EPPAC: Entity Pre-typing Relation Classification with Prompt Answer Centralizing

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Abstract

Relation classification (RC) aims to predict the relationship between a pair of subject and object in a given context. Recently, prompt tuning approaches have achieved high performance in RC. However, existing prompt tuning approaches have the following issues: (1) numerous categories decrease RC performance; (2) manually designed prompts require intensive labor. To address these issues, a novel paradigm, Entity Pre-typing Relation Classification with Prompt Answer Centralizing (EPPAC)\(^1\) is proposed in this paper. The entity pre-tying in EPPAC is presented to address the first issue using a double-level framework that pre-types entities before RC and prompt answer centralizing is proposed to address the second issue. Extensive experiments show that our proposed EPPAC outperformed state-of-the-art approaches on TACRED and TACREV by 14.4% and 11.1%, respectively. The code is provided in the Supplementary Materials.

1 Introduction

Named entity recognition (NER) and relation classification (RC) are the two key steps in extracting relations from the raw context. NER focuses on extracting entities from a text, whereas RC aims to predict the possible relationship between the two entities. Researchers have achieved satisfactory results in the NER (Wang et al., 2021). Nevertheless, RC continues to remain a challenge because its key information is not relatively opaque in the context sequence.

Transformer-based pre-trained language models (PLMs) such as BERT (Devlin et al., 2019) are suitable for handling sequence-based tasks and obtaining promising performance in RC. However, there is a gap between pre-training and downstream tasks. To narrow this gap, PTR (Han et al., 2021) and KnowPrompt (Chen et al., 2021) adopted prompt tuning. Prompt tuning reformulated RC to be more similar to the cloze-style word-predicting task during pre-training. However, existing prompt tuning approaches for RC still have the following issues.

- First, as illustrated in Figure 1, TACRED (Zhang et al., 2017) has 42 categories. Numerous categories in an answer space result in too many category intersections, which limits RC performance. In real-world circumstances, the number of categories will increase further.

- Second, current prompt tuning strategy requires manually designed templates to directly compare with prompt answers (used by PTR) or to initialize continuous prompts (used by KnowPrompt). The process of template engineering is cumbersome and inefficient, as much labor is required in the template selection (illustrated in Figure 2). Additionally, once the dataset has changed, the templates need to be redesigned.

In this paper, we propose a novel paradigm, called entity pre-typing relation classification (EPPAC) with prompt answer centralizing to address the above issues. To reduce the number of categories, entity pre-typing with a double-level framework was proposed. Each level contain several categories.

\(^1\)Our code is publicly available at https://github.com/plageon/EPPAC

Figure 1: Numerous categories for traditional relation classifiers. The overlap of the disks shows the intersection between categories.
specialized classifiers. In the first level, we build two specialized classifiers to pre-type subject and object, respectively, with the prompt “[entity] is a [mask].” In the second level, each subject and object type pair correspond to a specialized classifier. Each specialized classifier handles samples matching the subj-obj type pair with the prompt “[subject] [mask] [mask] [mask] [object].” Under the premise of a specific subj-obj type pair, possible relations are reduced to a small subset of relations in the dataset.

To avoid manually designing templates, effective prompt answer centralizing is proposed to work reliably with randomly initialized templates. We apply it to all specialized classifiers in entity pre-typing with a double-level framework. For each iteration, we obtain prompt answers from PLM and maximize their similarity to the correct category templates while minimizing wrong ones so that prompt answers are centralized around templates. To further enhance the performance of the centralizing algorithm, we experimented on various similarity measures, including the Manhattan distance and cosine similarity. We even manage to remove templates by appending a dense neural network classifier to prompt answers.

To summarize, our major contributions are as follows:

- A novel entity pre-typing method that pre-types entity before RC is proposed, which maintains high performance despite continuously growing categories.
- To remove manual templates, an effective prompt answer centralizing is proposed to work with randomly initialized prompts.
- We achieve a 14.4% and 11.1% improvement over state-of-the-art approaches on TACRED and TACREV, respectively.

2 Related work

To tackle RC, several attempts have been made using recurrent neural networks(Zhang et al., 2017) or graph convolutional networks(Zhang et al., 2018). However, these conventional approaches perform poorly when the context sequence becomes longer. Recently, transformer-based models such as BERT(Devlin et al., 2019) have been widely applied to various downstream NLP tasks for outstanding performance in handling long sequences. Through unsupervised pre-training with large-scale corpora, PLM masters abundant semantic or syntactic knowledge. ERNIE(Zhang et al., 2019) and FINE-TUNING(Devlin et al., 2019) fine-tune PLM with downstream training data and apply PLM in RC. However, in contrast to a cloze-style task in the pre-training stage, RC models are expected to learn a classification standard based on annotated data. Such a gap between the PLM and RC circumscribes the PLM to achieve better performance in RC.

To narrow the gap between PLM and RC, some researchers have attempted to adjust the PLM structures. SpanBERT(Joshi et al., 2020) designed lengthened word masks so that masked words can contain more information, and RECENT(Tong et al., 2021) further improved SpanBERT’s performance by adding entity type restrictions. KnowBERT(Peters et al., 2019) integrates a knowledge graph during pre-training. LUKE(Yamada et al., 2020) introduced deep entity embeddings containing entity types in the pre-training stage. However, these PLM adjustments ignore a critical issue: a sentence typically contains much more noise information than relation information between two given entities. Without a proper way to focus on key information, these approaches are vulnerable to noise.

Meanwhile, prompt tuning has been proven to be an efficient way to reformulate downstream tasks to cloze-style tasks in the hope of bridging the gap (e.g., Brown et al. (2020); Liu et al. (2021b); Schick and Schütze (2021); Gao et al. (2021)). Liu et al. (2021a) summarize this paradigm as “pre-train, prompt, and predict.” Prompt tuning appends a short textual prompt (e.g., Paris is [MASK]) to the end of the original sequence and induces PLM to yield an answer for the masked slot. In this manner, we can manipulate the PLM behavior and induce
it to yield the expected output while reducing the disturbance caused by noise information. PTR(Han et al., 2021) introduced prompt tuning to RC, which applies hybrid prompt tuning. Their final templates were decomposed into manually designed subtemplates based on logical rules. KnowPrompt(Chen et al., 2021) used continuous prompt tuning with knowledge injection.

Compared to previous approaches that use prompt tuning, our approach, EPPAC, has the following major improvements. First, through entity pre-typing with a double-level framework, we could reduce the number of categories a classifier must handle. Thus, our specialized classifiers can learn more accurate and efficient classification standards. Second, prompt answer centralizing can work with randomly initialized templates, which reduces the labor required in designing manual templates and makes them more adaptable to other datasets.

3 Methodology

In this section, the detailed implementation process of EPPAC is presented. We focus mainly on entity pre-typing with a double-level framework and prompt answer centralizing.

3.1 Entity pre-typing

In a traditional RC task setting, the input \( X = \{x, s_x, o_x\} \) contains three parts: the original sequence \( x = \{x_1, x_2, \cdots, x_{|X|}\} \), subject \( s_x = \{x^s_1, \cdots, x^s_{|s|}\} \), and object \( o_x = \{x^o_1, \cdots, x^o_{|o|}\} \), \( s, o \in X \). The expected output is the relation \( y = r_x \). Entity pre-typing is a double-level framework. The first level contains two specialized classifiers: subject type classifier \( M_s \) and object type classifier \( M_o \). In the second level, for each subj-obj type pair, there is a specialized relation classifier \( M(P_k) \). To determine the extent to which specialized relation classifiers are needed, the entire training set is analyzed for the correlation between the subj-obj type pair \( (t(s), t(o)) \) and the relation \( r(x) \). \( T^s = \{t^s_1, t^s_2, \cdots\} \) accounts for all subject types, and \( T^o = \{t^o_1, t^o_2, \cdots\} \) accounts for all object types. The entire subj-obj-type pair set is denoted as \( P = \{p_1, p_2, \cdots\} \), where \( p_k = (t^s_1, t^o_1), t^s_1, t^o_1 \in T^s, t^o_1 \in T^o \). All relations in the dataset are in \( R_{tot} = \{r_1, r_2, \cdots, R_{tot}\} \). However, for each subj-obj pair, the relations between the given entity type pair are limited, which are denoted as \( R(p_k) = \{r^{pk}_1, r^{pk}_2, \cdots\} \), \( p_k \in P \). Notably the same relation might be present in the small relation set of different subj-obj type pairs and, in particular, the special relation "no_relation"
is inevitably contained by every $R(p_k)$.

EPPAC is trained and tested on different scales: each specialized classifier is trained separately, and testing is performed in collaboration with all specialized classifiers from entity pre-typing with a double-level framework. As shown in Figure 3, the subject-type classifier $M_s$ and object type classifier $M_o$ are fed with all data $D = \{(X, t(s))\}, D_o = \{(X, t(o))\}$; however, a specialized relation classifier $M_p$ only obtains training samples that match the classifier’s subj-obj type pair $D_{p_k} = \{(X, y)((t(s_x), t(s_o)) = p_k\}$. As shown in Figure 4, in the testing phase, specialized classifiers work collaboratively in a double-level framework. When we input a test sample $X = \{x, s_x, o_x\}$, the subject-type classifier and object-type classifier first predict the subj-obj type pair $\tilde{p} = \{\tilde{p}^s, \tilde{p}^o\}$ in the first level. Then, a corresponding specialized relation classifier is selected for the sample at the second level and finally outputs the predicted relation $\hat{r}$.

### 3.2 Prompt construction

An appropriate prompt manipulates the PLM’s behavior, inducing the PLM to output intended prompt answers. In the first level, we design the same prompt for the subject and object type classifiers, $P_s = P_o = "[entity] is a [mask], \cdots [mask]."$ In the second level, we design the same prompt for all specialized relation classifiers, $P_r = "[object] [mask] \cdots [mask] [subject]."$ Then, the original sequence and the prompt are concatenated to form a new sequence $\chi = \{x, P\}$. The new sequence is the input for the encoder layer of the PLM. Notably, the length of the masked words in the prompt can vary.

To eliminate manually designed templates, templates are initialized with random vectors $C_s = \{c_{1s}^s, c_{2s}^s, \cdots, c_{T_m}^s\}, C_o = \{c_{1o}^o, c_{2o}^o, \cdots, c_{T_m}^o\}, C_{p_k} = \{c_{1p_k}^{p_k}, c_{2p_k}^{p_k}, \cdots, c_{T_m}^{p_k}\}$, $p_k \in P$. A random value between 0 and 0.1 is chosen for each dimension of these random vectors.

### 3.3 Prompt Answer Centralizing

Because templates are initialized with random vectors, we design a prompt answer centralizing, which works reliably with randomly initialized templates. The overall structure of prompt answer centralizing is illustrated in Figure 5. After the concatenation of the original sequence and prompt, $\chi = \{x, P\}$ is input to the encoder layer of PLM, PLM outputs contextualized word embedding of masked words $v_x = f_0(\chi)$, which is known as a prompt answer. Here, the encoder layer of the PLM is a mapping function $f_0 : \{\chi\} \rightarrow \text{Encoder}_V$, where $\theta$ denotes all trainable parameters of the encoder layer. The prompt answer $\tau_x$ and template $\tau$ share the same size and are all in the answer space $V$. RoBERTa-base(Liu et al., 2019) was selected as the base model.

In the training phase, our goal is to find the best parameters for both the PLM encoder layer $f_0$ and template set $C$, which maximize the probability $P(X|t(s)), P(X|t(o)), \text{and} P(X|y)$ for the correct category. The parameter set is denoted by $\Theta_s = \{\theta_s, C_s\}, \Theta_o = \{\theta_o, C_o\}, \Theta_{p_k} = \{\theta_{p_k}, C_{p_k}\}$. Then, the probability is calculated using the similarity between the prompt answer and template $D(f_0(\chi), \tau)$. The more similar the prompt answer $f_0(\chi)$ is to a template $C$, the larger the probability that the sample belongs to that category, namely,

$$P(X|\gamma) \propto D(f_0(\chi), \tau)$$

Based on Equation 1, our goal is to find the parameter set that maximizes the sum of similarity $D$ for the prompt answer and template for the correct category.

$$\Theta_s = \max_{\Theta_s} \sum_{i=1}^{N_s} D(f_{\theta_s}(\chi_{i}^{s}), c_{t(s)})$$

$$\Theta_o = \max_{\Theta_o} \sum_{i=1}^{N_o} D(f_{\theta_o}(\chi_{i}^{o}), c_{t(o)})$$

$$\Theta_{p_k} = \max_{\Theta_{p_k}} \sum_{i=1}^{N_{p_k}} D(f_{\theta_{p_k}}(\chi_{i}^{p_k}), c_{j}^{p_k})$$

The similarity $D$ is calculated by applying normalization to the distance $d$, with the following definition: Let $X$ be a random variable with a probability distribution function $f(x)$ and $E(x)$ be the expectation of $X$: $E(d) = \int_{-\infty}^{\infty} x f_X(x) dx$. $\text{Var}(x)$ is the variance of $X$: $\text{Var}(d) = E(X^2) - (E(X))^2$. Then, a normalization layer is ready to calculate the similarity, which can be expressed (with parameters $\gamma, \beta$) as follows:

$$D = \text{Softmax}(\frac{d_k - E(d)}{\sqrt{\sum_{i=1}^{n}(d_i - \text{Var}(d))} + \sigma} + \gamma + \beta)$$

(5)
The distance between the prompt answer $v$ and the template $c$ can be calculated in various ways, $d_k = d(v, c_k)$. The distance function can be defined simply as the Euclidean distance as follows:

$$d(v, c) := -\sqrt{\sum_{i=1}^{n}(v_i - c_i)^2}$$

or the Manhattan distance as follows:

$$d(v, c) := -\sum_{i=1}^{n}||(v_i - c_i)||$$

Notably, because the similarity is negatively correlated with the Euclidean and Manhattan distance, we take the opposite number of Euclidean and Manhattan distance to represent $d_k$. In addition to $p$-norm measures, we have other measures to represent distance, such as the dot product:

$$d(v, c) := v \cdot c = \sum_{i=1}^{n}v_ic_i$$

and cosine similarity:

$$d(v, c) := \frac{v \cdot c}{||v|| \times ||c||}$$

PLM parameters and templates are both optimized according to their contribution to the loss, $\theta^k = \theta^{k-1} - \nabla_{\theta^k}L, C^k = C^{k-1} - \nabla_{C^k}L$. With the similarity given by Equation 5, the loss function can be expressed as follows:

$$L = -\log\left(\frac{e^{D(f_\theta(\chi), c_t)}}{\sum_{k=1}^{n}e^{D(f_\theta(\chi), c_k)}}\right)$$  (6)

### 3.4 Predicting Details

In the testing phase, EPPAC first pre-types the subject and object according to the following rule:

$$\hat{s} = \max_{t^s \in T^s} D(f_{\theta^s}(\chi), c_{t^s})$$  (7)

$$\hat{o} = \max_{t^o \in T^o} D(f_{\theta^o}(\chi), c_{t^o})$$  (8)

Then, every sample is mapped to a subj-obj type pair $\hat{p} = (\hat{s}, \hat{o})$ and sent to the next layer. In the testing phase, we predict the relation within the possible relation category set $R(\hat{p}), \hat{p} \in P$, according to their probability in each category. The prediction rule can be expressed as follows:

$$\hat{r} = \max_{r \in R(\hat{p})} D\left(f_{\theta_{R(\hat{p})}}(\chi), c_{r \hat{p}}\right)$$  (9)

In rare cases, it is possible that some samples may not fall into any predefined subj-obj type pairs, namely, $(\hat{t}^s, \hat{t}^o) \notin P$. Under such circumstances, we have no choice but to assume them as "no relation" because no classifier can deal with these samples.

### Algorithm 1 EPPAC

**Input:** Dataset, PLM

**Output:** Specialized classifiers

**Training:**

for all classifier $M$ In $\{M_s, M_o, \cdots, M_{p[P]}\}$ do

Initialize templates $C^s \in \{C^s_1, \cdots, C^s_{p[P]}\}$

Prepare data segment $D \in \{D_s, \cdots, D_{p[P]}\}$

Initialize $f_\theta$ with pre-trained parameter $\theta^*$

Apply prompt answer centralizing:

Calculate loss $L$ with equation 6

Update $\Theta = \{\theta, C\}$ for epochs

end for

**Testing:**

**Input:** Sample $X = \{x, s, o\}$

**Output:** Relation $\hat{r}$

predict subject type with Equation 7

predict object type with Equation 8

⇒ subj-obj pair: $\hat{p} \leftarrow (\hat{t}^s, \hat{t}^o)$

if $\hat{p} \in P$ then

possible relations: $R(\hat{p}) \leftarrow \{r_1^\hat{p}, r_2^\hat{p}, \cdots\}$

predict relation with Equation 9

else

$\hat{r} \leftarrow "no\_relation"

end if

return $\hat{r}$

### 4 Experiments

#### 4.1 Datasets

- **TACRED** (Zhang et al., 2017) consists of three segments: train, development, and test, containing 68124, 22631, and 15509 samples, respectively. TACRED is one of the most widely used large-scale datasets of RC, containing 41 relations and no relation.

- **TACREV** (Alt et al., 2020) applies patching to development and test segment of the original TACRED dataset, while remains the training set intact.

- **Re-TACRED** (Stoica et al., 2021) applies patching to all three segments of the TACRED
Figure 5: Illustration of prompt answer centralizing. The initial sample distribution (left) goes through prompt answer centralizing (middle) and turns into a centralized distribution (right).

dataset, and several samples are dropped. Consequently, the number of different relations was reduced to 40.

• **SEMEVAL** ([Hendrickx et al., 2010]) is a traditional dataset that contains 8000 training samples and 2717 testing samples distributed on nine relations with two directions and no relation.

• **Wiki80** ([Han et al., 2019]) was recently published with 44800 training and 5600 testing samples and contains up to 80 distinct relations.

4.2 Baselines

Several representative previous approaches that handle RC from different perspectives were selected as baselines for comparison with EPPAC. For typical sequence-based neural models, PALSTM ([Zhang et al., 2017]) represents a recurrent neural network, and C-GCN ([Zhang et al., 2018]) represents a graph neural network. For those that use transformer-based models, ERNIE ([Zhang et al., 2019]) SPANBERT ([Joshi et al., 2020]), RECENT ([Tong et al., 2021]), LUKE ([Yamada et al., 2020]), and KNOWBERT ([Peters et al., 2019]) were selected as the baseline. To represent recent work that uses the prompt tuning, PTR ([Han et al., 2021]) and KnowPrompt ([Chen et al., 2021]) are selected.

4.3 Training configurations

Hyper-parameters are set according to previous work and parameter experiment results for specialized classifier training for EPPAC. The learning rates for the PLM parameters and templates were set as 1e-5 and 3e-5, respectively. The optimization strategy for the PLM parameters was chosen as Adam with a weight decay of 1e-2 and Adam epsilon of 1e-6. The optimization strategy for the templates was SGD with a momentum of 0.9. We trained the subject-type classifier for two epochs, the object-type classifier for six epochs, and specialized relation classifiers for eight epochs. The remaining problems are the similarity measure and which length of the prompt yields the best performance.

**Similarity measures** Because similarity calculation is a key step in prompt answer centralizing, we conducted experiments on various similarity measures. Cosine similarity measures the cosine of the angle between the two vectors. The dot product measures the projection of one vector onto another. The result is a number between -1 and 1, where 1 means the vectors are identical, and -1 means they are diametrically opposite.

Table 1: Parameter experiment for template length. The metrics include subject and object typing accuracy (%), overall precision (%), recall (%), and F1 score (%) on TACRED.

| Length | Subj | Obj | Relation |
|--------|------|-----|----------|
|        | Prec | Rec | F1       |
| 1[mask] | 97.2 | 92.8 | 89.5 | 85.1 | 87.3 |
| 3[mask] | 97.2 | 94.2 | 89.8 | 89.0 | 89.4 |
| 5[mask] | 97.1 | 94.3 | 90.0 | 89.2 | 89.6 |
| 7[mask] | 97.2 | 94.3 | 90.2 | 89.0 | 89.5 |

Evaluating the performance of EPPAC on TACRED, the results show that the model achieves high accuracy, precision, recall, and F1 scores for subject and object typing, as well as specialized relation classification.

The table above demonstrates the effectiveness of EPPAC in handling relation classification tasks. The model achieves high performance across different template lengths, with the 3[mask] length showing the best overall results in terms of accuracy, precision, recall, and F1 score. This suggests that a moderate template length is optimal for prompt answer centralizing, allowing the model to leverage more information from the context while avoiding excessive length that could diminish the connection between the prompt and the PLM.
product considers both the angle and the vector length. The Manhattan distance is the distance between two points along the axes at right angles. The Euclidean distance is the length of a segment connecting two points, which is the most intuitive method. Additionally, we substitute templates with a dense neural network to serve as a classifier. As shown in Figure 6, dot products outperform other approaches in many specialized classifiers, but they do not always perform the best. The dot product, cosine distance, and dense neural network are comparably more reliable, but the performance of the Manhattan distance and Euclidean distance fluctuates.

4.4 Overall results

We conducted experiments on the EPPAC and several baseline models. Considering all factors, the template length for the subject type classifier is finally set to three, and the template length for other specialized classifiers is set as five. Similarity measures for all specialized models were set as dot products. The overall results are shown in Table 2, where we observe some key facts.

(1) For those that adjust PLM structures or add more information during pre-training, such as SPANBERT and LUKE, enhance RC performance. However, they are not as efficient as prompt tuning, which reformulates downstream tasks.

(2) EPPAC significantly outperforms state-of-the-art approaches on TACRED and TACREV, where relations are closely correlated with entity types. EPPAC exceeded the best previous result by 14.4 F1 points on TACRED and 11.1 on TACREV. Re-TACRED is also derived from TACRED, and EPPAC has a minor improvement over previous approaches. This is because the applied patching throws away some hard categories and samples. Thus, EPPAC loses part of its edge over previous approaches when handling troublesome samples.

(3) EPPAC achieves or slightly exceeds state-of-the-art approaches on SEMEVAL and Wiki80, where relations are weakly correlated with entity types. As a result, EPPAC is unaware of the clear correlation between relations and entity types and is unable to fully apply entity pre-typing.

4.5 Analysis on specialized classifiers

Entity pre-typing is a double-level framework, and in entity-typing level and RC level, the encoder layer of PLM inevitably focuses on different aspects of the context. The encoder layer of PLM focuses on either paying attention to inherent entity information or mutual relations between entities. Taking TACRED as an example, EPPAC contains two entity type classifiers and 26 RC classifiers.
Table 2: Overall performance of baselines and EPPAC for all five datasets.

| Model                     | TACRED | TACREV | Re-TACRED | SEMEVAL | Wiki80 |
|---------------------------|--------|--------|-----------|---------|--------|
| PA-LSTM (Zhang et al. (2017)) | 65.1   | 73.3   | 79.4      | 84.8    | -      |
| C-GCN (Zhang et al. (2018)) | 66.3   | 74.6   | 80.3      | -       | -      |
| RoBERTa-Large (Liu et al., 2019) | 70.5   | 80.6   | 89.3      | 88.0    | -      |
| KNOWBERT (Peters et al. (2019)) | 71.5   | 79.3   | 89.1      | -       | -      |
| SPANBERT (Joshi et al. (2020)) | 70.8   | 78.0   | 85.3      | 78.5    | 62.6   |
| RECENT (Tong et al., 2021) | 75.2   | -      | -         | -       | -      |
| LUKE (Yamada et al., 2020) | 72.7   | 80.6   | 90.3      | -       | -      |
| MTB (Baldini Soares et al., 2019) | 70.1   | -      | -         | 89.5    | -      |
| PTR (Han et al., 2021)     | 72.4   | 80.2   | 89.0      | 89.9    | 85.5   |
| KnowPrompt (Chen et al., 2021) | -      | 80.8   | 89.8      | 90.1    | 85.7   |
| EPPAC                      | 89.6   | 91.9   | 89.9      | 90.0    | 87.2   |

Wiki80 is measured by accuracy (%), while others are measured by F1 score (%).

(subj-obj type pairs that are only correlated with "no relation" are excluded), as illustrated in Figure 6. EPPAC successfully reduces the number of categories that specialized classifiers must handle. The subject-type classifier has two categories, whereas the object-type classifier has 17. Most relation classifiers have only two to five categories. Even the relation classifier with most categories (11) is far easier to handle than all 42 categories.

Both the subject-type and object-type classifiers are reliable, with accuracies of over 97% and 94%, respectively. Therefore, RC faces the most difficult challenge in the second level. The amount of training data for each relation classifier is skewed, and their performance varies. Furthermore, there is no clear connection between the amount of training data and performance because some relations are generally difficult, while some are easy. Therefore, it is not advisable to mix them up and perform the classification all at once, because paying too much attention to minor or difficult categories may affect the overall performance. This is why a combination of specialized classifiers can outperform traditional classifiers.

### 4.6 Ablation study of prompt answer centralizing

An ablation study on prompt answer centering was conducted to validate the effectiveness of its components. For "-Template optimizing," templates are frozen during training. For "+Manual Template," manually designed templates are added to test whether they can impact EPPAC’s performance. We initialize our templates with manually designed templates following PTR (subject and object type classifiers have templates with length 1, and relation classifiers have templates with length 3). We compare the performance of prompt answer centralizing under randomly initialized templates (EPPAC) and manually initialized templates. As shown in Table 3, the freezing templates decrease the final performance. Manual templates also result in a subtle drop because inappropriate lengths for templates are chosen. Randomly initialized templates do cause fluctuation in final results, but the deviation is rather small, as is marked with "± ."

| Method            | Subj accuracy | Obj accuracy | Relation accuracy | F1 score  |
|-------------------|---------------|--------------|-------------------|-----------|
| EPPAC             | 97.2±(±0.1)   | 94.3±(±0.1)  | 94.3±(±0.1)       | 89.6±(±0.1) |
| -Template optimizing | 97.1(±0.1)   | 94.2(±0.1)   | 89.1(±0.5)        |           |
| +Manual Template  | 97.2(±0.0)    | 94.2(±0.1)   | 89.4(±0.2)        |           |

Table 3: Ablation study for prompt answer centralizing results on TACRED. The metrics include subject-and object-type classifier accuracy (%) and overall F1 score (%).

5 Conclusion

In this paper, we propose EPPAC, an effective approach for RC based on entity pre-typing and prompt answer centralizing. EPPAC significantly improves RC performance by reducing the number of categories for classifiers and reducing the required labor by eliminating manually designed templates. Future work involves the following key domains: (1) simplify specialized classifiers to reduce algorithm complexity, and (2) improve EPPAC performance on datasets where relations are weakly correlated with entity types.
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