Dan Jurafsky and James Martin

Speech and Language Processing

Chapter 6

Vector Semantics, Part 2

Tf-idf and PPMI are sparse representations

tf-idf and PPMI vectors are

- **long** (length |V|= 20,000 to 50,000)
- **sparse** (most elements are zero)

Alternative: dense vectors

vectors which are

- **short** (length 50-1000)
- **dense** (most elements are non-zero)

Sparse versus dense vectors

Why dense vectors?

- Short vectors may be easier to use as **features** in machine learning (fewer weights to tune)
- Dense vectors may **generalize** better than storing explicit counts
- They may do better at capturing synonymy:
  - *car* and *automobile* are synonyms; but are distinct dimensions in sparse vectors
    - a word with *car* as a neighbor and a word with *automobile* as a neighbor should be similar, but aren't
- **In practice, they work better**

Dense embeddings you can download!

Word2vec (Mikolov et al.)
https://code.google.com/archive/p/word2vec/

Fasttext http://www.fasttext.cc/

Glove (Pennington, Socher, Manning)
http://nlp.stanford.edu/projects/glove/

Word2vec

Popular embedding method

Very fast to train

Code available on the web

Idea: **predict** rather than **count**

Word2vec

- Instead of **counting** how often each word *w* occurs near "*apricot*"
- Train a classifier on a binary **prediction** task:
  - Is *w* likely to show up near "*apricot*"?
- We don’t actually care about this task
  - But we'll take the learned classifier weights as the word embeddings

Brilliant insight: Use running text as implicitly supervised training data!

- A word *s* near *apricot*
  - Acts as gold ‘correct answer’ to the question
  - “Is word *w* likely to show up near *apricot*?”
- No need for hand-labeled supervision
- The idea comes from **neural language modeling**
  - Bengio et al. (2003)
  - Collobert et al. (2011)

Word2Vec: **Skip-Gram** Task

Word2vec provides a variety of options. Let's do

- "skip-gram with negative sampling" (SGNS)

Skip-gram algorithm

1. Treat the target word and a neighboring context word as positive examples.
2. Randomly sample other words in the lexicon to get negative samples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the weights as the embeddings

Skip-Gram Training Data

Training sentence:

... lemon, a tablespoon of **apricot** jam a pinch ...

c1 c2 target c3 c4

Asssume context words are those in +/- 2 word window

Skip-Gram Goal

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

- (*apricot*, *jam*)
- (*apricot*, *aardvark*)

Return probability that c is a real context word:

$P(+|t,c)$

$P(-|t,c) = 1 - P(+|t,c)$

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

Intuition:

- Words are likely to appear near similar words
- Model similarity with dot-product!
- Similarity(t,c) ≈ t · c

Problem:

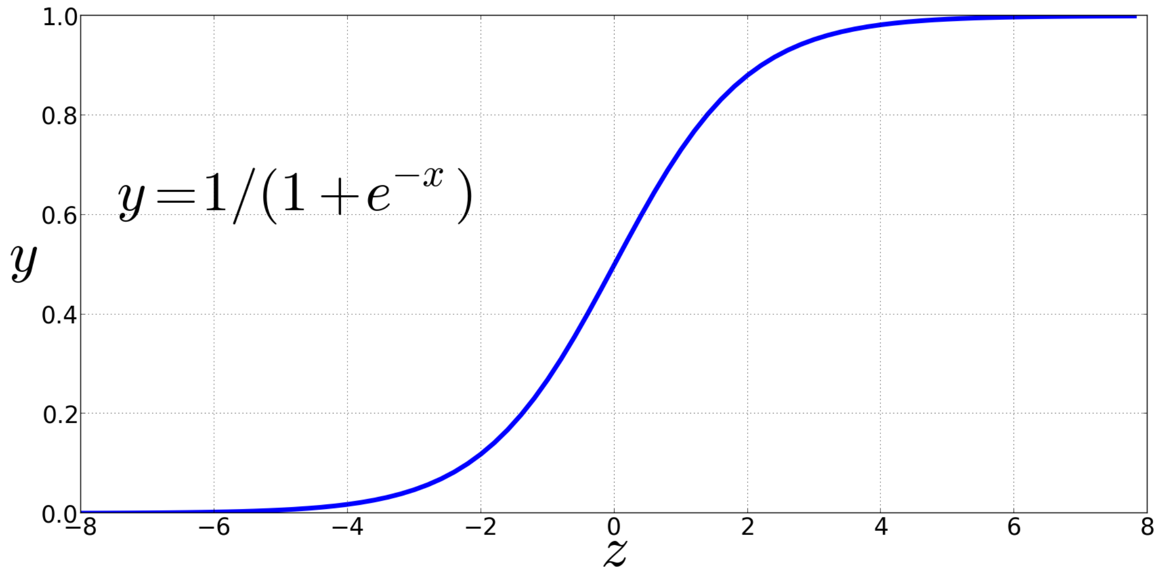
- *Dot product is not a probability!*
  - *(Neither is cosine)*

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

Turning dot product into a probability

The sigmoid lies between 0 and 1:

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



Turning dot product into a probability

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

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

For all the context words:

Assume all context words are independent

$$P(+|t, c_{1:k}) = \prod_{i=1}^{\kappa} \frac{1}{1+e^{-t \cdot c_i}}$$

$$\log P(+|t, c_{1:k}) = \sum_{i=1}^{k} \log \frac{1}{1+e^{-t \cdot c_i}}$$

Popping back up

Now we have a way of computing the probability of p(+ | t, c), which is the probability that c is a real context word for t.

BUT, we need embeddings for **t** and **c** to do it.

Where do we get those embeddings?

Word2vec learns them automatically!

It starts with an initial set of embedding vectors and then iteratively shifting the embedding of each word *w* to be more like the embeddings of words that occur nearby in texts, and less like the embeddings of words that don't occur nearby.

Skip-Gram Training Data

Training sentence:

... lemon, a tablespoon of **apricot** jam a pinch ...

c1 c2 t c3 c4

Training data: input/output pairs centering on *apricot*

Assume a +/- 2 word window

Skip-Gram Training

Training sentence:

... lemon, a tablespoon of **apricot** jam a pinch ...

c1 c2 t c3 c4

positive examples +

t	c
apricot	tablespoon
apricot	of
apricot	preserves
apricot	or

- For each positive example, we'll create *k* negative examples.
- Using *noise* words
- Any random word that isn't *t*

Skip-Gram Training

Training sentence:

... lemon, a tablespoon of apricot jam a pinch ...

c1 c2 t c3 c4

positive examples +

t	c
apricot	tablespoon
apricot	of
apricot	preserves
apricot	or

negative examples - k=2

t	c	t	c
apricot	aardvark	apricot	twelve
apricot	puddle	apricot	hello
apricot	where	apricot	dear
apricot	coaxial	apricot	forever

Choosing noise words

Could pick w according to their unigram frequency P(w)

More common to chosen then according to $p_\alpha(w)$

$$P_\alpha(w) = \frac{count(w)^\alpha}{\sum_w count(w)^\alpha}$$

α= ¾ works well because it gives rare noise words slightly higher probability

To show this, imagine two events p(a)=.99 and p(b) = .01:

$$P_\alpha(a) = \frac{.99^{.75}}{.99^{.75} + .01^{.75}} = .97$$

$$P_\alpha(b) = \frac{.01^{.75}}{.99^{.75} + .01^{.75}} = .03$$

Setup

Let's represent words as vectors of some length (say 300), randomly initialized.

So we start with 300 * V random parameters

Over the entire training set, we'd like to adjust those word vectors such that we

- Maximize the similarity of the target word, context word pairs (t,c) drawn from the positive data
- Minimize the similarity of the (t,c) pairs drawn from the negative data.

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:

Objective Criteria

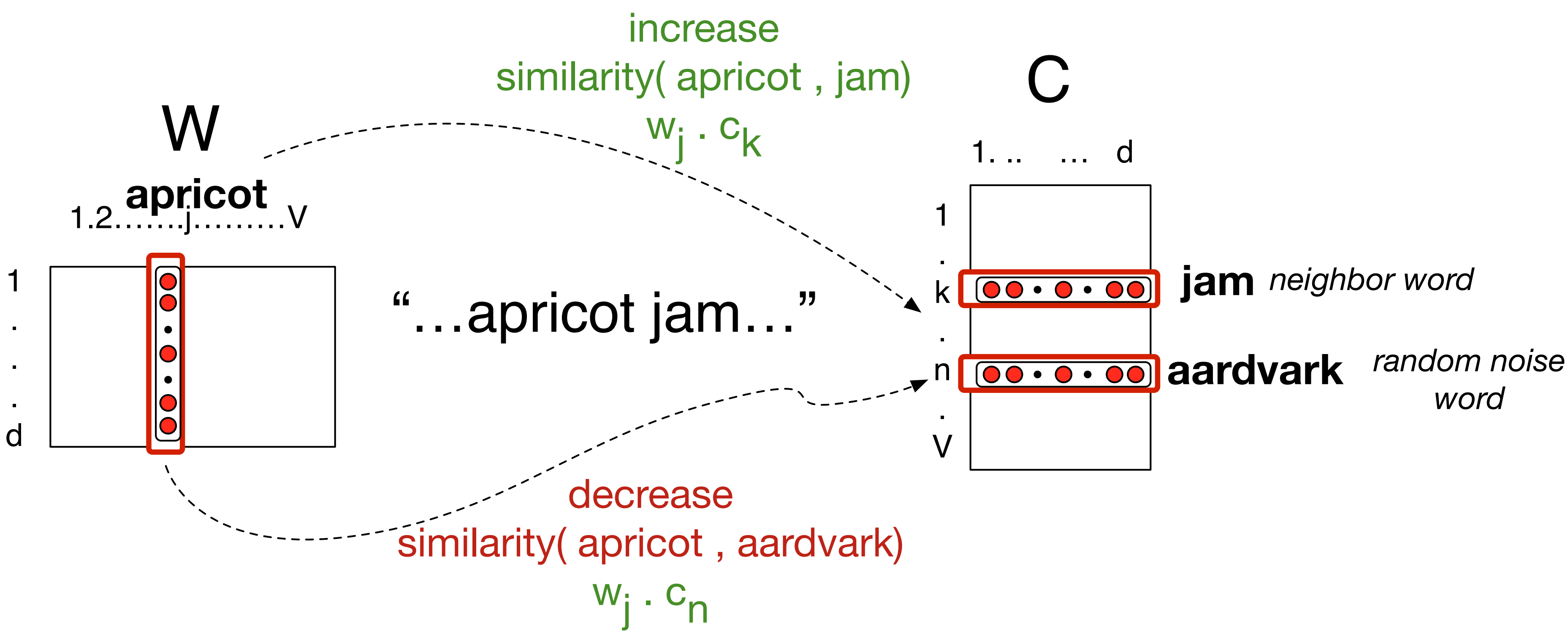
We want to maximize…

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

Maximize the + label for the pairs from the positive training data, and the – label for the pairs sample from the negative data.

Focusing on one target word t:

$$
\begin{aligned}
L(\theta) &= \log P(+|t,c) + \sum_{i=1}^{k} \log P(-|t,n_i) \\
&= \log \sigma(c \cdot t) + \sum_{i=1}^{k} \log \sigma(-n_i \cdot t) \\
&= \log \frac{1}{1+e^{-c \cdot t}} + \sum_{i=1}^{k} \log \frac{1}{1+e^{n_i \cdot t}}
\end{aligned}
$$



increase
similarity(apricot , jam)
$w_j \cdot c_k$
W
apricot
1.2…….j………V
1
.
.
.
d
C
1. ..   … d
1
.
k
.
n
.
V
jam
neighbor word
aardvark
random noise word
"…apricot jam…"
decrease
similarity(apricot , aardvark)
$w_j \cdot c_n$

Train using gradient descent

Actually learns two separate embedding matrices W and C

Can use W and throw away C, or merge them somehow

Summary: How to learn word2vec (skip-gram) embeddings

Start with V random 300-dimensional vectors as initial embeddings

Use logistic regression, the second most basic classifier used in machine learning after naïve Bayes

- Take a corpus and take pairs of words that co-occur as positive examples
- Take pairs of words that don't co-occur as negative examples
- Train the classifier to distinguish these by slowly adjusting all the embeddings to improve the classifier performance
- Throw away the classifier code and keep the embeddings.

Evaluating embeddings

Compare to human scores on word similarity-type tasks:

- WordSim-353 (Finkelstein et al., 2002)
- SimLex-999 (Hill et al., 2015)
- Stanford Contextual Word Similarity (SCWS) dataset (Huang et al., 2012)
- TOEFL dataset: *Levied is closest in meaning to: imposed, believed, requested, correlated*

Intrinsic evalation

Psycholinguistic experiment

cos sim	$\hat{u}$	$\hat{v}$	mean 10 judges
	Love ,	Sex	6.8
⋮	tiger ,	cat	7.3
⋮	tiger ,	tiger	10
⋮	fertility ,	egg	6.7
	stock ,	egg	1.8
	professor ,	Cucumber	0.3

WordSim 353

GOLD STANDARD

Compute correlation

· Kendall's tau " " "

$$\tau = \frac{(\text{number of concordant pairs}) - (\text{\# of discordant pairs})}{\underbrace{N(N-1)/2}_{\text{total pairs}}}$$

Human ordering

sex, love > prof., cucumber

system ordering predicts < ⇒ discordant pair

> ⇒ concordant pair

range −1 to 1

Properties of embeddings

Similarity depends on window size C

C = ±2 The nearest words to *Hogwarts:*

- *Sunnydale*
- *Evernight*

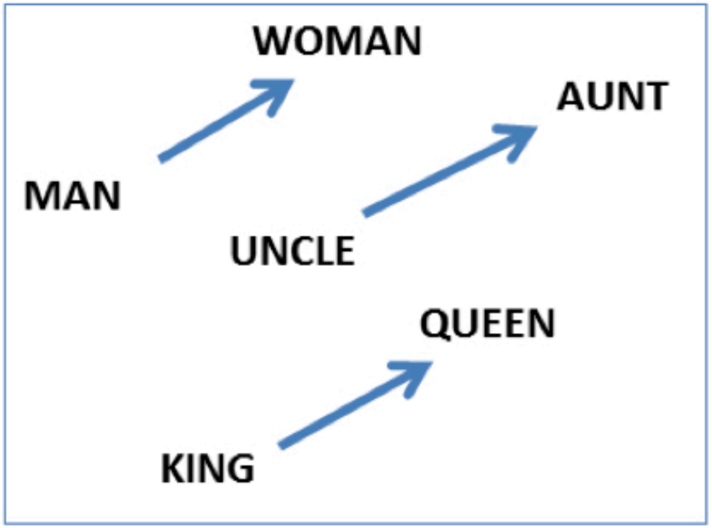
C = ±5 The nearest words to *Hogwarts:*

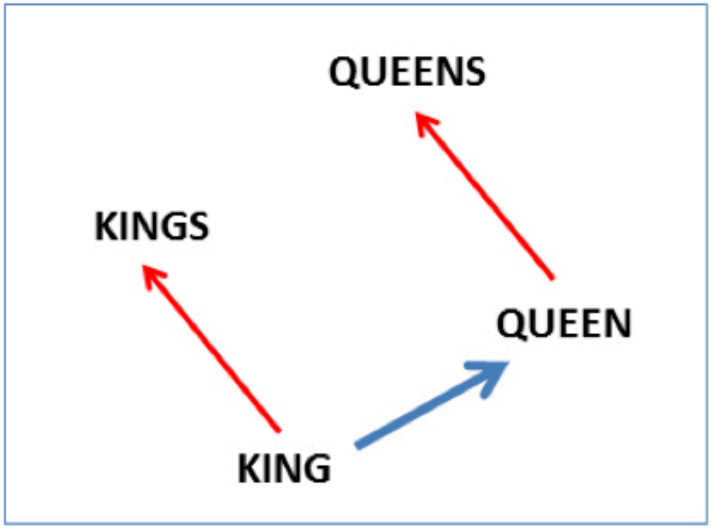
- *Dumbledore*
- *Malfoy*
- *halfblood*

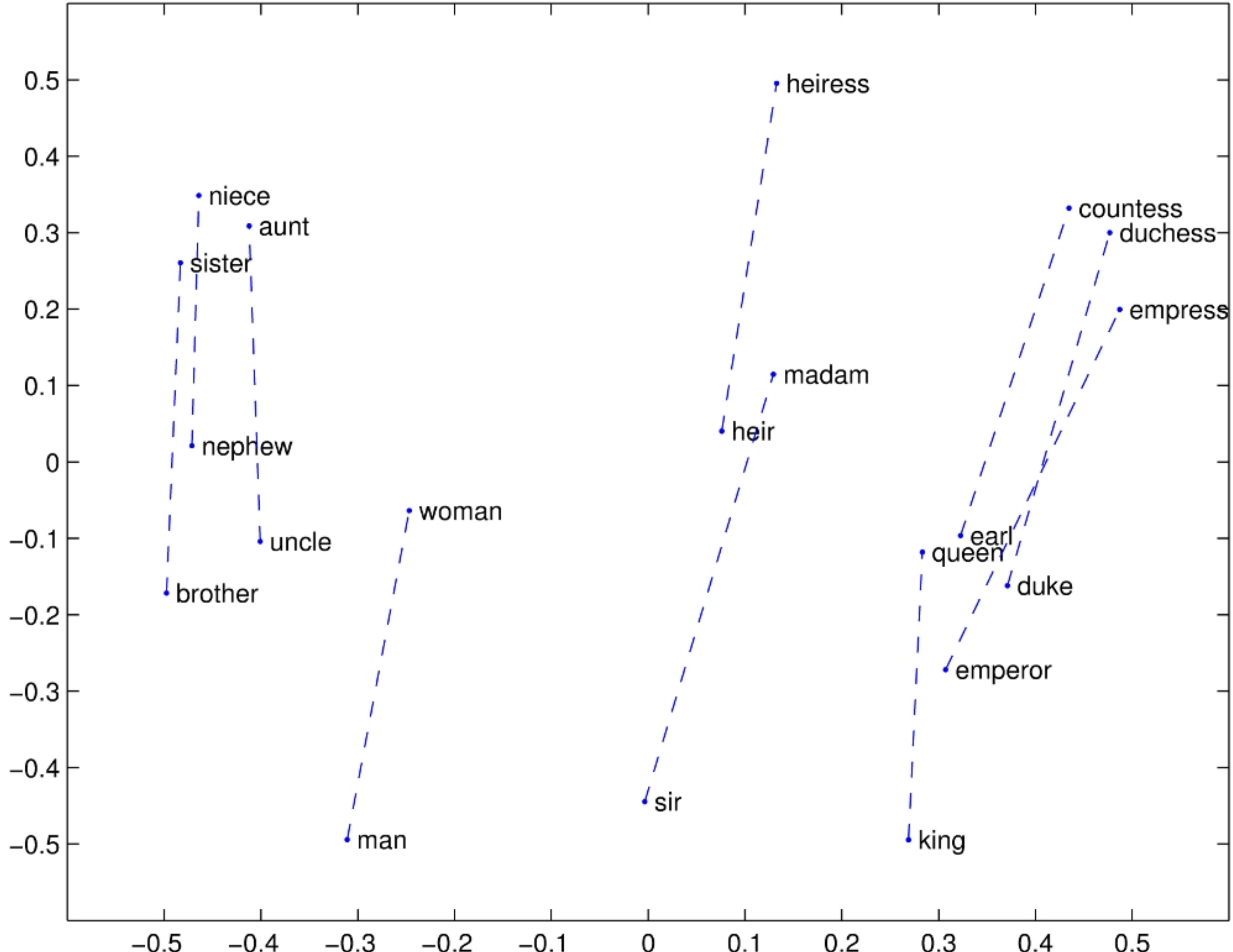
Analogy: Embeddings capture relational meaning!

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

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







heiress
niece
aunt
sister
countess
duchess
empress
madam
heir
nephew
woman
uncle
earl
queen
duke
brother
emperor
sir
man
king
0.5
0.4
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
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0
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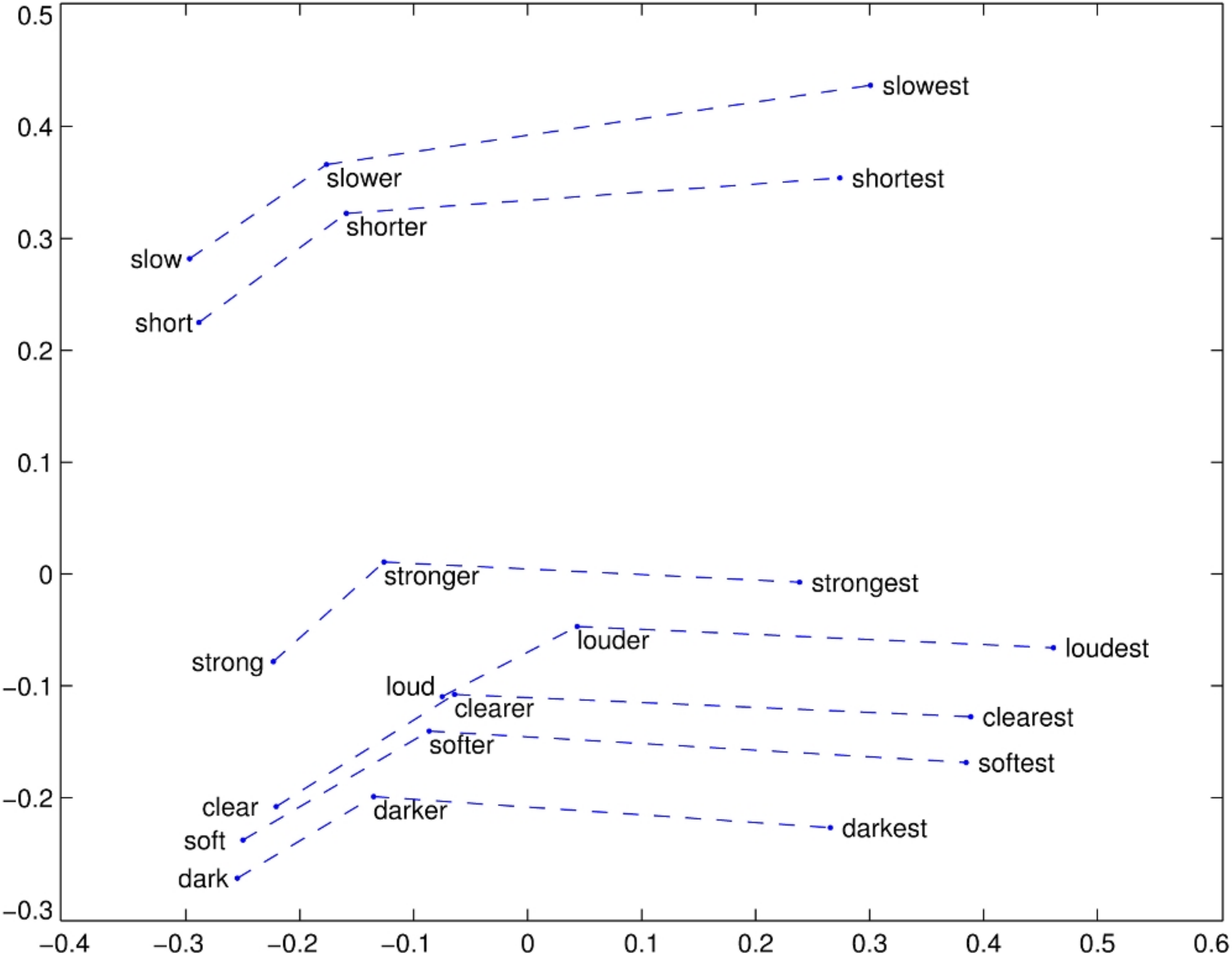


slowest
slower
shortest
shorter
slow
short
stronger
strongest
louder
loudest
strong
loud
clearer
clearest
softer
softest
clear
soft
darker
darkest
dark
0.5
0.4
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
−0.3
−0.2
−0.1
0
0.1
0.2
0.3
0.4
0.5
0.6

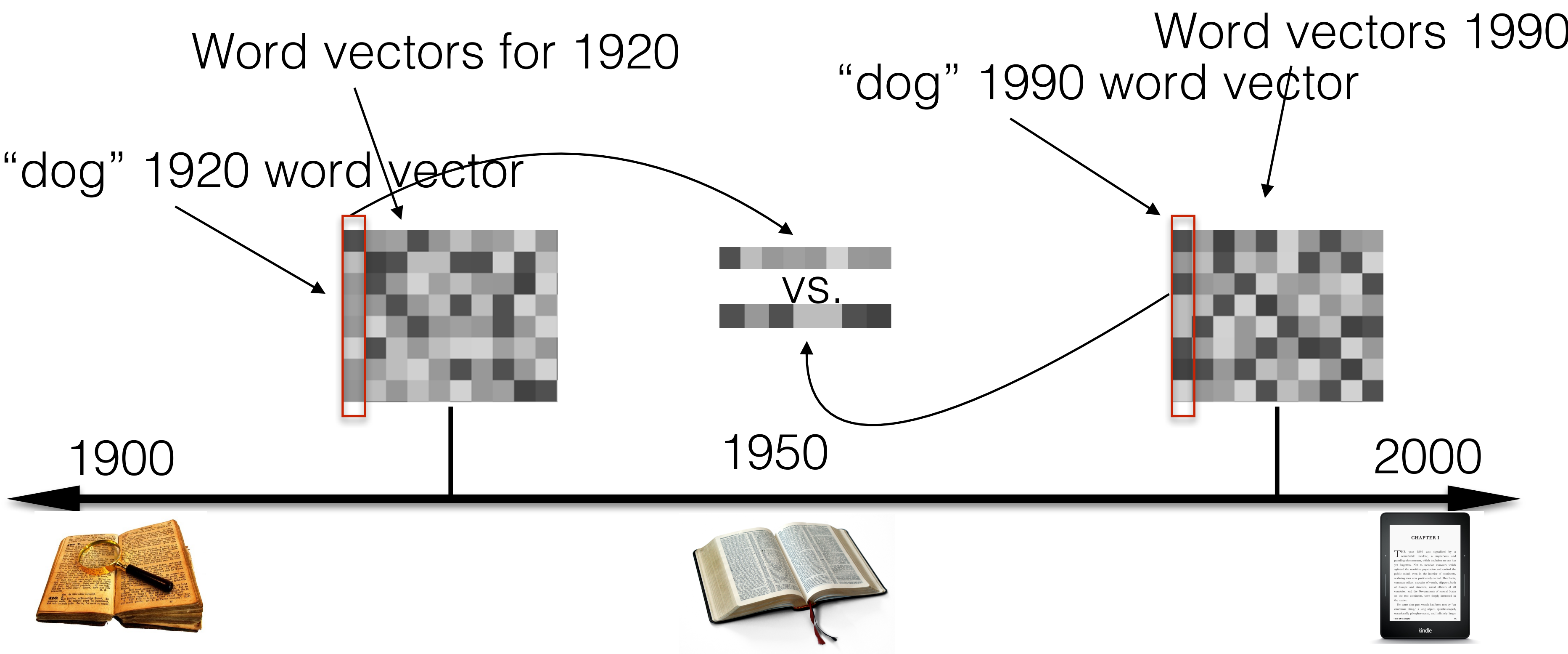
Embeddings can help study word history!

Train embeddings on old books to study changes in word meaning!!

Dan Jurafsky

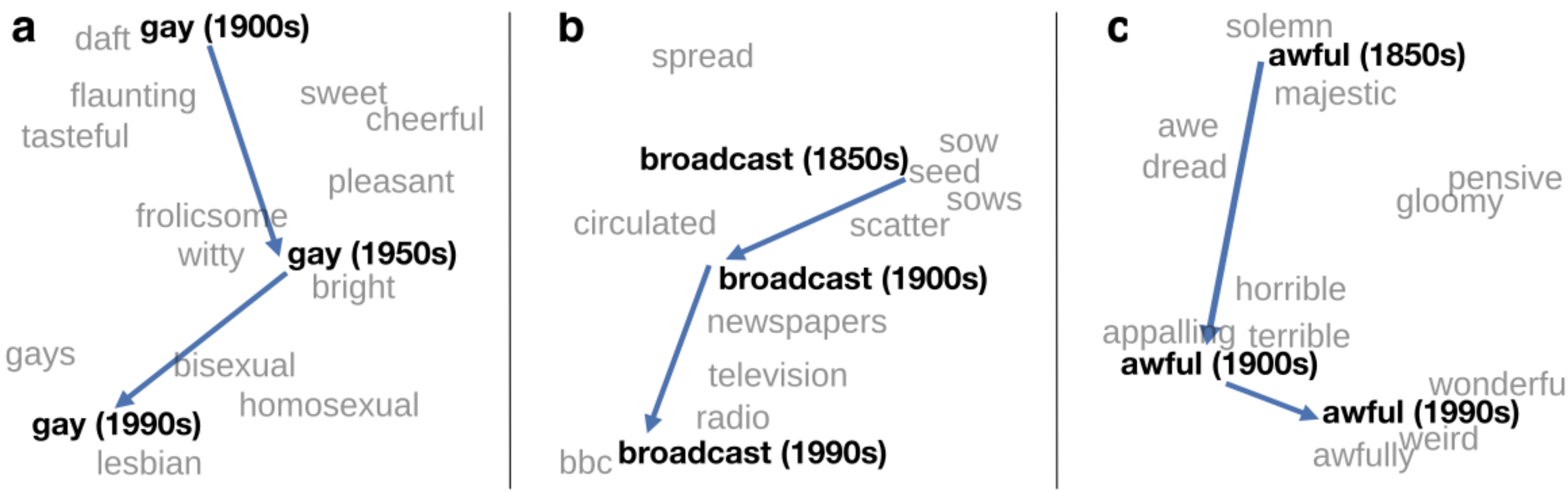
Will Hamilton

Diachronic word embeddings for studying language change!



Visualizing changes

Project 300 dimensions down into 2



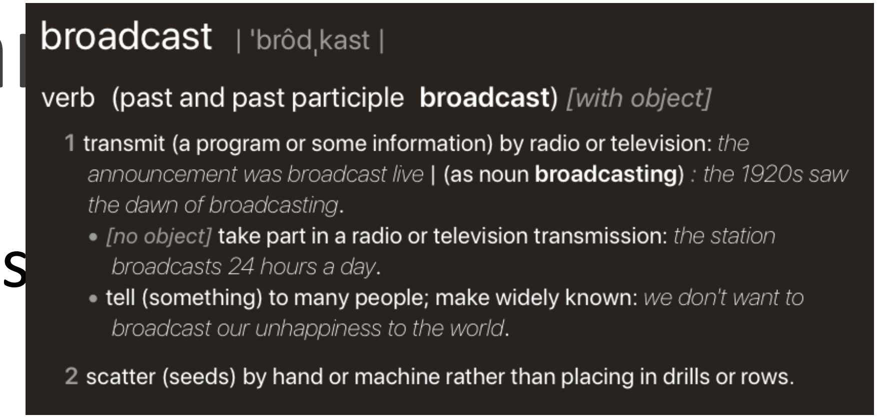
~30 million books, 1850-1990, Google Books data

gay | gā |

adjective (**gayer, gayest**)

1 (of a person) homosexual (used especially of a man): *that friend of yours, is he gay?*
• relating to or used by homosexuals: *a gay bar* | *the gay vote can decide an election.*

2 *dated* lighthearted and carefree: *Nan had a gay disposition and a very pretty face.*
• brightly colored; showy; brilliant: *a gay profusion of purple and pink sweet peas.*

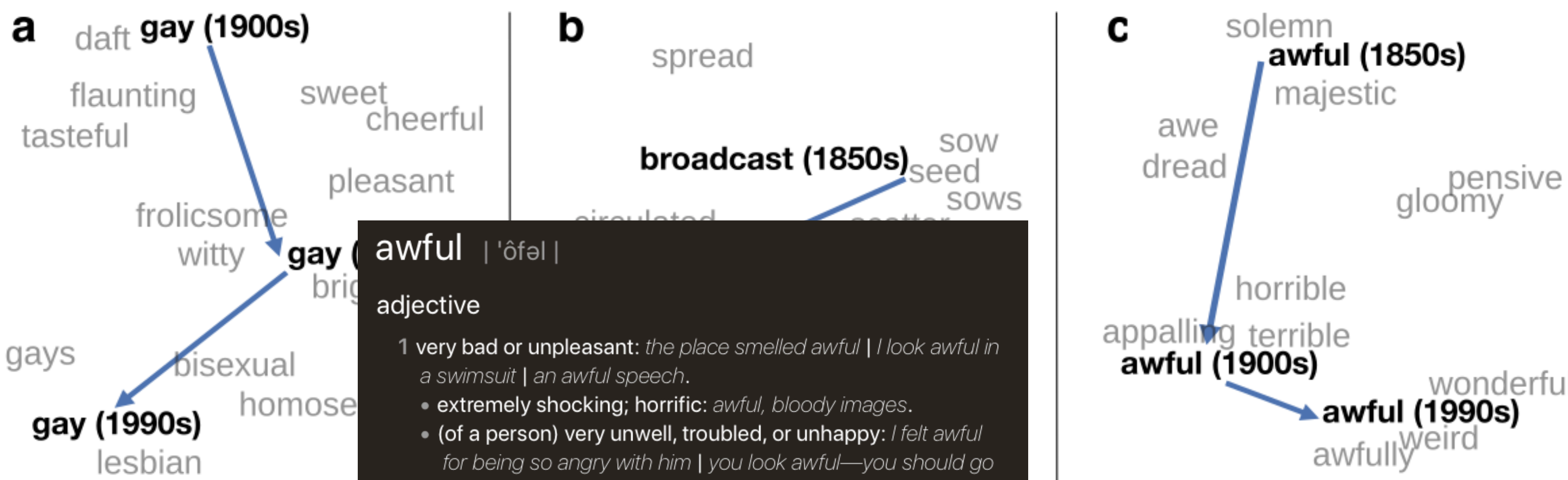


broadcast | 'brôdˌkast |

verb (past and past participle **broadcast**) *[with object]*

1 transmit (a program or some information) by radio or television: *the announcement was broadcast live* | (as noun **broadcasting**) *: the 1920s saw the dawn of broadcasting.*
• *[no object]* take part in a radio or television transmission: *the station broadcasts 24 hours a day.*
• tell (something) to many people; make widely known: *we don't want to broadcast our unhappiness to the world.*

2 scatter (seeds) by hand or machine rather than placing in drills or rows.



awful | 'ôfəl |

adjective

1 very bad or unpleasant: *the place smelled awful* | *I look awful in a swimsuit* | *an awful speech.*
• extremely shocking; horrific: *awful, bloody images.*
• (of a person) very unwell, troubled, or unhappy: *I felt awful for being so angry with him* | *you look awful—you should go and lie down.*

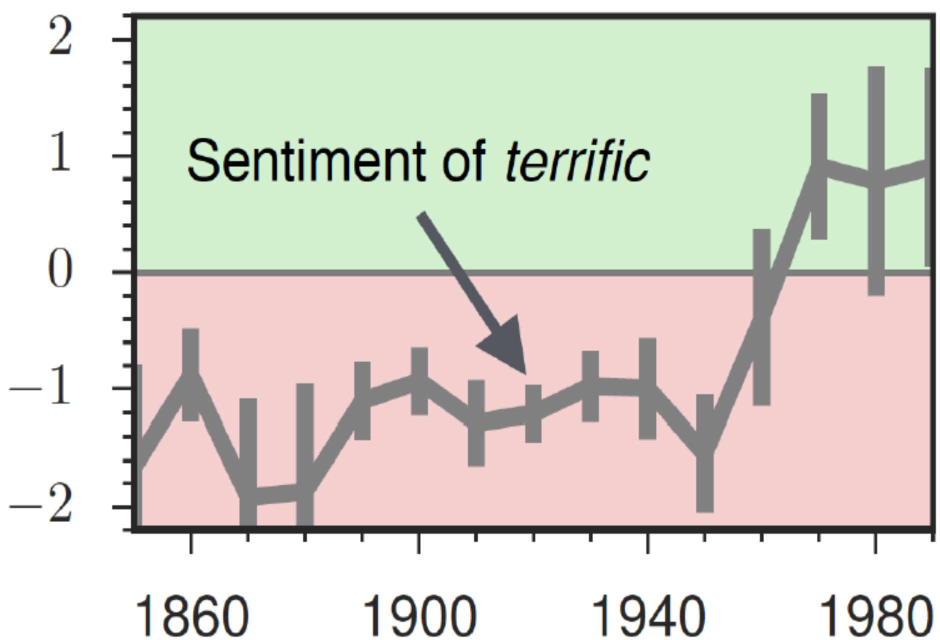
2 *[attributive]* used to emphasize the extent of something, especially something unpleasant or negative: *I've made an awful fool of myself.*

3 *archaic* inspiring reverential wonder or fear.

~30 million boo

The evolution of sentiment words

Negative words change faster than positive words



Embeddings and bias

Embeddings reflect cultural bias

Bolukbasi, Tolga, Kai-Wei Chang, James Y. Zou, Venkatesh Saligrama, and Adam T. Kalai. "Man is to computer programmer as woman is to homemaker? debiasing word embeddings." In *Advances in Neural Information Processing Systems*, pp. 4349-4357. 2016.

Ask "Paris : France :: Tokyo : x"

- x = Japan

Ask "father : doctor :: mother : x"

- x = nurse

Ask "man : computer programmer :: woman : x"

- x = homemaker

Embeddings reflect cultural bias

Caliskan, Aylin, Joanna J. Bruson and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. Science 356:6334, 183-186.

Implicit Association test (Greenwald et al 1998): How associated are

- concepts (*flowers*, *insects*) & attributes (*pleasantness*, *unpleasantness*)?
- Studied by measuring timing latencies for categorization.

Psychological findings on US participants:

- African-American names are associated with unpleasant words (more than European-American names)
- Male names associated more with math, female names with arts
- Old people's names with unpleasant words, young people with pleasant words.

Caliskan et al. replication with embeddings:

- African-American names (*Leroy, Shaniqua*) had a higher GloVe cosine with unpleasant words (*abuse, stink, ugly*)
- European American names (*Brad, Greg, Courtney*) had a higher cosine with pleasant words (*love, peace, miracle*)

Embeddings reflect and replicate all sorts of pernicious biases.

Directions

Debiasing algorithms for embeddings

- Bolukbasi, Tolga, Chang, Kai-Wei, Zou, James Y., Saligrama, Venkatesh, and Kalai, Adam T. (2016). Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In *Advances in Neural Information Processing Systems*, pp. 4349–4357.

Use embeddings as a historical tool to study bias

Embeddings as a window onto history

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

Use the Hamilton historical embeddings

The cosine similarity of embeddings for decade X for occupations (like teacher) to male vs female names

- Is correlated with the actual percentage of women teachers in decade X

History of biased framings of women

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

Embeddings for competence adjectives are biased toward men

- *Smart, wise, brilliant, intelligent, resourceful, thoughtful, logical, etc.*

This bias is slowly decreasing

Embeddings reflect ethnic stereotypes over time

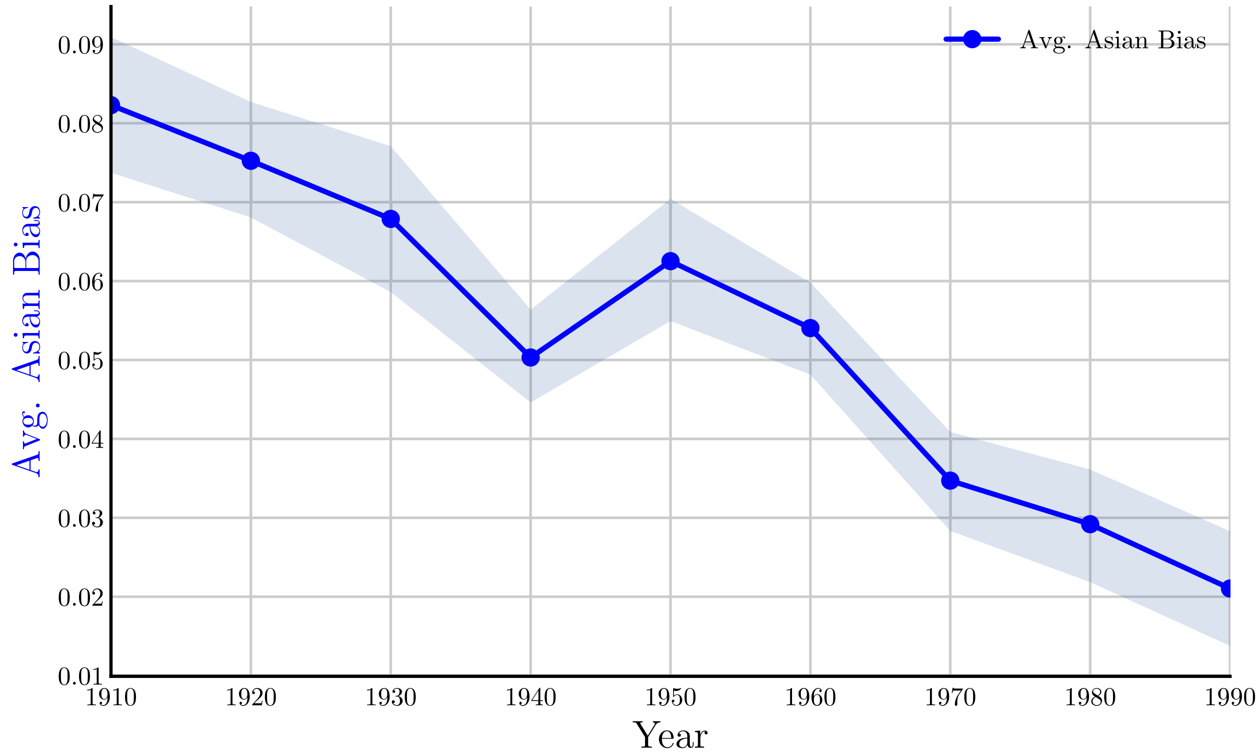
Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

- Princeton trilogy experiments
- Attitudes toward ethnic groups (1933, 1951, 1969) scores for adjectives
  - *industrious, superstitious, nationalistic*, etc
- Cosine of Chinese name embeddings with those adjective embeddings correlates with human ratings.

Change in linguistic framing 1910-1990

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

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



Changes in framing: adjectives associated with Chinese

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

1910	1950	1990
Irresponsible	Disorganized	Inhibited
Envious	Outrageous	Passive
Barbaric	Pompous	Dissolute
Aggressive	Unstable	Haughty
Transparent	Effeminate	Complacent
Monstrous	Unprincipled	Forceful
Hateful	Venomous	Fixed
Cruel	Disobedient	Active
Greedy	Predatory	Sensitive
Bizarre	Boisterous	Hearty

Conclusion

Embeddings = vector models of meaning

- More fine-grained than just a string or index
- Especially good at modeling similarity/analogy
  - Just download them and use cosines!!
- Can use sparse models (tf-idf) or dense models (word2vec, GLoVE)
- Useful in practice but know they encode cultural stereotypes