Deep Learning based Information Extraction Framework on Chinese Electronic Health Records

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Abstract

Electronic Health Records (EHRs) store a large amount of clinical data associated with each patient. Information extraction on unstructured clinical notes in EHRs is important which could contribute to huge improvement in patient health management. Previous studies mainly focused on English corpus. However, at the same time there are very limited research work on Chinese EHRs. Due to the challenges brought by the characteristics of Chinese, it is difficult to apply existing techniques for English on Chinese corpus. In this paper, we propose a deep learning based framework for information extraction from clinical notes in Chinese EHRs. Our framework consists of three components: data preprocessing, feature generation and entity and relation extractor. For clinical entity recognition, we propose a novel Conditional Random Field (CRF) based model and introduce effective features by leveraging the characteristics of Chinese language. For relation extraction, we utilize Convolutional Neural Network (CNN) to obtain high quality entity-relation facts. To the best of our knowledge, this is the first framework to apply deep learning to information extraction from clinical notes in Chinese EHRs. We conduct extensive sets of experiments on real-world datasets from hospital. The experimental results show the effectiveness of our framework, indicating its practical application value.

Key words: Electronic Health Records; Deep learning; Information extraction; Entity recognition; Chinese

1 Introduction

Electronic Health Records (EHRs) store a large amount of clinical data associated with each patient encounter, including demographic information, current and past diagnoses, prescriptions etc [1]. Information extraction from unstructured clinical notes in EHRs, which serves as the first step towards constructing medical-domain specific knowledge graph, can be beneficial for many fields such as disease inference, clinical decision support systems and risk prediction etc [2, 3, 4]. As such, recently years have seen lots of studies concentrated on information extraction from English clinical notes.

However, when it comes to Chinese domain, very limited work has been done especially for relation extraction due to the challenges brought by the Chinese clinical notes. On one hand, the different characteristics of Chinese language determine that the methods on English corpus can not be directly applied on Chinese documents. For example, there is no blank space representing word boundaries between Chinese words, and words have no morphological changes in different situations. Besides, some Chinese function words which are important for semantic understanding, such as ”的”, ”等” are often omitted. On the other hand, since there are a large number of professional terms, abbreviations and medical-domain based knowledge contained in clinical notes. It is difficult to adopt existing Chinese-based work focusing on other domains, such as Chinese social media [5, 6], to our problem.

To address these challenges, we propose a deep learning based information extraction framework on clinical notes in Chinese EHRs. Our framework contains three major components: data preprocessing, feature generation and entity and relation extractor. For data preprocessing, we clean the raw corpus and invite medical experts to make necessary annotations. For feature generation, we then select high quality features from multiple aspects according to the characteristics of clinical notes and Chinese language. For relation extraction, we utilize Convolutional Neural Network (CNN) to obtain high quality entity-relation facts. To the best of our knowledge, this is the first framework to apply deep learning to information extraction from clinical notes in Chinese EHRs. We conduct extensive sets of experiments on real-world datasets from hospital. The experimental results show the effectiveness of our framework, indicating its practical application value.

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perimental results demonstrate the effectiveness of our proposed framework.

The rest of the paper is organized as follows. Section 2 provides an overview of the existing information extraction approaches. Section 3 introduces our deep learning-based information extraction framework. Section 4 and Section 5 respectively describe our clinical entity recognition and relation extraction methods in detail. Section 6 reports the experiments and discusses the results. Finally, we draw our conclusions in Section 7.

2 Related Work

In this section, we first review the related work about information extraction on English clinical notes and then introduce the information extraction methods on Chinese and their applications in health-related domain.

Recently, a large amount of work has focused on information extraction on English clinical notes. Due to the unstructured nature, most work utilize the statistical machine learning methods. For example, Seol et al. [10] proposed a clinical Problem-Action relation extraction framework based on CRF and Support Vector Machine (SVM). Skeppstedt et al. [11] studied the usefulness of features extracted from unsupervised methods and applied them in clinical named entity recognition problem. It is noteworthy that these methods have depended on manually engineered features which have seen limited adoption. As such, some recent studies have proposed several methods using deep learning. Jagannatha et al. [12] regarded clinical named entity recognition as a sequence labeling problem and utilized Recurrent Neural Network (RNN) based model. Sahu et al. [13] focused on extracting relations from clinical discharge summaries and exploited the power of CNN to learn features automatically.

Despite the great challenges of information extraction on Chinese documents, there has been a lot of work focused on it recently. For example, in Chinese social media domain, Peng et al. [5] jointly trained word segmentation with an LSTM-CRF model for named entity recognition problem. He et al. [6] further improved the performance for named entity recognition on the same datasets by proposing a unified model combining cross-domain learning and semi-supervised learning. In health-related domain, Yao et al. [14] focused on the text classification on traditional Chinese medicine (TCM) clinical records and proposed a novel method combining deep learning text representation with TCM domain knowledge. He et al. [15] studied the corpus construction of Chinese clinical texts.

3 Framework Architecture

The key idea of our framework is extracting clinical entities and relations between them. As shown in Figure 1, there are three main components in our framework: data preprocessing, feature generation, and entity and relation extractor. The data preprocessing component processes the raw clinical notes from hospital. Firstly, to generate a high quality corpus for training and testing, we have invited professionals from hospital to help annotate the corpus. And to apply CRF based algorithms to the entity recognition problem, annotated entities should be typically converted into a BIO format. Specifically, it assigns each word into a class as follows: B means the beginning of an entity, I means inside an entity, and O means outside of an entity. For the sentence “患者无明显诱因出现胸痛，服用硝酸甘油可缓解” (No obvious cause of chest pain, taking nitroglycerin can relieve symptoms), the BIO format of annotation is shown in Figure 2. Annotated relations are expressed in a triple format \([h, r, t]\), the triple means there exists a relation named \(r\) between the entities named \(h\) and \(t\). Secondly, considering most relations are existed within one sentence, the preprocessing component splits the clinical notes into sentences using natural language processing tools.

Feature generation component is mainly designed to generate features needed in entity and relation extractor component and normalizes the format of training data so that it can meet the requirements of extractor component. Generally speaking, the data should consist of multiple tokens, and a token consists of multiple columns representing the features.

The entity and relation extractor component learns two extractors: CRF-based clinical entity recognition and CNN-based relation extraction. The two extractors enable extracting clinical entities and relations from clinical notes automatically. Clinical entities and relationships are actually the knowledge contained in clin-
4 Clinical Entity Recognition

In this section, we apply the CRF-based model to Chinese Entity recognition problem. First we introduce the features we choose and then we propose our CRF-based model based on these features.

4.1 Features

According to the characteristics of clinical notes and Chinese language, we select the bag-of-characters feature, Part of Speech(POS) tag feature, and dictionary feature etc. as our feature sets for clinical entity recognition problem.

**Bag-of-characters feature** As the basic units of Chinese, both characters and phrases can express basic information of Chinese documents. For clinical entity problem, the operations on phrases to generate bag-of-words tend to be more synonymous to complex model than to better performance. So in this paper, we select the bag-of-characters as our feature rather than bag-of-words.

**POS tag feature** Besides bag-of-characters feature, the POS tag information can help improve the efficiency and precision of clinical entity recognition. Through the analysis of clinical notes, we find that different kinds of clinical entities show different characteristics in the POS tag composition. In addition, usually there will be a verb in front of the entity “test” and “treatment” etc. POS tag features can be generated through the existing natural language processing tools.

**Dictionary feature** Clinical notes are highly specialized medical relevant texts which contain a large number of medical terminology. Therefore, the introduction of medical entity dictionaries can effectively improve the accuracy of clinical entity recognition. But there are no such dictionaries available in Chinese domain yet. Considering this situation, we construct a Chinese-based medical dictionary as our feature by cooperating with the professionals from hospital. We first extract numerous clinical entities by referring to large amounts of books and literatures as our basic dictionary and then expand it by crawling and filtering data from Internet. The details of the dictionary are shown in Table 1.

4.2 CRF-based Model

In natural language processing domain, CRF is mainly used to solve sequence annotation problems.

**Table 1: Medical Entity dictionary**

<table>
<thead>
<tr>
<th>Entity</th>
<th>Example</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disease</td>
<td>胸椎键盘突出 (Thoracic keyboard protrusion)</td>
<td>31450</td>
</tr>
<tr>
<td>Medicine</td>
<td>接骨续筋片 (Fracture tablets)</td>
<td>38726</td>
</tr>
<tr>
<td>Treatment</td>
<td>骨髓再造术 (Guttural reconstruction surgery)</td>
<td>8493</td>
</tr>
<tr>
<td>Test</td>
<td>胸片增强扫描 (CT)</td>
<td>3473</td>
</tr>
<tr>
<td>Organ</td>
<td>胸口 (Chest)</td>
<td>6089</td>
</tr>
<tr>
<td>Physical indicator</td>
<td>血清触球蛋白 (Serum haptoglobin)</td>
<td>3314</td>
</tr>
</tbody>
</table>

**Figure 3: Chain Structure of CRF**

Not only can it capture a large amount of human observational experience but also enable capture Markov-chain dependencies between different tags. What's more, by adding customized features according to specific task, CRF has achieved good results on many entity recognition problems.

In this paper, we regard the clinical entity recognition as a sequence labelling problem. Under this situation, we believe that the CRF dependency graph is a chain structure. And what we attempt to do is modelling the conditional probability of multiple variables by giving their observation values. Specifically, as shown in Figure 3, assuming that the observation sequence is $\mathbf{x} = (x_1, x_2, \ldots, x_n)$. $\mathbf{y} = (y_1, y_2, \ldots, y_n)$ is the corresponding labelling sequence, and $y_i$ means the label of the $i$th instance of sequence $X$. Our goal is to construct the conditional probability model $P(\mathbf{y} | \mathbf{x})$. Here, $\mathbf{x}$ is the entire Chinese character sequence of a sentence in the clinical notes. $\mathbf{y}$ is the sequence of entity labels corresponding to each word in the sequence $\mathbf{x}$. And we define our feature function as $f_{a,i}(y_{i-1}, y_i, \mathbf{x}, i)$. In this function, $a \in A$ represents the type of feature, $x_i$ is the word that we are going to label. $\lambda_a$ are the corresponding parameters we need to train. For observation sequence $\mathbf{x}$ and labelling sequence $\mathbf{y}$, the conditional probability is as follows:

$$p(\mathbf{y} | \mathbf{x}, \lambda) = \frac{1}{Z(\mathbf{x}, \lambda)} \exp\left(\sum_{a \in A, y_1, y_2 \in \mathbf{y}} \lambda_{a,y_1,y_2} \sum_{i=1}^{n} f_{a,i,y_1,y_2}(y_{i-1}, y_i, \mathbf{x}, i)\right)$$

where $Z(\mathbf{x}, \lambda)$ is the regularization term. And the final labelling sequence we get based on this model is as follows:

$$\hat{y}^* \defeq \arg\max_{\mathbf{y} \in Y^*} p(\mathbf{y} | \mathbf{x}, \lambda)$$
5 Relation Extraction

Relation extraction is the process of identifying how the given clinical entities are related within the clinical note where they exist. And these relationships contain a lot of clinical semantic knowledge. And these knowledge can then be applied in many fields \[16, 17\]. For this task, we creatively design a CNN-based model and achieve exciting results. First of all, we identify 12 common relation types. Their names and occurrence frequencies are shown in Table 2.

### 5.1 CNN-based Model Architecture

As shown in Figure 4, in the training process, the outermost layer of the model is initial input. It is the sentence in clinical notes. The last layer refers the output which is a vector and each value of the vector corresponds the possibility of a relation. Besides these, there are 5 more layers in the model including feature layer, embedding layer, convolution layer, pooling layer and fully connected layer.

<table>
<thead>
<tr>
<th>Relation</th>
<th>Type</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment and disease</td>
<td>治疗施加于疾病 (TrAD)</td>
<td>1460</td>
</tr>
<tr>
<td></td>
<td>治疗改善疾病 (TrID)</td>
<td>260</td>
</tr>
<tr>
<td>Treatment and symptom</td>
<td>治疗改善症状 (TrIS)</td>
<td>910</td>
</tr>
<tr>
<td></td>
<td>治疗导致症状 (TrCS)</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>治疗施加于症状 (TrFAS)</td>
<td>2760</td>
</tr>
<tr>
<td></td>
<td>治疗改善症状 (TrNAS)</td>
<td>10</td>
</tr>
<tr>
<td>Test and disease</td>
<td>检查证实疾病 (TeRD)</td>
<td>440</td>
</tr>
<tr>
<td></td>
<td>证实疾病而检查 (TeCD)</td>
<td>90</td>
</tr>
<tr>
<td>Test and symptom</td>
<td>检查证实症状 (TeRS)</td>
<td>3340</td>
</tr>
<tr>
<td></td>
<td>证实症状而检查 (TeAS)</td>
<td>3010</td>
</tr>
<tr>
<td>Disease and symptom</td>
<td>疾病导致症状 (DCS)</td>
<td>1930</td>
</tr>
<tr>
<td></td>
<td>症状表明疾病 (SID)</td>
<td>300</td>
</tr>
</tbody>
</table>

For word embedding, we used word2vec tool \(^1\) to train the word vectors on 55000 clinical notes from a famous medical institute and Q & A data from Chinese medical platform 39 Health \(^2\).

#### Convolution Layer

In convolution layer, we obtain the local features of the sentence by convolution operations. Supposing \(x^1, x^2, x^3, ..., x^m\) is a feature vector sequence of a sentence with length \(m\), where \(x^i\) is the feature vector of the \(i\)th word and the length of the filter is \(c\), then the output sequence of the convolution layer is computed as given below:

\[
h^i = f(w \cdot x^{i+c-1} + b) \quad (4)
\]

\(f(x)\) is the ReLU function: \(f(x) = max(0, x)\). \(w\) and \(b\) are the parameters we need to train.

#### Pooling Layer

In the pooling layer, we choose the max-pooling to obtain the global feature of each sentence. Not only does this reduce the dimensions of the output, but it still retains the most salient features.

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\(^1\)https://code.google.com/archive/p/word2vec/

\(^2\)http://www.39.net/
We started with the model which only use the bag-of-characters feature and dictionary feature and used window sizes of 3 to 6. As we can see from the figure, with the different size of context window, the templates with the POS tag feature and the templates with the dictionary feature showed the same changing trend and the better performance was generated when the window size is 3. At the same time, the best performance, F1 score of 88.825% was achieved when bag-of-characters feature, POS tag feature and dictionary feature were combined in template 6(T6).

6.3 Experimental Results on Relation extraction

Implementation While implementing our model, we set the word embedding dimension to be 50 and the other 4 feature dimensions to be 5. In other words, the dimension of each word is 70. In convolution layer, we use the combination of filter lengths 3, 4 and 5 together empirically. And we set the number of filters as 100 for every length. Moreover, we use dropout with a probability of 0.50 to prevent overfitting.
Comparison with featured based models As described before, existing studies for relation extraction problem are mainly based on statistical machine learning methods which heavily depend on manual feature engineering. Here, we compare the performance of our CNN-based model with two state-of-the-art SVM-based models. And we build the SVM classifiers using features defined, respectively, in [9] and [10]. Table 5 shows the comparison of best results obtained by SVM-based models and our CNN-based model.

From the results, we can see that the single SVM model has the lowest precision. But it achieves higher recall than multi-class SVM model since it introduces some new features. And our CNN based model all significantly outperform the two baseline methods, which indicates the effectiveness of our approach.

7 Conclusion

We worked on information extraction on unstructured clinical notes in Chinese EHRs from hospital. Our framework consists of three components: data preprocessing, feature generation and entity and relation extractor. For clinical entity recognition, we propose a novel CRF based model and introduce effective features by leveraging the characteristics of clinical notes and Chinese language. For relation extraction, we utilize CNN to obtain high quality entity-relation facts. A series of experimental results showed that our methods are significantly effective comparing with existing state-of-the-art models.

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