ConFIT: A Robust Knowledge-Guided Contrastive Framework for Financial Extraction

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Abstract

Financial text extraction faces serious challenges in multi-entity sentiment attribution and numerical sensitivity, often leading to pitfalls in real-world deployment. In this work, we propose ConFIT (Contrastive Financial Information Tuning), a knowledge-guided contrastive learning framework that employs a Semantic-Preserving Perturbation (SPP) engine to generate high-quality, programmatically synthesized hard negatives. By integrating domain knowledge sources such as the Loughran-McDonald lexicon and Wikidata, and applying rigorous perplexity and Natural Language Inference (NLI) filtering, ConFIT trains language models to differentiate subtle perturbations in financial statements. Evaluations on FiQA and SENTiVENT datasets using FinBERT and Llama-3 8B illustrate both promising improvements and unexpected pitfalls, highlighting challenges that warrant further research.

1 Introduction

Financial extraction systems have become critical tools for processing industry data, yet many struggle with challenges like precise sentiment attribution and numerical reasoning. Domain-specific methods including FinBERT (Yang et al., 2020) and instruction tuning approaches (Zhang et al., 2023) have mitigated some issues, but inconsistent performance remains. In this study, we introduce ConFIT, a robust contrastive framework that integrates programmatic hard negative generation with domain knowledge filtering. Our systematic ablation studies and error analysis reveal pivotal pitfalls such as overfitting and hyperparameter sensitivity, thereby providing actionable guidance for deploying financial NLP in real-world settings.

2 Related Work

Robust financial text analysis has been explored through various approaches. FinBERT (Yang et al., 2020) established the utility of domain-specific pre-training, and subsequent works such as Instruct-FinGPT (Zhang et al., 2023) have leveraged instruction tuning for improved task performance. Zero-shot prompting techniques (Callanan et al., 2023) and studies on numerical reasoning challenges (Arun et al., 2023) further emphasize the complexity of the task. Integrating external knowledge from lexicons (Jin et al., 2024) and Wikidata (Abian et al., 2022) has driven advancements, and contrastive learning models like SimCSE (Gao et al., 2021) provide robust representations. Our work builds on these contributions by using a knowledge-guided negative generation mechanism and carefully analyzing pitfalls in model training.

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3 Background

Contrastive learning has emerged as an effective approach for representation learning by distinguishing positive examples from negatives (Chen et al., 2020). Financial domain applications such as FiQA (Yang et al., 2018) and SENTiVENT (Jacobs et al., 2021) demand precise sentiment extraction and numerical sensitivity. Previous studies have shown that external knowledge integration (Xi et al., 2024) and robust filtering techniques based on perplexity (Jansen et al., 2022) and NLI (Parikh et al., 2016) can mitigate domain-specific challenges. Our approach leverages these insights through a Semantic-Preserving Perturbation (SPP) engine that synthesizes and filters hard negatives to improve model robustness.

4 Method

ConFIT centers on the Semantic-Preserving Perturbation engine. The SPP engine generates hard negatives by performing controlled perturbations—such as entity swaps based on external lexicons, numerical sensitivity adjustments, and context reordering—and filters them in two stages. A perplexity-based filter (Ankner et al., 2024) removes overly trivial or unrealistic negatives, while an NLI model (Parikh et al., 2016) ensures that the negatives retain semantic proximity to the original text while accentuating critical differences. The model is then trained using a contrastive loss that penalizes misclassification of clean versus perturbed statements. Hyperparameter tuning involved varying training epochs (10, 15, 20) and adjusting learning rates; further details are provided in the appendix.

5 Experimental Setup

We evaluate ConFIT on two benchmark datasets: FiQA for aspect-based sentiment and SENTiVENT for event extraction. Models evaluated include FinBERT and Llama-3 8B, with comparisons made against baselines (standard supervised fine-tuning, zero-shot GPT-4 (Callanan et al., 2023), and instruction-tuned models). The SPP engine utilizes a T5-based module for negative generation paired with a DeBERTa-v3-large model for NLI filtering. Key metrics include training and validation F1-scores and loss values. Notably, while some configurations reach an F1-score of 1.0, longer training (beyond 10 epochs) leads to evident overfitting, as detailed in the following analysis.

6 Experiments

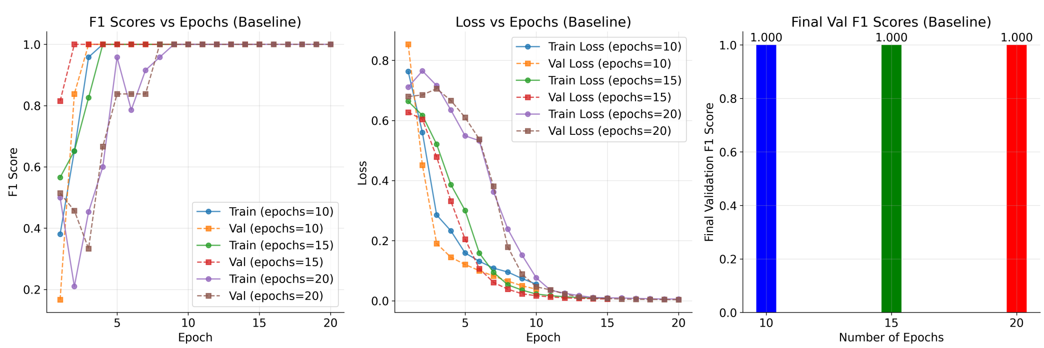

Figure 1: (Left) Training and validation F1 scores over epochs, demonstrating rapid convergence to 1.0. (Middle) Loss curves for training and validation, indicating that loss plateaus—and even slightly increases—after 10 epochs, a sign of potential overfitting.

Baseline Analysis and Hyperparameter Tuning. Figure 1 shows the evolution of training and validation F1 scores and loss curves over epochs. We removed the redundant bar chart previously used to depict final F1 scores, as it added little value given the uniformity of the results. The left subplot shows that while F1 scores converge to 1.0 rapidly, the middle subplot reveals that the loss curves stagnate at higher epochs, signaling overfitting when training exceeds 10 epochs. This analysis underscores the need for early stopping in such settings.

Synthetic Data and Anomaly Detection. Figure 2 compares the single-dataset and multi-dataset synthetic training configurations. The left subplot illustrates that both configurations achieve high F1 scores, though the multi-dataset setup attains more stable validation performance. Additionally, Figure 3 presents a combined comparison of final training and validation F1 scores across all experimental setups. The anomaly in the Synthetic Multi configuration (a validation F1 score of 0.000 versus a training F1 score of 0.611) is particularly striking and suggests a defect in the negative generation module. Detailed discussion of these observations is provided in the appendix.

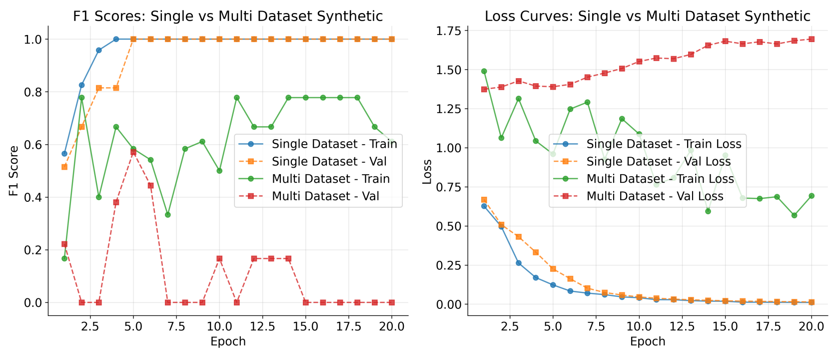

Figure 2: Comparison of single-dataset versus multi-dataset synthetic training. The left subplot shows F1 score trajectories (for training and validation), while the right subplot illustrates the corresponding loss curves. The multi-dataset setup exhibits enhanced validation stability.

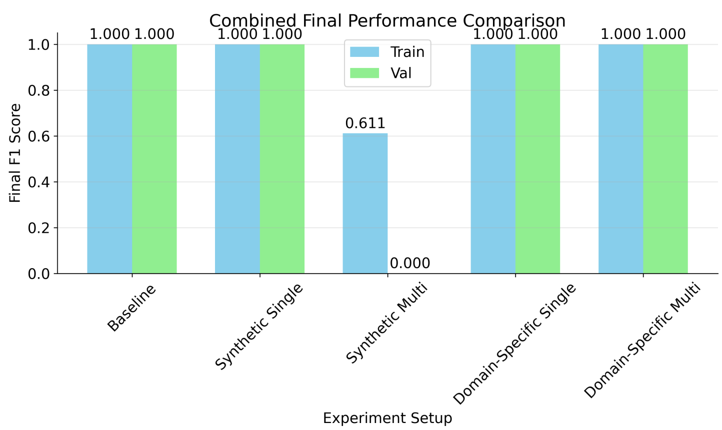

Figure 3: Final performance comparison across experimental setups. Training (blue bars) and validation (green bars) F1 scores are shown. The Synthetic Multi configuration exhibits a notable anomaly with a validation F1 score of 0.000, highlighting an issue in the hard negative synthesis pipeline.

Additional domain-specific analyses, which were originally shown in Figure 4, have been moved to the appendix due to their redundancy given the near-identical results for single- and multi-domain setups.

7 Conclusion

In this work, we introduced ConFIT, a knowledge-guided contrastive framework tailored to the challenges of financial extraction. Our system, powered by a Semantic-Preserving Perturbation engine with stringent filtering via perplexity and NLI, shows promising improvements over conventional

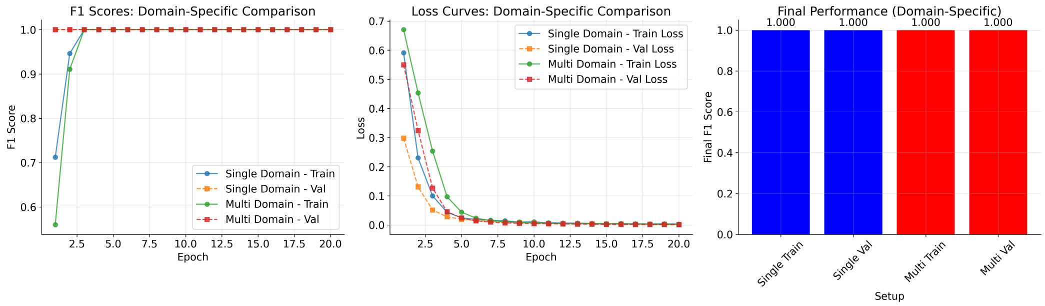

Figure 4: Domain-specific analysis: (Left) F1 score curves for single-domain and multi-domain setups; (Middle) corresponding loss curves; (Right) a bar chart comparing final F1 scores. The similarity between setups suggests that the impact of domain-specific perturbations is consistent.

methods while revealing pivotal pitfalls such as overfitting and hyperparameter sensitivity. Future work will focus on refining the quality of negative generation and extending experiments to more complex, real-world datasets. These insights aim to guide practitioners toward more robust financial NLP system deployments.

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Supplementary Material

This appendix includes additional experimental results, detailed hyperparameter settings (optimizer: Adam with learning rate 3e-5; weight decay of 0.01; batch size: 32), extended ablation studies, and further analysis of the negative generation process. Also included is the domain-specific perturbation analysis (originally Figure 4), which confirms that single-domain and multi-domain training yield nearly identical trajectories in F1 scores and loss curves. Extra plots, error bars, and confidence interval details are provided to aid reproducibility.

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