Outline

Recap: dependency grammars and arc-standard dependency parsing

Structured Meaning: Semantic Frames and Roles
   What problem do they solve?
   Theory
   Computational resources: FrameNet, VerbNet, Propbank
   Computational Task: Semantic Role Labeling

Selectional Restrictions
   What problem do they solve?
   Computational resources: WordNet
   Some simple approaches
Labeled Dependencies

Word-to-word labeled relations

governor (head)

dependent

Constituency trees/analyses (PCFGs): based on hierarchical structure

Dependency analyses: based on word relations
(Labeled) Dependency Parse

Directed graphs

Vertices: linguistic blobs in a sentence
Edges: (labeled) arcs

Often directed trees

1. A single root node with no incoming arcs
2. Each vertex except root has exactly one incoming arc
3. Unique path from the root node to each vertex
Shift-Reduce Dependency Parsing

Tools: input words, some special root symbol ($), and a stack to hold configurations

**Shift:**
- move tokens onto the stack
- decide if top two elements of the stack form a valid (good) grammatical dependency

**Reduce:**
- If there’s a valid relation, place head on the stack

**Decide how?**
Search problem!

**What is valid?**
Learn it!

**What are the possible actions?**
Arc Standard Parsing

\[
\text{state} \leftarrow \{[\text{root}], [\text{words}], [] \}
\]

while \(\text{state} \neq \{[\text{root}], [], [(\text{deps})]\}\) {

\[
t \leftarrow \text{ORACLE}(\text{state})
\]

\[
\text{state} \leftarrow \text{APPLY}(t, \text{state})
\]

}\n
return \text{state}

<table>
<thead>
<tr>
<th>Possibility</th>
<th>Action Name</th>
<th>Action Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assign the current word as the head of some previously seen word</td>
<td>LEFTARC</td>
<td>Assert a head-dependent relation between the word at the top of stack and the word directly beneath it; remove the lower word from the stack</td>
</tr>
<tr>
<td>Assign some previously seen word as the head of the current word</td>
<td>RIGHTARC</td>
<td>Assert a head-dependent relation between the second word on the stack and the word at the top; remove the word at the top of the stack</td>
</tr>
<tr>
<td>Wait processing the current word; add it for later</td>
<td>SHIFT</td>
<td>Remove the word from the front of the input buffer and push it onto the stack</td>
</tr>
</tbody>
</table>
Arc Standard Parsing

Q: What is the time complexity?
A: Linear

Q: What’s potentially problematic?
A: This is a greedy algorithm
Learning An Oracle (Predictor)

Training data: dependency treebank

Input: configuration

Output: \{LEFTARC, RIGHTARC, SHIFT\}

t ← ORACLE(state)

- Choose \texttt{LEFTARC} if it produces a correct head-dependent relation given the reference parse and the current configuration
- Choose \texttt{RIGHTARC} if
  - it produces a correct head-dependent relation given the reference parse and
  - all of the dependents of the word at the top of the stack have already been assigned
- Otherwise, choose \texttt{SHIFT}
Training the Predictor

Predict action $t$ give configuration $s$

\[ t = \phi(s) \]

Extract *features* of the configuration

Examples: word forms, lemmas, POS, morphological features

How? Perceptron, Maxent, Support Vector Machines, Multilayer Perceptrons, Neural Networks

Take CMSC 478 (678) to learn more about these
From Dependencies to Shallow Semantics
From Syntax to Shallow Semantics

“Open Information Extraction”

Angeli et al. (2015)
From Syntax to Shallow Semantics

“Open Information Extraction”

Angeli et al. (2015)

http://corenlp.run/ (constituency & dependency)

https://github.com/hltcoe/predpatt

http://openie.allenai.org/

http://www.cs.rochester.edu/research/knext/browse/ (constituency trees)

http://rtw.ml.cmu.edu/rtw/
Outline

Recap: dependency grammars and arc-standard dependency parsing

Structured Meaning: Semantic Frames and Roles
  What problem do they solve?
  Theory
  Computational resources: FrameNet, VerbNet, Propbank
  Computational Task: Semantic Role Labeling

Selectional Restrictions
  What problem do they solve?
  Computational resources: WordNet
  Some simple approaches
Semantic Roles

Who  
did what to whom  
 at where?

The police officer detained the suspect at the scene of the crime

Agent  
Predicate  
Theme  
Location

Following slides adapted from SLP3
Predicate Alternations

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 a situation

Semantic (thematic) roles express the abstract role that arguments of a predicate can take in the event

Different schemes/annotation styles have different specificities

More specific

buyer

agent

proto-agent

More general

Label an annotation might use
Thematic roles

Sasha broke the window

Pat opened the door

Subjects of break and open:
Breaker and Opener

Specific to each event
Thematic roles

Sasha broke the window

Pat opened the door

Subjects of break and open:

Breaker and Opener

Specific to each event:

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.
Thematic roles

Sasha broke the window

Pat opened the door

Subjects of break and open: Breaker and Opener

Specific to each event

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

Sasha broke the window

Pat opened the door

Subjects of break and open: Breaker and Opener

Specific to each event

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

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
## Typical Thematic Roles

<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 <em>Benjamin Franklin</em> broke <em>the ice</em>...</td>
</tr>
<tr>
<td>RESULT</td>
<td>The end product of an event</td>
<td><em>The city</em> 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><em>Mona</em> 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><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</em> 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><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>
Verb Alternations (Diathesis Alternations)

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

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

*Break:* AGENT, INSTRUMENT, or THEME as subject

*Give:* THEME and GOAL in either order
Verb Alternations (Diathesis Alternations)

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

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

*Levin (1993):* 47 semantic classes ("Levin classes") for 3100 English verbs and alternations. In online resource [VerbNet](https://verbnet.princeton.edu/).
Issues with Thematic Roles

Hard to create (define) a standard set of roles

Role **fragmentation**
Issues with Thematic Roles

Hard to create (define) a standard set of roles

Role *fragmentation*

For example: 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

2. **More roles**: Define roles specific to a group of predicates
agree.01
Arg0: Agreeer
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].
View Commonalities Across Sentences

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

[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%].
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
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**

Frames can be *related* (inherited, demonstrate alternations, etc.)

Each frame can be triggered by different “lexical units”

*See: Baker et al. 1998, Fillmore et al. 2003, Fillmore and Baker 2009, Ruppenhofer et al. 2006*
Example:
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)

1) [ITEM Oil] rose [ATTRIBUTE in price] [DIFFERENCE by 2%].
2) [ITEM It] has increased [FINAL_STATE to having them 1 day a month].
3) [ITEM Microsoft shares] fell [FINAL_VALUE to 7 5/8].
4) [ITEM Colon cancer incidence] fell [DIFFERENCE by 50%] [GROUP among men].
5) a steady increase [INITIAL_VALUE from 9.5] [FINAL_VALUE to 14.3] [ITEM in dividends]

6) a [DIFFERENCE 5%] [ITEM dividend] increase...
Lexical Triggers

### Verbs:
- advance
- climb
- decline
- decrease
- diminish
- dip
- double
- drop
- dwindle
- edge
- explode
- fall
- fluctuate
- grow
- increase
- jump
- move
- mushroom
- plummet
- reach
- rise
- rocket
- shift
- slide
- soar
- swell
- swing
- triple
- tumble

### Nouns:
- escalation
- explosion
- fall
- fluctuation
- gain
- growth
- hike
- increase
- rise

### Adverbs:
- increasingly
- shift
- tumble

---

*The “Change position on a scale” Frame*
# Frame Roles (Elements)

## 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>

---

*The “Change position on a scale” Frame*
FrameNet and PropBank representations

PropBank annotations are layered on CFG parses
FrameNet and PropBank representations

PropBank annotations are layered on CFG parses

FrameNet annotations can be layered on either CFG or dependency parses

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

<table>
<thead>
<tr>
<th></th>
<th>English Gigaword, v5</th>
<th>Annotated NYT</th>
<th>English Wikipedia</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Documents</td>
<td>8.74M</td>
<td>1.81M</td>
<td>5.06M</td>
<td>15.61M</td>
</tr>
<tr>
<td>Sentences</td>
<td>170M</td>
<td>70M</td>
<td>154M</td>
<td>422M</td>
</tr>
<tr>
<td>Tokens</td>
<td>4.3B</td>
<td>1.4B</td>
<td>2.3B</td>
<td>8B</td>
</tr>
<tr>
<td>Vocabulary (≥ 100)</td>
<td>225K</td>
<td>120K</td>
<td>264K</td>
<td>91K</td>
</tr>
<tr>
<td>Semantic Frames</td>
<td>2.6B</td>
<td>780M</td>
<td>1.1B</td>
<td>4.4B</td>
</tr>
</tbody>
</table>

Source: Ferraro et al. (2014)

[https://goo.gl/BrsG4x](https://goo.gl/BrsG4x) (or Globus---talk to me)
Outline

Recap: dependency grammars and arc-standard dependency parsing

Structured Meaning: Semantic Frames and Roles
   What problem do they solve?
   Theory
   Computational resources: FrameNet, VerbNet, Propbank
   Computational Task: Semantic Role Labeling

Selectional Restrictions
   What problem do they solve?
   Computational resources: WordNet
   Some simple approaches
Semantic Role Labeling (SRL)

Find the semantic roles of each argument of each predicate in a sentence.
Why Semantic Role Labeling

A useful shallow semantic representation

Improves NLP tasks:

  question answering (Shen and Lapata 2007, Surdeanu et al. 2011)
  machine translation (Liu and Gildea 2010, Lo et al. 2013)
A Simple Parse-Based Algorithm

Input: sentence
Output: Labeled tree

parse = GETPARSE(sentence)
for each predicate in parse {
  for each node in parse {
    fv = EXTRACTFEATURES(node, predicate, parse)
    CLASSIFYNODE(node, fv, parse)
  }
}
Simple Predicate Prediction

PropBank: choose all verbs

FrameNet: choose every word that was labeled as a target in training data
SRL Features

Headword of constituent: Examiner

Headword POS: NNP

Voice of the clause: Active

Subcategorization of pred: VP -> VBD NP PP

Named Entity type of constituent: ORGANIZATION

First and last words of constituent: The, Examiner

Linear position re: predicate: before

Path Features
Path Features

Path in the parse tree from the constituent to the predicate
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>Other</td>
<td>no matching parse constituent</td>
</tr>
<tr>
<td>31.4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Palmer, Gildea, Xue (2010)
3-step SRL

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.
3-step SRL

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.

**Pruning & Identification**

Prune the **very** unlikely constituents first, and then use a classifier to get rid of the rest.

Very few of the nodes in the tree could possibly 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)
Features for Frame Identification

the POS of the parent of the head word of $t_i$
the set of syntactic dependencies of the head word\textsuperscript{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\textsuperscript{22} $\rho$ holds between $\ell$ and $t_i$
WordNet relation\textsuperscript{22} $\rho$ holds between $\ell$ and $t_i$, and the prototype is $\ell$
WordNet relation\textsuperscript{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 $\pi_t$

Das et al (2014)
Joint-Inference SRL: Reranking

Stage 1: SRL system produces multiple possible labels for each constituent

Stage 2: Find the best **global** label for all constituents
Joint-Inference SRL: Factor Graph

Make a large, probabilistic factor graph

Run (loopy) belief propagation

Take CMSC 678 (478) to learn more
Joint-Inference SRL: Neural/Deep SRL

Make a large (deep) neural network

Run back propagation

Take CMSC 678 (478) to learn more
PropBank: Not Just English

“The police are thoroughly investigating the cause of the accident.”
Not Just Verbs: NomBank

Figure from Jiang and Ng 2006
Additional Issues for Nouns

Features:
Nominalization lexicon (employment → employ)
Morphological stem

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”
Outline

Recap: dependency grammars and arc-standard dependency parsing

Structured Meaning: Semantic Frames and Roles
   What problem do they solve?
   Theory
   Computational resources: FrameNet, VerbNet, Propbank
   Computational Task: Semantic Role Labeling

Selectional Restrictions
   What problem do they solve?
   Computational resources: WordNet
   Some simple approaches
Selectional Restrictions

I want to eat someplace nearby.
Selectional Restrictions

I want to eat someplace nearby.
Selectional Restrictions

I want to eat someplace nearby.
Selectional Restrictions

I want to eat someplace nearby.

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

I want to eat someplace nearby.

(a)

(b)

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

The THEME of eating tends to be something edible
Selectional Restrictions and Word Senses

The restaurant *serves* green-lipped mussels.

**THEME** is some kind of food

Which airlines *serve* Denver?

**THEME** is an appropriate location
One Way to Represent Selectional Restrictions

\[ \exists e, x, y \text{Eating}(e) \land \text{Agent}(e, x) \land \text{Theme}(e, y) \]

\[ \exists e, x, y \text{Eating}(e) \land \text{Agent}(e, x) \land \text{Theme}(e, y) \land \text{EdibleThing}(y) \]

but do have a large knowledge base of facts about edible things?!  

(do we know a hamburger is edible? sort of)
WordNet

Knowledge graph containing concept relations

hamburger  hero  gyro
WordNet

Knowledge graph containing *concept* relations

A hamburger is-a sandwich
WordNet

Knowledge graph containing concept relations

hyponym: general to specific

hamburger -> sandwich

hero -> sandwich

gyro -> sandwich

a hamburger is-a sandwich
WordNet

Knowledge graph containing *concept* relations

Other relationships too:
- meronymy, holonymy (part of whole, whole of part)
- troponymy (describing *manner* of an event)
- entailment (what else *must* happen in an event)
WordNet Knows About Hamburgers

hamburger
sandwich
snack food
dish
nutriment
food
substance
matter
physical entity
entity
WordNet Synsets for Selectional Restrictions

“The THEME of eat must be WordNet synset \{food, nutrient\}”

Similarly

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

Allows:

imagine a hamburger and lift a hamburger,

Correctly rules out:

diagonalize a hamburger.
Selectional Preferences

Initially: strict constraints (Katz and Fodor 1963)
Eat [+FOOD]

which turned into preferences (Wilks 1975)

“But it fell apart in 1931, perhaps because people realized you can’t eat gold for lunch if you’re hungry.”
Computing Selectional Association (Resnik 1993)

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 Semantic Class</th>
<th>Assoc</th>
<th>Direct Object Semantic Class</th>
<th>Assoc</th>
</tr>
</thead>
<tbody>
<tr>
<td>read</td>
<td>WRITING</td>
<td>6.80</td>
<td>ACTIVITY</td>
<td>-0.20</td>
</tr>
<tr>
<td>write</td>
<td>WRITING</td>
<td>7.26</td>
<td>COMMERCE</td>
<td>0</td>
</tr>
<tr>
<td>see</td>
<td>ENTITY</td>
<td>5.79</td>
<td>METHOD</td>
<td>-0.01</td>
</tr>
</tbody>
</table>
A Simpler Model of Selectional Association
(Brockmann and Lapata, 2003)

Model just the association of predicate \( v \) with a single noun \( n \)

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)
A Simpler Model of Selectional Association (Brockmann and Lapata, 2003)

Model just the association of predicate $v$ with a single noun $n$

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)

<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>

See: Bergsma, Lin, Goebel (2008) for evaluation/comparison
Outline

Recap: dependency grammars and arc-standard dependency parsing

Structured Meaning: Semantic Frames and Roles
   What problem do they solve?
   Theory
   Computational resources: FrameNet, VerbNet, Propbank
   Computational Task: Semantic Role Labeling

Selectional Restrictions
   What problem do they solve?
   Computational resources: WordNet
   Some simple approaches