Semantic Role Labeling
Semantic Role Labeling

Introduction
Semantic Role Labeling

Who did what to whom at where?

The police officer detained the suspect at the scene of the crime.
Can we figure out that these have the same meaning?

XYZ corporation bought the stock.
They sold the stock to XYZ corporation.
The stock was bought by XYZ corporation.
The purchase of the stock by XYZ corporation...
The stock purchase by XYZ corporation...
A Shallow Semantic Representation: Semantic Roles

Predicates (bought, sold, purchase) represent an event. Semantic roles express the abstract role that arguments of a predicate can take in the event.

More specific          More general

buyer  agent  proto-agent
Semantic Role Labeling

Semantic Roles
Getting to semantic roles

Neo-Davidsonian event representation:

Sasha broke the window

\( \exists e, x, y \text{ Breaking}(e) \land \text{Breaker}(e, \text{Sasha}) \land \text{BrokenThing}(e, y) \land \text{Window}(y) \)

Pat opened the door

\( \exists e, x, y \text{ Opening}(e) \land \text{Opener}(e, \text{Pat}) \land \text{OpenedThing}(e, y) \land \text{Door}(y) \)

Subjects of break and open: **Breaker** and **Opener**

**Deep roles** specific to each event (breaking, opening)

Hard to reason about them for NLU applications like QA
Thematic roles

• **Breaker** and **Opener** have something in common!
  • Volitional actors
  • Often animate
  • Direct causal responsibility for their events
• Thematic roles are a way to capture this semantic commonality between *Breakers* and *Eaters*.
• They are both **AGENTS**.
• The *BrokenThing* and *OpenedThing*, are **THEMES**.
  • prototypically inanimate objects affected in some way by the action
Thematic roles

• One of the oldest linguistic models
  • Indian grammarian Panini between the 7th and 4th centuries BCE

• Modern formulation from Fillmore (1966, 1968), Gruber (1965)
  • Fillmore influenced by Lucien Tesnière’s (1959) *Éléments de Syntaxe Structurale*, the book that introduced dependency grammar
  • Fillmore first referred to roles as *actants* (Fillmore, 1966) but switched to the term *case*
# Thematic roles

- A typical set:

<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><em>The waiter</em> spilled the soup.</td>
</tr>
<tr>
<td>EXPERIENCER</td>
<td>The experiencer of an event</td>
<td><em>John</em> has a headache.</td>
</tr>
<tr>
<td>FORCE</td>
<td>The non-volitional causer of the event</td>
<td><em>The wind</em> 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 <em>the ice</em>...</td>
</tr>
<tr>
<td>RESULT</td>
<td>The end product of an event</td>
<td>The city built a <em>regulation-size baseball diamond</em>...</td>
</tr>
<tr>
<td>CONTENT</td>
<td>The proposition or content of a propositional event</td>
<td>Mona asked “<em>You met Mary Ann at a supermarket</em>?””</td>
</tr>
<tr>
<td>INSTRUMENT</td>
<td>An instrument used in an event</td>
<td>He poached catfish, stunning them <em>with a shocking device</em>...</td>
</tr>
<tr>
<td>BENEFICIARY</td>
<td>The beneficiary of an event</td>
<td>Whenever Ann Callahan makes hotel reservations <em>for her boss</em>...</td>
</tr>
<tr>
<td>SOURCE</td>
<td>The origin of the object of a transfer event</td>
<td>I flew in <em>from Boston</em>.</td>
</tr>
<tr>
<td>GOAL</td>
<td>The destination of an object of a transfer event</td>
<td>I drove <em>to Portland</em>.</td>
</tr>
</tbody>
</table>
Thematic grid, case frame, θ-grid

Example usages of “break”

John broke the window.
AGENT THEME

John broke the window with a rock.
AGENT THEME INSTRUMENT

The rock broke the window.
INSTRUMENT THEME

The window broke.
THEME

The window was broken by John.
THEME AGENT

thematic grid, case frame, θ-grid

Break:
AGENT, THEME, INSTRUMENT.

Some realizations:

AGENT/Subject, THEME/Object
AGENT/Subject, THEME/Object, INSTRUMENT/PP with
INSTRUMENT/Subject, THEME/Object
THEME/Subject
Diathesis alternations (or verb alternation)

**Doris** gave the book to Cary.
**AGENT** THEME GOAL

**Doris** gave Cary the book.
**AGENT** GOAL THEME

**Dative alternation:** particular semantic classes of verbs, “verbs of future having” *(advance, allocate, offer, owe)*, “send verbs” *(forward, hand, mail)*, “verbs of throwing” *(kick, pass, throw)*, etc.

**Levin (1993):** 47 semantic classes *(“Levin classes”)* for 3100 English verbs and alternations. In online resource VerbNet.
Problems with Thematic Roles

Hard to create standard set of roles or formally define them. Often roles need to be fragmented to be defined.

Levin and Rappaport Hovav (2015): two kinds of INSTRUMENTS

intermediary instruments that can appear as subjects

The cook opened the jar with the new gadget.
The new gadget opened the jar.

enabling instruments that cannot

Shelly ate the sliced banana with a fork.
*The fork ate the sliced banana.
Alternatives to thematic roles

1. **Fewer roles**: generalized semantic roles, defined as prototypes (Dowty 1991)
   PROTO-AGENT
   PROTO-PATIENT
   PropBank

2. **More roles**: Define roles specific to a group of predicates
   FrameNet
Semantic Role Labeling

The Proposition Bank (PropBank)
PropBank

PropBank Roles

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

Following Dowty 1991
PropBank Roles

• Following Dowty 1991
  • Role definitions determined verb by verb, with respect to the other roles
  • Semantic roles in PropBank are thus verb-sense specific.

• Each verb sense has numbered argument: 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 really that consistent, causes a problem for labeling)
PropBank Frame Files

agree.01
Arg0:  Agreer
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].

fall.01
Arg1:  Logical subject, patient, thing falling
Arg2:  Extent, amount fallen
Arg3:  start point
Arg4:  end point, end state of arg1

Ex1:  [Arg1 Sales] fell [Arg4 to $25 million] [Arg3 from $27 million].
Ex2:  [Arg1 The average junk bond] fell [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

| ArgM-TMP  | when?               | yesterday evening, now |
| LOC       | where?              | at the museum, in San Francisco |
| DIR       | where to/from?      | down, to Bangkok |
| MNR       | how?                | clearly, with much enthusiasm |
| PRP/CAU   | why?                | because ... , in response to the ruling |
| REC       |                      | themselves, each other |
| ADV       | miscellaneous       | ... |
| PRD       | secondary predication | ...ate the meat raw |
Analysts have been expecting a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.
Analysts have been expecting a GM-Jaguar pact that would give \*T*-1 the US car maker an eventual 30% stake in the British company.

**Expectation**

**Arg0**: Analysts

**Arg1**: a GM-Jaguar pact

**Arg2**: the US car maker

**Role Labels**

- Arg0
- Arg1
- Arg2

**Predicates**

- 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
Count of word sense (lexical units)

<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$_{ARG1}$]”

Slide from Palmer 2013
Semantic Role Labeling

FrameNet
Capturing descriptions of the same event by different nouns/verbs

[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].
FrameNet

• Roles in PropBank are specific to a verb
• Role in FrameNet are specific to a **frame**: a background knowledge structure that defines a set of frame-specific semantic roles, called **frame elements**,
  • includes a set of predicates that use these roles
  • each word evokes a frame and profiles some aspect of the frame
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).

ITEM Oil rose [Attribute in price] [Difference by 2%].
ITEM It has increased [Final State to having them 1 day a month].
ITEM Microsoft shares] fell [Final Value to 7 5/8].

a steady increase [Initial Value from 9.5] [Final Value to 14.3] [Item in dividends]

a [Difference 5%] [Item dividend] increase...
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></td>
</tr>
<tr>
<td>decrease</td>
<td>fluctuate</td>
<td>rise</td>
<td>tumble</td>
<td></td>
<td></td>
</tr>
<tr>
<td>diminish</td>
<td>gain</td>
<td>rocket</td>
<td>gain</td>
<td>growth</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></td>
<td>decrease</td>
<td>increment</td>
<td></td>
</tr>
<tr>
<td>drop</td>
<td>jump</td>
<td>slide</td>
<td>increase</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] raised [ITEM the price of their soda] [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.
### 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>
Relation between frames

Inherits from:
Is Inherited by:
Perspective on:
Is Perspectivized in:
Uses:
Is Used by:
Subframe of:
Has Subframe(s):
Precedes:
Is Preceded by:
Is Inchoative of:
Is Causative of:
Relation between frames

“cause change position on a scale”

Is Causative of: **Change_position_on_a_scale**

Adds an agent Role

\[ \text{AGENT They} \] raised \[ \text{ITEM the price of their soda} \] \[ \text{DIFFERENCE by 2\%}. \]

- *add.v, crank.v, curtail.v, cut.n, cut.v, decrease.v, development.n, diminish.v, double.v, drop.v, enhance.v, growth.n, increase.v, knock down.v, lower.v, move.v, promote.v, push.n, push.v, raise.v, reduce.v, reduction.n, slash.v, step up.v, swell.v*
Relations between frames

Figure from Das et al 2010
Computational Linguistics Volume 40, Number 1

1. Introduction

FrameNet (Fillmore, Johnson, and Petruck 2003) is a linguistic resource storing considerable information about lexical and predicate-argument semantics in English. Grounded in the theory of frame semantics (Fillmore 1982), it suggests—but does not formally define—a semantic representation that blends representations familiar from word-sense disambiguation (Ide and Véronis 1998) and semantic role labeling (SRL; Gildea and Jurafsky 2002). Given the limited size of available resources, accurately producing richly structured frame-semantic structures with high coverage will require data-driven techniques beyond simple supervised classification, such as latent variable modeling, semi-supervised learning, and joint inference.

In this article, we present a computational and statistical model for frame-semantic parsing, the problem of extracting from text semantic predicate-argument structures such as those shown in Figure 1. We aim to predict a frame-semantic representation with two statistical models rather than a collection of local classifiers, unlike earlier approaches (Baker, Ellsworth, and Erk 2007). We use a probabilistic framework that cleanly integrates the FrameNet lexicon and limited available training data. The probabilistic framework we adopt is highly amenable to future extension through new features, more relaxed independence assumptions, and additional semi-supervised models.

Carefully constructed lexical resources and annotated data sets from FrameNet, detailed in Section 3, form the basis of the frame structure prediction task. We decompose this task into three subproblems: target identification (Section 4), in which frame-evoking predicates are marked in the sentence; frame identification (Section 5), in which the evoked frame is selected for each predicate; and argument identification (Section 6), in which arguments to each frame are identified and labeled with a role from that frame. Experiments demonstrating favorable performance to the previous state of the art on SemEval 2007 and FrameNet data sets are described in each section. Some novel aspects of our approach include a latent-variable model (Section 5.2) and a semi-supervised extension of the predicate lexicon (Section 5.5) to facilitate disambiguation of words not in the FrameNet lexicon; a unified model for finding and labeling arguments.
FrameNet Complexity

But there still are n't enough ringers to ring more than six of the eight bells.

Frame  LU

Agent  NOISE_MAKERS

Sound_maker  CAUSE_TO_MAKE_NOISE

Item  SUFFICIENCY

Enabled_situation  EXISTENCE

Entity

From Das et al. 2010
FrameNet and PropBank representations

In that time more than 1.2 million jobs have been created and the official jobless rate has been pushed below 17% from 21%.
Semantic Role Labeling

Semantic Role Labeling Algorithm
Semantic role labeling (SRL)

- The task of finding the semantic roles of each argument of each predicate in a sentence.
- FrameNet versus PropBank:

[You] can’t [blame] [the program] [for being unable to identify it]
COGNIZER TARGET EVALUEE REASON

[The San Francisco Examiner] issued [a special edition] [yesterday]
ARG0 TARGET ARG1 ARGM-TMP
History

- Semantic roles as a intermediate semantics, used early in
  - machine translation (Wilks, 1973)
  - question-answering (Hendrix et al., 1973)
  - spoken-language understanding (Nash-Webber, 1975)
  - dialogue systems (Bobrow et al., 1977)
- Early SRL systems
  Simmons 1973, Marcus 1980:
    - parser followed by hand-written rules for each verb
    - dictionaries with verb-specific case frames (Levin 1977)
Why Semantic Role Labeling

• A useful shallow semantic representation

• Improves NLP tasks like:
  • question answering
    Shen and Lapata 2007, Surdeanu et al. 2011
  • machine translation
    Liu and Gildea 2010, Lo et al. 2013
A simple modern algorithm

```
function SEMANTICROLELABEL(words) returns labeled tree

parse ← PARSE(words)
for each predicate in parse do
    for each node in parse do
        featurevector ← EXTRACTFEATURES(node, predicate, parse)
        CLASSIFYNODE(node, featurevector, parse)
```
How do we decide what is a predicate

- If we’re just doing PropBank verbs
  - Choose all verbs
  - Possibly removing light verbs (from a list)
- If we’re doing FrameNet (verbs, nouns, adjectives)
  - Choose every word that was labeled as a target in training data
Figure 22.5

Parse tree for a PropBank sentence, showing the PropBank argument labels. The dotted line shows the path feature NP-SBJ = ARG0, the NP-SBJ constituent.

- The headword of the constituent, Examiner.
- The headword part of speech, NNP.
- The path in the parse tree from the constituent to the predicate. This path is marked by the dotted line in Fig. 22.5. Following Gildea and Jurafsky (2000), we can use a simple linear representation of the path, NP "S#VP#VBD."
- The voice of the clause in which the constituent appears, in this case, active (as contrasted with passive). Passive sentences tend to have strongly different linkings of semantic roles to surface form than do active ones.
- The binary linear position of the constituent with respect to the predicate, either before or after.
- The subcategorization of the predicate, the set of expected arguments that appear in the verb phrase. We can extract this information by using the phrase-structure rule that expands the immediate parent of the predicate; VP ! VBD NP PP for the predicate in Fig. 22.5.
- The named entity type of the constituent.
- The first words and the last word of the constituent.

The following feature vector thus represents the first NP in our example (recall that most observations will have the value NONE rather than, for example, ARG0, since most constituents in the parse tree will not bear a semantic role):

ARG0: [issued, NP, Examiner, NNP, NP "S#VP#VBD, active, before, VP ! NP PP, ORG, The, Examiner]
Features

Headword of constituent

Examiner

Headword POS

NNP

Voice of the clause

Active

Subcategorization of pred

VP -> VBD NP PP

Named Entity type of constit

ORGANIZATION

First and last words of constit

The, Examiner

Linear position, clause re: predicate

before
Path Features

Path in the parse tree from the constituent to the predicate

NP↑S↓VP↓VBD
Frequent path features

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Path</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.2%</td>
<td>VB↑VP↓PP</td>
<td>PP argument/adjunct</td>
</tr>
<tr>
<td>11.8</td>
<td>VB↑VP↑S↓NP</td>
<td>subject</td>
</tr>
<tr>
<td>10.1</td>
<td>VB↑VP↓NP</td>
<td>object</td>
</tr>
<tr>
<td>7.9</td>
<td>VB↑VP↑VP↑S↓NP</td>
<td>subject (embedded VP)</td>
</tr>
<tr>
<td>4.1</td>
<td>VB↑VP↓ADVP</td>
<td>adverbial adjunct</td>
</tr>
<tr>
<td>3.0</td>
<td>NN↑NP↑NP↓PP</td>
<td>prepositional complement of noun</td>
</tr>
<tr>
<td>1.7</td>
<td>VB↑VP↓PRT</td>
<td>adverbial particle</td>
</tr>
<tr>
<td>1.6</td>
<td>VB↑VP↑VP↑VP↑S↓NP</td>
<td>subject (embedded VP)</td>
</tr>
<tr>
<td>14.2</td>
<td>no matching parse constituent</td>
<td></td>
</tr>
<tr>
<td>31.4</td>
<td>Other</td>
<td></td>
</tr>
</tbody>
</table>

From Palmer, Gildea, Xue 2010
Final feature vector

- For “The San Francisco Examiner”,
- Arg0, [issued, NP, Examiner, NNP, active, before, VP→NP PP, ORG, The, Examiner, NP↑S↓VP↓VBD]

- Other features could be used as well
  - sets of n-grams inside the constituent
  - other path features
    - the upward or downward halves
    - whether particular nodes occur in the path
3-step version of SRL algorithm

1. **Pruning**: use simple heuristics to prune unlikely constituents.

2. **Identification**: a binary classification of each node as an argument to be labeled or a NONE.

3. **Classification**: a 1-of-\(N\) classification of all the constituents that were labeled as arguments by the previous stage.
Why add Pruning and Identification steps?

• Algorithm is looking at one predicate at a time
• Very few of the nodes in the tree could possible be arguments of that one predicate
• Imbalance between
  • positive samples (constituents that are arguments of predicate)
  • negative samples (constituents that are not arguments of predicate)
• Imbalanced data can be hard for many classifiers
• So we prune the very unlikely constituents first, and then use a classifier to get rid of the rest.

- Add sisters of the predicate, then aunts, then great-aunts, etc
- But ignoring anything in a coordination structure
A common final stage: joint inference

- The algorithm so far classifies everything *locally* – each decision about a constituent is made independently of all others.
- But this can’t be right: Lots of *global* or *joint* interactions between arguments.
  - Constituents in FrameNet and PropBank must be non-overlapping.
    - A local system may incorrectly label two overlapping constituents as arguments.
    - PropBank does not allow multiple identical arguments.
      - labeling one constituent ARG0
      - Thus should increase the probability of another being ARG1.
How to do joint inference

• Reranking
  • The first stage SRL system produces multiple possible labels for each constituent
  • The second stage classifier the best global label for all constituents
  • Often a classifier that takes all the inputs along with other features (sequences of labels)
More complications: FrameNet

We need an extra step to find the frame

```
function SEMANTICROLELABEL(words) returns labeled tree
    parse ← PARSE(words)
    for each predicate in parse do
        Predicatevector ← ExtractFrameFeatures(predicate,parse)
        Frame ← ClassifyFrame(predicate,Predicatevector)
    for each node in parse do
        featurevector ← EXTRACTFEATURES(node,predicate,parse)
        Featurevector ← CLASSIFYNODE(node,featurevector,parse,Frame)
```
Features for Frame Identification

Das et al (2014)

the POS of the parent of the head word of \( t_i \)
the set of syntactic dependencies of the head word\(^{21} \) of \( t_i \)
if the head word of \( t_i \) is a verb, then the set of dependency labels of its children
the dependency label on the edge connecting the head of \( t_i \) and its parent
the sequence of words in the prototype, \( w_\ell \)
the lemmatized sequence of words in the prototype
the lemmatized sequence of words in the prototype and their part-of-speech tags \( \pi_\ell \)
WordNet relation\(^{22} \) \( \rho \) holds between \( \ell \) and \( t_i \)
WordNet relation\(^{22} \) \( \rho \) holds between \( \ell \) and \( t_i \), and the prototype is \( \ell \)
WordNet relation\(^{22} \) \( \rho \) holds between \( \ell \) and \( t_i \), the POS tag sequence of \( \ell \) is \( \pi_\ell \), and the POS tag sequence of \( t_i \) is \( \pi_t \)
Not just English

The police are thoroughly investigating the cause of the accident.
Not just verbs: NomBank

Meyers et al. 2004

Figure from Jiang and Ng 2006
Additional Issues for nouns

• Features:
  • Nominalization lexicon (employment → employ)
  • Morphological stem
    • Healthcare, Medicate → care

• Different positions
  • Most arguments of nominal predicates occur inside the NP
  • Others are introduced by support verbs
  • Especially light verbs “X made an argument”, “Y took a nap”
Semantic Role Labeling

Conclusion
Semantic Role Labeling

- A level of shallow semantics for representing events and their participants
  - Intermediate between parses and full semantics
- Two common architectures, for various languages
  - FrameNet: frame-specific roles
  - PropBank: Proto-roles
- Current systems extract by
  - Parsing sentence
  - Finding predicates in the sentence
    - For each one, classify each parse tree constituent