Abstract

We study question-answering over semi-structured data. We introduce a new way to apply the technique of semantic parsing by applying machine learning only to provide annotations that the system infers to be missing; all the other parsing logic is in the form of manually authored rules. In effect, the machine learning is used to provide non-syntactic matches, a step that is ill-suited to manual rules. The advantage of this approach is in its debuggability and in its transparency to the end-user. We demonstrate the effectiveness of the approach by achieving state-of-the-art performance of 40.42% on a standard benchmark dataset over tables from Wikipedia.

1 Introduction

We investigate the problem of answering questions about semi-structured data. More specifically, we consider questions about tabular data. Individual entries may represent entities, numeric values or dates, though the list of these types is not specified a priori.

We illustrate our techniques and measure our performance using the WikiTableQuestions data set that was first studied by Pasupat and Liang (Pasupat and Liang, 2015). This data set was derived from tables in Wikipedia articles, and consists of a list of crowdsourced (question, answer, table) triples. For instance, one table is about the movies that the actress Mischa Barton has acted in. The questions in this data set includes simple factual lookups (“In which movies was Mischa Barton also a producer?”), or may involve a composition of several analytic functions (“which was the first year after 1995 in which Mischa Barton acted in more than 4 movies?”).

Most previous approaches to the problem of question answering have been based on semantic parsing, machine learning, or mixes of the two. Rule-based systems and machine learning both have strengths and weaknesses, and we apply a combination of the two in order to gain some of the advantages from both.

1.1 Our Contributions

The approach we take is to apply machine-learning to providing abductive (speculative) matches when we detect that we are missing an operand. As an example, for the question [in what movie was barton also the producer?], the terms “barton”, “producer” all have near exact syntactic matches to various table entities. The term “movie” is supposed to match the column called “title”. This is the kind of match we use machine learning to discover.

As a consequence, this allows the system to remain transparent. By this we mean that the system is be able to provide information about aspects of the logic that are speculative, and provide provenance for parts of the query that generate the answer. This will be described in more detail in section 3.7. We do not use machine learning either to score parses as in (Liang, 2016) or (Haug et al., 2017), or to solve the problem end-to-end like in (Nee-lakantan et al., 2017).

The advantages of our approach are as follows:

- It becomes much easier to debug and iterate on quality in the system.
- It allows the system to be “self-aware” as to when it is guessing, and to express
doubt in communication back to the user. 
(For instance: We think you meant: In what [title] was barton also the producer.)

Such human-readable justifications were suggested in (Raina et al., 2005).

We achieve a 40.42% accuracy on the question answering task on the WikiTables dataset (Pasupat and Liang, 2015); this is higher than the best published result we are aware of: 38.7% in (Haug et al., 2017); see Table 1. While our approach achieves higher overall accuracy, there are some questions that previous approaches answer correctly but our system does not. We leave a detailed comparison of the the various methods to future work.

| System                | Test accuracy |
|-----------------------|---------------|
| Baselines             |               |
| (Pasupat and Liang, 2015) | 37.1%         |
| (Neelakantan et al., 2017) | 34.2%         |
| (Neelakantan et al., 2017) Ensemble [15 models] | 37.7%         |
| (Haug et al., 2017)    | 38.7%         |
| Our system            |               |
| Without ML-based abduction | 35.22%       |
| With ML-based abduction | 40.42%       |

Table 1: Comparison of results

2 Prior work

The problem of factual question answering is by now quite old, but the formulation of the problem and the approaches depend in part upon the type of corpus that contains the answers. At one extreme is the case of a full text corpus in which answers are embedded in linguistic prose (Hirschman and Gaizauskas, 2001). At the other end of the spectrum is when answers are encoded in fully structured databases, in which case the problem is cast as a natural language interface to databases (cf. (Androutsopoulos et al., 1995)).

Due to lack of space, we are only able to describe a few of the previous contributions on question answering. For instance, (Berant et al., 2013; Cai and Yates, 2013; Berant and Liang, 2014) use a semantic parsing approach for answering questions on an open-end knowledge based like Freebase; see (Liang, 2016) for a description of the approach and a survey of related work. Yin et al. (Yin et al., 2016) proposes a neural network that encodes both the query and table using distributed representations, and passes it through a series of “executor” networks to generate the answer. The entire network is trained using question-answer pairs obtained from a synthetic dataset. Andreas et al. (Andreas et al., 2016) propose a hybrid approach where a neural network for answering questions is obtained by composing smaller neural “modules” (operators) with the composition layout generated from a syntactic parse of the question.

The first work on the WikiTableQuestions data set appeared in (Pasupat and Liang, 2015), and used semantic parsing to parse questions into logical forms, with a machine-learned component to score the logical forms. The logical forms are represented in lambda dependency-based compositional semantics (Liang et al., 2013). The scoring component is a regression model over features extracted from the query, table and the logical form. The model is tuned on the training set. There is also a semantic function abstraction that invalidates certain logical forms. The accuracy that they achieve on this data set was 37.1%.

More recently, the problem has also been tackled using end to end deep learning (Neelakantan et al., 2017). Their approach derives from the “Neural Programmer” work of Neelakantan et al. (Neelakantan et al., 2015) wherein the question and the table are fed as input to a recursive neural network that selects operators and operands at each step of the recursion. The result of applying the operator at each step is supplied to the next step. The best single model achieves an accuracy of 34.2%, while an ensemble of 15 models achieves an accuracy of 37.7%.

Finally, there is the work of (Haug et al., 2017) that uses a hybrid of the previous two approaches. It replaces the linear regression model used to score parses by (Pasupat and Liang, 2015) with a deep neural network that is featurized much like the one in (Neelakantan et al., 2017); that is, it uses a deep neural network only for scoring, still relying on the grammar-annotator-semantic function framework to generate candidate parses. Their best single model achieves an accuracy of 34.8% and an ensemble of 15 models achieves an accuracy
Finally, we are not the first to have applied abductive reasoning in NLP applications. In (Raina et al., 2005), the authors applied a combination of an abductive theorem prover and machine learning to the task of whether one sentence implies the other.

3 Our approach

The overall architecture of the system is derived from a rule-based semantic parsing system described in a previous paper (Dhamdhere et al., 2017). The system described in that paper is currently used by two Google products, namely Google Analytics and Google Spreadsheets.

In this paper we compose the previous system with a machine learning step to backfill missing pieces that correspond to unrecognized terms. The resulting architecture is shown in Figure 1. Our main conceptual contribution is to isolate the use of machine learning to identifying non-obvious term matches, and we only apply it when abductive reasoning tells us to. This modularization of the problem raises the question of how to use the Wikitables training data to learn such matches. The training data has the form of triples (Question, Table, Answer), so it is not immediately clear how to generate training data to identify query-term, table-entity matches. The details of this crucial training process are described in Section 3.5.

The parsing phase consists of a standard framework using an annotator and context-free grammar that is designed to recognize different classes of questions for which there are factual answers within the tables (see (Liang, 2016)). The output from the parsing phase is a data structure called semantic parse described in the next section. Following this parse phase, we attempt to identify the question type from among a set of question types (see Table 2). Based on this classification, we enter a phase where we apply abductive reasoning (see Section 3.5) to fill in missing semantics based on the unmatched terms and question type.

Once the semantic types have been identified, we convert the data structure into a SQL query on the underlying table. The use of SQL is a convenience that matches the rectangular structure of the tables, but can easily be replaced by a query language that is more appropriate to the underlying data storage.

3.1 Semantic Types

The semantic parse contains place holders for the typed concepts that make up the formal query. The types of these concepts include metrics (numerical columns), dimensions (string valued columns), filters (on dimensions and metrics), and ranges of datetime values. In addition, the semantic parse contains elements like sort order, limit, aggregation type, and what type of answer is expected. Not all the fields of the semantic parse are filled in for every query. Further details on the architecture can be found in (Dhamdhere et al., 2017).

3.2 Table comprehension

We chose SQL as our formal language for representing logical forms. This differs somewhat from the approach used in (Pasupat and Liang, 2015) where the structured representation was a more expressive knowledge graph format, with entity normalization nodes to facilitate the final step of answer extraction. Rather than using a “next” relation, we simply use a RowID column in the table. The one case in which these two methods seem to differ is when a cell contains a list of individual items (e.g., scores of tennis matches). In this case, we would need to post-process the cells that are needed to extract the answer, but we found these to be quite rare in the Wikitables data set.

One of the challenges of unstructured data
is that structure is not explicitly represented in the data, but considerable structure may still be implicitly represented. As an example, a string like 2005/06/27 will instantly be recognized by a human as a structured representation for a date without being told it is a date. There is a limit to how much effort should be put into hand-crafted parsers for such structures, but we found that the Wikitables data had several very common features that are explicitly referenced in questions. We therefore employed several simple parsers to recognize a few structures, including various date formats, times written as HH:MM:SS, numbers formatted in various ways, common units such as km/h, and scores of sporting events written as W 21–14. In some cases the preprocessing step allows us to split a column into two or three separate columns. In case a column contains numeric values, we keep both the original string values for a column as a dimension, but may also create a separate metric column. The creation of multiple columns allows us to easily perform aggregation or differences on numeric values, but also perform lookups by treating them as string values. Finally, some tables are already adorned with “Total” rows that contain sums of values above them. In order to allow aggregation over parts of the table, we separated out these rows when they could be easily recognized.

3.3 Annotation and Grammar

The output from table comprehension is a knowledge base that maps table entities to (possibly multiple) types. The goal of the annotator is to use this knowledge base to map phrases in the user’s query with the entities and intent word types. It uses simple string matching to perform this mapping, augmented by standard stemming and spell correction. Phrases can have multiple annotations, and subsequent steps of parsing (such as scoring) perform disambiguation. The annotator also identifies the headword in the question, and annotates it as a placeholder entity.

We use a context-free grammar to parse the annotated query. The grammar rules are written in terms of the types. Most of the grammar rules are “floating” in the sense of (Pasupat and Liang, 2015), i.e., they ignore the ordering of query terms. We make a few exceptions, for instance when we parse inequality conditions on numeric values (“more than 10 wins”). Here we use the sequence of comparison words, a bound and a metric.

3.4 Scoring

We use scoring to produce a soft ranking among candidate parses. A parse with higher annotation coverage should be ranked higher. The main feature in ranking is the number of annotated question words for a parse. Tie-breaking among the candidates with same number of annotated words is done using features like number of exact matches vs approximate matches, number of column header matches vs cell matches. This logic is implemented as a linear model with manually assigned weights. In the training set, on average our system generated 8.7 candidate parses for each question. By contrast, in (Pasupat and Liang, 2015) the number of parses may be exponential in the number of question terms, but they truncate to 200.

After scoring, we perform the abductive matching step that is our main contribution. This is described in the next section. After this step, the semantic parse is turned into an executable SQL query with up to one level of nesting. By contrast, (Liang, 2016) uses a lambda DCS abstraction, which allows for unlimited composition of operators. Our semantic parse/SQL abstraction restricts the amount of composition possible, but we achieve quite good results in spite of this limitation. Following execution of the SQL, there is a normalization step to extract the final answer based on the question type. We extract a list answer if the headword in the question is plural.

3.5 The Operand Predictor

A key conceptual contribution of our work is to separate deductive reasoning from abductive reasoning. Essentially, we can factor our system into two parts, namely a rule-based grammar-annotator component that produces a potentially incomplete parse, followed by a statistical component called an operand predictor that does its best to fill in the value of missing operands.

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1In this paper, a headword is the noun or noun-phrase that succeeds the question-word, for instance, in our running example, “movie” is headword.
The operand predictor is abductive in the sense of Mooney (Mooney, 2000) that defines abductive reasoning as the “constructing explanations of observed events”. In other words, the operand predictor explains the incomplete, invalid parse by adding operands that make the new parse valid, in the sense that it contains all the required operands. For our running example, the additional match of the query term “movie” to the column 'Title', constitutes an explanation that makes the incomplete parse a valid lookup query.

**Identifying missing operands:** This step is purely deductive: Suppose that the question is: “in what movie was barton also the producer?”. The intent word “what” implies that the answer is most likely a cell of the table, i.e., it is a lookup question. Second, such a lookup requires the specification of a row and a column. Third, the word “producer” from the question syntactically matches the phrase “also producer” from a cell of the table. The row of this cell specifies the row of the answer. Unfortunately, there isn’t a simple syntactic match between a query term and a column heading, so we are missing information that identifies the column.

Our approach was to identify a list of question types and required operands with each type. These are listed in Table 3. The detection of the question types is entirely rule-based, using a combination of intent words and syntactically matched entities. Some question types are determined purely from the intent words, e.g. “after” indicates **BEF_AFTER** and “how many” suggests **HOW_MANY**. On the other hand, to detect **A_OR_B**, we look for the existence of two row filters along with an intent word like “or”. Both **SORT_DIM** and **SORT_MET** use words that indicate ordering (e.g. highest, most). To distinguish between the two, we use presence of a dimension or metric. The logic for type detection assumes that all row filters and intent words are identified correctly, but does not require all columns to have been identified. Questions that don’t fall under these types (e.g. yes/no questions) also get mapped to **OTHER_TYPE**.

**Predicting operand values:** In our running example, we have detected a row filter (“producer”), but we are still missing a dimension operand, and we need to predict its value. The dimension must be one of the column headings in the table, which, from left to right are: “Year”, “Title”, “Role” and “Notes”, and it turns out that the correct dimension is “Title”.

In predicting the correct dimension, the number of column headings is usually quite small (4-10). There are probably a number of ways to implement this prediction. For instance, by examining the contents of the column, and using the semantic web to infer that every entry in the column is a movie. Our machine learning approach is described in the next section.

It is worth noting that this abductive process is closely related to the fact that real-world questions are often under-specified (see e.g. (Small et al., 2004)). For example, the question “How much traffic did my website receive?” is lacking a time range over which to compute the answer. It make sense to assume some value for this time range while answering the question and reflect this assumption back to the user, and we used this approach in our previous work (Dhamdhere et al., 2017). This situation does not arise in the WikiTableQuestions data set, but offers further evidence for why abduction is important to the process of question answering.

### 3.6 Machine Learning for Abduction

We notice that there is a frequent co-occurrence of certain query terms and column headings in the data set. For instance, we notice that the query term “movie” occurs in questions against 43 tables, and 20 of these contain the column named “Title”. This suggests that we can learn associations “movie” → “Title” and apply these generally to the test set. See Table 3 for some examples that we learned. One could also imagine learning a mapping between a query phrase “did not swim” and the cell entry “DNS”. Unfortunately they don’t co-occur in the training data frequently enough to learn, so we constrained the learning to only learn the mapping between query terms and column headings. By learning such a mapping, we are able to achieve a nearly 5.2% gain in test accuracy.

We train a machine learning model that,
Table 2: Question types used in the statistical component.

| Question type | Example | Required Operands |
|---------------|---------|------------------|
| **SORT_DIM**  | which movie has the most budget? | Dimension, Metric |
| **SORT_MET**  | First movie by Tom Cruise | Metric |
| **FIRST_LAST**| What was the highest attendance | Dimension |
| **BEF_AFTER** | Actor who won before Tom Cruise | Filter |
| **SAME_VALUE**| Which city from same state as Boston | Two Dimensions, Filter |
| **POS_BOTH**  | LA and SF are both in which state? | Dimension, Two Filters |
| **A_OR_B**    | Who has 4 world cup wins, Germany or Brazil? | Two Filters |
| **DIFFERENCE**| What is the difference in height between x and y | Metric, Two Filters |
| **HOW_MANY**  | How many cities with ... | Metric |
| **LOOKUP**    | Location of Boston Celtics game | Dimension, Filter |
| **OTHER_TYPE**| (a catch-all for cases we have no semantics for) | at least one column |

given a set of query terms that are either unmatched or assigned to a placeholder (see Section 3.3), and a list of columns, assigns probabilities to each column indicating the likelihood of it being the correct guess. An unmatched term in the question is a term that cannot be matched to an intent word from the grammar or column heading or cell value in the table or a placeholder entity.

### 3.6.1 Training data generation

The Wikitables training data set provided only the answer as a label for a question. For the aforementioned task we seek training data for intermediate annotation steps. We obtain such data from our parses.

Given parses for the questions that have missing operands, we construct counter-factual parses as follows: We try out all possible columns for the missing operand in the parse, generating a new parse for each alternative. We then generate SQL for each of these parses, and evaluate the SQL over the table comparing the result to the known correct answer. There are three possibilities. First, it is possible that none of the SQL queries lead to the correct answer. This means that we have not detected the intent correctly, or we do not support the semantics of the question. Second, it is possible that more than one of these parses produces a correct answer. This may happen by accident. For example, in the question “how many movies did barton act in?”, it is possible that the number of distinct values in the “Title” and the “Role” both result in the right answer. Third, there is exactly one query leading to the correct answer. Our training data is constructed from these examples.

For each such example, the training data consists of a triple \( \langle W, C, \text{ind} \rangle \) where \( W \) is a set of query words, \( C \) is a list of columns in the table, and \( \text{ind} \) is a one-hot vector (has value 1 the correct column). Notice that this process of generating training data is only tractable because there is a closed, small world of choices among the columns.

### 3.6.2 Training set-up

We use a very simple neural network for training. We embed each term into a 50 dimensional embedding space. We construct query embedding by adding the embeddings of the query terms together, and a column embedding by adding the embeddings of the column heading terms together. We then take the dot product of the two and apply a softmax that produces a prediction for the correct choice. The loss function is cross-entropy. We split our training dataset into 70/30 train-test split. When we use the model in serving, it generates approximately a 5.2% gain in accuracy; see Table 1. Note also that simply guessing the left-most string-valued column would give a third of this gain. In our running example, “Title” is the left-most string-valued column.

Tables 3 and 4 show the query term to column heading matches learned by our model. Table 3 shows examples where the model’s prediction is correct while Table 4 shows examples where the model’s prediction is semantically related but leads to an incorrect answer. Notice that the correct matches predicted by the model are non-syntactic. Of the original 14,152 training questions, we derived a training set of only 1,392 examples. Despite this, certain term/column associations occur

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While the embeddings could be combined using a more complex architecture such as an LSTM or a CNN, we prefer our simple averaging method for its interpretability.
Table 3: Examples of correct mappings from terms to column names.

| Terms     | Column             | Frequency |
|-----------|--------------------|-----------|
| who       | name               | 114       |
| country   | nation             | 38        |
| who       | player             | 38        |
| player    | name               | 15        |
| film      | title              | 13        |
| who       | opponent           | 12        |
| team      | opponent           | 11        |
| year      | season             | 11        |
| episode   | title              | 10        |
| movie     | title              | 10        |
| movie     | film               | 8         |
| competitor| name               | 5         |

Table 4: Examples of incorrect mappings from terms to column names.

| Terms     | Predicted        | Correct                  |
|-----------|------------------|--------------------------|
| tier      | division         | level                    |
| size      | area (mm2)       | diagonal (mm)            |
| who       | name             | president served under   |
| who       | party            | senator                  |
| game      | date             |                          |
| win       | score            | outcome                  |

frequently enough to allow for learning.

3.7 Transparency

One of our main motivations was to deploy a system that offers a high level of transparency to both the user and the developer. The user benefits from seeing how their question was interpreted, and the developer benefits from being able to debug and iteratively improve the system.

Most of our system consists of hand-written rules that are easy to debug in isolation, though the interaction between rules can be quite complex. Most of the complexity in debugging arises from the annotator and the abductive matching components. Errors manifest either as a query-term being unmatched to any entity or intent word, or by a query term being matched incorrectly. Consequently, our debugging information consists of all the entity/intent-word annotations we produced, including the list of unmatched query terms. For each of these we include the provenance. The types of provenances include exact syntactic match, approximate syntactic match, machine-learned abductive match, or rule-based abductive match. The developer can use this information in several ways:

- To identify unhandled intents by inspecting the list of frequently occurring unmatched terms. For instance, we found the terms “next” and “previous” as frequently unmatched in an earlier version. This indicated the need to implement position-based selection operator.
- To debug the approximate matching logic in the annotator and the abductively added machine-learning matches.

Though it does not apply to the WikiTables exercise, we envision warning the user whenever we use an approximate syntactic match, or any abductive match: We could preface the response with “We think the answer is”, and also identify which query terms if any were used in the matching. This will help the user decide whether to trust the response.

4 Evaluation

We chose to evaluate our methodology on version 1.0.2 of the WikiTableQuestions data set (Pasupat and Liang, 2015). This dataset consists of a set of 22,033 (table, question, answer) triples, where the table is from an HTML page on wikipedia. The data set is divided into a training set of 14,152 examples and a test set of 4,344 examples, plus an extra set of 3,537 examples that we did not use. The objective for this data set is to get as many right answers as possible on the test set, though we are only ever allowed to inspect the training set. The questions were sourced through Mechanical Turk by showing the pages to users and prompting them to ask a question of a given form. The answers were then collected via Mechanical Turk by asking other users to answer the questions. In our evaluation we confined ourselves to using only the CSV form of the tables, though it is evident from some of the questions in the training data set that users were shown something more than this. See Section 7.2 from (Pasupat and Liang, 2015) for further details about the dataset.

We have achieved an accuracy of 41.35% on the training set, which translates into an accuracy of 40.42% on the test set (see Table 1). We believe that this represents the best published results on this test set so far.

We expect our system to have different wins and losses from that of (Pasupat and Liang, 2015) and (Neelakantan et al., 2017). For
instance, (Pasupat and Liang, 2015) does not handle questions with Yes/No answers. The end-to-end trained model of (Neelakantan et al., 2017) does not support comparison operators on derived values and therefore cannot handle questions of type \textit{SAME_VALUE} e.g., “which nation won the same number of bronze medals as Peru?”.

Our parse and SQL have bounded “formula size” in the terminology of (Pasupat and Liang, 2015). This is possibly where many of our losses lie. In contrast, their system allows for arbitrarily long chains of operator composition (“what are the number of movies that Barton acted in the year after she acted in three movies, two of which were documentaries?”). On the other hand, our abduction approach (cf. Section 3.5) lets us match query terms and column name that aren’t close synonyms of each other while their system is limited in this aspect (Pasupat and Liang, 2015, Section 7.5). Given the somewhat complementary strengths, it might be interesting to compose our abduction approach with their system and see what the gain is.

A More Meaningful Evaluation

While the WikiTableQuestions data set represents a worthwhile evaluation set to compare the results from different approaches, we believe that it is not an accurate representation of what a human would expect from a question-answering system. In particular, there should be a consequence of giving a wrong answer, but the metrics proposed with the WikiTableQuestions data set focus only on how many questions are answered correctly. If a human was asking questions of an analyst or expert, then they would quickly lose faith in an expert who routinely produced a significant number of answers that are just wrong. The goal of building reliable question-answering systems has been previously discussed in (Khani et al., 2016).

As an example, consider the case of yes/no questions. The WikiTableQuestions training data set has 182 questions of this type, for which 95 (52%) have a “yes” answer. A system that always answered “yes” would therefore do better than average across all questions, but would clearly result in an unsatisfying system. We therefore believe that a metric that penalizes for wrong answers would better reflect what a real system should deliver.

There are other factors that a real question answering system should address, such as ambiguity in questions and conversation. In previous work we have discussed our approach to these issues (Dhamdhere et al., 2017).

5 Summary and Conclusions

Rule-based systems are transparent, but often not extensible without significant manual effort. In contrast, machine-learning systems are extensible, but are often not transparent. We propose an architecture that combines the best of the two approaches, by using machine-learning only to supply missing operands. This use of machine-learning is minimal in the sense that everything that can be easily expressed as rules is expressed as such. This allows the overall system to be transparent and debuggable, as discussed in section 3.7. While we use machine learning in a limited way, it still has a significant impact on the accuracy of our system. We expect our architecture with the use of machine-learnt embeddings within the annotator, combined with a hand-written grammar, to apply to question-answering on other corpora.

References

Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Dan Klein. 2016. Learning to compose neural networks for question answering. \textit{CoRR} abs/1601.01705. \url{http://arxiv.org/abs/1601.01705}.

I. Androutsopoulos, G. D. Ritchie, and P. Thanisch. 1995. Natural language interfaces to databases - an introduction. \textit{Natural Language Engineering} 1(1):29–81. \url{https://arxiv.org/pdf/cmp-lg/9503016.pdf}.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on freebase from question-answer pairs. In \textit{Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, EMNLP 2013, 18-21 October 2013, Grand Hyatt Seattle, Seattle, Washington, USA, A meeting of SIGDAT, a Special Interest Group of the ACL}. pages 1533–1544. \url{https://arxiv.org/pdf/cmp-lg/9503016.pdf}.

Jonathan Berant and Percy Liang. 2014. Semantic parsing via paraphrasing. In \textit{Proceedings of the 52nd Annual Meeting of the Association for
Qingqing Cai and Alexander Yates. 2013. Large-scale semantic parsing via schema matching and lexicon extension. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, ACL 2013, 4-9 August 2013, Sofia, Bulgaria, Volume 1: Long Papers. pages 423–433.

Kedar Dhamdhere, Kevin S. McCurley, Ralfi Nahmias, Mukund Sundararajan, and QiQi Yan. 2017. Analyza: Exploring data with conversation. In Proceedings of the 22nd International Conference on Intelligent User Interfaces, IUI 2017, Limassol, Cyprus, March 13-16, 2017. pages 493–504. http://doi.acm.org/10.1145/3025171.3025227.

Till Haug, Octavian-Eugen Ganea, and Paulina Grnarova. 2017. Neural multi-step reasoning for question answering on semi-structured tables. CoRR abs/1702.06589. http://arxiv.org/abs/1702.06589.

L. Hirschman and R. Gaizauskas. 2001. Natural language question answering: The view from here. Nat. Lang. Eng. 7(4):275–300. https://doi.org/10.1017/S1351324901002807.

F. Khani, M. Rinard, and P. Liang. 2016. Unanimous prediction for 100% precision with application to learning semantic mappings. In Association for Computational Linguistics (ACL). https://arxiv.org/abs/1606.06368.

Percy Liang. 2016. Learning executable semantic parsers for natural language understanding. Commun. ACM 59(9):68–76. https://doi.org/10.1145/2866568.

Percy Liang, Michael I. Jordan, and Dan Klein. 2013. Learning dependency-based compositional semantics. Comput. Linguist. 39(2):389–446.

Raymond J. Mooney. 2000. Integrating abduction and induction in machine learning. In P. A. Flach and A. C. Kakas, editors, Abduction and Induction, Kluwer Academic Publishers, pages 181–191. http://www.cs.utexas.edu/users/ailab/?mooney:bkchapter00.

Arvind Neelakantan, Quoc V. Le, Martin Abadi, Andrew McCallum, and Dario Amodei. 2017. Learning a natural language interface with neural programmer. https://arxiv.org/abs/1611.08945.

Arvind Neelakantan, Quoc V. Le, and Ilya Sutskever. 2015. Neural programmer: Inducing latent programs with gradient descent. CoRR abs/1511.04834. http://arxiv.org/abs/1511.04834.

Panupong Pasupat and Percy Liang. 2015. Compositional semantic parsing on semi-structured tables. ACL. See also https://github.com/ppasupat/WikiTableQuestions. https://arxiv.org/pdf/1508.06305.pdf.

Rajat Raina, Andrew Y Ng, and Christopher D Manning. 2005. Robust textual inference via learning and abductive reasoning. In AAAI. pages 1099–1105. https://nlp.stanford.edu/manning/papers/aaai05-learnabduction.ps.

Sharon Small, Tomek Strzalkowski, Ting Liu, Sean Ryan, Robert Salkin, Nobuyuki Shimizu, Paul Kantor, Diane Kelly, Robert Rittman, and Nina Wacholder. 2004. Hitqa: Towards analytical question answering. In Proceedings of the 20th International Conference on Computational Linguistics, Association for Computational Linguistics, Stroudsburg, PA, USA, COLING ’04. https://doi.org/10.3115/1220355.1220544.

Pengcheng Yin, Zhendong Lu, Hang Li, and Ben Kao. 2016. Neural enquirer: Learning to query tables in natural language. In Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, IJCAI 2016, New York, NY, USA, 9-15 July 2016. pages 2308–2314.