Modeling the Noise in Distantly Supervised Relation Extraction with Transition Matrix

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Abstract

TODO: add abstract

1 Introduction

Distant supervision is a way of exploiting existing (prior) knowledge to construct training data for classification tasks, without relying on laborious human annotation.

The basic distant supervision paradigm lies in making proper assumptions according to a task, distilling feasible and effective rules from prior knowledge and applying those rules to automatically prepare training data. Successful distant supervision applications include, relation extraction (Mintz et al., 2009), cross-lingual semantic analysis (Fang and Cohn, 2016), and so on. The former assumes that the sentences containing both the subject and the object of a (subject $subj$, relation rel, object obj) triple are support for the existence of relation rel between $subj$ and obj, and aligns triples in knowledge base with free text to automatically create training data. The latter assumes that words of different languages which share similar meaning should have similar POS tags, and thus automatically create training data for low-resourced languages according to their English translations.

Distant supervision significantly reduces the cost of obtaining training data for these tasks. However, since the assumptions may be imperfect, it also inevitably brings noise to the training data. Sometimes the positive data may actually be negative (*false positive*), while sometimes the negative data may actually be positive (*false negative*). Furthermore, sometimes there may also be confusion between positive labels (*positive label confusion*). This noisy data may disturb the training procedure, and lead to a model with inaccurate performance.

We need to note that, the noise introduced by distant supervision is not random, and the input data may consist of useful clues for us to identify its noise pattern. In relation extraction, for example, some sentences labeled by distant supervision to express the relation *place_of_birth* between a person and place actually only talks about the work place of the person. Since we also find many sentences labeled as *place_lived* talks about the person's work place, we can reasonably assume that if a sentence is talking about the work place of a person, although the real relation expressed by the sentence is *place_lived*, there is still some chance that it is erroneously labeled as *place_of_birth* by distant supervision.

This observation shows that it is possible to identify the noise pattern by analyzing the input data. In this paper, we propose to dynamically produce a transition matrix $\mathbf{T}$ for each datum to model the transition from the true label to the observed label. Here T_{ij} represents the conditional probability that the observed label is j given the true label is i. Since the label modeled by the transition matrix can be both positive and negative, it actually has the ability to model all the three types of noise introduced by distant supervision.

In this paper, we focus specifically on the relation extraction task. The data is noisy because not all sentences containing $subj$ and obj support the ($subj$, rel, obj) triple. TODO: for example... In previous literature, this noise is often implicitly handled by the *at-least-one assumption* that at least one of the sentences containing both $subj$ and obj support the ($subj$, rel, obj) triple. The sentences that containing both $subj$ and obj are therefore aggregated into a sentence bag, and the problem becomes classifying the relation expressed by the sentence bag instead (Riedel et al., 2010; Lin et al., 2016).

However, the at-least-one assumption is not

perfect either, and therefore introduces bag level noise. First, if all the retrieved sentences do not support the $(subj, rel, obj)$ triple, then this bag is false positive. Second, if the $(subj, rel, obj)$ triple is true but is missing in the KB, then the bag is false negative.

We apply our transition matrix method to both sentence level and bag level models. We also propose to combine curriculum learning and trace normalization for training to deal with the lack of guidance over the noise. The experiments show that our transition matrix method improve both of these models in two datasets. By experimenting on the dataset proposed by (Luo et al., 2016), which contains both reliable and unreliable data, we show that our training procedure can make use of the prior knowledge of the data quality and help the transition matrix model the noise better. We find that, the at-least-one assumption works better than the sentence level transition matrix model if no prior knowledge of the data quality is used. However, if we know which data are reliable, the sentence level transition matrix model works significantly better than bag level transition models. This shows that, with some indirect guidance, explicitly modeling the noise works better than using heuristics to implicitly handle the noise.

2 Related Work

TODO: add more description about DS Relation extraction aims at extracting (subject s, relation r, object o) triples from free text. This task is often conducted in the distant supervision paradigm (Mintz et al., 2009), which tries to automatically build noisy training set with the guidance of knowledge base. Specifically, it considers the sentences containing both the subject $subj$ and the object obj as supports for the triple $(subj, rel, obj)$. Since not all sentences retrieved by distant supervision are true positive, (Riedel et al., 2010) propose to consider the relation extraction task as a multi-instance classification problem based on the assumption that at least one of the retrieved sentences (sentence bag) are support for the triple. (Hoffmann et al., 2011; Surdeanu et al., 2012) further considers the problem as a multi-instance multi-label problem and uses graphic models to solve the problem. (Zeng et al., 2015) proposes to use piece-wise convolutional neural network (PCNN) model in the multi-instance paradigm and (Lin et al., 2016) further uses attention mechanism to better distinguish true positive ones from false positive ones. These models actually only tries to identify the noisy sentences and reduce their influence. However, our method has the ability to model the noise and can further make use of the noise.

Although the multi-instance assumption can significantly reduce the noise, this assumption is not perfect. First, there are situations where all the retrieved sentences are false positive. Second, the KB is not complete, and there may exist false negative problems. (Takamatsu et al., 2012) considers the denoising problem as a pre-processing problem, and removes potential noisy sentences by identifying bag syntactic patterns. Another thread of work tries to alleviate the false negative problem. (Xu et al., 2013) use pseudo-relevance feedback to find possible false negative data. (Ritter et al., 2013) and (Min et al., 2013) adds a set of latent variables to the MultiR model (Hoffmann et al., 2011) and the MIML model (Surdeanu et al., 2012) respectively to model the true relation before the variables representing observed relations. Our method shares similar spirit to (Ritter et al., 2013) and (Min et al., 2013) that we all try to generate the true relation before the observed relation. The differences between our models are three-fold. First, our model is designed in the neural network framework and their models are designed in the probabilistic graphic model framework. Second, the noise modeling part in our model is fully differentiable while their parameters used to model the transition from true relation to observed relation need to be set by hand or with some heuristics. Third, our transition matrix model can model fine grained transition from true relation to observed relation (the sentence level noise is fine grained), while their methods only deals with false negative and false positive noise.

Our method is also closely related to the thread of work of designing denoising neural network component in the computer vision field. The noise can come from automatically constructed dataset like Tiny Images dataset (Torralba et al., 2008) where the images are gathered from web search engine and can also come from human labeled dataset (Misra et al., 2016) like the MS COCO Captions dataset (Chen et al., 2015). (Sukhbaatar et al., 2014) propose to use a global transition matrix to transform the true label distribution to the observed label distribution and use weight decay

on the transition matrix during training. (Reed et al., 2014) also use a hidden layer to represent the true label distribution but try to force it to predict both the noisy label and the input. (Chen and Gupta, 2015; Xiao et al., 2015) first estimates the transition matrix on the clean data set and use it in the noisy data set. (Misra et al., 2016) generates the transition matrix dynamically for each training instance.

In contrast to computer vision, the research on denoising with neural network is limited in the field of natural language processing (NLP). (Fang and Cohn, 2016) also uses a global transition matrix to model the noise introduced by cross-lingual projection of training data in the task of POS tagging for low-resource languages and propose to train the basic model on the clean data first and add the transition matrix when using noisy data afterwards. Similar to (Misra et al., 2016), we also dynamically generate a transition matrix for each training data, but our datum can be a bag of instances. Furthermore, we combine curriculum learning and trace normalization for training and we also discuss the training procedure under various situations.

3 Task Description

Relation extraction aims at extracting (subject $subj$, relation rel, object obj) triples from free text. In this paper, we consider two kinds of models. Sentence level models take a sentence s containing both $subj$ and obj as input. We want to identify the relation expressed by the sentence between $subj$ and obj. Bag level models take a bag of sentences S as input and each sentence $s \in S$ contains both $subj$ and obj. We need to identify the relation expressed by the sentence bag between $subj$ and obj. Distant supervision considers all the sentences containing both $subj$ and obj to express relation rel for sentence level models, and considers the sentence bag containing both $subj$ and obj to express relation rel for bag level models.

We also consider two types of relation extraction tasks. The first task aims at extracting relations between entity and time. Specifically, it requires the object to be an time expression and the subject to be an entity. As suggested by (Luo et al., 2016), the distant supervision dataset in this task can be naturally divided into several subsets with different levels of reliability. The basic idea is that number of important things related to one entity increases as the time scope becomes larger. For example, a sentence containing both *Alphabet* and *October_2_2015* is very likely to express the foundation time of *Alphabet*, while a sentence containing both *Alphabet* and *2015* may instead talk about its financial report of year 2015. We experiment with this task because it has a public dataset that contains both reliable and unreliable data, which enables us to conduct all of our experiments.

The second task aims at extracting relations between entities, which is extensively studied in relation extraction. We experiment with this task to see if our transition matrix method generalizes well in different datasets.

4 Method

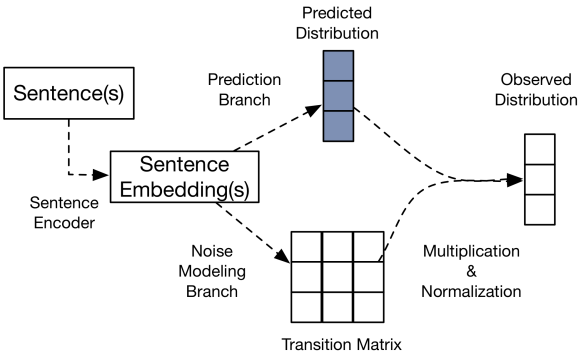


Figure 1: The architecture of our denoising model

The overview of our model is shown in Figure 1. First, the input sentence (or sentence bag) is passed to a sentence encoder to get sentence embedding(s). After that, the model is split into two branches. The prediction branch generates the predicted relation distribution $\mathbf{p}$ of the input sentence (or sentence bag). The noise modeling branch generates the transition matrix $\mathbf{T}$. Finally, the predicted distribution is multiplied by the transition distribution to generate the observed relation distribution $\mathbf{o}$. The predicted relation distribution $\mathbf{p}$ is the output of the model while the observed relation distribution $\mathbf{o}$ is used to simulate the relation assigned by distant supervision. In this way, the noise is modeled by the transition matrix and the real prediction is protected from the influence of the noise.

4.1 Sentence Encoder

TODO: add distance embedding Similar to previous researches in relation extraction, we also

use the piecewise convolutional neural network (PCNN) model (Zeng et al., 2015) as our sentence encoder. The PCNN model first divides the input sentence into three pieces by the subject and the object. After that, it will apply convolutional neural network (CNN) to each piece to calculate the piece embedding. The final sentence embedding is the concatenation of the embeddings of the three pieces.

4.2 Prediction Branch

The prediction branch can be implemented by the prediction part of almost all the relation extraction neural network models. As for sentence level models, we use the settings of (Luo et al., 2016). Specifically, we first feed the sentence embedding to a full connection layer, and use softmax classifier for relation classification. As for bag level models, the key problem is how to aggregate the embeddings of each sentence in a bag. Similar to (Lin et al., 2016), we experiment with two settings: average aggregation and attention aggregation. The average aggregation calculates the bag embedding $\mathbf{s}$ by averaging the embeddings of each sentence, and the resultant bag embedding is fed to a softmax classifier for relation classification. The attention aggregation method (Lin et al., 2016) calculates bag embeddings with respect to each relation. For example, the bag embedding with respect relation j is:

$$\mathbf{s}_j = \sum_i^n \alpha_{ij}\mathbf{x}_i \tag{1}$$

$$\alpha_{ij} = \frac{exp(\mathbf{x}_i^T \mathbf{A}\mathbf{r}_j))}{\sum_i exp(\mathbf{x}_i^T \mathbf{A}\mathbf{r}_j)} \tag{2}$$

where and α_{ij} is the attention over sentence i with respect to relation j, $\mathbf{A}$ is a diagonal matrix and $\mathbf{r_j}$ is the randomly initialized embedding of relation j. The resultant bag embedding is fed to a softmax classifier to predict the probability of relation j.

4.3 Noise Modeling Branch

Parallel to the prediction branch, the noise modeling branch calculates a transition matrix dynamically for each sentence (or sentence bag) to model its noise pattern.

Sentence Level Transition Matrix As for sentence level models, the sentence embedding $\mathbf{x}$ is passed to another full connection layer to obtain the sentence embedding $\mathbf{x}_n$ used specifically for the noise branch. After that, the transition matrix $\mathbf{T}$ is calculated using a softmax classifier:

$$T_{ij} = \frac{exp((\mathbf{w}_t^{ij})^T \mathbf{x}_n + b_t)}{\sum_{j=1}^{|\mathbb{C}|} exp((\mathbf{w}_t^{ij})^T \mathbf{x}_n + b_t)} \tag{3}$$

where T_{ij} is the conditional probability that this sentence is labeled as relation j by distant supervision given the true relation is i, $\mathbf{w}_t^{ij}$ is the weight vector for this situation, b_t is a scalar bias and $|\mathbb{C}|$ is the number of relations.

Bag Level Transition Matrix As for bag level models, we first use the attention mechanism to calculate the bag embedding with respect to each relation:

$$\mathbf{s}_j = \sum_i^n \alpha_{ij}\mathbf{x}_i \tag{4}$$

$$\alpha_{ij} = \frac{exp(\mathbf{x}_i^T \mathbf{r}_t^j)}{\sum_i^n exp(\mathbf{x}_i^T \mathbf{r}_t^j)} \tag{5}$$

where $\mathbf{s}_j$ is the bag embedding with respect to relation j, $\mathbf{x}_i$ is the embedding of sentence i, α_{ij} is the attention value and $\mathbf{r}_t^j$ is another randomly initialized embedding of relation j used specifically for noise modeling branch.

Then the transition matrix $\mathbf{T}$ is calculated by:

$$T_{ij} = \frac{exp((\mathbf{r}_t^j)^T \mathbf{s}_i + b_t)}{\sum_{j=1}^{|\mathbb{C}|} exp((\mathbf{r}_t^j)^T \mathbf{s}_i + b_t)} \tag{6}$$

where $\mathbf{s}_i$ is the bag embedding with respect to relation i, $\mathbf{r}_t^j$ is the embedding of relation j mentioned above, and b_t is a scalar bias.

Note that the softmax function guarantees that each row of the transition matrix $\mathbf{T}$ sums to 1 in both sentence level and bag level models. Here T_{ij} represents the conditional probability that the relation labeled by distant supervision is j given the true relation is i.

4.4 Observed Relation Distribution

Given the predicted relation distribution $\mathbf{p}$ calculated by the prediction branch, and the transition matrix $\mathbf{T}$ calculated by the noise modeling branch, the observed relation distribution $\mathbf{o}$ is calculated by:

$$\mathbf{o} = \mathbf{T}^T \cdot \mathbf{p} \tag{7}$$

$$o_i = \frac{o_i}{\sum_i o_i} \tag{8}$$

where $\cdot$ represents dot product and Equation 8 normalizes the elements of $\mathbf{o}$ so that $\sum_i o_i = 1$

Different from previous works that use the predicted relation distribution $\mathbf{p}$ to directly match the relation labeled by distant supervision. We instead use $\mathbf{o}$ to match the relation assigned by distant supervision. In this way, we can model the procedure of how the noisy label is produced and thus protect our prediction $\mathbf{p}$ from the influence of the noise.

Note that the noise modeling branch and $\mathbf{o}$ is only used in the training phase. In the test phase, we only use the prediction brach and take the predicted relation distribution $\mathbf{p}$ as our output.

5 Training Procedure

Note that if we apply the transition matrix model directly to the training data, there is no incentive for the predicted relation distribution $\mathbf{p}$ to model the true relation distribution, instead it will probably be treated as a normal hidden layer. In this section, we show how to combine the curriculum learning framework and a novel normalization strategy to solve this problem. We describe the training procedure in the situation with and without the prior knowledge of the data quality.

5.1 Curriculum Learning over Dataset

TODO: describe the curriculum learning for bag level methods in experiment part The basic idea of curriculum learning is simple: start with the easiest aspect of a task, and level up the difficulty gradually.

The most straight forward way to build a curriculum is by controlling the training data. If we have both reliable and unreliable data, we can first train the prediction branch on the reliable data for t_1 epochs so that the prediction branch will have the basic classification ability. Then we add the unreliable data as well as the noise modeling branch. In this way, the prediction branch will already possess the tendency to predict true relation distribution before exposed to noisy data.

Specifically, in the dataset of (Luo et al., 2016), we have three subsets with decreasing reliability. We first train the prediction branch on the reliable subset for t_1 epochs. After that, we add the less reliable subset and the most unreliable subset consecutively and train for t_2 and t_3 epochs respectively (for simplicity, here we set $t_1 = t_2 = t_3$).

5.2 Trace Normalization

The curriculum learning method above only works when we know which data are reliable. Here we introduce how to use trace normalization to control the behavior of the transition matrix and how to use this method to build a more general curriculum in the next section.

Intuitively, if the noise is small, the transition matrix $\mathbf{T}$ will tend to become an identity matrix. Therefore, we can utilize our prior knowledge of the data quality by controlling the similarity between $\mathbf{T}$ and identity matrix. In the situation where we do not know which data are reliable, we can first force the transition matrix to be similar to identity matrix until the prediction branch is roughly trained. Then by gradually relax the constraint, the model will gradually learn to model the noise in the dataset.

Specifically, since each row of $\mathbf{T}$ sums to 1, the similarity between the transition matrix and the identity matrix can be represented by the trace of the transition matrix $\mathbf{T}$. The larger the $trace(\mathbf{T})$ is, the smaller the elements that do not lie in the diagonal are, and the similar the transition matrix $\mathbf{T}$ is to identity matrix.

Since we have the prior knowledge of the quality of the three subsets of the dataset of Luo et.al, we can further use three hyper-parameters $\{\beta_1, \beta_2, \beta_3\}$ to control the $trace(\mathbf{T})$ of the three subsets. For reliable subset, we want $trace(\mathbf{T})$ to be large (negative β_1) so that the element values of $\mathbf{T}$ will be centralized to the diagonal. As for unreliable subsets, we want the $trace(\mathbf{T})$ to be small (positive β_2 and β_3) so that the element values of their transition matrices will be diffusive. Note that this method only works for sentence level models, since reliable sentences and unreliable ones are all aggregated into a sentence bag in bag level models and therefore we can not determine which bag is reliable. and which is not. We use cross entropy as our basic loss function, and the loss function of the sentence level model is defined as follows:

$$J(\theta) = \sum_{i=1}^{3} \sum_{j=1}^{N_i} -log(o_{ijy_{ij}}) + \beta_i trace(\mathbf{T}_{ij}) \tag{9}$$

where θ represents all the parameters in our model, i is the index of the three subsets, j is the index of sentence, $\mathbf{T}_{ij}$ is the transition matrix of sentence

s_{ij}, y_{ij} is the relation assigned by distant supervision for sentence s_{ij}, and $o_{ijy_{ij}}$ is the probability that the observed relation for sentence s_{ij} is y_{ij}.

5.3 Curriculum Learning over Noise Modeling Strength

As for bag level models, and in the situation where we do not have prior knowledge of the data quality, we can build a curriculum by controlling our expectation for the model to model the noise. Specifically, the loss function is defined as follows:

$$J(\theta) = \sum_{i=1}^{N} -(\alpha log(o_{iy_i}) + (1-\alpha) log(p_{iy_i})) + \beta trace(\mathbf{T}_i) \tag{10}$$

where $0 \leq \alpha \leq 1$, y_i is the relation assigned by distant supervision for sentence s_i, o_{iy_i} and p_{iy_i} is the probability that the observed and predicted relation for setnence s_i is y_i. TODO: polish the statement before Instead of only using the observed relation distribution $\mathbf{o}$ to simulate the relation labeled by distant supervision, we use the linear combination of the cross entropy of both the observed relation distribution $\mathbf{o}$ and the predicted relation distribution $\mathbf{p}$.

At the start of the training, we set $\alpha = 1$ and $\beta < 0$, which means we do not expect the model to model the noise (easy part of the problem). As the training proceeds, the prediction branch gradually learns the basic prediction ability. Therefore, we decrease α and the absolute value of β by d every τ epochs to gradually lead the model to learn to model the noise.

5.4 Constraint Transition Matrix

Recall that the bag level noise mainly consists of false negative and false positive, but our transition matrix also has the ability to model the confusion among positive relations. To prevent overfitting and make the model concentrate on the false negative and false positive noise, we restrict the transition matrix for bag level models so that only the diagonal, the first column and the first row of the transition matrix do not equal to zero (assume the index of *no-relation* is 0).

6 Experiments

6.1 Data Set

We experiment our model on two datasets. The first one is proposed by (Luo et al., 2016) and aims at extraction relations between entity and time (*time RE data*). The dataset is constructed by aligning Wikidata triples with Wikipedia corpus. Based on the granularity of the time expression in the sentence, this dataset can be split into 3 subsets with different levels of reliability. The reliable subset is used as basic training data, validation data and test data which contains 22,214, 2,776 and 2,771 positive sentences respectively. The two less reliable subset contains 2,094 and 53,469 positive sentences and are used as additional training data. Negative data are constructed with two heuristic strategies. We use this dataset because this is a public dataset on relation extraction that has both reliable and unreliable data, which is suitable for all of our experiment settings.

We also conduct our experiment on the dataset proposed by (Riedel et al., 2010), which is a commonly used dataset in relation extraction (*entity RE*). This dataset is generated by aligning triples in Freebase with the New York Times corpus (NYT corpus). The training data contains 522,611 sentences and 281,270 entity pairs. The test set contains 172,448 sentences and 96,678 entity pairs. We experiment our bag level models in this dataset to see the generalization ability of our transition matrix model.

6.2 Hyper-parameters

Sentence Level Model We experiment our sentence level model on time RE data. We use 100-dimensional word embedding pre-trained using GloVe (Pennington et al., 2014) on Wikipedia and Gigaword, and 20-dimensional vector for distance embedding. The convolution window is 3 and the number of convolution kernels is 200. The size of the full connection layer is also 200. As for training, we use stochastic gradient descend (SGD) for optimization with batch size 20, learning rate 0.1. We also use dropout with probability 0.5 upon the sentence embedding. Each phase of the curriculum learning over dataset contains 15 epochs. The trace normalization parameters for three subsets are $\beta_1 = -0.01$, $\beta_2 = 0.01$ and $\beta_3 = 0.1$ (the ratio of β_3 and β_2 is fixed to 10 and 5 when tuning hyper-parameters).

Bag Level Model The parameters of the bag level model is almost the same as the sentence level model on time RE data, except that the learning rate is 0.01. As for entity RE data, our settings for prediction branch is similar to (Lin et al., 2016). The word embedding is of dimension 50 and is pre-trained on the NYT corpus using word2vec[1]. The convolution window is 3 and the number of convolution kernels is 256, distance embedding size is 5, batch size is 16 and learning rate is 0.01. For all the bag level models, the linear combination parameter α is 1 and trace normalization parameter β is -0.1 at the start of training. We experiment with decay rate $\{0.95, 0.9, 0.8\}$ and decay step $\{3, 5, 8\}$. We find that using decay rate 0.9 and decay step 5 performs well in most situations.

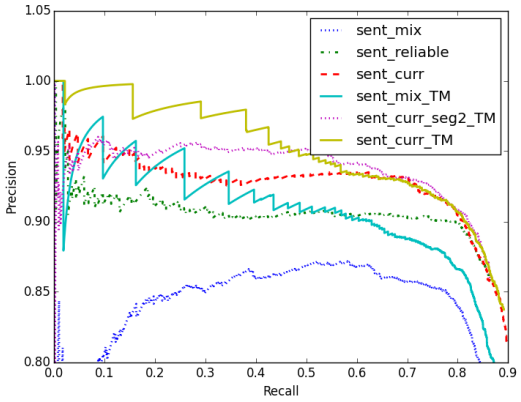


Figure 2: Sentence Level Results on Time RE

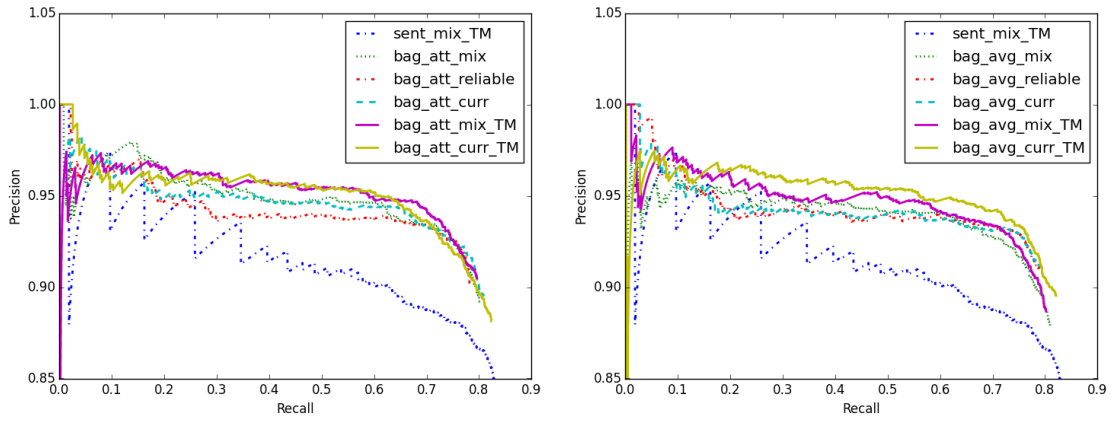
6.3 Results on Time RE Data

We exhibit the results in the form of precision recall curves (PR curves).

Sentence Level Models The results of sentence level models is shown in Figure 2. We can see that the performance of the model trained on all subsets mixed together (*sent_mix*) is very bad, which is significantly worse than the model trained only on the reliable subset (*sent_reliable*). This shows that the noise problem is innegligible and have bad influence on the training of the model. However, with the help of transition matrix, the model obtains the ability of modeling noise (*sent_mix_TM*), which significantly improves the performance of the model. By using the reliable subset first and gradually adding less reliable data (*sent_curr*), we can see that the model can actually make use of the noisy data and performs better than the model trained only on the reliable subset. If we further use the transition matrix under the curriculum learning framework (*sent_curr_TM*), the transition matrix will model the noise better and further improve the model performance. Apart from the experiments above, we also experiment our model in the situation where all the unreliable data are merged into one subset (*sent_seg2_curr_TM*), which means there are only two subsets: reliable subset and unreliable subset. We conduct this experiment because this setting will reduce the hyper-parameters and make the training easier to perform. We can see the, although this setting is not as good as using the full information of the data quality (using 3 subsets), it still has reasonable performance and also significantly outperforms the model which only use curriculum learning over dataset.

Bag Level Attention Aggregation Models The results of the bag level models with attention aggregation is shown in Figure 3(a). We can see that the basic bag level attention aggregation model (*bag_att_mix*) performs very good and significantly outperforms the *sent_mix_TM* model. Recall that the bag level model is based on the at-least-one assumption that at least one of the sentences in the sentence bag support the $(subj, rel, obj)$ triple, and the *sent_mix_TM* model do not use any assumption about the dataset. This shows that prior knowledge of the data quality plays an important role in the situation where the dataset is noisy. In the bag level models, the curriculum learning over dataset can be conducted by using only the reliable sentences in the sentence bag, and add unreliable sentences gradually. However, we find that using only reliable subset (*bag_att_reliable*) or using curriculum learning over dataset alone (*bag_att_curr*) does not improve the bag level attention aggregation model. This shows that the less reliable data in the sentence bag may provide additional side information or possibly plays the role of avoiding overfitting. TODO: polish the explanation. Also note that the at-least-one assumption does not always hold and there are also false negative and false positive problems in bag level. Therefore, we can see that using transition matrix with or without curriculum learning over the dataset (*bag_att_curr_TM* and *bag_att_mix_TM*) all improve the model perfor-

[1] https://code.google.com/p/word2vec/



(a) Attention Aggregation (b) Average Aggregation

Figure 3: Bag Level Results on Time RE

mance, and the *bag_att_curr_TM* model performs better in the low recall region.

Bag Level Average Aggregation Models The results of the bag level models with average aggregation is shown in Figure 3(b). The ranking of each setting is similar to the attention aggregation models. One interesting thing is that our transition matrix method improves the average aggregation models more significantly than the attention aggregation models. Note that the average aggregation model actually do not have good ability of handling sentence level noise. Therefore, the unhandled sentence level noise may further propagate to the bag level, which gives the transition matrix more chance to help model the noise. Also note that the *bag_avg_curr_TM* model significantly outperforms the *bag_avg_mix_TM*, this shows that curriculum learning over dataset helps the transition matrix more when the noise is more severe.

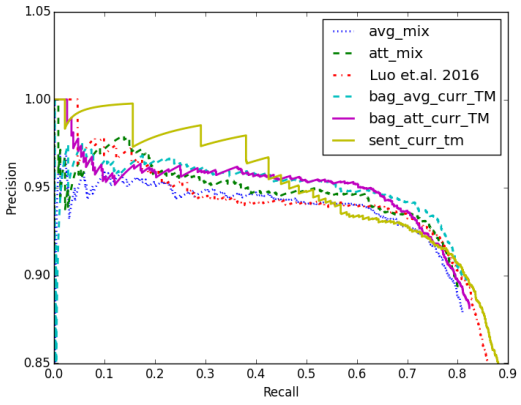


Figure 4: Comparison on Time RE

Comparison TODO: polish this part The comparison of the best settings of each model family is shown in Figure 4. We can see that all of our models outperforms the model of (Luo et al., 2016). With the help of transition matrix, although the basic version of average aggregation is not as good as attention aggregation, its transition matrix version is similar to the attention aggregation. Also note that although the sentence level models trained on mixed data do not perform very good, the sentence level model can use transition matrix to model the sentence level noise and thus performs best in all these models. Recall that the transition matrix can model the noise rather than just reduce the influence of noisy sentences as in bag level models, the sentence level model actually has the ability to make use of the noisy data. This shows that sentence level noise is more important than the bag level noise in relation extraction, and modeling noise works better than just trying to reducing the influence of noise.

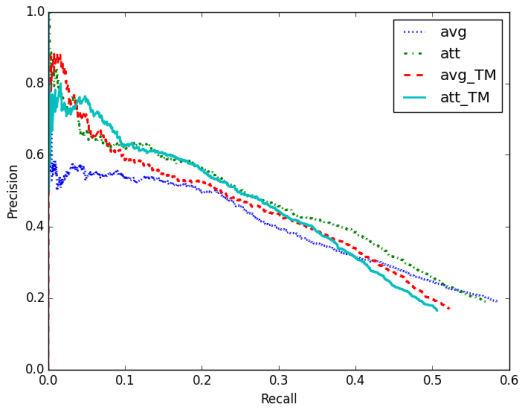


Figure 5: Results on Dataset of Riedel et.al.

6.4 Performance on Entity RE Data

To show the generalization ability of our proposed transition matrix method, we also conduct experiments on the entity RE dataset proposed by (Riedel et al., 2010), which is a commonly used dataset in relation extraction. We implement the average aggregation method (*avg*) and the attention aggregation method (*att*) proposed by (Lin et al., 2016) as well as the corresponding transition matrix version (*avg_TM* and *att_TM*). The results are shown in Figure 5. We can see that, since the average aggregation method do not have good ability in handling sentence level noise, it performs significantly worse than the attention aggregation method. Similar to the results in time RE data, since the unhandled sentence level noise propagates to the bag level, which makes the bag level noise become more severe, the transition matrix has more chance to model the noise. Therefore, the *avg_TM* model significantly outperforms the *avg* model. As for attention aggregation, this model already have good ability in reducing the impact of sentence level noise. Since the bag level noise is less important than the sentence level noise, the improvement of our transition matrix model is limited, which only improves the model on the low recall part. Note that the low recall part corresponds to high precision, which is more useful than the rest of the extraction results in practice. Therefore, our transition matrix method is also useful in this situation.

7 Conclusion

TODO: re-write

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