

Supervised Relation Extraction via Generative Adversarial Network

1st Yanhua Yu
Beijing University of
Posts and Telecommunications
Beijing, China
yuyanhua@bupt.edu.cn

2nd Kanghao He
Beijing University of
Posts and Telecommunications
Beijing, China
hkh@bupt.edu.cn

3rd Jie Li
Beijing University of
Posts and Telecommunications
Beijing, China
jli@bupt.edu.cn

Abstract—Most supervised methods for relation extraction(RE) need lots of time-consuming human annotation. Distant supervision for relation extraction is an efficient method to obtain large corpora which contains thousands of instances and various relations. However, the existing approaches rely on sophisticated pre-defined rules as well as knowledge base(e.g Freebase) for automatic annotation and thus suffer from data noise. Various relations and noisy labeling instances make the issue harder to be solved. To address these issues, we build a relation candidate set and then apply an adversarial training mechanism to filter out those noisy instances from the candidate set and identify informative ones. The experiments on the extended dataset show that our candidate selection and generative adversarial network can cooperate together to obtain more accurate training data for RE and significantly outperforms several competitive baseline models.

Index Terms—relation extraction, adversarial training, generative adversarial network

I. INTRODUCTION

Relation extraction(RE), which aims to extract relations between entity pairs from the sentences containing them, is of great importance for many natural language applications, such as information extraction, question answering and constructiong of knowledge base(KB) [1]–[3].

Most prior methods for RE follow a supervised learning approach to train models on human-annotated data, such as SemEval-2010 Task 8 [4] and ACE 2005 [5]. These methods are limited by the amount of labeled training data, thus Mintz [6] proposes distant supervision to automatically generate training data based on knowledge bases. It assumes that if two entities have a relation in KBs, then all sentences mentioning these two entities express this relation. Thus, distant supervision can generate abundant amounts of labeled data without intensive labor. Simultaneously, it always suffers from wrong labeling problem. For example, (Apple, founder, Steve Jobs) is a relational fact in KB, the sentence "Steve Jobs passed away the day before Apple unveiled iPhone 4s in late 2011." does not express the relation founder but will still be regarded as a training instance. To combat the noisy training data, Riedel and Hoffmann [7], [8] propose multi-instance learning, assuming only that at least one of the sentences containing entities are expressing the relation. Zeng and Santos attempt to incorporate multi-instance learning with neural network model [9]–[11].

Recently, attention mechanism have been proposed to select valid instances from the auto-annotated sentence set [12], [13].

Although these methods achieve significant improvement in relation extraction, there are still some severe problems for these RE methods: (1)Most supervised datasets lack sufficient training data. (2)Distant supervision naturally suffers from the inevitable noisy data, and the supervision is much weaker due to the multi-instance framework.

In this paper, we propose an approach which use generative adversarial network to take advantage of the noisy data and a discovery strategy to obtain more labeled data. Considering the weakness of distant supervision, we use supervised dataset and adopt a discovery strategy similar to distant supervision, assuming that if two entities have a relation in supervised training set, then all instances mentioning these two entities express this relation. Hence, we obtain a supervised dataset and a noisy dataset. These noisy data that come from heuristic labeling are natural adversarial training samples. We design a generative adversarial network consist of a selector and a discriminator like Goodfellow [14], as shown in Figure 1.

The selector is used to select the most confusing instance from the noisy data and the discriminator is used to judge whether a instance is annotated correctly. During the training process, the discriminator will influence the selector to select the more informative data and thus the discriminator will integrate information from supervised data and adversarial data. When the selector and the discriminator reach a balance, the selector can effectively select valid instances to the discriminator and the discriminator can boost resistance to noise and improve the relation extraction. Instances from the noisy dataset selected by the selector and regarded as being labeled correctly by the discriminator will be judged as valid data and enrich the supervised dataset.

Our main contributions are listed as follows:

- Compared with existing neural relation extraction model, we propose a novel adversarial training mechanism to make full use of all informative sentences of noisy data.
- The discovery strategy and the selector can cooperate to obtain more valid training data and extend the original supervised dataset.
- Experiments on the extension of SemEval-2010 Task 8 dataset have demonstrated that our model significantly

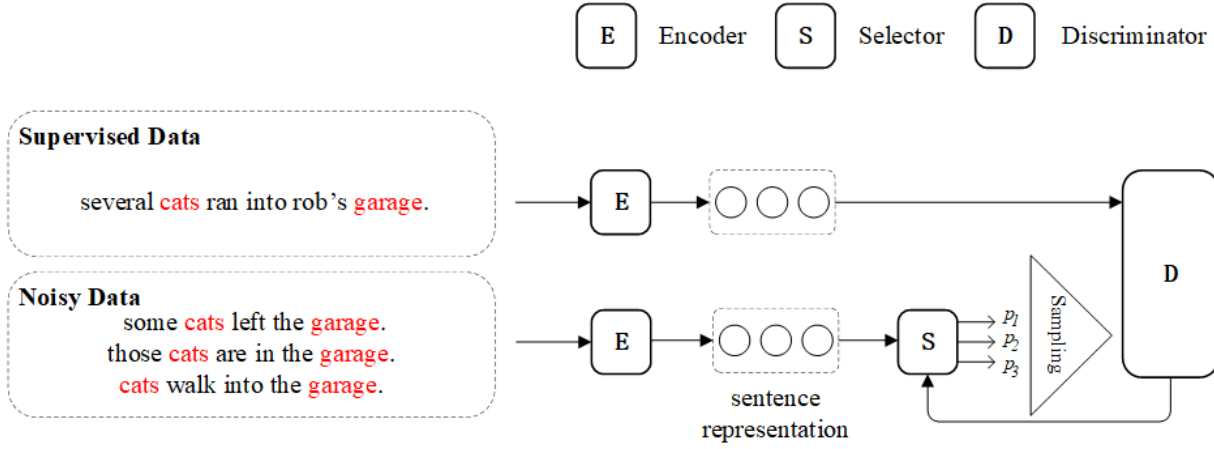


Fig. 1. The overall architecture of generative adversarial network. The relation type is *Entity-Destination*($e1, e2$).

outperforms the previous models, and the new dataset improve the performance of previous models as well.

II. RELATED WORK

This paper is mainly related to neural networks and adversarial training. Most traditional supervised RE models [11], [15], [16] heavily rely on abundant amounts of annotated data, which are labor intensive and time consuming. To address this issue, Mintz [6] proposed a distantly supervised model for RE. Distant supervision aligns plain text with Freebase to automatically label large-scale training data. However, the training data generated by distant supervision inevitably accompany with the mislabeling problem. Therefore, mainstream methods of distant supervision focus on reducing noise.

To alleviate the noise issue, Riedel [7] and Hoffmann [8] proposed multi-instance learning (MIL) mechanisms for single-label and multi-label problems respectively, where instances are processed at a bag level. But these feature-based methods depend strongly on the handcrafted features. Most features are explicitly generated by NLP tools, which will suffer from error propagation problem. With the development of neural networks, various neural methods have been proposed. Zeng [9] attempted to integrate piecewise convolution neural network (PCNN) into distant supervision. The method assumes that at least one sentence that mentions these two entities will express their relation and select the most reliable sentence as the bag representation. Lin [12] further proposed attention mechanism to jointly consider all sentences containing same entity pairs and distribute different weights to each sentence. Attention-based neural relation extraction (NRE) model has become a foundation for some recent works [13], [17]. Yuan [18] conduct MIL with a cross-relation cross-bag selective attention in order to reduce the impact of noisy data. Ye [19] adopted both intra-bag and inter-bag attention to deal with the noisy training data. Apart from that, some efforts have been made to improve the performance of RE with external knowledge, entity description, and reinforcement learning [20]–[22]. Nevertheless, due to the restriction of

knowledge bases as well as the lack of external information, those methods still suffer from the noise at sentence-level and bag-level respectively.

Adversarial training has been widely exploited in NLP applications recently to resist noise including text classification and relation extraction [23]–[25]. For example, Wu [24] generated adversarial instances by adding simple noise perturbation to embeddings. Qin [25] adopted adversarial training to denoise data and neglect to discover more training instances from raw data.

Different from the existing methods, our work regard the real-world data as adversarial samples rather than add pseudo noisy perturbations. Furthermore, we propose a discovery strategy similar to distant supervision and train a selector (the generator) so that our model not only resist the noisy data but also discover valid labeled data to extend datasets. Our discovery strategy can obtain specific relation type to deal with the imbalanced dataset.

III. METHODOLOGY

In this section, we present the overall framework of our model for supervised relation extraction with discovery strategy. After that, we present each module in details.

A. Preliminaries

The architecture of the generative adversarial network is illustrated in Figure 1, which has three main modules including sentence encoder, selector and discriminator.

The sentence encoder is applied to transform sentences into low-dimensional vectors. Given a sentence s and two target entities, a piecewise convolution neural network (PCNN) [9] is used to derive the sentence representation x . Details of the sentence encoder are shown in Section III-B.

After that, we introduce an adversarial learning pipeline to train a selector which can select the valid instances from the noisy dataset ND under the guidance of the discriminator. The discriminator is responsible for judging whether the given instance express its relation. The adversarial training strategy

is the core of our method. We will give its details in Section III-C.

Our discovery strategy is based on a heuristic assumption that if a given pair of entities have a relation in supervised dataset SD, all other sentences mentioning these two entities express this relation. If an instance does not contain a pair of entities shown in SD, it will be labeled with NA. It is effective to obtain abundant amounts of adversarial noisy data ND. The details of automatically labeling ND and utilizing selector to extend SD will be introduced in Section III-E.

B. Sentence Encoder

Input representation: Word Embeddings. Given a sentence x consisting of m words $x = \{w_1, w_2, \dots, w_m\}$, each word w_i is mapped into a d_w -dimensional word embedding \mathbf{w}_i , where \mathbf{w}_i is the pre-trained word vector of w_i .

Position Embeddings. The position features (PFs) proposed by [16] are adopted in our work to describe the position information of two entities. PFs describe the relative distances from the current word to the two entities.

For each word, we compute the relative distances to the two entities and embed the distances in two d_p -dimensional vectors $p_i^{e_1}$ and $p_i^{e_2}$.

The final representation \mathbf{x}_i of each word w_i is the concatenation of the word embedding and two position embeddings as follows:

$$\mathbf{x}_i = \mathbf{w}_i \oplus p_i^{e_1} \oplus p_i^{e_2} \quad (1)$$

The symbol \oplus represents concatenation operator. Then the input representation part transforms an instance into a matrix $\mathbf{X} \in \mathbb{R}^{m \times d}$, where m is the sentence length and $d = d_w + 2d_p$. The matrix \mathbf{X} is subsequently fed into the convolutional part.

Piecewise CNN: After representing all words in the sentence x into their input embeddings, we employ PCNN as our feature extractor. PCNN uses a piecewise max-pooling layer to capture sentence structure information. A sentence is divided into three segments by two entity words, then max-pooling is executed on each segment respectively. Inheriting the settings from Zeng et al. [9], we apply tanh as activation function. We denote convolution kernel channels by d_s , and the output of PCNN by $\mathbf{f}_x \in \mathbb{R}^{3d_s}$. Figure 2 shows PCNN architecture for input representation.

C. Adversarial Training

The purpose of discriminator is to identify relation types for each instance in datasets. When given a noisy instance, the discriminator is also expected to resist noise and explicitly classify it into the correct label. Unlike the generator applied in computer vision field [26] that generates a new image from the input noise, our generator aims to select instances from ND to confuse the discriminator as much as possible. So we denote the generator as selector.

As shown in Figure 1, we exploit a supervised dataset SD and a noisy dataset ND. Each instance $x \in SD$ express its relation type r explicitly. On the contrary, each instance $x \in ND$ is assumed to be unreliable. However, there is a certain probability that it is labeled correctly. Therefore,

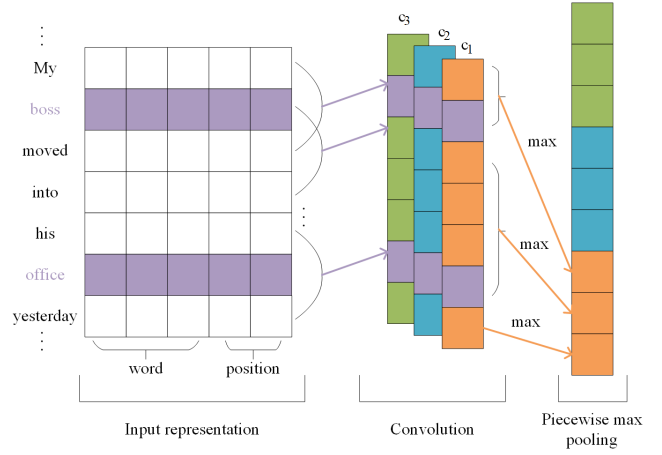


Fig. 2. PCNN Module is used to extract features.

we train the selector to select the instances that are most likely to be labeled correctly to fool the discriminator by conditional probability $P(r | x)$, $x \in ND$. Meanwhile, we design the discriminator as a multi-class classifier, which aims at maximizing the conditional probability $P(r | x)$, $x \in SD$ and $1 - P(r | x)$, $x \in ND$. Based on the notion of adversarial training, we define the training process as an adversarial min-max game as follows:

$$\begin{aligned} & \max_{\theta_D} \mathbb{E}_{x \sim P_{SD}} [\log(P(r | x))] + \\ & \mathbb{E}_{x \sim P_{ND}} [\log(1 - P(r | x))], \quad (2) \\ & \max_{\theta_S} \mathbb{E}_{x \sim P_{ND}} [\log(P(r | x))], \end{aligned}$$

where θ_D and θ_S are the parameters of discriminator and selector respectively. P_{SD} is the supervised data distribution and selector samples adversarial examples from ND according to the probability distribution P_{ND} . After our adversarial training process, we obtain a robust discriminator that can boost resistance to noise and better categorize relations and a selector that can select those informative instances with a higher probability compared with those noisy ones.

Discriminator

Given a sentence x and its relation type $r \in \varepsilon$, the discriminator is responsible for predicting the relation type of this sentence. After representing the sentence x with its embedding \mathbf{f}_x , the feature vector \mathbf{f}_x is fed into a softmax classifier, the discriminator calculates the probability of each relation type as follows,

$$\mathbf{o} = \mathbf{W}_1 \mathbf{f}_x + \mathbf{b} \quad (3)$$

$\mathbf{W}_1 \in \mathbb{R}^{n_1 \times 3d_s}$ is the transformation matrix, where n_1 is equal to the number of relation types. To obtain the conditional probability $P(r | x)$, we utilize the one-hot embedding of relation type:

$$P(r | x) = \frac{\exp(\mathbf{r} \cdot \mathbf{o})}{\sum_{k=1}^{n_1} \exp(o_k)} \quad (4)$$

where \mathbf{r} is the one-hot embedding of the relation type $r \in \varepsilon$. The optimized discriminator will assign high scores to those

instances from SD and conversely distrust those instances in ND. Hence, the objective of the discriminator can be formulated as minimizing the following loss function:

$$L_D = - \sum_{x \in SD} \frac{1}{|SD|} \log(P(r|x)) - \sum_{x \in ND} P_{ND}(x) \log(1 - P(r|x)) \quad (5)$$

where $P_{ND}(x)$ is a probability computed by selector. The update of discriminator contains the parameters of encoder and θ_D .

Selector

The selector is used to select the most confusing instances from ND to confuse the discriminator. After representing the sentence x with its embedding \mathbf{f}_x , the selector computes confusing probability $P_{ND}(x)$ for all instances in ND as follows,

$$P_{ND}(x) = \frac{1}{1 + \exp(-(\mathbf{W}_2 \mathbf{f}_x + b))} \quad (6)$$

where $\mathbf{W}_2 \in \mathbb{R}^{1 \times 3d_s}$ is the transformation matrix. In order to confuse the discriminator, the objective of the selector is to maximize the probabilities P_{ND} . Hence, we can formalize the loss function to optimize the selector as follows,

$$L_S = - \sum_{x \in ND} P_{ND}(x) \log(P(r|x)) \quad (7)$$

where $P(r|x)$ is computed by the discriminator. What needs to be explained is that, because the selector and the discriminator share one sentence encoder, we freeze the parameters of the encoder when optimizing the selector.

D. Implementation Details

As the common setting for GANs [25], [27], we propose a pre-train process. The discriminator and the selector share one sentence encoder, therefore we just pre-train the discriminator with SD.

In the implementation, we employ dropout [28] on the output layer of the encoder. The dropout layer is defined as an element-wise multiplication with a vector \mathbf{h} of Bernoulli random variables with probability p . Then final sentence representation becomes:

$$\mathbf{f}_x = \tanh(\mathbf{p} \circ \mathbf{h}) \quad (8)$$

E. Extend Dataset with Selector

We construct the noisy dataset based on our discovery strategy with the entity pairs in the supervised data as heuristic seed. For example, the entity pair “suicide” and “death” in the instance “suicide is one of the leading causes of death among pre adolescents and teens, and victims of bullying are at an increased risk for committing suicide” expresses the relation “Cause-Effect”, then all instances in unlabeled data containing the entity pair “suicide” and “death” will be automatically labeled the relation “Cause-Effect”. Different from the distant supervision, our discovery strategy

is restrictive, which can discover specific relation type to deal with the imbalance problem of the original dataset. After our adversarial training process, we obtain a selector that can select the most confusing instances from noisy dataset meanwhile those instances are most likely to be labeled correctly. All instances from ND selected by the selector and regarded as being labeled correctly by the discriminator will be adjusted from ND to SD. Thus, we obtain an extension of SD.

IV. EXPERIMENTS

Our experiments are intended to demonstrate that our method can obtain a large amount of data for supervised relation extraction and alleviate the noisy labeling problem. To this end, we first introduce the dataset and evaluation metrics used. Next, we show the detailed experimental settings, then compare the performance of our model to those several traditional methods. Finally, we evaluate the effects of our selector and discriminator.

A. Datasets and Evaluation

To evaluate the performance of our model, we conduct experiments on the **SemEval-2010 Task 8** dataset [4]. The dataset consists of 9 relations including a special relation NA indicating that there is no relation between entities. We construct a noisy dataset from the New York Times corpus with discovery strategy and use our adversarial training strategy to filter out the noisy instances to build a new dataset. **SemEval-2010 Task 8** defines 9 relation types and a tenth type *Other* when two entities have none of these relations. We take direction into consideration except *Other* and the total number of relation types is 19. The dataset consists of 8,000 training and 2,717 test sentences, and each sentence is annotated with a relation between two given entities. For balance, we discover 8000 instances as noisy data. Figure 3 shows the proportion of each relation type. We followed the official task setting, and report the official macro-averaged F1-score (Macro-F1) on the 9 relation types (excluding *Other*).

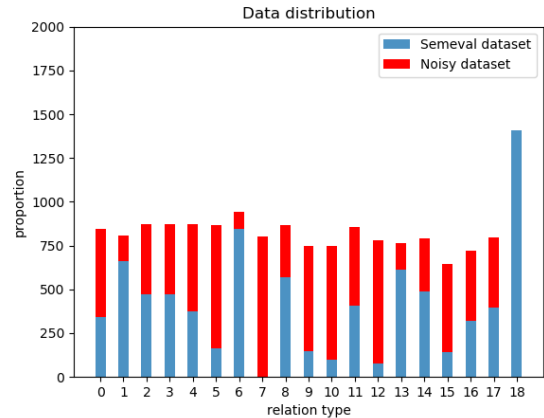


Fig. 3. Data distribution. Considering direction, We use two numbers to represent each relation type respectively.

TABLE I
HYPERPARAMETER SETTINGS

Hyperparameter	Value
Window size	3
Feature maps	230
Word embedding	50
Position embedding	5
Max sequence length	128
Training epochs	5.0
Learning rate of S, D	0.005, 0.01
Dropout rate	0.5

B. Experimental Settings

In this paper, we use the pre-trained word embeddings Glove [29] as the initial word embeddings. For PCNN encoder, we follow the settings used in their papers [9] for fair comparisons. For adversarial training, we use a grid search to determine the optimal parameters and select learning rate λ_1 for S among $\{0.1, 0.01, 0.001, 0.005\}$ and λ_2 for D among $\{0.1, 0.01, 0.001\}$. Table I shows the main parameters used in the experiments.

C. Comparison with other Methods

Overall Evaluation Results: Results of various neural models are demonstrated in table II. We compare our model with various neural baselines, including SVM, RNN, CNN, Attention CNN and Attention BiLSTM. Table II reports the results. We can see that our model significantly beats all the baseline models. The MACRO F1 value of PCNN-AD is 87.61, which is much better than the previous methods.

TABLE II
COMPARISON WITH RESULTS IN THE LITERATURE.

Method	F1
SVM	82.2
RNN	77.6
CNN	82.7
CR-CNN	84.1
Attention CNN	85.9
Attention BiLSTM	85.2
PCNN-AD	87.61

In order to avoid the impact of the augmented data on the results, we add noisy data and filtered data to the original dataset respectively, and conduct experiments with CNN and PCNN model. Table III shows the results on three datasets. We can see that adding noisy data to the original data has no effect on the model even reduces its accuracy, and models trained on the filtered dataset perform better. That demonstrates that our selector can select valid training instance which labeled correctly and improve the accuracy of models.

D. Case Study

To demonstrate that our approach does select effective noisy instances, we give an example in Table IV. All hyperparameter are the same as those described in Section IV-B.

The instance in the “Semeval” row is a typical instance of the *Entity-Destination* relation, the instances in the “Discovered” row are sampled from the noisy dataset constructed by

TABLE III
THE F1 RESULTS(EXCLUDING OTHER) ON DIFFERENT DATASETS OF PREVIOUS MODELS.

Method	dataset	F1
CNN	SemEval	82.7
	+Noisy	81.8
	+Filtered	83.3
PCNN	SemEval	83.1
	+Noisy	82.9
	+Filtered	84.5

our discovery strategy, and the instance in the “Extended” row is select from the noisy dataset by our selector. Compared to most of discovered instances which are totally unrelated, the instances selected by selector always express this relation. This demonstrates that our methods can filter out noisy instances and accomplish utilizing large amount of unlabeled data to enrich labeled data.

TABLE IV
THE EXAMPLE OF EXTENDED DATA.

dataset	Entity-Destination(e1, e2)
Semeval	several cats ran into rob’s garage
Discovered	some cats left the garage those cats are in the garage cats walk into the garage
Extended	cats walk into the garage

V. CONCLUSION AND FUTURE WORK

In this paper, we take advantages of adversarial training and propose an effective method for supervised RE. To be specific, we designed a selector and discriminator framework with PCNN. The selector selects higher quality adversarial examples, which allow the discriminator model to learn better, as well as automatically construct a large dataset. The experiments show that the adversarial training framework brought significant improvements to relation extraction. In the future, we plan to explore the following directions: (1)We will propose our adversarial training method based on advanced sentence encoder. (2)We will develop a large-scale and clean dataset for RE based on our method, which will benefit further research in this field.

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