Logical & Shallow Semantics

CMSC 723 / LING 723 / INST 725

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Recall: A CFG specification of the syntax of First Order Logic Representations

\[
\begin{align*}
\text{Formula} & \rightarrow \text{AtomicFormula} \\
& \quad | \quad \text{Formula Connective Formula} \\
& \quad | \quad \text{Quantifier Variable, \ldots Formula} \\
& \quad | \quad \neg \text{Formula} \\
& \quad | \quad (\text{Formula}) \\
\text{AtomicFormula} & \rightarrow \text{Predicate}(\text{Term}, \ldots) \\
\text{Term} & \rightarrow \text{Function}(\text{Term}, \ldots) \\
& \quad | \quad \text{Constant} \\
& \quad | \quad \text{Variable} \\
\text{Connective} & \rightarrow \land | \lor | \Rightarrow \\
\text{Quantifier} & \rightarrow \forall | \exists \\
\text{Constant} & \rightarrow \text{A} | \text{VegetarianFood} | \text{Maharani} \cdots \\
\text{Variable} & \rightarrow x | y | \cdots \\
\text{Predicate} & \rightarrow \text{Serves} | \text{Near} | \cdots \\
\text{Function} & \rightarrow \text{LocationOf} | \text{CuisineOf} | \cdots
\end{align*}
\]
Principle of Compositionality

• The meaning of a whole is derived from the meanings of the parts

• What parts?
  – The constituents of the syntactic parse of the input
Augmented Rules

• We’ll accomplish this by attaching semantic formation rules to our syntactic CFG rules

• Abstractly

\[ A \rightarrow \alpha_1...\alpha_n \quad \{ f(\alpha_1.sem,...\alpha_n.sem) \} \]

– This should be read as: “the semantics we attach to A can be computed from some function applied to the semantics of A’s parts.”
Compositional Analysis: use syntax to guide semantic analysis
Example

- Lexicon: attaches semantics to individual words
  
  - PropNoun -> Frasca \{Frasca\}
  - PropNoun -> Franco \{Franco\}
  - Verb -> likes \( \lambda x \lambda y \exists e Liking(e) \land Liker(e, y) \land Liked(e, x) \)

- Composition rules
  
  - S -> NP VP VP.sem(NP.sem)
  - VP -> Verb NP Verb.sem(NP.sem)
Complications: Complex NPs

– The previous example simplified things by only dealing with constants (FOL Terms).

– What about...
  • A menu
  • Every restaurant
  • Not every waiter
  • Most restaurants
Complications: Complex NPs

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– What about...
  • A menu
  • Every restaurant
  • Not every waiter
  • Most restaurants
Complex NPs: Example

Every restaurant closed.

\( \forall x \, \text{Restaurant}(x) \Rightarrow \exists e \, \text{Closed}(e) \land \text{ClosedThing}(e, x) \)
Complex NPs: Example

- Roughly “every” in an NP like this is used to stipulate something (VP) about every member of the class (NP)

- So the NP can be viewed as the following template

\[ \forall x \text{Restaurant}(x) \Rightarrow Q(x) \]
Complex NPs: Example

• But that’s not combinable with anything so wrap a lambda around it...

$$\lambda Q. \forall x \text{Restaurant}(x) \Rightarrow Q(x)$$

• Note: this requires a change to the kind of things that we’ll allow lambda variables to range over...
  – Now its both FOL predicates and terms.
Resulting CFG rules augmented with semantics

\[ NP \rightarrow Det\ Nominal \quad \{Det.\text{Sem}(Nominal.\text{Sem})\} \]

\[ Det \rightarrow \text{every} \quad \{\lambda P.\lambda Q.\forall x P(x) \Rightarrow Q(x)\} \]

\[ Nominal \rightarrow Noun \quad \{Noun.\text{sem}\} \]

\[ Noun \rightarrow \text{restaurant} \quad \{\lambda x.\text{Restaurant}(x)\} \]
Every Restaurant Closed
Note on S Rule

– For “Franco likes Frasca”
  • We were applying the semantics of the VP to the semantics of the NP
    $S \rightarrow NP\ VP\ \ VP.Sem(NP.Sem)$

– “Every restaurant closed” requires a new rule
  $S \rightarrow NP\ VP\ \ NP.Sem(VP.Sem)$
Every Restaurant Closed
Recap: Logical Meaning Representations

• Representation based on **First Order Logic**
• In Syntax-driven semantic analysis, meaning of a phrase is **composed** by meaning of its syntactic constituents
• Compositional creation of FOL formulas requires extensions such as **lambda expressions**
• Logical representations offer a natural way to capture contradiction, entailment, synonymy
• Semantic parsers can be learned from data
  – E.g using latent variable perceptor
Semantic Parsing

• Task where
  – Input: a natural language sentence
  – Output: a semantic representation (such as FOL with lambda calculus)

• Parsers can be learned from data
Supervised Semantic Parsers

- Using gold logical analyses (e.g., Zettlemoyer & Collins [2005]*)
  - Each syntactic-semantic rule is a feature with a weight
  - Learning: latent variable perceptron

\[
\hat{y}, \hat{z} = \arg \max_{y, z} \theta^\top f(w, y, z)
\]

\[
\theta^{(t+1)} \leftarrow \theta^{(t)} + f(w, y, z^*) - f(w, \hat{y}, \hat{z}),
\]

*Note: uses Combinatory Categorial Grammars instead of CFGs
SEMANTIC ROLE LABELING

Slides Credit: William Cohen, Scott Yih, Kristina Toutanova
Yesterday, Kristina hit Scott with a baseball

Scott was hit by Kristina yesterday with a baseball

Yesterday, Scott was hit with a baseball by Kristina

With a baseball, Kristina hit Scott yesterday

Yesterday Scott was hit by Kristina with a baseball

Kristina hit Scott with a baseball yesterday

Agent, hitter  Thing hit  Instrument  Temporal adjunct
Semantic Role Labeling – Giving Semantic Labels to Phrases

• \([\text{AGENT}\, \text{John}]\) broke \([\text{THEME}\, \text{the window}]\)

• \([\text{THEME}\, \text{The window}]\) broke

• \([\text{AGENT}\, \text{Sotheby’s}]\) .. offered \([\text{RECIPIENT}\, \text{the Dorrance heirs}]\)
  \([\text{THEME}\, \text{a money-back guarantee}]\)

• \([\text{AGENT}\, \text{Sotheby’s}]\) offered \([\text{THEME}\, \text{a money-back guarantee}]\) to
  \([\text{RECIPIENT}\, \text{the Dorrance heirs}]\)

• \([\text{THEME}\, \text{a money-back guarantee}]\) offered by \([\text{AGENT}\, \text{Sotheby’s}]\)

• \([\text{RECIPIENT}\, \text{the Dorrance heirs}]\) will \([\text{ARM-NEG}\, \text{not}]\)
  be offered \([\text{THEME}\, \text{a money-back guarantee}]\)
SRL: useful level of abstraction for many applications

• Question Answering
  – Q: When was Napoleon defeated?
  – Look for: $[\text{PATIENT Napoleon}]$ $[\text{PRED defeat-synset}]$ $[\text{ARGM-TMP *ANS*}]$

• Machine Translation
  English (SVO)  
  $[\text{AGENT The little boy}]$ $[\text{PRED kicked}]$ $[\text{THEME the red ball}]$ $[\text{ARGM-MNR hard}]$
  Farsi (SOV)  
  $[\text{AGENT pesar koocholo}]$ boy-little $[\text{THEME toop germezi}]$ ball-red $[\text{ARGM-MNR moqtam}]$ hard-adverb $[\text{PRED zaad-e}]$ hit-past

• Document Summarization
  – Predicates and Heads of Roles summarize content
SRL: REPRESENTATIONS & RESOURCES
FrameNet [Fillmore et al. 01]

Frame: Hit_target
(hit, pick off, shoot)

Lexical units (LUs):
Words that evoke the frame
(usually verbs)

Frame elements (FEs):
The involved semantic roles

[Agent Kristina] hit [Target Scott] [Instrument with a baseball] [Time yesterday].
Methodology for FrameNet

1. Define a frame (eg DRIVING)
2. Find some sentences for that frame
3. Annotate them

- Corpora
  - FrameNet I – British National Corpus only
  - FrameNet II – LDC North American Newswire corpora

- Size
  - >8,900 lexical units, >625 frames, >135,000 sentences

http://framenet.icsi.berkeley.edu
Proposition Bank (PropBank) [Palmer et al. 05]

- Transfer sentences to propositions
  - Kristina hit Scott → hit(Kristina, Scott)

- Penn TreeBank → PropBank
  - Add a semantic layer on Penn TreeBank
  - Define a set of semantic roles for each verb
  - Each verb’s roles are numbered

...[A0 the company] to ... offer [A1 a 15% to 20% stake] [A2 to the public]
...[A0 Sotheby’s] ... offered [A2 the Dorrance heirs] [A1 a money-back guarantee]
...[A1 an amendment] offered [A0 by Rep. Peter DeFazio] ...
...[A2 Subcontractors] will be offered [A1 a settlement] ...
Proposition Bank (PropBank)  
Define the Set of Semantic Roles

• It’s difficult to define a general set of semantic roles for all types of predicates (verbs).
• PropBank defines semantic roles for each verb and sense in the frame files.
• The (core) arguments are labeled by numbers.
  – A0 – Agent; A1 – Patient or Theme
  – Other arguments – no consistent generalizations
• Adjunct-like arguments – universal to all verbs
  – AM-LOC, TMP, EXT, CAU, DIR, PNC, ADV, MNR, NEG, MOD, DIS
Proposition Bank (PropBank)
Frame Files

• hit.01 “strike”
  A0: agent, hitter; A1: thing hit; A2: instrument, thing hit by or with
  
  \[ A_0 \text{Kristina} \text{hit} A_1 \text{Scott} \text{with a baseball} \text{yesterday.} \]

• look.02 “seeming”
  A0: seemer; A1: seemed like; A2: seemed to
  
  \[ A_0 \text{It} \text{looked} A_2 \text{to her} \text{like} A_1 \text{he deserved this}. \]

• deserve.01 “deserve”
  A0: deserving entity; A1: thing deserved; A2: in-exchange-for
  
  \[ \text{It looked to her like } A_0 \text{he} \text{deserved} A_1 \text{this}. \]
FrameNet vs PropBank

**FRAMENET ANNOTATION:**


**PROPBNANK ANNOTATION:**

[Arg0 Chuck] bought [Arg1 a car] [Arg2 from Jerry] [Arg3 for $1000].

[Arg0 Jerry] sold [Arg1 a car] [Arg2 to Chuck] [Arg3 for $1000].
FrameNet vs PropBank

FRAMENET ANNOTATION:

[Goods A car] was bought [Buyer by Chuck].
[Goods A car] was sold [Buyer to Chuck] [Seller by Jerry].
[Buyer Chuck] was sold [Goods a car] [Seller by Jerry].

PROPBNANK ANNOTATION:

[Arg1 A car] was bought [Arg0 by Chuck].
[Arg1 A car] was sold [Arg2 to Chuck] [Arg0 by Jerry].
[Arg2 Chuck] was sold [Arg1 a car] [Arg0 by Jerry].
Proposition Bank (PropBank)
Add a Semantic Layer

Kristina hit Scott with a baseball yesterday

[A0 Kristina] hit [A1 Scott] [A2 with a baseball] [AM-TMP yesterday].
Proposition Bank (PropBank) Statistics

• Proposition Bank I
  – Verb Lexicon: 3,324 frame files
  – Annotation: ~113,000 propositions
    http://www.cis.upenn.edu/~mpalmer/project_pages/ACE.htm

• Alternative format: CoNLL-04,05 shared task
  – Represented in table format
  – Has been used as standard data set for the shared tasks on semantic role labeling
    http://www.lsi.upc.es/~srlconll/soft.html
SRL: TASKS & SYSTEMS
Semantic Role Labeling: Subtasks

• **Identification**
  – Very hard task: to separate the argument substrings from the rest in this exponentially sized set
  – Usually only 1 to 9 (avg. 2.7) substrings have labels ARG and the rest have NONE for a predicate

• **Classification**
  – Given the set of substrings that have an ARG label, decide the exact semantic label

• **Core argument** semantic role labeling: (easier)
  – Label phrases with core argument labels only. The modifier arguments are assumed to have label NONE.
Evaluation Measures

Correct: \[ A_0 \text{The queen} \] broke \[ A_1 \text{the window} \] \[ \text{AM-TMP yesterday} \]
Guess: \[ A_0 \text{The queen} \] broke the \[ A_1 \text{window} \] \[ \text{AM-LOC yesterday} \]

<table>
<thead>
<tr>
<th>Correct</th>
<th>Guess</th>
</tr>
</thead>
<tbody>
<tr>
<td>{The queen} → A0</td>
<td>{The queen} → A0</td>
</tr>
<tr>
<td>{the window} → A1</td>
<td>{window} → A1</td>
</tr>
<tr>
<td>{yesterday} → AM-TMP</td>
<td>{yesterday} → AM-LOC</td>
</tr>
<tr>
<td>all other → NONE</td>
<td>all other → NONE</td>
</tr>
</tbody>
</table>

– Precision, Recall, F-Measure
– Measures for subtasks
  • Identification (Precision, Recall, F-measure)
  • Classification (Accuracy)
  • Core arguments (Precision, Recall, F-measure)
What information can we use for Semantic Role Labeling?

- Syntactic Parsers

- Shallow parsers

- Semantic ontologies (WordNet, automatically derived), and named entity classes

(v) **hit** (cause to move by striking)

WordNet hypernym

**propel, impel** (cause to move forward with force)
Arguments often correspond to syntactic constituents!

Most commonly, substrings that have argument labels correspond to syntactic constituents

- **In Propbank**, an argument phrase corresponds to exactly one parse tree constituent in the correct parse tree for 95.7% of the arguments;
- **In Propbank**, an argument phrase corresponds to exactly one parse tree constituent in Charniak’s automatic parse tree for approx 90.0% of the arguments.
- **In FrameNet**, an argument phrase corresponds to exactly one parse tree constituent in Collins’ automatic parse tree for 87% of the arguments.
Labeling Parse Tree Nodes

- Given a parse tree $t$, label the nodes (phrases) in the tree with semantic labels.
Combining Identification and Classification Models

**Step 1. Pruning.**
Using a hand-specified filter.

**Step 2. Identification.**
Identification model (filters out candidates with high probability of NONE)

**Step 3. Classification.**
Classification model assigns one of the argument labels to selected nodes (or sometimes possibly NONE)
Combining Identification and Classification Models

\[ P(l|c, t, p) = P_{ID}(Id(l)|\Phi(c, t, p)) \times P_{CLS}(l|Id(l), \Phi(c, t, p)) \]

or

\[ P(l|c, t, p) = P(l|\Phi(c, t, p)) \]

**One Step.**

Simultaneously identify and classify using \( P(l|c, t, p) \)
What are useful features?

- **Gildea & Jurafsky 2002**
  - Key early work
  - Future systems use these features as a baseline

- **Constituent Independent**
  - Target predicate (lemma)
  - Voice
  - Subcategorization

- **Constituent Specific**
  - Path
  - Position (*left, right*)
  - Phrase Type
  - Governing Category (*S* or *VP*)
  - Head Word

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**Example:**

```
She broke the expensive vase

PRP VBD DT JJ NN
```

- **Target:** broke
- **Voice:** active
- **Subcategorization:** *VP* → *VBD NP*
- **Path:** *VBD* ↑ *VP* ↑ *S* ↓ *NP*
- **Position:** left
- **Phrase Type:** *NP*
- **Gov Cat:** *S*
- **Head Word:** She
She broke the expensive vase.
Recap: Semantic Role Labeling

- A shallow approach to semantics
- Useful for many applications
- Can leverage standard classification
- Requires manual creation of resources
  - FrameNet
  - PropBank