Semantic Parsing for Question Answering

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Semantic Parsing

- Semantic Parsing: Transforming natural language (NL) sentences into completely formal logical forms or meaning representations (MRs).
- Sample application domains where MRs are directly executable by another computer system to perform some task.
  - Database/knowledge-graph queries
  - Robot command language

Geoquery: A Database Query Application

- Query application for U.S. geography database containing about 800 facts [Zelle & Mooney, 1996]

Which rivers run through the states bordering Texas?

Answer (traverse(next_to(stateid('texas'))))

Answer (traverse(next_to(stateid('texas'))))

Arkansas, Canadian, Cimarron, Gila, Mississippi, Rio Grande ...

answer(traverse(next_to(stateid('texas'))))

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Most existing work on computational semantics is based on predicate logic.

What is the smallest state by area?
answer(x_1, smallest(area(x_1, x_2)))

x_1 is a logical variable that denotes “the smallest state by area”

Functional Query Language (FunQL)

• Transform a logical language into a functional, variable-free language (Kate et al., 2005)

What is the smallest state by area?
answer(x_1, smallest(area(x_1, x_2)))

answer(smallest_one(area_1(state(all))))

Learning Semantic Parsers

• Manually programming robust semantic parsers is difficult due to the complexity of the task.
• Semantic parsers can be learned automatically from sentences paired with their logical form.
Compositional Semantics

- Approach to semantic analysis based on building up an MR compositionally based on the syntactic structure of a sentence.
- Build MR recursively bottom-up from the parse tree.

\[
\text{BuildMR}(\text{parse-tree})
\]

If parse-tree is a terminal node (word) then
return an atomic lexical meaning for the word.
Else
For each child, subtree, of parse-tree
Create its MR by calling \text{BuildMR}(\text{subtree}_i)
Return an MR by properly combining the resulting MRs for its children into an MR for the overall parse-tree.

Composing MRs from Parse Trees

What is the capital of Ohio?
\[S \text{ answer(capital(loc_2(stateid('ohio'))))}\]

Disambiguation with Compositional Semantics

- The composition function that combines the MRs of the children of a node, can return \(\otimes\) if there is no sensible way to compose the children’s meanings.
- Could compute all parse trees up-front and then compute semantics for each, eliminating any that ever generate a \(\otimes\) semantics for any constituent.
- More efficient method:
  - When filling (CKY) chart of syntactic phrases, also compute all possible compositional semantics of each phrase as it is constructed and make an entry for each.
  - If a given phrase only gives \(\otimes\) semantics, then remove this phrase from the table, thereby eliminating any parse that includes this meaningless phrase.
Composing MRs from Parse Trees

What is the capital of Ohio?

Experimental Corpora

- GeoQuery [Zelle & Mooney, 1996]
  - 250 queries for the given U.S. geography database
  - 6.87 words on average in NL sentences
  - 5.32 tokens on average in formal expressions
  - Also translated into Spanish, Turkish, & Japanese.
Experimental Methodology

- Evaluated using standard 10-fold cross validation
- Correctness
  - CLang: output exactly matches the correct representation
  - Geoquery: the resulting query retrieves the same answer as the correct representation
- Metrics
  \[
  \text{Precision} = \frac{|\text{Correct Completed Parses}|}{|\text{Completed Parses}|}
  \]
  \[
  \text{Recall} = \frac{|\text{Correct Completed Parses}|}{|\text{Sentences}|}
  \]

Precision Learning Curve for GeoQuery

Recall Learning Curve for GeoQuery
Precision Learning Curve for GeoQuery (WASP)

Recall Learning Curve for GeoQuery (WASP)

Conclusions

- Semantic parsing maps NL sentences to completely formal computer language.
- Semantic parsers can be effectively learned from supervised corpora consisting of only sentences paired with their formal representations.
- Can reduce supervision demands by training on questions and answers rather than formal representations.
  - Results on FreeBase queries and queries to corpora of web tables.
- Full question answering is finally taking off as an application due to:
  - Availability of large-scale, open databases such as FreeBase, DBPedia, Google Knowledge Graph, Bing Satori
  - Availability of speech interfaces that allow more natural entry of full NL questions.