Lecture 7

Semantic Role Labelling (SRL)/Predicate Argument Structure (PAS)

(II)

Marina Santini
Uppsala University
Sweden
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Thanks!
Basically...

- **Semantic roles** are semantic interpretations that we can use to fill up the arguments of a predicate.

- **Semantic role labelling** is the task of finding semantic roles for each predicate in the sentence.
We said...

- A variety of semantic role labels have been proposed, common ones are:
  - Agent: Actor of an action
  - Patient: Entity affected by the action
  - Instrument: Tool used in performing action.
  - Beneficiary: Entity for whom action is performed
  - Source: Origin of the affected entity
  - Destination: Destination of the affected entity
  - Etc.

- Frequently semantic role is indicated by a particular syntactic position (e.g. object of a particular preposition):
  - Agent: subject
  - Patient: direct object
  - Instrument: object of “with” PP
  - Beneficiary: object of “for” PP
  - Source: object of “from” PP
  - Destination: object of “to” PP
  - What about “about”? 

- There are different naming conventions, but one common set of names for semantic roles are agent, patient, means/instrument, ....
Some constraints

1. Only certain kinds of phrases can fill certain kinds of semantic roles
   “with a hammer” will never be an agent
   But many are ambiguous:
   “hammer” → patient or instrument?

2. Syntax provides a clue, but it is not the full answer
   Subject → Agent? Patient? Instrument?
Semantic Role Labelling (SRL)/Predicate Argument Structure (PAS) & co.

- Predicate argument structure analysis
  (more semantics-oriented perspective)
- Semantic role labeling
  (more surface-oriented perspective)
- very closely related tasks

Other names for the same or similar tasks:
- Thematic role labelling
- Case role assignment
- Shallow semantic parsing
- Etc.
We also said...

- Many lexical ambiguities can be resolved using selectional restrictions. For ex:
  - Ambiguous verbs
    - “John fired the secretary.”
    - “John fired the rifle.”
  - This sense of ’fire’ requires an argument that must be animate
  - This sense of ’fire’ requires an argument that must be an instrument

- Definition: A selectional restriction is a kind of semantic type constraint that a verb imposes on the kind of concepts that are allowed to fill its argument roles. (J&M2009: 661)
We have experienced its limitations...

- One way to overcome these limitations and to capture the semantics of selectional restrictions is to use a *neo-Davidsonian* representation, which can be used both:

1. for the semantics of events, for ex: ’I ate turkey sandwich’ (j&m2009: 597ff)
   
   \[ \exists e \text{ Eating}(e) \land \text{ Eater}(e,\text{Speaker}) \land \text{ Eaten}(e,\text{TurkeySandwich}) \]

2. for representing the meanings of arguments.
Neo-Davidsonian Representation of the semantics of arguments

• Instead of using specific semantic roles (as we did in the practical task), we can use:
  – A **variable** that stands for the event
  – A **predicate** denoting the type of event
  – **Variables and relations** for the event roles.

  • *eat* = \( \exists e,x,y \text{Eating}(e) \land \text{Agent}(e,x) \land \text{Theme}(e,y) \)
  • *I ate a hamburger* =
    – \( \exists e,x,y \text{Eating}(e) \land \text{Eater}(e,x) \land \text{Theme}(e,y) \land \text{EdibleThing}(y) \land \text{Hamburger}(y) \)
Two main drawbacks

1. FOL is too costly! Simpler formalisms can do the job with much less computational cost

2. We need a large, logical, common-sense KB of facts about concepts that make up the selectional restrictions.

3. We can use WordNet hyperonym/hyponym hierarchy of the synsets, but at this point in time it is unlikely that WordNet has all relevant synsets to specify selectional restrictions for all possible words...
Thematic Roles Model

• In a neo-Davidsonian event representation, the two sentences:
  – Ate an hamburger
  – Pat opened the door

• Would be represented as:

  • $\exists e, x, y \text{ Eating}(e) \land \text{ Eater}(e, x) \land \text{ Theme}(e, y) \land \text{ EdibleThing}(y) \land \text{ Hamburger}(y)$
  • $\exists e, x, y \text{ Opening}(e) \land \text{ Opener}(e, \text{Pat}) \land \text{ Theme}(e, y) \land \text{ OpenedThing}(e, y) \land \text{ Door}(y)$
Thematic Roles Model is...

• An attempt to capture this semantic commonality between *eaters and openers*:
  – *The subjects are both AGENTS*
  – *The objects are both THEMES*

• *Thematic roles are one of the oldest linguistic models* (Indian grammarian Panini 7th-4th century BC)

• *Modern formulation by Fillmore (1968) and Gruber (1965)*

• *There is no universally-agreed upon set of thematic roles!*
Predicates and Arguments, quick definitions

- **Predicate** – a general concept that applies or doesn’t apply to a particular arrangement of entities (arguments).

- **Arity** – number of arguments: one-place, two-place, etc.
  
  *Pompe was a dog*: *dog* – one-place.

  *Charles XII was the owner of Pompe*: *owner_of*: two-place.

  Or three-place if time is counted as an argument.

- **Argument roles** are important: *Charles XII was the owner of Pompe* and *Pompe was the owner of Charles XII* are different propositions, as are *Charles XII loved Pompe* and *Pompe loved Charles XII*.

Predicate words: verbs, adjectives, nouns adverbs
Same event - different sentences

John broke the window.

John broke the window with a hammer.

The hammer broke the window.

The window broke.
Same event - different syntactic frames

John broke the window.

SUBJ VERB OBJ

John broke the window with a hammer.

SUBJ VERB OBJ MODIFIER

The hammer broke the window.

SUBJ VERB OBJ

The window broke.

SUBJ VERB
Thematic role example

\textit{break(AGENT, THEME, INSTRUMENT)}

\begin{itemize}
  \item \textbf{AGENT} \quad \textbf{THEME}
    \begin{itemize}
      \item John broke the window
    \end{itemize}
  \item \textbf{AGENT} \quad \textbf{THEME} \quad \textbf{INSTRUMENT}
    \begin{itemize}
      \item John broke the window with a hammer.
    \end{itemize}
  \item \textbf{INSTRUMENT} \quad \textbf{THEME}
    \begin{itemize}
      \item The hammer broke the window.
    \end{itemize}
  \item \textbf{THEME}
    \begin{itemize}
      \item The window broke.
    \end{itemize}
\end{itemize}
Slot Filling

Phrases

John

broke

the window

with a hammer

Slots

Pred

Agent

Theme

Instrument

Argument Classification

Lecture 7: SRL/PAS II
Slot Filling

Phrases

The hammer
broke
the window

Slots

Pred
Agent
Theme
Instrument

Argument Classification
Slot Filling

Phrases
- The window
- broke

Slots
- Pred
- Agent
- Theme
- instrument

Argument Classification
Slot Filling and Shallow Semantics

Phrases: John, broke, the window, with a hammer

Slots: Pred, Agent, Theme, (Instrument)

Shallow Semantics: broke(John, the window, with a hammer)
Slot Filling and Shallow Semantics

Phrases

- The window
- broke

Slots

- Pred
- Agent
- Theme

(Instrument)

Shallow Semantics

\texttt{broke( \ ?x \ , the window, \ ?y \ )}
Thematic Role Representation

• Seems like it should be useful in dealing with different surface forms. However...
  – it is difficult to come up with a standard set of roles
  – It is difficult to produce a formal definition of roles like: AGENT, THEME, or INSTRUMENT
Alternatives... Generalized Semantic Roles

• PROTO-ROLES
  – PROTO-AGENT
  – PROTO-PATIENT

• Proto-roles are generalized semantic roles that abstract over specific thematic roles.
  – The more an argument desplay displays agent like properties (e.g. intentionality, causality, etc) the greater the likelihood that the argument can be called pro-agent.
Alternatives... semantic roles specific to particular lexical items

- **PropBank**: uses both proto-roles and verb-specific semantic roles
- **FrameNet**: uses frame-specific semantic roles
PropBank

• Project at U Penn lead by Martha Palmer to add semantic roles to the Penn Treebank (parsed corpus; ex

• (S
  – (NP (NNP John))
    • (VP (VPZ loves)
      – (NP (NNP Mary)))
    • (..))

• Roles (Arg0 to ArgN) specific to each individual verb to avoid having to agree on a universal set.
  – Arg0 basically “agent”
  – Arg1 basically “patient”

• Annotated over 1M words of Wall Street Journal text with existing gold-standard parse trees.

• Statistics:
  – 43,594 sentences  99,265 propositions (verbs + roles)
  – 3,324 unique verbs  262,281 role assignments
ProBank: Semantic Roles

- “neutral” semantic roles, as opposed to verb-specific ones
- E.g. *give*:
  - Arg0: giver
  - Arg1: thing given
  - Arg2: entity given to
- Rather than giver, gift, recipient.
Sample PropBank: Lexicon & Annotation

- PropBank consists of Lexicon and Annotation
- Lexicon
  - Each verb is associated with 1 or more rolesets (~senses)
  - Each roleset lists the **core** arguments of the verb
    - These are numbered: ARG0, ARG1, ARG2, ...
    - Additional information intended for annotation purposes
      - But possibly usable for other purposes as well (see later slide)
- Annotation: points to annotated PTB constituents
  - Verb
  - Core arguments: subset of \{ARG0, ..., ARG9\}
  - Non-core ARGM-XXX arguments:
    - -TMP, -LOC, -MNR, -CAU, -MOD
FrameNet

- Project at UC Berkeley led by Chuck Fillmore for developing a database of frames, general semantic concepts with an associated set of roles.

- Roles are specific to frames, which are “invoked” by multiple words, both verbs and nouns.
  - JUDGEMENT frame
    - Invoked by: V: blame, praise, admire; N: fault, admiration
    - Roles: JUDGE, EVALUEEE, and REASON

- Specific frames chosen, and then sentences that employed these frames selected from the British National Corpus and annotated by linguists for semantic roles.

- Initial version: 67 frames, 1,462 target words, 49,013 sentences, 99,232 role fillers
In summary, SRL Datasets

• FrameNet:
  – Developed at Univ. of California at Berkeley
  – Based on notion of Frames

• PropBank:
  – Developed at Univ. of Pennsylvania
  – Based on elaborating their Treebank

• Others
  – Salsa:
    • Developed at Universität des Saarlandes
    • German version of FrameNet
  – NomBank: annotation project at New York University that is related to the PropBank project at the University of Colorado.
  – VerbNet: maps PropBank verb types to their corresponding Levin classes.
    • Beth Levin showed, for a large set of English verbs (about 3200), the correlations between the semantics of verbs and their syntactic behavior. More precisely, she shows that some facets of the semantics of verbs have strong correlations with the syntactic behavior of these verbs and with the interpretation of their arguments.
Semantic Role Labeling Techniques
In Language Technology, SRL is...

• the task of automatically finding the semantic roles for each predicate in a sentence.

• SRL ia a way of linking word meaning (eg lexical entries in WordNet) to sentence meaning by determining which constituents in a sentence are semantic arguments for a given predicate and the then determining the appropriate role for each of these arguments (J&M2009:704)
Current Approaches to SRL

• Supervised machine learning: annotated data for training and testing is required
  – FrameNet and PropBank are often used for supervised ML approaches to SRL
Semantic Role Labeling

Semantic role labeling is the computational task of assigning semantic roles to phrases. It’s usually divided into three subtasks:

1. Predicate identification
2. Argument Identification
3. Argument Classification -- assigning *semantic roles*

```
Agent  
Arg    

Pred   
John   
broke  

Patient 
Arg     

Instrument 
Arg     

the    
window 
with    
a      
hammer.
```
• Function
  – For each parse(sentence)
    • For each node(parse)
      – EXTRACT_FEATURES
      – CLASSIFY_ARGUMENT
Semantic Role Labeling Technique: Basic Approach

Gildea and Jurafsky 2002: **Automatic Labeling of Semantic Roles**
([http://acl.ldc.upenn.edu/J/J02/J02-3001.pdf](http://acl.ldc.upenn.edu/J/J02/J02-3001.pdf))

From the Abstract:

We present a system for identifying the semantic relationships, or semantic roles, filled by constituents of a sentence within a semantic frame. Given an input sentence and a target word and frame, the system labels constituents with either abstract semantic roles, such as Agent or Patient, or more domain-specific semantic roles, such as Speaker, Message, and Topic. The system is based on statistical classifiers trained on roughly 50,000 sentences that were hand-annotated with semantic roles by the FrameNet semantic labeling project. We then parsed each training sentence into a syntactic tree and extracted various lexical and syntactic features, including the phrase type of each constituent, its grammatical function, and its position in the sentence. These features were combined with knowledge of the predicate verb, noun, or adjective, as well as information such as the prior probabilities of various combinations of semantic roles...
Feature Extraction
(Gildea and Jurafsky, 2002)

- Predicate
- Phrase type
- Headword
- Headword POS
- Path
- Voice
- Linear position
- subcategorization

**Figure:** Figure 20.16 Jurafsky & Martin

ARG0: [issued, NP, Examiner, NNP, NP↑S↓VP↓VBD, active, before, VP, →NP PP]
FrameNet Results

• Gildea and Jurafsky (2002) performed SRL experiments with initial FrameNet data.

• Assumed correct frames were identified and the task was to fill their roles.

• Automatically produced syntactic analyses using Collins (1997) statistical parser.

• Used simple Bayesian method with smoothing to classify parse nodes.

• Achieved 80.4% correct role assignment.
  – (Increased to 82.1% when frame-specific roles were collapsed to 16 general thematic categories.)
Supervised Learning

- Devide these observations into a training and a test set
- Use training examples in any ML algorithm
  - SVM and Maximum entropy classifiers are among the best
- Once trained, the classifier can be used on unlabeled sentences to propose a role for each constituent in the sentence.

ARG0: [issued, NP, Examiner, NNP, NP↑S↓VP↓VBD, active, before, VP, → NP PP]
The End