

Grasping the Essentials: Tailoring Large Language Models for Zero-Shot Relation Extraction

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Abstract

Relation extraction (RE) aims to identify semantic relationships between entities within text. Despite considerable advancements, existing models predominantly require extensive annotated training data, which is both costly and labor-intensive to collect. Moreover, these models often struggle to adapt to new or unseen relations. Few-shot learning, aiming to lessen annotation demands, typically provides incomplete and biased supervision for target relations, leading to degraded and unstable performance. To accurately and explicitly describe relation semantics while minimizing annotation demands, we explore the *definition only zero-shot RE* setting where *only* relation definitions expressed in natural language are used to train a RE model. We introduce REPAL, comprising three stages: (1) We leverage large language models (LLMs) to generate initial seed instances from relation definitions and an unlabeled corpus. (2) We fine-tune a bidirectional Small Language Model (SLM) with initial seeds to learn relations for the target domain. (3) We expand pattern coverage and mitigate bias from initial seeds by integrating feedback from the SLM’s predictions on the unlabeled corpus and the synthesis history. To accomplish this, we leverage the multi-turn conversation ability of LLMs to generate new instances in follow-up dialogues, informed by both the feedback and synthesis history. Studies reveal that definition-oriented seed synthesis enhances pattern coverage whereas indiscriminately increasing seed quantity leads to performance saturation. Experiments on two datasets show REPAL significantly improved zero-shot performance by large margins.

1 Introduction

Relation extraction is a pivotal task in Information Extraction (IE) that involves identifying and classifying semantic relationships between entities within texts. It has wide applications in various

<u>Seeds for Low-Resource RE</u>		
1. Label Names: location		
2. Definitions: <ENT1> was/is the location of <ENT0> (a structure or event)		
3. Patterns:	ENT0 Types	Trigger Words
	Structure type	located at
	Event type	happened in
	----	-----
		ENT1 Types
		Loc type
		Loc type

4. Triplets/Entity Pairs: (White House, Washington, D.C.), (White House, U.S.)		
5. Instances:		
- London held the 2012 Olympics		
- The French Revolution took place in Paris		

Figure 1: Different types of initial seeds for low-resource RE approaches for example relation P276. It shows using only two instances as seeds fail to cover *structure* type head entities.

downstream tasks including knowledge graph construction (Lin et al., 2015; Yu et al., 2020), question answering (QA) (Wang et al., 2012, 2016) and event mining (Jiao et al., 2022; Li et al., 2023c). Traditional RE works train models with human-labeled data (Han et al., 2018a, 2020; Yamada et al., 2020). However, acquiring large-scale, high-quality datasets is challenging and costly in reality. To address this data scarcity, few- and zero-shot RE works try to leverage knowledge from LM pre-training or auxiliary sources (Petroni et al., 2019; Chia et al., 2022; Han et al., 2022; Chen et al., 2022a; Zhao et al., 2023; Zhou et al., 2023a; Wan et al., 2023; Li et al., 2023b; Sun et al., 2024).

Despite these advancements, two issues persist in low-resource RE. The first issue is the *underutilization of relation definitions*. Relation semantics are generally directional and multifaceted which involve entity-entity interactions and entity-related requirements (see Fig. 1). Thus, target relation semantics typically can only be partially reflected by most low-resource supervision, such as seed instances, triples, or label names. Such relation semantic complexity requires detailed elaborations described by relation definitions. Another issue is the *underutilization of LLMs for zero-shot RE*.

Most LLMs are designed to perform multi-turn conversations and excel in seeking feedback from the dialogue history. Such a feature has shown great potential in knowledge-intensive or complex reasoning question-answering tasks (Trivedi et al., 2022; Zhou et al., 2023b,c). Nevertheless, LLM-based low-resource RE works typically rely on single-turn usages.

To address the first issue, this work introduces a new zero-shot RE setting where only relation definitions, instead of seen instances, are provided. In addition to the fact that relation definitions serve as more precise and less biased initial seeds, such a task setup is realistic as: (1) downstream applications such as QA tasks already have explicit definitions of interested relations and obtaining such supervision is generally straightforward; and (2) such a setting highlights the importance for RE systems to continuously adapt to new relation types based on corresponding definitions without maintaining a large amount of seen instances and re-training models.

To address the second issue, we propose a novel zero-shot RE framework, REPAL. Firstly, REPAL prompts LLMs to generate positive instances conditioned on the definition and samples negative instances from unlabeled corpus, thus constructing an initial training set. A SLM is then trained on this training set for performance and efficiency of inference. Secondly, to enhance pattern coverage of instance generation and to rectify the bias introduced by instance generation and SLM training, REPAL then acquires feedback as reflection inputs to LLMs to guide followup instance synthesis for iterative refinements. For robustness, the feedback consists of two independent components: the synthesis dialogues and sampled SLM’s inference results on the massive unlabeled corpus. The feedback is utilized to: (1) leverage LLMs’ multi-turn conversational ability to recognize the pattern coverage bias, synthesis error, and then generate instances with new or rectified positive patterns, and (2) leverage LLMs’ reasoning ability to diagnose the SLM’s bias and further generate targeted or near-miss negative instances to rectify such bias by explicitly deriving negative definitions. The whole framework performs iterative refinements in which more and better-quality relation instances are accumulated to improve the task-specialized RE model. Our contributions are as follows:

- We demonstrate the partial coverage issue

of few-shot RE’s initial seeds. Our studied definition-oriented RE setting can seamlessly leverage few-shot supervision for better pattern coverage and better performance by definition derivation and instance augmentation.

- We propose a novel zero-shot RE framework, REPAL, that only requires relation definitions and an unlabeled corpus. REPAL iteratively synthesizes both positive and negative instances to enhance pattern coverage and addresses biases by automatically mining and reflecting on feedback from multiple sources, leveraging the multi-turn conversation capability of LLMs.
- Extensive quantitative and qualitative experiments demonstrate the effectiveness and the potential of our task setup and framework.

2 Background

2.1 Definition Only Zero-Shot Relation Extraction Task

Task Definition 2.1. Definition Only Zero-Shot Relation Extraction. We assume that, for any target relation $r(E_0, E_1) \in \mathcal{R}(E_0, E_1)$ ¹, only one associated relation definition $d(E_0, E_1)$ is given. Here $\mathcal{R}(E_0, E_1)$ denotes the whole binary relation space and $d(E_0, E_1)$ can be a single sentence or a document specifying the target relation $r(E_0, E_1)$. E_0 and E_1 are two entity placeholders.

The goal of *Definition Only Zero-Shot Relation Extraction* task is to extract all relation instances that belong to target relation $r(E_0, E_1)$ from any given set of relation instances $\{(s^i, e_0^i, e_1^i)\}_{i=1}^n$ in a binary classification manner. Here s^i denotes the i -th context text, while e_0^i and e_1^i denote two entity mentions inside s^i . Compared with the traditional zero-shot RE task settings, our task assumes no seen data but only target relation definitions. Our task also assumes the unknown negative relation space while mainstream zero-shot RE assumes known information of all test relations. This makes our task more challenging, but aligns better with real-world scenarios. Further details and discussions are in Appendix A.

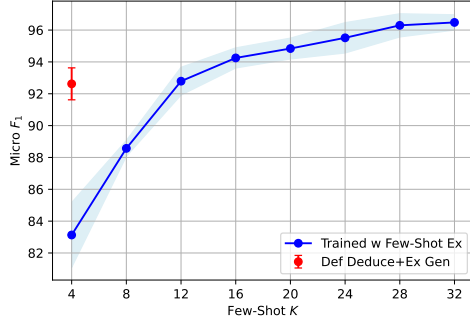


Figure 2: Micro F_1 (%) score of model trained with few-shot instances (*Trained w Few-Shot Ex*) and model trained with instances from our relation definition derivation and instance generation approach (*Def Deduce+Ex Gen*). The error bar/band denotes averaged value \pm standard deviation.

2.2 From Few-Shot to Definition-Oriented Low-Resource RE

In this section, we reveal the partial relation pattern coverage issue of commonly adopted RE few-shot setup and further show that the few-shot setup can be converted to our definition-oriented setup while achieving much better results. We take KNOWPROMPT (Chen et al., 2022b) as the underlying N-way classification model where N equals the number of test relations. It’s a prompt tuning model with robust and strong few-shot performance and does not require hand-crafted prompts.

We experiment on two groups: (1) *Trained w Few-Shot Ex* (baseline group) which has KNOWPROMPT trained on few-shot instances for evaluation, and (2) *Def Deduce+Ex Gen* which uses GPT-4 to derive each relation’s definition given 4-shot instances, generate 15 new instances based on the definition, and train KNOWPROMPT for evaluation.

The LLM derived relation definitions compared with original relation definitions are shown in Appendix G.1 and the experiment results are shown in Fig. 2 and Fig. 7 (in Appendix G.2). The derived relation definitions show that LLM is capable of deducing suitable yet generalizable relation definitions based on few-shot instances. However, the coverage of derived definitions is limited by the coverage of few-shot instances. This is in accordance with our motivation for definition-based low-resource RE setup.

Fig. 2 and Fig. 7 show that our definition derivation and instance generation approach achieves much better performance than the model trained

only on few-shot instances. This indicates the approach extends the relation patterns conveyed by the few-shot instances. However, we can see our (15 generated + 4 gold shots) trained model has slightly lower performance than 16 gold shots trained model which is due to the partial coverage of relation semantics conveyed by the 4 gold shots instances. This further illustrates the importance of capturing actual relation definitions instead of few-shot data for low-resource RE approaches.

3 Methodology

Our proposed REPAL is an iterative framework which consists of three major components: (1) Definition-based seed construction with LLM and the unlabeled corpus (Sec. 3.1). This step leverages rich semantics in relation definitions for informed LLM-based initial data synthesis and randomly samples negative instances from unlabeled corpus. (2) Pattern learning with RE-specialized SLM (Sec. 3.2) which trains a SLM extractor with initial seeds for inference performance and efficiency. (3) Feedback-driven instance improvement and bias rectification (Sec. 3.3) by providing LLMs with independent feedbacks (SLM’s inference on unlabeled corpus and synthesis history) and leveraging LLMs’ multi-turn conversations for followup positive and negative instance synthesis. The overview of REPAL can be found in Fig. 3.

3.1 Definition-Based Seed Construction with LLM and Unlabeled Corpus

LLMs, such as the GPT family, are pre-trained for the domain adaptation ability (Radford et al., 2019). They have demonstrated to contain factual relation knowledge (Petroni et al., 2019) and are widely used as data generator for various tasks such as text classification (Meng et al., 2022) and dialogue systems (Abdullin et al., 2024). Follow-up evaluation studies have shown that LLMs are relatively skilled at constrained content generation, storytelling, and rationale generation (Sun et al., 2023; Keskar et al., 2019). Following such observations as well as the goal to tackle the data scarcity issue of zero-shot RE, REPAL first leverages LLMs to generate K_{p_0} positive seeds, $\{(s_p^i, e_{0,p}^i, e_{1,p}^i)\}_{i=1}^{K_{p_0}}$, conditioned on the target relation definition $r(E_0, E_1)$. We carefully design three prompts for this step (shown in Appendix B) to encourage the LLM to generate comprehensive patterns from three perspectives in terms of complexity: brief, medium,

¹This work focuses on sentence-level binary relation extraction setting, so two entity mentions are considered for each instance.

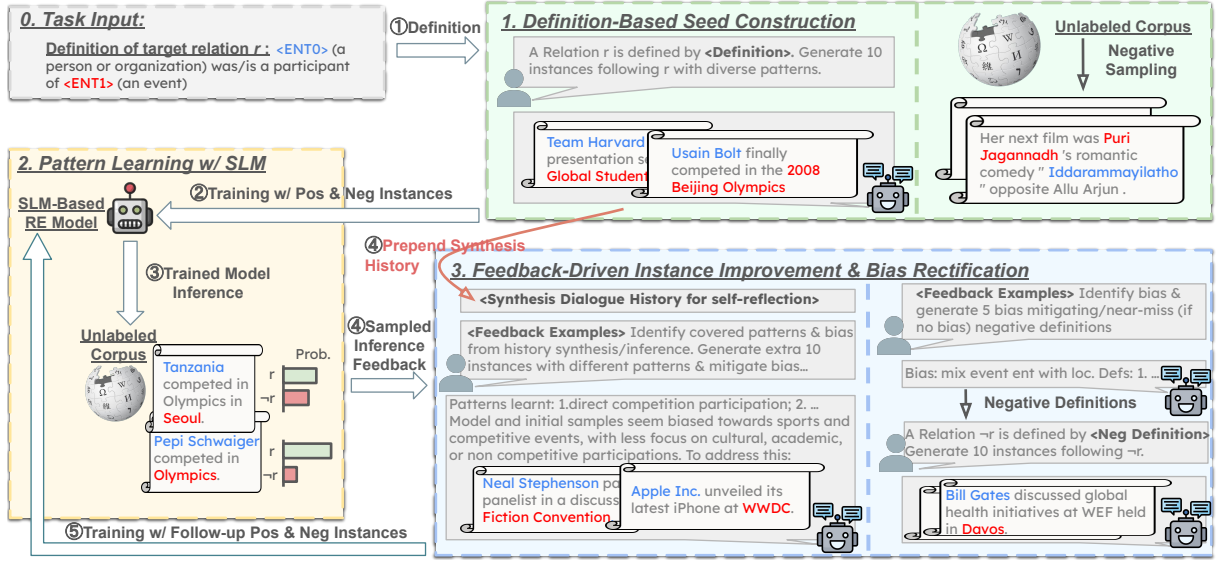


Figure 3: REPAL framework. The trained SLM-Based RE Model is used in inference stage.

and implicit. Based on exploratory experiments, they yield different types of relation patterns in accordance with our design expectations. Details of experiments and quantitatively how choice of different prompts affect the results are in Sec. 5.3.

In addition to positive seed generation, constructing negative seeds is also vital for better extraction for the target relation $r(E_0, E_1)$, as our task setting assumes no prior knowledge on the negative relation space in order to mimic the real-life deployments (Li et al., 2022). Our negative seed construction is based on the hypothesis that, with a normal large-scale unlabeled corpus, the proportion of target relation instances is relatively small. Thus REPAL conducts random sampling over the unlabeled corpus, which is expected to yield an acceptable set of negative instances denoted as $\{(s_n^i, e_{0,n}^i, e_{1,n}^i)\}_{i=1}^{K_{n0}}$. In case of extreme cases, REPAL designs counter-measures in Sec. 3.3.

3.2 Pattern Learning with RE-Specialized SLM

Given the fact that LLMs are computationally expensive to be fine-tuned, while pure in-context learning (ICL) is hindered by LLM’s capability to comprehend long-context demonstrations and its temporal and monetary expense (Ma et al., 2023), we leverage SLMs as tunable and task-specialized extractors. SLMs also enable faster inference on massive unlabeled corpus to mine feedback in Sec. 3.3. Specifically, we adapt a natural language inference (NLI) model (Obamuyide and Vlachos, 2018; Liu et al., 2019; Sainz et al., 2021) to be relation-specific binary classifiers for simplicity

and leave other architectures or LLMs for future research.

For each training instance (s^j, e_0^j, e_1^j) , the input is formulated as in NLI style:

$$\text{Premise}_j := s^j,$$

$$\text{Hypothesis}_j := d(E_0 = e_0^j, E_1 = e_1^j).$$

Given a SLM model \mathcal{M} , we obtain the encoded sequence hidden states \mathbf{H} by:

$$\mathbf{H} = \mathcal{M}(\text{Premise}_j [\text{SEP}][\text{SEP}] \text{Hypothesis}_j)$$

and the NLI logits $\mathbf{z} = [z_E, z_N, z_C] \in \mathbb{R}^3$ is computed as:

$$\mathbf{z} = \mathbf{W} \cdot \mathbf{H}_{[CLS]} + \mathbf{b}.$$

Finally, P_j , the probability of instance (s^j, e_0^j, e_1^j) following relation $r(E_0, E_1)$, is computed as the normalized logit of ENTAILMENT label:

$$P_j = \frac{e^{z_E}}{\sum_{c \in \{C, N, E\}} e^{z_c}},$$

where C, N, E denote logits \mathbf{z} ’s indices for NLI label CONTRADICTION, NEUTRAL, ENTAILMENT respectively. And the binary classification loss (Shannon, 1948) for relation $r(E_0, E_1)$ is defined as:

$$\mathcal{L} = -\frac{1}{|B|} \sum_{(s^j, e_0^j, e_1^j) \in B} [y_j \log(P_j) + (1 - y_j) \log(1 - P_j)], \quad (1)$$

where B denotes the batched data sampled from $\{(s_p^i, e_{0,p}^i, e_{1,p}^i)\}_{i=1}^{K_{p0}} \cup \{(s_n^i, e_{0,n}^i, e_{1,n}^i)\}_{i=1}^{K_{n0}}$.

3.3 Feedback-Driven Instance Improvement and Bias Rectification

After obtaining the trained SLM relation extractor, REPAL further introduces a follow-up feedback-driven iterative refinement approach with intuitions listed as follows: (1) the initially generated positive seeds might only have a partial relation pattern coverage or concentrate on common patterns due to LLM’s longtail deficiency (Mallen et al., 2022). Instead of one-time generation, iterative follow-up generations by incorporating feedback from examining previously generated results are better for pattern coverage. (2) bias or errors could be introduced by previous two steps (Sec. 3.1 and 3.2). One potential source of bias is the generated positive seeds or the randomly sampled negative seeds. Another potential source of bias is the randomness of SLM training over limited training samples (see Fig. 8 and Fig. 9). Identifying and rectifying bias requires a feedback-driven follow-up refinement approach.

Specifically, we first obtain the inference results on the unlabeled corpus leveraging trained SLM extractor. The first component of the feedback is constructed by randomly sampling instances within a predicted probability range (see Appendix F for details). It is constructed for follow-up positive instance and follow-up negative instance generation respectively, differing only on the probability ranges.

The other component of the feedback is LLMs’ synthesis history. For follow-up positive instance generation, we leverage the multi-turn conversational feature of LLMs where the positive instance synthesis history is prepended to a new turn of conversation asking for positive instances with different patterns. The SLM’s inference feedback is integrated into the new turn of conversation so that LLMs can identify the correct and incorrect patterns learned by SLMs. The double channel feedback design, incorporating both SLM inference and synthesis history, enhances the robustness of this step as the followup synthesis can still rely on LLMs’ self-reflection if the inference feedback is uninformative.

For follow-up negative instance generation, we divide it into two sub-steps following the divide-and-conquer philosophy: the first sub-step is feedback-driven negative relation definition generation and the subsequent sub-step is negative instance generation based on the negative relation

definitions. LLM is queried to examine the SLM’s inference feedback and identify the incorrect patterns learned by SLM so that newly generated negative relations can address such patterns. Similarly, for robustness in cases where SLM’s inference feedback is uninformative, we query LLM to generate near-miss negative relation definitions based on the positive relation definition to better distinguish hard cases. After acquiring the negative relation definitions, the second sub-step is the same as the initial positive seed generation process in Sec. 3.1. The prompts used in this section are placed in Appendix C. After obtaining all the follow-up positive and negative instances, we iteratively train the SLM extractor.

4 Experiments

4.1 Evaluation Dataset Construction

We first construct datasets for model evaluation on the *Definition Only Zero-Shot Relation Extraction* task. Our constructed datasets are based on FewRel (Han et al., 2018b) and Wiki-ZSL (Chen and Li, 2021) respectively². The public portion of FewRel contains 80 relations, each comes with 700 instances annotated by crowd workers. Wiki-ZSL consists of 113 relations with total 93,383 instances obtained by distant supervision. As their relations are from WikiData’s³ properties, we query the property definitions and slightly modify them to become complete sentences with entity placeholders [ENT0] and [ENT1] (corresponding to E_0 and E_1 as in definition notation $d(E_0, E_1)$). For evaluation, we sample 5 groups of 14 FewRel relations and 3 groups of 15 Wiki-ZSL relations as test sets.

To construct unlabeled corpus, for each group of the test set, we down-sample 10,000 instances from the unlabeled corpora used by Gao et al. for few-shot relation learning which contains 744 distantly supervised relations (labels are not used in this work) and totally 899,996 instances (2020). The final test sets with the corpus are denoted as DefOn-FewRel and Defon-Wiki-ZSL respectively.

²An ideal test set for our setting should follow: (1) annotations should follow the officially documented relation definitions and the sentences should be sufficient to deduce the target relations without external knowledge; (2) relations are better semantically disjoint without ambiguity so that we do not need to manually adjust binary test labels for overlapped relations in each test iteration. These principles also apply to existing multi-way classification RE datasets. However, we leave these for future dataset related works.

³WikiData main page

Model	DefOn-FewRel				DefOn-Wiki-ZSL			
	Precision	Recall	F ₁	Macro-F ₁	Precision	Recall	F ₁	Macro-F ₁
<i>Fully-Supervised</i>								
ROBERTA NLI	79.36	98.46	86.99	-	68.66	97.14	78.46	-
<i>Zero-Shot</i>								
RANDOM GUESS	7.14	50.77	12.52	-	6.67	51.01	11.67	-
GPT-3.5	55.09	61.81	53.94	-	42.64	45.70	39.60	-
ROBERTA NLI	48.79	81.17	55.07	-	36.23	62.65	35.28	-
ZS-BERT	35.91	35.70	-	35.78	37.11	33.85	-	35.26
RELATIONPROMPT	74.39	66.89	-	67.78	71.89	60.50	-	61.08
RE-MATCHING	77.49	72.95	-	75.11	73.10	68.99	-	70.97
REPAL (Ours)	71.17	82.34	73.02	88.44	62.12	52.99	48.17	81.25

Table 1: Evaluation results of relation extraction models under zero-shot and fully-supervised settings. REPAL is trained on 15p15n initial instances and further trained with additional 15p15n follow-up instances.

4.2 Baseline Methods

We compare our method with the following baselines under *Fully-Supervised* and *Zero-Shot* settings: (1) RANDOM GUESS: gives uniform random binary predictions. (2) GPT-3.5 (Brown et al., 2020; Ouyang et al., 2022): uses gpt-3.5-turbo-0125 model and formulates RE as a double choice problem, answering whether two entity mentions in each test instance follow the given target relation definition. (3) ROBERTA NLI (Devlin et al., 2018; Liu et al., 2019): our adopted SLM RE backbone model (Sec. 3.2). It adopts 100 gold positive and 100 gold negative instances for each relation under the *Fully-Supervised* setting. (4) ZS-BERT (Chen and Li, 2021): a Siamese-based zero-shot RE framework trained on seen labeled instances and gives prediction by nearest neighbour search comparing encoded sentence representations and relation definition representations. (5) RELATIONPROMPT (Chia et al., 2022): a Seq2Seq-based zero-shot RE framework that trains GPT-2 (Radford et al., 2019) to generate relation instances conditioned on relation names and train BART (Lewis et al., 2020) to generate the extracted relation triple on seen data. For unseen data, it fine-tune BART on synthetic data generated by trained GPT and then predicts. (6) RE-MATCHING (Zhao et al., 2023): a Siamese-based zero-shot RE model that encodes entity types and relation definitions for each relation on seen data and conducts nearest neighbour search for prediction on unseen data.

Note that ZS-BERT, RELATIONPROMPT and RE-MATCHING require being trained on labeled seen data and their predictions on unseen data need to be conducted in a multi-way classification manner where information of all relations is leveraged. These three baselines are trained on the relation in-

stances not in the test set while leaving 5 relations’ instances for dev set.

4.3 Experiment Setup

Evaluation Methods. Following our *Definition Only Zero-Shot Relation Extraction* setting, evaluation is conducted similar to cross validation where each iteration one test relation is treated as the gold positive target relation and remaining test relations serve as gold negative test relations (our setting assumes all negative relations are unknown in terms of relation definitions and any distribution information). Each test iteration is a binary classification problem with precision, recall and F₁ calculated. Table 1 shows the main results where Precision, Recall and F₁ indicates the corresponding binary classification metric scores averaged across all test iterations. Since ZS-BERT, RELATIONPROMPT and RE-MATCHING require the traditional zero-shot RE setting where multi-way classification is assumed, we further train the KNOWPROMPT (Chen et al., 2022b) multi-way RE classifier with all instances of test relations synthesized by REPAL for comparison. This leads to the Macro-F₁ column.

Random seeds used for this work are from 1 to 5. See Appendix F for further implementation details and see Appendix A for details of our definition only zero-shot RE setting and justifications.

5 Results and Analysis

5.1 Main Results

The main results are shown in Table 1. REPAL achieves much better performance compared with all zero-shot baselines with large margins for both evaluation datasets. This shows the effectiveness of our method in low-resource settings and the robustness across different benchmarks.

The advance of REPAL is slightly lower in DefOn-Wiki-ZSL compared to DefOn-FewRel which is because Wiki-ZSL is much more noisy due to distant supervised annotations. By comparing the absolute values of F_1 scores derived for our zero-shot RE setting with the Macro- F_1 scores derived for traditional zero-shot RE setting, it can be concluded that our definition only zero-shot setting is much more challenging. Once we break the assumption of unknown negative relation space, models can take shortcuts to distinguish different relations without actually comprehending the relations.

Compared with fully-supervised baselines, it shows there is still room for improvement. This is related to our task’s assumption on unknown negative test relation space which is normally avoided in mainstream zero-shot RE works.

5.2 Ablation Study

Model	DefOn-FewRel		
	Precision	Recall	F_1
REPAL	76.99	82.87	77.09
- N_feedback	72.39	87.54	76.01
- P_feedback	69.34	88.05	74.33
- P_init	39.67	94.34	49.40

Table 2: Ablation results with 15p15n as initial setting. P_init, P_feedback, and N_feedback denote initial positive generation, feedback-driven follow-up positive generation and negative generation respectively. The ablations are conducted with one group of FewRel relations over 5 random seeds.

To investigate the effectiveness of our framework design, we conduct ablation studies with results shown in Table 2. The initial seed generation brings considerable performance advance which shows LLM’s power of domain adaptation is fully leveraged given a clear relation definition. Based on experiments on Sec. 5.4, the best F_1 achieved by a single seed among all initial seed generation setups is 75.92 (p=60, n=60, random seed=3). By adopting our feedback-driven follow-up generation design, the average performance of in total p=30 & n=30 surpasses this upper bound by approximately 1 points.

Furthermore, the negative follow-up instance generation further boosts the precision score, demonstrating its effectiveness on rectifying SLM’s bias in distinguishing positive and negative relations.

5.3 Effect of Positive Templates

Model	DefOn-FewRel		
	Precision	Recall	F_1
REPAL	68.25	86.85	73.42
- implicit	68.57	88.52	74.38
- brief	67.93	86.40	72.77

Table 3: Evaluation results w/o follow-up generation and conditioned only on different initial positive generation templates. 30p30n instances are gathered for all settings.

Table 5 in Appendix B shows the adopted initial positive seed construction templates. Note that no ICL is adopted in REPAL’s generation step. Analysis in Appendix B yields the conclusion that the generated instance’s patterns generally follow the prompt instructions well, covering instances with brief, medium-length, and implicit patterns respectively.

The quantitative results with different combinations of positive instance generation prompts are shown in Table 3. We can see that results are generally robust against different prompt combinations. And leveraging medium and brief prompts yields the best result. It’s likely because two evaluation datasets have short or medium length/complexity instances. However, in our main experiments, all three prompts are adopted to cover diverse types of generated patterns.

5.4 Effect of More Initial Seeds

As recent LLMs have enabled larger context windows, a naïve method for improving framework performance is to directly query LLMs for more generated instances. So we conduct such trials on our definition only zero-shot RE task (Sec. 3.1) to investigate whether more initially generated seeds can bring more benefits. The quantitative results are shown in Fig. 5, Fig. 6, and Fig. 4. We can see that synthetic data by LLM is generally beneficial, but generating more initial seeds does not guarantee better results. Larger p&n or larger n:p ratio both lead to higher precision and lower recall⁴.

One explanation for these trends is that more positive seeds does not bring larger positive pattern coverage but results in over-fitting. However, more randomly sampled negative seeds lead to larger negative pattern coverage. So the model tends to give positive predictions on instances with some

⁴We abbreviate the number of positive instances for each target relation as p and the number of negative instances as n.

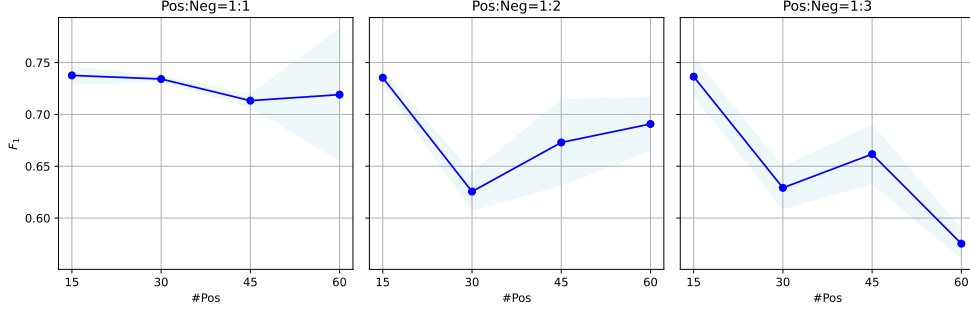


Figure 4: F_1 (%) scores for different setups in REPAL’s first step of *Definition-Based Seed Construction with LLM and Unlabeled Corpus*.

dominant positive patterns but identify other minority patterns as negative. Also note that when n&p are small, usually recall is pretty high while precision is low. This may also be caused by our task assumption on unknown negative relation space. The above observations and analysis further justify our design of feedback-driven follow-up generation and refinement paradigm.

5.5 Error Analysis

Table 4 shows the major source of false positive predictions of the final tuned SLM RE model, it can be seen that the majority of false positive predictions are concentrated on a few similar negative relations. As our proposed task setting assumes the unknown negative relation space, one challenge appears to be learning the positive relation against the unknown and infinitely many negative relations. To address such challenge, our model derive targeted negative relations based on the feedback of model inference. Based on the results in Table 4, we can see that the challenge is not fully eliminated which serves as a promising future research direction. Another feature seen from the false positive predicted instances is that some typical false positive instances actually express the target relation in addition to its gold relation. However, the target relation is not expressed by the tagged entity mention pair. This may indicate that better RE architectures which well model the position awareness of target entity pairs can be adopted for improving the overall performance. We also leave this for future studies.

6 Related Work

Zero-Shot Relation Extraction Our work is related to zero-shot RE (Levy et al., 2017). Majority zero-shot RE approaches mainly leverage clustering, label-verbalization, or Siamese-based architectures (Rahimi and Surdeanu, 2023; Chen and Li,

2021; Chia et al., 2022; Li et al., 2023a) which seek for the instance-instance similarity or the similarity between the relation instances and the unseen relations’ information. Chen and Li (2021) utilize relation descriptions for zero-shot RE but their approach still relies on seen data to align relation descriptions with instances in a supervised manner. Li et al. (2023b) adopt the relation descriptions but only for verifying synthesized data with the instance-level seeds. LLM-based RE works focus on designing prompting strategies or LLM alignment to tackle zero-shot RE (Li et al., 2023a; Zhang et al., 2023; Wei et al., 2023; Wadhwa et al., 2023). Our work is distinguished from pre-LLM zero-shot RE works as they heavily rely on the supervision from massive seen data and the complete negative relation space. And the majority do not focus on relation definitions. Our work is different from LLM-based zero-shot RE works as we emphasize both the rich relation definitions for data synthesis and synergy between SLM and LLM.

Definition-Driven Text Mining Another related line of research is definition-driven text mining. BERTNet (Hao et al., 2023) applies definitions for distilling entities from LM parametric knowledge. Label definitions/descriptions have also been proven to be powerful in text classification (Gao et al., 2023). In zero-shot RE, several PLM-based works have utilized relation definitions (Chen and Li, 2021; Zhao et al., 2023) but they mainly focus on computing instance-definition similarities. In our work, LLM is used to distill patterns described in definitions and extend or rectify the learning of SLM starting from definitions.

7 Conclusion

In this work, we have introduced a new zero-shot RE task where only relation definitions instead of seen-unseen relation instances are provided. Cor-

Example Target Relation	Majority False Positive Predicted Relations	Example Instance of False Positive Predicted Relations
P40: <ENT1> was/is the child (not stepchild) of <ENT0>	<ol style="list-style-type: none"> 1. P26 (218): <ENT1> was/is the married spouse (husband, wife, partner, etc.) of <ENT0> 2. P3373 (165): <ENT1> and <ENT0> had/have at least one common parent (<ENT1> is the sibling, brother, sister, etc. including half-sibling of <ENT0>) 	<ol style="list-style-type: none"> 1. <ENT1> Lord Louis Mountbatten </ENT1> (Hugh Bonneville) arrives at Viceroy 's House in Delhi in 1947 with his strong - willed wife <ENT0> Edwina </ENT0> (Gillian Anderson) and daughter Pamela . (Gold: P26 Pred: P40 Pos Prob: 0.995) 2. Daughter of <ENT1> Sancho IV </ENT1> and of <ENT0> María de Molina </ENT0> , Infanta Beatrice was born in Toro . (Gold: P26 Pred: P40 Pos Prob: 0.998) 3. <ENT1> Ruby Aldridge </ENT1> is the daughter of former Playboy playmate Laura Lyons and artist and graphic designer Alan Aldridge , and younger sister of fashion model <ENT0> Lily Aldridge </ENT0> . (Gold: P3373 Pred: P40 Pos Prob: 0.959) 4. <ENT0> Jan van Hoogstraten </ENT0> (1628–1654) was a Dutch Golden Age painter who died young in Vienna , where he was living with his older brother <ENT1> Samuel van Hoogstraten </ENT1> . (Gold: P3373 Pred: P40 Pos Prob: 0.998)
P410: <ENT1> was/is the military rank achieved by or associated with <ENT0> (a person or a position)	P241 (376): <ENT1> was/is the military branch to which <ENT0> (a military unit, award, office, or person) belonged/belongs	<ol style="list-style-type: none"> 1. In November 1966 , retired <ENT1> USMC </ENT1> Major <ENT0> Donald Keyhoe </ENT0> and Richard H. Hall , both of NICAP , briefed the panel . (Gold: P241 Pred: P410 Pos Prob: 0.996) 2. General Sir <ENT0> Hew Whitefoord Dalrymple </ENT0> , 1st Baronet (3 December 1750 – 9 April 1830) was a <ENT1> British Army </ENT1> general and Governor of Gibraltar . (Gold: P241 Pred: P410 Pos Prob: 0.995)
P57: <ENT1> was/is the director(s) of <ENT0> (a film, TV-series, stageplay, video game or similar)	P84 (131): <ENT1> was/is the architect or architectural firm responsible for designing <ENT0> (a building)	<ol style="list-style-type: none"> 1. The <ENT0> Yokosuka Arts Theatre </ENT0> , part of the Bay Square complex by <ENT1> Kenzo Tange </ENT1> , is a venue for opera , orchestral concerts , chamber music , and films . (Gold: P84 Pred: P57 Pos Prob: 0.981) 2. Memorials such as <ENT1> Maya Lin </ENT1> 's <ENT0> Vietnam Veterans Memorial </ENT0> and Peter Eisenman 's Memorial to the Murdered Jews of Europe are also said to reflect themes of trace and erasure . (Gold: P84 Pred: P57 Pos Prob: 0.979)

Table 4: Error analysis of the predictions made by SLM-based RE model. The contents in red denote the number of false positive predictions for a specific relation. The contents in blue denote the prediction details made by SLM-based RE model. *Gold* refers to the gold relation label of an instance. *Pred* refers to the predictions made by our model. *Pos Prob* means the predicted probability of the instance following the target relation.

respondingly, we have proposed REPAL which leverages LLMs and unlabeled corpora to generate relation instances and iteratively self-improves the generation pattern coverage while rectifying the bias by automatically acquiring and reflecting over sampled feedback from multiple sources. Quantitative experiments and qualitative analysis on our two modified datasets show the effectiveness and robustness of our framework as well as our large-margin advance over SOTA baselines. Exploratory experiments show that generating more data in a single-turn conversation does not yield larger pattern coverage. We also proposed a derive-definition-and-then-generate approach which achieves much better performance than just utilizing few-shot instances. This gives insights into low-resource RE works to capture the complete relation semantics to avoid partial coverage by few-shot instances.

Limitations

In this work, we mainly experimented on GPT-3.5 and GPT-4 as their instruction following performance is competent so that we do not need to introduce in-context learning in most of the time. So one follow-up work is to explore other LLMs to see their generation capability compared to the GPT series. Besides, new RE datasets tailored for our definition only zero-shot RE still can be created as RE still lacks large scale yet high quality datasets. Thirdly, prompt engineering and hyperparameter search are not conducted. For the sake of better performance in downstream tasks, future works could compensate this.

Ethics Statements

Since our goal is to solve sentence-level RE tasks where the text contexts are sufficient to derive the relation, factualness of the relation triples is not a strict requirement or a vital factor for the training instances. Therefore, in generative data synthesis, we do not further verify the factualness of the gen-

eration results and we simply count on the GPT-4 model. So follow-up works could explore this and other related approaches should also be careful if they want to adapt our work to downstream tasks necessitating factualness such as factual question answering.

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A Detailed Discussions on Definition Only Zero-Shot Relation Extraction Setup

A.1 Task Setup and Evaluation Process

Suppose the RE test set contains R relations and each relation r has N_r instances. Then the evaluation will be conducted in R iterations and the final score will be calculated by averaging over the individual scores from the total R iterations.

For each test iteration, we take one test relation r as the target relation (gold positive relation) with N_r gold positive instances. All the other test relations will be treated as negative relations and all their associated instances are gold negative instances. So each iteration is in the format of binary classification, targeting at the set of gold positive instances and gold negative instances. Additionally, we assume the negative relation space is unknown, which means that for each test iteration, we only know the relation definition of the gold positive relation r , and we do not know any information about the negative test relations. Such cross-validation evaluation is designed for robustness as the results are averaged over all different test relations. For the evaluation complexity, if we assume each test relation has balanced N instances, the complexity is proportional to $N \cdot R^2$.

A.2 Distinctions with Traditional Zero-Shot RE

Traditional zero-shot relation extraction models are trained on a large set of seen relations with corresponding labeled instances. During evaluation, the trained model will deal with a set of unseen relations with corresponding relation instances. The trained model will have access to the information of all unseen relations (at the same time) in the format such as relation label names, or relation descriptions/definitions, or other more fine-grained information (e.g., extended possible entity type lists). Then the final model is required to conduct multi-way classification over all unseen relations.

For our newly defined Definition Only Zero-Shot Relation Extraction task:

- We do not rely on any seen relation or any labeled relation instance.
- We only assume a clear and complete relation definition for each target positive relation and an unlabeled corpora.
- We assume unknown negative relation space which means for each test iteration, in addition

to the single positive target test relation, all the other test relations are treated as negative relations and we do not know any information about how many negative relations are and what the negative relations are.

- The evaluation process is completely different from traditional zero-shot RE as described above.

A.3 Motivations and Practical Values

We design our Definition Only Zero-Shot Relation Extraction in order to accommodate more realistic and more challenging applications as the fast developing LMs, especially LLMs, are enabling the design of such advanced systems. Here we will emphasize the motivations and values of the setup of our Definition Only Zero-Shot Relation Extraction task.

First, the assumption that the definition of the target unseen relation is given instead of assuming and using annotated data of other seen relations accommodates various applications scenarios. When people deal with domain specific problems, the definitions of interested relations are normally clear and explicit. For instance, an expert in the geographic information system (GIS) domain might want to model textual patterns which describe two geospatial entities “touches” with each other (their interiors do not intersect and only their boundaries intersect). They already have well defined terminologies and associated definitions for such relations but the annotations are expensive. Another example lies in the question answering task where one can derive the “<ENT0> is youngest birth child of <ENT1>” definition if they are interested in extracting instances (text contexts and tuples) for the question “Who is the youngest child of Person A?”. Additionally, when crowdsource workers are annotating RE samples, they are often provided with the relation definitions to guide their annotation work. So it’s realistic to assume that a clear and explicit relation definition is given. From the above cases, it can also be seen that the potential relations of interest are infinite which emerge with different problems in different domains. But annotating in-domain samples are expensive and time consuming. So it’s also meaningful to tackle RE from the source. Namely, focusing on definitions which capture the complete relation semantics compared to other types of starting seeds and leveraging the domain adaptation power and the constrained gen-

eration power of LLMs to alleviate the annotation scarcity issue.

Second, the assumption of unknown negative relation space is to mimic the real world setting where the number of interested relations is extremely small compared to the number of negative relations between entities. For example, one may be interested in one Wikidata property relation but the number of total Wikidata properties is massive. In such cases, approximately, we barely know anything about the negative relation space. But to train a good relation extractor that can distinguish interested target relations against all the other negative relations in the corpus, we will need some method designs to deal with such unknown negative relation space. Our assumption of unknown negative relation space can also be considered as a more challenging version of “None” or “No Relation” relation labels for traditional multi-classification RE datasets.

Third, the assumption of a large unlabeled corpus is natural as the unlabeled corpus usually come together with specific domains. Still taking the geospatial RE as an example, it’s relatively easy to acquire documents that mention about geospatial entities and potentially their mutual relations. Some experts from GIS could also be able to provide such corpus. Since the corpus do not need to be labeled with relations, it’s much more convenient and efficient to get such unlabeled corpus set up instead of gathering domain-specific annotations. Besides, our framework does not solely rely on the unlabeled corpus as we have designed follow-up positive and negative instance generation processes to rectify the bias and extend the relation pattern coverage which synthesizes follow-up positive and negative instances. LLMs will conduct self-reflection on the given relation definition, synthesis dialogue history, and the sampled inference results on the unlabeled corpora. Among those sampled inference results, LLM will judge whether the prediction is correct or wrong. If the sampled inference results contain correct predictions, LLM can analyze the instances which convey the information on the patterns learnt by SLM. If the sampled inference results contain wrong predictions, LLM can summarize their relations and generate follow-up similar negative relations and corresponding instances to correct the learning of SLM. Even if the feedback does not contain useful information, LLM can still generate more positive relation patterns based on the previously generated instances.

And LLM can also generate near-miss negative relations simply based on the definition of the positive target relation. With LLMs becoming more powerful in inference and having longer context window sizes, the performance gain of follow-up feedback driven generation process can be further improved.

Finally, our setting of binary NLI is versatile and has great potential to adapt to multi-way classification and multi-label classification settings. Based on the task setup and evaluation process, we can see there will be one binary relation classifier for each target relation. This is versatile because if we stick to the multi-classification setting based on data synthesis approach, we would need to re-train our multi-way classifier on synthesized data if there is an additional new relation coming in. Furthermore, the setup of R binary classifiers accommodates the scenarios where there are relations entailed by other relations or the contexts indicate two possible relations which are not allowed by multi-way classification setup. If we have multiple interested relations and the number of such relations are large, there are various methods to reduce the cost of adapting binary classifiers for multi-class/label problems. One method is to use some rules (e.g., mismatched entity types) or some coarse-grained NLI methods to first filter impossible relation candidates to reduce the candidate relation space and then apply our trained relation classifiers.

B Prompt Templates Used in Definition-Based Seed Construction with LLM

Table 5 contains the three prompt templates used for generating initial positive seeds using LLMs. Example instances generated by corresponding prompts are also shown inside the table. Our goal of designing such prompts is to cover all the patterns for target relations. From the generated example instances, we can see that the pattern complexity (or more naïvely, the sentence length) exhibits significant distinctions, especially between implicit and other two prompts. The pattern complexity (or more naïvely, the sentence length) well follows the instructions conveyed by each type of prompt and well represents the prompt name, brief, medium, and implicit correspondingly.

Prompt Name	Prompt Template	Example Generated Instances (Relation=P106)
brief	A binary relation between entity placeholders <ENT0> and <ENT1> is defined by “ \${Relation Definition} ”. Under sentence-level relation extraction setting, generate \${Number of Examples} examples (numbered from 1 to \${Number of Examples}) expressing the same relation, where <ENT0> is replaced with actual entity mention and is prefixed with tag <ENT0> and suffixed with tag </ENT0> , <ENT1> is replaced with actual entity mention and is prefixed with tag <ENT1> and suffixed with </ENT1> . Do not overfit the pattern of the definition. Try as many different relation patterns or relation expressions as possible.	<ol style="list-style-type: none"> Before becoming a renowned author, <ENT0>Agatha Christie</ENT0> had a career as a <ENT1>nurse</ENT1> during the World War I period. The award-winning film director <ENT0>Quentin Tarantino</ENT0> once worked at a video rental store, which heavily influenced his future as a <ENT1>filmmaker</ENT1>. Known for his groundbreaking theories in physics, <ENT0>Albert Einstein</ENT0> held the position of a <ENT1>patent clerk</ENT1> in his early career, which gave him the time to develop his early theories.
medium	A binary relation between entity placeholders <ENT0> and <ENT1> is defined by “ \${Relation Definition} ”. Under sentence-level relation extraction setting, generate \${Number of Examples} examples (numbered from 1 to \${Number of Examples}) expressing the same relation, where <ENT0> is replaced with actual entity mention and is prefixed with tag <ENT0> and suffixed with tag </ENT0> , <ENT1> is replaced with actual entity mention and is prefixed with tag <ENT1> and suffixed with </ENT1> . Other content requirements: 1. Do not overfit the pattern of definition. Try as many different relation patterns or relation expressions as possible. 2. Generate rich and informative related contexts before and after each entity.	<ol style="list-style-type: none"> During the 1990s, the renowned physicist <ENT0>Stephen Hawking</ENT0> dedicated his life to unraveling the mysteries of the universe, a commitment that made him synonymous with the role of <ENT1>theoretical physicist</ENT1>. Before stepping into the political arena, <ENT0>Barack Obama</ENT0> honed his skills and passion for change as a <ENT1>community organizer</ENT1> in Chicago, working tirelessly on initiatives that aimed to improve living conditions for the city’s residents. In her illustrious career spanning several decades, <ENT0>Marie Curie</ENT0> shattered gender barriers and set new benchmarks in scientific research, earning worldwide acclaim as a pioneering <ENT1>chemist</ENT1> and physicist.
implicit	A binary relation between entity placeholders <ENT0> and <ENT1> is defined by “ \${Relation Definition} ”. Under sentence-level relation extraction setting, generate \${Number of Examples} examples (numbered from 1 to \${Number of Examples}) expressing the same relation, where <ENT0> is replaced with actual entity mention and is prefixed with tag <ENT0> and suffixed with tag </ENT0> , <ENT1> is replaced with actual entity mention and is prefixed with tag <ENT1> and suffixed with </ENT1> . Other content requirements: 1. Do not overfit the pattern of definition. Try as many different relation patterns or relation expressions as possible. 2. Generate rich and informative related contexts before and after each entity. 3. The relation patterns or relation expressions should be implicit or complicated	<ol style="list-style-type: none"> Born into a family with a history of academic excellence, it was no surprise when <ENT0>Albert Einstein</ENT0> ventured into the realms of theoretical physics, a field where he made his mark by unraveling the mysteries of the universe, thus becoming synonymous with the profession that <ENT1>theoretical physicist</ENT1> would forever be associated with his name. The battlefields of ancient Macedonia were graced by the strategic genius of <ENT0>Alexander the Great</ENT0>, whose military campaigns across the vast expanses of the known world were unmatched, firmly establishing him not just as a king but as one of the greatest <ENT1>military leaders</ENT1> history has ever witnessed, shaping the course of the civilizations that came after him. In the annals of crime-solving history, <ENT0>Sherlock Holmes</ENT0> stands out as a fictional detective who, through his acute observation and deductive reasoning, set the gold standard for the <ENT1>detective</ENT1> profession, influencing countless others in the field of criminal investigation despite his creator, Sir Arthur Conan Doyle’s, initial reluctance to make him a permanent fixture in literary history.

Table 5: Prompt templates used in Definition-Based Seed Construction with LLM (Sec. 3.1). Words in blue denote the placeholders for filling in contents indicated by their surface names.

C Prompt Templates Used in Feedback-Driven Instance Improvement and Bias Rectification

Table 6 contains prompt templates for our feedback-driven follow-up positive instance generation and negative relation definition generation respectively. After obtaining the negative relation definitions, we simply leverage the medium instance generation template in Table 5 to generate negative relation instances. We take this template as our purpose of negative instance generation is to rectify the ex-

isting bias instead of pursuing complete negative relation pattern coverage. Furthermore, Table 3 demonstrates that the performance difference between the usages of different templates is minor.

D Details of Constructed DefOn-FewRel and DefOn-Wiki-ZSL Datasets

Table 7 shows the example relation labels and constructed definitions. Please see the associated anonymous Github repo for detailed relations and definitions.

Prompt Name	Prompt Template
Follow-up Positive Instance Generation	Typical examples predicted as positive by my relation extraction model are:\n\n\${Feedback Examples}\n\nBased on these predicted examples and your previously generated examples, generate \${Number of Examples} additional examples (numbered from 1 to \${Number of Examples}) expressing the same pre-defined relation: \${Positive Relation Definition}. Other requirements are: 1. Identify what relation patterns have been learnt by my model or covered by your previously generated examples and your newly generated examples should have different and diverse relation patterns. 2. Identify model’s bias from the typical predicted examples which do not express the correct relation definition and your newly generated examples should try to mitigate the bias.
Follow-up Negative Relation Definition Generation	A binary relation between entity placeholders <ENT0> and <ENT1> is defined by: “\${Positive Relation Definition}”. In relation examples or relation instances, <ENT0> is replaced with actual entity mention and is prefixed with tag <ENT0> and suffixed with tag </ENT0> , <ENT1> is replaced with actual entity mention and is prefixed with tag <ENT1> and suffixed with </ENT1> .\n\nTypical examples predicted as positive by current relation extraction model are:\n\n\${Feedback Examples}\n\nBased on the positive relation definition and the typical predicted examples, generate \${Number of Follow-Up Negative Relations} negative binary relation definitions (numbered from 1 to \${Number of Follow-Up Negative Relations}) in the same format as the above positive relation definition (including entity placeholders and entity type constraints). Other requirements are: 1. Identify false positive predictions from the typical predicted examples and your generated negative relations should teach model to mitigate such bias. 2. After addressing the previous requirement, consider generating near-miss negative relations.

Table 6: Prompt templates used in Feedback-Driven Instance Improvement and Bias Rectification (Sec. 3.3). Words in blue denote the placeholder for filling in contents indicated by their surface names.

To get quality evaluation samples, we conduct test data cleaning with the requirements as: (1) The two entity mentions should not overlap; (2) The entity mentions should not be pronouns such as *I*, *he*, and *she*. Note these two requirements only give negligible impact on the number of relation instances. Furthermore, we clean the unlabeled corpora before down-sampling by requiring that selected unlabeled samples should not be repeated. Namely, for any two unlabeled samples, the sentence, the head entity mention and the tail entity mention can not all be the same.

E Effect of More Initial Seeds

The precision (%) scores and recall (%) scores discussed in Sec. 5.4 are shown in Fig. 5 and Fig. 6 respectively.

F Implementation Details

F.1 Baselines

In consideration of OpenAI API calling expense, the GPT-3.5 baseline results are from the evaluation over down-sampled test sets (30 down-sampled

test instances for each relation). For all the other baselines, we adopted their original hyperparameters reported in corresponding publications.

F.2 REPAL

The LLM model we use is gpt-4-0125-preview with max tokens set to 4,096, presence penalty set to 0.15 and temperature set to 1.0⁵. The OpenAI API cost to reproduce one random seed’s results of REPAL in Table 1 is around 2.5 dollars (far cheaper than direct inference with GPT-3.5 on test sets). The SLM checkpoint used is ROBERTA-LARGE-MNLI. All model training is conducted on 2 or 4 NVIDIA RTX A6000 GPUs.

For the step of *Definition-Based Seed Construction with LLM and Unlabeled Corpus*, we follow the templates in Table 5. For the results reported in Table 1, we choose the setting of 15 initial positive seeds and 15 initial negative seeds based on the analysis in Sec. 5.4. As we have

⁵For reproducibility, the temperature for REPAL’s follow-up instance generation is set to 0 even though higher temperature could lead to better performance.

Original Dataset	Relation Label : Definition	Frequency
FewRel	P106: <ENT1> was/is the occupation of <ENT0> (a person)	700
FewRel	P1344: <ENT0> (a person or organization) was/is a participant of <ENT1> (an event)	700
FewRel	P136: <ENT1> was/is the genre or the field of work of <ENT0> (a creative work or an artist)	700
FewRel	P1411: <ENT1> was/is the award nomination received by <ENT0> (a person, organisation, or creative work)	698
FewRel	P241: <ENT1> was/is the military branch to which <ENT0> (a military unit, award, office, or person) belonged/belongs	700
FewRel	P26: <ENT1> was/is the married spouse (husband, wife, partner, etc.) of <ENT0>	700
FewRel	P276: <ENT1> was/is the location of <ENT0> (an object, structure or event)	700
FewRel	P3373: <ENT1> and <ENT0> had/have at least one common parent (<ENT1> is the sibling, brother, sister, etc. including half-sibling of <ENT0>)	700
FewRel	P40: <ENT1> was/is the child (not stepchild) of <ENT0>	700
FewRel	P400: <ENT1> was/is the platform or platform version for which <ENT0> (a work or a software product) was/is developed or released	700
FewRel	P410: <ENT1> was/is the military rank achieved by or associated with <ENT0> (a person or a position)	700
FewRel	P57: <ENT1> was/is the director(s) of <ENT0> (a film, TV-series, stageplay, video game or similar)	700
FewRel	P84: <ENT1> was/is the architect or architectural firm responsible for designing <ENT0> (a building)	700
FewRel	P974: <ENT1> was/is the watercourse that flowed/flows into <ENT0> (a watercourse)	700

Table 7: Example DefOn-FewRel relation labels, definitions, and corresponding instance frequencies.

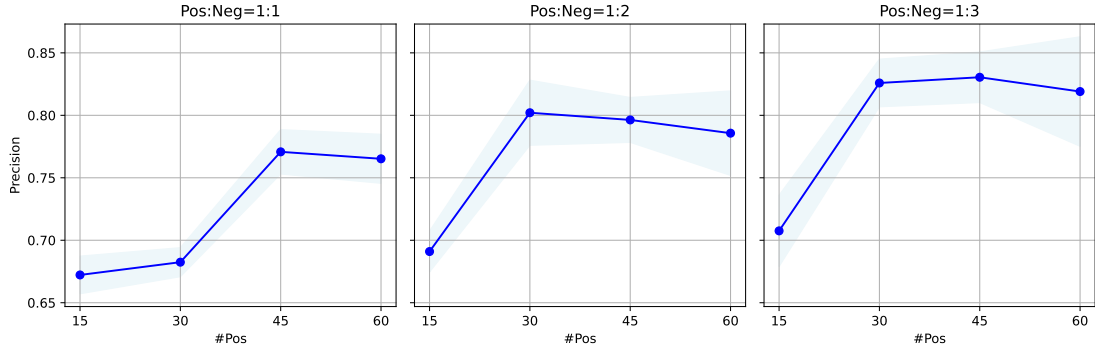


Figure 5: Precision (%) scores for different set-ups in REPAL’s first step of *Definition-Based Seed Construction* with *LLM* and *Unlabeled Corpus*.

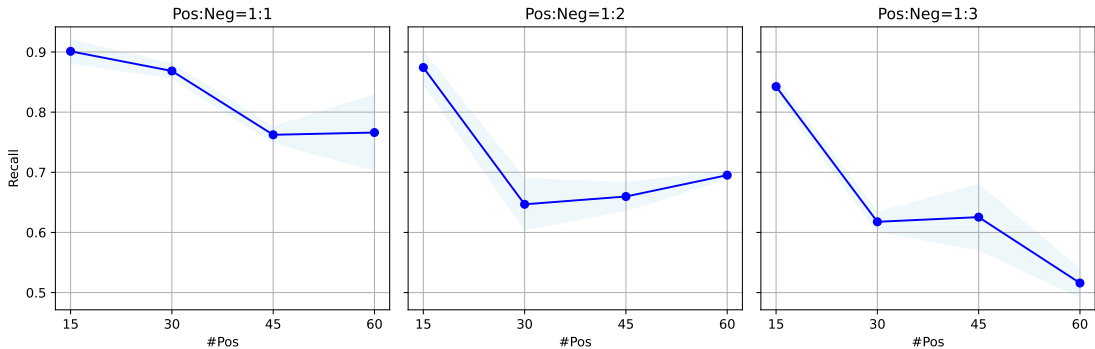


Figure 6: Recall (%) scores for different set-ups in REPAL’s first step of *Definition-Based Seed Construction* with *LLM* and *Unlabeled Corpus*.

three types of prompts for positive seeds generation, each prompt will contribute to generating 5 initial positive seeds. For the step of *Pattern Learning with RE-Specialized SLM*, we train the SLM with 5 epochs using AdamW optimizer (Loshchilov and Hutter, 2017) with learning rate equal to $3e-5$ and batch size equal to 64.

For the step of *Feedback-Drive Instance Improvement and Bias Rectification*, we first leverage the trained SLM to conduct inference on the unlabeled corpus after which each unlabeled instance will be associated with a score as the probability of being positive. Then, for follow-up positive instance generation, we conduct random sampling from all instance with score higher than 0.85 as we want the sampled feedback instances to reflect the model’s learning outcome for the target positive relation. For follow-up negative relation definition generation, we conduct random sampling from all instances with score higher than 0.50 as we want to see both the confident predictions and less confident predictions to identify the existing bias. Note that continuing from the initial positive seed generation, there will be three threads of dialogue history for follow-up positive instance generation corresponding to three types of prompts in Table 5. So for each thread of dialogue, we fill in different groups of sampled feedback instances to maximize the feedback coverage. For both the follow-up positive instance generation and the follow-up negative instance generation, the number of feedback instances for each prompt input is set to 10. For follow-up negative relation definition generation, we set the number of generated negative relation definitions to be 5 and the number of total follow-up negative instances to be 15. After obtaining the feedback-driven follow-up instances, we continue to train the SLM RE model for 5 epochs with all the other hyperparameters the same as our previous SLM training step.

G LLM-Based Relation Definition Derivation

Our adopted prompt template for deriving relation definitions based on few-shot instances is shown in Table 8. Note that we leveraged a fixed 3 relation definition demonstrations for in-context learning across all relations so that the LLM can give the relation definition in our desired format for automatic parsing. After getting the relation definition, we use the prompt template in Table 8 to generate

15 instances for each derived relation. Note that the instance generation prompt is basically the same as brief prompt in Table 5 except that it integrates the gold few-shot instances as in-context learning demonstrations.

G.1 Relation Definitions Derived by LLM From Few-Shot Instances

Table 9 and Table 10 show the LLM derived relation definitions based on the gold 4-shot instances. The table also contains the ground truth relation definitions for reference. We can see that for most of the FewRel relations, LLM successfully recovers the gold relation definitions. The derived definitions also reveal that one major difficulty is to specify the entity type constraints as few-shot instances may only convey a partial set of entity types which misguides LLMs to deduce a partial entity type constraints in the derived relation definitions.

G.2 Macro F1 Scores of Few-Shot Method against Definition-Based Method

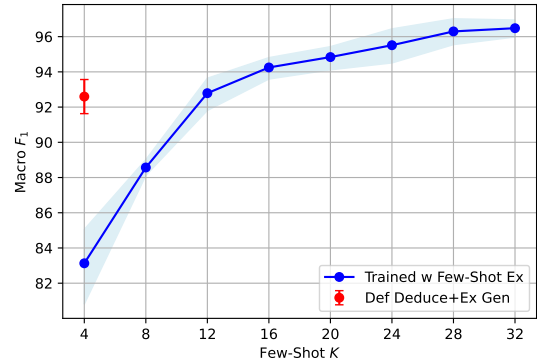


Figure 7: Macro F_1 (%) scores of model trained with few-shot instances (*Trained w Few-Shot Ex*) and model trained with instances from our relation definition derivation and instance generation approach (*Def Deduce+Ex Gen*). The error bar/band denotes averaged value \pm standard deviation.

The macro F_1 scores of the experiments conducted in Sec. 2.2 are shown in Table 7. Since the DefOn-FewRel dataset is almost balanced, the micro F_1 and macro F_1 are close. So we put macro F_1 here for reference.

H Case Study

In order to showcase how LLMs function in accordance with our design expectations, we provide some dialogue cases in Fig. 8 and Fig. 9. From the example dialogues, we can see that GPT-4 is

Prompt Name	Prompt Template
Few-Shot Definition Derivation	<p>Given a list of relation instances/examples of a binary relation defined between two entities <ENT0> and <ENT1>, derive the relation definition in a single sentence. Note that in relation instances/examples, actual entity mention for <ENT0> is prefixed with tag <ENT0> and suffixed with tag </ENT0>, and actual entity mention for <ENT1> is prefixed with tag <ENT1> and suffixed with </ENT1> . Your derived relation definition should use entity placeholders <ENT0> and <ENT1> to refer to the two entities and the relation definition should try to contain entity type constraints. Example relation definitions are:\n\n1. <ENT1> is the league in which <ENT0> (team or player) plays or has played in.\n\n2. <ENT1> is the organization or person responsible for publishing <ENT0> (books, periodicals, printed music, podcasts, games or software).\n\n3. <ENT1> is the city, where <ENT0> (an organization)'s headquarters is or has been situated.\n\nThe list of relation instances/examples is:\n\n\${Few-Shot Instances for One Relation}\n\n</p>
Train Instance Generation	<p>A binary relation between entity placeholders <ENT0> and <ENT1> is defined by "\${Derived Relation Definition}". Under sentence-level relation extraction setting, generate additional \${Number Of Additional Examples to Generate} examples (numbered from 1 to \${Number Of Additional Examples to Generate}) expressing the same relation, where <ENT0> is replaced with actual entity mention and is prefixed with tag <ENT0> and suffixed with tag </ENT0> , <ENT1> is replaced with actual entity mention and is prefixed with tag <ENT1> and suffixed with </ENT1> . \${Gold Few-Shot Examples for ICL} Do not overfit the pattern of the definition. Try as many different relation patterns or relation expressions as possible.</p>

Table 8: Prompt template used in deriving original relation definitions given few-shot relation instances and generating new relation instances based on the derived relation definition and gold few-shot instances (Sec. 2.2). Words in blue denote the placeholder for filling in contents indicated by their surface names.

A binary relation between entity placeholders <ENT0> and <ENT1> is defined by "<ENT1> was/is the military branch to which <ENT0> (a military unit, award, office, or person) belonged/belongs". Under sentence-level relation extraction setting, generate 5 examples (numbered from 1 to 5) expressing the same relation, where <ENT0> is replaced with actual entity mention and is prefixed with tag <ENT0> and suffixed with tag </ENT0> , <ENT1> is replaced with actual entity mention and is prefixed with tag <ENT1> and suffixed with </ENT1> . Do not overfit the pattern of the definition. Try as many different relation patterns or relation expressions as possible.

1. The <ENT0>42nd Infantry Division</ENT0> is currently part of the <ENT1>Army National Guard</ENT1>.

2. During World War II, <ENT0>Ernest Hemingway</ENT0> served in the <ENT1>United States Army</ENT1> as an ambulance driver.

3. The prestigious <ENT0>Victoria Cross</ENT0> is awarded by the British <ENT1>Royal Navy</ENT1>, Army, and Air Force for valor in the face of the enemy.

4. As a member of the <ENT0>Blue Angels</ENT0>, she represents the elite flight demonstration squadron of the <ENT1>United States Navy</ENT1>.

.....

Typical examples predicted as positive by my relation extraction model are:

1. <ENT0>Junius Wallace Jones</ENT0> , who later rose to the rank of Major General and was the first Inspector - General of the <ENT1>United States Air Force</ENT1> received his flight training here .

2. A detachment of the Special Investigation Branch of the Royal Air Force Police headed by <ENT1>Wing Commander</ENT1> <ENT0>Wilfred Bowes</ENT0> was given the assignment of tracking down the killers of the 50 officers .

.....

Based on the observation of the predicted examples and the previous examples generated, it's evident that **the model can efficiently recognize direct associations between military personnel, units, or awards and their corresponding military branches**. However, there may be **biases or gaps in recognizing broader or more nuanced relations, such as civilian roles within military contexts, historical context of service not explicitly mentioned as military, and relations involving military infrastructure or events**.

To address these gaps and diversify the relation patterns, I propose the following new examples, intentionally designed to mitigate identified biases and introduce variance in expressing the relation between entity mentions and their military branches:

1. During the Siege of Sarajevo, UN peacekeeping forces included troops from the <ENT0>Irish Regiment</ENT0>, which was under the operational command of the <ENT1>United Nations Protection Force</ENT1>.

2. In 1945, <ENT0>Karl Donitz</ENT0> assumed the position of President of Germany and supreme commander of the Armed Services, particularly the <ENT1>Kriegsmarine</ENT1>, during the final phase of World War II.

3. The <ENT0>Joint Base Pearl Harbor-Hickam</ENT0> symbolizes a unique integration of Air and Naval military capabilities, co-administered by the <ENT1>United States Navy</ENT1> and the United States Air Force.

.....

By crafting these examples, I aimed to showcase:

- **International or non-traditional military branch affiliations (Example 1).**
- **Leadership roles that encompass command over specific military branches, addressing historical military structures (Example 2).**
- **Joint military installations showing cooperation between different military branches (Example 3), thereby going beyond the direct person-to-branch or unit-to-branch affiliations observed in the model's predictions.**

.....These examples are intended to guide the model towards recognizing a wider array of relations that convey military affiliation without being explicitly framed as traditional command or unit membership relations.

Figure 8: Example interaction dialogue which demonstrates the initial seed generation and feedback-driven follow-up positive instance generation.

considerably capable of identifying and summarizing the existing patterns in the dialogue history. The conversational feature also improves the in-

terpretability of the results which can be further exploited with human-in-the-loop methods for future research or downstream applications.

Gold Definition	Gold Few-Shot Instances For Derivation	Derived Definition
<ENT1> was/is the occupation of <ENT0> (a person)	<ol style="list-style-type: none"> 1. <ENT0>Pierre Maudru</ENT0> (1892\u20131992) was a French <ENT1>screenwriter</ENT1> . Goble p.189 He also directed three films . 2. WWF Hall of Famer Bob Backlund and Extreme Championship Wrestling <ENT1>manager</ENT1> <ENT0>Bill Alfonso</ENT0> also made surprise appearances during the event . 3. In May 2010 , Paratici moved from Sampdoria to Juventus , along with Director General Giuseppe Marotta and <ENT1>Manager</ENT1> <ENT0>Luigi Delneri</ENT0> . 4. <ENT0>Else Reval</ENT0> (14 June 1893 \u201325 January 1978) was a German <ENT1>film actress</ENT1> . Giesen p.210 	<ENT1> is the profession in which <ENT0> (a person) works or has worked.
<ENT0> (a person or organization) was/is a participant of <ENT1> (an event)	<ol style="list-style-type: none"> 1. He only saw limited action in <ENT1>Euro 2000</ENT1> as cover for left - back <ENT0>Arthur Numan</ENT0> . 2. <ENT0>Francesco Cameli</ENT0> was a sailor from Italy , who represented his country at the <ENT1>1928 Summer Olympics</ENT1> in Amsterdam , Netherlands . 3. <ENT0>Giannin Andreossi</ENT0> (born July 2 , 1902 , date of death unknown) was a Swiss ice hockey player who competed in the <ENT1>1928 Winter Olympics</ENT1> . 4. <ENT0>Ren\u00e9 Sch\u00f6fisch</ENT0> (born February 3 , 1962) is a German speed skater who competed for East Germany in the <ENT1>1984 Winter Olympics</ENT1> . 	<ENT1> is the major international sports competition in which <ENT0> (an athlete) has competed.
<ENT1> was/is the genre or the field of work of <ENT0> (a creative work or an artist)	<ol style="list-style-type: none"> 1. Another version , dating from c. 1616 , was given in c. 1790 to <ENT0>Joshua Reynolds</ENT0> by the Duke of Leeds in exchange for a Reynolds self - <ENT1>portrait</ENT1> . 2. Teixeira is a former member of indie rock bands Ik Mux and Boris Ex - Machina , as well as the <ENT1>hip hop</ENT1> group <ENT0>Da Weasel</ENT0> and industrial metal band Bizarra Locomotiva . 3. Beautiful Stories for Ugly ChildrenMUSHROOMHEAD To Release ' Beautiful Stories For Ugly Children ' In September is the seventh studio album by <ENT1>industrial metal</ENT1> band <ENT0>Mushroomhead</ENT0> . 4. Wales is portrayed in the 1976 <ENT1>western film</ENT1> “ <ENT0>The Outlaw Josey Wales</ENT0> ” by actor and director Clint Eastwood . 	<ENT1> is the genre or type of art (music, painting, film) associated with <ENT0> (an artist, band, or cultural artifact).
<ENT1> was/is the award nomination received by <ENT0> (a person, organisation, or creative work)	<ol style="list-style-type: none"> 1. On January 24 , 2012 , he was nominated for an <ENT1>Academy Award for Best Adapted Screenplay</ENT1> for the movie “ <ENT0>Moneyball</ENT0> ” . 2. “ <ENT0>The Great Santini</ENT0> ” received two Academy Award nominations : <ENT1>Best Actor in a Leading Role</ENT1> (Duvall) and Best Actor in a Supporting Role (O’Keefe) . 3. “ <ENT0>Born This Way</ENT0> ” (2011) , Gaga ’s second studio album , accrued three nominations at the 54th Annual Grammy Awards , including her third consecutive nomination for <ENT1>Album of the Year</ENT1> . 4. As a producer , he has been nominated for <ENT1>Best Picture</ENT1> for three other films : “ Raging Bull ” , “ <ENT0>The Right Stuff</ENT0> ” , and “ Goodfellas ” . 	<ENT1> is the award category for which <ENT0> (films, albums, or individuals associated with entertainment productions) has been nominated.
<ENT1> was/is the military branch to which <ENT0> (a military unit, award, office, or person) belonged/belongs	<ol style="list-style-type: none"> 1. General Sir (William) <ENT0>Henry Mackinnon</ENT0> , (15 December 1852 \u201317 March 1929) was a <ENT1>British Army</ENT1> General during World War I. 2. Lieutenant - Colonel <ENT0>Gordon Graham Donaldson</ENT0> was a senior officer in the <ENT1>British Army</ENT1> who died as a result of illness contracted during the disastrous Walcheren Campaign in 1809 . 3. <ENT0>Raphael Semmes</ENT0> was an officer in the <ENT1>United States Navy</ENT1> from 1826 to 1860 and the Confederate States Navy from 1860 to 1865 . 4. <ENT0>Isaac Townsend</ENT0> (“ c. ” 1685 \u201321 November 1765) was an admiral in the <ENT1>British Royal Navy</ENT1> and a Member of Parliament . 	<ENT1> is the military organization (such as an army or navy) with which <ENT0> (an individual, specified by their role or rank) has served or been associated.
<ENT1> was/is the married spouse (husband, wife, partner, etc.) of <ENT0>	<ol style="list-style-type: none"> 1. The film is about <ENT0>Carolyn Cassady</ENT0> ’s recollection of life with husband <ENT1>Neal Cassady</ENT1> and Jack Kerouac , and her concern that the truth about these men is being lost in their myths . 2. Maximilian married Duchess Helene in Bavaria , daughter of <ENT1>Duke Maximilian Joseph in Bavaria</ENT1> and his wife <ENT0>Princess Ludovika of Bavaria</ENT0> , on 24 August 1858 at Possenhofen Castle . 3. In 1916 his younger daughter , <ENT0>Nadejda</ENT0> (“ Nada ”) married <ENT1>Prince George of Battenberg</ENT1> , older son of Prince Louis by Queen Victoria ’s granddaughter , Princess Victoria of Hesse - Darmstadt . 4. The fourth and youngest son of King <ENT1>John II of France</ENT1> and his wife , <ENT0>Bonne of Luxembourg</ENT0> , Philip was the founder of the Burgundian branch of the House of Valois . 	<ENT1> is the spouse or partner of <ENT0> (an individual), indicating a marital, romantic, or partnership connection between the two entities.
<ENT1> was/is the location of <ENT0> (an object, structure or event)	<ol style="list-style-type: none"> 1. At the <ENT0>2014 Winter Olympics</ENT0> , Hudec won the bronze medal in the super - G at <ENT1>Rosa Khutor</ENT1> . 2. On the night of 22 January 1942 during the <ENT0>Battle of the Points</ENT0> , Japanese troops of the 16th Division attempted a landing on the west coast of southern <ENT1>Bataan</ENT1> . 3. Since the Netherlands did boycott the Moscow Olympic Games Brasser represented his National Olympic Committee at the <ENT0>1980 Summer Olympics</ENT0> in <ENT1>Tallinn</ENT1> , USSR under the Dutch NOC flag . 4. The bridge Norrbro stretches past the Riksdag on <ENT0>Helgeandsholmen</ENT0> and further south to <ENT1>Stockholm Old Town</ENT1> and the Royal Palace . 	<ENT1> is the location or venue where <ENT0> (an event such as sports competitions, battles, or significant historical or cultural events) took place or was hosted.
<ENT1> and <ENT0> had/have at least one common parent (<ENT1> is the sibling, brother, sister, etc. including half-sibling of <ENT0>)	<ol style="list-style-type: none"> 1. Together they had three sons : Antonio , <ENT1>Arturo</ENT1> , and <ENT0>Alejandro</ENT0> . 2. Portuguese and Spanish conquerors made use of these weapons , including Vasco da Gama and his sons <ENT1>Crist\u00f3v\u00e1o da Gama</ENT1> and the younger brother <ENT0>Est\u00e1\u00e7o da Gama</ENT0> . 3. <ENT1>Arjuna</ENT1> was the fourth one to fall after Draupadi , <ENT0>Sahadeva</ENT0> and Nakula . 4. His nephews , Andr\u00e9 , <ENT0>Jordan</ENT0> and <ENT1>Rahim</ENT1> , also played the sport professionally . 	<ENT1> is the sibling, specifically the brother, of <ENT0>.

Table 9: Comparison between gold relation definitions and few-shot (4-shot) derived relation definitions (random seed=1).


We can also see that feedback-driven negative relation definition generation is of great potential. As the feedback instances may contain false predic-

tions which can be directly taken by LLM to generate new negative relations and effectively rectify the SLM’s bias. Such feature directly boost the pre-

Gold Definition	Gold Few-Shot Instances For Derivation	Derived Definition
<ENT1> was/is the child (not stepchild) of <ENT0>	<ol style="list-style-type: none"> 1. He was the son of Flemish painter <ENT1>Jan Massys , Matsys , or Metsys</ENT1> and the grandson and namesake of <ENT0>Quentin Massys or Metsys</ENT0> . 2. She married <ENT1>Lu Jing</ENT1> , who was born to <ENT0>Lu Kang</ENT0> and another daughter of Zhang Cheng ; both Sun He 's daughter and Lu Jing therefore were Zhang Cheng 's maternal grandchildren . 3. She is the wife of Bollywood actor , <ENT0>Jackie Shroff</ENT0> and mother of <ENT1>Tiger Shroff</ENT1> and Krishna Shroff . 4. His uncle was polymath <ENT0>Lionel Penrose</ENT0> , whose children include mathematician <ENT1>Oliver Penrose</ENT1> , polymath Sir Roger Penrose , chess grandmaster Jonathan Penrose , and geneticist Shirley Hodgson . 	<ENT1> is a direct family member (such as a son, grandson, wife, or mother) of <ENT0>, specified by their familial relationship.
<ENT1> was/is the platform or platform version for which <ENT0> (a work or a software product) was/is developed or released	<ol style="list-style-type: none"> 1. The <ENT1>NES</ENT1> version of <ENT0>Shadowgate</ENT0> also carries the distinction of being one of the few NES games to be available in a Swedish language version . 2. In case of incidents <ENT0>Plumbr</ENT0> provides its users with information on problem severity , problem 's root cause location in source code or <ENT1>JVM</ENT1> configuration and lists steps needed to take to remediate the problem . 3. In 2013 , " <ENT0>Mega Man Xtreme</ENT0> " was made available on the Virtual Console of Japan 's Nintendo eShop for the <ENT1>Nintendo 3DS</ENT1> . 4. Prior to <ENT0>Windows 2000</ENT0> , Windows NT (and thus PE) supported the MIPS , Alpha , and <ENT1>PowerPC</ENT1> ISAs . 	<ENT1> is the platform, console, or environment for which <ENT0> (software applications, games, or operating systems) is designed or available.
<ENT1> was/is the military rank achieved by or associated with <ENT0> (a person or a position)	<ol style="list-style-type: none"> 1. The son of Robert Langton Douglas , he was a half - brother to <ENT1>Marshal of the Royal Air Force</ENT1> <ENT0>William Sholto Douglas , 1st Baron Douglas of Kirtleside</ENT0> . 2. <ENT0>Dwight Edward Aultman</ENT0> , <ENT1>Brigadier General</ENT1> , United States Army . 3. He then served in the 27th U - boat Flotilla along with " <ENT1>Korvettenkapit��n</ENT1> " <ENT0>Erich Topp</ENT0> . 4. <ENT0>Axel Schimpf</ENT0> (born 1 October 1952) is a retired " <ENT1>Vizeadmiral</ENT1> " (vice admiral) of the German Navy . 	<ENT1> is the military rank of <ENT0> (a military personnel).
<ENT1> was/is the director(s) of <ENT0> (a film, TV-series, stage-play, video game or similar)	<ol style="list-style-type: none"> 1. Cummins 's photographs have been used extensively in cinema and TV documentaries including <ENT1>Grant Gee</ENT1> 's <ENT0>Joy Division</ENT0> and John Dower 's . 2. In 2014 , Zhang starred in <ENT1>Tsui Hark</ENT1> 's wuxia film " <ENT0>The Taking of Tiger Mountain</ENT0> " . 3. Starting her career in 2005 , she acted in the Malayalam film " <ENT0>Boyy Frienn</ENT0> " directed by <ENT1>Vinayan</ENT1> . 4. Kaif had her first success in Bollywood when she appeared opposite Salman Khan in <ENT1>David Dhawan</ENT1> 's romantic comedy " <ENT0>Maine Pyaar Kyun Kiya ?</ENT0> " . 	<ENT1> is the director who directed the movie <ENT0>.
<ENT1> was/is the architect or architectural firm responsible for designing <ENT0> (a building)	<ol style="list-style-type: none"> 1. The <ENT0>Hotel Attraction</ENT0> project by Catalan architect <ENT1>Antoni Gaud��</ENT1> was built in 1908 in the parallel universe , whereas in our world it never went past initial planning . 2. Tampere Cathedral (Lars Sonck , 1900) , <ENT0>National Museum</ENT0> , Helsinki (<ENT1>Herman Gesellius , Armas Lindgren and Eliel Saarinen</ENT1> , 1902) . 3. Its designer was <ENT1>George Gilbert Scott</ENT1> , <ENT0>Busbridge Church</ENT0> \2013 Church of England Official gateway to the church . 4. He served a seven - year apprenticeship with <ENT1>Sir Charles Barry</ENT1> , the architect of the <ENT0>Houses of Parliament</ENT0> and Manchester Art Gallery . 	<ENT1> is the architect or group of architects who designed <ENT0> (a building or architectural project).
<ENT1> was/is the watercourse that flowed/flows into <ENT0> (a watercourse)	<ol style="list-style-type: none"> 1. The <ENT1>Cerchez River</ENT1> is a tributary of the <ENT0>Ceair River</ENT0> in Romania . 2. The lake flows into the <ENT1>River Mangfall</ENT1> , a tributary of the <ENT0>River Inn</ENT0> and thence the River Danube . 3. The <ENT1>Veljul Mic River</ENT1> is a tributary of the <ENT0>Veljul Mare River</ENT0> in Romania 4. A small part of the district along the eastern boundary drains into the east - flowing <ENT1>River Loud</ENT1> , a tributary of the <ENT0>Hodder</ENT0> . 	<ENT1> is a tributary of the <ENT0> (rivers or water bodies).

Table 10: (Continued from Table 9) Comparison between gold relation definitions and few-shot (4-shot) derived relation definitions (random seed=1).

cision score as shown in Sec. 5.2. Hence, we can see that our design expectations are well fulfilled and this also qualitatively explains the performance boost of our proposed model.



A binary relation between entity placeholders <ENT0> and <ENT1> is defined by: "**<ENT1> was/is the military rank achieved by or associated with <ENT0> (a person or a position)**". In relation examples or relation instances, <ENT0> is replaced with actual entity mention and is prefixed with tag <ENT0> and suffixed with tag </ENT0>, <ENT1> is replaced with actual entity mention and is prefixed with tag <ENT1> and suffixed with </ENT1> .

Typical examples predicted as positive by current relation extraction model are:

1. A different installation , as of May 2004 elements of <ENT1>United States Army</ENT1> <ENT0>1st Armored Division</ENT0> were operating at FOB Delta near al - Kut .
2. Its jurisdiction extends over the entire maritime branch of the <ENT1>armed forces</ENT1> and it is subordinate to the <ENT0>Chief of the Defence Staff</ENT0> .
3. Edward John Dorn

Edward J. Dorn (January 12 , 1854 – December 10 , 1937) was a <ENT0>captain</ENT0> in the <ENT1>United States Navy</ENT1> .

4. <ENT0>Yoshikazu Okada</ENT0> was born into a wealthy family as the son of Inasaburo , a major general in the <ENT1>Imperial Japanese Army</ENT1> .
5. <ENT0>Harold Sturtevant</ENT0>

Harold Sturtevant was a sailor in the <ENT1>United States Navy</ENT1> .


6. Lechasseur served in the <ENT1>Canadian Army</ENT1> with the <ENT0>Les Voltigeurs de Québec</ENT0> and saw action in France and the Netherlands completing World War II with the rank of major .
7. <ENT0>Frederick Rosier</ENT0>

<ENT1>Air Chief Marshal</ENT1> Sir Frederick Rosier , (13 October 1915 – 10 September 1998) was a senior Royal Air Force commander .

8. He attended Columbia on a football scholarship , interrupted by his service with the <ENT1>United States Navy</ENT1> as a <ENT0>Seabee</ENT0> in the South Pacific during World War II .

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Based on the positive relation definition and the typical predicted examples, generate 5 negative binary relation definitions (numbered from 1 to 5) in the same format as the above positive relation definition (including entity placeholders and entity type constraints). Other requirements are: 1. Identify false positive predictions from the typical predicted examples and your generated negative relations should teach model to mitigate such bias. 2. After addressing the previous requirement, consider generating near-miss negative relations.



Given the task to generate negative binary relation definitions based on the provided positive relation examples, here are five negative relation definitions that attend to the details of entity types and relation specifications:

1. A binary relation between entity placeholders <ENT0> and <ENT1> is defined by: "**<ENT1> was/is the geographical location or operation base associated with <ENT0> (a military unit or formation)**". Negative instances would illustrate that the location or base of operation of a military unit does not equate to the military rank of individuals or the unit.
2. A binary relation between entity placeholders <ENT0> and <ENT1> is defined by: "**<ENT1> is the parent branch or larger organizational unit <ENT0> (a specific role or office) is part of**". This definition inaccurately associates a person's or position's parent organization as their rank.
3. A binary relation between entity placeholders <ENT0> and <ENT1> is defined by: "**<ENT1> is the overarching entity or government that <ENT0> (a military rank) served under or was part of**". This misinterprets the entity or government as the rank itself.
4. A binary relation between entity placeholders <ENT0> and <ENT1> is defined by: "**<ENT1> is the conflict or war <ENT0> (a person or a position) participated in**". This would incorrectly suggest the conflict itself as the rank or military status of the individual.
5. A binary relation between entity placeholders <ENT0> and <ENT1> is defined by: "**<ENT1> is the educational qualification or civilian occupation achieved by <ENT0> before or after military service**". This erroneously associates civilian roles or education as military ranks.

These negative definitions aim to instruct the model to distinguish between actual military ranks associated with individuals, and locations, broader organizations, historical conflicts, and civilian occupations or qualifications which are not indicative of military rank.

Figure 9: Example interaction dialogue which demonstrates the feedback-driven generation of negative relation definitions.