JPMC Meme Stock Challenge

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1 Introduction

1.1 Objective

The purpose behind this project is to help determine if there is a relationship between the sentiment of a company and its respective stock price at that time. We will attempt to predict which stocks will become "meme stocks" based on online public sentiment by developing a program that automatically extracts data on specified companies to generate a visualization that will improve stock prediction performance.

1.2 Motivation

1.2.1 General Industry

This project could help determine the relationship between the stock price of a publicly traded company at a given time, and the online public sentiment and social presence of that company at that same time.If such a relationship exists, this could help predict future meme stocks and changes in stock values.

1.2.2 Implications for JP Morgan and Chase

JP Morgan and Chase (JPMC) is a company that specializes in financial services, specifically asset management and investment advising. Predicting significant changes in stocks could help JPMC investment advisors to better advise their clients. Additionally, since JPMC is a publicly traded company itself, JPMC can take advantage of any relationship found between public sentiment and stock price by utilizing marketing tactics and altering public image to cater to such a relationship in order to maximize the benefit on their stock price.

1.3 Traditional Stocks vs. Meme Stocks

Meme stocks gained popularity in 2020, originating from the subreddit r/wall -streetbets. Generally, they are memes that rise to popularity not due to the success of the company, but beacause they go viral with internet popularity, often at the whim of amateur investors that lurk on social media. The value of meme stocks often stems from public sentiment, and the stock value tends to not follow patterns in the stock market, nor show any of the corporate indicators of a potential increase in value. As a result, meme stocks are highly volatile, and come with a very high risk, but also monumental potential gains at a far higher percentage than that of traditional stocks. There is also a difference between Traditional Investors and 'Meme Stock Investors'. Traditional investors will read the news, consider market sentiment and trends, and analyze technical details when considering what to invest in, while those who invest in meme stocks are more risk-prone, evaluate sentiment on social media sites such as Reddit and Twitter, and are more likely to invest on a whim or with no reason at all.

2 Data

Over six weeks, we created a compilation of tweets scraped using Twitter API, each tweet containing the ticker of a stock in a list of nine stocks we selected: GameStop (GME), AMC, Tesla (TSLA), Bank of America (BAC), Amazon (AMZN), Facebook/Meta (FB), JP Morgan & Chase (JPM), Starbucks (SBUX), and Nokia (NOK). The specific features we received from Twitter API for each tweet were the date the tweet was posted, the text the tweet contained, whether the tweet was favorited, and the number of times it was favorited, whether the tweet scraped was a retweet, the stock ticker in the tweet used to identify the tweet ('GME', 'AMZN', 'TSLA', etc.). The feed of tweets averaged at about 4000 total tweets per day, with about 500 tweets per stock ticker. Additionally, we compiled daily stock prices for each stock from Yahoo Finance, and ran the text of the tweet through a sentiment analyzer, that returned a decimal score from -1 to 1. All of these features were put into a pandas dataframe that was then converted to a .csv file.

3 Methodology

3.1 vaderSentiment

For this project, we used the vaderSentiment analysis tool to calculate the sentiment scores for each tweet pulled from the Twitter API. There are multiple commonly used sentiment analyzers; however, compared to other sentiment analyzers such as LIWC (Linguistic Inquiry Word Count), vaderSentiment is the best tool for our project. VaderSentiment does not require any training data, works exceedingly well on social media type text - in fact better than other popular tools, generates a score based on the strength of a sentiment, and interprets text containing emoticons, slangs, conjunctions, capital words and punctuations. The algorithm for vaderSentiment is based on the idea that more than one stock of interest may be present within a tweet comment. Therefore, a dictionary is used to keep track of the average sentiments of individual sentences that may have a stock we are interested in. From there, a dictionary of stocks with its respective sentiment score is printed out.

3.2 Compound Score

The vaderSentiment Sentiment Analysis algorithm returns a compound score, which is a number between -1 and +1, that indicates whether the text analyzed has positive or negative sentiment, with -1 being the most negative, and +1 being the most positive. We used this range to classify each tweet as positive, negative, or neutral. Positive tweets had compound scores greater than +0.5, negative tweets had compound scores less than -0.5, and tweets with compound scores within this range, inclusive, were classified as neutral.

4 Results & Analysis

When determining the relationship between the stock price and sentiment, we considered the sentiment scores and the stock price as time series variables, and plotted both accordingly. We decided to calculate and analyze the Pearson correlation coefficient, or Pearson's r and respective P value, of each stock.

Note: The P-value is the probability that you would have found the current result if the correlation coefficient were in fact zero (null hypothesis). If this probability is lower than the conventional 5% (P¡0.05) the correlation coefficient is statistically significant.
Out of the nine stock we chose, four were used as a control group: BAC, JPM, SBUX, and AMZN. These four are considered traditional stocks, and the online sentiment of each was expected to have little effect on the stock price of the company, and as such were predicted to have very insignificant correlation scores. The remaining five stocks, AMC, TSLA, GME, FB, and NOK, were tested as meme stocks, so we expected a stronger correlation between the two time series in these five stocks, than the four in the control group. The calculated correlation coefficients and P- values are displayed in the table below:

Stock	r	P
GME	-.32083	.20926
AMC	.05422	.83072
TSLA	.03838	.88776
NOK	.03302	.91078
JPM	-.05421	.84194
BAC	.10169	.70786
SBUX	.16398	.55925
AMZN	.15576	.56459
FB	.22147	.40975

5 Conclusion

As seen in the table, all of the P-values are well above .05, and all of the r-values are relatively close to zero, regardless of whether they are part of the control group. Thus, we were unable to find a correlation between the stock price and sentiment scores of the selected meme stocks with the data and calculations we performed. However, the relationship between public sentiment and stock price of meme stocks is a reactionary one, meaning that any effects one may have on the other do not immediately take effect; there will be a delay between when the sentiment of a company experiences significant changes and when such changes are reflected in the stock price. Our calculations did not account for this fact, and we believe if there had been an offset of about one day, the r values calculated would have shown a stronger correlation between the two. Additionally, a disproportionately large number of tweets collected returned a neutral sentiment (approx. 65%) and very few tweets returned a negative sentiment. This fact may have skewed the averages of the compound scores, and thus the r-values.