Natural Language Processing

Compositional Semantics

Joakim Nivre

Uppsala University
Department of Linguistics and Philology
joakim.nivre@lingfil.uu.se
Do we need semantics?

- For many NLP tasks, we can sidestep semantic analysis:
  - Statistical MT: direct mapping from source to target sentences
  - WSD: surface context features as proxy for semantics
Do we need semantics?

- For many NLP tasks, we can sidestep semantic analysis:
  - Statistical MT: direct mapping from source to target sentences
  - WSD: surface context features as proxy for semantics
- But some tasks require semantic reasoning
  - Question answering
    - What is the capital of Liechtenstein?
    - Why does a rainbow form?
    - Did Marilyn Monroe and Cary Grant ever appear in a movie together?
  - Textual entailment
    - Text: If you help the needy, God will reward you.
    - Hypothesis: Giving money to a poor man has good consequences.
From Word to Sentence Meaning

- Word senses are not enough

  Ann robbed a bank \neq A bank robbed Ann
From Word to Sentence Meaning

- Word senses are not enough
  \[ \text{Ann robbed a bank} \neq \text{A bank robbed Ann} \]
- Adding syntax is not sufficient
  \[ \text{Ann robbed a bank} \neq \text{A bank was robbed by Ann} \]
From Word to Sentence Meaning

- Word senses are not enough
  \[ \text{Ann robbed a bank} \neq \text{A bank robbed Ann} \]
- Adding syntax is not sufficient
  \[ \text{Ann robbed a bank} \neq \text{A bank was robbed by Ann} \]
- Compositional semantics: combining word senses using syntax
Meaning Representations

- Logic:
  \[ \exists x : \text{bank}(x) \land \text{robbed}(\text{Ann}, x) \]

- Semantic roles in proposition/frame:
  \[[\text{Arg}_0 \text{ Ann} ] [\text{rob}_1 \text{ robbed} ] [\text{Arg}_1 \text{ a bank} ]\]

- Vector space model:
  [0.8, 1.3, −2.0, 3.4, −0.2, 0.0, 1.2, ... 0.2]
Logical Semantics

- Logic:
  - Formal language with precise semantics (model theory)
  - Unambiguous, facilitates logical reasoning
- Predicate logic:
  - Predicates denote $n$-ary relations
  - Constants denote entities
  - Variables range over a set of entities
- Atomic formulas ($a$ and $b$ are constants; $x$ is a variable):
  - $\text{bank}(b) = \text{"b is a bank"}$
  - $\text{rob}(a, b) = \text{"a robs b"}$
  - $\text{rob}(a, x) = \text{"a robs (some unknown) x"}$
Logical Semantics

- Logical connectives produce complex formulas:
  \[ \text{bank}(b) \lor \text{cinema}(b) = \text{“b is a bank or b is a cinema”} \]
  \[ \text{bank}(b) \land \text{rob}(a, b) = \text{“b is a bank and a robs b”} \]
  \[ \text{bank}(b) \rightarrow \text{rob}(a, b) = \text{“if b is a bank, then a robs b”} \]

- Quantifiers:
  \[ \exists x \ [\text{bank}(x) \land \text{rob}(a, x)] = \text{“a robs a bank”} \]
  \[ \forall x \ [\text{bank}(x) \rightarrow \text{rob}(a, x)] = \text{“a robs every bank”} \]
Logical Semantics

- How map natural language sentences to logical formulas?
  - The rule-to-rule hypothesis
  - For every syntactic rule, there is a corresponding semantic rule

- Example (simplified):
  \[ S \rightarrow NP \ VP \ : \ [S] = [VP](NP) \]
  \[ NP \rightarrow Ann \ : \ [NP] = a \]
  \[ VP \rightarrow sleeps \ : \ [VP] = sleep \]

- Long tradition of research on logical compositional semantics
  - Pros: expressive and precise; supports logical inference
  - Cons: complex; hard to achieve large coverage and robustness
Semantic Role Labeling

- Shallow semantic analysis of predicate-argument relations
- PropBank links semantic roles to predicate senses:
  \[\text{Args}_0 \text{ Ann } \text{rob}_1 \text{ robbed } \text{Args}_1 \text{ a bank }\]
  \[\text{Args}_1 \text{ a bank } \text{was rob}_1 \text{ robbed } \text{Args}_0 \text{ by Ann}\]
- FrameNet links semantic roles to frames
  \[\text{Perpetrator Ann } \text{Robbery robbed } \text{Source a bank }\]
  \[\text{Victim Ann } \text{was Robbery mugged } \text{Perpetrator by a stranger}\]
Semantic Role Labeling

- Typical SRL algorithm:
  1. Identify predicates and their senses/frames (essentially WSD)
  2. Identify argument candidates (usually from a syntactic parse)
  3. Classify argument candidates by relevant roles (or none)
  4. Apply post-processing to enforce global coherence

- State of the art:
  - Pros: robust and efficient; sufficient for shallow semantic tasks
  - Cons: only partial semantics; limited support for inference
For an example of textual entailment, consider this “text”:

- Merkel attended a ceremony in Washington to commemorate the landings in Normandy.

Which of these “hypotheses” are entailed by the text?

1. Merkel was in Washington.
2. Merkel was in Normandy.
3. Washington is in Normandy.
4. Normandy is in France.
PropBank and FrameNet

Slides adapted from Dan Jurafsky and James Martin
Background: Thematic Roles

- One of the oldest linguistic models
  - Indian grammarian Panini between the 7th and 4th centuries BCE
- Modern formulation from Fillmore (1966, 1968)

<table>
<thead>
<tr>
<th>Thematic Role</th>
<th>Definition</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGENT</td>
<td>The volitional causer of an event</td>
<td>The waiter spilled the soup.</td>
</tr>
<tr>
<td>EXPERIENCER</td>
<td>The experincer of an event</td>
<td>John has a headache.</td>
</tr>
<tr>
<td>FORCE</td>
<td>The non-volitional causer of the event</td>
<td>The wind blows debris from the mall into our yards.</td>
</tr>
<tr>
<td>THEME</td>
<td>The participant most directly affected by an event</td>
<td>Only after Benjamin Franklin broke the ice...</td>
</tr>
<tr>
<td>RESULT</td>
<td>The end product of an event</td>
<td>The city built a regulation-size baseball diamond...</td>
</tr>
<tr>
<td>CONTENT</td>
<td>The proposition or content of a propositional event</td>
<td>Mona asked “You met Mary Ann at a supermarket?”</td>
</tr>
<tr>
<td>INSTRUMENT</td>
<td>An instrument used in an event</td>
<td>He poached catfish, stunning them with a shocking device...</td>
</tr>
<tr>
<td>BENEFICIARY</td>
<td>The beneficiary of an event</td>
<td>Whenever Ann Callahan makes hotel reservations for her boss...</td>
</tr>
<tr>
<td>SOURCE</td>
<td>The origin of the object of a transfer event</td>
<td>I flew in from Boston.</td>
</tr>
<tr>
<td>GOAL</td>
<td>The destination of an object of a transfer event</td>
<td>I drove to Portland.</td>
</tr>
</tbody>
</table>
PropBank Roles

Following Dowty 1991

Proto-Agent

- Volitional involvement in event or state
- Sentience (and/or perception)
- Causes an event or change of state in another participant
- Movement (relative to position of another participant)

Proto-Patient

- Undergoes change of state
- Causally affected by another participant
- Stationary relative to movement of another participant
PropBank Frames

• Lexicon of verb senses (later extended to other classes)
• Each verb sense has numbered arguments: Arg0, Arg1, Arg2,...
  Arg0: PROTO-AGENT
  Arg1: PROTO-PATIENT
  Arg2: usually: benefactive, instrument, attribute, or end state
  Arg3: usually: start point, benefactive, instrument, or attribute
  Arg4: the end point
  (Arg2-Arg5 are not always consistent across verbs)
PropBank Frame Files

agree.01
Arg0: Agreeer
Arg1: Proposition
Arg2: Other entity agreeing

Ex1: [Arg0 The group] agreed [Arg1 it wouldn’t make an offer].
Ex2: [ArgM-TMP Usually] [Arg0 John] agrees [Arg2 with Mary]
[Arg1 on everything].

grow.01
Arg1: Logical subject, patient, thing growing
Arg2: Extent, amount grown
Arg3: start point
Arg4: end point, end state of arg1

Ex1: [Arg1 Sales] grew [Arg4 to $25 million] [Arg3 from $27 million].
Ex2: [Arg1 The average junk bond] grew [Arg2 by 4.2%].
**Advantage of a ProbBank Labeling**

increase.01 “go up incrementally”
- Arg0: causer of increase
- Arg1: thing increasing
- Arg2: amount increased by, EXT, or MNR
- Arg3: start point
- Arg4: end point

This would allow us to see the commonalities in these 3 sentences:

- [Arg0 Big Fruit Co. ] increased [Arg1 the price of bananas].
- [Arg1 The price of bananas] was increased again [Arg0 by Big Fruit Co. ]
- [Arg1 The price of bananas] increased [Arg2 5%].
Modifiers or adjuncts of the predicate: Arg-M

<table>
<thead>
<tr>
<th>ArgM-TMP</th>
<th>when?</th>
<th>yesterday evening, now</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOC</td>
<td>where?</td>
<td>at the museum, in San Francisco</td>
</tr>
<tr>
<td>DIR</td>
<td>where to/from?</td>
<td>down, to Bangkok</td>
</tr>
<tr>
<td>MNR</td>
<td>how?</td>
<td>clearly, with much enthusiasm</td>
</tr>
<tr>
<td>PRP/CAU</td>
<td>why?</td>
<td>because ... , in response to the ruling</td>
</tr>
<tr>
<td>REC</td>
<td></td>
<td>themselves, each other</td>
</tr>
<tr>
<td>ADV</td>
<td>miscellaneous</td>
<td></td>
</tr>
<tr>
<td>PRD</td>
<td>secondary predication</td>
<td>...ate the meat raw</td>
</tr>
</tbody>
</table>
Analysts have been expecting a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.
The same sentence, PropBanked

Analysts have been expecting a GM-Jaguar pact that would give the US car maker an eventual 30% stake in the British company.

expect(Analysts, GM-J pact) give(GM-J pact, US car maker, 30% stake)
Annotated PropBank Data

- Penn English TreeBank, OntoNotes 5.0.
  - Total ~2 million words
- Penn Chinese TreeBank
- Hindi/Urdu PropBank
- Arabic PropBank

### 2013 Verb Frames Coverage

<table>
<thead>
<tr>
<th>Language</th>
<th>Final Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>English</td>
<td>10,615*</td>
</tr>
<tr>
<td>Chinese</td>
<td>24,642</td>
</tr>
<tr>
<td>Arabic</td>
<td>7,015</td>
</tr>
</tbody>
</table>

From Martha Palmer 2013 Tutorial
Plus nouns and light verbs

Example Noun: Decision
- Roleset: Arg0: decider, Arg1: decision…

- “…[your$_{ARG0}$] [decision$_{REL}$]
  [to say look I don't want to go through this anymore$_{ARG1}$]”

Example within an LVC: Make a decision
- “…[the President$_{ARG0}$] [made$_{REL-LVB}$]
  the [fundamentally correct$_{ARGM-ADJ}$]
  [decision$_{REL}$] [to get on offense$_{ARG1}$]”
FrameNet

- Roles in PropBank are specific to a verb
  
  \[ \text{[Arg1 The price of bananas] increased [Arg2 5%].} \]
  
  \[ \text{[Arg1 The price of bananas] rose [Arg2 5%].} \]
  
  \[ \text{There has been a [Arg2 5%] rise [Arg1 in the price of bananas].} \]

- Roles in FrameNet are specific to a frame: a background knowledge structure that defines a set of frame-specific semantic roles, called frame elements
The “Change position on a scale” Frame

- This frame consists of words that indicate the change of an ITEM’s position on a scale (the ATTRIBUTE) from a starting point (INITIAL VALUE) to an end point (FINAL VALUE)

\[
\text{[ITEM Oil] } rose \ [\text{ATTRIBUTE in price}] \ [\text{DIFFERENCE by 2\%}].
\]

\[
\text{[ITEM It] has } increased \ [\text{FINAL_STATE to having them 1 day a month}].
\]

\[
\text{[ITEM Microsoft shares] } fell \ [\text{FINAL_VALUE to 7 5/8}].
\]
The “Change position on a scale” Frame

<table>
<thead>
<tr>
<th>VERBS:</th>
<th>dwindle</th>
<th>move</th>
<th>soar</th>
<th>escalation</th>
<th>shift</th>
</tr>
</thead>
<tbody>
<tr>
<td>advance</td>
<td>edge</td>
<td>mushroom</td>
<td>swell</td>
<td>explosion</td>
<td>tumble</td>
</tr>
<tr>
<td>climb</td>
<td>explode</td>
<td>plummet</td>
<td>swing</td>
<td>fall</td>
<td></td>
</tr>
<tr>
<td>decline</td>
<td>fall</td>
<td>reach</td>
<td>triple</td>
<td>fluctuation</td>
<td>gain</td>
</tr>
<tr>
<td>decrease</td>
<td>fluctuate</td>
<td>rise</td>
<td>tumble</td>
<td>growth</td>
<td></td>
</tr>
<tr>
<td>diminish</td>
<td>gain</td>
<td>rocket</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dip</td>
<td>grow</td>
<td>shift</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>double</td>
<td>increase</td>
<td>skyrocket</td>
<td>decline</td>
<td>increase</td>
<td>rise</td>
</tr>
<tr>
<td>drop</td>
<td>jump</td>
<td>slide</td>
<td>decrease</td>
<td>rise</td>
<td></td>
</tr>
</tbody>
</table>

ADVERBS: increasingly

FrameNet also codes relationships between frames, allowing frames to inherit from each other, or representing relations between frames like causation (and generalizations among frame elements in different frames can be represented by inheritance as well). Thus, there is a Cause change of position on a scale frame that is linked to the Change of position on a scale frame by the cause relation, but that adds an AGENT role and is used for causative examples such as the following:

(22.26) They [AGENT They] raised [AGENT] the price of their soda [ARG0] [DIFFERENCE by 2%].

Together, these two frames would allow an understanding system to extract the common event semantics of all the verbal and nominal causative and non-causative usages.

FrameNets have also been developed for many other languages including Spanish, German, Japanese, Portuguese, Italian, and Chinese.
# The “Change position on a scale” Frame

## Core Roles

<table>
<thead>
<tr>
<th>Role</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATTRIBUTE</td>
<td>The ATTRIBUTE is a scalar property that the ITEM possesses.</td>
</tr>
<tr>
<td>DIFFERENCE</td>
<td>The distance by which an ITEM changes its position on the scale.</td>
</tr>
<tr>
<td>FINAL_STATE</td>
<td>A description that presents the ITEM’s state after the change in the ATTRIBUTE’s value as an independent predication.</td>
</tr>
<tr>
<td>FINAL_VALUE</td>
<td>The position on the scale where the ITEM ends up.</td>
</tr>
<tr>
<td>INITIAL_STATE</td>
<td>A description that presents the ITEM’s state before the change in the ATTRIBUTE’s value as an independent predication.</td>
</tr>
<tr>
<td>INITIAL_VALUE</td>
<td>The initial position on the scale from which the ITEM moves away.</td>
</tr>
<tr>
<td>ITEM</td>
<td>The entity that has a position on the scale.</td>
</tr>
<tr>
<td>VALUE_RANGE</td>
<td>A portion of the scale, typically identified by its end points, along which the values of the ATTRIBUTE fluctuate.</td>
</tr>
</tbody>
</table>

## Some Non-Core Roles

<table>
<thead>
<tr>
<th>Role</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DURATION</td>
<td>The length of time over which the change takes place.</td>
</tr>
<tr>
<td>SPEED</td>
<td>The rate of change of the VALUE.</td>
</tr>
<tr>
<td>GROUP</td>
<td>The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.</td>
</tr>
</tbody>
</table>
FrameNet and PropBank representations

(a) A phrase-structure tree taken from the Penn Treebank and annotated with PropBank predicate-argument structures. The verbs created and pushed serve as predicates in this sentence. Dotted arrows connect each predicate to its semantic arguments (bracketed phrases).

(b) A partial depiction of frame-semantic structures for the same sentence. The words in bold are targets, which instantiate (lemmatized and part-of-speech–tagged) lexical units and evoke as semantic frames. Every annotation is enclosed in borders and its argument labels are shown together on the same vertical tier below the sentence. See text for explanation of abbreviations.

There are many instances of influential work on semantic role labeling using PropBank conventions. Pradhan et al. (2004) present a system that uses support vector machines (SVMs) to identify the arguments in a syntax tree that can serve as semantic roles, followed by classification of the identified arguments to role names via a collection of binary SVMs. Punyakanok et al. (2004) describe a semantic role labeler that uses integer linear programming for inference and uses several global constraints to find the best...
Quiz

• In which of these sentences does Susan fill an agent role?

1. Susan had a headache.
2. Susan ordered a sandwich.
3. Susan was insulted by the waiter.
4. The restaurant was sued by Susan.