Leveraging Domain Agnostic and Specific Knowledge for Acronym Disambiguation

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Abstract
An obstacle to scientific document understanding is the extensive use of acronyms which are shortened forms of long technical phrases. Acronym disambiguation aims to find the correct meaning of an ambiguous acronym in a given text. Recent efforts attempted to incorporate word embeddings and deep learning architectures, and achieved significant effects in this task. In general domains, kinds of fine-grained pretrained language models have sprung up, thanks to the large-scale corpora which can usually be obtained through crowdsourcing. However, these models based on domain agnostic knowledge might achieve insufficient performance when directly applied to the scientific domain. Moreover, obtaining large-scale high-quality annotated data and representing high-level semantics in the scientific domain is challenging and expensive. In this paper, we consider both the domain agnostic and specific knowledge, and propose a Hierarchical Dual-path BERT method coined hdBERT to capture the general fine-grained and high-level specific representations for acronym disambiguation. First, the context-based pretrained models, RoBERTa and SciBERT, are elaborately involved in encoding these two kinds of knowledge respectively. Second, multiple layer perceptron is devised to integrate the dual-path representations simultaneously and outputs the prediction. With a widely adopted SciAD dataset contained 62,441 sentences, we investigate the effectiveness of hdBERT. The experimental results exhibit that the proposed approach outperforms state-of-the-art methods on various evaluation metrics. Specifically, its macro F1 achieves 93.73%.

Introduction
In recent years, it has witnessed the vigorous development of deep learning. Among the most successful scenarios, natural language processing (NLP) is advancing steadily. However, natural language is frequently ambiguous, so many words and phrases can be interpreted in many ways depending on the context in which they appear (Navigli 2009). Specifically, an obstacle to scientific document understanding (SDU) is the widespread use of acronyms, which are shortened forms of long technical phrases (Veyseh et al. 2020b; Beltagy, Lo, and Cohan 2019). In order to understand the document correctly, the SDU system should be able to identify acronyms and their correct meanings. The goal of acronym disambiguation (AD) is to determine the correct long form of an ambiguous acronym in a given text (Veyseh et al. 2020a). It is usually formulated as a sequence classification problem in general (Veyseh et al. 2020b). For instance, a toy sample of this task is shown in Table 1. In this example, the “CNN” might be an acronym for “Conventional Neural Network”, “Cable News Network” or “Condensed Nearest Neighbor”. Given a sentence “They use CNN in the proposed model,” and a dictionary with possible expansions (i.e., long forms) of the acronym “CNN”, the expected prediction for its correct meaning is “Conventional Neural Network”. Recent efforts attempted to incorporate hand crafted features (Li et al. 2018), word embeddings (Charbonnier and Wartena 2018), Ciosici, Sommer, and Assent 2019), graph structures (Prokofyev et al. 2013), Veyseh et al. 2020b), and deep learning architectures (Jin, Liu, and Lu 2019; Blevins and Zettlemoyer 2020) and achieved significant effects in this task.

In this paper, we pay more attention to the scenario of scientific acronym disambiguation. Some observations are still worthy of further investigation. Generally, large-scale training data for natural language processing tasks in general domains is often possible to obtain through crowdsourcing, emerging a variety of domain-independent fine-grained pretrained models. However, these models based on domain agnostic knowledge might achieve insufficient performance when applied to the specific domain (Beltagy, Lo, and Cohan 2019). Furthermore, obtaining large-scale annotated data in the scientific domain is challenging and expensive (Beltagy, Lo, and Cohan 2019), which leads to the shortage of high-level semantic expression to some extent.

To remedy these challenges, we fully consider both the domain agnostic and specific knowledge, and propose a Hierarchical Dual-path BERT method coined hdBERT to fusion the general fine-grained and high-level specific representations for acronym disambiguation. The overall architecture is illustrated in Figure 1. We pinpoint that hdBERT is a BERT-based supervised method adopting the now ubiquitous transformer architecture (Vaswani et al. 2017). First, RoBERTa (Liu et al. 2019) and SciBERT (Beltagy, Lo, and Cohan 2019) modules are elaborately involved to distill representations from inputs consist of sentence and candidate long forms. Specifically, we utilize RoBERTa, a ro-
Word Sense Disambiguation

Word sense disambiguation (WSD) is an open problem concerned with identifying which sense of a word is used in a text (Navigli 2009). It is a core and difficulty in natural language processing tasks, which affects the performance of almost all downstream tasks. The methods to solve word sense disambiguation are usually divided into two categories: knowledge-based and supervised (Wang, Wang, and Fujita 2020; Barba et al. 2020).

Knowledge-based methods usually rely on amounts of statistical information and can be easily extended to other low-resource languages (Agirre, López de Lacalle, and Soroa 2014; Scarlini, Pasini, and Navigli 2020). For example, SensEmBERT (Scarlini, Pasini, and Navigli 2020), a knowledge- and BERT-based method that combines the expressive power of language modeling with the vast amount of knowledge contained in the semantic network, produces high-quality latent semantic representations of the meanings of the word in different languages. And it can achieve competitive results attained by most of the supervised neural approaches on the WSD tasks. On the other hand, supervised methods require lots of labeled data to learn word representations (Bevilacqua and Navigli 2019; Wang, Wang, and Fujita 2020). Of course, this defect can be alleviated through semi-supervised methods (Barba et al. 2020) by jointly leveraging contextualized word embedding and the multilingual information to project some sense labels.

Furthermore, acronym disambiguation is more challenging since we need to identify the acronym first and then to understand the text to determine the correct meaning of acronyms. Recently, an effective solution is to extract acronym definitions from unstructured texts by computing the Levenshtein string edit distance between any pair of long forms (Ciosici, Sommer, and Assent 2019), which is an entirely unsupervised acronym disambiguation method. And researches also attempt to incorporate hand crafted features (Li et al. 2018), word embeddings (Charbonnier and Wartena 2018; Ciosici, Sommer, and Assent 2019), graph structures (Prokofyev et al. 2013; Veyseh et al. 2020b), and deep learning architectures (Jin, Liu, and Lu 2019; Blevins and Zettlemoyer 2020), and have achieved significant effects in this task. Specifically, a supervised method named GAD (Veyseh et al. 2020b), which utilizes the syntactic structure of sentences to extend ambiguous acronyms in sentences by combining Bidirectional Long Short-Term Memory (BiLSTM) with Graph Convolutional Networks (GCN), provides a strong baseline on acronym disambiguation tasks in the scientific domain.

**Table 1: A toy sample of acronym disambiguation.**

| Input - Sentence | They use CNN in the proposed model. |
|------------------|-------------------------------------|
| Input - Dictionary | CNN: 1. Convolutional Neural Network, 2. Cable News Network, 3. Condensed Nearest Neighbor |
| Output | Convolutional Neural Network |

BERT-based Methods

Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2019) is a self-supervised learning method that trains based on a large number of corpora to express better features for word embedding. And its network architecture utilizes the multi-layer transformer structure (Vaswani et al. 2017). The feature representation of BERT could be directly adopted as word embedding features for downstream tasks. Besides, BERT provides a model for transfer learning of other tasks. It can be fine-tuned or fixed according to tasks and then treated as a feature extractor. BERT was significantly undertrained, and there have been many fine-grained improvements or specific domain variants of it (Beltgay, Lo, and Cohan 2019; Liu et al. 2019; Scarlini, Pasini, and Navigli 2020; Lee et al. 2020).

RoBERTa. RoBERTa (Liu et al. 2019) is mainly trained on general domain corpora via byte-level Byte-Pair-Encoding (Sennrich, Haddow, and Birch 2016) based on the structure of BERT and can supply more fine-grained representation. This encoding scheme can process amounts of words that are common in natural language corpora and is

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SciBERT. SciBERT (Beltagy, Lo, and Cohan 2019) is a specific pretrained language model for scientific domain texts. This model follows the same architecture as BERT to solve the lack of high-quality, large-scale labeled scientific data. It significantly outperforms previous BERT-based methods and achieves new state-of-the-art results on some scientific NLP tasks.

**Methodology**

In this section, we first introduce the problem statement of acronym disambiguation and then describe the overall architecture and details of our proposed hdBERT model.

**Problem Statement**

Acronym disambiguation is formulated as a sequence classification problem in general (Veyseh et al. 2020b). Formally, given an input sentence $s = w_1, w_2, ..., w_n$ and the position of the acronym, i.e., $p$, the goal is to disambiguate the acronym $w_p$, that is, predicting the true long form $l$ from all candidate long forms of $w_p$. Specifically, in this paper, we simplify it into a binary classification problem. That is, given an input sample consists of the sentence $s$ with acronym $w_p$ and the candidate long form $l$, i.e., $x = (s; l)$, our purpose is to predict the probability of $l$ being the right long form of $w_p$. We assign a label $y \in \{0, 1\}$ on each sample in training dataset to indicate whether $l$ is a true long form of $w_p$ in sentence $s$ or not. In the testing phase, the long form with the highest prediction probability among the candidate long form set of a sentence would be chosen as its final result.

**Overview**

Figure 1 exhibits the schematic illustration of the proposed hdBERT model. As mentioned previously, we design a hierarchical integration model comprising three major components, each plays a different role in final prediction. The first two context-based components, i.e., RoBERTa (Liu et al. 2019) and SciBERT (Beltagy, Lo, and Cohan 2019) modules, distill representations of the sentence and the candidate long forms. Specifically, as a robustly optimized method trained on vast amounts of general domain corpora, we use RoBERTa to capture the general and fine-grained semantic information via byte-level Byte-Pair-Encoding (Sennrich, Haddow, and Birch 2016). Moreover, SciBERT, which leverages unsupervised pretraining on a large scientific corpus by WordPiece (Wu et al. 2016) tokenization strategy, is exploited to represent the high-level scientific domain information. Finally, a multiple layer perceptron network is devised to fusion these two kinds of representations. In the following, we present detail of each major component.

**Information Distillation**

**General and Fine-grained Information.** We involve RoBERTa to capture domain agnostic and fine-grained information of the sentence and its candidate long form. RoBERTa uses the now ubiquitous transformer architecture (Vaswani et al. 2017) via byte-level Byte-Pair-Encoding (BPE), which is a hybrid between character- and word-level representations that allow handling large vocabularies common in natural language corpora. Instead of full words, BPE relies on subwords units, which are extracted by performing statistical analysis of the training corpus. The size of the original vocabulary released with RoBERTa is about 50K, which is 20K more than BERT’s.

We define the encoding of a sample $x = (s, l)$ after the BPE strategy as $e_{BPE}$ and the output representation throughout the RoBERTa model as $h_{RoBERTa}$.

$$e_{BPE} = \text{BPE}(x)$$

$$h_{RoBERTa} = \text{RoBERTa}(e_{BPE})$$

**High-level Scientific Domain Information.** To handle the high-level scientific domain information, SciBERT is chosen elaborately. SciBERT follows the same architecture
### Statistical Information

|                          | SciAD          |
|--------------------------|----------------|
| number of acronyms       | 732            |
| average number of long form per acronym | 3.1           |
| overlap between sentence and long forms | 0.32          |
| average sentence length  | 30.7           |
| number of training       | 50,034         |
| number of development    | 6,189          |
| number of test           | 6,218          |

Table 2: The statistical information of original SciAD dataset. Note that the third row shows the ratio of sentences that have at least one word in common with the long forms of the acronyms appearing in the sentence.

As BERT but is instead pretrained on the scientific texts. It constructed a new WordPiece vocabulary on scientific corpus using the SentencePiece library and trained on a random sample of 1.14M papers from Semantic Scholar (Ammar et al. 2018). Its corpus consists of 18% papers from the computer science domain and 82% from the broad biomedical domain. The size of the original vocabulary released with SciBERT is about 30K, which is 20K less than RoBERTa. The resulting token overlap between SciBERT and BERT is 42%, which illustrates the significant difference in common terms between scientific and general domain texts.

We define the encoding of a sample $x = (s, l)$ after SciBERT’s encoding strategy (noted as WPE) as $e_{WPE}$ and the output representation throughout the SciBERT model as $h_{SciBERT}$:

$$e_{WPE} = WPE(x)$$

$$h_{SciBERT} = SciBERT(e_{WPE})$$

### Integration

After modeling the two complex representations above, the obtained concatenation $h$ is fed into multiple layer perceptron network and followed by a regression layer with sigmoid unit, as follows:

$$h = [h_{RoBERTa}; h_{SciBERT}]$$

$$p = \text{sigmoid}(W^T \text{MLP}(h) + b)$$

where $W$ is the weight vector, $b$ is the bias, and $\text{MLP}(\cdot)$ represents the operation of multiple layer perceptron shown in Figure 1. Here $p$ is the predicted probability.

Finally, our model is trained with cross entropy loss with regularization. The loss function is defined as

$$L(\theta) = - \sum_{D} (y \log(p) + (1 - y) \log(1 - p)) + \lambda \|\theta\|_2^2$$

where $y$ is the ground truth, $\theta$ is the parameter set of the proposed model, $\lambda$ is the regularizer parameter, and $D$ is the training dataset.

### Experiments

In this section, we first illustrate the datasets, evaluation metrics, and implementation details, then demonstrate the experimental results and further studies.

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1. We won second place in the acronym disambiguation competition. [https://sites.google.com/view/sdu-aaai21/shared-task]
Table 3: Architecture and hyper parameters information. Our proposed hdBERT model ensembles RoBERTa and SciBERT via three MLP layers.

| Parameter | BERT | RoBERTa | SciBERT |
|-----------|------|---------|---------|
| pretrained model | bert-large-uncased | roberta-large | allenai/scibert_scivocab_uncased |
| architecture | sequence classification | sequence classification | sequence classification |
| attention_probs_dropout_prob | 0.1 | 0.1 | 0.1 |
| hidden_act | gelu | gelu | gelu |
| hidden_dropout_prob | 0.1 | 0.1 | 0.1 |
| hidden_size | 1024 | 1024 | 768 |
| initializer_range | 0.02 | 0.02 | 0.02 |
| intermediate_size | 4096 | 4096 | 3072 |
| layer_norm_eps | 1e-12 | 1e-05 | 1e-12 |
| max_position_embeddings | 512 | 514 | 512 |
| model_type | bert | roberta | bert |
| num_attention_heads | 16 | 16 | 12 |
| num_hidden_layers | 24 | 24 | 12 |
| position_embedding_type | absolute | absolute | absolute |
| vocab_size | 30522 | 50265 | 31090 |
| learning_rate | 2e-5 | 2e-5 | 2e-5 |
| epoch | 5 | 5 | 5 |

If a long form $l$ is true for $w_p$, while $y = 0$ for other false candidate long forms of $w_p$. Specifically, to alleviate the imbalance problem during training, we upsample each positive sample to equal the number of candidate long forms of its acronym. More statistics of SciAD\textsubscript{BI} is shown in Table 4.

Table 4: The statistical information of SciAD\textsubscript{BI} dataset.

| Statistical Information | SciAD\textsubscript{BI} |
|-------------------------|-------------------------|
| number of training      | 352,366                 |
| number of development   | 28,286                  |
| number of test          | 28,364                  |

Evaluation Metrics

To evaluate the performance of different methods, three popular metrics are adopted, namely Macro Precision, Macro Recall and Macro F1. The definitions are as follows:

\[
\text{Precision}_{\text{MACRO}} = \frac{\sum_{i=1}^{n} \text{Precision}_i}{n} \quad (8)
\]

\[
\text{Recall}_{\text{MACRO}} = \frac{\sum_{i=1}^{n} \text{Recall}_i}{n} \quad (9)
\]

\[
\text{F1}_{\text{MACRO}} = \frac{2 \times \text{Precision}_{\text{MACRO}} \times \text{Recall}_{\text{MACRO}}}{\text{Precision}_{\text{MACRO}} + \text{Recall}_{\text{MACRO}}} \quad (10)
\]

where $n$ is the number of total classes, Precision, and Recall, represent the precision and recall of class $i$ respectively. The higher $\text{Precision}_{\text{MACRO}}, \text{Recall}_{\text{MACRO}}$ and $\text{F1}_{\text{MACRO}}$ indicate the higher performance of approaches.
Methodology

| Model  | Macro Precision (%) | Macro Recall (%) | Macro F1 (%) |
|--------|---------------------|------------------|--------------|
| MF     | 89.03               | 42.20            | 57.26        |
| ADE (Li et al. 2018) | 86.74               | 43.25            | 57.72        |
| NOA (Charbonnier and Wartena 2018) | 78.14               | 35.06            | 48.40        |
| UAD (Ciosici, Sommer, and Assent 2019) | 89.01               | 70.08            | 78.37        |
| BEM (Blevins and Zettlemoyer 2020) | 86.75               | 35.94            | 50.82        |
| DECBAE (Jin, Liu, and Lu 2019) | 88.67               | 74.32            | 80.86        |
| GAD (Veyseh et al. 2020b) | 89.27               | 76.66            | 81.90        |
| Human Performance (Veyseh et al. 2020b) | 97.82               | 94.45            | 96.10        |

Table 5: Performance of models in acronym disambiguation.

Implementation Details

For models ADE, NOA, UAD, DECBAE, BEM, and GAD, please refer to Veyseh et al. for more implementation information. We implement the proposed model based on PyTorch (Paszke et al. 2019) and Transformers (Wolf et al. 2020). For models BERT, RoBERTa, and SciBERT, we fine-tune them on dataset based on their popular pretrained models. The implementation details of these models are shown in Table 3. Moreover, the information distillation components of our model are the same as model RoBERTa and SciBERT respectively. And we simply adopt three MLP layers for integration simultaneously. As mentioned previously, in the testing phase, the long form with the highest prediction probability in the candidate long form set of a sentence would be chosen as its final result. In addition, we use two V100 GPUs with 12 cores to complete all these experiments.

Performance Comparison

Table 5 demonstrates the main results of all compared methods on the dataset. The major findings from the experimental results can be summarized as follows:

First, GAD achieves a better result than methods such as ADE, NOA, UAD, DECBAE, BEM, and GAD, showing the importance of syntactic structure for the acronym disambiguation task. But it still far worse than pretrained-based models like BERT and RoBERTa. Second, between the two general-domain models, RoBERTa gets better performance than BERT, indicating the advantage of more fine-grained encoding. Moreover, SciBERT is more advanced than the domain agnostic methods, i.e., BERT and RoBERTa, with about 2.26% and 1.03% increased macro F1 respectively, showing the importance of the scientific domain pretraining for this task. Furthermore, we can clearly observe that our hdBERT model outperforms all the baselines by a large margin. Its macro F1, with the reported value of 93.73%, is about 1.88% and 0.84% higher than state-of-the-art RoBERTa and SciBERT respectively. And its loss curve falls faster and converges lower than the two pretrained methods on the development dataset, as shown in Figure 4. These observations demonstrate that it is effective to model both fine-grained domain agnostic and high-level domain specific knowledge simultaneously.

However, despite the significant improvements among these approaches, performances of all models are still not as effective as humans on the dataset, especially on macro recall and macro F1, thus providing many further research opportunities for this scenario.

Case Study

We further focus on studying both success and failure cases of pretraining-based models to provide more insight into acronym disambiguation. Specifically, for success case of our model in which RoBERTa and SciBERT fail, e.g., “Each SP within an SM shares an instruction unit, dedicated to the management of the instruction flow of the threads.” (DEV-6156), the true long form of “SM” is “Streaming Multiprocessors”. While both BERT and SciBERT output “Shared Memory”, which may often appear in deep learning publications. It might benefit from the additional integration modeling of two different information from RoBERTa and SciBERT. However, all the three models fail in this exam-
ple: “In the first stage, we train the SPM, and extract the FL and FR.” (DEV-4604) with the wrong prediction “Federated Learning” for “FL”. The true long form of “FL” is “Fixed Locations”. We guess that all models pay too much attention to “Federated Learning”, a hot phrase nowadays, and ignore the subtle information among the sentence and its different candidate long forms. It also indicates the necessity of more advanced models for this task.

Further Discussion
As mentioned previously and shown in Table 5, all the current models are still less effective than humans in this scenario. There are still many samples that all models fail in. Some further research opportunities on this dataset are discussed in this section. First, as shown in Table 6, there are some noise data, i.e., conflicted annotation, in the SciAD dataset. For example, the acronym “RF” in boldface in sentence “Just like RF, QRF is a set of binary regression trees.” gets two different long form “Regression Forest” (TR-43200) and “Regression Function” (TR-49535) respectively. It will be some negative impacts on modeling to some extent. Furthermore, to a certain extent, samples constructed from the same sentence with different long forms are independent during our training stage. It might lose more subtle information among them. Therefore, recent methods such as self-training (Peng et al., 2019; Chi et al., 2020), adversarial learning (Goodfellow, Shlens, and Szegedy, 2015; Miyato, Dai, and Goodfellow, 2017; Zhu et al., 2021), and contrastive learning (Hadsell, Chopra, and LeCun, 2006) are worth studying to further improve the performance.

Conclusions
An obstacle to scientific document understanding is the widespread use of acronyms which are shortened forms of long technical phrases. Acronym disambiguation aims to find the correct meaning of an ambiguous acronym in a given text. However, it is challenging and expensive to obtain large-scale high-quality annotated data in the scientific domain. In this paper, we present a hierarchical dual-path BERT method coined hdBERT for acronym disambiguation to resolve the special challenges in this scenario. The method is equipped with pretrained models RoBERTa and SciBERT and integrates their dual-path representations simultaneously to leveraging domain agnostic and specific knowledge. Experiments on real-world datasets demonstrate the effectiveness of the proposed approach. It achieves competitive performance and outperforms state-of-the-art methods among various evaluation metrics. Moreover, there are still many research opportunities in this task, approaches such as self-training, adversarial learning, and contrastive learning are worth studying to further improve the performance.

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