Know What I don't Know: Handling Ambiguous and Unanswerable Questions for Text-to-SQL

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Abstract

The task of text-to-SQL aims to convert a natural language question into its corresponding SQL query within the context of relational tables. Existing text-to-SQL parsers generate a "plausible" SQL query for an arbitrary user question, thereby failing to correctly handle problematic user questions. To formalize this problem, we conduct a preliminary study on the observed ambiguous and unanswerable cases in text-to-SQL and summarize them into 6 feature categories. Correspondingly, we identify the causes behind each category and propose requirements for handling ambiguous and unanswerable questions. Following this study, we propose a simple yet effective counterfactual example generation approach that automatically produces ambiguous and unanswerable text-to-SQL examples. Furthermore, we propose a weakly supervised DTE (**D**etecting-**T**hen-**E**xplaining) model for error detection, localization, and explanation. Experimental results show that our model achieves the best result on both real-world examples and generated examples compared with various baselines. We release our data and code at: https://github.com/wbbeyourself/DTE.

Movie	IMDB Rating	Rotten Tomatoes Rating	Content Rating
Titanic	7.9	86%	7.6
Avatar	7.8	87%	7.7

(a) **Ambiguous Question:** Show me the top rating movie.
Previous: SELECT [Movie] ORDER BY [IMDB Rating] DESC LIMIT 1
Ours: Oops, this question has multiple answers. "rating" may refer to either "IMDB Rating", "Rotten Tomatoes Rating", or "Content Rating".

Brand	Sales	Year
Toyota	1,933,099	2021
Ford	1,804,824	2021

(b) **Unanswerable Question:** Show me model name sorted by sales.
Previous: SELECT [Brand] ORDER BY [Sales] DESC
Ours: Sorry, we can't find an answer for you since "model name" cannot be mapped to any concepts in your table.

Figure 1: Ambiguous and unanswerable examples in text-to-SQL task as well as our explanations. Blue font denotes the problematic question span and red font means the "plausible" column name selected by previous models.

1 Introduction

Text-to-SQL task aims to generate an executable SQL query given a natural language (NL) question and corresponding tables as inputs. It builds a natural language interface to the database to help users access information in the database (Popescu et al., 2003), thereby receiving considerable interest from both industry and academia (Guo et al., 2019; Wang et al., 2020; Liu et al., 2021). Correspondingly, a series of new model architectures have been proposed, such as IRNet (Guo et al., 2019), RAT-SQL (Wang et al., 2020), ETA (Liu et al., 2021), etc. These models have achieved satisfactory results on well-known benchmarks, including Spider (Yu et al., 2018) and WikiSQL (Zhong et al., 2017).

However, state-of-the-art models trained on the leaderboard datasets still demonstrate inadequate performance in practical situations, where user queries are phrased differently, which can be problematic. Concretely, from our study with real-world text-to-SQL examples (Sec. 2), it is found that about 20% of user questions are problematic, including but not limited to *ambiguous* and *unanswerable* questions. Ambiguous questions refer to those which can have multiple semantic meanings based on a single table. For instance, in Figure 1(a), the word "rating" in a user's query could be mapped to disparate columns, such as "IMDB Rating", "Rotten Tomatoes Rating", or "Content Rating". On the other hand, unanswerable questions pertain to those that cannot be answered based on the information provided by the tables. For example, in Figure 1(b), there is no column about "model name" in the table. State-of-the-art models

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are capable of generating "plausible" SQL queries, even in the presence of ambiguous or unanswerable questions.

This phenomenon reveals two problems of previous methods. Firstly, with regard to data, the training samples utilized in these approaches lack ambiguous and unanswerable questions. Current training datasets gather queries by either using templates (Zhong et al., 2017) or by manually annotating controlled questions and filtering out poorly phrased and ambiguous ones (Yu et al., 2018). This data-gathering approach ensures that a correct answer exists within the table context. Secondly, in regards to the model, end-to-end parsing models ignore modeling questions in a fine-grained manner, which results in an inability to precisely detect and locate the specific reasons for ambiguous or unanswerable questions.

To address the data shortage problem, we propose a counterfactual examples generation approach that automatically produces ambiguous and unanswerable text-to-SQL examples using existing datasets. Given the free-form nature of the text, conventional natural language modification techniques are not always accurate. In contrast to plain text, tables exhibit well-defined structures, usually consisting of rows and columns. Consequently, table modification is more controllable. In light of this, we propose to generate ambiguous and unanswerable examples by modifying the structured table.

Furthermore, we propose a weakly supervised model DTE (**D**etecting-**T**hen-**E**xplaining) for handling ambiguous and unanswerable questions. To locate ambiguous or unanswerable tokens in user questions, we formulate the location process as a sequence labeling problem, where each token in the user question will be tagged as being related to an ambiguous label, an unanswerable label, or others (Sec. 4.1). Since there is no labeled data for sequence labeling, we extract the set of column names and cells appearing in the SQL query and use this set as the weak supervision. In this way, we could generate explicit explanations for ambiguous and unanswerable questions to end users. Note that the sequence labeling information is pseudo and derived from our model, thus alleviating heavy manual efforts for annotation.

Experimental results show that our approach achieves the best results on both real-world examples collected from realistic applications and automatically generated ambiguous and unanswerable examples, compared with various baselines. Our contributions are as follows:

- We conduct a preliminary study on the ambiguous and unanswerable questions in text-to-SQL and summarize 6 featured categories. We also identify the causes behind each category and propose requirements that should be met in explainable text-to-SQL systems.
- We propose a counterfactual examples generation approach that automatically produces ambiguous and unanswerable text-to-SQL examples via modifying structured tables.
- We propose a weakly supervised model for ambiguous and unanswerable question detection and explanation. Experimental results show that our approach brings the model with the best explainability gain compared with various baselines.

2 Preliminary Study on Ambiguous and Unanswerable Problem

To understand user behaviors in a real-world application, we conduct a comprehensive user study on our commercial text-to-SQL product. Firstly, around 3,000 failed user questions in the product are collected. They obtained over 30 data tables from multiple domains, including education, finance, government, etc. Then, we manually group these questions into multiple categories. At last, we explore the causes and potential solutions to deal with them. According to our analysis, nearly 20% of the questions are problematic, including 55% ambiguous and 45% unanswerable questions respectively, revealing the importance of handling problematic questions. In the following, we will introduce their categories, causes, and potential solutions for handling them.

2.1 Problem Categories

In this section, we formalize ambiguous and unanswerable questions and identify 6 sub-categories.

Ambiguous Problem In the text-to-SQL task, ambiguity means that one user question could have multiple semantic meanings (e.g., SQL query) based on one table. Specifically, we can subdivide them into two sub-categories, namely column ambiguity and value ambiguity, which account for 45% and 10% of all problematic questions, respectively.

Ambiguous Problem		
Category	**Example**	**Percentage**
Column Ambiguity	Question: Show me the top rating movie. Columns: Movie, IMDB Rating, Rotten Tomatoes Rating, Content Rating Note: The token "rating" in question is ambiguous because there are 3 column names containing "rating".	45%
Value Ambiguity	Question: For Jack, show me the date of license issued and license expires. Columns: Engineer, Constructor, License issued, License expires, … Values: Jack::Engineer, Jack::Constructor Note: The token "Jack" in question is ambiguous because both column "Engineer" and "Constructor" have the same cell value "Jack".	10%
Unanswerable Problem		
Category	**Example**	**Percentage**
Column Unanswerable	Question: Show me model name by sales. Columns: Brand, Sales, Year Note: The span "model name" is unanswerable because no such a column named "model name".	30%
Value Unanswerable	Question: Count the total of Private hospitals. Columns: NHHospitalCategory, State, Year, BenefitsPaid Note: The span "Private hospitals" is unanswerable because no such value in column "NHHospitalCategory".	7%
Calculation Unanswerable	Question: What is the balance of trade of China ? Columns: Country, Imports, Exports, … Note: The span "balance of trade" is unanswerable, because model does not know the calculation formula : Balance of Trade = Exports – Imports.	6%
Out of Scope	Question: Bar chart showing the Word count of every character. Columns: ChapterNo, WordCount, ChScID, SceneName Note: The span "Bar chart" is out of the model's scope, the model does not support the graphic operation.	2%

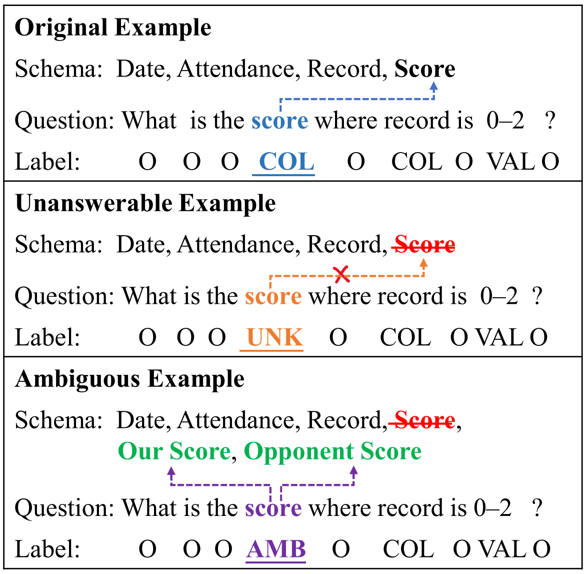
Table 1: Ambiguous and unanswerable problem categories in text-to-SQL task. The red font with a dashed line denotes the ambiguous or unanswerable question span. The green font means a related concept (columns or values) to the red span. Note sentence explains why the example is ambiguous or unanswerable.

Column ambiguity means that some tokens in the user question could be mapped to multiple columns. For example in Table 1, we don't know exactly which "Rating" the user wants since there are three *rating* columns. Value ambiguity means that some tokens in the user question could be mapped to multiple cell values in the table. For example in Table 1, *Jack* in the user question can be mapped to the name of either an "Engineer" or a "Constructor".

Unanswerable Problem The unanswerable problem can be classified into four categories: column unanswerable, value unanswerable, calculation unanswerable, and out-of-scope, which account for 30%, 7%, 6%, and 2% of all problematic questions, respectively, as shown in the bottom part of Table 1. (1) The column unanswerable means that the concepts mentioned in the question do not exist in table columns. In the first example, the *model name* does not exist in the given columns, but our product incorrectly associates it with the irrelevant column "Brand". (2) The value unanswerable indicates that the user question refers to cell values that do not exist in the table. As the second example shows, no such *Private hospitals* value exists in the table. (3) The calculation unanswerable category is more subtle. It requires mapping the concept mentioned in the user question to composite operations over existing table columns. For example, the *balance of trade* is a concept derived from "$Exports - Imports$". Such mapping functions require external domain knowledge. Our product which is trained from a general corpus captures limited domain knowledge, and thus often fails. (4) The out-of-scope category means that the question is out of SQL's operation scope, such as chart operations.

2.2 Causes

Through communicating with end users and analyzing the characteristic of questions as well as corresponding table contexts, we identify three fundamental causes for ambiguous and unanswerable questions: (1) end users are unfamiliar with the content of the table and don't read the table carefully, causing unanswerable questions; (2) ambiguity arises due to the richness of natural language expressions and the habitual omission of expressions by users (Radhakrishnan et al., 2020); (3) the emergence of similar concepts in the table tends to cause more ambiguous questions. Note that around 95% of problematic questions are constructed un-



Original Example

Schema: Date, Attendance, Record, **Score**

Question: What is the score where record is 0–2 ?

Label: O O O COL O COL O VAL O

Unanswerable Example

Schema: Date, Attendance, Record, ~~Score~~

Question: What is the score where record is 0–2 ?

Label: O O O UNK O COL O VAL O

Ambiguous Example

Schema: Date, Attendance, Record, ~~Score~~, **Our Score**, **Opponent Score**

Question: What is the score where record is 0–2 ?

Label: O O O AMB O COL O VAL O

Figure 2: Ambiguous and unanswerable examples generated by our approach.

	NoisySP	WikiSQL	WTQ
Train			
# ambiguous	4,760	0	0
# unanswerable	10,673	0	0
# answerable	0	56,350	7,696
# tables	4,861	17,984	1,283
Development			
# ambiguous	1,581	0	0
# unanswerable	1,652	0	0
# answerable	0	8,142	1,772
# tables	1,232	2,614	325
Test			
# ambiguous	2,332	0	0
# unanswerable	2,560	0	0
# answerable	0	15,362	0
# tables	1,993	5,031	0

Table 2: Dataset statistics of NoisySP, compared to the original WikiSQL and WTQ dataset.

intentionally, revealing the importance of making users *conscious of being wrong*.

2.3 Explainable Parser Requirements

Based on the findings and analysis above, to deal with ambiguous and unanswerable questions, we propose to make a text-to-SQL system *know-what-I-don't-know*. On one hand, a parsing system should detect ambiguous and unanswerable questions. On the other hand, a parsing system should locate the specific reasons and generate corresponding explanations to guide the user in rectification.

Achieving *know-what-I-don't-know* can benefit from two aspects: (1) from model view: enhances models' ability to deal with problematic questions and improve user trust; (2) from user view: makes it clear to users which part of their questions are problematic, guiding them to revise their questions. In our user study experiments, we find that 90% of the problematic questions can be corrected by prompting users with explanations shown in Table 1, and the remaining 10% of questions can only be solved by injecting external knowledge into the model. In the following, we will introduce how we mitigate the challenges mentioned in Sec. 1

3 Counterfactual Examples Generation

To alleviate the data shortage issue, we propose a counterfactual examples generation approach for automatically generating problematic text-to-SQL examples. In our approach, we mainly focus on generating two major types of problematic examples: column ambiguity and column unanswerable, which account for 75% [1] of all problematic examples based on our preliminary study. Note that the counterfactual examples are generated via modifying structured tables instead of natural language questions. The reason is that conditional modification on a structured table is more controllable than unstructured text. Finally, 23k problematic examples are obtained based on two text-to-SQL datasets, i.e., WikiSQL (Zhong et al., 2017) and WTQ (Shi et al., 2020). Next, we will introduce the details of our approach.

3.1 Our Approach

Given an answerable text-to-SQL example that contains a question $Q = (q_1, \ldots, q_m)$, a DB schema (also a column set) $\mathcal{C} = \{c_1, \ldots, c_n\}$ and a SQL query S, our goal is to generate problematic examples, denoting as $(Q, \mathcal{C}', S)$ triplets. By removing evidence supporting Q from $\mathcal{C}$ or adding ambiguous ones, a new DB schema $\mathcal{C}'$ is generated.

Unanswerable Examples Generation Specifically, we randomly sample a target column c_t in the SQL query S. Then we delete c_t from $\mathcal{C}$ to remove the supporting evidence for question spans $Q_s = (q_i, \ldots, q_j)$ that mentioned c_t. At last, the question span Q_s is labeled as UNK. For instance, in the unanswerable example of Figure 2, given an original question "What is the score where record is 0–2?", the question span "score" is grounded to the column "Score". By deleting the column "Score", we obtain an unanswerable example.

[1] Proposal for handling the remaining 25% questions can be found in Appendix

Labels	Description	Example(Token:Label)
COL	Column Mention	sales: B-COL
VAL	Value Mention	godfather: B-VAL
AMB	Ambiguous Span	rating: B-AMB
UNK	Unanswerable Span	model: B-UNK
O	Nothing	the: O

Table 3: Labeling categories of question tokens

Ambiguous Examples Generation Similar to unanswerable examples generation, we generate an ambiguous example by firstly deleting a column c_t and then adding two new columns. The critical point is that newly added columns are expected to (1) fit nicely into the table context; (2) have high semantic associations with the target column c_t yet low semantic equivalency (e.g. "opponent score" is semantically associated with "score", but it is not semantic equivalent). To achieve this, we leverage an existing contextualized table augmentation framework, CTA (Pi et al., 2022), tailored for better contextualization of tabular data, to collect new column candidates. We select target columns from within the SQL, and typically choose 2-3 near-synonyms for each column candidate. After that, we rerank the column candidates by their length and similarity with the column c_t, and keep the top 2 as our newly added columns. As shown in the ambiguous example of Figure 2, we first delete the original column "Score", then add two domain-relevant and semantically associated columns "Our Score" and "Opponent Score".

3.2 Dataset Statistic

Leveraging our counterfactual examples generation approach, we obtain a dataset, called NoisySP based on two cross-domain text-to-SQL datasets, i.e., WikiSQL (Zhong et al., 2017) and WTQ (Shi et al., 2020). Consistent with our preliminary study, we generate 20% of the original data count as problematic examples. Finally, we get 23k problematic examples. Detailed statistics can be seen in Table 2. To ensure the quality of the development set and test set, we hired 3 annotators to check the candidate set of newly added columns for ambiguous examples and then drop low-quality ones. Note that the rate of low quality is only 5%, demonstrating the effectiveness of our approach.

4 Model: DTE

In this section, we introduce our **D**etecting-**T**hen-**E**xplaining (DTE) model to handle ambiguous and unanswerable questions. To generate a fine-grained explanation, we formulate it as a sequence labeling problem, where each token in the user question will be tagged as being related to an ambiguous label, an unanswerable label, or others. Concretely, DTE consists of three modules: concept prediction module, grounding module, and sequence labeling module. The grounding module generates pseudo-label information to guide the training of the sequence labeling module. The overall architecture of DTE is shown in Figure 3.

4.1 Task definition

Given an input question $Q = (q_1, \ldots, q_m)$, a data table (with a concept set $C = c_1, \ldots, c_k$, containing columns and cell values), the goal of sequence labeling is to output a labeling sequence $L = (l_1, \ldots, l_m)$ for each token in Q. It can be represented by tagging each token in the question with a set of BIO labels (Tjong Kim Sang and Veenstra, 1999). Specifically, we define 5 kinds of labels for question tokens, namely COL, VAL, AMB, UNK, and O. Their descriptions and examples are shown in Table 3.

4.2 Preliminaries: ETA for grounding

In this work, we formulate problematic question detection as a sequence labeling task, whose training process requires large-scale label annotations as supervision. However, such annotations are expensive and time-consuming. To obtain label information in an efficient and cheap way, we propose to leverage the grounding result of the text-to-SQL task and transform it into a pseudo-labeling sequence. Particularly, we use ETA (Liu et al., 2021), a pretrained probing-based grounding model, as the backbone of our approach. The major advantage of ETA is that, compared with models relying on expensive annotations of grounding, it only needs supervision that can be easily derived from SQL queries.

4.3 Sequence Labeling Module

To meet the requirements of detecting and locating ambiguous and unanswerable question spans, we design a sequence labeling module, which is intuitively suitable for our sequential modeling purpose. The sequence labeling module consists of a dropout layer, a linear layer, and a CRF layer, following best practices in previous work (Yang et al., 2018). Given a contextualized embedding sequence $(e_{q_1}, \ldots, e_{q_m})$, the goal of the sequence

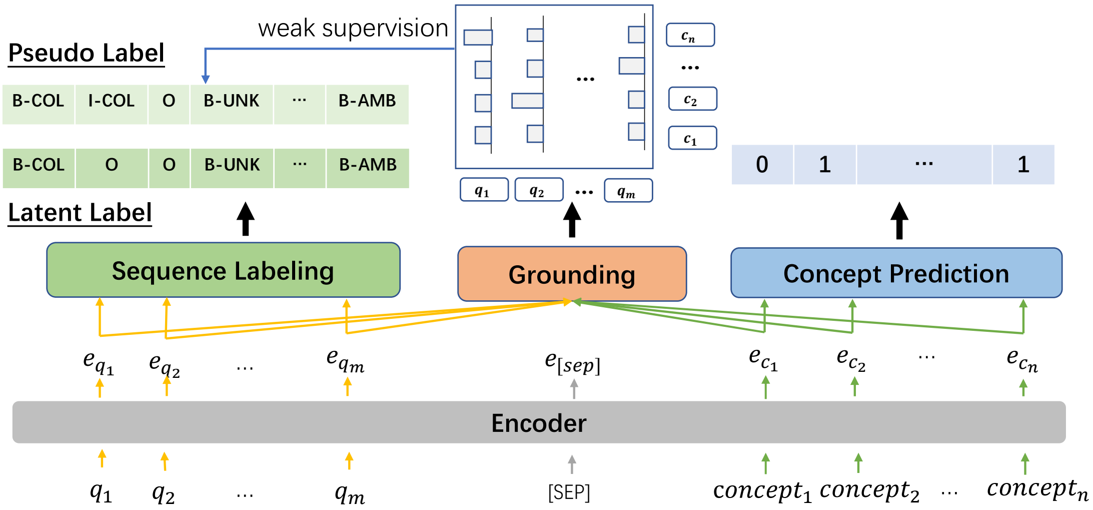


Figure 3: The overall architecture of DTE.

labeling module is to output the label sequence $L = l_1, \ldots, l_m$ with the highest likelihood probability.

4.4 Multi-Task Training

Our multi-task training process involves three steps: (1) train the concept prediction module. (2) warm-up grounding module to get alignment pairs. (3) train the sequence labeling module with the pseudo tag derived from the grounding module.

4.5 Response Generation

At the inference step, given a question and the table information, DTE predicts labels for each question token and outputs grounding pairs between question tokens and table entities. If the AMB (or UNK) label occurs, it means it is an ambiguous (or unanswerable) question. To generate corresponding interpretations to end users, we carefully design two response templates. More details about the templates could be found in Appendix A.3.

5 Experiments

In this section, we systematically evaluate the effectiveness of DTE. Specifically, we examine DTE's performance in two aspects: (1) the performance of the sequence labeling module in detecting ambiguous and unanswerable tokens; (2) the grounding performance for each label to provide evidence for generating explainable responses to end users. In addition, we report the evaluation results on text-to-SQL tasks.

5.1 Experimental Setup

Datasets We conduct experiments based on the following datasets: (1) NoisySP with 23k automatically generated examples, (2) two cross-domain text-to-SQL datasets, i.e., WikiSQL (Zhong et al., 2017) and WTQ (Shi et al., 2020)[2], (3) 3,000 real-world examples collected by us (Sec. 2). All models are trained with the NoisySP, WikiSQL, and WTQ datasets. Specifically, real-world examples are only used for testing. Dataset statistics are shown in Table 2.

Evaluation Metric To evaluate sequence labeling performance, we report accuracy for each label category. For grounding performance evaluation, we report grounding accuracy for each label, except for UNK and O, which have no grounding results.

Baseline Models We choose two types of representative models for comparison: (1) the heuristic-based method (Sorokin and Gurevych, 2018), which is widely used in entity linking and grounding tasks; (2) the learning-based method, ETA (Liu et al., 2021), which is a strong grounding baseline, leveraging the intrinsic language understanding ability of pretrained language models. We update them with a little modification to fit our task because their vanilla version is not directly applicable. More implementation details about the baseline and DTE could be found in Appendix A.

[2] Note that we use the version with SQL annotations provided by Shi et al. (2020) , since the original WTQ (Pasupat and Liang, 2015) only contains answer annotations.

Models	COL	VAL	AMB	UNK	O
Heuristic	61.7	66.8	57.8	60.7	72.1
ETA+BERT	83.4	87.9	75.6	70.2	80.9
ETA+BERT$_L$	85.7	90.4	76.4	71.4	82.7
DTE +BERT	88.2	94.1	81.4	78.6	90.7
DTE +BERT$_L$	**89.4**	**95.7**	**83.2**	**80.3**	**92.4**

Table 4: Sequence labeling accuracy of DTE compared with baselines in NOISYSP test set.

Models	COL	VAL	AMB
Heuristic	55.9	67.2	56.2
ETA+BERT	71.4	75.3	60.7
ETA+BERT$_L$	72.4	77.8	62.4
DTE +BERT	73.4	78.2	79.8
DTE +BERT$_L$	**75.1**	**80.7**	**82.4**

Table 5: Grounding accuracy of DTE compared with baselines in NOISYSP test set.

5.2 Experimental Results on NOISYSP

Sequence Labeling Results As shown in Table 4, we compare the performances of DTE with various baselines on the test set of NOISYSP. DTE outperforms previous baselines across all label categories, which demonstrates the superiority of our DTE model. Compared with the heuristic-based method, DTE significantly improves performances by 25% average gains of all label categories, which shows that our NOISYSP dataset is challenging and the heuristic-based method is far from solving these questions. Besides, DTE consistently outperforms the ETA+BERT baseline by a large margin, not only improving the ambiguous and unanswerable label accuracy by 7% and 11%, respectively, but also improving column and value detecting accuracy, demonstrating the effectiveness of our approach for detection.

Grounding Results In order to identify the specific reasons for ambiguous questions, we need to not only identify the target spans, but also establish grounding by finding the linked concept (column or value). As shown in Table 5, we compare DTE's grounding performance with various baselines. Note that the unanswerable span in question does not require grounding to any concept, thus we do not report the grounding result of it. We observe that DTE consistently outperforms baselines across three label categories on grounding performance, especially on the ambiguous grounding whose linked concepts are more varied and diverse.

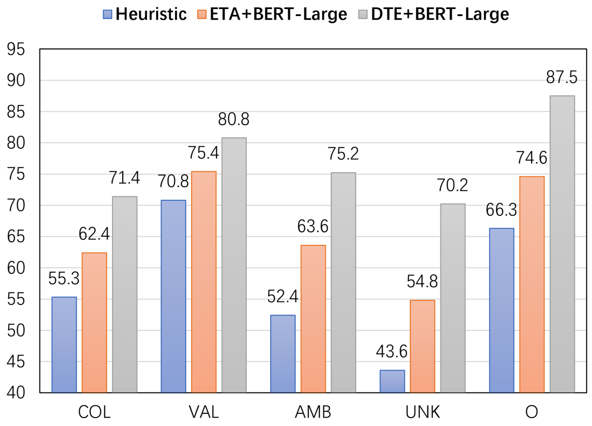


Figure 4: Sequence labeling accuracy of DTE compared with baselines in realistic data.

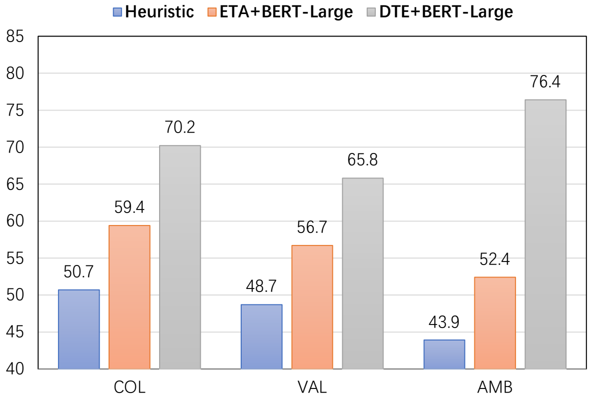


Figure 5: Grounding accuracy of DTE compared with baselines in realistic data.

5.3 Generalization on Realistic Data

We verify the generalization ability of DTE by conducting *out-of-distribution* experiments on 3,000 realistic datasets that we collected from our commercial products. These datasets cover more than 30 data tables from multiple domains such as education, finance, government, etc. As shown in Figure 4, our DTE model still outperforms all baselines consistently and achieves promising performance in ambiguous and unanswerable detection with 75.2% and 70.2% sequence labeling accuracy, respectively. From Figure 5, we observe that our DTE model outperforms other baselines by a large margin in grounding accuracy of ambiguous spans. These results indicate the generalization ability of DTE for handling ambiguous and unanswerable questions and the effectiveness of realistic data.

5.4 Text-to-SQL Results

To verify the influence of DTE on the text-to-SQL task, we report the exact match accuracy (Ex.Match) and execution accuracy (Ex.Acc) on

Model	Dev		Test
	Ex.Match	Ex.Acc	Ex.Acc
ALIGN	37.8	56.9	46.6
ALIGN+BERT	44.7	63.8	51.8
ETA+BERT	47.6	**66.6**	53.8
DTE+BERT	**48.1**	66.5	**54.2**

Table 6: Ex.Match and EX.ACC of text-to-SQL results on the dev and test set of WTQ.

Models	COL	VAL	O
DTE w/ SL	**75.1**	**80.7**	**90.5**
DTE w/o SL	72.6	75.2	82.8

Table 7: Ablation study of DTE model with BERT-large in the grounding accuracy on the test set of NOISYSP. SL means sequence labeling module.

WTQ dataset. As shown in Table 6, compared with ALIGN (Lei et al., 2020) and ETA (Liu et al., 2021), DTE shows slightly better performance in both exact match accuracy and execution accuracy. It should be noted that all questions in this experiment are normal questions, i.e., without ambiguous and unanswerable questions. The result shows that DTE can boost text-to-SQL performance instead of damaging it.

5.5 Discussion

What are the remaining errors? We manually analyze 20% of the remaining errors in the NOISYSP dataset and summarize four main error types: (1) wrong detection (25%) - where our model either misses or over-predicts the ambiguous or unanswerable label. (2) widened span (30%) - where our model predicts a longer span than the golden result. (3) narrowed span (25%) - where the model infers a narrowed span than the golden result. (4) other errors (20%) are caused by the grounding module. This error analysis indicates the main challenge of DTE is precise localization rather than detection because the second and third errors (55%) are caused by the wrong span boundary. More detailed examples can be seen in Appendix B.

Can sequence labeling module benefit grounding module? As a multi-task training approach, it is critical to determine the effect of introducing extra tasks on the models' performance on original tasks. To verify the influence of the sequence labeling module on grounding results, we conduct an ablation study with or without the sequence labeling module. As we can see in Table 7, the grounding module does achieve better performance on columns and values alignment with the sequence labeling module. Through our analysis, we find the performance gain mainly comes from *long concept mention* (with token length > 4). The reason is that the CRF layer in the sequence labeling module can strengthen the grounding module's ability to capture long-distance dependency. In summary, we can conclude that the sequence labeling task can fit in well with the grounding task.

6 Related Work

Problematic Question Detection. Existing works on problematic question detection can be classified into two categories: (1) heuristic-based methods leverage elaborate rules to detect and locate problematic questions span (Sorokin and Gurevych, 2018; Li et al., 2020; Wu et al., 2020), suffering from heavy human efforts on feature engineering. Besides, some approaches (Dong et al., 2018; Yao et al., 2019) estimate the confidence of parsing results, relying on existing parsing models; (2) on the contrary, learning-based methods don't rely on heuristic rules and parsing models. For example, Arthur et al. (2015) jointly transforms an ambiguous query into both its meaning representation and a less ambiguous NL paraphrase via a semantic parsing framework that uses synchronous context-free grammars. Zeng et al. (2020) trains a question classifier to detect problematic questions and then employed a span index predictor to locate the position. However, the index predictor can only find one error span per example, which limits its usage. In this work, we propose a learning-based approach that could handle multiple errors in problematic questions.

Uncertainty Estimation. Recent works on uncertainty estimation of neural networks explore diverse solutions, such as deep ensembles in prediction, calibration, and out-of-domain detection (Liu et al., 2020). However, these methods need network and optimization changes, generally ignore prior data knowledge (Loquercio et al., 2020), and can only provide uncertainty in predictions without identifying the reasons. In this work, we propose the counterfactual examples generation approach to adding prior knowledge to the training data and then propose a weakly supervised model for problematic span detection and give explainable reasons.

7 Conclusion

We investigate the ambiguous and unanswerable questions in text-to-SQL and divide them into 6 categories, then we sufficiently study the characteristics and causes of each category. To alleviate the data shortage issue, we propose a simple yet effective counterfactual example generation approach for automatically generating ambiguous and unanswerable text-to-SQL examples. What's more, we propose a weakly supervised model for ambiguous and unanswerable question detection and explanation. Experimental results verify our model's effectiveness in handling ambiguous and unanswerable questions and demonstrate our model's superiority over baselines.

Limitations

Among the six ambiguous and unanswerable problem categories in Table 1, our counterfactual example generation approach can not cover the calculation unanswerable and out-of-scope examples generation. The reason is that our approach focuses on the table transformation ways while generating the calculation unanswerable and out-of-scope examples requires conditional NL modification techniques. We leave this as our future work.

Ethics Statement

Our counterfactual examples generation approach generates a synthesized dataset based on two mainstream text-to-SQL datasets, WikiSQL (Zhong et al., 2017) and WTQ (Shi et al., 2020), which are free and open datasets for research use. All claims in this paper are based on the experimental results. Every experiment can be conducted on a single Tesla V100. No demographic or identity characteristics information is used in this paper.

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A Implementation Details

A.1 Baselines Implementation

We modified ETA since the vanilla version (Liu et al., 2021) does not support ambiguous and unanswerable span detection. For a fair comparison, we update the vanilla ETA in two ways. Firstly, in the original inference part, the vanilla version of ETA applies the greedy linking algorithm to only keep the top 1 confidence score-related schema item (column or value). We change the selection process by allowing the top 3 candidates to be chosen, whose confidence score should be greater than the threshold. We consider those spans with multi-grounding results as ambiguous spans. Second, to enable ETA to handle unanswerable questions, we add a UNK column to the schema part and train the model to enable unanswerable span to get closer to the UNK column. We consider those linked with the UNK column as unanswerable spans. The heuristic-based baseline (Sorokin and Gurevych, 2018) is n-gram matching via enumerating all n-gram ($n \leq 5$) phrases in a natural language question and links them to schema items by fuzzy string matching. We consider a span as an ambiguous one when it can fuzzy match multiple results. Similarly, if a noun phrase span can match no results, it is considered to unanswerable span.

A.2 DTE Implementation

Our DTE model consists of a BERT encoder, and three task modules, namely the concept prediction module, grounding module, and sequence labeling module. We implement the first two modules following the implementation details mentioned in Liu et al. (2021) and use the same hyperparameters. In addition, the sequence labeling module is built by a dropout layer, a linear layer, and a CRF layer which is based on the open-source repository pytorch-crf[3]. The response template for ambiguous questions is “Oops, this question has multiple semantic meanings. X may refer to either "concept1", "concept2", or "c_3"”. What’s more, we design the template for unanswerable questions as “ Sorry, we can’t find an answer for you since "X" cannot be mapped to any concepts in your table”. Examples can be seen in Figure 1.

A.3 Response Templates

The response template for ambiguous questions is “Oops, this question has multiple semantic meanings. X may refer to either "concept1", "concept2", or "c_3"”. What’s more, we design the template for unanswerable questions as “ Sorry, we can’t find an answer for you since "X" cannot be mapped to any concepts in your table”. Examples can be seen in Figure 1.

A.4 Training Hyper-parameters

For all experiments, we employ the AdamW optimizer and the default learning rate schedule strategy provided by Transformers library (Wolf et al., 2020). The learning rate of other non-BERT layers is 1×10^{-4}. The max training step is 100,000 and our training batch size is 35. The training process last 6 hours on a single 16GB Tesla V100 GPU.

B Examples of NoisySP dataset

In this section, we demonstrate some good and bad cases of our DTE model prediction. Good case examples are shown in Table 8 and Table 9. Bad case examples are shown in Table 10 and Table 11.

Ambiguous Good Case of NoisySP
Q: What is the minimum **population** of the parish with a 750.51 km area ? **Gold:** O O O O **B-AMB** O O O O O B-VAL I-VAL I-VAL O **Pred:** O O O O **B-AMB** O O O O O B-VAL I-VAL I-VAL O **Schema**: Official Name || Area km 2 || foreign-born **population** || total estimated **population** **Description**: correct prediction
Q: Which **name** has a state of Yan ? **Gold:** O **B-AMB** O O B-COL O B-VAL O **Pred:** O **B-AMB** O O B-COL O B-VAL O **Schema**: State || Type || born **name** || first **name** || Title || Royal house || From **Description**: correct prediction

Table 8: Ambiguous good cases by DTE on the NoisySP data.

Unanswerable Good Case of NoisySP
Q: Which players college is Tennessee ? **Gold:** O B-UNK B-COL O B-VAL O **Pred:** O B-UNK B-COL O B-VAL O **Schema**: Pick # || NFL Team || Position || College **Description**: correct prediction
Q: What prefecture is listed in the map as number 39 ? **Gold:** O B-UNK O O O O B-COL O B-COL B-VAL O **Pred:** O B-UNK O O O O B-COL O B-COL B-VAL O **Schema**: Number in map || Area (km²) || Population (2001) || Pop. density (/km²) **Description**: correct prediction

Table 9: Unanswerable good cases by DTE on the NoisySP data.

[3] https://github.com/kmkurn/pytorch-crf

Ambiguous Bad Case of NoisySP

Q:	I	want	the	date	of	appointment	for	manner	of	departure	being	sacked
Gold:	O	O	O	B-AMB	O	O	O	B-COL	I-COL	I-COL	O	B-VAL
Pred:	O	O	O	B-UNK	I-UNK	I-UNK	O	B-COL	I-COL	I-COL	O	B-VAL

Schema: Team || Manner of departure || busy date || date of vacancy
Description: widened span error

Q:	What	is	the	winning	score	on	Feb	12	,	1978	?
Gold:	O	O	O	O	B-AMB	O	B-VAL	I-VAL	I-VAL	I-VAL	O
Pred:	O	O	O	B-AMB	I-AMB	O	B-VAL	I-VAL	I-VAL	I-VAL	O

Schema: home team score || score || Margin of Victory || Runner(s)-up || Date || Tournament
Description: widened span error

Table 10: Ambiguous bad cases by DTE on the NoisySP data.

Unanswerable Bad Case of NoisySP

Q:	How	many	hectars	of	land	is	in	Kaxholmen	?
Gold:	O	O	B-UNK	I-UNK	I-UNK	O	O	B-VAL	O
Pred:	O	O	O	O	B-UNK	O	O	B-VAL	O

Schema: Urban area (locality) || Municipality || Population || Density (inh./km²) || Code
Description: narrowed span error

Q:	What	was	the	elimination	number	of	the	fighter	who	fought	within	26:15	?
Gold:	O	O	O	B-UNK	I-UNK	O	O	O	O	O	O	B-VAL	O
Pred:	O	O	O	O	O	O	O	O	O	O	O	B-VAL	O

Schema: Wrestler || Entered || Eliminated by || Method of elimination || Time
Description: wrong detection error

Table 11: Unanswerable bad cases by DTE on the NoisySP data.

C Proposal for remaining 25% problematic questions

The remaining categories are (1) Value Ambiguity (10%); (2) Value Unanswerable (7%); (3) Calculation Unanswerable (6%); and (4) Out of Scope (2%). Although our data generation method does not cover these categories, our DTE model trained with our generated dataset NoisySP can generalize to questions of these categories (results are shown in Sec. 5.3), especially for Value Ambiguity and Value Unanswerable. This is because columns and values are treated as concepts that share the same pattern.

For the Calculation Unanswerable category, formulaic knowledge is needed to inject the model with the necessary background information. Existing works, such as KnowSQL (Dou et al., 2022), are intended to solve this kind of problem.

As for the Out of Scope problem, which usually calls for graphic operation or other unsupported operations, it can be easily handled with a blacklist or a simple classifier.

ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
Limitations

☒ A2. Did you discuss any potential risks of your work?
Left blank.

☑ A3. Do the abstract and introduction summarize the paper's main claims?
abstract, introduction

☒ A4. Have you used AI writing assistants when working on this paper?
Left blank.

B ☑ Did you use or create scientific artifacts?

4.2

☑ B1. Did you cite the creators of artifacts you used?
4.2

☑ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
Ethics Statement

□ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
Not applicable. Left blank.

☑ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
3

☒ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
Left blank.

☑ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
Left blank.

C ☑ Did you run computational experiments?

5

☑ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
A

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

☑ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
5, A

☑ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
5.2, 5.3, 5.4

☑ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
5

D ☑ Did you use human annotators (e.g., crowdworkers) or research with human participants?
3

☑ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
3

☒ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
China

☒ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
no

☑ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
3

☒ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
no