Bachelor Thesis

Examinations of Stock Trading Algorithms and Applications of Twitter Sentiment for Trading Strategies

Alex Thomas

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Advisor: Prof. Darren Strash, Prof. Aaron Gember Jacobson

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Department of Computer Science
Colgate University
Hamilton, New York

Abstract

Algorithmic Trading (AT) is a financial sector that trades financial instruments, such as stocks, with algorithms and no human interaction. This allows the largest prop-trading firms in the world to conduct thousands of trades per second. In practice, the vast majority of strategies are implemented using mathematical formulas based on a variety of stock metrics, such as closing price or volume. However, the effectiveness of these algorithms isn't publicly available due to the necessity of secrecy of implementation details. Part of the thesis aims to uncover and examine the effectiveness of existing metrics-based strategies. We find both Pairs Trading and a combined RSI and MACD momentum algorithm to be incredibly effective.

Moving beyond traditional AT strategies, this thesis further aims to investigate using news- or media-content-based strategies. By using Twitter data and Natural Language Processing (NLP), we create a unique trading strategy based on Twitter sentiment of publicly traded companies' tweets using a bevy of machine learning algorithms and a deep learning algorithm. We use models which have simplistic or extended features and apply these features to a stacking model and a deep learning model. We find the simplistic model to be very ineffective while the extended model beats the baseline measure for 87.5% of stocks tested generating profits of up to 529%. Even though the stacked model only beats the baseline for 62.5% of stocks tested, it proves to be very effective for certain stocks and have far more consistent performances while the deep learning model is far more risk averse than any of the other models explored.

Acknowledgments

I would like to thank both of my thesis advisors Prof. Darren Strash and Prof. Aaron Gember-Jacobson. The former had an incredibly involved role throughout my independent study and development of my thesis. I would not have been able to complete this thesis without his organization, incredible experience, and mentorship. I cannot stress enough how lucky I am to have him acting as the chief advisor of my thesis. I have had the privilege of being advised by Prof. Gember-Jacobson for both this thesis and as my computer science advisor. Both have taught me in the classroom and have had profound impact on my experience and enjoyment as a computer science major as well as giving industry guidance for my pursuits after Colgate. I also would like to thank Prof. Will Cipoli. He provided valuable consultation related to machine learning algorithms and feedback on my various models implemented for my Twitter sentiment trading contributions. I would additionally like to thank my parents, friends, and family for allowing me to complete this thesis.

I declare that I have developed and written the enclosed thesis completely by myself, and have not used sources or means without declaration in the text.

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(Alex Thomas)

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1 Introduction

Algorithmic Trading (AT) is the generation and submission of orders of a financial asset by an algorithm, or set of instructions [28]. The trading of stocks is one of the most important and prominent profit making utilities in the world. The introduction of 401k's in 1978 into employment benefits has caused the majority of families in the United States to be invested in the stock market [27]. Each individual's portfolio has a unique distribution of stocks. Because the average person doesn't have enough knowledge to day trade productively, this has created the need for owning stocks that provide safe and constant returns. This is realized in mutual funds, which are collections of funds invested into a variety of different stocks and often compose large percentages of 401k portfolios. These funds often utilize algorithmic trading to produce maximum profit, motivating our study to understand how these strategies work. This has allowed millions of people to maximize longterm savings [28].

To enter into the stock market one must purchase a specified number of shares of a particular security or mutual fund, which consist of companies, individuals, institutions, currencies, and more. However, this is a two-way transaction. To purchase a specific number of shares at a particular price, another party must agree to sell at least as many shares at that same price. This happens via broker or in modern times, via computer. From the trader's standpoint, it is as simple as logging onto a stock trading website and clicking "execute trade".

There are many different types of transactions in financial markets. *Buying* and *selling* of shares are among the most common stock orders. *Limit orders* are buy and sell transactions that are only executed at a given limit price threshold. These orders are generally used to minimize loss and risk as trades will only occur when specific market conditions hold [2]. *Shorting* of stocks works the opposite way of buying. With shorting, the trader is betting against the performance of the stock. The short sellers borrow shares of stock they don't own and sell them at market price. The goal is to re-buy the stock at a later date and return the borrowed shares to the lender by repurchasing the stocks at a lower price than the initial purchase. *Options* trading has gained recent popularity and is comprised of call and put options. This is a derivative type of security, as it is intrinsically linked to the price of something else. *Call options* give the owners the right to buy stock at a certain price, while *put options* gives the holder the right to sell stock at a certain price. Here, we are chiefly concerned with buying and selling transactions, however further study could examine some of the other types of orders mentioned above.

The intended outcome for any trade or transaction is always the same: to maximize profit. However, it is often difficult to pinpoint the exact moment in time that a particular trade maximizes profit. As computers and network connections have improved, trading financial instruments via automation has become more prominent. By using advanced mathematical models and measures, automated financial trading aims to maximize profit, executing up to thousands of trades a day of a particular security. While not often widely publicized, millions of trades each day are made by computer algorithms and not humans. In 2011, over 73% of all equity trading volume in the U.S. was performed algorithmically [28]. However, much of this trading is done by large financial institutions or prop-trading firms. Few studies look at the efficacy and inner workings of prominent trading algorithms [10] [13].

The stock market at its inception was entirely analog and trades of stock were carried out in person. Rapid trading traces its roots back to the early 1930s. Specialists and pit traders bought and sold positions and broadcasted trades via new high speed telegram services [28]. Computerization of trades started in the 1980s when the NASDAQ was the first exchange to introduce purely electronic trading. This trend of stock markets moving towards computers opened the gate for the use of Today, trading time has changed from a matter of seconds to microseconds [28]. The stock market moving entirely electronic gives motivation and reason for automated trading.

Just like the stock market moving entirely electronic, modern news has also moved entirely online. Social media or news websites are often the most effective way for a company to create news in the modern day. This allows companies to share news in the matter of seconds. Social media websites like Twitter or Facebook allow companies to create incredible amounts of content and instantly share it with the entire world. Previous research has looked to leverage news sentiment for algorithmic trading strategies, as it has been proved that news affects stock price[15]. Behavioral finance suggests that emotions, mood, and sentiments in response to news play a significant role in investment and affect the price of stocks.

Algorithmic trading has not always had a positive impact on the market. There have been some negative consequences. The May 6th, 2010 “Flash Crash” brought the public’s attention to the little publicized, but very heavily used algorithmic trading in financial markets [18]. This happened with E-mini, denoted by ES, which is a stock market index futures contract that trades for around 50 times the value of the S&P. A mutual fund complex sold 75,000 of these contracts valued at approximately $4.1 billion - resulting in the largest net change in daily position of any trader in the E-mini since the beginning of the year. This caused a cascading effect, as other traders reacted to this massive momentary plunge and sold accordingly, with over 20,000 trades across 300 separate securities executing at prices 60 percent away from their initial prices a mere half hour earlier. The Dow Jones Industrial Average fell over 1,000 points in a matter of moments, causing over $1 trillion to evaporate within 10 minutes.

1.1 Motivation

AT is the generation and submission of orders of a financial asset by an algorithm, or set of instructions, that processes current market data and places orders in stock marketplaces without human interaction. More formally, Chaboud et al. [7] define AT as:

> "In algorithmic trading (AT), computers directly interface with trading platforms, placing orders without immediate human intervention. The computers observe market data and possibly other information at very high frequency, and, based on a built-in algorithm, send back trading instructions, often within milliseconds. A variety of algorithms are used: for example, some look for arbitrage opportunities, including small discrepancies in the exchange rates between three currencies; some seek optimal execution of large orders at the minimum cost; and some seek to implement longer-term trading strategies in search of profits."

High Frequency Trading (HFT), is a subset of algorithmic trading and a far newer phenomenon that has been made possible by the rapid improvement of computerized trading speed [14]. This is the primary form of algorithmic trading found in financial markets today, with billions of dollars constantly traded by machines every second. However, it is difficult for trading of this type to occur at an individual level. Companies have the capital and resources to pay millions of dollars for their own fiber-optic cable connections across the United States and into Wall Street and up to the millisecond stock data whereas the individual doesn't.

This provides an interesting conundrum for the individual trader. Much of AT done in the market is done by large banks or massive prop-trading firms trading billions of dollars of existing capital per day. Is it possible for an individual with much less capital to engage in AT and be significantly profitable? With the current market trend of no-commission brokers such as Robinhood or developer friendly API's such as Alpaca, it has become ever the more possible for individuals to become algorithmic-traders [4]. However, what strategies can be implemented to obtain profits? Is it feasible to use small amounts of capital to have significant returns? While sentiment plays a role in the stock market, is it possible to quantify via Twitter and build a model that predicts stock price? All of these questions provide motivation for this study. In particular, the last question is of utmost importance.

Social networks have provided large companies a platform for mass public communication with the entire planet. This data is publicly available and could provide helpful insight into trading decisions.

1.2 Our Contribution

Because AT is an unsurprisingly secretive industry, we look to examine the effectiveness of both typical and atypical trading strategies. We give an in-depth analysis of a variety of both AT and HFT strategies. Specifically, we examine momentum, arbitrage and mean reversion measures and methods [2]. While many of these methods can be applied to other financial markets, such as Bitcoin markets, we use data exclusively from the US stock market. We develop a test suite that runs a variety of different algorithmic trading strategies on two different periods of data. Some of the strategies tested focus on HFT and use intra-day, minute-by-minute stock data. Others look at a period of over 7 years of closing price data. By using different types of data, we are able to examine strategies in both an AT and a HFT context.

Additionally, we contribute unique trading algorithms using both Machine and Deep Learning using Twitter *sentiment* data. We collect tweets from publicly traded companies twitter pages from the inception of their account until 2017. We then using Natural Language Processing (NLP) to construct average sentiment values for tweets on each day. While we find weak linear correlation with price and average tweet sentiment, we expect more advanced models that use machine learning to be able to more accurately apply this data. We investigate the effectiveness and fit of machine learning classifiers and reggressors, such as decision trees, k-nearest neighbors, and MLP, and random forest. We also investigate the effectiveness of LSTM neural networks using deep learning.

1.3 Organization

In Chapter 3 we give…, in Chapter 4…

THIS NEEDS TO BE FILLED IN ONCE STRUCTURE IS DONE AT[1]

[1] AT: ToDo

2 Related Work

Many researchers have studied AT and HFT in the context of specific algorithms, the state of the industry, and greater topics [28]. Because of the secretive nature of AT due to the direct effect of money making, research on specific algorithms often doesn't include specific implementations or pseudo-code of algorithms. This is because they would lose the advantage their particular algorithm has by making it publicly available.

2.1 Algorithmic Stock Trading

Algorithmic stock trading is a rare combination of being both an academic discipline and a multi-billion dollar industry. Academically, it is often studied in a general context. Specifically, research highlights how AT has a dysfunctional role in the stock market or may take a general look at how HFT can undercut normal trading. For example, articles review components of AT trading systems, which generally includes data access and cleaning, pre-trade analysis, trading signal generation, trade execution, and post-trade analysis [28]. Other research takes a deep dive into particular experimental algorithms, like *gated Bayesian networks* (GBN) [5]. GBN's are models that combine several Bayesian networks in a manner that acts like gates – making specific networks inactive or active based on logic. This method is applied to AT systems and performs better than the benchmark of buy-and-hold while simultaneously substantially decreasing risk of invested capital.

However, the research also has very practical applications. Numerous textbooks exist that take a very general, overarching dive into algorithmic-trading. Aldridge's textbook [2], which is one of the most cited works on AT, looks at market structure, HFT data fetching, risk management of HFT, and a variety of naïve strategies, such as market making or statistical arbitrage. Gomber et al. [14] focus on the evolution of AT and take a look at very specific regulations in European and American markets. These practical applications all reinforce the barriers of entry for an individual trader, as acquiring raw and cleaned data is highly expensive and time consuming due to the time sensitivity of trading algorithms [28].

2.2 Sentiment Analysis, Twitter, and Stock Trading

The stock market often behaves as a function of news sentiment. Behavioral finance suggests that emotions, mood, and sentiments in response to news play a significant role in investment [15]. Particularly, Ho and Wang identify that sentiment has the most significant impact on investors in the market [15]. Take the GE downswing on April 8, 2019 as an applicable case study. GE's stock plunged over 6% in pre-market trading as an influential J.P. Morgan analyst slashed his rating on the stock [26]. Significant actors can have major effects on the entire market purely based on sentiment of the actor's remarks. This makes sentiment analysis and stock trading a particular area of interest academically.

2.2.1 Sentiment Analysis Application to Machine Learning and Classification

Previous literature often uses machine learning for sentiment classification problems. Pang et al. [23] employ different machine learning methods on movie review data and find that while it does vastly outperform human-produced baseline, it is not as nearly as effective on traditional topic-based categorization. Their work stems from the issue of automatically classifying the vast amount of online text documents' sentiment, which would be incredibly useful for business intelligence applications and review sites. Using naïve Bayes, a maximum entropy model, and support vector machines (SVM), they find that they aren't able to produce very accurate topic-based categorization results. They estimate that a large problem with their sentiment analysis is authors' uses of deliberate contrast in the data, which humans could easily discern unlike machines. Their paper shows how even though machine learning is often relied on for classification and does outperform the baseline, it isn't incredibly effective. These discrepancies could potentially lead to challenges for our own methods.

2.2.2 Past Examinations of Sentiment and Stock Trading

Using sentiment as an indicator for stock trading has been heavily studied in academia. Li et al. study news impact on stock price using sentiment analysis [19]. Because financial news articles are believed to have an impact on stock price return, they use news sentiment to implement a stock price prediction framework using the Harvard psychological dictionary and the Loughran-McDonald financial sentiment dictionary. This sentiment analysis framework outperforms previous *bag-of-words* stock price prediction frameworks [19]. This literature demonstrates how news impacts the stock market and can be used to predict stock price movement, which is at the crux of our study.

Financial markets outside of the major United States heavyweights like the *Dow Jones Industrial Average* (DJIA) have also been studied using sentiment analysis. Garcia et al. use social signals to create a Bitcoin trading algorithm that is highly profitable [12]. They integrate various datasources that provide social signal data on information search, word of mouth volume, emotional valence and opinion polarization in the analysis of Bitcoin, a cryptocurrency that is extremely volatile and known for sustained price fluctuations. Their analysis reveals that increases in opinion polarization and exchange volume precede rising Bitcoin prices and are able to create a Bayesian model that is highly profitable. Shah et al. [25] discuss the efficacy of Bayesian regressions on predicting Bitcoin price variation. They use a latent-source model for the purpose of binary classification, which has been previously established as effective for this specific scenario. They are able to predict price change every 10 seconds accurately enough to double the initial investment in less than 60 days. While these studies consider use of cryptocurrency markets, it still proves that financial instruments are correlated with social signals, or sentiment.

2.2.3 Past Examinations of Twitter as a Valid Means of Stock Trading

Past literature has extensively examined using Twitter as a means of data for input into trading algorithms. Mao et al. [22] use Twitter volume spikes to S&P 500 stocks and wether or not they are useful for stock trading. They find that Twitter volume spikes are correlated with stock price movement, acting as a surprise to market participants based on implied volatility. The authors use a Bayesian classifier to develop a trading strategy that has significant returns in a short period of time. Zhang et al. [29] look to predict stock market indicators through Twitter. After collecting randomized twitter posts for six months, the researchers measure collective hope and fear each day and analyze the correlation between those and stock market indicators. They find that emotional tweet percentage is significantly negatively correlated with all of the major United States stock markets. Bollen et al. [6] use Twitter mood to predict the movement of the stock market by classifying specific tweets into six different categories or moods. The authors use a Granger causality analysis and a self-organizing fuzzy neural network to investigate how indicative public mood states are of the DJIA closing prices. They use large-scale Twitter feeds and determine the mood of tweets over 6 dimensions and find that Twitter mood can predict the movement of the DJIA with incredible accuracy. All of these works suggest that Twitter activity can be applied to stock prices and thus used in trading algorithms, which is precisely what we aim to exploit in our study.

3 Stock Trading Preliminaries

In this study we examine numerous algorithmic trading methods. To measure the effectiveness of a particular strategy, we use a quality metric to analyze productivity. Different denominations of purchasing powers are used and compared against a *buy-and-hold baseline*. The baseline measure is created by holding a long position of a specific denomination throughout the entire period of trading. Simply put, shares are bought at the beginning of the period and sold at the end. The profit level is then compared against the performance of the AT strategy. Much of the literature actively study the best performance of these strategies over different periods and use the same baseline comparison [20] [2] [12]. We therefore include the same baseline in this study.

The stocks used in all strategies are found in Figure 3.2. These stocks were chosen given the availability of NASDAQ and S&P500 stocks in the Quandl dataset and cover a variety of industries. This is important because we need to account for different performances of stocks. Certain large tech stocks like FB or GOOG have had incredible trajectories and performances whereas other stocks outside of the tech industry like HAS, have performed more moderately. The range of stocks chosen encompass nearly all of the major industries throughout the world.

Buy and *sell signals* are used throughout the study. Algorithms can generate a variety of buy and sell signals at a specific point in time, indicating that some denomination of stocks should be purchased or sold at that specific point in time. To measure how a given algorithm performs, different denominations of shares are purchased and compared. The strategies use closing price data from October 1st, 2006 to January 1st, 2017. Some strategies use intra-day stock data, which is minute-by-minute data of stock prices from October 26, 2018. Other additional terms need to be defined. *Securities* and *stocks* are used interchangeably throughout the paper and effectively have the same meaning. Specifically, securities have more of a broad definition, as securities include stocks, bonds, mortgages, and others. When discussing how stocks will move in the future, we use *bearish signals* to signal trends of downturn and *bullish signals* for positive, upward trends [2].

Graphs can be interpreted as follows. Figure 3.1 shows the Simple Moving Average strategy applied to GOOG. Purple triangles, which are angled upwards, are buy signals while black triangles angled downwards are sell signals. On June 2015, the strategy generated a sell signal, denoted by the black triangle. In the following couple of months, a subsequent buy signal was generated as denoted by the purple triangle. The orange line is the long moving average, the blue line is the short moving average, and the red line gives the price of GOOG throughout the time.

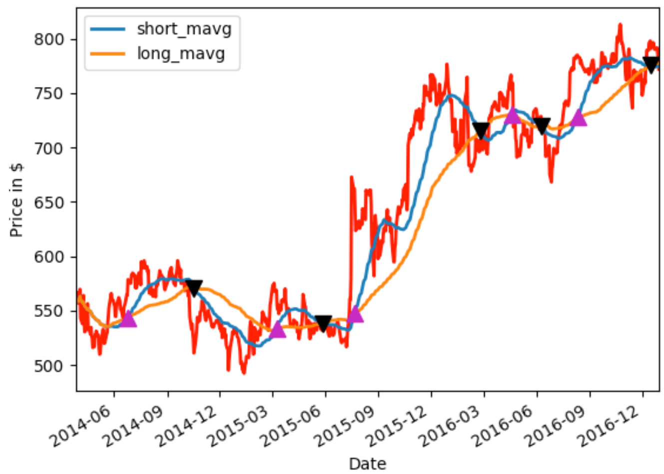


Figure 3.1: Simple Moving Average - "Golden Cross" Strategy applied to GOOG

Stock Ticker	Stock Name	Stock Market
AAL	American Air Lines	Nasdaq
AAPL	Apple, Inc.	Dow Jones Industrial Average
AMD	Advanced Micro Devices, Inc.	Nasdaq
AXP	American Express Company	Dow Jones Industrial Average
BA	The Boeing Company	Dow Jones Industrial Average
BIG	Big Lots!, Inc.	New York Stock Exchange
CAT	Caterpillar Inc.	Dow Jones Industrial Average
COLM	Columbia Sportswear Company	Nasdaq
CSCO	Cisco Systems, Inc.	Dow Jones Industrial Average
CVX	Chevron Coporation	Dow Jones Industrial Average
DIS	Walt Disney Co.	New York Stock Exchange
EBAY	eBay Inc	Nasdaq
FB	Facebook, Inc.	Nasdaq
GE	General Electric Company	Dow Jones Industrial Average
GOOG	Alphabet, Inc.	Nasdaq
GS	The Goldman Sachs Group, Inc.	Dow Jones Industrial Average
HAS	Hasbro, Inc.	Nasdaq
HD	The Home Depot, Inc.	Dow Jones Industrial Average
IBM	International Business Machines Corporation	Dow Jones Industrial Average
INTC	Intel Corporation	Dow Jones Industrial Average
JNJ	Johnson & Johnson	Dow Jones Industrial Average
JPM	JPMorgan Chase & Co.	Dow Jones Industrial Average
KO	The Coca-Cola Company	Dow Jones Industrial Average
MCD	McDonald's Coporation	Dow Jones Industrial Average
MMM	3M Compnany	Dow Jones Industrial Average
MNST	Monster Beverage Corp	Nasdaq
MRK	Merck & Co., Inc.	Dow Jones Industrial Average
MSFT	Microsoft Corporation	Dow Jones Industrial Average
NKE	Nike, Inc.	Dow Jones Industrial Average
PFE	Pfizer Inc.	Dow Jones Industrial Average
PG	The Procter & Gamble Company	Dow Jones Industrial Average
PYPL	Paypal Holdings, Inc.	Nasdaq
QCOM	QUALCOMM, Inc.	Nasdaq
SBUX	Starbucks Corporation	Nasdaq
TRV	The Travelers Companies, Inc.	Dow Jones Industrial Average
UNH	UnitedHealth Group Inc.	Dow Jones Industrial Average
UTX	United Technologies Corporation	Dow Jones Industrial Average
V	Verizon Communications, Inc.	Dow Jones Industrial Average
VOD	Vodafone Group Plc	Nasdaq
VZ	Visa Inc.	Dow Jones Industrial Average
WMT	Walgreens Boots Alliance, Inc.	Dow Jones Industrial Average
XOM	Exxon Mobil Corporation	Dow Jones Industrial Average

Figure 3.2: Table of stocks used in our study

4 Examination of Trading Algorithms

4.1 Data

We use Quandl, a financial data platform, to obtain the different stock ticker data. Specifically, we used the WIKI and AS500 datasets to acquire stock data. The former contains end-of-day stock pricing data while the former contains intraday data, with updated pricing for each minute in the day. While these datasets include numerous stock statistics, such as volume and adjusted price metrics, we only consider closing price for both of our datasets.

4.2 Momentum Trading Strategies

4.2.1 Simple Moving Average

Simple Moving Average (SMA) is an elementary AT measure. It is mostly used to measure average stock price over a period of time, however certain strategies solely rely on SMA. It looks at a rolling average of a specified window. Mathematically this can be defined as [3]:

$$SMA(t) = 1/n \sum_{i=t-n}^{t} x(i)$$

In words, this gets the average price over a specified window of time for a specified function. In the context of the stock market, SMA can be applied for both short term and long term averages, with the former under an hour while the latter can be hundreds of days or more. In application to the stock market and closing prices, this creates an average closing price for a specified amount of time, which gives an indicator of price swings in that period of time.

SMA is commonly leveraged into a strategy that uses a dual moving average [3]. It works by taking two different SMA's - a short window and a long window. In our implementation, we chose a 40-day window and 200-day window, giving insight into a strategy that uses longer averages. The short window crossing below the long window gives a buy signal reinforced by high trading volumes. The long window crossing below the short window is considered bearish and gives a sell signal, as this signals that the stock is currently overvalued and will devalue. As demonstrated in Figure 3.1, the strategy generates 10 buy or sell signals over the period tested. Taking March 2015 as a specific example, buy signals are generated when the orange line - the long moving average, crosses the blue line - the short moving average, from below. Sell signals occur, like on June 2015, when the opposite occurs.

4.2.2 Expected Moving Average

Expected Moving Average (EMA) is closely linked to SMA. Like SMA, EMA functions over a rolling window; however, it is calculated differently. Mathematically, EMA is calculated with F_i = the value associated with the moving average at period 0, α = smoothing constant, and X_i = closing price of the security at period i [17]:

$$F_i = F_{i-1} + \alpha(X_i - F_{i-1})$$

In words, the EMA is found by multiplying the close subtracted by EMA from the previous day times a multiplier plus that prior day's average. This makes this measure far more weighted towards recent prices than SMA.

Like our implementation of SMA, EMA is commonly implemented with dual high and low value average. It takes two different EMA's, one with a low window and the second with a high window. However, because EMA reacts more closely to recent stock prices shorter windows are more commonly chosen. For our implementation, 12-day and 26-day windows were used. The short window crossing below the long window gives a buy signal reinforced by high trading volumes while the opposite is considered bearish and gives a sell signal. Figure 4.1 demonstrates the EMA trading strategy applied to GOOG. Because smaller windows are used than our SMA implementation, we see far more buy and sell signals. Additionally, we see the short and long expected moving average lines follow the price line far closer than the SMA implementation.

4.2.3 Bollinger Bands

Bollinger Bands were introduced by John Bollinger in the 1980s[20]. They provide a relative definition for high and low stock prices. This strategy uses 3 bands, with the 2 outer bands derived from a standard deviation of the moving average. Bollinger bands are great measures of market conditions of a particular security. Just like the previously examined techniques,

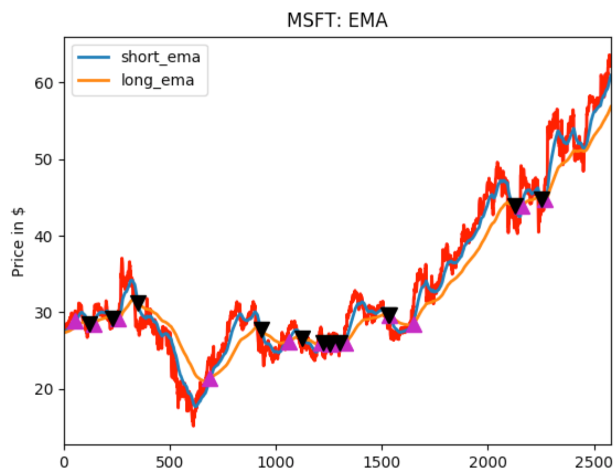


Figure 4.1: Dual Moving Average Strategy with Exponential effects applied to MSFT

the method uses a simple moving average as its basis, but instead incorporates 3 different bands separated by standard deviation. Because of this use of standard deviation, which is determined by market volatility, Bollinger Bands adjust themselves to market conditions. Precisely, the bands are calculated as follows with M - Middle Band, U - Upper Band, L - Lower Band, STD(x) - standard deviation of period x:

$$M = SMA(12), U = M + 2 * STD(12), L = M - 2 * STD(12)$$

When the market is more volatile the bands widen and when the market becomes less erratic, the bands move closer together [20]. Unlike the previous techniques, this strategy uses market conditions to evaluate trading orders.

This strategy is implemented with these 3 bands as mentioned above. For our implementation, a 12 day window was chosen to test out the algorithm, as this has been proven to be the most effective [20]. When the closing price drops below the lower band, this gives a buy signal, as once a lower band has been broken due to heavy selling, the stock price will revert back and head towards the middle band. The opposite is true for when the closing price breaks the upper band, as this is indicative of heavy buying. The closing price approaching the upper band gives a bearish signal while approaching the lower band gives a bullish signal. This strategy is showing in Figure 4.2. This measure can generate multiple buy or sell signals in a row. Looking at the first 100 days of the strategy, 5 straight sell signals are generated. The following 100 days subsequently generate 4 straight buy signals. This trend is indicative of the market giving only bearish indicators followed by a period of only bullish indicators stemming from the use of standard deviation in the measure.

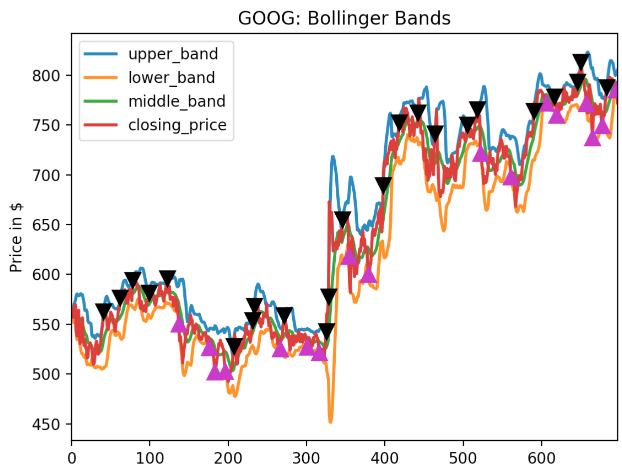


Figure 4.2: Bollinger Bands strategy applied to GOOG

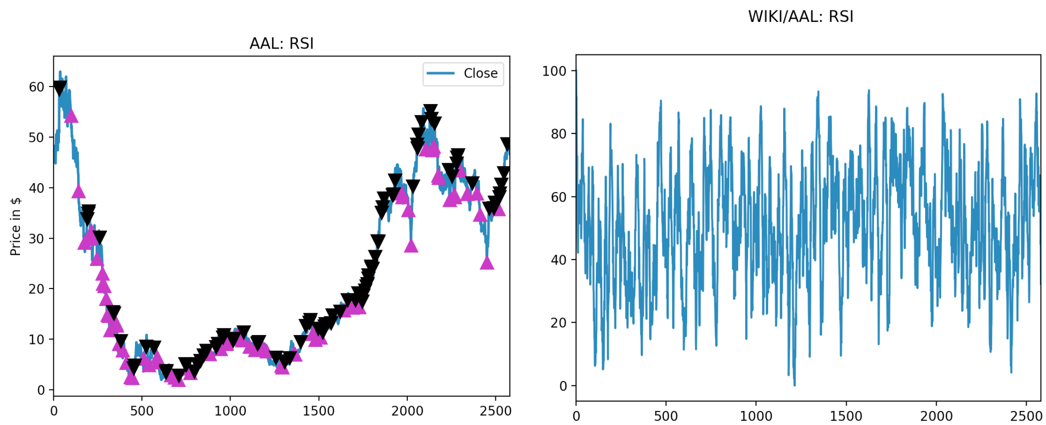
4.2.4 RSI - Relative Strength Index

Relative Strength Index (RSI) is a momentum indicator that measures the magnitudes of price changes to analyze overbought or oversold stocks. It demonstrates a particular security's recent performance over a relatively short window compared to the mean. This indicator is widely used today in algorithmic trading. The measure is a value between 0 and 100 at a specific date. The equation for RSI is as follows with *RS* defined as average gain of up periods divided by the average gain of down periods over a specified window x [8]:

$$RSI = 100.0 - (100.0/(1.0 + RS(x))$$

Therefore, a large RSI value is indicative of stocks that have had recent larger gains compared to losses while a low RSI value is indicative of stocks with poor recent performance compared to the mean.

This strategy takes advantage of mean reversion. Our implementation uses a very simple method. Sell signals are generated when the RSI is over 70 and buy signals are generated when the RSI is under 30 [8]. This is very logical, as expected gains are the largest when a stock has performed poorly recently and is expected to revert back to the mean. This strategy also uses a 14 day window, which is standard across the industry. Figure 4.3 shows this strategy when run on AAL. The second subfigure generates the buy and sell signals, as it shows the RSI of the stock throughout the period tested. These signals generated from the second subfigure are then plotted on the first subfigure over the stock price. Clearly, this strategy generates a large quantity of trading signals over the period.



(a) RSI Strategy

(b) RSI of AAL

Figure 4.3: RSI strategy applied to AAL

4.2.5 Combining Momentum Indicators - RSI and Moving Average Convergence-Divergence (MACD)

MACD uses two moving averages to identify trend changes while RSI performs exactly as stated in the above section. The MACD is constructed by subtracting two different sized exponential moving averages from each other. The equation for MACD is as follows and uses $EMA(x)$, with x representing the period in minutes [8]:

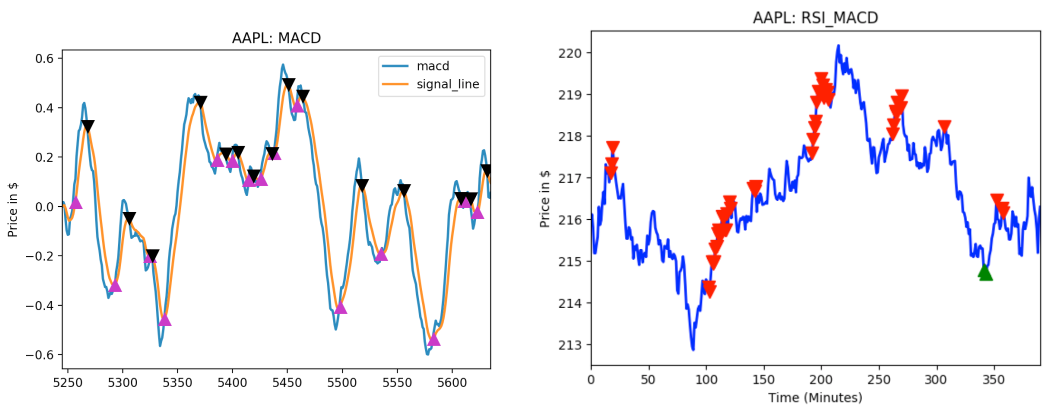
$$MACD = EMA(12) - EMA(16)$$

The MACD is then plotted against a signal line, which is defined as S and is the EMA of the 9 minute MACD:

$$S = EMA(MACD(9))$$

Buy and sell signals are then generated by the “golden cross" method. Specifically, this is when the MACD crosses the signal line from below - signaling a momentum swing and a bullish buy signal. A sell signal is the reverse - when the MACD crosses the signal live from above. Figure 4.4a shows the MACD strategy applied to AAPL. This strategy behaves the exact same way as both Figure 4.1 and Figure 3.1.

Unlike the previously mentioned strategies, this one combines indicators to generate more robust trading signals. Because there are two different measures working at the same time, buy signals are generated by both the RSI and MACD measures giving bullish signals within 3 minutes of each other. Sell signals are generated by either one of the measures producing a sell. Under this strategy, buy signals are very rarely generated while either strategy generating a sell denotes all shares to be sold. Because of the selectivity of buy signals, we can expect this technique to be very profitable. This strategy is most effective when run over intra-day data because of the relative infrequency of buy signals as demonstrated in Figure 4.4b. Throughout an entire day, only 2 buy signals were generated.



(a) MACD Strategy

(b) RSI and MACD strategy buy and sell signals

Figure 4.4: RSI and MACD combination strategy applied to AAPL

4.3 Pairs Trading - Arbitrage and Mean Reversion

Pairs trading is an algorithmic trading strategy that chooses two economically linked stocks and profits off the divergence in spread of prices. Pairs trading uses statistical arbitrage, which is attempted profit from pricing inefficiencies identified through mathematical models. The most basic assumption is that prices will move towards their historical average, which pairs trading takes advantage of and is also known as mean reversion. However, unlike other instances of mean-reversion, this strategy has a distinct advantage of always being hedged against market movements.

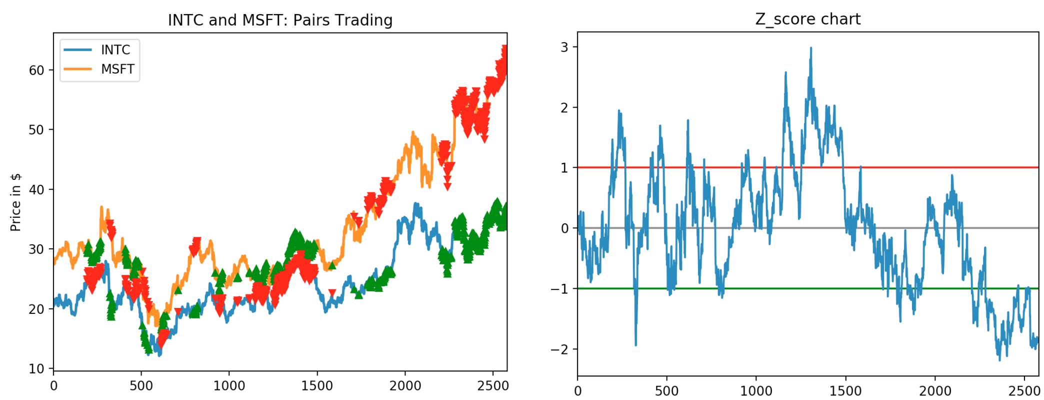
Pairs trading is motivated by statistical arbitrage and mean reversion[11]. When given two stocks that are linked economically (i.e. Pepsi and Coca-Cola), we expect the spread to remain relatively constant over time. However, there might be divergence in the spread between these two pairs cause by factors such as supply/demand changes or changes in volume in a particular stock. Another problem with this is finding stocks that are closely related. Because we need to have stocks that behave similarly, we use cointegration to identify pairs of similarly behaving stocks.

Cointegration is a stationary measure that highlights horizontal trends [13]. Unlike correlation, which only tracks similarly moving magnitudes over time, it instead tells how the difference between two regression lines changes over time. The implementation uses the python extension statsmodels to generate the p-value for cointegration. It is absolutely key to have related stocks, as this strategy takes advantage of mean reversion, or in other words, stocks reverting back to their original mean in relation to other similarly behaving ones. Now this is quite difficult, as it is very difficult to find stocks that are behave very similarly. After running comparisons of cointegration, certain tech stocks such as INTC and MFST were found to behave similarly.

To generate trading signals, a Zscore is generated from the ratio of prices R(i) = ClosingPriceStockX/ClosingPriceStockY on a particular day *i*, the overall mean of ratio of prices M = AVG(R), and the standard deviation of the price ratio STD = STD(R):

$$Z = (R(i) - M)/STD$$

The Zscore is a measure of how far away the current ratio of prices is away from its mean. Figure 4.5b shows the Zscore of both INTC and MSFT. Because of mean reversion, we can use this as a good indicator for buy and sell signals. A buy signal is generated when the zscore drops below -1, as we expect the zscore to return to its mean of 0. A sell signal is generated when the zscore goes above 1, as the stock is currently overvalued because we expect the stock to return to its mean of 0[11]. These thresholds are shown in Figure 4.5b. In context of the pair of stocks, on buy signals the first stock in the pair is bought while the second is sold or shorted. The reverse is true on sell signals. Figure 4.5 shows this strategy applied to INTC and MSFT. The red triangles represent sell signals while the green triangles show buy signals. Each time a buy signal is generated at a particular day the other stock has a matching sell signal and vice versa.



(a) Pairs Trading Strategy

(b) Zscore of INTC and MSFT

Figure 4.5: Pairs Trading strategy applied to INTC and MSFT

5 Experimental Results of Standard Algorithms

The test suite runs all of the algorithms discussed above on a subset of stocks and generates profit figures for different denominations of stocks purchased. For every buy signal generated, the strategies ran on purchasing 10, 100, and 1000 stocks at a time. The strategies were implemented in Python and accessed stock data stored in csv files. The implementation leveraged Pandas Dataframes to store and manipulate the stock data. Pandas is a python data analysis package and is perhaps the most powerful open source data analysis or manipulation tool available. See Section 9.1 for pseudocode of each strategy's implementation. The best way to understand how effective a particular strategy is to compare against a baseline, which is discussed above, helping us analyze the effectiveness of each strategy.

5.1 Momentum Strategies

Standalone momentum strategies as a whole very rarely beat out the baseline measure. Figure 9 displays the results of AAPL, GOOG, HAS, QCOM, and AMD when using SMA, EMA, Bollinger Bands, and RSI. Only a few stocks had any strategies beat the baseline. One was GOOG, with both Bollinger Bands and RSI outperforming the baseline profit significantly. AMD for both SMA and EMA proved to be effective as well. However, for most it was more profitable to simply just buy and hold over the period. Figure 5.1 demonstrates this poor performance. The baseline bar chart on the right side of the graph outperforms nearly every strategy. This however seems counterintuitive, as we should be generating profitable buying and selling trading signals with all of the computation, but that is clearly not the case. Clearly, these strategies aren't viable as standalone trading algorithms. Now we will discuss why we observed overall poor performance.

The dual moving average algorithm when applied to both SMA and EMA isn't particularly effective. Due to the nature of SMA, which generally looks at long periods of time to highlight trends, this can induce a lagged effect to the buy and sell orders. A lagged effect in the context of moving averages is that the current moving average doesn't react to the current trend because of this longer observation window, often making this method ineffective. This lagged effect can be fixed by looking at an Exponential Moving Average analysis [10]. However, unlike the literature suggests, in practice this doesn't translate to profit. AAPL nearly doubled its profit from using the exponential window that removes the lagged effect yet still had 2.53% less returns than the baseline. While as a whole the strategy was more effective than SMA and did come closer to baseline performance, it rarely ended up beating it. This suggests that these indicators should be looked at in a different, combined context where multiple indicators could provide more robust trading signals. See the following section for discussion.

With Bollinger Bands, buy and sell signals are still reliant on changes in rolling average prices. However, because of the incorporation of standard deviation, this strategy uses volatility in the market to further base buy and sell decisions. While a significant portion of the chosen stocks didn't end up actually out performing the baseline, a majority of them were within 1-2 percent performance of the baseline. 33% of stocks tested on the strategy out performed each of its own baseline measure of buying and holding a specific denomination of shares throughout the entire period. Most notably, GOOG outperformed the baseline by 2.77% while the implementations of SMA and EMA had abysmal performances of -30.25% and -19.41% respectively. While still not a passable standalone algorithm, the improvement over SMA and EMA is encouraging.

RSI takes advantage of over-purchasing or overselling of securities to predict convergence back to the mean. So, this strategy does take advantage of mean reversion. Unfortunately, most RSI implementations didn't outperform the baseline. The performance was comparable to EMA but slightly worse, as we see less stocks beating out the baseline. GOOG beat the baseline by 12.88% while on the other hand DIS massively underperformed and posted a -7.08% performance.

5.2 Combination Momentum Strategies

The RSI and MACD combined implementation performed incredibly well. The most notable performances were from AAPL and HD. When purchasing 1000 shares at each buy signal, AAPL out-gained the baseline by $9070 while HD had $4990 of profit with the strategy while the baseline lost $3750. Of all 30 stocks tested, only 3 stocks ended up with negative profit at the end of the day. AXP is a good example - generating a loss of $1300 more than the baseline. With enough capital, this strategy could be used to generate incredible returns on a daily basis. Figure 5.2 shows this strong performance. The green bar - the profit of the strategy buying or selling 1000 shares at a time, beats out the correspond baseline purple bar for every single stock, giving truly significant results.

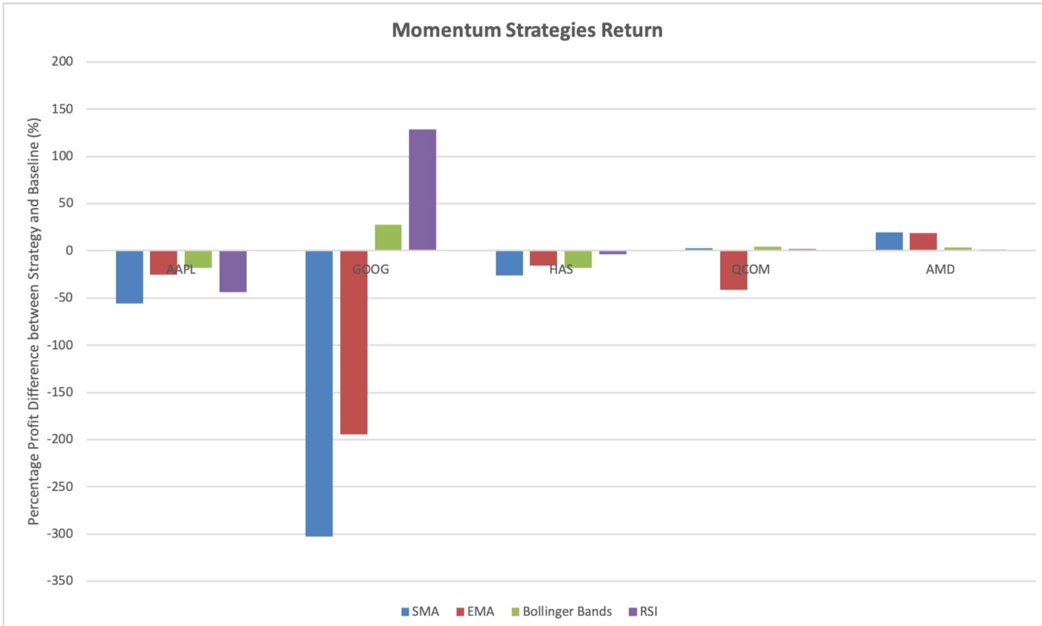


Figure 5.1: Momentum Strategies Results

This algorithm generates incredibly robust buy signals and frequent sell signals which can nearly guarantee gains after buy signals. Therefore, utilizing strategies where 1000 shares of a given stock can generate massive profits with less risk of massive losses. It is also important that each transaction purchases a large amount of shares because it is necessary to offset the transaction cost charged by brokers. However, rather than focusing on individual stocks over time, this combination strategy is best implemented over a pool of multiple stocks because it isn't uncommon for days to generate absolutely no buy signals.

5.3 Pairs Trading

Just like the above strategy, our pairs trading implementation performed incredibly well. Compared against the baseline of SPY, a mutual fund that is the industry standard for baseline comparison of AT strategies, this strategy has amazing performance. When using AMD against SBUX, the strategy profited 2143.28%. QCOM and SBUX performed similarly - culminating in 1748.06% returns. However, even the lowest performing combination, AMD and VOD, beat out the baseline by over 138%. Figure 5.3 shows these truly astounding results. Furthermore, this strategy would need to be tested on a larger pool of stocks, as only 5 combinations of stocks were cointegrated enough to justify trading together.

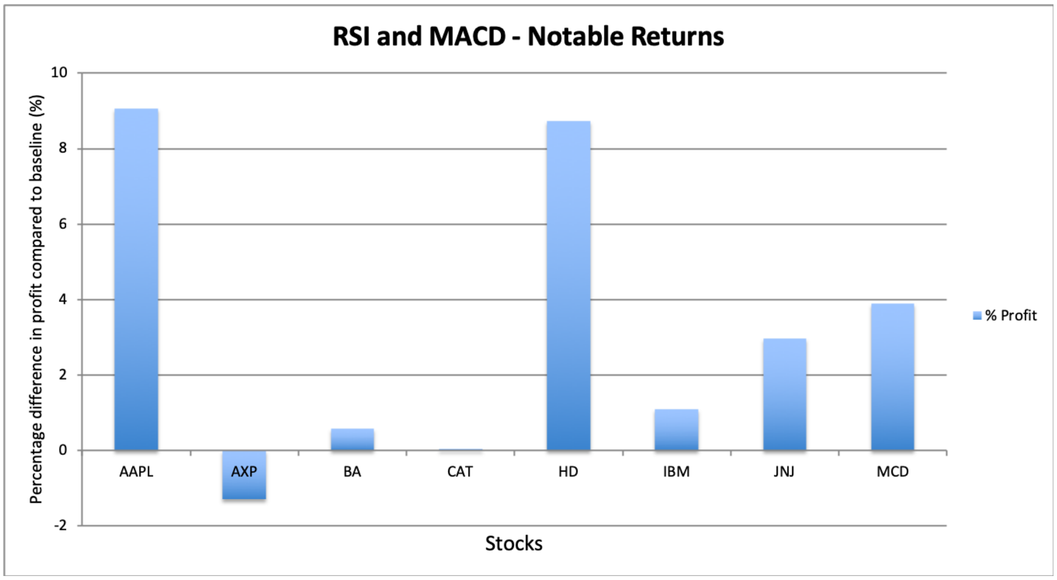


Figure 5.2: RSI and MACD strategy

This highlights a common trend. More involved strategies that use multiple measures or inputs always perform better than single measures and nearly always beat the baseline. Just like the combination momentum strategies, the results are incredible. With both pairs trading and as well as the above strategy, someone who implements either strategy could make incredible profits. The barrier to entry however for individuals to truly generate these massive profits, is being able to access up to the minute stock data. All data found via the internet or Quandl is delayed by upwards of 20 minutes, which can make the difference between thousands of dollars and profits and thousands of dollars of losses. However, because pairs trading uses closing prices, one wouldn't have to pay for the end of day closing data.

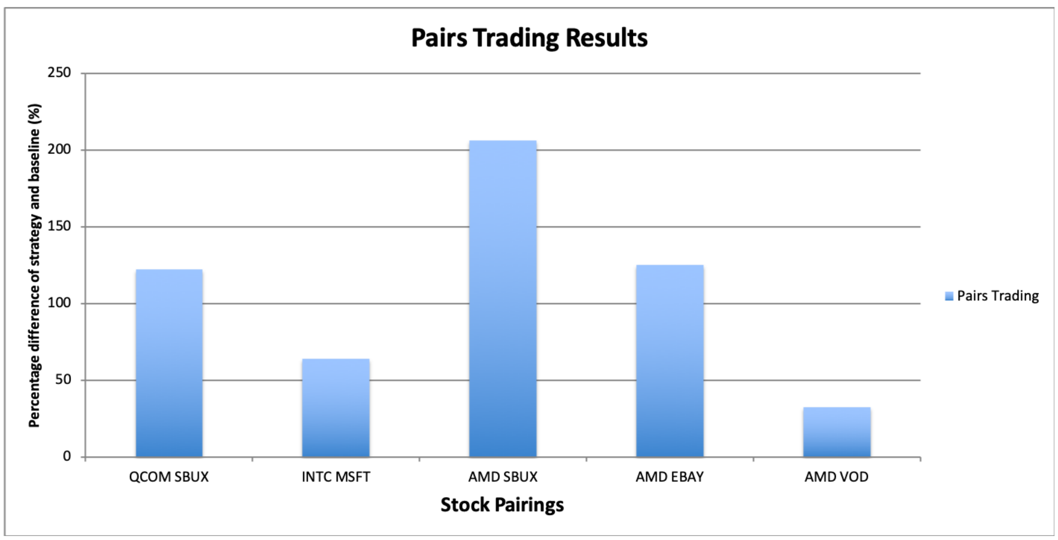


Figure 5.3: Pairs Trading Results

6 Twitter Sentiment and Stock Trading

We create unique twitter sentiment stock trading algorithms using a variety of different models. As mentioned in the literature review, sentiment can be used to effectively trade in the stock market. While a variety of different papers have looked at more general tweet sentiment directed at particular stocks, such as specific stock ticker mentions [22], we choose a different method. Unlike previous literature, we instead leverage large companies own twitter activity. The motivation is that companies often use social media as a primary medium for announcements, product launches, and generally important events. While mentions of a particular stock can gage the public's reaction or sentiment to a particular event, we attempt to circumvent this reactionary sentiment measure and look at the sentiment of the content the company is producing on Twitter. By analyzing a companies Twitter output for a day, we expect that we can use that information to more effectively predict the following days stock price movement and thus generate more profit. This method has the added benefit of not only gaging the sentiment of a companies tweets, but also identifying the public's reaction to particular tweets measured by retweets and favorites. We consider 5 different learning algorithms and 4 different models that use Twitter sentiment. Below we discuss why we choose such algorithms and how they work.

6.1 Twitter Data and Aggregation

To acquire tweets from the companies, we use a slightly modified version of Github user *bpb27*'s repository *twitter_scraping* [1]. We scrape tweets from within our trading period of 2006 until the start of 2017. We found that most major companies didn't start tweeting until after the start of our initial trading period so our models trade over the time from the companies first tweet until the start of 2017. We use 16 major companies tweets and stock data for our experiments, which cover a variety of different industries as shown in Figure 3.2.

To acquire Twitter sentiment values, we use Natural Language Processing (NLP). NLP is a branch of artificial intelligence that allows machines to understand and decipher human

[1] https://github.com/bpb27/twitter_scraping

language. For our implementation, we used the textblob python library to perform NLP on the Twitter data [21]. We perform sentiment analysis on the text from the tweets and use the *polarity* score, which is a float from -1 to 1, to understand the sentiment of individual tweets. The textblob library generates polarity from a naïve Bayesian classifier that has been pre-trained on a movie review data corpus by identifying positive and negative words from the input text. While it is possible there are differences between the movie review corpus and the language used in tweets, it is impossible to quantify. While building our own NLP Bayesian classifier would have potentially made Twitter sentiment more accurate, future work could look to implement a tweet-based NLP classifier.

We then aggregate the Twitter data over each day of stock trading by merging both the Twitter data and stock data Pandas DataFrames. Replies, which are tweets directed in response to particular users, are dropped from the models, as this would skew the intent of the data as we are concerned with tweets directed at the general public.We create inputs for our model over each day of average tweet sentiment, amount of tweets, total favorites, and total retweets. After, we then generate indicators for supervised learning: closing price change and closing price signed change. For the regression model we use the float value of change in closing price while the classifier models only accept integer values for the y-value input. Therefore, a 1 signals a positive change in price while a -1 signals a negative change in price from day to day.

6.2 Statistical Approach

We look to understand if there is any statistical correlation between closing price and average tweet sentiment. We find that there is very minimal correlation. Figure 6.1 shows this lack of correlation. We find BIG to have the most correlation of any stock tested of a measly 0.30. The vast majority of the stocks are under +/- 0.15 correlation. This lack of correlation could have negative implications for a very basic trading strategy that uses sentiment values statistically.

Because there is little correlation between closing price and average sentiment we should expect a naïve strategy to perform poorly. We create a simple strategy that generates a buy signal when the average tweet sentiment is above .25 and generates a sell signal when it is below 0. We choose these values because of what we find in the data. Companies often have tweets that are positive, which is logical. Twitter is used as a means of promotion and sharing of news that is often positive so if the companies tweets for the day were on average negatively, we could expect the stock to perform poorly the next day. Figure 6.2 shows the abysmal performance for this naïve strategy. Only 25% of the stocks end up beating the baseline, with the underperforming stocks performing terribly. EBAY characterizes the

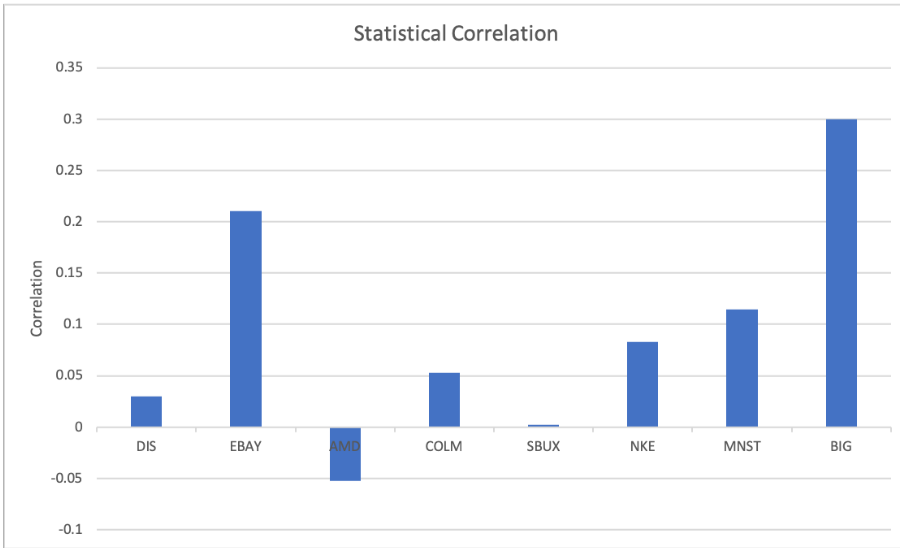


Figure 6.1: Correlation Results

overall performance of this strategy well – with the strategy returning 47.2% while the baseline nets a 237.6% profit. If sentiment was more correlated with closing price, we would expect this strategy to be more profitable. This lack of correlation motivates the need for a more sophisticated approach, such as using machine learning.

6.3 Stock Trading and Machine Learning Algorithms

Our implementation uses the both the Scikit-learn and TensorFlow Python libraries [24] [1]. We use Natural Language Processing to conduct a sentiment analysis of tweets for our models. We then aggregate the twitter data across days of stock trading and then feed the combined stock and twitter data into a variety of different machine learning algorithms. WHY DO WE USE THIS VARIETY OF ML ALGOS?[AT2] We use this variety of machine learning algorithms to attempt to understand if one in particular works well with Twitter sentiment data or if the effectiveness of each algorithm varies from stock to stock. We discuss the different types of features inputted to these algorithms in section 6.4.

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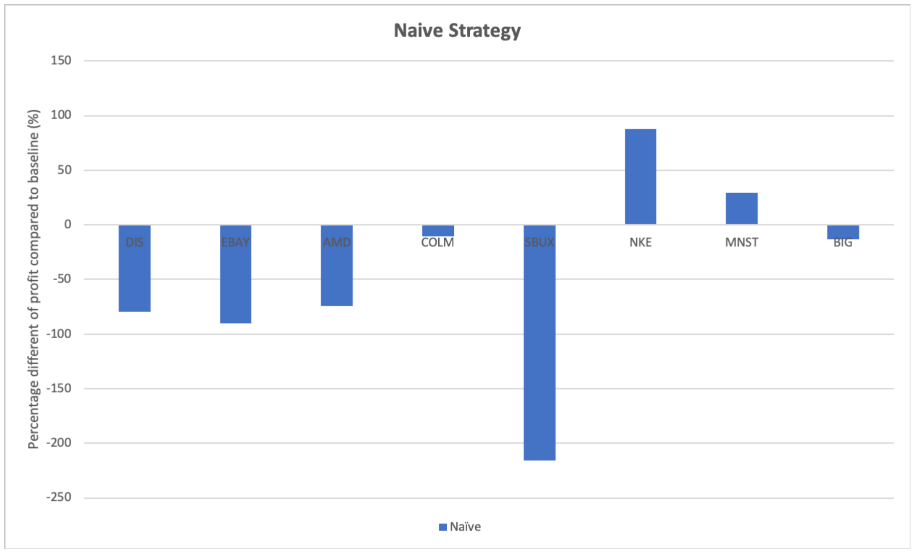

Figure 6.2: Naive Strategy Results

6.3.1 Trees

Decision Tree Classifier

Decision trees are models that predict the value of a target variable by learning simple decision rules inferred from the data features [24]. It breaks down a dataset into smaller and smaller subsets, with the leaf nodes representing the classification prediction based on information gain. For features into the classifier, we use the default features specified in the Scikit-learn library. Specifically, we use a Gini impurity for criterion, we choose the best split, and use 2 as the minimum number of samples to split a node. Because we are using a classifier, our implementation predicts whether or not the following days closing price will be higher or lower, which is represented by a 1 or -1. Another benefit of decision trees is that they can be visualized easily. Figure 6.3 shows the decision tree fitted to DIS. However, due to the complexity of our model it is difficult to interpret the visualization.

RandomForest Regressor

This module builds off of the above's section decision tree implementation. It instead uses a randomized decision tree making a diverse set of classifiers by introducing randomness in the classifier construction [24]. This prediction of the ensemble is then given as an averaged prediction of the individual classifiers. Each tree in the ensemble when it is constructed is

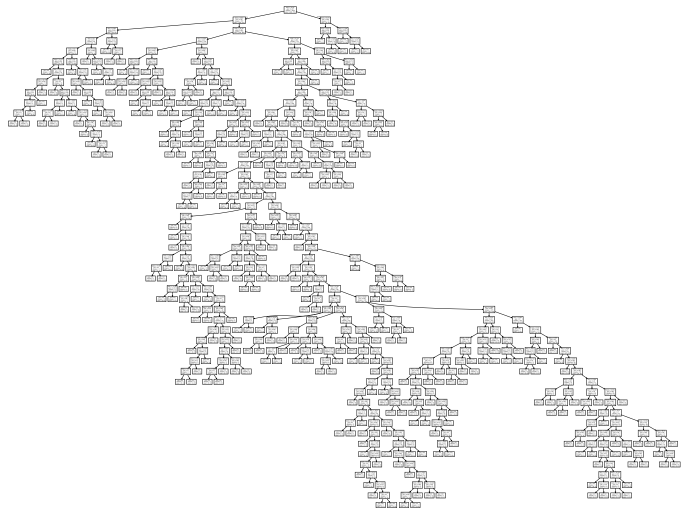

Figure 6.3: Decision Tree Visualization of DIS

built from a random sample drawn from the training set. More randomness is added during construction by choosing the best split of nodes from a random subset of the features. This generally induces more bias from the randomness, but due to averaging often decreases variance and hence yields a better overall model [24]. Just like the features used in the decision tree, we use the default values in the Scikit-learn library. We use 10 trees in the forest and measure quality of a split using mean squared error. Unlike a classifier, a regressor is able to predict and model float values, giving us a different insight, as our implementation predicts the magnitude of change in closing price rather than just the direction of price movement.

6.3.2 Other Classifiers

K-nearest Neighbors Classifier

This algorithm is one of the simplest machine learning algorithms that exists. After choosing a k, or amount of nearest neighbors, it calculates the distance between the query sample and all of the training samples via Euclidian distance [24]. The algorithm then sorts the ordered collection of distances and chooses the mode of the k selected labels for classification. In a regression, it would choose the mean of the k selected labels. For our algorithm, we choose $k = 5$. We do this because of the variety of different features that some of our models take will generate different groups of neighbors. Because we are doing classification, our algorithm predicts binary price change, as in the other classification algorithms discussed above.

MLP Classifier

An MLP is a neural network of percpetrons that perform binary classification. They have an input layer, a certain number of hidden layers, and an output layer which makes a decision about the given input and are generally used in a supervised learning context. The network *learns* by using a back-propagation algorithm consisting of two steps [16]. In the forward pass, predicted outputs from a given input are evaluated mathematically. In the backwards pass, partial derivatives of the cost function are propagated back through the network. Figure 6.4 shows how a signal flows through a simple MLP with one hidden layer.

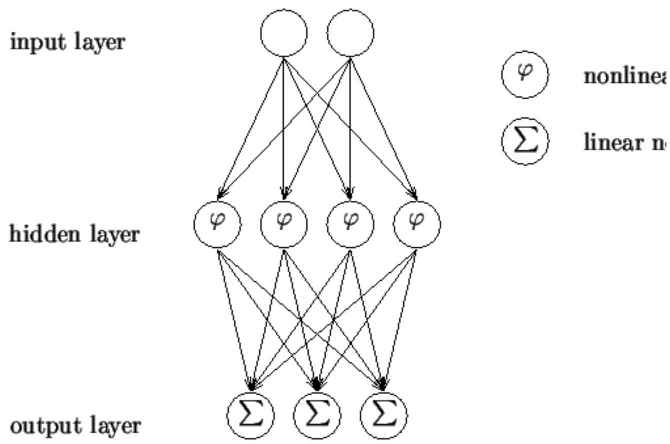

Figure 6.4: Signal-flow graph of an MLP

We choose a classifier with 3 hidden layers, each with 100 neurons, and use a stochastic gradient descent for the solver. While MLP classifiers can handle a variety of different layers and solvers, this combination proved to be most effective during testing of the algorithm for our combined Twitter and stock data. The MLP classifier predicts a 1 or -1, signaling a price rise or alternatively a price drop the following day. WHY DO WE DO THIS? not entirely sure

6.3.3 Deep Learning

We implement a Long Short Term Memory model (LSTM) using the TensorFlow Python library [1]. This is an example of a recurrent neural network (RNN). Unlike traditional neural networks, RNN's use previous data to help classify or predict the current value [9].

RNN's have persistence and are networks with loops in them. LSTM networks are a special type of RNN that is capable of learning long-term dependencies unliked traditional neural networks which struggle with this problem. They are trained via back-propogation over time and instead of neurons have memory blocks that are connected through layers. Each block contains 3 different types of gates which are triggered by sigmoid activation units: forget, input, and output gates. The first decides wether or not to throw away information from the block. The second decides which values from the input should be allocated to update the memory state. The third decides what to output based on input and memory state. Because the structure of an RNN allows the model to use past events to aid future states unlike a typical neural network, this has an ideal application for long term time-series based data, which makes an LSTM model ideal for our use case [9].

should i give an explanation behind math/ graph??? - to be honest not entirely sure I understand it[AT3]

The model for our implementation has a look back of 60 days to give the model enough input to predict the following closing price. At its core, our LSTM model processes 60 days prior of inputs including closing price, tweet sentiment, and a variety of Twitter data, and then predicts the following days closing price. Unlike the above methods which predict signaled change, this model predicts the stock price. Furthermore, we add a second layer into our model. This stacked LSTM makes the output of the first layer become the input to the second layer, giving our model more depth and accuracy. To verify that our model is accurately predicting the following days stock prices well, we check the efficacy of the predictions by looking at mean squared error regression loss. This is done in Scikit-learn metrics function call to `mean_squared_error()`.

6.4 Models with Different Features applying Machine Learning Algorithms

Each model, besides Deep Learning, run on the 4 different machine learning techniques described in the preliminaries: Random Forest Regressor, MLP classifier, decision tree classifier, and k-nearest neighbors classifier. We use a variety of different models to try to better understand the efficacy of particular machine learning techniques, or if a particular model is more effective than the others. For each model, all of the data is scaled using Sckit-learn's `minmaxscaler()` preprocessing tool to remove skew from the data. Most companies tweets aren't overwhelmingly negative and are far more positive. To test the effectiveness of the models, we trade with starting capital of $1000. Using the predicted changes in price,

[3]AT: should i insert a graph?

we buy as many shares as possible when the price is predicted to close higher the next day. The strategy sells all shares when the price is predicted to close lower the next day. The baseline is obtained by buying $1000 worth of shares at the beginning of the trading period and selling on the last day.

6.4.1 Simplistic Features

The most simplistic model employed in our research only uses two inputs: closing price and average tweet sentiment.

6.4.2 Complex Features

Building on the simplistic features, we add other twitter features to the input. We use amount of tweets, favorites, and retweets to provide a more detailed input to the model, which should translate to more accurate results.

6.4.3 Stacked Features

Using complex features, we use stacking to find more consistent performance with the particular machine learning algorithms. Stacking works by aggregating the buy or sell signal from each machine learning technique on each day of stock trading. We employ two different strategies – one that behaves more conservatively and another that behaves generates buy signals far more leniently. The former sells all positions if any machine learning model generates a sell signal and only buys when all 4 models generate a buy signal. The latter gives a buy signal if more than half of the models generate a buy signal and sells if under half give buy signals.

6.4.4 Deep Learning

Our Deep Learning model uses complex features. As described above, we employ an LSTM neural network to predict stock price for the following day. To generate buy sell signals, we compare the predicted price to the current close. A positive difference signals a buy while a negative difference signals a sell just like the above models.

7 Twitter Sentiment Results

We find each of our different Twitter sentiment strategies have overall strong results. Different models have differing effects on various stocks. For all of our models, 100% beat the baseline for all stocks with baseline *buy-and-hold* losses. This unanimous success for poor performing stocks gives great promise towards a live-trading implementation during poor overall stock market performances. Stocks that have a strong baseline performances are rarely beaten by any of our strategies, but still mostly generate positive profits within roughly 10% of the strong baseline measure. Although, each specific model utilizing the extended feature sentiment finds at least two stocks with performances that beat the baseline by over 50%. On an individual stock level, our results have somewhat random performances on each model for different stocks. This lack of consistency is due to the difference in data and sentiment for each stock. Because we fit the model for each stock on each machine learning algorithm, it would be highly improbable to see one model give persistent and consistent results due to the random nature of market movement.

Of the 16 stocks we tested, we examine 8 in-depth that have the most remarkable results across different algorithms. However, we do discuss the overall results using all of the stocks that we tested at the end of this chapter. We exclude the lowest performing in our in-depth discussion of the models to emphasize the highest performing stocks for our strategies. Common practice in the field is to focus on and examine the highest performing stocks across different strategies [2]. Therefore, we choose `DIS, EBAY, SBUX, BIG, NKE, AMD, COLM, and MNST`. Most of these stocks share a common feature: the baseline strategy posts sizable losses, whereas our trading algorithms make profit when the stock does poorly. Therefore, stocks that had strong baseline performances during the trading period such as `HAS` or `FB`, were excluded from individual analysis of each of the models and are instead examined in Figure 7.5.

As a whole, it would be difficult to trade using this entire group of tested stocks, but our testing reveals some encouraging results. Trading on this Twitter sentiment strategy certainly comes with lots of risk and is at an individuals discretion. However, individual results that beat the baseline by nearly 80 or more percentage points offer some starting points for making a live trading implementation. Specifically, using our deep learning strategy on `SBUX` nets a 54.5% profit over the trading period, while the baseline *buy-and-hold* nets a loss of 23.7%. The stacking lenient strategy for `MNST` nets a 50% profit while the baseline nets a loss of 31.2%. Another encouraging result worth pursuing in live trading is the extended model decision tree algorithm for `AMD`. For this particular stock, our algorithm nets a 529.1% profit, more than doubling the baseline's already impressive 207.3% profit. Our research shows that starting with these three stocks and the associated strategies would be a great start to a sample portfolio.

7.1 Simplistic Model

Our simplistic model has the worst performance of any of the tested strategies. Only a few of the stocks tested had truly notable performances. Figure 7.1 shows the performance of a selection of stocks that were tested. We rarely find any machine learning algorithm actually beat the baseline. Only 29.4% of stocks tested ended up beating the baseline. The vast majority of stocks tested performed like `COLM`, with all four of our machine learning algorithms generating profits slightly below or right at the baseline. However, some did actually find success. `MNST`'s MLP beat the baseline by 31.2% whereas `SBUX`'s decision tree classifier beat the baseline by 50.7%. Only a minority of stocks show profitable trading margins. We need to utilize a more advanced feature set to more effectively predict following day stock price movement. We find improvement across the board by adding more inputs into the model as seen in the following section.

7.2 Extended Model

By adding total tweets, retweets, and favorites as additional features, we see an overall improvement over the simplistic model that only uses closing price and twitter sentiment. Figure 7.2 shows the performance of a selection of stocks that were tested. We find that 82.4% of the stocks tested have a particular algorithm that beats the baseline. This is an improvement of 53% moving to a model with more features. This means that including features such as amount of tweets and retweets are useful for stock trading. Specifically, `AMD` has the most remarkable performance, with the decision tree classifier generating 529.1% profit and more than doubling the baseline profit. We find `MNST` to also have impressive returns with this model. The decision tree classifier generates a 79% profit while the baseline nets a loss of 31.2%. The random forest regressor of `BIG` generates 88.7% profit, beating the baseline by 55.7%. These returns for specific models on specific stocks are significant enough to implement for a realtime for-profit trading algorithm, showing that Twitter sentiment can be used to aid stock trading.

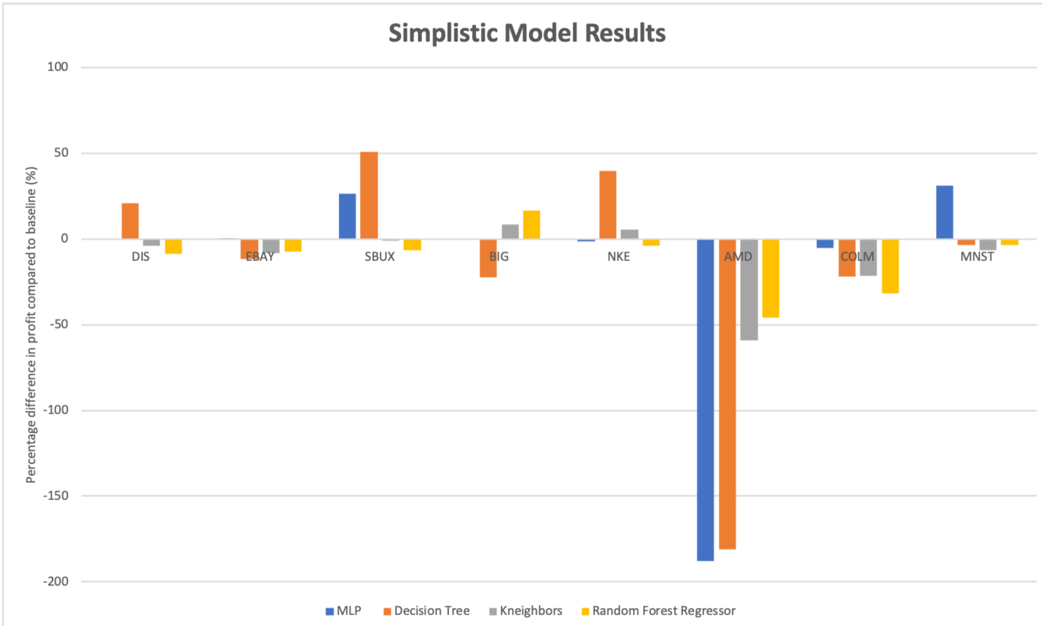

Figure 7.1: Simplistic Model Results

7.3 Stacking Model

Our stacking model that aggregates all of our various machine learning models into one buy or sell signal doesn't perform as well as the extended model, but handily beats the basic model. Figure 7.2 shows the performance of a selection of stocks that were tested. We find that 58.8% of the stocks using the conservative strategy beat the baseline, while only 29.4% of the lenient strategy beat the baseline. These results show how the conservative strategy performs far more consistently than the lenient strategy. `EBAY's` conservative strategy has a 6.9% return while the baseline has a 39.5% loss. `MNST` nets a 50% profit while the baseline records a loss of 31.2% while using the lenient strategy. This performance sets a high individual performance threshold for this model, as the baseline measure is significantly negative while our strategy has large positive returns. In these results, the stocks that end up beating the baseline are correlated with baseline losses over the trading period. While a few stocks do end up beating a high performing baseline, this strategy like others using Twitter sentiment, performs much better when the stock does poorly over the trading period.

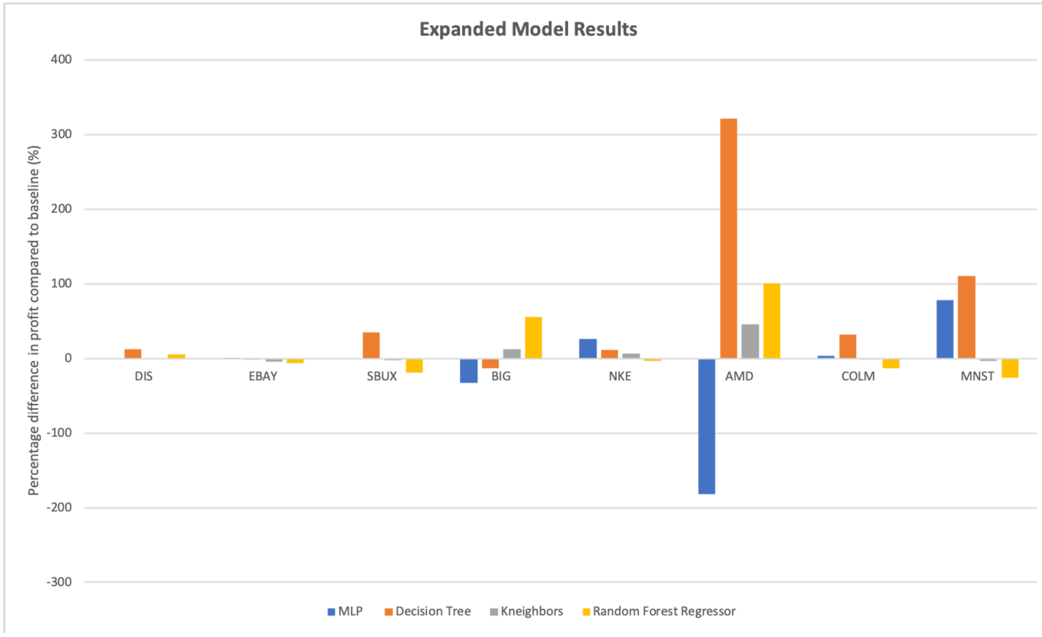

Figure 7.2: Extended Model Results

7.4 Deep Learning Model

Our deep learning model acts differently than any of the above models, as it predicts the price of the following days close. This model has more average performance, but is far more consistent. Rarely does a particular stock trading on the strategy fall significantly below the baseline. Figure 7.4 shows our results for some specific stocks within the data. `DIS`, `NKE`, and `COLM` categorize the results of this model well – showing how the strategy hovers close to the baseline and gives consistent performance. Interestingly, `EBAY` and `SBUX`, perform far better than the baseline. There is a respective improvement of $559.53 and $785.71 for our strategy over the baseline.

For this model we don't find as many instances of beating the baseline as some of our other models. This is most likely attributed to the accuracy of the predicted stock prices. The RMSE of all of our stocks range between 1.5 and 2.5, signifying that our model is able to predict the closing price of stocks extremely closely. While the predicted price is close, it isn't accurate enough to be consistently profitable. This performance is most likely due the model predicting stock prices for multiple days in a row either above or below the current price. This prediction differs from the other models that all predict price signal changes. We find that this change in prediction hampers performance for our end-of-day trading strategy that is entirely reliant on price signal changes. Future work could predict multiple

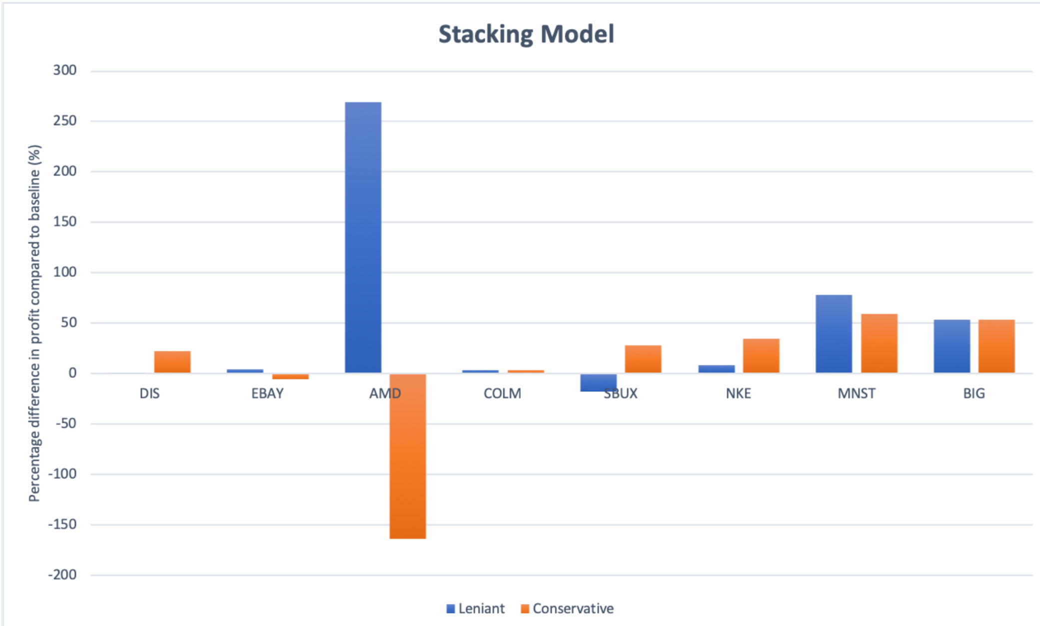

Figure 7.3: Stacking Model Results

days of stock prices in the future and then act on sustained performance rather than specific day-by-day changes to help with this issue in our strategy.

7.5 Discussion and Comparison

Now that we have examined some particular notable performances of specific models, we must identify trends between all of our models. Figure 7.5 shows our results for all 16 stocks tested. We don't find that one model has particularly astounding performance across all of the stocks tested. However, the decision tree classifier is the most successful of the models examined. With a median score of 6.4% and an upper quartile score of 28.7%, this classifier has the most positive results as it has the largest concentration of the models with performances that beat the baseline. Both of our strategies that use the stacking model have positive medians, signaling its effectiveness. We additionally find that the upper quartile performances for each model are all greater than the baseline. Excepting the decision tree classifier and conservative stacking model, we see a consistent spread between the upper and lower quartiles of roughly 25 percentage points. As discussed in the above sections, each of our strategies has a few stocks that generate incredible performance. This performance is reflected in Figure 7.5 as we see a collection of positive outlier datapoints above each

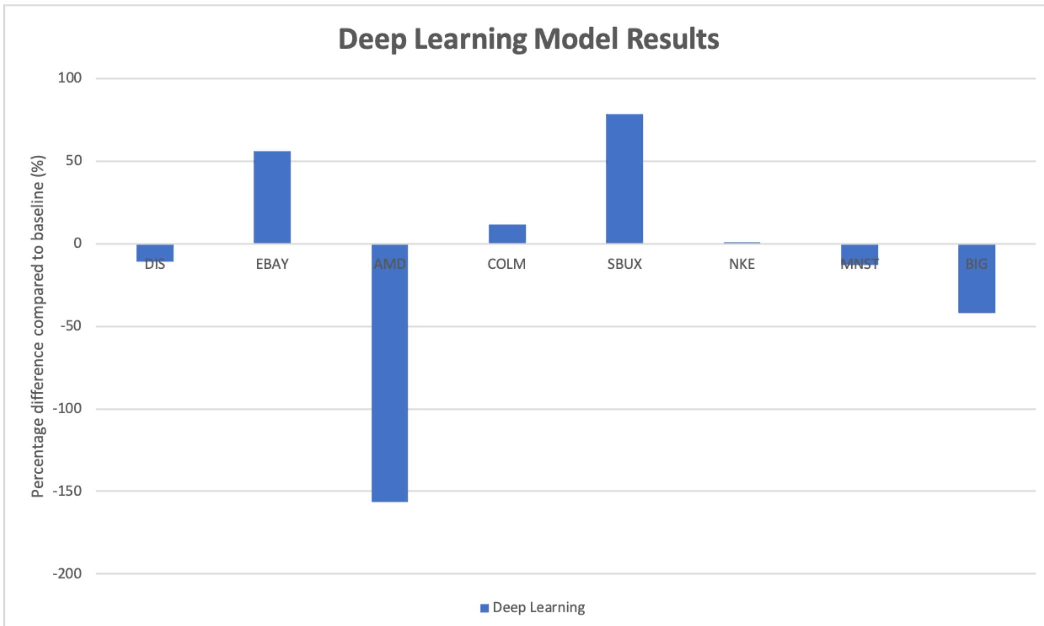

Figure 7.4: Deep Learning Model Results

different model.

However, we also find some limitations with our models and data. Even though the 16 stocks we examined for our sentiment strategies were spread across different industries, it is still possible that skew exists within our data. Incorporating many more stocks to test our models would give more basis to our findings. We are looking at a very small subset of the entire market. But, this small subset is a result of data availability and expense. For acquiring Twitter data, Twitter makes data available at a fee that is prohibitively expensive. Our method for scraping twitter data is incredibly time intensive and restricts our study to 16 stocks. A more thorough study would examine a greater collection of stocks. Additionally, examining more classifiers and regressors could lead to discovering more machine learning algorithms that are highly productive.

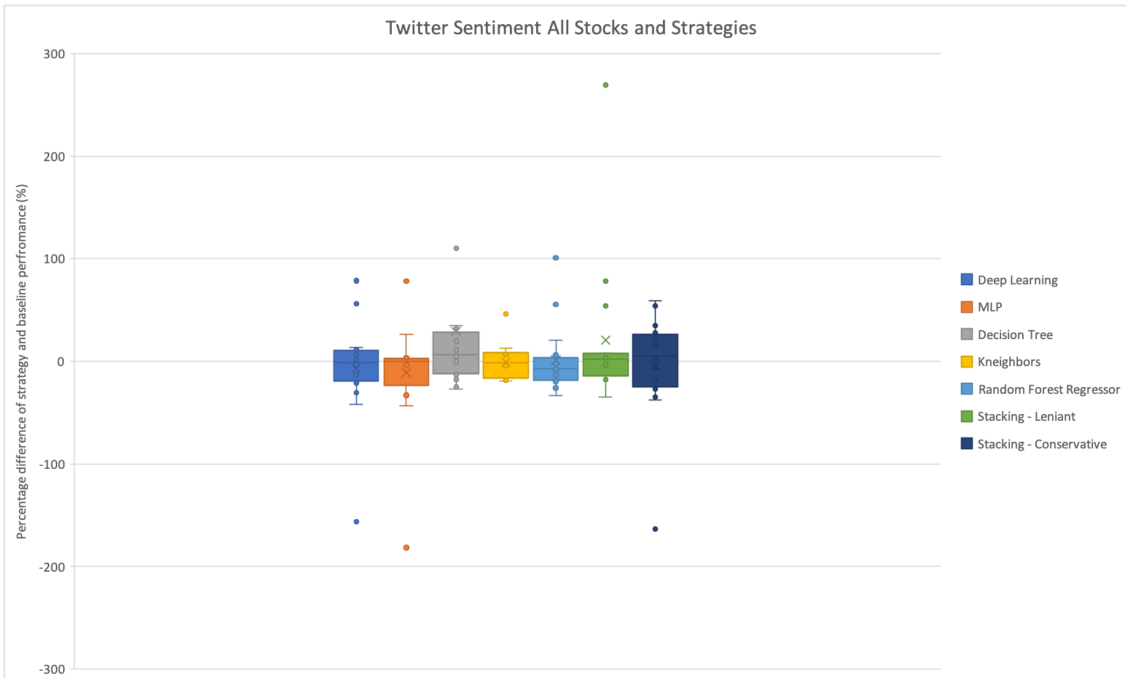

Figure 7.5: Twitter Sentiment Results Compared

8 Conclusion

8.1 Contributions

We make 2 different contributions to AT. Our first contribution examines existing AT strategies to understand how they work mathematically to generate buy and sell signals. We then run these different strategies using our test suite to understand the effectiveness of different strategies. We find that combining momentum indicators, specifically RSI and MACD, and pairs trading to be by far and away the most effective.

Our second part of research looks at using Twitter sentiment as a means of stock trading. We find a lack of statistical correlation between average sentiment and price, motivating our use of different machine learning algorithms. We test two different feature sets for our models, and find that a complex feature set using additional Twitter features such as total retweets to be far more effective than a simplistic feature set. Using this complex feature set, we test the effectivness of each machine learning algorithm, combine multiple signals into a stacking model, and additionally use a deep learning model. We find that our strategies nearly always turn a profit while the baseline measure often posts losses. Even when the stock performs well and the baseline posts profits, our strategies are able to match the performance.

8.2 Future Work

In the future, our study could be extended greatly. First, the NLP component of the research could be tailored exactly to Twitter. Currently we use the textblob implementation trained on movie review data. Training on tweets would be more applicable to our research and potentially give more accurate sentiment measures. Some of the existing literature looks at applying sentiment classification to cryptocurrencies. Extending this model to other financial markets, such as cryptocurrency, could give differing results. Also, we could extend our models to predict overall market movement. Rather than our models using individual stocks as input, our models could instead use a collection of stocks as input to try to predict

DJIA price movement. This mixed effects model for market prediction could be used as an overall portfolio management tool.

9 Appendix

9.1 Implementation

Included in this section is all of the pseudocode for the implementations described above.

9.1.1 SMA

```
def execute(stock, start_date, end_date):
    stock = stockDataRetriever(stock, start_date, end_date).getStock()

    # Initialize the short and long windows and buy sell in df
    short_window = 40
    long_window = 100

    # set Pandas df with stock data
    df = pd.DataFrame(index=stock.index)

    # Create short and long simple moving average
    df['short_moving_average'] = df.movingWindow(short_window)
    df['long_moving_average'] = df.movingWindow(long_window)

    # mark signal based on comparison of the two averages
    df['signal'] = df.compare(short_moving_average, long_moving_average,1,0)

    # when signal changes from 1 to 0 or 0 to 1 - is a buy or sell
    df['positions'] = df['signal'].diff()

```

9.1.2 EMA

```
def execute(stock, start_date, end_date):
```

```
    stock = stockDataRetriever(stock, start_date, end_date).getStock()

    # Initialize the short and long windows and buy sell in df
    short_window = 12
    long_window = 26

    # set Pandas df with stock data
    df = pd.DataFrame(index=stock.index)

    # Create short and long simple moving average
    df[short_ema] = df.ema(short_window)
    df[long_ema] = df.ema(long_window)

    # mark signal based on comparison of the two averages
    df[signal] = df.compare(short_ema, long_ema,1,0)

    # when signal changes from 1 to 0 or 0 to 1 - is a buy or sell
    df[positions] = df[signal].diff()
```

9.1.3 Bollinger Bands

```
def execute(stock, start_date, end_date):
    stock = stockDataRetriever(stock, start_date, end_date).getStock()

    # Initialize the window
    window = 12

    # set Pandas df with stock data
    df = pd.DataFrame(index=stock.index)

    # Create the bollinger bands
    df['middle_band] = df.sma(window)
    df['moving_deviation'] = df.std(window)
    df['upper_band'] = df['middle_band'] + df['moving_deviation'] * 2
    df['lower_band'] = df['middle_band'] - df['moving_deviation'] * 2

    # mark signal based on upper or lower prices
```

```
    df[signal] = df.compare((df_closing_price, df_lower band),
          (df_closing_price, df_upper_band),1,0)

    # when signal changes from 1 to 0 or 0 to 1 - is a buy or sell
    df[positions] = df[signal].diff()
```

9.1.4 RSI

```
def execute(stock1, stock2, start_date, end_date):
    stock = stockDataRetriever(stock1, start_date, end_date).getStock()

    # set Pandas df with both stocks
    df = pd.DataFrame(index=stock.index)

    # create measures of up and down performance
    delta = stock['Close'].diff()
    roll_up = delta[delta > 0].rolling.mean()
    roll_down = delta[delta > 0].rolling.mean()

    # create RSI
    RS = roll_up/roll_down
    RSI = 100.0 - (100.0 / (1.0 + RS))

    # create the buy and sell commands
    df['buy'] = np.where(RSI < 30, 1, 0)
    df['sell'] = np.where(RSI > 70, -1, 0)
    df['signal'] = df['buy'] + df['sell']

    # when signal changes from 1 to 0 or 0 to 1 - is a buy or sell
    df[positions] = df[signal].diff()
```

9.1.5 Combination Momentum Strategies

```
def execute(stock, start_date, end_date):
    stock = stockDataRetrieverIntraday(stock, start_date, end_date).getStock()
```

```
    # create df for both RSI and MACD and merge
    rsi_df = RSI(name, stock)
    macd_df = MACD(name, stock)
    df = pd.merge(rsi_df, macd_df)

    # buy signals when both rsi and macd indicate buy
    # sell signals when either one of rsi or macd indicate sell
    df['buy'] = (df['signal_rsi'] == 1) & (df['signal_macd'] == 1)
    df['sell'] = (df['signal_rsi'] == -1) | (df['signal_macd'] == -1)
    df['signal] = df['buy'] + df['sell']
```

9.1.6 Pairs Trading

```
def execute(stock1, stock2, start_date, end_date):
    stock_1 = stockDataRetriever(stock1, start_date, end_date).getStock()
    stock_2 = stockDataRetriever(stock2, start_date, end_date).getStock()

    # set Pandas df with both stocks
    df = pd.DataFrame(index=stock_1.index, stock_2.index)

    # create zscore from price ratios
    ratios = df['Close_stock1']/df['Close_stock2']
    zscore = (ratios - ratios.mean())/ np.std(ratios)

    # Create the buy and sell commands
    df['buy'] = np.where(zscore < -1, 1, 0)
    df['sell'] = np.where(zscore > 1, -1, 0)
    df['signal'] = df['buy'] + df['sell']

    # when signal changes from 1 to 0 or 0 to 1 - is a buy or sell
    df[positions] = df[signal].diff()
```

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