Predicting Stock Trends using Twitter Sentiment

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ABSTRACT

With social media on the rise, the amount of data available for processing is growing at an increasing rate. It is an advanced area of research to be able to use that data to predict or better understand the world around us. In our project we attempted to discover a relationship between twitter sentiment and stock values the next day. Unfortunately, we failed at determining a relationship, but, to quote Thomas Edison, we did not fail, we found exactly how *not* to predict changes in the stock market. In addition, We were able to create a real-time sentiment engine that allows our mobile application to get real time sentiment analysis.

Categories and Subject Descriptors

H.3.4 [Information Systems Applications-Systems and Software]: Information networks; J.4 [Social and Behavioral Sciences]: Economics

General Terms

Algorithms, Measurement, Economics, Experimentation, Human Factors

Keywords

Social Networks, Trends, Blogging, Tweets, Hashtag, Twitter, Stock

Goal

To determine if there is a relationship between the sentiment of tweets and the change in stock price for the next day. Then to create a user friendly mobile application to display real time sentiment analysis.

1. INTRODUCTION

The recent rise in popularity of online social media has led to a huge amount of social data available online for analysis. The popular social media site, Twitter, gets an average of 6,000 tweets posted per second and 500 million per day. We originally set out to determine that a relationship exists between the sentiment of tweets and stock values for the next day. For the purposes of this project we looked at four companies, Amazon, Apple, Google, and Samsung.

The first step in determining a relationship was to collect data. To do this we had to gather information from two sources, Twitter, and Yahoo. Twitter allowed us to open a connection to the streaming API. Using this API we receive anywhere between 1% and 40% of all the tweets being tweeted at any given time of the day. This percentage depends on the current Twitter load and how many things we are filtering on. Once we received a tweet we would store it in a database for latter processing. In addition to collecting twitter data we also collected historical stock data. Yahoo provides historical stock data for companies going back many years. Once we collected all our tweets we gathered the stock data for the same intervals of time.

Once we had all the data, we had to pre-process it before we could do any analysis. Each dataset needed to be preprocessed in order to perform efficient analysis. For Twitter we had to filter each tweet and remove all unnecessary words. We needed to try to strip down the information as much as possible or else the classifier would become unreasonable slow. The stock data was another challenge all together. Since the tweets were not received on a constant time bases, we had to filter all the stock data to match up correctly with tweets. Once we preprocessed, we were then able to pass them to the sentiment analysis step.

Before we could actually determine the correlation between the data sets, we had to classify all the tweets. To do this we used a Naive Bayes Classifier. Our classifier was built to extract each word from the preprocessed text. Each word was then added to a dictionary to describe the sentiment of each tweet. This phase our project easily took the most time and effort. We attempted to build the most accurate classifier and experimented with different types of feature

vectors. We discovered classifying on words yielded the best results.

Once we had the sentiment for each tweet we ran multiple tests to determine the correlation. The tests were mostly based off a linear regression model fitted to the data with Ordinary Least Squares estimators. The model was not at all adequate, but allowed us to perform many conclusive statistical tests for correlation including a t-test and R^2 value examination.

Once we determined there was no correlation, we had to decided what our next step was. Originally, We were hoping to find a correlation but because we determined that there wasn't one we were no longer able to create a mobile app that predicted stock trends. However, it is still very useful to have a sentiment analyzer so we decided that it would be best to create an mobile application to shows sentiment analysis instead. To do this we had two parts: The REST API and the mobile application. The REST API was written in Haskell and performed the real time sentiment analysis. The mobile application was written for android and reaches out to the REST API in order to get the sentiment. The two work together to create a user friendly, easy to use application.

2. AUTHORS

The authors of this project are Nicolas Broeking, Anna Hoffee, and Joshua Rahm. Broeking and Rahm are graduate students at the University of Colorado at Boulder. Hoffee is an undergraduate student at the University of Colorado.

Nicolas Broeking has worked on embedded systems and mobile applications for the past four years. Broeking's contributions were in the data collection, preprocessing, sentiment analysis, optimizations, and creation of the mobile application.

Josh Rahm has spent his career working with embedded devices, cellular technologies and billing platforms. Rahm contributions were with sentiment analysis, optimizations, and converting the tools to be used in a real time system on the server. He also created the REST API that allows the mobile application to get the real time sentiment analysis.

Anna Hoffee is a student in the mathematics department. She has spent her career working on similar projects attempting to find patterns in other live data sets. Hoffee contributed by taking the sentiment data and determining that there was no correlation.

3. MOTIVATION

The Stock Market is one of the largest entities in Western and World economies. In a world where a 15% increase is assets per year is massive, even the ability to increase certainty in the market by a few percentage points is appreciable. Companies and individuals can harness this technology make billions and secure investments, producing and saving billions for the economy. While making billions is outside the scope of this project, we thought it was possible to significantly increase the accuracy of stock predictions. We know that public image is critical to stock value; therefore, we predicted that if a company's public sentiment, displayed on Twitter, were to decrease, then it would stand to reason that there would be a drop in the stock value of said company. This ended up to be an incorrect prediction and we were able to show that there exists no correlation between twitter sentiment and changes in stock value.

Even with this failure, we still have motivation for sentiment analysis. Companies still have an interest in a positive public image. There are many ways for companies to get this information but none are as convenient as having a phone in your pocket that easily shows you this information. The need for an app like this was the motivation for us to take our original tools and customize them to do real time analysis.

4. LITERATURE SURVEY

Many similar experiments have been done in the field of data mining. The first and probably the closest to our project is Correlating Financial Time Series with Micro-Blogging. This project looks at 150 random companies stock prices over a six month time period. Then they take all the tweets with specific hashtags related to the company and construct a context graph. In this graph the tweets themselves were nodes and any actions on the tweets were edges. They then use this graph to find relationships with the stock price. This project looked for other things than just stock trends though. They wanted to find relationships between the data and how much a stock will change, and what the values of the stock will be. They determined that the most reliable way to determine the information is by looking at the number of edges in the graph. However, even in this case however they were not able to find a reliable correlation but they did give us a start with where to begin our search[1]

Another team, Twitter Mood Predicts the Stock Market, attempted to determine how twitter mood affects the stock price. They grouped tweets into 6 dimensions Calm, Alert, Sure, Vital, Kind, and Happy. Then they took these categories and created a relationship between to the closing value of the Dow Jones. They only wanted to determine though if there was a relationship at all. On a very specific data set they were able to find a correlation between the values however on a large scale their data did not work out. They showed very similar results to what we showed. d[2]

Many other studies have been done similar to the first two on how to use twitter to predict stock prices. The one thing that has been determined for sure is that there is a high correlation between peoples' attitudes and stock value. However, it hasn't been determined if twitter accurately reflects

market sentiment and therefore is the basis of our project. In one situation Twitter was used in 2013, to predict a drop in Royal Caribbean's stock value when people started tweeting about the flu spreading on one of its cruises. Researchers were able to predict the drop in price 48 minutes before the stock plunged about 3%. This was only a rare case however and worked under a very specific set of circumstances.[3]

Once we found information regarding other studies that have been done in sentiment analysis and stock price correlation we started looking into the best ways to actually do sentiment analysis. After the midway presentation, we were not happy with our accuracies. We talked with Jamie Wood from Waylin. Waylin specializes in performing sentiment analysis at an industrial scale. Sentiment analysis on twitter data is a very challenging task because tweets are a form of natural language. Mr. Wood advised us that a 65% accuracy is something that is considered to be a good analyzer and any point upwards of that is a great classification. Using this information we set a goal to achieve an accuracy upwards of 65

We also used several blogs online from software engineers who have performed Twitter sentiment. [5][6] They provided a good starting place for us to easily learn the language and the toolkit before creating our own custom sentiment analyzer.

5. TASKS

In order to successfully prove or in our case, disprove, a correlation and then to create an application we split our project into ten different sub tasks. These tasks, explained below, allowed us to split the workload among the group and to ensure that we stayed on a schedule for a successful project.

5.1 Data Collection

To collect all the data that we needed to get it from two sources. First we had to get a decent volume of tweets to perform the sentiment analysis. Then we had to gather data from Yahoo that matched the same time period os the twitter data.

5.1.1 Twitter Collection

In order to collect the tweets from Twitter we needed to set up a channel to the Twitter Streaming API. The API allows us to request all tweets related to Amazon, Apple, Google, or Samsung. Depending on the current load to the twitter servers this provided anywhere from 4% to 40% of all tweets being posted at any given time. In order to create the streaming tool we used python and a library called Tweepy. Tweepy allows a call back event system that will notify every time Twitter has more tweets for us.

Once we had the tweets we immediately stored them in a SQLite database. We had a lot of discussion about what would be the best way to store the tweets. We had to make sure that we kept up with the streaming API or else twitter would block our connection. SQlite is a lightweight fast database that is reliable and easy to use. We also didn't have to worry about other processes attempting to access the same service so SQLite seemed like a great choice. For each tweet we stored the text, its re-tweeted count, time of the tweet, user id and the tweet id. For each user we also stored the user id, the followers count, friend count, and their name. We ended up not using all this information but we wanted to store all relevant information during the data collection phase so we would have it just in case it became relevant later.

Every time we received a tweet from twitter a callback was called that allowed us to put it in the database. This function is shown below.

```
def on_data(self, data):
    broadcast_sock.sendto(data, to_addr)
    d = json.loads(data.strip())
    try:
        if d['lang'] == "en":
            cursor = self.db.cursor()

            cursor.execute('INSERT INTO Tweets( text,
                retweeted, retweeted_count,
                time, userid, tweetId)
                VALUES(?,?,?,?,?,?,?)',
                [d['text'], bool(d['retweeted']),
                int(d['retweet_count']),
                d['created_at'], int(d['user']['id']),
                int( d['id'])])

            cursor.execute('INSERT INTO Users( userID,
                followers_count, friendcount,
                name) VALUES (?,?,?,?)',
                [d['user']['id'],
                d['user']['followers_count'],
                d['user']['friends_count'],
                d['user']['name']])

            self.db.commit()
            return True

    except: # catch *all* exceptions
        e = sys.exc_info()[0]
        print( e )
```

5.1.2 Stock Collection

To get the stock data we needed to collect historical data fore each of our four companies. Yahoo Finances has a great API that allowed us to download the data at the day granularity going back a couple years. We only took the data for the same time period as our tweets and then stored them in a

comma separated text format. This data source provides us with the Open, Close, High, Low, and Data attributes. Similarly, to the tweets, we stored more information than we needed to make sure that we had extra information in case we needed it.

5.2 Data Preprocessing

The preprocessing step, like the data collection step, was done in two parts. First we did the preprocessing of the tweets to prepare for the sentiment analysis. Then we preprocessed the stock data to fit with the twitter data to allow us to compare between the two data sets.

5.2.1 Tweet Preprocessing

Our twitter preprocessing step went through many versions of development before it arrived in its current state. In the first version we removed all words under three letters and then passed on the full tweet to the classifier. Unfortunately, this did not give us any good results. There were too many words to add to our feature vector and so we ended up with a lot of irrelevant features. The next iteration of the project used a different feature extractor. In this step we refactored our pre processor to strip away all non alpha characters.

Finally, before the midway presentation we refactored again to a more complex pre processor. In this version we removed all urls and replaced it with the string URL. Then we tool all hashtags and replaced it with the string TAG. After the feedback from the midway presentation we decided that we weren't satisfied with our pre processor and so we did research. We added other functions that allowed our preprocessor to become the most effective. The first major thing we did was to replace all repeating characters with two of the same. In the tweet "I looooooooooooooove hamburgers" compared against "I looooove pickles" we would get two different words for love. We really only want one though because they represent the same word.

Our first pre processor step would change this to "I loove hamburgers" The first logical question is then why do we leave two o in the word. This is because people use repeating characters to stress emotion so we want to treat loove and love differently. In addition to this we also changed all the characters to lowercase, changed any username to AT_USER, removed additional white space, and stripped any punctuation. The code for these two steps is shown below.

```
#start replaceTwoOrMore
def replaceTwoOrMore(s):
    pattern = re.compile(r"(.)\1{1,}", re.DOTALL)
    return pattern.sub(r"\1\1", s)

#Preprocess the tweet
def PreprocessTweet(tweet):
    #Convert to lower case
    tweet = tweet.lower()
    #Convert www.* or https?://* to URL
    tweet = re.sub('((www\.[^\s]+)|
        (https?://[^\s]+))','URL',tweet)

    #Convert @username to AT_USER
    tweet = re.sub('@[^\s]+','USER',tweet)

    #Remove additional white spaces
    tweet = re.sub('[\s]+', ' ', tweet)

    #Replace hashtag with the word
    tweet = re.sub(r'#([^\s]+)', r'\1', tweet)

    #trim
    tweet = tweet.strip('\'"')

    return tweet
```

After these two steps, we also filtered out any stop words. Stop words are a list of words that are proven to have no sentiment value but will sway the classifier. The combination of all these steps brought us to our final pre processor.

5.2.2 Stock Preprocessing

The last step in pre-processing, after sentiment analysis was performed on the tweets, was to combine the twitter data with the stock data. Since the two came from very different sources and in different formats work had to be done before they could be combined for correlation analysis. The goal was to calculate the change in stock value from day n to day $n+1$ and pair it with the percent of positive tweets on day n, This proved to be not straightforward due to the fact that there were arbitrary sized missing blocks of days in the twitter data, as well as no stock data on weekends. A day of twitter data had to be thrown out if there wasn't stock values available for that day and the preceding, and stock values had to be thrown out if their wasn't the appropriate twitter and additional stock data to go along with it. A function to determine weather or not two days are one day apart aided a lot in the pre-processing:

```
one.day <- function(date1,date2) {

  daysPerMonth <- c(0, 31, 28, 31, 30, 31,
                    30, 31, 31, 30, 31, 30,
                    31)

      month1 <- as.numeric(date1[2])
      day1<- as.numeric(date1[3])

      month2 <- as.numeric(date2[2])
    day2 <- as.numeric(date2[3])

    if (abs(month2 - month1) > 1){
        return (0)
        }

    if(month1 == month2){
        if(abs(day2-day1) > 1){
            return (0)
              }
        else{
            return (1)
             }
       }
    lastDayMonth1 = daysPerMonth[month1]
    lastDayMonth2 = daysPerMonth[month2]

    if(day1 == lastDayMonth1 && day2 == 1){
        return (1)
         }
    if(day2 == lastDayMonth2 && day1 == 1){
        return (1)
        }

    return (0)

}
```

After the stock and twitter data was converted to the same format and reorganized into consecutive days the correlation analysis could begin.

5.3 Sentiment Analysis

After creating the Preprocessing tools, we created the sentiment analyzer. We wrote the sentiment analyzer in python using the natural language tool kit library. In the final version we trained the classifier on 15000 tweets and then test its accuracy with 10000 tweets. Like the preprocessing step this phase went through a few iterations as well. We started with basic classifier and ended up with a high performing Naive Bayes Classifier that performed in real time.

The major part of the sentiment analysis was choosing features to use for our classifier. At first we just looked at raw words. However, with our less than good pre processor we weren't able to get reasonable results. In this first version we were only able to train on 2000 tweets because our memory got so bloated that training on anymore would cause the process to get killed. The accuracy in this step lied somewhere between the 50% and 55% mark. In order to try to create a better classifier we attempted to try other features. We found examples of people using letters to classify gender of a name and thought we could apply this to our classifier. We turned out to be very wrong. Our letter classifier showed about a 50% accuracy. This is about the accuracy we would expect to see if we were to randomly guess. After this slight set back, we went back to the drawing board. We talked with a Jamie Wood from Waylin. Waylin specializes in twitter sentiment and provides similar services to their customers. Mr. Wood told us that a 65% accuracy would be considered a very good accuracy and anything above that would require a much larger training set. After talking to Mr. Wood we refactored again to use words as features but created a smarter feature extractor, shown below, that utilized the new preprocessing steps.

```
#start extract_features
def extractFeatures(tweet):

    if not isinstance(tweet, list):
        tweet = tweet.split(' ')

    class default_dict(dict):
        def __init__(self):
            super(default_dict,
            self).__init__()

        def __getitem__(self, k):
            self.get(k, False)

    features = default_dict()

    for word in tweet:
        if word in word_features:
            features[word] = True

    return features
```

,:

As a Part of the new steps we also improved the training data that we fed to the classifier. We made sure to have the same amount of positive tweets as negative tweets and we applied the new pre processing steps. In our final version our training looked like below.

```
#Train the classifier
def train():
    global word_features

    f = open('training.csv')
    lines = f.read().splitlines()

    #Create a list of training data
    trainingdata = []
    testingdata = []
    i = 0
    needPos = True
    for x in lines:
        line = x.split(",")

        #If we have a good formed data string
        if len(line) is 4:

            text = PreprocessTweet(line[3])
            featureVec = getFeatureVector(text)

            word_features.update(featureVec)

            tup = (text, 'pos' if int(line[1]) == 1
                else 'neg')

            if i <= 20000:
                if( needPos and tup[1] == 'pos'):
                    trainingdata.append(tup)
                    needPos = False
                    i+=1;

                if( (needPos is False) and tup[1]
                    == 'neg'):
                    trainingdata.append(tup)
                    needPos = True
                    i+=1;

            elif i <= 100000:
                if( needPos and tup[1] == 'pos'):
                    testingdata.append(tup)
                    needPos = False
                    i+=1;

                if( (needPos is False) and tup[1]
                    == 'neg'):
                    testingdata.append(tup)
                    needPos = True
                    i+=1;
            else:
                break

    training_set = nltk.classify.util.apply_features(
                    extractFeatures,
                    trainingdata)

    classifier = nltk.NaiveBayesClassifier.train(
        training_set)

    testing_set = nltk.classify.util.apply_features(
                    extractFeatures,
                    testingdata)

    return classifier
```

The new feature extractor worked really well with an accuracy at about 64% but still wasn't as good as we wanted. We realized the problem was most likely with the slowness of our code. We then spend the next week attempting to optimize it even further. We started by using sets instead of lists and then using these sets to reverse how we were determining the feature vector. By iterating on the tweets instead of the feature vector and by using a dictionary with default values we were able to speed up the performance of our code by about 1000 times. At the midway demo we were processing about 5 to 10 tweets a second. After our optimizations we started classifying over 4000 tweets per second. This brought our runtime from about $O((nm)^2)$ where n is the number of tweets and m is the words in each tweet, to $O(nm)$ These optimizations then allowed us to train on 15000 tweets instead of just 5000. The extra volume of training jumped our accuracy up to about 90%. This was a huge success in the project because the jump in accuracy allows for us to find the correlation with a much higher accuracy.

When we brought our classifier to the full dataset, we ran into one more problem. Previously when we were running our classifier we did it on such a small database that we could fit it all into memory. However, when we stepped up the full dataset the operating system would start killing our process for using so much memory. This led to the last optimization we had to do on our classifier. We used a generator on the SQLite database to only return 1000 stored tweets at a time, shown below. These optimizations dramatically increased the effectiveness of our classification step.

```
#Used to Iterate the cursor
def ResultIter(cursor, arraysize=1000):
    'An iterator that uses fetchmany
        to keep memory usage down'
    while True:
        results = cursor.fetchmany(arraysize)
        if not results:
            break
        for result in results:
            yield result
```

The final piece of our classifier was putting it all together. After training our classifier we needed to read all the stored

tweets from the database and export them to a comma separated list for the Correlation analysis. To do this step we had a function that read from the database and echoed the tweet into the correct company bin.

```
def convertDatabase(classifier):
    fapple = open('results/apple.csv','w')
    google = open('results/google.csv','w')
    samsung = open('results/samsung.csv','w')
    amazon = open('results/amazon.csv', 'w')

    try:
        con = lite.connect(sys.argv[1])

        cur = con.cursor()
        cur.execute('SELECT Tweets.id, text,
                    retweeted,
                    retweeted_count, time,
                    followers_count,
                    friendcount from Tweets
                    LEFT JOIN Users on
                    Tweets.userid == Users.userid
                    group by Tweets.id;');

        f = fapple
        i = 0;
        for row in ResultIter(cur):
            i+=1
            if "apple" in row[1].lower():
                f = fapple
            if "google" in row[1].lower():
                f = google

            if "samsung" in row[1].lower():
                f = samsung

            if "amazon" in row[1].lower():
                f = amazon

            f.write("%d, %s, %r, %d, %s, %d, %d\n"
                % (row[0],
                classifier.classify(
                    extractFeatures(
                        getFeatureVector(
                        PreprocessTweet(row[1])))),
                row[2], row[3],
                row[4], row[5],
                row[6]))

            if i %100 == 0:
                print (i)

    except lite.Error, e:
        print ( "Error %s:" % e.args[0])
        sys.exit(1)

    finally:
        if fapple:
            fapple.close()
        if google:
            google.close()
        if samsung:
            samsung.close()
        if amazon:
            amazon.close()
        if con:
            con.close()
```

This classifier was able to sort all of our 10 gb of tweet data into the separate company bins in about 10 hours using 3 different processes.

5.4 Correlation Analysis

After the sentiment analysis is completed and we had all the tweets classified as positive or negative we could begin the correlation analysis.

We were then able to graphically examine the relationship between the percent of positive tweets and the change in stock price. As well, we well perform a few different statistical tests to determine if there is any use full correlation.

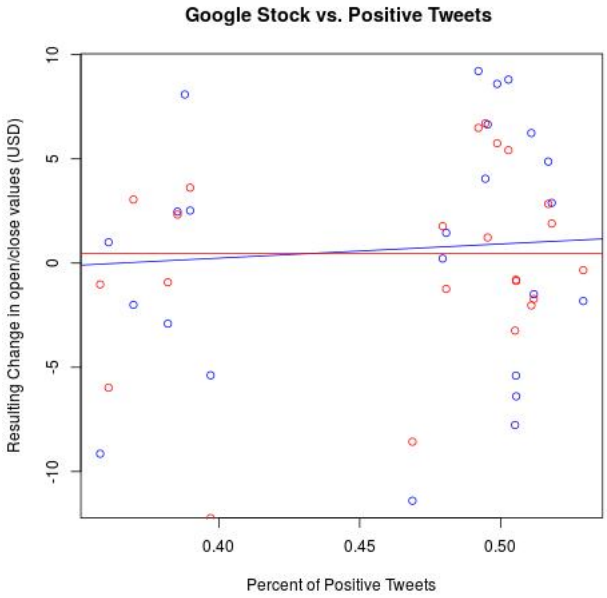
Test One: Linear Regression

Assume $y = \beta_0 + \beta_1 x$ where y = change in stock value, x = percent of positive tweets. I'll use the Ordinary Least Squares estimators to derive the regression parameters. To use OLS estimators we assumed that there was a linear relationship between response variable and the regressor. We also assumed that the residuals of this model will be uncorrelated and have constant variance. The $lm()$ function in R will perform the regression.

Regression models for open and close values for each company were created and all came out with very similar results. One example, change in Google Open values regressed on percent of positive tweets:
$\hat{Y} = -2.48 + 6.794x$the
and the model summary is:

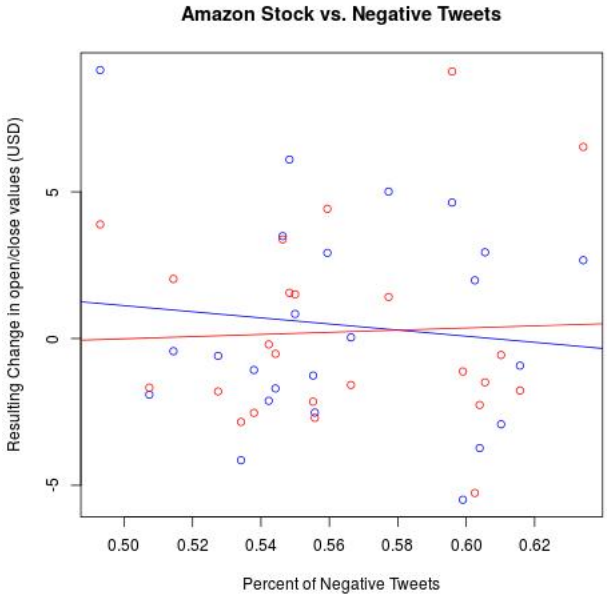
```
lm(formula = open.vec ~ percent.pos)

Residuals:
     Min       1Q   Median       3Q      Max
-12.4474  -2.1983  -0.3133   3.1269  13.2047

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   -2.480      8.597  -0.289    0.776
percent.pos    6.794     18.524   0.367    0.717

Residual standard error: 5.392 on 22 degrees of freedom
```

```
Multiple R-squared:  0.006077,  Adjusted R-squared:  -0.
F-statistic: 0.1345 on 1 and 22 DF,  p-value: 0.7173
```



Then we did a hypothesis test, specifically a T-test, to see if β_1 should equal 0, this would indicate that there is no relationship between x - percent of positive tweets, and y - change in stock price. We set $\alpha = .05$ meaning that theoretically 5% of the time we would reject the null hypothesis (H_0) in favor of the alternate hypothesis (H_1) when $_0$ is actually true.

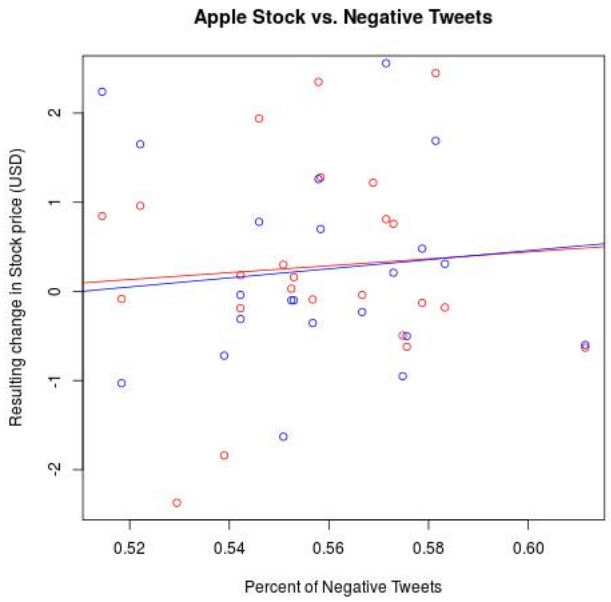
$H_0 : \beta_1 = 0 \quad H_1 : \beta_1 \neq 0$
$T_{calc} = \frac{\hat{\beta_1} - 0}{s.e.(\hat{\beta_1})} = \frac{6.794}{18.524} = 0.367$
$t_{(n-2,\alpha/2)} = 2.07$
$|T_{calc}| < t_{(n-2,\alpha/2)}$ so we fail to reject the null hypothesis that there is no relationship between positive tweets and changes in stock price.



In the model summary given above the p-value for β_1 is .717. This means that for us to reject the null hypothesis that $H_0 = 0$ we would have to set $\alpha = .717$ meaning would have had to allow the test to reject the null hypothesis when it's true 71% of the time. This is unheard of.

As well, given in the model summary is the R^2 value. This measures the percent of variance in y that is explained by x. In a perfect linear model it would be 1. In our mode it is .006, indicating that .6% of the variance in the stock price can be explained by twitter data. This is an extremely low R^2 value. As well as quantitive evidence there is qualitative evidence of an absence of linear relationship between x and y.

See the graphs below. Note that the blue data points/regression lines correspond to the change in close values, and the red data points/lines correspond to the change in stock open values.



from these graphs it's very clear that there is no relationship between x and y.

Test Two: Correlation Coefficient $\mathrm{Cor}(X,Y) = \frac{E(X-\mu_x)(Y-\mu_y)}{\sigma_x \sigma_y}$

This tests for linear correlation between x and y. If the correlation coefficient is -1, the variables are perfectly negatively correlated. If it is 1 then they are perfectly positively correlated.

For Apple stock the correlation between the open values and the percent of positive tweets is 0.079. This indicates that there is little to no relationship between the two.

5.5 Accuracy and Error Analysis

To evaluate the accuracy of the model we looked at the R^2 value, which shows the percent change in Y that is explained by X. We can also look at the standard errors the of regression coefficients and the residuals of the models. If there is much correlation in the errors we can try using the generalized least squares estimators instead.

It's clear that our original goal of predicting the stock market with twitter sentiment was not achieved. We may have gotten these results because we did not split up the data enough into sub-categories. We might have found more interesting patterns if we had split tweets up into categories based off what else was in the tweet about the company, i.e. look at all the tweets about a new product that Google/Amazon/Samsung/Apple came out with. We could have performed data mining on the positive and negative tweets to see if there were any similarities between them (other than positive/negative words). Sometimes when too much data is meshed together patterns are masked; we don't know if this did or didn't happen. This is clearly a place that our project could be extend for future work. It is hard to be able to detect every pattern out there. We only looked at one specific pattern and just because the one we were looking for didn't exist it doesn't mean there are not others out there that would prove to have a correlation.

5.6 Application

Even though we were not able to determine a correlation between the data sets, it didn't mean that we didn't have useful tools. Companies are still very interested in what their company looks like in the public eye even if it doesn't have a direct relation to their stock price. There are a lot of complex tools out there that can help a CEO but nothing that is quick and easy and fits in his pocket. To do this we created an application that does just this. We can analyze the sentiment of these companies in real time and then display that information to the user. In order to do this we have two parts. The server side that does real time sentiment analysis and hosts a rest API for devices to use. The mobile side is the client side that allows users to see the sentiment in real time.

5.6.1 Rest API

The REST API is an application written in Haskell and Python in two distinct parts. The Python section is responsible for collecting and analyzing incoming tweets. It then broadcasts that information on a UDP socket. The Haskell side collects the data from the UDP socket and is responsible for aggregating and storing the data as well as maintaining a HTTP service that responds to a GET request and regurgitates the necessary information in JSON form.

5.6.2 Mobile Application

We built the mobile application for the android system. We can run it on any android device that runs Android Lollipop or greater. This gives the user a lot of flexibility. It is really easy for anyone to install the application to their phone and instantly get real time sentiment analysis. When the phone starts up, it reaches out via a web request the Rest API that is doing the sentiment analysis. It gets the JSON back and parses it for the values. It then calculates the percent positive and uses that to update its GUI. For the GUI we chose to display a smiley face for a positive sentiment and a frowny face for a negative sentiment. A screen shot of the application running in the android simulator can be seen below.

6. CONCLUSION

In conclusion we were able to determine that there is no relationship between twitter sentiment and the change in stock price the next day. The stock market is a complex system that is clearly not influenced by just one thing. Our calculations showed that less than 1% of the change is stock value could be predicted using our methods.

Even though we weren't able to find a relationship our project was still a success. We were able to turn our sentiment analysis into a real-time tool that allows anyone to open up their phone and get real-time sentiment analysis.

Through this data mining process we learned many things about mining for sentiment.

1) Your preprocessing step must be tailored to your data. At first we were just doing minimal work with our preprocessing and letting the classifier do most of the work. This however proved to be very inefficient in both time and accuracy. Getting to know the data and then removing the stuff that you don't need proved to not only speed up the classifier but also to provide more accurate results.

2.) Feature extraction is the key to a good Naive Bayes Classifier. If you choose the wrong features you just wont get accurate results. In addition to the accuracy if you are inefficient in your feature extraction it will bog down the whole system.

3.) Just because you don't find a correlation doesn't mean that the project is a failure. We were able to prove that there is no correlation which helps further research in the area. This also led us to be able to create a useful application that shows real time sentiment analysis

7. FUTURE WORK

In our project we determined that there is no correlation between stock and twitter sentiment on a day by day basis. This does not rule out many other granularities though. One could potentially find a relationship hour to hour, minute to minute, week to week, or even year to year. There are so many timeframes that could be researched that we were not even able to scratch the surface on what is possible. In future work more research should be done to see if one could predict stocks on another level.

Even though we found no correlation to be able to predict stock prices that doesn't necessarily mean there is no value in knowing the sentiment of a company. One might be able to discovery that only very large changes in sentiment can detect a change in stock prices. It was already shown from other studies that researches were able to see a dip in the stock price by watching what was being posted on twitter. It would be interesting to investigate phenomenon such as this more in depth.

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