Relational semantics

CS 690N, Spring 2017
Advanced Natural Language Processing
http://people.cs.umass.edu/~brenocon/anlp2017/

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Why semantics?

**Goal** is to convert text into structured knowledge representations.

Some motivations:

- Automatically update databases of facts
- Infer new facts and relationships
- Answer complex questions, e.g., what cheese-exporting countries are hereditary monarchies?
- Logic-check written arguments
- ...
Why semantics?

Semantics is a stumbling block for NLP at all levels:

- I shot an elephant in my pajamas
- How to solve PP attachment question?
- Bilexical probabilities are just a noisy approximation
Can your computer ever *really* understand you?

What does it really mean to understand language anyway?
Can your computer ever really understand you?

What does it really mean to understand language anyway?

Some functional answers:

- Answer reading comprehension tests
- Determine whether a statement is true or false
- Choose the appropriate action
- Convert text to a meaning representation
Language to Meaning

Information Extraction

Recover information about pre-specified relations and entities

Example Task

Relation Extraction

is_a(Obama, President)
Language to Meaning

Broad-coverage Semantics

Focus on specific phenomena (e.g., verb-argument matching)

More informative

Example Task

Summarization

Obama wins election. Big party in Chicago. Romney a bit down, asks for some tea.
Language to Meaning

Example Task

Database Query

What states border Texas?

Semantic Parsing

Recover complete meaning representation

More informative

Oklahoma
New Mexico
Arkansas
Louisiana

[Slides: ACL 2013 CCG tutorial]
Language to Meaning

Example Task

Instructing a Robot

at the chair, turn right
Meaning

- Lexical semantics: individual words/phrases
  - KBs, embeddings, etc.
- Logical semantics
  - [e.g. questions as database queries ... theorem proving ...]
- Compositional semantics
- “Shallow” semantics: predicates, arguments
  - who did what to whom?
  - I bought a car from him <=> he sold me a car
- Practical examples: Information Extraction
- Major subtasks
  - Entities and coreference
    - I saw Bob, and he said hi
  - Time and Events
Desiderata for an MR

• Truth-conditional semantics
  • Every sentence is a logical statement (boolean, first order...)
  • Model-theoretic denotations: possible worlds (database states?) licensed by the sentence
• Entailment and equivalence
• Non-ambiguity
• Expressiveness
• Maps to applications
Semantic parsing

- Semantic parsing: from NL to an MR
  - Typically “sem parse” applies to sentence-only analysis
- Lambda calculus: one common approach
  - Tie it to syntax: e.g. CFG extension (Montague-style semantics)
  - Current research: combinatory categorial grammar (CCG)

\[
S : \beta(\alpha) \rightarrow NP : \alpha \quad VP : \beta \\
VP : \beta(\alpha) \rightarrow V : \beta \quad NP : \alpha
\]

\[
P = \lambda y. \lambda x. \text{LIKES}(x, y)(\text{MAX})(\text{ABIGAIL}) \\
= \lambda x. \text{LIKES}(x, \text{ABIGAIL})(\text{MAX}) \\
= \text{LIKES}((\text{MAX}, \text{ABIGAIL})
\]

\[
\text{Abigail}, NP : \text{ABIGAIL} \\
\text{Max}, NP : \text{MAX} \\
\text{likes}, V : \lambda y. \lambda x. \text{LIKE}(x, y)
\]
I want to go to New York on Sunday
I want to go to New York on Sunday
Natural Language Understanding

Shallow Semantics: *Frames and Roles*

I want to go to New York on Sunday

Encode an event or scenario

[Slides: Dipanjan Das]
Natural Language Understanding

Shallow Semantics: *Frames and Roles*

I want to go to New York on Sunday

Traveler

Goal

Time

Traveler

Goal

Time

[Slides: Dipanjan Das]
Natural Language Understanding

Shallow Semantics: Frames and Roles

I want to go to New York on Sunday

participant or role for the frame

Traveler

Goal

Time

Travel

[Slides: Dipanjan Das]
I want to go to New York on Sunday
I want to go to New York on Sunday.
The entity-relation paradigm

http://thelousylinguist.blogspot.com/2017/03/using-ibm-watson-knowledge-studio-to.html
The entity-relation paradigm
According to Ginsburg, we have an obligation to provide others with contraception.

- Annotations reflect a *neo-Davidsonian* logical representation
  - Broad event/predicate classes (“frames”)
  - No deeper sharing of frames across lexical items (buy vs. sell)

https://github.com/nschneid/amr-tutorial/tree/master/slides
Event analysis in intl. relations
(Narrow-coverage MR)

- Analyze time-series of friendly vs. hostile country-country interactions, coded from newswire text
  - Manual coding (~1960’s): hire people to read thousands of articles (inconsistencies!)
  - Machine coding (KEDS) -- rule-based S-V-O or S-V-PP extraction [Phil Schrodt (1993, 1994... 2011)]
- Various current efforts: ICEWS, OEDA, etc.
Event analysis in Intl. relations
(Narrow-coverage MR)

Examples of WEIS Event Codes

11. REJECT

111  Turn down proposal; reject protest demand; threat
112  Refuse; oppose; refuse to allow

12. ACCUSE

121  Charge, criticize, blame, disapprove
122  Denounce, denigrate, abuse

13. PROTEST

131  Make complaint (not formal)
132  Make formal complaint or protest

17. THREATEN

171  Threat without specific negative sanctions
172  Threat with specific nonmilitary negative sanctions
173  Threat with force specified
174  Ultimatum: threat with negative sanctions and time

18. DEMONSTRATE

181  Non-military demonstration; walk out on
182  Armed force mobilization, exercise and/or display

Table 2: WEIS Coding of 1990 Iraq-Kuwait Crisis

<table>
<thead>
<tr>
<th>Date</th>
<th>Source</th>
<th>Target</th>
<th>WEIS Code</th>
<th>Type of Action</th>
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<tr>
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<td>IRQ</td>
<td>KUW</td>
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<td>CHARGE</td>
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<td>DENOUNCE</td>
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Event analysis in intl. relations
(Narrow-coverage MR)

These graphs are from manual coding; IE evaluations in Schrodt and Gerner 1994, King and Lowe 2001
Message Understanding Conferences (MUC)

- Bakeoff format: shared task, dataset, hidden test set for competitive evaluation
- Different domains – involving specific events
  - (1987) MUC-1: Fleet operations
  - (1991-2) MUC-3, 4: Terrorist activities in Latin America
  - (1993-7) Corporate Joint Ventures, Microelectronic production, Negotiation of Labor Disputes, Airplane crashes, and Rocket/Missile Launches
- ACE (1999-2008) – Automated Content Extraction
MUC Template-Filling IE

Input: text

San Salvador, 19 Apr 89 (ACAN-EFE) – [TEXT] Salvadoran President-elect Alfredo Cristiani condemned the terrorist killing of Attorney General Roberto Garcia Alvarado and accused the Farabundo Marti National Liberation Front (FMLN) of the crime.

...Garcia Alvarado, 56, was killed when a bomb placed by urban guerrillas on his vehicle exploded as it came to a halt at an intersection in downtown San Salvador.

...Vice President-elect Francisco Merino said that when the attorney general’s car stopped at a light on a street in downtown San Salvador, an individual placed a bomb on the roof of the armored vehicle.

...According to the police and Garcia Alvarado’s driver, who escaped unscathed, the attorney general was traveling with two bodyguards. One of them was injured.

Output: extract an event record (“terrorist attack”) with the following attributes:

- Incident: Date
- Incident: Location
- Incident: Type
- Perpetrator: Individual ID
- Perpetrator: Organization ID
- Perpetrator: Organization
- Physical Target: Description
- Physical Target: Effect
- Human Target: Name
- Human Target: Description
San Salvador, 19 Apr 89 (ACAN-EFE) – [TEXT] Salvadoran President-elect Alfredo Cristiani condemned the terrorist killing of Attorney General Roberto Garcia Alvarado and accused the Farabundo Marti National Liberation Front (FMLN) of the crime.

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Pipeline
(finite-state transducers)

Text

1. Complex Words
2. Basic Phrases
3. Complex Phrases
4. Domain Events
5. Merging Structures

Structure

Syntax steps
Names, multiwords...
NPs, verb groups, phrase structure...

Domain-specific semantics

Thursday, April 6, 17
Bridgestone Sports Co. said Friday it has set up a joint venture in Taiwan with a local concern and a Japanese trading house to produce golf clubs to be shipped to Japan.

The joint venture, Bridgestone Sports Taiwan Co., capitalized at 20 million new Taiwan dollars, will start production in January 1990 with production of 20,000 iron and “metal wood” clubs a month.
Bridgestone Sports Co. said Friday it has set up a joint venture in Taiwan with a local concern and a Japanese trading house to produce golf clubs to be shipped to Japan.

The joint venture, Bridgestone Sports Taiwan Co., capitalized at 20 million new Taiwan dollars, will start production in January 1990 with production of 20,000 iron and “metal wood” clubs a month.
### Domain Events

#### Merge Structures

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<tr>
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<tbody>
<tr>
<td>Company:</td>
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</tr>
<tr>
<td>Product:</td>
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(4/5) Domain Events

(5/5) Merge Structures

Decide identity coreference through name-matching and type compatibility; if arguments are coreferent, merge events

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| Joint Venture Company: | — |
| Activity: | — |
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Empirical Rule-based NLP

- Originally FASTUS was just a preprocessor for a more complex system. It was too slow, they threw it out -- deadline pressure
- Hours vs Minutes runtime on development set -- much faster development iterations
Empirical Rule-based NLP

- Originally FASTUS was just a preprocessor for a more complex system. It was too slow, they threw it out -- deadline pressure

- Hours vs Minutes runtime on development set -- much faster development iterations

January: Designed FASTUS
Jan-May: Development
May 6: First test of the FASTUS system on a blind test set of 100 terrorist reports, which had been withheld as a fair test, and we obtained a score of 8% recall and 42% precision.

At that point we began a fairly intensive effort to hill-climb on all 1300 development texts then available, doing periodic runs on the fair test to monitor our progress. This effort culminated in a score of 44% recall and 57% precision in the wee hours of June 1, when we decided to run the official test. The rate of progress was rapid enough that even a few hours of work could be shown to have a noticeable impact on the score. Our scarcest resource was time, and our supply of it was eventually exhausted well before the point of diminishing returns.

We were thus able, in three and a half weeks, to increase the system’s F-score by 36.2 points, from 13.5 to 49.7.
- Current work in supervised event extraction (feature-based, neural network...)
- ACE entity/event dataset: ~dozen event types and mention-level annotations

In Baghdad, a cameraman **died** when an American tank **fired** on the Palestine Hotel.
<table>
<thead>
<tr>
<th>Category</th>
<th>Type</th>
<th>Feature Description</th>
</tr>
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</table>
| Trigger        | Lexical     | 1. unigrams/bigrams of the current and context words within the window of size 2  
                                                                 2. unigrams/bigrams of part-of-speech tags of the current and context words within the 
                                                                 window of size 2  
                                                                 3. lemma and synonyms of the current token  
                                                                 4. base form of the current token extracted from Nomlex (Macleod et al., 1998)  
                                                                 5. Brown clusters that are learned from ACE English corpus (Brown et al., 1992; Miller et al., 2004; Sun et al., 2011). We used the clusters with prefixes of length 13, 16 and 20 for each token. |
|                | Syntactic   | 6. dependent and governor words of the current token  
                                                                 7. dependency types associated the current token  
                                                                 8. whether the current token is a modifier of job title  
                                                                 9. whether the current token is a non-referential pronoun |
|                | Entity Information | 10. unigrams/bigrams normalized by entity types  
                                                                 11. dependency features normalized by entity types  
                                                                 12. nearest entity type and string in the sentence/clause |
| Argument       | Basic       | 1. context words of the entity mention  
                                                                 2. trigger word and subtype  
                                                                 3. entity type, subtype and entity role if it is a geo-political entity mention  
                                                                 4. entity mention head, and head of any other name mention from co-reference chain  
                                                                 5. lexical distance between the argument candidate and the trigger  
                                                                 6. the relative position between the argument candidate and the trigger: \{before, after, overlap, or separated by punctuation\}  
                                                                 7. whether it is the nearest argument candidate with the same type  
                                                                 8. whether it is the only mention of the same entity type in the sentence |
|                | Syntactic   | 9. dependency path between the argument candidate and the trigger  
                                                                 10. path from the argument candidate and the trigger in constituent parse tree  
                                                                 11. length of the path between the argument candidate and the trigger in dependency graph  
                                                                 12. common root node and its depth of the argument candidate and parse tree  
                                                                 13. whether the argument candidate and the trigger appear in the same clause |

Table 1: Local features.
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[Li et al. 2013]
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| Trigger  | 1. bigram of trigger types occur in the same sentence or the same clause  
           2. binary feature indicating whether synonyms in the same sentence have the same trigger label  
           3. context and dependency paths between two triggers conjuncted with their types |
| Argument | 4. context and dependency features about two argument candidates which share the same role within the same event mention  
           5. features about one argument candidate which plays as arguments in two event mentions in the same sentence  
           6. features about two arguments of an event mention which are overlapping  
           7. the number of arguments with each role type of an event mention conjuncted with the event subtype  
           8. the pairs of time arguments within an event mention conjuncted with the event subtype |

Table 2: Global features.