# IN2110: Språkteknologiske metoder Ord: Leksikalsk semantikk og ordvektorer

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- Evaluation of classifiers.
- ► Unsupervised machine learning for class discovery: Clustering.
- ► k-means clustering.



- Focus on *words* rather than documents.
- Distributional models of word meaning (lexical semantics).
- ► Vector Semantics.
- ► Words and Vectors.
- Example tasks for evaluating word vectors.

## Lexical Semantics



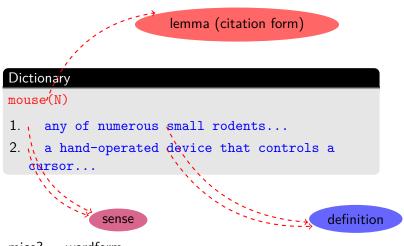
- Lexical Semantics = linguistic study of word meaning.
- How should we represent the meaning of a word?
- What do we want a word meaning model to do for us?

We want a model of word meaning to tell us (e.g.):

- ▶ words have similar meanings (*cat* is similar to *dog*).
- ▶ words are antonyms (*cold* is the opposite of *hot*).
- words have positive or negative connotations (*happy* and *sad* respectively).
- the meaning of *sell*, *pay*, *buy* are different perspectives on the same underlying purchasing event.

### What do words mean?





mice? = wordform



- ► A sense or "concept" is the meaning component of a word.
- Important component of word meaning = relationships between word senses.



- Synonyms have the same meaning in some or all contexts.
  - ► couch & sofa, big & large, automobile & car, vomit & throw up, water & H<sub>2</sub>0
- Synonymy between senses: "a word sense whose meaning is (nearly) identical to a sense of another word". Chapter 6, p.3.
- Synonymy between words (more formal): "two words are synonyms if they are substitutable one for the other in any sentence without changing the *truth conditions* of the sentence, the situations in which the sentence would be true." Chapter 6, p.3.
- No examples of perfect synonymy.
- The Linguistic Principle of Contrast:
  - Difference in form  $\rightarrow$  difference in meaning.
  - ► water & H<sub>2</sub>0: H<sub>2</sub>0 appropriate in scientific contexts, inappropriate in hiking guide.



Senses that are opposites with respect to one feature of meaning. Otherwise, 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



### How to automatically distinguish synonyms from antonyms ?



Words don't have many synonyms, but have lots of similar words.

From synonymy to similarity:

• relations between senses  $\rightarrow$  relations between words.

Words with similar meanings. Not synonyms, but sharing some element of meaning:

#### Examples

- ► alligator, crocodile
- love, affection
- ► cat, dog



Word relatedness (or word association): words are related if they do not share features, but commonly "participate" in a shared event.

### Similarity VS Relatedness

- ► car , bicycle: similar.
- car , gasoline: related, not similar.

#### Word Relatedness

- car , tyre
- car , motorway
- ► car , crash
- ► coffee , cup

Words can be related in any way, e.g. via a semantic frame or semantic field.

# Values of word similarity



How to get values for word similarities?

How to automatically differentiate between word similarity and word relatedness?

► Ask human judges!

SimLex-999 dataset (Hill et al., 2015):

- ► gold standard resource for evaluating distributional semantic models.
- quantifies similarity rather than relatedness.

| word1  | word2      | similarity |
|--------|------------|------------|
| vanish | disappear  | 9.8        |
| behave | obey       | 7.3        |
| belief | impression | 5.95       |
| muscle | bone       | 3.65       |
| modest | flexible   | 0.98       |
| hole   | agreement  | 0.3        |



Words that:

- cover a particular semantic domain.
- bear structured relations with each other.

### Examples

- ► hospitals: surgeon, scalpel, nurse, anesthetic, hospital
- ► restaurants: waiter, menu, plate, food, chef
- ► houses: door, roof, kitchen, family, bed



Closely related to semantic fields.

"A semantic frame is a set of words that denote perspectives or participants in a particular type of event." Chapter 6, p.4.

Frames have semantic roles, and words in a sentence can take on these roles.

- ► buy, sell, pay.
- buyer, seller, goods, money.

Semantic frames makes it possible for systems to recognize paraphrases.

- Sam bought the book from Ling.
- Ling sold the book to Sam.



Word senses can be related taxonomically.

### hyponyms and hypernyms:

- ► a word (sense) is a hyponym of another word (sense) if the first is more specific, denoting a subclass of the other.
- ► a word (sense) is a hypernym of another word (sense) if the first one is more general.

#### Examples

- car is a hyponym of vehicle.
- mango is a hyponym of fruit.
- vehicle is a hypernym of car.
- fruit is a hypernym of mango.



Hypernymy can be defined in terms of entailment:

- ► sense A is a hyponym of B if everything that is A is also B.
- being A entails being B.

Hyponymy and hypernymy are transitive: A hyponym of B, B hyponym of C, then A is hyponym of C.

Hyponyms and hypernyms structure is the IS-A hierarchy: A IS-A B, or B subsumes A.

Hyponym and hypernym too similar: easily confused.

The words subordinate and superordinate are used instead.

| Superordinate | vehicle | fruit | furniture |
|---------------|---------|-------|-----------|
| Subordinate   | car     | mango | chair     |



### Words have affective meanings or connotations.

Connotations are aspects of a word's meaning related to a writer/reader's emotions, sentiment, opinions, or evaluations.

- ► positive connotations (happy).
- negative connotations (sad).
- ► positive evaluation (great, love) sentiment.
- ▶ negative evaluation (terrible, hate) sentiment.

In affective meaning (Osgood et al., 1957) – words vary along 3 dimensions:

- ► valence, arousal, and dominance represented by numbers.
- word meaning can be represented as a vector, a list of numbers, point in a dimensional space.



Concepts or word senses

- Have a complex many-to-many association with words (homonymy, multiple senses)
- Have relations with each other
  - Synonymy , Antonymy, Similarity, Relatedness, Superordinate/subordinate, Connotation

How to build a computational model that successfully deals with the different aspects of word meaning?

How to define word meaning for a computational model?

# Distributional hypothesis

- ► A perfect model that can deal with all the aspects of word meaning is very difficult to find!
- Linguistic and philosophical works from the 1950's inspired the current best model: vector semantics
- "The meaning of a word is its use in the language" (Ludwig Wittgenstein, 1953, PI 43).
- ► The linguistic distributionalists Joos (1950), Harris (1954), Firth (1957):
  - words are defined by their environments or distributions (the words around them).
  - a word's distribution is the set of contexts in which it occurs: the neighboring words or grammatical environment.
- "If A and B have almost identical environments we say that they are synonyms." (Zellig Harris, 1954).

 $\rightarrow$  two words that occur in very similar distributions (context, similar words) tend to have the same meaning.





Suppose you see these sentences:

- Ongchoi is delicious sautéed with garlic.
- Ongchoi is superb over rice.
- Ongchoi **leaves** with salty sauces.

And you've also seen these:

- ...spinach sautéed with garlic over rice.
- Chard stems and **leaves** are **delicious**.
- Collard greens and other **salty** leafy greens.

Conclusion:

 Ongchoi is a leafy green like spinach, chard (bladbete), or collard greens (en type grønnkål).



Computationally:

- count words in the context of *ongchoi*:
  - ▶ find words like *sauteed*, *eaten*, *garlic*.
  - ► these words occur around *spinach/collard green*.

 $\rightarrow$  there is a similarity between *ongchoi* and *spinach/collard green*.

Vector semantics combines two intuitions:

- distributional intuition.
- ▶ vector intuition (Osgood et al., 1957, slide 22)

# Model of word meaning



Build a model of meaning focused on similarity:

- Each word = a vector.
- ► Similar words are "nearby in space".

| to   | by   | 's  |     | not good bad   |       |
|------|------|-----|-----|----------------|-------|
| that | now  |     | are | dislike        | worst |
| а    | i    | you |     | incredibly bad |       |
| than | with | is  |     |                | worse |





A word vector is called an "embedding" (embedded into a space).

The standard way to represent meaning in NLP.

Fine-grained model of meaning for similarity:

We focus on 2 kinds of embeddings:

- ► Tf-idf:
  - Sparse vectors and common baseline model.
  - ► Words are represented by a simple function of the counts of nearby words.
- ► Word2vec (next week with Fredrik):
  - Dense vectors.
  - Representation is created by training a classifier to distinguish nearby and far-away words.

## Vectors and documents VS Words and vectors



Distributional models of meaning (vectors) generally based on a co-occurrence matrix.

Term-document matrix VS word-word matrix:

|        | As You Like It |  | Twelfth Night |  | Julius Caesar |  | Henry V |  |
|--------|----------------|--|---------------|--|---------------|--|---------|--|
| battle | 1              |  | 0             |  | 7             |  | 13      |  |
| good   | 114            |  | 80            |  | 62            |  | 89      |  |
| fool   | 36             |  | 58            |  | 1             |  | 4       |  |
| wit    | 20             |  | 15            |  | 2             |  | 3       |  |

|        | As ۱ | ou Like It | Twelfth Night | Julius Caesar | Henry V | / |
|--------|------|------------|---------------|---------------|---------|---|
| battle |      | 1          | 0             | 7             | 13      |   |
| good   | (    | 114        | 80            | 62            | 89      | ) |
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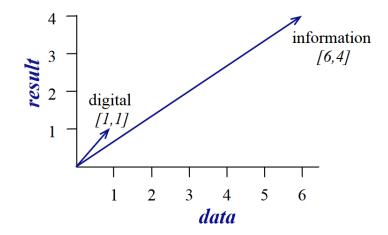


#### word-word matrix or term-term matrix or term-context matrix.

Two words are similar in meaning if their context vectors are similar.

|            | aardvark | <br>computer | data | pinch | result | sugar |
|------------|----------|--------------|------|-------|--------|-------|
| apricot    | 0        | <br>0        | 0    | 1     | 0      | 1     |
| pineapple  | 0        | <br>0        | 0    | 1     | 0      | 1     |
| digital    | 0        | <br>2        | 1    | 0     | 1      | 0     |
| infomation | 0        | <br>1        | 6    | 0     | 4      | 0     |







Based on all we've seen so far, how to compute word similarity? (Eivind will tell you more about it!)