Predicting Stock Market Prices

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Figure 1: An image of S&P 500 prices since inception. X-axis is year, y-axis is price

ABSTRACT

In this paper, we describe a project concerning mining the stock market for data in order to search for discernible statistical trends. Many statistical methods have been used to mine the stock market for information in order to predict which direction a given stock will move. By definition, a stock market prediction is "the act of trying to determine the future value of a company stock or other financial instrument traded on an exchange." The counter to the idea that stock market prices can be predicted is based on the efficient-market hypothesis. This hypothesis suggests "that stock prices reflect all currently available information and any price changes that are not based on newly revealed information thus are inherently unpredictable." Prediction methods of the stock market consist of fundamental analysis, technical analysis, and data mining technologies. In this paper, we are focusing solely on the latter.

- Is it possible to find patterns in previous stock prices and the history of the stock market in order to predict its future performance?
- Can we utilize data mining and machine learning to recognize discernible patterns in stock prices?

Over the course of the project, we found out that it is hard to predict the price that a certain stock will sell at on a certain day, because there are so many external factors that come into play. Our model attempts to predict a stock price using only the history of previous prices, and doesn't take into account other influences that may affect the price. Our predictions seemed to either rise or fall before hitting a plateau where the price would stay pretty consistent over the course of a few days. This was in line with many stocks we tried to predict, as their prices seemed relatively stable, but our predictions were either too high or too low, so while the correct behavior was predicted (a steady price), the amount itself was not able to be predicted accurately using only historical data.

CCS CONCEPTS

• Information Systems -> **Data Mining**

KEYWORDS
Finance, Economics, Stocks, Stock market, Trends, Prediction, Prices, Patterns, Future performance, NASDAQ, Machine learning, Python, Data mining

1 INTRODUCTION

Since the stock market was created, investors have taken numerous measures in order to try and increase their income from the stock market. While there have been very few successful investors, the stock market has proven to be very difficult to predict. Burton Malkiel, a well-known name in the world of finance, attributes this fact to what he calls the efficient-market hypothesis. The theory states that "stock prices are a function of information and rational expectations, and that newly revealed information about a company's prospects is almost immediately reflected in the current stock price. This would imply that all publicly known information about a company, which obviously includes its prices history, would already be reflected in the current price of the stock. Accordingly, changes in the stock price reflect release of new information, changes in the market generally, or random movements around the value that reflects the existing information set." Malkiel addressed this theory in his book A Random Walk Down Wall Street, arguing that stock prices could therefore "not be accurately predicted by looking at prices history." In this paper, we plan to challenge the theory that stock prices cannot be predicted using data mining methods found in Python's scikit-learn.

Whether or not stock prices can be predicted is an important question to answer, as it will affect trading heavily. If we are able to prove that you can use machine learning techniques to predict the behavior of the stock market, this opens up a lot of possibilities for both professional traders and casual traders, and allows them to make more well informed decisions. Even if we don't end up predicting the stock prices completely, we can predict the expected behavior using historical data, that will give a better understanding of what the market might do. Combining this with things like sentiment analysis or some outside research about the standing of a stock, brokers and traders will be able to make much better decisions when it comes to trading stocks.

2 PREVIOUS WORK

- Genetic algorithms have been used to try and predict the stock market.
- Banks and high frequency trading firms hire analysts to predict the stock market and have talented developers writing algorithms and utilizing machine learning to try and predict the stock market.
- There are many papers written on the subject and a lot of academic research going into utilizing machine learning in order to predict the stock market.

2.1 Application of data mining techniques in stock markets; A survey by Ehsan Hajizadeh, Hamed Davari Aradakani, and Jamal Shahrabi ("Applying Data Mining Techniques." *Data Mining for Managers* (n.d.): n. pag. Web.)

- Keywords: Stock market, data mining, decision tree, neural network, clustering, association rules, factor analysis, time series
- "In this paper, an overview of application of data mining techniques such as decision tree, neural network, association rules, factor analysis, and etc in stock markets is provided."

2.2 Financial Stock Market Forecast using Data Mining Techniques by K. Senthamarai Kannan, P. Sailapathi Sekar, M. Mohamed Sathik and P. Arumugam ("Financial Forecasting Problem and Data Mining Techniques." *Ordinary Shares, Exotic Methods* (2003): 1-4. Web.)

- Keywords: Data mining, Time series Analysis, Binomial test, Typical Price, Bollinger Bands, Relative Strength Index and Moving Average
- "This paper attempts to determine if it is possible to predict if the closing price of stocks will increase or decrease on the following day. The approach taken in this paper was to combine six methods of analyzing stocks and use them to automatically generate a prediction of whether or not stock prices will go up or down. After the predictions were made they were tested with the following day's closing price. If the following day's closing price can be predicted to increase or decrease 70% of the time at the .07 confidence level, then this analysis would be an easy and useful aid in financial investing. Furthermore, the results would show that the results are better than random at a reasonable level of significance."

2.3 Stock market time series forecasting with data mining methods by Milan Csaba Badics (Milan Csaba Badics, Awar, Kochmeister. *Stock Market Time Series Forecasting with Data Mining* (n.d.): n. pag. Web.)

- Keywords: Stock time series forecasting, Trading strategy, Neural networks, ICA, EMD, Data mining methods
- "This paper focuses on the best-known data mining methods suitable for active portfolio management, as well as their advantages and disadvantages, discussing which should be used when and how, and also touching upon the most important current research trends. The objective is to present the entire process, from the selection of stock prices to forecastic (OTP

and MOL daily closing prices in this paper), through the definition of the necessary input variables and available data mining methods right up to the execution of the trade, essentially giving the reader a roadmap for forecast-based active portfolio management.

3 WORK THAT WE DID

Over the course of the project, we fed preexisting datasets that contain stock prices over a period of time into machine learning models in order to make more educated predictions about the future prices of individual stocks. We used Python for all of our programming, and utilized tools available in the Scikit-Learn library for our machine learning. We used support vector regression in order to generate a model that we then used to predict stock prices on certain dates. After getting these predictions, we gathered more data, consisting of the actual stock prices on the dates that we predicted. We used this newly gathered data in order to compare our predictions to the actual closing prices on those days. We have developed a program that places our stock data into a machine learning algorithm using Python library Scikit-Learn. After the data is inputted, the system uses Support Vector Regression in order to predict the stock price of a stock on a certain day. The original data will be plotted, with the model over it, and the prediction will be printed to the terminal. The graphs of these results can be seen below.

4 DATA SET

Our data set consists of .CSV files of past stock performance of the following: AAPL, AXP, BA, CAT, CSCO, CVX, DD, DIS, GE, GS, HD, IBM, INTC, JNJ, JPM, KO, MCD, MMM, MRK, MSFT, NKE, NVDA, PFE, PG, TRV, UNH, UTX, V, VZ, WMT, and XOM. Each individual CSV file has the following attributes: Volume, Symbol, Adjusted Close, High, Low, Date, Close, Open. The volume is defined as the number of shares that changed hands during a given day. The ticker symbol or stock symbol is an abbreviation used to uniquely identify publicly traded shares of a particular stock on a particular stock market. A stock symbol may consist of letters, numbers or a combination of both. The adjusted close is defined as a stock's closing price on any given day of trading that has been amended to include any distributions and corporate actions that occurred at any time prior to the next day's open. The high is defined as a security's intraday high trading price. Low is defined as a security's intraday low trading price. Open is defined as the price of the stock as the market opens and close is defined as the price of a stock as the market closes for the business day.

5 TOOLS

We used Python in order to write code that will use machine learning in order to make predictions. We will be using the Scikit-Learn library in Python in order to help us make calculations. Scikit-Learn provides more than one method of mining for data so this will suffice as our tool for the duration of the project.

6 TECHNIQUES USED

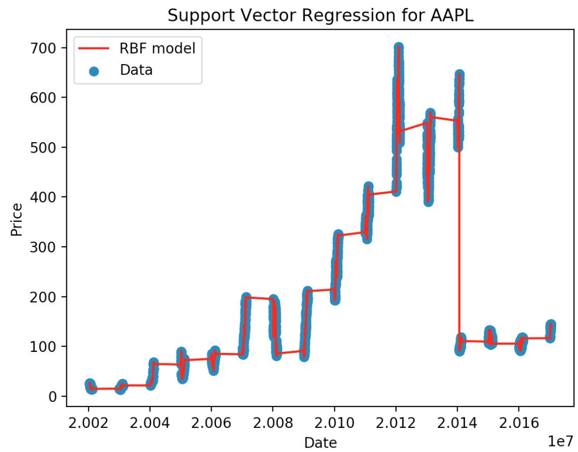
First, to gather the data, we used the Yahoo Finance API in order to pull the histories of various stocks, mentioned in the data set section of this paper. After the data was collected, we decided to use the closing price attribute in order to predict closing prices at future dates.

After the data was gathered, we used Support Vector Regression in order to generate a model that we would use to make our predictions. Support Vector Regression is a special use case of a Support Vector Machine, which is a classifier that uses supervised learning in order to label data. Support Vector Machines can also be used for regression, which is what we used it for. Initially, we ended up making 3 different regression models to see which one would best fit the data that we collected. We made a linear regression model, a polynomial regression model, and an RBF regression model. The model that we generated using RBF was the best fit for our data, so that is the model we used to make the predictions. Our code generates a separate model for each stock, so that each different stock has it's own unique model, which means that the predictions are specific and accurate to each stock, giving us better results over all. For each stock we predicted prices for, we entered in a range of dates for which prices would be predicted. The model that was generated takes these dates in, and gives us predictions for what the stock closing prices are going to be on those dates.

7 RESULTS

Here are the generated models, predicted prices, and comparison to the actual prices for stocks AAPL, AXP, BA, CAT, CSCO, JPM, NKE, NVDA, PFE, and PG.

AAPL:

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The predicted price for AAPL on 2017-04-05 is 153.245313003
The predicted price for AAPL on 2017-04-06 is 164.882718812
The predicted price for AAPL on 2017-04-07 is 175.336304217
The predicted price for AAPL on 2017-04-10 is 187.506859127
The predicted price for AAPL on 2017-04-11 is 188.018500349
The predicted price for AAPL on 2017-04-12 is 188.158078234
The predicted price for AAPL on 2017-04-13 is 188.1891061
The predicted price for AAPL on 2017-04-17 is 188.195688106
The predicted price for AAPL on 2017-04-18 is 188.195688932
The predicted price for AAPL on 2017-04-19 is 188.195688987
The predicted price for AAPL on 2017-04-20 is 188.19568899
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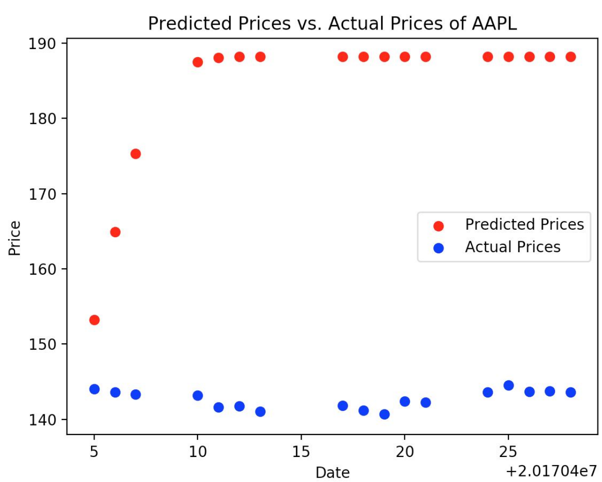
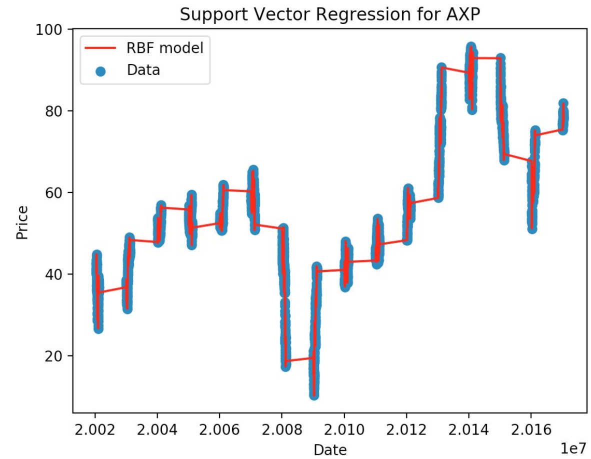


AXP:

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The predicted price for AXP on 2017-04-05 is 73.8353747496
The predicted price for AXP on 2017-04-06 is 67.6137815882
The predicted price for AXP on 2017-04-07 is 61.9149506445
The predicted price for AXP on 2017-04-10 is 55.1303787573
The predicted price for AXP on 2017-04-11 is 54.8369995402
The predicted price for AXP on 2017-04-12 is 54.7562125436
The predicted price for AXP on 2017-04-13 is 54.7381043651
The predicted price for AXP on 2017-04-17 is 54.7342310634
The predicted price for AXP on 2017-04-18 is 54.7342305679
The predicted price for AXP on 2017-04-19 is 54.7342305346
The predicted price for AXP on 2017-04-20 is 54.7342305328
The predicted price for AXP on 2017-04-21 is 54.7342305327
The predicted price for AXP on 2017-04-24 is 54.7342305327
The predicted price for AXP on 2017-04-25 is 54.7342305327
The predicted price for AXP on 2017-04-26 is 54.7342305327
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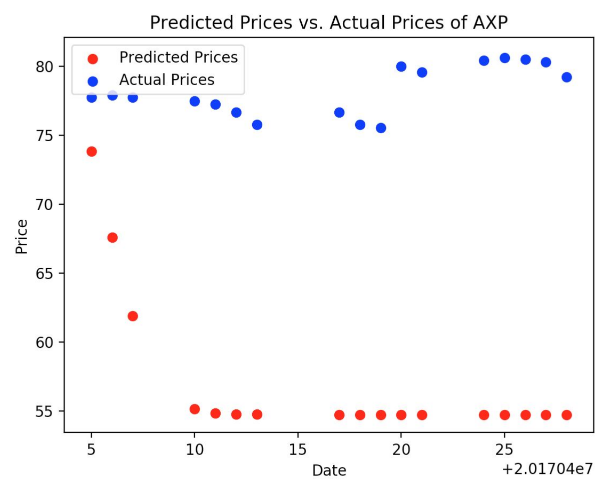
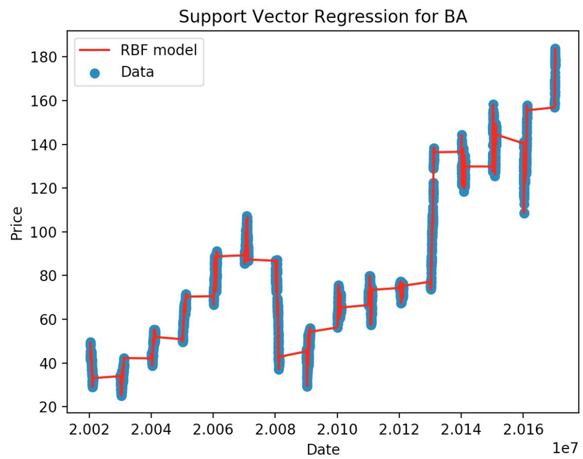


BA:

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The predicted price for BA on 2017-04-05 is 163.422743057
The predicted price for BA on 2017-04-06 is 138.530543358
The predicted price for BA on 2017-04-07 is 114.19692656
The predicted price for BA on 2017-04-10 is 83.1834836251
The predicted price for BA on 2017-04-11 is 81.7334586071
The predicted price for BA on 2017-04-12 is 81.3244113494
The predicted price for BA on 2017-04-13 is 81.2308037165
The predicted price for BA on 2017-04-17 is 81.2103735161
The predicted price for BA on 2017-04-18 is 81.2103707817
The predicted price for BA on 2017-04-19 is 81.2103705969
The predicted price for BA on 2017-04-20 is 81.2103705867
The predicted price for BA on 2017-04-21 is 81.2103705863
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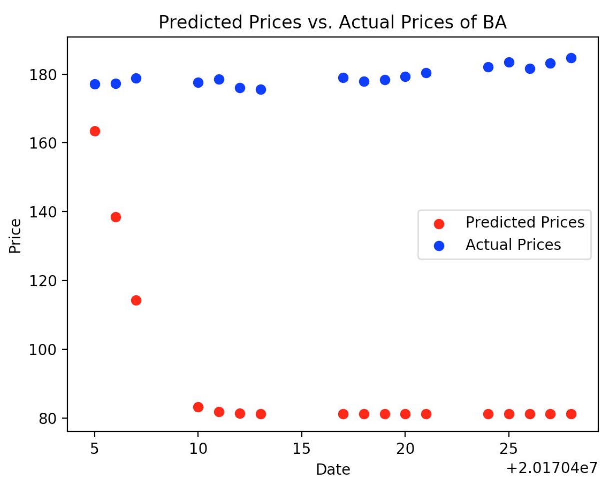
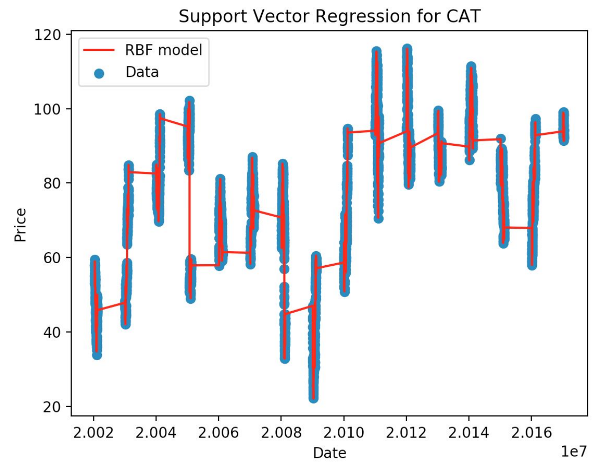


CAT:

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The predicted price for CAT on 2017-04-06 is 87.8363656711
The predicted price for CAT on 2017-04-07 is 82.8809283527
The predicted price for CAT on 2017-04-10 is 75.7555189954
The predicted price for CAT on 2017-04-11 is 75.3820601367
The predicted price for CAT on 2017-04-12 is 75.2733689869
The predicted price for CAT on 2017-04-13 is 75.2478540528
The predicted price for CAT on 2017-04-17 is 75.2421519097
The predicted price for CAT on 2017-04-18 is 75.2421511078
The predicted price for CAT on 2017-04-19 is 75.2421510532
The predicted price for CAT on 2017-04-20 is 75.2421510502
The predicted price for CAT on 2017-04-21 is 75.24215105
The predicted price for CAT on 2017-04-24 is 75.24215105
The predicted price for CAT on 2017-04-25 is 75.24215105
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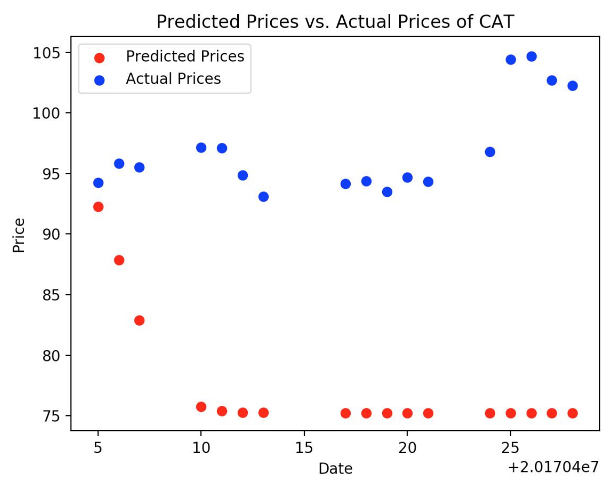
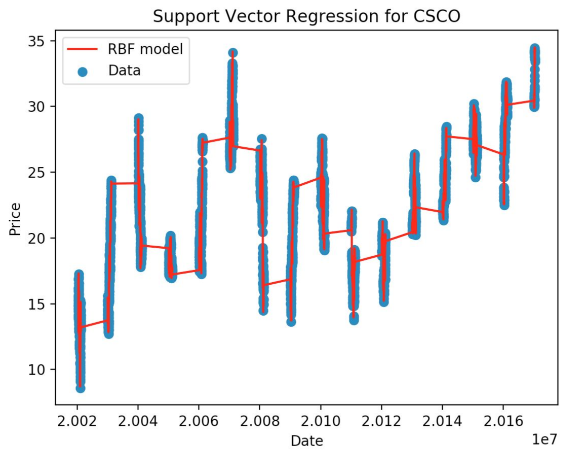


CSCO:

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The predicted price for CSCO on 2017-04-05 is 31.2200610036
The predicted price for CSCO on 2017-04-06 is 28.2230150792
The predicted price for CSCO on 2017-04-07 is 25.4828360828
The predicted price for CSCO on 2017-04-10 is 22.2273226181
The predicted price for CSCO on 2017-04-11 is 22.0869057589
The predicted price for CSCO on 2017-04-12 is 22.0482716745
The predicted price for CSCO on 2017-04-13 is 22.0396182727
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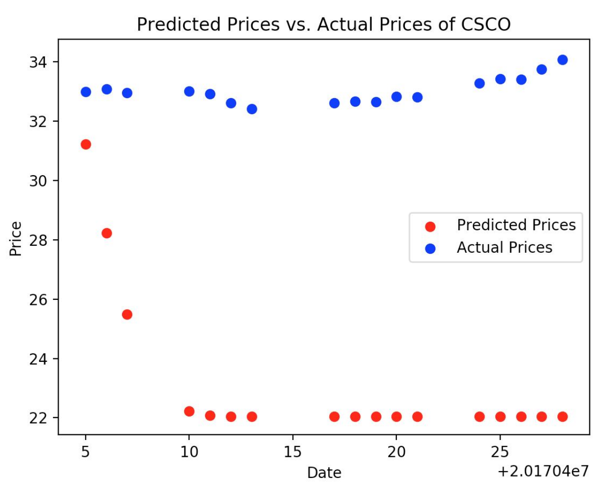
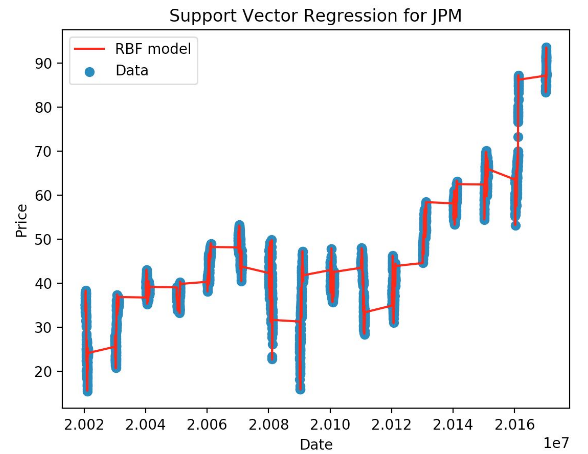


JPM:

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The predicted price for JPM on 2017-04-05 is 79.7274057218
The predicted price for JPM on 2017-04-06 is 68.6179363942
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The predicted price for JPM on 2017-04-10 is 45.7188917272
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The predicted price for JPM on 2017-04-12 is 45.0099975597
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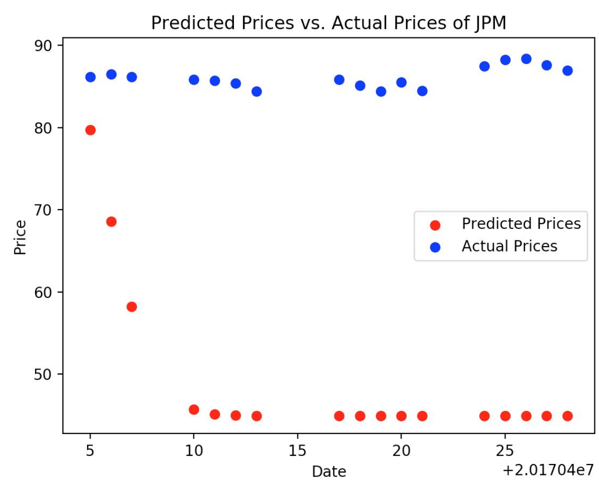
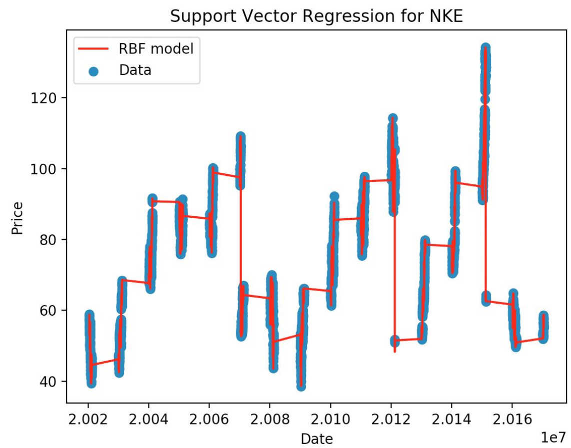


NKE:

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The predicted price for NKE on 2017-04-10 is 73.4124826708
The predicted price for NKE on 2017-04-11 is 73.6988983926
The predicted price for NKE on 2017-04-12 is 73.7800001244
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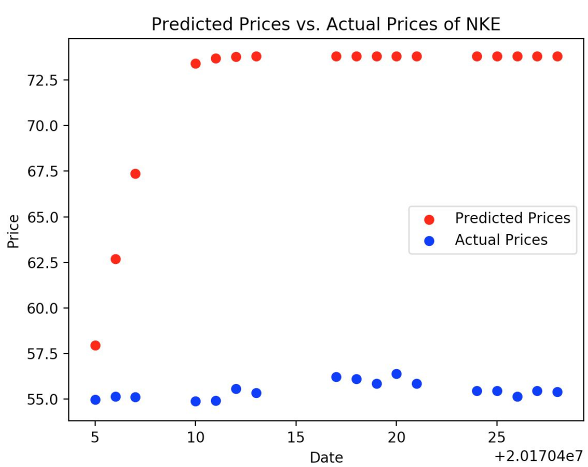
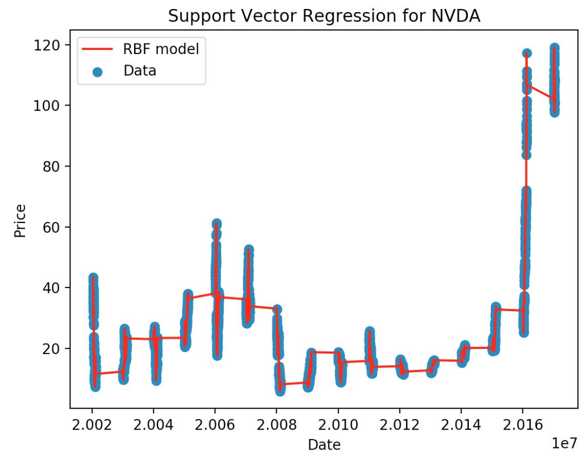


NVDA:

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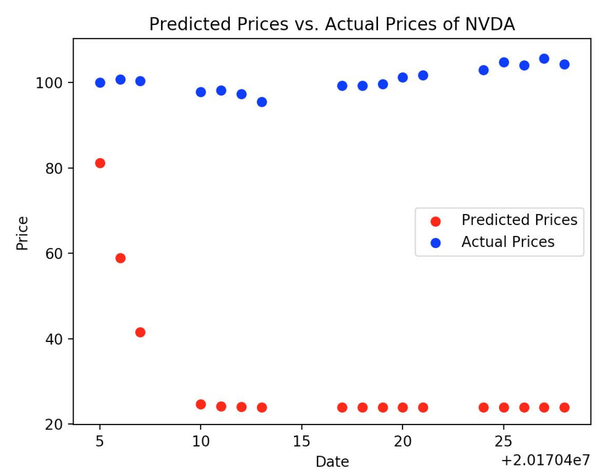
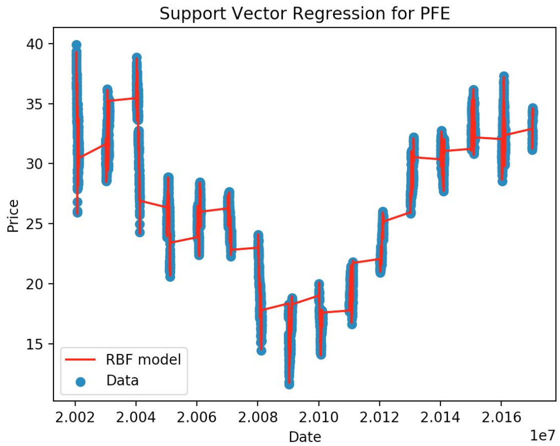


PFE:

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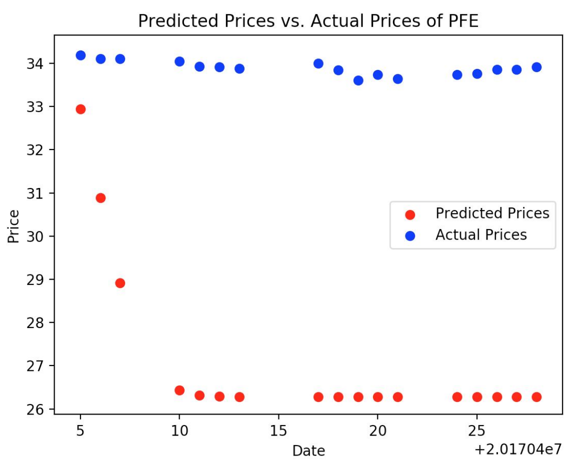
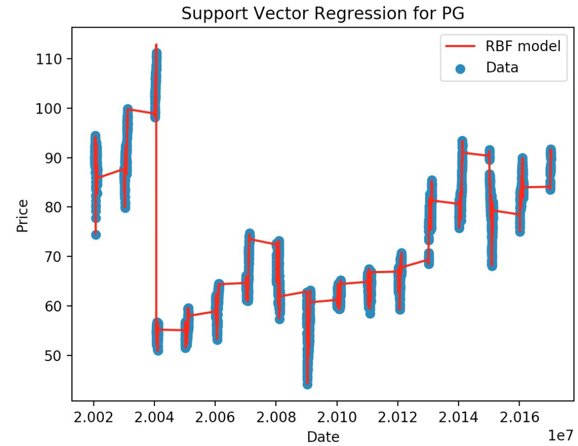


PG:

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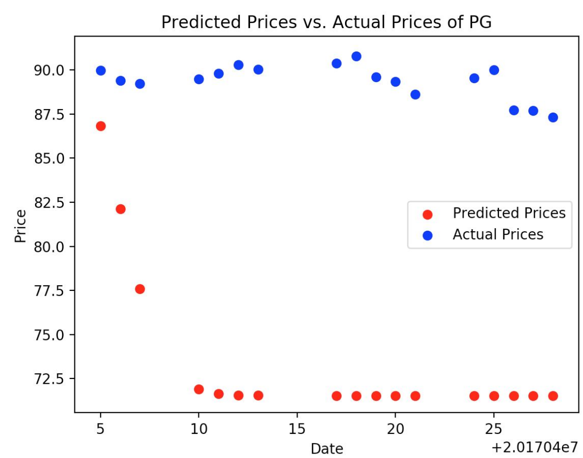
The predicted price for PG on 2017-04-25 is 71.5406405848
The predicted price for PG on 2017-04-26 is 71.5406405848
The predicted price for PG on 2017-04-27 is 71.5406405848
The predicted price for PG on 2017-04-28 is 71.5406405848
```



8 EVALUATING THE RESULTS

After gathering predictions for multiple stocks from April 5 to April 28, we plotted the predicted values against the actual values on those dates, which we again pulled from the Yahoo Finance API. After plotting these values, we found that the predictions generated using our model were not very accurate. For every stock we attempted to predict, our predicted prices were either higher or lower than the actual prices by a fair amount. While the actual prices were inaccurate, the behavior predicted by the model was closer to the behavior of the actual market. As you can see from the data, most stocks stay relatively steady over the course of a few days, and the data that we predicted using the model shows this. After a rise or fall in the predicted prices, they level out and remain relatively level for the duration of the dates, this is a similar behavior to what the actual stocks did, as they showed very little change over the course of the time period that we predicted.

This goes to show that the stock market is heavily affected by outside forces other than previous prices, forces that our model does not account for. If a stock were to drop due to a controversial announcement by a company, our model would not be able to predict that drop. Our data shows that while the stock market can be extremely volatile, if outside factors are limited, stock prices tend to remain relatively even over a short period of time of about a month, and our model shows this. In order to get more accurate predictions that take into account other factors, a more advanced model is needed.

9 APPLICATIONS

There are many different areas that our findings may be applied to. For one, this model can be used to help study the general behavior of the stock market. While our model wasn't the best at determining specific prices, it did show us that the stock market remains fairly constant if there are no extreme outside factors that swing the prices. This finding can be used to help study these factors, to see what specific things cause these disruptions in the market, and cause a stock from being steadily priced to either plummeting or skyrocketing.

Another thing we learned, is that the stock market is heavily influenced by outside factors unaccounted for in price history. We can use this finding in order to generate better models, to maybe predict stock prices more accurately in the future (Possible improvements to the model will be discussed in the next section). The data that we gathered can definitely be applied to future machine learning applications.

10 FUTURE IMPROVEMENTS

There is a lot more that goes into stock prices than the history of past prices. Things like public perception, scandals, political climate, the economy, and many more factors affect the prices of stocks. In order to have a more accurate model, these factors need to be taken into account.

One improvement we can make is to include sentiment analysis through Twitter in our model. We would scrape Twitter for tweets regarding the companies we are predicting, and perform sentiment analysis in these tweets in order to see what the public's perception of the company is like. If people like the company, there is a good chance their stock is going to be priced higher than that of a company that people are talking negatively about. We see this in the real world all the time, most recently with American Airlines, whose stock plummeted after dragging a passenger off a flight. Our sentiment analysis would factor this into the model, and provide for a more accurate prediction.

Another way to improve the model would be to use some more advanced machine learning methods, such as neural networks. Regression is fairly simple, and there are too many outside factors with stocks to make it accurate. A more advanced method would be able to more accurately learn patterns in the data, and give us better predictions.

11 CONCLUSION

We found that the stock market is very difficult to predict. Our model was unsuccessful in accurately predicting the prices of stocks in the future, but was successful in predicting the behavior of stocks. As far as prices go, there are too many unpredictable factors at play that can heavily affect the prices of stocks, factors that aren't going to be accounted for by simply looking at data. While the results may be better with a model that takes into account these outside factors, they are still unpredictable and hard to find patterns in. In conclusion, the stock market is volatile and unpredictable, and it is rather difficult to accurately predict stock prices by looking at price history.

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