Bridging the Data Gap in Financial Sentiment: LLM-Driven Augmentation

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Abstract

Static and outdated datasets hinder the accuracy of Financial Sentiment Analysis (FSA) in capturing rapidly evolving market sentiment. We tackle this by proposing a novel data augmentation technique using Retrieval Augmented Generation (RAG). Our method leverages a generative LLM to infuse established benchmarks with up-to-date contextual information from contemporary financial news. This RAG-based augmentation significantly modernizes the data's alignment with current financial language. Furthermore, a robust BERT-BiGRU judge model verifies that the sentiment of the original annotations is faithfully preserved, ensuring the generation of high-quality, temporally relevant, and sentiment-consistent data suitable for advancing FSA model development.

1 Introduction

Financial Sentiment Analysis (FSA) is pivotal for extracting actionable insights from the vast corpus of financial text, thereby informing investment decisions and risk assessment strategies (Kearney and Liu, 2021). Nevertheless, the development of robust FSA systems is frequently impeded by significant data-related obstacles. A primary challenge is the reliance on established, human-annotated benchmarks like the Financial PhraseBank (Fin). While invaluable for their reliable annotations, such datasets are increasingly outdated and may not reflect contemporary financial language, evolving market narratives, or the subtle contextual shifts in modern economies. This issue of "data staleness" is compounded by the inherent class imbalances often present in these resources and the considerable expense and specialized expertise needed to annotate new, large-scale financial datasets Consequently, even advanced Large Language Models (LLMs) can struggle to deliver optimal performance in FSA when their training is rooted in temporally misaligned, potentially biased, or scarce annotated data (Stureborg et al., 2024).

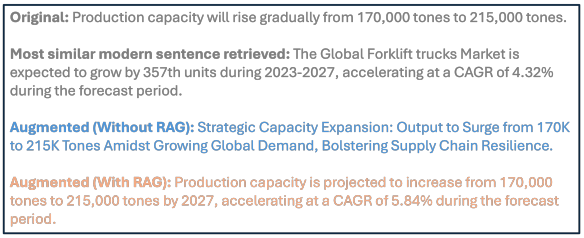

Figure 1: Figure showing different sentences, 1) Original sentence from Financial Phrasebank dataset, 2) The most similar modern sentence retrieved from Yahoo Finance Headlines, 3) Augmented Sentence without RAG, and 4) augmented sentence with RAG

To surmount these critical data challenges, we propose a novel data augmentation framework centered on Retrieval Augmented Generation (RAG) (Lewis et al., 2020). Our methodology is designed to modernize and expand existing reliable benchmarks by injecting contemporary contextual information, while also systematically addressing class imbalance. Specifically, we leverage a generative LLM, guided by RAG, to synthesize new training instances. The RAG mechanism retrieves pertinent information from modern, unlabeled financial news (specifically, Yahoo Finance News from 2021-2022) to inform the generation process. This allows for the creation of synthetic data that not only aims to preserve the original sentiment from datasets like Financial PhraseBank but is also imbued with current financial vernacular and themes. Our augmentation strategy further ensures a balanced class distribution in the generated data by augmenting samples to achieve a target equilibrium (e.g., 50% positive, 50% negative).

Our empirical evaluation of the augmentation process, conducted using an unseen corpus of Yahoo Finance News from 2023 to ensure robust,

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leakage-free assessment, demonstrates the efficacy of our RAG-based approach. Comparative analysis against non-RAG augmentation and the original dataset revealed that RAG-augmented samples exhibited the closest semantic alignment (lowest L2 distance) to contemporary financial language. Furthermore, our RAG-augmented data also showed a slightly closer semantic proximity to the original sentences compared to non-RAG augmented data, indicating effective modernization while maintaining high fidelity to the original semantic core. To rigorously assess the sentiment preservation of these augmented instances, we developed a "judge" model: a hybrid BERT-base (Devlin et al., 2018) and Bidirectional Gated Recurrent Unit (BiGRU) architecture, incorporating Monte Carlo (MC) layers to mitigate overfitting. This specific architecture was selected as it demonstrated superior performance in classifying the sentiment of our RAG-augmented data when compared against alternative recurrent head configurations (BERT-GRU, BERT-LSTM, BERT-BiLSTM).

This fine-tuned judge model (itself trained on the original Financial PhraseBank) served a key role in meticulously filtering the augmented data to ensure sentiment consistency. The judge's evaluation confirmed a very high degree of sentiment preservation in the RAG-augmented data, with its classifications aligning more closely with the original intended sentiment for RAG samples compared to non-RAG samples. This underscores the quality and reliability of the RAG-generated data for FSA tasks.

Our contributions are thus:

1. A novel RAG-informed LLM-driven data augmentation framework that injects contemporary context (from 2021-2022 financial news) into established benchmarks, addressing data staleness and class imbalance, with robust evaluation against unseen 2023 data.

2. The design and empirical validation of a high-performing hybrid judge model (BERT-BiGRU with MC layers), optimized for classifying augmented financial text, for meticulous sentiment-based filtering and quality assurance of the augmented data.

3. Comprehensive experimental results demonstrating that RAG-augmentation significantly enhances the temporal relevance of datasets while maintaining high sentiment fidelity and internal consistency, rendering the data highly suitable for developing robust FSA models.

This work charts a course towards more resilient and contextually-aware FSA systems by effectively addressing pervasive data limitations, thereby paving the way for more reliable financial intelligence.

2 Related Work

Our research is situated at the intersection of several dynamic areas within natural language processing: data augmentation strategies tailored for specialized domains such as finance, the application of retrieval-augmented generation for enhancing contextual understanding, and addressing the distinct challenges inherent in financial sentiment analysis.

2.1 Data Augmentation in Financial NLP

The problem of data scarcity presents a significant challenge in specialized NLP domains like finance. High-quality labeled data is often in limited supply, costly to produce through expert annotation, and can quickly become outdated due to the evolving nature of financial markets and discourse. Traditional data augmentation (DA) techniques, such as synonym replacement or back-translation, have been explored to artificially expand training datasets (Wei and Zou, 2019; Feng et al., 2021). More recently, Large Language Models (LLMs) have emerged as powerful instruments for DA, demonstrating capabilities in generating diverse synthetic data or enriching existing samples with new contextual information.

A key development in LLM-based DA is the shift from mere data volume expansion towards *semantic augmentation*, which aims to enrich the data's feature space and contextual depth (Kumar et al., 2020). For instance, LLMs can be employed to refine noisy textual data or generate explanatory content, thereby improving overall data quality. In the financial sector, LLM-driven DA has shown promise, with studies indicating its potential to achieve performance levels comparable to those obtained with human-annotated data, but at a substantially reduced cost. However, a critical and often overlooked issue is the "data staleness" of many widely-used financial benchmarks, where the language, themes, and market context may no longer accurately reflect current financial realities. Our work directly addresses this gap by proposing

a DA methodology specifically focused on generating *temporally-aware* data, ensuring that the augmented samples are aligned with contemporary financial discourse.

2.2 Retrieval Augmented Generation for Contextual Data Augmentation

Retrieval Augmented Generation (RAG) has become a prominent technique for grounding the outputs of LLMs in external knowledge sources. This approach helps to mitigate issues such as model hallucination and significantly enhances the factual accuracy and relevance of generated content (Lewis et al., 2020; Gao et al., 2023). Within the financial domain, RAG applications have primarily concentrated on tasks like question answering over dense and often static financial documents, such as 10-K filings or research reports (Wu et al., 2023). These systems are typically designed to retrieve precise factual information from fixed, historical corpora.

Our research introduces a novel application of RAG, employing it as a core component of a *data augmentation* pipeline for FSA, with a specific emphasis on *temporal relevance*. Unlike conventional financial RAG systems that query static archives, our method retrieves contextual information from a dynamic stream of contemporary financial news (specifically, Yahoo Finance News from 2021-2022). This retrieved, up-to-date information is then used to guide an LLM in augmenting an older, established labeled dataset (Financial PhraseBank, (Fin)). This strategic use of RAG is intended to "rejuvenate" existing reliable resources, making the resultant augmented data more reflective of current market narratives and sentiment indicators. This constitutes a less explored yet vital application of RAG for DA, particularly in rapidly evolving domains such as finance where the context is paramount.

2.3 Hybrid Models and Domain Adaptation in FSA

Financial Sentiment Analysis has significantly benefited from the advent of pre-trained language models (PLMs) like BERT (Devlin et al., 2018) and its domain-specific adaptations such as FinBERT (Yang et al., 2020), which are adept at capturing nuanced semantic information from financial texts. Hybrid neural architectures, notably those that combine the rich contextual embeddings from BERT with sequential modeling capabilities of recurrent layers like Bidirectional Gated Recurrent Units (BiGRU), have demonstrated strong performance across various NLP classification tasks by leveraging both contextual understanding and sequential patterns (Nadeem et al., 2022). Our choice of a BERT-BiGRU architecture for our "judge" model is informed by these successes, aiming for robust sentiment classification.

Adapting general-purpose LLMs to the specialized language and complexities of the financial domain, through techniques such as continual pre-training on financial corpora or instruction tuning with finance-specific tasks, remains a critical area of research (Wu et al., 2023; Chen et al., 2023). The financial domain is particularly challenging due to its unique jargon, the rapid evolution of market narratives influenced by global events, and the inherent subjectivity in interpreting financial communications (Kearney and Liu, 2021). Ongoing efforts to develop more robust, comprehensive, and context-aware financial datasets continue to drive progress in the field (Ma et al., 2021; Shah et al., 2022).

3 Our Approach

We propose a two-stage framework to address data scarcity, temporal misalignment, and class imbalance in Financial Sentiment Analysis (FSA). First, a Retrieval Augmented Generation (RAG)-enhanced LLM augments existing benchmarks with modernized, contextually relevant, and class-balanced data. Second, a hybrid "judge" model validates these augmentations and serves as a robust sentiment classifier. Figure 2 outlines this pipeline.

3.1 RAG-Driven Data Augmentation

Our augmentation aims to enrich datasets like Financial PhraseBank (Fin) by generating contemporary, sentiment-preserving samples and ensuring class balance.

Methodology. We use an instructive prompt for a generative LLM, providing the original sentence and its sentiment label to guide sentiment preservation. To incorporate modern context, RAG retrieves the top-K semantically similar sentences from a corpus of Yahoo Financial News (2021-2022). The LLM then generates an augmented sentence conditioned on the original sentence, its sentiment, and these retrieved contemporary examples. This process is controlled to produce a class-balanced

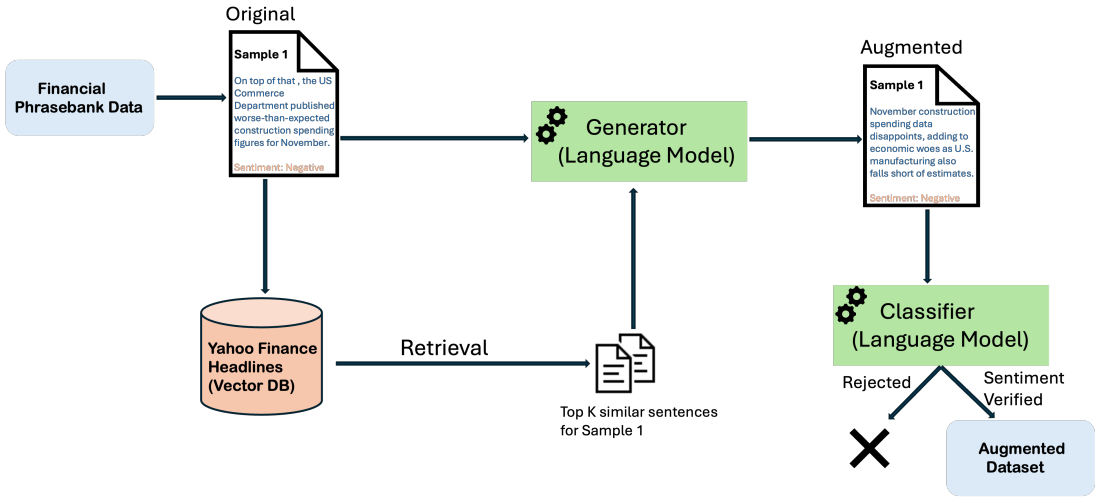

Figure 2: The proposed two-stage framework: RAG-driven augmentation using 2021-2022 news to modernize benchmarks, followed by a hybrid sentiment judge for validation and filtering.

augmented dataset. Details on K and the LLM are in Section 4.

Baseline. A non-RAG baseline, where augmentation relies only on the original sentence and sentiment, is used to isolate RAG's impact on modernization.

3.2 Hybrid Sentiment Judge

A specialized "judge" model ensures augmented data quality and acts as a reliable sentiment classifier for the augmented samples.

Architecture. The judge combines a BERT-base (Devlin et al., 2018) with a Bi-GRU classification head and Monte Carlo (MC) dropout layers to mitigate overfitting. This hybrid structure leverages BERT's contextual understanding and Bi-GRU's sequential pattern recognition (Nadeem et al., 2022). The choice of BERT-BiGRU was based on its superior performance in classifying our RAG-augmented data compared to other recurrent head configurations, as detailed in Section 5.2.

Training and Application. The judge model is fine-tuned on the original Financial PhraseBank using a staged regimen: initial head-only training followed by full-model fine-tuning with differential learning rates to effectively adapt BERT. Once trained, this judge is applied to filter both RAG and non-RAG augmented data by verifying whether the sentiment of the augmented sentences aligns with the original intended labels. This cross-verification assesses the sentiment preservation quality of the augmentation process.

4 Experimental Setup

This section details the datasets employed, the metrics and protocols for evaluating our data augmentation strategy and the sentiment judge, and the specific implementation choices made throughout our experiments.

4.1 Datasets

Primary Annotated Dataset: Financial PhraseBank. For our core annotated data, we utilized the widely recognized Financial PhraseBank (FPB) dataset (Fin). This dataset consists of sentences extracted from English financial news articles and stock market reports, manually annotated by finance and language professionals with sentiment labels: positive, negative, or neutral. We used the version containing 4,840 sentences. We adhered to standard splits often used with this dataset (e.g., 80% train, 20% test) for the initial training of our sentiment judge model. The pre-2013 origin of FPB's primary sources makes it a suitable candidate for our temporal augmentation task.

Contemporary Context Corpus for RAG: Yahoo Financial News (2021-2022). To provide modern contextual information for our RAG-driven augmentation, we compiled a corpus from Yahoo Financial News headlines published between January 2021 and December 2022. This resulted in a corpus of approximately 45,000 unique headlines, which were used to populate our vector database for retrieval during augmentation.

Modern Evaluation Corpus: Yahoo Financial News (2023). To assess the "modernity" of our aug-

mented data against a truly unseen contemporary context, we collected a separate corpus of Yahoo Financial News headlines published throughout 2023. This corpus was exclusively used for evaluation purposes as described in Section 4.2 and was not seen during the RAG augmentation process.

Data Splits for Judge Model. The Financial PhraseBank dataset was divided into training (80%) and testing (20%) sets for the initial fine-tuning of the sentiment judge architectures.

4.2 Augmentation Quality Assessment

We employed quantitative semantic metrics and qualitative human inspection to rigorously evaluate the augmented data generated by both RAG-informed and non-RAG methods.

Semantic Distance Metrics. We assessed semantic relationships against two references: (1) the original Financial PhraseBank sentences and (2) the unseen contemporary Yahoo Financial News (2023) headlines representing modern context. Sentence embeddings were obtained using a pre-trained Sentence-BERT model ('all-mpnet-base-v2' (Reimers and Gurevych, 2019)), chosen for its strong semantic capture. We then calculated:

- *Euclidean Distance (L2):* To measure proximity in vector space (lower values are better).

This metric compared how RAG-augmented and non-RAG-augmented data aligned with original and modern contexts.

Qualitative Inspection Protocol. A subset of augmented sentences from both methods was manually inspected by two authors familiar with financial language, focusing on fluency, coherence, sentiment preservation (relative to the original sentence), and perceived contemporariness.

4.3 Judge Model Evaluation

The performance of our sentiment judge and its architectural variants in classifying the augmented data was evaluated based on standard classification metrics.

Classification Performance Metrics. We used Accuracy, Precision, Recall, F1-score (macro-averaged), and Matthews Correlation Coefficient (MCC) to evaluate the judge's classifications of test data (20 % samples from Financial Phrasebank, reserved for testing) against their original sentiment labels.

Ablation Study for Judge Head Architecture. To validate our choice of a Bi-GRU head for the BERT-based judge, we compared its performance against GRU, LSTM, and Bi-LSTM recurrent heads. All configurations were trained on the original Financial PhraseBank training set (80% of total samples), and then their performance was specifically evaluated on their ability to classify the *Financial Phrasebank test dataset* according to its original sentiment labels. This allowed us to select the architecture most adept at interpreting our synthetically generated contemporary data.

4.4 Implementation Details

Models and Libraries. The generative LLM for data augmentation was Google's Gemini Flash model (Hassabis and Kavukcuoglu, 2024) (version used consistent with experiments conducted early 2024). For the sentiment judge, we utilized bert-base-uncased from Hugging Face Transformers (Wolf et al., 2020). RAG retrieval employed ChromaDB. All models were implemented in PyTorch (Paszke et al., 2019). Sentence embeddings for RAG retrieval used all-MiniLM-L6-v2, while all-mpnet-base-v2 was used for semantic similarity assessment (Section 4.2), both via Sentence Transformers (Reimers and Gurevych, 2019).

Key Hyperparameters and Procedures.

- *RAG Retriever:* The Yahoo Financial News (2021-2022) corpus was embedded using all-MiniLM-L6-v2 and stored in ChromaDB. For each FPB sentence, its embedding queried ChromaDB for the top-$K = 5$ most similar headlines using cosine similarity.

- *LLM API Usage:* To manage API rate limits (e.g., 15 RPM for Gemini Flash free tier during our experiments), a 5-second wait time was implemented between API calls. Prompt templates. Default generation temperature settings were used.

- *Judge Model Training:* The BERT-BiGRU judge was trained for 10 epochs. Initial head-only training (BERT frozen) lasted 2 epochs (LR 1×10^{-3}). Full model fine-tuning (last 2 BERT layers unfrozen) used LRs of 2×10^{-5} (BERT) and 5×10^{-5} (Bi-GRU head), with linear decay and AdamW (Loshchilov and Hutter, 2017). The Bi-GRU hidden dimension was set to 256. MC dropout rates were $p = 0.1$ (BERT's layers) and $p = 0.2$ (Bi-GRU head).

Computational Resources. Judge model fine-tuning was performed on NVIDIA T4 GPUs, with

each configuration training in approximately 1.5 hours. Augmenting roughly 1,000 sentences took about 2.5 hours, inclusive of API wait times.

5 Results and Analysis

This section presents the empirical evaluation of our proposed framework. We first assess the quality of the augmented data in terms of its modernization and fidelity to the original content. Subsequently, we evaluate the performance of different hybrid model architectures when tasked with classifying our RAG-augmented data, thereby identifying the most suitable "judge" configuration. Finally, we compare the chosen judge's performance across both RAG-augmented and non-RAG augmented datasets to further assess sentiment preservation.

5.1 Augmented Data Quality Assessment

We evaluated the augmented data generated by our RAG-informed method and the non-RAG baseline against two key criteria: (1) alignment with contemporary financial language, and (2) semantic proximity to the original Financial PhraseBank (FPB) sentences. As described in Section 4.2, L2 (Euclidean) distance was used as the primary metric, calculated on sentence embeddings.

Alignment with Modern Context. To assess how well each dataset reflects current financial discourse, we measured the average L2 distance between sentences from each dataset (original FPB, non-RAG augmented, RAG-augmented) and their closest semantic match retrieved from an unseen corpus of Yahoo Financial News headlines from 2023. Lower distances indicate closer alignment with modern context.

Table 1 summarizes these findings. The RAG-augmented data exhibits the lowest mean L2 distance (0.86) to the modern 2023 headlines, followed by the non-RAG augmented data (0.96), with the original FPB data being the most distant (1.05). This quantitatively supports our hypothesis that RAG-informed augmentation effectively modernizes the dataset, bringing its semantic content closer to contemporary financial narratives than both the original data and a simpler non-RAG augmentation approach.

Figure 3 visually corroborates these results, illustrating the distribution of L2 distances for each dataset. The RAG-augmented data's distribution is visibly shifted towards lower distances compared to the other two, indicating a more consistent alignment with the modern context.

Table 1: Mean L2 Distance to Modern Context (Yahoo Finance News 2023). Lower is better. Standard deviations in parentheses.

Dataset	Mean L2 Distance (std)
Original FPB	1.05 (0.12)
Non-RAG Augmented	0.96 (0.11)
RAG-Augmented	0.86 (0.17)

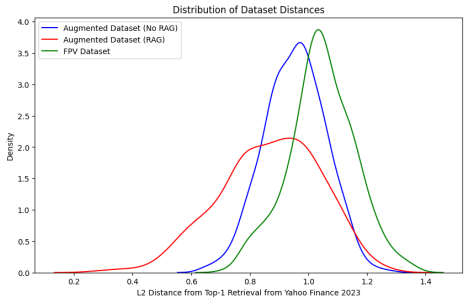

Figure 3: Distribution of L2 distances from sentences in each dataset to their top-1 retrieved semantic match from Yahoo Finance News 2023, illustrating the RAG-augmented data's closer proximity to modern context.

Fidelity to Original Content. We also measured the L2 distance between the augmented sentences and their corresponding original sentences from the FPB. This assesses how much the augmentation process alters the core semantic content. The results were:

- RAG-Augmented vs. Original FPB: Mean L2 Distance = 0.77 (std = 0.11)
- Non-RAG Augmented vs. Original FPB: Mean L2 Distance = 0.82 (std = 0.14)

Notably, the RAG-augmented data (0.77) shows a slightly lower mean distance (i.e., is closer) to the original sentences than the non-RAG augmented data (0.82). This indicates that our RAG-based approach, while effectively infusing modern context, does so with remarkable fidelity. It suggests that the RAG mechanism guides the LLM to make targeted and nuanced modifications that align with contemporary language without fundamentally distorting the original semantic core, even more so than the non-RAG baseline. Qualitative inspections further supported these findings, noting high fluency and sentiment preservation in RAG-augmented samples.

Table 2: Performance of Hybrid Model Architectures in Classifying Financial Phrasebank Test Dataset (against original labels).

Model Architecture	Acc.	Prec. (M)	Rec. (M)	F1 (M)	MCC
BERT + GRU	0.9822	0.9823	0.9822	0.9822	0.9645
BERT + BiGRU	**0.9873**	**0.9873**	**0.9873**	**0.9873**	**0.9746**
BERT + LSTM	0.9772	0.9775	0.9772	0.9771	0.9545
BERT + BiLSTM	0.9822	0.9823	0.9822	0.9822	0.9645

5.2 Sentiment Judge Performance on Augmented Data

To validate the sentiment consistency of our augmented data and identify a robust judge architecture, we evaluated several BERT-based hybrid models. These models were tasked with classifying the sentiment of the RAG-augmented data, with performance measured against the original (pre-augmentation) sentiment labels. This assesses how well the intended sentiment is preserved and recognizable in the synthetic data.

Table 2 presents the performance of different recurrent heads combined with BERT when classifying the RAG-augmented dataset. The BERT-BiGRU configuration achieves the highest scores across all metrics, with an accuracy of 0.9873 and an MCC of 0.9746. These near-perfect scores indicate that the sentiment within the RAG-augmented data is highly discernible and internally consistent when analyzed by a suitable hybrid architecture. The superior performance of BERT-BiGRU identifies it as the most effective "judge" configuration for interpreting the nuances of our augmented data.

Further, we used the selected BERT-BiGRU judge (trained on the original FPB as per Section 3.2) to compare the sentiment consistency of the non-RAG augmented data versus the RAG-augmented data. Table 3 details this comparison, again evaluating against the original intended sentiment labels.

The BERT-BiGRU judge demonstrates exceptionally high agreement with the intended sentiment for RAG-augmented samples (0.9880 Accuracy, 0.9760 MCC), surpassing its already high agreement with non-RAG samples (0.9660 Accuracy, 0.9325 MCC). This superior performance on RAG-augmented data implies that the contextual grounding provided by RAG not only helps in modernizing the text but also contributes to generating sentiment expressions that are clearer, more consistent, and more robustly aligned with the original intent. These results provide strong quantitative evidence for the high quality and sentiment integrity of data produced by our RAG-driven augmentation framework, making it highly suitable for subsequent use in training or fine-tuning FSA models.

6 Conclusion

This paper addressed the critical challenge of data staleness and imbalance in Financial Sentiment Analysis (FSA) by introducing a novel framework for RAG-driven, LLM-based data augmentation. Our approach successfully enriches existing reliable benchmarks, like the Financial PhraseBank, with contemporary financial context sourced from recent news (2021-2022), while strategically managing class balance. We demonstrated through quantitative L2 distance metrics that our RAG-augmented data achieves significantly closer alignment with modern financial narratives (evaluated against unseen 2023 data) compared to both the original dataset and a non-RAG augmentation baseline. Notably, this modernization is achieved with high fidelity to the original semantic content, with RAG-augmented data exhibiting a remarkable proximity to the original sentences.

Furthermore, we developed a hybrid BERT-BiGRU "judge" model, which, when applied to the augmented data, confirmed the high degree of sentiment preservation, particularly in samples generated via RAG. The judge's near-perfect agreement with the intended sentiment of RAG-augmented

Table 3: Chosen Judge (BERT-BiGRU) Performance in Classifying Non-RAG vs. RAG Augmented Data (against original intended labels).

Dataset Classified by Judge	Acc.	Prec. (M)	Rec. (M)	F1 (M)	MCC
Non-RAG Augmented Samples	0.9660	0.9700	0.9700	0.9700	0.9325
RAG-Augmented Samples	**0.9880**	**0.9900**	**0.9900**	**0.9900**	**0.9760**

data underscores the clarity and consistency of these synthetic samples. Our findings collectively indicate that the proposed RAG-informed augmentation strategy is a robust method for generating high-quality, temporally relevant, and sentiment-consistent data. This work provides a valuable methodology for revitalizing existing annotated resources, paving the way for the development of more accurate and contextually aware FSA systems capable of navigating the dynamic financial landscape. Future work could explore the application of this enriched data in complex downstream FSA tasks and investigate adaptive RAG components that dynamically update their knowledge sources.

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