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J&M Ch. 16, 17–17.3 (1st ed); J&M Ch. 19, 20–20.5 (2nd ed); J&M Ch. 6.1; 23.2 – 23.5 (3rd ed older version)

Review Quiz

What are the components of a PCFG?

Vanilla PCFGs

Estimate of rule probabilities:

MLE estimates:

$$Pr(\alpha \to \beta) = \frac{\#(\alpha \to \beta)}{\#\alpha}$$

- e.g., Pr(S -> NP VP) = #(S -> NP VP) / #(S)
 - Recall: these distributions are normalized by LHS symbol

Even with smoothing, doesn't work very well:

- Not enough context
- Rules are too sparse

Subject vs Object NPs

NPs in subject and object positions are not identically distributed:

- Obvious cases pronouns (I vs me)
 - But both appear as NP -> PRP -> I/me
- Less obvious: certain classes of nouns are more likely to appear in subject than object position, and vice versa.
 - For example, subjects tend to be animate (usually, humans, animals, other moving objects)

Many other cases of obvious dependencies between distant parts of the syntactic tree.

Sparsity

Consider subcategorization of verbs, with modifiers

• *ate* VP -> VBD

ate quickly
 VP -> VBD AdvP

ate with a fork
 VP -> VBD PP

ate a sandwich
 VP -> VBD NP

ate a sandwich quickly
 VP -> VBD NP AdvP

ate a sandwich with a fork
 VP -> VBD NP PP

quickly ate a sandwich with a fork VP -> AdvP VBD NP PP

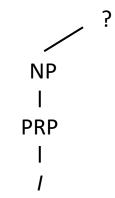
We should be able to factorize the probabilities:

 of having an adverbial modifier, of having a PP modifier, etc.

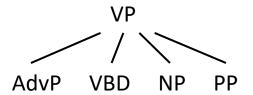
Wrong Independence Assumptions

Vanilla PCFGs make independence assumptions that are too strong AND too weak.

Too strong: vertically, up and down the syntax tree



Too weak: horizontally, across the RHS of a production



Adding Context

Add more context vertically to the PCFG

Annotate with the parent category

```
Before: NP -> PRP, NP -> Det NN, etc.
```

Now:

Subjects:

NP^S -> PRP, NP^S -> Det NN, etc.

Objects:

NP^VP -> PRP, NP^VP -> Det NN, etc.

Learn the probabilities of the rules separately (though they may influence each other through interpolation/smoothing)

Example

Let's help Pierre Vinken find his ancestors.

```
( (S
    (NP
      (NP (NNP Pierre) (NNP Vinken) )
      (,,)
      (ADJP
        (NP (CD 61) (NNS years) )
        (JJ old) )
      (,,)
    (VP (MD will)
      (VP (VB join)
        (NP (DT the) (NN board) )
        (PP (IN as)
          (NP (DT a) (JJ nonexecutive) (NN director) ))
        (NP (NNP Nov.) (CD 29) )))
    (. .) ))
```

Note that the tree here is given in bracket parse format, rather than drawn out as a graph.

Removing Context

Conversely, we break down the RHS of the rule when estimating its probability.

```
Before: Pr(VP -> START AdvP VBD NP PP END) as a unit
```

Now: Pr(VP -> START AdvP) *

Pr(VP -> AdvP VBD) *

Pr(VP -> VBD NP) *

Pr(VP -> NP PP) *

Pr(VP -> PP END)

- In other words, we're making the same N-gram assumption as in language modelling, only over nonterminal categories rather than words.
- Learn probability of factors separately

Example

Let's help Pierre Vinken find his children.

```
( (S
    (NP
      (NP (NNP Pierre) (NNP Vinken) )
      (,,)
      (ADJP
        (NP (CD 61) (NNS years) )
        (JJ old) )
      (,,)
    (VP (MD will)
      (VP (VB join)
        (NP (DT the) (NN board) )
        (PP (IN as)
          (NP (DT a) (JJ nonexecutive) (NN director) ))
        (NP (NNP Nov.) (CD 29) )))
    (. .) ))
```

Markovization

Vertical markovization: adding ancestors as context

- Zeroth order vanilla PCFGs
- First order the scheme we just described
- Can go further:
 - e.g., Second order: NP^VP^S -> ...

Horizontal markovization: breaking RHS into parts

- Infinite order vanilla PCFGs
- First order the scheme we just described
- Can choose any other order, do interpolation, etc.

Effect of Category Splitting

		Horizontal Markov Order				
Vertical Order		h = 0	h = 1	$h \leq 2$	h=2	$h = \infty$
v = 1	No annotation	71.27	72.5	73.46	72.96	72.62
		(854)	(3119)	(3863)	(6207)	(9657)
$v \leq 2$	Sel. Parents	74.75	77.42	77.77	77.50	76.91
		(2285)	(6564)	(7619)	(11398)	(14247)
v=2	All Parents	74.68	77.42	77.81	77.50	76.81
		(2984)	(7312)	(8367)	(12132)	(14666)
$v \leq 3$	Sel. GParents	76.50	78.59	79.07	78.97	78.54
		(4943)	(12374)	(13627)	(19545)	(20123)
v=3	All GParents	76.74	79.18	79.74	79.07	78.72
		(7797)	(15740)	(16994)	(22886)	(22002)

Figure 2: Markovizations: F₁ and grammar size.

WSJ results by Klein and Manning (2003)

- With additional linguistic insights, they got up to 87.04 F1
- Current best is around 94-95 F1

Where Are We In the Course?

Single decisions → Text classification

Sequences \rightarrow Language modelling

Sequence labelling

Structure → Parsing

Next big topic: semantics

Semantics

The study of **meaning** in language

What does meaning mean?

- Relationship of linguistic expression to the real world
- Relationship of linguistic expressions to each other

Let's start by focusing on the meaning of words—lexical semantics.

Later on:

- meaning of phrases and sentences
- how to construct that from meanings of words

From Language to the World

What does telephone mean?

 Picks out all of the objects in the world that are telephones (its referents)

Its extensional definition





Relationship of Linguistic Expressions

How would you define *telephone*? e.g, to a three-year-old, or to a friendly Martian.

Dictionary Definition

http://dictionary.reference.com/browse/telephone

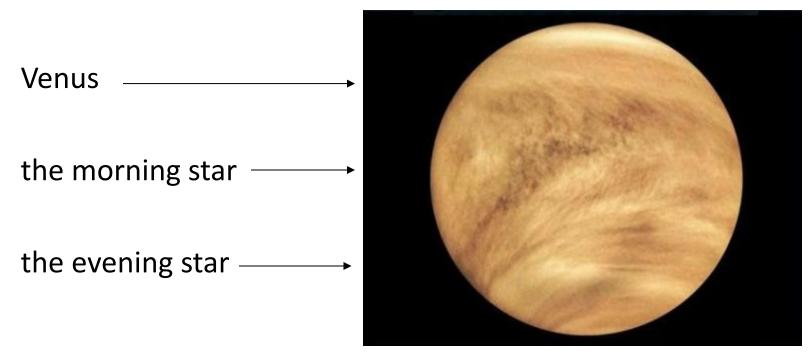
Its intensional definition

• The necessary and sufficient conditions to be a telephone This presupposes you know what "apparatus", "sound", "speech", etc. mean.

Sense and Reference (Frege, 1892)

Frege was one of the first to distinguish between the sense of a term, and its reference.

Same referent, different senses:



Lexical Semantic Relations

How specifically do terms relate to each other? Here are some ways:

Hypernymy/hyponymy

Synonymy

Antonymy

Homonymy

Polysemy

Metonymy

Synecdoche

Holonymy/meronymy

Hypernymy/Hyponymy

ISA relationship

Hyponym Hypernym

monkey mammal

Montreal city

red wine beverage

Synonymy and Antonymy

Synonymy

```
(Roughly) same meaning offspring descendent spawn happy joyful merry
```

Antonymy

(Roughly) opposite meaning synonym antonym happy sad descendant ancestor

Homonymy

Same form, different (and unrelated) meaning

Homophone – same sound

e.g., son vs. sun

Homograph – same written form

• e.g., lead (noun) vs. lead (verb)

Polysemy

Multiple related meanings

- S: (n) newspaper, paper (a daily or weekly publication on folded sheets; contains news and articles and advertisements) "he read his newspaper at breakfast"
- S: (n) newspaper, paper, newspaper publisher (a business firm that publishes newspapers) "Murdoch owns many newspapers"
- <u>S:</u> (n) **newspaper**, <u>paper</u> (the physical object that is the product of a newspaper publisher) "when it began to rain he covered his head with a newspaper"
- S: (n) **newspaper**, <u>newsprint</u> (cheap paper made from wood pulp and used for printing newspapers) "they used bales of newspaper every day"

Homonymy vs Polysemy

- Homonymy: <u>unrelated</u> Polysemy: <u>related</u> meaning
 - <u>S:</u> (n) **position**, <u>place</u> (the particular portion of space occupied by something) "he put the lamp back in its place"
 - <u>S:</u> (n) <u>military position</u>, **position** (a point occupied by troops for tactical reasons)
 - <u>S:</u> (n) **position**, <u>view</u>, <u>perspective</u> (a way of regarding situations or topics etc.)"*consider what follows from the positivist view*"
 - <u>S:</u> (n) **position**, <u>posture</u>, <u>attitude</u> (the arrangement of the body and its limbs) "he assumed an attitude of surrender"
 - <u>S:</u> (n) <u>status</u>, **position** (the relative position or standing of things or especially persons in a society) "he had the status of a minor"; "the novel attained the status of a classic"; "atheists do not enjoy a favorable position in American life"
 - <u>S:</u> (n) **position**, <u>post</u>, <u>berth</u>, <u>office</u>, <u>spot</u>, <u>billet</u>, <u>place</u>, <u>situation</u> (a job in an organization) "he occupied a post in the treasury"

Metonymy

Substitution of one entity for another related one

We ordered many delicious dishes at the restaurant.

I worked for the local paper for five years.

Quebec City is cutting our budget again.

The loonie is at a 11-year low.

Synecdoche – a specific kind of metonymy involving whole-part relations

All hands on deck!

Don't be a <censored body part>

Holonymy/meronymy

Some kind of whole/part relationship

Subtypes Holonym Meronym

groups and members class student

whole and part car windshield

whole and substance chair wood

Quiz

Classify the following examples in terms of what lexical semantic relation they exhibit

cold freezing

they're their

hair head

enemy friend

cut (hair) cut (bread)

George Clooney actor

WordNet (Miller et et., 1990)

WordNet is a lexical resource organized by synsets

- Nodes: synsets
- Edges: lexical semantic relation between two synsets

Separate hierarchy for different parts of speech

Nouns, verbs, adjectives, adverbs

WordNet online:

http://wordnetweb.princeton.edu/perl/webwn

A Synset Entry

S: (n) hand, manus, mitt, paw (the (prehensile) extremity of the superior limb) "he had the hands of a surgeon"; "he extended his mitt"

direct hyponym / full hyponym

- S: (n) fist, clenched fist (a hand with the fingers clenched in the palm (as for hitting))
- S: (n) hooks, meat hooks, maulers (large strong hand (as of a fighter)) wait till I get my hooks on him
- <u>S:</u> (n) <u>right</u>, <u>right hand</u> (the hand that is on the right side of the body) "he writes with his right hand but pitches with his left"; "hit him with quick rights to the body"
- S: (n) left, left hand (the hand that is on the left side of the body) "jab with your left"

part meronym

<u>direct hypernym / inherited hypernym / sister term</u>

part holonym

- <u>S:</u> (n) <u>arm</u> (a human limb; technically the part of the superior limb between the shoulder and the elbow but commonly used to refer to the whole superior limb)
- <u>S:</u> (n) <u>homo</u>, <u>man</u>, <u>human being</u>, <u>human</u> (any living or extinct member of the family Hominidae characterized by superior intelligence, articulate speech, and erect carriage)

<u>derivationally related form</u>

WordNet Has an NLTK Interface

>>> from nltk.corpus import wordnet

Some useful functions:

```
>>> wordnet.synsets(<query_term>)
```

>>> wordnet.synset(<synset_name>)

Remember you can use dir and help to get a list of functions in Python.

Word Sense Disambiguation

Figuring out which word sense is expressed in context

His **hands** were tired from hours of typing.

 \rightarrow hand.n.01

Due to her superior education, her **hand** was flowing and graceful.

 \rightarrow hand.n.03

General idea: use words in the context to disambiguate. Which words above would help with this?

Possible Computational Approaches

A heuristic algorithm

Lesk's algorithm

Supervised machine learning

 Possible, but requires a lot of work to annotate word sense information that we want to avoid

Unsupervised, or minimally supervised machine learning

Yarowsky's algorithm

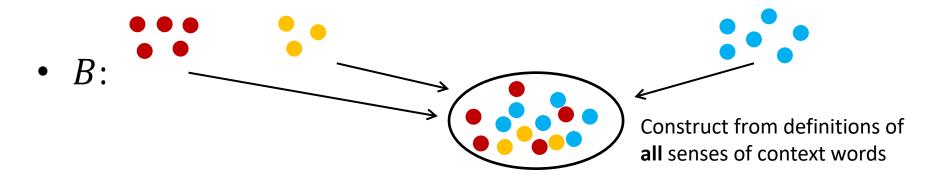
Lesk's Algorithm (1986)

Use the dictionary definitions of a word's senses Steps to disambiguate word w:

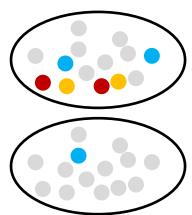
- 1. Construct a bag of words representation of the context, B
- 2. For each candidate sense s_i of word w:
 - Calculate a signature of the sense by taking all of the words in the dictionary definition of s_i
 - Compute Overlap(B, signature(s_i))
- 3. Select the sense with the highest overlap score

Financial Bank or Riverbank?

... deposit a cheque at the bank before it closed ...



- overlap(bank#1,B)
 - 6 overlaps found
- overlap(bank#2,B)
 - 1 overlap found
- Decision: select sense 1.



Model Variations

Which dictionary to use? NLTK?

Use only dictionary definitions? Or include example sentences?

Ignore uninformative stopwords (e.g., the, a, of)?

Lemmatize when considering matches (tomatoes matches tomato)?

Exercise

Run the Lesk algorithm using NLTK/WordNet. Ignore stop words, include examples, count lemma overlap. Consider only the top two senses of bank.

- 1. I'll deposit the cheque at the bank.
- 2. The bank overflowed and water flooded the town.

Yarowsky's Algorithm (1995)

A method based on **bootstrapping**

Steps:

- 1. Gather a data set with target word to be diambiguated
- 2. Automatically label a small seed set of examples
- Repeat the following for a while:
 - Train a supervised learning algorithm from the seed set
 - Apply the supervised model to the entire data set
 - Keep the highly confident classification outputs to be the new seed set
- 4. Use the last model as the final model

Yarowsky's Example

Step 1: Disambiguating *plant*

Sense	Training Examples (Keyword in Context)
?	company said the plant is still operating
?	Although thousands of plant and animal species
?	zonal distribution of plant life
?	to strain microscopic plant life from the
? ? ? ? ?	vinyl chloride monomer plant, which is
	and Golgi apparatus of plant and animal cells
? ? ?	computer disk drive plant located in
?	divide life into plant and animal kingdom
?	close-up studies of plant life and natural
?	Nissan car and truck plant in Japan is
? ? ?	keep a manufacturing plant profitable without
?	molecules found in plant and animal tissue
	union responses to plant closures
? ? ?	animal rather than plant tissues can be
?	many dangers to plant and animal life
?	company manufacturing plant is in Orlando
	growth of aquatic plant life in water
? ? ?	automated manufacturing plant in Fremont,
?	Animal and plant life are delicately
?	discovered at a St. Louis plant manufacturing
?	computer manufacturing plant and adjacent
?	the proliferation of plant and animal life
?	

Step 2: Initial Seed Set

Sense A:

• plant as in a lifeform

Other data

Sense B:

plant as in a factory

Sense	Training Examples (Keyword in Context)
A	used to strain microscopic plant life from the
A	zonal distribution of plant life
A	close-up studies of plant life and natural
A	too rapid growth of aquatic plant life in water
A	the proliferation of plant and animal life
A	establishment phase of the plant virus life cycle
A	that divide life into plant and animal kingdom
A	many dangers to plant and animal life
A	mammals . Animal and plant life are delicately
A	beds too salty to support plant life . River
A	heavy seas, damage, and plant life growing on
A	
?	vinyl chloride monomer plant, which is
?	molecules found in plant and animal tissue
?	Nissan car and truck plant in Japan is
?	and Golgi apparatus of plant and animal cells
?	union responses to plant closures
???????????	
?	
?	cell types found in the plant kingdom are
?	company said the plant is still operating
?	Although thousands of plant and animal species
?	animal rather than plant tissues can be
	computer disk drive plant located in
В	
В	automated manufacturing plant in Fremont
В	vast manufacturing plant and distribution
В	chemical manufacturing plant, producing viscose
В	keep a manufacturing plant profitable without
В	computer manufacturing plant and adjacent
В	discovered at a St. Louis plant manufacturing
В	copper manufacturing plant found that they
В	copper wire manufacturing plant, for example
В	's cement manufacturing plant in Alpena
В	polystyrene manufacturing plant at its Dow
В	company manufacturing plant is in Orlando

Step 3: Train a Classifier

He went with a **decision-list** classifier (we didn't cover this one in class)

Initia	decision list for plant (abbrevia	ated)
LogL	Collocation	Sense
8.10	plant life	$\Rightarrow A$
7.58	${f manufacturing} \ plant$	\Rightarrow B
7.39	life (within $\pm 2\text{-}10 \text{ words}$)	$\Rightarrow A$
7.20	manufacturing (in $\pm 2\text{-}10 \text{ words}$)	\Rightarrow B
6.27	animal (within ± 2 -10 words)	$\Rightarrow A$
4.70	equipment (within $\pm 2\text{-}10 \text{ words}$)	\Rightarrow B
4.39	employee (within $\pm 2\text{-}10 \text{ words}$)	\Rightarrow B
4.30	assembly plant	\Rightarrow B
4.10	plant closure	\Rightarrow B
3.52	plant species	$\Rightarrow A$
3.48	automate (within $\pm 2\text{-}10 \text{ words}$)	\Rightarrow B
3.45	microscopic plant	$\Rightarrow A$

Note how new collocations are found for each sense

Step 3: Change Seed Set

Use only the cases where classifier is highly confident

Labeling previously untagged contexts

using the one-sense-per-discourse property

	~	
Change	Disc.	
in tag	Numb.	Training Examples (from same discourse)
$A \rightarrow A$	724	the existence of plant and animal life
$A \rightarrow A$	724	classified as either plant or animal
? → A	724	Although bacterial and plant cells are enclosed
$A \rightarrow A$	348	the life of the plant, producing stem
$A \rightarrow A$	348	an aspect of plant life, for example
? → A	348	tissues ; because plant egg cells have
? → A	348	photosynthesis, and so plant growth is attuned

Results

96% on binary word sense distinctions

Same result as with supervised methods, but with minimal amounts of annotation effort!