Natural Language Processing

Lexical semantics

Yulia Tsvetkov

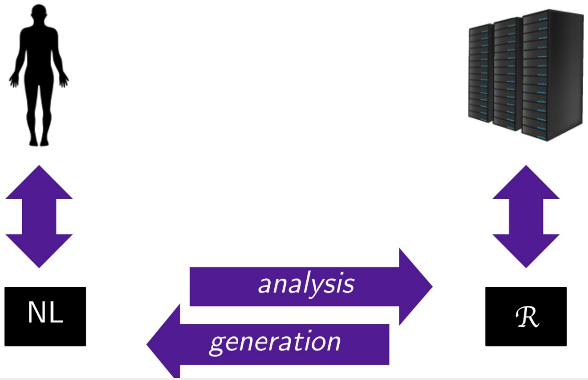
yuliats@cs.washington.edu

PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

Lexical Semantics

What is Natural Language Processing (NLP)?

- NL $\in$ {Mandarin Chinese, Hindi, Spanish, Arabic, English, … Inuktitut, Njerep}
- Automation of NLs:
  - analysis of (“understanding”) what a text means, to some extent (NL $\rightarrow \mathcal{R}$)
  - generation of fluent, meaningful, context-appropriate text ($\mathcal{R} \rightarrow$ NL)
  - acquisition of $\mathcal{R}$ from knowledge and data



Lexical 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!

What are various ways to represent the meaning of a word?

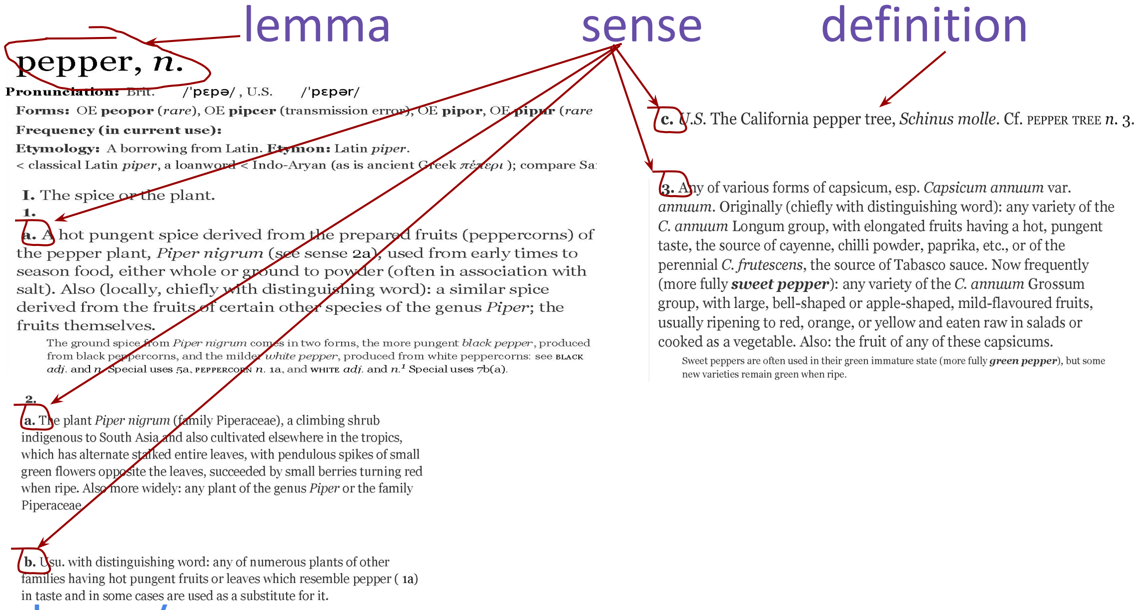
Desiderata

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

Lexical semantics

- How should we represent the meaning of the word?
  - Words, lemmas, senses, definitions



pepper, *n.*

Pronunciation: Brit. /ˈpɛpə/ , U.S. /ˈpɛpər/

Forms: OE **peopor** (*rare*), OE **pipcer** (transmission error), OE **pipor**, OE **pipur** (*rare*

Frequency (in current use):

Etymology: A borrowing from Latin. **Etymon:** Latin *piper*.

< classical Latin *piper*, a loanword < Indo-Aryan (as is ancient Greek *πέπερι*); compare Sa

I. The spice or the plant.

1.

a. A hot pungent spice derived from the prepared fruits (peppercorns) of the pepper plant, *Piper nigrum* (see sense 2a), used from early times to season food, either whole or ground to powder (often in association with salt). Also (locally, chiefly with distinguishing word): a similar spice derived from the fruits of certain other species of the genus *Piper*; the fruits themselves.

The ground spice from *Piper nigrum* comes in two forms, the more pungent *black pepper*, produced from black peppercorns, and the milder *white pepper*, produced from white peppercorns: see BLACK *adj.* and *n.* Special uses 5a, PEPPERCORN *n.* 1a, and WHITE *adj.* and *n.*[1] Special uses 7b(a).

2.

a. The plant *Piper nigrum* (family Piperaceae), a climbing shrub indigenous to South Asia and also cultivated elsewhere in the tropics, which has alternate stalked entire leaves, with pendulous spikes of small green flowers opposite the leaves, succeeded by small berries turning red when ripe. Also more widely: any plant of the genus *Piper* or the family Piperaceae.

b. Usu. with distinguishing word: any of numerous plants of other families having hot pungent fruits or leaves which resemble pepper (1a) in taste and in some cases are used as a substitute for it.

c. *U.S.* The California pepper tree, *Schinus molle*. Cf. PEPPER TREE *n.* 3.

3. Any of various forms of capsicum, esp. *Capsicum annuum* var. *annuum*. Originally (chiefly with distinguishing word): any variety of the *C. annuum* Longum group, with elongated fruits having a hot, pungent taste, the source of cayenne, chilli powder, paprika, etc., or of the perennial *C. frutescens*, the source of Tabasco sauce. Now frequently (more fully ***sweet pepper***): any variety of the *C. annuum* Grossum group, with large, bell-shaped or apple-shaped, mild-flavoured fruits, usually ripening to red, orange, or yellow and eaten raw in salads or cooked as a vegetable. Also: the fruit of any of these capsicums.

Sweet peppers are often used in their green immature state (more fully ***green pepper***), but some new varieties remain green when ripe.

http://www.oed.com/

Lemmas and senses

lemma

sense

mouse (N)
1. any of numerous small rodents...
2. a hand-operated device that controls a cursor...

Modified from the online thesaurus WordNet

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

Relation: synonymity

- Synonyms have the same meaning in some or all contexts.
  - filbert / hazelnut
  - couch / sofa
  - big / large
  - automobile / car
  - vomit / throw up
  - Water / H_20

The Linguistic Principle of Contrast

Difference in form → difference in meaning

- Note that there are probably no examples of perfect synonymy
  - Even if many aspects of meaning are identical
  - Still may not preserve the acceptability based on notions of politeness, slang, register, genre, etc.
    - Water / H20 in a surfing guide?
    - my big sister != my large sister

Relation: antonymy

Senses that are opposites with respect to 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

Relation: similarity

Words with similar meanings.

- Not synonyms, but sharing some element of meaning
  - car, bicycle
  - cow, horse

Ask humans how similar two 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)

Relation: word relatedness

Also called "word association"

- Words be related in any way, perhaps via a semantic frame or field
  - car, bicycle: similar
  - car, gasoline: related, not similar

Semantic field

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

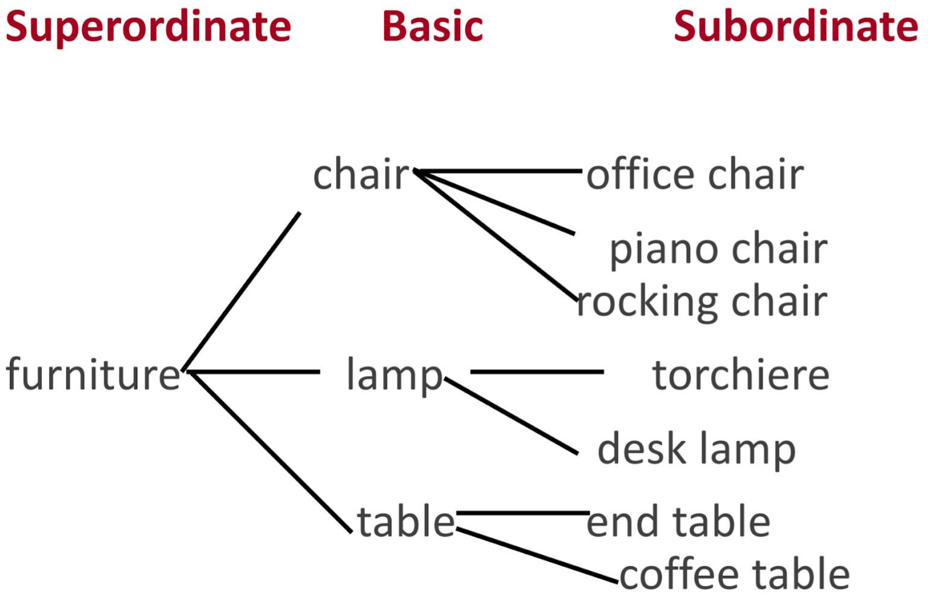
door, roof, kitchen, family, bed

Taxonomic relation: superordinate/ subordinate

- One sense is a subordinate (hyponym) of another if the first sense is more specific, denoting a subclass of the other
  - car is a subordinate of vehicle
  - mango is a subordinate of fruit

- Conversely superordinate (hypernym)
  - vehicle is a superordinate of car
  - fruit is a subordinate of mango

Taxonomy


Superordinate
Basic
Subordinate
furniture
chair
lamp
table
office chair
piano chair
rocking chair
torchiere
desk lamp
end table
coffee table

Lexical semantics

- How should we represent the meaning of the word?
  - Dictionary definition
  - Lemma and wordforms
  - Senses
  - Relationships between words or senses
  - Taxonomic relationships
  - Word similarity, word relatedness
  - Semantic frames and roles
  - Connotation and sentiment

Lexical semantics

- How should we represent the meaning of the word?
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  - Relationships between words or senses
  - Taxonomic relationships
  - Word similarity, word relatedness
  - Semantic frames and roles
    - *John hit Bill*
    - *Bill was hit by John*

Lexical Semantics

- How should we represent the meaning of the word?
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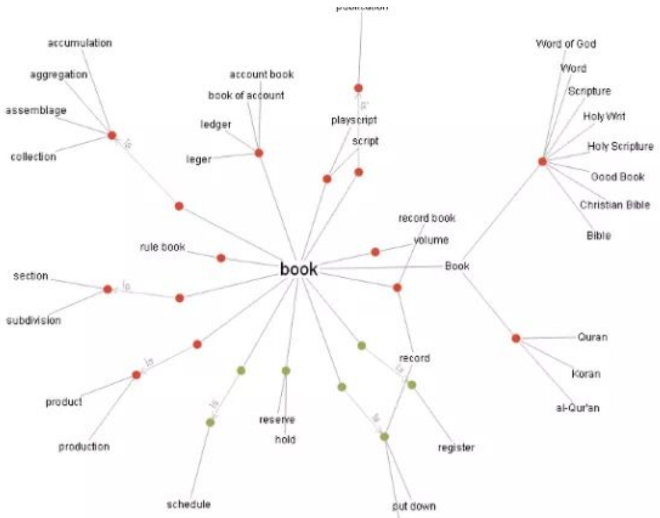
  - Senses
  - Relationships between words or senses
  - Taxonomic relationships
  - Word similarity, word relatedness
  - Semantic frames and roles
  - Connotation and sentiment
    - *valence*: the pleasantness of the stimulus
    - *arousal*: the intensity of emotion
    - *dominance*: the degree of control exerted by the stimulus

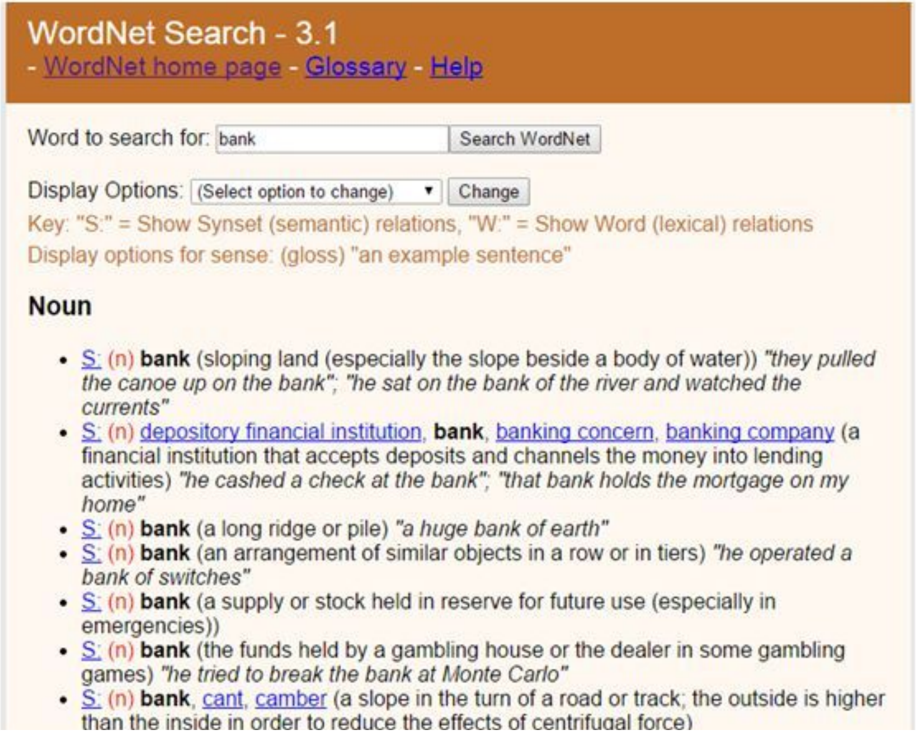
	Valence	Arousal	Dominance
courageous	8.05	5.5	7.38
music	7.67	5.57	6.5
heartbreak	2.45	5.65	3.58
cub	6.71	3.95	4.24
life	6.68	5.59	5.89

Electronic Dictionaries

WordNet

https://wordnet.princeton.edu/





Electronic Dictionaries

WordNet

```
from nltk.corpus import wordnet as wn
panda = wn.synset('panda.n.01')
hyper = lambda s: s.hypernyms()
list(panda.closure(hyper))
```

```
[Synset('procyonid.n.01'),
Synset('carnivore.n.01'),
Synset('placental.n.01'),
Synset('mammal.n.01'),
Synset('vertebrate.n.01'),
Synset('chordate.n.01'),
Synset('animal.n.01'),
Synset('organism.n.01'),
Synset('living_thing.n.01'),
Synset('whole.n.02'),
Synset('object.n.01'),
Synset('physical_entity.n.01'),
Synset('entity.n.01')]
```

NLTK www.nltk.org

Problems with discrete representations

- Too coarse
  - *expert ↔ skillful*
- Sparse
  - *wicked, badass, ninja*
- Subjective
- Expensive
- Hard to compute word relationships

S: (adj) full, good
S: (adj) estimable, good, honorable, respectable
S: (adj) beneficial, good
S: (adj) good, just, upright
S: (adj) adept, expert, good, practiced, proficient, skillful
S: (adj) dear, good, near
S: (adj) good, right, ripe
...
S: (adv) well, good
S: (adv) thoroughly, soundly, good
S: (n) good, goodness
S: (n) commodity, trade good, good

expert [0 0 0 **1** 0 0 0 0 0 0 0 0 0 0 0]

skillful [0 0 0 0 0 0 0 0 0 0 **1** 0 0 0 0]

- dimensionality: PTB: 50K, Google1T 13M

Distributional hypothesis

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

[Wittgenstein PI 43]

"You shall know a word by the company it keeps"

[Firth 1957]

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

[Harris 1954]

Example

What does ongchoi mean?

Example

- 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

Ongchoi: Ipomoea aquatica "Water Spinach"

Ongchoi is a leafy green like spinach, chard, or collard greens

空心菜
kangkong
rau muống
...

Yamaguchi, Wikimedia Commons, public domain

Model of meaning focusing on similarity

- Each word = a vector
  - not just “word” or word45.
  - similar words are “nearby in 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
- The standard way to represent meaning in NLP

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

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!!!

How to represent the meaning of a word?

What property we want the mapping to have?

We want vectors of similar words to be close. And dissimilar words to be away from each other.

distance(f(apple), f(orange)) <- small

distance(f(computer), f(rabbit)) <- large

There are many kinds of embeddings

- Count-based
  - Words are represented by a simple function of the counts of nearby words
- Class-based
  - Representation is created through hierarchical clustering, Brown clusters
- Distributed prediction-based (type) embeddings
  - Representation is created by training a classifier to distinguish nearby and far-away words: word2vec, fasttext
- Distributed contextual (token) embeddings from language models
  - ELMo, BERT

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
  - https://fasttext.cc/docs/en/crawl-vectors.html
  - Later we'll discuss extensions called contextual embeddings

Vector Semantics

Term-document matrix

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	17
soldier	2	80	62	89
fool	36	58	1	4
clown	20	15	2	3

Context = appearing in the same document.

Term-document Matrix

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	17
soldier	2	80	62	89
fool	36	58	1	4
clown	20	15	2	3

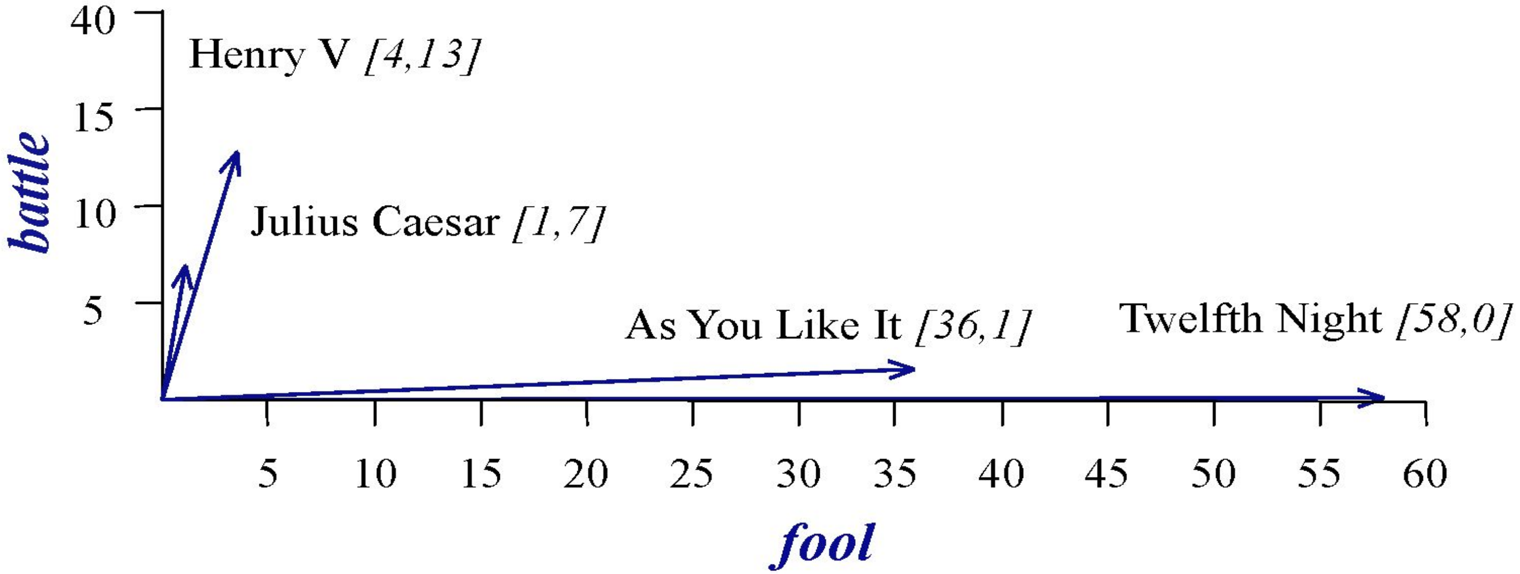
Each document is represented by a vector of words

Vectors are the basis of information retrieval

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
soldier	2	80	62	89
fool	36	58	1	4
clown	20	15	2	3

- Vectors are similar for the two comedies
- Different than the history
- Comedies have more fools and wit and fewer battles.

Visualizing Document Vectors



Words can be vectors too

	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
clown	20	15	2	3

- battle is "the kind of word that occurs in Julius Caesar and Henry V"
- fool is "the kind of word that occurs in comedies, especially Twelfth Night"

More common: word-word matrix (“term-context matrix”)

	knife	dog	sword	love	like
knife	0	1	6	5	5
dog	1	0	5	5	5
sword	6	5	0	5	5
love	5	5	5	0	5
like	5	5	5	5	2

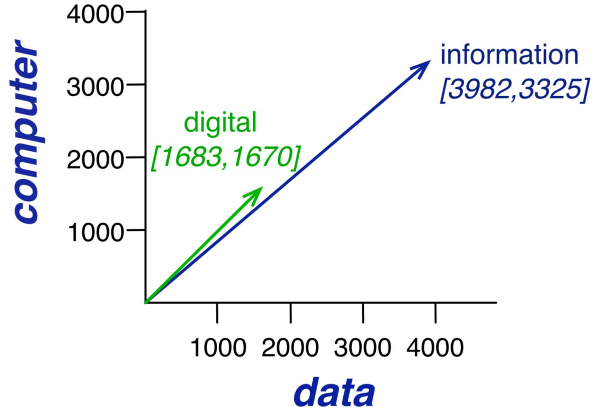
- Two words are “similar” in meaning if their context vectors are similar
  - Similarity == relatedness

Term-context matrix

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

is traditionally followed by	**cherry**	pie, a traditional dessert
often mixed, such as	**strawberry**	rhubarb pie. Apple pie
computer peripherals and personal	**digital**	assistants. These devices usually
a computer. This includes	**information**	available on the internet

	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	...
strawberry	0	...	0	0	1	60	19	...
digital	0	...	1670	1683	85	5	4	...
information	0	...	3325	3982	378	5	13	...



Computing word similarity

The dot product between two vectors is a scalar:

$$\text{dot product}(\mathbf{v}, \mathbf{w}) = \mathbf{v} \cdot \mathbf{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \ldots + v_N w_N$$

- The dot product tends to be high when the two vectors have large values in the same dimensions
- Dot product can thus be a useful similarity metric between vectors

Problem with raw dot-product

- Dot product favors long vectors
  - Dot product is higher if a vector is longer (has higher values in many dimension)
    Vector length:

$$|\mathbf{v}| = \sqrt{\sum_{i=1}^{N} v_i^2}$$

- Frequent words (of, the, you) have long vectors (since they occur many times with other words).
  - So dot product overly favors frequent words

Alternative: cosine for computing word similarity

$$\text{cosine}(\vec{v},\vec{w}) = \frac{\vec{v}\cdot\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

Based on the definition of the dot product between two vectors a and b

$$\mathbf{a}\cdot\mathbf{b} = |\mathbf{a}||\mathbf{b}|\cos\theta$$

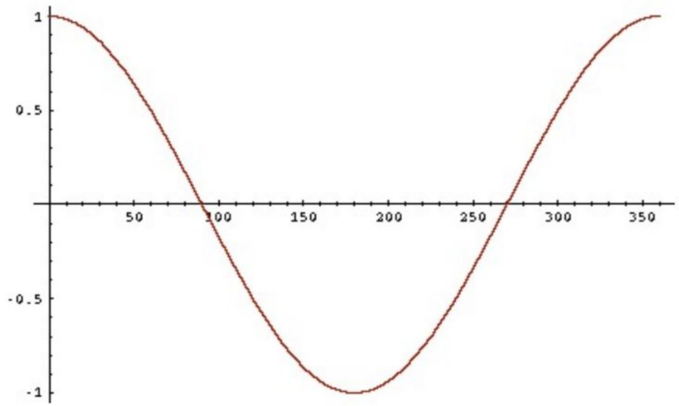
$$\frac{\mathbf{a}\cdot\mathbf{b}}{|\mathbf{a}||\mathbf{b}|} = \cos\theta$$

Cosine as a similarity metric

-1: vectors point in opposite directions

+1: vectors point in same directions

0: vectors are orthogonal



- But since raw frequency values are non-negative, the cosine for term-term matrix vectors ranges from 0–1

Cosine examples

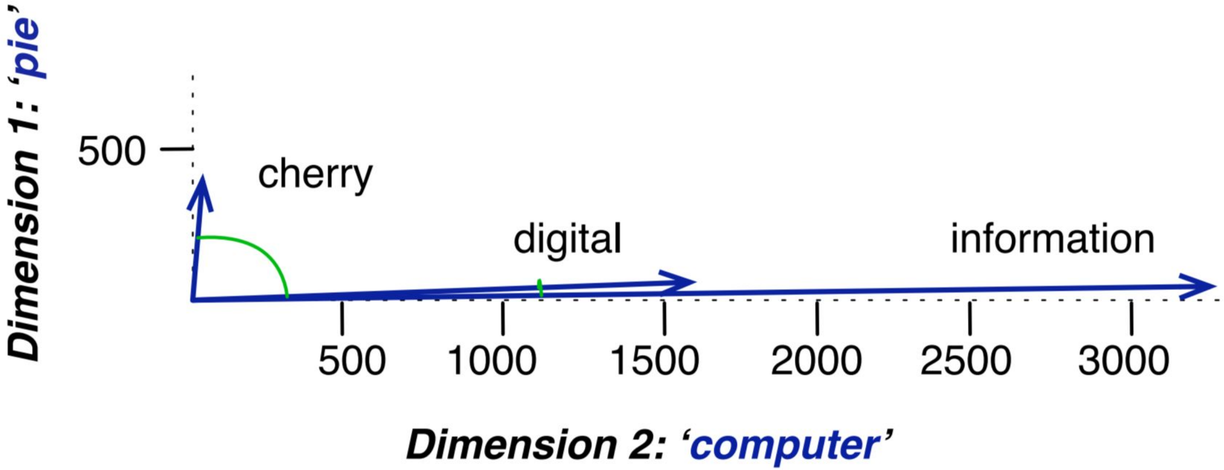
$$\cos(\vec{v},\vec{w}) = \frac{\vec{v}\bullet\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\vec{v}}{|\vec{v}|}\bullet\frac{\vec{w}}{|\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

	pie	data	computer
cherry	442	8	2
digital	114	80	62
information	36	58	1

$$\cos(\text{cherry}, \text{information}) = \frac{442 * 5 + 8 * 3982 + 2 * 3325}{\sqrt{442^2 + 8^2 + 2^2}\sqrt{5^2 + 3982^2 + 3325^2}} = .017$$

$$\cos(\text{digital}, \text{information}) = \frac{5 * 5 + 1683 * 3982 + 1670 * 3325}{\sqrt{5^2 + 1683^2 + 1670^2}\sqrt{5^2 + 3982^2 + 3325^2}} = .996$$

Visualizing angles



Count-based representations

	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

- Counts: term-frequency
  - remove stop words
  - use $\log_{10}(tf)$
  - normalize by document length

But raw frequency is a bad representation

- The co-occurrence matrices we have seen represent each cell by word frequencies
- Frequency is clearly useful; if sugar appears a lot near apricot, that's useful information
- But overly frequent words like the, it, or they are not very informative about the context
- It's a paradox! How can we balance these two conflicting constraints?

Two common solutions for word weighting

tf-idf: tf-idf value for word t in document d:

$$w_{t,d} = \mathrm{tf}_{t,d} \times \mathrm{idf}_t$$

Words like “the” or “it” have very low idf

PMI: Pointwise mutual information

$$\mathrm{PMI}(w_1, w_2) = log \frac{p(w_1,w_2)}{p(w_1)p(w_2)}$$

See if words like “good” appear more often with “great” than we would expect by chance

TF-IDF

- What to do with words that are evenly distributed across many documents?

$$\mathrm{tf}_{t,d} = \log_{10}(\mathrm{count}(t,d)+1)$$

$$\mathrm{idf}_i = \log\left(\frac{N}{\mathrm{df}_i}\right)$$

Total # of docs in collection

# of docs that have word i

Words like "the" or "good" have very low idf

$$w_{t,d} = \mathrm{tf}_{t,d} \times \mathrm{idf}_t$$

Positive Pointwise Mutual Information (PPMI)

- In word--context matrix
- Do words w and c co-occur more than if they were independent?

$$\text{PMI}(w,c) = \log_2 \frac{P(w,c)}{P(w)P(c)}$$

$$\text{PPMI}(w,c) = \max(\log_2 \frac{P(w,c)}{P(w)P(c)}, 0)$$

- PMI is biased toward infrequent events
  - Very rare words have very high PMI values
  - Give rare words slightly higher probabilities α=0.75

$$\text{PPMI}_\alpha(w,c) = \max(\log_2 \frac{P(w,c)}{P(w)P_\alpha(c)}, 0) \qquad P_\alpha(c) = \frac{count(c)^\alpha}{\sum_c count(c)^\alpha}$$

# name	formula	reference
1. **Joint probability**	$p(xy)$	(Giuliano, 1964)
2. **Conditional probability**	$p(y\|x)$	(Gregory et al., 1999)
3. **Reverse cond. probability**	$p(x\|y)$	(Gregory et al., 1999)
4. **Pointwise mutual inf. (*MI*)**	$\log \frac{p(xy)}{p(x*)p(*y)}$	(Church and Hanks, 1990)
5. **Mutual dependency (*MD*)**	$\log \frac{p(xy)^2}{p(x*)p(*y)}$	(Thanopoulos et al., 2002)
6. **Log frequency biased *MD***	$\log \frac{p(xy)^2}{p(x*)p(*y)} + \log p(xy)$	(Thanopoulos et al., 2002)
7. **Normalized expectation**	$\frac{2f(xy)}{f(x*)+f(*y)}$	(Smadja and McKeown, 1990)
8. **Mutual expectation**	$\frac{2f(xy)}{f(x*)+f(*y)} \cdot p(xy)$	(Dias et al., 2000)
9. **Salience**	$\log \frac{p(xy)^2}{p(x*)p(*y)} \cdot \log f(xy)$	(Kilgarriff and Tugwell, 2001)
10. **Pearson's χ^2 test**	$\sum_{i,j} \frac{(f_{ij}-\hat{f}_{ij})^2}{\hat{f}_{ij}}$	(Manning and Schütze, 1999)
11. **Fisher's exact test**	$\frac{f(x*)!f(\bar{x}*)!f(*y)!f(*\bar{y})!}{N!f(xy)!f(x\bar{y})!f(\bar{x}y)!f(\bar{x}\bar{y})!}$	(Pedersen, 1996)
12. **t test**	$\frac{f(xy)-\hat{f}(xy)}{\sqrt{f(xy)(1-(f(xy)/N))}}$	(Church and Hanks, 1990)
13. **z score**	$\frac{f(xy)-\hat{f}(xy)}{\sqrt{\hat{f}(xy)(1-(\hat{f}(xy)/N))}}$	(Berry-Rogghe, 1973)
14. **Poisson significance**	$\frac{\hat{f}(xy)-f(xy)\log \hat{f}(xy)+\log f(xy)!}{\log N}$	(Quasthoff and Wolff, 2002)
15. **Log likelihood ratio**	$-2\sum_{i,j} f_{ij} \log \frac{f_{ij}}{\hat{f}_{ij}}$	(Dunning, 1993)
16. **Squared log likelihood ratio**	$-2\sum_{i,j} \frac{\log f_{ij}^2}{\hat{f}_{ij}}$	(Inkpen and Hirst, 2002)
17. **Russel-Rao**	$\frac{a}{a+b+c+d}$	(Russel and Rao, 1940)
18. **Sokal-Michiner**	$\frac{a+d}{a+b+c+d}$	(Sokal and Michener, 1958)
19. **Rogers-Tanimoto**	$\frac{a+d}{a+2b+2c+d}$	(Rogers and Tanimoto, 1960)
20. **Hamann**	$\frac{(a+d)-(b+c)}{a+b+c+d}$	(Hamann, 1961)
21. **Third Sokal-Sneath**	$\frac{b+c}{a+d}$	(Sokal and Sneath, 1963)
22. **Jaccard**	$\frac{a}{a+b+c}$	(Jaccard, 1912)
23. **First Kulczynsky**	$\frac{a}{b+c}$	(Kulczynski, 1927)
24. **Second Sokal-Sneath**	$\frac{a}{a+2(b+c)}$	(Sokal and Sneath, 1963)
25. **Second Kulczynski**	$\frac{1}{2}(\frac{a}{a+b}+\frac{a}{a+c})$	(Kulczynski, 1927)
26. **Fourth Sokal-Sneath**	$\frac{1}{4}(\frac{a}{a+b}+\frac{a}{a+c}+\frac{d}{d+b}+\frac{d}{d+c})$	(Kulczynski, 1927)
27. **Odds ratio**	$\frac{ad}{bc}$	(Tan et al., 2002)
28. **Yulle's ω**	$\frac{\sqrt{ad}-\sqrt{bc}}{\sqrt{ad}+\sqrt{bc}}$	(Tan et al., 2002)
29. **Yulle's Q**	$\frac{ad-bc}{ad+bc}$	(Tan et al., 2002)
30. **Driver-Kroeber**	$\frac{a}{\sqrt{(a+b)(a+c)}}$	(Driver and Kroeber, 1932)

# name	formula	reference
31. **Fifth Sokal-Sneath**	$\frac{ad}{\sqrt{(a+b)(a+c)(d+b)(d+c)}}$	(Sokal and Sneath, 1963)
32. **Pearson**	$\frac{ad-bc}{\sqrt{(a+b)(a+c)(d+b)(d+c)}}$	(Pearson,1950)
33. **Baroni-Urbani**	$\frac{a+\sqrt{ad}}{a+b+c+\sqrt{ad}}$	(Baroni-Urbani and Buser, 1976)
34. **Braun-Blanquet**	$\frac{a}{\max(a+b,a+c)}$	(Braun-Blanquet, 1932)
35. **Simpson**	$\frac{a}{\min(a+b,a+c)}$	(Simpson, 1943)
36. **Michael**	$\frac{4(ad-bc)}{(a+d)^2+(b+c)^2}$	(Michael, 1920)
37. **Mountford**	$\frac{2a}{2bc+ab+ac}$	(Kaufman and Rousseeuw, 1990)
38. **Fager**	$\frac{a}{\sqrt{(a+b)(a+c)}} - \frac{1}{2}\max(b,c)$	(Kaufman and Rousseeuw, 1990)
39. **Unigram subtuples**	$\log \frac{ad}{bc} - 3.29\sqrt{\frac{1}{a}+\frac{1}{b}+\frac{1}{c}+\frac{1}{d}}$	(Blaheta and Johnson, 2001)
40. ***U* cost**	$\log(1+\frac{\min(b,c)+a}{\max(b,c)+a})$	(Tulloss, 1997)
41. ***S* cost**	$\log(1+\frac{\min(b,c)}{a+1})^{-\frac{1}{2}}$	(Tulloss, 1997)
42. ***R* cost**	$\log(1+\frac{a}{a+b}) \cdot \log(1+\frac{a}{a+c})$	(Tulloss, 1997)
43. ***T* combined cost**	$\sqrt{U \times S \times R}$	(Tulloss, 1997)
44. **Phi**	$\frac{p(xy)-p(x*)p(*y)}{\sqrt{p(x*)p(*y)(1-p(x*))(1-p(*y))}}$	(Tan et al., 2002)
45. **Kappa**	$\frac{p(xy)+p(\bar{x}\bar{y})-p(x*)p(*y)-p(\bar{x}*)p(*\bar{y})}{1-p(x*)p(*y)-p(\bar{x}*)p(*\bar{y})}$	(Tan et al., 2002)
46. ***J* measure**	$\max[p(xy)\log\frac{p(y\|x)}{p(*y)} + p(x\bar{y})\log\frac{p(\bar{y}\|x)}{p(*\bar{y})},$ $p(xy)\log\frac{p(x\|y)}{p(x*)} + p(\bar{x}y)\log\frac{p(\bar{x}\|y)}{p(\bar{x}*)}]$	(Tan et al., 2002)
47. **Gini index**	$\max[p(x*)(p(y\|x)^2+p(\bar{y}\|x)^2)-p(*y)^2$ $+p(\bar{x}*)(p(y\|\bar{x})^2+p(\bar{y}\|\bar{x})^2)-p(*\bar{y})^2,$ $p(*y)(p(x\|y)^2+p(\bar{x}\|y)^2)-p(x*)^2$ $+p(*\bar{y})(p(x\|\bar{y})^2+p(\bar{x}\|\bar{y})^2)-p(\bar{x}*)^2]$	(Tan et al., 2002)
48. **Confidence**	$\max[p(y\|x), p(x\|y)]$	(Tan et al., 2002)
49. **Laplace**	$\max[\frac{Np(xy)+1}{Np(x*)+2}, \frac{Np(xy)+1}{Np(*y)+2}]$	(Tan et al., 2002)
50. **Conviction**	$\max[\frac{p(x*)p(*y)}{p(x\bar{y})}, \frac{p(\bar{x}*)p(*y)}{p(\bar{x}y)}]$	(Tan et al., 2002)
51. **Piatersky-Shapiro**	$p(xy)-p(x*)p(*y)$	(Tan et al., 2002)
52. **Certainity factor**	$\max[\frac{p(y\|x)-p(*y)}{1-p(*y)}, \frac{p(x\|y)-p(x*)}{1-p(x*)}]$	(Tan et al., 2002)
53. **Added value (*AV*)**	$\max[p(y\|x)-p(*y), p(x\|y)-p(x*)]$	(Tan et al., 2002)
54. **Collective strength**	$\frac{p(xy)+p(\bar{x}\bar{y})}{p(x*)p(y)+p(\bar{x}*)p(*y)} \cdot \frac{1-p(x*)p(*y)-p(\bar{x}*)p(*y)}{1-p(xy)-p(\bar{x}\bar{y})}$	(Tan et al., 2002)
55. **Klosgen**	$\sqrt{p(xy)} \cdot AV$	(Tan et al., 2002)

(Pecina'09)

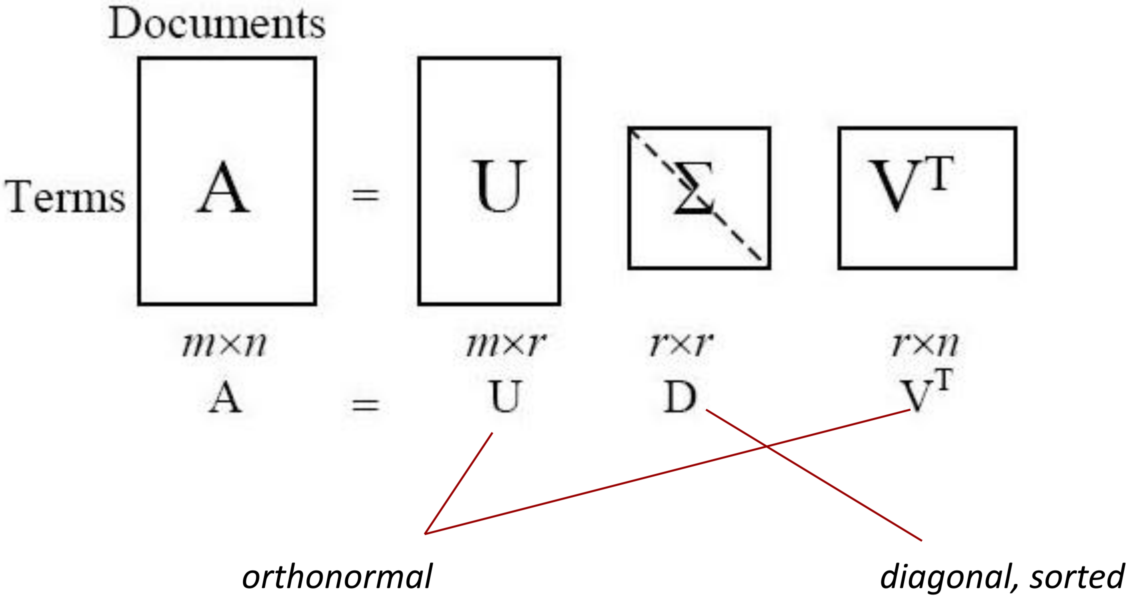
Dimensionality Reduction

- Wikipedia: ~29 million English documents. Vocab: ~1M words.
  - High dimensionality of word--document matrix
    - Sparsity
    - The order of rows and columns doesn't matter
- Goal:
  - good similarity measure for words or documents
  - dense representation
- Sparse vs Dense vectors
  - Short vectors may be easier to use as features in machine learning (less weights to tune)
  - Dense vectors may generalize better than storing explicit counts
    - They may do better at capturing synonymy
    - In practice, they work better

A	0
a	0
aa	0
aal	0
aalii	0
aam	0
Aani	0
aardvark	**1**
aardwolf	0
...	0
zymotoxic	0
zymurgy	0
Zyrenian	0
Zyrian	0
Zyryan	0
zythem	0
Zythia	0
zythum	0
Zyzomys	0
Zyzzogeton	0

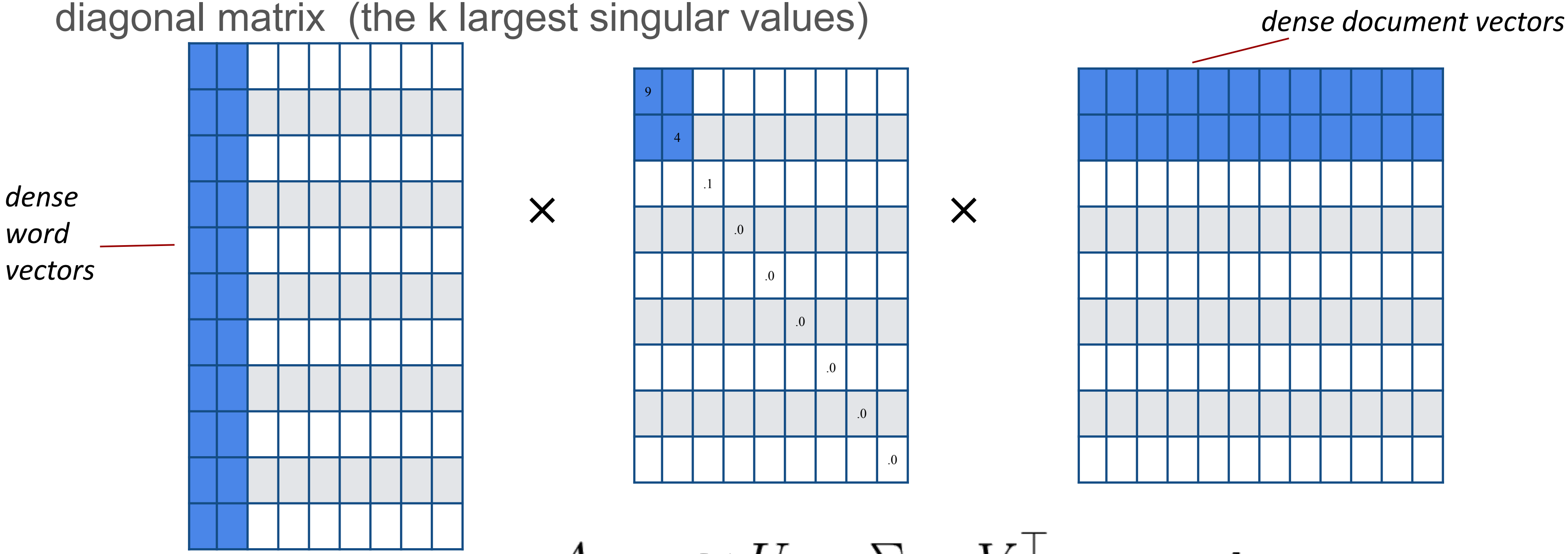
Singular Value Decomposition (SVD)

- Solution idea:
  - Find a projection into a low-dimensional space (~300 dim)
  - That gives us a best separation between features



Truncated SVD

We can approximate the full matrix by only considering the leftmost k terms in the diagonal matrix (the k largest singular values)



$$A_{m\times n} \approx U_{m\times k}\Sigma_{k\times k}V^{\top}_{k\times n} \qquad k \ll m, n$$

Latent Semantic Analysis

#0	#1	#2	#3	#4	#5
we	music	company	how	program	10
said	film	mr	what	project	30
have	theater	its	about	russian	11
they	mr	inc	their	space	12
not	this	stock	or	russia	15
but	who	companies	this	center	13
be	movie	sales	are	programs	14
do	which	shares	history	clark	20
he	show	said	be	aircraft	sept
this	about	business	social	ballet	16
there	dance	share	these	its	25
you	its	chief	other	projects	17
are	disney	executive	research	orchestra	18
what	play	president	writes	development	19
if	production	group	language	work	21

[Deerwester et al., 1990]

Evaluation

- Intrinsic
- Extrinsic
- Qualitative

WORD	d1	d2	d3	d4	d5	...	d50
summer	0.12	0.21	0.07	0.25	0.33	...	0.51
spring	0.19	0.57	0.99	0.30	0.02	...	0.73
fall	0.53	0.77	0.43	0.20	0.29	...	0.85
light	0.00	0.68	0.84	0.45	0.11	...	0.03
clear	0.27	0.50	0.21	0.56	0.25	...	0.32
blizzard	0.15	0.05	0.64	0.17	0.99	...	0.23

Extrinsic Evaluation

- Topic categorization
- Sentiment analysis
- Metaphor detection
- Machine translation
- etc.
-

Intrinsic Evaluation

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

similarity (embeddings)
1.1
0.5
0.3
1.7
0.98
0.3

Spearman's rho (human ranks, model ranks)

- WS-353 (Finkelstein et al. '02)
- MEN-3k (Bruni et al. '12)
- SimLex-999 dataset (Hill et al., 2015)

Visualisation

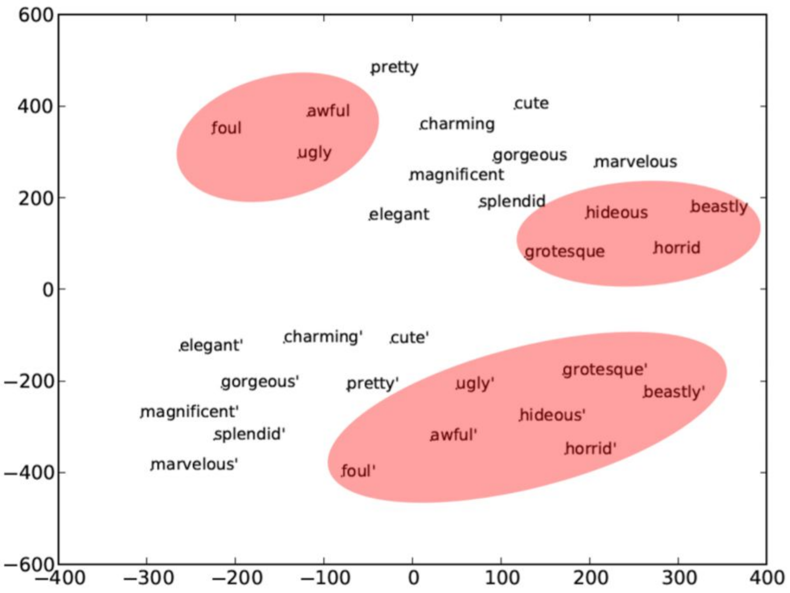


Figure 6.5: Monolingual (top) and multilingual (bottom; marked with apostrophe) word projections of the antonyms (shown in red) and synonyms of "beautiful".

- Visualizing Data using t-SNE (van der Maaten & Hinton'08)

Distributed representations

Word Vectors

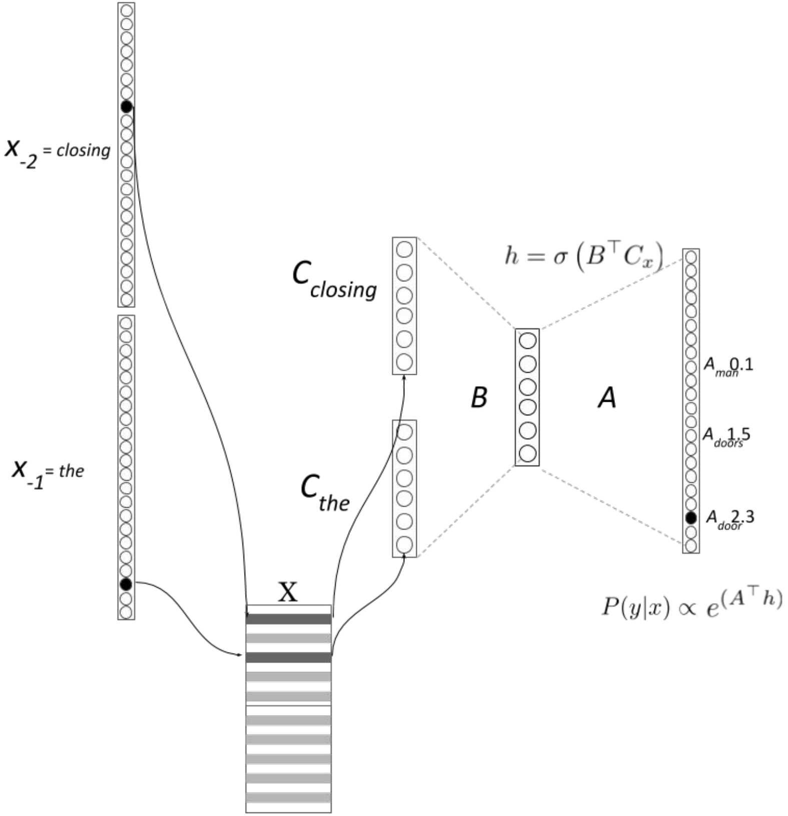
WORD	d1	d2	d3	d4	d5	...	d50
summer	0.12	0.21	0.07	0.25	0.33	...	0.51
spring	0.19	0.57	0.99	0.30	0.02	...	0.73
fall	0.53	0.77	0.43	0.20	0.29	...	0.85
light	0.00	0.68	0.84	0.45	0.11	...	0.03
clear	0.27	0.50	0.21	0.56	0.25	...	0.32
blizzard	0.15	0.05	0.64	0.17	0.99	...	0.23

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
  - https://fasttext.cc/docs/en/crawl-vectors.html
  - Later we'll discuss extensions called contextual embeddings

"One hot" vectors and dense word vectors (embeddings)

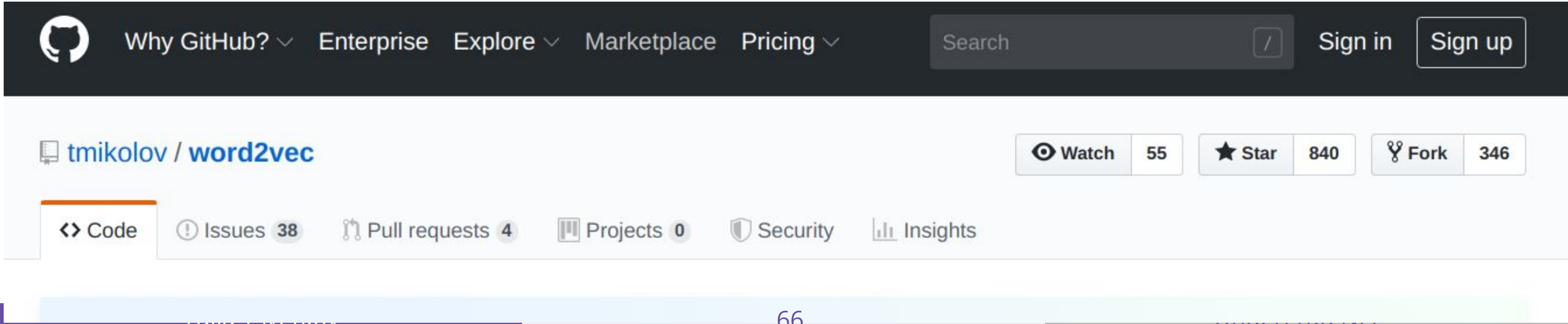


Low-dimensional word representations

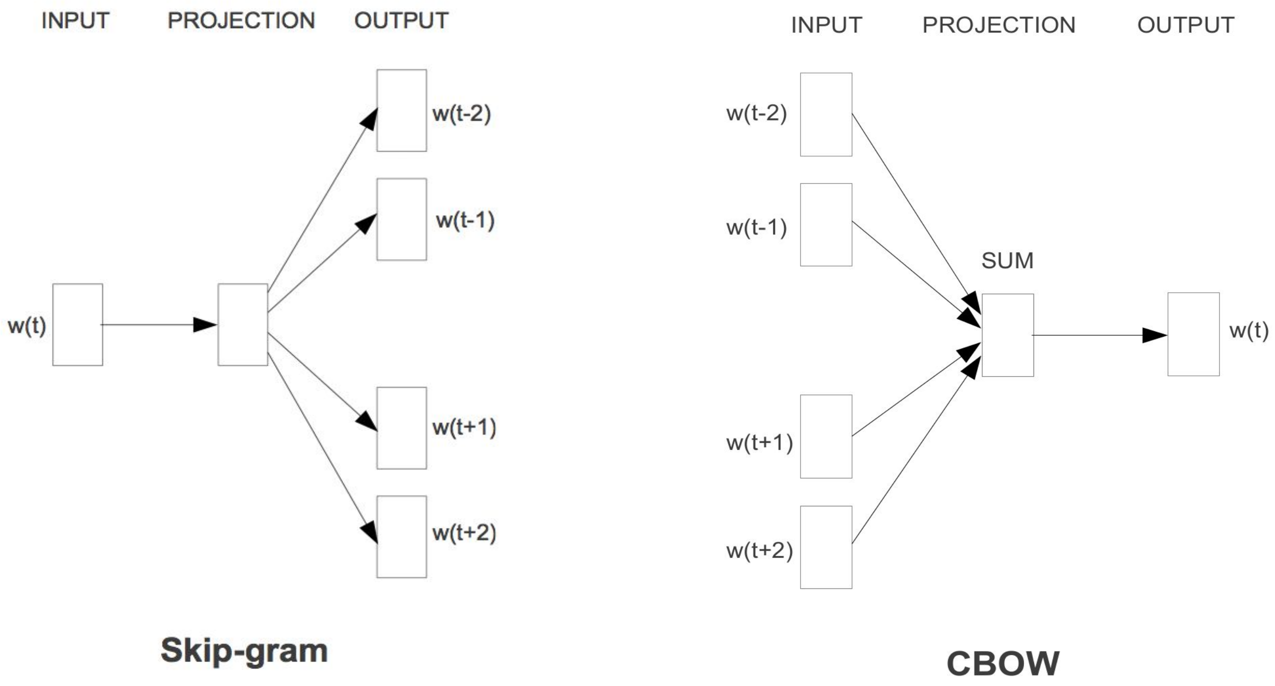
- Learning representations by back-propagating errors
  - Rumelhart, Hinton & Williams, 1986
- A neural probabilistic language model
  - Bengio et al., 2003
- Natural Language Processing (almost) from scratch
  - Collobert & Weston, 2008
- Word representations: A simple and general method for semi-supervised learning
  - Turian et al., 2010
- Distributed Representations of Words and Phrases and their Compositionality
  - Word2Vec; Mikolov et al., 2013

Word2Vec

- Popular embedding method
- Very fast to train
- Code available on the web
- Idea: predict rather than count



Word2Vec

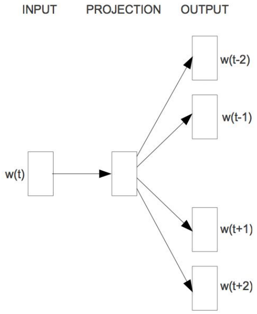


- [Mikolov et al.’ 13]

Skip-gram Prediction

- Predict vs Count

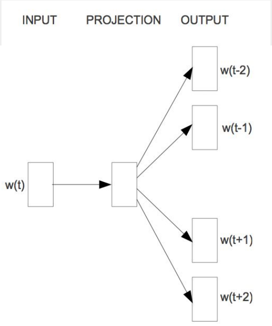
the cat sat on the mat



Skip-gram

Skip-gram Prediction

- Predict vs Count



Skip-gram

the cat sat on the mat

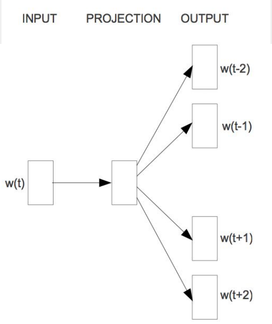
w_t = the → CLASSIFIER →

w_{t-2} = <start$_{-2}$>
w_{t-1} = <start$_{-1}$>
w_{t+1} = cat
w_{t+2} = sat

context size = 2

Skip-gram Prediction

- Predict vs Count



Skip-gram

the cat sat on the mat

w_t = cat → CLASSIFIER →

w_{t-2} = <start$_{-1}$>
w_{t-1} = the
w_{t+1} = sat
w_{t+2} = on

context size = 2

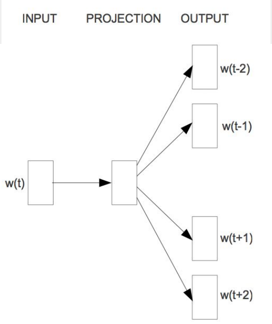
Skip-gram Prediction

- Predict vs Count

the cat sat on the mat

w_t = sat → **CLASSIFIER** →

w_{t-2} = the
w_{t-1} = cat
w_{t+1} = on
w_{t+2} = the



Skip-gram

context size = 2

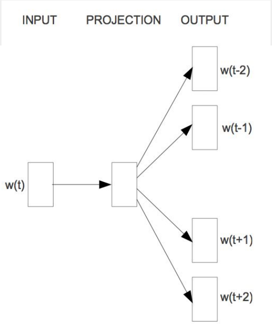
Skip-gram Prediction

- Predict vs Count

the cat sat <u>on</u> the mat

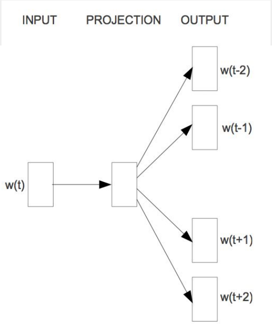
w_t = on → **CLASSIFIER** → w_{t-2} = cat, w_{t-1} = sat, w_{t+1} = the, w_{t+2} = mat

context size = 2



Skip-gram

Skip-gram Prediction



Skip-gram

- Predict vs Count

the cat sat on the mat

w_t = the → **CLASSIFIER** →

w_{t-2} = sat
w_{t-1} = on
w_{t+1} = mat
$w_{t+2} = \langle end_{+1} \rangle$

context size = 2

Skip-gram Prediction

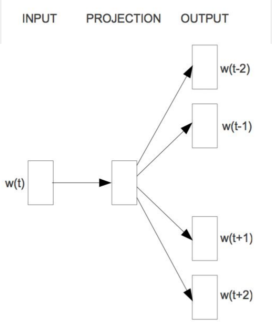
- Predict vs Count

the cat sat **on the <u>mat</u>**

w_t = mat → **CLASSIFIER** →

w_{t-2} = on
w_{t-1} = the
w_{t+1} = <end$_{+1}$>
w_{t+2} = <end$_{+2}$>

context size = 2



Skip-gram

Skip-gram Prediction

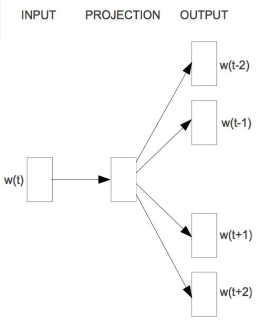
- Predict vs Count

w_t = the → CLASSIFIER →

w_{t-2} = sat
w_{t-1} = on
w_{t+1} = mat
$w_{t+2} = \langle end_{+1} \rangle$

w_t = the → CLASSIFIER →

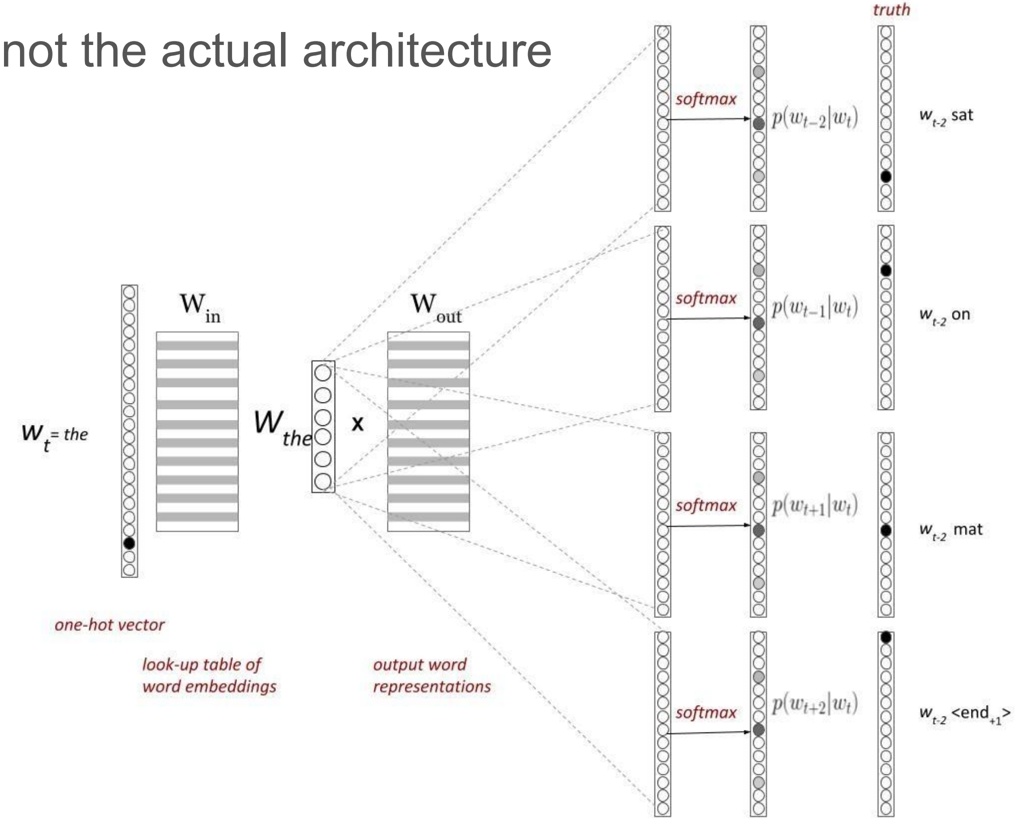
$w_{t-2} = \langle start_{-2} \rangle$
$w_{t-1} = \langle start_{-1} \rangle$
w_{t+1} = cat
w_{t+2} = sat

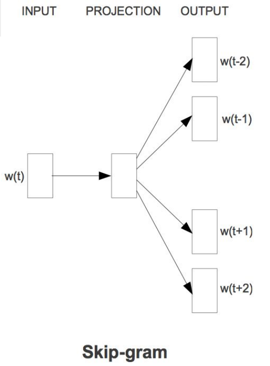


Skip-gram

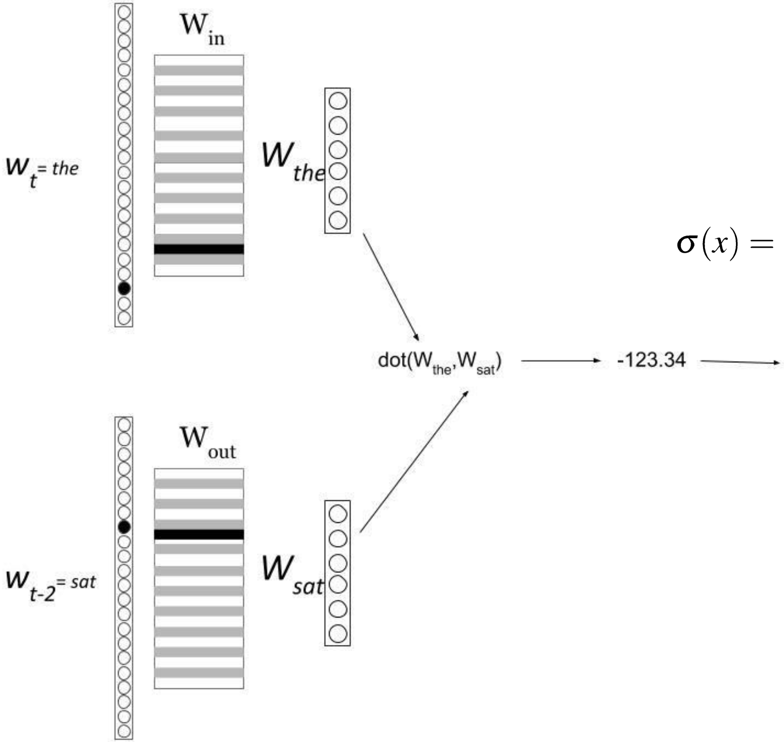
Skip-gram Prediction

Conceptual idea, not the actual architecture

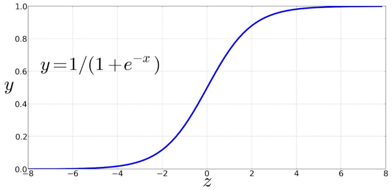




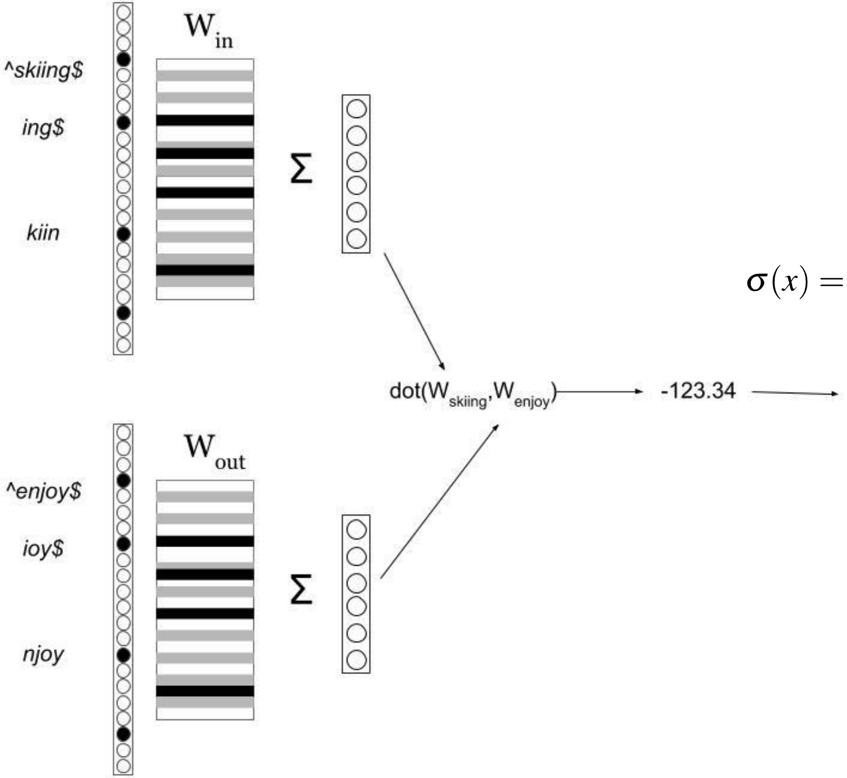
How to compute p(+|t,c)?



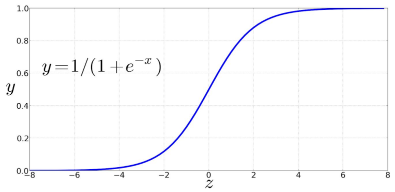
$$\sigma(x) = \frac{1}{1+e^{-x}}$$



FastText



$$\sigma(x) = \frac{1}{1+e^{-x}}$$



SGNS

Given a tuple (t,c) = target, context

- (cat, sat)
- (cat, aardvark)

Return probability that c is a real context word:

$$P(+|t,c) = \frac{1}{1+e^{-t\cdot c}}$$

$$\begin{aligned} P(-|t,c) &= 1-P(+|t,c) \\ &= \frac{e^{-t\cdot c}}{1+e^{-t\cdot c}} \end{aligned}$$

Learning the classifier

- Iterative process
  - We'll start with 0 or random weights
  - Then adjust the word weights to
    - make the positive pairs more likely
    - and the negative pairs less likely
  - over the entire training set:

$$\sum_{(t,c)\in+} logP(+|t,c) + \sum_{(t,c)\in-} logP(-|t,c)$$

- Train using gradient descent

BERT

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin Ming-Wei Chang Kenton Lee Kristina Toutanova
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html

Properties of Embeddings

The kinds of neighbors depend on window size

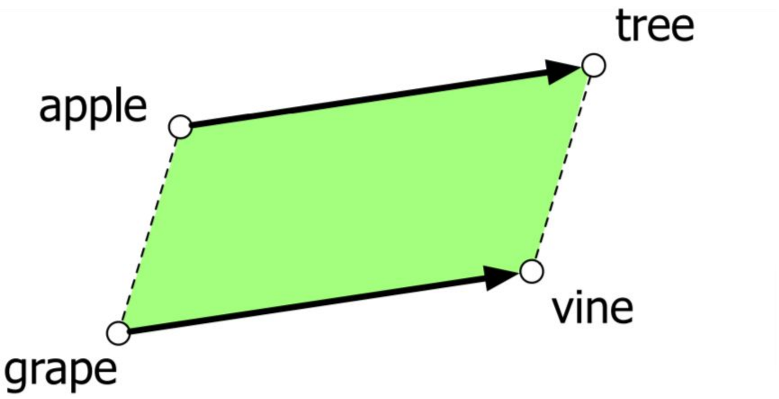
- Small windows (C= +/- 2) : nearest words are syntactically similar words in same taxonomy
  - Hogwarts nearest neighbors are other fictional schools
  - Sunnydale, Evernight, Blandings
- Large windows (C= +/- 5) : nearest words are related
  - Hogwarts nearest neighbors are Harry Potter world:
  - Dumbledore, half-blood, Malfoy

Analogical relations

The classic parallelogram model of analogical reasoning (Rumelhart and Abrahamson 1973)

To solve: "apple is to tree as grape is to __________"

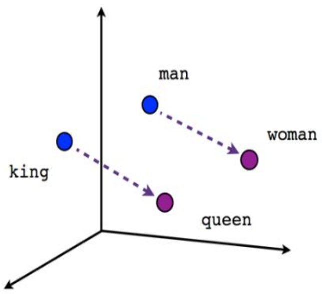
Add $\overrightarrow{\text{tree}} - \overrightarrow{\text{apple}}$ to $\overrightarrow{\text{grape}}$ to get $\overrightarrow{\text{vine}}$



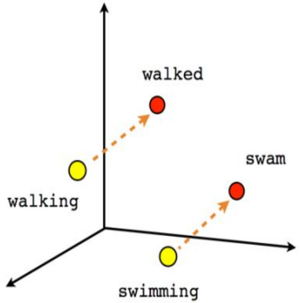
Analogy: Embeddings capture relational meaning!

vector(*'king'*) - vector(*'man'*) + vector(*'woman'*) ≈ vector('queen')

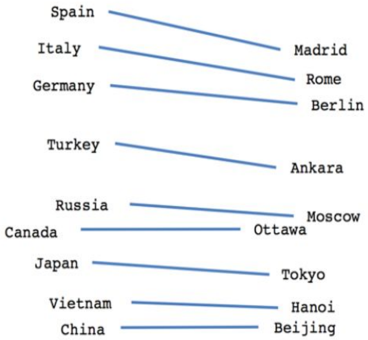
vector(*'Paris'*) - vector(*'France'*) + vector(*'Italy'*) ≈ vector('Rome')



Male-Female



Verb tense



Country-Capital

$$\min cos(man - woman,\ king - x)\ s.t.\ ||king - x||_2 < \delta$$

Analogical relations via parallelogram

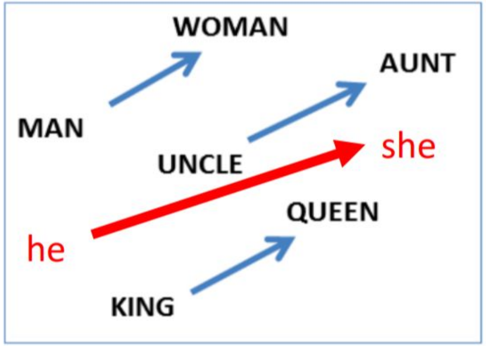
The parallelogram method can solve analogies with both sparse and dense embeddings (Turney and Littman 2005, Mikolov et al. 2013b)

$$\overrightarrow{\text{king}} - \overrightarrow{\text{man}} + \overrightarrow{\text{woman}} \text{ is close to } \overrightarrow{\text{queen}}$$

$$\overrightarrow{\text{Paris}} - \overrightarrow{\text{France}} + \overrightarrow{\text{Italy}} \text{ is close to } \overrightarrow{\text{Rome}}$$

Bias in word embeddings

Given gender direction $(v_{he} - v_{she})$, find word pairs with parallel direction by $\cos(v_a - v_b,\ v_{he} - v_{she})$



he: ________	she:________
brother	sister
beer	
physician	
professor	

Google w2v embedding trained from the news

Bias in literature

Male Verbs

Female Verbs

Bias in literature

Male
strong
arrogant
sexual
active
dominant
violent
beautiful
angry

Male Adjectives

Female Adjectives

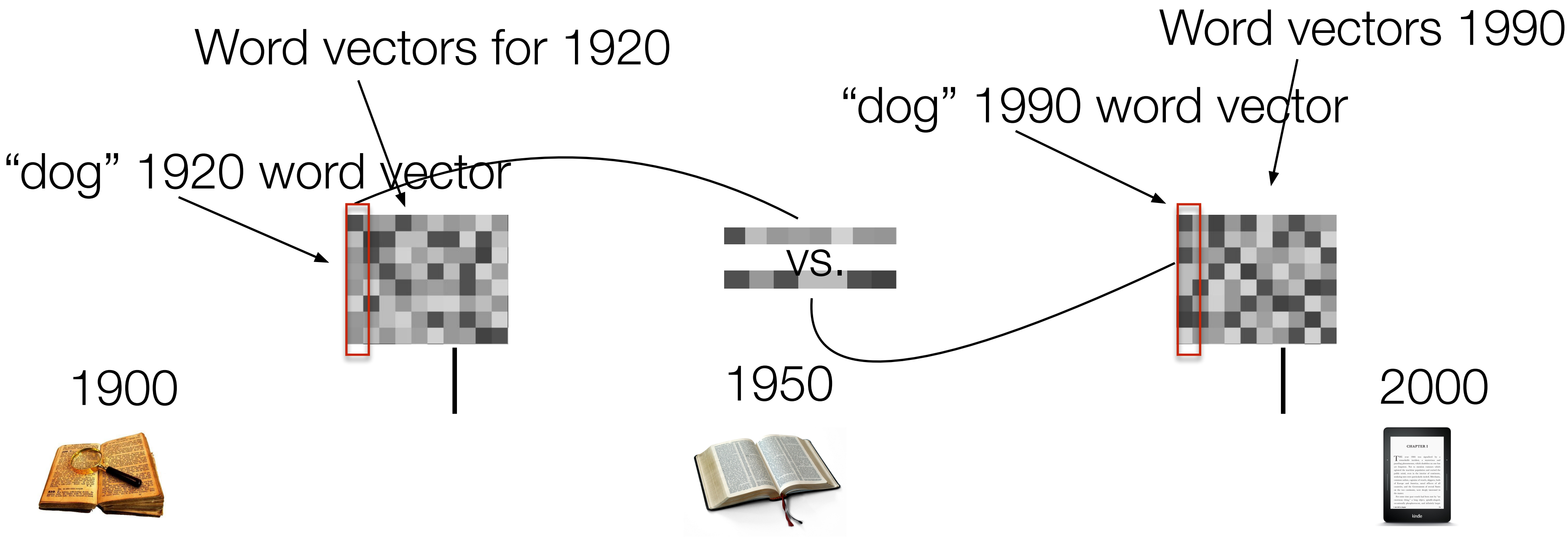
Female
weak
submissive
childish
afraid
dependent
hysterical
domestic
emotional

Embeddings can help study word history!

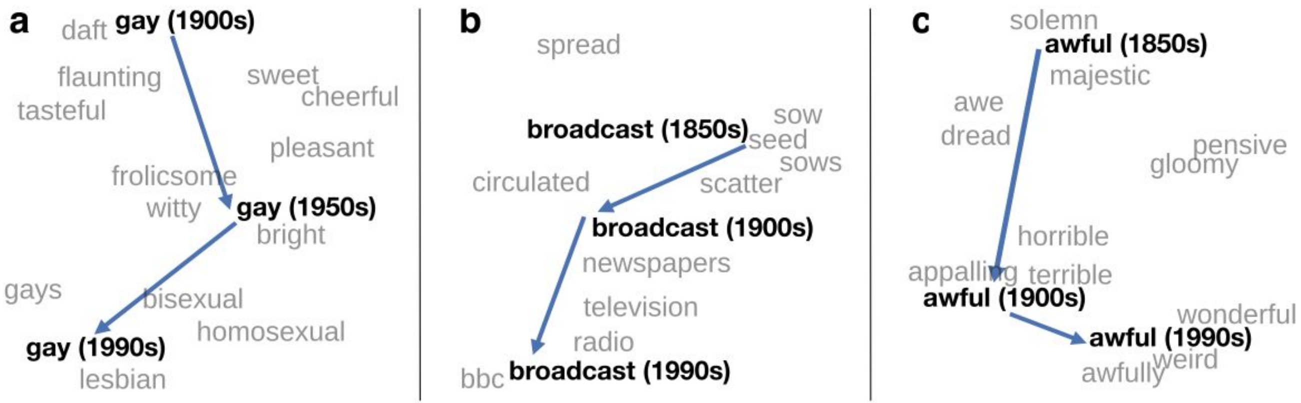
Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change

William L. Hamilton, Jure Leskovec, Dan Jurafsky
Department of Computer Science, Stanford University, Stanford CA, 94305
wleif,jure,jurafsky@stanford.edu

Diachronic Embeddings

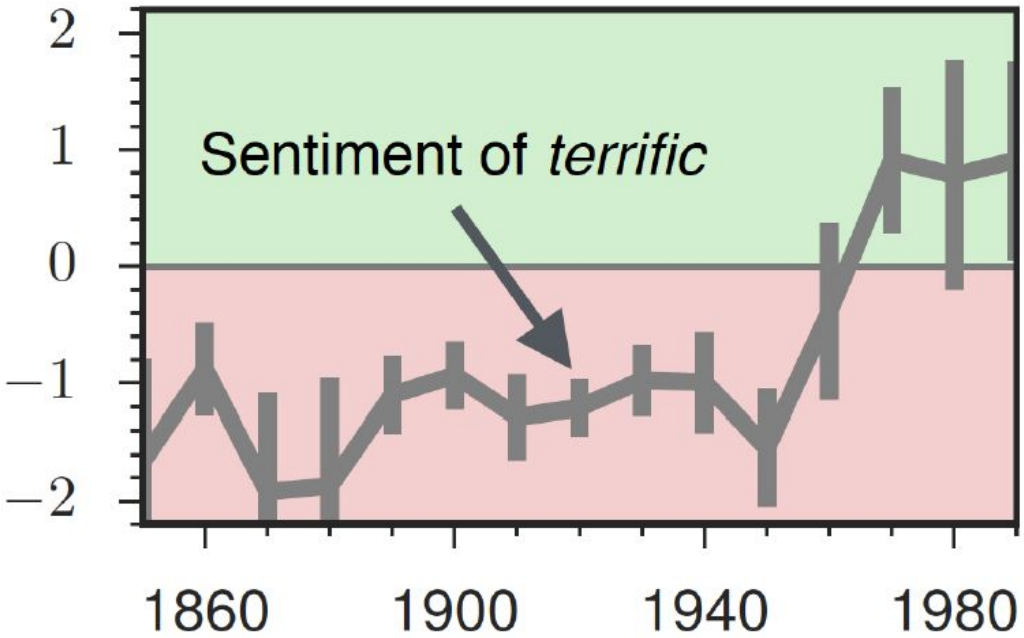


Project 300 dimensions down into 2

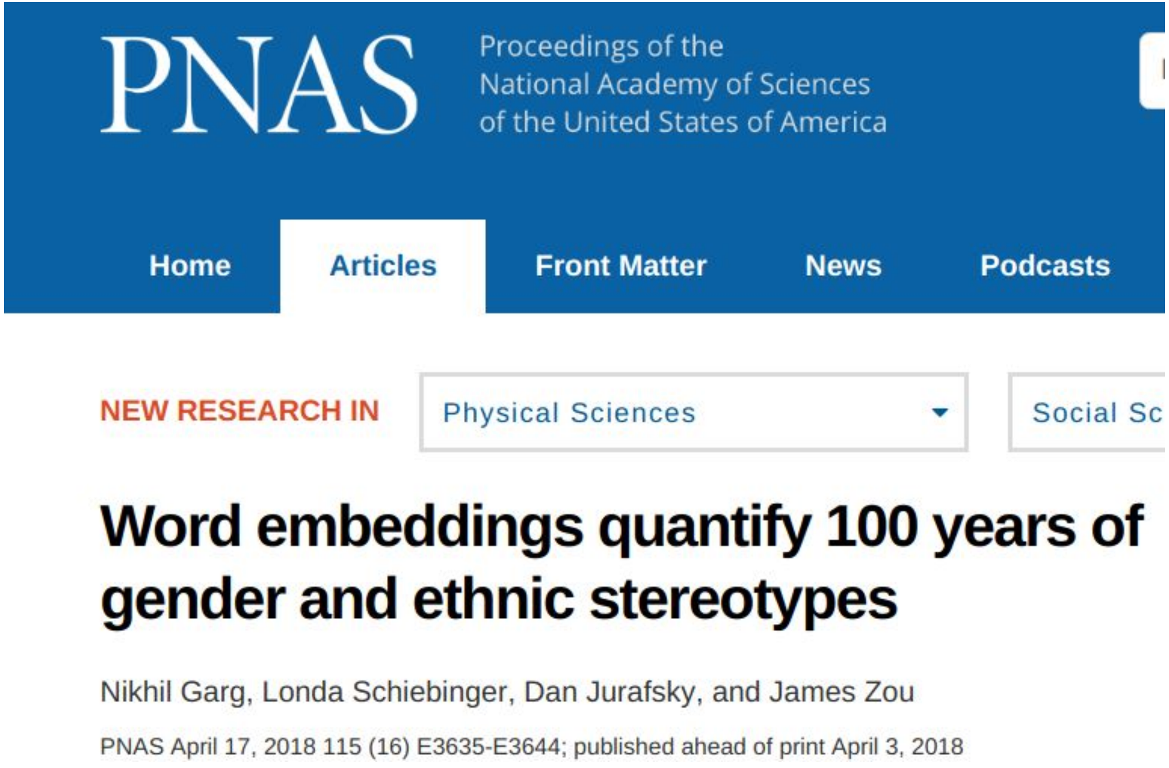


~30 million books, 1850-1990, Google Books data

Negative words change faster than positive words



Embeddings reflect ethnic stereotypes over time


PNAS Proceedings of the National Academy of Sciences of the United States of America

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Word embeddings quantify 100 years of gender and ethnic stereotypes

Nikhil Garg, Londa Schiebinger, Dan Jurafsky, and James Zou

PNAS April 17, 2018 115 (16) E3635-E3644; published ahead of print April 3, 2018

Change in linguistic framing 1910-1990

Change in association of Chinese names with adjectives framed as "othering" (barbaric, monstrous, bizarre)