RxWhyQA: a clinical question-answering dataset with the challenge of multi-answer questions

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Keywords: Question Answering, Multiple Answers, Dataset, Artificial Intelligence, Natural Language Processing

Word count: 1,899
ABSTRACT:

Objectives
Create a dataset for the development and evaluation of clinical question-answering (QA) systems that can handle multi-answer questions.

Materials and Methods
We leveraged the annotated relations from the 2018 National NLP Clinical Challenges (n2c2) corpus to generate a QA dataset. The 1-to-0 and 1-to-N drug-reason relations formed the unanswerable and multi-answer entries, which represent challenging scenarios lacking in the existing clinical QA datasets.

Results
The result RxWhyQA dataset contains 91,440 QA entries, of which half are unanswerable, and 21% (n=19,269) of the answerable ones require multiple answers. The dataset conforms to the community-vetted Stanford Question Answering Dataset (SQuAD) format.

Discussion
The RxWhyQA is useful for comparing different systems that need to handle the zero- and multi-answer challenges, demanding dual mitigation of both false positive and false negative answers.

Conclusion
We created and shared a clinical QA dataset with a focus on multi-answer questions to represent real-world scenarios.
BACKGROUND AND SIGNIFICANCE

Introduction

The thought process involved in clinical reasoning and decision-making can be naturally framed into a series of questions and answers [1, 2]. Achieving human-like question-answering (QA) capability is highly regarded in artificial intelligence (AI). Medical QA research has garnered terrific momentum over the past decade, and a new generation of AI scientists are updating “state-of-the-art” at a daunting pace of almost every month, if not week. One of the very sought-after applications is to find the answer within a given document (a.k.a. reading comprehension), which enables patient-specific QA based on the information mentioned in the clinical text. As an essential component in most AI engineering, QA training data determines the likelihood of success not only in terms of annotation quality but the fidelity of representing the target scenario. Along with other issues observed in existing medical QA corpora [3], the mainstream annotation approach knowingly simplifies the task into a “one answer per document” scheme. Although the simplification makes development and evaluation easier for promoting the initial growth of the field, it is unrealistic because medical QA can naturally have multiple qualified answers (or answer components) within one document and often all of them must be captured to sufficiently answer a question. To address this gap, we created a clinical QA dataset that involves realistic, multi-answer cases by converting the concept-relation annotations from an existing natural language processing (NLP) challenge dataset. Our generated RxWhyQA dataset includes a total of 91,440 QA entries, of which 21% require identification of multiple answers.

Related work
The reading comprehension QA task in general NLP has more than a decade of research, with the Stanford Question Answering Dataset (SQuAD) [4] long serving as an iconic corpus and a benchmark for AI solutions. A notable enhancement in the later SQuAD 2.0 task [5] also requires a QA system to refrain from answering when no suitable answer is present in the text. In the clinical domain, there have been corpora developed for reading comprehension QA based on electronic health records (EHR). In Raghavan et al. [6], medical students were presented with structured and unstructured EHR information of each patient to come up with realistic questions for a hypothetical office encounter. The patient’s notes were then loaded into an annotation tool for them to mark answer text spans. Pampari et al. [7] developed the emrQA, a large clinical QA corpus generated through template-based semantic extraction from the i2b2 NLP challenge datasets. We took a similar approach as emrQA, but additionally included unanswerable questions like SQuAD 2.0 and multi-answer questions that better reflect natural clinical QA scenarios.

MATERIALS AND METHODS

Generating the RxWhyQA dataset from a relation identification challenge

Our source data was based on the annotations originally created for the National NLP Clinical Challenges (n2c2) of 2018, which aimed to identify adverse drug events (ADEs) by extracting various drug-related concepts and classifying their relations in clinical text [8]. Their final gold standard included 83,869 concepts and 59,810 relations in 505 discharge summaries. For the RxWhyQA, we focused on generating whyQA pairs from the subset of drug and reason concepts (i.e., more about the prescribing indication or justification) and the relations between the concepts. Each drug-reason relation consisted of two arguments: a drug concept and a reason
concept, e.g., *drug-reason* (morphine, pain). Accordingly, we could derive a question around the drug concept: “Why morphine was prescribed to the patient?” and the reason concept “pain” was designated as an answer. In the n2c2 corpus, each pair of drug and reason concepts also had their text mentions annotated in the corresponding clinical note.

From the n2c2 annotations on each clinical note, we leveraged several relation types between the drug and reason concepts: 1 drug 0 reason, 1 drug 1 reason, 1 drug N reasons, or N drugs 1 reason. The most straightforward were the 1 drug 1 reason relations (e.g., the morphine-pain relation above), each translated into a 1-to-1 QA. The 1 drug 0 reason relations apparently corresponded to the 1-to-0 (unanswerable) QA entries. To conform to the community-established SQuAD format with a single concept in question, we preserved the 1 drug N reasons directly as 1-to-N QAs, while breaking each N drugs 1 reason relation into N 1-to-1 QAs. That is, instead of asking “Why amlodipine, metoprolol, and isorbide were prescribed to the patient?”, we put only one drug a time and made three separate questions to avoid overloading one question with the combinatorial specifics. On top of the generated QA entries, we also supplemented paraphrastic questions [9] that may benefit the generalizability of the systems potentially trained on RxWhyQA.

**Quantitative and qualitative analyses of the derived RxWhyQA dataset**

**Identify the frequent question and answer concepts**

In addition to summary statistics of the QA entries and the number of answers per question, we computed frequencies of the specific drug and reason concept terms (after applying lexical
normalization such as lowercase) among the QA entries. The frequencies were meant to offer an intuitive estimate for the abundance of train/test data available for each specific concept or concept pair.

Measure the distance between the question and answer concepts

A rule-based sentence splitter was implemented to preprocess the clinical notes, allowing us to measure the distance (by the number of sentences) between the question and answer concepts. For each specific drug-reason pair, we took that with the shortest distance if there were multiple occurrences of either concept. The distance was deemed 0 if the pair occurred within the same sentence. Such distance may serve as a surrogate for measuring potential difficulty, where a longer distance implies a more challenging task.

Identify common contextual patterns relevant to the QA inferences

We randomly sampled 100 QA entries for manual review: 50 from those with a single answer and 50 from those with multiple answers. The common patterns informative to QA inference were summarized, offering a clue on what the potential AI solutions could leverage.

RESULTS

Summary of the RxWhyQA dataset

We leveraged a total of 10,489 relations from the n2c2 ADEs NLP challenge and derived the RxWhyQA dataset, consisting of 91,440 QA entries. Table 1 summarizes the four major drug-reason relation categories in the n2c2 corpus, the strategies that we implemented to convert them into QA entries and the resulted QA frequency in RxWhyQA. About half (51%) of QA entries
are unanswerable, and the other answerable half consisted of 1-to-1 QAs (28%) and 1-to-N QAs (21%). Figure 1 shows the detailed distribution for the number of answers per question. Note that duplicate answer terms located at different positions of the clinical notes were retained. For example, the procedure “CT” might occur at several places in the text and be recorded as the answer to “Why was the patient prescribed contrast?” We included each such identical term and their different offset as multiple answers so that AI solutions may leverage such nuances. The final RxWhyQA was formatted into a SQuAD-compatible JSON file and shared through the n2c2 community annotations repository (https://portal.dbmi.hms.harvard.edu/projects/n2c2-du/).

Figure 2 illustrates a multi-answer QA entry in RxWhyQA.

### Table 1. Categories, examples, and conversion strategies for making the drug-reason relations into the QA entries of RxWhyQA.

| Category in the n2c2 corpus | Example | Conversion strategy | Frequency (%) in RxWhyQA |
|-----------------------------|---------|---------------------|--------------------------|
| 1 Drug, no Reason           | Mirtazapine 15 mg PO QHS. [only the drug is mentioned but no reason is documented] | Make an unanswerable QA entry | 46,278 (51%) (1-to-0 QA) |
| 1 Drug, 1 Reason            | The patient received morphine for pain as needed. | Make a 1-to-1 QA entry | 25,893 (28%) (1-to-1 QA) |
| N Drugs, 1 Reason           | Hypertension: Severely elevated blood pressure. Started amlodipine, metoprolol, and isorbide. | Break into N separate 1-to-1 relation and make each a 1-to-1 QA entry | 25,893 (28%) (1-to-1 QA) |
1 Drug, N Reasons

*albuterol sulfate* 90 mcg… Puff Inhalation Q4H for sob or wheeze.

List the N reasons under answer block to form a 1-to-N QA entry

19,269 (21%)

(1-to-N QA)

**Figure 1.** Distribution for the number of answers per question in the RxWhyQA dataset. The 0 means an unanswerable question.
Figure 2. A multi-answer entry in the RxWhyQA. The “id” field is the unique ID for the QA entry in the dataset. The “_mname” field indicates medication name, i.e., the anchor concept in the question. The “answer_start” is character offset where the answer term occurs in the clinical note, which is hosted in the “context” field (not shown here). When “is_impossible” is false, which means this is an answerable QA entry.

Content analysis of the RxWhyQA dataset

The five most frequently asked drug terms (noting the number of QA entries) in the answerable questions are: coumadin (1,278), vancomycin (1,170), Lasix (963), acetaminophen (801), and antibiotics (783). Interestingly without any overlap, the five most frequent drug terms in the unanswerable questions are: docusate sodium (648), metoprolol tartrate (504), aspirin (468), pantoprazole (450), and penicillins (414). Among the answerable QA entries, the five most frequently seen pairs are: acetaminophen-pain (504), senna-constipation (369), oxycodone-pain
(261), coumadin-afib (252), and acetaminophen-fever (234). As a potential surrogate measure of the task difficulty, Figure 3 shows the distribution for the number of sentences between the question anchor and answer term in each answerable QA entry. The majority (72%, n=32,409) of the drug and reason terms occur within the same sentence, and the portion increases to 90% (72%+18%) when adding those with the drug and reason occurring in an adjacent sentence (i.e., distance=1). In the extreme case, the drug and reason terms are 16 sentences apart from each other. Table 2 summarizes the commonly observed contexts from manually reviewing 100 random samples of the answerable QA entries.

![Figure 3](image.png)

**Figure 3.** Distribution for the distance between the question anchor (drug) and answer term (reason). A distance of 0 indicates that the drug and reason terms occur within the same sentence.
**Table 2.** Common patterns (observed >10 times) between the question and answer terms in 100 random QA entries. Each **Reason** or **Drug** represents where a question or answer anchor term occurs in the pattern. The shorthands are used as follows: ellipsis stands for zero to multiple words, round brackets are for scoping, square brackets with pipes indicate a boolean ORed set, and a question mark is a binary quantifier for presence or absence.

| Pattern | Frequency |
|---------|-----------|
| **Reason** … (being)? [received|started|restarted|required|maintained|continued?] (on)? **Drug** | 25 |
| **Drug** … [prn|PRN|[as needed for]?] **Reason** | 18 |
| **Drug** … (was)? [attempted|given|dosing|taking] for (any)? [possible|likely|presumed]? **Reason** | 14 |
| **Reason** … (was)? [managed|treated|improved|recommended|downtrended|resolved|reversed|needed] with **Drug** | 13 |

**DISCUSSION**

The generated RxWhyQA dataset can serve training and testing AI systems that target excerpting pertinent information in a clinical note to answer patient-specific questions. In addition to the unanswerable questions that require a system to refrain from extracting false positive answers, the RxWhyQA features 21% of multi-answer QA entries (n=19,269) that represent a realistic challenge in clinical QA. The multi-answer scenario is a key improvement beyond existing datasets, which are limited to a single answer per question and therefore preclude AI solutions
from learning to accept multiple targets that are equally legitimate or desirable. The number of answers per question (Figure 1) reflects the proportion as in the original relation annotations, but the users can adjust for any desirable distribution (e.g., down-sampling the unanswerable entries) per their development needs.

The frequently observed drugs and drug-reason pairs likely imply the clinical practice in the original n2c2 cohort. The finding that the top five drugs in the unanswerable questions were disjoint from that in the answerable questions suggests that prescription of certain drugs might be self-evident in context even without documenting the reason. It is expected that the performance of AI solutions on those terms with more abundant training examples will have an advantage, but there also appear to be general patterns such as “PRN” (pro re nata) or “as needed for” (Table 2) that can be learned to facilitate locating answers around those typical contexts. Our question-answer mentioning distance analysis showed that 90% of the drug-reason pairs were within the same or an adjacent sentence, suggesting the demand for long-distance inference to be modest in the RxWhyQA dataset.

Although why-question answering only covers a subdomain of clinical QA, it represents a unique category that deals with cause, motivation, circumstance, and justification. It was estimated that 20% of the top ten question types asked by family physicians [10] can be paraphrased into a why-question. Clinical whyQA is important because: 1) the ultimate task resembles expert-level explanatory synthesis of knowledge and evidence, 2) it aligns with identifying reasons for the decisions documented in clinical text. Therefore, we consider the
contents and challenges offered by the RxWhyQA dataset itself have independent, practical value for developing clinical QA applications.

We are aware of the following limitations: 1) the source n2c2 corpus represented a specific cohort that may not generalize to any clinical notes, 2) the quality of our QA entries is dependent on that of the original n2c2 annotations, 3) the drug-reason relations confer only moderate linguistic diversity that will not fully challenge or prepare AI solutions for every potential clinical QA application. Nonetheless, it is fair to reason that any AI model and QA solution capable of handling multi-answer questions should be able to pass the RxWhyQA challenge before conquering any broader scope.

**CONCLUSION**

We derived and shared the RxWhyQA, a reading comprehension style clinical QA dataset for training and testing systems to answer patient-specific questions based on clinical notes. The RxWhyQA includes 19,269 entries that require identification of multiple answers in text, which is an essential scenario not well covered by existing datasets. Although the RxWhyQA focuses on why-questions derived from a specific corpus and drug-reason relations, it offers an initial benchmark of multi-answer clinical QA and a reference for future work to repurpose other annotations likewise.

**COMPETING INTERESTS STATEMENT**

The authors have no competing interests to declare.
CONTRIBUTORSHIP STATEMENT

JWF conceived the study. HL offered scientific consultation. SM implemented the data conversion and analysis. HH assisted in implementing the data conversion. JWF and SM drafted the manuscript. All authors contributed to the interpretation of the results, critical revision of the manuscript, and approved the final submission.

ACKNOWLEDGEMENT

We thank the n2c2 organizers for making the annotations available to the research community. The study was partly supported by the Mayo Clinic Kern Center for the Science of Health Care Delivery.
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