Natural Language Processing
SoSe 2016

Lexical Semantics

Dr. Mariana Neves

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Outline

- Lexical Semantics
- Word Sense Disambiguation
- Word Similarity
- Semantic Role Labeling

Outline

- Lexical Semantics
- Word Sense Disambiguation
- Word Similarity
- Semantic Role Labeling

Word Meaning

- Considering the meaning(s) of a word in addition to its written form
- Word Sense
  - A discrete representation of an aspect of the meaning of a word

Berlin, Maryland

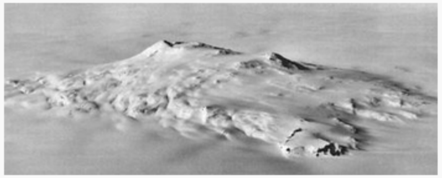
Town

Downtown Berlin, Maryland

Berlin

Berlin, 1982. L-R: David Diamond, Rob Brill, Terri Nunn, John Crawford, Matt Reid, and Ric Olsen.

Mount Berlin



Aerial view of Mount Berlin from the northwest

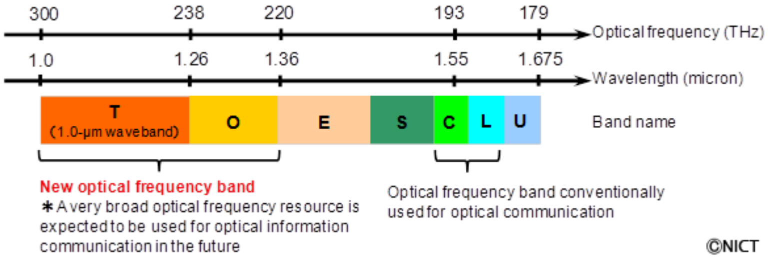
Elevation	3,478 m (11,411 ft)
Location	
Location	Marie Byrd Land, Antarctica

Berlin

State of Germany

Lexeme

- An entry in a lexicon consisting of a pair: a form with a single meaning representation
  - band (music group)
  - band (material)
  - band (wavelength)



(http://www.nict.go.jp/en/press/2011/12/26-01.html)
(http://www.weiku.com/products/12426189/Polyester_Elastic_band_for_garment_underwear_shoe_bags.html)
(http://clipart.me/band-material-with-the-enthusiasm-of-the-audience-silhouette-19222)

Lemma

- The grammatical form that is used to represent a lexeme
  - Berlin
  - band

Homonymy

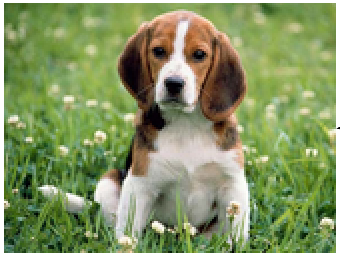
- Words which have similar form but different meanings
  - Homographs:
    - Berlin (Germany's capital); Berlin (music band)
    - band (music group); band (material); band (wavelength)

Homophones

- Word which have similar pronunciation but different writing and meaning
  - write
  - right

Semantics Relations

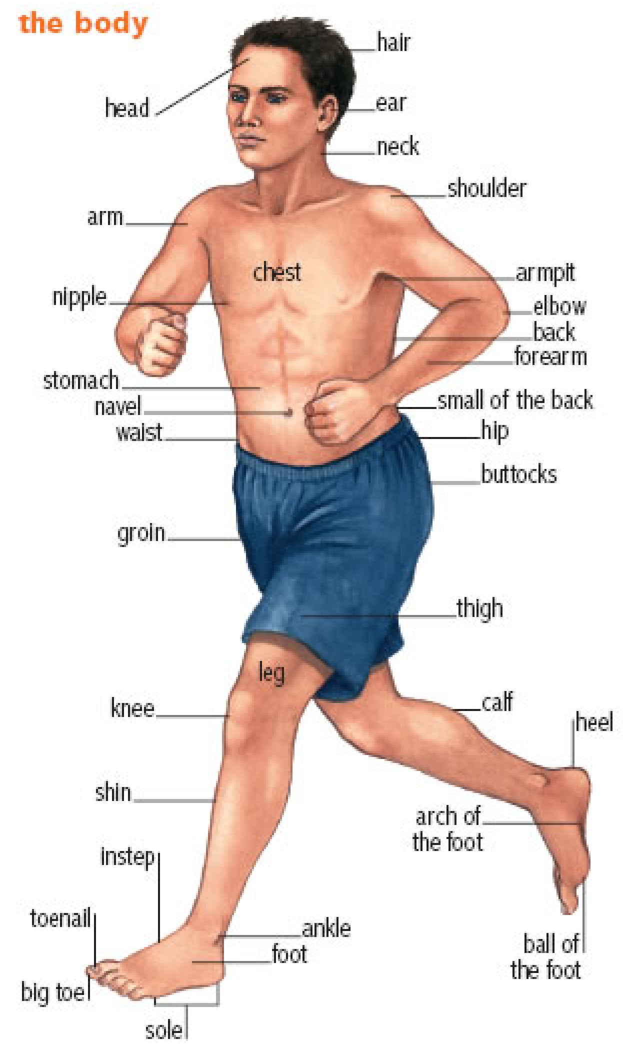
- Lexical relations among words (senses)
  - Hyponymy (is a) {parent: hypernym, child: hyponym}
    - dog & animal



(http://animalia-life.com/dogs.html)
(http://pic-zoom.com/pictures-animals.html)

Semantics Relations

- Lexical relations among words (senses)
  - Meronymy (part of)
    - arm & body



(http://www.oxfordlearnersdictionaries.com/definition/american_english/arm_1)

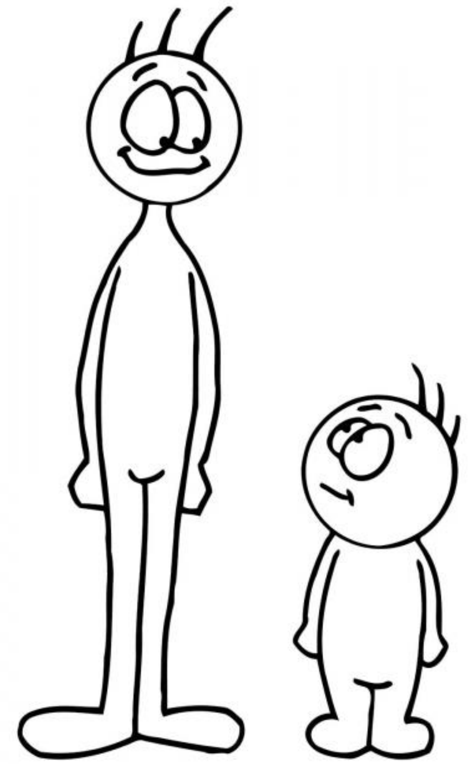
Semantics Relations

- Lexical relations among words (senses)
  - Synonymy
    - fall & autumn

(http://pinitgallery.com/photo/f/fall-background/7/)

Semantics Relations

- Lexical relations among words (senses)
  - Antonymy
    - tall & short



(http://pixgood.com/tall-short.html)

WordNet

- A hierarchical database of lexical relations
- Three Separate sub-databases
  - Nouns
  - Verbs
  - Adjectives and Adverbs
- Each word is annotated with a set of senses
- Available online or for download
  - http://wordnetweb.princeton.edu/perl/webwn

Word sense

- Synset
(synonym set)

Noun

- S: (n) set, circle, **band**, lot (an unofficial association of people or groups) *"the smart set goes there"; "they were an angry lot"*
- S: (n) **band** (instrumentalists not including string players)
- S: (n) **band**, banding, stria, striation (a stripe or stripes of contrasting color) *"chromosomes exhibit characteristic bands"; "the black and yellow banding of bees and wasps"*
- S: (n) **band**, banding, stripe (an adornment consisting of a strip of a contrasting color or material)
- S: (n) dance band, **band**, dance orchestra (a group of musicians playing popular music for dancing)
- S: (n) **band** (a range of frequencies between two limits)
- S: (n) **band** (a thin flat strip of flexible material that is worn around the body or one of the limbs (especially to decorate the body))
- S: (n) isthmus, **band** (a cord-like tissue connecting two larger parts of an anatomical structure)
- S: (n) ring, **band** (jewelry consisting of a circlet of precious metal (often set with jewels) worn on the finger) *"she had rings on every finger"; "he noted that she wore a wedding band"*
- S: (n) **band** (a driving belt in machinery)
- S: (n) **band** (a thin flat strip or loop of flexible material that goes around or over something else, typically to hold it together or as a decoration)
- S: (n) **band**, ring (a strip of material attached to the leg of a bird to identify it (as in studies of bird migration))
- S: (n) **band** (a restraint put around something to hold it together)

Verb

- S: (v) **band** (bind or tie together, as with a band)
- S: (v) ring, **band** (attach a ring to the foot of, in order to identify) *"ring birds"; "band the geese to observe their migratory patterns"*

Word Relations (Hypernym)

- S: (n) ring, **band** (jewelry consisting of a circlet of precious metal (often set with jewels) worn on the finger) *"she had rings on every finger"; "he noted that she wore a wedding band"*
  - *direct hyponym* / *full hyponym*
    - S: (n) engagement ring (a ring given and worn as a sign of betrothal)
    - S: (n) mourning ring (a ring worn as a memorial to a dead person)
    - S: (n) ringlet (a small ring)
    - S: (n) signet ring, seal ring (a ring bearing a signet)
    - S: (n) wedding ring, wedding band (a ring (usually plain gold) given to the bride (and sometimes one is also given to the groom) at the wedding)
  - ***direct hypernym*** / *inherited hypernym* / *sister term*
    - S: (n) jewelry, jewellery (an adornment (as a bracelet or ring or necklace) made of precious metals and set with gems (or imitation gems))

Outline

- Lexical Semantics
- Word Sense Disambiguation
- Word Similarity
- Semantic Role Labeling

Motivation: Information retrieval

Berlin is the capital of Germany.

Berlin may also refer to:

Individuals [edit]

- Berlin (surname)
- Berlin Ndebe-Nlome (born 1987), Cameroonian football player
- Berlin, former stage name for professional wrestler Alex Wright

Places [edit]

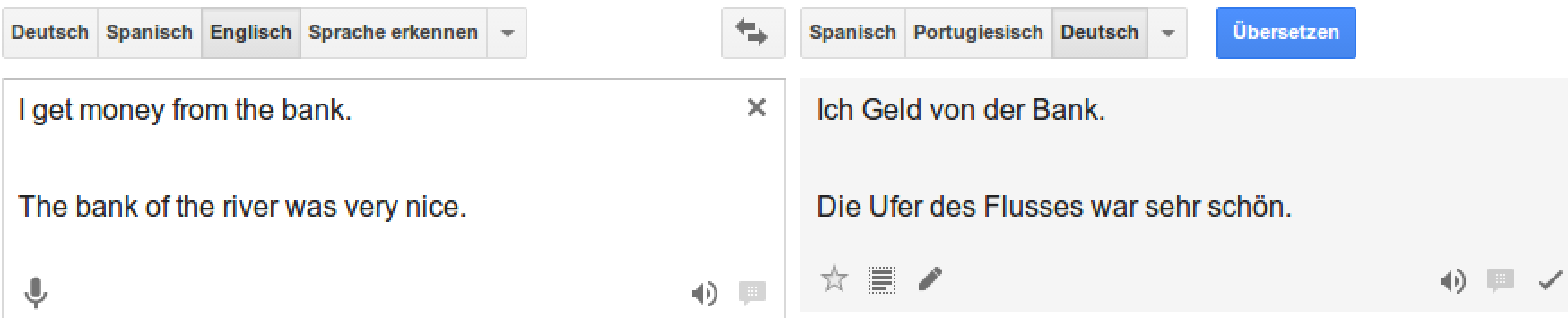
Canada [edit]

- Berlin, former name of Kitchener, Ontario
  - Berlin to Kitchener name change

United States [edit]

- Berlin, California, the former name of Genevra, California
- Berlin, Connecticut
  - Berlin (Amtrak station), rail station in Berlin, Connecticut
- Berlin, Georgia
- Berlin, Illinois
- Berlin, Indiana, extinct town
- Berlin, Kentucky
- Berlin, Maryland

Motivation: Machine translation



(http://translate.google.de)

Motivation: Speech recognition

- You have to process it write.

- You have to process it right.

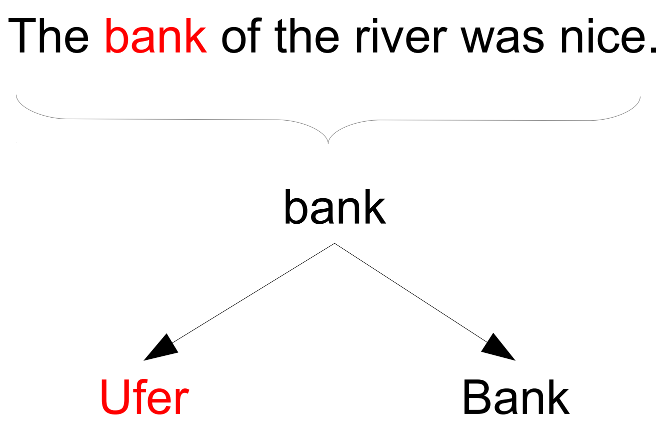
Motivation: Speech synthesis

- Eggs have a high protein content.

- She was content to step down after four years as chief executive.

Word Sense Disambiguation

- Input
  - A word
  - The context of the word
  - Set of potential senses for the word
- Output
  - The best sense of the word for this context



Approaches

- Thesaurus-based
- Supervised learning
- Semi-supervised learning

Thesaurus-based

- Extracting sense definitions from existing sources
  - Dictionaries
  - Thesauri
  - Wikipedia

Science and technology [edit]

- BAND (application), a private space for groups
- Band (mathematics), an idempotent semigroup
- Band (radio), a range of frequencies or wavelengths used in radio transmission and radar
- Band cell, a type of white blood cell
- Gastric band, a weight-control measure
- Bird banding, placing numbered bands of metal on birds' legs for identification

Organizations [edit]

- Band (channel), nickname of Brazilian broadcast television network Rede Bandeirantes
- Bands (Italian Army irregulars), military units once in the service of the Italian Regio Esercito
- The Band (professional wrestling), the Total Nonstop Wrestling name for the professional wrestling stable New World Order

Music [edit]

- Band (music), a group of people who perform instrumental or vocal music
  - Concert band, an ensemble of woodwind, brass, and percussion instruments
  - School band, a group of student musicians who rehearse and perform instrumental music together
  - Marching band, a group of instrumental musicians who generally perform outdoors incorporating some type of marching
  - Jazz band, a musical ensemble that plays jazz music
- The Band, a Canadian-American rock and roll group
  - *The Band* (album), its eponymous album released in 1969

Clothing, jewelry, and accessories [edit]

- Bands (neckwear), two pieces of cloth fitted around the neck as part of formal clothing for clergy, academics, and lawyers
- Bandolier or bandoleer, an ammunition belt
- Wedding band, a metal ring indicating the wearer is married
- Belt (clothing), a flexible band or strap, typically made of leather or heavy cloth, and worn around the waist
- Strap, an elongated flap or ribbon, usually of fabric or leather

The Lesk Algorithm

- Selecting the sense whose definition shares the most words with the word's context

```
function SIMPLIFIED LESK(word,sentence) returns best sense of word
    best-sense <- most frequent sense for word
    max-overlap <- 0
    context <- set of words in sentence
    for each sense in senses of word do
        signature <- set of words in the gloss and examples of sense
        overlap <- COMPUTEOVERLAP (signature,context)
        if overlap > max-overlap then
            max-overlap <- overlap
            best-sense <- sense
end return (best-sense)
```

(http://en.wikipedia.org/wiki/Lesk_algorithm)

The Lesk Algorithm

- Simple to implement
- No training data needed, „only" a lexicon
- Relatively bad results

Supervised Learning

- Training data:
  - A corpus in which each occurrence of the ambiguous word „w" is annotated with its correct sense
    - SemCor : 234,000 sense-tagged from Brown corpus
    - SENSEVAL-1: 34 target words
    - SENSEVAL-2: 73 target words
    - SENSEVAL-3: 57 target words (2081 sense-tagged)

SemCor corpus

```
<s snum=2>
<wf cmd=tag pos=NNP>Mr._Hawksley</wf>
<wf cmd=done pos=VB lemma=say wnsn=1 lexsn=2:32:00::>said</wf>
<wf cmd=tag pos=NN>yesterday</wf>
<wf cmd=ignore pos=PRP>he</wf>
<wf cmd=ignore pos=MD>would</wf>
<wf cmd=done pos=VB ot=metaphor>be</wf>
<wf cmd=tag pos=JJ>willing</wf>
<wf cmd=ignore pos=TO>to</wf>
<wf cmd=done pos=VB lemma=go wnsn=1 lexsn=2:38:00::>go</wf>
<wf cmd=ignore pos=IN>before</wf>
<wf cmd=ignore pos=DT>the</wf>
<wf cmd=tag pos=NN>city_council</wf>
<punc>``</punc>
<wf cmd=ignore pos=CC>or</wf>
<wf cmd=tag pos=NN>anyone</wf>
<wf cmd=tag pos=RB>else</wf>
<wf cmd=tag pos=RB>locally</wf>
<punc>''</punc>
<wf cmd=ignore pos=TO>to</wf>
<wf cmd=done pos=VB lemma=outline wnsn=1 lexsn=2:32:00::>outline</wf>
<wf cmd=ignore pos=PRP$>his</wf>
<wf cmd=tag pos=NN>proposal</wf>
<wf cmd=ignore pos=IN>at</wf>
<wf cmd=ignore pos=DT>the</wf>
<wf cmd=tag pos=RBS>earliest</wf>
<wf cmd=tag pos=JJ>possible</wf>
<wf cmd=tag pos=NN>time</wf>
<punc>.</punc>
</s>
```

(http://web.eecs.umich.edu/~mihalcea/downloads/semcor/semcor3.0.tar.gz)

Feature Selection

- Using the words in the context with a specific window size
  - Collocation
    - Considering all words in a window (as well as their POS) and their position:

$$\{W_{n-3}, P_{n-3}, W_{n-2}, P_{n-2}, W_{n-1}, P_{n-1}, W_{n+1}, P_{n+1}, W_{n+2}, P_{n+2}, W_{n+3}, P_{n+3}\}$$

Collocation: example

- band:

  „There would be equal access to all currencies financial instruments and financial services dash and no major constitutional change. As realignments become more rare and exchange rates waver in narrower bands the system could evolve into one of fixed exchange rates."

- Window size: +/- 3
- Context: waver in narrower bands the system could
- $\{W_{n-3}, P_{n-3}, W_{n-2}, P_{n-2}, W_{n-1}, P_{n-1}, W_{n+1}, P_{n+1}, W_{n+2}, P_{n+2}, W_{n+3}, P_{n+3}\}$
- {waver, NN, in , IN , narrower, JJ, the, DT, system, NN , could, MD}

Feature Selection

- Using the words in the context with a specific window size
  - Bag-of-word
    - Considering the frequent words regardless their position
    - Deriving a set of k most frequent words in the window from the training corpus
    - Representing each word in the data as a k-dimension vector
    - Finding the frequency of the selected words in the context of the current observation

{ 0 , 0 , 0 , 0 , 0 , 1 , 0 , 0 , 1 , ... }

Bag-of-words: example

- band:

  „There would be equal access to all currencies financial instruments and financial services dash and no major constitutional change. As realignments become more rare and exchange rates waver in narrower bands the system could evolve into one of fixed exchange rates."

- Window size: +/- 3
- Context: waver in narrower bands the system could
- k frequent words for „band":
  - {circle, dance, group, jewelery, music, narrow, ring, rubber, wave}
  - { 0 , 0 , 0 , 0 , 0 , 1 , 0 , 0 , 1 }

Naïve Bayes Classification

- Choosing the best sense $\hat{s}$ out of all possible senses s_i for a feature vector $\vec{f}$ of the word w

$$\hat{s} = argmax_{s_i} P(s_i | \vec{f})$$

$$\hat{s} = argmax_{s_i} \frac{P(\vec{f} | s_i) P(s_i)}{P(\vec{f})}$$

$$P(\vec{f})\, has\, no\, effect$$

$$\hat{s} = argmax_{s_i} P(\vec{f} | s_i) P(s_i)$$

Naïve Bayes Classification

$$\hat{s} = argmax_{s_i} P(\vec{f} | s_i) P(s_i)$$

Likelihood probability

Prior probability

$$\hat{s} = argmax_{s_i} P(s_i) \prod_{j=1}^{m} P(f_j | s_i)$$

$$P(s_i) = \frac{\#(s_i)}{\#(w)}$$

$\#(s_i)$: number of times the sense s_i is used for the word w in the training data
$\#(w)$: the total number of samples for the word w

Naïve Bayes Classification

$$\hat{s} = argmax_{s_i} P(\vec{f}|s_i) P(s_i)$$

Likelihood probability

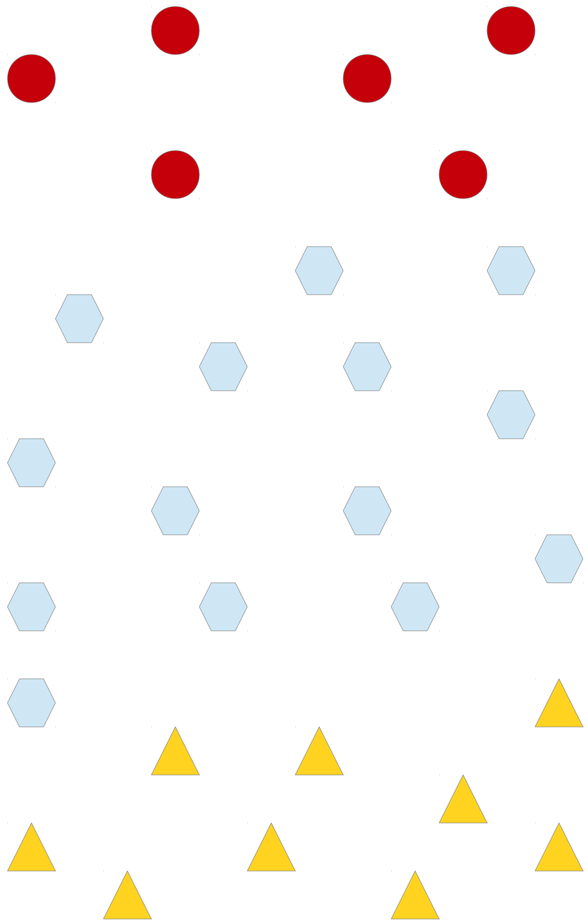
Prior probability

$$\hat{s} = argmax_{s_i} P(s_i) \prod_{j=1}^{m} P(f_j|s_i)$$

$$P(f_j|s_i) = \frac{\#(f_j, s_i)}{\# s_i}$$

$\#(f_j,s_i)$: the number of times the feature f_j occurred for the sense s_i of word w
$\#(s_i)$: the total number of samples of w with the sense s_i in the training data

Semi-supervised Learning



- A small amount of labeled data
- A large amount of unlabeled data

- Solution:
- Finding the similarity between the labeled and unlabeled data
- Predicting the labels of the unlabeled data

Semi-supervised Learning

- For each sense of „band“:
  - Select the most important word which frequently co-occurs with the target word only for this particular sense
    - „play“ (music)
    - „elastic“ (rubber)
    - „spectrum“ (range)

Semi-supervised Learning

- For each sense of „band“:
  - Find the sentences from unlabeled data which contain the target word and the selected word

For example the Jamaican reggae musician Bob Marley and his band The Wailers were known to play the concerts ….

A rubber band, also known as a binder, elastic band, lackey band, laggy band, "gum band", or elastic, is a short length of rubber and latex, elastic in nature and formed ...

The band spectrum is the combination of many different spectral lines

(http://en.wikipedia.org/wiki/Encore_(concert))
(http://en.wikipedia.org/wiki/Rubber_band)
(http://en.wikipedia.org/wiki/Spectral_bands)

Semi-supervised Learning

- For each sense,
  - Label the sentence with the corresponding sense
  - Add the new labeled sentences to the training data

Outline

- Lexical Semantics
- Word Sense Disambiguation
- Word Similarity
- Semantic Role Labeling

Word similarity

- Task
  - Finding the similarity between two words in a wide range of relations (e.g., relatedness)
  - Different of synonymy
  - Being defined with a score (degree of similarity)

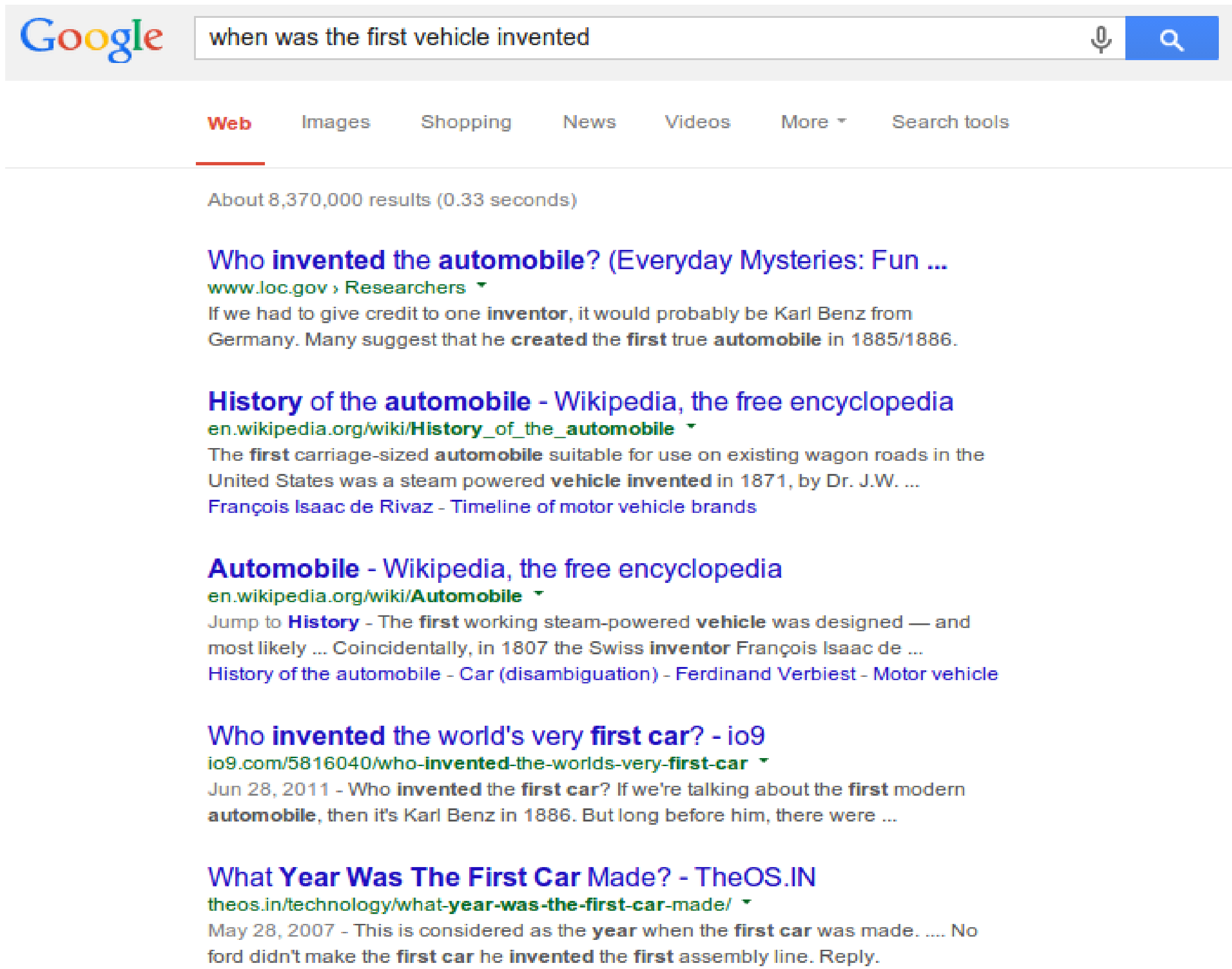
Word similarity

bank $\xleftrightarrow{0.8}$ fund

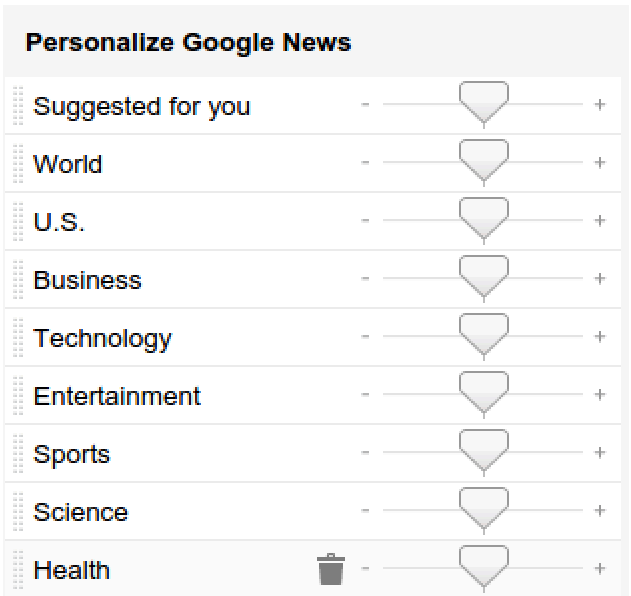
car $\xleftrightarrow{0.5}$ bicycle

car $\xleftrightarrow{0.2}$ gasoline

Motivation: Information retrieval & Question Answering



Motivation: Document categorization



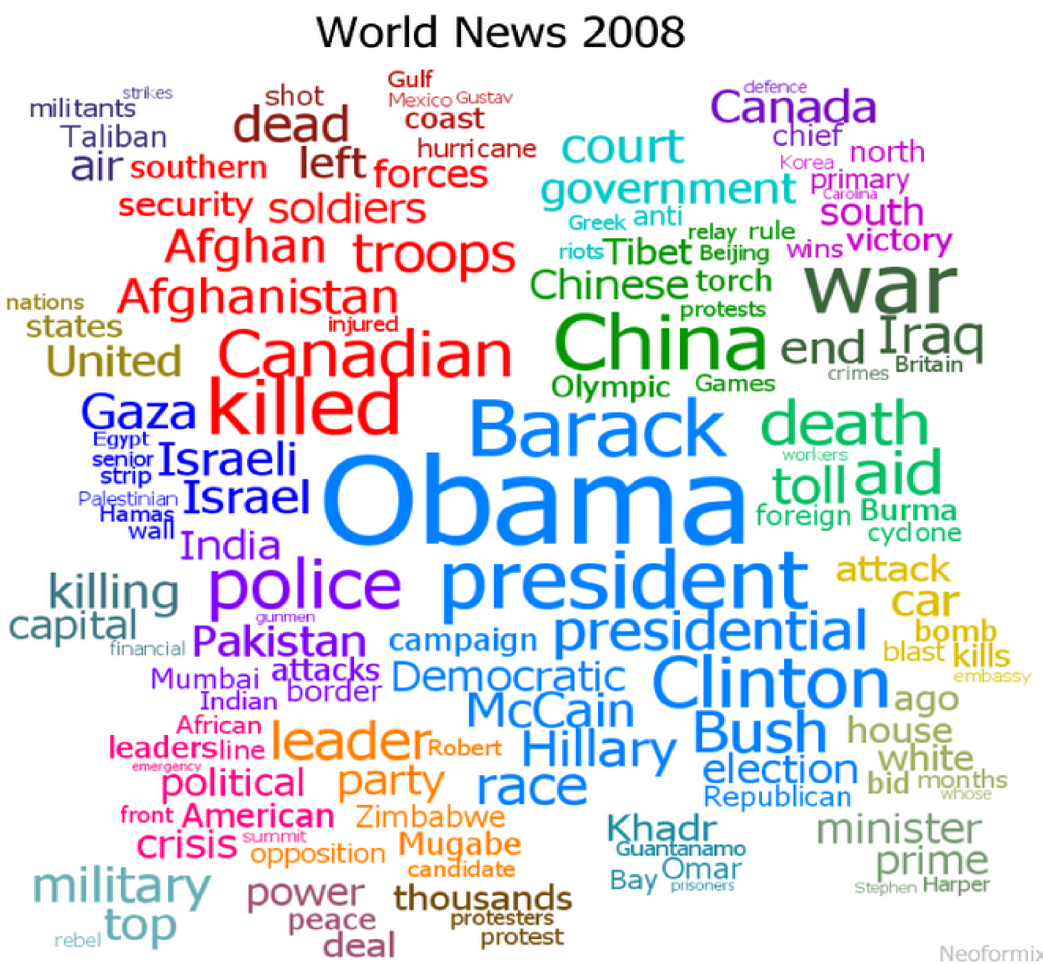
Motivation: Machine translation, summarization, text generation

- Substitution of one word for other in some contexts
  - „The bank is on the left bank of the river“
    - „The financial institution is on the left bank of the river“

Motivation: Language modeling

- Cluster words for class-based models
  - „to London“, „to Beijing“, „to Denver“
  - Classes: CITY_NAME, AIRLINE, DAY_OF_WEEK, MONTH, etc.

Motivation: Word clustering



(http://neoformix.com/2009/WorldNewsClusteredWordCloud.html)

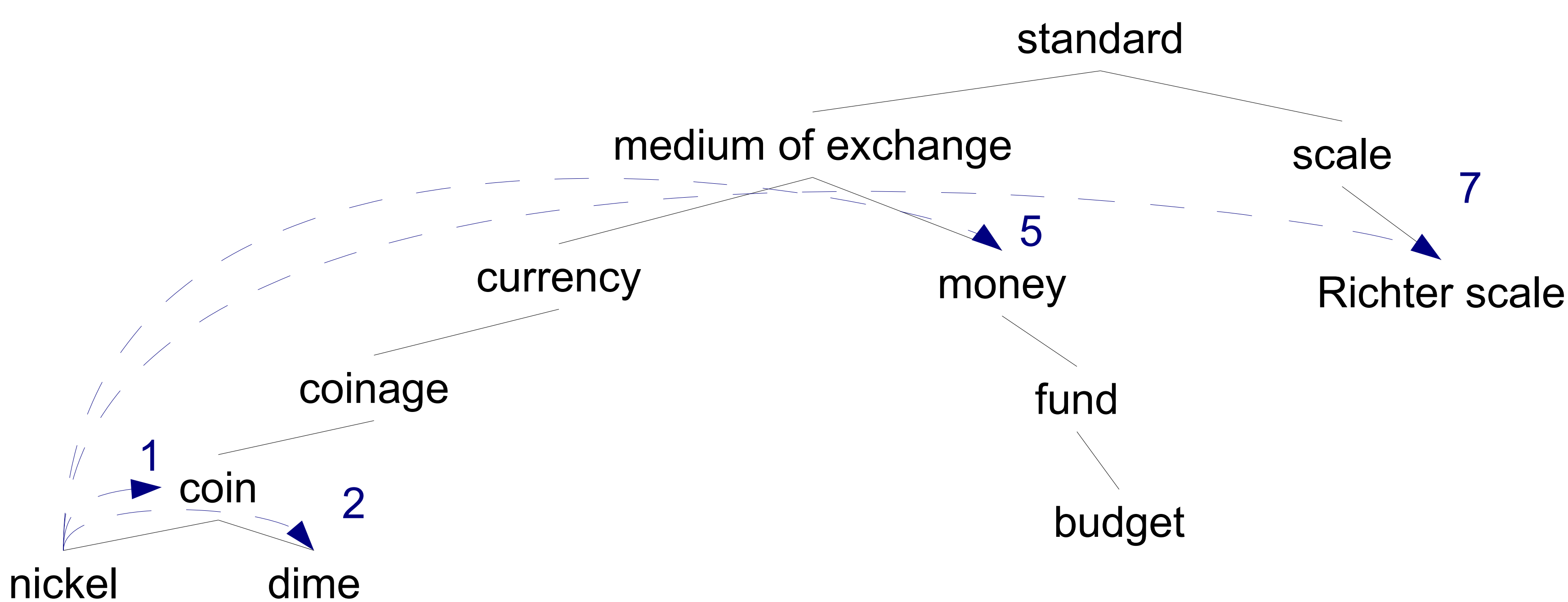
Approaches

- Thesaurus-based
  - Based on their distance in a thesaurus
  - Based on their definition in a thesaurus (gloss)

- Distributional
  - Based on the similarity between their contexts

Thesaurus-based Methods

- Two concepts (sense) are similar if they are “nearby” (short path in the hypernym hierarchy)



Path-base Similarity

- $\text{pathlen}(c_1,c_2)$ = 1 + number of edges in the shortest path between the sense nodes c_1 and c_2

- $\text{sim}_{\text{path}}(c_1,c_2) = -\log \text{pathlen}(c_1,c_2)$

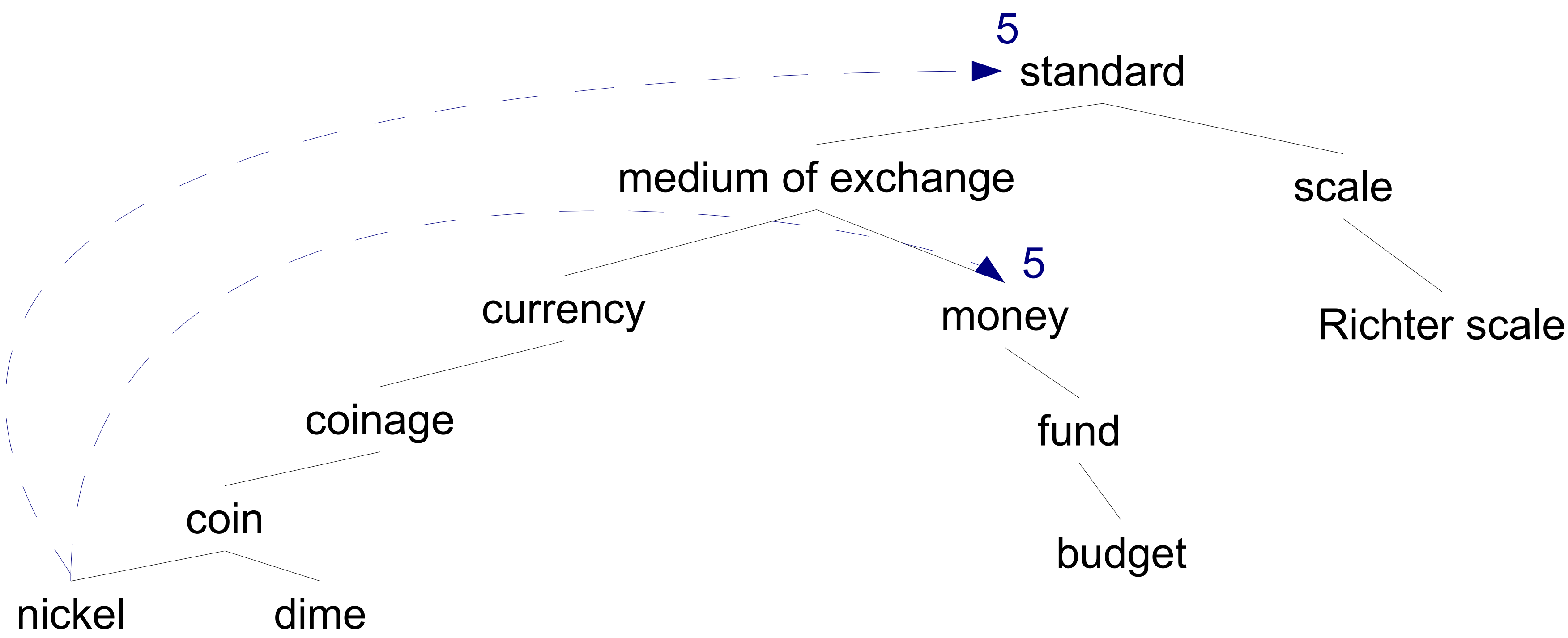
- $\text{wordsim}(w_1,w_2) = \max_{c1 \in \text{senses}(w1),\ c2 \in \text{senses}(w2)} \text{sim}(c_1,c_2)$

  when we have no knowledge about the exact sense

  (which is the case when processing general text)

Path-base Similarity

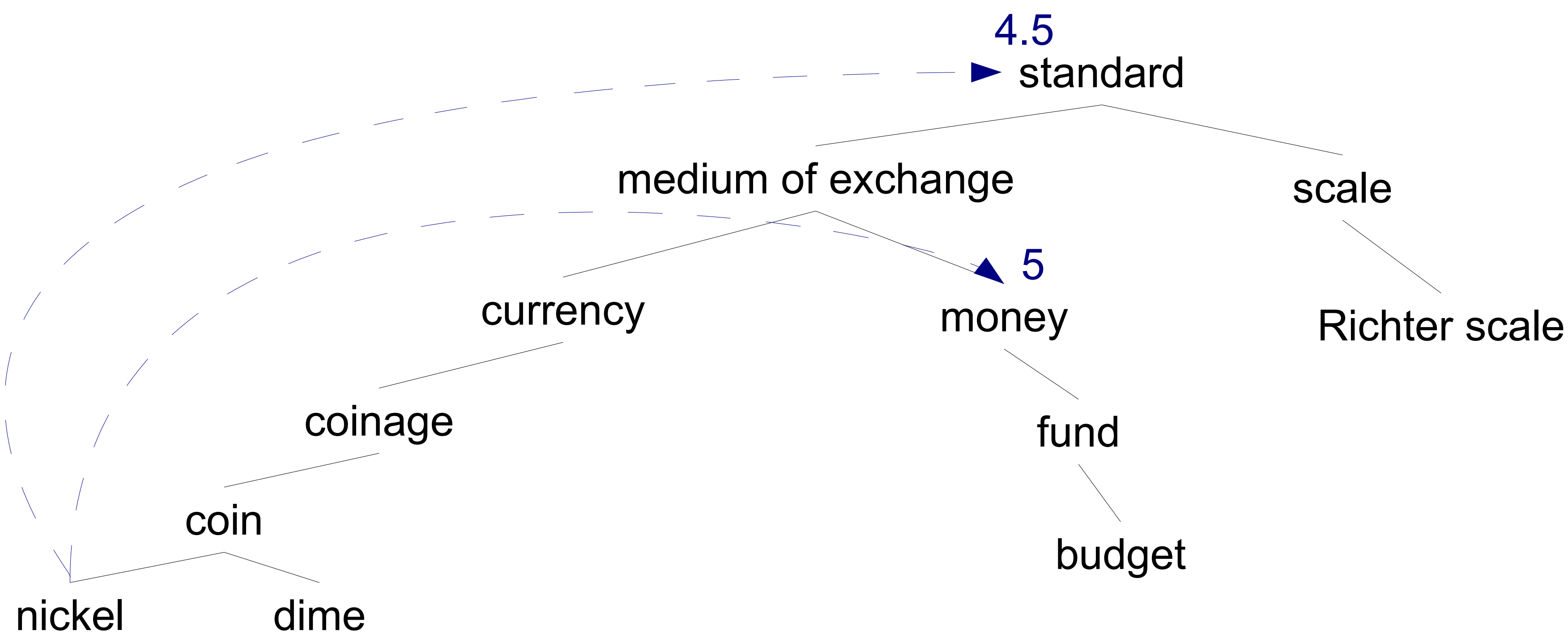
- Shortcoming
  - Assumes that each link represents a uniform distance
    - „nickel" to „money" seems closer than „nickel" to „standard"



Path-base Similarity

- Solution
  - Using a metric which represents the cost of each edge independently

    ⇒ Words connected only through abstract nodes are less similar



Information Content Similarity

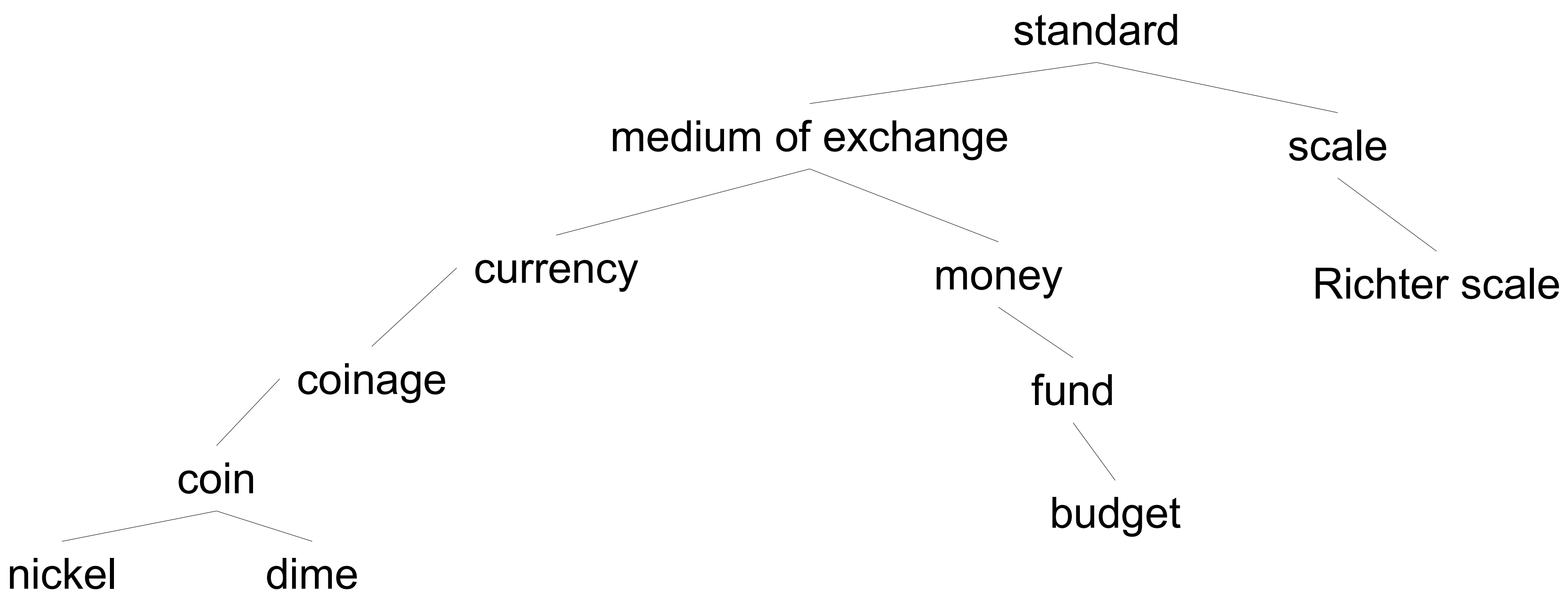
- Assigning a probability P(c) to each node of thesaurus
  - P(c) is the probability that a randomly selected word in a corpus is an instance of concept c

    ⇒ P(root) = 1, since all words are subsumed by the root concept
  - The probability is trained by counting the words in a corpus
  - The lower a concept in the hierarchy, the lower its probability

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

- *words(c)* is the set of words subsumed by concept c
- *N* is the total number of words in the corpus that are available in thesaurus

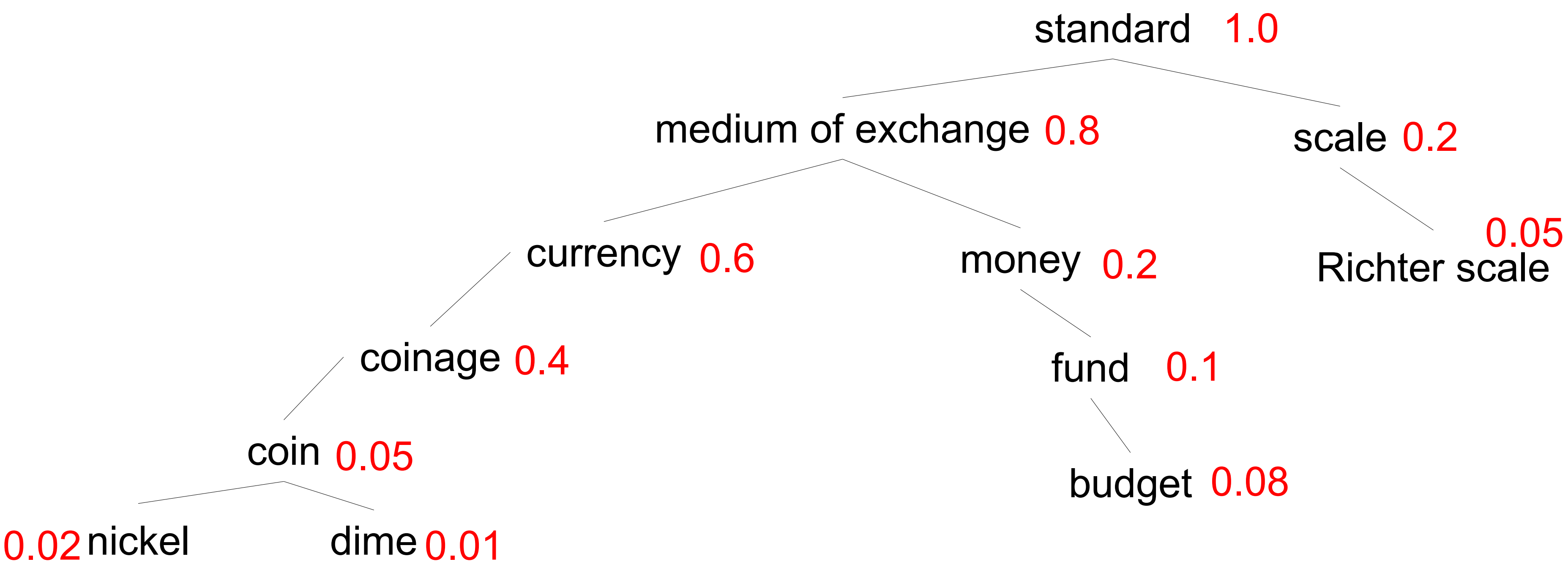
Information Content Similarity



words(coin) = {nickel, dime}
words(coinage) = {nickel, dime, coin}
words(money) = {budget, fund}
words(medium of exchange) = {nickel, dime, coin, coinage, currency, budget, fund, money}

Information Content Similarity

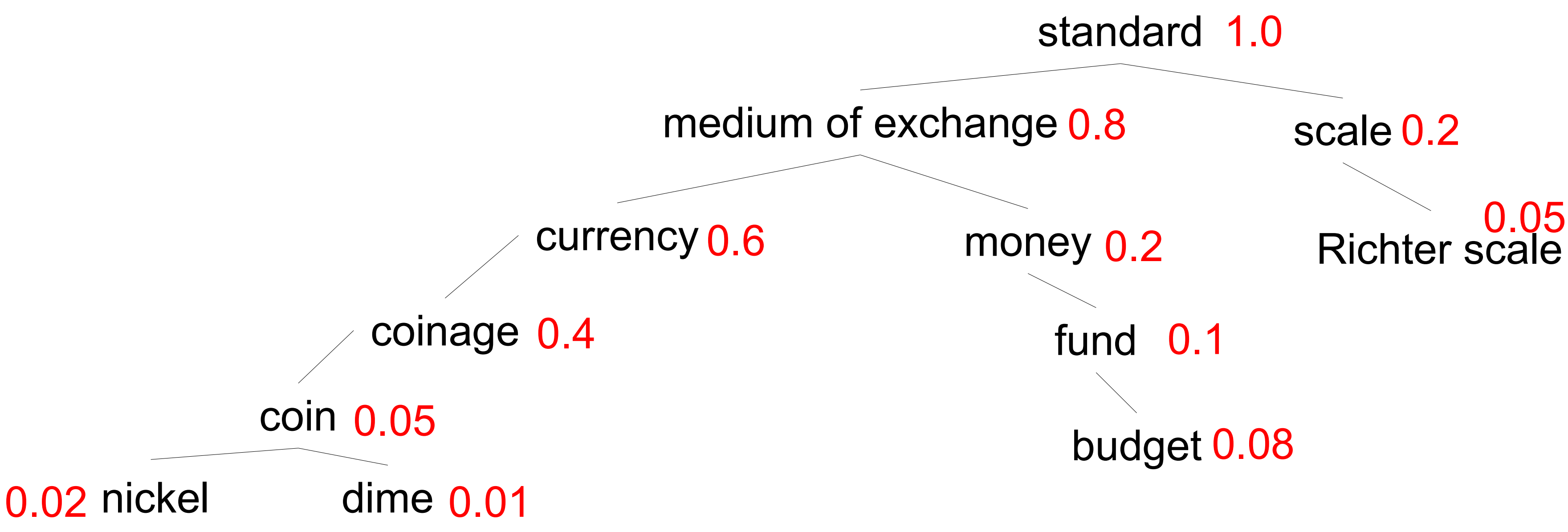
- Augmenting each concept in the hierarchy with a probability P(c)



Information Content Similarity

- Information Content (self-information):

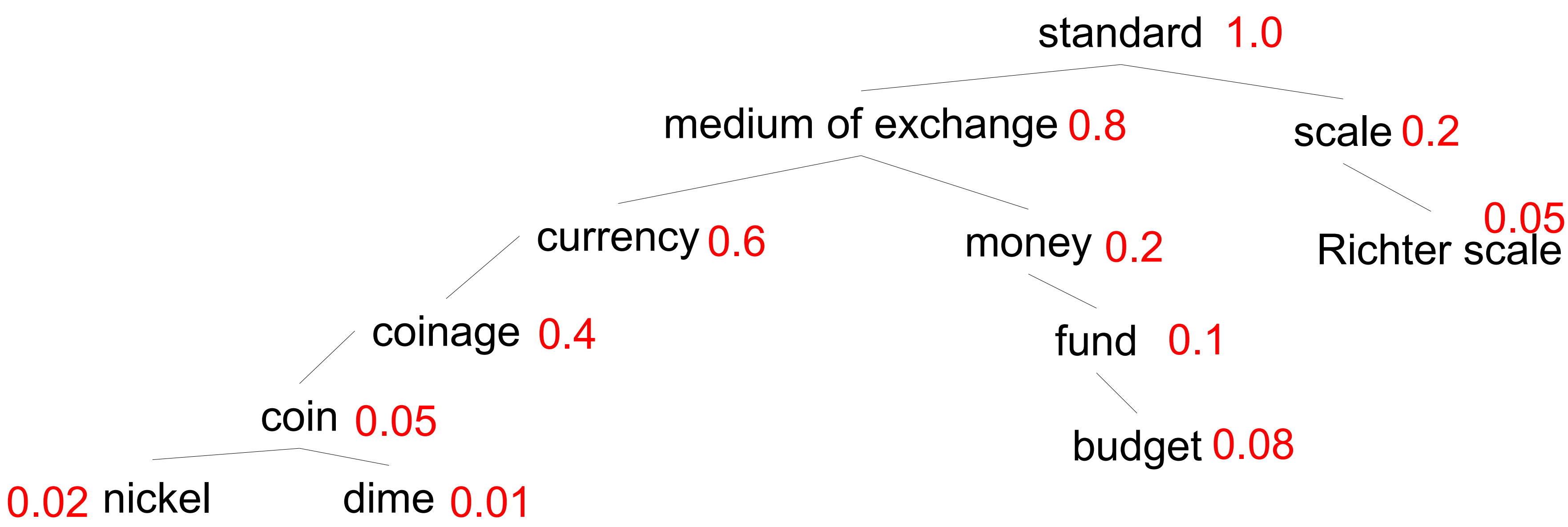
  IC(c) = − log P(c)



Information Content Similarity

- Lowest common subsumer:

  $LCS(c_1,c_2)$ = the lowest node that subsumes c_1 and c_2



Information Content Similarity

- Resnik similarity
  - Measuring the common amount of information by the information content of the lowest common subsumer of the two concepts

$$sim_{resnik}(c_1,c_2) = -\log P(LCS(c_1,c_2))$$

$$sim_{resnik}(dime,nickel) = -\log P(coin)$$

Information Content Similarity

- Lin similarity
  - Measuring the difference between two concepts in addition to their commonality

$$similarity_{LIN}(c_1, c_2) = \frac{2 \log P(LCS(c_1, c_2))}{\log P(c_1) \log P(c_2)}$$

$$similarity_{LIN}(dime, nickel) = \frac{2 \log P(coin)}{\log P(dime) \log P(nickel)}$$

Information Content Similarity

- Jiang-Conrath similarity

$$similarity_{JC}(c_1, c_2) = \frac{1}{\log P(c_1) + \log P(c_2) - 2 \log P(LCS(c_1, c_2))}$$

Extended Lesk

- Looking at word definitions in thesaurus (gloss)
- Measuring the similarity base on the number of common words in their definition
- Adding a score of n^2 for each n-word phrase that occurs in both glosses

$$similarity_{eLesk} = \sum_{r,q \in RELS} overlap\left(gloss\left(r\left(c_1\right)\right), gloss\left(q\left(c_2\right)\right)\right)$$

Extended Lesk

- Computing overlap for other relations as well (gloss of hypernyms and hyponyms)

  - similarity(A,B) = overlap(gloss(A),gloss(B))

    + overlap(gloss(hypo(A)),gloss(hypo(B)))

    + overlap(gloss(A),gloss(hypo(B)))

    + overlap(gloss(hypo(A)),gloss(B))

Extended Lesk

- 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
- common phrases: specially prepared and paper

$$similarity_{eLesk} = 1^2 + 2^2 = 1 + 4 = 5$$

Available Libraries

- WordNet::Similarity
  - Source:
    - http://wn-similarity.sourceforge.net/
  - Web-based interface:
    - http://marimba.d.umn.edu/cgi-bin/similarity/similarity.cgi

Thesaurus-based Methods

- Shortcomings
  - Many words are missing in thesaurus
  - Only use hyponym info
    - Might useful for nouns, but weak for adjectives, adverbs, and verbs
  - Many languages have no thesaurus

- Alternative
  - Using distributional methods for word similarity

Distributional Methods

- Using context information to find the similarity between words

- Guessing the meaning of a word based on its context

Distributional Methods

- tezgüino?
  - A bottle of tezgüino is on the table
  - Everybody likes tezgüino
  - Tezgüino makes you drunk
  - We make tezgüino out of corn

tezgüino = an alcoholic beverage

Context Representations

- Considering a target term t
- Building a vocabulary of M words ($\{w_1, w_2, w_3, \ldots, w_M\}$)
- Creating a vector for t with M features ($t = \{f_1, f_2, f_3, \ldots, f_M\}$)
- f_i means the number of times the word w_i occurs in the context of t

Context Representations

- tezgüino?
  - A bottle of tezgüino is on the table
  - Everybody likes tezgüino
  - Tezgüino makes you drunk
  - We make tezgüino out of corn

- t = tezgüino

  vocab = {book, bottle, city, drunk, like, water,...}

  t = { 0, 1 , 0 , 1 , 1 , 0 ,...}

Context Representations

- Term-term matrix
  - The number of times the context word „c“ appear close to the term „t“ within a window

term / word	art	boil	data	function	large	sugar	summarize	water
apricot	0	1	0	0	1	2	0	1
pineapple	0	1	0	0	1	1	0	1
digital	0	0	1	3	1	0	1	0
information	0	0	9	1	1	0	2	0

Context Representations

- Goal: finding a good metric that based on the vectors of these four words shows
  - [apricot, pineapple] and [digital, information] to be highly similar
  - the other four pairs to be less similar

	art	boil	data	function	large	sugar	summarize	water
apricot	0	1	0	0	1	2	0	1
pineapple	0	1	0	0	1	1	0	1
digital	0	0	1	3	1	0	1	0
information	0	0	9	1	1	0	2	0

Distributional similarity

- Size of the context:
  - How the co-occurrence terms are defined? (What is a neighbor?)
    - Window of k words
    - Sentence
    - Paragraph
    - Document

Distributional similarity

- Weighting: How terms are weighted?
  - Binary
    - 1, if two words co-occur (no matter how often)
    - 0, otherwise

term / word	art	boil	data	function	large	sugar	summarize	water
apricot	0	1	0	0	1	1	0	1
pineapple	0	1	0	0	1	1	0	1
digital	0	0	1	1	1	0	1	0
information	0	0	1	1	1	0	1	0

Distributional similarity

- Weighting: How terms are weighted?
  - Frequency
    - Number of times two words co-occur with respect to the total size of the corpus

$$P(t,c)=\frac{\#(t,c)}{N}$$

Distributional similarity

(t,c)

	art	boil	data	function	large	sugar	summarize	water
apricot	0	1	0	0	1	2	0	1
pineapple	0	1	0	0	1	1	0	1
digital	0	0	1	3	1	0	1	0
information	0	0	9	1	1	0	2	0

P(t, c) {N = 28}

	art	boil	data	function	large	sugar	summarize	water
apricot	0	0.035	0	0	0.035	0.071	0	0.035
pineapple	0	0.035	0	0	0.035	0.035	0	0.035
digital	0	0	0.035	0.107	0.035	0	0.035	0
information	0	0	0.321	0.035	0.035	0	0.071	0

Distributional similarity

- Weighting: How terms are weighted?
  - Pointwise Mutual information
    - Number of times two words co-occur, compared with what we would expect if they were independent

$$PMI(t,c) = \log \frac{P(t,c)}{P(t)P(c)}$$

Pointwise Mutual Information

	art	boil	data	function	large	sugar	summarize	water
apricot	0	0.035	0	0	0.035	0.071	0	0.035
pineapple	0	0.035	0	0	0.035	0.035	0	0.035
digital	0	0	0.035	0.107	0.035	0	0.035	0
information	0	0	0.321	0.035	0.035	0	0.071	0

P(digital, summarize) = 0.035
P(information, function) = 0.035

P(digital, summarize) = P(information, function)

PMI(digital, summarize) =?
PMI(information, function) =?

Pointwise Mutual Information

	art	boil	data	function	large	sugar	summarize	water
apricot	0	0.035	0	0	0.035	0.071	0	0.035
pineapple	0	0.035	0	0	0.035	0.035	0	0.035
digital	0	0	0.035	0.107	0.035	0	0.035	0
information	0	0	0.321	0.035	0.035	0	0.071	0

P(digital, summarize) = 0.035
P(information, function) = 0.035

P(digital) = 0.212
P(function) = 0.142

P(summarize) = 0.106
P(information) = 0.462

$$PMI(digital, summarize) = \frac{P(digital, summarize)}{P(digital) \cdot P(summarize)} = \frac{0.035}{0.212 . 0.106} = 1.557$$

$$PMI(information, function) = \frac{P(information, function)}{P(information) \cdot P(function)} = \frac{0.035}{0.462 . 0.142} = 0.533$$

P(digital, summarize) > P(information, function)

Distributional similarity

- Weighting: How terms are weighted?
  - t-test statistic
    - How much more frequent the association is than chance

$$t-test(t,c)=\frac{P(t,c)-P(t)P(c)}{\sqrt{P(t)P(c)}}$$

Distributional similarity

- Vector similarity: What vector distance metric should be used?
  - Cosine

$$similarity_{cosine}(\vec{v}, \vec{w}) = \frac{\sum_i v_i \times w_i}{\sqrt{\sum_i v_i^2}\sqrt{\sum_i w_i^2}}$$

  - Jaccard, Tanimoto, min/max

$$similarity_{jaccard}(\vec{v}, \vec{w}) = \frac{\sum_i min(v_i, w_i)}{\sum_i max(v_i, w_i)}$$

  - Dice

$$similarity_{dice}(\vec{v}, \vec{w}) = \frac{2 \cdot \sum_i min(v_i, w_i)}{\sum_i (v_i + w_i)}$$

Outline

- Lexical Semantics
- Word Sense Disambiguation
- Word Similarity
- Semantic Role Labeling

Semantic Role Labeling (SRL)

- Also called
  - Thematic role labeling, case role assignment, shallow semantic parsing
- The task of automatic finding the semantic roles for each predicate in a sentence.
  - Which constituents are semantic arguments for a given predicate?

predicate

Mary didn't slap the green witch with a frozen trout in the park.

agent　　theme　　instrument

Semantic Role Labeling

- Can potentially improve any natural language understanding (NLU) task
- Applications:
  - Question answering
  - Information extraction

PropBank/VerbNet

- Around 5,000 verb senses
- „slap“ verb:
  - Roleset id: **slap.01**
  - Role:
    - **Arg0-PAG**: agent, hitter - animate only!
    - **Arg1-PPT**: thing hit
    - **Arg2-MNR**: instrument, thing hit by or with

(http://verbs.colorado.edu/verb-index/index.php
http://verbs.colorado.edu/propbank/framesets-english/slap-v.html)

Methods for SRL

- Usually based on supervised learning
  - Annotated training data is necessary
  - Also need to rely on syntactic parsing or chunking

- Simple algorithm:
  - Parse the sentence
  - For each predicate in the parse tree
    - For each node in the parse tree
      - Create a feature set
      - Classify node

Features for SRL

- Predicate (verb): e.g., „slap“
- Phrase type: e.g., „NP“, „PP“
- Headword: e.g., „Mary“, „witch“, „trout“
- Path in parse tree: e.g., „VP↑VB“, „S↑VP↓VP↓VB“
- Voice: „active“ or „passive“
- Linear position: „before“ or „after“
- Verb subcategorization: e.g., whether it requires objects (VP → NP PP)
- Named entities: e.g., „Mary [PERSON]“

```
(ROOT
  (S
    (NP (NNP Mary))
    (VP (VBD did) (RB n't)
      (VP (VB slap)
        (NP (DT the) (JJ green) (NN witch))
        (PP (IN with)
          (NP
            (NP (DT a) (JJ frozen) (NNS trout))
            (PP (IN in)
              (NP (DT the) (NN park)))))))
    (. .)))
```

Methods for SRL

- A classifier might include a pre-processing **pruning** step to eliminate some constituents
- Classification is taken place for each node and each argument (e..g, ARG1-PPT)
- A post-processing step is necessary to check if a constituent has been assigned to more than one argument
  - Further, one argument is not independent of the others

Summary

- Semantics
  - Senses, relations
- Word disambiguation
  - Thesaurus-based, (semi-) supervised learning
- Word similarity
  - Thesaurus-based
  - Distributional
    - Features, weighting schemes and similarity algorithms
- Semantic role labeling

Further Reading

- Speech and Language Processing
  - Chapters 19, 20