http://poloclub.gatech.edu/cse6242
CSE6242: Data & Visual Analytics

Text Analytics (Text Mining)

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Text is everywhere

We use documents as primary information artifact in our lives

Our access to documents has grown tremendously thanks to the Internet

- *WWW:* webpages, Twitter, Facebook, Wikipedia, Blogs, ...
- *Digital libraries:* Google books, ACM, IEEE, ...
- Lyrics, closed caption... (youtube)
- Police case reports
- Legislation (law)
- Reviews (products, rotten tomatoes)
- Medical reports (EHR - electronic health records)
- Job descriptions

Big (Research) Questions

... in understanding and gathering information from text and document collections

- establish authorship, authenticity; plagiarism detection
- classification of genres for narratives (e.g., books, articles)
- tone classification; sentiment analysis (online reviews, twitter, social media)
- code: syntax analysis (e.g., find common bugs from students' answers)

Popular **Natural Language Processing** (NLP) libraries

- **Stanford NLP**
- **OpenNLP**
- **NLTK** (python)

tokenization, sentence segmentation, part-of-speech tagging, named entity extraction, chunking, parsing

Image source: https://stanfordnlp.github.io/CoreNLP/

Outline

- **Preprocessing** (e.g., stemming, remove stop words)
- **Document representation** (most common: bag-of-words model)
- **Word importance** (e.g., word count, TF-IDF)
- **Latent Semantic Indexing** (find “concepts” among documents and words), which helps with **retrieval**

To learn more:
CS 4650/7650 Natural Language Processing

Stemming

Reduce words to their **stems** (or base forms)

Words: compute, computing, computer, ...

Stem: comput

Several classes of algorithms to do this:

- Stripping suffixes, lookup-based, etc.

http://en.wikipedia.org/wiki/Stemming
Stop words: http://en.wikipedia.org/wiki/Stop_words

Bag-of-words model

Represent each **document** as a **bag of words**, ignoring words' ordering. Why? For **simplicity**.

Unstructured text becomes **a vector of numbers**

e.g., docs: "I like visualization", "I like data".

1 : "I"

2 : "like"

3 : "data"

4 : "visualization"

"I like visualization" ➞ [1, 1, 0, 1]

"I like data" ➞ [1, 1, 1, 0]

TF-IDF

A word's importance score in a **document**, among **N documents**

When to use it? Everywhere you use "word count", you can likely use TF-IDF.

TF: **term** frequency
= #appearance a **document**
(high, if terms appear many times in this document)

IDF: inverse document frequency
= log(**N** / #document containing that **term**)
(penalize "common" words appearing in almost any documents)

Final score = TF * IDF
(higher score ➞ more "characteristic")

Example: http://en.wikipedia.org/wiki/Tf–idf#Example_of_tf.E2.80.93idf

Vector Space Model

Why?

Each document → vector
Each query → vector

Search for documents → find “similar” vectors
Cluster documents → cluster “similar” vectors

Latent Semantic Indexing (LSI)

Main idea

- map each **document** into some **‘concepts’**
- map each **term** into some **‘concepts’**

‘Concept’ : ~ a set of terms, with weights.

For example, DBMS_concept:
“data” (0.8),
“system” (0.5),
“retrieval” (0.6)

Latent Semantic Indexing (LSI)

~ pictorially (before) ~

document-**term** matrix

	data	system	retireval	lung	ear
doc1	1	1	1		
doc2	1	1	1		
doc3				1	1
doc4				1	1

Latent Semantic Indexing (LSI)

~ pictorially (after) ~

term-concept matrix

	database concept	medical concept
data	1	
system	1	
retrieval	1	
lung		1
ear		1

… and

document-concept matrix

	database concept	medical concept
doc1	1	
doc2	1	
doc3		1
doc4		1

Latent Semantic Indexing (LSI)

Q: How to search, e.g., for "system"?

A: find the corresponding concept(s); and the corresponding documents

	database concept	medical concept
data	1	
system	1	
retrieval	1	
lung		1
ear		1

	database concept	medical concept
doc1	1	
doc2	1	
doc3		1
doc4		1

Latent Semantic Indexing (LSI)

Works like an **automatically constructed thesaurus**

We may retrieve documents that **DON’T** have the term “system”, but they contain almost everything else (“data”, “retrieval”)

LSI - Discussion

Great idea,

- to derive **‘concepts’** from documents
- to build a **‘thesaurus’** automatically
- to reduce dimensionality (down to few “concepts”)

How does LSI work?

Uses **Singular Value Decomposition** (SVD)

Singular Value Decomposition (SVD)

Motivation

Problem #1

Find “concepts” in matrices

Problem #2

Compression / dimensionality reduction

	bread	lettuce	tomatos	beef	chicken
vegetarians	1	1	1		
	2	2	2		
	1	1	1		
	5	5	5		
meat eaters				2	2
				3	3
				1	1

SVD is a **powerful**, **generalizable** technique.

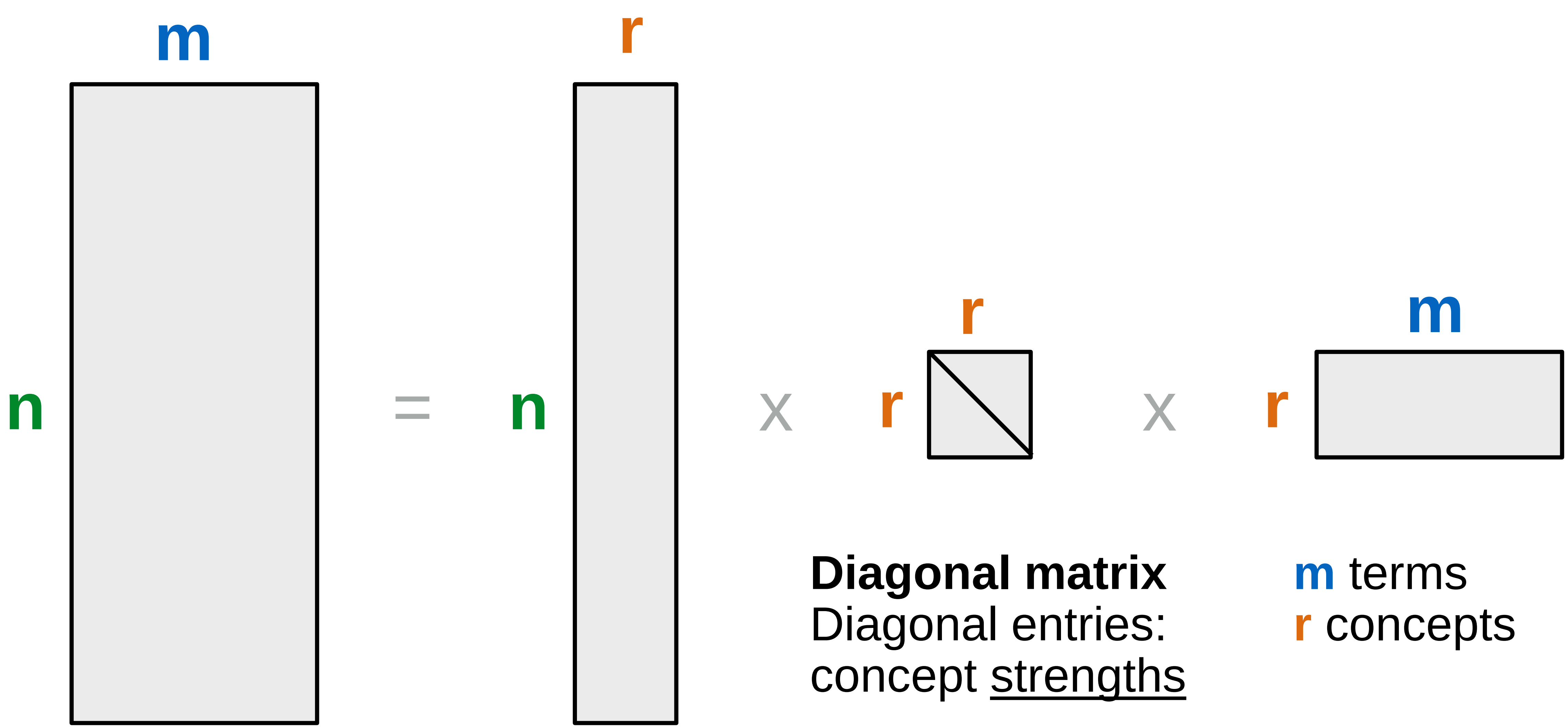
Songs / Movies / Products

Customers

1	1	1		
2	2	2		
1	1	1		
5	5	5		
			2	2
			3	3
			1	1

SVD Definition (pictorially)

$$\mathbf{A}_{[n \times m]} = \mathbf{U}_{[n \times r]} \, \Lambda_{[r \times r]} \, (\mathbf{V}_{[m \times r]})^T$$



n documents
m terms

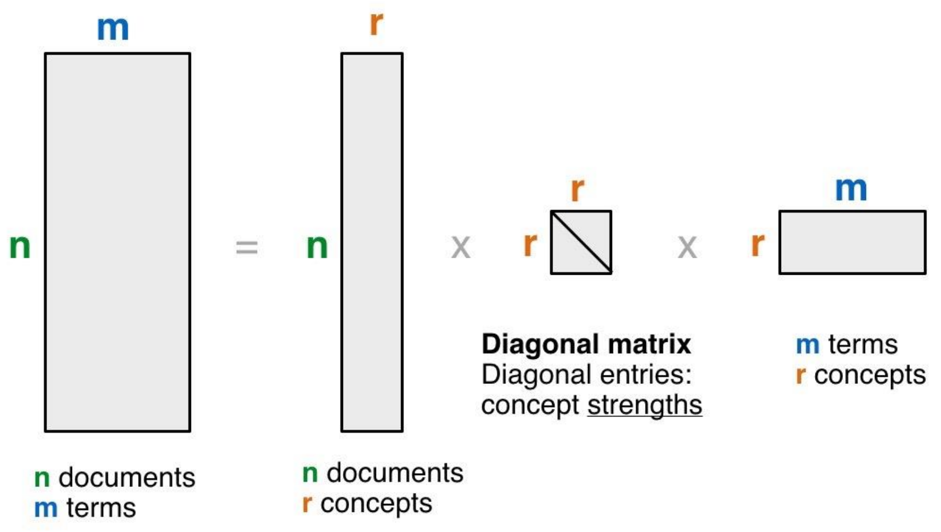
n documents
r concepts

Diagonal matrix
Diagonal entries:
concept <u>strengths</u>

m terms
r concepts

SVD Definition (in words)

$$\boxed{\mathbf{A}_{[n \times m]} = \mathbf{U}_{[n \times r]}\, \Lambda_{[r \times r]}\, (\mathbf{V}_{[m \times r]})^T}$$



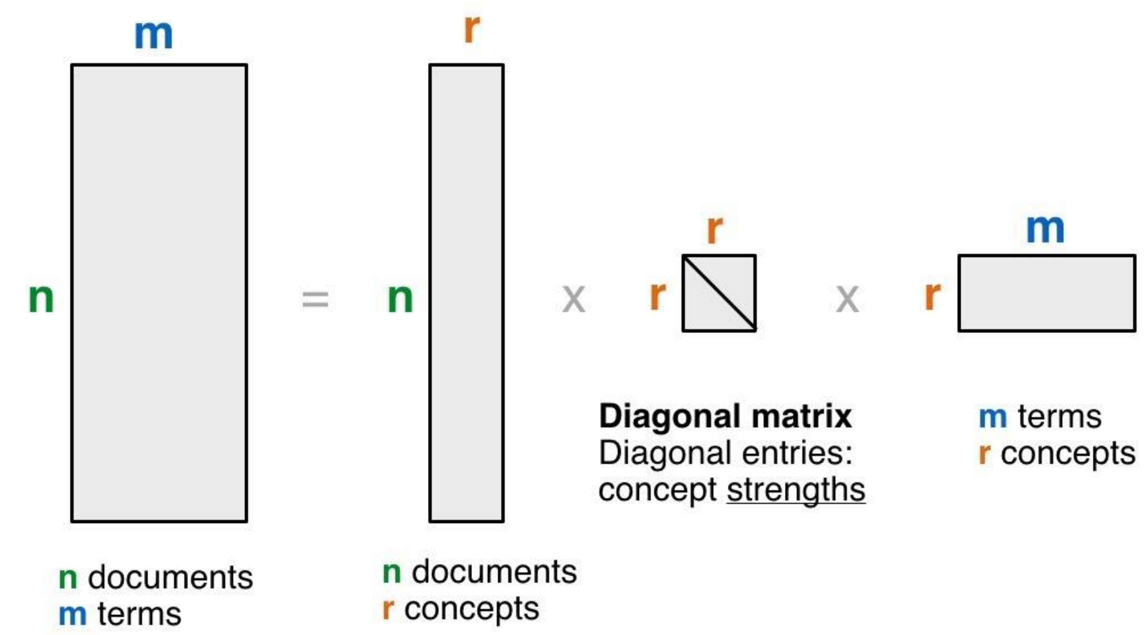
A: n x m matrix
e.g., n documents, m terms

U: n x r matrix
e.g., n documents, r concepts

Λ: r x r diagonal matrix
r : rank of the matrix; strength of each ‘concept’

V: m x r matrix
e.g., m terms, r concepts

SVD - Properties



THEOREM [Press+92]:

always possible to decompose matrix **A** into

$\mathbf{A} = \mathbf{U}\ \Lambda\ \mathbf{V}^T$

U, Λ, **V**: **unique**, most of the time

U, **V**: column **orthonormal**

i.e., columns are unit vectors, and orthogonal to each other

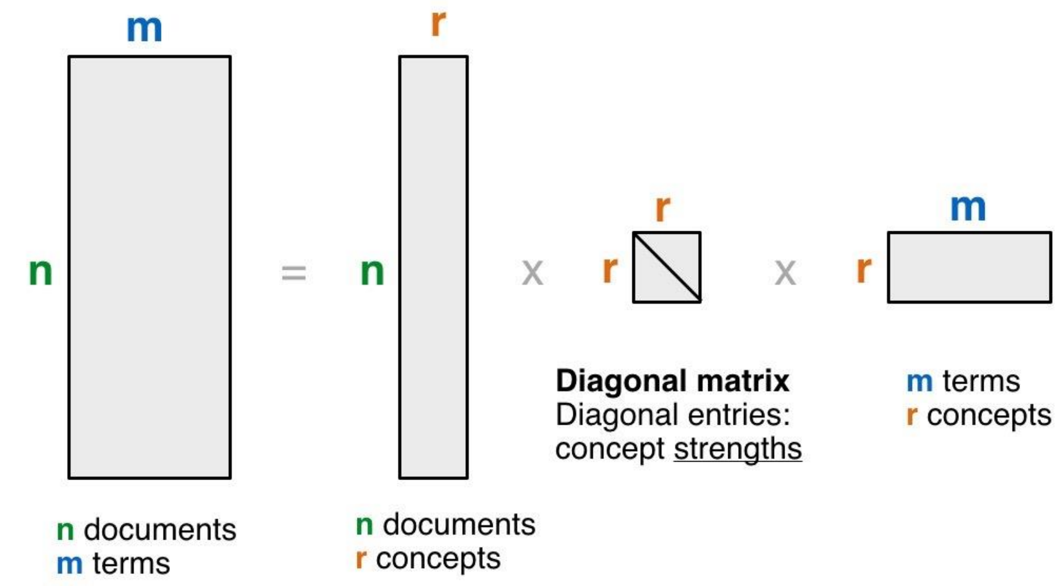
$\mathbf{U}^T\ \mathbf{U} = \mathbf{I}$

$\mathbf{V}^T\ \mathbf{V} = \mathbf{I}$ **(I:** identity matrix**)**

Λ**: diagonal** matrix with non-negative diagonal entires, sorted in decreasing order

SVD - Example

$$A = U \Lambda V^T$$



$$
\begin{array}{c|ccccc}
 & \text{data} & \text{info} & \text{retrieval} & \text{brain} & \text{lung} \\
\hline
\text{CS docs} & 1 & 1 & 1 & 0 & 0 \\
 & 2 & 2 & 2 & 0 & 0 \\
 & 1 & 1 & 1 & 0 & 0 \\
 & 5 & 5 & 5 & 0 & 0 \\
\text{MD docs} & 0 & 0 & 0 & 2 & 2 \\
 & 0 & 0 & 0 & 3 & 3 \\
 & 0 & 0 & 0 & 1 & 1
\end{array}
=
\begin{bmatrix}
0.18 & 0 \\
0.36 & 0 \\
0.18 & 0 \\
0.90 & 0 \\
0 & 0.53 \\
0 & 0.80 \\
0 & 0.27
\end{bmatrix}
\times
\begin{bmatrix}
9.64 & 0 \\
0 & 5.29
\end{bmatrix}
\times
\begin{bmatrix}
0.58 & 0.58 & 0.58 & 0 & 0 \\
0 & 0 & 0 & 0.71 & 0.71
\end{bmatrix}
$$

SVD - Example

	data	info	retrieval	brain	lung
CS docs	1	1	1	0	0
	2	2	2	0	0
	1	1	1	0	0
	5	5	5	0	0
MD docs	0	0	0	2	2
	0	0	0	3	3
	0	0	0	1	1

=

CS concept	MD concept
0.18	0
0.36	0
0.18	0
0.90	0
0	0.53
0	0.80
0	0.27

document-concept
similarity matrix

x

"strength" of CS-concept

9.64	0
0	5.29

x

	data	info	retrieval	brain	lung
CS concept	0.58	0.58	0.58	0	0
MD concept	0	0	0	0.71	0.71

term-concept
similarity matrix

SVD - Interpretation #1

‘documents’, ‘terms’ and ‘concepts’:

U: document-concept similarity matrix

V: term-concept similarity matrix

Λ: diagonal elements: concept “strengths”

SVD - Interpretation #1

'documents', 'terms' and 'concepts':

Q**:** if **A** is the document-to-term matrix, what is the similarity matrix $\mathbf{A}^T \mathbf{A}$?

A:

Q: $\mathbf{A} \mathbf{A}^T$?

A:

SVD - Interpretation #1

'documents', 'terms' and 'concepts':

Q**:** if **A** is the document-to-term matrix,
what is the similarity matrix $\mathbf{A}^T \mathbf{A}$?

A: term-to-term ([m x m]) similarity matrix

Q: $\mathbf{A}\,\mathbf{A}^T$?

A: document-to-document ([n x n]) similarity matrix

SVD properties

V are the eigenvectors of the *covariance matrix*
$\mathbf{A}^{\mathsf{T}}\mathbf{A}$ (term-to-term [m x m] similarity matrix)

$$\mathbf{A}^{\mathsf{T}}\mathbf{A} = \left(\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathsf{T}}\right)^{\mathsf{T}}\left(\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathsf{T}}\right) = \mathbf{V}\boldsymbol{\Sigma}^{2}\mathbf{V}^{\mathsf{T}}$$

U are the eigenvectors of the *Gram (inner-product) matrix*
$\mathbf{A}\mathbf{A}^{\mathsf{T}}$ (doc-to-doc [n x n] similarity matrix)

$$\mathbf{A}\mathbf{A}^{\mathsf{T}} = \left(\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathsf{T}}\right)\left(\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathsf{T}}\right)^{\mathsf{T}} = \mathbf{U}\boldsymbol{\Sigma}^{2}\mathbf{U}^{\mathsf{T}}$$

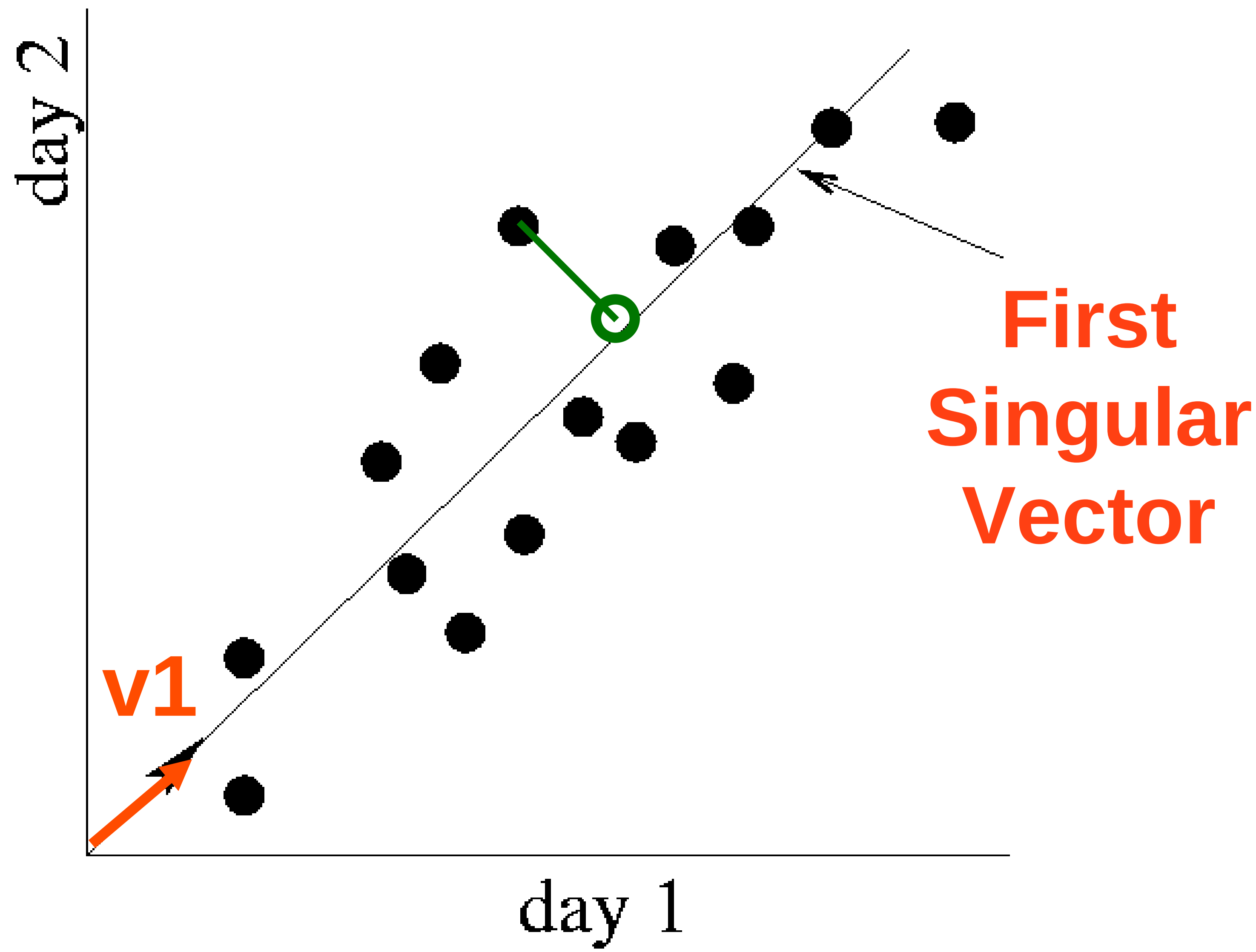
SVD is closely related to PCA, and can be numerically more stable.
For more info, see:

http://math.stackexchange.com/questions/3869/what-is-the-intuitive-relationship-between-svd-and-pca
Ian T. Jolliffe, Principal Component Analysis (2nd ed), Springer, 2002. Gilbert Strang, Linear Algebra and Its Applications (4th ed), Brooks Cole, 2005.

SVD - Interpretation #2

Find the best axis to project on.

("best" = minimize sum of squares of projection errors)

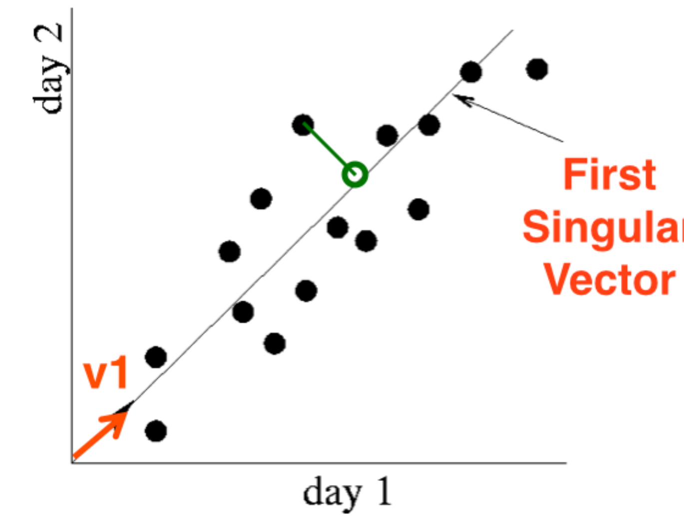


inimizes
MS error

Beautiful visualization explaining PCA:
http://setosa.io/ev/principal-component-analysis/

SVD - Interpretation #2

U Λ gives the **coordinates** of the points in the projection axis



variance ('spread') on the v1 axis

v1

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \times \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \times \begin{bmatrix} \boxed{0.58 \quad 0.58 \quad 0.58 \quad 0 \quad 0} \\ 0 \quad 0 \quad 0 \quad 0.71 \quad 0.71 \end{bmatrix}$$

$$\mathbf{A} = \mathbf{U} \quad \Lambda \quad \mathbf{V}^T$$

SVD - Interpretation #2

More details

Q: how exactly is dim. reduction done?

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \times \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \times \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

SVD - Interpretation #2

More details

Q: how exactly is dim. reduction done?

A: set the smallest singular values to zero:

$$
\begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
2 & 2 & 2 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 \\
0 & 0 & 0 & 3 & 3 \\
0 & 0 & 0 & 1 & 1
\end{bmatrix}
=
\begin{bmatrix}
0.18 & 0 \\
0.36 & 0 \\
0.18 & 0 \\
0.90 & 0 \\
0 & 0.53 \\
0 & 0.80 \\
0 & 0.27
\end{bmatrix}
\times
\begin{bmatrix}
9.64 & 0 \\
0 & \cancel{5.29}
\end{bmatrix}
\times
\begin{bmatrix}
0.58 & 0.58 & 0.58 & 0 & 0 \\
0 & 0 & 0 & 0.71 & 0.71
\end{bmatrix}
$$

SVD - Interpretation #2

More details

Q: how exactly is dim. reduction done?

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\begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
2 & 2 & 2 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 \\
0 & 0 & 0 & 3 & 3 \\
0 & 0 & 0 & 1 & 1
\end{bmatrix}
=
\begin{bmatrix}
0.18 & 0 \\
0.36 & 0 \\
0.18 & 0 \\
0.90 & 0 \\
0 & 0.53 \\
0 & 0.80 \\
0 & 0.27
\end{bmatrix}
\times
\begin{bmatrix}
9.64 & 0 \\
0 & 5.29
\end{bmatrix}
\times
\begin{bmatrix}
0.58 & 0.58 & 0.58 & 0 & 0 \\
0 & 0 & 0 & 0.71 & 0.71
\end{bmatrix}
$$

SVD - Interpretation #2

More details

Q: how exactly is dim. reduction done?

A: set the smallest singular values to zero:

$$
\begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
2 & 2 & 2 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 \\
0 & 0 & 0 & 3 & 3 \\
0 & 0 & 0 & 1 & 1
\end{bmatrix}
=
\begin{bmatrix}
0.18 & \\
0.36 & \\
0.18 & \\
0.90 & \\
0 & \\
0 & \\
0 &
\end{bmatrix}
\times
\begin{bmatrix}
9.64 & 0 \\
0 &
\end{bmatrix}
\times
\begin{bmatrix}
0.58 & 0.58 & 0.58 & 0 & 0 \\
 & & & &
\end{bmatrix}
$$

SVD - Interpretation #2

More details

Q: how exactly is dim. reduction done?

A: set the smallest singular values to zero:

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \sim \begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

SVD - Interpretation #3

finds non-zero 'blobs' in a data matrix

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \times \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \times \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

SVD - Interpretation #3

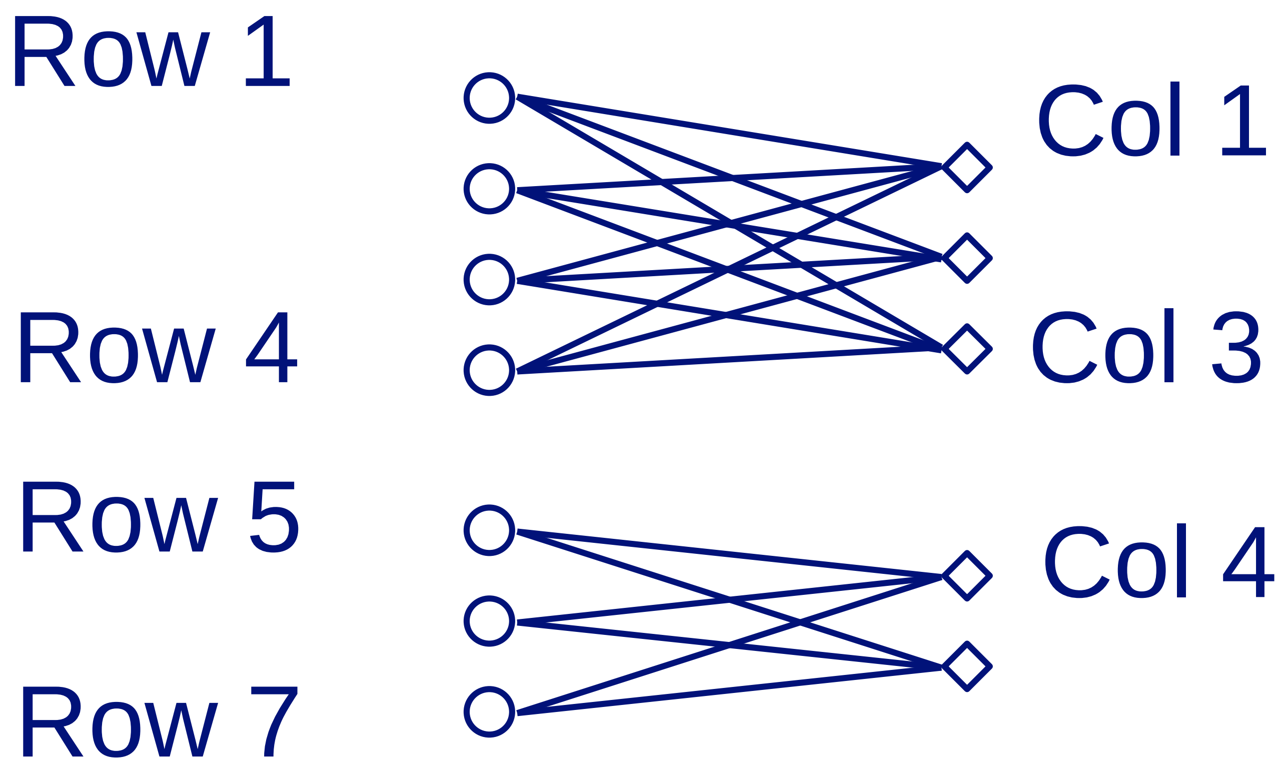
finds non-zero ‘blobs’ in a data matrix

$$\left[\begin{array}{ccc|cc} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ \hline 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{array}\right] = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \times \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \times \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

SVD - Interpretation #3

- finds non-zero ‘blobs’ in a data matrix =
- ‘communities’ (bi-partite cores, here)

$$\left[\begin{array}{ccc|cc} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ \hline 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{array}\right]$$



SVD - Complexity

O(n*m*m) or O(n*n*m) (whichever is less)

Faster version, if just want singular values

or if we want first *k* singular vectors

or if the matrix is sparse [Berry]

No need to write your own!

Available in most linear algebra packages (LINPACK, matlab, Splus/R, mathematica ...)

Case Study

How to do queries with LSI?

Case Study

How to do queries with LSI?

For example, how to find documents with ‘data’?

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \text{data} & \text{info} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \\
\begin{array}{c} \text{CS} \\ \text{docs} \\ \\ \\ \text{MD} \\ \text{docs} \\ \\ \end{array} &
\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix}
\end{array}
=
\begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix}
\text{x}
\begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix}
\text{x}
\begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}
$$

Case Study

How to do queries with LSI?

For example, how to find documents with ‘data’?
A: map query vectors into ‘concept space’ – how?

$$\begin{array}{cc} & \begin{array}{ccccc} \text{data} & \text{info} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \\ \begin{array}{c} \text{CS docs} \\ \\ \\ \\ \text{MD docs} \\ \\ \\ \end{array} & \begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \end{array} = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \times \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \times \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

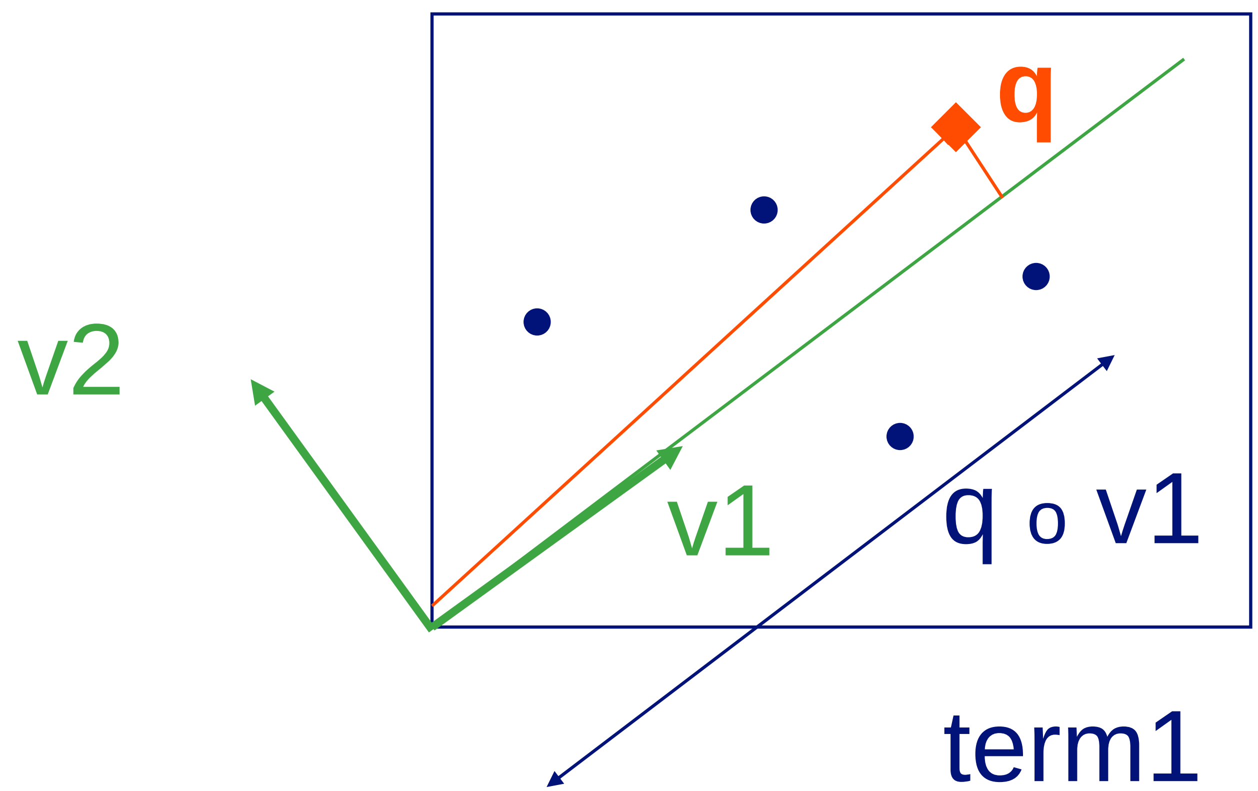
Case Study

How to do queries with LSI?

For example, how to find documents with ‘data’?
A: map query vectors into ‘concept space’, using **inner product** (cosine similarity) with each **‘concept’ vector v_i**

q =

data	info	retrieval	brain	lung
1	0	0	0	0



Case Study

How to do queries with LSI?

Compactly, we have:

$$\mathbf{q}\,\mathbf{V} = q_{concept}$$

$$\begin{array}{c}\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix} \\ \begin{array}{ccccc} \text{data} & \text{info} & \text{retrieval} & \text{brain} & \text{lung} \end{array}\end{array} \begin{bmatrix} 0.58 & 0 \\ 0.58 & 0 \\ 0.58 & 0 \\ 0 & 0.71 \\ 0 & 0.71 \end{bmatrix} = \begin{array}{c}\begin{bmatrix} 0.58 & 0 \end{bmatrix} \\ \text{CS concept}\end{array}$$

term-concept
similarity matrix

Case Study

How would the document (‘information’, ‘retrieval’) be handled?

Case Study

How would the document ('information', 'retrieval') be handled?

SAME!

$$\mathbf{d}\ \mathbf{V} = d_{concept}$$

$$\begin{array}{c} \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \end{bmatrix} \\ \begin{array}{ccccc} \text{data} & \text{info} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \end{array} \begin{bmatrix} 0.58 & 0 \\ 0.58 & 0 \\ 0.58 & 0 \\ 0 & 0.71 \\ 0 & 0.71 \end{bmatrix} = \begin{bmatrix} 1.16 & 0 \end{bmatrix}$$

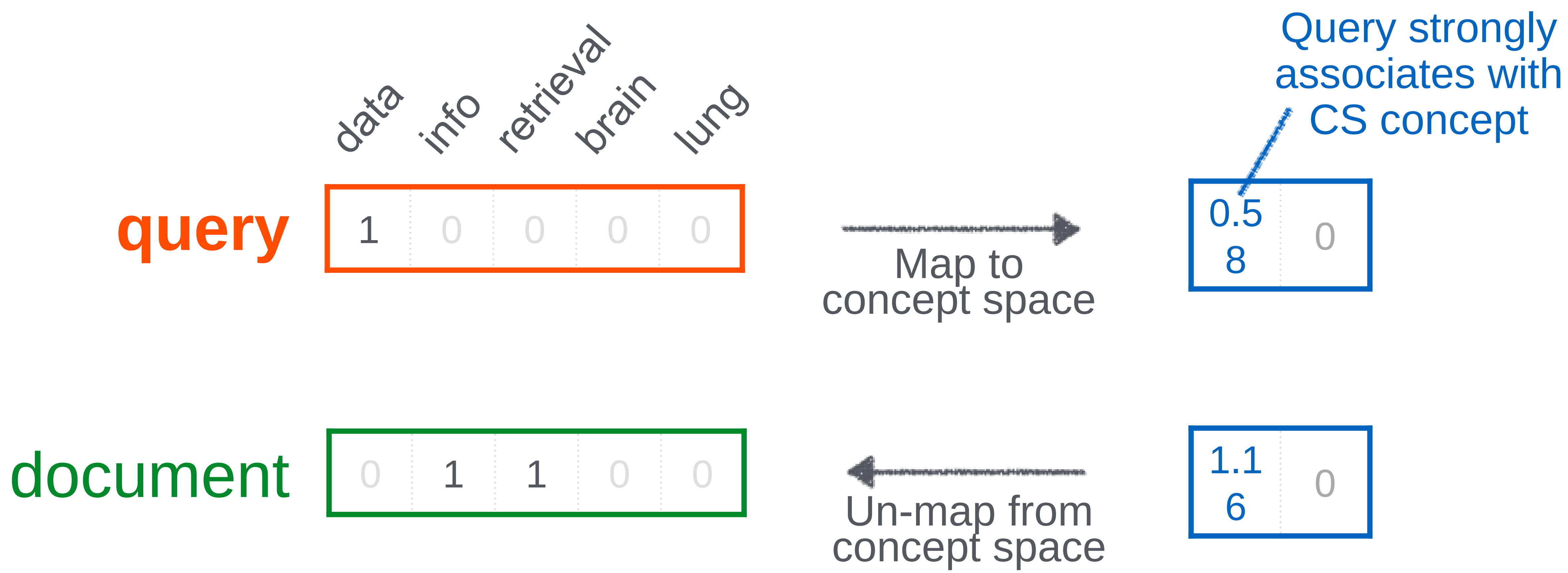
CS concept

term-concept
similarity matrix

Case Study

Observation

Document ('information', 'retrieval') will be retrieved by **query** ('data'), even though it does not contain 'data'!!



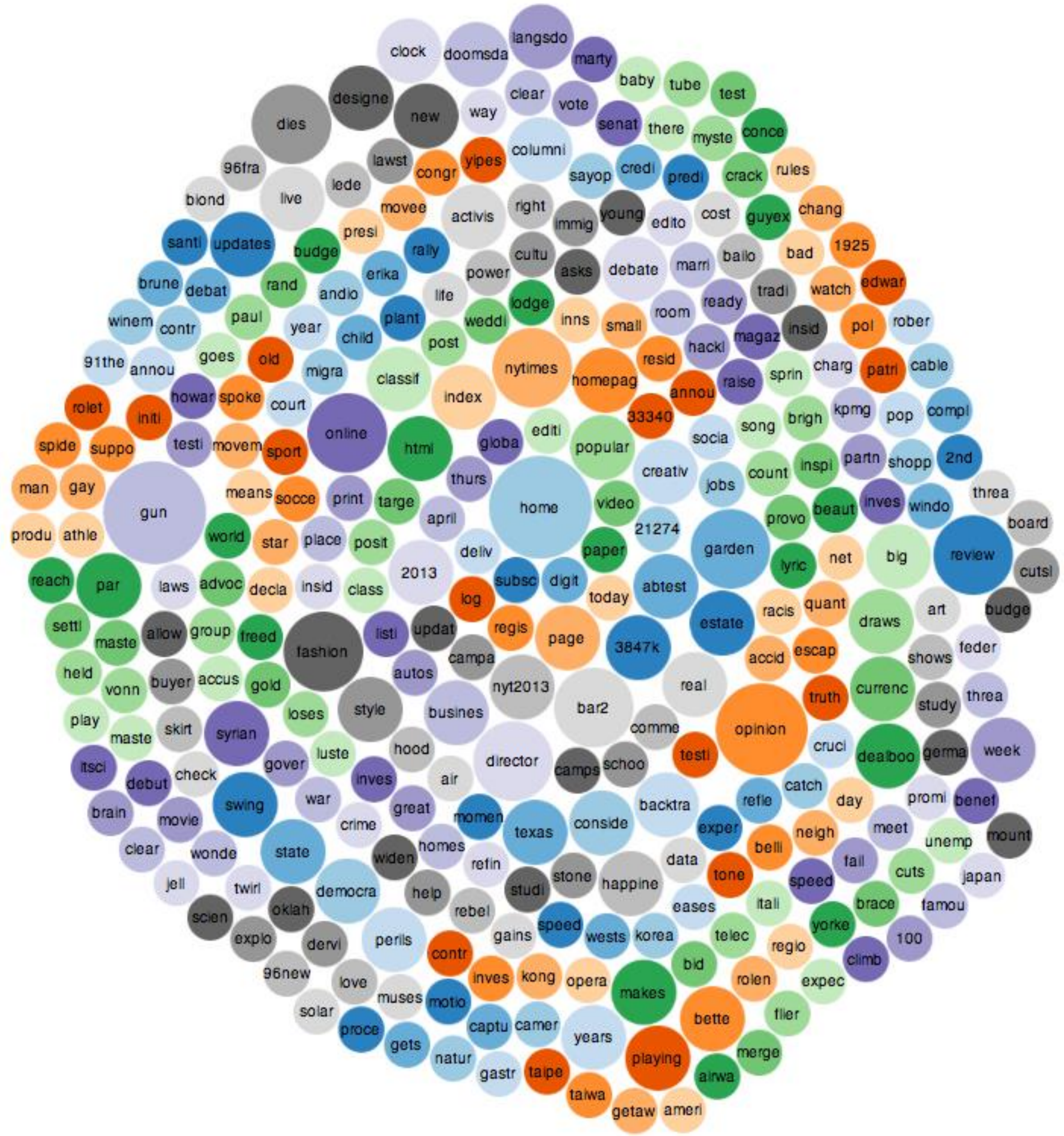
Switch Gear to

Text Visualization

Word/Tag Cloud (still popular?)

http://www.wordle.net

Word Counts (words as bubbles)



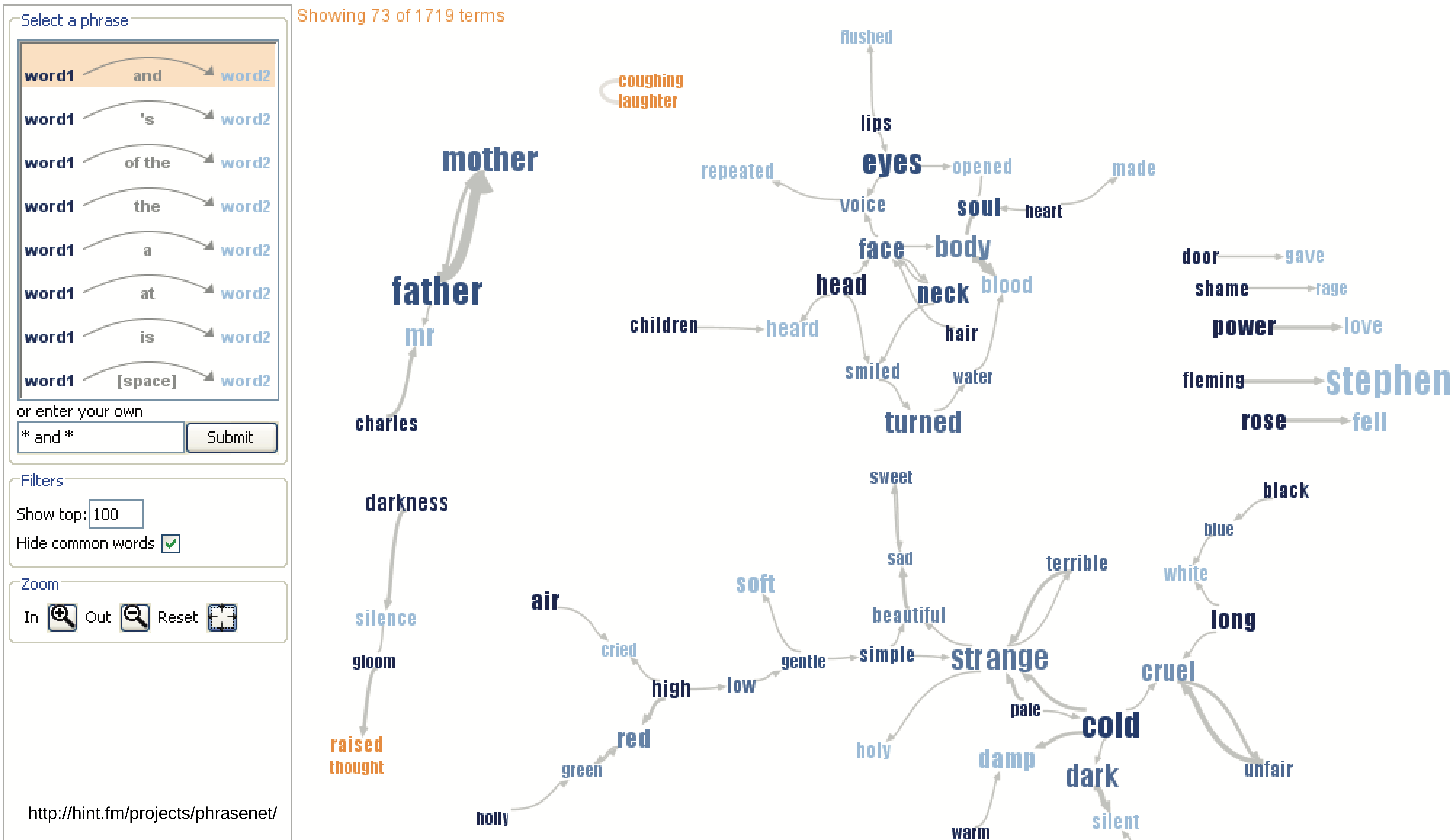
http://www.infocaptor.com/bubble-my-page

Word Tree

http://www.jasondavies.com/wordtree/

Phrase Net

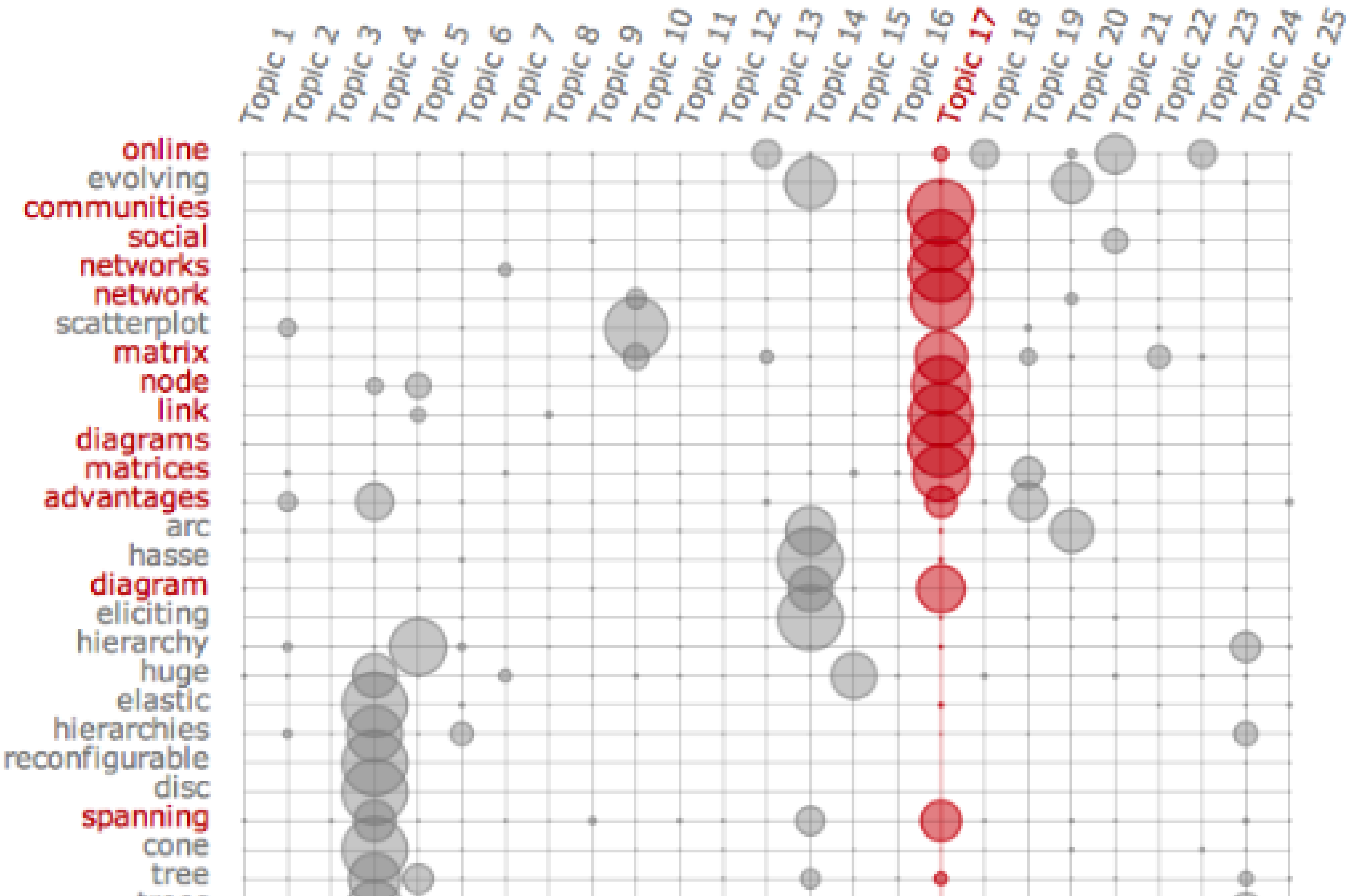
Visualize pairs of words satisfying a pattern ("X and Y")



http://hint.fm/projects/phrasenet/

Termite: Topic Model Visualization

http://vis.stanford.edu/papers/termite



Termite: Topic Model Visualization

http://vis.stanford.edu/papers/termite