Measuring the Impact of Influential Tweets on Apple Stock Prices: An Event-Based Sentiment Analysis

Abstract

Through an event-based sentiment analysis framework, this project investigates the influence of sentiment expressed in AAPL-related tweets on Apple stock prices. By leveraging advanced natural language processing (NLP) models like VADER and FinBERT, combined with market data, the study explores how social media sentiment correlates with stock price movements. Key findings highlight behavioral biases such as loss aversion and herd behavior, offering a nuanced understanding of the interplay between sentiment and market dynamics.

Introduction

Understanding the stock market's dynamics is a complex and multifaceted challenge. Investor sentiment, a key driver of market behavior, is influenced by a myriad of factors, including emotions, cognitive biases, and external events. The increasing integration of social media in financial markets has provided investors with an abundance of real-time information. Social media platforms, particularly Twitter, are characterized by their ability to amplify opinions and disseminate information at an unprecedented scale and speed and have become a valuable source for understanding market sentiment, as influential tweets often generate significant market reactions.

This project explores the relationship between social media sentiment and Apple stock prices, employing natural language processing (NLP) techniques to predict stock movements based on Twitter content. Previous studies have explored the influence of aggregated market sentiment on financial indicators. However, less attention has been paid to individual high-impact tweets and their direct effects on specific company's stock performance. Given the prominence of Apple as a market leader and its high visibility on social media, this research aims to bridge this gap by leveraging advanced Natural Language Processing (NLP) techniques to quantify the effect of influential tweets on AAPL stock prices. Combining the model's performance with results, we try to explain and interpret them by connecting them to investors' behavioral biases.

Literature Review

The interplay between behavioral economics and market sentiment has been extensively studied. Kahneman and Tversky's Prospect Theory (1979) provides the theoretical foundation for understanding loss aversion, highlighting the asymmetric perception of gains and losses among investors. Subsequent research has demonstrated how loss aversion contributes to market anomalies, including overreactions to negative news and underreactions to positive developments (Barberis et al., 1998).

Recent advancements in NLP have enabled researchers to analyze large-scale textual data, uncovering sentiment patterns that correlate with market behavior. Bollen et al. (2011) pioneered the use of social media sentiment to predict stock market movements, finding significant correlations between collective mood states and market performance.

In addition to sentiment analysis, the role of specific biases in market behavior has gained attention. Research by Tetlock (2007) highlights how negative sentiment in financial news predicts lower stock returns, reinforcing the importance of loss aversion in shaping market outcomes. Similarly, studies by Zhang et al. (2021) reveal that integrating behavioral biases into sentiment models improves the accuracy of stock price predictions.

This project contributes to the existing literature by integrating behavioral economics theories with advanced NLP techniques to analyze Twitter sentiment. By focusing on Apple stock prices, it examines the extent to which event-specific sentiment and behavioral biases, such as loss aversion, influence market dynamics. This approach provides a deeper understanding of the psychological underpinnings of market behavior and offers practical applications for investors and analysts.

Data

The project utilized two primary datasets to analyze the relationship between social media sentiment and Apple stock price behavior. The Twitter dataset was sourced from Kaggle and included tweets mentioning "AAPL." To ensure data relevance, preprocessing steps were applied to filter high-engagement tweets, specifically those with at least 10 comments, retweets, or likes. Text cleaning was performed using the Natural Language Toolkit (NLTK), which involved removing stop words, punctuation, and extraneous characters to prepare the content for sentiment analysis.

The stock data was collected from Nasdaq's website and included Apple's daily closing prices, returns, and volatility metrics. (please fill free to add some other details about the stock data)

Methodology

Stock Price Model

Although this report primarily covers the topic from a deep learning perspective, it would be naive not to consider the theoretical undertones of the data we are examining. This is done primarily by consulting financial theory and metrics that may be significantly influenced by Twitter data.

We want to predict Apple stock price data, so we decided to consult a variety of metrics that are commonly used to forecast prices. These include daily returns, close prices, and trade volume. The close price metric is especially important because of how we used it to perform gap analysis. This involves calculating the percentage change between the current close price and the previous day's close price. Deciding the thresholds for the gap is something that we also had to fine-tune specifically because it would significantly impact the sentiment classifications if done incorrectly. We decided to choose a range of -0.5% to 0.5%, with values below -0.5% being classified as negative sentiment, above 0.5% as positive sentiment, and in between as neutral. This was decided because Apple stock's beta value is historically around 1.24, which only makes it slightly more volatile than the rest of the market. We know this because the average beta value of the S&P 500 as a whole is 1.0. If we were to consider other stocks, we would naturally have to design different thresholds, such as for more volatile stocks like Tesla (2.34).

After defining the correct thresholds, we simply take our available data and classify each daily close price value using the gap and daily returns. We chose to incorporate daily returns in our classifications primarily because it is known to frequently cause investor sentiment to fluctuate. This is rather self-explanatory because the returns an investor makes is likely to affect their wellbeing and subsequently their reported sentiment.

VADER Sentiment Analysis

The first sentiment model implemented in this project was VADER (Valence Aware Dictionary and Sentiment Reasoner). VADER is a lexicon and rule-based sentiment analysis tool designed for social media text, making it particularly suitable for our Twitter dataset. It is pre-trained and does not require additional training, which makes it efficient for quick deployment. VADER is also capable of handling emoticons, slangs, punctuation, and other informal language often seen on platforms like Twitter.

VADER provides four sentiment scores to classify text:

1. Compound Score: A normalized score reflecting the overall sentiment polarity, ranging from -1 (most negative) to +1 (most positive).
2. Positive (pos): The proportion of positive sentiment words in the text.
3. Negative (neg): The proportion of negative sentiment words in the text.
4. Neutral (neu): The proportion of neutral sentiment words in the text.

The compound score plays a crucial role in this analysis because it balances positive and negative words to determine the text's overall sentiment. Importantly, the compound score can lean positive even when neutral words dominate, as long as a single strongly positive word appears. For example, a sentence like "The product is great but nothing extraordinary" contains mostly neutral words, but the word "great" carries enough weight to produce a positive compound score. Similarly, for the compound score to be negative, the negative sentiment must outweigh any positive sentiment.

Sentiment Distribution Analysis *(See where to put?)*

The sentiment distribution from VADER reveals a distinct bias toward positive sentiment. As shown in the Distribution of Compound Sentiment Scores, most compound scores are concentrated on the positive end of the spectrum. This observation aligns with the frequency distribution of sentiment categories, where positive sentiment clearly dominates, followed by negative and then neutral sentiment.

This outcome arises because VADER assigns a positive compound score when even a small portion of the text contains strongly weighted positive words. Consequently, even with a high proportion of neutral words, the compound score can still reflect an overall positive sentiment.

Sentiment Scores Over Time

Analyzing the sentiment scores over time reveals key trends in public sentiment regarding Apple. The Sentiment Scores Over Time graph highlights the following observations:

1. Compound Sentiment Fluctuations: The compound sentiment fluctuates significantly, reflecting variability in public opinion. These fluctuations are likely tied to specific events such as product launches, earnings reports, or broader market changes.
2. Positive vs. Negative Sentiment: The positive sentiment (represented by the orange line) consistently outweighs the negative sentiment (green line). This pattern indicates a general optimism in tweets mentioning Apple.

Results

Over the observed time period (2015 to 2020), the overall trajectory of Apple's stock price shows a significant upward trend, indicating long-term positive market performance despite short-term fluctuations.

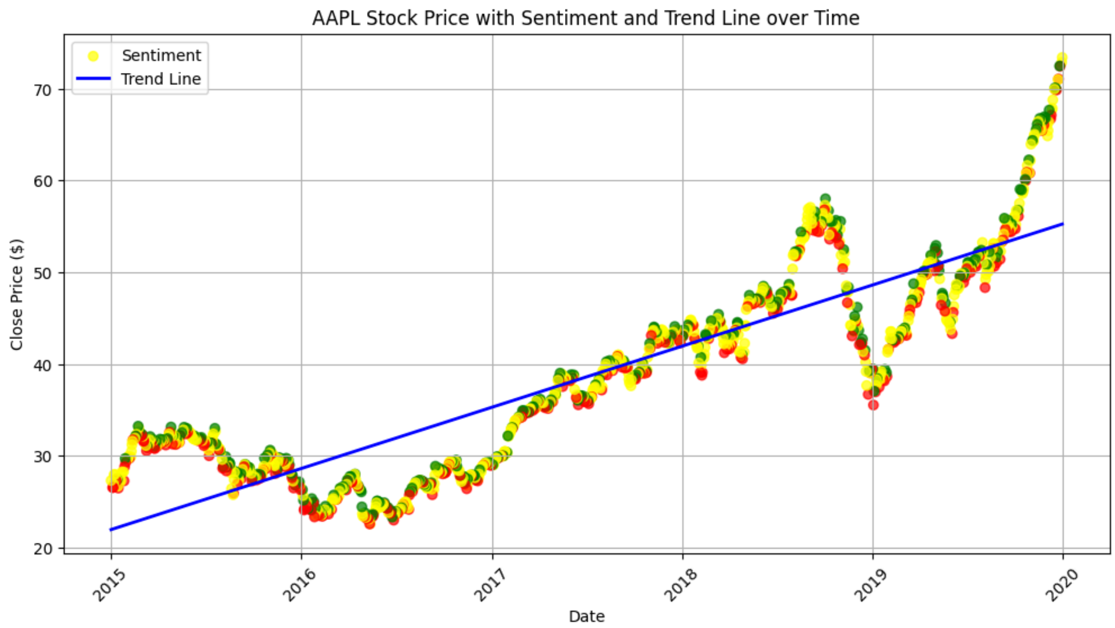
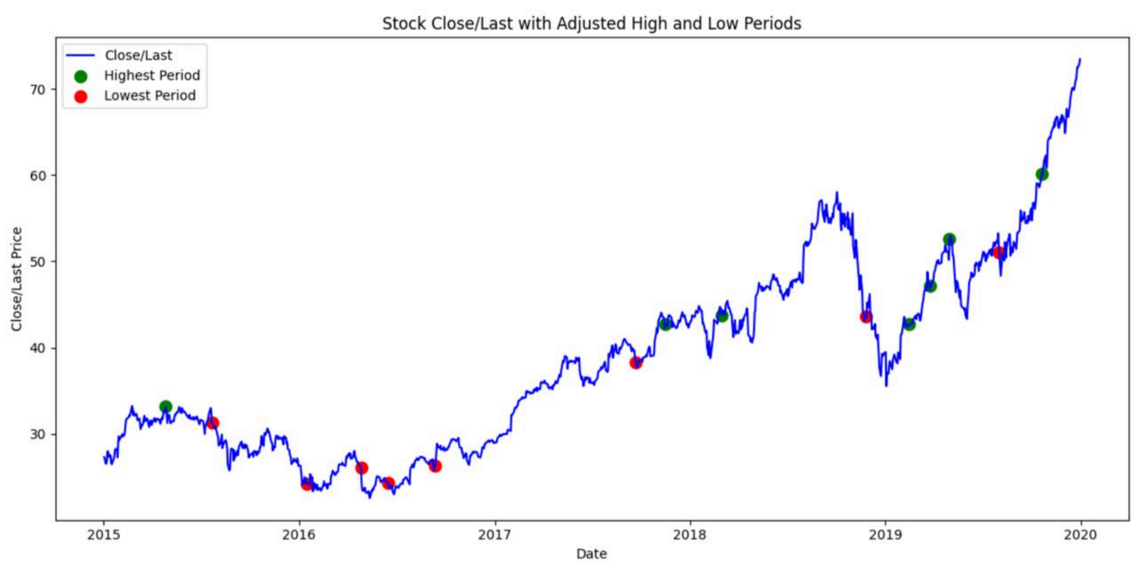


Figure 1–Apple Stock Price Sentiment and Trend Line

We found that most of the close price values were designated as ‘neutral’ with 619 classifications, while the positive and negative classifications had an even split. We observed 322 negative classifications and 317 positive ones. We visualized this to get a better idea of the trend as well as point out any potential patterns *(Figure 1)*. Although the price of stock has been increasing steadily with few dips over this period, sentiment remains relatively balanced, which is an interesting observation. However, it is important to highlight that each classification only represents a single day in isolation and does not account for the overall upward trend in price observed here.

Looking at *Figure 2,* sharp price movements often surround the green and red points. Those fluctuations suggest that extreme sentiment, whether positive or negative, corresponds to periods of high volatility, where investor reactions—driven by optimism or fear—lead to rapid price fluctuations.

Figure 2–Stock Price with Sentiment Period Dots



More specifically, the highest points of sentiment periods (green points) generally align with or closely precede local stock price peaks, indicating that positive Twitter sentiment often captures investor optimism in real-time. This might suggest that investors respond quickly and more normally to favorable sentiment, leading to a predictable rise in stock prices. In contrast, the lowest points of sentiment periods (red points) do not immediately correspond to the lowest stock prices. These points are usually not located at the lowest point of price curve fluctuations but often appear in the middle of price declines. We can observe from the graph that the stock price tends to continue declining after periods of extreme negative sentiment.

This delayed and prolonged effect can be attributed to behavioral biases, particularly loss aversion and herd behavior. Loss aversion theory explains why investors react more strongly to negative sentiment than to positive sentiment, as the psychological weight of potential losses outweighs the perception of equivalent gains. Consequently, negative sentiment triggers not only immediate selling but also sustained downward pressure on stock prices as investors internalize the pessimistic outlook and gradually adjust their portfolios through actions such as selling off shares or rebalancing their holdings. At the same time, herd behavior amplifies this effect, as pessimistic sentiment spreads among market participants and reinforces group behavior by spreading and repeating the pessimistic mood on Twitter.

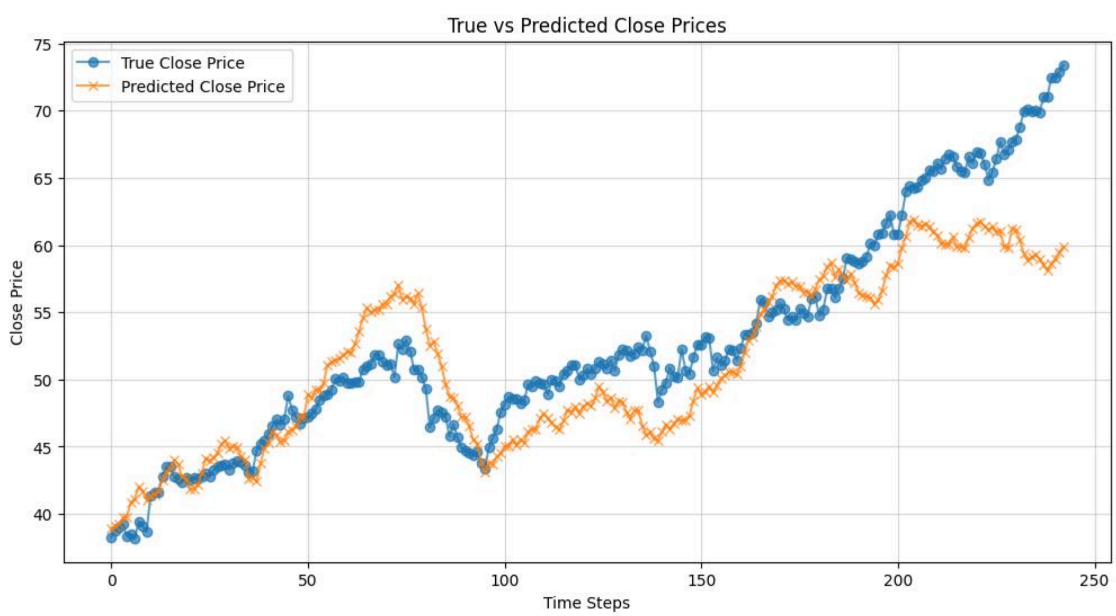


Figure 3–True Closing Price vs. Predicted Closing Price

Figure 3 visually demonstrates the overall predictive performance of the model. The blue line (True Close Price) and the orange line (Predicted Close Price) generally follow a similar upward trend, indicating that the model captures the long-term directional movements of Apple's stock prices. As a company that has positive long-term performance, Apple has overall market optimism that is driven by positive sentiment from investors.

However, the model shows underperformance in volatile periods, particularly between time steps 50 and 100, where the predicted line lags behind sharp rises and declines in stock prices. This difficulty in adapting to volatility also highlights the potential behavioral biases in the stock market that emotions cause either over or under-reaction. Besides, sudden declines or raises in stock price may reflect collective overreactions, like herd behavior, causing volatility that the model struggles to predict accurately.

There are also noticeable prediction gaps during periods of sharp upward or downward momentum. While the model aligns closer with true prices in stable phases, it fails to fully capture abrupt increases. This could reflect anchoring and status quo biases, where prior price levels constrain investor expectations. Even when positive news emerges, investors may be slow to react fully, leading to a gradual adjustment rather than an immediate surge, which the model fails to replicate. These gaps could be linked to the fact that our model did not incorporate behavioral bias to adjust or fine-tune the model, which can be improved in the future.

The performance of the model and our analysis emphasize the importance of incorporating behavioral biases when using sentiment to predict stock prices. This also explains why prior research has focused on improving predictive models by integrating these biases. However, human emotions and behaviors are inherently complex and difficult to forecast. To address this challenge, we hope to build closer collaboration with psychological scientists to develop more robust mechanisms for capturing and understanding investor behavior in future research.

Conclusion

By utilizing VADER for general sentiment extraction and FinBERT for domain-specific financial sentiment, our group established a robust methodology to analyze Apple-related tweets. Fine-tuning FinBERT using the Masked Language Model (MLM) approach further enhanced its ability to capture nuanced sentiment trends within financial discussions.

The integration of processed sentiment data with market metrics in the LSTM model enabled us to predict Apple's stock prices effectively, demonstrating the value of sentiment-driven features in financial forecasting. While positive sentiment often aligned with stock price peaks, negative sentiment exhibited a deeper and longer-lasting impact, reflecting behavioral biases such as loss aversion and emotional contagion.

Despite the performance of our models, limitations remain. The reliance on Twitter data may exclude significant sentiment signals from other platforms or traditional financial news sources. Additionally, the models showed reduced accuracy during periods of extreme volatility, where investor reactions are less predictable. (any other limitations?)

In conclusion, this study lays a foundation for future research that integrates emotional insights and potential irrational investment behaviors with computational models. Collaborating with behavioral scientists and expanding sentiment data sources will be key to building more accurate and resilient predictive frameworks for financial markets.

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