Application of Machine Learning on Fundamental Stock Price Analysis

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Abstract:

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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

The original dataset was obtained from Kaggle. Five datasets were combined together containing stock information for different years: 2014, 2015, 2016, 2017 and 2018, respectively. There were 225 columns in the original dataset. However, after curating the data, only 66 columns were chosen as fundamental columns and were included in the project.

Missingness

The dataset was assessed for missing values. Any columns that had more then 1/3 of the data as missing values were removed. For the rest of the columns, data imputation was performed using the MICE package in R. We used the CART method to impute the data. CART imputes values by using classification and regression trees. Four columns were left with missing values after imputation. Those columns were removed leaving the final dataset with a total of 62 columns.

Feature Selection

It is important to note that this project contains both unsupervised and supervised learning. Decision Tree was used for feature selection. Decision tree is a classification algorithm used for classification problems, as well as detecting variable importance in a dataset. The top 10 important variables from the decision tree were selected as the features. They were used to run k-means unsupervised learning, which determined 4 clusters of data. Then, for the supervised learning dataset, we used the top 10 variables selected from the decision tree plus the cluster number obtained from k-means model (as a categorical variable) and the Sector of the stock. Thus, the unsupervised learning data contained 10 features, while the supervised learning data contained 12.

Table 1: Common Predictor variables

Variable	Type
Consolidated.Income	numeric
Dividend.payments	numeric
Stock.based.compensation	numeric
Income.Tax.Expense	numeric
Retained.earnings deficit	numeric
Operating.Cash.Flow	numeric
Operating.Expenses	numeric
R.D.Expenses	numeric
Total.debt	numeric
Long.term.debt	numeric

Principal Component Analysis

We applied Principal Component Analysis (PCA) to our feature dataset for dimension reduction before doing unsupervised learning using the k-Means clustering algorithm. PCA creates orthogonal ‘principal components’ of the feature set, reducing multicollinearity within the data. Although the k-means algorithm is non-parametric, the reduction in multicollinearity by PCA could lead to greater discrimination between the observations.

Unsupervised Learning

The k-Means algorithm was performed in order to cluster the data before supervised learning. The number of clusters were 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

Supervised learning was performed using three algorithms: XGBoost, Random Forest and GBM Model. XGBoost is a very powerful algorithm which drives fast learning and offers efficient usage of storage. XGBoost uses ensemble learning, which is a systematic solution that combines the predictive power of multiple learners. It outputs a single model that gives the combined output from many models. This allows the opportunity to not rely on the result of a single machine learning model. In this particular model, the trees are built sequentially, such that the next tree focuses on reducing the errors of the previous tree. Random forest is another supervised machine learning model that uses the "ensemble" method to fit many decision trees by using a subset of the rows and then taking the "mode" of the predicted class. GBM, which stands for Gradient Boosting Machine, is also a gradient boosting algorithm that works similar to XGBoost. However, XGBoost has more tuning parameters, thus both algorithms were chosen for comparison. All models were ran and then evaluated using the k-fold cross validation method. Three accuracy metrics: Root Mean-Squared Error (RMSE), Pearson correlation (R^2), and Mean Average Error (MAE) were used to chose the final model.

Deployment

Due to its accuracy, size, and speed in predicting, we chose the XGBoost model to include in our application. The application's main function is to provide a recommendation for a stock based on the financial information released by the company. The application is built to be used by financial advisers and portfolio managers. The main page allows the user to input a ticker ID. If the ID is in the database, the application will pull the latest financial data for the company and run the model on that data. The application then compares the predicted market cap with the current market cap and provides a recommendation based on the difference. If the ID is not in the database, the user can manually enter the financial data for the company in order to produce a recommendation. The application uses data provided by the API from https://financialmodelingprep.com/. The application is limited by the availability of the financial data and the restrictions provided by the free account on financialmodelingprep.com. For a full deployment, a paid account would be needed.

The application can be found here: https://colin-green.shinyapps.io/stock-evaluator/ # Results

Table 2: Data Dictionary

Variable	Type
X.1	Index of the records

Variable	Type
X	Stock ticker symbol
Consolidated.Income	Describe all changes in equity except investments made by owners in a period of time
Dividend.payments	A dividend payment to shareholders
Stock.based.compensation	Describe the rewords to employees in lieu of cash made by stock or stock options
Income.Tax.Expense	Total amount of tax
Retained.earnings deficit	Represent the negative or debt banlance
Operating.Cash.Flow	Measuremnent of the amount of cash the company generated
Operating.Expenses	The amount of expense of a company
R.D.Expenses	Research and development of tax return
Total.debt	Sum of long term debt and short term debt
Long.term.debt	Value of long term debt
Market.Cap	market capitalization for a company

Data Preparation

Five containing stock information from a different years (2014, 2015, 2016, 2017 and 2018) were merged into one dataset. Analysis was performed on the data and after some research, 66 columns were selected as fundamental columns needed for analysis. The non-fundamental columns were removed from the dataset. A column was added for the year that the dataset came from.

Missing Values

After preparing the dataset, we assessed the data for missing values. As shown in the plot, a few columns had a large amount of missing data. We decided to remove any columns that were missing more then 1/3 of the data. This left a total of 66 columns on the dataset. After we removed the missing data columns, we set the Sector and year columns as a factor and saved the new data set into a new CSV file for further data exploration.

To account for missing values, we chose to use the CART (Classification and Regression Trees) method of imputation. After imputation, 4 columns still had missing values, which were then subsequently removed.

Correlation Plot

There were 62 columns after we finished data cleaning and we wanted to select only significant features for our target variable before modeling. Before focusing on feature selection, we had to check for correlation between the independent variables. We performed a correlation analysis based on Pearson's coefficient between each numeric predictor first. We considered a $|\text{correlation}| > 0.8$, with $p < 0.05$ as a significant correlation. Figure 3 demonstrates significant correlation between many of our predictor variables. However, due to the large amount of variables, the correlation plot was not interpretable if all the variables were plotted together. Therefore, we filtered the correlation plot by keeping only variables that had a correlation with absolute value greater than 0.8.

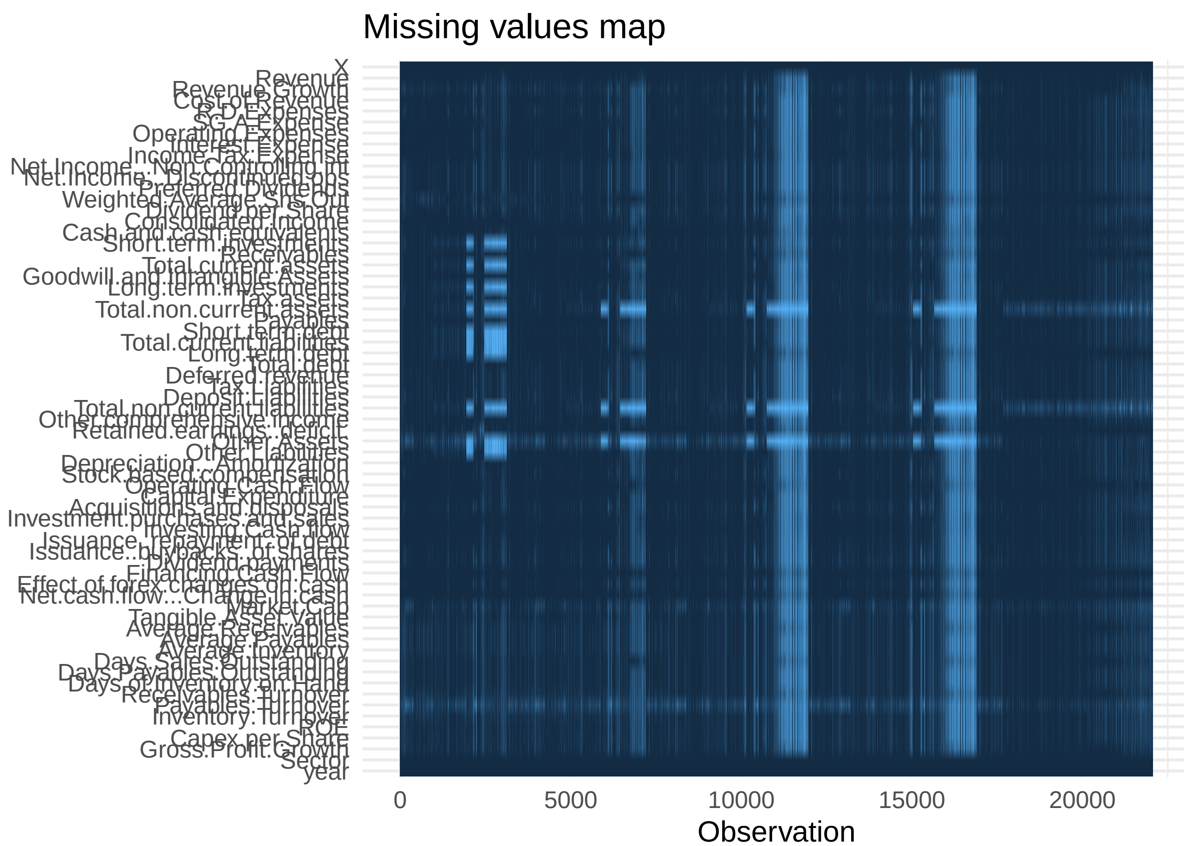


Figure 1: Missing values map before imputation

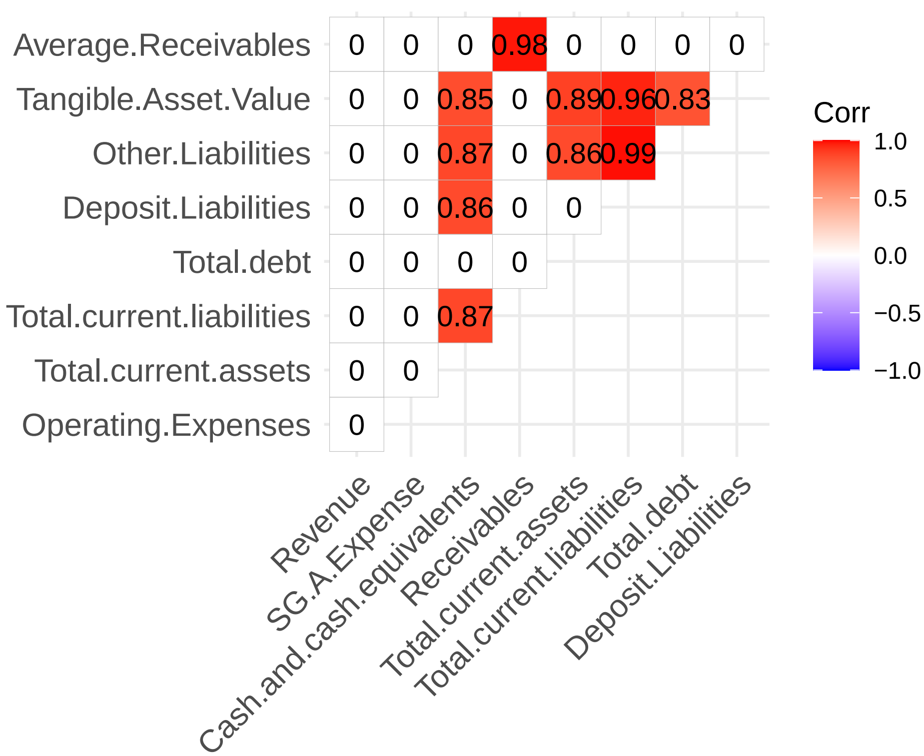


Figure 2: Correlogram of variables with |R| > 0.8

Data Distribution

We to observe the means, and check for outliers. Most variables were not normally distributed and had a clear skew. In Figure 3, we show a subset of the variable distributions.

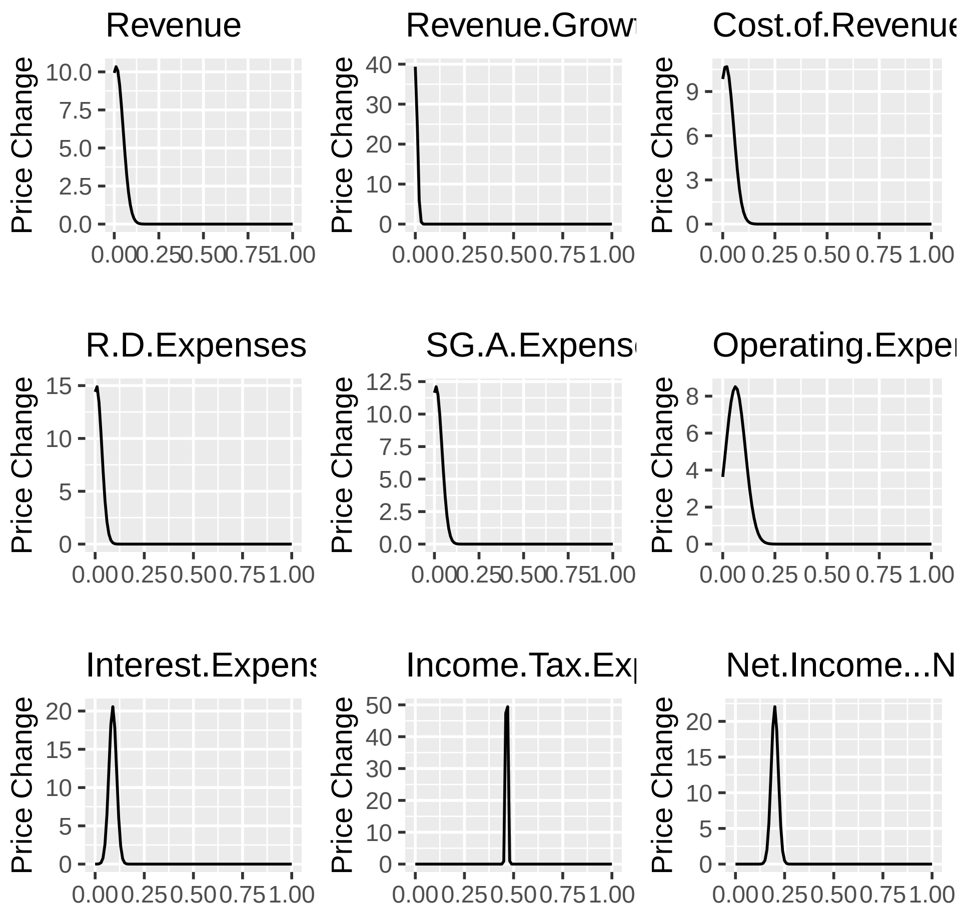


Figure 3: Column distributions

Feature Selection

Since there were 62 columns on our dataset, we ran a decision tree model to determine the most important variables to be included in modelling. Below are plots showing the importance of each variable. We also ran a correlation to ensure that the features were not highly correlated.

Principal Component Analysis

We performed PCA to reduce the dimensionality of our feature dataset. The Scree plot shows the overall variance explained by each principal 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.

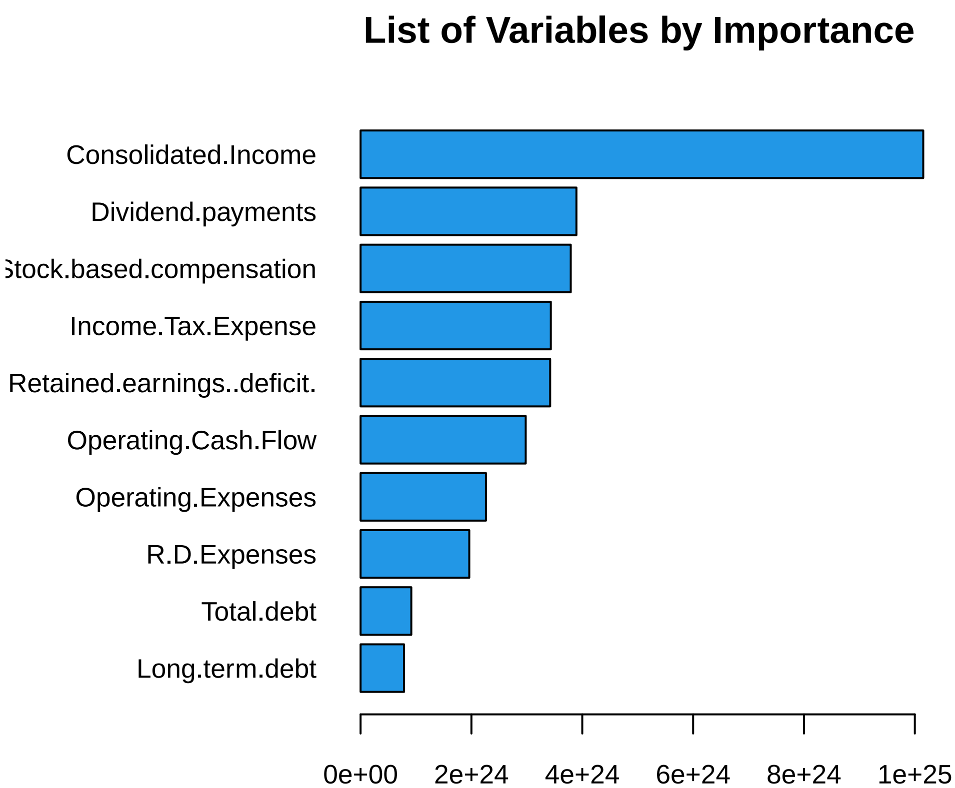


Figure 4: Top 10 variable importance, determined by Decision Tree

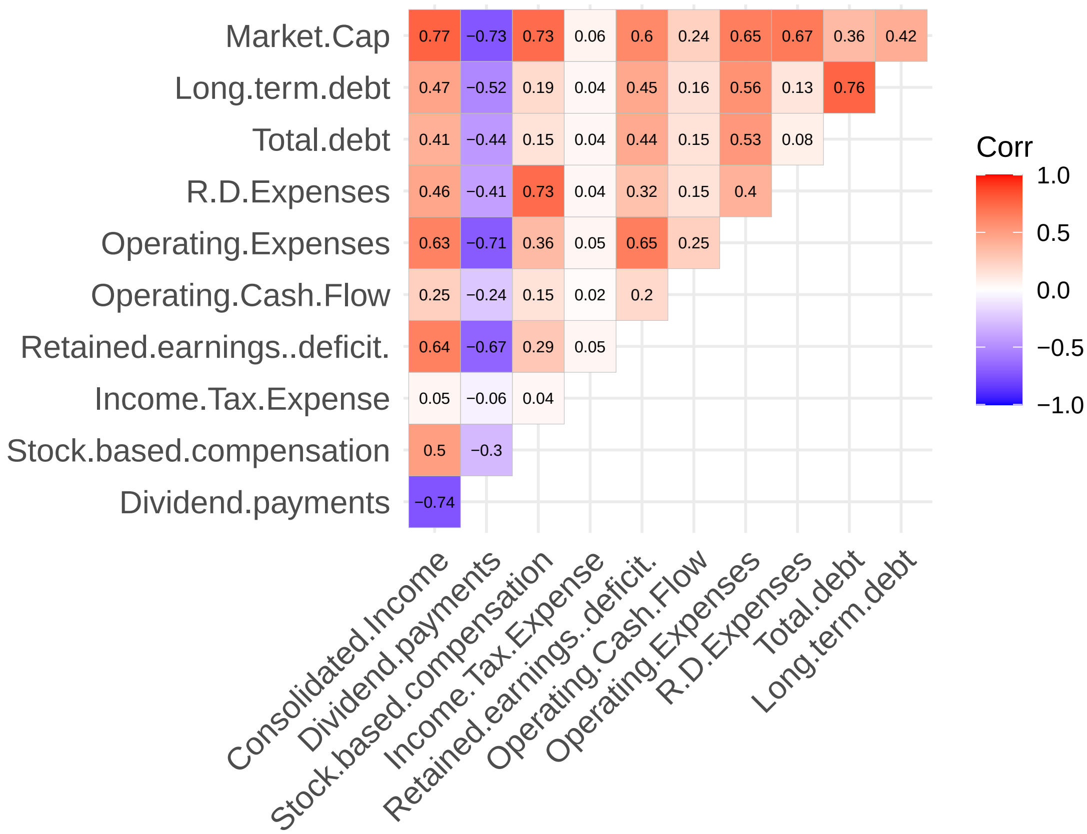


Figure 5: Correlogram of Top 10 Variables

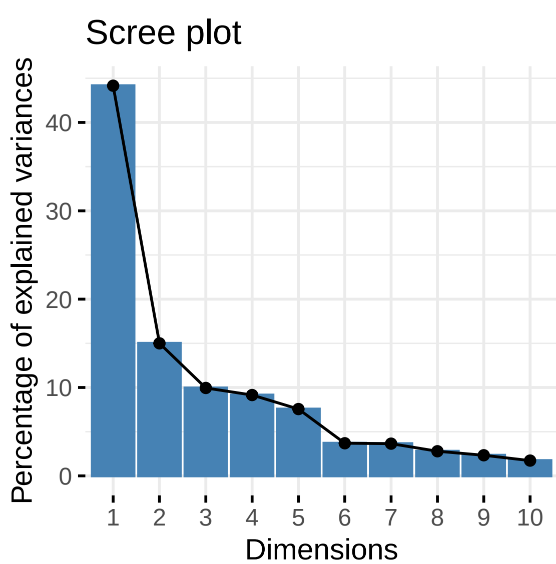


Figure 6: Scree plot

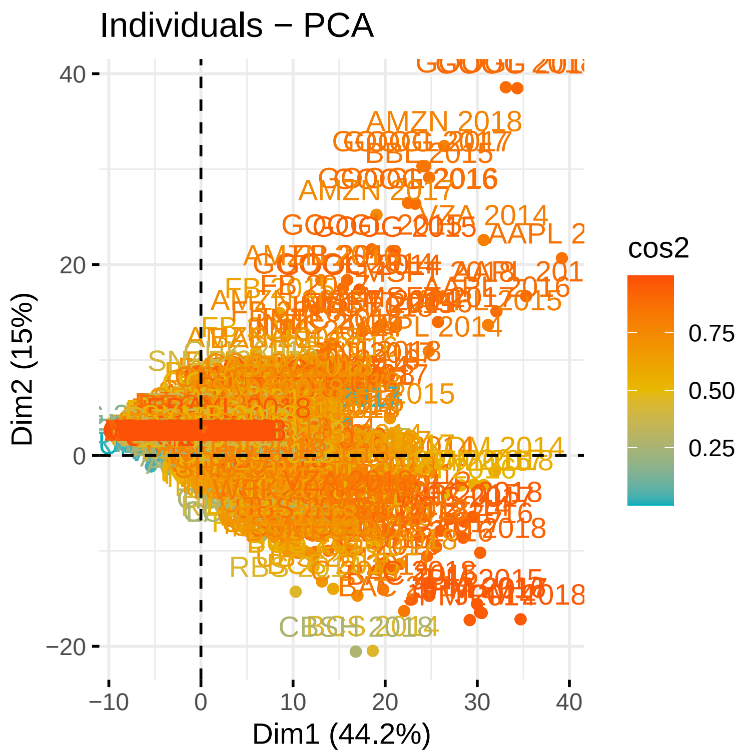


Figure 7: Effect of Individual points - PCA

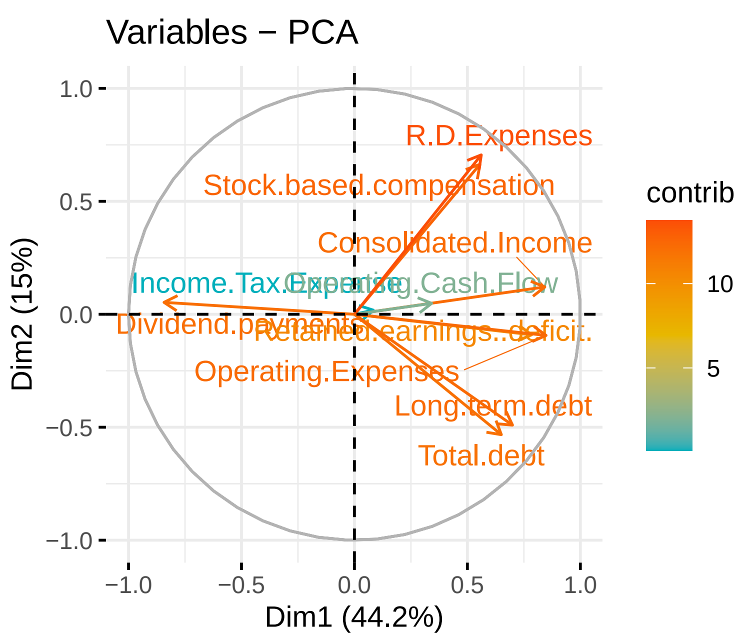


Figure 8: Effect of Variables - PCA

K Means Clustering

The “silhouette” method was first performed to determined number of clusters. It suggested a number of cluster of 2 (k=2). The ‘elbow method’ was then 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.

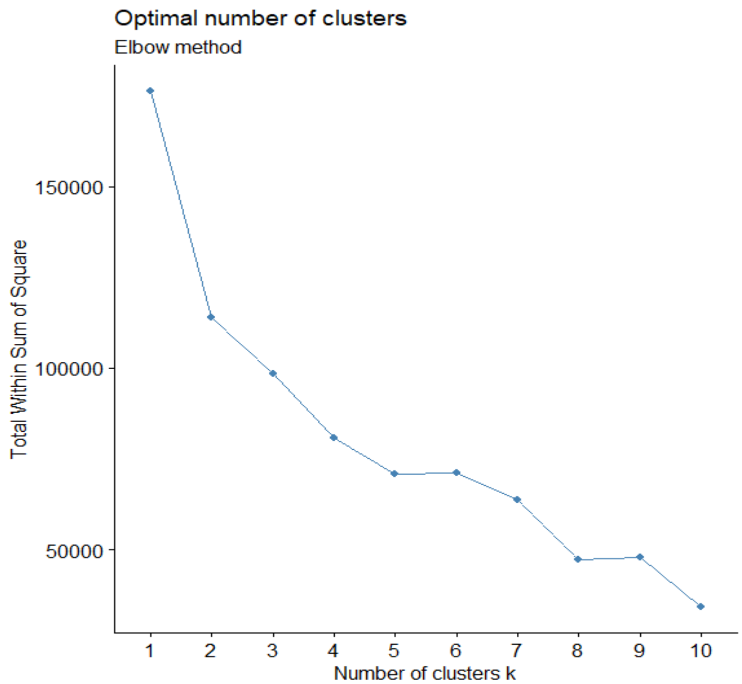


Figure 9: Elbow method

The following figure displays our datapoints in a 2-D space based on 4 clusters.

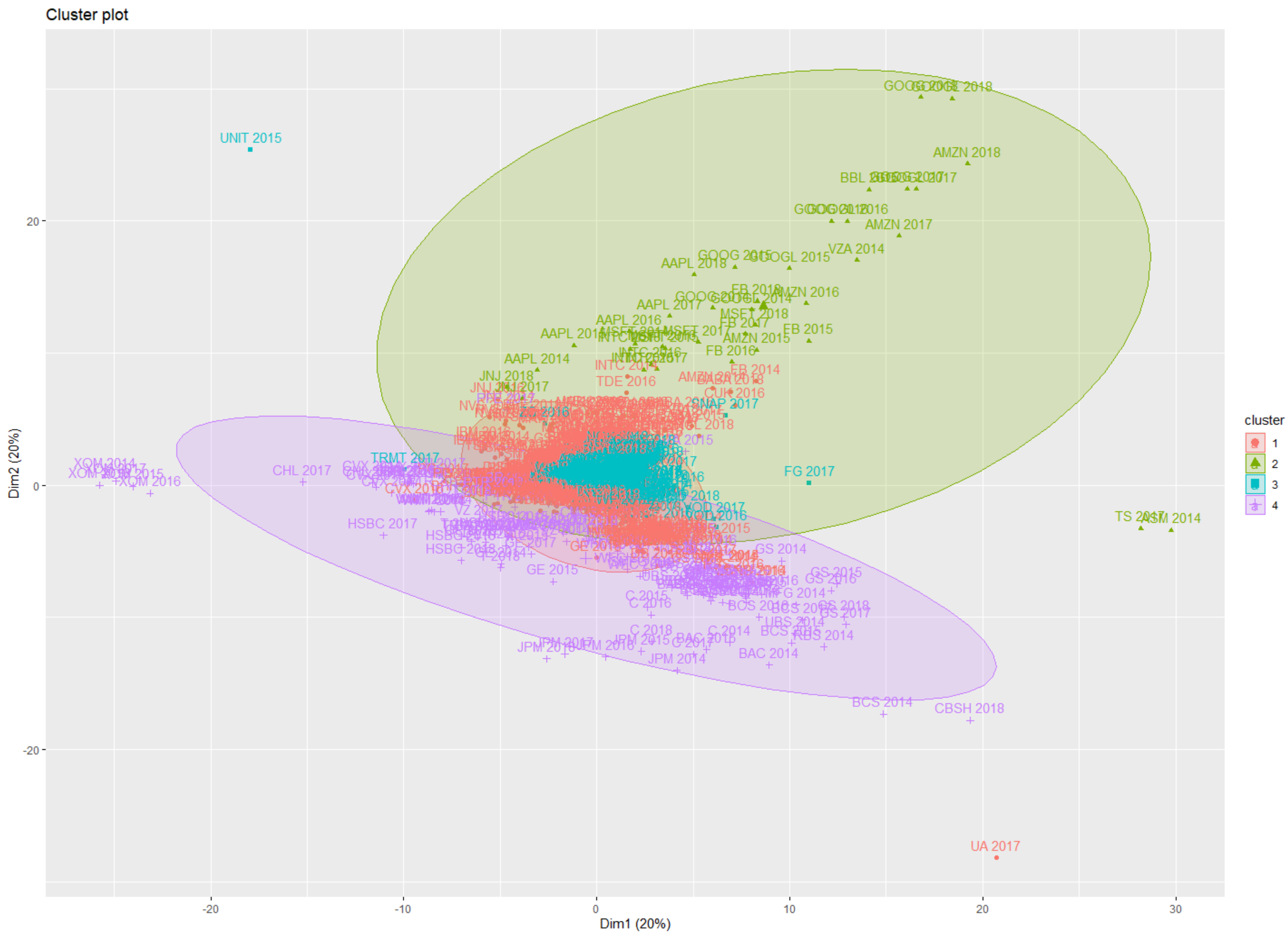


Figure 10: K means clustering, k = 4

Cluster Interpretation

We performed some exploratory visualizations to interpret how the data was clustered by k-means. Cluster 1 contained the majority of observations, with n=19759. Cluster 2 had 35 observations, cluster 3 had 126, and cluster 4 had 586. On average, cluster 1 contained more small- and medium-sized companies compared to other clusters, with 89% of observations falling under a market cap of $10 billion.

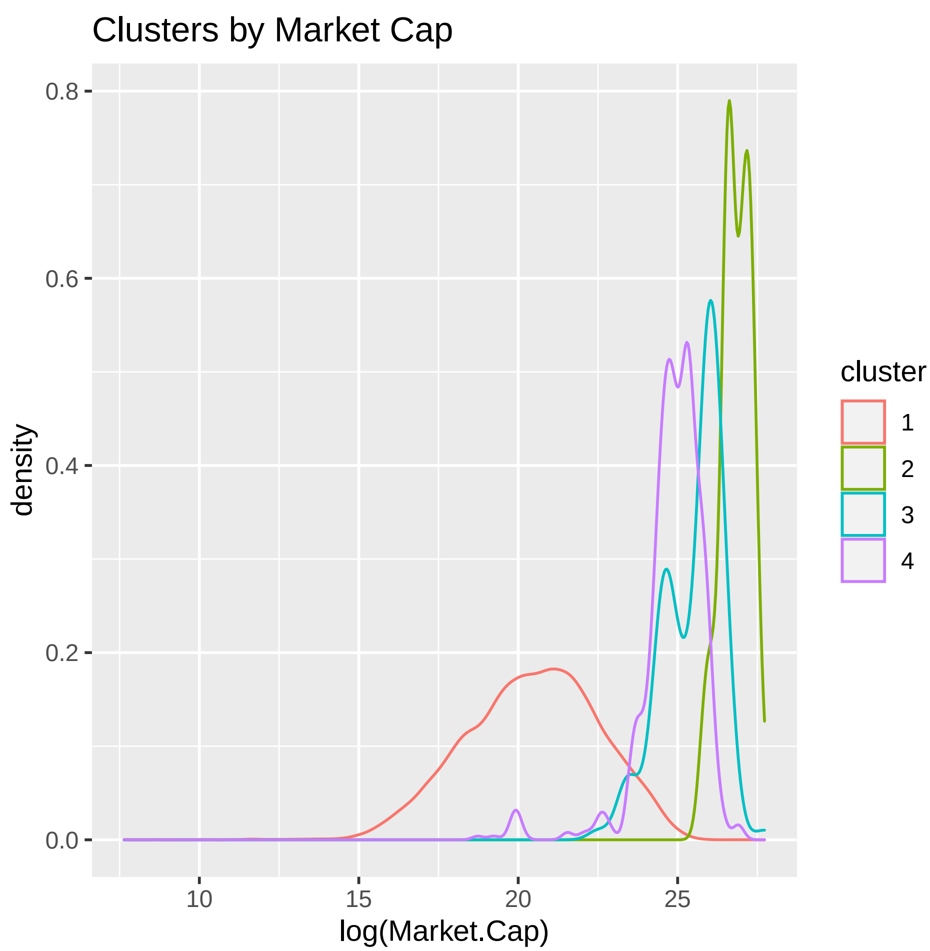


Figure 11: Clusters by Market Cap

K-means was able to segregate the large high-tech companies: Facebook, Apple, Amazon, Google, Intel, and Microsoft all into one cluster (Cluster 2). We noted that these companies trended towards large market capitalization, high stock compensation, and high R & D expenses. Cluster 3 contained a significant majority of big banks, such as JP Morgan, Wells Fargo, and Bank of America, as well as large energy corporations such as ExxonMobil and Chevron. Clusters 1 and 4 had similar sector distributions, although companies in cluster 4 were all large cap. Interesting to note that the top 20 big pharmaceutical and healthcare companies were mainly in cluster 4, such as Johnson & Johnson, Roche, and Abbvie.

Price-to-earnings ratio is a common method of determining how a company is valued by in-

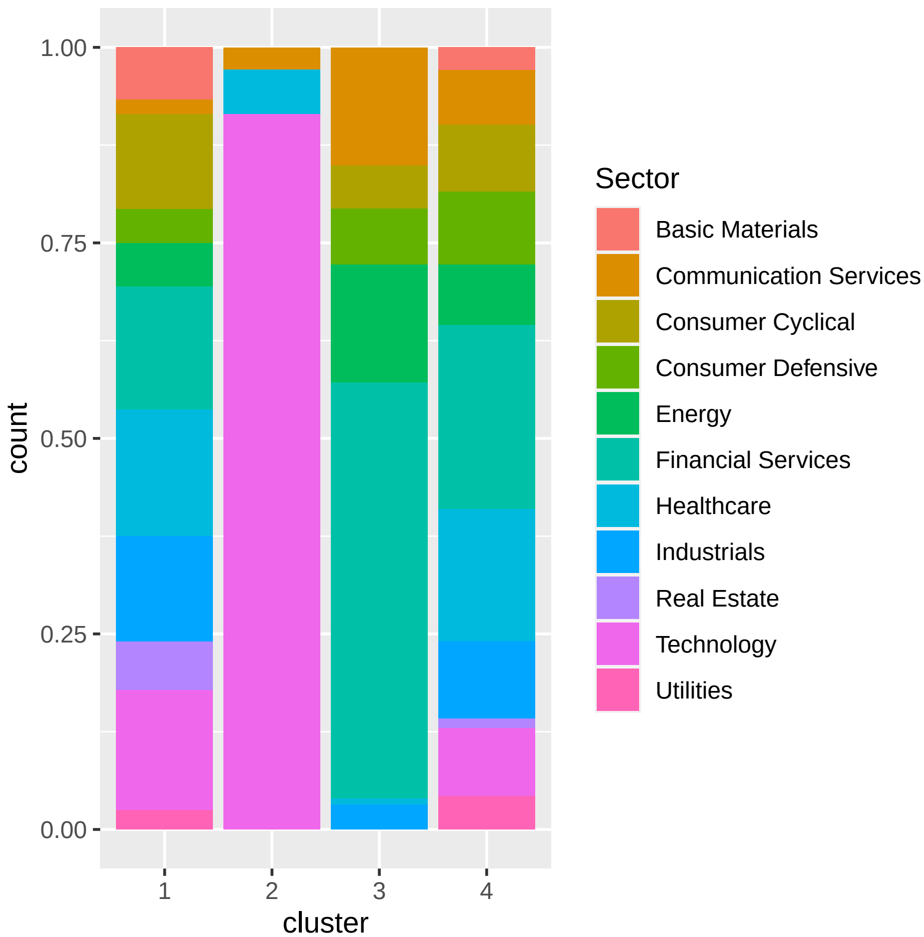


Figure 12: Clusters by Sector

vestors. A high P/E ratio may suggest that investors are willing to pay a higher price for that company's share price because of future growth expectations. Here, we see that cluster 2, composed largely of high-tech companies such as Google, had high P/E ratios - aligning with investor sentiments about the growth of the industry. Cluster 1 maintains an interesting bimodal distribution of positive and negative P/E ratios. Stocks with negative P/E ratio suggest that these companies are reporting a loss.

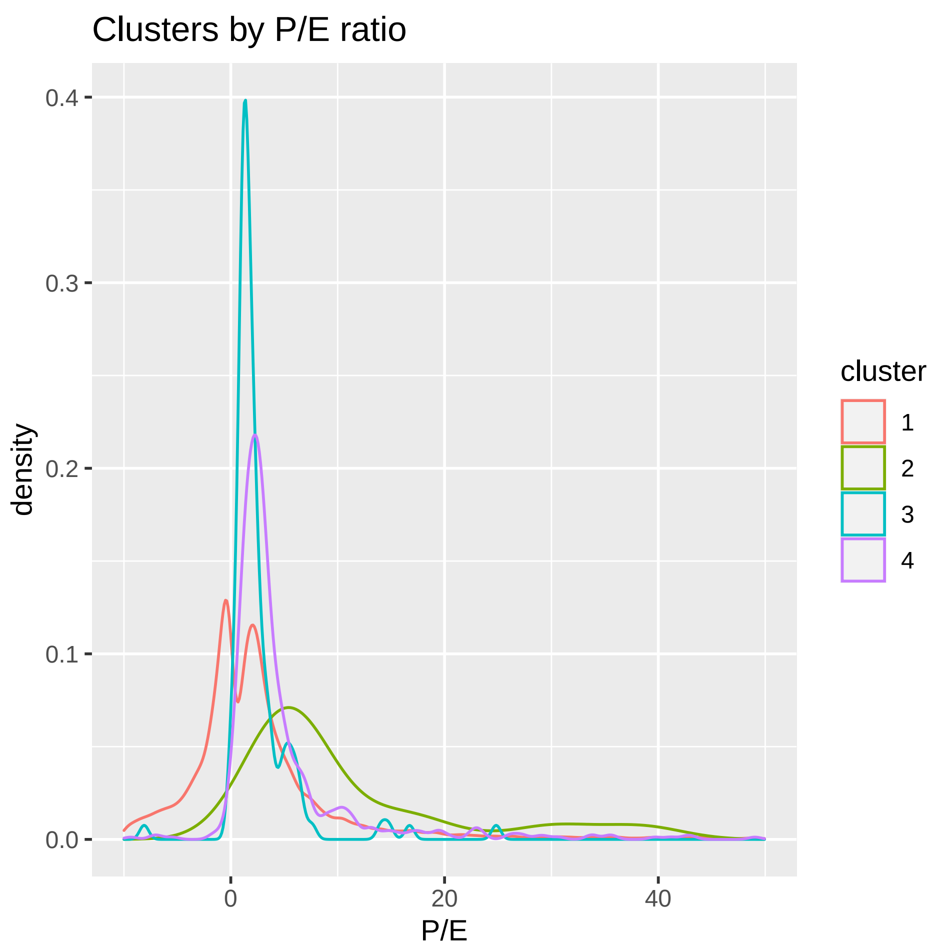


Figure 13: Clusters by P/E ratio

Normalizing for the proportion of small-medium and large cap stocks in cluster 1, we noted that small to medium-sized companies were 2 to 3 times more likely to have a negative P/E ratio compared to large companies. The bimodal distribution in cluster 1 can therefore be partially explained by a split between the distribution of company size.

Modeling

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

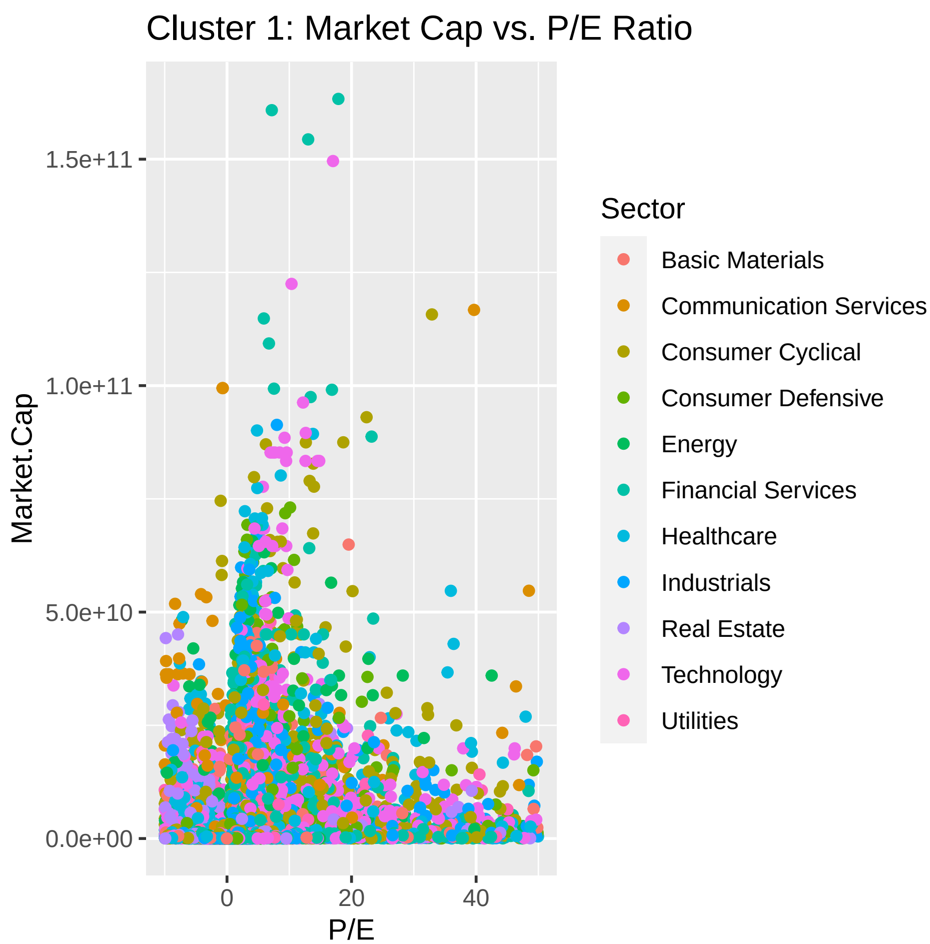


Figure 14: Cluster 1: Market Cap vs. P/E Ratio

XGBoost

The XGBoost model was ran and was parametrized using grid method. The final parameter values used by the best model were nrounds = 200, max_depth = 6, eta = 0.1, gamma = 0, colsample_bytree = 0.5, min_child_weight = 1 and subsample = 0.8.

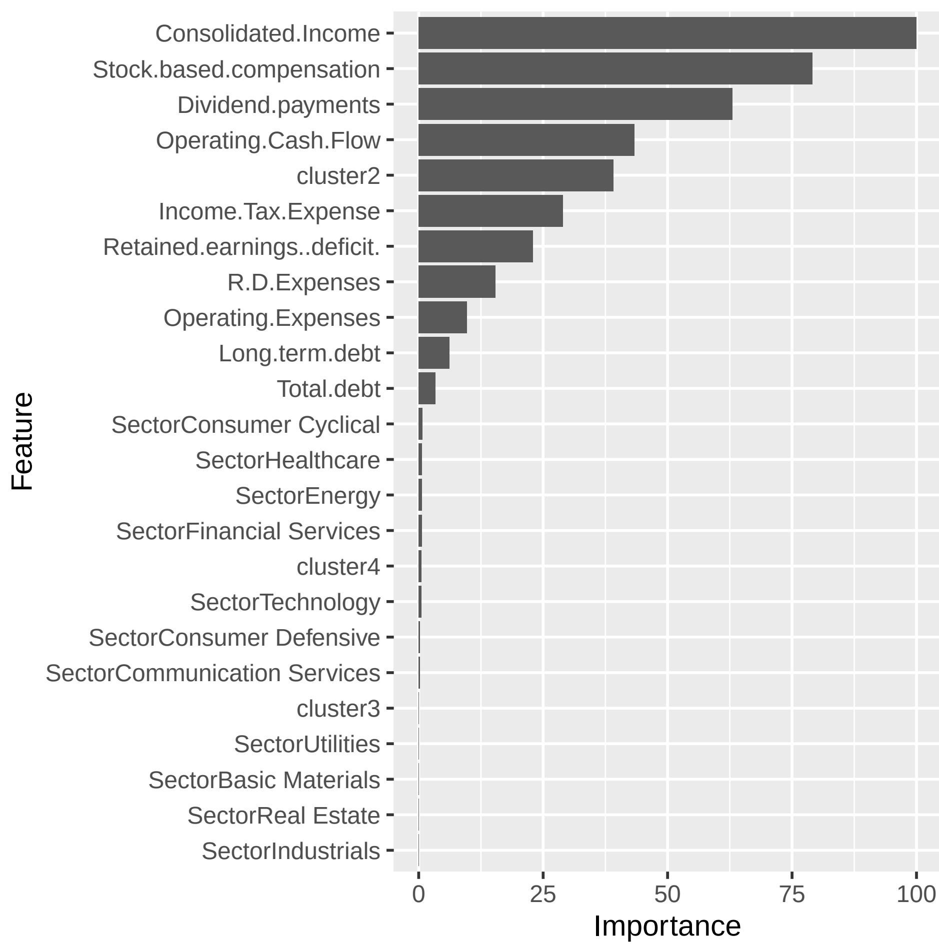


Figure 15: XGBoost Tuning Parameters

Gradient Boosting

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

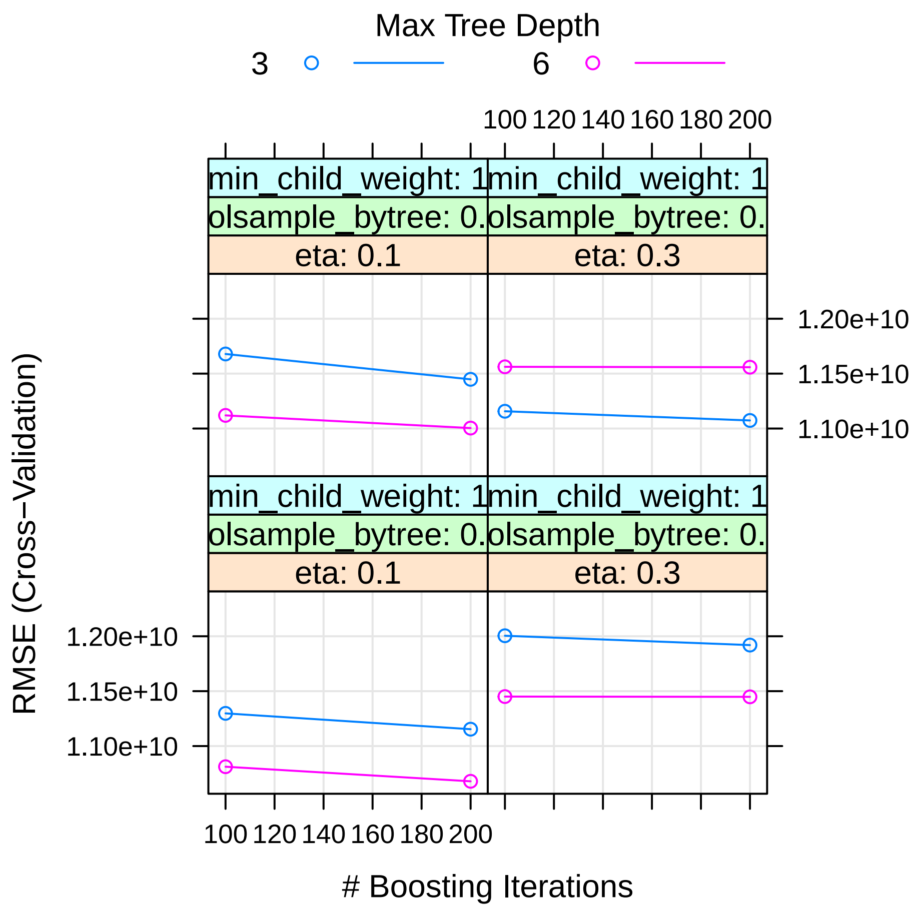


Figure 16: XGBoost Tuning Parameters

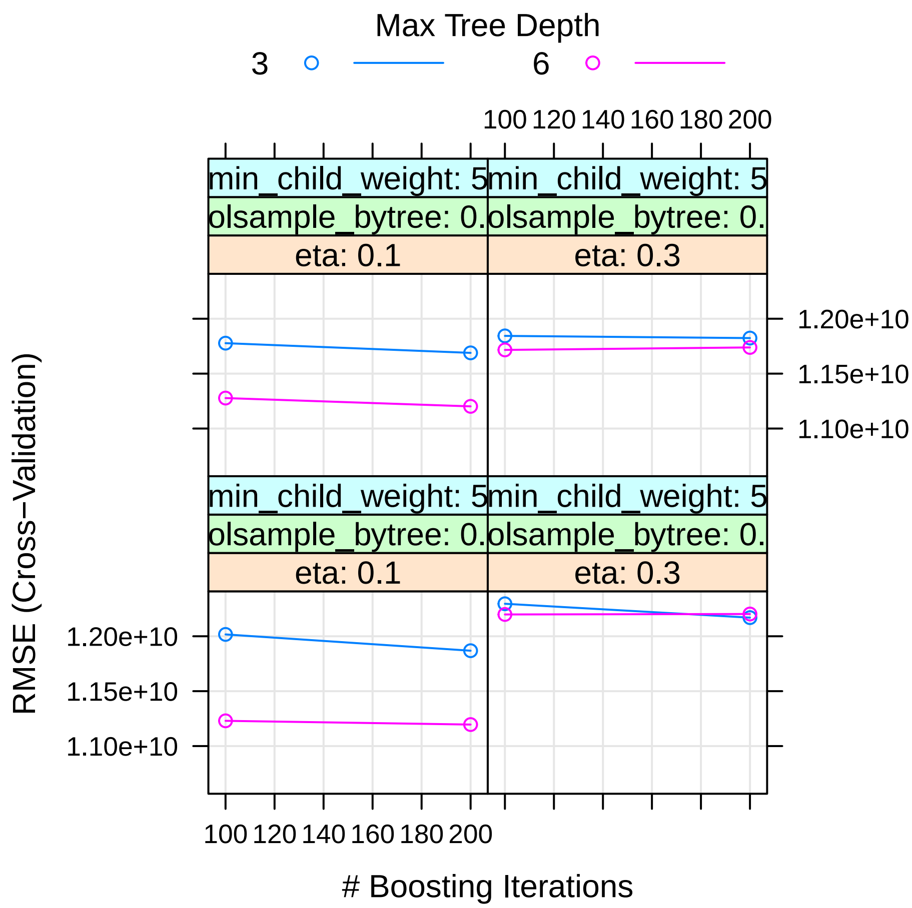
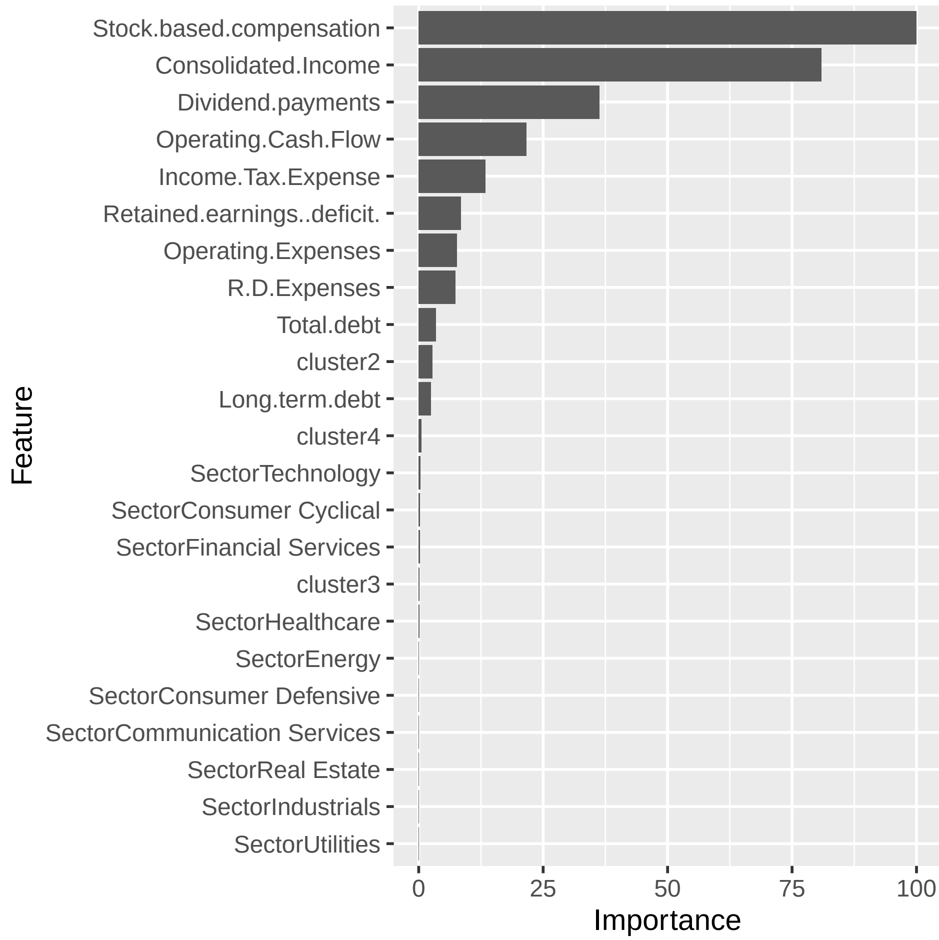


Figure 17: XGBoost Tuning Parameters



##Random Forest The Random Forest model was ran using its normal parameters. The model was not tuned due to the long running time and the limited timeframe of this project.

Model Selection

All models found *ConsolidatedIncome* and *StockbasedCompensation* and *DividendPayments* to be important predictors of Market.Cap. Mean Absolute Error (MAE) shows the average error of the predicted variable. Root Mean-Squared Error (RMSE) is similar with MAE but it is more useful when we are interested in fewer large errors over many small errors. Overall, we prioritized model stability by prioritizing RMSE over MAE. R^2 computes how well the regression model fits the data. The higher the R^2 value, the better the model fits the data. 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 3: Model Accuracy

model	RMSE	R2	MAE
random_forest	2.75e+05	0.81	1.36e+05
extreme_gradient_boosting	1.08e+10	0.90	2.70e+09

model	RMSE	R2	MAE
gradient_boosting	1.18e+10	0.88	2.92e+09

Discussion

This project focused on applying unsupervised and supervised learning on stock data. We merged 5 datasets from different years of stock data with the same attributes, containing a total of 225 columns. We cleaned the data by adding by chosing fundamental columns and imputing missing values using the MICE package. We then ran a decision tree model which chose the most important variables which were used as the features for our modeling. Unsupervised learning using the K-means algorithm was used to cluster the data into 4 different clusters. Cluster 1 was the largest and had 19759 observations. It included small-medium sized companies, where 89% of the observations fell under a market cap of $10 billion. Cluster 2 was the smallest with 35 observations and it included the large high-tech companies, such as Amazon, Apple, Facebook and Google. Cluster 3 had 126 observations and included majority of the big banks such as Bank of America and large energy corporations such as Chevron. Cluster 4 had 568 observations similar sector distribution to cluster one, however, the companies all had a large market cap. In this cluster 20 large pharmaceutical and healthcare companies were found. It was interesting to see how well the clustering algorithm was able to cluster the data in different sections based on the type of company they were, their market cap and other attributes. However, it is notable to discuss that the clusters were not equally distributed and cluster 1 was harder to interpret due to the large number of observations. A larger number of cluster could be considered in future work in order to make the clusters smaller and more interpretable. It is important to note that both the elbow method and silhouette method to chose the number of clusters suggested a cluster number of 2, which when was ran resulted in a very large cluster and a negligible second cluster. Thus, we observed that algorithms determining cluster numbers should be used as a guide and tuned when needed. We also learned that it is important to change the number of cluster to make the data as interpretable as possible. Supervised learning was applied on the 10 important features plus Sector and cluster # as features. Three algorithms, XGBoost, GBM and Random Forest were ran using the cross-validation method. XGBoost and GBM models were tuned with several parameters, while Random Forest was not due to its high running time. The models were evaluated using R^2, RMSE and MAE and XGBoost was the best performer, with Random Forest being the second best and GBM being the worst performer. It is important to note that Random Forest performed almost as well as XGBoost without tuning, thus, if the model was tuned it could have achieved higher performance then the XGBoost. However, this was not possible due to the short time frame of this project and the running time of the model. Therefore, we realized that it is important to consider modeling running time and project timeline when choosing our models. XGBoost achieved a R^2 value of 0.9010295. This means that the std (standard deviation) of the error of the regression model is 1/3 of the std of the error that would be achieved with a constant-only model (a regression model without predictors). Thus the model is quite accurate in prediction, however, there is still error present. A higher R^2 value and lower RMSE and MAE values could have been achieved if the model parameters were tuned further. However, due to the limited time frame, the model's parameters were tuned only by values, rather then value range. Using value range instead of values on the grid tuning algorithm would have allowed for more possibility of achieving a more highly accurate model. Our project had several limitations. First of all the data was old, from 2014-2018 and could not reflect the situation of the stocks currently. In addition, it is important to note that COVID-19 has dramatically changed the economy and affected the prices of stocks. Thus, while using this app, users might not get a reflection of the current marketplace. Furthermore, the supervised learning gave many unbalanced clusters, one of them containing 19759 observations, which was hard to interpret. Thus, this could have given error in our interpretation of the cluster. In addition, these clusters were used in our modelling, thus the unbalanced or non-interpretable clusters could misguide the users. Ethical considerations It is important to note that this app contains data from 2014-2018, thus it is not to be used as a reflection of the current marketplace, considering the COVID-19 pandemic.

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