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 and semantic roles express the abstract role that arguments of a predicate can take in the event

<table>
<thead>
<tr>
<th>More specific</th>
<th>More general</th>
</tr>
</thead>
<tbody>
<tr>
<td>buyer</td>
<td>agent</td>
</tr>
</tbody>
</table>
Getting to semantic roles

What roles are involved in a breaking event?

First order logic event representation for Sasha broke the window:

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

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

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 *Openers*.
- 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 cause of an event</td>
<td><em>The waiter spilled the soup.</em></td>
</tr>
<tr>
<td>EXPERIENCER</td>
<td>The experiencer of an event</td>
<td><em>John has a headache.</em></td>
</tr>
<tr>
<td>FORCER</td>
<td>The non-volitional cause of the event</td>
<td><em>The wind blows debris from the mall into our yards.</em></td>
</tr>
<tr>
<td>THEME</td>
<td>The participant most directly affected by an event</td>
<td><em>Only after Benjamin Franklin broke the ice...</em></td>
</tr>
<tr>
<td>RESULT</td>
<td>The end product of an event</td>
<td><em>The city built a regulation-size baseball diamond...</em></td>
</tr>
<tr>
<td>CONTENT</td>
<td>The proposition or content of a propositional event</td>
<td><em>Mona asked “You met Mary Ann at a supermarket?”</em></td>
</tr>
<tr>
<td>INSTRUMENT</td>
<td>An instrument used in an event</td>
<td><em>He poached catfish, stunning them with a shocking device...</em></td>
</tr>
<tr>
<td>BENEFICIARY</td>
<td>The beneficiary of an event</td>
<td><em>Whenever Ann Callahan makes hotel reservations for her boss...</em></td>
</tr>
<tr>
<td>SOURCE</td>
<td>The origin of the object of a transfer event</td>
<td><em>I flew in from Boston.</em></td>
</tr>
<tr>
<td>GOAL</td>
<td>The destination of an object of a transfer event</td>
<td><em>I drove to Portland.</em></td>
</tr>
</tbody>
</table>

Thematic grid, case frame

Example usages of “break”
- John broke the window
- John broke the window with a rock
- The rock broke the window
- The window broke
- The window was broken by John
Thematic grid, case frame

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
Diathesis alternations (or verb alternation)

*Doris gave the book to Cary.*  
**Break:** AGENT, INSTRUMENT, or THEME as subject

*Doris gave Cary the book.*  
**Give:** THEME and GOAL in either order

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

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

PropBank

- http://verbs.colorado.edu/~mpalmer/projects/ace.html
PropBank Roles

Following Dowty 1991

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

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)
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:

- Big Fruit Co. increased the price of bananas.
- The price of bananas was increased again by Big Fruit Co.
- The price of bananas increased 5%
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:

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

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.

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

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
• https://framenet.icsi.berkeley.edu/fndrupal/

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].
[ITEM Colon cancer incidence] fell [DIFFERENCE by 50%] [GROUP among men].
  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

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

---

The “Change position on a scale” Frame

<table>
<thead>
<tr>
<th>Core Roles</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATTRIBUTE</td>
</tr>
<tr>
<td>DIFFERENCE</td>
</tr>
<tr>
<td>FINAL_STATE</td>
</tr>
<tr>
<td>INITIAL_STATE</td>
</tr>
<tr>
<td>INITIAL_VALUE</td>
</tr>
<tr>
<td>ITEM</td>
</tr>
<tr>
<td>VALUE_RANGE</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Some Non-Core Roles</th>
</tr>
</thead>
<tbody>
<tr>
<td>DURATION</td>
</tr>
<tr>
<td>SPEED</td>
</tr>
<tr>
<td>GROUP</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:

“cause change position on a scale”
Is Causative of: Change_position_on_a_scale
Adds an agent Role

[AGENT They] raised [ITEM the price of their soda] [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

Schematic of Frame Semantics

Figure from Das et al 2010

Figure from Das et al (2014)
Homework 3

<table>
<thead>
<tr>
<th>Minimum</th>
<th>0.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>100.00</td>
</tr>
<tr>
<td>Average</td>
<td>86.175</td>
</tr>
<tr>
<td>Median</td>
<td>93.00</td>
</tr>
</tbody>
</table>

Observations from Rav

- Using other algorithms such as NB didn’t improve the baseline with statistical significance.
- Addressing the data imbalance directly, e.g. regrouping the labels or oversampling, did find an improvement ... sometimes.
- Pre-processing and manipulating how many words to consider: there is some number of features (between 2000 and 8000) that maximizes the accuracy, and that normalizing the text too much hurts the performance.
  - No one handled unknown words though
- General summary: the best performance is achieved through proper and thoughtful feature extraction and management.
Review

- Semantic roles
- Human-created resources
  - PropBank
  - FrameNet

FrameNet and PropBank representations

In that time more than 1.2 million jobs have been created and the official address rate has been pushed below 37% from 21%.
Semantic role labeling (SRL) algorithms

- 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 EVALUER 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 downstream NLP tasks like
  • question answering
  • machine translation

A simple modern algorithm

```plaintext
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

• If we’re doing FrameNet (verbs, nouns, adjectives)
  • Choose every word that was labeled as a target in training data

Semantic Role Labeling

[Diagram of semantic role labeling with POS tags and labels such as S, VP, NP-SBJ, VBD, NP, PP-TMP, NNP, NNP, NNP, NNP, NNP, DT, JJ, NN, IN, NN, NP, and labels like TARGET, ARG0, ARG1, ARGM-TMP, issue, special, edition, around, noon, yesterday]
### Features: 1st constituent

- **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:

\[ NP \uparrow S \downarrow VP \downarrow VBD \]
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>Other</td>
<td>no matching parse constituent</td>
</tr>
<tr>
<td>31.4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

From Palmer, Gilda, 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 be possible 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 \texttt{global} label for all constituents
  • Often a classifier that takes all the inputs along with other features (sequences of labels)

Neural Approaches too

• Typically same models as used for other “tagging” tasks (e.g., POS, NER)
• Instead of parsing first, uses and end-to-end (map straight from words) approach
Neural Approaches too

- Typically model used for other “tagging” tasks (e.g., POS, NER)

More complications: FrameNet

We need an extra step to find the frame

```plaintext
function SEMANTIC_ROLE_LABEL(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
    FrameFeatures ← ExtractFeatures(node, predicate, parse)
    Frame ← 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 $t_i$
- 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, $w_t$
- the lemmatized sequence of words in the prototype
- the lemmatized sequence of words in the prototype and their part-of-speech tags $\pi_t$
- WordNet relation, $p$ holds between $t$ and $t_i$
- WordNet relation, $p$ holds between $t$ and $t_i$, and the prototype is $t$
- WordNet relation, $p$ holds between $t$ and $t_i$, the POS tag sequence of $t$ is $\pi_t$, and the POS tag sequence of $t_i$ is $\pi_t$

Evaluation

- Each argument label must be assigned to the exactly correct word sequence or parse constituent
- Recall/Precision/F
- Common to use shared task datasets from CoNLL (Computational Natural Language Learning)
SRL Summary

• 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

Selectional Restrictions

Consider:

I want to eat someplace nearby.
Selectional Restrictions

Consider the two interpretations of:

I want to eat someplace nearby.

a) sensible:
   Eat is intransitive and “someplace nearby” is a location adjunct

b) Speaker is Godzilla
   Eat is transitive and “someplace nearby” is a direct object

How do we know speaker didn’t mean b) ?

Because the THEME of eating tends to be something *edible*

Selectional restrictions are associated with senses

- The restaurant serves *green-lipped mussels*.
  - THEME is some kind of food
- Which airlines serve *Denver*?
  - THEME is an appropriate location
Selectional restrictions vary in specificity

I often ask the musicians to imagine a tennis game. To diagonalize a matrix is to find its eigenvalues. Radon is an odorless gas that can’t be detected by human senses.

Representing selectional restrictions

Instead of representing “eat” as:
\[ \exists e, x, y \ Eats(e) \wedge Agent(e, x) \wedge Theme(e, y) \]
Just add:
\[ \exists e, x, y \ Eats(e) \wedge Agent(e, x) \wedge Theme(e, y) \wedge EdibleThing(y) \]
And “eat a hamburger” becomes
\[ \exists e, x, y \ Eats(e) \wedge Eater(e, x) \wedge Theme(e, y) \wedge EdibleThing(y) \wedge Hamburger(y) \]

But this assumes we have a large knowledge base of facts about edible things and hamburgers and whatnot.
Let’s use WordNet synsets to specify selectional restrictions

• The THEME of eat must be WordNet synset \{food, nutrient\}
  “any substance that can be metabolized by an animal to give energy and build tissue”

• Similarly
  THEME of imagine: synset \{entity\}
  THEME of lift: synset \{physical entity\}
  THEME of diagonalize: synset \{matrix\}

• This allows
  imagine a hamburger and lift a hamburger,

• Correctly rules out
  diagonalize a hamburger.

Selectional Preferences

• In early implementations, selectional restrictions were strict constraints
  • Eat [+FOOD]

• But it was quickly realized selectional constraints are really preferences
  • But it fell apart in 1931, perhaps because people realized you can’t eat gold for lunch if you’re hungry.
  • In his two championship trials, Mr. Kulkarni ate glass on an empty stomach, accompanied only by water and tea.
Selectional Association (Resnik 1993)

• **Selectional preference strength**: amount of information that a predicate tells us about the semantic class of its arguments.
  - *eat* tells us a lot about the semantic class of its direct objects
  - *be* doesn’t tell us much

• The selectional preference strength
  - difference in information between two distributions:
    - $P(c)$ the distribution of expected semantic classes for any direct object
    - $P(c | v)$ the distribution of expected semantic classes for this verb
  - The greater the difference, the more the verb is constraining its object

Selectional preference strength

• Relative entropy, or the Kullback-Leibler divergence is the difference between two distributions
  \[
  D(P||Q) = \sum_x P(x) \log \frac{P(x)}{Q(x)}
  \]

• Selectional preference: How much information (in bits) the verb expresses about the semantic class of its argument
  \[
  S_R(v) = D(P(c | v) || P(c)) = \sum_c P(c | v) \log \frac{P(c | v)}{P(c)}
  \]

• Selectional Association of a verb with a class: The relative contribution of the class to the general preference of the verb
  \[
  A_R(v, c) = \frac{1}{S_R(v)} P(c | v) \log \frac{P(c | v)}{P(c)}
  \]
Computing Selectional Association

- A probabilistic measure of the strength of association between a predicate and a semantic class of its argument
  - Parse a corpus
  - Count all the times each predicate appears with each argument word
  - Assume each word is a partial observation of all the WordNet concepts associated with that word
  - Some high and low associations:

<table>
<thead>
<tr>
<th>Verb</th>
<th>Direct Object</th>
<th>Semantic Class</th>
<th>Assoc</th>
</tr>
</thead>
<tbody>
<tr>
<td>read</td>
<td>Direct Object</td>
<td>WRITING</td>
<td>6.80</td>
</tr>
<tr>
<td>write</td>
<td>Direct Object</td>
<td>WRITING</td>
<td>7.26</td>
</tr>
<tr>
<td>see</td>
<td>Direct Object</td>
<td>ENTITY</td>
<td>5.79</td>
</tr>
<tr>
<td></td>
<td>Direct Object</td>
<td>ACTIVITY</td>
<td>-0.20</td>
</tr>
<tr>
<td></td>
<td>Direct Object</td>
<td>COMMERCE</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Direct Object</td>
<td>METHOD</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Instead of using classes, a simpler model of selectional association

- Model just the association of predicate $v$ with a noun $n$
  (one noun, as opposed to the whole semantic class in WordNet)
  - Parse a huge corpus
  - Count how often a noun $n$ occurs in relation $r$ with verb $v$:
    \[ \log \text{count}(n, v, r) \]
  - Or the probability:
    \[
P(n|v, r) = \begin{cases} 
\frac{C(n,v,r)}{C(v,r)} & \text{if } C(n, v, r) > 0 \\
0 & \text{otherwise}
\end{cases}
\]
Evaluation from Bergsma, Lin, Goebel

<table>
<thead>
<tr>
<th>Verb</th>
<th>Plaus./Implaus.</th>
</tr>
</thead>
<tbody>
<tr>
<td>see</td>
<td>friend/method</td>
</tr>
<tr>
<td>read</td>
<td>article/fashion</td>
</tr>
<tr>
<td>find</td>
<td>label/fever</td>
</tr>
<tr>
<td>hear</td>
<td>story/issue</td>
</tr>
<tr>
<td>write</td>
<td>letter/market</td>
</tr>
<tr>
<td>urge</td>
<td>daughter/contrast</td>
</tr>
<tr>
<td>warn</td>
<td>driver/engine</td>
</tr>
<tr>
<td>judge</td>
<td>contest/climate</td>
</tr>
<tr>
<td>teach</td>
<td>language/distance</td>
</tr>
<tr>
<td>show</td>
<td>sample/travel</td>
</tr>
<tr>
<td>expect</td>
<td>visit/mouth</td>
</tr>
<tr>
<td>answer</td>
<td>request/tragedy</td>
</tr>
<tr>
<td>recognize</td>
<td>author/pocket</td>
</tr>
<tr>
<td>repeat</td>
<td>comment/journal</td>
</tr>
<tr>
<td>understand</td>
<td>concept/session</td>
</tr>
<tr>
<td>remember</td>
<td>reply/smoke</td>
</tr>
</tbody>
</table>

Evaluation

- Pseudowords
  - Choose between real argument and created confounders

- Compare to human preferences
Primitive Decomposition of Predicates

- Semantic roles define the roles that arguments play for a predicate in a decompositional way based on finite lists
- Can do something similar to define predicate meaning itself!

Summary: Selectional Restrictions

- Two classes of models of the semantic type constraint that a predicate places on its argument:
  - Represent the constraint between predicate and WordNet class
  - Represent the constraint between predicate and a word