

# LLMAAA: Making Large Language Models as Active Annotators

Ruoyu Zhang<sup>1\*</sup>, Yanzeng Li<sup>1</sup>, Yongliang Ma<sup>2</sup>, Ming Zhou<sup>2</sup>, Lei Zou<sup>1</sup>

<sup>1</sup>Wangxuan Institute of Computer Technology, Peking University, Beijing, China

<sup>2</sup>Langboat Technology, Beijing, China

{ry\_zhang, zoulei}@pku.edu.cn, liyanzeng@stu.pku.edu.cn,  
{mayongliang, zhouming}@langboat.com

## Abstract

Prevalent supervised learning methods in natural language processing (NLP) are notoriously data-hungry, which demand large amounts of high-quality annotated data. In practice, acquiring such data is a costly endeavor. Recently, the superior performance of large language models (LLMs) has propelled the development of dataset generation, where the training data are solely synthesized from LLMs. However, such an approach usually suffers from low-quality issues and requires orders of magnitude more labeled data to achieve satisfactory performance. To fully exploit the potential of LLMs and make use of massive unlabeled data, we propose LLMAAA, which takes LLMs as annotators and puts them into an active learning loop to determine what to annotate efficiently. To learn robustly with pseudo labels, we optimize both the annotation and training processes: (1) we draw  $k$ -NN samples from a small demonstration pool as in-context examples, and (2) we adopt the automatic reweighting technique to assign training samples with learnable weights. Compared with previous approaches, LLMAAA features both **efficiency** and **reliability**. We conduct experiments and analysis on two classic NLP tasks, named entity recognition and relation extraction. With LLMAAA, task-specific models trained from LLM-generated labels can outperform their teacher LLMs within only hundreds of annotated examples, which is much more cost-effective than other baselines<sup>1</sup>.

## 1 Introduction

Large language models (LLMs) have exhibited remarkable few-shot performance in a wide range of tasks, with only a few demonstrations and well-designed prompts (Brown et al., 2020; Ding et al., 2022; Liu et al., 2023). However, with rapid ad-

\*This work was done during an internship at Langboat Technology.

<sup>1</sup>Our code and data are available at <https://github.com/ridiculouz/LLMAAA>.

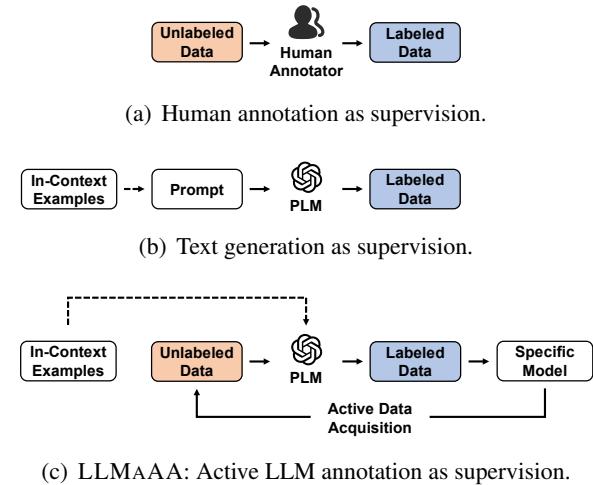


Figure 1: Comparing LLMAAA with other frameworks. We actively acquire annotations from LLM for efficiency, requiring little human effort.

vancements comes vast potential risks in adopting LLMs for widespread downstream production applications. One of the main concerns is about data privacy and security. Under the prevalent “Language-Model-as-a-Service” (LMaaS, Sun et al., 2022) setting, users are required to feed their own data, potentially including sensitive or private information, to third-party LLM vendors to access the service, which increases the risk of data leakage (Lyu et al., 2020; Yu et al., 2022; Li et al., 2023). Besides, LLMs usually consume abundant tokens by continuous requests to APIs, where the marginal cost and latency become substantial in large-scale or real-time applications, hindering LLMs’ practical deployment in cost-sensitive scenarios (Goyal et al., 2020; Cao et al., 2023).

On the other hand, training task-specific models (TAMs) for NLP tasks necessitates extensive amounts of labeled data. Due to the superior generative capacity of LLMs, some researchers attempt to synthesize training data with text generation (Meng et al., 2022; Ye et al., 2022), as depicted

in Figure 1. However, the generated text usually struggles with low-quality issues and may exhibit domain shifts with test data (Gao et al., 2023). To exploit the abundant unlabeled corpus, an alternative is to employ LLMs as annotators, which generate labels in a zero-shot or few-shot manner. While this approach seems promising, it is important to acknowledge that LLM-generated labels inevitably contain noise, especially when applied to challenging tasks and domain-specific data (Agrawal et al., 2022; Kazemi et al., 2023). Besides, larger models come with heavier expenses, and it is also crucial to reduce the annotation cost when the budget is restricted.

To enhance the **reliability** (i.e. accuracy) of TAMs’ performance as well as to ensure the data **efficiency** in annotation cost, we propose LLMAAA, an innovative framework that integrates active learning into the LLM annotation process, i.e., making LLMs as Active Annotators. By exploring different active acquisition strategies, LLMAAA enables the LLM to annotate more informative instances that benefit model performance more. To train TAMs reliably, we optimize both the annotation and training processes within LLMAAA framework. Firstly, we employ prompt engineering techniques to enhance LLMs’ performance by (1) selecting  $k$ -NN samples from a demonstration pool as in-context examples, and (2) building fine-level descriptions aligned with natural language for unnatural labels (e.g., category labels in the RE task). The valuable contextual information helps improve the quality of LLM annotations substantially. During training, we adopt the automatic reweighting technique (Ren et al., 2018) to assign learnable weights to the *silver*<sup>2</sup> training samples. This strategy allows the model to prioritize more informative and representative samples while simultaneously reducing the impact of noisy annotations.

We evaluate LLMAAA on two practical NLP tasks: named entity recognition (NER) and relation extraction (RE). Experiments show that: (1) with small-scale *gold* data ( $\sim 100$  examples) serving for demonstration and validation, the trained TAMs can outperform their teacher LLMs within hundreds of *silver* samples via LLMAAA; (2) our approach is significantly more data efficient compared to prevalent data generation methods, which

usually require large-scale synthetic training data (size varying from 10k to 200k, Ye et al., 2022; Gao et al., 2023). These results confirm the potential of LLMAAA as a practical and cost-efficient solution to make LLMs as *good* annotators. The TAMs created through our framework offer advantages in terms of task-specific performance, data privacy, and inference costs, which release the capacity of LLMs for real-world productivity.

We summarize our contributions as follows:

- We propose LLMAAA, a framework to employ LLMs as annotators, featuring both efficiency and reliability.
- LLMAAA is capable to train TAMs that outperform teacher LLMs within hundreds of annotated samples, on classic NLP tasks like NER and RE.
- LLMAAA sheds light on the practical substitution of LLMs, with a cost-effective, privacy-ensured, yet well-performing solution.

## 2 Related Work

**LLM and In-Context Learning** Large language models (LLMs), usually pretrained on large-scale corpora to capture rich linguistic patterns and generate coherent text (Brown et al., 2020; Raffel et al., 2020; Chowdhery et al., 2022; OpenAI, 2023; Touvron et al., 2023), have shown remarkable performance in a wide range of NLP tasks (Min et al., 2021; Zhao et al., 2023). With the proposal of in-context learning (Brown et al., 2020), prompt engineering has been extensively explored to steer LLMs’ behavior for desired outcomes. These techniques design specific prompts or instructions to guide models’ outputs (Ding et al., 2022; Liu et al., 2023), either in rule-based (Shin et al., 2020) or learning-based (Lester et al., 2021) manners. Recent trend focuses on the strong reasoning capabilities of LLMs and enhances LLMs’ performance on complex task with chain-of-thought (CoT) prompting (Wei et al., 2023a). In general, prompt engineering improves the controllability and performance of LLMs in few-shot and zero-shot settings (Zhong et al., 2021), and enables LLMs to solve specific tasks, e.g. information extraction (Wei et al., 2023b; Wang et al., 2023).

**Dataset Synthesis** Supervised learning methods in NLP are often limited by high-quality annotated data. To address the bottleneck, researchers have explored techniques to synthesize training

---

<sup>2</sup>We refer *gold* data to ground-truth/human-labeled samples, and *silver* data to LLM-labeled samples.

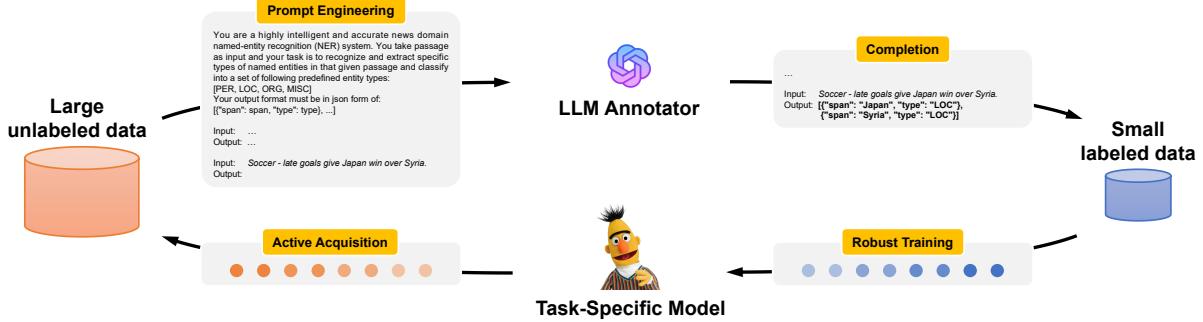


Figure 2: LLMAAA puts the LLM annotator in an active learning iteration, which mainly consists of three novel components: (1) an LLM annotator optimized with prompt engineering that generates pseudo labels, (2) an active acquisition mechanism for efficient data selection, and (3) an automatic reweighting technique to ensure robust learning with noisy labels. The annotation and training stages run iteratively and gradually produce labeled data for task-specific models.

data with LLMs, either by annotation or by generation. Following the first line of research, Feng et al. (2021); Chen et al. (2023) employ LLMs as unsupervised annotators to generate dialogue datasets. Recently, AnnoLLM (He et al., 2023) makes LLMs’ performance on par with crowd-source annotators by chain-of-thought prompting and self-generated explanations. As a contemporary work, Bansal and Sharma (2023) use LLMs for annotation in the domain transfer setting. Under the formulation of active learning, they propose a new metric, conditional informativeness, that works well with noisy labels. Among generation-based methods, Wang et al. (2021) first use LLM with few-shot prompts to generate training data. Schick and Schütze (2021) attempt to generate labeled text counterparts and text pairs for semantic textual similarity tasks. ZEROGEND (Ye et al., 2022) and SUNGEN (Gao et al., 2023) further extend this practice to zero-shot learning by training small models with zero-shot LLM-generated datasets. However, these approaches still suffer the low-quality and domain-shift issues of the synthetic data, and *none* of them consider the cost efficiency of data generation via LLMs.

**Labor Efficiency and Active Learning** Active learning is a technique proposed to minimize the annotation cost during the labeling process (Settles, 2009; Ren et al., 2021). A popular setting for active learning is the pool-based paradigm, which aims to select the most beneficial samples from an unlabeled data pool based on criteria including uncertainty (Lewis and Gale, 1994; Houlsby et al., 2011; Gal et al., 2017), diversity (Huang et al., 2010; Sener and Savarese, 2018), and hybrid ob-

jectives (Du et al., 2017; Yang et al., 2017; Ash et al., 2020; Margatina et al., 2021). The selected samples are annotated by human annotators and then added into the labeled dataset iteratively.

### 3 LLM as Active Annotator

To exploit LLMs’ superior few-shot performance and leverage abundant unlabeled data, we attempt to take LLM as annotator and train task-specific models for inference. An ideal process should be both **efficient** and **reliable**: we want to learn TAMs robustly with minimal LLM-generated labels.

Concretely, our solution is to make LLMs as Active Annotator. As shown in Figure 2, LLMAAA comprises three key components: (1) an LLM annotator that generates pseudo labels of given data, (2) an active acquisition mechanism for efficient data selection, and (3) an automatic reweighting technique to ensure robust learning with noisy labels. LLMAAA iterates the three stages to gradually produce stronger TAMs.

#### 3.1 Optimizing LLM as Better Annotator

In-context learning (i.e. PROMPTING) enables LLM to conduct few-shot inference without fine-tuning. Given a manually-designed prompt  $T(\cdot, \cdot)$ , a demonstration set  $\mathcal{S} = \{\mathbf{x}^i, y^i\}_{i=1}^k$  and the query example  $\mathbf{x}_q$ , PROMPTING first builds a sentence  $T(\mathcal{S}, \mathbf{x}_q)$ , conditioned on which LLM then generates a text sequence

$$\mathbf{y}_q = \underset{\mathbf{y}}{\operatorname{argmax}} P_{LM}(\mathbf{y}|T(\mathcal{S}, \mathbf{x}_q)).$$

Finally,  $\mathbf{y}_q$  is mapped to the label space  $\mathcal{Y}$ .

Despite the decent abilities, previous studies show that the design of task-specific prompts has

a large impact on performance, varying between near state-of-the-art and random guess (Gao et al., 2021; Lu et al., 2022b). Finding the *best* prompts for given tasks and given data points is intractable. However, there are several principles turn out to be effective, compared with plain instruction.

**$k$ -NN Example Retrieval** To select good in-context examples, Liu et al. (2022) propose a  $k$ -NN retrieval strategy, which first embeds the demonstration pool  $\mathcal{D}_{\text{demo}}$  and query sample to vector representations, and then retrieves the nearest  $k$  neighbors of the query to form its exemplars. The rationale behind this is that semantically similar examples may help LLM answer the query better. Following their practice, we use Sentence-BERT (Reimers and Gurevych, 2019, 2020) to build the representations.

**Label Verbalizer** In classification tasks, the surface forms of labels may induce difficulties and ambiguities. Taking relation classification for instance, the label “per:parents” can indicate either “subject is the parent of object” or “object is the parent of subject”, depending on its definition. To address this problem, we utilize a label verbalizer to transform the surface forms to natural language descriptions with pre-defined templates (Sainz et al., 2021; Lu et al., 2022a), serving as fine-level guidance. The semantic templates we use are shown in Table 7.

### 3.2 Active Data Acquisition

Active learning (AL) seeks to reduce labeling efforts by strategically choosing which examples to annotate. We consider the standard *pool-based* setting, assuming that a large pool of unlabeled data  $\mathcal{D}_{\text{pool}}$  is available. AL loop starts with a seed labeled set  $\mathcal{D}_{\text{labeled}}$ . At each iteration, we train a model  $M$  on  $\mathcal{D}_{\text{labeled}}$  and then use acquisition function  $f(\cdot, M)$  to acquire a batch  $\mathcal{B}$  consisting of  $b$  examples from  $\mathcal{D}_{\text{pool}}$ . We then query the LLM annotator to label  $\mathcal{B}$ . The labeled batch is then removed from the pool  $\mathcal{D}_{\text{pool}}$  and added to labeled set  $\mathcal{D}_{\text{labeled}}$ , and will serve as training data for the next iteration. The process is repeated for  $t$  times.

Active acquisition strategies generally maximize either *uncertainty* or *diversity*. On one hand, uncertainty-based methods leverage model predictions to select *hard* examples. On the other hand, diversity-based methods exploit the heterogeneity of sampled data. We will cover some common

strategies for thorough comparisons, and illustrate with classification task for simplicity<sup>3</sup>.

**Random** We consider random selection as baseline, which samples uniformly from  $\mathcal{D}_{\text{pool}}$ . Typically pool data and test data share the same distribution, thus the sampled batch is expected to be i.i.d. with test data.

**Maximum Entropy** Entropy is one of the most widely used estimations of uncertainty (Settles, 2009). Data for which the model  $M$  has the highest entropy are sampled for annotation according to

$$\underset{\mathbf{x} \in \mathcal{D}_{\text{pool}}}{\operatorname{argmax}} - \sum_{y \in \mathcal{Y}} P_M(y|\mathbf{x}) \log P_M(y|\mathbf{x}).$$

**Least Confidence** Culotta and McCallum (2005) propose to sort examples with the probability assigned by  $M$  to predicted class  $\hat{y}$ , which samples

$$\underset{\mathbf{x} \in \mathcal{D}_{\text{pool}}}{\operatorname{argmax}} (1 - P_M(\hat{y}|\mathbf{x})).$$

**$K$ -Means** Diversity sampling intends to select batches of data that is heterogeneous in the feature space. Following Yuan et al. (2020), we apply  $k$ -means clustering to the  $l_2$ -normalized embeddings of  $M^4$ , and sample the nearest neighbors of the  $k$  cluster centers.

### 3.3 Robust Learning with Noisy Labels

LLM annotators inevitably produce noisy labels, especially with harder tasks and domain-specific data. To stay robust against training label bias, we adopt the automatic reweighting technique (Ren et al., 2018) to assign different weights to training examples adaptively.

We assume that a small-scale validation set  $\mathcal{D}_{\text{val}}$  with clean labels (e.g. human annotations) is available throughout learning, with  $|\mathcal{D}_{\text{val}}| \ll |\mathcal{D}_{\text{pool}}|$ . Concisely, automatic reweighting learns sample weights  $\mathbf{w}$  by a meta-learning objective that minimizes validation loss w.r.t.  $\mathbf{w}$ , and uses online approximation to eliminate the nested loop of optimization. The training process of TAM is shown in Algorithm 1.

## 4 Tasks

We instantiate LLMAAA with two tasks: named entity recognition (NER) and relation extraction

<sup>3</sup>Adaptation to other settings (e.g. sequence tagging) will be introduced in § 4.

<sup>4</sup>We use BERT family as  $M$ ’s encoder, and the embeddings refer to BERT output.

---

**Algorithm 1:** Automatic Reweighting

---

**Input:** Noisy data  $\mathcal{D}_{\text{train}}$ , clean data  $\mathcal{D}_{\text{val}}$ , batch size  $n, m$ , initial parameter  $\theta_0$ , step  $S$

**Output:** Trained parameter  $\theta_S$

**for**  $s = 0, \dots, S - 1$  **do**

```
 $\mathcal{B}_{\text{train}} \leftarrow \text{SampleBatch}(\mathcal{D}_{\text{train}}, n)$ 
 $\mathcal{B}_{\text{val}} \leftarrow \text{SampleBatch}(\mathcal{D}_{\text{val}}, m)$ 
 $\{\hat{y}_{\text{train}}^i\}_{i=1}^n \leftarrow \text{Forward}(\mathcal{B}_{\text{train}}, \theta_s)$ 
// build computation graph with automatic differentiation
 $\epsilon \leftarrow 0; l_{\text{train}} \leftarrow \sum_{i=1}^n \epsilon_i \mathcal{L}(y_{\text{train}}^i, \hat{y}_{\text{train}}^i)$ 
 $\nabla \theta_s \leftarrow \text{Backward}(l_{\text{train}}, \theta_s)$ 
 $\hat{\theta}_s \leftarrow \theta_s - \alpha \nabla \theta_s$ 
 $\{\hat{y}_{\text{val}}^i\}_{i=1}^m \leftarrow \text{Forward}(\mathcal{B}_{\text{val}}, \hat{\theta}_s)$ 
 $l_{\text{val}} \leftarrow \frac{1}{m} \sum_{i=1}^m \mathcal{L}(y_{\text{val}}^i, \hat{y}_{\text{val}}^i)$ 
 $\nabla \epsilon \leftarrow \text{Backward}(l_{\text{val}}, \epsilon)$ 
// truncate weights to zero, and normalize to one
 $\tilde{w} \leftarrow \max(-\nabla \epsilon, 0);$ 
 $w \leftarrow \frac{\tilde{w}}{\sum_j \tilde{w} + \delta(\sum_j \tilde{w})}$ 
 $\hat{l}_{\text{train}} \leftarrow \sum_{i=1}^n w_i \mathcal{L}(y_{\text{train}}^i, \hat{y}_{\text{train}}^i)$ 
 $\nabla \theta_s \leftarrow \text{Backward}(\hat{l}_{\text{train}}, \theta_s)$ 
 $\theta_{s+1} \leftarrow \text{OptimizerStep}(\theta_s, \nabla \theta_s)$ 
```

---

(RE). We opt for two simple yet effective models as TAMs, and leave other choices for future study.

#### 4.1 Named Entity Recognition

**Formulation** NER aims to extract entities  $\{e_i\}$  from text  $x$ , where  $e_i$  can be expressed as a continuous span of sequences with predefined type. We consider the flat scenario (i.e. no overlapping entities), in which NER can be reformulated as a sequence tagging problem with BIO label.

To smoothly adapt uncertainty-based active functions from classification task to sequence tagging, we provide three pooling options: average, sum, and max. In practice, we adopt average and sum operations for better empirical performance.

**Model** Following Devlin et al. (2019), we leverage BERT to convert tokens into vectorized features, and use a linear classifier with activation to predict the {class}-BIO label for each token.

#### 4.2 Relation Extraction

**Formulation** Given subject entity  $e_{\text{subj}}$  and object entity  $e_{\text{obj}}$  in a sentence, RE classifies their relation into a predefined set  $\mathcal{R} \cup \{\text{NA}\}$ .

**Model** We use the same model architecture as Baldini Soares et al. (2019), which first encloses entity spans with special tokens [E] and [\E], then encodes the sentence with BERT. The concatenated embedding of subject and object is fed into a linear classifier with activation for final prediction.

## 5 Experiments and Analysis

### 5.1 Setup

**Dataset** We experiment with three different NLP datasets: Chinese OntoNotes 4.0 (Weischedel et al., 2011) and English CoNLL03 (Tjong Kim Sang and De Meulder, 2003) for NER, and Re-TACRED (Stoica et al., 2021) for RE. For Re-TACRED, we select a subset describing personal relationships and balance the NA relation instances to the original portion. Details of dataset statistics are described in Appendix A. We report the precision, recall, and micro F1 for both tasks.

**Baselines** We compare LLMAAA with the following baselines: (1) PROMPTING. The prompt-based direct inference on test data, using the same engineering techniques as LLMAAA’s teacher LLMs. (2) SUPERVISED. The TAMs are trained on clean-labeled data  $\mathcal{D}_{\text{val}}$  used in LLMAAA’s demonstration/validation. (3) ZEROGEND (Ye et al., 2022). Zero-shot data synthesis method via text generation. (4) FEWGEN. A data synthesis method that enhances ZEROGEND with in-context examples uniformly sampled from the demonstration pool.

**Implementation** We use ChatGPT<sup>5</sup> as LLM annotator for main experiments, and adopt BERT (Devlin et al., 2019; Cui et al., 2021) as TAM’s encoder. We also explore with other LLM annotators, GPT-3 (Brown et al., 2020) and GPT-4 (OpenAI, 2023), in § 6. We randomly sample 100 examples from the original validation sets as *gold* data, reusing the same set for demonstration  $\mathcal{D}_{\text{demo}}$  and validation  $\mathcal{D}_{\text{val}}$ . We use the original training sets as  $\mathcal{D}_{\text{pool}}$  and randomly initialize seed labeled set  $\mathcal{D}_{\text{labeled}}$  with a size of 50 and acquire 50 samples per batch for 9 iterations, which generates 500 *silver* annotated samples in total. We generate 500 and 5,000 samples via ZEROGEND and FEWGEN for comparison. TAMs under all settings are trained three times with different random seeds, and we report the mean and standard deviation in the results. The training process and hyperparameters are detailed in Appendix B.

<sup>5</sup><https://openai.com/blog/chatgpt>

Method	#Data	Chinese OntoNotes 4.0			English CoNLL03			Re-TacRED-subset			Avg. F1
		P	R	F1	P	R	F1	P	R	F1	
PROMPTING	100 / -	67.72	74.02	70.73	79.18	<b>83.59</b>	81.33	64.21	86.68	73.77	75.28
SUPERVISED	100 / -	70.54 <sub>1.33</sub>	<b>75.66<sub>1.14</sub></b>	73.00 <sub>0.84</sub>	77.16 <sub>0.31</sub>	78.52 <sub>0.52</sub>	77.94 <sub>0.10</sub>	62.36 <sub>2.35</sub>	91.88 <sub>1.90</sub>	74.28 <sub>2.05</sub>	75.07
ZEROGEN	- / 500	62.10 <sub>1.70</sub>	71.87 <sub>0.68</sub>	66.62 <sub>1.05</sub>	71.14 <sub>2.64</sub>	71.10 <sub>2.08</sub>	71.07 <sub>0.36</sub>	61.60 <sub>7.21</sub>	78.25 <sub>5.37</sub>	68.57 <sub>3.14</sub>	68.75
FEWGEN	- / 5000	62.00 <sub>0.92</sub>	72.84 <sub>2.50</sub>	66.97 <sub>0.61</sub>	74.23 <sub>3.32</sub>	71.78 <sub>1.97</sub>	72.99 <sub>2.61</sub>	51.46 <sub>0.82</sub>	94.28 <sub>0.65</sub>	66.57 <sub>0.66</sub>	68.84
	100 / 500	71.78 <sub>4.34</sub>	71.06 <sub>1.66</sub>	71.35 <sub>1.80</sub>	73.06 <sub>2.31</sub>	69.87 <sub>2.23</sub>	71.43 <sub>2.21</sub>	69.21 <sub>2.49</sub>	77.84 <sub>11.21</sub>	73.12 <sub>6.46</sub>	71.97
LLMAAA-random	100 / 5000	68.05 <sub>0.81</sub>	75.17 <sub>0.48</sub>	71.43 <sub>0.52</sub>	75.93 <sub>2.67</sub>	72.93 <sub>1.80</sub>	74.40 <sub>2.20</sub>	68.07 <sub>3.08</sub>	92.24 <sub>5.23</sub>	78.20 <sub>0.99</sub>	74.68
	LLMAAA-confidence	100 / 500	<b>72.66<sub>2.42</sub></b>	75.49 <sub>1.67</sub>	<b>74.00<sub>0.44</sub></b>	<b>82.91<sub>0.83</sub></b>	82.78 <sub>0.63</sub>	<b>82.84<sub>0.31</sub></b>	<b>71.49<sub>4.76</sub></b>	93.28 <sub>5.18</sub>	<b>80.79<sub>2.63</sub></b>

Table 1: Evaluation results for LLMAAA and other baselines across three different datasets, using ChatGPT as LLM backbone. We report the mean and standard deviation of three separate runs for each method. Since we set the temperature to 0 in PROMPTING, its results are deterministic and we only run evaluation once. We also denote the amount of data (gold/silver) that TAM used for training.

Relation	Generated Data
per:parents	<u>Mary</u> <sub>subj</sub> 's father is <u>Adam</u> <sub>obj</sub> . <u>Tom</u> <sub>subj</sub> 's mother, <u>Mary</u> <sub>obj</sub> , lives in New York.
	<u>Michelle Obama</u> <sub>subj</sub> 's parents are <u>Fraser C. Robinson III</u> and <u>Marian Shields Robinson</u> <sub>obj</sub> .
per:children	<u>Mike</u> <sub>subj</sub> 's son is named <u>Jack</u> <sub>obj</sub> . <u>Lily</u> <sub>subj</sub> 's children are <u>Alex and Bella</u> <sub>obj</sub> . <u>Sarah</u> <sub>subj</sub> has a daughter named <u>Emily</u> <sub>obj</sub> .

Table 2: A case study of generated data with ZEROGEN on Re-TACRED. We leverage ChatGPT as the text generator, and the full prompts we use can be found in Appendix B.3.

We follow consistent principles in prompt design. Empirically, we find that in-context examples bring marginal benefit to RE, while label verbalizer is a technique specifically designed for the classification task. Therefore, We apply  $k$ -NN example retrieval to NER and label verbalizer to RE separately. We set  $k$  to 5 for all experiments, including FEWGEN. Refer to Appendix B.3 for full prompts.

## 5.2 Overall Results

Table 1 denotes our main experiment results. LLMAAA with least confidence as acquisition function outperforms all comparative baselines across all datasets, with 74.00%, 82.84% and 80.79% F1 scores on Chinese OntoNotes 4.0, English CoNLL03 and Re-TACRED-subset, respectively.

Comparing with PROMPTING (i.e. the LLM annotator), LLMAAA shows steady improvement (4% in average score) with TAMs of much fewer parameters and lower inference latency, indicating that LLMAAA provides a decent substitute for LLMs in real-world deployments. LLMAAA also surpasses SUPERVISED, where TAMs are trained on clean-labeled but smaller-scale data. This suggests that LLMAAA is capable of deriving rich knowledge beyond the limited demonstration/vali-

dation set on unlabeled data, which benefits generalization.

We also notice that generation-based methods, i.e. ZEROGEN and FEWGEN, fail to establish on-par results, even with 10 $\times$  more data in zero-shot setting. We argue that the text-generation abilities of LLMs are exaggerated in complex scenarios. To demystify the illusion, we devise a case study on Re-TACRED, as is shown in Table 2. ZEROGEN tends to generate simple templated sentences that deviate from the news domain, i.e. the original corpus of Re-TACRED. These results may induce low-quality and domain-shift issues that hamper TAMs' performance. FEWGEN's performance improves with in-context examples, however, it still lags far behind LLMAAA. In contrast, exploiting the unlabeled data effectively alleviates these problems with much higher efficiency, where only hundreds of annotated samples are sufficient for satisfactory performance.

## 5.3 Ablations

### 5.3.1 Effects of Prompt Engineering

Though ChatGPT can well follow human instructions in general, it still struggles with difficult tasks and domain-specific data. We compare the infer-

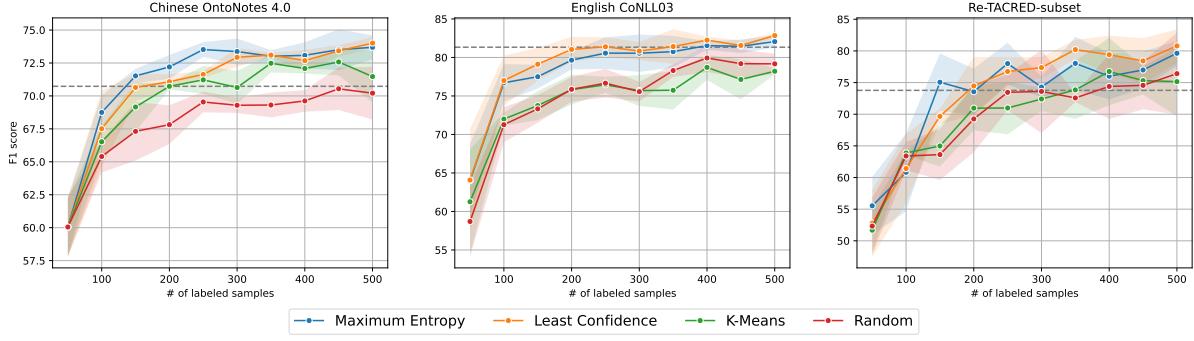


Figure 3: LLMAAA’s performance with different active acquisition strategies, shown by F1 scores. The dashed lines denote PROMPTING’s results. For each method, we report the mean and standard deviation of three runs initialized with different random seeds.

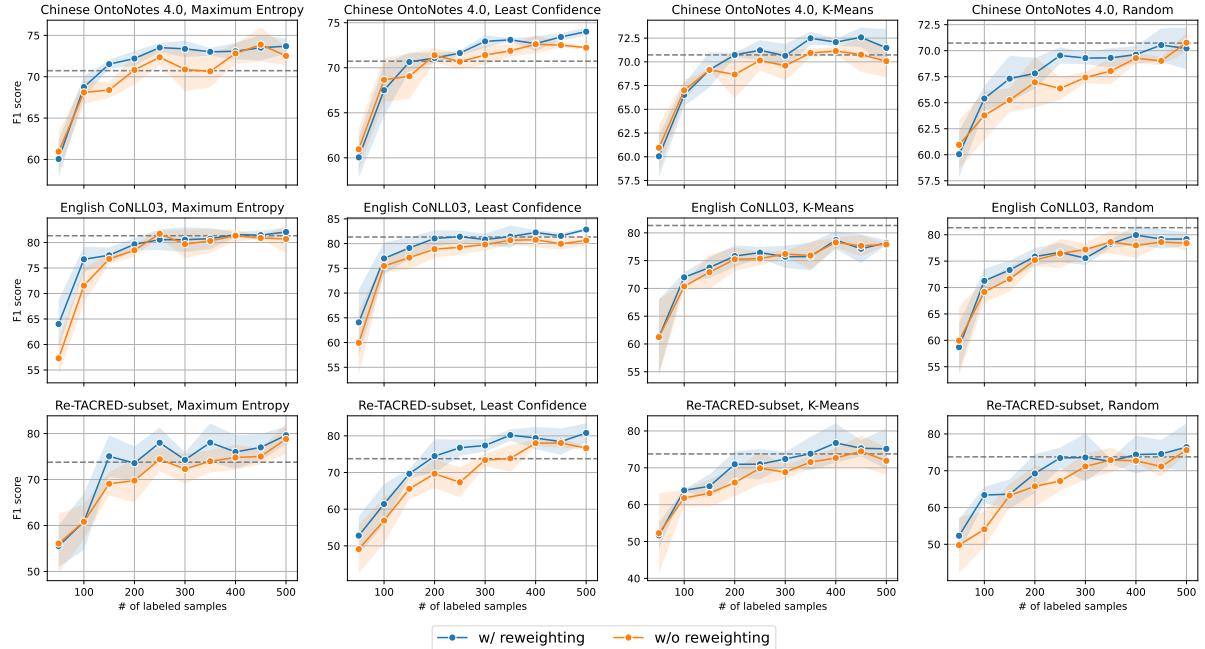


Figure 4: Results for analyzing the effects of automatic reweighting. We remove the online-approximated sample weights and train TAMs with standard loss objectives for ablation. The dashed lines denote PROMPTING’s performance. For each method, we report the mean and standard deviation of F1 scores within three different runs.

	<b>OntoNotes</b>	<b>CoNLL</b>	<b>Re-TacRED</b>
Base Instruction	49.62	55.74	70.94
+ $k$ -NN Examples	<b>70.73</b>	<b>81.33</b>	-
+Label Verbalizer	-	-	<b>73.77</b>

Table 3: Comparison results between plain instructions and optimized prompts in F1 scores.

ence performance of plain instructions with optimized prompts in Table 3. Without  $k$ -NN example retrieval module (i.e. in zero-shot manners), the LLM annotator is unable to extract entities well in NER task, shown by a drastic drop in F1 scores (21% on OntoNotes and 25% on CoNLL). This result highlights the need for demonstrations, where

LLMs’ zero-shot performance is unsatisfactory. In addition, the label verbalizer can help align unnatural labels with natural language descriptions, which improves the performance in RE (from 70.94% to 73.77% in F1). These findings emphasize that prompt engineering is crucial for building strong annotators, and incorporating similar and aligned contexts contributes to better inference.

### 5.3.2 Accelerating with Active Learning

Figure 3 shows LLMAAA performance with different active learning strategies across all datasets.

Uncertainty-based methods, i.e. **maximal entropy** and **least confidence**, perform significantly better than the random baseline, with faster con-

<b>Backbone</b>	<b>Method</b>	<b>P</b>	<b>R</b>	<b>F1</b>
GPT-3	PROMPTING	41.82	22.77	29.49
	LLMAAA-confidence	<b>57.26</b>	<b>56.09</b>	<b>56.63</b>
ChatGPT	PROMPTING	67.72	74.02	70.73
	LLMAAA-confidence	<b>72.66</b>	<b>75.49</b>	<b>74.00</b>
GPT-4	PROMPTING	68.70	<b>79.42</b>	73.68
	LLMAAA-confidence	<b>73.47</b>	76.42	<b>74.90</b>

Table 4: Results on Chinese OntoNotes 4.0 for PROMPTING and LLMAAA with different LLMs. LLMAAA uses least confidence as the acquisition function, and annotates 500 samples for TAM training.

vergence and higher F1 scores at the end of iterations. It is worth noting that (1) uncertainty-based methods are able to achieve on-par performance with random selection with only 30%~40% training data, (2) they surpass PROMPTING consistently within 500 LLM-annotated training samples. In summary, uncertainty-based active learning strategies enable LLMAAA to be more efficient and more capable.

Though *k-means* clustering encourages diversity in feature space, it only outperforms random sampling on OntoNotes, while yielding similar results on CoNLL03 and Re-TacRED. This suggests that it may require more training data for finetuned BERT to learn informative representations, and such a diversity-based method may fail in low-resource environments, e.g. at early iterations of the loop.

### 5.3.3 Reweighting Helps Robust Training

Figure 4 depicts the learning trials with and without the automatic reweighting technique. We observe that reweighting training samples consistently help improve performance across all datasets and methods. This finding proves that the training process of TAMs is more noise-tolerant with automatic reweighting, even with only a small-scale clean-labeled set (100 samples) serving for validation.

In particular, the performance gain from automatic reweighting is more prominent on OntoNotes and Re-TACRED, and diminishes on CoNLL03. We argue that automatic reweighting plays a crucial role when the LLM annotators are relatively poor (as in OntoNotes and Re-TACRED). In such scenarios, the online approximation of the validation set serves as an effective estimation of unbiased data distribution, and helps prevent TAMs from overfitting noisy labels.

## 6 Analysis

### 6.1 LLMAAA with Different Annotators

To guarantee the universal effectiveness of LLMAAA, we further investigate the performance with other LLM annotators, i.e. GPT-3 (Brown et al., 2020) and GPT-4 (OpenAI, 2023). Due to budgetary considerations, we opt to restrict our experiments to OntoNotes. The precision, recall and F1 score are shown in Table 4. The results indicate that LLMAAA benefits from better annotators with continuous improvements, and more importantly, TAMs trained by LLMAAA outperform the LLM annotators consistently. The student outperforms the weak teacher by a large margin (27% in F1 for GPT-3). As the teacher grows stronger, this gap narrows down. This trend meets our expectations: since student TAMs are trained with a fixed budget of data (500 samples), enhancing the capabilities of teacher LLMs will gradually approach the performance ceiling of the students. More annotation budget and more powerful TAMs can help extend this limit, while we leave the exploration for future research.

### 6.2 Why Can Students Outperform Teachers?

An interesting observation across our experiments is that student TAMs trained with generated labels can outperform teacher LLMs, i.e. LLMAAA > PROMPTING, even without sample reweighting, as shown by Figure 4. Such results partially align with previous findings in knowledge distillation (Wang, 2021; Song et al., 2021) and pseudo-label-based learning (Lee, 2013; Sanyal et al., 2022; Min et al., 2023), which share similar yet slightly different settings with LLMAAA.

We attempt to further explain the phenomenon in a simplified setting, where we consider a binary classification task that predicts  $y$  for  $\mathbf{x} \sim \mathcal{D}(\mathbf{x})$ , where  $\mathcal{D}(\mathbf{x})$  is discrete as in language space. For simplicity, we let  $y = 1$  denote the **correct** label and  $y = 0$  otherwise. We first make the natural assumption that the teacher’s performance is above chance, i.e. the accuracy  $p > 0.5$ . Querying teacher for target sample  $\mathbf{x}_t$  will generate pseudo label  $y_t \sim \text{Bernoulli}(p)$ . If the student is a universal function approximator  $S(\mathbf{x}; \theta)$  that outputs a scalar as probability that  $\hat{y} = 1$ , then minimizing the

cross-entropy loss

$$\min_{\theta} \mathbb{E}_{\mathbf{x}_t \sim \mathcal{D}(\mathbf{x}), y_t \sim \mathcal{B}(p)} [-y_t \log(S(\mathbf{x}_t; \theta)) - (1 - y_t) \log(1 - S(\mathbf{x}_t; \theta))]$$

will reach optimal with  $S(\mathbf{x}; \theta) = p$ . Usually we predict with heuristics that  $\hat{y} = 1$  if  $S(\mathbf{x}; \theta) > 0.5$ . With the previous assumption, we have  $\hat{y} = 1$ , which means that  $S$  always predicts correctly. This toy case nonetheless explains that *an ordinary teacher can raise better students*. Though teacher LLMs are deterministic for specific  $\mathbf{x}$  when the temperature is set to 0, their predictions are yet statistically random in  $\mathcal{D}(\mathbf{x})$ , where the same conclusion holds.

We shall point out that the above discussion considers a much-relaxed setting, where we attempt to account for an intuitive understanding on why students outperform teachers in the hard label distillation problem. We leave the rigorous theoretical analysis for future work.

## 7 Conclusion

In this work, we propose LLMAAA, a framework that uses LLMs as active annotators to address the challenges of data scarcity in NLP tasks. With active learning strategies, LLMAAA allows LLMs to label more informative samples that promote TAMs performance efficiently. We also optimize for reliability within the framework, which uses prompt engineering techniques and automatic reweighting to improve annotation quality and to reduce the impact of noisy labels, respectively. Experiments on NER and RE tasks demonstrate the effectiveness of LLMAAA. The evaluation results highlight the **efficiency** and **reliability** of LLMAAA. Trained with just hundreds of LLM-annotated samples, TAMs are able to outperform their teacher LLMs substantially. Besides, LLMAAA is also much more efficient compared to prevalent data generation methods, which usually require orders of magnitude more synthetic training data. These findings reveal that LLMAAA offers a cost-effective, privacy-ensured, yet well-performing solution to apply LLMs in practical scenarios.

## Limitations

Although LLMAAA demonstrates success in transferring and exceeding LLMs’ capabilities with cheaper TAMs, it does come with certain limitations. The main difference between the setting

in LLMAAA and previous zero-shot generation-based methods, e.g. ZERGEN and SUNGEN, is that we use an unlabeled data pool  $\mathcal{D}_{\text{pool}}$  and oracle-annotated data  $\mathcal{D}_{\text{demo}}/\mathcal{D}_{\text{val}}$ , to provide extra knowledge. However, we shall point out that unlabeled text is readily available in many real-world scenarios, thus it is practical to make the pool-based assumption. Additionally, in complex tasks where zero-shot inference fails (like NER in our experiments), it is costly yet necessary to incorporate demonstrations for LLMs. In LLMAAA, we strive for minimizing human efforts by restricting the oracle-annotated data to a small scale (100 samples), and exploiting the same data for demonstration and validation. Another bottleneck is the model capacities of teacher LLMs and student TAMs. On one hand, a weak teacher is unable to teach excellent students that are ready to be used for applications (e.g. GPT-3). On the other hand, TAMs are bounded depending on their architectures. When the teacher surpasses the ceiling, it will be theoretically impossible for students to outperform teachers. Despite these cases, we are optimistic that LLMAAA is effective in most situations.

We adopt the proprietary GPT family as annotators in experiments, which are provided by OpenAI in a black-box manner. Though powerful, this practice may raise several concerns, e.g. the potential exposure to test data. Nevertheless, we believe that given the comprehensive analysis in § 6.1, it does not affect the effectiveness of our method.

## Ethics Statement

This work utilizes publicly available benchmark datasets, and we respect and adhere to their licenses and agreements. Our proposed method involves the use of LLMs for data annotation, as discussed in GPT3Mix (Yoo et al., 2021). This paradigm still poses several challenges, such as the potential biases or toxic content in the generated data. Therefore, it is crucial to exercise caution when employing our method to invoke LLMs for generating data and when utilizing TAMs trained on such generated data. Applying our work to downstream tasks such as NER and RE may result in issues such as mis-extraction and false information, and may fail in some cases. When employing our method, it is essential to consider using debiasing (Schick et al., 2021) or manual checking to mitigate these concerns.

## Acknowledgements

We appreciate the anonymous reviewers for their valuable advice on this manuscript. We would like to thank Tianhao Wu for the insightful discussion and feedback. This work was supported by NSFC under grant 61932001 and U20A20174. The corresponding author of this paper is Lei Zou (zoulei@pku.edu.cn).

## References

- Monica Agrawal, Stefan Heggelmann, Hunter Lang, Yoon Kim, and David Sontag. 2022. [Large language models are few-shot clinical information extractors](#). In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 1998–2022, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Jordan T. Ash, Chicheng Zhang, Akshay Krishnamurthy, John Langford, and Alekh Agarwal. 2020. [Deep batch active learning by diverse, uncertain gradient lower bounds](#). In *International Conference on Learning Representations*.
- Livio Baldini Soares, Nicholas FitzGerald, Jeffrey Ling, and Tom Kwiatkowski. 2019. [Matching the blanks: Distributional similarity for relation learning](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2895–2905, Florence, Italy. Association for Computational Linguistics.
- Parikshit Bansal and Amit Sharma. 2023. [Large language models as annotators: Enhancing generalization of nlp models at minimal cost](#).
- Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. [Language models are few-shot learners](#). In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.
- Qingqing Cao, Bhargavi Paranjape, and Hannaneh Hajishirzi. 2023. [Pumer: Pruning and merging tokens for efficient vision language models](#).
- Wanxiang Che, Mengqiu Wang, Christopher D. Manning, and Ting Liu. 2013. [Named entity recognition with bilingual constraints](#). In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 52–62, Atlanta, Georgia. Association for Computational Linguistics.
- Maximillian Chen, Alexandros Papangelis, Chenyang Tao, Seokhwan Kim, Andy Rosenbaum, Yang Liu, Zhou Yu, and Dilek Hakkani-Tur. 2023. [PLACES: Prompting language models for social conversation synthesis](#). In *Findings of the Association for Computational Linguistics: EACL 2023*, pages 844–868, Dubrovnik, Croatia. Association for Computational Linguistics.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. [Palm: Scaling language modeling with pathways](#).
- Yiming Cui, Wanxiang Che, Ting Liu, Bing Qin, and Ziqing Yang. 2021. [Pre-training with whole word masking for chinese bert](#). *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:3504–3514.
- Aron Culotta and Andrew McCallum. 2005. [Reducing labeling effort for structured prediction tasks](#). In *Proceedings of the 20th National Conference on Artificial Intelligence - Volume 2, AAAI’05*, page 746–751. AAAI Press.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [BERT: Pre-training of deep bidirectional transformers for language understanding](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Ning Ding, Shengding Hu, Weilin Zhao, Yulin Chen, Zhiyuan Liu, Haitao Zheng, and Maosong Sun. 2022. [OpenPrompt: An open-source framework for prompt-learning](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics*:

- System Demonstrations*, pages 105–113, Dublin, Ireland. Association for Computational Linguistics.
- Bo Du, Zengmao Wang, Lefei Zhang, Liangpei Zhang, Wei Liu, Jialie Shen, and Dacheng Tao. 2017. Exploring representativeness and informativeness for active learning. *IEEE Transactions on Cybernetics*, 47(1):14–26.
- Xiachong Feng, Xiaocheng Feng, Libo Qin, Bing Qin, and Ting Liu. 2021. Language model as an annotator: Exploring DialoGPT for dialogue summarization. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1479–1491, Online. Association for Computational Linguistics.
- Yarin Gal, Riashat Islam, and Zoubin Ghahramani. 2017. Deep Bayesian active learning with image data. In *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 1183–1192. PMLR.
- Jiahui Gao, Renjie Pi, Lin Yong, Hang Xu, Jiacheng Ye, Zhiyong Wu, Weizhong Zhang, Xiaodan Liang, Zhengu Li, and Lingpeng Kong. 2023. Self-guided noise-free data generation for efficient zero-shot learning. In *The Eleventh International Conference on Learning Representations*.
- Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making pre-trained language models better few-shot learners. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3816–3830, Online. Association for Computational Linguistics.
- Saurabh Goyal, Anamitra Roy Choudhury, Saurabh Raje, Venkatesan T. Chakaravarthy, Yogish Sabharwal, and Ashish Verma. 2020. Power-bert: Accelerating BERT inference via progressive word-vector elimination. In *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event*, volume 119 of *Proceedings of Machine Learning Research*, pages 3690–3699. PMLR.
- Xingwei He, Zhenghao Lin, Yeyun Gong, A-Long Jin, Hang Zhang, Chen Lin, Jian Jiao, Siu Ming Yiu, Nan Duan, and Weizhu Chen. 2023. Annollm: Making large language models to be better crowdsourced annotators.
- Neil Houlsby, Ferenc Huszár, Zoubin Ghahramani, and Máté Lengyel. 2011. Bayesian active learning for classification and preference learning.
- Sheng-Jun Huang, Rong Jin, and Zhi-Hua Zhou. 2010. Active learning by querying informative and representative examples. In *Advances in Neural Information Processing Systems 23: 24th Annual Conference on Neural Information Processing Systems 2010. Proceedings of a meeting held 6-9 December 2010, Vancouver, British Columbia, Canada*, pages 892–900. Curran Associates, Inc.
- Mehran Kazemi, Sid Mittal, and Deepak Ramachandran. 2023. Understanding finetuning for factual knowledge extraction from language models.
- Dong-Hyun Lee. 2013. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In *Workshop on challenges in representation learning, ICML*, volume 3, page 896.
- Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3045–3059, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- David D. Lewis and William A. Gale. 1994. A sequential algorithm for training text classifiers. In *Proceedings of the 17th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '94*, page 3–12, Berlin, Heidelberg. Springer-Verlag.
- Yansong Li, Zhixing Tan, and Yang Liu. 2023. Privacy-preserving prompt tuning for large language model services.
- Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. 2022. What makes good in-context examples for GPT-3? In *Proceedings of Deep Learning Inside Out (DeeLIO 2022): The 3rd Workshop on Knowledge Extraction and Integration for Deep Learning Architectures*, pages 100–114, Dublin, Ireland and Online. Association for Computational Linguistics.
- Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2023. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys*, 55(9):1–35.
- Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In *International Conference on Learning Representations*.
- Keming Lu, I-Hung Hsu, Wenxuan Zhou, Mingyu Derek Ma, and Muha Chen. 2022a. Summarization as indirect supervision for relation extraction. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 6575–6594, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Yao Lu, Max Bartolo, Alastair Moore, Sebastian Riedel, and Pontus Stenetorp. 2022b. Fantastically ordered prompts and where to find them: Overcoming few-shot prompt order sensitivity. In *Proceedings of the*

- 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 8086–8098, Dublin, Ireland. Association for Computational Linguistics.
- Lingjuan Lyu, Xuanli He, and Yitong Li. 2020. Differentially private representation for NLP: Formal guarantee and an empirical study on privacy and fairness. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2355–2365, Online. Association for Computational Linguistics.
- Katerina Margatina, Giorgos Vernikos, Loïc Barrault, and Nikolaos Aletras. 2021. Active learning by acquiring contrastive examples. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 650–663, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Yu Meng, Jiaxin Huang, Yu Zhang, and Jiawei Han. 2022. Generating training data with language models: Towards zero-shot language understanding. In *Advances in Neural Information Processing Systems*.
- Bonan Min, Hayley Ross, Elior Sulem, Amir Pouran Ben Veyeh, Thien Huu Nguyen, Oscar Sainz, Eneko Agirre, Ilana Heinz, and Dan Roth. 2021. Recent advances in natural language processing via large pre-trained language models: A survey. *arXiv preprint arXiv:2111.01243*.
- Zeping Min, Qian Ge, and Cheng Tai. 2023. Why the pseudo label based semi-supervised learning algorithm is effective?
- OpenAI. 2023. Gpt-4 technical report.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21:140:1–140:67.
- Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.
- Nils Reimers and Iryna Gurevych. 2020. Making monolingual sentence embeddings multilingual using knowledge distillation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4512–4525, Online. Association for Computational Linguistics.
- Mengye Ren, Wenyuan Zeng, Bin Yang, and Raquel Urtasun. 2018. Learning to reweight examples for robust deep learning. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 4331–4340. PMLR.
- Pengzhen Ren, Yun Xiao, Xiaojun Chang, Po-Yao Huang, Zhihui Li, Brij B Gupta, Xiaojiang Chen, and Xin Wang. 2021. A survey of deep active learning. *ACM computing surveys (CSUR)*, 54(9):1–40.
- Oscar Sainz, Oier Lopez de Lacalle, Gorka Labaka, Ander Barrena, and Eneko Agirre. 2021. Label verbalization and entailment for effective zero and few-shot relation extraction. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1199–1212, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Sunandini Sanyal, Sravanti Addepalli, and R Venkatesh Babu. 2022. Towards data-free model stealing in a hard label setting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15284–15293.
- Timo Schick and Hinrich Schütze. 2021. Generating datasets with pretrained language models. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6943–6951, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Timo Schick, Sahana Udupa, and Hinrich Schütze. 2021. Self-diagnosis and self-debiasing: A proposal for reducing corpus-based bias in NLP. *Transactions of the Association for Computational Linguistics*, 9:1408–1424.
- Ozan Sener and Silvio Savarese. 2018. Active learning for convolutional neural networks: A core-set approach. In *International Conference on Learning Representations*.
- Burr Settles. 2009. Active learning literature survey.
- Taylor Shin, Yasaman Razeghi, Robert L. Logan IV, Eric Wallace, and Sameer Singh. 2020. AutoPrompt: Eliciting Knowledge from Language Models with Automatically Generated Prompts. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4222–4235, Online. Association for Computational Linguistics.
- Dandan Song, Jing Xu, Jinhui Pang, and Heyan Huang. 2021. Classifier-adaptation knowledge distillation framework for relation extraction and event detection with imbalanced data. *Information Sciences*, 573:222–238.
- George Stoica, Emmanouil Antonios Platanios, and Barnabas Poczos. 2021. Re-tacred: Addressing shortcomings of the tacred dataset. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(15):13843–13850.
- Tianxiang Sun, Yunfan Shao, Hong Qian, Xuanjing Huang, and Xipeng Qiu. 2022. Black-box tuning for language-model-as-a-service. In *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pages 20841–20855. PMLR.

- Erik F. Tjong Kim Sang and Fien De Meulder. 2003. *Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition*. In *Proceedings of the Seventh Conference on Natural Language Learning at HLT-NAACL 2003*, pages 142–147.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.
- Shuhe Wang, Xiaofei Sun, Xiaoya Li, Rongbin Ouyang, Fei Wu, Tianwei Zhang, Jiwei Li, and Guoyin Wang. 2023. Gpt-ner: Named entity recognition via large language models.
- Zi Wang. 2021. Zero-shot knowledge distillation from a decision-based black-box model. In *Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event*, volume 139 of *Proceedings of Machine Learning Research*, pages 10675–10685. PMLR.
- Zirui Wang, Adams Wei Yu, Orhan Firat, and Yuan Cao. 2021. Towards zero-label language learning.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. 2023a. Chain-of-thought prompting elicits reasoning in large language models.
- Xiang Wei, Xingyu Cui, Ning Cheng, Xiaobin Wang, Xin Zhang, Shen Huang, Pengjun Xie, Jinan Xu, Yufeng Chen, Meishan Zhang, et al. 2023b. Zero-shot information extraction via chatting with chatgpt. *arXiv preprint arXiv:2302.10205*.
- Ralph Weischedel, Martha Palmer, Mitchell Marcus, Eduard Hovy, Sameer Pradhan, Lance Ramshaw, Ni-anwen Xue, Ann Taylor, Jeff Kaufman, Michelle Franchini, et al. 2011. Ontonotes 4.0. *Linguistic Data Consortium LDC2011T03*.
- Lin Yang, Yizhe Zhang, Jianxu Chen, Siyuan Zhang, and Danny Z. Chen. 2017. Suggestive annotation: A deep active learning framework for biomedical image segmentation. In *Medical Image Computing and Computer Assisted Intervention - MICCAI 2017: 20th International Conference, Quebec City, QC, Canada, September 11-13, 2017, Proceedings, Part III*, page 399–407, Berlin, Heidelberg. Springer-Verlag.
- Jiacheng Ye, Jiahui Gao, Qintong Li, Hang Xu, Jiangtao Feng, Zhiyong Wu, Tao Yu, and Lingpeng Kong. 2022. ZeroGen: Efficient zero-shot learning via dataset generation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11653–11669, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Kang Min Yoo, Dongju Park, Jaewook Kang, Sang-Woo Lee, and Woonyoung Park. 2021. GPT3Mix: Leveraging large-scale language models for text augmentation. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 2225–2239, Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Da Yu, Saurabh Naik, Arturs Backurs, Sivakanth Gopi, Huseyin A. Inan, Gautam Kamath, Janardhan Kulkarni, Yin Tat Lee, Andre Manoel, Lukas Wutschitz, Sergey Yekhanin, and Huishuai Zhang. 2022. Differentially private fine-tuning of language models. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net.
- Michelle Yuan, Hsuan-Tien Lin, and Jordan Boyd-Graber. 2020. Cold-start active learning through self-supervised language modeling. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7935–7948, Online. Association for Computational Linguistics.
- Yuhao Zhang, Victor Zhong, Danqi Chen, Gabor Angeli, and Christopher D. Manning. 2017. Position-aware attention and supervised data improve slot filling. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 35–45, Copenhagen, Denmark. Association for Computational Linguistics.
- Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. 2023. A survey of large language models. *arXiv preprint arXiv:2303.18223*.
- Ruiqi Zhong, Kristy Lee, Zheng Zhang, and Dan Klein. 2021. Adapting language models for zero-shot learning by meta-tuning on dataset and prompt collections. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 2856–2878, Punta Cana, Dominican Republic. Association for Computational Linguistics.

## A Dataset Statistics

In this section, we describe the statistics and pre-processing of each dataset in detail.

**OntoNotes 4.0** (Weischedel et al., 2011) is a large corpus comprising various genres of text (news, web text, etc.) in three languages (English, Chinese, and Arabic) with structural information and shallow semantics, and has been widely used for NER. We use the Chinese text data and take the same data split as Che et al. (2013), which uses four most common entity types, i.e. PER (person), LOC (location), ORG (organization) and GPE (geo-political entities). We truncate token length within 512 (i.e. split long input to multiple chunks) to

	Training	Validation	Testing
per:age	421	256	208
per:nationality	295	222	115
per:parents	182	69	106
per:children	275	114	55
per:siblings	211	33	66
per:spouse	271	189	73
no_relation	2,482	1,324	934
<b>Total</b>	<b>4,137</b>	<b>2,207</b>	<b>1,557</b>

Table 5: Statistics of relation types in each split of Re-TACRED-subset. We replace the label "per:origin" with "per:nationality" for clarity.

fit in BERT input limit. The processed data contains 15,724/4,301/4,346 samples for training/validation/testing, respectively.

The **English CoNLL 2003** shared task ([Tjong Kim Sang and De Meulder, 2003](#)) is a NER dataset that contains four entity types: PER (person), LOC (location), ORG (organization), and MISC (miscellaneous entities), which consists of 14,041/3,250/3,453 sentences for training/validation/testing.

**Re-TACRED** ([Stoica et al., 2021](#)) is a revised version of TACRED ([Zhang et al., 2017](#)), a large-scale crowdsource-annotated RE dataset. It originally has 40 relation types. Including all these types will lead to much longer prompts, which may exceed the API length limit and receive responses with higher latency. Therefore, we opt to select a subset of relations that describe personal relationships for study. We keep all these relation instances in training/validation/testing sets, and balance the NA relation instances to the original portion. The statistics for each relation type is shown in Table 5.

For all three datasets, we randomly sample 100 examples from the original validation sets and reuse the same data for demonstration  $\mathcal{D}_{\text{demo}}$  and validation  $\mathcal{D}_{\text{val}}$ . We use the full training sets as the initial  $\mathcal{D}_{\text{pool}}$ , from which we randomly sample active learning's seed labeled sets  $\mathcal{D}_{\text{labeled}}$  with a size of 50.

## B Implementations

### B.1 LLM Inference APIs

We access OpenAI APIs by Azure service. The API we use for each model is depicted in Table 6. Since ChatGPT and GPT-4 will continue to be updated, they may generate different responses as time changes, even when the temperature is 0.

Model	API
GPT-3	text-curie-001
ChatGPT	gpt-35-turbo
GPT-4	gpt-4

Table 6: Azure OpenAI service API that we use.

### B.2 Training Task-Specific Models

For all experiments that train TAMs for inference (i.e. LLMAAA, ZEROGEN, FEWGEN and SUPERVISED), we repeat each with three random seeds, resulting in different parameter initialization and random data sampling. We report the mean and standard deviation in our results.

We use bert-base-cased ([Devlin et al., 2019](#)) as TAMs' encoders with a learning rate of 5e-5 for English data (CoNLL03 and Re-TACRED), and chinese-bert-base-wwm ([Cui et al., 2021](#)) with a learning rate of 2e-5 for Chinese data (OntoNotes 4.0). The learning rate of other parameters (i.e. linear classifiers) is set to 1e-4. We optimize the models via AdamW ([Loshchilov and Hutter, 2019](#)), with  $\epsilon = 1e-6$ , under a linear warmup schedule for the first 6% steps. We train all TAMs with a batch size of 8 for 40 epochs and take the checkpoint with the highest validation performance for final prediction.

### B.3 Prompts

The full prompts we use for annotation are shown in Table 7. In Re-TACRED, we provide prompts both with and without verbalized labels. To add demonstration, we insert each sample's text into input and label to output. The target sample is added to the last input, and the last output is left blank for prediction.

We also show the prompts for generation in Table 8. We use them similarly to annotation. In the zero-shot setting, to help models generate desired outputs, we use a default example to inform LLMs about the output format.

## C Annotation Examples

We show two annotation examples of correct/partially wrong annotations from the CoNLL 2003 NER dataset in Listing 1. The first example is exactly correct, and the second example contains hallucinations that do not exist in ground truth: "April", "March", and "Thursday".

Task	Prompting
CoNLL 03	<p><b>Description</b> You are a highly intelligent and accurate news domain named-entity recognition (NER) system. You take passage as input and your task is to recognize and extract specific types of named entities in that given passage and classify into a set of following predefined entity types: [person (PER), location (LOC), organization (ORG), miscellaneous entity (MISC)] Your output format must be in json form of: [“span”: span, “type”: type, ...]</p> <p><b>Instruction</b> The span must be exactly the same as the original text, including white spaces.</p> <p><b>Format</b></p> <p><b>Input:</b> “Input: {}”</p> <p><b>Output:</b> “Output: {}”</p>
	<p>你是一名通用领域的命名实体识别（NER）标注者，给定一段输入文本和 NER 类型，你需要以 json 格式返回 NER 的 span 和类型。</p> <p><b>Description</b> 类型: [人物 (PER) , 组织机构 (ORG) , 地缘政治实体 (GPE) , 地理位置 (LOC) ] 输出格式: [“span”: span, “type”: type, ...]</p>
	<p><b>Format</b></p> <p><b>Input:</b> “输入: {}”</p> <p><b>Output:</b> “输出: {}”</p>
OntoNotes 4.0	<p><b>Description</b> Given a sentence, and two entities within the sentence, classify the relationship between the two entities based on the provided sentence. If no relation of interest exists, strictly return “no_relation”. All possible relationships are listed below:</p> <ul style="list-style-type: none"> <li>- per:age</li> <li>- per:parents</li> <li>- per:spouse</li> <li>- per:siblings</li> <li>- per:children</li> <li>- per:nationality</li> <li>- no_relation</li> </ul> <p><b>Instruction</b></p> <p><b>Format</b></p> <p><b>Input:</b> “Sentence: {}”</p> <p><b>Output:</b> “Relationship: {}”</p> <p><b>Struct:</b> “e1: {} e2: {}”</p>
	<p><b>Description</b> Given a sentence, and two entities within the sentence, classify the relationship between the two entities based on the provided sentence. If no relation of interest exists, strictly return “no_relation”. All possible relationships and explanations are listed below:</p> <ul style="list-style-type: none"> <li>- per:age : the age of {e1} is {e2}</li> <li>- per:parents : {e1}’s parent is {e2}</li> <li>- per:spouse : {e1}’s spouse is {e2}</li> <li>- per:siblings : {e1} is the sibling of {e2}</li> <li>- per:children : {e1}’s children is {e2}</li> <li>- per:nationality: {e1}’s nationality is {e2}</li> <li>- no_relation : {e1} has no known relations to {e2}</li> </ul> <p><b>Instruction</b></p> <p><b>Format</b></p> <p><b>Input:</b> “Sentence: {}”</p> <p><b>Output:</b> “Relationship: {}”</p> <p><b>Struct:</b> “e1: {} e2: {}”</p>
	<p><b>Description</b> Given a sentence, and two entities within the sentence, classify the relationship between the two entities based on the provided sentence. If no relation of interest exists, strictly return “no_relation”. All possible relationships and explanations are listed below:</p> <ul style="list-style-type: none"> <li>- per:age : the age of {e1} is {e2}</li> <li>- per:parents : {e1}’s parent is {e2}</li> <li>- per:spouse : {e1}’s spouse is {e2}</li> <li>- per:siblings : {e1} is the sibling of {e2}</li> <li>- per:children : {e1}’s children is {e2}</li> <li>- per:nationality: {e1}’s nationality is {e2}</li> <li>- no_relation : {e1} has no known relations to {e2}</li> </ul> <p><b>Instruction</b></p> <p><b>Format</b></p> <p><b>Input:</b> “Sentence: {}”</p> <p><b>Output:</b> “Relationship: {}”</p> <p><b>Struct:</b> “e1: {} e2: {}”</p>
Re-TACRED (Original)	
Re-TACRED (Verbalized)	

Table 7: Annotator’s prompts for each task.

```
{
  "text": "Celtic 's Jackie McNamara , who did well with last season 's successful under-21 team , earns a call-up to the senior squad .",
  "labels": [{"span": "Celtic", "type": "ORG"}, {"span": "Jackie McNamara", "type": "PER"}]
},
{
  "text": "Finland 's trade surplus rose to 3.83 billion markka in April from 3.43 billion in March , the National Customs Board ( NCB ) said in a statement on Thursday .",
  "labels": [{"span": "NCB", "type": "ORG"}, {"span": "Finland", "type": "LOC"}, {"span": "National Customs Board", "type": "ORG"}, {"span": "April", "type": "MISC"}, {"span": "March", "type": "MISC"}, {"span": "Thursday", "type": "MISC"}]
}
```

Listing 1: Annotation examples.

Task	Prompting
CoNLL 03	<p><b>Description</b> You are an intelligent text data generator. Generate {} high-quality and diverse sentences in news domain containing entities for the following types: [person (PER), location (LOC), organization (ORG), miscellaneous entity (MISC)] Write one sample per line. No other output.</p>
	<p><b>Format</b> <b>Example:</b> “Example: {}” <b>Output:</b> “Output: {}”</p>
	<p><b>Default Example</b> {“text”: text, “entities”: [{“name”: name, “type”: type}]} </p>
OntoNotes 4.0	<p><b>Description</b> 你是一名新闻领域的文本生成助手。生成{}个流畅、通顺、多样的中文句子，并包含下面这些类型的命名实体 (entity)： [人名 (PER)， 组织机构名 (ORG)， 地缘政治实体 (GPE)， 地理位置 (LOC) ] 每行输出一个样本，不要有任何额外的输出。</p>
	<p><b>Format</b> <b>Example:</b> “示例: {}” <b>Output:</b> “输出: {}”</p>
	<p><b>Default Example</b> {“text”: text, “entities”: [{“name”: name, “type”: type}]} </p>
Re-TACRED	<p>You are an intelligent text data generator. Generate {} high-quality and diverse sentences in news domain containing relational triplet for the following relation types:</p> <ul style="list-style-type: none"> <li>- per:age : the age of SUBJ is OBJ</li> <li>- per:parents : SUBJ’s parent is OBJ</li> <li>- per:spouse : SUBJ’s spouse is OBJ</li> <li>- per:siblings : SUBJ is the sibling of OBJ</li> <li>- per:children : SUBJ’s children is OBJ</li> <li>- per:nationality: SUBJ’s nationality is OBJ</li> <li>- no_relation : SUBJ has no known relations to OBJ</li> </ul> <p>Write one sample per line in json format. Subject and object must appear in the sentence. No other output.</p>
	<p><b>Format</b> <b>Example:</b> “Example: {}” <b>Output:</b> “Output: {}”</p>
	<p><b>Default Example</b> {“text”: text, “subject”: subject, “object”: object, “relation”: relation} </p>

Table 8: Generator’s prompts for each task.