# Semantic Analysis

Ling571
Deep Processing Techniques for NLP
February 14, 2011

## **Updating Attachments**

Noun -> restaurant

 $\{\lambda x.Restaurant(x)\}\$ 

• Nom-> Noun

{ Noun.sem }

Det -> Every

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

NP -> Det Nom

{ Det.sem(Nom.sem) }

 $\lambda P.\lambda Q. \forall x P(x) \Rightarrow Q(x)(\lambda x. \text{Re } staurant(x))$   $\lambda P.\lambda Q. \forall x P(x) \Rightarrow Q(x)(\lambda y. \text{Re } staurant(y))$   $\lambda Q. \forall x \lambda y. \text{Re } staurant(y)(x) \Rightarrow Q(x)$  $\lambda Q. \forall x \text{Re } staurant(x) \Rightarrow Q(x)$ 

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## Generalizing Attachments

ProperNoun -> Maharani

{Maharani}

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- New style:  $\lambda x.x(Maharani)$

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  - Verb -> opened

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 $\lambda w. \lambda z. w(\lambda x. \exists eOpened(e) \land Opener(e,z) \land OpenedThing(e,x))$ 

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- Use transitive verb structure with new predicate
  - eq(y,x)

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# Strategy for Semantic Attachments

- General approach:
  - Create complex, lambda expressions with lexical items
    - Introduce quantifiers, predicates, terms
  - Percolate up semantics from child if non-branching
  - Apply semantics of one child to other through lambda
    - Combine elements, but don't introduce new

# Sample Attachments

Grammar Rule	Semantic Attachment
$S \rightarrow NP VP$	$\{NP.sem(VP.sem)\}$
$NP \rightarrow Det Nominal$	$\{Det.sem(Nominal.sem)\}$
$NP \rightarrow ProperNoun$	{ProperNoun.sem}
$Nominal \rightarrow Noun$	{Noun.sem}
$VP \rightarrow Verb$	{Verb.sem}
$VP \rightarrow Verb NP$	$\{Verb.sem(NP.sem)\}$
$Det \rightarrow every$	$\{\lambda P.\lambda Q. \forall x P(x) \Rightarrow Q(x)\}$
$Det \rightarrow a$	$\{\lambda P.\lambda Q.\exists x P(x) \land Q(x)\}$
<i>Noun</i> → <i>restaurant</i>	$\{\lambda r.Restaurant(r)\}$
ProperNoun → Matthew	$\{\lambda m.m(Matthew)\}$
ProperNoun → Franco	$\{\lambda f. f(Franco)\}$
ProperNoun → Frasca	$\{\lambda f. f(Frasca)\}$
$Verb \rightarrow closed$	$\{\lambda x. \exists eClosed(e) \land ClosedThing(e,x)\}$
$Verb \rightarrow opened$	$\{\lambda w. \lambda z. w(\lambda x. \exists eOpened(e) \land Opener(e, z)\}$
	$\land Opened(e,x))\}$

- Ambiguity:
  - Every restaurant has a menu

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- Only derived one

 $\exists y Menu(y) \land \forall x (\text{Re } staurant(x) \Rightarrow \exists e Having(e) \land Haver(e, x) \land Had(e, y)))$ 

- Potentially O(n!) scopings (n=# quantifiers)
- There are approaches to describe ambiguity efficiently and recover all alternatives.

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  - Augment grammar rules with semantic field
  - Augment chart states with meaning expression
  - Completer computes semantics e.g. unifies
    - Can also fail to unify
      - Blocks semantically invalid parses
    - Can impose extra work

## Sidelight: Idioms

- Not purely compositional
  - E.g. kick the bucket = die
  - tip of the iceberg = beginning
- Handling:
  - Mix lexical items with constituents (word nps)
  - Create idiom-specific const. for productivity
  - Allow non-compositional semantic attachments
- Extremely complex: e.g. metaphor

## Semantic Analysis

- Applies principle of compositionality
  - Rule-to-rule hypothesis
  - Links semantic attachments to syntactic rules
    - Incrementally ties semantics to parse processing
    - Lambda calculus meaning representations
    - Most complexity pushed into lexical items
    - Non-terminal rules largely lambda applications

## Semantics Learning

 Zettlemoyer & Collins, 2005, 2007, etc; Mooney 2007

- Given semantic representation and corpus of parsed sentences
  - Learn mapping from sentences to logical form
    - Structured perceptron
    - Applied to ATIS corpus sentences

- Motivation: Word sense disambiguation
- Meaning at the word level
  - Issues
    - Ambiguity
    - Meaning
    - Meaning structure
      - Relations to other words
      - Subword meaning composition
  - WordNet: Lexical ontology

## What is a plant?

There are more kinds of plants and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of plants and animals live in the rainforest. Many are found nowhere else. There are even plants and animals in the rainforest that we have not yet discovered.

The Paulus company was founded in 1938. Since those days the product range has been the subject of constant expansions and is brought up continuously to correspond with the state of the art. We're engineering, manufacturing, and commissioning world-wide ready-to-run plants packed with our comprehensive know-how.

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  - Internal meaning structure of words
    - Basic internal units combine for meaning

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    - E.g. bank: money, organ, blood,...
  - Big issue in lexicography
    - # of senses, relations among senses, differentiation
    - E.g. serve breakfast, serve Philadelphia, serve time

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    - Register:
      - social factors: e.g. politeness, formality

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  - Organize as ontology/taxonomy

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- Relations between entries:
  - Synonymy: in synset
  - Hypo(per)nym: Isa tree

#### WordNet

The noun "bass" has 8 senses in WordNet.

- 1. bass<sup>1</sup> (the lowest part of the musical range)
- 2. bass<sup>2</sup>, bass part<sup>1</sup> (the lowest part in polyphonic music)
- 3. bass<sup>3</sup>, basso<sup>1</sup> (an adult male singer with the lowest voice)
- 4. sea bass<sup>1</sup>, bass<sup>4</sup> (the lean flesh of a saltwater fish of the family Serranidae)
- 5. freshwater bass<sup>1</sup>, bass<sup>5</sup> (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
- 6. bass<sup>6</sup>, bass voice<sup>1</sup>, basso<sup>2</sup> (the lowest adult male singing voice)
- 7. bass<sup>7</sup> (the member with the lowest range of a family of musical instruments)
- 8. bass<sup>8</sup> (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

The adjective "bass" has 1 sense in WordNet.

1. bass<sup>1</sup>, deep<sup>6</sup> - (having or denoting a low vocal or instrumental range)

"a deep voice"; "a bass voice is lower than a baritone voice";

"a bass clarinet"

#### Noun WordNet Relations

Relation	Also Called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	$breakfast^1 \rightarrow meal^1$
Hyponym	Subordinate	From concepts to subtypes	$meal^1 \rightarrow lunch^1$
Instance Hypernym	Instance	From instances to their concepts	$Austen^1 \rightarrow author^1$
Instance Hyponym	Has-Instance	From concepts to concept instances	$composer^1 \rightarrow Bach^1$
Member Meronym	Has-Member	From groups to their members	$faculty^2 \rightarrow professor^1$
Member Holonym	Member-Of	From members to their groups	$copilot^1 \rightarrow crew^1$
Part Meronym	Has-Part	From wholes to parts	$table^2 \rightarrow leg^3$
Part Holonym	Part-Of	From parts to wholes	$course^7  o meal^1$
Substance Meronym		From substances to their subparts	$water^1 \rightarrow oxygen^1$
Substance Holonym		From parts of substances to wholes	$gin^1 \rightarrow martini^1$
Antonym		Semantic opposition between lemmas	$leader^1 \iff follower^1$
Derivationally		Lemmas w/same morphological root	$destruction^1 \iff destroy^1$
Related Form			

# WordNet Taxonomy

```
Sense 3
bass, basso --
(an adult male singer with the lowest voice)
=> singer, vocalist, vocalizer, vocaliser
   => musician, instrumentalist, player
      => performer, performing artist
         => entertainer
            => person, individual, someone...
               => organism, being
                  => living thing, animate thing,
                     => whole, unit
                        => object, physical object
                           => physical entity
                              => entity
               => causal agent, cause, causal agency
                  => physical entity
                     => entity
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    - The window<sub>THEME</sub> was broken by John<sub>AGENT</sub>

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  - Group verbs into classes based on shared patterns

# Canonical Roles

Thematic Role	Example
AGENT	The waiter spilled the soup.
EXPERIENCER	John has a headache.
FORCE	The wind blows debris from the mall into our yards.
THEME	Only after Benjamin Franklin broke the ice
RESULT	The French government has built a regulation-size baseball
	diamond
CONTENT	Mona asked "You met Mary Ann at a supermarket?"
INSTRUMENT	He turned to poaching catfish, stunning them with a shocking
	device
BENEFICIARY	Whenever Ann Callahan makes hotel reservations for her boss
SOURCE	I flew in from Boston.
GOAL	I drove to Portland.

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  - Standard definition of roles
    - Most AGENTs: animate, volitional, sentient, causal
    - But not all....
- Strategies:
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    - Ex1: [Arg0 The group] agreed [Arg1 it wouldn't make an offer]

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  - Relationships b/t frames, frame elements
    - Add causative: cause\_change\_position\_on\_scale

Core Roles	
ATTRIBUTE	The ATTRIBUTE is a scalar property that the ITEM possesses.
DIFFERENCE	The distance by which an 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 ends up.
INITIAL_STATE	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 end points, along which the values of the ATTRIBUTE fluctuate.
Some Non-Core Roles	
DURATION	The length of time over which the change takes place.
SPEED	The rate of change of the VALUE.
GROUP	The GROUP in which an ITEM changes the value of an
	ATTRIBUTE in a specified way.

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#### Selectional Restrictions

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  - Associate with WordNet synset (and hyponyms)

### Primitive Decompositions

- Jackendoff(1990), Dorr(1999), McCawley (1968)
- Word meaning constructed from primitives
  - Fixed small set of basic primitives
    - E.g. cause, go, become,
    - kill=cause X to become Y
  - Augment with open-ended "manner"
    - Y = not alive
    - E.g. walk vs run
- Fixed primitives/Infinite descriptors

### Word Sense Disambiguation

- Selectional Restriction-based approaches
  - Limitations
- Robust Approaches
  - Supervised Learning Approaches
    - Naïve Bayes
  - Bootstrapping Approaches
    - One sense per discourse/collocation
  - Unsupervised Approaches
    - Schutze's word space
  - Resource-based Approaches
    - Dictionary parsing, WordNet Distance
  - Why they work
  - Why they don't

### Word Sense Disambiguation

- Application of lexical semantics
- Goal: Given a word in context, identify the appropriate sense
  - E.g. plants and animals in the rainforest
- Crucial for real syntactic & semantic analysis
  - Correct sense can determine
    - Available syntactic structure
    - Available thematic roles, correct meaning,...

#### Selectional Restriction Approaches

- Integrate sense selection in parsing and semantic analysis – e.g. with Montague
- Concept: Predicate selects sense
  - Washing dishes vs stir-frying dishes
    - Stir-fry: patient: food => dish~food
  - Serve Denver vs serve breakfast
    - Serve vegetarian dishes
      - Serve1: patient: loc; serve1: patient: food
      - => dishes~food: only valid variant
- Integrate in rule-to-rule: test e.g. in WN

#### Selectional Restrictions: Limitations

- Problem 1: Predicates too general
  - Recommend, like, hit....
- Problem 2: Language too flexible
  - "The circus performer ate fire and swallowed swords"
    - Unlikely but doable
  - Also metaphor
- Strong restrictions would block all analysis
  - Some approaches generalize up hierarchy
    - Can over-accept truly weird things

### Robust Disambiguation

- More to semantics than P-A structure
  - Select sense where predicates underconstrain
- Learning approaches
  - Supervised, Bootstrapped, Unsupervised
- Knowledge-based approaches
  - Dictionaries, Taxonomies
- Widen notion of context for sense selection
  - Words within window (2,50,discourse)
  - Narrow cooccurrence collocations

### Disambiguation Features

- Key: What are the features?
  - Part of speech
    - Of word and neighbors
  - Morphologically simplified form
  - Words in neighborhood
    - Question: How big a neighborhood?
      - Is there a single optimal size? Why?
  - (Possibly shallow) Syntactic analysis
    - E.g. predicate-argument relations, modification, phrases
  - Collocation vs co-occurrence features
    - Collocation: words in specific relation: p-a, 1 word +/-
    - Co-occurrence: bag of words...

### Naïve Bayes' Approach

- Supervised learning approach
  - Input: feature vector X label
- Best sense = most probable sense given V  $\hat{s} = \arg\max \dot{P}(s \mid V)$

$$\hat{s} = \underset{s \in S}{\operatorname{arg\,max}} \frac{P(V \mid s)P(s)}{P(V)}$$

 $P(V|s) = \prod_{j=1}^{n} P(v_{j}|s)$ • "Naïve" assumption: features independent

$$\hat{s} = \underset{s \in S}{\operatorname{arg\,max}} P(s) \prod_{j=1}^{n} P(v_j \mid s)$$

# Example: "Plant" Disambiguation

There are more kinds of plants and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of plants and animals live in the rainforest. Many are found nowhere else. There are even plants and animals in the rainforest that we have not yet discovered.

#### **Biological Example**

**Industrial Example** 

The Paulus company was founded in 1938. Since those days the product range has been the subject of constant expansions and is brought up continuously to correspond with the state of the art. We're engineering, manufacturing and commissioning worldwide ready-to-run plants packed with our comprehensive know-how. Our Product Range includes pneumatic conveying systems for carbon, carbide, sand, lime and many others. We use reagent injection in molten metal for the...

Label the First Use of "Plant"

#### Yarowsky's Decision Lists: Detail

- One Sense Per Discourse Majority
- One Sense Per Collocation
  - Near Same Words
- → Same Sense

#### Yarowsky's Decision Lists: Detail

- Training Decision Lists
  - 1. Pick Seed Instances & Tag
  - 2. Find Collocations: Word Left, Word Right, Word <u>+</u>K
    - (A) Calculate Informativeness on Tagged Set,
      - Order:
    - (B) Tag New Instances with Rules
    - (C)\* Apply 1 St  $abs(\log \frac{Pr(sense_1|Collocation)}{Pr(sense_2|Collocation)})$
    - (D) If Still Unlabeled, Go To 2
  - 3. Apply 1 Sense/Discouse
- Disambiguation: First Rule Matched

# Sense Choice With Collocational Decision Lists

- Use Initial Decision List
  - Rules Ordered by  $abs(\log \frac{Pr(sense_1|Collocation)}{Pr(sense_2|Collocation)})$
- Check nearby Word Groups (Collocations)
  - Biology: "Animal" in  $\pm$  2-10 words
  - Industry: "Manufacturing" in ± 2-10 words
- Result: Correct Selection
  - 95% on Pair-wise tasks

### Semantic Ambiguity

- "Plant" ambiguity
  - Botanical vs Manufacturing senses
- Two types of context
  - Local: 1-2 words away
  - Global: several sentence window
- Two observations (Yarowsky 1995)
  - One sense per collocation (local)
  - One sense per discourse (global)

### Schutze's Vector Space: Detail

97 Real Values

- Build a co-occurrence matrix
  - Restrict Vocabulary to 4 letter sequences
  - Exclude Very Frequent Articles, Affixes
  - Entries in 5000-5000 Matrix
- Word Context
  - 4grams within 1001 Characters
  - Sum & Normalize Vectors for each 4gram
  - Distances between Vectors by dot product

# Schutze's Vector Space: continued

- Word Sense Disambiguation
  - Context Vectors of All Instances of Word
  - Automatically Cluster Context Vectors
  - Hand-label Clusters with Sense Tag
  - Tag New Instance with Nearest Cluster

# Sense Selection in "Word Space"

- Build a Context Vector
  - 1,001 character window Whole Article
- Compare Vector Distances to Sense Clusters
  - Only 3 Content Words in Common
  - Distant Context Vectors
  - Clusters Build Automatically, Label Manually
- Result: 2 Different, Correct Senses
  - 92% on Pair-wise tasks

#### Resnik's WordNet Labeling: Detail

- Assume Source of Clusters
- Assume KB: Word Senses in WordNet IS-A hierarchy
- Assume a Text Corpus
- Calculate Informativeness  $(I) = -\log(\frac{\sum_{w \in C} Count(w)}{N})$ 
  - For Each KB Node:
    - Sum occurrences of it and all children
    - Informativeness
- Disambiguate wrt Cluster & WordNet
  - Find MIS for each pair, I
  - For each subsumed sense, Vote += I
  - Select Sense with Highest Vote

## Sense Labeling Under WordNet

- Use Local Content Words as Clusters
  - Biology: Plants, Animals, Rainforests, species...
  - Industry: Company, Products, Range, Systems...
- Find Common Ancestors in WordNet
  - Biology: Plants & Animals is a Living Thing
  - Industry: Product & Plant isa Artifact isa Entity
  - Use Most Informative
- Result: Correct Selection

$$(I) = -\log(\frac{\sum_{w \in C} Count(w)}{N})$$

### The Question of Context

- Shared Intuition:
  - ContextSense
- Area of Disagreement:
  - What is context?
- Wide vs Narrow Window
- Word Co-occurrences

# Taxonomy of Contextual Information

- Topical Content
- Word Associations
- Syntactic Constraints
- Selectional Preferences
- World Knowledge & Inference

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## Context All Words within X words of Target

- Many words: Schutze 1000 characters, several sentences
- Unordered "Bag of Words"
- Information Captured: Topic & Word Association
- Limits on Applicability
  - Nouns vs. Verbs & Adjectives
  - Schutze: Nouns 92%, "Train" -Verb, 69%

#### Limits of Wide Context

- Comparison of Wide-Context Techniques (LTV '93)
  - Neural Net, Context Vector, Bayesian Classifier, Simulated Annealing
    - Results: 2 Senses 90+%; 3+ senses ~ 70%
    - People: Sentences ~100%; Bag of Words: ~70%
- Inadequate Context
- Need Narrow Context
  - Local Constraints Override
  - Retain Order, Adjacency

# Surface Regularities = Useful Disambiguators

- Not Necessarily!
- "Scratching her nose" vs "Kicking the bucket" (deMarcken 1995)
- Right for the Wrong Reason
  - Burglar Rob... Thieves Stray Crate Chase Lookout
- Learning the Corpus, not the Sense
  - The "Ste." Cluster: Dry Oyster Whisky Hot Float Ice
- Learning Nothing Useful, Wrong Question
  - Keeping: Bring Hoping Wiping Could Should Some Them Rest

# Interactions Below the Surface

- Constraints Not All Created Equal
  - "The Astronomer Married the Star"
  - Selectional Restrictions Override Topic
- No Surface Regularities
  - "The emigration/immigration bill guaranteed passports to all Soviet citizens
  - No Substitute for Understanding

#### What is Similar

- Ad-hoc Definitions of Sense
  - Cluster in "word space", WordNet Sense, "Seed Sense": Circular
- Schutze: Vector Distance in Word Space
- Resnik: Informativeness of WordNet Subsumer + Cluster
  - Relation in Cluster not WordNet is-a hierarchy
- Yarowsky: No Similarity, Only Difference
  - Decision Lists 1/Pair
  - Find Discriminants