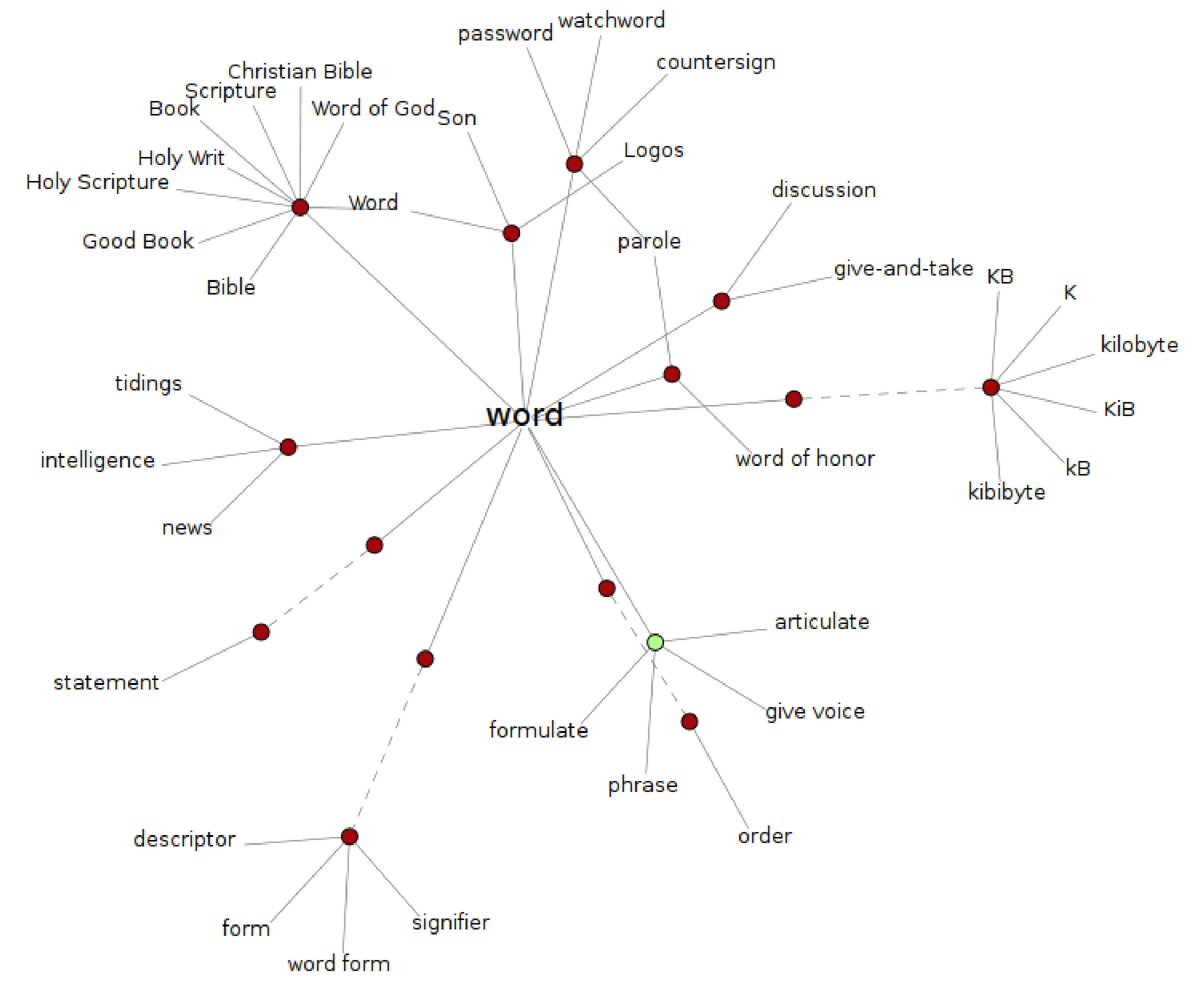


COMP90042 LECTURE 8

LEXICAL SEMANTICS

WHAT DO WORDS MEAN?

- Referents in the physical or social world
  - But not usually useful in text analysis
- Their dictionary definition
  - But dictionary definitions are necessarily circular
  - Only useful if meaning is already understood
- Their relationships with other words
  - Also circular, but more practical

THREE KINDS OF SEMANTICS

- Logical semantics
  - How facts about the world can be represented
- Distributional semantics
  - How word co-occurrence reflect their meaning
- Lexical semantics
  - How the meanings of words connect to one another

WORDS AND SENSES

- Orthographic word type is wrong unit for semantic analysis

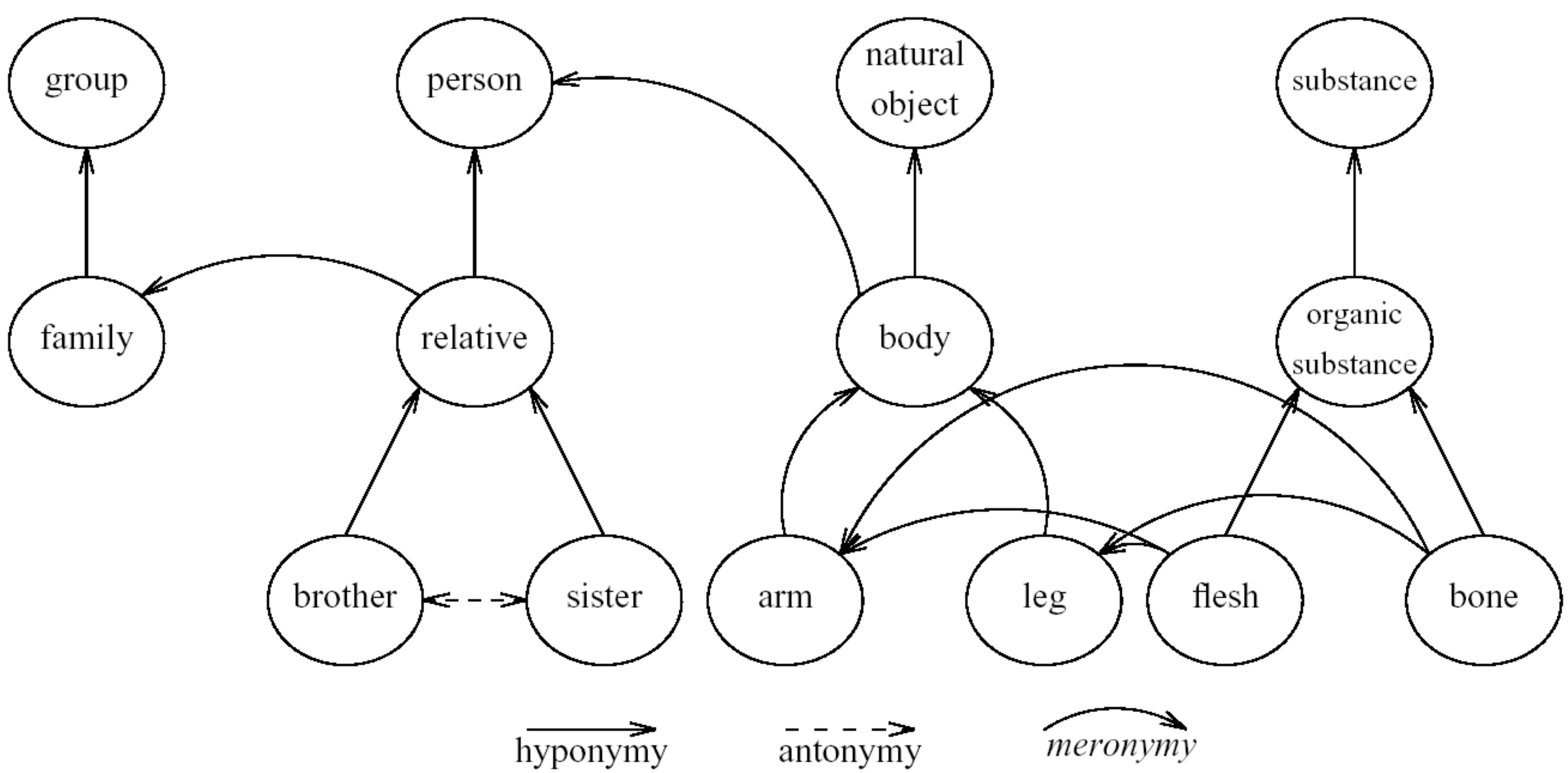
Bank (noun):

> *1. A financial institution; a building where a financial institution offers services; a repository; a container for holding money*
> *2. Land sloping down to a body of water*

- *Bank* has many senses (more than just these)
- 1 and 2 are *homonyms*
  - Considered different lexical items by lexicographers
- 1 shows *polysemy*
  - Related senses of the same lexical item

BASIC LEXICAL RELATIONS

- Synonyms (same) and antonyms (opposite/complementary)
- Hypernyms (generic), hyponyms (specific)
- Holoynms (whole) and meronyms (part)



WORDNET

- A database of lexical relations
- English WordNet includes ~120,000 nouns, ~12,000 verbs, ~21,000 adjectives, ~4,000 adverbs
- WordNets available in most major languages (www.globalwordnet.org)
- English version freely available (accessible via NLTK)

SYNSETS

- The nodes of WordNet are not words, but meanings
- There are represented by sets of synonyms, or *synsets*

>>> nltk.corpus.wordnet.synsets('bank')

[Synset('bank.n.01'), Synset('depository_financial_institution.n.01'), Synset('bank.n.03'), Synset('bank.n.04'), Synset('bank.n.05'), Synset('bank.n.06'), Synset('bank.n.07'), Synset('savings_bank.n.02'), Synset('bank.n.09'), Synset('bank.n.10'), Synset('bank.v.01'), Synset('bank.v.02'), Synset('bank.v.03'), Synset('bank.v.04'), Synset('bank.v.05'), Synset('deposit.v.02'), Synset('bank.v.07'), Synset('trust.v.01')]

>>> nltk.corpus.wordnet.synsets('bank')[0].definition()

u'sloping land (especially the slope beside a body of water)'

>>> nltk.corpus.wordnet.synsets('bank')[1].lemma_names()

[u'depository_financial_institution', u'bank', u'banking_concern', u'banking_company']

LEXICAL RELATIONS IN WORDNET

- Connections between nodes are lexical relations
- Including all the major ones mentioned earlier

```
>>> nltk.corpus.wordnet.synsets('relative')[0].hypernyms()

[Synset('person.n.01')]

>>> nltk.corpus.wordnet.synsets('body')[0].part_meronyms()

[Synset('arm.n.01'), Synset('articulatory_system.n.01'), Synset('body_substance.n.01'),
Synset('cavity.n.04'), Synset('circulatory_system.n.01'), Synset('crotch.n.02'),
Synset('digestive_system.n.01'), Synset('endocrine_system.n.01'), Synset('head.n.01'), Synset('leg.n.01'),
Synset('lymphatic_system.n.01'), Synset('musculoskeletal_system.n.01'), Synset('neck.n.01'),
Synset('nervous_system.n.01'), Synset('pressure_point.n.01'), Synset('respiratory_system.n.01'),
Synset('sensory_system.n.02'), Synset('torso.n.01'), Synset('vascular_system.n.01')]

>>> print nltk.corpus.wordnet.lemmas('sister')[0].antonyms()

[Lemma('brother.n.01.brother')]
```

WORD SIMILARITY WITH PATHS

- Want to go beyond specific lexical relations
  - E.g. *money* and *nickel* are related, despite no direct lexical relationship
- Given WordNet, find similarity based on path length in hypernym/hyponym tree

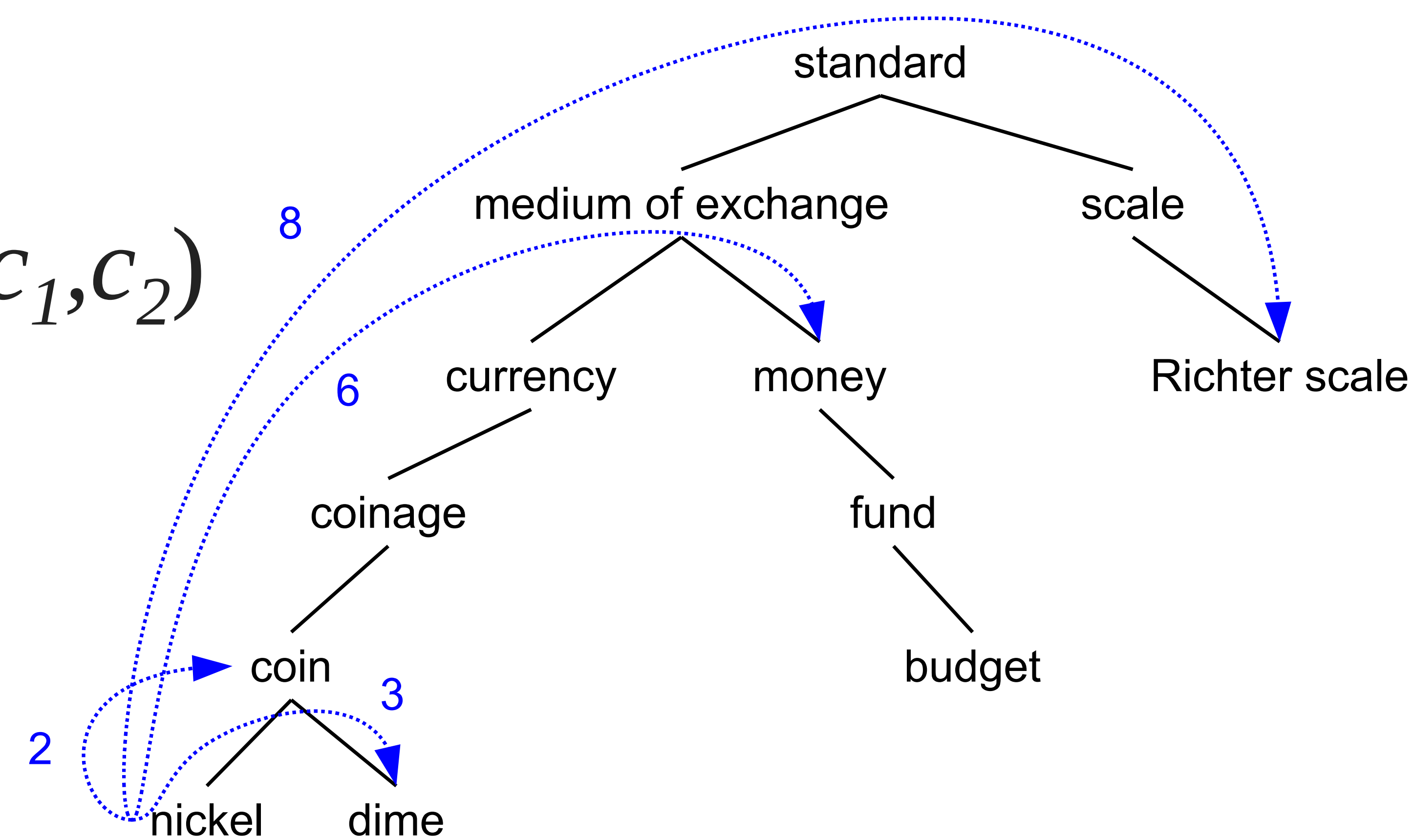
$$\text{simpath}(c_1,c_2) = 1/\text{pathlen}(c_1,c_2)$$

simpath(*nickel,coin*) = 1/2 = .5

simpath(*nickel,currency*) = 1/4 = .25

simpath(*nickel,money*) = 1/6 = .17

simpath(*nickel,Richter scale*) = 1/8 = .13



BEYOND PATH LENGTH

- Problem: edges vary widely in actual semantic distance
  - Much bigger jumps near top of hierarchy
- Solution 1: include depth information (Wu & Palmer)
  - Use path to find lowest common subsumer (LCS)
  - Compare using depths

$$\text{simwup}(c_1,c_2) = \frac{2*\text{depth}(\text{LCS}(c_1,c_2))}{\text{depth}(c_1) + \text{depth}(c_2)}$$

simwup(*nickel*,*money*) = 2*2/(3+ 6) = .44

simwup(*nickel*,*Richter scale*) = 2*1/(3 + 6) = .22

INFORMATION CONTENT

- But count of edges is still poor semantic distance metric
- Solution 2: include statistics from corpus (Resnik; Lin)
  - P(c): probability that word in corpus is instance of concept *c*

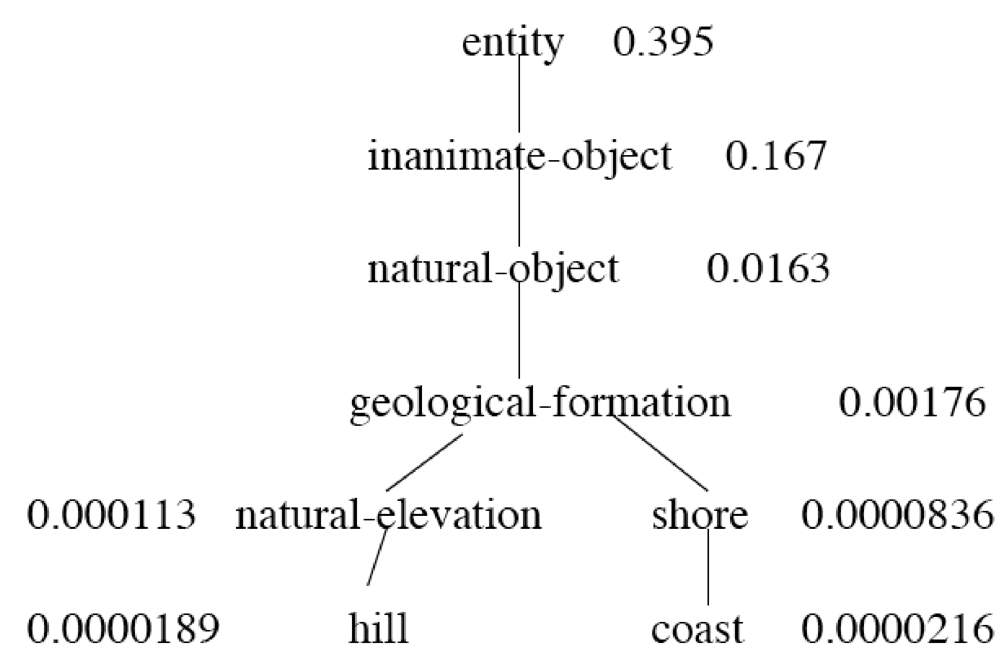
$$P(c) = \frac{\sum_{w \in words(c)} count(w)}{N}$$

  - information content (IC)

$$IC(c) = -\log P(c)$$

  - Lin distance

$$\text{simlin}(c_1,c_2) = \frac{2 * \text{IC}(\text{LCS}(c_1,c_2))}{\text{IC}(c_1) + \text{IC}(c_2)}$$



WORD SENSE DISAMBIGUATION

- But how to go from words in text to senses in WordNet?
  - Hacky (but popular) "solutions":
    - Assume the most popular sense
    - For word similarity, take minimum across senses
  - The proper (but difficult) solution: Word Sense Disambiguation
- Good WSD potentially useful for many tasks in NLP
  - In practice, often ignored because good WSD too hard
- WordNet as sense inventory a great resource for WSD
  - Also problematic, because too comprehensive

SUPERVISED WSD

- Apply standard machine classifiers
- Feature vectors typically words and syntax around target
  - But context is ambiguous too!
  - How big should context window be? (typically very small)
- Requires sense-tagged corpora
  - E.g. SENSEVEL, SEMCOR (available in NLTK)
  - Very time consuming to create!

LESS SUPERVISED APPROACHES

- Lesk: Choose sense whose dictionary gloss from WordNet most overlaps with the context
- Yarowsky: Bootstrap method
  - Create a small seed training set
    - *plant* (factory vs. vegetation): *manufacturing plant*, *plant life*
  - Iteratively expand training set with untagged examples
    - Train a statistical classifier on current training set
    - Add confidently predicted examples to training set
  - Uses *one sense per collocation*, *one sense per document*
- Graph methods in WordNet

FRAMENET

- A lexical data base of *frames*, typically prototypical situations
  - E.g. "apply_heat" frame
- Includes lists of *lexical units* that evoke the frame
  - E.g. *cook*, *fry*, *bake*, *boil*, etc.
- Lists of *semantic roles* or *frame elements*
  - *E.g.* "the cook", "the food", "the container", "the instrument"
- Semantic relationships among frames
  - "apply_heat" is Causitive of "absorb_heat", is Used by "cooking_creation"

LEXICONS FOR TEXT ANALYSIS

- General Inquirer lexicon
  - Large set of words tagged for 150+ categories
  - Tags for psychological, social, and topic distinctions
  - Best known in NLP for positive/negative tags
- Linguistic Inquiry and Word Count (LIWC) lexicons
  - Largest and most well known text analysis tool
  - Major lexical categories: affect; social; cognitive processes; perpetual processes; biological processes; core drives and needs; time orientation; relativity; personal concerns; informal speech

OTHER USEFUL LEXICONS IN NLTK

- Names: List of male and female names
- Gazetteer List: lists of cities and countries
  - Comprehensive lists of locations at www.geonames.org
- WordList: lists of words for various languages
- Stopwords: list of stopwords for various languages
- Cmudict: a pronounciation dictionary

MULTIWORD LEXICONS

- Many lexical items involve multiple words
  - Semantically *non-compositional* (United States ≠ United + States)
  - Sometimes non-contiguous (*take him/her/them for a ride*)
- Both WordNet and FrameNet contain *multiword expressions* (MWEs)
  - But far from comprehensive
- In fact, no comprehensive collection of MWEs exists
  - MWE/collocation identification is a classic NLP task
- See http://www.cs.cmu.edu/~ark/LexSem/ for a good collection taken from various sources

MOVING ON TO THE CORPUS

- Manually-tagged lexical resources an important starting point for text analysis
- But much modern work attempts to derive semantic information directly from corpora, without human intervention
- Let's add some distributional information

FURTHER READING

- JM2 19.1-19.4 (lexical semantics and Word/FrameNet)
- JM2 20.1-20.6 (WSD and word similarity)