

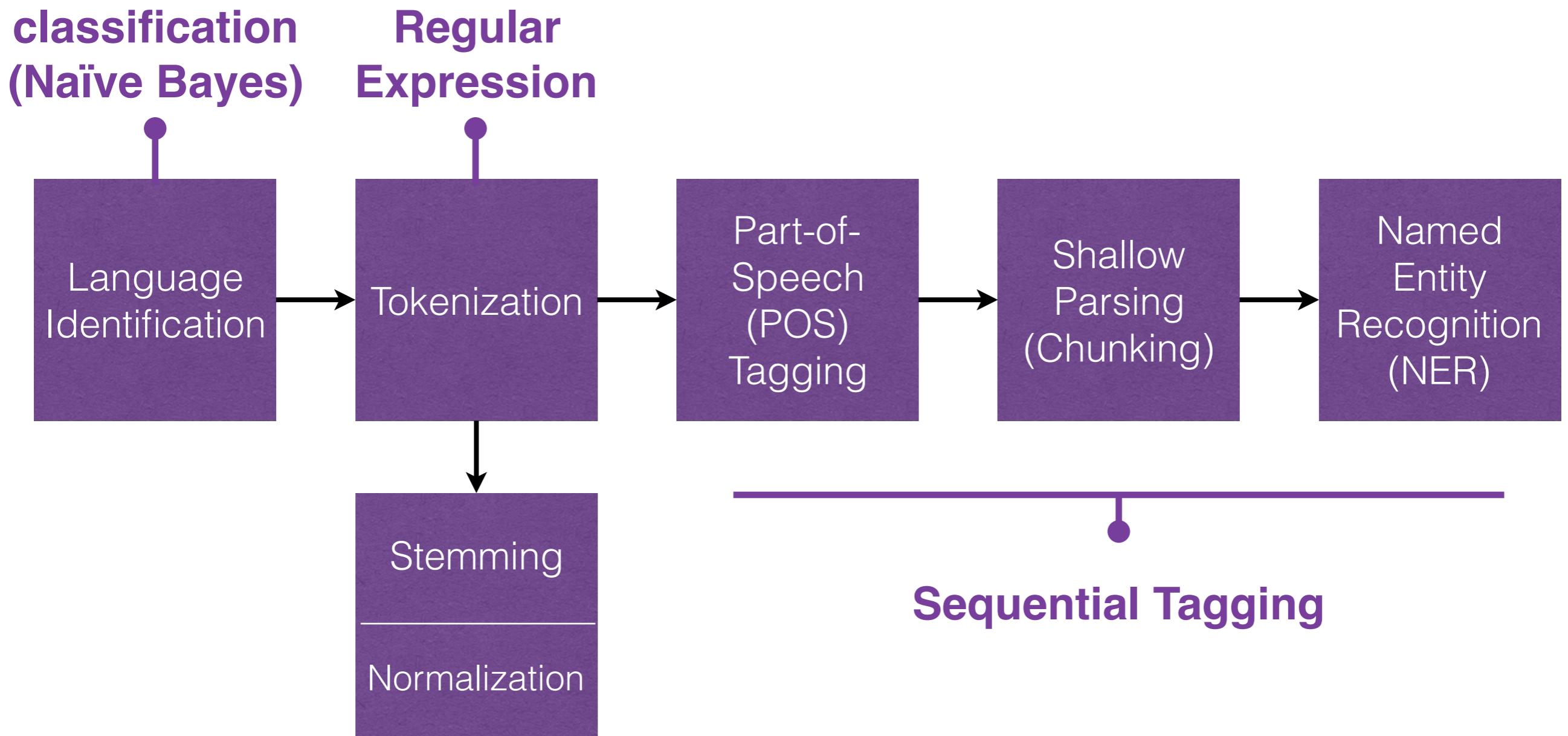
Social Media & Text Analysis

lecture 5 - Vector Semantics

CSE 5539-0010 Ohio State University
Instructor: Alan Ritter
Website: socialmedia-class.org

some slides are adapted from Michael Collins, Dan Jurafsky, Richard Socher,, Chris Manning

NLP Pipeline



Part-of-Speech (POS) Tagging

Cant	MD
wait	VB
for	IN
the	DT
ravens	NNP
game	NN
tomorrow	NN
...	:
go	VB
ray	NNP
rice	NNP
!!!!!!	.



Named Entity Recognition

India vs Australia 2014-15 , 4th Test in Sydney

Samsung to launch Galaxy S6 in March

New Suits and Brooklyn Nine-Nine tomorrow ... Happy days

The diagram shows three sentences with entities annotated using green boxes and labels:

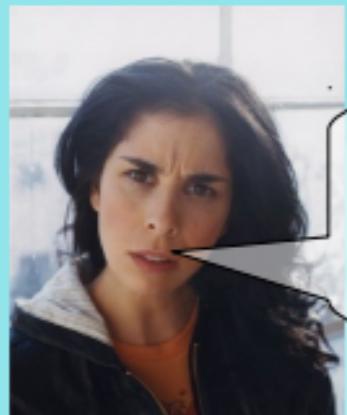
- India vs Australia 2014-15 , 4th Test in Sydney**
 - India: sportsteam
 - vs: (unlabeled)
 - Australia: sportsteam
 - 2014-15: (unlabeled)
 - 4th: (unlabeled)
 - Test: (unlabeled)
 - Sydney: geo-loc
- Samsung to launch Galaxy S6 in March**
 - Samsung: company
 - to launch: (unlabeled)
 - Galaxy S6: product
 - in March: (unlabeled)
- New Suits and Brooklyn Nine-Nine tomorrow ... Happy days**
 - New: tvshow
 - Suits: tvshow
 - and: (unlabeled)
 - Brooklyn Nine-Nine: tvshow
 - tomorrow: (unlabeled)
 - ... Happy: (unlabeled)
 - days: (unlabeled)

Source: Strauss, Toma, Ritter, de Marneffe, Xu

Results of the WNUT16 Named Entity Recognition Shared Task (WNUT@COLING 2016)

BAD LANGUAGE!

...on the INTERNET!!



Boom! Ya ur
website suxx bro

...dats why pluto is pluto
it can neva be a star



Jacob EISENSTEIN
GEORGIA Institute of **TECH**nology

michelle obama great.
job. and. whit all my.
respect she. look. great.
congrats. to. her.



I now h v an iphone

What can we do about it?

*Why don't they just write **NORMALLY**??*

*Can our software ever **ADAPT**???*

How does language go bad?

Illiteracy? No.

(Tagliamonte and Denis 2008;
Drouin and Davis 2009)

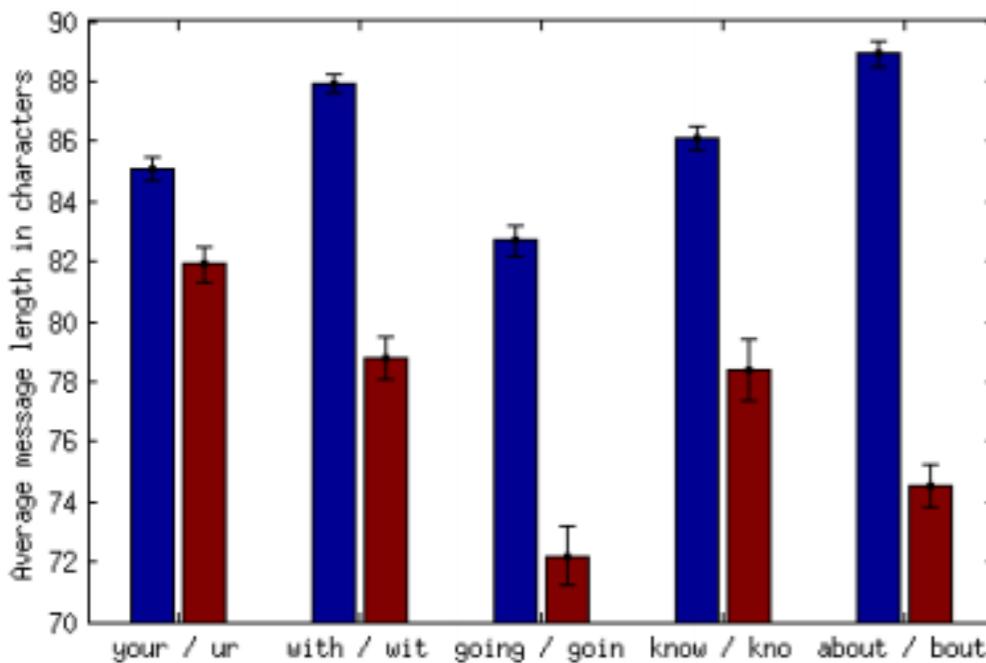


rob delaney @robdelaney

1 Jun

Great. Now a bunch of illiterate teens claim to be "powning" me with their insults. Heads up jerks my wife & children love me & are proud of
[Expand](#) [Reply](#) [Classic RT](#) [Retweet](#) [Favorite](#) [More](#)

Length limits? (probably not)

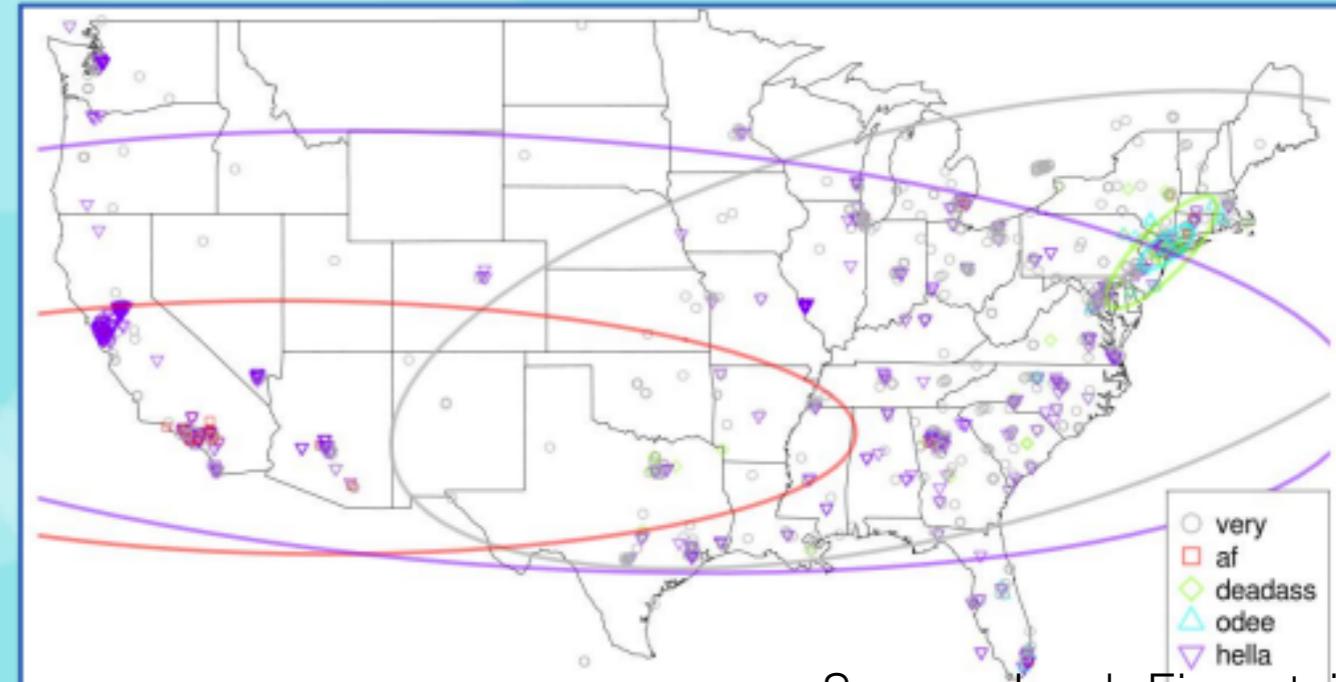


Hardware input constraints? (Gouws et al 2011)



Social variables

- Non-standard language does *identity work*, signaling authenticity, solidarity, etc.
- Social variation is usually inhibited in written language, but social media is less regulated than other written genres.



Source: Jacob Eisenstein

Why is Social Media Text “Bad”?

- Lack of literacy? no [Drouin and Davis, 2009]
- Length restrictions? not primarily [Eisenstein, 2013]
- Text input method? to some degree, yes [Gouws et al., 2011]
- mimicking prosodic effects etc. in speech? yeeeees [Eisenstein, 2013]
- Social variables/markers of social identity? blood oath! [Eisenstein, 2013]

Why is Social Media Text “Bad”?

- mimicking prosodic effects etc. in speech? *yeeeess* [Eisenstein, 2013]

HELLA 🔊

Derived from "hell of a lot". Similar to "very, really, a lot," etc.

Used mostly in Northern California though has been heard in other parts of CA and even in the media such as an infamous "hella" South Park episode. (Cartman used it outside of its meaning to annoy Kyle.)

Before: There's a hell of a lot of beer in that fridge.

After: There's hella beer in that fridge.

As "very" or "really":

"That's hella far away!"

Why is Social Media Text “Bad”?

- Social variables/markers of social identity? **blood oath!** [Eisenstein, 2013]



“I would like to believe he’s **sick** rather than just mean and evil.”



“You could’ve been getting down to this **sick** beat.”

Text Normalization

- convert non-standard words to standard

Original tweet

@USER, r u cuming 2 MidCorner dis Sunday?

Normalized tweet

@USER, are you coming to MidCorner this Sunday?

Original tweet

Still have to get up early 2mr thou 😞 so Gn 😴

Normalized tweet

Still have to get up early tomorrow though 😞 so Good night 😴

An Unsupervised Learning Method:

(1) Brown Clustering

- Input:
 - a (large) text corpus
- Output:
 1. a partition of words into word clusters
 2. or a hierarchical word clustering (generalization of 1)

Brown Clustering

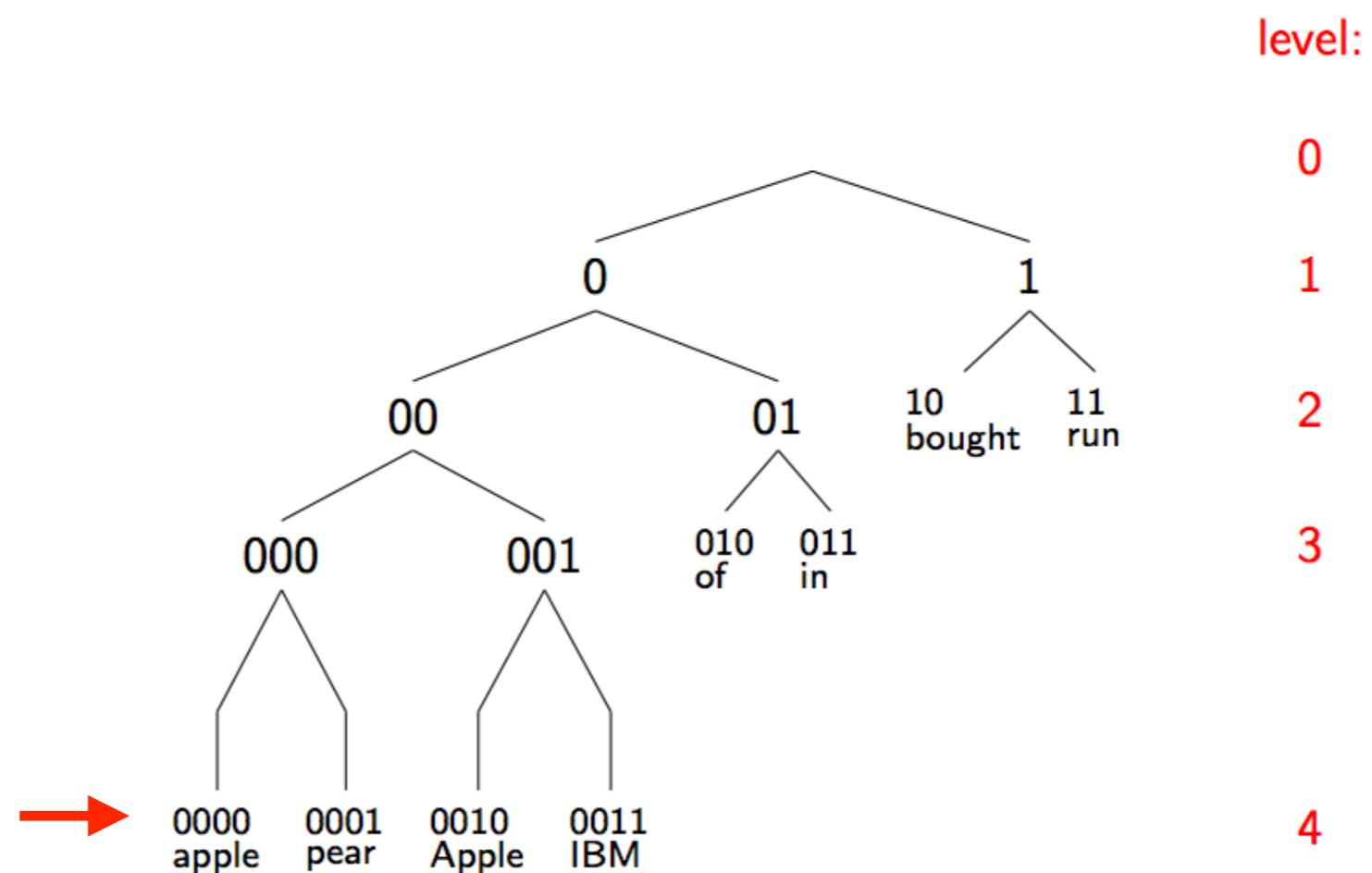
- Example Clusters (from Brown et al. 1992)

Friday Monday Thursday Wednesday Tuesday Saturday Sunday weekends Sundays Saturdays
June March July April January December October November September August
people guys folks fellows CEOs chaps doubters commies unfortunates blokes
down backwards ashore sideways southward northward overboard aloft downwards adrift
water gas coal liquid acid sand carbon steam shale iron
great big vast sudden mere sheer gigantic lifelong scant colossal
man woman boy girl lawyer doctor guy farmer teacher citizen
American Indian European Japanese German African Catholic Israeli Italian Arab
pressure temperature permeability density porosity stress velocity viscosity gravity tension
mother wife father son husband brother daughter sister boss uncle
machine device controller processor CPU printer spindle subsystem compiler plotter
John George James Bob Robert Paul William Jim David Mike
anyone someone anybody somebody

Source: Miller, Guinness, Zamanian (NAACL 2004)
Name Tagging with Word Clusters and Discriminative Training

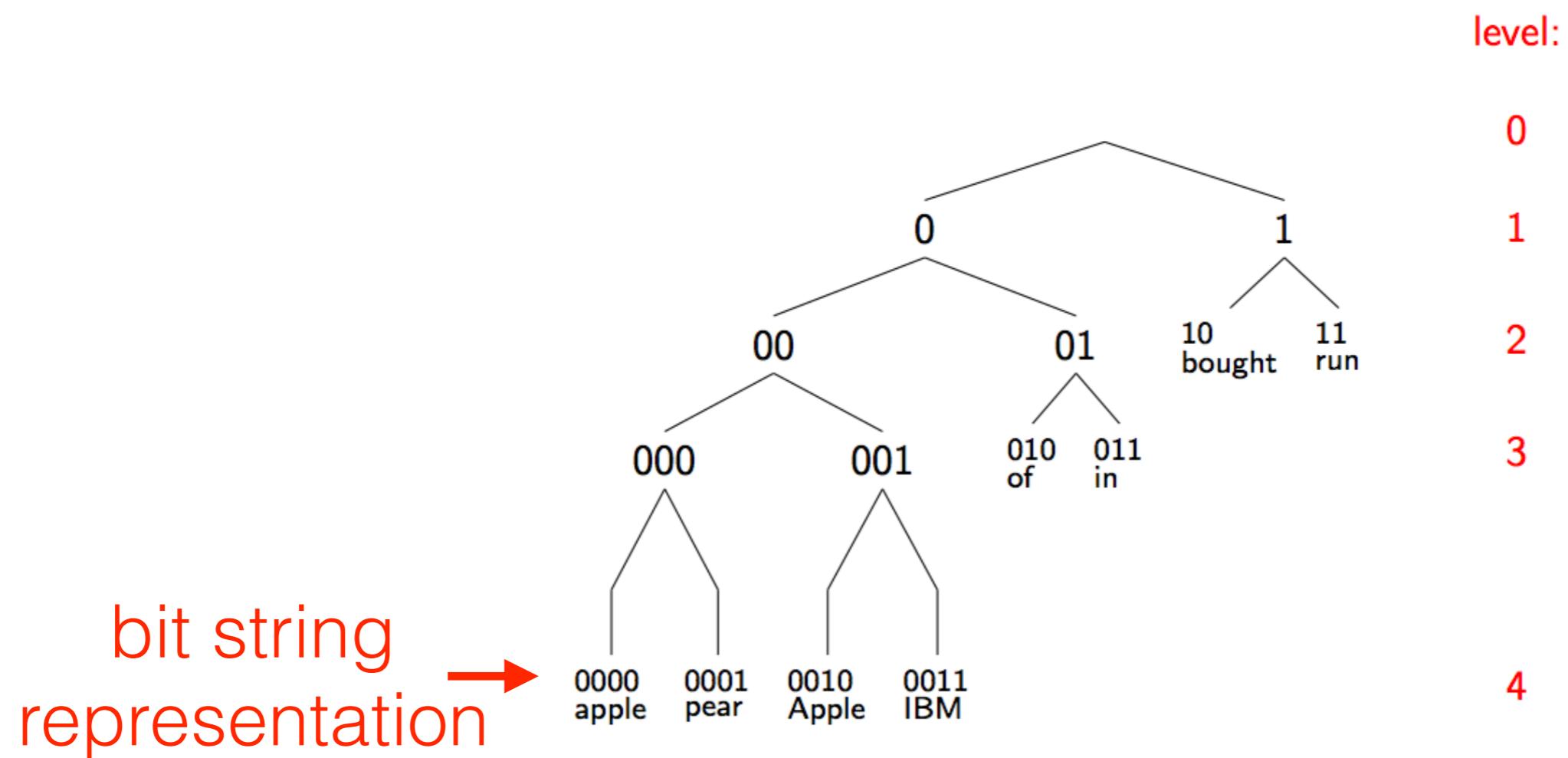
Hierarchical Word Clustering

- Each intermediate node is a cluster:



Hierarchical Word Clustering

- Each intermediate node is a cluster:



Hierarchical Word Clustering

mailman	10000011010111
salesman	100000110110000
bookkeeper	1000001101100010
troubleshooter	10000011011000110
bouncer	10000011011000111
technician	1000001101100100
janitor	1000001101100101
saleswoman	1000001101100110
...	
Nike	1011011100100101011100
Maytag	10110111001001010111010
Generali	10110111001001010111011
Gap	1011011100100101011110
Harley-Davidson	10110111001001010111110
Enfield	101101110010010101111110
genus	101101110010010101111111
Microsoft	10110111001001011000
Ventrity	101101110010010110010
Tractebel	1011011100100101100110
Synopsys	1011011100100101100111
WordPerfect	1011011100100101101000
....	
John	101100100000000000
Consuelo	101100100000000001
Jeffrey	101100100000000010
Kenneth	10110010000000001100
Phillip	101100100000000011010
WILLIAM	101100100000000011011
Timothy	10110010000000001110

- Example Clusters
(from Miller et al. 2004)

Hierarchical Word Clustering

mailman	10000011010111
salesman	100000110110000
bookkeeper	1000001101100010
troubleshooter	10000011011000110
bouncer	10000011011000111
technician	1000001101100100
janitor	1000001101100101
saleswoman	1000001101100110
...	
Nike	1011011100100101011100
Maytag	10110111001001010111010
Generali	10110111001001010111011
Gap	10110111001001010111110
Harley-Davidson	10110111001001010111110
Enfield	101101110010010101111110
genus	101101110010010101111111
Microsoft	10110111001001011000
Ventrity	101101110010010110010
Tractebel	1011011100100101100110
Synopsys	1011011100100101100111
WordPerfect	1011011100100101101000
....	
John	10111001000000000000
Consuelo	10111001000000000001
Jeffrey	10111001000000000010
Kenneth	101110010000000001100
Phillip	1011100100000000011010
WILLIAM	1011100100000000011011
Timothy	101110010000000001110

- Example Clusters
(from Miller et al. 2004)

Source: Miller, Guinness, Zamanian (NAACL 2004)

Name Tagging with Word Clusters and Discriminative Training

Hierarchical Word Clustering

mailman
salesman
bookkeeper
troubleshooter
bouncer
technician
janitor
saleswoman

10000011010111
100000110110000
1000001101100010
10000011011000110
10000011011000111
1000001101100100
1000001101100101
1000001101100110

...
Nike
Maytag
Generali
Gap
Harley-Davidson
Enfield

1011011100100101011100
10110111001001010111010
10110111001001010111011
1011011100100101011110
10110111001001010111110
101101110010010101111110
101101110010010101111111
1011011100100101011111111
10110111001001011000
101101110010010110010
1011011100100101100110
1011011100100101100111
1011011100100101101000

genus
Microsoft
Ventrity
Tractebel
Synopsys
WordPerfect

10111001000000000000
10111001000000000001
10111001000000000010
1011100100000000001100
10111001000000000011010
10111001000000000011011
1011100100000000001110

- Example Clusters
(from Miller et al. 2004)

word cluster features
(bit string prefix)

....
John
Consuelo
Jeffrey
Kenneth
Phillip
WILLIAM
Timothy

Source: Miller, Guinness, Zamanian (NAACL 2004)

Name Tagging with Word Clusters and Discriminative Training

Challenges in Twitter

2m 2ma 2mar 2mara 2maro 2marrow 2mor 2mora
2moro 2morow 2morr 2morro 2morrow 2moz 2mr
2mro 2mrrw 2mrw 2mw tmmrw tmo tmoro tmorrow
tmoz tmr tmro tmrow tmrrow tmrrw tmrw tmrww tmw
tomaro tomarow tomarro tomorrow tomm
tommarow tomamarow tommoro tommorow
tommorrow tommorw tommrow tomo tomolo tomoro
tomorow tomorro tomorrw tomoz tomrw tomz

Clusters in Twitter NER

Brown clusters, for each i s.t. $s \leq i < t$:

$$\{[y_j, brn(n, x_i), n]\}_{n \in \{2, 4, 8, 12\}},$$
$$\{[y_j, er_{s,t}(i), brn(n, x_i), n]\}_{n \in \{2, 4, 8, 12\}}$$

Word vectors, for each i s.t. $s \leq i < t$:

$$\{[y_j, n] = w2v(n, x_i)\}_{n=1}^{300},$$
$$\{[y_j, er_{s,t}(i), n] = w2v(n, x_i)\}_{n=1}^{300}$$

Table 2: Word representation features in $\phi(s, t, y_j, x)$.
 $brn(n, x_i)$ maps a word x_i to the first n bits of its Brown cluster bit sequence. $w2v(n, x_i)$ maps x_i to the n^{th} component of its word vector, and $[str] = v$ stands for a real-valued feature with name str and value v .

Clusters in Twitter NER

System	Fin10Dev	Rit11	Fro14	Avg
CoNLL + Brown + Vector + Reps	27.3	27.1	29.5	28.0
	38.4	39.4	42.5	40.1
	40.8	40.4	42.9	41.4
	42.4	42.2	46.2	43.6
Fin10 + Brown + Vector + Reps	36.7	29.0	30.4	32.0
	59.9	53.9	56.3	56.7
	61.5	56.4	58.4	58.8
	64.0	58.5	60.2	60.9
CoNLL+Fin10 + Brown + Vector + Reps + Weights	44.7	39.9	44.2	42.9
	54.9	52.9	58.5	55.4
	58.9	55.2	59.9	58.0
	58.9	56.4	61.8	59.0
	64.4	59.6	63.3	62.4

Table 5: Impact of our components on Twitter NER performance, as measured by F1, under 3 data scenarios.

Source: Colin Cherry, Hongyu Guo (NAACL 2015)

The Unreasonable Effectiveness of Word Representations for Twitter Named Entity Recognition

Brown Clustering

- The Intuition:
 - similar words appear in similar contexts
 - more precisely: similar words have similar distributions of words to their immediate left and right



Brown Clustering Algorithm

- An agglomerative clustering algorithm:
 - take the top m most frequent words, put each into its own cluster, $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_m$
 - repeat for $i = (m+1) \dots |V|$
 - create a new cluster \mathbf{c}_{m+1} for the i 'th most frequent word
 - choose two clusters from $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_{m+1}$ to be merged, which give the highest **Quality** based on a *training corpus*

Brown Clustering Algorithm

- maximize the **Quality** function that score a given partitioning **C**: **parameters**

$$\begin{aligned} \text{Quality}(C) &= \sum_i^n \log e(w_i | C(w_i)) q(C(w_i) | C(w_{i-1})) \\ &= \sum_{c=1}^k \sum_{c'=1}^k p(c, c') \log \frac{p(c, c')}{p(c)p(c')} + G \end{aligned}$$

- **n(c)** : count of class **c** seen in the corpus
- **n(c,c')** : counts of **c'** seen following **c**

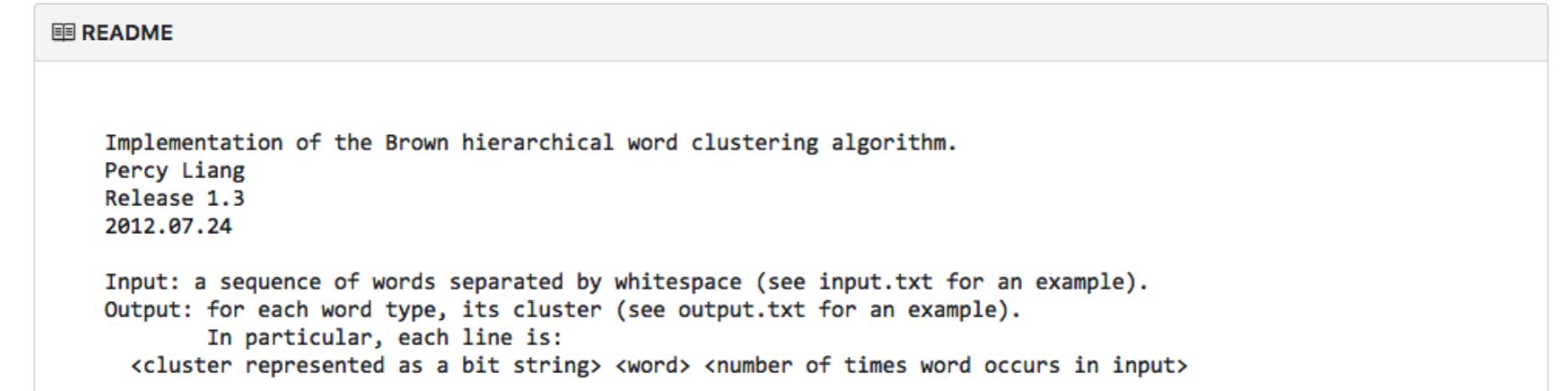
$$p(c, c') = \frac{n(c, c')}{\sum_{c, c'} n(c, c')}$$

$$p(c) = \frac{n(c)}{\sum_c n(c)}$$

Brown Clustering

A screenshot of a GitHub repository page for 'percyliang/brown-cluster'. The repository title is 'percyliang / brown-cluster'. The header includes 'Watch 29', 'Star 203', 'Fork 79', and tabs for 'Code', 'Issues 9', 'Pull requests 0', 'Projects 0', 'Wiki', 'Pulse', and 'Graphs'. Below the header is a description: 'C++ implementation of the Brown word clustering algorithm.' A summary bar shows '20 commits', '1 branch', '0 releases', and '4 contributors'. The commit list shows the following commits:

Author	Commit Message	Date
percyliang	Merge pull request #15 from mannby/large_corpora	Latest commit d9dff3b on Mar 26
	Enable >= 2^31 tokens in input data	8 months ago
	cluster-viewer final	3 years ago
	turn on -O3 optimization, add gitignore	3 years ago
	small fix to makefile	3 years ago
	Merge branch 'master' of https://github.com/percyliang/brown-cluster	3 years ago
	Version 1.2	4 years ago
	Version 1.3: incorporate Chris Dyer's g++ compatibility changes; smal...	4 years ago
	Enable >= 2^31 tokens in input data	8 months ago

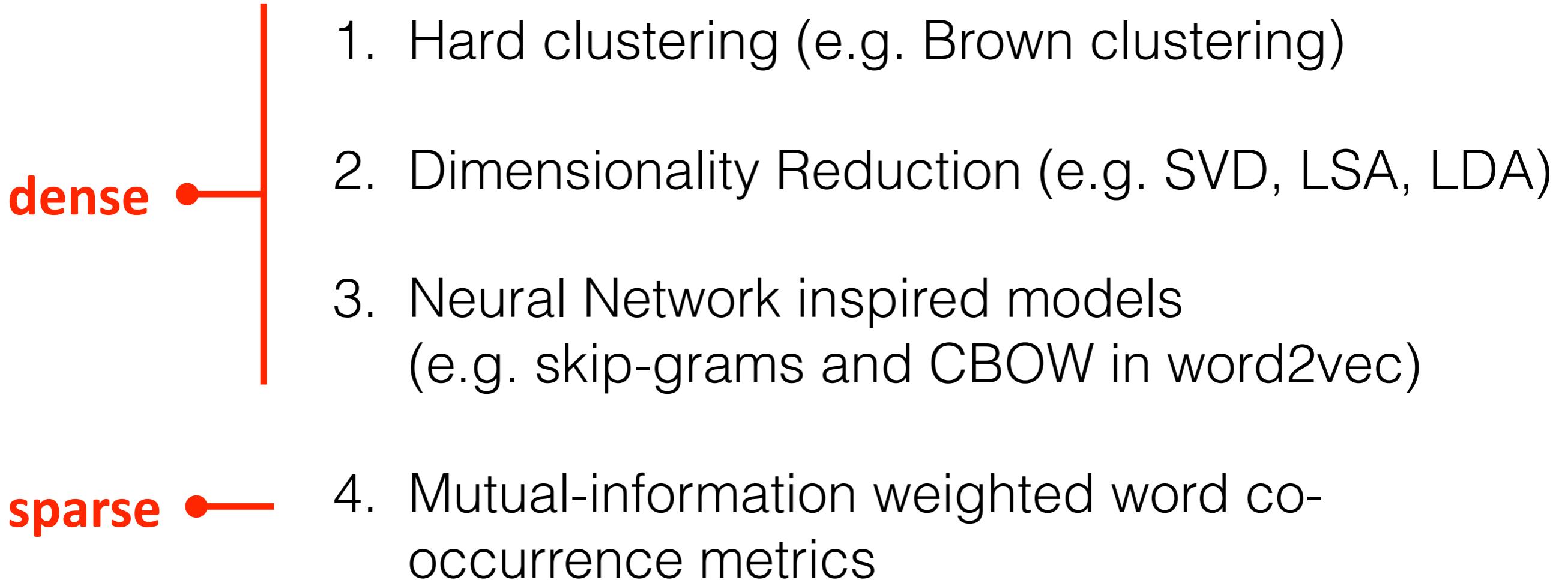
The 'README' file content is as follows:

```
Implementation of the Brown hierarchical word clustering algorithm.  
Percy Liang  
Release 1.3  
2012.07.24  
  
Input: a sequence of words separated by whitespace (see input.txt for an example).  
Output: for each word type, its cluster (see output.txt for an example).  
In particular, each line is:  
<cluster represented as a bit string> <word> <number of times word occurs in input>
```

Word Vector Representations

(a.k.a. “word embeddings”)

- 4 kinds of vector semantic models



In Contrast To

represent word meaning by a taxonomy like 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')]
```

synonym sets (good):

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

In Contrast To

represent word meaning by a taxonomy like WordNet

- problems with this discrete representation:
 - missing new words (impossible to keep up-to-date): *wicked, badass, nifty, crack, ace, wizard, genius, ninja*
 - requires human labor to create and adapt
 - hard to compute accurate word similarity
 - and apparently not enough to handle social media data!

Distributional Intuition

- From context words, human can guess a word's meaning:

A bottle of ***tesgüino*** is on the table

Everybody likes ***tesgüino***

Tesgüino makes you drunk

We make ***tesgüino*** out of corn.

“You shall know a word by the company it keeps”

— J. R. Firth 1957

Distributional Intuition

- From context words, human can guess a word's meaning:

A bottle of ***tesgüino*** is on the table

Everybody likes ***tesgüino***

Tesgüino makes you drunk

We make ***tesgüino*** out of corn.

- similar words = similar contexts = similar vectors
- word meaning is represented by a vector of numbers

Simple Co-occurrence Vectors

- Option #1: word-document co-occurrence counts

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

this will give general topics (e.g. sports terms will have similar entries), leading to **Latent Semantic Analysis**

Simple Co-occurrence Vectors

- Option #2: use a sliding window over a big corpus of text and count word co-occurrences:

example corpus:

- I like deep learning.
- I like NLP.
- I enjoy flying.

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

this captures both syntactic (POS) and semantic information

Simple Co-occurrence Vectors

- Problems with this representation of raw counts:
 - increase in size with vocabulary
 - high dimensionality and very sparse!
 - not a great measure of association between words:

“the” and “of” are very frequent, but maybe not the most discriminative

Lower Dimensional Vectors

- **The Idea:** use dense vectors to store “most” of the important information in a fixed, small number of dimensions
- usually around 25 ~1000 dimensions

Lower Dimensional Vectors

- Word meaning is represented as a **dense** vector

“linguistic” =

$$\begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix}$$

How to reduce the dimensionality?

(2) Matrix Factorization

- Singular Value Decomposition (SVD)

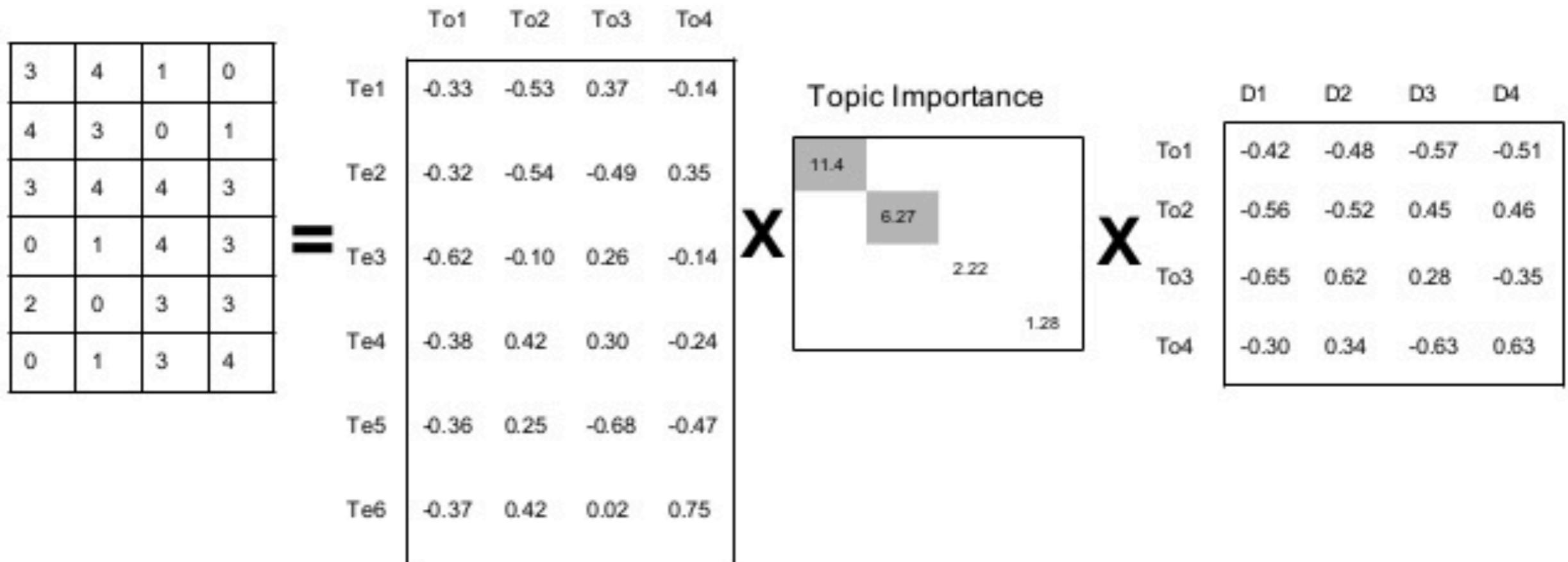
$$\begin{array}{c} m \\ n \end{array} \boxed{X} = \begin{array}{c} r \\ n \end{array} \boxed{U} = \begin{array}{c} r \\ r \end{array} \boxed{S} = \begin{array}{c} m \\ r \end{array} \boxed{V^T}$$
$$\begin{array}{c} m \\ n \end{array} \boxed{\hat{X}} = \begin{array}{c} k \\ n \end{array} \boxed{\hat{U}} = \begin{array}{c} k \\ k \end{array} \boxed{\hat{S}} = \begin{array}{c} m \\ k \end{array} \boxed{\hat{V}^T}$$

\hat{X} is the best rank k approximation to X , in terms of least squares.

(2) Matrix Factorization

- Latent Semantic Analysis (LSA)

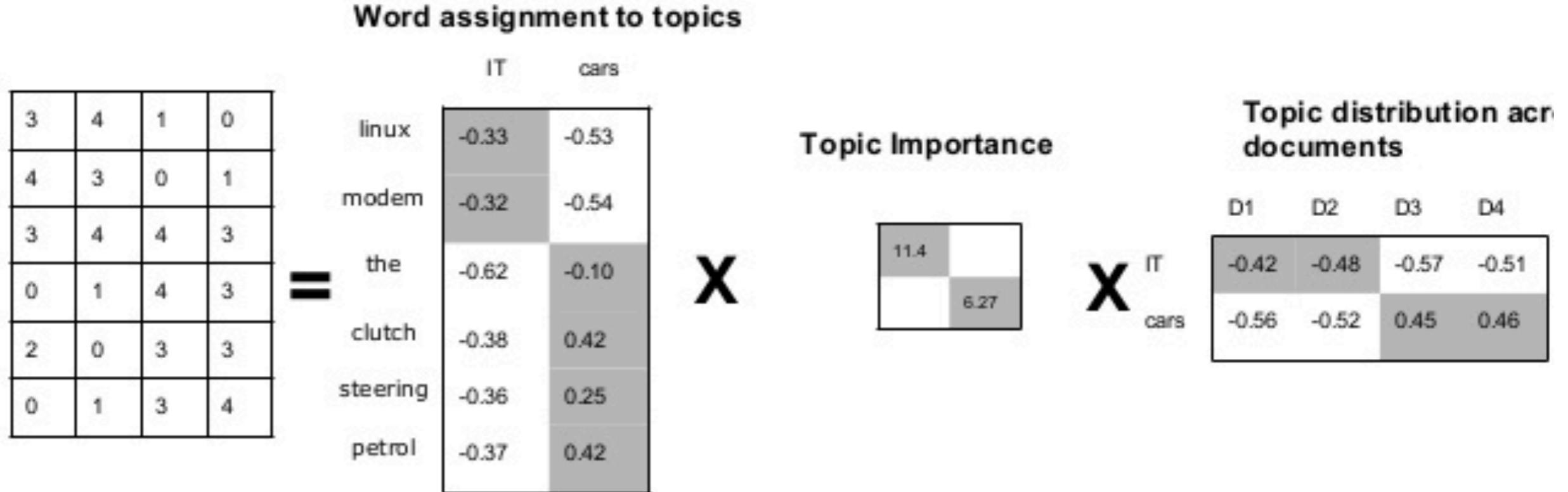
LSA is essentially low-rank approximation of document term-matrix.



(2) Matrix Factorization

- Latent Semantic Analysis (LSA)

LSA is essentially low-rank approximation of document term-matrix.



SVD Word Vectors

example corpus:

- I like deep learning.
- I like NLP.
- I enjoy flying.

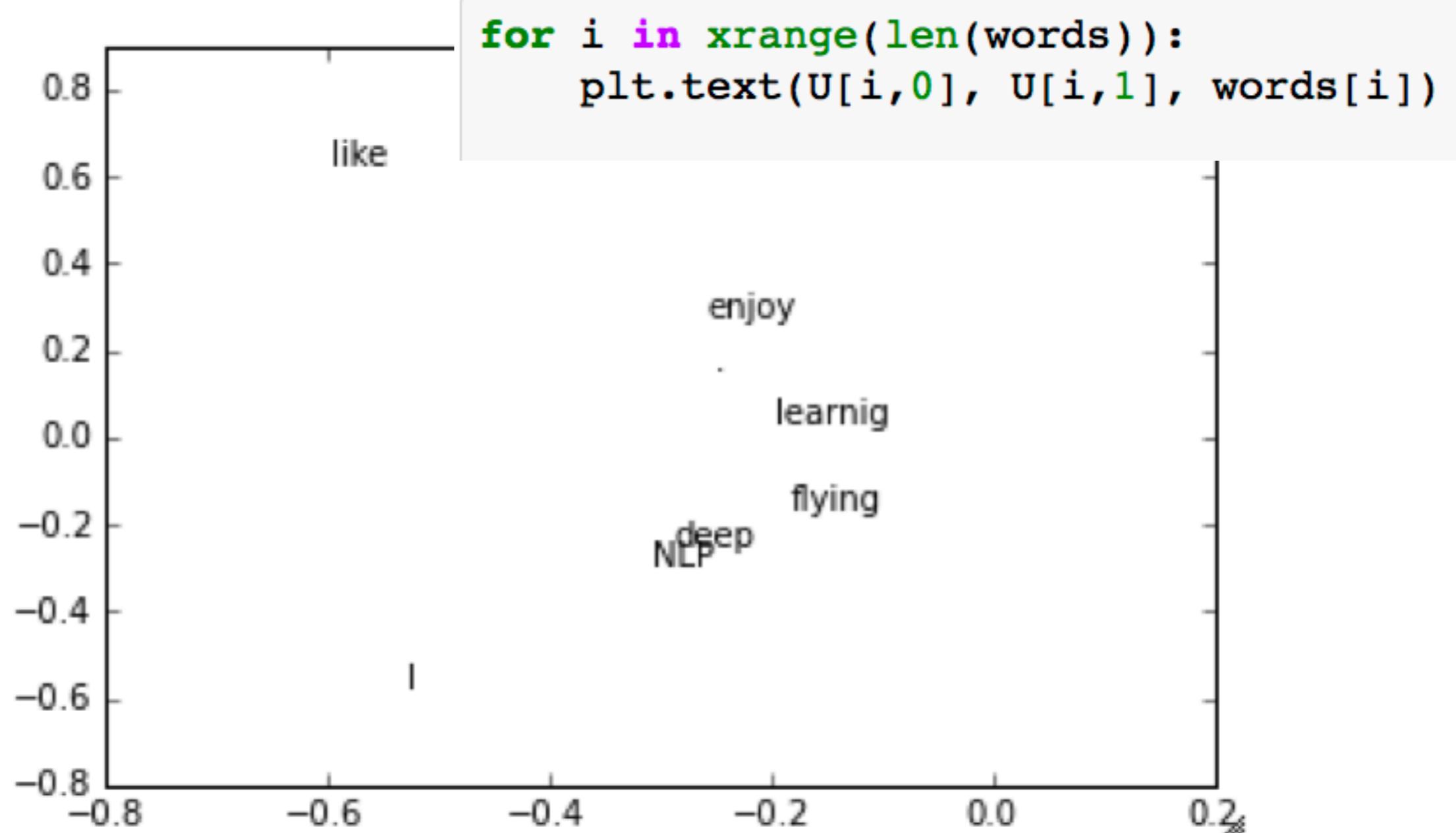
```
import numpy as np
la = np.linalg
words = ["I", "like", "enjoy",
          "deep", "learning", "NLP", "flying", ".."]
X = np.array([[0,2,1,0,0,0,0,0],
              [2,0,0,1,0,1,0,0],
              [1,0,0,0,0,0,1,0],
              [0,1,0,0,1,0,0,0],
              [0,0,0,1,0,0,0,1],
              [0,1,0,0,0,0,0,1],
              [0,0,1,0,0,0,0,1],
              [0,0,0,0,1,1,1,0]])
```



```
U, s, Vh = la.svd(X, full_matrices=False)
```

SVD Word Vectors

- plot first 2 columns of U corresponding to the 2 biggest singular values:



Some Hacks

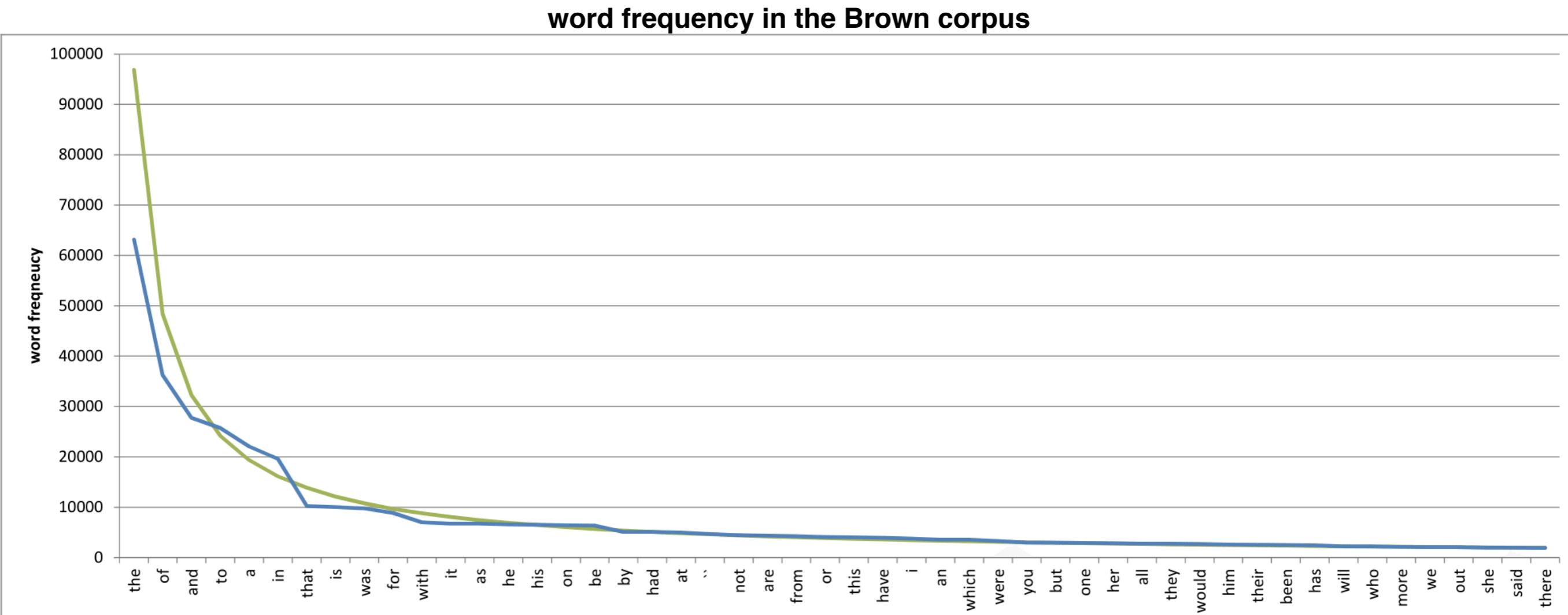
- Problem: function words (“the”, “he”, “has”) are too frequent → syntax has too much impact.
 - fixes: cap the counts, or ignore them all
- ramped windows that count closer words more
- etc ...

Source: Rohde et al. (2005)

An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence

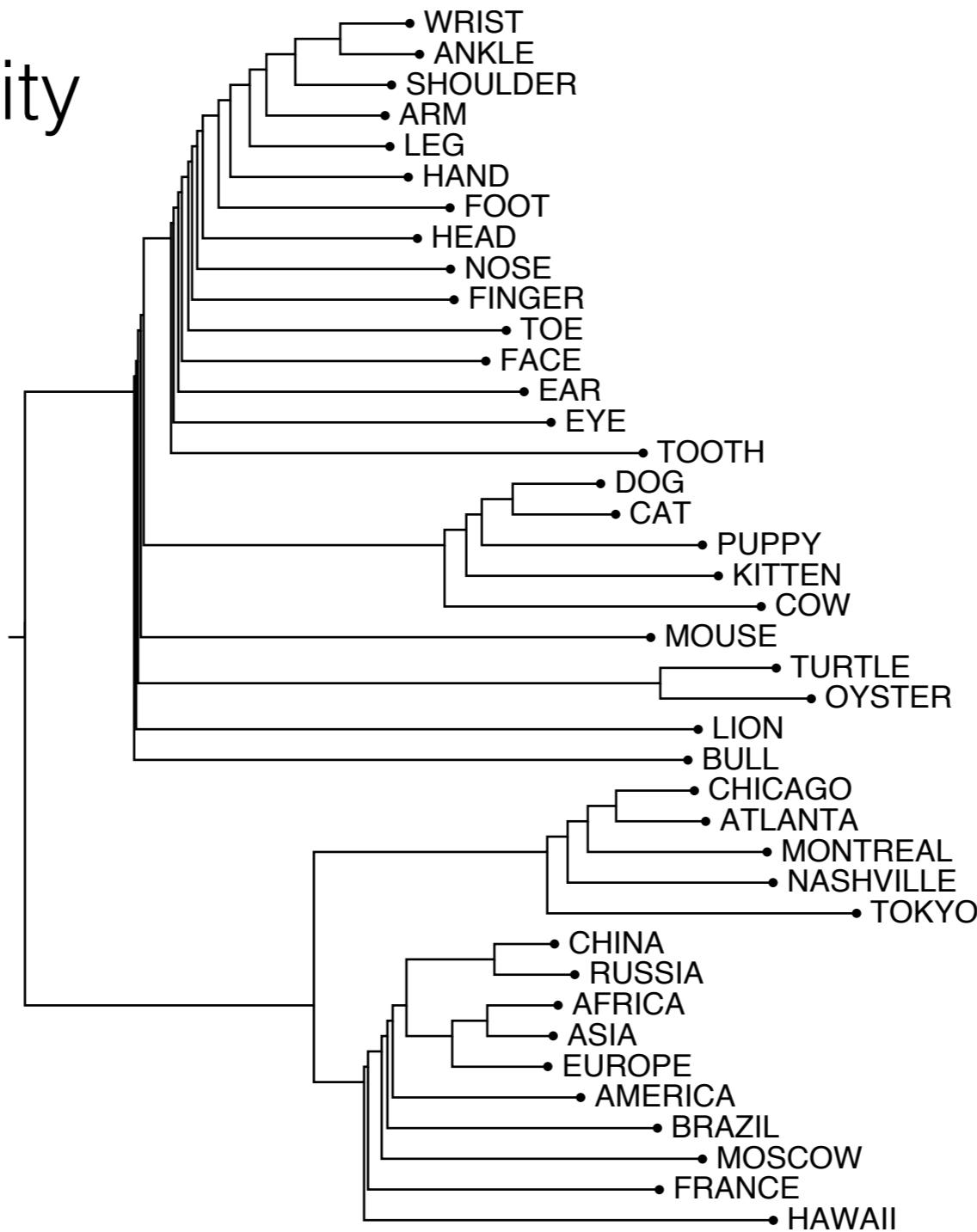
Zipf's (Power) Law

- frequency of word is inversely proportional to its rank in the frequency table



Clustering Vectors

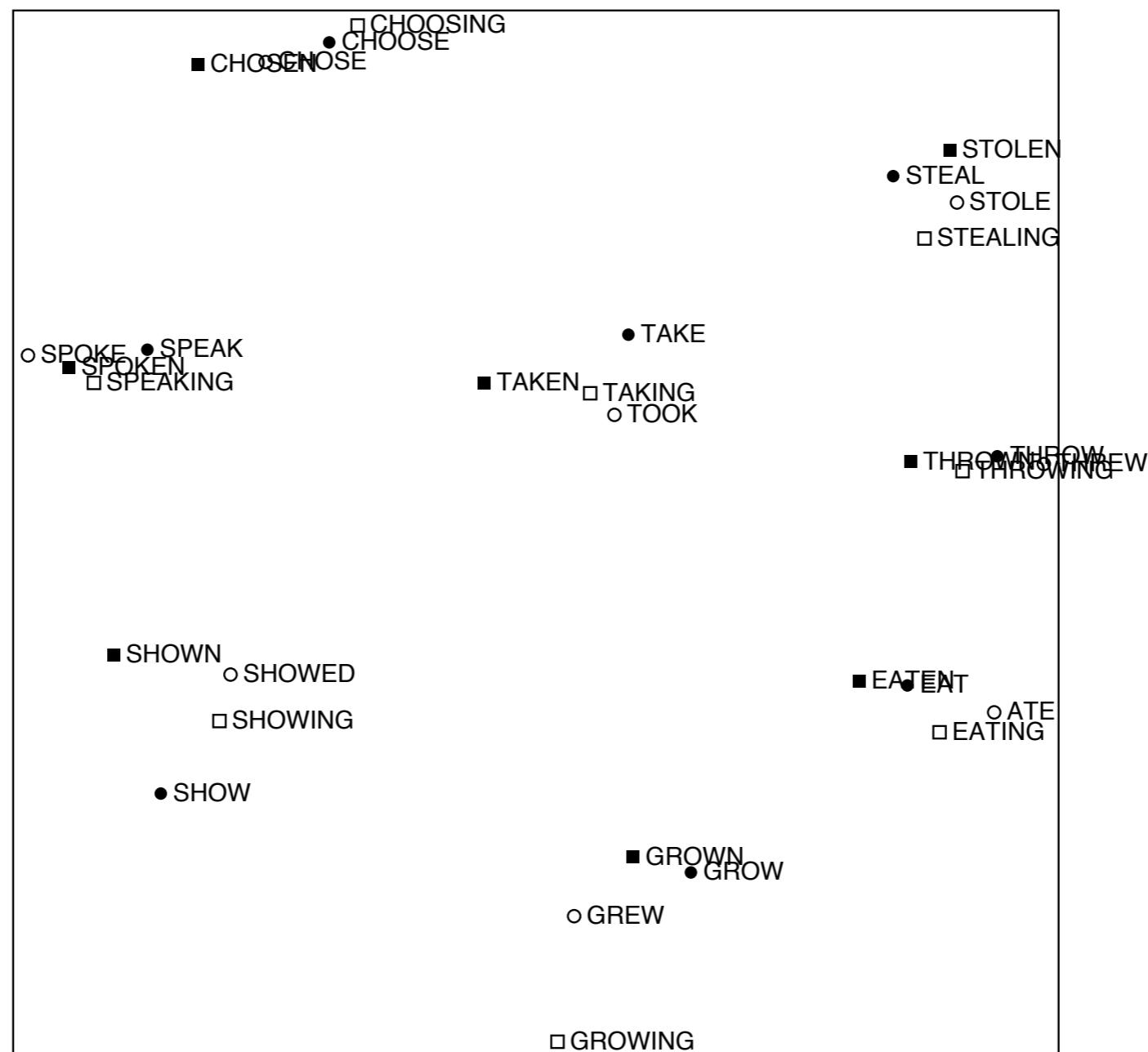
- visualize similarity



Source: Rohde et al. (2005)

An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence

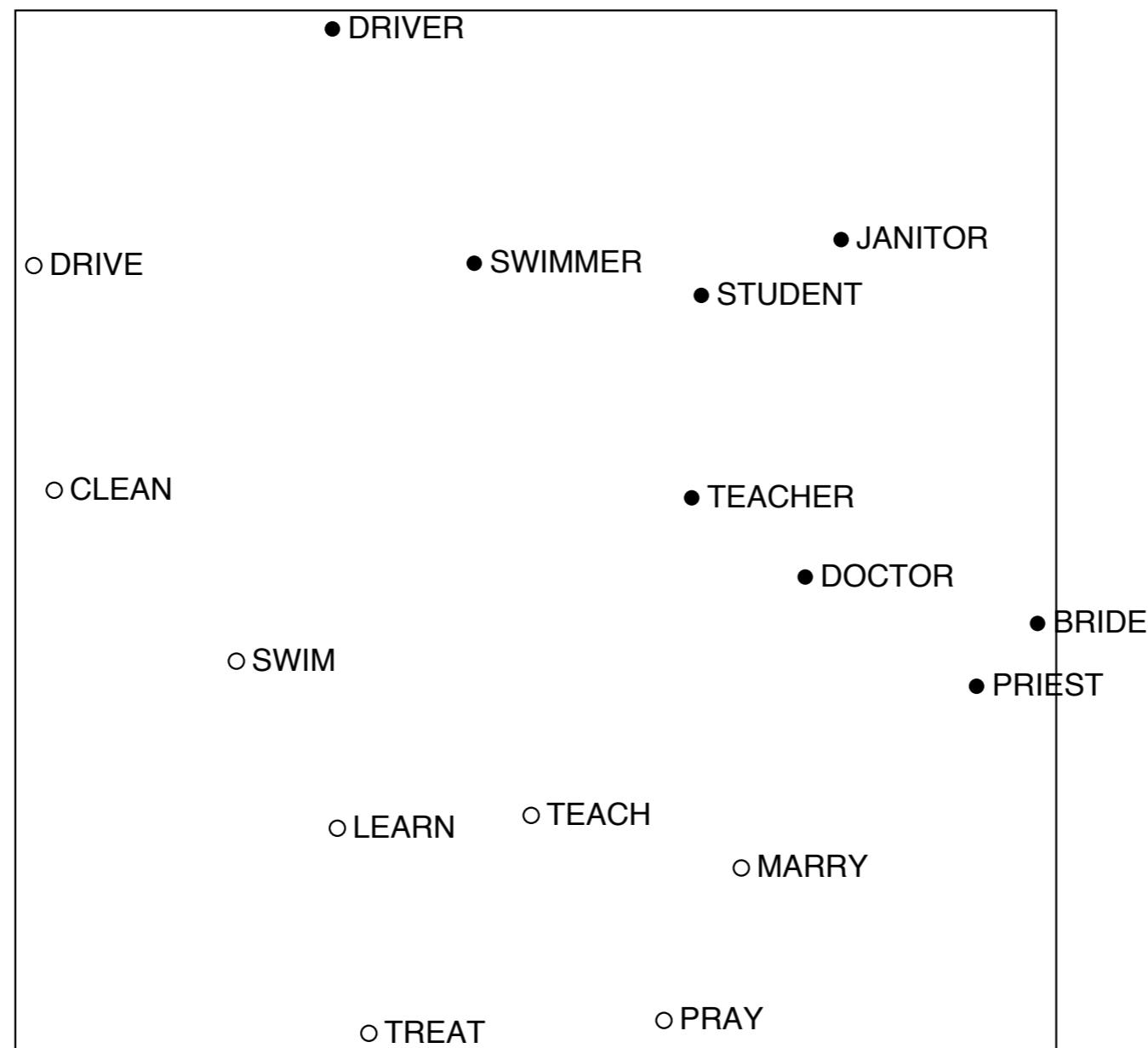
Interesting Syntactic Patterns



Source: Rohde et al. (2005)

An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence

Interesting Semantic Patterns



Source: Rohde et al. (2005)

An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence

SVD Word Vectors

- Still some problems:
 - computational cost scales quadratically for $m \times n$ matrix — $O(mn^2)$ when $n < m$
 - hard to use large corpus (and vocabulary)
 - hard to incorporate new words or documents

(3) Neural Word Embeddings

- **The Idea:** directly learn low-dimensional word vectors
- ... can go back to 1980s:
 - Learning Representations by Back-Propagating Errors (Rumelhart et al., 1986)
 - **A Neural Probabilistic Language Model** (Bengio et al., 2003)
 - NLP from Scratch (Collobert & Weston, 2008)
 - **Word2vec** (Mikolov et al. 2013), GloVe (Pennington et al. 2014)
 - ELMo (Peters et al. 2018), BERT (Devlin et al. 2019)

A Neural Probabilistic Language Model (Bengio et al., 2003)

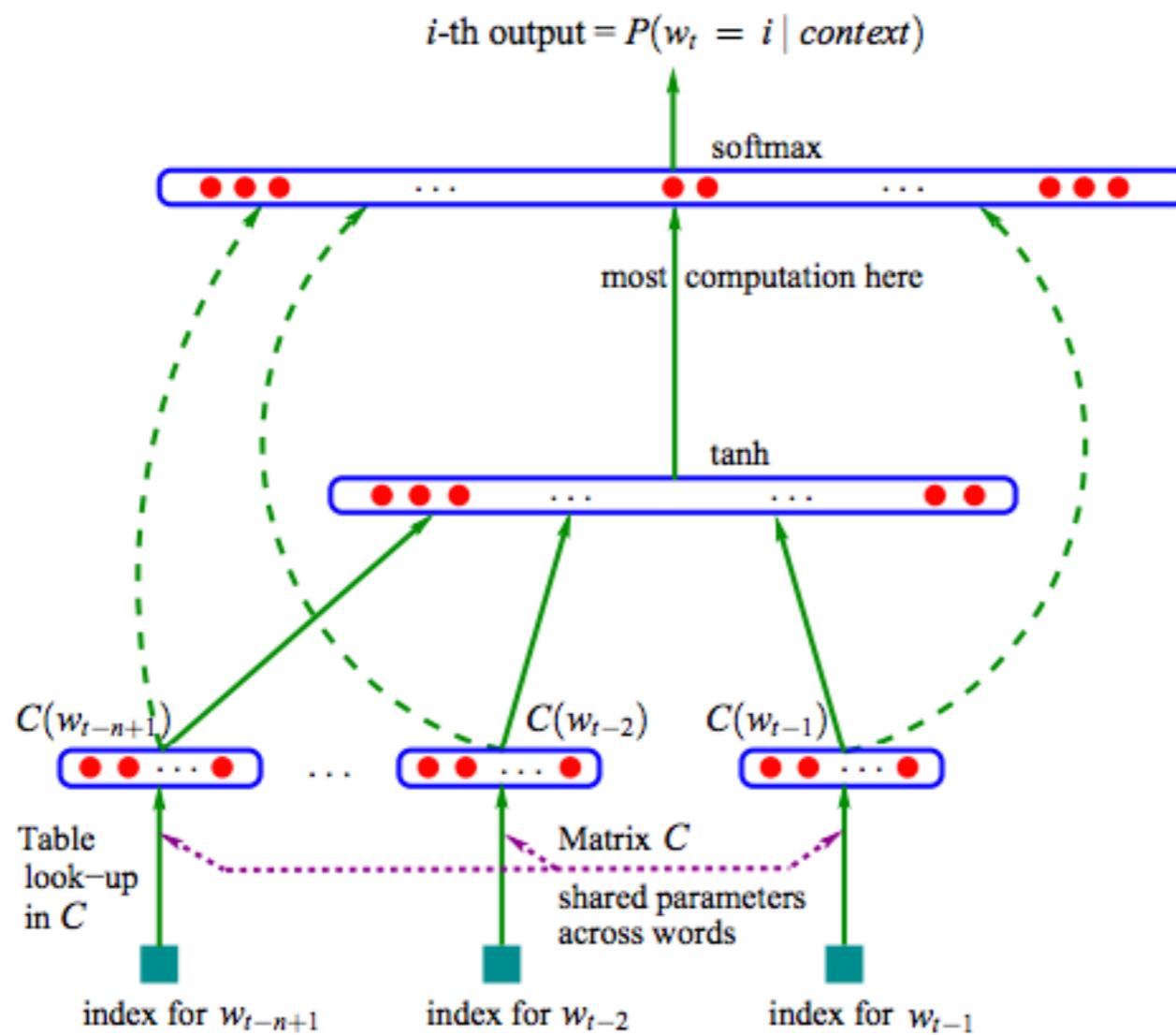


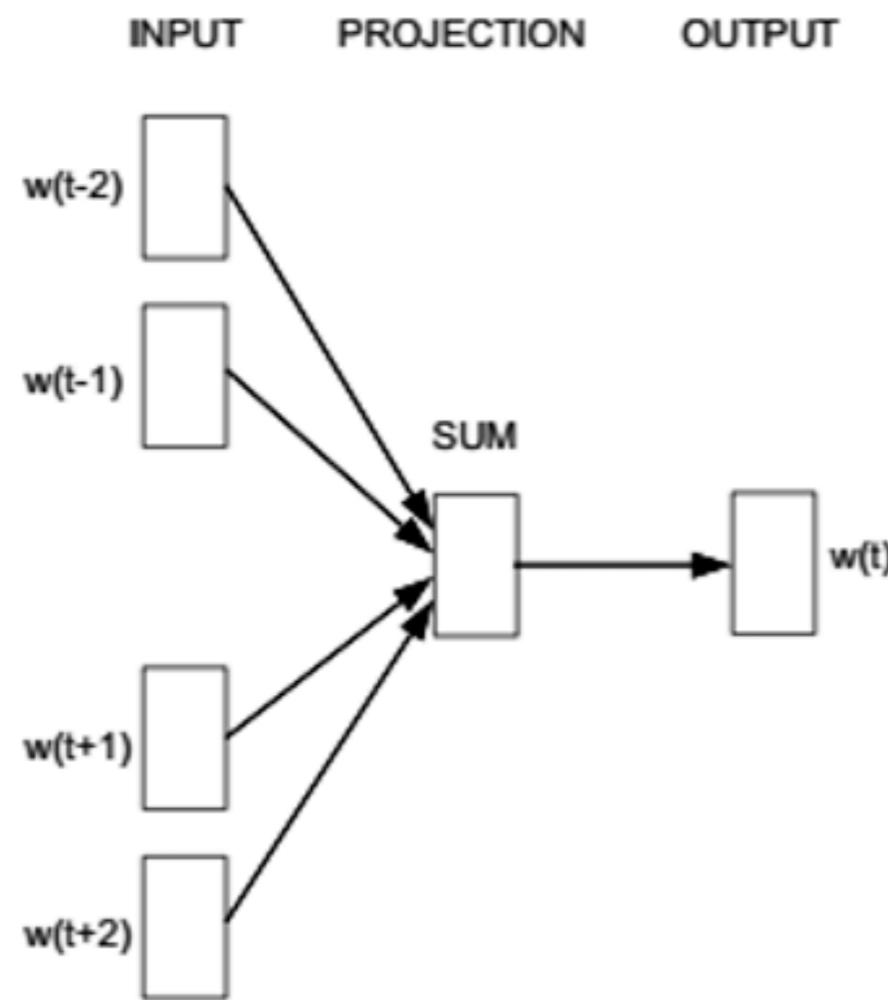
Figure 1: Neural architecture: $f(i, w_{t-1}, \dots, w_{t-n+1}) = g(i, C(w_{t-1}), \dots, C(w_{t-n+1}))$ where g is the neural network and $C(i)$ is the i -th word feature vector.

Neural Word Embeddings

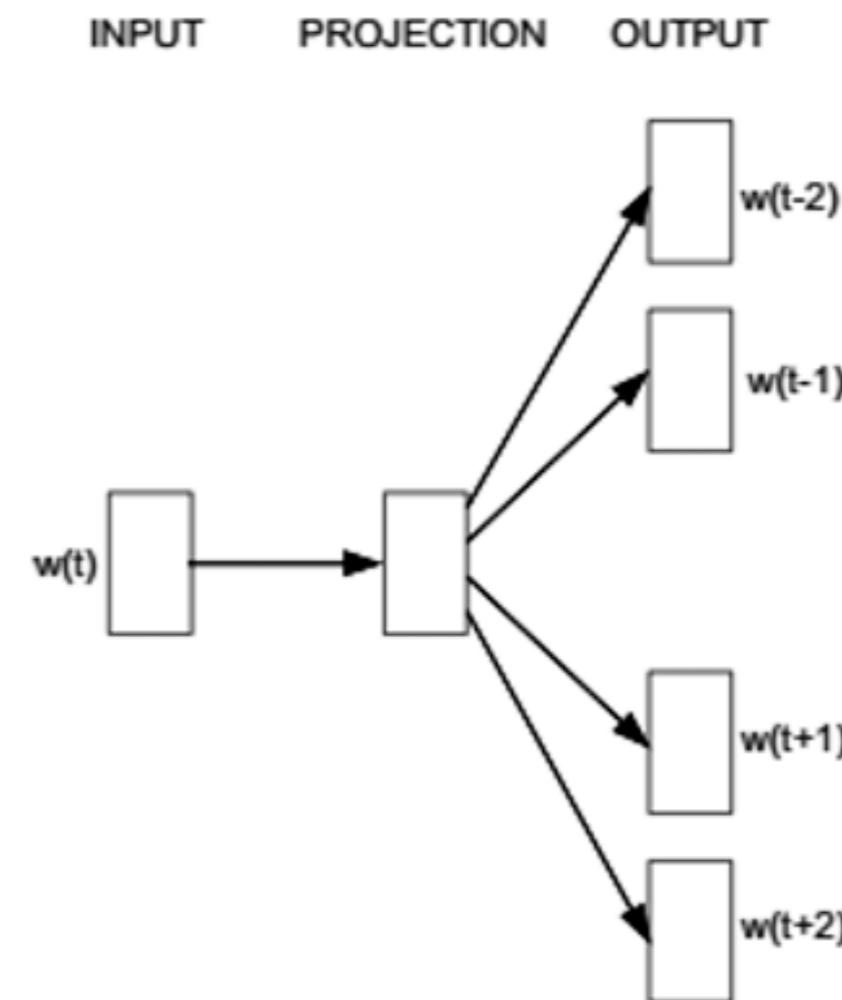
- **The Basic Idea:**
 - We define a model that aims to predict a word given its context words (word vectors), which has a loss function, e.g. $J = 1 - P(\text{context} \mid w_t)$
 - We look at many positions of t in a big text corpus,
 - and keep adjusting the word vectors to minimize this loss.

Word2vec

- simple and efficient



CBOW



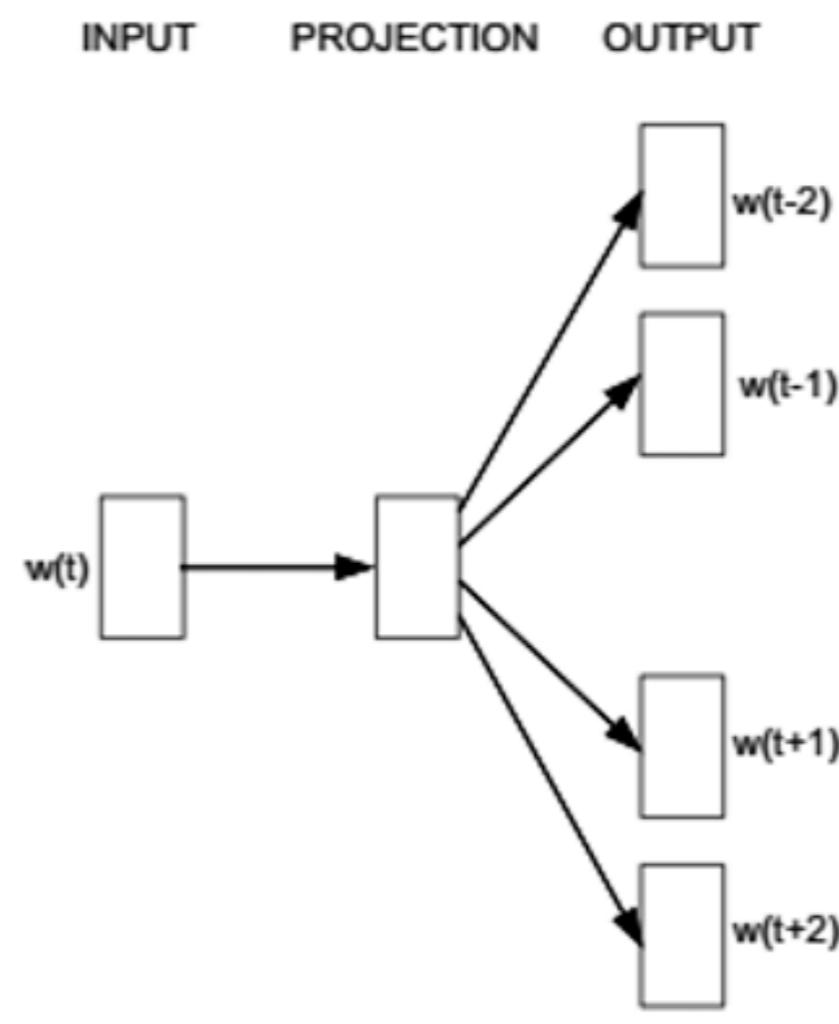
Skip-gram

Source: Mikolov et al. (NIPS 2013)

Distributed Representations of Words and Phrases and their Compositionality

Word2vec

- Skip-gram — predicts surrounding “outside” words given the “center” word



Skip-gram

Word2vec

- Skip-gram — predicts surrounding “outside” words given the “center” word

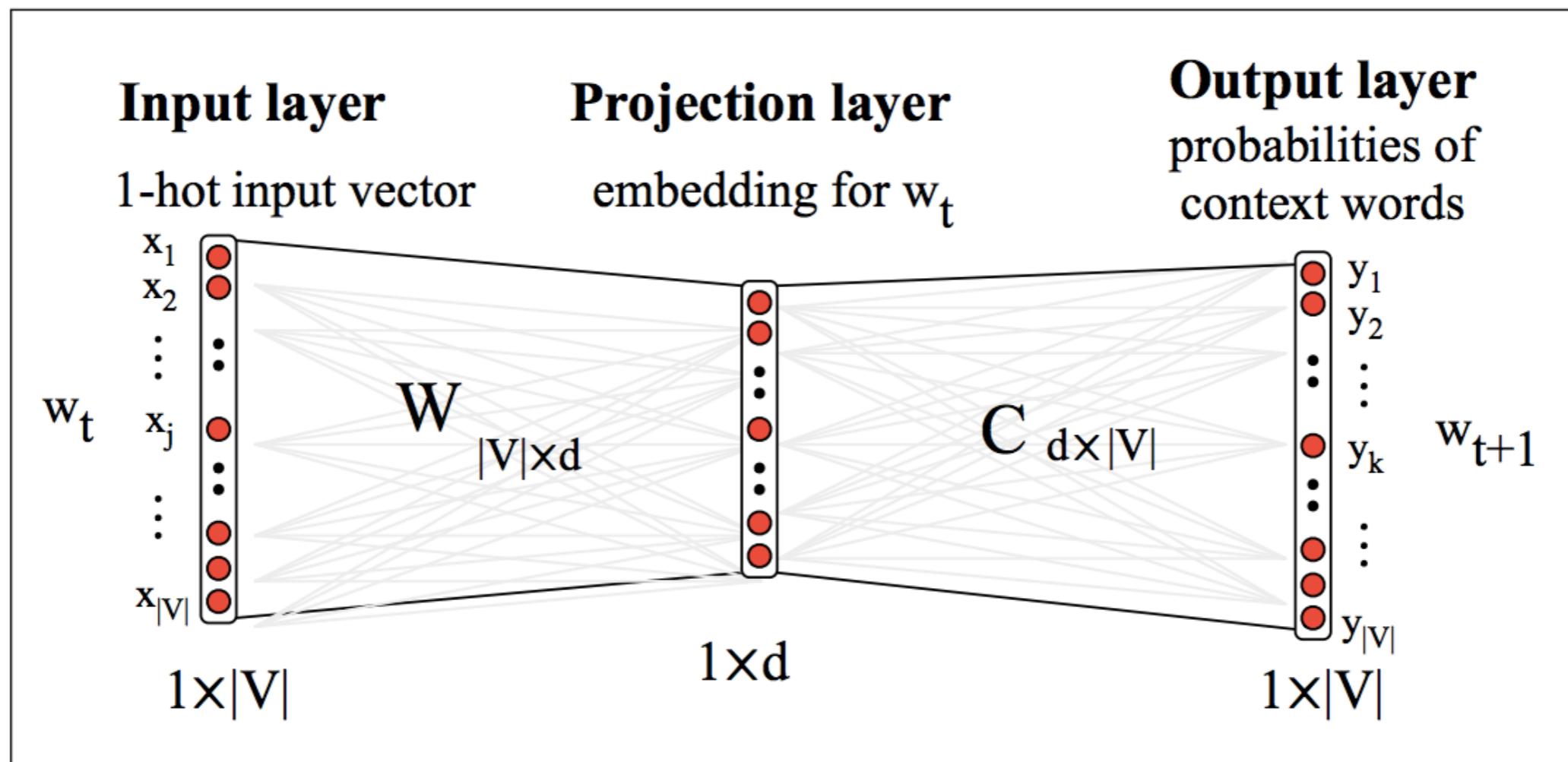
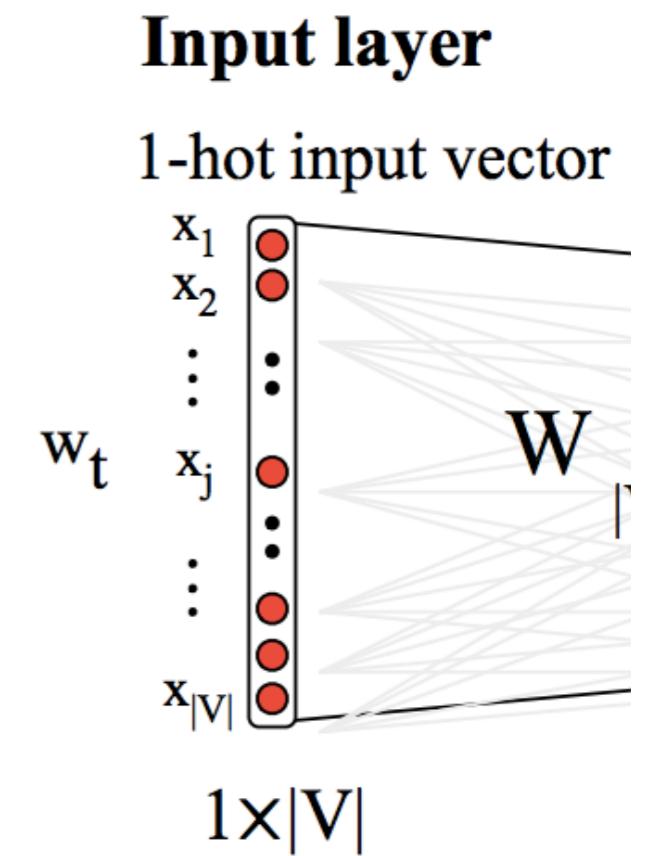


Figure 16.5 The skip-gram model viewed as a network (Mikolov et al. 2013, Mikolov et al. 2013a).

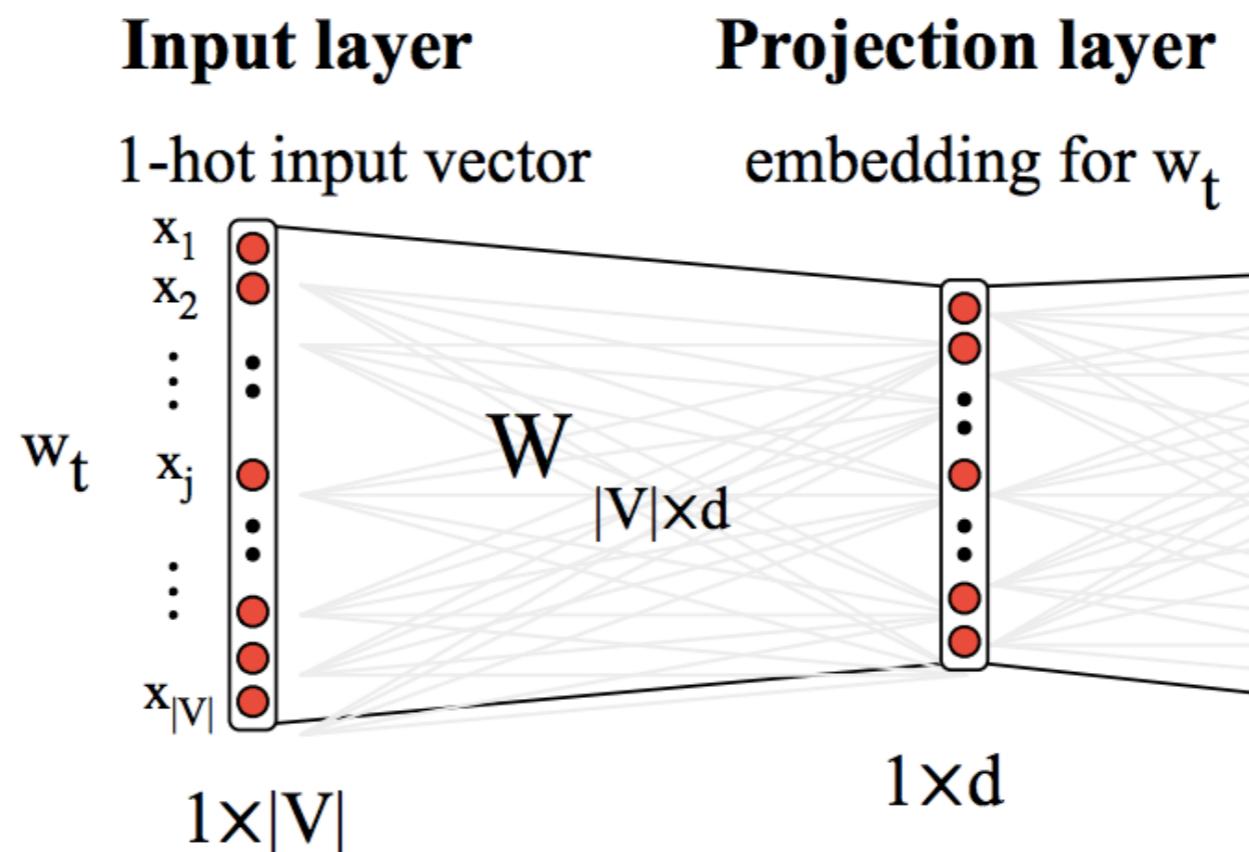
Input Layer

- “one-hot” word vectors
 - a vector of dimension $|V|$ (size of vocabulary)
 - all “0”s expect a single “1” in the vector
 - different positions of that “1” represent different words



Hidden (Projection) Layer

- A simple look up — the rows of this weight matrix are actually “input” word vectors



Hidden (Projection) Layer

- A simple look up — the rows of this weight matrix are actually “input” word vectors

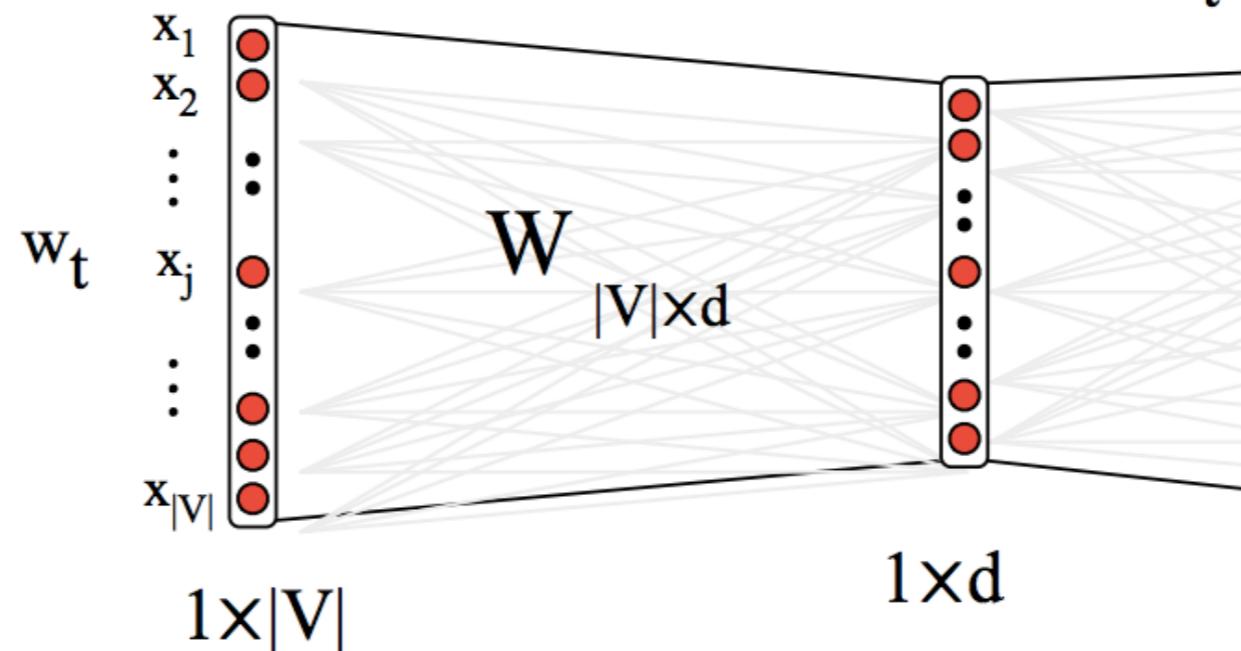
$$\begin{bmatrix} 0 & 0 & 0 & \boxed{1} & 0 \end{bmatrix} \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ \boxed{10} & \boxed{12} & \boxed{19} \\ 11 & 18 & 25 \end{bmatrix} = \begin{bmatrix} 10 & 12 & 19 \end{bmatrix}$$

Input layer

1-hot input vector

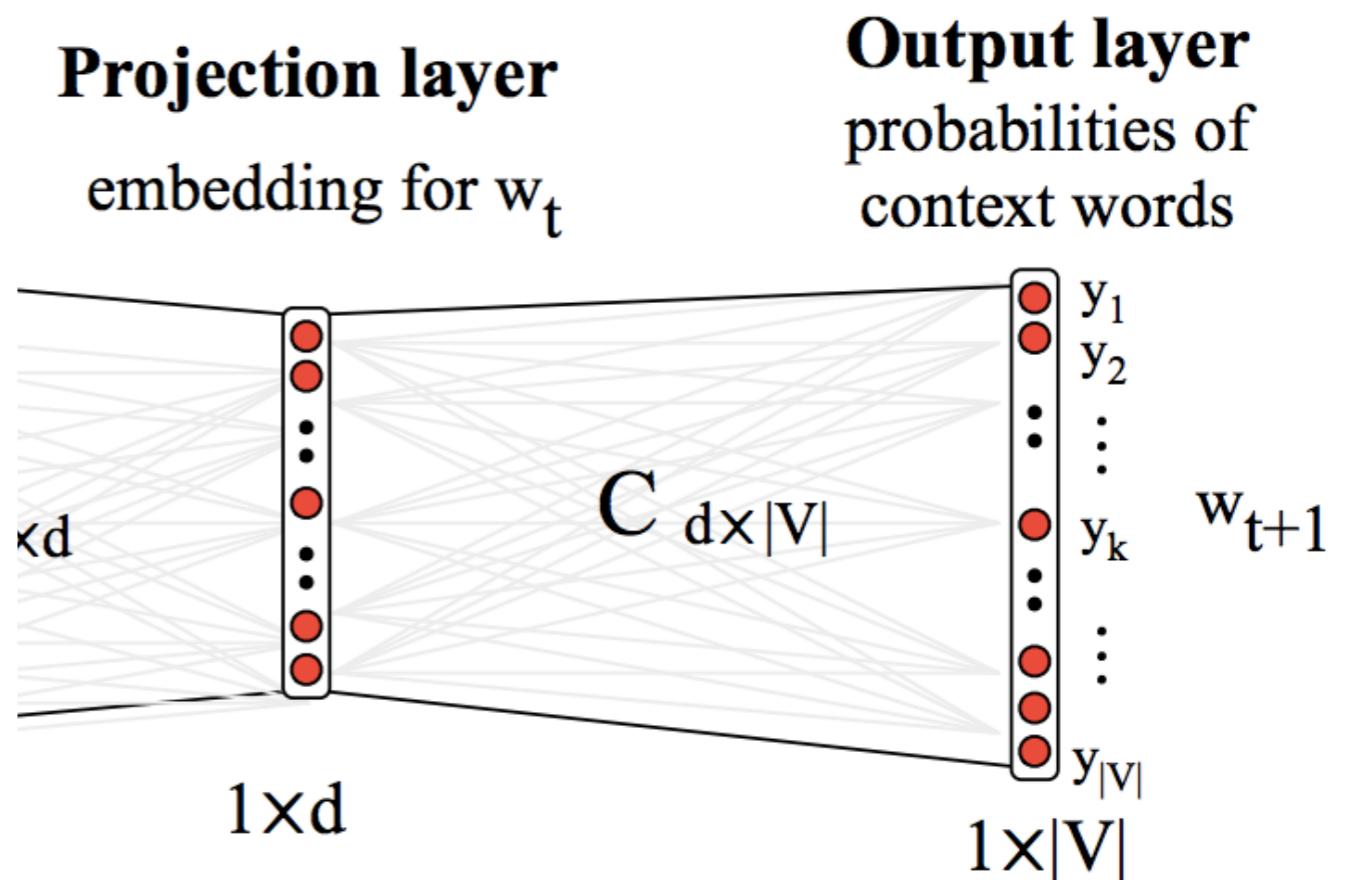
Projection layer

embedding for w_t



Output Layer

- predicts surrounding “outside” (context) words given the “center” word → A classification problem!
- Softmax Regression = Multi-class Logistic Regression



Softmax Function

- Softmax function is a generalization of logistic function

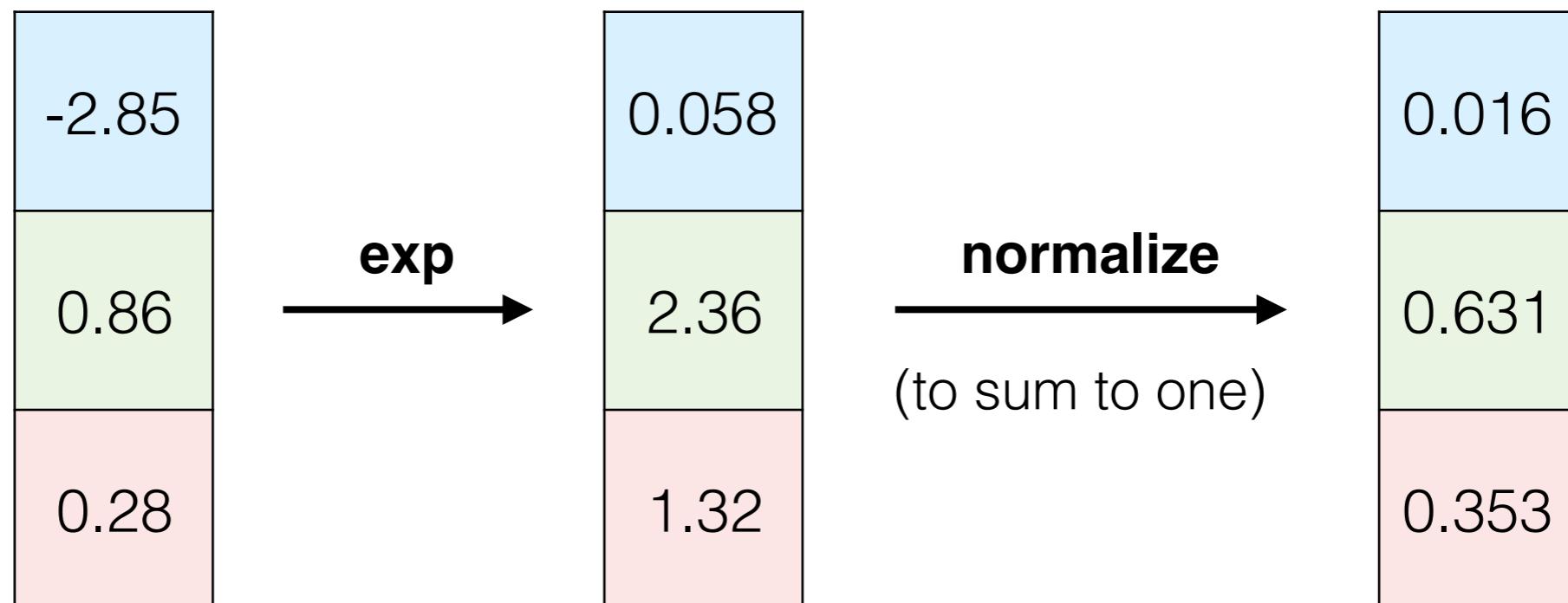
$$\text{softmax}(\mathbf{x})_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

exponentiate to make positive ← **normalized to give probability**

Softmax Function

- Softmax function is a generalization of logistic function

$$\text{softmax}(\mathbf{x})_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$$



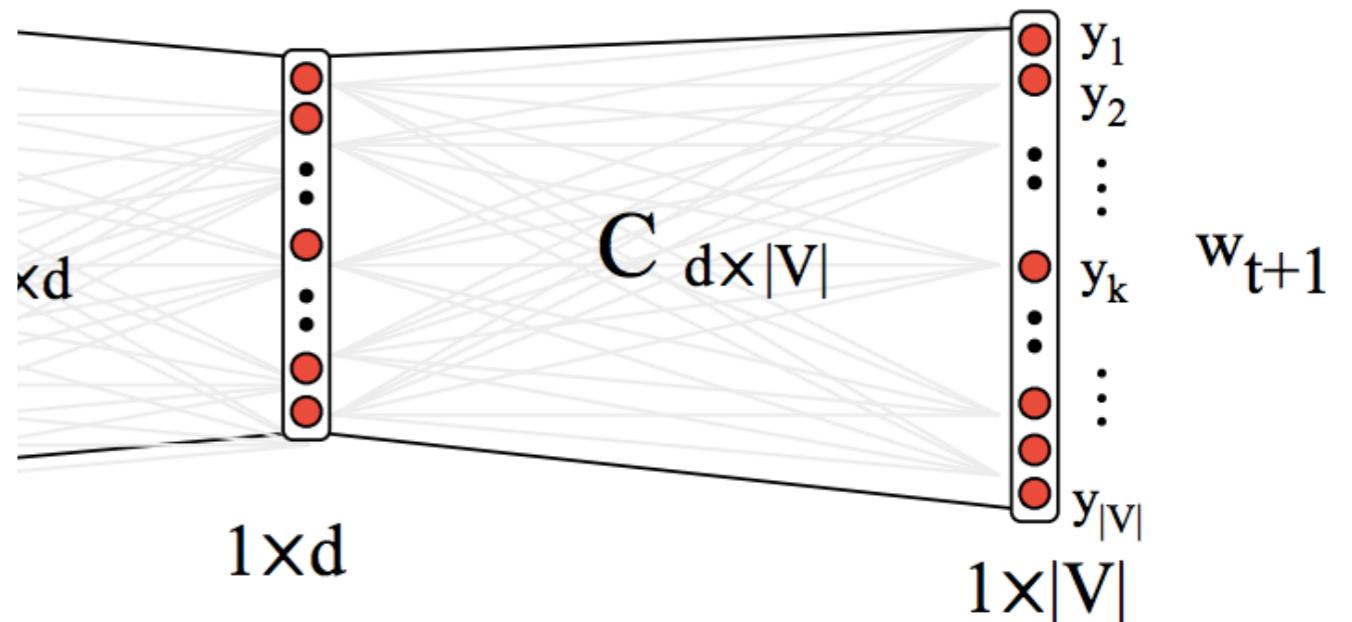
Output Layer

- Objective function: maximize the log probability of any “outside” (context) word given the “center” word

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{-m \leq j \leq m, j \neq 0} \log p(w_{t+j} | w_t)$$

Projection layer
embedding for w_t

Output layer
probabilities of
context words

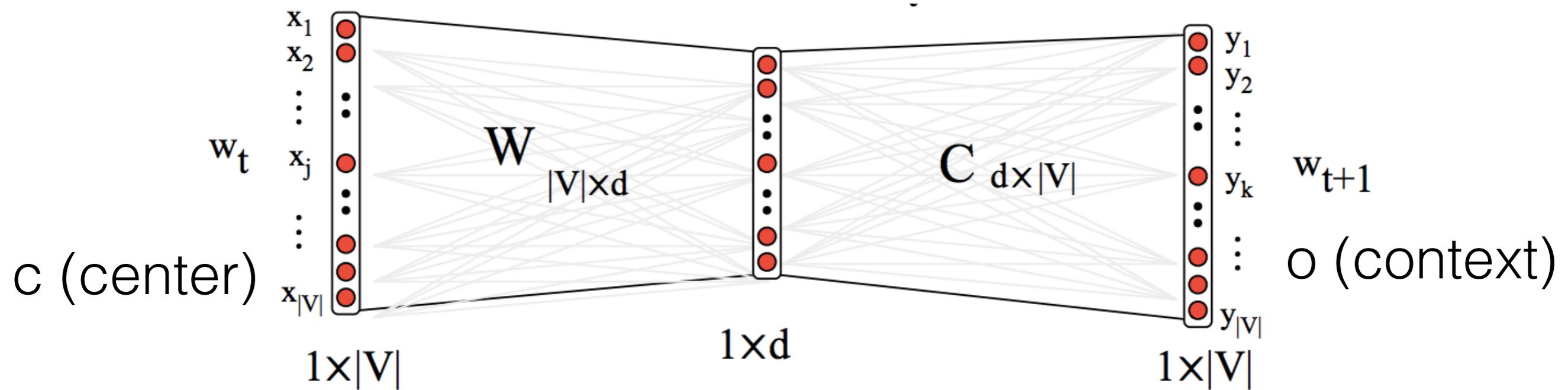


Output Layer

- predicts surrounding “outside” (context) words given the “center” word

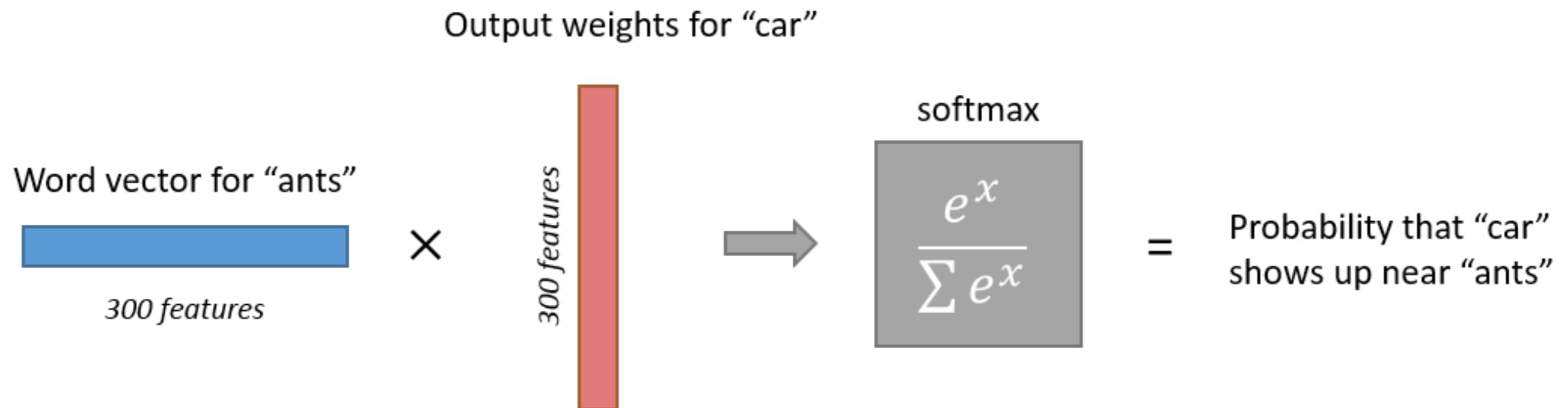
$$p(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w=1}^W \exp(u_w^T v_c)}$$

- so, every word has two vectors!



Output Layer

- Intuition



Objective Function

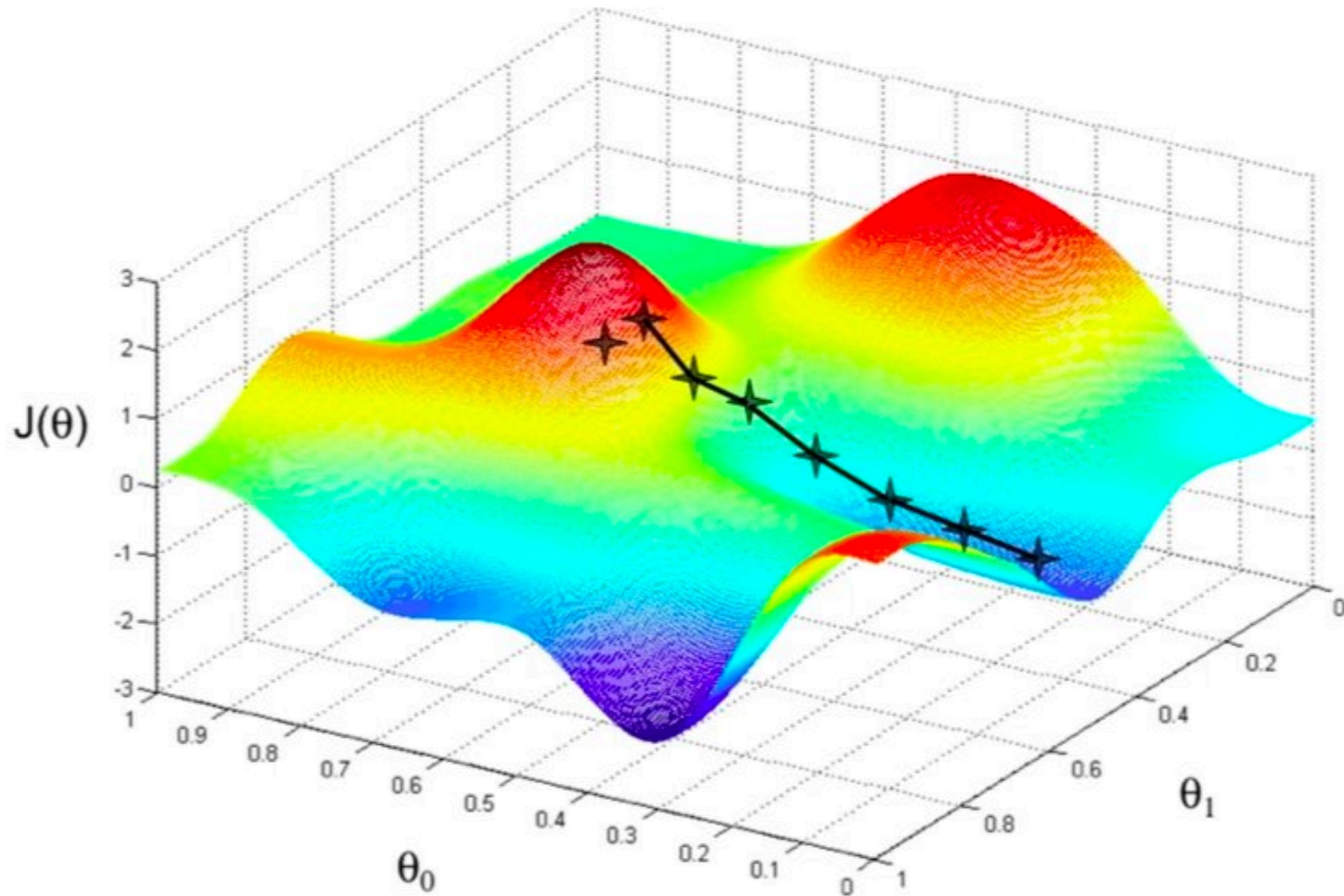
- Cost/Objective function:

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{-m \leq j \leq m, j \neq 0} \log p(w_{t+j} | w_t)$$

- For a “center” word and an “outside” word:

$$\log p(o|c) = \log \frac{\exp(u_o^T v_c)}{\sum_{w=1}^W \exp(u_w^T v_c)}$$

Gradient Descent



Gradient Descent

- Basics:

$$\frac{\partial \mathbf{x}^T \mathbf{a}}{\partial \mathbf{x}} = \frac{\partial \mathbf{a}^T \mathbf{x}}{\partial \mathbf{x}} = \mathbf{a}$$

$$\frac{\partial e^x}{\partial x} = e^x \qquad \qquad \frac{\partial \log x}{\partial x} = \frac{1}{x}$$

- Chain Rule:

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g} \frac{\partial g}{\partial x} = \frac{\partial f(g)}{\partial g} \frac{\partial g(x)}{\partial x}$$

Word2vec

- Word2vec is not a single algorithm, but a toolkit
 - which contains two distinct algorithms (Skip-gram & CBOW), two training methods (negative sampling & hierarchical softmax)
- Word2vec is not deep learning, but neural-inspired
 - only one hidden layer followed by softmax, no non-linear activation function

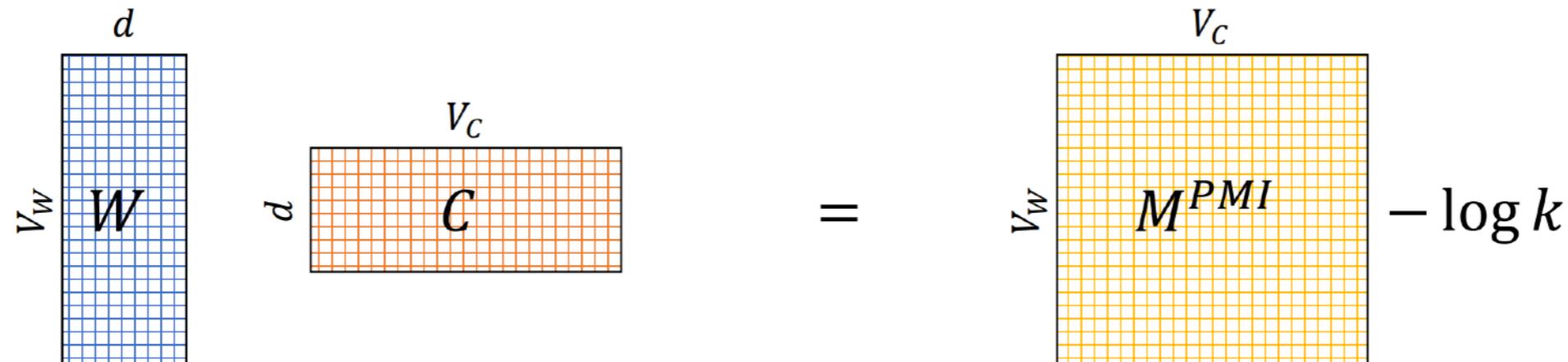
Learn more: Omer Levy's answer on Quora

<https://www.quora.com/How-does-word2vec-work-Can-someone-walk-through-a-specific-example>

Relation between Skip-gram and SVD

- Levy and Goldberg (2014) show that skip-gram is factorizing (a shifted version of) the traditional word-context PMI matrix:

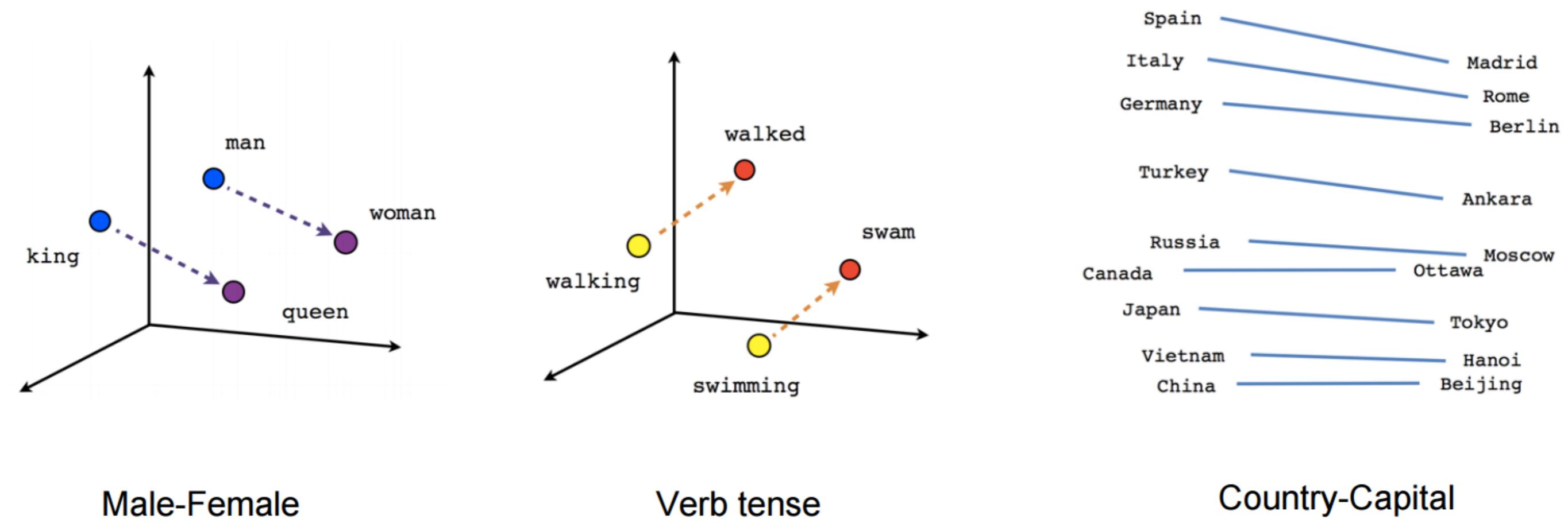
$$Opt(\vec{w} \cdot \vec{c}) = PMI(w, c) - \log k$$



- So does SVD!

Source: Omer Levy and Yoav Goldberg (NIPS 2014)
Neural Word Embedding as Implicit Matrix Factorization

Visualization



Visualization

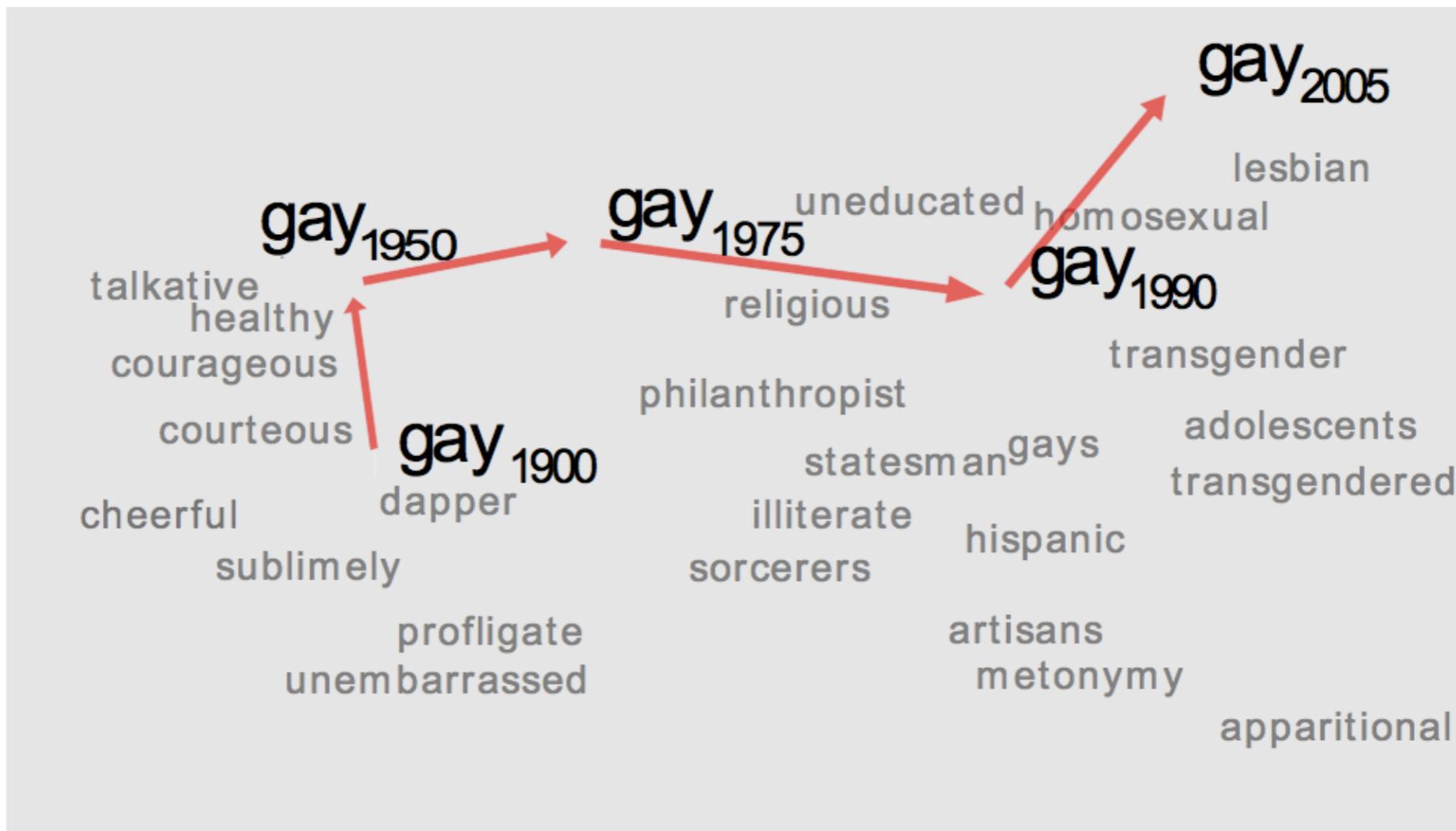


Figure 1: A 2-dimensional projection of the latent semantic space captured by our algorithm. Notice the semantic trajectory of the word **gay** transitioning meaning in the space.

Source: Kulkarni et al. (WWW 2015)
Statistically Significant Detection of Linguistic Change