Application of Machine Learning on Fundamental Stock Price Analysis

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Abstract:

Keywords: stock price, fundamental analysis, machine learning, R

Introduction

Background

The stock market is a marketplace where investors can purchase or sell shares of publicly traded companies. As of 2019, the amount of money invested in the global stock market has surpassed over $85 trillion. Since the inception of the stock market, investors have continuously sought to develop methods of improving their returns. Currently, there are two main schools of thought when it comes to stock market analysis: technical analysis and fundamental analysis.

Technical analysis looks at buying and selling trends of a particular stock. The core theory of technical analysis assumes that all information is already factored into the stock price. As such, technical analysis prioritizes identifying patterns or trends in time-series data to predict stock price at a particular time point.

Fundamental analysis attempts to measure the intrinsic value of a company by studying information from that company's balance sheet, such as revenue or debt. Fundamental analysis attempts to identify companies that appear to be 'undervalued' or 'overvalued' to inform buy or sell recommendations.

Previous machine learning models that simulated stock market returns have largely focused on using time series data to predict stock trends, which is more akin to technical analysis. However, such models have run into challenges such as overfitting or a lack of interpretability. One benefit of fundamental analysis is that it allows the investor to learn about which aspects of a company's financials will influence that company's stock price; it is more interpretable. As there are dozens to hundreds of variables on a company's balance sheet, the use of machine-learning approaches may augment fundamental analysis by pinpointing important markers of a company's financials and their relationship with the stock price.

Objective

In this project, we apply machine learning and data science techniques to predict the market capitalization, which is how much company is worth on the stock market. Stock price can then be calculated by dividing market capitalization by total number of stocks issued. We also create an application using R shiny to be used as a guide for investors. This application would be used individuals interested in checking their stock analyses with a machine learning prediction. The application could be used by financial analysts, portfolio managers, or non-professional investors with an interest in fundamental analysis.

Methodology

Data Preprocessing

Missing Values

Data Curation

Modeling

Feature Selection

Talk about the decision tree here

Principle Component Analysis

We applied Principle Component Analysis (PCA) to our feature dataset for dimensionality reduction before unsupervised learning with k-Nearest Neighbor (kNN). PCA creates orthoganal 'principle components' of the feature set, reducing multicollinearity within the data. While k-NN is non-parametric, reducing multicollinearity before performing k-NN could lead to greater discrimination in-between points.

Unsupervised Learning

The k-NN algorithm was run to cluster the data before supervised learning. The number of clusters was evaluated by plotting the within-cluster sum of squares (WSS) against the number of clusters (k). The optimal number of clusters was chosen based on a combination of the 'elbow method' and domain knowledge.

Supervised Learning

Deployment

Results

Data Exploration

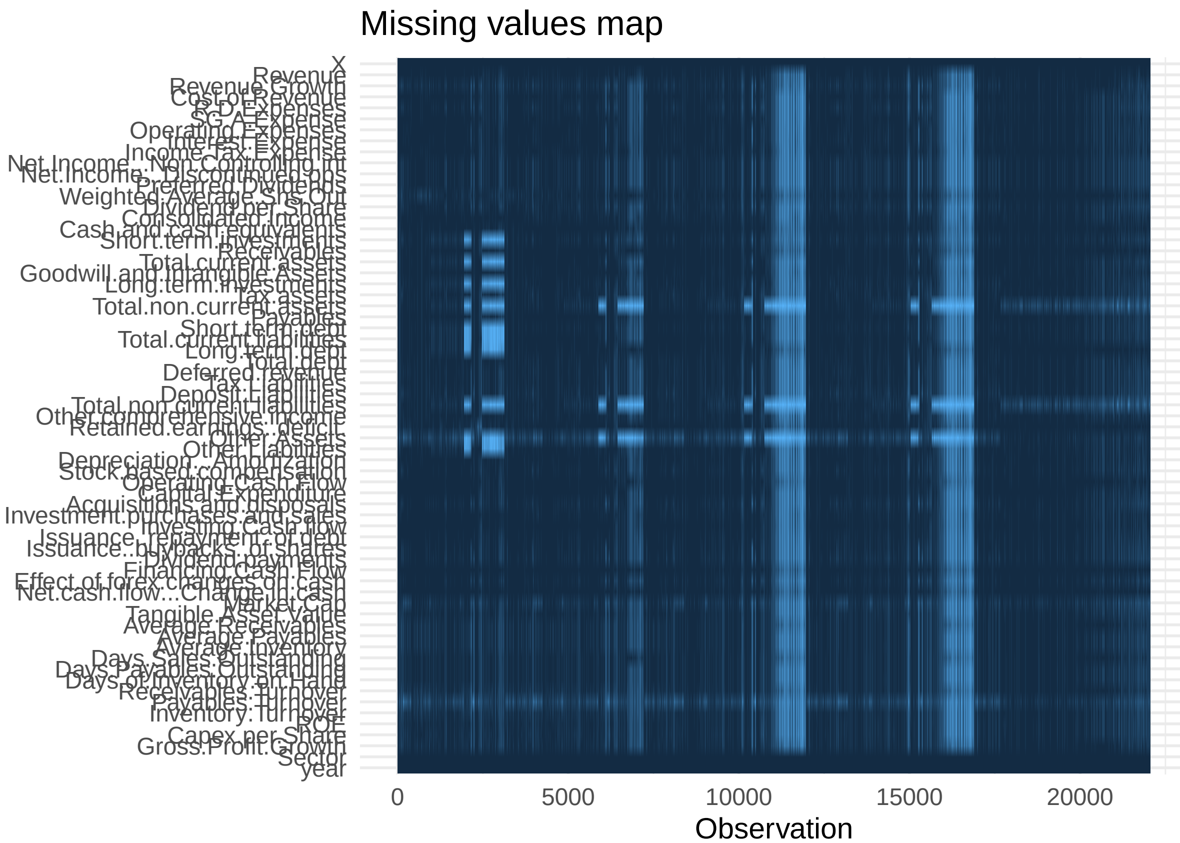
###Data Preparation The original data is from Kaggle and have several different CSV files include the stock information for different years. We combined the CSV files into one full data set for our project

```
#load in the first file
data_2014 <- read.csv('2014_Financial_Data.csv')
data_2015 <- read.csv('2015_Financial_Data.csv')
data_2016 <- read.csv('2016_Financial_Data.csv')
data_2017 <- read.csv('2017_Financial_Data.csv')
data_2018 <- read.csv('2018_Financial_Data.csv')

#add a column for year
data_2014 <- data_2014 %>% mutate(year=2014)
data_2015 <- data_2015 %>% mutate(year=2015)
```

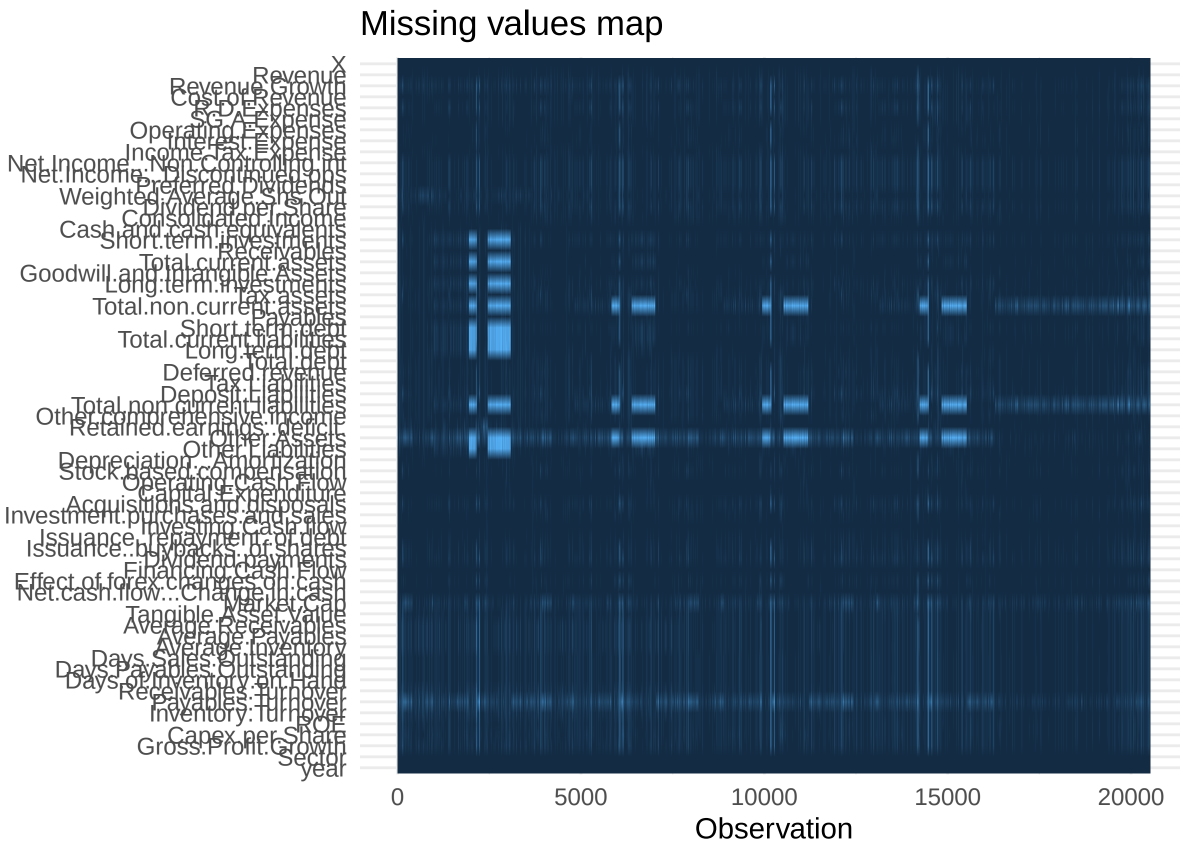
```
data_2016 <- data_2016 %>% mutate(year=2016)
data_2017 <- data_2017 %>% mutate(year=2017)
data_2018 <- data_2018 %>% mutate(year=2018)

#fix the column name
colnames(data_2014)[224] <- 'PRICE.VARR'
colnames(data_2015)[224] <- 'PRICE.VARR'
colnames(data_2016)[224] <- 'PRICE.VARR'
colnames(data_2017)[224] <- 'PRICE.VARR'
colnames(data_2018)[224] <- 'PRICE.VARR'

complete_data <- rbind(data_2014, data_2015, data_2016, data_2017, data_2018)

#only include fundamental columns
complete_data <- subset(complete_data[,c(1:4,6:8,10,12:14,16,20,22,30,33,34,36,38,40:43,45:53,55
complete_data <- complete_data[complete_data$X != 'IGLD', ]
complete_data <- complete_data[complete_data$X != 'SBT', ]
complete_data <- complete_data[complete_data$X != 'KST', ]
complete_data <- complete_data[complete_data$X != 'AMX', ]
```

After we finished the first step of data cleaning, we want to do the data validation. For missing values, as the plot shown, a lot of observations make up the majority of the missing data and we decided to remove observations that have more than a third of the columns NA.After we removed those observations, we set the sector and year columns as a factor and saved the new data set into a new CSV files for futhur data exploration.

```
missing_plot(complete_data)
```




```
#sort((sapply(complete_data, function(x) sum(is.na(x)))), decreasing=TRUE)

complete_data_remove<-complete_data[which(rowMeans(!is.na(complete_data))>(1/3)),]
missing_plot(complete_data_remove)
```




```r
#sort((sapply(complete_data_remove, function(x) sum(is.na(x)))), decreasing=TRUE)

complete_data_remove$Sector <- as.factor(complete_data_remove$Sector)
complete_data_remove$year <- as.factor(complete_data_remove$year)

#save the new data set as a csv
#write.csv(complete_data_remove,"fundamental_data.csv")
pvq <- quantile(complete_data_remove$Market.Cap, probs = c(0.01,0.99), names=FALSE, na.rm=TRUE)
plot_data <- complete_data_remove
plot_data[plot_data==0] <- NA
```

To account for missing values, we chose to use the CART (Classification and Regression Trees) method of imputation (Figure 2). Blue represents the distribution of the original data, while red represents the distribution of imputed data. After the imputation there are still 4 columns has missing values.

```
##       X                 Revenue             Revenue.Growth
##  Length:20526       Min.   :-6.276e+08   Min.   :   -6.87
##  Class :character   1st Qu.: 6.567e+07   1st Qu.:   -0.01
##  Mode  :character   Median : 4.684e+08   Median :    0.06
##                     Mean   : 4.883e+09   Mean   :    5.72
##                     3rd Qu.: 2.367e+09   3rd Qu.:    0.18
##                     Max.   : 5.003e+11   Max.   :42138.66
```

```
## Cost.of.Revenue       R.D.Expenses         SG.A.Expense
## Min.   :-2.987e+09   Min.   :-1.098e+08   Min.   :-1.402e+08
## 1st Qu.: 3.380e+06   1st Qu.: 0.000e+00   1st Qu.: 1.778e+07
## Median : 1.519e+08   Median : 0.000e+00   Median : 8.048e+07
## Mean   : 2.942e+09   Mean   : 1.037e+08   Mean   : 8.508e+08
## 3rd Qu.: 1.171e+09   3rd Qu.: 1.235e+07   3rd Qu.: 3.698e+08
## Max.   : 3.771e+11   Max.   : 2.884e+10   Max.   : 1.065e+11
## Operating.Expenses   Interest.Expense     Income.Tax.Expense
## Min.   :-5.496e+09   Min.   :-1.711e+09   Min.   :-7.380e+11
## 1st Qu.: 3.582e+07   1st Qu.: 0.000e+00   1st Qu.: 0.000e+00
## Median : 1.565e+08   Median : 3.684e+06   Median : 3.374e+06
## Mean   : 1.354e+09   Mean   : 9.349e+07   Mean   : 1.242e+08
## 3rd Qu.: 6.233e+08   3rd Qu.: 4.994e+07   3rd Qu.: 4.443e+07
## Max.   : 1.065e+11   Max.   : 1.845e+10   Max.   : 8.490e+11
## Net.Income...Non.Controlling.int Net.Income...Discontinued.ops
## Min.   :-1.587e+09               Min.   :-1.591e+10
## 1st Qu.: 0.000e+00               1st Qu.: 0.000e+00
## Median : 0.000e+00               Median : 0.000e+00
## Mean   : 1.343e+07               Mean   :-4.430e+06
## 3rd Qu.: 0.000e+00               3rd Qu.: 0.000e+00
## Max.   : 6.431e+09               Max.   : 8.368e+09
## Preferred.Dividends  Weighted.Average.Shs.Out Dividend.per.Share
## Min.   :-161000000   Min.   :0.000e+00        Min.   :    0.000
## 1st Qu.:         0   1st Qu.:1.743e+07        1st Qu.:    0.000
## Median :         0   Median :4.421e+07        Median :    0.000
## Mean   :   4816894   Mean   :2.620e+08        Mean   :    1.197
## 3rd Qu.:         0   3rd Qu.:1.196e+08        3rd Qu.:    0.720
## Max.   :2741588000   Max.   :1.113e+11        Max.   :10100.664
## Consolidated.Income  Cash.and.cash.equivalents Short.term.investments
## Min.   :-2.244e+10   Min.   :0.000e+00         Min.   :0.000e+00
## 1st Qu.:-9.438e+06   1st Qu.:1.809e+07         1st Qu.:0.000e+00
## Median : 1.950e+07   Median :7.410e+07         Median :0.000e+00
## Mean   : 3.798e+08   Mean   :1.538e+09         Mean   :1.483e+09
## 3rd Qu.: 1.643e+08   3rd Qu.:2.976e+08         3rd Qu.:1.800e+07
## Max.   : 5.953e+10   Max.   :5.123e+11         Max.   :8.000e+11
##  Receivables        Total.current.assets Goodwill.and.Intangible.Assets
## Min.   :0.000e+00   Min.   :0.000e+00    Min.   :0.000e+00
## 1st Qu.:2.169e+06   1st Qu.:6.823e+07    1st Qu.:0.000e+00
## Median :4.472e+07   Median :2.822e+08    Median :3.743e+07
## Mean   :8.594e+08   Mean   :5.709e+09    Mean   :1.708e+09
## 3rd Qu.:2.889e+08   3rd Qu.:1.234e+09    3rd Qu.:4.915e+08
## Max.   :1.624e+11   Max.   :1.181e+12    Max.   :2.931e+11
## Long.term.investments   Tax.assets           Payables
## Min.   :-8.000e+07    Min.   :0.000e+00   Min.   :-2.059e+10
## 1st Qu.: 0.000e+00    1st Qu.:0.000e+00   1st Qu.: 2.801e+06
## Median : 0.000e+00    Median :0.000e+00   Median : 2.620e+07
## Mean   : 3.621e+09    Mean   :1.498e+08   Mean   : 8.274e+08
## 3rd Qu.: 6.371e+07    3rd Qu.:1.566e+07   3rd Qu.: 1.820e+08
```

```
##  Max.   : 9.970e+11    Max.   :4.262e+10   Max.   : 2.136e+11
##  Short.term.debt      Total.current.liabilities Long.term.debt
##  Min.   :-1.375e+09   Min.   :-2.108e+10        Min.   :-8.446e+09
##  1st Qu.: 0.000e+00   1st Qu.: 2.838e+07        1st Qu.: 7.345e+05
##  Median : 1.666e+06   Median : 1.810e+08        Median : 1.504e+08
##  Mean   : 6.148e+08   Mean   : 8.541e+09        Mean   : 2.999e+09
##  3rd Qu.: 4.003e+07   3rd Qu.: 1.040e+09        3rd Qu.: 1.285e+09
##  Max.   : 2.192e+11   Max.   : 2.095e+12        Max.   : 7.330e+11
##    Total.debt         Deposit.Liabilities Other.comprehensive.income
##  Min.   :-9.290e+09   Min.   :0.000e+00   Min.   :-9.478e+10
##  1st Qu.: 5.916e+06   1st Qu.:0.000e+00   1st Qu.:-2.083e+07
##  Median : 2.131e+08   Median :0.000e+00   Median :-2.335e+05
##  Mean   : 4.158e+09   Mean   :4.917e+09   Mean   : 8.310e+10
##  3rd Qu.: 1.486e+09   3rd Qu.:0.000e+00   3rd Qu.: 0.000e+00
##  Max.   : 1.014e+12   Max.   :1.471e+12   Max.   : 1.709e+15
##  Retained.earnings..deficit.  Other.Assets        Other.Liabilities
##  Min.   :-2.800e+11          Min.   :-9.120e+11   Min.   :-9.923e+10
##  1st Qu.:-1.190e+08          1st Qu.: 1.878e+06   1st Qu.: 7.704e+06
##  Median : 2.056e+07          Median : 1.542e+07   Median : 6.580e+07
##  Mean   : 2.005e+09          Mean   : 1.430e+09   Mean   : 7.223e+09
##  3rd Qu.: 5.367e+08          3rd Qu.: 9.163e+07   3rd Qu.: 4.791e+08
##  Max.   : 4.217e+11          Max.   : 6.010e+11   Max.   : 1.866e+12
##  Depreciation...Amortization Stock.based.compensation Operating.Cash.Flow
##  Min.   :-8.336e+07          Min.   :-137000000       Min.   :-3.180e+11
##  1st Qu.: 2.046e+06          1st Qu.:    496050       1st Qu.: 1.018e+06
##  Median : 2.086e+07          Median :   3811000       Median : 5.854e+07
##  Mean   : 3.358e+08          Mean   :  31793457       Mean   : 8.704e+08
##  3rd Qu.: 1.256e+08          3rd Qu.:  14953500       3rd Qu.: 3.394e+08
##  Max.   : 7.510e+11          Max.   :9353000000       Max.   : 9.600e+11
##  Capital.Expenditure  Acquisitions.and.disposals Investment.purchases.and.sales
##  Min.   :-9.662e+10   Min.   :-5.100e+10         Min.   :-1.930e+11
##  1st Qu.:-1.291e+08   1st Qu.:-1.153e+07         1st Qu.:-1.017e+07
##  Median :-1.700e+07   Median : 0.000e+00         Median : 0.000e+00
##  Mean   :-3.608e+08   Mean   :-1.030e+08         Mean   :-1.764e+08
##  3rd Qu.:-1.344e+06   3rd Qu.: 0.000e+00         3rd Qu.: 0.000e+00
##  Max.   : 5.823e+09   Max.   : 6.987e+10         Max.   : 1.499e+11
##  Investing.Cash.flow  Issuance..repayment..of.debt
##  Min.   :-1.980e+11   Min.   :-8.488e+10
##  1st Qu.:-2.887e+08   1st Qu.:-1.045e+07
##  Median :-4.875e+07   Median : 0.000e+00
##  Mean   :-6.591e+08   Mean   : 6.767e+07
##  3rd Qu.:-1.848e+06   3rd Qu.: 4.738e+07
##  Max.   : 1.446e+11   Max.   : 6.268e+10
##  Issuance..buybacks..of.shares Dividend.payments    Financing.Cash.Flow
##  Min.   :-7.207e+10            Min.   :-1.603e+10   Min.   :-1.875e+11
##  1st Qu.:-8.241e+06            1st Qu.:-5.092e+07   1st Qu.:-7.786e+07
##  Median : 0.000e+00            Median : 0.000e+00   Median : 0.000e+00
##  Mean   :-1.140e+08            Mean   :-1.854e+08   Mean   :-6.441e+07
```

```
##  3rd Qu.: 6.221e+06           3rd Qu.: 0.000e+00   3rd Qu.: 5.758e+07
##  Max.   : 1.444e+11           Max.   : 0.000e+00   Max.   : 2.260e+11
##  Effect.of.forex.changes.on.cash Net.cash.flow...Change.in.cash
##  Min.   :-1.000e+12              Min.   :-1.525e+11
##  1st Qu.:-2.668e+05              1st Qu.:-1.689e+07
##  Median : 0.000e+00              Median : 7.057e+05
##  Mean   :-6.421e+07              Mean   : 7.016e+07
##  3rd Qu.: 0.000e+00              3rd Qu.: 2.900e+07
##  Max.   : 9.993e+09              Max.   : 4.050e+11
##    Market.Cap        Tangible.Asset.Value Average.Receivables
##  Min.   :0.000e+00   Min.   :-2.422e+10   Min.   :0.000e+00
##  1st Qu.:1.970e+08   1st Qu.: 1.681e+08   1st Qu.:2.378e+06
##  Median :9.249e+08   Median : 9.063e+08   Median :4.341e+07
##  Mean   :8.305e+09   Mean   : 1.611e+10   Mean   :8.522e+08
##  3rd Qu.:4.029e+09   3rd Qu.: 4.047e+09   3rd Qu.:2.831e+08
##  Max.   :1.098e+12   Max.   : 2.568e+12   Max.   :1.614e+11
##  Average.Payables     Average.Inventory   Days.Sales.Outstanding
##  Min.   :-2.037e+10   Min.   :0.000e+00   Min.   :-165044.9
##  1st Qu.: 2.911e+06   1st Qu.:0.000e+00   1st Qu.:     10.6
##  Median : 2.619e+07   Median :1.693e+06   Median :     45.4
##  Mean   : 9.308e+08   Mean   :4.189e+08   Mean   :    197.2
##  3rd Qu.: 1.783e+08   3rd Qu.:1.009e+08   3rd Qu.:     72.3
##  Max.   : 7.124e+11   Max.   :4.560e+11   Max.   :1504680.2
##  Days.Payables.Outstanding Days.of.Inventory.on.Hand Receivables.Turnover
##  Min.   :-207232.5         Min.   :-5182867          Min.   :   -27.99
##  1st Qu.:     10.3         1st Qu.:     -70          1st Qu.:     2.70
##  Median :     26.8         Median :      -5          Median :     5.96
##  Mean   :    404.2         Mean   :    -650          Mean   :    44.53
##  3rd Qu.:     55.7         3rd Qu.:       0          3rd Qu.:     9.89
##  Max.   :1043413.3         Max.   :     976          Max.   :164428.50
##  Payables.Turnover  Inventory.Turnover      ROE            Capex.per.Share
##  Min.   : -41.096   Min.   :    0.00   Min.   :  -34772   Min.   :-73354000
##  1st Qu.:   0.784   1st Qu.:    0.00   1st Qu.:       0   1st Qu.:       -2
##  Median :   2.543   Median :    3.18   Median :       0   Median :        0
##  Mean   :   7.394   Mean   :   33.30   Mean   :    1583   Mean   :   -19086
##  3rd Qu.:   4.913   3rd Qu.:   10.63   3rd Qu.:       0   3rd Qu.:        0
##  Max.   :8650.316   Max.   :95827.71   Max.   :11141142   Max.   :  1255873
##  Gross.Profit.Growth    Sector              year
##  Min.   : -5536.5    Length:20526       2014:3758
##  1st Qu.:     0.0    Class :character   2015:3976
##  Median :     0.1    Mode  :character   2016:4210
##  Mean   :    19.6                       2017:4343
##  3rd Qu.:     0.2                       2018:4239
##  Max.   :336767.8
```

###Feature Selection

####Correlation Plot There are 62 columns after we finished data cleaning, and we want to select the important features to do modeling. We performed a correlation analysis based on Pearson's coefficient between each numeric predictor first. We considered a correlation > 0.5, with p < 0.05 as a significant correlation. Figure 3 demonstrates significant correlation between many of our predictor variables.

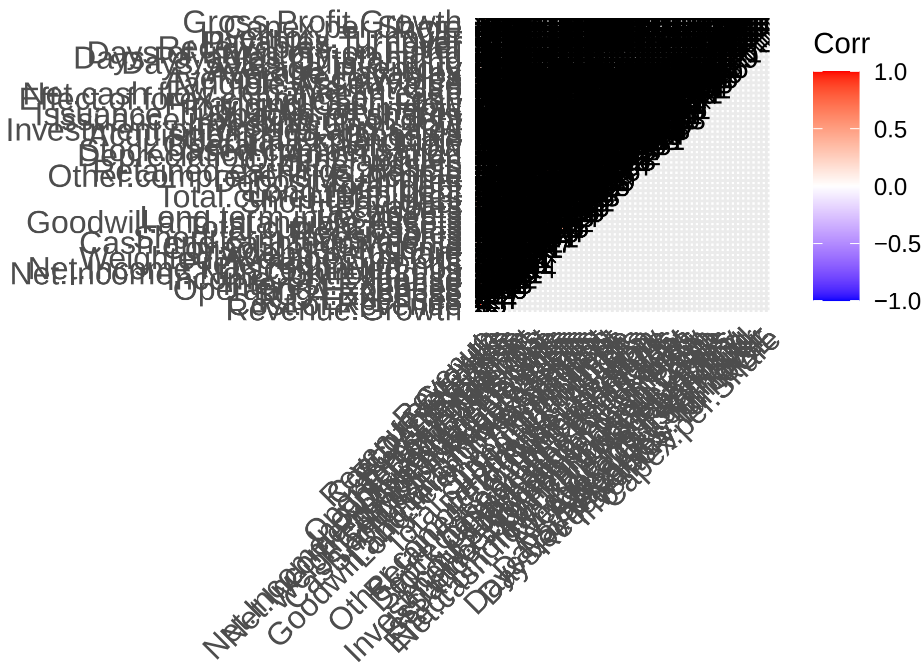


Figure 1: Correlogram

###Data Normal Distribution

```
plot_index <- list()
for (i in c(1:58)){

  plot_index[[names(df_full_numeric[i])]] <- ggplot(df_full_numeric, aes(x = df_full_numeric[[i]
    stat_function(
      fun = dnorm,
      args = with(df_full_numeric, c(mean = mean(df_full_numeric[[i]], na.rm=TRUE),
                                    sd = sd(df_full_numeric[[i]], na.rm=TRUE))))+
    labs(title=as.list(names(df_full_numeric[i])), x='',y='Price Change')
  #print(plot_index[[names(df[i])]])
}
```

####Varaible Importance We decided to use decision tree to check the variable importance as a important reference for us to do feature selection.

```r
#decision_tree_model <-readRDS('decision_tree_model.rds')
#print(decision_tree_model)
#dTreeImp <- varImp(decision_tree_model, scale = FALSE)
#plot(dTreeImp, top = 10)
#invisible(model_importance <- summary(decision_tree_model$finalModel))
```

We also did some data visualization for our final data set which we will use for modeling. Correlation plot for the final dataset

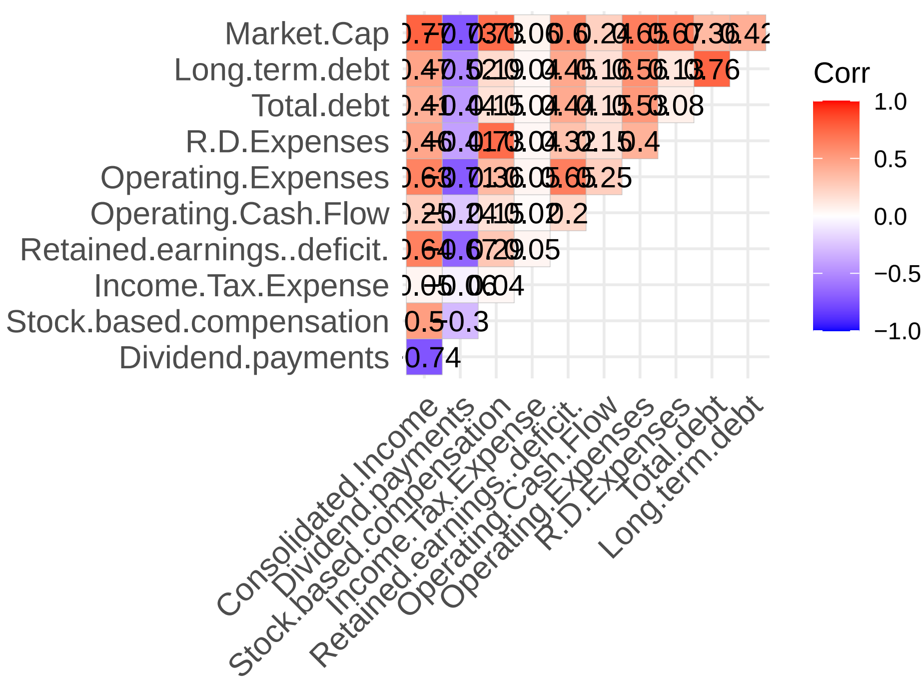


Figure 2: Correlogram

Principle Component Analysis

We performed PCA to reduce the dimensionality of our feature dataset. The Scree plot shows the overall variance explained by each principle component. The top 5 dimensions explained approximately 90% of the total variance within the data. Individual datapoints involving large technology companies (Google, Apple, Amazon) had high contributions to the overall variance. R&D Expenses and Stock-based compensation were two variables with high contribution to variance, while Income Tax Expense and Operating Cash Flow had more negligible contribution.

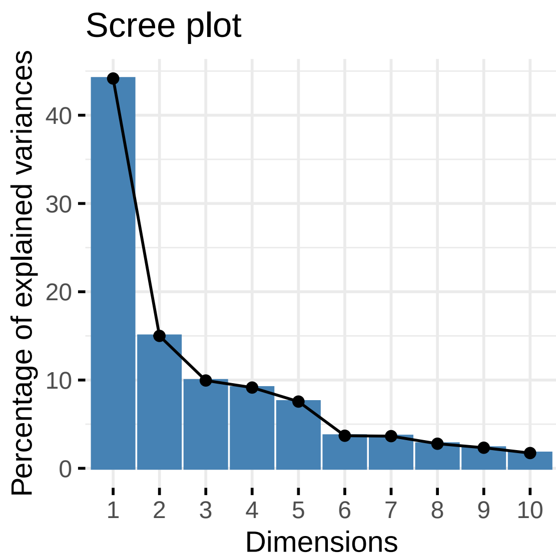


Figure 3: Scree plot

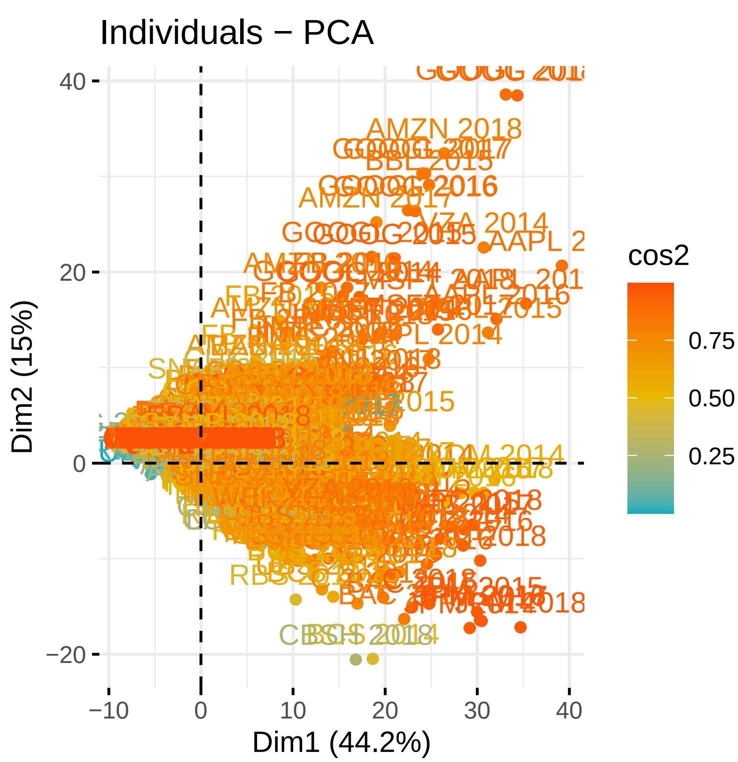


Figure 4: Effect of Individual points - PCA

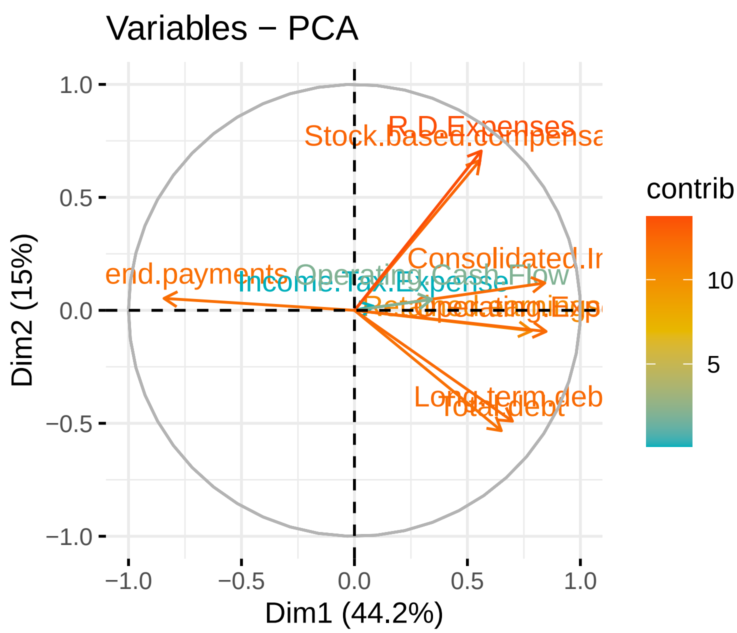


Figure 5: Effect of Variables - PCA

K Means Clustering

The 'elbow method' was first performed to determine an optimal number of k clusters. However, there was no significant drop in within-cluster sum of squares with k besides k=2. As two clusters did not provide much discrimination for our observations, we instead used k=4 as the final number of clusters.

The following figure displays our datapoints in a 2-D space based on 4 clusters. (will show the cluster plots and more by tomorrow evening)

Modeling

The k-fold cross-validation method evaluates the model performance on different subsets of the training data calculates the average prediction error rate. We used k = 10 for our project,and this method was used instead of the simple train-test-split as it gives a more valid estimation of model effectiveness.

###Random Forest

```
Lasso_Regression_Model <- readRDS("Lasso_Model.rds")
invisible(model_importance <- summary(Lasso_Regression_Model$finalModel))
print(Lasso_Regression_Model)
```

```
## The lasso
##
## 20526 samples
```

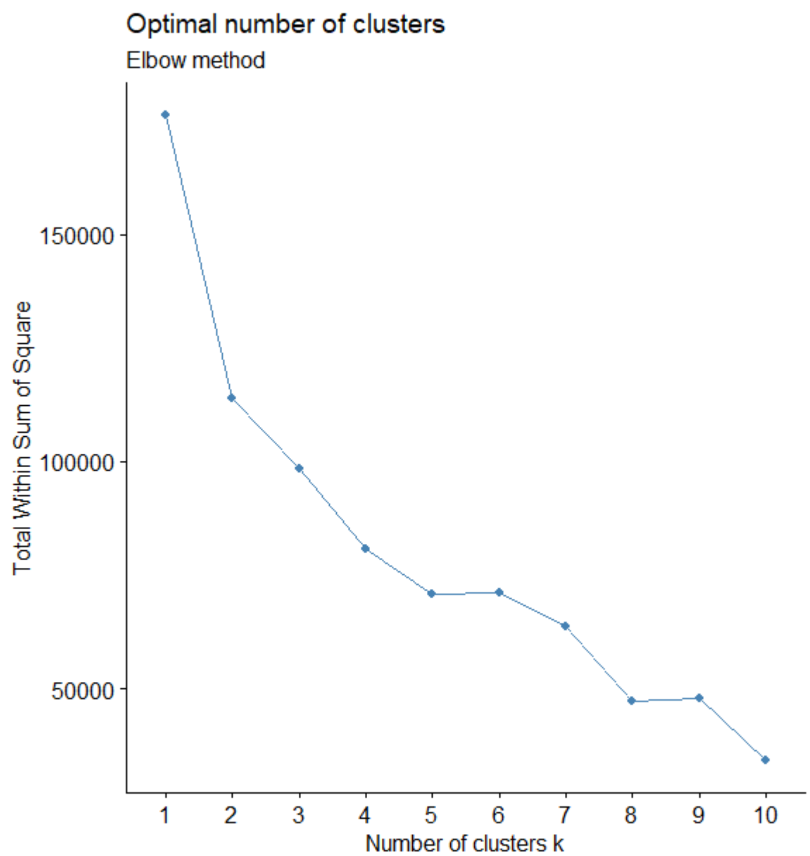


Figure 6: Elbow method

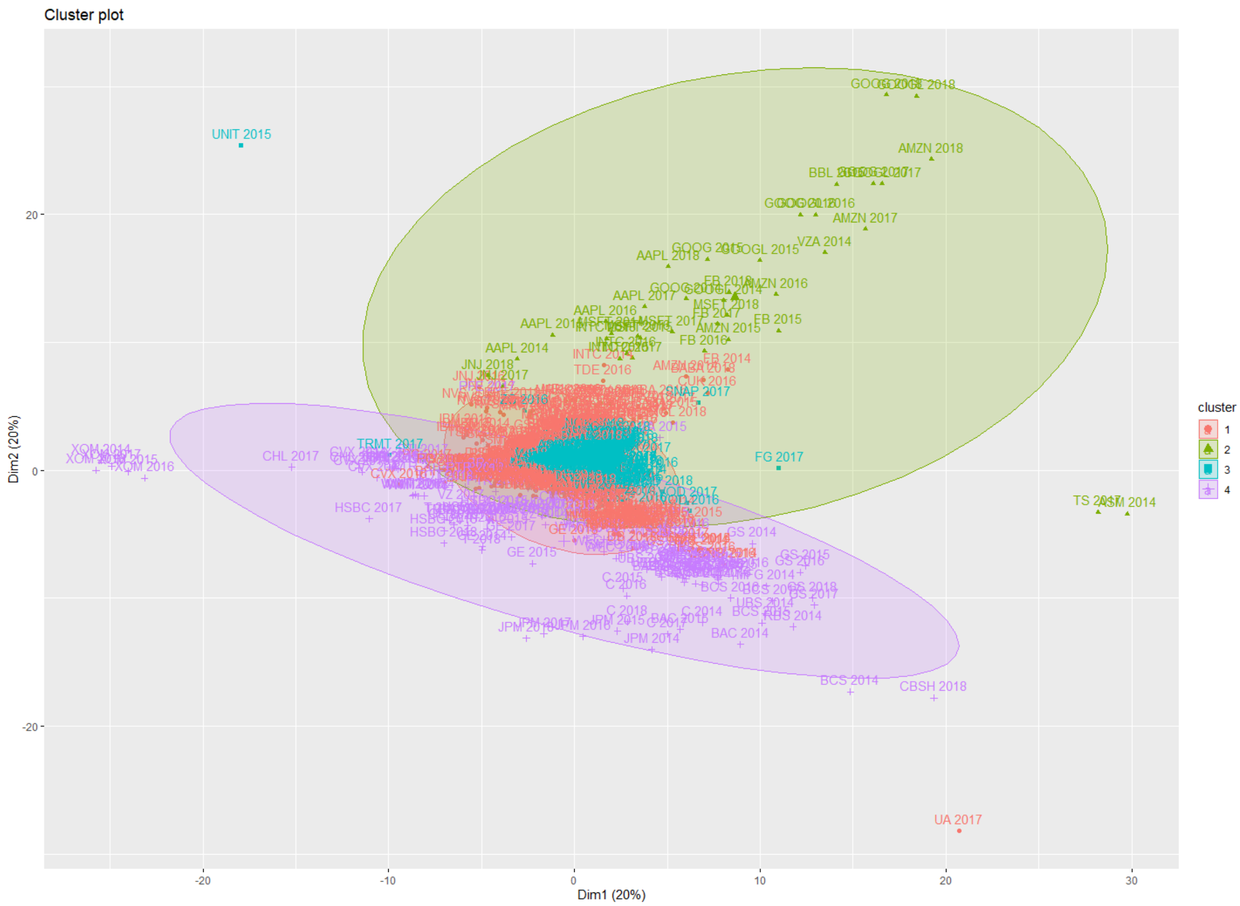


Figure 7: K means clustering, k = 4

```
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 18474, 18473, 18474, 18474, 18474, 18474, ...
## Resampling results across tuning parameters:
##
##   fraction  RMSE         Rsquared   MAE
##   0.1       29847119786  0.6657088  10396703438
##   0.5       18268035966  0.8275453   6331689880
##   0.9       14502322435  0.8229718   3748806832
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was fraction = 0.9.
```

###XGBoost

```
XGB_model_albina_updated <- readRDS("XGB_model_albina_updated.rds")
invisible(model_importance <- summary(XGB_model_albina_updated$finalModel))
print(XGB_model_albina_updated)
```

```
## eXtreme Gradient Boosting
##
## 20526 samples
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 18473, 18473, 18474, 18473, 18473, 18474, ...
## Resampling results across tuning parameters:
##
##   eta  max_depth  colsample_bytree  min_child_weight  nrounds  RMSE
##   0.1  3          0.5               1                 100      11297769319
##   0.1  3          0.5               1                 200      11153696935
##   0.1  3          0.5               5                 100      12016959672
##   0.1  3          0.5               5                 200      11868472990
##   0.1  3          0.8               1                 100      11678940749
##   0.1  3          0.8               1                 200      11448075994
##   0.1  3          0.8               5                 100      11777602876
##   0.1  3          0.8               5                 200      11689135589
##   0.1  6          0.5               1                 100      10811777965
##   0.1  6          0.5               1                 200      10678931438
##   0.1  6          0.5               5                 100      11229919521
##   0.1  6          0.5               5                 200      11195832518
##   0.1  6          0.8               1                 100      11119571865
##   0.1  6          0.8               1                 200      11003973857
##   0.1  6          0.8               5                 100      11277492870
##   0.1  6          0.8               5                 200      11201950013
```

```
##    0.3  3          0.5               1                 100      12004655198
##    0.3  3          0.5               1                 200      11919821202
##    0.3  3          0.5               5                 100      12296068467
##    0.3  3          0.5               5                 200      12169722999
##    0.3  3          0.8               1                 100      11157193541
##    0.3  3          0.8               1                 200      11073495053
##    0.3  3          0.8               5                 100      11843686785
##    0.3  3          0.8               5                 200      11823850264
##    0.3  6          0.5               1                 100      11450646224
##    0.3  6          0.5               1                 200      11448380352
##    0.3  6          0.5               5                 100      12198763314
##    0.3  6          0.5               5                 200      12202859349
##    0.3  6          0.8               1                 100      11562180036
##    0.3  6          0.8               1                 200      11558531210
##    0.3  6          0.8               5                 100      11716036086
##    0.3  6          0.8               5                 200      11738642412
##    Rsquared   MAE
##    0.8896248  3025597071
##    0.8933700  2899449245
##    0.8734745  3105472498
##    0.8775792  2994044894
##    0.8819070  3036077796
##    0.8868560  2918699879
##    0.8802254  3080889131
##    0.8829531  2974229345
##    0.9010295  2699512435
##    0.9036540  2607174685
##    0.8923127  2799146431
##    0.8937549  2739344610
##    0.8948140  2701522279
##    0.8970401  2608294734
##    0.8914582  2785358189
##    0.8937160  2715321747
##    0.8740762  3014788294
##    0.8763696  2921411076
##    0.8705632  3036350817
##    0.8739974  2955711950
##    0.8949485  2925883336
##    0.8977816  2835624149
##    0.8810923  3029991331
##    0.8823128  2940958333
##    0.8833500  2770283506
##    0.8835000  2746961666
##    0.8719434  2899255791
##    0.8723048  2864715871
##    0.8864085  2750904184
##    0.8866565  2724649496
##    0.8858417  2800341939
```

```
##   0.8860739  2777264655
##
## Tuning parameter 'gamma' was held constant at a value of 0
## Tuning
##  parameter 'subsample' was held constant at a value of 0.8
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were nrounds = 200, max_depth = 6, eta
##  = 0.1, gamma = 0, colsample_bytree = 0.5, min_child_weight = 1 and subsample
##  = 0.8.
```

###Lasso Regression For the lasso regression model, RMSE was used to select the optimal model using the smallest value. The final value used for the model was fraction = 0.9.

```r
Lasso_Regression_Model <- readRDS("Lasso_Model.rds")
invisible(model_importance <- summary(Lasso_Regression_Model$finalModel))
print(Lasso_Regression_Model)
```

```
## The lasso
##
## 20526 samples
##    12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 18474, 18473, 18474, 18474, 18474, 18474, ...
## Resampling results across tuning parameters:
##
##   fraction  RMSE         Rsquared   MAE
##   0.1       29847119786  0.6657088  10396703438
##   0.5       18268035966  0.8275453   6331689880
##   0.9       14502322435  0.8229718   3748806832
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was fraction = 0.9.
```

###GBM The gradient boosting model was tuned by several different parameters. The final values used for the model were n.trees = 600, interaction.depth = 9, shrinkage = 0.1 and n.minobsinnode = 20

```r
Gradient_Boosting_model <- readRDS("GBM_Model.rds")
invisible(model_importance <- summary(Gradient_Boosting_model$finalModel))
print(Gradient_Boosting_model)
```

```
## Stochastic Gradient Boosting
##
## 20526 samples
##    12 predictor
##
```

```
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 18474, 18474, 18472, 18474, 18474, 18472, ...
## Resampling results across tuning parameters:
##
##   interaction.depth  n.trees  RMSE         Rsquared   MAE
##   1                    50     14124027037  0.8282571  4524926616
##   1                   100     13475650086  0.8389626  3825603267
##   1                   150     13365749192  0.8410406  3724044548
##   1                   200     13353144492  0.8416811  3680094274
##   1                   250     13323269670  0.8421521  3646635546
##   1                   300     13329642771  0.8420975  3627441365
##   1                   350     13300458638  0.8425506  3605545712
##   1                   400     13312545492  0.8423640  3590860917
##   1                   450     13317023702  0.8421014  3581140723
##   1                   500     13320927593  0.8422359  3572912367
##   1                   550     13322782291  0.8419982  3566080839
##   1                   600     13302580737  0.8422658  3560307032
##   1                   650     13338961270  0.8416355  3553447340
##   1                   700     13341267742  0.8416673  3546548078
##   1                   750     13354057666  0.8413850  3544247718
##   1                   800     13359836135  0.8413913  3538673311
##   1                   850     13350326616  0.8416304  3534223726
##   1                   900     13363343195  0.8413422  3529176977
##   1                   950     13335452450  0.8417824  3521059418
##   1                  1000     13361242334  0.8413842  3520745451
##   1                  1050     13365369621  0.8410382  3513989472
##   1                  1100     13348842447  0.8412774  3506770469
##   1                  1150     13385849634  0.8407678  3507684517
##   1                  1200     13395769483  0.8406162  3507000822
##   1                  1250     13392702202  0.8406493  3500566401
##   1                  1300     13406045359  0.8403595  3501399478
##   1                  1350     13410628101  0.8402051  3495703464
##   1                  1400     13426400401  0.8399945  3494010620
##   1                  1450     13432769866  0.8396457  3493631728
##   1                  1500     13433438947  0.8397093  3490245293
##   5                    50     12903152478  0.8534757  3354961782
##   5                   100     12458841182  0.8624257  3228082896
##   5                   150     12250649248  0.8660799  3169130805
##   5                   200     12129449136  0.8685640  3134719618
##   5                   250     12062559122  0.8697808  3109598404
##   5                   300     11995730502  0.8708580  3085232662
##   5                   350     11966444010  0.8713883  3074406207
##   5                   400     11954469252  0.8716856  3062709008
##   5                   450     11905424273  0.8725703  3050056406
##   5                   500     11921270049  0.8722154  3044743321
##   5                   550     11908331249  0.8724540  3034945267
##   5                   600     11901258092  0.8726158  3027942695
```

```
## 5 650 11902503609 0.8725331 3021776728
## 5 700 11895878497 0.8728508 3015437864
## 5 750 11894272104 0.8728781 3008456036
## 5 800 11887933129 0.8730051 3003053684
## 5 850 11878373142 0.8732005 2996049715
## 5 900 11883079046 0.8731064 2991892089
## 5 950 11884223872 0.8731104 2986787476
## 5 1000 11879031553 0.8732858 2981375114
## 5 1050 11876935870 0.8733356 2977307111
## 5 1100 11880804062 0.8733136 2973393351
## 5 1150 11875363470 0.8734460 2967940339
## 5 1200 11870385335 0.8735441 2963275929
## 5 1250 11879869337 0.8733253 2960820486
## 5 1300 11875704728 0.8733549 2956959782
## 5 1350 11872847047 0.8733816 2952436000
## 5 1400 11872510798 0.8734766 2948797795
## 5 1450 11868690394 0.8734593 2945797530
## 5 1500 11874193568 0.8733932 2942017449
## 9 50 12691857472 0.8585558 3168255203
## 9 100 12240157913 0.8670912 3064499366
## 9 150 12047638628 0.8706164 3026983169
## 9 200 11956476324 0.8722903 3004688724
## 9 250 11913471784 0.8729673 2988978306
## 9 300 11836366415 0.8743434 2969185947
## 9 350 11804416302 0.8751054 2958019394
## 9 400 11800513944 0.8750533 2948483073
## 9 450 11767921349 0.8753353 2938473982
## 9 500 11769637298 0.8754723 2930924396
## 9 550 11768569790 0.8753808 2923634572
## 9 600 11765977743 0.8754267 2917376718
## 9 650 11776513745 0.8752992 2912991756
## 9 700 11790816976 0.8750239 2908677978
## 9 750 11792220980 0.8749711 2903907450
## 9 800 11802391094 0.8748958 2900130822
## 9 850 11801055334 0.8749229 2897142151
## 9 900 11799437488 0.8748676 2892760682
## 9 950 11818394082 0.8745360 2891477902
## 9 1000 11814961987 0.8746040 2887018925
## 9 1050 11827491498 0.8744384 2886020799
## 9 1100 11817481328 0.8746387 2882768265
## 9 1150 11819744616 0.8745512 2879531189
## 9 1200 11821439738 0.8745366 2877197968
## 9 1250 11829390076 0.8743817 2876140776
## 9 1300 11830716619 0.8743222 2874157802
## 9 1350 11828238004 0.8744165 2871981694
## 9 1400 11833140422 0.8743391 2871295497
## 9 1450 11828226701 0.8744637 2868531435
## 9 1500 11837750727 0.8742912 2867884814
```

```
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 20
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were n.trees = 600, interaction.depth =
##  9, shrinkage = 0.1 and n.minobsinnode = 20.
```

###Model Selection All models found *nmnmb* and *hghh* to be important predictors of Market.Cap. Mean Absolute Error (MAE) tells the average error of the variable we want to predict. Root Mean-Squared Error (RMSE) is similar with MAE but it is more useful when we are interested in fewer larger errors over many small errors. Overall, we prioritize model stability and thus prioritized RMSE over MAE. R^2 computes how much better the regression fits the data than the mean line, which gives an overall score.For predicting market cap, we desired a model with the lowest RMSE and MAE to keep the high accuracy of prediction. The XGBoost model had the highest R^2 as well as the lowest RMSE and MAE, thus, it was chosen for deployment.

Table 1: Model Accuracy

model	RMSE	R2	MAE
random_forest	274957.8	0.81	135701.0
extreme_gradient_boosting	233734.1	0.85	119745.2
Lasso_Regression	257316.5	0.83	134117.1
gradient_boosting	220850.4	0.86	116308.5

Discussion