A Robust and Domain-Adaptive Approach for Low-Resource Named Entity Recognition

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Abstract—Recently, it has attracted much attention to build reliable named entity recognition (NER) systems using limited annotated data. Nearly all existing works heavily rely on domain-specific resources, such as external lexicons and knowledge bases. However, such domain-specific resources are often not available, meanwhile it’s difficult and expensive to construct the resources, which has become a key obstacle to wider adoption. To tackle the problem, in this work, we propose a novel robust and domain-adaptive approach RDANER for low-resource NER, which only uses cheap and easily obtainable resources. Extensive experiments on three benchmark datasets demonstrate that our approach achieves the best performance when only using cheap and easily obtainable resources, and delivers competitive results against state-of-the-art methods which use difficulty obtainable domain-specific resources. All our code and corpora can be found on https://github.com/houking-can/RDANER.

Keywords—named entity recognition, low resource, domain-adaptive

I. INTRODUCTION

Named entity recognition (NER) is a fundamental task which is often used as a first step in numerous natural language processing (NLP) tasks, including relation extraction [1], [2] and knowledge graph construction [3], [4]. Most existing NER approaches such as neural network-based methods [5]–[7], often require a large amount of training data (annotated entity spans and types) to achieve satisfactory performance. It is clearly expensive, and sometimes impossible, to obtain a large amount of annotated data in a new domain for the NER task. Under such circumstance, low-resource NER has attracted much deserved attention recently, which aims to build reliable NER systems using limited annotated data.

Many approaches have been proposed to address low-resource NER. Early works are mainly based on hand-crafted rules [8]–[10], but they suffer from limited performance in practice. More recently, researches on low-resource NER focus on learning information and knowledge from extra domain-specific resources to improve the NER performance. According to the required resources, they can be divided into two types: learning-based methods [4], [11], [12] and domain-specific pre-training methods [13], [14]. Learning-based methods belong to supervised learning in some sense, such as transfer learning, multi-task learning and distantly-supervised learning, which leverage information and knowledge provided by external lexicons and knowledge bases. In fact, it needs extensive amount of experts effort to construct such resources. Unlike learning-based methods, domain-specific pre-training methods adopt transfer-based pre-training (unsupervised learning) on large amount of in-domain corpora to enable knowledge transfer. Domain-specific pre-training methods need less manual effort, but GPU clusters or TPUs (quite expensive) are required to speed up the training process. Both kinds of methods utilize extra knowledge, either from experts or in-domain corpora, which have been shown to be effective for low-resource NER.

Most existing methods for low-resource NER are summarized in Table I. From the table, we observe that these methods highly dependent on the availability of domain-specific resources. However, these resources are often not available, meanwhile it’s difficult and expensive to construct them, which has become a key obstacle to wider adoption. For example, it’s easy to obtain a general domain knowledge base (like Wikipedia), but we could hardly find a publicly financial knowledge base. In fact, it requires large amounts of experts effort and money to build a domain-specific knowledge base.

To tackle the problem, we propose a novel robust and domain-adaptive approach RDANER for low-resource NER only using cheap and easily obtainable resources. Specifically, the proposed approach consists of two steps: transformer-based language model fine-tuning (LM fine-tuning) and bootstrapping. Here, LM refers specifically to the transformer-based language model. Firstly, we fine-tune a general domain pre-trained LM on in-domain corpora to make it fit on the target domain. Fortunately, it’s easy to obtain a general domain pre-trained LM and a large amount of unannotated in-domain corpora. Then we perform a bootstrapping process, starting from an initial NER model trained on the small fully-annotated seed data, and then we use it to predict on an unannotated corpus which is further used to train the model iteratively until convergence. Our proposed approach alleviates the requirements of difficulty obtainable domain-specific resources, and builds reliable
NER systems under low-resource conditions, which is a trade-off between effectiveness and efficiency.

To evaluate our proposed approach, we conduct low-resource experiments on three benchmark datasets in two challenging domains: computer science and biomedical. Extensive experiments demonstrate that our proposed approach is not only effective but also efficient. When only using cheap and easily obtainable resources, our approach outperforms baselines with an average improvement of 3.5 F1. Beside, the proposed approach achieves competitive performance against the state-of-the-art methods which utilize expensive and time-consuming resources.

Another trend for better low-resource NER performance is DSL, which has attracted much attention in recent times. Researches on domain-specific pre-training [13], [14] are two domain-specific BERT variants for scientific text and biomedical text respectively, showing powerful performance in corresponding domains. Different from learning-based methods, pre-training doesn’t depend on the resources required experts effort to construct. Unfortunately, it is quite expensive to pre-train LMs from scratch, needing GPU clusters or TPUs to speed up the training processes.

Most existing works heavily rely on difficultly obtainable domain-specific resources, requiring either experts effort or high-performance hardware. However, they are often not available or cost lots of money to construct them. Without corresponding domain-specific resources, it’s hard for these methods to be applied in a new domain. To solve this problem, we propose a novel robust and domain-adaptive approach RDANER for low-resource NER, which only uses cheap and easily obtainable resources.

### II. RELATED WORK

Named entity recognition (NER) has been studied widely for decades. Traditionally, NER is concerned with identifying general named entities, such as person, location, and organization names in unstructured text. Nowadays, researches have been extended to many specific domains, including biomedical, financial and academic. Most early NER works are based on hand-crafted rules designed by experts [8]–[10]. Recently, neural network-based NER models [5]–[7] have yielded great improvement over the early features-based models, meanwhile, requiring little feature engineering and domain knowledge [6], [9]. The biggest limitation of such neural models is that they highly dependent on large amounts of annotated data. As a result, the performance of these models degrades dramatically in low-resource settings. Low-resource NER, which aims to build reliable NER systems, has attracted much attention in recent times. Researches on low-resource NER mainly focus on utilizing extra domain-specific resources to improve the performance. There are mainly two types methods: learning-based methods and domain-specific pre-training methods. We introduce the related works of them respectively as follows.

#### A. Learning-based Methods

Learning-based methods for low-resource NER assume some domain-specific resources are available, such as lexicons, parallel corpora and knowledge bases. These methods can be divided into three types: transfer learning (TL), multi-task learning (MTL) and distantly-supervised learning (DSL). TL has been extensively used for improving low-resource NER [20], [21]. Most of them focus on transferring cross-domain knowledge into NER, which rely on annotation projection methods where annotations in high-resource domains are projected to the low-resource domains leveraging parallel corpora [22], [23] and shared representation [11], [15], [24]. In fact, many TL methods are designed for general domain NER tasks, because it is easier to obtain parallel corpora or bilingual dictionaries from the general domain than from a specific domain.

Similarly, MTL utilizes knowledge from extra annotations provided by the dataset, and adopts jointly training on multiple tasks to help improve NER performance [4], [16], [17]. Different from TL, MTL aims at improving the performance of all the tasks instead of low-resource task only. The requirements of MTL methods for low-resource NER are manual-labeled annotations for other tasks.

Another trend for better low-resource NER performance is DSL, which has attracted many attentions to alleviate human efforts. DSL methods use domain-specific dictionaries and knowledge bases to generate large mount of weakly-annotated data. SwellShark [19] and AutoNER [12] use dictionary matching for named entity span detection. Reference [25] combines bootstrapping and weakly-annotated data augmentation by using a reference set. Their approaches work well only when domain-specific resources are available.

#### B. Domain-specific Pre-training Methods

Transformer-based pre-training have been shown to be powerful for NLP tasks [26], [27], including low-resource NER. But most publicly pre-trained LMs (like GPT, BERT) are trained on general domain corpora, they often yields unsatisfactory results in many specific domains. A solution for this problem is domain-specific pre-training, which trains LMs on in-domain corpora. SciBERT [13] and BioBERT [14] are two domain-specific BERT variants for scientific text and biomedical text respectively, showing powerful performance in corresponding domains. Different from learning-based methods, pre-training doesn’t dependent on the resources required experts effort to construct. Unfortunately, it is quite expensive to pre-train LMs from scratch, needing GPU clusters or TPUs to speed up the training processes.

Table I: Summarization of the existing low-resource NER methods.

| Methods                        | Required resources                  | Limitations                      |
|--------------------------------|-------------------------------------|----------------------------------|
| Transfer learning [11], [15]   | Parallel corpora, dictionary       | Difficult to obtain and          |
| Multi-task learning [4], [16], [17] | Annotations for other tasks         | expensive to construct          |
| Distantly supervised learning [12], [18], [19] | Knowledge bases, lexicons           |                                  |
| Domain-specific pre-training [13], [14] | Pre-trained language models        | Time-consuming and              |

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Most existing works heavily rely on difficultly obtainable domain-specific resources, requiring either experts effort or high-performance hardware. However, they are often not available or cost lots of money to construct them. Without corresponding domain-specific resources, it’s hard for these methods to be applied in a new domain. To solve this problem, we propose a novel robust and domain-adaptive approach RDANER for low-resource NER, which only uses cheap and easily obtainable resources.
The most related works to ours are semi-supervised methods, which have been explored to further improve the accuracy by either augmenting labeled datasets or bootstrapping techniques [15], [25], [28]. Reference [15] uses a combination of cross-lingual transfer learning and active learning for bootstrapping low-resource entity recognizers. Reference [25] combines bootstrapping and weakly-annotated data augmentation by using an external lexicon to improve NER performance. Different from [15], [25], our proposed approach assumes no parallel corpora or lexicons.

We describe our approach RDANER in detail as follows.

III. APPROACH: RDANER

For a specific low-resource NER task, we assume to have (1) a small fully-annotated seed dataset \( D_s \) that has every token tagged by entity type, (2) a small in-domain corpus \( D_c \), which is used to generate weakly-annotated data, (3) a general domain pre-trained language model \( \text{LM} \) and (4) a large-scale in-domain corpus \( C_T \) of the target domain \( T \).

As noted in the introduction, RDANER consists of two processes: LM fine-tuning and the bootstrapping. Fig. 1 shows the architecture of the proposed approach. We will describe each of them in follow sections.

A. LM Fine-tuning

Given a general domain pre-trained language model \( \text{LM} \) and a domain-specific corpus \( C_T \), our goal is to make \( \text{LM} \) fit on the target domain \( T \). In this work, \( \text{LM} \) is BERT, and we follow the work of pre-training BERT [26]. Before feeding word sequences into BERT, 15% of the words in each sequence are replaced with a [MASK] token at random. BERT attempts to predict the original value of the masked words, based on the context provided by the other non-masked words in the sequence. The objective is masked language modeling (MLM) cross-entropy [26], which measures the likelihood of predictions for masked words. When fine-tuning has completed, we get a BERT variant, BERT\(_T\).

B. Bootstrapping

Bootstrapping is proposed to further improve the accuracy. First, we train an initial NER model \( M_0 \) using the small seed dataset \( D_s \). We use BERT\(_T\) as the word-level encoder, and a linear-chain CRF after a softmax layer. For an input sequence \( X = (x_1, x_2, \ldots, x_n) \), and a sequence of tag predictions \( y = (y_1, y_2, \ldots, y_n) \), BERT\(_T\) converts \( x_i \) into a fixed-length vector \( w_i \), and outputs the probability distributions \( h \) on \( \mathbb{R}^K \):

\[
h = \text{softmax}(w)
\]

where \( w = (w_1, w_2, \ldots, w_n) \), \( K \) is the number of tags and depends on the the number of classes and on the tagging scheme. The linear-chain CRF model defines the posterior probability of \( y \) given \( X \) to be:

\[
p(y|X; A) = \frac{1}{Z(X)} \exp \left( \sum_{k=0}^{n-1} h_k(y_k; X) + \sum_{k=1}^{n-1} A_{y_k, y_{k+1}} \right)
\]

where \( Z(X) \) is a normalization factor over all possible tags of \( X \), \( h_k(y_k; X) \) indicates the probability of taking the \( y_k \) tag at position \( k \), \( y_0 \) and \( y_{n+1} \) are start and end tags. \( A \) is the transfer matrix, and \( A_{y_k, y_{k+1}} \) means the probability of a transition from tag states \( y_k \) to \( y_{k+1} \). The most likely tag sequence of \( X \) is represented as follows:

\[
y^* = \arg\max_{y \in \mathbb{R}^K} p(y|X; A)
\]

A is learnt through the maximum log-likelihood estimation, which maximizes the log-likelihood function \( L \) of training set sequences in seed dataset \( D_s \):

\[
L(D_s, A) = \sum_{m=1}^{M} \log p(Y^{(m)}|X^{(m)}; A)
\]

where \( M \) is the size of the fully-annotated seed dataset \( D_s \).

Then, we use the initial NER model \( M_0 \) to assign labels on \( D_c \), and get a weakly-annotated dataset \( D_c^* \). Moreover, we combine \( D_s \) with \( D_c^* \) and get an augmented dataset. Different from training, we set thresholds \( \theta \) to filter tags with low probabilities outputted by the softmax layer. Finally, we iteratively train the NER model with \( D_c^* \), until the model has achieved an acceptable level of accuracy, or until the maximum number of iterations. Algorithm1 show the overall process of assigning weakly labels, where 0 stands for none tag.

IV. EXPERIMENTS

We conduct experiments on three benchmark datasets in two challenging domains to evaluate and compare our proposed approach with state-of-the art methods. We further investigate the effectiveness of LM fine-tuning and the bootstrapping process respectively.

A. Datasets

- SciERC [4] annotates entities, their relations, and coreference clusters. Four relations are annotated.
Algorithm 1: Weakly labels assignment

Input: Annotated seed data ($\mathcal{D}_s$)  
Input: Unannotated corpus ($\mathcal{D}_c$)  
Output: NER model ($\mathcal{M}_K$)  

Train NER model $\mathcal{M}_0$ on $\mathcal{D}_s$  

for $i$ in 1...$K$ do  

\[
\mathcal{D}_s^{(i-1)*} \leftarrow \text{Predict using } \mathcal{M}_{i-1}
\]

\[
\mathcal{D}_c^{(i-1)} \leftarrow \text{Relabel } \mathcal{D}_c^{(i-1)*}
\]

s.t.

if $p(y^*_k) < \theta$ then

\[
y^*_k \leftarrow 0
\]

end

Train model $\mathcal{M}_i$ on $\mathcal{D}_s + \mathcal{D}_c^{(i-1)}$

end

return $\mathcal{M}_K$

Table II: Datasets overview.

| Seed  | Sci-ERC | BC5CDR | NCBI-Disease |
|-------|---------|--------|--------------|
| 10%   | 189     | 485    | 626          |
| 20%   | 359     | 960    | 1,171        |
| 30%   | 540     | 1,348  | 1,737        |
| 50%   | 895     | 2,319  | 2,943        |
| 100%  | 1,857   | 4,611  | 5,825        |

| Domain | CS | Biomedical | Biomedical |
|--------|----|------------|------------|
| Entity types | 6 | 2 | 1 |

- BC5CDR [1] is from the most recent BioCreative V Chemical and Disease Mention Recognition task. Two relations are annotated.
- NCBI-Disease [29] focuses on Disease Name Recognition. Only 1 relation is annotated.

Table II gives the statistics of the datasets used in this work. To be directly comparable with previous works, we used the official train/dev/test set splits on all datasets.

B. Cheap and Easily Obtainable Resources

- General Domain Pre-trained LM: We use BERT$_{BASE}^1$, which trained on a general domain corpora including English Wikipedia and BooksCorpus.
- In-domain Corpora: We construct two in-domain corpora, CS and BIO, to fine-tune BERT$_{BASE}$. The CS consists of 40k papers from AI conference proceedings and 87k papers in AI community from arXiv. The BIO consists of 200k abstracts which are randomly sampled from PubMed.

C. Evaluation Metric

Following previous works [11], [13], [15], the micro-averaged F1 score is used as the evaluation metric.

D. Baselines

We evaluate our proposed approach RDANER with BERT$_{BASE}$, which is the strongest baseline in our work. Then, we compare RDANER against two domain-specific BERT variants to show the effectiveness of LM fine-tuning. Furthermore, we show the performance of bootstrapping process and compare RDANER with state-of-the-art learning-based methods which use difficulty obtainable domain-specific resources. More details are as follows.

- BERT$_{BASE}$ [26] is a transformer-based language model which has been shown to be powerful for general domain NER tasks.
- SCIBERT [13] is trained on scientific corpora including 18% papers from the computer science domain and 82% from the broad biomedical domain.
- BIOBERT [14] is initialized with BERT, then fine-tuned on PubMed abstracts and PMC full text articles.
- DyGIE++ [16] has achieved best performance on NER, especially on Sci-ERC dataset. However, DyGIE++ requires extra annotations including relation, coreference and event labels.
- SpERT [17] is an attention model for span-based joint entity and relation extraction. It requires relation annotations for training.
- SwellShark [19] is an excellent distantly supervised model in the biomedical domain, which needs no human annotated data. However, it requires extra expert effort for designing effective regular expressions.
- AutoNER [12] circumvents the requirements of extra human effort, however, it needs large high-quality dictionaries to achieve satisfactory performance.

E. Implementation Details

Our model is implemented with AllenNLP$^2$. For all pre-trained BERT variants, we use PyTorch version of them and the original code released publicly. All experiments are conducted on a single GTX 1080Ti GPU (12GB).

We fine-tune BERT$_{BASE}$ on two large-scale in-domain corpora: CS and BIO using transformers library$^3$, and get two BERT variants BERT$_{CS}$ and BERT$_{BIO}$ respectively. We initialize BERT$_{CS}$ and BERT$_{BIO}$ with weights from BERT$_{BASE}$, and we use the same vocabulary as BERT$_{BASE}$. Different from original BERT code, we set a maximum sentence length of 120 tokens for CS corpus and 80 tokens for BIO corpus, which are in line with most sentence length in the corresponding corpus. Both of them are fine-tuned for 1 epoch, and we don’t continue train the model allowing longer sentence length as BERT does.

To simulate a limited annotated data setting, we randomly select subsets of training data as seed training datasets with varying data ratios at 10%, 20%, 30%, 50% and 100%.

1https://github.com/google-research/bert

2https://github.com/allenai/allennlp

3https://github.com/huggingface/transformers
remaining training data simulate small in-domain corpora. Numbers of sentences of each ratio are shown in Table II.

The maximum number of iterations is set to 10, and we take the average of last 5 iterations as the result of each model. In order to reduce training time, we set different epochs for different seed training datasets, epochs decrease as seed increase.

To investigate the effectiveness of the proposed approach, all parameters are fine-tuned on the dev set and we do not perform extensive hyperparameter search. For all compared methods, we use the code published in their papers, and follow the same experimental settings. We add a CRF layer after the softmax layer for all BERT variants.

V. RESULTS AND DISCUSSION

In this section, we evaluate our proposed approach from the following aspects. First, we evaluate the proposed approach against BERT\textsubscript{BASE} to investigate the effectiveness of LM fine-tuning process. Second, we show the performance of the bootstrapping process and investigate the impact of the threshold $\theta$. Furthermore, we compare our proposed approach with domain-specific BERT variants and state-of-the-art learning-based methods which use difficultly obtainable domain-specific resources.

A. Effectiveness of LM Fine-tuning

Table III shows the test set evaluation results of LM fine-tuning on the three datasets. The reported results are the mean across five different runs with different random seeds. As introduced before, we use BERT\textsubscript{CS} for Sci-ERC dataset, BERT\textsubscript{HC} for BC5CDR and Disease datasets. We observe that LM fine-tuning consistently outperform BERT\textsubscript{BASE} on all three datasets. More specifically, LM fine-tuning gains an average improvement of 3.35 F1 on Sci-ERC, 2.02 F1 on BC5CDR and 1.24 F1 on NCBI-Disease. It indicates that LM fine-tuning on in-domain corpora is effective and domain-adaptive. We also note that there is performance gap degradation when training data increase for each dataset, which indicates that LM fine-tuning works better on less training data. This is due to the text representation has greater impact on NER models when less training data are provided.

B. Performance of Bootstrapping

Table III shows the performance of the RDANER on the three datasets. RDANER consists two processes: LM fine-tuning and bootstrapping. We observe that the bootstrapping process can always further improve the accuracy of NER models, which indicates the bootstrapping process is reliable. Based on LM fine-tuning, the bootstrapping process gains an average improvement of 1.29 F1. Using only 50% of training data, RDANER achieves reasonable performance, which BERT\textsubscript{BASE} needs 100% of training data to achieve.

In order to get a further understanding of the bootstrapping process, the iteratively training process with 10% of the training data is shown in Table IV. Iteration 0 is the initial model trained on seed dataset, and we use the model to predict labels for unknown tokens repeatedly, which yields a jump in performance in the first iteration (Iter 1), since the predicted labels are informative. We observe that the bootstrapping process gains an average improvement of 1.86 F1 on initial models across the three datasets. The improvement achieved on Sci-ERC and BC5CDR is mainly due to the gain in recall. On the contrary, the improvement achieved on NCBI-Disease is mainly due to the gain in precision. Because there is only 1 type of entity needed to be recognized on NCBI-Disease dataset, NER on NCBI-Disease is more likely to achieve a high precision.

Impact of $\theta$: Fig. 2 shows the F1 scores curves on development sets with different thresholds of label assignment probability. This experiment is to find the optimal thresholds for different ratios of training data. Theoretically, increasing the threshold does result in a lower number of false positives, leading to higher precision. Instead, lower thresholds lead to higher recalls. For Sci-ERC, slowly increasing the threshold results in a slightly more balanced F1 measure. But the F1 scores start decreasing when precision is higher than a threshold. We observe that the less training data, the smaller the optimal thresholds, indicating recall has a greater impact on F1 under lower resources. Different from Sci-ERC, curves on BC5CDR and NCBI-Disease are more stable, increasing the threshold does little impact on F1 scores except using 10% of the training data. This demonstrates that entity annotated by models have a very high accuracy. We attribute this to the fact that BC5CDR and NCBI-Disease have fewer entity types, resulting in high accuracy of classification.

C. Comparison with Domain-specific Pre-training Methods

Table V shows the performance of domain-specific BERT variants on the three datasets. We observe that SciBERT and BioBERT perform well on their corresponding domains. SciBERT achieves satisfactory F1 scores on Sci-
Table IV: Performance of iterative bootstrapping process using 10% training data. (P: Precision, R: Recall)

| Iter | Sci-ERC | BC5CDR | NCBI-Disease |
|------|---------|--------|-------------|
|      | P       | R     | F1         | P       | R     | F1         | P       | R     | F1         |
| 0    | 53.84   | 61.44 | 57.39      | 77.42   | 75.82 | 76.61      | 75.62   | 76.56 | 76.09      |
| 1    | 55.26   | 61.84 | 58.36      | 77.13   | 76.88 | 77.75      | 76.72   | 77.56 | 77.14      |
| 2    | 55.34   | 61.62 | 58.31      | 78.65   | 77.14 | 78.87      | 77.23   | 77.71 | 77.47      |
| 3    | 55.18   | 62.10 | 58.43      | 78.36   | 77.77 | 78.76      | 76.43   | 77.71 | 77.07      |
| 4    | 55.14   | 62.22 | 58.47      | 77.13   | 77.26 | 77.45      | 75.22   | 80.31 | 77.68      |
| 5    | 55.69   | 62.64 | 58.96      | 77.40   | 77.45 | 77.26      | 77.04   | 77.60 | 77.32      |
| 6    | 55.30   | 63.00 | 59.11      | 77.77   | 77.81 | 77.72      | 78.12   | 77.25 | 77.68      |
| 7    | 55.23   | 62.16 | 58.49      | 77.77   | 78.26 | 78.01      | 78.16   | 77.19 | 77.67      |
| 8    | 56.24   | 63.00 | **59.20**  | 77.75   | 78.41 | **78.08**  | 80.33   | 76.56 | **78.40**  |

Table V: NER F1 scores of domain-specific BERT variants on Sci-ERC, BC5CDR and NCBI-Disease with varying training data ratios.

| Dataset       | Seed | SciBERT | BioBERT | R DANER |
|---------------|------|---------|---------|--------|
| Sci-ERC       | 10%  | 57.59   | 57.68   | **58.83** |
|               | 20%  | 62.05   | 61.84   | **62.28** |
|               | 30%  | **65.63** | 63.35   | 64.61 |
|               | 50%  | 66.95   | 64.66   | 65.48 |
|               | 100% | 68.55   | 67.89   | **68.96** |
| BC5CDR        | 10%  | 81.92   | **83.56** | 78.25 |
|               | 20%  | 84.85   | 85.57   | 82.35 |
|               | 30%  | 86.14   | 86.87   | 83.55 |
|               | 50%  | 87.50   | **87.94** | 85.26 |
|               | 100% | **90.01** | 89.11   | 87.38 |
| NCBI-Disease  | 10%  | 80.82   | **81.08** | 78.14 |
|               | 20%  | 83.69   | **85.82** | 83.46 |
|               | 30%  | 86.35   | 87.02   | 85.46 |
|               | 50%  | 87.37   | **88.53** | 86.80 |
|               | 100% | 88.57   | **89.36** | 87.89 |

Table VI: Resources required by domain-specific BERT variants and RDANER. R DANERCS use BERTCS and R DANERBio use BERTBio as the text encoder. (B: billion, M: million; d: day, h: hour)

| Variants | SciBERT | BioBERT | R DANERCS | R DANERBio |
|----------|---------|---------|-----------|------------|
| Tokens   | 3.2B    | 18.0B   | 17.2M     | 37.7M      |
| GPU Time | 42d     | 254d    | **2.5h**  | **3.5h**   |

Figure 2: F1 scores curves on development set vs. thresholds of label assignment probability.
science domain currently. We attribute this to the fact that Sci-ERC is a small dataset with only 1,857 annotated sentences. Unfortunately, bootstrapping is prone to over-fitting on small dataset. What’s more, NER on Sci-ERC sentences. Unfortunately, bootstrapping is prone to over-

Table VII: NER F1 scores of state-of-the-art learning-based methods using full training data. AutoNER and SwellShark require domain-specific lexicons that are unavailable for Sci-ERC.

| Models          | Sci-ERC | BC5CDR  | NCBI-Disease |
|-----------------|---------|---------|--------------|
| AutoNER [12]    | -       | 84.80   | 75.52        |
| SwellShark [19] | -       | 84.23   | 80.80        |
| SpERT [17]      | 67.62   | 86.65   | 86.12        |
| DyGIE++ [16]    | 69.80   | 85.44   | 84.11        |
| RDANER          | 68.96   | 87.38   | 87.71        |

D. Comparison with State-of-the-art Learning-based Methods

In this section, we exploit all training data and use the perfect thresholds of label assignment probability to improve the performance of RDANER. The averaged results over 5 repetitive runs are summarized in Table VII. We observe that RDANER performs reasonably well when compared to various state-of-the-art methods that use difficulty obtainable domain-specific resources, including distantly supervised learning-base (DSL) methods and multi-task learning-based (MTL) methods. Because we can’t find any parallel resources in computer science and biomedical domains, we don’t compare RDANER with transfer learning methods.

AutoNER and SwellShark are two DSL methods, and we observe that RDANER consistently outperforms them. We can’t apply AutoNER and SwellShark on Sci-ERC dataset, because the domain-specific lexicons are unavailable. This also shows DSL methods are highly dependent on the availability of domain-specific resources. Although AutoNER and SwellShark claim that they don’t use any human-annotated data, they actually leverage the information of large domain-specific lexicons. For example, AutoNER uses a lexicon contains 322,882 chemical and disease entity surfaces, and SwellShark uses ontologies for generating weakly-annotated data. Such resources are often not available, leading DSL methods less adaptable. Interestingly, we notice that our approach achieves close results to AutoNER and SwellShark using 20% of the training data (960 sentences) of BC5CDR, and 10% of the training data (626 sentence) of NCBI-Disease. Since it is much more challenging to construct big domain-specific lexicons, we suggest using RDANER to build reliable NER systems when domain-specific lexicons are unavailable.

DyGIE++ and SpERT are two latest state-of-the-art MTL methods, and both of them are built on top of BERT encodings and utilize extra annotations of other tasks. DyGIE++ achieves best F1 score on Sci-ERC, indicating that the extra annotations for other tasks, such as relation, event and coreference labels are helpful to improve performance. However, DyGIE++ perform mediocrly on BC5CDR and NCBI-Disease dataset, due to the lack of extra annotations of the two datasets. We note that SpERT performs better than DyGIE++ on BC5CDR and NCBI-Disease. This is partly due to SpERT only uses relation labels, lacking of extra annotations has less impact on SpERT than DyGIE++. Surprisingly, without extra annotations, RDANER achieves the second best F1 score on Sci-ERC. Besides, RDANER outperforms DyGIE++ and SpERT on BC5CDR and NCBI datasets. It demonstrates our proposed approach is not only effective but also domain-adaptive.

VI. Conclusions

In this paper, we propose a novel robust and domain-adaptive approach RDANER for low-resource NER only using cheap and easily obtainable resources. We conduct low-resource experiments in two challenging domains and find that: 1) RDANER is effective and efficient for low-resource NER, and it achieves competitive performance against the state-of-the-art methods which utilize difficultly obtainable domain-specific resources. 2) Beside, RDANER is domain-adaptive, which can be easily applied to a new domain.

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