Semantic Role Labeling
CS 224N, Spring 2008
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Slides mainly from a tutorial from Scott Wen-tau Yih and Kristina Toutanova (Microsoft Research) with additional slides from Sameer Pradhan (BBN) as well as Chris Manning and myself.

Syntactic Variations versus Semantic Roles

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.

The baseball with which Kristina hit Scott yesterday was hard.

Kristina hit Scott with a baseball yesterday.

Syntactic Variations (as trees)

Semantic Role Labeling

Giving Semantic Labels to Phrases

• [AGENT John] broke [THEME the window]

• [THEME The window] broke

• [AGENT Sotheby’s] offered [RECIPIENT the Dorrance heirs] [THEME a money-back guarantee]

• [AGENT Sotheby’s] offered [THEME a money-back guarantee] to [RECIPIENT the Dorrance heirs]

• [THEME a money-back guarantee] offered by [AGENT Sotheby’s]

• [RECIPIENT the Dorrance heirs] will [ARM-NEG not] be offered [THEME a money-back guarantee]

What is SRL good for?

Question Answering

Q: What was the name of the first computer system that defeated Kasparov?
A: [PATIENT Kasparov] was defeated by [AGENT Deep Blue] [TIME in 1997].

Q: When was Napoleon defeated?

Look for: [AGENT Napoleon] [PRED defeat-synset] [ARGM-TMP *ANS*]

More generally:

What is SRL good for?

Applications as a simple meaning rep’n

• Machine Translation

  English (SVO) [AGENT The little boy] [PRED kicked] [THEME the red ball] [ARGM-MNR hard-adverb]

  Farsi (SOV) [AGENT koocholo] [PRED zaad-e] [THEME moqtam] [ARGM-MNR hit-past]

• Document Summarization

  • Predicates and Heads of Roles summarize content

• Information Extraction

  • SRL can be used to construct useful rules for IE
Application: Semantically precise search

Query: afghans destroying opium poppies

Some typical semantic roles

<table>
<thead>
<tr>
<th>Thematic Role</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGENT</td>
<td>The volitional causer of an event</td>
</tr>
<tr>
<td>EXPERIENCER</td>
<td>The experiencer of an event</td>
</tr>
<tr>
<td>FORCE</td>
<td>The non-volitional causer of the event</td>
</tr>
<tr>
<td>THEME</td>
<td>The participant most directly affected by an event</td>
</tr>
<tr>
<td>RESULT</td>
<td>The end product of an event</td>
</tr>
<tr>
<td>CONTENT</td>
<td>The proposition or content of a propositional event</td>
</tr>
<tr>
<td>INSTRUMENT</td>
<td>An instrument used in an event</td>
</tr>
<tr>
<td>BENEFICIARY</td>
<td>The beneficiary of an event</td>
</tr>
<tr>
<td>SOURCE</td>
<td>The origin of the object of a transfer event</td>
</tr>
<tr>
<td>GOAL</td>
<td>The destination of an object of a transfer event</td>
</tr>
</tbody>
</table>

Some typical semantic roles

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

Problems with those semantic roles

- It’s very hard to produce a formal definition of a role
- There are all sorts of arbitrary role splits
- Intermediary instruments (1-2) vs. enabling instruments (3-4):
  1. The cook opened the jar with the new gadget
  2. The new gadget opened the jar
  3. Sally ate the sliced banana with a fork
  4. *The fork ate the sliced banana

Diathesis alternations

John broke the window.
- AGENT: Theme

John broke the window with a rock.
- AGENT: Theme, Instrument

The rock broke the window.
- Theme: Instrument

The window was broken by John.
- Theme: Agent

Doris gave the book to Cary.
- Agent: Theme, Goal

Doris gave Cary the book.
- Agent: Goal, Theme

Solutions to the difficulty of defining semantic roles

- Ignore semantic role labels, and just mark arguments of individual verbs as 0, 1, 2
  - PropBank
- Define semantic role labels for a particular semantic domain
  - FrameNet
Proposition Bank (PropBank) [Palmer et al. 05]

- Transfer sentences to propositions
  - Kristina hit Scott \rightarrow hit(Kristina,Scott)
- Penn TreeBank \rightarrow PropBank
  - Add a semantic layer on Penn TreeBank
  - Define a set of semantic roles for each verb
  - Each verb’s roles are numbered
    - \[A0\text{ the company}] to \ldots \[A1 a 15\% to 20\% stake] \[A2 to the public]
    - \[A0 Sotheby’s] \ldots offered \[A2 the Dorrance heirs] \[A1 a money-back guarantee]
    - \[A1 an amendment] offered \[A0 by Rep. Peter DeFazio] \ldots
    - \[A2 Subcontractors] will be offered \[A1 a settlement] \ldots
- Penn TreeBank \rightarrow 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 \ldots offer \[A1 a 15\% to 20\% stake] \[A2 to the public]
  - \[A0 Sotheby’s] \ldots offered \[A2 the Dorrance heirs] \[A1 a money-back guarantee]
  - \[A1 an amendment] offered \[A0 by Rep. Peter DeFazio] \ldots
  - \[A2 Subcontractors] will be offered \[A1 a settlement] \ldots

...[A0 Big Fruit Co.] increased [A1 the price of bananas].

[A1 The price of bananas] was increased again [A0 by Big Fruit Co.]

[A0 The company] to [A1 a 15\% to 20\% stake] [A2 to the public]

Proposition Bank (PropBank)

- A corpus of labeled sentences
- The arguments of each verb are labeled with numbers rather than names

PropBank

- A corpus of labeled sentences
- The arguments of each verb are labeled with numbers rather than names

Application of PropBank labels

(19.31) **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

\[
\begin{align*}
\text{Arg0 Big Fruit Co.} & \text{ increased } \text{[Arg1 the price of bananas].} \\
\text{[Arg1 The price of bananas] was increased again } \text{[Arg0 by Big Fruit Co.]} \\
\text{[Arg1 The price of bananas] increased } \text{[Arg2 5\%].}
\end{align*}
\]

.......

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
  - \[\text{[A0 Kristina] hit [A1 Scott] with a baseball} \text{ yesterday.}\]

- look.02 “seeming”
  - A0: seer, A1: seemed like; A2: seemed to
  - \[\text{[A0 It looked [A1 to her] like [A2 he deserved this]} \text{.}\]

- deserve.01 “deserve”
  - A0: deserving entity; A1: thing deserved;
  - A2: in-exchange-for
  - It looked to her like [A0 deserved [A1 this]

Proposition Bank (PropBank)

Add a Semantic Layer

\[
\begin{align*}
\text{Kristina} & \text{ hit } \text{[A1 Scott] with a baseball} \text{ yesterday.}
\end{align*}
\]
Proposition Bank (PropBank)

Add a Semantic Layer – Continued

```
S
NP A1
NP

S

PP VP NP A0

S

VP C-A1

"The worst thing about him" said [A8 Kristina] [A8 is his laziness].
```

Other Corpora

- Chinese PropBank [http://www.cis.upenn.edu/~chinese/cpb/]
  - Similar to PropBank, it adds a semantic layer onto Chinese Treebank
- NomBank [http://nlp.cs.nyu.edu/meyers/NomBank.html]
  - Label arguments that co-occur with nouns in PropBank
  - [A8 Her] [REL gift] of [A1 a book] [A2 to John]

Problem with PropBank Labels

- Propbank has no nouns
- Nombank adds nouns, but
- We’d like to also get similar meanings in these cases using
  - Increase (verb)
  - Rose (verb)
  - Rise (noun)

```
[Arg1] The price of bananas increased [Arg2 5%].
[Arg1] The price of bananas rose [Arg2 5%].
There has been a [Arg2 5%] rise [Arg1 in the price of bananas].
```

Proposition Bank (PropBank)

Final Notes

- Current release (Mar 4, 2005): 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]

FrameNet [Fillmore et al. 01]

```
Frame: Hit_target
      (Hit, pick off, shoot)

Agent      Target       Place       Non-Core
Means      Instrument  Manner       Frame elements (FEs): The involved semantic roles
Purpose     Subregion    Time

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

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

- A frame is a semantic structure based on a set of participants and events
- Consider the “change_position_on_scale” frame

Examples from this frame

(19.38) [ITEM Oil] rose [ATTRIBUTE in price] [DIFFERENCE by 2%].
(19.39) [ITEM R] has increased [FINAL_STATE to having them 1 day a month].
(19.40) [ITEM Microsoft shares] fell [FINAL_VALUE to 7 5/8].
(19.41) [ITEM Colon cancer incidence] fell [DIFFERENCE by 50%] [GROUP among men].
(19.42) a steady increase [INITIAL_VALUE from 9.5] [FINAL_VALUE to 14.5] [ITEM in dividends].
(19.43) a [DIFFERENCE] 5% [ITEM dividend] increase...

Verbs: advance, climb, decline, edge, explode, fall, diminish, drop, double, dig, grow, increase, jump, soar, shrink, swell, tumble, rise, slide, shift, soar, swim, explode, fluctuation, increase, grow, increasingly, rise, decrease, +ADVERBS

Attributes: accelerating, elevation, shift, expansion, tumble, fall, roach, triple, cancer, gain, rocket, shift, shrink, decline, decrease.

Some History

- Fillmore 1968: The case for case
- Simmons 1973:
  - Built first automatic semantic role labeler
  - Based on first parsing the sentence

Roles in this frame

<table>
<thead>
<tr>
<th>Core Roles</th>
<th></th>
<th></th>
</tr>
</thead>
</table>
| ATTRIBUTE | The ATTRIBUTE is a scalable property that has the ITEM possess.
| DIFFERENCE | The distance by which the ITEM changes its position on the scale.
| FINAL_STATE | A description that presents the ITEM's state after the change in the ATTRIBUTE's value as an independent predication.
| FINAL_VALUE | The position on the scale where the ITEM ended up.
| INITIAL_VALUE | A description that presents the ITEM's state before the change in the ATTRIBUTE's value as an independent predication.
| INITIAL_VALUE | The initial position on the scale from which the ITEM moves away.
| ITEM | The entity that has a position on the scale.
| VALUE_RANGE | A portion of the scale typically identified by its endpoints, along which the values of the ATTRIBUTE fluctuate.

<table>
<thead>
<tr>
<th>Some Non-Core Roles</th>
<th></th>
<th></th>
</tr>
</thead>
</table>
| DURATION | The length of time over which the change takes place.
| START | The start of change of the VALUE.
| GROUP | The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.

Problems with FrameNet

- Example sentences are chosen by hand
  - Not randomly selected
  - Complete sentences not labeled
  - Since TreeBank wasn’t used
  - No perfect parses for each sentence
  - Still ongoing (that’s good and bad)

Methodology for FrameNet

While (remaining funding > 0) do
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
FrameNet vs PropBank -1

**FRAMENET ANNOTATION:**
[Inch] Chuck bought [Gboat a car] [Inst from Jerry] [Prent for $1000].
[Inst] Jerry sold [Gboat a car] [Inst to Chuck] [Prent for $1000].

**PROPBank ANNOTATION:**
[Inch] Chuck bought [Iarg a car] [Iarg from Jerry] [Iarg for $1000].
[Iarg] Jerry sold [Iarg a car] [Iarg to Chuck] [Iarg for $1000].

Information Extraction versus Semantic Role Labeling

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>IE</th>
<th>SRL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coverage</td>
<td>narrow</td>
<td>broad</td>
</tr>
<tr>
<td>Depth of semantics</td>
<td>shallow</td>
<td>shallow</td>
</tr>
<tr>
<td>Directly connected to application</td>
<td>sometimes</td>
<td>no</td>
</tr>
</tbody>
</table>

Subtasks

- **Identification:** \(2^{(1,2, \ldots, m)} \rightarrow \text{(NONE, ARG)}\)
  - 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:** \(2^{(1,2, \ldots, m)} \rightarrow L \setminus \{\text{NONE}\}\)
  - 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.

FrameNet vs PropBank -2

**FRAMENET ANNOTATION:**
[Inch] A car was bought [Iarg by Chuck].
[Inst] A car was sold [Iarg to Chuck] [Inst by Jerry].
[Inst] Chuck was sold [Iarg a car] [Inst by Jerry].

**PROPBank ANNOTATION:**
[Iarg] A car was bought [Iarg by Chuck].
[Iarg] A car was sold [Iarg to Chuck] [Iarg by Jerry].
[Iarg] Chuck was sold [Iarg a car] [Iarg by Jerry].

Overview of SRL Systems

- Definition of the SRL task
- Evaluation measures
- General system architectures
- Machine learning models
  - Features & models
  - Performance gains from different techniques

Evaluation Measures

<table>
<thead>
<tr>
<th>Correct</th>
<th>Guess</th>
</tr>
</thead>
<tbody>
<tr>
<td>[The queen] broke [the window] [yesterday]</td>
<td>[The queen] broke the [window] [yesterday]</td>
</tr>
<tr>
<td>[The queen] -&gt; A0 (the window) -&gt; A1 (yesterday) -&gt; AM-TMP</td>
<td>[The queen] -&gt; A0 (window) -&gt; A1 (yesterday) -&gt; AM-LOC</td>
</tr>
<tr>
<td>all other -&gt; NONE</td>
<td>all other -&gt; NONE</td>
</tr>
</tbody>
</table>

- Precision, Recall, F-Measure (\(p=1/2, f=1/3, m=2\)) \(p=1/3, f=2/3\)
- Measures for subtasks
  - Identification (Precision, Recall, F-measure) (\(p=2, f=1, m=1\)) \(p=1/3, f=2/3\)
  - Classification (Accuracy) acc = 5 (labeling of correctly identified phrases)
  - Core arguments (Precision, Recall, F-measure) (\(p=1, f=1, m=1\)) \(p=1/2, f=1/2\)
What’s the problem with these evaluations?

- Approximating human evaluations is dangerous
  - Humans don’t always agree
  - Not clear if it’s good for anything
  - Sometimes called the “match-a-linguist” task
- What’s a better evaluation?

Basic Architecture of a Generic SRL System

Sentence s, predicate p

- Local scores for phrase labels do not depend on labels of other phrases
- Joint scores take into account dependencies among the labels of multiple phrases

Why this parse-tree architecture?

Semantic role chunks tend to correspond to syntactic constituents

- Propbank:
  - 96% of arguments = 1 (gold) parse tree constituent
  - 90% of arguments = 1 (Charniak) parse tree constituent
  - Simple rules can recover missing 4-10%
- FrameNet:
  - 87% of arguments = 1 ( Collins) parse tree constituent

Why?
- They were labeled from parse trees
- By humans trained in syntax

SRL architecture:
Walk the tree, labeling each parse tree node

- Given a parse tree t, label the nodes (phrases) in the tree with semantic labels

Parsing Algorithm

- Use a syntactic parser to parse the sentence
- For each predicate (non-copula verb)
  - For each node in the syntax tree
    - Extract a feature vector relative to the predicate
    - Classify the node
  - Do second-pass informed by global info

Baseline Features [Gildea & Jurafsky, 2000]

- Predicate (verb)
- Path from constituent to predicate
- Phrase type (syntactic)
- Position (before/after)
- Voice (active/passive)
- Head Word
- Sub-categorization
Pradhan et al. (2004) Features

- Predicate cluster
- Noun head and POS of PP constituent
- Verb sense
- Partial path
- Named entities in constituent \([\text{Surdeanu et al., 2003}]\)
- Head word POS \([\text{Surdeanu et al., 2003}]\)
- First and last word in constituent and their POS
- Parent and sibling features
- Constituent tree distance
- Ordinal constituent position
- Temporal cue words in constituent
- Previous 2 classifications

<table>
<thead>
<tr>
<th>Predicate cluster, automatic or WordNet</th>
</tr>
</thead>
<tbody>
<tr>
<td>![Predicate cluster diagram]</td>
</tr>
</tbody>
</table>

Noun Head and POS of PP

![Noun Head and POS diagram]

Partial Path

![Partial Path diagram]

Named Entities and Head Word POS

![Named Entities and Head Word diagram]

First and Last Word and POS

![First and Last Word diagram]
Parent and Sibling features

Constituent tree distance

Ordinal constituent position

Temporal Cue Words (~50)

time
recently
days
end
period

Previous 2 classifications

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

- **Classification Models**
  - which maximizes a combination of local and a joint score

There are many statistical tendencies for the sequence

**Exact search for**

**Tight integration of local and joint scoring in a**

**Combining Local and Joint Scoring Models**

- **Tight integration of local and joint scoring in a single probabilistic model and exact search [Cohn & Brunson 05]**
  - When the joint model makes strong independence assumptions
- **Re-ranking or approximate search to find the labeling which maximizes a combination of local and a joint score**
  - Usually exponential search required to find the exact maximizer
- **Exact search for best assignment by local model satisfying hard joint constraints**
  - Using Integer Linear Programming [Punyakanok et al. 04, 05] (worst case NP-hard)

**Joint Scoring Models**

- These models have scores for a whole labeling of a tree (not just individual labels)
  - Encode some dependencies among the labels of different nodes
  - One Step. Simultaneously identify and classify using $P(l|c,t,p)$

**Joint Scoring: Integrating Soft Preferences**

- **Joint Scoring: Integrating Soft Preferences**
  - There are many statistical tendencies for the sequence of roles and their syntactic realizations
  - When both are before the verb, AM-TMP is usually before Ao
  - Usually, there aren’t multiple temporal modifiers
  - Many others which can be learned automatically

**Joint Scoring: Enforcing Hard Constraints**

- **Constraint 1: Argument phrases do not overlap**
  - By $\{a_1, working (a_1, hard) \}$, he said, you can achieve a lot.
  - Pradhan et al. (04) - greedy search for a best set of non-overlapping arguments
  - Toutanova et al. (05) - exact search for the best set of non-overlapping arguments (dynamic programming, linear in the size of the tree)
  - Punyakanok et al. (05) - exact search for best non-overlapping arguments using integer linear programming
  - **Other constraints** (Punyakanok et al. 04, 05)
    - no repeated core arguments (good heuristic)
    - phrases do not overlap the predicate

**Joint Scoring: Enforcing Hard Constraints**

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  - There are many statistical tendencies for the sequence of roles and their syntactic realizations
  - When both are before the verb, AM-TMP is usually before Ao
  - Usually, there aren’t multiple temporal modifiers
  - Many others which can be learned automatically
Semantic roles: joint models boost results [Toutanova et al. 2005]

Accuracies of local and joint models on core arguments

System Properties

- Features
  - Most modern systems use the standard set of Gildea, Pradhan, and Surdeanu features listed above
  - Lots of features important for building a good system

- Learning Methods
  - SNoW, MaxEnt, AdaBoost, SVM, CRFs, etc.
  - The choice of learning algorithms is less important.

System Properties – Continued

- Syntactic Information
  - Charniak’s parser, Collins’ parser, clauser, chunker, etc.
  - Top systems use Charniak’s parser or some mixture
  - Quality of syntactic information is important

- System/Information Combination
  - Greedy, Re-ranking, Stacking, ILP inference
  - Combination of systems or syntactic information is a good strategy to reduce the influence of incorrect syntactic information!

Per Argument Performance

CoNLL-05 Results on WSJ-Test

<table>
<thead>
<tr>
<th>Core Arguments (Freq. ~70%)</th>
<th>Adjuncts (Freq.</th>
<th>Freq.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best F.</td>
<td>Freq.</td>
<td>Best F.</td>
</tr>
<tr>
<td>A0 88.31</td>
<td>5.58%</td>
<td>TMP 78.21</td>
</tr>
<tr>
<td>A1 79.91</td>
<td>35.36%</td>
<td>ADV 59.73</td>
</tr>
<tr>
<td>A2 70.26</td>
<td>8.26%</td>
<td>DIS 80.45</td>
</tr>
<tr>
<td>A3 65.26</td>
<td>1.39%</td>
<td>MNR 59.22</td>
</tr>
<tr>
<td>A4 77.25</td>
<td>1.09%</td>
<td>LOC 60.99</td>
</tr>
<tr>
<td>MOD 98.47</td>
<td>3.83%</td>
<td>CAU 64.62</td>
</tr>
<tr>
<td>NEG 98.91</td>
<td>1.36%</td>
<td></td>
</tr>
</tbody>
</table>

Arguments that need to be improved

Data from Carreras&Màrquez’s slides (CoNLL 2005)

Summary

- Semantic role labeling
  - An important attempt at shallow semantic extraction
  - Relatively successful in terms of approximating
    - Human FrameNet labels
    - Human PropBank labels
  - Are these good for anything?
  - We don’t know yet