Did You Ask a Good Question? A Cross-Domain Question Intention Classification Benchmark for Text-to-SQL

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Abstract

Neural models have achieved significant results on the text-to-SQL task, in which most current work assumes all the input questions are legal and generates a SQL query for any input. However, in the real scenario, users can input any text that may not be able to be answered by a SQL query. In this work, we propose TRIAGE SQL, the first cross-domain text-to-SQL question intention classification benchmark that requires models to distinguish four types of unanswerable questions from answerable questions. The baseline RoBERTa model achieves a 60% F1 score on the test set, demonstrating the need for further improvement on this task. Our dataset is available at https://github.com/chatc/TriageSQL.

1 Introduction

Text-to-SQL has attracted much attention as a translation task from a natural language question to an executable SQL query. As large-scale datasets are proposed (Zhong et al., 2017; Yu et al., 2018), recent works have achieved significant results via neural architecture improvements (Lyu et al., 2020; Guo et al., 2019; Wang et al., 2020). Those works assume all the user inputs are legal, i.e. answerable by a SQL query, which makes models focus on translating input questions to SQL queries.

Nevertheless, in the real scenario, a text-to-SQL system needs to handle any types of inputs including answerable questions and unanswerable questions. In Figure 1, we provide different types of user inputs and the corresponding actions of a text-to-SQL system. For answerable questions, the system activates a text-to-SQL translation model to generate SQL queries, while it also needs to rule out all illegal questions with different actions.

In this work, we propose TRIAGE SQL, a cross-domain text-to-SQL question intention classification benchmark. We formalize four types of unanswerable questions differentiated from answerable questions and construct our benchmark dataset containing 34K databases and 390K questions from 20 existing datasets. We further revised and annotated data to construct a high-quality test set with 500 examples in each type. A Transformer-based model achieved a 60% F1 score when trained and tested on our benchmark for a five-class classification model, which indicates the challenge of this task.

We summarize our contributions as below:

1) To the best of our knowledge, this work is the first to focus on the unanswerable questions in the text-to-SQL task. We construct a five-class question

Figure 1: A realistic text-to-SQL system framework where the system distinguishes answerable questions from other possible inputs and then triggers different actions for different types of unanswerable inputs.
Improper (Improper) Some questions such as small talk or asking-opinion questions are not proper to any databases. Apparently, users who asked those questions are not familiar with the function of databases, so the best strategy of the system is to return a tutorial instead of trying to answer those questions.

Require external knowledge (ExtKnow) Users are likely to ask unanswerable questions because the questions require extra information which is not in the database. This is common especially when users are not familiar with the database schema or its meaning. The following action of a system is to detect what information is required by the user but not included in the database.

Ambiguous (Ambiguous) The system may not answer the question correctly due to the ambiguity of user questions. These ambiguous questions can usually be paraphrased into more than one SQL parses in our settings, because they contain some words not explicitly pointing to either 1) column/table names (ambiguity in schema elements), such as finding the “name” of a person for a schema containing “last name” as well as “first name”; or 2) conditions of operators (ambiguity in values), such as finding the “good” movie while “good” is an ambiguous measurement for selecting a correct value. The system should indicate the ambiguous part and ask the user to clarify.

Unanswerable by common SQL grammar (Non–SQL) This type contains the questions and corresponding queries that are not executable by text-to-SQL systems with common SQL grammar, i.e. the grammar only containing operators in the current mainstream text-to-SQL systems (Zhong et al., 2017; Yu et al., 2018), due to the limitation of current text-to-SQL datasets and models.

First, this type contains some questions that are totally unanswerable by any SQL grammar, such as declarative statements and multi-modality questions. Furthermore, we also add some questions beyond the reach of current text-to-SQL systems because they are answerable only by uncommon grammar. For example, as shown in Table 1, users may query information about the database table itself, such as column/table names and the order of records, or about the return values of SQL queries. Since such questions are reasonable questions but out of the capability of text-to-SQL models, the system needs to know its limit.

Answerable (Answerable) This type refers to regular questions that a text-to-SQL translation model can handle.

3 Dataset Construction

We construct our benchmark from 21 text-to-SQL, question answering, and table-to-text datasets. Table 2 summarizes the dataset source of each question type, and we briefly describe our construction procedure below.
3.1 Data Sources and Construction Methods

**Spider, SparC, CoSQL** are cross-domain text-to-SQL datasets containing 162 different databases and corresponding questions (Yu et al., 2018, 2019b,a). Spider is single-turn, while the other two are multi-turn. To collect Answerable questions, we collect questions from Spider and the first-turn questions from SparC and CoSQL since we focus on context-independent questions in this work. We also collect the Ambiguous questions annotated in CoSQL. In addition, the schemas of these dataset are paired with the chit-chat questions, e.g. Alexa, to form Improper questions. Furthermore, we construct ExtKnow questions by ablating the database schema. To build ExtKnow questions, we randomly remove 1-3 columns that are mentioned in SQL from the database schema, so that the database does not contain sufficient information to answer the question. To prevent models from recognizing ExtKnow questions by simply detecting incomplete database schema, we also add some answerable questions by removing 1-3 unmentioned columns from the schema. In Section 4.3, we will show that these examples make it particularly challenging for the model to distinguish ExtKnow and Answerable questions.

**WikiSQL** is a cross-domain text-to-SQL dataset over Wikipedia tables (Zhong et al., 2017). WikiSQL is also used to construct Answerable and ExtKnow questions in a similar way to Spider/SparC/CoSQL.

In addition, WikiSQL contributes to the construction of Ambiguous questions as well. To achieve this, we firstly apply two rules to generate the candidates of ambiguous questions. The first rule is to use the overlapped words between two columns in a schema to replace a column name in question, e.g. "away team" in question would be changed to "team" since both “home team” as well as “away team” are in the schema. The second rule is simply to use some ambiguous concepts to replace the numbers or strings in the questions, such as changing “15” to “around 15”. Then, secondly, we further label about 200 samples from the generated candidates manually to make sure the correctness.

**Restaurants, Scholar, Yelp, IMDB** are four single-database text-to-SQL datasets where some questions are ambiguous during their annotation process (Tang and Mooney, 2000; Iyer et al., 2017; Yaghmazadeh et al., 2017; Finegan-Dollak et al., 2018). We first manually annotate the ambiguous questions in these four datasets to construct Ambiguous questions. Then, the remaining questions are used to construct Answerable and ExtKnow questions.

**TabFact, ToTTo, LogicNLG** are table-to-text datasets where the text is the description or statement of a part of the database information instead of questions to them (Chen et al., 2020b; Parikh et al., 2020; Chen et al., 2020a). Therefore, we extract the text-schema pairs in these three datasets as Non-SQL type because they are related to the database but not answerable by SQL.

**HybridQA** is a question answering dataset requiring the combination of a Wikipedia table and a paragraph to answer a question (Chen et al., 2020c). We generate ExtKnow questions naturally by removing the needed passages for inferring correct answers. In this way, these questions become unanswerable due to the lack of information out of databases.

**WikiTableQuestions (WTQ)** is a question answering dataset over Wikipedia tables annotated with corresponding answers instead of SQL (Pasupat and Liang, 2015). Some of its questions cannot be answered by SQL or require uncommon SQL grammar which is never covered by any existing text-to-SQL datasets. Therefore, WTQ is mainly used for constructing Non-SQL questions.

Similar to ambiguous question generation, we first use two rules to detect such questions. The first one is to extract the questions with string-type

| Improper | ExtKnow | Ambiguous | Non-SQL | Answerable |
|----------|---------|-----------|---------|------------|
| Spider | SparC, CoSQL | Restaurants, Scholar, Yelp | IMDB, Geo, Academic | TabFact, ToTTo, LogicNLG, HybridQA | Alexa, NQ, MARCO, WikiQA, CoQA, QuAC |

Table 2: The source of each question type in TRIAGE SQL.
answers not appearing in the content of databases, since most common grammar is not able to return the string type values other than the content of database. The second one is to extract the questions related to the information about the DB itself using keyword matching, such as “chart” and “row”.

Alexa, Natural Questions (NQ), MARCO, WikiQA, CoQA, QuAC contains chat-chat questions (or statements) of passages, concepts, documents, and web searches instead of relational databases (Gopalakrishnan et al., 2019; Kwiatkowski et al., 2019; Nguyen et al., 2016; Yang et al., 2015; Reddy et al., 2019; Choi et al., 2018). Therefore, all of these questions are not answerable by SQL, so we use them to construct Improper questions.

To make sure the consistency with other type of questions, we sample 1/10 of questions from these dataset. For each question, we randomly choose a schema from datasets containing DBs, e.g. Spider, as the corresponding schema of the question.

3.2 Train, Dev, Test split

To make TRIAGE SQL a cross-domain dataset, we first merge the databases from different sources with the same schema and their corresponding questions. Second, we randomly select 80% of databases for training and development set and leave the rest 20% as test set candidates (Table 3). We split questions based on schema, which means there is no overlap of schema in train, development, and test set. Finally, two students with SQL expertise manually pick 500 high-quality examples from test set candidates for each type (including manually labeled extra 200 ambiguous questions from WikiSQL), 2500 examples in total and another 2 students confirm the examples in test set. In this way, this test set is sampled and then revised by humans to make it high-quality and representative.

4 Experiment and Result

4.1 Model

We use RoBERTa (Liu et al., 2019) as the baseline model to test the difficulty of our task. RoBERTa is a strong pre-trained language model based on Transformers (Vaswani et al., 2017; Devlin et al., 2019) which has been widely used in encoding text and DB schema (Hwang et al., 2019). Given a pair of question and schema, we use a special token to separate question and each column in the schema and fine-tune a pre-trained RoBERTa-base model on a sampled training set with at most 10k samples in each type.

4.2 Result

Table 4 shows the result of the RoBERTa model on the proposed test set, achieving a 60% F1 score on average. Some question types can be classified with high F1 scores, such as Improper questions.
and Non-SQL questions unanswerable by common SQL grammar. However, it only obtains 17% F1 score on Ambiguous questions. The lower scores could be the result of inherent difficulty of ambiguous questions.

To further analyze the distribution of prediction, Figure 2 displays the confusion matrix of the results. As shown in the figure, the model is likely confused with ExtKnow and Answerable questions, demonstrating that it is challenging to figure out the missing column in the database and classify them as unanswerable questions. In addition to this, ambiguous questions are relatively hard to be classified as the correct type, demonstrating the difficulties of our task.

4.3 Discussion

|                | Precision | Recall | F1  |
|----------------|-----------|--------|-----|
| w/ non-mentioned |           |        |     |
| Answerable     | 0.55      | 0.73   | 0.63|
| ExtKnow        | 0.63      | 0.41   | 0.49|
| w/o non-mentioned |         |        |     |
| Answerable     | 0.69      | 0.88   | 0.78|
| ExtKnow        | 0.87      | 0.64   | 0.74|

Table 5: Scores of ExtKnow and Answerable questions on the development set. w/ non-mentioned is the dataset containing the answerable questions with non-mentioned column removed, while w/o non-mentioned does not contains.

To further explore the factors of confusion between ExtKnow and Answerable questions, we hypothesize that the Answerable questions constructed by removing one to three non-mentioned columns make it challenging for the model to distinguish the two types. To test this, we modify the dataset by deleting the samples in Answerable questions which are constructed by removing one to three non-mentioned columns, and then evaluate the model on both the original and this modified dataset. For each dataset, we randomly sample a development set (10k samples for each type). As shown in Table 5, the model evaluated on the original dataset obtains lower scores although it uses more training data. This result demonstrates that non-mentioned columns are able to confuse the model. Adding this type of data into the dataset would largely increase the difficulty of the task.

5 Related Work

While Text-to-SQL and natural language interface to database systems have been studied for decades (Warren and Pereira, 1982; Miller et al., 1996; Popescu et al., 2003; Li and Jagadish, 2014; Zhong et al., 2017; Finegan-Dollak et al., 2018; Yu et al., 2018), most of the prior work assume the user question is answerable by SQL queries and can be handled by the system. The only text-to-SQL work to study out-of-scope user questions is CoSQL (Yu et al., 2019a) where they perform dialog act classification to identify ambiguous and answerable questions in a conversational setting. Furthermore, question intent classification and out-of-scope detection has been studies for task-oriented dialog systems (Braun et al., 2017; Coucke et al., 2018; Larson et al., 2019; Zheng et al., 2020; Yilmaz and Toraman, 2020; Feng et al., 2020; Casanueva et al., 2020; and Anthony Zheng et al., 2020), community question answering (Chen et al., 2012), and machine comprehension (Rajpurkar et al., 2018). By contrast, our paper focuses on the cross-domain text-to-SQL task and proposes the first benchmark to provide a systematic taxonomy and comprehensive analysis of different question types for text-to-SQL systems.

6 Conclusion

We proposed TRIAGESQL, a cross-domain benchmark for text-to-SQL intention classification. In addition to the answerable questions, it contains four types of unanswerable questions to help text-to-SQL systems deal with different inputs. We use a baseline RoBERTa model to measure the difficulty of human refined test set. The result demonstrates a significant space for improvement. The future study includes collecting naturally occurring examples of questions that fit our criteria (de Vries et al., 2020), reducing the training and test set gap, and creating better models. Also, another direction is to generate suggestions by the system based on the classification results, e.g. provide users the missed columns or the required knowledge in ExtKnow questions.

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