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...
of supervision. Traditionally, training data is completeness natural utterances few to paraphrase each canonical utterance into a forms. Third, the builder leverages crowdsourcing but they should retain the semantics of the logical forms. These utterances need not be the most elegant, 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 crowdsource 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 \( \langle t \rightarrow s[p] \rangle \), where \( t \) is a natural language phrase (e.g., “publication date”) and \( s \) is a syntactic cat-

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forms and canonical utterances GEN
phrasing, in the spirit of Berant and Liang (2014).
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) ∈ GEN(G ∪ L) and x ∈ 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
pθ(z, c | 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 GEN(G ∪ L) =
\{(z, c)\}; (3) the builder (via crowdsourcing) uses
P(·) to produce a dataset D = \{(x, c, z)\}; and (4)
the framework uses D to train a semantic parser
pθ(z, c | 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
unary (denoting a set of entities) or a binary (de-
noting a set of entity-pairs). In the base case, each
entity e (e.g., 2015) is a unary denoting the single-
ton set: [e]w = \{e\}; and each property p (e.g.,
publicationDate) is a binary denoting all entity-
pairs (e1, e2) 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 e1 for
which there exists an e2 ∈ [u]w with (e1, e2) ∈
[b]w. For example, 
publicationDate.2015 denote entities published in 2015.
The intersection u1 ∩ u2, union u1 ∪ u2, com-
plement ¬u denote the corresponding set operations on the denotations. We let R(b) denote the reversal of b: (e1, e2) ∈ [b]w iff
(e2, e1) ∈ [R(b)]w. This allows us to define
R(publicationDate).article1 as the publica-
tion 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: λx.u denotes a set of (e1, e2) where
e1 ∈ [u[x/e2]]w and u[x/e2] is the logical form
where free occurrences of x are replaced with e2.
For example, R(λx.count(R(cites).x)) denotes the
set of entities (e1, e2), where e2 is the number of entities that e1 cites.

3 Generation and canonical
compositionality
Our functionality-driven process hinges on having a
domain-general grammar that can connect logi-
cal forms with canonical utterances composi-
tionally. 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)
Using a small grammar, all logical forms ex-
pressible in natural language can be realized
compositionally based on the logical form.
Grammar. We target database querying appli-
cations, where the parser needs to handle superla-
tives, comparatives, negation, and coordination.
We define a simple grammar that captures these
forms of compositionality using canonical utter-
ances in a domain-general way. Figure 2 illustrates
a derivation produced by the grammar.
The seed lexicon specified by the builder con-
tains canonical utterances for types, entities, and
properties. All types (e.g., person) have the syn-
tactic category TypeNP, and all entities (e.g.,
Figure 2: Deriving a logical form $z$ (red) and a canonical utterance $c$ (green) from the grammar $G$. Each node contains a syntactic category and a logical form, which is generated by applying a rule. Nodes with only leaves as children are produced using the seed lexicon; all other nodes are produced by rules in the domain-general grammar.

Alice) are ENTITYNP's. Unary predicates are realized as verb phrases VP (e.g., "has a private bath"). The builder can choose to represent binaries as either relational noun phrases (RELNP) or generalized transitive verbs (VP/RELNP). RELNP's are usually used to describe functional properties (e.g., "publication date"), especially numerical properties. VP/RELNP's include transitive verbs ("cites") but also longer phrases with the same syntactic interface ("is the president of"). Table 1 shows the seed lexicon for the SOCIAL domain.

From the seed lexicon, the domain-general grammar (Table 2) constructs noun phrases (NP), verbs phrases (VP), and complementizer phrase (CP), all of which denote unary logical forms. Broadly speaking, the rules (R1)–(R4), (C1)–(C4) take a binary and a noun phrase, and compose them (optionally via comparatives, counting, and negation) to produce a complementizer phrase CP representing a unary (e.g., "that cites article 1" or "that cites more than three article"). (G3) combines these CP's with an NP (e.g., "article"). In addition, (S0)–(S4) handle superlatives (we include argmin in addition to argmax), which take an NP and return the extremum-attaining subset of its denotation. Finally, we support transformations such as join (T1) and disjunction (T4), as well as aggregation (A1)–(A2).

Rendering utterances for multi-arity predicates was a major challenge. The predicate instances are typically reified in a graph database, akin to a neo-Davidsonian treatment of events: There is an abstract entity with binary predicates relating it to its arguments. For example, in the SOCIAL domain, Alice's education can be represented in the database as five triples:

| birthdate | → RELNP[birthdate] |
| person/university/field | → RELNP[person] |
| company/job title | → RELNP[company] |
| student/university/field of study | → RELNP[student] |
| employee/employer/job title | → RELNP[employee] |
| start date/end date | → RELNP[startDate] |
| is friends with | → VP/RELNP[friends] |

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).

(e17, student, alice), (e17, university, ucla), (e17, fieldOfStudy, music), (e17, startDate, 2005), (e17, endDate, 2009).

All five properties here are represented as RELNP's, with the first one designated as the subject (RELNP$_0$). 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/RELNP's as context-independent as possible; e.g., using "publication date" instead of "date". In cases where more context is required, we use parenthetical marks (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.
4 Paraphrasing and bounded non-compositionality

While the canonical utterance $c$ is generated compositionally along with the logical form $z$, natural paraphrases $x \in \mathbf{P}(c)$ 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 (Bounded 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 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 (“black” 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 1 cites ⇒ person whose article 1 cited ⇒ 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 (2015 → NP[2015]) and (article 1 → NP[article 1]). Let $L_x$ be the rules in the seed lexicon $L$ where the entity rules (e.g., (alice → NP[alice])) are replaced by $T(x)$.

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

$$p_\theta(z, c \mid x, w) \propto \exp(\phi(c, z, x, w)^T \theta),$$  \hspace{1cm} (1)

where $\phi(c, z, x, w) \in \mathbb{R}^d$ 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 $\text{count}(\text{type.article})$. 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 $O(\theta) =$
∀ 32 1657 long unary relations
x:
meeting whose date is at least date of weekly standup
c:
meeting whose date is at least date of weekly standup

∀ 19 1995 spatial language
x:
block that is to the furthest left.
c:
block that is to the furthest left.

∀ 24 941 measurement units
x:
housing unit whose size is at least 800 square feet.
c:
housing unit whose size is at least 800 square feet.

∀ 15 801 sublexical compositionality
x:
author of article whose author is efron.
c:
author of article whose author is efron.

EX. A
ber).
pos
a paraphrased utterance

compute conditional probabilities of aligning one
in the PPDB resource (Ganitkevitch et al., 2013).

compute a maximum weight alignment
maximize, we use AdaGrad (Duchi et al., 2010).

Features

Table 4: Features for the paraphrasing model. pos(x_i) is the POS tag; type([z]_w) is a coarse semantic type for the denotation (an entity or a number). A is a maximum weight alignment between x and c.

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.

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 Kollar, 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; Wor 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/0x269ef752f8c344a283383240f7bb2be9c/.

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