Knowledge-Empowered Representation Learning for Chinese Medical Reading Comprehension: Task, Model and Resources

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Abstract

Machine Reading Comprehension (MRC) aims to extract answers to questions given a passage, which has been widely studied recently especially in open domains. However, few efforts have been made on closed-domain MRC, mainly due to the lack of large-scale training data. In this paper, we introduce a multi-target MRC task for the medical domain, whose goal is to predict answers to medical questions and the corresponding support sentences from medical information sources simultaneously, in order to ensure the high reliability of medical knowledge serving. A high-quality dataset (more than 18k samples) is manually constructed for the purpose, named Multi-task Chinese Medical MRC dataset (CMedMRC), with detailed analysis conducted. We further propose a Chinese medical BERT model for the task (CMedBERT), which fuses medical knowledge into pre-trained language models by the dynamic fusion mechanism of heterogeneous features and the multi-task learning strategy. Experiments show that CMedBERT consistently outperforms strong baselines by fusing context-aware and knowledge-aware token representations.\textsuperscript{1}

1 Introduction

Machine Reading Comprehension (MRC) has become a popular task in NLP, aiming to understand a given passage and answer the relevant questions. With the wide availability of MRC datasets (Rajpurkar et al., 2016; He et al., 2018; Cui et al., 2019) and deep learning models (Yu et al., 2018; Ding et al., 2019) (including pre-trained language models such as BERT (Devlin et al., 2019)), significant progress has been made.

Despite the success, a majority of MRC research has focused on open domains. For specific domains, however, the construction of high-quality MRC datasets, together with the design of corresponding models is considerably deficient (Welbl et al., 2017, 2018). The causes behind this phenomenon are threefold. Take the medical domain as an example. i) Data annotators are required to have medical backgrounds with high standards. Hence, simple crowdsourcing (Rajpurkar et al., 2016; Cui et al., 2019) often leads to poor annotation results. ii) Due to the domain sensitivity, people are more concerned about the reliability of the information sources where the answers are extracted, and the explainability of the answers themselves (Lee et al., 2014; Dalmer, 2017). This is fundamentally different from the task requirements of open-domain MRC. iii) From the perspective of model learning, it is difficult for pre-trained language models to understand the meaning of the questions and passages containing a lot of specialized terms (Chen et al., 2016; Bauer et al., 2018). Without the help of domain knowledge, state-of-the-art models can perform poorly. As shown in Figure 1, BERT (Devlin et al., 2019) and MC-BERT (Zhang et al., 2020) only predict part of the correct answer, i.e., “torso” and “buttocks”, instead of generating the complete answer to the medical question.

In this paper, we present a comprehensive study on Chinese medical MRC, including i) how the task is formulated, ii) the construction of the Chinese medical dataset and iii) the MRC model with rich medical knowledge injected. To meet the requirements of medical MRC, we aim to predict both the answer spans to a medical question, and the support sentence from the passage, indicating

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\textsuperscript{1}The code and dataset will be available at https://github.com/MatNLP/CMedMRC
we find that comprehensive skills are required for answering 31% of the questions, and for medical professionals to assess the trustworthiness of model output results.

For the dataset, we construct a highly-quality Chinese medical MRC dataset, named the Multi-task Chinese Medical MRC dataset (CMedMRC). It contains 18,153 quads. Based on the analysis of CMedMRC, we summarize four special challenges for Chinese medical MRC, including long-tail terminologies, synonym terminology, terminology combination and paraphrasing. In addition, we find that comprehensive skills are required for MRC models to answer medical questions correctly. For answer extraction in CMedMRC, direct token matching is required for answering 31% of the questions, co-reference resolution for 11%, multi-sentence reasoning for 18% and implicit causality for 22%. In addition, the answers to the remaining questions (16%) are extremely difficult to extract without rich medical background knowledge.

To address the medical MRC task, we propose the multi-task dynamic heterogeneous fusion network (CMedBERT) based on the MC-BERT (Zhang et al., 2020) model and a Chinese medical knowledge base (see Appendix).

The technical contributions of CMedBERT are twofold:

- **Heterogeneous Feature Fusion**: We mimic humans’ approach of reading comprehension (Wang et al., 1999) by learning attentively aggregated representations of multiple entities in the passage. Different from the knowledge fusion method used by KBLSTM (Yang and Mitchell, 2017) and KT-NET (Yang et al., 2019), we propose a two-level attention and a gated-loop mechanism to replace the knowledge sentinel, so that rich knowledge representations can be better integrated into the model.

- **Multi-task Learning**: Parameters of CMedBERT are dynamically learned by capturing the relationships between the two tasks via multi-task learning. We regard the semantic similarities between support sentences and answers to questions as the task similarities.

We compare CMedBERT against six strong baselines. For answer prediction, compared to the strongest competitor, the EM (Exact Match) and F1 scores are increased by +3.88% and +1.46%, respectively. Meanwhile, the support sentence prediction task result is increased by a large margin, i.e., +7.81% of EM and +4.07% of F1.

### 2 Related Work

**MRC Datasets and Models.** Due to the popularity of the MRC task, there exist many types of MRC datasets, such as span-extraction (Rajpurkar et al., 2016; Yang et al., 2018), multiple choices (Richardson et al., 2013; Lai et al., 2017), cloze-style (Hermann et al., 2015), cross-lingual (Jing et al., 2019; Yuan et al., 2020). For specific domains, however, the number of publicly available MRC datasets remains few, including SciQ (Welbl et al., 2017), Quasar-S (Dhingra et al., 2017) and Biology (Berant et al., 2014). CLiCR (Suster and Daelemans, 2018) is a cloze-style single-task English medical MRC dataset. However, it contains a relatively small variety of medical questions, automatically generated from clinical case reports. Recently, (Li et al., 2020) propose a multi-choice Chinese medical QA dataset, retrieving text snippets as the passage and the task only chooses an existing correct option from candidate set. Our work specifically focuses on the fine-grained medical
MRC tasks and deep domain knowledge reasoning, with a manually constructed high-quality dataset released.

The model architecture of MRC mostly takes advantage of neural networks to learn token representations of passages and questions jointly (Qiu et al., 2019a; Liu et al., 2019). The interaction between questions and passages is modeled based on attention mechanisms. The rapid development of deep learning leads to a variety of models, such as the QANet (Yu et al., 2018), SAN (Liu et al., 2018). Graph neural networks have been used in MRC recently by modeling the relations between entities in the passage (Ding et al., 2019) and multi-grained tokens representation (Zheng et al., 2020).

Pre-trained Language Models and Knowledge Fusion. Pre-trained language models (e.g., BERT (Devlin et al., 2019), ERNIE-THU (Zhang et al., 2019), K-BERT (Liu et al., 2020a)) have successfully improved the performance of the MRC task, which even exceed the human level in some datasets. This is because these models obtain better token representations and capture lexical and syntactic knowledge in different layers (Guan et al., 2019). For specific domain, there also have some pre-trained models (Beltagy et al., 2019; Zhang et al., 2020).

A potential drawback is that pre-trained language models of open domains only learn general representations, lacking domain-specific knowledge to deepen the understanding of entities and other nouns (Ostendorff et al., 2019) (which are often the answers in span-extraction MRC tasks). Without proper descriptions of such entities in the passage, MRC models often fail to understand and extract key information (Das et al., 2019). Hence, the explicit fusion of knowledge in MRC models is vital for learning context-aware token representations (Pan et al., 2019; Qiu et al., 2019b; Liu et al., 2020b). Instead of encoding entities appearing in both knowledge bases and passages into the MRC model only (Chen et al., 2018), our proposed model encodes all the triples from a medical KG and then employs heuristic rules to retrieve relevant entities. This practice allows the model to acquire deeper understanding of domain-specific terms.

| Challenges         | Characteristics                     | Example                                                                 |
|--------------------|-------------------------------------|-------------------------------------------------------------------------|
| Long-tail terminology | 冈上肌肌腱断裂试验是冈上肌肌腱是否存在断裂进行检查。(supraspinatus tendon rupture test is to check whether the supraspinatus tendon is ruptured.) |
| Lexical-Level       | Synonym terminology                  | ...本药物对过敏性鼻炎和上呼吸道感染引起的鼻黏膜有效，可用于感冒或鼻窦炎...(This medicine is effective for nasal congestion caused by allergic rhinitis and upper respiratory tract infection, and can be used for colds or sinusitis...) |
| Terminology combination | ...糖尿病性视网膜病(diabetic retinopathy)是糖尿病性微血管病中最重要的表现。(...Diabetic retinopathy (DR) is the most important manifestation of diabetic microangiopathy...) |
| Sentence-Level      | Paraphrasing                         | Passage: 如果在糖尿病患者血糖控制的地方进行冷敷，一方面冷敷物品不干净的话会致感染。另一方面局部温度降低之后，反而会延缓伤口的愈合。如果采用冷敷材料的角落的嘴，如果冷敷材料不干净，它会造感染；如果用冷敷的材料的角落的嘴，如果冷敷材料不干净，它会延缓伤口的愈合。...  Question: 为什么糖尿病患者不建议进行冷敷？(Why is it not recommended to apply cold compresses when the corners of the mouth are rotten or crusted?) |

Table 1: Two levels of challenges in processing Chinese medical texts. The blue and underscore contents in brackets indicate why this example belongs to its corresponding “Characteristics” category. (Best viewed in color.)
Table 2: Reading comprehension skills of models required to answer questions in CMedMRC. The blue and underscored contents in brackets indicate why the sample belongs to its category. (Best viewed in color)

| Skills              | Example                                                                 | Percentage |
|---------------------|-------------------------------------------------------------------------|------------|
| Token matching      | Passage: ...amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy. (...it is less likely to secrete too much acute amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy...). | 31%        |
| Co-reference resolution | Passage: ...amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy. (...it is less likely to secrete too much acute amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy...). | 11%        |
| Multi-sentence reasoning | Passage: ...amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy. (...it is less likely to secrete too much acute amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy...). | 18%        |
| Implicit casuality  | Passage: ...amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy. (...it is less likely to secrete too much acute amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy...). | 22%        |
| Domain knowledge    | Passage: ...amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy. (...it is less likely to secrete too much acute amniotic fluid. The disease is most common in the 20th to 24th weeks of pregnancy...). | 16%        |

3.2 Quality Control

During the dataset collection process, we take the following measures to ensure the quality of the dataset. i) The Knowledge source (DXY Medical) contains high-quality medical articles which are written by medical personnel and organized based on different topics in the medical domain. ii) Our annotators are all engaged in medical-related professions rather than annotators with short-term medical guidance only. iii) We further hire 12 medical experts to check all the collected samples rather than checking a randomly selected sample only. The experts remove out-of-domain questions and questions that are unhelpful to medical practice. In this stage, the experts are divided into two groups and cross-check their judgments.

3.3 Challenges of Understanding Texts

Due to the closed-domain property of our dataset, there are some domain-specific textual features in both passages and questions that the model needs to understand. Based on our observations of the CMedMRC, we summarize the following two major challenges. These challenges can be also regarded as key reasons why some recent state-of-the-art MRC models cannot address the medical MRC task on CMedMRC well.

*Lexical-Level:* i) Long-tail terminology means these medical terms occur very infrequently and are prone to Out-Of-Vocabulary (OOV) problems. ii) Synonym terminology means that some medical terms may express the same meaning, but there is a distinction between colloquial expressions and professional terms. The above two points require the model to have rich domain knowledge to solve. iii) Terminology combination means these terms are usually formed by a combination of multi-

medical knowledge and annotate the answers from these passages. The annotation results are in the form of question-answer pairs. Following SQUAD, we ask annotators to provide 2 additional answers for each question in the DEV and TEST sets.

Since people are concerned about the scientific explanation and sources of answers in the medical domain, we ask annotators to select the support sentence of their annotated answer similar to those of CoQA (Reddy et al., 2019) and QuAC (Choi et al., 2018). Finally, CMedMRC consists of three parts: 12,700 training samples, 3,630 development samples and 1,823 testing samples.
We randomly select 100 samples from the development set to analyze what skills the model should have in order to answer the questions correctly. We divide the reasoning skills corresponding to these samples into five major categories, namely token matching, co-reference resolution, multi-sentence reasoning, implicit causality and domain knowledge. Examples are shown in Table 2. It is particularly noteworthy that the fifth type is the need of domain knowledge to answer medical questions. Consider the example:

**Passage:** ... The incidence of thrombotic cell weakness is most common in childhood with an incidence rate of 0.01 / 10,000 ...

**Question:** What is the incidence rate of blood platelet weakness?

**Answer:** 0.01/10,000.

We know that the blood platelet in the question refers to the thrombotic cell described in the passage through the medical knowledge base. It shows that the rich information of the knowledge base can help the model obtain a better understanding of domain terms to improve the MRC performance.

4 The CMedBERT Model

4.1 Task Formulation and Model Overview

For our task, the input includes a medical question $Q$ together with the passage $P$. Let $\{p_1, p_2, \cdots, p_m\}$ and $\{q_1, q_2, \cdots, q_n\}$ represent the passage and question tokens, respectively. In the answer prediction task, the goal is to train an MRC model which extracts the answer span $\{p_i, p_{i+1}, \cdots, p_j\}$ ($0 \leq i \leq j \leq m$) from $P$ that correctly answers the question $Q$. Additionally, the model is required to predict the support sentence tokens $\{p_k, p_{k+1}, \cdots, p_l\}$ ($0 \leq k \leq l \leq m$) from $P$ to provide additional medical knowledge and to enhance interpretability of the extracted answers. We constrain that $\{p_k, p_{k+1}, \cdots, p_l\}$ must form a complete sentence, instead of incomplete semantic units and the support sentence tokens contain the answer span. The high-level architecture of the CMedBERT model is shown in Figure 2. It mainly includes four modules: BERT encoding, knowledge embedding and retrieval, heterogeneous feature fusion and multi-task training.

4.2 BERT Encoding

This module is used to learn context-aware representations of question and the passage tokens. For each input pair (the question $Q$ and the passage $P$), we treat $[(CLS), Q, (SEP), P, (SEP)]$ as the input sequences for BERT. We denote $\{h_i\}_{i=1}^{m+n+3}$ as the hidden layer representations of tokens, where $m$ and $n$ are the length of passage tokens and question tokens, respectively.

4.3 Knowledge Embedding and Retrieval

In the knowledge bases, relational knowledge is stored in the form of $(subject, relation, object)$ triples. In order to fuse knowledge into token representations, we first encode all entities in the knowledge base into a low-dimensional vector space. Here, we employ PTransE (Lin et al., 2015a) to learn entity representations, and denote the underlying entity embedding as $e_j$. Because existing medical NER tools do not have high coverage over our corpus, we consider five types of token strings as candidate entities: noun, time, location, direction and numeric. Two matching strategies are then employed to retrieve relevant entities from the knowledge base: (i) The two strings match exactly. (ii) The number of overlapped tokens is larger than a threshold. After relevant entities are retrieved, we can fuse the knowledge into contextual representations, introduced below.

4.4 Heterogeneous Feature Fusion

In this module, we fuse heterogeneous entity features retrieved from the knowledge base into the question and passage tokens representations.

**Local Fusion Attention.** We observe that each token is usually related to multiple entities of varying importance. Thus, we assign different weights to the entity embedding $e_j$ corresponding to the token representation $h_i$ using attention mechanism:

$$
\alpha_{i,j} = \frac{\exp(e_j^T W h_i)}{\sum_{k=1}^{K} \exp(e_k^T W h_i)}
$$

(1)
we have the following update process:

\[ G_i^t = \sigma(\tanh(W^t h_i^t, e_i, \hat{e}_i)) \]

\[ h_i^{t+1} = G_i^t \odot h_i^t \]  

This process runs for \( L \) loops and this fusion process output is \( h_i^L \). The loop process mimics the human’s behavior of reading the passage repeatedly to find the most accurate answers.

4.5 Multi-task Training

The output layer of CMedBERT is extended from BERT. We first concatenate two types of token representations and calculate the probability of the \( i \)th token being selected in the support sentence as follows:

\[ o_i = \sigma(W_i^g h_i^L) \]

\[ p_i^{support} = \sigma(W o_i) \]  

We also calculate its probabilities as the starting and ending positions of the answer span, respectively:

\[ p_i^{start} = \frac{\exp(w_1^T o_i)}{\sum_j \exp(w_1^T o_j)} \]

\[ p_i^{end} = \frac{\exp(w_2^T o_i)}{\sum_j \exp(w_2^T o_j)} \]

The loss function of the answer prediction task is the negative log-likelihood of the starting and ending positions of ground-truth answer tokens:

\[ \mathcal{L}_A = -\frac{1}{N} \sum_{j=1}^N (\log p_{y_{start}} + \log p_{y_{end}}) \]

For the extraction of support sentences, the loss function is defined by cross-entropy:

\[ \mathcal{L}_S = -\frac{1}{N} \sum_{j=1}^N \sum_{i=1}^M (y_{support} \log p_{y_{support}}) \]
## 5 Experiments and Result Analysis

### 5.1 Experimental Setups

We evaluate CMedBERT on CMedMRC, and compare it against six strong baselines: DrQA (Chen et al., 2017), BERT\_base (Devlin et al., 2019), ERNIE (Zhang et al., 2019), KT\_NET (Yang et al., 2019), MC-BERT (Zhang et al., 2020) and KMQA (Li et al., 2020). KT\_NET is the first model to leverage rich knowledge to enhance pre-trained language models for MRC. MC-BERT is the first Chinese biomedical pre-trained model fine-tuned on BERT\_base. We only use the encoder layer in KMQA removing the answer layer due to the different answer type.

For evaluation, we use EM (Exact Match) and F1 metrics for answer and support sentence tasks. We calculate character-level overlaps between prediction and ground truth for the Chinese language, rather than token-level overlaps for English. To assess the difficulty of solving CMedMRC tasks, we select 100 testing samples to evaluate human performance. Human scores of EM and F1 are 85.00% and 96.69% for answer prediction, respectively.

In the implementation, we set the learning rate as 5e-5 and the batch size as 16, and the max sequence length as 512. Other BERT’s hyper-parameters are the same as in Google’s settings \(^3\). Each model is trained for 2 epochs by the Adam optimizer (Kingma and Ba, 2015). Results are presented in average with 5 random runs with different random seeds. Other implementation details are in Appendix C.

### 5.2 Model Results

Table 3 and Table 4 show the multi-task and single-task results on the CMedMRC development and testing sets. CMedBERT has a great improvement compared to four strong baseline models in both tasks. Specifically, our CMedBERT outperforms the state-of-the-art model by a large margin in multi-task results, with +3.88%EM / +1.46%F1 improvements, which shows the effectiveness of our model. Meanwhile, in the support sentence task, our model also has the best performance, improving (+7.81%EM / +4.07%F1) over the testing set. In single task evaluation, we remove the

\(^3\)https://github.com/google-research/bert
| Model       | Exact Match (EM) | F1       |  |  |
|-------------|-----------------|----------|  |  |
|              | Dev  | Test  | Dev | Test |  |  |
| DrQA        | 34.50%| 32.10%| 56.67%| 56.64%|  |  |
| BERT_base   | 63.39%| 68.29%| 81.48%| 83.70%|  |  |
| ERNIE       | 63.18%| 66.92%| 81.74%| 83.41%|  |  |
| KT-NET♠     | 64.64%| 66.26%| 82.48%| 83.61%|  |  |
| MC-BERT     | 63.39%| 68.38%| 81.86%| 83.88%|  |  |
| KMQA        | 64.37%| 67.48%| 81.95%| 83.74%|  |  |
| CMedBERT♣   | 72.91%| 85.64%| 25.51%| 52.41%|  |  |
| w/o Local Att. | 68.93%| 83.89%| 19.75%| 49.45%|  |  |
| w/o Global Att. | 71.71%| 84.96%| 17.59%| 47.01%|  |  |
| w/o λ       | 71.91%| 85.09%| 21.09%| 48.80%|  |  |

Table 4: Result of single-task (answer prediction).

and ♠ indicate that CMedBERT uses BERT_base and MC-BERT as the encoder, respectively.

| Model       | Answer Sentence | EM | F1 | EM | F1 |
|-------------|-----------------|----|----|----|----|
| CMedBERT♣   | 72.91%| 85.64%| 25.51%| 52.41%|  |  |
| w/o Local Att. | 68.93%| 83.89%| 19.75%| 49.45%|  |  |
| w/o Global Att. | 71.71%| 84.96%| 17.59%| 47.01%|  |  |
| w/o λ       | 71.91%| 85.09%| 21.09%| 48.80%|  |  |

Table 5: Ablation study of CMedBERT (testing set).

5.3 Ablation study

In Table 5, we choose three important model components for our ablation study and report the results over the testing set. When the dynamic parameter λ of the loss function is removed from the model, the performance of the model on two tasks is decreased by (-1.00%EM and -0.55%F1) and (-4.42%EM and -3.61%F1), respectively. Without local attention, the EM performance in the answer prediction task decreases by (-3.98%EM and -1.75%F1). Experiments have shown that the model performs worse without the local fusion attention than without the global fusion attention and the dynamic parameter λ. However, the performance of support sentence task is decreased significantly by (-7.92%EM and -3.61%F1) without global fusion attention. It shows that local fusion attention is more important for extracting answer spans, while global fusion attention plays a larger role in support sentence prediction.

5.4 Case Study

In Figure 3, we use our motivation example to conduct a case study. In BERT, we can see that the difference among the probability values of different words is small, especially when predicting the probability of ending positions. The ending position probabilities of token “部” token “皮” are 0.3 and 0.25, leading the model to extract the wrong answer span. However, in the knowledge retrieval module of CMedBERT, multiple entities representation are fused into the context-aware latent space representation to enhance the medical text semantic understanding. Therefore, in our CMedBERT model, the starting position probability is 0.95 and the end position probability is 0.8. In this case, the CMedBERT model can easily choose the correct range of the answer span.

5.5 Discussion of Support Sentence Task

Compared with the answer prediction task, existing models have poor prediction results on the EM metric in the support-sentence task. In prediction results, we randomly select 100 samples for analysis. We divide the error types into the following three main types (see Appendix): i) starting position cross ii) ending position cross iii) answer substring. The most common error type is the answer substring, accounting for 46%. In this error type, the predicted result of our model is part of the true result, which shows the model cannot predict long answers completely (Yuan et al., 2020) and reduce...
the accuracy of the results greatly.

6 Conclusion

In this work, we address medical MRC with a new dataset CMedMRC constructed. An in-depth analysis of the dataset is conducted, including statistics, characteristics, required MRC skills, etc. Moreover, we propose the CMedBERT model, which can help the pre-trained model better understand domain terms by retrieving entities from medical knowledge bases. Experimental results confirm the effectiveness of our model. In the future, we will explore how knowledge can improve the performance of models in the medical domain.

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A Detailed Dataset Construction Process of CMedMRC

A.1 Medical Passage Curation
We use the following rules to obtain 20,000 passages from DXY as the inputs to human annotators:

- We use regular expressions to filter out images, tables, hyperlinks, etc. The English-Chinese translations of medical terms are also provided if the passages contain medical terms in English.
- We find that if we follow (Rajpurkar et al., 2016) to limit the lengths of the passages within 500 tokens, our human annotators could not ask 4 high-quality medical questions easily. Hence, our passage length limit is 1000 tokens.

A.2 Medical Question-Answer Pair Collection
We employ a group of annotators with professional medical background to generate question-answer pairs from the medical passages. Here are some general guidelines:

- We encourage our annotators to ask questions to which the answers are uniformly distributed in different positions of medical passages.
- For each medical passage, we limit the number of questions to 4.
- Each question should be strictly related to the medical domain. When creating the questions, no any part of the texts can be directly copied and pasted from the given medical passages.
- We limit the number of answer tokens to no more than 40.

A.3 Support Sentence Selection
In our dataset, we add an index to each sentence in the passages. Annotators are required to select the support sentence index and mark the range of the answer spans on the user interface.

### Table 6: Statistical results for answer types.

| Answer Type | Pct. | Example |
|-------------|------|---------|
| Numeric     | 6%   | 20%     |
| Time/Date   | 11%  | 1-3小时 (1-3 Hours) |
| Person      | 8%   | 儿童 (Child) |
| Location    | 5%   | 安徽, 云南, 湖北 (Anhui, Yunnan, Hubei) |
| Noun Phrase | 18%  | 输卵管炎 (Salpingitis) |
| Verb Phrase | 6%   | 清洗、干燥和粉碎 (Wash, dry and crush) |
| Yes/No      | 1%   | 不会感染 (Will not infect) |
| Description | 44%  | 维生素缺乏 (Vitamin deficiency) |
| Other       | 1%   | 严重 (Severe) |

Table 7: Statistical results of text length in our CMedMRC dataset.

|                      | Train | Dev  | Test |
|----------------------|-------|------|------|
| # Questions          | 12,700| 3,630| 1,823|
| Avg. tokens of passages | 883.64| 743.10| 745.52|
| Avg. tokens of questions | 15.40 | 14.85 | 15.23 |
| Avg. tokens of answers | 19.69 | 18.48 | 16.57 |
| Avg. tokens of support sen. | 57.50 | 48.19 | 42.70 |

### B Statistical Analysis of the CMedMRC Dataset

B.1 Question and Answer Types
Due to the special characteristics of the Chinese language, the question types cannot be simply classified by prefix words of questions (Rajpurkar et al., 2016). Here, we manually define 8 common question types in the user annotation interface. The statistics of each question type are shown in Figure 4. The first seven question types usually correspond to special medical
Genetic factors play a role in this disease. Anti-inflammatory, improve capillary permeability, reduce edema, pain relief, etc., (The following people are at high risk: people with chronic hepatitis B and C virus infections, suffering from diseases such as rheumatoid arthritis, lupus, and scleroderma; smoking... Genetic factors play a role in this disease.)

We further analyze to what degree there exists domain knowledge in CMedMRC, in terms of medical entities and other terms. In this study, we employ the POS and NER toolkits\(^4\) to tag medical entities and terms from 100 samples in the development set of CMedMRC. We also compare the statistics against those of two other Chinese MRC datasets, namely CMRC (Cui et al., 2019) and DuReader (He et al., 2018). The proportions of entities and five frequent POS tags in the three datasets are summarized in Figure 5. Comparing to the other two open-domain datasets, the proportion of entities in CMedMRC is very high (11%). In addition, the proportion of nouns (27%) is much higher than the other four POS tags in CMedMRC. The most likely cause is that existing datasets are relatively large. The results are consistent with Figure 4, since most of What questions need to be answered with the above two answer types. Table 7 shows the text length of four input data.

### B.2 Analysis of Domain Knowledge

We further analyze to what degree there exists domain knowledge in CMedMRC, in terms of medical entities and other terms. In this study, we employ the POS and NER toolkits\(^4\) to tag medical entities and terms from 100 samples in the development set of CMedMRC. We also compare the statistics against those of two other Chinese MRC datasets, namely CMRC (Cui et al., 2019) and DuReader (He et al., 2018). The proportions of entities and five frequent POS tags in the three datasets are summarized in Figure 5. Comparing to the other two open-domain datasets, the proportion of entities in CMedMRC is very high (11%). In addition, the proportion of nouns (27%) is much higher than the other four POS tags in CMedMRC. The most likely cause is that existing

\(^4\)We use jieba toolkit with additional medical term dictionaries. See [https://pypi.org/project/jieba/](https://pypi.org/project/jieba/).
models have difficulty recognizing all the medical terms, and treat them as common nouns. Among the three Chinese datasets, CMedMRC has the largest proportion (38%) of nouns and entities. Therefore, it is difficult for pre-trained language models to understand so many medical terms without additional medical background knowledge.

C Experimental Settings

C.1 Medical Knowledge Base and Corpora
The underlying medical knowledge base is constructed by DXY, containing 44 relation types and over 4M relation triples. The KGs embedding trained by TransR (Lin et al., 2015b) on DXY-KG 5 containing 152,508 entities. In knowledge retrieval, the threshold of overlapped tokens is set to half of its own length. The medical pre-training corpora used in ERNIE-THU(Zhang et al., 2019) contains 5,937,695 text segments with 3,028,224,412 tokens (4.9 GB) after pre-processing.

C.2 Additional Training Details
In average, the training time for DrQA, BERT_base, MC-BERT, KT-NET, ERNIE, KMQA and CMedBERT takes 10, 16, 16, 27, 29, 28 and 25 minutes per epoch on a TiTAN RTX GPU. All the models are implemented by the PyTorch deep learning framework 6.

5https://portal.dxy.cn/
6https://pytorch.org/