**ChiMed: A Chinese Medical Corpus for Question Answering**

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**Abstract**

Question answering (QA) is a challenging task in natural language processing (NLP), especially when it is applied to specific domains. While models trained in the general domain can be adapted to a new target domain, their performance often degrades significantly due to domain mismatch. Alternatively, one can require a large amount of domain-specific QA data, but such data are rare, especially for the medical domain. In this study, we first collect a large-scale Chinese medical QA corpus called ChiMed; second we annotate a small fraction of the corpus to check the quality of the answers; third, we extract two datasets from the corpus and use them for the relevance prediction task and the adoption prediction task. Several benchmark models are applied to the datasets, producing good results for both tasks.

**1 Introduction**

In the big data era, it is often challenging to locate the most helpful information in many real-world applications, such as search engine, customer service, personal assistant, etc. A series of NLP tasks, such as text representation, text classification, summarization, keyphrase extraction, and answer ranking, are able to help QA systems in finding relevant information (Siddiqi and Sharan, 2015; Allahyari et al., 2017; Yang et al., 2016; Joulin et al., 2016; Song et al., 2017, 2018).

Currently, most QA corpora are built for the general domain focusing on extracting/generating answers from articles, such as CNN/Daily Mail (Hermann et al., 2015), SQuAD (Rajpurkar et al., 2016), Dureader (He et al., 2017), SearchQA (Dunn et al., 2017), CoQA (Reddy et al., 2018), etc., with few others from community QA forums, such as TrecQA (Wang et al., 2007), WikiQA (Yang et al., 2015), and SemEval-2015 (Nakov et al., 2015).

In the medical domain, most medial QA corpora consist of scientific articles, such as BioASQ (Tsatsaronis et al., 2012), emrQA (Pampari et al., 2018), and CliCR (Šuster and Daelemans, 2018). Although some studies were done for conversational datasets (Wang et al., 2018a,b), corpora designed for community QA are extremely rare. Meanwhile, given that many online medical service forums have emerged (e.g. MedHelp1), there are increasing demands from users to search for answers for their medical concerns. One might be tempted to build QA corpora from such forums. However, in doing so, one must address a series of challenges such as how to ensure the quality of the derived corpus despite the noise in the original forum data.

In this paper, we introduce our work on building a Chinese medical QA corpus named ChiMed by crawling data from a big Chinese medical forum2. In the forum, the questions are asked by web users and all the answers are provided by accredited physicians. In addition to (Q, A) pairs, the corpus contains rich information such as the title of the question, key phrases, age and gender of the user, the name and affiliation of the accredited physicians who answer the question, and so on. As a result, the corpus can be used for many NLP tasks. In this study, we focus on two tasks: relevance prediction (whether an answer is relevant to a question) and adoption prediction (whether an answer will be adopted).

1https://www.medhelp.org

2The code for constructing the corpus and the datasets used in this study are available at https://github.com/yuanheTian/ChiMed.
| # of As per Q | # of Qs | % of Qs |
|-------------|-------|--------|
| 1           | 5,517 | 11.8   |
| 2           | 39,098| 83.7   |
| ≥3          | 2,116 | 4.5    |
| Total       | 46,731| 100.0  |

Table 1: Statistics of ChiMed with respect to the number of answers (As) per question (Q).

2 The ChiMed Corpus

To benefit NLP research in the medical domain, we create a Chinese medical corpus (ChiMed). This section describes how the corpus was constructed, the main content of the corpus, and its potential usage.

2.1 Data Collection

Ask39 is a large Chinese medical forum where web users (to avoid confusion, we will call them patients) can post medical questions and receive answers provided by licensed physicians. Each question, together with its answers and other related information (e.g., the names of physicians and similar questions), is displayed on a page (aka a QA page) with a unique URL. Currently, approximately 145 thousand forum-verified physicians have joined the forum to answer questions and there are 17.6 million QA pages. We started with fifty thousand URLs from the URL pool and downloaded the pages using the selenium package. After removing duplicates or pages with no answers, 46,731 pages remain and most of the questions (83.7%) have two answers (See Table 1).

2.2 QA Records

From each QA page, we extract the question, the answers and other related information, and together they form a QA record. Table 2 displays the main part of a QA record, which has five fields that are most relevant to this study: (1) “Department” indicates which medical department the question is directed to; (2) “Title” is a brief description of disease/symptoms (5-20 characters); (3) “Question” is a health question with a more detailed description of symptoms (at least 20 characters); (4) “Keyphrases” is a list of phrases related to the question and the answer(s); (5) The last field is a list of answers, and each answer has an Adopted flag indicating whether it has been adopted. Among the five fields, Title and Question are entered by patients; Answers are provided by physicians; Department is determined by the forum engine automatically when the question is submitted. As for the Keyphrases field and the Adopted flag, it is not clear to us whether they are created manually (if so, by whom) or generated automatically. In addition to these fields, a QA record also contains other information such as the name and affiliation of the physicians who answer the question, the patient’s gender and age, etc.

Table 3 shows the statistics of ChiMed in terms of QA records. On average, each QA record contains one question, 1.96 answers, and 4.48 keyphrases. Overall, 69.1% of the answers in the corpus have an adopted flag.

2.3 Potential Usage of the Corpus

Given the rich content of the QA record, ChiMed can be used in many NLP tasks. For instance, one can use the corpus for text classification (to predict the medical department that a Q should be directed to), text summarization (to generate a title given a Q), keyphrase generation (to generate keyphrases given a Q and/or its As), answer ranking (to rank As for the same Q, if adopted As are indeed better than unadopted As), and question answering (retrieve/generate As given a Q).

Because the content of the corpus comes from an online forum, before we use the corpus for any NLP task, it is important to check the quality of the corpus with respect to that task. As a case study, for the rest of the paper, we will focus on three closely related tasks, all taking a question and an answer (or a set of answers) as the input: The first one determines whether the answer is relevant to the question; the second determines whether the answer will be adopted for the question (as indicated by the Adopted flag in the corpus); the third one ranks all the answers for the question if there are more than one answer. We name them the relevancy task, the adoption prediction task, and the answer ranking task, respectively. The first two are binary classification tasks, while the last one is a ranking task. In the next section, we will manually check a small fraction of the corpus to determine whether its quality is high for those tasks.

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http://ask.39.net
https://github.com/SeleniumHQ/selenium

There are 13 departments such as pediatrics, infectious diseases, and internal medicine.

We have made many attempts to no avail to contact the forum about those and other questions.
### Answer 1

In general, this is caused by Helicobacter pylori infection and does not cause cancer. So do not panic. It is recommended to have a regular diet, eat digest friendly food and chew slowly. Do not eat much in one meal and no spicy food is allowed.

**Adopted** True

### Answer 2

This is a common chronic gastric mucosal inflammation and has a relationship with Helicobacter pylori infection. You can choose amoxicillin for treatment.

**Adopted** False

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| # of Questions | 46,731 |
|----------------|--------|
| # of Answers   | 91,416 |
| Avg. # of Answers per Question | 1.96 |
| # (%) of Answers Adopted | 63.153 (69.1%) |
| # of Keyphrases | 209,261 |
| # of Keyphrases per Q | 4.48 |
| # of Unique Keyphrases | 10,360 |

**Table 3**: Statistics of *ChiMed*.

### 3 Relevancy, Answer Ranking, and Answer Adoption

Given *ChiMed*, it is easy to synthesize a “labeled” dataset for the relevancy task. E.g., given a question, we can treat answers in the same QA record as relevant, and answers in other QA records as irrelevant. The quality of such a synthesized dataset will depend on how often answers in a QA record are truly relevant to the question in the same record. For the adoption prediction task, we can directly use the *Adopted* flag in the QA records.

For the answer ranking task, the answers in a QA record are not ranked. However, if adopted answers are often better than unadopted answers, the former can be considered to rank higher than the latter if both answers come from the same QA record. For example, 65.46% of QA records with exactly two answers have one adopted answer and 34.46% have two adopted answers. We can use these 65.46% of QA records as a labeled dataset for the answer ranking task. However, the quality of such a dataset will depend on the correlation between the *Adopted* flag and the high quality of an answer.

To evaluate whether the answers are relevant to the question in the same QA record, and whether adopted answers are better than unadopted ones, we randomly sampled QA records containing exactly two questions, and picked 60 records with exactly one adopted and one unadopted answers (called *Subset-60*) and 40 records with both answers adopted (called *Subset-40*). The union of subset-60 and subset-40 is called *Full-100*, and it contains 100 questions, 200 answers (140 answers are adopted and 60 are not).

#### 3.1 Annotating Relevancy and Answer Ranking

To determine the quality of *ChiMed*, we manually added two types of labels to each QA record in
Possible Relevancy Labels for a (Q, A) pair:
1: The A fully answers the Q
2: The A partially answers the Q
3: The A does not answer the Q
4: Cannot tell whether the A is relevant to Q

Possible Ranking Labels for one Q and two As:
1: The first A is better
2: The second A is better
3: The two As are equally good
4: Neither of As is good (fully answers the Q)
5: Cannot tell which A is better

Properties of Good As:
1: Answer more sub-questions
2: Analyze symptoms or causes of disease
3: Offer advice on treatments or examinations
4: Offer instructions for drug usage
5: Soothe patients’ emotions

Properties of Bad As:
1: Answer the Q indirectly
2: The A has grammatical errors
3: Offer irrelevant information

Table 5: Labels and part of annotation Guidelines for relevancy and ranking annotation.

Table 6: Inter-annotator agreement for relevancy and ranking labeling on the Full-100 set in terms of percentage (%) and Cohen’s Kappa (κ). I and II refer to the annotations by the two annotators before any discussion, and Agreed is the annotation after the annotators have resolved their disagreement.

3.2 Inter-annotator Agreement on Relevancy and Answer Ranking

We hired two annotators without medical background to first annotate the Full-100 set independently and then resolve any disagreement via discussion. The results in terms of percentage and Cohen’s Kappa are in Table 6. Inter-annotator agreement on the relevancy label is quite high (90.5% in percentage and 55.6% in kappa), while the agreement on the ranking label is much lower (62.0% in percentage and 43.0% in kappa).

Table 7: The confusion matrices of two annotators on relevancy labels and ranking labels on the Full-100 set.
For ranking annotation, disagreement tends to occur when the two answers are very similar. That is why the majority of disagreed annotations (22 out of 38) occur when one annotator chooses one answer to be better while the other annotator considers the two answers to be equally good (an example is given in Table 8). There are 13 examples where annotators have completely opposite annotation (e.g., one annotates “1” while the other annotates “2”), which further shows the difficulty in identifying which answer is better.

3.3 The Adopted flag in ChiMed

As is mentioned above, each answer in ChiMed has a flag indicating whether or not the answer has been adopted. While we do not know the exact meaning of the flag and whether the flag is set manually (e.g., by the staff at the forum) or automatically (e.g., according to factors such as the physicians’ past performance or seniority), we would like to know whether the flag is a good indicator of relevant or better answers.

Among four relevancy labels, we regard answers with label “1” or “2” as relevant answers because they fully or partially answer the question, and answers with label “3” or “4” as irrelevant answers. Table 9 shows that 98.0% of the answers in the Full-100 set are considered to be relevant, according to the Agreed relevancy annotation. In other words, approximately 98% of (Q, A) pairs in the corpus are good question-answer pairs. On the other hand, the adopted answers are not more likely to be relevant to the question than the unadopted ones. Therefore, the Adopted flag is not a good indicator of an answer’s relevancy.

The next question is whether adopted answers tend to be better answers than unadopted ones. If so, we can use the Adopted flag to infer ranking labels as follows: if a QA record in the Full-100 set has exactly one adopted answer, we rank that answer higher than the unadopted one in the same record; if both answers in a QA record are adopted, they are considered to be equally good. Table 10 shows such inferred labels do not correlate well with human annotation. In fact, the correlation between inferred labels and the Agreed human annotation is only 0.068, when we use the 97 QA records with ranking label “1”, “2”, or “3”. Therefore, the Adopted flag is not a good indicator of relevant or better answers.
3.4 Two Datasets from ChiMed

As shown in Table 9, the majority of answers in ChiMed are relevant to the questions in the same QA records. To create a dataset for the relevancy task, we start with the 25,594 QA records which have exactly one adopted and one unadopted answer (see Table 4). Next, we filter out QA records whose questions or answers are too long or too short, because very short questions or answers tend to be lack of crucial information, whereas very long ones tend to include much redundant or irrelevant information. The remaining dataset contains 24,940 QA records. We divide it into training/development/testing subsets to distinguish relevant vs. irrelevant answers. We call this synthesized dataset ChiMed-QA2. We will use those two datasets for the adoption prediction task and the relevancy task (see the next section). We are not able to use the corpus for the answer ranking task as we cannot infer the ranking label from the Adopted flag.

3.4.1 Datasets.

For the relevancy task, we need both positive and negative examples. We start with ChiMed-QA1, and for each QA record, we keep the adopted answer as a positive instance, and replace the unadopted answer with an adopted answer from another QA record randomly selected from the same training/dev/testing subsets to distinguish relevant vs. irrelevant answers. We call this synthesized dataset ChiMed-QA2. We will use those two datasets for the adoption prediction task and the relevancy task (see the next section). We are not able to use the corpus for the answer ranking task as we cannot infer the ranking label from the Adopted flag.

Table 11: The answer does not directly answer the question, but it has an adopted flag.

| Q       | A                                               |
|---------|-------------------------------------------------|
| Why does gallstone always occur at night?    | 有些人会表现出过度劳累、腹胀、打鼾症状。可能是胆结石的原因，且通常晚上疼痛更严重，可以选择药物治疗。手术复发的可能性很大。建议平时多运动。Some people have symptoms of fatigue, bloating and snoring. They may be caused by gallstones, and usually the pain is more severe at night. You can choose medication. There is a high probability of recurrence of surgery. It is recommended to exercise more usually. |

Table 12: Statistics of the two ChiMed-QA Datasets. Average lengths of Qs and As are in characters.

|                  | Train | Dev | Test |
|------------------|-------|-----|------|
| # of Qs          | 19,952| 2,494| 2,494|
| # of As          | 39,904| 4,988| 4,988|
| Avg. Length of Qs| 63.5  | 63.8 | 63.3 |
| Avg. Length of As in ChiMed-QA1 | 118.7 | 118.6 | 118.0 |
| Avg. Length of As in ChiMed-QA2 | 128.0 | 127.6 | 127.1 |

3.4.2 Datasets.

For the relevancy task, we need both positive and negative examples. We start with ChiMed-QA1, and for each QA record, we keep the adopted answer as a positive instance, and replace the unadopted answer with an adopted answer from another QA record randomly selected from the same training/dev/testing subsets to distinguish relevant vs. irrelevant answers. We call this synthesized dataset ChiMed-QA2. We will use those two datasets for the adoption prediction task and the relevancy task (see the next section). We are not able to use the corpus for the answer ranking task as we cannot infer the ranking label from the Adopted flag.
Figure 1: The architecture of CNN- and LSTM-based systems under A-Only setting.

Figure 2: The architecture of our systems under A-A setting. The architecture of answer encoder is identical with the one in Figure 1. Prediction 1 and 2 means the prediction for answer 1 and 2, respectively.

Table 12 shows the statistics of the two datasets. The first three rows are the same for the two datasets; the average length of As in ChiMed-QA2 is slightly longer than that in ChiMed-QA1 because adopted answers tend to be longer than un-adopted ones.

4 Experiments on Two Prediction Tasks

In this section, we use ChiMed-QA1 and ChiMed-QA2 (See Table 12) to build NLP systems for the adoption prediction task and the relevancy prediction task, respectively. Both tasks are binary classification tasks with the same type of input; the only difference is the meaning of class labels (relevancy vs. adopted flag). Therefore, we build a set of NLP systems and apply them to both tasks.

4.1 Systems and Settings

We implemented both CNN- and LSTM-based systems, and applied three state-of-the-art sentence matching systems to the two tasks. The three existing systems are: (1) ARC-I (Hu et al., 2014) matches questions and answers by directly concatenating their embeddings; (2) DUET (Mitra et al., 2017) computes the Q-A similarity by matching exact terms and high-level sentence embeddings (Hadamard production) simultaneously; (3) DRMM (Guo et al., 2016) makes its final prediction based on the similarity matrix of each pair of word embeddings in a question and an answer.

We run our CNN- and LSTM-based systems under four different settings: (1) A-Only where an answer is the only input (See Figure 1); (2) A-A where both answers are input (See Figure 2); (3) Q-A where a question and one of its answers are input (See Figure 3); (4) Q-As where a question and both of its answers are input (See Figure 4). ARC-I, DUET, and DRMM are run under the settings of Q-A and Q-As, because the systems require a question to be one of the input. The reason we apply the A-Only and A-A settings to the adoption prediction task is that it helps identify whether features from an answer itself will contribute to its adopted flag assignment without knowing its question. To compare the relevancy task and the adoption prediction task, we also apply these two settings to the former task although they are not common settings in previous studies (Lai et al., 2018).

Word segmentation has always been a challenge in Chinese NLP especially when it is applied to a particular domain (Song et al., 2012; Song and Xia, 2012, 2013). Therefore, instead of word embeddings (Song et al., 2018), we use Chinese-character-based embeddings to avoid word segmentation errors. We set the embedding size to 150. We use 155 and 245 as the lengths of questions and answers respectively. Short texts are padded with blank characters. We use 32 filters
Table 13: Results of all systems under different settings with respect to (Q, A) pair prediction accuracy with (+CR) and without (-CR) conflict resolution. We do not present results of +CR in A-A and Q-As settings because they are equivalent to the results of -CR.

Table 13 shows the experimental results of running the five predictors on the testing set under four different settings. There are a few observations.

First, for the relevancy task, by designing only half of the (Q, A) pairs in ChiMed-QA2 come from the same QA records. When Q is not given as part of the input (System 1-4), it is impossible for the predictors to determine whether an answer is relevant; therefore, the system performances are no better than random guesses. In contrast, for the adoption prediction task, by designing all the (Q, A) pairs in ChiMed-QA1 come from the same QA records, and according to Table 9 we also know that about 98% of the answers, regardless of whether they are adopted or not, are relevant. Therefore, the absence of Qs in System 1-4 does not affect system performance a lot.

Second, when both Q and A are present (System 5-9), the accuracy of relevancy prediction is higher than that of adoption prediction, because the former is an easier task (at least for humans). The only exception is ARC-I (System 7), whose results on relevancy is close to random guess (50.34% and 50.60%) while the result on adoption is comparable with other systems. This is due to the way that ARC-I matches questions and answers. Because embeddings of a question and an answer are directly concatenated in ARC-I, Q-A similarity are not fully captured, leading to low performance on relevancy. On the contrary, the adoption prediction does not rely much on the Q-A similarity (as explained above).

Third, for the relevancy task, systems that capture more features of Q-A similarity tend to have a better result. For example, under the Q-A setting, DUET (System 8) outperforms CNN, LSTM and ARC-I (System 5-7) because DUET has an additional model of exact phrase matching between questions and answers. DRMM (System 9) performs better than DUET (System 8) because DRMM uses word embedding instead of exact phrase when matching pairs of phrases between a question and an answer. In contrast, the performances of the five systems on the adoption task are very similar.

In addition, except for the relevancy task evaluated with CR, the contrast between System 10-14 vs. System 5-9 indicates comparing two As always helps predictors in both tasks because intuitively knowing both answers would help us to decide which one is relevant/adopted. On the contrary, the comparison between the same two groups of systems with CR in the relevancy task indicates comparing two As may hurt the relevancy predictors (System 5, 7, 8) because the relevancy is really between Q and A, which might be affected by the existence of other As.

Finally, all the systems under A-Only and Q-A settings (Systems 1-2 and 5-9) benefit from CR. It

| Sys ID | Input Setting | NLP System | Relevancy Prediction | Adoption Prediction |
|--------|---------------|------------|----------------------|---------------------|
|        |               |            | -CR | +CR | -CR | +CR |
| 1      | A-Only        | CNN        | 50.80 | 51.64 | 74.10 | 81.64 |
| 2      | LSTM          | 50.66 | 50.72 | 74.24 | 82.00 |
| 3      | A-A           | CNN        | 49.40 | -  | 84.20 | -  |
| 4      | LSTM          | 50.28 | -  | 85.00 | -  |
| 5      | Q-A           | CNN        | 74.32 | 81.84 | 74.84 | 81.07 |
| 6      | LSTM          | 80.19 | 87.09 | 75.28 | 83.64 |
| 7      | ARC-I         | 50.34 | 50.60 | 75.20 | 82.64 |
| 8      | DUET          | 81.03 | 91.74 | 75.28 | 82.48 |
| 9      | DRMM          | 93.60 | 98.16 | 71.49 | 83.88 |
| 10     | Q-As          | CNN        | 76.98 | -  | 83.52 | -  |
| 11     | LSTM          | 88.41 | -  | 84.24 | -  |
| 12     | ARC-I         | 48.84 | -  | 83.88 | -  |
| 13     | DUET          | 87.17 | -  | 83.36 | -  |
| 14     | DRMM          | 98.32 | -  | 83.28 | -  |
is also worth noting that running the models under Q-A setting and to evaluate them without CR in previous studies (Lai et al., 2018) is much more common. Under this setting, the highest performance achieved is 93.60% (System 9). The score is not as high as our expectation and there still exist room for improvement.

4.3 Error Analysis for Relevancy Prediction

We go through errors of system 9 in the relevancy prediction task without CR and find three main types of errors. Note that we artificially build ChiMed-QA2 for the relevancy prediction task by keeping the adopted answer \( a \) of a question \( q \) and replacing the unadopted answer of \( q \) with an adopted answer \( a' \) from another question \( q' \). And we therefore regard \( a \) as a relevant answer of \( q \) and \( a' \) as an irrelevant answer of \( q \) (See Section 3.4).

The first type of error is that the answer \( a \) is actually irrelevant to the question \( q \). In other words, the gold standard is wrong; system 9 does make a correct prediction. This is not surprising as there are around 2% irrelevant answers in the dataset according to our annotation (See Table 9).

Second, the system fails to capture the relationship between a disease and a corresponding treatment. E.g., a patient describes his/her symptoms and asks for treatment. The doctor offers a drug directly without analyzing the symptoms and causes of disease. In that case, the overlap between the question and the answer is relatively low. The system therefore cannot predict the answer to be relevant without the help of a knowledge base.

Finally, it is quite common that a patient describes his/her symptoms at the beginning of the question \( q \) and asks something else at the end (e.g., whether drug X will help with his/her illness). In this case, if \( q' \) (the original question of the irrelevant answer \( a' \)) describes similar symptoms, the system may fail to capture what exactly \( q \) wants to ask and therefore mistakes \( a' \) for a relevant answer. Table 14 gives an error in this type where \( q \) and \( q' \) describe similar diseases but they are in fact expecting totally different answers.

Given the three types of errors, we find out the latter two are relatively challenging. This therefore requires further exploration on the way of modeling (Q, A) pairs in the relevancy prediction task. In addition, because current irrelevant answers are randomly sampled from the entire dataset, the current dataset does not include many challenging examples. This makes relevancy prediction task appear easier than what it could be. For future work, we plan to balance the easy and hard instances in the dataset by adding more challenging examples to ChiMed-QA2.

5 Conclusion and Future Work

In this paper, we present ChiMed, a Chinese medical QA corpus collected from an online medical forum. Our annotation on a small fraction of the corpus shows that the corpus is of high quality as approximately 98% of the answers successfully address the questions raised by the forum users. To demonstrate the usage of the corpus, we extract two datasets and use them for two prediction tasks. A few benchmark systems yield good performance on both tasks.

For the future work, we are collecting data to expand the corpus and plan to add more challenging samples to the datasets. In addition, we plan to use ChiMed for other NLP tasks such as automatic answer generation, keyphrase generation, summarization, and question classification. We also plan to explore various methods of adding more annotations (e.g., answer ranking) to the corpus.
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