LEXICAL SEMANTICS

CS 224N – 2011
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Slides largely adapted from ones by Christopher Manning, Massimo Poesio, Ted Pedersen, Dan Jurafsky, and Jim Martin

Lexical information and NL applications

- NL applications often need to know the MEANING of words at least
- Word meaning is tricky, messy stuff!
- IBM Watson: “Words by themselves have no meaning”
- Many word strings express apparently unrelated senses / meanings, even after their POS has been determined
  - Well-known examples: BANK, SCORE, RIGHT, SET, STOCK
  - Homonymy affects the results of applications such as IR and machine translation
- The opposite case of different words with the same meaning (SYNONYMY) is also important
  - NOTEBOOK/LAPTOP
  - E.g., for IR systems (synonym expansion)

An example LEXICAL ENTRY from a machine-readable dictionary: STOCK,from the LDOCE

- 0100 a supply (of something) for use: *a good stock of food*
- 0200 goods for sale: *Some of the stock is being taken without being paid for*
- 0300 the thick part of a tree trunk
- 0400 (a) a piece of wood used as a support or handle, as for a gun or tool (b) the piece which goes across the top of an ANCHOR^1 (1) from side to side
- 0500 (a) a plant from which CUTTINGs are grown (b) a stem onto which another plant is GRAFTed
- 0600 a group of animals used for breeding
- 0700 farm animals usu. cattle; LIVESTOCK
- 0800 a family line, esp. of the stated character
- 0900 money lent to a government at a fixed rate of interest
- 1000 the money (CAPITAL) owned by a company, divided into SHAREs
- 1100 a type of garden flower with a sweet smell
- 1200 a liquid made from the juices of meat, bones, etc., used in cooking …..

Homonymy, homography, homophony

- HOMONYMY: Word-strings like STOCK are used to express apparently unrelated senses / meanings, even in contexts in which their part-of-speech has been determined
  - Other well-known examples: BANK, RIGHT, SET, SCALE
- HOMOGRAPHS: BASS
  - The expert angler from Dora, Mo was fly-casting for BASS rather than the traditional trout.
  - The curtain rises to the sound of angry dogs baying and ominous BASS chords sounding.
  - Problems caused by homography: text to speech synthesis
- Many spelling errors are caused by HOMOPHONES – distinct lexemes with a single pronunciation
  - *Its* vs. *it's*
  - *weather* vs. *whether*
  - *their vs. there*

POLYSEMY vs HOMONYMY

- In cases like BANK, it's fairly easy to identify two distinct senses (etymology also different). But in other cases, distinctions more questionable
  - E.g., senses 0100 and 0200 of stock clearly related, like 0600 and 0700, or 0900 and 1000
- POLYSEMOUS WORDS: meanings are related to each other
  - Cf. human's foot vs. mountain's foot
  - Commonly the result of some kind of metaphorical extension
- In some cases, syntactic tests may help.
  - Claim: can conjoin, do ellipsis, etc. over polysemy not homonymy
- In general, distinction between HOMONYMY and POLYSEMY not always easy

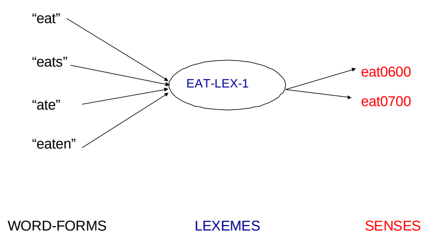
Meaning in MRDs, 2: SYNONYMY

- Two words are SYNONYMS if they have the same meaning at least in some contexts
- E.g., PRICE and FARE; CHEAP and INEXPENSIVE; LAPTOP and NOTEBOOK; HOME and HOUSE
  - I'm looking for a CHEAP FLIGHT / INEXPENSIVE FLIGHT
- From Roget's thesaurus:
  - OBLITERATION, erasure, cancellation, deletion
- But very few words are truly synonymous in ALL contexts:
  - HOME/??HOUSE is where the heart is
  - The flight was CANCELLED / ?? OBLITERATED / ??? DELETED
- Knowing about synonyms may help in IR:
  - NOTEBOOK (get LAPTOPs as well)
  - CHEAP PRICE (get INEXPENSIVE FARE)

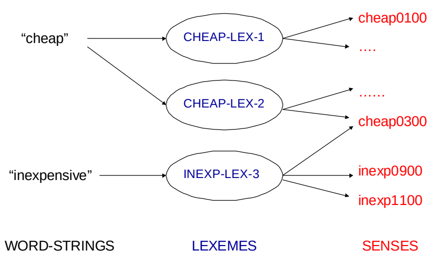
Hyponymy and Hypernymy

- HYPONYMY is the relation between a subclass and a superclass:
  - CAR and VEHICLE
  - DOG and ANIMAL
  - BUNGALOW and HOUSE
- Generally speaking, a hyponymy relation holds between X and Y whenever it is possible to substitute Y for X:
  - That is a X -> That is a Y
  - E.g., That is a CAR -> That is a VEHICLE.
- HYPERONYMY is the opposite relation
- Knowledge about TAXONOMIES useful to classify web pages
  - Eg., Semantic Web. ISA relation of AI
- This information not generally contained explicitly in a traditional or machine-readable dictionary (MRD)

The organization of the lexicon



The organization of the lexicon: Synonymy



A free, online, more advanced lexical resource: WordNet

- A lexical database created at Princeton
  - Freely available for research from the Princeton site
  - http://wordnet.princeton.edu/
- Information about a variety of SEMANTICAL RELATIONS
- Three sub-databases (supported by psychological research as early as (Fillenbaum and Jones, 1965))
  - NOUNs
  - VERBS
  - ADJECTIVES and ADVERBS
    - But ***no*** coverage of closed-class parts of speech
- Each database organized around SYNSETS

The noun database

- About 90,000 forms, 116,000 senses
- Relations:

hyper(o)nym	breakfast -> meal
hyponym	meal -> lunch
has-member	faculty -> professor
member-of	copilot -> crew
has-part	table -> leg
part-of	course -> meal
antonym	leader -> follower

Synsets

- Senses (or `lexicalized concepts') are represented in WordNet by the set of words that can be used in AT LEAST ONE CONTEXT to express that sense / lexicalized concept
  - the SYNSET
- E.g.,

{chump, fish, fool, gull, mark, patsy, fall guy, sucker, shlemiel, soft touch, mug}

(gloss: *person who is gullible and easy to take advantage of*)

Hyperonyms

2 senses of robin

Sense 1
robin, redbreast, robin redbreast, Old World robin, Erithacus rubecola -- (small Old World songbird with a reddish breast)
=> thrush -- (songbirds characteristically having brownish upper plumage with a spotted breast)
=> oscine, oscine bird -- (passerine bird having specialized vocal apparatus)
=> passerine, passeriform bird -- (perching birds mostly small and living near the ground with feet having 4 toes arranged to allow for gripping the perch; most are songbirds; hatchlings are helpless)
=> bird -- (warm-blooded egg-laying vertebrates characterized by feathers and forelimbs modified as wings)
=> vertebrate, craniate -- (animals having a bony or cartilaginous skeleton with a segmented spinal column and a large brain enclosed in a skull or cranium)
=> chordate -- (any animal of the phylum Chordata having a notochord or spinal column)
=> animal, animate being, beast, brute, creature, fauna -- (a living organism characterized by voluntary movement)
=> organism, being -- (a living thing that has (or can develop) the ability to act or function independently)
=> living thing, animate thing -- (a living (or once living) entity)
=> object, physical object --
=> entity, physical thing --

Meronymy

$ wn beak –holon

Holonyms of noun beak

1 of 3 senses of beak

Sense 2
beak, bill, neb, nib
PART OF: bird

The verb database

- About 10,000 forms, 20,000 senses
- Relations between verb meanings:

Hyperonym	fly-> travel
Troponym	walk -> stroll
Entails	snore -> sleep
Antonym	increase -> decrease

V1 ENTAILS V2
when *Someone V1* (logically) entails *Someone V2*
- e.g., *snore* entails *sleep*

TROPONYMY
when *To do V1* is *To do V2 in some manner*
- e.g., *limp* is a troponym of *walk*

The adjective and adverb database

- About 20,000 adjective forms, 30,000 senses
- 4,000 adverbs, 5600 senses
- Relations:

Antonym (adjective)	heavy <-> light
Antonym (adverb)	quickly <-> slowly

How to use

- Online: http://wordnet.princeton.edu/perl/webwn
- Download (various APIs; some archaic)
- C. Fellbaum (ed), *Wordnet: An Electronic Lexical Database*, The MIT Press

WORD SENSE DISAMBIGUATION

Identifying the sense of a word in its context

- The task of Word Sense Disambiguation is to determine which of various senses of a word are invoked in context:
  - *the seed companies cut off the tassels of each plant, making it male sterile*
  - *Nissan's Tennessee manufacturing plant beat back a United Auto Workers organizing effort with aggressive tactics*
  - This is generally viewed as a categorization/tagging task
    - So, similar task to that of POS tagging
    - But this is a simplification!
    - Less agreement on what the senses are, so the UPPER BOUND is lower
- Word sense discrimination is the problem of dividing the usages of a word into different meanings, without regard to any particular existing sense inventory. Involves unsupervised techniques.
- Clear potential uses include Machine Translation, Information Retrieval, Question Answering, Knowledge Acquisition, even Parsing.
  - Though in practice the implementation path hasn't always been clear

Early Days of WSD

- Often taken as a proxy for Machine Translation (Weaver, 1949)
  - A word can often only be translated if you know the specific sense intended (A bill in English could be a pico or a cuenta in Spanish)
- Bar-Hillel (1960) posed the following problem:
  - *Little John was looking for his toy box. Finally, he found it. The box was in the pen. John was very happy.*
  - Is “pen” a writing instrument or an enclosure where children play?

…declared it unsolvable, and left the field of MT (!):

- “Assume, for simplicity's sake, that *pen* in English has only the following two meanings: (1) a certain writing utensil, (2) an enclosure where small children can play. I now claim that no existing or imaginable program will enable an electronic computer to determine that the word *pen* in the given sentence within the given context has the second of the above meanings, whereas every reader with a sufficient knowledge of English will do this ‘automatically’.” (1960, p. 159)

Bar-Hillel

- "Let me state rather dogmatically that there exists at this moment no method of reducing the polysemy of the, say, twenty words of an average Russian sentence in a scientific article below a remainder of, I would estimate, at least five or six words with multiple English renderings, which would not seriously endanger the quality of the machine output. Many tend to believe that by reducing the number of initially possible renderings of a twenty word Russian sentence from a few tens of thousands (which is the approximate number resulting from the assumption that each of the twenty Russian words has two renderings on the average, while seven or eight of them have only one rendering) to some eighty (which would be the number of renderings on the assumption that sixteen words are uniquely rendered and four have three renderings apiece, forgetting now about all the other aspects such as change of word order, etc.) the main bulk of this kind of work has been achieved, the remainder requiring only some slight additional effort" (Bar-Hillel, 1960, p. 163).

Identifying the sense of a word in its context

- Most early work used semantic networks, frames, logical reasoning, or ``expert system'' methods for disambiguation based on contexts (e.g., Small 1980, Hirst 1988).
- The problem got quite out of hand:
  - The word expert for `throw' is ``currently six pages long, but should be ten times that size'' (Small and Rieger 1982)
- Supervised machine learning sense disambiguation through use of context is frequently extremely successful -- and is a straightforward classification problem
- However, it requires extensive annotated training data
- Much recent work focuses on minimizing need for annotation.

Philosophy

- “You shall know a word by the company it keeps”
  - -- J. R. Firth (1957)
- “You say: the point isn't the word, but its meaning, and you think of the meaning as a thing of the same kind as the word, though also different from the word. Here the word, there the meaning. The money, and the cow that you can buy with it. (But contrast: money, and its use.)”
  - Wittgenstein, *Philosophical Investigations*
- “For a large class of cases—though not for all—in which we employ the word ‘meaning’ it can be defined thus: the meaning of a word is its use in the language.”
  - Wittgenstein, *Philosophical Investigations*

U.S. Supreme Court

- ”[it is a] fundamental principle of statutory construction (and, indeed, of language itself) that the meaning of a word cannot be determined in isolation, but must be drawn from the context in which it is used”

  Deal v. United States 508 U.S. 129, 132 (1993)

Corpora used for word sense disambiguation work

- **Sense Annotated (**Difficult and expensive to build)
  - Semcor (200,000 words from Brown)

    DSO (192,000 semantically annotated occurrences of 121 nouns and 70 verbs),

    Classic words: *interest, line, …*
  - Training data for Senseval competitions (lexical samples and running text)
- **Non Annotated (**Available in large quantity)
  - Brown, newswire, Web

SEMCOR


```
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<context filename="br-h15" paras="yes">
…..
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<wf cmd="done" pos="NN" lemma="fig" wnsn="1" lexsn="1:10:00::">fig.</wf>
<wf cmd="done" pos="NN" lemma="6" wnsn="1“ lexsn="1:23:00::">6</wf>
<punc>)</punc>
<wf cmd="done" pos="VBP" ot="notag">are</wf>
<wf cmd="done" pos="VB" lemma="slip" wnsn="3" lexsn="2:38:00::">slipped</wf>
<wf cmd="ignore" pos="IN">into</wf>
<wf cmd="done" pos="NN" lemma="place" wnsn="9" lexsn="1:15:05::">place</wf>
<wf cmd="ignore" pos="IN">across</wf>
<wf cmd="ignore" pos="DT">the</wf>
<wf cmd="done" pos="NN" lemma="roof" wnsn="1" lexsn="1:06:00::">roof</wf>
<wf cmd="done" pos="NN" lemma="beam" wnsn="2" lexsn="1:06:00::">beams</wf>
<punc>,</punc>
```


Dictionary-based approaches

- Lesk (1986):
  1. Retrieve from MRD all sense definitions of the word to be disambiguated
  2. Compare with sense definitions of words in context
  3. Choose sense with most overlap
- Example:

  PINE
  - 1 kinds of evergreen tree with needle-shaped leaves
  - 2 waste away through sorrow or illness

  CONE
  - 1 solid body which narrows to a point
  - 2 something of this shape whether solid or hollow
  - 3 fruit of certain evergreen trees
- Disambiguate: *PINE CONE*

Frequency-based word-sense disambiguation

- If you have a corpus in which each word is annotated with its sense, you can collect class-based unigram statistics (count the number of times each sense occurs in the corpus)

  P(SENSE)

  P(SENSE|WORD)
- E.g., if you have

  5845 uses of the word bridge,

  5641 cases in which it is tagged with the sense STRUCTURE

  194 instances with the sense DENTAL-DEVICE
- Frequency-based WSD can get about 60-70% correct!

  The WordNet first sense heuristic is good!
- To improve upon these results, need context

Traditional selectional restrictions

- One type of contextual information is the information about the type of arguments that a verb takes – its SELECTIONAL RESTRICTIONS:

  AGENT EAT FOOD-STUFF

  AGENT DRIVE VEHICLE
- Example:

  Which airlines serve DENVER?

  Which airlines serve BREAKFAST?
- Limitations:

  In his two championship trials, Mr. Kulkarni ATE GLASS on an empty stomach, accompanied only by water and tea.

  But it fell apart in 1931, perhaps because people realized that you can't EAT GOLD for lunch if you're hungry
- Resnik (1998): 44% with these methods

Context in general

- But it's not just classic selectional restrictions that are useful context

  Often simply knowing the topic is really useful!

Supervised approaches to WSD: the rebirth of Naïve Bayes in CompLing

- A Naïve Bayes Classifier chooses the most probable sense for a word given the context:

$$s = \text{argmax } P(s_k|C)$$

- As usual, this can be expressed as:

$$s = \text{argmax} \frac{P(C|s_k)P(s_k)}{P(C)}$$

- The "NAÏVE BAYES" ASSUMPTION: all the features are independent

$$P(C|s_k) \approx \prod_{j=1}^{n} P(v_j|s_k)$$

An example of use of Naïve Bayes classifiers: Gale et al (1992)

- Used this method to disambiguated word senses using an ALIGNED CORPUS (Hansard) to get the word senses

English	French	Sense	Number of examples
duty	droit devoir	tax obligation	1114 691
drug	medicament drogue	medical illicit	2292 855
land	terre pays	property country	1022 386

Gale et al: words as contextual clues

- Gale et al. view a *context* as a substring of words of some length (how long?) at some distance away (how far?)
- Good clues for the different senses of DRUG:
  - Medication: *prices, prescription, patent, increase, consumer*
  - Illegal substance: *abuse, paraphernalia, illicit, cocaine, trafficking*
- To determine which interpretation is more likely, extract words (e.g. ABUSE) from context, and use P(abuse|medicament), P(abuse|drogue) estimated as smoothed relative frequency
- Gale et al (1992): disambiguation system using this algorithm correct for about 90% of occurrences of six ambiguous nouns in the Hansard corpus:
  - duty, drug, land, language, position, sentence
- BUT THIS WAS FOR TWO CLEARLY DIFFERENT SENSES, i.e. homonymy disambiguation

Gale, Church, and Yarowsky (1992): Even Remote Context is Informative

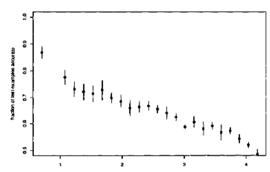


Figure II. Remote context is informative.
The horizontal axis shows the distance of context words from an ambiguous word, while the vertical scale shows the percent correct when using ten context words at the specified distance in doing the disambiguation. The vertical lines show the mean and standard deviation of mean for six disambiguations. With two equiprobable choices, 50 percent represents chance performance. Performance remains above chance for ten word contexts up to ten thousand words away from the ambiguous word.

Gale, Church, and Yarowsky (1992): Wide Contexts are Useful

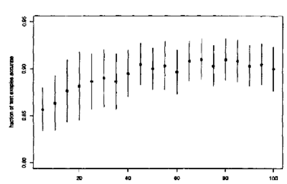


Figure III. Wide contexts are useful.
The horizontal axis shows the maximum distance of context words from an ambiguous word, while the vertical scale shows the percent correct when using all context words out to the specified distance in disambiguation. While performance rises very rapidly with the first few words, it clearly continues to improve through about twenty words, and is not worse by fifty words.

Gale, Church, and Yarowsky (1992): Even just a few training instances help

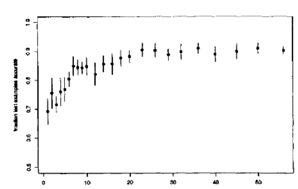


Figure IV. Just a few training examples do surprisingly well.
The horizontal axis shows the number of examples used in training while the vertical scale shows the mean percent correct in six disambiguations. The performance increases rapidly for the first few examples, and seems to have reached a maximum by 50 or 60 examples.

Other methods for WSD

- Supervised:
  - Brown et al, 1991: using mutual information to combine senses into groups
  - Yarowsky (1992): using a thesaurus and a topic-classified corpus
  - More recently, any machine learning method whose name you know
- Unsupervised: sense DISCRIMINATION
  - Schuetze 1996: using EM algorithm based clustering, LSA
- Mixed
  - Yarowsky's 1995 bootstrapping algorithm
    - Quite cool
    - A pioneering example of using context and content to constrain each other. More on this later
- Principles
  - One sense per collocation
  - One sense per discourse
  - Broad context vs. collocations: both are useful when used appropriately

Evaluation

- Baseline: is the system an improvement?
  - **Unsupervised**: Random, Simple-Lesk
  - **Supervised**: Most Frequent, Lesk-plus-corpus.
- Upper bound: agreement between humans?

SENSEVAL

- Goals:
  - Provide a common framework to compare WSD systems
  - Standardise the task (especially evaluation procedures)
  - Build and distribute new lexical resources
- Web site: http://www.senseval.org/
  - *"There are now many computer programs for automatically determining the sense of a word in context (Word Sense Disambiguation or WSD). The purpose of Senseval is to evaluate the strengths and weaknesses of such programs with respect to different words, different varieties of language, and different languages."* from: *http://www.sle.sharp.co.uk/senseval2*
- ACL-SIGLEX workshop (1997): Yarowsky and Resnik paper
- SENSEVAL-I (1998); SENSEVAL-II (Toulouse, 2001)
  - Lexical Sample and All Words
- SENSEVAL-III (2004); SENSEVAL-IV -> SEMEVAL (2007)

WSD at SENSEVAL-II

- Choosing the right sense for a word among those of WordNet

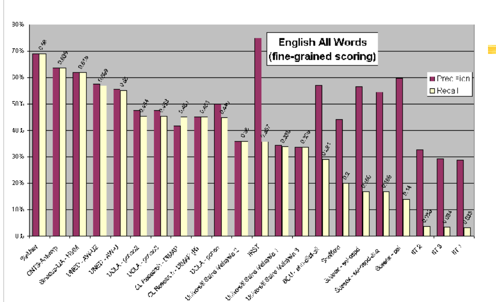
Corton has been involved in the design, manufacture and installation of ***horse*** *stalls and horse-related equipment like external doors, shutters and accessories.*

Sense 1: horse, Equus caballus -- (solid-hoofed herbivorous quadruped domesticated since prehistoric times)
Sense 2: horse -- (a padded gymnastic apparatus on legs)
Sense 3: cavalry, horse cavalry, horse -- (troops trained to fight on horseback: "500 horse led the attack")
Sense 4: sawhorse, horse, sawbuck, buck -- (a framework for holding wood that is being sawed)
Sense 5: knight, horse -- (a chessman in the shape of a horse's head; can move two squares horizontally and one vertically (or vice versa))
Sense 6: heroin, diacetyl morphine, H, horse, junk, scag, shit, smack -- (a morphine derivative)

English All Words: All N, V, Adj, Adv

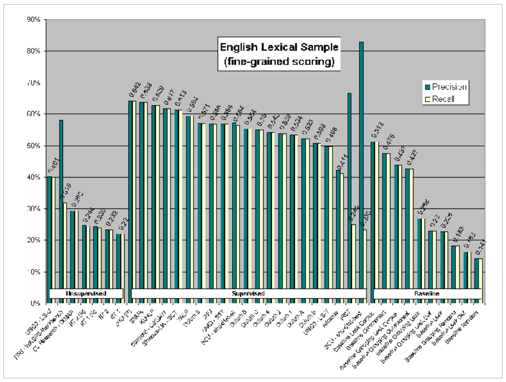
- **Data**: 3 texts for a total of 1770 words
- **Average "polysemy"**: 6.5
- **Example**: (part of) Text 1

The **art** of **change-ringing is peculiar** to the **English** and, like **most English peculiarities** , **unintelligible** to the **rest** of the **world** . -- Dorothy L. Sayers , " The Nine **Tailors** " ASLACTON , **England** -- Of all **scenes** that **evoke rural England** , this is one of the **loveliest** : An **ancient stone church stands** amid the **fields** , the **sound** of **bells cascading** from its **tower** , **calling** the **faithful** to **evensong** . The **parishioners** of St. Michael and All Angels **stop** to **chat** at the **church door** , as **members here always** have . […]



English Lexical Sample

- **Data**: 8699 texts for 73 words
- **Average WN polysemy**: 9.22
- **Training Data**: 8166 (average 118/word)
- **Baseline (commonest)**: 0.47 precision
- **Baseline (Lesk)**: 0.51 precision



Quiz

Which of the following was not one of Church and Gale's (1992) claims about WSD?

a) Context helps, even if very distant

b) Context helps, even if very wide

c) Context helps, even if POS tags are used instead of words

d) Context helps, even if only a few training examples

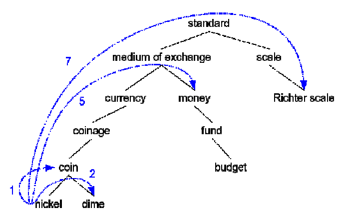
LEXICAL ACQUISITION: Lexical and Distributional notions of meaning similarity

Thesaurus-based word similarity

- How can we work out how similar in meaning words are?
- We could use anything in the thesaurus
  - Meronymy
  - Glosses
  - Example sentences
- In practice
  - By "thesaurus-based" we usually just mean
    - Using the is-a/subsumption/hyperonym hierarchy
- Word similarity versus word relatedness
  - Similar words are near-synonyms
  - Related could be related any way
    - Car, gasoline: related, not similar
    - Car, bicycle: similar

Path based similarity

- Two words are similar if nearby in thesaurus hierarchy (i.e. short path between them)



Problem with basic path-based similarity

- Assumes each link represents a uniform distance
- Nickel to money seems closer than nickel to standard
- Instead:
  - Want a 'metric' which lets us represent the cost of each edge independently
- There have been a whole slew of methods that augment thesaurus with notions from a corpus (Resnik, Lin, …)
  - But we won't cover them here.

The limits of hand-encoded lexical resources

- Manual construction of lexical resources is very costly
- Because language keeps changing, these resources have to be continuously updated
- Some information (e.g., about frequencies) has to be computed automatically anyway

The coverage problem

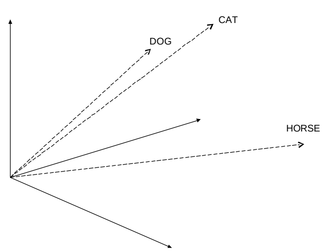
- Sampson (1989): tested coverage of Oxford ALD (~70,000 entries) looking at a 45,000-token subpart of the LOB. About 3% of tokens not listed in dictionary
- Examples:

Type of problem	Example
Proper noun	*Caramello, Chateau-Chalon*
Foreign word	*perestroika*
Rare/derived words	*reusability*
Code	*R101*
Non-standard English	*Havin'*
Hyphen omitted	*bedclothes*
Technical vocabulary	*normoglycaemia*

Vector-based lexical semantics

- Very old idea in NL engineering: the meaning of a word can be specified in terms of the values of certain `features' (`COMPONENTIAL SEMANTICS')
  - dog : ANIMATE= +, EAT=MEAT, SOCIAL=+
  - horse : ANIMATE= +, EAT=GRASS, SOCIAL=+
  - cat : ANIMATE= +, EAT=MEAT, SOCIAL=-
- Similarity / relatedness: proximity in feature space

Vector-based lexical semantics



General characterization of vector-based semantics

- Vectors as models of concepts
- The CLUSTERING approach to lexical semantics:
  1. Define properties one cares about, and give values to each property (generally, numerical)
  2. Create a vector of length n for each item to be classified
  3. Viewing the n-dimensional vector as a point in n-space, cluster points that are near one another
- What changes between models:
  1. The properties used in the vector
  2. The distance metric used to decide if two points are `close'
  3. The algorithm used to cluster
- For similarity based approaches, skip the 3rd step

Distributional Similarity: Using words as features in a vector-based semantics

- The old decompositional semantics approach requires
  1. Specifying the features
  2. Characterizing the value of these features for each lexeme
- Simpler approach: use as features the WORDS that occur in the proximity of that word / lexical entry
  - Intuition: Firth's "You shall know a word by the company it keeps."
- More specifically, you can use as `values' of these features
  - The FREQUENCIES with which these words occur near the words whose meaning we are defining
  - Or perhaps the PROBABILITIES that these words occur next to each other
- Some psychological results support this view. Lund, Burgess, et al (1995, 1997): lexical associations learned this way correlate very well with priming experiments. Landauer et al (1987): good correlation on a variety of topics, including human categorization & vocabulary tests.

Using neighboring words to specify the meaning of words

- Take, e.g., the following corpus:
  1. John ate a banana.
  2. John ate an apple.
  3. John drove a lorry.
- We can extract the following co-occurrence matrix:

	john	ate	drove	banana	apple	lorry
john	0	2	1	1	1	1
ate	2	0	0	1	1	0
drove	1	0	0	0	0	1
banana	1	1	0	0	0	0
apple	1	1	0	0	0	0
lorry	1	0	1	0	0	0

Acquiring lexical vectors from a corpus (Schuetze, 1991; Burgess and Lund, 1997)

- To construct vectors *C(w)* for each word *w*:
  1. Scan a text
  2. Whenever a word *w* is encountered, increment all cells of *C(w)* corresponding to the words *v* that occur in the vicinity of *w*, typically within a window of fixed size
- Differences among methods:
  - Size of window
  - Weighted / dampened or not
  - Whether every word in the vocabulary counts as a dimension (including function words such as *the* or *and*) or whether instead only some specially chosen words are used (typically, the m most common content words in the corpus; or perhaps modifiers only). The words chosen as dimensions are often called CONTEXT WORDS
  - Whether dimensionality reduction methods are applied

Variant: using modifiers to specify the meaning of words

- …. The Soviet cosmonaut …. The American astronaut …. The red American car …. The old red truck … the spacewalking cosmonaut … the full Moon …

	cosmonaut	astronaut	moon	car	truck
Soviet	1	0	0	1	1
American	0	1	0	1	1
spacewalking	1	1	0	0	0
red	0	0	0	1	1
full	0	0	1	0	0
old	0	0	0	1	1

Measures of semantic similarity

- Euclidean distance:

$$d=\sqrt{\sum_{i=1}^{n}\left(x_i-y_i\right)^2}$$

- Cosine:

$$\cos(\alpha)=\frac{\sum_{i=1}^{n}x_i y_i}{\sqrt{\sum_{i=1}^{n}x_i^2}\sqrt{\sum_{i=1}^{n}y_i^2}}$$

- Manhattan (L1) Metric:

$$d=\sum_{i=1}^{n}\left|x_i-y_i\right|$$

The HAL model (Burgess and Lund, 1995, 1997)

- A 160 million words corpus of articles extracted from all newsgroups containing English dialogue
- Context words: the 70,000 most frequently occurring symbols within the corpus
- Window size: 10 words to the left and the right of the word
- Measure of similarity: cosine

- *Frightened: scared, upset, shy, embarrassed, anxious, worried, afraid*
- *Harmed: abused, forced, treated, discriminated, allowed, attracted, taught*
- *Beatles: original, band, song, movie, album, songs, lyrics, British*

Latent Semantic Analysis (LSA) (Landauer et al, 1997)

- Goal: extract relatons of expected contextual usage from passages
- Steps:
  1. Build a word / document co-occurrence matrix
  2. `Weight' each cell (e.g., tf.idf)
  3. Perform a DIMENSIONALITY REDUCTION with SVD
- Argued to correlate well with humans on a number of tests

Detecting hyponymy and other relations

- Could we discover new hyponyms, and add them to a taxonomy under the appropriate hypernym?
- Why is this important?

  "**insulin**" and "**progesterone**" are in WordNet 2.1,
  but "**leptin**" and "**pregnenolone**" are not.

  "**combustibility**" and "**navigability**",
  but not "**affordability**", "**reusability**", or "**extensibility**".

  "**HTML**" and "**SGML**", but not "**XML**" or "**XHTML**".

  "**Google**" and "**Yahoo**", but not "**Microsoft**" or "**IBM**".
- This **unknown word problem** occurs throughout NLP

Hearst (1992) Approach

- Agar is a substance prepared from a mixture of red algae, such as Gelidium, for laboratory or industrial use.
- What does Gelidium mean? How do you know?

$$NP_0 \textit{ such as } NP_1\{, NP_2 \ldots, (and|or) NP_i\}, i \geq 1$$
implies the following semantics
$$\forall NP_i, i \geq 1, \text{hyponym}(NP_i, NP_0)$$
allowing us to infer
$$\text{hyponym(Gelidium, red algae)}$$

Hearst's hand-built patterns

$NP\{, NP\} * \{,\}$ (and|or) other NP_H	…temples, treasuries, and other important civic buildings.
NP_H such as $\{NP,\}^*$ (or and) NP	red algae such as Gelidium
such NP_H as $\{NP,\}^*$ (or and) NP	works by such authors as Herrick, Goldsmith, and Shakespeare
NP_H $\{,\}$ including $\{NP,\}^*$ (or|and) NP	All common law countries, including Canada and England
NP_H $\{,\}$ especially $\{NP,\}^*$ (or|and) NP	…most European countries, especially France, England, and Spain

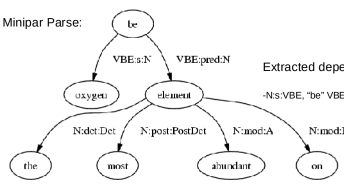
Recording the Lexico-Syntactic Environment with MINIPAR Syntactic Dependency Paths

MINIPAR: A dependency parser (Lin, 1998)

Example Word Pair: "**oxygen / element**"

Example Sentence: "Oxygen is the most abundant element on the moon."

Minipar Parse:



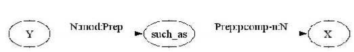
Extracted dependency path:

-N:s:VBE, "be" VBE:pred:N

Each of Hearst's patterns can be captured by a syntactic dependency path in MINIPAR:

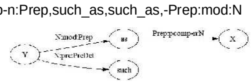
Hearst Pattern — **MINIPAR Representation**

Y such as X…



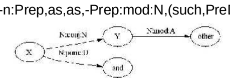
-N:pcomp-n:Prep,such_as,such_as,-Prep:mod:N

Such Y as X…



-N:pcomp-n:Prep,as,as,-Prep:mod:N,(such,PreDet:pre:N)}

X… and other Y



(and,U:punc:N),N:conj:N, (other,A:mod:N)

Algorithm (Snow, Jurafsky, and Ng 2005)

- Collect noun pairs from corpora
  - (752,311 pairs from 6 million words of newswire)
- Identify each pair as positive or negative example of hyperonym-hyponym relationship
  - (14,387 yes, 737,924 no)
- Parse the sentences, extract patterns
  - (69,592 dependency paths occurring in >5 pairs)
- Train a hyperonym classifier on these patterns
  - We could interpret each path as a binary classifier
  - Better: **logistic regression** with 69,592 features
    - (actually converted to 974,288 bucketed binary features)

Using Discovered Patterns to Find Novel Hyponym/Hyperonym Pairs

Example of a discovered high-precision path:
-N:desc:V,call,call,-V:vrel:N: **“<hyperonym> ‘called’ <hyponym>”**

Learned from cases such as:

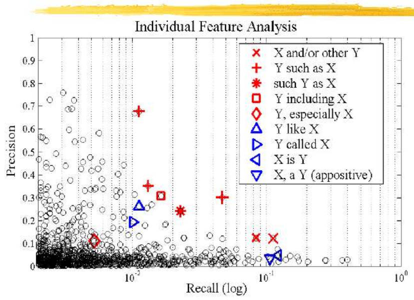
“sarcoma / cancer”: …an uncommon bone **cancer called osteogenic sarcoma** and to…
“deuterium / atom” ….heavy water rich in the doubly heavy hydrogen **atom called deuterium**.

May be used to discover new hyperonym pairs not in WordNet:

“*efflorescence / condition*”: …and a **condition called efflorescence** are other reasons for…
“*’neal_inc / company*” …The **company, now called O'Neal Inc.**, was sole distributor of E-Ferol…
“*hat_creek_outfit / ranch*” …run a small **ranch called the Hat Creek Outfit**.
“*tardive_dyskinesia / problem*”: ... irreversible **problem called tardive dyskinesia**…
“*hiv-1 / aids_virus*” …infected by the **AIDS virus, called HIV-1**.
“*bateau_mouche / attraction*” …local sightseeing **attraction called the Bateau Mouche**...
“*kibbutz_malkiyya / collective_farm*” …an Israeli **collective farm called Kibbutz Malkiyya**…

But 70,000 patterns are better than one!

Using each pattern/feature as a binary classifier: Hyperonym Precision / Recall



There are lots of fun lexical semantic tasks: Logical Metonymy

- (Pustejovsky 1991, 1995, Lapata and Lascarides 1999)
- Additional meaning arises from chracterization of an event:
  - Mary finished her dinner -->
    - Mary finished eating her dinner
  - Mary finished her beer -->
    - Mary finished drinking her beer
    - NOT Mary finished eating her beer
  - Mary finished her sweater -->
    - Mary finished knitting her sweater
    - NOT Mary finished eating her sweater

- How can we work out the implicit activities?

Logical metonymy

- Easy cake --> easy cake to bake
- Good soup --> good to eat NOT enjoyable to make
- Fast plane --> flies fast NOT fast to construct

- There is a default interpretation, but it depends on context:
  - All the office personnel took part in the company sports day last week.
  - One of the programmers was a good athlete, but the other was struggling to finish the events.
  - The fast programmer came first in the 100m.

- Some cases seem to lack default metonymic interpretations
  - ? John enjoyed the dictionary

How can you learn them? (Lapata and Lascarides 1999)

- Corpus statistics!
- But cases that fill in the metonymic interpretation (*begin V NP* or *like V NP*) are too rare -- not regularly used
- So just use general facts about verb complements
  - The likelihood of an event is assumed to be independent of whether it is the complement of another verb.
    - $P(o|e,v) \approx P(o|e)$
- Examples learned by model:
  - Begin story --> begin to tell story
  - Begin song --> begin to sing song
  - Begin sandwich --> begin to bite into sandwich
  - Enjoy book --> enjoy reading book

- This doesn’t do context-based interpretation, of course!