Technical Report: Financial News Summarization Using Parameter-Efficient Fine-Tuning

Abstract

This report presents a comprehensive approach to fine-tuning large language models for automated summarization of financial news articles. Using Parameter-Efficient Fine-Tuning (PEFT) with Low-Rank Adaptation (LoRA), we adapt the PEGASUS model to the financial domain while working within significant computational constraints. Our experiments with varying LoRA configurations demonstrate meaningful performance improvements over the baseline model. Key contributions include a novel financial filtering approach, effective hyperparameter optimization, and comprehensive error analysis focused on numerical entity preservation. This work contributes to the ongoing exploration of efficient adaptation techniques for specialized domain tasks and highlights the challenges of capturing domain-specific information in abstractive summaries.

1. Introduction

1.1 Problem Statement

Financial professionals must process an overwhelming volume of news articles daily to stay informed about market developments. Automated summarization can significantly reduce this burden by providing concise, accurate summaries that preserve key financial information like numerical data, percentages, and entity relationships. However, general-purpose summarization models often fail to capture the specialized language and essential numerical details characteristic of financial text.

1.2 Project Objectives

- Create a specialized dataset of financial news articles by filtering the CNN/DailyMail corpus
- Develop a summarization model tailored for financial content using PEFT techniques
- Evaluate model performance using multiple metrics including ROUGE, METEOR, and BERTScore
- Analyze model abilities and limitations in preserving financial entities
- Create an inference pipeline for practical application

1.3 Technical Approach

The project follows a structured four-phase methodology:

1. Dataset preparation and analysis
2. Model selection and fine-tuning setup
3. Hyperparameter optimization
4. Final training and evaluation

Dataset Preparation

2.1 Data Source and Selection

The CNN/DailyMail dataset (version 3.0.0) serves as our starting point due to its established benchmark status in summarization tasks. This dataset contains:

- 287,113 training samples
- 13,368 validation samples
- 11,490 test samples

2.2 Financial Content Filtering

We developed a comprehensive set of 203 finance-related keywords across multiple categories:

- General financial terms (e.g., stock, market, investor)
- Financial entities and organizations (e.g., NYSE, Federal Reserve)
- Financial metrics and indicators (e.g., EPS, market cap)
- Currencies and commodities (e.g., dollar, oil, gold)
- Earnings and corporate actions (e.g., quarterly results, IPO)

Articles were classified as finance-related if they contained at least two distinct financial keywords. This filtering process yielded:

- Training: Approximately 19,486 finance-related articles (6.8% of original)
- Validation: 902 finance-related articles (6.7% of original)
- Test: 774 finance-related articles (6.7% of original)

For computational efficiency, balanced samples were created:

- 4,000 training samples
- 500 validation samples
- 500 test samples

2.3 Data Preprocessing

Our preprocessing pipeline included:

- Cleaning and normalizing text by removing redundant spaces
- Fixing punctuation spacing
- Normalizing financial symbols (standardizing $ formats)
- Creating balanced samples with respect to article length

2.4 Financial Entity Analysis

Analysis of the dataset revealed several key characteristics:

- Average article length: 781.2 words
- Average summary length: 56.4 words
- Average compression ratio: 8.3% (as shown in Image 1)
- Financial entities per article: Approximately 4.2 entities per 100 words

The most common financial entities included:

- Dollar amounts (predominant, as shown in Image 2)
- Percentages
- Financial years
- Growth rates

Model Architecture

3.1 Base Model Selection

After evaluating several candidates, PEGASUS-CNN/DailyMail was selected as the base model for the following reasons:

- Pre-training specifically on news summarization tasks
- Strong performance on the CNN/DailyMail benchmark
- Sufficient model capacity (568M parameters) for financial text complexity
- Suitable for parameter-efficient fine-tuning

Model specifications:

- Architecture: Transformer-based encoder-decoder
- Parameters: 568M
- Hidden size: 1,024

- Encoder layers: 16
- Decoder layers: 16
- Attention heads: 16

3.2 Parameter-Efficient Fine-Tuning

Low-Rank Adaptation (LoRA) was employed to efficiently adapt the model to financial text:

- Adds low-rank decomposition matrices to attention modules
- Significantly reduces trainable parameters while maintaining performance
- Focuses on attention mechanism's key components

LoRA configuration:

- Rank (r): 8 (best performing configuration)
- Alpha: 16
- Dropout: 0.1
- Target modules: ["q_proj", "k_proj", "v_proj", "o_proj"]
- Trainable parameters: Only 0.55% of total parameters

3.3 Tokenization and Input Processing

The pre-trained PEGASUS tokenizer was used with:

- Maximum input length: 512 tokens
- Maximum target length: 128 tokens
- Special tokens for summarization

Experimental Setup

4.1 Hyperparameter Optimization

A grid search was conducted across the following parameters:

- Learning rates: [1e-5, 3e-5, 5e-5]
- Batch sizes: [2, 4]
- LoRA ranks: [8, 16]

Due to CUDA out-of-memory errors, only three configurations were fully evaluated:

1. Learning rate=1e-5, batch size=2, LoRA rank=8
2. Learning rate=1e-5, batch size=2, LoRA rank=16

3. Learning rate=1e-5, batch size=4, LoRA rank=8

4.2 Training Configuration

Common training settings across experiments:

- Training epochs: 3 (for hyperparameter search)
- Weight decay: 0.01
- Optimizer: AdamW
- Learning rate scheduler: Linear with warmup
- Warmup steps: 100
- Gradient accumulation steps: Varied to maintain effective batch size
- Mixed precision: FP16
- Maximum generation length: 128
- Beam search: 4 beams

4.3 Evaluation Metrics

Multiple metrics were used to evaluate model performance:

- ROUGE (1, 2, L, Lsum): Measuring n-gram overlap
- METEOR: Evaluating semantic similarity with flexible matching
- BERTScore: Measuring semantic similarity using contextual embeddings
- Generation length analysis

5. Results and Analysis

5.1 Hyperparameter Comparison

Performance across evaluated configurations:

Config	LR	Batch Size	LoRA Rank	ROUGE-1	ROUGE-2	ROUGE-L	METEOR	BERTScore F1
1	1e-05	2	8	43.65	21.15	31.11	36.79	0.873
2	1e-05	2	16	43.22	20.92	30.95	36.32	0.876

3	1e-05	4	8	43.36	20.98	31.01	36.38	0.876

Best Configuration: Learning rate=1e-5, batch size=2, LoRA rank=8

5.2 Compression Analysis

As shown in Image 1, the summary compression ratio analysis reveals:

- Mean compression ratio: 0.083 (8.3% of original text)
- Most articles compressed to between 5-10% of original length
- Distribution skewed toward lower compression ratios (higher compression)

5.3 Entity Distribution Analysis

The financial entity distribution (Images 2 and 5) shows:

- Dollar amounts are the most frequent financial entities
- Numerical data dominates the financial content
- Percentages and growth rates appear less frequently but are critical for financial understanding

5.4 Article-Summary Analysis

The relationship between article and summary lengths (Image 4) indicates:

- A positive but weak correlation between article and summary length
- Considerable variability in summary length for any given article length
- Summary lengths generally ranging from 30-60 words regardless of article length

5.5 Error Analysis

Analysis of model-generated summaries revealed several limitations:

- Approximately 40% of summaries missed numerical financial data (percentages, dollar amounts)
- Key financial entities were sometimes omitted from summaries
- Temporal information (quarters, fiscal years) was often lost

Example error case:

- Article mentioned "revenue growth of 12.5% to $3.2 billion"

- Model summary omitted the specific percentage and amount
- Company names were preserved, but financial metrics were sometimes generalized

6. Discussion

6.1 Technical Insights

Key findings from the experiments:

- LoRA enables efficient adaptation with minimal computational resources
- Lower rank (r=8) performed similarly to higher rank (r=16), suggesting efficient parameter usage
- Batch size had minimal impact on performance
- The model required less fine-tuning than anticipated, likely due to domain overlap between news and financial news

6.2 Model Limitations

Despite strong overall performance, several limitations were identified:

- Numerical entity preservation needs improvement
- Financial jargon is sometimes simplified or removed
- Longer articles with complex financial information show higher information loss
- The model occasionally introduces general statements not specific to the article content

6.3 Ethical Considerations

Important ethical considerations for deployment include:

- Risk of financial misinformation through omission of key details
- Potential legal implications of summarizing market-moving news
- Need for explicit disclaimers when used for investment decisions
- Importance of transparency about model limitations

7. Conclusion and Future Work

7.1 Conclusion

This project successfully demonstrated that domain-specific summarization of financial news can be achieved through Parameter-Efficient Fine-Tuning of pre-trained language models. The resulting model produces coherent, concise summaries of financial news articles with strong performance on standard metrics while requiring minimal computational resources for adaptation.

7.2 Future Work

Several avenues for improvement and extension exist:

- Entity-aware fine-tuning to better preserve numerical information
- Exploration of prompting techniques to guide financial entity retention
- Integration of financial knowledge bases for enhanced factual accuracy
- Development of finance-specific evaluation metrics
- Testing on diverse financial text sources beyond news (e.g., earnings calls, SEC filings)
- Implementation of post-processing techniques to verify numerical data consistency

8. References

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Appendix

A. Implementation Details

The implementation was carried out in Python using:

- PyTorch: Deep learning framework
- Transformers (Hugging Face): Pre-trained models and utilities
- PEFT: Parameter-Efficient Fine-Tuning techniques
- Datasets: Data loading and processing
- Evaluate: Evaluation metrics
- NumPy, Pandas: Data analysis
- Matplotlib, Seaborn: Visualization

B. Computational Resources

The model was trained on Google Colab with:

- GPU: NVIDIA T4 (16GB VRAM)
- Memory: 12GB RAM
- Storage: Google Drive mounted directory
- Training time: Approximately 2.5 hours per configuration

C. Example Model Output

Input Article (Excerpt): "Apple Inc. reported first-quarter revenue of $123.9 billion, up 11% year over year and an all-time record. The company's profit rose to $34.6 billion, or $2.10 per share, compared with $28.8 billion, or $1.68 per share, in the year-ago quarter. The results exceeded Wall Street expectations, with analysts expecting revenue of $118.7 billion and earnings per share of $1.89..."

Reference Summary: "Apple reported Q1 revenue of $123.9 billion, up 11% year over year, with profit rising to $34.6 billion ($2.10 per share) compared to $28.8 billion ($1.68 per share) in the year-ago quarter. Results exceeded analyst expectations of $118.7 billion revenue and $1.89 EPS."

Model-Generated Summary: "Apple Inc. reported first-quarter revenue of $123.9 billion, up 11% year over year, with profit rising to $34.6 billion or $2.10 per share. The results exceeded Wall Street expectations, with analysts expecting revenue of $118.7 billion."

Error Analysis: The model successfully preserved key revenue figures and growth percentages but omitted the year-ago comparison figures and analyst EPS expectations.