

Text Analysis and Retrieval

5. Semantics

Prof. Jan Šnajder

University of Zagreb
Faculty of Electrical Engineering and Computing (FER)

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v3.0

Computational semantics

(*Wikipedia*)

Computational semantics is the study of how to automate the process of constructing and reasoning with meaning representations of natural language expressions.

- **Word-level (lexical) semantics:** meaning of words
- **Sentence-level semantics:** representing the meaning of a sentence comprised of the meaning of its parts
- **Discourse-level semantics:** meaning of text that goes beyond a single sentence (coreferences/anaphors, discourse structures)

We'll look into (some of) word- and sentence-level semantics...

Outline

- 1 Lexical semantics
- 2 Semantic parsing
- 3 Distributional semantics

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- Lexical semantics is concerned with the meaning of words
 - What the words mean and how they relate to each other
 - Verb and event semantics (semantic roles)
 - Distributional semantics \Rightarrow we'll cover in part 3
 - ...

Word senses and polysemy

- Lemma vs. wordform vs. sense
 - **lemma** = dictionary/citation form of the word (mouse)
 - **wordform** = the specific form of the word (mouses)
 - **sense** = the meaning of the word
- **Polysemy** = the capacity of a word to have multiple senses
 - Many words are **polysemous** (have many senses)
 - Word senses are listed and defined in dictionaries
- **Homonymy** = the relation between different words that share the same surface form
 - e.g., mouse as a noun and mouse as a verb
 - e.g., saw as a verb (inflected) and saw as a noun

Word senses and polysemy

Mouse – two words (homonyms):

The noun “mouse” (4 senses)

- any of numerous small rodents typically resembling diminutive rats having pointed snouts and small ears on elongated bodies with slender usually hairless tails
- shiner, black eye, mouse (a swollen bruise caused by a blow to the eye)
- person who is quiet or timid
- computer mouse (a hand-operated electronic device that controls the coordinates of a cursor on your computer screen as you move it around on a pad)

The verb “mouse” (2 senses)

- sneak, creep, pussyfoot (to go stealthily or furtively) “..stead of sneaking around spying on the neighbor’s house”
- manipulate the mouse of a computer

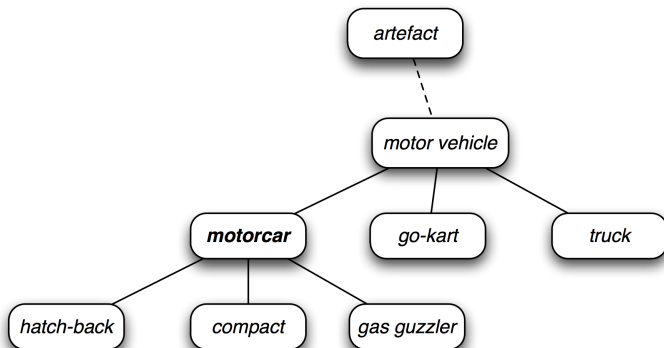
Relationship between senses is an important aspect of word meaning!

- **Synonymy** – identical or nearly identical senses \Rightarrow **synonyms**
 - couch/sofa, car/automobile, mouse/black eye
- **Antonymy** – senses with opposite meanings \Rightarrow **antonyms**
 - long/short, fast/slow, rise/fall
- **Hypernymy** – one sense is more general \Rightarrow **hypernyms**
 - vehicle/car, fruit/mango, mammal/dog
- **Hyponymy** – one sense is more specific \Rightarrow **hyponyms**
 - car/vehicle, mango/fruit, dog/mammal

- Manually constructed lexical database (Fellbaum, 2005)
 - <https://wordnet.princeton.edu/>
- Covers nouns, verbs, adjectives, and adverbs
- Words are organized into **synsets** – sets of words with the same sense
- For each synset WordNet provides:
 - a list of words that can be used in that sense
 - a gloss – a short description of the sense
 - semantic relations to other synsets (hyponymy, meronymy, ...)
- Over 100k synsets for English, coverage is still an issue
- Expensive to build, there are smaller wordnets for other languages

WordNet hierarchy

- Example of the hierarchy from WordNet:



WordNet search

<https://wordnet.princeton.edu/>

WordNet Search - 3.1

- [WordNet home page](#) - [Glossary](#) - [Help](#)

Word to search for:

Display Options:

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Display options for sense: (gloss) "an example sentence"

Noun

- [S:](#) (n) **wing** (a movable organ for flying (one of a pair))
- [S:](#) (n) **wing** (one of the horizontal airfoils on either side of the fuselage of an airplane)
 - [part meronym](#)
 - [direct hypernym](#) / [inherited hypernym](#) / [sister term](#)
 - [part holonym](#)
 - [derivationally related form](#)
- [S:](#) (n) **wing**, [offstage](#), [backstage](#) (a stage area out of sight of the audience)
- [S:](#) (n) **wing** (a unit of military aircraft)
- [S:](#) (n) **flank**, **wing** (the side of military or naval formation) "*they attacked the enemy's right flank*"
- [S:](#) (n) **wing** (a hockey player stationed in a forward position on either side)
- [S:](#) (n) **wing** ((in flight formation) a position to the side and just to the rear of another aircraft)
- [S:](#) (n) **wing** (a group within a political party or legislature or other organization that

Word sense disambiguation

- **Word-sense disambiguation** (WSD) is the task of identifying which sense (meaning) of a polysemous word is used in a sentence

Distinct senses of the word

The newspaper fired the editor. (The company/organization)
John spilled coffee on the newspaper. (The physical newspapers)

- Approaches:
 - Dictionary-based
 - Supervised WSD
 - Unsupervised WSD

- The meanings of verbs are more difficult to classify/systematize
Why?
- Nouns describe **objects**, verbs describe **events**
- Objects can be classified into a hierarchy based on their type
- Verbs: type + temporal dimension + arguments
 - ① Requires a larger set of relations
 - Entailment, Event/Subevent, Causation, . . .
 - No clear single hierarchy!
 - ② Requires a level of description for arguments

Frame semantics

- Theory of frame semantics (Fillmore, 1977):
 - Predicates define frames and frames define arguments with their semantic roles
 - Frames are listed in resources such as FrameNet (Baker et al., 1998)

FrameNet frame

[*VICTIM* A one-year-old baby] was **snatched** [*SOURCE* from a shopping centre][*TIME* last night].

[*PERPETRATOR* The thief] **snatched** [*GOODS* a 32 million dollar worth Dalí painting][*SOURCE* from Louvre].

Hiring

Definition:

An **Employer** hires an **Employee**, promising the **Employee** a certain **Compensation** in exchange for the performance of a job. The job may be described either in terms of a **Task** or a **Position**. In some cases, the **Employee** FE will also indicate the **Position** (see fourth example below).

John was **HIRED** to clean up the file system.

IBM **HIRED** Gates as chief janitor.

I was **RETAINED** at \$500 an hour.

The A's **SIGNED** a new third baseman for \$30M.

The same sentence (above) should also have the FE **Position** on the second layer:

The A's **SIGNED** a new third baseman for \$30M.

FEs:

Core:

Employee [Empee] The person whom the **Employer** takes on as an **Employee**, obligating them to perform some **Task** in order to receive **Compensation**.
I was just **HIRED** yesterday!

Employer [Emper] The person (or institution) that takes on an **Employee**, giving them **Compensation** in return for the performance of an assigned **Task**.
Last month, IBM **HIRED** Mike Zisman to head up its storage software group.

Field [Field] The **Field** that the **Employee** is going to work in for their **Employer**.
It's not easy to get **HIRED** in academia.

Position [Posit] The label given to a particular type of employment.
Look, I wasn't **HIRED** as your waitress!

Task [Task] The action that the **Employee** is taken on by the **Employer** to do.
I was **HIRED** just to empty the trash cans.

Non-Core:

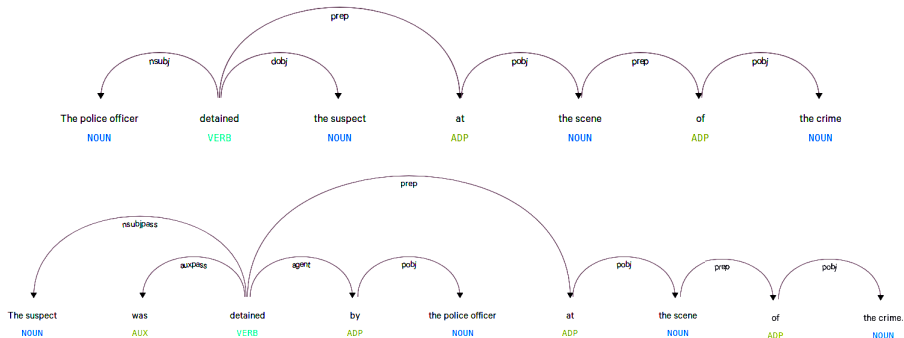
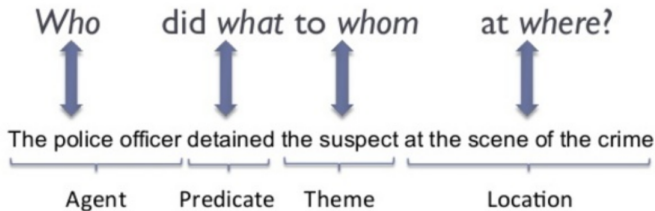
Compensation [Compense] The **Compensation** is the payment that the **Employee** is set to receive for performing an assigned **Task**.
They fired our management, **HIRED** him for 20% more and gave him a free office to set up his own company.

- 1 Define and exemplify polysemy and the main lexical relations
- 2 Describe WordNet and give an example of synsets involving a polysemous word
- 3 Describe the purpose and the main approaches to word sense disambiguation
- 4 Describe frame semantics and FrameNet, and give an example of a frame

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Syntactic vs. semantic parsing

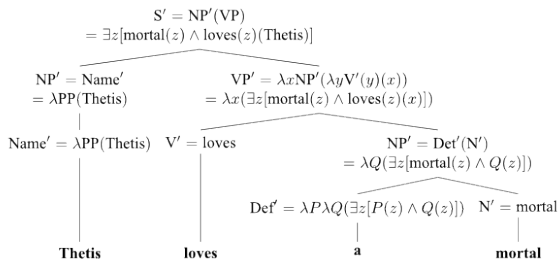


Semantic parsing

- **Semantic parsing** – mapping natural-language sentences (or, generally, text) to a formal representation of meaning
 - **Deep semantic parsing** – mapping to a **complete** meaning representations (including negation, quantifiers, determiners, etc.), which has a rich ontology of types and supports automated reasoning
 - **Shallow semantic parsing** aka **Semantic role labeling (SRL)** – identifying the main semantic roles (constructing the predicate-argument structure)
- Both deep and shallow approaches rely on some formal theory that defines the meaning representations
 - Abend, O., & Rappoport, A. (2017). **The State of the Art in Semantic Representation**. ACL 2017
http://www.cs.huji.ac.il/~oabend/papers/sem_rep_survey.pdf
 - SRL: FrameNet or PropBank

Deep parsing \Rightarrow Formal semantics

- **Formal semantics:** Traditional approach to natural language semantics, focused at sentence-level and discourse-level semantics
- **Montague grammar:** based on predicate logic and lambda calculus, constructs predicate formulas based on parse trees:



- Example: Groningen Meaning Bank – a semantically annotated corpus (<http://gmb.let.rug.nl>)
- Semantically brilliant, but of limited use for practical TAR

Groningen Meaning Bank

<https://gmb.let.rug.nl/>

Bottles
NNS
NP
 $\lambda v0. (x2 : (v0 @ x2))$
bottle(x2)

contain
VBP
(S[dcf]\NP)/NP
 $\lambda v0. \lambda v1. \lambda v2. (v1 @ \lambda v3. (v0 @ \lambda v4. (e6 : (v2 @ e6)) : (v2 @ e6)))$
contain(e6)
Theme(e6, v3)
Co-Theme(e6, v4)

250
CD
NP/N
 $\lambda v0. \lambda v1. (x3 : ((v0 @ x3) : (v1 @ x3)))$
 $x3 = 250$

film-coated
JJ
N/N
 $\lambda v0. \lambda v1. (: (v0 @ v1))$
film-coated(v1)

tablets
NNS
N
 $\lambda v0.$
tablet(v0)

film-coated tablets

N
 $\lambda v0.$
film-coated(v0)
tablet(v0)

250 film-coated tablets

NP
 $\lambda v0. (x2 : (v0 @ x2))$
 $x2 = 250$
film-coated(x2)
tablet(x2)

contain 250 film-coated tablets

S[dcf]\NP
 $\lambda v0. \lambda v1. (v0 @ \lambda v2. (x4 e5 : (v1 @ e5)))$
 $x4 = 250$
film-coated(x4)
tablet(x4)
contain(e5)
Theme(e5, v2)
Co-Theme(e5, x4)

Bottles contain 250 film-coated tablets

S[dcf]
 $\lambda v0. (x2 x3 e4 : (v0 @ e4))$
bottle(x2)
 $x3 = 250$
film-coated(x3)
tablet(x3)
contain(e4)
Theme(e4, x2)
Co-Theme(e4, x3)

Learning outcomes 2

- 1 Define semantic parsing and explain how it differs from syntactic parsing
- 2 Differentiate between deep and shallow semantic parsing
- 3 Define semantic role labeling and how it can be framed as a machine learning task
- 4 Differentiate between FrameNet and PropBank semantic roles

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Distributional semantics

- Representation of word meaning based on **distributional hypothesis**:

Distributional hypothesis (Harris, 1954)

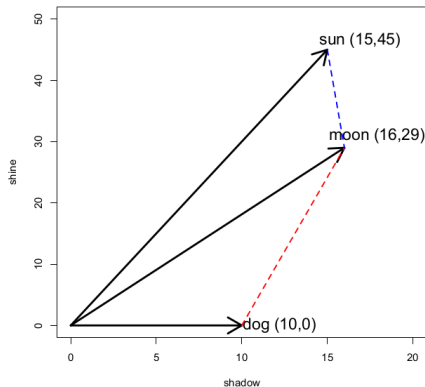
Words that occur in **similar contexts** tend to have **similar meanings**

⇒ correlation between context similarity and meaning similarity

- **Distributional semantics** – represents each word via a distribution of words (or other elements) in its context
- **Distributional semantic model (DSM)** – represents words as vectors of context features obtained from corpus
- Semantic similarity predicted via vector similarity

Distributional semantic models

	planet	night	full	shadow	shine	crescent
moon	10	22	43	16	29	12
sun	14	10	4	15	45	0
dog	0	4	2	10	0	0



Word representations

- Words are discrete objects. We have to figure out a way to represent them in a feature vector for a machine learning model
- Options:
 - ① **One-hot representation**
 - ② **Distributional vectors** (count-based)
 - ③ **Word-embeddings** (aka “distributed representations”)
 - (3a) Dimension-reduced count-based vectors
 - (3b) Trained using a neural network
- (1) and (2) give “sparse representations” \Rightarrow large vectors with many zero elements
- (3) gives “dense representations” \Rightarrow small vectors filled with real-valued numbers

Pretrained dense representations

- word2vec
<https://code.google.com/archive/p/word2vec/>
- Pretrain models for EN:
<https://github.com/mmihaltz/word2vec-GoogleNews-vectors>
- 30+ other languages:
<https://github.com/Kyubyong/wordvectors>
- Alternatives:
 - GloVe (<https://nlp.stanford.edu/projects/glove/>)
 - fastText (<https://fasttext.cc/>) – uses character n-grams
 - ...

word2vec: results

airplane

word	cosine
plane	0.835
airplanes	0.777
aircraft	0.764
planes	0.734
jet	0.716
airliner	0.707
jetliner	0.706

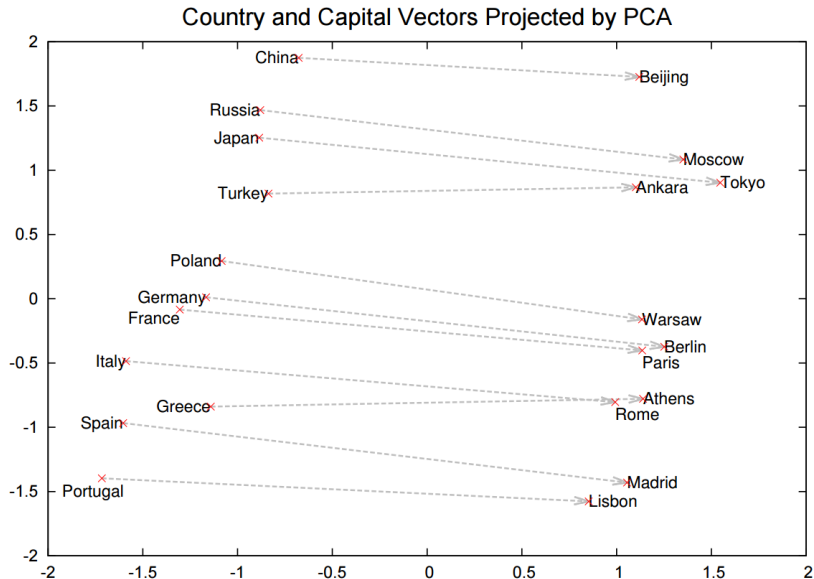
cat

word	cosine
cats	0.810
dog	0.761
kitten	0.746
feline	0.732
puppy	0.707
pup	0.693
pet	0.689

dog

word	cosine
dogs	0.868
puppy	0.811
pit_bull	0.780
pooch	0.763
cat	0.761
pup	0.741
canines	0.722

Word2Vec: results



Semantic composition

- **Semantic composition** = composing the meaning of phrases, sentences or longer text fragments from the meaning of individual words
 - “red” + “apple” = “red apple”
- Language is mostly compositional (we can express an infinitude of meanings using a finite set of words)
- How to automate semantic composition to represent the meaning of text fragments?
- We need this for text classification, comparing text similarity, etc. ... basically, all tasks that work with text fragments!
- The simplest option: **just add up the vectors**
- Alternatives: see study slides

Learning outcomes 3

- 1 State the distributional hypothesis and give an example
- 2 Explain what a distributional semantic model is, how it's constructed, and what it's used for
- 3 Differentiate between three generations of DSMs
- 4 Define distributional semantic composition and the simplest approach to it

Study assignment

① Watch TAR “Semantics” video lectures:

- <https://youtu.be/2h3yvm5qqMM>
- <https://youtu.be/tAZQb5y2tio>
- <https://youtu.be/VBhrgBj5SxA>

② Read chapter on SRL from Jurafsky’s book, sections 24.1–24.6:

<https://web.stanford.edu/~jurafsky/slp3/24.pdf>

③ Read (Lenci et al., 2022), first two sections:

<https://arxiv.org/pdf/2105.09825.pdf>

④ Self-check against learning outcomes!