Introduction to Human Language Technologies
5. Lexical semantics

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FIB

Outline

Semantics

Semantics deals with the meaning:

- Lexical semantics: deals with the meaning of individual words
- Compositional semantics: deals with the construction of meaning usually in high concordance with syntax

This session focuses on lexical semantics

Outline

Motivation of lexical semantics

Some examples of usefulness:

- Discovery of semantic patterns
  - Ex: USA bombed Hiroshima
    They began to bombard the defenses
    → A sense_12533 B
- Determine discourse relations
  - Ex: [Anna will show up later.] [She has missed the train.] → explanation
  - Ex: [Mathew is good cooking.] [Albert fails making every dish] → contrast
- Twitter sentiment analysis
  - Ex: @vooda1: CNN Declines to Air White House Press Conference Live YES! THANK YOU @CNN FOR NOT LEGITIMI...
    positive
  - Ex: @Slate: Donald Trump's administration: "Government by the worst men."
    negative

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Resources of lexical semantics

- Knowledge-based resources: represented as graphs

  Ex: WordNet (English lexical ontology)
  SentiWordNet (sentiment polarity into WordNet)
  BabelNet (Wikipedia+WordNet)
  VerbNet (syntactic/semantic verbal behaviour)
  FrameNet (conceptual behaviour –fine-grained event representation–)
  ConceptNet (common sense knowledge)

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  ConceptNet (common sense knowledge)
- Corpus-based resources: contextual usage of words
  Ex: Latent Semantic Analysis (LSA)
  Word embeddings , sense embeddings
  We will study them in AHLT

Resources of lexical semantics

WordNet	`https://wordnet.princeton.edu/`
SentiWordNet	`https://github.com/aesuli/SentiWordNet`
BabelNet	`https://babelnet.org/`
VerbNet	`https://verbs.colorado.edu/verbnet/`
FrameNet	`https://framenet.icsi.berkeley.edu/fndrupal/`
LSA	accessible from
Word embeddings	`https://radimrehurek.com/gensim/`

Outline

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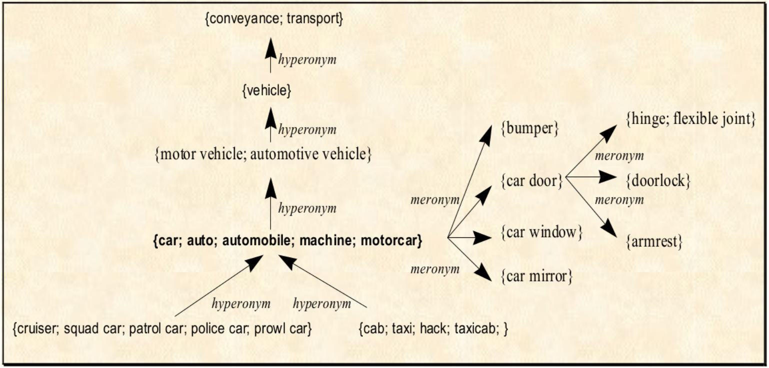
WordNet

- Free large lexical database of English
- Contains only nouns, verbs, adjectives and adverbs
- Words are grouped into synonyms sets (*synsets*)
- each *synset* has an associated gloss and some examples
- *synsets* are interlinked by means of lexical relations

https://en-word.net/lemma/demo

Lexical relations

Example of Lexical Relation Net



Lexical relations

- Synonym: same meaning. Ex: age - historic_period
- Antonym: opposite meaning. Ex: dark - light
- Homophome: same sound. Ex: son - sun
- Homograph: same written form. Ex: lead (noun - verb)
- Polysemy: different related meaning. Ex: newspaper (paper - firm)
- Homonymy: different unrelated meaning. Ex: position (place - status)
- Hypernym: parent. Ex: cat - feline
- Hyponym: child. Ex: feline - cat
- Holonym: group, whole. Ex: student - class
- Meronym: member, part. Ex: class - student
- Metonym: substitution of entity. Ex: We ordered many delicious dishes at the restaurant.

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Similarities in WordNet

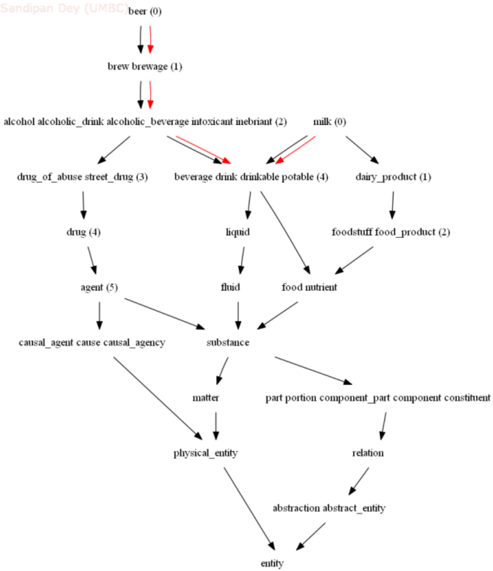
- Shortest Path Length: $Sim(s_1, s_2) = \frac{1}{SPL(s_1,s_2)}$
  where $SPL(s_1, s_2)$ = Shortest Path Length from s_1 to s_2 as vertex-countings

- Leacock & Chodorow: $Sim(s_1, s_2) = -log_2 \frac{SPL(s_1,s_2)}{2 \cdot MaxDepth}$
  where $depth(s)$ = SPL(TopSynset,s)
  $MaxDepth = \max_{s \in WN} depth(s)$

- Wu & Palmer:
  $Sim(s_1, s_2) = \frac{2 \cdot depth(LCS(s_1,s_2))}{depth_{LCS(s_1,s_2)}(s_1) + depth_{LCS(s_1,s_2)}(s_2)}$
  where $LCS(s_1, s_2)$ = Lowest Common Subsumer of s_1 and s_2
  $depth_{s'}(s)$ = SPL(TopSynset,s) through s'

- Lin: $Sim(s_1, s_2) = \frac{2 \cdot IC(LCS(s_1,s_2))}{IC(s_1) + IC(s_2)}$
  where $IC(s) = -log_2 P(s)$ = information content of s (from frequencies in a corpus)

Example / exercise



$spl(beer, milk) = 5$
$Sim_{spl}(beer, milk) = 0.2$

$Sim_{wp}(beer, milk) = 0.75$

$Sim_{spl}(drug, milk)$?
$Sim_{wp}(drug, milk)$?

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Definition

Extension of wordnet that adds for each synset 3 measures:

- positive_score
- negative_score
- objective_score = 1 - positive_score - negative_score

Wordnet		SentiWordnet		
Antonym Synsets	Gloss	obj	pos	neg
bad.a.01	having undesirable or negative qualities	0.375	0.0	0.625
good.a.01	having desirable or positive qualities. . .	0.25	0.75	0.0
bad.n.01	that which is below standard or expectations as of ethics or decency	0.125	0.0	0.875
good.n.03	that which is pleasing, valuable, useful	0.375	0.625	0.0

Outline

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Sentiment analysis

Different subtasks:

- Opinion detection: given a piece of text (document or sentence), is it an objective text or a subjective one?
- Polarity classification: given a subjective piece of text, is it a positive opinion or a negative one?
- Opinion extraction: given a subjective piece of text, recognise the focuses of the opinion (templates <entity, aspect, polarity>).

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Unsupervised sentiment analysis

Possible solution:

$$h(D) = \sum_{s \in \hat{D}} score(s)$$

$\hat{D}$ is usually the set of synsets related to adjectives, or to nouns and adjectives, or to nouns, verbs, adjectives and adverbs.

- Opinion detection:

$$score(s) = 1 - obj_s \quad or \quad score(s) = obj_s$$

- Polarity classification:

$$score(s) = pos_s - neg_s$$

Pros:

- no need for training corpora

Cons:

- low results
- need for POS and WSD taggers

Supervised sentiment analysis

Possible solution:

Bag of words with Naïve Bayes

$$h(D) = h(w_1, \ldots, w_n) = \operatorname*{argmax}_y P(y) \prod_{i=1}^{n} P(w_i|y)$$

where y is the category (positive/negative, subjective/objective), and $w_1, \ldots, w_n$ is the bag of words related to D

- Given a training corpus $C = \{d_i\}$ partitioned into subsets Y_1 and Y_2
  - $P(y) \approx P_{MLE}(y) = \frac{|Y_i|}{|C|}$
  - $P(w_i|y) \approx P_{MLE}(w_i|Y_j) = \frac{c(w_i, Y_j)}{\sum_{w_i \in Y_j} c(w_i, Y_j)}$

Pros:

- higher results
- no need for POS and WSD taggers

Cons:

- need for training corpora

Hybrid approach for sentiment analysis

Possible solution:

- Combine two supervised methods with SentiWordnet method
- I.e., consensuate the output of the three methods, using *voting*, for instance:

  if at least 2 of the methods answer y then output y
  else output the answer of the method with better accuracy in the training corpus

The combination improves the results of the isolated methods

Annex

- Base on the Bayes' theorem:

$$P(y|x_1,\dots,x_n) = \frac{P(y)P(x_1,\dots,x_n|y)}{P(x_1,\dots,x_n)}$$

- Naïve assumption of independence between features:

$$P(y|x_1,\dots,x_n) \approx P(y)\prod_{i=1}^{n} P(x_i|y)$$

- *Maximum likelihood estimation* of $P(y)$ and $P(x_i|y)$ as training model
- Test prediction as:

$$h(x_1,\dots,x_n) = \operatorname*{argmax}_y P(y)\prod_{i=1}^{n} P(x_i|y)$$

- Need a smoothing technique to avoid zero counts:
  in NLTK never seen features are discarded