Distributional Similarity / Semantics

CS 585, Fall 2016

Introduction to Natural Language Processing

http://people.cs.umass.edu/~brenocon/inlp2016/

Brendan O'Connor

College of Information and Computer Sciences

University of Massachusetts Amherst

[Slides borrowed from Dan Jurafsky and David Belanger]

Why vector models of meaning? computing the similarity between words

“**fast**” is similar to “**rapid**”

“**tall**” is similar to “**height**”

Question answering:

*Q: “How **tall** is Mt. Everest?”*

*Candidate A: “The official **height** of Mount Everest is 29029 feet”*

Word similarity for plagiarism detection

MAINFRAMES

Mainframes are primarily referred to large computers with rapid, advanced processing capabilities that can execute and perform tasks equivalent to many Personal Computers (PCs) machines networked together. It is characterized with high quantity Random Access Memory (RAM), very large secondary storage devices, and high-speed processors to cater for the needs of the computers under its service.

Consisting of advanced components, mainframes have the capability of running multiple large applications required by many and most enterprises and organizations. This is one of its advantages. Mainframes are also suitable to cater for those applications (programs) or files that are of very high

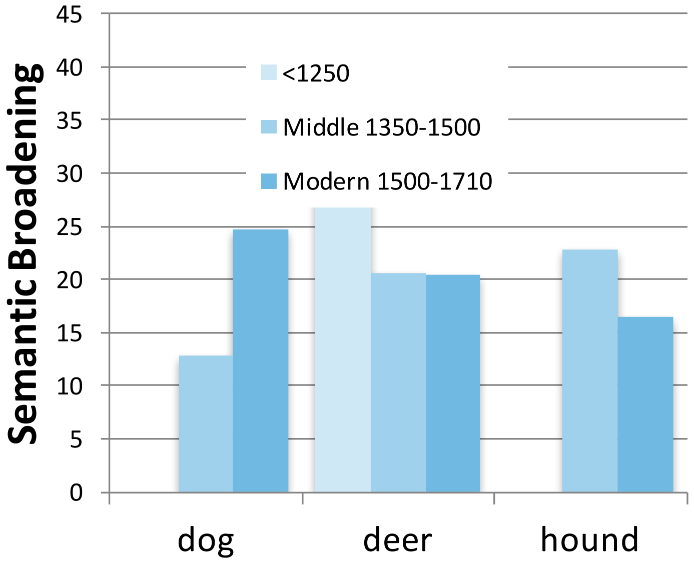
MAINFRAMES

Mainframes usually are referred those computers with fast, advanced processing capabilities that could perform by itself tasks that may require a lot of Personal Computers (PC) Machines. Usually mainframes would have lots of RAMs, very large secondary storage devices, and very fast processors to cater for the needs of those computers under its service.

Due to the advanced components mainframes have, these computers have the capability of running multiple large applications required by most enterprises, which is one of its advantage. Mainframes are also suitable to cater for those applications or files that are of very large demand

Word similarity for historical linguistics: semantic change over time

Sagi, Kaufmann Clark 2013



Kulkarni, Al-Rfou, Perozzi, Skiena 2015

Distributional models of meaning
= vector-space models of meaning
= vector semantics

Intuitions: Zellig Harris (1954):

- “oculist and eye-doctor … occur in almost the same environments”
- “If A and B have almost identical environments we say that they are synonyms.”

Distributional models of meaning
= vector-space models of meaning
= vector semantics

Intuitions: Zellig Harris (1954):

- “oculist and eye-doctor … occur in almost the same environments”
- “If A and B have almost identical environments we say that they are synonyms.”

Firth (1957):

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

Intuition of distributional word similarity

- Nida example:

```
A bottle of tesgüino is on the table
Everybody likes tesgüino
Tesgüino makes you drunk
We make tesgüino out of corn.
```

- From context words humans can guess **tesgüino** means...

Intuition of distributional word similarity

- Nida example:

```
A bottle of tesgüino is on the table
Everybody likes tesgüino
Tesgüino makes you drunk
We make tesgüino out of corn.
```

- From context words humans can guess **tesgüino** means…
- an alcoholic beverage like **beer**
- Intuition for algorithm:
  - Two words are similar if they have similar word contexts.

Question:

What do ‘art’ and ‘pharmaceuticals’ have in common?

What are contexts that they would both have?

What are contexts that they wouldn’t share?

Comparing Context Vectors

common contexts for "art" but not "pharmaceuticals" [7394 total]	common contexts for both "art" and "pharmaceuticals" [165 total]	common contexts for "pharmaceuticals" but not "art" [206 total]
'm into _	areas such as _	a greater amount of _
's interested in _	prices of _	standards for _
A collection of _	storage of _	marketer of _
_ has been described by	producers of _	market for _
structure of _	_ designed for	prescriptions for _
study in _	the provision of _	the supply of _
_ have been shown in	_ sold in	the availability of _
The knowledge of _	the same way as _	advertising for _
_ is a commodity	_ are among	the appropriate use of _
_ is a creation	The production of _	shipment of _
_ is a world	the analysis of _	a cocktail of _
an exhibition of _	advances in _	classes of _
the commercialization of _	specialising in _	a complete inventory of _
the confinement of _	a career in _	_ related downloads
_ is cast in	_ stolen from	new generations of _

Four kinds of vector models

Sparse vector representations

1. Mutual-information weighted word co-occurrence matrices

Dense vector representations:

2. Singular value decomposition (and Latent Semantic Analysis)
3. Neural-network-inspired models (skip-grams, CBOW)
4. Brown clusters

Shared intuition

Shared intuition

- Model the meaning of a word by “embedding” in a vector space.

Shared intuition

- Model the meaning of a word by "embedding" in a vector space.
- The meaning of a word is a vector of numbers
  - Vector models are also called "**embeddings**".

Shared intuition

- Model the meaning of a word by "embedding" in a vector space.
- The meaning of a word is a vector of numbers
  - Vector models are also called "**embeddings**".
- Contrast: word meaning is represented in many computational linguistic applications by a vocabulary index ("word number 545")

Shared intuition

- Model the meaning of a word by "embedding" in a vector space.
- The meaning of a word is a vector of numbers
    - Vector models are also called "**embeddings**".
- Contrast: word meaning is represented in many computational linguistic applications by a vocabulary index ("word number 545")
- Old philosophy joke:

  Q: What's the meaning of life?

  A: LIFE'

Term-document matrix

- Each cell: count of term *t* in a document *d*: $\mathrm{tf}_{t,d}$:
  - Each document is a count vector in $\mathbb{N}^{v}$: a column below

	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

Term-document matrix

- Two documents are similar if their vectors are similar

	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

Term-document matrix

- Two documents are similar if their vectors are similar

	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

Term-document matrix

- Two documents are similar if their vectors are similar

	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

The words in a term-document matrix

- Each word is a count vector in $\mathbb{N}^D$: a row below

	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

The words in a term-document matrix

- Each word is a count vector in $\mathbb{N}^D$: a row below

	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

The words in a term-document matrix

- Two **words** are similar if their vectors are similar

	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

The words in a term-document matrix

- Two **words** are similar if their vectors are similar

	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

The words in a term-document matrix

- Two **words** are similar if their vectors are similar

	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

Term-context matrix for word similarity

- Two **words** are similar in meaning if their context vectors are similar

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	

Term-context matrix for word similarity

- Two **words** are similar in meaning if their context vectors are similar

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	

Term-context matrix for word similarity

- Two **words** are similar in meaning if their context vectors are similar

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	

Term-context matrix for word similarity

- Two **words** are similar in meaning if their context vectors are similar

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	

Term-context matrix for word similarity

- Two **words** are similar in meaning if their context vectors are similar

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	

The word-word or word-context matrix

- Instead of entire documents, use smaller contexts
  - Paragraph
  - Window of $\pm$ 4 words
- A word is now defined by a vector over counts of context words
- Instead of each vector being of length D
- Each vector is now of length |V|
- The word-word matrix is |V|x|V|

Word-Word matrix
Sample contexts ± 7 words

sugar, a sliced lemon, a tablespoonful of	**apricot**	preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first	**pineapple**	and another fruit whose taste she likened
well suited to programming on the digital	**computer**.	In finding the optimal R-stage policy from
for the purpose of gathering data and	**information**	necessary for the study authorized in the

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	
…	…						

Word-Word matrix
Sample contexts $\pm$ 7 words

sugar, a sliced lemon, a tablespoonful of	**apricot**	preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first	**pineapple**	and another fruit whose taste she likened
well suited to programming on the digital	**computer**.	In finding the optimal R-stage policy from
for the purpose of gathering data and	**information**	necessary for the study authorized in the

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	
…	…						

Word-Word matrix
Sample contexts ± 7 words

sugar, a sliced lemon, a tablespoonful of	**apricot**	preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first	**pineapple**	and another fruit whose taste she likened
well suited to programming on the digital	**computer**.	In finding the optimal R-stage policy from
for the purpose of gathering data and	**information**	necessary for the study authorized in the

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	
…	…						

Word-Word matrix
Sample contexts $\pm$ 7 words

sugar, a sliced lemon, a tablespoonful of	**apricot**	preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first	**pineapple**	and another fruit whose taste she likened
well suited to programming on the digital	**computer**.	In finding the optimal R-stage policy from
for the purpose of gathering data and	**information**	necessary for the study authorized in the

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	
…	…						

Word-Word matrix
Sample contexts ± 7 words

sugar, a sliced lemon, a tablespoonful of	**apricot**	preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first	**pineapple**	and another fruit whose taste she likened
well suited to programming on the digital	**computer**.	In finding the optimal R-stage policy from
for the purpose of gathering data and	**information**	necessary for the study authorized in the

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	
…	…						

Word-word matrix

- We showed only 4x6, but the real matrix is 50,000 x 50,000
  - So it's very **sparse**
    - Most values are 0.
  - That's OK, since there are lots of efficient algorithms for sparse matrices.
- The size of windows depends on your goals
  - The shorter the windows , the more **syntactic** the representation

    $\pm$ 1-3 very syntacticy
  - The longer the windows, the more **semantic** the representation

    $\pm$ 4-10 more semanticy

2 kinds of co-occurrence between 2 words

(Schütze and Pedersen, 1993)

- First-order co-occurrence (**syntagmatic association**):
  - They are typically nearby each other.
  - *wrote* is a first-order associate of *book* or *poem*.
- Second-order co-occurrence (**paradigmatic association**):
  - They have similar neighbors.
  - *wrote* is a second- order associate of words like *said* or *remarked*.

*which gets **syntactic** sim? which gets **topical** sim?*

Problem with raw counts

- Raw word frequency is not a great measure of association between words
  - It's very skewed
    - "the" and "of" are very frequent, but maybe not the most discriminative
- We'd rather have a measure that asks whether a context word is **particularly informative** about the target word.
  - Positive Pointwise Mutual Information (PPMI)

Pointwise Mutual Information

- **Pointwise mutual information:**

  Do events x and y co-occur more than if they were independent?

$$\text{PMI}(X, Y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

PMI between two words: (Church & Hanks 1989)

Do words x and y co-occur more than if they were independent?

$$\text{PMI}(word_1, word_2) = \log_2 \frac{P(word_1, word_2)}{P(word_1)P(word_2)}$$

Positive Pointwise Mutual Information

- PMI ranges from $-\infty$ to $+\infty$
- But the negative values are problematic
  - Things are co-occurring **less than** we expect by chance
  - Unreliable without enormous corpora
    - Imagine w1 and w2 whose probability is each 10^{-6}
    - Hard to be sure p(w1,w2) is significantly different than 10^{-12}
  - Plus it's not clear people are good at "unrelatedness"
- So we just replace negative PMI values by 0
- Positive PMI (PPMI) between word1 and word2:

$$\text{PPMI}(word_1, word_2) = \max\left(\log_2 \frac{P(word_1, word_2)}{P(word_1)P(word_2)}, 0\right)$$

Measuring similarity

- Given 2 target words *v* and *w*
- We'll need a way to measure their similarity.
- Most measure of vectors similarity are based on the:
- **Dot product** or **inner product** from linear algebra

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

  - High when two vectors have large values in same dimensions.
  - Low (in fact 0) for **orthogonal vectors** with zeros in complementary distribution

31

Solution: cosine

- Just divide the dot product by the length of the two vectors!

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|}$$

- This turns out to be the cosine of the angle between them!

$$\begin{aligned} \vec{a} \cdot \vec{b} &= |\vec{a}||\vec{b}| \cos\theta \\ \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} &= \cos\theta \end{aligned}$$

Cosine

Dot product

Unit vectors

$$\cos(\vec{v},\vec{w}) = \frac{\vec{v}\bullet\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\vec{v}}{|\vec{v}|}\bullet\frac{\vec{w}}{|\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

v_i is the PPMI value for word *v* in context *i*
w_i is the PPMI value for word *w* in context *i*.

Cos($\vec{v},\vec{w}$) is the cosine similarity of $\vec{v}$ and $\vec{w}$

$$\cos(\vec{v},\vec{w}) = \frac{\vec{v} \bullet \vec{w}}{|\vec{v}||\vec{w}|} = \frac{\vec{v}}{|\vec{v}|} \bullet \frac{\vec{w}}{|\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2} \sqrt{\sum_{i=1}^{N} w_i^2}}$$

	large	data	computer
apricot	2	0	0
digital	0	1	2
information	1	6	1

Which pair of words is more similar?

cosine(apricot,information) = $\frac{2+0+0}{\sqrt{2+0+0}\sqrt{1+36+1}} = \frac{2}{\sqrt{2}\sqrt{38}} = .23$

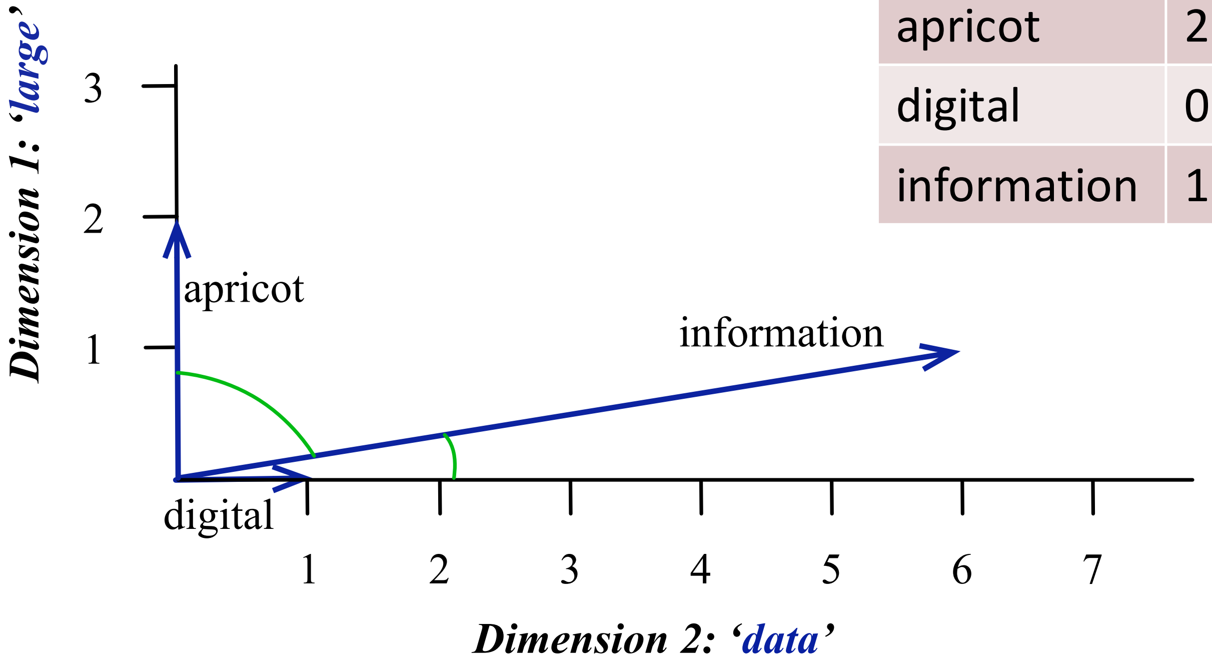
cosine(digital,information) = $\frac{0+6+2}{\sqrt{0+1+4}\sqrt{1+36+1}} = \frac{8}{\sqrt{38}\sqrt{5}} = .58$

cosine(apricot,digital) = $\frac{0+0+0}{\sqrt{1+0+0}\sqrt{0+1+4}} = 0$

36

Visualization

	large	data
apricot	2	0
digital	0	1
information	1	6



7

WORD EMBEDDINGS

Word Embeddings

Sparse Context Vector (10 million+ dimensional):

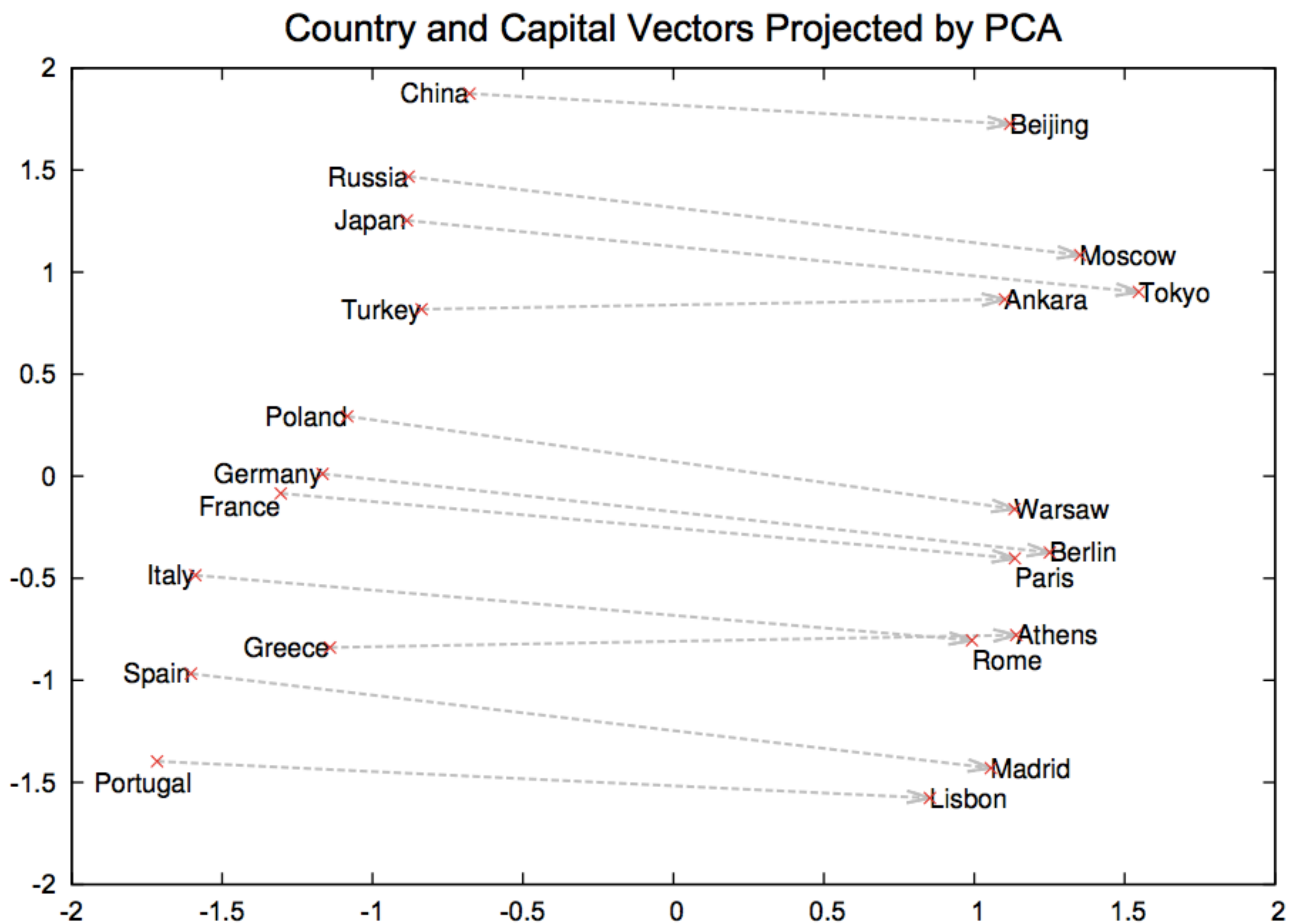
$$V_i = [0, 1, 0, 0, 0, 4, 0, 0, 0, 2, 0, 0, 1, \ldots]$$

[This can be directly used, but maybe too slow, sparse]

Instead represent every word type as a low-dimensional dense vector (about 100 dimensional).

$$E_i = [.253, 458, 4.56, 78.5, 120, \ldots]$$

These don't come directly from the data. They need to be learned.



Country and Capital Vectors Projected by PCA
China
Beijing
Russia
Japan
Moscow
Tokyo
Turkey
Ankara
Poland
Germany
France
Warsaw
Berlin
Paris
Italy
Greece
Spain
Athens
Rome
Madrid
Portugal
Lisbon
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2

Nearest Neighbors

- deals --> checks approvals vents stickers cuts
- warned --> suggested speculated predicted stressed argued
- ability --> willingness inability eagerness disinclination desire
- dark --> comfy wild austere cold tinny
- possibility --> possiblity possibilty dangers notion likelihood

Nearest Neighbors

- deals --> checks approvals vents stickers cuts
- warned --> suggested speculated predicted stressed argued
- ability --> willingness inability eagerness disinclination desire
- dark --> comfy wild austere cold tinny
- possibility --> possiblity possibilty dangers notion likelihood

Question:

What are the pros and cons of representing word types with such small vectors?

Answer:

Pro:

It requires less annotated data to train an ML model on low dimensional features.

Con:

You can't capture all of the subtlety of language in 100 dimensions. (...can you?)

Learning Embeddings by Preserving Similarity

- Given long, sparse context cooccurrence vectors V_i and V_j

- Goal: Choose Embeddings E_i and E_j such that similarity is approximately preserved

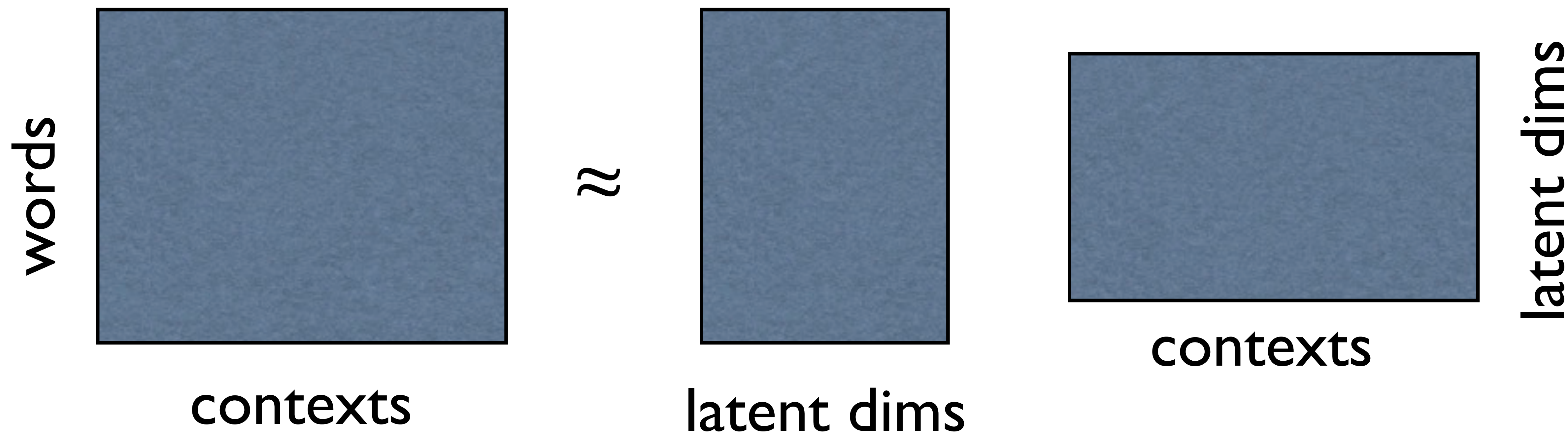
$$V_i^\top V_j \approx E_i^\top E_j$$

- Difficulty: need to do this for all words jointly.
- Solution: Use an eigen-decomposition (implemented in every language).

Matrix factorization

V ≈ E B

(counts) (embeddings)



Reconstruct the co-occurrence matrix

$$V_{i,c} \approx \sum_k E_{i,k} B_{k,c}$$

Singular Value Decomposition learns E,B
(or other matrix factorization techniques)

Preserve pairwise distances between words i, j

$$V_i^{\top} V_j \approx E_i^{\top} E_j$$

Eigen Decomposition learns E