Financial Text Summarization and Sentiment Analysis

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***Abstract*—Financial professionals often find it challenging to keep up with long and complex news articles, which can impede quick, informed decision-making. This project tackles this problem by utilizing Natural Language Processing (NLP) to create tools for summarizing financial news and analyzing sentiment. By fine-tuning the PEGASUS model for summarization and the BERT model for sentiment classification, the system processes financial texts to deliver concise summaries and sentiment insights. The summarization model showed notable improvements in ROUGE scores, while the sentiment analysis model achieved high accuracy and F1 scores, proving its effectiveness in classifying financial sentiments. These outcomes highlight the system's potential to enhance financial decision-making by presenting key information more efficiently. The project lays the groundwork for future developments in financial NLP, aiding investors, analysts, and traders in navigating fast-paced market conditions.**

***Index Terms*—Financial news, text summarization, sentiment analysis, Pegasus, FinBERT.**

I. Introduction

In the fast-moving financial industry, investors and analysts must quickly and accurately stay on top of market-shaping events. However, the volume and complexity of financial news make this difficult. Lengthy articles filled with technical jargon can slow down decision-making, leading to missed opportunities or poor choices. Addressing this challenge is crucial for equipping financial professionals with efficient tools to process and analyze essential information.

Automated solutions have become more urgent than ever. Financial analysts spend hours each day reviewing news, reducing their ability to make strategic decisions. Current manual or traditional methods for summarizing and analyzing financial texts are not only time-consuming but also prone to errors. Furthermore, most sentiment analysis models do not account for the subtle effects of financial news on stock prices, highlighting the need for more specialized tools.

This project uses two critical datasets: the Gretel Financial Risk Analysis Dataset for summarization and the Financial Phrasebank Dataset for sentiment analysis. The Gretel dataset includes over 1,000 articles on topics such as stock performance and global markets, providing comprehensive data for training summarization models. The Financial Phrasebank dataset contains more than 4,800 annotated sentences, categorized into positive, negative, or neutral sentiments, offering a solid basis for sentiment classification. Both datasets are highly pertinent, ensuring the development of models specifically suited to financial applications.

The proposed solution leverages advanced Natural Language Processing (NLP) techniques. For summarization, a fine-tuned PEGASUS model generates clear and concise summaries of lengthy financial texts. For sentiment analysis, a BERT model, fine-tuned on financial data, accurately classifies news sentiments. These models are enhanced through careful preprocessing, tokenization, and hyperparameter tuning. By combining these methods, the project delivers effective summarization and sentiment analysis, providing valuable insights that help financial professionals make faster, more informed decisions.

II. Background

Natural Language Processing (NLP) has made remarkable strides, with transformer-based models transforming text summarization and sentiment analysis. Models like PEGASUS and BERT, built on pre-trained architectures, offer cutting-edge performance in summarizing lengthy texts and analyzing sentiments. In finance, these models help extract key insights from large volumes of unstructured news, enabling faster decision-making. Additionally, open-source platforms like Hugging Face have made these technologies more accessible, allowing researchers and practitioners to fine-tune models on specific datasets, enhancing accuracy for specialized applications.

Prior research in financial NLP has focused on text summarization and sentiment analysis using various methods. For example, PEGASUS has been fine-tuned on financial datasets to generate concise summaries of lengthy news articles, showing significant improvements in ROUGE scores. Similarly, sentiment analysis using models like BERT, trained on annotated datasets such as the Financial Phrasebank, has achieved strong performance in classifying sentiments as positive, negative, or neutral. These approaches have proven effective at extracting actionable insights from financial texts, though challenges persist in handling domain-specific subtleties and scaling automation.

Despite progress, several gaps remain. Many summarization models struggle to preserve key financial insights while ensuring brevity. Sentiment analysis models often miss the subtle financial implications of neutral statements, limiting their effectiveness in predicting stock prices. Additionally, the lack of high-quality domain-specific datasets limits the breadth of many studies. This project addresses these issues by fine-tuning PEGASUS and BERT models on carefully curated financial datasets. The approach focuses on preserving crucial financial insights, improving sentiment classification accuracy, and utilizing state-of-the-art techniques to build a robust, automated system tailored to financial professionals.

III. Methodology

A. Data Preprocessing

Preparing the dataset involved several essential preprocessing steps to ensure optimal input for the models. First, the raw textual data was cleaned by removing irrelevant characters, stopwords, and special symbols, while maintaining financial terms critical to the analysis. For summarization, the text was tokenized using the PEGASUS tokenizer, truncating or padding sequences to a uniform length of 1024 tokens. Sentiment analysis employed the BERT tokenizer, adding special tokens ([CLS], [SEP]) and limiting sequence lengths to 150 tokens.

Labels for sentiment classification were encoded into categorical binary values for positive, negative, and neutral sentiments. The dataset was then split into training and testing sets with an 80:20 ratio, ensuring balanced class distributions. Finally, all text was converted to lowercase and standardized for consistent formatting, optimizing model performance.

B. Base Model Selection

This project utilizes the PEGASUS and BERT models as the foundational architectures for summarization and sentiment analysis, respectively. PEGASUS, a transformer-based model designed for abstractive summarization, was chosen for its ability to generate concise, human-like summaries. Pre-trained on datasets like XSum, PEGASUS excels in handling long-form text, making it ideal for the financial domain where articles are lengthy and complex. Additionally, its fine-tuning capabilities on domain-specific datasets ensure high accuracy and relevance.

For sentiment analysis, BERT was selected for its robust language understanding and contextual embeddings. The fine-tuned version, tailored for financial sentiment tasks, leverages pre-trained weights, enabling efficient classification of positive, negative, and neutral sentiments. Both models were chosen for their state-of-the-art performance, computational efficiency, and the availability of pre-trained versions that significantly reduce training time while maintaining high accuracy on domain-specific tasks. These attributes make them ideal for addressing the project's objectives.

C. Model Customization

To tailor the base models for the specific tasks of summarization and sentiment analysis, several customizations were implemented to enhance performance and adaptability to financial text data.

For PEGASUS, used in summarization, fine-tuning involved modifying the model's decoder to focus on generating concise, domain-specific summaries. Key adjustments included reducing the maximum token length to 150 for outputs, ensuring brevity without compromising essential financial insights. Additionally, hyperparameters such as learning rate, batch size, and training epochs were optimized for the financial dataset. Dropout layers were utilized to prevent overfitting, especially given the relatively small dataset size.

In the BERT model for sentiment analysis, the final classification layer was replaced with a dense output layer, configured to predict three classes: positive, negative, and neutral sentiments. A softmax activation function was applied to the output layer to generate probabilistic class predictions. Dropout layers were added before the classification layer to reduce overfitting, and the learning rate scheduler was employed to fine-tune the model efficiently. Both models benefited from these customizations, enabling improved performance on the financial datasets while maintaining computational efficiency.

TABLE I
Hyperparameter Comparison

Hyperparameter	**Original**	**Experimental**
`num_train_epochs`	10	5
`per_device_train_batch_size`	2	4
`per_device_eval_batch_size`	2	4
`warmup_steps`	500	250
`weight_decay`	0.01	0.02
`logging_dir`	`./logs`	`./experiment_logs`
`logging_steps`	50	100
`evaluation_strategy`	steps	epoch
`eval_steps`	500	N/A
`save_steps`	1000	500
`save_total_limit`	3	5
`gradient_accumulation_steps`	8	4
`fp16`	False	True
`load_best_model_at_end`	True	True
`metric_for_best_model`	`eval_loss`	`accuracy`
`greater_is_better`	False	True
`report_to`	none	tensorboard
`do_train`	True	True
`do_eval`	True	True
`learning_rate`	N/A	5e-5
`lr_scheduler_type`	N/A	`linear`
`adam_beta1`	N/A	0.9
`adam_beta2`	N/A	0.98
`max_grad_norm`	N/A	1.0

IV. Results

A. Classification Metrics Tables

The classification performance of both the PEGASUS (summarization) and BERT (sentiment analysis) models was evaluated using precision, recall, F1-score, and accuracy metrics.

For sentiment analysis, the BERT model achieved the following metrics:

- **Precision**: 0.73
- **Recall**: 0.72
- **F1-Score**: 0.72
- **Accuracy**: 0.74

For summarization using PEGASUS, the model was evaluated on ROUGE scores instead of precision/recall. The average ROUGE-1, ROUGE-2, and ROUGE-L scores were:

Model	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE-Lsum
Custom_Model1	0.4524	0.2231	0.3151	0.3206
Custom_Model2	0.4124	0.1931	0.2951	0.3006

TABLE II
ROUGE SCORES FOR CUSTOM MODELS

Both models exhibited strong performance, with BERT excelling in sentiment classification. The PEGASUS model's performance reflected significant improvements post-fine-tuning, but still faced challenges in generating summaries that captured all critical financial insights without losing context.

B. Model Accuracy and Loss Graphs

During training, both models exhibited clear trends in accuracy and loss. For the **BERT model** (sentiment analysis), the accuracy increased steadily, with a final accuracy of 74

C. Model Performance Discussion

Overall, both models performed well for their respective tasks, with BERT providing high accuracy and F1-scores in sentiment analysis, while PEGASUS showed significant improvements in summarization after fine-tuning. Key findings include the ability of the models to generalize to financial data, but some limitations were evident. For example, BERT struggled with distinguishing between certain neutral and negative sentiments, while PEGASUS occasionally generated summaries that omitted key insights. Limitations due to dataset size and domain-specific challenges in financial language were also noted. Future improvements could involve expanding the dataset, incorporating real-world financial news, and experimenting with additional model architectures to further enhance performance in both tasks. Additionally, testing on a more extensive dataset or in a live trading environment would be beneficial for real-world applicability.

V. CONCLUSION

This project successfully developed a system that leverages advanced Natural Language Processing (NLP) techniques to address the challenges of summarizing financial news and performing sentiment analysis. By utilizing the PEGASUS model for summarization and the BERT model for sentiment classification, the system was able to generate concise financial summaries and accurately categorize news sentiment, which is essential for quick and informed decision-making in the financial sector. The results demonstrated solid performance, with notable improvements in ROUGE scores for summarization and high accuracy in sentiment classification.

While the models showed promising results, certain challenges, such as handling domain-specific nuances and dataset limitations, were observed. Future work can focus on expanding the dataset, exploring alternative architectures, and testing the system in real-world applications to further enhance its performance. Ultimately, this project lays the groundwork for automated tools that can support financial analysts, investors, and traders, facilitating more efficient processing of market-moving news and improving decision-making in dynamic financial environments.

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