Abstract

Distant supervision has been widely used for relation extraction but suffers from noise labeling problem. Neural network models are proposed to denoise with attention mechanism but cannot eliminate noisy data due to its non-zero weights. Hard decision is proposed to remove wrongly-labeled instances from the positive set though causes loss of useful information contained in removed instances. In this paper, we propose a novel generative neural framework named **RDSGAN** (Rank-based Distant Supervision GAN) which automatically generates valid instances for distant supervision relation extraction. Our framework combines soft attention and hard decision to learn the distribution of true positive instances via adversarial training and selects valid instances conforming to the distribution via rank-based distant supervision, which addresses the false positive problem. Experimental results show the superiority of our framework over strong baselines.

1 Introduction

Relation extraction is fundamental for constructing large scale knowledge bases, which aims to extract the relations between entity pairs. One popular way to handle this task is distant supervision (Mintz et al., 2009) which automatically generates numerous labeled data via aligning text with the existing knowledge bases. However, generated training data contains numerous noisy samples due to the strong assumption. To tackle this issue, most recent state-of-the-art methods perform neural networks (Du et al., 2018; Li et al., 2019; Beltagy et al., 2019) on denoising operation with distant supervision. Various attention mechanisms (Lin et al., 2016; Han et al., 2018; Gao et al., 2019) are proposed for calculating precise attention weights over instances, but soft attention mechanism usually assigns non-zero weights to noisy instances, which does not eliminate noisy data. Qin et al. (2018a,b); Ma et al. (2019) argue that wrongly-labeled instances must be treated with hard decision by removing false positive instances from the positive set, though hard decision may cause loss of useful information contained in removed instances. In order to keep as much useful information and reduce as much noise as possible, combining both soft attention and hard decision to learn the distribution of true positive instances is a better choice.

In this paper, we propose a novel generative neural framework Rank-based Distant Supervision GAN (named RDSGAN). Firstly, we train the framework to learn the distribution of true positive instances excluding false positive instances via adversarial training and selects valid instances conforming to the distribution via rank-based distant supervision, which addresses the false positive problem. Finally, the framework can automatically generate massive valid instances\(^1\) and thus provide a clean dataset for distant supervision relation extraction.

Our contributions are summarized as follows:

1. We propose a novel generative neural framework which learns the distribution of true positive instances and automatically generates massive valid instances to provide a clean dataset for distant supervision relation extraction.

2. We propose the method of rank-based distant supervision to address the false positive problem.

2 Methodology

In this section, we present the procedure of our framework, details of adversarial training and rank-based distant supervision as follows.

\(^1\)Valid instances include true positive and true negative instances.
Figure 1: Overview of RDSGAN. Input instances are the concatenation (denoted by ⊕) of encoded embeddings including: a) sentence 0 from the generator (denoted by G) with the triplet (head, relation, tail), and b) sentence 1 to m from instances in NYT dataset. Firstly, input instances are fed into the discriminator (denoted by D) for adversarial training. Secondly, we fix D and rank instances in the ranking module (denoted by Ranking) and also perform relation classification for rank-based distant supervision. Please see Section 2 for more details.

### 2.1 Framework

As illustrated in Figure 1, input instances are the concatenation of encoded embeddings of sentence 0 to m, we initialize the discriminator (D) and the generator (G) with random weights \( \theta_d \) and \( \theta_g \). In the first phase, input instances are fed to train D to learn the distribution of true positive instances, then G is trained to generate instances more similar to real ones. In the second phase, we fix D and use ranking module to rank mixed instances, then we select instances conforming to the distribution based on selective attention (Lin et al., 2016), which produces the bag representation for relation classification. Rank loss \( L_1 \) and relation classification loss \( L_2 \) are added (denoted by \( \oplus \)) with weights to optimize G to generate a valid instance in one bag for building up a clean dataset for distant supervision. The complete training procedure of the framework is shown in Algorithm 1.

### 2.2 Adversarial Training

#### 2.2.1 Generator

The target of the generator is to generate a vector sequence representing a clean and valid instance which conforms to the distribution of true positive data. As shown in Figure 1, The decoder-based generator is fed into a triplet \((h, r, t)\) and outputs a valid vector sequence. Hence, given the triplet of \((h, r, t)\), we first map \( h \) and \( t \) into vectors via their word embeddings and map \( r \) via a relation matrix \( A \in \mathbb{R}^{N_r \times d_r} \), i.e. \( e_r = Ae_r \), where \( N_r \) is the number of all relation classes, and \( d_r \) is the dimension of sentence embedding, \( r \) is the query vector associated with relation \( r \). The input of the generator is the sum of the three vectors:

\[
z = e_h + W_g e_r + e_t \tag{1}\]

In detail, we utilize Bidirectional-GRU (BiGRU) for the decoder and place dropouts on the hidden states of BiGRU. The generation process can be formulated as:

\[
h_{i+1} = BiGRU(h_i) \tag{2}\]

where \( h_i \in \mathbb{R}^d \) is the hidden vector of the BiGRU and \( h_0 = z \). The generation process goes on until it reaches the aligned sentence length \( L \). After the generation, we obtain a sentence bag \( X = \{x_0, x_1, \ldots, x_m\} \) shown in Figure 1, then we feed the sentence bag into the discriminator.
2.2.2 Discriminator

The discriminator is designed to learn the distribution of the true positive data, for each instance in a sentence bag, the discriminator calculates its probability of coming from the real data as follows:

\[ L_D(x_i, \theta_d) = \log D(x_i) + \log(1 - D(x_i)) \]  

(3)

where \( i = 0, 1, \ldots, m \) and \( m \) is the number of instances in a bag. Hence, as for instances \( x \) in the \( j \)-th bag \( M_j \) in the training data, the discrimination loss \( L_D \) can be formulated as:

\[ L_{D(M_j)} = \sum_{x_i \in M_j} (\log D(x_i) + \log(1 - D(x_i))) \]  

(4)

2.3 Rank-based Distant Supervision

As shown in Figure 1, Ranking and Classifier perform rank-based distant supervision. Given a bag \( M \) containing \( m \) instances related to entity pair \((h, t)\), the representation of \( M \) and the conditional probability of \((h, t)\) expressing relation \( r \) are respectively calculated as:

\[ q = \sum_{i=1}^{N_r} \alpha_i x_i, \quad p(r|M; \Theta) = \frac{\exp(o_r)}{\sum_{i=1}^{N_r} \exp(o_i)} \]  

(5)

where \( q \) is the representation of \( M \), \( \alpha_i \) is the attention weight for each sentence \( x_i \). \( N_r \) is the total number of relation classes. \( \Theta \) represents all the parameters, and \( o_r \) is the score for relation \( r \):

\[ o = W_r q + b_2 \]  

(6)

where \( W_r \) is weight matrix and \( b_2 \) is a bias vector.

We further define the loss function for rank-based distant supervision as the sum of rank loss \( L_1 \) and relation classification loss \( L_2 \) with their respective weights \( \lambda_1, \lambda_2 > 0 \):

\[ L = \lambda_1 L_1 + \lambda_2 L_2 \]  

(7)

**Rank Loss:** In the ranking module, for all the instances in one bag, an instance containing less or no noise has higher attention weights and thus ranks higher. Hence, we attempt to make the generated instance rank in top-\( k \) (\( k \) is a hyperparameter), and rank loss of the generated instance \( L^{G}_{rank} \) in a bag is calculated as follows:

\[ L^{G}_{rank} = \frac{\exp(e_i)}{\sum_{i=1}^{k} \exp(e_i)} \]  

(8)

where \( e_i \) is referred to as a query-based function which scores how well the input instance \( x_i \) and the predicting relation \( r \) matches. The rank loss \( L_1 \) can be calculated as the average of the rank loss of each bag, where \( m \) is the number of instances in a sentence bag:

\[ L_1 = \frac{1}{m} \sum_{i=1}^{m} L^{G}_{rank} \]  

(9)

**Relation Classification Loss:** We define the loss of relation classification \( L_2 \) using cross-entropy:

\[ L_2 = \sum_{i=1}^{N_r} \log p(r_i|M_i; \Theta) \]  

(10)

3 Experiments

3.1 Experiment Setup

We conduct experiments on Riedel dataset (Riedel et al., 2010), which aligns Freebase relations with the New York Times (NYT) corpus. The dataset contains 53 relations including no relation “NA”. There are 522,611 sentences linked to 281,270 entity pairs for training and 172,448 sentences linked to 96,678 entity pairs for testing.

In our experiments, we adopt stochastic gradient descent (SGD) as optimization strategy. We select the word dimension as 50, position dimension as 10, kernel size as 3, the number of feature maps or filters as 230, batch size as 160, aligned sentence length \( L \) as 120, and the dropout probability as 0.5. We also set the learning rate of generator and discriminator as 1e-5 and 1e-4 respectively.

Following previous works, we evaluate our framework on the held-out evaluation. We adopt Precision@N (P@N), area under curve (AUC) and aggregated Precision-Recall (PR) curves as evaluation metrics to illustrate the performance of our proposed framework.

3.2 Performance Evaluation of RDSGAN

We adopt following baselines for distant supervised relation extraction. Mintz (Mintz et al., 2009), MultiR (Hoffmann et al., 2011) and MIML (Surdeanu et al., 2012): Non-neural models based on handcrafted features. CNN+ATT and PCNN+ATT (Lin et al., 2016): Robust CNN-based models reducing noisy data based on selective attention mechanism. DSGAN+ATT (Qin et al., 2018a): A robust model using GAN to recognize true positive data. PDCNN+ATT (Peng et al., 2019): A dilated CNN-based model with soft entity type constraints.
The overall performance of our method compared with aforementioned baselines for distant supervised relation extraction is shown in Table 1. We can see that our method achieves much better results on P@N (100, 200, 300) metrics, and improves the AUC value by 8.98% and 7.69% compared to DSGAN+ATT and PDCNN+ATT respectively. The huge improvement comes from rank-based distant supervision which reduces much false positive data for relation extraction.

| P@N  | 100  | 200  | 300  | Mean | AUC  |
|------|------|------|------|------|------|
| CNN+ATT | 76.2 | 68.6 | 59.8 | 68.2 | 0.33 |
| PCNN+ATT | 76.2 | 73.1 | 67.4 | 72.2 | 0.35 |
| DSGAN+ATT | 78.0 | 75.5 | 72.3 | 75.3 | 0.35 |
| PDCNN+TATT | 83.2 | 81.1 | 76.4 | 80.2 | 0.36 |
| RDGSAN+ATT | 88.9 | 85.3 | 81.1 | 85.1 | 0.39 |

Table 1: Overall performance at P@Ns(%) and AUC values of different models on the NYT dataset

We also plot PR curves between different models shown in Figure 2 with recall number smaller than 0.4. From the overall result, we can see that: (1) All the non-neural baselines perform poorly as their features used by them are mostly derived from NLP tools, which can be erroneous. (2) CNN+ATT and PCNN+ATT improve the performance because they utilize sentence-level selective attention to reduce noise in the bag of entity pair. (3) PDCNN+TATT further enhances the performance as it incorporates soft entity type constraints to improve attention mechanism. (4) Our method RDGSAN+ATT achieves the best precision over the entire range of recall on the NYT dataset. As the recall rate increases, the precision rate of RDGSAN+ATT decreases more slowly than other models and outperforms PDCNN+ATT by 6% on average. It shows that our proposed framework can consistently generate valid instances to promote the performance for distant supervision relation extraction.

4 Related Work

**Generative Adversarial Training:** Recent studies have proposed several GAN-based methods utilizing gradient information in adversarial training to generate instances for relation extraction. Qin et al. (2018a) proposes DSGAN to recognize true positive instances from noisy dataset via reinforcement learning (Yu et al., 2017). Li et al. (2019) uses GAN-driven semi-distant supervision approach to construct accurate instances and avoid wrong negative labeling. Zhao (2019) proposes an auxiliary classifier in the discriminator to generate high-quality training data for relation classifiers. Unlike previous models focusing on discrimination, we focus on generating valid instances to provide a clean dataset for relation extraction.

**Neural Relation Extraction:** In recent years, neural network models have shown superior performance on denoising operation over relation extraction. Zhang et al. (2018) explores the attention-based capsule networks in a multi-instance multi-label learning (MIML) framework. Bai and Ritter (2019) employs minimally structured learning to predict instance-level relation mentions. Beltagy et al. (2019) utilizes joint training on distant supervision to identify noisy sentences. Most recently, BERT (Devlin et al., 2018) and its variants (Shi and Lin, 2019; Soares et al., 2019; Papanikolaou et al., 2019) have been proposed to leverage attention mechanism and transformer to learn word contextual relations. Unlike previous approaches, we utilizes rank-based distant supervision which combines both soft attention and hard decision to reduce noise.

5 Conclusion

In this paper, we propose RDGSAN, a novel generative neural framework which learns the distribution of true positive instances and automatically generates massive valid instances to provide a clean dataset for distant supervision relation extraction. We propose the method of rank-based distant supervision to address the false positive problem. Experimental results on the NYT dataset shows the superiority of our framework over strong baselines.
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