Directional Prediction of Stock Prices using Breaking News on Twitter

by

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A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved May 2016 by the
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ARIZONA STATE UNIVERSITY

August 2016

ABSTRACT

Stock market news and investing tips are popular topics in Twitter. In this dissertation, first I utilize a 5-year financial news corpus comprising over 50,000 articles collected from the NASDAQ website matching the 30 stock symbols in Dow Jones Index (DJI) to train a directional stock price prediction system based on news content. Next, I proceed to show that information in articles indicated by breaking Tweet volumes leads to a statistically significant boost in the hourly directional prediction accuracies for the DJI stock prices mentioned in these articles. Secondly, I show that using document-level sentiment extraction does not yield a statistically significant boost in the directional predictive accuracies in the presence of other 1-gram keyword features. Thirdly I test the performance of the system on several time-frames and identify the 4 hour time-frame for both the price charts and for Tweet breakout detection as the best time-frame combination. Finally, I develop a set of price momentum based trade exit rules to cut losing trades early and to allow the winning trades run longer. I show that the Tweet volume breakout based trading system with the price momentum based exit rules not only improves the winning accuracy and the return on investment, but it also lowers the maximum drawdown and achieves the highest overall return over maximum drawdown.

To the loving memory of my mother Howa Hussain, my role-model for hard work, persistence and personal sacrifices, no words are sufficient to describe my late mother's contribution to my life, I owe every bit of my existence to her.

To my father Hassan Alostad, circumstances didn't give him a chance to get any education, yet he continuously emphasized the importance of pursuing and gaining a higher education, this dissertation is dedicated to you.

ACKNOWLEDGMENTS

Firstly, I would like to express my very great appreciation to Prof. Hasan Davulcu my supervisor for the continuous support, patience, motivation, immense knowledge, valuable and constructive suggestions during the planning and development of this research work.

Besides my supervisor, I would like to thank the members of my committee: Prof. Steven Corman, Prof. Jingrui He, and Prof. Hanghang Tong, for their insightful comments and encouragement.

I also would like to thank my fellow labmates in the Cognitive Information Processing Systems (CIPS) lab for their continues advice, and support during the course of my graduate studies.

Special thanks to my friends who helped me stay sane through these difficult years. Their support and care helped me overcome setbacks and stay focused on my graduate study. I greatly value their friendship and I deeply appreciate their belief in me.

Last but not the least, none of this would have been possible without the love and patience of my family to whom this dissertation is dedicated to, they have been a constant source of love, concern, support and strength all these years.

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Chapter 1

INTRODUCTION

Online social networks, like Twitter, are enabling people who are passionate about trading and investing to break critical financial news faster and they also go deep into relevant areas of research and sources leading to real-time insights. Recently Twitter has been used to detect and forecast civil unrest (Compton *et al.*, 2014), criminal incidents (Wang *et al.*, 2012), box-office revenues of movies (Asur and Huberman, 2010), and seasonal influenza (Achrekar *et al.*, 2012).

Stock market news and investing tips are popular topics in Twitter. In this dissertation, first we utilize a 5-year financial news corpus comprising over 50,000 articles collected from the NASDAQ website for the 30 stock symbols in Dow Jones Index (DJI) to train a directional stock price prediction system based on news content. Next we collect over 750,000 Tweets during a 6 month period in 2014 that mention at least one of the 30 DJI stock symbols. We utilize the 68-95-99.7 rule, also known as the three-sigma rule or empirical rule (Pukelsheim, 1994), to define a simple method for detecting hourly stock symbol related Tweet volume breakouts. Then we proceed to test our hypothesis to determine if "information in articles indicated by breaking Tweet volumes will lead to a statistically significant boost in the hourly directional prediction accuracies for the prices of DJI stocks mentioned in these articles". The contributions of the reserach can be summarized as follows:

- Firstly, we show that sparse logistic regression (Liu *et al.*, 2009) for this text based classification task with 1-gram keyword features filtered by a Chi2 (Liu and Setiono, 1997) feature selection algorithm lead to the best overall directional prediction accuracy among a set of other classifiers and feature sets that we tested.

- Secondly, we show that using document-level sentiment extraction does not yield to a statistically significant boost in the predictive accuracies in the presence of other 1-gram keyword features.

- Thirdly, we show that information in articles indicated by Tweet volume breakouts leads to a statistically significant boost in the hourly directional prediction accuracies for the DJI stocks mentioned in the articles linked by Tweets.

- Fourthly, we compare the performance of the breaking Tweet volumes based trading system on different time-frames. We identify the 4 hour time-frame for both price charts and for Tweet volume breakouts detection as the best time-frame.

- Finally, we develop a set of price momentum based trade exit rules to cut losing trades early and to allow the winning trades run longer. We show that the Tweet volume breakouts based trading system with the momentum based trade exit rules not only improves the average winning accuracy and the return on investment, but it also lowers the maximum drawdown and yields the highest overall return over maximum drawdown (RoMaD).

The rest of the dissertation is organized as follows. Chapter 2 presents related work. Chapter 3 presents the problem definition for the directional prediction of stock prices. The design of experiments to evaluate the performance of various trading systems and strategies are presented in Chapter 4. Chapter 5 describes the experimental data we used and the simulated financial backtesting results for the experiments. Chapter 6 concludes the dissertation and discusses future work.

Chapter 2

RELATED WORK

Table 2.1 contains a summary of previous research findings related to stock price or direction prediction; the input data sets used, the time-frames used for prediction, the length of the period of collected data, prediction algorithms used, and the resulting overall accuracies.

These systems have different prediction time-frames and goals. Some of them predict stock price for the intended time-frame like (Roy *et al.*, 2015), (Schumaker and Chen, 2006), (Deng *et al.*, 2011), and (Mao *et al.*, 2013). Time frames vary between next 20 minutes to up to next month. Works such as (Bollen *et al.*, 2011), (Hagenau *et al.*, 06), (Kaya and Karsligil, 2010), (Lauren and Harlili, 2014),(Mao *et al.*, 2012) , (Patel, 2015), (Xu and Keelj, 2014), and (Vu *et al.*, 2012) predict stock price direction for the next day. (Mao *et al.*, 2011) predict stock price direction for both the next day and next week. (Nassirtoussi *et al.*, 2015) aims to predict the price direction every 2-hours, and (Gong and Sun, 2009) aims to predict monthly direction. (Bordino *et al.*, 2012), and (Bordino *et al.*, 2014) predicts daily trading volume, and (Oliveira *et al.*, 2013) predicts daily return, trading volume, and volatility. Related systems collected their input data from various sources and exchanges: (Schumaker and Chen, 2006),(Mao *et al.*, 2012), and (Mao *et al.*, 2013) collected stock news, Tweets and price charts related to S&P 500 companies. (Vu *et al.*, 2012) collected Tweets and stock price data related to Nasdaq stocks, (Bollen *et al.*, 2011) collected Tweets and stock price charts related to Dow Jones Industrial Average (DJIA), (Kaya and Karsligil, 2010) collected one year of data related to Microsoft company. (Xu and Keelj, 2014) collected stock price charts and tweets from a social media platform used

Table 2.1: Summary of Previous Research Results

Reference	Data set: Stock Price	Data set: Online News	Data set: Microblogs	Data set: Search Engine	Time-frame	Period	Prediction	Algorithm	Accuracy
Patel (2015)	✓	✗	✗	✗	Daily	9 Yrs	Direction	Naive Bayes	90%
(Gong and Sun, 2009)	✓	✗	✗	✗	Monthly	2 Yrs	Direction	Log. Reg	83%
(Roy *et al.*, 2015)	✓	✗	✗	✗	Daily	13 Yrs	Price	Linear Reg	2.54 (RMSE)
(Nassirtoussi *et al.*, 2015)	✓	✓	✗	✗	2 Hrs	4 Yrs	Direction	SVM	83%
(Hagenau *et al.*, 06)	✓	✓	✗	✗	Daily	14 Yrs	Direction	SVM	79%
(Kaya and Karsligil, 2010)	✓	✓	✗	✗	Daily	1 Yr	Direction	SVM	61%
(Schumaker and Chen, 2006)	✓	✓	✗	✗	20 Min	1 Mo	Price	SVR	51%,
(Lauren and Harlili, 2014)	✓	✓	✗	✗	Daily	1 Yr	Direction	Neural Network	3.70 (RMSE)
(Bollen *et al.*, 2011)	✓	✗	✓	✗	Daily	10 Mos	Direction	Neural Network	88%
(Vu *et al.*, 2012)	✓	✗	✓	✗	Daily	2 Mos	Direction	Decision Tree	77%
(Mao *et al.*, 2012)	✓	✗	✓	✗	Daily	3 Mos	Direction	Liner Reg	68%
(Xu and Keelj, 2014)	✓	✗	✓	✗	Daily	2 Yrs	Direction	SVM	58.9%
(Mao *et al.*, 2013)	✓	✗	✓	✗	Daily	1 Yr	Price	Bayesian	0.3% (daily)
(Deng *et al.*, 2011)	✓	✗	✓	✗	Daily	3 Yrs	Price	MKL	0.3 (RMSE)
(Oliveira *et al.*, 2013)	✓	✗	✓	✗	Daily	2 Yrs	Return, Vol., VIX.	Liner Reg	-
(Bordino *et al.*, 2012)	✓	✗	✗	✓	Daily	1 Yr	Trade Vol.	Regression	0.3 (RMSE)
(Bordino *et al.*, 2014)	✓	✗	✗	✓	Hourly, Daily	1 Mos	Trade Vol.	Correlation	-
(Mao *et al.*, 2011)	✓	✓	✓	✓	Daily, Weekly	1 Yr	Direction	Liner Reg	70%

by traders called Stocktwits for 16 stocks symbols, (Oliveira *et al.*, 2013) collected one year of stock price data and tweets from Stocktwits for 6 major stocks (AAPL, AMZN, GS, GOOG, IBM, SPX). (Deng *et al.*, 2011) collected historical stock price from Google finance, news, and comments from a microblog site called Endaget for the three major technology companies AMZN, MSFT, and GOOG.

(Bordino *et al.*, 2012) collected one year of search volume on Yahoo! search engine, and the trading volume for NASDAQ exchange. (Bordino *et al.*, 2014) data set collected web browsing volume, web search volume from from Yahoo Finance!, and trading volume for some stock symbols in NYSE, NASAQ, and NSP. (Mao *et al.*, 2011) collected DJIA price, volatility, trading volume, Gold, Investor Intelligence survey data, news, Twitter, and Google search volume for directional prediction of Dow Jones Industrial Average (DJIA).

(Gong and Sun, 2009) collected stock price charts from Shenzhen Development Stock A (SDSA) exchange. (Nassirtoussi *et al.*, 2015) collected currency price and news data related to foreign exchange market (Forex). (Patel, 2015) collected stock price data from CNX Nifty, S&P BSE Sensex exchanges and finally (Roy *et al.*, 2015) collected thirteen years of stock price charts data related to Goldman Sachs Group Inc.

(Gong and Sun, 2009), (Patel, 2015), and (Roy *et al.*, 2015) used only stock price as input to predict stock price or direction with accuracies varying between 83% and 90%. (Hagenau *et al.*, 06), (Kaya and Karsligil, 2010),(Lauren and Harlili, 2014), and (Nassirtoussi *et al.*, 2015) are examples of papers which utilize news as well as stock prices to predict price direction with varying accuracies between 51% and 83%.

(Deng *et al.*, 2011) used historical price and volume for three major technology companies AMZN, MSFT, and GOOG, with some features related to news, and comments like volume of news, and volume comments from Endaget microbloging site to predict next day price using multiple kernel learning (MKL), the performance of the proposed model in this paper outperforms the other presented methods under MAE, MSPE, and RMSE performance measures.

(Mao *et al.*, 2012) made correlation analysis between the stock price and the Tweet volume, and used it to predict stock market direction with 68% accuracy. Following work by (Mao *et al.*, 2013) analyzed Tweet spikes in combination with price action based technical indicators such as price breakout direction as an input to a Bayesian classifier for stock price prediction, yielding a daily average gain of approximately 0.3% during a period of 55 days generating a total gain of 15%. (Bollen *et al.*, 2011) used extracted sentiment information from Twitter data and a neural network classifier to predict Dow Jones Industrial average (DJIA) daily price direction with 88% accuracy. (Vu *et al.*, 2012) also used sentiment information extracted from Twitter as input to a decision tree classifier to predict price direction for four companies in NASDAQ stock exchange with average accuracy of 77% distributed as APPL at 77%, GOOG at 77%, MSFT at 69% and AMZN at 85% during a two months period of evaluations.

(Oliveira *et al.*, 2013) used sentiment indicators, daily volume of tweets, and 5 days moving average of tweets volume from StockTwits social media platform as features in several regression models to predict return, volatility, and trading volume, while in this paper the performance of trading volume regression models was found to be statistically significant to the baseline model under RMSE metric, the forecasting results of regression models for both return and volatility was not statistically significant to the baseline model.

(Mao *et al.*, 2011) collected daily and weekly price, trading volume, volatility (VIX) from Yahoo finance for Dow Jones Industrial Average (DJIA), they also extracted news headlines from URLs that was mentioned in tweets of some famous news media outlets like Wall Street Journal, Forbes.com, CNN-Money,.. etc, then calculated the Negative News Sentiment score of news headline, next they used Google Insights Search to get the search volume on specific seed queries, this procedure resulted into 26 financial search terms, following that they calculated the investors sentiment of public tweets and tweets volume of the 26 financial search terms, then they used the previous features as an input to multiple regression model, resulting into a directional accuracy to predict DJIA price, Volume, and VIX using weekly search volumes of 70%, 55%, and 65%, and a daily directional accuracy of 63%, 60%, and 67%.

Chapter 3

PROBLEM DEFINITION

The correction effect of online news articles covering company related events, announcements and technical analyst reports on the stock price may take some time to show. Depending on the severity and impact of the news announcement this period may vary between few minutes to an hour, and the effect may sometimes determine the trend direction of the financial instrument for upcoming weeks or months.

One way to measure the impact of news on a stock price is to analyze the trading volume following the news announcement. Another indicator of news impact is the diffusion rates and volumes of messages on social media containing the stock symbol and news links of interest.

Twitter provides a suitable platform to investigate properties of such information diffusion. Diffusion analysis can harness social media to investigate "viral Tweets" to create early-warning indicators that can signal if a breakout started to emerge in its nascent stages. In this research, we utilize the 68-95-99.7 rule to define a simple method of Tweet volume breakouts. In statistics, the 68-95-99.7 rule, also known as the three-sigma rule or empirical rule (Pukelsheim, 1994), states that nearly all values lie within three standard deviations (σ) of the mean (μ) in a normal distribution. We utilize a fixed sized sliding window (of length 20 hour intervals that was determined experimentally), to compute a running average and standard deviation for the hourly volumes of Tweets that mention a stock symbol. Then, we identify *breakout* signals within a time-series of hourly Tweet volumes for each stock symbol whenever its hourly volume exceeds ($\mu(20) + 2\sigma$) of the previous 20 hour periods. We consider a breakout as an indication that traders or technical analysts are sharing some exciting or important new information regarding the company or a group of companies. Next, we collect the URL links mentioned within the breaking-news hour of Tweets and we designed a pair of experiments to test the hypothesis whether "information in news indicated by breaking Tweet volumes will lead to statistically significant boost in the directional prediction accuracy for the prices of the related stock symbols mentioned in these articles".

Our system has the following characteristics:

1. Input Data: Hourly stock price charts of the 30 stocks comprising the Dow Jones Index (DJI), online stock news articles for a 5 year period spanning 2010 and 2014 from NASDAQ [1] news website, the Tweets related the 30 stock symbols collected from Twitter Streaming API [2] spanning a 6 months period between March 2014 and September 2014, and online news articles mentioned in Tweets during breaking news hours.

2. Prediction Time-Frame: The collected data is analyzed and predictions are made on hourly bases.

3. Prediction Goal: To predict the hourly price direction for the stocks mentioned in Tweets during breaking news hours.

The distinguishing features of our system compared to systems mentioned in the related work section are: (1) (Mao *et al.*, 2013) used Tweeter volume spikes alongside stock price-based technical indicators for stock price turning point prediction where as our system utilizes textual content of the news mentioned in Tweets during breaking Twitter volume hours to predict the hourly direction of the stock price following a breakout period. (2) (Bollen *et al.*, 2011) and (Vu *et al.*, 2012) used extracted

[1] http://www.nasdaq.com/symbol/ibm/news-headlines

[2] https://dev.twitter.com/streaming/overview

sentiment information alongside stock price-based technical indicators to determine if sentiment information leads to a boost in the predicted direction accuracy. Our system primarily relies on textual content of the news linked from breaking Tweet volumes to predict the direction of the stock price in the next hour. We also experimented with extracted sentiment as an additional feature to determine if it leads to a boost in the overall prediction accuracy. Unlike (Bollen *et al.*, 2011) and (Vu *et al.*, 2012), our system did not experience a statistically significant boost in predictive accuracies as a result of including sentiment information alongside other textual content features. (Bollen *et al.*, 2011)'s accuracy is not comparable to ours since they are reporting the daily directional prediction accuracy for the Dow Jones Index Average (DJIA). Compared to predictive accuracies for four companies listed in (Vu *et al.*, 2012), we have only one stock in common with their experiments, i.e. MSFT, where their system reported a daily directional predictive accuracy of 69% and our system reported an hourly directional accuracy of 82%.

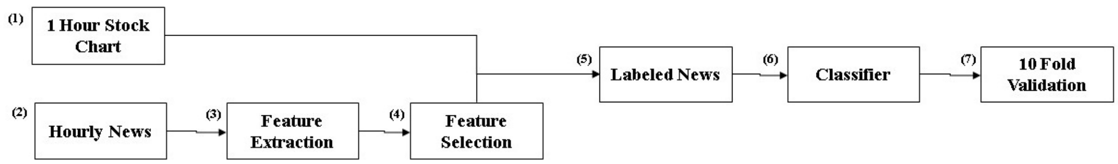

Figure 4.1: Illustration of System Architecture of Experiment-1

Chapter 4

DESIGN OF EXPERIMENTS

In order to test the hypothesis that "information in news indicated by *breaking* Tweet volumes will lead to statistically significant boost in the directional prediction accuracy for the prices of the relevant stock symbols mentioned in such articles", we designed two experiments. In the first experiment we trained a classifier using *all* stock news articles for a 5 year period spanning 2010 and 2014 from NASDAQ news website. Figure 4.1 illustrates the system architecture used for the first experiment. For comparison purposes we experimented with three different types of features extracted from text: 1-gram keywords, 2-gram phrases, and bi-polar sentiment (i.e. positive and negative) extracted from text. We grouped news hourly, and categorized each hourly collection as one of two categories: (1) those that led to an increased stock price or (2) those that led to a price reduction during the next hour. Next, we applied a feature selection method to reduce the number of features to only relevant ones. The details of these steps are presented in Section 4.1. Finally we experimented with two types of text classifiers and evaluated their directional predictive accuracy using 10-fold cross validation. The results of the first experiment utilizing all stock news for all 30 company stocks are reported in Section 5.2. In our second experiment, we tested the directional predictive accuracy of our classifier (i.e. trained in the first

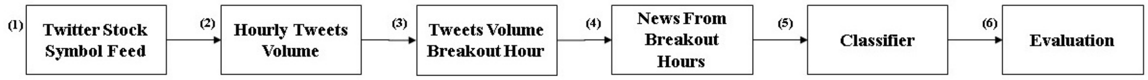

Figure 4.2: Illustration of System Architecture of Experiment-2

experiment above) using *only* online articles collected during hourly breaking Tweet volume periods. Figure 4.2 illustrates the system architecture used for our second experiment. Steps involved in the second experiment were hourly profiling of the Tweets mentioning a stock symbol, detection of Tweet volume breakout periods, collection of online news mentioned in Tweets during the breaking hours, feature extraction from news, and running of the classifier to predict the stock price direction of the next hour using the collected news content. We compared the accuracies of the classifiers in both first and second experiments to test the validity of our hypothesis. The details of the steps involved in the second experiment are explained in Section 4.2, and the experimental results and evaluations are presented in Section 5.3. In the third experiment, we compared the performance of the breaking Tweet volumes system based on different time-frames, the experimental results and evaluations for the third experiment are presented in Section 5.4. In Experiment-4 we developed a simulated trading system using the best performing time-frame resulted from Experiment-3 and evaluated its performance, the experimental results and evaluations for Experiment-4 are presented in Section 5.5. Finally, in the fifth experiment, we developed a set of price momentum based trade exit rules to cut losing trades early and to allow the winning trades run longer, the experimental results and evaluations for Experiment-5 are presented in Section 5.6.

4.1 Experiment-1: Hourly Price Direction Prediction Using Online News

The following is a detailed description of each step used in Experiment-1:

1. One Hour Stock Chart: We collected hourly stock financial price charts for all the companies comprising the Dow Jones Index (DJI) using an API from ActiveTick [1]. For each trading hour the price direction was calculated based on the difference between hourly Open and Close prices according to the Formula 4.1 below, where d represents the trading date and h represents the trading hour:

$$Dir(d,h) = \begin{cases} 1 & \text{if } Open(d,h) \leq Close(d,h) \text{)} \\ -1 & \text{otherwise} \end{cases} \tag{4.1}$$

2. Hourly News: We used Web Content Extractor [2] to collect online news articles from NASDAQ website. We stored all metadata information related to the articles like their title, url, date, time, and source in a database table. We fetched the news content using their urls and performed content extraction using Boilerpipe [3].

3. Feature Extraction:

   - N-gram Features from News: R for Text Mining(TM) [4] package was used to extract keyword features from the news corpus. First all whitespaces, stop words, numbers, punctuation were removed from the documents, then all the terms were converted to lowercase and stemmed into their root words. Next features were recorded in a document-term matrix. For each stock symbol we created a pair of document-term matrices: one with 1-gram features and another with 2-gram features represented in a binary form. We used R.Matlab [5] package to create Matlab format files for these matrices.

[1]http://www.activetick.com/

[2]http://www.newprosoft.com/

[3]http://code.google.com/p/boilerpipe/

[4]http://cran.r-project.org/web/packages/tm/index.html

[5]http://cran.r-project.org/web/packages/R.matlab/index.html

- Sentiment Features: To detect sentiment in news content we used a Java version of SentiStrength library [6] . SentiStrength is a classifier that uses a predefined sentiment word list with human polarity and strength judgments, then it applies rules to detect sentiment in short text (Thelwall *et al.*, 2012). (Loughran and McDonald, 2011) showed that using general word lists for sentiment analysis of large financial text leads into mis-classification of common words in the financial domain. So alongside SentiStrenght dictionary (Loughran and McDonald, 2011) we also used Loughran and McDonald Financial Sentiment Dictionaries [7] to compute sentiment. Besides using different sentiment word lists, we also need to get the sentiment for each document. We used OpenNLP [8] Sentence Detector to extract sentences mentioning a stock symbol from each document, and then we applied the SentiStrenght classifier on each sentence. We determined the majority polarity for the sentences contained in a document and used the majority polarity (i.e. positive or negative) as the sentiment for each stock symbol mentioned in the document.

4. Feature Selection: Feature selection in text mining reduces the number of features to only relevant and discriminative set of features. We used *Chi2* (Liu and Setiono, 1997) feature selection algorithm from a feature selection package [9] . Chi2 is a two phase general algorithm that automatically selects a proper critical value for statistical χ^2 test and then it removes all irrelevant and redundant features (Liu and Setiono, 1997).

5. News Labeling: Figure 4.3 is an illustration of the news labeling step. In

[6]http://sentistrength.wlv.ac.uk/

[7]http://www3.nd.edu/~mcdonald/Word_Lists.html

[8]https://opennlp.apache.org/

[9]http://featureselection.asu.edu/software.php

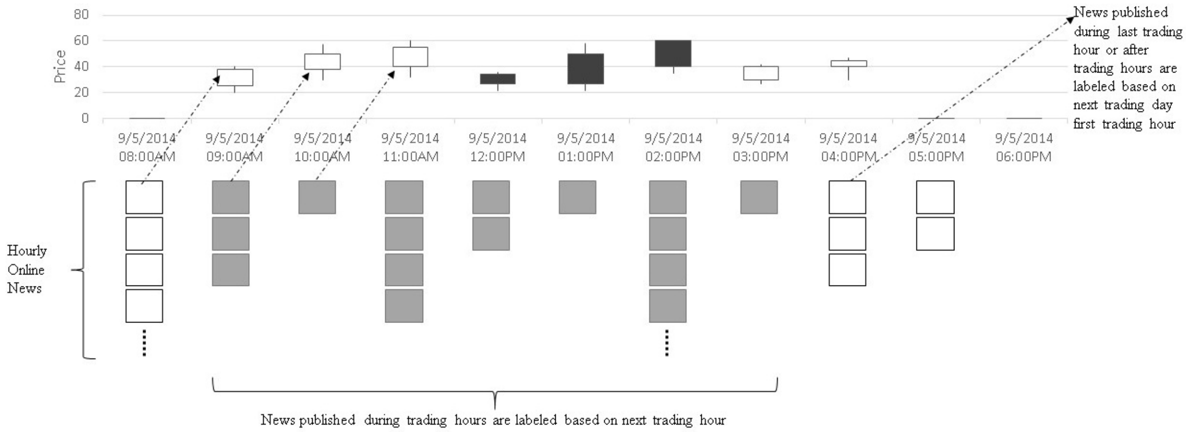

Figure 4.3: Illustration of News Labeling

this phase we used the stock price direction of the following hour to categorize the directionality of the hourly collections of news articles. In order to align the news article hours with the stock chart hours we had to standardize and adjust their time zones. Formula 4.2 is used to label the news articles where d represents the publishing date, and h represents the publishing hour.

$$Label(d, h) = Dir(d, Next(h)) \tag{4.2}$$

In this research we initially assume that the effect of published news articles will be reflected on the stock price direction during the next hour. Later we relax this assumption and test the system for all time periods varying between 5 mins up to 4 hours. Formula 4.2 applies to all the news articles published during official trading hours which starts at 9AM and ends on 3PM in EST time zone.

For articles that are published during the last trading hour, or after trading hours, or during holidays and weekends we assumed that their effect will be seen on the direction of the first trading hour of the next trading day. For this case Formula 4.3 is used to label those news articles.

$$Label(d,h) = Dir(Next(d), First(h)) \tag{4.3}$$

6. Classifier: We formulate price direction prediction problem as a classification problem in a general structured sparse learning framework (Liu *et al.*, 2009). In particular, the logistical regression formulation presented below fits this application, since it is a dichotomous classification problem (e.g. upwards vs. downwards price correction), In the formula 4.4, a_i is the vector representation of the news during the i^{th} hour, w_i is the weight assigned to the i^{th} document (w_i=1/m by default), and A=[a_1, a_2, , a_m] is the document n-gram matrix, y_i is the directionality of each hour based upon the stock price action of the next hour, and the unknown x_j , the j-th element of x, is the weight for each n-gram feature, $\lambda > 0$ is a regularization parameter that controls the sparsity of the solution, $|x|_1 = \Sigma|x_i|$ is 1-norm of the x vector. We used the SLEP (Liu *et al.*, 2009) sparse learning package that utilizes gradient descent approach to solve the above convex and non-smooth optimization problem. The n-grams with non-zero values on the sparse x vector yield the discriminant factors for classifying a news collection as leading to upwards or downwards price correction. n-grams with positive polarity correspond to upward direction indicators, and those with negative polarity correspond to downward direction indicators.

$$\min_x \sum_{i=1}^{n} w_i \log(1 + \exp(1 + y_i(x^t a_i + c))) + \lambda|x| \tag{4.4}$$

We also utilized an SVM classifier in our experiments using LIBSVM [10] library.

7. 10-fold cross validation: We run a total of 8 experiments for each stock symbol where we experimented: (1) with SVM and sparse logistic regression classi-

[10] http://www.csie.ntu.edu.tw/~cjlin/libsvm/

fiers, (2) with 1-gram and 2-gram features, and (3) with and without extracted sentiment features. After the training phase of the classifier, we validated the accuracies using 10-fold cross validation. The evaluation results for the first experiment are presented in Section 5.2.

4.2 Experiment-2: Hourly Price Direction Prediction Using Breaking News

We selected the classifier with the best performance emerging from Experiment-1 to use in Experiment-2. Experiment-2 was designed to test if the online news indicated by *breaking* Tweet volumes would lead to a statistically significant boost in the directional prediction accuracy for the prices of the relevant stock symbols mentioned in such news. The system architecture figure in Figure 4.2 shows the steps used in this experiment. The following is a detailed description of each step:

1. Twitter Stock Symbol Feed: Twitter streaming API was used to collect Tweets related to companies in the Dow Jones Index (DJI). In order to collect relevant Tweets we used a keyword filter made from the stock symbols, either prefixed by a dollar sign ($) or prefixed by "NYSE:" or "NASDAQ:". For example, the keyword filter for Microsoft Corporation are $MSFT and NYSE:MSFT. For each matching Tweet we stored the stock symbol, Tweet text, date, time, and the set of URLs mentioned in the Tweet. If the Tweet text contained more than one stock symbol then we stored the same Tweet information for each mentioned stock symbol.

2. Hourly Tweets Volume Profiling: We utilize a fixed sized sliding window (of length 20 hour intervals) where the 20 hour intervals was determined by conducting several experiments with different intervals, to compute a running average $\mu[20]$ and standard deviation σ for the hourly volumes of Tweets that

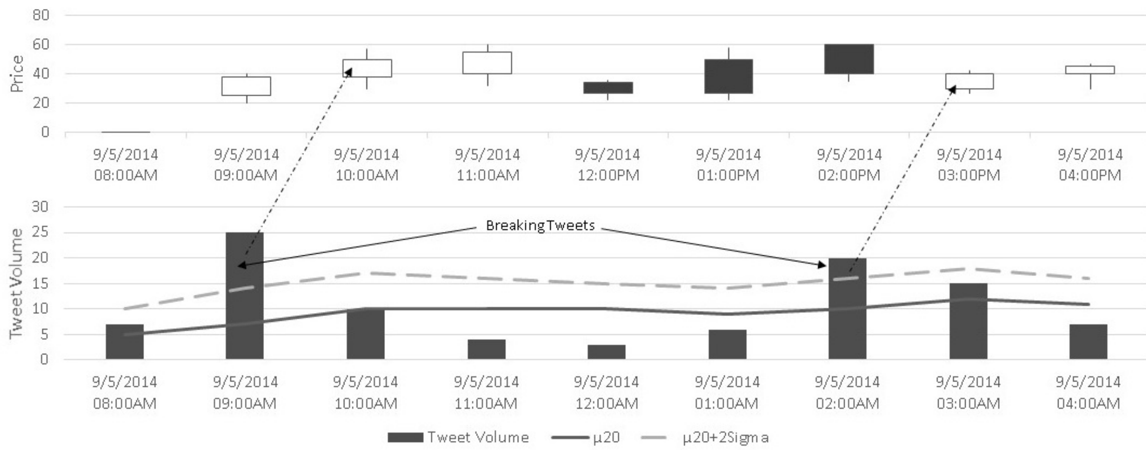

Figure 4.4: Illustration of Breaking Tweets

mention a stock symbol.

3. Tweets Volume Breakout Hour: We identify *breakout* signals within a time-series of hourly Tweet volumes for each stock symbol using Formula 4.5.

$$Breakout = \begin{cases} True & \text{if } N(d,h) \geq \mu[20](d,h) + 2\sigma(d,h)) \\ False & \text{otherwise} \end{cases} \tag{4.5}$$

In Formula 4.5, N represents Tweet volume on specific date d, and hour h. $\mu[20]$ is 20-hour simple moving average applied on Tweets' volume, $\mu[20](d,h)+2\sigma(d,h)$ represents the upper band for simple moving average - a 20-hour moving average plus 2-times standard deviation. If the volume of hourly Tweets N exceeds the upper band value, this would indicate a volume breakout. Otherwise the Tweet volume is non-breaking. In Figure 4.4, the pair of dotted arrows shows two instances of Tweet volume breakouts at 9/5/2014 at 9AM and 9/5/2014 at 2PM, where the corresponding articles from these hours will be used to predict the price directions of the mentioned stocks at the following hours.

4. News From Breaking Tweets: In this step the news content of URLs found in the Tweets during the breaking hours are downloaded and their textual contents

are extracted using the following steps:

(a) For each breaking hour of a specific stock symbol we fetch the URLs found in Tweets during the breaking hour, i.e. Breakout = True. In some cases the URLs were mentioned in their short URL forms, so before fetching them, they were converted to their long forms.

(b) Fetch the URL links' content and perform content extraction from the HTML documents using the JSoup HTML parser [11] .

5. Classifier: After extracting the hourly breaking news and their 1-gram features we utilized the logistic regression classifier to predict the price direction for the next hour.

6. Evaluation: The predictive accuracies of the news classifier for the price direction following the breaking Tweet volume hours are presented in Section 5.3.

4.3 Experiment-3: Comparison Between Different Time-Frames For Price Direction Prediction Using Breaking News

In Experiment-3 we used the same steps of the system architecture of Experiment-2 shown in Figure 4.2, but instead of using the 1 hour time-frame for news grouping and the price direction labeling, we tested the prediction performance of the news content based classifier using all possible time-frame combinations (i.e. 4 hours, 1 hour, 30 minutes, 15 minutes, and 5 minutes) for both news grouping and news price effects labeling. Table 4.1 lists the evaluated time-frame combinations for news grouping and news effect labeling. The goal of this experiment is to identify the best time-frame combination that should be used for (i) news grouping and (ii) news

[11] http://jsoup.org/

Table 4.1: Tweets Breaking News Grouping and Prediction Time-Frames

News grouping Time-frames	Price Direction Labeling Time-frames				
	4h	1h	30m	15m	5m
4h	✓	✓	✓	✓	✓
1h		✓	✓	✓	✓
30m			✓	✓	✓
15m				✓	✓

effect labeling which yields the highest directional stock price prediction accuracy. The findings of Experiment-3 is presented in Section 5.4.

4.4 Experiment-4: Tweets Volume Breakout Based Trading System

We selected the classifier with the best performance emerging from Experiment-3 for use in Experiment-4. Experiment-4 is designed to test if prediction with the online news linked from *breaking* Tweet volumes would lead to a higher performance directional stock price prediction system. Figure 4.5 shows the flowchart of the proposed system for Experiment-4. The following are the trade entry and exit rules that we used:

1. ENTER a trade at the beginning of the next trade period, if there was a Tweet volume breakout for Tweets matching a stock's symbol in the preceding time-frame.

2. The trade DIRECTION (i.e. buy or sell) is determined by the news content-based classifier applied to the content linked from the Tweets matching a stock's symbol during the proceeding Tweet volume breakout period.

3. EXIT the trade at the end of the next time-frame period.

4. Evaluate the performance of the resulting trade (i.e. a win or a loss) and the

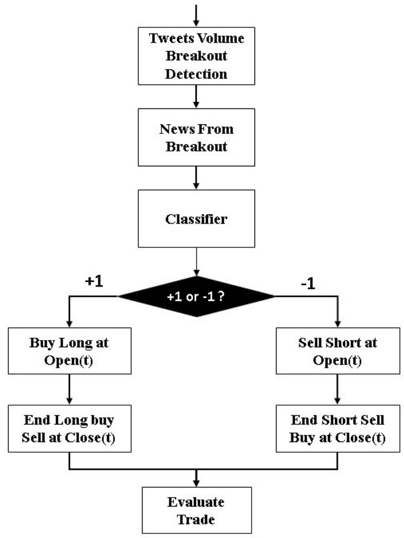

Figure 4.5: A Flowchart of Tweets Breakout Trading Strategy

corresponding amount according to the real stock price movement during the trade period.

In order to evaluate the performance of the above trading system we performed a backtesting of the system on real data, recorded the outcomes of its trades accounting for its wins and losses, as follows:

- Percentage of winning trades (Won%)
- Percentage of long positions (Long Won%)
- Percentage of short positions (Short Won%)
- Percentage of Return On Investment (ROI%) according to Equation 4.6

$$ROI = \frac{Gain - Cost}{Cost} \tag{4.6}$$

ROI is a performance measure used to evaluate the efficiency of an investment or to compare the efficiency of a number of different investments (ROI, 2016). The higher the value of ROI% the better.

- Percentage of Maximum Drawdown (MDD%), is the maximum loss from a peak to a trough of a portfolio, before a new peak is attained. It is an indicator of downside risk over a specified time period (MDD, 2016). The lower the value of MDD% the better for investment.

- Return Over Maximum Drawdown (RoMaD) shown in Equation 4.7

$$RoMaD = \frac{ROI}{MDD} \tag{4.7}$$

  RoMad is a risk-adjusted return metric. It enables investors to ask the question: Are they willing to accept an occasional drawdown of X% in order to generate an average return of Y%? (RoM, 2016), for example: An investment with a MDD of 20% and ROI= 10% (RoMAD = 2.0) would be considered the more attractive investment than one with a MDD of 50% and a ROI of 10% (RoMAD = 0.2).

The experimental results for the Tweets volume breakout based trading system are presented in Section 5.5.

4.5 Experiment-5: Price Momentum Based Trade EXIT Rules

In this experiment we develop a set of price momentum based trade exit rules to cut losing trades early and to allow the winning trades run longer. We apply these price momentum based EXIT rules to the trading system developed in Experiment-4, and compare their performance in Section 5.6. The rules are based on the Squeeze Momentum Indicator (Squ, 2016), which is a derivative of John Carter's "TTM Squeeze" volatility indicator (Carter, 2007). This indicator has been used to detect periods while the market is quiet (i.e. squeeze) and the periods while the market is volatile (i.e. price breakouts). Squeeze Momentum Indicator is comprised of three components:

1. Bollinger Bands (bol, 2016).

$$\begin{aligned} UpperBollingerBand &= \mu[20] + 2\sigma, \\ LowerBollingerBand &= \mu[20] - 2\sigma, \\ MiddleBollingerBand &= \mu[20] \end{aligned} \tag{4.8}$$

where $\mu[20]$ is the average of the closing prices for the previous 20 time-periods and σ is their standard deviation.

2. Keltner Channels (Kel, 2016).

$$\begin{aligned} UpperChannelLine &= \mu[20] + 2ATR(10), \\ LowerChannelLine &= \mu[20] - 2ATR(10) \end{aligned} \tag{4.9}$$

where ATR (ATR, 2016) is defined as follows:

$$ATR(t) = \frac{ATR(t-1) \times (n-1) + TR}{n}$$

$$TR = max[(high - low), abs(high, close_{Prev}), abs(low - close_{prev})]$$

ent time, n=10, and true range TR is the largest of either the most recent period's high minus the most recent period's low, or the absolute value of the most recent period's high minus the previous close, or the absolute value of the most recent period's low minus the previous close.

3. Momentum Indicator (Squ, 2016).

$$Momentum = close[0] - \mu[\mu[highest[high, 20], lowest[low, 20]], \mu[20]] \tag{4.10}$$

where Momentum is the difference between the current close values to the average of the average between highest high of the previous 20 time periods and lowest low of the previous 20 time periods, to the average of the closing prices for the previous 20 time-periods.

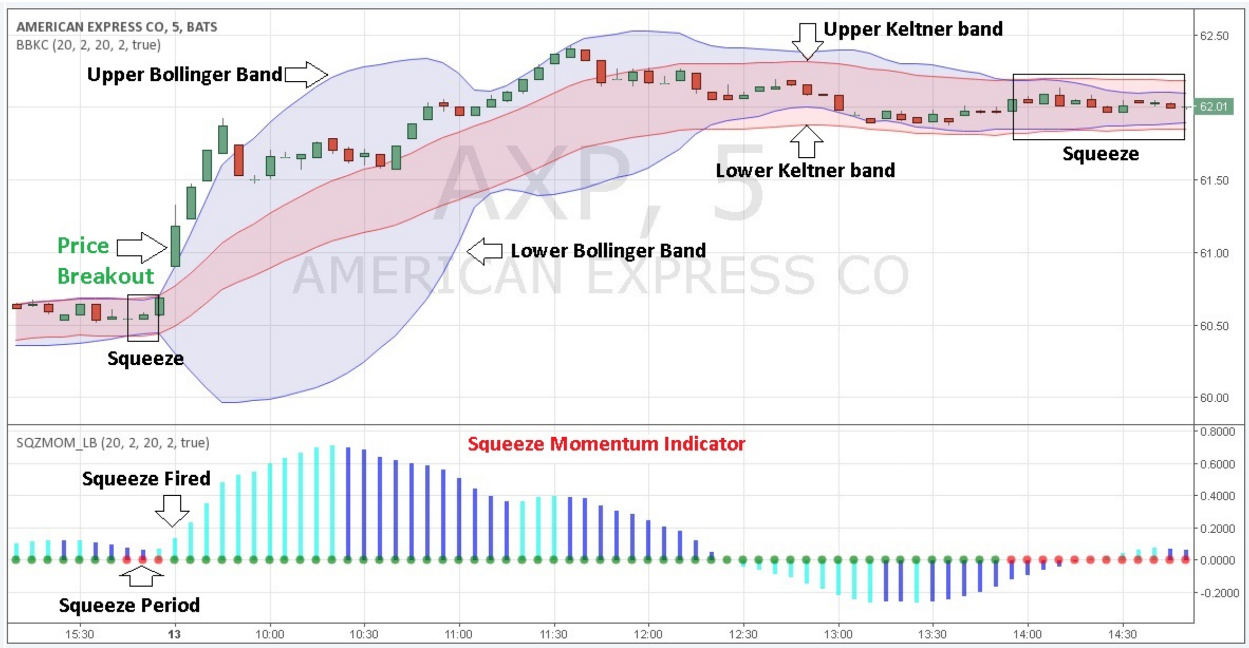

Figure 4.6: Squeeze Momentum Indicator for AXP Stock symbol on 5 min Chart. Chart created using https://www.tradingview.com site charts

Figure 4.6 illustrates the Squeeze Momentum Indicator components. The Squeeze Momentum Indicator is used as follows: It signals a red dot when the Bollinger Bands are inside of the Keltner Channel, whence the market is said to be in a *squeeze*. Otherwise, it signals a green dot signaling that the market is *volatile* (i.e. price breakout). In order to determine the direction of the volatility, we inspect the sign of the Momentum Indicator. If it is positive, then the price momentum is in the upward direction, otherwise it is in the downward direction.

The momentum based trade EXIT rules are defined as follows:

- Cut Losses Early (CLE) EXIT Rule is defined in Section 4.5.1.
- Conservative Let the Winners Run (ConsLWR) EXIT Rule is defined in Section 4.5.2.
- Aggressive Let the Winners Run (AggLWR) EXIT Rule is defined in Section

4.5.3

- Cut Losses Early (CLE) + Conservative Let the Winners Run (ConsLWR) EXIT Rule is defined in Section 4.5.4

- Cut Losses Early (CLE) + Aggressive Let the Winners Run (AggLWR) EXIT Rule is defined in Section 4.5.5

4.5.1 Trading With Cut Losses Early (CLE) EXIT Rule

This rule applies during the initial fixed time-period of the trade, where we track the price action on the 5 minute chart to cut the losses early if the price is *volatile* and the Momentum Indicator points to a direction that is opposite to that of the trade's direction.

1. Stock price is volatile and not in a squeeze period i.e. TTM squeeze indicator should be off (i.e. green)

2. The momentum indicator for the previous pair of bars are rising in an opposite direction.

   - Long EXIT: Momentum indicator for the previous pair of bars are both negative and declining.

   - Short EXIT: Momentum indicator for the previous pair of bars are positive and rising.

4.5.2 Trading With the Conservative Let the Winners Run (ConsLWR) EXIT Rule

In this strategy a trade is allowed to run, past its fixed time period, if it is in profit at the end of its fixed time-period and while the following conditions remain true on the 5 minute price chart:

- Long/Buy Continuation: Momentum indicator for the previous pair of bars are rising.
- Short/Sell Continuation: Momentum indicator for the previous pair of bars are declining.

The trade is exited, using the 5 minute chart when one of the following conditions are met:

- Long/Buy EXIT: Momentum indicator for the previous pair of bars are declining.
- Short/Sell EXIT: Momentum indicator for the previous pair of bars are rising.

4.5.3 Trading With the Aggressive Let the Winners Run (AggLWR) EXIT Rule

In this strategy a trade is allowed to run, past its fixed time period, if it is in profit at the end of its fixed time-period and while the following conditions remain true on the 5 minute price chart:

- Long/Buy Continuation: Momentum indicator for the previous pair of bars are positive.
- Short/Sell Continuation: Momentum indicator for the previous pair of bars are negative.

The trade is exited, using the 5 minute chart when one of the following conditions are met:

- Long EXIT: Momentum indicator for the previous bar is negative (i.e. opposite direction)
- Short EXIT: Momentum indicator for the previous bar is positive (i.e. opposite direction)

4.5.4 CLE + ConsLWR Trading Strategy

This strategy combines the CLE exit rule during the initial time-frame with the ConsLWR rule following the initial time-frame.

4.5.5 CLE + AggLWR Trading Strategy

This strategy combines the CLE exit rule during the initial time-frame with the AggLWR rule following the initial time-frame.

The detailed results of financial back-testing of the Tweets volume breakout trading system with the price momentum based trade EXIT rules are presented in Section 5.6.

Chapter 5

EXPERIMENTS RESULTS AND EVALUATION

5.1 Experimental Data

Table 5.1: Counts of Collected News Articles, and Tweets for 30 Dow Jones Stock Symbols

Stock Symbol	News	Tweets	Stock Symbol	News	Tweets
$AXP	1614	15251	$MCD	1879	21419
$BA	2006	19041	$MMM	1183	11438
$CAT	1842	19303	$MRK	1573	28882
$CSCO	1984	26611	$MSFT	1733	59469
$CVX	2168	15897	$NKE	1080	18206
$DD	1553	11218	$PFE	1841	50859
$DIS	1870	25014	$PG	1781	15097
$GE	2260	31336	$T	1784	30128
$GS	1878	52888	$TRV	968	8858
$HD	1743	18459	$UNH	1133	11224
$IBM	2188	80412	$UTX	1278	10872
$INTC	2157	30724	$V	1683	19174
$JNJ	2232	18236	$VZ	2194	20896
$JPM	1543	33658	$WMT	2216	30448
$KO	1899	22688	$XOM	2378	22433

We collected online news articles and stock price charts related to 30 stock symbols in Dow Jones Index for the period between October, 2009 and September, 2014. We also collected Tweets matching stock symbols for the period between March, 2014 and September, 2014. The total number of news articles collected from the NASDAQ website for the 30 stock symbols in Dow Jones Index is 53,641. The total number of

Table 5.2: Counts of Breaking Tweets for 30 Dow Jones Stock Symbols based on Different Time-frames

Symbol	4H	1H	30m	15m	Symbol	4H	1H	30m	15m
$AXP	77	155	309	289	$MCD	93	228	404	424
$BA	81	207	374	404	$MMM	81	122	218	190
$CAT	83	188	350	353	$MRK	83	199	394	385
$CSCO	78	285	505	574	$MSFT	83	272	598	854
$CVX	87	202	363	369	$NKE	71	196	293	288
$DD	70	63	192	201	$PFE	104	292	452	586
$DIS	79	199	436	444	$PG	82	192	226	318
$GE	87	274	552	659	$T	86	263	405	562
$GS	89	246	518	606	$TRV	65	52	97	145
$HD	81	164	335	349	$UNH	78	144	134	170
$IBM	92	248	513	761	$UTX	73	68	142	177
$INTC	85	273	501	597	$V	74	190	268	280
$JNJ	78	224	366	393	$VZ	91	252	364	440
$JPM	84	274	510	590	$WMT	89	236	395	488
$KO	74	208	369	470	$XOM	84	248	386	446

collected Tweets matching 30 stock symbols is 780,139. Table 5.1 shows the number of news articles, total number of collected Tweets. Table 5.2 shows Counts of breaking tweets for 30 Dow Jones Stock Symbols based on different time-frames, table 5.2 shows that the count of breaking tweets decreases as we move from lower to higher time-frames.

We used equation 5.1 to measure the skewness ratio of our data towards the positive and the negative labels, when skewness ratio equals 1 it indicates that the data set is fully balanced, on the other a skewness ratio value greater than 1 indicates that the data set is imbalanced toward the negative labels, and finally, when skewness

Table 5.3: Dataset Skewness Ratio for each Stock Symbol based on Different Time-frames

Symbol	4H	1H	30m	15m	Symbol	4H	1H	30m	15m
$AXP	0.638	0.797	0.876	0.883	$MCD	0.715	0.855	0.994	0.967
$BA	0.692	0.820	0.887	0.938	$MMM	0.655	0.878	0.823	0.866
$CAT	0.702	0.925	0.925	0.978	$MRK	0.658	0.798	0.856	0.862
$CSCO	0.660	0.753	0.770	0.758	$MSFT	0.759	0.981	1.017	1.023
$CVX	0.752	0.957	0.979	1.141	$NKE	0.695	0.852	0.907	0.929
$DD	0.701	0.941	0.990	1.015	$PFE	0.729	0.803	0.818	0.830
$DIS	0.577	0.781	0.789	0.747	$PG	0.720	0.765	0.771	0.879
$GE	0.738	0.928	0.947	1.059	$T	0.730	1.023	1.021	1.003
$GS	0.632	0.801	0.855	0.881	$TRV	0.771	0.869	0.972	0.926
$HD	0.736	0.806	0.817	0.846	$UNH	0.629	0.816	1.004	0.896
$IBM	0.669	0.811	0.906	0.939	$UTX	0.680	0.871	0.985	0.961
$INTC	0.650	0.786	0.796	0.802	$V	0.698	0.928	1.080	1.062
$JNJ	0.683	0.908	0.971	0.975	$VZ	0.672	0.943	0.932	1.173
$JPM	0.775	0.879	0.909	0.922	$WMT	0.616	0.816	0.866	0.927
$KO	0.638	0.897	0.974	0.976	$XOM	0.655	0.824	0.832	0.939

ratio is less than 1 it means that the data imbalnce is toward the positive labels.

$$skewratio = \frac{NegativeTrainingData}{PositiveTrainingData} \tag{5.1}$$

Table 5.3 shows the skewness ratio for each stock symbol based on different time-frames, it shows that our data set has small skewness toward positive labels in some time-frames and in a small number of cases a small skewness towards the negative labels, the imbalance in our data set in either case is very small, the majority of skewness ratio of our data set was very close to 1 either >0.5 or <2, meaning that our data set is very close to be fully balanced.

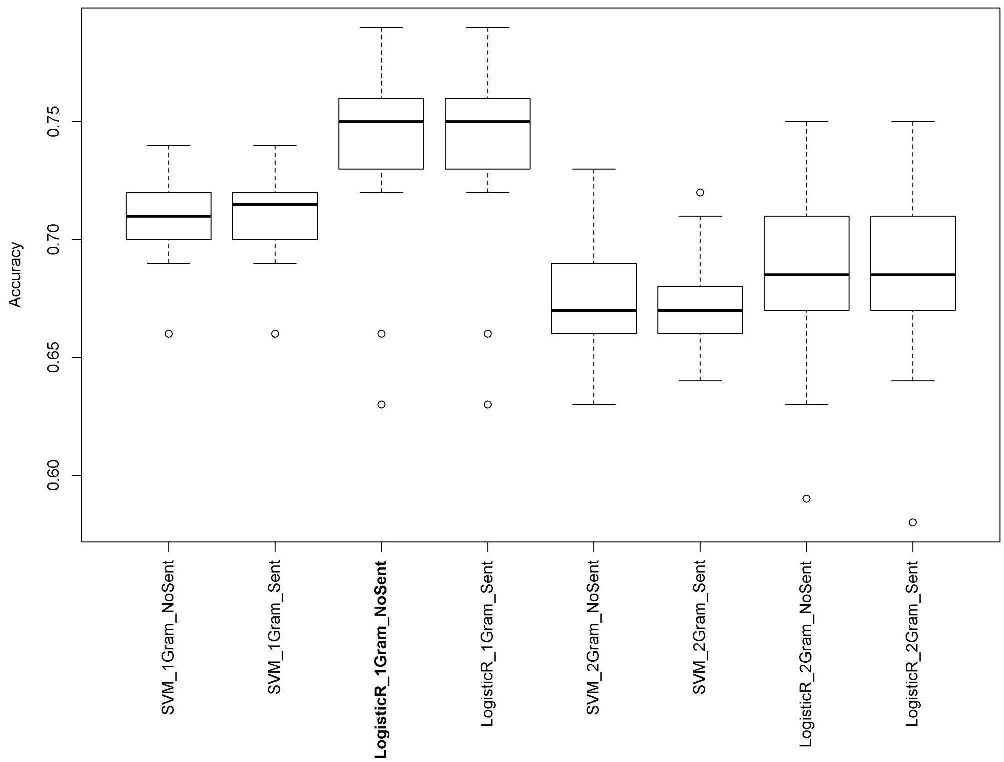

Figure 5.1: Whisker Plot of Experiment-1 Accuracy

5.2 Experiment-1: Hourly Price Direction Prediction Using Online News

We executed the steps described in Figure 4.1 on data sets collected for the 30 Dow Jones Index companies. In order to identify the best set of text features and the best classifier we had to perform several experiments. We run a total of 8 experiments for each stock symbol where we experimented: (1) with SVM and sparse logistic regression classifiers, (2) with 1-gram and 2-gram keyword features, and (3) with and without extracted sentiment for documents. After the training phase of the classifier, we validated the accuracies using 10-fold cross validation. The results for this first experiment is presented as whisker plot in Figure 5.1 and in Table 5.4. The bold numbers on each row indicate the experimental setup which led to the best accuracy for each stock symbol. The evaluations show that 1-gram features led to higher overall accuracies compared to 2-gram features for both SVM and LogisticR

Table 5.4: Accuracy Results of Experiment-1: Hourly Price Direction Prediction using Online News

Classification Method	SVM		LogisticR		SVM		LogisticR	
Feature Representation	1-Gram				2-Gram			
Sentiment Features	No	Yes	No	Yes	No	Yes	No	Yes
$AXP	71.44%	70.19%	**75.47%**	74.28%	67.72%	67.66%	70.82%	70.26%
$BA	68.70%	69.39%	72.64%	**72.98%**	66.60%	66.50%	68.29%	68.29%
$CAT	72.21%	72.47%	**76.49%**	75.95%	65.15%	65.63%	66.18%	67.21%
$CSCO	70.36%	71.17%	**72.83%**	72.68%	67.19%	66.58%	70.51%	70.11%
$CVX	69.00%	69.01%	**75.19%**	**75.19%**	65.96%	64.62%	65.82%	65.27%
$DD	66.39%	66.19%	71.73%	**72.18%**	65.29%	64.97%	68.19%	68.12%
$DIS	72.03%	72.41%	74.76%	**75.40%**	66.04%	65.99%	68.82%	68.29%
$GE	**70.31**%	69.78%	63.36%	63.19%	64.96%	64.56%	58.76%	58.19%
$GS	71.19%	71.14%	**74.60%**	74.07%	66.35%	65.55%	67.62%	68.00%
$HD	70.74%	71.95%	73.84%	**74.76%**	67.18%	67.64%	67.98%	68.15%
$IBM	70.47%	70.48%	**73.99%**	73.81%	67.46%	66.68%	66.69%	67.37%
$INTC	69.17%	69.49%	73.39%	**73.85%**	68.20%	69.36%	69.87%	70.01%
$JNJ	70.39%	70.75%	**72.72%**	72.18%	64.87%	64.20%	66.22%	66.62%
$JPM	72.13%	72.01%	76.22%	**76.54%**	66.37%	65.58%	68.38%	67.20%
$KO	72.88%	73.83%	**76.20%**	76.04%	70.67%	69.88%	70.93%	70.62%
$MCD	71.42%	71.64%	74.30%	**74.93%**	68.02%	67.91%	70.62%	70.73%
$MMM	73.96%	74.22%	**77.85%**	77.85%	72.87%	72.44%	74.22%	74.72%
$MRK	72.60%	72.54%	**76.10%**	75.27%	68.91%	68.34%	70.95%	71.27%
$MSFT	73.92%	73.98%	**77.85%**	77.84%	68.72%	68.27%	71.61%	71.33%
$NKE	73.24%	72.31%	**79.17%**	78.80%	72.13%	71.67%	74.54%	73.80%
$PFE	72.95%	72.03%	**76.32%**	75.83%	70.07%	70.18%	72.03%	71.86%
$PG	71.48%	72.26%	75.91%	**76.47%**	67.94%	68.16%	67.83%	68.72%
$T	70.90%	70.90%	**75.67%**	**75.67%**	63.34%	64.57%	62.95%	65.14%
$TRV	69.83%	70.98%	**75.42%**	75.11%	69.52%	67.66%	71.79%	72.00%
$UNH	72.11%	72.64%	**76.08%**	75.82%	71.31%	71.32%	74.76%	74.24%
$UTX	70.89%	71.76%	**75.90%**	75.67%	67.30%	68.86%	70.51%	70.89%
$V	71.90%	73.50%	75.22%	**76.30%**	68.15%	67.32%	69.87%	68.87%
$VZ	70.14%	68.96%	**72.56%**	71.83%	65.36%	64.31%	66.46%	66.22%
$WMT	**70.31**%	69.90%	65.97%	65.57%	63.81%	64.53%	64.62%	63.99%
$XOM	69.89%	69.72%	**72.75%**	71.70%	66.48%	66.53%	67.70%	68.04%

experiments. Also, the experimental setup with the LogisticR classifier using 1-Gram features where the sentiment features were excluded led to the maximal accuracies in 19 out of 30 cases. The second best experimental setup that achieved the maximal accuracies was also with the LogisticR classifier with 1-gram features integrated with the sentiment feature. Hence, in order to determine the utility of extracted sentiment features we formulated the following hypotheses and applied the non-parametric sign test (Lehmann, 2006) at confidence level 95% to test if sentiment features would yield a statistically significant boost in the overall prediction accuracies:

1. Null Hypothesis (h0): 1-gram LogisticR classifier without sentiment features accuracies' mean = 1-gram LogisticR classifier with sentiment accuracies' mean, indicating that they are at the same level of performance.

2. Alternative Hypothesis (h1): 1-gram LogisticR classifier without sentiment features accuracies' mean ≠ 1-gram LogisticR classifier with sentiment features accuracies' mean, indicating that they are not at the same level of performance.

The p-value of the sign test to compare 1-gram LogisticR classifier without sentiment features with 1-gram LogisticR classifier with sentiment features at significance level 0.05 equals to 0.1221, which leads to the acceptance of the null hypothesis h0 and the rejection of the alternative hypothesis h1, concluding that using sentiment would *not* yield a statistically significant boost in the overall prediction accuracy in this setup.

5.3 Experiment-2: Hourly Price Direction Prediction Using Breaking News

In Experiment-2 we applied steps outlined in Figure 4.2 to 30 stock symbols in Dow Jones Index using breaking news periods only as trade triggers. Table 5.5 shows that Experiment-2 led to a boost in predictive accuracies for 70% of the stock symbols

Table 5.5: Accuracy Results of Experiment 2: Hourly Price Direction Prediction using Breaking News

Stock Symbol	Experiment-1 Accuracy	Experiment-2 Accuracy	Stock Symbol	Experiment-1 Accuracy	Experiment-2 Accuracy
$AXP	67.84%	**69.66**%	$MCD	67.80%	65.30%
$BA	68.20%	**79.00**%	$MMM	70.60%	**76.50**%
$CAT	65.37%	**68.39**%	$MRK	69.30%	64.80%
$CSCO	67.70%	**69.55**%	$MSFT	72.60%	**81.80**%
$CVX	66.60%	65.22%	$NKE	70.30%	**71.30**%
$DD	67.93%	66.67%	$PFE	70.70%	59.50%
$DIS	65.60%	64.75%	$PG	70.80%	**72.70**%
$GE	66.60%	**66.67**%	$T	75.80%	**82.90**%
$GS	68.30%	**71.60**%	$TRV	65.40%	**75.00**%
$HD	68.70%	**75.00**%	$UNH	68.40%	**75.20**%
$IBM	66.10%	**80.80**%	$UTX	67.80%	58.60%
$INTC	69.60%	67.30%	$V	71.20%	71.00%
$JNJ	64.40%	**69.20**%	$VZ	65.30%	**72.80**%
$JPM	67.50%	**74.00**%	$WMT	66.60%	**71.00**%
$KO	67.90%	**68.60**%	$XOM	65.20%	**67.30**%

(i.e. 21 out of 30 cases). In order to prove that Experiment-2 yields a statistically significant boost in prediction accuracy compared to Experiment-1 we applied sign test at confidence level 95%. We formulated the following hypotheses:

1. Null Hypothesis (h0): Experiment-1 accuracies mean = Experiment-2 accuracies mean, indicating that they are at the same level of performance.

2. Alternative Hypothesis (h1): Experiment-1 accuracies mean $\neq$ Experiment-2 accuracies mean, indicating that they are not at the same level of performance.

The p-value of the sign test to compare Experiment-1 with Experiment-2 at significance level 0.05 equals to 0.0357, which leads to the rejection of the null hypothesis h0 and the accepting of the alternative hypothesis h1 thus confirming that using 1-gram

Table 5.6: Accuracy Results of Experiment-3: Performance Comparison Between Different Time-frames for News Grouping and Direction Labaling

News grouping Time-frames	Price Direction Labeling Time-frames				
	4h	1h	30m	15m	5m
4h	**75%**	71%	74%	74%	74%
1h	–	71%	72%	73%	71%
30m	–	–	68%	68%	68%
15m	–	–	–	65%	66%

based LogisticR classifier with *breaking news* yields a *statistically significant boost* in directional prediction accuracy for 30 DJI stocks compared to using the same classifier with *all* of the stock news every hour.

5.4 Experiment-3: Comparison Between Different Time-frames For Price Direction Prediction Using Breaking News

13 pairs of time-frame combinations were tested in Experiment-3 where we applied the steps outlined in Figure 4.2 to each of the 30 stock symbols in Dow Jones Index using breaking news periods. Table 5.6 shows that in this experiment 4h4h time-frame combination yields the best average predictive accuracy for the price direction. This experiment indicates that (i) the 4 hour time period is the best time-period for detecting Tweet volume breakouts, and (ii) the 4 hour time-period is also the best time-frame to label and predict the trend direction following a Tweet volume breakout session. The detailed accurcy results for each stock symbol is listed in table A.1.

5.5 Experiment-4: Tweets Volume Breakout Based Trading System

We performed a simulated financial evaluation of the proposed trading system by back-testing its trades and accounting for its return on investment (ROI%) for a period of 6 months, between March 2014 and September 2014. In this simulation it is assumed that no commissions or fees are charged for each trade. Since the 4h4h time-frame yield the best accuracy results from Experiment-3 the system was tested using the 4 hours breaking Tweets on the 4 hour stock chart, for its trade entries and exists. The system entered a trade following a Tweet volume breakout session for Tweets matching a stock's symbol, with a trade fired in the direction (e.g. a long/buy or short/sell trade) predicted by our classifier based on the content that was collected by following the links from the Tweets during the breakout period, for a fixed duration of 4 hours. For each company, we measured the percentage of winning trades (Won%), percentage of long positions (Long Won%), percentage of short positions (Short Won%), return on investment (ROI%), maximum drawdown (MDD%), and risk adjusted return over maximum drawdown (RoMad).

Table 5.7 shows the results of the simulated back-testing evaluations. The results show that during this period our system was profitable overall on its recommended trades with each stock symbol. Since each stock has a different stock price, we performed simulated trading using a diversified portfolio based on equal exposure to risk or gains from each stock in order to calculate the total and monthly average return on investment (ROI%). The simulated trades show that trading with the system during the 6 months period results in a winning ratio of 74% for its long/buy directional trades and 80% winning ratio for its short/sell directional trades. Trading with an equally diversified portfolio yields a total (ROI%) of 14% for 6 months, indicating an average monthly (ROI%) of 2.22% and RoMad value of 6.09. The highest total (ROI%) achieved was 31.9% with Intel corporation($INTC), and the lowest total (ROI%) was 0.50% with Mcdonald's ($MCD), the highest RoMad value was achieved by trading AT&T ($T) equals 26.84 and the lowest RoMaD was 0.21 achieved by trading Mcdonald's ($MCD).

Table 5.7: Experiment-4 Financial Evaluation of Tweets Breakout Trading System

Stock Symbol	Won%	Short Won%	Long Won%	ROI%	MDD	RoMaD
$AXP	66%	100.00%	61.76%	6.90%	4.17	1.65
$BA	65%	60.61%	68.75%	13.94%	3.52	3.96
$CAT	69%	63.64%	72.00%	6.06%	2.66	2.28
$CSCO	77%	74.19%	78.72%	15.10%	1.47	10.27
$CVX	82%	85.00%	80.60%	13.67%	1.69	8.09
$DD	76%	88.24%	71.70%	7.70%	2.39	3.22
$DIS	78%	100.00%	75.00%	6.42%	3.99	1.61
$GE	78%	83.87%	75.00%	14.96%	2.65	5.65
$GS	76%	67.50%	83.67%	18.45%	1.52	12.14
$HD	79%	100.00%	76.06%	20.20%	1.07	18.88
$IBM	79%	83.33%	78.38%	10.46%	1.48	7.07
$INTC	81%	100.00%	77.14%	31.90%	1.19	26.81
$JNJ	77%	82.61%	74.55%	8.61%	2.60	3.31
$JPM	77%	67.39%	89.47%	16.96%	2.83	5.99
$KO	77%	86.67%	74.58%	12.46%	1.11	11.23
$MCD	62%	60.42%	64.44%	0.50%	2.39	0.21
$MMM	67%	88.89%	63.89%	0.65%	2.97	0.22
$MRK	80%	85.00%	77.78%	31.41%	2.38	13.20
$MSFT	80%	95.83%	72.88%	12.56%	2.64	4.76
$NKE	75%	50.00%	75.36%	11.22%	1.61	6.97
$PFE	61%	56.52%	68.57%	12.12%	2.97	4.08
$PG	76%	82.14%	72.22%	14.12%	0.91	15.52
$T	86%	95.00%	83.33%	20.13%	0.75	26.84
$TRV	62%	64.71%	60.42%	1.08%	2.04	0.53
$UNH	73%	85.71%	70.31%	22.28%	1.70	13.11
$UTX	67%	76.19%	63.46%	3.15%	5.79	0.54
$V	77%	94.12%	71.93%	12.24%	2.51	4.88
$VZ	87%	80.00%	90.16%	26.46%	1.17	22.62
$WMT	73%	68.97%	75.00%	13.55%	1.85	7.32
$XOM	80%	81.08%	78.72%	20.09%	0.65	30.91
Average	**74.73 %**	**80.25 %**	**74.20%**	**13.51 %**	**2.22**	**6.09**

Table 5.8: Experiment-5: Comparison Between Different Trading Strategy Results

Trading Strategy	Won%	Short Won%	Long Won%	ROI%	MDD	RoMaD
Tweets breakout	75%	80%	74%	14%	2%	7.00
Tweets breakout + CLE	79%	83%	77%	16%	2%	8.00
Tweets breakout + ConsLWR	74%	79%	73%	14%	3%	4.66
Tweets breakout + AggLWR	72%	78%	72%	16%	6%	2.66
Tweets breakout + CLE + ConsLWR	78%	83%	77%	17%	2%	8.5
Tweets breakout + CLE + AggLWR	**78%**	**83%**	**77%**	**19%**	**2%**	**9.5**

5.6 Experiment-5: Tweets Breakout Stock Trading System With Price Momentum Based Trade EXIT Rules

We performed a simulated financial evaluation of the Tweets breakout stock trading system with the price momentum based trade EXIT rules defined in Section 4.5. Table 5.8 shows a comparison of the average results of the proposed trading strategies based on the Won%, Short Won%, Long Won%, ROI%, MDD, and RoMaD. The results show that Tweets Breakout+CLE+AggLWR trading strategy yielded the best risk adjusted return metric value (RoMad) of 9.5 - meaning that, this system would yield 9.5% returns for an occasional drawdown risk of 1%, or 95% returns for an occasional drawdown risk of 10%, essentially almost doubling the initial investment in 6 months. The second best trading strategy was obtained by the Tweets Breakout + CLE + ConsLWR with RoMaD value of 8.5. Detailed Experiment-5 results can be found in Appendix A tables A.2 ,A.3, A.4, A.5, and A.6.

Chapter 6

CONCLUSION AND FUTURE WORK

In this dissertation we start with a system to predict the hourly stock price direction based on the textual analysis of news articles' content mentioning a stock symbol. First, we show that using LogisticR classifier with 1-gram keyword features leads to the best overall directional prediction accuracy based on news articles. Next, we showed that using extracted document-level sentiment features do not yield to a statistically significant boost in directional predictive accuracies in the presence of other 1-gram features. Then, we proceed to show that information in articles indicated by breaking Tweet volumes leads to a statistically significant boost in the hourly directional prediction accuracies for the prices of DJI stocks mentioned in these articles. We experiment with all time-frame combinations and identify the 4h time period as the best time-period for detecting Tweet volume breakouts, and it is also as the best time-frame for the price-charts to label and predict the trend direction following a Tweet volume breakout session. Finally, we develop price momentum based trade exit rules to cut losing trades early and to allow the winning trades run longer. We show that the Tweet volume breakout based trading system with the momentum based exit rules not only improves the winning accuracy and the return on investment, but it also lowers the maximum drawdown and achieves the highest overall return over maximum drawdown. Our future work includes developing a real-time distributed trading system to monitor the Tweeter streams of different categories of stocks (i.e. large cap, mid cap and small cap) and trade with the their breaking volumes. We also plan to develop online learning methods to maintain the currency of the predictive models.

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APPENDIX A

EXPERIMENTAL RESULTS

Table A.1: Accuracy Results of Experiment-3 For Each Time-frame

Symbol	4h4	4h1h	4h30m	4h15m	4h15m	1h1h	1h30m	1h15m	1h5m	30m30m	30m15m	30m5m	15m15m	15m5m
$AXP	66%	62%	81%	75%	75%	70%	72%	80%	71%	71%	64%	59%	74%	64%
$BA	65%	77%	64%	69%	69%	79%	82%	77%	80%	64%	55%	74%	60%	65%
$CAT	69%	60%	71%	75%	75%	68%	60%	70%	68%	67%	67%	68%	69%	69%
$CSCO	77%	56%	69%	77%	77%	70%	72%	68%	70%	62%	66%	66%	67%	65%
$CVX	82%	74%	74%	60%	60%	65%	68%	67%	69%	58%	60%	55%	67%	61%
$DD	76%	67%	76%	73%	73%	67%	89%	56%	75%	71%	78%	76%	58%	85%
$DIS	78%	73%	77%	76%	76%	65%	65%	70%	72%	70%	63%	68%	63%	64%
$GE	78%	84%	69%	75%	75%	67%	63%	66%	84%	70%	67%	70%	67%	64%
$GS	76%	67%	73%	81%	81%	72%	75%	84%	79%	75%	69%	70%	65%	66%
$HD	79%	74%	73%	60%	60%	75%	70%	71%	68%	66%	64%	63%	59%	66%
$IBM	79%	79%	78%	87%	87%	81%	70%	75%	78%	81%	78%	65%	69%	67%
$INTC	81%	78%	82%	67%	67%	67%	68%	74%	61%	58%	68%	64%	69%	61%
$JNJ	77%	81%	78%	86%	86%	69%	79%	78%	72%	68%	61%	71%	66%	68%
$JPM	77%	83%	89%	83%	83%	74%	78%	79%	76%	72%	76%	61%	68%	62%
$KO	77%	68%	65%	70%	70%	69%	65%	70%	63%	55%	65%	64%	69%	62%
$MCD	62%	67%	56%	83%	83%	65%	72%	69%	70%	75%	60%	70%	69%	68%
$MMM	67%	73%	69%	64%	64%	77%	84%	79%	77%	69%	61%	60%	60%	63%
$MRK	80%	73%	69%	82%	82%	65%	58%	71%	68%	56%	73%	72%	69%	67%
$MSFT	80%	72%	94%	80%	80%	82%	87%	75%	75%	74%	73%	63%	58%	66%
$NKE	75%	76%	86%	70%	70%	71%	79%	67%	66%	62%	65%	73%	56%	70%
$PFE	61%	54%	68%	63%	63%	60%	68%	71%	79%	68%	65%	76%	64%	62%
$PG	76%	68%	77%	79%	79%	73%	77%	76%	69%	70%	67%	57%	69%	66%
$T	86%	58%	76%	83%	83%	83%	77%	83%	84%	63%	75%	74%	68%	70%
$TRV	62%	63%	72%	66%	66%	75%	50%	69%	58%	68%	74%	65%	54%	62%
$UNH	73%	73%	67%	71%	71%	75%	69%	66%	60%	69%	67%	82%	63%	45%
$UTX	67%	59%	63%	75%	75%	59%	69%	76%	58%	76%	70%	71%	76%	83%
$V	77%	73%	78%	80%	80%	71%	72%	69%	76%	61%	73%	77%	62%	68%
$VZ	87%	82%	66%	75%	75%	73%	69%	70%	73%	63%	65%	74%	60%	65%
$WMT	73%	88%	88%	76%	76%	71%	73%	80%	74%	71%	65%	69%	67%	70%
$XOM	80%	75%	71%	73%	73%	67%	78%	75%	70%	74%	74%	61%	71%	69%

Table A.2: Experiment-5 Financial Evaluation of Tweets Breakout Trading System With Cut Losses Early (CLE) EXIT Rule

Stock Symbol	Won%	Short Won%	Long Won%	ROI%	MDD%	RoMaD
$AXP	71.43%	100.00%	67.65%	6.22%	5.44%	1.14
$BA	74.07%	75.76%	72.92%	16.63%	2.70%	6.16
$CAT	75.90%	66.67%	82.00%	19.99%	1.27%	15.74
$CSCO	80.77%	77.42%	82.98%	20.86%	1.41%	14.79
$CVX	86.21%	95.00%	83.58%	15.57%	0.90%	17.30
$DD	82.86%	82.35%	83.02%	11.58%	2.07%	5.59
$DIS	83.54%	100.00%	80.88%	17.88%	0.78%	22.92
$GE	80.46%	83.87%	78.57%	16.59%	2.52%	6.58
$GS	80.90%	77.50%	83.67%	22.42%	1.35%	16.61
$HD	82.72%	100.00%	80.28%	20.04%	0.79%	25.37
$IBM	82.61%	100.00%	78.38%	33.90%	0.51%	66.47
$INTC	77.65%	93.33%	74.29%	29.18%	1.39%	20.99
$JNJ	85.90%	91.30%	83.64%	15.25%	1.87%	8.16
$JPM	82.14%	78.26%	86.84%	19.37%	1.40%	13.84
$KO	82.43%	93.33%	79.66%	12.97%	1.19%	10.90
$MCD	73.12%	77.08%	68.89%	5.47%	1.96%	2.79
$MMM	71.60%	88.89%	69.44%	4.57%	1.58%	2.89
$MRK	81.93%	85.00%	80.95%	32.21%	1.93%	16.69
$MSFT	80.72%	95.83%	74.58%	15.18%	2.07%	7.33
$NKE	80.28%	50.00%	81.16%	15.33%	1.04%	14.74
$PFE	72.12%	72.46%	71.43%	15.86%	2.98%	5.32
$PG	69.51%	75.00%	66.67%	1.62%	4.91%	0.33
$T	79.07%	85.00%	77.27%	12.92%	1.16%	11.14
$TRV	75.38%	76.47%	75.00%	1.76%	1.53%	1.15
$UNH	76.92%	92.86%	73.44%	22.38%	1.11%	20.16
$UTX	65.75%	66.67%	65.38%	1.04%	3.80%	0.27
$V	77.03%	76.47%	77.19%	19.44%	2.12%	9.17
$VZ	83.52%	86.67%	81.97%	21.83%	1.57%	13.90
$WMT	75.28%	75.86%	75.00%	11.22%	1.19%	9.43
$XOM	83.33%	83.78%	82.98%	18.95%	0.77%	24.61

Table A.3: Experiment-5 Financial Evaluation of Tweets Breakout Trading System With the Conservative Let the Winners Run (ConsLWR) EXIT Rule

Stock Symbol	Won%	Short Won%	Long Won%	ROI%	MDD%	RoMaD
$AXP	67.53%	100.00%	63.24%	2.68%	9.39%	0.29
$BA	67.90%	66.67%	68.75%	11.57%	4.00%	2.89
$CAT	71.08%	66.67%	74.00%	16.27%	1.42%	11.46
$CSCO	75.64%	70.97%	78.72%	17.22%	2.16%	7.97
$CVX	81.61%	90.00%	79.10%	12.40%	2.25%	5.51
$DD	80.00%	76.47%	81.13%	9.95%	2.03%	4.90
$DIS	75.95%	100.00%	72.06%	13.00%	4.50%	2.89
$GE	72.41%	70.97%	73.21%	10.69%	2.76%	3.87
$GS	75.28%	75.00%	75.51%	16.98%	1.80%	9.43
$HD	80.25%	100.00%	77.46%	28.00%	1.31%	21.37
$IBM	81.52%	88.89%	79.73%	32.31%	1.56%	20.71
$INTC	75.29%	86.67%	72.86%	37.29%	1.38%	27.02
$JNJ	83.33%	86.96%	81.82%	14.10%	1.56%	9.04
$JPM	79.76%	76.09%	84.21%	16.83%	2.52%	6.68
$KO	70.27%	80.00%	67.80%	12.91%	1.94%	6.65
$MCD	65.59%	66.67%	64.44%	-0.11%	3.77%	-0.03
$MMM	65.43%	88.89%	62.50%	0.16%	2.92%	0.05
$MRK	75.90%	85.00%	73.02%	29.89%	2.60%	11.50
$MSFT	79.52%	95.83%	72.88%	11.73%	4.22%	2.78
$NKE	71.83%	50.00%	72.46%	8.71%	2.37%	3.68
$PFE	62.50%	57.97%	71.43%	8.55%	2.70%	3.17
$PG	65.85%	71.43%	62.96%	0.60%	6.62%	0.09
$T	80.23%	90.00%	77.27%	15.40%	1.17%	13.16
$TRV	60.00%	52.94%	62.50%	-1.38%	2.95%	-0.47
$UNH	69.23%	85.71%	65.63%	19.80%	1.80%	11.00
$UTX	61.64%	66.67%	59.62%	-0.38%	4.55%	-0.08
$V	72.97%	94.12%	66.67%	16.43%	4.24%	3.88
$VZ	83.52%	83.33%	83.61%	28.91%	1.70%	17.01
$WMT	73.03%	65.52%	76.67%	12.98%	2.55%	5.09
$XOM	83.33%	86.49%	80.85%	23.80%	1.02%	23.33

Table A.4: Experiment-5 Financial Evaluation of Tweets Breakout Trading System With the Aggressive Let the Winners Run (AggLWR) EXIT Rule

Stock Symbol	Won%	Short Won%	Long Won%	ROI%	MDD%	RoMaD
$AXP	66.23%	100.00%	61.76%	3.34%	9.48%	0.35
$BA	65.43%	66.67%	64.58%	12.96%	5.38%	2.41
$CAT	69.88%	66.67%	72.00%	13.86%	2.87%	4.83
$CSCO	71.79%	64.52%	76.60%	9.45%	8.97%	1.05
$CVX	78.16%	80.00%	77.61%	10.95%	3.70%	2.96
$DD	77.14%	76.47%	77.36%	10.81%	2.54%	4.26
$DIS	74.68%	100.00%	70.59%	11.95%	4.50%	2.66
$GE	75.86%	80.65%	73.21%	14.84%	2.37%	6.26
$GS	74.16%	75.00%	73.47%	21.73%	1.79%	12.14
$HD	80.25%	100.00%	77.46%	35.47%	1.33%	26.67
$IBM	79.35%	88.89%	77.03%	33.93%	1.54%	22.03
$INTC	75.29%	86.67%	72.86%	44.68%	1.38%	32.38
$JNJ	82.05%	86.96%	80.00%	18.94%	1.67%	11.34
$JPM	78.57%	73.91%	84.21%	16.78%	2.52%	6.66
$KO	68.92%	80.00%	66.10%	12.84%	1.76%	7.30
$MCD	65.59%	66.67%	64.44%	2.19%	3.17%	0.69
$MMM	65.43%	88.89%	62.50%	1.94%	2.65%	0.73
$MRK	75.90%	85.00%	73.02%	33.92%	2.53%	13.41
$MSFT	75.90%	91.67%	69.49%	12.36%	4.95%	2.50
$NKE	70.42%	50.00%	71.01%	10.29%	72.12%	0.14
$PFE	61.54%	56.52%	71.43%	9.96%	2.89%	3.45
$PG	67.07%	71.43%	64.81%	2.84%	6.09%	0.47
$T	76.74%	90.00%	72.73%	8.70%	4.13%	2.11
$TRV	58.46%	52.94%	60.42%	-1.55%	3.54%	-0.44
$UNH	73.08%	85.71%	70.31%	27.97%	1.80%	15.54
$UTX	58.90%	66.67%	55.77%	1.39%	4.69%	0.30
$V	71.62%	88.24%	66.67%	18.88%	4.16%	4.54
$VZ	84.62%	83.33%	85.25%	31.60%	1.72%	18.37
$WMT	73.03%	65.52%	76.67%	14.66%	2.44%	6.01
$XOM	78.57%	81.08%	76.60%	27.19%	1.41%	19.28

Table A.5: Experiment-5 Financial Evaluation of Tweets Breakout Trading System With the CLE + ConsLWR EXIT Rules

Stock Symbol	Won%	Short Won%	Long Won%	ROI%	MDD%	RoMaD
$AXP	72.73%	100.00%	69.12%	6.98%	6.09%	1.15
$BA	74.07%	75.76%	72.92%	17.30%	2.66%	6.50
$CAT	74.70%	63.64%	82.00%	20.68%	1.22%	16.95
$CSCO	79.49%	77.42%	80.85%	22.64%	1.62%	13.98
$CVX	86.21%	95.00%	83.58%	15.81%	0.90%	17.57
$DD	82.86%	82.35%	83.02%	13.96%	1.96%	7.12
$DIS	81.01%	100.00%	77.94%	17.33%	0.78%	22.22
$GE	79.31%	77.42%	80.36%	16.47%	2.50%	6.59
$GS	80.90%	77.50%	83.67%	22.92%	1.34%	17.10
$HD	82.72%	100.00%	80.28%	23.11%	0.79%	29.25
$IBM	82.61%	100.00%	78.38%	35.65%	0.51%	69.90
$INTC	78.82%	93.33%	75.71%	30.17%	1.36%	22.18
$JNJ	85.90%	91.30%	83.64%	15.86%	1.87%	8.48
$JPM	82.14%	78.26%	86.84%	20.91%	1.42%	14.73
$KO	82.43%	93.33%	79.66%	11.58%	1.21%	9.57
$MCD	73.12%	77.08%	68.89%	5.64%	1.73%	3.26
$MMM	72.84%	88.89%	70.83%	4.46%	1.83%	2.44
$MRK	80.72%	85.00%	79.37%	34.20%	2.10%	16.29
$MSFT	78.31%	91.67%	72.88%	15.43%	1.58%	9.77
$NKE	80.28%	50.00%	81.16%	16.04%	1.17%	13.71
$PFE	71.15%	71.01%	71.43%	18.19%	3.19%	5.70
$PG	69.51%	75.00%	66.67%	1.73%	4.94%	0.35
$T	79.07%	85.00%	77.27%	13.84%	1.16%	11.93
$TRV	75.38%	76.47%	75.00%	3.15%	1.51%	2.09
$UNH	75.64%	92.86%	71.88%	22.33%	1.14%	19.59
$UTX	65.75%	66.67%	65.38%	2.11%	4.23%	0.50
$V	78.38%	82.35%	77.19%	19.58%	2.12%	9.24
$VZ	83.52%	86.67%	81.97%	22.96%	1.72%	13.35
$WMT	75.28%	79.31%	73.33%	13.35%	0.86%	15.52
$XOM	84.52%	86.49%	82.98%	23.10%	0.77%	30.00

Table A.6: Experiment-5 Financial Evaluation of Tweets Breakout Trading System With the CLE + AggLWR EXIT Rules

Stock Symbol	Won%	Short Won%	Long Won%	ROI%	MDD%	RoMaD
$AXP	72.73%	100.00%	69.12%	8.90%	6.00%	1.48
$BA	74.07%	75.76%	72.92%	21.72%	2.83%	7.67
$CAT	74.70%	63.64%	82.00%	20.46%	1.22%	16.77
$CSCO	78.21%	74.19%	80.85%	27.51%	1.60%	17.19
$CVX	85.06%	90.00%	83.58%	15.86%	0.90%	17.62
$DD	81.43%	82.35%	81.13%	15.24%	1.97%	7.74
$DIS	83.54%	100.00%	80.88%	19.10%	0.78%	24.49
$GE	80.46%	83.87%	78.57%	19.89%	2.15%	9.25
$GS	80.90%	77.50%	83.67%	26.13%	1.47%	17.78
$HD	82.72%	100.00%	80.28%	26.96%	0.79%	34.13
$IBM	80.43%	100.00%	75.68%	38.80%	0.73%	53.15
$INTC	78.82%	93.33%	75.71%	36.18%	1.36%	26.60
$JNJ	84.62%	91.30%	81.82%	20.28%	1.98%	10.24
$JPM	82.14%	78.26%	86.84%	20.78%	1.42%	14.63
$KO	82.43%	93.33%	79.66%	12.19%	1.21%	10.07
$MCD	72.04%	77.08%	66.67%	8.03%	1.71%	4.70
$MMM	72.84%	88.89%	70.83%	6.17%	1.80%	3.43
$MRK	80.72%	85.00%	79.37%	39.80%	2.03%	19.61
$MSFT	78.31%	91.67%	72.88%	18.18%	1.62%	11.22
$NKE	80.28%	50.00%	81.16%	16.75%	1.17%	14.32
$PFE	70.19%	71.01%	68.57%	21.57%	3.19%	6.76
$PG	70.73%	75.00%	68.52%	4.77%	4.78%	1.00
$T	79.07%	85.00%	77.27%	15.47%	1.16%	13.34
$TRV	75.38%	76.47%	75.00%	3.41%	1.51%	2.26
$UNH	75.64%	92.86%	71.88%	26.95%	1.14%	23.64
$UTX	61.64%	66.67%	59.62%	2.68%	3.85%	0.70
$V	75.68%	76.47%	75.44%	22.03%	2.07%	10.64
$VZ	83.52%	86.67%	81.97%	24.78%	1.68%	14.75
$WMT	75.28%	79.31%	73.33%	14.82%	0.78%	19.00
$XOM	83.33%	83.78%	82.98%	27.64%	0.76%	36.37