LTP: A New Active Learning Strategy for Bert-CRF Based Named Entity Recognition

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ABSTRACT

In recent years, deep learning has achieved great success in many natural language processing tasks including named entity recognition. The shortcoming is that a large amount of manually-annotated data is usually required. Previous studies have demonstrated that both transfer learning and active learning could elaborately reduce the cost of data annotation in terms of their corresponding advantages, but there is still plenty of room for improvement. We assume that the convergence of the two methods can complement with each other, so that the model could be trained more accurately with less labelled data, and active learning method could enhance transfer learning method to accurately select the minimum data samples for iterative learning. However, in real applications we found this approach is challenging because the sample selection of traditional active learning strategy merely depends on the final probability value of its model output, and this makes it quite difficult to evaluate the quality of the selected data samples. In this paper, we first examine traditional active learning strategies in a specific case of BERT-CRF that has been widely used in named entity recognition. Then we propose an uncertainty-based active learning strategy called Lowest Token Probability (LTP) which considers not only the final output but also the intermediate results. We test LTP on multiple datasets, and the experiments show that LTP performs better than traditional strategies (including LC and NLC) on both token-level $F_1$ and sentence-level accuracy, especially in complex imbalanced datasets.

KEYWORDS

active learning, named entity recognition, transfer learning, CRF

1 INTRODUCTION

Over the past few years, papers applying deep neural networks (DNNs) to the task of named entity recognition (NER) have achieved noteworthy success [3], [11],[13]. However, under typical training procedures, the advantages of deep learning are established mostly relied on the huge amount of labeled data. When applying these methods on domain-related tasks, their main problem lies in their need for considerable human-annotated training corpus, which requires tedious and expensive work from domain experts. Thus, to make these methods more widely applicable and easier to adapt to various domains, the key is how to reduce the number of manually annotated training samples.

Both transfer learning and active learning are designed to reduce the amount of data annotation. However, the two methods work differently. Transfer Learning is the migration of trained model parameters to new models to facilitate the new model training. We can share the learned model parameters into the new model in a certain way to accelerate and optimize the learning efficiency of the model, instead of learning from zero. So transfer learning could help to achieve better results on a small dataset. However, it should be noted that transfer learning works well only when the sample distributions of the source and target domain are similar. While significant distribution divergence might cause a negative transfer.

Unlike the supervised learning setting, in which samples are selected and annotated at random, the process of Active Learning employs one or more human annotators by asking them to label new samples that are supposed to be the most informative in the creation of a new classifier. The greatest challenge in active learning is to determine which sample is more informative. The most common approach is uncertainty sampling, in which the model preferentially selects samples whose current prediction is least confident.

Quite a lot of works have been done to reduce the amount of data annotation for NER tasks through either transfer learning or active learning, but few researches have combined these two techniques to reduce labeling cost and avoid negative transfer. In this work, we try to integrate a widely used transfer learning based NER model, called Bert-CRF, with active learning.

When evaluating the effect of NER, most of the works only use the value of the token-level $F_1$ score or entity-level $F_1$ score. However, in some cases, this could be misleading, especially for languages that do not have a natural separator, such as Chinese. And the NER task is often used to support downstream tasks, which prefer that all entities in the sentence are correctly identified. Figure 1 shows an example where only one token gets the wrong label (the corresponding token-level and entity-level $F_1$ values are 0.947 and 0.857). When this wrong result is used in the user intention understanding, the phone will be considered as the user demand rather than the phone cases. So in this work, we not only evaluate the token-level $F_1$ score but also the sentence-level accuracy.
We first experiment with the traditional uncertainty-based active learning algorithms, and then we proposed our own active learning strategy based on the lowest token probability with the best labeling sequence. Experiments show that our selection strategy is superior to traditional uncertainty-based active selection strategies in multiple Chinese datasets both in token-level $F_1$ score and overall sentence-level accuracy. Especially in the case of a large number of entity types.

Finally, we make empirical analysis with different active selection strategies and give some suggestions for using them.

The remainder of this paper is organized as follows. In Section 2 we summarize the related works in transfer learning and active learning. In section 3 we introduce an NER model called Bert-CRF, and the active learning framework. Section 4 describes in details the active learning strategies we propose. Section 5 describes the experimental setting, the datasets, and discusses the empirical results.

## 2 RELATED WORK

### 2.1 Named entity recognition

The framework of NER using deep neural network can be regarded as a composition of encoder and decoder. For encoders, there are many options. Collobert et al. [5] first used convolutional neural network (CNN) as the encoder. Traditional CNN cannot solve the problem of long-distance dependency. In order to solve this problem, RNN[17], BiLSTM[9], Dilated CNN[24] and bidirectional Transformers[8] are proposed to replace CNN as encoder. For decoders, some works used RNN for decoding tags [15], [17]. However, most competitive approaches relied on CRF as decoder[11],[27].

### 2.2 Transfer learning

Transfer learning could help have satisfied results on small datasets. There are two methods to apply the pre-training language model to downstream tasks. Feature-based approach (eg. Word2Vec[16], ELMo[18]) that includes pre-trained representations as additional features into embedding. Fine-tuning approach (eg. GPT[19], BERT[8]) that fine-tunes the pre-trained parameters in the specific downstream tasks. In this work, we use BERT (as encoder) in upstream to do pre-training and CRF (as decoder) in downstream to fine-tune.

### 2.3 Active learning

Active learning strategies have been well studied [7], [1], [23]. These strategies can be grouped into following categories: Uncertainty sample [12][6][20][10], query-by-committee[22] [25], information density[26], fisher information[21]. There were some works that compared the performance of different types of selection strategies in NER/sequence labeling tasks with CRF model [2] [14] [21][4]. These results show that, in most case, uncertainty-based methods perform better and cost less time. However, we found that these traditional uncertainty-based strategies did not perform well with transfer learning. So, we propose our own uncertainty-based strategy in this work.

## 3 NER MODEL

### 3.1 Architecture

The entire learning processing is shown in Figure 2. There are two main stages in the process, model training (discussed in detail in this section) and sample selection (discussed in detail in Section 4). Through multiple iterations of two stages, we can get the ideal results in quite low annotation cost.

The architecture of the NER network comprises of an input layer, a pre-training language model, a fully connected layer and finally a CRF (conditional random field) layer, which simulates label dependencies in the output. It is must be noted that while some work have been done with Bert-BiLSTM-CRF that replace the full connectivity layer in the Bert-CRF with BiLSTM layer. However, we found in the experiment that there was no significant difference between the performance of Bert-BiLSTM-CRF and Bert-CRF, and the network structure of Bert-BiLSTM-CRF is more complex than Bert-CRF and with slower training speed. So Bert-CRF was selected in this paper.

### 3.2 Data Representation

We represent each input sentence following Bert format; Each token in the sentence is marked with BIO scheme tags. Special [CLS] and [SEP] tokens are added at the beginning and the end of the tag sequence, respectively. [PAD] tokens are added at the end of sequences to make their lengths uniform. The formatted sentence in length $N$ is denoted as $x = <x_1, x_2, \ldots, x_N>$, and the corresponding tag sequence is denoted as $y = <y_1, y_2, \ldots, y_N>$. 
3.3 Bert & CRF Layer

Bert is one of the most successful pre-training language models, here we use it as the character-level encoder. For each character \( x_i \) in the input sequence \( x \), bert will convert it into a fixed-length vector \( w \). CRF are statistical graphical models which have demonstrated state-of-art accuracy on virtually all of the sequence labeling tasks including NER task. Particularly, we use linear-chain CRF that is a popular choice for tag decoder, adopted by most DNNs for NER.

A linear-chain CRF model defines the posterior probability of \( y \) given \( x \) to be:

\[
P(y|x; A) = \frac{1}{Z(x)} \exp \left( h^1(y_1|x) + \sum_{k=1}^{n-1} h^{k+1}(y_{k+1}|x) + A_{y_k y_{k+1}} \right)
\]

where \( Z(x) \) is a normalization factor over all possible tags of \( x \), and \( h^k(y_k|x) \) (#TODO: ambiguous?) indicates the probability of taking the \( y_k \) tag at position \( k \) which is the output of the previous softmax layer. \( A \) is a parameter called a transfer matrix, which can be set manually or by model learning. In our experiment, we let the model learn the parameter by itself. \( A_{y_k y_{k+1}} \) means the probability of a transition from tag states \( y_k \) to \( y_{k+1} \). We use \( y^* \) to represent the most likely tag sequence of \( x \):

\[
y^* = \arg \max_y P(y|x)
\]

The parameters \( A \) are learnt through the maximum log-likelihood estimation, that is to maximize the log-likelihood function \( \ell \) of training set sequences in the labeled data set \( \mathcal{L} \):

\[
\ell(\mathcal{L}; A) = \frac{1}{L} \sum_{l=1}^{L} \log P(y|l|x|l; A)
\]

where \( L \) is the size of the tagged set \( \mathcal{L} \).

4 ACTIVE LEARNING STRATEGIES

The biggest challenge in active learning is how to select instances that need to be manually labeled. A good selection strategy \( \phi(x) \), which is a function used to evaluate each instance \( x \) in the unlabeled pool \( \mathcal{U} \), will select the most informative instance \( x^* \).

Algorithm 1 illustrate the entire pool-based active learning process. In the remainder of this section, we describe various query strategy formulations of \( \phi(\cdot) \) in detail.

4.1 Least Confidence (LC)

Culotta and McCallum employ a simple uncertainty-based strategy for sequence models called least confidence(LC), which sort examples in ascending order according to the probability assigned by the model to the most likely sequence of tags:

\[
\phi^{LC}(x) = 1 - P(y^*|x; A)
\]

This confidence can be calculated using the posterior probability given by Equation 1. Preliminary analysis revealed that the LC strategy prefer selects longer sentences:

\[
P(y^*|x; A) = \exp \left( h^1(y_1^*|x) + \sum_{k=1}^{n-1} h^{k+1}(y_{k+1}^*|x) + A_{y_k^* y_{k+1}^*} \right)
\]

Since Equation 5 contains summation over tokens, LC method naturally favors longer sentences. Although the LC method is very simple and has some shortcomings, many works prove the effectiveness of the method in sequence labeling tasks.

4.2 Normalized Least Confidence (NLC)

As mentioned in Section 4.1, LC favors longer sentences which requires more labor for annotation. To overcome this drawback, we normalize the confidence as follow:

\[
\phi^{NLC}(x) = 1 - \frac{1}{N} P(y^*|x; A)
\]

where \( N \) is the length of \( x \).

4.3 Lowest Token Probability (LTP)

Inspired by Minimum Token Probability (MTP) strategies that select the most informative tokens, regardless of the assignment performed by CRF. This strategy greedily samples the tokens whose highest probability among the labels is lowest:

\[
\phi^{MTP}(x) = 1 - \min_{i j} h^i(y_i = j|x; A)
\]

\( h^i(y_i = j|x; A) \) is the probability that \( j \) is the label at position \( i \) in the sequences.

Unlike MTP, we believe that the sequence selected by CRF is valuable. We look for the most probable sequence assignment, and hope that each token in the sequence has a high probability.

\[
\phi^{LTP}(x) = 1 - \min_{y^* \in y^*} h^i(y_i^*|x; A)
\]
We proposed our select strategy called Lowest Token Probability (LTP), which selects the tokens whose probability under the most likely tag sequence $y^*$ is lowest.

5 EXPERIMENTS

5.1 Datasets

We have experimented and evaluated the active learning strategies of Section 4 on three Chinese datasets. People’s Daily is a collection of newswire articles annotated with three entities: person, organization, location. Boson-NER\(^1\) is a set of online news annotations published by bosonNLP, which contains 6 entities, such as person, product, time. OntoNotes-5.0 Chinese data (bn part) (#TODO: cite) which contains 18 entities. All corpora are formatted in the “BIO” sequence representation(#TODO cite). Table 2 shows some statistics of the datasets in terms of dimensions, number of entity types, distribution of the labels, etc.

5.2 Experimental Setting

We randomly chose an initial training set $L_1$ of 99 sentences on People’s Daily dataset, 75 sentences on Boson-NER dataset, 76 sentences on OntoNotes-5.0 dataset. The dimension of the batch update $B$ has been seen as a trade-off between an ideal case in which the system is retrained after every single annotation and a practical case with higher $B$ to limit the algorithmic complexity and improve manual labeling efficiency in real-world. In our experiment, $B$ is setting to 200. We fixed the number of active learning iterations at 12 because of each algorithm does not improve obviously after 12 iterations.

In the NER Model, we use BERT-Base-Chinese\(^2\) which has 110M parameters. The training batch size is set to 32, and the max_seq_length is set to 80. We set the learning rate to 0.00001. For each iteration, we train 30 epoch to ensure model convergence. And other parameters related to BERT are set to default values. In the fully connected layer, we set the dropout rate to be 0.9 to prevent overfitting. The transfer matrix in CRF is also left to the model to learn by itself.

We empirically compare the selection strategy proposed in Section 4, as well as the uniformly random baseline (RAND). We evaluate each selection strategy by constructing learning curves that plot the overall $F_1$ (for tokens, $O$ tag doesn’t in the metric) and accuracy (for sentences). In order to prevent the contingency of the experiment, we have done 10 experiments for each selection strategy using different random initial training sets $L_1$. All results are averaged across these experiments.

5.3 Results

From the learning curves of Figure 3, it is clear that all active learning algorithms perform better than the random baseline on People’s Daily and Boson-NER datasets. On OntoNote5.0 dataset, LC and NLC are better than RAND in the early iteration. Our approach LTP performs best on all datasets. Figure 3 also shows that combining transfer learning with appropriate active learning strategy, the amount of data that needs to be labeled can be greatly reduced. For example, LTP achieves 99% performance of FULL using only 4.3% (5.0%, 5.4%) of training sentences (tokens, entities) on People’s Daily dataset, 22.8% (31.1%, 40.8%) of training sentences (tokens, entities) on Boson-NER dataset and 19.32% (26.1%, 30.2%) of training sentences (tokens, entities) on OntoNote5.0 dataset.

Figure 4 shows the results of sentence-level accuracy on three datasets. The results exceeded our expectations and were very interesting. Firstly, the results confirm that the token-level $F_1$ value is sometimes misleading what we mentioned in Section 1. For example, on Boson-NER dataset, although the token-level $F_1$ scores of LTP and LC are similar in the last few iterations, the sentence-level accuracy is 2% difference. Secondly, in the experiment, LTP is much better than the rest of the methods, and can be close to the use of all training data especially on complex datasets (eg. Boson-NRR, OntoNotes). Thirdly, LC and NLC perform poorly at sentence-level accuracy.

The two operations that are time-consuming in the actual sequence labeling process are the amount of text that the labeler needs to read and the amount of text that the labeler needs to label. In Figure 5, we use the total number of tokens and the total number of entities to represent these two factors. One can see that compared with LC, LTP can achieve better performance with less label effort.

6 DISCUSSION AND SUGGESTION

In this section, we will discuss possible reasons for the gap between different selection strategies. Then we give some suggestions on how to choose different active learning strategies in practical applications.

\(^1\)https://bosonnlp.com/resources/BosonNLP_NER_6C.zip
\(^2\)https://github.com/google-research/bert

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Table 2: Training(Testing) Data Statistics. #S is the number of total sentences in the dataset, #T is the number of tokens in the dataset, #E is the number of entity types, ASL is the average length of a sentence, ASE is the average length of a sentence, AEL is the average length of a entity, %PT is the percentage of tokens with positive label, %AC is the percentage of a sentences with more than one entity, %DAC is the percentage of sentences that have two or more entities.

| Corpus         | #S   | #T   | #E   | ASL | ASE  | AEL  | %PT   | %AC   | %DAC  |
|----------------|------|------|------|-----|------|------|-------|-------|-------|
| People’s Daily | 38950| (16608) | 3 | 42.4 | 1.45 | 3.24 | 11.1% | 57.8% | 34.9% |
| Boson-NER      | 7348 | (3133) | 6 | 51.5 | 2.20 | 3.99 | 17.1% | 73.2% | 50.3% |
| OntoNotes-5.0  | 7637 | (917)  | 18 | 48.2 | 3.45 | 3.14 | 22.4% | 87.5% | 71.8% |
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(a) People’s Daily
(b) Boson-NER
(c) OntoNote5.0 Chinese

Figure 3: Token-level $F_1$ results on three datasets

(a) People’s Daily
(b) Boson-NER
(c) OntoNote5.0 Chinese

Figure 4: Sentence-level accuracy on three corpus

(a) People’s Daily
(b) Boson-NER
(c) OntoNote5.0 Chinese

Figure 5: Total number of selected tokens and entities.

Table 3: Entity Distribution in People’s Daily Training dataset.

|          | Person | Location | Organization |
|----------|--------|----------|--------------|
| Percentage | 23.85% | 48.88%   | 27.27%       |

Table 4: Entity Distribution in Boson-NER Training dataset.

|          | PER    | LOC    | ORG    | TIM    | PRODUCT | COMPANY |
|----------|--------|--------|--------|--------|---------|---------|
| Percentage | 22.92% | 21.46% | 12.46% | 18.79% | 13.63%  | 10.75%  |

We first give the detailed distribution of the entities under different datasets as shown in Table 3 - 5. One can see that the biggest difference between OntoNote dataset and the remaining two datasets is that the entity distribution is extremely unbalanced. The number of GPE is approximately 162 times the number of LANGUAGE in the OntoNote5.0 dataset.

Due to page limitations, we are unable to present the analysis results for all datasets here. So we select the first 6 iterations of OntoNote dataset for explanation, for two reasons:

1. On the OntoNote dataset, the difference in the effect of the different strategies is most obvious.
2. The first 6 iterations have large performance changes.

Figure 7 shows the deviation between the sample distribution selected by different selection strategies and the overall sample distribution. We can see two differences between LTP and other active learning strategies in sampling:

...
This sampling strategy is consistent with our intuition, that is, to indicate stability:  

$$o_f s e t_i = \sum_{e \in \mathcal{E}} |p_{\hat{e}}(e) - p_{\hat{e}_{i-1}}(e)|$$  

(9)

Where $E$ is a set of entity types, $p_{\hat{e}}(e)$ represents the proportion of entity class $e$ in iteration $i$. Figure 6 shows this result. We found that LTP can obtain stable sampling distribution faster, which means that LTP is more stable than other active learning strategies.

Based on the discussion above, we give several suggestions here.

1. For entities with high overall proportion (such as GPE, PERSON, ORG), LTP samples consistently below overall proportion.
2. For entities with low overall proportion (such as LAW, LANGUAGE, PRODUCT), LTP samples consistently above overall proportion.

Finally, we explore the stability of sampling with different active selection strategies. We use two adjacent sampling offsets to indicate stability:

$$o_f s e t_i = \sum_{e \in \mathcal{E}} |p_{\hat{e}}(e) - p_{\hat{e}_{i-1}}(e)|$$  

(9)

7 CONCLUSION

We proposed a new active learning strategy for Bert-CRF based named entity recognition. The experiment shows that compared with the traditional active selection strategies, our strategy has better performance, especially in complex datasets. Further, we analyze the different selection strategies and give some Suggestions on how to use them.

8 ACKNOWLEDGMENTS

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Figure 7: Comparison of selected entities distribution and overall entities distribution for first 6 iterations on OntoNote dataset.

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