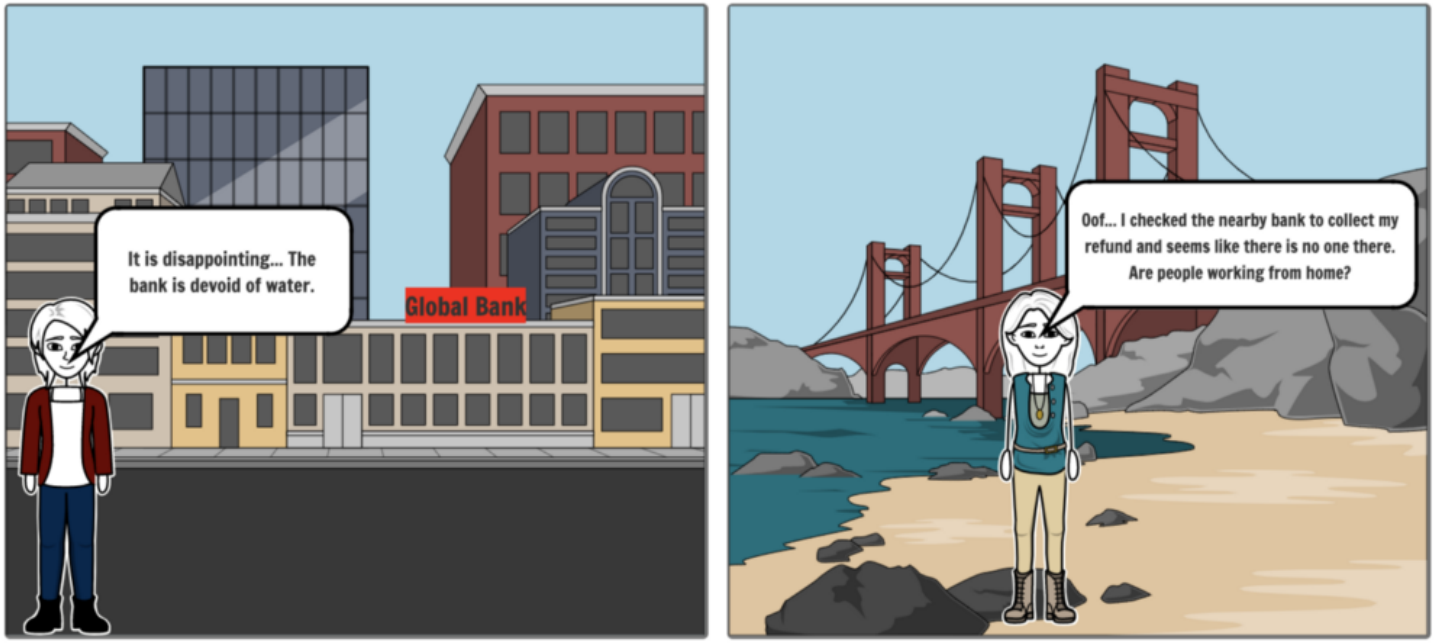
University of Ljubljana, Faculty of Computer and Information Science

Word senses and word sense disambiguation



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Natural Language Processing, Edition 2022

Contents

- Lexical semantics
- Computational lexical semantics
- Wordnet
- Word-sense disambiguation

- Literature and many slides: Jurafsky and Martin, 3rd edition, version 2021

Terminology: lemma and wordform

- A **lemma** or **citation form**
  - Same stem, part of speech, rough semantics
- A **wordform**
  - The inflected word as it appears in text

Wordform	Lemma
banks	bank
sung	sing
duermes	dormir
pleše	plesati

Lemmas have senses

- One lemma "bank" can have many meanings:

Sense 1: …a **bank** can hold the investments in a custodial account…

Sense 2: "…as agriculture burgeons on the east **bank** the river will shrink even more"

- **Sense** (or **word sense**)
  - A discrete representation of an aspect of a word's meaning.
- The lemma **bank** here has two senses

Homonymy

Homonyms (slo. homonimi, enakozvočnice): words that share a form but have unrelated, distinct meanings:

- $bank_1$: financial institution, $bank_2$: sloping land
- bat_1: club for hitting a ball, bat_2: nocturnal flying mammal

- prst (del roke) in prst (zemlja)
- klop (sedež) in klop (zajedalec)
- list (del rastline) in list (papir)
- dolg (pridevnik, lastnost) in dolg (samostalnik, finance)

1. Homographs (slo. homografi, enakopisnice) (bank/bank, bat/bat)
2. Homophones (slo. homofoni, enakoglasnice)
    1. Write and right
    2. Piece and peace
    3. bel (barva) in bev (mijavk)

Homonymy causes problems for NLP applications

- Information retrieval
  - "`bat care`"
- Machine Translation (to Spanish)
  - `bat`: murciélago (animal) or bate (for baseball)
- Text-to-Speech
  - `bass` (stringed instrument) vs. `bass` (fish)

Polysemy

- 1. The **bank** was constructed in 1875 out of local red brick.
- 2. I withdrew the money from the **bank**
- Are those the same sense?
  - Sense 2: “A financial institution”
  - Sense 1: “The building belonging to a financial institution”
- A **polysemous** word has **related** meanings
  - In English, most non-rare words have multiple meanings

Metonymy or Systematic Polysemy: A systematic relationship between senses

- Lots of types of polysemy are systematic
  - `School, university, hospital`
  - All can mean the institution or the building.
- A systematic relationship:
  - Building <--> Organization
- Many more such kinds of systematic polysemy:

Author (`Jane Austen wrote Emma`) <--> Works of Author (`I love Jane Austen`)

Tree (`Plums have beautiful blossoms`) <--> Fruit (`I ate a preserved plum`)

How do we know when a word has more than one sense?

- The "zeugma" test: Two senses of `serve`?
  - `Which flights **serve** breakfast?`
  - `Does Lufthansa **serve** Philadelphia?`
  - ?Does Lufthansa serve breakfast and San Jose?
- Since this conjunction sounds weird,
  - we say that these are **two different senses of "serve"**

Synonyms

- Word that have the same meaning in some or all contexts.
  - filbert / hazelnut
  - couch / sofa
  - big / large
  - automobile / car
  - vomit / throw up
  - Water / H_20
- Two lexemes are synonyms
  - if they can be substituted for each other in all situations
  - If so, they have the same propositional meaning

Synonyms

- But there are few (or no) examples of perfect synonymy.
  - Even if many aspects of meaning are identical
  - Still may not preserve the acceptability based on notions of politeness, slang, register, genre, etc.
- Example:
  - Water/H_20
  - Big/large
  - Brave/courageous

Synonymy is a relation between senses rather than words

- Consider the words *big* and *large*
- Are they synonyms?
  - How **big** is that plane?
  - Would I be flying on a **large** or small plane?
- How about here:
  - Miss Nelson became a kind of **big** sister to Benjamin.
  - ?Miss Nelson became a kind of **large** sister to Benjamin.
- Why?
  - *big* has a sense that means being older, or grown up
  - *large* lacks this sense

Antonyms

- Senses that are opposites with respect to one feature of meaning
- Otherwise, they are very similar!

  `dark/light  short/long  fast/slow  rise/fall`

  `hot/cold  up/down  in/out`

- More formally: antonyms can
  - define a binary opposition or be at opposite ends of a scale
    - `long/short, fast/slow`
  - Be **reversives**:
    - `rise/fall, up/down`

Hyponymy and Hypernymy

- One sense is a **hyponym** of another if the first sense is more specific, denoting a subclass of the other
  - *car* is a hyponym of *vehicle*
  - *mango* is a hyponym of *fruit*
- Conversely **hypernym/superordinate** ("hyper is super")
  - *vehicle* is a **hypernym** of *car*
  - *fruit* is a hypernym of *mango*

Superordinate/hyper	vehicle	fruit	furniture
Subordinate/hyponym	car	mango	chair

Hyponymy more formally

- Extensional:
  - The class denoted by the superordinate extensionally includes the class denoted by the hyponym
- Entailment:
  - A sense A is a hyponym of sense B if *being an A* entails *being a B*
- Hyponymy is usually transitive
  - (A hypo B and B hypo C entails A hypo C)
- Another name: the **IS-A hierarchy**
  - A IS-A B (or A ISA B)
  - B **subsumes** A

Hyponyms and Instances

- WordNet has both **classes** and **instances**.
- An **instance** is an individual, a proper noun that is a unique entity
  - `San Francisco` is an **instance** of `city`
  - But `city` is a class
    - `city` is a **hyponym** of `municipality...location...`

Meronymy

- The part-whole relation
  - A *leg* is part of a *chair*; a *wheel* is part of a *car*.
- *Wheel* is a **meronym** of *car*, and *car* is a **holonym** of *wheel*.

WordNet 3

- A hierarchically organized lexical database
- On-line thesaurus + aspects of a dictionary
    - Many other languages available
        - –(Arabic, Finnish, German, Portuguese, Slovene, Polish, …)

Category	Unique Strings
Noun	117,798
Verb	11,529
Adjective	22,479
Adverb	4,481

Senses of “bass” in Wordnet

Noun

- S: (n) **bass** (the lowest part of the musical range)
- S: (n) **bass**, bass part (the lowest part in polyphonic music)
- **S: (n) bass, basso (an adult male singer with the lowest voice)**
- S: (n) sea bass, **bass** (the lean flesh of a saltwater fish of the family Serranidae)
- S: (n) freshwater bass, **bass** (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
- S: (n) **bass**, bass voice, basso (the lowest adult male singing voice)
- S: (n) **bass** (the member with the lowest range of a family of musical instruments)
- S: (n) **bass** (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

Adjective

- S: (adj) **bass**, deep (having or denoting a low vocal or instrumental range) *"a deep voice"; "a bass voice is lower than a baritone voice"; "a bass clarinet"*

How is “sense” defined in WordNet?

- **The synset (synonym set),** the set of near-synonyms, instantiates a sense or concept, with a gloss
- Example: chump as a noun with the gloss:

  “a person who is gullible and easy to take advantage of”
- This sense of “chump” is shared by 9 words:

  chump[1], fool[2], gull[1], mark[9], patsy[1], fall guy[1], sucker[1], soft touch[1], mug[2]
- Each of **these** senses have this same gloss
  - (Not **every** sense; sense 2 of gull is the aquatic bird)

WordNet Hypernym Hierarchy for “bass”

- S: (n) **bass**, basso (an adult male singer with the lowest voice)
  - *direct hypernym* / ***inherited hypernym*** / *sister term*
    - S: (n) singer, vocalist, vocalizer, vocaliser (a person who sings)
      - S: (n) musician, instrumentalist, player (someone who plays a musical instrument (as a profession))
        - S: (n) performer, performing artist (an entertainer who performs a dramatic or musical work for an audience)
          - S: (n) entertainer (a person who tries to please or amuse)
            - S: (n) person, individual, someone, somebody, mortal, soul (a human being) *"there was too much for one person to do"*
              - S: (n) organism, being (a living thing that has (or can develop) the ability to act or function independently)
                - S: (n) living thing, animate thing (a living (or once living) entity)
                  - S: (n) whole, unit (an assemblage of parts that is regarded as a single entity) *"how big is that part compared to the whole?"; "the team is a unit"*
                    - S: (n) object, physical object (a tangible and visible entity; an entity that can cast a shadow) *"it was full of rackets, balls and other objects"*
                      - S: (n) physical entity (an entity that has physical existence)
                        - S: (n) entity (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))

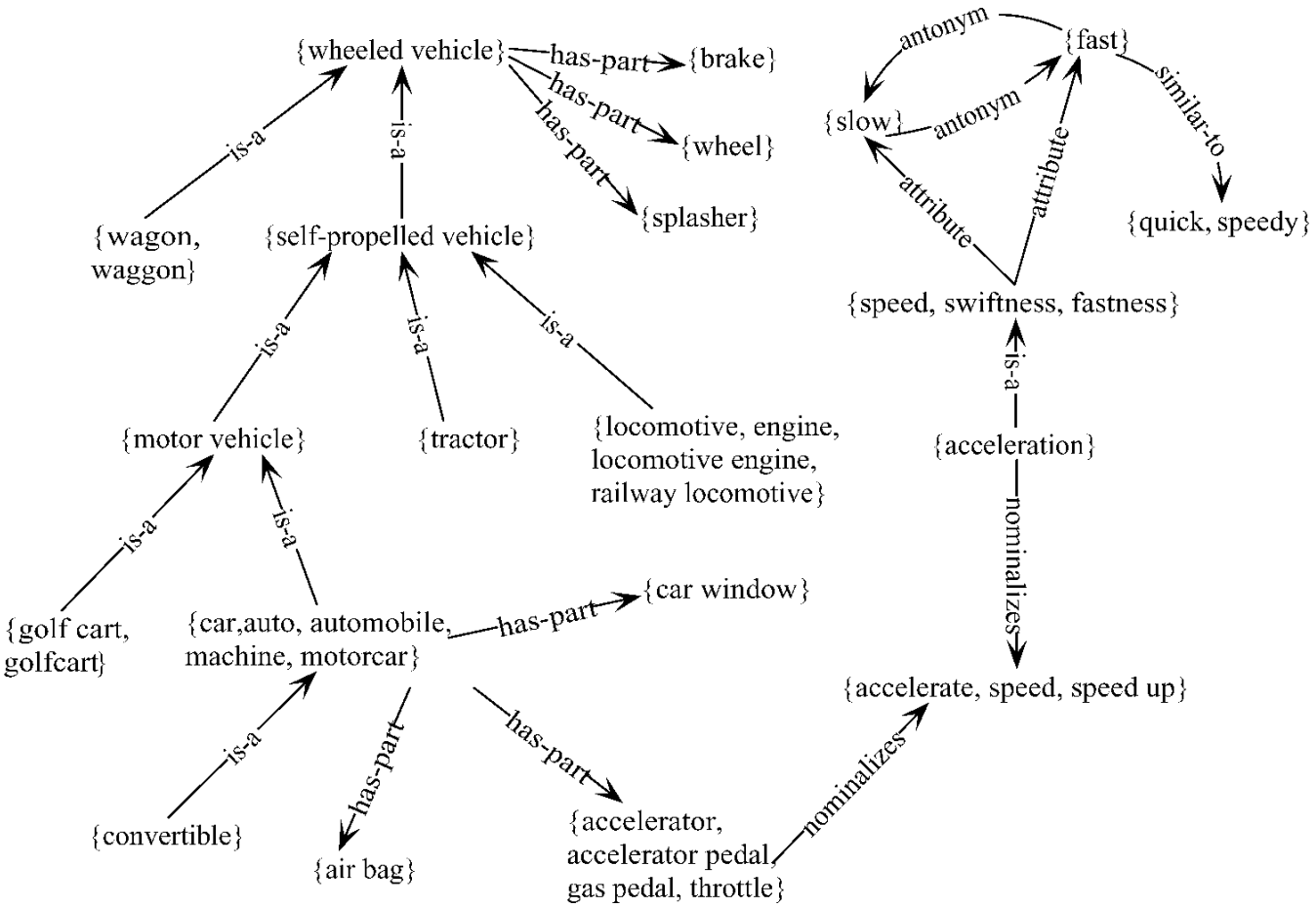
WordNet Noun Relations

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	$course^7 \rightarrow meal^1$
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	$leader^1 \Longleftrightarrow follower^1$
Derivationally Related Form		Lemmas w/same morphological root	$destruction^1 \Longleftrightarrow destroy^1$

WordNet Verb Relations

Relation	Definition	Example
Hypernym	From events to superordinate events	*fly*^{9} $\rightarrow$ *travel*^{5}
Troponym	From events to subordinate event (often via specific manner)	*walk*^{1} $\rightarrow$ *stroll*^{1}
Entails	From verbs (events) to the verbs (events) they entail	*snore*^{1} $\rightarrow$ *sleep*^{1}
Antonym	Semantic opposition between lemmas	*increase*^{1} $\Longleftrightarrow$ *decrease*^{1}
Derivationally Related Form	Lemmas with same morphological root	*destroy*^{1} $\Longleftrightarrow$ *destruction*^{1}

WordNet: Viewed as a graph



"Supersenses"
The top level hypernyms in the hierarchy

(counts from Schneider and Smith 2013's Streusel corpus)

Noun

GROUP	1469	*place*
PERSON	1202	*people*
ARTIFACT	971	*car*
COGNITION	771	*way*
FOOD	766	*food*
ACT	700	*service*
LOCATION	638	*area*
TIME	530	*day*
EVENT	431	*experience*
COMMUNIC.*	417	*review*
POSSESSION	339	*price*
ATTRIBUTE	205	*quality*
QUANTITY	102	*amount*
ANIMAL	88	*dog*
BODY	87	*hair*
STATE	56	*pain*
NATURAL OBJ.	54	*flower*
RELATION	35	*portion*
SUBSTANCE	34	*oil*
FEELING	34	*discomfort*
PROCESS	28	*process*
MOTIVE	25	*reason*
PHENOMENON	23	*result*
SHAPE	6	*square*
PLANT	5	*tree*
OTHER	2	*stuff*

Verb

STATIVE	2922	*is*
COGNITION	1093	*know*
COMMUNIC.*	974	*recommend*
SOCIAL	944	*use*
MOTION	602	*go*
POSSESSION	309	*pay*
CHANGE	274	*fix*
EMOTION	249	*love*
PERCEPTION	143	*see*
CONSUMPTION	93	*have*
BODY	82	*get…done*
CREATION	64	*cook*
CONTACT	46	*put*
COMPETITION	11	*win*
WEATHER	0	—

Supersenses

- A word's supersense can be a useful coarse-grained representation of word meaning for NLP tasks

I googled$_{\texttt{communication}}$ restaurants$_{\texttt{GROUP}}$ in the area$_{\texttt{LOCATION}}$ and Fuji_Sushi$_{\texttt{GROUP}}$ came_up$_{\texttt{communication}}$ and reviews$_{\texttt{COMMUNICATION}}$ were$_{\texttt{stative}}$ great so I made_ a carry_out$_{\texttt{possession}}$ _order$_{\texttt{communication}}$

WordNet and BabelNet

- Where is WordNet:
  - http://wordnetweb.princeton.edu/perl/webwn
- Global WordNet Association
  - http://globalwordnet.org/
- Libraries
  - Python: WordNet from NLTK
    - http://www.nltk.org

- BabelNet links Wikipedia, WordNet, Wiktionary, Wikidata, FrameNet, VerbNet, etc. Uses Babel synsets with glosses; available in many languages harvested from both WordNet and Wikipedia. Freely available at
  - https://babelnet.org/

An example of domain specific thesaurus: MeSH: Medical Subject Headings thesaurus from the National Library of Medicine

- **MeSH (Medical Subject Headings)**
  - 177,000 entry terms that correspond to 26,142 biomedical "headings"

- **Hemoglobins**

  Entry Terms: Eryhem, Ferrous Hemoglobin, Hemoglobin

  Definition: The oxygen-carrying proteins of ERYTHROCYTES. They are found in all vertebrates and some invertebrates. The number of globin subunits in the hemoglobin quaternary structure differs between species. Structures range from monomeric to a variety of multimeric arrangements

Synset

The MeSH Hierarchy

- a

1. + Anatomy [A]
2. + Organisms [B]
3. + Diseases [C]
4. − Chemicals and Drugs [D]
    - Inorganic Chemicals [D01] +
    - Organic Chemicals [D02] +
    - Heterocyclic Compounds [D03] +
    - Polycyclic Compounds [D04] +
    - Macromolecular Substances [D05] +
    - Hormones, Hormone Substitutes, and Hori
    - Enzymes and Coenzymes [D08] +
    - Carbohydrates [D09] +
    - Lipids [D10] +
    - Amino Acids, Peptides, and Proteins [D12]
    - Nucleic Acids, Nucleotides, and Nucleoside
    - Complex Mixtures [D20] +
    - Biological Factors [D23] +
    - Biomedical and Dental Materials [D25] +
    - Pharmaceutical Preparations [D26] +
    - Chemical Actions and Uses [D27] +
5. + Analytical, Diagnostic and Therapeutic Techniques and Equipment [E]
6. + Psychiatry and Psychology [F]
7. + Phenomena and Processes [G]

Amino Acids, Peptides, and Proteins [D12]
- Proteins [D12.776]
  - Blood Proteins [D12.776.124]
    - Acute-Phase Proteins [D12.776.124.050] +
    - Anion Exchange Protein 1, Erythrocyte [D12.776.124.078
    - Ankyrins [D12.776.124.080]
    - beta 2-Glycoprotein I [D12.776.124.117]
    - Blood Coagulation Factors [D12.776.124.125] +
    - Cholesterol Ester Transfer Proteins [D12.776.124.197]
    - Fibrin [D12.776.124.270] +
    - Glycophorin [D12.776.124.300]
    - Hemocyanin [D12.776.124.337]
    - ➤ Hemoglobins [D12.776.124.400]
      - Carboxyhemoglobin [D12.776.124.400.141]
      - Erythrocruorins [D12.776.124.400.220]

Uses of the MeSH Ontology

- Provide synonyms ("entry terms")
  - E.g., glucose and dextrose
- Provide hypernyms (from the hierarchy)
  - E.g., glucose ISA monosaccharide
- Indexing in MEDLINE/PubMED database
  - NLM's bibliographic database:
    - >20 million journal articles
    - Each article hand-assigned 10-20 MeSH terms

Word Similarity

- **Synonymy**: a binary relation
  - Two words are either synonymous or not
- **Similarity** (or **distance**): a looser metric
  - Two words are more similar if they share more features of meaning
- Similarity is properly a relation between **senses**
  - The word "`bank`" is not similar to the word "`slope`"
  - Bank^1 is similar to fund^3
  - Bank^2 is similar to slope^5
- But we sometimes compute similarity over both words and senses

Why word similarity

- A practical component in lots of NLP tasks
  - Question answering
  - Natural language generation
  - Automatic essay grading
  - Plagiarism detection
- A theoretical component in many linguistic and cognitive tasks
  - Historical semantics
  - Models of human word learning
  - Morphology and grammar induction

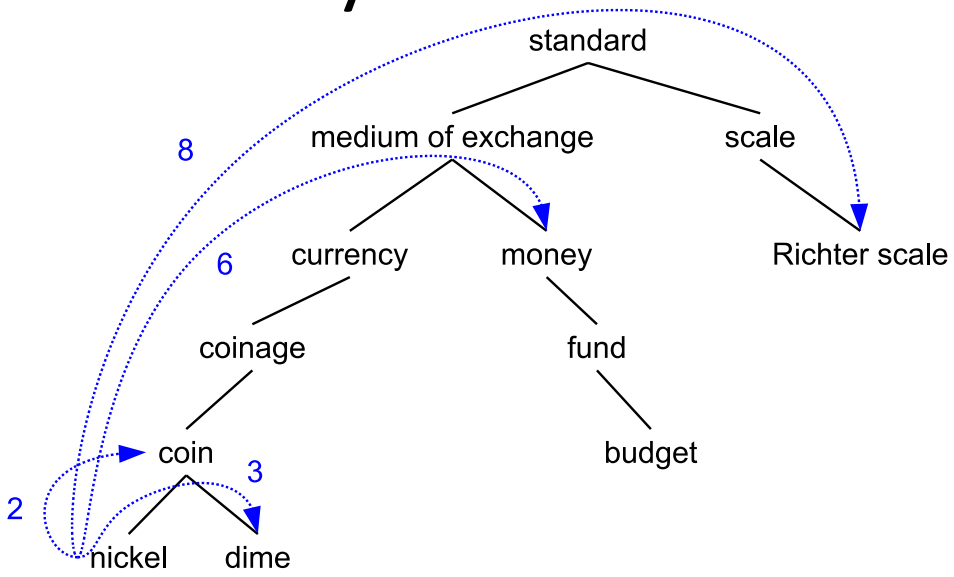
Word similarity and word relatedness

- We often distinguish **word similarity** from **word relatedness**
  - **Similar words**: near-synonyms
  - **Related words**: can be related any way
    - `car, bicycle`: **similar**
    - `car, gasoline`: **related**, not similar

Two classes of similarity algorithms

- Thesaurus-based algorithms
  - Are words “nearby” in hypernym hierarchy?
  - Do words have similar glosses (definitions)?
- Distributional algorithms
  - Do words have similar distributional contexts?
  - Distributional (vector) semantics (requires description, i.e. a gloss)

Path based similarity



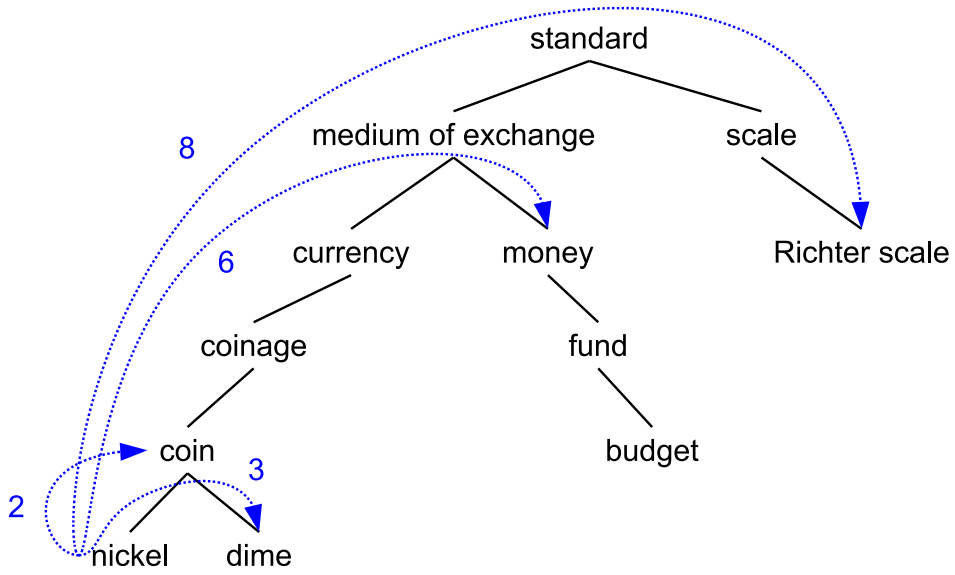
- Two concepts (senses/synsets) are similar if they are near each other in the thesaurus hierarchy
  - =have a short path between them
  - concepts have path 1 to themselves

Refinements to path-based similarity

- pathlen(c_1,c_2) = 1 + number of edges in the shortest path in the hypernym graph between sense nodes c_1 and c_2
- ranges from 0 to 1 (identity)
- $\text{simpath}(c_1,c_2) = \dfrac{1}{\text{pathlen}(c_1,c_2)}$
- $\text{wordsim}(w_1,w_2) = \max_{c_1 \in \text{senses}(w_1), c_2 \in \text{senses}(w_2)} \text{simpath}(c_1,c_2)$

Example: path-based similarity

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



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

simpath(*fund,budget*) = 1/2 = .5

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

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

simpath(*coinage,Richter scale*) = 1/6 = .17

Problem with basic path-based similarity

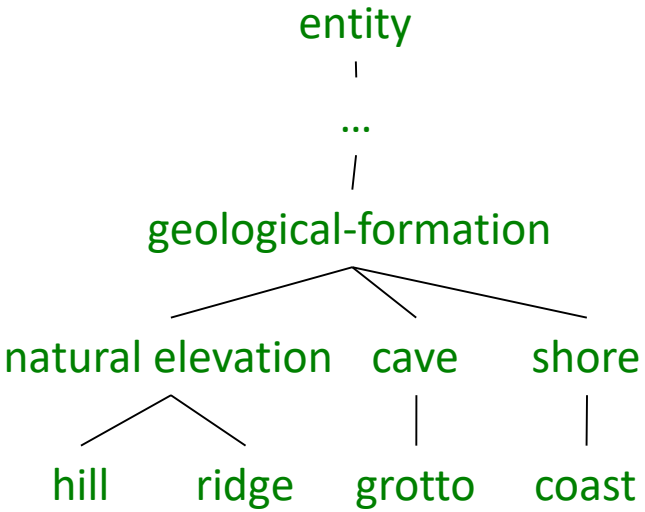
- Assumes each link represents a uniform distance
  - But *nickel* to *money* seems to us to be closer than *nickel* to *standard*
  - Nodes high in the hierarchy are very abstract
- We instead want a metric that
  - Represents the cost of each edge independently
  - Words connected only through abstract nodes are less similar

Information content similarity metrics

Resnik 1995

- Let's define P(c) as:
  - The probability that a randomly selected word in a corpus is an instance of concept *c*
  - Formally: there is a distinct random variable, ranging over words, associated with each concept in the hierarchy
    - for a given concept, each observed noun is either
      - a member of that concept with probability P(c)
      - not a member of that concept with probability 1-P(c)
  - All words are members of the root node (Entity)
    - P(root)=1
  - The lower a node in hierarchy, the lower its probability

Information content similarity



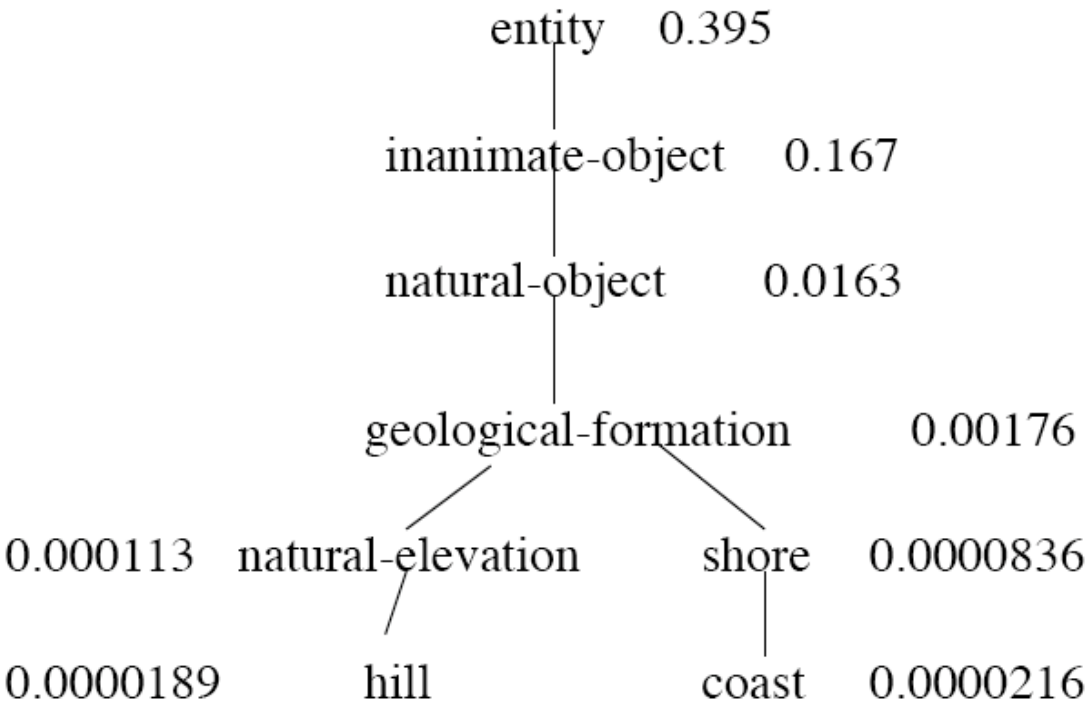
- Train by counting in a corpus
  - Each instance of hill counts toward frequency of *natural elevation*, *geological formation*, *entity*, etc
  - Let words(c) be the set of all words that are children of node c
    - words("geo-formation") = {hill,ridge,grotto,coast,cave,shore,natural elevation}
    - words("natural elevation") = {hill, ridge}

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

Information content similarity

- WordNet hierarchy augmented with probabilities P(c)

  D. Lin. 1998. An Information-Theoretic Definition of Similarity. ICML 1998



Information content and probability

- The **self-information** of an event, also called its **surprisal:**
  - how surprised we are to know it; how much we learn by knowing it.
  - The more surprising something is, the more it tells us when it happens
  - We'll measure self-information in **bits**.

  I(w)= -log2 P(w)
- I flip a coin; P(heads)= 0.5
- How many bits of information do I learn by flipping it?
  - I(heads) = -log2(0.5) = -log2 (1/2) = log2 (2) = 1 bit
- I flip a biased coin: P(heads)= 0.8 I don't learn as much
  - I(heads) = -log2(0.8) = -log2(0.8) = .32 bits

Information content: definitions

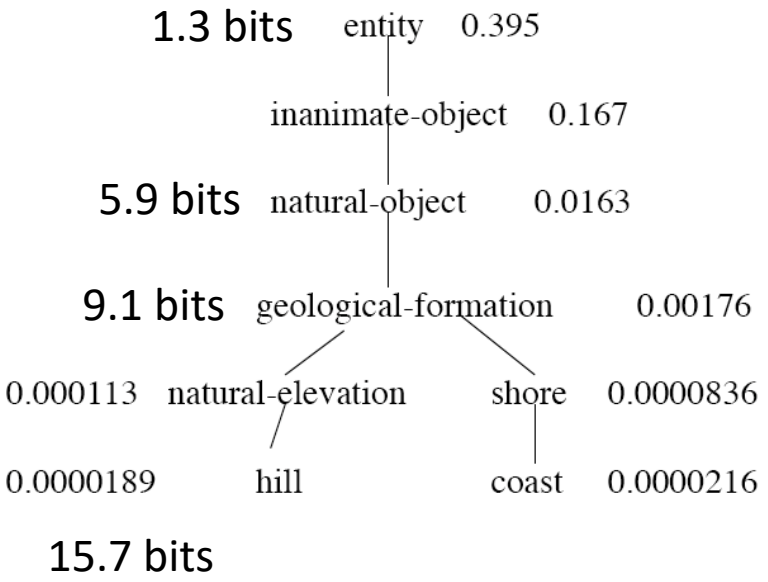
- Information content:

  IC(c) = -log P(c)

- Most informative subsumer (Lowest common subsumer)

  $LCS(c_1,c_2)$ =

  The most informative (lowest) node in the hierarchy subsuming both c_1 and c_2



Using information content for similarity: the Resnik method

Philip Resnik. 1995. Using Information Content to Evaluate Semantic Similarity in a Taxonomy. IJCAI 1995.
Philip Resnik. 1999. Semantic Similarity in a Taxonomy: An Information-Based Measure and its Application to Problems of Ambiguity in Natural Language. JAIR 11, 95-130.

- The similarity between two words is related to their common information
- The more two words have in common, the more similar they are
- Resnik: measure common information as:
  - The information content of the most informative (lowest) subsumer (MIS/LCS) of the two nodes
  - $\text{sim}_{\text{resnik}}(c_1,c_2) = -\log P(\text{LCS}(c_1,c_2))$

Dekang Lin method

Dekang Lin. 1998. An Information-Theoretic Definition of Similarity. ICML

- Intuition: Similarity between A and B is not just what they have in common
- The more **differences** between A and B, the less similar they are:
  - Commonality: the more A and B have in common, the more similar they are
  - Difference: the more differences between A and B, the less similar
- Commonality: IC(common(A,B))
- Difference: IC(description(A,B)-IC(common(A,B))

Dekang Lin similarity theorem

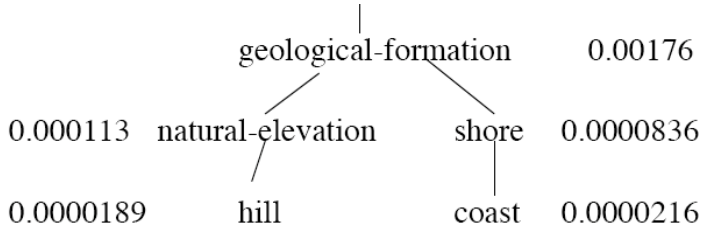
- The similarity between A and B is measured by the ratio between the amount of information needed to state the commonality of A and B and the information needed to fully describe what A and B are

$$sim_{Lin}(A,B)\,\mu\,\frac{IC(common(A,B))}{IC(description(A,B))}$$

- Lin (altering Resnik) defines IC(common(A,B)) as 2 x information of the LCS

$$sim_{Lin}(c_1,c_2)=\frac{2\log P(LCS(c_1,c_2))}{\log P(c_1)+\log P(c_2)}$$

Lin similarity function



$$sim_{Lin}(A,B) = \frac{2\log P(LCS(c_1,c_2))}{\log P(c_1)+\log P(c_2)}$$

$$sim_{Lin}(\text{hill},\text{coast}) = \frac{2\log P(\text{geological-formation})}{\log P(\text{hill})+\log P(\text{coast})}$$

$$= \frac{2\ln 0.00176}{\ln 0.0000189 + \ln 0.0000216}$$

$$= .59$$

The (extended) Lesk Algorithm

- A thesaurus-based measure that looks at **glosses**
- Two concepts are similar if their glosses contain similar words
  - ***Drawing paper***: paper that is specially prepared for use in drafting
  - ***Decal***: the art of transferring designs from specially prepared paper to a wood or glass or metal surface

- For each *n*-word phrase that is in both glosses
  - Add a score of n^2
  - Paper and specially prepared for $1 + 2^2 = 5$
  - Compute overlap also for other relations
    - glosses of hypernyms and hyponyms

Summary: thesaurus-based similarity

$$\text{sim}_{\text{path}}(c_1, c_2) = \frac{1}{pathlen(c_1, c_2)}$$

$$\text{sim}_{\text{resnik}}(c_1, c_2) = -\log P(LCS(c_1, c_2)) \quad \text{sim}_{\text{lin}}(c_1, c_2) = \frac{2\log P(LCS(c_1, c_2))}{\log P(c_1) + \log P(c_2)}$$

$$\text{sim}_{\text{jiangconrath}}(c_1, c_2) = \frac{1}{\log P(c_1) + \log P(c_2) - 2\log P(LCS(c_1, c_2))}$$

$$\text{sim}_{eLesk}(c_1, c_2) = \sum_{r,q \hat{\imath} RELS} \text{overlap}(\text{gloss}(r(c_1)), \text{gloss}(q(c_2)))$$

Evaluating similarity

- Extrinsic (task-based, end-to-end) Evaluation:
  - Question Answering
  - Spell Checking
  - Essay grading
- Intrinsic Evaluation:
  - Correlation between algorithm and human word similarity ratings
    - Wordsim353: 353 noun pairs rated 0-10. *sim(plane,car)=5.77*
  - Taking TOEFL multiple-choice vocabulary tests
    - Levied is closest in meaning to:

      imposed, believed, requested, correlated

Word Sense Disambiguation

Word Sense Disambiguation (WSD)

- Given
  - A word in context
  - A fixed inventory of potential word senses
  - Decide which sense of the word this is
- Why? Machine translation, QA, speech synthesis
- What set of senses?
  - English-to-Spanish MT: set of Spanish translations
  - Speech Synthesis: homographs like *bass* and *bow*
  - In general: the senses in a thesaurus like WordNet

Two variants of WSD task

- Lexical Sample task
  - Small pre-selected set of target words (*line, plant*)
  - And inventory of senses for each word
  - **Supervised machine learning: train a classifier for each word**
- All-words task
  - Every word in an entire text
  - A lexicon with senses for each word
  - Data sparseness: can't train word-specific classifiers

WSD Methods

- Supervised Machine Learning
- Thesaurus/Dictionary Methods
- Semi-Supervised Learning

Supervised Machine Learning Approaches

- Supervised machine learning approach:
  - a training corpus of words tagged in context with their sense
  - used to train a classifier that can tag words in new text
- Summary of what we need:
  - the **tag set** ("sense inventory")
  - the **training corpus**
  - For classical **classifiers:** a set of **features** extracted from the training corpus
  - For neural classifiers: **contextual embeddings** like ELMo or BERT

Supervised WSD 1: WSD Tags

- What's a tag?

  A dictionary sense?

- For example, for WordNet an instance of "bass" in a text has 8 possible tags or labels (bass1 through bass8).

8 senses of “bass” in WordNet

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

Inventory of sense tags for *bass*

WordNet Sense	Spanish Translation	Roget Category	Target Word in Context
bass^4	lubina	FISH/INSECT	. . . fish as Pacific salmon and striped **bass** and. . .
bass^4	lubina	FISH/INSECT	. . . produce filets of smoked **bass** or sturgeon. . .
bass^7	bajo	MUSIC	. . . exciting jazz **bass** player since Ray Brown. . .
bass^7	bajo	MUSIC	. . . play **bass** because he doesn't have to solo. . .

Supervised WSD 2: Get a corpus

- Lexical sample task:
  - *Line-hard-serve* corpus - 4000 examples of each
  - *Interest* corpus - 2369 sense-tagged examples
- All words:
  - **Semantic concordance**: a corpus in which each open-class word is labeled with a sense from a specific dictionary/thesaurus.
    - SemCor: 234,000 words from Brown Corpus, manually tagged with WordNet senses
    - SENSEVAL-3 competition corpora - 2081 tagged word tokens
    - BabelNet works for many languages

SemCor

<wf pos=PRP>**He**</wf>

<wf pos=VB lemma=recognize wnsn=4 lexsn=2:31:00::>**recognized**</wf>

<wf pos=DT>**the**</wf>

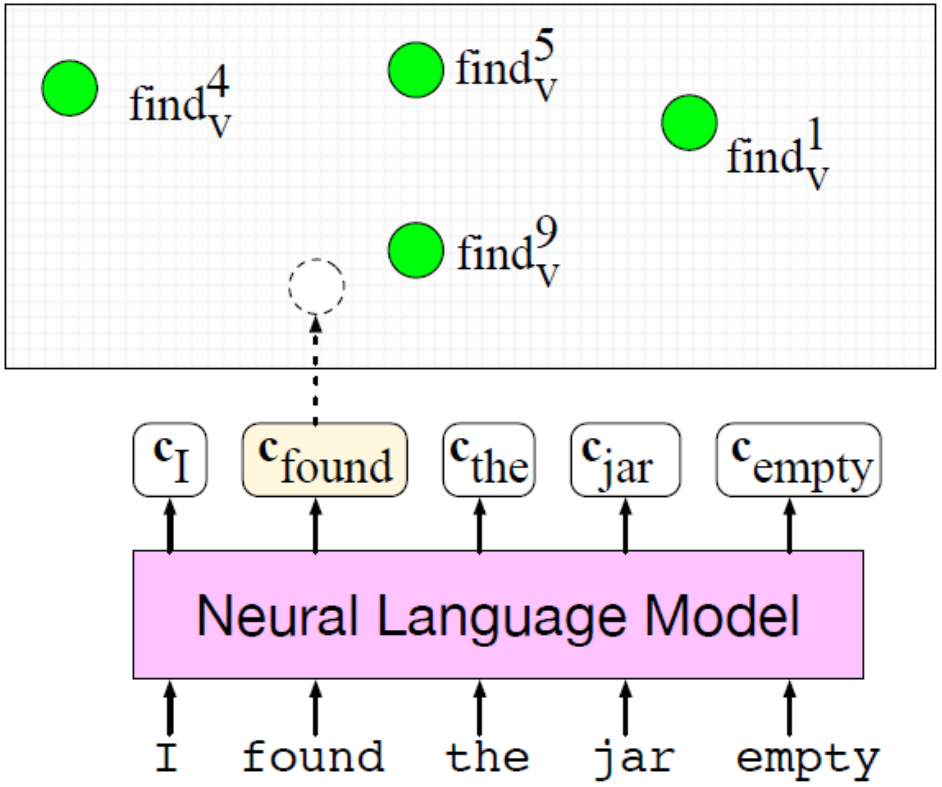
<wf pos=NN lemma=gesture wnsn=1 lexsn=1:04:00::>**gesture**</wf>

<punc>.</punc>

Classification with vectors and NN classifier: WSD with contextual embeddings

- after transforming each word in context into contextual embeddings (ELMo, BERT), we can use 1-NN algorithm
- for words not in the training set of e.g., in SemCor, we fall back to other methods,
  - the Most Frequent Sense baseline, i.e. taking the first sense in WordNet
  - impute the missing sense embeddings, bottom-up, by using the WordNet taxonomy and supersenses.

  We get a sense embedding for any higher-level node in the WordNet taxonomy by averaging the embeddings of its children.



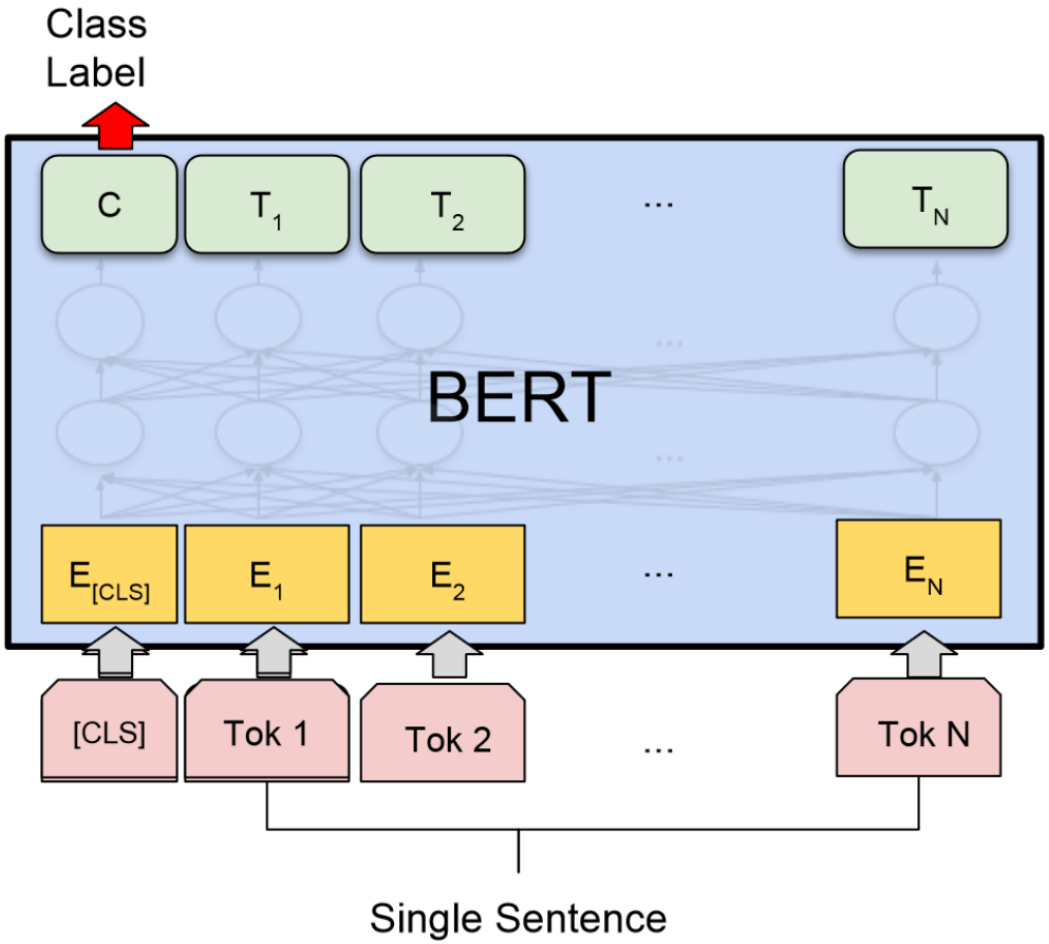
WSD with contextual embeddings

- No explicit features
- Compute the contextual embedding of the word in context, where the context is typically the sentence
- add a classification layer (typically softmax) and fine-tune the network
- Example text (WSJ):

  An electric guitar and **bass** player stand off to one side not really part of the scene

- Predict the correct sense label, 7 in our case.

WSD using BERT



Classical ML approaches: feature based

Supervised WSD 3: Extract feature vectors
Intuition from Warren Weaver (1955):

"If one examines the words in a book, one at a time as through an opaque mask with a hole in it one word wide, then it is obviously impossible to determine, one at a time, the meaning of the words…

But if one lengthens the slit in the opaque mask, until one can see not only the central word in question but also say N words on either side, then if N is large enough one can unambiguously decide the meaning of the central word…

The practical question is : ``What minimum value of N will, at least in a tolerable fraction of cases, lead to the correct choice of meaning for the central word?"

Feature vectors

- A simple representation for each observation
  (each instance of a target word)
  - **Vectors** of sets of feature/value pairs
  - Represented as a ordered list of values
  - These vectors represent, e.g., the window of words around the target

Two kinds of features in the vectors

- **Collocational** features and **bag-of-words** features
  - **Collocational**
    - Features about words at **specific** positions near target word
      - Often limited to just word identity and POS
  - **Bag-of-words**
    - Features about words that occur anywhere in the window (regardless of position)
      - Typically limited to frequency counts

Examples

- Example text (WSJ):

  An electric guitar and **bass** player stand off to one side not really part of the scene

- Assume a window of +/- 2 from the target

Examples

- Example text (WSJ)

  An electric guitar and **bass** player stand off to one side not really part of the scene,

- Assume a window of +/- 2 from the target

Collocational features

- Position-specific information about the words and collocations in window
- guitar and bass player stand

$$[w_{i-2}, \text{POS}_{i-2}, w_{i-1}, \text{POS}_{i-1}, w_{i+1}, \text{POS}_{i+1}, w_{i+2}, \text{POS}_{i+2}, w_{i-2}^{i-1}, w_{i}^{i+1}]$$

```
[guitar, NN, and, CC, player, NN, stand, VB, and guitar, player stand]
```

- word 1,2,3 grams in window of ±3 is common

Bag-of-words features

- “an unordered set of words” – position ignored
- Counts of words occur within the window.
- First choose a vocabulary
- Then count how often each of those terms occurs in a given window
  - sometimes just a binary “indicator” 1 or 0

Co-Occurrence Example

- Assume we've settled on a possible vocabulary of 12 words in "bass" sentences:

[*fishing, big, sound, player, fly, rod, pound, double, runs, playing, guitar, band*]

- The vector for:

  guitar and bass player stand

  [0,0,0,1,0,0,0,0,0,0,1,0]

Classification: definition

- *Input*:
  - a word w and some features f
  - a fixed set of classes $C = \{c_1, c_2, \ldots, c_J\}$

- *Output*: a predicted class $c \in C$

Classification Methods: Supervised Machine Learning

- *Input:*
  - a word *w in a text window d (which we'll call a "document")*
  - a fixed set of classes $C = \{c_1, c_2, \ldots, c_J\}$
  - A training set of *m* hand-labeled text windows again called "documents" $(d_1,c_1),\ldots,(d_m,c_m)$
- *Output:*
  - a learned classifier $\gamma:d \rightarrow c$

Standard classification Methods: Supervised Machine Learning

- Any kind of classifier
  - Naive Bayes
  - Logistic regression
  - Neural Networks
  - Support-vector machines
  - k-Nearest Neighbors
  - …

Applying Naive Bayes to WSD

- P(c) is the prior probability of that sense
  - Counting in a labeled training set.
- P(w|c) conditional probability of a word given a particular sense
  - P(w|c) = count(w,c)/count(c)
- We get both of these from a tagged corpus like SemCor

- Can also generalize to look at other features besides words.
  - Then it would be P(f|c)
    - Conditional probability of a feature given a sense

$$\hat{P}(c) = \frac{N_c}{N}$$

$$\hat{P}(w \mid c) = \frac{count(w,c)+1}{count(c)+|V|}$$

	Doc	Words	Class
Training	1	fish smoked fish	f
	2	fish line	f
	3	fish haul smoked	f
	4	guitar jazz line	g
Test	5	line guitar jazz jazz	?

Priors:

$P(f) = \frac{3}{4}$

$P(g) = \frac{1}{4}$

V = {fish, smoked, line, haul, guitar, jazz}

Choosing a class:

$P(f|d5) \propto 3/4 * 2/14 * (1/14)^2 * 1/14$
≈ 0.00003

$P(g|d5) \propto 1/4 * 2/9 * (2/9)^2 * 2/9$
≈ 0.0006

Conditional Probabilities:

P(line|*f*) = (1+1) / (8+6) = 2/14
P(guitar|*f*) = (0+1) / (8+6) = 1/14
P(jazz|*f*) = (0+1) / (8+6) = 1/14
P(line|*g*) = (1+1) / (3+6) = 2/9
P(guitar|*g*) = (1+1) / (3+6) = 2/9
P(jazz|*g*) = (1+1) / (3+6) = 2/9

WSD Evaluations and baselines

- Best evaluation: **extrinsic ('end-to-end', `task-based') evaluation**
  - Embed WSD algorithm in a task and see if you can do the task better!
- What we often do for convenience: **intrinsic evaluation**
  - Exact match **sense accuracy**
    - % of words tagged identically with the human-manual sense tags
  - Usually evaluate using **held-out data** from same labeled corpus
- Baselines
  - Most frequent sense
  - The Lesk algorithm

Evaluation with WiC dataset

- Word in Contex (WiC) dataset: determine if two sentences contain a word with the same or different sense
- Contains senses mostly from the WordNet
- WordNet senses are sometimes too fine-grained for machine recognition

F	There's a lot of trash on the **bed** of the river — I keep a glass of water next to my **bed** when I sleep
F	**Justify** the margins — The end **justifies** the means
T	**Air** pollution — Open a window and let in some **air**
T	The expanded **window** will give us time to catch the thieves — You have a two-hour **window** of clear weather to finish working on the lawn

Most Frequent Sense

- WordNet senses are ordered in frequency order
- So "most frequent sense" in WordNet = "take the first sense"
- Sense frequencies come from the *SemCor* corpus

Freq	Synset	Gloss
338	plant[1], works, industrial plant	buildings for carrying on industrial labor
207	plant[2], flora, plant life	a living organism lacking the power of locomotion
2	plant[3]	something planted secretly for discovery by another
0	plant[4]	an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience

Ceiling

- Human inter-annotator agreement
  - Compare annotations of two humans
  - On same data
  - Given same tagging guidelines
- Human agreements on all-words corpora with WordNet style senses
  - 75%-80%

Word Sense Disambiguation

Dictionary and Thesaurus Methods

The Simplified Lesk algorithm

- Let's disambiguate "**bank**" in this sentence:

  The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

- given the following two WordNet senses:

bank^1	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	"he cashed a check at the bank", "that bank holds the mortgage on my home"
bank^2	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	"they pulled the canoe up on the bank", "he sat on the bank of the river and watched the currents"

The Simplified Lesk algorithm

Choose sense with most word overlap between gloss and context (not counting function words)

The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

bank[1]	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	"he cashed a check at the bank", "that bank holds the mortgage on my home"
bank[2]	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	"they pulled the canoe up on the bank", "he sat on the bank of the river and watched the currents"

The Corpus Lesk algorithm

- Assumes we have some sense-labeled data (like SemCor)
- Take all the sentences with the relevant word sense:

  These short, "streamlined" meetings usually are sponsored by local ***banks***^{1}*, Chambers of Commerce, trade associations, or other civic organizations.*
- Now add these to the gloss + examples for each sense, call it the "signature" of a sense.
- Choose sense with most word overlap between context and signature.

Corpus Lesk: IDF weighting

- Instead of just removing function words
  - Weigh each word by its `promiscuity' across documents
  - Down-weights words that occur in every `document' (gloss, example, etc)
  - These are generally function words, but is a more fine-grained measure
- Weigh each overlapping word by **inverse document frequency**

Corpus Lesk: IDF weighting

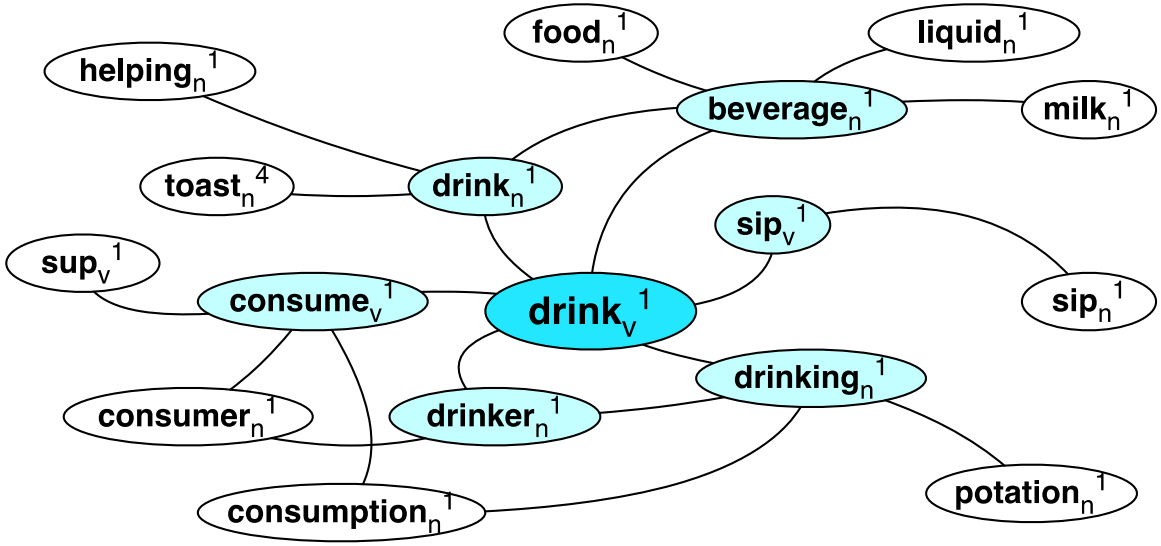
- Weigh each overlapping word by **inverse document frequency**
  - N is the total number of documents
  - df_i = "document frequency of word *i*"
  - = # of documents with word *I*

$$\text{idf}_i = \log\left(\frac{N}{df_i}\right)$$

$$score(sense_i, context_j) = \sum_{w \in overlap(signature_i, context_j)} \text{idf}_w$$

Graph-based methods

- WordNet can be viewed as a graph
  - senses are nodes
  - relations (hypernymy, meronymy) are edges
  - Also add edge between word and unambiguous gloss words



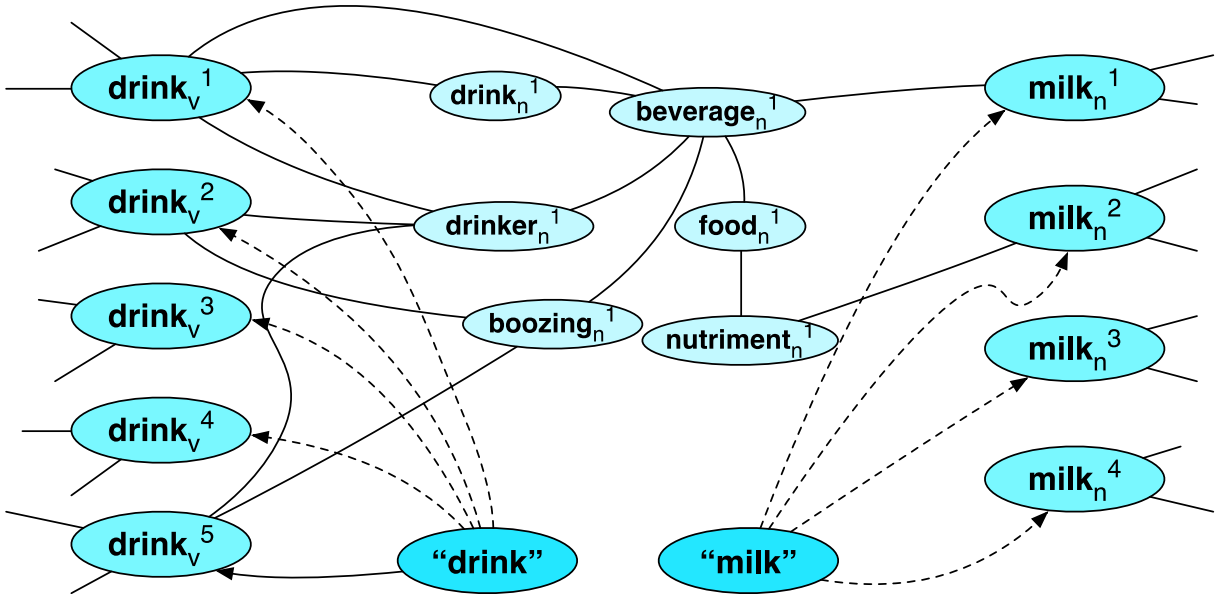
How to use the graph for WSD

- Insert target word and words in its sentential context into the graph, with directed edges to their senses

"She drank some milk"

- Now choose the *most central* sense

Add some probability to "drink" and "milk" and compute node with highest "pagerank"



Word Sense Disambiguation

Semi-Supervised Learning

Semi-Supervised Learning

Problem: supervised and dictionary-based approaches require large hand-built resources

What if you don't have so much training data?

Solution: Bootstrapping

Generalize from a small hand-labeled seed-set.

Bootstrapping

- For `bass`
  - Rely on “One sense per collocation” heuristic rule
    - A word reoccurring in collocation with the same word will almost surely have the same sense.
  - the word `play` occurs with the music sense of bass
  - the word `fish` occurs with the fish sense of bass

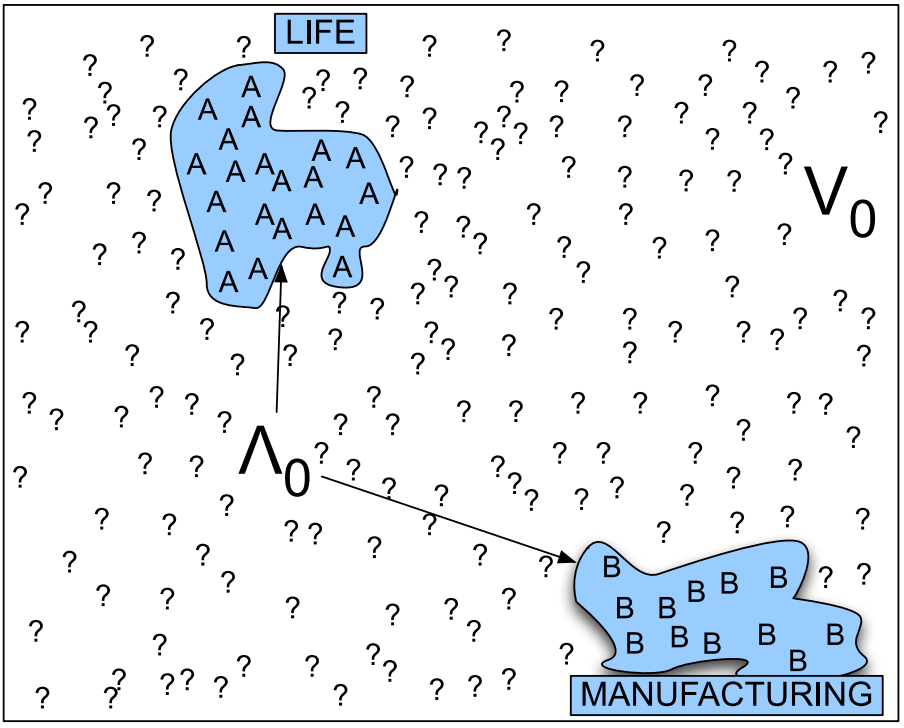
Sentences extracting using “fish” and “play”

We need more good teachers – right now, there are only a half a dozen who can **play** the free **bass** with ease.
An electric guitar and **bass play**er stand off to one side, not really part of the scene, just as a sort of nod to gringo expectations perhaps.
The researchers said the worms spend part of their life cycle in such **fish** as Pacific salmon and striped **bass** and Pacific rockfish or snapper.
And it all started when **fish**ermen decided the striped **bass** in Lake Mead were too skinny.

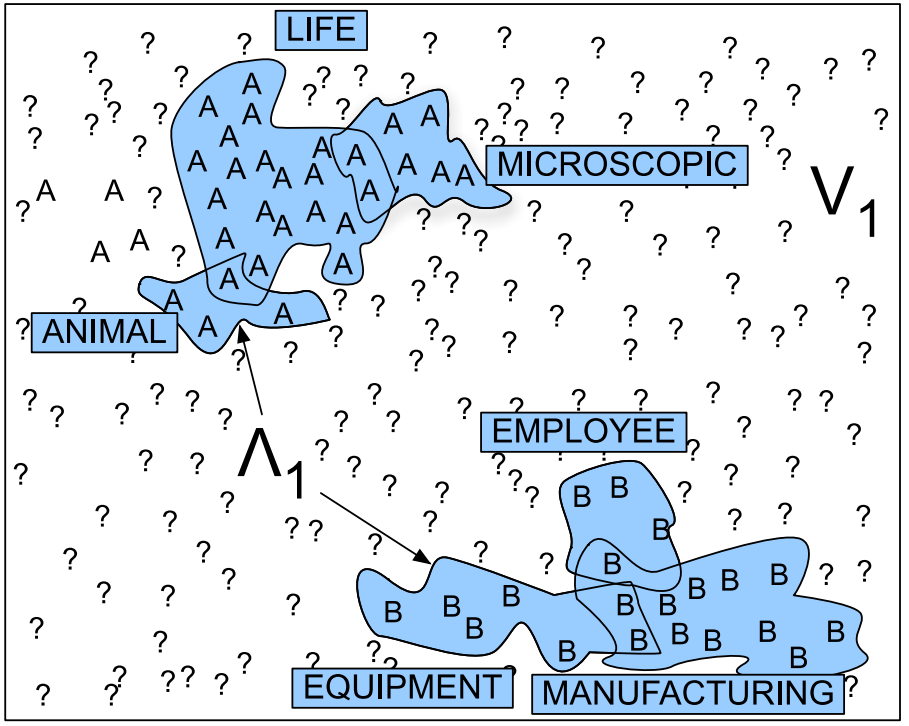
Summary: generating seeds

1) Hand labeling
2) “One sense per collocation”:
   - A word reoccurring in collocation with the same word will almost surely have the same sense.
3) “One sense per discourse”:
   - The sense of a word is highly consistent within a document - Yarowsky (1995)
   - (At least for non-function words, and especially topic-specific words)

Stages in the Yarowsky bootstrapping algorithm for the word “plant”



(a)



(b)

Summary

- Word Sense Disambiguation: choosing correct sense in context
- Applications: MT, QA, etc.
- Three classes of Methods
  - Supervised Machine Learning: Naive Bayes classifier, BERT
  - Thesaurus/Dictionary Methods
  - Semi-Supervised Learning
- Main intuition
  - There is lots of information in a word's context
  - Simple algorithms based just on word counts can a good baseline
  - contextual embeddings greatly improved the performance

Word Sense Induction (WSI)

- It is expensive and difficult to build large labelled corpora for WSD
- many languages do not have freely available (large) word inventories
- solution: unsupervised approach
- idea: don’t use human-defined word senses but induce senses of each word from te instances of each word in the training set
- typical approach: use clustering over word embeddings

WSI algorithm

1. For each token w_i of word w in a corpus, compute a context vector c.
2. Use a clustering algorithm to cluster these word-token context vectors c into a predefined number of groups or clusters. Each cluster defines a sense of w.
3. Compute the vector centroid of each cluster. Each vector centroid s_j is a sense vector representing that sense of w.

- Weakness: the gained clusters have no names,
- we can assign words to cluster based on the closest cluster
- evaluation with a hand-labelled gold-standard set