Semantic Parsing for Question Answering

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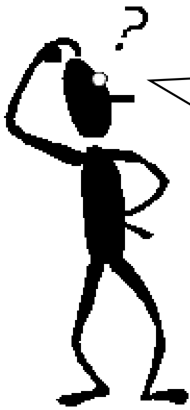
Semantic Parsing

- ***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?

Semantic Parsing

answer(traverse(next_to(stateid(‘texas’))))

Query

Answer

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

Predicate Logic Query Language

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

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

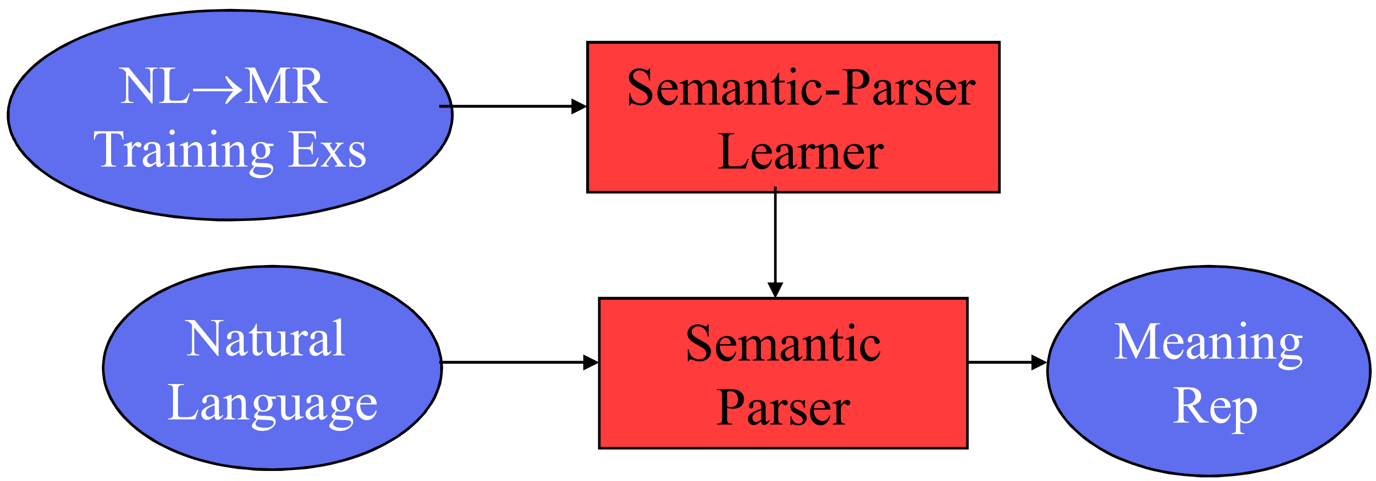
What is the smallest state by area?

~~$answer(x_1,smallest(x_2,(state(x_1),area(x_1,x_2))))$~~

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.



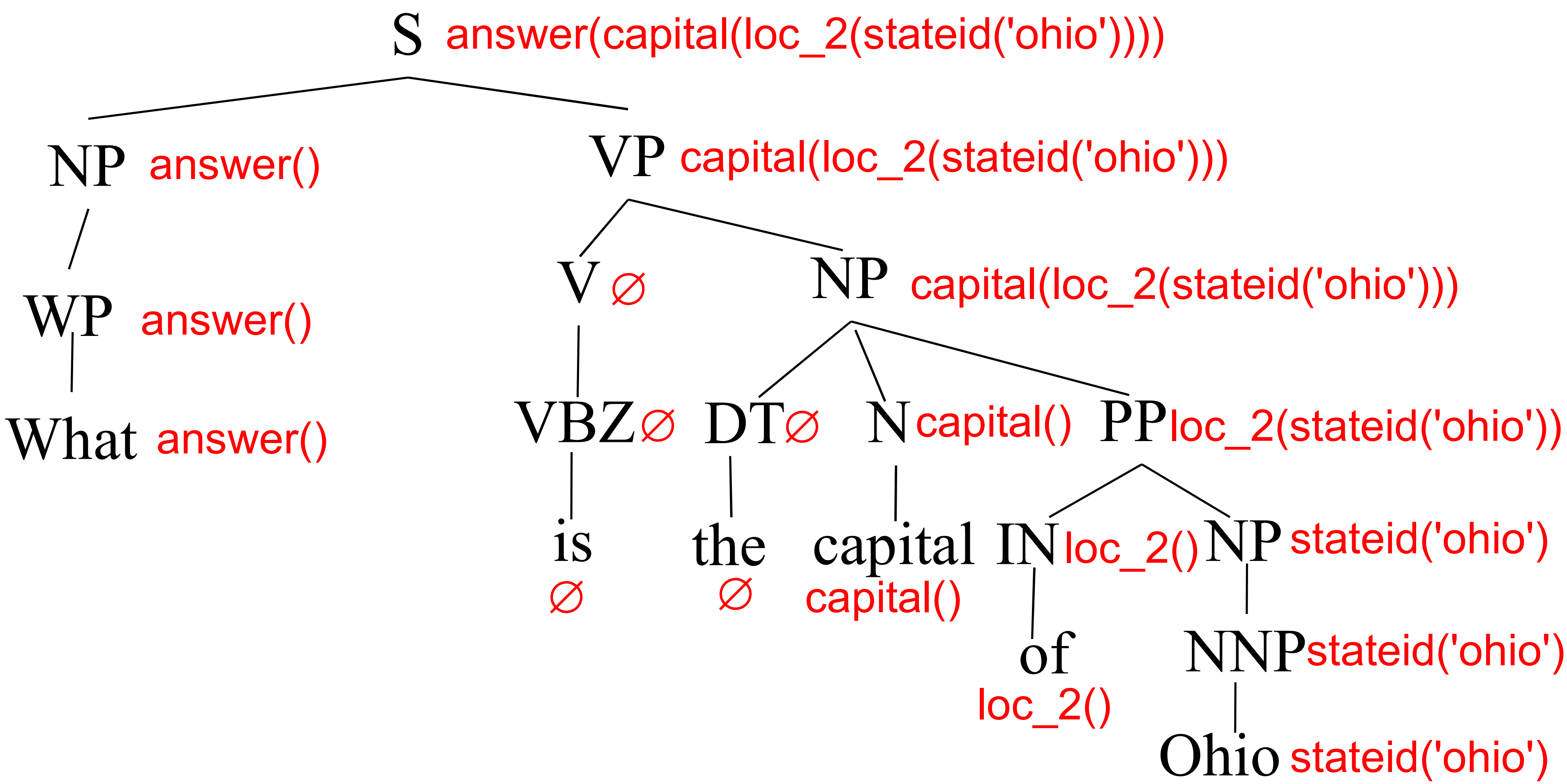
Compositional Semantics

- 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.

BuildMR(parse-tree)
    If parse-tree is a terminal node (word) then
        return an atomic lexical meaning for the word.
    Else
      For each child, subtree$_i$, of parse-tree
          Create its MR by calling BuildMR(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?



Disambiguation with Compositional Semantics

- The composition function that combines the MRs of the children of a node, can return ⊗ 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 ⊗ 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 ⊗ semantics, then remove this phrase from the table, thereby eliminating any parse that includes this meaningless phrase.

Composing MRs from Parse Trees

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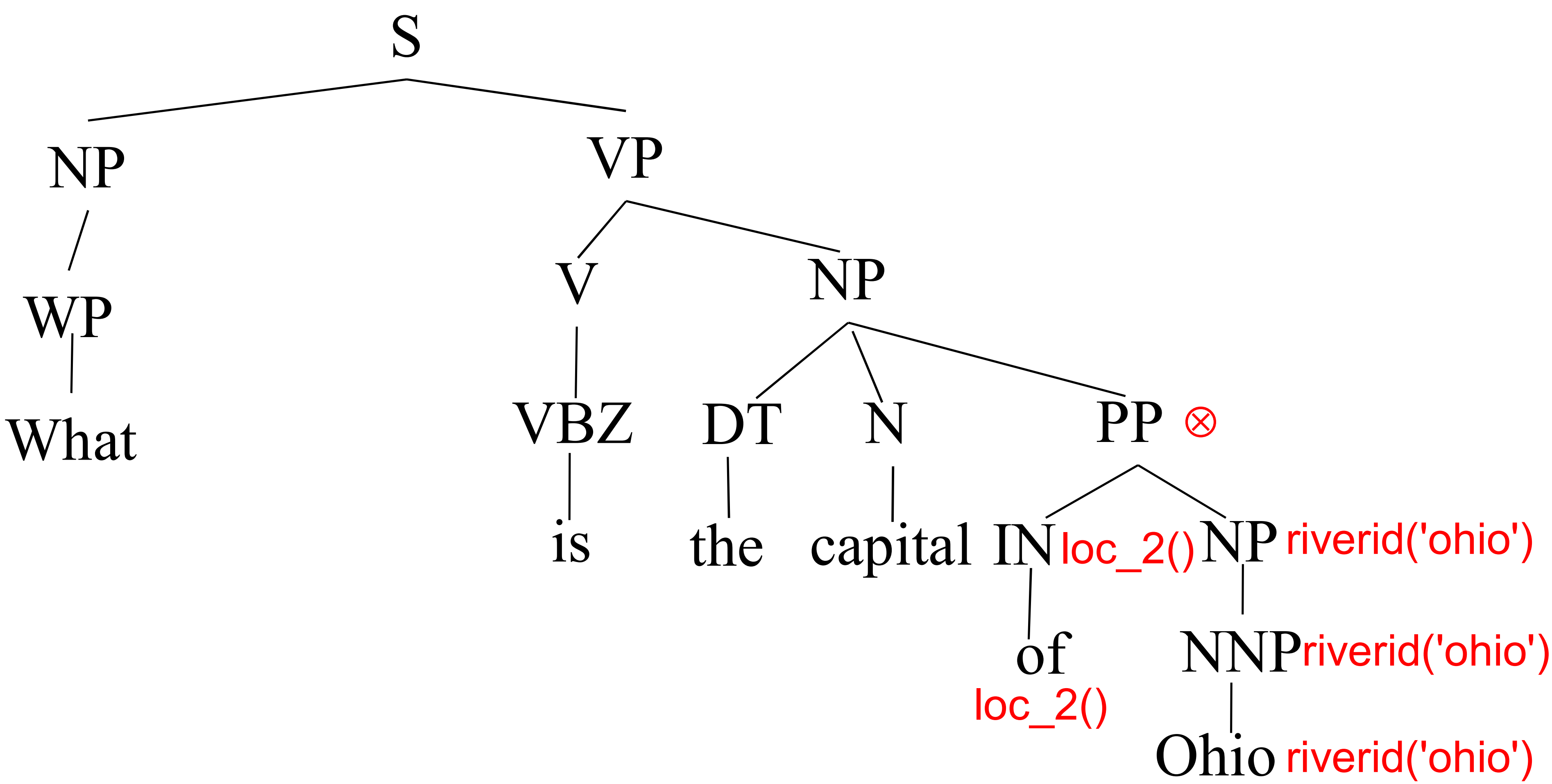
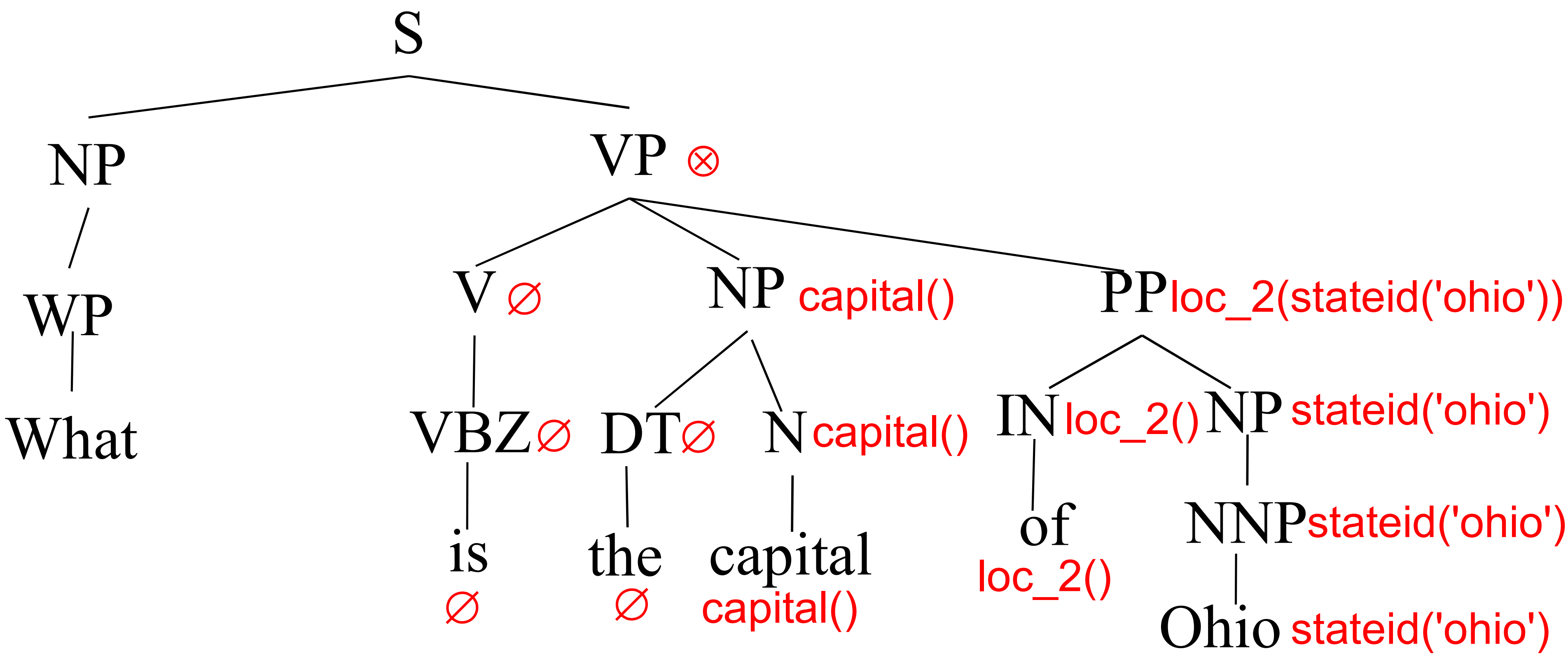


Composing MRs from Parse Trees

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.

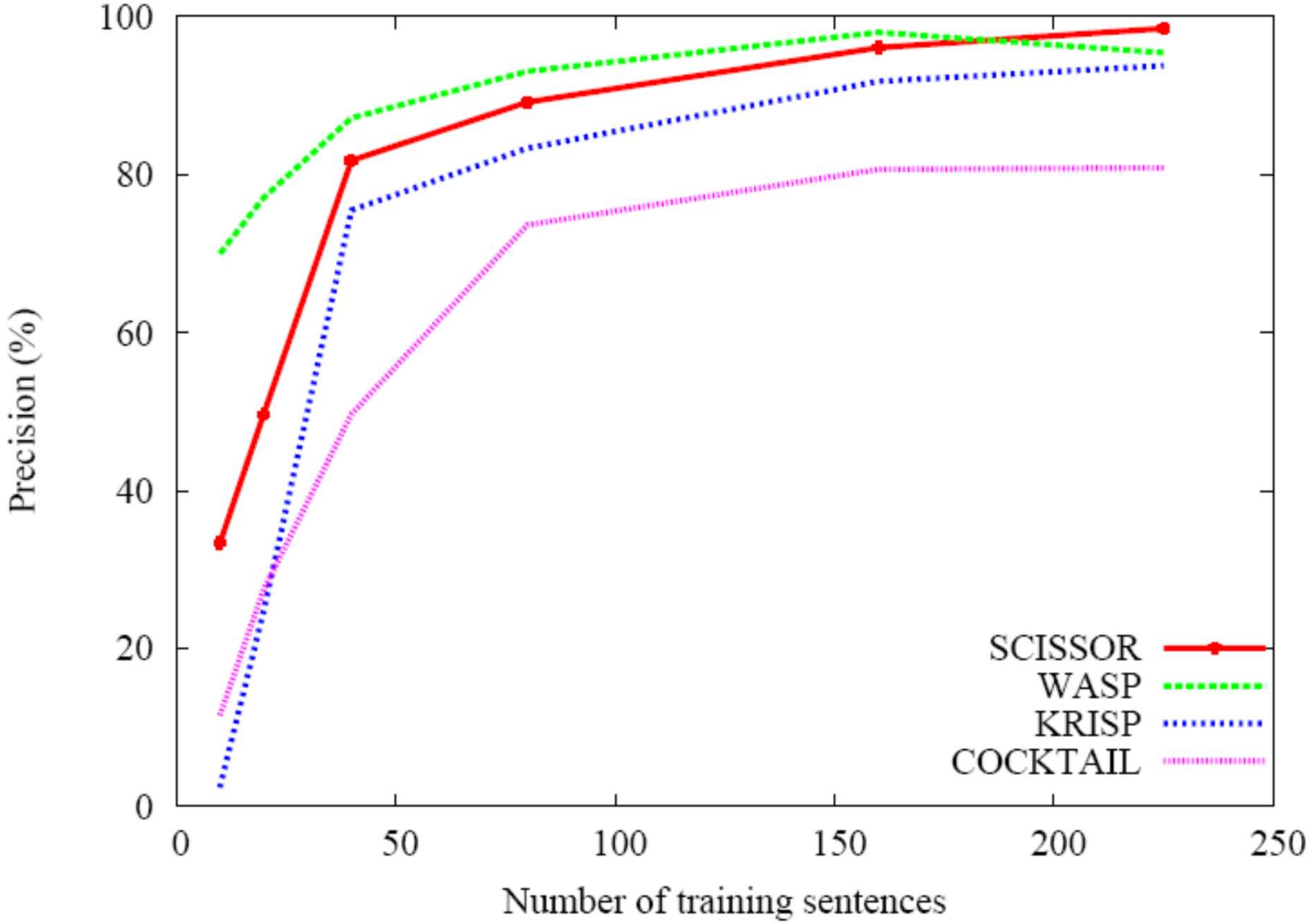
Experimental Methodology

- 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

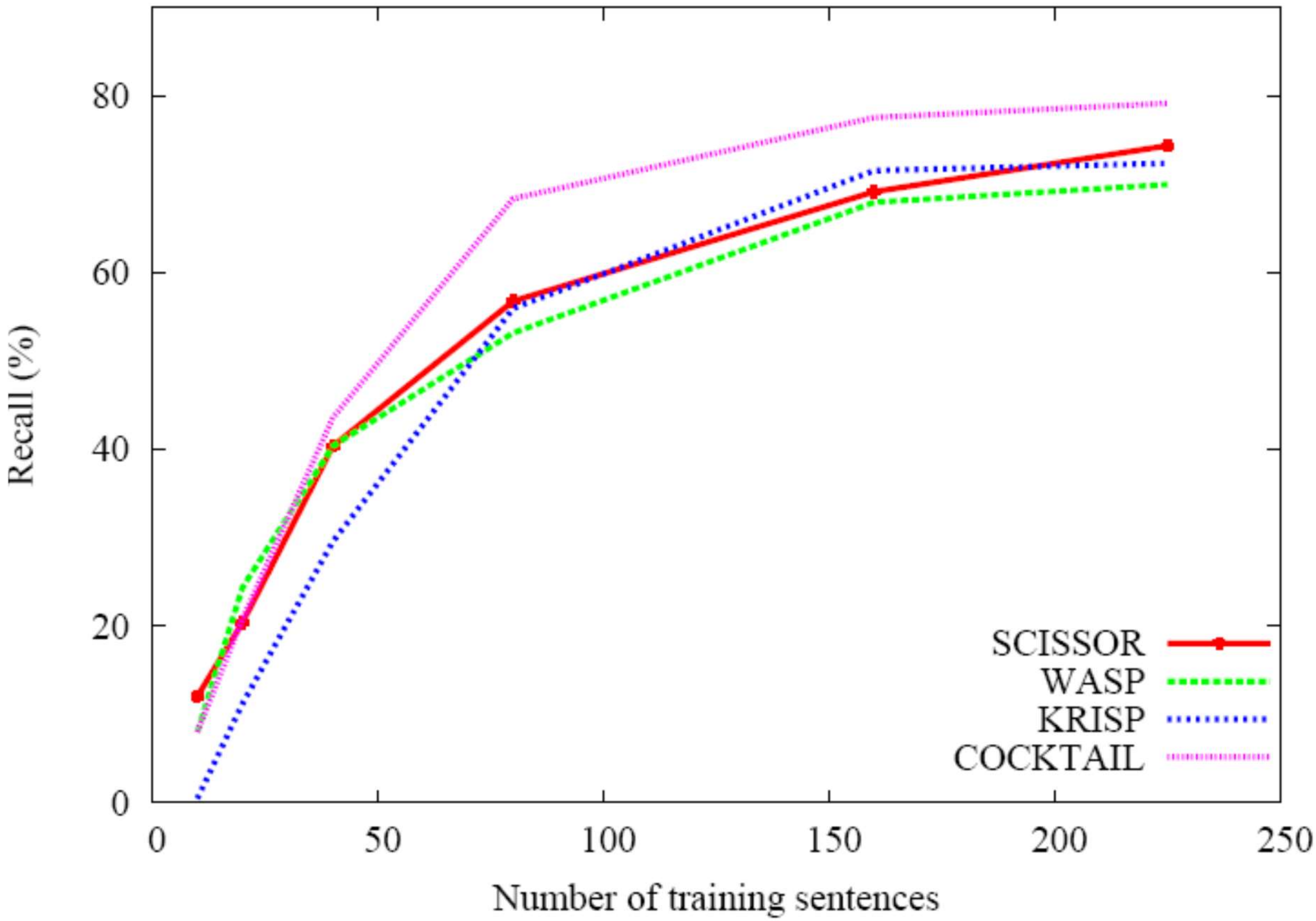
$$Precision = \frac{|Correct\ Completed\ Parses|}{|Completed\ Parses|}$$

$$Recall = \frac{|Correct\ Completed\ Parses|}{|Sentences|}$$

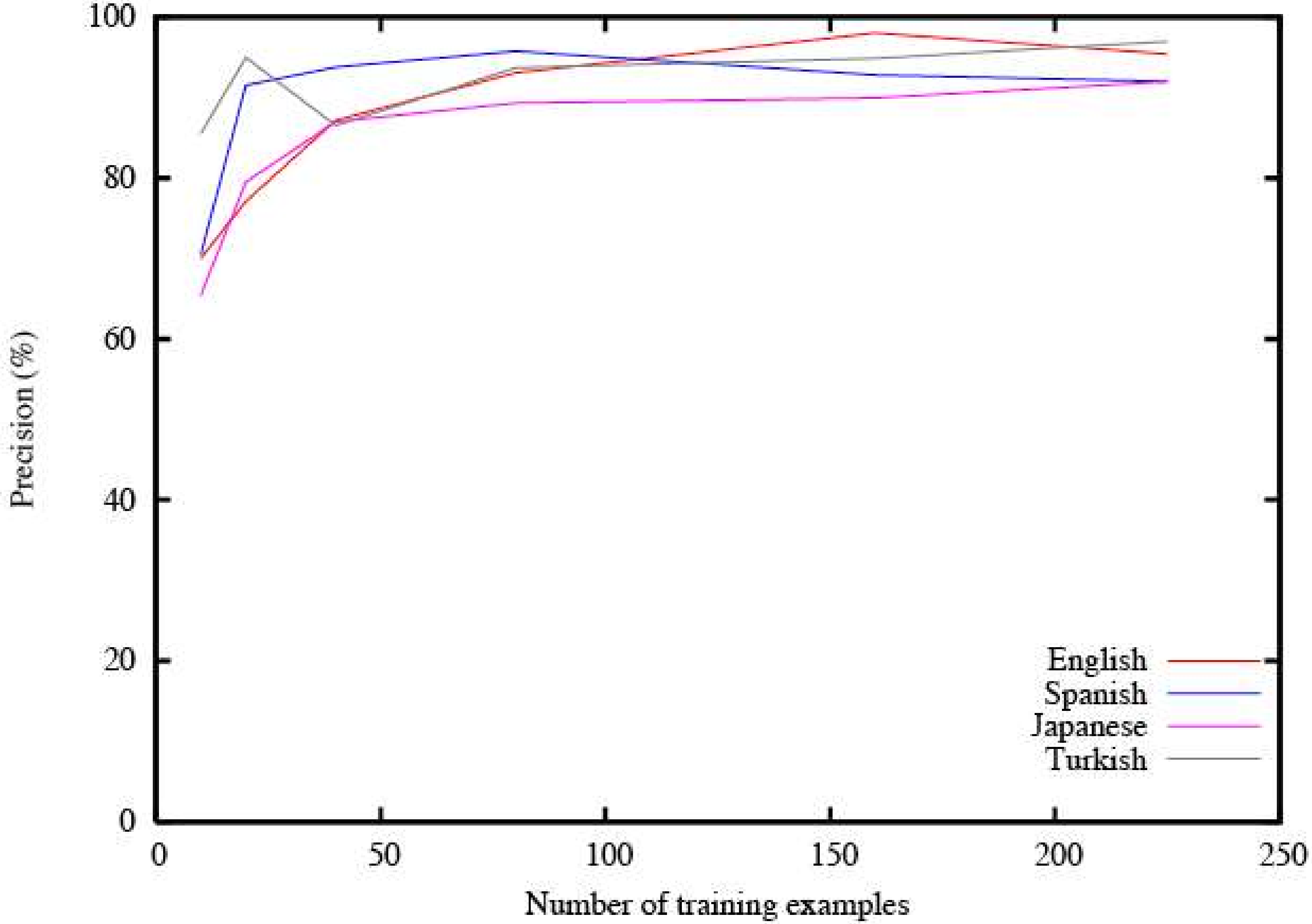
Precision Learning Curve for GeoQuery



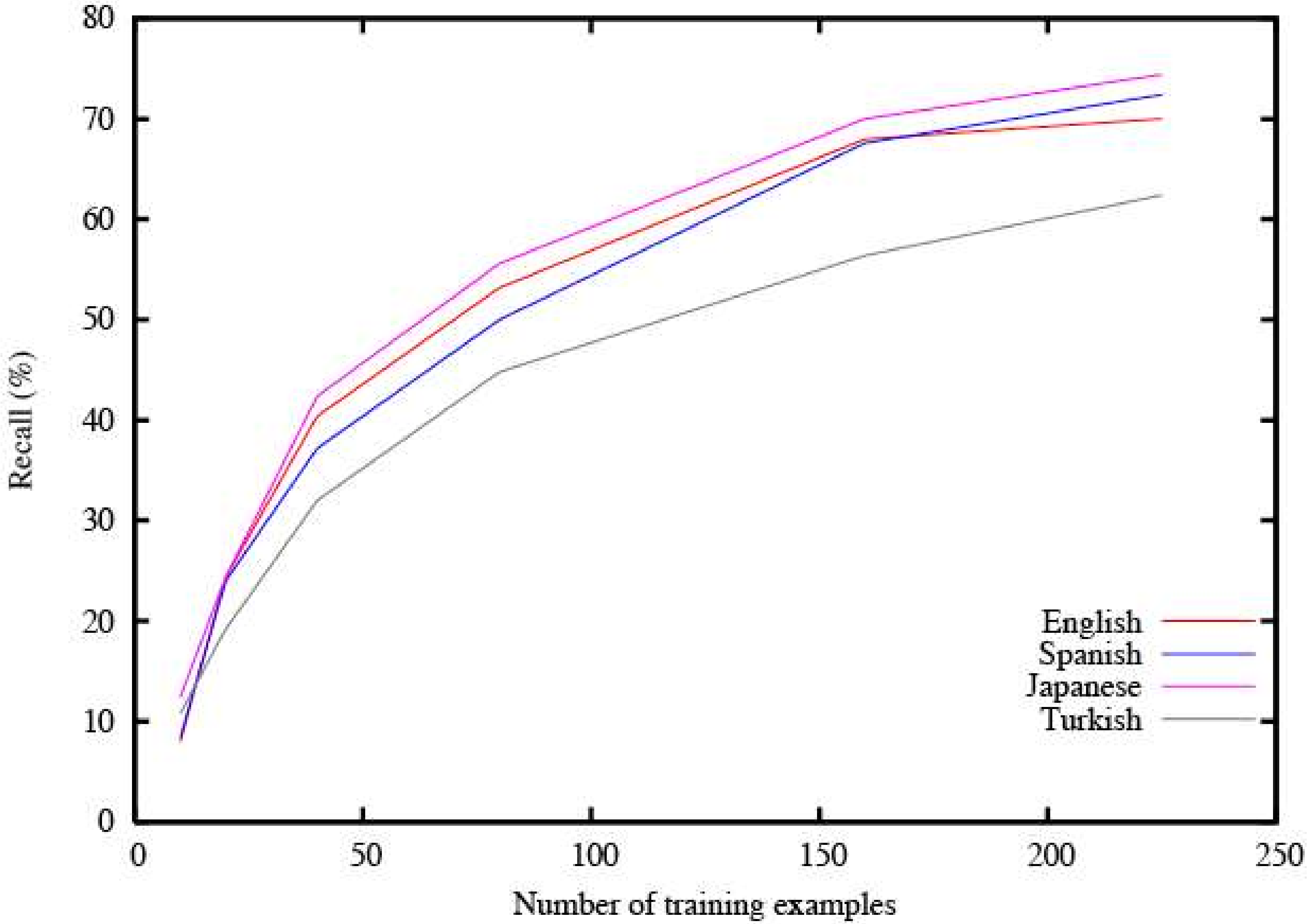
Recall Learning Curve for Geoquery



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.