EMPIRICAL ANALYSIS OF UNLABELED ENTITY PROBLEM IN NAMED ENTITY RECOGNITION

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ABSTRACT

In many scenarios (e.g., distantly supervised learning), named entity recognition (NER) models severely suffer from *unlabeled entity problem*, where the entities of a sentence may not be fully annotated. Through empirical studies performed on synthetic datasets, we find that the main cause of performance degradation is treating unlabeled entities as negative instances, which seriously misguides the models in training. Another cause is the reduction of annotated entities. However, it can be mitigated well by adopting pre-training language models. Inspired by recent span-based models, we propose a general method that is capable of eliminating the misguidance brought by unlabeled entities. The core idea is to utilize negative sampling to keep the probability of training with unlabeled entities at a very low level. On standard datasets (e.g., CoNLL-2003), our model is competitive with current state-of-the-art approach. Experiments on synthetic datasets and real-world datasets show that our model is robust to *unlabeled entity problem* and significantly outperforms prior baselines[1].

1 INTRODUCTION

Named entity recognition (NER) is an important task in information extraction. Previous methods typically cast it into a sequence labeling problem by adopting IOB tagging scheme (Huang et al., 2015; Ma & Hovy, 2016; Akbik et al., 2018). A representative model is Bi-LSTM CRF (Lample et al., 2016). The great success achieved by these methods benefits from massive correctly labeled data. However, in some real scenarios, not all the entities in the corpus are annotated, which largely degrades the performances of models. We refer this to *entity unlabeled problem*. For example, in fine-grained NER (Ling & Weld, 2012), the datasets contain hundreds of entity types and a mention may be associated with multiple labels. Since manual annotation is too hard, many entities are ignored by human annotators. The situation in distantly supervised NER (Ren et al., 2015; Fries et al., 2017) is even more serious. To reduce handcraft annotation, distant supervision (Mintz et al., 2009) is applied to automatically produce labeled data. As a result, large amounts of entities in the corpus are missed due to the limited coverage of knowledge resources.

There are several approaches used in prior works to alleviating this problem. Fuzzy CRF and AutoNER (Shang et al., 2018b) allow the models to learn from the phrases that may be potential entities. However, since these phrases are obtained by using a distantly supervised phrase mining method (Shang et al., 2018a), many unlabeled entities in the training data may still not be recalled. In the context of only resorting to unlabeled corpus and an entity ontology, Peng et al. (2019) use positive-unlabeled (PU) learning (Li & Liu, 2005) to unbiasedly and consistently estimate the task loss. In implementations, they build a distinct binary classifiers for each label. Nevertheless, the unlabeled entities still impact on the classifiers of the corresponding entity types and, importantly, the model can't disambiguate neighboring entities. Partial CRF (Tsuboi et al., 2008) is an extension of commonly used CRF (Lafferty et al., 2001) that supports learning from incomplete annotations. Yang et al. (2018); Nooralahzadeh et al. (2019) use it to circumvent the unlabeled entities. However, as fully annotated corpus is still required to get true negative instances, this approach is not applicable to the cases where no high-quality data is available.

In this work, our goal is to study what are the impacts of unlabeled entities on the models and how to effectively eliminate them by a general method. Initially, we construct some synthetic datasets

[1]The source code of this work is publicly available at https://XXX.

and introduce degradation rates. The datasets are constructed by randomly removing the annotated named entities in standard datasets, e.g., CoNLL-2003 (Sang & De Meulder, 2003), with different probabilities. The degradation rates measure how severe an impact of unlabeled entities degrades the performances of models. Comprehensive studies are investigated on synthetic datasets. We find that the primary cause is treating unlabeled entities as negative instances, which seriously misleads the models during training. Even in less severe cases, it can sharply reduce the F1 score by about 20%. Another cause is the reduction of annotated entities. While this is quite obvious, we find that its effect is much smaller than the misguidance and can be mitigated well by adopting a pre-training language model, like BERT (Devlin et al., 2018), as the sentence encoder. Inspired by recent span-based models (Stern et al., 2017; Li et al., 2019; Yu et al., 2020), we present a method that can almost completely eliminate the misguidance from unlabeled entities. The core idea is to apply negative sampling, which keeps training with unlabeled entities at a very low level.

To verify the effectiveness of our method, we conduct extensive experiments on standard datasets (e.g., CoNLL-2003), synthetic datasets, and real-world datasets (e.g., EC). On the one hand, our model is competitive with current state-of-the-art method. On the other hand, experiments on synthetic datasets and real-world datasets demonstrate that our model is capable of handling unlabeled entities well and notably outperforms prior baselines.

2 PRELIMINARIES

In this section, we formally define the *entity unlabeled problem* and briefly describe a strong baseline, BERT Tagging (Devlin et al., 2018), used in empirical analysis.

2.1 ENTITY UNLABELED PROBLEM

We denote an input sentence as $\mathbf{x} = [x_1, x_2, \cdots, x_n]$ and the annotated named entity set as $\mathbf{y} = \{y_1, y_2, \cdots, y_m\}$. n is the sentence length and m is the amount of entities. Each member y_k of set $\mathbf{y}$ is a tuple (i_k, j_k, l_k). (i_k, j_k) is the span of an entity which corresponds to the phrase $\mathbf{x}_{i_k,j_k} = [x_{i_k}, x_{i_k+1}, \cdots, x_{j_k}]$. l_k is the label of an entity. The *entity unlabeled problem* is defined as, in some situations, a few entities $\widetilde{\mathbf{y}}$ may be omitted by annotators, and thus not covered by set $\mathbf{y}$, which severely degrades the performances of NER models.

2.2 BERT TAGGING

BERT Tagging adopts IOB format, where each token x_i in a sentence $\mathbf{x}$ is labeled as B-tag if it's the beginning of an entity, I-tag if it's inside but not the first one within the entity, or O otherwise. Under this scheme, the output is a n-length label sequence.

Firstly, it uses BERT to compute the representation $\mathbf{h}_i$ for every token x_i:

$$[\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_n] = \mathrm{BERT}(\mathbf{x}). \tag{1}$$

Then, the label distribution $\mathbf{q}_i$ is predicted as

$$\mathbf{q}_i = \mathrm{Softmax}(\mathbf{W}\mathbf{h}_i). \tag{2}$$

During training, a hybrid cross entropy loss is induced as $\sum_{1 \le i \le n} -\log \mathbf{q}_i[y_i]$. At test time, the label for each token x_i is obtained by $\arg\max \mathbf{q}_i$.

3 EMPIRICAL STUDIES

To understand the impacts of *unlabeled entity problem*, we conduct empirical studies over multiple synthetic datasets, different methods, and various metrics.

3.1 PREPARATIONS

Synthetic Datasets. To simulate poorly annotated datasets, we randomly remove the labeled entities of standard datasets with different masking probabilities. The standard datasets are CoNLL-2003 (Sang & De Meulder, 2003) and OntoNotes 5.0 (Pradhan et al., 2013). Both of datasets are

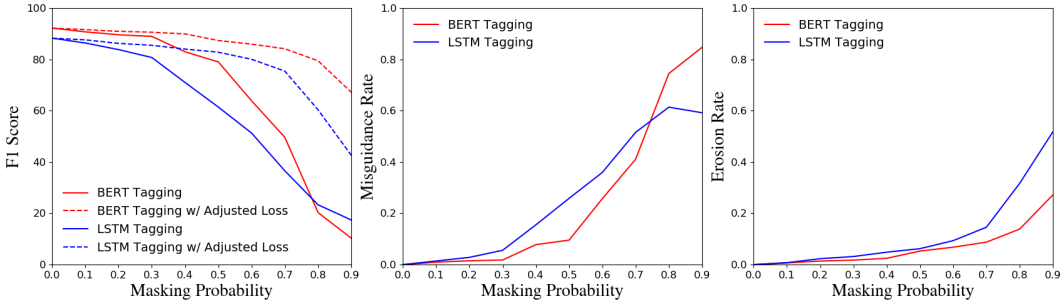

Figure 1: The empirical studies conducted on CoNLL-2003 dataset.

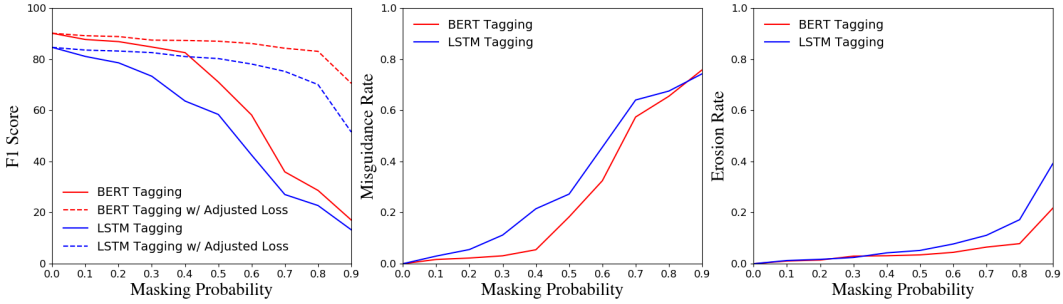

Figure 2: The empirical studies investigated on OntoNotes 5.0 dataset.

usually adopted to evaluate the performances of NER models. The probabilities p are respectively set as $0.0, 0.1, 0.2, \cdots, 0.9$. In this way, 2×10 synthetic datasets are constructed.

Methods. We adopt two models. One of them is BERT Tagging, which has long been regarded as a strong baseline. The other is LSTM Tagging that replaces the original encoder (i.e., BERT) of BERT Tagging with LSTM (Hochreiter & Schmidhuber, 1997). We use it to study the effect of using pretraining language model. To explore the negative impacts brought by unlabeled entities in training, we present an adjusted training loss for above two models:

$$\Big(\sum_{1\le i\le n} -\log \mathbf{q}_i[y_i]\Big) - \Big(\sum_{(i',j',l')\in\widetilde{\mathbf{y}}} \sum_{i'\le l\le j'} -\log \mathbf{q}_l[y_l]\Big). \tag{3}$$

The idea here is to remove the incorrect loss incurred by unlabeled entities. Note that missed entity set $\widetilde{\mathbf{y}}$ is reachable in synthetic datasets but unknown in real-world datasets.

Metrics. Following prior works, the F1 scores of models are tested by using conlleval script[2]. We also design two degradation rates to measure the different impacts of *unlabeled entity problem*. One is misguidance rate α_p and the other is erosion rate β_p:

$$\alpha_p = \frac{f_p^a - f_p}{f_p^a}, \quad \beta_p = \frac{f_0^a - f_p^a}{f_0^a}. \tag{4}$$

For a synthetic dataset with the masking probability being p, f_p and f_p^a are the performances of a model and its adjusted version, respectively. Misguidance rate α_p measures how serious unlabeled entities mislead a model during training. Erosion rate β_p measures how severe the reduction of annotated entities degrades the F1 scores of a model.

3.2 Result Analysis

The left parts of Figure 1 and Figure 2 show the results of empirical studies. From them, we can draw the following information. Firstly, the significant downward trends of solid lines confirm the

[2]https://www.clips.uantwerpen.be/conll2000/chunking/conlleval.txt.

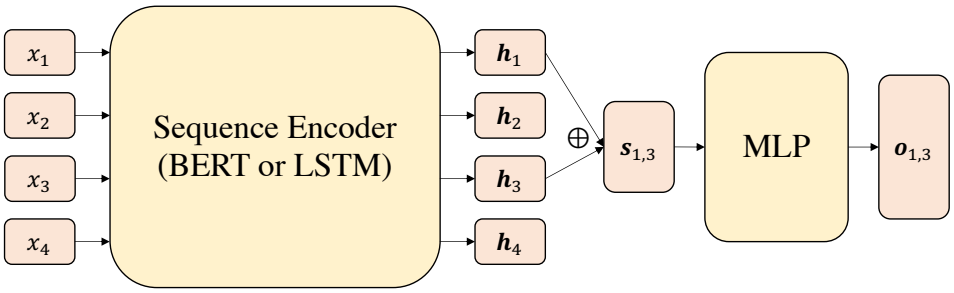

Figure 3: This demonstrates how our model scores possible entities.

fact that NER models severely suffer from *unlabeled entity problem*. For example, by setting the masking probability as 0.4, the performances of LSTM Tagging decrease by 33.01% on CoNLL-2003 and 19.58% on OntoNotes 5.0. Secondly, in contrast, the dashed lines change very slowly, indicating that the models with adjusted training loss (see Equation 3) are much less impacted by the issue. For instance, when masking probability is 0.7, adopting adjusted loss preserves the F1 scores of BERT Tagging by 41.04% on CoNLL-2003 and 57.38% on OntoNotes 5.0. Lastly, for high masking probabilities, even though the negative impacts of unlabeled entities are eliminated by adjusting the training loss, the performances still decline to a certain extent. For example, when masking probability is set as 0.8, the F1 scores of adjusted LSTM Tagging decrease by 31.64% on CoNLL-2003 and 17.22% on OntoNotes 5.0.

3.3 Misguidance of Unlabeled Entities

From the second observation in Section 3.2, we can conclude that the major cause of performance degradation is treating unlabeled entities as negative instances, which severely misleads the models during training. To better understand it, in the middle parts of Figure 1 and Figure 2, we plot the change of misguidance rates α_p (see Equation 4) with masking probabilities. These rates are essentially the percentage decreases of F1 scores. From them, we can see that the impact of misguidance is very much serious even when in low masking probabilities.

3.4 Reduction of Annotated Entities

From the third observation in Section 3.2, we can infer that another cause is the reduction of annotated entities. In the right parts of Figure 1 and Figure 2, we plot the change of erosion rates β_p (see Equation 3) with respect to masking probabilities. We can see that its impact is much smaller than that of misguidance but can't be neglected with high masking probabilities. Besides, adopting pre-training language models greatly mitigates the problem. As an example, when masking probability is 0.8, on both CoNLL-2003 and OntoNotes 5.0, the erosion rates of adjusted BERT Tagging are only about half of those of adjusted LSTM Tagging.

4 Methodology

Inspired by recent span-based models, we propose a general method that is capable of addressing *unlabeled entity problem* well. We illustrate it in Figure 3.

4.1 The Model

Based on the finding of Section 3.4, we adopt BERT as the encoder by default. Given a sentence $\mathbf{x}$, we firstly obtain the token representations $\mathbf{h}_i$ using Equation 1.

Then, we get the representation for every phrase $\mathbf{x}_{i,j}$ as

$$\mathbf{s}_{i,j} = \mathbf{h}_i \oplus \mathbf{h}_j \oplus (\mathbf{h}_i - \mathbf{h}_j) \oplus (\mathbf{h}_i \odot \mathbf{h}_j), \tag{5}$$

where $\oplus$ is vector concatenation and $\odot$ is element-wise product.

Finally, multi-layer perceptron (MLP) computes the label distribution $\mathbf{o}_{i,j}$ for a span (i, j):

$$\mathbf{o}_{i,j} = \mathrm{Softmax}(\mathbf{U} \tanh(\mathbf{V}\mathbf{s}_{i,j})). \tag{6}$$

The term $\mathbf{o}_{i,j}[l]$ is the predicted score for an entity (i, j, l).

4.2 Training and Inference

From Section 3.3, we know that treating unlabeled entities as negative instances severely misleads the models in training. Our solution to this issue is randomly sampling negative instances, which keeps the probability of training with unlabeled entities at a very low level.

Given the annotated entity set $\mathbf{y}$, all negative instance candidates are

$$\{(i, j, \mathrm{O}) \mid (i, j) \notin \{(i', j') \mid (i', j', l') \in \mathbf{y}\}, 1 \leq i \leq j \leq n\}, \tag{7}$$

where O is the label for non-entity spans. Because of the *unlabeled entity problem*, some members of the set may be unlabeled entities. We randomly sample a small set $\widehat{\mathbf{y}}$ from it. The size of this sample set $\widehat{\mathbf{y}}$ is $\mathrm{INT}(\lambda * n), 0 < \lambda < 1$, where INT is the ceiling function.

A span-level cross entropy loss used for training is incurred as

$$\Big(\sum_{(i,j,l) \in \mathbf{y}} -\log(\mathbf{o}_{i,j}[l]) \Big) + \Big(\sum_{(i',j',l') \in \widehat{\mathbf{y}}} -\log(\mathbf{o}_{i',j'}[l']) \Big). \tag{8}$$

At test time, firstly, the label for every span (i, j) is obtained by $\arg\max_l \mathbf{o}_{i,j}[l]$. Then, we select the ones whose label l is not O as predicted entities. When the spans of inferred entities intersects, we preserve the one with the highest predicted score and discard the others.

4.3 Discussion

We prove that, through negative sampling, the probability of not treating a specific missed entity in a n-length sentence as the negative instance is larger than $1 - \frac{2}{n-5}$:

$$\begin{aligned} \prod_{0 \leq i < \mathrm{INT}(\lambda n)} \Big(1 - \frac{1}{\frac{n(n-1)}{2} - m - i}\Big) &> \Big(1 - \frac{1}{\frac{n(n-1)}{2} - m - \mathrm{INT}(\lambda n)}\Big)^{\mathrm{INT}(\lambda n)} \\ &> \Big(1 - \frac{1}{\frac{n(n-1)}{2} - n - n}\Big)^{n} \geq \Big(1 - n * \frac{1}{\frac{n(n-1)}{2} - n - n}\Big) = 1 - \frac{2}{n-5} \end{aligned} . \tag{9}$$

Here $\frac{n(n-1)}{2} - m$ is the amount of negative instance candidates. Note that we use the facts $\lambda < 1$, $m \leq n$, and $(1 - z)^n \geq 1 - nz, 0 \leq z \leq 1$ during the proof.

5 Experiments

We have conducted extensive experiments on multiple datasets to verify the effectiveness of our method. Studies on synthetic datasets show that our model can almost eliminate the misguidance brought by unlabeled entities during training. On standard datasets, our model is competitive with current state-of-the-art method. On real-world datasets, our model has significantly outperformed prior baselines and achieved the state-of-the-art performances.

5.1 Settings

The setups of synthetic datasets and standard datasets are the same as what we describe in Section 3.1. For real-world datasets, we use EC and NEWS, both of which are collected by (Yang et al., 2018). EC is in e-commerce domain, which has 5 entity types: Brand, Product, Model, Material, and Specification. The data contains 2400 sentences tagged by human annotators and are divided into three parts: 1200 for training, 400 for dev, and 800 for testing. Yang et al. (2018) also construct an entity dictionary of size 927 and apply distant supervision on a raw corpus to obtain additional 2500 sentences for training. NEWS is from MSRA dataset (Levow, 2006). Yang et al. (2018) only adopt the PERSON entity type. Training data of size 3000, dev data of size 3328, and testing data of

Masking Prob.	CoNLL-2003		OntoNotes 5.0	
	BERT Tagging	Our Model	BERT Tagging	Our Model
0.1	90.71	**91.37**	87.69	**89.20**
0.2	89.57	**91.25**	86.86	**89.15**
0.3	88.95	**90.53**	84.75	**88.73**
0.4	82.94	**89.73**	82.55	**88.20**
0.5	78.99	**89.22**	71.07	**88.17**
0.6	63.84	**87.65**	58.17	**87.53**

Table 1: The experiment results on two synthetic datasets.

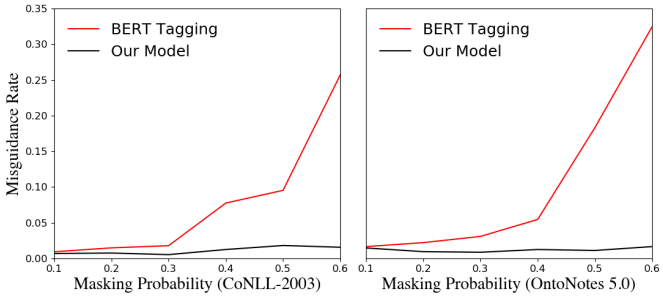

Figure 4: The misguidance rates of BERT Tagging and our model.

size 3186 are all sampled from MSRA. They collect an ontology of size 71664 and perform distant supervision on the rest data to obtain extra 3722 training cases.

We adopt the same neural network configurations for all the datasets. L2 regularization and dropout ratio are respectively set as 1×10^{-5} and 0.4 for reducing overfit. The dimension of scoring layers are 256. Ratio λ is set as 0.35. When the sentence encoder is LSTM, we set the hidden dimension as 512 and use cased, 300d GloVe (Pennington et al., 2014) to initialize the word embedding. We utilize Adam (Kingma & Ba, 2014) as the optimization algorithm and adopt the suggested hyper-parameters. At test time, we convert the predictions of our models into IOB format and use conlleval script to compute the F1 score. In all the experiments, the improvements of our models over the baselines are statistically significant with $p < 0.05$.

5.2 Results on Synthetic Datasets

In this section, our model is compared with BERT Tagging on the synthetic datasets of the masking probabilities being $0.1, 0.2, \cdots, 0.6$. From Table 1, we can get two conclusions. Firstly, our model significantly outperforms BERT Tagging, especially in high masking probabilities. For example, on CoNLL-2003, our F1 scores outnumber those of BERT Tagging by 1.88% when the probability is 0.2 and 27.16% when the probability is 0.6. Secondly, our model is very robust to the *unlabeled entity problem*. When increasing the masking probability from 0.1 to 0.5, the results of our model only decrease by 2.35% on CoNLL-2003 and 1.91% on OntoNotes 5.0.

Figure 4 demonstrates the misguidance rate comparisons between BERT Tagging and our models. The way to adjust our model is reformulating Equation 8 as

$$\{(i, j, \mathrm{O}) \mid (i, j) \notin \{(i', j') \mid (i', j', l') \in \mathbf{y} \cup \widetilde{\mathbf{y}}\}, 1 \leq i \leq j \leq n\}. \tag{10}$$

The idea here is to avoid the unlabeled entities being sampled. From Figure 4, we can discover that, in all the masking probabilities, the misguidance rates of our model are far smaller than those of BERT Tagging and are consistently lower than 2.50%. These indicate that, in training, our model can well eliminate the misguidance brought by unlabeled entities.

5.3 Results on Standard Datasets

As shown in Table 2, our model is compared with the following baselines. Akbik et al. (2018) present Flair Embedding that pretrains character embedding in a large corpus and directly uses it,

Method	CoNLL-2003	OntoNotes 5.0
Flair Embedding (Akbik et al., 2018)	93.09	89.3
BERT-MRC (Li et al., 2019)	93.04	91.11
HCR w/ BERT (Luo et al., 2020)	93.37	90.30
BERT-Biaffine Model (Yu et al., 2020)	**93.5**	**91.3**
Our Model	93.42	90.59

Table 2: The experiment results on two standard datasets.

Method		EC	NEWS
Yang et al. (2018)	String Matching via Ontology	44.02	47.75
	BiLSTM + CRF	54.59	69.09
	BiLSTM + CRF w/ RL	56.23	73.19
	BiLSTM + Partial CRF	60.08	78.38
	BiLSTM + Partial CRF w/ RL	61.45	79.22
Nooralahzadeh et al. (2019)	BiLSTM + Partial CRF w/ RL	63.56	80.04
This Work	Our Model	**66.17**	**85.39**
	Our Model w/o BERT, w/ BiLSTM	**64.68**	**82.11**

Table 3: The experiment results on two real-world datasets.

instead of word representations, to encode a sentence. BERT-MRC (Li et al., 2019) regard NER as a machine reading comprehension (MRC) task, where entities are recognized as retrieving answer spans. Luo et al. (2020) use hierarchical contextualized representations to incorporate document-level information. BERT-Biaffine Model is the existing state-of-the-art method, which ranks all the labeled spans in terms of the scores predicted by a bi-affine mode (Dozat & Manning, 2016). We follow all the results of baselines as reported in their papers.

The F1 scores of our model are very close to current best results. Our model slightly underperforms BERT-Biaffine Model by only 0.09% on CoNLL-2003 and 0.78% on OntoNotes 5.0. Besides, our model surpasses many other strong baselines. On OntoNotes 5.0, our model outperforms HCR w/ BERT by 0.32% and Flair Embedding by 1.44%. On CoNLL-2003, the improvements of F1 scores are 0.41% over BERT-MRC and 0.35% over Flair Embedding. All these results indicate that our model is still very effective when applied to high-quality data.

5.4 Results on Real-world Datasets

For the two datasets, a large portion of training data is obtained via distant supervision. As stated in (Yang et al., 2018), the F1 scores of string matching through ontology are notably declined by the low recall scores. Meanwhile, its precision scores are much higher than those of other methods. Therefore, *unlabeled entity problem* is serious in the datasets.

As demonstrated in Table 3, the baselines come from two works (Yang et al., 2018; Nooralahzadeh et al., 2019). Yang et al. (2018) use Partial CRF to circumvent all possible unlabeled entities and leverage reinforcement learning (RL) to skip the noisy annotations in an adaptive manner. A disadvantage of Partial CRF is that it can't be trained with the true negative instances in poorly labeled corpora. Nooralahzadeh et al. (2019) further optimize the policy of RL.

Our model has significantly outperformed prior baselines and obtained new state-of-the-art results. Compared with prior best model (Nooralahzadeh et al., 2019), we achieve the improvements of 3.94% on EC and 6.27% on NEWS. Compared with strong baseline, BiLSTM + Partial CRF, the increases of F1 scores are 9.20% and 8.21%. To make fair comparisons, we replace BERT with LSTM. Even so, we still outperform (Nooralahzadeh et al., 2019) by 1.76% on EC and 2.52% on NEWS. All these strongly confirm the effectiveness of our model.

5.5 Ratio λ in Negative Sampling

Intuitively, setting ratio λ (see Section 4.2) as too large values or too small values both are inappropriate. Large ratios increase the probability of training with labeled entities. Small ratios reduce the

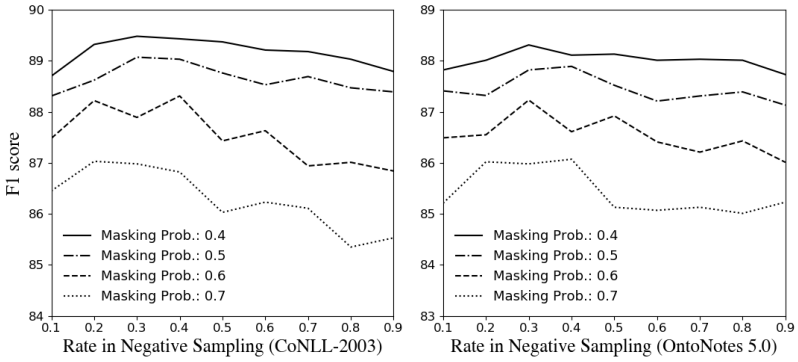

Figure 5: The results of our models with different ratio λ on synthetic datasets.

amount of negative instances used for training, leading to over fitting. Figure 5 shows the experiments on some synthetic datasets with the ratio λ of our method being $0.1, 0.2, \cdots, 0.9$. From it, we can see that all the score curves are roughly arched, which verifies our intuition. Besides, we find that $0.3 < \lambda < 0.4$ performs well in all the cases.

6 Related Work

NER is a classical task in information extraction. Previous works generally regard it as a sequence labeling problem by using IOB tagging scheme (Huang et al., 2015; Lample et al., 2016; Akbik et al., 2018; Luo et al., 2020). Each word in the sentence is labeled as B-tag if it is the beginning of an entity, I-tag if it's inside but not the first one within the entity, or O otherwise. This approach is extensively studied in prior works. For example, Akbik et al. (2018) propose Flair Embedding that pretrains character embedding in large corpora and uses it rather than token representations to represent a sentence. Recently, there is a growing interest in span-based models (Li et al., 2019; Yu et al., 2020). They treat the spans, instead of single words, as the basic units for labeling. For example, (Li et al., 2019) present BERT-MRC that regards NER as a MRC task, where named entities are extracted as retrieving answer spans.

In some practical applications (e.g., data annotation in fine-grained NER), NER models are faced with *unlabeled entity problem*, where the unlabeled entities seriously degrade the performances of models. Several approaches to this issue have been proposed. Fuzzy CRF and AutoNER (Shang et al., 2018b) allow learning from high-quality phrases. However, since these phrases are obtained through distant supervision, the unlabeled entities in the corpora may still be missed. PU learning (Li & Liu, 2005) unbiasedly and consistently estimates the training loss. Nevertheless, the unlabeled entities still impact on the classifiers of the corresponding entity types and, importantly, the model can't disambiguate neighboring entities. Partial CRF (Yang et al., 2018; Nooralahzadeh et al., 2019) supports learning from incomplete annotations. However, because fully annotated corpus is still in need to traing the models with true negative instances, this type of approach is not applicable to the situations where no high-quality data is available.

7 Conclusion

In this work, we study what are the impacts of unlabeled entities on NER models and how to effectively eliminate them. Through empirical studies on synthetic datasets, we find the main cause is treating unlabeled entities as negative instances, which seriously misleads the models in training. Another cause is the reduction of annotated entities, which can be mitigated by using pretraining language models. Inspired by recent span-based models, we propose a general model that can almost completely eliminate the misguidance of unlabeled entities in training. The core idea is using negative sampling to keep the probability of training with unlabeled entities at a very low level. Experiments on synthetic datasets and real-world datasets show that our model can handle unlabeled entities well and notably outperforms prior baselines. Besides, on standard datasets, our model is competitive with current state-of-the-art method.

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