INTRODUCTION:

In the era of COVID-19, many aspects of day-to-day life are uncertain and subject to rapid change. Meetings and social engagements are cancelled, deadlines are missed, and local government guidelines change frequently. Each of these events have major impacts on our daily lives, and rippling impacts on the economy as a whole. Beyond these local disturbances, large scale events like positive study results for a vaccine or passage of federal stimulus have major implications for global markets.

By carefully tracking major news stories, one can often identify events that will trigger upwards or downwards trends in the market. Since the market is efficient, any newly available information is quickly incorporated into share prices. Once this information is "built in" to the price, it is no longer of much value for any person trying to gain an inside track. For this reason, it is important to have a method for identifying relevant information and its impact on the economy.

One particular example of this phenomenon is that on Monday, March 16th 2020, the S&P 500 fell by nearly 11%. This drop came on the coattails of President Trump's declaration of a national emergency for Coronavirus after the markets closed the previous Friday. Although it seems intuitive that this type of thing is prone to happen, it is not clear where the line should be drawn between events that will impact the market and events that should be classified as simply “noise.” Scaling down from the global economy, this phenomenon clearly also effects security prices for individual companies. For Tesla, Elon Musk’s tweet on May 1st 2020 (shown below) immediately precipitated a 10% drop in the company’s valuation. Just like a snap news story, it is hard to capture and quantify the instantaneous impact of tweets. Certainly not every tweet from Mr. Musk has huge consequences, but these micro-events could potentially be linked to a noticeable effect on the market.

RELATED WORK

There are some works related to this project that we found during the course of our research. The first related work is “Twitter mood predicts the stock market,” by Bollen, Mao, and Zeng [1]. This paper uses the communal “mood” of Twitter on any given day to make predictions about future of the Dow Jones Industrial Average. In order to calculate their prediction, they ingest and aggregate a large amount of data from Twitter, and then using natural language processing to classify the mood and predict the directionality and magnitude of changes in the DJIA. These researchers found an accuracy of over 86% for their model in predicting the daily changes in the market, with only 6% mean error. The second paper, “Stock Prediction Using Twitter

Sentiment Analysis" [2], follows the same methods as presented in [1], but chooses a different validation approach. In their research, the accuracy of the model dropped to roughly 75%, which is still very good. Another nice conclusion that these authors were able to draw was a prescription for how many DJIA points a person would have gained using this computational trading approach.

From our perspective, both of these papers lacked two things: First, they were not targeted at specific phenomena, rather the market average over a day. In this sense, the opportunities for financial gain are limited because the market is inherently much less volatile than individual securities. Second, both of these papers lacked interesting visualizations that would allow a reader or researcher to identify other trends in the data that could provide insight about the relationship and directionality of the connection between twitter data and security pricing.

METHODS

With the idea that tweets could have a measurable consequence on markets in mind, we sought out to develop our own approach through which we could systematically record and visualize the effect of tweets in real time. The first, and most crucial step in our approach was collection of data. For our large time scale data, we used the Yahoo Finance API to get historic information about stock closing prices. For our short term data (minute scale) we wrote a program to query the twitter API, parse tweets, classify their sentiment, and group the Twitter data with the market price of the stock at that exact time.

Twitter data was collected through queries on the Twitter API, using a developer account that we applied for in order to do this process. After collecting the tweets relevant to our query, sentiment classification was performed using the python package TextBlob, which is a natural language processing suite with many features. After collecting all of our data and running it through our classifier, we performed various transformations on the data as shown in our Streamlit application and below. By performing these transformations, we were able to produce visualizations that went far beyond what the previous papers written on this topic had done. Source code for each aspect of the project is available in our GitHub repository, https://github.com/CMU-IDS-2020/fp-holmesandwatson.

RESULTS:

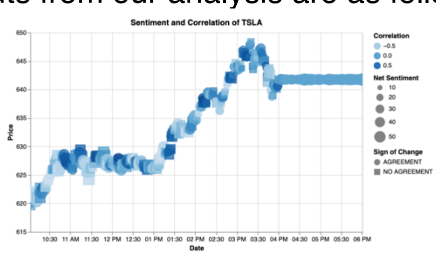
In the long term, the trends of asset prices can be closely tied to major developments in the news. For example, a world-wide pandemic will cause asset prices to fall, while government stimulus will cause these prices to rise. Moreover, federal monetary policies such as raising interest rates will cause stock prices to fall, while quantitative easing will cause prices to rise.

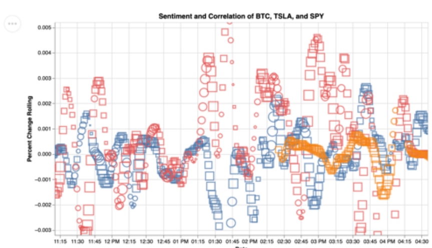
However, the price of an asset is affected by more than these long-term trends alone. Therefore, an important part of this study is examining the effects of breaking news on asset pricing. For the purpose of this analysis, we use Twitter data as a proxy for breaking news. The motivation for this idea is that it can take hours for a journalist to write a proper news story, but it only takes seconds to send out a 280-character tweet. For this reason, we believe that parsing and analyzing Twitter data is the closest we will reasonably get to “breaking news.”

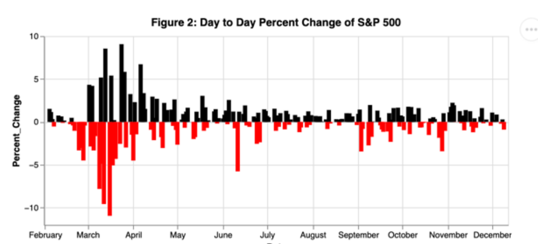
In this section, typical outputs of our visualizations appear in the figures below. The horizontal axis denotes time, and the vertical axis denotes the price of the asset, or the percent change of the asset. Our contribution has to do with the selection of the particular encodings used in this visualization. After considering different possibilities for the most useful encodings, we settled on the following three, which will be detailed more in the following section:

1. Correlation: this is the correlation between the asset price and the sentiment of relevant Twitter data
2. Net Sentiment: recall that we collected sentiment data as percentages. That is, we collected a “positivity rate,” which was the percentage of tweets classified as positive, and we collected a “negativity rate,” which was the percentage of tweets classified as negative. Accordingly, we calculated the net sentiment as follows:
$$net\ sentiment = positivity\ rate - negativity\ rate$$
3. Sign of Change: this actually turned out to be one of the most important pieces of data we calculated. The “sign of change” encoding has to do with comparing the derivative of the asset price with the derivative of the tweet sentiment. If the derivatives were both negative or both positive, then the “sign of change” was said to be in agreement. Otherwise, if one was positive while the other was negative, then the “sign of change” was said to have no agreement.

Sample outputs from our analysis are as follows:

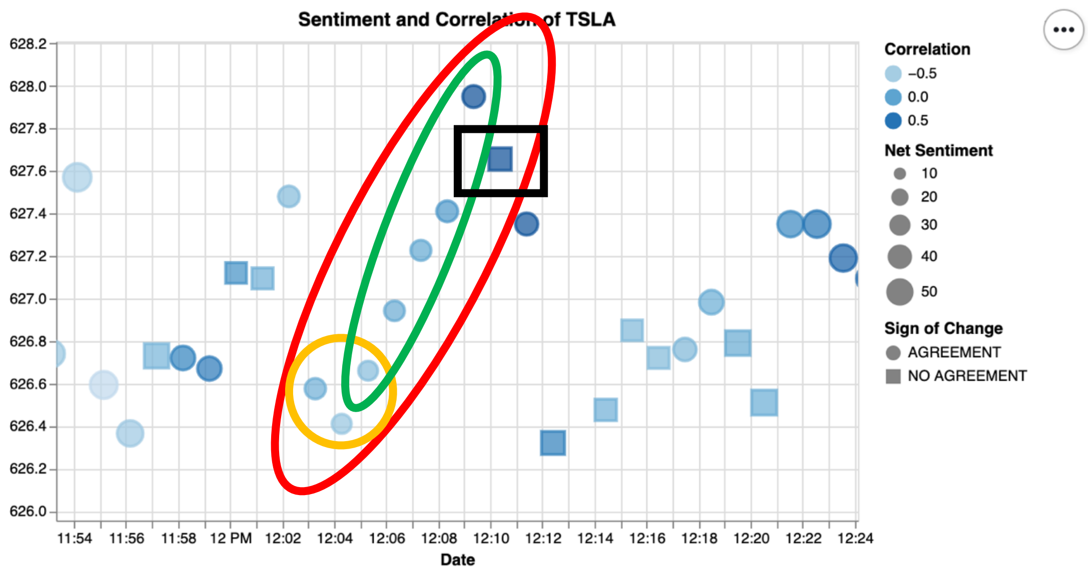






DISCUSSION

In practice, examining a full day’s worth of data at a time was not particularly useful. Instead, we conducted the majority of our analysis by looking at data on the scale of 5-15 minutes. A more typical example of our analysis appears below.



Here, we are really just looking at roughly 5 minutes' worth of data. Specifically, the period from 12:04 to 12:10. This is the type of data (and the typical time interval) that a day-trader might use. What we see in this example (the data in the **red oval**) is actually rather striking. The relevant facts are below:

1. At 12:05, we see a reversal in the downward trend that began at 12:02 (the reversal is shown in the **orange circle**).
2. At the start of the reversal, the net sentiment is 25% and the correlation is -40%. However, the important observation is that the derivatives of the price change and sentiment change are both positive.
3. From 12:05 to 12:09 (the **green oval**), we see increasing sentiment and correlation, and at 12:09 we have net sentiment of 33% and correlation of 86%.
4. Finally, at 12:10 (the **black rectangle**), we begin to see the next reversal. Interestingly, the sentiment (34%) and correlation (87%) have actually grown since 12:09. Therefore, the indication of the reversal is actually the disagreement of the derivatives between the price data and the sentiment data, which is denoted by the square marker used in the visualization.

FUTURE WORK

We were fairly encouraged by the results of this study. It is not surprising that asset prices are tied to major news developments. However, the exciting prospect is that they may also be tied to net tweet sentiment on the minute-by-minute level. Our next step would be to develop a machine learning algorithm to recognize patterns in this data (such as the pattern we demonstrated/analyzed above by hand). Then, we would want to develop a program to make trading decisions (on the scale of minutes) based on the identified patterns.

REFERENCES

[1] “Twitter mood predicts the stock market.” https://arxiv.org/pdf/1010.3003&.

[2] “Stock Prediction Using Twitter Sentiment Analysis” http://cs229.stanford.edu/proj2011/GoelMittal-StockMarketPredictionUsingTwitterSentimentAnalysis.pdf