# RCL: Relation Contrastive Learning for Zero-Shot Relation Extraction

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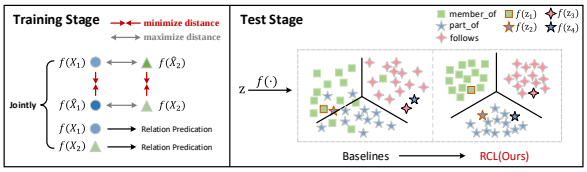
## Abstract

Zero-shot relation extraction aims to identify novel relations which cannot be observed at the training stage. However, it still faces some challenges since the unseen relations of instances are similar or the input sentences have similar entities, the unseen relation representations from different categories tend to overlap and lead to errors. In this paper, we propose a novel Relation Contrastive Learning framework (RCL) to mitigate above two types of similar problems: Similar Relations and Similar Entities. By jointly optimizing a contrastive instance loss with a relation classification loss on seen relations, RCL can learn subtle difference between instances and achieve better separation between different relation categories in the representation space simultaneously. Especially in contrastive instance learning, the dropout noise as data augmentation is adopted to amplify the semantic difference between similar instances without breaking relation representation, so as to promote model to learn more effective representations. Experiments conducted on two well-known datasets show that RCL can significantly outperform previous state-of-the-art methods. Moreover, if the seen relations are insufficient, RCL can also obtain comparable results with the model trained on the full training set, showing the robustness of our approach[1].


## 1 Introduction

Relation extraction is a fundamental problem in natural language processing, which aims to identify the semantic relation between a pair of entities mentioned in the text. Recent progress in supervised relation extraction has achieved great successes (Zeng et al., 2014; Zhou et al., 2016; Soares et al., 2019), but these approaches usually require large-scale labeled data. While in practice, human annotation is time-consuming and labor-intensive.

[1]We will release our code after blind review.




| Error Type | Input Sentence | Ground Truth | Baseline Pred | RCL Pred(Ours) |
|---|---|---|---|---|
| Similar Relation | $Z_1$ : In 1978, he replaced Thomas Erdelyi in the Ramones, assuming the name Marky Ramone. | member_of | member_of | member_of |
| | $Z_2$ : The Doctor tries to restore the universe with the help of River and the alternative universe versions of his companions Amy Pond(Karen Gillan) and Rory Williams(Arthur Darvill). | part_of | member_of | part_of |
| Similar Entity | $Z_3$ : In May 2015, Vienna hosted the Eurovision Song Contest following Austria 's victory in the 2014 contest. | follows | follows | follows |
| | $Z_4$ : Thus, the song was succeeded as Romanian repre-sentative at the 2002 Contest by Monica Anghel & Marcel Pavel with "Tell Me Why". | part_of | follows | part_of |

Figure 1: **Top:** Overview of the proposed RCL at the training and test stage. $f(\cdot)$ is a learnable projection function that projects the input sentence $X_i$ to its corresponding relation representation $f(X_i)$. $f(\hat{X}_i)$ is the augmented view of $f(X_i)$ and $Z$ is the whole test set. **Bottom:** Four examples at the test stage and their corresponding relation representations are shown in the right of Top. The entities are marked in orange.

To alleviate the human annotation efforts in relation extraction, some recent studies use distant supervision to generate labeled data for training (Mintz et al., 2009; Lin et al., 2016). However, in the real-world setting, the relations of instances are not always included in the training data, and existing supervised methods cannot well recognize unobserved relations due to weak generalization ability.

To address the aforementioned limitations, zero-shot relation extraction has been proposed to extract relational facts where the target relations cannot be observed at the training stage. The challenge of zero-shot relation extraction models is how to learn effective representations based on seen relations at the training stage and well generalize to unseen relations at the test stage. Two studies (Levy et al., 2017; Obamuyide and Vlachos, 2018) treat zero-shot relation extraction as a different task (i.e., question answering and textual entailment), but they both need human annotation auxiliary in-

formation for input, i.e., pre-defining question templates and relation descriptions. ZS-BERT (Chen and Li, 2021) predicts unseen relations with attribute representation learning. Despite promising improvements on directly predicting unseen relations, ZS-BERT still makes wrong predictions due to similar relations or similar entities. The same problem arises in supervised methods under the zero-shot settings.

As shown in Figure 1, there are two types of similar errors: **Similar Relations** and **Similar Entities**. For similar relations (see $Z_1$ and $Z_2$), existing methods predict wrongly results because the unseen relations possess similar semantics and data points belong to two relations in the representation space are overlapped. For similar entities (i.e., *2014 contest* and *2002 Contest*), since entities are the context of relation and relation representations are derived from entities, the relation representations containing similar entities are close (see $f(Z_3)$ and $f(Z_4)$) and baselines wrongly consider $f(Z_4)$ belongs to *follows* in the representation space, even if two unseen relations are not related. Recently, Instance-wise Contrastive Learning (Instance-CL) (He et al., 2020; Chen et al., 2020; Yan et al., 2021; Gao et al., 2021; Zhang et al., 2021) has achieved remarkable success in representation learning. Instance-CL is used to learn an effective representation by pulling together the instances from the same class, while pushing apart instances from different classes. Inspired by Instance-CL, we attempt to use Instance-CL on seen relations to learn the difference between similar relations and the divergence of relation representations derived from similar entities.

In this paper, we propose a novel Relation Contrastive Learning framework (RCL) to solve the above-mentioned problems. Figure 1 depicts the overview of the proposed model, which consists of four steps: (i) The input for RCL is a batch of sentences containing the pair of target entities and each sentence is sent into input sentence encoder to generate the contextual sentence embeddings[2]. (ii) Taking the sentence embeddings as input, relation augmentation layer is designed to obtain the relation representations $f(X_i)$ and their corresponding augmented views $f(\hat{X}_i)$. (iii) By jointly optimizing a contrastive loss and a relation classification loss on seen relations, RCL can learn subtle difference between instances and achieve better separation between relations in the representation space simultaneously to obtain an effective projection function $f$. (iv) With the learned $f$, the whole test set $Z$ can be projected for unseen relation representations in the representation space and zero-shot prediction is performed on unseen relation representations by K-Means.

To summarize, the major contributions of our work are as follows: (i) We propose a novel framework based on contrastive learning for zero-shot relation extraction. It effectively mitigates two types of similar problems: similar relations and similar entities by learning representations jointly optimized with contrastive loss and classification loss. (ii) We explore various data augmentation strategies in relation augmentation to minimize semantic impact for contrastive instance learning and experimental results show dropout noise as minimal data augmentation can help RCL learn the difference between similar instances better. (iii) We conduct experiments on two well-known datasets. Experimental results show that RCL can advance state-of-the-art performance by a large margin. Besides, even if the number of seen relations is insufficient, RCL can also achieve comparable results with the model trained on the full training set.

## 2 Related Work

**Relation Extraction.** Relation extraction aims at extracting relation between entities within a given sentence. Many relation extraction methods (Qian et al., 2008; Zeng et al., 2014; Zhou et al., 2016) are supervised model. Recently, some studies focus on pre-training language model (Devlin et al., 2019; Liu et al., 2019; Lan et al., 2020) because of its powerful capability of semantic representation. Wu and He (2019) propose R-BERT that uses BERT to extract relation features and incorporates entity information to perform relation extraction. Soares et al. (2019) propose a relation representation learning method based on BERT and have shown promising results. However, these models require labeled data. Unsupervised relation extraction (Yu et al., 2017; Saha et al., 2018; Stanovsky et al., 2018) can discover semantic relation feature from data without human annotations. One representative work is Open relation extraction. Wu et al. (2019) propose a novel model to learn a similarity metric of relations from labeled data, and identify unseen relations by transferring knowledge learned from seen relations. While OpenRE method can

[2]The words, "embeddings", and "representations", are used interchangeably throughout this paper.

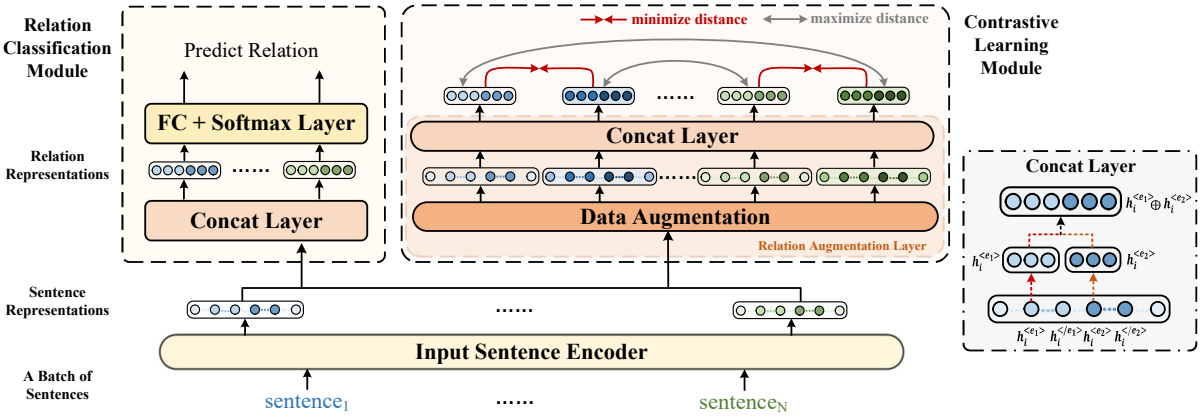



Figure 2: Architecture of the RCL, which consists of three components, and the details are introduced in Section 3. Note that relation augmentation layer contains data augmentation and a concat layer.

identify novel relation without annotations and external resources, it cannot effectively discard irrelevant information and severely suffers from the instability.

**Zero-shot Relation Extraction.** Zero-shot relation extraction aims to identify novel relation without training instances. Existing zero-shot relation extraction methods are few and most rely on human annotation auxiliary information for input. Levy et al. (2017) reduce zero-shot relation extraction to a question answering task. They use 10 predefining question templates to represent relations, and then train a reading comprehension model to infer which relation satisfies the given sentence and question. Obamuyide and Vlachos (2018) treat zero-shot relation extraction as a textual entailment task, which requires the model to input descriptions of relations. They train a textual entailment model to predict whether the input sentence containing two entities matches the description of a given relation, identifying novel relations by generalizing from the descriptions of seen relations at the training stage to those of unseen relations at test time. Chen and Li (2021) propose ZS-BERT to tackle zero-shot relation extraction task with attribute representation learning. ZS-BERT learns the representations of relations based on their descriptions during the training time, and generates the prediction of unseen relation for new sentence by nearest neighbor search. However, ZS-BERT suffers from similar relation error and similar entity error, and it needs human annotation auxiliary information for input, i.e., relation descriptions. In this paper, we do not require any human annotation auxiliary information for input.

**Contrastive Learning.** In the field of image and natural language processing, many recent successes are inspired by contrastive learning (He et al., 2020; Chen et al., 2020; Yan et al., 2021; Gao et al., 2021). Contrastive learning regards the input data and corresponding augmented views as an independent class. The goal of contrastive learning is to pull together representations from the same class, while keeping representations from different classes away. Therefore, the representations learned from contrastive learning are better separated and good for clustering. Gao et al. (2021) propose a novel sentence embeddings learning framework based on contrastive learning to produce superior sentence embeddings and show that dropout is an effective data augmentation. SCCL (Zhang et al., 2021) jointly optimizes a contrastive loss and a clustering loss to disperse overlap categories in the representation space. Inspired by contrastive learning, we leverage contrastive learning to help the model learn an effective representation.

## 3 Proposed Model

### 3.1 Model Overview

As illustrated in Figure 2, the proposed model RCL consists of three components: input sentence encoder, contrastive learning module and relation classification module. Given a batch of sentences containing two entities, the sentence representations are generated by input sentence encoder and then are sent to relation classification module and contrastive learning module. For contrastive learning module, the relation representations and their corresponding augmented views generated by a relation augmentation layer are used to perform contrastive instance learning to learn difference between instances. For relation classification module, the relation representations generated by the

concat layer are used to identify seen relations to achieve better separation between relations. We train RCL under a multi-task learning structure with contrastive learning module and relation classification module to learn effective representations for unseen relations. At the test stage, we obtain the unseen relation representations by input sentence encoder and concat layer, and then send them into K-Means to predict the unseen relations.

### 3.2 Input Sentence Encoder

Input Sentence Encoder aims to generate the contextual representation of each token. In this work, we assume entities contained in the sentence have been recognized before input. For a sentence $X_i = \left[x_i^1, .., x_i^L\right]$ where two entities $e_1$ and $e_2$ are mentioned, we use the ENTITY MARKERS (Soares et al., 2019) to augment $X_i$ to better extract relation features from context. Specifically, we introduce four special tokens to mark the beginning and the end of each entity mentioned in the sentence. The input token sequence $X_i$ for input sentence encoder is as follows:

$$X_i = [x_i^1, \ldots, <e_1>, x_i^i, \ldots, x_i^{j-1}, </e_1>, \ldots, <e_2>, x_i^k, \ldots, x_i^{l-1}, </e_2>, \ldots, x_i^L] \tag{1}$$

where $<e_1>, </e_1>, <e_2>, </e_2>$ are four special tokens to mark the beginning and the end of each entity mentioned in the sentence, $L$ is the length of sentence. Then we use BERT (Devlin et al., 2019) to obtain the sentence embeddings $\boldsymbol{h}_i \in \mathbb{R}^{L \times d}$:

$$\mathbf{h_i} = [\mathbf{h_i^1}, \ldots, \mathbf{h_i^{<e_1>}}, \ldots, \mathbf{h_i^{</e_1>}}, \ldots, \mathbf{h_i^{<e_2>}}, \ldots, \mathbf{h_i^{</e_2>}}, \ldots, \mathbf{h_i^L}] \tag{2}$$

where $d$ is the hidden dimension.

### 3.3 Contrastive Learning Module

Contrastive Learning Module aims at learning the difference between a batch of instances to better represent relations.

**Contrastive Instance Learning.** After we obtained $\boldsymbol{H} = \{\boldsymbol{h}_1, \ldots, \boldsymbol{h}_N\}$ from $N$ input sentences using input sentence encoder, relation augmentation layer is used to generate relation representations and their augmented views. More specifically, the relation augmentation layer consists of data augmentation and a concat layer. For each sentence embeddings $\boldsymbol{h}_i$, a transformation $T(\cdot)$ is applied to generate its augmented view: $\hat{\boldsymbol{h}}_i = T(\boldsymbol{h}_i)$, where $\hat{\boldsymbol{h}}_i \in \mathbb{R}^{L \times d}$.

After obtaining sentence embeddings $\boldsymbol{h}_i$ and its augmentation $\hat{\boldsymbol{h}}_i$, we obtain relation representations and its augmentation by a concat layer. Specifically, we use the token embeddings corresponding to $<e_1>, <e_2>$ positions as the entity representation and concatenate them to derive a contextualized relation representation and its augmented view $\boldsymbol{r}_i, \hat{\boldsymbol{r}}_i \in \mathbb{R}^{2 \cdot d}$:

$$\begin{aligned} \mathbf{r_i} &= \mathbf{h_i^{<e_1>}} \oplus \mathbf{h_i^{<e_2>}} \\ \hat{\mathbf{r}}_\mathbf{i} &= \hat{\mathbf{h}}_\mathbf{i}^{<\mathbf{e_1}>} \oplus \hat{\mathbf{h}}_\mathbf{i}^{<\mathbf{e_2}>} \end{aligned} \tag{3}$$

where $\oplus$ is the concatenation operator and $\boldsymbol{r}_i, \hat{\boldsymbol{r}}_i$ are both fixed-length vector.

To better learn effective relation representations, we optimizes a contrastive objective, which disperses different relation of instances apart while implicitly bringing the same relation of instances together. Let $\boldsymbol{R} = \{\boldsymbol{r_1}, \ldots, \boldsymbol{r_N}\}$ and $\hat{\boldsymbol{R}} = \{\hat{\boldsymbol{r}}_\boldsymbol{1}, \ldots, \hat{\boldsymbol{r}}_\boldsymbol{N}\}$ denote a mini-batch of relation representations and its augmented views respectively. We regard $(\boldsymbol{r}_i, \hat{\boldsymbol{r}}_i)$ as a positive pair and other $N-1$ augmented views as negative instances. For a mini-batch with N pairs, we follow the contrastive framework in SimCSE (Gao et al., 2021) and take a cross-entropy objective with in-batch negatives (Chen et al., 2017) and the training objective for $(\boldsymbol{r}_i, \hat{\boldsymbol{r}}_i)$ is:

$$\ell_i^{cl} = -\log \frac{e^{\mathrm{sim}(\mathbf{r_i}, \hat{\mathbf{r}}_\mathbf{i})/\tau}}{\sum_{j=1}^{N} e^{\mathrm{sim}(\mathbf{r_i}, \hat{\mathbf{r}}_\mathbf{j})/\tau}} \tag{4}$$

where $\boldsymbol{r}_i \in \boldsymbol{R}, \hat{\boldsymbol{r}}_i \in \hat{\boldsymbol{R}}$, $\mathrm{sim}\left(\mathbf{r_1}, \mathbf{r_2}\right)$ is the cosine similarity $\frac{\mathbf{r}_1^\top \mathbf{r}_2}{\|\mathbf{r}_1\| \cdot \|\mathbf{r}_2\|}$ ,and $\tau$ is a temperature hyperparameter.

**Data Augmentation Strategies.** To amplify the semantic difference between similar instances without breaking the semantic of relation representations, we explore five different data augmentations $T(\cdot)$ for contrastive instance learning, including feature cutoff (Shen et al., 2020), random mask (Hinton et al., 2012), dropout (Gao et al., 2021), composition of dropout and feature cutoff and composition of dropout and random mask.

Feature cutoff is a simple and efficient data augmentation strategy to introduce minimal semantic impact for relation instances. Specifically, we randomly erase some feature dimensions in the sentence embeddings produced by input sentence encoder.

Random mask is proved its effectiveness as an augmentation strategy (Yan et al., 2021). In our experiments, we randomly drop elements in the

sentence embeddings by a specific probability and sets their values to zero.

Dropout has been shown its effectiveness as minimal data augmentation by SimCSE (Gao et al., 2021). Thus, similar to SimCSE, we augment sentence embeddings by feeding the same input sentence to BERT again.

Composition of augmentations is an effective strategy in image domain (Chen et al., 2020). Based on dropout, we explore two strategies of composition of data augmentations. Composition of dropout and feature cutoff is a strategy that we first use dropout to obtain augmented view and then send it into feature cutoff to obtain the final augmented view. Similarly, composition of dropout and random mask is a strategy that dropout first and then random mask. We present the experimental results of these strategies and analyze their effects for contrastive learning in Section 4.4.

### 3.4 Relation Classification Module

Relation Classification Module aims to identify seen relations. With sentence embeddings $\boldsymbol{h_i}$ from input sentence encoder, we obtain relation representation $\boldsymbol{r_i}$ by the concat layer, following the way same as Equation (3). Let $n$ denotes the number of seen relations and $Y_s$ denotes the set of seen relations. By transforming the relation representation $\boldsymbol{r_i}$, along with a softmax layer, we generate the n-dimensional classification probability distribution of the i-th sample over seen relations:

$$p\left(y_i \mid X_i, \theta\right) = \operatorname{softmax}\left(W\left(\tanh\left(\mathbf{r_i}\right)\right) + b\right) \tag{5}$$

where $X_i$ is the input sentence containing two entities, $y_i \in Y_s$ is the seen relation, $\theta$ is the model parameter, $W \in \mathbb{R}^{n \times 2 \cdot d}$, and $b \in \mathbb{R}^n$. Note that we use the relation representation $\boldsymbol{r_i}$ produced intermediately for predicting unseen relations under the zero-shot settings instead of the probability distribution. For each data point $X_i$, we use cross-entropy to calculate classification loss:

$$\ell_i^{rc} = CrossEntropy(p(y_i \mid X_i, \theta), \hat{y}_i) \tag{6}$$

where $\hat{y}_i$ is the ground-truth label of the i-th sample.

### 3.5 Train and Test

At the training stage, We train the model with two objectives under the multi-task learning structure. The first is to minimize the distance between the relation representation and its augmented view, while keeping the relation representation distant from other augmented relation representations in a mini-batch. The second objective is to bring high prediction accuracy of seen relations. For a mini-batch of input sentences, the training objective of RCL is as follows:

$$\begin{aligned} &\mathcal{L}_{\text{CL}} = -\frac{1}{N}\sum_{i=1}^{N} \ell_i^{cl}, \mathcal{L}_{\text{RC}} = -\frac{1}{N}\sum_{i=1}^{N} \ell_i^{rc} \\ &\mathcal{L}_{\text{joint}} = \mathcal{L}_{\text{RC}} + \alpha \mathcal{L}_{\text{CL}} \end{aligned} \tag{7}$$

where $N$ is the number of input sentences, $\alpha$ is a hyper-parameter to balance two objectives.

At the test stage, we send the new-coming sentences into input sentence encoder and concat layer to generate unseen relation representations, and the prediction on unseen relations can be achieved by K-Means.

## 4 Experiments

### 4.1 Datasets

Two datasets are used to evaluate our model: SemEval2010 Task8 (Hendrickx et al., 2010) and FewRel (Han et al., 2018). **SemEval2010 Task8** has been widely used in relation extraction task, which contains 9 relations and an Other relation. There are 10,717 instances in the dataset and the number of instances of each relation is not equal. Each relation has direction in the dataset, but in our experiments, we do not consider the direction of 9 relations and not use the Other relation. For each relation, we combine the instances of training set with instances of test set to obtain overall instances of each relation. **FewRel** is a public dataset based on Wikipedia, and it contains 80 types of relations, each with 700 instances. Although FewRel is widely used in few-shot learning setting, it is also suitable for zero-shot learning as long as we disjoint the relation labels within training and test data.

### 4.2 Evaluation Settings

**Zero-shot Learning Settings.** Let $m$ denotes the number of unseen relations, and $Y_u$ denotes the set of unseen relations. We randomly select $m$ relations as unseen relations and the rest of relations $n$ as seen relations. Note that $Y_s \cap Y_u = \emptyset$. Then we split the whole dataset into training and test data. The training data only contains the instances of seen relations, in contrast to test data only with the instances of unseen relations. We repeat experiments 5 times on SemEval2010 Task8

and FewRel and then report the average results. As for implementation details for RCL, we implement our model based on `Transformers` package (Wolf et al., 2020). And we use an Adam optimizer (Kingma and Ba, 2014), in which the learning rate is $5e-5$. Please refer to the Appendix for more implementation details.

**Evaluation Metrics.** We follow the setting in the previous work (Simon et al., 2019) to convert pseudo labels predicted by clustering to relation labels. In each cluster, the relation label with the largest proportion among the cluster is assigned to all samples as the prediction label. For evaluation metrics, we adopt three commonly-used metrics (Wu et al., 2019; Hu et al., 2020; Zhang et al., 2021) to measure the effectiveness of clustering : $B^3$ (Bagga and Baldwin, 1998), Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI). For $B^3$, $B^3$ precision and recall correspondingly measure the correct rate of putting each sentence in its cluster or clustering all samples into a single class. Then $B^3$ $F_1$ is computed as the harmonic mean of the $B^3$ precision and recall:

$$B^3\text{precision} = \mathop{\mathbb{E}}_{X,Y} P(g(X) = g(Y) \mid c(X) = c(Y))$$
$$B^3\text{recall} = \mathop{\mathbb{E}}_{X,Y} P(c(X) = c(Y) \mid g(X) = g(Y))$$

NMI measures the information shared between the predicted label and the ground truth. When data are partitioned perfectly, the NMI score is 1, while it becomes 0 when prediction and ground truth are independent. ARI is a metric to measure the degree of agreement between the cluster and golden distribution, which ranges in [-1,1]. The more consistent two distributions, the higher the score.

**Baselines.** We compare RCL to previous methods consisting of CNN (Zeng et al., 2014), Attention BiLSTM (Zhou et al., 2016), RSNs (Wu et al., 2019), MTB (Soares et al., 2019), ZS-BERT (Chen and Li, 2021). For CNN, Attention BiLSTM and MTB, these methods have great success in supervised relation extraction (SRE) but fail to perform zero-shot prediction. Specifically, we consider two variations of MTB which only differ in the backbone (MTB-BERT and MTB-RoBERTa). For fair comparison and zero-shot prediction, we make the relation representation from encoder become the output of the SRE model, instead of originally outputting a probability vector whose dimension is equal to the seen relations. The dimension of output vector is same as RCL. The K-Means is applied over output vector to generate zero-shot prediction. Although RSNs is a open relation extraction method, its Supervised RSN model also meets the setting of zero-shot. For ZS-BERT, the original relation descriptions are used for FewRel and we collect the descriptions of relations for SemEval2010 Task8 from open resources. Then we use the sentence embeddings for K-Means to predict unseen relations. Note that we set the dimension of sentence embeddings same as RCL for fair comparison.

| SemEval2010 Task8 | | | | | |
|---|---|---|---|---|---|
| **Model** | **P** | **R** | **F1** | **NMI** | **ARI** |
| CNN | 38.37 | 38.49 | 38.42 | 17.06 | 15.43 |
| Att-BiLSTM | 41.46 | 41.79 | 41.6 | 21.45 | 19.97 |
| Supervised RSN | 33.14 | 47.06 | 38.41 | 11.98 | 10.96 |
| MTB-BERT | 45.1 | 46.35 | 45.71 | 28.12 | 23.69 |
| MTB-RoBERTa | 42.71 | 44.84 | 43.71 | 24.52 | 21.01 |
| ZS-BERT | 33.86 | 36.33 | 35.03 | 12.47 | 9.53 |
| RCL w/o RC | 50.31 | 54.87 | 52.45 | 34.55 | 28.97 |
| RCL | **68.1** | **67.95** | **68.02** | **55.91** | **54.71** |

Table 1: Experimental results(%) on SemEval2010 Task8 in terms of $B^3$ precision, $B^3$ recall, $B^3$ F1, Normalized Mutual Information, Adjusted Rand Index.

### 4.3 Experimental Results

**Results on SemEval2010 Task8.** Table 1 show the comparison results on SemEval2010 Task8. RCL achieves the best performance, significantly outperforming the previous state-of-the-art with 22.31% F1, 27.79% NMI and 31.02% ARI improvements. Due to the relations of SemEval2010 Task8 dataset with high similarity, baseline models severely suffer from similar errors and the performances of baselines are poor. Another reason why baselines perform poorly is that small number of seen relations and class imbalance are more challenging for model. Moreover, SemEval2010 Task8 is much less related to the general domains on which the transformers are pretrained. However, comparing with baselines, experimental results show RCL can effectively mitigates similar problems and better use the general knowledge of the pre-training language model.

**Results on FewRel.** For FewRel, the experimental results are shown in Table 2. From the results, we observe that our model RCL outperforms existing baselines on FewRel when targeting at different numbers of unseen relations $m$. Specifically, RCL achieves an average of 2.87% F1, 1.98% NMI and 2.98% ARI improvements compared to previous best results. Since relations on FewRel are class balance and sufficient, MTB-BERT and MTB-RoBERTa perform well among competing models

| | FewRel | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | m=5 | | | m=10 | | | m=15 | | | m=30 | | | m=40 | | | Avg. | | |
| **Model** | **F1** | **NMI** | **ARI** | **F1** | **NMI** | **ARI** | **F1** | **NMI** | **ARI** | **F1** | **NMI** | **ARI** | **F1** | **NMI** | **ARI** | **F1** | **NMI** | **ARI** |
| CNN | 74.47 | 68.51 | 66.31 | 60.87 | 64.59 | 53.79 | 55.3 | 62.35 | 49.87 | 39.15 | 54.61 | 35.49 | 34.09 | 53.46 | 30.37 | 52.78 | 60.7 | 47.17 |
| Att-BiLSTM | 82.75 | 79.36 | 76.63 | 75.89 | 79.1 | 71.46 | 69.84 | 75.94 | 66.03 | 50.76 | 66.99 | 47.64 | 45.01 | 64.66 | 42.23 | 64.85 | 73.21 | 60.8 |
| Supervised RSN | 73.33 | 67.89 | 64.49 | 59.11 | 64.96 | 48.66 | 50.99 | 59.98 | 39.74 | 26.01 | 44.31 | 18.71 | 23.55 | 48.26 | 18.08 | 46.6 | 57.08 | 37.94 |
| MTB-BERT | 88.06 | 85.32 | 84.03 | 81.08 | 83.95 | 76.22 | 78.62 | 83.57 | 74.83 | 63.51 | 76.61 | 59.98 | 60.35 | 75.9 | 54.54 | 74.32 | 81.07 | 69.92 |
| MTB-RoBERTa | 90.14 | 87.12 | 86.7 | 82.39 | 84.77 | 78.03 | 79.78 | 84.35 | 76.82 | 62.98 | 75.91 | 58.83 | 60.58 | 75.99 | 55.08 | 75.17 | 81.63 | 71.15 |
| ZS-BERT | 74.51 | 69.24 | 66.96 | 70.63 | 74.1 | 65.23 | 63.33 | 70.7 | 59.24 | 46.43 | 61.66 | 42.94 | 45.68 | 64.43 | 42.68 | 60.12 | 68.03 | 55.41 |
| RCL w/o RC | 73.58 | 68.23 | 64.5 | 70.52 | 74.28 | 59.53 | 58.02 | 64.67 | 51.74 | 39.89 | 54.62 | 33.7 | 33.09 | 50.15 | 28.57 | 55.02 | 62.39 | 47.61 |
| RCL | **90.73** | **87.41** | **86.72** | **84.52** | **86.73** | **80.23** | **81.48** | **85.64** | **78.18** | **67.75** | **79.21** | **64.43** | **65.74** | **79.09** | **61.1** | **78.04** | **83.61** | **74.13** |

Table 2: Experimental results(%) produced by the baseline models and the proposed model RCL on FewRel dataset in terms of $B^3$ F-score, NMI, ARI. $m$ is the number of unseen relations, and we vary $m$ in [5, 10, 15, 30, 40] to examine how performance is affected. RCL w/o RC means RCL without relation classification module.

but their performance is still lower than RCL. The reason is that their approaches cannot well deal with similar problems. ZS-BERT performs worse than most competing models because ZS-BERT severely relies on the unseen relation descriptions for prediction, while our approach can perform well without external resources. In addition, we find that the improvement of RCL gets larger when $m$ is larger, especially when $m = 40$. It is obvious that it becomes more difficult for prediction since the number of unseen relations increases leading to more seriously similar problems.

**Ablation Study.** To better validate our model, we conduct an ablation study on each module by correspondingly ablating one. Note that MTB-BERT is the version of RCL without contrastive learning module. From Table 1 and Table 2, we can see that combining these two modules can result in a noticeable performance gain over two datasets. Especially in SemEval2010 Task8, RCL w/o RC outperforms existing baselines by all evaluation metrics, which prove the effectiveness of contrastive learning. However, our proposed RCL significantly outperforms RCL w/o RC with 15.57% F1, 21.36% NMI and 25.74% ARI improvements. It demonstrates that these two modules are complementary on relation representation learning: contrastive learning focuses on learning the difference between instances and implicitly obtaining some knowledge about the difference between relations while relation classification can explicitly learn the difference between relations by identifying the relations but cannot learn the difference between similar instances and suffers from similar problems. When the number of unseen relations increases on FewRel, RCL w/o RC performs worse than competing methods due to without effectively learning relation difference, which also shows that both two modules are important to the final model performance.

| | SemEval2010 Task8 | FewRel |
|---|---|---|
| **Data augmentation** | **F1** | **F1** |
| None | 58.14 | 86.95 |
| Random Mask | 60.25 | 87.42 |
| Feature Cutoff | 59.92 | 88.46 |
| Dropout | **68.02** | **90.73** |
| Dropout+Random Mask | 67.53 | 89.84 |
| Dropout+Feature Cutoff | 65.51 | 89.23 |

Table 3: Experimental results(%) with different data augmentation strategies over two datasets in term of $B^3$ F1 score. For FewRel, we report the results on $m = 5$.

### 4.4 Qualitative Analysis

**Effect of Data Augmentations.** To study the effect of data augmentations, we consider six different data augmentation strategies for contrastive learning in our experiments, including None (i.e. doing nothing), Random Mask, Feature Cutoff, Dropout, Composition of Dropout and Feature Cutoff (Dropout+Feature Cutoff) and Composition of Dropout and Random Mask (Dropout+Random Mask).

The results are shown in Table 3. We can make the following observations: (a) Dropout is the most effective strategy, outperforming all competing strategies. It demonstrate that Dropout essentially acts as minimal data augmentation (Gao et al., 2021) and the noise produced by Dropout can make model learn the difference between similar instances better. (b) When compared with None, Random Mask and Feature Cutoff also improve performance across two datasets. Moreover, Dropout+Random Mask and Dropout+Feature Cutoff significantly outperform Random Mask and Feature Cutoff with roughly 6 and 2 points gain respectively while Dropout still outperforms these two composition of augmentations. It shows that different from the image domain (Chen et al., 2020), composition of augmentations is not always effective for the text domain. (c) We find that our model can improve performance on two datasets

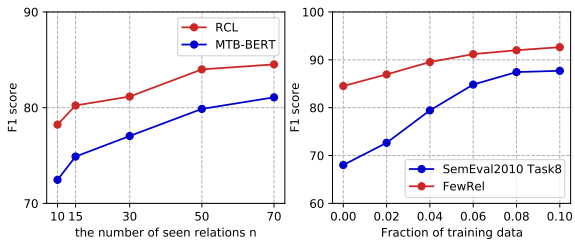



Figure 3: Left: The results of RCL and MTB-BERT with different numbers of seen relations. Right: The performance of RCL with different fractions of unseen instances available for training. The number of unseen relations is set to 10 on FewRel.

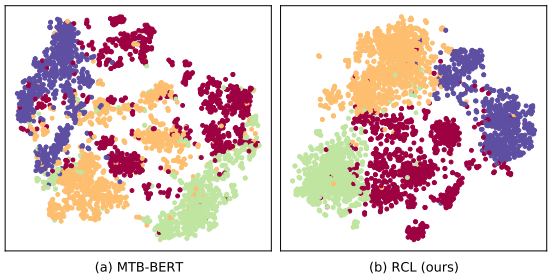



Figure 4: t-SNE visualization of unseen relation representations learned by MTB-BERT and RCL on SemEval2010 Task8 dataset.

even without any data augmentation (None), especially for SemEval2010 Task8 (from 45.71 to 58.14). This is because None tunes the representation space by keeping each representation away from others, even if it has no effect on minimizing the distance between instance and its augmented view since the embeddings of augmented view are same with original instance. It also demonstrates that the effectiveness of the contrastive learning without external resources.

**Effect of Number of Seen Relations.** In this section, we study the effect of the number of seen relations on FewRel which contains sufficient relations. In our experiment, we vary the number of seen relations $n$ from 10 (insufficient) to 70 (sufficient) and consistently set the number of unseen relations $m$ to 10. Experimental results are presented in Figure 3. As the number of seen relations increases, RCL continuously outperforms MTB-BERT, which shows the effectiveness of our approach. More specifically, when $n$ is set to 10, RCL can achieve 90% F1 score of the model trained on the full seen relations. In addition, the performance of RCL declines more slighter and smoother than MTB-BERT when seen relations gradually become insufficient (from 30 to 10), showing the robustness of our approach.

**Capability under Few-shot Settings.** In this section, we conduct the experiment of few-shot prediction by following the setting of Chen and Li (2021) to understand the capability of RCL. We move a small fraction of sentences of each unseen relation from test data to training data. Experimental results are shown in Figure 3. As expected on two datasets, RCL achieves more F1 score improvement with more unseen relation instances available at the training stage. When the fraction is set to 4%, RCL can achieve 90% F1 score on FewRel and 80% F1 score on SemEval2010 Task8. It shows the capability of few-shot learning for RCL.

**Visualization of Relation Representations.** To intuitively show how our approach helps to learn better relation representations on seen relations, we visual the representations of unseen relations by using t-SNE (Van der Maaten and Hinton, 2008) to reduce the dimension to 2. We randomly choose 4 relations as unseen relation from SemEval2010 Task8 and the visualization results are shown in Figure 4. In each figure, relation instances are colored according to their ground-truth labels.

As we can see from Figure 4(a), the data points from MTB-BERT are mingled with different clusters, especially for red points. The reason is these instances possess similar relations or similar entities and MTB-BERT has not learned the corresponding knowledge to deal with similar problems. However, as illustrate in Figure 4(b), RCL effectively mitigates these two types of similar problems since our approach can learn the difference between instances and the difference between seen relations. It again exhibits the effectiveness of the contrastive loss and multi-task learning structure. We also provide a case study in the Appendix.

## 5 Conclusion

In this paper, we propose a jointly framework for zero-shot relation extraction to mitigate two types of similar errors: Similar Relations and Similar Entities. Different from conventional zero-shot relation extraction models which require external resources for training and test, our model does not require external resources. We demonstrate the effectiveness of our framework on two datasets, and our method achieves new state-of-the-art performance. Furthermore, we compare various data augmentation strategies for contrastive learning and provide fine-grained analysis for interpreting how our approach works.

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## A Statistics of Datasets

The statistics of SemEval2010 Task8 and FewRel are shown in Table 4. For SemEval2010 Task8, we use 9 relations except the Other relaiton. Because of small number of relations, class imbalance and relations with high similarity, the experiment on SemEval2010 Task8 is more challenging and close to real world setting. For FewRel, we use the train and valid split but not test split, because the test split is not publicly available.

| | #Instances | #Entities | #Relations | Avg.Len. |
|---|---|---|---|---|
| **SemEval2010 Task8** | 10,717 | 7,984 | 10 | 18.84 |
| **FewRel** | 56,000 | 72,954 | 80 | 24.95 |

Table 4: Statistics of two datasets. "Avg.Len." means the average length of sentences.

## B Implementation Details

We implement RCL based on `Transformers` package (Wolf et al., 2020), where we use *Bert-base-uncased* as backbone. We set the maximum input length to 96 for SemEval2010 Task8 and 80 for FewRel. The epoch is set to 6 for training and we use an Adam optimizer (Kingma and Ba, 2014) with a batch size of 32. The learning rate is set to $5e-5$ and the weight decay is set to 0.1. Same as SimCSE (Gao et al., 2021), the dropout probability of data augmentation is set to 0.1. The temperature $\tau$ is set to 0.05 across two datasets and we set $\alpha$ to 0.4 and 0.6 on SemEval2010 Task8 and FewRel respectively. The hidden size of fully-connected layer is set to 1536.

## C More Ablation Studies

The effects of hyper-parameters are shown in Table 5 and Table 6. For hyper-parameter $\alpha$, we vary $\alpha$ in the list of [0.0, 0.2, 0.4, 0.6, 0.8, 1.0] and find RCL can achieve the best performance when $\alpha$ is set to 0.4 on SemEval2010 Task8 or 0.6 on Fewrel. For temperature hyper-parameter $\tau$, we vary $\tau$ in the list of [0.001, 0.01, 0.05, 0.1, 1.0] and find $\tau = 0.05$ can achieve the best performance across two datasets.

| $\alpha$ | 0.0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 |
|---|---|---|---|---|---|---|
| **SemEval2010 Task8** | 45.71 | 65.45 | **68.02** | 67.08 | 66.00 | 64.46 |
| **FewRel** | 81.08 | 82.32 | 82.94 | **84.52** | 83.35 | 83.11 |

Table 5: Experimental results(%) with different $\alpha$ in term of $B^3$ F1 score. For FewRel, we report the results on the unseen relation number $m = 10$.

| $\tau$ | 0.001 | 0.01 | 0.05 | 0.1 | 1.0 |
|---|---|---|---|---|---|
| **SemEval2010 Task8** | 44.99 | 47.18 | **68.02** | 61.85 | 42.23 |
| **FewRel** | 82.23 | 83.51 | **84.52** | 83.11 | 77.29 |

Table 6: Experimental results(%) with different temperatures over two datasets in term of $B^3$ F1 score. For FewRel, we report the results on the unseen relation number $m = 10$.

## D Different Clustering methods for Zero-shot Prediction

Figure 5 shows the results of different clustering methods for RCL, including Mini-Batch K-Means (Sculley, 2010), Gaussian Mixture Model (GMM), Hierarchical Agglomerative Clustering (HAC), Birch (Zhang et al., 1996), K-Means. We can find that the performance of K-Means is much better than other clustering methods on two datasets. Moreover, Mini-Batch K-Means still outperforms MTB-BERT on SemEval2010 Task8, even its performance is worse than other clustering methods, showing the effectiveness of our model.

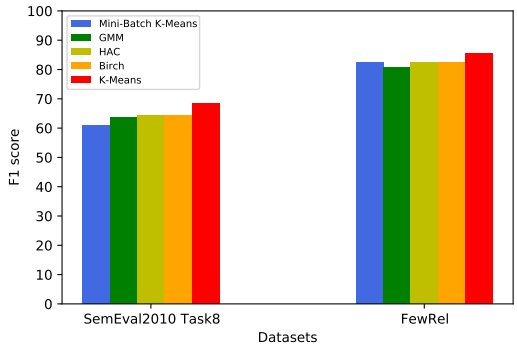


Figure 5: Different clustering methods for our proposed RCL model on two datasets. For FewRel, the number of unseen relations is set to 10.

## E Case Study

To intuitively show how RCL helps to solve two types of similar problems (similar relations and similar entities), we conduct some case studies on two datasets. As shown in Figure 6, it is clear to see that RCL effectively solves these two problems under the multi-task learning structure. Specifically, RCL can better represent two sentences which have similar relations or similar entities, and then make their euclidean distance closer to the cluster corresponding to their ground truth.

| SemEval 2010 Task8 | Sentence | Label | Cluster Center | Euclidean Distance | | |
|---|---|---|---|---|---|---|
| | | | | ZS-BERT | MTB-BERT | RCL |
| Similar Relations | The **envelope** contained an important intelligence **discovery** of the war. | Content-Container | **Member-Collection** | **12.08** | **9.92** | 8.55 |
| | | | **Content-Container** | 12.18 | 12.42 | **8.36** |
| | The **kitchen** holds patient **drinks** and snacks. | Content-Container | **Member-Collection** | **10.41** | **8.68** | 8.52 |
| | | | **Content-Container** | 11.71 | 10.66 | **8.41** |
| Similar Entities | ***Group1:*** China has tested Barack Obama early in his presidency, with a **flotilla** of naval **vessels** surrounding and harassing a US spy ship in the South China Sea. | Member-Collection | Member-Collection | **11.59** | **7.02** | **6.83** |
| | | | Instrument-Agency | 11.83 | 12.41 | 8.30 |
| | ***Group1:*** Until 1864 **vessels** in the service of certain UK public offices defaced the Red Ensign with the **badge** of their office. | Instrument-Agency | **Member-Collection** | **11.84** | **8.62** | 8.20 |
| | | | **Instrument-Agency** | 13.74 | 11.02 | **7.70** |
| | ***Group2:*** The **puppy** was inside a sealed **garbage bag** lying in vomit and near death. | Content-Container | Content-Container | **9.65** | **7.83** | **7.00** |
| | | | Entity-Origin | 16.97 | 13.69 | 8.93 |
| | ***Group2:*** The **puppy** was born in a **barn** where Layla made a soft, bed out of hay in an empty horse stall. | Entity-Origin | **Content-Container** | **13.49** | **9.29** | 10.14 |
| | | | **Entity-Origin** | 15.49 | 11.78 | **9.37** |

| FewRel | Sentence | Label | Cluster Center | Euclidean Distance | | |
|---|---|---|---|---|---|---|
| | | | | ZS-BERT | MTB-BERT | RCL |
| Similar Relations | The Doctor tries to restore the universe with the help of River and the alternative universe versions of his **companions** Amy Pond (Karen Gillan) and **Rory Williams** (Arthur Darvill). | part_of | **member_of** | **16.55** | **26.13** | 28.76 |
| | | | **part_of** | 17.90 | 26.42 | **26.06** |
| | Later in the game, she joins Snake in rescuing Dr Marv, but dies when Jaeger (as **Gray Fox** in **Metal Gear** D) destroys the bridge she is on. | part_of | **member_of** | **16.10** | **25.63** | 31.34 |
| | | | **part_of** | 16.85 | 26.10 | **27.19** |
| Similar Entities | ***Group1:*** In May 2015, Vienna hosted the **Eurovision Song Contest** following Austria's victory in the **2014 contest**. | follows | follows | **13.57** | **7.52** | **11.41** |
| | | | part_of | 16.11 | 26.01 | 26.01 |
| | ***Group1:*** Thus, the song was succeeded as Romanian representative at the **2002 Contest** by Monica Anghel & Marcel Pavel with "**Tell Me Why**". | part_of | **follows** | **14.89** | **25.46** | 28.22 |
| | | | **part_of** | 18.11 | 26.54 | **27.78** |
| | ***Group2:*** On 1 September 1939, the **Second World War** began with the German **Invasion of Poland**, and two days later the United Kingdom declared war on Germany. | part_of | part_of | **15.16** | **22.98** | **21.81** |
| | | | follows | 18.64 | 30.77 | 28.90 |
| | ***Group2:*** During the **War of 1812**, Rolette, like many other French-Canadian Fur Traders in the Old Northwest, was an active supporter of the British Empire against the **United States**. | follows | **part_of** | **15.15** | **24.63** | 25.00 |
| | | | **follows** | 18.13 | 25.28 | **23.54** |

Figure 6: Case study of similar relations and similar entities on two datasets. "Euclidean Distance" is the euclidean distance between the relation representation of input sentence and the cluster center of the relation. The target entities of input sentence are marked in orange.