Distantly Supervised Relation Extraction in Federated Settings

Dianbo Sui$^{1,2}$, Yubo Chen$^1$, Kang Liu$^{1,2}$, Jun Zhao$^{1,2}$

$^1$ National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, Beijing, 100190, China

$^2$ University of Chinese Academy of Sciences, Beijing, 100049, China

{dianbo.sui, yubo.chen, kliu, jzhao}@nlpr.ia.ac.cn

Abstract

This paper investigates distantly supervised relation extraction in federated settings. Previous studies focus on distant supervision under the assumption of centralized training, which requires collecting texts from different platforms and storing them on one machine. However, centralized training is challenged by two issues, namely, data barriers and privacy protection, which make it almost impossible or cost-prohibitive to centralize data from multiple platforms. Therefore, it is worthy to investigate distant supervision in the federated learning paradigm, which decouples the model training from the need for direct access to the raw data. Overcoming label noise of distant supervision, however, becomes more difficult in federated settings, since the sentences containing the same entity pair may scatter around different platforms. In this paper, we propose a federated denoising framework to suppress label noise in federated settings. The core of this framework is a multiple instance learning based denoising method that is able to select reliable instances via cross-platform collaboration. Various experimental results on New York Times dataset and miRNA gene regulation relation dataset demonstrate the effectiveness of the proposed method.

1 Introduction

Relation extraction (RE) is a fundamental task for knowledge base (KB) construction. It aims to mine factual knowledge from free texts by labeling relations between entity mentions. Most existing supervised RE systems, such as Zeng et al. (2014); Zhang and Wang (2015); Wang et al. (2016); Zhou et al. (2016), rely on large-scale manually annotated training data, which is labor-intensive and time-consuming.

To ease the reliance on annotated data, Mintz et al. (2009) proposed the distant supervision to automatically generate training data by aligning a KB and unlabeled texts. The key assumption of distant supervision is that if two entities have a relation in the KB, then all sentences that mention these two entities will express this relation. A set of sentences containing the same entity pair is called a bag. Although distant supervision can scale up training data, the automatic labeling inevitably accompanies with label noise, which means not all sentences that mention an entity pair can represent the relation between them. Training on such noisy data will hinder the performance of the RE model.

There is a rich literature on handling label noise in distant supervision, such as Riedel et al. (2010); Hoffmann et al. (2011); Zeng et al. (2015); Lin et al. (2016); Ye and Ling (2019). However, it should be noted that all these studies were conducted under the assumption of centralized training. In other words, all these approaches require centralizing texts from different platforms to one machine and then conduct training. Centralized training faces two major challenges (Yang et al., 2019). The first challenge is the data barrier, caused by the reluctance of data holders in most industries to share the underlying data. The second challenge is the fact that states across the world have been strengthening relevant laws in privacy protection, such as GDPR $^1$, which places a significant compliance burden on data collection. These two challenges make it almost impossible or cost-prohibitive to integrate data from multiple platforms. Therefore, it is worthy to investigate distant supervision under the federated learning paradigm (McMahan et al., 2016), which permits learning to be done while local data of each platform stays in its local environment.

Federated learning decouples the model training from the need for direct access to raw training

$^1$https://en.wikipedia.org/wiki/GDPR
data. The learning task is solved by a loose federation of platforms coordinated by a master server. Each platform has a local training dataset that is never uploaded to the master server. Instead, each platform computes an update to the current global model maintained by the master server, and only this update is communicated between platforms and the master server.

Although in federated learning, texts from multiple platforms can be used to collaboratively train the model without considering data barriers and privacy issues, overcoming label noise of distant supervision becomes more arduous. In detail, the sentences in a bag may scatter around different platforms. As shown in Figure 1, \( S_1 \) and \( S_2 \) contain the same entity pair (“Steve Jobs”, “Apple”) but are distributed on two platforms. \( S_1 \) is true positive while \( S_2 \) is a false positive instance, which does not express the “founder” relation. Under the assumption of centralized training, considering \( S_1 \) and \( S_2 \) simultaneously can easily denoise via only selecting \( S_1 \) (Zeng et al., 2015) or placing a small weight on \( S_2 \) (Lin et al., 2016; Ye and Ling, 2019). However, due to data barriers or privacy issues, data exchange between platforms is prohibited. Without \( S_1 \), the false positive sentence \( S_2 \) is retained as training data instead of being removed as a noise. As a result, the local model in platform 2 is poisoned by the false positive instance \( S_2 \), which would in turn affect the global model.

To suppress label noise of distant supervision in federated settings, we propose a federated denoising framework in this paper. The core of this framework is a multiple instance learning (MIL) (Dietterich et al., 1997; Maron and Lozano-Pérez, 1998) based denoising algorithm, called Lazy MIL, which is only executed at the beginning of each communication round and then would rest until the next round. Since the instances in a bag may scatter around different platforms, Lazy MIL algorithm coordinates multiple platforms to jointly select reliable instances without exposing underlying texts. Once instances have been selected, they would be used repeatedly to train local models until the end of this round.

In summary, the contributions of this paper are

- Considering data barriers and privacy protection, we investigate distant supervision under the federated learning paradigm, which decouples the model training from the need for direct access to the raw training data.
- To suppress label noise of distant supervision in federated settings, we present a multiple instance learning based denoising method, which can select reliable instances via cross-platform collaboration.
- The method yields promising results on two benchmarks datasets, and we perform various experiments to verify the effectiveness of the proposed method. The code will be released at https://github.com/DianboWork/FedDS.

2 Related Work

In this section, we will briefly review the recent progress in distantly supervised relation classification and existing studies on federated learning.

2.1 Distantly Supervised Relation Extraction

Relation extraction is a task of mining factual knowledge from free texts by labeling relations. To alleviate the dependence of supervised methods on annotated data, Mintz et al. (2009) proposed distant supervision by using an existing knowledge base to automatically annotating large-scale datasets. However, distant supervision often suffers from label noise. To deal with label noise, most distantly supervised approaches (Riedel et al., 2010; Hoffmann et al., 2011; Surdeanu et al., 2012; Zeng et al., 2015; Lin et al., 2016; Ye and Ling, 2019) fall under the framework of multiple instance earning, which assumes that at least one sentence expresses the relation in a bag. Our work is in line with this framework and, moreover, we extend this framework to federated settings. Another line of work aims to reduce label noise at sentence level prediction, some studies (Zeng et al., 2018; Feng et al., 2018; Qin et al., 2018a,b) use reinforcement learning or adversarial training to selects trustable relation labels by matching the predicted label of the learned model with distant supervision generated label.
2.2 Federated Learning

Recently, federated learning (McMahan et al., 2016; Konečný et al., 2016a,b) has become a rapidly developing topic in the research community, since it provides a new communication-efficient way of learning models over a collection of highly distributed platforms while still preserving data privacy. According to distribution characteristics of the data, federated learning can be classified into horizontal federated learning, vertical federated learning and federated transfer learning (Yang et al., 2019). This work is in line with the horizontal federated learning, where data sets share the same feature space but different in samples.

Federated learning has witnessed many successful applications in various fields. Kim et al. (2017) introduced federated tensor factorization for computational phenotyping without sharing patient-level data. Chen et al. (2018) combined federated learning with meta learning for the recommendation. Liu and Miller (2020) presented federated pre-training of BERT model using clinical notes from multiple silos. Ge et al. (2020) applied federated learning to medical NER. In contrast to the previous work, we focus on applying federated learning to a noisy environment. To this end, we introduce a federated denoising framework.

3 Federated Denoising Framework

3.1 Task Definition

In this paper, we focus on distant supervision in federated settings. Define $K$ platforms $\{P_1, \ldots, P_K\}$ with respective data $\{D_1, \ldots, D_K\}$. Under the assumption of centralized training, each platform transfers its local data to a server, and the server will take the integrated data $D = D_1 \cup \ldots \cup D_K$ to conduct training, while the task of distant supervision in federated settings requires any platform $P_i$ does not expose its data $D_i$ to others (including the server). In distant supervision, a knowledge base (KB) is required to automatically label the underlying texts. In this paper, we only focus on the data security of underlying texts, so the KB is public available for platforms. The issue of protecting the security of KB is beyond the scope of the current work.

To solve this task, we propose a federated denoising framework. The overall of this framework is shown in Figure 2 and the key components of this framework will be elaborated in the following section. Concretely, we first introduce the basic relation extractor in Section 3.2, which is the network architecture shared by the global model and the local model. Then we present how to select
reliable instance via cross-platform collaboration in Section 3.3. Next, we describe how to use the selected instances to train the local model in Section 3.4. Finally, we present how to use federated averaging algorithm to update the global model in Section 3.5.

3.2 Relation Extractor

Following previous studies (Zeng et al., 2015; Lin et al., 2016; Ye and Ling, 2019), we adopt the Piecewise Convolutional Neural Network (PCNN) as our relation extractor.

Given a sentence $s$ and two entities within this sentence, we first split the sentence into tokens, and then each token $w_i$ is mapped into a dense word embedding $e_i \in \mathbb{R}^{d_w}$. To specify entity pairs, the relative distances between the current token and the two entities are transformed into two positional features by looking up the position embedding matrices. Next, the token representation is represented as the concatenation of the word embedding and two positional features, and is fed into the convolutional neural network. Then, piecewise max pooling (Zeng et al., 2015) is employed to extract the high-level sentence representation from three segments of CNN outputs, and the boundaries of segments are determined by the positions of the two entities. After that, we apply a single fully connected layer to output the logit value $o$. Finally, the conditional probability of $j$-th relation is denoted as follows:

$$p(\text{rel}_j | s, \Theta) = \frac{\exp(o_j)}{\sum_{i=1}^{M} \exp(o_i)}$$

(1)

where $\Theta$ is the model parameter and $M$ is the total number of relation.

3.3 Lazy Multiple Instance Learning

To avoid the local relation extractor being poisoned by false positive instances, we propose the lazy multiple instance learning (Lazy MIL), which can select reliable instances via cross-platform collaboration. The overall of Lazy MIL is illustrated in Algorithm 1.

Suppose that there is a triple $(h, r, t)$ in the public KB\(^2\), the set of sentences containing the head entity $h$ and tail entity $t$ is represented as \{$(s^1_1, s^1_2, \ldots, s^1_{n_1}), \ldots, (s^K_1, s^K_2, \ldots, s^K_{n_1})$\}, where $s^j_i$

\(^2\)We assume there are triples with ‘NA’ relation in the public KB. In other words, we treat ‘NA’ as a normal relation.

| Algorithm 1 Lazy Multiple Instance Learning |
| --- |
| **Input:** $\Theta$ is the global model parameters, and $A$ is the set of activated platforms. |
| **Output:** $V$ is a dictionary about denoising information |
| **Function Lazy_MIL ($\Theta$, $A$)*** |
| Define a dictionary on the server, named $V$ |
| Distribute $\Theta$ to each platform in $A$ |
| // Run on activated platforms |
| for each platform $i \in A$ in parallel do |
| for each triple $(h, r, t)$ in KB do |
| for each sentence $s^j_i$ in bag $b^i$ do |
| Compute $p(r|s^j_i, \Theta)$ |
| $v^i, id^i \leftarrow \max_z(p(r|s^j_z, \Theta))$, $s^j_z \in b^i$ |
| Upload $[v^i, id^i, i]$ to the server |
| // Run on the master server |
| Add $[v^i, id^i, i]$ to $V(h, r, t)$ |
| // Run on the master server |
| for each key $(h, r, t)$ in $V$ do |
| // The sorted list is in descending order |
| $\text{tmp} \leftarrow \text{sorted}(V(h, r, t), \text{key} = \lambda x:x[0], \text{reverse}=\text{True})$ |
| $V(h, r, t) \leftarrow \text{tmp[0]}$ |
| return $V$ |

indicates the $i$-th instance in the platform $j$. In the $q$-th communication round, assume that only platform $i$ and platform $j$ are activated. At the beginning of this round, the parameters of the global model $\Theta_q$ are distributed to the activated platforms $i$ and $j$ for initializing local models, which ensures that all activated local models share the same parameters in Lazy MIL. In platform $i$, the sentences in the set $(s^1_i, s^K_i)$ are fed into the local model to get conditional probabilities associated with the $r$ relation according to Equation 1, where $r$ is the predicate of the triple. The value $v^i$ and index $id^i$ of the instance with the maximum conditional probability associated with the $r$ relation is computed as follows\(^3\):

$$v^i, id^i = \max_z(p(r|s^j_z, \Theta_q)) \ 1 \leq z \leq n_i$$

(2)

\(^3\)The max function returns the maximum value and the index location of the maximum value.

After computation, platform $i$ uploads the value $v^i$ and index $id^i$ to the master server. At the same time, the same procedure is performed on platform $j$, and the value $v^j$ and index $id^j$ are also uploaded to the server.

The master server decides which local instance
can be selected among all activated platforms based on the uploaded values. If \( v^i > v^j \), then the \( id^i \)-th sentence in platform \( i \) is selected as the reliable sentence that expresses this triple \((h, r, t)\) in this round. This decision, called denoising information, is broadcast to all activated platforms. Each activated platform selects reliable training instances from its local data according to this denoising information. Note that, since only values and indices of conditional probabilities are uploaded to the master server, Lazy MIL does not leak the information of texts in each platform.

3.4 Local Model Training

After platform \( i \) selects reliable instances from its local data \( D_i \), the selected reliable instance set \( D_i^* \) is used for training the local relation extractor. We use the cross-entropy loss function to optimize parameters \( \Theta_q \), which is defined as follows:

\[
J(\Theta_q; D_i^*) = -\frac{1}{|D_i^*|} \sum_{u=1}^{|D_i^*|} \log p(r_u; s_u^*, \Theta_q) \tag{3}
\]

where \( s_u^* \) indicates the \( u \)-th sentence in the selected reliable instance set \( D_i^* \). After training \( E \) epochs on the selected reliable instance set, the trained parameters \( \Theta_{q+1}^i \) are uploaded to the master server, where the superscript \( i \) indicates the parameters are trained on platform \( i \).

3.5 Global Model Update

Suppose \( A_q \) is the set of activated platforms in the \( q \)-th communication round. After all activated platforms finish local training, the master server collects all trained parameters \( \{\Theta_{q+1}^i \mid i \in A_q\} \) to update the global model. We define the goal of the global model as follows:

\[
\min_{\Theta_q} \frac{1}{|A_q|} \sum_{i \in A_q} J(\Theta_q; D_i^*) \tag{4}
\]

where \( J(\Theta_q; D_i^*) \) is the local loss function for the platform \( i \). Follow previous studies (McMahan et al., 2016), we optimize this global objective function via taking an average of all trained parameters, which is shown as follows:

\[
\Theta_{q+1} = \frac{1}{|A_q|} \sum_{i \in A_q} \Theta_{q+1}^i \tag{5}
\]

where \( \Theta_{q+1}^i \) is the optimal parameters obtained by minimizing the local loss function on the local data of platform \( i \). Since all trained parameters from different platforms are aggregated together, the information of texts in each platform is hard to be inferred. Thus, texts in platforms are well-protected. Complete pseudo-code of this framework is given in Algorithm 2.

|Algorithm 2 Federated Denoising Framework.|
|---|
|**Hyperparameters:**|
|\( K \) is the total number of platforms;|
|\( C \) is the fraction of platforms;|
|\( B \) is the local minibatch size;|
|\( E \) is the number of local epochs;|
|\( \eta \) is the learning rate.|
|**Master server executes:**|
|Initialize \( \Theta_0 \)
|for each communication round \( q = 0,1,... \) do
|// Select activated platforms
|\( m \leftarrow \max(C \times K, 1) \)
|\( A_q \leftarrow \text{(random set of } m \text{ platforms)} \)
|// Lazy MIL is defined in Algorithm 1
|\( V \leftarrow \text{Lazy}_\text{MIL}(\Theta_q, A_q) \)
|Broadcast \( V \) to each platform in \( A_q \)
|for each platform \( i \in A_q \) in parallel do
|\( \Theta_{q+1}^i \leftarrow \text{Local}_\text{Training}(i, \Theta_q) \)
|Upload \( \Theta_{q+1}^i \) to the server
|\( \Theta_{q+1} \leftarrow \frac{1}{|A_q|} \sum_{i \in A_q} \Theta_{q+1}^i \)
|**Function Local\_Training(i, \Theta_q):**|
|// Run on platform \( i \)
|Generate denoised dataset \( D_i^* \) from \( D_i \) based on the denoising information \( V \)
|\( B \leftarrow \text{(split } D_i^* \text{ into batches of size } B) \)
|for each local epoch \( e \) from 1 to \( E \) do
|for batch \( b \in B \) do
|// \( J \) is defined in Equation 3
|\( \Theta \leftarrow \Theta - \eta \nabla J(\Theta; b) \)
|return \( \Theta \) |

4 Experiments

4.1 Datasets and Evaluation Metrics

We conduct experiments on two public available distantly supervised relation extraction data, i.e., NYT 10 dataset (Riedel et al., 2010)\(^4\) and miRNA gene regulation relation (MIRGENE) dataset (Li et al., 2017)\(^5\), to investigate the effectiveness of our method.

\[^4\]https://github.com/thunlp/OpenNRE
\[^5\]https://github.com/leebird/bionlp17
NYT 10 is a standard benchmark distantly supervised dataset in news domain. It was automatically generated by aligning Freebase relations with the New York Times corpus, with the years 2005-2006 reserved for training and validation and 2007 for testing. The training data contains 466,876 sentences, 251,928 entity pairs and 16,444 relational facts. The test data contains 172,448 sentences, 96,678 entity pairs and 1,950 relational facts. There are 52 actual relations and a special relation NA for representing no relation between two entities.

MIRGENE is a large biomedical with 172,727 sentences in the training set and 1239 sentences in the test set, and is generated by aligning Tarbase and miRTarBase with the Medline abstract. An example is shown in the following: “MicroRNA-223 regulates FOXO1 expression and cell proliferation”, where MicroRNA-223 is a miRNA and FOXO1 is a gene.

Data Partitioning. To study distant supervision in federated settings, we need to specify how the data is distributed over the platforms. In this paper, we focus on the IID situation, where the training data is shuffled and then partitioned into $K$ (the total number of platforms) platforms.

Evaluation Metrics. We evaluate our approach and baseline methods on the held-out test set of these two datasets. Precision-recall (PR) curves, area under curve (AUC) values and Precision@N (P@N) values are adopted as evaluation metrics in our experiments.

4.2 Experimental Settings

For a fair comparison, we implemented our method and all baselines in the same experimental settings. We divide the hyperparameters into three parts, i.e., fixed hyperparameters, unfixed hyperparameters and federated hyperparameters. Fixed hyperparameters follow the hyperparameter settings in Lin et al. (2016), including the 50-dimensional pretrained word embeddings for NYT, the 5-dimensional position embeddings, and CNN module which includes 230 filters with a window size of 3. For MIRGENE, 200-dimensional word embeddings pretrained on PubMed and MIMIC-III texts are used. The optimal unfixed hyperparameters are determined by a grid search, and the search space of unfixed hyperparameters is shown in Table 1. Federated hyperparameters include the total number of platforms $K$, the fraction of platforms $C$, the local minibatch size $B$, the number of local epochs $E$. All of these control the amount of computation. In the end-to-end comparison, we fix the $K$ to 100, $B$ to 32, $E$ to 3, and set the hyperparameter space of $C$ as $\{0.1, 0.2, 0.5, 1\}$ following (McMahan et al., 2016). We use stochastic gradient descent as the local training optimizer and all experiments can be done by using a single GeForce GTX 1080 Ti.

4.3 Baselines

We compare our method with the following denoising baselines in federated settings: (1) Zeng et al. (2015) proposed to leverage multi-instance learning to choose the most reliable sentence as the bag representation, and we abbreviate this method as ONE; (2) ATT is proposed by Lin et al. (2016), which uses the attention mechanisms to place soft weights on a set of noisy sentences and select samples; (3) AVE (Lin et al., 2016) is a naive version of ATT and represents each sentence set as the average vector of sentences inside the set; (4) ATT RA (Ye and Ling, 2019) is a variant of ATT, which calculates the bag representations in a relation-aware way. For a fair comparison, we keep the other modules unchanged and only replace the denoising module in this work with the baseline models.

4.4 Results

4.4.1 Results on NYT 10

We plot PR curves of all methods with the top 2000 points in Figure 3, present detailed precision values measured at different points along these curves in Table 2, and show the AUC values of these curves in Table 3. We find that: (1) Our method significantly outperforms all baselines in federated settings. We believe the reason is that our denoising method can hinder false positive instances from poisoning local models, which leads to a better performance of the global model. (2) $C$ is the fraction of platforms that are activated on each round, which controls the amount of multi-platform parallelism. With increasing platform parallelism, the performance of all baselines declines slightly while our method performs better. Intuitively, increasing platform parallelism is able to lead to better

| Hyperparameter     | Search Space       |
|--------------------|--------------------|
| Learning Rate ($\eta$) | 0.05, 0.08, 0.1, 0.2 |
| Learning Rate Decay | 0.01, 0.05          |
| Dropout            | 0.1, 0.2, 0.5      |
| Weight Decay       | 1e-5, 1e-6          |

Table 1: The search space of unfixed hyperparameter.
results, since involving more platforms in training can increase the likelihood that all sentences with the same entity pair appear simultaneously. However, due to lack of cross-platform collaboration, all baselines handle label noise only based on its own local data, which may hamper the performance. In contrast, our method selects reliable instances among all activated platforms, which can effectively reap the benefits of increasing platform parallelism. (3) Leveraging attention mechanisms to denoise, which is an effective solution in centralized settings, seems not to work in federated settings. Compared with centralized training, the sentences in a bag may scatter around different platforms in federated settings, so the number of the sentences with the same entity pair on a platform is small, which may lead to placing large attention weights on noisy sentences due to lack of inter-bag contrast.

4.4.2 Results on MIRGENE

Figure 4, Table 4, and Table 5 show the comparison results in terms of PR curves, detailed precision values, and AUC values respectively on MIRGENE datasets. We notice that: (1) Our method achieves the best performance compared to all baselines, demonstrating the effectiveness of our denoising method. (2) With increasing platform parallelism (increasing \( C \)), baselines do not achieve better performance. In contrast, our method achieves better performance with the increase of parallelism. Unlike the significant performance improvement in NYT, the improvement of our method is not very obvious in MIRGENE. We conjecture this is largely due to the characteristic of the dataset. Concretely, the average number of sentences containing same entity pairs with non-“NA” relation is about 8 in NYT 10 while the number is about 4 in MIRGENE, which means that with lower parallelism, there is a high probability that all sentences with the same entity pairs appear simultaneously in MIRGENE.

4.5 Savings of Local Computation

In the real-world scenario, platforms are controlled by data holders or users, which require conducting local training with the least computation cost. Therefore, we investigate the impact of varying the number of local updates in this section. The number of local updates is given by \( E \left| D^*_i \right| \), where \( \left| D^*_i \right| \)
is the size of the denoised dataset in platform $i$ at a round, $B$ is the local minibatch size and $E$ is the number of local epochs. Increasing $B$, decreasing $E$, or both will reduce computation on each round. We fix $C$ to 0.1 and only $B$ and $E$ are varied in this section.\footnote{The lr, lr decay, weight decay and dropout are fix to is 0.1, 0.01, 1e-5 and 0.1 respectively, which are not the optimal hyperparameters for most experiments}. The results are shown in Figure 5. We find that: (1) When setting $B$ to 64 and $E$ to 1, our method achieves the best AUC value. In this case, the number of local updates is the least. (2) Increasing the local minibatch $B$ may improve the performance. (3) Increasing the local epoch $E$ can make training more stable and speed up converge, but may not make the global model converge to a higher level of AUC value. These findings are in line with McMahan et al. (2016), which shows it may hurt performance when over-optimize on the local dataset. We also present the results of other baselines in the Appendix due to page limits.

5 Conclusion

Due to data barriers and privacy protection, it is almost impossible or cost-prohibitive to integrate the data from multiple platforms. In this paper, we investigate distant supervision under the federated learning paradigm, which permits learning to be done while data stays in its local environment. To suppress label noise in federated settings, we propose a federated denoising framework, which can select reliable instances via cross platform collaboration. Extensive experiments on two datasets have demonstrated the effectiveness of our model.
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