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Applying Data Analytics to Improve Multi-Asset Portfolio Performance

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Applying Data Analytics to Improve Multi-Asset Portfolio Performance

by

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Dedication

To my parents Ravi and Viji, for their unwavering support through my education and ultimately in the completion of my Master's degree.

And to Dr. Raj, for having the highest level of patience to guide me through a Master's degree in Computer Science.

Abstract

Applying Data Analytics to Improve Multi-Asset Portfolio Performance

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The number of casual investors allocating funds into financial exchanges has surged due to the increased availability of trading accounts on multiple platforms. These investors quite often invest only in one type of asset, stocks. Stocks are known to experience sudden market shifts and extreme volatility based on factors that the investors may not be able to control. Existing applications of data mining stocks perform well, but if the entire stock market performs poorly, investors can face severe losses. This study utilized a data mining tool that evaluates two other classes of investments: the commodities market and the currency exchange market. Three avenues of data mining were implemented as solutions, a neural network, logistic regression and a decision tree, to classify the buying and selling of investments. The results presented that unless in a bullish market scenario, utilizing a multi-asset portfolio with backed by a data mining tool can prove beneficial to an investor. In a bearish market, this study outlined how the performance of the multi-asset portfolio is drastically better than investing using a standalone stock classifier or investing in an index tracked product. In a volatile market, results showed that a multi-asset portfolio is competitive with a standalone stock classifier and in many scenarios even out performed. Overall, the data and resulting analysis provides a good basis for further research.

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Chapter 1

Introduction

In recent years, many secure financial applications have been developed for the end user, lowering barriers between the potential investors and financial exchanges. Bank of America recently noted that mobile stock trading went up 200% year over year between 2012 and 2013, and mobile trading now accounts to be between 10% to 20% of its total trading volume [5]. MarketWatch explains that this trend is not isolated to banks but is also prevalent in all major providers of equity trading [5]. As a result, many new or casual investors may not be aware of sudden market shifts, trends in the market, or they may be distracted by other facets of life. I plan to create a portfolio maintenance mechanism that allows for users to diversify their investments from just stocks, into commodities and bonds through the use of futures contracts. Using data-mining techniques, we can inform these end users about when to reconsider their investments in one particular asset class and shift it to another.

Example 1: Consider that a similar recession like scenario is reached where consumers are afraid to spend money and insist on saving. This causes weak demand for products, which in turn curtails the sales of the companies making the products causing investors in these companies to panic. In such a situation, we can see that many investors diversify their investments into other stable products such as commodities - which include gold, silver, crude oil and other staples. Investors also choose to invest in bonds such as the United States Treasury Bond, which provides them interest over year in the form of coupons.

In our example if the S&P 500 index is observed between July 8th 2011, and the index's basis points on September 2nd 2011 is compared, we can see a change of -12.6%. The S&P 500 indicates the weighted price movements of stocks in the US market. In the same time

period investigating spot gold prices per ounce reveals a change 21.5%. Ideally, if market forces could have been predicted, and an investor could have shifted their investments into commodities like gold, Figure 1 represents the change in price and points over this time period. Now if we shift the time period to September 2nd 2011 to November 2nd 2011, spot gold prices reduced from $1854 per ounce to $1731 per ounce, a change of -6.63%. At the same time however the S&P 500 Index rose from 1173.91 basis points to 1237.90 basis points, an increase of 5.45%. In this scenario, it would have been highly advantageous for an investor to shift their investments from being heavy on the gold and other commodities to stocks and other equities resulting in a tidy profit.
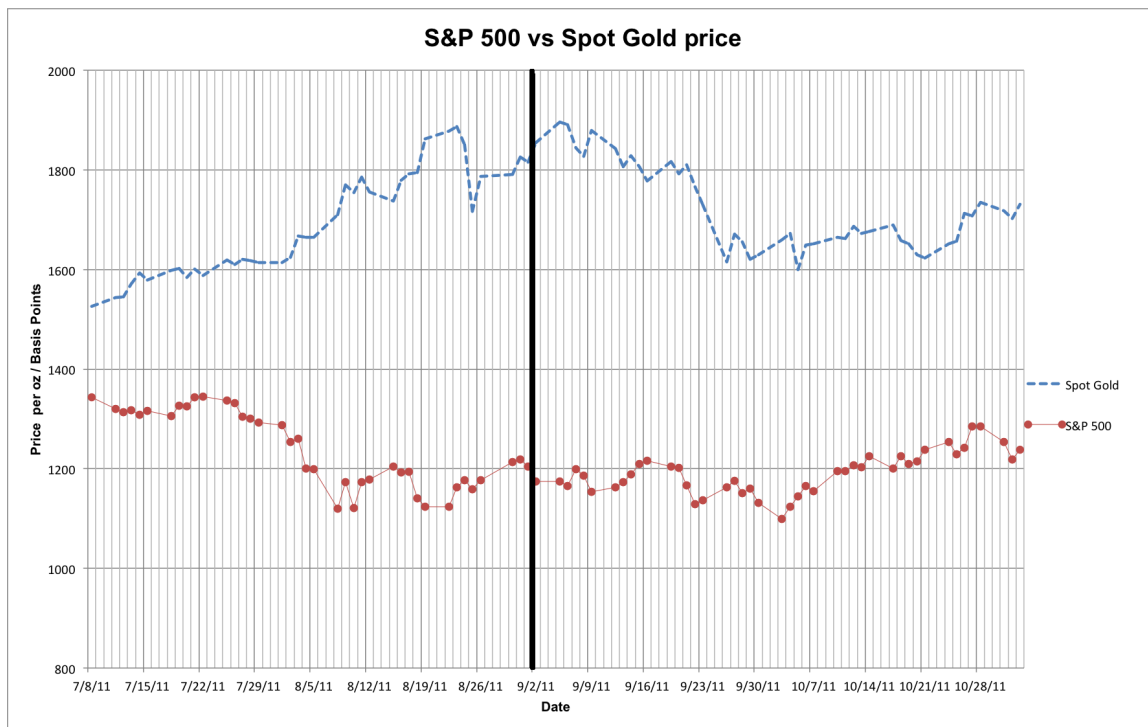
Figure 1.1: The change in price per ounce of gold and basis points of the S&P 500 between July 8th 2011 and November 2nd 2011. Between July 8th and September 2nd, gold prices increased while the S&P 500 Index fell. In the next two months gold prices fell 6.63% while the S&P 500 Index rose 5.45%.

If we look at the data for stocks and futures, we can get information from a significant time period, and down to fine grade time slices. Studies such as Haregreaves et al. have looked into strategies to pick stocks in a portfolio, but they haven't explored the possibility

of adding more choices to the same portfolio such as commodities and currencies. When investing in futures, buying and selling the position are represented as contracts that can be called or put. By purchasing the option on calling, the investor has the right to purchase the underlying security at the stated price. If the prevailing market price of the security is greater than the price of the contract, the investor is "in the money" and can liquidate his position for a profit. In the currency market, major markets include the trading of international currencies with the U.S. Dollar. As this study utilizes the U.S. Dollar as the base currency for investment, if the reciprocal foreign currency gains in value, an investor owning the foreign currency would have a bigger position if they were to liquidate back to U.S. Dollars. As each of these different asset types have unique economic and market factors that affect the performance, it will be vital to identify those factors into quantifiable attributes. By utilizing those attributes with reference to the market price, one can create a data mining tool to identify the opportune time to buy and sell a position in the given market. The remainder of this introduction focuses on describing the data mining tools utilized to a success in past studies and creating a strategy to invest and proactively maintain a portfolio.

1.1 Background

1.1.1 Stocks and Data Mining

By investigating stock prices over a large period of time coupled with large attribute sets, researchers have utilized techniques such as neural networks and logistic regression to identify opportunities to purchase and sell stocks where underlying trends are observed and market changes can be predicted[6]. Data mining allows end users to make sense of the data, and as stock prices and economic factors are routinely recorded they test the abilities of data mining techniques in a real world environment. The real strength in data mining stock data is that due to its periodical nature and the ability to classify stocks either as a buy, sell or hold, it is possible to identify a possible gain or loss.

1.1.2 Artificial Neural Networks

An artificial neural network operates on the divide and conquer paradigm[7]. They emulate biological neural systems by representing the network as massively parallel process that involve processing elements connected together. This representation starts by receiving inputs analogous to electrochemical impulses as x_i. Next these inputs are multiplied by weights, which represent the strength of these input signals, w_{ij}. This helps compute the activation of a neuron, wherein once the summation of these inputs and weights surpass a certain threshold, an output is triggered. Overall we can represent the equation as $U_j = \Sigma(X_i \cdot W_{ij})$[10].

Backpropagation and learning are features of neural networks currently in use in many studies[2]. A new layer, *the hidden layer,* is placed between the input and output layers where all input nodes connect to each of the hidden layer nodes and all the hidden layer nodes connect to the output nodes, but not to any nodes in the same layer. By utilizing one or more hidden layers, the weights in the network will be updated to prevent loss. A multilayer neural network escapes the linear limitation of a single layer network and allows internal classification rules to be created where features can be learnt in each layer[8]. We can further this learning by training the network, this is done by determining the *error*, a difference between the desired response and the actual response. By propagating this error backward through the network, we can further adjust the weights of the neurons to minimize the error of the network for the same outputs.

In the stock data mining studies, the attributes attached to the stock are deemed the weights and the output is traditionally the outcome the researcher desires: buy, sell or hold. By sequentially training the neural network with data we can train the network to optimize the weights and establish patterns to which our classification occurs. Over time the total error will become smaller and after we set a specified threshold we can begin testing the neural network on data used in the training to test the validity of the training. In terms of stocks and futures classification, the assets neural networks posses include the ability to cope with patterns that are hard to place into precise rules. Using techniques like

backpropagation and learning - as market trends change so can the neural network, thus adapting to newer trends. Lastly, by assigning and altering weights to the inputs and the hidden layers, we can interpret what variables to investigate when looking at past data.

1.1.3 Logistic Regression

To classify the stocks and futures into buy, sell and hold a multinomal logistic regression classifier can be used. This classifier uses a combination of binary logistic regressions which are traditionally a binary classifier. In this scenario the classifier will compare buy and not buy, sell and not sell and hold and not hold. Thus performing two comparisons for each of our independent variables. The logistic regression model works on the reasoning that the probability of a system S_p corresponding to a certain input x_p results in the system's output y_q. This is modeled as equation 1.

$$P(y_q/S_p, x_q) \tag{1.1}$$

Logistic regression uses the sigmoid function to aid in the learning of classification of data points by employing multiple regression coefficients. This model can be represented as equation 2.

$$P(y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 ... + \beta_p x_p)}} \tag{1.2}$$

Equation 1 represents the probability of our event, in this paper either a buy, a sell or a hold. β represents the regression coefficients that are applied to linear models x that represent patterns in the data[4]. Using this model, we can predict a discrete outcome, such as group membership, from a set of variables that may be continuous, discrete, dichotomous, or a combination of these. When we apply this scenario to stock and future data, we can take into account a series of attributes upon which this classifier can be built[1].

When considering the application of logistic regression as a classifier, one of the major advantages is that it is noise insensitive and avoids overfitting to the training data. While not in use in this study, logistic regression can be utilized in a distributed setup, where the efficiency of the of the classifier is greatly improved. Lastly, when considering our scenario

of picking best performing investment options, logistic regression provides a probability of classification which can be used in this scenario[1]. By using the probability as a rank, logistic regression provides an alternative tool to pick investment options in a scenario where multiple options exist.

1.1.4   Decision Tree

In the field of data mining and its application of identifying stocks, decision trees are used in several studies to positive effect[2]. They can be used to represent both classifiers and regression models, while offering a hierarchical model of decisions. They are particularly useful when investigating the relationship between large number of attributes and the target variable.

A C5.0 decision tree has been used successfully by Hargreaves et. al in their study investigating stocks in the Australian stock market. A decision tree itself is composed of its training data set of $S = s_1, s_2, ..., s_i$. This series represents a set of data which has been already classified. Each data point is further broken down into a vector composed of attributes represented as $(x_{1,i}, x_{2,i}, ..., x_{p,i})$. The attributes x also include the class which the set s_i falls into. The decision tree then starts to create decision points between classes based on each attribute which most effectively splits the data into one or more of the classes based on information gained from the entropy of a data set. Entropy is represented as the equation 3.

$$Entropy = \sum_i -p_i log_2 p_i \tag{1.3}$$

Entropy is measured as the probability p of class i in the data set. Information gain is calculated by looking at the entropy of the children and comparing that to the entropy of the parent. This is represented as equation 4.

$$InformationGain = Entropy(Parent) - AverageEntropy(Children) \tag{1.4}$$

Once the attribute with the most information gain has been identified, it will be used as the decision point and this process repeats recursively until all attributes have been visited[9].

An advantage of decision trees is that the rules that are derived can be easily interpreted and applied to queries for manual selection. The rule definition is easily interpreted and can be applied on the data set. The disadvantage of having these rules defined and of decision trees in general is that learning is not supported as well as neural networks and as a result the weights of each of the attributes will not be changed unless the tree is retrained. This may not be a problem in a stock and futures situation where markets operate between 9:30am and 4pm, but over time the training the decision tree with more data points will take more time.

1.2   Problem Statement

The aim of the proposed work in this thesis is the investigation and development of a multi-asset based investment classifier backed by data mining. Each classification technique has been described with how the information gained from the attributes will build towards overcoming existing limitations of investing in stocks singularly. By adding varied investment choices, the correlating attributes will be key to mitigate loses in the event that the entire economy performs poorly. The goal of this project is to reflect an investor's portfolio and replicate investment decisions as they would occur in the market and utilize the strength of the information stored in the classifiers to make rewarding investment choices.

1.3   Related Work

There is concerted effort in the field of computer science to use data mining techniques to pick stocks, whereas futures are often overlooked. Muh-Cherng et. al applied a decision tree based classifier to pick stocks in the Taiwan and NASDAQ stock exchanges. In their study, the comparison uses a classifier to a selling or buying stocks when they surpass a certain price threshold. In their study, they also utilize CPI(consumer price index) as one of the attributes to represent the inflation rate, which has been known to have an effect on stock price growth. Muh-Cherng et. al also utilize a metric, average compound annual rate of

return (ACARR), which calculates the return made on investment taking into consideration trading taxes and fees in addition to the actual performance of the stock. This metric can be useful for portfolios that range for more than one year[11].

Hargreaves et. al present a study that investigates both decision trees as well as a neural network. Their paper presents several concepts that will be useful to build upon. Both Muh-Cherng et. al and Hargreaves et. al limit the scope of the market in their papers to one field. By choosing a sector in the stock market, we can limit the data preparation required aggregating economic and historical data. For example, there are 1033 companies listed in the financial sector in NASDAQ, NYSE and AMEX exchanges. Hargreaves et. al however utilize this sector selection as the first point in the stock picking process[3]. They investigated each of the sectors and selected the sector that performed the best over 3 months prior to the period they were performing the tests. When selecting futures based on commodities contracts, there is some variation based on the contract size and the exchange which this commodity is traded on, however the best performing futures will be picked using the classifiers rather than selecting an sector.

Another interesting correlation between both Muh-Cherng et. al and Hargreaves et. al is that they utilized some form of trading strategy to determine when to buy and when to sell their positions. Hargreaves et. al use a 10% gain as an exit strategy. This infers that assuming that a stock grows more than 10% over the period that the portfolio is holding this script, the portfolio then executes a sell on all the shares for that particular script. Conversely, a 5% loss was utilized as an exit strategy to liquidate positions held which resulted in losses. This ensures that even with unpredictable swings in the market, the investor can exit their positions and use the data mining tools to re-invest their capital.

Hargreaves et. al also utilize some useful attributes in their classifiers, these attributes will be key to ensuring the success of the stock classifiers. Some attributes include return on equity, return on assets, earnings per share, revenue per share, and quarterly revenue growth. When it comes to the futures, there are fewer attributes that indicate when it comes to the commodities - instead they must be supplanted with economic indicators such as oil

production, unemployment rate and oil rig data that are available through public databases. These attributes can be evaluated by using the random forest model. This model produces a score that represents the link between the attribute and the output hence ensuring that appropriate attributes are chosen for the classifiers[3].

1.4   Hypothesis

Current studies have investigated using stocks and implementing data mining solutions to adequate success, however this is not enough in the situation where the entire economy does poorly or if other avenues of investment such as currency or commodity futures present themselves. Hence, to take into consideration these other avenues of investment, a solution must be probed where in economic factors are coupled with data mining tools that take into account new economic trends.

The hypothesis underlying this study is that a two stage data mining solution would help allocate capital into varied investments by utilizing classification, neural networks and logistic regression in a manner that utilizes their classification abilities in more avenues. As the result of this expanded investment choice, one would expect greater growth of a portfolio over a similar period of investment. The hypothesis can be validated by investigating three periods in the market: a growing market, a declining market and a volatile market. In each scenario, by classifying the best available options to invest and utilizing a second classification to identify which market to invest in, this solution should provide the best investment scenario.

To further evaluate the hypothesis, the performance of the multi-asset portfolio will be compared to a portfolio that only utilized data mining for investing in stocks only. The performance will also be compared to an index based investment strategy, investing in the S&P 500 index and the underlying stocks. By training the classifiers with a dataset that includes a large history, multiple scenarios can be trained into the data mining algorithms allowing for more successful investment decisions.

1.4.1 Initial Portfolio Distribution Consideration

As this study proposes a novel solution to the security investment problem where the funds can be split into the asset types, the initial split into each asset class may impact the performance of the portfolio. As a result, it is worth investigating four basic scenarios of how these funds are distributed. In the first scenario, the funds should be split evenly between the stocks, currencies and commodities. This split will create a diversified portfolio that should be prone to less risk, but at the same time it may compromise the gain achievable by investing more in one type of asset. The other three scenarios would involve investing predominantly in one of the three asset classes. These three scenarios would rely on the data mining algorithm to determine the most opportune time to re-evaluate the market conditions and appropriately reinvest into a different asset type. An additional benefit of this strategy is that by exposing more risk by investing in one asset type, a greater profit is also possible.

1.4.2 Gain Threshold

Another major factor in this study is the investment strategy that identifies when to close the existing position. As mentioned, existing studies that have mined stocks have used a strategy of 10% gain and 5% loss as entry and exit strategies respectively[3]. However, as currencies and commodities have not been investigated in a similar manner, this study will also investigate the appropriate trading strategy. By investigating a range of values at which this strategy is used, we can determine the most effective trading strategy. In figure 2, data points where trends change between a buy and sell set by the 10% gain and 5% loss threshold have been identified. It will be key to identify similar points across all available investment securities over the training data period.
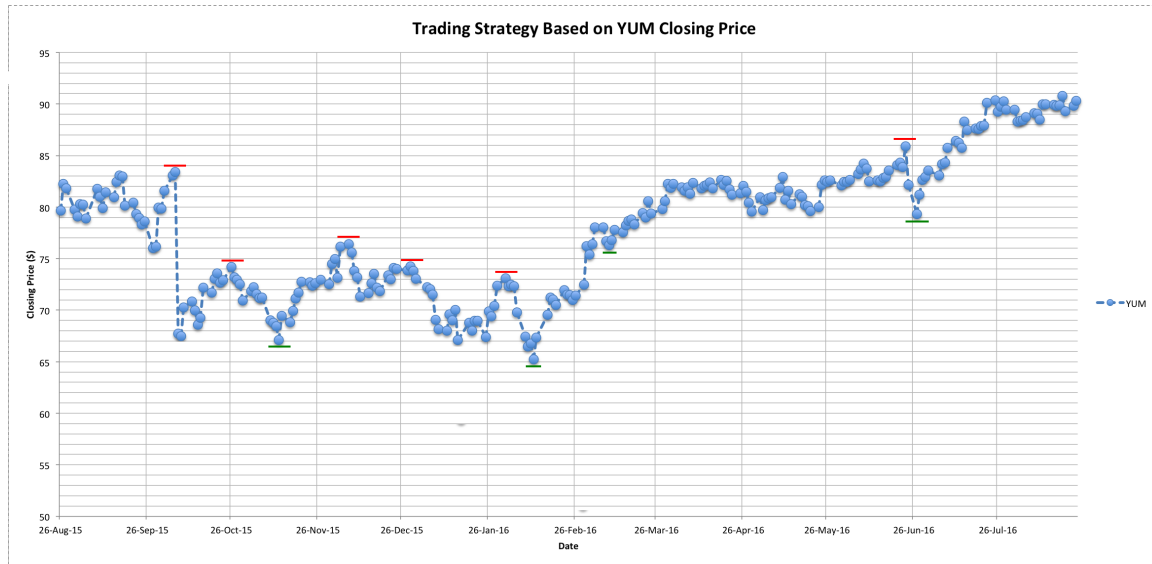
Figure 1.2: This graph displays the closing price of the YUM company stock between 26th August 2015 and 26th August 2016. On this graph, based on the 10% gain and 5% loss strategy, key data points have been identified, where red indicates sell and green indicates the buy classification.

1.5 Roadmap

The remainder of this report is dedicated to the detailed implementation and analysis of the results obtained from utilizing the multi-asset classifier. Design and implementation information are described in section 2. Section 3 contains the results and testing methodologies. Future work and conclusions are discussed in section 4.

Chapter 2

Design and Implementation

2.1 Design

To investigate the performance of a multi-asset based classifier, the project focused on the recreation of an investment situation by creating datasets that is available to common investors. This allows for day by day application of investment decisions based on the two level classifier that has been created. At each of the two levels, the data output from the classifier and appropriately equating the investment choices in dollar value is key to the successful implementation and verification of the declared hypothesis. The application maintaining the portfolio is designed to maintain the investment choices and accurately aggregating the portfolio's value based on the day value of the actual investment choice. The same application is also used to evaluate the performance of the single asset type portfolio's performance for comparison.

2.1.1 Application Design

The application design involves primarily in a Java application that maintains the user's state on a daily basis. This state will be altered on a daily basis based on the choices made by the data mining sub-algorithms. These data mining algorithms will be created and maintained using an implementation of the R statistical programming language. R provides a configurable environment into which the training data can be loaded as a .csv file. The java program will handle the decisions created as a result of the data mining tools and apply the subsequent action, maintain the portfolio value, and add new daily data into the

data mining algorithms. For each asset type, the subset of securities closing price per day data will be acquired for a common 8 year period that includes all three market scenarios $bull, bear, volatile$. Other attributes are also applied to each of days where available. Once the data is compiled, data warehousing techniques will be used to identify missing data and evaluate the best possible action to remedy the data. For each of the security available to invest, a simple evaluation of the closing price is conducted for training the classifier on when to buy and when to sell as the base classification. Similarly, a classification must be made on the picking which of the asset type to invest in based on an index value. Finally, when the algorithm is ready to test, each day's closing price is added to the data mining tool to evaluate the actions that should be performed at each given day. As the actions are performed, the investment choices are updated with the new profit or loss and restated.

Another aspect of the solution is the application of attributes to aid the data mining process and discover statistically significant trends in the data which may be used to the create decisions. One key principle of this study is that by broadening the scope of the assets available to invest in, the risk is equally mitigated. Hence to ensure that similar data mining techniques can be applied to the new assets, attributes that relate to the price and environment of currency and commodity investment choices are presented in Table 1. In addition to attributes proven to provide success in mining stocks, economic attributes are included in Table 1. Using methods such as the random forest model suggested by Hargreaves et. al[3], and accuracy tests on trained classifiers the following attributes were utilized in the study.

The day to day management of the portfolio's assets is illustrated in Figure 3. In this study, a top level decision is made to identify which of the three asset classes best suits the current market and economic conditions. After identifying the market market to invest in, a lower level data miner evaluates the available securities and identifies the product with best gain potential based on learnt data. The lower level classifiers have been illustrated with the sample exit strategies based of the original acquisition price, where a profit of 10% results in the current position being liquidated and a loss of 5% involves the same to minimize

loss. The last exit strategy is when stagnation occurs, if an investment remains inside the +10% and -5% threshold for over 30 days, the position will be liquidated on the 30th day.
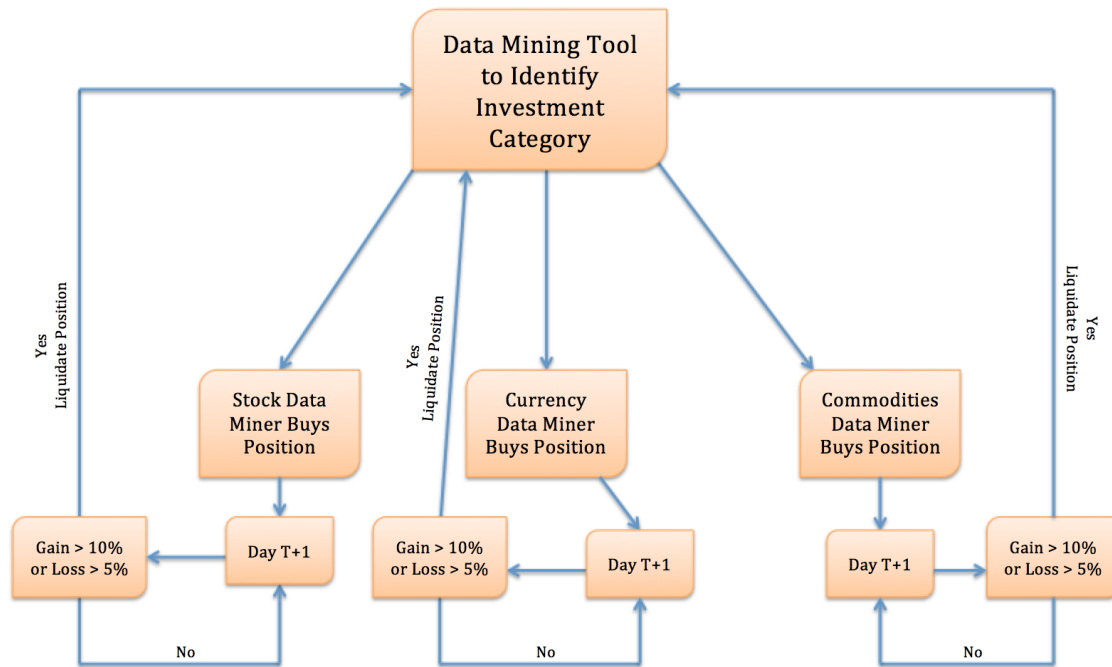
Figure 2.1: This workflow represents the day to day evaluation of the portfolio and the application of the two stage data mining tool to pick investment choices.

To streamline of the implementation and validation of the hypothesis, the following assumptions are required.

- The data investigated will be utilized as a numeric type and similarly data such as analyst ratings will be similarly converted to maintain consistency.

- All data will be presented as closely as possible to a daily basis, matching the price of security, present as an end of day value.

- An average profit and loss exit strategy will be applied across each asset type to simplify the execution of the strategy.

- The data presented will be evaluated using open refine to identify anomalies and clean data.

- Holidays across the markets will be normalized by excluding that particular day from the data.

- A constant exchange rate and end of day values will be maintained to calculate the current portfolios value.

- The time period of the investigation will range for 1 year, loading these data points into the algorithm for learning where applicable.

- A visualization of the portfolio's performance will be provided, a comparison between the portfolio and popular indices will be available.

- The same data provided to the multi-asset classifier will be provided to the stock classifier for an easier comparison.

- The stocks in the Dow Jones Industrial Average will be used as the core stock investment option, reflecting multiple large, popular and diverse companies not limited to a single industry.

- Investments held after 30 days but still inside 10% gain and 5% loss threshold will be liquidated.

- Each investment block will be $10,000 totaling a sum of $100,000 at the start of each scenario.

- Each investment block will carry forward earned appreciation or depreciation, and no more than three blocks can be invested into a sub-investment choice.

2.2 Implementation

The implementation of the multi-asset classifier was guided by the design scheme and employed the trading strategy as the basis for the creation of Java application. This application was created in the Java SE 6.0 environment, relying on CSV data generated by the classifiers trained in R version 3.2.4. Within R, the neuralnet package was used to train then neural network based classifier, the nnet package was used to train the logistic regression based and lastly the ctree package was used to train the decision tree classifier. Additionally Python 2.7.4 was utilized with the Yahoo Finance API to allow for the retrieval of financial data used to train the classification tools. Lastly, OpenRefine 2.6 was utilized to normalize the data utilized in this project.

During the initial creation of the training data, it was observed that a significant set can be obtained from Yahoo Finance. As a result, the Yahoo Finance API was utilized in Python to generate custom CSV files containing the appropriate data sets. After analyzing the patterns in historical data, the training set was created with a range from January 1, 1999 to December 31 2007. As discussed previously this training set encompasses the bull, bear and volatile market appropriate for holistically validating the hypothesis. To test the trained classifiers, 2008 is utilized as the bear market data set, 2016 was utilized as the bull market data set and 2015 was utilized as the volatile market.

Additional observations indicated that the stock data set contained the most exchange holidays. Considering that this data set is the key indicator, OpenRefine was utilized to create a normalized dataset per asset for the 8 year training period. During the creation of the R based classifiers it became apparent that utilizing the Java based libraries would become cumbersome, and instead the CSV output from the classifiers was used as an input in the Java Application instead. Similarly, the output of the Java application was utilized in the individual asset classifiers to test the model. Additionally, the neural network and logistic regression classifiers provided output indicating the probability of classification into buy or sell. The decision tree classifier however, would rather classify the test data into the class, hence if multiple stocks were indicated as a buy on a particular date, a strategy of

Table 2.1: Attributes for Data Mining Strategies

Attributes Investigated	Description	Type
Return on Assets	Profit of company relative to total assets	Integer
Return on Equities	Net Income as a percentage of shareholders equity	Float
Earnings per share	Companies profit allocated to each outstanding stock	Float
Revenue per share	Total revenue earned per share	Float
Quarterly revenue growth	Current quarter growth compared to last fiscal year	Float
Annual Growth	Percentage of growth of this years earnings	Float
Price per book	Closing price of the stock by the latest quarter's book value	Float
Price per sales	Company's market cap divided by the revenue	Float
Analyst Rating	Average analyst recommendation to buy or sell	Float
Gross Shipping Volume	Published shipping volumes of commodities	Integer
Production of Commodities	Published production volumes of commodities	Integer
Crude Oil Price per Barrel	Close price of a barrel of WTI Crude	Float
Volumes Traded	Relevant volumes at end of trading	Integer

testing the same set 10 times was used as a decider.

2.3   Testing

Four major components were developed for the validation of this projects hypothesis. First the datasets would be created using the python utilizing the end of day recorded values populating the attributes described in Table 2.1. This dataset allows for the appropriate information gain used in the creation and testing of classifiers. To train the asset type classification, the training dataset based on the S & P 500 Index and custom currency and commodities index. These two indexes were weighted by the volume, creating a buffered index, and linked to the relevant economic attributes below.

Chapter 3

Analysis

3.1 Analysis Methodology

The approach to testing, analysis and evaluation of the results of this project is focused on investigating the performance of each of the classifiers both by exploring the monetary results of the portfolio and by statistically evaluating the results of the classifiers to known values. Testing has been split first into two major branches, dividing the testing between the initial distribution investment into One Asset Type and Equally Split Between All Asset Types. In the One Asset Type section, the testing is further split into the three scenarios of bull, bear and volatile market. In the testing scenario where the initial distribution is split between all three asset classes validates its results in a volatile market scenario. Additionally these four scenarios are compared to a benchmark performance of a singular stock classifier, utilizing stocks as its only investment option. Another benchmark is the S&P 500, a flat investment at the start of the year is also utilized as a metric. It is key to identify the different investment choices observed within each individual market scenario and observe the trajectory of the portfolio's value. Success within each individual test scenario in relation to the stated hypothesis would reflect a higher portfolio balance at the end of the year, additionally confusion matrices can be employed to test the efficacy of each individual classification technique, with the more precise classifier performing the best. The remainder of this section focuses on results and discussion of each the individual test scenarios.

3.2 Environment

Project implementation and all testing has been performed on an Apple MacBook Pro, utilizing an Intel Core i7 2.3GHz processor and 8GB of system memory. While future performance of the portfolio should remain independent of the machine, the training time for each classification model would be dependent on the host machine capabilities.

3.3 One Asset Type Distribution

The first test scenario describes a new investor scenario as the first day in each test scenario will have a singular asset type classification. To test this scenario, an investment of $100,000 was divided into ten investment blocks and subsequently tested into the appropriate asset level classifier. Each initial investment block will remain consistent across the three market scenarios and the reciprocal gain or loss will be reinvested based on the classification. The three market scenarios are designed to test multiple economic forces influencing the asset prices and ensure that no unintentional bias or bell-weather pattern is introduced into the training set.

3.3.1 Bull Market

This test scenario representing fiscal year 2016 is indicative of the economy doing well and similarly reflecting in the stock market's performance as well. Ideally the gains of the stock market showcase the performance of the economy and produce the most gains, however in the testing observed the initial investment type is in the currencies asset class. Figure 3.1 tracks the investment performance for 2016, comparing the results to a standalone stock classifier and the S&P 500 Index.

From the results it is observable that the standalone stock classifier performed had the best end performance by ending with the portfolio with the highest asset value. When comparing the returns, the standalone classifier produced returns of nearly 42%. The neural network tool produced a return of 33.9%, the logistic regression tool produced a return
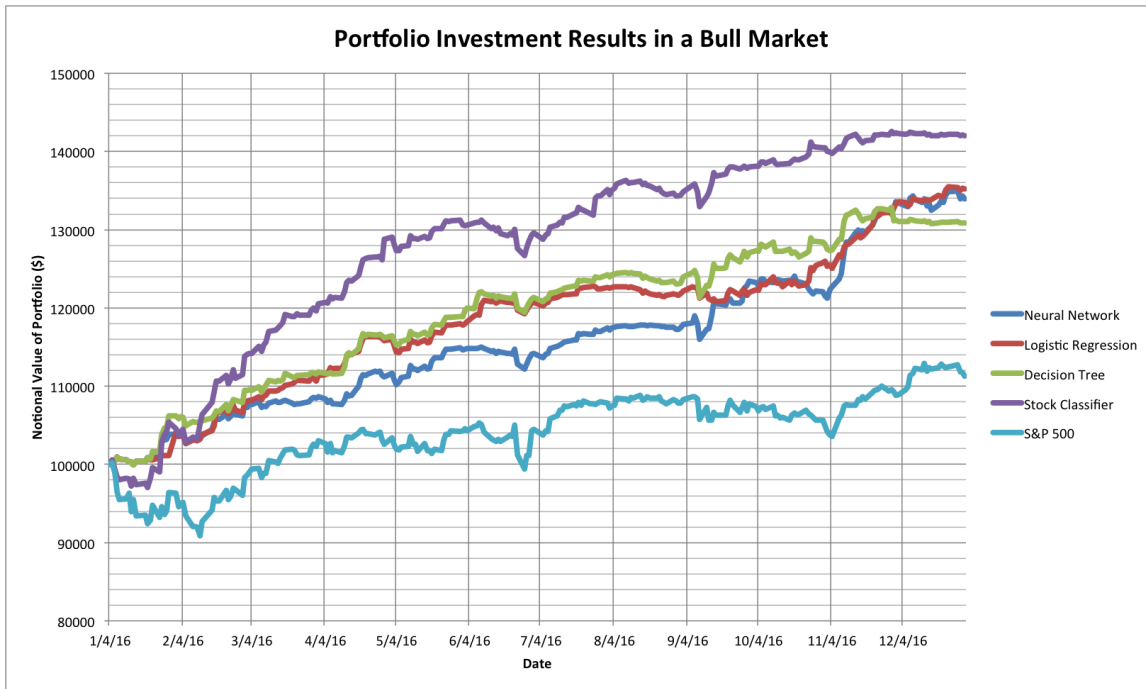
Figure 3.1: This graph displays the resulting portfolio value change over the fiscal year 2016. The results of investments based on the three classification techniques are presented with a stock market focused investment tool and the S & P 500 Index for comparison.

of 35.2% and lastly the decision tree produced a return of 30.8%. A quarterly breakdown of each tool investigated is highlighted in Table 3.1. First and foremost, all data mining techniques performed better than the S&P500 Index, which returned a gain of 11.1%, indicating that the training data set and the economic factors were able to add useful information gain to assist an investor.

To analyze further, one of the interesting results is the underperformance of the Decision Tree, considering that it uses the same classification technique as the standalone stock classifier, it produced a return of nearly 11.2% less that the stand alone stock classifier. Using Figure 3.1 we can see that while the Decision Tree had a stronger initial month than stand alone stock classifier, the performance slowly starts to widen. Another point to notice in Figure 3.1 is that although the Neural Network and the Logistic Regression based portfolios had a strong December, the Decision Tree portfolio starts to flatline. This pattern is also observable in the performance of the stand alone stock classifier.

Table 3.1: Portfolio Values in Bull Market per Quarter 2016

Date	Neural Network	Logistic Regression	Decision Tree	Stock Classifier	S&P 500
01/04/16	100000	100000	100000	100000	100000
03/31/16	108451.83	110637.92	111559.48	119655.43	102339.19
06/30/16	114073.27	120622.68	121180.28	129340.96	104282.89
9/30/16	123449.80	121996.92	127058.93	138011.28	107731.56
12/30/16	133948.52	135220.66	130828.73	142008.4466	111237.37

Digging deeper, utilizing the output from the Java application to see the raw investment choices, it is observable that the decision tree missed out on investing in the USD / Yen currency exchange. This one asset appreciated nearly 16.2% between October and its peak in December. Investigating the overall classification performance of the Decision Tree, we can see that the True Positives indicate the actual predicted classification which corresponds to an actual classification. In Table 3.2, we can see that the Decision Tree has 15 True Positives, dividing the True Positives by the sum of True Positives and False Positives we arrive at the Precision for this classification. In this scenario the Precision for Currency Investments by the Decision Tree stands at 55.6%. This strongly provides a reason why the USD / Yen currency investment choice was not utilized by the Decision Tree.

The specificity of the Decision Tree for Currency is calculated by dividing the True Negatives by the Sum of True Negatives and False Positives. In this scenario, there are 218 True Negatives and 12 False Positives. This results in a specificity of 94.8%, indicating that the decision tree will rarely register a false positive that is not the target for testing. Considering that in the bull market example where stocks were shown to represent majority of the economic benefits, being highly specific for investing in the currency market which had the fewest individual gains does have some meaningful result.

The Decision Tree had a stronger performance in the Commodities investment category. From Table 3.2, the True Positives for Commodities was at 61.8%, and the True Positive rate for stocks was at 89.3%, which is definitely helpful in a bull market. Looking at data in Table 3.3 and 3.4, the Neural Network and the Logistic Regression tools produce a Precision rate of 70.8% and 64.3% respectively. Again these numbers are low but, due to

Table 3.2: Confusion Matrix for Decision Tree in Bull Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	151	5	13	169
Predicted Outcome	Invest Currency	8	15	4	27
	Invest Commodities	20	1	34	55
	Sum	179	21	51	251

the lack of overall attempts to test the classification of investment in Currency Exchange, a lower True Positive can be observed. Additionally, a specificity of 97% and 95.7% is calculated based on the results obtained from the Neural Network and Logistic Regression tools respectively.

Table 3.3: Confusion Matrix for Neural Network in Bull Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	150	3	4	157
Predicted Outcome	Invest Currency	4	17	3	24
	Invest Commodities	25	1	44	70
	Sum	179	21	51	251

Table 3.4: Confusion Matrix for Logistic Regression in Bull Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	152	1	6	159
Predicted Outcome	Invest Currency	6	18	4	28
	Invest Commodities	21	2	41	64
	Sum	179	21	51	251

3.3.2   Bear Market

A bear market represents the economy doing poorly, and this is reflected by the stock market ending significantly lower that how it started. In the past 10 years, only 2008 shows

a significant degradation of the market value over the fiscal year. The year 2008 exhibits some unique characteristics, there is an initial dip of more than 10% within the first three months, however by June of 2008 these losses are pared. The stock market in the second half of the year significantly responds to the financial uncertainties and loses nearly 48.1% by November 20th. Figure 3.2 presents these market conditions by plotting the S & P 500 Index and compares the performance of the data mining algorithms in 2008.
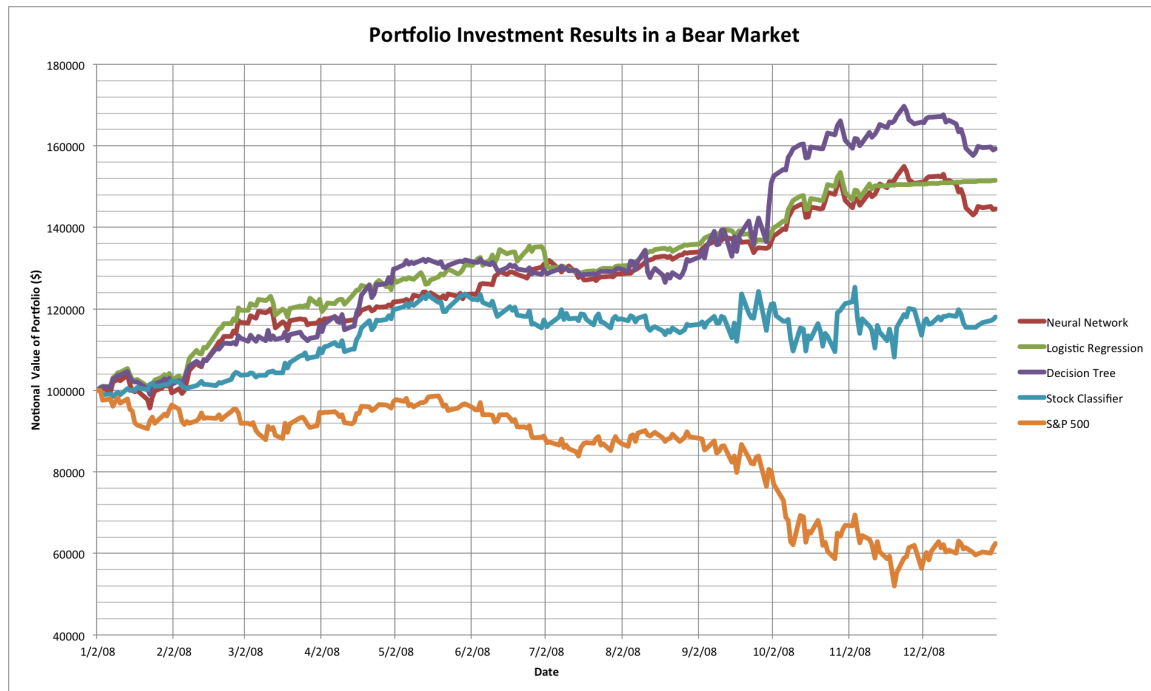
Figure 3.2: This figure presents the resulting portfolio value change over the fiscal year 2008. The results of investments based on the three classification techniques are presented with a stock market focused investment tool and the S & P 500 Index for comparison.

The results infer that due to the major financial crisis the stock market performed extremely poorly, an investor with capital invested in a fund tracking the S & P 500 Index would have lost 37.6% of the value over the course of 2008. With that being said, the stand alone stock classifier produced a return of 11.8% over the same period. This indicates that despite the market tumbling, certain stocks were still able to appreciate in value. The neural network tool produced a return of 44.5%, the logistic regression tool produced a return of 51.5% and lastly the decision tree produced a return of 59.2%. A quarterly breakdown of

each tool investigated is highlighted in Table 3.5.

Looking at the results, the multi-asset based classification tools performed significantly better than the stand alone stock classifier and they completely out performed the S & P 500 Index. Using Figure 3.2, it is observable that all three multi-asset algorithms start to appreciate in value significantly after October 2nd. Looking at the underlying investment choice, all three algorithms shifted investments from stocks to currencies during the month of June. Currencies such as the Korean Won and Mexican Peso increased appreciated in values of roughly 44% and 34% respectively using June 1st 2008 as a base value date. This point is most observable in the performance of the decision tree classifier, although this portfolio was lagging behind the other two tools as of June 6st, aggressive investments into the Currency Exchange market ultimately yielded with the best performing portfolio.

Table 3.5: Portfolio Values in Bear Market per Quarter 2008

Date	Neural Network	Logistic Regression	Decision Tree	Stock Classifier	S&P 500
01/02/08	100000	100000	100000	100000	100000
03/31/08	116470.73	121182.94	113164.99	108396.91	91399.70
06/30/08	130290.30	135308.26	128490.53	115274.50	88449.10
9/30/08	135165.53	137130.62	145204.58	118966.50	80596.48
12/30/08	144574.98	151522.07	159246.38	118083.95	62415.35

In the first quarter of 2008, from the performance of S & P 500 Index it can be observed that the stock market is performing poorly. During this period, all three tools investigated invest in the commodities market with varying strategy. In Figure 3.2, it is observable that Logistic Regression and Decision Tree portfolios had a notional value above the standalone stock classifier throughout this time frame. The Neural Network however did have some points in the first quarter where it fell below the stock classifier. Investigating the performance of these classifiers in Tables 3.6-3.8, the Neural Network appears to be over fitted to the commodities asset type and has less precision when compared to the Logistic Regression and Decision Tree based tools. Despite the Neural Network being overfitted, ultimately all three algorithms have a higher portfolio value at the end of the first quarter.

From Tables 3.6-3.8, the Precision for commodities is calculated to be 77.9% for the

Table 3.6: Confusion Matrix for Neural Network in Bear Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	77	11	8	96
Predicted Outcome	Invest Currency	3	68	9	80
	Invest Commodities	9	8	60	77
	Sum	89	87	77	253

Table 3.7: Confusion Matrix for Logistic Regression in Bear Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	79	5	6	90
Predicted Outcome	Invest Currency	5	75	4	84
	Invest Commodities	5	7	67	79
	Sum	89	87	77	253

Neural Network, 84.8% for the logistic regression and 84% for the decision tree. Looking at the performance in the first quarter as discussed, these results provide some basis to indicate why the Logistic Regression and Decision Tree performed better. Furthermore, the False Positives in commodities for the Neural Network was the highest at 17 compared to 12 False Positives obtained by the other two tools investigated. The specificity is calculated to be 89.8% for the Neural Network, 94.3% for the logistic regression and 92.1% for the decision tree, further highlighting the performance of the Logistic Regression tool. Lastly, the performance edge in the months of November and December where the Logistic Regression portfolio outperforms Decision Tree and Neural Network, could also be attributed to the improved precision and specificity.

3.3.3 Volatile Market

A volatile market unlike the bear and bull market does not trend significantly up or down. This type of market has a tendency to rise or fall rapidly in a short period of time. As a result, investing and liquidating investments at the opportune time is key to maintain a portfolio with gains. Looking at the year 2015, for the first 8 months of the S & P 500

Table 3.8: Confusion Matrix for Decision Tree in Bear Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	83	8	10	101
Predicted Outcome	Invest Currency	2	71	4	77
	Invest Commodities	4	8	63	75
	Sum	89	87	77	253

Index, there is significant movement in both directions of up to 3.5%. Between the months of August and November, the market dips 9.3% but is able to recover all these losses by the start of November. Figure 3.2 presents these market conditions by plotting the S & P 500 Index and compares the performance of the data mining algorithms in 2015.
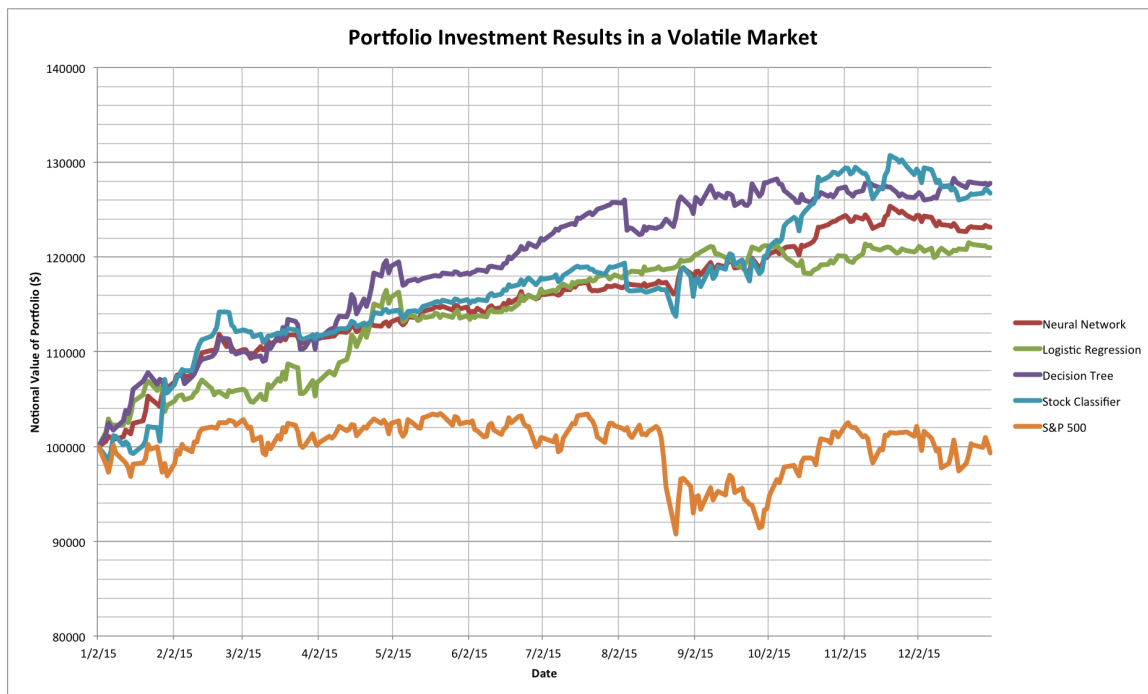
Figure 3.3: This figure presents the resulting portfolio value change over the fiscal year 2015. The change in value of the assets identified by the three classification techniques are presented with a stock market focused investment tool and the S & P 500 Index for comparison.

Considering that the Index is weighted, these fluctuations indicate strong, quick movements in stock prices. Figure 3.2 presents some of the volatility observed by presenting

several dips in the value of the portfolio such as March 25th or May 6th. These occurrences upon deeper investigation were caused by the sudden nature of the share price dropping intra-day. Next, either the classification tool or the investment strategy of limiting losses to 5% triggers liquidation of the asset. Looking at the notional values of the portfolios, the standalone classifier produced returns of roughly 26.8%. The neural network tool produced a return of 23.1%, the logistic regression tool produced a return of 21% and lastly the decision tree produced a return of 27.8%. A quarterly breakdown of each tool investigated is highlighted in Table 3.9.

The results indicate that overall the Decision Tree performed the best, relying on a significant appreciation of its assets between the months of May and August. These results were produced with a significant distribution in stocks, most notably in Goldman Sachs. This performance was followed closely by the stand alone stock classifier. Right after this steady appreciation between May and August, the stock market tumbles. Again, the Decision Tree and stand alone stock classifier represent this crash by the portfolio losing value. Much like the Bear year test scenario, the Neural Network had shifted the investments into currencies at this point and avoid the crash. The Decision Tree follows ensuite, and invests aggressively into currencies avoiding the impact from the slump in the stock market.

Table 3.9: Portfolio Values in Bear Market per Quarter 2008

Date	Neural Network	Logistic Regression	Decision Tree	Stock Classifier	S&P 500
1/2/15	100000	100000	100000	100000	100000
3/31/15	111050.28	105332.40	110304.52	111319.61	100470.79
6/30/15	115727.25	115912.47	121373.84	117431.31	100238.56
9/30/15	119955.25	121192.84	127886.26	120088.28	93286.85
12/31/15	123121.63	121029.24	127758.91	126754.83	99307.16

Another key investment decision by all three algorithms was to invest in commodities at the start of the fiscal year. The performance of the Neural Network and Decision Tree at the end of the first quarter are similar at 11.1% and 10.3% respectively. The Logistic Regression model on the other hand only presents a return of 5.3% at this time period. Investigating the investment choices, the Logistic Regression tool included investments in

copper and crude. These two assets produced a gradual return over the first three months, unlike the investments in gold and silver also utilized by the other tools. This is reflected in the confusion matrices in Tables 3.10-3.12. From these tables the Precision of commodities can be calculated 70% for the Neural Network, 61.3% for the Logistic Regression and 70.6% for the Decision Tree. The specificity for the same three tools remains comparable at 95.8% for the Neural Network, 94.4% for the Logistic Regression and 95.3% for the Decision Tree tool.

Another point of divergence observed between the classification tools investigated is the choice of investments after the market crash between August and November. From Figure 3.3, it is observable that at the start of October, the stock market initiates its recovery. This recovery is reflected in the stand alone stock classifier, appreciating from a value of 120088.28 to a peak of 130735.57 as of November 20th. The Neural Network's performance also replicates this trend, choosing to invest in stocks. The decision tree on the other hand was unable to invest into stocks as the portfolio was invested in currencies at that point and due to the investments being stuck in the 10% appreciation and 5% depreciation limits, the gains were unrealized. A key point to note at this juncture is that the precision for stocks by the decision tree was at 85.1% where as the Neural Network was marginally lower at 84%. Hence it can be inferred that in this scenario, due to the prior investment commitments the precision is not always a guarantee of performing the best.

Table 3.10: Confusion Matrix for Neural Network in Volatile Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	100	11	8	119
Predicted Outcome	Invest Currency	12	82	9	103
	Invest Commodities	6	3	21	30
	Sum	118	96	38	252

Table 3.11: Confusion Matrix for Logistic Regression in Volatile Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	98	14	15	127
Predicted Outcome	Invest Currency	15	75	4	94
	Invest Commodities	5	7	19	31
	Sum	118	96	38	252

Table 3.12: Confusion Matrix for Decision Tree in Volatile Market

		Actual Outcome			
		Invest Stocks	Invest Currency	Invest Commodities	Sum
	Invest Stocks	103	8	10	121
Predicted Outcome	Invest Currency	8	85	4	97
	Invest Commodities	7	3	24	34
	Sum	118	96	38	252

3.4 Equal Distribution in Three Assets

In this scenario, the top level classification is bypassed for the initial distribution to validate if the initial distribution would impact the resulting gain on the portfolio. Utilizing figure 3.4 to identify the results, it can be observed that despite the change in initial distribution and its associated gains, ultimately the investment decisions were fairly consistent after February and December. The Decision Tree again produced the best results, a gain of 31.3% in this scenario compared to a gain of 27.8% previously in the dynamic allocation scenario based on the volatile market. The Neural Network produced the second best gains, a return on 25.3%, besting the return of 23.1%. Lastly, the Logistic Regression portfolio also improved, producing a return of 22.5%, greater than the 21% return observed previously. These results are summarized in Table 3.13.

Table 3.13 highlights the gains made per quarter in 2015. At the end of the first quarter, the Neural Network portfolio increased by $2,135.5, the Logistic Regression portfolio increased in value by $1493.5 and the decision tree increased in value by $3533.1. Having a deeper look at the investment choices, in addition the commodities chosen previously,
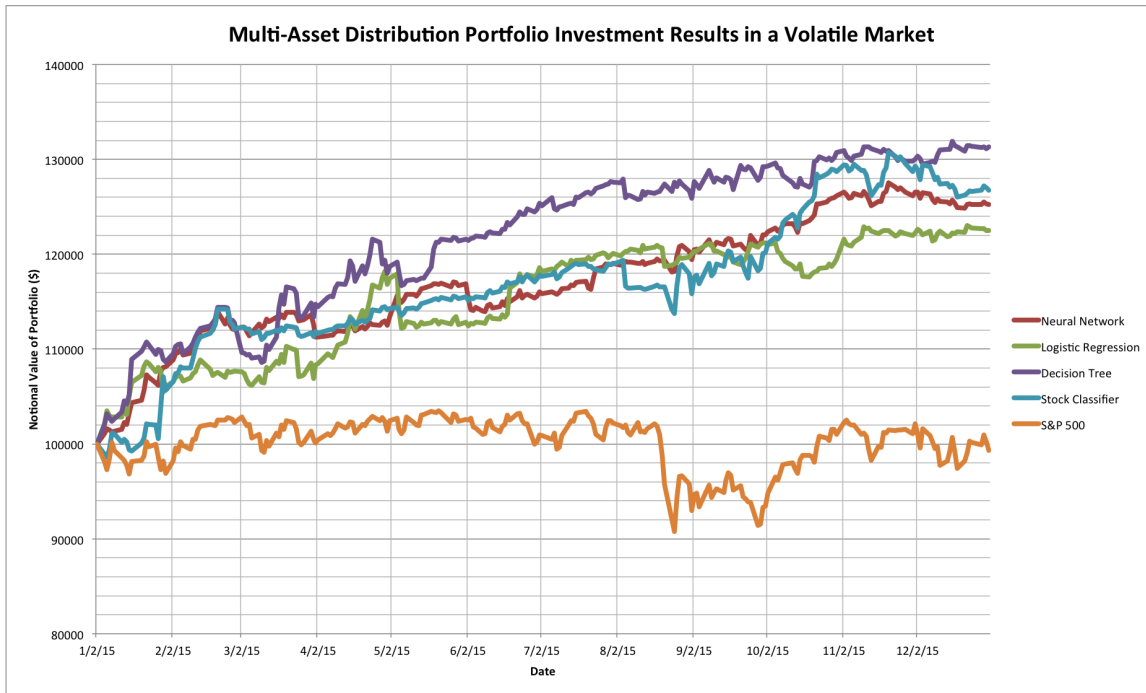
Figure 3.4: This figure presents the resulting portfolio value change over the fiscal year 2015 where the initial distribution of assets was evenly split between the asset classes. The change in value of the assets identified by the three classification techniques are presented with a stock market focused investment tool and the S & P 500 Index for comparison.

the currency exchange assets of USD/AUD, USD/GBP, USD/EUR had some gains in early 2015. The Decision Tree invested significantly in the USD/EUR category to boost its gains and the Neural Network invested equally in all three currency exchange options.

Considering that the top level classifier was suspended for the initial distribution, this scenario provides a good opportunity to evaluate the performance of the asset level classifiers, classifying between buy, hold, or selling of any particular investment. Tables 3.14 to 3.16 represent the calculated Precision and Specificity of each asset class split by the classification tool employed. Specific results include the Decision Tree being the most precise when buying any of the three asset types, this is most prominent in the currencies asset type with a precision of 80.4%. The Logistic Regression tool performs the worst across all three asset types, dropping its precision to 66.1% when buying commodities. Lastly, the Neural Network operates in the middle ground, averaging a precision of 75.8% when

Table 3.13: Portfolio Values in Volatile Market per Quarter 2015 with Split Initial Distribution

Date	Neural Network	Logistic Regression	Decision Tree	Stock Classifier	S&P 500
1/2/15	100000	100000	100000	100000	100000
3/31/15	112567.678	106866.7847	113354.9071	111319.6133	100470.7969
6/30/15	115560.6036	117857.4849	124730.3389	117431.3157	100238.5655
9/30/15	122035.8742	121192.8419	129248.5931	120088.284	93286.85622
12/31/15	125257.1824	122522.7466	131291.986	126754.8379	99307.1611

averaged across the three asset classes.

Table 3.14: Performance Evaluation for Stock Level Classifier

		Neural Network	Logistic Regression	Decision Tree
Buy	Precision	74.3%	69.4%	78.3%
	Sensitivity	93.5%	85.3%	91.4%
Hold	Precision	75.1%	68.4%	79.2%
	Sensitivity	92.2%	84.7%	90.6%
Sell	Precision	78.1%	76.2%	72.1%
	Sensitivity	91.2%	83.8%	90.8%

3.4.1 Review

The hypothesis stated that implementing a multi-asset portfolio with a two stage classification setup would yield in greater returns than a regular stock based classification tool. Reviewing the results, in the bull market, the stand alone stock classifier outperformed the implementations investigated in this study. In a bull market, results indicate that majority of the time investing in stocks is the best option. The bear and volatile markets allow for further analysis of the implementation. In the bear market, all three tools comprehensively outperformed the stock based classifier, achieved by altering investments from stocks to currencies at specific points in the fiscal year. Lastly, the volatile market produced another validation, with the decision tree performing the best. In this scenario the stock classifier and neural network were inside one percentage point of each other's performance.

Table 3.15: Performance Evaluation for Commodity Level Classifier

		Neural Network	Logistic Regression	Decision Tree
Buy	Precision	75.3%	66.1%	78.3%
	Sensitivity	90.9%	84.6%	92.6%
Hold	Precision	78.1%	69.7%	79.2%
	Sensitivity	91.1%	82.9%	90.8%
Sell	Precision	72.1%	67.3%	72.1%
	Sensitivity	94.3%	83.8%	92.9%

Table 3.16: Performance Evaluation for Currency Level Classifier

		Neural Network	Logistic Regression	Decision Tree
Buy	Precision	77.9%	67.5%	80.4%
	Sensitivity	90.7%	87.1%	94.4%
Hold	Precision	72.3%	78.3%	77.9%
	Sensitivity	90.8%	88.4%	92.0%
Sell	Precision	77.8%	66.5%	75.7%
	Sensitivity	92.1%	83.2%	94.3%

The use of precision and specificity derived from confusion matrices helped identify useful trends such as the logistic regression performing poorly in the volatile market scenario. This particular classification technique had the lowest precision and appropriately reflected on the net gain in that portfolio. Having stated this fact, it was also observed that despite the Decision Tree having the best precision in the same scenario, due to prior investments it was unable to liquidate and re-invest itself into a better performing asset. Ultimately investigating these observances, exploring a wider set of products and flattening the two level classifier into a single level classifier will further strengthen the hypothesis. These avenues are discussed further in the next section.

Chapter 4

Conclusions

4.1 Current Status

This report demonstrates that a multi-asset based portfolio backed by decisions made using data mining techniques provides improved performance in many market scenarios when compared to a stand alone stock classifier. The application framework outlined in the hypothesis and subsequently tested upon functions as outlined in the report. There are some incomplete operational aspects, improving these aspects could lead towards creating a better application and experience for the end user. A list of these aspects include the following items:

- Tighter integration between the R based tools and the Java application - Currently the .CSV training and test files are manually loaded into the R application and subsequently loaded in to the Java Application for portfolio maintenance. Localizing the classification tools into the Java application will allow for a stand alone application.

- Investigate/Subscribe to data sources - A significant subset of the data used to train and validate the analytical tools investigated in this study is paid and free data is often more periodical. Exploring paid sources of reliable data will streamline training and testing dataset creation.

- Improve output of asset decisions to visual cues - Currently the final Java Application output includes a list of the investment decisions made and notional value of the

portfolio. For and end user using this application to invest, the output should be altered to state instructions on what actions to take.

These operational updates highlight some improvements that will aid the ultimate usability of the application created in this study. The next section outlines some function aspects to investigate further to strengthen the hypothesis validation.

4.2   Future Work

The testing and hypothesis validation performed in this study have demonstrated that a multi-asset portfolio in many market scenarios builds on a stand alone stock classifier and can help mitigate economic and market risks for new investors, however there are some further avenues to research to improve and fine tune the resulting solution.

To limit the scope of this study the products available to invest were the: 30 Stocks in the Dow Jones Industrial Average, top 10 most traded currency pairs, and the top 10 most traded commodities. Widening the range of these products will help reduce any inherent bias introduced by limiting the choice. Considering that the 30 Stocks in the Dow Jones Industrial Average are themselves chosen on a unique set of economic criteria, a wider set would help increase the diversity in both the training set and risk mitigation.

Another aspect that can be further investigated is the ability to short sell or use the alternate currency exchange pair, allowing the investor to bet against the market. Short selling involves selling a borrowed set of stocks with the motivation that the price will drop. Once the price has dropped, it can be bought and returned to the loaner, allowing the investor to utilize the differential. Reverse currency exchange follows the same principle, utilizing borrowed foreign funds to bet against the US Dollar.

This study also utilized the 10% appreciation and 5% depreciation limits as a trading strategy coupled with the 30 day forced liquidation. To validate the hypothesis more rigorously, all three factors must be manipulated. In some test scenarios reflected in this study, it was identified that even though a certain classification tool is more precise in identifying

the investment choices, if the portfolio is already distributed and unable to re-invest, greater returns could be missed.

The top level training set utilized to distinguish between the three asset classes in this study utilized a training set based on the S & P 500 Index and custom currency and commodities index. These two indexes were weighted by the volume, creating a buffered index. Hence in some scenarios it is observable that although one sub asset like crude oil may be performing well, if other commodities are not performing well, this investment choice may be excluded. Hence future studies should investigate flattening the two level classification tool, and identifying best investment choices as a comparison to the two stage method utilized in this study. Additionally this study utilized three market scenarios, often providing distinct choices between investment categories. More market scenarios must be validated against to investigate the effectiveness of the solution.

4.3   Lessons Learned

The testing and analysis in this study has presented that unless in a bull market scenario, utilizing a multi-asset portfolio with a data mining tool can prove beneficial to a novice investor. In a bear market, this study outlined how the performance of the multi-asset portfolio is drastically better than investing using a standalone stock classifier or investing in an index tracked product. In a volatile market, this study showed that a multi-asset portfolio is competitive with a standalone stock classifier and in many scenarios even out perform it. Looking at the underlying data mining techniques used and test results, the Logistic Regression preformed best when long term trends were available. The Decision Tree and Neural Network performed better in volatile market conditions, owing to better fitting to that training data set. Lastly, a key point that although the tool utilized may be the most precise in that scenario, ultimately the trading strategy and existing investment decisions can also impact the gains made. Overall, based on the results and issues identified, this study provides a good basis to build further research upon. Ultimately, the end goal would be to take the lessons and investment advice generated using the techniques stated build a

consumer facing product to assist and stimulate more trading.

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