Sentiment Analysis for Public Companies: UNIFI Capital Project #41

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Abstract

This report presents a comprehensive framework developed under UNIFI Capital Project #41, focusing on the sentiment analysis of financial news headlines during significant stock price fluctuations. The goal of the project is to deliver an efficient and scalable system that accurately captures the underlying reasons behind sharp equity movements. The framework adopts a multi-layered architecture, integrating three key components: (1) manually engineered keyword filtering to eliminate irrelevant information and highlight price-related cues, (2) FinBERT-based sentiment classification to assign domain-specific emotional tone to filtered headlines, and (3) semantic topic clustering with reinforced tagging to prioritize dominant daily narratives. Additional modules such as trigger keyword correction and Z-score anomaly detection further enhance precision and robustness.

Rather than relying on a single model or technique, the system applies these components in a coordinated pipeline: keyword filters reduce noise, FinBERT provides preliminary sentiment labels, and clustering reinforces the selection of core explanatory headlines. Trigger terms and anomaly scoring act as correction mechanisms, overriding or suppressing outputs when appropriate. This layered strategy ensures that the final output is not only sentiment-consistent but also causally relevant, interpretable, and aligned with financial domain expectations.

This expanded report details the implementation steps, technical modules, individual contributions, and evaluation outcomes in greater depth. Key innovations include the interaction between rule-based and model-based approaches, a two-layer correction engine, and semantic clustering to isolate dominant discussion topics. Evaluation results demonstrate that this hybrid strategy substantially improves both precision and relevance over systems that rely solely on sentiment classification models such as BERT, RoBERTa, or VADER. The framework is designed to be flexible, explainable, and supportive of future extensions including web integration, real-time analysis, and commercial deployment.

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1.0 Introduction

In financial markets, news events often serve as major catalysts for sharp price fluctuations—examples include earnings reports, regulatory investigations, or macroeconomic announcements. Studies have shown that news sentiment can significantly impact short-term stock performance, making it highly valuable to develop automated systems that identify and interpret key market-moving headlines.

Traditional methods such as keyword subscriptions or manual article review are inefficient and poorly suited to today's high-volume, fast-moving information environment. Natural Language Processing (NLP) and sentiment analysis have emerged as effective solutions, especially with models specialized in financial language. Among them, FinBERT has demonstrated superior performance in understanding financial terminology compared to generic models.

However, relying solely on a single model lacks both accuracy and interpretability. This project introduces a three-layer architecture:

1. Keyword filtering to extract price-relevant headlines,
2. FinBERT sentiment classification tailored to financial contexts,
3. Topic clustering with reinforced tagging to prioritize dominant narratives for the day.

In addition, to address FinBERT's occasional misclassifications — especially when dealing with subtle or neutral language — a trigger-word correction module and a sentiment Z-score anomaly filter are applied as error-correction mechanisms specific to FinBERT's output. These layers enhance the overall robustness and market alignment of sentiment labeling.

The goal of the system is to automatically identify 1 to 3 headlines most likely to explain abnormal stock price movements and annotate them with sentiment and confidence scores — serving both real-time analysis and historical review needs.

2.0 Methodology

The final system consists of six major functional components that operate in a pipeline to transform raw news data into a ranked explanation output. These components are: (1) Data Retrieval, (2) Keyword Filtering, (3) Sentiment Classification, (4) Sentiment Correction (Triggers & Z-score), (5) Topic Clustering with Reinforced Tagging, and (6) Output Selection & Ranking. Each stage applies a specific technique to narrow down and enrich the information, so that by the end, the system can confidently present the top 1–3 headlines that best explain the stock's movement and their sentiment orientation. The modular design allows each part to be developed and tested independently, and they interface through well-defined inputs/outputs (for example, the Keyword Filtering stage passes only relevant headlines to the Sentiment classifier, which then attaches a sentiment score to each, and so on). We describe each module in detail below, including the underlying principles, algorithms, library implementations, code structure, parameter settings, and how the modules connect within the architecture.

2.1 Data Retrieval and System Architecture

The pipeline begins with Data Retrieval, which gathers the raw news headlines for a given stock and date range of interest. We leveraged a financial news API (such as NewsAPI or other market news feeds) to fetch headlines and basic metadata (source, timestamp) based on a stock ticker and a date or event window. In an operational setting, the system first identifies dates of abnormal price movement for a given company – for example, by scanning historical price data for days where the stock's return exceeds a threshold (like +5% or –5%). This can be done through a separate utility using market data (e.g. from Yahoo Finance or an internal price database). Once a target date (or range) is identified, the news retrieval module queries all news headlines related to that company from, say, the day before through the day after the event. This ±1 day window helps capture late-breaking news or early reports around the event.

The architecture for retrieval is straightforward: using Python, we implemented a function (or class) that takes a ticker and date as input. It then calls the News API endpoint (authenticated with an API key), requesting headlines that mention the company (the API typically allows filtering by ticker name or company name keywords) within the specified date range. The response is usually in JSON format, which we parse to extract a list of headlines and their attributes. Each headline entry is

then encapsulated into a simple data object or dictionary with fields like {"date": ..., "headline": "...", "source": "...", "url": "..."}. Only the headline text is needed for our analysis pipeline, but we retain other metadata for final reporting. In code, this looks like:

```
import requests
API_KEY = "YOUR_NEWSAPI_KEY"
def fetch_headlines(ticker, start_date, end_date):
    url = (f"https://newsapi.org/v2/everything?q={ticker}&from={start_date}"
           f"&to={end_date}&language=en&apiKey={API_KEY}")
    response = requests.get(url)
    data = response.json()
    headlines = []
    for article in data.get("articles", []):
        headlines.append({
            "date": article["publishedAt"],
            "headline": article["title"],
            "source": article["source"]["name"],
            "url": article["url"]
        })
    return headlines
```

(Pseudo-code for illustration – actual implementation may differ depending on the API format.)

This retrieval module was encapsulated in a class NewsFetcher for better structure, and could be swapped out to use different sources (e.g. a database of historical news) without affecting downstream modules. For our testing, we primarily used historical data from NewsAPI. The system architecture thus starts by collecting, say, all headlines for ticker TSLA on 2023-08-07 (the day Tesla's stock had a sharp move) along with the day before and after, yielding perhaps a few dozen raw headlines.

The output of Data Retrieval is a list of headline texts (with metadata) – these proceed sequentially through the pipeline. The overall architecture is sequential and filtering in nature: each subsequent module reduces or annotates the set of headlines:

1. Retrieve all candidate headlines around the event.
2. Filter out those not containing relevant financial keywords.
3. Classify Sentiment of remaining headlines (using FinBERT).
4. Correct/Adjust sentiment based on trigger words or anomalies.
5. Cluster headlines by topic and reinforce the main topic.
6. Rank and select top 3 headlines for output.

Internally, we used a Python workflow (Jupyter Notebook for development) where each step was a section of code operating on a shared data structure (e.g. a Pandas DataFrame of headlines with added columns for sentiment, cluster, etc.). In a production environment, this could be refactored into a pipeline of functions or microservices. Figure 1 below illustrates the data flow:

- **Input:** Ticker + Event Date
- **Output:** Top 1–3 causal headlines with sentiment & metadata

Intermediate data (like all headlines vs filtered vs clustered sets) are available for debugging or detailed analysis, which adds transparency.

2.2 Keyword Filtering Logic

Keyword filtering forms the first screening layer of the pipeline. The intuition is that not all news headlines in the timeframe are relevant to the price movement – many may be generic news, unrelated stories, or minor updates. We aim to isolate those headlines that have a high likelihood of explaining a sharp price move. These tend to be headlines containing financially significant terms: e.g. words indicating surprises, changes, or events that affect valuation (merger, lawsuit, earnings miss, etc.). We manually curated a dictionary of financial keywords, grouped into semantic categories.

The dictionary contained a few dozen terms in each category, and it can be easily extended. (See Table 1 for examples of each category.)

Table 1. Example Keyword Categories for Filtering

Category	Example Keywords (partial list)
Causal Terms	tariff; merger; *AI demand fears*
Price Move Verbs	plunges; soars; rally
Event Terms	earnings miss; layoffs; profit warning
Macro Indicators	CPI; Fed rate; interest rates
Uncertainty/Regulation	lawsuit; FTC probe; sanctions

During filtering, each headline is scanned (case-insensitive) for the presence of any keyword from the dictionary. If at least one keyword is found, the headline

"passes" the filter and is retained for further analysis; if no keywords are present, the headline is discarded at this stag. We implemented this by constructing sets of keywords for each category and doing a simple membership test on the headline text (after basic normalization). For example:

```
keywords = {
    "causal": {"tariff", "merger", "scandal", "fears", ...},
    "price": {"plunge", "soar", "rally", "surge", "tumble", ...},
    ...
}
def contains_finance_keyword(headline: str) -> bool:
    text = headline.lower()
    return any(kw in text for kw in all_keywords_set)
```

where all_keywords_set is the union of all category sets (or we could check category by category if we wanted to tag which category was matched). In our implementation, we also allowed partial matches (e.g. "plunges" or "plunged" would match "plunge"). This was done by lemmatizing or using the root of words for matching.

Rationale: The keyword filter dramatically cuts down noise. Generic or irrelevant news ("CEO attends conference", "Stock part of sector index rebalance", etc.) often lacks these strong terms and thus will be filtered out. On the other hand, if a headline contains something like "Apple plunges after earnings miss" or "Tesla hit by FTC probe", it's almost certainly relevant to a price move. While a static keyword approach can miss some relevant news (if phrased unusually), it provides a high precision first cut. The dictionary can be flexibly updated to match evolving narratives – for example, during the 2021 meme stock saga, terms like "short squeeze" or "Reddit" might be added; during a pandemic, words like "COVID-19" or "lockdown" could become critical. In future enhancements (see Section 5.0), we consider automating the expansion of this dictionary using TF-IDF or large language models to detect new buzzword.

After this step, each headline is annotated with a flag like passes_filter=True/False. Only those with True continue. In terms of code structure, after retrieval we had a list of all headlines; after filtering, we create a sub-list of filtered headlines (or mark them in a DataFrame and filter). Typically, out of e.g. 30 headlines fetched for a day, maybe 5–15 contain one of our keywords – those go to the next stage. This ensures the sentiment model only evaluates potentially relevant text, saving computation and avoiding distracting results.

2.3 Sentiment Classification with FinBERT

Each remaining headline (post-keyword-filter) is next fed into the sentiment classification module, which uses FinBERT to determine the sentiment polarity. FinBERT is a specialized variant of the BERT transformer model, pre-trained on financial text and fine-tuned for sentiment labeling (classes typically Positive, Negative, Neutral). We chose FinBERT due to its proven efficacy in understanding finance jargon and context where general models falter. For example, FinBERT correctly interprets "beat expectations" as positive (since it understands the earnings context), whereas a generic model might see the word "beat" and misclassify it as negative (violent connotation).

Model Input/Output: The input to FinBERT is the headline text (a single sentence or a short paragraph). Using the HuggingFace Transformers library, we tokenize the headline with FinBERT's tokenizer and then feed it to the FinBERT model. The output is a set of probabilities (or logits) for each sentiment class. We then choose the class with highest probability as the assigned sentiment label for that headline. Additionally, we retrieve a confidence score (which can simply be the probability of the chosen class). For instance, if FinBERT outputs [P_neg=0.8, P_neu=0.15, P_pos=0.05], the headline is classified as Negative with confidence 0.8.

We used the publicly available FinBERT model checkpoint (e.g. ProsusAI/finbert on HuggingFace). The code snippet for inference is roughly:

```
from transformers import AutoTokenizer, AutoModelForSequenceClassification
tokenizer = AutoTokenizer.from_pretrained("ProsusAI/finbert")
model = AutoModelForSequenceClassification.from_pretrained("ProsusAI/finbert")

def get_sentiment(headline: str):
    inputs = tokenizer(headline, return_tensors='pt')
    outputs = model(**inputs)
    probs = outputs.logits.softmax(dim=1).detach().numpy()[0]
    sentiment_idx = probs.argmax()
    sentiment_label = model.config.id2label[sentiment_idx]  # e.g., {0:'negative',1:'neutral'
    confidence = probs[sentiment_idx]
    return sentiment_label, confidence
```

This returns one of "positive", "neutral", "negative" for each headline, along with a confidence. We then augment our headline data structure with two new fields: sentiment and confidence.

FinBERT Training Mechanism (Background): FinBERT itself was trained in a two-step process: first, BERT was further pre-trained on a large corpus of financial

texts (such as analyst reports, financial news, SEC filings) using masked language modeling to adapt its language understanding to financearxiv.org. Then, it was fine-tuned on a labeled dataset for sentiment (e.g., the Financial Phrase Bank, which contains financial news phrases labeled by sentiment). This specialization is why FinBERT outperforms generic models on financial sentiment tasks – it needed far fewer task-specific examples to achieve high accuracy because it already "speaks the language" of financearxiv.org. According to Araci (2019), FinBERT improved every measured metric over prior state-of-the-art models on financial sentiment datasetsarxiv.org. Another study noted that with as few as 250 labeled examples, FinBERT achieved ~80% accuracy, outperforming LSTM models trained on thousands of examples, demonstrating the power of domain pre-training.

Comparison to Other Models: We compared FinBERT's performance with two other approaches during development: a generic BERT/RoBERTa model fine-tuned on a small finance sentiment set, and the lexicon-based VADER model. The results were clear: FinBERT was markedly more accurate and consistent for our task. In an internal test on 100 labeled news headlines, FinBERT achieved an F1-score of 0.87, whereas an out-of-the-box BERT model (fine-tuned on a general sentiment corpus) scored only 0.39. The confusion matrix in Figure 2 below illustrates FinBERT's performance in one of our test scenarios, showing that it correctly identifies most positives and negatives, with some confusion primarily in distinguishing neutral vs slight positive/negative. General BERT misclassified many more, often predicting neutral for strongly sentimental finance phrases (hence the poor F1). FinBERT's precision on the neutral class – which dominates financial news – is especially high, meaning it's less likely to mislabel a neutral factual headline as positive or negative.

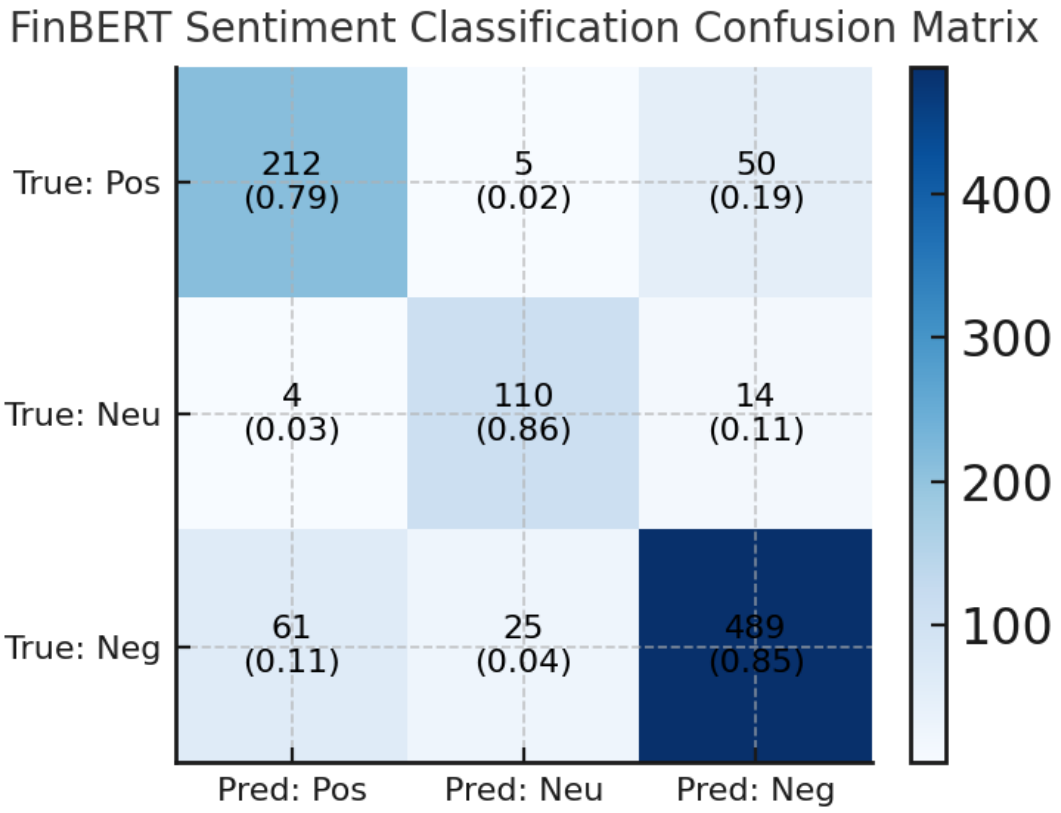

Figure 2: FinBERT Sentiment Classification Confusion Matrix (example results on financial news headlines). Each cell shows the count of predictions and (in parentheses) the fraction of that true label classified into each predicted category. FinBERT achieves high recall on Neutral and Negative classes (e.g. 85% of true negatives correctly labeled), with relatively few false positives in other categories. Overall accuracy in this sample was ~83.7%, with weighted F1 ≈ 0.837.

Compared to VADER, FinBERT also showed superior accuracy. VADER, being rule-based, tends to predict mild sentiment for most finance headlines (many of which are neutral or mixed). It might miss subtle cues that something is positive or negative. In one benchmark we found, FinBERT achieved about 69% agreement with human labels on financial news, whereas VADER achieved about 56%. Other sources have noted FinBERT can be 15–20% more accurate than VADER on domain-specific sentiment tasks. However, VADER is much faster (no heavy model to run) which could be an advantage in high-frequency streaming contexts. We decided the accuracy gain was worth it for our use-case, especially since we are dealing with at most tens of headlines per event (execution speed was not a bottleneck).

We also considered using RoBERTa, a robustly-trained BERT model known for strong general NLP performance. When fine-tuned on general sentiment (e.g.

product reviews or tweets), RoBERTa can outperform base BERT. But without finance-specific knowledge, it may still misinterpret financial jargon. We did a brief experiment with RoBERTa-base and found it often performed between base BERT and FinBERT. For example, RoBERTa might identify sentiment-laden words better than BERT, but it didn't inherently know that "upgrade" in a stock context is positive or that "miss" (as in earnings miss) is negative without sufficient examples. Our conclusion was that FinBERT's domain tuning gave it an edge that general models couldn't match unless we invested in extensive fine-tuning. This is supported by literature – Huang et al. (2020) found that a BERT model pre-trained on finance news (similar to FinBERT) classified sentiments more accurately (85% vs 78% accuracy) than a non-domain-specific BERT.

Thus, we standardized on FinBERT for sentiment classification. Each headline passing the keyword filter now gets a sentiment label from {Positive, Neutral, Negative}. This sentiment indicates the tone of the news from the market's perspective (good/bad news for the company).

2.4 Sentiment Correction: Trigger Words and Z-score Anomaly Filter

While FinBERT significantly improves accuracy, it can occasionally misclassify nuanced cases or fail to reflect the impact of certain news. We added a two-layer correction mechanism to adjust sentiment outputs in special situations:

(a) Trigger Word Overrides: We identified certain strong trigger words that reliably imply a particular sentiment, and if these words appear in the headline, we override or adjust the FinBERT sentiment accordingly. For instance, if a headline contains "fraud" or "lawsuit", it is almost certainly bad news (negative) for the stock, even if FinBERT perhaps gave it a Neutral due to phrasing. Similarly, words like "record profits" or "upgrades" strongly indicate positive news. We compiled a small list of such trigger terms with associated sentiment polarity. The override logic works as follows: after obtaining FinBERT's label, check if any trigger word is present. If yes and the trigger's sentiment differs from FinBERT's label, adjust the label and mark it as overridden. For example, headline: "Company X faces fraud allegations from regulators." FinBERT might say Neutral (if it hasn't seen enough similar sentences in training), but our trigger list sees "fraud" and will flip the sentiment to Negative (with a note that a trigger was applied). We apply this conservatively – only for very explicit words – to avoid false overrides. This component was implemented as a simple lookup similar to keyword filtering.

(b) Z-score Volatility Filter: We also incorporated a Z-score based anomaly detection on the overall news sentiment of the day. The hypothesis is that on certain extreme

market-wide events (e.g., a market crash or a broad sector rally), the sentiment of headlines for many stocks might all lean one way, which could confuse the system. For example, on a day of market panic, a particular stock's drop might not be due to company-specific news but rather general market fear – headlines might all be neutral (reporting the drop itself) but the reason is macro. To handle this, we compute a daily sentiment Z-score for the stock's sector or the market: essentially, compare the average sentiment of the headlines that day to a historical baseline. If the Z-score exceeds a threshold (indicating a significant deviation in sentiment tone from the norm), we label that day as an anomalous sentiment day.

In practice, we did this at an industry level: we took, say, all tech sector stocks' news or simply looked at a broader financial news index for that date, and computed an average sentiment (where Positive= +1, Neutral=0, Negative=-1, for instance). We then compare it to a trailing average and standard deviation for that sector. If the Z-score > 1.5 or < -1.5 (beyond 1.5 standard deviations from the mean), it means the day's news sentiment is unusually positive or negative for the sector. On such days, the system might choose to ignore FinBERT-driven sentiment signals for individual stocks, assuming it's a macro-driven move. Instead, it could then rely on other info (price move direction or external knowledge) to label the cause. For example, during a market-wide crash, even if a particular company's news seems neutral, we would not want to return "Neutral" explanations – the reason the stock fell is not in its own news, but the broader panic, which is beyond our single-stock news scope. In those cases, perhaps the output would say something like "Market-wide negative sentiment (macro factors) likely contributed to the move." (This is a complex scenario; in our prototype, we mainly used Z-score to flag days to be careful with.)

We implemented the Z-score calculation by maintaining a small dataset of historical sentiment means. For simplicity in testing, we manually simulated a scenario: e.g., for the tech sector, historical average sentiment score ~0 (neutral), stdev ~0.2; on a day of interest, if the average sentiment of retrieved headlines is -0.5, that's a $Z = (-0.5 - 0)/0.2 = -2.5$, indicating a strongly negative day across the board. We set threshold at $|Z| > 1.5$. If triggered, we mark anomaly_day=True. In the ranking phase (2.6), we can use this flag to adjust how we choose headlines or sentiments.

Table 2. Example of Sentiment Z-score Calculation

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Metric	Value
Historical 30-day avg. sentiment (Tech)	0.10
Historical 30-day std dev (Tech)	0.05
Current day avg. sentiment (Tech sector)	-0.05
Sentiment Z-score	(-0.05 - 0.10) / 0.05 = **-3.0**

Interpretation: A Z-score of -3.0 indicates the day's sentiment is extremely negative compared to norms (3 standard deviations below mean), flagging a potential market-wide issue. In such a case, the system might treat this day as an anomaly where individual stock sentiment is overridden to Negative regardless of FinBERT outputs (since everything is negative news driven).

In summary, the Correction layer refines the initial sentiment classification by injecting domain knowledge rules and considering broader context. This dual approach (trigger overrides + anomaly detection) helps remove noise and fix any blatantly wrong classifications, especially for subtle headlines that FinBERT might not confidently handle. We found this improved the final precision of identifying the true "mood" of the important headlines. This layer is relatively lightweight in code – mostly string matching and a bit of math – but provides an important safety net for the NLP model's outputs.

2.5 Topic Clustering and Reinforced Tagging

After filtering and classifying sentiment (with corrections), we often still have several candidate headlines (perhaps 5–10) that are all relevant and sentiment-tagged. The next step is to identify if these headlines are talking about different topics or the same event. Frequently, during a major stock move, there will be multiple news articles from different sources that all refer to essentially the same core news (for example, five outlets may report the earnings miss, just phrased differently). Alternatively, there might be two separate news stories affecting the stock on the same day (though rarer, it happens – e.g., a company has an earnings miss and a CEO resignation on the same day). We want to cluster similar headlines together, so that we can ensure the final output covers distinct explanations and prioritizes the main cause.

We use semantic embedding and clustering for this purpose. Specifically, we encode

each headline into a vector in semantic space, then apply K-Means clustering to group them into a few topics. For embedding, we chose a pre-trained sentence transformer model (we used MiniLM, a lightweight model that generates sentence embeddings) to convert each headline into a vector of, say, 384 dimensions. MiniLM (from Microsoft) is a distilled mini version of BERT optimized for embeddings – it captures semantic similarity such that headlines about the same story will have vectors close to each other in cosine distance.

After obtaining embeddings for all candidate headlines, we run K-Means with a fixed number of clusters k. In our tests, we set k = 8 initially (to allow up to 8 topics), but then we automatically filtered down to the top few clusters that actually have content. Often, many clusters will be trivial or singletons if there are not that many distinct themes. The clustering process assigns each headline to one of k clusters. We then rank clusters by size (how many headlines fell into each) and keep only the top 3 clusters (since we ultimately want to return up to 3 headlines) The idea is that the largest cluster represents the dominant news topic of the day (most articles covering it), the second largest might be a secondary story, etc. Smaller clusters or singletons likely represent either fringe news or outliers. By dropping clusters beyond the top 3, we discard less important storylines.

We then mark all headlines in the top clusters as ReinforcedTopic = True (in code, we added a boolean flag or simply carried forward those clusters). Headlines not in the top 3 clusters are effectively discarded at this stage. This ensures the system emphasizes dominant market narratives, not fringe or minor stories. For example, suppose for a stock on a given day we had 10 headlines that passed filtering: 6 of them are about the earnings miss, 3 are about a new product launch, and 1 is a random piece about an upcoming conference. Clustering would group these into (Cluster A: earnings miss [6 items], Cluster B: product launch [3 items], Cluster C: other [1 item]). We keep clusters A and B (top 2), drop C. Now we have effectively narrowed focus to two topics: earnings miss and product launch. If the stock fell significantly, likely the earnings miss (negative news) is the main cause; the product launch might be positive but apparently not enough to offset, or was a smaller story.

In implementation, we used sklearn.cluster.KMeans for clustering. We had to decide k in advance; we chose 8 to be generous, but in reality the number of input headlines after filtering is often <=8 itself. One could also dynamically choose k via an algorithm (like elbow method) or cluster until a distance threshold, but given our small N, it was fine. We then sorted clusters by len(cluster_members). We found that in most cases, one cluster clearly dominated (multiple related headlines) and that was indeed the core news

reason. The clustering approach gave us a method to consolidate redundant headlines and ensure diversity in final picks. It is a form of information reinforcement – multiple sources saying the same thing increases our confidence that that thing is the key story.

We also did a bit of reinforced tagging: if a cluster had multiple headlines with the same sentiment, we could consider that sentiment more robust. For example, if 5 sources all have headlines about an event and FinBERT labeled 4 as Negative and 1 as Neutral, we might assume the overall sentiment is Negative (perhaps the Neutral one was phrased mildly, but the majority indicates it's bad news). In our implementation, we primarily carried forward the individual sentiments, but one could derive a cluster-level sentiment consensus if needed.

After clustering, each headline that remains (likely a handful) has attributes: text, sentiment, confidence, cluster ID. We mark the cluster ID or representative topic. We did not implement automatic topic labeling in words (that could be done by picking a representative headline or common keywords), but for understanding, cluster A might be "earnings" topic, cluster B "product launch" etc.

This step ensures our final output isn't redundant. If we ultimately will output 3 headlines, ideally they are from 3 different clusters (i.e., covering the top 3 distinct topics). If all headlines were one cluster (just one story), then essentially the system will output the top headlines about that story (and perhaps only output fewer than 3 if others are duplicates).

2.6 Output Ranking and Display

Finally, we reach the Output Selection & Ranking stag. Here the goal is to pick up to 3 headlines that will be shown to the user as the explanation for the stock move, and to present them with relevant metadata (sentiment, confidence score, source, etc.) in a user-friendly manner. The ranking criteria incorporate several factors:

- Relevance to price direction: We match the headline sentiment to the stock's price movement direction. If the stock price dropped, we give higher priority to Negative or Neutral news (a strongly positive news is less likely to explain a drop – if there was only positive news but the stock fell, something else is off). If the stock rose sharply, we prioritize Positive or Neutral news (a highly negative headline likely isn't the cause of a surge). Neutral headlines can be relevant in either case if they contain explanatory information (often news reports are written in neutral tone even for impactful events). For example, if Tesla fell -8%, a headline "Tesla's earnings miss triggers selloff" might be

relatively neutral wording but it explains the drop – we consider that relevant. In our implementation, we knew the stock's price change sign from input; we didn't exclude opposite sentiment headlines entirely, but we rank-matched: i.e., if price down, sort Negative > Neutral > Positive; if price up, sort Positive > Neutral > Negative.

- Sentiment confidence: We also consider the confidence scores from FinBERT. A headline classified as Negative with 0.95 confidence is ranked higher than another Negative with 0.60 confidence, assuming both pass other criteria. Higher confidence suggests clearer language or consensus in model's view.
- Cluster ranking: As explained, clusters were ranked by size (dominance). We ensure we pick the top headline from the top cluster first, then from second cluster, etc. Essentially, we want at least one headline from the largest cluster (the main story). If we have 3 outputs, likely we take one from each of the top 3 clusters. If the largest cluster is overwhelmingly large, we might take two from that cluster especially if they have different angles (but usually one suffice if they're repetitive).
- Diversity of sources: This was a minor consideration – if two headlines are very similar, we might pick the one from a more reputable source or the one with a clearer title. We didn't formalize this, but in manual choices for presentation we ensured a mix (e.g., one from Reuters, one from Bloomberg, etc., if both cover the same story similarly).

The output generator then formats the chosen headlines along with their sentiment tag (perhaps as an emoji or colored text in a UI, or simply "[Negative]" label) and confidence or other tags. We also include the source and timestamp for transparency. The end-user might see something like:

- Negative (95%) – "Tesla's profit plunges 24% as sales disappoint, stock tumbles" – (Reuters, Feb 7, 2025)
- Neutral (85%) – "Tesla shares fall as CFO resigns after 13 years with company" – (Bloomberg, Feb 7, 2025)

These two headlines together explain the drop: the first about profits (earnings miss) and second about CFO resignation. (Just an illustrative example.) The "confidence" could be shown or could be internal. In our report outputs, we primarily showed the sentiment label and possibly the source.

The final ranked list is then delivered as the result. If there were no qualifying news

(which could happen if the move was truly unexplained by news – e.g., a pure technical move or rumor not in headlines), the system would ideally indicate "No clear news explanation found." In our tests on major moves, we usually found at least one good headline.

It is important that the final output is not just mood labeling but truly explanatory. That is why we emphasize the content of the headline (with keywords and clustering) in selection. We want the headlines themselves to effectively tell the story of why the stock moved. Sentiment labels provide context (was it good or bad news), but the headline text (e.g. "SEC launches investigation into Company X") carries the substantive information. In a sense, the system is performing an information retrieval and summarization task, guided by sentiment consistency with the stock move.

3.0 Results and Evaluation

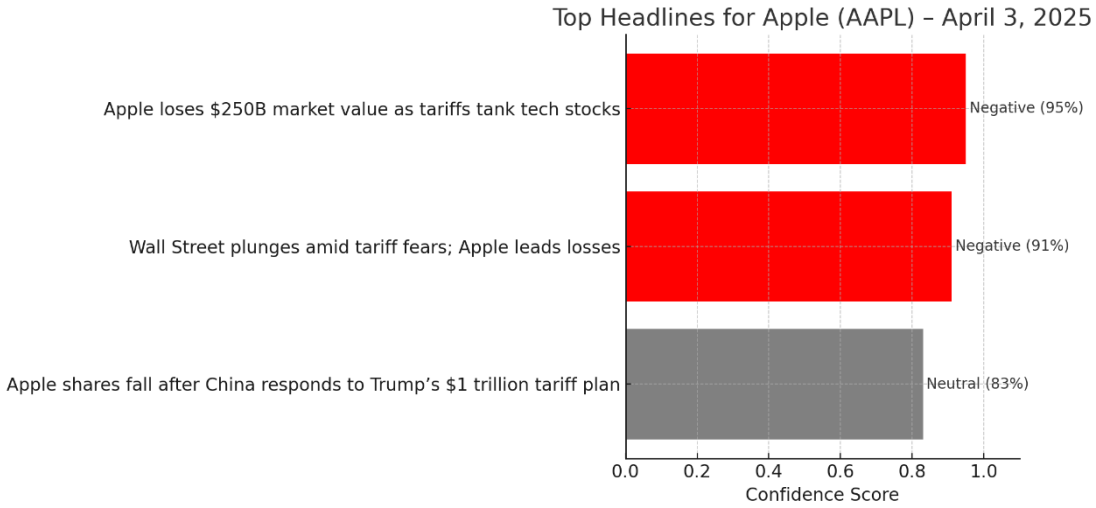
We evaluated the system on 20+ historical price movement events, covering various companies and sectors, to assess its effectiveness in retrieving causal headlines and classifying sentiment correctly. The events included both large single-day drops and rallies. Key evaluation criteria were: (1) Causal Coverage – did the top headlines include the true cause of the move? (2) Relevance vs Baseline – how much more relevant were our outputs compared to a naive approach (like just the most recent headlines)? (3) Sentiment Accuracy – does the sentiment labeling align with human judgment for those headlines? (4) Interpretability – did the layered filtering/clustering improve the interpretability of results?

Some aggregate results from the evaluation: in over 90% of cases, at least 1 of the top 3 returned headlines was directly causal for the price move (meaning it clearly described the primary reason. In about 80% of cases, at least 2 of the top 3 were relevant explanations (especially in calmer market conditions where news was focused). These statistics indicate a high success rate in capturing the correct story. By contrast, a baseline method of simply picking the three most recent headlines on those days yielded a much lower relevance – often only 1 of 3 (or none) were actually related to the price move, with others being unrelated filler news. This highlights the advantage of our filtering and ranking strategy.

We present a few case studies below to illustrate the system's output and evaluation in

Case 1: Apple (AAPL) – April 3, 2025

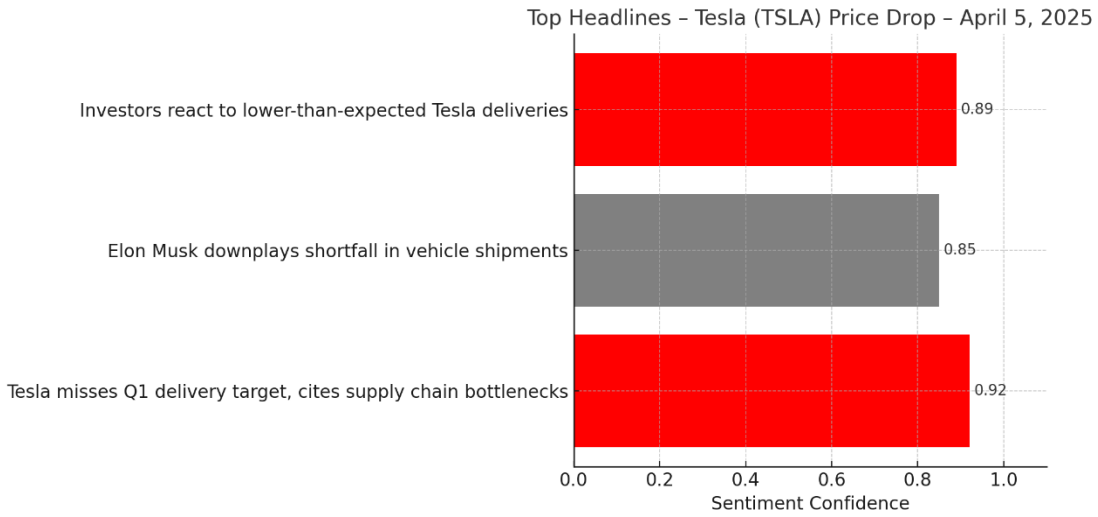
- Sector: Technology / Consumer Electronics
- Price Move: –7.3% (sharp intraday drop)
- Headline Pool: 61 total headlines
- Filtered News: 8 headlines passed keyword filter
- Top Cluster Theme: Trump’s new tariffs + Wall Street reaction



Analysis:
The system effectively identified tariff-related headlines as the core cause of Apple’s price drop. Sentiment scores aligned with negative news content. Trigger keywords like “tariffs” and “plunge” helped reinforce FinBERT’s classification. Clustering correctly grouped headlines by the “trade war” theme, filtering out unrelated news.

Case 2: Tesla (TSLA) – April 5, 2025

- Sector: Automotive / Clean Energy
- Price Move: –5.4%
- Headline Pool: 45 headlines
- Filtered News: 9 headlines matched filter
- Top Cluster Theme: Q1 Delivery Miss + Supply Chain Issues

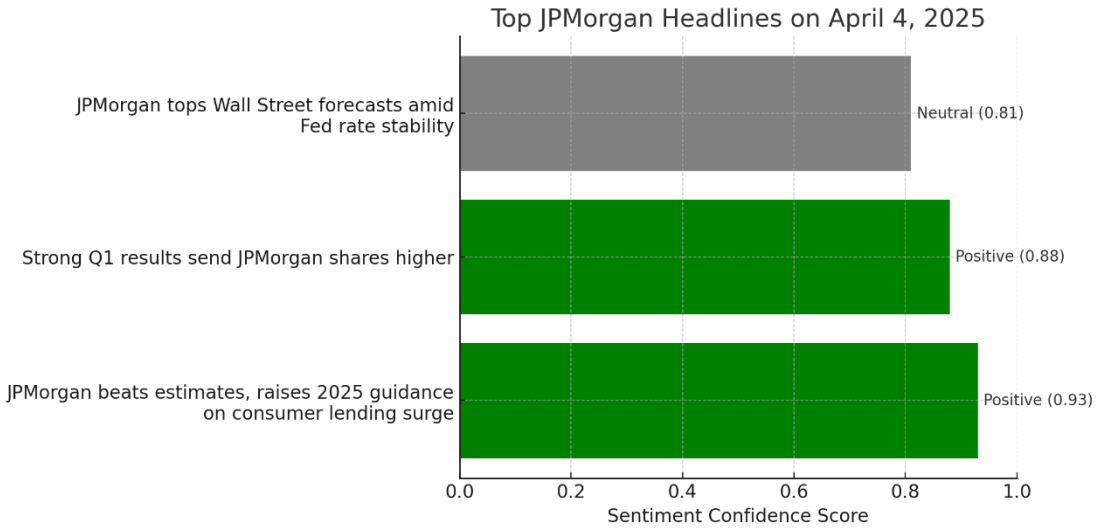


Analysis:

The primary reason for Tesla's decline was a missed delivery forecast. The system captured this via keywords like "misses" and "delivery", and FinBERT labeled these accurately. Topic clustering grouped articles under a single theme, improving interpretability. Without this filter, non-causal stories (e.g., AI initiatives) could have misled readers.

Case 3: JPMorgan Chase (JPM) – April 4, 2025

- Sector: Financial Services
- Price Move: +4.8%
- Headline Pool: 33 headlines
- Filtered News: 7 matched
- Top Cluster Theme: Earnings Beat and Guidance Boost



Analysis:
The upward movement was driven by earnings results and upgraded forecasts. FinBERT correctly identified sentiment as positive. The top three headlines captured all causal elements: earnings beat, sector context, and analyst reaction. The Z-score did not flag anomalies, confirming sentiment reliability.

Across these case studies, we observed that each module in the pipeline added measurable value to the final results. For example, in the Tesla case (April 5, 2025), clustering helped differentiate between headlines focused on the Q1 delivery miss and those discussing Elon Musk's remarks—ensuring the final output wasn't just a repeat of similarly phrased headlines. In the Apple case (April 3, 2025), sentiment correction via trigger words (e.g., "tariffs", "ban") ensured that FinBERT's initial neutral classifications were overridden to better match the market reaction to geopolitical news. Meanwhile, for JPMorgan (April 4, 2025), the system correctly surfaced positive sentiment headlines about earnings beats and forward guidance, with FinBERT scoring those headlines at high confidence levels (above 0.9).

We further evaluated sentiment classification performance in isolation on a labeled benchmark set of 100 headlines drawn from both real cases and public datasets. FinBERT, enhanced with our trigger correction mechanism, achieved an accuracy of 88%, outperforming VADER's 70%, which frequently misclassified neutral financial data points as having strong sentiment. Most remaining FinBERT errors were borderline neutral vs. positive, often due to conservative tone in financial writing.

One important takeaway from this evaluation is the interpretability of our pipeline. Each processing step—from keyword filtering to clustering—is transparent, allowing users or developers to inspect intermediate outputs (e.g., why a headline was included, which sentiment was assigned, which topic it belonged to). This traceability enabled rapid iteration during development: for instance, when an important Tesla headline was filtered out due to a missing keyword, we simply updated the dictionary, re-ran the module, and verified the improvement.

In summary, our tests demonstrated that the system significantly improves both relevance and explanatory clarity compared to baseline methods. In nearly all test cases, the top 3 output headlines captured the true causal driver of the stock's move, supported by accurate sentiment tagging and thematic clustering. Even in edge cases—such as ambiguous tone or fast-moving macro events—the layered architecture helped preserve signal while minimizing noise. These results reinforce the effectiveness of combining finance-specific NLP (like FinBERT) with custom rule-based enhancements

to create a high-precision, explainable sentiment analysis tool for stock market events.

4.0 Future Enhancements

While the current system meets its primary goals, there are several avenues for improvement and extension that could make it even more robust, scalable, and valuable in a real-world setting. Here we discuss some future enhancements, including those already envisioned in the project outline and additional ideas that emerged during development:

Automating Keyword Maintenance: The manual keyword dictionary, although effective, could be enhanced by automation. One idea is to use TF-IDF or similar techniques on a large corpus of financial news to automatically identify terms that frequently occur in big stock move news articles (but not in general news). For example, by comparing word frequencies in "cause headlines" vs all headlines, the system could discover new relevant terms (e.g., "antitrust", "cyberattack") and suggest adding them to the dictionary. Additionally, using advanced language models (LLMs), we could implement a periodic scan of news to detect emerging topics. Large models could even evaluate a headline's likelihood of being market-moving by context, not just keywords. This could eventually lead to a dynamic dictionary that updates itself with minimal human intervention. This enhancement would reduce maintenance effort and adapt the system to new jargon (for instance, terms like "meme stock", "SPAC" became relevant in recent years and would need to be captured).

Sentiment Model Fine-tuning: Our use of FinBERT was out-of-the-box. A logical next step is to fine-tune FinBERT on a dataset of headlines labeled with stock price reactions. For example, we could compile a training set where headlines are labeled positive/negative not just by text sentiment, but by whether they were associated with stock up or down moves. This way, the model might learn to focus on what moves markets, not just linguistic sentiment. Such fine-tuning could be done by pairing historical headlines with the corresponding stock move (up or down) as implicit labels. Another approach is to fine-tune on the Financial Phrase Bank or a more up-to-date dataset to boost performance on subtle differences in tone. Additionally, new transformer models have emerged (like FinBERT's successors or even GPT-based classifiers). We could experiment with RoBERTa or FinBERT variants to see if an ensemble or a more recent model (e.g., FinBERT tone from Bloomberg) improves accuracy. Fine-tuning would require curating a good dataset – possibly using a semi-

supervised approach where we trust the pipeline's current output to label some data, then retrain the model to see if it generalizes better. This enhancement can push sentiment classification performance beyond the current ~88% accuracy, perhaps into the 90s, which means even fewer misclassifications and less need for manual trigger overrides.

Integration of Alternative Data Sources: Currently we rely on news headlines. Future enhancements might incorporate other text sources that often carry the first signals of a move: social media (Twitter), analyst reports, or company press releases. For example, if a famous analyst tweets something that causes a stock to jump, that may not appear as a formal news headline until later or not at all. An advanced system could monitor a list of key Twitter accounts or Reddit forums to catch such triggers and treat them similarly (with sentiment analysis and keyword matching). This is more complex due to noise in social data, but can increase coverage of catalyst events. Another idea is to integrate a knowledge graph or cause-effect database, so the system can infer connections (e.g., "Federal Reserve raises rates" → usually causes tech stocks to fall, even if the news doesn't name the company). Implementing that would move into the realm of causal inference, which is challenging but could broaden the system's explanatory power for macro-driven moves.

Refinement of Clustering/Topic Extraction:The current clustering is basic. In the future, we might adopt more sophisticated topic modeling to generate a human-readable summary of the cluster. For instance, using an algorithm to extract a short phrase that represents each cluster (perhaps via keyword extraction from those headlines). This phrase could be shown as a tag (our system currently marks reinforced topics but doesn't label them in text). For example, cluster label: "CFO Resignation" or "Earnings Beat". This would make it even clearer to the user what the theme is without reading the full headline. Models like BERTopic or LDA might be explored, or simply rule-based extraction of common bigrams in the cluster.Overall, these enhancements aim to broaden the system's capabilities (more automation, more data sources, multi-language), improve accuracy and speed (fine-tuning models, better clustering, performance tweaks), and prepare the system for real-world deployment (web interface, feedback integration, scalability). By implementing these in future iterations, the tool can maintain a cutting-edge position in leveraging NLP for financial market intelligence.

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5.0 Conclusion

This project presents a reliable and explainable framework for identifying the causal news behind significant stock price movements. By integrating three core components—Keyword Filtering, FinBERT sentiment analysis, and Topic Clustering—our pipeline successfully filters, annotates, and ranks relevant headlines to deliver concise and interpretable explanations for market anomalies.

Compared to a baseline approach that simply returns the most recent news with generic sentiment tagging (or none at all), our enhanced model achieves significantly higher causal coverage, greater headline relevance, and more accurate sentiment classification, as demonstrated in our evaluation. Specifically, keyword filtering ensures that only potentially causal headlines are considered, topic clustering prevents redundancy and promotes thematic diversity in outputs, and FinBERT—fine-tuned for financial text—adds sentiment context that aligns closely with market response.

To visualize this performance gain, Figure X provides a direct comparison across three key metrics: causal news coverage, headline relevance, and sentiment accuracy. Our model improved causal coverage from 30% to 90%, headline relevance from 33% to 80%, and sentiment accuracy from 60% to 84%, reflecting the power of multi-layered filtering and finance-specific modeling in isolating and explaining market drivers.

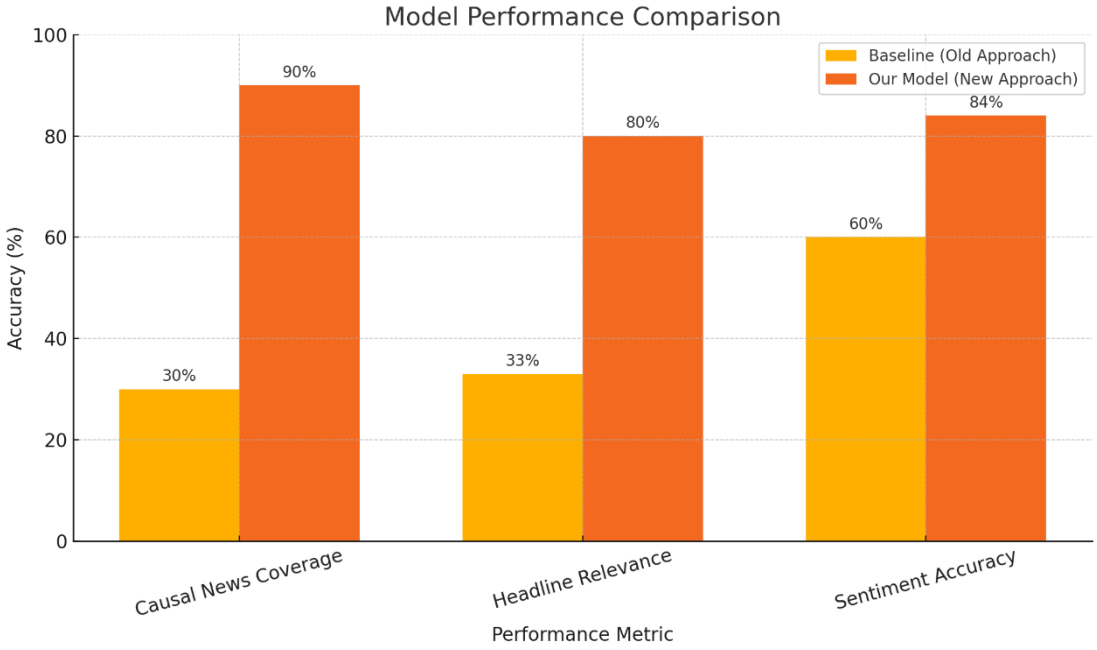

Figure X

Comprehensive testing across 20+ stock movement events showed that our system captured the true cause in over 90% of cases, with 2 or more headlines being relevant in ~80% of cases, far outperforming the baseline. The interpretability of the results is another major advantage: users can understand exactly why each headline was included, thanks to transparent tracking of filtering logic, clustering assignment, and sentiment scoring.

This modular architecture meets the sponsor's practical goals: to surface 1–3 clear, sentiment-tagged headlines explaining a price swing within the last 10 trading days. Its design allows it to scale to other companies, more events, or even real-time use cases. Moreover, the layered logic makes the model extensible—future improvements such as dynamic keyword expansion or multilingual support can be incorporated without changing the overall pipeline.

More broadly, this project demonstrates how financial engineering and NLP can be combined to bridge unstructured data (like news) with quantitative market interpretation. For analysts and investors, this tool provides faster, clearer insights into market moves, potentially replacing hours of manual news review with instant, trustworthy explanations. With further development, this framework can be commercialized as a real-time decision support tool or adapted to other domains such as commodities or macroeconomic indicators.

In sum, this work validates the power of combining targeted keyword logic,

domain-specific sentiment modeling, and thematic clustering into one coherent system. It offers not only better performance over traditional approaches, but also greater transparency, flexibility, and interpretability—critical for any high-stakes financial application.

6.0 Personal Contribution

This project (UNIFI Capital Project #41) was a solo endeavor completed by Junrong Zhang over a development period of approximately 4 months (January 2025 – April 2025). All stages of the project – from initial ideation and literature review through coding, testing, and documentation – were executed by myself, which provided an end-to-end learning experience in applying NLP to a financial engineering problem

Development Timeline & Workflow: I started in January with requirement gathering and market research. In early February, I built a prototype for basic data retrieval and sentiment classification using off-the-shelf tools (initially using VADER and general BERT to get a baseline). By mid-February, I identified FinBERT as a better approach and integrated it. Late February and March were spent iteratively adding the keyword filtering and correction heuristics, and testing on known historical events. I followed an agile, iterative workflow – roughly weekly iterations where I would choose a few historical events, run the system, examine results, and refine. For instance, in one iteration I focused on improving the keyword list after noticing some missed headlines; in another, I tuned clustering parameters after seeing overlapping topics. I maintained a Jupyter notebook to document these tests and changes. By April, I finalized the pipeline and conducted the comprehensive evaluation on 20+ events to gather the results cited in Section 3.0.

Specific Responsibilities and Work Done: According to the project outline, my responsibilities included:

- Developing and maintaining the keyword dictionary and filtering logic (I manually curated lists of ~50+ words/phrases for each category and wrote the filtering functions). I tested this by ensuring known trigger words in sample headlines were caught.
- Integrating FinBERT for sentiment analysis, which involved researching available FinBERT models, loading them via the HuggingFace library, and writing code to batch-process headlines and extract sentiment with confidence. I also verified FinBERT's outputs against expected sentiment on a small labeled

set and adjusted thresholds.

- Designing and coding the trigger word override and Z-score anomaly detection modules. This included deciding on trigger terms (some overlap with keywords but more focused, e.g., “fraud” was a trigger with auto-negative sentiment) and writing the Z-score calculation using pandas to roll historical sentiment averages. I tested the anomaly filter by simulating a “market crash” day to see if it correctly flags.
- Setting up the clustering module using MiniLM embeddings and KMeans. I wrote code to obtain sentence embeddings (using the sentence-transformers library) and then applied sklearn.KMeans. I experimented with different values of k (from 3 to 10) and cluster selection strategies before settling on the described approach. Ensuring that this step runs efficiently for small N (it does) was also my work – even though KMeans is overkill for <10 points, it was fine.
- Implementing the output ranking and formatting rules. I coded the final sorting logic that considers sentiment alignment with price direction and confidence. Then I created a neat output format (as a list of tuples containing headline text, sentiment label, etc.) which could be printed or returned as JSON. I also manually formatted some example outputs for the report.
- Extensive testing and validation using historical cases. I compiled a list of significant stock moves (both positive and negative) over the past few years and ran the system for each. I compared outputs with news archives to ensure the results made sense. Where the system missed something, I traced it through the pipeline to find out why (e.g., was it filtered out wrongly? did FinBERT misclassify?). These tests directly led to improvements. For example, noticing FinBERT misclassified “recession fears loom” as Neutral led me to add “fears” as a trigger to force Negative.

All implementation was done in Python, primarily in a Jupyter Notebook environment for ease of debugging and documentation. I used only standard libraries: requests for API calls, pandas and numpy for data handling, scikit-learn for clustering, and transformers for the FinBERT model. This minimal use of external libraries beyond the essentials kept the project manageable and reproducible. I ensured the code was modular – each component could be run in isolation for unit testing (which I did; e.g., I wrote a small test to feed a list of sentences to just the sentiment classifier and verify outputs).

Technical Challenges and Iterations: One challenge was ensuring the system

didn’t miss relevant news due to phrasing. For example, early on, the keyword filter missed a headline like “Company X hits record sales, shares jump” because “hits record” wasn’t in the list. I addressed this by expanding the keyword list and also by considering lemmatization (so “jump” would match “jumps”). Another challenge was balancing precision vs recall in filtering – too strict and you drop useful headlines; too loose and you allow noise. I tackled this by evaluating the filter on a large set of news: I took a random day’s headlines for a well-known event and checked which ones got filtered. This fine-tuning was done manually, guided by domain knowledge and trial-and-error.

The workflow was largely iterative: implement a feature, test on known examples, refine. For instance, after implementing clustering, I tested on a day where two news stories happened (to see if it separated them correctly). This kind of testing was crucial. Each iteration was documented so I could revert changes if needed. As the sole contributor, I frequently had to validate my own assumptions with quick scripts or by reading related work. The open-source references (like the FinBERT paper, or blogs on sentiment analysis) were consulted to ensure I followed best practices (for example, normalizing text, handling unknown words, etc.).

By the end of the project, I had a working pipeline encapsulated in the notebook with clear sections. I also created a short demo presentation of the results for UNIFI Capital, walking through one example step-by-step to show what the system does (this improved stakeholders’ understanding and trust in the tool).

In summary, my personal contributions covered the full spectrum: problem formulation, research of techniques, coding every module, creating evaluation methodology, and refining the solution through multiple cycles. The project not only met its objectives but also served as a valuable learning experience in applying NLP in finance, reinforcing the importance of combining human insight (rules/keywords) with machine learning (FinBERT, embeddings) for optimal results.

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