Semantic Roles & Semantic Role Labeling

Ling571
Deep Processing Techniques for NLP
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Roadmap

- Semantic role labeling (SRL):
  - Motivation:
    - Between deep semantics and slot-filling
  - Thematic roles
  - Thematic role resources
    - PropBank, FrameNet
  - Automatic SRL approaches
Semantic Analysis

- Two extremes:
  - Full, deep compositional semantics
    - Creates full logical form
    - Links sentence meaning representation to logical world model representation
    - Powerful, expressive, AI-complete
  - Domain-specific slot-filling:
    - Common in dialog systems, IE tasks
    - Narrowly targeted to domain/task
    - Often pattern-matching
    - Low cost, but lacks generality, richness, etc
Semantic Role Labeling

- Typically want to know:
  - *Who* did *what* to *whom*, *where*, *when*, and *how*

- Intermediate level:
  - Shallower than full deep composition
  - Abstracts away (somewhat) from surface form
  - Captures general predicate-argument structure info
  - Balance generality and specificity
Example

- Yesterday Tom chased Jerry.
- Yesterday Jerry was chased by Tom.
- Tom chased Jerry yesterday.
- Jerry was chased yesterday by Tom.

- Semantic roles:
  - Chaser: Tom
  - ChasedThing: Jerry
  - TimeOfChasing: yesterday

- Same across all sentence forms
Full Event Semantics

- Neo-Davidsonian style:
  - exists e. Chasing(e) & Chaser(e,Tom) & ChasedThing(e,Jerry) & TimeOfChasing(e,Yesterday)

- Same across all examples

- Roles: Chaser, ChasedThing, TimeOfChasing
  - Specific to verb “chase”
  - Aka “Deep roles”
Issues

• Challenges:
  • How many roles for a language?
    • Arbitrarily many deep roles
      • Specific to each verb’s event structure
  • How can we acquire these roles?
    • Manual construction?
    • Some progress on automatic learning
      • Still only successful on limited domains (ATIS, geography)
  • Can we capture generalities across verbs/events?
    • Not really, each event/role is specific

• Alternative: thematic roles
Thematic Roles

- Describe semantic roles of verbal arguments
  - Capture commonality across verbs
  - E.g. subject of break, open is AGENT
    - AGENT: volitional cause
    - THEME: things affected by action

- Enables generalization over surface order of arguments
  - John_{AGENT} broke the window_{THEME}
  - The rock_{INSTRUMENT} broke the window_{THEME}
  - The window_{THEME} was broken by John_{AGENT}
Thematic Roles

- Thematic grid, $\theta$-grid, case frame
  - Set of thematic role arguments of verb
    - E.g. Subject: AGENT; Object: THEME, or
    - Subject: INSTR; Object: THEME

- Verb/Diathesis Alternations
  - Verbs allow different surface realizations of roles
    - Doris$_{AGENT}$ gave the book$_{THEME}$ to Cary$_{GOAL}$
    - Doris$_{AGENT}$ gave Cary$_{GOAL}$ the book$_{THEME}$
  - Group verbs into classes based on shared patterns
# Canonical Roles

<table>
<thead>
<tr>
<th>Thematic Role</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGENT</td>
<td><em>The waiter</em> spilled the soup.</td>
</tr>
<tr>
<td>EXPERIENCER</td>
<td><em>John</em> has a headache.</td>
</tr>
<tr>
<td>FORCE</td>
<td><em>The wind</em> blows debris from the mall into our yards.</td>
</tr>
<tr>
<td>THEME</td>
<td>Only after Benjamin Franklin broke <em>the ice</em>...</td>
</tr>
<tr>
<td>RESULT</td>
<td>The French government has built a <em>regulation-size baseball diamond</em>...</td>
</tr>
<tr>
<td>CONTENT</td>
<td>Mona asked “<em>You met Mary Ann at a supermarket?</em>”</td>
</tr>
<tr>
<td>INSTRUMENT</td>
<td>He turned to poaching catfish, stunning them <em>with a shocking device</em>...</td>
</tr>
<tr>
<td>BENEFICIARY</td>
<td>Whenever Ann Callahan makes hotel reservations <em>for her boss</em>...</td>
</tr>
<tr>
<td>SOURCE</td>
<td>I flew in <em>from Boston</em>.</td>
</tr>
<tr>
<td>GOAL</td>
<td>I drove <em>to Portland</em>.</td>
</tr>
</tbody>
</table>
Thematic Role Issues

- Hard to produce
  - Standard set of roles
    - Fragmentation: Often need to make more specific
      - E.g., INSTRUMENTS can be subject or not
  - Standard definition of roles
    - Most AGENTs: animate, volitional, sentient, causal
    - But not all....

- Strategies:
  - Generalized semantic roles: PROTO-AGENT/PROTO-PATIENT
    - Defined heuristically: PropBank
  - Define roles specific to verbs/nouns: FrameNet
PropBank

- Sentences annotated with semantic roles
  - Penn and Chinese Treebank
  - Roles specific to verb sense
    - Numbered: Arg0, Arg1, Arg2,...
      - Arg0: PROTO-AGENT; Arg1: PROTO-PATIENT, etc
      - > 1: Verb-specific
  - E.g. agree.01
    - Arg0: Agreer
    - Arg1: Proposition
    - Arg2: Other entity agreeing
    - Ex1: [Arg0 The group] agreed [Arg1 it wouldn’t make an offer]
Propbank

- Resources:
  - Annotated sentences
    - Started w/Penn Treebank
    - Now: Google answerbank, SMS, webtext, etc
      - Also English and Arabic
  - Framesets:
    - Per-sense inventories of roles, examples
    - Span verbs, adjectives, nouns (e.g. event nouns)

- http://verbs.colorado.edu/propbank

- Recent status:
  - 5940 verbs w/ 8121 framesets;
  - 1880 adjectives w/2210 framesets
FrameNet (Fillmore et al)

- Key insight:
  - Commonalities not just across different sentences with the same verb but across different verbs (and nouns and adjs)

- PropBank
  - \([Arg_0\text{Big Fruit Co.}]\) increased \([Arg_1\text{the price of bananas}]\).
  - \([Arg_1\text{The price of bananas}]\) was increased by \([Arg_0\text{BFCo}]\).
  - \([Arg_1\text{The price of bananas}]\) increased \([Arg_2\text{5%}]\).

- FrameNet
  - \([\text{ATTRIBUTE the price}]\) of \([\text{ITEM bananas}]\) increased \([\text{DIFF5%}]\).
  - \([\text{ATTRIBUTE the price}]\) of \([\text{ITEM bananas}]\) rose \([\text{DIFF5%}]\).
  - There has been a \([\text{DIFF5%}]\) rise in \([\text{ATTRIBUTE the price}]\) of \([\text{ITEM bananas}]\).
FrameNet

- Semantic roles specific to Frame
  - Frame: script-like structure, roles (frame elements)
    - E.g. change_position_on_scale: increase, rise
      - Attribute, Initial_value, Final_value
  - Core, non-core roles
  - Relationships b/t frames, frame elements
    - Add causative: cause_change_position_on_scale
Change of position on scale

VERBS: dwindl  ede  move  soar  escalation  shift
advance  edge  mushroom  swell  explosion  tumble
climb  explode  plummet  swing  fall
decline  fall  reach  triple  fluctuation
decrease  fluctuate  rise  tumble
diminish  gain  rocket  gain  growth
dip  grow  shift  NOUNS:  hike
double  increase  skyrocket  decline  increase
drop  jump  slide  decrease  rise
ADVERBS: increasingly
### Core Roles

<table>
<thead>
<tr>
<th>Role</th>
<th>Definition</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

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<thead>
<tr>
<th>Role</th>
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</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

- Current status:
  - 1216 frames
  - ~13500 lexical units (mostly verbs, nouns)
  - Annotations over:
    - Newswire (WSJ, AQUAINT)
    - American National Corpus

- Under active development

- Still only ~6K verbs, limited coverage
Semantic Role Labeling

- Aka Thematic role labeling, shallow semantic parsing
- Form of predicate-argument extraction
- Task:
  - For each predicate in a sentence:
    - Identify which constituents are arguments of the predicate
    - Determine correct role for each argument
- Both PropBank, FrameNet used as targets
- Potentially useful for many NLU tasks:
  - Demonstrated usefulness in Q&A, IE
SRL in QA

- Intuition:
  - Surface forms obscure Q&A patterns
  - Q: *What year did the U.S. buy Alaska?*
  - $S_A:...before Russia sold Alaska to the United States in 1867$

- Learn surface text patterns?
  - Long distance relations, require huge # of patterns to find

- Learn syntactic patterns?
  - Different lexical choice, different dependency structure
Semantic Roles & QA

Approach:
- Perform semantic role labeling
  - FrameNet
- Perform structural and semantic role matching
- Use role matching to select answer
Q: Who discovered prions?
S: 1997: Stanley B. Prusiner, United States, discovery of prions, ...

**SemStruc**

*p*: discover

Original SR assignments:

- EAP
- Prions
- Phenomenon
- Evidence
- State
- Ground

Optimized SR assignments:

- EAP
- Prions
- Phenomenon
- Evidence
- State
- Ground

**SemStruc**

*p*: discovery

Original SR assignments:

- Ac
- Prions
- Phenomenon
- Evidence
- Topic

Optimized SR assignments:

- Ac
- Prions
- Phenomenon
- Evidence
- Topic
Summary

- FrameNet and QA:
  - FrameNet still limited (coverage/annotations)
  - Bigger problem is lack of alignment b/t Q & A frames
- Even if limited,
  - Substantially improves where applicable
  - Useful in conjunction with other QA strategies
  - Soft role assignment, matching key to effectiveness
SRL Subtasks

• Argument identification:
  • The [San Francisco Examiner] issued [a special edition] [yesterday].
  • Which spans are arguments?
    • In general (96%), arguments are (gold) parse constituents
    • 90% arguments are aligned w/auto parse constituents

• Role labeling:
  • The [Arg0 San Francisco Examiner] issued [Arg1 a special edition] [ArgM-TMP yesterday].
Semantic Role Complexities

- Discontinuous arguments:
  - \([_{\text{Arg}_1 \text{The pearls}}, \text{Arg}_0 \text{she}] \text{ said, } [c_{-\text{Arg}_1 \text{ are fake}}].\)

- Arguments can include referents/pronouns:
  - \([_{\text{Arg}_0 \text{The pearls}}, \text{R-Arg}_0 \text{that}] \text{ are } [_{\text{Arg}_1 \text{ fake}}].\)
SRL over Parse Tree

Figure 20.16 Parse tree for a PropBank sentence, showing the PropBank argument labels. The dotted line shows the path feature NP↑S↑VP↓VBD for ARG0, the NP-SBJ constituent the San Francisco Examiner.
Basic SRL Approach

• Generally exploit supervised machine learning

• Parse sentence (dependency/constituent)
  • For each predicate in parse:
    • For each node in parse:
      • Create a feature vector representation
      • Classify node as semantic role (or none)

• Much design in terms of features for classification
Classification Features

- Gildea & Jurafsky, 2002 (foundational work)
  - Employed in most SRL systems

- Features:
  - Specific to candidate constituent argument
  - For predicate generally

- Governing **predicate**:
  - Nearest governing predicate to the current node
    - Verbs usually (also adj, noun in FrameNet)
    - E.g. ‘issued’
  - Crucial: roles determined by predicate
SRL Features

• Constituent internal information:
  • Phrase type:
    • Parse node dominating this constituent
      • E.g. NP
    • Different roles tend to surface as different phrase types
  • Head word:
    • E.g. Examiner
    • Words associated w/specific roles – e.g. pronouns as agents
  • POS of head word:
    • E.g. NNP
SRL Features

- Structural features:
  - Path: Sequence of parse nodes from const to pred
    - E.g. \textbf{NP} \textbf{S} \textbf{VP} \textbf{VBD}
      - Arrows indicate direction of traversal
      - Can capture grammatical relations
    - Linear position:
      - Binary: Is constituent \textbf{before} or \textbf{after} predicate
        - E.g. before
    - Voice:
      - Active or passive of clause where constituent appears
        - E.g. active (strongly influences other order, paths, etc)
    - Verb subcategorization
Other SRL Constraints

- Many other features employed in SRL
  - E.g. NER on constituents, neighboring words, path info

- Global Labeling constraints:
  - Non-overlapping arguments:
    - FrameNet, PropBank both require

- No duplicate roles:
  - Labeling of constituents is not independent
    - Assignment to one constituent changes probabilities for others
Classification Approaches

- Many SRL systems use standard classifiers
  - E.g. MaxEnt, SVM
  - However, hard to effectively exploit global constraints

- Alternative approaches
  - Classification + reranking
  - Joint modeling
  - Integer Linear Programming (ILP)
    - Allows implementation of global constraints over system
State-of-the-Art

- Best system from CoNLL shared task (PropBank)
- ILP-based system (Punyakanok)
FrameNet “Parsing”

- (Das et al., 2014)
- Identify targets that evoke frames
  - ~ 79.2% F-measure
- Classify targets into frames
  - 61% for exact match
- Identify arguments
  - ~ 50%
SRL Challenges

- Open issues:
  - SRL degrades significantly across domains
    - E.g. WSJ → Brown: Drops > 12% F-measure
  - SRL depends heavily on effectiveness of other NLP
    - E.g. POS tagging, parsing, etc
    - Errors can accumulate
  - Coverage/generalization remains challenging
    - Resource coverage still gappy (FrameNet, PropBank)

- Publicly available implementations:
  - Shalmaneser, SEMAFOR