
Empirical Methods in Natural Language Processing

Lexical Semantics:

Word senses, relations, and classes

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(based on slides by Philipp Koehn and Sharon Goldwater)

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A Concrete Goal

- We would like to build
 - a machine that answers questions in natural language.
 - may have access to knowledge bases
 - may have access to vast quantities of English text
- Basically, a smarter Google
- This is typically called **Question Answering**

Semantics

- To build our QA system we will need to deal with issues in **semantics**, i.e., meaning.
- Lexical semantics: the meanings of individual words (next few lectures)
- Sentential semantics: how word meanings combine (after that)
- Consider some examples to highlight problems in lexical semantics

Example Question

- Question

When was Barack Obama born?

- Text available to the machine

Barack Obama was born on August 4, 1961

- This is easy.

- just phrase a Google query properly:

- "Barack Obama was born on *"

- syntactic rules that convert questions into statements are straight-forward

Example Question (2)

- Question

What plants are native to Scotland?

- Text available to the machine

A new chemical plant was opened in Scotland.

- What is hard?

- words may have different meanings (**senses**)
- we need to be able to disambiguate between them

Example Question (3)

- Question

Where did David Cameron go on vacation?

- Text available to the machine

David Cameron spent his holiday in Cornwall

- What is hard?

- words may have the same meaning (**synonyms**)
- we need to be able to match them

Example Question (4)

- Question

Which animals love to swim?

- Text available to the machine

Polar bears love to swim in the freezing waters of the Arctic.

- What is hard?

- words can refer to a subset (**hyponym**) or superset (**hypernym**) of the concept referred to by another word
- we need to have database of such **A is-a B** relationships, called an **ontology**

Example Question (5)

- Question

What is a good way to remove wine stains?

- Text available to the machine

Salt is a great way to eliminate wine stains

- What is hard?

- words may be related in other ways, including **similarity** and **gradation**
- we need to be able to recognize these to give appropriate responses

Example Question (6)

- Question

Did Poland reduce its carbon emissions since 1989?

- Text available to the machine

Due to the collapse of the industrial sector after the end of communism in 1989, all countries in Central Europe saw a fall in carbon emissions.

Poland is a country in Central Europe.

- What is hard?

- we need to do inference
- a problem for sentential, not lexical, semantics

WordNet

- Some of these problems can be solved with a good ontology, e.g., **WordNet**
- WordNet (English) is a hand-built resource containing 117,000 **synsets**: sets of synonymous words (See <http://wordnet.princeton.edu/>)
- Synsets are connected by relations such as
 - hyponym/hypernym (IS-A: chair-furniture)
 - meronym (PART-WHOLE: leg-chair)
 - antonym (OPPOSITES: good-bad)
- globalwordnet.org now lists wordnets in over 50 languages (but variable size/quality/licensing)

Word Sense Ambiguity

- Not all problems can be solved by WordNet alone.
- Two completely different words can be spelled the same (**homonyms**):

I put my money in the *bank*. vs. He rested at the *bank* of the river.
You *can* do it! vs. She bought a *can* of soda.

- More generally, words can have multiple (related or unrelated) senses (**polysemes**)
- Polysemous words often fall into (semi-)predictable patterns: see next slides (from Hugh Rabagliati in PPLS).

Pattern	Participating Senses	Example Sentences
Animal for fur	Mink, chinchilla, rabbit, beaver, raccoon*, alpaca*, crocodile*	The <i>mink</i> drank some water / She likes to wear <i>mink</i>
Animal/Object for personality	Chicken, sheep, pig, snake, star*, rat*, doll*	The <i>chicken</i> drank some water / He is a <i>chicken</i>
Animal for meat	Chicken, lamb, fish, shrimp, salmon*, rabbit*, lobster*	The chicken drank some water / The <i>chicken</i> is tasty
Artifact for activity	Shower, bath, sauna, baseball,	The <i>shower</i> was leaking / The <i>shower</i> was relaxing
Body part for object part	Arm, leg, hand, face, back*, head*, foot*, shoulder*, lip*,	John's <i>arm</i> was tired / The <i>arm</i> was reupholstered
Building for people	Church, factory, school, airplane,	The <i>church</i> was built 20 years ago / The <i>church</i> sang a song
Complement Coercion	Begin, start, finish, try	John <i>began</i> reading the book / John <i>began</i> the book
Container for contents	Bottle, can, pot, pan, bowl*, plate*, box*, bucket*	The <i>bottle</i> is made of steel / He drank half of the <i>bottle</i>
Word for question	Price, weight, speed	The <i>price</i> of the coffee was low / John asked the <i>price</i> of the coffee

Pattern	Participating Senses	Example Sentences
Figure for Ground	Window, door, gate, goal	The window is broken / The cat walked through the window
Grinding	Apple, chair, fly	The apple was tasty / There is apple all over the table
Instrument for action	Hammer, brush, shovel, tape, lock*, bicycle*, comb*, saw*	The hammer is heavy / She hammered the nail into the wall
Instance of an entity for kind	Tennis, soccer, cat, dog, class*, dinner*, chair*, table*	Tennis was invented in England / Tennis was fun today
Location / Place at location	Bench, land, floor, ground, box*, bottle*, jail*	The bench was made of pine / The coach benched the player
Object for placing at goal	Water, paint, salt, butter, frame*, dress*, oil*	The water is cold / He watered the plant.
Object for taking from source	Milk, dust, weed, peel, pit*, skin*, juice*	The milk tastes good / He milked the cow
Material for artifact	Tin, iron, china, glass, linen*, rubber*, nickel*, fur*	Watch out for the broken glass / He filled the glass with water
Occupation for role in action	Boss, nurse, guard, tutor	My boss is nice / He bossed me around

Pattern	Participating Senses	Example Sentences
Place for an event	Vietnam, Korea, Waterloo, Iraq	It is raining in <i>Vietnam</i> / John was shot during <i>Vietnam</i>
Place for an institution	White House, Washington, Hollywood, Pentagon, Wall Street*, Supreme Court	The <i>White House</i> is being repainted / The <i>White House</i> made an announcement
Plant for food or material	Corn, broccoli, coffee, cotton, lettuce*, eggs*, oak*, pine*	The large field of <i>corn</i> / The <i>corn</i> is delicious
Portioning	Water, beer, jam	She drank some <i>water</i> / She bought three <i>waters</i>
Publisher for product	Newspaper, magazine, encyclopedia, Wall Street Journal*, New York Times*,	The <i>newspaper</i> is badly printed / The <i>newspaper</i> fired three employees
Artist for product	Writer, artist, composer, Shakespeare, Dickens*, Mozart*, Picasso*	The <i>writer</i> drank a lot of wine / The <i>writer</i> is hard to understand
Object for contents	Book, CD, DVD, TV*, magazine*, newspaper*	The heavy, leather- bound <i>book</i> / The <i>book</i> is funny.
Visual Metaphor	Beam, belt, column, stick, bug*, leaf*	Most of the weight rests on the <i>beam</i> / There was a <i>beam</i> of light

How many senses?

- 5 min. exercise: How many senses does the word [interest](#) have?

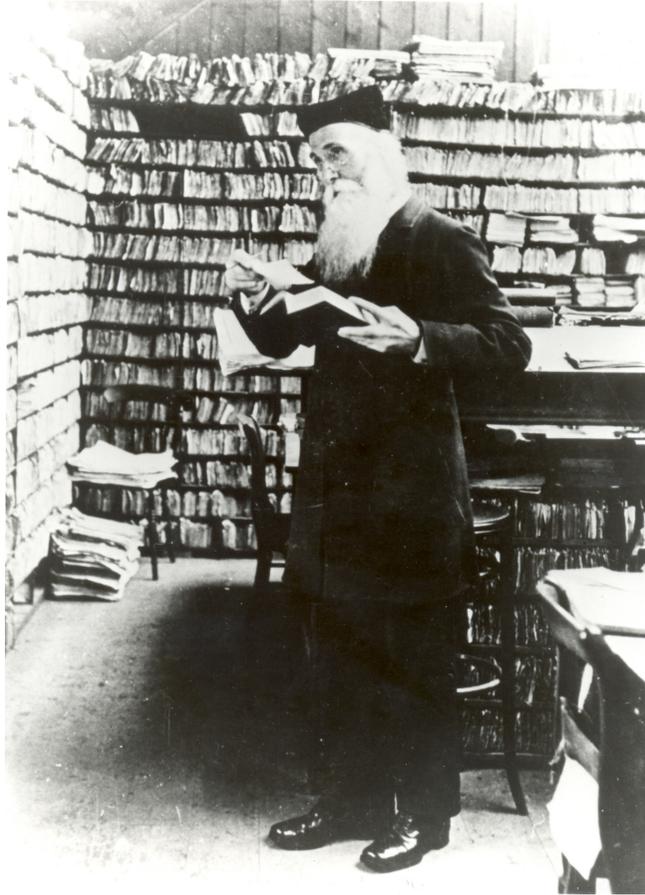
How many senses?



How many senses?

- How many senses does the word **interest** have?
 - She pays 3% **interest** on the loan.
 - He showed a lot of **interest** in the painting.
 - Microsoft purchased a controlling **interest** in Google.
 - It is in the national **interest** to invade the Bahamas.
 - I only have your best **interest** in mind.
 - Playing chess is one of my **interests**.
 - Business **interests** lobbied for the legislation.
- Are these seven different senses? Four? Three?
- Also note: distinction between polysemy and homonymy not always clear!

Lexicography requires data



Lumping vs. Splitting

- For any given word, lexicographer faces the choice:
 - **Lump** usages into a small number of senses? or
 - **Split** senses to reflect fine-grained distinctions?

WordNet senses for interest

- S1: a sense of concern with and curiosity about someone or something, Synonym: involvement
- S2: the power of attracting or holding one's interest (because it is unusual or exciting etc.), Synonym: interestingness
- S3: a reason for wanting something done, Synonym: sake
- S4: a fixed charge for borrowing money; usually a percentage of the amount borrowed
- S5: a diversion that occupies one's time and thoughts (usually pleasantly), Synonyms: pastime, pursuit
- S6: a right or legal share of something; a financial involvement with something, Synonym: stake
- S7: (usually plural) a social group whose members control some field of activity and who have common aims, Synonym: interest group

Synsets and Relations in WordNet

- **Synsets** (“synonym sets”, effectively senses) are the basic unit of organization in WordNet.
 - Each synset is specific to nouns (.n), verbs (.v), adjectives (.a, .s), or adverbs (.r).
 - Synonymous words belong to the same synset: `car1` (car.n.01) = {`car`,`auto`,`automobile`}.
 - Polysemous words belong to multiple synsets: `car1` vs. `car4` = {`car`,`elevator car`}. Numbered roughly in descending order of frequency.
- Synsets are organized into a **network** by several kinds of relations, including:
 - **Hypernymy** (Is-A): hyponym {`ambulance`} is a kind of hypernym `car1`
 - **Meronymy** (Part-Whole): meronym {`air bag`} is a part of holonym `car1`

Using WordNet

- NLTK provides an excellent API for looking things up in WordNet:

```
>>> from nltk.corpus import wordnet as wn
>>> wn.synsets('car')
[Synset('car.n.01'), Synset('car.n.02'), Synset('car.n.03'),
Synset('car.n.04'), Synset('cable_car.n.01')]
>>> wn.synset('car.n.01').definition()
u'a motor vehicle with four wheels; usually propelled by an
internal combustion engine'
>>> wn.synset('car.n.01').hypernyms()
[Synset('motor_vehicle.n.01')]
```

- (WordNet uses an obscure custom file format, so reading the files directly is not recommended!)

Polysemy and Coverage in WordNet

- Online stats:
 - 155k unique strings, 118k unique synsets, 207k pairs
 - nouns have an average 1.24 senses (2.79 if excluding monosemous words)
 - verbs have an average 2.17 senses (3.57 if excluding monosemous words)
- Too fine-grained?
- WordNet is a snapshot of the English lexicon, but by no means complete.
 - E.g., consider **multiword expressions** (including noncompositional expressions, idioms): [hot dog](#), [take place](#), [carry out](#), [kick the bucket](#) are in WordNet, but not [take a break](#), [stress out](#), [pay attention](#)
 - Neologisms: [hoodie](#), [facepalm](#)
 - Names: [Microsoft](#)

Different sense = different translation

- Another way to define senses: if occurrences of the word have different translations, these indicate different sense
- Example [interest](#) translated into German
 - [Zins](#): financial charge paid for loan (WordNet sense 4)
 - [Anteil](#): stake in a company (WordNet sense 6)
 - [Interesse](#): all other senses
- Other examples might have distinct words in English but a polysemous word in German.

Word sense disambiguation (WSD)

- For many applications, we would like to disambiguate senses
 - we may be only interested in one sense
 - searching for [chemical plant](#) on the web, we do not want to know about chemicals in bananas
- Task: Given a polysemous word, find the sense in a given *context*
- Popular topic, data driven methods perform well

WSD as classification

- Given a word token in context, which sense (class) does it belong to?
- We can train a supervised classifier, assuming sense-labeled training data:
 - She pays 3% **interest/INTEREST-MONEY** on the loan.
 - He showed a lot of **interest/INTEREST-CURIOSITY** in the painting.
 - Playing chess is one of my **interests/INTEREST-HOBBY**.
- **SensEval** and later **SemEval** competitions provide such data
 - held every 1-3 years since 1998
 - provide annotated corpora in many languages for WSD and other semantic tasks

What kind of classifier?

Lots of options available:

- Naïve Bayes
- MaxEnt
- Decision lists (see J&M, 20.2.2)
- Decision trees (see any ML textbook)

Naïve Bayes for WSD

- Naïve Bayes requires estimates of:
 - The prior probability of each class (sense)
 - The probability of each feature given each class
- These can be estimated from the training data.
- But what features to use? (Same question for other classifiers!)

Simple features

- Directly neighboring words
 - **interest** paid
 - rising **interest**
 - lifelong **interest**
 - **interest** rate
 - **interest** piqued
- Any content words in a 50 word window
 - pastime
 - financial
 - lobbied
 - pursued

More features

- Syntactically related words
- Syntactic role in sense
- Topic of the text
- Part-of-speech tag, surrounding part-of-speech tags

Of course, with NB we have the usual problem with correlated features. MaxEnt doesn't assume they are independent.

Evaluation

- Extrinsic: test as part of IR, QA, or MT system
- Intrinsic: evaluate classification accuracy or precision/recall against gold-standard senses
- Baseline: choose the most frequent sense (sometimes hard to beat)

Issues with WSD

- Not always clear how fine-grained the gold-standard should be
- Difficult/expensive to annotate corpora with fine-grained senses
- Classifiers must be trained separately for each word
 - Hard to learn anything for infrequent or unseen words
 - Requires new annotations for each new word
 - Motivates unsupervised and semi-supervised methods (see J&M 20.5, 20.10)

Semantic Classes

- Other approaches, such as **named entity recognition** and **supersense tagging**, define coarse-grained semantic categories like PERSON, LOCATION, ARTIFACT.
- Like senses, can disambiguate: **APPLE** as ORGANIZATION vs. FOOD.
- Unlike senses, which are *refinements* of particular words, classes are typically larger groupings.
- Unlike senses, classes can be applied to words/names not listed in a lexicon.

Named Entity Recognition

- Recognizing and classifying **proper names** in text is important for many applications. A kind of **information extraction**.
- Different datasets/named entity recognizers use different inventories of classes.
 - Smaller: PERSON, ORGANIZATION, LOCATION, MISCELLANEOUS
 - Larger: sometimes also PRODUCT, WORK_OF_ART, HISTORICAL_EVENT, etc., as well as numeric value types (TIME, MONEY, etc.)
- NER systems typically use some form of feature-based sequence tagging, with features like capitalization being important.
- Lists of known names called **gazetteers** are also important.

Supersenses

- As a practical measure, WordNet noun and verb synset entries were divided into multiple files (“lexicographer files”) on a semantic basis.
- Later, people realized these provided a nice inventory of high-level semantic classes, and called them **supersenses**.
- Supersenses offer an alternative, broad-coverage, language-neutral approach to corpus annotation.

Supersenses

N:TOPS	N:OBJECT	V:COGNITION
N:ACT	N:PERSON	V:COMMUNICATION
N:ANIMAL	N:PHENOMENON	V:COMPETITION
N:ARTIFACT	N:PLANT	V:CONSUMPTION
N:ATTRIBUTE	N:POSSESSION	V:CONTACT
N:BODY	N:PROCESS	V:CREATION
N:COGNITION	N:QUANTITY	V:EMOTION
N:COMMUNICATION	N:RELATION	V:MOTION
N:EVENT	N:SHAPE	V:PERCEPTION
N:FEELING	N:STATE	V:POSSESSION
N:FOOD	N:SUBSTANCE	V:SOCIAL
N:GROUP	N:TIME	V:STATIVE
N:LOCATION	V:BODY	V:WEATHER
N:MOTIVE	V:CHANGE	

- The **supersense tagging** goes beyond NER to cover all nouns and verbs.

Summary (1)

- In order to support technologies like question answering, we need ways to reason computationally about **meaning**. **Lexical semantics** addresses meaning at the word level.
 - Words can be ambiguous (**polysemy**), sometimes with related meanings, and other times with unrelated meanings (**homonymy**).
 - Different words can mean the same thing (**synonymy**).
- Computational lexical databases, notably WordNet, organize words in terms of their meanings.
 - **Synsets** and relations between them such as hypernymy and meronymy.

Summary (2)

- **Word sense disambiguation** is the task of choosing the right sense for the context.
 - Classification with contextual features
 - Relying on dictionary senses has limitations in granularity and coverage
- **Semantic classes**, as in NER and supersense tagging, are a coarser-grained representation for semantic disambiguation and generalization.