

# Calculating Media's Impact on Stock Price

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# Motivation

- Financial markets are unpredictable
- Stock prices take into account many factors, from past performance to politics
- Media stories are often how these factors are reported

**Question:** how much impact do media stories have on stock price?

# Background

- A share of **stock** is a portion of ownership in a company; owning shares of a stock means you own part of that business.
- The **price of a stock** changes based on how much buyers and sellers are willing to pay.
- Many things can affect how a stock's price moves, including:
  - Company news, financial results, or big announcements
  - Overall economic health, interest rates, inflation, and employment
  - Public opinion and how confident investors feel about the future
- **Sentiment analysis** is a computer technique that tries to measure how people feel, based on the words they use.
- **BERT** is a machine learning model that can understand context and subtle meanings, making it ideal for sentiment analysis

# Related Work

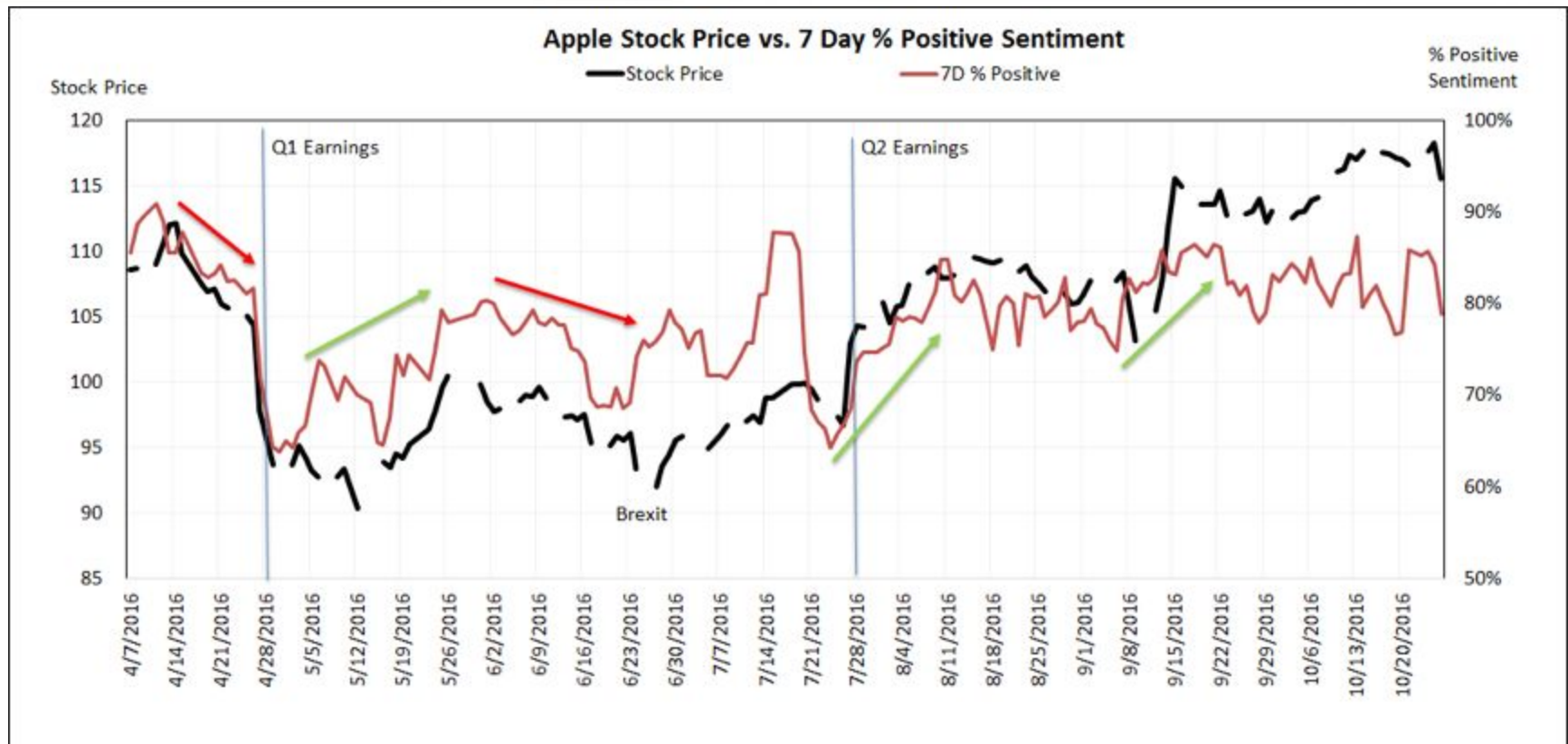
- "BERTopic-Driven Stock Market Predictions: Unraveling Sentiment Insights" analyses comment sentiment and integrates it with deep learning models for stock price prediction.
  - <https://arxiv.org/pdf/2404.02053>
- "Market Trend Prediction using Sentiment Analysis: Lessons Learned and Paths Forward" examines how both sentiment attitude and emotion from financial news and tweets can, in certain cases, help predict market movements.
  - <https://arxiv.org/pdf/1903.05440>
- "A Sentiment Analysis Approach to the Prediction of Market Volatility" investigates correlations between sentiment from news headlines and tweets with next-day market volatility and returns, finding clear links in some cases.
  - <https://arxiv.org/pdf/2012.05906>

# Claim / Target Task

- How much do media stories impact stock price?



# An Intuitive Figure Showing WHY Claim



As can be seen in this graph, Apple's stock price is sometimes highly correlated with the sentiment analysis, and sometimes not. We proposed to do a multi-stock analysis to find a good overall correlation coefficient between sentiment and price.

# Proposed Solution

- 1) Perform a sentiment analysis of media stories on specific stocks using a BERT model
- 2) Using statistics, determine the correlation between sentiment and stock price
- 3) Find the overall correlation coefficient between media sentiment and stock price

# Implementation

**Data:** We will use a kaggle financial news dataset, which contains thousands of financial news articles from trusted outlets and their date of publication, and append financial stock info from finance for that day.

(<https://www.kaggle.com/datasets/rdolphin/financial-news-with-ticker-level-sentiment> )

**Sentiment Analysis:** We plan on using finBERT, a BERT model on HuggingFace fine-tuned on financial data, to assign a sentiment analysis score for each article.

(<https://huggingface.co/ProsusAI/finbert>)

**Correlation:** We can perform a linear regression to measure the relationship between sentiment and price change. An average & standard deviation of all stock correlations will be taken for our final answer.



# Data Summary

- 13,386 headlines
- 2,833 missing/incomplete rows
- ~78% data is usable
- Data columns:

{  
– Headline  
– Date  
– Stock Ticker  
}

Extracted from raw Kaggle dataset

{  
– Open Price  
– Close Price  
– Price Change  
– Price Change Percent  
}

Added using yfinance API in python.

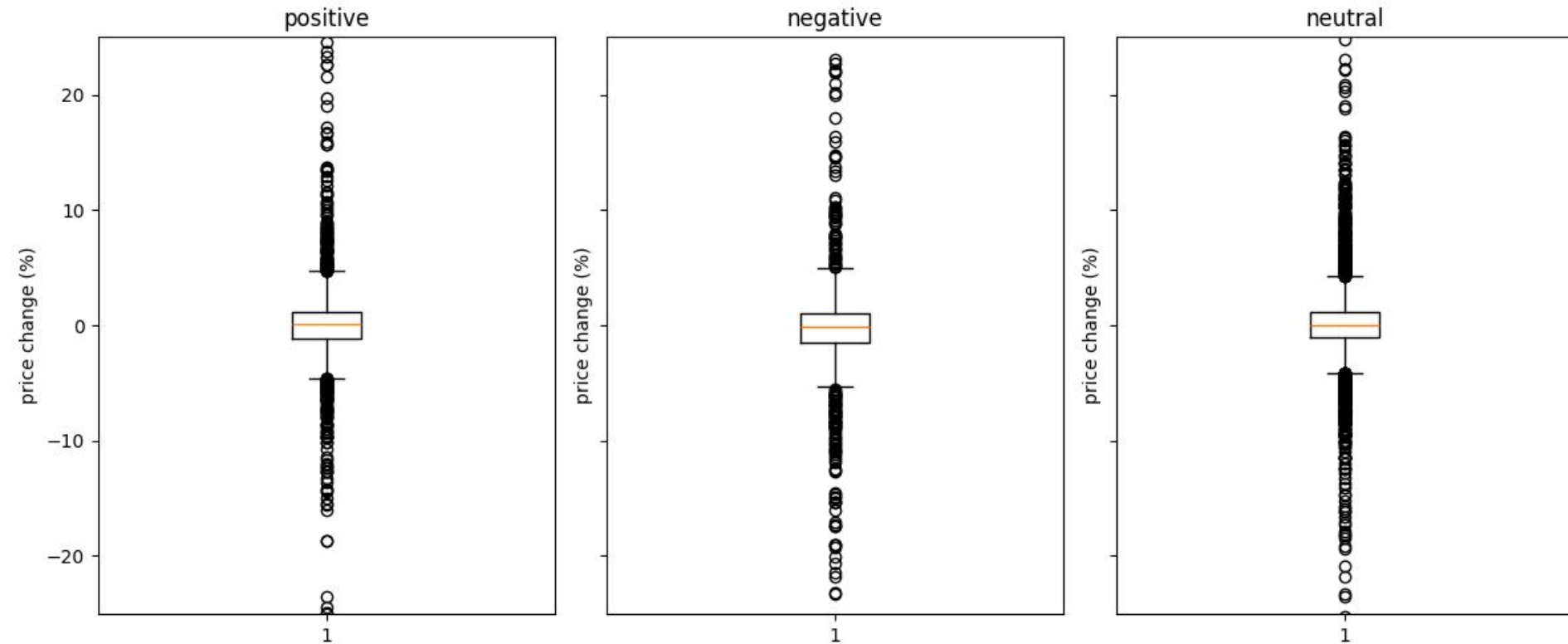
# Experimental Results

|                      | Correlation Coefficient | Mean % change in price | standard deviation of % change in price |
|----------------------|-------------------------|------------------------|---|
| BERT positive rating | 0.0159                  | 0.137                  | 4.478                                   |
| BERT neutral rating  | -0.0016                 | 0.104                  | 3.568                                   |
| BERT negative rating | -0.0158                 | -0.052                 | 8.622                                   |

Key Takeaway: all the correlation coefficients are very low

# Experimental Results

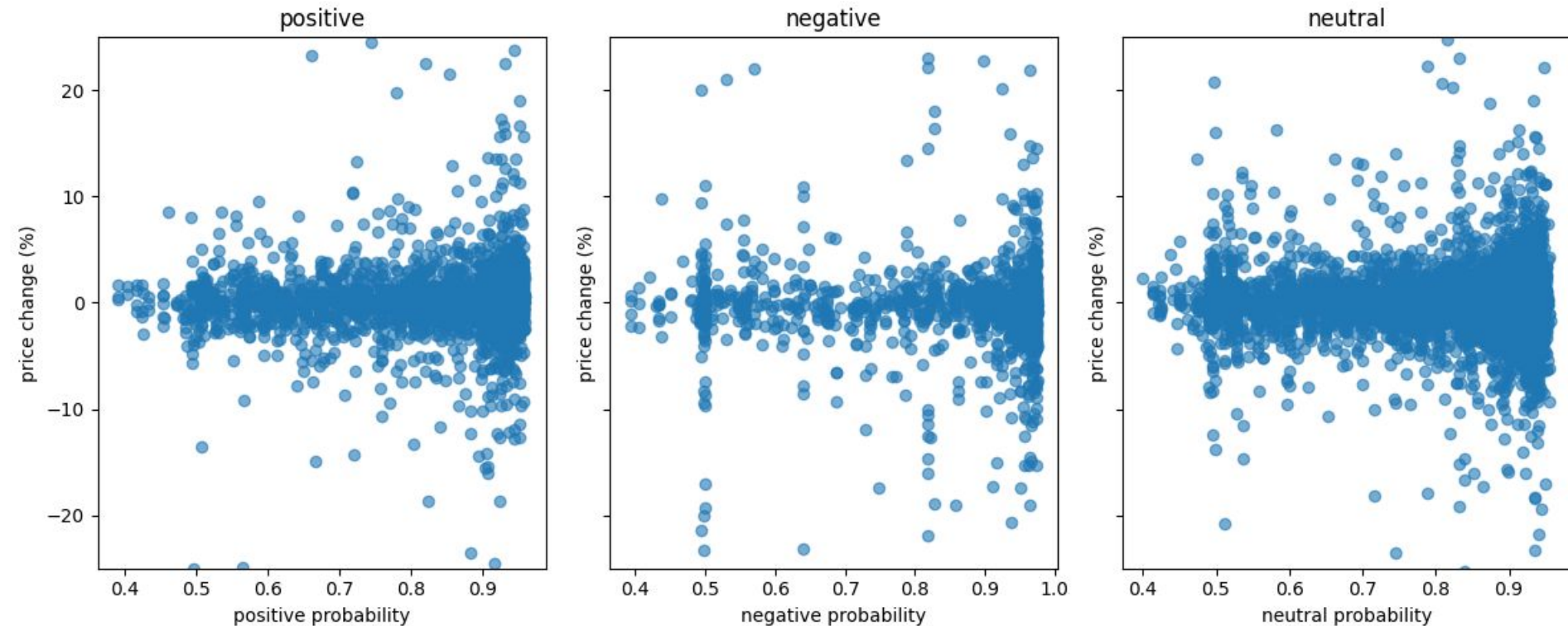
Boxplot of price change percentage for each sentiment



Key Takeaway: with all classes, all the data, except a few outliers, is near zero

# Experimental Results

Scatter plot of price change percentage for each sentiment



Key Takeaway: for most of the data, BERT was confident (high probability) in its classifications

# Experimental Analysis

- Correlation coefficients are very low
  - All are under 0.02 - very weak!
- Mean for each class is near zero and standard deviation is large
  - Standard deviation for negative is unusually large
- Vast majority of headlines are classified as 'neutral'
  - This could be a dataset peculiarity. Using another dataset with better headlines could be a solution.
  - This could also be a market issue: prices are too volatile, and media headlines are only one of several factors affecting price

# Conclusion and Future Work

## **Conclusions:**

- There is very little correlation between news coverage sentiment and stock price change by day
- Even a BERT model fine-tuned for finance does not discern good and bad news from neutral news very well

## **Possible Improvements:**

- Include news article body or a summary in the input to BERT for inference
- Fine-tune a BERT model for each news source or journalist, to try and learn individual writing styles

# Breakdown of Contributions

## Flavien

- Performed research on topic, finding useful datasets, models, & previous work
- Did slides 2-9
- Wrote Python script for extracting data from the Kaggle dataset & enriching it with yfinance API

## Colby

- Did slides 10-14
- Wrote Python Script for finding sentiment scores for each headline
- Wrote Python script for statistical analysis & creating the graphs

Due to different schedules & workloads, Flavien did more work towards the beginning of the project, & Colby did more at the end of it. Each person dedicated roughly the same amount of hours towards the project.

Code Demo Video:

[https://drive.google.com/file/d/1\\_knZ4cJ5R\\_Vtlu8JD36AL0irAj8IVv1H/view?usp=sharing](https://drive.google.com/file/d/1_knZ4cJ5R_Vtlu8JD36AL0irAj8IVv1H/view?usp=sharing)

# References

- Deveikyte, J., Geman, H., Piccari, C., & Provetti, A. (2020). A sentiment analysis approach to the prediction of market volatility. *arXiv:2012.05906* [q-fin.ST]. <https://doi.org/10.48550/arXiv.2012.05906>
- Mudinas, A., Zhang, D., & Levene, M. (2019). Market trend prediction using sentiment analysis: Lessons learned and paths forward. *arXiv:1903.05440* [cs.CL].
- Zhu, E., et al. (2024). BERTopic-driven stock market predictions: Unraveling sentiment insights. *arXiv:2404.02053* [cs.CL]. <https://doi.org/10.48550/arXiv.2404.02053>