Investment and Trading Capstone Project | Ricardo Cortez

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PROJECT OVERVIEW

Predicting future stock prices based on the analysis of past data have been widely used for several decades. Predicting future values, in this sense, is about understanding the underlying behavior of the data, the interrelation among input features and their individual contributions to the target data. The ability to extract information from past data becomes a challenge in which the developer must answer several questions such as: in what space is the data better represented? How many features should be used? How far back should data be analyze? What algorithms are available for this sort of problem?

There are several articles in the literature covering prediction of stock market prices. Methods go from classical regression methods, filtering, pattern findings, Bollinger bands, to artificial intelligence, and supervised machine learning methods. In this project, the supervised method Support Vector Regressor, is used to make recommendations of future prices. In order to make the predictions, it makes use of historical data exported from Yahoo Finance API. This historical data is used to train the predictor model as well as well as to analyze the performance of the model.

Problem Statement

In a world were internet allows to get instant stock quotes and recommendations from several sources, it becomes overwhelming the amount of information that a person needs to filter based on his personal financial interests. In a similar way, many times the information provided is biased or subject to other information that is not always transparent. Even if the source can be trusted and the predictions accurate, some questions remains: How many shares of this company should I buy? And what would be the expected overall return?

The project provides a solution for both of these problems: a prediction for tomorrow's prices for the stocks based historical prices and the weight distribution of the portfolio, thus indicating the budget allocation for each asset. The following steps summarize the strategy of the program:

- Read portfolio (stock symbols) from input user
- Search for historical data in the data project folder, if the data is not available then download it from Yahoo Finance API
- Use mean-variance analysis to estimate and provide the optimal weights for each asset. The Sharpe ratio provides a measure of the portfolio performance
- Use the supervised learning method Support Vector Regressor to fit our model and generate a predictor model that predict the next day Adj. Close prices.
- Apply the model to predict tomorrow's Adj. Close price. Based on this results provide a recommendation on whether the investor should 'Buy', or 'Sell', for each of the stocks in the portfolio.

METRICS

In this project we use a regression method, Support Vector Regressor, to predict the future prices of a stock. The coefficient of determination (r-square) is used to measure the performance of the model. R-square provides a measure of how well the model is predicting future outcomes. A good model will produce r-square values closer to 1 and very poor performances will produce negative values. In this project, r-square is used during the cross-validation and backtesting stage. During the cross-validation stage, it is passed as an input parameter for the model fitting during the exhaustive parameter search (Sklearn GridSearchCV). It is used to measure performance of a model as it goes through models with different parameters. During the backtesting part, it is used to measure the performance of the predicted prices for different supervised learning methods.

The predicted error is defined as the average percentage of the predicted value that falls within the actual value (see Equation 1). This metric is used to analyze how close the predicted values are from the actual prices, in average.

$$P_e = 100 * np.mean\left(\frac{target - predicted}{target}\right)$$

Another useful metric is the Sharpe ratio, this metric is used to calculate the performance of the portfolio (risk-adjusted return). By definition the Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility. For simplicity, the risk-free rate is considered to be zero. The Sharpe ratio, calculated as:

$$Sharpe\ Ratio = \frac{\mu_p - r_f}{\sigma_p} = \frac{\mu_p}{\sigma_p}$$

$$\mu_p\!: Average\ portfolio\ return$$

$$r_f\!: risk - free\ return$$

$$\sigma_p\!: standard\ deviation$$

ANALYSIS

Data Exploration

The historical data is exported from the web using Yahoo Finance API. The data is saved in the /data/ folder within the project using the ticker symbol as the filename (e.g. AMZN.csv for Amazon). Files are saved in csv format. These files contain the fields: High, Low, Volume, Close, Adjusted Close indexed by date. Adjusted Close Price is the feature considered for the analysis and it is preferred against Close Price because its price includes any distributions and corporate actions that incurred at any time prior to the next day's open.

SYMBOL	Mean	Median	Min	Max	Std. Dev	Kurtosis daily ret.
GOOG	492.6	518.34	237.2	813.11	166.98	14.45
AMZN	371.07	310.04	160.97	844.36	184.3	8.48
IBM	160.26	161.36	114.68	193.6	15.88	5.52
AAPL	82.26	79.11	41.03	128.52	24.93	5.16
NFLX	54.4	48.09	7.69	130.93	35.39	26.89

Table 1 Data statistics. Period 2011-2016

Table 1 shows the statistics of stock market data for the companies: Google, Amazon, IBM, Apple, and Netflix. Google and Amazon share prices are considerably higher than the others while Netflix price per share are the lowest. Netflix price per share at some point traded at $7.69. Market volatility is determined by their standard deviation, in this case, we can say that during 2011 through 2016 Amazon was the more volatile company.

It often occurs that some data points are not available for the selected dates. This can be caused by connectivity problems with the API, or the ticker symbol has changed, other reasons could be that data was not available because the stock did not trade on those dates. Since gaps in the data could lead to distorted or biased results; the program will first load the data into a pandas DataFrame and then it will verify the existence of all data points for the specified range. If a symbol contains dates with missing data, it will be eliminated from the DataFrame and thus, from the analysis. In this way, although some stocks might not be available for analysis and prediction, the underlying characteristics from point to point remain the same from stock to stock. Eliminating stocks with missing points allows us to make better statistical inferences such as the mean and variance, which will be of great importance during the portfolio analysis and computation of Sharpe ratios. The latter is used to measure the performance of a portfolio given its return and standard deviation.

Exploratory Visualization

The portfolio used for analysis of the predictor algorithm consists in 5 stocks: Google (GOOG), Apple (AAPL), IBM (IBM), Netflix (NFLX), and Amazon (AMZN). Figure 1 shows the prices, during the testing period, for all 5 stocks and the benchmark. During this period, AMZN and GOOG prices are much higher than the others, and also more volatile (higher standard deviation) as it can be verified from Table 1.

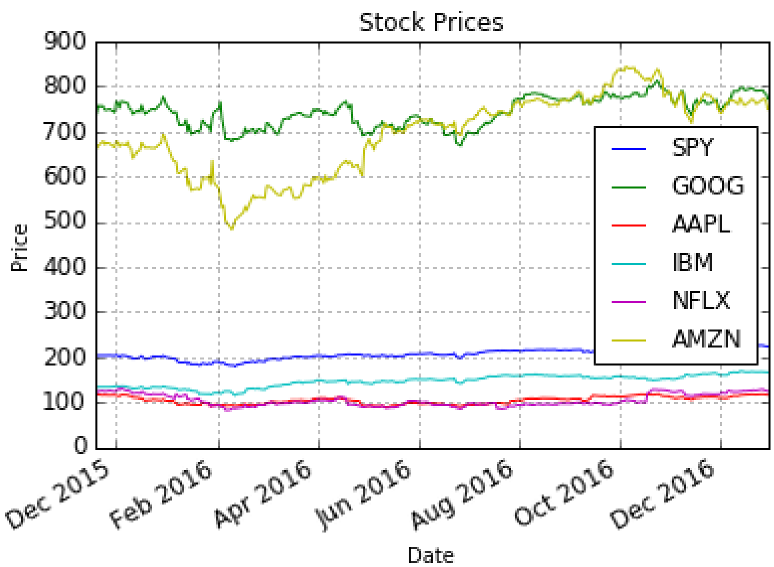
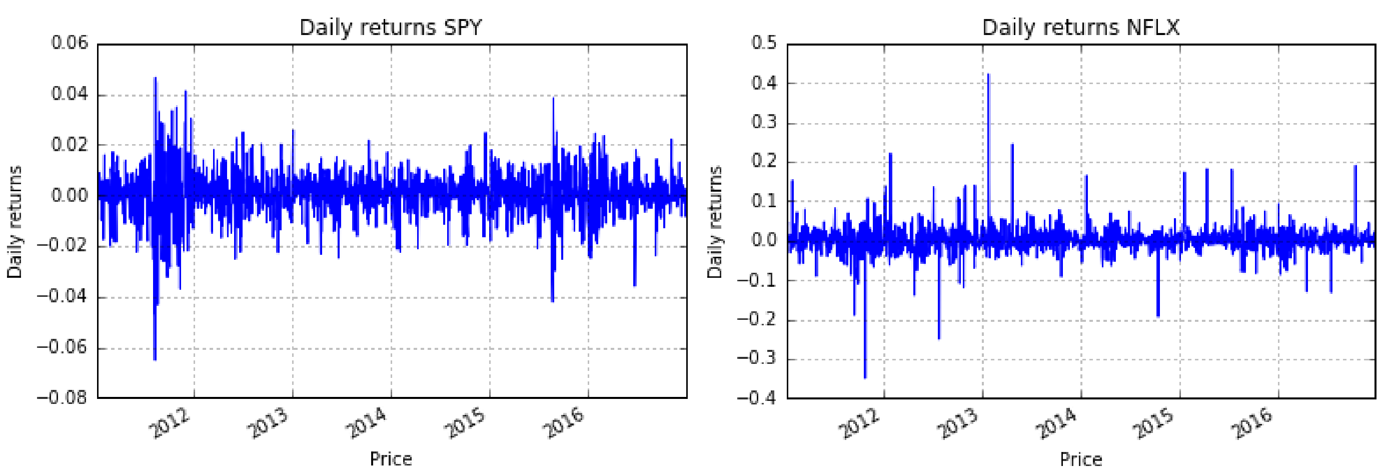


Figure 1. Stock prices for 5 portfolio companies and the benchmark SPY (S&P 500)



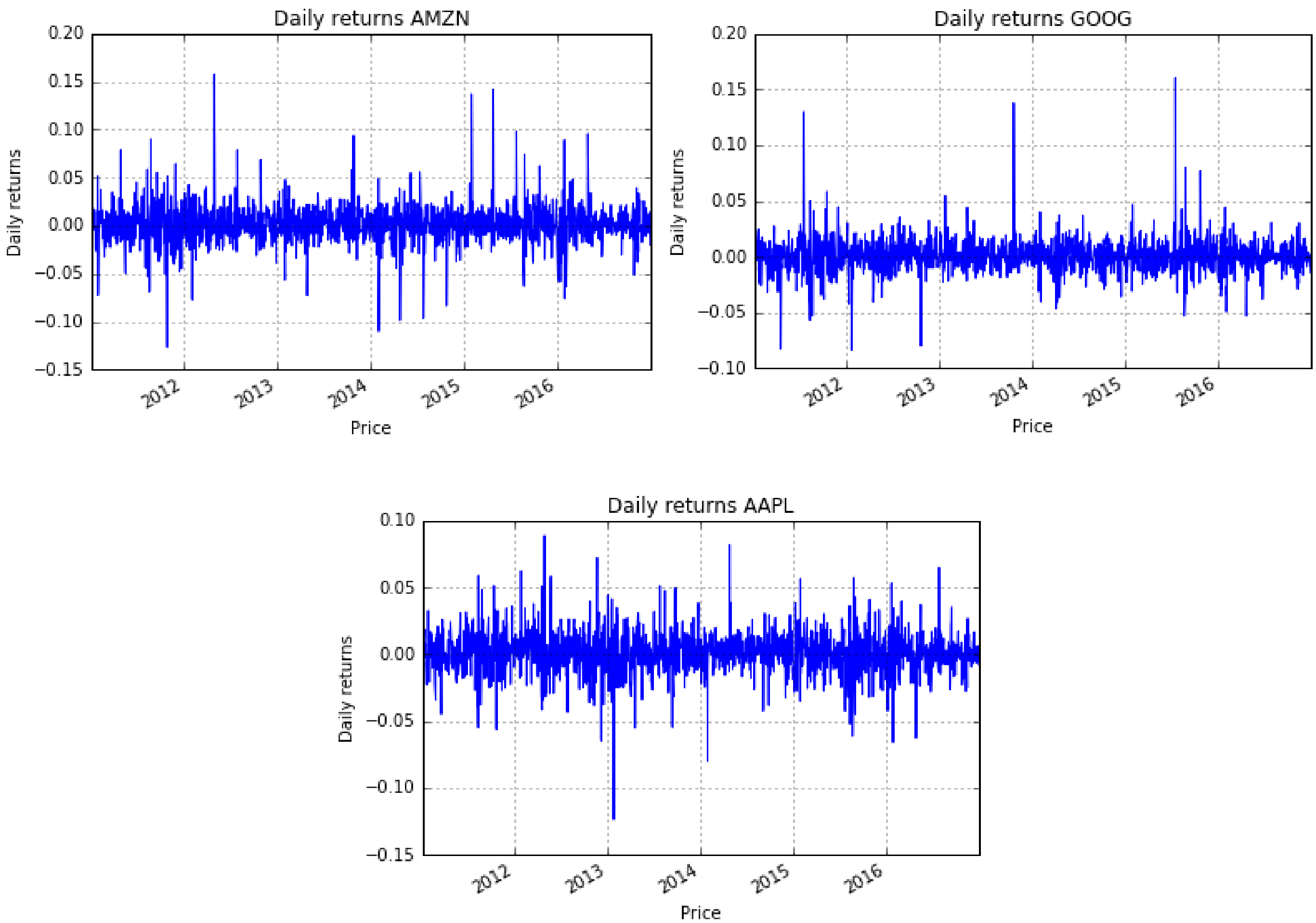


Figure 2. Daily returns for portfolio stocks and companies.

Figure 2. Shows daily returns for the companies and the benchmark. By simple observation they seem to be normally distributed but the Kurtosis measure from Table 1 indicates that they are not completely normal. Kurtosis is a measure of whether the daily returns are heavy-tailed or light-tailed relative to a normal distribution. Table 1 provides the Kurtosis for the daily returns, positive Kurtosis indicated heavy tails. The mean-variance analysis is based on the assumption that daily returns can be modeled as normal distribution. For the purposes of this project, we assume that the daily returns are close enough to be considered normally distributed.

Algorithms and Techniques

The executable program sets most of the variables to their default values but it allows some flexibility for the user. There are some default parameters that can be easily adjusted such as the test size and the number of prior closing prices days (features). See Table 1 for default parameters.

Parameter	Default Value
Starting Training Date	1/1/2011
Ending Training Date	1/1/2017
Number of Prior Adjusted Closing Dates (features)	100
Test size	80%
KFold (used in Cross-Validation)	10
Predict stock value X-days out	1 day (tomorrow's price)

Table 2. Default Parameters

Algorithm (see Figure 3):

1. Program reads and loads file from /data/ directory into a pandas DataFrame. If file does not exist, program downloads stock prices from Yahoo Finance API
2. Delete stocks with missing data from DataFrame
3. For each stock do:
   A. Generate a DataFrame with X prior adjusted closing prices for each of the dates. See Table 2.
   B. Split the DataFrame into training and testing sets (80% for training)
   C. Generate Cross-Validation indexing sets
   D. Apply Support Vector regressor to training data using GridSearchCV with r-square as performance metric
   E. Obtain a regressor model from GridSearchCV.best_estimator_
   F. Backtest regressor model against testing set
4. Display results and recommendations for future day

The program uses the python command line user interface. When the program is executed, the user will be prompt to choose to either load a file with symbols or enter symbols directly in the command line interface. The program can take standard text files (.txt) with comma separated symbols or pickle files containing a list of symbols. Stock symbols entered directly through the command line must to be comma separated (e.g. >>> GOOG, IBM, RTN).

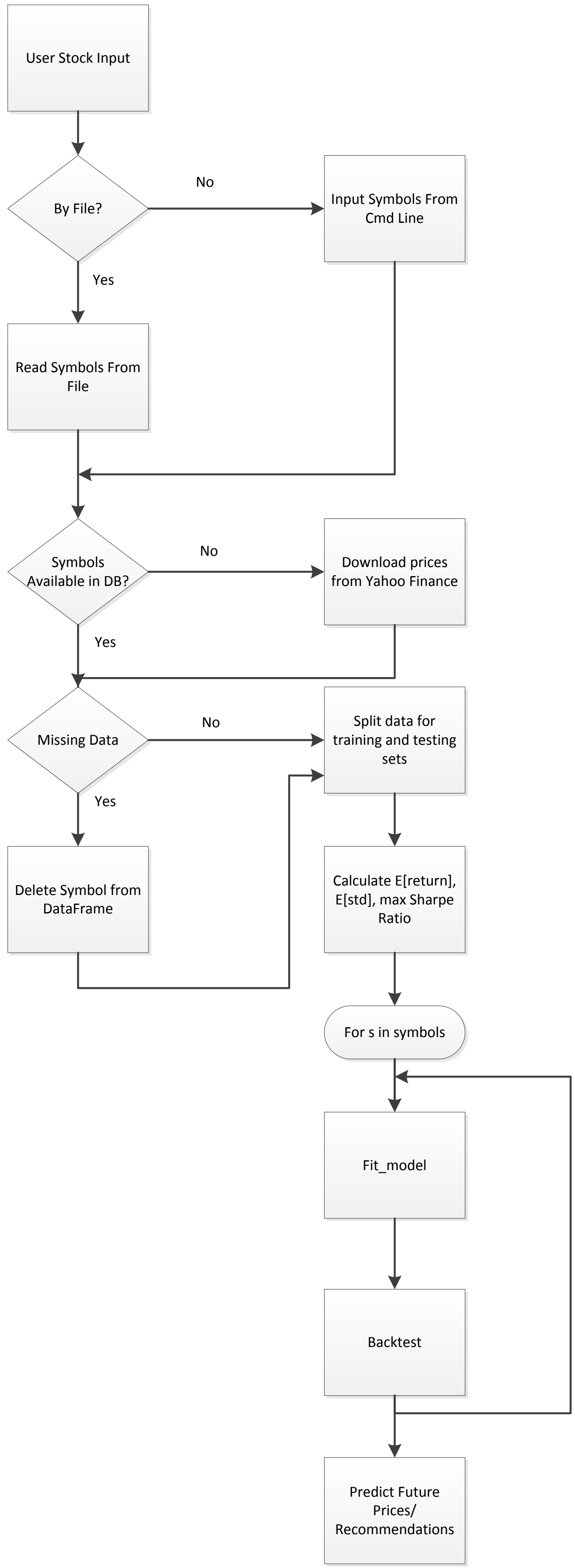


Figure 3. Algorithm flow diagram

BENCHMARK

The ETF fund SPY is an index tracker that follows the S&P 500 Index. For the purpose of this project, the SPY will be used as a benchmark to analyze the performance of the portfolio. The performance of SPY during the test period will be used as a benchmark against the performance of the predictions over the same period of time. The S&P 500 is widely used as a benchmark by financial analysts, it is an American stock market index based on 500 large companies listed on NYSE or NASDAQ.

METHODOLOGY

Data Preprocessing

During the user interface and data reading, the load_symbols function is used for reading symbols in either .txt or .pickle extension. A .txt file must contain comma separated stock symbols. A pickle must contain a python list of comma separated symbols (e.g. [‘AAPL’, ‘IBM’, ‘BK’, …]

The data exported from Yahoo Finance API provides 7 fields for each stock: Date, Open, High, Low, Close, Volume and Adj.Close. where Date is the date when the stock traded, Open is the opening price for that day, High and Low are the highest and lowest price the stock traded, Close is the price at the end of the day, Volume is the number of share transaction on that given day, and Adj. Close is a stock closing price after any distribution and corporate action have been factored in.

Once exported, the data is saved in the /data/ directory as a XXX.csv file for future queries, where XXX represents the 3 or 4 stock ticker symbol. Once in a .csv file, the Date and Adj. Close fields is loaded into a DataFrame. The ‘Adj Close’ label is then renamed with the stock ticker symbol. The generated DataFrame contains as indexes the dates and as columns the Adj. Close for each of the symbols. Next, a new DataFrame is created, for each symbol. This DataFrame will contain in each row the Adj. Close price for N consecutive days. The first N-1 columns are the features corresponding to the N-1 prior Adjusted Close prices. The N-th column is the target, corresponding to the Adjusted Close price for the date specified by its index. See Table 3 for details. .

DATES	Adj Cls - 100	Adj Cls - 99	Adj Cls - 98		Adj Cls		Adj Cls + 1
start date							
start date + 1							
start date + 2							
⋮	⋮	⋮	⋮		⋮		⋮
end date - 3							
end date - 2							
end date - 1							
end date							
	FEATURES						TARGET

Table 3. DataFrame containing features and target data. Feature

The split in training and testing sets occurs after a DataFrame containing N prior days is generated. Default parameters are 80/20 for training and testing respectively. No random shuffle is applied since it is important to keep the day-to-day correlation of the stock prices. In order to obtain the best parameters from a set of values the sklearn.model_selection.GridSearchCV is used during model fitting. Sub-sets for parameter validation are created within the training set. Generating these sets allow the parameter estimator to validate the model performance over multiple sets during GridSearchCV. The default number of subsets is set to 10. The generation of this subsets is similar to the KFold validation technique from sklearn. It provides K-Fold-like index sets to GridSearchCV using python generator, but in order to keep the linearity each set is generated with continuous dates (unshuffled). These sets are generated in the get_partition function. The get_partition function yields a set of indexes each time it is called (each set differs from the prior set by an offset). See Figure 4.

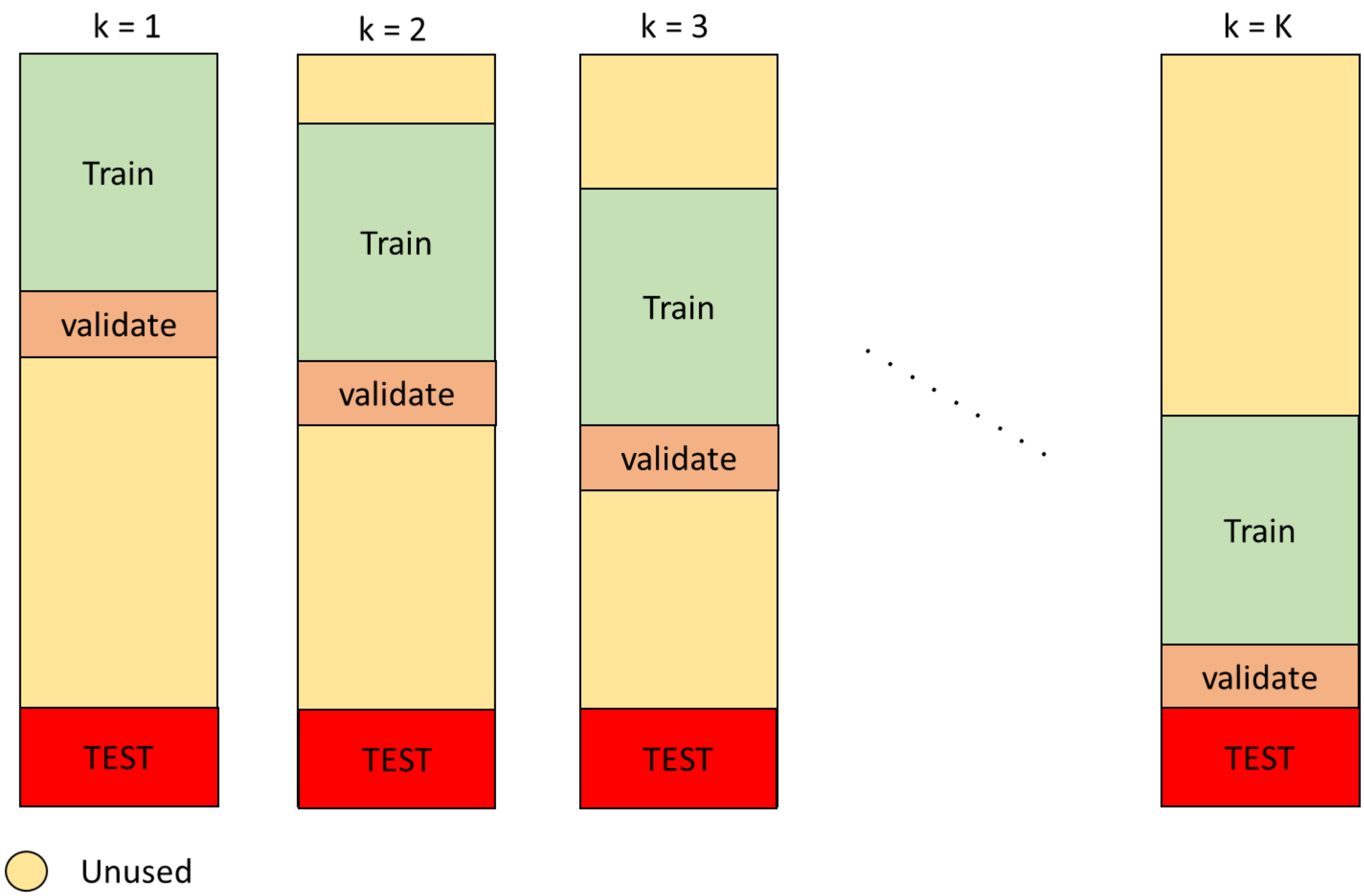


Figure 4. Train and test partition. Validate sets are for validation of parameters during GridSearchCV

IMPLEMENTATION

Mean-Variance Analysis

The project uses mean-variance analysis, which is a component of modern portfolio theory (MPT) created by Harry Markowitz (1952). A mean-variance analysis is the process of weighting the risk (variance) against the expected return in a portfolio. Thus, weighting the contribution (weights) of the assets in the portfolio. This approach assumes the investor is only interested in long positions (does not provide analysis for portfolios with short positions), thus the entire investment is to be divided among the portfolio stocks and the positions add up to 100%. Modern portfolio theory assumes that the asset returns are normally distributed, in reality asset returns are said to be heavy tailed distributed or to have positive Kurtosis.

The expected portfolio return is calculated as:

$$\mu_p = E\left(\sum_I w_i r_i\right), I = 0,1,2,\dots.,s-1\ assets$$

$$\mu_p = \sum_I w_i E(r_i) = \sum_I w_i \mu_i = w^T \mu$$

The expected portfolio risk is calculated as:

$$\sigma_p^2 = w^T \Sigma w, \quad \Sigma\text{: covariance matrix}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1I} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2I} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{I1} & \sigma_{I2} & \cdots & \sigma_I^2 \end{bmatrix}$$

The Sharpe ratio is used to measure the portfolio performance by calculating the Risk-adjusted return. The Sharpe ratio is defined as the average return earned in excess of the risk-free return divided by the volatility or total risk. By allocating weights to the portfolio assets, the expected portfolio returns and standard deviations become variables in a maximization problem. Maximizing the Sharpe ratio in this sense becomes an optimization problem. There are available python libraries for optimization problems. In this project we use the library scipy.optimize to find the optimal weight for each asset in the portfolio.

$$\Theta = {}_{max}(SharpeRatio)$$

Under the constraints: $\{ \sum_i w_i = 1; 0 < w_i < 1, \vee\, i \}$

Support Vector Regressor:

The continuous price fluctuations where there is an infinite range of price possibilities indicates a regression problem (as opposed to a classification problem). In this project, three supervised regression methods were tested: DecisionTreeRegressor, AdaBoostRegressor, and Suppor Vector Regressor (SVR). During the model fitting, for the case of SVR, an exhaustive search was performed over the parameter values for C, Gamma and the kernel function. The SVR model also takes other input parameters such as the scoring function, and cross-validation sets. The scoring_function wraps the r-quare function and it is used to evaluate the model performance through each parameter iteration. It is also important to note that the algorithm generates a model for each stock symbol and saves it to a dictionary for future queries

After the model is fit, the program proceeds to backtesting using the test set to test the model. At this point, predictions are made for each asset during the testing period. Based on this next-day predictions a ‘Buy’ signal (signal = 1) is generated when the predictor ‘predicts’ a higher price the next day. Similarly, a ‘Sell’ signal is generated when a lower than the current price is predicted. The asset return, over the testing period, is calculated by dividing the sum of all the positive and negative profits by the price at the beginning of the period.

$$Ret(a_i) = \frac{\sum_S profit_{a_i}}{a_0}$$

Where: a_o is the price at the start of the period, s is the number of securities in the portfolio

The process of model selection takes into account 2 metric: r-square and prediction error. Considering both metrics over one of them was preferred because, in many cases, even though the prediction error was low, the model performed poorly.

Refinement

During the process improvement, one of the biggest challenges was to find a regressor model that meets the performance requirements. The methods analyzed were Decision Tree Regressor (DTR), AdaBoost and Support Vector Regressor. The three model were tuned from a range of input parameters using GridSearchCV.

DTR dictionary of parameters considered:

- ‘max_depth’: [2, 3, 4, 5, 7, 8, 20]
- ‘min_samples_split’: [2, 8, 16, 32]

AdaBoost dictionary of parameters considererd:

- n_estimator : [50, 200, 500]

Support Vecto Regressor dictionary of parameters considered:

- $'C'$: $[1exp^{-6}, 1exp^{-3}, 1, 10]$
- ‘gamma’ : [$1exp^{-6}$, 1exp^{-4} ,$1exp^{-3}, 1, 10$]
- ‘kernel’ : [‘rbf’, ‘linear’, ‘poly’]

Table 4 shows the 3 models r-square and average predicted percentage error. The test was performed over the information technology sector of the S&P 500 index in which 61 technology companies are trading. The r-square coefficient for SVR was significantly larger than the other 2 models. Also, the predicted percentage error,P_e, for SVR was smaller when compared to the other models. During the refinement for the SVR model, the parameter that contribute with the most significant improvement was the kernel function. The model performed poorly, with respect to P_e and r-square, when used with the default kernel (‘rbf’).

The mean-variance analysis literature provides a way of calculating a set of weights for optimal performance of the portfolio. The set of weights is based on historical data, but the length of the period from which to extract the weights was found to have a significant contribution in the overall performance of the portfolio. It was found that short period lengths produced more unbalanced weightings where in some cases the weights were distributed among only 1 or 2 assets. Larger periods such as 6 to 12 months produces more balance weightings. It is important to emphasize that these observation where performed over a small subset of stocks, predominantly in the sector of technology.

RESULTS

Model Evaluation and Validation

For the results, a portfolio of with 5 stocks were analyzed. See Table 4.

Parameter	Input
Companies:	Google, IBM, Apple, Netflix, Amazon
Symbol Tickers:	GOOG, IBM, AAPL, NFLX, AMZN
Training Period:	2011-05-26 to 2015-11-17
Testing Period:	2015-11-18 to 2016-12-30
SVR parameter 'C'	0.001
SVR parameter 'Gamma'	0.0001
SVR parameter 'Kernel'	'Linear'

Table 4. Stocks analyzed and model parameters

As expected DecisionTreeRegressor was the most computation efficient but prediction accuracy was low. AdaBoostRegressor also produced poor results although further analysis is required to maximize the performance of this method. Support Vector Regressor (SVR) produced the best result, it was also computational efficient. Table 5 shows the performance relative to metrics r-quare and P_e for the 3 methods analyzed.

Model	r-square (avg)	Predicted Error (% avg)
Decision Tree Regressor	0.22	1.98
Adaboost Regressor	0.23	2
Support Vector Regressor	0.95	-1.57

Table 5. Methods performance

The results for the portfolio are shown in Table 6 and correspond to the testing period. The first 2 columns represent the amount of profit from 'Buying' and 'Selling' based on predictor recommendations. The next column, 'Asset Return' was calculated by dividing the sum of profits and initial price by the initial price. The following column corresponds to the coefficient of determination and the prediction percentage error (r-square/Pe). Both, r-square and P_e coefficients are calculated during the testing period. The next column, 'Weight', corresponds to the contribution of each asset to the portfolio. Finally, the last column, 'Weighted Return' corresponds to the product of the columns 'Asset Return' and 'Weight'. It is interesting to note that for the companies 'AAPL', 'IBM', and 'NFLX' the weight was zero, therefore their contribution to the portfolio was zero. From the algorithm perspective, it makes sense that 'AAPL' and 'IBM' have zero weight given their negative overall returns. On the other hand, NFLX generated over 48% in returns but weren't considered either. Maximizing the Sharpe ratio is about maximizing the expected return constrained to the expected volatility. Since the weights are calculated during the training period, it is possible that during the training period, NFLX performed poorly compared to Google and Amazon but during the testing period it significantly improved its performance.

Date	Profits ('Buy')	Profits ('Sell')	Asset Return	r-square/Pe(%)	Weight	Weighted return
GOOG	198.441	152	0.473	0.917/-0.19	0.09	0.043
AAPL	-7.473	-12.078	-0.17	0.953/-1.93	0	0
IBM	11.066	-26.016	-0.114	0.98/-0.84	0	0
NFLX	32.62	25.92	0.485	0.947/-0.65	0	0
AMZN	90.17	-16.4	0.111	0.98/-1.42	0.91	0.101

Table 6. Prediction results, Profits and Asset Return are based on the assumption that the investor followed the 'Buy/Sell' recommendations every day during the testing period.

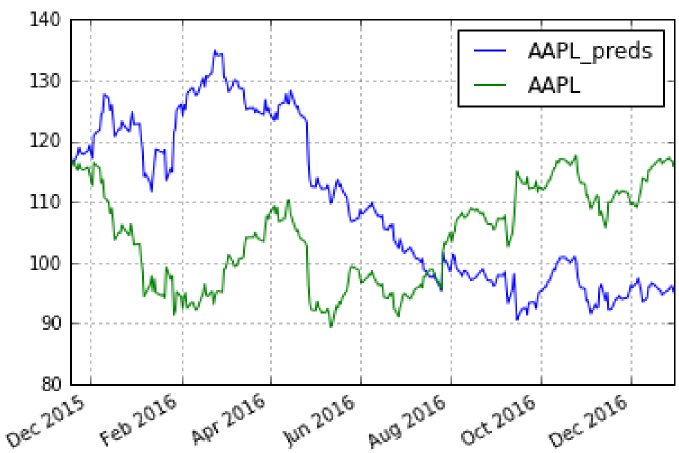
Results	Value
Total Number of Traded days	282
Sharpe Ratio	2.681
Long Position Portfolio Return	12.20%
Portfolio Return	14.39%

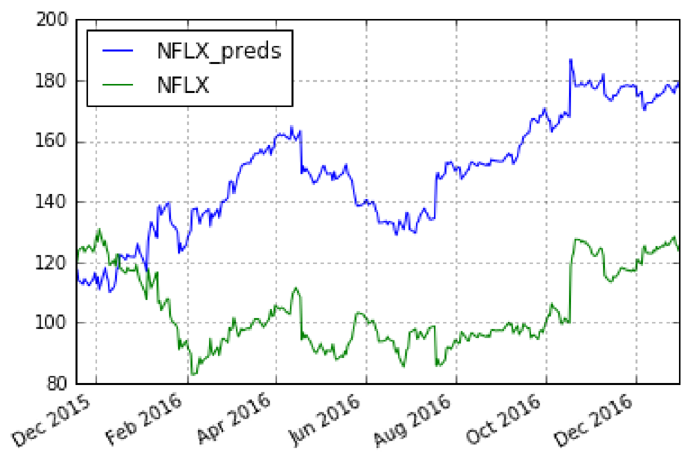
Table 7. Portfolio parameters and return over testing period

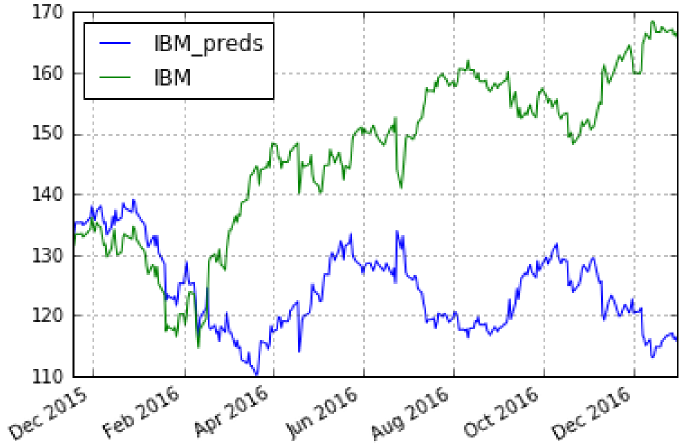
Table 7 shows information relative to the portfolio return. The testing period covered 282 days. The maximum Sharpe ratio for this portfolio is 2.681. It is interesting to note that if we consider the case where all assets were bought on the first day of the testing period and sold only at the of the period (long position), the return was 12.2%. Also, the overall portfolio return using the predictive algorithm is obtained from the sum of the weighted returns. The portfolio return obtained was 14.39% which is considerably lower than returns from GOOG (47.3%) and NLFX (48.5%) but higher than the other ones, thus balancing the ups and downs of the securities by weighting their volatility.

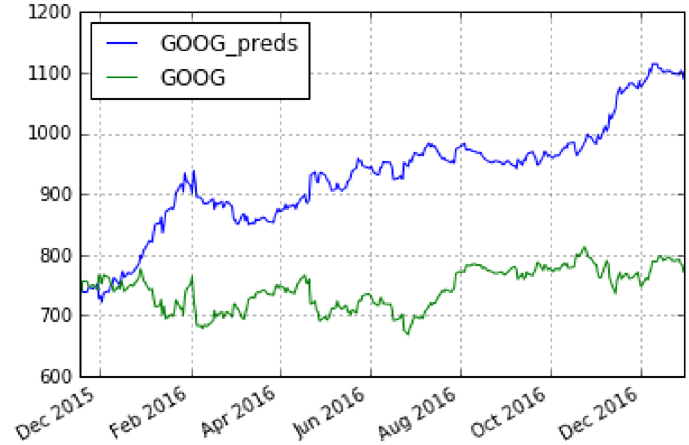
Justification

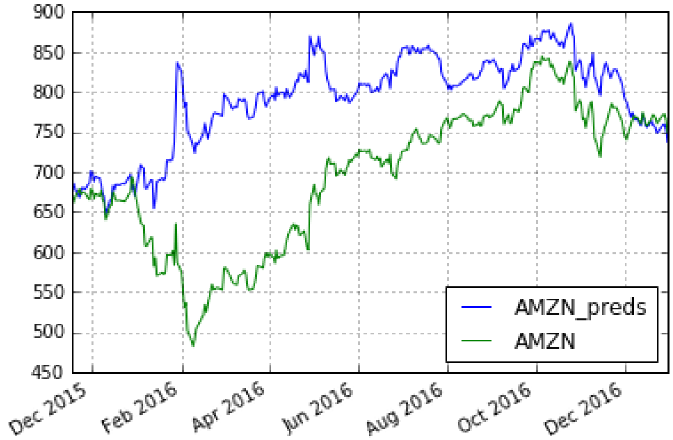
Figure 5 shows 5 plots and the long term position returns (bottom right). The plots compare the performance of the stock predictor relative to the stock they predict. In order to generate a plot for the predictor, a cumulative predicted profit (normalized) was generated based on the assumption that the investor followed the recommendations ('Buy/Sell') during the testing period. A similar approach was used to generate Figure 8.











Long term position	Return (%)
GOOG	4.3
IBM	26.9
NFLX	2.6
AMZN	13
AAPL	0.9

Figure 5 Predicted cumulative prices against actual prices. GOOG_preds and NFLX_preds produced better returns than their corresponding baselines (GOOG, NFLX). AMZN_preds produced positive returns but not significant when compared to its baseline AMZN. AAPL_preds and IBM_pred not only produced negative returns but also underperformed their corresponding baselines. Bottom right displays long term position returns (buy at the beginning and sell at the end of the period)

GOOG_preds produced 47.3% returns compared to the long position performance 4.3%. IBM_preds generated 11.4% in loses, clearly underperforming the long position performance of IBM 26.9%. NFLX_preds generated 48.5% in returns against 2.6%. AMZN_preds and AMZN produced similar returns. AAPL_preds produced negative returns, -17%. The two models that produced negative results: AAPL and IBM have zero weight allocation in the portfolio, along with NFLX. Note from Table 6 that the prediction errors are well within 5%, in average the prediction error is 1.005%, indicating that the predictor is closely following the fluctuations.

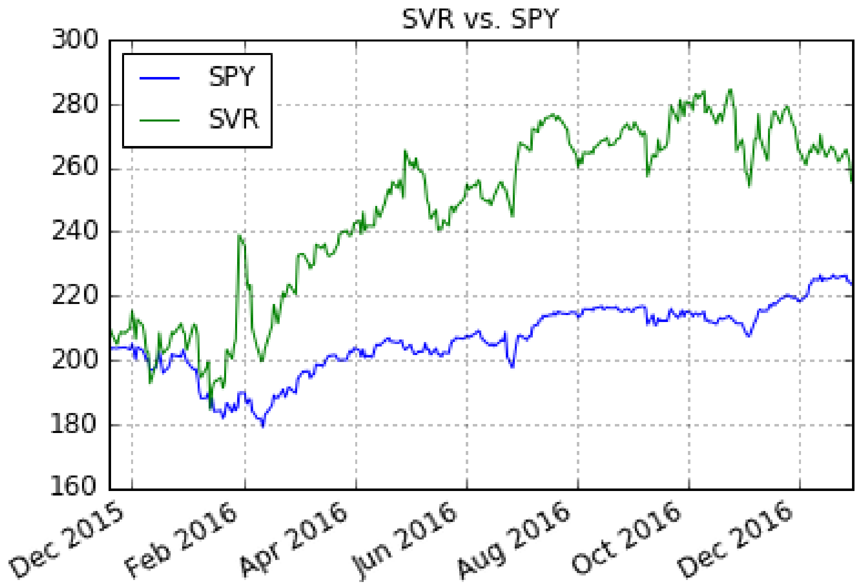


Figure 8. Portfolio performance (SVR) against benchmark SPY

Figure 8 plot compares the performance of the portfolio relative to the benchmark. The benchmark, SPY, produced a performance of 10.04%, the algorithm produced a portfolio allocation and recommendations that generated 14.39% in returns.

CONCLUSION

Reflection

The project provides a stock market portfolio prediction tool with recommendations for the next day close. In order to provide recommendations, it analyzes past performances to create a predictive model using the Support Vector Regressor method. Along with the recommendations, the program also include metrics from past performances to help the user making a final decision.

One of the many interesting aspects while developing a model that accurately predicts stock prices is the predicted percentage error, in particular, its reliability on the actual prediction. In many cases, even though this average fell within 2%, the model performed poorly. Similarly, the coefficient of determination (r-square) in many cases reached over .98 but the model performance was lower than expected. Small fluctuations in the daily prices are generating 'Buy/Sell' signals that in some cases should be avoided. A possible solution to this problem could be to define a 'neutral band' around the price from which if the prediction falls within this gap it generates a 'Hold' signal as oppose to 'Buy/Sell' signal

Another interesting aspect was finding the optimal weights for the portfolio assets. The program uses an optimization technique based on modern portfolio theory which provides the set of weights that maximizes the Sharpe ratio. The overall return of the portfolio is the dot product of the weights and the asset returns. Depending on the period over which the weights were calculated, the portfolio performance can vary significantly. As pointed earlier, smaller periods produced uneven weightings while larger periods tended to produced evenly distributed weights. Some questions remain to be answered: What is the optimal period of time to calculate the weights? Are these periods vary depending on the sector/volatility? During the test of this project it was observed that a 6 months' period provided better overall portfolio results than shorter or longer periods.

Improvement

The following are things to consider for future improvements of the project:

- Analyze in depth what is the period duration that should be used for the calculation of the portfolio weights (3 months, 6 months, 1 year) and its dependencies with the market sector
- Analyze performance for each of the S&P 500 sectors:
    - Costumer discretionary
    - Consumer staples
    - Energy
    - Financials
    - Health care
    - Industrial
    - Information Technology
    - Materials
    - Real state
    - Telecommunication services
    - Utilities

  Then analyze if there is any correlation between the model performance and the sector (based on the assumption, some sectors are more volatile than others, therefore, more unpredictable) and use these findings to select portfolio stocks
- Use K-fold for the testing. Currently only used during model fitting. Testing over different periods of time would provide more solid performance results.
- Portfolio selector- Use clustering techniques to analyze the correlation among a pool of securities, select the ones with the lowest correlation, analyze their performance, choose the ones high performance and compare them to other well-known performing portfolios. This is based on the assumption of securities with low dependencies with other sectors or securities would be affected less by the fluctuations in other sectors, thus, more predictable.
- Include transaction costs and any other fees into the final performance/results.
- Consider implementing a ‘Hold’ signal to reduce the overall number of transactions.