

# Improving Distantly Supervised Relation Extraction with Neural Noise Converter and Conditional Optimal Selector

**Shanchan Wu**

Alibaba Group (U.S.) Inc.  
shanchan.wu@alibaba-inc.com

**Kai Fan**

Alibaba Group (U.S.) Inc.  
k.fan@alibaba-inc.com

**Qiong Zhang**

Alibaba Group (U.S.) Inc.  
qz.zhang@alibaba-inc.com

## Abstract

Distant supervised relation extraction has been successfully applied to large corpus with thousands of relations. However, the inevitable wrong labeling problem by distant supervision will hurt the performance of relation extraction. In this paper, we propose a method with neural noise converter to alleviate the impact of noisy data, and a conditional optimal selector to make proper prediction. Our noise converter learns the structured transition matrix on logit level and captures the property of distant supervised relation extraction dataset. The conditional optimal selector on the other hand helps to make proper prediction decision of an entity pair even if the group of sentences is overwhelmed by no-relation sentences. We conduct experiments on a widely used dataset and the results show significant improvement over competitive baseline methods.

## Introduction

The task of relation extraction (RE) is to predict semantic relations between pairs of entities in text. To alleviate the work load of obtaining the training data for relation extraction, distant supervision is applied to collect training data for learning a model. Relation extraction (RE) under distant supervision heuristically aligns entities in texts to some given knowledge bases (KBs). For a triplet  $(e_1, r, e_2)$ , where  $e_1$  and  $e_2$  are a pair of entities with relation type  $r$  in KBs, distant supervision assumes that all sentences that contain both entities  $e_1$  and  $e_2$  will express the same relation type  $r$  which will be used in training.

Although distant supervision is an effective way to automatically label training data, it always suffers from the problem of wrong labeling. For example, *(Mark Zuckerberg, founder, Facebook)* is a relational triplet in KBs. Distant supervision will regard all sentences that contain *Mark Zuckerberg* and *Facebook* as the instances containing relation *founder*. For example, the sentence “*Mark Zuckerberg uses Facebook to visit Puerto Rico in VR.*” does not express the relation *founder* but will still be regarded as a positive instance containing that relation type. This will introduce noise into the training data.

Tackling the noisy data problem for distant supervision is a non-trivial problem, as there is not any explicit supervision for the noisy data. Some previous work tries to clean

the noisy training data. Takamatsu, Sato, and Nakagawa propose a solution to identify those potential noisy sentences and remove them from training data by syntactic patterns during the preprocessing stage. Although the effort of removing noise during preprocessing is practically effective, it has to rely on manual rules and hence is unable to scale. Some other work directly makes effort to reduce the impact of the noisy data during the training process. Riedel, Yao, and McCallum make the *at-least-one* assumption that if two entities participate in a relation, at least one sentence that mentions these two entities might express that relation. They then propose a graphical model to build relation classifier. There are some following works based on this assumption using probabilistic graphic models (Hoffmann et al. 2011; Surdeanu et al. 2012), and neural network methods (Zeng et al. 2015). The methods based on *at-least-one* assumption can reduce the impact of some noisy sentences. However, it can also lose a large amount of useful information containing in neglected sentences. Lin et al. propose to use sentence-level selective attention mechanism to reduce the noise through a sentence bag. The selective attention mechanism represents a group of sentences including the same entity pair into a vector representation, and then use it for classification. This method has very significant improvement over other previous methods. The selective attention mechanism uses the information of all sentences in the group containing the entity pair. Moreover, it still considers that the label of the group of sentences in the training data is always correct, and it is further used to derive the loss function. However, under distant supervision, it is very likely that none of the sentences in the same sentence group with the same entity pair express the semantic relation decided by KBs. Neither *at-least-one* solution nor selective attention solution is able to handle this situation properly.

In this paper, we propose a model with neural noise converter and conditional optimal selector for distant supervised relation extraction to tackle the noisy data problem. We regard the relation label for a pair of entities decided by KBs as a noisy label for the corresponding group of sentences obtained by distant supervision. We build a neural noise converter which tries to build the connection between true labels and noisy labels. Our final prediction output is then based on the prediction of true labels rather than noisy labels using a conditional optimal selector. Some previous works in com-

puter vision such as (Sukhbaatar et al. 2015) have used a “noise” layer on top of the softmax layer to adapt the softmax output to match the noise distribution. Our noise converter is different from theirs as our noise converter is on top of logits rather than softmax, and we take advantage of the properties in the distantly supervised relation dataset and impose a reasonable constraint to the transition matrix. One advantage is that we do not need to project the transition matrix to the space representing a valid probability distribution for each update. Another advantage is that the linear transition on hidden vectors can achieve non-linear transition results on probability space. Our noise converter can also theoretically converge to its optimal value. The conditional optimal selector on the other hand helps to make proper prediction decision of an entity pair even if the corresponding group of sentences are overwhelmed by no-relation sentences.

Our main contributions in this paper are: (1) We propose a novel model named neural noise converter to better deal with noisy relational data. (2) We design a conditional optimal selector to help make proper prediction among sentence bags. (3) Our experimental results demonstrate the effectiveness of our approach over the state-of-the-art method.

## Related Work

In recent years, convolutional neural networks (CNN) have been successfully applied to relation extraction (Santos, Xiang, and Zhou 2015; Nguyen and Grishman 2015). Besides the typical CNN, variants of CNN have also been developed to relation extraction, such as piecewise-CNN (PCNN) (Zeng et al. 2015), split CNN (Adel, Roth, and Schütze 2016), CNN with sentencewise pooling (Jiang et al. 2016) and attention CNN (Wang et al. 2016). Furthermore, recurrent neural networks (RNN) are another successful choice for relation extraction, such as recurrent CNNs (Cai, Zhang, and Wang 2016) and attention RNNs (Zhou et al. 2016).

For relation extraction, the effect of wrongly labeled training data has been attracted attention and some recent works have been proposed to reduce the influence. Among the works, some of them attempt to clean the noisy training data, such as (Takamatsu, Sato, and Nakagawa 2012). The work in (Xu et al. 2013) tries to find possible false negative data through pseudo-relevant feedback to expand training data. Some other works directly make effort to reduce the impact of the noisy data during the training process, such as (Riedel, Yao, and McCallum 2010; Hoffmann et al. 2011; Surdeanu et al. 2012; Zeng et al. 2015). Lin et al. propose to use instance-level selective attention mechanism to reduce the noise through a sentence bag. The approach has significantly improved the prediction accuracy for several baselines of deep learning models.

Out of the NLP domain, in computer vision, recently there are some proposed methods to fit the noisy data. Reed et al. propose a bootstrapping mechanism by augmenting the prediction objective with a concept of perceptual consistency to make the model more robust to noise. Sukhbaatar et al. add a linear “noise” layer on top of the softmax layer which adapts the softmax output to match the noise distribution. The main issue in (Sukhbaatar et al. 2015) is that the parameters of the extra layer in their proposed model is not

identifiable, and they circumvent this problem by using a tricky optimization process. Rather than optimizing a global transition matrix, Misra et al. generate the transition matrix in an amortized way for each training instance. In NLP, as far as we know, the only couple of works that are based on neural network noise model are (Fang and Cohn 2016) and (Luo et al. 2017). The key difference is that we do not follow the previous work by directly adapting the softmax output. Instead, we creatively make transition on logits output and we address the identifiable issue by adding extra constraint to the transition matrix.

## Methodology

Given a set of sentences  $\{s_1, s_2, \dots, s_N\}$ , with each containing a corresponding pair of entities, our model predicts the relation type  $r$  for each entity pair. Figure 1 shows the overall neural network architecture of our model. It primarily consists of three parts: Sentence Encoder Module, Neural Noise Converter Module, and Conditional Optimal Selector Module. Sentence Encoder uses a variant of convolutional neural network (CNN) to process a given sentence with a pair of target entities to a vector representation. After constructing the vector representation of the sentence, Neural Noise Converter Module converts the hidden state with respect to the true label to the hidden state with respect to the noise label. Conditional Optimal Selector is a mechanism to make prediction based on a group of sentences with the same entity pair. We describe these parts in details below.

### Sentence Encoder

Similar to (Zeng et al. 2015; Lin et al. 2016; Ji et al. 2017), we transform a sentence into its vector representation by piecewise CNN (PCNN, a variant of CNN). First a sentence is transformed into a matrix with word embeddings and position embeddings. Then a convolutional layer, max-pooling layer and non-linear layer are used to construct a vector representation of the sentence.

**Word Embeddings and Position Embeddings** Word embeddings are distributed representations of words, which are usually pre-trained from a text corpus and can capture syntactic and semantic meanings of the words. Similar to (Zeng et al. 2014), we use the word position information besides the word embeddings. The position information has shown its importance in relation extraction. The position feature values of a word are determined by the distances between this word and the two target entity words. Each relative position value is encoded as a vector which is randomized at the beginning and updated during the training. Then the word embeddings and position embeddings are concatenated, and a sentence is then originally encoded as a vector sequence  $X = \{x_1, x_2, \dots, x_{|X|}\}$ , where  $x_i \in \mathbb{R}^d$  ( $d = d^a + d^b \times 2$ ),  $d^a$  is the dimension of a word embedding, and  $d^b$  is the dimension of a position embedding.

**Convolution** Suppose matrix  $A$  and  $B$  has the same dimension  $t_1 \times t_2$ , then the convolution operation between  $A$  and  $B$  is defined as  $A \otimes B = \sum_{i=1}^{t_1} \sum_{j=1}^{t_2} A_{ij} B_{ij}$

Given an input vector sequence  $X = \{x_1, x_2, \dots, x_{|X|}\}$

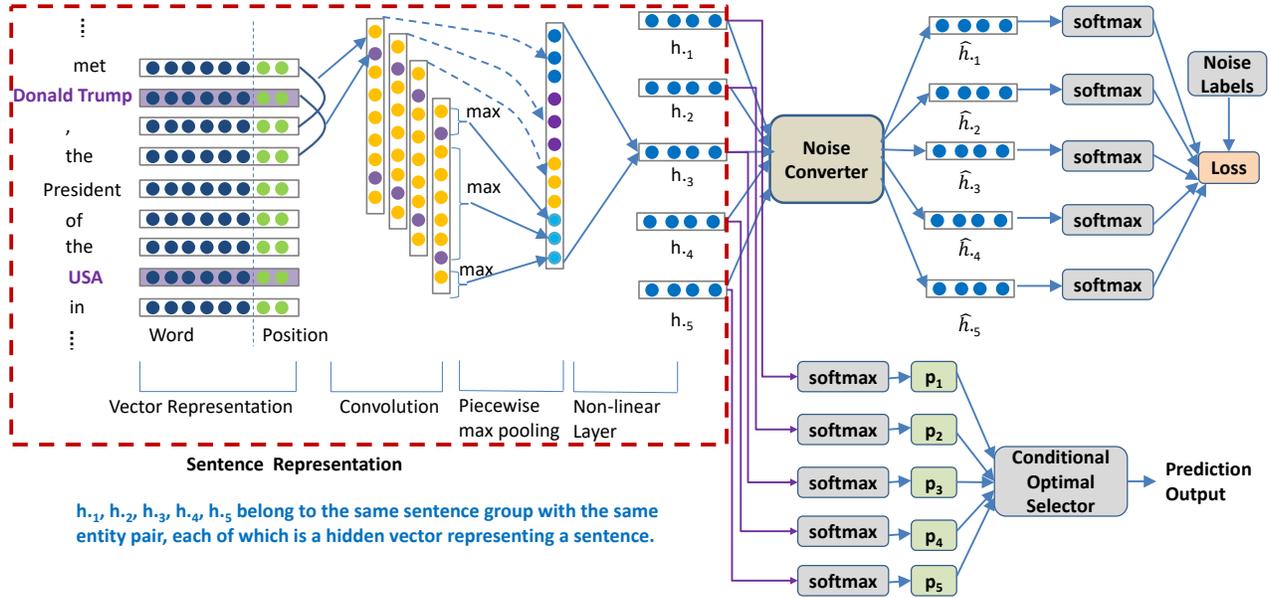


Figure 1: The model architecture. The left side shows the sentence encoder by PCNN. The example sentence is encoded to a hidden vector  $h_{i,3}$ . Four other sentences with the same entity pair are encoded as  $h_{i,1}, h_{i,2}, h_{i,4}, h_{i,5}$ . The noise converter converts each hidden vector. Softmax and loss function are applied thereafter. The conditional optimal selector is used to make prediction based on the hidden vectors which the noise converter is applied to.

of a sentence, where  $x_i \in \mathbb{R}^d$  represents the vector of the  $i$ -th word in the sentence. Let  $X_{i:j} = [x_i : x_{i+1} : \dots : x_j]$  be a matrix by concatenating the vectors from the  $i$ -th vector to the  $j$ -th vector, and let  $U = \{U_1, U_2, \dots, U_m\}$  be a list of filter matrixes, where the  $t$ -th filter matrix is  $U_t \in \mathbb{R}^{l \times d}$ . The convolution operation output between  $X$  and  $U_t$  will be a new vector  $c_t \in \mathbb{R}^{|X|-l+1}$ , the  $i$ -th element of which is  $c_{ti} = U_t \otimes X_{i:(i+l-1)}$ . Through the convolution operation between  $X$  and the list of filter matrixes  $U = \{U_1, U_2, \dots, U_m\}$ , we get a list of output vectors  $C = \{c_1, c_2, \dots, c_m\}$ .

**Max-pooling and non-linear layer** The max-pooling operation is a widely used method to extract the most significant features inside a feature map. To capture the structure information, PCNN divides a sequence into three parts based on the positions of the two target entities which cut the sequence into three pieces. Then the piecewise max pooling procedure returns the maximum value in each subsequence instead of a single maximum value. As shown in Figure 2, the output vector  $c_i$  from convolution operation is divided into three segments,  $\{c_{i1}, c_{i2}, c_{i3}\}$  by *Donald Trump* and *USA*. The piecewise max pooling procedure is applied to each of the three segments separately:

$$p_{i1} = \max(c_{i1}), p_{i2} = \max(c_{i2}), p_{i3} = \max(c_{i3})$$

So for each convolution filter, we can get a vector  $p_i = \{p_{i1}, p_{i2}, p_{i3}\}$  with 3 elements. After that, we can concatenate the vectors from  $p_1$  to  $p_m$  to obtain the final max pooling output vector  $P \in \mathbb{R}^{3m}$ .

We then apply a non linear layer on the max pooling output. We also apply dropout on this layer for regularization during training.



Figure 2: An example of relative distances

## Neural Noise Converter

For the training data obtained from distant supervision, their labels are usually noisy or incorrect. To incorporate the noise information, we propose a neural noise converter module that can capture the relationship between the underlying true labels and the noisy labels.

We denote  $y^*$  and  $\tilde{y}$  to be the true label and the observed label (i.e., the noisy label) of the sentence  $s$ , where  $y^*, \tilde{y} \in \{1, \dots, K\}$ . In addition, we define two probabilistic models  $p(y^*|s)$  and  $p(\tilde{y}|s)$  to represent the distributions of true and noisy labels, respectively. For notation simplicity, we abuse using  $p(y^* = k)$  as the alternative of  $p(y^* = k|s)$ .

A natural way to convert the true label to the noisy one is to build a linear transformation by assuming the existence of an optimal probabilistic transition matrix  $Q^* = (q_{uv}^*) \in \mathbb{R}^{K \times K}$  where  $q_{uv}^* = p(\tilde{y} = u|y^* = v)$  (Sukhbaatar et al. 2015). That is to say we can build the following connection

$$p(\tilde{y} = u) = \sum_{v=1}^K q_{uv}^* p(y^* = v). \quad (1)$$

However, we extend it to an implicit transformation by a

neural noise converter module, via enforcing a linear transformation on the softmax logits which are used to calculate the relation type distribution.

To make it concrete, we define  $p(y^*) \sim \text{softmax}(h^*)$ , where the hidden vector  $h^*$  is the softmax logits for true labels. Similarly, we have  $p(\tilde{y}) \sim \text{softmax}(\tilde{h})$  and the hidden vector  $\tilde{h}$  for noisy labels. In other words, we have

$$\begin{aligned} p(y^* = k) &= \frac{\exp(h_k^*)}{\sum_{j=1}^K \exp(h_j^*)} \\ p(\tilde{y} = k) &= \frac{\exp(\tilde{h}_k)}{\sum_{j=1}^K \exp(\tilde{h}_j)} \end{aligned} \quad (2)$$

Unlike the explicit transformation in probability space (Sukhbaatar et al. 2015), we assume an optimal logits transition matrix  $W^* = (w_{ij}^*) \in R^{K \times K}$ , such that

$$\tilde{h} = W^* h^*. \quad (3)$$

A special case is that if  $W^*$  is an identity matrix, then it means there is no noise in the observed data. Equivalently, we can rewrite Equation (2) and (3) to obtain the following approximate linear transformation (due to the presence of  $\tilde{Z}$  and  $Z^*$  in Equation (4), it is not exact linear) in the log-space of probability,

$$\log p(\tilde{y} = k) = \sum_{j=1}^K w_{kj}^* (\log p(y^* = j) + \log Z^*) - \log \tilde{Z} \quad (4)$$

where  $Z^*$  and  $\tilde{Z}$  are two normalizing terms in Equation (2). In this case, we can not analytically provide the total probability rule as Equation (1), but we actually define it in the implicit way. Notice that the biggest issue in (Sukhbaatar et al. 2015) is the identifiable problem of  $Q^*$ , which also appears in the above definition of  $W^*$ , since there are  $K^2$  free parameters involving only  $K$  equations. To make our model robust and well-defined during optimization, we suggest imposing some constraint on  $W^*$  according to specific tasks.

### Structured Transition Matrix

In this section, we take advantage of the properties in the distantly supervised relation dataset to impose the restriction on the transition matrix  $W^*$ . When two entities are labeled by some relation type, there should be some sentences with that two entities showing that relation type somewhere in the world, but not necessarily in the sentences extracted by distant supervision. Meanwhile, that pair of entities in the extracted sentences will rarely show relation types other than ‘no-relation’ or the types that are assigned to this pair from the knowledge base used for distant supervision. So the transition matrix should primarily transfer ‘no-relation’ (which is labeled as ‘1’, or negative relation) to positive relations (labeled other than ‘1’), but unlikely between positive relations or from positive relations to ‘no-relation’. Hence, in the situation of this distant supervised relation extraction task, the transition matrix is assumed in the following form in Equation (5), where the values in diagonal are all 1 except

the first one, the rest values except those in the first column and the diagonal are all 0s.

$$W^* = \begin{bmatrix} w_{11}^* & 0 & 0 & \dots & 0 \\ w_{21}^* & 1 & 0 & \dots & 0 \\ w_{31}^* & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{K1}^* & 0 & 0 & \dots & 1 \end{bmatrix} \quad (5)$$

Besides the identifiable issue, another purpose to introduce the structured constraint is to guarantee the softmax operation invertible with respect to  $W^*$  when  $h^*$  is given.

### Transition Matrix Estimation

Let  $\hat{p}(y^*|\theta)$  be the prediction probability of true labels by the classification model parameterized by  $\theta$ . Therefore, we can build an extra affine layer with the parameter  $W$  (same structure as  $W^*$ ) on top of the softmax logits layer of the true label prediction, converting the distribution of the true labels to the distribution of the noisy labels, i.e.,  $\hat{p}(\tilde{y}|\theta, W)$ .

Due to the mechanism of distant supervision, the collected dataset are naturally divided into several groups with the same observed entity pairs. Thus we can define a customized loss function for the combined noisy model by maximizing the cross-entropy between the observed noisy labels and the model prediction of  $\hat{p}(\tilde{y}|\theta, W)$  for the sentences in each group. The equivalent loss function to minimize is

$$\mathcal{L}(\theta, W) = -\frac{1}{G} \sum_{g=1}^G \frac{1}{|\mathcal{S}_g|} \sum_{n_g=1}^{|\mathcal{S}_g|} \log \hat{p}(\tilde{y} = r_g | s_{n_g}, \theta, W) \quad (6)$$

where  $G$  is the total number of entity pairs in the training data,  $r_g$  is the observed noisy label in the sentence group  $\mathcal{S}_g$  which contains entity pair  $E_g$ , and  $s_{n_g}$  is the sentence included in  $\mathcal{S}_g$ .

Our purpose is to learn a model such that  $W$  is close the underlying optimal  $W^*$ . Let  $\hat{h}$  be the model output of the hidden vector before softmax operation for the noisy labels, and  $h$  be the model output of hidden vector before softmax operation for the true labels. Similar to Equation (3) we have  $\hat{h} = Wh$ , thus resulting the following categorical distribution.

$$\begin{aligned} \hat{p}(\tilde{y} = k | s, \theta, W) &= \frac{\exp(\sum_{j=1}^K w_{kj} h_j)}{\sum_{i=1}^K \exp(\sum_{j=1}^K w_{ij} h_j)} \\ &= \frac{\exp(w_{k1} h_1 + h_k \mathbb{I}_{k \neq 1})}{\sum_{i=1}^K \exp(w_{i1} h_1 + h_i \mathbb{I}_{i \neq 1})} \end{aligned} \quad (7)$$

By the above Equation (7), we can further reformulate the

loss function and derive a non-negative lower bound,

$$\begin{aligned} \mathcal{L}(\theta, W) &= \frac{1}{G} \sum_{g=1}^G \frac{1}{|\mathcal{S}_g|} \sum_{n_g=1}^{|\mathcal{S}_g|} \left( \log \sum_{i=1}^K \exp \left( \sum_{j=1}^K w_{ij} h_{j,n_g} \right) \right. \\ &\quad \left. - \sum_{j=1}^K w_{r_g j} h_{j,n_g} \right) \\ &\geq \frac{1}{G} \sum_{g=1}^G \frac{1}{|\mathcal{S}_g|} \sum_{n_g=1}^{|\mathcal{S}_g|} \left( \max_{1 \leq i \leq K} (w_{i1} h_{1,n_g} + h_{i,n_g} \mathbb{I}_{i \neq 1}) \right. \\ &\quad \left. - w_{r_g 1} h_{1,n_g} - h_{r_g,n_g} \mathbb{I}_{r_g \neq 1} \right) \geq 0 \end{aligned} \quad (8)$$

where  $h_{j,n_g}$  is the  $j$ th element of the hidden vector for the sentence  $s_{n_g}$ . Based on Equation (8), when  $G \rightarrow \infty$  and  $|\mathcal{S}_g| \rightarrow \infty$ , an ideal optimization of  $\mathcal{L}(\theta, W)$  (i.e., loss approaches 0) will push  $w_{r_g 1} h_{1,n_g} + h_{r_g,n_g} \mathbb{I}_{r_g \neq 1}$  towards the maximum  $w_{i1} h_{1,n_g} + h_{i,n_g} \mathbb{I}_{i \neq 1}$  among all entity pairs, for  $\forall s_{n_g} \in \mathcal{S}_g$ . It implies that the distribution of the noisy label for each sentence can be calculated after an ideal optimization. However, we only care about the distribution of underlying real label during inference, i.e.,  $\hat{p}(y^*|\theta)$ .

In (Sukhbaatar et al. 2015), the total probability rule of the predicted model is explicitly defined in  $\hat{p}(\tilde{y}) = Q\hat{p}(y^*)$ , which implicitly defined via neural noise converter. By a deliberate optimization strategy,  $Q$  can tend to converge to the optimal unknown  $Q^*$  (Sukhbaatar et al. 2015). Using this argument, we want to show that our transition matrix  $W$  on hidden vectors can also converge to the true transformation matrix  $W^*$  by bridging  $W$  and  $Q$ . The total probability rule is always hold, thus we have

$$\hat{p}(\tilde{y}) = \text{softmax}(Wh) = Q\hat{p}(y^*) = Q\text{softmax}(h) \quad (9)$$

By the constraint of the structured transition matrix, the softmax operation is invertible with respect to  $W$ , i.e., given  $h$ , the solution of  $W$  for Equation (9) is unique. Notice the right side  $Q\hat{p}(y^*)$  is a  $K$ -dimensional vector, while the constraint  $W$  has only  $K$  free parameters. As long as  $Q$  is able to converge to the optimal  $Q^*$ , our structured transition matrix can converge to  $W^*$ .

### Conditional Optimal Selector

After the model is trained, our prediction is then based on the hidden vectors which are the input to the neural noise converter. For each pair of entities, a typical solution is to represent the group of sentences with that pair of entities as a single vector by some attention mechanism and then apply softmax to get the prediction output. However, it is difficult for a single vector representation to make correct prediction for a group overwhelmed by ‘no-relation’ sentences if only very few sentences with positive relations are included. In this situation, the solution for such a label-imbalance group will tend to make ‘no-relation’ prediction. However, the correct label for the target entity pair should be the positive relation type expressed in those few sentences.

Instead of directly computing the label distribution of the group with one single vector representation, we first consider to derive all label distributions over sentences, and then select the most representative one for the group label. The

selection criteria is basically based on the portion of predicted ‘no-relation’ type of all sentences within each group. Thus, we call it ‘‘Conditional Optimal Selector’’. For a pair of entity, if all sentences in the group are predicted to be negative (i.e. ‘no-relation’ type), we make ‘no-relation’ prediction for the entire group. Otherwise, if any sentence is predicted to be some positive relation, we will predict the group label based on the sentences with positive relation predictions, regardless of the ‘no-relation’ sentences. To be precise, the probability distribution of the group label can be formally expressed as follows.

$$\begin{aligned} &\text{if } \forall s_i, \arg \max_k \hat{p}(y_i^* = k | s_i \in \mathcal{S}_g) = 1 : \\ &\quad j = \arg \max_i \hat{p}(y_i^* = 1 | s_i \in \mathcal{S}_g) \\ &\text{else :} \\ &\quad j, \kappa = \arg \max_{(i,k), k \neq 1} \hat{p}(y_i^* = k | s_i \in \mathcal{S}_g) \\ &\hat{P}(E_g) = \hat{p}(y_j^* | s_j), \end{aligned} \quad (10)$$

Furthermore, one side-product is that the multiple positive relation types can also be learned as the final prediction if the task of multiple labels learning is required.

### Model Training

We first pretrain the model by replacing  $W$  with an identity matrix for several epochs, and then we set  $W$  to trainable parameters.

Since we have fixed value 1 in the diagonal of  $W$  (See Equation (5)), we initialize the variables in the first column in the way with their summation equal to 1, in order to make all elements in the matrix at the same scale.

One advantage of modeling  $W$  on hidden vector rather than modeling  $Q$  on probability output is that we do not need to project  $Q$  to the space representing a valid probability transition matrix for each update. Another advantage is that the linear transition on hidden vectors can achieve non-linear transition results on probability space.

## Experiments

In this section, we demonstrate that our method with noise converter and conditional optimal selector can reduce the impact of the wrong labels for relation extraction on distant supervised dataset. We first describe the dataset and the evaluation metrics that are used in our experiments, and then compare with several baseline methods. In addition, we analyze our proposed components by ablation study.

### Dataset and Evaluation Metrics

To evaluate our model, we experiment on a widely used dataset which is developed by (Riedel, Yao, and McCallum 2010) and has also been tested by (Hoffmann et al. 2011; Surdeanu et al. 2012; Zeng et al. 2015; Lin et al. 2016). We use the preprocessed version<sup>1</sup> which is made publicly available by Tsinghua NLP Lab. This dataset was generated by aligning Freebase relations with the New York Times corpus

<sup>1</sup><https://github.com/thunlp/OpenNRE>

(NYT). The Freebase relations are divided into two parts for training and testing. The training set aligns the sentences from the corpus of the years 2005-2006, and the testing one aligns the sentences from 2007. The dataset contains 53 possible relationships including a special relation type ‘NA’ which indicates no relation between the mentioned two entities. The resulted training and testing data contain 570,088 and 172,448 sentences, respectively. We further randomly extract 10 percent of relation pairs and the corresponding sentences from the training data as the validation data for model selection and parameter tuning, and leave the rest as the actual training data.

Similar to previous works (Mintz et al. 2009; Lin et al. 2016), we evaluate our model in the held-out testing data. The evaluation compares the extracted relation instances discovered from the test sentences against Freebase relation data. It makes the assumption that the inference model has similar performance in relation instances inside and outside Freebase. We report the precision/recall curves, Precision@N (P@N), and average precision in our experiments.

### Parameter Settings

We tune the parameters of maximum sentence length, learning rate, weight decay, and batch size by testing the performance on the validation dataset. For other parameters, we use the same parameters as (Lin et al. 2016). Table 1 shows the major parameters used in our experiments.

Table 1: Parameter settings.

Convolution filter window size $l$	3
Number of convolution filters	230
Sentence hidden vector size	690
Word dimension $d^a$	50
Position dimension $d^b$	5
Batch size $B$	50
Max sentence length	100
Adam learning rate $\lambda$	0.001
Adam weight decay	0.0001
Dropout rate	0.5

For the initialization of  $W$ , we use the following strategy. We define a ratio  $e$ , and assign  $w_{11} = 1 - e$ , and the rest  $K - 1$  elements to be  $e/(1 - K)$ . We do evaluation on the validation dataset and pick  $e = 0.1$  in the candidate set  $\{0.001, 0.01, 0.1, 0.2, 0.3, 0.5\}$ . We pretrain our model for 2 epochs by setting  $W$  as an identity matrix and then fine tune our model for another 18 epochs with trainable  $W$ .

### Comparison with Baseline Methods

To evaluate our proposed approach, we select several baseline methods for comparison by held-out evaluation:

**Mintz** (Mintz et al. 2009) is a traditional distant supervised model.

**MultiR** (Hoffmann et al. 2011) is a probabilistic, graphical model for multi-instance learning that can handle overlapping relations.

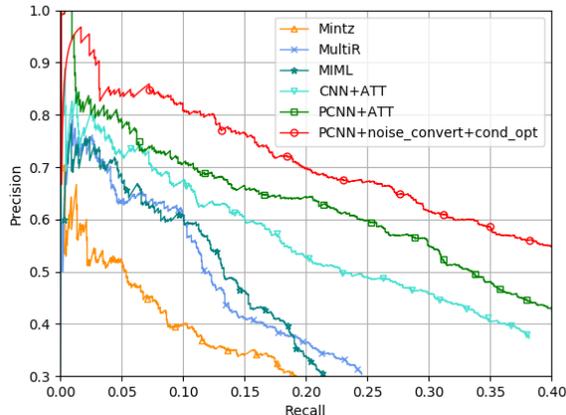


Figure 3: Performance comparison of proposed model and baseline methods. Our model and our implementation of PCNN+ATT both pick the model with the highest accuracy on the validation dataset.

**MIML** (Surdeanu et al. 2012) is a method that models both multiple instances and multiple relations.

**CNN + ATT** and **PCNN+ATT** (Lin et al. 2016) are two methods that first represent a sentence by CNN and PCNN respectively, and then use sentence-level selective attention to model a group of sentences with the same entity pair.

For the above baseline methods, we implement the state of the art method **PCNN+ATT**. To make fair comparison, we use the same implementation of the component PCNN in our model and **PCNN+ATT**, and use the same hyperparameters. For other methods, we use the results from the source code released by the authors.

For our method and **PCNN+ATT**, we run 20 epochs in total, and track the accuracy on the validation dataset. The model is saved for every 200 batches during training. We use the saved model that has the highest accuracy on the validation dataset for making predictions on the testing dataset.

Figure 3 shows the precision/recall curves for all methods, including ours (labeled as **PCNN+noise\_convert+cond\_opt**). For all of the baseline methods, we can see that PCNN+ATT shows much better performance than others, which demonstrates the effectiveness of the sentence-level selective attention. Although PCNN+ATT has shown significant improvement over other baselines, our method still gains great improvement over PCNN+ATT. Particularly, Table 2 compares the precision@N (P@N) between our model and PCNN+ATT. For PCNN+ATT, we report both the P@N numbers from the authors’ original paper and the results based on our implementation. Our method achieves the highest values for P@100, P@200, P@300, with mean value of 9.1 higher than original report of PCNN+ATT, and 7.1 higher than our implementation of PCNN+ATT. To avoid randomness in the best single model, we also compare our method and PCNN+ATT on ensemble of several saved models in one single training run. For each method, the corresponding

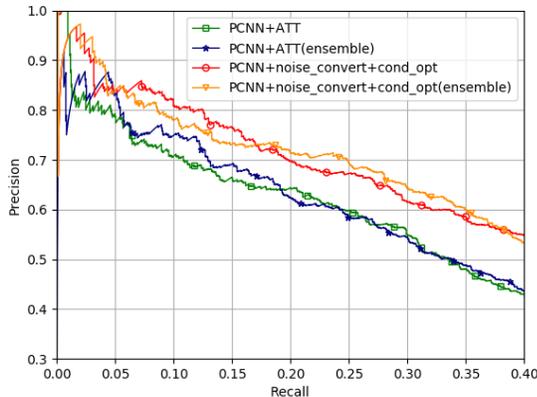


Figure 4: Performance comparison of proposed model and PCNN+ATT model, and their corresponding ensemble versions.

Table 2: Comparison of P@N for relation extraction for our model PCNN+nc+cond\_opt (same notation as PCNN+noise\_convert+cond\_opt) and PCNN+ATT

P@N (%)		100	200	300	Mean
PCNN+ATT	original report	76.2	73.1	67.4	72.2
	our implementation	81.0	72.5	69	74.2
PCNN+nc+cond_opt		<b>85.0</b>	<b>82.0</b>	<b>77.0</b>	<b>81.3</b>

ensemble model averages the probability scores for each test instance from the 5 last saved trained single models, and use the average score for prediction. Figure 4 shows the precision/recall curves of the corresponding methods with or without ensemble. We observe that the performance of the ensemble method of our method is still much better than the ensemble method of PCNN+ATT. We further compare the average precision of our method and PCNN+ATT on both single model and ensemble model, achieving 7.0 and 7.3 higher average precision scores respectively.

### Ablation Study

To understand the impact of the neural noise converter and conditional optimal selector in our model, we do two more experiments. The first one is to enforce the transition matrix in our model to be identity matrix, and keep other components and loss function remain unchanged, in order to validate the neural noise converter. We call this method as **PCNN+identity\_matrix+cond\_opt** (or PCNN+ $I_W$ +cond\_opt). Figure 5 illustrates the precision/recall curves of all comparison methods, and Table 4

Table 3: Comparison of average precision for relation extraction for our model and PCNN+ATT model

Average Precision (%)	Single model	Ensemble model
PCNN+ATT	36.5	37.9
PCNN+nc+cond_opt	<b>43.5</b>	<b>45.2</b>

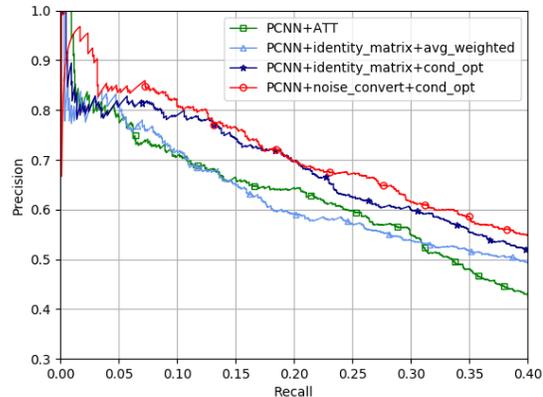


Figure 5: Performance comparison of PCNN+ATT model and our models with different components.

Table 4: Comparison of P@N for PCNN+ATT model, and our model with avg\_weighted, cond\_opt and our model with both cond\_opt and noise\_convert

P@N (%)		100	200	300	Mean
PCNN+ATT	original report	76.2	73.1	67.4	72.2
	our implementation	81.0	72.5	69	74.2
PCNN + $I_W$ +avg_weighted		83.0	74.5	68.3	75.2
PCNN + $I_W$ +cond_opt		81.0	78.5	<b>77.0</b>	78.8
PCNN+nc+cond_opt		<b>85.0</b>	<b>82.0</b>	<b>77.0</b>	<b>81.3</b>

shows the P@N values. We can see that without neural noise converter, our method is still better than the baseline method PCNN+ATT, but with neural noise converter, our method gains significantly more improvement.

In addition, we conduct the second experiment to compare our conditional optimal selector with another selector which uses the average label distribution of all sentences within each group, called **PCNN+identity\_matrix+avg\_weighted** (or PCNN+ $I_W$ +avg\_weighted). In practice, we only consider averaging the distribution in the second condition of Equation (10). In other words, this method uses the average probability of all positive predicted sentences. The results also show in Figure 5 and Table 4. We can see that this method is slightly better than PCNN+ATT, but worse than PCNN+ $I_W$ +cond\_opt.

### Conclusions

In this paper, we develop a novel model by incorporating neural noise converter and conditional optimal selector to a variant of convolutional neural network for distantly supervised relation extraction. We evaluate our model on the distantly supervised relation extraction task. The experimental results demonstrate that our model significantly and consistently outperforms state-of-the-art methods. One possible future work is to relax the constraint of  $W^*$  such that our method can be applied to a more general framework, and benefit other NLP tasks.

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