Semantic Parsing
Claudio Delli Bovi
Tommaso Pasini
Roberto Navigli
The fish trap exists because of the fish. Once you've gotten the fish you can forget the trap. The rabbit snare exists because of the rabbit. Once you've gotten the rabbit, you can forget the snare. Words exist because of meaning. Once you've gotten the meaning, you can forget the words. Where can I find a man who has forgotten words so I can talk with him?

-- The Writings of Chuang Tzu, 4th century B.C.
Semantic Parsing: What is it exactly?

- Transforming Natural Language (NL) sentences into **computer executable** and **complete** Meaning Representations (MRs)

\[ f : \text{sentence} \rightarrow \text{logical form} \]

I want a flight to New York \( \lambda x. \text{flight}(x) \land \text{to}(x, \text{NYC}) \)

- MRs are fully formal languages that:
  - Have a rich **ontology** of types, properties, and relations
  - Support **automated reasoning** and/or **execution**

- Semantic parsers (especially earlier ones) are often designed with some **application domain** in mind
Semantic Parsing: Application Domains/Benchmarks

- **ATIS: Air Travel Information Service**
  - Interface to an air travel database (Price, 1990); widely-used benchmark for spoken language understanding
  - "May I see all the flights from Cleveland to Dallas?"
    - Show: (Flight-Number)
    - Origin: (City “Cleveland”)
    - Destination: (City “Dallas”)
    - NA 1439, TQ 23, ...

- **CLang: Robocup Coach Language**
  - Coaching instructions to simulated players are given in a language called CLang (Chen et al., 2003)
    - "If the ball is in our goal area then player 1 should intercept it"
    - (bpos (goal-area our) (do our {1} intercept))

- **GeoQuery: A Database Query Application**
  - Query application for U.S. geography database (Zelle and Mooney, 2006)
    - "Which rivers run through the states bordering Texas?"
    - answer(traverse(next_to(stateid('texas'))))
Differences with other NLP tasks

- **“Shallow”** semantic processing:
  - Information Extraction
  - Semantic Role Labeling

- **Intermediate** linguistic representations:
  - Part-of-speech Tagging
  - Syntactic Parsing
  - Semantic Role Labeling

- Output meant for **humans**:
  - Question Answering
  - Text Summarization
  - Machine Translation

Semantic parsing involves **deeper** semantic analysis to understand the whole sentence.

Semantic parsing generates a **“final”** representation that assumes no further processing.

Semantic parsing outputs a formal language for **computers to read**, with no room for implicit/incomplete output.
Relations with other NLP tasks

- Tasks being performed **within** semantic parsing:
  - Word Sense Disambiguation
  - Syntactic Parsing

- Tasks **closely related** to semantic parsing:
  - Natural Language Generation
  - Machine Translation

Any MR language can be looked upon as just another NL language! *(more on this later)*

Reversing a semantic parsing system yields a natural language generation system (Wong and Mooney, 2007)
Outline

- Frame-semantic Parsing
- Supervised Semantic Parsing
- Semantic Parsing with CCG
- Unsupervised Semantic Parsing
- Semi-Supervised Semantic Parsing
- Learning from Q&A pairs
- Semantic Parsing with AMR (latest trend!)
Frame-semantic Parsing

- Given a text/sentence, analyze its **frame semantics**:
  - Identify the **frame(s)** evoked by the sentence
  - Match **frame elements** with their realizations

> “Sir, the possibility of successfully navigating an asteroid field is approximately 3,720 to 1.”

ATTENTION GETTING \(\rightarrow\) LIKELIHOOD

> “Sir, the **possibility** of successfully navigating an asteroid field is approximately 3,720 to 1.”
Frame-semantic Parsing

- Given a text/sentence, analyze its frame semantics:
  - Identify the frame(s) evoked by the sentence
  - Match frame elements with their realizations

“Sir, the possibility of successfully navigating an asteroid field is approximately 3,720 to 1.”

- Address Term
- ATTENTION GETTING
- LIKELIHOOD
- Hypothetical Event
- Degree
Frame-semantic Parsing

- Given a text/sentence, analyze its **frame semantics**:
  - Identify the **frame(s)** evoked by the sentence
  - Match **frame elements** with their realizations

- Strictly speaking, frame-semantic parsing is **not** semantic parsing!
  - Frame semantics does not yet provide a **formal meaning representation** (frames have human-level descriptions!)
  - On the practical ground, it can be seen as an “enhanced” Semantic Role Labeling task (Gildea and Jurafsky, 2002)
Frame-semantic Parsing: SEMAFOR (Das et al. 2012)

- **SEMantic Analyzer of Frame Representations**: State-of-the-art frame-semantics parser, discriminatively trained on the full-text annotated sentences in FrameNet

- **(Semi)supervised model** based on features over observable parts of the sentence (words, lemmas, POS-tags, dependency edges, …)

Open-source software available at: [http://www.cs.cmu.edu/~ark/SEMAFOR/](http://www.cs.cmu.edu/~ark/SEMAFOR/)
Frame-semantic Parsing: SEMAFOR (Das et al. 2012)

- Three-stages pipeline:
  - Target Detection
  - Frame Disambiguation
  - Argument Detection and Labeling

Preprocessed sentence (dependency parse, etc.)
Frame-analyzed sentence
Frame-semantic Parsing: SEMAFOR (Das et al. 2012)

- Three-stages pipeline:

  - **Target Detection**
  - **Frame Disambiguation**
  - **Argument Detection and Labeling**

  

  Identify the target frame-evoking elements (FEEs):
  - Whitelist + small set of rules based on POS criteria (Johansson and Nugues, 2007)
Frame-semantic Parsing: SEMAFOR (Das et al. 2012)

- **Three-stages pipeline:**

  ![Diagram](attachment:image)

  \[ f = \langle f_1, \ldots, f_m \rangle \]

  **Conditional log-linear model** to identify the set of frames \( f = \langle f_1, \ldots, f_m \rangle \) from the targets, trained to maximized trained data log-likelihood on a frame-annotated corpus (SemEval 2007, FrameNet 1.5 full-text annotations)
Frame-semantic Parsing: SEMAFOR (Das et al. 2012/2014)

- Three-stages pipeline:

  - Target Detection
  - Frame Disambiguation
  - Argument Detection and Labeling

*Conditional log-linear model* to map, for each frame $f_i$, a subset of the set of roles $R_i = \{ r_1, \ldots, r_{|f_i|} \}$ to spans of the input sentence + *joint decoding/inference* using *beam search* (approximate) or *dual decomposition* (exact)
Frame-semantic Parsing: SEMAFOR (Das et al. 2012/2014)

● Frame Element constraints (example):

**Beam search**

The next morning his households and neighbors started **talking to** the tribe, saying it was the national guards, they added that they heard some of them speaking English, meaning that the Americans are the ones who took Abu Dhari (Sheik Nasr al-Fahdawi).

**Dual decomposition**

The next morning his households and neighbors started **talking to** the tribe, saying it was the national guards, they added that they heard some of them speaking English, meaning that the Americans are the ones who took Abu Dhari (Sheik Nasr al-Fahdawi).
Frame-semantic Parsing: Unknown Predicates

- Problem: sparseness/lack of labeled data
  Many frame-evoking predicates are seen neither in lexicon nor in training data!
Frame-semantic Parsing: Unknown Predicates

- **Solution:**
  Propagate frame labels from known predicates to unknown predicates in a **similarity graph** (Das et al., 2014)
Frame-semantic Parsing: Recent Advances

- **Frame Embeddings (Hermann et al., 2014):**
  Starting from frame-annotated data, learn an embedding model that projects the set of word representations for the *syntactic context* around a predicate to a low-dimensional representation.

  ⬡ Frame identification in the vector space (e.g. cosine similarity)

- **Dynamic Programming (Täckström et al., 2015):**
  A frame’s arguments should not overlap, but this means *classification decisions are not independent*: use a dynamic program to label Frame Elements (Google’s variant of SEMAFOR).
Outline

- Frame-semantic Parsing
- **Supervised Semantic Parsing**
- Semantic Parsing with CCG
- Unsupervised Semantic Parsing
- Semi-Supervised Semantic Parsing
- Learning from Q&A pairs
- **Semantic Parsing with AMR** *(latest trend!)*
Supervised Semantic Parsing: Syntax-based Approaches

Intuition:
- Semantic parsing is a compositional process
- Sentence structures are key in building MRs

Syntax-based approach:
meaning composition follows the tree structure of a syntactic parse
(meaning of a constituent from the meaning of its sub-constituents)

Hand-built approaches (Warren and Pereira, 1982)
Learning approaches (Tang and Mooney, 2001; Kate and Mooney, 2006)
Supervised Semantic Parsing: SCISSOR (Ge and Mooney, 2005)

- SCISSOR (Semantic Composition that Integrates Syntax and Semantics to get Optimal Representations):
  - Allows both syntax and semantics to be used simultaneously to obtain a syntactic-semantic analysis
  - Based on a statistical parser to generate a semantically-augmented parse tree (SAPT)
Supervised Semantic Parsing: SCISSOR (Ge and Mooney, 2005)

- SAPT example:
Supervised Semantic Parsing: SCISSOR
(Ge and Mooney, 2005)

- SAPT example:
Supervised Semantic Parsing: SCISSOR (Ge and Mooney, 2005)

- SAPT example:

```
player(our,2)

S

bowner(_)

our

PRP$

player(_,_) 2

NP

VP

our

player

2

VB

has

DT

the

NN

ball

null

null

NP

null

null

null

S
```
Supervised Semantic Parsing: SCISSOR (Ge and Mooney, 2005)

- SAPT example:
Supervised Semantic Parsing: SCISSOR (Ge and Mooney, 2005)

- Limitations:
  - Knowledge of syntax (vs. flexibility loss) provides a limited gain for short sentences
  - Requires MR annotation + extra SAPT annotation for training
  - Must learn both syntax and semantics from the same training corpus (while high-performance syntactic parsers trained on larger corpora are available)

\[ \text{SYNSEM (Ge and Mooney, 2009): syntactic and semantic parsers trained separately} \]
Supervised Semantic Parsing: Machine Translation Approaches

Intuition:

- MR languages can be statistically modeled exactly as human languages!
- In this perspective, MR-annotated corpora becomes parallel corpora (EN-MR)

Semantic Parsing as Machine Translation:
Syntax-based statistical machine translation (Chiang, 2005) can be used to learn semantic grammars as synchronous context-free grammars (Aho and Ullman, 1972)
Supervised Semantic Parsing: WASP (Wong and Mooney, 2006; 2007)

- WASP (Word Alignment-based Semantic Parsing):
  - A word alignment model is used to acquire a **bilingual lexicon** consisting of NL substrings coupled with their translations in the target MR language (CLang, GeoQuery, etc.)
  - Complete MRs are formed by combining NL-MRL substring pairs using **SCFG parsing** as in syntax-based translation models (Yamada and Knight, 2001; Chiang, 2005)

```
( (bowner our {4} )
 ( do our {6} (pos (left (half our)))) )
```

If our player 4 has the ball, then our player 6 should stay in the left side of our half.

Target Source
Supervised Semantic Parsing: WASP (Wong and Mooney, 2006; 2007)

Training NL-MR sentence pairs

Lexical Acquisition

Unambiguous CFG for MRs

Lexicon L

Parameter Estimation

Feature weights $w$

Semantic Parser

Sentence

MR

answer(capital(loc_2 (riverid("Ohio"))))

What is the capital of Ohio?

QUERY → What is CITY
CITY → the capital CITY
CITY → of STATE
STATE → Ohio
Supervised Semantic Parsing: Kernel-based Classification

Intuition:

- Statistical feature-based methods struggle to capture the full variety of natural language by only enumerating all the possible contexts in which a NL-MR mapping occurs!
- **Kernel methods** implicitly work with a potentially infinite number of features in order to deal with sparseness and noise.

Semantic Parsing as Kernel-based Classification:
For each production of a MR grammar, a classifier based on string kernels estimates its probability over different substrings of the input sentence.
Supervised Semantic Parsing: KRISP (Kate and Mooney, 2006; Kate, 2008)

- **KRISP (Kernel-based Robust Interpretation of Semantic Parsing):**
  - Semantic parsing means finding the **most probable derivation** of an input sentence
    - Dynamic programming algorithm with beam search (Kate & Mooney, 2006)
  - Takes pairs of NL sentences and their respective MRs and induces the semantic parser through an **iterative process** of labeling **positive** and **negative samples** based on a SVM classifier with string-subsequence kernel (Lodhi et al., 2002)
Supervised Semantic Parsing: KRISP (Kate and Mooney, 2006; Kate, 2008)

- Further improvements:
  - Dependency-based word subsequence kernel (Kate, 2008) to count the number of common paths in the dependency tree

```
was
  cat
    a fat
  chased
    by
      dog
        a

was
  cat
    a with
      collar
        a red
      dog
        a fat
da
```
Supervised Semantic Parsing: KRISP (Kate and Mooney, 2006; Kate, 2008)

- Further improvements:
  - **SEMISUP-KRISP** (Kate and Mooney, 2007) adopts a semi-supervised learning approach where *unlabeled examples* are considered in the iterative training algorithm.
Outline

- Frame-semantic Parsing
- Supervised Semantic Parsing
- Semantic Parsing with CCG
- Unsupervised Semantic Parsing
- Semi-Supervised Semantic Parsing
- Learning from Q&A pairs
- Semantic Parsing with AMR (latest trend!)
Semantic Parsing using CCG

Wait! What is CCG?

- **Combinatory Categorial Grammar (CCG)** is an alternative approach to syntax compared to CFG
  - Transparent interface between **syntax** and **semantics**;
  - Instead of rules and constituents, we have **categories** associated with each element in the lexicon:

Lexeme: `write`  \[ \rightarrow (S\setminus NP)/NP \lambda y.\lambda x.\text{write}ʻ(x, y) \]

Category
Semantic Parsing using CCG

Wait! What is CCG?

- **Combinatory Categorial Grammar (CCG)** is an alternative approach to syntax compared to CFG
  - Transparent interface between **syntax** and **semantics**;
  - Instead of rules and constituents, we have **categories** associated with each element in the lexicon:

  ```latex
  write \vdash (S \backslash NP)/NP \lambda y. \lambda x. \text{write}'(x, y)
  ```

  **Syntax** (Lambek notation): reads as a function that takes as input a NP on the **left** ("\") and a NP on the **right** ("/") and output a sentence S

  **Semantics**: λ-calculus in this case, but can be any other formal language!
Semantic Parsing using CCG

Why CCG?

- Complex categories, but very few combination operations that are naturally based on function composition:

\[
\begin{align*}
\text{Texas} & \quad \text{borders} & \quad \text{New Mexico} \\
\text{NP} & \quad (S \setminus \text{NP}) / \text{NP} & \quad \text{NP} \\
\text{texas} & \quad \lambda x.\lambda y.\text{borders}(y,x) & \quad \text{new\_mexico} \\
& \quad S \setminus \text{NP} & \quad \lambda y.\text{borders}(y,\text{new\_mexico}) \\
& \quad \text{borders}(\text{texas, new\_mexico}) & \quad S
\end{align*}
\]
Semantic Parsing using CCG

CCG is much more than this!

- Generalized type-raising operations
- Cross composition operations for cross serial dependencies
- Various associated semantic theories
- Part of a larger family (Categorial Grammar) which is in turn part of a class of “mildly context-sensitive” grammars

Have a look at my tutorial!
“CCG: a (gentle) introduction”

Training sentences and logical forms

Lexical Acquisition

Lexicon L

Parameter Estimation

Feature weights w

CCG parser

Sentence

Logical form

Unambiguous grammar for MRs

Log-linear model:

\[ p(y|x) = \frac{e^{w \cdot f(x,y)}}{\sum_{y'} e^{w \cdot f(x,y')}} \]

Best derivation:

\[ y^* = \arg \max_y w \cdot f(x, y) \]

Texas := NP : texas
borders := (S\NP)/NP : \( \lambda x.\lambda y.\text{borders}(y,x) \)
Mexico := NP
New Mexico := NP
...
Supervised Semantic Parsing: Wrapping up!
Supervised Semantic Parsing: Wrapping up!

Commonalities:

- A model to connect **language** and **meaning**
- A mechanism for meaning composition
- **Parameters** to weight a given meaning representations
- An **iterative learning** algorithm
- A **generalization** mechanism

---

**SCISSOR**: Semantically Annotated Parse Trees (SAPT)

**WASP**: Synchronous CFG

**KRISP**: Probabilistic string classifiers

**Zettlemoyer & Collins**: CCG with semantic types
Supervised Semantic Parsing: Wrapping up!

Commonalities:

- A model to connect **language** and **meaning**
- A mechanism for meaning composition
- **Parameters** to weight a given meaning representations
- An **iterative learning** algorithm
- A **generalization** mechanism

SCISSOR: Semantically Annotated Parse Trees (SAPT)
WASP: MR grammar
KRISP: MR grammar
Zettlemoyer & Collins: CCG parsing rules
Supervised Semantic Parsing: Wrapping up!

Commonalities:

- A model to connect **language** and **meaning**
- A mechanism for meaning **composition**
- **Parameters** to weight a given meaning representations
- An **iterative learning** algorithm
- A **generalization** mechanism

**Semantic Parsing**
Claudio Delli Bovi

**SCISSOR**: Parsing model weights
**WASP**: Grammar production weights
**KRISP**: SVM weights
**Zettlemoyer & Collins**: Weights for lexical items and parsing rules
Supervised Semantic Parsing: Wrapping up!

Differences:

- Learn lexicon or not
- Exploit general syntactic parsing or not
- Use matching patterns or not

**SCISSOR:** No
**WASP:** Yes
**KRISP:** No
**Zettlemoyer & Collins:** Yes
Supervised Semantic Parsing: Wrapping up!

Differences:

- Learn lexicon or not
- Exploit general syntactic parsing or not
- Use matching patterns or not

SCISSOR: CFG
WASP: No
KRISP: No
Zettlemoyer & Collins: CCG

Pro: Leverage knowledge of natural language

Con: Not immediately portable to other languages
Supervised Semantic Parsing: Wrapping up!

Differences:

- Learn lexicon or not
- Exploit general syntactic parsing or not
- Use matching patterns or not

**Pro:** The parser can be “inverted” to form a generation system

**Con:** Affected by noise and data sparseness
Outline

- Frame-semantic Parsing
- Supervised Semantic Parsing
- Semantic Parsing with CCG
- **Unsupervised Semantic Parsing**
- Semi-Supervised Semantic Parsing
- Learning from Q&A pairs
- **Semantic Parsing with AMR**  (latest trend!)
Unsupervised Systems

  - Based on Markov Logic (Richardson & Domingos 2006)
  - Can be used in general domains
Key idea #1:

- Clusters of syntactic or lexical variations with same meaning
  - Buy = \{buy, acquire, purchase, \ldots\}
  - MICROSOFT = \{Microsoft, Bill Gates’ company, \ldots\}

- Target predicates and objects can be learned
Unsupervised Semantic Parsing - USP

- **Key idea #2:**
  - **Relational clustering:** cluster relations with similar subexpressions

Example:
- Microsoft buys Powerset
- Microsoft acquires semantic search engine Powerset
- Powerset is acquired by Microsoft Corporation
- The Redmond software giant buys Powerset
- Microsoft’s purchase of Powerset, …
Key idea #2:

- **Relational clustering**: cluster relations with similar subexpressions

Example:
- Microsoft buys Powerset
- Microsoft acquires semantic search engine Powerset
- Powerset is acquired by Microsoft Corporation
- The Redmond software giant buys Powerset
- Microsoft’s purchase of Powerset, …
Key idea #2:

- **Relational clustering**: cluster relations with similar subexpressions

Example:
- Microsoft buys Powerset
- Microsoft acquires semantic search engine Powerset
- Powerset is acquired by Microsoft Corporation
- The Redmond software giant buys Powerset
- Microsoft’s purchase of Powerset, …
Unsupervised Semantic Parsing - USP

- Key idea #2:
  - Relational clustering: cluster relations with similar subexpressions

Example:
- Microsoft buys Powerset
- Microsoft acquires semantic search engine Powerset
- Powerset is acquired by Microsoft Corporation
- The Redmond software giant buys Powerset
- Microsoft’s purchase of Powerset, …
Unsupervised Semantic Parsing - USP

- **Key idea #2:**
  - **Relational clustering:** cluster relations with similar subexpressions

Example:
- Microsoft buys Powerset
- Microsoft acquires semantic search engine Powerset
- Powerset is acquired by Microsoft Corporation
- The Redmond software giant buys Powerset
- Microsoft’s purchase of Powerset, …
Unsupervised Semantic Parsing - USP

- Key idea #3:
  - Starts directly from syntactic analyses
  - Focus on translating syntax trees in semantic trees
  - Leverage rapid progress in syntactic parsing
Practical example

- Syntax tree

```
buys
  nsubj
  Microsoft

  dobj
  Powerset
```
Unsupervised Semantic Parsing - USP

Practical example

- Vertices conversion into unary atoms

\[
\text{buys}(n1) \\
\text{nsubj} \quad \text{dobj} \\
\text{Microsoft}(n2) \quad \text{Powerset}(n3)
\]

n1, n2 and n3 are Skolem constants
Unsupervised Semantic Parsing - USP

Practical example

- Edge conversion into binary atoms

\[
\begin{align*}
\text{buys}(n1) \\
\text{nsubj}(n1, n2) & \quad \text{dobj}(n1, n3) \\
\text{Microsoft}(n2) & \quad \text{Powerset}(n3)
\end{align*}
\]
Unsupervised Semantic Parsing - USP

Practical example

- Partitioning of Quasi-Logical Forms into sub-formulas

\[
\begin{array}{c}
\text{buys(n1)} \\
\text{nsubj(n1, n2)} & \text{dobj(n1, n3)} \\
\text{Microsoft(n2)} & \text{Powerset(n3)}
\end{array}
\]
Unsupervised Semantic Parsing - USP

Practical example

- Partitioning of Quasi-Logical Forms into sub-formulas

\[
\lambda x_2. \text{nsubj}(n1, x_2) \quad \lambda x_3. \text{dobj}(n1, x_3)
\]

\[
\text{buys}(n1) \\
\text{Microsoft}(n2) \quad \text{Powerset}(n3)
\]
Unsupervised Semantic Parsing - USP

Practical example

- Assign subformula to lambda-form clusters

\[
\lambda x_2.\text{nsubj}(n_1, x_2) \quad \lambda x_3.\text{dobj}(n_1, x_3) \quad \text{buys}(n_1) \quad \text{C(buys)}
\]

\[
\text{Microsoft}(n_2) \quad \text{C(Microsoft)}
\]

\[
\text{Powerset}(n_3) \quad \text{C(Powerset)}
\]
Unsupervised Semantic Parsing - USP

Practical example

- Abstract lambda formula

\[
\text{buys}(n_1)^\lambda x_2.\text{nsubj}(n_1, x_2)^\lambda x_3.\text{dobj}(n_1, x_3)
\]

\[
C(\text{buys})(n_1)^\lambda x_2.\text{A(buyer)}(n_1, x_2)^\lambda x_3.\text{A(bought)}(n_1, x_3)
\]
Outline

- Frame-semantic Parsing
- Supervised Semantic Parsing
- Semantic Parsing with CCG
- Unsupervised Semantic Parsing
- Semi-Supervised Semantic Parsing
- Learning from Q&A pairs
- Semantic Parsing with AMR (latest trend!)
Semi-Supervised Semantic Parsing

- **SEMISUP-KRISP** (unambiguous supervision)

- **KRISPER** (ambiguous supervision)
  (Learning Language Semantics from Ambiguous Supervision, Kate, Mooney 2007)
Semi-Supervised Semantic Parsing: Ambiguous Supervision

Cats love boxes

John bought a new car

Steve Jobs created Apple inc.

Bill Gates is the father of Windows

love(cats, boxes)

ate(dog, bone)

bought(John, car)

broke(Mike, bike)

created(Steve Jobs, Apple inc)

won(Einstein, Nobel prize)

Is_the_father_of(Bill Gates, Windows)

eat(Mary, apple)

did(students, homework)
Semi-Supervised Semantic Parsing: KRISPER

- Extends KRISP to handle ambiguous training set:
  - **Assigns weights** to each pair (NL-sentence, MR) equals to 1 over the number of MR for NL-sentence in the dataset.
  - During the SVM iterations the “penalization score” is increased in order to allow incorrect classifications at the beginning.
  - Once all NL-sentences have been paired at most with 1 MR, then the original KRISP algorithm is called in order to learn a better semantic parser.
Outline

● Frame-semantic Parsing
● Supervised Semantic Parsing
● Semantic Parsing with CCG
● Unsupervised Semantic Parsing
● Semi-Supervised Semantic Parsing
● Learning from Q&A pairs
● Semantic Parsing with AMR (latest trend!)
Learning from Q&A pairs: Semantic Parsing on Freebase from Question-Answer Pairs (Berant et al. 2013)

- Available at http://nlp.stanford.edu/software/sempre/

- Exploits available **dataset of question-answer pairs** to automatically train a semantic parser.

- Does not need a dataset with Natural Language sentences and their associated Meaning Representations.

- Exploits **Freebase** (a huge knowledge base) in order to find the right Meaning Representations for a query, which, if used on the knowledge base, comes out with the right answer.
Learning from Q&A pairs: Semantic Parsing on Freebase from Question-Answer Pairs (Berant et al. 2013)

Which college did Obama go to?
Learning from Q&A pairs:
Semantic Parsing on Freebase from Question-Answer Pairs (Berant et al. 2013)

Which college did Obama go to?

Barack Obama

Type.University
Learning from Q&A pairs:
Semantic Parsing on Freebase from Question-Answer Pairs (Berant et al. 2013)

Which college did Obama go to?

Type.University

Barack Obama

Education

bridging

bridging
Learning from Q&A pairs: Semantic Parsing on Freebase from Question-Answer Pairs (Berant et al. 2013)

Which college did Obama go to?

Barack Obama

Type.University

Education

Type.University AND Education.BarackObama
Learning from Q&A pairs: Semantic Parsing on Freebase from Question-Answer Pairs (Berant et al. 2013)

Which college did Obama go to?

Barack Obama

Type.University bridging Education

Type.University AND Education.BarackObama

FreeBase Query

Occidental College, Columbia University
Bridging aims at establish novel relations between distinct parts of a sentence.

Generates a binary predicate based on neighboring logical predicates rather than on explicit lexical material.

Given a pair of unaries $u_1$, $u_2$ (e.g. BarackObama and Type. University) with type $t_1, t_2$ (Person, University), given the binary operator $b(t_1, t_2)$ (Education(Person, University)), then the formula $u_1 \text{ AND } b.u_2$ will be produced (e.g. Type.University AND Education. BarakObama).
Learning from without Q&A pairs:
Large-scale Semantic Parsing without Question-Answer Pairs (Reddy, Lapata, Steedman 2014)

- Exploits existing **CCG syntactic parser** in order to build a **semantic parse**

- Builds a graph for the semantic parse

- **Grounds** the previously extracted **graph on FreeBase**

- **Matches the grounded graph on FreeBase** in order to retrieve the correct answer for the question expressed by the graph.
Learning from without Q&A pairs: Large-scale Semantic Parsing without Question-Answer Pairs (Reddy, Lapata, Steedman 2014)

Austin is the capital of Texas

CCG Parser

capital(Austin) ^ UNIQUE(Austin) ^ capital.of.arg1(e, Austin) ^ capital.of.arg2(e, Texas)
Learning from without Q&A pairs: Large-scale Semantic Parsing without Question-Answer Pairs (Reddy, Lapata, Steedman 2014)
Learning from without Q&A pairs:
Large-scale Semantic Parsing without Question-Answer Pairs (Reddy, Lapata, Steedman 2014)

- Uses **features** (F) in order to find the **best grounded graph**
- Uses **Perceptron** in order to **learn weights** (W) for each features
- Chooses the **grounded graph** that **maximize** the **dot-product** between F and W.
Recap

- Parsing
- Learning
- Modeling
Recap

SAPT (SCISSOR)  Synchronous CFG

Parsing

Learning

Modeling

String Kernels (KRISP)

CCG
Recap

Semantic Parsing
Tommaso Pasini
13/05/2016

SAPT (SCISSOR)
Synchronous CFG

Unsupervised

Supervised

Parsing

Learning

Modeling

String Kernels (KRISP)

CCG

Q&A Pairs

Semi-supervised
(ambiguous / unambiguous)
Recap

Parsing

- SAPT (SCISSOR)
- Synchronous CFG
- CCG
- String Kernels (KRISP)
- Semi-supervised (ambiguous / unambiguous)

Learning

- Supervised
- Unsupervised
- Q&A Pairs

Modeling

- AMR (coming soon!!!)
- Grounded Semantic Graph

λ
References

● Frame-semantic Parsing


● Supervised Semantic Parsing


References

● Supervised Semantic Parsing (cont.)


● Unsupervised/Semi-Supervised Semantic Parsing


References

- Semi-Supervised Semantic Parsing (cont.)


- Abstract Meaning Representation

Complete tutorial at: https://github.com/nschneid/amr-tutorial/tree/master/slides

Video of the talk also available at: http://techtalks.tv/talks/the-logic-of-amr-practical-unified-graph-based-sentence-semantics-for-nlp/61564/