

Stock Price Predictor

Matthew Bozelka

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Project Overview

The Stock Market is a large collection of markets and exchanges where equities of publicly held companies can be traded. Trading in stocks has many benefits, and can be a lucrative income if the market is well understood. Companies are able to gain access to capital by selling off slices of ownership to investors, and the investors have the opportunity to gain income and assets. The Stock Market can also be one of the better predictors in determining the health and direction of an economy. It can help predict if economic and political policies are paying off, whether or not housing prices are going to rise, and influence the size of a nation's workforce (Leads, 2017).

For these reasons, predicting the Stock Market can be very advantageous. The issue is the market is very volatile and influenced by a large number of factors. Many argue that the market cannot be predicted, and in a strong definition that is likely correct. However, the market often does have concrete trends that can be analyzed, and therefore may still be able to be reasonably predicted in short periods of time.

In this project, I am going to combine Machine Learning concepts with a technical analysis of individual stocks from the NYSE or NASDAQ (American Stock Markets) in an attempt to predict their stock prices. I will report future stock predictions over a 14-day period in intervals of 7 days. Ex: 1 day out, 7 days out, 14 days out from the current date. All data sets were obtained from Yahoo Finances (Data Sets, N.d). The final implementation will be in the form of a web application that allows users to select up to 4 stock symbols, and the application will then output the predicted results and analysis of each stock.

My prior knowledge of the Stock Market was minimal, which was also a driving factor in my personal reasoning for taking on this project. Much of my understanding and knowledge of the Stock Market, and how to interpret it through technical analysis came from Udacity's course Machine Learning for Trading (Balch, N.d), Khan Academy's overview of Stocks and Bonds (Stocks and Bonds, N.d), and the book "How to Day Trade for a Living: Tools, Tactics, Money Management, Discipline and Trading Psychology" (Aziz, A. N.d).

Problem Statement

The goal of this project is to reasonably predict the price of individual stocks in the American Stock Market over a short period of time in the future, 14-days, with the expectation that the 14th day will be less accurate than the 1st. A secondary goal will be to advise an action on those predicted days of either "None", "Sell", or "Buy". The following outlines the steps involved in accomplishing the task:

1. Obtain data sets of 4 individual stocks and the S&P 500 (explained in detail in coming sections) from Yahoo Finances.

2. Process the data to ensure it includes any missing information, and does not include any dates the market was not trading.
3. Analyze each of the stocks individually, compare them against the S&P 500, and determine the best features to utilize in my predictions.
4. Train the data against a few models to determine which delivers the best results. The problem will be modeled as a regression task given its continuous nature.
5. Tweak the results of the models if necessary.
6. Develop a web application that allows a user to select up to four stocks, run the stocks through the model, and present them an analysis of the stocks with predictions based on my chosen model.

The web application will be intended only for educational purposes, and not to be utilized in actual market trading.

Metrics

In order to provide metrics for my solution I will be using the coefficient of R^2 (R squared) of the prediction. R^2 is used in models with the purpose of predicting future outcomes. The coefficient R^2 is defined as:

$(1 - u/v)$, where u is the residual sum of squares, and v is the total sum of squares.

The residual sum of squares (u) can be defined as:

$$u = \sum_i (y_i - f_i)^2, i = \text{all training points}, f = \text{predicted values of training points}$$

The total sum of squares (v) can be defined as:

$$v = \sum_i (y_i - \bar{y})^2, i = \text{all training points}, \bar{y} \text{ is the mean of the observed data.}$$

The best possible score for a R^2 metric evaluation is 1, and the score can also be negative. A negative score can indicate that a particular model is unusable for the problem, and if R^2 is consistently 1 then the model is disregarding the input features (Sklearn.metrics.r2_score, N.d).

The R^2 value represents how well observed outcomes are reproduced by a model, compared to the total variance explained by the model. In other words, how much of the change in the output can be explained by the change in the input. In comparison, another popular Linear Regression metric is the Mean Squared Errors (MSE) which measures the difference between the actual output and the prediction. With MSE, a good score would be closer to zero.

R^2 was chosen as the metrics evaluation over other Regression scorers because of its strong use in predicting future outcomes, and because it attempts to explain how the variance of an input explains the variance in the output.

Analysis

Data Exploration

During the data exploration phase of the project multiple sets of historical stock data was obtained. The data was downloaded from Yahoo finance in the form of CSV files. The reason for downloading the files in the beginning stages, instead of using the Yahoo API utilized in the final implementation, was to ensure any procedures were reproducible and not affected by stock market factors such as stock splits. The data sets used during this phase are included in the final project files, so any procedures can be reproduced in the future.

There are two main components needed for data exploration to satisfy the problem domain; A date range to gather historical values, and stock indexes that represent a company traded in the American Stock Market (NYSE or NASDAQ) on those dates. To satisfy the former the dates from July 7th, 2015 – July 7th, 2017 were chosen (At the time July 7th was the most recent trading date). This results in 2 years of historical data. To satisfy the latter stock indexes for Google (GOOG), Apple (AAPL), IBM (IBM), Nvidia (NVDA), and the S&P 500 (SPY) were chosen. Google, Apple, IBM, and Nvidia were chosen at random, and four indexes were chosen since that will be the max allowed in the final implementation of the user interface. The S&P 500, however, is a unique stock market index in that it is a weighted representation of around 500 American Stock Market indexes with the nice side effect that any null values in the data set will represent days not traded. By removing these dates, we are left with only dates the stock market was open and trading. This is useful information as it helps determine true null data values in other stocks such as dates it may not have existed, dates when the stock market was trading but the stock was not, or just missing data. For this reason, the S&P 500 has been chosen as a benchmark index to evaluate all stock data against.

When retrieving data from Yahoo Finances multiple features of the stock are returned. These features include the chosen stocks “Open”, “High”, “Close”, “Adjusted Close”, “Volume”, and are all indexed by the dates traded. The below table is a visual representation from the S&P 500 data.

SPY						
Date	Open	High	Low	Close	Adj Close	Volume
2010-07-15	109.610001	110.059998	108.169998	95.017952	109.680000	232337900
2010-07-16	109.089996	109.209999	106.449997	92.401672	106.660004	282693400
2010-07-19	107.050003	107.629997	106.220001	92.947449	107.290001	186709000
2010-07-20	105.870003	108.559998	105.820000	93.978371	108.480003	258162400
2010-07-21	109.040001	109.070000	106.629997	92.756844	107.070000	264527000

The above data example represents various features of the S&P 500 over a 5-day period. They each have their own significance depending on what is trying to be determined, but ultimately, they mostly describe the price of a given Stock at different portions of the day. In the defined domain problem of this project, our target is the Adjusted Close prices of each day since our ultimate goal is to predict future Adjusted Close prices. Therefore, the other data features will be discarded and not used in our exploration and implementation. This is an interesting problem and

divergence from many other data sets used for predictions. After dropping the other data features we are left only with our target values and no features in the given set to learn from. The solution will be to derive new features that are calculated from basic statistics and the previous days Adjusted Close. A few of these new features that will be processed and explored are the Standard Moving Average, Momentum, and the Bollinger Bands ratios. In upcoming sections, there will be discussion on how these features were processed and used, but for now they will only be defined.

Simple Moving Average (SMA): The SMA is derived by calculating the mean of the data over intervals. For example, an interval may be every 20 days, and the SMA for a particular day would be represented by the mean calculated from the previous 20 days. This is also referred to as the Rolling Mean. In order to use this as a technical analysis we use the following equation to obtain values around -0.50 to 0.50.

$$\text{Simple Moving}[\text{day}] = (\text{price}[\text{day}] / \text{price}[\text{day} - \text{interval}] .\text{mean}()) - 1$$

Bollinger Bands (BB): BB bands are simply the upper and lower bands created when calculating data points two standard deviations above and below the SMA. In order to use this as a technical analysis we use the following equation to obtain values around -1.0 to 1.0.

$$\text{BB}[\text{day}] = \text{price}[\text{day}] - \text{sma}[\text{day}] / 2 * \text{std}[\text{day}]$$

Momentum: Momentum gives directionality to a stock over a given interval. It indicates if the stock has a positive momentum (going up), or a negative momentum (going down). In order to use this as a technical analysis we use the following equation to obtain values around -0.50 to 0.50.

$$\text{momentum}[\text{day}] = \text{price}[\text{day}] / \text{price}[\text{day} - \text{interval}] - 1$$

Now that we have our feature set the below table gives an example of what it would look like for the S&P 500.

	BB	Momentum	SMA
2015-07-28	-0.305356	-0.006408	-0.025181
2015-07-29	0.053972	0.000760	-0.018476
2015-07-30	0.108938	-0.006971	-0.018243
2015-07-31	0.082941	-0.009319	-0.019733
2015-08-03	-0.045573	-0.013171	-0.023039

Given the high volatility of the Stock Market it was decided it was not necessary to locate or remove outliers. In this situation, what may be seen as an outlier is still valuable information in understanding how a particular stock is behaving and therefore is not truly an outlier.

The below table lists the basic statistics of the data sets used. The adjusted closing price has been normalized so each stock is evaluated on a level playing field. This allows for a more accurate representation of how the stocks are behaving compared to each other.

	Mean	Median	Standard Deviation
SPY	1.021891	1.008686	0.072933
NVDA	3.246513	2.654098	1.982375
IBM	0.910470	0.909703	0.078761
GOOG	1.357082	1.347870	0.154974
AAPL	0.927906	0.899809	0.134810

Of these basic statistical measurements, the Standard Deviation holds a lot of value. Higher values indicate the stock is more volatile which could result in less certain predictions. As we can see NVDA has a much larger standard deviation than the other stocks.

Exploratory Visualization

The following graph (**Fig. 1**) is a visualization of the Rolling Mean and the Bollinger Bands. The visualization is useful to see how they relate to the Adjusted Close values over a given period of time.

Fig. 1 - SMA/Bollinger Bands of SPY

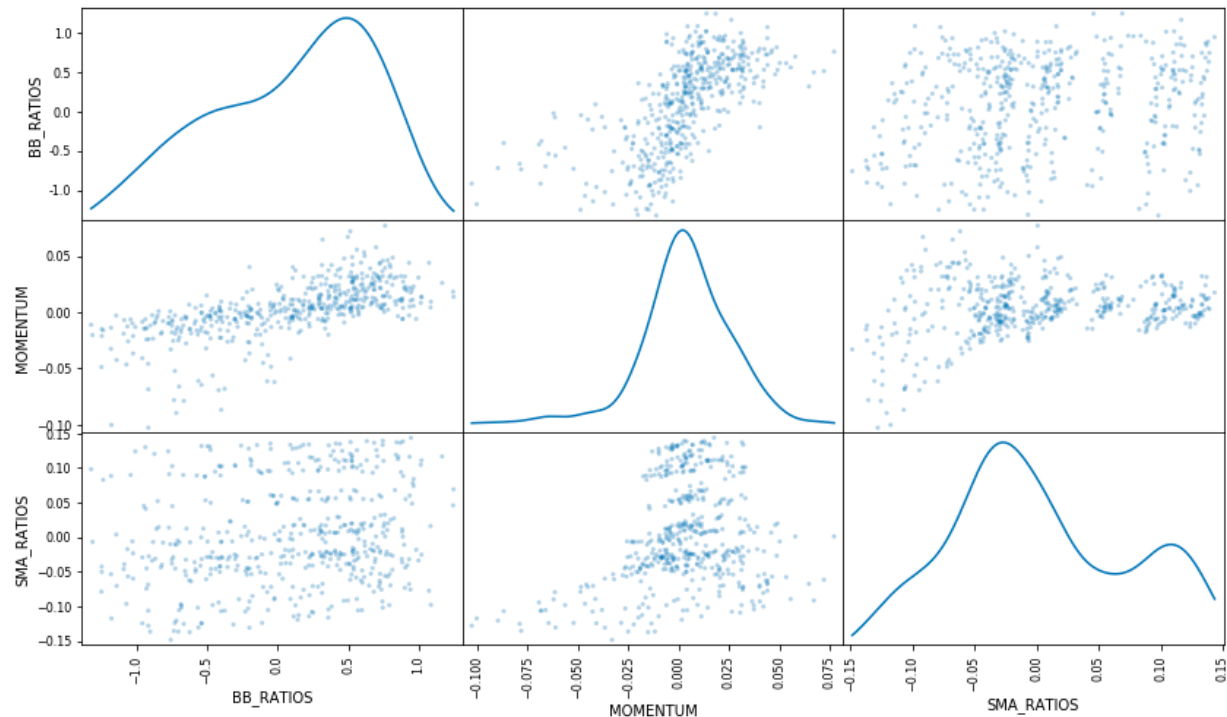


The Bollinger Bands in **Fig 1**. will be how the action for a prediction is chosen. They represent a statistical indicator of 2 standard deviations above or below a day's SMA. An example situation of when a "Sell" action will be predicted, is when the Adjusted Closing value is outside the upper band the day before, and on the current day is between the upper band and the SMA. This

indicates the stock may be coming back down after a statistically significant high, and therefore may be time to sell.

The following graph (**Fig.2**) illustrates the correlations between the selected features. If a feature is correlated to another feature it would be visualized in a linear fashion. If two features are highly correlated they may not offer unique enough information to the final model. Based on the visualization it would appear the features are unique enough to be useful.

Fig. 2 - Feature Correlation Based on SPY



Algorithms and Techniques

The problem is a Supervised Learning problem given we are attempting to predict future stock prices based on learning and training from historical data. The continuous nature of the data makes it particularly suitable for regression type algorithms. After evaluating the types of algorithms available I have decided to use an Ordinary Least Squares Linear Regression algorithm, the K-Nearest Neighbor (KNN) Regressor algorithm, and a Random Forest Regressor algorithm to evaluate which returns the best results. Each of these algorithms are available in the Scikit Learn Python library. Another technique that will be utilized for all three models is Time Series Splitting for cross-validation.

Linear Regression: In this model, one technique that will be utilized is to pass the model what is known as a Standard Scalar. The idea of it is to bring each of the features passed to the linear regression within the same numerical scale as well as try representing the features as a normal distribution. The goal of the Linear Regression model is to fit a line to the data that can best

generalize any trends. The output of the model will be an equation that can then be used to make future predictions.

K-Nearest Neighbor (KNN) Regressor: The K-Nearest Neighbor Regression is a regression variant of the class based K-Nearest Neighbor algorithm. In this model, the same Standard Scalar technique utilized in the Linear Regression model will be utilized. One of the fundamental differences in this model is the historical data the model is trained on needs to be retained in order to make future predictions, whereas in Linear Regression the historical data is no longer needed once the model equation is obtained. The idea behind this model is it will use a variable amount of the closest historical values, take their average, and use that to make its predictions. Different variable amounts will be tested to see what number of neighbors return the best results. The weights parameter will also be set to “distance” so that closer query points will have greater influence than those further away.

Random Forest Regressor: A Random Forest Regression is a model that fits multiple Decision Trees and uses averaging to improve predictive accuracy and control overfitting. In this model, we will not need to use the Standard Scalar used on the previous models because the decision-making process is not affected by features of differing scales. The only parameter that will be tuned is the `n_estimators` parameter which determines the number of trees the model will use.

Time Series Splitting: Cross-validation is a useful technique for training and testing a model by utilizing all the available data for testing and training. The goal is to reduce overfitting. However, traditional cross-validation does not preserve data ordering in the process which is important in our problem domain. Time Series Split will preserve the ordering solving this issue.

Benchmark

I will benchmark stock predictions against the online Stock Forecasting tool found at <https://www.stock-forecasting.com/RealtimeDemo.aspx>. During my research, this was the only free and accessible stock predicating tool that I could locate. The tool attempts to predict a few more variables than my model will and only for the next trading day, but they both will predict closing values and a possible action for a chosen stock such as “Buy”, or “Sell”.

As mentioned earlier a secondary benchmark for the model will be the S&P 500. The S&P 500 is a weighted representation of around 500 American Stock Market indexes and attempts to capture the market as a whole. By using this as a Benchmark we can properly prepare the data for our predictions, and ensure we are not using erroneous values generated from non-trading days. We can also visualize a stocks historical data against the S&P 500 along the way to evaluate how each stock is doing against the market as whole, and we can use it to help determine if our features are appropriate. In the end, we can attempt to predict the S&P 500 along with other stocks and see if it follows a similar trend.

Methodology

Data Preprocessing

During the preprocessing stage I began by pulling data for the S&P 500, and used it as a benchmark for finding null values in other stocks. The following steps were taken:

1. Decide on a historical date range to explore. The dates July 7th, 2015 – July 7th, 2017 were used in the analysis process.
2. Gather data on the S&P 500 based on the chosen dates.
3. Gather data on 4 other stocks based on the chosen dates. GOOG, NVDA, AAPL, and IBM were used during this phase.
4. Drop all data values except for the Adjusted Close values.
5. Drop all dates in all chosen stocks where the S&P 500 is null. These represent dates the stock market was closed.
6. Locate null values in the other stocks and fill in values forward. This means taking the last known value that was not-null, and filling that value forward until you reach the next non-null value.
7. Locate any more null values in the other stocks and fill backwards. If a particular stock has null values at the start of the date range, find the first non-null value and use that value to fill back to the start of the date range.

At this point the data is ready to be explored. There is no need to search for outliers, as all historical data values represent the nature of the stocks.

Now that the data has been pre-processed the next step is to calculate the desired features from the Adjusted Close values. The technical indicators chosen for the purposes of this project were the stocks Momentum, the Bollinger Band values, and Simple Moving Average values. These indicators were talked about more thoroughly in the Data Exploration section.

The features are not on the same scale and so they were scaled using Scikit Learn's Standard Scalar. This was required for the Linear Regression model and the KNN Regressor model.

Implementation

Once the data was fully processed and features were evaluated I decided to run the data through 3 different models to determine which gave the best results. The algorithms chosen were a simple Linear Regression, A KNN Regressor, and a Random Forest Regressor.

To begin I ran the data and the models through the Scikit Learn Pipeline. A pipeline is a chaining of estimators applying a fixed sequence of steps. It was used to first scale the features before running the code through the model. This was used for the Linear Regression as well as the KNN Regressor. There was no need to use it for the Random Forest as that particular regressor does not benefit from scaling of data.

A common procedure in training a model is cross-validation (CV) with K-folds being one of the more common CV techniques. In K-folds you split the data into k smaller sets, then use k – 1 folds as training data, validate on the remaining data, and then repeat until all the folds have been used for training and testing. However, this technique does not work in situations where the order of the data is important such as a time series. In order to achieve similar effects, a

technique known as a Time Series Split was used. In each split of a Time Series Split CV, the test indices are higher than the previous split preserving order while still maximizing the data used for training and testing.

The CV was set to N splits, and therefore the data was put through N sets of training and testing for each algorithm. The R^2 scores for each split was collected and an overall mean score was calculated as the metrics value. The score was calculated for the training sets as well as the testing sets to determine if there was any overfitting.

During the final split, where the training set was the largest, the predicted values and actual values were plotted on a scatter plot and fit with a linear line as a visual metric.

Once the final model was decided upon, the final application was built using the Python web development micro framework Flask for the server side code, Angular JS to handle the front-end code presentation, and D3.js for data visualization. During each load of the application, a user selects up to 4 stock symbols to explore, then each stock is trained on the model, and the user is presented with the predictions and analysis of each stock.

Refinement

After the first few runs of training the models the results were not as expected. The KNN Regressor and the Random Forest Regressor performed very poorly. The Linear Regression model, however, had pleasing results. I decided to move forward with the Linear Regression model and see if it could be improved upon.

Overall the scores of the Linear Regression were considered acceptable compared to the metrics, so refinement strategies were minimal.

A few areas that were tweaked to increase performance did not relate directly to the model itself, but how the data was processed, and the calculation of the features. Multiple date ranges were tested to see what was the least amount of data needed to increase speed and still obtain good metric scores. Ultimately, I settled on *2 years of data to be analyzed during the model training.

**Note: There was an error in my initial reporting. I suggested 1 year was satisfactory, but as the results below show 2 years did significantly better, and 2 years was utilized in the web application. The documentation has been updated to address this.*

Linear Regression Scores from Date Range Trials		
2017-01-14 – 2017-07-14	2016-07-14 – 2017-07-14	2015-07-14 – 2017-07-14
0.28	0.87	0.93

To calculate the features, it was required to use what is referred to in the documentation and project code as a window size. What this represents is how many previous days were used to calculate a particular days Momentum, Bollinger Bands, and SMA values. The window size was adjusted to see if it had an effect on the final results, and the values 10, 20, and 30 were tested. The final chosen window size was 10 days.

Linear Regression Scores from Window Size Trials		
Window Size of 10	Window Size of 20	Window Size of 30
0.93	0.92	0.90

Results

Model Evaluation and Validation

The original intent was to use an Ensemble model that took the average of multiple models. However, after the initial testing it was decided to use only use the Linear Regression for the final model. The contents of the following table are the training and testing mean scores for each model.

	Training Mean Score for SPY	Testing Mean Score for SPY
KNN Regressor	1	-1.95
Linear Regression	0.92	0.93
Random Forest Regressor	0.9	-1.6

The values in the previous table illustrate that the KNN Regressor and the Random Forest Regressor generalized very poorly to unseen data. The values for the Linear Regression suggest it did well in generalizing to unseen data, and had scores that satisfy the solution.

The parameters used for the KNN Regressor model were as follows:

1. n_neighbors: value of 5, the number of nearest neighbors to utilize
2. weights: value of distance, the closer the neighbor the more influence it has
3. algorithm: value of 'auto', the regressor attempts to decide the most appropriate
4. leaf_size: default of 30
5. p: default of 2
6. metric: default of "minkowski"
7. metric_params: none
8. n_jobs: default of 1

The parameters of the Linear Regression model were as follows:

1. fit_intercept: default value of True
2. normalize: default value of False, this was handled by the Scaler
3. copy_X: default value of True
4. n_jobs: default value of 1

The parameters of the Random Forest Regressor model were as follows:

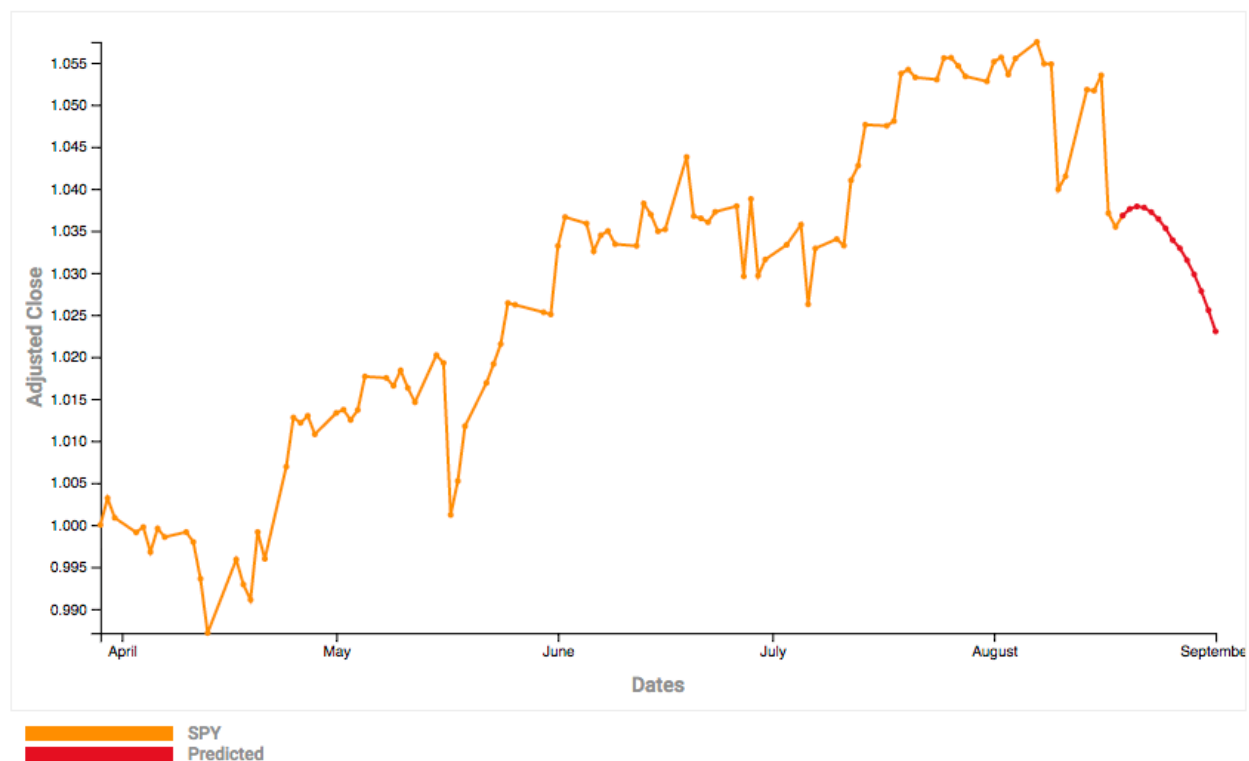
1. n_estimators: value of 5
2. criterion: default of "mse"

3. max_features: default value of auto
4. max_depth: None
5. min_samples_leaf: default value of 1
6. min_weight_fraction_leaf: default value of 0
7. max_leaf_nodes: None
8. min_impurity_decrease: default value of 0
9. bootstrap: default value of 1
10. oob_score: Default value of False
11. n_jobs: default value of 1
12. random_state: none
13. verbose: default of 0
14. warm_start default value of False

Each model was tested against the four other sets of stock data and similar results were obtained.

As anticipated due to the problem domain, the further out the predictions are made the worse the model does. There is also a tapering effect of further out predictions that cause a distinct visual pattern (**Fig. 3**). I believe this pattern is evidence that predicting the stock market more than a few days out is unreliable. However, I do believe the model can be trusted if approached appropriately. Predicting exact values is highly unlikely, but can give insight as to how the stock may behave a few days into the future.

Fig. 3 Normalized Adjusted Closing Values of SPY



Justification

To visualize the final model's solution against the benchmark, I compared the model with the stock prices of eBay. I chose eBay specifically because the benchmark forecasting tool found at Stock-Forecasting.com does not offer a wide range of available stocks but both models have eBay as an option, and eBay was at the time unseen data to the final model. The values in **Fig. 4** are the predicted values reported by Stock-Forecasting.com, with a next day closing value of 34.88 and a reported accuracy of 99.12%. The reported values from the final model has the next day adjusted closing value at 34.82 (**Fig. 5**) and a reported accuracy of 92.07% (**Fig. 6**) for the testing set. The 92.07% is the R^2 metrics outlined earlier in the "Metrics" portion of the report. The R^2 was obtained by splitting the data into 3 Time Series Splits (cross-validation technique for time series data), calculating the R^2 for each split, then taking the average of all 3. The R^2 was calculated for the testing and training sets to ensure the model was not overfitting.

A few differences are Stock-Forecasting.com lists the action as a "Buy" strategy and my results list the action as "None". The difference here is most likely explained by a difference in how the action is calculated. Stock-Forecasting.com does not mention the exact mathematical calculations involved in their predictions. Stock-Forecasting.com also does not outline their accuracy methods.

The second part of my benchmark strategy was to compare the eBay stock to the S&P 500. All along the way the eBay data was processed utilizing the trading dates from the S&P 500 ensuring no erroneous values were added in skewing results. As you can also see in **Fig. 7** and **Fig. 8** the prediction trend over the 14 predicted days is similar. While this does not suggest the predicted prices are correct it is another reassurance that nothing went askew in the processing and prediction steps. Ultimately, I consider the final model to be significant enough to be a success.

Fig. 4 – Stock-Forecasting.com Predictions

Predicted Data. EBAY - Next Business Day

Date	Open	Close	Low	High	Vector**	Strategy***
Aug 21, 2017	35.12	34.88	34.75	35.23	▲ +0.20%	Buy
Accuracy, %*	98.95	99.12	99.00	98.93		

Fig. 5 – Model Predictions for eBay and Spy




	18-08-2017 1 Day Out	25-08-2017 7 Days Out	31-08-2017 14 Days Out
Prediction Confidence			
SPY	\$243.03 Action: None	\$242.34 Action: None	\$239.79 Action: None
EBAY	\$34.82 Action: None	\$34.56 Action: None	\$34.25 Action: None

Fig. 6 – Model Metric Scores for eBay and SPY

	Training Score Mean	Testing Score Mean
SPY	%95.07	%95.33
EBAY	%95.14	%92.07

Fig. 7 – SPY Adjusted Close and Bollinger Band Visualizations

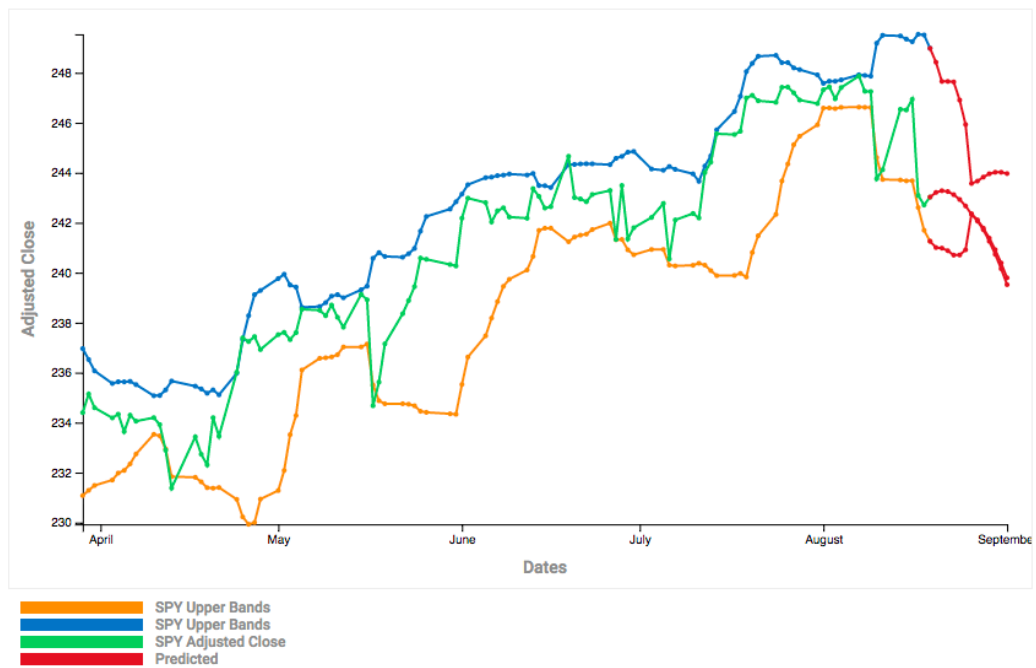
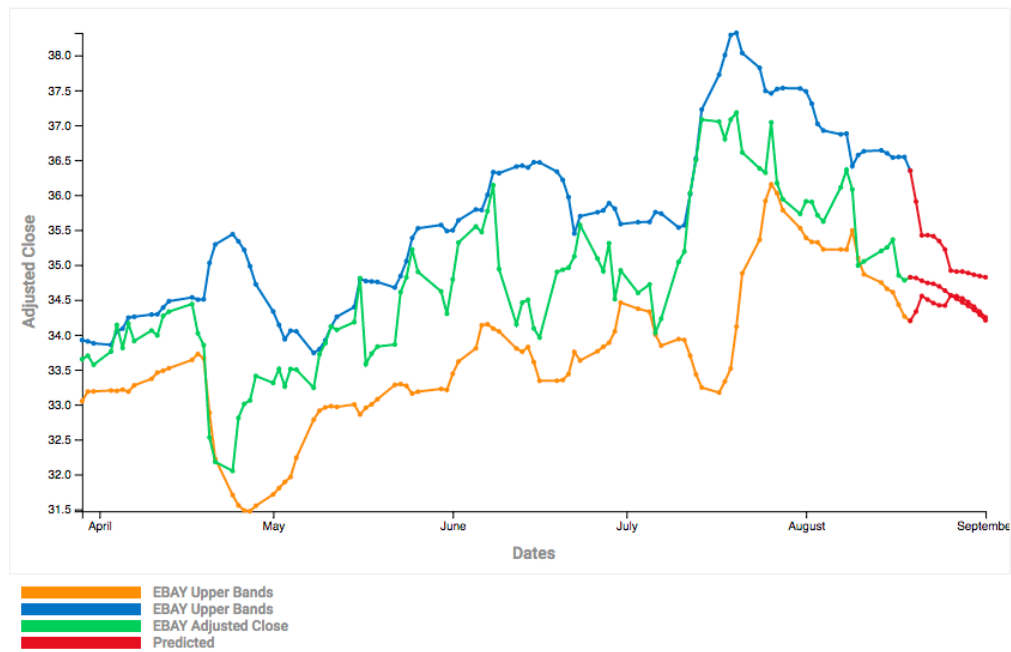


Fig. 8 – eBay Adjusted Close and Bollinger Band Visualizations

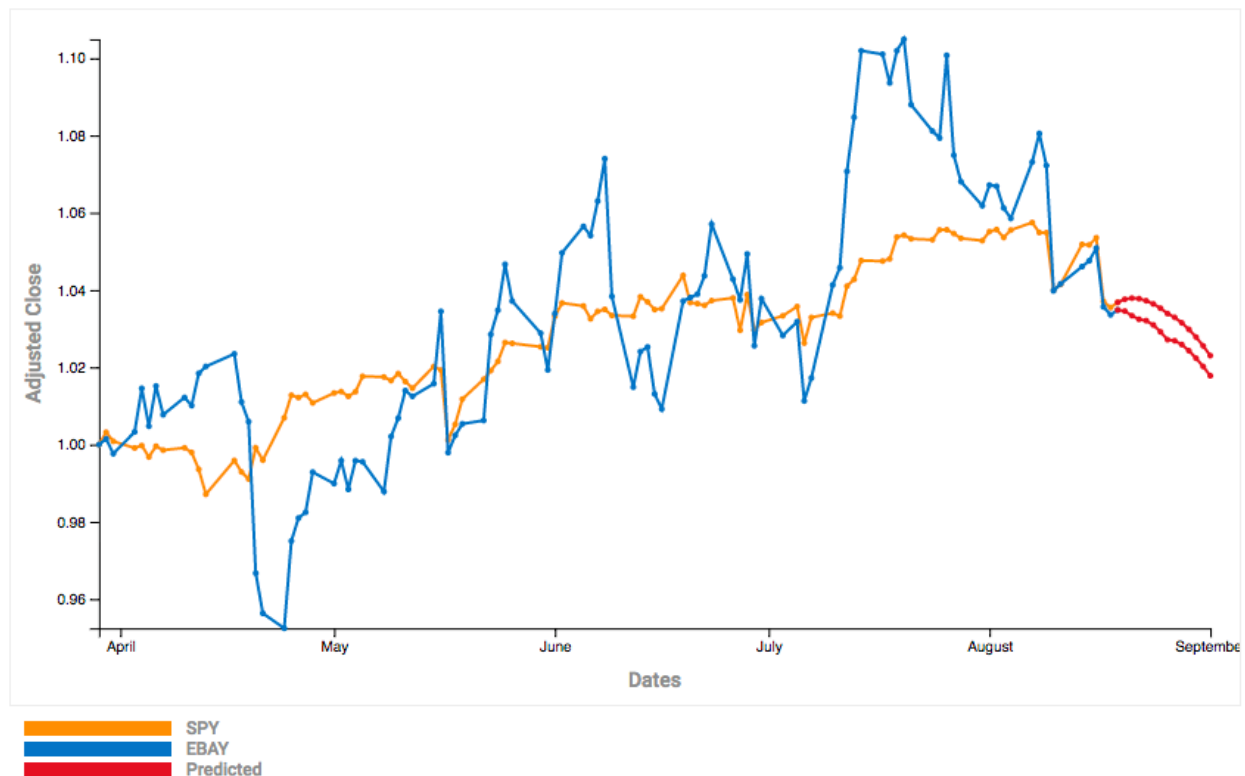


Conclusion

Free-Form Visualization

One interesting quality about the problem domain of the project is how dependent a stock prediction is on previous historical dates and values. Given its continuous nature one can reason why predicting the future of a stock over long periods of time purely from technical analysis is a futile task. In my model that surmounts to only a few days. A stocks motion (rise or fall in value) is only evident in comparison to a defined amount of dates prior. This concept is illustrated by the trend noticed in the predicted values. In the final model, the further out the prediction dates are the prediction values start to see a steady decline. This can be seen in **Fig. 9**.

Fig. 9 – Normalized Adjusted Close of SPY and EBAY



Reflection

The final steps in conducting the project where:

1. Define a problem statement
2. Define a metric to score the final solutions accuracy
3. Define a benchmark to evaluate the final solution
4. Locate and process the required data
5. Analyze the data and determine the appropriate features
6. Determine the best model appropriate to the data and the features
7. Train and test the model with the processed data and features
8. Analyze the results
9. Adjust the model if necessary
10. Extend the final solution to a web application that can generalize unseen data from a set of user chosen stocks.

One of the most interesting and troubling portions of the project for me was the nature of the features. Features for a particular day were concocted entirely from the previous days target values. This was a new use case for me and took some time for me to fully understand the idea.

The hardest aspect of the project was understanding the domain. Since features did not come with the data set one could not learn about the domain from the features and the values

themselves. It required understanding the nature of the Stock Market, and that took a lot of research and time.

Ultimately, the final model and solution fits my expectations for the problem. The solution should not be used to make stock predictions on its own, and it was not intended to. It should be considered another tool in a kit to analyze stocks before making a final trading decision.

Improvement

To achieve stronger results future iterations of the solution should consider more features to be utilized. Given my weak understanding of the domain when I began the problem the selected features were what I was able to gather. If I improve on the project in the future I would certainly do more research into the domain.

Ideally more models should also be considered. The chosen model works as intended but could possibly be enhanced by more modern techniques or an ensemble of techniques. I have read of successful results obtained from Neural Net Classifiers and would consider looking more into one as a solution.

The final web application can also be improved upon in terms of efficiency. I would improve the backend code to speed up stock evaluations, improve the D3.js implementations, and properly package and minify the front-end code for production.

The final improvement that should be made is to ensure the predicted days are actual trading days. The predictions given were just “days out”, and did not take this into consideration.

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