  ylim (-5000, 8000) +
  xlim (0, 10000) +
  ggtitle("Tree, Prediction Error vs Actual Bike Count") +
```

```r
  labs(x = "Actual Bike Count", y = "Tree Prediction Error")

grid.arrange(h_error_tree, p_error_tree)

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

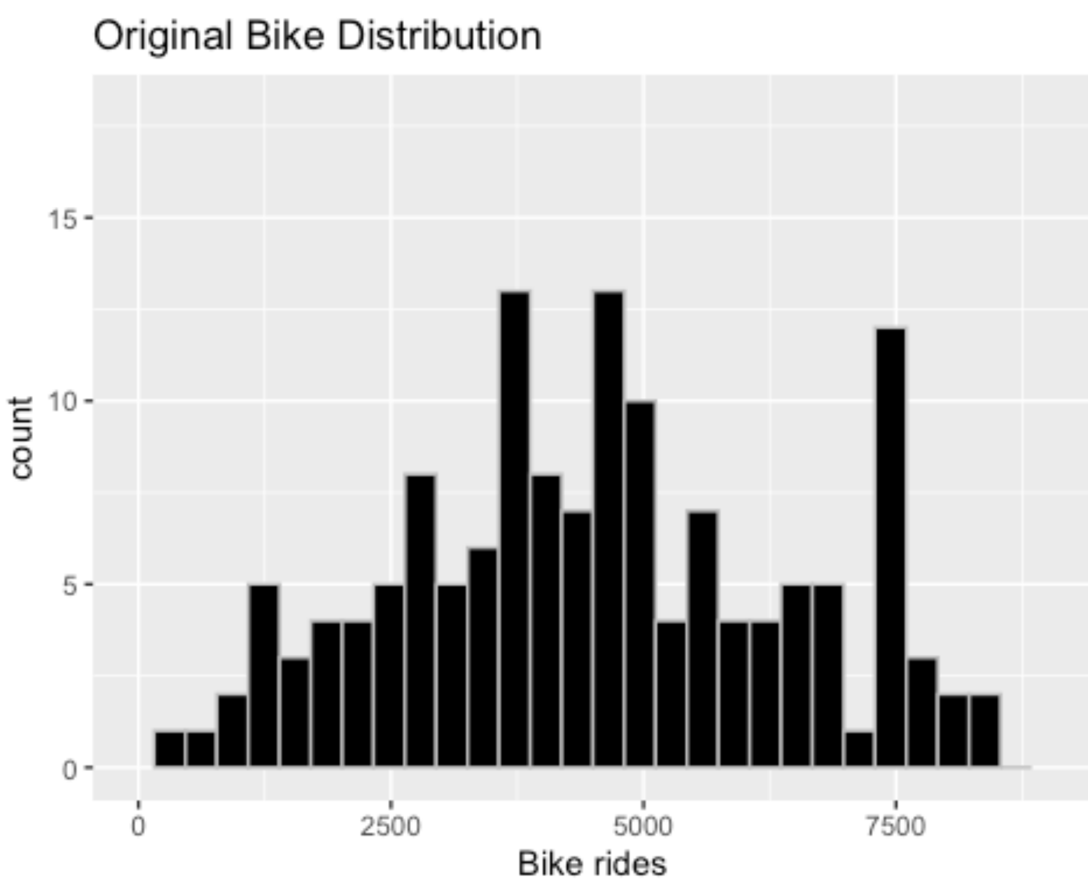



```r
# The distribution of Prediction Error looks like there might be a little
more error on the left side.
# It is interesting how we could draw three lines in this scatter plot, and
those would represent the three bars in “Distribution of prediction” graph. I
think the algorithm is doing a good job not over-Estimating nor under-
estimating too much.

# i,b) Compute the ME and RMSE for the regression tree
ME_tree <- mean(tree_error)
treeRMSE <- RMSE(pred = treePred, obs = test_set$cnt_bike)
ME_tree

## [1] -53.61088

treeRMSE

## [1] 1435.095
```

```
# ME of -53 means that on average RegressionTree under predicts
# by 53

# RMSE of 1435 meants that on average RegressionTree's prediction
# is off by 1435 bike counts




# Train a Linear Regression
#a) Decide whether you need to standardize the data
A. No. I do not have to use standardized data in Linear Regression

#b) Check and comment on whether using the attributes used for the
prediction.
bike_dist
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```



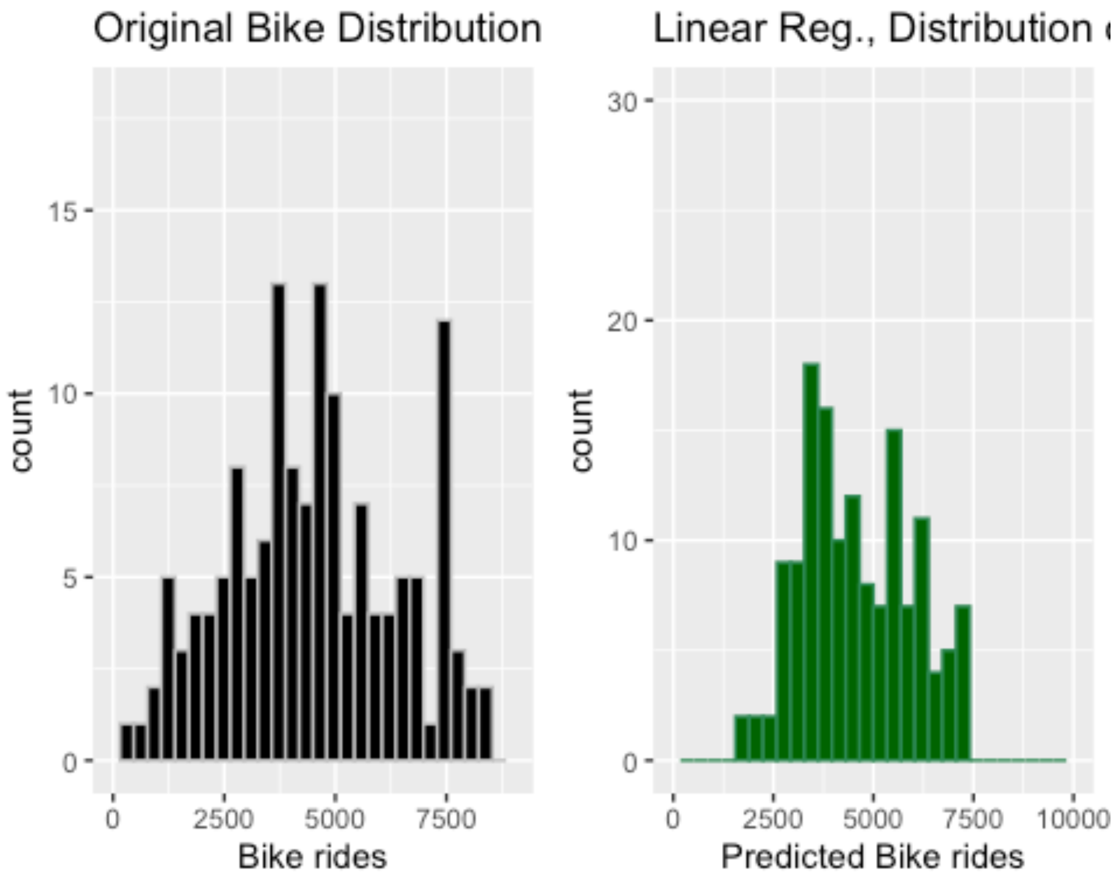

```
# A. Yes. There are some outliers, but it is somewhat normally distributed
```

```
#c) Create a correlation matrix using the attributes used for the prediction,
cor(df[,c(2:7)])

##                  atemp         hum    windspeed        temp      holiday
## atemp       1.00000000  0.14000432 -0.183668766  0.99169797 -0.032502593
## hum         0.14000432  1.00000000 -0.248509797  0.12695001 -0.015927598
## windspeed  -0.18366877 -0.24850980  1.000000000 -0.15792514  0.006288675
## temp        0.99169797  0.12695001 -0.157925143  1.00000000 -0.028556898
## holiday    -0.03250259 -0.01592760  0.006288675 -0.02855690  1.000000000
## workingday  0.05215699  0.02432579 -0.018791911  0.05267624 -0.253022700
##             workingday
## atemp       0.05215699
## hum         0.02432579
## windspeed  -0.01879191
## temp        0.05267624
## holiday    -0.25302270
## workingday  1.00000000

# I will exclude atemp from the attributes because it is highly correlated
# with temp (0.99169).
train_set_lr <- train_set %>% select(1:1, 3:7)
test_set_lr <- test_set %>% select(1:1, 3:7)

# d) Train a linear regression model
lin_reg <- train(cnt_bike~., train_set_lr, method = "lm")
lin_reg

## Linear Regression
##
## 587 samples
##   5 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 587, 587, 587, 587, 587, 587, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   1437.873  0.4553024  1184.21
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

#Summarize final model
fit <- lin_reg$finalModel
options(scipen = 999) #this is to avoid scientific notation
summary(fit)

##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4917.8 -1075.7   -96.7  1070.7  3635.1
##
## Coefficients:
##             Estimate Std. Error t value             Pr(>|t|)
## (Intercept) 4053.062    392.155  10.335 < 0.0000000000000002 ***
## hum          -32.192      4.338  -7.422    0.000000000000413 ***
## windspeed    -67.318     11.863  -5.674    0.000000021967255 ***
## temp         163.722      8.058  20.318 < 0.0000000000000002 ***
## holiday     -727.827    371.818  -1.957               0.0508 .
## workingday    57.799    129.667   0.446               0.6559
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1420 on 581 degrees of freedom
## Multiple R-squared:  0.4681, Adjusted R-squared:  0.4636
## F-statistic: 102.3 on 5 and 581 DF,  p-value: < 0.00000000000000022
```

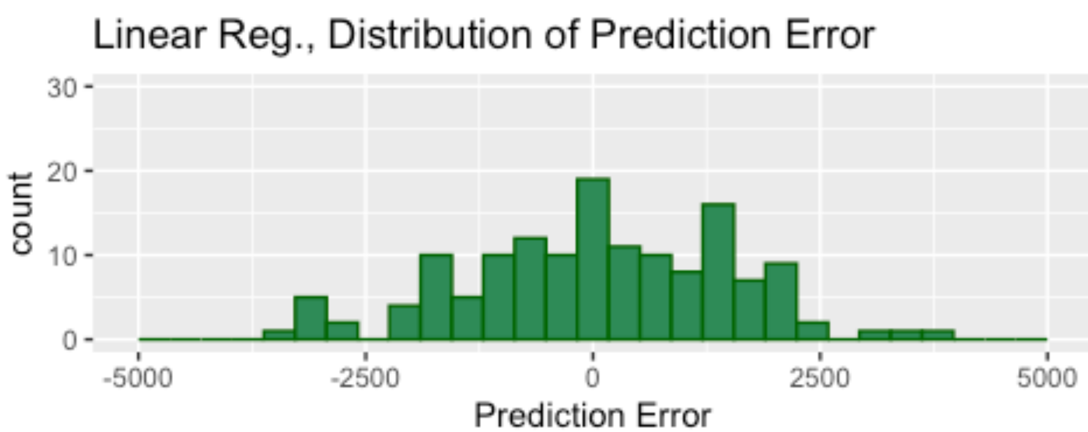
```r
# j) Get the predictions from the linear regression model and
# use ggplot to create a histogram of the distribution of the predicted
# bike rides

lin_pred <- predict(lin_reg, newdata = test_set_lr)

#Visualize the predictions
#Create a histogram for the distribution of predicted prices
h_pred_lm <- ggplot(data= test_set_lr, aes(x = lin_pred)) +
  geom_histogram(colour = "seagreen", fill = "darkgreen") +
  xlim (0,10000) +
  ylim (0, 30) +
  ggtitle("Linear Reg., Distribution of Predictions") +
  labs(x = "Predicted Bike rides")

#compare to the actual price distribution
grid.arrange(bike_dist, h_pred_lm, nrow = 1)
```

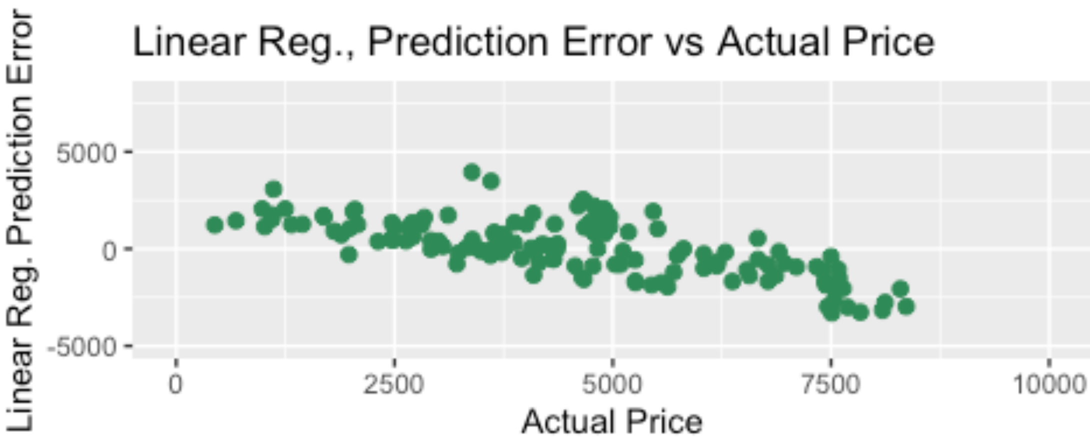
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 2 rows containing missing values (geom_bar).

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
# By looking at the graph it seems like linear regression
# model is doing a good job because the graph has similar
# overall shape. But it does not capture all the details.

#k) Compute the prediction error for the linear regression model and create
# a ggplot histogram for the distribute of the prediction error
#Compute Prediction error
lm_error <- lin_pred - test_set_lr$cnt_bike
#Visualize the prediction error
#Histogram of the distribution of prediction errors
h_error_lm <- ggplot(data= test_set_lr, aes(x = lm_error)) +
  geom_histogram(colour = "darkgreen", fill = "seagreen") +
  xlim (-5000, 5000) +
  ylim (0, 30) +
  ggtitle("Linear Reg., Distribution of Prediction Error") +
  labs(x = "Prediction Error")

#Plot of the Prediction Error vs Actual Price
p_error_lm<- ggplot(data = test_set_lr, aes(x=cnt_bike, y=lm_error)) +
  geom_point(size=2, color = "seagreen") +
  ylim (-5000, 8000) +
  xlim (0, 10000) +
  ggtitle("Linear Reg., Prediction Error vs Actual Price") +
```

```
  labs(x = "Actual Price", y = "Linear Reg. Prediction Error")

grid.arrange(h_error_lm, p_error_lm)

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```






```
# By looking at these two graphs we can say that linear
# regression is doing a good job not over predicting nor
# under-predicting.
# Also the model tends to over predict when actual price is < 5000 and under-
predict when actual price is > 5000.
#e)
ME_lin <- mean(lm_error)
#RMSE
lin_RMSE <- RMSE(pred = lin_pred, obs = test_set_lr$cnt_bike)
ME_lin

## [1] 61.8804

lin_RMSE

## [1] 1440.201
```

```r
# ME of 61 means that on average Linear Regression model is
# underpredicting by 61.
# RMSE of 1440 means that on average the model is off by
# 1440 bike counts
######
# Product Insights
#Put together the error metrics

error_table <- c(knnME, knnRMSE, ME_tree, treeRMSE, ME_lin, lin_RMSE)
names(error_table) <- c("KNN ME", "KNN RMSE", "TREE ME", "TREE RMSE", "LR
ME", "LR RMSE")
error_table <- set_label(error_table, "Error table")
error_table

## Error table
##      KNN ME   KNN RMSE    TREE ME  TREE RMSE      LR ME    LR RMSE
##   -20.23920 1359.40552  -53.61088 1435.09505   61.88040 1440.20087

# Report the histogram for the distribution of the prediction errors
grid.arrange(h_error_knn,h_error_tree,h_error_lm, nrow = 1)

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

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```

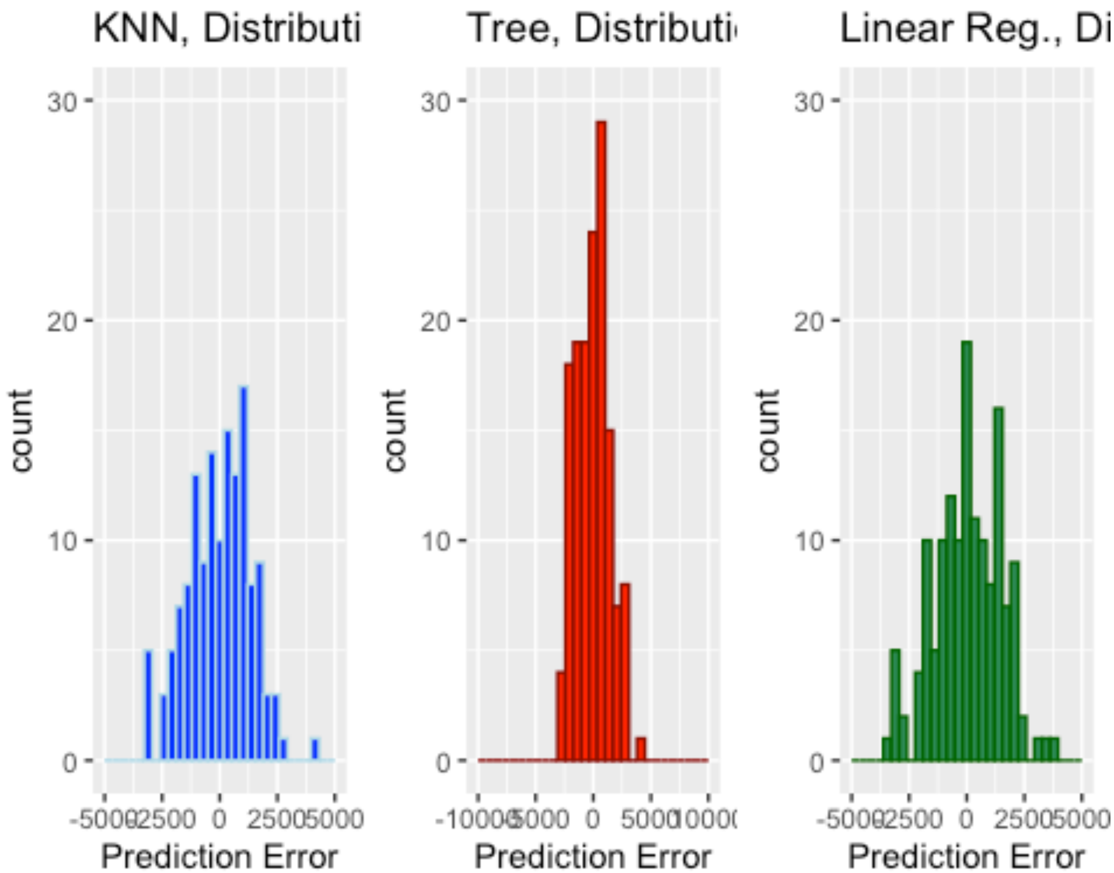

 # I would suggest the company to implement the K-NN model. This is because the K-NN model has lowest abs (ME) and lowest RMSE. This means K-NN model did the best job not overpredicting nor underpredicting as well as minimizing the overall error. I would not suggest the company to use Regression Tree model and Linear Regression model because ME and RMSE are higher than K-NN's ME and RMSE.

Also in the histogram, Regression tree has higher Prediction Error count because the model only has 3 values to return. We could see that from Regression Tree's distribution of prediction.

K-NN might did a better job than Regression Tree and Linear Regression because the data points were pretty close to each other and there weren't that many outliers.