ChiMST: A Chinese Medical Corpus for Word Segmentation and Medical Term Recognition

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Abstract

Chinese word segmentation (CWS) and named entity recognition (NER) are two important tasks in Chinese natural language processing. To achieve good model performance on these tasks, existing neural approaches normally require a large amount of labeled training data, which is often unavailable for specific domains such as the Chinese medical domain due to privacy and legal issues. To address this problem, we have developed a Chinese medical corpus named ChiMST which consists of question-answer pairs collected from an online medical healthcare platform and is annotated with word boundary and medical term information. For word boundary, we mainly follow the word segmentation guidelines for the Penn Chinese Treebank (Xia, 2000); for medical terms, we define 9 categories and 18 sub-categories after consulting medical experts. To provide baselines on this corpus, we train existing state-of-the-art models on it and achieve good performance. We believe that the corpus and the baseline systems will be a valuable resource for CWS and NER research on the medical domain.

Keywords: Chinese medical corpus, Chinese word segmentation, named entity recognition

1. Introduction

In the past decade, there have been tremendous progress in applying natural language processing (NLP) techniques to medical text, with the hope that the progress will lead to real-world applications that improve healthcare quality. When analyzing Chinese medical text, Chinese word segmentation (CWS) and named entity recognition (NER) are often two of the early steps whose outputs are needed by downstream modules, and they have thus attracted attentions from both academia and industry (e.g., (Xing et al., 2018; Wang et al., 2018; Zhang et al., 2019; Wang et al., 2019; Luo et al., 2019; Chang et al., 2021; Li et al., 2021)). Building high-quality systems for the two tasks often requires large labeled datasets, which are usually unavailable for special domains such as the Chinese medical domain. While there are studies (Xu et al., 2014; Jinfeng et al., 2016; He et al., 2017; Gao et al., 2019; Xiong et al., 2019; Su et al., 2019; Zan et al., 2020; Zhang et al., 2020a) that annotated Chinese medical text with CWS and NER labels, most of them use electronic medical records (EMR) collected from hospitals and thus are not publicly available due to privacy and legal issues. Meanwhile, little attention has been paid to medical text from online healthcare platforms especially the ones with questions from patients and answers from doctors. In addition, the named entities in most studies use common categories such as disease and symptom, without including fine-grained medical term types such as abnormality types (e.g., 貓型 (Type II)) and body functions (e.g., 消化 (digestion)).

In this paper, we introduce ChiMST, a Chinese Medical Corpus with Word Segmentation and Medical Term Annotation. Specifically, the raw text in the corpus comes from ChiMed (Tian et al., 2019), a Chinese medical question answering (QA) corpus collected from a Chinese online healthcare platform\(^2\) where the registered doctors verified by the platform answer the questions raised by the patients (i.e., the platform users). For word segmentation, our annotation guidelines follow the segmentation guidelines for the Penn Chinese Treebank (CTB) (Xia, 2000), with more detailed specifications and examples added to accommodate the language use in the medical domain. For medical terms, we start with the medical taxonomy proposed by unified medical language system (UMLS) semantic groups (Lindberg et al., 1993). After consulting physicians, we choose a label set with 9 categories and 18 sub-categories for medical terms (see Section 3.3 for more details). Because our corpus consists of QA pairs from online QA healthcare platform rather than EMRs from hospitals, it is available to the public under a data license agreement\(^3\).

To test the usefulness of the ChiMST corpus as well as providing baseline results on CWS and medical term recognition (MTR) tasks\(^2\), we train several state-of-the-art models for CWS and MTR on the corpus; some of the models are enhanced by word n-grams and syntactic information, and the experimental results show that leveraging such extra information is able to improve model performance on both tasks.

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\(^2\)See https://github.com/synlp/ChiMST for details.

\(^3\)Because some medical term categories such as Medical Order are not normally regarded as named entity types, for the rest of the paper we will call the task of identifying medical terms Medical Term Recognition (MTR), instead of Named Entity Recognition (NER).
2. Related Work

Applying NLP techniques to processing Chinese medical text has attracted much attention in recent years (e.g., Xue et al. (2012), Xu et al. (2015), Li et al. (2019), Wang et al. (2020), Song et al. (2020), Chang et al. (2021), etc.). Because the performance of the models trained on general domain data tends to drop significantly when they are tested on medical text, previous studies (Xu et al., 2015; Li et al., 2015; Zhang et al., 2016; He et al., 2017; Chowdhury et al., 2018) often rely on annotated medical corpus to achieve better performance. For CWS and MTR, many datasets have been created for them (Xu et al., 2014; Jinfeng et al., 2016; He et al., 2017; Gao et al., 2019; Xiong et al., 2020; Su et al., 2019; Zhang et al., 2020a; Zhang et al., 2020b).

For example, Jinfeng et al. (2016) constructed a Chinese corpus containing 992 Chinese EMRs with annotations of named entities and their relations. They mark five types of named entities in Chinese EMRs: diseases, type of disease diagnosis, symptoms and signs, test, and treatments. Their innovation in the definition of named entities was to split medical problems into diseases and symptoms, and further split the symptoms into two subcategories: self-reported symptoms and abnormal examination results. Zhang et al. (2020a) divided medical entities into nine categories (i.e., disease, clinical manifestation, medical procedure, medical equipment, drug, medical test, body, department, and microbe) for primary classification, where some of them are further divided into sub-categories.

Most existing datasets for CWS and MTR use EMRs and thus are not publicly available due to privacy and legal issues. In our study, we annotate medical text collected from online healthcare platforms with a more fine-grained set of categories.

3. The ChiMST Corpus

The raw data of the current version of the ChiMST corpus come from the QA records in the ChiMed corpus (Tian et al., 2019). After a brief introduction to ChiMed, we describe ChiMST’s annotation guidelines and report annotation results.

3.1. Data from the ChiMed Corpus

The ChiMed corpus contains over 200 thousand QA records collected from a Chinese online healthcare platform called 39ask. A QA record contains five main fields: department, title, keyphrases, the question, and the answers. Among the five fields, the department and keyphrases are provided by the platform managers; the question and the title fields, which describe the problem the patient has, are written by the patient; the answers are written by physicians who have registered and verified by the platform. All the QA records come from 15 different departments and there are exactly two answers in each QA record.

To create the ChiMST corpus, we randomly sampled 1,000 QA records from ChiMed. The annotation is done only on the question and answer fields of the QA records. We segment text in those fields into sentences by three punctuation marks (i.e., delimiters period, question marks, and exclamation marks), resulting in a corpus of 6,646 sentences and 222,465 Chinese characters. Table 1 shows an example QA record with word boundary and medical terms annotated as explained below.

3.2. Annotation Guidelines

Two graduate students in the field of NLP developed the annotation guidelines for CWS and MTR. They consulted two physicians when defining the category set for the medical terms.

For word segmentation, we follow the segmentation guidelines of the Penn Chinese Treebank (CTB) (Xia, 2000), which is one of the most widely used guidelines for CWS. Since the CTB guidelines focus on the general domain and do not include many examples from the medical domain, we add more specifications and examples from the medical domain to help our annotators. For example, the CTB guidelines do not specify how to segment medical terms. Following CTB’s approach for segmenting names of organization/country/school, we add examples for medical terms, such as “神经内科” (nerve internal medicine), “营养科” (nutrition), “淋巴细胞” (lymphocytes), and “膝间反射” (knee-jerk reflex).

For the medical terms, we start with the medical taxonomy proposed by unified medical language system (UMLS) semantic groups (Lindberg et al., 1993) and choose categories that are widely used in our corpus. After consulting two physicians, we define a set consisting of 9 medical term categories and 18 subcategories, shown in Table 2.

Compared with previous Chinese datasets with medical term annotations, our medical term categories are more fine-grained. For instance, the category “Abnormality” has two subtypes: “Symptom” is the patient’s self-experience and feeling to the physiological function of the body abnormal, such as “瘙痒” (pruritus), “疼痛” (pain), “紧张” (distension), “胀闷” (stuffy), and “头晕” (dizziness), whereas “Sign” represents the perceptible changes in the body’s internal structure, such as “心尖杂音” (heart murmur) and “肝脾大” (enlarged liver and spleen). The category “Illness” includes “Disease” and “Injured or Poisoned”, which correspond to different physical condition for patients. “Medical Test” has three subcategories: “Imaging Test”, “Laboratory Test”, and “General Test”, where the first two labels are for tests involving images and laboratory examinations, respectively. “Treatment” has four subcate-

In the future, we plan to extend ChiMST with data from other sources.

The English translation is not part of the corpus.

"/" marks the word boundary.
| Title | 近视不想戴眼镜改怎么办? | What should I do if I am nearsighted but do not want to wear glasses? |
|---|---|---|
| Keyphrases | 眼睛，视力，眼科检查，屈光不正，eyes, vision, eye examination, refractive error |
| Question | 我 [nearsighted@DI]，五六百度了， | I am [nearsighted@DI], five or six hundred degrees. |
| | 看电脑都累，晚上玩游戏的时候戴戴，平常不戴。 | It takes a lot of effort to work on the computer. I wear glasses when playing (games) on computer at night, otherwise I do not normally wear glasses. |
| | 请问 [nearsighted@DI]会越来越严重吗，不想戴眼镜该怎么办？ | Will my [nearsightedness@DI] get worse? What should I do if I do not want to wear glasses? |
| Answer 1 | 从你的描述来看，考虑同时 [睡眠@BF] 缺乏用眼不合理，导致 [疲劳@SP]和 [屈光不正@DI]有关系。 | From your description, your condition could have something to do with lack of [sleep@BF] and unreasonable use of eyes in daily life, which cause [fatigue@SP] and [refractive errors@DI]. |
| | 建议去正规医院的 [眼科@DEP] 检查，然后佩戴合适的眼镜，平时 [注意休息@MO]， [合理用眼@MO]，控制手机，电脑的使用，做 [眼部@BP]的 [热敷@TT]，可以使用滋润性的眼药水，比如 [贝复舒滴眼液@DR]。 | It is recommended to go to the [ophthalmology department@DEP] of a hospital for an eye examination, and then wear suitable glasses, [rest more@MO] at ordinary times, fuse your [eyes@BP] rationally, control the use of mobile phones and computers, do [hot compress@TT] for [eyes@BP], and use moisturizing eye drops, such as [Beifu Shu eye drops@DR]. |
| Answer 2 | 你好， [nearsighted@DI]了，建议还是配戴眼镜。 | Hello. If you are [nearsighted@DI], it is still recommended to wear glasses. |
| | 配戴眼镜的作用： | The purpose of wearing glasses: |
| | 一是为了矫正屈光，达到清晰视力的效果； | One is to correct the refractive and achieve the effect of clear vision; |
| | 二是为了防止造成 [眼睛@BP]的 [调节和功能@BF] 失去平衡。 | It is recommended to do the following: |
| | The second is to prevent the [assembly and adjustment function@BF] of [eyes@BP] from losing balance. | |
| | 如果确实不想戴眼镜，可考虑通过 [近视手术@SR] 来提高裸眼视力。 | If you really do not want to wear glasses, you can consider [myopia surgery@SR] to improve your vision. |

Table 1: An example of annotated QA record in ChiMST, where the question and two answers are annotated with word boundaries and medical terms. Word boundaries are illustrated by white spaces. Medical terms are highlighted in blue and marked by the brackets. The label of each medical term follows the schema in Table2, and it is attached to the corresponding medical term by “@”. For example, [贝复舒滴眼液@DR] ([Beifu Shu eye drops@DR]) is a medical term of type Drug (DR) consisting of two words (i.e., 贝复舒 and 滴眼液). The English translation is included only for reference; it is not part of the corpus.

Medical categories depending on the types of treatment, namely, "Drug", “Surgery”, “Targeted Treatment”, and “Medical Order”. “Body” and “Abnormality Type” are categories that are rarely used in previous studies, but they are useful when we want to accurately identify the detail of a disease and obtain more accurate information for the follow-up diagnosis and treatment. The remaining three categories (namely, “Department”, “Medical Equipment”, and “Pathogen”) are widely used categories, which also play an important role in the clinical process of diagnosis and treatment.

To help annotators to distinguish similar medical term (sub-)categories, our annotation guidelines include detailed specifications and examples such as the following:

- **Symptom and Sign**: If the abnormality can be detected without requiring professional medical equipment (excluding common home medical equipment such as thermometer, sphygmomanometer, blood glucose meter, etc.), annotate it as “Symptom” (e.g., “疼痛” (pain) and “发烧” (fever)). Otherwise, annotate it as “Sign”.

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### Table 2: Types of medical terms (there are 9 categories and 18 sub-categories) used in ChiMST. The last two columns show the label and explanation for each sub-category.

| Category                  | Sub-category | Labels | Explanations                                                                 |
|---------------------------|--------------|--------|-------------------------------------------------------------------------------|
| 1 Abnormality             | Symptom      | SP     | Symptom that is directly observed or felt by the patient, such as “疼痛” (pain) and “恶心” (nausea). |
|                           | Sign         | SG     | Sign that is diagnosed or detected by the doctor or medical equipment, such as “心悸” (heart murmur) and “肝脾大” (enlarged liver and spleen). |
| 2 Abnormality Type        | Abnormality Type | DT   | The type and degree of an abnormality, such as “极高危险组” (very high risk group) and “轻度” (mild). |
| 3 Body                    | Body Part    | BP     | Body part such as “头” (head) and “腰” (waist).                               |
|                           | Body Substance | BS    | Substance produced or excreted from the body, such as “血” (blood) and “尿” (urine). |
|                           | Body Function | BF     | The general function of human body, such as “消化” (digestion) and “怀孕” (pregnant). |
| 4 Department              | Department   | DEP    | A hospital department such as “外科” (surgical department) and “妇科” (department of gynecology). |
| 5 Illness                 | Injured or Poisoned | IOP | The name of injury and poison, such as “皮肤受伤” (skin injury) and “酒精中毒” (alcoholism). |
|                           | Disease      | DI     | The name of disease excluding injury and poison, such as “肺癌” (lung cancer) and “皮疹” (rash). |
| 6 Medical Equipment       | Medical Equipment | ME | Medical equipment, such as “鼻镜” (rhinoscope) and “呼吸机” (ventilator). |
| 7 Pathogen                | Pathogen     | PG     | Pathogen, such as “细菌” (germ) and “病毒” (virus).                           |
| 8 Medical Test            | Imaging Test | IMT    | Image medical examination, such as “腹部CT” (abdominal CT) and “心电图” (electrocardiography). |
|                           | Laboratory Test | LT | Laboratory medical examination, such as “血常规” (complete blood count) and “凝血四项” (blood clotting tetrachoric). |
|                           | General Test  | GT     | General medical examination excluding image tests and laboratory tests, such as “体温” (body temperature) and “呼吸” (breathe). |
| 9 Treatment               | Drug         | DR     | The name of drugs, such as “青霉素” (penicillin) and “泰勒” (Taylor).            |
|                           | Surgery      | SR     | The name of surgeries, such as “吸脂手术” (liposuction) and “心脏搭桥术” (heart bypass surgery). |
|                           | Targeted Treatment | TT | Targeted treatment, such as “抗病毒治疗” (antiviral therapy) and “中频疗法” (intermediate frequency therapy). |
|                           | Medical Order | MO     | The suggestions from doctors for daily medical care, such as “过量饮酒” (drinking alcohol is strictly prohibited) and “多喝水” (drink more water). |

- **Body function, Imaging test, and Laboratory test:** If the word “做” (do) can be added before the medical term, then annotate the term as Imaging Test or Laboratory Test according to its meaning (e.g., “血常规” (complete blood count)). Otherwise, annotate the term as Body Function (e.g., “视力” (vision) and “肝功能” (liver function)).

Moreover, following the convention in previous studies, we do not annotate medical terms embedded in another larger medical term. For example, in the Body Function term “肝功能” (liver function), we do not mark the body part “肝” (liver) as a Body Part.

### 3.3. Annotation Process

Since questions and answers are the most important fields of QA records, we ask two annotators who have background in the medical domain to annotate them: word segmentation first, followed by medical term annotation. We train the two annotators and ask them to first annotate a small set of sample data to ensure they fully un-
Table 3: The inter-annotator agreement (Cohen’s kappa) of two annotators on the 300 double-annotated QA records. The average F1 scores of the annotators are computed with respect to the agreed annotation.

| # of QA records annotated by both annotators | 300 |
| # of QA records annotated by one annotator  | 700 |
| Agreement (Cohen’s kappa) for CWS           | 0.934 |
| Agreement (Cohen’s kappa) for MTR           | 0.907 |
| Avg. F1 of annotators for CWS              | 0.974 |
| Avg. F1 of annotators for MTR              | 0.931 |

Table 4: The statistics of the ChiMST corpus.

| # of QA records | 1,000 |
| # of questions  | 1,000 |
| # of answers    | 2,000 |
| # of characters | 222,465 |
| # of words      | 142,455 |
| # of medical terms | 13,695 |
| # of sentences  | 6,646 |
| # of character types | 2,455 |
| # of word types | 8,982 |
| # of medical term (sub-)categories | 18 |
| Avg. # of characters per sentence | 33.5 |
| Avg. # of words per sentence | 21.4 |
| Avg. # of medical terms per sentence | 2.1 |

Table 5: The number of medical terms in each subcategory in the annotated ChiMST corpus.

| Sub-categories       | Labels | Count |
|----------------------|--------|-------|
| 1 Symptom            | SP     | 1,946 |
| 2 Sign               | SG     | 164   |
| 3 Abnormality Type   | DT     | 374   |
| 4 Body Parts         | BP     | 2,408 |
| 5 Body Substance     | BS     | 407   |
| 6 Body Function      | BF     | 913   |
| 7 Department         | DEP    | 231   |
| 8 Injured or Poisoned| IOP    | 72    |
| 9 Disease            | DI     | 3,520 |
| 10 Medical Equipment | ME     | 78    |
| 11 Pathogen          | PG     | 116   |
| 12 Imaging Test      | IMT    | 242   |
| 13 Laboratory Test   | LT     | 171   |
| 14 General Test      | GT     | 124   |
| 15 Drug              | DR     | 1,338 |
| 16 Surgery           | SR     | 142   |
| 17 Targeted Treatment| TT     | 517   |
| 18 Medical Order     | MO     | 932   |
| Total                |        | 13,695|

4. Experiments

To test the usefulness of ChiMST, we train and evaluate CWS and MTR systems on the corpus.

4.1. Tasks

Following the convention in most previous studies (Tseng et al., 2005; Song et al., 2009; Zhang et al., 2010; Song and Xia, 2012; Pei et al., 2014; Lample et al., 2016; Nie et al., 2020b; Tian et al., 2020a; Tian et al., 2021), we regard CWS and MTR as sequence labeling tasks using the BIO scheme (or its variants such as the BIES scheme). That is, each character is assigned a CWS label and an MTR label according to its position in a word or in a medical term.

For example, if a character is the first character of a word, its CWS label would be “B”; if it is part of a medical term of type department (DEP) but is not in the beginning position, its MTR label would be “I-DEP”. The object of the models for CWS and MTR is to predict the corresponding CWS and MTR label according to its position in a word or in a medical term.

In our experiments, the input to the MTR models is a character sequence, not a word sequence. Therefore, the BIO label is on each character.
the context information for different tasks (Pennington et al., 2014; Song and Shi, 2018; Bae et al., 2019; Chen et al., 2020; Rafief et al., 2020; Tian et al., 2020; Mandya et al., 2020; Ribeiro et al., 2021; Qin et al., 2021a; Herzig and Berant, 2021; Qin et al., 2021b; Paolini et al., 2021; Rothe et al., 2021; Pasupat et al., 2021; Tian et al., 2022), in the experiments, we train four state-of-the-art character-based models for CWS and MTR with widely used pre-trained language models for Chinese. Specifically, the four models are BERT (Devlin et al., 2019), ZEN (Diao et al., 2020; Song et al., 2021), WMSeg (Tian et al., 2020c), and AESINER (Nie et al., 2020a), where all of them follow the standard encoding-decoding paradigm in Figure 1. The details of the models are illustrated as follows:

BERT. BERT is a pre-trained language model in the general domain that has achieved state-of-the-art performance on many NLP tasks. We used the base version of Chinese BERT as the text encoder and use softmax or conditional random field (CRF) as the decoder to predict the CWS and MTR labels for each character. We use the default setting for the BERT encoder, which uses 12 layers of multi-head attentions and 768 dimensional vectors for the hidden states.

ZEN. ZEN is another pre-trained language model for Chinese in the general domain. It enhances BERT by modeling n-gram information through the encoding process of the running text and thus achieves better performance on many Chinese NLP tasks. We use the large version of ZEN with the default setting (i.e., 24 layers of multi-head attentions and 1024 dimensional hidden states) and use softmax or CRF as the decoder.

WMSeg. WMSeg is a model for CWS, which uses either BERT or ZEN as the text encoder and CRF as the decoder. WMSeg improves CWS by leveraging the wordhood information in n-grams to achieve better performance. We follow the default settings specified in the original paper and apply it to CWS only.

AESINER. AESINER proposes an attentive ensemble mechanism to leverage different types of syntactic information (namely, part-of-speech (POS) labels, syntactic constituents, and dependency relations) and achieves state-of-the-art performance on NER in the general domain. Similar to WMSeg, the text encoder of AESINER is either BERT or ZEN and the decoder is CRF. We use the default settings of AESINER in the original paper and apply it only to MTR.

4.3. Settings

For the data, we split ChiMST into training, development, and test sets, where both CWS and MTR tasks use the same train/dev/test split. The training set contains the 700 QA records, each being annotated by one of the annotators; the development and test set contains 100 and 200 QA records, respectively, and each being double annotated. The statistics of the train/dev/test sets are reported in Table 6. In addition, since our CWS annotation follows the CTB guideline, for CWS we use the training set of CTB5 (Xue et al., 2005).

Table 6: The statistics of the training, development, and test sets of ChiMST in the experiments. “Double annotated” indicates whether the data is annotated by both annotators.

| Hyper-parameters | Values |
|------------------|--------|
| Learning Rate    | $5e^{-6}$, $1e^{-5}$, $2e^{-5}$ |
| Warmup Rate      | 0.06, 0.1 |
| Dropout Rate     | 0.1 |
| Batch Size       | 8, 16, 32 |

4.3.1. Hyper-parameters

Table 7: The hyper-parameter values tested when tuning our models, and the ones used in our final experiments are in boldface.

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AESINER. AESINER proposes an attentive ensemble mechanism to leverage different types of syntactic information (namely, part-of-speech (POS) labels, syntactic constituents, and dependency relations) and achieves state-of-the-art performance on NER in the general domain. Similar to WMSeg, the text encoder of AESINER is either BERT or ZEN and the decoder is CRF. We use the default settings of AESINER in the original paper and apply it only to MTR.
Table 8: CWS performance for different composition of training data, namely, the CTP data only ("CTB only"), the CTB data and our data ("CTB+ChiMST"), and our data only ("ChiMST Only"). BERT and ZEN refer to the models with the softmax decoder. WMSeg (BERT) and WMSeg (ZEN) denote the WMSeg models using BERT and ZEN encoder, respectively.

| Methods         | Prec. | Recall | F1   |
|-----------------|-------|--------|------|
| CTB Only        |       |        |      |
| BERT            | 94.61 | 94.81  | 94.71|
| BERT + CRF      | 94.50 | 95.11  | 94.80|
| WMSeg (BERT)    | 94.81 | 95.02  | 94.92|
| ZEN             | 94.58 | 94.93  | 94.75|
| ZEN + CRF       | 94.70 | 94.89  | 94.79|
| WMSeg (ZEN)     | 95.14 | 94.90  | 95.02|
| CTB+ChiMST      |       |        |      |
| BERT            | 97.93 | 97.65  | 97.79|
| BERT + CRF      | 97.89 | 97.76  | 97.82|
| WMSeg (BERT)    | 98.04 | 97.91  | 97.97|
| ZEN             | 98.21 | 97.99  | 98.10|
| ZEN + CRF       | 98.23 | 98.01  | 98.12|
| WMSeg (ZEN)     | 98.39 | 98.04  | 98.21|
| ChiMST Only     |       |        |      |
| BERT            | 97.82 | 98.15  | 97.98|
| BERT + CRF      | 97.90 | 98.16  | 98.03|
| WMSeg (BERT)    | 98.00 | 98.23  | 98.11|
| ZEN             | 98.22 | 98.18  | 98.20|
| ZEN + CRF       | 98.29 | 98.21  | 98.25|
| WMSeg (ZEN)     | 98.05 | 98.41  | 98.38|

Table 9: The performance of different models on the MTR task in terms of precision, recall, and F1 scores. Herein, AESINER models use all three types of syntactic information (i.e., POS labels, syntactic constituents, and dependency relations).

| Methods         | Prec. | Recall | F1   |
|-----------------|-------|--------|------|
| BERT            | 79.19 | 83.81  | 81.43|
| BERT + CRF      | 78.60 | 84.79  | 81.57|
| AESINER (BERT)  | 79.15 | 84.87  | 81.91|
| ZEN             | 82.17 | 85.52  | 83.81|
| ZEN + CRF       | 82.44 | 85.59  | 83.98|
| AESINER (ZEN)   | 82.67 | 86.25  | 84.41|

Table 10: The performance of AESINER model (using ZEN encoder) using different types of syntactic information. “POS”, “SC”, and “DR” denote POS labels, syntactic constituents, and dependency relations, respectively. The performance of the model where all types of syntactic information are used (i.e., “All”) is also reported for reference.

Syntactic Info. | Prec. | Recall | F1   |
----------------|-------|--------|------|
POS Only        | 82.31 | 85.83  | 84.03|
SC Only         | 82.55 | 86.04  | 84.25|
DR Only         | 82.30 | 85.98  | 84.10|
All             | 82.67 | 86.25  | 84.41

5. Results and Discussion

5.1. Performance on CWS

For CWS, we run the three models (i.e., BERT, ZEN, and WMSeg) with different settings and report system performance (precision, recall, and F1 scores) on the test set of ChiMST in Table 8. Herein, “CTB only” refers to the cross-domain experiment setting where the models are trained on the training set of CTB5; “CTB+ChiMST” denotes the setting where the training data is the union of CTB5 and ChiMST training sets; “ChiMST Only” is the in-domain setting where the models are trained and evaluated on ChiMST.

There are some observations. First, all models achieve outstanding performance when the training data is ChiMST Only. Second, CTB only results are worse than both CTB+ChiMST and ChiMST only, confirming that the gaps between the domains remarkably affect the performance of WSD models and demonstrating the benefits of constructing annotated corpus for special domains such as medical domain. Third, for all three settings, WMSeg with ZEN encoder achieves the highest F1 scores, because this model can leverage n-gram information to improve CWS performance.

5.2. Performance on MTR

For MTR, we run BERT, ZEN, and AESINER models with different configurations on ChiMST. We report...
we further conduct experiments on label sets in previous studies. Able to release the corpus to the public. In addition, the form rather than EMRs in the hospitals; thus we are uses QA records from a public healthcare plat-
ChiMST and 18 sub-categories. Specifically, the corpus includes 1,000 QA records with annotations for CWS and MTR. The experimental results in Table 10: the first three rows use only one type of syntactic information, and the last row uses all three types. Among the three types, syntactic information (SC) works the best. One possible explanation is that the syntactic constituents suggest the boundary information of a medical term (medical terms are more likely to be noun phrases) and thus contribute more to identifying the medical terms than the other two types of syntactic information.

6. Conclusion
In this paper, we describe a Chinese medical corpus named ChiMST with annotations for CWS and MTR. Specifically, the corpus includes 1,000 QA records from the ChiMed corpus, where the question and answer fields are annotated with word segmentation and medical term information. The annotation guidelines for CWS follows CTB’s segmentation guidelines; medical term annotation uses a label set with 9 categories and 18 sub-categories.

Compared with existing datasets for CWS and MTR, ChiMST uses QA records from a public healthcare platform rather than EMRs in the hospitals; thus we are able to release the corpus to the public. In addition, the 18-subcategory label set is more fine-grained than the label sets in previous studies.

We further conduct experiments on ChiMST with state-of-the-art sequence labeling models. The experimental results on CWS show the performance in the cross-domain setting is much worse than the in-domain setting, demonstrating the benefit of having labeled data for special domains. In addition, WMSeg and AESINER, which leverage n-gram and syntactic information, achieve the best performance for CWS and MTR, respectively, demonstrating that extra information (such as n-gram and syntactic information) is helpful to improve model performance.

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