Improving Reinforcement Learning for Neural Relation Extraction with Hierarchical Memory Extractor

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ABSTRACT

Distant supervision relation extraction (DSRE) is an efficient method to extract semantic relations on a large-scale heuristic labeling corpus. However, it usually brings in a massive noisy data. In order to alleviate this problem, many recent approaches adopt reinforcement learning (RL), which aims to select correct data autonomously before relation classification. Although these RL methods outperform conventional multi-instance learning-based methods, there are still two neglected problems: 1) the existing RL methods ignore the feedback of noisy data, 2) the reduction of training corpus exacerbates long-tail problem. In this paper, we propose a novel framework to solve the two problems mentioned above. Firstly, we design a novel reward function to obtain feedback from both correct and noisy data. In addition, we use implicit relations information to improve RL. Secondly, we propose the hierarchical memory extractor (HME), which utilizes the gating mechanism to share the semantics from correlative instances between data-rich and data-poor classes. Moreover, we define a hierarchical weighted ranking loss function to implement top-down search processing. Extensive experiments conducted on the widely used NYT dataset show significant improvement over state-of-the-art baseline methods.

CCS CONCEPTS

• Computing methodologies \rightarrow Machine learning; Artificial intelligence.

KEYWORDS

knowledge graph, relation extraction, distant supervision, deep reinforcement learning, long-tail, noisy reduction

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1 INTRODUCTION

Relation extraction (RE) is a preliminary task in natural language processing (NLP) for knowledge graph (KG) construction [24], question answering (QA) [39] and recommendation system (RS) [30], which aims to capture the relation between two target entities. Recently, RE based on conventional supervised learning has made a great success [42]. However, it heavily relies on human annotation.

In order to obtain large-scale training corpus, distant supervision relation extraction (DSRE) [17] was proposed to generate heuristic labeling data by aligning entity pairs in raw text. As shown in Figure 1 (a), it assumes that if two target entities have a semantic relation in KG, all the raw text containing the two entities can be labeled as this relation class. However, this solution makes an over-strong assumption and inevitably brings in massive wrong labeling data. To alleviate this problem, recent researches based on deep learning roughly full into two categories: 1) **Soft-strategy**, which is the common way based on multi-instance learning (MIL) with attention mechanism [9, 12, 41]. 2) **Hard-strategy** is the other novel strategy to improve RE by directly splitting the original data into credible and noisy set, and then training RE on the credible set [3, 20, 21, 43].

Despite the success and popularity of these strategies, there are still two remaining problems: 1) Exist RL methods [3, 21, 43] ignore the contributions of noisy data and only consider the feedback of selected instances from credible set, so that the agent tend to pick few instances with prejudice. In a word, it might miss a lot of correct labeling data. According to our investigations, some new works proposed to address this issue by designing extra loss on unlabeled data [7] to leverage this semantics, or employing unsupervised deep clustering to generate reliable labels [23]. Unfortunately, availability and time-consume of relevant text corpora is a challenge which limits broad-coverage applicability of such methods. 2) By intuition, hard-strategy reduces the number of corpus both on sentence-level and bag-level. Under the circumstances, it exacerbates the long-tail problem, the number of different labels is quite imbalance. Some recent works [12] [31] have introduced additional knowledge and information to make a success enhancement. Han [6] and Zhang [45] improved long-tail relation extraction via hierarchical structural representations, which enable to transfer knowledge from datarich and semantically similar head classes to data-poor tail classes. However, they still train the model directly on the noisy data which inevitably results in the wrong mapping relations.

In this paper, we propose a novel framework to solve the problems mentioned above. For the first problem, We improve the RL by designing a novel reward function to fully consider the feedback of credible and noisy data. Specifically, given an original bag of sentences, the agent splits its into credible set and noisy set. As

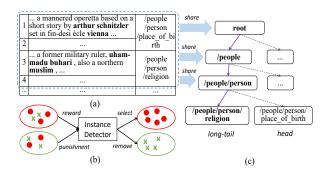


Figure 1: The example of our method. The red filled circle and ellipse is the correct labeling data and credible set, respectively. The green cross and ellipse is the wrong labeling data and noisy set, respectively. The purple solid lines are the searching path, while the dash lines are the other branches.

shown in Figure 1 (b), if there are more ground truth in the credible set, the agent may be given a higher reward. Conversely, if there are more ground truth in the noisy set, it means that the agent makes selection with prejudice, which should be given a punishment. In addition, we also utilize the implicit relation through t-h instead of the original relation embedding [7], where h(t) is the pre-trained entity embedding of head entity h(t) (tail entity h(t)) by TransE [2].

For the second problem, by the intuition that the semantics of data-rich can be shared with the similar data-poor relations. For example in Figure 1 (c), the data-rich relation /people/person/place_of-_birth in NYT corpus can represent a four-layers tree, from top to down are root, /people, /people/person and /people/person/place of-_birth, respectively, where root is virtual node, /people and /people/person are sub-relations. When given a data-poor relation people-/person/religion, it can be integrated with related instances at the layer of root, /people, and /people/person. Different from [6] and [45], we view RE as a tree search task from the root to the leaf node. During the search processing, we selectively save and combine the semantics of related instances at the current node, and calculate the score of each candidate child nodes and choose the maximum one. When training this module, we find that conventional ranking loss is not suitable for it. In order to ensure the convergence, we consider three challenges, and then define a hierarchical weighted ranking loss function to train this module. The specific details will be described later. The contributions of this paper are as follows:

- To improve the RL-based denoising method, we introduce implicit relation information, and design a novel reward function to take into account the feedback of both credible and noisy data.
- To the best of our knowledge, we are the first to transform the DSRE into a tree search task to solve long-tail problem. We propose the hierarchical memory extractor (HME) with gating mechanism to share the correlated instance semantics at the each node. We also design a hierarchical weighted ranking loss to train this module.
- We propose a novel framework to simultaneously solve the noisy and long-tail problems. Extensive experiments on the

NYT dataset demonstrate that our method outperforms stateof-the-art baselines. Specially, our proposed framework can address both on noisy and long-tail scenes.

2 RELATED WORK

Distant supervision (DS) [17] was proposed to automatically label large-scale corpus to overcome the time-consuming and human-intensive problem, which is one of the popular methods for the semi-supervised relation extraction. However, it suffers from too many noisy data, which causes from the over-strong heuristic assumption. Some recent researches solving this problem roughly full into two categories:

The first category is **soft-strategy**, which employees multi-instance learning (MIL) for bag-level classification [8, 22]. Inspired by MIL, [9, 10, 15, 34, 41, 42] address this problem by sentence-level attention, which can make the model focus on the high quality sentence and reduce the influence of noise. Other works [38, 40] denoise by extra bag-level attention to capture the correlation semantics between sentence and bag.

The other category is **hard-strategy**, which is a novel way to directly select correct data. [3] is the first to utilize RL for RE. The instance selector (agent) is modeled as a binary-classifier, where 1 represents select action and 0 denotes remove action. The relation classifier is trained on the selected set and returns a reward through validation loss to the instance selector. [7] and [21] improved RL by using Q-network. In addition, [5, 13, 20] leverage generative adversarial network (GAN) to filter noisy data by iterative training generator and discriminator. Different from them, we improve RL to denoise by proposed instance detector with a novel reward function which considers the drawback from both selected and removed instance. In addition, we also utilize the implicit relation information to make semantics enhancement.

Additionally, some recent researches start to focus on the long-tail problem. For example, [12, 14, 28, 35] utilize side information to realize semantics enhancement. [1, 32] make data enhancement by multi-task learning, such as entity type information, implicit or explicit relation-aware knowledge or unstructure text, etc. Unfortunately, availability and quality of extra data is a challenge which limits broad-coverage applicability of such methods. [6, 45] leverage hierarchical attention to transfer data-rich information to data-poor class at the tail of distribution, which succeed in overcoming the long-tail problem without explicit external data.

We also investigate some researches on hierarchical tree structure, which intuitively and explicitly reflects the hierarchical structure of data. For instances, [18] extracts entity relation by transforming the sentence into dependency tree and learns it by Bi-TreeLSTM. [44] proposes ASTNN to represent the source code of abstract syntax tree (AST), which is better for code classification and code clone detection. [16] proposes the hierarchical softmax algorithm to predict the masked word through a binary-tree, which aims to reduce search space and improve the efficiency of pre-trained word embedding. In addition, [4, 27, 36, 37, 46] consider the correlation between different labels and perform hierarchical CNN or attention for image or text classification, which outperform than the traditional classification models. Inspired by this structure, we treat the

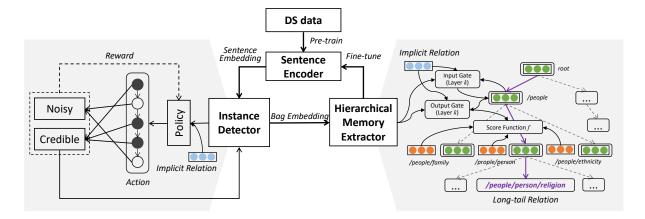


Figure 2: The architecture of our framework with three modules. The sentence encoder aims to represent each sentence into a vector. The instance detector proposed to select the correct labeling sentences based on RL. The hierarchical memory extractor aims to search the truly relation on credible subset. Three modules joint interacts with each other during training process. The blue, orange and green color circles denote implicit relation, pre-trained relation and memory cell embedding, respectively.

RE as a tree search task, which can share the associated instances semantics at each nodes to alleviate the long-tail problem.

3 METHODOLOGY

In this section, we present our framework of DSRE. The overview of proposed architecture as illustrated in Figure 2. It has three main modules:

- Sentence Encoder. When given a sentence, we encoder it
 into a vector by PCNN [41], which is basic model to encode
 the long sentence with piece-wise max-pooling. The input
 of PCNN are pre-trained word embedding and the position
 embedding while the output is corresponding sentence-level
 vector.
- Instance Detector. We use RL to alleviate the noisy problem. Given a sentence from the bag, the instance detector decides to whether select for correct data set or remove for noisy data set. To improve the instance detector, we design a novel reward function to both consider the feedback of two set, and then introduce the implicit relation by pre-trained knowledge base embedding (KBE). The output is a bag-level embedding of the correct data set.
- Hierarchical Memory Extractor. We propose to solve the insufficient and long-tail problem. Firstly, we transform the origin relation labels into four layers, where the first layer is itself, the second and third layer is the sub-relation and the top layer is virtual root node. Secondly, we construct the hierarchical tree. Each node has two vectors consists of pre-trained relation embedding and memory cell embedding. Thirdly, we make decision which path to go at each node, and combine the semantics of data-rich and data-pool relations at each nodes with gating mechanism. We propose a hierarchical weighted ranking loss to train this module.

We first give the notations, and then introduce three modules. At last, we present the training algorithm about proposed framework.

3.1 Task and Notations

Given a KG $\mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{F})$, where \mathcal{E} represents the set of entities, \mathcal{R} is the set of relations, $\mathcal{F} \subseteq \mathcal{E} \times \mathcal{R} \times \mathcal{E}$ denotes the facts, where $(h, r, t) \in \mathcal{F}, r \in \mathcal{E}$ is the semantic relation between head entity $h \in \mathcal{E}$ and tail entity $t \in \mathcal{E}$. Given a DS dataset T, where $B \in T$ is the bag of sentences S with corresponding aligned triple (h_B, r_B, t_B) . The task of our framework aims to select the credible sentences from bag, and to predict the semantic relation by hierarchical tree search process.

3.2 Sentence Encoder

We use PCNN [41] to represent the sentence into a low-dimension vector. Given a input of sentence: $X = [w_1, w_2, ..., w_n]$, where $w_i \in \mathbb{R}^{d_w + 2 \times d_p}$ is the *i*-th word vector consists of d_w -dimension pretrained word embedding by GloVe [19] and d_p -dimension position embedding. We then use CNN with K different l-dimension filters to encode sentence by:

$$L = CNN(X) \tag{1}$$

where $\mathbf{L} = [\mathbf{L}^{(1)}, \mathbf{L}^{(2)}, ..., \mathbf{L}^{(K)}] \in \mathbb{R}^{K \times (n-l+1)}$. The piece-wise max pooling vector of the *j*-filter can be calculated by :

$$c_{j} = [max(L_{0:p_{1}}^{(j)}); max(L_{p_{1}:p_{2}}^{(j)}); max(L_{p_{2}:n}^{(j)})]$$
 (2)

where p_1, p_2 is the position of two entities h_B, t_B . $[\cdot; \cdot]$ is the concatenate operation. We denote the parameters as Π .

At last, we can output the sentence-level embedding represents $c = [c_1; c_2; ...; c_K] \in \mathbb{R}^{d_c}$, where $d_c = 3K$. We use cross entropy [41] to train this module:

$$\mathcal{L}(\Pi) = -\frac{1}{N'} \sum_{i=1}^{N'} log p(r_i | S_i; \Pi) + \frac{\lambda_1}{2} ||\Pi||_2^2$$
 (3)

where Π denotes the parameters of sentence encoder, λ_1 is the L2 regularization parameters.

3.3 Instance Detector

We propose the instance detector module based on RL to automatically split the original bag into credible and noisy set. We follow [3] to define the state, action and reward function.

State. RL can be abstracted as the Markov decision process (MDP) of iterative interaction between the agent and the environment. In this paper, we regard the selection of a bag as an episode, and define the state embedding \mathbf{s}_t consists of: 1) the average vector of selected sentences from credible set $\hat{\mathbf{x}} \in \mathbb{R}^{d_c}$, 2) the last state embedding $\mathbf{s}_{t-1} \in \mathbb{R}^{d_s}$, 3) the current sentence embedding $\mathbf{c}_t \in \mathbb{R}^{d_c}$ and 4) the implicit relation information $\mathbf{r}^* \in \mathbb{R}^{d_r}$. In contrast to [3, 7], we leverage a feed-forward network with implicit relation to encode the state embedding. Formally:

$$\mathbf{s}_t = [tanh(\mathbf{W}_q[\mathbf{s}_{t-1}; \mathbf{c}_t; \mathbf{r}^*]); \hat{\mathbf{x}}_t]$$
(4)

where $W_q \in \mathbb{R}^{(d_s-d_c)\times(d_s+d_c+d_r)}$ is the trainable matrix. $r^*=t-h$, where t, h denotes the knowledge base embedding pre-trained by TransE [2].

Action. At each time t, the instance detector takes an action to decide whether to select for credible set or remove for noisy set. It can be viewed as a binary-classifier refers to the policy $\pi_{\Theta}(a_i|\mathbf{s}_t)$:

$$\pi_{\Theta}(a_i|\mathbf{s}_t) = a_i \sigma(\mathbf{W}_p \mathbf{s}_t) + (1 - a_i)(1 - \sigma(\mathbf{W}_p \mathbf{s}_t))$$
 (5)

where $\sigma(\cdot)$ is the sigmoid function, W_p is the training matrix. $a_i \in \{0,1\}$ is the action space, where 1 denotes select action and 0 denotes remove action. The training parameters of instance detector denotes $\Theta = \{W_q, W_p\}$.

Reward. Generally, the reward function is used to evaluate the utility of agent. Different from existing methods [3, 7, 21], we design a novel reward function to consider the feedback both from two subsets. Given a credible set B_{cre} and noisy set B_{noi} , where $B_{cre} \cap B_{noi} = \emptyset$ and $B_{cre} \cup B_{noi} = B$. We assume that the model has a terminal reward when it finishes all the selection. The terminal reward function is defined as:

$$\begin{split} R(B) &= \frac{M_{cre}}{M(M_{cre} + \gamma)} \big[\sum_{S_i \in B_{col}} p(r_B | S_i) + \gamma \big] \\ &+ \frac{M_{noi}}{M} \big\{ 1 - \frac{1}{M_{noi} + \gamma} \big[\sum_{S_j \in B_{noi}} p(r_B | S_j) + \gamma \big] \big\} \end{split} \tag{6}$$

where M is the number of sentences (episodes) in bag B, M_{cre} , M_{noi} is the number of sentences in correct set B_{cre} and B_{noi} , respectively. In order to explicitly reflect the effect of instance detector, we accumulate the probability of each sentence $p(r_B|S_i)$ in each subset to represent the occurrence probability of ground truth. Obviously, the reward function mainly contains both feedback from two subset, which enable to train this module instructively. Note that, the instance detector sometimes selects all the sentences for B_{cre} or remove all for B_{noi} . To avoid the denominator being 0, we add a small smoothing coefficient $\gamma(>0)$.

We train this module by policy gradient algorithm [26, 33] and following the same settings by [3]. The loss function as follow:

$$\mathcal{L}(\Theta) = -\frac{1}{M} \sum_{i=1}^{M} R(B_i) log \pi_{\Theta}(a_i | \mathbf{s}_i)$$
 (7)

At last, we can obtain the credible set $B_{cre} \subseteq B$ and corresponding bag-level embedding $\hat{\mathbf{x}}$.

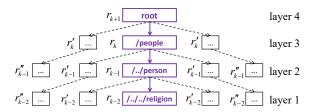


Figure 3: The hierarchical tree structure

3.4 Hierarchical Memory Extractor (HME)

After denoising, we use the HME to extract the semantics relation. We introduce this module from three aspects:

The construction of hierarchical relation tree. As shown in Figure 3, given an original relation label $r \in \mathcal{R}$, it can be represented as a path from root (layer4) to the leaf (layer1), and the node at layer k denotes r_k ($k \in \{1, 2, 3, 4\}$). In addition, we suppose that r_k' is the sibling node of r_k . The child nodes set of r_k , r_k' represents $N_k(r)$ and $\overline{N_k(r)}$, respectively, where $\overline{N_k(r)}$ is the complement set of $N_k(r)$. Therefore, we have $r_{k-1}, r_{k-1}' \in N_k(r), r_{k-1}'' \notin N_k(r)$, where r_{k-1} is the true path at layer k-1, r_{k-1}' is the negative but share the same parent node, r_{k-1}'' is the negative but not share the same parent node.

As shown in Figure 2, each node consists of sub-relation embedding and memory cell embedding. The original relation embedding at layer 1 is pre-trained by TransE [2], and then we recursively calculate the embedding of each sub-relation from layer 2 to 4. Formally:

$$r_k = \frac{1}{|\mathcal{N}_k(r)|} \sum_{r_{k-1} \in \mathcal{N}_k(r)} r_{k-1}$$
 (8)

where $\mathbf{r}_k \in \mathbb{R}^{d_r}$ is the sub-relation embedding of node r_k , $|\mathcal{N}_k(r)|$ denotes the number of child nodes. The memory cell embedding aims to preserve the semantics of instances¹, which initialed as zeros vector $\mathbf{C}_k(r) = 0 \in \mathbb{R}^{d_{cell}}$.

The search processing with gating mechanism. Given a bag B and the bag-level embedding $\hat{\mathbf{x}}$ which outputs from instance detector. HME aims to search a path from the root to the leaf node, which can be also viewed as a multi-branch classification between two adjacent layers. Specifically, we first obtain the fusion of implicit relation information and bag-level embedding $G = tanh(W_G[\hat{\mathbf{x}}; \mathbf{r}^*] + \mathbf{b}_G)$, where $\mathbf{r}^* = \mathbf{t} - \mathbf{h}$ denotes implicit relation, $W_G \in \mathbb{R}^{d_{cell} \times d_c}$ and $\mathbf{b}_G \in \mathbb{R}^{d_{cell}}$ is the trainable parameters. $G \in \mathbb{R}^{d_{cell}}$ is the fusion information of one bag. Suppose that the bag at node r_k , inspired by GRUs and LSTMs, we use an input gate $i_k(r)$ to selective save this fusion information to update the memory cell $C_k^{old}(r)$ to $C_k^{new}(r)$ at the node r_k :

$$i_k(r) = \sigma(\mathbf{W}_{i,k}[\hat{\mathbf{x}}; \mathbf{C}_k(r)] + \mathbf{b}_{i,k}) \tag{9}$$

$$C_k^{new}(r) = i_k(r) \cdot G + (1 - i_k(r)) \cdot C_k^{old}(r)$$
(10)

We then use an output gate $o_k(r)$ to extract the mixed semantics from memory cell at the node r_k :

$$o_k(r) = \sigma(\mathbf{W}_{o,k}[\hat{\mathbf{x}}; \mathbf{C}_k^{new}(r)] + \mathbf{b}_{o,k})$$
(11)

¹Instance is referred to a bag in the HME module

$$\mathbf{Z}_k(r) = o_k(r) \cdot \mathbf{C}_k^{new}(r) + (1 - o_k(r)) \cdot \mathbf{G}$$
 (12)

where $W_{i,k}, W_{o,k}, b_{i,k}, b_{o,k}$ are the trainable matrices and bias at the layer $k, \sigma(\cdot)$ is the sigmoid function, $[\cdot; \cdot]$ is the concatenate operation. $Z_k(r)$ is the mixed semantics of bag B at the node r_k , we can calculate the score of each next branch to child node $r_{k-1} \in \mathcal{N}_k(r)$, and choose the maximum one r_{k-1}^* as the next node.

$$f(\mathbf{Z}_k(r), \mathbf{r}_{k-1}) = softmax(\mathbf{Z}_k(r)\mathbf{W}_{f,k}\mathbf{r}_{k-1}^{\mathbb{T}})$$
 (13)

$$r_{k-1}^* = \arg\max_{r_{k-1}} f(\mathbf{Z}_k(r), \mathbf{r}_{k-1})$$
 (14)

where $W_{f,k}$ is the matrix of score function $f(\cdot)$ at layer k.

The hierarchical weighted ranking loss. Different from existing works [44, 46], we have only one specific tree in our method, which relies on hierarchical relation label, so the learning of the parameters on this tree is completely dependent on the top-down search of each instances. However, we find three challenges: 1) each node has a different number of branches, 2) the parameters of each layer are shared, so that when training one node, parameters of the other nodes will change which results in local optimum or divergence, 3) each layer or node has different influence degree on the loss. Therefore, series existing strategy such as cross entropy or hierarchical metric learning [29] are unable to train this module.

In order to train the HME module, we propose hierarchical weighted ranking loss. To satisfy the first challenge, we use the ranking loss to replace conventional cross entropy loss. In other word, we use the opposite of the score as the loss function, and train to maximize the score of the correct path. For the second challenge, we additionally perform negative sampling from two aspects: 1) $r'_{k-1} \in \mathcal{N}_k(r)$ and 2) $r''_{k-1} \in \overline{\mathcal{N}_k(r)}$. Therefore, the loss function at the layer $k(k \in \{2,3,4\})$ can be defined as follows:

$$\mathcal{L}_{k}(B, r) = \sum_{\substack{r'_{k-1} \in \mathcal{N}_{k}(r)}} ||f(\mathbf{Z}_{k}(r), \mathbf{r'}_{k-1}) + \mu - f(\mathbf{Z}_{k}(r), \mathbf{r}_{k-1})||_{+} \\ + \sum_{\substack{r''_{k-1} \in \overline{\mathcal{N}_{k}(r)}}} ||f(\mathbf{Z}_{k}(r), \mathbf{r''}_{k-1}) + \mu - f(\mathbf{Z}_{k}(r), \mathbf{r}_{k-1})||_{+}$$
(15)

where $\mu \in [0, 1]$ is the margin hyper-parameter, $|| \cdot ||_+$ is the hinge function.

We consider the third challenge into two corners: 1) if the wrong path selected at the beginning, subsequent searches will be meaningless, and 2) it is more difficult when there are too many branches. We think the model should pay more attention to the node which is near to root or has too many child nodes. Simply, we define the weighted value as follow:

$$\alpha_k(r) = \frac{|\mathcal{N}_k(r)| + k - 1}{\sum_{j=2}^4 (|\mathcal{N}_j(r)| + j - 1)}$$
(16)

The final loss defined as:

$$\mathcal{L}(B, r, \Phi) = \sum_{k=2}^{4} \alpha_k(r) \mathcal{L}_k(B, r) + \frac{\lambda_2}{2} ||\Phi||_2^2$$
 (17)

where Φ denotes the parameters of HME module, λ_2 is the L2 regularization parameters.

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Algorithm 1: The Framework for DSRE
```

Input: DS training data B, pre-trained sentence encoder Π

```
and instance detector \Theta, initialized HME \Phi, iteration
        number L, a small \tau.
Output: Parameter \Pi', \Theta' and \Phi';
Initialize sentence encoder \Pi' = \Pi, instance detector
 \Theta' = \Theta and HME \Phi' = \Phi;
for iteration l=1 to L do
    Shuffle training data B, credible set B_{cre} = \emptyset;
    foreach B_i \in B do
        For each sentence, obtain the state and sample
          action by Equal 4 and 5 with \Theta';
        Comput delayed reward by Equal 6;
        Update the parameter \Theta by calculating Equal 7;
    end
    \Theta' = \tau\Theta + (1 - \tau)\Theta';
    foreach B_i \in B do
        Obtain credible set \hat{B}_i of B_i with \Theta';
        Add \hat{B}_i into B_{cre};
    foreach B_i \in B_{cre} do
        Obtain the bag-level embedding of B_i;
        while not at leaf (layer k > 1) do
             Save semantics by Equal 9 and 10;
             Obtain mixed semantics Z_k by Equal 11 and 12;
             Search for next node by Equal 14;
        Calculate the loss of the HME by Equal 17 and
          update parameter \Phi;
    end
    Update the sentence encoder \Pi by calculating Equal 3;
    \Phi' = \tau \Phi + (1 - \tau) \Phi';
    \Pi' = \tau \Pi + (1 - \tau) \Pi';
```

3.5 The training strategy

end

In this section, we present the training algorithm for DSRE. As shown in Figure 2, we first pre-train the sentence encoder to obtain sentence-level embedding, and then pre-train the instance detector by computing the reward function. The pre-train stage of RL is crucial for our experiment. We then train three modules jointly. The training strategy is shown in Algorithm 1. We first train the instance detector and obtain the credible set. Then, we train the HME module based on credible set. We fine-tune the sentence encoder and go into next iteration. We follow [3] to use a hyper-parameter $\tau(\ll 1)$ to make the stable update.

4 EXPERIMENT

4.1 Dataset and Evaluation Metrics

We evaluate the proposed framework on widely used DS dataset NYT [22]. The dataset 2 has 52 semantic relations and a special

 $^{^2{\}rm The~NYT~dataset~can~be~download~from~http://iesl.cs.umass.edu/riedel/ecml/$

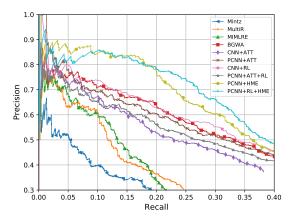


Figure 4: Comparison with previous baselines.

NA label which means that no relation between entity pair. The training set contains 522611 sentences, 281270 entity pairs and 18252 relational facts. The testing set contains 172448 sentences, 96678 entity pairs and 1950 relational facts.

To fairly compare with some baselines³, we follow [7, 15] to evaluate our method in the held-out evaluation and manual evaluation. The held-out evaluation aims to compare the predicted relational fact from the test data with the facts in Freebase, but it does not consider the efficient on predicting NA class. The manual evaluation is performed to avoid the influence of the noisy testing data by manually checking the efficiency. We select precision-recall (P-R) curve, P@N and Hits@K metrics to report the results of the experiment.

4.2 Experiment Settings

In sentence encoder, we use the same hyper-parameters as previous works [41]. The word embedding size $d_w=50$, The position embedding size $d_p=5$. The filters K=230 and the window size l is set to 3. The implicit relation and memory cell embedding dimension $d_r=d_{cell}=50$. The batch size is 64. The learning rate as 0.02, 0.01 at the pre-training and joint training stage, respectively. We employ a dropout strategy with a probability of 0.5. The small constant $\gamma=0.01$, $\mu=0.5$ and $\tau=0.001$. The L2 regularization parameters $\lambda_1=\lambda_2=1.0$. We pre-train sentence encoder and instance detector for 5 epoches. The joint training iteration number L is 30. We apply Adam [11] method to optimize parameters both on pre-training and joint training stage.

4.3 Main Results

We use held-out evaluation to compare our model **PCNN+HME** and **PCNN+RL+HME** with several baselines, which fall into three categories:

• Feature-based methods utilize traditional feature engineering and machine learning, such as Mintz [17], MultiR [8] and MIML [25]. Mintz is a traditional method for DSRE via human designed features and multi-class logistic regression. MultiR leverages MIL to reduce the noise and handle

Table 1: The selection result of RL baselines

baselines	TC	TN	FC	FN	Acc(%)
CNN+RL[3]	54	61	36	149	67.7
PCNN+PU[7]	83	32	30	155	79.3
ours	94	21	14	171	88.3

the overlapping problem by proposed probabilistic graphical module. **MIML** utilizes multi-instance multi-label method for extracting semantics relation between two entities.

- Soft-strategy methods leverage sentence-level attention mechanism to reduce the influence of noisy, including BGW-A [9], CNN +ATT and PCNN +ATT [15]. BGWA is a bidirectional GRU based RE model with piecewise max pooling. CNN +ATT is a basic CNN module with sentence-level attention mechanism. PCNN +ATT combines the sentence-level attention with PCNN to capture structure information between two entities.
- Hard-strategy methods aim to filter noisy before RE, consisting of CNN +RL [3] and PCNN +ATT +RL [21]. CNN +RL is a novel method to reduce noisy labeling data by RL, and achieves rewards from CNN to evaluate the RL. PCNN +ATT +RL also introduce the RL, but it redistributes noisy sentences into negative examples.

As shown in Figure 4, we use P-R curve to make comparison without NA label 4, where x-axis denotes the recall and y-axis denotes the precision. The main results indicate that 1) both soft-strategy and hard-strategy based on deep learning methods outperform the feature-based methods, it means that the representation and generalization of traditional feature engineering unable to improve the performance. 2) The performance of CNN-based method is worse than PCNN-based, this is due to the factor that CNN ignores the entity structure information, while other methods consist of piecewise max-pooling can make reliable promotion. 3) We also find that both PCNN+HME and PCNN+RL+HME outperform all other baselines by large margin, which demonstrates that the successful improvement of transforming relation extraction into tree search processing, and sharing the semantics of data-poor and data-rich class. 4) In addition, the PCNN+RL+HME makes a bit improvement than PCNN+HME. By intuitive, the RL, which aims to filter out noisy data, is also helpful for RE.

4.4 The performance of different layers

To validate the results of search processing at each layer in HME, we also report the P-R curve without NA label. Specifically, if one test instance reach one node r_k ($k \in \{1, 2, 3\}$), we will obtain the corresponding score probability of the current path $r_4 \to \dots \to r_k$, and preserve the precision and recall values by the comparison with ground truth. In other words, if all given test instances finish the complete tree search processing, we will get three P-R values pairs of different layers from layer 1-3, respectively. The top layer which contains only one class (virtual node) *root*, so we ignore it. For each layers, We choose CNN and PCNN to make comparison.

 $^{^3} https://github.com/thunlp/OpenNRE\\$

 $^{^4\}mathrm{We}$ follow previous works to only preserve the precision and recall value of no-NA labels, because that the prediction of NA is useless.

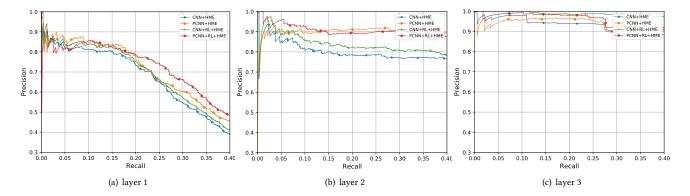


Figure 5: The results of relation search processing at different layers.

Table 2: The marco accuracy of Hits@K on long-tail relations

T	T t		100			200	
Trainii	ng Instances		<100		<200		
Hits@	ФК(Marco)	10	15	20	10	15	20
CNN	+ATT	< 5.0	< 5.0	18.5	< 5.0	16.2	33.3
	+HATT	5.6	31.5	57.4	22.7	43.9	65.1
	+KATT	9.1	41.3	58.5	23.3	44.1	65.4
	+HME	9.5	40.2	59.6	23.9	47.0	66.6
	+RL+HME	11.3	41.5	60.1	25.0	47.1	66.9
PCNN	+ATT	< 5.0	7.4	40.7	17.2	24.2	51.5
	+HATT	29.6	51.9	61.1	41.4	60.6	68.2
	+KATT	35.3	62.4	65.1	43.2	61.3	69.2
	+HME	36.8	64.0	68.8	44.8	62.0	71.5
	+RL+HME	36.6	64.1	68.9	44.5	62.3	71.7

As shown in Figure 5, we observe that: 1) PCNN+RL+HME almost outperforms other models, which indicates that both consider noisy reduction and long-tail can improve the efficient of DSRE. 2) For each method, the result of DSRE decreases as k decreases, which shows that the searching accuracy of the lower layer depends on that of the upper layer. 3) PCNN is more efficient than CNN at layer 1 and 2 regardless of whether considering denoising. However, CNN+RL+HME is the best choice at layer 3. We guess that PCNN is suitable for handling low-layer while CNN is suitable for high layer. 4) We randomly choose some instances both from long-tail and data-rich classes, we find that most long-tail classes instances can successfully reach to corresponding leaf node, which indicates that the success of sharing semantics between data-rich and data-poor classes. 5) The most obvious improvement is from the layer 3 to the layer 2, we guess that the long tail problem corresponding to the second layer is more serious than others. Therefore, through our HME module, the prediction effect of long-tail instances can be greatly improved.

4.5 The manual results of instance detector

We randomly select 300 sentences from testing data, then manually label them as true or false. In order to clearly compare the efficient of RL, we statistic four numbers:

- TC is the number of sentences manually labeled as true but selected in credible set.
- TN is the number of sentences manually labeled as true but removed in noisy set.
- FC is the number of sentences manually labeled as false but selected in credible set
- FN is the number of sentences manually labeled as false but removed in noisy set.

The accuracy can be calculate by (TC+FN)/300. We select two baselines consists of CNN+RL [3] and PCNN+PU[7]. As shown in Table 1, we manually label 115 sentences as true and 185 sentences as false. We find that our proposed instance detector can achieve the highest TC, FN and corresponding accuracy, it benefits from the consideration of feedback both from selected and noisy data.

Although, we have further improved the accuracy of noise recognition, some of the noise are still recognized incorrectly. 1) For the original correct but identified as noise, it may be due to the incomplete of the knowledge base which causes that some entities really contain semantics relation but viewed as noise. 2) For the original noise but identified as correct labeling data, we guess that some instance is really hard to recognize them, which is also the bottleneck problem of deep learning so far.

4.6 The results for long-tail relations

We also demonstrate the improvements for long-tail relations. We choose three attention based models +ATT [15], +HATT [6] and +KATT [45]:

- +ATT is the traditional sentence-level attention mechanism over instances, such as CNN+ATT and PCNN+ATT[15].
- +HATT is the hierarchical attention method over the instances, the different is that it considers the hierarchical structure of semantic relation.
- +KATT is also an attention-based method, which utilizes knowledge base embedding (KBE) and graph neural network (GNN) to represent the hierarchical relational label.

To make fair comparison, we follow the same evaluation strategy by them. Specifically, we obtain a subset from testing data in which all the relations have fewer than 100 or 200 instances, we leverage macro Hits@K metric, which meas that the accuracy of the golden

Methods		PCNN+	-HME			PCNN+R	L+HME	
P@N	P@100	P@200	P@300	Avg.	P@100	P@200	P@300	Avg.
origin	88.00	82.50	78.67	83.06	90.00	84.50	79.33	84.61
w/o NR	-	-	-	-	88.18	82.09	77.67	82.65
w/o IR	86.23	81.29	78.33	81.95	88.11	81.93	77.50	82.51
w/o GM	81.00	73.33	62.76	72.36	82.19	74.00	63.33	73.17
w/o WL	83.18	78.00	74.67	78.62	83.26	77.33	71.35	77.31

Table 3: The ablation results of PCNN+HME and PCNN+RL+HME

Table 4: Some sentences for case study

Sentences	Original label	Predicted label	Is noise?
Kuhn and his wife luisa relocated to ponte vedra beach , florida in	/location/location/contains	/location/location/contains	No
1990 ,			
a former military ruler , muhammadu buhari , also a northern muslim	/people/person/religion	/people/person/religion	No
, is a leading candidate ,			
the american rights to jonathan littell's novel les bienveillantes,	/people/person/nationality	NA	Yes
which became a publishing sensation in france , have been sold to harper-			
collins,			
the annual meeting morphed into a three and a half hour celebration	/business/company/advisors	/business/company/founders	No
of sanford i. weill, citigroup 's departing chairman.			

relation in the top K candidate relations recommended by our model. In this experiment, we select K from $\{10, 15, 20\}$.

As shown in Table 2, it illustrates that: 1) The PCNN-based encoder is better than CNN, which indicates that the piecewise information is also useful for long-tail prediction. 2) HME module with both CNN and PCNN outperforms than previous works, it verifies that the hierarchical tree processing is really better than simple attention. 3) If we use RL to filter the noisy data before relation extraction, despite obtaining a bit improvement, it is still hard to extract the long-tail relations because of the reduction of data

4.7 Ablation Study

We perform ablation experiments to validate the contributions of different components of our models. We report the P@N metric, which denotes the top N of precision. Specifically, we evaluate all the testing instances and achieve the corresponding sorted precision value at the layer 1, and then we choose the N-th value as P@N. We choose PCNN as the encoder, PCNN+HME and PCNN+RL+HME are two corresponding methods. We remove the following settings:

- w/o NR is the method without considering the feedback of noisy data, which is the same as CNN+RL [3].
- w/o IR is the method without implicit relation in instance detector or HME.
- w/o GM is the method without gating mechanism, which calculates the score function by only the semantics of instance itself.
- w/o WL is the method without the weighted influence of different layers or nodes, it means that we replace the Equal 14 with a simple average operation.

As shown in Table 3, we find that if we remove one of these components, the performance of both PCNN+HME and PCNN+RL+HME will be worse. Specifically, 1) if we ignore the feedback of

noisy data, the average of P@N will reduce by 1.96%, owing to the agent missing some semantics of correct labeling sentence. 2) the implicit relation make a success improvement on our framework. 3) when we remove the gating mechanism, the average of P@N will reduce by more than 10% both on two methods, it illustrates that it is important to share the knowledge between related instances. 4) the weighted sum loss of different layers or nodes makes the positive contributions on training.

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4.8 Case Study

We further present some sentences in Table 4 for case study. The text in bold represents the entity. The first two sentences which belong to long-tail class, successfully selected by instance detector and predicted by HME. The third noisy sentence is removed for noisy set and directly predicted as NA. Our method makes wrong prediction on the last sentence, we analyze that the sample number of <code>/business/company/advisors</code> is too small to predict the third layer, but our HME still performs well in the first two layers.

5 CONCLUSION

In this paper, we propose a novel framework to alleviate both noisy labeling and long-tail problem. We apply RL to select the credible data, and improve the RL by implicit relation information and a novel reward function that consider the contributions of both credible and noisy data. For the long-tail problem, we newly transform the relation extraction into a tree searching task, and share the semantics of related instances between data-rich classes at the head of distribution and data-poor classes at the tail. We also provide hierarchical weighted loss function to train this module. Extensive experimental results on NYT dataset show that our method outperforms than state-of-the-art baselines. In the future, we will pay attention to the overlapping problem. We also decide to apply this proposed framework to few-shot RE task.

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