

# Attention-based Aspect Reasoning for Knowledge Base Question Answering on Clinical Notes

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Question Answering (QA) in clinical notes has gained a lot of attention in the past few years. Existing machine reading comprehension approaches in clinical domain can only handle questions about a single block of clinical texts and fail to retrieve information about different patients and clinical notes. To handle more complex questions, we aim at creating knowledge base from clinical notes to link different patients and clinical notes, and performing knowledge base question answering (KBQA). Based on the expert annotations in n2c2, we first created the ClinicalKBQA dataset that includes 8,952 QA pairs and covers questions about seven medical topics through 322 question templates. Then, we proposed an attention-based aspect reasoning (AAR) method for KBQA and investigated the impact of different aspects of answers (e.g., entity, type, path, and context) for prediction. The AAR method achieves better performance due to the well-designed encoder and attention mechanism. In the experiments, we find that both aspects, type and path, enable the model to identify answers satisfying the general conditions and produce lower precision and higher recall. On the other hand, the aspects, entity and context, limit the answers by node-specific information and lead to higher precision and lower recall.

CCS Concepts: • **Mathematics of computing** → **Graph algorithms**; • **Computing methodologies** → **Neural networks**; **Learning latent representations**; **Information extraction**.

Additional Key Words and Phrases: Clinical knowledge base, question answering, aspect representation, attention mechanism.

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## 1 INTRODUCTION

Electronic Health Records (EHR) provide comprehensive information that can assist doctors with their clinical decision making. Traditionally, doctors retrieve the information of patients via accessing structured databases with rule-based systems and reading their clinical notes. Recently, several attempts have been made to build Question-Answering (QA) systems on EHR [16, 22, 30], so doctors can get answers for their questions more efficiently. Generally speaking, QA systems can be grouped into several categories according to the format of data sources. For example, machine reading comprehension (MRC) performs QA on plain text data [18]. Text-to-SQL problem performs QA on database [33, 34]. Knowledge Base QA (KBQA) [6] aims at finding answers from the underlying Knowledge Base (KB), such as Freebase [4]. Wang *et al.* introduced a MIMICSQL dataset for Text-to-SQL generation on MIMIC III database [30].

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Table 1. Comparisons of the answerable questions over different types of EHR, including Clinical Notes (CN), Structured Tables (ST) and Knowledge Base (KB). The symbol “✓” indicates that the questions are answerable.

Questions	CN	ST	KB
Q1: What medications has patient P939003 ever been prescribed?	✓	✓	✓
Q2: For patient P164, what are the comorbidities associated with Asthma?	✓	✓	✓
Q3: What does patient P961115 take ibuprofen for?	✓		✓
Q4: Give me all diseases that are revealed by non contrast head ct scan on patient P0126.	✓		✓
Q5: Which patients have been diagnosed with both Gout and GERD?		✓	✓
Q6: Give me all patients who have been prescribed with propofol.		✓	✓
Q7: Which medications can be prescribed for preventing creatinine?			✓
Q8: What are the obese indicators of heart disease in all medical records of patient P258?			✓

However, their system is limited to retrieving answers from a database, which does not have information that cannot be quantified, such as family history and discharge conditions. Pampari *et al.* proposed an emrQA dataset for MRC on clinical notes [16]. However, their model can only access information from a single block of texts, which is not practical for doctors who may need information from a collection of clinical notes.

In this work, we present ClinicalKBQA, a dataset for QA on clinical KB (ClinicalKB) constructed from clinical notes, which alleviates the problems encountered with emrQA by allowing doctors to access information across different notes. ClinicalKBQA is composed of two subsets, namely, Clinical Knowledge Base (ClinicalKB) and Question-Answering (QA) pairs, both of which are constructed by leveraging existing annotations of clinical notes that are available for various NLP tasks in n2c2 (previously known as i2b2).

ClinicalKB integrates advantages of both structured database and unstructured clinical notes. On the one hand, the intrinsic graph structure of ClinicalKB connects the information of different patients and clinical notes via relations/edges, which allows it to answer questions associated with many patients and clinical notes (e.g., Q5-Q8 in Table 1). On the other hand, ClinicalKB includes comprehensive patient information as in clinical notes, which makes it possible to answer questions not covered in database (e.g., Q3, Q4, Q7, and Q8 in Table 1).

To tackle the KBQA challenges in ClinicalKBQA dataset, we proposed an attention-based aspect reasoning (AAR) approach. Specifically, for each input question, we represent each candidate answer as four aspects, including entity, type, path, and context, and analyze the matching scores between the input question and candidate answers based on their embeddings. Through the results analysis, we found that the impact of different candidate aspects on retrieving final answers tends to be different. Two aspects, entity and context, provides the node specific information, which helps to retrieve nodes that satisfy the constraints specified in the questions. While the general information included in the other two aspects, type and path, are helpful for the model to filter out more nodes that satisfy the constraints of the node type and path.

In summary, the major contributions of this work are as follows.

- Created a dataset for knowledge base question answering task in healthcare domain, namely ClinicalKBQA, which consists of two sets: (i) ClinicalKB: which is a comprehensive clinical knowledge base created based on the expert annotations in n2c2 dataset, and (ii) QA pairs: a large-scale question answering dataset on ClinicalKB.
- Proposed an attention-based aspect-level reasoning (AAR) method for KBQA.
- Conducted experimental analysis on ClinicalKBQA dataset to demonstrate the effectiveness of AAR model and analyzed the significance of different aspects in providing accurate answers. We aim at improving current

Table 2. Comparison of ClinicalKBQA with other datasets for QA in healthcare domain.

Dataset	Data Source	QA Task	Answer Type
BioASQ	Biomedical Articles	MRC	Text Span
CliCR	Clinical Reports	MRC	Text Span
PubMedQA	Biomedical research	MRC	Text Span
emrQA	Clinical Notes	MRC	Text Span
MIMICSQL	Structured Clinical Tables	Text-to-SQL	SQL Query
ClinicalKBQA	Clinical Notes	KBQA	KB Entity

KBQA models in healthcare QA systems via addressing challenges presented by ClinicalKBQA and provide more efficient assistance for doctors to retrieve, understand, and utilize the clinical information in clinical notes.

## 2 RELATED WORKS

Question-Answering (QA) aims at automatically answering natural language questions about data sources in a variety of formats, including free text [18], knowledge base [8], and database [34]. Knowledge base question answering (KBQA) has gained a lot of attention in recent years with the rapid growth of large-scale knowledge bases, such as YAGO2 [11] and Freebase [4]. Advances in deep neural networks also allowed KBQA models to be trained in an end-to-end manner [5, 7, 10] and achieve competitive performance compared to traditional semantic parsing based methods [1, 15].

QA in the healthcare domain is still an underexplored research topic, especially due to the lack of large-scale annotated datasets and patient privacy issues [13]. Traditional biomedical QA depends on rule-based or heuristic feature-based methods [2]. Recently, several datasets have been created for machine reading comprehension (MRC), including BioASQ for semantic indexing and QA [23], CliCR for MRC on clinical case reports [22], PubMedQA for MRC on biomedical research texts [12] and emrQA for MRC on clinical notes [16]. MIMICSQL [30] was presented for QA on structured EMR data by translating questions to SQL queries. These datasets allow researchers to handle unique challenges present in the healthcare domain. Table 2 shows a comparison of our ClinicalKBQA to these datasets for QA in healthcare. There are several works about knowledge base in healthcare. SNOMED [9] is a KB with standard clinical terminologies for healthcare documentation. Unified Medical Language System (UMLS) [3] is an integration of medical terminology, classification and coding standards including SMOMED. Rotmensch *et al.* [19] learnt a knowledge graph of symptom and disease from EMR by considering the importance measure between terms.

## 3 THE CLINICALKBQA DATASET

ClinicalKBQA consists of two subsets, i.e., ClinicalKB and QA pairs. In this section, we will explain how we created the clinical knowledge base and the question answering dataset.

### 3.1 ClinicalKB

The n2c2 challenge data provide fine-grained document-level expert annotations of clinical records for various NLP tasks in clinical domain. We leverage the annotations about seven tasks to build the clinical knowledge base.

- **Smoking status classification** [26]: Each clinical record is annotated with the smoking status from five possible categories (including current smoker, past smoker, non-smoker, smoker and unknown) along with the smoking-related facts mentioned in the records.

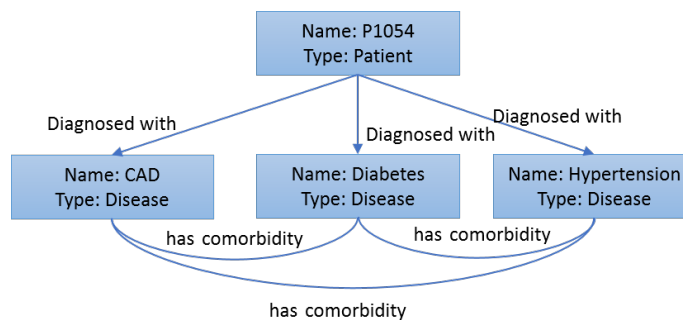


Fig. 1. A subgraph example about diagnosed diseases and their comorbidity relationships in *Obesity* dataset.

- **Identification of obesity and its co-morbidities** [24]: Each clinical record is annotated with obesity and co-morbidities using both textual judgments (explicitly) and intuitive judgments (implicitly).
- **Medication extraction** [27]: The medication-related information including medication name, dosage along with the mode, frequency, duration and reason of the administration, is annotated in each clinical record.
- **Analysis of relations of medical problems, tests and treatments** [28, 29]: The annotations for concept, assertion, and relation information are provided in each clinical record.
- **Co-reference resolution** [25]: Each clinical record is annotated with concept mentions that are referring to the same entity.
- **Temporal information extraction and reasoning** [21]: The clinically significant events and temporal expressions are annotated along with the temporal relation between them in each clinical record.
- **Risk factors identification of heart disease** [20]: Each clinical record provides the annotation of medically relevant information about heart disease risk factors including the status of smoking, obesity, medication and hypertension.

The narrative blocks in clinical notes, such as family history, provide more detailed clinical information from different aspects and can be efficiently extracted with rule-based methods as additional annotations.

Grounded on domain expert annotated clinical notes in the n2c2 challenge data, we construct clinical KB by following two steps: (1) *Identify entities*. An entity is represented by its name and type. For example, {name: “ibuprofen”, type: “medication”}. (2) *Build triples*, i.e., (subject, predicate, object). Here, both subject and object are entities, and predicate is a relation between them. For example, we can construct a triple (“P961115”, “prescribed with”, “ibuprofen”) based on “a patient with ID P961115 has medication ibuprofen”. In addition, we have also fixed some problems in the annotations during pre-processing, such as pronouns like “this/a/his/her” and irrelevant punctuation.

**3.1.1 Subgraph Examples in ClinicalKB.** We provide a subgraph example in Obesity dataset about diagnosed diseases for patient P1054 and their comorbidity relationships in Figure 1. Based on the clinical note of patient P1054, he/she has been diagnosed with three diseases, including CAD, Diabetes and Hypertension. Since the annotations in Obesity dataset focus on the comorbidities relations of different diseases, we include such comorbidity relation between these three diseases.

Figure 2 shows the relationships between patient P961115 and the prescribed medications along with other detailed attribute information including dosage, frequency, duration, and reason. We observe that not all attribute information is

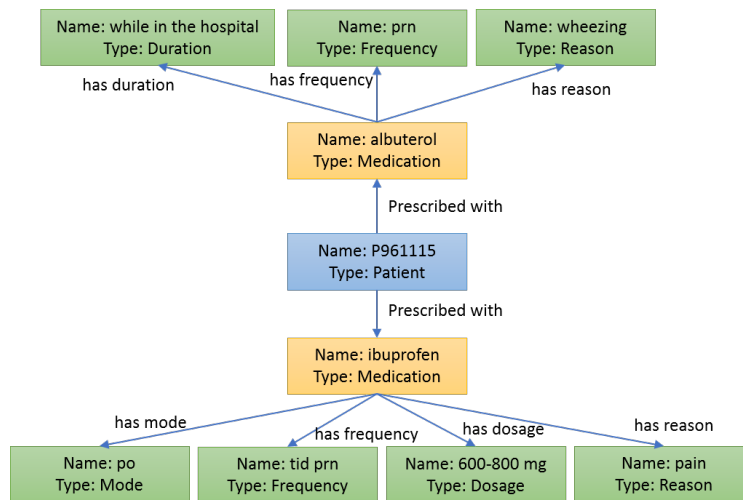


Fig. 2. A subgraph example about prescribed medications along with their related information in *medication* dataset.

available for each medication. For example, the duration is only mentioned for albuterol, while the mode and dosage are mentioned only for ibuprofen. We hope that these two subgraph examples can provide an overview for understanding about patient information covered in ClinicalKB. Detailed statistics about ClinicalKB are summarized in Table 3.

### 3.2 Question-Answer (QA) Pairs

**Question Collection:** We first collect a set of questions by polling real interests of physicians and considering existing clinical question resources, including emrQA and MIMICSQL, and further identify questions that can be answered by ClinicalKB. Compared with QA on structured tables [30] and clinical notes [16], we found that questions on ClinicalKB cover a wide range of topics (see Table 1). Some questions are not answerable by structured tables or a single clinical note. Take Q8 as an example, “indicators of diseases” is usually not included in structured tables, and “all medical records” indicates answers cannot be found in a single note.

We then manually identified specific entities in the selected questions and replace them with generic placeholders to normalize and form question templates. In total, we generated a set of 322 question templates, including various paraphrases of questions with the same meanings. For example, the template for Q3 in Table 1 is “*What does patient |Patient| take |Medication| for?*”, where the generic placeholders *|Patient|* and *|Medication|* are the topic entities of the question that need to be replaced by the corresponding ClinicalKB entities during question generation. We hope that the questions we collected from domain experts and the existing clinical question sources recognized by the community can provide a helpful resource of QA for researchers in both the medical domain and NLP community.

**QA Pairs Generation:** This step focuses on populating question templates and identifying corresponding answers. Since patient private information is de-identified in n2c2, we use patient IDs instead of names in patient-specific questions. Each question template may have multiple ways to populate. For example, the template of Q3 mentioned previously can be populated with different combinations of *|Patient|* and *|Medication|*. However, we do not need to enumerate all possible questions for it. In practice, we applied two constraints to limit repetitions: (1) Set a threshold to

Table 3. Statistics of ClinicalKB and QA pairs created based on the n2c2 dataset. Here, QuesLen, GoldAns and CandAns represent question length, gold-standard answers and candidate answers, respectively.

Metric	Smoking	Obesity	Medications	Relations	Co-reference	Temporal	Risk
# Patients	502	1,103	261	426	424	310	119
# Entities	6,160	17,861	28,821	20,031	1,581	127,772	6,984
# Entity types	49	42	46	7	7	20	15
# Triples	9,730	42,474	53,519	30,401	1,378	276,513	24,553
# Relations	5	8	14	11	7	13	11
# Question Templates	26	37	59	74	18	29	79
# QA pairs	600	1,126	1,847	2,389	444	626	1,920
Min/Max/Avg QuesLen	4/10/8	5/14/9	5/17/10	6/21/11	8/17/12	8/19/11	8/21/17
Min/Max/Avg # GoldAns	1/82/5	1/816/27	1/111/10	1/29/3	1/2/2	1/239/19	1/69/5
Min/Max/Avg # CandAns	5/2,665/999	3/8,686/2,261	2/6,240/68	4/679/79	3/6/4	5/1,543/175	2/74/17

the total number of questions generated for each template. (2) Remove questions without answers. The corresponding answers to each question is simultaneously extracted from clinical notes when generating questions.

### 3.3 Data Analysis

**Basic Statistics:** The statistics of ClinicalKB and QA pairs are presented in Table 3. From this table, we can observe that our ClinicalKB covers seven important medical topics in n2c2. The total number of QA pairs is 8,952. We created more question templates and QA pairs for *Medications*, *Relations* and *Risk* because their annotations are more comprehensive. The average question length is 12 in terms of tokens. Each question has at least one gold-standard answer and a lot of questions have multiple answers. In this work, we refer to the collection of ClinicalKB and QA pairs as the ClinicalKBQA dataset. The number of entities in golden and candidate answers are 9 and 402 in average, respectively. The number of golden and candidate answers for questions in *Co-reference* is relatively small since the variety of annotated terms with the same meaning are small. More details about ClinicalKBQA are provided in Table 3.

**Question Types:** Our primary goal of knowledge base question answering on clinical notes is to extract patient information from unstructured clinical text. Therefore, all questions included in our ClinicalKBQA dataset are factoid questions which aim to seek reliable and concise medical history information about patients. We group the questions in ClinicalKBQA dataset into different types based on the starting words. The distributions of question types showed in Figure 3(a) are generated based on the most common first two starting words in all questions. Table 4 provides the quantitative percentage of various question types along with specific examples. It can be observed that the questions starting with “What”, “List/Search/Give/Provide” and “Which” account for a large proportion of the dataset and aim to ask for detailed medical facts, such as prescribed medications and the smoking status. The questions starting with “Why” and “How” tend to be open-ended in many open-domain question answering datasets. However, in the ClinicalKBQA dataset, the “Why” and “How” types of questions are mainly included for retrieving attribute facts about medication, including prescribed reason, dosage, frequency, and duration. In addition, the question type “When” are included for extracting the admission and discharge time of patients.

In Figure 3(b), we also show a distribution of the most common bigrams used in all questions in ClinicalKBQA dataset. It provides an overview about the specific patient information that various questions aim to extract from clinical notes.

**Question Coverage:** Table 1 provides a comparison of questions that can be answered on different types of EHR data including clinical notes (CT), structured tables (ST) and knowledge base (KB). We can observe that knowledge base of patient clinical information is able to answer the basic questions that are answerable by QA on both clinical notes and



Q5 and Q6, the machine reading comprehension on emrQA cannot provide answers since these questions are related to multiple clinical notes. ClinicalKB is able to integrate the information in different clinical notes or about different patients into a general network structure, which makes it feasible to handle more complexed questions about patients.

## 4 KNOWLEDGE BASE QUESTION ANSWERING MODELING

### 4.1 Candidate Generation

It will be computationally expensive for KBQA models to directly search answers from ClinicalKB. Therefore, we first generate a candidate subgraph for each question in two steps: (1) We identify one of the entities in the question template as the topic entity (root), and collect all entities connected to it within 3-hop as a candidate subgraph. Each entity in the subgraph except the root is viewed as a candidate answer. For the ClinicalKBQA dataset, the answers to all questions are reachable within 3-hop of their topic entities. (2) We treat the remaining entities in the question as constraints to the candidate sub-graph, and further prune the graph to ensure that paths to the topic entity satisfy the constraints and include entities with expected answer type. For example, the answer type for Q3 is “disease”. Topic entities are “P961115” and “ibuprofen”. If we treat “P961115” as root, then, one possible path is [“P961115”, “*prescribed with*”, “ibuprofen”, “*has reason*”, “right leg pain”, “*has comorbidity*”, “pain control”] since it has “ibuprofen”. This path is further pruned to [“P961115”, “*prescribed with*”, “ibuprofen”, “*has reason*”, “right leg pain”] because answer type is “disease”. We show the statistics of candidate answers in Table 3.

### 4.2 Attention-based Aspect Reasoning

Generally speaking, there are two groups of methods for KBQA task, i.e., semantic parsing-based [32] and information retrieval-based (IR-based) [31] methods. As an important category of information retrieval-based KBQA methods, embedding-based approaches [5, 10] usually map questions and answer candidates onto a common embedding space and directly calculate their matching scores. Then, ranking techniques are adopted to search answers from KB for given questions. We proposed an embedding-based End-to-End model on ClinicalKBQA dataset that incorporates an attention mechanism between question representations and aspect-level answer candidate representations to calculate matching scores. We will introduce this Attention-based Aspect Reasoning (AAR) approach for knowledge base question answering with more details as follows. Specifically, there are mainly four components in the AAR model: (1) Question Representation: the vector representations of the input question are obtained by a single-layer bidirectional Long short-term memory (LSTM). (2) Graph Representation: for each candidate answer, we considered four aspects based on the answer subgraph, including entity, entity type, path to topic entities, and context entities. Hereafter, we refer them as entity, type, path, and context, respectively. (3) Attention Mechanisms: this reasoning process allows us to capture the underlying dependencies between input question and different aspects of the candidate answers. (4) Scoring: first, distances (i.e., similarity scores) between the input question and the candidate answers in the hidden space are calculated; and then, predicted answers are selected via re-ranking based on the scores. Figure 4 shows the framework of our AAR model. In the following section, we will introduce more details of each component.

**Question Representations:** The question encoder is composed of a word-embedding layer followed by a bi-directional LSTM layer, which encodes a question  $q = (q_1, q_2, \dots, q_{|q|})$  into a sequence of hidden states  $H^q = (h_1^q, h_2^q, \dots, h_{|q|}^q)$ , where  $q_i$  and  $h_i^q$  represent the  $i^{th}$  token and its corresponding hidden state, respectively.  $|q|$  is the length of the input question.



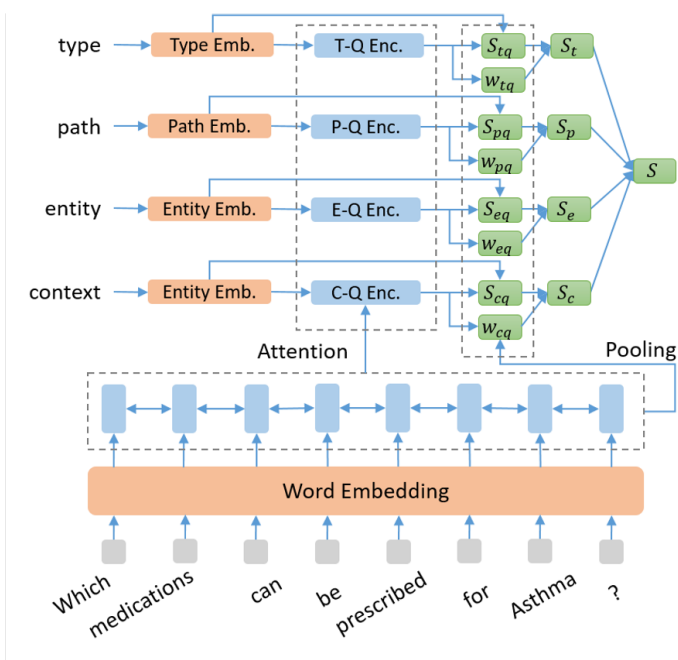


Fig. 4. The overall framework of AAR model.

**Graph Representation:** To encode candidate subgraphs of the knowledge base, we first convert each subgraph to a candidate answer set, where each element (i.e., node) in the set represents an entity in the subgraph, which has four aspects of information:

- Entity ( $h_k^e$ ) represents the embedding of the node  $k$  in a knowledge base.
- Type ( $h_k^t$ ) denotes the entity type of the node  $k$ . It provides important clue for finding an answer. For example, given a question such as “Give me all patients who have been diagnosed with heart failure.”, the answer type should be “Patients”.
- Path ( $h_k^p$ ) represents a path from the topic entity node of a subgraph to the current candidate node. Thus, the path provides relationships between the topic entity and the candidate answer. In the above example, the topic entity is “heart failure”.
- Context consists of all neighboring nodes of the current candidate node  $k$ . We encoded the context of each candidate answer  $c_k = (c_{k_1}, c_{k_2}, \dots, c_{k_c})$  as a list of hidden states  $H_k^c = (h_{k_1}^e, h_{k_2}^e, \dots, h_{k_c}^e)$ , where  $c_{k_i}$  is the  $i^{th}$  context node in the context of node  $k$ , and  $h_{k_i}^e$  represents its corresponding entity embedding. For simplicity, in the following part of the section, we will use  $h^e$ ,  $h^t$ ,  $h^p$  and  $H^c$  to represent  $h_k^e$ ,  $h_k^t$ ,  $h_k^p$  and  $H_k^c$ , respectively.

Among these four aspects, the entity and context provide node-specific information, which help us identify more specific nodes in the graph. On the other hand, the type and path represent general information and help us filter out nodes in the graph that satisfy the constraints of the node type and path.

**Attention Mechanisms:** Now, we discuss the reasoning process over a candidate graph through attention mechanisms, which can discover underlying correlations between a question and different features/aspects of any candidate node. Here, we will use the attention between aspect “type” and the input question, namely type-to-question attention, to

illustrate how the attention mechanism works. Given the question representation  $H^q = (h_1^q, h_2^q, \dots, h_{|q|}^q)$ , and the type embedding  $h^t$ , the alignment score  $u^{t2q}$  and attention weight  $\alpha^{t2q}$  are calculated as follows.

$$u_i^{t2q} = (h^t)^T \tanh(W_{t2q} h_i^q + b_{t2q}) \quad (1)$$

$$\alpha_i^{t2q} = \frac{\exp(u_i^{t2q})}{\sum_{j=1}^{|q|} \exp(u_j^{t2q})} \quad (2)$$

where  $W_{t2q}$  and  $b_{t2q}$  are model parameters. Finally, the type-related question representation, namely type-to-question representation, is obtained by

$$r^{t2q} = \sum_{j=1}^{|q|} \alpha_j^{t2q} h_j^q \quad (3)$$

where,  $r^{t2q}$  can be considered as a question representation which incorporates type information. Similarly, we can also obtain such representations for other aspects, including path, entity, and context. Hereafter, they are denoted as  $r^{e2q}$ ,  $r^{p2q}$  and  $r^{c2q}$ , respectively.

**Scoring Answers:** The prediction of answers is made based on the similarity score between the input question and each answer candidate, which is a weighted average score of distances between questions and different answer aspects of each candidate. For each aspect, we first calculate the similarity of its embedding and aspect-to-question representation as follows:

$$s_{tq} = (h^t)^T r^{t2q} \quad (4)$$

Since different aspects of candidate answers are not equally important to the final predictions, we also calculate the weight of each aspect as follows.

$$w_{tq} = (H_{avg}^q)^T r^{t2q} \quad (5)$$

where  $H_{avg}^q$  represents the question representation obtained by performing average-pooling over the sequence of hidden states of the question  $H^q = (h_1^q, h_2^q, \dots, h_{|q|}^q)$ . Therefore, the final score of each candidate answer  $a$  can be obtained as follows:

$$S(q, a) = w_{eq} s_{eq} + w_{tq} s_{tq} + w_{pq} s_{pq} + w_{cq} s_{cq} \quad (6)$$

In the testing phase, candidate answers are ranked based on their scores.

**Training:** In the ClinCalcKBQA task, we treat the answer retrieval problem as a ranking problem and adopt a pair-wised strategy to train our model. Intuitively, ground truth answers should have higher scores than the other candidate answers. Therefore, during training, for each ground-truth answer node  $a$  (positive example), we randomly select a candidate node (not an answer)  $a'$  as a negative example. The training loss is a max-margin hinge loss and defined as follows:

$$L = \min \frac{1}{|B^q|} \sum_{(a, a') \in B^q} [\gamma + S(q, a) - S(q, a')]_+ \quad (7)$$

where  $S(q, a)$  and  $S(q, a')$  are the final scores of nodes  $a$  and  $a'$ , respectively.  $\gamma \in (0, 1)$  is a real number that indicates the margin between the positive and negative examples.  $[\cdot]_+$  represents the hinge loss, which is defined by  $\max(0, \cdot)$ . Here,  $B^q$  denotes a set of positive-negative example pairs  $(a, a')$ , and  $|B^q|$  is the batch size. Intuitively, the hinge loss function increases the margin between the positive and negative examples and allows us to select multiple answers from a set of candidate answers instead of the best answer only.

Table 5. Performance results on ClinicalKBQA. # Ans denotes the number of answers predicted by models on testing set. Number of ground-truth answers is 16,251.

Models	# Ans	Precision	Recall	Accuracy	Micro-F1	Macro-F1
<b>SGEmb</b> (full)	2,726	0.7447	0.1249	0.5105	0.2139	0.6617
<i>entity &amp; sub-graph</i>	3,153	0.3866	0.0750	0.2370	0.1256	0.3807
<i>path</i>	26,597	0.4870	0.7966	0.7260	0.6045	0.8583
<b>AAR</b> (full)	3,492	<b>0.8072</b>	0.1735	0.6525	0.2856	0.7973
<i>entity &amp; context</i>	3,707	0.5964	0.1360	0.4725	0.2216	0.6645
<i>type</i>	120,128	0.1205	<b>0.8908</b>	0.3685	0.2123	0.6177
<i>path</i>	26,900	0.4780	0.7913	0.7665	0.5960	<b>0.9057</b>
<i>type &amp; path</i>	16,297	0.6598	0.6616	<b>0.7745</b>	<b>0.6607</b>	0.8980

**Inference:** During the testing, for each input question, we first retrieve a set of candidate answers  $C^q$  from the corresponding knowledge base, and then calculate the score for each candidate answer  $a \in C^q$ . The best answer is obtained by

$$a_{best} = arg \max_{a \in C^q} S(q, a) \quad (8)$$

Usually, there are multiple answers for each question, therefore, the candidate answers whose scores are close to the highest score within a margin can also be considered as answers. This inference process can be formulated as  $f(q, a) = 1$  if  $S(q, a) > S(q, a_{best}) - \gamma$ . Otherwise,  $f(q, a) = 0$ . Here  $f(q, a) = 1$  indicates that node  $a$  is the answer to the question  $q$ .

## 5 EXPERIMENTS AND ANALYSIS

### 5.1 Experimental Settings

We implemented both models and variants of AAR. Following prior work, we adopted micro-averaged precision, recall, and F1 score to evaluate different models. In our experiment, we split the data into training/development/testing sets with a proportion of 5952/1000/2000. We implemented the AAR model using Pytorch [17] and the best set of parameters are selected based on the development set. We set the size of embeddings for words, entities, entity types, and paths to topic entities to 300. The word embeddings are learnt from scratch. We adopted a single layer Bi-LSTM with the hidden size 150. All parameters were trained using ADAM [14] optimizer with a constant learning rate of 0.0001 for 10 epochs. In addition, we compare the performance of AAR with a subgraph-based approach SGEmb [5], which first calculates embeddings of words, entities, and path to topic entities. Then, each question representation is obtained by applying average pooling to word embeddings. Answer candidates are represented by entities, paths to topic entities, and subgraphs. This method is known as subgraph embedding. The ClinicalKBQA dataset and our implementation is made publicly available at this website<sup>1</sup>.

### 5.2 Experimental Results

From Table 5, we can observe that AAR achieves better results than SGEmb, which is because AAR is equipped with a better encoder, attention mechanisms, and entity *type* information. To explore the impact of each aspect in our ClinicalKBQA, we studied models with only one aspect of information. SGEmb-*entity & sub-graph* and AAR-*entity & context*, which only leverage entity embeddings, achieve relatively higher precision and lower recall, and the number of

<sup>1</sup><https://github.com/wangpinggl/Clinical-KBQA>

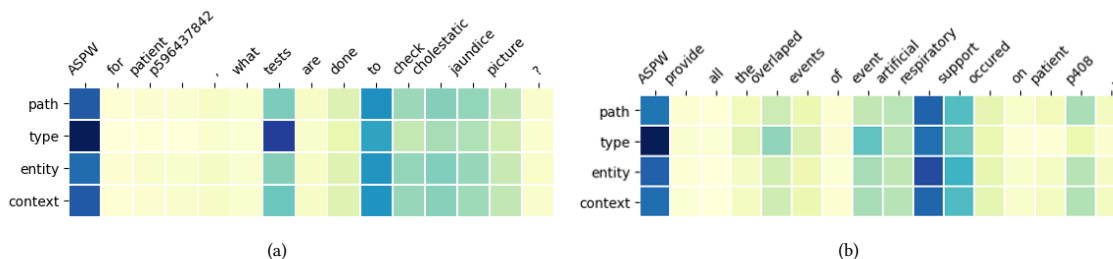


Fig. 5. Attention heatmaps generated by the cross-attention module. ASPW denotes weights for different aspects, which are *path*, *type*, *entity*, and *context*.

predicted answers is much fewer than that of ground-truth. This is because different answer candidates have different entity embeddings and matching scores, which makes the model favor the answer with the highest score.

On the other hand, models that only consider *path* and *type* achieve relatively lower precision and higher recall since different candidates may share common *type* and *path* embeddings and have the same matching score. Thus, the number of predicted answers are much more than that of the ground-truth. Models with only *path* information perform significantly better than other variants with only one aspect, which indicates *path* is the most significant factor for our ClinicalKBQA. Finally, *AAR-type & path* achieves the best accuracy and Micro-F1 score.

We have also shown the heat-map based on the attention mechanism for two input questions in Figure 5. In the first example in Figure 5(a), the model gives more weight to the aspect “type” among all four aspects, which indicates that the aspect “type” of candidate answers are the most important features for the final prediction. For aspect-towards-question attention, all four aspects capture the keywords “tests” and “to check cholestatic jaundice picture”. These important keywords are serving as the query conditions to identify qualified candidate answers whose node “type” is “test” and can be used “to check cholestatic jaundice picture”. For the second example in Figure 5(b), we can find that the aspect “type” is also the most important aspect for the candidate answers to satisfy the query conditions of “event” and “artificial respiratory support”. This analysis of attention weights is helpful for us to explain how the AAR model identifies correct answers for an input question. It also provides us insights about the impactful aspects of candidate answers to match the input questions on the ClinicalKBQA dataset.

## 6 CONCLUSIONS

In this work, we introduced a dataset for question answering (QA) on ClinicalKB, namely ClinicalKBQA, which is composed of two subsets, i.e., ClinicalKB and QA pairs. ClinicalKB is built from expert annotated clinical notes; thus, it allows doctors to ask questions on a collection of notes for different patients. We have also introduced a procedure for generating answer candidate subgraphs from ClinicalKB for given questions. In addition, an attention-based aspect-level reasoning model is developed for KBQA on the new created dataset. Finally, we conducted experimental analysis and studied the significance of different aspects in providing accurate answers.

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