Use Machine Learning To Possibly Become A Millionaire: Predicting The Stock Market?

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Objectives:

Use Machine Learning To Possibly Become A Millionaire: Predicting The Stock Market? The stock market is one of the most well-known infrastructures through which anyone can potentially make a fortune. If anyone could crack the code to predicting what future stock prices are, they'll practically rule the world.here's just one problem. It's pretty much impossible to accurately predict the future of the stock market.

In this project, we will work with historical data about the stock prices of a publicly listed company. We will implement a mix of machine learning algorithms to predict the future stock price of the company, starting with simple algorithm like linear regression, and then move on to advanced techniques like Auto ARIMA and Neural Networks.

Data Import

- The data set we will be working with is from the New York Stock Exchange (NYSE) and represent the historical prices and other fundamental data points of the S&P 500 from 2010 to the end of 2016. Dataset consists of following files:
- prices.csv: raw, as-is daily prices. Most of data spans from 2010 to the end 2016, for companies new on stock market date range is shorter. There have been approx. 140 stock splits in that time, this set doesn't account for that.
- prices-split-adjusted.csv: same as prices, but there have been added adjustments for splits.
- securities.csv: general description of each company with division on sectors
- fundamentals.csv: metrics extracted from annual SEC 10K fillings (2012-2016), should be enough to derive most of popular fundamental indicators.

- The majority of our focus will be on the prices-split-adjusted.csv file, as this contains the adjusted prices for the stocks we will be trying to predict.

Description of fundamentals.csv

Names	Description
Stocks Variable Columns	Categorical - Ticker.Symbol,Period.Ending
Stocks Technical Indicator Columns	Numerical - Accounts.Payable, Accounts.Receivable, Add.l.income.expense.items, After.Tax.ROE, Capital.Expenditures, Capital.Surplus, Cash.Ratio, Cash.and.Cash.Equivalents, Changes.in.Inventories,Common.Stocks, Cost.of.Revenue,Current.Ratio, Deferred.Asset.Charges,Total.Assets, Deferred.Liability.Charges, Depreciation,Earnings.Before.Interest.and.Tax, Earnings.Before.Tax,Net.Income.Adjustments, Effect.of.Exchange.Rate, Equity.Earnings.Loss.Unconsolidated.Subsidiary, Fixed.Assets,Goodwill,Gross.Margin, Gross.Profit,Income.Tax, Intangible.Assets,Interest.Expense, Inventory,Investments,Liabilities, Long.Term.Debt,Long.Term.Investments, Minority.Interest,Misc..Stocks, Net.Borrowings,Net.Cash.Flow , Net.Cash.Flow.Operating,Net.Cash.Flows.Financing, Net.Cash.Flows.Investing,Net.Income, Net.Income.Applicable.to.Common.Shareholders, Net.Income.Cont..,Operations, Net.Receivables,Non.Recurring.Items, Operating.Income,Operating.Margin, Other.Assets,Other.Current.Assets, Other.Current.Liabilities, Other.Equity,Other.Financing.Activities, Other.Investing.Activities,Other.Liabilities, Other.Operating.Activities,Pre.Tax.Margin Other.Operating.Items,Pre.Tax.ROE, Profit.Margin,Quick.Ratio, Research.and.Development, Retained.Earnings,Short.Term.Debt Sale.and.Purchase.of.Stock, Sales..General.and.Admin., Current.Portion.of.Long.Term.Debt, Short.Term.Investments,Equity, Total.Current.Assets,For.Year Total.Current.Liabilities, Total.Equity,Total.Liabilities, Total.Revenue,Treasury.Stock, Earnings.Per.Share, Estimated.Shares.Outstanding

Description of securities.csv

Names	Description
Ticker.symbol	Categorical - Ticker.Symbol
GICS.Sector	Categorical -Industry of the ticker
GICS.Sub.Industry	Categorical -Sub.Industry of the ticker

Description of sprice.csv

Names	Description
Date	Date - Date for which prices are recorded
Symbol	Categorical - Ticker.Symbol
Open	Numerical - Opening price of the stock on a particular day
Close	Numerical - Closing price of the stock on a particular day
Low	Numerical -Low price of the stock on a particular day
High	Numerical -High price of the stock on a particular day
Volume	Numerical -Volume of the stock on a particular day

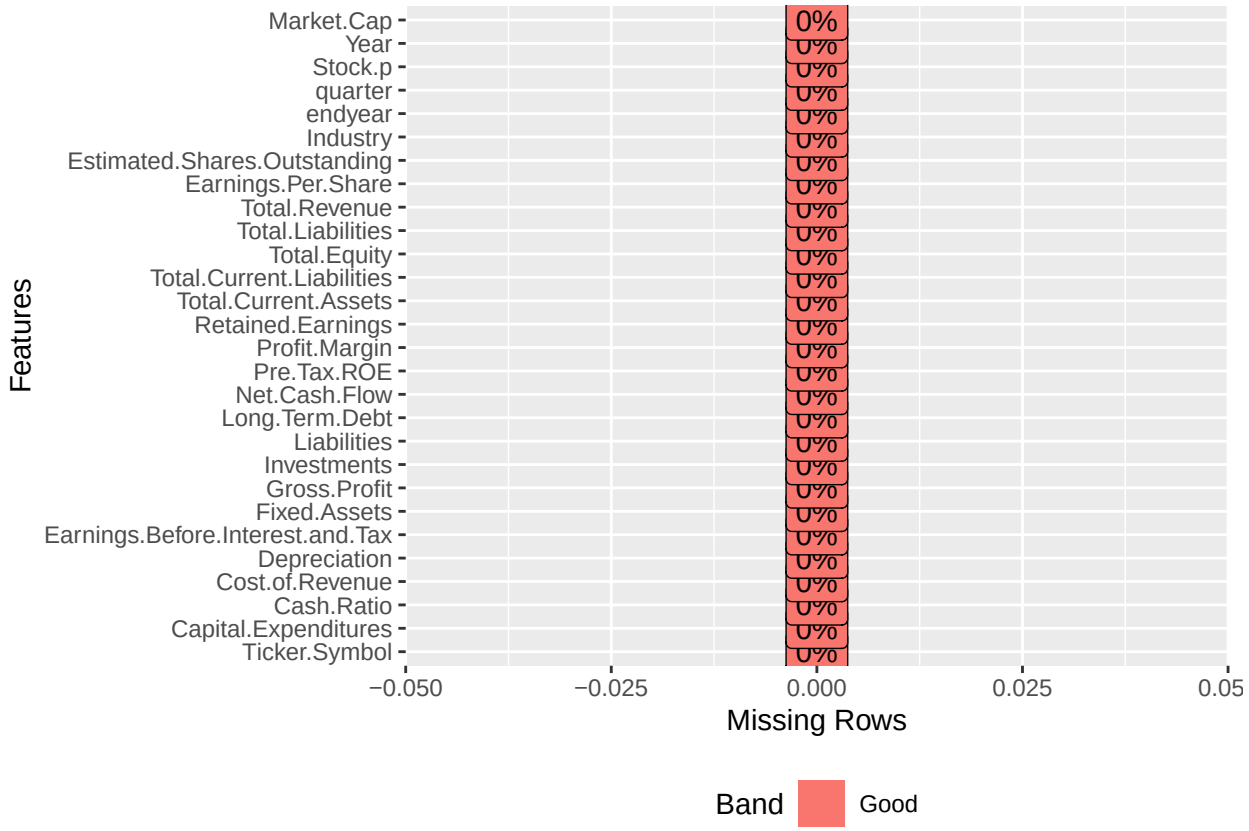
Data Structure and manipulation.

- Merge the three dataframe to combine information about a stock grouped by year.
- Filter out unnecessary columns and display the final dataset which we will work on.
- Final data after merging info from three dataframes

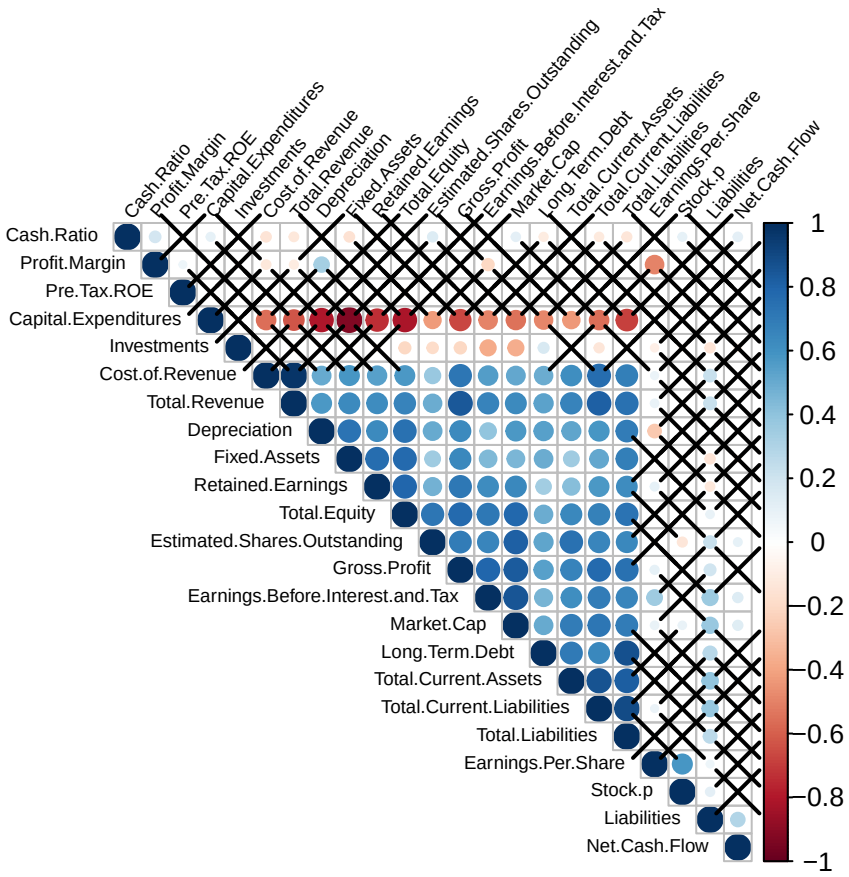
Names	Description
Ticker.Symbol	Categorical - Stock Symbol
Industry	Categorical - Idustry of the Stock
endyear	Date - Year of the revenue
quarter	Date - Quarter of the revenue
Stock.p	Numerical - Mean of Close price
Capital.Expenditures	Numerical - Technical Indicator
Cash.Ratio	Numerical - Technical Indicator
Cost.of.Revenue	Numerical - Technical Indicator
Depreciation	Numerical - Technical Indicator
Earnings.Before.Interest.and.Tax	Numerical - Technical Indicator
Effect.of.Exchange.Rate	Numerical - Technical Indicator
Fixed.Assets	Numerical - Technical Indicator
Gross.Profit	Numerical - Technical Indicator
Investments	Numerical - Technical Indicator
Liabilities	Numerical - Technical Indicator
Long.Term.Debt	Numerical - Technical Indicator
Long.Term.Investments	Numerical - Technical Indicator
Net.Cash.Flow	Numerical - Technical Indicator
Net.Income	Numerical - Technical Indicator
Pre.Tax.ROE	Numerical - Technical Indicator
Profit.Margin	Numerical - Technical Indicator
Retained.Earnings	Numerical - Technical Indicator
Total.Current.Assets	Numerical - Technical Indicator
Total.Current.Liabilities	Numerical - Technical Indicator
Total.Equity	Numerical - Technical Indicator
Total.Liabilities	Numerical - Technical Indicator
Total.Revenue	Numerical - Technical Indicator
Earnings.Per.Share	Numerical - Technical Indicator
Estimated.Shares.Outstanding	Numerical - Technical Indicator

Data Science Analysis

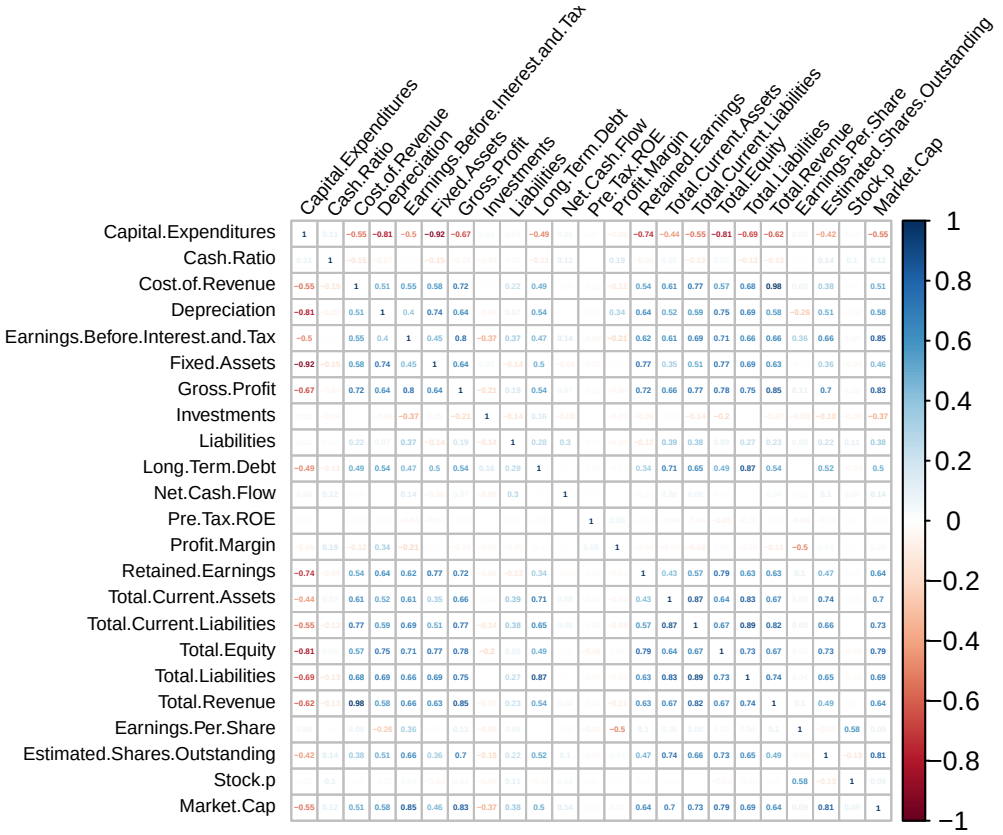
- Plot the percentage of missing data for each attribute.



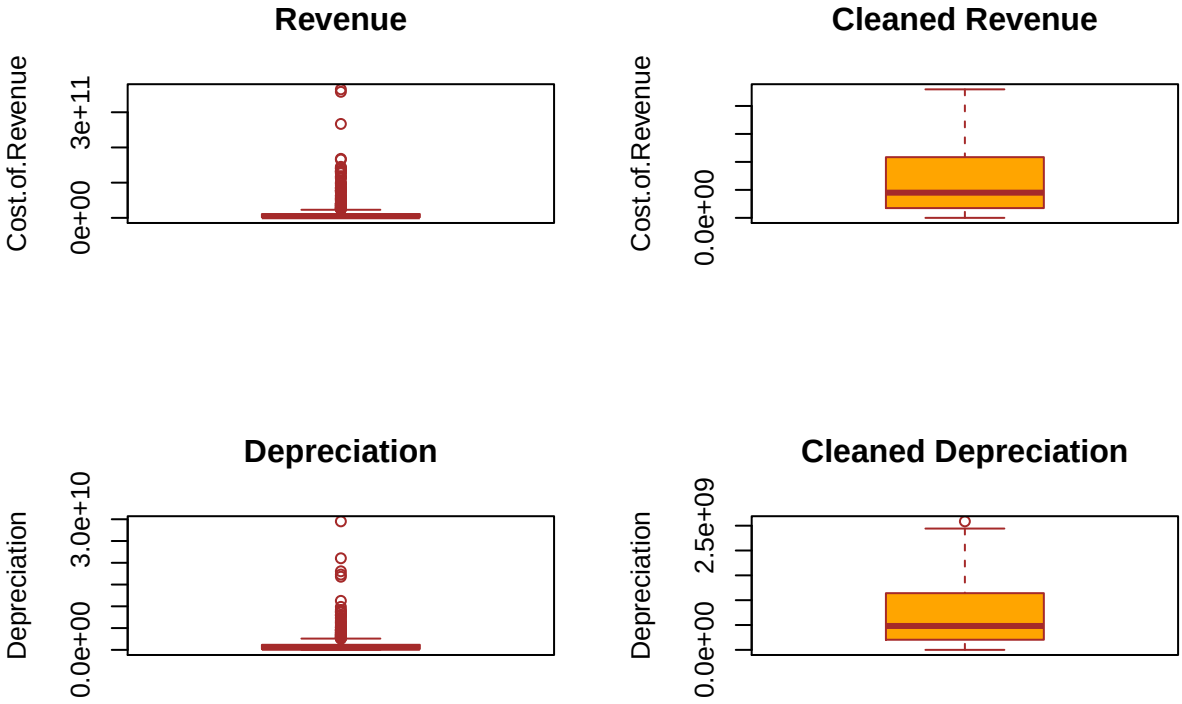
- Correlation plot with correlation coefficient before data clean up

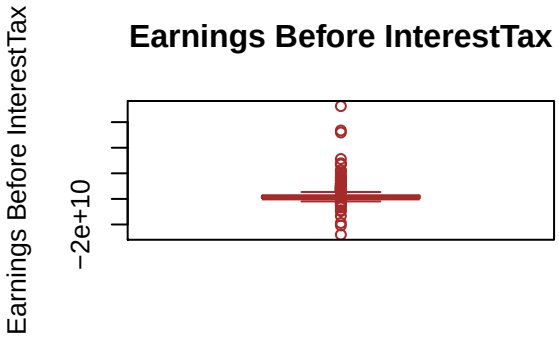


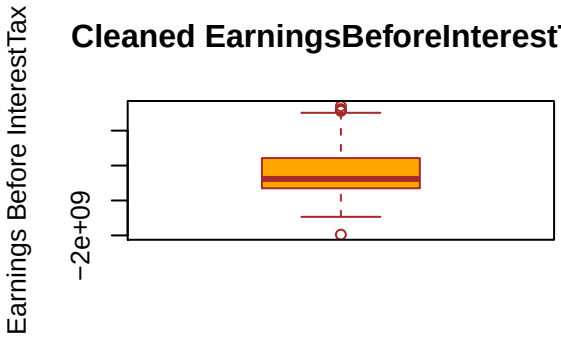
Corrplot With Correlation Coefficient

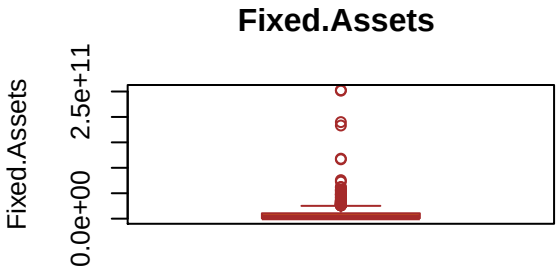


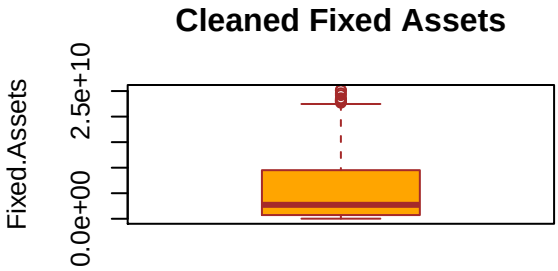
- Remove outliers of the features and replace them with the mean of the value.
- Replacing the missing values with the mean / median / mode is a best way of treating missing values.
  + Depending on the context, like if the variation is low or if the variable has low leverage over the response, such a rough approximation is acceptable and could possibly give satisfactory results.

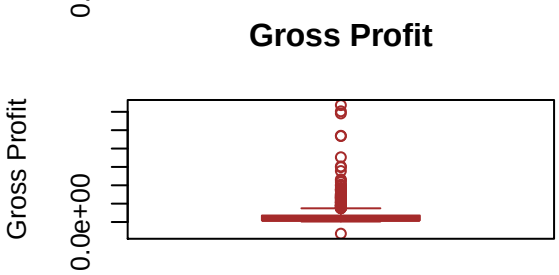


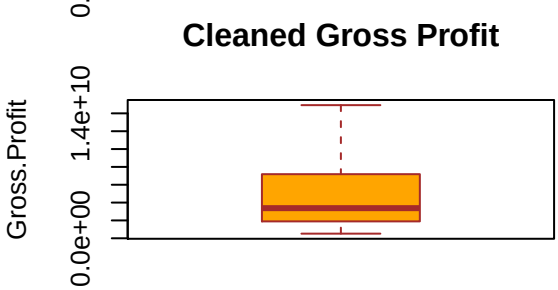

Earnings Before InterestTax
Earnings Before InterestTax
−2e+10

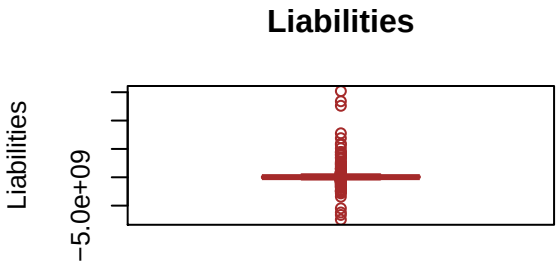

Cleaned EarningsBeforeInterestTax
Earnings Before InterestTax
−2e+09

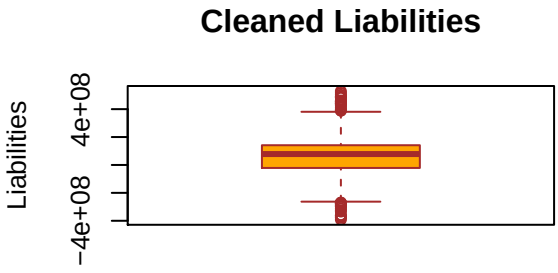

Fixed.Assets
Fixed.Assets
0.0e+00
2.5e+11

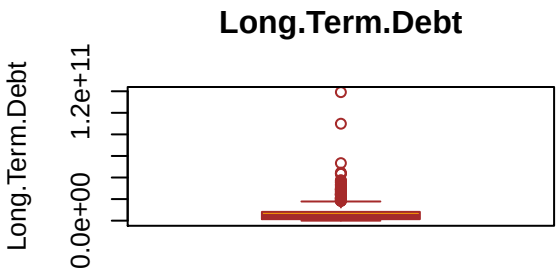

Cleaned Fixed Assets
Fixed.Assets
0.0e+00
2.5e+10

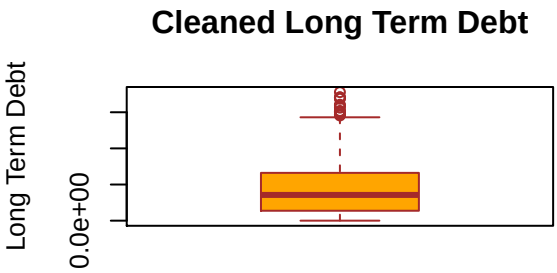

Gross Profit
Gross Profit
0.0e+00

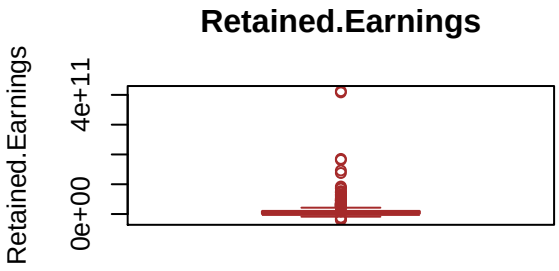

Cleaned Gross Profit
Gross.Profit
0.0e+00
1.4e+10

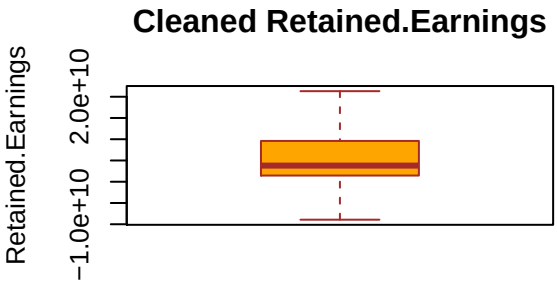

Liabilities
Liabilities
−5.0e+09

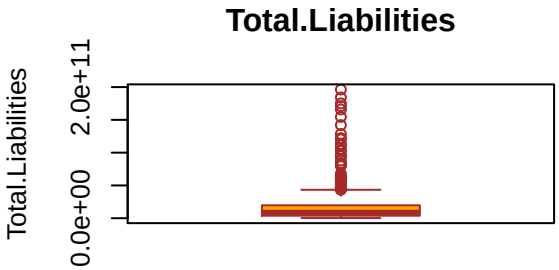

Cleaned Liabilities
Liabilities
−4e+08
4e+08

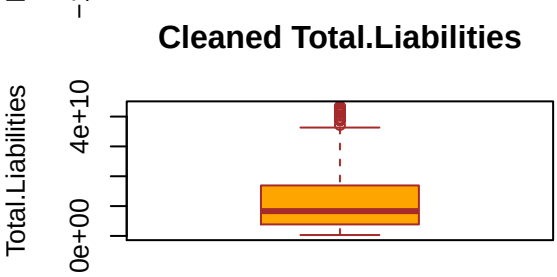

Long.Term.Debt
Long.Term.Debt
0.0e+00
1.2e+11

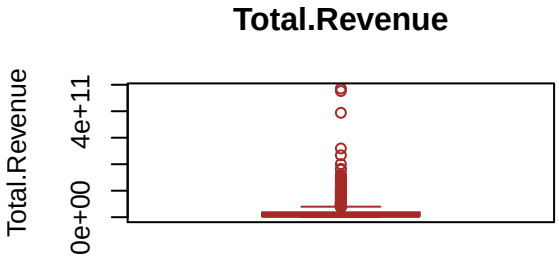

Cleaned Long Term Debt
Long Term Debt
0.0e+00

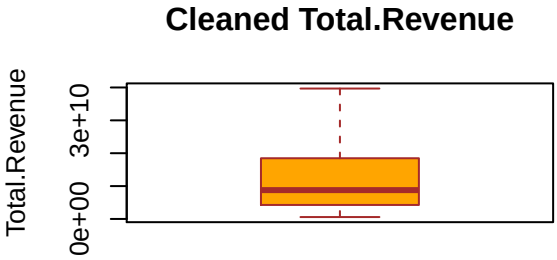

Retained.Earnings
Retained.Earnings
0e+00
4e+11

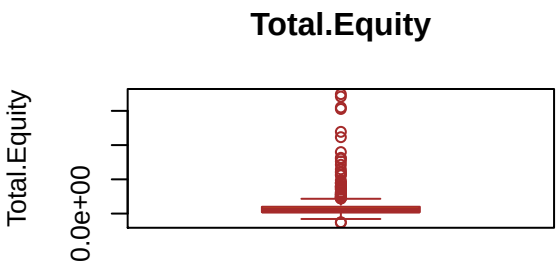

Cleaned Retained.Earnings
Retained.Earnings
−1.0e+10
2.0e+10

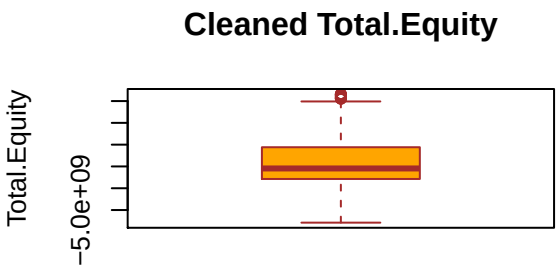

Total.Liabilities
Total.Liabilities
0.0e+00
2.0e+11

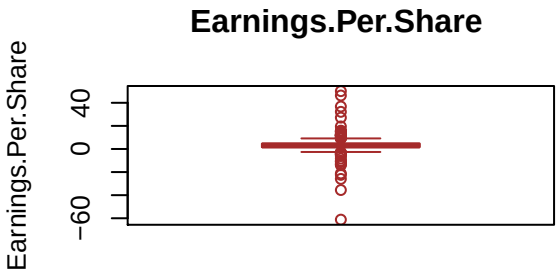

Cleaned Total.Liabilities
Total.Liabilities
0e+00
4e+10

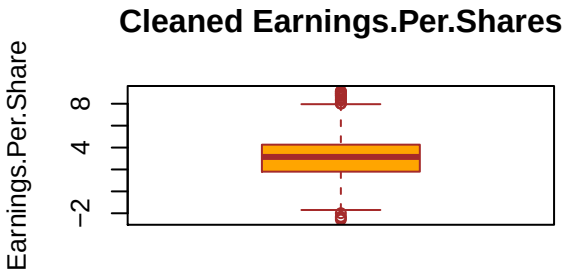

Total.Revenue
Total.Revenue
0e+00
4e+11

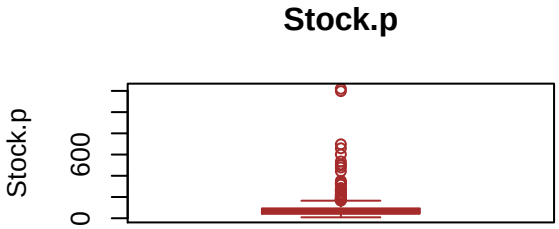

Cleaned Total.Revenue
Total.Revenue
0e+00
3e+10

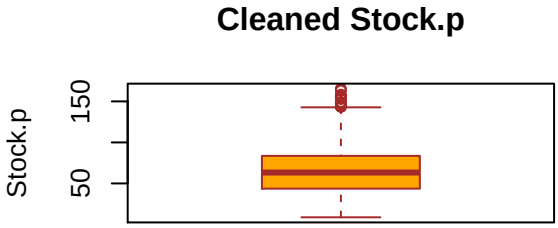

Total.Equity
Total.Equity
0.0e+00

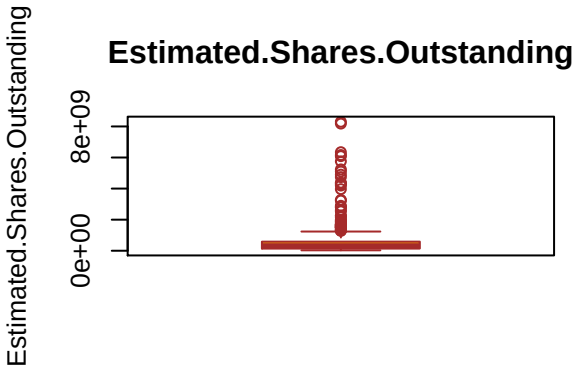

Cleaned Total.Equity
Total.Equity
−5.0e+09

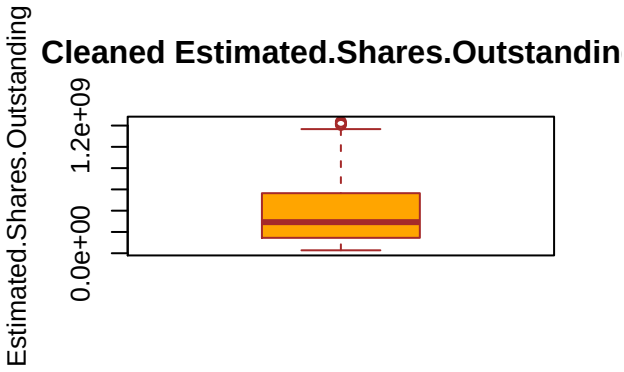

Earnings.Per.Share
Earnings.Per.Share
−60
0
40


Cleaned Earnings.Per.Shares
Earnings.Per.Share
−2
4
8

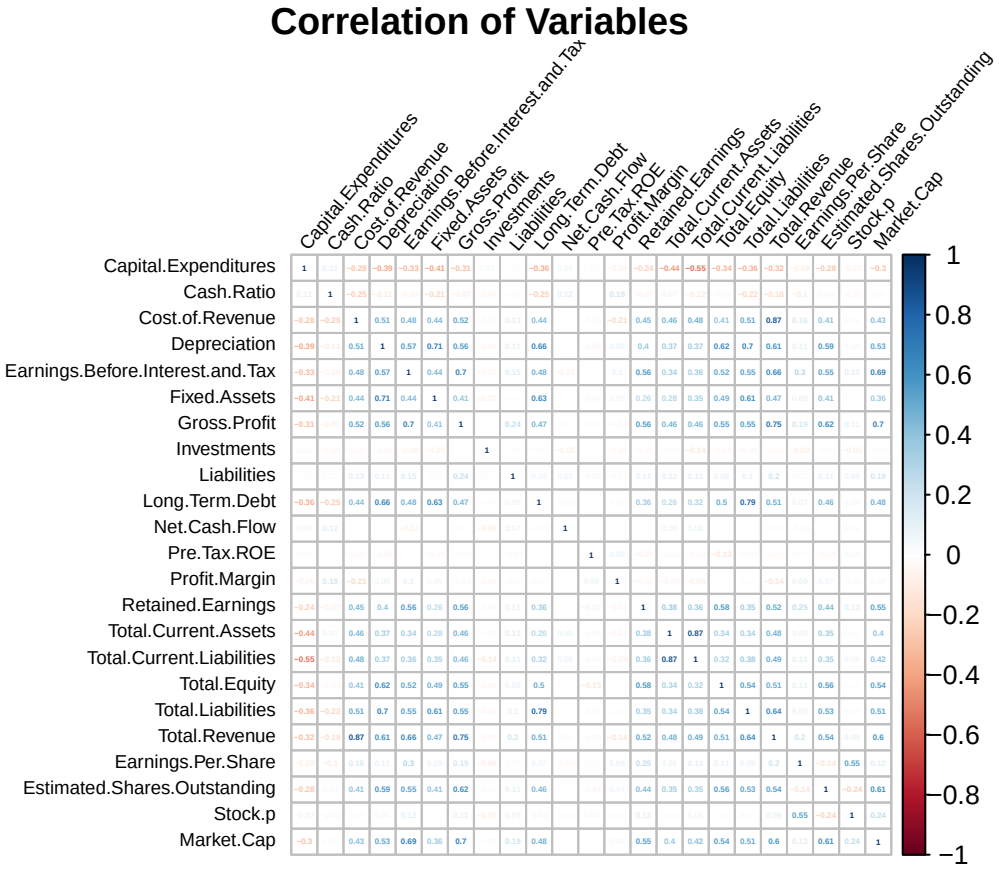

Stock.p
Stock.p
0
600


Cleaned Stock.p
Stock.p
50
150


Estimated.Shares.Outstanding
Estimated.Shares.Outstanding
0e+00
8e+09


Cleaned Estimated.Shares.Outstandin
Estimated.Shares.Outstanding
0.0e+00
1.2e+09

- Correlation plot with correlation coefficient after data clean up



Numerical Summaries

- Frequency distribution, calculate relevant proportions, and contingency tables for categoricalvariable marketCapIndicator (Low/Medium/High) & industry.

```
Frequency Table for Industry:
```

```
Consumer Discretionary       Consumer Staples                Energy
                   120                     50                    58
            Financials            Health Care            Industrials
                    10                     74                   120
Information Technology              Materials           Real Estate
                   108                     44                    14
             Utilities
                    42
```

```
Frequency Table for MarketCapIndiactor:
```

```
  high    low medium
   292    301     47
```

```
Contingency Table for Industry/ MarketCapIndiactor:
```

```
                          high low medium
  Consumer Discretionary    46  67      7
  Consumer Staples          28  18      4
```

```
  Energy                   32  23      3
  Financials                3   4      3
  Health Care              45  23      6
  Industrials              47  65      8
  Information Technology   49  52      7
  Materials                17  24      3
  Real Estate               6   6      2
  Utilities                19  19      4
```

Proportions Table for Industry/ MarketCapIndiactor:

```
                            high       low    medium
  Consumer Discretionary 0.0718750 0.1046875 0.0109375
  Consumer Staples       0.0437500 0.0281250 0.0062500
  Energy                 0.0500000 0.0359375 0.0046875
  Financials             0.0046875 0.0062500 0.0046875
  Health Care            0.0703125 0.0359375 0.0093750
  Industrials            0.0734375 0.1015625 0.0125000
  Information Technology 0.0765625 0.0812500 0.0109375
  Materials              0.0265625 0.0375000 0.0046875
  Real Estate            0.0093750 0.0093750 0.0031250
  Utilities              0.0296875 0.0296875 0.0062500
```

Summary MarketCapIndiactor

```
   Length     Class      Mode
      640 character character
```

Summary Industry

```
Consumer Discretionary       Consumer Staples                 Energy
                   120                     50                     58
            Financials            Health Care             Industrials
                    10                     74                    120
Information Technology              Materials            Real Estate
                   108                     44                     14
             Utilities
                    42
```

Numerical Summary of Market Cap

```
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
2.609e+09 1.030e+10 1.678e+10 3.534e+10 3.393e+10 6.907e+11
```

Numerical Summary of Market Cap grouped by Industry

```
# A tibble: 10 x 6
   Industry                 sum         mean        min          max      median
   <fct>                  <dbl>        <dbl>      <dbl>        <dbl>       <dbl>
 1 Consumer Discretion~ 3.33e12 27755715066.     4.62e9      2.23e11     1.38e10
 2 Consumer Staples     2.74e12 54777333131.     4.69e9      2.53e11     2.83e10
 3 Energy               2.44e12 42025301685.     4.57e9      4.16e11     2.27e10
 4 Financials           1.55e11 15499103508.     7.49e9      2.69e10     1.60e10
 5 Health Care          3.31e12 44710159546.     3.22e9      2.08e11     2.31e10
 6 Industrials          3.04e12 25355115660.     4.07e9      1.01e11     1.38e10
 7 Information Technol~ 5.52e12 51151898108.     2.61e9      6.91e11     1.61e10
 8 Materials            9.05e11 20569895953.     4.04e9      5.99e10     1.44e10
 9 Real Estate          3.33e11 23773975192.     5.95e9      4.93e10     1.81e10
```

```
10 Utilities             8.41e11 20019656246.      3.28e9       5.23e10      1.63e10
```

- Does skewness deviate a lot from 1 ?
  - Skewness for Industry is left skewed.It has longer tail on the left side of distribution.
  - Skewness for MarketCapIndiactor is right skewed.It has longer tail on the right side of distribution.
  - Skewness for Market.Cap is right skewed.It has longer tail on the right side of distribution.
  - Skewness for Total.Revenue is right skewed.It has longer tail on the right side of distribution.
  - Skewness for Gross.Profit is right skewed.It has longer tail on the right side of distribution.

```
[1] "skewness  of Industry -0.051643"
```

```
[1] "skewness  of MarketCapIndiactor 0.476626"
```

```
[1] "skewness  of Market.Cap 5.468953"
```

```
[1] "skewness  of Total.Revenue 6.125020"
```

```
[1] "skewness  of Gross.Profit 5.369591"
```

- Shapiro Wilkes Test for Normality.
  - Industry -> p-value < 8.458e-09 < 0.05 = not normaly distributed

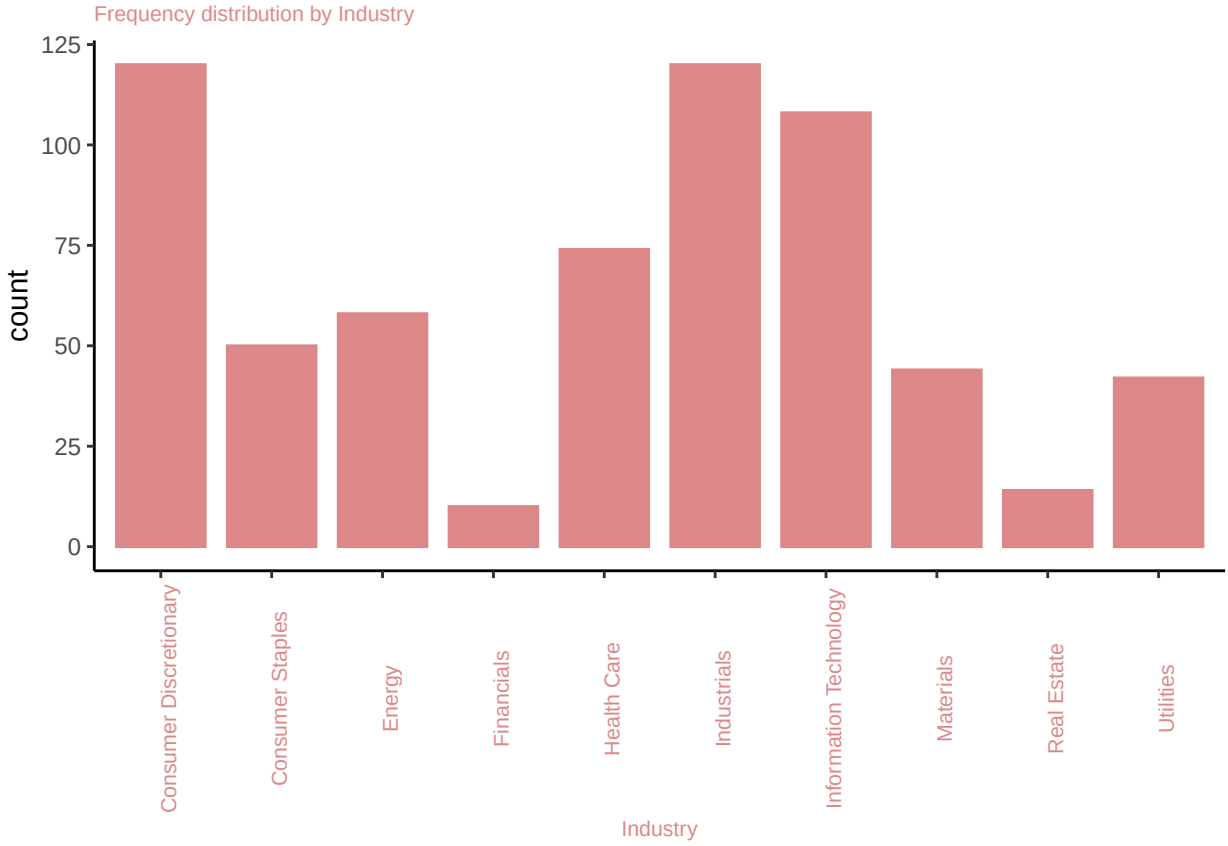
```
Shapiro Wilkes Test
```

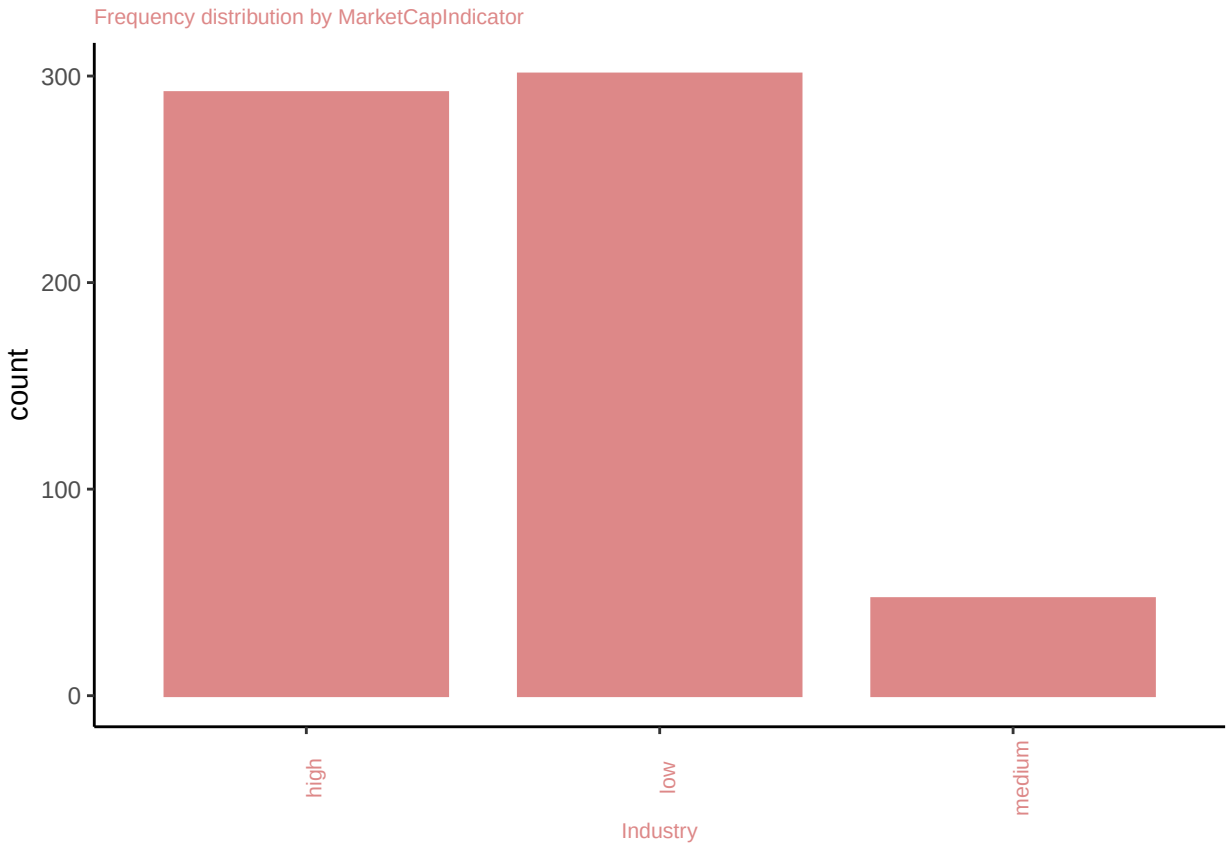
```
    Shapiro-Wilk normality test

data:  as.numeric(as.factor(s$Industry))[0:200]
W = 0.92219, p-value = 8.452e-09
```

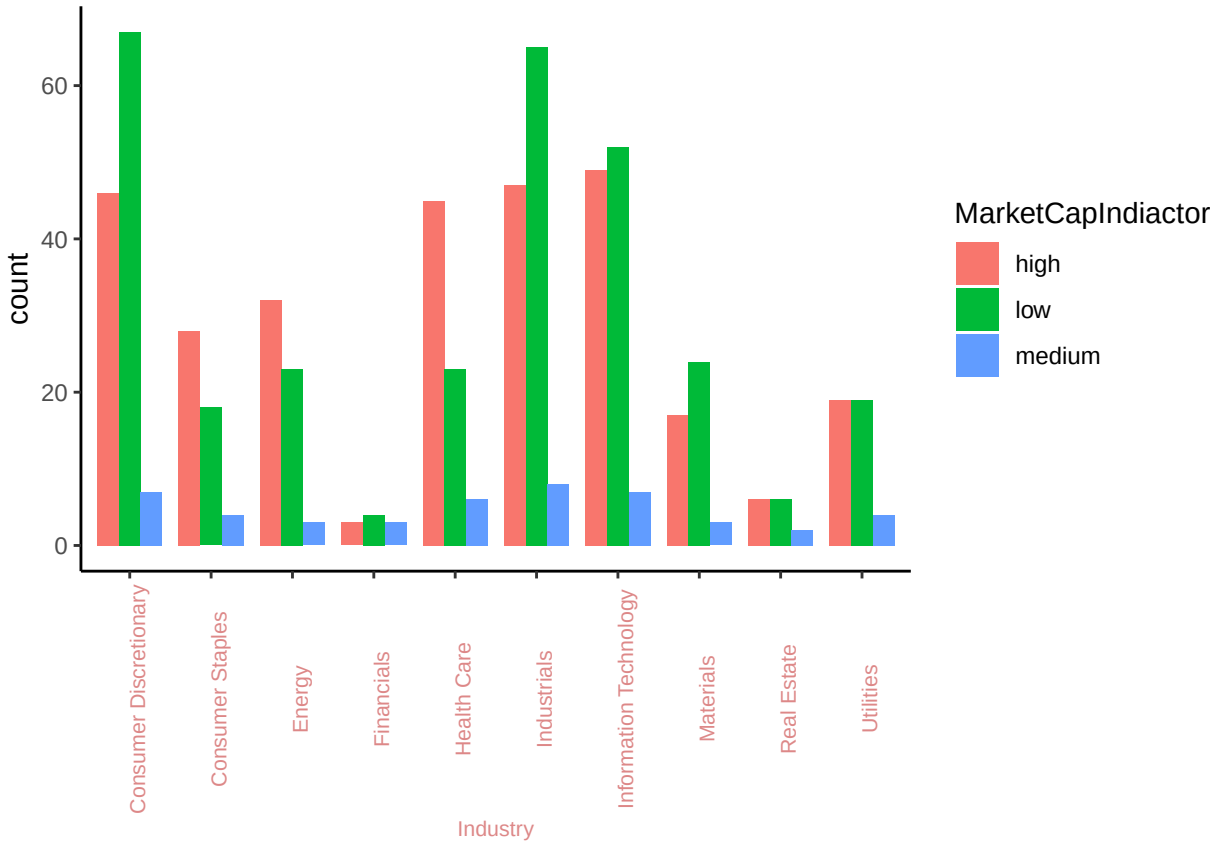
###Graphical Summaries

- Graphical Summary of categorical variable Industry & marketCapIndiactor

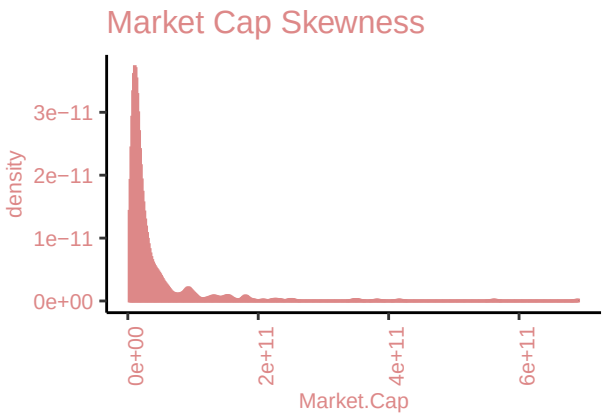


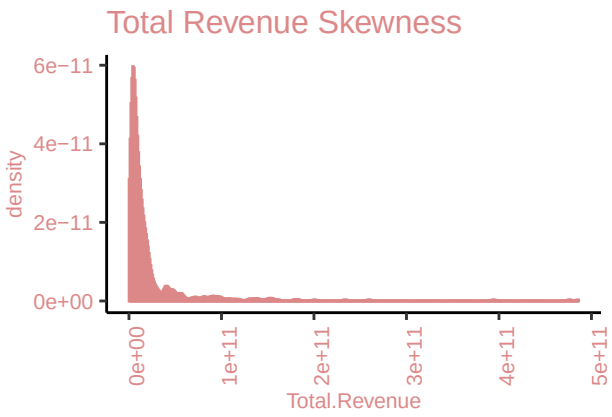


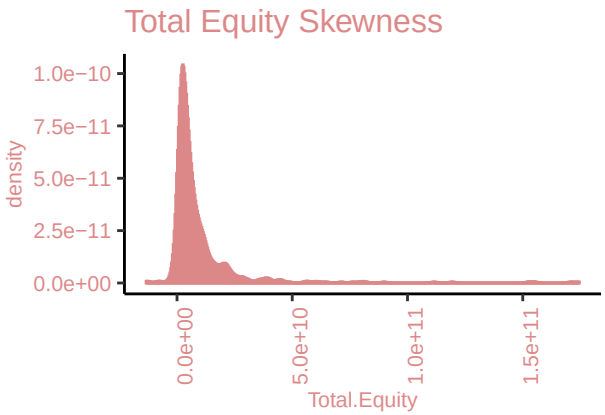
- Graphical Summary of categorical variable Industry grouped by MarketCapIndiactor

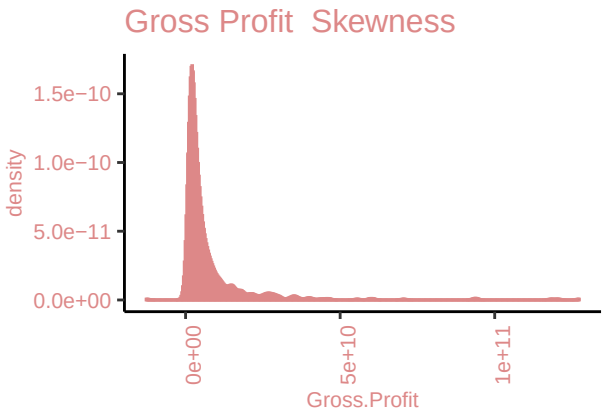


- Graphical summary of numerical variable Market.Cap,Total.Revenue,Total.Equity,Gross.Profit

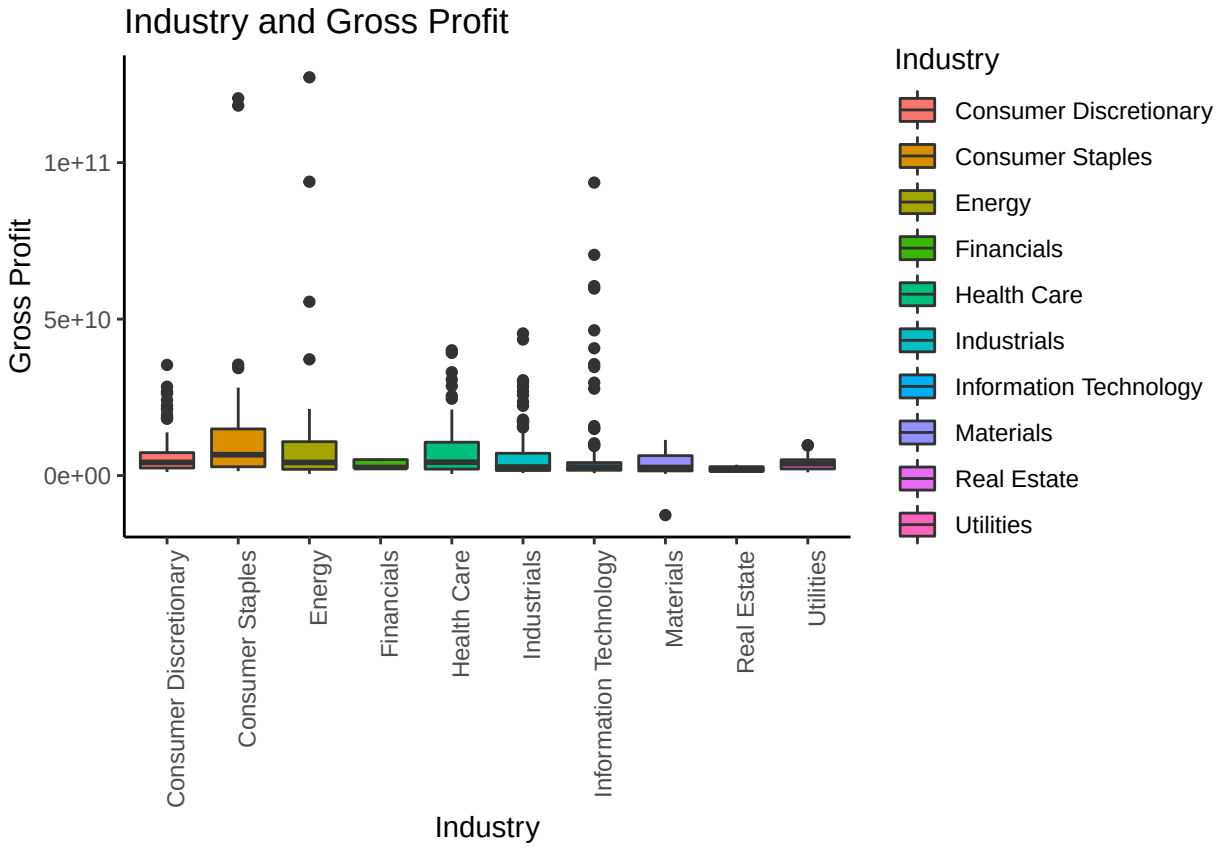


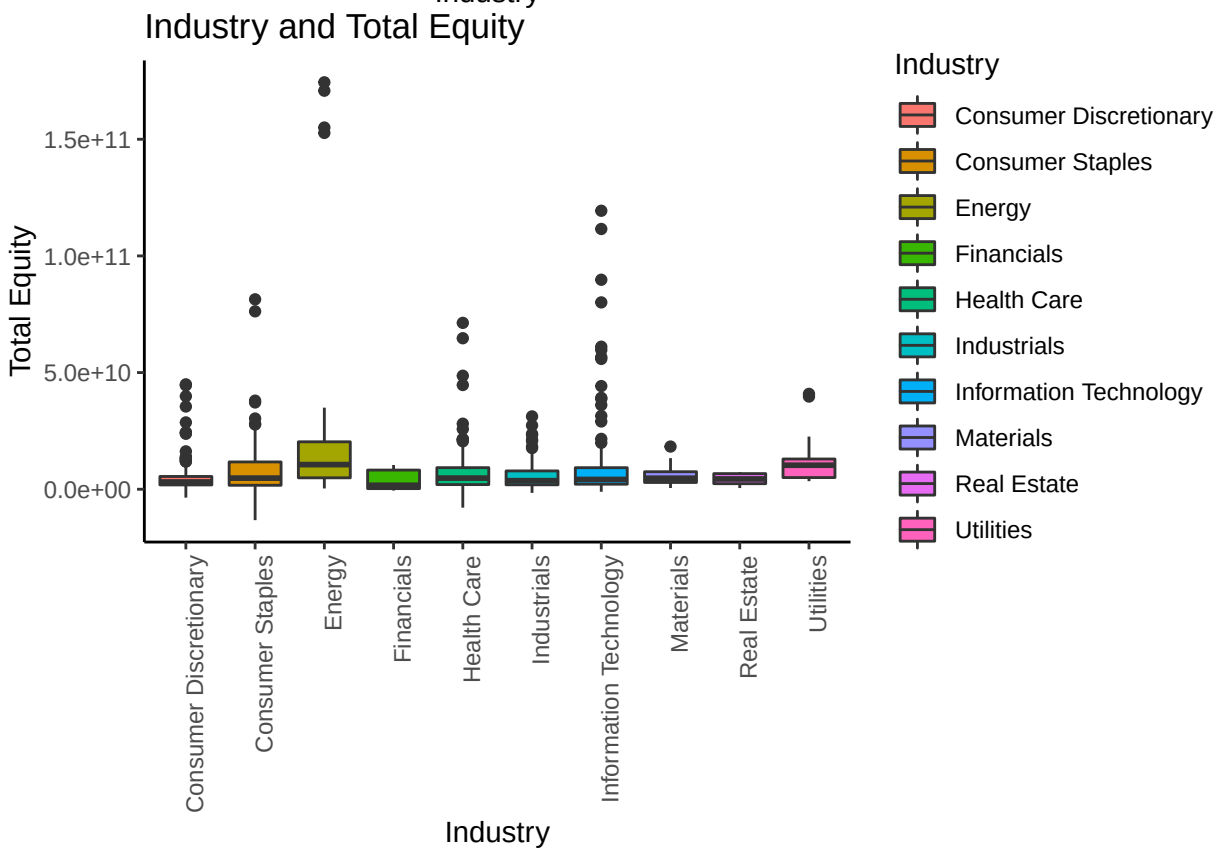


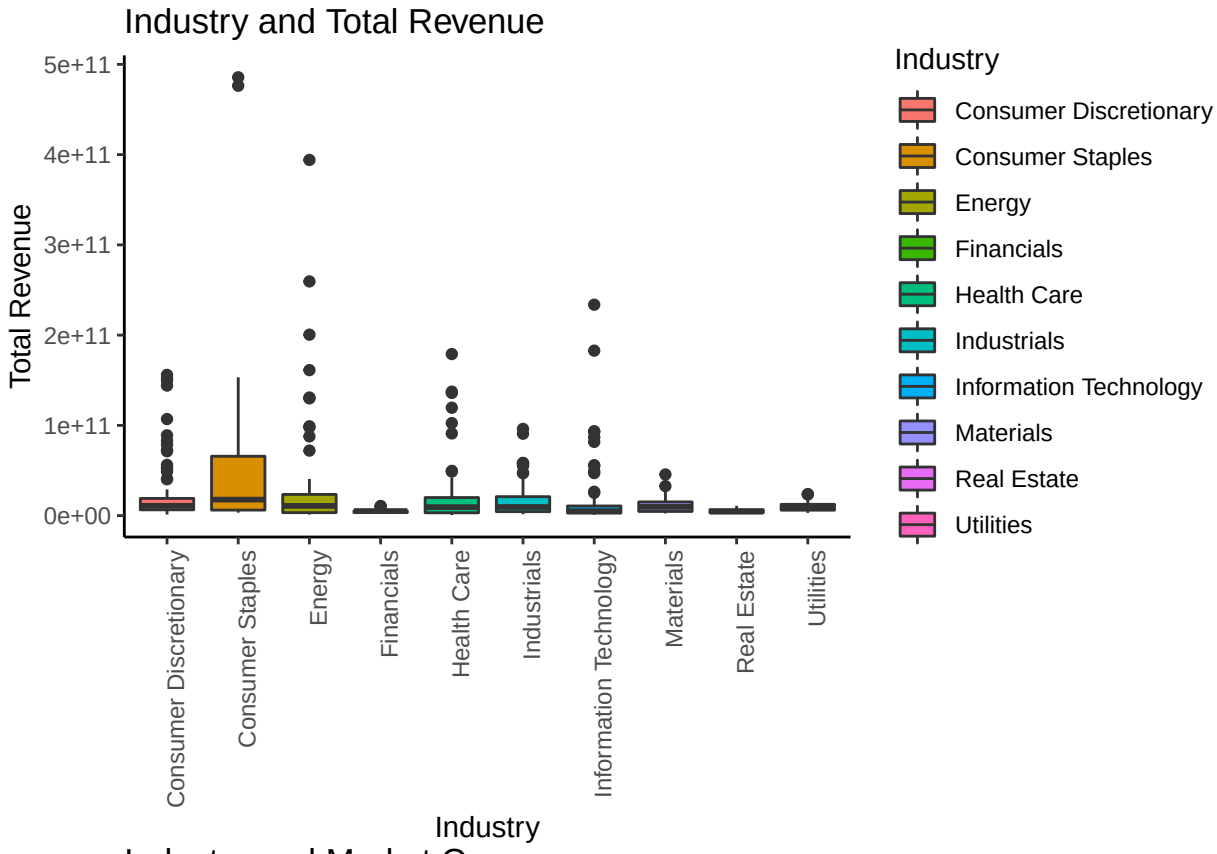


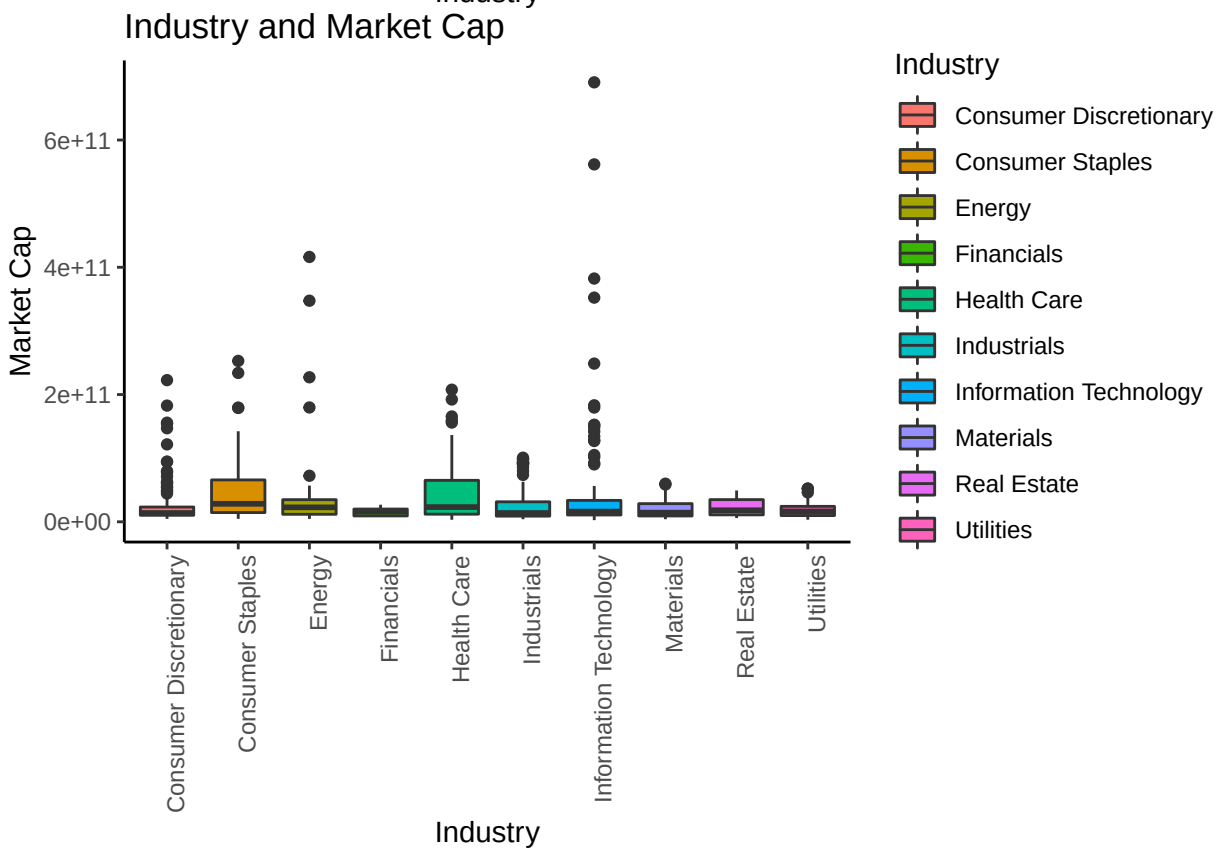


- Graphical summary of numerical variable Market.Cap,Total.Revenue,Total.Equity,Gross.Profit grouped by categorical variable Industry


Industry and Gross Profit
Gross Profit
1e+11
5e+10
0e+00
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities
Industry
Industry
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities


Industry and Total Equity
Total Equity
1.5e+11
1.0e+11
5.0e+10
0.0e+00
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities
Industry
Industry
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities

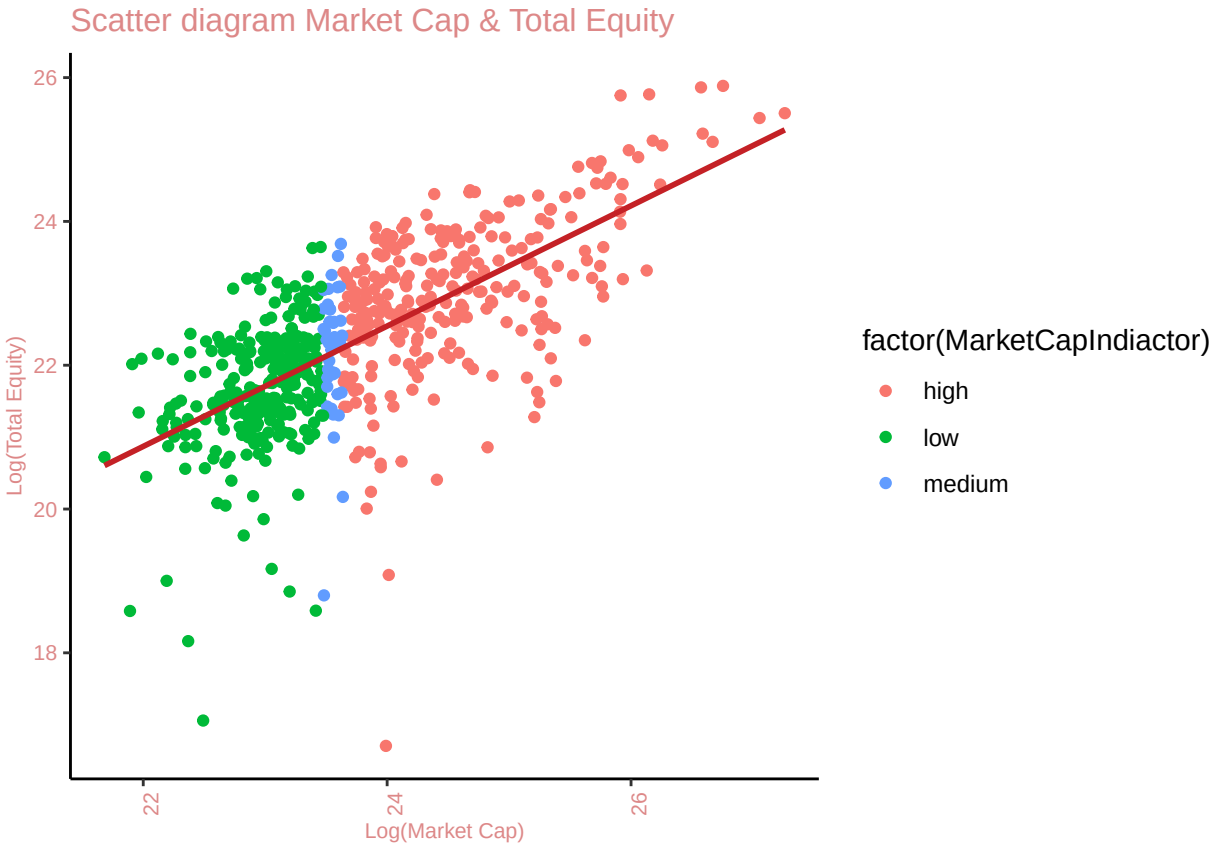

Industry and Total Revenue
Total Revenue
5e+11
4e+11
3e+11
2e+11
1e+11
0e+00
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities
Industry
Industry
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities


Industry and Market Cap
Market Cap
6e+11
4e+11
2e+11
0e+00
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities
Industry
Industry
Consumer Discretionary
Consumer Staples
Energy
Financials
Health Care
Industrials
Information Technology
Materials
Real Estate
Utilities

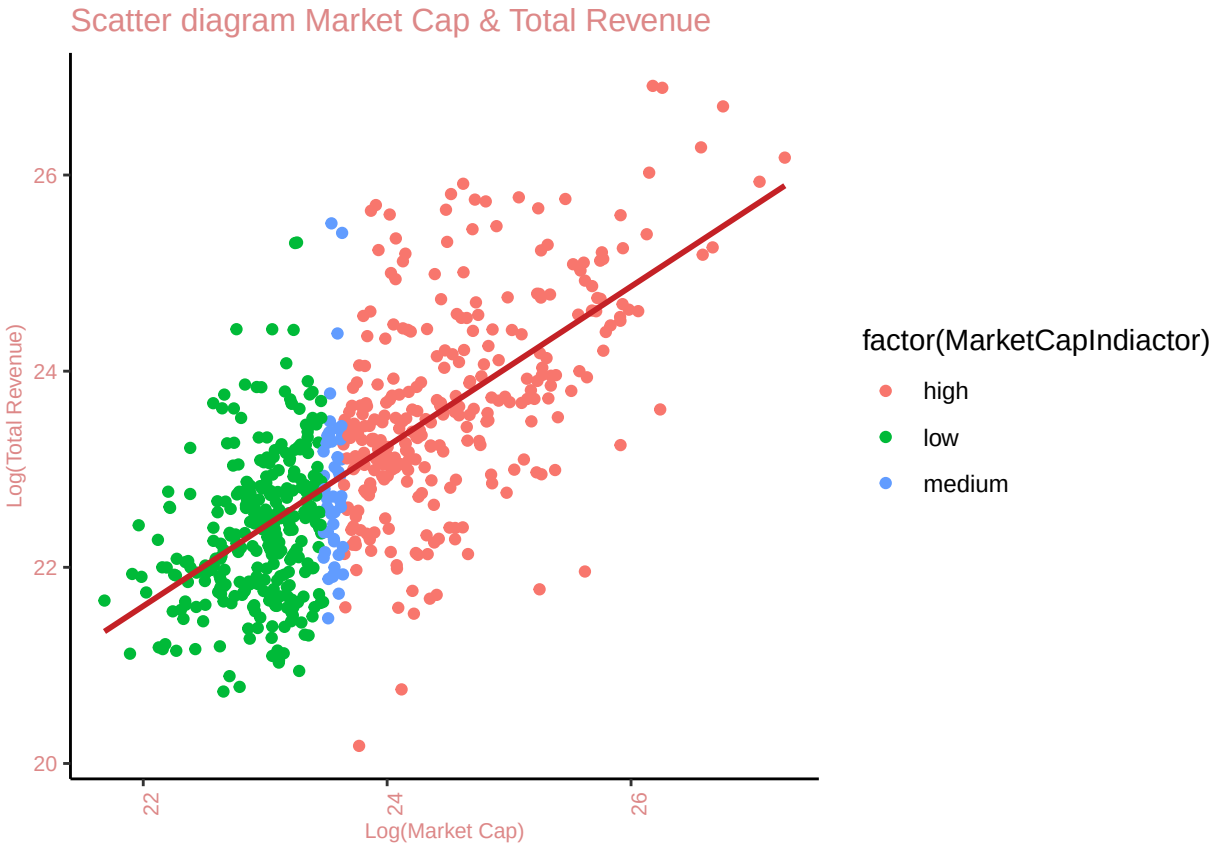
Correlation and Regression

- Scatter Plot for Market.Cap & Total.Equity.

```
'data.frame':   640 obs. of  29 variables:
 $ Ticker.Symbol                   : Factor w/ 320 levels "AAL","AAPL","ABBV",..: 1 1 2 2 3 3 4 4 5 5 .
 $ Capital.Expenditures            : num  -5.31e+09 -6.15e+09 -9.57e+09 -1.12e+10 -6.12e+08 ...
 $ Cash.Ratio                      : num  60 51 40 52 74 77 10 10 43 67 ...
 $ Cost.of.Revenue                 : num  1.56e+10 1.11e+10 1.12e+11 1.40e+11 4.43e+09 ...
 $ Depreciation                    : num  1.34e+09 1.49e+09 7.95e+09 1.13e+10 7.86e+08 ...
 $ Earnings.Before.Interest.and.Tax: num  4.10e+09 5.50e+09 5.35e+10 7.25e+10 2.76e+09 ...
 $ Fixed.Assets                    : num  2.31e+10 2.75e+10 2.06e+10 2.25e+10 2.48e+09 ...
 $ Gross.Profit                    : num  2.70e+10 2.99e+10 7.05e+10 9.36e+10 1.55e+10 ...
 $ Investments                     : num  1.80e+09 4.43e+08 -9.03e+09 -4.44e+10 3.08e+08 ...
 $ Liabilities                     : num  -1.03e+09 -6.33e+08 1.34e+10 1.52e+10 -1.93e+08 ...
 $ Long.Term.Debt                  : num  1.60e+10 1.83e+10 2.90e+10 5.33e+10 1.05e+10 ...
 $ Net.Cash.Flow                   : num  -1.46e+08 -6.04e+08 -4.15e+08 7.28e+09 -1.25e+09 ...
 $ Pre.Tax.ROE                     : num  159 82 48 61 136 168 34 44 12 15 ...
 $ Profit.Margin                   : num  7 19 22 23 9 23 0 0 11 22 ...
 $ Retained.Earnings               : num  -8.56e+09 -1.23e+09 8.72e+10 9.23e+10 5.35e+08 ...
 $ Total.Current.Assets            : num  1.18e+10 9.98e+09 6.85e+10 8.94e+10 1.61e+10 ...
 $ Total.Current.Liabilities       : num  1.34e+10 1.36e+10 6.34e+10 8.06e+10 1.14e+10 ...
 $ Total.Equity                    : num  2.02e+09 5.64e+09 1.12e+11 1.19e+11 1.74e+09 ...
 $ Total.Liabilities               : num  4.12e+10 4.28e+10 1.20e+11 1.71e+11 2.58e+10 ...
 $ Total.Revenue                   : num  4.26e+10 4.10e+10 1.83e+11 2.34e+11 2.00e+10 ...
 $ Earnings.Per.Share              : num  4.02 11.39 6.49 9.28 1.11 ...
 $ Estimated.Shares.Outstanding    : num  7.17e+08 6.68e+08 6.09e+09 5.75e+09 1.60e+09 ...
 $ Industry                        : Factor w/ 10 levels "Consumer Discretionary",..: 6 6 7 7 5 5 5 5 5
 $ endyear                         : Factor w/ 2 levels "2014","2015": 1 2 1 2 1 2 1 2 1 2 ...
 $ quarter                         : Factor w/ 4 levels "1","2","3","4": 4 4 3 3 4 4 3 3 4 4 ...
 $ Stock.p                         : num  38.9 45.1 92.3 120 55.5 ...
 $ Year                            : Factor w/ 2 levels "2014","2015": 1 2 1 2 1 2 1 2 1 2 ...
 $ Market.Cap                      : num  2.79e+10 3.01e+10 5.62e+11 6.91e+11 8.86e+10 ...
 $ MarketCapIndiactor              : chr  "high" "high" "high" "high" ...
```



- R2 value for Market.Cap and Total.Equity
- Scatter Plot for Market.Cap & Total.Revenue



- R2 value for Market.Cap and Total.Revenue
- Statistical Hypothesis Testing can be categorized into two types as below:
  - t-test command prints out the p-value for the data. The p-value can then be readily compared to the significance level. The null hypothesis is then rejected if the p-value is less than the significance level.

```
    Welch Two Sample t-test

data:  visualization_data$Market.Cap and visualization_data$Total.Revenue
t = 4.908, df = 1179.8, p-value = 1.049e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  8411277703 19614850898
sample estimates:
  mean of x   mean of y
35337997368 21324933067

[1] "P value for Market cap & Total revenue 0.000001"

[1] "Group Means for Market cap & Total revenue 35337997367.965248"
[2] "Group Means for Market cap & Total revenue 21324933067.187500"

[1] "Confidence interval for difference for Market cap & Total revenue 8411277703.442698"
[2] "Confidence interval for difference for Market cap & Total revenue 19614850898.112801"

[1] "Confidence level for Market cap & Total revenue 0.950000"
```

Inferential Statistics

```
[1] "GOOGL"
```

Hypothesis Test, Mean Change Price

- We want to do a hypothesis about the daily change of price of stock trading. Price may be volatile for stocks which are trending, but it might also be stable over the long-haul.
- Testing to see if daily price change has changed would make sense if we wanted to evaluate stability over two time frames. For example, if we wanted to do a pre-post analysis after a sales / marketing event, then we would test two samples (one before and one after).
- Test is two-tailed, meaning we want to know if price increased or decreased.
- Once again, we have a very small p-value (near zero), meaning we need to reject the null hypothesis. Mean daily price change is not equal to the baseline price change.Obviously, changing the alpha level makes no difference, because p is so close to zero.

```
    One Sample t-test

data:  DataSetGoogle$Price2012
t = -33.718, df = 501, p-value < 2.2e-16
alternative hypothesis: true mean is not equal to 6.241242
95 percent confidence interval:
 -0.1912902  0.5170744
sample estimates:
mean of x
0.1628921
```

Paired Tests

- To conduct a matched t-test, we simply need to compare prices of google between 2012 & 2014.
- From the results of the F test, we can see that the null hypothesis that the variances are equal is rejected, because the p-value is below .05. This means we should use the unequal variance t-test (also known as the Welch.)
- The results of this test are also clear. Reject the null hypothesis that that years 2012 adjusted closing prices are less than or equal to years 2014. That is nice to know. We would definitely want to investigate further, but we would surmise that if a company invested five years ago in a long-term position, they would not have greater gains!

```
    F test to compare two variances

data:  DataSetGoogle$Price2012 and DataSetGoogle$Price2014
F = 0.32317, num df = 501, denom df = 501, p-value < 2.2e-16
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.2711993 0.3851034
sample estimates:
ratio of variances
         0.3231715

    Two Sample t-test

data:  DataSetGoogle$Price2012 and DataSetGoogle$Price2014
t = 1.6032, df = 1002, p-value = 0.1092
alternative hypothesis: true difference in means is not equal to 0
```

```
95 percent confidence interval:
 -0.1310177  1.3005862
sample estimates:
 mean of x  mean of y
 0.1628921 -0.4218921
```

```
    Welch Two Sample t-test

data:  DataSetGoogle$Price2012 and DataSetGoogle$Price2014
t = 1.6032, df = 794.2, p-value = 0.1093
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.1312443  1.3008127
sample estimates:
 mean of x  mean of y
 0.1628921 -0.4218921
```

Independent Tests

- The independent-samples test can take one of three forms, depending on the structure of your data and the equality of their variances. The general form of the test is t.test(y1, y2, paired=FALSE).
- Here for Independent test, we will conduct price comparison between Amazon & Google.
- Test for equality of variances in the data prior to running an independent-samples t-test,can be done by var.test() function:

```
[1] "GOOGL"
```

```
[1] "AMZN"
```

```
    Two Sample t-test

data:  pairedtestdataset$PriceGoogle and pairedtestdataset$PriceAmazon
t = -0.41406, df = 1002, p-value = 0.6789
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.3699250  0.2410143
sample estimates:
  mean of x   mean of y
-0.12885399 -0.06439866
```

```
    Welch Two Sample t-test

data:  pairedtestdataset$PriceGoogle and pairedtestdataset$PriceAmazon
t = -0.41406, df = 828.45, p-value = 0.6789
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.3700024  0.2410917
sample estimates:
  mean of x   mean of y
-0.12885399 -0.06439866
```

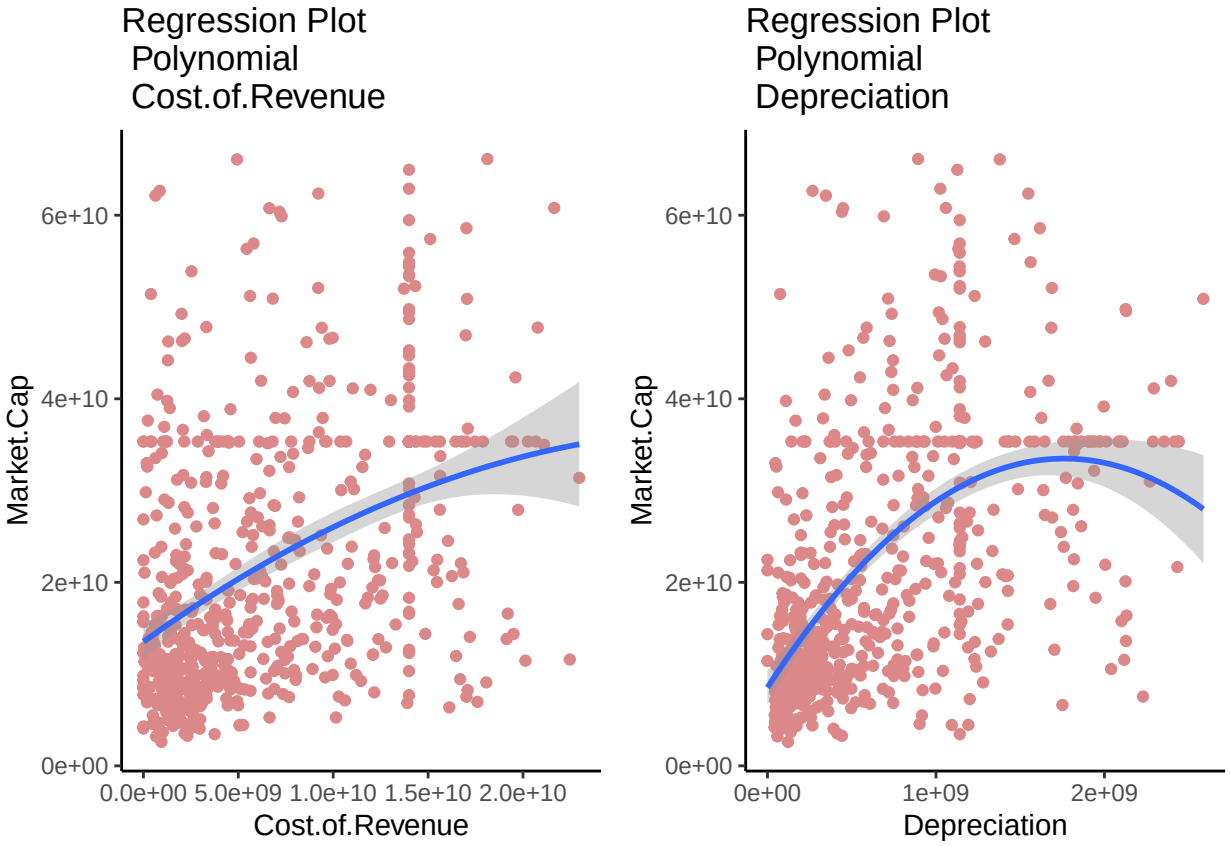
```
    F test to compare two variances

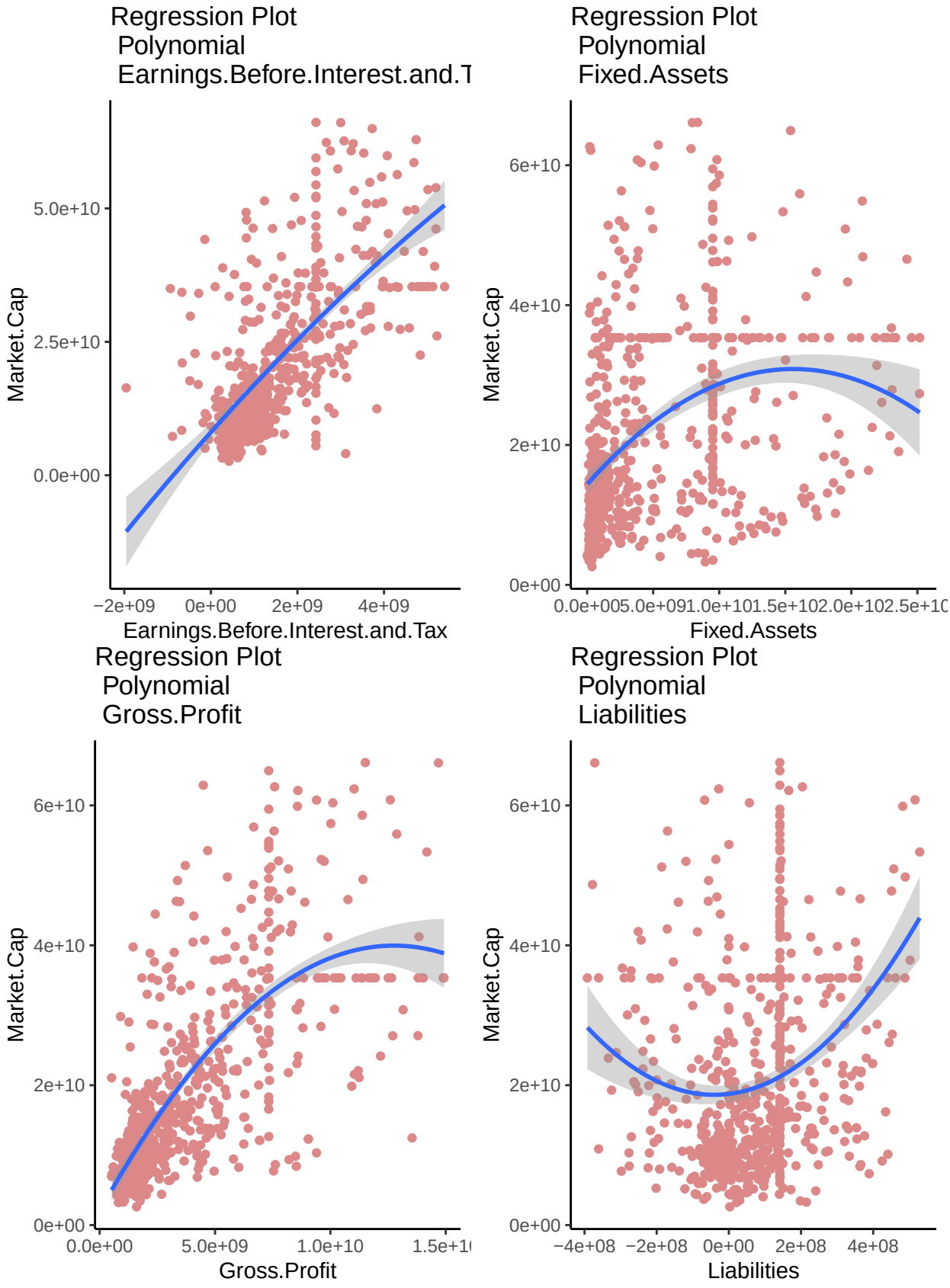
data:  pairedtestdataset$PriceGoogle and pairedtestdataset$PriceAmazon
F = 2.688, num df = 501, denom df = 501, p-value < 2.2e-16
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
```

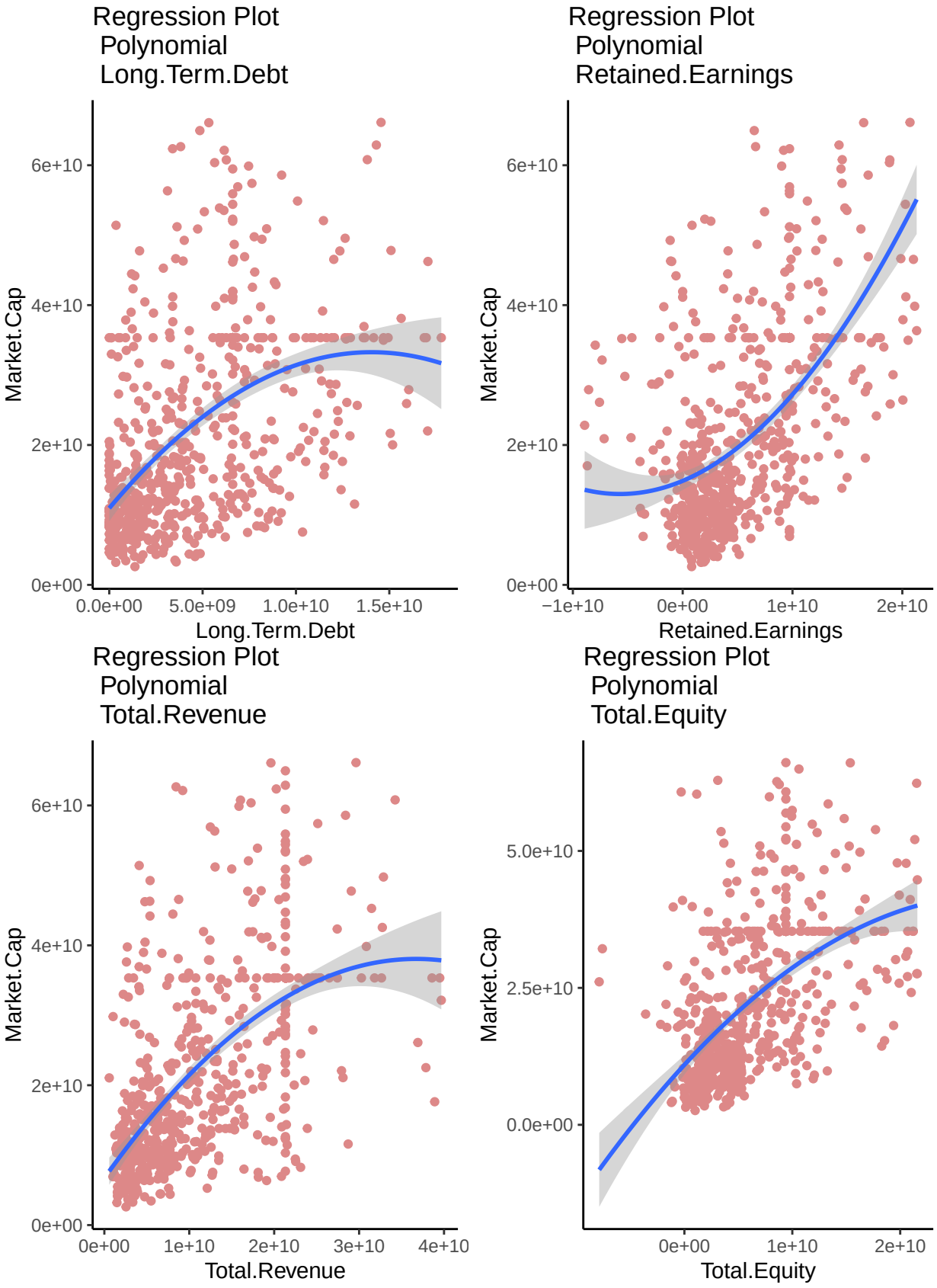
```
 2.255708 3.203109
sample estimates:
ratio of variances
          2.687988
```

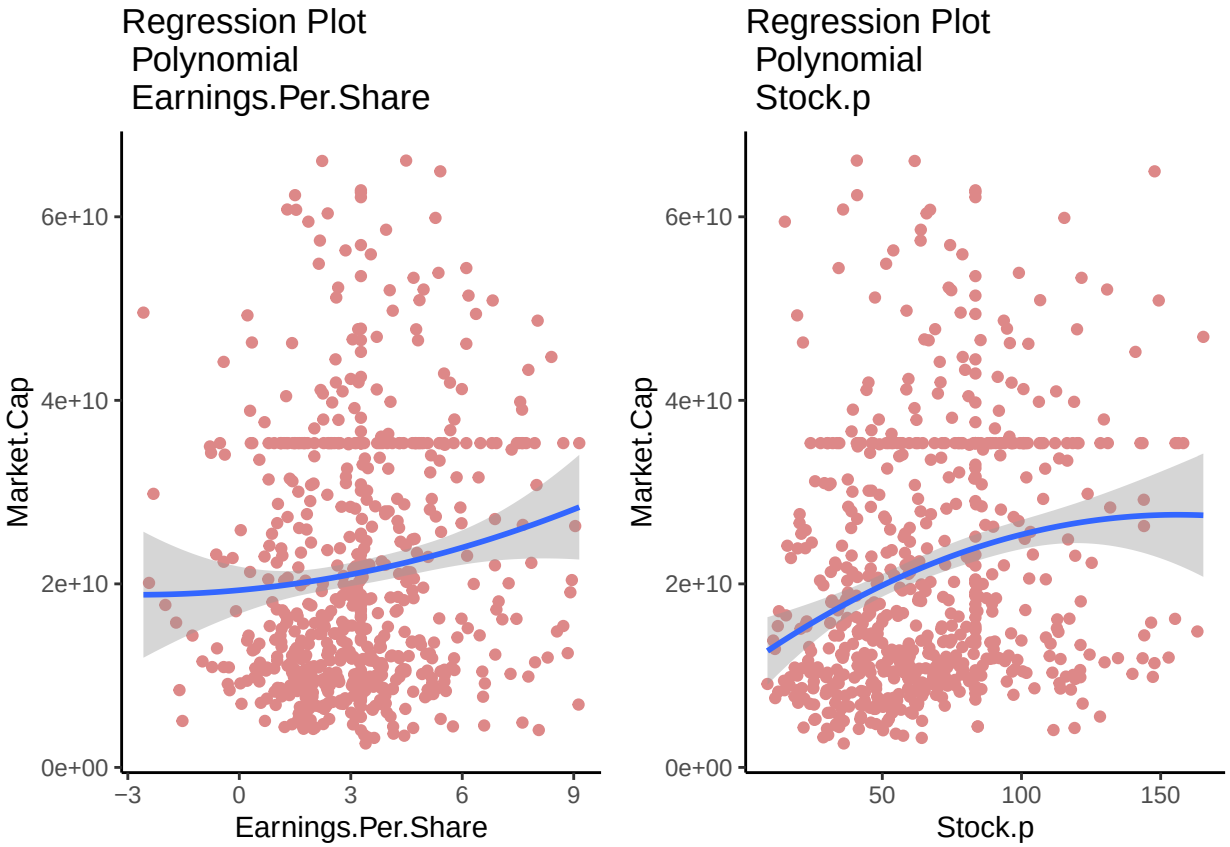
Regression Diagnostic Plots

- Regression plot for Market.Cap with other features

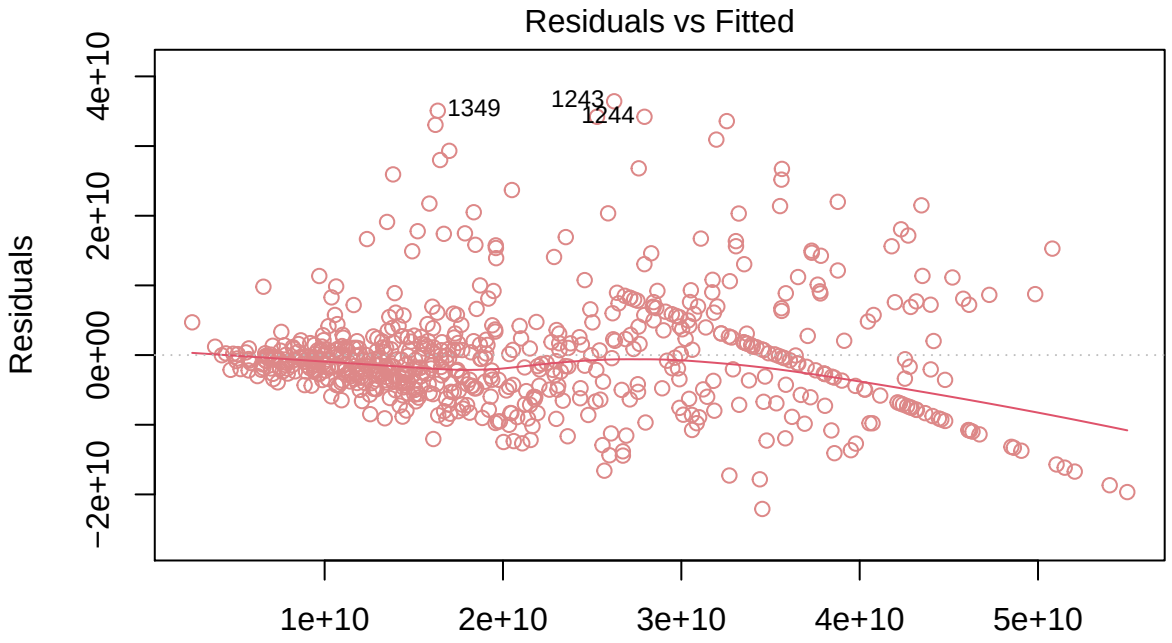


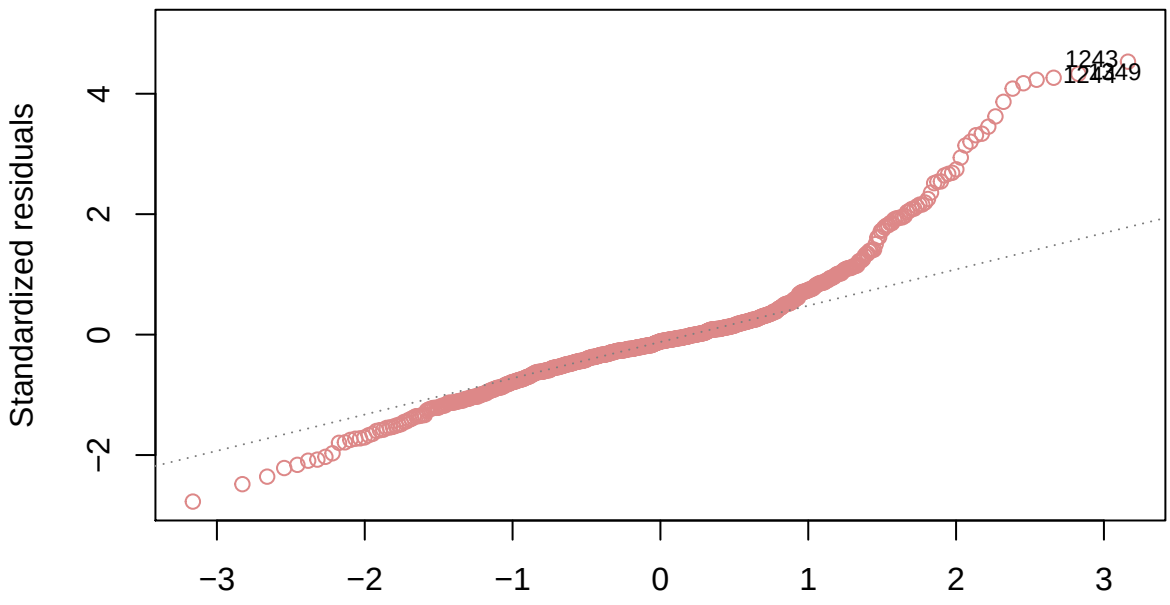

Regression Plot
Polynomial
Earnings.Before.Interest.and.T
Market.Cap
5.0e+10
2.5e+10
0.0e+00
−2e+09
0e+00
2e+09
4e+09
Earnings.Before.Interest.and.Tax
Regression Plot
Polynomial
Fixed.Assets
Market.Cap
6e+10
4e+10
2e+10
0e+00
0.0e+00
5.0e+09
1.0e+10
1.5e+10
2.0e+10
2.5e+10
Fixed.Assets
Regression Plot
Polynomial
Gross.Profit
Market.Cap
6e+10
4e+10
2e+10
0e+00
0.0e+00
5.0e+09
1.0e+10
Gross.Profit
Regression Plot
Polynomial
Liabilities
Market.Cap
6e+10
4e+10
2e+10
0e+00
−4e+08
−2e+08
0e+00
2e+08
4e+08
Liabilities

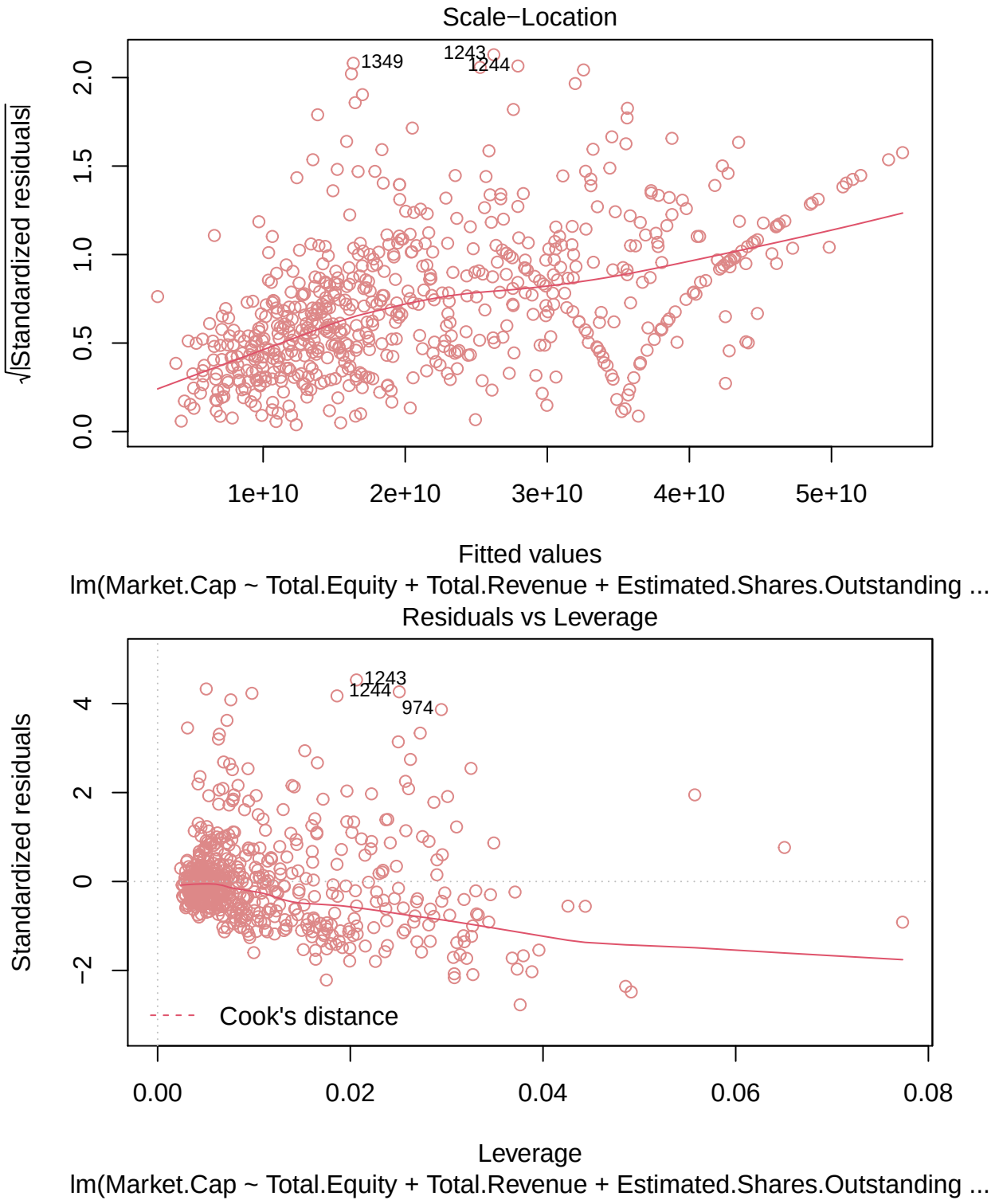

Regression Plot
Polynomial
Long.Term.Debt
Market.Cap
Long.Term.Debt
0e+00
2e+10
4e+10
6e+10
0.0e+00
5.0e+09
1.0e+10
1.5e+10
Regression Plot
Polynomial
Retained.Earnings
Market.Cap
Retained.Earnings
−1e+10
0e+00
1e+10
2e+10
Regression Plot
Polynomial
Total.Revenue
Market.Cap
Total.Revenue
0e+00
1e+10
2e+10
3e+10
4e+10
Regression Plot
Polynomial
Total.Equity
Market.Cap
Total.Equity
0.0e+00
2.5e+10
5.0e+10



- The diagnostic plots of availability with price show residuals in four different ways:
- Residuals vs Fitted: This diagnostic plot is an indicator of the Linearity or Non Linearity of the relationship.If there is no perceivable pattern around the central horizontal curve then the relationship is linear.
- Normal Q-Q: This diagnostic plot ascertains whether the residuals are normally distributed.If the resiuals are algned to the central diagonal then the residuals follow a straight line.
- Scale-Location: This diagnostic is to evaluate the homogeneity of variance of the residuals .If the residuals are spread uniformly around the central line then the residuals are homoscedastic.
- Residuals vs Leverage. Used to identify influential cases, that is extreme values that might influence the regression results when included or excluded from the analysis.


Residuals vs Fitted
Residuals
4e+10
2e+10
0e+00
−2e+10
1349
1243
1244
1e+10
2e+10
3e+10
4e+10
5e+10
Fitted values
lm(Market.Cap ~ Total.Equity + Total.Revenue + Estimated.Shares.Outstanding ...


Normal Q−Q
Standardized residuals
4
2
0
−2
1243
1244
1349
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(Market.Cap ~ Total.Equity + Total.Revenue + Estimated.Shares.Outstanding ...



MultiCollinearity

- Collinearity implies two variables are near perfect linear combinations of one another. Multicollinearity involves more than two variables. In the presence of multicollinearity, regression estimates are unstable and have high standard errors.
- Variance inflation factors measure the inflation in the variances of the parameter estimates due to

collinearities that exist among the predictors.

- The general rule of thumb is that VIFs exceeding 4 warrant further investigation, while VIFs exceeding 10 are signs of serious multicollinearity requiring correction.
- In our example, the VIF score all the Total.Equity,Total.Revenue , Estimated.Shares.Outstanding Earnings.Before.Interest.and.Tax ,Gross.Profit is very high . This might be problematic.

```
[1] "VIF score for all features"
```

```
                   Total.Equity                    Total.Revenue
                       3.198600                         3.939829
    Estimated.Shares.Outstanding Earnings.Before.Interest.and.Tax
                       2.732357                         3.040498
                   Gross.Profit                          Stock.p
                       7.184466                         1.062775
```

Regression- Find if Market.Cap is affected by trading technical indicators

Linear Regression

- Objective: Check if Market.Cap is affected by "Total.Equity","Total.Revenue", "Estimated.Shares.Outstanding","Earni
- Import the dataset, and clean the dataset for target and feature variables.
- Data slicing:
  - Dataset is split into 75 percent of training data, 25 % of test set.
- Preprocessing:
  - We scale and center the predictor & feature variables before passing to models.
- Training the Multiple Linear Regression:
  - Training the Multiple Linear Regression with metric as "RMSE".
  - train() method is passed with repeated cross-validation resampling method for 10 number of resampling iterations repeated for 3 times.The default method for optimizing tuning parameters in train is to use a grid search.Hyperparameter Tuning using Grid Search Cross Validation
- Trained classifier results
  - We can check the result of our train() method by a print fit.LR variable.

```
+ Fold1.Rep1: intercept=TRUE
- Fold1.Rep1: intercept=TRUE
+ Fold2.Rep1: intercept=TRUE
- Fold2.Rep1: intercept=TRUE
+ Fold3.Rep1: intercept=TRUE
- Fold3.Rep1: intercept=TRUE
+ Fold1.Rep2: intercept=TRUE
- Fold1.Rep2: intercept=TRUE
+ Fold2.Rep2: intercept=TRUE
- Fold2.Rep2: intercept=TRUE
+ Fold3.Rep2: intercept=TRUE
- Fold3.Rep2: intercept=TRUE
+ Fold1.Rep3: intercept=TRUE
- Fold1.Rep3: intercept=TRUE
+ Fold2.Rep3: intercept=TRUE
- Fold2.Rep3: intercept=TRUE
+ Fold3.Rep3: intercept=TRUE
- Fold3.Rep3: intercept=TRUE
Aggregating results
Fitting final model on full training set

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

```
Residuals:
       Min         1Q     Median         3Q        Max
-2.233e+10 -4.448e+09 -9.596e+08  2.379e+09  3.628e+10

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                      2.139e+10  2.102e+08 101.771  < 2e-16 ***
Total.Equity                     9.649e+08  2.724e+08   3.542 0.000409 ***
Total.Revenue                   -5.398e+07  3.301e+08  -0.164 0.870121
Estimated.Shares.Outstanding     4.801e+09  3.153e+08  15.226  < 2e-16 ***
Earnings.Before.Interest.and.Tax 3.977e+09  3.150e+08  12.623  < 2e-16 ***
Gross.Profit                     3.104e+09  3.696e+08   8.397  < 2e-16 ***
Stock.p                          3.654e+09  2.338e+08  15.632  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.237e+09 on 1529 degrees of freedom
Multiple R-squared:  0.6548,    Adjusted R-squared:  0.6534
F-statistic: 483.3 on 6 and 1529 DF,  p-value: < 2.2e-16
```

- Prediction
  - We are ready to predict classes for our test set using predict() method, and calculate error rate and rmse.We get Multiple R-squared value as 0.99499149, and error rate as 0.2309932.

```
RMSE:  4968177423 Error:  0.2309932 R2:  0.9949914
```

- Interpretation of results
  - R-squared has the useful property that its scale is intuitive: it ranges from zero to one, with zero indicating that the proposed model does not improve prediction over the mean model, and one indicating perfect prediction. Improvement in the regression model results in proportional increases in R-squared.
  - The RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data–how close the observed data points are to the model's predicted values. Whereas R-squared is a relative measure of fit, RMSE is an absolute measure of fit. Lower values of RMSE indicate better fit.
  - Since error percentage is 23, R2=0.99, RMSE is , it is safe to assume that market cap is affected by "Total.Equity","Total.Revenue", "Estimated.Shares.Outstanding","Earnings.Before.Interest.and.Tax","Gross.Prof

Polynominal Regression

- Polynomial regression is a special case of linear regression where we fit a polynomial equation on the data with a curvilinear relationship between the target variable and the independent variables.
- In a curvilinear relationship, the value of the target variable changes in a non-uniform manner with respect to the predictor (s).
- poly function returns or evaluates orthogonal polynomials of degree 1 to degree over the specified set of points x: these are all orthogonal to the constant polynomial of degree 0.

```
+ Fold1.Rep1: intercept=TRUE
- Fold1.Rep1: intercept=TRUE
+ Fold2.Rep1: intercept=TRUE
- Fold2.Rep1: intercept=TRUE
+ Fold3.Rep1: intercept=TRUE
- Fold3.Rep1: intercept=TRUE
+ Fold1.Rep2: intercept=TRUE
```

```
- Fold1.Rep2: intercept=TRUE
+ Fold2.Rep2: intercept=TRUE
- Fold2.Rep2: intercept=TRUE
+ Fold3.Rep2: intercept=TRUE
- Fold3.Rep2: intercept=TRUE
+ Fold1.Rep3: intercept=TRUE
- Fold1.Rep3: intercept=TRUE
+ Fold2.Rep3: intercept=TRUE
- Fold2.Rep3: intercept=TRUE
+ Fold3.Rep3: intercept=TRUE
- Fold3.Rep3: intercept=TRUE
Aggregating results
Fitting final model on full training set

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

Residuals:
       Min          1Q      Median          3Q         Max
-1.693e+10 -3.719e+09 -1.128e+09  1.712e+09  4.125e+10

Coefficients:
                                          Estimate Std. Error t value
(Intercept)                               2.139e+10  1.893e+08 112.981
`poly(Total.Equity, 2)1`                  6.920e+08  2.562e+08   2.701
`poly(Total.Equity, 2)2`                 -3.021e+08  2.006e+08  -1.506
`poly(Total.Revenue, 2)1`                -1.022e+09  3.300e+08  -3.096
`poly(Total.Revenue, 2)2`                 4.368e+08  2.210e+08   1.976
`poly(Estimated.Shares.Outstanding, 2)1`  6.839e+09  3.241e+08  21.099
`poly(Estimated.Shares.Outstanding, 2)2` -3.001e+09  2.174e+08 -13.804
`poly(Earnings.Before.Interest.and.Tax, 2)1`  2.823e+09  3.021e+08   9.345
`poly(Earnings.Before.Interest.and.Tax, 2)2`  7.322e+08  2.015e+08   3.633
`poly(Gross.Profit, 2)1`                  2.982e+09  3.786e+08   7.876
`poly(Gross.Profit, 2)2`                 -7.289e+08  2.282e+08  -3.195
`poly(Stock.p, 2)1`                       4.900e+09  2.256e+08  21.724
`poly(Stock.p, 2)2`                      -2.355e+09  2.020e+08 -11.659
                                         Pr(>|t|)
(Intercept)                               < 2e-16 ***
`poly(Total.Equity, 2)1`                  0.00700 **
`poly(Total.Equity, 2)2`                  0.13233
`poly(Total.Revenue, 2)1`                 0.00199 **
`poly(Total.Revenue, 2)2`                 0.04833 *
`poly(Estimated.Shares.Outstanding, 2)1`  < 2e-16 ***
`poly(Estimated.Shares.Outstanding, 2)2`  < 2e-16 ***
`poly(Earnings.Before.Interest.and.Tax, 2)1`  < 2e-16 ***
`poly(Earnings.Before.Interest.and.Tax, 2)2`  0.00029 ***
`poly(Gross.Profit, 2)1`                 6.37e-15 ***
`poly(Gross.Profit, 2)2`                  0.00143 **
`poly(Stock.p, 2)1`                       < 2e-16 ***
`poly(Stock.p, 2)2`                       < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.42e+09 on 1523 degrees of freedom
```

```
Multiple R-squared:  0.721, Adjusted R-squared:  0.7188
F-statistic: 327.9 on 12 and 1523 DF,  p-value: < 2.2e-16
```

- Polynomial Regression Prediction & Accuracy

```
RMSE:  5761789130 Error:  0.2309932 R2:  0.9938427
```

Spline Regression

- Spline is a special function defined piece-wise by polynomials. The term "spline" is used to refer to a wide class of functions that are used in applications requiring data interpolation and/or smoothing. The data may be either one-dimensional or multi-dimensional.
- Spline Regression is one of the non-parametric regression technique. In this technique the dataset is divided into bins at intervals or points which we called as knots. Also this bin has its separate fit.
- The disadvantages of the polynomial regression can be overcome by using Spline Regression. Polynomial regression only captures a certain amount of curvature in a nonlinear relationship. An alternative, and often superior, approach to modeling nonlinear relationships is to use splines.
- Splines provide a way to smoothly interpolate between fixed points, called knots. Polynomial regression is computed between knots. In other words, splines are series of polynomial segments strung together, joining at knots.
- The generic function quantile produces sample quantiles corresponding to the given probabilities.
- bs {splines} Generate the B-spline basis matrix for a polynomial spline.bs uses knots which is the internal breakpoints that define the spline.Typical values are the mean or median for one knot, quantiles for more knots.

```
'data.frame':   640 obs. of  23 variables:
 $ Capital.Expenditures            : num  -5.31e+09 -6.15e+09 -9.57e+09 -1.12e+10 -6.12e+08 ...
 $ Cash.Ratio                      : num  60 51 40 52 74 77 10 10 43 67 ...
 $ Cost.of.Revenue                 : num  1.56e+10 1.11e+10 1.40e+10 1.40e+10 4.43e+09 ...
 $ Depreciation                    : num  1.34e+09 1.49e+09 1.14e+09 1.14e+09 7.86e+08 ...
 $ Earnings.Before.Interest.and.Tax: num  4.10e+09 2.43e+09 2.43e+09 2.43e+09 2.76e+09 ...
 $ Fixed.Assets                    : num  2.31e+10 9.51e+09 2.06e+10 2.25e+10 2.48e+09 ...
 $ Gross.Profit                    : num  7.33e+09 7.33e+09 7.33e+09 7.33e+09 7.33e+09 ...
 $ Investments                     : num  1.80e+09 4.43e+08 -9.03e+09 -4.44e+10 3.08e+08 ...
 $ Liabilities                     : num  1.41e+08 1.41e+08 1.41e+08 1.41e+08 -1.93e+08 ...
 $ Long.Term.Debt                  : num  1.60e+10 6.61e+09 6.61e+09 6.61e+09 1.05e+10 ...
 $ Net.Cash.Flow                   : num  -1.46e+08 -6.04e+08 -4.15e+08 7.28e+09 -1.25e+09 ...
 $ Pre.Tax.ROE                     : num  159 82 48 61 136 168 34 44 12 15 ...
 $ Profit.Margin                   : num  7 19 22 23 9 23 0 0 11 22 ...
 $ Retained.Earnings               : num  -8.56e+09 -1.23e+09 9.73e+09 9.73e+09 5.35e+08 ...
 $ Total.Current.Assets            : num  1.18e+10 9.98e+09 6.85e+10 8.94e+10 1.61e+10 ...
 $ Total.Current.Liabilities       : num  1.34e+10 1.36e+10 6.34e+10 8.06e+10 1.14e+10 ...
 $ Total.Equity                    : num  2.02e+09 5.64e+09 9.41e+09 9.41e+09 1.74e+09 ...
 $ Total.Liabilities               : num  4.12e+10 4.28e+10 1.69e+10 1.69e+10 2.58e+10 ...
 $ Total.Revenue                   : num  2.13e+10 2.13e+10 2.13e+10 2.13e+10 2.00e+10 ...
 $ Earnings.Per.Share              : num  4.02 3.27 6.49 3.27 1.11 ...
 $ Estimated.Shares.Outstanding    : num  7.17e+08 6.68e+08 5.64e+08 5.64e+08 5.64e+08 ...
 $ Stock.p                         : num  38.9 45.1 92.3 120 55.5 ...
 $ Market.Cap                      : num  2.79e+10 3.01e+10 3.53e+10 3.53e+10 3.53e+10 ...
```

```
Call:
lm(formula = Market.Cap ~ bs(Total.Equity, knots = knots) + bs(Total.Revenue,
    knots = knots) + bs(Estimated.Shares.Outstanding, knots = knots) +
    bs(Earnings.Before.Interest.and.Tax, knots = knots) + bs(Gross.Profit,
    knots = knots), data = splineDatasetSubTrain)
```

```
Residuals:
       Min         1Q     Median         3Q        Max
-2.800e+10 -4.215e+09 -6.977e+08  2.852e+09  3.430e+10

Coefficients: (12 not defined because of singularities)
                                                      Estimate Std. Error
(Intercept)                                           3.427e+10  6.318e+09
bs(Total.Equity, knots = knots)1                     -1.727e+10  6.381e+09
bs(Total.Equity, knots = knots)2                     -5.320e+09  3.911e+09
bs(Total.Equity, knots = knots)3                     -8.529e+09  5.238e+09
bs(Total.Equity, knots = knots)4                     -8.703e+09  4.685e+09
bs(Total.Equity, knots = knots)5                     -9.102e+09  5.085e+09
bs(Total.Equity, knots = knots)6                             NA         NA
bs(Total.Equity, knots = knots)7                             NA         NA
bs(Total.Revenue, knots = knots)1                    -2.704e+09  2.740e+09
bs(Total.Revenue, knots = knots)2                    -7.207e+09  1.720e+09
bs(Total.Revenue, knots = knots)3                    -5.667e+09  2.841e+09
bs(Total.Revenue, knots = knots)4                    -2.484e+09  3.860e+09
bs(Total.Revenue, knots = knots)5                    -5.955e+09  5.374e+09
bs(Total.Revenue, knots = knots)6                    -1.659e+10  4.956e+09
bs(Total.Revenue, knots = knots)7                            NA         NA
bs(Estimated.Shares.Outstanding, knots = knots)1     1.295e+09  2.767e+09
bs(Estimated.Shares.Outstanding, knots = knots)2     1.918e+10  2.905e+09
bs(Estimated.Shares.Outstanding, knots = knots)3     9.242e+08  2.432e+09
bs(Estimated.Shares.Outstanding, knots = knots)4    -5.107e+09  5.035e+09
bs(Estimated.Shares.Outstanding, knots = knots)5             NA         NA
bs(Estimated.Shares.Outstanding, knots = knots)6             NA         NA
bs(Estimated.Shares.Outstanding, knots = knots)7             NA         NA
bs(Earnings.Before.Interest.and.Tax, knots = knots)1 -4.189e+10  8.942e+09
bs(Earnings.Before.Interest.and.Tax, knots = knots)2  1.181e+10  3.244e+09
bs(Earnings.Before.Interest.and.Tax, knots = knots)3 -3.521e+08  5.359e+09
bs(Earnings.Before.Interest.and.Tax, knots = knots)4  3.307e+09  1.027e+10
bs(Earnings.Before.Interest.and.Tax, knots = knots)5         NA         NA
bs(Earnings.Before.Interest.and.Tax, knots = knots)6         NA         NA
bs(Earnings.Before.Interest.and.Tax, knots = knots)7         NA         NA
bs(Gross.Profit, knots = knots)1                     1.185e+10  2.733e+09
bs(Gross.Profit, knots = knots)2                     1.652e+10  2.554e+09
bs(Gross.Profit, knots = knots)3                     1.585e+10  2.959e+09
bs(Gross.Profit, knots = knots)4                     1.685e+10  2.868e+09
bs(Gross.Profit, knots = knots)5                             NA         NA
bs(Gross.Profit, knots = knots)6                             NA         NA
bs(Gross.Profit, knots = knots)7                             NA         NA
                                                     t value Pr(>|t|)
(Intercept)                                            5.424 6.77e-08 ***
bs(Total.Equity, knots = knots)1                      -2.706 0.006888 **
bs(Total.Equity, knots = knots)2                      -1.360 0.173932
bs(Total.Equity, knots = knots)3                      -1.628 0.103653
bs(Total.Equity, knots = knots)4                      -1.858 0.063417 .
bs(Total.Equity, knots = knots)5                      -1.790 0.073660 .
bs(Total.Equity, knots = knots)6                          NA       NA
bs(Total.Equity, knots = knots)7                          NA       NA
bs(Total.Revenue, knots = knots)1                     -0.987 0.323903
bs(Total.Revenue, knots = knots)2                     -4.190 2.95e-05 ***
bs(Total.Revenue, knots = knots)3                     -1.995 0.046232 *
```

```
bs(Total.Revenue, knots = knots)4                    -0.643 0.520074
bs(Total.Revenue, knots = knots)5                    -1.108 0.267934
bs(Total.Revenue, knots = knots)6                    -3.346 0.000839 ***
bs(Total.Revenue, knots = knots)7                        NA       NA
bs(Estimated.Shares.Outstanding, knots = knots)1      0.468 0.639956
bs(Estimated.Shares.Outstanding, knots = knots)2      6.602 5.59e-11 ***
bs(Estimated.Shares.Outstanding, knots = knots)3      0.380 0.703998
bs(Estimated.Shares.Outstanding, knots = knots)4     -1.014 0.310574
bs(Estimated.Shares.Outstanding, knots = knots)5         NA       NA
bs(Estimated.Shares.Outstanding, knots = knots)6         NA       NA
bs(Estimated.Shares.Outstanding, knots = knots)7         NA       NA
bs(Earnings.Before.Interest.and.Tax, knots = knots)1  -4.684 3.06e-06 ***
bs(Earnings.Before.Interest.and.Tax, knots = knots)2   3.640 0.000282 ***
bs(Earnings.Before.Interest.and.Tax, knots = knots)3  -0.066 0.947627
bs(Earnings.Before.Interest.and.Tax, knots = knots)4   0.322 0.747503
bs(Earnings.Before.Interest.and.Tax, knots = knots)5      NA       NA
bs(Earnings.Before.Interest.and.Tax, knots = knots)6      NA       NA
bs(Earnings.Before.Interest.and.Tax, knots = knots)7      NA       NA
bs(Gross.Profit, knots = knots)1                      4.336 1.54e-05 ***
bs(Gross.Profit, knots = knots)2                      6.471 1.31e-10 ***
bs(Gross.Profit, knots = knots)3                      5.355 9.87e-08 ***
bs(Gross.Profit, knots = knots)4                      5.875 5.18e-09 ***
bs(Gross.Profit, knots = knots)5                         NA       NA
bs(Gross.Profit, knots = knots)6                         NA       NA
bs(Gross.Profit, knots = knots)7                         NA       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.429e+09 on 1512 degrees of freedom
Multiple R-squared:  0.6425,    Adjusted R-squared:  0.637
F-statistic: 118.1 on 23 and 1512 DF,  p-value: < 2.2e-16
```

- Spline Regression Prediction & Accuracy

```
RMSE:  4626494209 Error:  0.2151068 R2:  0.8751914
```

Generalized Linear Model

Why Use GAM?Relationships between the individual predictors and the dependent variable follow smooth patterns that can be linear or nonlinear. + Mathematically speaking, GAM is an additive modeling technique where the impact of the predictive variables is captured through smooth functions which—depending on the underlying patterns in the data—can be nonlinear. + GAM can capture common nonlinear patterns that a classic linear model would miss. + GAM framework allows us to control smoothness of the predictor functions to prevent overfitting. By controlling the wiggliness of the predictor functions, we can directly tackle the bias/variance tradeoff.

```
Family: gaussian
Link function: identity

Formula:
Market.Cap ~ Total.Equity + Earnings.Before.Interest.and.Tax

Parametric coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                2.173e-09  5.850e-11   37.14   <2e-16 ***
Total.Equity               1.052e+00  5.873e-02   17.92   <2e-16 ***
```

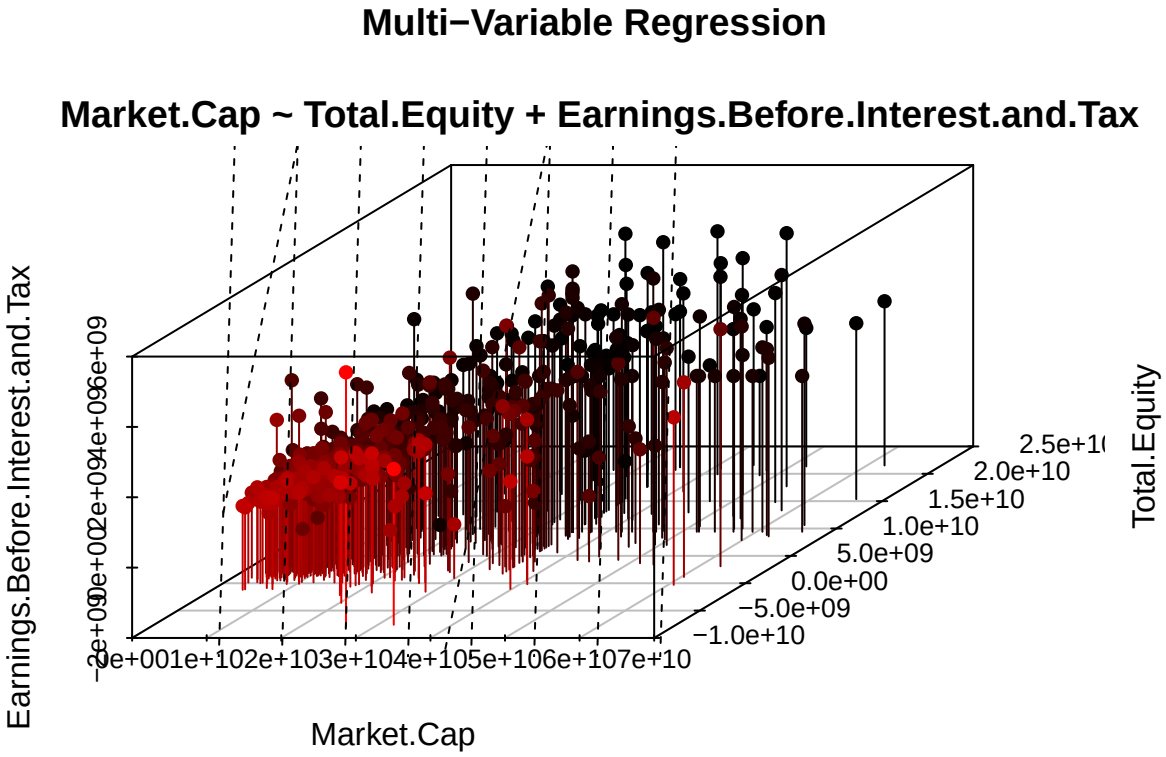
```
Earnings.Before.Interest.and.Tax 8.172e+00  2.327e-01   35.11   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Rank: 2/3
R-sq.(adj) =  0.461   Deviance explained = 43.4%
GCV = 1.1162e+20  Scale est. = 1.1147e+20  n = 1536
```

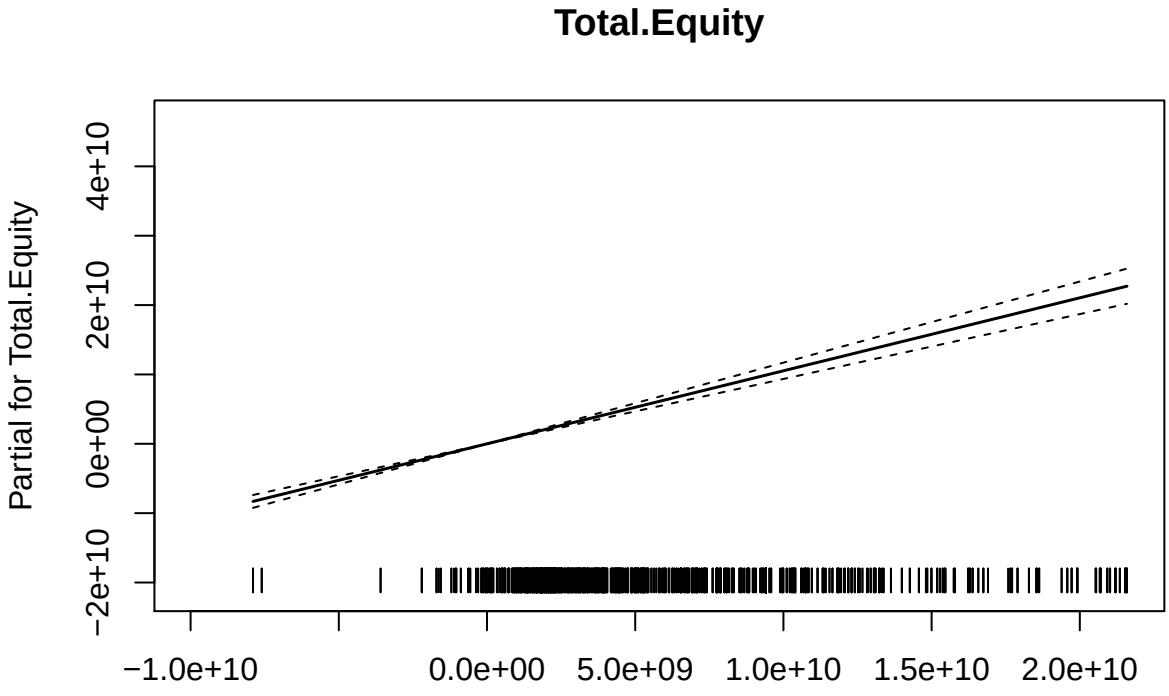
- GAM Regression Prediction & Accuracy

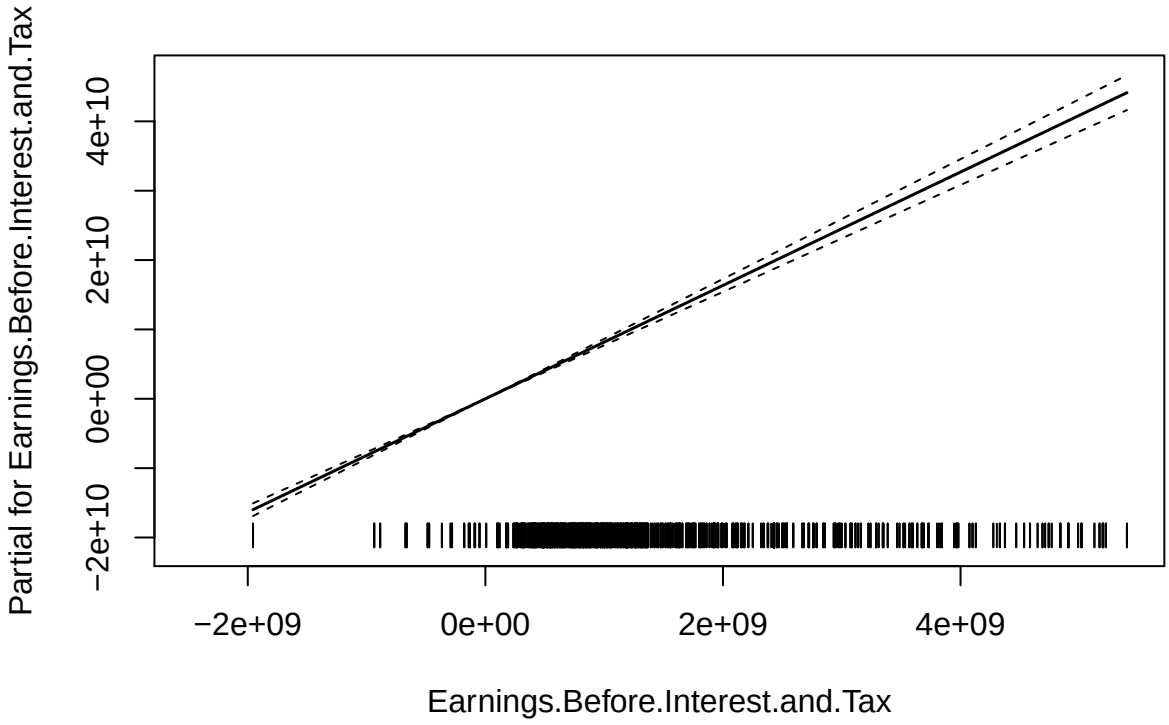
```
RMSE:  6937151743 Error:  0.354476 R2:  0.6515361
```

- GAM Scatter Plot 3D Visualization

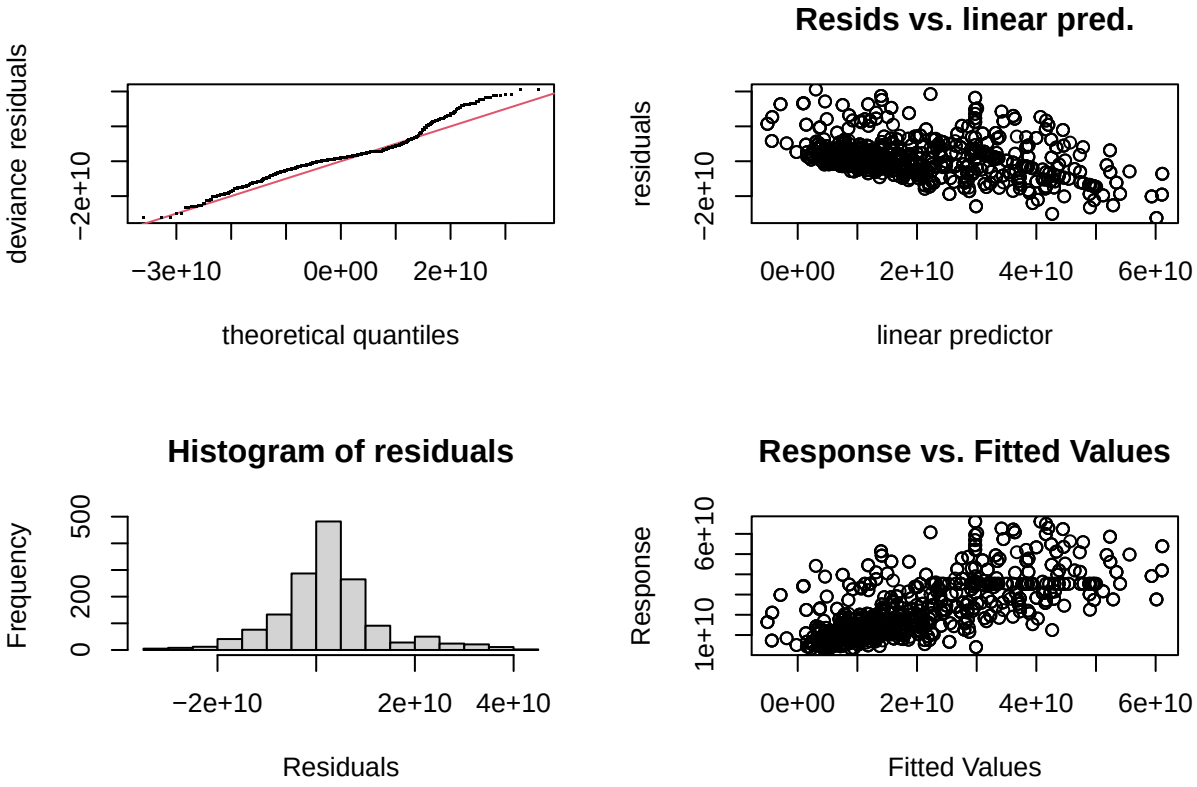


- Visualization part of gam model





- Diagnosing GAM model issues




```
Method: GCV   Optimizer: magic
Model required no smoothing parameter selectionModel rank =  2 / 3
```

Penalized Cubic Regression Spline

- Cubic Regression Spline is specified by bs="cr". These have a cubic spline basis defined by a modest sized set of knots spread evenly through the covariate values. They are penalized by the conventional intergrated square second derivative cubic spline penalty.

```
Family: gaussian
Link function: identity

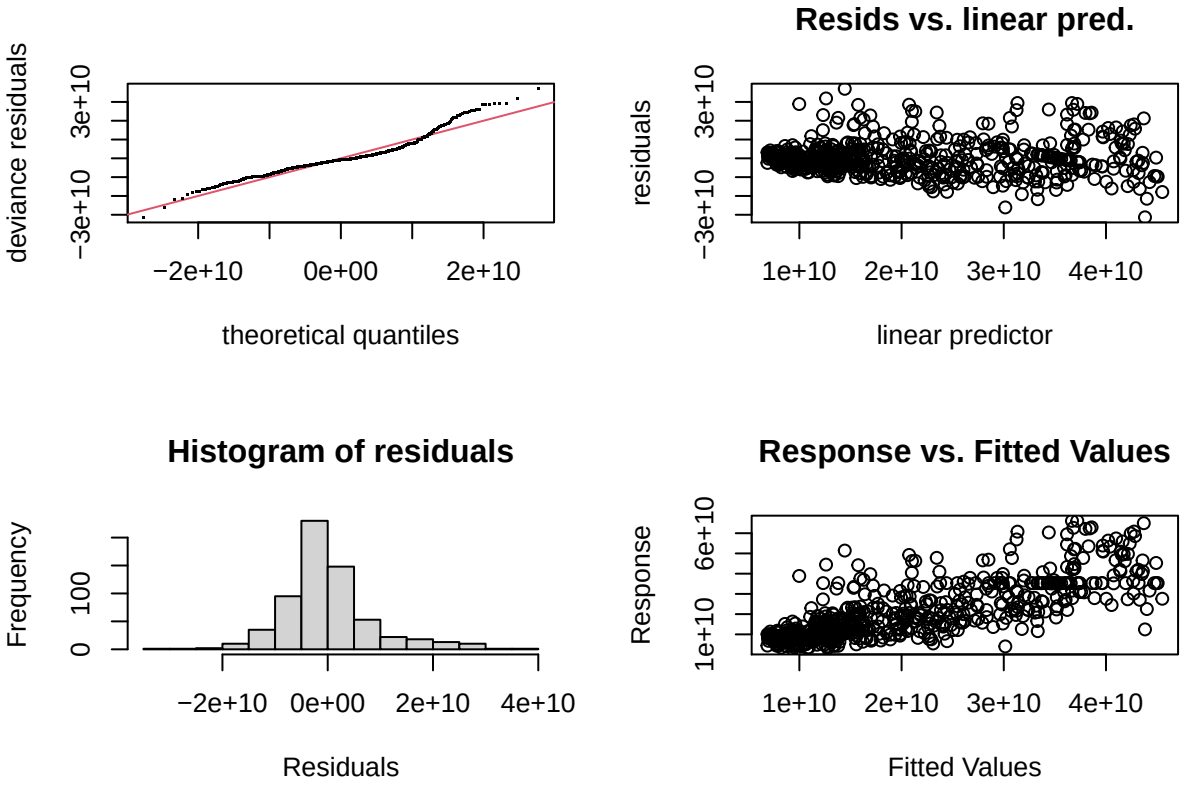
Formula:
Market.Cap ~ s(Total.Equity, bs = "cr") + s(Total.Revenue, bs = "cr") +
    s(Earnings.Before.Interest.and.Tax, bs = "cr")

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.144e+10  3.458e+08      62   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                                   edf Ref.df      F  p-value
s(Total.Equity)                  8.091  8.625  6.858  < 2e-16 ***
s(Total.Revenue)                 4.292  5.027  4.697 0.000331 ***
s(Earnings.Before.Interest.and.Tax) 8.418  8.829 22.214  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
R-sq.(adj) =  0.607   Deviance explained =   62%
GCV = 7.9235e+19  Scale est. = 7.6536e+19  n = 640
```

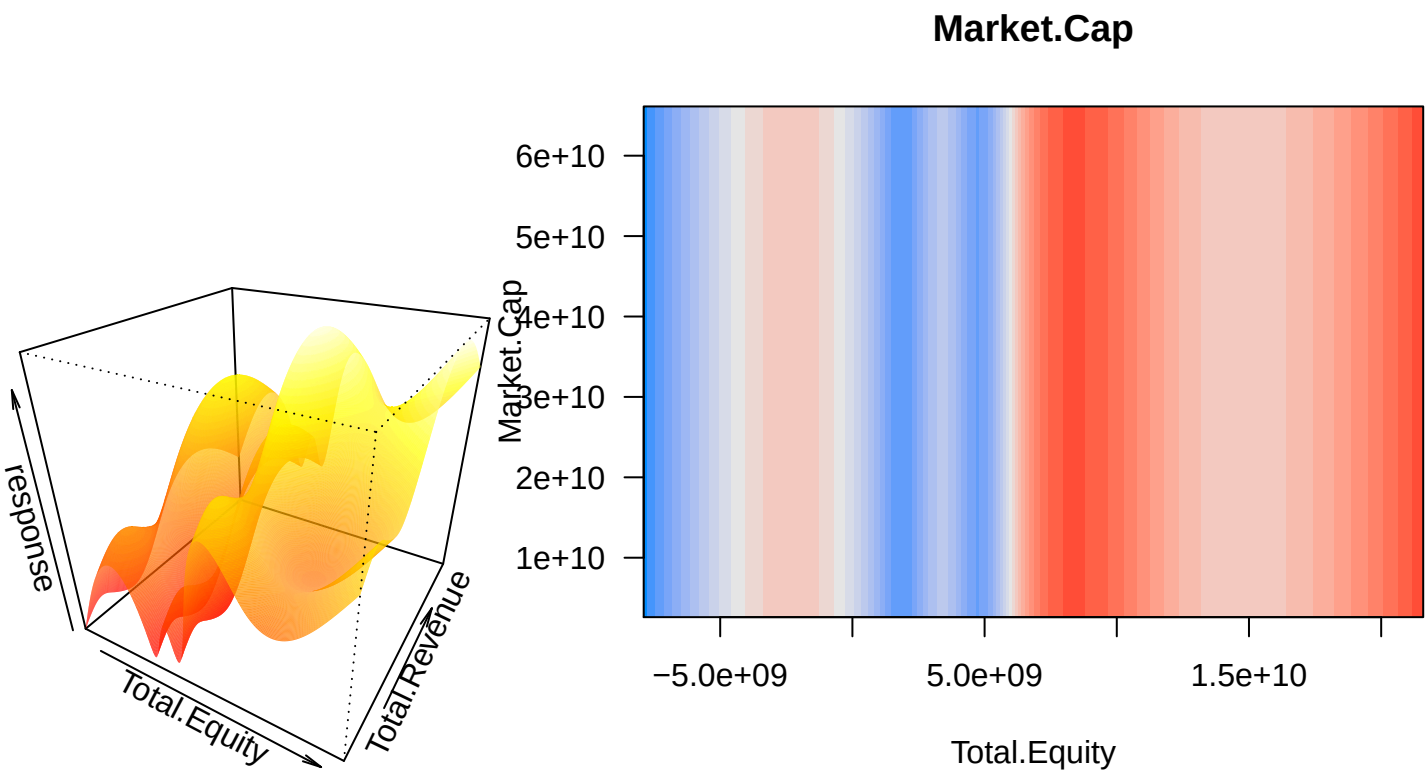
- Diagnosing Penalized Cubic Regression Spline GAM model issues




```
Method: GCV   Optimizer: magic
Smoothing parameter selection converged after 7 iterations.
The RMS GCV score gradient at convergence was 2.367604e+13 .
The Hessian was positive definite.
Model rank =  28 / 28

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                                    k'  edf k-index p-value
s(Total.Equity)                   9.00 8.09    1.07   0.956
s(Total.Revenue)                  9.00 4.29    0.95   0.088 .
s(Earnings.Before.Interest.and.Tax) 9.00 8.42    1.03   0.798
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



- Cubic Regression Spline Prediction & Accuracy

```
RMSE:  5328801306 Error:  0.2722922 R2:  0.9062193
```

Extreme Gradient Boosting

- XGBoost is an implementation of the Gradient Boosted Decision Trees algorithm.
- XGBoost supports various objective functions, including regression, classification and ranking.
- XGBoost gives among the best performances in many machine learning applications. It is optimized gradient-boosting machine learning library. The core algorithm is parallelizable and hence it can use all the processing power of your machine and the machines in your cluster. In R, according to the package documentation, since the package can automatically do parallel computation on a single machine, it could be more than 10 times faster than existing gradient boosting packages.
- XGBoost shines when we have lots of training data where the features are numeric or mixture of numeric and categorical fields. It is also important to note that xgboost is not the best algorithm out there when all the features are categorical or when the number of rows is less than the number of fields (columns).
- The data argument in the xgboost R function is for the input features dataset. It accepts a matrix, dgCMatrix, or local data file. The nrounds argument refers to the max number of iterations (i.e. the number of trees added to the model).
- There are different hyperparameters that we can tune and the parametres are different from baselearner to baselearner. In tree based learners, which are the most common ones in xgboost applications, the following are the most commonly tuned hyperparameters:
- learning rate: learning rate/eta- governs how quickly the model fits the residual error using additional base learners. If it is a smaller learning rate, it will need more boosting rounds, hence more time, to achieve the same reduction in residual error as one with larger learning rate. Typically, it lies between 0.01 - 0.3

- The three hyperparameters below are regularization hyperparameters.
- gamma: min loss reduction to create new tree split. default = 0 means no regularization.
- lambda: L2 reg on leaf weights. Equivalent to Ridge regression.
- alpha: L1 reg on leaf weights. Equivalent to Lasso regression.
- max_depth: max depth per tree. This controls how deep our tree can grow. The Larger the depth, more complex the model will be and higher chances of overfitting. Larger data sets require deep trees to learn the rules from data. Default = 6.
- subsample: % samples used per tree. This is the fraction of the total training set that can be used in any boosting round. Low value may lead to underfitting issues. A very high value can cause over-fitting problems.
- colsample_bytree: % features used per tree. This is the fraction of the number of columns that we can use in any boosting round. A smaller value is an additional regularization and a larger value may be cause overfitting issues.
- n_estimators: number of estimators (base learners). This is the number of boosting rounds.

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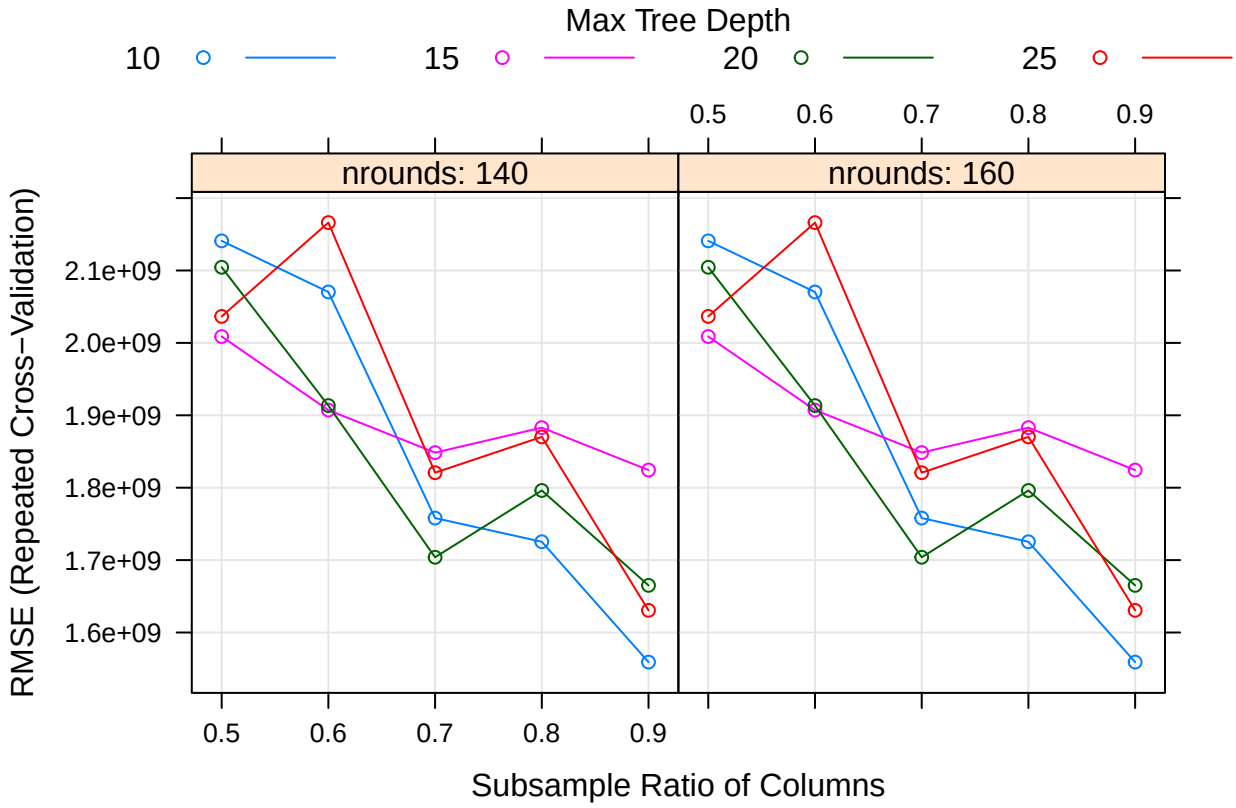
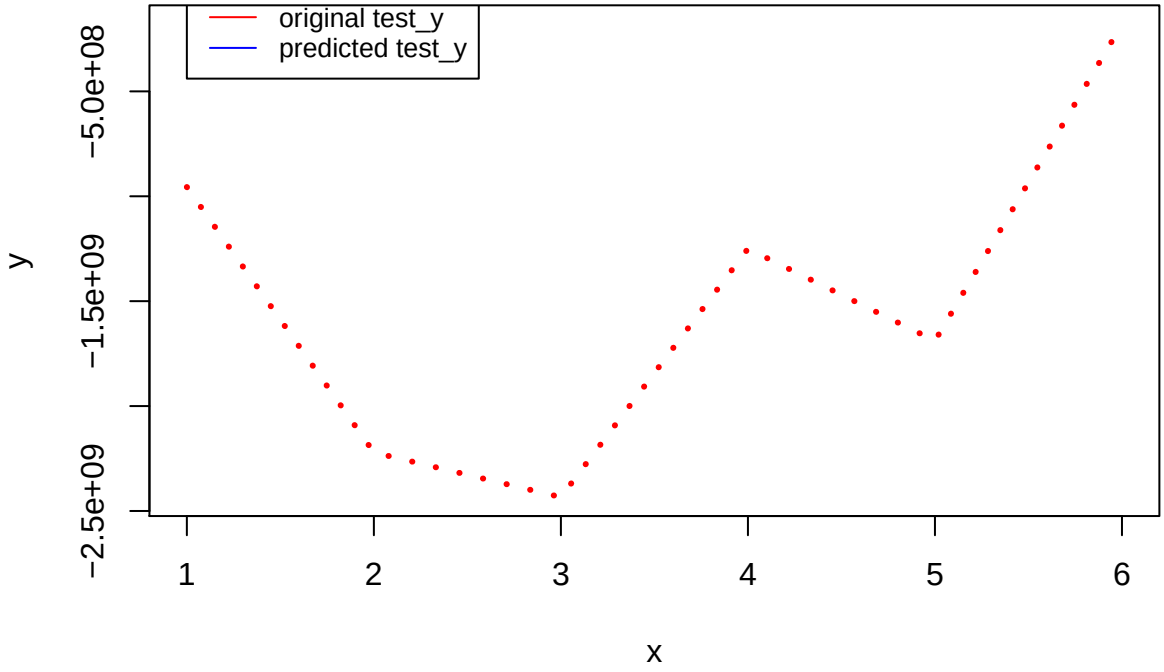


- Extreme Gradient Boosting Prediction & Accuracy

```
MSE:  3.852715e+20 MAE:  18121969088  RMSE:  19628334514
```




```
[1] 3988987596
[1] 0.2038301
[1] 0.8701342
```

```
RMSE:  3988987596 Error:  0.2038301 R2:  0.8701342
```

Compare Regression Models

X.Algorithm.	X.RMSE.	X.R2.	X.Error.
Algorithm	RMSE	R2	Error
ExtremeGradinetBoosting	3988987596.3155	0.870134218809127	0.203830128687742
Cubic Regression Spline	5328801306.20932	0.906219318025209	0.272292211938517
GAM	6937151742.56324	0.651536114257158	0.354476041419414
Spline Regression	4626494208.87458	0.875191434305949	0.215106804884498
PolynomialRegression	0.99384270252873	0.230993214992809	5761789129.92617

Conclusion

As such, we provide evidence suggesting that stock technical indicator has influence in stock market market cap. PolynomialRegression outperforms other model with lesser error and with R2=0.994 the model completely fit.

Generalized Linear Model

Why Use GAM?Relationships between the individual predictors and the dependent variable follow smooth patterns that can be linear or nonlinear. + Mathematically speaking, GAM is an additive modeling technique where the impact of the predictive variables is captured through smooth functions which—depending on the underlying patterns in the data—can be nonlinear. + GAM can capture common nonlinear patterns that a classic linear model would miss. + GAM framework allows us to control smoothness of the predictor functions to prevent overfitting. By controlling the wiggliness of the predictor functions, we can directly tackle the bias/variance tradeoff.

```
Family: gaussian
Link function: identity

Formula:
Market.Cap ~ Total.Equity + Earnings.Before.Interest.and.Tax

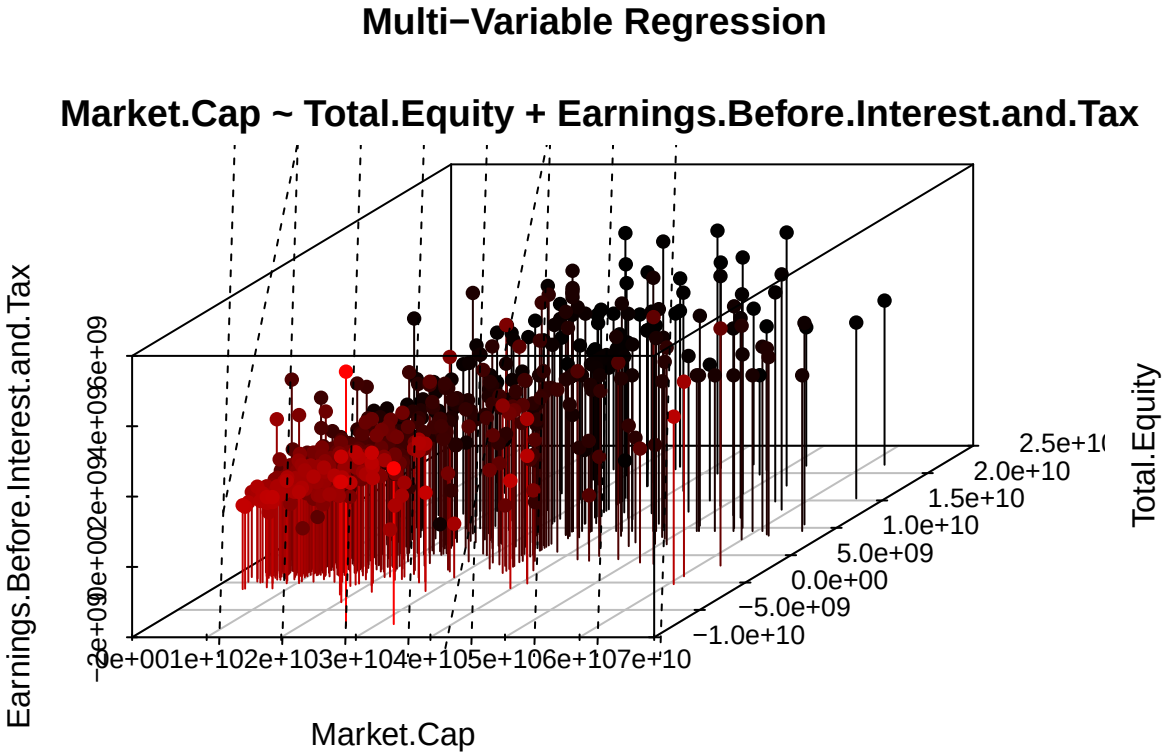
Parametric coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                     2.173e-09  5.850e-11   37.14   <2e-16 ***
Total.Equity                    1.052e+00  5.873e-02   17.92   <2e-16 ***
Earnings.Before.Interest.and.Tax 8.172e+00  2.327e-01   35.11   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Rank: 2/3
R-sq.(adj) =  0.461   Deviance explained = 43.4%
GCV = 1.1162e+20  Scale est. = 1.1147e+20  n = 1536
```

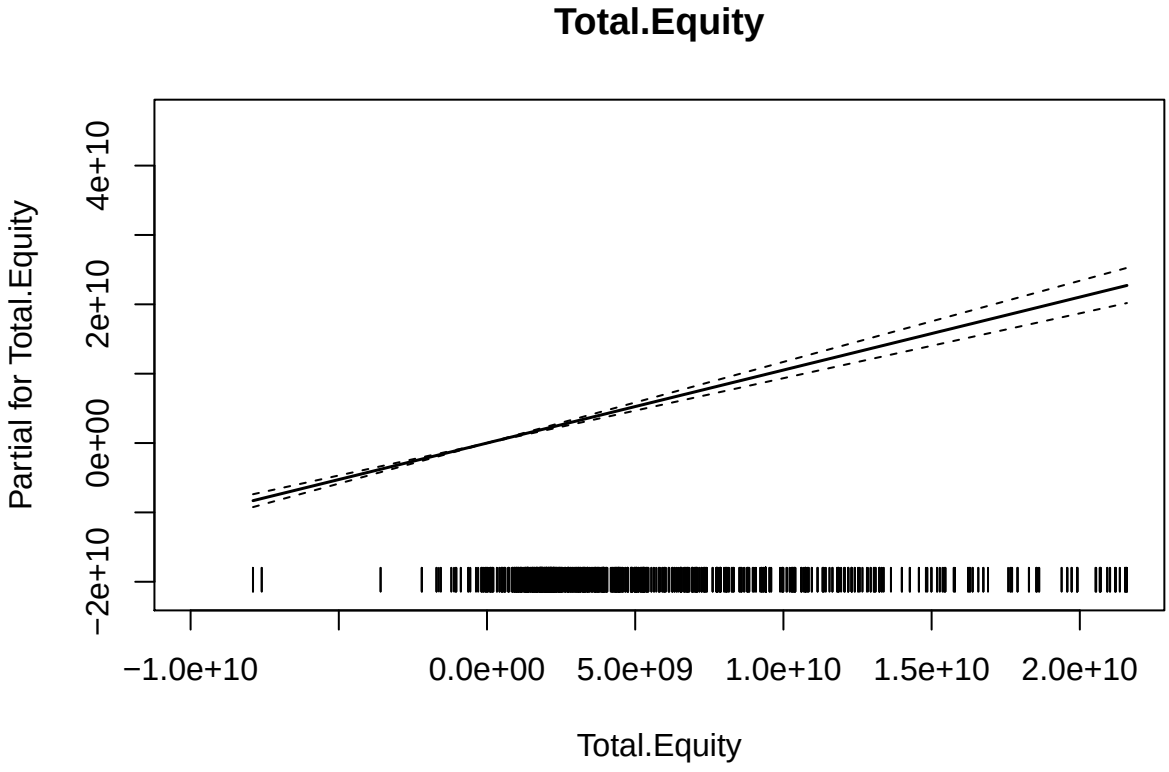
GAM Regression Prediction & Accuracy

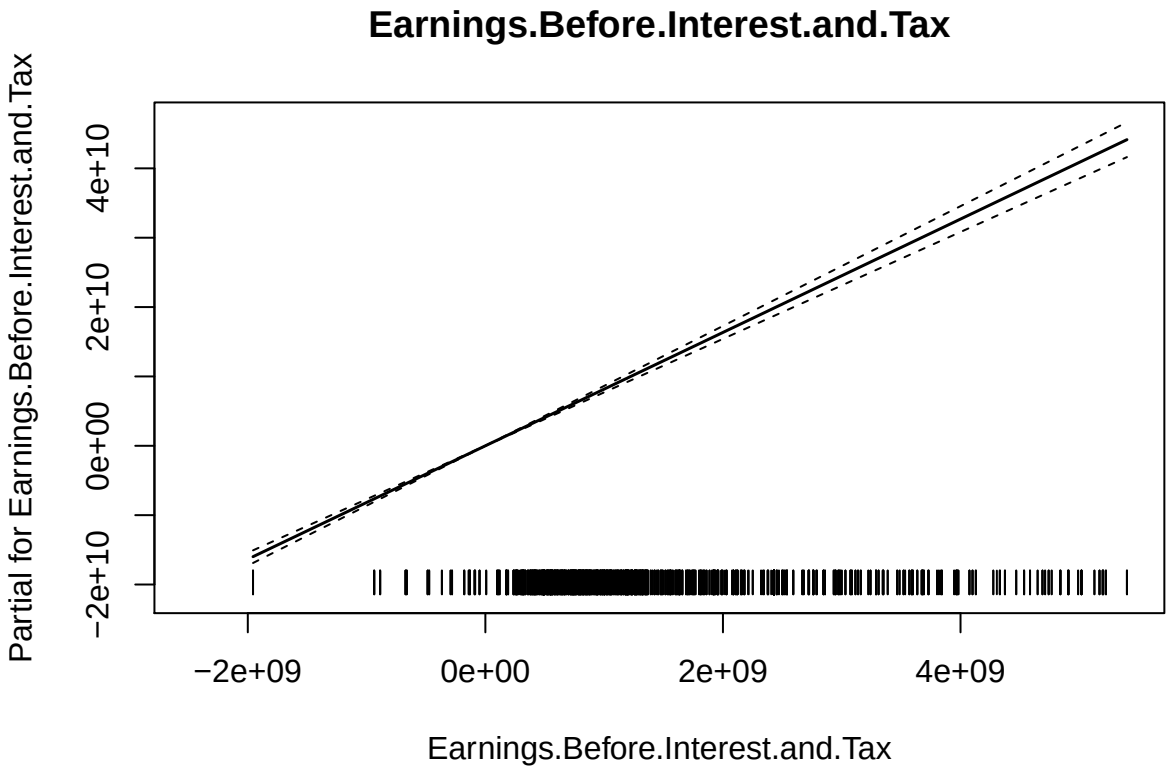
```
RMSE:  6937151743 Error:  0.354476 R2:  0.6515361
```

GAM Scatter Plot 3D Visualization

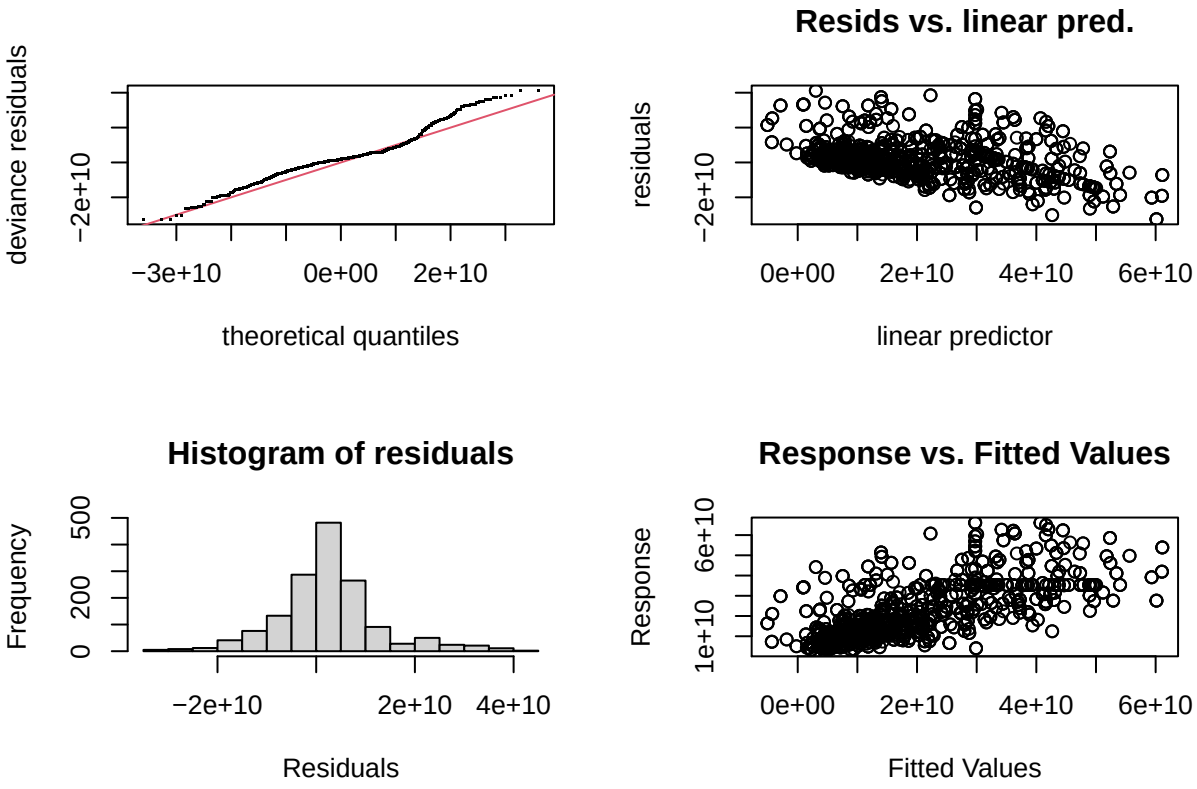


- Visualization part of gam model





- Diagnosing GAM model issues




```
Method: GCV   Optimizer: magic
Model required no smoothing parameter selectionModel rank =  2 / 3
```

Extreme Gradient Boosting

- XGBoost is an implementation of the Gradient Boosted Decision Trees algorithm.
- XGBoost supports various objective functions, including regression, classification and ranking.
- XGBoost gives among the best performances in many machine learning applications. It is optimized gradient-boosting machine learning library. The core algorithm is parallelizable and hence it can use all the processing power of your machine and the machines in your cluster. In R, according to the package documentation, since the package can automatically do parallel computation on a single machine, it could be more than 10 times faster than existing gradient boosting packages.
- XGBoost shines when we have lots of training data where the features are numeric or mixture of numeric and categorical fields. It is also important to note that xgboost is not the best algorithm out there when all the features are categorical or when the number of rows is less than the number of fields (columns).
- The data argument in the xgboost R function is for the input features dataset. It accepts a matrix, dgCMatrix, or local data file. The nrounds argument refers to the max number of iterations (i.e. the number of trees added to the model).
- There are different hyperparameters that we can tune and the parametres are different from baselearner to baselearner. In tree based learners, which are the most common ones in xgboost applications, the following are the most commonly tuned hyperparameters:
- learning rate: learning rate/eta- governs how quickly the model fits the residual error using additional base learners. If it is a smaller learning rate, it will need more boosting rounds, hence more time, to achieve the same reduction in residual error as one with larger learning rate. Typically, it lies between 0.01 - 0.3
- The three hyperparameters below are regularization hyperparameters.
- gamma: min loss reduction to create new tree split. default = 0 means no regularization.
- lambda: L2 reg on leaf weights. Equivalent to Ridge regression.
- alpha: L1 reg on leaf weights. Equivalent to Lasso regression.
- max_depth: max depth per tree. This controls how deep our tree can grow. The Larger the depth, more complex the model will be and higher chances of overfitting. Larger data sets require deep trees to learn the rules from data. Default = 6.
- subsample: % samples used per tree. This is the fraction of the total training set that can be used in any boosting round. Low value may lead to underfitting issues. A very high value can cause over-fitting problems.
- colsample_bytree: % features used per tree. This is the fraction of the number of columns that we can use in any boosting round. A smaller value is an additional regularization and a larger value may be cause overfitting issues.
- n_estimators: number of estimators (base learners). This is the number of boosting rounds.

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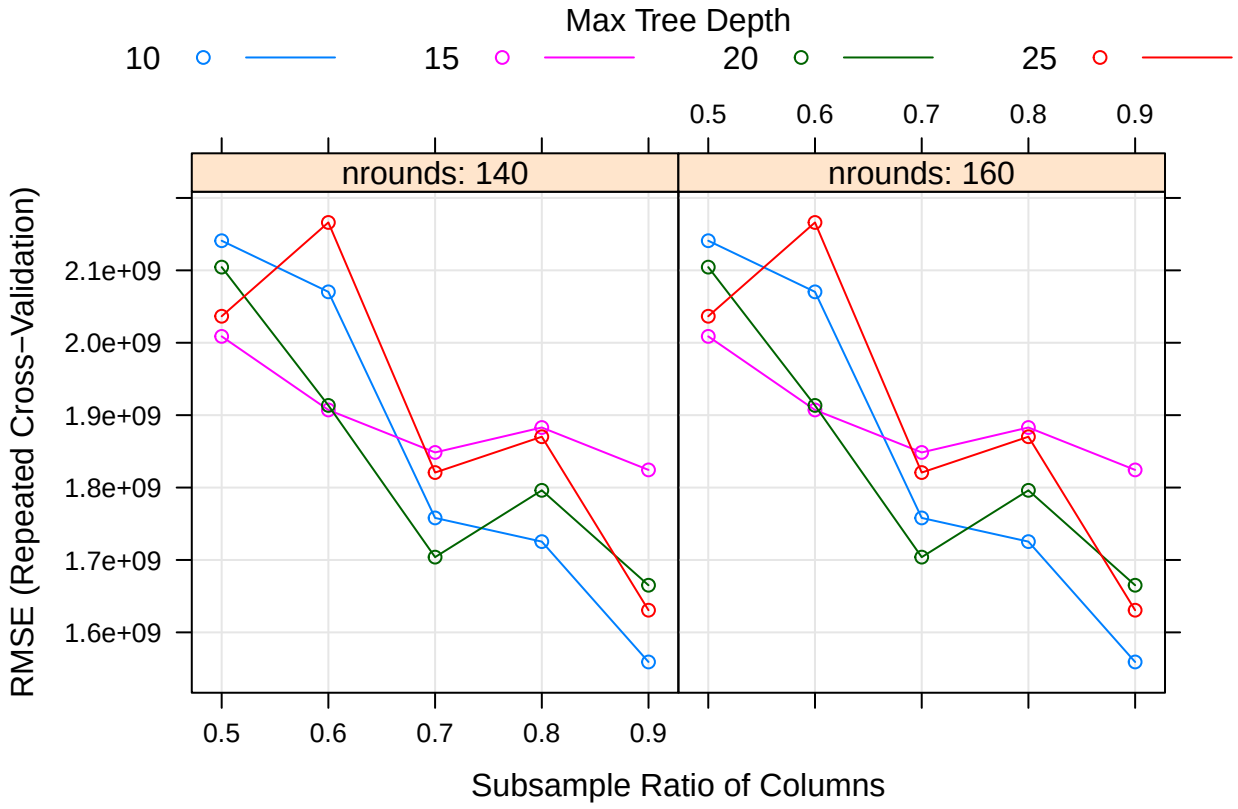
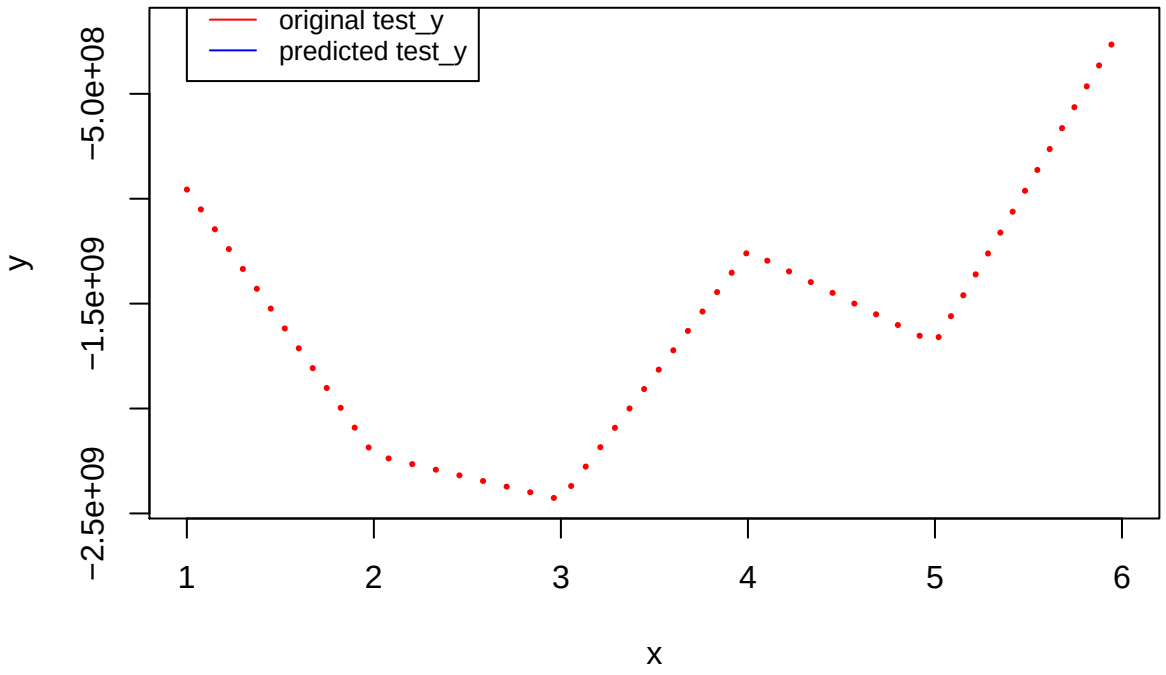
[18:29:18] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:18] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
```

```
[18:29:19] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:19] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:19] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:19] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:19] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:20] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:20] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:20] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:21] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:21] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:22] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:22] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:22] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:23] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:23] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:24] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:24] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:24] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:25] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:25] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
[18:29:26] WARNING: amalgamation/../src/objective/regression_obj.cu:174: reg:linear is now deprecated in
```



Extreme Gradient Boosting Prediction & Accuracy

```
MSE:  3.852715e+20 MAE:  18121969088  RMSE:  19628334514
```




```
[1] 3988987596
```

```
[1] 0.2038301
```

```
[1] 0.8701342
```

```
RMSE:  3988987596 Error:  0.2038301 R2:  0.8701342
```

Decision Tree to Trade Bank of America Stock (Real Time Value Analysis)

- Decision trees are one of the more popular machine-learning algorithms for their ability to model noisy data, easily pick up non-linear trends, and capture relationships between your indicators; they also have the benefit of being easy to interpret.
- Decision trees take a top-down, "divide-and-conquer" approach to analyzing data. They look for the indicator, and indicator value, that best splits the data into two distinct groups.
- The algorithm then repeats this process on each subsequent group until it correctly classifies every data point or a stopping criteria is reached.
- Each split, known as a "node", tries to maximize the purity of the resulting "branches". The purity is basically the probability that a data point falls in a given class, in our case "up" or "down", and is measured by the "information gain" of each split.
- In this model, we are going to use real time data of bofa stock from 2000- 2020.For this we will use quantmod package

Building a Strategy

- Let's see how we can quickly build a strategy using 4 technical indicators to see whether today's price of BoA's stock is going to close up or down.The 4 technical indicators are:
  - RSI -> Calculate a 3-period relative strength index (RSI) off the open price
  - EMA -> Calculate a 5-period exponential moving average (EMA)
  - MACD -> Calculate a MACD with standard parameters
  - SMI -> Stochastic Oscillator with standard parameters
- Then we calculate the variable we are looking to predict and build our data sets.
  - Class -> Calculate the difference between the close price and open price. If PriceChange>0,"UP","DOWN"

```
[1] "BAC"
```

```
[1] "RSI3"       "EMAcross"   "MACDsignal" "Stochastic" "Class"
```

- Data slicing is a step to split data into train and test set. Training data set can be used specifically for our model building. Test dataset should not be mixed up while building model. Even during standardization, we should not standardize our test set.75 percent contributes to training & 25 percent of data contributes to test.
- Training the Decision Tree classifier with criterion as information gain
- We are setting 3 parameters of trainControl() method. The "method" parameter holds the details about resampling method. We can set "method" to use repeatedcv i.e, repeated cross-validation.
- The "number" parameter holds the number of resampling iterations. The "repeats" parameter contains the complete sets of folds to compute for our repeated cross-validation. We are using setting number =10 and repeats =3. This trainControl() methods returns a list. We are going to pass this on our train() method.
- To select the specific strategy for decision tree, we need to pass a parameter "parms" in our train() method. It should contain a list of parameters for our rpart method. For splitting criterions, we need to add a "split" parameter with values either "information" for information gain & "gini" for gini index. We are using information gain as a criterion.

Trained Decision Tree classifier results

```
+ We can check the result of our train() method by a print dtree_fit variable. It is showing us the accu
```

```
CART

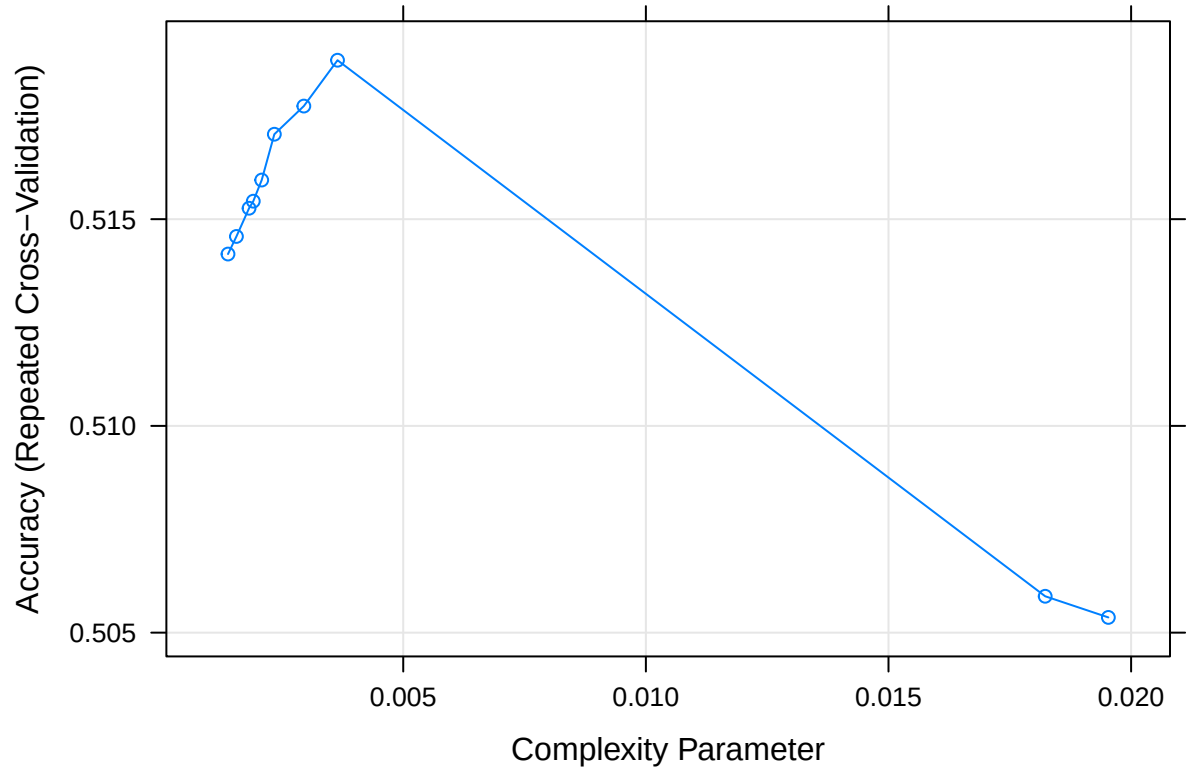
3908 samples
   4 predictor
   2 classes: 'DOWN', 'UP'

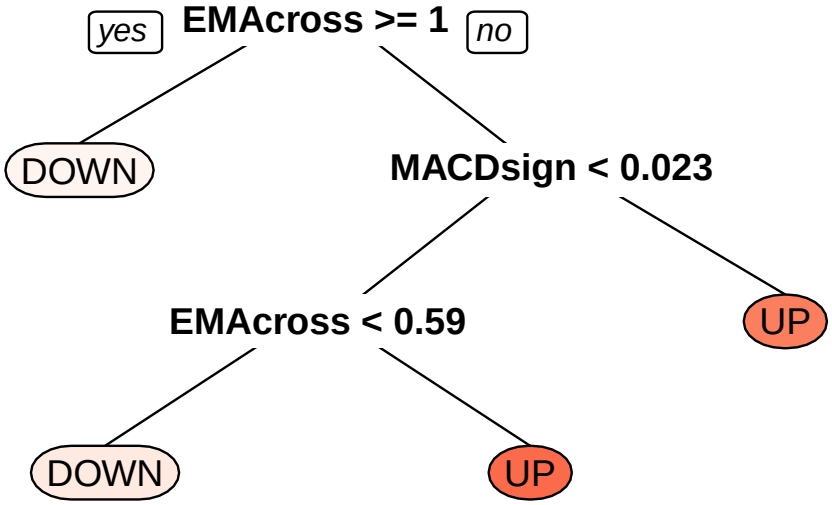
Pre-processing: centered (4), scaled (4)
Resampling: Cross-Validated (10 fold, repeated 3 times)
Summary of sample sizes: 3517, 3518, 3517, 3517, 3517, 3517, ...
Resampling results across tuning parameters:

  cp           Accuracy   Kappa
  0.001388889  0.5141566   0.0301167276
  0.001562500  0.5145822   0.0308771188
  0.001822917  0.5152644   0.0322216484
  0.001909722  0.5154349   0.0325509692
  0.002083333  0.5159460   0.0335094058
  0.002343750  0.5170542   0.0345975203
  0.002951389  0.5177349   0.0358283997
  0.003645833  0.5188436   0.0377622413
  0.018229167  0.5058795   0.0006184276
  0.019531250  0.5053680  -0.0004969420

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was cp = 0.003645833.
```

Plot Decision Tree





Decision Tree Prediction

Now, our model is trained with cp = 0.003645833.Accuracy of the model is 0.5141566.

```
Confusion Matrix and Statistics

          Reference
Prediction DOWN  UP
      DOWN  317 279
      UP    345 360

               Accuracy : 0.5204
                 95% CI : (0.4928, 0.5478)
    No Information Rate : 0.5088
```

```
   P-Value [Acc > NIR] : 0.210682

                 Kappa : 0.0422

 Mcnemar's Test P-Value : 0.009266

            Sensitivity : 0.4789
            Specificity : 0.5634
         Pos Pred Value : 0.5319
         Neg Pred Value : 0.5106
             Prevalence : 0.5088
         Detection Rate : 0.2437
   Detection Prevalence : 0.4581
      Balanced Accuracy : 0.5211

       'Positive' Class : DOWN
```

KNN Classifier to predict if daily stock price will increase

- kNN algorithm is a non-parametric algorithm that can be used for either classification or regression. Non-parametric means that it makes no assumption about the underlying data or its distribution.
- For each data point, the algorithm finds the k closest observations, and then classifies the data point to the majority. Usually, the k closest observations are defined as the ones with the smallest Euclidean distance to the data point under consideration.
- K-Nearest Neighbors computes the likelihood of each share closing price based on other technical indicator.

Building KNN model

- Data Model which we will use for ML is listed below. Here, the 3 columns represent the closing price,opening price,High price, volume of the stock on the given date.
- The Increase column represents whether the price of stock rose or fell as compared to the previous day.
- We are using caret's KNN to sample the data (for training and testing), preprocessing, evaluating the model etc.,
- ***Step 1: Data Splicing***
  - KNN algorithm is applied to the training data set and the results are verified on the test data set.
  - I used 25% to test data and 75% to train the data.
  - After obtaining training and testing data sets, then we will create a separate data frame from testing data set which has values to be compared with actual final values
  - Predictor variables are Open ,increase ,Volume,High. Target variable is Close
- ***Step 2:Data Pre-Processing With Caret***
  - We need to pre-process our data before we can use it for modeling.
  - The caret package in R provides a number of useful data transforms.
  - Training transforms can prepared and applied automatically during model evaluation.
  - Transforms applied during training are prepared using the preProcess() and passed to the train() function via the preProcess argument.
  - Combining the scale and center transforms for preprocessing will standardize the data.
  - The scale transform calculates the standard deviation for an attribute and divides each value by that standard deviation.

- The center transform calculates the mean for an attribute and subtracts it from each value.
- Attributes after preprocessing will have a mean value of 0 and a standard deviation of 1.

- ***Step 3:Model Training and Tuning***
  - To control parameters for train, trainControl function is used. "trainControl" allows estimation of parameter coefficients through resampling methods like cross validation, repeatedcv,boosting etc.
  - The option "repeatedcv" method which we used in traincontrol method controls the number of repetitions for resampling used in repeated K-fold cross-validation.

```
  colnames(bny_raw)
1              Date
2              Open
3          increase
4            Volume
5             Close
6              High
```

- ***Step 4:How to choose value for K to improve performance***
  - Time to fit a knn model using caret with preprocessed values.
  - From the output of the knn model ,maximum RSquared(0.9983847) is achieved by k = 5
  - Now we can plot our KNN , and view summary of the model

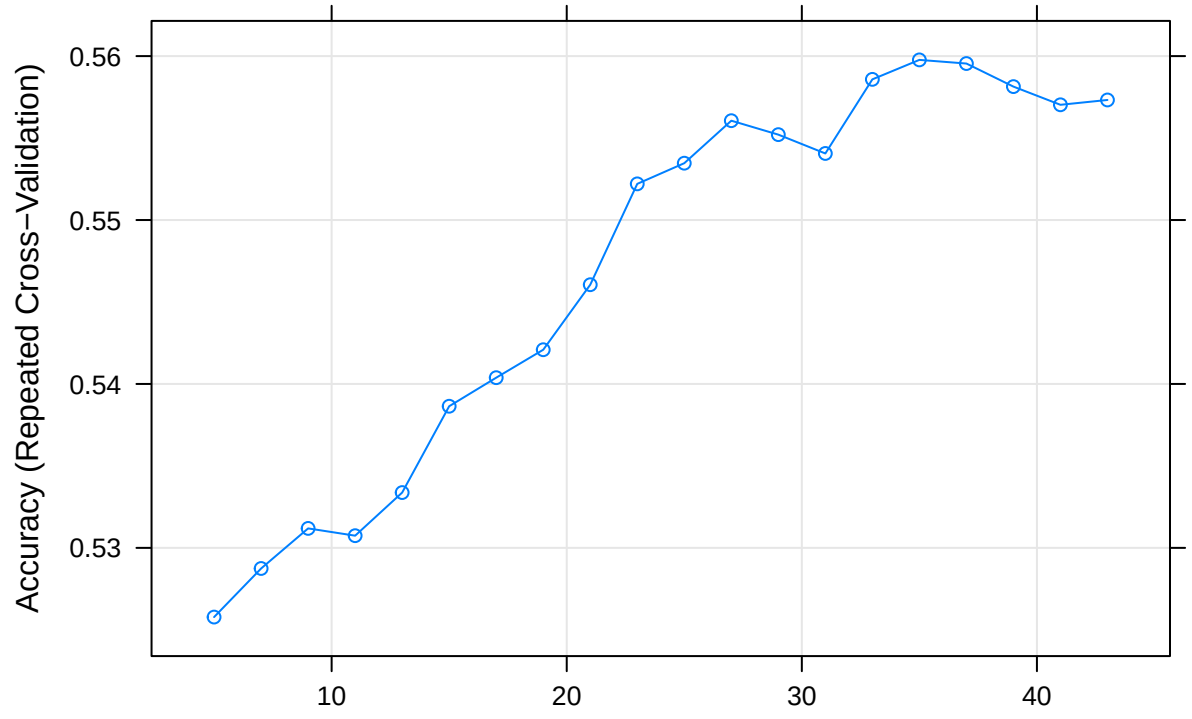
```
k-Nearest Neighbors

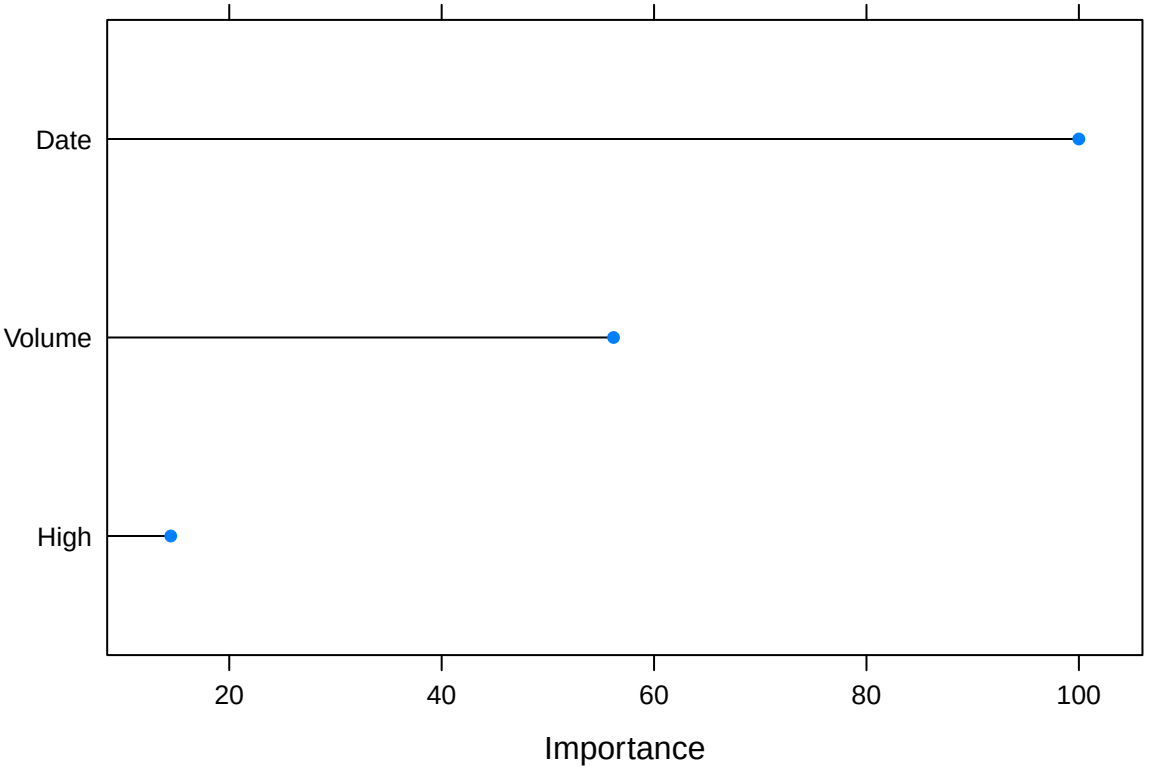
8993 samples
   5 predictor
   2 classes: 'FALSE', 'TRUE'

Pre-processing: centered (5), scaled (5)
Resampling: Cross-Validated (10 fold, repeated 3 times)
Summary of sample sizes: 8093, 8094, 8093, 8094, 8094, 8095, ...
Resampling results across tuning parameters:

  k   Accuracy   Kappa
   5  0.5257777  0.02578255
   7  0.5287424  0.02899955
   9  0.5311870  0.03274320
  11  0.5307430  0.02950820
  13  0.5333738  0.03257598
  15  0.5386393  0.04107065
  17  0.5403822  0.04288474
  19  0.5420874  0.04482209
  21  0.5460535  0.05178726
  23  0.5522058  0.06325600
  25  0.5534678  0.06464222
  27  0.5560607  0.06852801
  29  0.5552093  0.06542168
  31  0.5540608  0.06233631
  33  0.5585827  0.07069766
  35  0.5597692  0.07214944
  37  0.5595463  0.07104593
  39  0.5581399  0.06758583
  41  0.5570294  0.06480353
  43  0.5573246  0.06410129
```

```
Accuracy was used to select the optimal model using the largest value.
The final value used for the model was k = 35.
```





KNN Accuracy

- ***Step 5: Making predictions***
  - We build knn by using training & test data sets. After building the model, then we can check the accuracy of forecasting using confusion matrix.
- ***Step 6: Interpretation of the results and prediction accuracy achieved.***
  - The accuracy of our model on the testing set is 55%.
  - We can visualise the model's performance using a confusion matrix.
  - We can also evaluvate the accuracy, precision and recall on the training and validation sets in confusion matrix to evaluate the performance of knn algorithm.

```
Confusion Matrix and Statistics

          Reference
Prediction FALSE TRUE
     FALSE   426  446
     TRUE    895 1229

               Accuracy : 0.5524
                 95% CI : (0.5344, 0.5703)
    No Information Rate : 0.5591
    P-Value [Acc > NIR] : 0.7748

                  Kappa : 0.0583

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.3225
            Specificity : 0.7337
         Pos Pred Value : 0.4885
         Neg Pred Value : 0.5786
             Prevalence : 0.4409
         Detection Rate : 0.1422
   Detection Prevalence : 0.2911
      Balanced Accuracy : 0.5281

       'Positive' Class : FALSE


Accuracy:  0.5524032
```

Overall insights obtained from the implemented project

- As we can see, the model has the highest accuracy of 55 when k = 5. While this may not seem any good, it is often extremely hard to predict the price of stocks. Even the 2.5% improvement over random guessing can make a difference given the amount of money at stake. After all, if it was that easy to predict the prices, wouldn't we all be trading in stocks for the easy money instead of learning these algorithms?
- Sensitivity for price increase is 0.3225 .
- Specificity for price increase is 0.7337.

K-means Clustering NYSE trades.

- K-means clustering is an unsupervised learning method used to uncover non-random structures in your data.

- It does so by creating labels for your training data, where each label is a cluster.
- An ideal cluster analysis groups points together on a scatterplot, with maximized space (seperation) between groups, and minimized space (cohesion) between points in the same group.
- Groups can be centered around a non-real point (k-means).
- ***Challenge: Group stock based on performances***
- Perform k-means clustering of the New York Stock Exchange (NYSE) dataset that has more than 9,211,031 NYSE trade data. Columns from 1 to 7 are:
  - ID INTEGER record ID
  - OPEN_P DOUBLE open price
  - HIGH_P DOUBLE highest price
  - LOW_P DOUBLE lowest price
  - CLOSE_P DOUBLE close price
  - VOLUME DOUBLE volume
  - CLOSE_ADJ_P DOUBLE close adjusted price
- ***Choose K Value***
  - Use columns 2 from the input data and perform the k-means clustering with k = 0 to 15. Set the maximum number of iterations to 10,000.
  - Use Within Cluster Sum of Squares as a measure to choose best K , which measures the squared average distance of all the points within a cluster to the cluster centroid. To calculate WCSS, you first find the Euclidean distance (see figure below) between a given point and the centroid to which it is assigned. You then iterate this process for all points in the cluster, and then sum the values for the cluster and divide by the number of points. Finally, you calculate the average across all clusters. This will give you the average WCSS.
- From the below plot we can see K=7 will not overfit/underfit the model.

Modelling

- We'll now use the k-means alogorithm to fit a model.
- It will divide all datapoints into 7 clusters, and allocate each point to a cluster group using a distance (euclidean) measurement.
- We'll set it to iteratively determine which point belongs to each cluster 10,000 times, allowing for each iteration to recalculate where the center of the groups is and which points are closest to those centers.
- We can visualize the coefficients with the following plot.

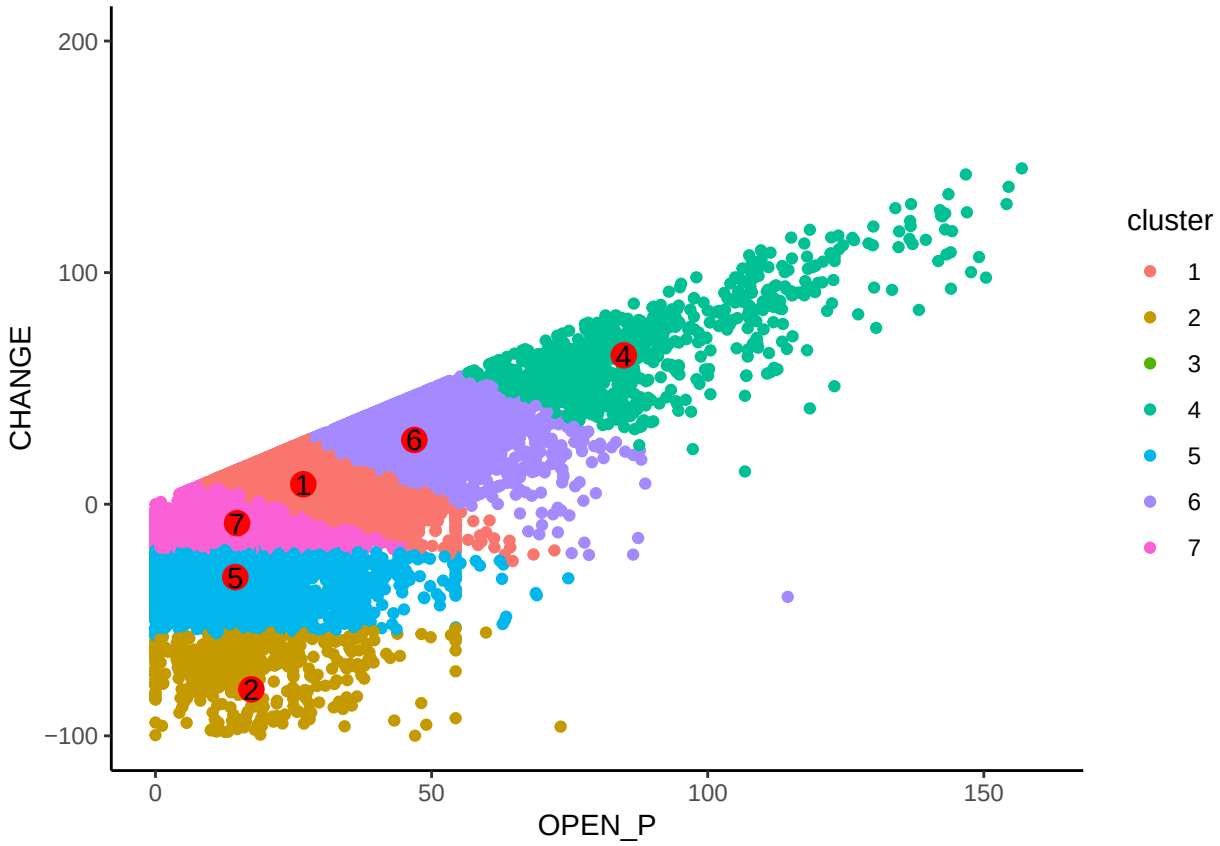
```
             Length Class  Mode
cluster      33333  -none- numeric
centers         14  -none- numeric
totss            1  -none- numeric
withinss         7  -none- numeric
tot.withinss     1  -none- numeric
betweenss        1  -none- numeric
size             7  -none- numeric
iter             1  -none- numeric
ifault           1  -none- numeric
```

```
Centers:  26.77171 17.36502 298.0009 84.80548 14.4589 46.8826 14.77272 8.621914 -79.9289 275.3313 64.273
```

```
No Of Records in Cluster:  10464 681 23 1032 5088 5087 10958
```

KNN Cluster Plotting

- Plot to see how opening prices have been distributed in clusters.



Overall Insights

- KNN is a lazy learner where generalization of the training data is delayed until a query is made to the system. Which means knn starts working only when you trigger it to, thus lazy learning methods can construct a different approximation or result to the target function for each encountered query.
- It is a good method for online learning but it requires a possibly large amount of memory to store the data, and each request involves starting the identification of a local model from scratch.

ARIMA Forecasting Expedia Stock Price incorporating COVID-19 (Real Time)

- The goal of this project is to predict the future stock price of Expedia using various predictive forecasting models and then analysing the models using ARIMA.
- The dataset for Expedia stocks is obtained from Yahoo Finance using Quantmod package in R.
- The timeline of the data is from 2019 till present day(11/26/2020).
- We shall also try and understand the impact of COVID-19 disaster on the stock prices of Expedia.
- ***Forecasting***
  - A forecasting algorithm is a process that seeks to predict future values based on the past and present data.
  - This historical data points are extracted and prepared trying to predict future values for a selected variable of the dataset.
- ***Data Preparation***
  - Importing the data : We obtain the data of Expedia from "2019-07-01" to "2020-11-26" of Expedia Stock price for our analysis using the quantmod package. To analyse the impact of COVID-19 on

the Expedia Stock price, we take two sets of data from the quantmod package.

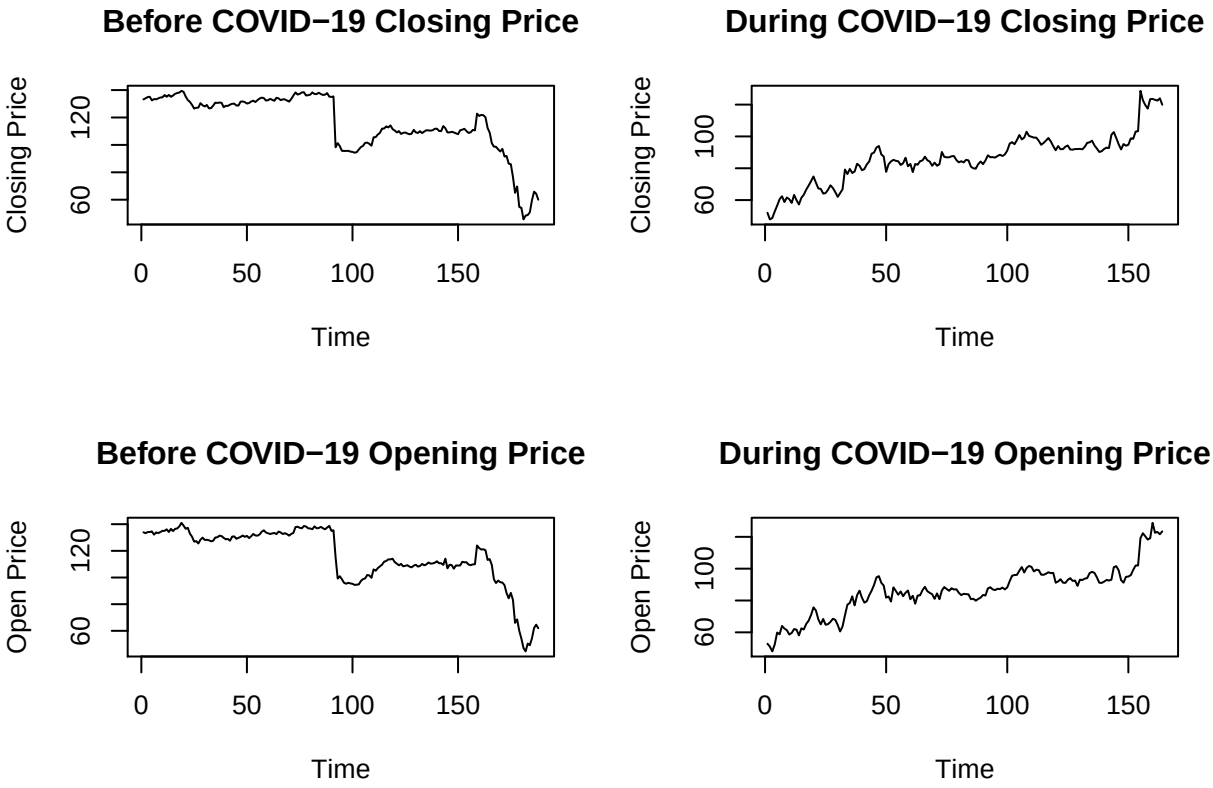
- Data from "2019-07-01" - "2020-03-28" is data before covid.
- Data from "2020-04-01" - "till date" is data before covid.
- All the analysis and the models will be made on both the datasets to analyse the impact of COVID-19, if any.

```
[1] "EXPE"
```

```
[1] "EXPE"
```

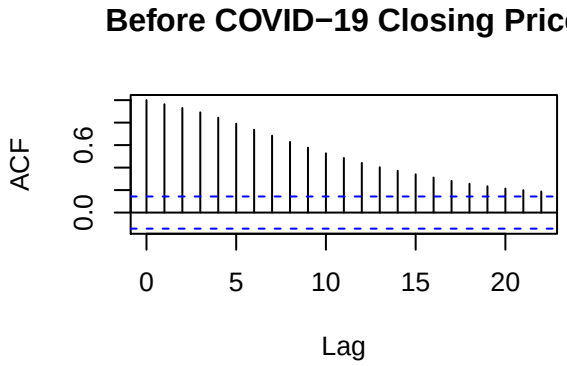
```
  colnames(google_data_after_covid)
1                          EXPE.Open
2                          EXPE.High
3                           EXPE.Low
4                         EXPE.Close
5                        EXPE.Volume
6                      EXPE.Adjusted
```

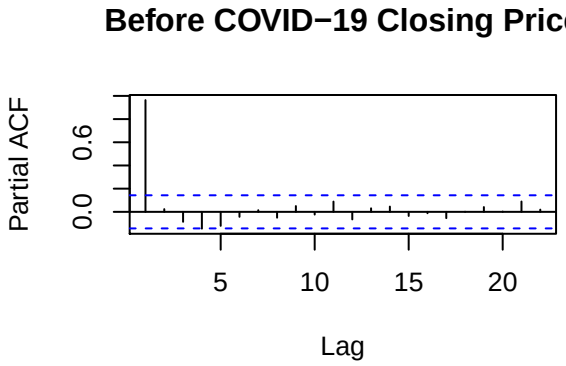
Graphical Representation of Data

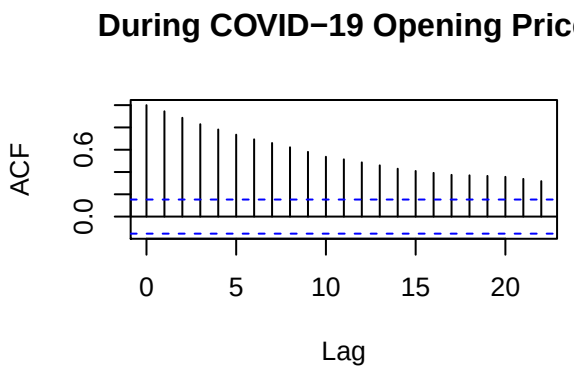


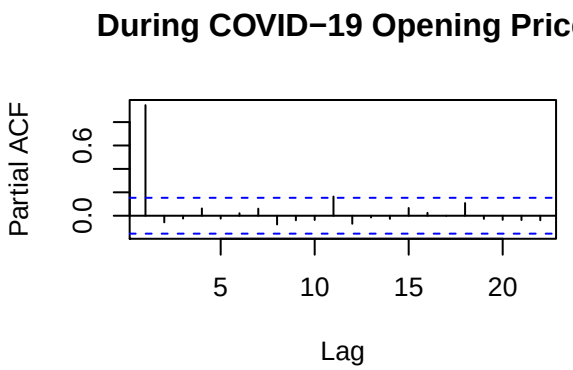
ARIMA Model

- Let us first analyse the ACF and PACF Graph of each of the two datasets.









- We then use the auto.arima function to determine the time series model for each of the datasets.

```
Series: tsData_before_covid_close
ARIMA(3,1,2)
Box Cox transformation: lambda= -0.5522943

Coefficients:
         ar1      ar2      ar3      ma1     ma2
      0.9436  -0.2552  -0.2793  -0.9659  0.7154
s.e.  0.1333   0.1520   0.0991   0.1174  0.1094

sigma^2 estimated as 1.264e-05:  log likelihood=791.34
AIC=-1570.69   AICc=-1570.22   BIC=-1551.3

Training set error measures:
                     ME     RMSE      MAE        MPE     MAPE     MASE
Training set -0.3468986 3.779995 2.064975 -0.4697368 2.119611 1.117624
                    ACF1
Training set -0.01611792
```

```
Series: tsData_after_covid_close
ARIMA(1,1,0) with drift
Box Cox transformation: lambda= 1.049021

Coefficients:
          ar1   drift
      -0.0993  0.5238
s.e.   0.0785  0.3099

sigma^2 estimated as 19.12:  log likelihood=-470.79
```

```
AIC=947.57   AICc=947.73   BIC=956.86

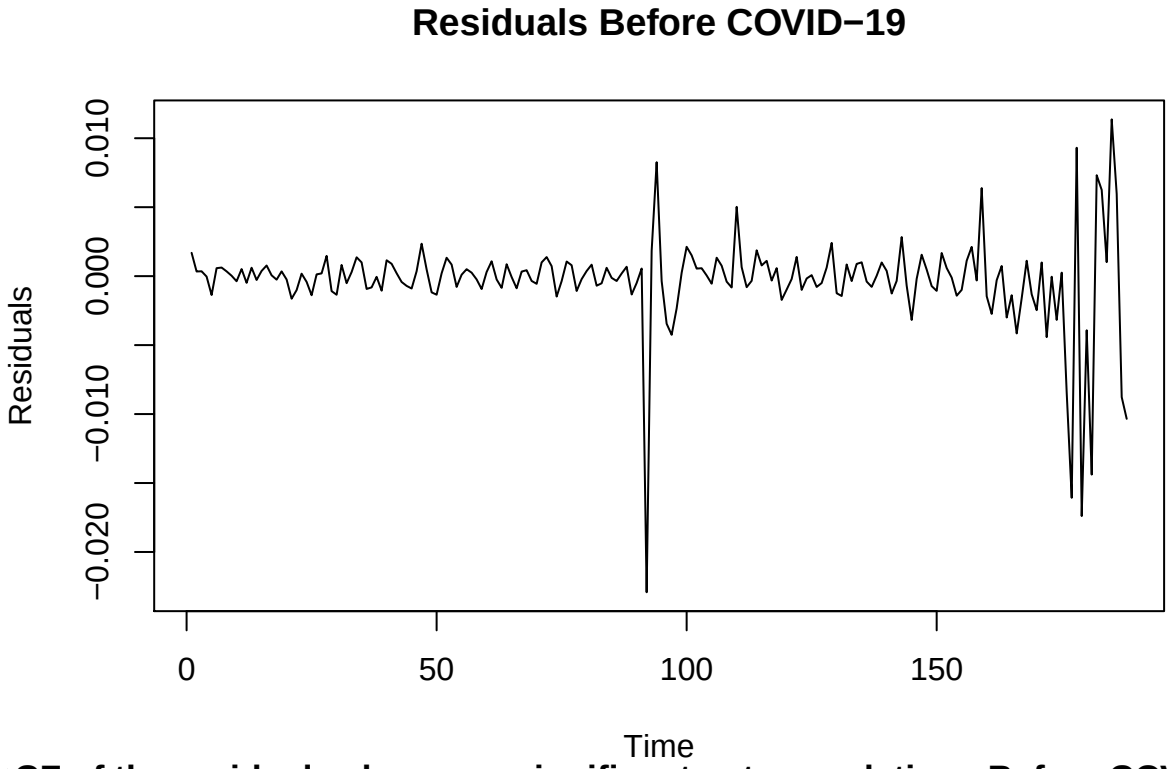
Training set error measures:
                      ME     RMSE      MAE         MPE     MAPE      MASE
Training set -0.002349432 3.471361 2.361182 -0.07665327 2.827689 0.9868023
                    ACF1
Training set 0.002088858
```

- From the auto.arima function, we conclude the following models for the two datasets:
  - Before COVID-19: ARIMA(3,1,2)
  - After COVID-19: ARIMA(1,1,0)
- After obtaining the model, we then perform residual diagnostics for each of the fitted models.
- From the residual plot , we can confirm that the residual has a mean of 0 and the variance is constant as well . The ACF is 0 for lag$>$ 0 , and the PACF is 0 as well.
- So, we can say that the residual behaves like white noise and conclude that the models ARIMA(3,1,2) and ARIMA(1,1,0) fits the data well. Alternatively, we can also test at a significance level using the Box-Ljung Test.

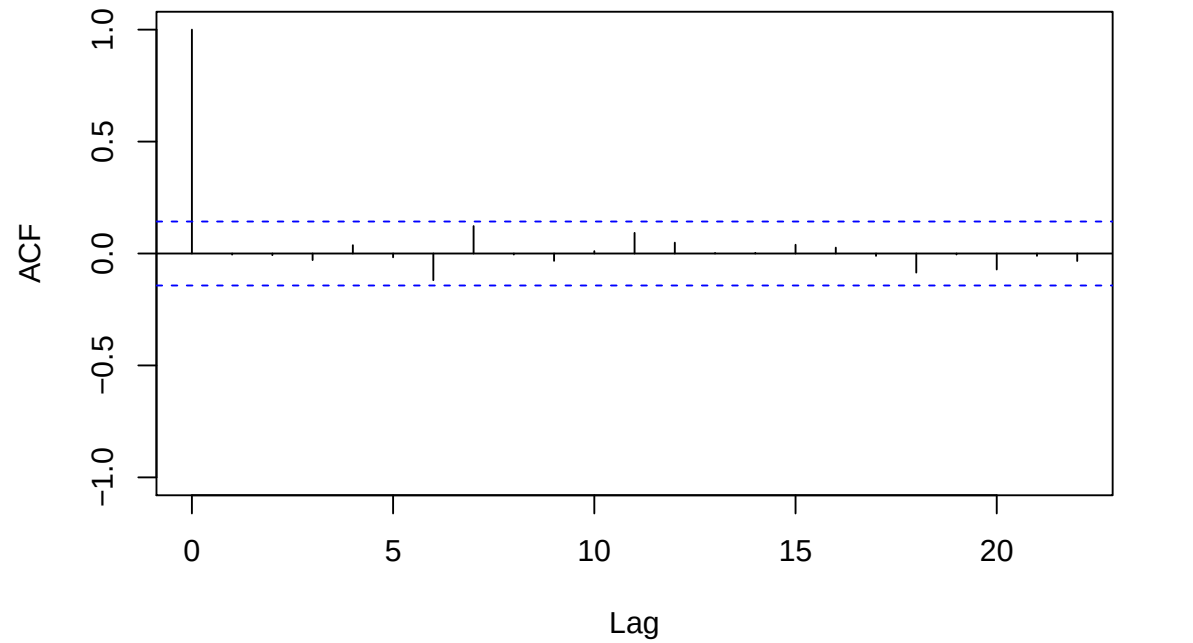
Diagnostic measures

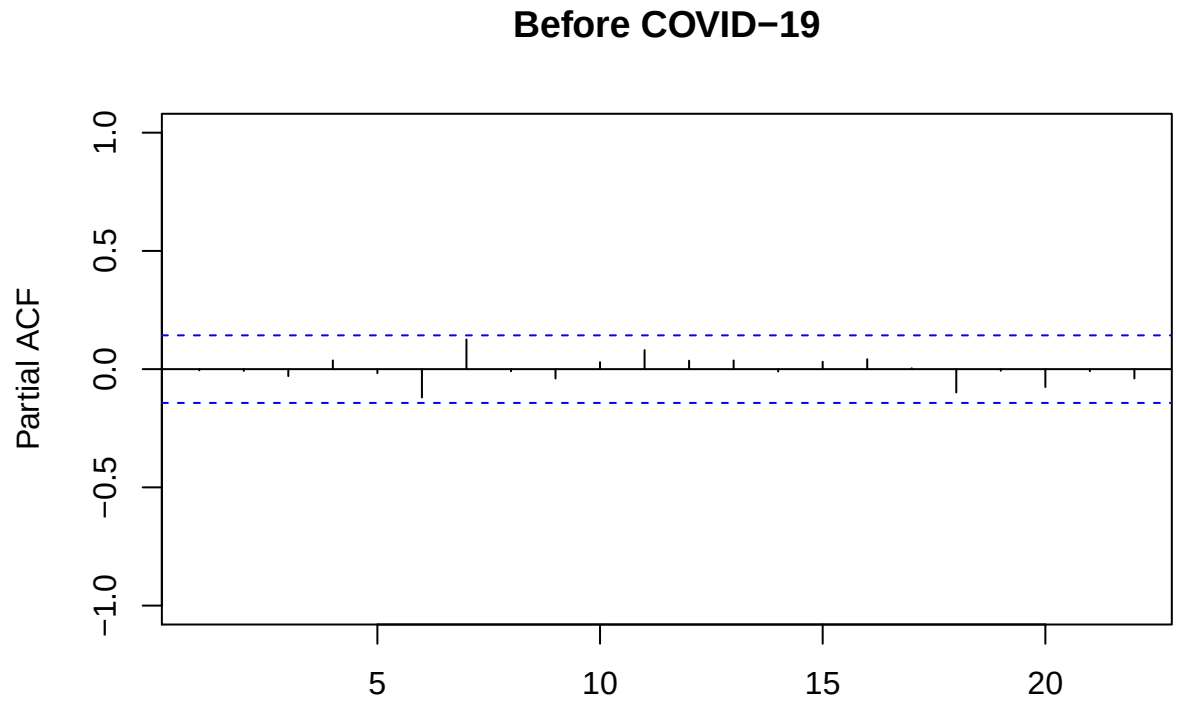
- Try to find out the pattern in the residuals of the chosen model by plotting the ACF of the residuals, and doing a portmanteau test. We need to try modified models if the plot doesn't look like white noise.
- Once the residuals look like white noise, calculate forecasts.
- Box-Ljung test is a test of independence at all lags up to the one specified. Instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags, and is therefore a portmanteau test. It is applied to the residuals of a fitted ARIMA model, not the original series, and in such applications the hypothesis actually being tested is that the residuals from the ARIMA model have no autocorrelation.
- The ACF of the residuals shows no significant autocorrelations.
- The p-values for the Ljung-Box Q test all are well above 0.05, indicating "non-significance." The values

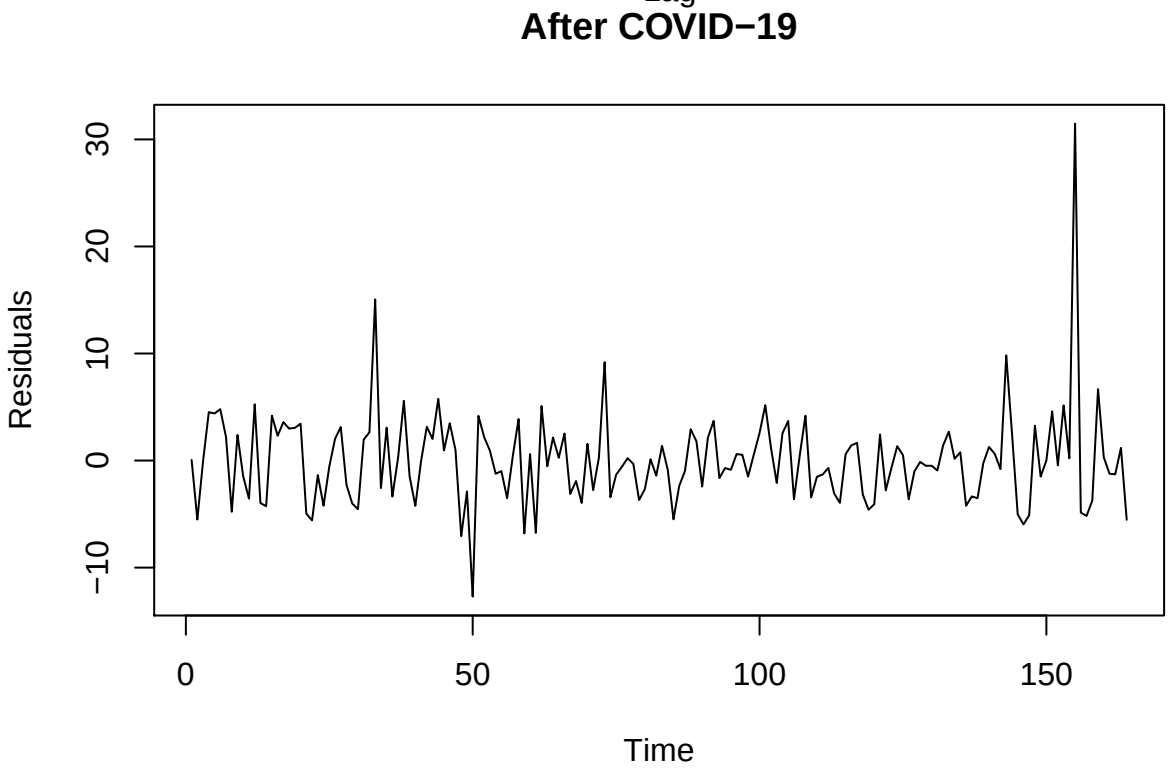
are normal as they rest on a line and aren't all over the place.

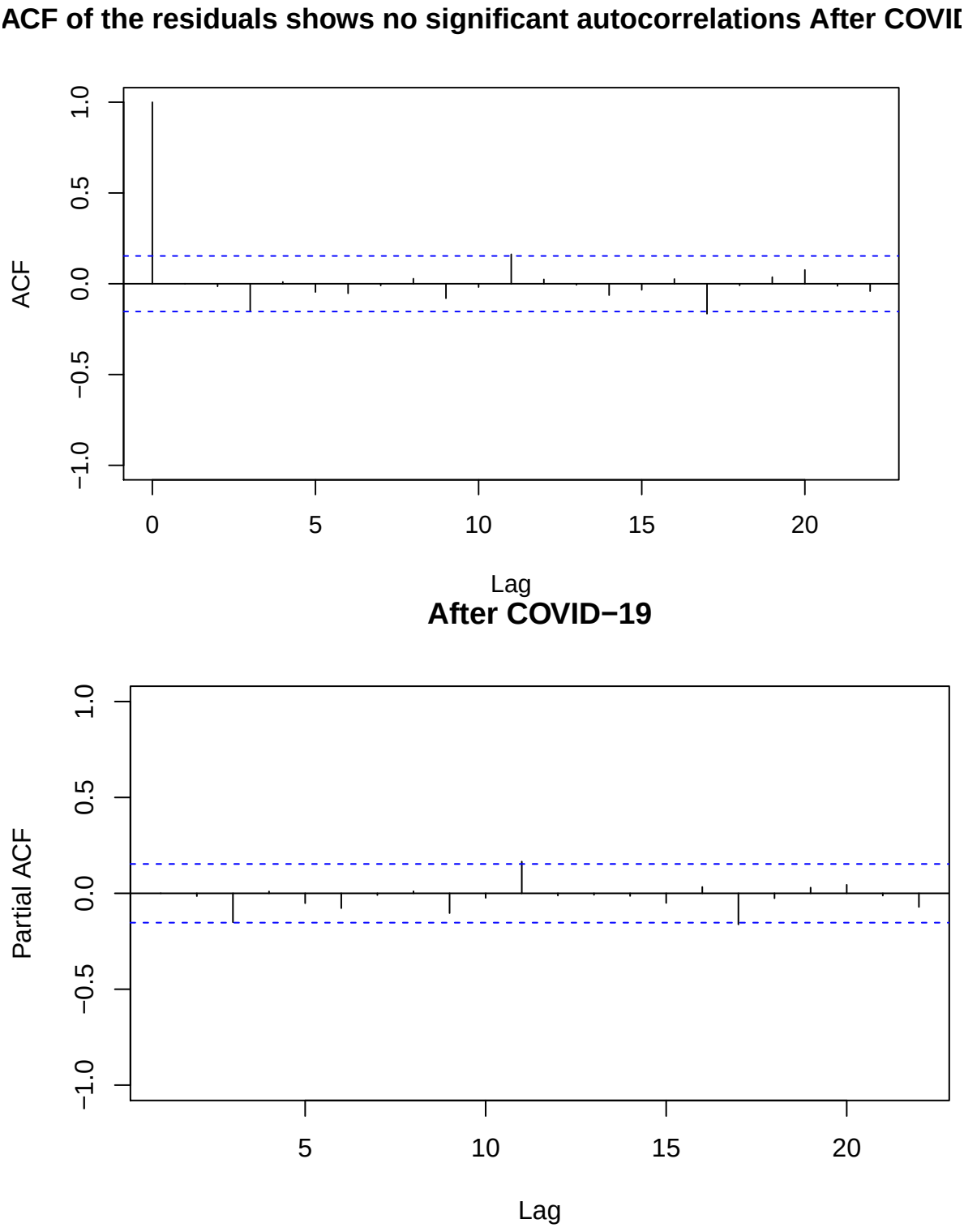


ACF of the residuals shows no significant autocorrelations Before COVI




Before COVID−19
Partial ACF
1.0
0.5
0.0
−0.5
−1.0
5
10
15
20
Lag


After COVID−19
Residuals
30
20
10
0
−10
0
50
100
150
Time



Augmented Dickey-Fuller & Kwiatkowski-Phillips-Schmidt-Shin

- We then conduct an ADF (Augmented Dickey-Fuller) test and KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test to check for the stationarity of the time series data for both the datasets closing price.

```
Augmented Dickey-Fuller Test
```

```
data:  tsData_before_covid_close
Dickey-Fuller = -2.1153, Lag order = 5, p-value = 0.5279
alternative hypothesis: stationary
```

```
    Augmented Dickey-Fuller Test

data:  tsData_after_covid_close
Dickey-Fuller = -2.4665, Lag order = 5, p-value = 0.3817
alternative hypothesis: stationary
```

- From the above ADF tests, we can conclude the following:
  - For the dataset before COVID-19, the ADF tests gives a p-value of 0.5279which is greater than 0.05, thus implying that the time series data is not stationary.
  - For the dataset after COVID-19, the ADF tests gives a p-value of 0.3817 which is lesser greater 0.05, thus implying that the time series data is not stationary.

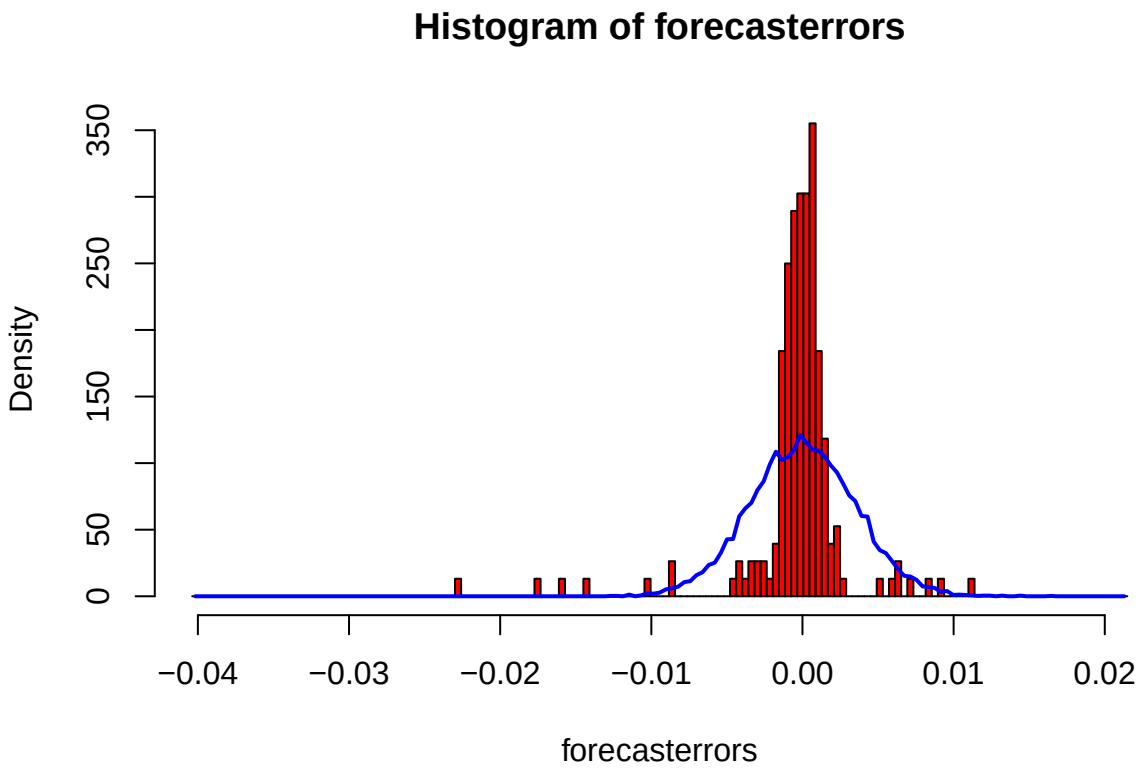
```
    KPSS Test for Level Stationarity

data:  tsData_before_covid_close
KPSS Level = 2.3907, Truncation lag parameter = 4, p-value = 0.01
```

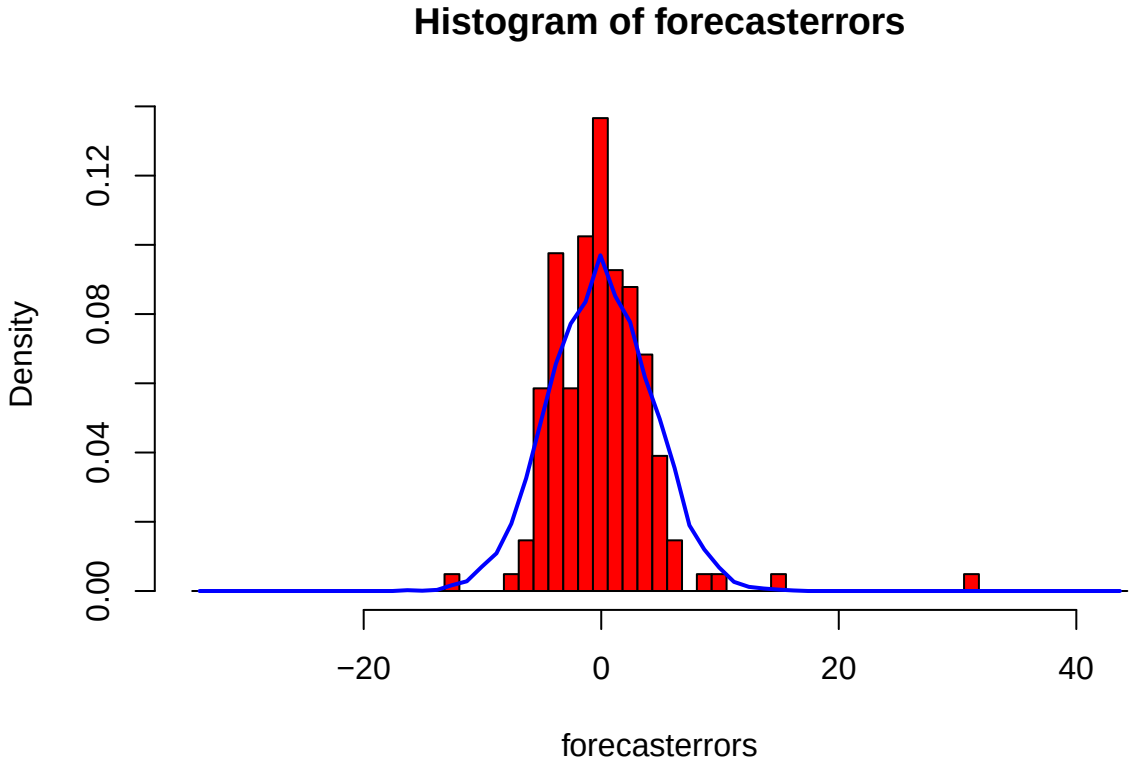
```
    KPSS Test for Level Stationarity

data:  tsData_after_covid_close
KPSS Level = 2.6532, Truncation lag parameter = 4, p-value = 0.01
```

- From the above KPSS tests, we can conclude the following:
- For the dataset before COVID-19, the KPSS tests gives a p-value of 0.01 which is less than 0.05, thus implying that the time series data is not stationary.
- For the dataset after COVID-19, the KPSS tests gives a p-value of 0.01 which is less than 0.05, thus implying that the time series data is not stationary.
- Thus, we can conclude from the above tests that the time series data is not stationary.
- ***Forecasting with ARIMA Models***
- Forecast errors for before covid dataset



- Forecast errors for after covid dataset



- ***Holt Winters***
  - To make forecasts using simple exponential smoothing in R, we can fit a simple exponential smoothing predictive model using the "HoltWinters()" function in R. To use HoltWinters() for

simple exponential smoothing, we need to set the parameters beta=FALSE and gamma=FALSE in the HoltWinters() function (the beta and gamma parameters are used for Holt's exponential smoothing, or Holt-Winters exponential smoothing, as described below).

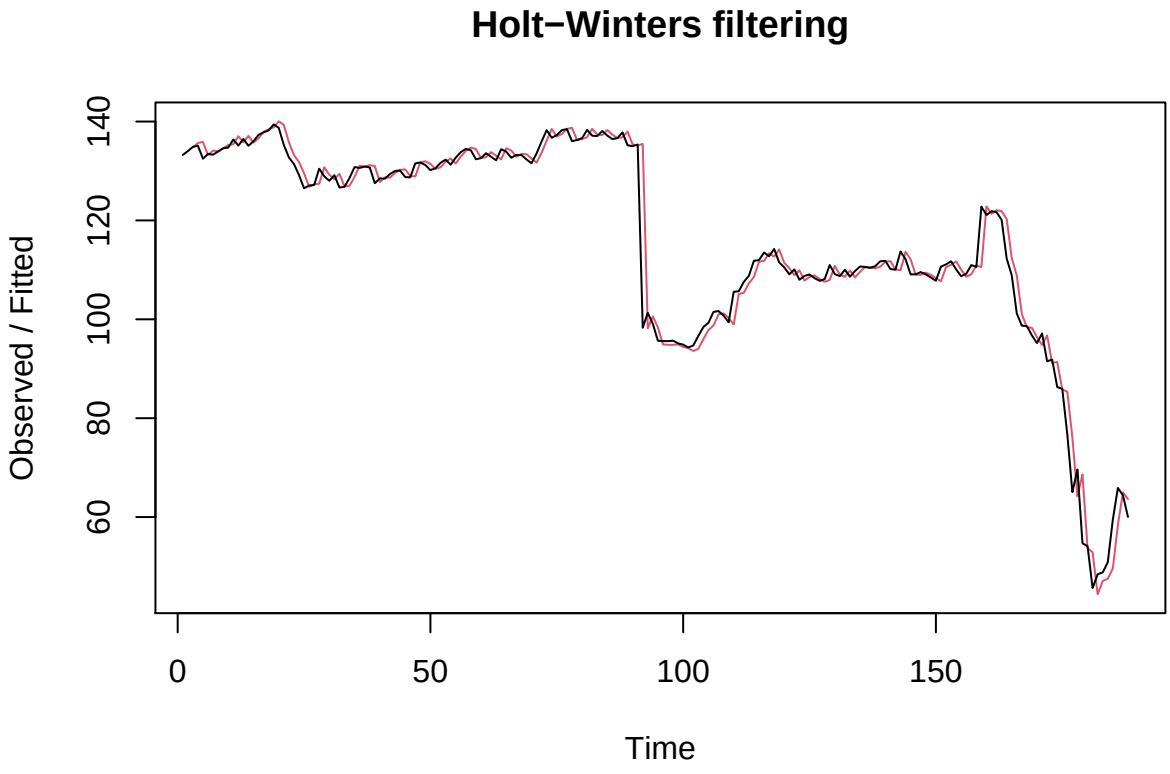
- HoltWinters() function returns a list variable, that contains several named elements.The output of HoltWinters() tells us that the estimated value of the alpha parameter is about 0.982813.
- We can plot the original time series.

```
Holt-Winters exponential smoothing with trend and without seasonal component.

Call:
HoltWinters(x = tsData_before_covid_close, gamma = FALSE)

Smoothing parameters:
 alpha: 0.982813
 beta : 0.02381423
 gamma: FALSE

Coefficients:
       [,1]
a 60.091954
b -0.869578
```



- As a measure of the accuracy of the forecasts, we can calculate the sum of squared errors for the in-sample forecast errors, that is, the forecast errors for the time period covered by our original time series. The sum-of-squared-errors is stored in a named element of the list variable "rainseriesforecasts" called "SSE", so we can get its value by typing:

```
[1] "skirtsseriesforecasts$SSE"
```

```
[1] 2798.291
```

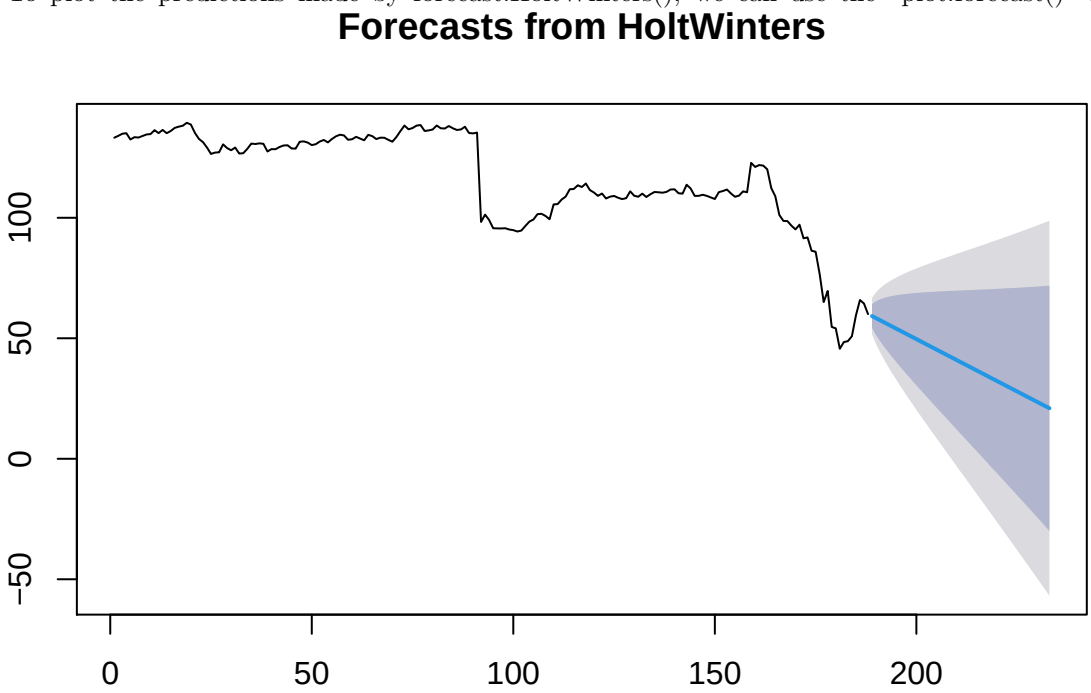
Forecasting with HoltWinters

- We can make forecasts for further time points by using the "forecast.HoltWinters()" function in the R "forecast" package.
- When using the forecast.HoltWinters() function, as its first argument (input), you pass it the predictive model that you have already fitted using the HoltWinters() function.
- You specify how many further time points you want to make forecasts for by using the "h" parameter in forecast.Here we are going to predict price for 45 days.
- forecast.HoltWinters() function gives you the forecast for a year, a 80% prediction interval for the forecast, and a 95% prediction interval for the forecast. For example, the forecasted stock price for 233 day is about 20.96095, with a 95% prediction interval of (-56.8291332 98.75102).

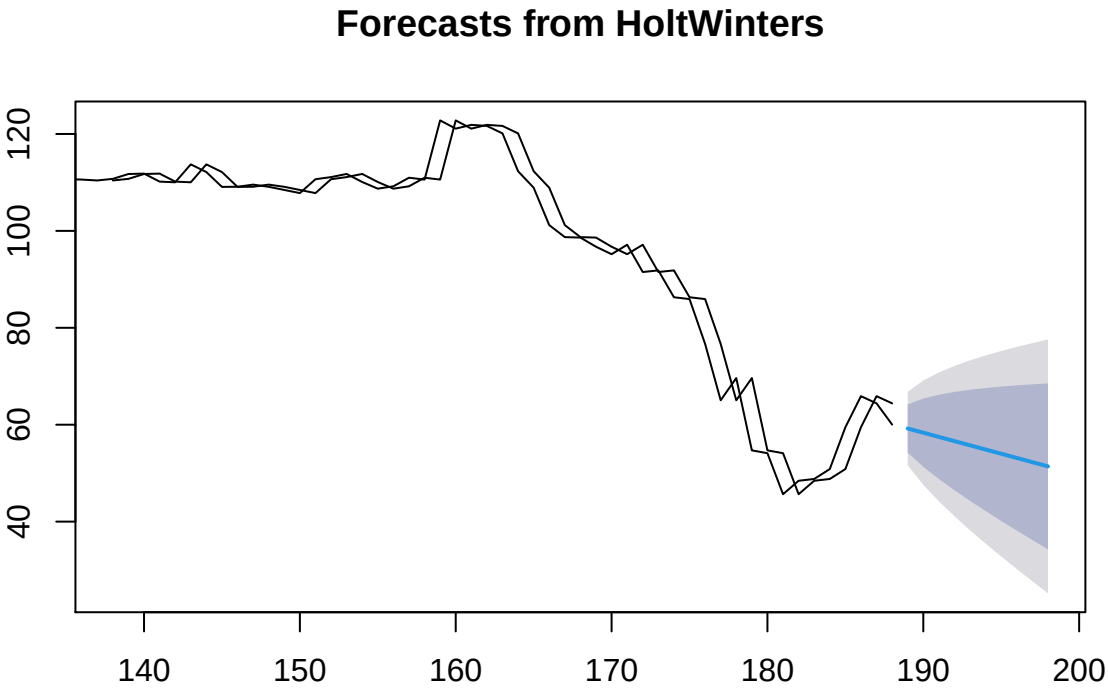
```
    Point Forecast      Lo 80    Hi 80       Lo 95    Hi 95
189       59.22238  54.261714 64.18304  51.6356981 66.80905
190       58.35280  51.315518 65.39008  47.5902068 69.11539
191       57.48322  48.787761 66.17868  44.1846635 70.78178
192       56.61364  46.469767 66.75752  41.0999238 72.12736
193       55.74406  44.280562 67.20757  38.2121512 73.27598
194       54.87449  42.178858 67.57011  35.4581988 74.29077
195       54.00491  40.140333 67.86948  32.8008698 75.20895
196       53.13533  38.149294 68.12137  30.2161653 76.05449
197       52.26575  36.194958 68.33655  27.6875932 76.84391
198       51.39617  34.269562 68.52279  25.2032811 77.58907
199       50.52660  32.367315 68.68588  22.7543724 78.29882
200       49.65702  30.483773 68.83026  20.3340704 78.97997
201       48.78744  28.615447 68.95943  17.9370389 79.63784
202       47.91786  26.759545 69.07618  15.5590078 80.27672
203       47.04828  24.913796 69.18277  13.1965057 80.90006
204       46.17871  23.076330 69.28108  10.8466714 81.51074
205       45.30913  21.245588 69.37267   8.5071196 82.11114
206       44.43955  19.420256 69.45884   6.1758412 82.70326
207       43.56997  17.599217 69.54073   3.8511288 83.28882
208       42.70039  15.781515 69.61927   1.5315205 83.86927
209       41.83082  13.966326 69.69531  -0.7842448 84.44588
210       40.96124  12.152934 69.76954  -3.0972610 85.01974
211       40.09166  10.340716 69.84261  -5.4084829 85.59180
212       39.22208   8.529124 69.91504  -7.7187474 86.16291
213       38.35250   6.717675 69.98733 -10.0287917 86.73380
214       37.48293   4.905945 70.05991 -12.3392679 87.30512
215       36.61335   3.093553 70.13314 -14.6507544 87.87745
216       35.74377   1.280164 70.20738 -16.9637667 88.45131
217       34.87419  -0.534523 70.28291 -19.2787648 89.02715
218       34.00461  -2.350779 70.36001 -21.5961611 89.60539
219       33.13504  -4.168844 70.43892 -23.9163256 90.18640
220       32.26546  -5.988937 70.51985 -26.2395913 90.77051
221       31.39588  -7.811255 70.60302 -28.5662585 91.35802
222       30.52630  -9.635974 70.68858 -30.8965985 91.94920
223       29.65672 -11.463254 70.77670 -33.2308566 92.54431
224       28.78715 -13.293243 70.86754 -35.5692552 93.14355
225       27.91757 -15.126070 70.96121 -37.9119963 93.74713
226       27.04799 -16.961857 71.05784 -40.2592630 94.35524
227       26.17841 -18.800712 71.15754 -42.6112221 94.96805
228       25.30884 -20.642734 71.26040 -44.9680254 95.58570
229       24.43926 -22.488014 71.36653 -47.3298109 96.20832
230       23.56968 -24.336634 71.47599 -49.6967045 96.83606
```

```
231       22.70010 -26.188669 71.58887 -52.0688212 97.46902
232       21.83052 -28.044188 71.70523 -54.4462656 98.10731
233       20.96095 -29.903253 71.82514 -56.8291332 98.75102
```

- To plot the predictions made by forecast.HoltWinters(), we can use the "plot.forecast()" function:



- Prediction for next ten days.



- ***Ljung-Box Tests***
- Box Test for modelfit_after_covid$residuals.
- To check for correlations between successive forecast errors, we can make a correlogram and use the

Ljung-Box test.

```
    Box-Ljung test

data:  modelfit_after_covid$residuals
X-squared = 1.6058e-05, df = 1, p-value = 0.9968
```

- Box Test for modelfit_before_covid$residuals

```
    Box-Ljung test

data:  modelfit_before_covid$residuals
X-squared = 0.0047812, df = 1, p-value = 0.9449
```

Conclusion

Here, the p value for both the models is greater than 0.05 . Hence, at a significance level of 0.05 we fail to reject the null hypothesis and conclude that the residual follows white noise. This means that the model fits the data well.

Using a Neural Network to Model the Amazon Stock Price Change (Real Time Analysis)

- Artificial neural networks are very powerful and popular machine-learning algorithms that mimic how a brain works in order find patterns in your data.
- In this project, we will build a basic neural network to model the price change of Amazon stocks in real Time.
- ANNs make predictions by sending the inputs (in our case, the indicators) through the network of neurons, with the neurons firing off depending on the weights of the incoming signals. The final output is determined by the strength of the signals coming from the previous layer of neurons.
- ***Data Import***
  - Use "quantmod" package to download information for Amazon stocks.
  - Let's see how we can quickly build a strategy using 4 technical indicators to see whether today's price of Amazon's stock .The 4 technical indicators are:
    - RSI -> Calculate a 3-period relative strength index (RSI) off the open price
    - EMA -> Calculate a 5-period exponential moving average (EMA)
    - MACD -> Calculate a MACD with standard parameters
    - SMI -> Stochastic Oscillator with standard parameters

```
[1] "AMZN"
```

Normalize Data

- One of the most important procedures when forming a neural network is data normalization. This involves adjusting the data to a common scale so as to accurately compare predicted and actual values. Failure to normalize the data will typically result in the prediction value remaining the same across all observations, regardless of the input values.
- Max-Min Normalization: For this method, we invoke the following function to normalize our data:
- Data slicing:
  - Data slicing is a step to split data into train and test set. Training data set can be used specifically for our model building. Test dataset should not be mixed up while building model. Even during

standardization, we should not standardize our test set.75 percent contributes to training & 25 percent of data contributes to test.

```
'data.frame':   5209 obs. of  5 variables:
 $ RSI3      : num  0.0853 0.0409 0.0402 0.6396 0.4188 ...
 $ EMAcross  : num  0.538 0.534 0.539 0.553 0.545 ...
 $ MACDsignal: num  0.727 0.705 0.681 0.661 0.643 ...
 $ BollingerB: num  0.423 0.353 0.362 0.477 0.408 ...
 $ Price     : num  0.417 0.424 0.444 0.422 0.433 ...
```

- TrainingParameters :
  - train() method is passed with repeated cross-validation resampling method for 10 number of resampling iterations repeated for 3 times.

Machine Learning: Classification using Neural Networks

- Model Training
  - We can us neuralnet() to train a NN model. Also, the train() function from caret can help us tune parameters. We can plot the result to see which set of parameters is fit our data the best.
  - nnnet package by defualt uses the Logisitc Activation function.
  - Data Pre-Processing With Caret: The scale transform calculates the standard deviation for an attribute and divides each value by that standard deviation.
  - The center transform calculates the mean for an attribute and subtracts it from each value.
  - Combining the scale and center transforms will standardize your data.
  - Attributes will have a mean value of 0 and a standard deviation of 1.
  - Training transforms can prepared and applied automatically during model evaluation.
  - Transforms applied during training are prepared using the preProcess() and passed to the train() function via the preProcess argument.
  - Backpropagation algorithm is a supervised learning method for multilayer feed-forward networks from the field of Artificial Neural Networks.
  - The principle of the backpropagation approach is to model a given function by modifying internal weightings of input signals to produce an expected output signal. The system is trained using a supervised learning method, where the error between the system's output and a known expected output is presented to the system and used to modify its internal state.
  - We use Backpropagation as algorithm in neural network package.

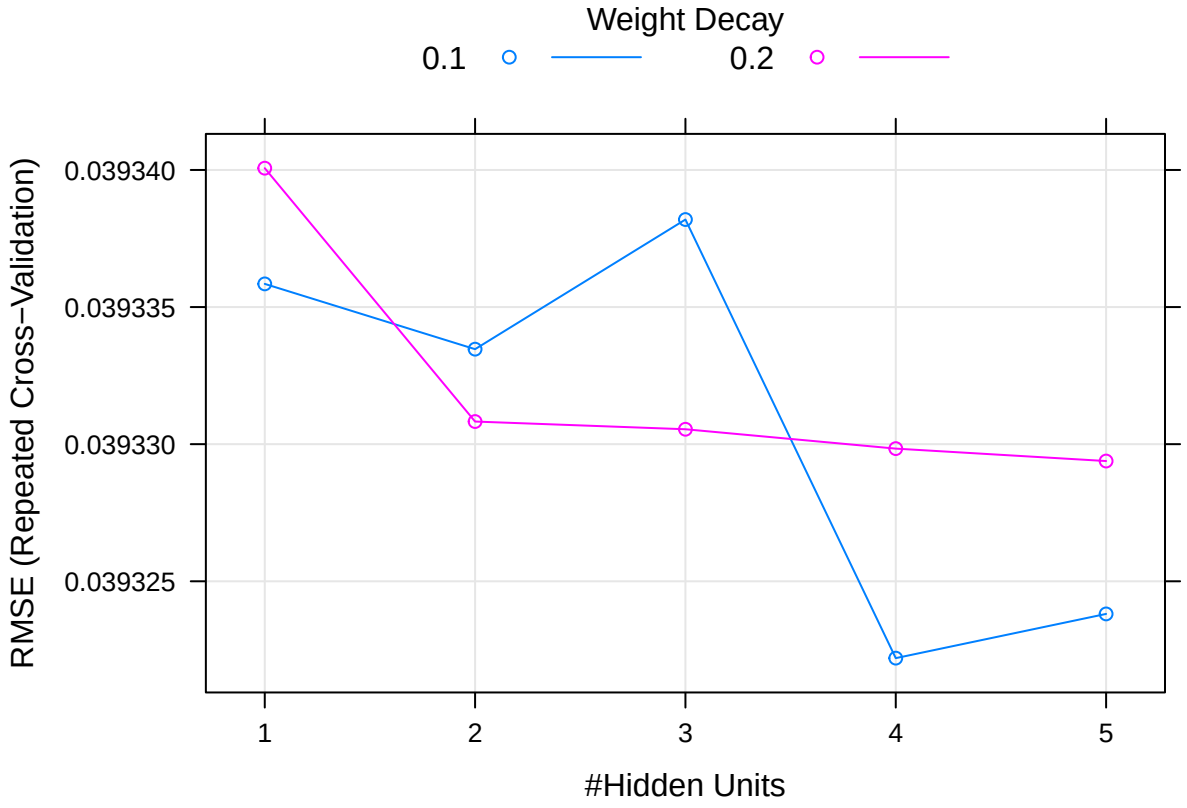
```
nnetGrid <-  expand.grid(size = seq(from = 1, to = 5, by = 1)
                         ,decay = seq(from = 0.1, to = 0.2, by = 0.1)
)
str(subTrain)
```

```
'data.frame':   12507 obs. of  5 variables:
 $ RSI3      : num  0.0853 0.0409 0.0402 0.4188 0.3651 ...
 $ EMAcross  : num  0.538 0.534 0.539 0.545 0.544 ...
 $ MACDsignal: num  0.727 0.705 0.681 0.643 0.625 ...
 $ BollingerB: num  0.423 0.353 0.362 0.408 0.386 ...
 $ Price     : num  0.417 0.424 0.444 0.433 0.426 ...
```

```
nn_model <- train(Price~RSI3+EMAcross+MACDsignal+BollingerB, subTrain,
                  method = "nnet",  algorithm = 'backprop',
                  trControl= TrainingParameters,
                  preProcess=c("scale","center"),
                  na.action = na.omit,
                  tuneGrid = nnetGrid,
                  trace=FALSE,
                  verbose=FALSE)
```

- Based on the caret neural network model, train sets hidden layer.caret neural network picks the best neural network based on size, decay. - We can visualize accuracy for different hidden layers below:

```
   size decay       RMSE   Rsquared        MAE      RMSESD RsquaredSD
1     1   0.1 0.03933584 0.01238798 0.01586244 0.002504076 0.01443134
2     1   0.2 0.03934006 0.01239107 0.01583777 0.002507265 0.01451383
3     2   0.1 0.03933346 0.01268185 0.01586449 0.002503906 0.01468389
4     2   0.2 0.03933083 0.01281302 0.01584319 0.002506894 0.01488929
5     3   0.1 0.03933819 0.01287279 0.01586899 0.002504096 0.01467428
6     3   0.2 0.03933054 0.01293707 0.01584766 0.002504418 0.01501688
7     4   0.1 0.03932220 0.01314280 0.01584623 0.002496180 0.01459575
8     4   0.2 0.03932984 0.01300564 0.01584778 0.002504590 0.01508909
9     5   0.1 0.03932381 0.01361986 0.01584481 0.002522508 0.01473453
10    5   0.2 0.03932938 0.01304931 0.01584684 0.002504771 0.01512491
          MAESD
1  0.0007305646
2  0.0007313067
3  0.0007312625
4  0.0007335536
5  0.0007326783
6  0.0007321606
7  0.0007377006
8  0.0007321347
9  0.0007322239
10 0.0007327730
```



- Prediction
  - Now, our model is trained with accuracy = 0.8889 We are ready to predict classes for our test set.

```
        actual prediction
7    0.4362379  0.4274795
10   0.4256909  0.4273008
97   0.4278731  0.4284938
139  0.4238725  0.4280213
483  0.4315391  0.4283605
783  0.4282804  0.4271653
896  0.4283095  0.4268096
908  0.4300552  0.4267116
911  0.4315391  0.4280867
952  0.4203374  0.4286907
1012 0.4257782  0.4279932
1711 0.4255164  0.4265486
1746 0.4299679  0.4280298
1804 0.4386092  0.4280147
2058 0.4317427  0.4280102
2073 0.4374163  0.4289039
2176 0.4056444  0.4292499
2276 0.4372417  0.4271038
2695 0.4251672  0.4280948
2746 0.4161477  0.4282272
2772 0.4228978  0.4272442
2784 0.4386092  0.4272447
3057 0.4236834  0.4273921
3139 0.4282513  0.4273274
3178 0.4408495  0.4281902
3220 0.4289496  0.4283887
3335 0.4316845  0.4266736
3443 0.4418097  0.4276801
3503 0.4245853  0.4275239
4018 0.4396857  0.4311302
4237 0.4353504  0.4281576
4261 0.4384055  0.4282462
4421 0.4145185  0.4284854
4526 0.5582194  0.4272961
4664 0.4444863  0.4258982
4786 0.4411985  0.4281155
4843 0.3776257  0.4279618
4865 0.4139076  0.4277111
4937 0.4610998  0.4286968
5030 0.5170493  0.4270784
```

Accuracy of Neural Network model:

99% accuracy is acheived to predict the price using the stock technical indicators.

```
          RSI3  EMAcross MACDsignal BollingerB     Price
7    0.32459911 0.5442847  0.6075494  0.3572573 0.4362379
10   0.20618845 0.5412815  0.5634201  0.3204323 0.4256909
97   0.24607269 0.5460137  0.2333221  0.3782227 0.4278731
139  0.84671114 0.5597144  0.7114260  0.7928638 0.4238725
483  0.80588690 0.5503068  0.6449523  0.7104961 0.4315391
783  0.54896975 0.5481855  0.7942074  0.5794676 0.4282804
896  0.36179313 0.5467044  0.7485756  0.4977961 0.4283095
908  0.36059256 0.5461656  0.7215884  0.5917109 0.4300552
```

```
911  0.87072321 0.5542228  0.7250983  0.8051809 0.4315391
952  0.72799440 0.5495230  0.5471357  0.5809809 0.4203374
1012 0.25508071 0.5462964  0.4156671  0.3042368 0.4257782
1711 0.17516899 0.5466259  0.7149182  0.3455139 0.4255164
1746 0.42878584 0.5473307  0.5385448  0.3833825 0.4299679
1804 0.95547536 0.5649359  0.7302750  0.9376553 0.4386092
2058 0.75475738 0.5528730  0.6755122  0.7233058 0.4317427
2073 0.85834756 0.5557843  0.6024193  0.5896256 0.4374163
2176 0.61647522 0.5560750  0.3465414  0.4212848 0.4056444
2276 0.38169960 0.5460403  0.7248211  0.4346285 0.4372417
2695 0.79630557 0.5568765  0.7103222  0.6807527 0.4251672
2746 0.86740868 0.5570476  0.6578077  0.8334958 0.4161477
2772 0.33325260 0.5425081  0.6137948  0.4871775 0.4228978
2784 0.11853439 0.5357345  0.5229431  0.2911652 0.4386092
3057 0.37948310 0.5450882  0.6474615  0.4269868 0.4236834
3139 0.47640198 0.5473919  0.6464690  0.6264217 0.4282513
3178 0.64602849 0.5532853  0.6476852  0.4856036 0.4408495
3220 0.78578515 0.5543646  0.6158716  0.6913156 0.4289496
3335 0.14403635 0.5345840  0.5990995  0.4992964 0.4316845
3443 0.95580068 0.6123559  0.6557729  0.9230118 0.4418097
3503 0.48426281 0.5469840  0.6377598  0.5614055 0.4245853
4018 0.04419073 0.4504553  0.4264717  0.1988550 0.4396857
4237 0.59029580 0.5558939  0.5694519  0.5221716 0.4353504
4261 0.87353837 0.5836426  0.6483177  0.7248558 0.4384055
4421 0.88473691 0.5823825  0.5743706  0.7673681 0.4145185
4526 0.59590136 0.5793888  0.7331421  0.5560403 0.5582194
4664 0.98636455 0.6589197  0.6674518  0.8129811 0.4444863
4786 0.62740722 0.5626872  0.5948031  0.5374183 0.4411985
4843 0.54126423 0.5618588  0.6234117  0.4116830 0.3776257
4865 0.63945676 0.5788562  0.5987941  0.6760626 0.4139076
4937 0.20789866 0.4876023  0.5509471  0.2674240 0.4610998
5030 0.44684424 0.5332037  0.7226938  0.6420079 0.5170493
```

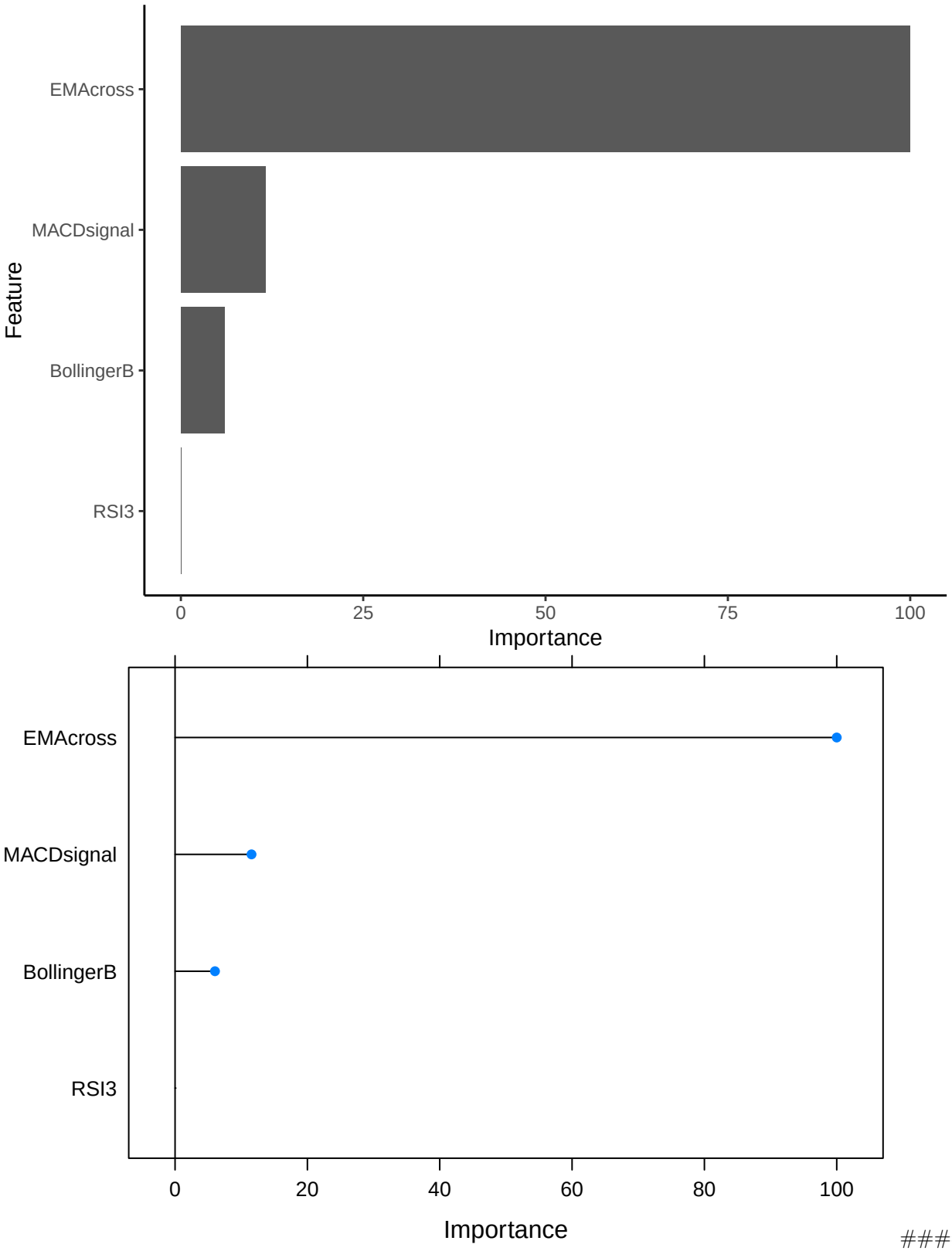
```
 [1]  0.0034655906 -0.0006396635 -0.0002464325 -0.0016497116  0.0012600367
 [6]  0.0004426085  0.0005953472  0.0013262634  0.0013685815 -0.0033262027
[11] -0.0008800795 -0.0004101826  0.0007687922  0.0041881569  0.0014795282
[16]  0.0033666456 -0.0094548054  0.0040098370 -0.0011635185 -0.0048179652
[21] -0.0017289311  0.0044925247 -0.0014748155  0.0003667483  0.0049999668
[26]  0.0002225924  0.0019863283  0.0055785501 -0.0011681378  0.0033806843
[31]  0.0028470762  0.0040164223 -0.0055743799  0.0494191079  0.0073310991
[36]  0.0051666092 -0.0203900965 -0.0055105203  0.0126964783  0.0344970986
```

```
[1] 0.9974791
```

- Plotting nnet variable importance

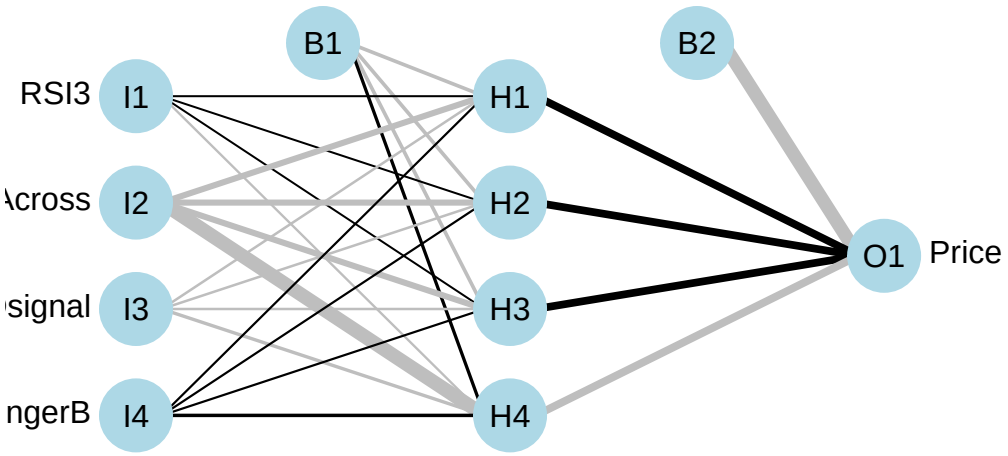
```
nnet variable importance
```

```
           Overall
EMAcross   100.000
MACDsignal  11.556
BollingerB   6.033
RSI3         0.000
```



####

Graphical Representation of our Neural Network



Conclusion

From the above implementation, the results are impressive(99% accuracy) and convincing in terms of using a machine learning algorithm to decide on the price of the stock Majority of the attributes in the dataset contribute significantly to the building of a predictive model.

Using SVM to predict price change for WALMART (Real Time Analysis)

Machine Learning: Classification using SVM

- SVM is another classification method that can be used to predict if a client falls into either 'yes' or 'no' class.
- The linear, polynomial and RBF or Gaussian kernel in SVM are simply different in case of making the hyperplane decision boundary between the classes.
- The kernel functions are used to map the original dataset (linear/nonlinear) into a higher dimensional space with view to making it linear dataset.
- Usually linear and polynomial kernels are less time consuming and provides less accuracy than the rbf or Gaussian kernels.
- The k cross validation is used to divide the training set into k distinct subsets. Then every subset is used for training and others k-1 are used for validation in the entire trainging phase. This is done for the better training of the classification task.Overall, if you are unsure which kernel method would be best, a good practice is use of something like 10-fold cross-validation for each training set and then pick the best algorithm.

```
   colnames(DataSetWalmart)
1                     Class
2                       RSI
3                 EMAcross
4                      MACD
5                       SMI
6                       WPR
7                       ADX
8                       CCI
9                       CMO
10                      ROC
```

SVM Classifier using Linear Kernel

- Caret package provides train() method for training our data for various algorithms. We just need to pass different parameter values for different algorithms. Before train() method, we will first use trainControl() method.
- We are setting 3 parameters of trainControl() method. The "method" parameter holds the details about resampling method. We can set "method" with many values like "boot", "boot632", "cv", "repeatedcv", "LOOCV", "LGOCV" etc. For this project, let's try to use repeatedcv i.e, repeated cross-validation.
- The "number" parameter holds the number of resampling iterations. The "repeats" parameter contains the complete sets of folds to compute for our repeated cross-validation. We are using setting number =10 and repeats =3. This trainControl() methods returns a list. We are going to pass this on our train() method.
- Before training our SVM classifier, set.seed().
- For training SVM classifier, train() method should be passed with "method" parameter as "svmLinear". We are passing our target variable Term_Deposit. The "Term_Deposit.~." denotes a formula for using all attributes in our classifier and Term_Deposit. as the target variable. The "trControl" parameter should be passed with results from our trianControl() method. The "preProcess" parameter is for preprocessing our training data.
- As discussed earlier for our data, preprocessing is a mandatory task. We are passing 2 values in our "preProcess" parameter "center" & "scale". These two help for centering and scaling the data. After preProcessing these convert our training data with mean value as approximately "0" and standard deviation as "1". The "tuneLength" parameter holds an integer value. This is for tuning our algorithm.

```
Support Vector Machines with Linear Kernel

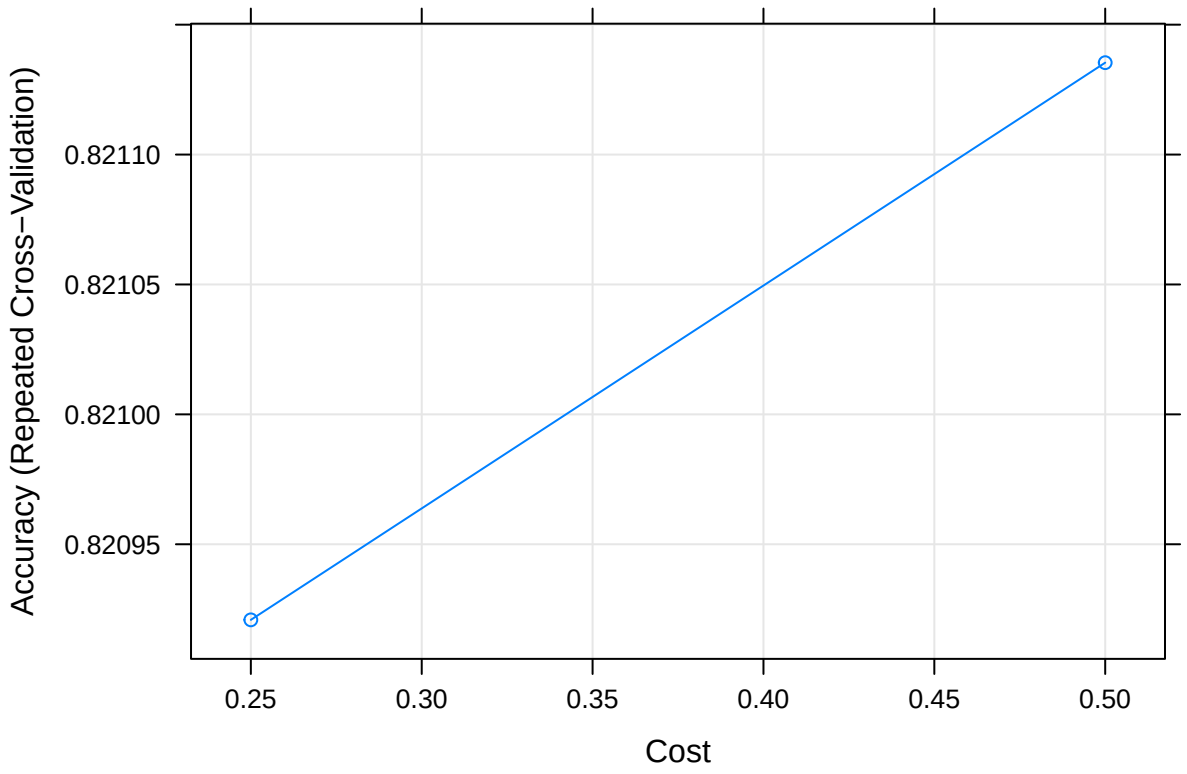
18651 samples
    7 predictor
    2 classes: 'DOWN', 'UP'

Pre-processing: centered (7), scaled (7)
Resampling: Cross-Validated (10 fold, repeated 1 times)
Summary of sample sizes: 16786, 16786, 16786, 16786, 16786, 16786, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.8209209  0.6412469
  0.50  0.8211354  0.6416789

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was C = 0.5.
```

- The above model is showing that our classifier is giving best accuracy on C = 0.25 Let's try to make predictions using this model for our test set and check its accuracy.




```
predictionsvm DOWN UP
         DOWN   28  8
         UP      5 28
```

- Accuracy on the test set by train control is 81% using C=0.25.

```
[1] 0.8115942
```

```
Confusion Matrix and Statistics

          Reference
Prediction DOWN UP
      DOWN   28  8
      UP      5 28

               Accuracy : 0.8116
                 95% CI : (0.6994, 0.8957)
    No Information Rate : 0.5217
    P-Value [Acc > NIR] : 5.253e-07

                  Kappa : 0.6239

 Mcnemar's Test P-Value : 0.5791

            Sensitivity : 0.8485
            Specificity : 0.7778
         Pos Pred Value : 0.7778
         Neg Pred Value : 0.8485
             Prevalence : 0.4783
         Detection Rate : 0.4058
```

```
   Detection Prevalence : 0.5217
      Balanced Accuracy : 0.8131

       'Positive' Class : DOWN
```

SVM Classifier using Non-Linear Kernel

- Now, we will try to build a model using Non-Linear Kernel like Radial Basis Function. For using RBF kernel, we just need to change our train() method's "method" parameter to "svmRadial". In Radial kernel, it needs to select proper value of Cost "C" parameter and "sigma" parameter.

```
Support Vector Machines with Radial Basis Function Kernel

18651 samples
    7 predictor
    2 classes: 'DOWN', 'UP'

Pre-processing: centered (7), scaled (7)
Resampling: Cross-Validated (10 fold, repeated 1 times)
Summary of sample sizes: 16786, 16786, 16786, 16786, 16786, 16786, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.8565757  0.7127826
  0.50  0.8618302  0.7233515

Tuning parameter 'sigma' was held constant at a value of 0.5
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were sigma = 0.5 and C = 0.5.
```

- SVM-RBF kernel calculates variations and will present us best values of sigma & C. Based on the output best values of sigma= 0.5 & C=0.5 Let's check our trained models' accuracy on the test set.

```
[1] 0.7971014
```

- Final prediction accuracy on the test set is 0.7971014

Comparision between SVM models

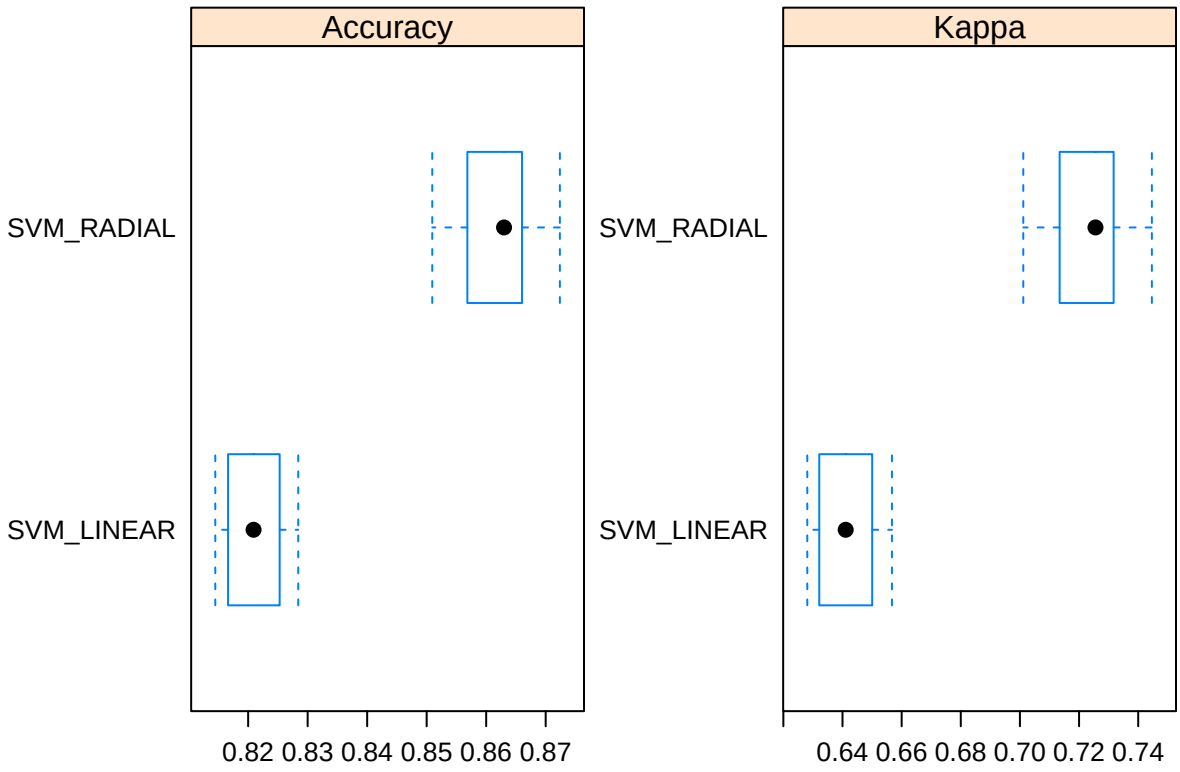
- Comparision between SVM Linear and Radial Models.

```
Call:
summary.resamples(object = algo_results)

Models: SVM_RADIAL, SVM_LINEAR
Number of resamples: 10

Accuracy
                Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
SVM_RADIAL 0.8509383 0.8571046 0.8630027 0.8618302 0.8657375 0.8723861    0
SVM_LINEAR 0.8144772 0.8171582 0.8209115 0.8211354 0.8248692 0.8284182    0

Kappa
                Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
SVM_RADIAL 0.7011356 0.7139651 0.7255579 0.7233515 0.7312067 0.7446252    0
SVM_LINEAR 0.6280912 0.6334363 0.6410743 0.6416789 0.6492305 0.6567207    0
```



Conclusion

From the above implementation, the results are impressive and convincing in terms of using a machine learning algorithm to decide on the price change of walmart . Majority of the attributes in the dataset contribute significantly to the building of a predictive model. All the two SVM approach acheives good accuracy rate(>80%) and are easier to implement.

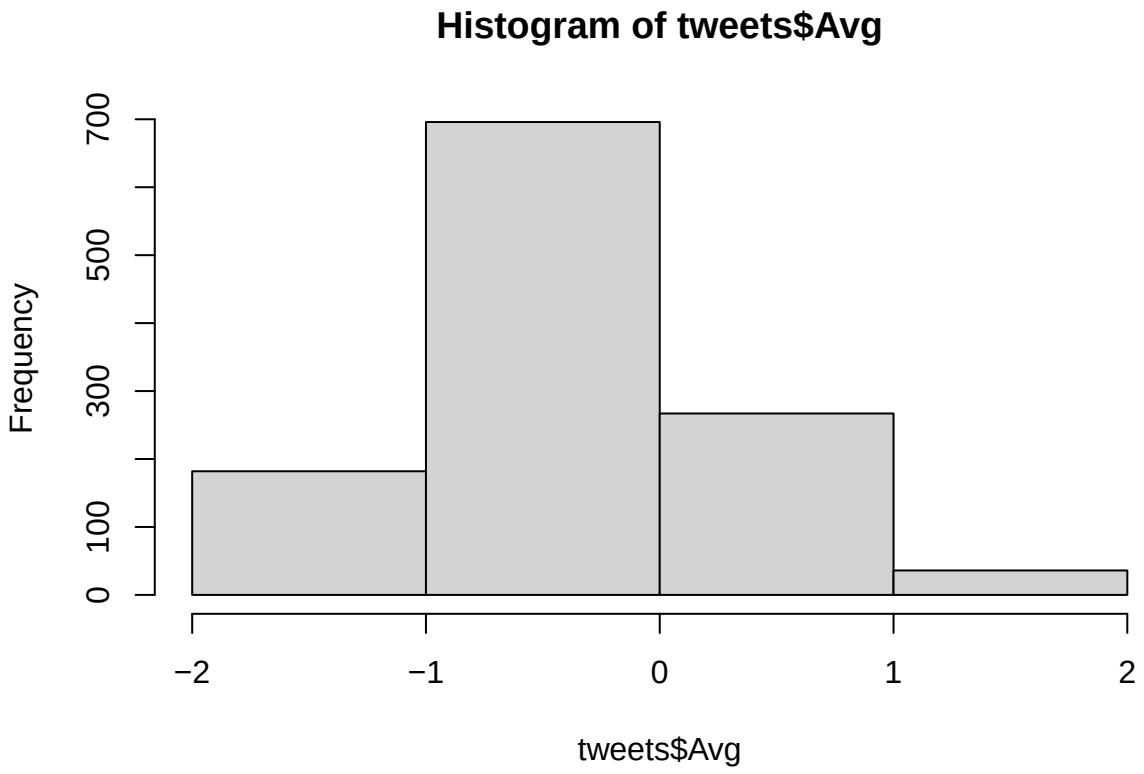
Naive Bayes Sentimental Analysis of Twitter Data for Apple Stock

- We will be trying to understand sentiment of tweets about the company Apple, By using the twitter for better understand public perception, Apple wants to monitor how people feel over time and how people receive new announcements.
- Our challenge in this project is to see if we can correctly classify tweets as being negative, positive, or neither about Apple.
- ***Sentiment Mining - Apple Stock***
  - Apple wants to monitor how people feel about them over time, and how people receive new announcements.
  - Challenge:Can we correctly classify tweets as being negative, positive, or neither about Apple?
- ***Preprocessing of Text data***
  - Change all the words in words in lower or upper
  - remove punctuation
  - remove stop words
  - stemming
- ***Data***

To collect the data needed for this task, we had to perform two steps.

- Collect Twitter data
- Construct the outcome variable for these tweets, which means that we have to label them as positive, negative, or neutral sentiment.These outcomes were represented as a number on the scale from -2 to 2.

The following graph shows the distribution of the number of tweets classified into each of the categories. We can see here that the majority of tweets were classified as neutral, with a small number classified as strongly negative or strongly positive.



Creating Corpus

- One of fundamental concepts in text analysis, implemented in the package tm as well, is that of a corpus.A corpus is a collection of documents.
- We will need to convert our tweets to a corpus for pre-processing. Various function in the tm package can be used to create a corpus in many different ways.
- We will create it from the tweet column of our data frame using two functions, Corpus() and VectorSource(). We feed to this latter the Tweets variable of the tweets data frame.
- ***Pre-processing steps***
  - To deal with text data following pre-processing is required.Follow the standard steps to build and pre-process the corpus:
    - Build a new corpus variable called corpus.
    - Using tm_map, convert the text to lowercase.
    - Using tm_map, remove all punctuation from the corpus.
    - Using tm_map, remove all English stopwords from the corpus.
    - Using tm_map, stem the words in the corpus.
  - Build a document term matrix from the corpus, called dtm. Each operation, like stemming or removing stop words, can be done with one line in R, where we use the tm_map() function which

takes as its first argument the name of a corpus and as second argument a function performing the transformation that we want to apply to the text.

Positive Bag Of Words

- Create a Document Term Matrix
- We are now ready to extract the word frequencies to be used in our prediction problem. The tm package provides a function called DocumentTermMatrix() that generates a matrix where:
  - the rows correspond to documents, in our case tweets, and
  - the columns correspond to words in those tweets.
  - The values in the matrix are the number of times that word appears in each document.
- Create word cloud for postive tweets

```
'data.frame':   61 obs. of  1 variable:
 $ text: chr  " say appl far best custom care servic ever receiv appl appstor" "io frick smooth beauti
```

Negative Bag Of Words & wordcloud for negative

```
<<DocumentTermMatrix (documents: 1181, terms: 3198)>>
Non-/sparse entries: 10102/3766736
Sparsity           : 100%
Maximal term length: 99
Weighting          : term frequency (tf)
Sample             :
      Terms
Docs   appl get ipad iphon ipod itun make new phone whi
  103     1   0    0     0    0    0    0   0     0   0
  1066    2   0    1     0    0    1    0   0     0   0
  215     3   0    2     0    0    0    0   0     0   0
  506     3   0    0     0    0    0    0   0     0   0
  592     1   0    0     0    0    0    0   0     1   1
  62      1   1    0     0    0    0    0   0     1   1
  740     1   1    0     0    0    0    0   1     0   0
  756     1   0    0     0    0    0    0   0     0   0
  86      1   0    0     2    0    0    0   1     0   0
  900     1   0    0     0    0    0    0   0     0   0
```

- ***Building machine learning model***
  - Before Building the machine learning model, we need to split our data in training and training dataset split data in training/testing sets
  - Lastly, let's split our data into a training set and a testing set, putting 70% of the data in the training set.
- ***Making predictions***
  - We build Naive Bayes by using training & test data sets.
  - We apply Laplace smoothing , which is a technique for smoothing categorical data.
  - A small-sample correction, or pseudo-count, will be incorporated in every probability estimate. Consequently, no probability will be zero. this is a way of regularizing Naive Bayes, and when the pseudo-count is zero, it is called Laplace smoothing.

```
model <- naive_bayes(as.data.frame(as.matrix(dtm_train)), dataset_train$positive, laplace = 1)
```

Interpretation of the results and prediction accuracy achieved

- ***Evaluate the model performance using confusionMatrix***
- The accuracy of our model on the testing set is 78%.
- We can visualise the model's performance using a confusion matrix.
- We can evaluvate the accuracy, precision and recall on the training and validation sets to evaluate the performance of naive bayes algorithm.

```
Confusion Matrix and Statistics

          Reference
Prediction FALSE TRUE
     FALSE   237    0
     TRUE     65    0

               Accuracy : 0.7848
                 95% CI : (0.7341, 0.8298)
    No Information Rate : 1
    P-Value [Acc > NIR] : 1

                  Kappa : 0

 Mcnemar's Test P-Value : 2.051e-15

            Sensitivity : 0.7848
            Specificity :     NA
         Pos Pred Value :     NA
```

```
         Neg Pred Value :     NA
             Prevalence : 1.0000
         Detection Rate : 0.7848
   Detection Prevalence : 0.7848
      Balanced Accuracy :     NA

       'Positive' Class : FALSE
```

- ***Evaluate the model performance using CrossTable***

```
   Cell Contents
|-------------------------|
|                       N |
|-------------------------|


Total Observations in Table:  302


              | dataset_test$positive
model_predict |     FALSE | Row Total |
--------------|-----------|-----------|
        FALSE |       237 |       237 |
--------------|-----------|-----------|
         TRUE |        65 |        65 |
--------------|-----------|-----------|
 Column Total |       302 |       302 |
--------------|-----------|-----------|
```

- ***Find 25 frequent words***

```
[1] "appl"  "iphon" "new"   "phone" "whi"   "get"   "ipad"  "itun"  "ipod"
```

Overall insights obtained from the implemented project

- Overall accuracy of the model is 78%.It is safe to assume that naive bayes models can be trained on to find the sentiment of the stocks.
- Sensitivity for finding ratings is 0.7848.
- Since the dataset was clean, and reviews are equally distributed between test & training set, adding laplace smoothing factor did not make much difference in the accuracy.

Amazon Price Trend Predict - Random Forest (Real Time Analysis)

- Stock market prediction is an incredibly difficult task, due to the randomness and noisiness found in the market. Yet, predicting market behaviors is a very important task. Correctly predicting stock price directions can be used to maximize profits, as well as to minimize risk. There are two types of methods to predicting market behavior. One is predicting the future price of an asset. This is usually done using time series analysis to fit a specific model, like ARIMA or GARCH, to some historical data. The other is predicting the future trend of an asset. That is, whether one thinks it will go up or down in price, treating it as a classification problem.
- The goal of this project is to create an intelligent model, using the Random Forest model, that can correctly forecast the behavior of a stock's price n days out.

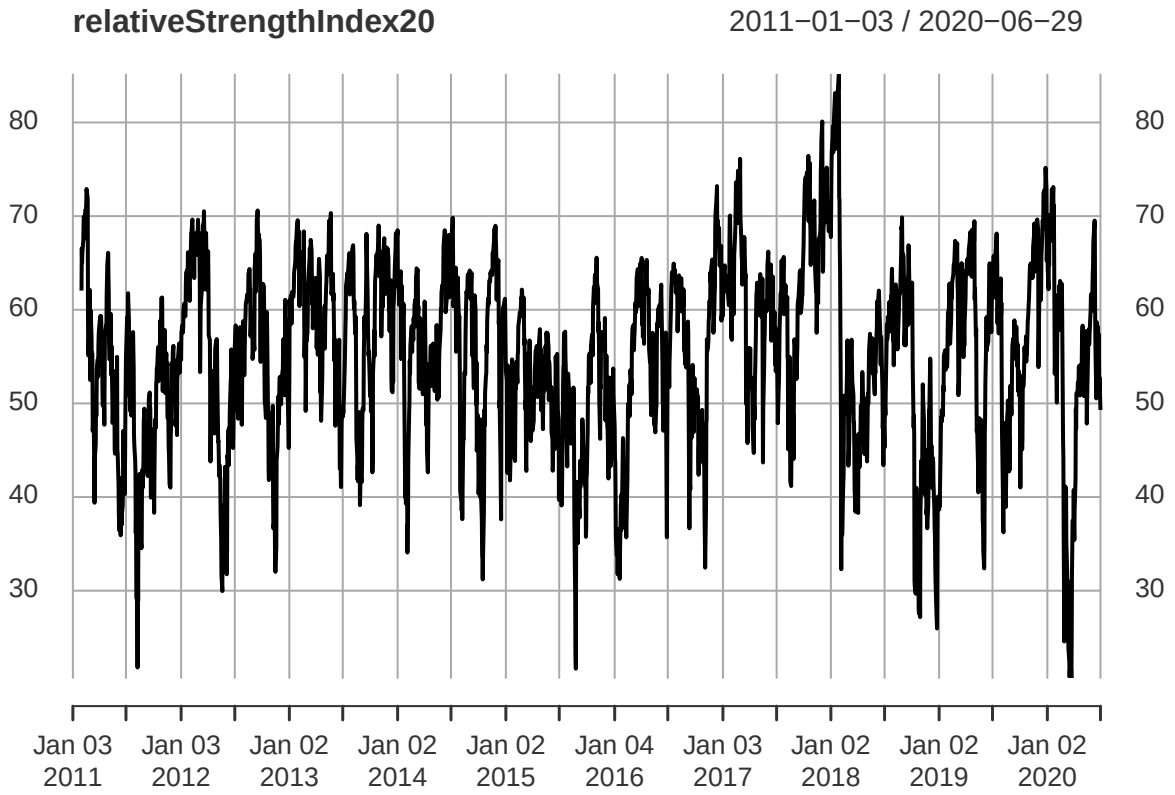
- ***Data Import***
  - Use "quantmod" package to download information for Amazon stocks.
  - The data used for this project consists of regular stock data (open, close, volume, etc.) from Yahoo finance, and ranges from the year 2000 to 2018.
  - From this data, technical indicators were calculated for every stock. Below are all the technical indicators used for this model:

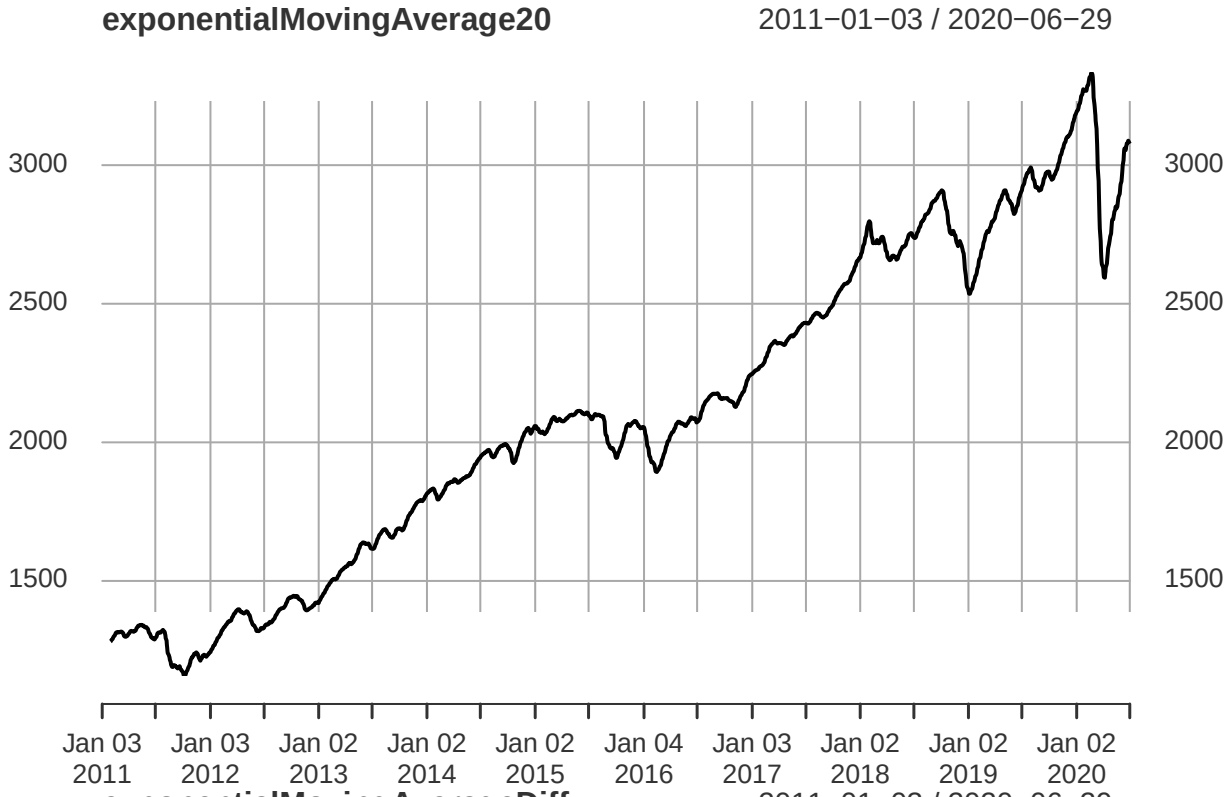
```
- Relative Strength Index
- Stochastic Oscillator
- William %R
- Moving Average Convergence Divergence
- Price Rate of Change
- On Balance Volume
```

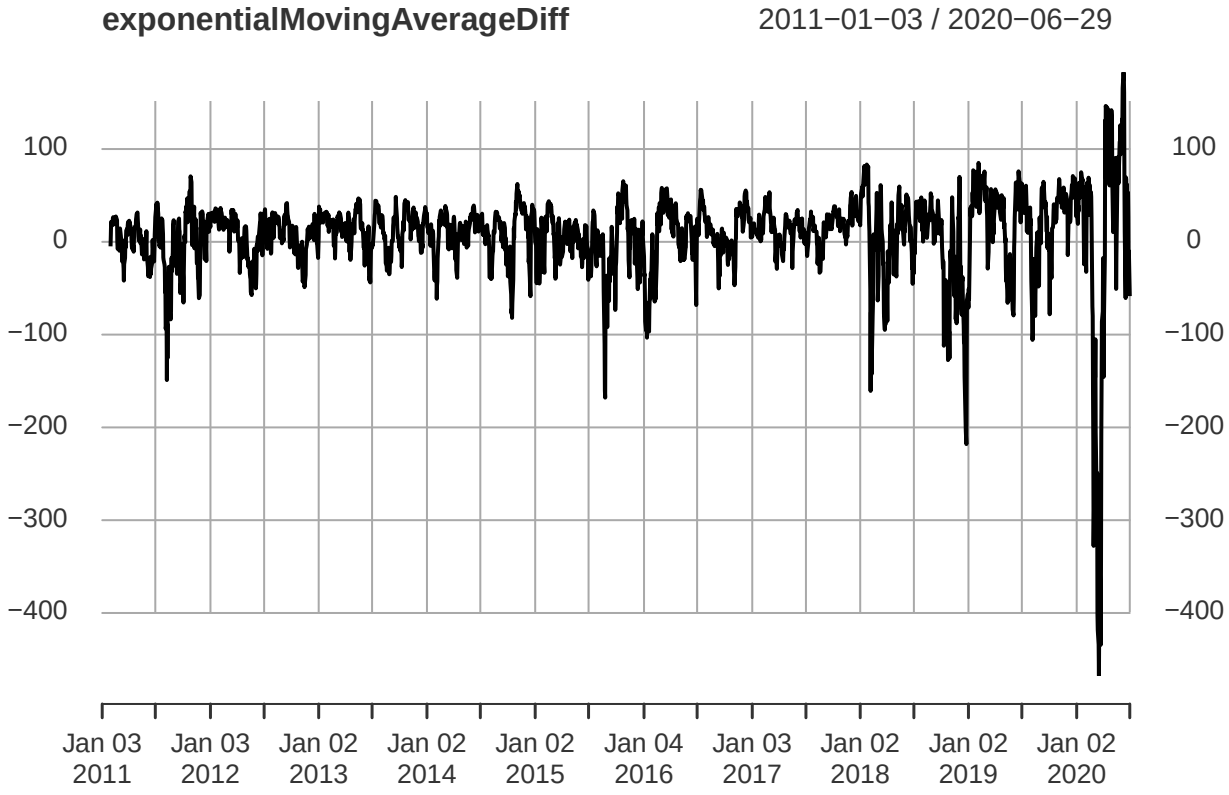
  - The last step of pre-processing the data was calculating the response variable. Since we are treating this as a classification problem, the response variable was binary. The equation for calculating the response variable is below:Response=Closet+n−Closet
  - It states that the adjusted close price at t+n, where n is the number of days out you want to predict, minus the current adjusted close price will map to a value that says the stock price went up from the point at time t, or that it went down.

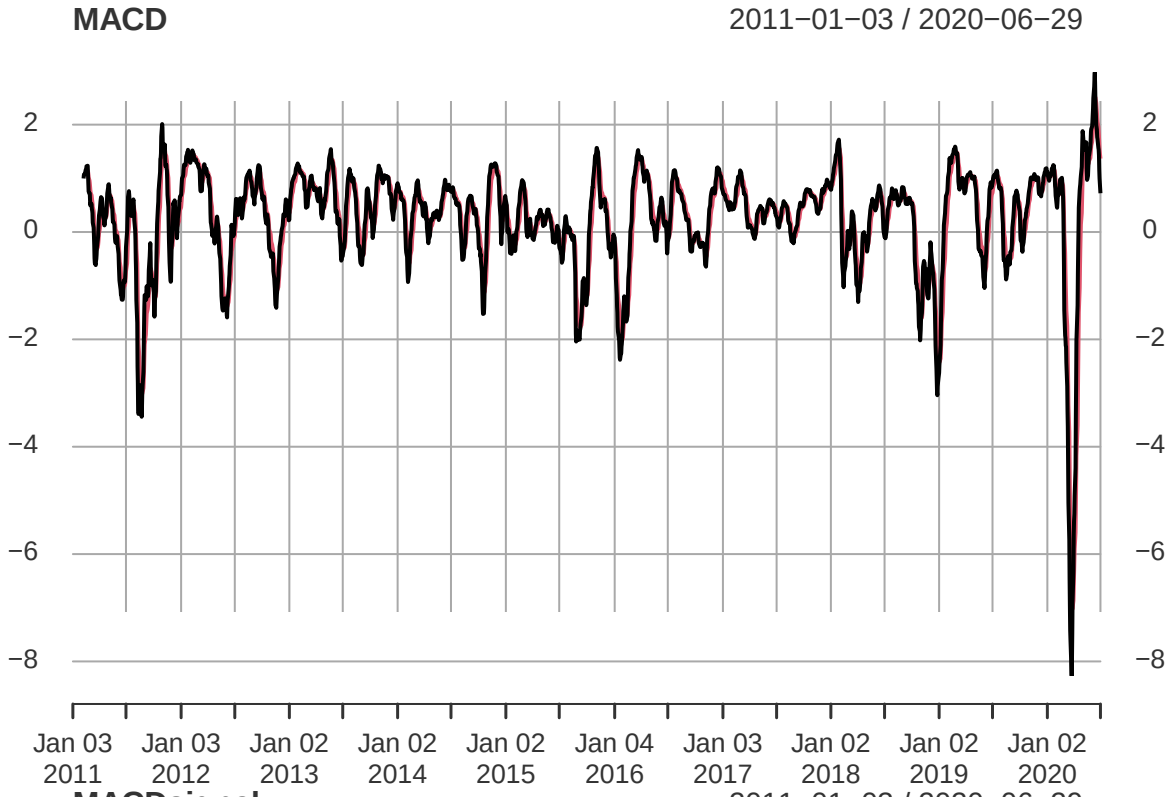
Methadology

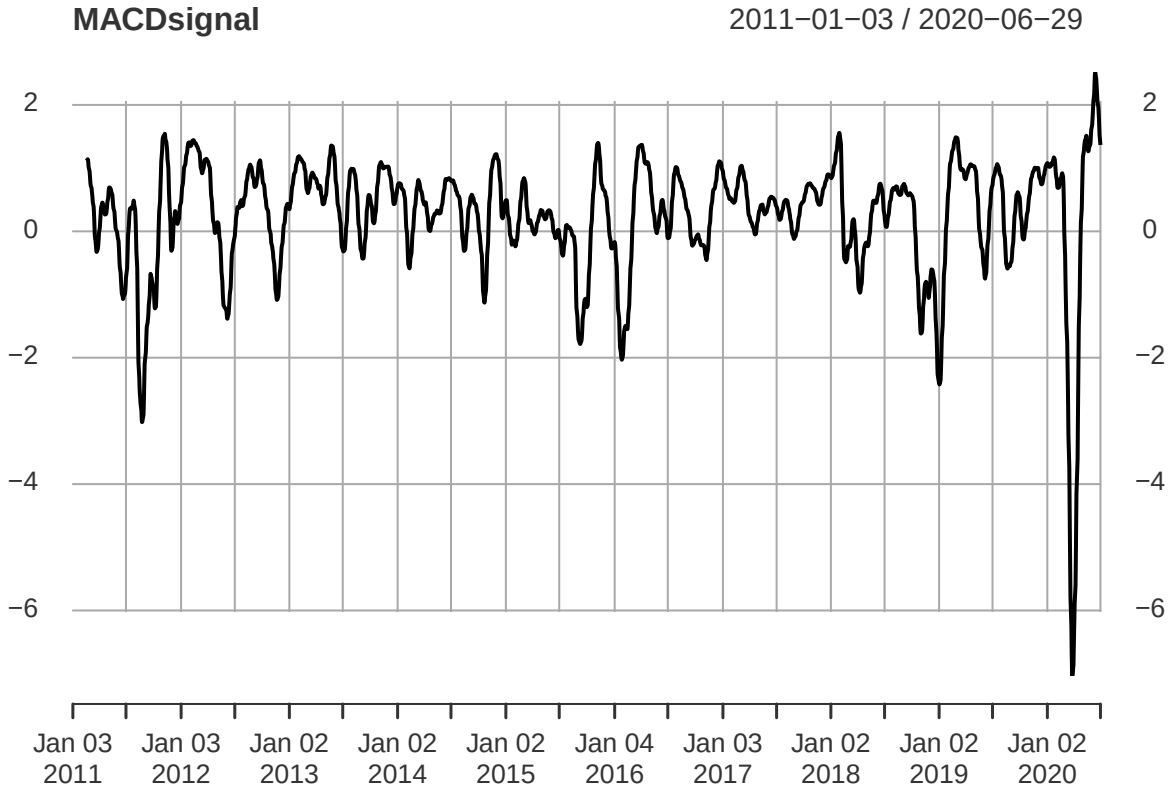
```
[1] "^GSPC"
```

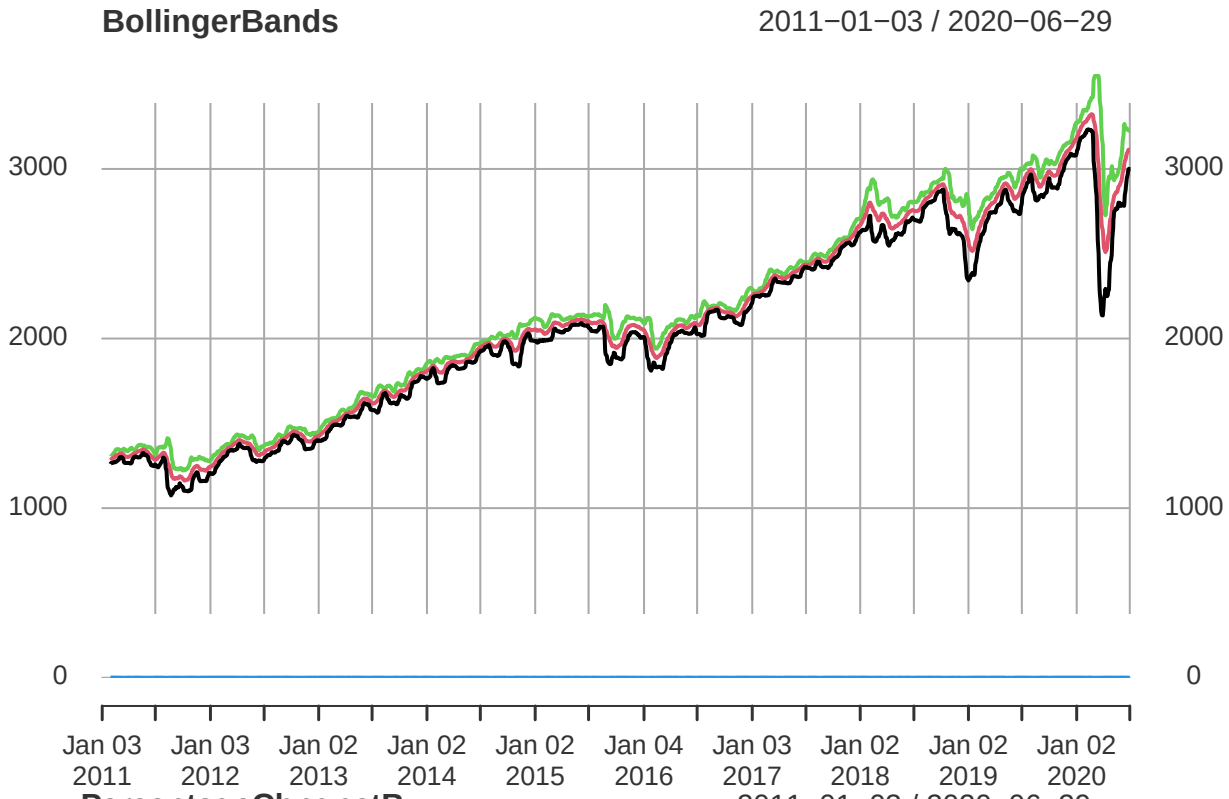


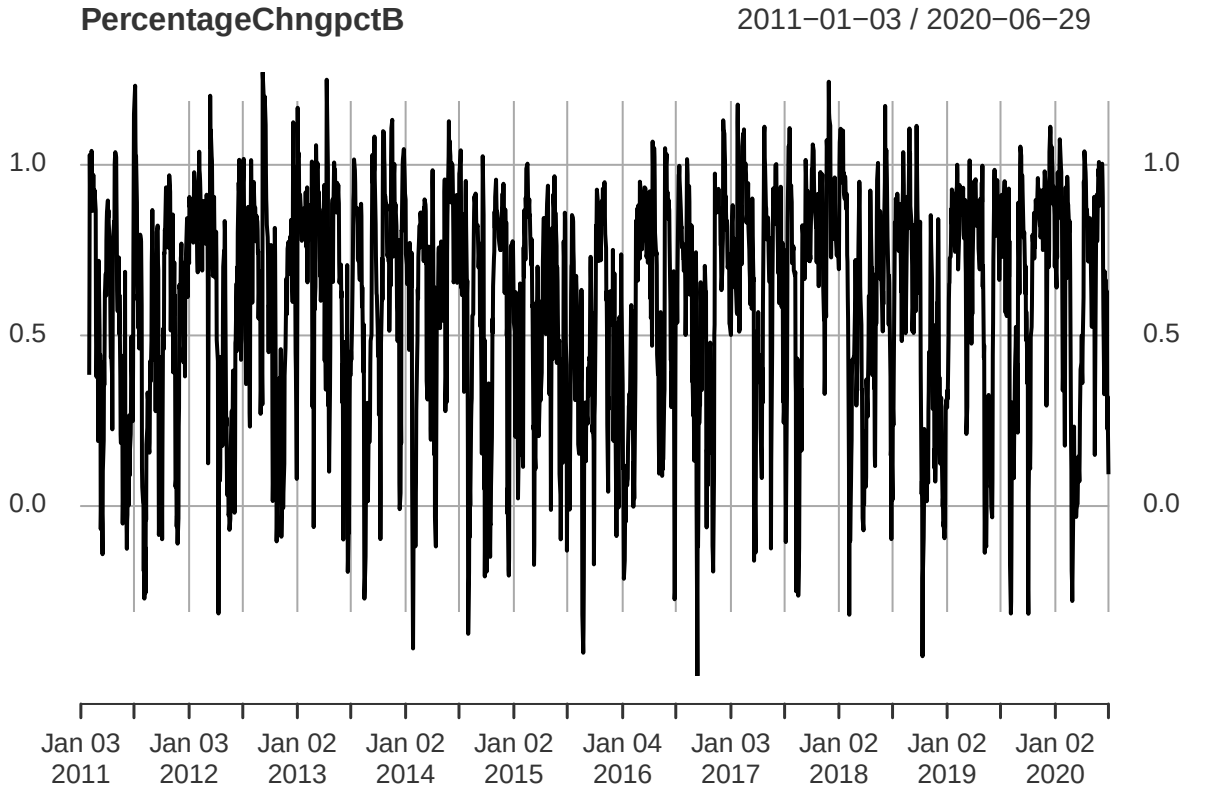

exponentialMovingAverage20
2011−01−03 / 2020−06−29
3000
2500
2000
1500
Jan 03 2011
Jan 03 2012
Jan 02 2013
Jan 02 2014
Jan 02 2015
Jan 04 2016
Jan 03 2017
Jan 02 2018
Jan 02 2019
Jan 02 2020

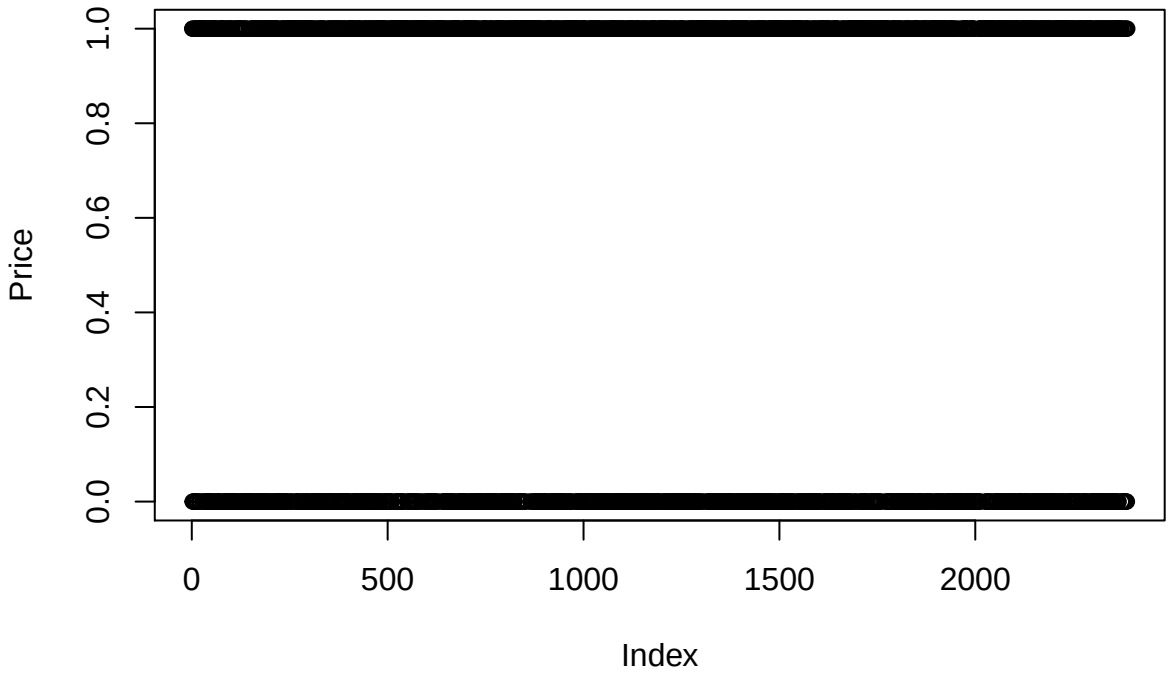

exponentialMovingAverageDiff
2011−01−03 / 2020−06−29
100
0
−100
−200
−300
−400
Jan 03 2011
Jan 03 2012
Jan 02 2013
Jan 02 2014
Jan 02 2015
Jan 04 2016
Jan 03 2017
Jan 02 2018
Jan 02 2019
Jan 02 2020


MACD
2011−01−03 / 2020−06−29
2
0
−2
−4
−6
−8
Jan 03 2011
Jan 03 2012
Jan 02 2013
Jan 02 2014
Jan 02 2015
Jan 04 2016
Jan 03 2017
Jan 02 2018
Jan 02 2019
Jan 02 2020


MACDsignal
2011−01−03 / 2020−06−29
2
0
−2
−4
−6
Jan 03 2011
Jan 03 2012
Jan 02 2013
Jan 02 2014
Jan 02 2015
Jan 04 2016
Jan 03 2017
Jan 02 2018
Jan 02 2019
Jan 02 2020


BollingerBands
2011−01−03 / 2020−06−29
3000
2000
1000
0
Jan 03 2011
Jan 03 2012
Jan 02 2013
Jan 02 2014
Jan 02 2015
Jan 04 2016
Jan 03 2017
Jan 02 2018
Jan 02 2019
Jan 02 2020


PercentageChngpctB
2011−01−03 / 2020−06−29
1.0
0.5
0.0
Jan 03 2011
Jan 03 2012
Jan 02 2013
Jan 02 2014
Jan 02 2015
Jan 04 2016
Jan 03 2017
Jan 02 2018
Jan 02 2019
Jan 02 2020



- Dataset used for this project:

```
  colnames(dataset1)
1                rsi
2                EMA
3             signal
4               pctB
5         GSPC.Close
```

- Check for missing data in relativeStrengthIndex20, exponentialMovingAverage20, MACDsignal, PercentageChngpctB, Price. Omit the n/a values in dataset.
- Print the number of missed value for each attribute in dataset.

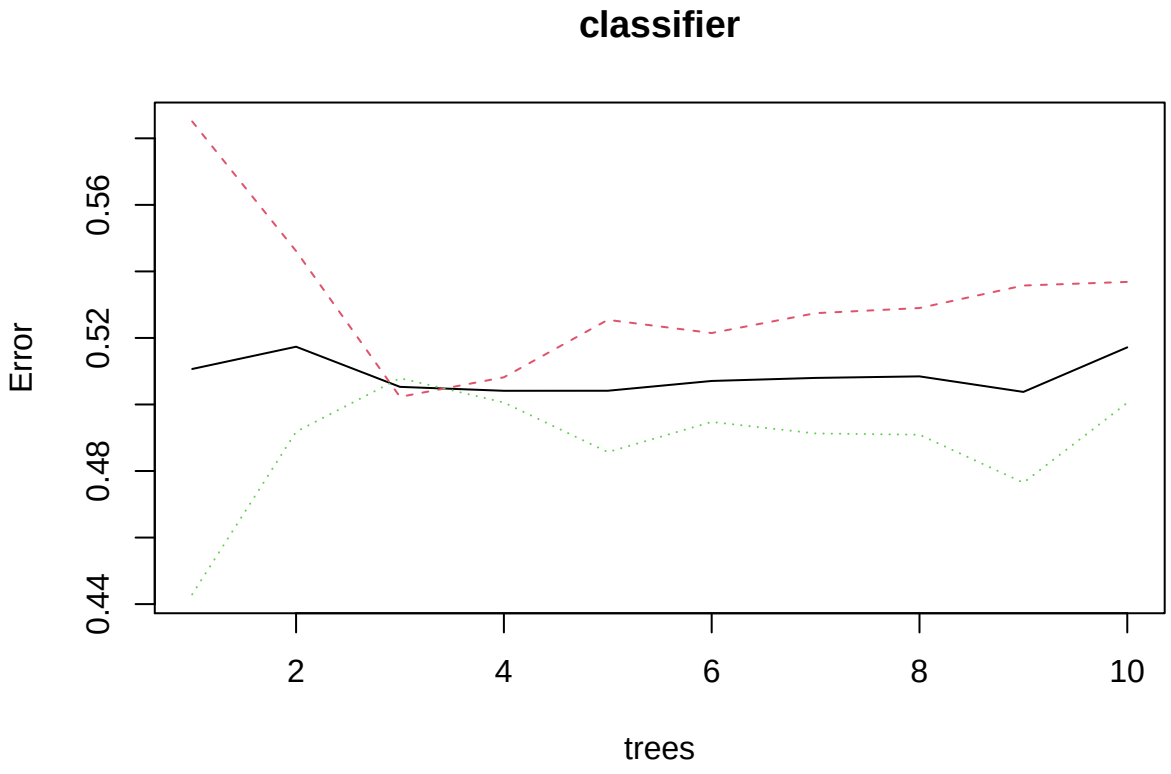
```
[1] "rsi"
[1] 20
[1] "EMA"
[1] 19
[1] "signal"
[1] 33
[1] "pctB"
[1] 19
[1] "GSPC.Close"
[1] 0
```

- RandoM Forest Machine Learning Model
  - Split the dataset into training & test dataset.80 % of the data is training data.20 % of the data is test dataset.
  - Feature Scaling -> Normalization /Scale and dropping the feature varaibles.

```
# Feature Scaling (Normalization and dropping the predicted variable)
training_set[-5] = scale(training_set[-5])
test_set[-5] = scale(test_set[-5])
```

- Applying Random Forest Model on the Training set.

```
                Length Class  Mode
call               4   -none- call
type               1   -none- character
predicted       1884   factor numeric
err.rate          30   -none- numeric
confusion          6   -none- numeric
votes           3768   matrix numeric
oob.times       1884   -none- numeric
classes            2   -none- character
importance         4   -none- numeric
importanceSD       0   -none- NULL
localImportance    0   -none- NULL
proximity          0   -none- NULL
ntree              1   -none- numeric
mtry               1   -none- numeric
forest            14   -none- list
y               1884   factor numeric
test               0   -none- NULL
inbag              0   -none- NULL
```



Prediction & Accuracy.

- After building the model, then we can check the accuracy of forecasting using confusion matrix.
- Final Model Accuracy of the model is 51 percent.

```
   predict_val
      0   1
  0  89 128
  1 102 152
```

```
[1] "Model Accuracy is"
```

```
[1] 0.5116773
```

Ensemble Method for Random Forest

```
Random Forest

1884 samples
   4 predictor
   2 classes: '0', '1'

No pre-processing
Resampling: Cross-Validated (3 fold)
Summary of sample sizes: 1257, 1256, 1255
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
  3     0.5058141  -0.003131317
  6     0.5021045  -0.009128875
  9     0.5132502   0.013836823

Kappa was used to select the optimal model using the largest value.
The final value used for the model was mtry = 9.
```

Overall insights obtained from the implemented project

- As we can see, the model has the highest accuracy of 51 percent . While this may not seem any good, it is often extremely hard to predict the price of stocks. Even the 2.5% improvement over random guessing can make a difference given the amount of money at stake. After all, if it was that easy to predict the prices, wouldn't we all be trading in stocks for the easy money instead of learning these algorithms?

Discussion and Conclusions

- This is a beginning of the use of ML algorithms for predicting the time series data or the stock prices.It can be modified and optimized in a lot of ways to produce much better and much more efficient and accurate results.
- Choosing the right technical indicators which will influence the price change is daunting.In this project we tried to predict the price change through variety of technical indicators in different ML algorithms.
- Although we have acheived accuracy of 80 percent in many ML algorithms and used ensembles to improve accuracy, there are many other things that impact the prices of stocks such as:Political and social upheavals ,current affairs etc
- Thus, we can say stock market price change is quite a dynamic movement.