Predicting Weeekly Sales from Store Features

Data Science: Capstone Project

Aditya Prasad Dash

Introduction

Understanding the structure and patterns in the data, developing data structures for effectively storing and visualizing it, and using insights from it to predict the target variable of interest from values of other variables is the realm of data science. In this project, I have used the Walmart dataset form kaggle [1] to predict the weekly sales of a store based on the various features of the store and the environment affecting the sales. In the first step, as the Weekly_Sales has numerical values, a linear regression model was trained to predict the Weekly_Sales from the other features. Then, a k-Nearest neighbors model was trained over the dataset for this regression task and the best value of k was found after evaluating the model performance for different k. Then, as sometimes it is more useful to understand if a given set of conditions would produce a high or low weekly_sales, the Weekly_Sales column was categorized into high, medium and low weekly sales and a knn model was trained to predict the class from the feature variables.

Methods

Reading, visualizing and preprocessing the data

The first step is to load the required libraries for the analysis[2,3].

```
if(!require(tidyverse)) install.packages("tidyverse")
library(tidyverse)
if(!require(tidyr)) install.packages("tidyr")
library(tidyr)
if(!require(caret)) install.packages("caret")
library(caret)
if(!require(stringr)) install.packages("stringr")
library(stringr)
if(!require(ggplot2)) install.packages("ggplot2")
library(ggplot2)
if(!require(lubridate)) install.packages("lubridate")
library(lubridate)
if(!require(corrplot)) install.packages("corrplot")
library(corrplot)
set.seed(1, sample.kind="Rounding")
```

I downloaded the dataset into my computer, therefore, I used the read.csv function in R to read the Walmart dataset and store it into a dataframe called walmart_dataset. The function str(walmart_dataset) displays information about the number of rows and columns of the dataset, the data type in each column and the first few entries of each column.

```
walmart_dataset <- read.csv("/Users/aditya/Documents/Coursework/Online_Courses/Machine_Learning_and_Deep
str(walmart_dataset)
```

```
## 'data.frame':    6435 obs. of  8 variables:
##  $ Store       : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Date        : chr  "05-02-2010" "12-02-2010" "19-02-2010" "26-02-2010" ...
##  $ Weekly_Sales: num  1643691 1641957 1611968 1409728 1554807 ...
##  $ Holiday_Flag: int  0 1 0 0 0 0 0 0 0 0 ...
##  $ Temperature : num  42.3 38.5 39.9 46.6 46.5 ...
##  $ Fuel_Price  : num  2.57 2.55 2.51 2.56 2.62 ...
##  $ CPI         : num  211 211 211 211 211 ...
##  $ Unemployment: num  8.11 8.11 8.11 8.11 8.11 ...
```

We notice that the dataset contains 6435 rows and 8 columns. As we want to predict Weekly_Sales from the other variables, I will refer to Weekly_Sales as the target variable and all other variables as feature variables. The data type of "Store" and "Holiday_Flag" is integer, that for "Date" is chr and that for "Weekly_Sales","Holiday_Flag","Temperature","Fuel_Price","CPI" and "Unemployment" is num.

The function head(dataset,n) displays the first n rows of the dataset, we can use it to visualize the entries of the first 5 rows of walmart_dataset.

```
head(walmart_dataset,5)
```

```
##   Store       Date Weekly_Sales Holiday_Flag Temperature Fuel_Price      CPI
## 1     1 05-02-2010      1643691            0       42.31      2.572 211.0964
## 2     1 12-02-2010      1641957            1       38.51      2.548 211.2422
## 3     1 19-02-2010      1611968            0       39.93      2.514 211.2891
## 4     1 26-02-2010      1409728            0       46.63      2.561 211.3196
## 5     1 05-03-2010      1554807            0       46.50      2.625 211.3501
##   Unemployment
## 1        8.106
## 2        8.106
## 3        8.106
## 4        8.106
## 5        8.106
```

We first omit all the rows with nan with the function na.omit(dataset) function. Then we check the range of our target variable Weekly_Sales. As both minimum and maximum Weekly sales are positive, it seems reasonable. Next we look at the store column which has integer entries. To find the number of stores included in the dataset we can use the unique() function with argument walmart_dataset$Store to find the unique store numbers.

```
walmart_dataset<-na.omit(walmart_dataset)
range(walmart_dataset$Weekly_Sales)
```

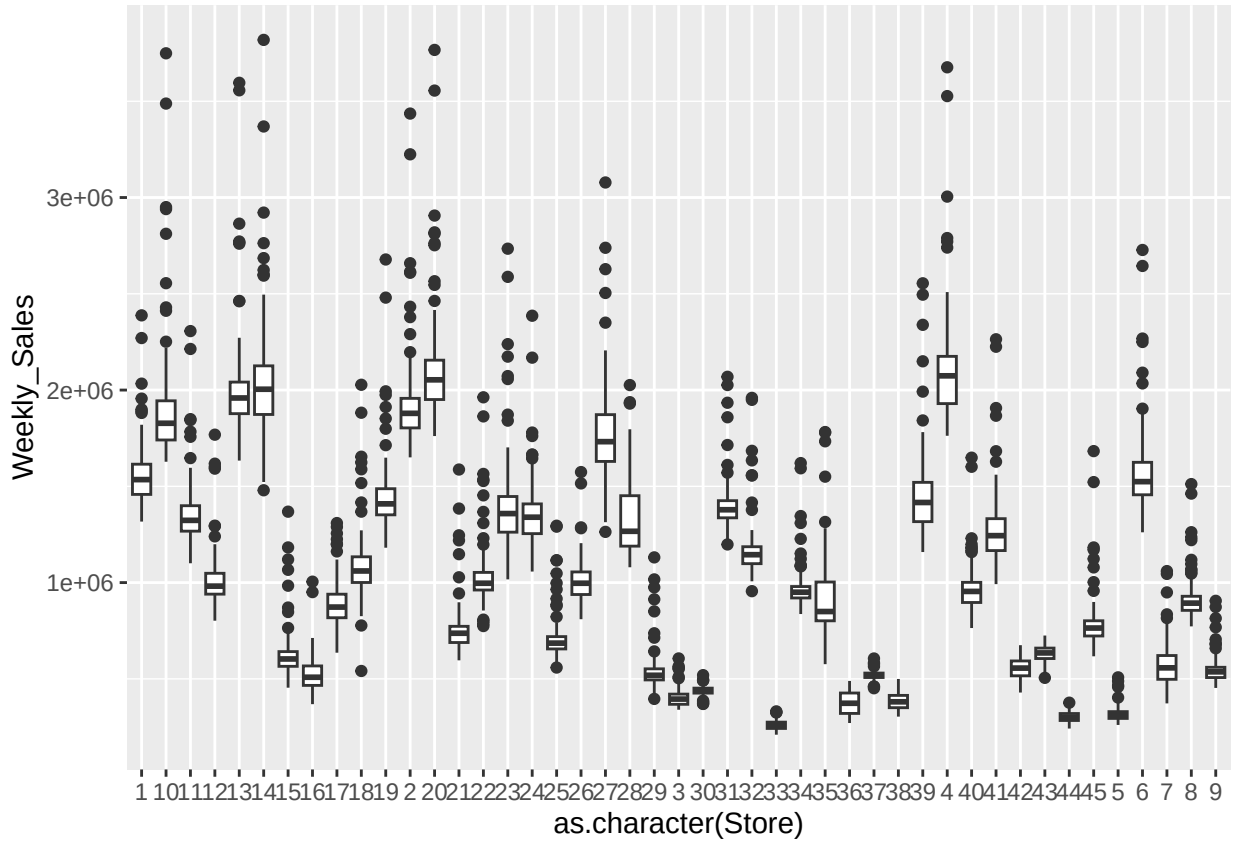
```
## [1]  209986.2 3818686.5
```

```
unique(walmart_dataset$Store)
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
## [26] 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45
```

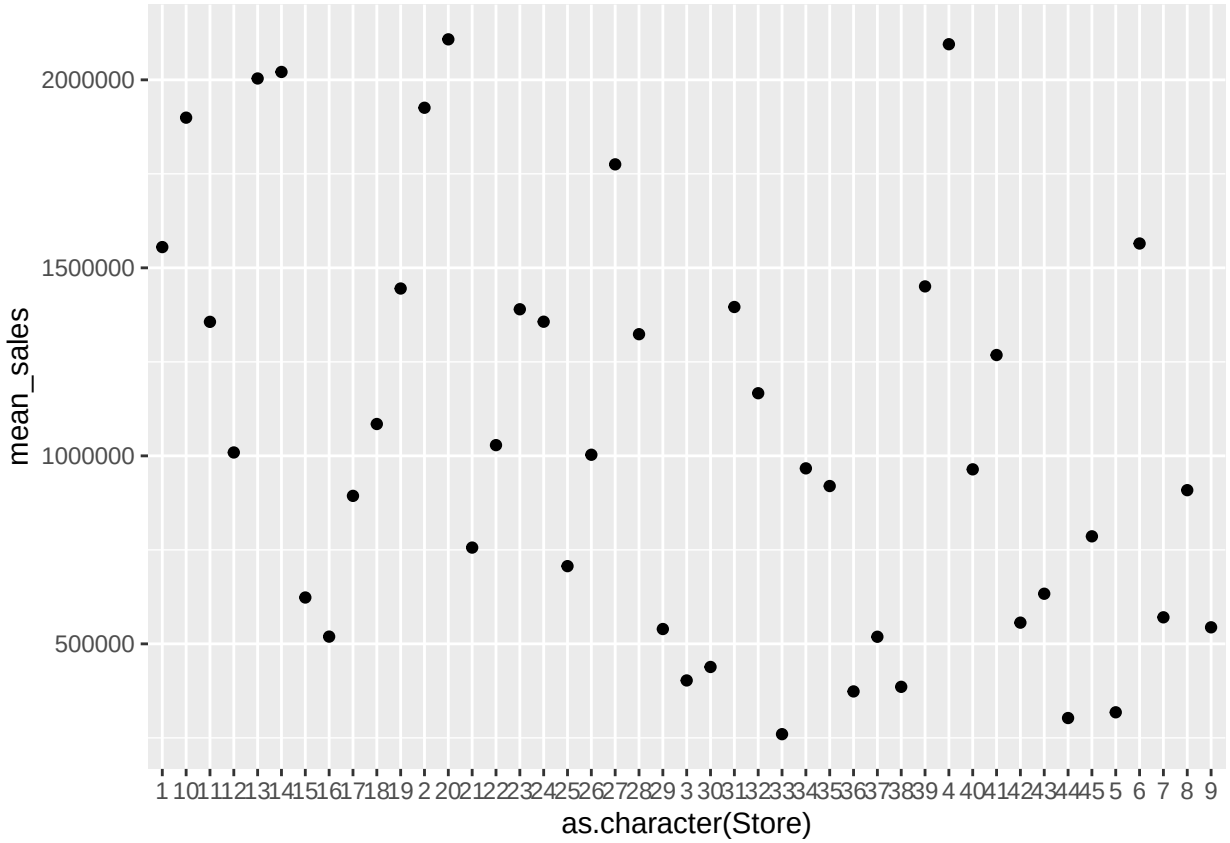
We can notice that there are 45 stores in the dataset with the store numbers ranging from 1 to 45. Some stores can have more sales than others due to location, total volume of products and other factors. Therefore, its useful to visualize the distribution of Weekly sales for different stores. For that, we can use a boxplot which displays the distribution of a numerical variable for each instance of a categorical variable.

```
walmart_dataset%>% ggplot(aes(as.character(Store), Weekly_Sales)) + geom_boxplot()
```



We see that for each store the weekly sales are distributed over a wide range. Moreover, the average (mean) weekly sales for a given store, shown by the central line in the boxplot is different accross different stores. To visualize the mean sales better, we can group the dataset by store numbers and then extract the mean sales for each store and store it in a tibble called mean_sales_store. Next, we can use ggplot and the geom_point function to make a scatterplot of mean scales as a function of the store number.

```
mean_sales_store<-walmart_dataset%>%group_by(Store)%>%summarise(mean_sales=mean(Weekly_Sales))
mean_sales_store %>% ggplot(aes(as.character(Store), mean_sales)) + geom_point()
```



We notice that the weekly sales are spread in each store and they have different averages for different stores, therefore it is useful to use this information in predicting weekly sales. As the store number should not have a heirarchy, we should use one-hot-encoding[4] to make separate columns for each store in which the entry for a row (observation) is 1 if the Store corresponds to that store and 0 otherwise. To do this, we can use the pivot wider function in R to separate the Store numbers into different columns and use length as a funcion to encode 1 if that observation is from that Store and 0 (values_fill is set to 0) otherwise and update the walmart_dataset.

```
walmart_dataset<-walmart_dataset%>% pivot_wider(names_from = Store, names_prefix="Store",values_from = S
```

Next we try to understand the date column. The format of the date in the dataset is day-month-year as a character. However, to extract meaningful insights from we should separate the month day and year into separate columns. To do this we can the dmy function in lubridate package to convert Date into the appropriate format and then mutate the dataset with the Day, Month and Year columns after extracting it from the Date variable. Displaying the first 5 entries using the head function shows that indeed we have created new columns corresponding to the day, month and year.

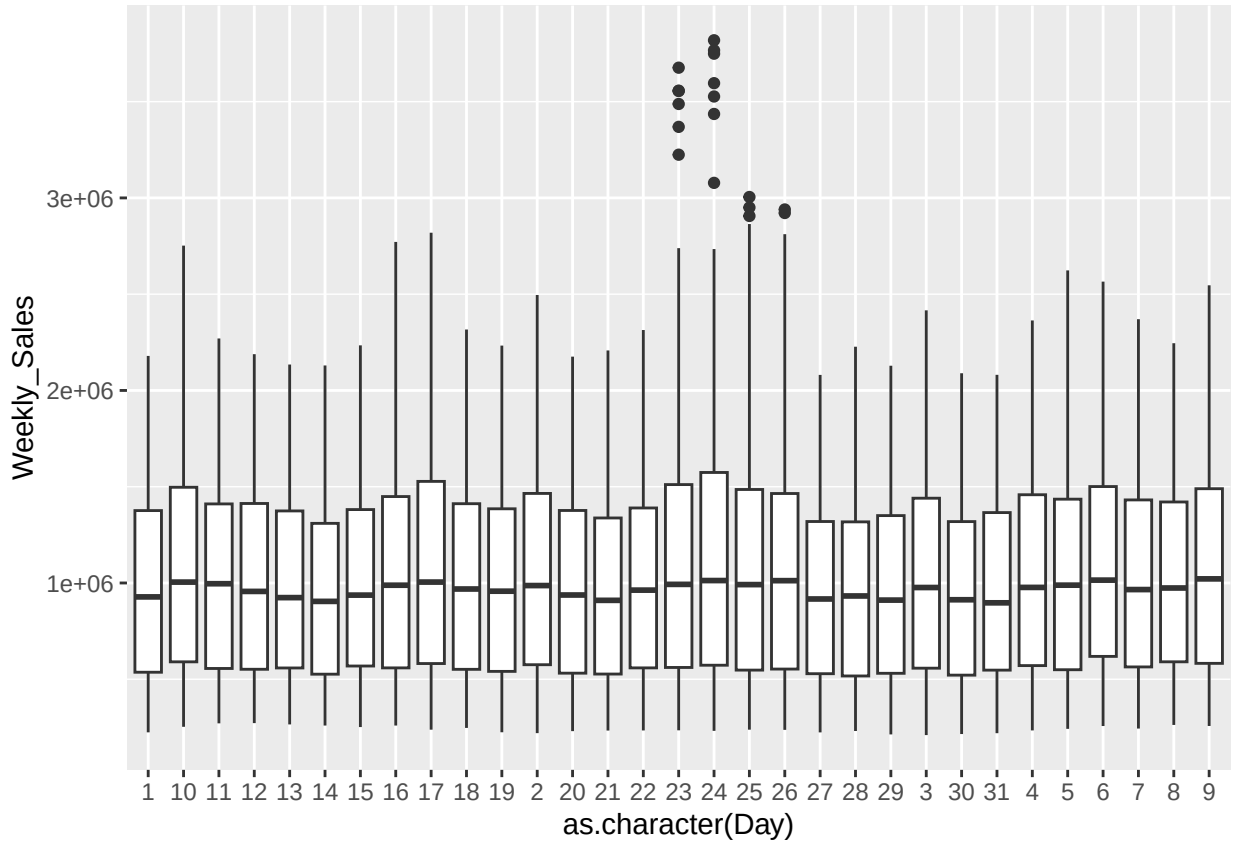
```
walmart_dataset<-walmart_dataset%>%mutate(Day=day(dmy(Date)),Month=month(dmy(Date)), Year=year(dmy(Date
head(walmart_dataset%>%select(c("Day","Month","Year")),5)
```

```
## # A tibble: 5 x 3
##     Day Month  Year
##   <int> <dbl> <dbl>
## 1     5     2  2010
## 2    12     2  2010
```

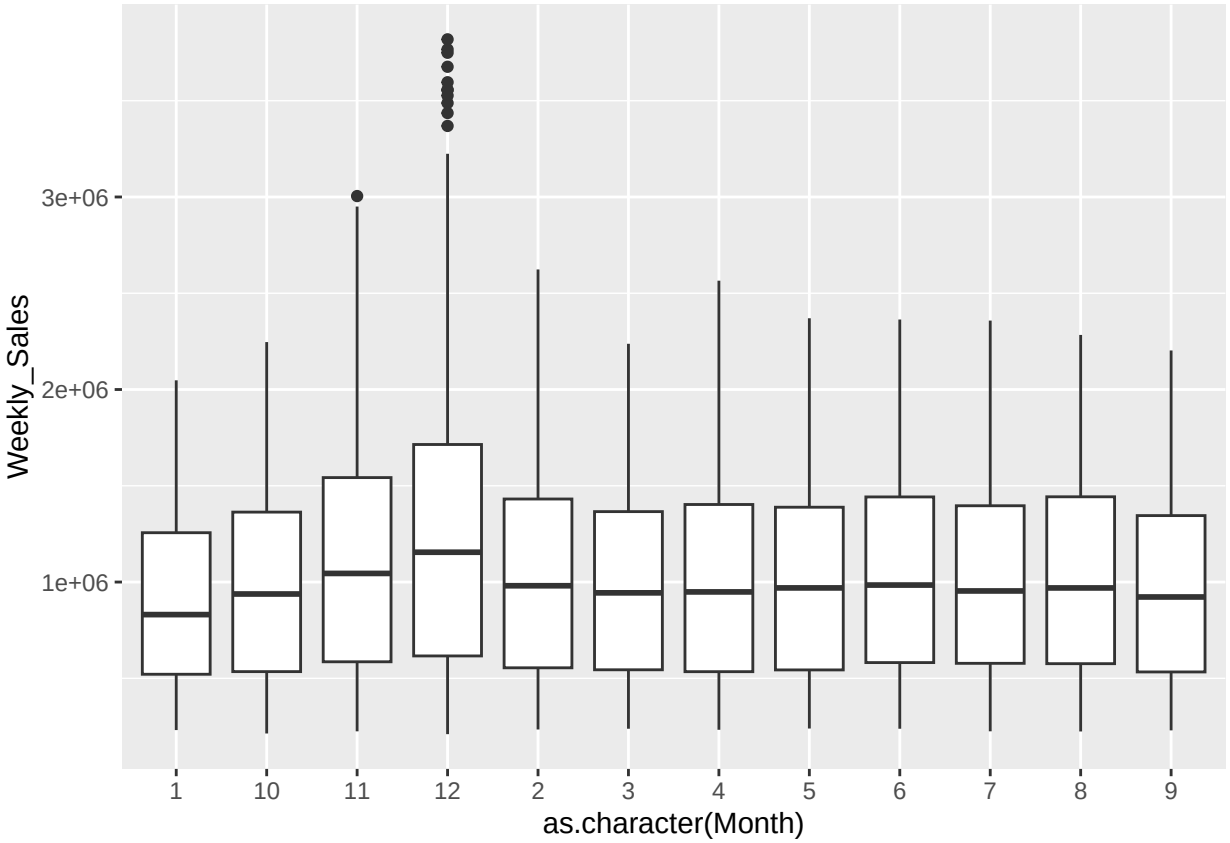
```
## 3     19      2  2010
## 4     26      2  2010
## 5      5      3  2010
```

Now, we try to visualize the distribution of weekly sales accross day, month and year by creating 3 different boxplots corresponding to each of them.

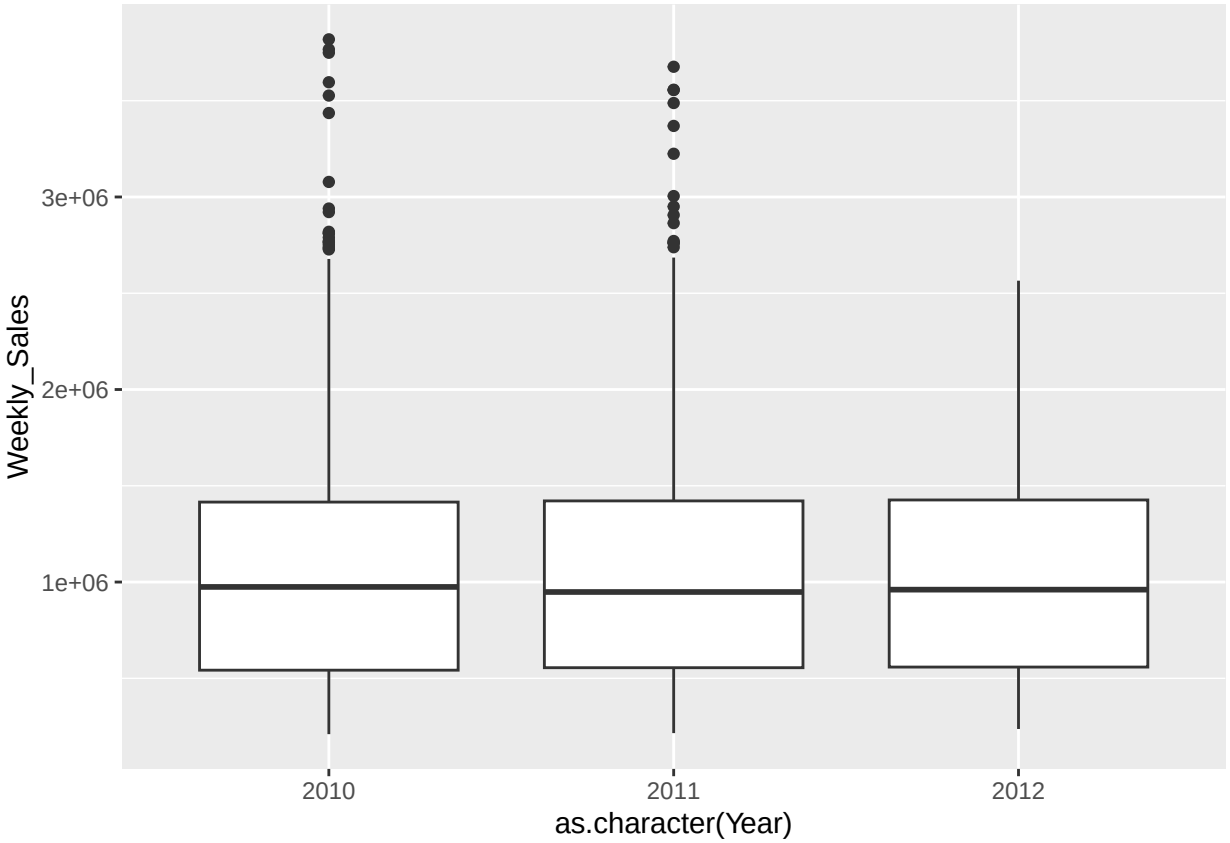
```
walmart_dataset%>% ggplot(aes(as.character(Day), Weekly_Sales)) + geom_boxplot()
```




```
walmart_dataset%>% ggplot(aes(as.character(Month), Weekly_Sales)) + geom_boxplot()
```

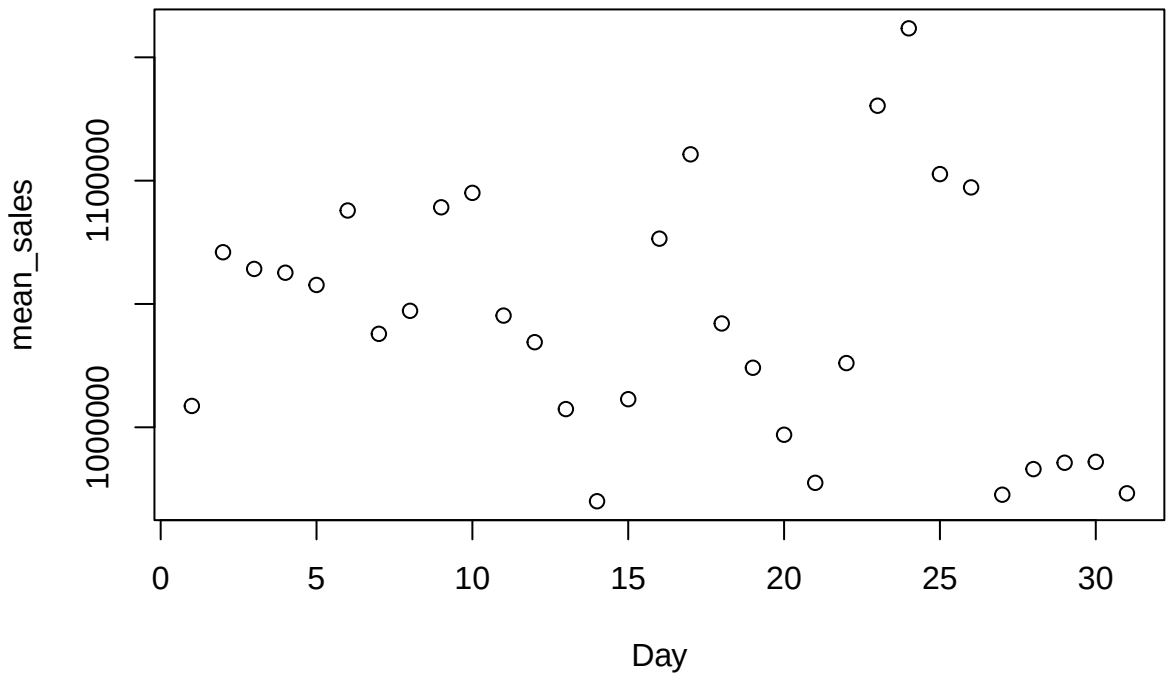



```
walmart_dataset%>% ggplot(aes(as.character(Year), Weekly_Sales)) + geom_boxplot()
```

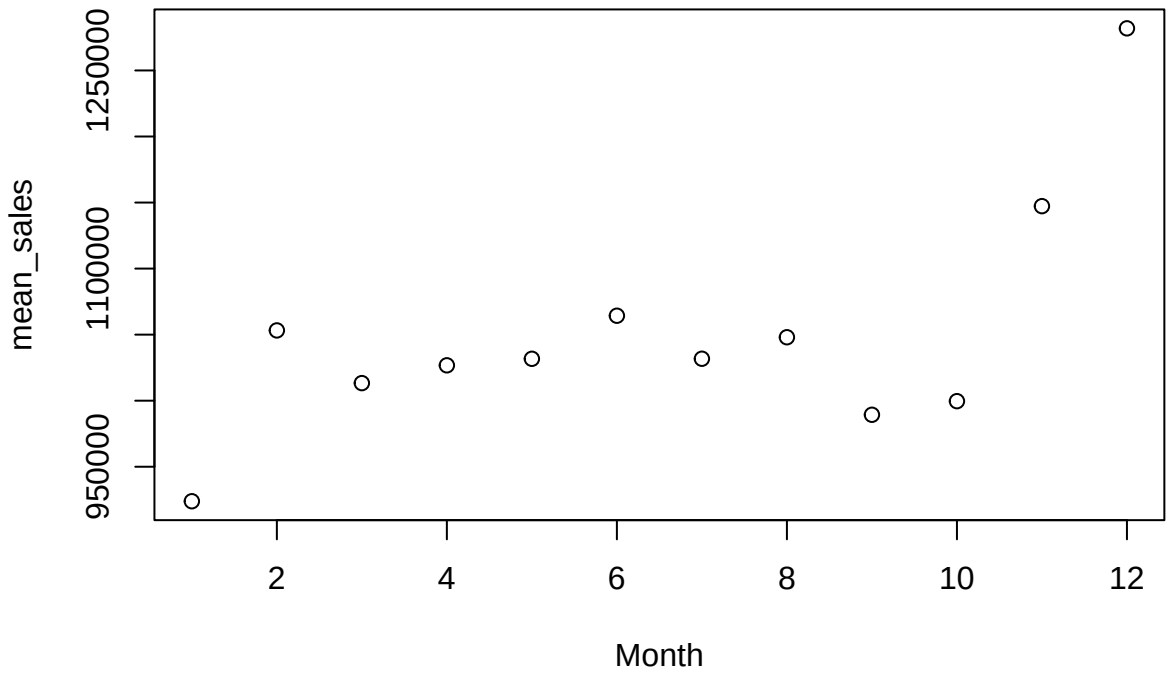


We see that the distribution of sales shows slight variation with day, month and year. Especially, the average sales is higher around december and 2010 had higher mean weekly sales than 2011 which was higher than that in 2012. To visualize the distribution of mean weekly sales, we can plot the scatter plot of the mean of the weekly sales with day, month and year which agrees with our findings from the boxplots.

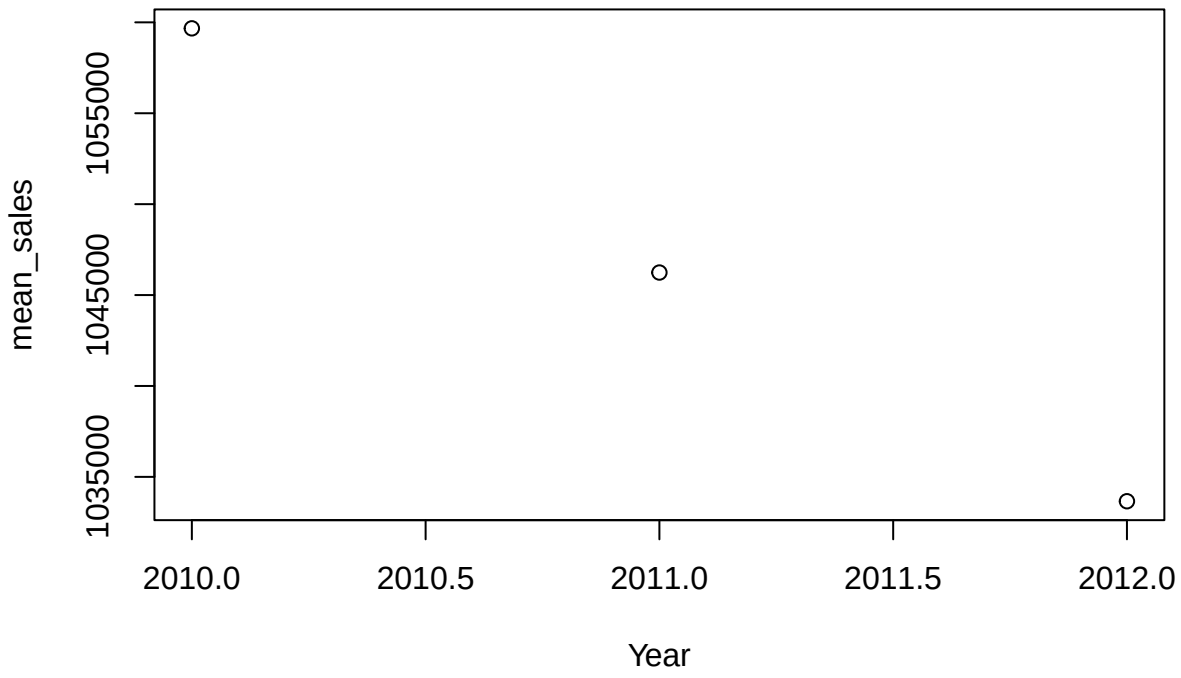
```
plot(walmart_dataset%>%group_by(Day)%>%summarise(mean_sales=mean(Weekly_Sales)))
```




```
plot(walmart_dataset%>%group_by(Month)%>%summarise(mean_sales=mean(Weekly_Sales)))
```




```
plot(walmart_dataset%>%group_by(Year)%>%summarise(mean_sales=mean(Weekly_Sales)))
```



To understand the dependence of the mean weekly sales on Day, Month and year we can group the dataset with the corresponding variable and arrange the categories with descending values of mean sales. We find that on average, the sales were highest on day and minimum on day 14, highest in December and lowest in January and highest in 2010 and lowest in 2012.

```
walmart_dataset%>%group_by(Day)%>%summarise(n=n(),mean_sales=mean(Weekly_Sales))%>%arrange(desc(mean_sa
```

```
## # A tibble: 31 x 3
##      Day     n mean_sales
##    <int> <int>      <dbl>
##  1    24   225   1161746.
##  2    23   225   1130371.
##  3    17   225   1110669.
##  4    25   225   1102654.
##  5    26   225   1097265.
##  6    10   225   1095039.
##  7     9   225   1089198.
##  8     6   225   1087901.
##  9    16   225   1076483.
## 10     2   225   1070976.
## # i 21 more rows
```

```
walmart_dataset%>%group_by(Month)%>%summarise(n=n(),mean_sales=mean(Weekly_Sales))%>%arrange(desc(mean_
```

```
## # A tibble: 12 x 3
```

```
##    Month     n mean_sales
##    <dbl> <int>      <dbl>
##  1    12   450   1281864.
##  2    11   360   1147266.
##  3     6   585   1064325.
##  4     2   540   1053200.
##  5     8   585   1048017.
##  6     7   630   1031748.
##  7     5   540   1031714.
##  8     4   630   1026762.
##  9     3   585   1013309.
## 10    10   585    999632.
## 11     9   585    989335.
## 12     1   360    923885.
```

```
walmart_dataset%>%group_by(Year)%>%summarise(n=n(),mean_sales=mean(Weekly_Sales))%>%arrange(desc(mean_sa
```

```
## # A tibble: 3 x 3
##    Year     n mean_sales
##   <dbl> <int>      <dbl>
## 1  2010  2160   1059670.
## 2  2011  2340   1046239.
## 3  2012  1935   1033660.
```

As we see a dependence of the weekly sales on day, month and year, we can separate them into different columns using one-hot encoding similar to that done for Stores [4]. However, as we have 31 days, including each day as a feature can over-complicate the model, therefore we only consider the effect of Month and Year. We can use pivot wider to create separate columns for each month and Year which takes the value 1 if the observation corresponds to that month or year and 0 otherwise.

```
walmart_dataset<-walmart_dataset%>% pivot_wider(names_from = Month, names_prefix="Month",values_from = M
walmart_dataset<-walmart_dataset%>% pivot_wider(names_from = Year, names_prefix="Year",values_from = Yea
colnames(walmart_dataset)
```

```
##  [1] "Date"         "Weekly_Sales" "Holiday_Flag" "Temperature"  "Fuel_Price"
##  [6] "CPI"          "Unemployment" "Store1"       "Store2"       "Store3"
## [11] "Store4"       "Store5"       "Store6"       "Store7"       "Store8"
## [16] "Store9"       "Store10"      "Store11"      "Store12"      "Store13"
## [21] "Store14"      "Store15"      "Store16"      "Store17"      "Store18"
## [26] "Store19"      "Store20"      "Store21"      "Store22"      "Store23"
## [31] "Store24"      "Store25"      "Store26"      "Store27"      "Store28"
## [36] "Store29"      "Store30"      "Store31"      "Store32"      "Store33"
## [41] "Store34"      "Store35"      "Store36"      "Store37"      "Store38"
## [46] "Store39"      "Store40"      "Store41"      "Store42"      "Store43"
## [51] "Store44"      "Store45"      "Day"          "Month2"       "Month3"
## [56] "Month4"       "Month5"       "Month6"       "Month7"       "Month8"
## [61] "Month9"       "Month10"      "Month11"      "Month12"      "Month1"
## [66] "Year2010"     "Year2011"     "Year2012"
```

Also, we remove the Date column from the dataset as its information is already contained in columns corresponding to different Month and Year.

```
walmart_dataset<-walmart_dataset%>%select(-c("Date"))
walmart_dataset<-walmart_dataset%>%select(-c("Day"))
```

Scaling the dataset

As the numerical values of each of the feature variables can have a different magnitude, giving unequal importance to the training parameters corresponding to them during the training process. Therefore, we should scale them to have similar magnitudes, two common methods of scaling are the standard scaler which centers the values of the column at the column mean and then divides each entry with the standard deviation. However, as the outliers are also included in calculating the mean standard deviation, it can bias the centering of the column. Therefore, we can use minmax scaling[5] in which we subtract the minimum value of the column from each entry and then divide each entry of the column by the range (max-min) of that column.

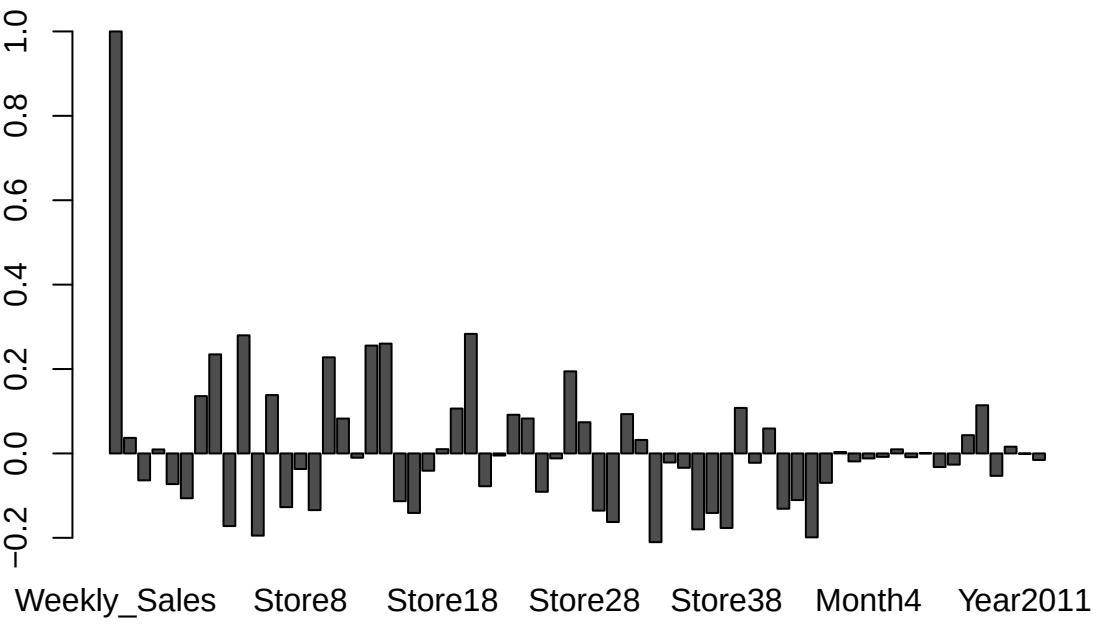
```
#Scaling the dataset
fMinMaxSclaer <- function(x) (
  (x - min(x)) / (max(x) - min(x))
)

walmart_dataset[-1]<-as.data.frame(lapply(walmart_dataset[-1],fMinMaxSclaer))
head(walmart_dataset)
```

```
## # A tibble: 6 x 66
##   Weekly_Sales Holiday_Flag Temperature Fuel_Price   CPI Unemployment Store1
##          <dbl>        <dbl>       <dbl>      <dbl> <dbl>        <dbl>  <dbl>
## 1     1643691.            0       0.434     0.0501 0.840        0.405      1
## 2     1641957.            1       0.397     0.0381 0.842        0.405      1
## 3     1611968.            0       0.411     0.0210 0.842        0.405      1
## 4     1409728.            0       0.476     0.0446 0.843        0.405      1
## 5     1554807.            0       0.475     0.0767 0.843        0.405      1
## 6     1439542.            0       0.586     0.0977 0.843        0.405      1
## # i 59 more variables: Store2 <dbl>, Store3 <dbl>, Store4 <dbl>, Store5 <dbl>,
## #   Store6 <dbl>, Store7 <dbl>, Store8 <dbl>, Store9 <dbl>, Store10 <dbl>,
## #   Store11 <dbl>, Store12 <dbl>, Store13 <dbl>, Store14 <dbl>, Store15 <dbl>,
## #   Store16 <dbl>, Store17 <dbl>, Store18 <dbl>, Store19 <dbl>, Store20 <dbl>,
## #   Store21 <dbl>, Store22 <dbl>, Store23 <dbl>, Store24 <dbl>, Store25 <dbl>,
## #   Store26 <dbl>, Store27 <dbl>, Store28 <dbl>, Store29 <dbl>, Store30 <dbl>,
## #   Store31 <dbl>, Store32 <dbl>, Store33 <dbl>, Store34 <dbl>, ...
```

Correlation between features and Weekly_Sales

To understand how each of the feature variable impacts the weekly sales, we can calculate the correlation [6] between the data of that feature variable with Weekly_Sales.

```
cor_data<-cor(walmart_dataset$Weekly_Sales,walmart_dataset%>%select(where(is.numeric)))
barplot(cor_data)
```



We see that different feature variables have different correlations with Weekly sales ranging from -0.2102702149 for Store33 to 0.2833633 for Store20.

Machine Learning Model

Partitioning the dataset into training and testing data A machine learning model is build to get trained on some dataset and be used to predict a quantity of interest in some unknown dataset which may not even exist at the present. Therefore, it is necessary to test the performance of the model by training it over a subset of the dataset(training_set) and test its performance over the other subset of the dataset (testing_set). The performance is evaluated by predicting the output for the target variable over the testing set and compare to the actual values of the target variable in it.

First, we find out indices of 15% of rows smapled randomly from the walmart_dataset (using Weekly_Sales column) using the createDataPartition function in R [1,2]. Then we use the test index to create the testing_set which will be used for testing the final model performance after fitting it over the training set which is the subset of the dataset excluding the testing set.

```
test_index <- createDataPartition(y = walmart_dataset$Weekly_Sales, times = 1,
                                  p = 0.15, list = FALSE)
testing_set <- walmart_dataset[test_index,]
training_set <- walmart_dataset[-test_index,]
```

We can see the number of observations in each set using the nrow function and see the first 5 rows of the training set using the head(training_set,5) function.

```
nrow(training_set)
```

```
## [1] 5467
```

```
nrow(testing_set)
```

```
## [1] 968
```

```
head(training_set,5)
```

```
## # A tibble: 5 x 66
##   Weekly_Sales Holiday_Flag Temperature Fuel_Price   CPI Unemployment Store1
##          <dbl>        <dbl>       <dbl>      <dbl> <dbl>        <dbl>  <dbl>
## 1     1643691.            0       0.434     0.0501 0.840        0.405      1
## 2     1611968.            0       0.411     0.0210 0.842        0.405      1
## 3     1409728.            0       0.476     0.0446 0.843        0.405      1
## 4     1554807.            0       0.475     0.0767 0.843        0.405      1
## 5     1439542.            0       0.586     0.0977 0.843        0.405      1
## # i 59 more variables: Store2 <dbl>, Store3 <dbl>, Store4 <dbl>, Store5 <dbl>,
## #   Store6 <dbl>, Store7 <dbl>, Store8 <dbl>, Store9 <dbl>, Store10 <dbl>,
## #   Store11 <dbl>, Store12 <dbl>, Store13 <dbl>, Store14 <dbl>, Store15 <dbl>,
## #   Store16 <dbl>, Store17 <dbl>, Store18 <dbl>, Store19 <dbl>, Store20 <dbl>,
## #   Store21 <dbl>, Store22 <dbl>, Store23 <dbl>, Store24 <dbl>, Store25 <dbl>,
## #   Store26 <dbl>, Store27 <dbl>, Store28 <dbl>, Store29 <dbl>, Store30 <dbl>,
## #   Store31 <dbl>, Store32 <dbl>, Store33 <dbl>, Store34 <dbl>, ...
```

Linear Regression Model In linear regression we fit the data to a function to the form $y = \Sigma c_i f_i$

where y is the target variable and f_i are the feature variables. The coefficients c_i are the machine learning parameters which need to be optimized from the training data. I use the caret package [7] to train a linear model to the training_data.

```
fit_lm<-train(Weekly_Sales~.,method="lm",data=training_set)
summary(fit_lm)
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -675097  -61415   -3875   45598 1610769
##
## Coefficients: (3 not defined because of singularities)
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   561736.5   105915.5   5.304 1.18e-07 ***
## Holiday_Flag   43720.1     8401.7   5.204 2.03e-07 ***
## Temperature    77738.1    37482.6   2.074 0.038128 *
## Fuel_Price      -770.3    27289.2  -0.028 0.977483
## CPI           404042.9   168184.3   2.402 0.016322 *
## Unemployment -398625.2    50148.2  -7.949 2.27e-15 ***
```

```
## Store1        596899.8    53843.8  11.086  < 2e-16 ***
## Store2        977376.0    53070.2  18.417  < 2e-16 ***
## Store3       -584930.6    59448.7  -9.839  < 2e-16 ***
## Store4       1427481.7    96614.0  14.775  < 2e-16 ***
## Store5       -690654.8    56495.3 -12.225  < 2e-16 ***
## Store6        558052.4    57459.7   9.712  < 2e-16 ***
## Store7       -233821.3    23044.6 -10.146  < 2e-16 ***
## Store8       -118660.8    61191.2  -1.939 0.052531 .
## Store9       -485018.9    61678.9  -7.864 4.47e-15 ***
## Store10      1323906.0    97325.6  13.603  < 2e-16 ***
## Store11       370194.0    59597.6   6.212 5.64e-10 ***
## Store12       611223.5   103072.3   5.930 3.22e-09 ***
## Store13      1383298.6    96754.7  14.297  < 2e-16 ***
## Store14      1228860.5    18484.2  66.482  < 2e-16 ***
## Store15        16223.9    86352.8   0.188 0.850979
## Store16      -372659.8    25688.2 -14.507  < 2e-16 ***
## Store17       266967.6    96641.8   2.762 0.005756 **
## Store18       507257.4    87188.7   5.818 6.30e-09 ***
## Store19       839403.2    86247.7   9.732  < 2e-16 ***
## Store20      1183078.5    43591.0  27.140  < 2e-16 ***
## Store21      -192415.2    53250.4  -3.613 0.000305 ***
## Store22       410639.6    80340.5   5.111 3.31e-07 ***
## Store23       668384.3    86057.3   7.767 9.57e-15 ***
## Store24       760882.6    86648.6   8.781  < 2e-16 ***
## Store25      -218545.7    43444.8  -5.030 5.05e-07 ***
## Store26       402200.4    86595.8   4.645 3.49e-06 ***
## Store27      1154210.3    80082.8  14.413  < 2e-16 ***
## Store28       931119.5   103146.5   9.027  < 2e-16 ***
## Store29         -470.3    88190.5  -0.005 0.995745
## Store30      -516198.0    53374.8  -9.671  < 2e-16 ***
## Store31       435997.1    53245.3   8.188 3.27e-16 ***
## Store32       354125.9    22294.7  15.884  < 2e-16 ***
## Store33      -317576.8    97446.2  -3.259 0.001125 **
## Store34       456534.8    99141.5   4.605 4.22e-06 ***
## Store35       314702.4    80761.1   3.897 9.87e-05 ***
## Store36      -568359.2    51564.5 -11.022  < 2e-16 ***
## Store37      -422490.7    51469.7  -8.209 2.77e-16 ***
## Store38       -10083.7   103064.7  -0.098 0.922064
## Store39       514155.8    51583.0   9.968  < 2e-16 ***
## Store40       241492.0    85907.7   2.811 0.004956 **
## Store41       399747.6    24581.3  16.262  < 2e-16 ***
## Store42       -23378.3    97087.1  -0.241 0.809721
## Store43      -196799.6    39820.0  -4.942 7.96e-07 ***
## Store44      -325291.8    96734.0  -3.363 0.000777 ***
## Store45             NA         NA      NA       NA
## Month2        116742.5    11279.4  10.350  < 2e-16 ***
## Month3         77420.4    13008.0   5.952 2.82e-09 ***
## Month4         81232.0    15267.5   5.321 1.08e-07 ***
## Month5         77455.5    17238.1   4.493 7.16e-06 ***
## Month6        103913.3    18522.5   5.610 2.12e-08 ***
## Month7         64315.3    19675.1   3.269 0.001087 **
## Month8         78554.3    19780.6   3.971 7.24e-05 ***
## Month9         15774.2    18430.2   0.856 0.392099
## Month10        36154.0    16102.5   2.245 0.024793 *
```

```
## Month11       197201.0    15612.9  12.631  < 2e-16 ***
## Month12       343262.9    14287.5  24.025  < 2e-16 ***
## Month1             NA         NA      NA       NA
## Year2010       56795.3    21422.2   2.651 0.008043 **
## Year2011       23136.4    10212.2   2.266 0.023517 *
## Year2012            NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 142400 on 5404 degrees of freedom
## Multiple R-squared:  0.9373, Adjusted R-squared:  0.9366
## F-statistic:  1303 on 62 and 5404 DF,  p-value: < 2.2e-16
```

The summary function displays the optimized fit coefficients after the training.with their standard errors and t values. The t-statistic is the ratio of the estimate of the parameter to its standard error (assuming the null-hypothesis is model parameter = 0). As the t-statistic follows a student-t distribution, we can estimate the probability that such a parameter could occur due to statistical fluctuations and it is mentioned in the Pr(>|t|) column. As lower Pr(>|t|) means that the non-zero value of the parameter is less likely to have arisen due to statistical fluctuations.The residual standard error is an estimate of the errors made by assuming the functional form of Weekly_Sales as a linear function of the feature variables.

Now, that we have fitted the linear model on the training set we can use it to predict the Weekly_Sales from the the other variables in the validation set using the predict function

```
y_hat<-predict(fit_lm,testing_set)
```

We can find out the mean absolute error between the predicted and actual Weekly_Sales in the validation_set by using the MAE function[3]

```
MAE<-function(true_values,predicted_values){
  mean(abs(predicted_values - true_values))
}
```

```
mae_lm<-MAE(testing_set$Weekly_Sales,y_hat)
```

We see that the mean absolute error (MAE) is 85775.22. Similarly the root mean square deviation can be found by defining the RMSE function[3]

```
RMSE <- function(true_values, predicted_values){
  sqrt(mean((true_values - predicted_values)^2))}
```

and using it to calculate the RMSE as

```
rmse_lm<-RMSE(testing_set$Weekly_Sales,y_hat)
```

which is calculated to be 139558.1. However, to get a sense of the model performance, we should calculate the ratio of the error to the mean of the Weekly_Sales, as scaling the Weekly_Sales would also scale up the errors in the prediction. This is known as the relative errors and can relative_mae and relative_rmse

```
rmse_lm<-RMSE(testing_set$Weekly_Sales,y_hat)
mean_weeklysales_val<-mean(testing_set$Weekly_Sales)
relative_mae_lm<-mae_lm/mean_weeklysales_val
```

```
relative_rmse_lm<-rmse_lm/mean_weeklysales_val

print(mae_lm)
```

```
## [1] 85775.22
```

```
print(relative_mae_lm)
```

```
## [1] 0.08226522
```

```
print(rmse_lm)
```

```
## [1] 139558.1
```

```
print(relative_rmse_lm)
```

```
## [1] 0.1338473
```

We find the relative_mae is 0.08226522 and the relative_rmse is 0.1338473 which are both around 10%. Thus, we find that using the linear model and just a handful of information about the store and environment, we can predict the weekly sales to an accuracy of around 10% relative error which is quite amazing.

K-Nearest Neighbors Model Usually the data points which are close in the feature space also have the same target value, for example the phones having similar features have similar price. We can utilize this information to make a prediction using the k-nearest neighbors (knn) model which uses knnreg for continuous variables (https://github.com/topepo/caret/blob/master/models/files/knn.R). In this model, for a given feature set, k observations in the training data are found which have the smallest distance to the given feature set. Then the predicted value is given by the average of the target value of these k-data points in the training set. However, we do not know which value of k should provide the best result, therefore I train the knn model using k values form 1-30 in steps of 2 and obtain the RMSE and print the RMSE vs k (#Neighbors) in a line plot.

```
fit_knnreg<-train(Weekly_Sales~.,method="knn",data=training_set,metric="RMSE",tuneGrid = data.frame(k =
summary(fit_knnreg)
```

```
##             Length Class      Mode
## learn        2     -none-     list
## k            1     -none-     numeric
## theDots      0     -none-     list
## xNames      65     -none-     character
## problemType  1     -none-     character
## tuneValue    1     data.frame list
## obsLevels    1     -none-     logical
## param        0     -none-     list
```

```
print(fit_knnreg)
```

```
## k-Nearest Neighbors
##
## 5467 samples
##   65 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 5467, 5467, 5467, 5467, 5467, 5467, ...
## Resampling results across tuning parameters:
##
##   k   RMSE      Rsquared   MAE
##    1  266704.5  0.7886575  122742.3
##    3  336673.3  0.6498059  195755.8
##    5  370695.1  0.5677560  247654.9
##    7  383340.3  0.5404550  271303.7
##    9  386369.9  0.5391055  280999.7
##   11  386755.4  0.5449030  285759.2
##   13  385872.4  0.5540074  288219.0
##   15  383822.8  0.5661387  288946.1
##   17  382288.2  0.5768737  289465.6
##   19  380827.0  0.5873379  289679.3
##   21  379620.5  0.5966719  289890.2
##   23  379582.6  0.6028080  290967.3
##   25  379499.0  0.6096647  292160.9
##   27  379818.1  0.6143320  293496.5
##   29  380460.2  0.6189726  295140.6
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 1.
```

```
fit_knnreg$bestTune
```

```
##   k
## 1 1
```

The k-value giving the lowest RMSE can be found using fit_knn$bestTune and is found to be 1 although there is a local minima of the RMSE at k=25. This value of k is used in the knn model. Comparing to the true values of the Weekly_Sales in the dataset the mae,relative_mae, rmse and relative_rmse can be found.

```
y_hat<-predict(fit_knnreg,testing_set)
mae_knnreg<-MAE(testing_set$Weekly_Sales,y_hat)
relative_mae_knnreg<-mae_knnreg/mean_weeklysales_val
rmse_knnreg<-RMSE(testing_set$Weekly_Sales,y_hat)
relative_rmse_knnreg<-rmse_knnreg/mean_weeklysales_val

print(mae_knnreg)
```

```
## [1] 88463.33
```

```
print(relative_mae_knnreg)
```

```
## [1] 0.08484333
```

```r
print(rmse_knnreg)
```

```
## [1] 182078.2
```

```r
print(relative_rmse_knnreg)
```

```
## [1] 0.1746274
```

We find the relative mae is 0.08484333 and the relative rmse is 0.1746274 which is slightly more than that from the linear model. It suggests that a linear model is not able to capture all the effect of the feature variables on weekly sales but it still provides an estimate with similar accuracy to the linear model.

Logistic Regression of the category of Weekly Sales Many a times, it is important to categorize the target variable into different classes ranging from its minimum to maximum value and use the Machine Learning model to output the category into which the target variables should fall given its set of feature values. For example, the store might be interested in making its overall strategy based on weather a given set of conditions would tend to produce high, medium or low weekly_sales and optimize the conditions based on that. Therefore, in this section, I create 3 classes of the weekly sales using its maximum and minimum values and mutate it as the Category_Weekly_Sales column.

```r
hist(training_set$Weekly_Sales)
```

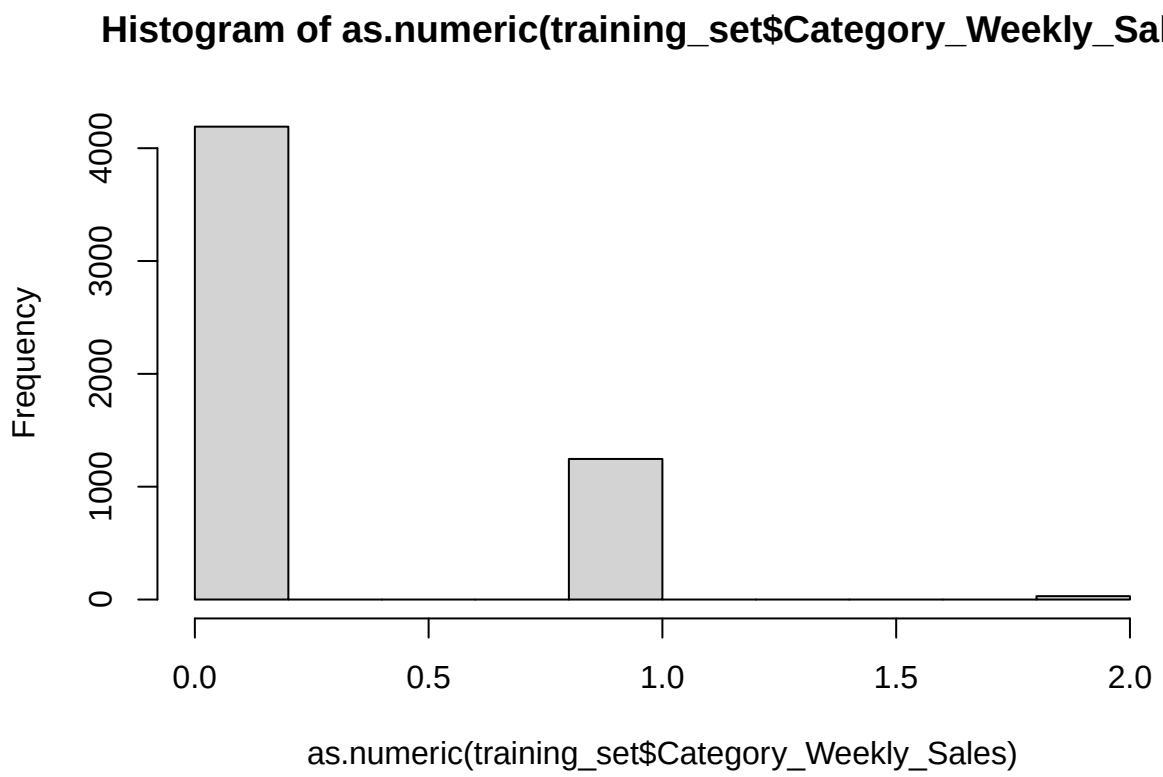
```
range(training_set$Weekly_Sales)
```

```
## [1]  209986.2 3818686.5
```

```
min_weekly_sales<-min(training_set$Weekly_Sales)
range_weekly_sales<-max(training_set$Weekly_Sales)-min(training_set$Weekly_Sales)

training_set<-training_set%>%mutate(Category_Weekly_Sales=floor((Weekly_Sales-min_weekly_sales)/range_we
testing_set<-testing_set%>%mutate(Category_Weekly_Sales=floor((Weekly_Sales-min_weekly_sales)/range_weel
```

We can visualize the distribution of Category_Weekly_Sales by plotting its histogram and also by using the group_by function to show the number of occurrences and the mean weekly sales in each of these categories. We observe that the categories 0, 1 and 2 contain 4191,1246 and 30 entries while the mean weekly sales in them are 799742, 1832458 and 3098531 respectively.

```
hist(as.numeric(training_set$Category_Weekly_Sales))
```




```
training_set%>%group_by(Category_Weekly_Sales)%>%summarise(n=n(), mean_weekly_sales=mean(Weekly_Sales))
```

```
## # A tibble: 3 x 3
##   Category_Weekly_Sales     n mean_weekly_sales
##                   <dbl> <int>             <dbl>
## 1                     0  4191           799742.
## 2                     1  1246          1832458.
## 3                     2    30          3098531.
```

Now, we can train a machine learning model to predict the category of Weekly_Sales from the other features (except Weekly_Sales as it was used to create the Category_Weekly_Sales so it should not be used as a feature variable). We can use knn, this time to be used for a classification task instead of the previous regression task. For that, we should first convert the Category_Weekly_Sales as factors and then train the knn model over it. As k=1 gave the lowest RMSE for regression, I have used k=1 although the model can be tested for different k values and the k value from the model with the lowest RMSE can be chosen for the final model.

```
training_set<-training_set%>%mutate(Category_Weekly_Sales=as.factor(Category_Weekly_Sales))
testing_set<-testing_set%>%mutate(Category_Weekly_Sales=as.factor(Category_Weekly_Sales))

fit_knncl<-train(Category_Weekly_Sales~.,method="knn",data=training_set[,-1],tuneGrid = data.frame(k = 
summary(fit_knncl)
```

```
##             Length Class      Mode
## learn        2     -none-     list
## k            1     -none-     numeric
## theDots      0     -none-     list
## xNames      65     -none-     character
## problemType  1     -none-     character
## tuneValue    1     data.frame list
## obsLevels    3     -none-     character
## param        0     -none-     list
```

Now, with the fitted knn model with the best tune, we can test its performance over the testing set.

```
y_hat_knncl<-predict(fit_knncl,testing_set[,-1],type="raw")
confusionMatrix(y_hat_knncl, testing_set$Category_Weekly_Sales)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1   2
##          0 713  32   0
##          1  29 184   1
##          2   0   6   3
##
## Overall Statistics
##
##                Accuracy : 0.9298
##                  95% CI : (0.9118, 0.945)
##     No Information Rate : 0.7665
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8045
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 0 Class: 1 Class: 2
## Sensitivity            0.9609   0.8288 0.750000
## Specificity            0.8584   0.9598 0.993776
```

```
## Pos Pred Value         0.9570   0.8598 0.333333
## Neg Pred Value         0.8700   0.9496 0.998957
## Prevalence             0.7665   0.2293 0.004132
## Detection Rate         0.7366   0.1901 0.003099
## Detection Prevalence   0.7696   0.2211 0.009298
## Balanced Accuracy      0.9097   0.8943 0.871888
```

The confusion matrix shows the comparison between the reference and prediction values, which should be a diagonal matrix in case of perfect prediction. The non-diagonal entries represent errors during the classification similar to the case when there are 2 classes in which false positive (when the prediction is positive and actual value is negative) and false_negatives (when the prediction is negative and actual value is positive) represent the errors made during the classification. Accuracy represents the ratio of number of instances which were correctly classified with the total number of instances. We find that the knn model gives an accuracy of 92.98%.

Summary of Results

In this project I have successfully built a machine learning model to predict the Weekly_Sales from the store number and other features in the dataset. In the first model, a linear model was used to regress the value of weekly sales from other features which was trained over the training set. To evaluate the model performance two different metrics, the mae (Mean absolute error) and rmse (Root Mean Squared Error) were used which were found to be 85775.22 and 139558.1 respectively for the linear regression model. To compare this error with the magnitude of the variable we are predicting, the relative_mae and relative_rmse which are the ratio of the mae and rmse to the mean of the Weekly_Sales were calculated and were found to be 0.08226522 and 0.1338473 respectively. Next a k-Nearest Neighbors model with regression mode was trained with different values of k to predict the weekly sales from other features. Although the RMSE showed a local minima at k=25, the lowest RMSE was found to be at k=1 which was chosen for the knn model. The mae, rmse, relative_mae and relative_rmse for the knn model were found to be 88463.33, 182078.2, 0.08484333 and 0.1746274 respectively. Next, the Weekly_Sales column was categorized into high, medium and low weekly sales and a knn model with classification mode was trained over the training set and used to predict the category of the Weekly_Sales in the testing set. The performance was visualized using the confusion matrix and the accuracy of the classification model was found to be 92.98%.

Conclusion

In this project, I have utilized the concepts of machine learning to build a model to predict the weekly sales of a store based on the store number and other conditions (Holiday, Temperature, Fuel_Price, CPI and Unemployment index). The dataset was first preprocessed, scaled and then partitioned into the training and testing sets. A linear model and a knn model with regression mode were then fitted over the training set and evaluated over the testing set. The linear model was found to have a better relatively mean absolute error and relative root mean squared error. The relative mean squared errors were different for different k in the knn model which shows that hyperparameter tunning is important during training a machine learning model. To estimate the overall nature of Weekly_Sales, the Weekly_Sales was columns was categorized into high, medium and low weekly sales and a knn model was fit with classification to predict the category of Weekly_Sales. It was found to have a classification accuracy of 92.98%. This model could be improved by using L1 and L2 type regularization and by using cross validation and decision trees for classification among other machine learning methods that can also be used and tested. Through this project, I have realized the importance of utilizing data to understand and predict quantities of interest from other features. This can be used in many practical applications for optimizing the parameters at hand (in this case to choose the location based on the feature parameters) to achieve the best possible value for a target variable (weekly sales of the store). This model can be generalized to predict the weekly sales of other stores by preprocessing the features of that store to the appropriate format used in the models in this project.

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