Automatic Keyphrase Extraction from Scientific Chinese Medical Abstracts Based on Character-Level Sequence Labeling

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ABSTRACT

Automatic keyphrase extraction (AKE) is an important task for quickly grasping the main points of the text. To improve the performance of keyphrase extraction from Chinese text, we regard AKE as a character-level sequence labeling task and initialize our model with pretrained language model BERT, which is released by Google in 2018. We collect data from Chinese Science Citation Database and construct a large-scale dataset from medical domain, which contains 100,000 abstracts as training set, 6,000 abstracts as trail set, 3,094 abstracts as test set. To validate the effectiveness of our character-level sequence labeling keyphrase extraction model, we use traditional statistical keyphrase extraction methods including term frequency (TF), TF-IDF, TextRank and machine learning methods including Conditional Random Field (CRF) , Bidirectional Long Short Term Memory Network (BiLSTM) and BiLSTM-CRF as our baselines. Compared with BiLSTM-CRF, which achieves the best performance among all baseline models with F1 score of 51.35%, our sequence labeling model obtains F1 score of 59.80%, getting 8.45% absolute improvement. And we make our IOB format dataset of automatic keyphrase extraction from scientific Chinese medical abstracts (AKESCMA) publicly available for the benefits of research community, which is available at: http://159.226.125.191:5000/HomePage.

KEYWORDS

Automatic Keyphrase Extraction, Character-Level Sequence Labeling, Pretraining-Finetuning, Scientific Chinese Medical Abstracts

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1 INTRODUCTION

Automatic keyphrase extraction (AKE) is a task to extract important and topical phrases from the body of a document [47], which is the basis of information retrieval [27], text summarization [56], text categorization [26], opinion mining [4], and document indexing [15]. It can help us quickly go through large amounts of textual

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information to find out the main stating point of the text. Appropriate keyphrases can serve as a highly concise summarization of the text and help us easily organize and retrieve text.

Classic keyphrase extraction algorithms usually contain two steps [20]. The first step is to generate candidate keyphrases, in which plenty of manually designed heuristics are combined to select potential candidate keyphrases. And the second step is to determine which of these candidate keyphrases are correct. For the second step, there are three common-used approaches: statistical approaches, supervised approaches and unsupervised approaches.

Statistical approaches use statistical features of words to identify keyphrases in text without training data. Supervised approaches usually formulate keyphrase extraction as a binary classification task, using annotated dataset and machine learning algorithms to train a classifier. Unsupervised approaches can mainly be divided into two types: graph-based ranking [39][18] and topic-based clustering [35][34].

One of the shared disadvantages in above-mentioned two-step approaches is that the model performance in second step is based on the quality of candidate keyphrases generated in the first step. So some researchers reformulate keyphrase extraction as a sequence labeling task and validate the effectiveness of this formulation.

In 2008, Zhang et al. [54] firstly reformulate keyphrase extraction as a sequence labeling task and construct a CRF model to extract keyphrases from Chinese text, which skips the step of candidate keyphrase generation. While their method still has room for improvements. They use word-level sequence labeling instead of character-level, tagging the words rather than characters, which still depends on the word segmentation results of Chinese tokenizer. Moreover, they use 600 documents to train the model and design lots of features manually.

By virtue of automatic extracting features, deep learning methods exceed machine learning methods and gradually become the mainstream in many natural language processing (NLP) tasks. Transformer [48] , an emerging model architecture for handling long-term dependencies, is a substitute to classic neural networks such as long short-term memory network. In 2018, Google releases BERT [12], which is a language model pre-trained on large-scale unannotated text and uses Transformer to capture deep semantic and syntactic features in text. In 2019, Sahrawat et al.[43] regards AKE as a sequence labeling task and applies lots of pretrained language models including BERT to English Automatic Keyphrase Extraction, showing the effectiveness of pretrained language model.

Compared with English keyphrase extraction, scientific Chinese medical keyphrase extraction is facing with three challenges: lacking of publicly available annotated dataset, relying on Chinese word segmentation and unique characteristics of scientific Chinese medical text. Firstly, machine learning methods need ground-truth keyphrases of the text to train the model, while there are few Chinese publicly annotated datasets, which makes it difficult to do objective evaluation among different researches. Secondly, English tokens is split by white space while there is no delimiter among Chinese words. The challenge of Chinese word segmentation causes great impacts on classic two-step keyphrase algorithms because candidate keyphrases generation relies on the word segmentation results of Chinese tokenizer and the quality of segmentation will further influence the performance of keyphrase extraction model. Thirdly, English words are interspersed with Chinese words, which increases the difficulty of data preprocessing.

To address the above-mentioned challenges, in this paper, we formulate automatic keyphrase extraction from scientific Chinese medical abstracts as a character-level sequence labeling task which doesn't need Chinese tokenizer to split words and we fine-tune the pretrained language model BERT to transfer to our target AKE task. And we use Unicode Coding to distinguish English and Chinese, which regards each English word as the elementary unit and each Chinese character as the elementary unit, to alleviate the problem that English words and Chinese words are mixed together. Furthermore, we propose a publicly available annotated sequence labeling dataset for keyphrase extraction (Automatic Keyphrase Extraction from Scientific Chinese Medical Abstracts, AKESCMA) to promote the development of Chinese AKE.

Our key contributions are summarized as follows:

(1) We regard AKE from scientific Chinese medical abstracts as a character-level sequence labeling task and fine-tune the parameters of BERT[12] to make it adapt to our large-scale keyphrase extraction dataset. Our approach skips the step of candidate keyphrase extraction and applies pretraining-finetuning this two-stage mode to Chinese AKE without complicated manually-designed features. And our model based on BERT outperforms BiLSTM-CRF, which is the best baseline model in our experiments, showing the effectiveness of pretrained language model.
(2) We process data from Chinese Science Citation Database and construct a large-scale dataset of scientific Chinese medical abstracts using Inside–Outside–Beginning tagging scheme (IOB format) [42], which is a common tagging format in chunking tasks such as named entity recognition task, to make it suitable for building sequence-labeling-based models. Our proposed dataset contains 100,000 abstracts in training set, 6,000 abstracts in trail set and 3,094 abstracts in test set. We make our processed large-scale dataset (AKESCMA) publicly available for the benefits of the research community.

2 RELATED WORK

2.1 Automatic Keyphrase Extraction

Automatic keyphrase extraction has received lots of attention for more than 20 years. Over this time, existing classic methods usually contain two steps: generating candidate keyphrases and determining which of these candidate keyphrases match ground-truth keyphrases. In the first step, candidate keyphrases generation relies on some heuristics such as extracting n-grams that appears in external knowledge base [18][38], extracting n-grams or noun phrases that satisfies pre-defined lexical patterns [2][24][32][50]. The classic approaches in second step can be divided into three categories: statistical approaches, supervised approaches and unsupervised approaches.

As for statistical approaches, these approaches don't need any training corpus and they are based on statistical features of the given text such as word frequency [36], TF*IDF [45], PAT-tree [8] and word co-occurrences [37]. And it's suitable for one single document because no prior information is needed. In 1995, Cohen uses N-gram statistical information to automatically index the document [9]. It doesn't use any stop list, stemmer or domain-specific external information, allowing for easy application in any language or domain with slight modification. In 1997, Chien uses PAT-tree and mutual information between words to extract Chinese keyphrases [8]. In 2009, Carpena et al. considers word frequency and spatial distribution features that keywords are clustered whereas irrelevant words distribute randomly in text [7]. These statistical approaches are usually easy to transfer to a new domain because no prior information is applied.

As for supervised approaches, classic keyphrase extraction is formulated as a binary classification problem [15][46] to determine whether the potential candidate keyphrases match ground-truth keyphrases for the text or not. Annotated datasets are needed to train a classifier, in which annotated candidate keyphrases serve as positive examples and unannotated candidate keyphrases serve as negative examples. Traditional machine learning algorithms such as Naïve Bayes [52], maximum entropy [59], decision trees [47], SVM [57], bagging [24], boosting [25] rely heavily on complicated manually-designed features which can be broadly divided into two categories: within collection features and external resource-bases features [20]. Within collection features use textual features within training data and can be further divided into statistical features such as term frequency [24], TF*IDF [44], syntactic features such as some linguistic patterns [29] and structural features such as location that keyphrases occur in [50]. External resource-based features consist of lexical knowledge bases such as Wikipedia [18][38], document citations [6], hyperlinks [28]. This method has some weaknesses. The prediction for each candidate keyphrases is independent to that of others, which means that the model can't capture the connection among keyphrases.

As for unsupervised approaches, keyphrase extraction is a ranking problem substantially. The model scores each candidate for its likelihood of being a ground-truth keyphrase and returns top-ranked keyphrases by setting a threshold. There are lots of popular unsupervised learning algorithms for keyphrases extraction, such as TextRank [39], LexRank [14], TopicRank [5], SGRank [11] and SingleRank [49].

This two-step keyphrase extraction method has some drawbacks. Firstly, error propagation. The candidate keyphrases generation errors occurring in the first step will be passed to the second step and influence the performance of the downstream methods including statistical methods, supervised and unsupervised methods. Secondly, the model performance relies heavily on some heuristic settings such as threshold, external resources (Wikipedia, domain ontology, lexicon dictionary etc.), and filtration patterns of POS tags, which make it difficult to transfer to a new domain. Thirdly, it's not able to find an optimal N value (number of keyphrases to extract for the text) based on article contents so it is usually set to a fixed parameter which results in keyphrase extraction performance varying with the value for N [37]. And also the number of keyphrases is same among text, ignoring the physical truth and bringing lots of redundant keyphrases or losing lots of import keyphrases. Fourthly, in the second step, the model just analyzes the semantic and syntactic properties of candidate keyphrases separately while losing the meaning of the whole text.

In 2008, Zhang et al.[54] reformulates keyphrase extraction to a sequence labeling task, and utilizes user-defined tagging scheme to annotate each phrase (word segmentation result) in Chinese text and indicate its chunk belonging. And they use conditional random field model, which shows great performance in sequence labeling task. While their method can improve further. Their sequence labeling model is word-level, which still needs Chinese tokenizer to segment words, and they use lot of manually-designed features such as POS tagging, TF*IDF, and other location features. Moreover, the training data scale is just 600 documents, which might not be enough to capture rich features for keyphrase extraction. In 2013, Li et al. [58] also use word-level sequence labeling model to extract keyphrases in automotive field for Chinese text.

Using deep learning method to automatically extract features has become the mainstream of many natural language processing tasks. There are some practices for English AKE. In 2016, Zhang et al. [55] casts keyphrase extraction as a sequence labeling task and proposes a joint-layer recurrent neural network model to extract keyphrases from tweets, which doesn't need complicated feature engineering. In 2019, Sahrawat et al. [43] constructs a BiLSTM-CRF model and uses contextualized word embedding from pre-trained language models to initialize the embedding layer. They evaluate model performance on three English benchmark datasets: Inspec [24], SemEval-2010 [30], SemEval-2017 [1] and their model achieves state-of-the-art results on these three benchmark datasets.

Casting keyphrase extraction as a sequence labeling task bypasses the step of candidate keyphrases generation and provides a unified method for automatic keyphrase extraction. Moreover, in sequence labeling, keyphrases are correlated to each other instead of being independent units. Furthermore, supervised machine learning methods require precise feature engineering and they rely heavily on manually-designed features, such as TF*IDF, POS tags, positional information, orthographic information[17].

Compared with English AKE, Chinese AKE is more complicated owing to the characteristic that there is no delimiter among Chinese words. So there is an additional step in most Chinese AKE models: using Chinese tokenizer to segment words. For traditional two-step keyphrase extraction models, generating Chinese candidate keyphrases needs to use Chinese tokenizer to segment words first. For Chinese AKE models based on sequence labeling, existing methods still use word-level tagging, restricted by the segmentation results of Chinese tokenizer. And for scientific Chinese medical abstracts, it's more difficult because English words are mixed in Chinese text so we need to distinguish English words and regard them as a whole instead of splitting them into characters.

2.2 Sequence Labeling Based on BERT

With the improvement of computer hardware and the increase of available data, deep learning based methods gradually occupy the dominant position in the field of natural language processing. Although deep neural networks can learn highly nonlinear features, they are prone to over-fitting without large amount of annotated data. And the objective functions of almost all deep learning architectures are highly non-convex function of the parameters, with the potential for many distinct local minima in the model parameter space[13]. Thus, how to initialize parameters has been a problem that puzzles researchers. The breakthrough comes in 2006 with the algorithms for deep belief networks [21] and stacked autoencoders[3], which are all based on a similar approach: greedy layer-wise unsupervised pre-training followed by supervised finetuning.

Compared with traditional supervised learning tasks that randomly initialize parameters then learn language representations directly from annotated text, pretraining-finetuning mode not only capture the syntactic and semantic features of words from large-scale unannotated text but also provide a good initial point for the downstream task, improving the generalization ability of the downstream supervised learning task.

Recently, BERT, short for Bidirectional Encoder Representations from Transformers, which is a pretrained language model receiving widespread concern and is believed to be a milestone in NLP. BERT is pretrained on large-scale unlabeled data from BooksCorpus and English Wikipedia, containing more than 3.3 billion tokens in total. Using BERT to fine-tune the downstream supervised tasks breaks the record for 11 NLP tasks which proves the feasibility of pretraining-finetuning mode. Using pretrained language models [10][40][41][22][12] has become a standard component of SOTA (state-of-the-art) model architecture in many natural language processing tasks.

Most previous works for sequence labeling are built upon different combinations of LSTM and CRF[16][19][51], Since the release of BERT[12], some researchers show the effectiveness of applying BERT or BERT-based models to sequence labeling task such as named entity recognition task. BERT has a simple architecture based on bidirectional transformers[48], which performs strongly on various tasks depending on its capability to capture long term frequency and parallelization. Lee et al. introduces BioBERT [33], which is pretrained on large-scale biomedical corpora using the model architecture same with BERT. They test BioBERT on several publicly datasets for named entity recognition such as NCBI disease, BC5CDR. The results show that BioBERT outperforms the state-of-the-art models on six of nine datasets.

In this paper, we combine the benefits of formulating keyphrase extraction from Chinese medical abstracts as a character-level sequence labeling task and the advantage of pretraining-finetuning mode, which can not only avoid errors occurring in Chinese tokenizer, but also extract features automatically rather than using complicated manually-designed features.

3 METHODOLOGY

3.1 Task Definition

We cast keyphrase extraction from Chinese medical abstracts as a sequence labeling task and use IOB format as the input format of the model. This task can be formally stated as:

Let $d = \{\omega_1, \omega_2, ..., \omega_n\}$ be an input text, where ω represents the t^{th} element. If the input text is mixed up with Chinese and English, the element is a Chinese character for Chinese and an English word for English. Assign each ω_t in the text one of the three class labels $Y = \{K_B, K_I, K_O\}$, where K_B denotes that ω_t locates in the beginning of a keyphrase, K_I denotes that ω_t locates in the inside or end of a keyphrase, and K_O denotes that ω_t is not a part of all keyphrases.

For example, there is a sentence ' 七例 X 连锁先天性肾上腺发育不良患儿的临床及 NR0B1 基因突变分析。' and the keyphrases in this sentence are 'X 连锁先天性肾上腺发育不良' and 'NR0B1 基因'.

After IOB format transformation, this sentence is formatted to : ' 七 → O'/' 例 → O'/'X→ B'/' 连 → I'/' 锁 → I'/' 先 → I'/' 天 → I'/' 性 → I'/' 肾 → I'/' 上 → I'/' 腺 → I'/' 发 → I'/' 育 → I'/' 不 → I'/' 良 → I'/' 患 → O'/' 儿 → O'/' 的 → O'/' 临 → O'/' 床 → O'/' 及 → O'/'NR0B1→ B'/' 基 → I'/' 因 → I'/' 突 → O'/' 变 → O'/' 分 → O'/' 析 → O'/'。→ O'

As you can see, we split the sentence according to the language which regards each English word as the elementary unit and each Chinese character as the elementary unit. This character-level segmentation formation avoids errors of Chinese tokenizer, which has been a troublesome problem in Chinese keyphrase extraction.

3.2 Dataset Construction

We collect data from Chinese Science Citation Database, which is a database contains more than 1000 kinds of excellent journals published in mathematics, physics, chemistry, biology, medicine and health etc. We set some constraints to restrict data to Chinese medical data as well as no incomplete and duplicated records included to ensure the quality of data. The constraints are listed as follows:

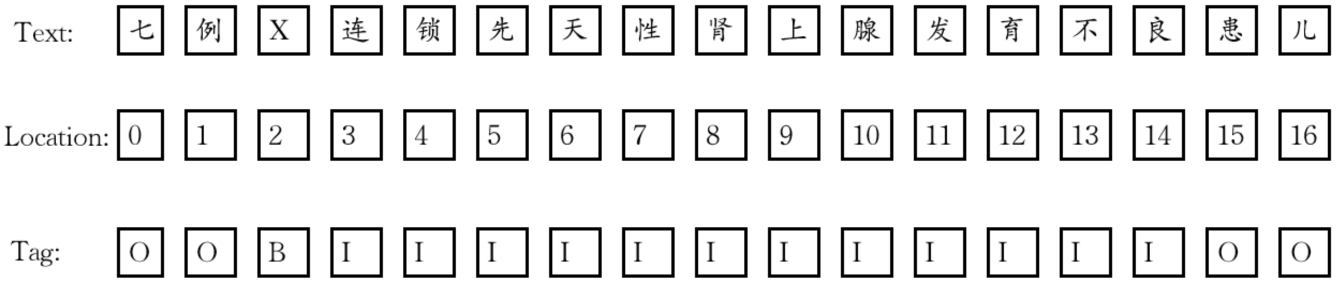
(1) According to Chinese Library Classification (CLC), the CLC code of medical data starts with the capital letter 'R'. So we restrict data to records that the metadata field of CLC code starts with the capital letter 'R'.
(2) The metadata field of language is set to Chinese.
(3) The metadata fields of title, abstract and keyphrases are not null. Here, keyphrases refer to author-assigned keyphrases.

Statistics shows that there are 757,277 records meeting the above-mentioned constraints in total. The title and the abstract of each article are concatenated as the source input text. And there are two types of keyphrases: extractive keyphrases and abstractive keyphrases. Extractive keyphrases refer to keyphrases that are present in the source input text while abstractive keyphrases refer to keyphrases that are not present in the source input text. Because we formulate keyphrase extraction as a character-level sequence labeling task and can only model the keyphrases that are present in the source input text, we just consider the extractive keyphrases.

To annotate as many extractive keyphrases as possible, we limit our dataset to records that all author-assigned keyphrases are extractive keyphrases to guarantee the number of keyphrases. After filtration, there are 169,094 records in total. We aim to construct a large-scale dataset for our deep neural network model because although deep neural networks can learn highly nonlinear features, they are prone to over-fitting compared with traditional machine learning methods.

We choose 100,000 records as our training data set, 6,000 records as our trail data set and 3,094 records as our test set. And there is no overlap among data sets. Next, we process these three data sets using IOB format to make them suitable for modeling sequence labeling task.

Before generating IOB format for each word, we do some pre-processing steps:



Text:	七	例	X	连	锁	先	天	性	肾	上	腺	发	育	不	良	患	儿
Location:	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Tag:	O	O	B	I	I	I	I	I	I	I	I	I	I	I	I	O	O

Figure 1: An Example of IOB Format Generation

(1) Using Unicode Coding to distinguish Chinese and English. To address the problem that English words and Chinese words are mixed together, we use Unicode Coding to distinguish English and Chinese. Our proposed data sets can greatly deal with the split of English words and Chinese characters, in which English word and Chinese character is the minimal unit respectively.

(2) Converting from all half width to full half width. Punctuations in Chinese medical text include two format: full width and half width. Authors may neglect the format of punctuations, which causes the problem that keyphrases can’t match with the abstract. For example, the authors might provide the keyphrase ’er:yag 激光’, but they use ’er：yag 激光’ in the abstract in which the colon is in full width format. So we transform all half width punctuations to full width punctuations except full stop.

(3) Dealing with special characters. There are lots of special characters in scientific Chinese medical abstracts and sometimes there are space characters next to these special characters while sometimes not. To unify the format, we drop all space characters next to special characters.

(4) Lowercase. We transform all English words to their lowercase format.

(5) Note that we try to keep the complete semantics for the source input text, we don’t use a stop words list or drop the punctuations.

After preprocessing procedures, we match keyphrases with source input text to find the locations of keyphrases present in the text and tag the characters within the locations with either label ’B’ or label ’I’ and characters not within the locations with label ’O’. For the first character in the keyphrase, tag it with label ’B’ and for the characters other than the first character in the keyphrase, tag them with label ’I’.

Figure 1 is an example of IOB format generation. In this example, the keyphrase is ’X 连锁先天性肾上腺发育不良’, and we match the keyphrase and return the location between 2 and 14. So we tag the character in location 2 with label ’B’ and the characters located between 3 and 14 with label ’I’. Other characters not within the location are tagged with label ’O’.

Note that there are two special occasions in our IOB generation process and we apply some tricks on it.

(1) If there is a containment relationship between two keyphrases, we use Maximum Matching Rule to tag the characters belonging to keyphrases. For example:
Text:’ 穴位注射罗哌卡因分娩镇痛对产妇产程的影响’ This text has two author-assigned keyphrases:’ 分娩’ and ’ 分娩镇痛’. And we choose the longest keyphrase ’ 分娩镇痛’ to tag. Therefore, the IOB generation results will be ’ 穴 → O’/’ 位 → O’/’ 注 → O’/’ 射 → O’/’ 罗 → O’/’ 哌 → O’/’ 卡 → O’/’ 因 → O’/’ 分 → B’/’ 勉 → I’/’ 镇 → I’/’ 痛 → I’/’ 对 → O’/’ 产 → O’/’ 妇 → O’/’ 产 → O’/’ 程 → O’/’ 的 → O’/’ 影 → O’/’ 响 → O’.

(2) If two keyphrases for a text share some characters in common, we will concatenate these two keyphrases by their common characters. For example, if a text has two author-assigned keyphrases: ’ 人工瓣膜’ and ’ 瓣膜功能异常’. Then we will tag the keyphrase ’ 人工瓣膜功能异常’ instead of ’ 人工瓣膜’ or ’ 瓣膜功能异常’.

To examine the quality of our data sets, we check the number of recognized phrases, the number of correct recognized keyphrases and the number of author-assigned ground-truth keyphrases to see the IOB generation performance. The results are summarized in Table 1. As for training set, there are 403,851 author-assigned ground-truth keyphrases in total, and we extract 403,406 phrases, in which 401,361 are correct keyphrases that match with the author-assigned ground-truth keyphrases. As for trail set, there are 25,777 author-assigned ground-truth keyphrases in total, and we extract 25716 phrases,in which 25,609 are correct keyphrases that match with the author-assigned ground-truth keyphrases. As for test set, there are 13,303 author-assigned ground-truth keyphrases in total, and we extract 13,259 phrases, in which 13,206 are correct keyphrases that match with the author-assigned ground-truth keyphrases. Owing to the tricks that we apply to IOB generation, the number of correct recognized keyphrases don’t match with the number of ground-truth keyphrases. But the IOB generation results on all three data sets still show that our data sets are of good quality.

3.3 Model Architecture

We initialize our sequence labeling keyphrase extraction model with pretrained BERT model. The architecture of BERT is based on a multi-layer bidirectional Transformers[48]. Instead of the traditional left-to-right language modeling objective, BERT is pretrained on two tasks: predicting randomly masked tokens and predicting whether two sentences follow each other. Our sequence labeling

Table 1: IOB Generation Results on Data Sets

Data Set	Number of Recognized Phrases	Number of Correct Recognized phrases	Number of Ground-Truth Keyphrases
Training Set	403,460	401,361	403,851
Trail Set	25,716	25,609	25,777
Test Set	13,259	13,206	13,303

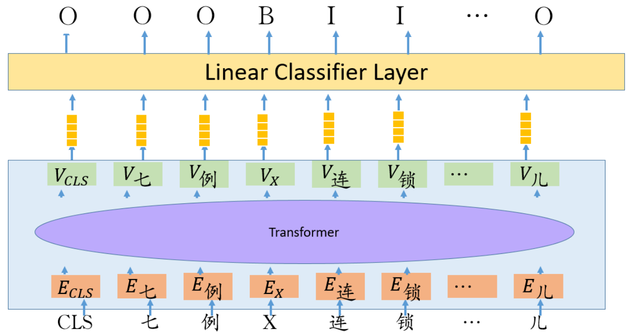


Figure 2: Character-Level Sequence Labeling Keyphrase Extraction Model Architecture

keyphrase extraction model follows the same architecture as BERT and is optimized on scientific Chinese medical abstracts. We use a linear classifier layer on top of the representations from the last layer of BERT to compute character level IOB probabilities. Our model architecture is shown in Figure 2.

For a given token, its input representation is constructed by summing the Wordpiece embeddings [53] of the corresponding token, segment embeddings and position embeddings. The first token of every sequence is always the special token [CLS]. The segment embeddings are useful in sentence-pairs task such as question answers to differentiate sentence. Sentence pairs are separated by a special token [SEP] and a sentence A embedding is added to every token in the first sentence and a sentence B embedding is added to every token in the second sentence. And our task is a single-sentence task, so we only use sentence A embeddings. And the positional embeddings for the max sentence lengths are up to 512. A visual representation of our input representations is given in Figure 3.

3.4 Keyphrase Extraction Evaluation Measures

Although there is a suit of evaluation measures for sequence labeling task, in automatic keyphrase extraction, what we really care about is whether we can extract correct keyphrases of the provided text. So we use precision, recall and F1-score based on actual matches against the ground-truth keyphrases for evaluation as used by previous studies [30].

Traditionally, automatic keyphrase extraction system have been accessed using the proportion of top-N candidates that exactly match the ground-truth keyphrases[13]. For keyphrase extraction based on sequence labeling, there is no need for N value and we just use the keyphrases predicted by the model to evaluate the AKE performance. But we need to firstly recognize the keyphrases from IOB format before evaluation. We concatenate characters between label 'B' and the last adjacent label 'I' behind label 'B' as predicted keyphrase.

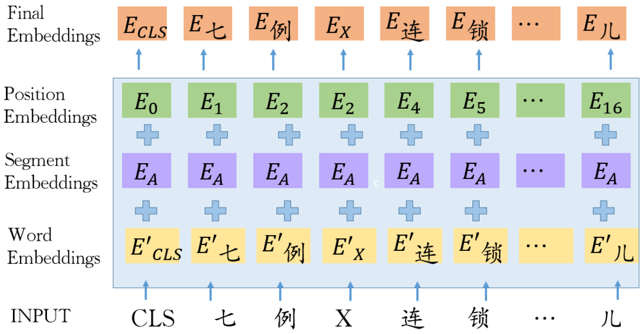


Figure 3: Input Representations of Sequence Labeling Keyphrase Extraction Model

We denote the total number of predicted keyphrases as r, number of predicted keyphrases matching with ground-truth keyphrases as c, number of ground-truth keyphrases as s. The evaluation measures are defined as follows:

$$Precision : P = \frac{c}{r}$$

$$Recall : R = \frac{c}{s}$$

$$F1 - score : F = \frac{2 \times P \times R}{P + R}$$

4 EXPERIMENTS & RESULTS

4.1 Experimental Design

In this paper, we use some traditional approaches including term frequency, TF*IDF based on single document, TF*IDF based on multi-documents, TextRank as the baselines to prove the effectiveness of regarding keyphrase extraction as sequence labeling task. Here, TF*IDF based on single document means that we just consider candidate keyphrases' term frequency and inverse document frequency based on one single document. While TF*IDF based on multi-documents means that we calculate the statistics based on the whole data set. As we know, the performance of traditional statistical approaches varies with the value for N (number of top ranked keyphrases), which is a parameter set manually. And traditional Chinese keyphrase extraction relies on Chinese tokenizer to generate candidate keyphrases. Usually, user-defined lexicon will make a great difference to the results of Chinese word segmentation.

So we design two groups of experiments for statistical baselines according to N value and lexicon scale. Group 1 keeps the same lexicon scale and compares the performance of baseline approaches at different N value of 3 and 5 to ensure the stability of the baseline approaches. Group 2 keeps the same N value and compares the performance of baseline approaches when the lexicon scale for the Chinese tokenizer is different to test the transferability of baseline approaches. We set two kinds of lexicon scales, one using all author-assigned keyphrases in training set, trail set and test set as lexicon, the other just using author-assigned keyphrases in training set.

In order to prove the effectiveness of pretrained language model BERT, we also design some machine learning baselines, which regard keyphrase extraction as sequence labeling task instead of binary classification task. We choose CRF, BiLSTM, BiLSTM-CRF as machine learning baselines.

We use the best baseline approach to compare with our character-level sequence labeling keyphrase extraction model. Note that we compare all results on the unified test set to ensure comparability.

4.2 Experimental Settings

As for statistical baseline approaches, we use Jieba tokenizer for Chinese word segmentation. Before generating candidate keyphrases, we do some preprocessing steps, such as removing stop words and some special characters. We restrict candidate keyphrases within our user-defined lexicon and noun phrases.

Of the three machine learning baseline approaches, CRF[31] is trained by regularized maximum likelihood estimation and uses Viterbi algorithm to find the optimal sequence of labels. BiLSTM and BiLSTM-CRF[23] are trained with Stochastic Gradient Descent (SGD). The learning rate is set to 0.01 and the model is trained for 10 epochs. The hidden layers are set to 128 units and the embedding size is 128 in both models.

For our BERT-based character-level sequence labeling keyphrase extraction model, namely, our model, due to system memory constraints, the batch size is set to 7 and we use SGD to optimize Cross Entropy Loss. The model is trained for 3 epochs and the initial learning rate is set to 5e-5 which decreases in the training process.

In this paper, we use F1-score to evaluate the data sets and model performance, which is the weighted average of precision and recall, taking both precision and recall into account.

4.3 Baseline Experiments

As for traditional statistical baseline experiments, we conduct two groups of baseline approaches comparison according to N value and lexicon scale as what we have mentioned in section 4.1.

For the group of N value experiments, we restrict the lexicon scale to whole lexicon, which contains author-assigned keyphrases in all the training set, trail set and test set as user-defined lexicon for Jieba word segmentation. Table 2 provides the results of N value comparison experiments of baseline approaches. Increasing the N value will improve the recall but lower the precision. We find that the F1-score of baseline approaches varies with the N value, but TF*IDF based on multi-documents achieves best performance among all baseline models no matter the N value. And when the N value is 3, the F1-score of TF*IDF based on multi-documents is 44.59%, which is higher than that when N value is 5.

For the group of lexicon scale experiments, we restrict N value to 3 to compare baseline approaches at different lexicon scales. Table 3 presents the results of lexicon scale comparison experiments of baseline approaches. As we can see, for all baseline approaches, the performance of using lexicon that only contains keyphrase in training set for Jieba word segmentation drops at least 7% compared to that of using whole lexicon. The results show that traditional keyphrases extraction approaches for Chinese medical abstracts have poor transferability so when transferring traditional models to a new domain and no lexicon can be used, the keyphrase extraction performance would be poor.

As for machine learning baselines, the experiment results are shown in Table 4. As we can see, BiLSTM-CRF achieves the best performance among all machine learning baselines, which gets 51.35% of F1 score. And compared with the best traditional statistical baseline TF*IDF, BiLSTM-CRF exceeds it by 6.76% without additional lexicon, which shows the effectiveness of deep learning and the rationality of regarding keyphrase extraction as sequence labeling task.

4.4 Sequence Labeling Experiments

We use the best baseline approach BiLSTM-CRF to compare with our BERT-based character-level sequence labeling model. The performance results are summarized in Table 5.

Compared with BiLSTM-CRF, our BERT-based model achieves F1-score of 59.80%, exceeding that of baseline approach by 8.45%, which shows that the pretrained language model captures rich features that are useful for downstream keyphrase extraction task.

And we compare the predicted phrases with author-assigned ground-truth keyphrases and find that some predicted phrases are concatenation of author-assigned keyphrases. For example, there are two author-assigned keyphrases ’ 卒中’ and ’ 抑郁’, while our model extracts keyphrases ’ 卒中后抑郁’. Another example, there are two author-assigned keyphrases ’ 急性肠胃炎’ and ’ 食源性疾病’, while our model extracts keyphrases ’ 食源性胃肠炎’. These examples indicate that as though our model get the F1-score of 59.80%， our model can achieve good practical application performance. In addition, it also indicates that the calculation of evaluation measure is an issue we need to consider further. Using the proportion of predicted phrases that exactly match the ground-truth keyphrases to assess the model is actually not appropriate because there are some biases for author-assigned keyphrases and sometimes the phrases predicted by our model are also concise descriptions for the text.

Moreover,owing to the limitation of BERT’s maximum sentence length, some source input text are truncated, causing the problem that our model will predict some single character as keyphrases. In most cases, single Chinese character makes no sense. To solve this problem, we decide to remove those nonsense single Chinese characters in the predicted phrases. When checking the predicted phrases, we find that some single Chinese characters are meaningful including chemical elements in The Periodic Table such as ’ 氢’,’ 氨’, organs such as ’ 胃’,’ 脾’ and animals such as ’ 鼠’,’ 鸡’. So we put these meaningful Chinese single characters in a list and remove single Chinese characters not in this list from predicted keyphrases. After removal, the keyphrase extraction performance of our adjusted model reaches to 60.56%.

5 CONCLUSIONS

In this paper,we formulate automatic keyphrase extraction as a character-level rather than word-level sequence labeling task and

Table 2: N-value Comparison Experiments of Baseline Approaches

Method	Top 3 Candidate Keyphrases			Top 5 Candidate Keyphrases		
	P	R	F	P	R	F
Term Frequency	47.66%	33.36%	39.24%	37.53%	43.78%	40.42%
TF*IDF Based on Single Document	50.56%	35.39%	41.61%	38.85%	45.33%	41.84%
TF*IDF Based on Multi Documents	**54.14%**	**37.90%**	**44.59%**	40.37%	47.11%	43.48%
TextRank	43.13%	30.19%	35.52%	33.29%	38.84%	35.85%

Table 3: Lexicon Scale Comparison Experiments of Baseline Approaches

Method	P	R	F
Term Frequency(whole lexicon)	47.66%	33.36%	39.24%
Term Frequency(training set lexicon)	37.31%	26.11%	30.72%
TF*IDF Based on Single Document(whole lexicon)	50.56%	35.39%	41.64%
TF*IDF Based on Single Document(training set lexicon)	40.03%	28.03%	32.97%
TF*IDF Based on Multi Documents(whole lexicon)	**54.14%**	**37.90%**	**44.59%**
TF*IDF Based on Multi Documents(training set lexicon)	42.18%	29.53%	34.74%
TextRank(whole lexicon)	43.13%	30.19%	35.52%
TextRank(training set lexicon)	34.37%	24.06%	28.30%

Table 4: Machine Learning Baseline Approaches

Method	P	R	F
CRF	42.05%	51.68%	46.37%
BiLSTM	30.43%	52.12%	38.42%
BiLSTM-CRF	**45.32%**	**59.23%**	**51.35%**

Table 5: Performance Evaluation of Keyphrase Extraction

Method	P	R	F
BiLSTM-CRF(Baseline)	45.32%	59.23%	51.35%
BERT-based Model(our model)	**60.33%**	**59.28%**	**59.80%**
Adjusted Model(our model)	**61.95%**	**59.22%**	**60.56%**

our model follows the same architecture of BERT and is optimized on scientific Chinese medical abstracts. Through our experimental work, we prove the benefits of this formulation with this architecture, which bypasses the step of Chinese tokenizer and the power of pretrained language model.

Our approach only deals with keyphrase extraction rather than keyphrase generation, so it can just handle extractive keyphrases. In the future, we plan to build keyphrase generation model to extract keyphrases. And also we will explore the solutions to solve the limitation of BERT's maximum sentence length to avoid being truncated. We expect some of the findings in this paper will provide valuable experiences for automatic keyphrase extraction and other NLP problems like document summarization, term extraction etc.

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