Data Mining and Business Intelligence

Lecture 4: Parsing and Quantifying Text

Jing Peng
University of Connecticut

2/13/20

Natural Language Processing

Natural Language Processing

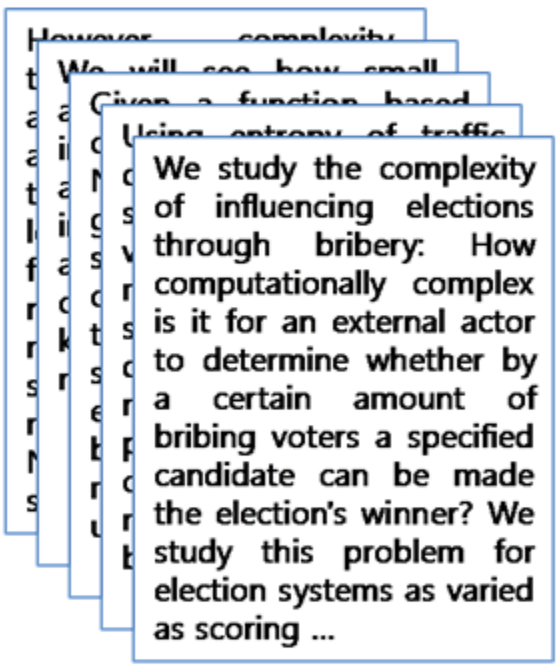
- Natural language processing (NLP) is
  - a field of computer science, artificial intelligence and computational linguistics
  - concerned with the interactions between computers and human (natural) languages

Natural Language vs. Computer Language

- Ambiguity is the primary different between natural and computer languages

Bag-of-Words Representation

Documents



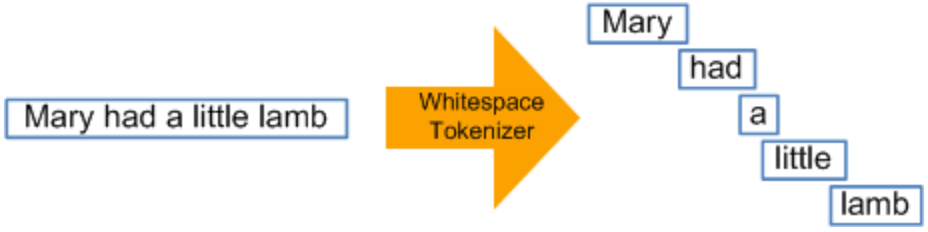
Vector-space representation

	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

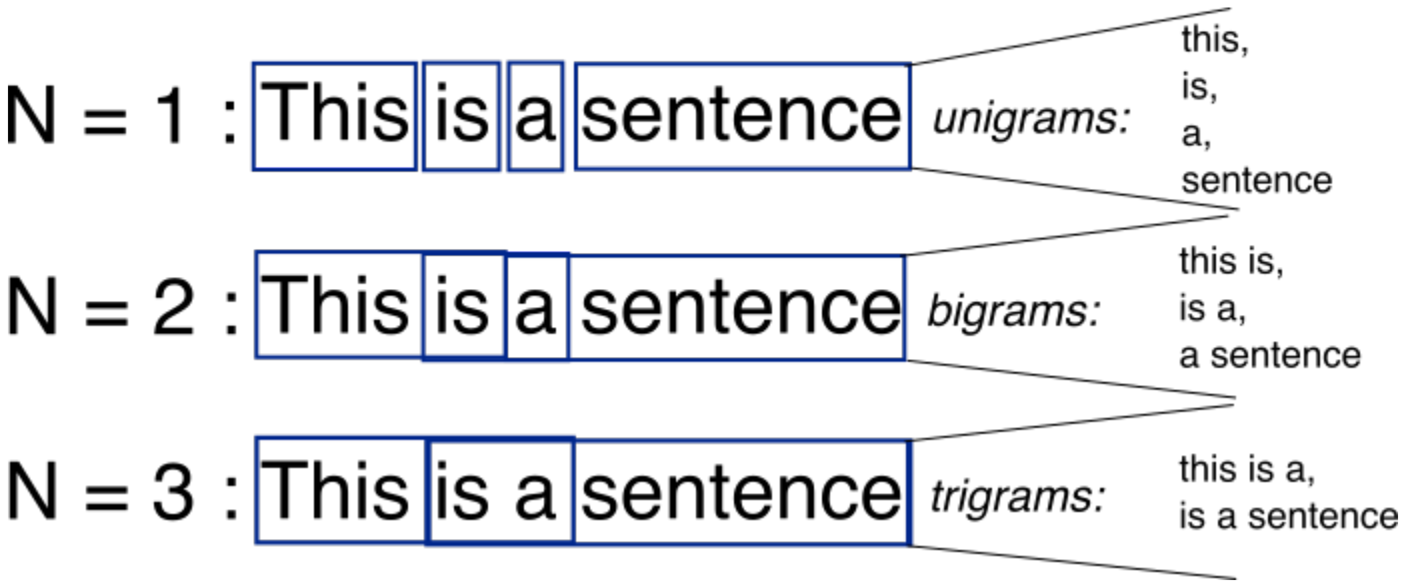
Term-document matrix

Tokenization

- Tokenization: breaking a stream of text up into words, phrases, symbols, or other meaningful elements called tokens
  - Name Entity: United Nation, United States of America, OPIM
  - Phrase: data mining, business analytics



Language Model: N-Gram



An **n-gram** is a contiguous sequence of **n** tokens

Part of Speech (POS) Tagging

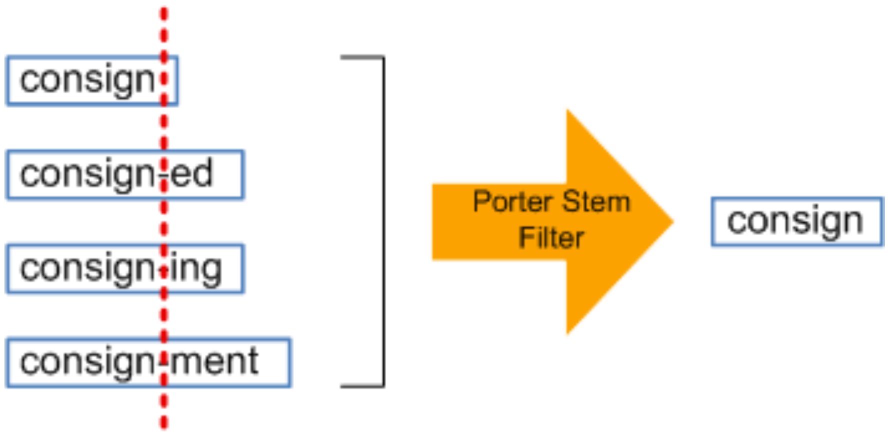
Text Mining is a lot of fun.

Word	Part of speech	Confidence
Text	Proper noun	0.52
Mining	Proper noun	0.98
is	Verb	0.99+
a	Determiner	0.99+
lot	Noun	0.99+
of	Adposition	0.99+
fun	Noun	0.99+
.	Punctuation	0.99+

by Amazon comprehend

Stemming and Lemmatization

- Stemming: reducing words to their base or root form (often rule-based)



- The objective of lemmatization is similar, but it is done in a more sophisticated way (uses context information)

Stemming and Lemmatization

```
> x = 'big bigger biggest bigly studies studying was is am'
> stem_strings(x)
[1] "big bigger biggest bigli studi studi wa i am"
> lemmatize_strings(x)
[1] "big big big bigly study study be be be"
```

Difference between Stemming and Lemmatization

Stemming	Lemmatization
Word Representation may not have any meaning	Word Representation has meaning
Takes Less Time	Takes More time than Stemming
Use stemming when the meaning of the word is not important for analysis. Example – Spam Detection	Use lemmatization when the meaning of the word is important for analysis. Example – Question Answering Application

source: https://hackernoon.com/nlp-core-4c16f379ced0

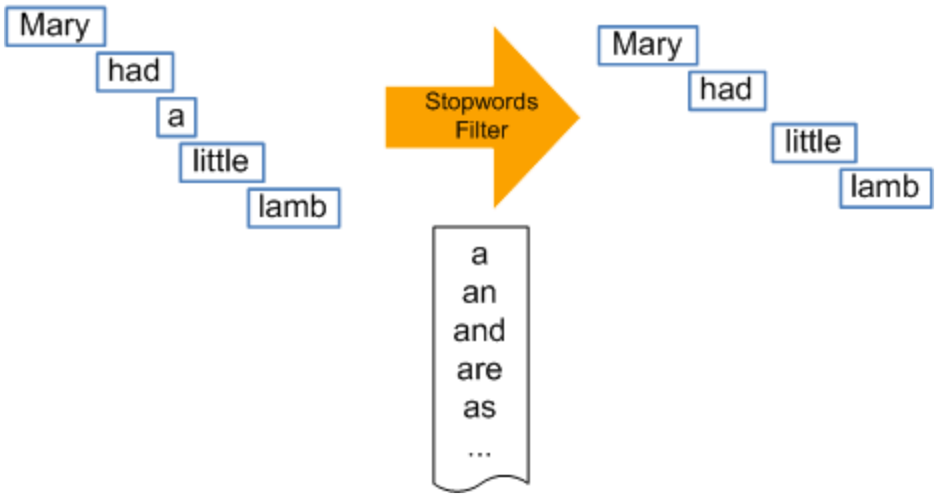
Stem_demo.R

Identifying Synonyms

- Synonym
  - car, vehicle, auto
  - sad, unhappy

Removing Stop Words

- Stop words: common words with no distinguishing power
  - a, the, and, or, is, it …
  - may depend on domain



Term-Document Matrix Weighting

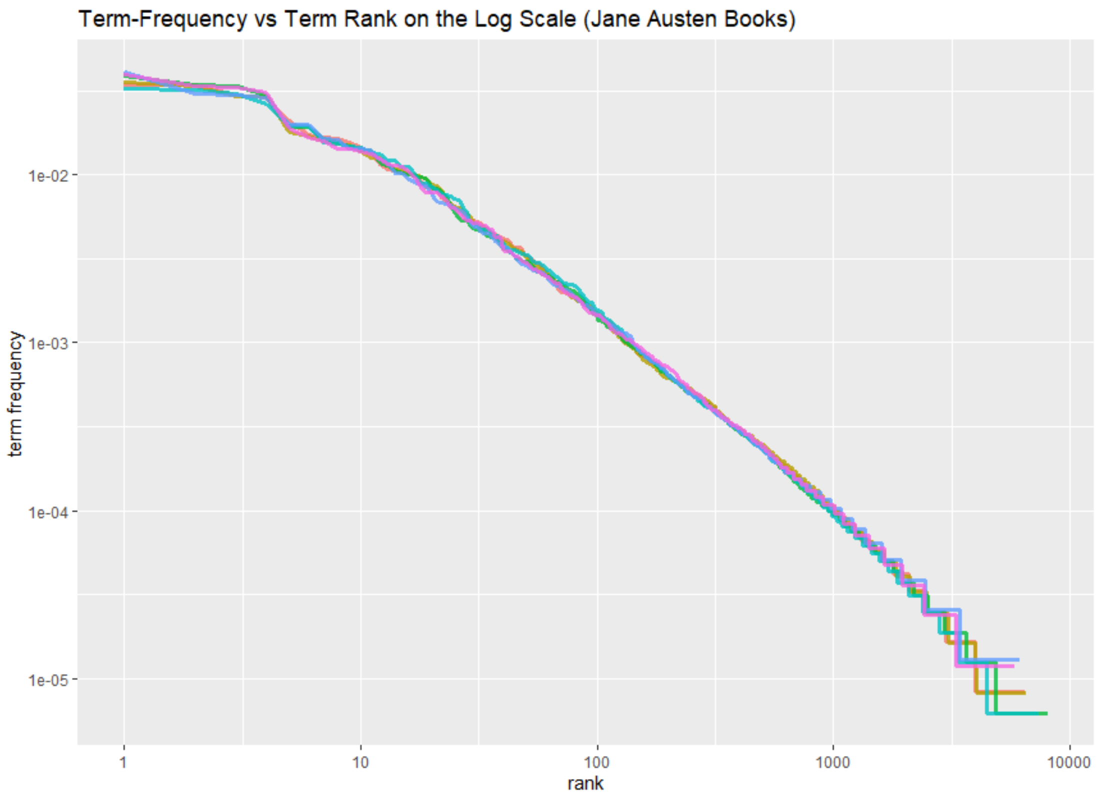
	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

Term-document matrix

Are all the terms with the same frequency equally important?

Zipf’s Law

- The frequency of any word is inversely proportional to its rank in the frequency table (empirical observation)



$$TF_i \cdot R_i = c$$

$$\Downarrow$$

$$\log(TF_i) = -\log(R_i) + \log(c)$$

Weighting Components

- Term Frequency: Relevance
  - Count
  - Log
  - Binary

- Term Weight: Distinguishing power
  - Inverse Document Frequency
  - Entropy
  - Mutual Information

TF-IDF Weighting

$$w_{t,d} = \log\left(1 + TF_{t,d}\right) * \log\left(\frac{N}{DF_t}\right)$$

- $TF_{t,d}$: Frequency of term t in document d
- DF_t: Number of documents containing term t
- N: Number of documents
- Many variants are used in practice

How to calculate TF-IDF weights for the matrix below?

	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

Term-document matrix

Summary: Steps to Parse and Quantify Texts

1. Tokenization
2. Part of Speech (POS) tagging (optional)
3. Stemming and lemmatization (recommended)
4. Synonyms (optional)
5. Removing stop words (optional)
6. Construct term-document matrix
7. Weighting (optional)

Data science is an art!

Many steps are optional and their order can be flexible!

THE VERGE

LONGFORM REVIEWS VIDEO TECH CIRCUIT BREAKER SCIENCE ENTERTAINMENT CARS TL;DR FORUMS

MICROSOFT WEB

TL;DR

Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day

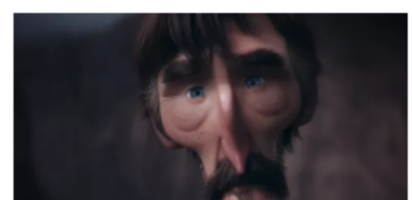
68 COMMENTS

by James Vincent · @jjvincent · Mar 24, 2016, 6:43a

SHARE TWEET LINKEDIN PIN

NEW TRENDING STORIES

Nintendo Switch: watch the first trailer for the new console



video

Garbage in, Garbage out!

Latent Semantic Analysis

Latent Semantic Analysis

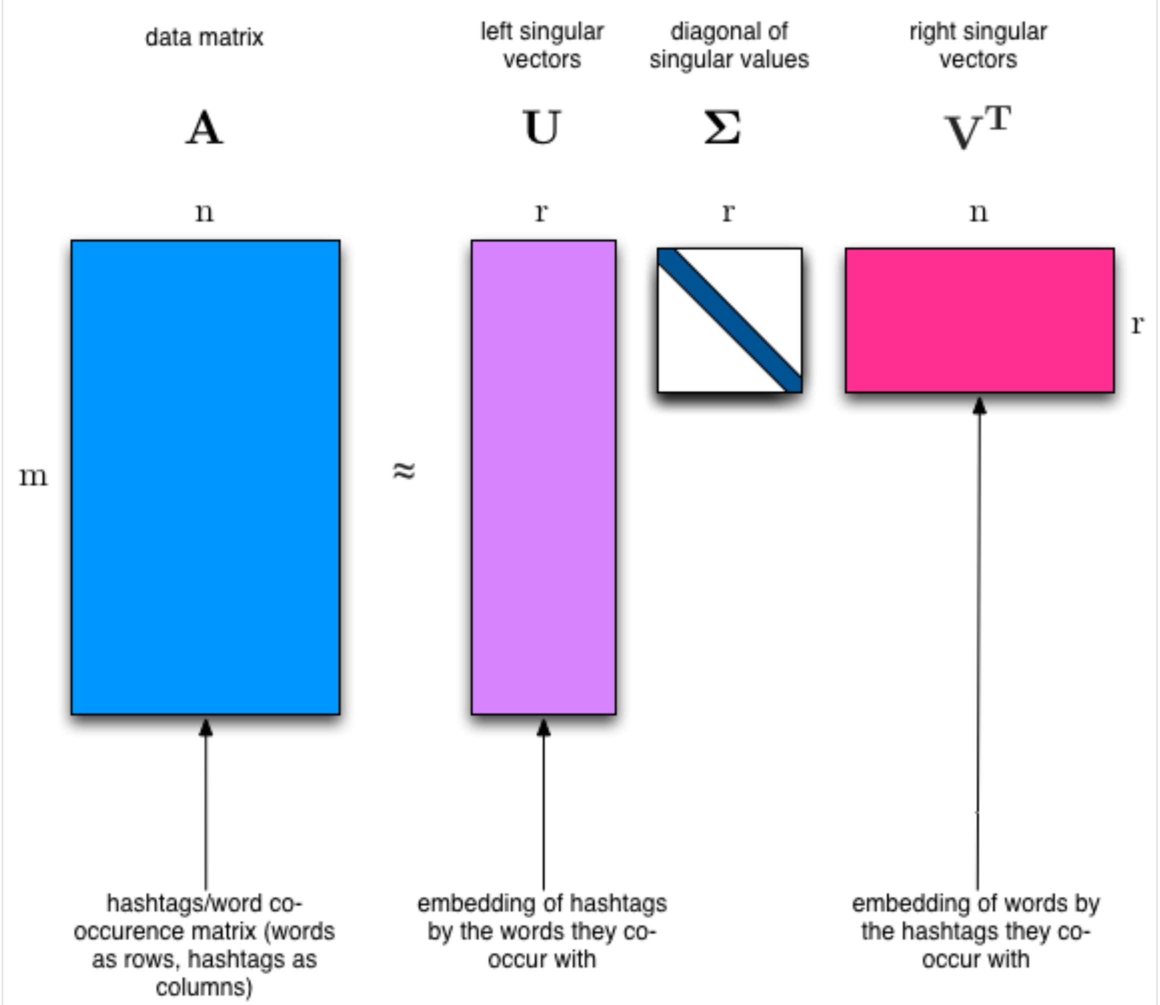
- **Latent semantic analysis** (**LSA**) is a technique in natural language processing of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms.

- **Implementation**: Singular Value Decomposition (SVD)

https://en.wikipedia.org/wiki/Latent_semantic_analysis

Singular Value Decomposition (SVD)

- SVD factors a large sparse term-by-document (m*n) matrix to a more compact latent space (r≤m), in which each latent dimension is a weighted combination of all terms



SVD Example

- Document 1 — deposit the cash and check in the bank
- Document 2 — the river boat is on the bank
- Document 3 — borrow based on credit
- Document 4 — river boat floats up the river
- Document 5 — boat is by the dock near the bank
- Document 6 — with credit, I can borrow cash from the bank
- Document 7 — boat floats by dock near the river bank
- Document 8 — check the parade route to see the floats
- Document 9 — along the parade route.

→

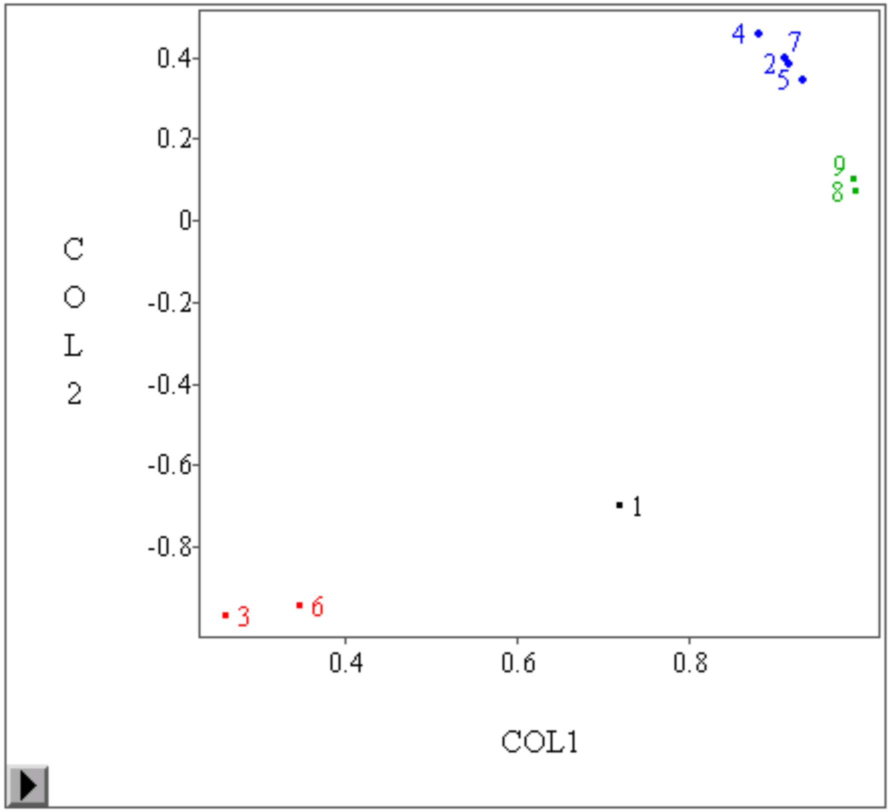
Term-by-Document Frequency Matrix

	d1	d2	d3	d4	d5	d6	d7	d8	d9
the	2	2	0	1	2	1	1	2	1
cash	1	0	0	0	0	1	0	0	0
check	1	0	0	0	0	0	0	1	0
bank	1	1	0	0	1	1	1	0	0
river	0	1	0	2	0	0	1	0	0
boat	0	1	0	1	1	0	1	0	0
+ be	0	1	0	0	1	0	0	0	0
on	0	1	1	0	0	0	0	0	0
borrow	0	0	1	0	0	1	0	0	0
credit	0	0	1	0	0	1	0	0	0
+ floats	0	0	0	1	0	0	1	1	0
by	0	0	0	0	1	0	1	0	0
dock	0	0	0	0	1	0	1	0	0
near	0	0	0	0	1	0	1	0	0
parade	0	0	0	0	0	0	0	1	1
route	0	0	0	0	0	0	0	1	1

Source: Help doc of SAS Enterprise Miner

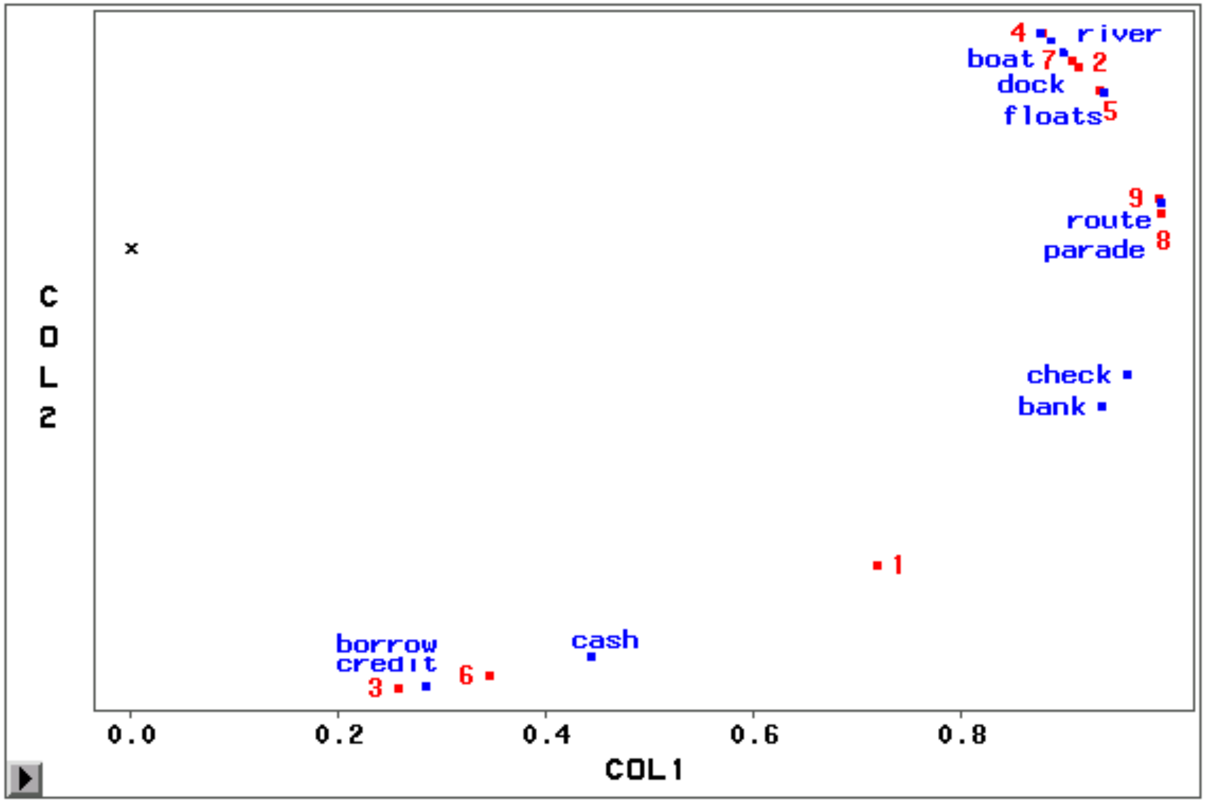
SVD Example (Cont.)

- If we compute similarity of documents based on co-occurrence of items, doc 2 will be considered more similar to 1 than to 3, due to the shared word “bank”
- SVD projects the documents to two latent “topic” space (described by combination of multiple terms). In the 2D latent space, doc 1 is closer to 3.



SVD Example (Cont.)

- Plot the locations of terms in the 2D space based on matrix V (blue points)



Another SVD Example

- $A = U \Sigma V^T$ **- example: Users to Movies**

$$
\begin{array}{cc}
 & \begin{matrix} \text{Matrix} & \text{Alien} & \text{Serenity} & \text{Casablanca} & \text{Amelie} \end{matrix} \\
\begin{matrix} \\ \text{SciFi} \\ \\ \\ \\ \text{Romance} \\ \\ \end{matrix} &
\begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
3 & 3 & 3 & 0 & 0 \\
4 & 4 & 4 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 2 & 0 & 4 & 4 \\
0 & 0 & 0 & 5 & 5 \\
0 & 1 & 0 & 2 & 2
\end{bmatrix}
\end{array}
=
\begin{array}{c}
\begin{matrix} \text{SciFi-concept} & \text{Romance-concept} & \end{matrix} \\
\begin{bmatrix}
\mathbf{0.13} & 0.02 & -0.01 \\
\mathbf{0.41} & 0.07 & -0.03 \\
\mathbf{0.55} & 0.09 & -0.04 \\
\mathbf{0.68} & 0.11 & -0.05 \\
0.15 & \mathbf{-0.59} & \mathbf{0.65} \\
0.07 & \mathbf{-0.73} & \mathbf{-0.67} \\
0.07 & \mathbf{-0.29} & \mathbf{0.32}
\end{bmatrix}
\end{array}
\times
\begin{bmatrix}
\mathbf{12.4} & 0 & 0 \\
0 & \mathbf{9.5} & 0 \\
0 & 0 & \mathbf{1.3}
\end{bmatrix}
\times
\begin{bmatrix}
\mathbf{0.56} & \mathbf{0.59} & \mathbf{0.56} & 0.09 & 0.09 \\
0.12 & -0.02 & 0.12 & \mathbf{-0.69} & \mathbf{-0.69} \\
0.40 & \mathbf{-0.80} & 0.40 & 0.09 & 0.09
\end{bmatrix}
$$

Relationship between SVD and PCA (optional)

- PCA can be done through SVD. Suppose $\mathrm{X} = \mathrm{USV}^{\mathrm{T}}$
  - V is the projection (rotation) matrix of PCA
    - Each column of V is a principle direction (axis)
    - Columns of V are orthogonal: $V^T V = I$
  - The principle scores are given by XV
    - $XV = USV^T V = US$
- Demo: svd.R

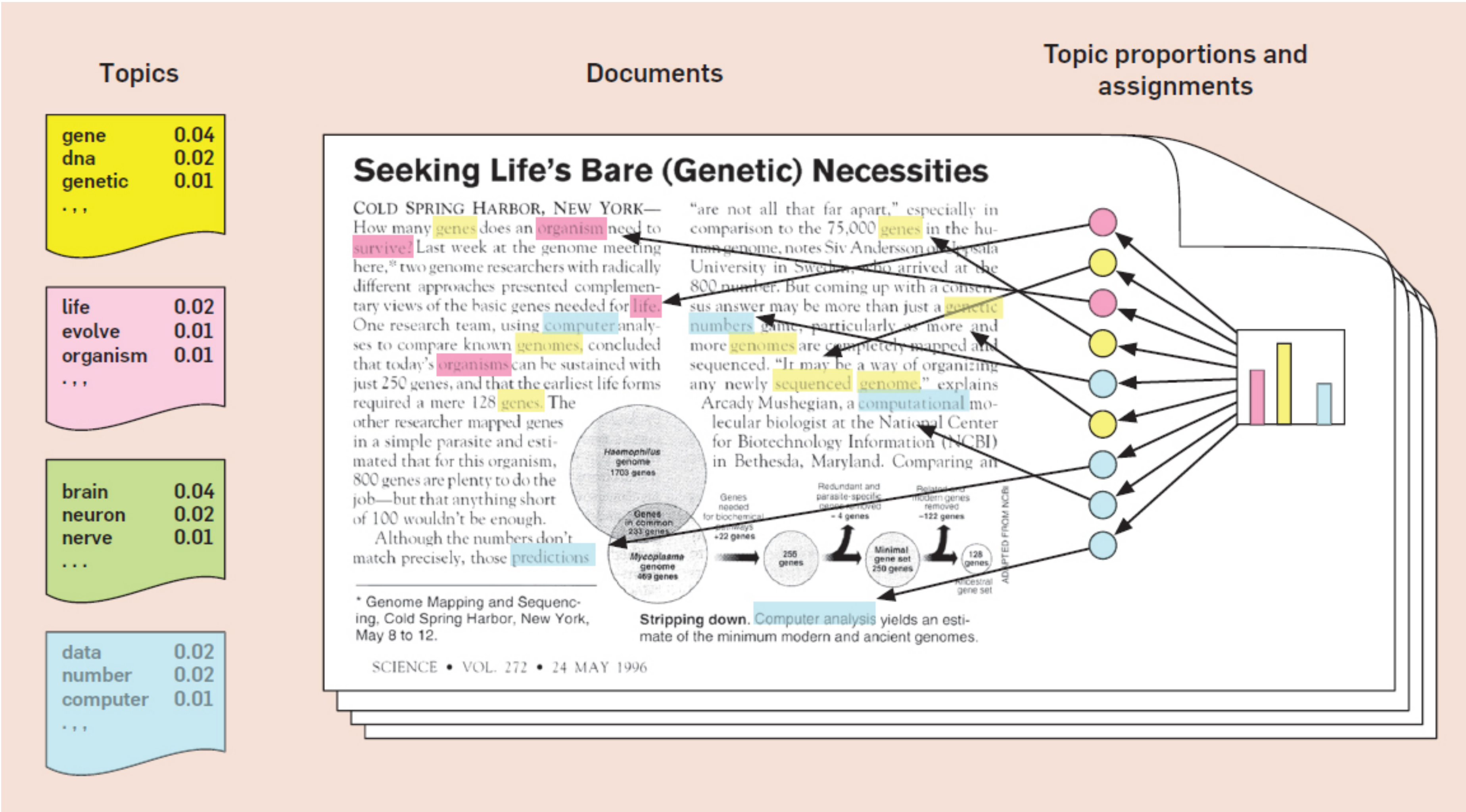
Discussions on SVD

- Pros
  - Reduces the dimensionality of the problem
  - Latent semantic analysis: may uncover transitive associations
  - More robust to noise

- Cons
  - SVD is time consuming
  - When r is small (<10), computation can be fast but may lose useful info
  - The meaning of the latent dimensions might be hard to interpret

- Choice of # dimensions (r)
  - Clustering: 2~50
  - Prediction: 30-200

Generalization: Latent Dirichlet Allocation



Readings

- TM Chapters 1-3
- **Highly Recommended**: Getting Started with SAS Text Miner
- SAS Enterprise Miner Documentation:  (press F1)
- Text Mining with R: ebook