

CHAPTER6: Vector Semantics and Embeddings

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Presentation Overview

1 Lexical Semantics

2 Vector Semantics

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1 Lexical Semantics

2 Vector Semantics

What do words mean?

N-gram or text classification methods we've seen so far

- Words are just strings (or indices w_i in a vocabulary list)
- That's not very satisfactory!

Introductory logic classes:

The meaning of "dog" is **DOG**; cat is **CAT**

$$\forall x, DOG(x) \longrightarrow MAMMAL(x)$$

Old linguistics joke by Barbara Partee in 1967:

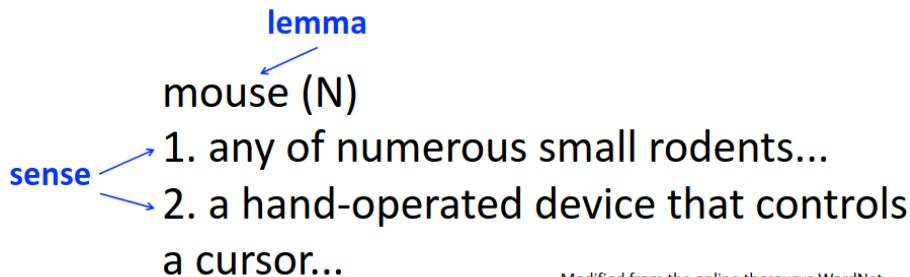
- **Q**: What's the meaning of life?
- **A**: LIFE

That seems hardly better!

What should a theory of word meaning do for us?

Let's look at some desiderata

From [lexical semantics](#), the linguistic study of word meaning



Modified from the online thesaurus WordNet

A **sense** or “**concept**” is the meaning component of a word Lemmas can be **polysemous** (have multiple senses)

Relations between senses: Synonymy

Synonyms have the same meaning in some or all contexts.

- filbert / hazelnut
- couch / sofa
- big / large
- automobile / car
- vomit / throw up
- water / H₂O

Relations between senses: Synonymy

Note that there are probably no examples of perfect synonymy.

- Even if many aspects of meaning are identical
- Still may differ based on politeness, slang, register, genre, etc.

water / H₂O

"H₂O" in a surfing guide?

big / large

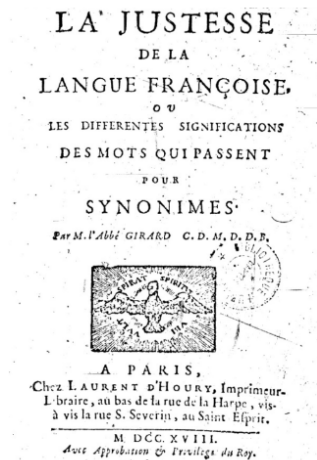
my big sister \neq my large sister

Difference in form \rightarrow difference in meaning

Re: "exact" synonyms

"je ne crois pas qu'il y ait de-
mot synonyme dans aucune
Langue."

[I do not believe that there is a synonymous
word in any language]



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

- car, bicycle
- cow, horse

Relation: **Similarity**

Ask humans how similar 2 words are

| 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 |

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

Also called "word association"

Words can be related in any way, perhaps via a semantic frame or field

- coffee, tea: **similar**
- coffee, cup: **related**, not similar

Words that:

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

hospitals

surgeon, scalpel, nurse, anaesthetic, hospital

restaurants

waiter, menu, plate, food, menu, chef

houses

door, roof, kitchen, family, bed

Relation: Antonymy

Senses that are opposites with respect to only one feature of meaning

Otherwise, they are 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

Connotation (sentiment)

Words have affective meanings

- Positive connotations (*happy*)
- Negative connotations (*sad*)

Connotations can be subtle:

- Positive connotation: *copy, replica, reproduction*
- Negative connotation: *fake, knockoff, forgery*

Evaluation (sentiment!)

- Positive evaluation (*great, love*)
- Negative evaluation (*terrible, hate*)

Connotation

Words seem to vary along 3 affective dimensions:

- **valence**: the pleasantness of the stimulus
- **arousal**: the intensity of emotion provoked by the stimulus
- **dominance**: the degree of control exerted by the stimulus

| | Word | Score | | Word | Score |
|------------------|------------|-------|--|-----------|-------|
| Valence | love | 1.000 | | toxic | 0.008 |
| | happy | 1.000 | | nightmare | 0.005 |
| Arousal | elated | 0.960 | | mellow | 0.069 |
| | frenzy | 0.965 | | napping | 0.046 |
| Dominance | powerful | 0.991 | | weak | 0.045 |
| | leadership | 0.983 | | empty | 0.081 |

Values from NRC VAD Lexicon (Mohammad 2018)

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
- Connotation

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Can we build a theory of how to represent word meaning, that accounts for at least some of the desiderata?

We'll introduce **vector semantics**

- The standard model in language processing!
- Handles many of our goals!

PI #43:

"The meaning of a word is its use in the language"

Let's define words by their usages

One way to define "usage":

words are defined by their environments (the words around them)

Zellig Harris (1954):

If A and B have almost identical environments we say that they are synonyms.

What does recent English borrowing *ongchoi* mean?

Suppose you see these sentences:

- Ong choi is delicious **sautéed with garlic**.
- Ong choi is superb **over rice**
- Ong choi **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, or collard greens
- We could conclude this based on words like "leaves" and "delicious" and "sauteed"

Ongchoi: *Ipomoea aquatica* "Water Spinach"

空心菜
kangkong
rau muống
...



Idea 1: Defining meaning by linguistic distribution

Let's define the meaning of a word by its distribution in language use, meaning its neighboring words or grammatical environments.

Idea 2: Meaning as a point in space (Osgood et al. 1957)

3 affective dimensions for a word:

- **valence**: pleasantness
- **arousal**: intensity of emotion
- **dominance**: the degree of control exerted

| | Word | Score | | Word | Score |
|------------------|------------|-------|--|-----------|-------|
| Valence | love | 1.000 | | toxic | 0.008 |
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Hence the connotation of a word is a vector in 3-space

Idea 1: Defining meaning by linguistic distribution

Idea 2: Meaning as a point in multidimensional space

Defining meaning as a point in space based on distribution

Each word = a vector (not just "good" or " w_{45} ")

Similar words are "**nearby in semantic space**"

We build this space automatically by seeing which words are **nearby in text**



We define meaning of a word as a vector

Called an "embedding" because it's embedded into a space (see textbook)

The standard way to represent meaning in NLP

Every modern NLP algorithm uses embeddings as the representation of word meaning

Fine-grained model of meaning for similarity

Intuition: why vectors?

Consider sentiment analysis:

- With **words**, a feature is a word identity
- Feature 5: 'The previous word was "terrible"'
- requires **exact same word** to be in training and test

With **embeddings**:

- Feature is a word vector
- The previous word was vector [35,22,17...]
- Now in the test set we might see a similar vector [34,21,14]
- We can generalize to **similar but unseen** words!!!

Intuition: why vectors?

We'll discuss 2 kinds of embeddings

Tf-idf

- Information Retrieval workhorse!
- A common baseline model
- **Sparse** vectors
- Words are represented by (a simple function of) the **counts** of nearby words

Word2vec

- **Dense** vectors
- Representation is created by training a classifier to **predict** whether a word is likely to appear nearby
- Later we'll discuss extensions called [contextual embeddings](#)

From now on: Computing with meaning representations instead of string representations

荃者所以在鱼，得鱼而忘荃 Nets are for fish;
Once you get the fish, you can forget the net.
言者所以在意，得意而忘言 Words are for meaning;
Once you get the meaning, you can forget the words
庄子(Zhuangzi), Chapter 26



Speech and Language Processing (3rd ed. draft)

Dan Jurafsky and James H. Martin

Part I: Fundamental Algorithms, *Chapter 6: Vector Semantics and Embeddings*

Thanks for listening!

Q&A section