

CIS 530: Vector Semantics part 2

JURAFSKY AND MARTIN CHAPTER 6

Reminders



HOMWORK 3 IS DUE ON
TONIGHT BY 11:59PM



HW4 WILL BE RELEASED
SOON



READ TEXTBOOK
CHAPTER 6

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/>

Magnitude (Patel and Sands)

<https://github.com/plasticityai/magnitude>

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))

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

Assume 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!
- $\text{Similarity}(t, c) \approx t \cdot c$

Problem:

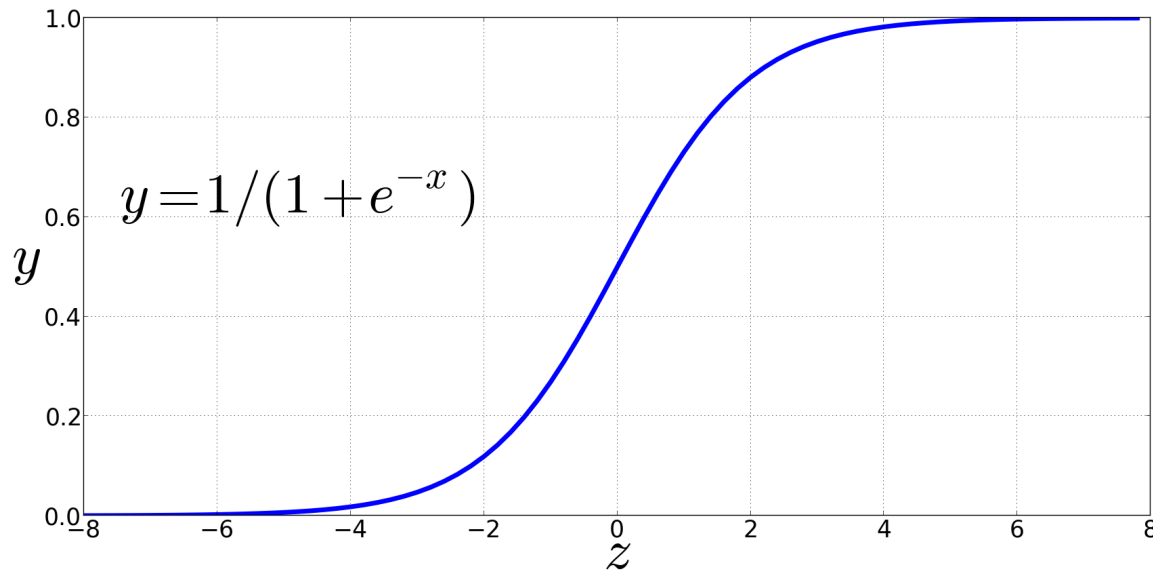
- *Dot product is not a probability!*
- *(Neither is cosine)*

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

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

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

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

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

For all the context words:

Assume all context words are independent

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

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

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 shifts 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

How many noise words?

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 $p_\alpha(w)$

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

$\alpha = \frac{3}{4}$ works well because it gives rare noise words slightly higher probability

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

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

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

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:

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.

Objective Criteria

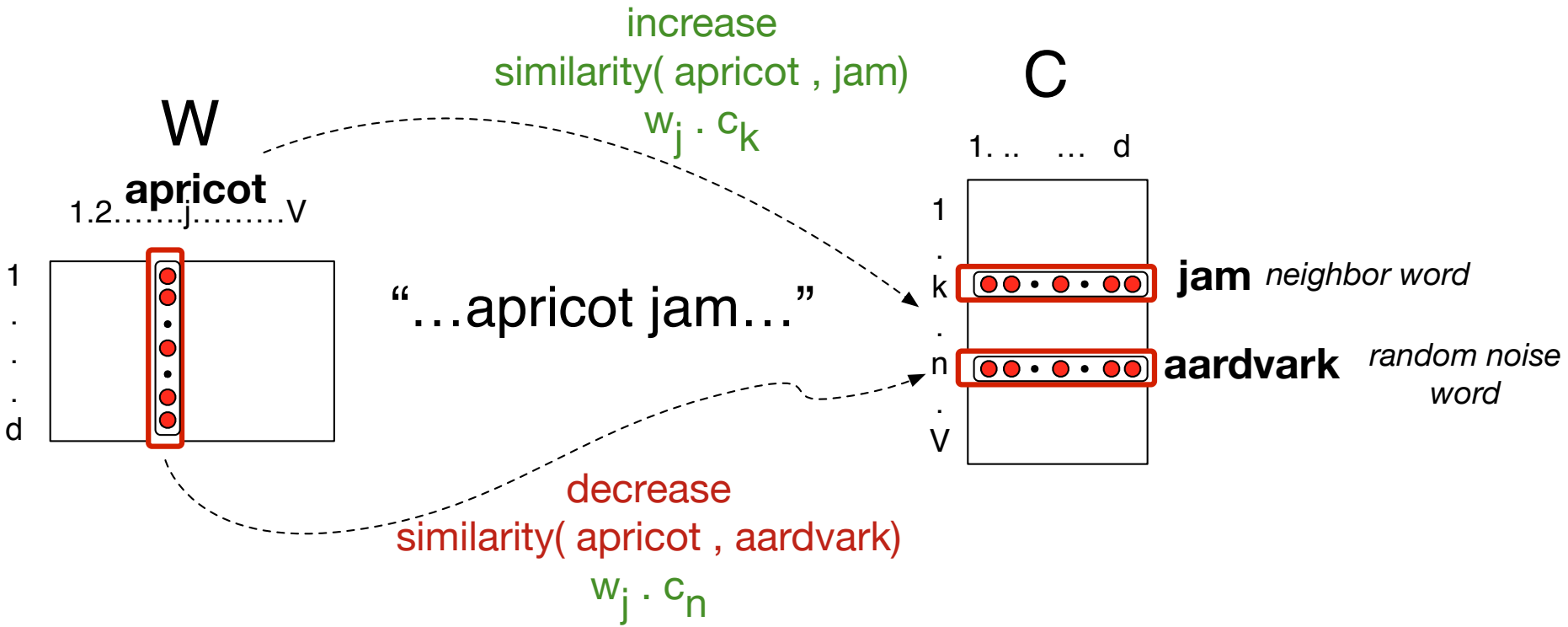
We want to maximize...

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

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 :

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



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:
(a) imposed, (b) believed, (c) requested, (d) correlated*

Intrinsic evaluation

cos sim	Psycholinguistic	experiment	mean 10 judges	WordSim 353
	<u>↑</u>	<u>↓</u>		
	Love,	sex	6.8	
:	tiger,	cat	1.3	
:	tiger,	tiger	10	
:	fertility,	egg	6.7	
:	stock,	egg	1.8	← GOLD STANDARD
	professor,	cucumber	0.3	

Compute correlation

• Kendall's tau " " "

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

total pairs

Human ordering

sex, love

>

prof., cucumber

System ordering

probiotics

<

⇒ discordant pair

>

⇒ concordant pair

range (−1) to (1)

Properties of embeddings

Similarity depends on window size C

$C = \pm 2$ The nearest words to *Hogwarts*:

- *Sunnydale*
- *Evernight*

$C = \pm 5$ The nearest words to *Hogwarts*:

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

How does context window change word embeddings?

Target Word	BoW5	BoW2	DEPS
batman	nightwing aquaman catwoman superman manhunter	superman superboy aquaman catwoman batgirl	superman superboy supergirl catwoman aquaman
hogwarts	dumbledore hallows half-blood malfoy snape	evernight sunnydale garderobe blandings collinwood	sunnydale collinwood calarts greendale millfield
florida	gainesville fla jacksonville tampa lauderdale	fla alabama gainesville tallahassee texas	texas louisiana georgia california carolina
	aspect-oriented	aspect-oriented	event-driven

Solving analogies with embeddings

In a word-analogy task we are given two pairs of words that share a relation (e.g. “man:woman”, “king:queen”).

The identity of the fourth word (“queen”) is hidden, and we need to infer it based on the other three by answering

“man is to woman as king is to — ?”

More generally, we will say **a:a*** as **b:b***.

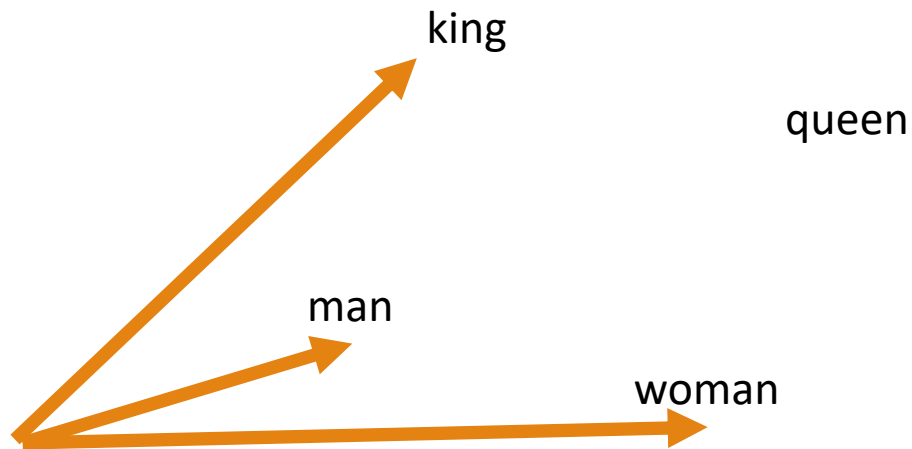
Can we solve these with word vectors?

Vector Arithmetic

$\mathbf{a}:\mathbf{a}^*$ as $\mathbf{b}:\mathbf{b}^*$. \mathbf{b}^* is a hidden vector.

\mathbf{b}^* should be similar to the vector $\mathbf{b} - \mathbf{a} + \mathbf{a}^*$

$\text{vector}('king') - \text{vector}('man') + \text{vector}('woman') \approx \text{vector}('queen')$

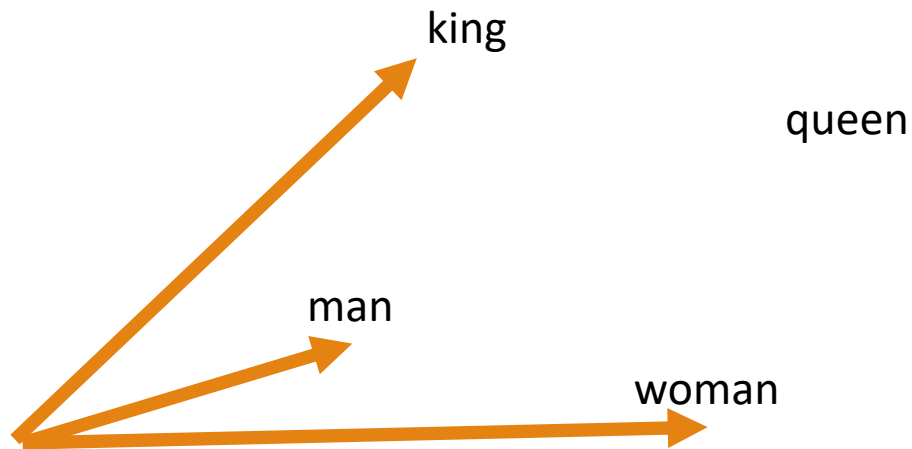


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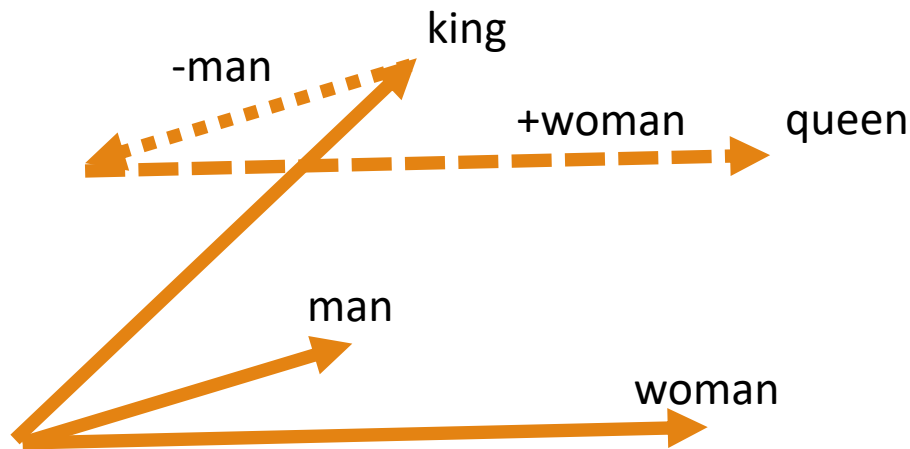


Analogy: Embeddings capture relational meaning!

$a:a^*$ as $b:b^*$. b^* is a hidden vector.

b^* should be similar to the vector $b - a + a^*$

$\text{vector}('king') - \text{vector}('man') + \text{vector}('woman') \approx \text{vector}('queen')$

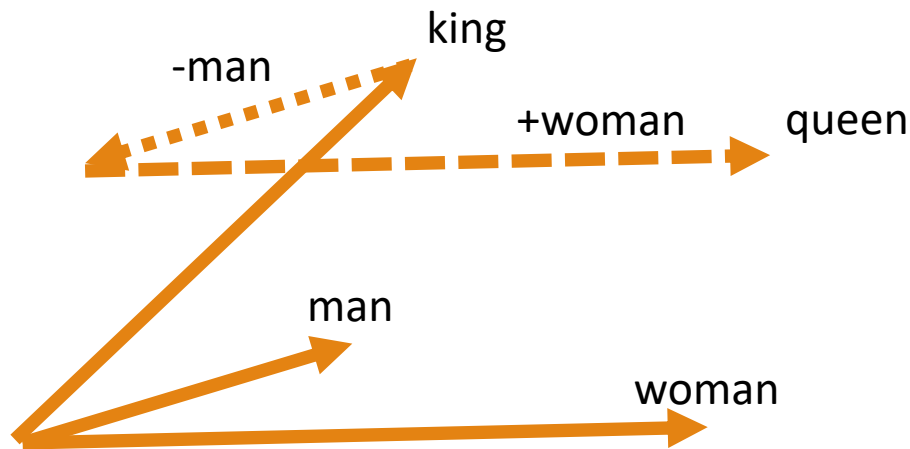


Vector Arithmetic

a:a* as **b:b***. **b*** is a hidden vector.

b* should be similar to the vector $b - a + a^*$

$\text{vector}('king') - \text{vector}('man') + \text{vector}('woman') \approx \text{vector}('queen')$

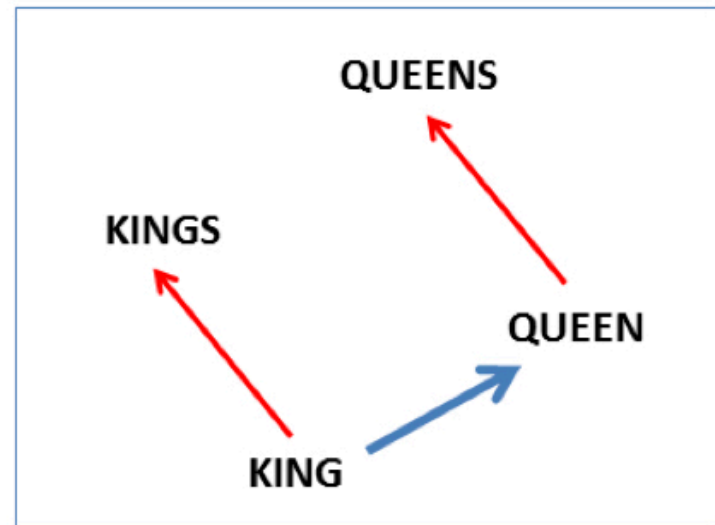
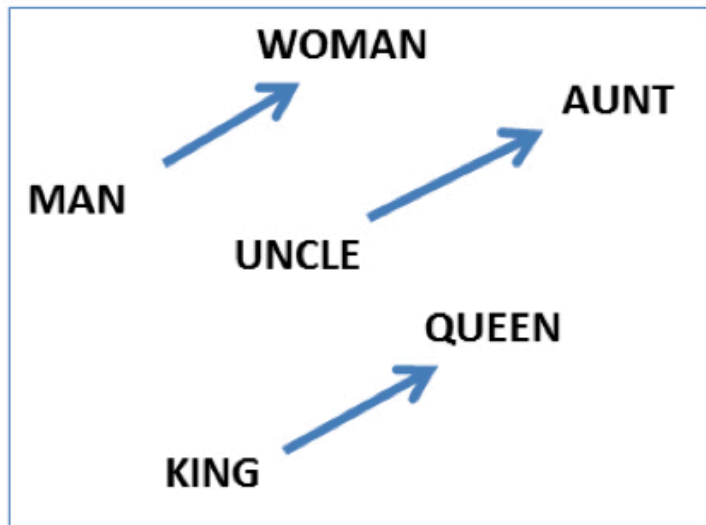


So the analogy question can be solved by optimizing: $\arg \max_{b^* \in V} (\cos(b^*, b - a + a^*))$

Analogy: Embeddings capture relational meaning!

$\text{vector}('king') - \text{vector}('man') + \text{vector}('woman') \approx \text{vector}('queen')$

$\text{vector}('Paris') - \text{vector}('France') + \text{vector}('Italy') \approx \text{vector}('Rome')$



Vector Arithmetic

If all word-vectors are normalized to unit length then

$$\arg \max_{b^* \in V} (\cos (b^*, b - a + a^*))$$

is equivalent to

$$\arg \max_{b^* \in V} (\cos (b^*, b) - \cos (b^*, a) + \cos (b^*, a^*))$$

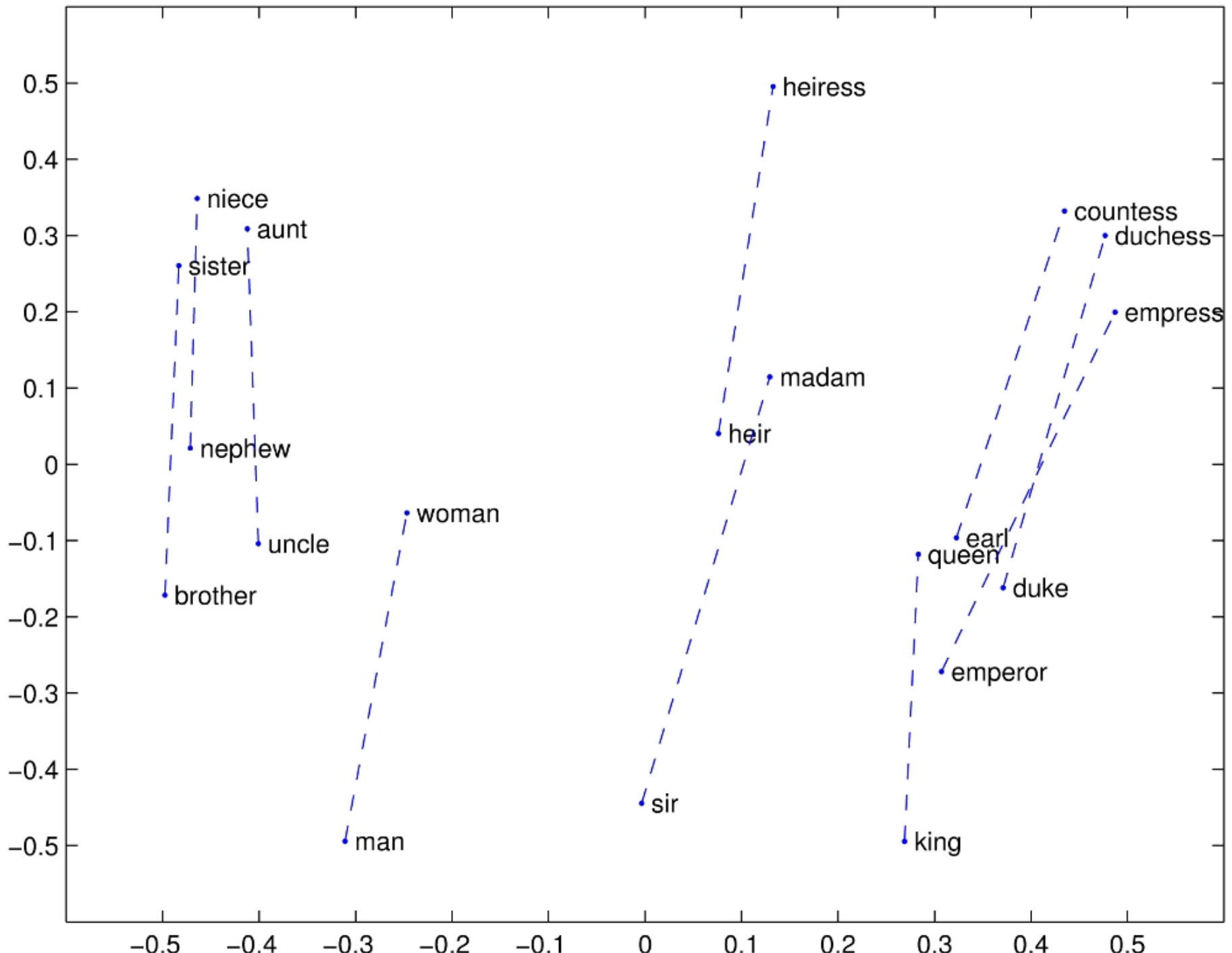
Vector Arithmetic

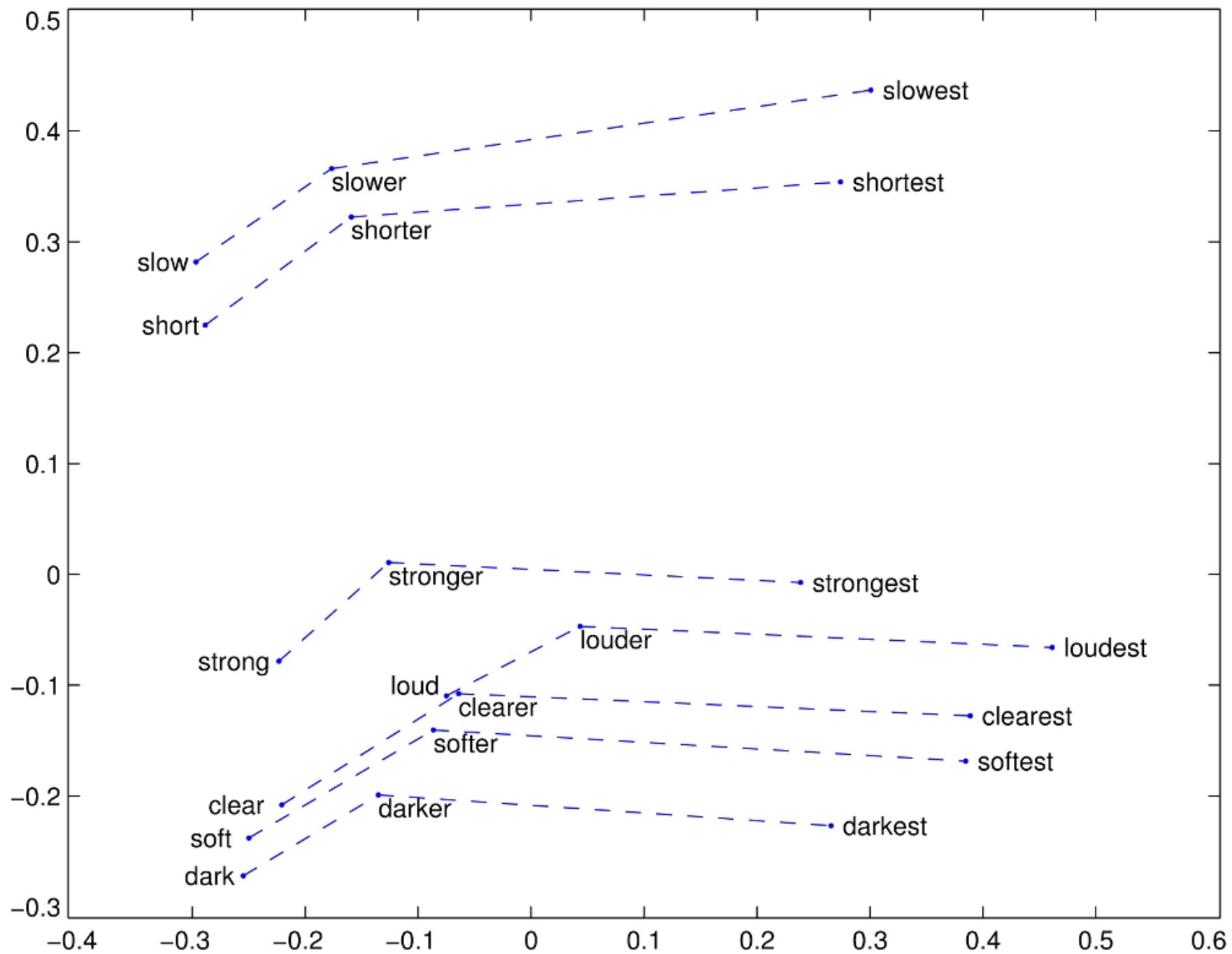
Alternatively, we can require that the direction of the transformation be maintained.

$$\arg \max_{b^* \in V} (\cos (b^*, b - a + a^*))$$

$$\arg \max_{b^* \in V} (\cos (b^* - b, a^* - a))$$

This basically means that $b^* - b$ **shares the same direction with** $a^* - a$, ignoring the distances





Representing Phrases with vectors

Mikolov et al constructed representations for phrases as well as for individual words.

To learn vector representations for phrases, they first find words that appear frequently together but infrequently in other contexts, and represent these n-grams as single tokens.

For example, “New York Times” and “Toronoto Maple Leafs” are replaced by `New_York_Times` and `Toronoto_Maple_Leafs`, but a bigram like “this is” remains unchanged.

$$\text{score}(w_i, w_j) = \frac{\text{count}(w_i w_j) - \delta}{\text{count}(w_i) \times \text{count}(w_j)}.$$

Analogical reasoning task for phrases

Newspapers			
New York San Jose	New York Times San Jose Mercury News	Baltimore Cincinnati	Baltimore Sun Cincinnati Enquirer
NHL Teams			
Boston Phoenix	Boston Bruins Phoenix Coyotes	Montreal Nashville	Montreal Canadiens Nashville Predators
NBA Teams			
Detroit Oakland	Detroit Pistons Golden State Warriors	Toronto Memphis	Toronto Raptors Memphis Grizzlies
Airlines			
Austria Belgium	Austrian Airlines Brussels Airlines	Spain Greece	Spainair Aegean Airlines
Company executives			
Steve Ballmer Samuel J. Palmisano	Microsoft IBM	Larry Page Werner Vogels	Google Amazon

Vector compositionality

Mikolov et al experiment with using element-wise addition to compose vectors

Czech + currency	Vietnam + capital	German + airlines
koruna	Hanoi	airline Lufthansa
Check crown	Ho Chi Minh City	carrier Lufthansa
Polish zolty	Viet Nam	flag carrier Lufthansa
CTK	Vietnamese	Lufthansa

Russian + river	French + actress
Moscow	Juliette Binoche
Volga River	Vanessa Paradis
upriver	Charlotte Gainsbourg
Russia	Cecile De

A SIMPLE BUT TOUGH-TO-BEAT BASELINE FOR SENTENCE EMBEDDINGS

Sanjeev Arora, Yingyu Liang, Tengyu Ma

Princeton University

{arora, yingyu, tengyu}@cs.princeton.edu

ABSTRACT

The success of neural network methods for computing word embeddings has motivated methods for generating semantic embeddings of longer pieces of text, such as sentences and paragraphs. Surprisingly, Wieting et al (ICLR'16) showed that such complicated methods are outperformed, especially in out-of-domain (transfer learning) settings, by simpler methods involving mild retraining of word embeddings and basic linear regression. The method of Wieting et al. requires retraining with a substantial labeled dataset such as Paraphrase Database (Ganitkevitch et al., 2013).

The current paper goes further, showing that the following completely unsupervised sentence embedding is a formidable baseline: Use word embeddings computed using one of the popular methods on unlabeled corpus like Wikipedia, represent the sentence by a weighted average of the word vectors, and then modify

Embeddings can help study word history!

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

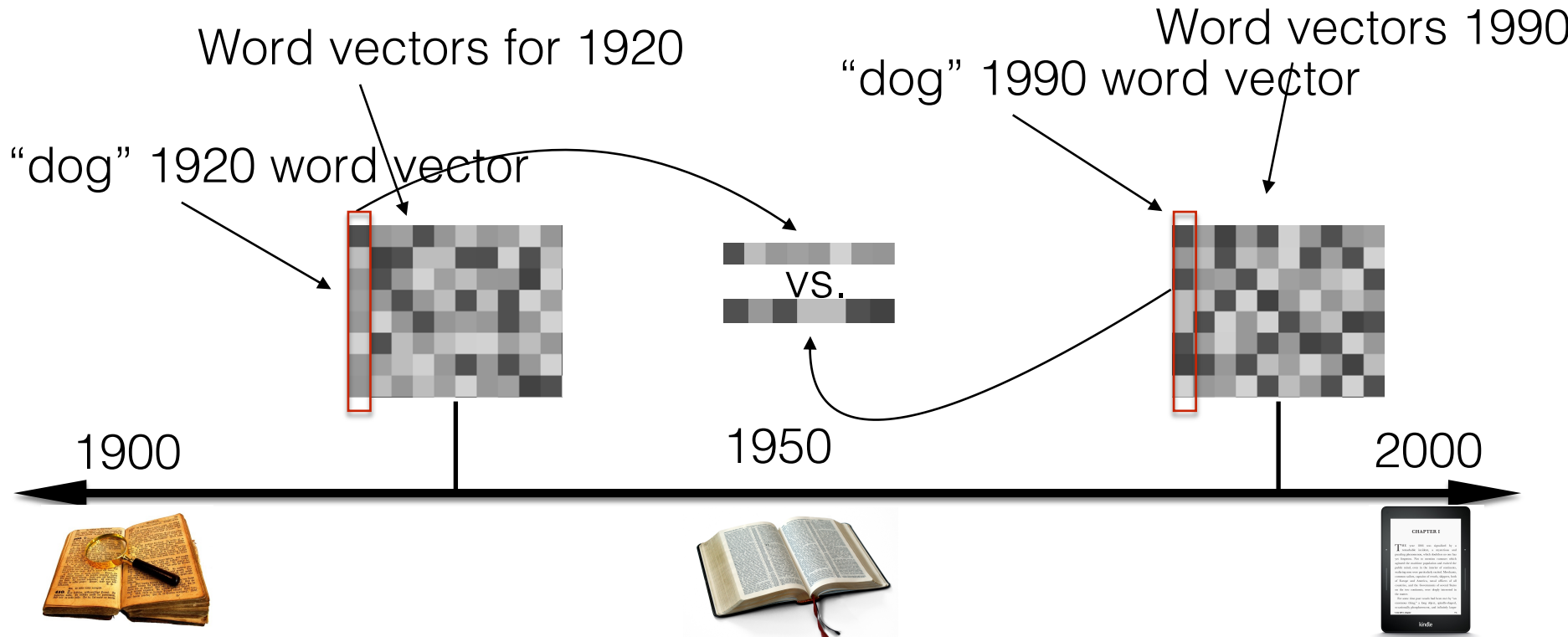


Dan Jurafsky



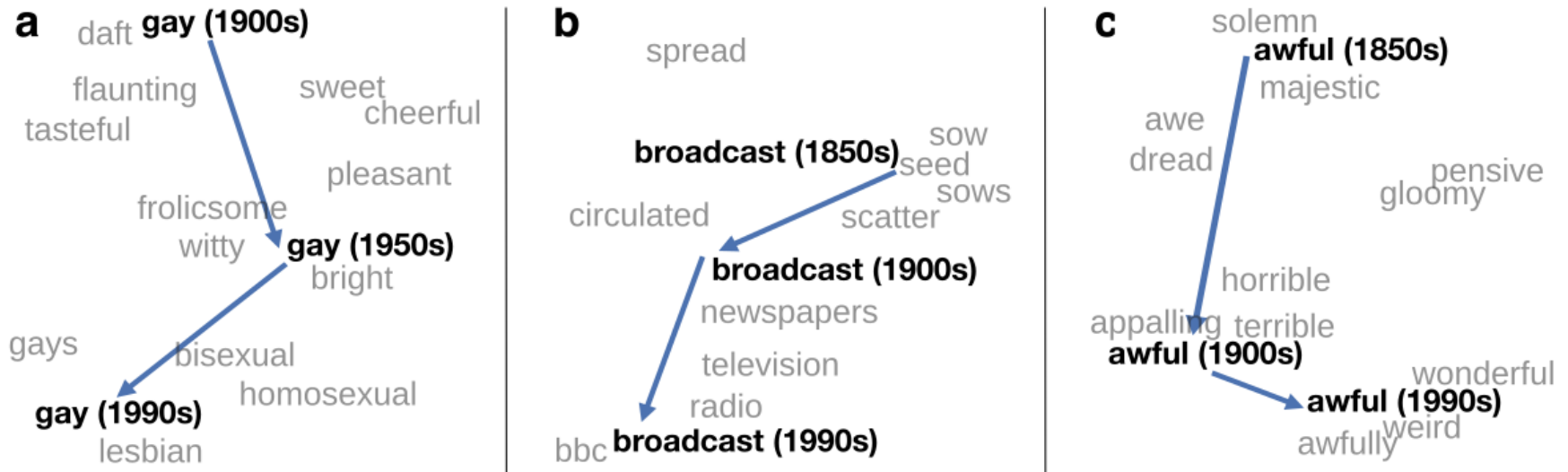
Will Hamilton

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 | 'brɒd,kast |

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.

a daft gay (1900s)

flaunting
tasteful
frolicsome
witty
gays
gay (1990s)
lesbian

sweet
cheerful
pleasant
brilliant
homosexual

b

spread
broadcast (1850s)
sow
seed
sows

awful | 'ɒfəl |

adjective

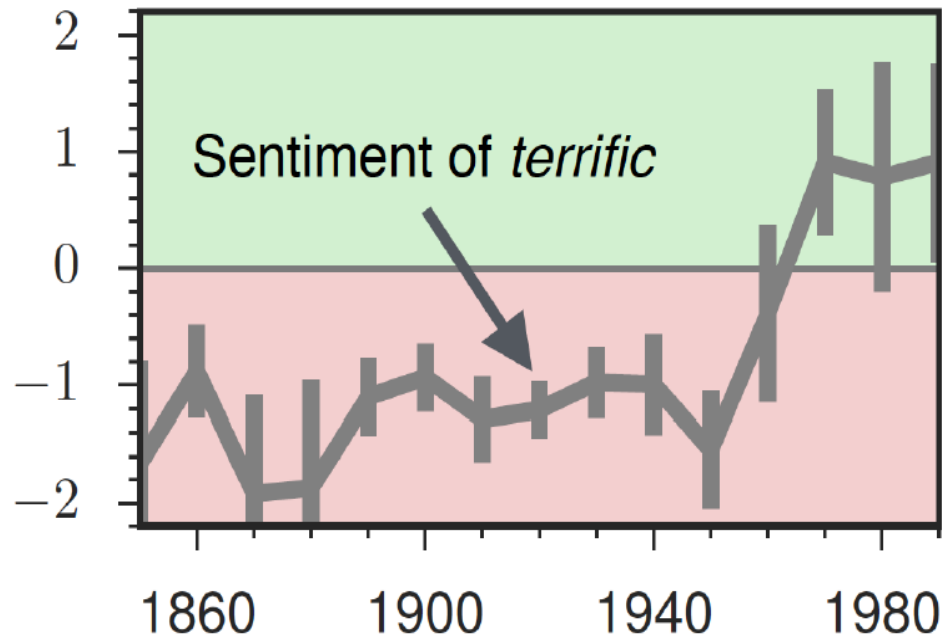
- 1 very bad or unpleasant: *the place smelled awful | I look awful in a swimsuit | an awful speech.*
 - extremely shocking; horrific: *awful, bloody images.*
 - (of a person) very unwell, troubled, or unhappy: *I felt awful for being so angry with him | you look awful—you should go and lie down.*
-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

c

solemn
awful (1850s)
majestic
awe
dread
horrible
appalling
awful (1900s)
terrible
awful (1990s)
awfully
wonderful
weird
pensive
gloomy

~30 million books

The evolution of sentiment words



ter·rif·ic | təˈrɪfɪk |

adjective

1 of great size, amount, or intensity: *there was a terrific bang.*

• *informal* extremely good; excellent: *it's been such a terrific day | you look terrific.*

2 *archaic* causing terror: *his body presented a terrific emblem of death.*

ORIGIN

mid 17th century (in [terrific](#) (sense 2)): from Latin *terrificus*, from *terrere* 'frighten'

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

Measuring cultural bias

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.

Embeddings reflect cultural bias

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

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

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

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

Princeton Trilogy experiments

Study 1: Katz and Braley (1933)

Investigated whether traditional social stereotypes had a cultural basis

Ask 100 male students from Princeton University to choose five traits that characterized different ethnic groups (for example Americans, Jews, Japanese, Negroes) from a list of 84 word

84% of the students said that Negroes were superstitious and 79% said that Jews were shrewd. They were positive towards their own group.

Study 2: Gilbert (1951)

Less uniformity of agreement about unfavorable traits than in 1933.

Study 3: Karlins et al. (1969)

Many students objected to the task but this time there was greater agreement on the stereotypes assigned to the different groups compared with the 1951 study. Interpreted as a re-emergence of social stereotyping but in the direction more favorable stereotypical images.

Embeddings reflect ethnic stereotypes over time

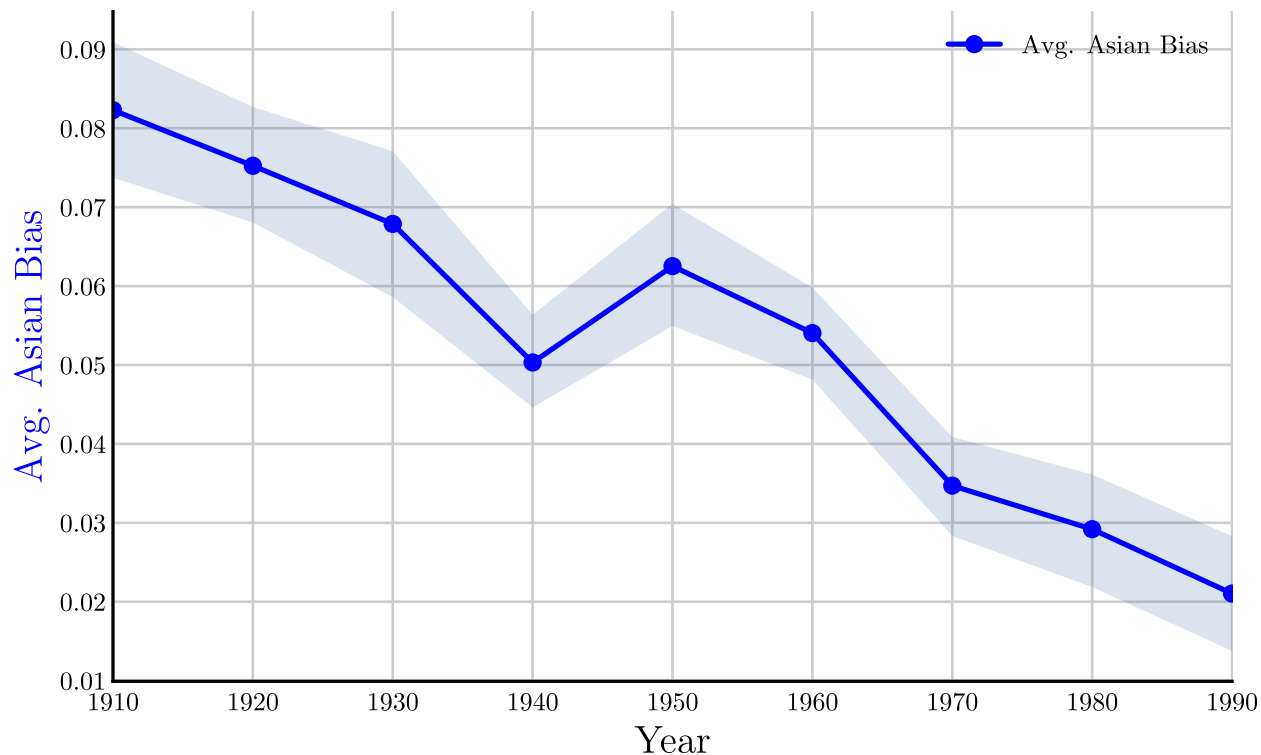
Nikhil Garg, Londa Schiebinger, Dan Jurafsky, and James Zou, (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, 115(16), E3635–E3644

- 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

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

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