MT-TEQL: Evaluating and Augmenting Consistency of Text-to-SQL Models with Metamorphic Testing

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Abstract

Text-to-SQL is a task to generate SQL queries from human utterances. However, due to the variation of natural language, two semantically equivalent utterances may appear differently in the lexical level. Likewise, user preferences (e.g., the choice of normal forms) can lead to dramatic changes in table structures when expressing conceptually identical schemas. Envisioning the general difficulty for text-to-SQL models to preserve prediction consistency against linguistic and schema variations, we propose MT-TEQL, a Metamorphic Testing-based framework for systematically evaluating and augmenting the consistency of Text-to-SQL models. Inspired by the principles of software metamorphic testing, MT-TEQL delivers a model-agnostic framework which implements a comprehensive set of metamorphic relations (MRs) to conduct semantics-preserving transformations toward utterances and schemas. Model Inconsistency can be exposed when the original and transformed inputs induce different SQL queries. In addition, we leverage the transformed inputs to retrain models for further model robustness boost. Our experiments show that our framework exposes thousands of prediction errors from SOTA models and enriches existing datasets by order of magnitude, eliminating over 40% inconsistency errors without compromising standard accuracy.

1 Introduction

Text-to-SQL is a task that translates natural language statements to SQL queries, which is expected to serve as a handy interface where even non-expert users can retrieve data from database. Recent advances show potentials of neural networks in synthesizing nested cross-domain SQL queries (Guo et al., 2019; Wang et al., 2019; Choi et al., 2020). Despite the spectacular progress, however, text-to-SQL models still face considerable challenges due to the high flexibility of natural language utterances and database schema design. One user intent can be expressed in multiple lexically different utterances. Similarly, one conceptual model (in the form of entity-relationship diagram) can be implemented in multiple structurally different schemas. Consider the erroneous predictions given in Figure 1, where given semantically equivalent utterances or schemas in different forms, text-to-SQL models yield inconsistent outputs.

Figure 1: Inconsistent predictions on semantically equivalent inputs.

These inconsistencies exhibit weakness of current models on generalization ability and robustness. Standard benchmarks, e.g., Spider (Yu et al., 2018c), are usually crafted following the best practice in schema design. In other words, standard benchmarks, as will be shown in our findings (see Sec. 4.3), are not sufficient to assess models under real-life noisy scenarios. For instance, users may denormalize schema for online analytical applications or may leverage an inadequate albeit functional database schema (e.g., lacking of foreign key constraints). Such variations, together
with insufficient metrics to assess the inconsistency of text-to-SQL models, likely become a practical challenge to impede the adoption of text-to-SQL models in real-world scenarios.

With recent progresses in testing NLP models (Ribeiro et al., 2020; Ma et al., 2020; Soremekun et al., 2020), testing-based approaches become popular to assess “in the wild” model robustness in addition to standard metrics on hold-out accuracy (Ribeiro et al., 2020). However, we note that adapting existing testing-based methods to assess text-to-SQL models are unattainable, whose reasons are three-fold. First, typical text-to-SQL models employ a unique learning paradigm that jointly learns the representations of utterances and database schemas in a common feature space. However, previous testing approaches are not designed to transform schemas, thus presumably neglecting inconsistency defects due to schema variations. Second, the problem of text-to-SQL is generally ill-posed, in the sense that some text inputs are not translatable into SQL queries. Some existing methods, by randomly substituting certain words with synonyms or typos, can likely induce such “unnatural” inputs which are undesired in testing text-to-SQL models (Zeng et al., 2020). Third, synthesizing text inputs based on hand-coded templates (Soremekun et al., 2020; Ribeiro et al., 2020), while producing generally translatable inputs, is difficult to cover nested SQL queries which are commonly seen in real-life usages. Given that SOTA models usually have very high performance on simple queries, e.g., RAT-SQL (Wang et al., 2019) has over 80% accuracy on “easy” questions but less than 40% accuracy on “extra hard” questions, we see a demand need to synthesize more comprehensive utterances rather than only simple cases.

To address above challenges, we propose MT-T\textsc{EQL}, a metamorphic testing-based framework for evaluating and augmenting text-to-SQL models. MT-T\textsc{EQL} transforms seed inputs (utterance-schema pairs) via a comprehensive set of metamorphic relations (MRs), where each MR specifies a semantics-preserving transformation scheme toward either utterances or schemas. By comparing SQL queries derived from the original and transformed inputs, we assess the consistency and coherence of the tested models. From 1,034 testing samples in the Spider dev set (Yu et al., 2018c), MT-T\textsc{EQL} automatically generates a total of 62,430 transformed testing samples. We test the consistency of popular text-to-SQL models, including the SOTA RAT-SQL (Wang et al., 2019), with the transformed samples and identify considerable inconsistency errors. We further augment models by extending the training dataset with those transformed inputs into a synthetic dataset. We show that training the text-to-SQL models with this dataset can effectively eliminate over 40% inconsistency errors while retaining comparable benchmark accuracy.

**Key Contributions.** 1) We propose MT-T\textsc{EQL}, a model-agnostic framework to test the consistency of text-to-SQL models without a requirement for manually labeled answers. 2) We design a comprehensive set of metamorphic relations (MRs) to conduct semantics-preserving transformations on utterances and schemas and expose inconsistency errors. 3) We propose three augmentation schemes by leveraging the transformed inputs to improve model consistency. 4) Our evaluation exposes considerable inconsistency defects, achieves effective model consistency augmentation, and also reveals insightful observations on de facto models that can be used for engineers to diagnose and improve models in real-life usage.

2 Metamorphic Testing (MT)

Determining the correctness of SQL queries generated by text-to-SQL models for arbitrary utterance-and-schema pairs generally requires human annotated ground truth. In contrast, MT specifies to benchmark testing targets via metamorphic relations (MRs) without the need of ground truth. Each MR denotes a general and usually invariant property of the testing targets. For instance, to test the implementation of $\sin(x)$, instead of knowing the expected output of arbitrary floating-point input $x$ (which requires considerable manual efforts), we assert that the MR $\sin(x) = \sin(\pi - x)$ always holds when arbitrarily mutating $x$. A bug in $\sin(x)$ is detected when input $x$ and its mutation $(\pi - x)$ induce inconsistent outputs. To date, MT has achieved major success in detecting bugs in software and AI systems (Chen et al., 1998; Segura et al., 2016). This research further leverages MT to evaluate the consistency of text-to-SQL models, by defining a comprehensive set of MRs to conduct semantics-preserving transformations toward natural language utterances and database schemas.
3 MT-TEQL

Alg. 1 depicts the overall workflow of MT-TEQL, where given seed utterance \( u_0 \), seed schema \( s_0 \), and model \( \mathcal{M} \). MT-TEQL first generates a collection \( T \) of transformed utterances and schemas based on a set of MRs (line 1). Then, for each pair of transformed utterances and schemas \((u', s')\), MT-TEQL checks the consistency between SQL queries derived from \((u', s')\) and queries derived from the original seed input \((u, s)\) (line 4). Inconsistency-triggering inputs will be collected for model augmentation (line 5).

Note that standard benchmark accuracy is generally measured by comparing prediction \( \mathcal{M}(u', s') \) with human annotated ground truth. In contrast, inspired by software metamorphic testing, MT-TEQL directly compares the consistency between \( \mathcal{M}(u, s) \) and \( \mathcal{M}(u', s') \) (line 4), thus alleviating manual efforts. In addition, considering text-to-SQL models typically develop a joint understanding of natural-language utterances and schemas, MT-TEQL transforms both utterances and database schemas with a set of semantics-preserving MRs (line 1), while existing general-purpose NLP model testing works can likely neglect certain model inconsistencies as they only focus on text (Ribeiro et al., 2020).

3.1 Metamorphic Relations (MRs)

In contrast with previous works, MT-TEQL does not mutate inputs from an adversarial perspective (e.g., substitute words with typos or unconstrained synonyms), nor does MT-TEQL break utterances/schemas into “untranslatable” forms to stress text-to-SQL models (Zeng et al., 2020). In fact, one key strength of MT-TEQL is to perform semantics-preserving transformation and check the logic consistency of generated SQL queries. This way, we alleviate the necessity of manually checking the correctness of SQL queries, and the entire workflow can be conducted fully automatically. As listed in Table 1, we instantiate a total of 12 MRs to systematically explore model defects. Following, we elaborate on the details of each MR.

3.1.1 Utterance Transformation

Usually, an utterance in the text-to-SQL task starts with a prefix (e.g., “what is” and “tell me”) and is followed by the real query body. We categorize frequently-used prefixes in utterances in Table 2. Here, common prefixes do not contain the user intents while special prefixes can implicitly indicate some user intents (e.g., desired columns or aggregate functions). Observing that the choice or even the occurrence of common prefixes usually does not affect the user intent, we design three MRs focusing on transforming prefixes as follows.

### Table 1: Categorizations of frequently-used prefixes in utterances

| Type                  | Illustrative Examples |
|-----------------------|-----------------------|
| Common Interrogative Prefix | what is/are, which is/are |
| Common Declarative Prefix | tell me, return, find, list |
| Special Interrogative Prefix | when, where, how many |
| Special Declarative Prefix | count |

### Table 2: Metamorphic relations in MT-TEQL

| Target | Metamorphic Relation          |
|--------|------------------------------|
| Utterance | Prefix Insertion  |
|          | Prefix Removal            |
|          | Prefix Substitution       |
|          | Synonym Substitution      |
the model. For example, “what is the age of all singers?”

**Prefix Substitution (PS).** Likewise, the choice of common prefixes before query body also does not affect user intents. Hence, we further define an MR to replace the prefix in an utterance with another prefix, e.g., “tell me what is the age of all singers?”

**Synonym Substitution (SS).** In addition to transforming prefixes, we further propose an MR focusing on replacing certain tokens in an utterance with their synonyms. While such “synonym transformation” scheme has been proposed in previous general-purpose NLP model testing frameworks (Ribeiro et al., 2020), Table 3 incorporates domain knowledge to manipulate a collection of specific synonyms tailored for the SQL language.

| AGG     | Textual Description |
|---------|---------------------|
| MIN     | minimal, minimum, lowest, smallest |
| MAX     | maximal, maximum, highest, largest |
| COUNT   | the (total) {number, count, amount} of |
| SUM     | the (total) {sum, amount} of |
| AVG     | the (mean, average) of |

Table 3: Illustrative mapping relations between aggregate functions (AGG) and textual descriptions.

We list the synonyms mapping rules in Table 3. Overall, one aggregate function in the SQL language can be expressed in multiple ways. For instance, the last row in Table 3 specifies that “the mean of” can be replaced into “the average of” while retaining the derived aggregate function AVG. Hence, by replacing tokens grouped together (e.g., “minimal” → “minimum”) in Table 3, the derived SQL queries should preserve the same aggregate function, e.g., MIN.

Note that different aggregate functions may also be expressed in the same form. For example, “the amount of” can indicate either SUM or COUNT aggregates in SQL (see the 3rd and 4th rows in Table 3). It is generally more challenging for models to infer an implicit aggregate function based on the context if we substitute “the sum of” to “the amount of”; however, as such opaque aggregate function indicators widely exist in the wild, we deem it necessary to stress models in this way.

### 3.1.2 Schema Transformation

As aforementioned, existing works generally test/augment models by transforming natural language text; nevertheless, given that utterances and database schemas are learnt jointly by typical text-to-SQL models, we see it as demanding to further transform database schemas to comprehensively explore model defects. At this step, we design eight MRs to conduct semantics-preserving transformations on schemas. We also note that, to preserve output invariance, MT-TeQL is carefully designed to only transform a part of schemas which does not change the ground-truth query (e.g., performing extra table joining). Illustrative examples of the schema-oriented MRs are shown in Figure 2.

From a holistic view, on the schema structural level, users may decide to normalize some inter-dependent column or denormalize two tables to boost query performance. In a more realistic setting, users may not explicitly declare foreign key constraints or primary key constraints to reduce database computational overheads. Also, the order of tables stored in the database should not affect the output, nor does the order of columns in the table. These observations motivate the design of the following schema-level transformations.

**Normalization.** Conducting normalization on columns that are irrelevant to the associated utterance should not change the model output. In principle, we can employ well-established functional dependency mining algorithms on the raw table content and normalize dependent columns accordingly. However, these heavy-weight algorithms are unaffordable when we are mutating considerable amount of tables to test text-to-SQL models. Instead, as shown in Figure 2, MT-TeQL launches a light-weight approach to extracting one unused
column each time to form a new table with two columns (one original column and one linking column). It then links the original table to the new table with the linking table.

**Flattening.** As a dual operation to normalization, we also implement MRs to flatten a table if there exists an explicit foreign key constraint. To be precise, MT-T-EQL piggybacks the reference table to the main table and drops the reference table. This way, we effectively changes the schema structure while retaining the high-level semantics.

**Opaque Key.** Explicit foreign key constraints and primary key constraints can sometimes give hints for models to perform table joining. However, in practice, explicit key constraints are not always available due to various reasons (e.g., performance boosts). Though key constraints can be used as a strong indicator for table joining, a model is expected to be consistent no matter an explicit key constraint exists or not, as the absence of key constraints often occurs in the wild. As shown in Figure 2, the explicit foreign key constraint between CAR.VENDOR.ID and VENDOR.VENDOR.ID is removed and it should still be feasible to infer their dependency relation based on the column names and table names.

**Table Shuffle.** It is easy to see that how tables are stored in the database system (reflected by the order of tables in the datasets) should not induce output changes. As shown in Figure 2, MT-T-EQL implements an MR to randomly shuffle tables within a schema and assert the output consistency.

**Column Shuffle.** Like table shuffle, how columns are stored in the database system (reflected by the order of columns in the datasets) should not induce inconsistent SQL queries. Therefore, MT-T-EQL implements an MR to randomly shuffle columns within a table.

**Column Removal+Renaming.** The name or occurrence of an irrelevant columns should not incur inconsistent outputs. If one column is not used in the ground-truth query, MT-T-EQL is implemented to change its name with some synonyms (e.g., “country” → “location” in the “Column Renaming” diagram in Figure 2) or simply drop that particular column.

**Column Insertion.** By querying the knowledge graph, we may know what attribute the object indicated by the table may have. As shown in the “Column Insertion” diagram in Figure 2, MT-T-EQL extends the schema by inserting an extra column named ENGINE.ID in the CAR table, since querying the knowledge graph with “car” returns an attribute of “engine.”

### 3.2 Augmentation

Our aforementioned MRs can induce a large volume of synthetic utterances and schemas (60x compared with the original dataset). We also confirm that these generated synthetic inputs are well formed and valid (see evaluation in Sec. 4.1). Nevertheless, despite this highly promising result, we note that it is extremely time-consuming, if at all possible, to directly augment models using such a large amount of synthetic inputs. Hence, this section proposes three sampling methods to reduce computational overhead and practically augment text-to-SQL models.

**Random Sampling (RS).** Suppose we have \( m \) synthetic test cases derived from the training dataset of \( n \) samples (where \( m \gg n \)), our first sampling strategy, random sampling (RS), randomly picks \( n \) test cases from those \( m \) synthetic data. We then extend the training set of \( n \) original samples with those \( n \) randomly-picked test cases. This way, the training cost should not be notably increased by only doubling the size of the training set.

**Stratified Sampling (SS).** Since \( m \gg n \), the RS strategy indeed picks a relatively small portion (\( n \) test cases) of the synthetic data set. In other words, RS may fail to retain inputs generated by certain MRs if such MRs are applicable to only small amount of data (see Table 4). To retain reasonable amount of data samples for each MR, we further propose the Stratified Sampling (SS) scheme. In particular, we first sample \( \min(m_i, n/k) \) test cases using each MR, where \( m_i \) is the total number of test cases synthesized using this MR and \( k \) is the number of MRs we have (\( k = 12 \) according to Table 1). In case \( \sum_{i=1,\ldots,k} \min(m_i, n/k) < n \), we further randomly sample \( n - \sum_{i=1,\ldots,k} \min(m_i, n/k) \) inputs from the synthetic test cases. This way, we use the SS scheme to prepare \( n \) synthetic test cases where the “minor” MRs are guaranteed to contribute all of its synthesized \( m_i \) test cases. We then extend the training set of \( n \) original samples with those \( n \) synthetic cases for model augmentation.

**Adaptive Sampling (AS).** Given that text-to-SQL models can exhibit inconsistency errors, one might wonder the feasibility of directly using the error-triggering inputs to augment the dataset. However,
we note that the total amount of error-triggering inputs are not directly comparable to the size of the standard training dataset. Hence, augmenting the training data with only error-triggering inputs are not realistic.

Instead, we design Adaptive Sampling (AS), as a practical error-aware sampling scheme. In particular, we first randomly split the standard training set into ten folds forming a nine-folds training set \( S_t \) and an one-fold validation set \( S_v \). A model \( m_0 \) is then trained on \( S_t \) using half of the standard model training epoch setting. Then, we transform test cases in \( S_v \) using our MRs, and evaluate \( m_0 \) in terms of its inconsistency rate \( r_i \) (see for Sec. 4.2 the definition of \( r_i \)) using the synthetic test cases generated by each MR. We then normalize \( r_i \) to \( \hat{r}_i \) such that \( \sum \hat{r}_i = 1 \). Then, similar to SS, we sample \( \min(m_i, \hat{r}_i) \) test cases from the synthetic data set generated by each MR and further sample from the remaining test cases to obtain a total of \( n \) sampled cases. We train the model with \( n \) original test cases and those \( n \) test cases sampled under the awareness of inconsistency errors.

\[
f(x) = \frac{1}{1 + H(x)}
\]

where \( H(x) \) is
\[
H(x) = -\sum_{i=1}^{|x|} \log P(x_i | x_{<i})
\]

\( P(x_i | x_{<i}) \) is the probability of \( x_i \) under given context \( x_{<i} \). We report that the average fluency score on the original utterances is 0.155 while the average fluency score of synthetic utterances is 0.148 (−4.5%). It shows that the synthetic utterances exhibit comparable fluency with the original utterances.

Figure 3 further reports the cumulative fluency scores distributions of original utterances and synthetic utterances. Particularly, in bottom 25%, the fluency score distributions of original utterances and synthetic utterances are very close, illustrating promising results that our MRs do not notably impede the readability of worse-case utterances in the original dataset.

### 4 Testing Models with MT-TEQL

Before testing text-to-SQL models with MT-TEQL, we first synthesize a total of 62,430 test cases from 1,034 data samples in the Spider dev set (Yu et al., 2018c). We report the distribution of test cases in terms of MRs in Table 4. A reasonable number of test cases can be synthesized by all MRs. We note that, as some MRs may have exponential test cases w.r.t. the input size (e.g., column shuffle), MT-TEQL only picks maximally ten possible candidates derived from one test case for each MR to avoid overwhelming test cases.

| Metamorphic Relation  | # Test Case |
|-----------------------|-------------|
| Prefix Insertion       | 6370        |
| Prefix Removal         | 199         |
| Prefix Substitution    | 8266        |
| Synonym Substitution   | 639         |
| Normalization          | 8707        |
| Flattening             | 2018        |
| Opaque Key             | 3079        |
| Table Shuffle          | 2575        |
| Column Shuffle         | 6675        |
| Column Removal         | 8707        |
| Column Renaming        | 11775       |
| Column Insertion       | 2802        |
| **Total**              | 62,430      |

Table 4: Distribution of generated test cases in terms of each MR.

### 4.1 Naturalness of Synthetic Utterances

As previously mentioned, instead of randomly transforming utterances (e.g., replacing certain words with typos) which likely induces ill-formed utterances, we aim to synthesize natural utterances whose incurred inconsistency likely denotes real-world defects that normal users can encounter. That is, we advocate the naturalness as an important metric to assess the quality of synthetic utterances. As there are no well-established metrics to quantify naturalness, we employ the fluency score (Ge et al., 2018) to practically approximate the naturalness of utterances, which is defined as follows:

\[
f(x) = \frac{1}{1 + H(x)}
\]
### 4.2 Setup

As summarized in Table 5, we reproduce six models and test them with MT-TEQL. The tested models feature diverse human utterance embedding techniques as well as schema learning modules, which, as will be shown in Sec. 4.3, incur different model consistency w.r.t. different MRs. We also report that, though we put much effort to resolve incompatibility issues (e.g., fixing buggy data reader and query parser) of the official model implementations, some models still fail to process a small proportion (≈3% on average) of our synthetic test cases. We ignore these test cases in the evaluation.

#### Inconsistency Rate

We first propose the formulation of inconsistency rate as a quantifier of the model robustness. Given a test suite $S_i = \{((u_1, s_1), (u_{11}, s_{11})), \cdots, ((u_n, s_n), (u_{nm}, s_{nm}))\}$, where $(u_i, s_i)$ denotes the $i$-th sample in the original dataset and $(u_{ij}, s_{ij})$ denotes the $j$-th test case derived from $(u_i, s_i)$, we define the inconsistency rate as follows:

$$r_i = \frac{\sum I_{eval}(M(u_i, s_i), M(u_{ij}, s_{ij}))}{|S_i|}$$

where $I_{eval}(M(u_i, s_i), M(u_{ij}, s_{ij}))$ is an indicator function and it returns 1 if the model $M$ yields inconsistent outputs over $(u_i, s_i)$ and $(u_{ij}, s_{ij})$. Here, $eval(\cdot, \cdot)$ can be any standard evaluation metrics, for instance, exact set match (EM) (Yu et al., 2018c) or semantics equivalence (Chu et al., 2017). At this step, we employ exact set match (EM) accuracy, the most widely-used metric, as our $eval(\cdot, \cdot)$.

**Table 5:** Information of our reproduced models.

| Model                  | Year | Utterance Encoder | Schema Learning Module | Accuracy |
|------------------------|------|-------------------|------------------------|----------|
| SyntaxSQLNet (Yu et al., 2018b) | 2018 | GloVe (Pennington et al., 2014) | Column Sequence | 22.4     |
| RAT-SQL (v1) (Wang et al., 2019) | 2019 | GloVe | Relation Encoding+Linking | 53.5     |
| IRNet (v1) (Guo et al., 2019) | 2019 | GloVe | Column Sequence+Linking | 52.8     |
| GNN (Bogin et al., 2019a) | 2018 | Bi-LSTM | Schema Graph | 46.0     |
| GlobalGNN+Linking (Bogin et al., 2019b; Chen et al., 2020) | 2020 | BERT-base (Devlin et al., 2019) | Schema Graph+Linking | 54.9     |

**Table 6:** Testing results of models under MT-TEQL (breakdown by MRs, measured by inconsistency rate).

| Model                  | PI   | PR   | PS   | SS   | NO   | FL   | OK   | TS   | CS   | CRm  | CRn  | CI   | ALL  |
|------------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| SyntaxSQLNet           | 8.2  | 10.0 | 6.7  | 13.5 | 2.4  | 2.7  | 1.3  | 2.1  | 1.1  | 1.5  | 1.7  | 0.8  | 3.2  |
| IRNet                  | 7.5  | 11.2 | 7.0  | 37.8 | 2.4  | 6.6  | 5.2  | 2.8  | 2.1  | 2.1  | 1.6  | 2.1  | 4.0  |
| GNN                    | 4.6  | 5.5  | 3.4  | 25.4 | 3.4  | 4.3  | 5.3  | 0.0  | 0.0  | 1.0  | 0.5  | 0.2  | 2.4  |
| GlobalGNN+Linking      | 4.0  | 7.5  | 3.3  | 18.3 | 5.8  | 6.9  | 6.1  | 0.4  | 0.2  | 2.9  | 1.1  | 3.0  | 3.2  |
| RAT-SQL (v1)           | 2.4  | 5.0  | 2.6  | 21.8 | 3.0  | 4.9  | 3.8  | 0.2  | 0.04 | 1.3  | 0.7  | 0.0  | 1.9  |
| **Average**            | 5.3  | 7.4  | 4.6  | 23.3 | 3.4  | 5.1  | 4.3  | 1.1  | 0.7  | 1.8  | 1.1  | 1.2  | 2.9  |

**Table 7:** Testing results of models under MT-TEQL (breakdown by hardness, measured by inconsistency rate).

| Model                  | Easy | Medium | Hard | Extra | All |
|------------------------|------|--------|------|-------|-----|
| SyntaxSQLNet           | 5.2  | 3.7    | 1.4  | 0.8   | 3.2 |
| IRNet                  | 2.1  | 4.7    | 2.1  | 6.9   | 4.0 |
| GNN                    | 1.9  | 2.5    | 2.4  | 2.6   | 2.4 |
| GlobalGNN+Linking      | 2.8  | 4.0    | 2.0  | 3.1   | 3.2 |
| RAT-SQL (v1)           | 1.2  | 2.4    | 1.5  | 1.7   | 1.9 |

### 4.3 Findings

We report the inconsistency rate of models in Table 6 and Table 7. MT-TEQL successfully finds considerable bugs from all the evaluated text-to-SQL models. Table 6 reports the evaluation results in terms of different MRs. We interpret that utterance transformations are all highly effective to expose inconsistent outputs. Synonym Substitution (SS) is particularly effective, given its high flexibility in perturbing natural language utterances. Relatively mundane prefix-oriented transformations, which impose easy challenge for human, are also very effective to stress text-to-SQL models.

Schema-based transformations also achieve reasonable performance in exposing model defects. We note that the consistency of models against schema-based transformations is highly influenced by its schema learning module (see Table 5). For example, SyntaxSQLNet and IRNet use the sequences of columns as input and are generally more sensitive to Table Shuffle (TS) and Column Shuffle (CS). In contrast, the other models learn from schema structural feature (e.g., graph-based method and relation encoding) and become more
resilient against such transformations. Moreover, more holistic structure changes, e.g., Normalization (NO) and Flattening (FL), impose noticeable challenges to these models, which are intuitive.

Table 7 further reports the inconsistency rates breakdown by the hardness. Overall, MT-TSQL effectively reveals subtle differences in the predictions of de facto models. Models of different architectures and data preprocessing show largely distinct robustness against questions of different hardness. For instance, SyntaxSQLNet performs apparently worse regarding “Easy” questions, while it shows high consistency regarding “Hard” and “Extra” questions. Overall, we view Table 6 and Table 7 have clearly illustrated the strength of our proposed approach, which can expose considerable defects from well-trained de facto models. Furthermore, as a by-product, MT-TSQL can serve as an assessment criteria to help engineers make fine-grained diagnosis on their text-to-SQL models, exposing their subtle difference and preference.

4.4 Case Study and Error Analysis

To understand the details of inconsistency errors, we report four representative cases of inconsistency errors in Figure 4. They are derived by transforming the Singer schema in the Spider dev set or transforming utterances associated with the schema.

We present the SQL query derived from the original inputs (Pred@O) and the query derived from the transformed inputs (Pred@T), accordingly.

We manually checked 500 pairs of inconsistency errors and find that most errors have correct query skeletons and incorrect or missing clauses. We also notice that there is no false negative cases in the inconsistency errors and presume the overall false negative should be lower than error cases reported by standard metrics. For example, it is reported that exact set matching has a 2.5% false negative rate on average and 8.1% in the worst case (Zhong et al., 2020). We hypothesis that, given two similar inputs (i.e., an original input and a transformed input), models are not likely to yield two semantically equivalent while syntactically different outputs. Therefore, we envision it as a useful by-product of MT compared with standard methods. Following, we discuss five major sources of inconsistency errors.

| Type            | # Errors |
|-----------------|----------|
| Column Prediction| 101      |
| Aggregate Function| 77       |
| Operator        | 13       |
| Table Joining   | 71       |
| Complex Query   | 48       |
| Others          | 30       |

Table 8: Error type distributions of 500 inconsistency errors.
referred to in the utterance. In contrast, as reported by the error analysis on the standard dataset (Guo et al., 2019), most column prediction errors are due to that the ground-truth column names are not explicitly (or merely partially) mentioned in the utterances. According to our observation, column prediction errors not only exist in the SELECT clause, but also occur in the GROUP BY and ORDER BY clauses. According to our manual study of 500 errors, erroneous column prediction account for 20.2% errors.

**Aggregate Function.** Among 500 manually checked errors, we report that 15.4% errors are caused by incorrect aggregate function. As discussed in Sec. 3.1, changing the aggregate function indicator can impose challenges to the text-to-SQL models. For instance, in the “Synonym Substitution” case of Figure 4, by replacing “sum” with “amount of”, the tested model fails to comprehend the transformed utterance and uses an incorrect aggregate function $\text{SUM}(\text{age})$ in $\text{Pred}@T$, although “age” was never mentioned in the original and the transformed utterances.

**Operator.** Predictions on operator is a major step towards identifying intended contents. Our manual study on the 500 erroneous cases report that 14.6% errors are due to incorrect operator predictions. For example, a LIKE operator may be mistakenly predicted as $=$. As shown in the “Flattening” erroneous case of Figure 4, some irreverent changes on schema structure can result in an incorrect prediction on the operator in the WHERE clause. Besides, we also observe errors in the HAVING clauses of the group-by operation. Overall, our manual study shows that such erroneous operators widely exist in almost all MRs.

**Table Joining.** Linking multiple tables in one query is challenging for models and is a major cause of inconsistency errors (34.2%). As an important table joining indicator, foreign key constraints help models link two tables to a large degree. Without explicit foreign key constraints in the schema, models may lack of guidance to link two tables. As shown in the “Opaque Key” case of Figure 4, though the model captures the need of table joining, it fails to make prediction on the joining condition (i.e., the ON clauses). Besides “Opaque Key”, our manual study shows that prefix- and column-based transformations can also trigger a considerable number of table joining errors.

**Complex Query.** In addition to the four basic types of inconsistency errors, we also observe that some “extra hard” queries in the Spider dev set, with multiple table joining and complex conditions, are itself hard for models, even for human experts, to translate. Hence, even subtle changes on the input can induce multiple errors in the corresponding output. Nevertheless, as will be reported in Sec. 5, dataset augmented by our transformed inputs can effectively enhance model performance toward “extra hard” challenges. Among the sampled 500 pairs, we observe that about 9.6% predictions have more than one errors.

**Discussion.** We have shown common weaknesses of the text-to-SQL models. Besides the mentioned types of errors, we also find some errors are less common, e.g., erroneous table predictions and unwanted conditions in WHERE clauses, which consist 6.0% of sampled errors. On the other hand, we find that substantial errors can be potentially eliminated with human annotation or interactive correction. For example, if users can explicitly specify their desired aggregate functions or interested columns in addition to the input utterances, the search space of the model can be effectively reduced, presumably enhancing the model accuracy. Hence, we envision adopting human-in-the-loop methods to further disambiguate user intents and reduce the model search space (e.g., by dropping irreverent columns and tables) (Andreas et al., 2020; Li et al., 2020). From the model design side, we have observed considerable potential improvements with more accurate natural language understanding. The model can generally yield more consistent outputs when processing utterances of different prefixes. In that sense, we presume task-oriented sentence representation learning techniques can facilitate natural language comprehension toward even noisy utterances (Yu et al., 2020). In terms of schema variations, we observe that graph neural networks have better robustness under subtle changes on schemas while become even more vulnerable on holistic structural changes. In general, it is hard for neural network models to maintain consistent performance under noisy schemas (Suhr et al., 2020). We observe that augmenting standard dataset with more schema variations can boost the model robustness, as will be shown shortly in Sec. 5.

## 5 MT-TEQL for Augmentation

In addition to model testing, we also seek to augment models with moderate cost, as discussed in
Sec. 3.2. To evaluate the proposed method, we perform three proposed sampling techniques on SyntaxSQLNet and IRNet. We also compare our method with the SyntaxSQLNet data augmentation module.

To present a fair comparison, all variants of SyntaxSQLNet are trained with 600 epochs on col model and 300 epochs on the remaining submodels; all variants of IRNet are trained with 50 epochs. Since the standard data augmentation module in SyntaxSQLNet uses 3x more data samples from external dataset, we additional design the “AS+” group that samples more synthetic data and makes the size of its training set equal to “aug” for a fair comparison.

We report the inconsistency rates in Table 9, subsuming the original model and also the augmented models with three schemes. Furthermore, we also report the accuracy of (augmented) models in Table 10. Overall, Table 9 shows that with augmentation, the model inconsistency is notably reduced. Consistent with our intuition, the adaptive sampling (AS) scheme (and AS+), which entails an “error-aware” augmentation, exhibits the best performance to reduce model prediction inconsistency.

Table 10 shows that the overall model performance is slightly reduced. On one hand, it is generally acknowledged that models with relatively higher robustness can exhibit lower accuracy to particular training data. In particular, Table 9 has shown that SyntaxSQLNet, with being augmented by previous work (the “SyntaxSQLNet+aug” row), becomes less robust with an average inconsistency rate of 3.4. On the other hand, we would like to point out that de facto models, with being augmented by the AS+ scheme, performs generally comparable in terms of “Hard” and “Extra” questions with “SyntaxSQLNet+aug” (see the last column of Table 10), while achieving much better robustness as shown in Table 9.

6 Related Work

Text-to-SQL and generalizability. Text-to-SQL (or NL2SQL) is a challenging topic which requires to comprehend and translate human utterances into corresponding structured SQL queries toward the given relational database. It has been actively studied by both NLP and database communities for decades (Kim et al., 2020). Recently, AI-powered models manifest highly promising performance on cross-domain and cross-table text-to-SQL tasks and show great potential for real-world usage (Zhong et al., 2017; Xu et al., 2017; Yu et al., 2018a,c,b; Bogin et al., 2019b; Guo et al., 2019; Wang et al., 2019; Chen et al., 2020). The generalizability of these models on unseen user cases is critical for commercial adaption but not systematically evaluated. Suhr et al. pinpoint the main challenge on linguistic variations, novel database and query structure and conventions in different datasets (Suhr et al., 2020). Data augmentation techniques are also extensively used to enrich utterances and achieve higher performance on standard metrics (Yu et al., 2018b, 2020; Weir et al., 2020). However, given the unbalanced size of schemas

Table 9: Inconsistency rate of augmented models. **aug**: SyntaxSQLNet standard data augmentation; **RS**: Random Sampling; **SS**: Stratified Sampling; **AS**: Adaptive Sampling.

| Model                  | Easy | Medium | Hard | Extra | All  | All* |
|------------------------|------|--------|------|-------|------|------|
| SyntaxSQLNet           | 41.9 | 19.3   | 17.8 | 6.6   | 22.4 | 12.4 |
| SyntaxSQLNet+aug       | 42.7 | 24.2   | 22.3 | 8.4   | 25.8 | 15.6 |
| SyntaxSQLNet+RS        | 37.9 | 20.6   | 23.0 | 6.0   | 22.8 | 14.7 |
| SyntaxSQLNet+SS        | 41.1 | 18.8   | 20.7 | 9.0   | 22.8 | 14.7 |
| SyntaxSQLNet+AS        | 37.5 | 18.4   | 19.3 | 7.2   | 21.4 | 13.5 |
| SyntaxSQLNet+AS+       | 42.3 | 21.7   | 21.3 | 8.4   | 24.5 | 15.0 |
| IRNet                  | 72.3 | 53.6   | 42.0 | 32.9  | 52.8 | 37.6 |
| IRNet+RS               | 70.3 | 52.9   | 47.7 | 30.5  | 52.6 | 39.3 |
| IRNet+SS               | 70.7 | 53.8   | 45.9 | 35.9  | 52.7 | 41.1 |
| IRNet+AS               | 70.3 | 54.3   | 44.8 | 29.3  | 52.5 | 39.3 |

Table 10: Standard accuracy results of augmented models (breakdown by hardness, measured by exact set matching rate (Yu et al., 2018c)).
and utterances, e.g., 166 schemas vs. 9693 utterances in the Spider dataset (Yu et al., 2018c), it is indeed necessary to further augment schemas in the standard dataset. In addition, given the variations of human languages, it may be difficult for existing template- or grammar-based augmentation methods to further enhance consistency w.r.t. noisy utterances in the wild.

Robustness of NLP Models and Model Testing. Adversarial examples, by substituting original tokens in an utterance with typos or synonyms, impede model performance deliberately (Zhang et al., 2020). Photon augments text-to-SQL models with untranslatable user inputs to improve the model robustness (Zeng et al., 2020). Furthermore, instead of evaluating adversarial robustness, some works advocate a focus on assessing models with software testing methods and expose prediction inconsistency (Ma et al., 2020; He et al., 2020; Ribeiro et al., 2020). By mostly preserving the “naturalness” of mutated inputs, their findings would presumably indicate defects and confusions that normal users can encounter in real-life scenarios. Compared with this line of work, this present research takes one major step further by systematically transforming both natural language texts and database schemas. We also propose practical (error-aware) data augmentation strategies using the mutated inputs to enhance model robustness.

7 Conclusion & Availability

We have presented MT-TEQL, a metamorphic testing framework conducting model-agnostic testing on the consistency and coherence of text-to-SQL models. Our evaluation shows that de facto models, despite its promising performance in standard benchmark accuracy, manifest considerable inconsistency errors with respect to either utterances or schema variants. We further propose data augmentation strategies to extend the standard benchmark set and train text-to-SQL models with much higher consistency and also retaining comparable benchmark accuracy. We commit to make MT-TEQL publicly available, including all the code, synthetic data and augmented models. We will maintain MT-TEQL to benefit follow-up research.

References

Jacob Andreas, John Bufe, David Burkett, Charles Chen, Josh Clausman, Jean Crawford, Kate Crim, Jordan DeLoach, Leah Dorner, Jason Eisner, et al. 2020. Task-oriented dialogue as dataflow synthesis. Transactions of the Association for Computational Linguistics, 8:556–571.

Ben Bogin, Jonathan Berant, and Matt Gardner. 2019a. Representing schema structure with graph neural networks for text-to-SQL parsing. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4560–4565, Florence, Italy. Association for Computational Linguistics.

Ben Bogin, Matt Gardner, and Jonathan Berant. 2019b. Global reasoning over database structures for text-to-sql parsing. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3650–3655.

Sanxing Chen, Aidan San, Xiaodong Liu, and Yangfeng Ji. 2020. A tale of two linkings: Dynamically gating between schema linking and structural linking for text-to-sql parsing. In Proceedings of the 28th International Conference on Computational Linguistics, pages 2900–2912.

Tsong Y Chen, Shing C Cheung, and Shiu Ming Yiu. 1998. Metamorphic testing: a new approach for generating next test cases. Technical report, Technical Report HKUST-CS98-01, Department of Computer Science, Hong Kong . . . .

DongHyun Choi, Myeong Cheol Shin, EungGyun Kim, and Dong Ryeol Shin. 2020. Ryansql: Recursively applying sketch-based slot fillings for complex text-to-sql in cross-domain databases. arXiv preprint arXiv:2004.03125.

Shumo Chu, Chenglong Wang, Konstantin Weitz, and Alvin Cheung. 2017. Cosette: An automated prover for sql. In CIDR.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT (1).

Tao Ge, Furu Wei, and Ming Zhou. 2018. Fluency boost learning and inference for neural grammatical error correction. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1055–1065.

Jiaqi Guo, Zecheng Zhan, Yan Gao, Yan Xiao, Jian-Guang Lou, Ting Liu, and Dongmei Zhang. 2019. Towards complex text-to-sql in cross-domain database with intermediate representation. arXiv preprint arXiv:1905.08205.

Pinjia He, Clara Meister, and Zhendong Su. 2020. Structure-invariant testing for machine translation. In Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering, pages 961–973.
Hyeonji Kim, Byeong-Hoon So, Wook-Shin Han, and Hong Rae Lee. 2020. Natural language to sql: Where are we today? *Proceedings of the VLDB Endowment*, 13(10):1737–1750.

Yuntao Li, Bei Chen, Qian Liu, Yan Gao, Jian-Guang Lou, Yan Zhang, and Dongmei Zhang. 2020. " what do you mean by that?" a parser-independent interactive approach for enhancing text-to-sql. *arXiv preprint arXiv:2011.04151*.

Pingchuan Ma, Shuai Wang, and Jin Liu. 2020. Metamorphic testing and certified mitigation of fairness violations in nlp models. In *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20*, pages 458–465.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. GloVe: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.

Marco Tulio Ribeiro, Tongshuang Wu, Carlos Guestrin, and Sameer Singh. 2020. Beyond accuracy: Behavioral testing of NLP models with CheckList. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4902–4912. Online. Association for Computational Linguistics.

Sergio Segura, Gordon Fraser, Ana B Sanchez, and Antonio Ruiz-Cortés. 2016. A survey on metamorphic testing. *IEEE Transactions on software engineering*, 42(9):805–824.

Ezekiel Soremekun, Sakshi Udeshi, and Sudipta Chattopadhyay. 2020. Astraea: Grammar-based fairness testing. *arXiv preprint arXiv:2010.02542*.

Alane Suhr, Ming-Wei Chang, Peter Shaw, and Kenton Lee. 2020. Exploring unexplored generalization challenges for cross-database semantic parsing. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8372–8388.

Bailin Wang, Richard Shin, Xiaodong Liu, Oleksandr Polozov, and Matthew Richardson. 2019. Rat-sql: Relation-aware schema encoding and linking for text-to-sql parsers. *arXiv preprint arXiv:1911.04942*.

Nathaniel Weir, Prasetya Utama, Alex Galakatos, Andrew Crotty, Amir Ilkhechi, Shekar Ramaswamy, Rohin Bhushan, Nadja Geisler, Benjamin Hättasch, Steffen Eger, et al. 2020. Dbpal: A fully pluggable nl2sql training pipeline. In *Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data*, pages 2347–2361.

Xiaojun Xu, Chang Liu, and Dawn Song. 2017. Sqlnet: Generating structured queries from natural language without reinforcement learning. *arXiv preprint arXiv:1711.04436*.