Building a Semantic Parser Overnight

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Abstract

How do we build a semantic parser in a new domain starting with zero training examples? We introduce a new methodology for this setting: First, we use a simple grammar to generate logical forms paired with canonical utterances. The logical forms are meant to cover the desired set of compositional operators, and the canonical utterances are meant to capture the meaning of the logical forms (although clumsily). We then use crowdsourcing to paraphrase these canonical utterances into natural utterances. The resulting data is used to train the semantic parser. We further study the role of compositionality in the resulting paraphrases. Finally, we test our methodology on seven domains and show that we can build an adequate semantic parser in just a few hours.

1 Introduction

By mapping natural language utterances to executable logical forms, semantic parsers have been useful for a variety of applications requiring precise language understanding (Zelle and Mooney, 1996; Zettlemoyer and Collins, 2005; Liang et al., 2011; Berant et al., 2013; Kwiatkowski et al., 2013; Artzi and Zettlemoyer, 2013). Previous work has focused on how to train a semantic parser given input utterances, but suppose we wanted to build a semantic parser for a new domain—for example, a natural language interface into a publications database. Since no such interface exists, we do not even have a naturally occurring source of input utterances that we can annotate. So where do we start?

In this paper, we advocate a functionality-driven process for rapidly building a semantic parser in a new domain. At a high-level, we seek to minimize the amount of work needed for a new domain by factoring out the domain-general aspects (done by our framework) from the domain-specific ones (done by the builder of the semantic parser). We assume that the builder already has the desired functionality of the semantic parser in mind—e.g., the publications database is set up and the schema is fixed. Figure 1 depicts the functionality-driven process: First, the builder writes a seed lexicon specifying a canonical phrase (“publication date”) for

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Each predicate (publicationDate). Second, our framework uses a domain-general grammar, along with the seed lexicon and the database, to automatically generate a few hundred canonical utterances paired with their logical forms (e.g., “article that has the largest publication date” and \( \arg \max(\text{type.article.publicationDate}) \)). These utterances need not be the most elegant, but they should retain the semantics of the logical forms. Third, the builder leverages crowdsourcing to paraphrase each canonical utterance into a few natural utterances (e.g., “what is the newest published article?”). Finally, our framework uses this data to train a semantic parser.

Practical advantages. There are two main advantages of our approach: completeness and ease of supervision. Traditionally, training data is collected in a best-effort manner, which can result in an incomplete coverage of functionality. For example, the WebQuestions dataset (Berant et al., 2013) contains no questions with numeric answers, so any semantic parser trained on that dataset would lack that functionality. These biases are not codified, which results in an idiosyncratic and mysterious user experience, a major drawback of natural language interfaces (Rangel et al., 2014). In contrast, our compact grammar precisely specifies the logical functionality. We enforce completeness by generating canonical utterances that exercise every grammar rule.

In terms of supervision, state-of-the-art semantic parsers are trained from question-answer pairs (Kwiatkowski et al., 2013; Berant and Liang, 2014). Although this is a marked improvement in cost and scalability compared to annotated logical forms, it still requires non-trivial effort: the annotator must (i) understand the question and (ii) figure out the answer, which becomes even harder with compositional utterances. In contrast, our main source of supervision is paraphrases, which only requires (i), not (ii). Such data is thus cheaper and faster to obtain.

Linguistic reflections. The centerpiece of our framework is a domain-general grammar that connects logical forms with canonical utterances. This connection warrants further scrutiny, as the structural mismatch between logic and language is the chief source of difficulty in semantic parsing (Liang et al., 2011; Kwiatkowski et al., 2013; Berant and Liang, 2014). There are two important questions here. First, is it possible to design a simple grammar that simultaneously generates both logical forms and canonical utterances so that the utterances are understandable by a human? In Section 3, we show how to choose appropriate canonical utterances to maximize alignment with the logical forms.

Second, our grammar can generate an infinite number of canonical utterances. How many do we need for adequate coverage? Certainly, single relations is insufficient: just knowing that “publication date of X” paraphrases to “when X was published” would offer insufficient information to generalize to “articles that came after X” mapping to “article whose publication date is larger than publication date of X”. We call this phenomena sublexical compositionality—when a short lexical unit (“came after”) maps onto a multi-predicate logical form. Our hypothesis is that the sublexical compositional units are small, so we only need to crowdsourcense a small number of canonical utterances to learn about most of the language variability in the given domain (Section 4).

We applied our functionality-driven process to seven domains, which were chosen to explore particular types of phenomena, such as spatial language, temporal language, and high-arity relations. This resulted in seven new semantic parsing datasets, totaling 12.6K examples. Our approach, which was not tuned on any one domain, was able to obtain an average accuracy of 59% over all domains. On the day of this paper submission, we created an eighth domain and trained a semantic parser overnight.

2 Approach Overview

In our functionality-driven process (Figure 1), there are two parties: the builder, who provides domain-specific information, and the framework, which provides domain-general information. We assume that the builder has a fixed database \( w \), represented as a set of triples \((e_1, p, e_2)\), where \( e_1 \) and \( e_2 \) are entities (e.g., article1, 2015) and \( p \) is a property (e.g., publicationDate). The database \( w \) can be queried using lambda DCS logical forms, described further in Section 2.1.

The builder supplies a seed lexicon \( L \), which contains for each database property \( p \) (e.g., publicationDate) a lexical entry of the form \((t \rightarrow s[p])\), where \( t \) is a natural language phrase (e.g., “publication date”) and \( s \) is a syntactic cat-
category (e.g., RELNP). In addition, \( L \) contains two typical entities for each semantic type in the database (e.g., \( \langle \text{alice} \rightarrow \text{NP[alice]} \rangle \) for the type \text{person}). The purpose of \( L \) is to simply connect each predicate with \text{some} representation in natural language.

The framework supplies a grammar \( G \), which specifies the modes of composition, both on logical forms and canonical utterances. Formally, \( G \) is a set of rules of the form \( \langle \alpha_1 \ldots \alpha_n \rightarrow s[z] \rangle \), where \( \alpha_1 \ldots \alpha_n \) is a sequence of tokens or categories, \( s \) is a syntactic category and \( z \) is the logical form constructed. For example, one rule in \( G \) is \( \langle \text{RELNP[r] of NP[x]} \rightarrow \text{NP[R(r).x]} \rangle \), which constructs \( z \) by reversing the binary predicate \( r \) and joining it with the unary predicate \( x \). We use the rules \( G \cup L \) to generate a set of \( (z,c) \) pairs, where \( z \) is a logical form (e.g., \( R(\text{publicationDate}.\text{article1}) \)) and \( c \) is the corresponding canonical utterance (e.g., “publication date of article 1”). The set of \( (z,c) \) is denoted by \( \text{GEN}(G \cup L) \). See Section 3 for details.

Next, the builder (backed by crowdsourcing) paraphrases each canonical utterance \( c \) output above into a set of natural utterances \( P(c) \) (e.g., “when was article 1 published?”). This defines a set of training examples \( D = \{(x,c,z)\} \), for each \( (z,c) \in \text{GEN}(G \cup L) \) and \( x \in P(c) \). The crowdsourcing setup is detailed in Section 5.

Finally, the framework trains a semantic parser on \( D \). Our semantic parser is a log-linear distribution \( p_\theta(z,c \mid x,w) \) over logical forms and canonical utterances specified by the grammar \( G \). Note that the grammar \( G \) will in general not parse \( x \), so the semantic parsing model will be based on paraphrasing, in the spirit of Berant and Liang (2014).

To summarize, (1) the builder produces a seed lexicon \( L \); (2) the framework produces logical forms and canonical utterances \( \text{GEN}(G \cup L) = \{(z,c)\} \); (3) the builder (via crowdsourcing) uses \( P(\cdot) \) to produce a dataset \( D = \{(x,c,z)\} \); and (4) the framework uses \( D \) to train a semantic parser \( p_\theta(z,c \mid x,w) \).

### 2.1 Lambda DCS

Our logical forms are represented in lambda DCS, a logical language where composition operates on sets rather than truth values. Here we give a brief description; see Liang (2013) for details.

Every logical form \( z \) in this paper is either a \text{unary} (denoting a set of entities) or a \text{binary} (denoting a set of entity-pairs). In the base case, each entity \( e \) (e.g., \( 2015 \)) is a unary denoting the singleton set: \( [e]_w = \{e\} \); and each property \( p \) (e.g., \text{publicationDate}) is a binary denoting all entity-pairs \((e_1,e_2)\) that satisfy the property \( p \). Unaries and binaries can be composed: Given a binary \( b \) and unary \( u \), the join \( b.u \) denotes all entities \( e_1 \) for which there exists an \( e_2 \in [u]_w \) with \((e_1,e_2) \in [b]_w \). For example, \( \text{publicationDate.2015} \) denote entities published in 2015.

The intersection \( u_1 \cap u_2 \), union \( u_1 \cup u_2 \), complement \( \neg u \) denote the corresponding set operations on the denotations. We let \( R(b) \) denote the reversal of \( b: (e_1,e_2) \in [b]_w \) iff \((e_2,e_1) \in [R(b)]_w \). This allows us to define \( R(\text{publicationDate}).\text{article1} \) as the publication date of article 1. We also include aggregation operations (count(\( u \)), sum(\( u \)) and average(\( u,b \)), and superlatives (argmax(\( u,b \))).

Finally, we can construct binaries using lambda abstraction: \( \lambda x.u \) denotes a set of \((e_1,e_2)\) where \( e_1 \in [u|x/e_2]_w \) and \( u|x/e_2 \) is the logical form where free occurrences of \( x \) are replaced with \( e_2 \). For example, \( R(\lambda x.\text{count}(R(\text{titles}).x)) \) denotes the set of entities \((e_1,e_2)\), where \( e_2 \) is the number of entities that \( e_1 \) cites.

### 3 Generation and canonical compositionality

Our functionality-driven process hinges on having a domain-general grammar that can connect logical forms with canonical utterances compositionally. The motivation is that while it is hard to write a grammar that parses all utterances, it is possible to write one that generates one canonical utterance for each logical form. To make this explicit:

**Assumption 1 (Canonical compositionality)**

\text{Using a small grammar, all logical forms expressible in natural language can be realized compositionally based on the logical form.}

**Grammar.** We target database querying applications, where the parser needs to handle superlatives, comparatives, negation, and coordination. We define a simple grammar that captures these forms of compositionality using canonical utterances in a domain-general way. Figure 2 illustrates a derivation produced by the grammar.

The seed lexicon specified by the builder contains canonical utterances for types, entities, and properties. All types (e.g., \text{person}) have the syntactic category \text{TypeNP}, and all entities (e.g.,
In addition, combines these CP’s with an NP (e.g., (T1) such as join its denotation. Finally, we support transformations include argmin in addition to argmax), which take or “that cites more than three article” can be represented in the database as five triples: 

<table>
<thead>
<tr>
<th>article</th>
<th>publication date</th>
<th>1950</th>
</tr>
</thead>
</table>

Table 1: The seed lexicon for the SOCIAL domain, which specifies for each predicate (e.g., birthdate) a phrase (e.g., “birthdate”) that realizes that predicate and its syntactic category (e.g., RELNP).

All five properties here are represented as RELNP’s, with the first one designated as the subject (RELNP₀). We support two ways of querying multi-arity relations: “student whose university is ucla” (T2) and “university of student Alice whose start date is 2005” (T3).

Generating directly from the grammar in Table 2 would result in many uninterpretable canonical utterances. Thus, we perform type checking on the logical forms to rule out “article that cites 2004”, and limit the amount of recursion, which keeps the canonical utterances understandable.

Still, the utterances generated by our grammar are not perfectly grammatical; we do not use determiners and make all nouns singular. Nonetheless, AMT workers found most canonical utterances understandable (see Table 3 and Section 5 for details on crowdsourcing). One tip for the builder is to keep the RELNP’s and VP/NP’s as context-independent as possible; e.g., using “publication date” instead of “date”. In cases where more context is required, we use parenthetical remarks (e.g., “number of assists (over a season)” → RELNP[. . .]) to pack more context into the confines of the part-of-speech.

Limitations. While our domain-general grammar covers most of the common logical forms in a database querying application, there are several phenomena which are out of scope, notably nested quantification (e.g., “show me each author’s most cited work”) and anaphora (e.g., “author who cites herself at least twice”). Handling these would require a more radical change to the grammar, but is still within scope.
\[
\text{(G1)} \quad \text{ENTITY}_{NP}[:z] \rightarrow NP[x], \\
\text{(G2)} \quad \text{TYPE}_{NP}[:x] \rightarrow NP[\text{type}, x], \\
\text{(G3)} \quad NP[x] \text{ CP}[f] (\text{and CP}[g])^* \rightarrow NP[x \land f \land g].
\]

Table 2: The domain-general grammar which is combined with the seed lexicon to generate logical forms and canonical utterances that cover the supported logical functionality.

4 Paraphrasing and bounded non-compositionality

While the canonical utterance \(c\) is generated compositionally along with the logical form \(z\), natural paraphrases \(x \in P(c)\) generally deviate from this compositional structure. For example, the canonical utterance “NP[number of NP[article CP[whose publication date is larger than NP[publication date of article 1]]]]” might get paraphrased to “How many articles were published after article 1?”. Here, “published after” non-compositionally straddles the inner NP, intuitively responsible for both instances of “publication date”. But how non-compositional can paraphrases be? Our framework rests on the assumption that the answer is “not very”:

Assumption 2 (Boundred non-compositionality)

Natural utterances for expressing complex logical forms are compositional with respect to fragments of bounded size.

In the above example, note that while “published after” is non-compositional with respect to the grammar, the rewriting of “number of” to “how many” is compositional. The upshot of Assumption 2 is that we only need to ask for paraphrases of canonical utterances generated by the grammar up to some small depth to learn about all the non-compositional uses of language, and still be able to generalize (compositionally) beyond that.

We now explore the nature of the possible paraphrases. Broadly speaking, most paraphrases involve some sort of compression, where the clunky but faithful canonical utterance is smoothed out into graceful prose.

Alternations of single rules. The most basic paraphrase happens at the single phrase level with synonyms (“block” to “brick”), which preserve the part-of-speech. However, many of our properties are specified using relational noun phrases, which are more naturally realized using prepositions (“meeting whose attendee is alice ⇒ meeting with alice”) or verbs (“author of article 1 ⇒ who wrote article 1”). If the RELNP is complex, then the argument can become embedded: “player whose number of points is 15 ⇒ player who scored 15 points”. Superlative and comparative constructions reveal other RELNP-dependent words: “article that has the largest publication date ⇒ newest article”. When the value of the
relation has enough context, then the relation is elided completely: “housing unit whose housing type is apartment ⇒ apartment”.

Multi-arity predicates are compressed into a single frame: “university of student alice whose field of study is music” becomes “At which university did Alice study music?”, where the semantic roles of the verb “study” carry the burden of expressing the multiple relations: student, university, and fieldOfStudy. With a different combination of arguments, the natural verb would change: “Which university did Alice attend?”

Sublexical compositionality. The most interesting paraphrases occur across multiple rules, a phenomenon which we called sublexical compositionality. The idea is that common, multi-part concepts are compressed to single words or simpler constructions. The simplest compression is a lexical one: “parent of alice whose gender is female ⇒ mother of alice”. Compression often occurs when we have the same predicate chained twice in a join: “person that is author of paper whose author is x ⇒ co-author of x” or “person whose birthdate is birthdate of x ⇒ person born on the same day as x”. When two CP’s combined via coordination have some similarity, then the coordination can be pushed down (“meeting whose start time is 3pm and whose end time is 5pm ⇒ meetings between 3pm and 5pm”) and sometimes even generalized (“that allows cats and that allows dogs ⇒ that allows pets”). Sometimes, compression happens due to metonymy, where people stand in for their papers: “author of article that article whose author is x cites ⇒ who does x cite”.

5 Crowdsourcing

We tackled seven domains covering various linguistic phenomena. Table 3 lists the domains, their principal phenomena, statistics about their predicates and dataset, and an example from the dataset.

We use Amazon Mechanical Turk (AMT) to paraphrase the canonical utterances generated by the domain-general grammar. In each AMT task, a worker is presented with four canonical utterances and is asked to reformulate them in natural language or state that they are incomprehensible. Each canonical utterance was presented to 10 workers. Over all domains, we collected 18,032 responses. The average time for paraphrasing one utterance was 28 seconds. Paraphrases that share the same canonical utterance are collapsed, while identical paraphrases that have distinct canonical utterances are deleted. This produced a total of 12,602 examples over all domains.

To estimate the level of noise in the data, we manually judged the correctness of 20 examples in each domain, and found that 17% of the utterances were inaccurate. There are two main reasons: lexical ambiguity on our part (“player that has the least number of team ⇒ player with the lowest jersey number”), and failure on the worker’s part (“restaurant whose star rating is 3 stars ⇒ hotel which has a 3 star rating”).

6 Model and Learning

Our semantic parsing model defines a distribution over logical forms given by the domain-general grammar $G$ and additional rules triggered by the input utterance $x$. Specifically, given an utterance $x$, we detect numbers, dates, and perform string matching with database entities to recognize named entities. This results in a set of rules $T(x)$. For example, if $x$ is “article published in 2015 that cites article 1”, then $T(x)$ contains $\langle 2015 \rightarrow \text{NP}[2015] \rangle$ and $\langle \text{article} 1 \rightarrow \text{NP[article1]} \rangle$. Let $L_x$ be the rules in the seed lexicon $L$ where the entity rules (e.g., $\langle \text{alice} \rightarrow \text{NP[alice]} \rangle$) are replaced by $T(x)$.

Our semantic parsing model defines a log-linear distribution over candidate pairs $(z,c) \in \text{GEN}(G \cup L_x)$:

$$p_\theta(z,c \mid x,w) \propto \exp(\phi(z,c,x,w)^T \theta), \quad (1)$$

where $\phi(z,c,x,w) \in \mathbb{R}^d$ is a feature vector and $\theta \in \mathbb{R}^d$ is a parameter vector.

To generate candidate logical forms, we use a simple beam search: For each search state, which includes the syntactic category $s$ (e.g., NP) and the depth of the logical form, we generate at most $K = 20$ candidates by applying the rules in Table 2. In practice, the lexical rules $T(x)$ are applied first, and composition is performed, but not constrained to the utterance. For example, the utterance “article” would generate the logical form count(type.article). Instead, soft paraphrasing features are used to guide the search. This rather unorthodox approach to semantic parsing can be seen as a generalization of Berant and Liang (2014) and is explained in more detail in Pasupat and Liang (2015).

Training. We train our model by maximizing the regularized log-likelihood $\mathcal{O}(\theta) =$
Table 3: We experimented on seven domains, covering a variety of phenomena. For each domain, we show the number of predicates, number of examples, and a (c, z) generated by our framework along with a paraphrased utterance x.

<table>
<thead>
<tr>
<th>Domain</th>
<th># pred.</th>
<th># ex.</th>
<th>Phenomena</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>CALENDAR</td>
<td>22</td>
<td>837</td>
<td>temporal language</td>
<td>x: “Show me meetings after the weekly standup day”</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>☰ type.meeting (\cap) date (\supset) R(date), weeklyStandup</td>
</tr>
<tr>
<td>BLOCKS</td>
<td>19</td>
<td>1995</td>
<td>spatial language</td>
<td>x: “Select the brick that is to the furthest left.”</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>☰ block that the most number of block is right of ({x} \cup {z})</td>
</tr>
<tr>
<td>HOUSING</td>
<td>24</td>
<td>941</td>
<td>measurement units</td>
<td>x: “Housing that is 800 square feet or bigger?”</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>☰ type.housingUnit (\cap) area (\supset) 800</td>
</tr>
<tr>
<td>RESTAURANTS</td>
<td>32</td>
<td>1657</td>
<td>long unary relations</td>
<td>x: “What restaurant can you eat lunch outside at?”</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>☰ restaurant that has outdoor seating and that serves lunch ({x} \cup {z})</td>
</tr>
<tr>
<td>PUBLICATIONS</td>
<td>15</td>
<td>801</td>
<td>sublexical compositionality</td>
<td>x: “Who has co-authored articles with Efron?”</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>☰ person that is author of article whose author is efron ({x} \cup {z})</td>
</tr>
<tr>
<td>SOCIAL</td>
<td>45</td>
<td>4419</td>
<td>multi-arity relations</td>
<td>x: “When did alice start attending brown university?”</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>☰ R(date), Student.Alice (\cap) University.Brown</td>
</tr>
<tr>
<td>BASKETBALL</td>
<td>24</td>
<td>1952</td>
<td>parentheticals</td>
<td>x: “How many fouls were played by Kobe Bryant in 2004?”</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>☰ count(R(fouls), player.KobeBryant (\cap) season.2004)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✷ person that is author of article whose author is efron ({x} \cup {z})</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✷ type.person (\cap) R(author), {type.article (\cap) author.efron}</td>
</tr>
</tbody>
</table>

Table 4: Features for the paraphrasing model. \(\text{pos}(x_{i,j})\) is the POS tag; \(\text{type}[z_\omega]\) is a coarse semantic type for the denotation (an entity or a number). \(\mathcal{A}\) is a maximum weight alignment between \(x\) and \(c\).

\[
\sum_{(x,c,z) \in D} \log p_\theta(z, c \mid x, w) - \lambda \|\theta\|_1. \quad \text{To optimize, we use AdaGrad (Duchi et al., 2010).}
\]

Features Table 4 describes the features. Our basic features mainly match words and bigrams in \(x\) and \(c\), if they share a lemma or are aligned in the PPDB resource (Ganitkevitch et al., 2013). We count the number of exact matches, PPDB matches, and unmatched words.

To obtain lexical features, we run the Berkeley Aligner (Liang et al., 2006) on the training set and compute conditional probabilities of aligning one word type to another. Based on these probabilities we compute a maximum weight alignment \(\mathcal{A}\) between words in \(x\) and \(c\). We define features over \(\mathcal{A}\) (see Table 4). We also use the word alignments to construct a phrase table by applying the consistent phrase pair heuristic (Och and Ney, 2004). We define an indicator feature for every phrase pair of \(x\) and \(c\) that appear in the phrase table. Examples from the PUBLICATIONS domain include fewest–least number and by–whose author is. Note that we do not build a hard lexicon but only use \(\mathcal{A}\) and the phrase table to define features, allowing the model to learn useful paraphrases during training. Finally, we define standard features on logical forms and denotations (Berant et al., 2013).

7 Experimental Evaluation

We evaluated our functionality-driven process on the seven domains described in Section 5 and one new domain we describe in Section 7.3. For each domain, we held out a random 20% of the examples as the test set, and performed development on the remaining 80%, further splitting it to a training and development set (80%/20%). We created a database for each domain by randomly generating facts using entities and properties in the domain (with type-checking). We evaluated using accuracy, which is the fraction of examples that yield the correct denotation.

7.1 Domain-specific linguistic variability

Our functionality-driven process is predicated on the fact that each domain exhibits domain-specific
phenomena. To corroborate this, we compare our full system to NoLEX, a baseline that omits all lexical features (Table 4), but uses PPDB as a domain-general paraphrasing component. We perform the complementary experiment and compare to NoPPDB, a baseline that omits PPDB match features. We also run Baseline, where we omit both lexical and PPDB features.

Table 5 presents the results of this experiment. Overall, our framework obtains an average accuracy of 59% across all eight domains. The performance of NoLEX is dramatically lower than Full, indicating that it is important to learn domain-specific paraphrases using lexical features. The accuracy of NoPPDB is only slightly lower than Full, showing that most of the required paraphrases can be learned during training. As expected, removing both lexical and PPDB features results in poor performance (Baseline).

**Analysis.** We performed error analysis on 10 errors in each domain. Almost 70% of the errors are due to problems in the paraphrasing model, where the canonical utterance has extra material, is missing some content, or results in an incorrect paraphrase. For example, “restaurants that have waiters and you can sit outside” is paraphrased to “restaurant that has waiter service and that takes reservations”. Another 12.5% result from reordering issues, e.g., we paraphrase “What venue has fewer than two articles” to “article that has less than two venue”. Inaccurate paraphrases provided by AMT workers account for the rest of the errors.

### 7.2 Bounded non-compositionality

We hypothesized that we need to obtain paraphrases of canonical utterances corresponding to logical forms of only small depth. We ran the following experiment in the CALENDAR domain to test this claim. First, we define by NP₀, NP₁, and NP₂ the set of utterances generated by an NP that has exactly zero, one, and two NPs embedded in it. We define the training scenario 0 → 1, where we train on examples from NP₀ and test on examples from NP₁; 0 ∪ 1 → 1, 0 ∪ 1 → 2, and 0 ∪ 1 ∪ 2 → 2 are defined analogously. Our hypothesis is that generalization on 0 → 1 should be better than for 0 → 1, since NP₁ utterances have non-compositional paraphrases, but training on NP₀ does not expose them.

The results in Table 6 verify this hypothesis. The accuracy of 0 → 1 is almost 65% lower than 0 ∪ 1 → 1. On the other hand, the accuracy of 0 ∪ 1 → 2 is only 19% lower than 0 ∪ 1 ∪ 2 → 2.

### 7.3 An overnight experiment

To verify the title of this paper, we attempted to create a semantic parser for a new domain (RECIPES) exactly 24 hours before the submission deadline. Starting at midnight, we created a seed lexicon in less than 30 minutes. Then we generated canonical utterances and allowed AMT workers to provide paraphrases overnight. In the morning, we trained our parser and obtained an accuracy of 70.8% on the test set.

### 7.4 Testing on independent data

Geo880. To test how our parser generalizes to utterances independent of our framework, we created a semantic parser for the domain of US geography, and tested on the standard 280 test examples from Geo880 (Zelle and Mooney, 1996). We did not use the standard 600 training examples. Our parser obtained 56.4% accuracy, which is substantially lower than state-of-the-art (~ 90%).

We performed error analysis on 100 random sentences from the development set where accuracy was 60%. We found that the parser learns from the training data to prefer shorter paraphrases, which accounts for 30% of the errors. In most of these cases, the correct logical form is ranked at the top-3 results (accuracy for the top-3 derivations is 73%). Geo880 contains highly compositional utterances, and in 25% of the errors...
the correct derivation tree exceeds the maximum depth used for our parser. Another 17.5% of the errors are caused by problems in the paraphrasing model. For example, in the utterance “what is the size of california”, the model learns that “size” corresponds to “population” rather than “area”. Errors related to reordering and the syntactic structure of the input utterance account for 7.5% of the errors. For example, the utterance “what is the area of the largest state” is paraphrased to “state that has the largest area”.

Calendar. In Section 7.1, we evaluated on utterances obtained by paraphrasing canonical utterances from the grammar. To examine the coverage of our parser on independently-produced utterances, we asked AMT workers to freely come up with queries. We collected 186 such queries; 5 were spam and discarded. We replaced all entities (people, dates, etc.) with entities from our seed lexicon to avoid focusing on entity detection.

We were able to annotate 52% of the utterances with logical forms from our grammar. We could not annotate 20% of the utterances due to relative time references, such as “What time is my next meeting?”. 14% of the utterances were not covered due to binary predicates not in the grammar (“What is the agenda of the meeting?”) or missing entities (“When is Dan’s birthday?”). Another 2% required unsupported calculations (“How much free time do I have tomorrow?”), and the rest are out of scope for other reasons (“When does my Verizon data plan start over?”).

We evaluated our trained semantic parser on the 95 utterances annotated with logical forms. Our parser obtained an accuracy of 46.3% and oracle accuracy of 84.2%, which measures how often the correct denotation is on the final beam. The large gap shows that there is considerable room for improvement in the paraphrasing model.

8 Related work and discussion

Much of current excitement around semantic parsing emphasizes large knowledge bases such as Freebase (Cai and Yates, 2013; Kwiatkowski et al., 2013; Berant et al., 2013). However, despite the apparent scale, the actual question answering datasets (Free917 and WebQuestions) are limited in compositionality. Moreover, specialized domains with specialized jargon will always exist, e.g., in regular expressions (Kushman and Barzilay, 2013) or grounding to perception (Matuszek et al., 2012; Tellex et al., 2011; Krishnamurthy and Kollár, 2013). Therefore, we believe building a targeted domain-specific semantic parser for a new website or device is a very practical goal.

Recent work has made significant strides in reducing supervision from logical forms (Zettlemoyer and Collins, 2005; Wong and Mooney, 2007) to denotations (Clarke et al., 2010; Liang et al., 2011) and to weaker forms (Artzi and Zettlemoyer, 2011; Reddy et al., 2014). All of these works presuppose having input utterances, which do not exist in a new domain. Our methodology overcomes this hurdle by exploiting a very lightweight form of annotation: paraphrasing.

Paraphrasing has been applied to single-property question answering (Fader et al., 2013) and semantic parsing (Berant and Liang, 2014). We not only use paraphrasing in the semantic parser, but also for data collection.

Table 2 might evoke rule-based systems (Woods et al., 1972; Warren and Pereira, 1982) or controlled natural languages (Schwitter, 2010). However, there is an important distinction: the grammar need only connect a logical form to one canonical utterance; it is not used directly for parsing. This relaxation allows the grammar to be much simpler. Our philosophy is to use the simple domain-general grammar to carry the torch just to the point of being understandable by a human, and let the human perform the remaining correction to produce a natural utterance.

In summary, our contributions are two-fold: a new functionality-driven process and an exploration of some of its linguistic implications. We believe that our methodology is a promising way to build semantic parsers, and in future work, we would like to extend it to handle anaphora and nested quantification.

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Reproducibility. All code, data, and experiments for this paper are available on the CodaLab platform at https://www.codalab.org/worksheets/0x269ef752f8c344a28383240f7bb2be9c/.

1Our system uses the SEMPRE toolkit (http://nlp.stanford.edu/software/sempre).
References


