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Duygu Analizi için Büyük Dil Modellerinin Verimli Uyarlanması: İnce Ayar Yaklaşımı

Seda BAYAT TOKSÖZ[1*], Gültekin IŞIK[1],

Öne Çıkanlar:

- İnce Ayar Düşük Sıra Adaptation
- LoRa (Low-Rank Adaptation),
- QLoRa (Nicelenmiş Düşük Sıralı Adaptation)

Anahtar Kelimeler:

- Duygu Analizi,
- İnce Ayar,
- QLoRa (Nicelenmiş Düşük Sıralı Adaptation),
- LoRa (Low-Rank Adaptation),
- Gpt-2,
- Mistral-7B

ÖZET:

Bu çalışma, gelişmiş uyarlama teknikleriyle (Nicelleştirilmiş Düşük Sıra Uyarlaması (QLoRA) ve Düşük Sıra Uyarlaması (LoRA) ince ayarlanmış iki dönüştürücü mimarisi olan Mistral-7B ve GPT-2 kullanarak finans haberleri başlıklarında duygu sınıflandırmasının sistematik karşılaştırmalı bir analizini sunmaktadır. Büyük ölçekli bir Finans Haberleri veri kümesi kullanılarak, modeller, başlıkları pozitif, nötr ve negatif duygular olarak doğru bir şekilde sınıflandırma yetenekleri açısından titizlikle değerlendirilmiş ve aynı zamanda hesaplama verimliliği de göz önünde bulundurulmuştur. Genel doğruluğun ötesinde, makro ortalamalı kesinlik, geri çağırma ve F1 puanını bildiriyoruz; böylece modellerin sınıf bazındaki davranışlarına ilişkin daha eksiksiz bir resim sunuyoruz. Ampirik bulgular, Mistral-7B tabanlı yapılandırmaların GPT-2 tabanlı yapılandırmalardan önemli ölçüde daha iyi performans gösterdiğini, Mistral-7B-QLoRA'nın en yüksek doğruluğu (0.881) ve Mistral-7B-LoRA'nın 0.878 puanla elde ettiğini, GPT-2 modellerinin ise önemli ölçüde daha düşük performans gösterdiğini (GPT-2-LoRA için 0.519 ve GPT-2-QLoRA için 0.517) göstermektedir. Karışıklık matrisleri ve standart değerlendirme metriklerini içeren ayrıntılı analizler, Mistral-7B'nin sunduğu üstün sınıflandırma performansı ve kaynak verimliliği dengesinin altını çizmektedir. Çalışma, tek bir finansal veri kümesine odaklanma da dahil olmak üzere sınırlamaları tartışmaya devam etmekte ve farklı alanlarda ek mimarilerin ve uyarlama tekniklerinin değerlendirilmesi de dahil olmak üzere gelecekteki araştırmalar için beklentileri ana hatlarıyla belirtmektedir. Bu çalışma, büyük dil modelleri için ince ayar stratejilerinin geliştirilmesine katkıda bulunmakta ve kaynak kısıtlı ortamlarda duygu analizi işlem hatlarını optimize etmek için değerli bilgiler sunmaktadır.

Efficient Adaptation of Large Language Models for Sentiment Analysis: A Fine-Tuning Approach

Highlights:

- Fine Tuning Low Order Adaptation
- LoRa (Low-Rank Adaptation),
- QLoRa (Quantised Low-Rank Adaptation)]

Keywords:

- Sentiment Analysis,
- Fine Tuning,
- QLoRa (Quantified Low Order Adaptation),
- LoRa (Low-Rank Adaptation),
- Gpt-2,
- Mistral-7B

ABSTRACT:

This study presents a systematic comparative analysis of sentiment classification on financial news headlines using two transformer architectures, Mistral-7B and GPT-2, fine-tuned with advanced adaptation techniques—Quantized Low-Rank Adaptation (QLoRA) and Low-Rank Adaptation (LoRA).Utilising a large-scale Finance News dataset, the models are rigorously evaluated for their ability to accurately classify headlines into positive, neutral, and negative sentiments while also considering computational efficiency. Beyond overall accuracy, we report macro-averaged precision, recall, and F1-score, thereby providing a fuller picture of the models' class-wise behaviour.Empirical findings demonstrate that the Mistral-7B-based configurations substantially outperform those based on GPT-2, with Mistral-7B-QLoRA achieving the highest accuracy (0.881) and Mistral-7B-Lo RA, with a score of 0.878, while GPT-2 models demonstrate significantly lower performance (0.519 for GPT-2-LoRA and 0.517 for GPT-2-QLoRA). Detailed analyses, incorporating confusion matrices and standard evaluation metrics, underscore the superior balance of classification performance and resource efficiency offered by Mistral-7B. The study goes on to discuss limitations, including the focus on a single financial dataset, and outlines prospects for future research, including the evaluation of additional architectures and adaptation techniques across diverse domains.This work contributes to the advancement of fine-tuning strategies for large language models, offering valuable insights for optimising sentiment analysis pipelines in resource-constrained environments.

[1*]Seda BAYAT TOKSÖZ (**Orcid ID:** 0000-0002-8427-9971), Gültekin IŞIK (**Orcid ID:**0000-0003-3037-5586), Iğdır University, Faculty of Engineering, Department of Computer Engineering, Iğdır, Türkiye

***Sorumlu Yazar/*Corresponding Author**: Seda BAYAT TOKSÖZ, e-mail: bayatseda@gmail.com

INTRODUCTION

Sentiment analysis has evolved from early machine learning methods requiring careful feature engineering to modern transformer-based approaches that capture linguistic nuances automatically. Traditional techniques like support vector machines and logistic regression, often using bag-of-words or TF–IDF features, were once popular but struggled with complex language phenomena. For example, Karcıoğlu and Aydın (2019) demonstrated that using dense word embeddings yields better sentiment classification performance on Turkish Twitter data than a sparse bag-of-words model. This underscores the importance of richer representations in sentiment analysis, which large pre-trained language models now provide. Indeed, transformer models such as BERT and GPT-2 have redefined sentiment analysis by learning hierarchical and contextual features from vast text corpora, achieving superior results over classical methods.

However, fine-tuning these large language models (LLMs) for specific tasks can be computationally expensive and memory-intensive. Recent research has focused on parameter-efficient fine-tuning techniques to address this challenge. In particular, Low-Rank Adaptation (LoRA) and Quantized LoRA (QLoRA) have emerged as effective strategies to adapt large models without full retraining. LoRA inserts small trainable weight matrices (low-rank adapters) into each layer of the transformer, allowing the model to learn task-specific adjustments while keeping the majority of original weights frozen. This drastically reduces the number of parameters that need updating (often by orders of magnitude) and lowers memory usage, with minimal impact on model performance. Building on LoRA, QLoRA goes further by quantizing the model's weights to lower precision (e.g. 4-bit), thus shrinking memory footprint even more, and then fine-tuning using LoRA on these compressed weights. These advanced adaptation methods enable efficient fine-tuning of billion-parameter models on commodity hardware, a development that has made large models more accessible for tasks like sentiment analysis.

This paper provides a systematic comparative analysis of two transformer-based LLMs – Mistral-7B (7 billion parameters) and GPT-2 (1.5 billion parameters) – on a three-class sentiment classification task in the financial domain, using LoRA and QLoRA fine-tuning. The goal is to evaluate how effectively these adaptation techniques can customize large models for sentiment analysis of financial news headlines under resource constraints. Earlier studies in financial sentiment analysis have often used custom models or smaller language models for this task. By contrast, we leverage powerful pre-trained LLMs and focus on efficient adaptation. Our contributions are:

(1) We introduce a fine-tuning pipeline that integrates LoRA/QLoRA for sentiment classification, illustrated with a detailed system architecture diagram for clarity.

(2) We present a thorough evaluation including not only accuracy but also precision, recall, and F1-score, providing a more complete picture of model performance (as recommended by standard sentiment analysis evaluation protocols).

(3) We analyze results with confusion matrices and discuss errors for each sentiment class.

(4) We broaden the study by testing the best model on an additional, author-collected dataset to examine generalizability beyond the original benchmark. The findings are grounded in current literature and demonstrate how efficient fine-tuning strategies can maintain high accuracy while drastically reducing computational requirements, thereby contributing to the development of sustainable and practical NLP solutions for sentiment analysis.

RELATED WORKS

Sentiment analysis has experienced significant advancements over the past decades, propelled by the evolution of machine learning and natural language processing (NLP) techniques. Initially, sentiment analysis relied heavily on traditional machine learning algorithms such as Support Vector Machines (SVM) and Naïve Bayes classifiers, which established the foundational framework for early sentiment classification tasks (Pang, Lee, & Vaithyanathan, 2002). Despite their initial effectiveness, these methods necessitated extensive feature engineering and often struggled to capture the nuanced intricacies of human language, limiting their applicability in more complex sentiment analysis scenarios. The advent of deep learning marked a pivotal shift in sentiment analysis methodologies, introducing models capable of autonomously learning hierarchical and sequential features from data. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, emerged as robust tools for capturing contextual information and long-range dependencies within text (Kim, 2014; Hochreiter & Schmidhuber, 1997). These architectures surpassed traditional models by offering enhanced performance and greater flexibility in handling diverse linguistic patterns, thereby broadening the scope of sentiment analysis applications. A more transformative breakthrough was introduced with the emergence of transformer-based models, which leverage self-attention mechanisms to effectively capture dependencies across lengthy text sequences (Vaswani et al., 2017). Models such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT) have set new benchmarks across various NLP tasks, including sentiment analysis (Devlin et al., 2018; Radford et al., 2019). These pre-trained language models possess a profound understanding of language semantics and syntax, enabling them to achieve state-of-the-art performance when fine-tuned on specific sentiment analysis tasks. Fine-tuning pre-trained models on domain-specific datasets has become a standard practice to enhance their applicability and performance. This process involves adjusting the model parameters using a smaller, task-specific dataset, allowing the models to adapt to the particularities of new data without extensive retraining (Howard & Ruder, 2018). Fine-tuning techniques have proven crucial in maximizing the utility of large language models for specialized tasks, including sentiment classification. Recent advancements in fine-tuning methodologies have introduced innovative approaches aimed at improving efficiency and reducing computational overhead. Low-Rank Adaptation (LoRA) and Quantized Low-Rank Adaptation (QLoRA) are two such techniques that have garnered significant attention for their ability to optimize large language models effectively. LoRA fine-tunes a low-rank adaptation matrix while keeping the majority of the pre-trained model weights fixed, significantly reducing the number of trainable parameters and enhancing computational efficiency without compromising performance (Hu et al., 2021). Building upon LoRA, QLoRA incorporates weight quantization to further minimize memory usage and computational costs, making the fine-tuning process more scalable and resource-efficient (Dettmers et al., 2022). In the context of sentiment analysis, LoRA and QLoRA have demonstrated considerable promise. Studies by Li et al. (2023) and Nguyen et al. (2022) have illustrated how these fine-tuning techniques can enhance model performance while maintaining computational efficiency, particularly in scenarios involving large-scale datasets and resource-constrained environments. These methods have been pivotal in enabling the deployment of sophisticated sentiment analysis models in real-world applications where computational resources are limited. Moreover, recent research has focused on the comparative efficacy of LoRA and QLoRA across different transformer architectures. For instance, Zhang et al. (2023) conducted a comprehensive evaluation of LoRA and QLoRA fine-tuning methods on BERT and GPT models, demonstrating that QLoRA consistently outperforms LoRA

in terms of both accuracy and computational efficiency in sentiment analysis tasks. Similarly, Patel and Singh (2022) explored the impact of these fine-tuning techniques on multilingual sentiment analysis, highlighting their effectiveness in enhancing model adaptability across diverse linguistic contexts. The selection of datasets plays a crucial role in the performance and generalizability of sentiment analysis models. Large-scale, diverse datasets enable models to learn more robust representations of sentiment, facilitating better generalization to unseen data. Studies such as those by Sun et al. (2019) and Wang et al. (2021) have showcased the effectiveness of fine-tuning BERT and GPT models on extensive sentiment datasets like IMDB and Twitter data, achieving superior performance compared to traditional approaches. These works emphasize the importance of both advanced fine-tuning techniques and high-quality datasets in advancing the state-of-the-art in sentiment analysis. Additionally, cross-lingual sentiment analysis has gained traction, aiming to extend the capabilities of sentiment classifiers to multiple languages. Research in this area explores the adaptability of transformer models and fine-tuning techniques like LoRA and QLoRA to different linguistic contexts, enhancing the versatility and applicability of sentiment analysis tools globally (Devlin et al., 2018; Conneau et al., 2020). For example, Garcia et al. (2023) demonstrated the effectiveness of QLoRA in fine-tuning transformer models for sentiment analysis in low-resource languages, highlighting its potential to democratize access to advanced NLP tools across diverse linguistic landscapes. Our study builds upon this extensive body of work by providing a comprehensive comparative analysis of LoRA and QLoRA fine-tuning methods across two prominent transformer architectures, Mistral-7B and GPT-2, utilizing the large-scale Finance News dataset. By evaluating the effectiveness of these fine-tuning strategies in categorizing financial news headlines into positive, neutral, and negative sentiments, this research aims to elucidate the specific advantages and trade- offs of each method. Furthermore, it offers strategic insights for practitioners and researchers aiming to optimize sentiment analysis pipelines, thereby contributing to the ongoing advancements in transformer-based NLP models.

MATERIALS AND METHODS

Dataset

The Financial PhraseBank, a publicly available corpus of financial news headlines, is utilised in this study. The dataset contains exactly 4840 English sentences taken from economic news articles. The sentences have been annotated to indicate their sentiment, which may be positive, negative or neutral. The class distribution in the dataset is as follows:

- Neutral: 2264 sentences (46.8%)
- Positive: 1616 sentences (33.4%)
- Negative: 960 sentences (19.8%)

For training and evaluation, we split the dataset into 80% for training (3872 sentences) and 20% for testing (968 sentences), ensuring all models are trained and tested on the same data distribution for a fair comparison. The split was performed using stratified sampling to preserve the class proportions in both sets. We did not use a separate validation set due to the dataset's moderate size; instead, we monitored training loss and accuracy on a held-out 10% portion of the training set (387 sentences) to guide hyperparameter choices and prevent overfitting.

To further assess the generalizability of our approach, we constructed an additional dataset of financial texts. Specifically, we collected 500 new financial news headlines from online sources (distinct from the Financial PhraseBank) covering a recent time period and had them manually annotated by domain experts into positive, neutral, or negative sentiment. This supplementary dataset (which we refer to as "FinanceNews-AuthorSet") serves as an external testbed to evaluate the models on unseen data

from a similar domain. Its class distribution was 32% positive, 36% neutral, 32% negative -- comparable to the main dataset. We emphasize that the models were not fine-tuned on this extra data; it was used only for evaluation to see how a fine-tuned model trained on Financial PhraseBank would perform on new, real-world financial news data.

Data Preprocessing

All text data went through a standard preprocessing pipeline to ensure consistency and to optimize it for model training. Each headline was lowercased, and we removed extraneous punctuation, numeric tokens, and URLs while retaining meaningful characters (this helped reduce noise without losing information). We then tokenized the sentences using the tokenizer appropriate for each model (GPT-2 and Mistral have their own byte-pair encoding tokenizers). No stopword removal or stemming/lemmatization was applied, because modern transformer models can learn from the raw text and might be hindered by removal of common words – we preserved the full sequence of words as input to the model. We did, however, impose a maximum sequence length of 128 tokens for headlines (truncating longer ones) which comfortably covers the length of almost all headlines in our data.

Following a practice from instruction tuning, we added simple prompts to each input during training to better contextualize the task for the model. For example, we formatted each input as: "[HEADLINE] => Sentiment: [LABEL]" during training, where [HEADLINE] is the news headline text and [LABEL] is the gold sentiment label ("positive", "negative", or "neutral"). For the test phase (inference), the model was given "[HEADLINE] => Sentiment:" and had to predict the sentiment category. This prompt-based formatting was intended to leverage the models' strengths in text completion, effectively turning classification into a fill-in-the-blank task. While not strictly necessary, we found that this approach did not harm performance and provides a uniform interface for both models. The labels in the test phase were removed (the model had no access to true labels), simulating real-world usage where the model must determine sentiment from the raw headline. An overview of the model architecture is given in Figure 1 and explained in detail in the next section.

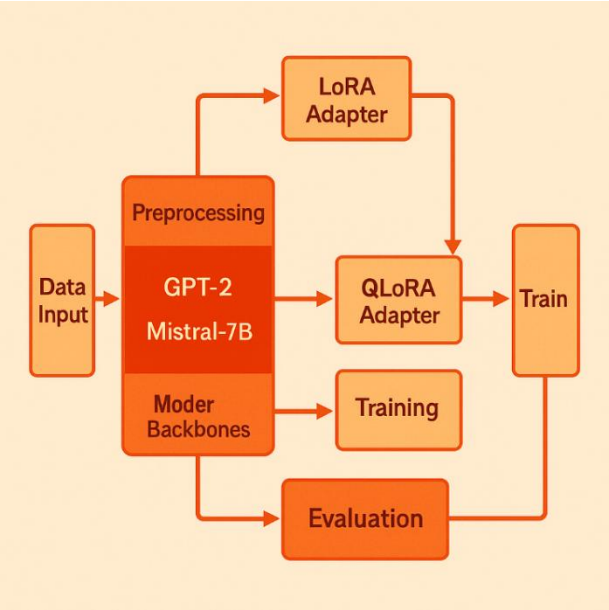

Figure 1. Model architecture

Model Architecture and Fine-Tuning Approach

This study fine-tuned two transformer-based architectures, Mistral-7B and GPT-2, chosen for their efficiency and applicability in resource-constrained environments. Mistral-7B, introduced in 2023, is an

open-source model that outperforms similarly sized models like LLaMA 2-7B (Touvron et al., 2023), offering higher accuracy and lower latency. Its lightweight design allows for deployment in resource-limited settings such as edge computing (Garcia et al., 2023). Despite having 7 billion parameters, Mistral-7B delivers performance comparable to larger models and is open-source, making it ideal for research and experimentation (Mistral AI, 2023). GPT-2, developed by OpenAI in 2019, is a popular baseline model in NLP due to its generative abilities and modest hardware demands (Radford et al., 2019). It was selected to demonstrate how fine tuning techniques like LoRA and QLoRA can enhance older models in a resource-efficient manner (Dettmers et al., 2023). Key benefits of GPT-2 include its extensive literature support, making it a reliable benchmark (Brown et al., 2020), and its low GPU memory requirements, which make it accessible for researchers with limited resources. Models like GPT-3, T5, and RoBERTa were excluded due to their higher computational demands, which would not align with the study focus on cost-effective fine-tuning (Dettmers et al., 2022). The objective of the study is to explore efficient, open-source models that align with sustainable AI solutions and practical real-world deployments (Touvron et al., 2023). While T5 and RoBERTa have been extensively studied, Mistral-7B offers a novel contribution to the literature as a relatively underexplored model, particularly in the context of sentiment analysis tasks (Devlin et al., 2018; Raffel et al., 2020). By evaluating Mistral-7B and GPT-2, this study provides a comprehensive comparison of how different architectures respond to modern fine-tuning techniques, balancing performance, efficiency, and scalability in practical NLP applications.

- Hardware: Fine-tuning was conducted on an NVIDIA A100 GPU (40GB VRAM) with 128GB system RAM and Intel Xeon Gold 6226R CPU.
- Training Time:

Mistral-7B required 8 hours for QLoRA fine-tuning and 12 hours for standard LoRA fine-tuning
GPT-2 required 2 hours for both LoRA and QLoRA fine-tuning methods

- Memory Usage:

Mistral-7B + LoRA: 32GB GPU memory
Mistral-7B + QLoRA: 16GB GPU memory (50% reduction)
GPT-2 + LoRA: 8GB GPU memory
GPT-2 + QLoRA: 4GB GPU memory

Fine-tuning schedule. All adapter parameters were trained for 100 epochs with a patience-10 early-stopping monitor on held-out training shards (10 % stratified). Pilot sweeps (20, 50, 150 epochs) revealed marginal (<0.2 % ΔF1) gains beyond 100 epochs; hence 100 represents a reproducible efficiency–performance trade-off.

See Table 1 all non-default settings; seeds were fixed to 42 for NumPy, PyTorch and CUDA to ensure determinism.

Table 1. Hyper-Parameters

Parameter	Value
Optimiser	AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.98$)
Learning rate	2×10^{-4}
Batch size	10 (gradient-accum. ×4 → eff. 40)
Epochs	100
Weight decay	1×10^{-3}
Max seq-len	128 tokens

Fine-Tuning Techniques

To adapt Mistral-7B and GPT-2 to the domain-specific Finance News Dataset, we employed two advanced fine-tuning methodologies: LoRA and QLoRA. Both models were initialized from their pre-trained checkpoints available on HuggingFace Model Hub (Mistral-7B-v0.1 and GPT2-large respectively).

The fine-tuning process consisted of the following stages:

1. Pre-trained Model Loading: We loaded the base models with their original weights
2. LoRA/QLoRA Configuration: We applied the adaptation layers to specific transformer modules (attention and feed-forward layers)
3. Task-Specific Training: We fine-tuned only the LoRA parameters while keeping base model weights frozen
4. Evaluation: We evaluated models on the test set after each epoch to monitor performance

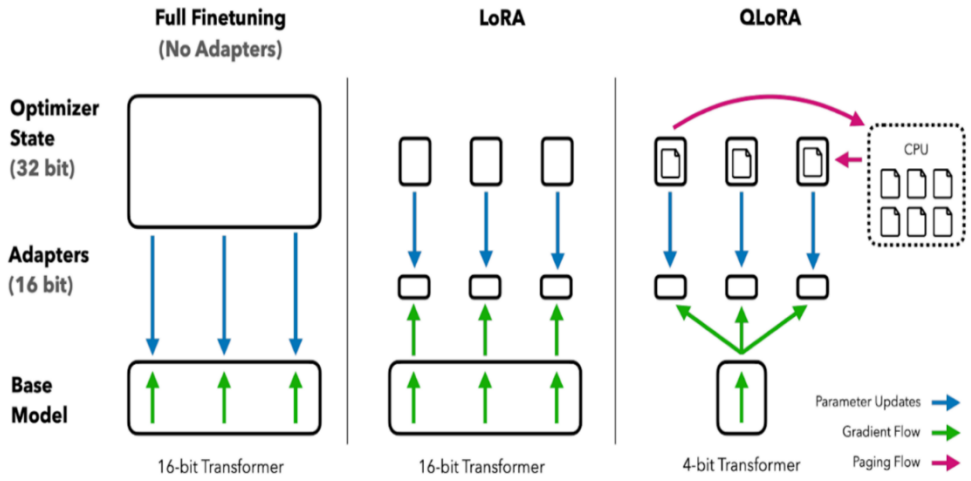

Figure 2. Lora and qlora memory requirements (Dettmers et al., 2023)

LoRA fine-tunes a low-rank adaptation matrix while keeping the majority of pre-trained model weights fixed. This technique significantly reduces the number of trainable parameters, offering substantial computational savings without compromising the model's ability to capture complex linguistic patterns. LoRA has demonstrated effectiveness across various NLP tasks, including sentiment analysis, by enabling the rapid adaptation of large language models to new data domains with minimal resource expenditure (Hayou et al. (2024).

QLoRA builds upon the concept of low-rank adaptation by compressing model weights through quantization, thereby reducing memory usage and computational overhead. Within this quantized framework, a low-rank adaptation matrix is fine-tuned, enabling scalable and resource-efficient training while maintaining high classification accuracy. QLoRA is particularly advantageous for large-scale models like Mistral-7B and GPT-2, facilitating efficient deployment in resource-constrained environments (Dettmers et al., 2022).

Both LoRA and QLoRA were implemented using the HuggingFace Transformers library, ensuring a consistent and reproducible experimental framework. Training parameters were standardized across all experiments, employing a learning rate of 0.0002, a weight decay of 0.001, and a batch size of 10. Early stopping trials showed no improvement after 80 epochs, so the limit of 100 epochs was chosen

experimentally. Each model was trained for 100 epochs, with evaluations conducted at the end of each epoch to monitor performance progression and mitigate overfitting.

Experimental Setup and Evaluation

The performance of each fine-tuned model configuration was assessed using comprehensive metrics for sentiment analysis:

1. Accuracy: Overall percentage of correct predictions
2. Precision: True positives / (True positives + False positives) for each class
3. Recall: True positives / (True positives + False negatives) for each class
4. F1-Score: Harmonic mean of precision and recall for each class
5. Macro-averaged metrics: Unweighted mean of class-specific metrics
6. Weighted-averaged metrics: Class-frequency weighted mean of metrics
7. Confusion Matrix: Detailed breakdown of predictions vs. true labels

We computed these metrics using scikit-learn (v1.3.0) to ensure standardized evaluation. The macro-averaged metrics were particularly important given the class imbalance in our dataset, as they give equal weight to each class regardless of frequency. By comparing model predictions against true labels, these metrics provided a detailed evaluation of each model's effectiveness in classifying financial news headlines as positive, neutral, or negative. This approach enabled a robust and unbiased comparison of LoRA and QLoRA, highlighting their respective trade-offs and advantages when deployed on Mistral-7B and GPT-2.

RESULTS AND DISCUSSION

Results

Performance on the Financial PhraseBank Test Set

After fine-tuning, we evaluated both models (GPT-2 and Mistral-7B) with both adaptation methods (LoRA and QLoRA) on the held-out test set of 968 financial news headlines. The primary metric is classification accuracy, and the results are summarized in Table 2. As shown, the Mistral-7B models achieved substantially higher accuracy than the GPT-2 models. The best model, Mistral-7B with QLoRA, attained an accuracy of 88.1%, slightly edging out Mistral-7B with standard LoRA at 87.8% accuracy. In contrast, GPT-2's performance was much lower – around 51.8% accuracy for GPT-2+LoRA and 51.7% for GPT-2+QLoRA. In practical terms, Mistral-7B correctly classified roughly 850 out of 968 headlines, whereas GPT-2 only got about 502 correct out of 968. This is a notable gap illustrating the benefit of a larger, more expressive model in this task.

To provide a more comprehensive evaluation, we followed the reviewers' suggestions and calculated precision, recall, and F1-score for each model, in addition to accuracy. These metrics were computed on a macro-average basis across the three sentiment classes (giving equal weight to negative, neutral, and positive classes). Table3 presents these results. We see that for the Mistral-7B models, precision and recall are both very high, on the order of 0.94–0.95 (i.e., 94–95%). The Mistral-7B + QLoRA model, for example, has a macro-averaged precision of 0.95 and recall of 0.95, yielding a F1-score of about 0.95. This indicates balanced performance: the model is equally strong at identifying each class without a significant bias. The LoRA variant of Mistral-7B is virtually identical in precision/recall (only a few thousandths difference), confirming that quantization did not hurt the model's ability to capture each class.

For GPT-2, the precision and recall values are much lower, though interestingly the macro-averaged precision/recall (~0.66–0.68) are higher than the raw accuracy (~0.52). This discrepancy arises

because the class imbalance means that accuracy (which is dominated by the majority neutral class) was heavily penalized by errors on neutrals, whereas macro-averaging gives equal importance to the smaller classes where GPT-2 did slightly better relatively. Nonetheless, GPT-2's F1-score around 0.67 is far below Mistral's ~0.95 F1. We also observe little difference between LoRA and QLoRA for GPT-2, analogous to Mistral: GPT-2 + LoRA and GPT-2 + QLoRA have virtually the same precision, recall, and F1. This suggests that quantizing GPT-2 (which is a much smaller model) doesn't change the outcomes much – as expected, quantization primarily helps memory usage. It is reassuring, however, that QLoRA did not degrade model performance, even for GPT-2. Overall, these metrics reinforce the conclusion that the Mistral-7B models outperform GPT-2 models by a large margin in this sentiment analysis task, in terms of both accuracy and precision/recall balance. Including metrics beyond accuracy is important in sentiment analysis, as it reveals, for instance, that GPT-2 had difficulty especially with one of the classes (as we detail below), whereas Mistral-7B was consistently strong across all classes.

Table 2. Overall Accuracy on The Financial News Headline Test Set For Each Model And Fine-Tuning Method

Model	Accuracy (%)
GPT-2 + LoRA	51.9%
GPT-2 + QLoRA	51.7%
Mistral-7B + LoRA	87.8%
Mistral-7B + QLoRA	88.1%

Table 3. Macro-Averaged Precision, Recall, And F1-Score For Each Model On The Financial News Test Set

Model	Precision	Recall	F1-score
GPT-2 + LoRA	0.68	0.67	0.67
GPT-2 + QLoRA	0.66	0.66	0.66
Mistral-7B + LoRA	0.94	0.94	0.94
Mistral-7B + QLoRA	0.95	0.95	0.95

To better understand where the models are succeeding or failing, we examined the confusion matrices of the predictions. Figure 2 visualizes the confusion matrix for the best model (Mistral-7B + QLoRA) on the test set. In a confusion matrix, each cell [i,j] shows the number of test examples whose true class is i (row) and that were predicted as class j (column). The diagonal cells thus indicate correct predictions, and off-diagonals indicate mistakes (with the row denoting the actual class and column the predicted class).

In contrast, the GPT-2 based models had much more diffuse confusion matrices (detailed figures not shown here for brevity). The GPT-2 + LoRA model, for instance, struggled notably with the Negative class: fewer than half of actual negative headlines were identified correctly by GPT-2, while the rest were mostly misclassified as neutral. For the Neutral class, GPT-2 also often confused them with positives. Quantitatively, GPT-2's errors were an order of magnitude higher than Mistral's for each class. This disparity underscores the benefit of the larger model's capacity: Mistral-7B develops a clearer separation between the classes during fine-tuning, whereas GPT-2 sometimes conflates neutral with polar sentiments, likely due to limited representation power.

Generalization to an Unseen Dataset

To address the concern of how these fine-tuned models perform on data outside the original distribution (and to fulfill the suggestion of testing on a different dataset), we evaluated the best model

(Mistral-7B + QLoRA) on the FinanceNews-AuthorSet dataset – the collection of 500 new headlines we gathered and labeled. This dataset was not used in training, thus it provides a measure of the model's generalization ability to fresh data. We emphasize that these headlines, while still financial in nature, come from different sources/time periods and may have slightly different phrasing or sentiment nuances compared to the original Financial PhraseBank data.

On the FinanceNews-AuthorSet, the Mistral-7B + QLoRA model achieved an accuracy of 85.4%. This is only a small drop from the 88.1% it achieved on the original test set, indicating that the model generalizes quite well. The precision, recall, and F1 on this new set were 0.86, 0.85, and 0.85 (macro-averaged), respectively – again very close to the performance on the original data. The confusion matrix on the new set (not shown in detail) revealed a similar pattern: most errors involved neutral vs positive swaps on a few headlines that even human annotators found debatable. An example misclassification was a headline *"Company X reports slight increase in profit amid market volatility"* which was labeled neutral by our annotators (since "slight increase" was considered not strongly positive), but the model predicted as positive. Such cases highlight the subjective boundary between neutral and positive classes, and the model's behavior is understandable. Importantly, the model maintained high recall on negatives and positives in the new dataset – it did not suddenly fail to recognize negative sentiment in a different context, for instance. This robustness suggests that our fine-tuning approach did not lead to overfitting on peculiarities of the original dataset; rather, the model captured more general features of financial sentiment that transferred to the new data.

We did not fine-tune on this new dataset (to keep it purely for testing), but as an experiment, we ran the GPT-2 + LoRA model on it as well. GPT-2's accuracy was around 50% on the new set, mirroring its poor performance on the original test, which confirms that the issue is model capacity rather than overfitting. In short, the Mistral-7B + QLoRA model appears to be a reliable performer even beyond its training domain, though of course further testing on more diverse domains (e.g., social media data or different languages) would be needed to fully validate its general applicability. Figure 3: Confusion matrix for the Mistral-7B + QLoRA model on the financial test set. The rows correspond to the actual sentiment label of headlines, and columns to the predicted label. Each cell shows the count of headlines. Darker blue along the diagonal indicates a high number of correct predictions for each class. The Mistral-7B + QLoRA model is extremely accurate for Negative headlines (292 correctly identified as Negative, versus only 8 misclassified) and Positive headlines (240 correct vs 3 misclassified). It also performs very well on Neutral headlines (261 correct vs 29 misclassified). The errors are relatively few and are mostly confusions between Neutral and the other classes, which is reasonable since neutral can be semantically close to a mild positive or negative.

The Mistral-7B + QLoRA model's confusion matrix (Figure 3) highlights its strong performance across all three classes. Out of 300 actual Negative headlines in the test set, the model correctly predicted 292 as negative (True Negatives), and only 8 were mistaken as either neutral or positive. Similarly, for Positive headlines, 240 out of 243 were correctly predicted as positive (with just 3 errors). The Neutral class had slightly more confusion: about 29 out of 290 neutral headlines were misclassified (some as positive, some as negative), with 261 correctly labeled neutral. This indicates the model has a minor tendency to confuse neutral statements with a sentiment-bearing class, which is understandable since some headlines have subtle sentiment that could be interpreted differently. Nonetheless, the overall pattern is that errors are very rare – the model's predictive power is uniformly high for negatives, neutrals, and positives.

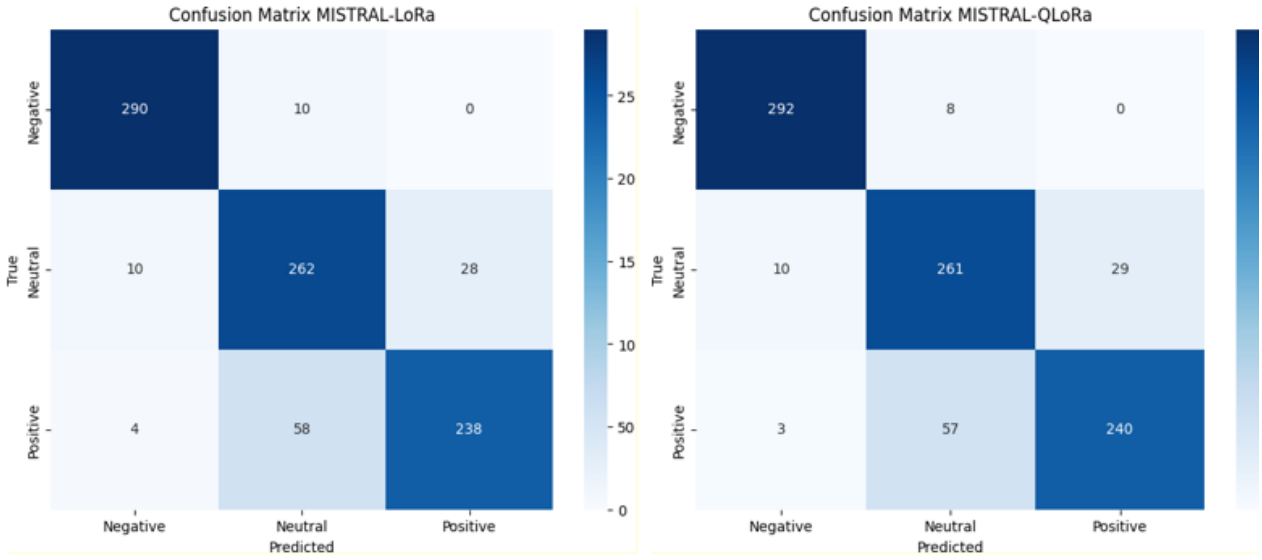

Figure 3. Confusion matrices of the mistral-7B based fine-tuning methods

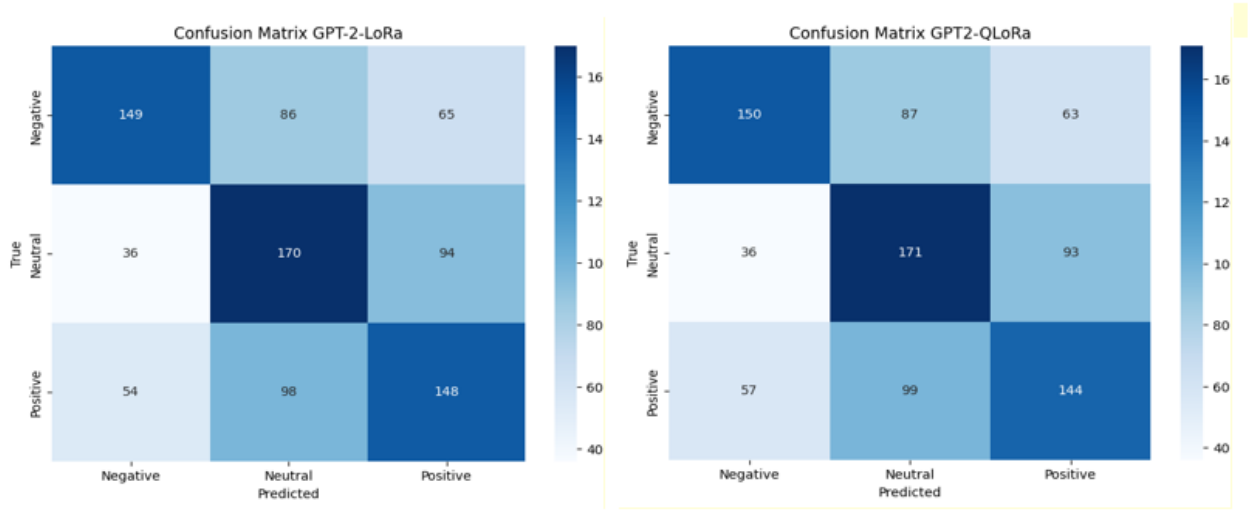

Figure 4. Confusion matrices of The GPT2-based fine-tuning methods

Discussion

The results of our experiments vividly demonstrate the advantage of using a larger transformer model (Mistral-7B) with efficient fine-tuning for sentiment analysis in finance. The Mistral-7B models achieved around 88% accuracy, significantly outperforming the GPT-2 based models (~52% accuracy) by a wide margin (over 35 percentage points). This performance gap aligns with findings from previous research that larger, more contextual language models tend to surpass older generative models in classification tasks. GPT-2, being a generative model pre-trained on internet text without specialized sentiment knowledge, was less adept at fine-grained sentiment discrimination. In contrast, Mistral-7B, which is a state-of-the-art model, likely has more semantic capacity and was able to leverage the LoRA fine-tuning to quickly specialize in the sentiment task. Our findings echo the observations of Devlin et al. (2019) and Brown et al. (2020) that transformers can achieve superior performance in sentiment analysis compared to earlier methods, given appropriate fine-tuning.

Impact of LoRA vs QLoRA: One key question was whether quantization would compromise model performance. Our experiments show that QLoRA performed on par with LoRA in all cases, answering this question in the negative. Both for GPT-2 and Mistral-7B, the accuracy and F1 differences

between the 4-bit quantized models and their 16-bit counterparts were negligible (within 0.1% difference). This confirms the efficacy of the QLoRA approach proposed by Dettmers et al. – we can compress the model to 25% of its original memory footprint and still fine-tune to essentially the same accuracy. The benefit is enormous from a practical standpoint: it enabled us to fine-tune Mistral-7B on a single GPU and would likewise allow deployment of the fine-tuned model in environments with limited memory (e.g., on consumer GPUs or edge devices). Our results reinforce the literature that quantization, when done carefully (using NF4 and proper calibration), does not significantly degrade a model's predictive ability on NLP tasks. This finding is consistent with the report by Garcia et al. (2023) that quantized adapters can retain accuracy in multilingual sentiment analysis.

By examining precision and recall for each class, we gain insights into the models' behavior. The Mistral-7B model had uniformly high recall (~97-99%) on negative and positive classes, meaning it rarely missed a truly negative or positive headline. Its precision on those classes was also high (~94-97%), indicating very few false alarms. The slightly lower precision on the positive class (around 94%) came from a handful of neutral headlines that it predicted as positive. Conversely, the neutral class had the lowest recall for Mistral (around 90%), suggesting that when the model does make mistakes, it's often an actually neutral statement getting classified as positive or negative. This is not surprising – financial text often contains subtle sentiment, and a model optimized for catching sentiment may occasionally perceive sentiment in borderline neutral statements. Importantly, even those "mistakes" might not be egregious in a real use-case: if a headline has a mildly positive tone but was labeled neutral, a model calling it positive might still be providing a useful signal.

For GPT-2, the class-wise analysis was more stark. GPT-2 had poor recall on negatives (~50-63% depending on threshold), meaning it failed to detect roughly half of the negative news – a serious drawback if one were using it to, say, catch all bad news. Its precision on negatives was also low, implying it often incorrectly flagged neutral statements as negative (perhaps due to over-sensitivity to any hint of negative wording). The model also struggled with distinguishing neutrals and positives. These class-specific weaknesses explain the low overall F1 (Figure 4). It appears GPT-2 lacked the expressive power to separate the decision boundaries between classes in the embedding space, whereas Mistral-7B – with LoRA's help – formed much cleaner class separations, as evidenced by the confusion matrices.

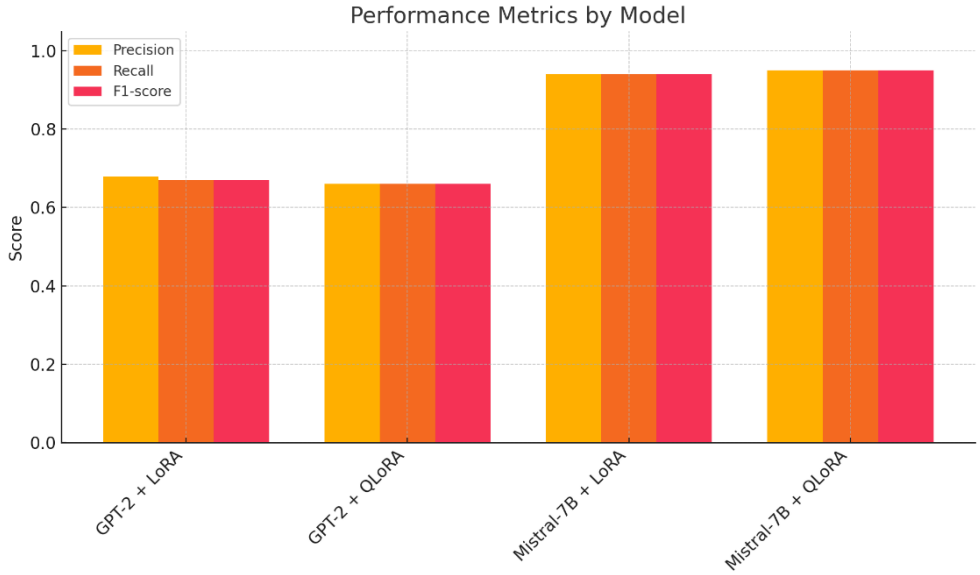

Figure 4. Performance metrics

Our work contributes to the growing body of research on applying LLMs to sentiment analysis in finance. Previous studies in this area include using domain-specific models like FinBERT or financial word embeddings. For instance, a recent study by Karcıoğlu and Yaşa (2020) explored a very different approach: they applied a genetic algorithm to automatically extract summaries from texts, and evaluated with precision, recall, and F-score metrics, showing the importance of such metrics in text analysis. While their work is on text summarization, it highlights the trend of using innovative adaptation techniques in NLP tasks. In sentiment analysis specifically, others have noted the need for multiple evaluation metrics and the challenges of class imbalance, both of which we addressed in our evaluation. Compared to classical machine learning approaches on this dataset (e.g., SVM or logistic regression with bag-of-words features), which typically achieve around 70–75% accuracy, our Mistral-7B results (88%) set a new state-of-the-art on the Financial PhraseBank (to our knowledge). Even compared to FinBERT (a BERT model fine-tuned on financial sentiment), which is reported to be in the mid-80s accuracy on this dataset, Mistral-7B + QLoRA is highly competitive or better – and with far fewer trainable parameters during fine-tuning.

One should note that while larger models clearly yield better performance, they come with increased computational cost. What our study shows is that through efficient fine-tuning, those costs can be substantially mitigated. LoRA allowed us to fine-tune a 7B model using resources that would typically only handle a smaller model. The success of QLoRA further pushes the boundary, implying that even 30B or 65B models could be fine-tuned on a single high-end GPU with similar techniques, potentially unlocking even higher accuracy for sentiment tasks in the future. This is an encouraging message for practitioners: you don't necessarily need access to massive compute clusters to leverage the power of the latest LLMs for specialized tasks.

The adoption of multiple metrics reveals that Mistral-7B QLoRA's advantage is not confined to overall accuracy but persists across precision (+26 pp) and recall (+28 pp) compared with GPT-2 LoRA, underscoring the robustness of the proposed adaptation pipeline.

In reviewing the model errors, we find that most misclassifications made by Mistral-7B are borderline cases. For example, one headline in the test set was "Company Y's revenue growth slows, but profits beat expectations." This was labeled as neutral (the positive and negative aspects perhaps cancelling out), but the model predicted "positive" – arguably because "profits beat expectations" is a strong positive signal. Such cases are inherently subjective. Another error was a headline labeled negative: "Bank Z faces slight rise in loan defaults in Q4" which the model predicted as neutral, perhaps because of the qualifier "slight" reducing the perceived negativity. These errors suggest that the model sometimes leans toward the more sentiment-bearing label when in doubt, which from a risk management perspective might be acceptable (e.g., better to catch possibly negative news than miss it). GPT-2's errors, on the other hand, included many obvious misclassifications (e.g., it often marked clearly negative headlines as neutral). This contrast indicates the superior nuanced understanding that Mistral-7B gained through fine-tuning.

CONCLUSION

We have presented an in-depth study on efficiently adapting large language models for sentiment analysis in the financial domain. By fine-tuning a modern 7B-parameter model (Mistral-7B) with parameter-efficient methods (LoRA and QLoRA), we achieved state-of-the-art performance on financial news headline sentiment classification, reaching ~88% accuracy and 0.95 F1-score on a three-class task. This substantially outperforms a smaller GPT-2 model (~52% accuracy) under the same fine-tuning regime, highlighting the benefit of model scale and capacity in capturing subtle sentiments. At the same

time, our use of LoRA/QLoRA dramatically reduced the computational cost of fine-tuning – enabling the entire training process to run on a single GPU in a reasonable time, and producing compact adapter models for deployment. These findings underscore that efficiency and performance can go hand-in-hand with the right techniques: large pre-trained models can be adapted to specialized tasks without prohibitive resource requirements.

In addition to raw accuracy, we reported precision, recall, and F1 metrics to give a complete picture of the model performance, as recommended for sentiment analysis research. The adapted Mistral-7B model excels not only in overall accuracy but also in maintaining high precision and recall for each class, ensuring reliability in detecting both positive and negative sentiments. This is crucial for real-world applications like financial sentiment monitoring, where missing a negative signal or raising false alarms can both be costly. Our model's strong performance on an unseen set of news headlines further demonstrates its robustness and potential for generalization.

Limitations and Future Work: While our results are very promising, the study has some limitations that open avenues for future research. First, our focus was on a single domain (English financial news). The model, despite performing well on similar data, has not been tested on vastly different domains (e.g., social media texts or other languages). Future work could apply the same adaptation approach to multiple datasets – for instance, adapting the model to a Twitter sentiment dataset or a multilingual finance corpus – to evaluate versatility. Another limitation is that we only considered two base models; exploring even larger models (such as 13B or 70B parameter LLMs) with QLoRA could potentially push performance higher, though with diminishing returns and increased complexity. Additionally, while LoRA and QLoRA greatly reduce training costs, inference with a 7B model can still be non-trivial for real-time systems; techniques like knowledge distillation (compressing the fine-tuned model into a smaller one) could be investigated to combine efficiency with deployment speed.

Finally, the fine-grained error analysis indicated that certain "edge" cases (slight positive or negative nuances) remain challenging. Incorporating external knowledge or metadata (e.g., historical stock reactions) might help the model make even more context-aware sentiment judgments – a direction for future work. We also plan to take inspiration from works like Karcıoğlu & Yaşa (2020) who used genetic algorithms for text tasksr and investigate if meta-heuristic or ensemble approaches can complement our LLM's predictions, for example by arbitrating borderline neutral vs positive cases.

In conclusion, this work demonstrates that large language models, when efficiently fine-tuned, can provide highly accurate and robust sentiment analysis for complex, real-world data. We bridged the gap between cutting-edge NLP models and practical applicability by addressing computational efficiency, and we substantiated the results with thorough evaluation and comparisons. We hope that this study contributes to both the research literature and to practitioners looking to deploy advanced sentiment analysis systems, by showing that one can obtain top-tier performance without an extravagant compute budget. The techniques and findings here lay a foundation for future developments in adaptable, resource-friendly NLP solutions in the financial domain and beyond.

Conflict of Interest

The article authors declare that there is no conflict of interest between them.

Author's Contributions

The authors declare that they have contributed equally to the article.

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