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# *Implicit In-context Learning for Few-Shot Relation Extraction*

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***Abstract:*** Relation Extraction (RE) is a key task in Natural Language Processing (NLP), aiming to identify semantic relations between entity pairs in text. While previous finetuning-based methods achieve strong performance with sufficient labeled data, their effectiveness drops sharply in low-resource settings. In-Context Learning (ICL) with Large Language Models (LLMs) has emerged as a promising alternative, enabling few-shot learning through few demonstrations. However, ICL suffers from high inference costs due to long input contexts and is sensitive to demonstration format and order, leading to unstable results. To address these limitations, we propose $I^2$CL-RE, a few-shot RE framework based on Implicit Contextual Learning. Instead of explicitly concatenating demonstrations, $I^2$CL-RE extracts a unified context representation from support examples and injects it into the hidden states of the LLM during inference. This method maintains the advantages of few-shot learning while significantly reducing inference overhead—approaching zero-shot efficiency. Experiments on four standard RE benchmarks show that $I^2$CL-RE consistently outperforms traditional ICL methods, both in accuracy and efficiency. The results demonstrate that implicit context integration can offer a more stable and cost-effective solution for relation extraction under low-resource conditions.

***Keywords:*** Few-Shot Learning, In-context Learning, Relation Extraction

## 1. Introduction

Relation Extraction (RE) is a core task in Natural Language Processing (NLP), aimed at identifying the semantic relationships between pairs of entities in text, or determining whether no relationship exists between them [1]. As a crucial prerequisite for constructing structured knowledge graphs and enabling knowledge retrieval, RE plays a key role in applications such as information extraction, question answering systems, and recommendation systems. Therefore, improving the generalization ability of RE models under low-resource conditions is of great significance for advancing the practical deployment of NLP systems. Early relation extraction methods [2-5] largely relied on the pretraining-and-finetuning paradigm. This approach typically involves first pretraining the model on large-scale unlabeled corpora, followed by fine-tuning on task-specific labeled datasets (such as BERT [2], RoBERTa [6]). Although these methods perform well with abundant supervised data, their

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heavy dependence on labeled data significantly degrades performance in low-resource scenarios, limiting their transferability and applicability in real-world settings.

With the emergence of large language models (LLMs) [7,8], a new training paradigm, namely In-Context Learning (ICL), which has been proposed. ICL enables models to perform downstream tasks without fine-tuning by providing task instructions and a small number of labeled examples, thereby greatly reducing the dependence on large amounts of annotated data. In recent years, ICL has been widely applied in few-shot RE tasks. For example, GPT-RE [1] enhances the performance of ICL by constructing chain-of-thought reasoning. Although ICL-based relation extraction methods show promising potential in low-resource scenarios, they still face two main challenges: (1) excessively long contexts result in high inference costs; (2) traditional ICL is highly sensitive to the format, order, and number of demonstrations, leading to unstable performance.

To address the aforementioned challenges, this paper proposes a few-shot relation extraction framework based on Implicit Contextual Learning [9], called $I^2$CL-RE. The framework aims to improve the performance of large language models in low-resource scenarios while maintaining high inference efficiency. Specifically, $I^2$CL-RE extracts a unified context vector from the example texts and injects it into the hidden space of the large model during inference to guide the reasoning process for test samples. Compared to explicit example concatenation, our method can reduce inference costs to zero-shot levels while achieving performance comparable to few-shot learning. We conducted extensive experiments on four standard relation extraction datasets, demonstrating that our approach significantly outperforms the traditional method GPT-RE [1], thereby validating the effectiveness and advancement of the proposed method in complex relation extraction tasks.

## 2. Related work

### 2.1. Few-Shot Relation Extraction

Few-shot Relation Extraction (FSRE) aims to enable models to quickly adapt to unseen relation types using only a small number of labeled examples, by training on a set of known relation categories. Among existing approaches, a prominent line of work is based on Transformer architectures. These methods leverage pre-trained language models (PLMs) to generate semantic representations of texts and entities, while implicitly capturing structural and discourse-level information such as dependency relations and coreference. For example, ATLOP [10] addresses the multi-label classification problem in relation extraction through adaptive thresholding and localized context pooling. Building upon this, DREEAM [11] introduces an evidence extraction module to further enhance performance. SRF [12] incorporates mention fusion, evidence extraction, and secondary reasoning to improve prediction accuracy, while TTM-RE [13] augments the model with memory components by introducing pseudo-entities and fine-tuning on large-scale distantly supervised data.

Another major line of research adopts graph-based approaches, which aim to model associations between entities by constructing document-level graphs, where entities and their mentions are treated as nodes. Through information propagation across the graph structure, these methods learn the underlying relational dependencies. For instance, DocuNet [14] captures both local and global contextual information by predicting an entity-level relation matrix, similar to semantic segmentation in computer vision. AA [15] combines graph structures with Transformer encodings to better capture fine-grained interactions between entities. However, a common limitation of these methods is their heavy reliance on large amounts of annotated data, making them less suitable for real-world scenarios where labeled examples are limited.

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However, the above methods typically rely on fine-tuning model parameters. With the advent of the era of large-scale models, the size of these models has grown exponentially, leading to a continuous increase in the computational cost required by such approaches.

### 2.2. In-context learning for Few-Shot RE

With the scaling of model size, in-context learning (ICL) has become a potent training-free paradigm for nature language processing (NLP), enabling LLMs to generalize to new tasks with a few demonstrations. In recent years, ICL has been widely applied to the few-shot relation extraction (FSRE) task. [16] prompt LLMs to solve the FSRE task via manually designed instructions directly. [17-19] introduced demonstrations into ICL and explored the optimization of demonstration arrangement within prompts. Recently, many researchers have focused on enhancing the demonstrations with Chain of Thought (CoT) [20], which illustrated the reasoning steps between the input text and relation label [21,1]. However, the performance of these CoT-based methods is heavily dependent on the quality of the generated CoT.

Although Chain-of-Thought (CoT) reasoning has indeed improved performance in in-context learning (ICL), it also significantly increases the complexity of prompts, thereby placing a heavier reasoning burden on the model. To address this issue, we propose a few-shot relation extraction framework based on implicit contextual learning, which effectively enhances the performance of large models in low-resource scenarios while maintaining inference efficiency.

## 3. Methodology

In this section, We first introduce the problem definition of FSRE, and then present how $I^2$CL is adapted and implemented for this setting, including its context vectorization and injection mechanisms.

### 3.1. Task definition under ICL

In the FSRE under In-Context Learning (ICL), given an unseen relation extraction task, ICL assumes the availability of a demonstration set $D = d_1, d_2, \ldots, d_N$ consisting of $N$ examples. Each example $d_i = (x_i, y_i)$ contains an input context $x_i$, including a pair of entities $(e_{\text{sub}}, e_{\text{obj}})$ within the context—and the corresponding relation label $y_i \in R \cup \text{NULL}$. Here, $R$ denotes a predefined set of relation types, and NULL indicates that there is no relation between the entity pair under any predefined class.

### 3.2. Context vectorization

We begin by independently vectorizing each demonstration example $d_i$ using a pre-trained large language model (LLM). Specifically, for each $d_i$, we extract its residual activations from both the multi-head attention (MHA) and feed-forward (MLP) modules at the final token position $e$, across all layers $l = 1, \ldots, L$:

$$d_i = \{a^e_{i,l}, m^e_{i,l}\}^L_{l=1} \tag{1}$$

Here, $a^e_{i,l}$ and $m^e_{i,l}$ denote the residual activations at layer $l$ from the MHA and MLP modules, respectively. These activations are assumed to encode the essential information of the input due to their role in next-token prediction.

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Next, we aggregate the extracted activations from all $N$ demonstration examples using an element-wise mean:

$$a_l^e = \frac{1}{N}\sum_{i=1}^{N} a_{i,l}^e, \quad m_l^e = \frac{1}{N}\sum_{i=1}^{N} m_{i,l}^e, \quad v = \{a_l^e, m_l^e\}_{l=1}^{L} \tag{2}$$

This produces a single context vector $v$, which captures the overall semantics of the demonstration set. The aggregation function is designed to be permutation-invariant, ensuring that the vector representation is independent of the order of examples.

This design is motivated by two key insights: (1) the residual stream at the final token position encodes crucial semantic information; (2) inspired by the linear representation hypothesis, contextual information from multiple examples can be linearly combined at different levels of abstraction.

### 3.3. Context injection

After obtaining the context vector $v$, we inject it into the forward pass of the query instance. Instead of concatenating demonstrations to the input, we modify the residual stream at each layer by linearly blending the context vector with the query activations. For the $t$-th token at layer $l$, the updated residual stream $r_l^t$ is computed as:

$$r_l^t = r_{l-1}^t + (\lambda_l^a a_l^e + \beta_l^a a_l^t) + (\lambda_l^m m_l^e + \beta_l^m m_l^t) \tag{3}$$

where $a_l^t$ and $m_l^t$ are the outputs of the MHA and MLP modules for the query token at layer $l$, and $\lambda_l^a, \beta_l^a, \lambda_l^m, \beta_l^m$ are learnable scalar coefficients that control the fusion between the context and query representations.

When $\lambda = 0$ and $\beta = 1$, the model reduces to standard zero-shot inference. Compared to attention-based methods, this approach introduces negligible computational overhead, involving only a few scalar multiplications and element-wise additions. This allows $I^2$CL to achieve inference speed comparable to that of zero-shot inference, while still incorporating demonstration information.

### 3.4. Coefficient optimization

Rather than manually tuning the scalar coefficients, we propose to optimize them via gradient descent using the demonstration set itself. Specifically, we minimize the perplexity of the label tokens in the demonstration examples:

$$\mathcal{L} = -\frac{1}{|D|}\sum_{(x,y)\in D} \log P(y \mid x, v, c) \tag{4}$$

where $c = \{\lambda_l^a, \beta_l^a, \lambda_l^m, \beta_l^m\}_{l=1}^{L}$ represents the set of layer-wise blending coefficients. This optimization process does not require any additional data beyond the few-shot examples, and enables the model to adaptively control the integration of contextual information across layers.

We initialize $\lambda = 0.1$ and $\beta = 1.0$, promoting a modest incorporation of context at the start of training, and update these coefficients jointly with inference.

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# 4. Experiments

## 4.1. Setup

### 4.1.1. Datasets

We conducted evaluations on three commonly used general-domain relation extraction (RE) datasets and one scientific-domain dataset. Due to the high cost of running models with GPT-3 via the API, we performed subset sampling of the original test sets for ACE2005 and TACRED two datasets in the main results (see Appendix C for details), as shown in Table 1.

Table 1: Statistics of datasets

| Dataset | #Relation | #Train | #Dev | #Test | NULL |
|---|---|---|---|---|---|
| Semeval | 9 | 6507 | 1493 | 2717 | 17.40% |
| TACRED | 41 | 68124 | 22631 | 15509 | 79.40% |
| SciERC | 7 | 16872 | 2033 | 4088 | 90.16% |
| ACE2005 | 6 | 121368 | 27597 | 24420 | 95.60% |

– **Semeval 2010 Task 8** [22] focuses on semantic relations between noun pairs collected from general-domain resources.
– **TACRED** [23] is a large-scale relation extraction dataset consisting of 106,264 samples, built on newswire and web text.
– **SciERC** [24] collects abstracts from papers in the artificial intelligence field along with annotated relations, specifically aimed at constructing scientific knowledge graphs.
– **ACE2005** includes annotations for entities, relations, and events, with data sourced from multiple domains including newswire, broadcast, and discussion forums.

### 4.1.2. Baselines

we chose the “text-davinci-003” model with a maximum input length of 4,097 tokens, and used the same prompt construction via the OpenAI API.

– **GPT-Random** [12] added an extra constraint to make the label distribution of the selected examples more balanced. Our preliminary experiments show that this is a stronger baseline than ordinary random selection.
– **GPT-Sent** [19] adopt SimCSE, which has been shown to be state-of-the-art in sentence similarity tasks.
– **GPT-RE** [1] generated the chain of thought for each example using a label-introduced approach, thereby enhancing the model’s contextual reasoning capabilities.

## 4.2. Main results

As shown in Table 2, The experimental results demonstrate that our proposed $I^2$CL-RE method achieves the best performance across all four relation extraction datasets. Compared with the closest baseline GPT-RE, $I^2$CL-RE improves performance by 2.64, 2.87, 1.74, and 2.68 points on Semeval, TACRED, SciERC, and ACE2005, respectively, with a relative gain of over 30% on ACE2005,

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Table 2: Main Results on four RE datasets. All results are given by Micro-F1.

| **Methods** | **Retriver** | **Semeval** | **TACRED** | **SciERC** | **ACE2005** |
|---|---|---|---|---|---|
| GPT-Random [12] | - | 70.04 | 32.49 | 17.92 | 9.04 |
| GPT-Sent [19] | SimCSE | 79.94 | 33.45 | 20.96 | 6.31 |
| GPT-RE [1] | SimCSE | 81.02 | 37.44 | 26.46 | 8.67 |
| $I^2$CL-RE (Ours) | SimCSE | **83.66** | **40.31** | **28.20** | **11.35** |

highlighting its strong advantage in low-resource and long-tail relation scenarios. Looking at different baselines, semantic similarity-based retrieval (GPT-Sent) brings notable improvements on some datasets (e.g., +9.90 on Semeval and +3.04 on SciERC) but even causes performance degradation on ACE2005, suggesting that retrieved examples may introduce noise when semantically similar but label-mismatched. By incorporating label-guided reasoning chains, GPT-RE effectively alleviates this issue and consistently boosts performance across all datasets, with the largest gain of +5.50. Building on this, $I^2$CL-RE further enhances performance by integrating instance-level contrastive learning, which better captures discriminative features among different relations, particularly on TACRED with its complex relation types and ACE2005 with its imbalanced label distribution. Overall, these results clearly validate the effectiveness of $I^2$CL-RE in leveraging retrieved examples and reasoning mechanisms to improve robustness and generalization in relation extraction.

Table 3: We evaluate the performance of our method under different ablation variants, conducting analyses on the example representation extraction module, the number of layers, and the injection position.

| Name | Semeval | TACRED |
|---|---|---|
| Target Module | | |
| MHA | 80.55 | 38.11 |
| MLP | 81.20 | 38.53 |
| Hidden | 75.98 | 32.96 |
| MHA+MLP (Ours) | **83.66** | **40.31** |
| Target Layers | | |
| Early | 70.53 | 29.33 |
| Middle | 78.96 | 37.63 |
| Late | 80.60 | 39.16 |
| All (Ours) | **83.66** | **40.31** |
| Injection Position | | |
| Random | 66.55 | 25.11 |
| First | 77.24 | 38.22 |
| Last | 81.98 | 39.55 |
| All (Ours) | **83.66** | **40.31** |

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### 4.3. Ablation study

The ablation results in Table 3 clearly demonstrate the impact of different design choices on model performance. First, regarding the example representation extraction module, using MHA, MLP, or Hidden vectors individually provides some improvement, but their effects remain limited. In contrast, combining MHA with MLP achieves significantly better performance, reaching 83.66 on Semeval and 40.31 on TACRED, which indicates that multi-module fusion offers stronger complementarity in capturing example representations. Second, when comparing different target layers, the Early, Middle, and Late layers show noticeable performance differences, with the Late layer outperforming the other two. More importantly, integrating information from all layers yields the best overall results, suggesting that cross-layer fusion can better exploit semantic features. Finally, for the injection position, random injection leads to substantial performance degradation, while fixed injection at the First or Last layer yields stronger results, with the Last layer performing better than the First. Once again, combining multiple positions produces the best outcome, further confirming that multi-position injection enhances the model's robustness and generalization ability. In summary, across all three aspects, the results consistently demonstrate that while each design choice is individually reasonable, the joint design of multi-module, multi-layer, and multi-position strategies delivers the strongest performance gains, thereby ensuring significant overall improvements.

## 5. Conclusion

In this paper, we proposed $I^2$CL-RE, a novel few-shot relation extraction framework based on Implicit Contextual Learning. Unlike traditional ICL-based methods that require concatenating explicit demonstrations during inference, $I^2$CL-RE generates a unified context representation from support examples and injects it directly into the hidden space of a large language model. This design significantly reduces inference costs while maintaining or even improving performance in low-resource settings. Through extensive experiments on the four datasets, we demonstrated that $I^2$CL-RE outperforms strong ICL baselines such as GPT-RE in both accuracy and efficiency. The results confirm the effectiveness of implicit context injection for guiding the model's reasoning process without relying on lengthy prompts, addressing key limitations of conventional ICL approaches. In future work, we plan to explore the generalizability of $I^2$CL to other NLP tasks such as named entity recognition and event extraction, as well as investigate adaptive context encoding strategies for further performance gains.

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