Dan Jurafsky and James Martin

Speech and Language Processing

Chapter 6:
Vector Semantics, Part II

Distributional similarity based representations

You can get a lot of value by representing a word by means of its neighbors

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

(J. R. Firth 1957: 11)

One of the most successful ideas of modern statistical NLP

…government debt problems turning into	***banking***	*crises as happened in 2009…*
…saying that Europe needs unified	***banking***	*regulation to replace the hodgepodge…*
…India has just given its	***banking***	*system a shot in the arm…*

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)

Low dimensional vectors

The number of topics that people talk about is small (in some sense)

- Clothes, movies, politics, …

- Idea: store "most" of the important information in a fixed, small number of dimensions: a dense vector
- Usually 25 – 1000 dimensions

- How to reduce the dimensionality?
  - Go from big, sparse co-occurrence count vector to low dimensional "word embedding"

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 (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)

BENGIO, YOSHUA, ET AL. "A NEURAL PROBABILISTIC LANGUAGE MODEL." JOURNAL OF MACHINE LEARNING RESEARCH 3.FEB (2003): 1137-1155.

Word2vec is a family of algorithms

[Mikolov et al. 2013]

Predict between every word and its context words!

Two algorithms

1. **Skip-grams (SG)**

   Predict context words given target (position independent)

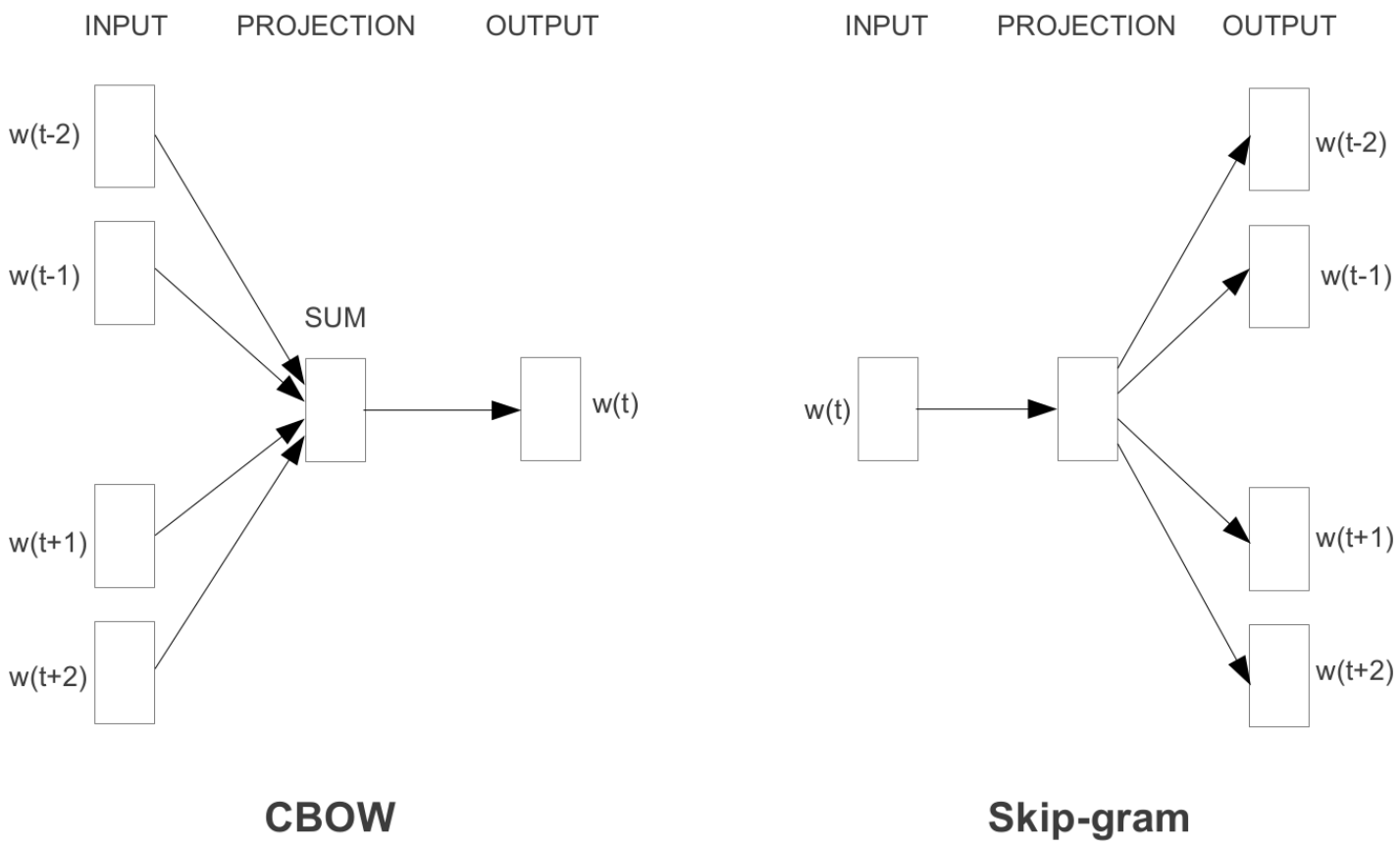
2. Continuous Bag of Words (CBOW)

   Predict target word from bag-of-words context

Two (moderately efficient) training methods

1. Hierarchical softmax
2. **Negative sampling**
3. Naïve softmax

Word2vec CBOW (Continuous Bag Of Words) and Skip-gram network architectures



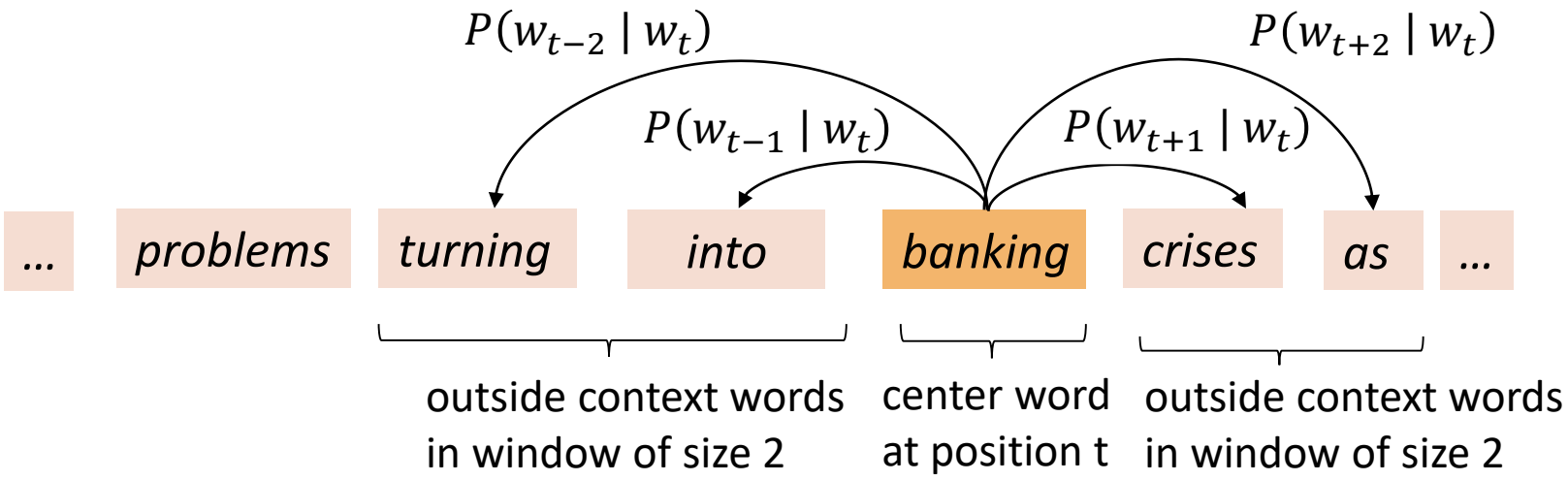
Word2Vec: **Skip-Gram** Task

Word2vec provides a variety of options. Let's do

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

Word2Vec Skip-gram Overview

Example windows and process for computing $P(w_{t+j} \mid w_t)$



WordToVec algorithm

1. Treat the target word and a neighboring context word as positive examples.
2. Use other words not in context as negative samples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights (parameters) of classifier 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

WordToVec 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) $\propto t \cdot c$

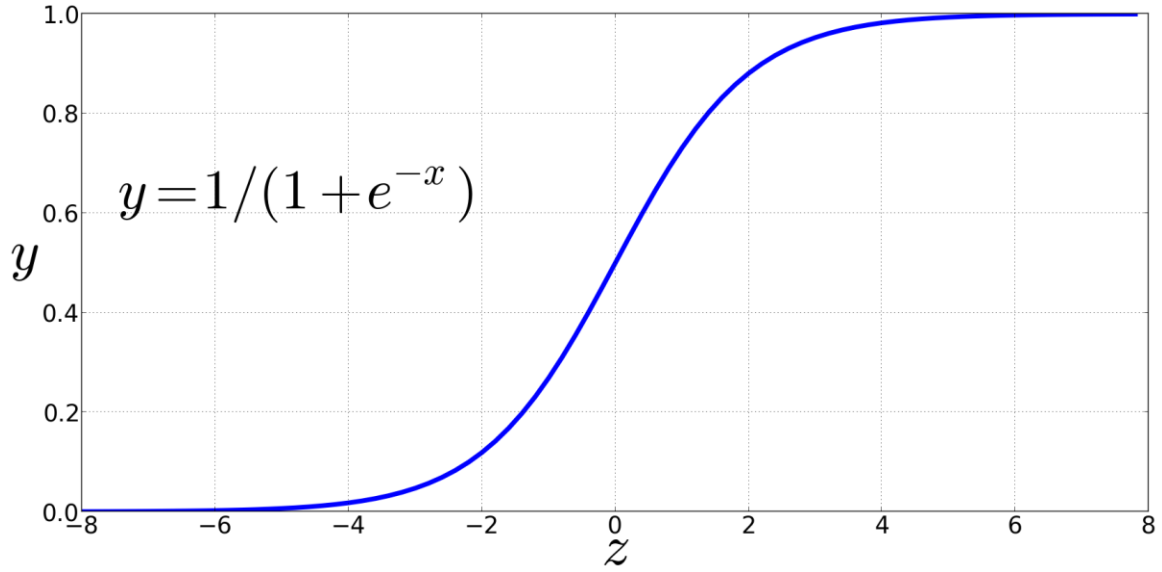
Problem:

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

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

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

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

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.

Loss Function: Binary Cross-Entropy / Log Loss

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

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

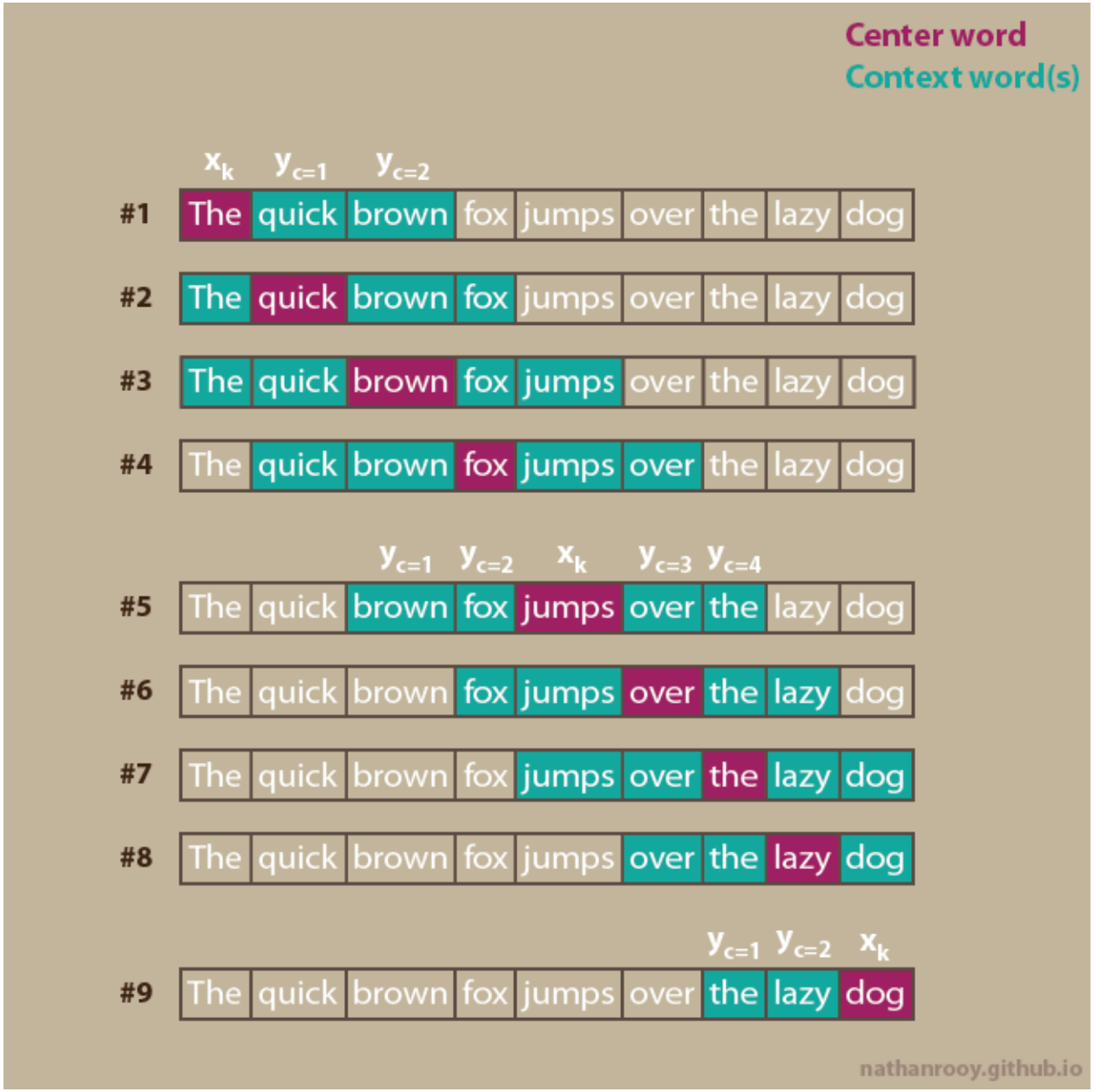
Iterative process.

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:



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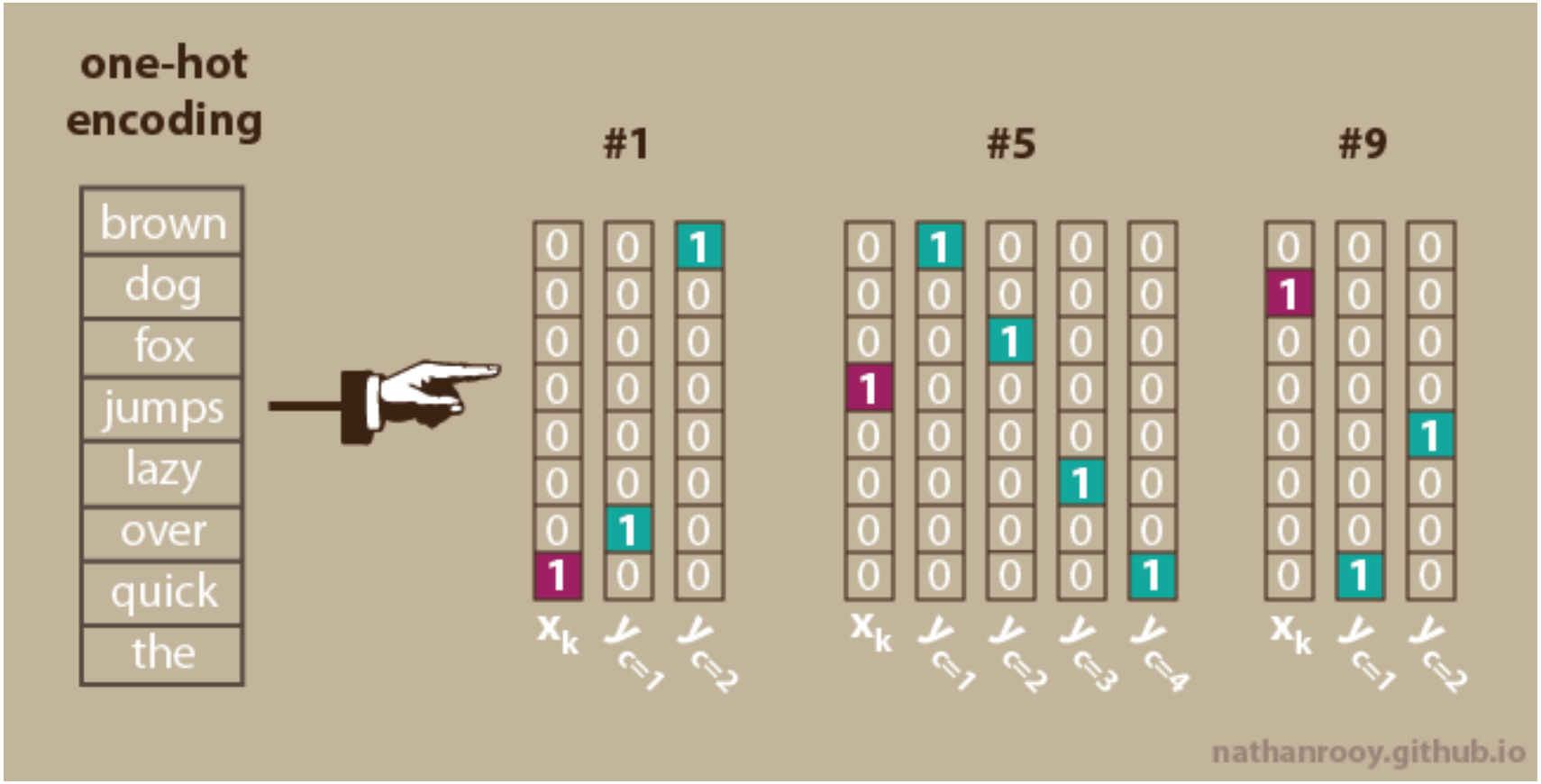

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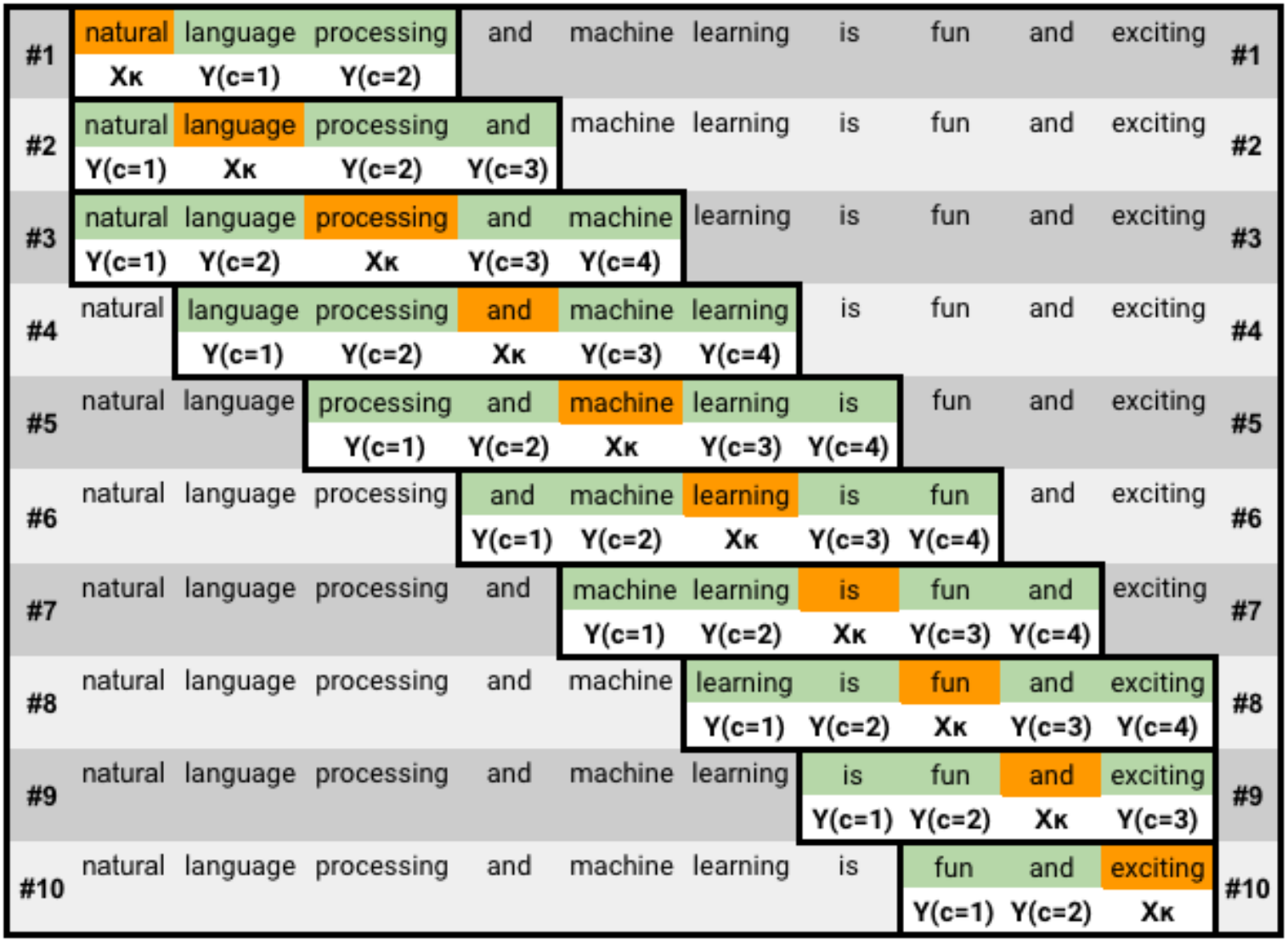

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#	Token	#1			#2				#3					#4					#5				
0	natural	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	language	0	1	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
2	processing	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0
3	and	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0
4	machine	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0
5	learning	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
6	is	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	fun	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	exciting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Xk	Y(c=1)	Y(c=2)	Xk	Y(c=1)	Y(c=2)	Y(c=3)	Xk	Y(c=1)	Y(c=2)	Y(c=3)	Y(c=4)	Xk	Y(c=1)	Y(c=2)	Y(c=3)	Y(c=4)	Xk	Y(c=1)	Y(c=2)	Y(c=3)	Y(c=4)

#	Token	#6					#7					#8					#9				#10		
0	natural	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	language	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	processing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	and	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1
4	machine	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	learning	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
6	is	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
7	fun	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	1	0
8	exciting	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0
		Xk	Y(c=1)	Y(c=2)	(c=3	Y(c=4)	Xk	Y(c=1)	(c=2	Y(c=3)	Y(c=4)	Xk	Y(c=1)	(c=2	Y(c=3)	Y(c=4)	Xk	Y(c=1)	(c=2	Y(c=3)	Xk	Y(c=1)	Y(c=2)

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first and last element in the first training window

*# 1 [Target (**natural**)], [Context (*language*,* processing*)]*
*[list(**[1, 0, 0, 0, 0, 0, 0, 0, 0]**)*
list([[0, 1, 0, 0, 0, 0, 0, 0, 0], [0, 0, 1, 0, 0, 0, 0, 0, 0]*])]*

first and last element in the last training window

*#10 [Target (**exciting**)], [Context (*fun*,* and*)]*
*[list(**[0, 0, 0, 0, 0, 0, 0, 0, 1]**)*
list([[0, 0, 0, 0, 0, 0, 0, 1, 0], [0, 0, 0, 1, 0, 0, 0, 0, 0]*])]*

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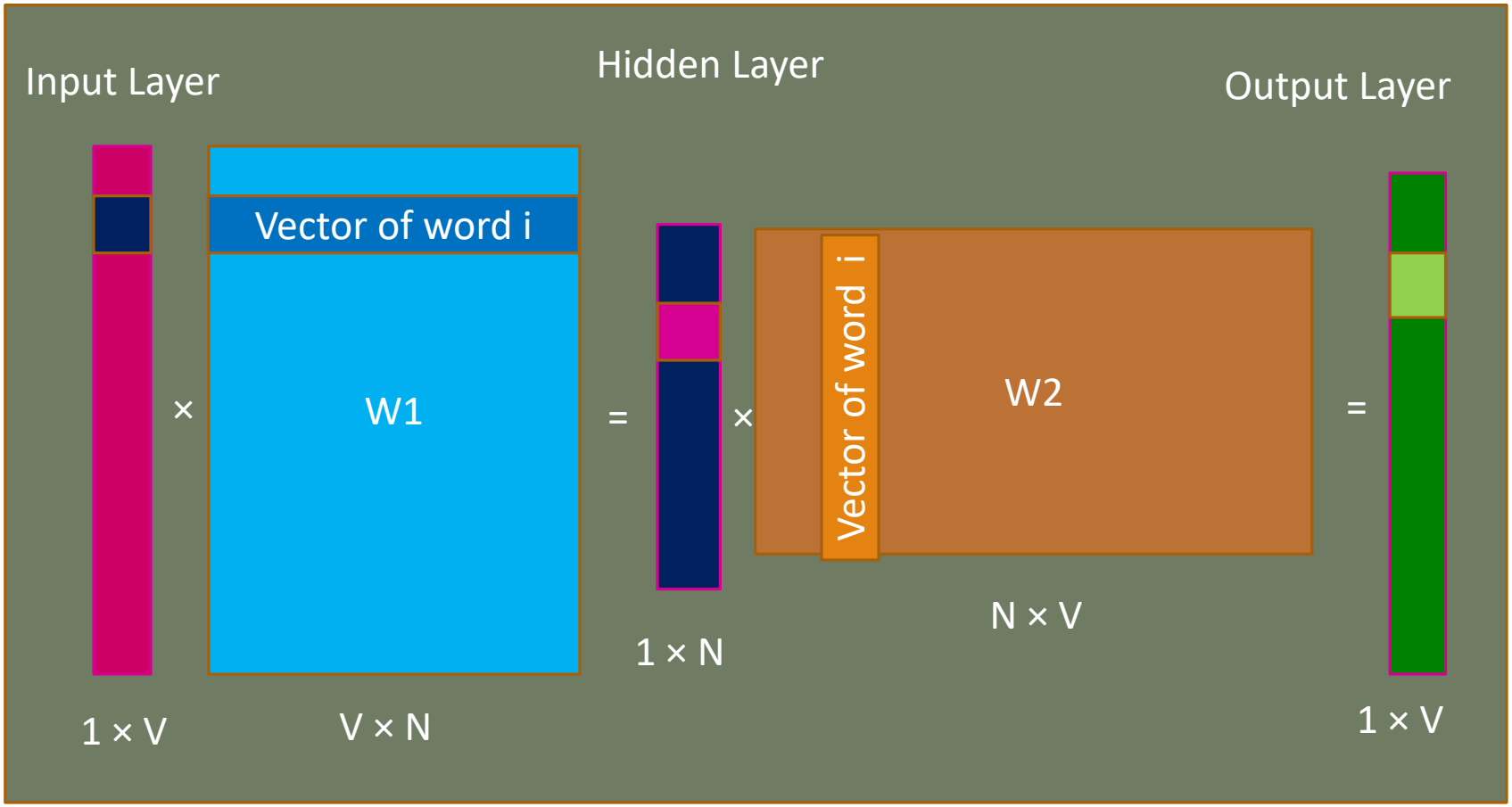
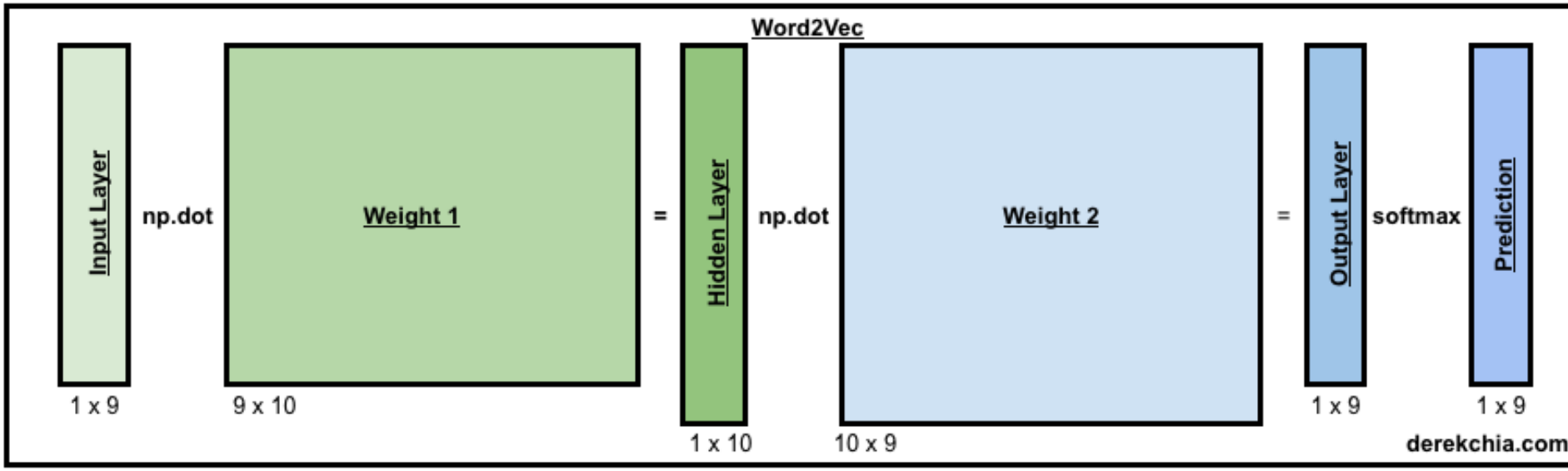
N = Dimensions, V = Vocabulary, unique words



Word2Vec — skip-gram network architecture



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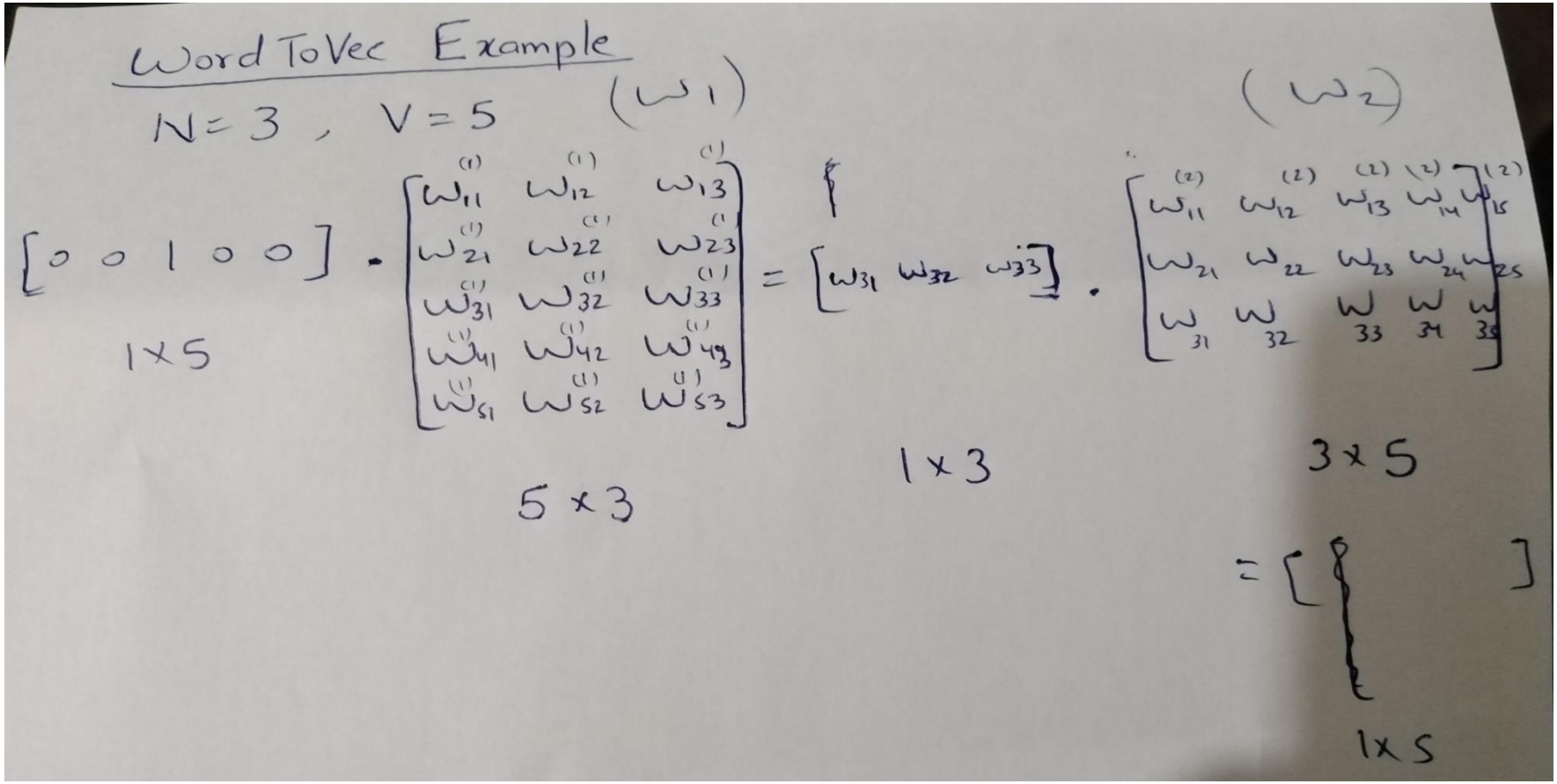
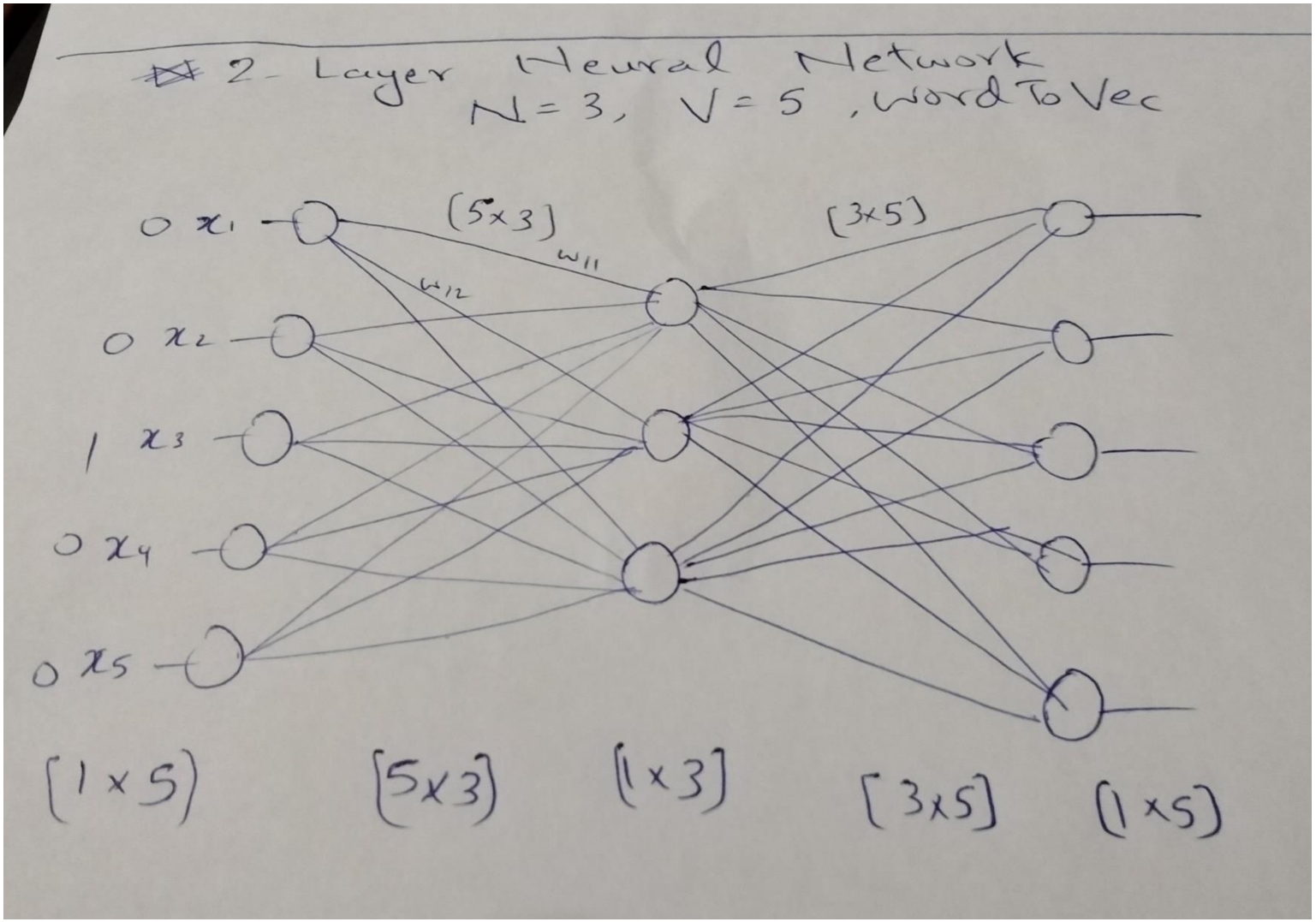
WordToVec Example



WordToVec Example 2 layer neural network



Word To Vec Example

$N = 3, \quad V = 5$

(W_1) (W_2)

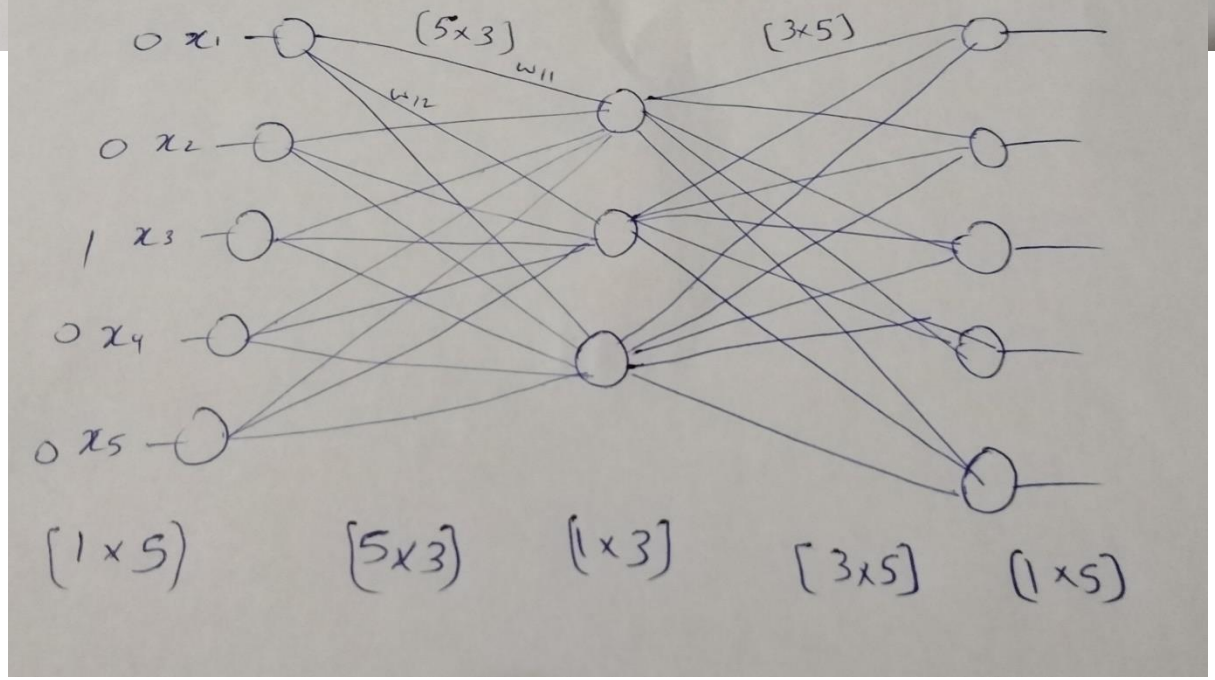
$$\begin{bmatrix} 0 & 0 & 1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} w_{11}^{(1)} & w_{12}^{(1)} & w_{13}^{(1)} \\ w_{21}^{(1)} & w_{22}^{(1)} & w_{23}^{(1)} \\ w_{31}^{(1)} & w_{32}^{(1)} & w_{33}^{(1)} \\ w_{41}^{(1)} & w_{42}^{(1)} & w_{43}^{(1)} \\ w_{51}^{(1)} & w_{52}^{(1)} & w_{53}^{(1)} \end{bmatrix} = \begin{bmatrix} w_{31} & w_{32} & w_{33} \end{bmatrix} \cdot \begin{bmatrix} w_{11}^{(2)} & w_{12}^{(2)} & w_{13}^{(2)} & w_{14}^{(2)} & w_{15}^{(2)} \\ w_{21} & w_{22} & w_{23} & w_{24} & w_{25} \\ w_{31} & w_{32} & w_{33} & w_{34} & w_{35} \end{bmatrix}$$

$1 \times 5 \qquad 5 \times 3 \qquad 1 \times 3 \qquad 3 \times 5$

$$= \begin{bmatrix} \{ & & & & \} \end{bmatrix}$$

1×5

2- Layer Neural Network
$N = 3, \quad V = 5$, Word To Vec



4. Skip-gram Model Architecture derekchia.com

Forward Pass for #1

Parameters - Embedding size 10

Random initialisation (Range) -1 to 1

Calculate Hidden Layer

#	Token	Input - w_t
0	natural	1
1	language	0
2	processing	0
3	and	0
4	machine	0
5	learning	0
6	is	0
7	fun	0
8	exciting	0

1 x 9

np.dot

Weight 1 - W1

0.236	**-0.962**	**0.686**	**0.785**	**-0.454**	**-0.833**	**-0.744**	**0.677**	**-0.427**	**-0.066**
-0.907	0.894	0.225	0.673	-0.579	-0.428	0.685	0.973	-0.070	-0.811
-0.576	0.658	-0.582	-0.112	0.662	0.051	-0.401	-0.921	-0.158	0.529
0.517	0.436	0.092	-0.835	-0.444	-0.905	0.879	0.303	0.332	-0.275
0.859	-0.890	0.651	0.185	-0.511	-0.456	0.377	-0.274	0.182	-0.237
0.368	-0.867	-0.301	-0.222	0.630	0.808	0.088	-0.902	-0.450	-0.408
0.728	0.277	0.439	0.138	-0.943	-0.409	0.687	-0.215	-0.807	0.612
0.593	-0.699	0.020	0.142	-0.638	-0.633	0.344	0.868	0.913	0.429
0.447	-0.810	-0.061	-0.495	0.794	-0.064	-0.817	-0.408	-0.286	0.149

9 x 10

=

Hidden Layer - h

0.236
-0.962
0.686
0.785
-0.454
-0.833
-0.744
0.677
-0.427
-0.066

1 x 10

Calculate y_pred

Hidden Layer - h

0.236
-0.962
0.686
0.785
-0.454
-0.833
-0.744
0.677
-0.427
-0.066

1 x 10

np.dot

Weight 2 - W2

-0.868	-0.406	-0.288	-0.016	-0.560	0.179	0.099	0.438	-0.551
-0.395	0.890	0.685	-0.329	0.218	-0.852	-0.919	0.665	0.968
-0.128	0.685	-0.828	0.709	-0.420	0.057	-0.212	0.728	-0.690
0.881	0.238	0.018	0.622	0.936	-0.442	0.936	0.586	-0.020
-0.478	0.240	0.820	-0.731	0.260	-0.989	-0.626	0.796	-0.599
0.679	0.721	-0.111	0.083	-0.738	0.227	0.560	0.929	0.017
-0.690	0.907	0.464	-0.022	-0.005	-0.004	-0.425	0.299	0.757
-0.054	0.397	-0.017	-0.563	-0.551	0.465	-0.596	-0.413	-0.395
-0.838	0.053	-0.160	-0.164	-0.671	0.140	-0.149	0.708	0.425
0.096	-0.995	-0.313	0.881	-0.402	-0.631	-0.660	0.184	0.487

10 x 9

=

Output Layer

1.258
-1.369
-1.828
1.196
0.545
1.113
1.333
-1.528
-2.335

1 x 9

Softmax - y_pred

0.218
0.016
0.010
0.205
0.107
0.189
0.235
0.013
0.006

1 x 9

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Read from following links for WordToVec example

https://towardsdatascience.com/an-implementation-guide-to-word2vec-using-numpy-and-google-sheets-13445eebd281

https://nathanrooy.github.io/posts/2018-03-22/word2vec-from-scratch-with-python-and-numpy/?source=post_page-----13445eebd281

Skip-Gram Training Data with Negative Sampling

Training sentence:

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

c1 c2 t c3 c4

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

Asssume a +/- 2 word window

Skip-Gram Training with Negative Sampling

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 with Negative Sampling

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 (negative samples)

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

More common to use $p_\alpha(w)$

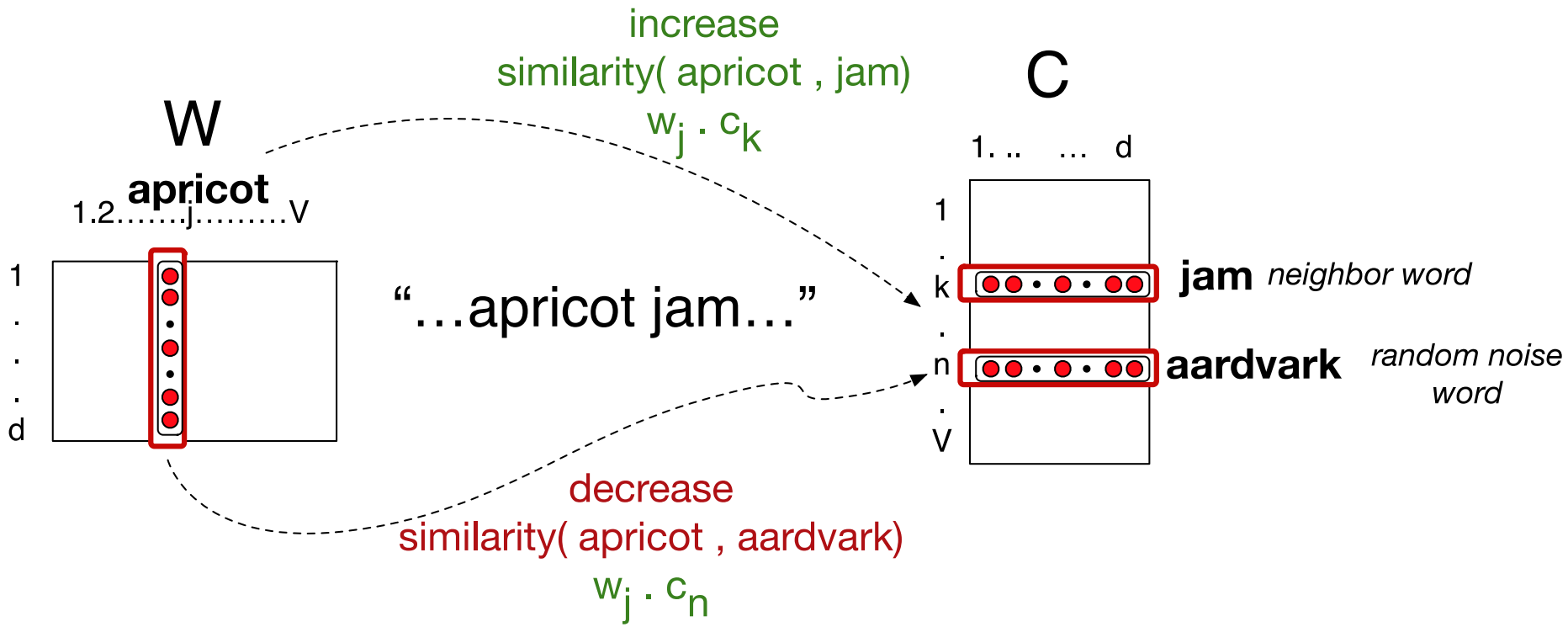
$$P_\alpha(w) = \frac{count(w)^\alpha}{\sum_w count(w)^\alpha}$$

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:

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

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


increase
similarity(apricot , jam)
$w_j \cdot c_k$
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)
$w_j \cdot c_n$

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.

Properties of embeddings

Similarity depends on window size C
(small window size, words that are syntactically similar and have same part of speech,
Large window size, words related but do not have same Part of speech)

C = ±2 The nearest words to *Hogwarts (name of school):*

- *Sunnydale (name of fictional school)*
- *Evernight (name of fictional school)*

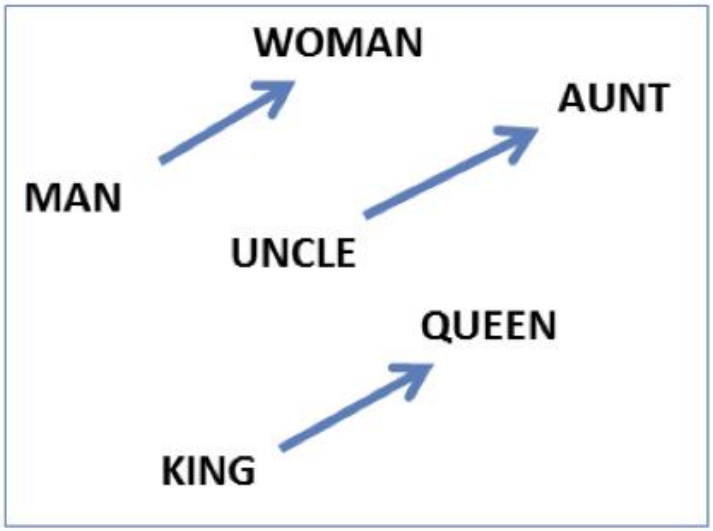
C = ±5 The nearest words to *Hogwarts:*

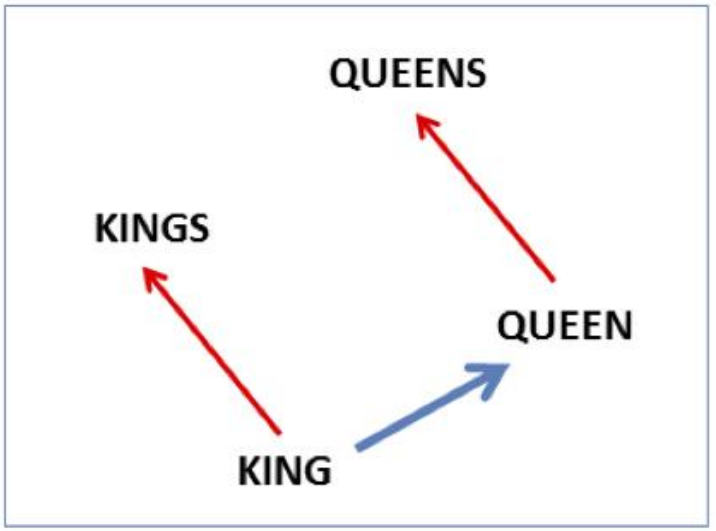
- *Dumbledore*
- *Malfoy*
- *halfblood*

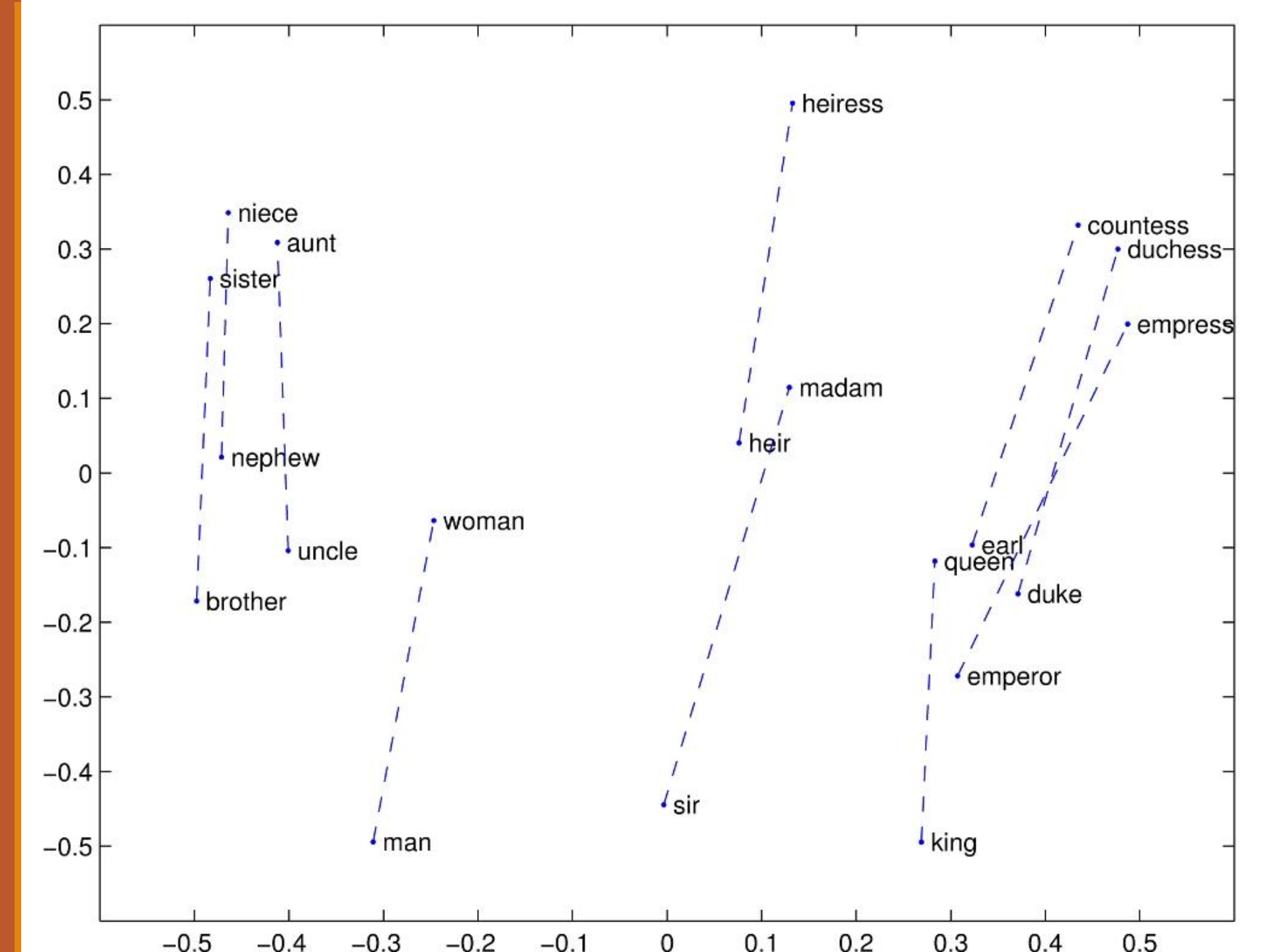
Analogy: Embeddings capture relational meaning!

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

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






heiress
niece
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sister
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duchess
empress
madam
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nephew
woman
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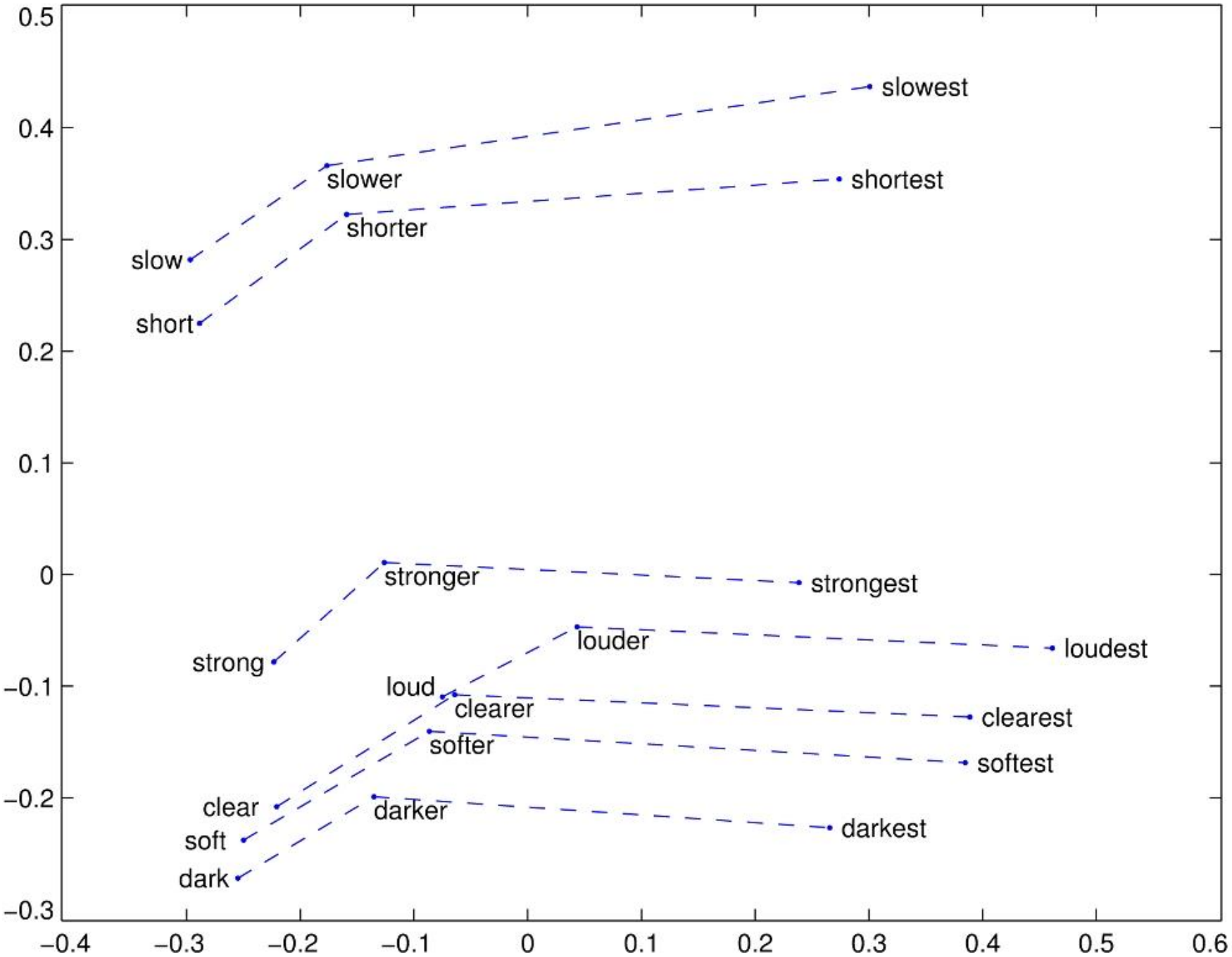
slowest
slower
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softest
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darker
darkest
soft
dark
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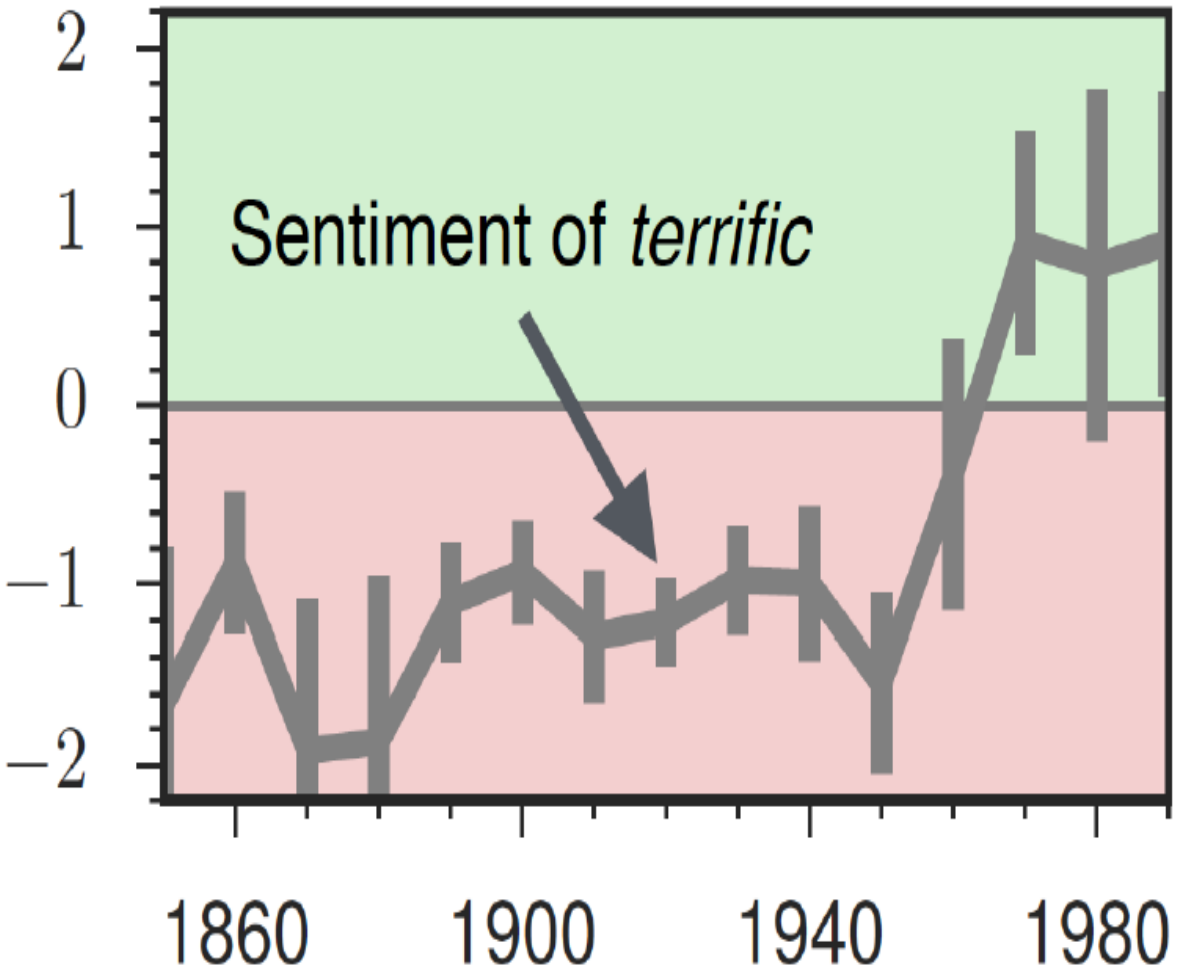
0.6

The evolution of sentiment words

Negative words change faster than positive words



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 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

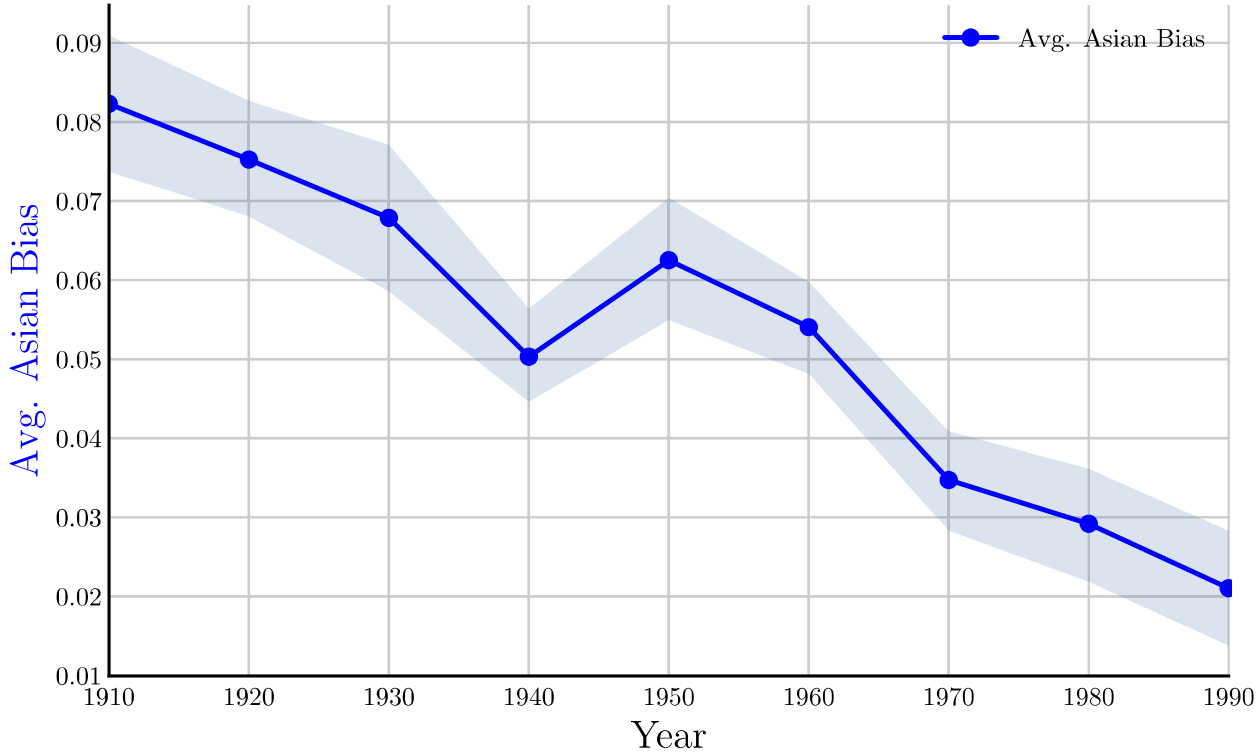
The cosine similarity of embeddings for decade X for occupations (like teacher) to male vs female names

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

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

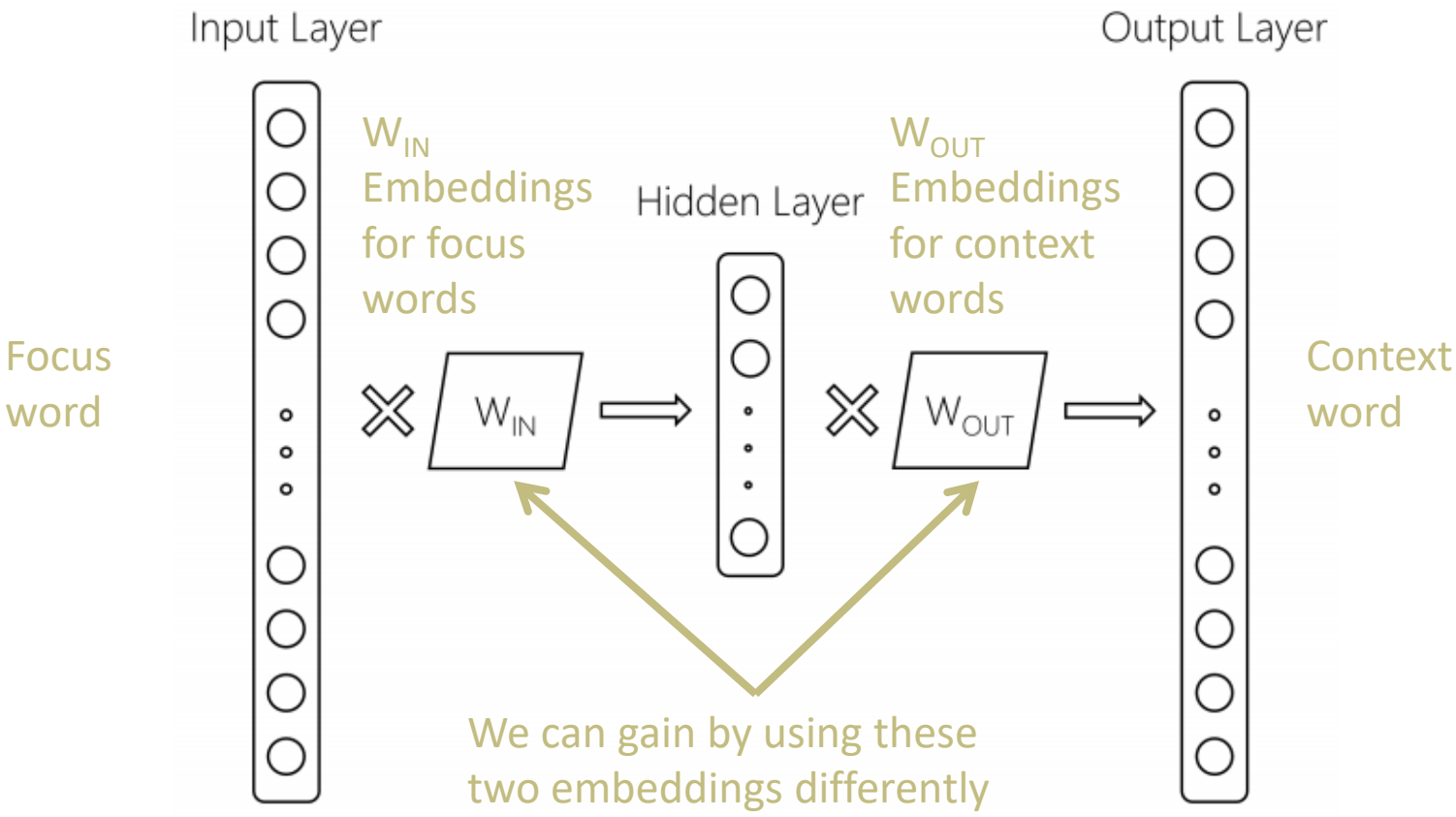
Conclusion

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

Using 2 word embeddings

word2vec model with 1 word of context



Dual Embedding Space Model (DESM)

Simple model

A document is represented by the centroid of its word vectors

$$\overline{\mathbf{D}} = \frac{1}{|D|} \sum_{\mathbf{d}_j \in D} \frac{\mathbf{d}_j}{\|\mathbf{d}_j\|}$$

Query-document simila e similarity

$$DESM(Q, D) = \frac{1}{|Q|} \sum_{q_i \in Q} \frac{\mathbf{q}_i^T \overline{\mathbf{D}}}{\|\mathbf{q}_i\| \|\overline{\mathbf{D}}\|}$$

Dual Embedding Space Model (DESM)

What works best is to use the OUT vectors for the document and the IN vectors for the query

$$DESM_{IN-OUT}(Q, D) = \frac{1}{|Q|} \sum_{q_i \in Q} \frac{q_{IN,i}^T \overline{D_{OUT}}}{\|q_{IN,i}\| \|\overline{D_{OUT}}\|}$$

This way similarity measures *aboutness* – words that appear with this word – which is more useful in this context than *(distributional) semantic similarity*

Experiments

Train word2vec from either

- 600 million Bing queries
- 342 million web document sentences

Test on 7,741 randomly sampled Bing queries

- 5 level eval (Perfect, Excellent, Good, Fair, Bad)

Two approaches

1. Use DESM model to rerank top results from BM25
2. Use DESM alone or a mixture model of it and BM25

$$MM(Q, D) = \alpha DESM(Q, D) + (1 - \alpha) BM25(Q, D)$$

$$\alpha \in \mathbb{R}, 0 \leq \alpha \leq 1$$

Results – reranking *k*-best list

	Explicitly Judged Test Set		
	NDCG@1	NDCG@3	NDCG@10
BM25	23.69	29.14	44.77
LSA	22.41*	28.25*	44.24*
DESM (IN-IN, trained on body text)	23.59	29.59	45.51*
DESM (IN-IN, trained on queries)	23.75	29.72	46.36*
DESM (IN-OUT, trained on body text)	24.06	30.32*	46.57*
DESM (IN-OUT, trained on queries)	**25.02***	**31.14***	**47.89***

Pretty decent gains – e.g., 2% for NDCG@3

Gains are bigger for model trained on queries than docs

Results – whole ranking system

	Explicitly Judged Test Set		
	NDCG@1	NDCG@3	NDCG@10
BM25	21.44	26.09	37.53
LSA	04.61*	04.63*	04.83*
DESM (IN-IN, trained on body text)	06.69*	06.80*	07.39*
DESM (IN-IN, trained on queries)	05.56*	05.59*	06.03*
DESM (IN-OUT, trained on body text)	01.01*	01.16*	01.58*
DESM (IN-OUT, trained on queries)	00.62*	00.58*	00.81*
BM25 + DESM (IN-IN, trained on body text)	21.53	26.16	37.48
BM25 + DESM (IN-IN, trained on queries)	**21.58**	26.20	37.62
BM25 + DESM (IN-OUT, trained on body text)	21.47	26.18	37.55
BM25 + DESM (IN-OUT, trained on queries)	21.54	**26.42***	**37.86***

Readings

1. Dan Jurafsky and James Martin, Speech and Language Processing
   Chapter 6: Vector Semantics

2. https://towardsdatascience.com/an-implementation-guide-to-word2vec-using-numpy-and-google-sheets-13445eebd281