Word meaning as classification

CMSC 723 / LING 723 / INST 725

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(Many slides c/o Dan Jurafsky & James Martin)

Announcements, logistics

- HW2 (ddl Sept 26 before class):
  - Written portion was posted last week
  - You should have received a login for Jupyter Hub server via email
    if not please contact us ASAP (either after class to talk to Amr)
  - Programming portion posted now or will be posted very soon!

- Readings for next few weeks are now posted

R 19 Sep	Data collection and annotation	DataInNLP, and AnnCaseStudy	
T 24 Sep	Measurement and validity	Measurement, and MeasurementCaseStudy, Sec "Reliability, Validity, ..."	
R 26 Sep	Crowdsourcing annotations	CrowdsourcingNLP, and AnnMyths	HW2
T 01 Oct	Multilinguality and linguistic variety	TheBenderRule, and Elicitation, Sec 3, and optional: ActiveElicitation	

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 (less 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
      - 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**
  - https://code.google.com/archive/p/word2vec/
- **Fasttext**
  - http://www.fasttext.cc/
- **Glove**
  - 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

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

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!
- Classification model
  - $P(+ \mid t, c) = 1/(1+\exp(-e_t \cdot e_c))$

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:

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

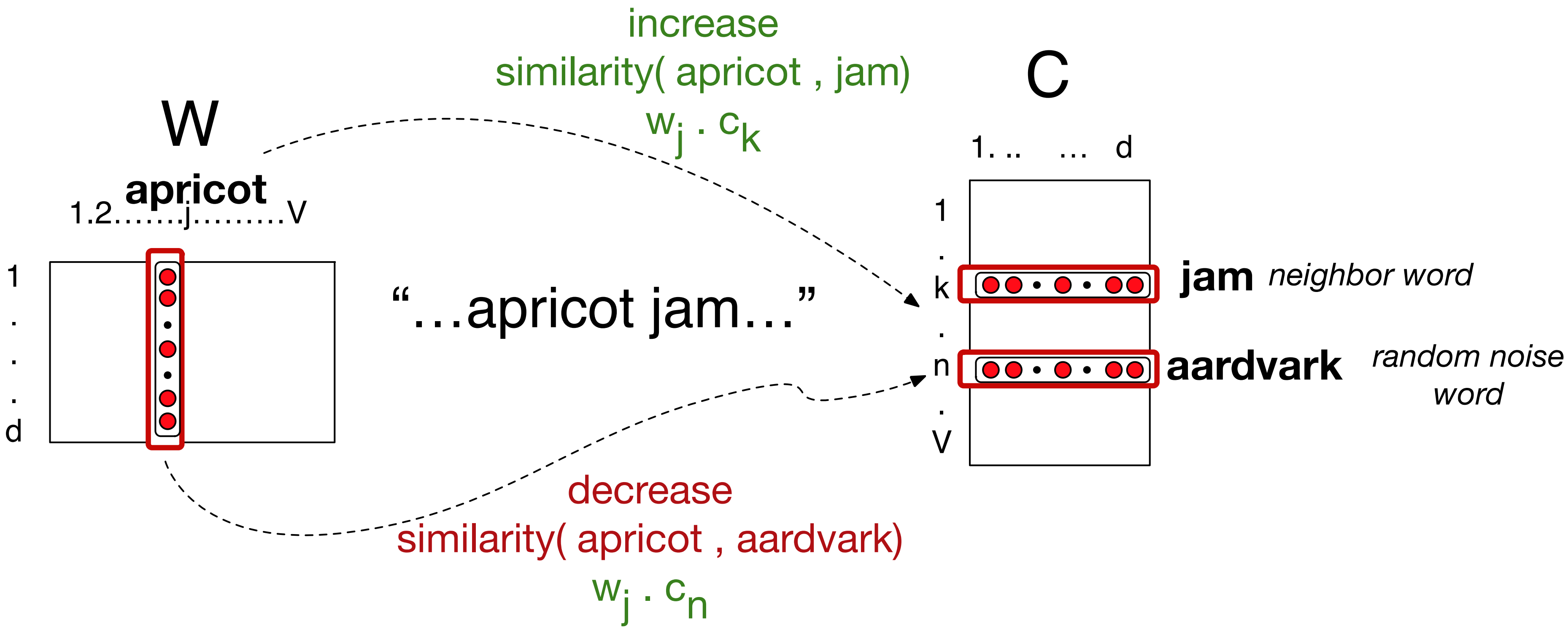
$$P_\alpha(b) = \frac{.01^{.75}}{.99^{.75} + .01^{.75}} = .03$$

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:


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

Properties of embeddings

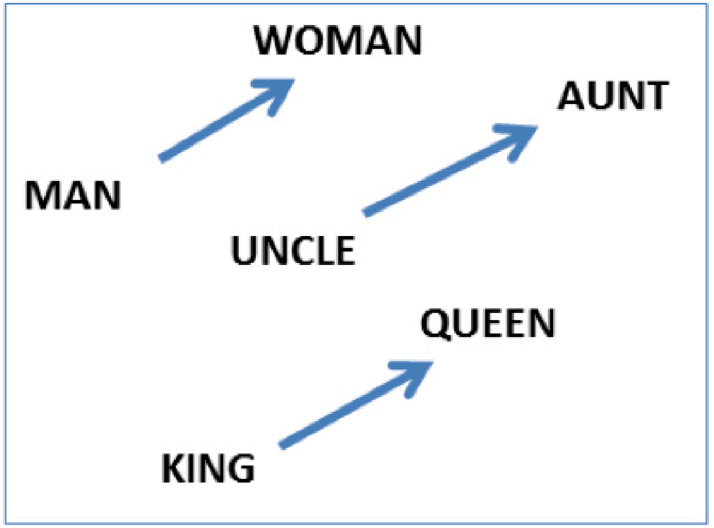
Similarity depends on window size C

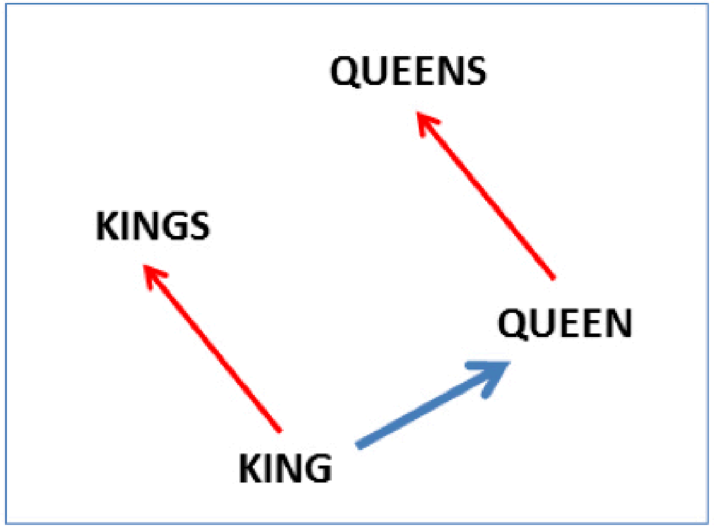
- C = ±2 The nearest words to *Hogwarts:*
  - *Sunnydale*
  - *Evernight*
- C = ±5 The nearest words to *Hogwarts:*
  - *Dumbledore*
  - *Malfoy*
  - *halfblood*

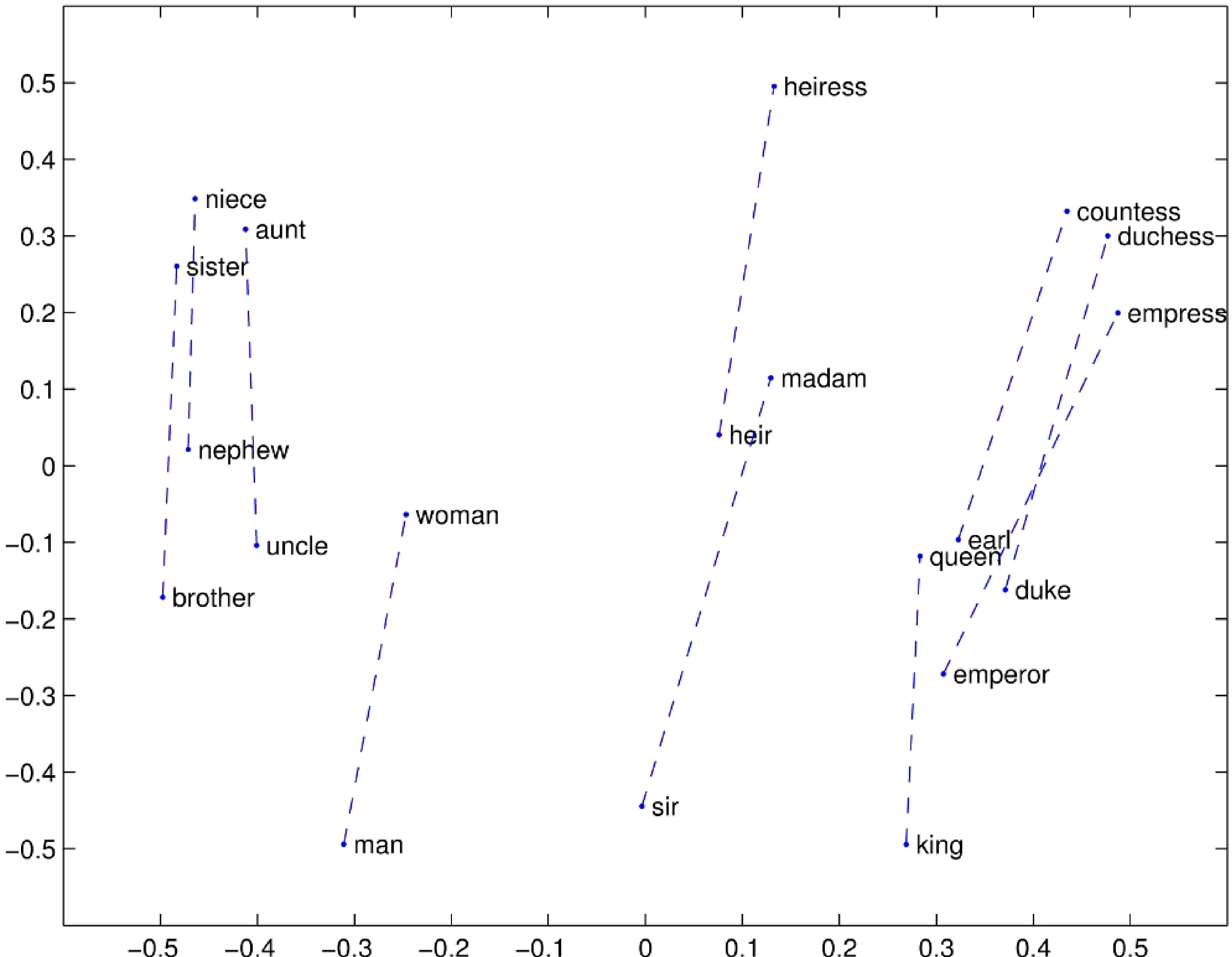
Analogy: Embeddings capture relational meaning!

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

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







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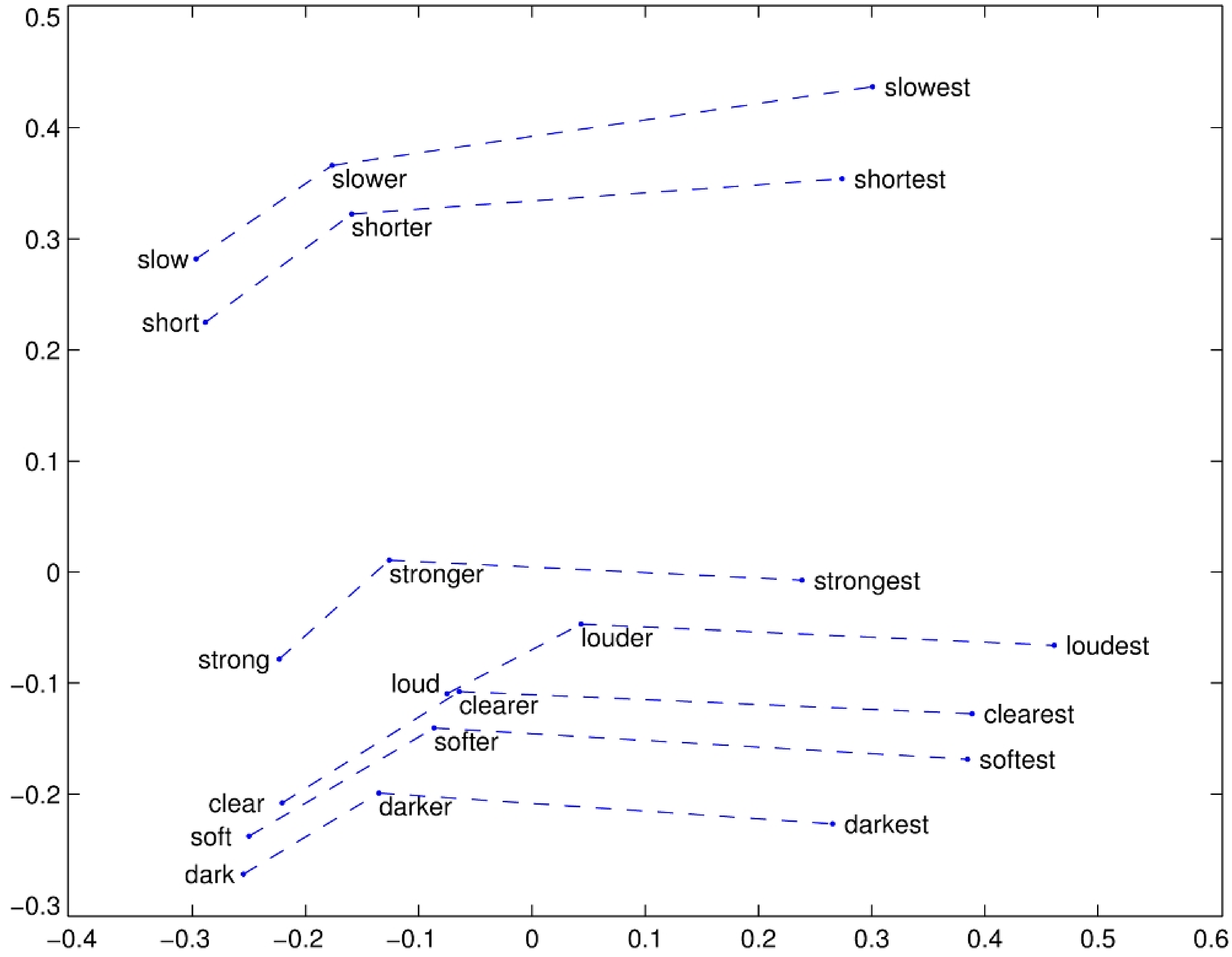
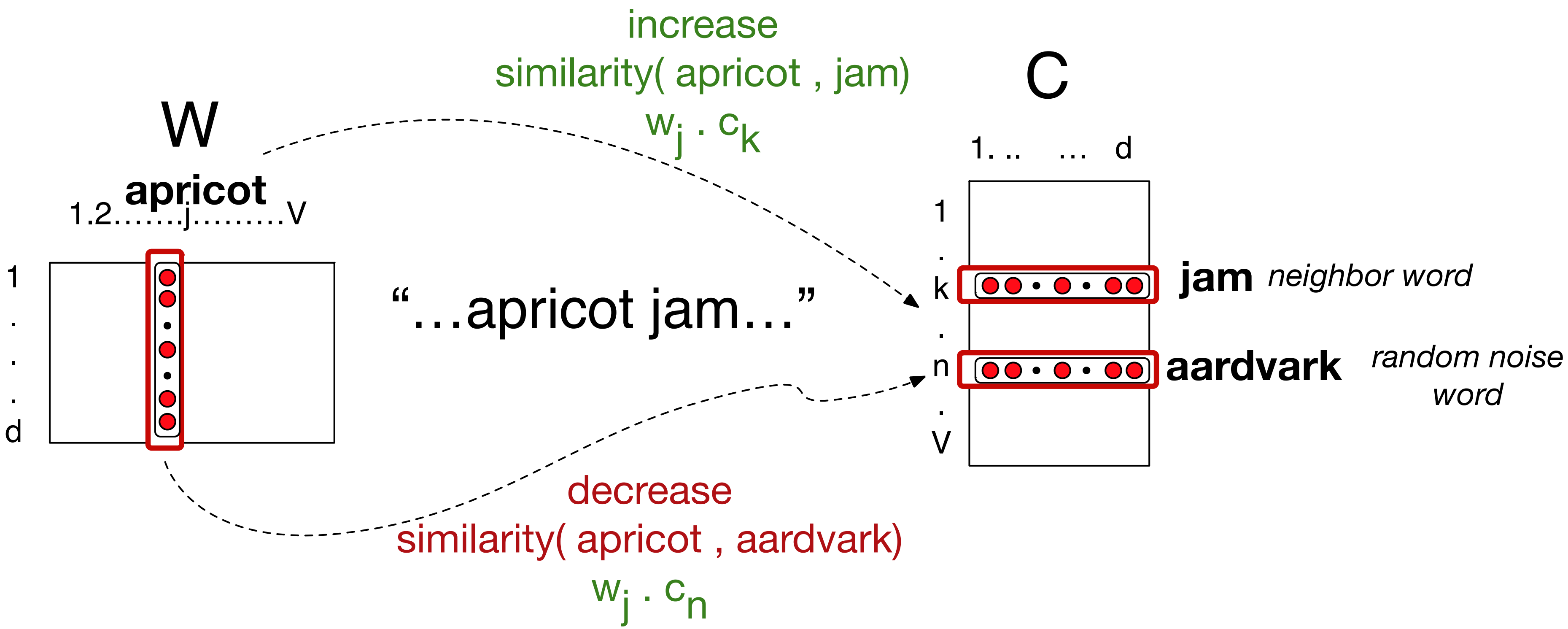


slowest
slower
shortest
shorter
slow
short
stronger
strongest
louder
loudest
strong
loud
clearer
clearest
softer
softest
clear
darker
darkest
soft
dark
0.5
0.4
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
−0.3
−0.2
−0.1
0
0.1
0.2
0.3
0.4
0.5
0.6

Are embeddings so magical?

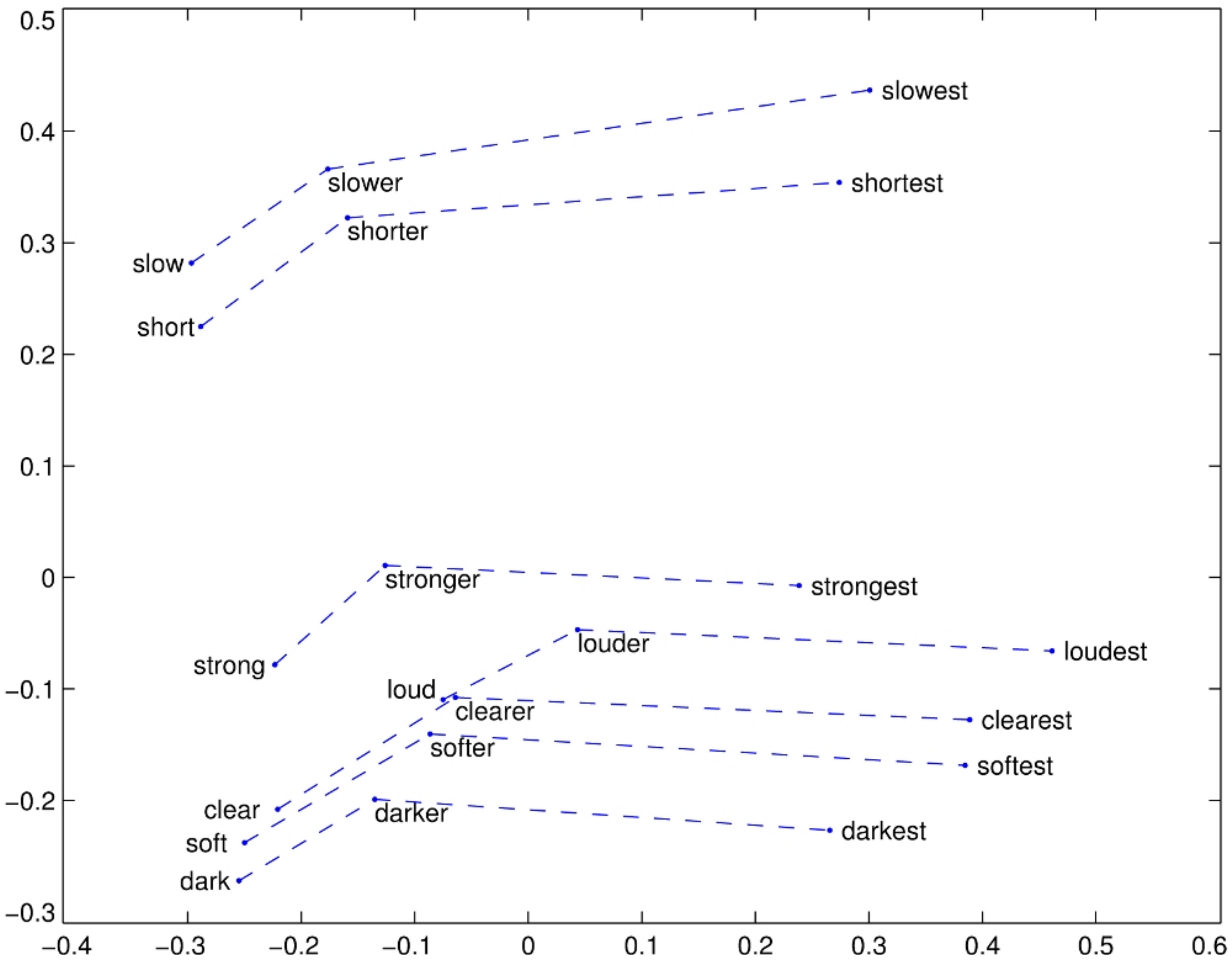
Word2vec as matrix factorization



M = WC, but… what is M? (Levy & Goldberg, NeurIPS 2014)

$$M = \log\left(\frac{\#(w,c)\cdot|D|}{\#(w)\cdot\#(c)}\right) - \log k = PMI(w_i, c_j) - \log k$$

How does this help us understand these “semantic” embedding dimensions?



Does this matter empirically?

WS353 (WordSim) [13]		MEN (WordSim) [4]		Mixed Analogies [20]		Synt. Analogies [22]	
Representation	Corr.	Representation	Corr.	Representation	Acc.	Representation	Acc.
SVD (k=5)	0.691	SVD (k=1)	0.735	SPPMI (k=1)	0.655	SGNS (k=15)	0.627
SPPMI (k=15)	0.687	SVD (k=5)	0.734	SPPMI (k=5)	0.644	SGNS (k=5)	0.619
SPPMI (k=5)	0.670	SPPMI (k=5)	0.721	SGNS (k=15)	0.619	SGNS (k=1)	0.59
SGNS (k=15)	0.666	SPPMI (k=15)	0.719	SGNS (k=5)	0.616	SPPMI (k=5)	0.466
SVD (k=15)	0.661	SGNS (k=15)	0.716	SPPMI (k=15)	0.571	SVD (k=1)	0.448
SVD (k=1)	0.652	SGNS (k=5)	0.708	SVD (k=1)	0.567	SPPMI (k=1)	0.445
SGNS (k=5)	0.644	SVD (k=15)	0.694	SGNS (k=1)	0.540	SPPMI (k=15)	0.353
SGNS (k=1)	0.633	SGNS (k=1)	0.690	SVD (k=5)	0.472	SVD (k=5)	0.337
SPPMI (k=1)	0.605	SPPMI (k=1)	0.688	SVD (k=15)	0.341	SVD (k=15)	0.208

Where did things go from here…

- Training objectives (fasttext, glove, etc.)
- Multilingual embeddings (also fasttext, others)
- Lots of “bias in embeddings” stuff
- Trying to tease out what embeddings are actually learning

- Using embeddings as an input representation is a very good default for dense models. But bag of n-grams still often wins

Side-note on biases

- There are >64 papers on biases and “debiasing”
- I have many thoughts on this, we’ll talk about it later

- For now:
  - Embeddings reflect co-occurance in data
  - Co-occurences reflect social structure as reflected in text
  - Text != the real world

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Today

- Embeddings
- Word2vec
- Word2vec isn’t magic