CoReX-GNN: A Co-reference-Aware Hybrid Transformer and Graph Neural Network for Document-Level Relation Extraction

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Abstract

Document-level relation extraction (RE) identifies relationships between entities across sentences within a document, requiring models to handle long-range dependencies and co-reference resolution. We propose **CoReX-GNN**, a novel hybrid model that integrates transformer-based architectures with graph neural networks (GNNs) for explicit reasoning over entities, sentences, and co-references. CoReX-GNN includes a neural co-reference resolution module and a multi-task framework for jointly optimizing named entity recognition (NER) and RE tasks. Evaluations on the DocRED dataset will use precision, recall, and F1 scores, with qualitative error analysis. This work advances document-level RE by addressing key challenges, including inter-sentence reasoning and interpretability.

1 Introduction

Document-level relation extraction is essential in natural language processing (NLP) applications, such as knowledge graph construction, biomedical research, and legal document analysis. Unlike sentence-level RE, document-level RE must resolve co-references and reason over long contexts, where entities and relationships are spread across multiple sentences.

For example, identifying a relationship between "John" and "Google" may require resolving "he" and other indirect references. Existing transformer-based models, such as BERT and Longformer, perform well in capturing local context but lack explicit mechanisms for reasoning over inter-sentence dependencies. To address this, we propose **CoReX-GNN**, a hybrid model that combines transformers and graph neural networks (GNNs) with co-reference resolution for enhanced document-level RE.

2 Related Work

The DocRED dataset [**?**] has become the standard benchmark for document-level RE, emphasizing multi-sentence reasoning. Pre-trained transformer models, such as BERT [**?**] and Longformer [**?**], provide strong baselines for RE tasks. Recent works have explored GNNs for inter-sentence reasoning [**?**] and co-reference resolution [**?**]. CoReX-GNN extends these efforts by integrating co-reference information directly into a multi-task learning framework.

3 Proposed Approach

CoReX-GNN consists of three main components:

1. **Transformer Encoder**: Longformer captures document-wide context with sparse attention, encoding sentence-level representations.

2. **Graph Neural Network**: A GNN models relationships between entities, sentences, and co-references as a heterogeneous graph. Nodes represent entities and sentences, while edges encode syntactic, positional, and semantic relationships.

3. **Co-reference Resolution Module**: A neural co-reference system identifies and resolves references, informing both the transformer and GNN components.

The model uses a multi-task framework to jointly optimize NER and RE, sharing parameters to enhance contextual understanding. Implementation tools include HuggingFace Transformers for Longformer, PyTorch Geometric for GNNs, and Stanza for co-reference resolution.

4 Data and Evaluation

The DocRED dataset will be used, containing over 5,000 documents with annotated entities and relationships. Preprocessing steps include tokenization, sentence segmentation, and co-reference annotation using neural resolution tools.

Performance metrics include precision, recall, and F1 scores for RE. Qualitative analysis involves error analysis and visualizing relationship graphs to assess the model's interpretability. Results will be compared against BERT and Longformer baselines.

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