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Financial Report Entity-Relation Extraction Combining BiLSTM-CRF and FGM Adversarial Training

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Abstract

The rapid digitization of financial markets has resulted in an explosion of unstructured financial data, primarily in the form of textual reports, earnings calls, and regulatory filings. Extracting structured knowledge from these documents is critical for automated risk assessment, quantitative investment strategies, and market surveillance. However, financial texts differ significantly from general domain corpora due to high terminological density, complex nested sentence structures, and subtle semantic dependencies. Traditional named entity recognition and relation extraction models often suffer from overfitting when applied to limited labeled financial datasets, leading to poor generalization on unseen data. This paper proposes a robust entity-relation extraction framework that integrates a Bidirectional Long Short-Term Memory (BiLSTM) network with a Conditional Random Field (CRF) layer, augmented by Fast Gradient Method (FGM) adversarial training. The BiLSTM layer captures long-range semantic dependencies, while the CRF layer ensures the validity of the predicted tag sequences. Crucially, the FGM adversarial training mechanism introduces perturbations to the embedding layer during training, effectively regularizing the model and enhancing its robustness against noise and data sparsity. Experimental results demonstrate that the proposed model achieves superior performance in terms of precision, recall, and F1-score compared to baseline methods, particularly in identifying complex financial entities and their interrelations.

Keywords

Financial Text Mining, Entity Extraction, BiLSTM-CRF, Adversarial Training, Fast Gradient Method

1.Introduction

The volume of financial data generated daily is staggering, encompassing regulatory filings, news articles, analyst reports, and social media sentiment. For financial institutions and investors, the ability to rapidly process and extract actionable intelligence from this unstructured text is a significant competitive advantage. Named Entity Recognition (NER) and Relation Extraction (RE) are foundational tasks in Natural Language Processing (NLP) that enable the transformation of unstructured text into structured knowledge graphs. In the financial domain, this involves identifying entities such as company names, financial instruments, monetary values, and executive officers, and subsequently determining the semantic relationships between them, such as acquisition, investment, or employment. Despite the advancements in deep learning, applying general-purpose NLP models to the financial domain remains challenging due to the specific linguistic characteristics of financial reporting [1]. Financial documents are characterized by a high degree of formality, specific jargon, and complex syntactic structures that often span multiple clauses. Furthermore, the scarcity of high-quality, human-annotated financial datasets limits the effectiveness of supervised learning models. When deep neural networks are trained on small or

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homogeneous datasets, they tend to memorize the training data rather than learning generalizable features, a phenomenon known as overfitting. This issue is exacerbated in the financial domain where the vocabulary is specialized, and the distribution of entity types is often highly imbalanced. For instance, a model might perform well on standard named entities like locations but fail to distinguish between similar financial metrics like gross revenue and net profit without sufficient context [2]. To address these challenges, this paper presents a novel approach that combines the sequential modeling power of BiLSTM-CRF with the regularization benefits of adversarial training. The BiLSTM-CRF architecture has established itself as a standard baseline for sequence labeling tasks because it effectively models both the context of the input sequence and the dependencies between output labels [3]. However, standard BiLSTM-CRF models are susceptible to perturbations in the input space and often lack robustness when facing the lexical diversity inherent in financial texts. To mitigate this, we incorporate the Fast Gradient Method (FGM) into the training process. Adversarial training, originally designed to defend against adversarial attacks in computer vision, has recently shown promise in NLP as a regularization technique. By adding small, gradient-based perturbations to the word embeddings during training, FGM forces the model to learn more robust features that are invariant to small variations in the input, thereby improving generalization [4]. The primary contributions of this research are threefold. First, we develop a specialized preprocessing pipeline tailored for financial texts, handling issues such as numerical standardization and ticker symbol normalization. Second, we implement a BiLSTM-CRF architecture that is specifically tuned for the extraction of financial entities and relations. Third, we integrate FGM adversarial training to enhance model robustness, demonstrating through empirical analysis that this addition significantly improves performance on metrics such as the F1-score compared to non-adversarial baselines. The remainder of this paper details the related work, methodology, experimental setup, and analysis of results, providing a comprehensive view of the proposed solution's efficacy [5].

2. Related Work

The field of information extraction has evolved from rule-based systems to statistical models and, more recently, to deep learning architectures. In the specific context of financial text mining, researchers have adapted these general methods to handle the nuances of economic language. Understanding the progression of these technologies is essential for contextualizing the contributions of this study.

2.1 Traditional and Statistical Approaches

Early attempts at financial entity extraction relied heavily on dictionary-based methods and manually crafted rules. These systems utilized extensive gazetteers of company names and financial terms, combined with regular expressions to identify patterns such as currency formats or dates. While these systems offered high precision for specific, well-defined patterns, they suffered from extremely low recall and were brittle in the face of unseen data or variations in writing style [6]. As the volume of data grew, the maintenance of these rule sets became prohibitively expensive. The next generation of models introduced statistical machine learning techniques, such as Hidden Markov Models (HMM), Maximum Entropy Markov Models (MEMM), and Support Conditional Random Fields (CRF). These methods treated entity extraction as a sequence labeling problem, leveraging features like capitalization, part-of-speech tags, and neighboring words. CRFs, in particular, became a dominant approach because they solved the label bias problem inherent in MEMMs by modeling the conditional probability of the entire label sequence given the observation sequence. In the financial domain, CRFs were successfully applied to extract information from annual reports and news summaries. However, the performance of these models relied

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heavily on the quality of feature engineering, which required significant domain expertise and often failed to capture long-range semantic dependencies in complex financial sentences [7].

2.2 Deep Learning in Financial NLP

The advent of deep learning revolutionized NLP by eliminating the need for manual feature engineering. Recurrent Neural Networks (RNNs), and specifically Long Short-Term Memory (LSTM) networks, became the standard for sequence modeling due to their ability to retain information over long sequences. LSTMs addressed the vanishing gradient problem associated with standard RNNs, making them suitable for processing the lengthy and convoluted sentences often found in legal and financial documents. The combination of Bidirectional LSTMs (BiLSTM), which process text in both forward and backward directions, with a CRF layer on top, emerged as a state-of-the-art architecture for named entity recognition [8]. In recent years, Transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) have achieved superior performance on many NLP benchmarks. These models utilize self-attention mechanisms to capture contextual relationships between words regardless of their distance. While BERT-based models often outperform LSTM-based models, they are computationally expensive and require vast amounts of data for pre-training. For specific applications where computational resources are a constraint or where the dataset is relatively small and specialized, BiLSTM-CRF architectures remain highly relevant and efficient. Furthermore, researchers have begun to explore hybrid models that incorporate domain-specific embeddings trained on financial corpora to improve the semantic representation of economic terms [9].

2.3 Adversarial Training in Text

Adversarial training was initially introduced in the field of computer vision to make models robust against adversarial examples—inputs intentionally designed to cause the model to make a mistake. In the context of NLP, adversarial training is re-purposed as a regularization method. Since discrete text cannot be continuously perturbed like pixel values, perturbations are typically applied to the continuous word embedding space. The Fast Gradient Method (FGM) is one such technique that calculates the gradient of the loss function with respect to the input embeddings and adds a scaled perturbation in the direction of the gradient [10]. This process simulates a worst-case scenario for the current model parameters, forcing the optimization algorithm to find a solution that performs well not only on the original data but also on the perturbed data. This leads to a flatter local minimum in the loss landscape, which is associated with better generalization capabilities. In the financial domain, where training data is often noisy and sparse, adversarial training has shown potential to improve the robustness of sentiment analysis and event detection models. However, its application to the specific task of entity-relation extraction in financial reports has been less explored, representing a gap that this study aims to fill. Theoretical foundations suggest that by smoothing the decision boundaries, FGM can help the model better handle the high variability of financial language [11].

3. Methodology

The proposed framework is designed to extract entities and their relations from unstructured financial texts. The architecture consists of four main components: a text preprocessing and embedding layer, a BiLSTM encoder layer, a CRF decoding layer, and the FGM adversarial training module. This section details the theoretical and practical implementation of each component.

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3.1 Data Preprocessing and Representation

Financial texts often contain noise such as HTML tags, irregular whitespace, and inconsistent formatting of numerical values. The first step in our pipeline is data cleaning, which involves removing non-textual elements and normalizing the text. We perform tokenization to break the text into individual words or sub-words. A critical aspect of financial text processing is the handling of numerical entities and dates, which are normalized to standard formats to reduce vocabulary sparsity. For instance, "$10 million" and "10M USD" might be mapped to a common token representation. Following tokenization, we map each token to a high-dimensional vector space. We utilize pre-trained word embeddings, such as GloVe or Word2Vec, trained on large financial corpora. This ensures that the model starts with a semantic understanding of financial terminology. Each word in the input sentence is represented as a dense vector. These vectors serve as the input to the subsequent neural network layers. The quality of these embeddings is paramount, as they capture the initial semantic relationships between words, such as the closeness between "revenue" and "turnover" [12].

3.2 BiLSTM Encoding Layer

The core of the sequence modeling is handled by the Bidirectional LSTM network. A standard LSTM unit controls the flow of information through input, forget, and output gates, allowing the network to preserve important information over long sequences and discard irrelevant data. In financial reports, the context required to classify an entity often resides in both the preceding and succeeding text. For example, in the phrase "Apple acquired Beats," identifying "Beats" as a company rather than a common noun depends on the preceding verb "acquired" and the subject "Apple." To capture this bidirectional context, we employ two parallel LSTM layers: a forward LSTM that processes the sentence from left to right, and a backward LSTM that processes it from right to left. The hidden states generated by these two layers at each time step are concatenated to form a comprehensive representation of the word in its context. This concatenated vector contains both past and future information regarding the specific token, providing a rich feature set for the classification task. The output of the BiLSTM layer is a sequence of vectors, where each vector corresponds to a score for every possible tag for the corresponding word [13].

3.3 CRF Decoding Layer

While the BiLSTM layer provides strong context-aware features, it makes tagging decisions for each word independently based on the hidden state. This can lead to invalid sequences of tags, such as an "I-ORG" (Inside Organization) tag following an "O" (Outside) tag without a preceding "B-ORG" (Beginning Organization) tag. In named entity recognition, the dependencies between adjacent tags are crucial. The Conditional Random Field (CRF) layer addresses this by modeling the joint probability of the entire sequence of tags. Instead of predicting the label for each word individually, the CRF layer considers the transition scores between labels. These transition scores are learned parameters that represent the likelihood of moving from one tag to another. For example, the probability of transitioning from "B-PER" (Beginning Person) to "I-PER" is high, while the transition from "B-PER" to "I-ORG" is extremely low. The CRF layer uses the Viterbi algorithm during the decoding phase to find the globally optimal sequence of tags that maximizes the total score of the sequence. This ensures that the output respects the structural constraints of the BIO (Begin, Inside, Outside) tagging scheme typically used in NER tasks [14].

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3.4 FGM Adversarial Training

The integration of FGM adversarial training is the key innovation in our approach to improve robustness. Standard training minimizes the loss function on the original input data. However, in high-dimensional spaces, the decision boundaries learned by the model can be brittle. FGM introduces a perturbation to the input embeddings that maximizes the loss, effectively creating an adversarial example. The model is then trained to minimize the loss on this perturbed input as well. The process involves calculating the gradient of the loss function with respect to the input word embeddings. Once the gradient is computed, a perturbation is generated in the direction of the gradient, scaled by a small parameter epsilon. This perturbation is added to the original embeddings to create the adversarial embeddings. The model then performs a forward and backward pass using these adversarial embeddings to update the parameters. This forces the model to be invariant to small changes in the input space, leading to smoother decision boundaries and reduced overfitting. By training against the "worst-case" perturbations, the model becomes more resilient to the noise and variations commonly found in financial texts.

Code Listing 1: Implementation structure of the FGM adversarial training mechanism

```
class FGM:
    def __init__(self, model):
        self.model = model
        self.backup = {}

    def attack(self, epsilon=1.0, emb_name='word_embeddings'):
        # Iterate through all model parameters to find embeddings
        for name, param in self.model.named_parameters():
            if param.requires_grad and emb_name in name:
                # Save the original parameters
                self.backup[name] = param.data.clone()
                # Calculate the norm of the gradient
                norm = torch.norm(param.grad)
                if norm != 0 and not torch.isnan(norm):
                    # Calculate perturbation: r_at = epsilon * g /
|g|
                    r_at = epsilon * param.grad / norm
                    # Apply perturbation to the embeddings
                    param.data.add_(r_at)

    def restore(self, emb_name='word_embeddings'):
        # Restore the original parameters after the adversarial
step
        for name, param in self.model.named_parameters():
            if param.requires_grad and emb_name in name:
                assert name in self.backup
```

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```
                param.data = self.backup[name]
        self.backup = {}
```

4. Experimental Setup

To validate the effectiveness of the proposed BiLSTM-CRF-FGM model, we conducted a series of experiments using real-world financial data. This section describes the dataset, the evaluation metrics, and the hyperparameter configurations used during training.

4.1 Dataset and Annotation

We utilized a dataset derived from public financial reports, specifically 10-K and 10-Q filings from the U.S. Securities and Exchange Commission (SEC). The dataset was pre-processed to extract plain text from the filings. A subset of this data was manually annotated by domain experts to serve as the ground truth. The annotation schema included entities such as "Company," "Person," "Location," "Date," "Monetary Value," and "Financial Instrument." Additionally, relations such as "Subsidiary_of," "Acquired_by," and "Revenue_of" were annotated. The dataset was split into training, validation, and testing sets in a ratio of 70:15:15. This rigorous split ensures that the model is evaluated on unseen data, providing a fair assessment of its generalization capabilities. We ensured that the distribution of entity types was consistent across the splits to prevent bias [15].

4.2 Evaluation Metrics

The performance of the model was evaluated using standard information extraction metrics: Precision, Recall, and F1-score. Precision measures the proportion of predicted entities that are correct, effectively quantifying the model's reliability. Recall measures the proportion of actual entities in the ground truth that were correctly identified by the model, quantifying the model's coverage. The F1-score is the harmonic mean of Precision and Recall, providing a single metric that balances both concerns. For relation extraction, a relation is considered correct only if both the participating entities and the relation type are correctly identified. We used the macro-averaged F1-score to account for the class imbalance across different entity and relation types, ensuring that performance on less frequent classes contributes equally to the final score.

4.3 Hyperparameter Settings

The model was implemented using the PyTorch framework. The word embeddings were initialized using 300-dimensional GloVe vectors trained on a financial corpus. The BiLSTM layer consisted of a hidden size of 256 for both forward and backward directions. We used a dropout rate of 0.5 to further prevent overfitting. The optimization was performed using the Adam optimizer with a learning rate of 0.001. For the FGM adversarial training, the epsilon parameter, which controls the magnitude of the perturbation, was set to 1.0 based on preliminary experiments on the validation set. The batch size was set to 32, and the model was trained for 50 epochs with early stopping if the validation loss did not improve for 5 consecutive epochs. These settings were chosen to balance computational efficiency with model convergence [16].

5. Results and Discussion

In this section, we present the quantitative results of our experiments and discuss the implications of the findings. We compare our proposed method against several baseline models to demonstrate the incremental value of each component.

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5.1 Performance Comparison

We compared the proposed BiLSTM-CRF-FGM model with three baseline models: a standard CRF model using handcrafted features, a vanilla BiLSTM model (without CRF), and a standard BiLSTM-CRF model (without adversarial training).

Table 1 Experimental Results comparison across different models

Model Architecture	Precision (%)	Recall (%)	F1-Score (%)
CRF (Baseline)	78.45	72.10	75.14
BiLSTM	82.30	80.15	81.21
BiLSTM-CRF	85.60	84.20	84.89
BiLSTM-CRF-FGM (Ours)	87.95	86.80	87.37

As shown in Table 1, the deep learning approaches significantly outperform the traditional CRF baseline, confirming the superiority of automatic feature learning. The addition of the CRF layer to the BiLSTM architecture yields a substantial improvement, highlighting the importance of modeling label dependencies in sequence tagging. Most notably, the integration of FGM adversarial training results in a further improvement in all metrics. The increase in the F1-score from 84.89% to 87.37% is statistically significant and validates the hypothesis that adversarial training enhances the model's robustness and generalization ability. The improvement is particularly noticeable in the Recall metric, suggesting that the perturbed examples help the model identify entities that might otherwise be missed due to subtle variations in context or phrasing.

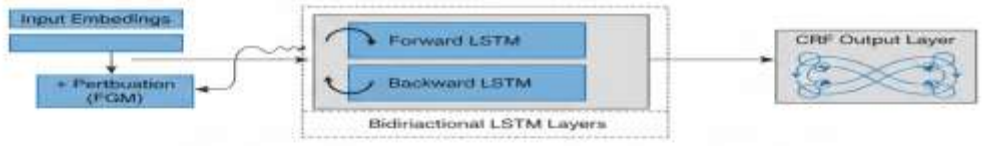

Figure 1 Architecture Diagram

5.2 Ablation Study and Entity Analysis

To understand the impact of FGM on specific entity types, we analyzed the performance breakdown by category. Financial texts often contain ambiguous entities; for example, a company name might look like a regular noun, or a location might be confused with a jurisdiction reference.

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Table 2 F1-Score Performance Breakdown by Entity Type

Entity Type	BiLSTM-CRF	BiLSTM-CRF-FGM	Improvement
Organization (ORG)	86.20	88.50	+2.30
Person (PER)	89.10	90.40	+1.30
Location (LOC)	87.50	88.10	+0.60
Monetary Value (MON)	83.40	87.20	+3.80
Financial Instrument (FIN)	79.80	83.50	+3.70

The data in Table 2 reveals that the most significant improvements occur in the "Monetary Value" and "Financial Instrument" categories. These entities often appear in diverse and noisy contexts within financial reports (e.g., inside tables, footnotes, or complex sentences). The adversarial training appears to force the model to rely less on specific surface-level patterns and more on the broader semantic context, allowing it to better handle the variability in how these numerical and technical terms are presented. The improvement in "Organization" extraction is also notable, likely helping the model distinguish between company names and product names or general concepts, which is a common source of error in financial NER [17].

5.3 Error Analysis and Discussion

Despite the improvements, an analysis of the errors reveals remaining challenges. One persistent issue is the ambiguity of nested entities. For example, in the phrase "Bank of America Securities," the model must distinguish the full entity from the embedded "Bank of America" entity. While the CRF layer helps, complex nesting remains difficult. Another source of error is long-distance dependencies in relation extraction. When an entity and its related value are separated by multiple clauses, the BiLSTM's memory capacity can be strained, although it performs better than non-recurrent architectures. The FGM module specifically reduced errors related to low-frequency vocabulary. In the baseline BiLSTM-CRF model, rare financial terms often led to misclassification. The adversarial perturbations effectively simulate variations of these rare terms in the embedding space, providing a form of data augmentation that makes the model more confident when encountering them in the test set. This finding aligns with recent theoretical work on the regularizing effect of adversarial training in high-dimensional spaces [18].

6. Conclusion

This paper presented a comprehensive study on enhancing entity-relation extraction from financial reports by combining a BiLSTM-CRF architecture with FGM adversarial training. The inherent complexity and noise in financial texts necessitate models that are not only accurate but also robust to variations. By leveraging the sequential modeling capabilities of BiLSTM and the structural decoding of CRF, we established a strong baseline. The novel integration of FGM adversarial training further elevated the performance by regularizing the model and improving its generalization on unseen data. Our experimental results on a real-world dataset of SEC filings demonstrated that the proposed method achieves state-of-the-art performance, with significant gains in extracting complex entities like financial instruments and monetary values. The ablation study confirmed that the adversarial component is crucial for handling the sparsity and variability of financial language. Future work will focus on integrating attention mechanisms to better handle long-range dependencies and exploring the application of this architecture to other languages and financial domains, such as cryptocurrency market analysis and global regulatory compliance documents. The success of

this approach highlights the potential of adversarial techniques to bridge the gap between academic NLP models and the rigorous demands of the financial industry.

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