Reference link to our project: https://waynegretzky1.github.io/stock-sentiment-analysis/

Stock Sentiment Analysis: The Social Media Effect

Why This Project?

In our day-to-day lives, almost everyone hears the word "stocks." But for most, it is either a mystery or just a number on a screen. Many see it as an investment, others a gamble. For a few, it is a passion, and for some, profit. Many people over the years have poured trillions into understanding what makes the market move, so we also wanted to take a shot at unraveling it through sentiment, voice, and the tweets of the world.

Our project, titled **Stock Sentiment Analysis: The Social Media Effect**, embarks on this exact journey using social media's chatter to analyze the living, breathing movement of stocks, and to ask a simple yet powerful question: "Does social media sentiment influence stock prices?"

We focus on the top 11 most-watched US stock tickers, tracking them over a full year from September 30, 2021, to September 30, 2022, and analyze how emotions expressed in over 860,000 tweets intersect with real market data. We calculated sentiment metrics using advanced NLP models and correlated them with 1-day, 2-day, 3-day, and 7-day returns.

Data Analysis

1. Preparation and Data Sources

Before the story began, we had to prepare the stage. We collected and merged multiple datasets:

- Twitter sentiment-tagged data with over 860K tweets
- Yahoo Finance API stock data (Opening, Closing prices, Return intervals)
- Kaggle financial sentiment datasets

We used multiple models for sentiment scoring such as TextBlob, LSTM-based sentiment analysis, and finally, the powerful transformer-based BERT for our primary sentiment measure. Then came the cleaning:

- We removed irrelevant tweets, null values, non-English posts, and emoji-heavy text.
- We ensured consistency by normalizing the sentiment scores across models.
- Every tweet was paired with its respective ticker's stock price and returns giving us a clean, synchronized timeline.

The result: a high-quality dataset where social chatter and stock behavior met in every row.

2. Analysis Techniques

We did not want just raw numbers, we wanted a story. A flow of questions, each one leading to the next, our key question was: *Does social media sentiment affect stock price?*

We listed 3 sub-questions that drove the story through analysis.

Q1: Is there a relationship between sentiment and stock price?

We plotted a line chart with average daily sentiment scores against returns across 1, 2, 3, and 7-day windows for all 11 stocks. With each interval, we watched the dance between two lines, the Sentiment and Returns that played out on the graph.

Yes! Our line charts painted a pattern: When sentiment rises, stock price tends to rise. When sentiment drops, so do prices. As one curved up or dipped down, so did the other. It was not just data; it felt like we were watching the mood of the market in motion.

But we noticed something irrelevant, a lag between sentiment changes and stock movement. This led to our second question below.

Q2: How can we measure sentiment-return relationships with lag time?

We delved into some mathematical calculations, rolled up our sleeves, and crunched the numbers as much as possible. By making the sentiment timeline ±7 days, we calculated correlation percentages at every shift. These were not merely numerical values on a spreadsheet; each bar on our interactive chart conveyed a distinct narrative. Hover or click, and the chart revealed exactly which lag had the strongest sentiment-return sync. A burst of color in the bar chart made it easy to spot the peaks where the connection between emotion and price was at its strongest.

Finding: 6 out of 11 stocks showed weak to moderate correlations with a 0-day lag, suggesting sentiment reacts almost immediately or simultaneously with price. However, the causation whether sentiment drives returns or vice versa remains unclear. So, we were not satisfied yet. We wanted to know: *who's leading this dance?*

Q3: Do tweets drive stock moves, or is it the other way around?

We looked for ways to do this and there came a statistical analysis test. The Granger Causality Test: A lie detector for cause and effect.

This test checks if sentiment helps predict returns, or vice versa. We used -log10(p) values to measure predictive strength; smaller p means higher predictive scores. We visualized results in a heatmap, displaying predictive strength for each stock in both directions. Each tile in our heatmap whispered (or shouted) whether sentiment or stock returns were doing the driving. Hovering over them revealed their predictive scores in real time.

Finding:

- **Sentiment → Returns:** Yes, predictive score is high, sentiment had a real, measurable impact.
- **Returns → Sentiment:** Weak or no predictive score.

Except for one, Tesla (TSLA). It was an anomaly. TSLA showed mutual causality: both its stock returns and sentiment drove each other. A livewire in the market. No wonder it was the most talked about stock all year (2021-2022).

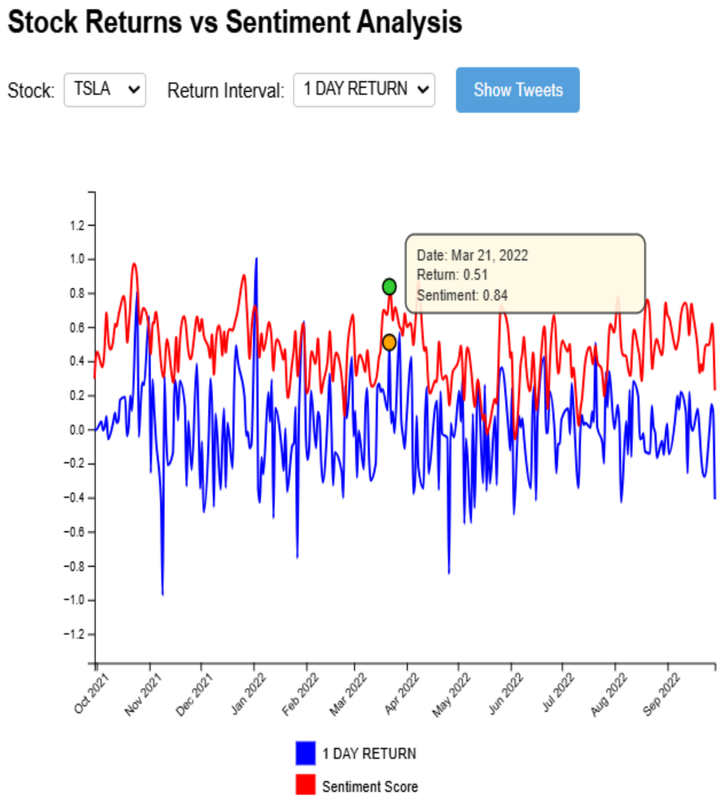
3. Summary of Insights:

We went in asking, *"Does sentiment drive stock prices?"* Summarizing the three insights that emerged from our deep-dive:

Insight 1: Sentiment and Returns Move Together

- **What we did:** We tracked average daily sentiment scores and compared them with stock returns over 1, 2, 3, and 7-day intervals.
- **How we did it:** Line Charts showing sentiment vs. return trajectories over time.
- **What we found:** A clear trend when sentiment climbed, stock returns often followed. When sentiment dropped, returns did too. The pattern held across most stocks, revealing an emotional pulse in the market. It felt like watching mood swings trigger price swings.

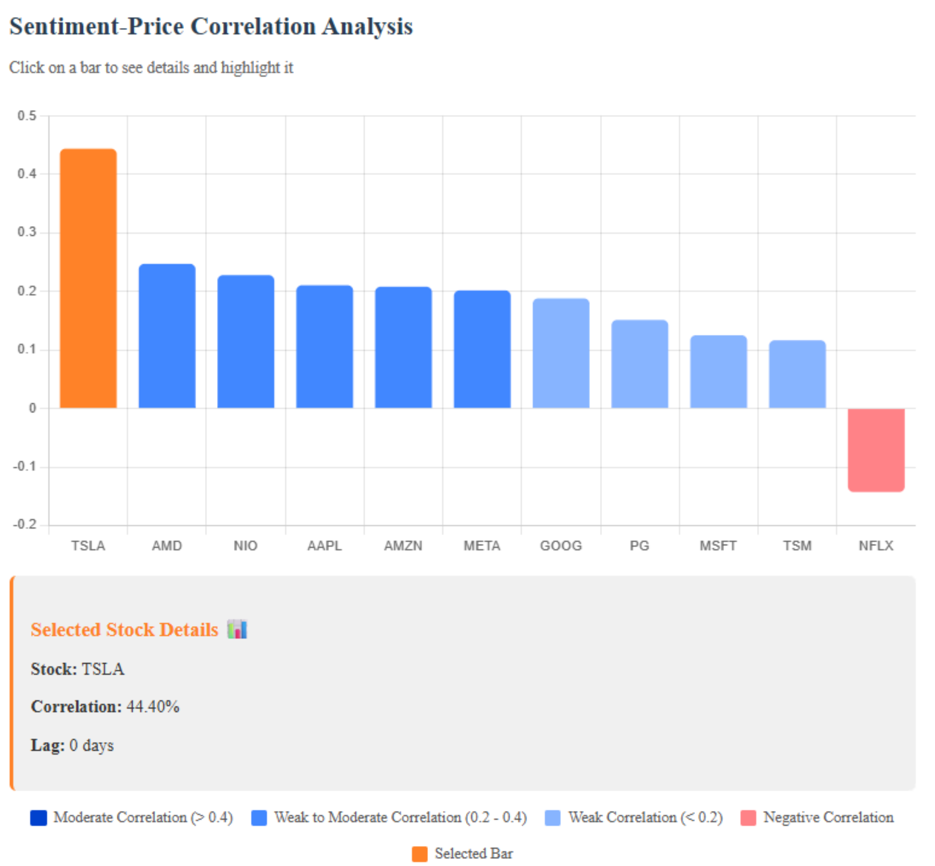
Below is the screenshot representing the line chart implemented for Stock Returns vs Sentiment Analysis:



Insight 2: Quantifying the relationship between sentiment and stock return with lag time:

- **What we did:** We investigated the relationship and time delay between sentiment shifts and stock return reactions.
- **How we did it:** Interactive Bar Chart showing correlation strength at different sentiment shift lags (from -7 to +7 days).
- **What we found:** 6 out of 11 stocks showed the strongest correlations at 0-day lag, meaning sentiment and returns moved *almost simultaneously*. The strongest response happened in real-time, suggesting markets are extremely reactive to public mood.

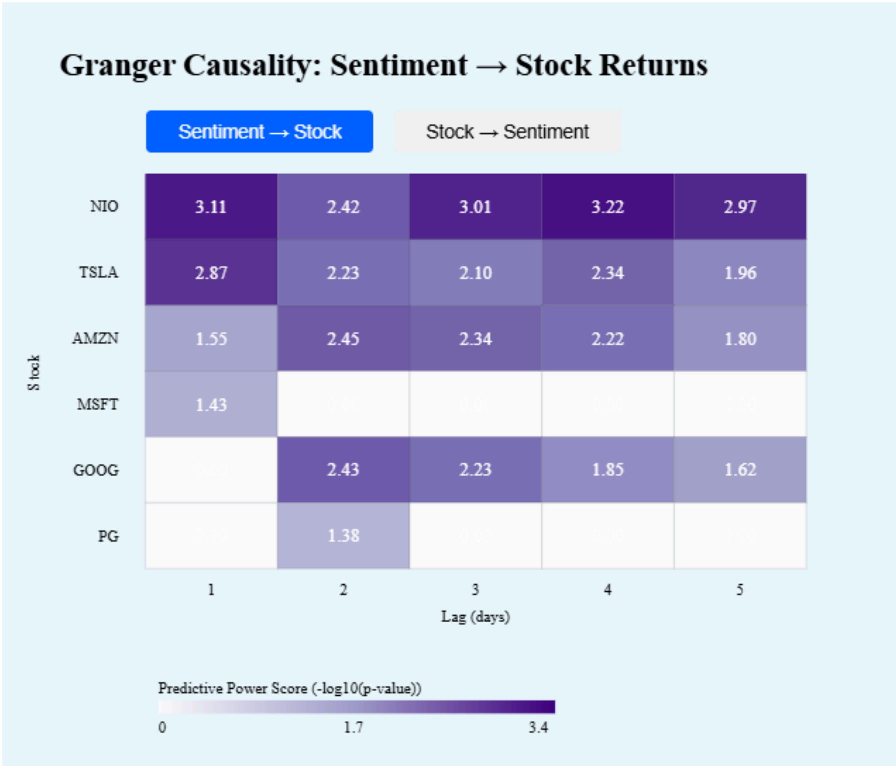
Below is the screenshot representing the Bar chart implemented for Sentiment Price Correlation Analysis:



Insight 3: Sentiment Predicts Returns, but Rarely the Other Way Around

- **What we did:** We tested for causality between sentiment and returns.
- **How we did it:** Heatmap of -log10(p) values from the Granger Causality Test, comparing two directions:
  - Sentiment → Returns
  - Returns → Sentiment
- **What we found:** In most stocks, sentiment successfully predicted returns, with high predictive scores (low p-values). However, returns almost never predicted sentiment except for Tesla (TSLA), which showed *mutual causality*. Tesla's feedback loop made it a high-volatility outlier, driven by and driving online emotion in equal measure.

Below is the screenshot representing the heat map implemented for Granger Causality Test:



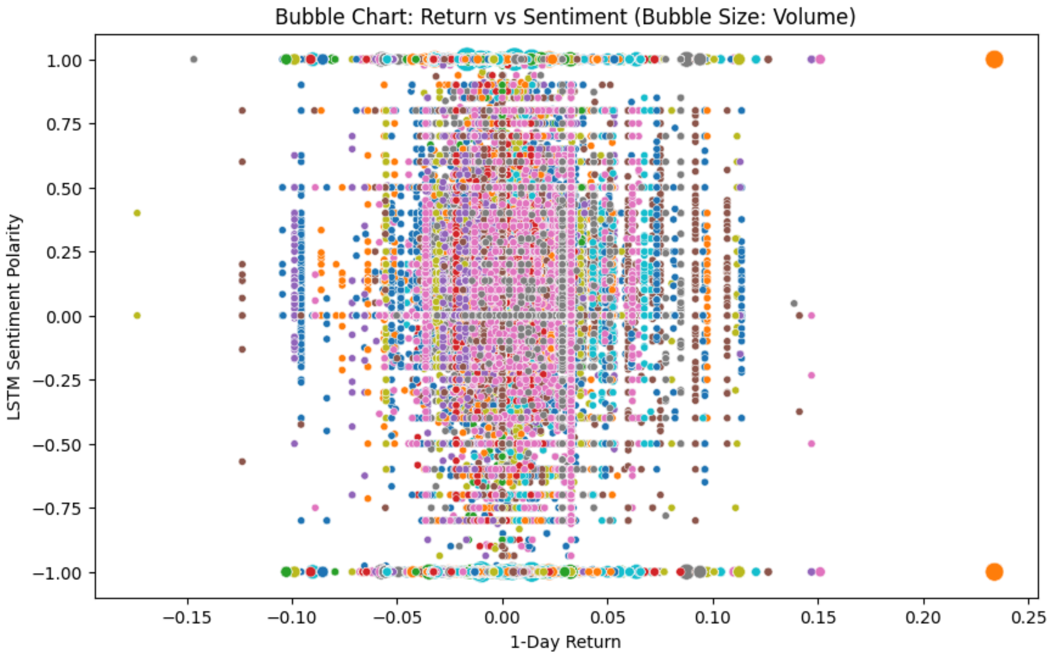
4. Choosing Insights

In the early stages of exploration, we cast a wide net, we built everything from bubble charts mapping sentiment volume vs. stock volatility, to Axis charts comparing tweet activity against sector-wise performance. We also experimented with volatility overlays, tweet-type clustering, and outlier detection on anomalous sentiment spikes.

However, not every analysis made the final cut. We filtered our insights by asking: *Does this analysis drive the core story forward?* If the answer was no, we set it aside. Here are three examples:

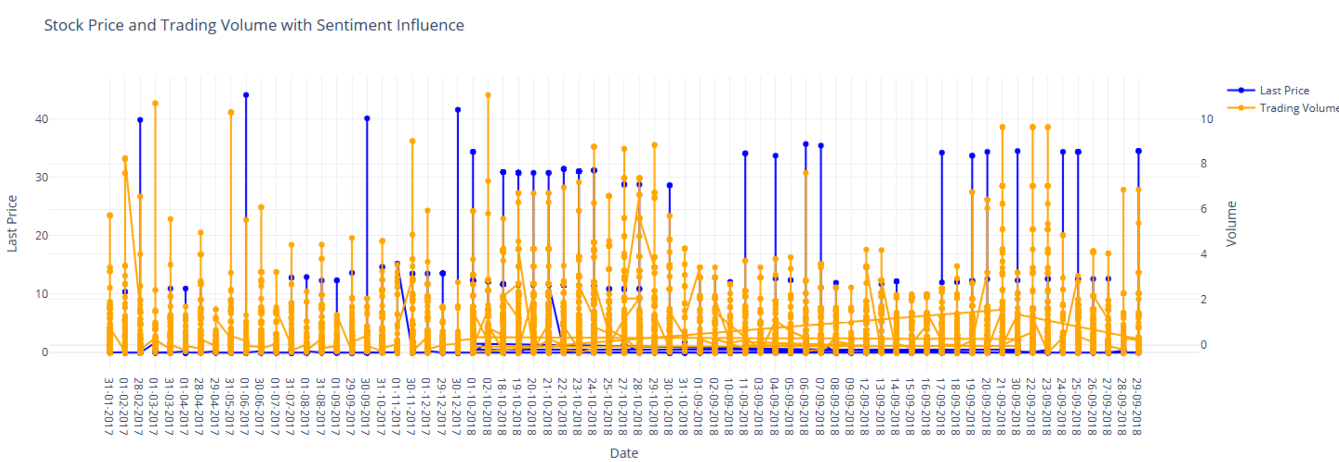
1. **Bubble Chart (Stock Return vs. Sentiment)**
   What we did: We plotted bubble sizes to represent tweet volume across different sentiment levels against stock return.
   Why we dropped it: While visually engaging, it failed to establish a clear link to stock returns or sentiment directionality. It was descriptive, not predictive, so it did not support our central hypothesis. Also, it was non-interpretable.

Below is the screenshot representing the Bubble Chart implemented for Stock Return vs Sentiment:



2. **Axis Chart (Trading volume with sentiment influence)**
   What we did: Compared stock performance alongside sentiment tweet spikes.
   Why we dropped it: The correlation was noisy, and sentiment tended to generalize across sectors, diluting specific stock-level insights. It added complexity without deepening the narrative.

Below is the screenshot representing the Axis Chart implemented for Stock Price and Trading Volume:



3. **Outlier Detection on Sentiment Spikes**
   What we did: Isolated days with extreme sentiment changes and mapped them to stock price anomalies.
   Why we dropped it: While intriguing, the insight lacked consistency across stocks. It felt anecdotal and did not scale well across our dataset.

We chose analyses that offered both clarity and continuity, line charts that visually paired sentiment and returns, lag correlation bar graphs that quantified alignment, and the Granger causality heatmap that anchored the narrative in statistical depth. These techniques allowed us to ask pointed questions, answer them with evidence, and transition seamlessly between phases of the story.

5. Tools, Frameworks, and Environment

This project was built on a tech stack optimized for data storytelling:

- **Python** (Pandas, NumPy, SciPy) – for data wrangling and correlation analysis
- **Matplotlib & Plotly** – for generating insights and test visuals
- **Svelte (JavaScript Framework)** – to create a smooth, scroll-based data story site
- **Google Colab** – cloud-based collaboration and large-scale processing

Data Communication

Before finalizing our current web-based interactive platform, we explored multiple visualization techniques, narrative structures, and user interactions. The goal was always clear: communicate complex sentiment-stock relationships in a way that is intuitive, engaging, and informative. Here is how our design journey evolved:

1. Static Charts vs Interactive Web Visualizations

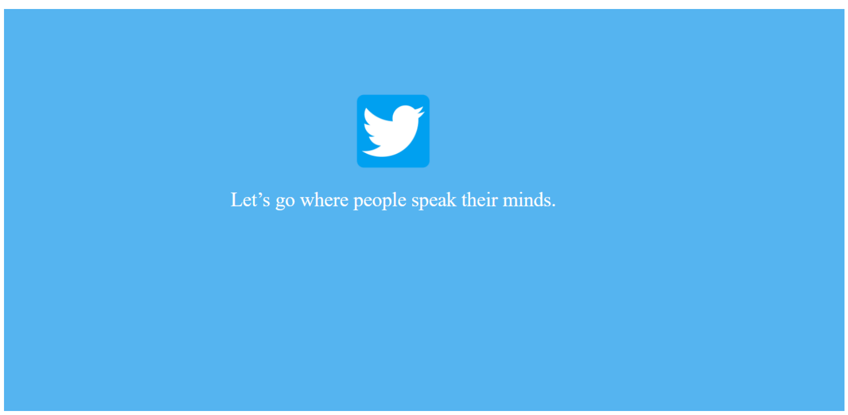
- **Alternative Explored:**
  We initially used static Matplotlib charts embedded within Jupyter Notebooks to explore sentiment-return correlations.
- **Problem Faced:**
  While they served our analytical needs, these charts were not interactive and made it difficult for users to explore patterns or feel immersed in the data. They lacked flexibility, and Python-based storytelling was limiting.
- **Design Decision Made:**
  We shifted to Svelte for building an interactive web application that included dynamic charts, tooltips, and user-driven exploration.
- **Reasoning:**
  Svelte allowed us to build a fluid, interactive experience that made the narrative more

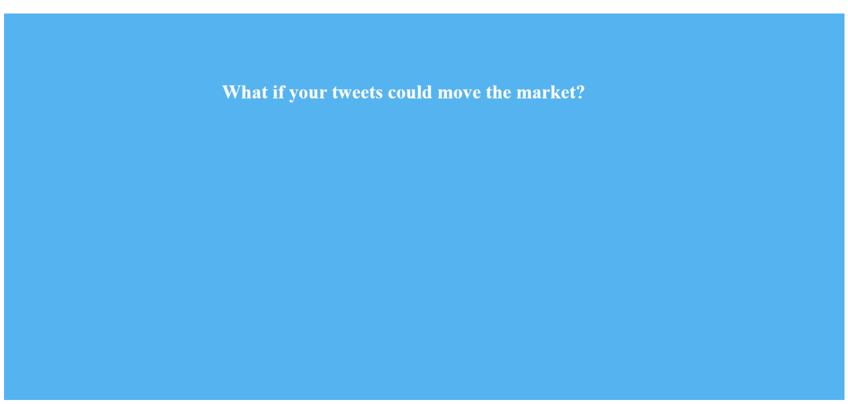
compelling. It also offered easier integration of scroll-based storytelling and live updates compared to Python's static environment.

2. Overuse of Animations and Lengthy Scroll Format

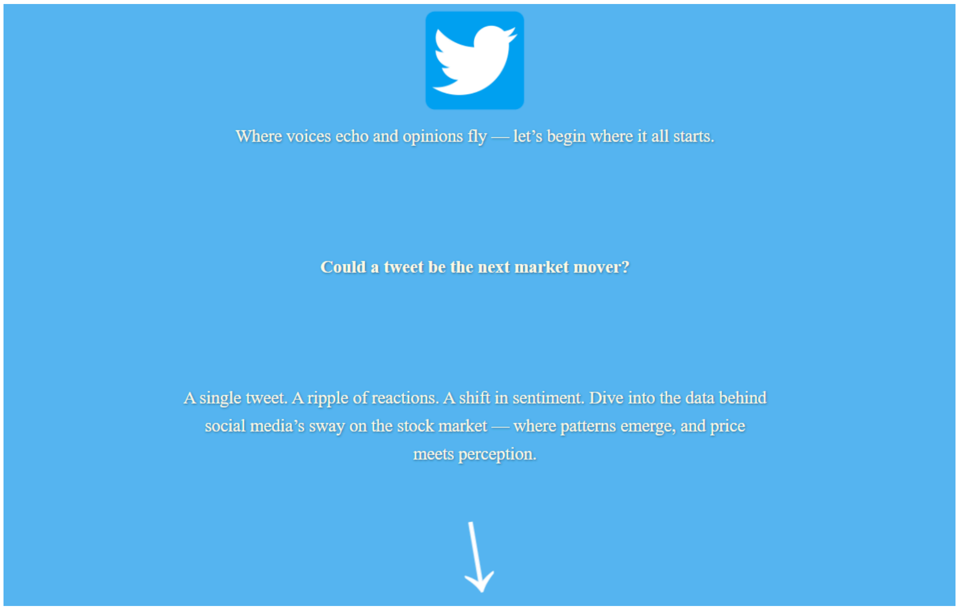
- **Alternative Explored:**
  We originally built a long scroll-based story with multiple animations (3-4) and extended introduction segments.
- **Problem Faced:**
  Peer feedback highlighted that the scroll was exhausting and animations, while visually interesting, were distracting. Users were losing track of the main message.
- **Design Decision Made:**
  We condensed the scroll, reduced the number of sections, and retained only one animation that served a meaningful purpose in the narrative.
- **Reasoning:**
  We realized visual clarity and narrative focus mattered more than aesthetic overload. One focused animation helped emphasize the turning point in our analysis without overwhelming the user.

Before:





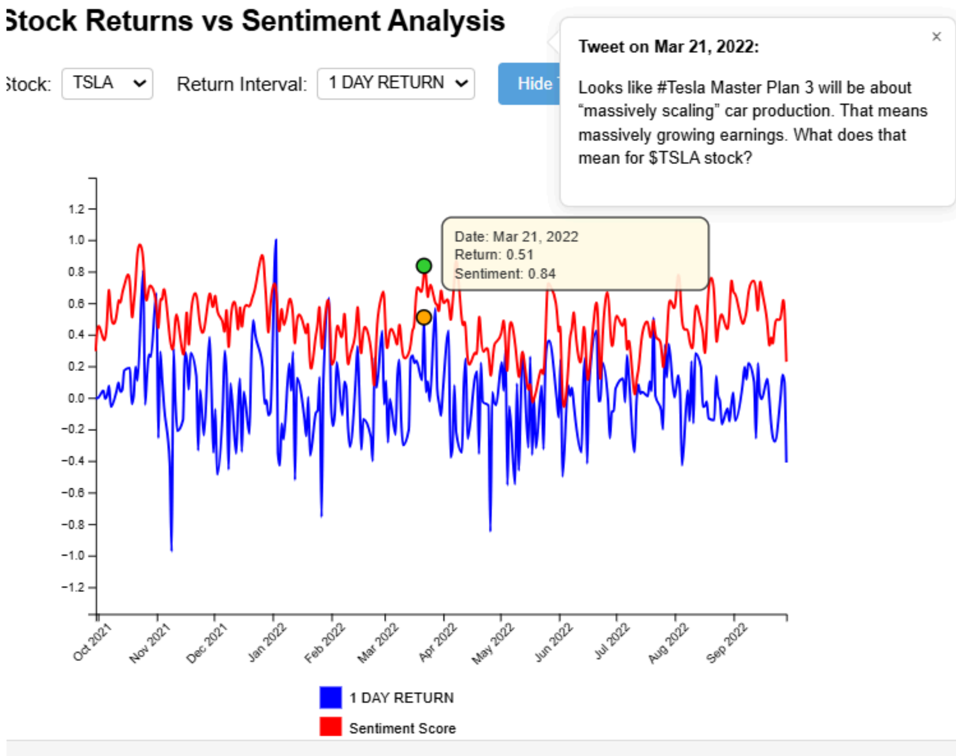
After:



3. Tweets as Data Points – Ignored vs Integrated

- **Alternative Explored:**
  Initially, we did not include individual tweets in the visualizations due to data clutter and integration complexity.
- **Problem Faced:**
  Our reviewers and testers were eager to understand what kinds of tweets were driving stock sentiment. The story lacked human context without tweet samples.
- **Design Decision Made:**
  We identified and integrated the most impactful tweets (based on sentiment scores) directly into the graph. When users hover over a stock's data point, the corresponding tweet appears, with a toggle to hide or show tweets.
- **Reasoning:**
  Since the project focused on social media influence, it was crucial to show real examples. This bridged the gap between raw sentiment scores and real-world signals, allowing users to correlate tweet tone with market reactions visually.

Below is the screenshot representing the real-time tweets displayed:



Finally, we shifted to a scrollable, interactive Svelte website, with real-time animation, incremental data reveals, and clear alignment of tweets and charts. This approach turned our findings into a “Twitter-thread” like experience where users learn in increments.

Evaluation

To assess the effectiveness and clarity of our interactive website, we conducted a small-scale usability evaluation involving three participants unfamiliar with the project.

Participants

- **Demographics**: Two graduate students and one undergraduate student.
- **Background**: All from non-finance domains to represent general users unfamiliar with stock sentiment analysis.

Evaluation Methodology

1. **Initial Exposure**
   Participants were asked to navigate the website independently, without any background or instructions. We then collected their first impressions and asked two open-ended questions:
    - *“What do you think this project is about?”*

    - *"What is one insight or finding that stood out to you?"*
2. **Contextual Explanation**
   After the first pass, we explained the core ideas of the project stocks, tweets, sentiment, and predictive relationships to the participants.
3. **Guided Evaluation**
   With context in place, we posed follow-up evaluation questions:
    - *"Were you able to detect the correlation between tweets and stock movements?"*
    - *"Did the visualizations feel self-explanatory and engaging?"*

Findings and Observations

Evaluation Criteria	**Observations**
Clarity of Purpose	All participants correctly identified the project as analyzing the influence of social media sentiment on stock prices.
Memorable Insight	Two users remembered the *lag effect* between tweets and stock reactions. One recalled the *causality patterns*.
Graph Comprehension	Participants found the visualizations intuitive and informative. However, they preferred slower transitions during sentiment trend animations.
User Engagement	All three reported that the dropdown-based stock selection and tweet display added a layer of interactivity that made them curious to explore more.
Suggestions for Improvement	One user suggested adjusting animation speed in sentiment graphs to allow better focus on changes and transitions.

The evaluation affirmed that even for users without domain expertise, our project effectively communicated its key message. The visual storytelling, stock selection interactivity, and tweet integration helped translate a complex concept into an engaging, digestible experience. Going forward, we will fine-tune animation pacing and consider adding brief tooltips or onboarding cues to support first-time users in exploring the data more comfortably.

Conclusion:

After a semester of learning, brainstorming, identifying the right datasets, building insightful analyses, crafting an interactive webpage, responding to peer feedback, debugging, and conducting user evaluations, we have reached a compelling realization:

Social media sentiment is no longer background noise, it is a measurable force actively shaping market dynamics.

Our project uncovered clear evidence that online emotion does not simply react to stock price movement; it often *leads* it. By analyzing tweets, tagging sentiment, and mapping it to stock behavior, we consistently observed short-term predictive patterns. These signals are not theoretical, they are visible, tangible, and actionable.

In an era where news spreads in 280 characters and market shifts can be sparked by a single viral post, *sentiment is the new signal.* Our analysis shows that the crowd does have a voice and sometimes, it speaks before the market does. In the world of stocks, emotion is not just a reflection, *it is a prediction.*

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