

# Information Retrieval

WS 2012 / 2013

Lecture 8, Wednesday December 12<sup>th</sup>, 2012  
(Synonyms, Latent Semantic Indexing)

Prof. Dr. Hannah Bast  
Chair of Algorithms and Data Structures  
Department of Computer Science  
University of Freiburg

# Overview of this lecture

---

## ■ Organizational

- Your experiences with [ES#7](#) (cookies, UTF-8)
- Date for the exam !

## ■ Synonyms

- Automatic approach: [latent semantic indexing \(LSI\)](#)
- Based on [singular value decomposition \(SVD\)](#) of the term-document matrix
- Effectively compute pairs of related terms
- [Exercise Sheet 8](#): create term-document matrix from our example collection, and get related terms via [LSI](#)

# Experiences with ES#7 (cookies, UTF-8)

---

- Summary / excerpts last checked December 12, 15:54
  - Confusion in Java, some file readers autocorrect the UTF-8
  - Some problems with Cookies and file://...
  - **Subscribe to the Announcements subforum, then you will get an email when something is posted there**  
Actually: best to subscribe to **all** subforums (one per ES)
  - "UTF-8 is a great topic ... lost my fear of text encoding issues"
  - Web stuff nice to look at, but not so nice to actually build it
  - Master solution for the chocolate chip cookies please
  - Last sheets took much longer than 8 hours, please reduce  
**I will do my best ... but please don't forget that most of the overtime is due to lack of programming skills / experience**

# Results for ES#6+7 (web apps)

---

- Let's look at some of the web apps
  - Suggestions also for multiple keywords
  - Result snippets
  - Nice layout
  - Postponed to next lecture ...

# Synonyms 1/4

---

- Problem: another source of word variation
  - We have already seen prefix search  
Type `uni` ... find `university`
  - And error-tolerant search  
Type `uniwercity` ... find `university`
  - But sometimes there are simply totally different words expressing more or less the same thing  
Type `university` ... find `college`  
Type `bringdienst` ... find `lieferservice`  
Type `cookie` ... find `biscuit`

# Synonyms 2/4

---

- Solution 1: Maintain a thesaurus
  - Hand-maintain a thesaurus of synonyms
    - university: uni, academy, college, ...
    - bringdienst:ieferservice, heimservice, pizzaservice, ...
    - cookie: biscuit, confection, wafer, ...
  - **Problem 1:** laborious, yet notoriously out of date
  - **Problem 2:** it depends on the context, which synonyms are appropriate
    - university award ≠ academy award
    - http cookie ≠ http biscuit
  - Anyway, that's not the topic of today's lecture ...

# Synonyms 3/4

---

- Solution 2: Track user behaviour
  - Investigate not just individual searches but whole **search sessions** (tracked using, guess what, cookies):
    - The initial query
    - The subsequent queries
    - What the user eventually clicked on
  - Interesting, but not the topic of today's lecture either ...

- Solution 3: Automatic methods
  - The text itself also tells us which words are related
  - For example: pizza delivery webpages they have similar contents (and style)  
some use the word **Bringdienst**  
some use the word **Lieferservice**
  - **Latent Semantic Indexing (LSI)** tries to find such relations, based on similar context, automatically
  - This is the topic of today's lecture !



# Latent Semantic Indexing 1/9

- An example term-document matrix

	D1	D2	D3	D4	D5	D6	Query
internet	0	1	1	0	1	0	0
web	1	0	1	0	1	0	1
surfing	1	1	1	0	1	1	1
beach	0	0	0	1	1	1	0

                                      

↖                      ↗

same sim.  
to query

4x6 matrix

# Latent Semantic Indexing 2/9

- Assume our matrix is a product of these two

$$\begin{array}{l} \text{internet} \\ \text{web} \\ \text{surfing} \\ \text{beach} \end{array} \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 & 2 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}$$

$4 \times 2$                        $2 \times 6$                        $4 \times 6$

- This is a matrix with **column rank 2**

- **column rank** = all columns can be written as a linear combination of that many "base" columns, but not less
- **row rank** = defined analogously
- Theorem: **column rank = row rank**

# Latent Semantic Indexing 3/9

- If we change only few entries in that matrix
  - we obtain a full-rank matrix again ... check in Octave
  - Let us assume that the matrix came from a rank-2 matrix by changing only a few entries ... which it did
  - Then it's not hard to guess that rank-2 matrix here
  - LSI does this recovering automatically

$$\begin{array}{l} \text{internet} \\ \text{web} \\ \text{surfing} \\ \text{beach} \end{array} \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 & 2 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}$$

$4 \times 2$                        $2 \times 6$                        $4 \times 6$

## ■ Definition of Latent Semantic Indexing (LSI)

- Given an  $m \times n$  term-document matrix  $A$
- And a rank  $k$ , typically  $\ll \min(m, n)$   
Note that the maximal rank is  $\min(m, n)$  ... why?
- Then LSI computes  $\operatorname{argmin}_{A_k, \operatorname{rank}(A_k) = k} \|A - A_k\|$   
that is, the rank- $k$  matrix  $A_k$  with minimal distance to  $A$
- Here  $\| \cdot \|$  is the Frobenius norm:  
For a matrix  $A = [a_{ij}]$  defined as  $\|A\| := \sqrt{\sum a_{ij}^2}$
- **How to compute this miraculous matrix ?**

## ■ Eigenvector decomposition (EVD)

- For an  $m \times m$  matrix  $A$ , and an  $m \times 1$  vector  $x$   
we say that  $x$  is an eigenvector of  $A$  if  $A \cdot x = \lambda \cdot x$   
 $\lambda$  is called an Eigenvalue of  $A$
- If  $A$  is symmetric,  $A$  has  $m$  linear independent eigenvectors, which hence form a basis of the  $\mathbb{R}^m$
- Then  $A$  can be written as  $U \cdot D \cdot U^T$   
where  $D$  is diagonal, containing the Eigenvalues  
and  $U$  is unitarian, that is,  $U \cdot U^T = U^T \cdot U = I$
- This is called the Eigenvector decomposition of  $A$   
sometimes also called Schur decomposition

$$A = \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \quad \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 3 \\ 3 \end{pmatrix} \quad EV = 3$$

$$\begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ -1 \end{pmatrix} = \begin{pmatrix} 1 \\ -1 \end{pmatrix} \quad EV = 1$$

$$U = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \quad ; \quad U U^T = \frac{1}{2} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} = \frac{1}{2} \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \\ = I_2$$

can write A as

$$\begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} = \frac{1}{2} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} 3 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

## ■ Singular Value Decomposition (SVD)

– Let  $A$  be an **arbitrary** rectangular  $m \times n$  matrix  $A$

– Then  $A$  can be written as  $U \cdot \Sigma \cdot V^T$

where  $U$  is  $m \times k$ ,  $\Sigma$  is  $k \times k$ , and  $V$  is  $n \times k$   $k = \text{rank}(A)$

and  $U^T \cdot U = I$  and  $V^T \cdot V = I$  (but not vice versa !)

and  $\Sigma$  is a diagonal matrix with the so-called **singular values** on its diagonal

– Let's look at an example in Octave ...

# Latent Semantic Indexing 7/9

## ■ How to compute the SVD

$$(A \cdot A^T)^T = A^T \cdot A^T = A \cdot A^T$$

- Easy to compute from the EVD ... see below
- In practice, use the more direct Lanczos method
- Which has complexity  $O(k \cdot \text{nnz})$ , where  $k$  is the rank and  $\text{nnz}$  is the number of non-zero values in the matrix
- Note that for term-document matrices  $\text{nnz} \ll n \cdot m$

$A \cdot A^T$  and  $A^T \cdot A$  are symmetric.

$$A^T = (U \cdot \Sigma \cdot V^T)^T = V \cdot \Sigma \cdot U^T$$

$$A = U \cdot \Sigma \cdot V^T \quad \text{SVD}, \quad U^T U = I, \quad V^T V = I$$

$$A \cdot A^T = U \cdot \Sigma \cdot \underbrace{V^T \cdot V}_{=I} \cdot \Sigma \cdot U^T = U \cdot \Sigma^2 \cdot U^T$$

$$A^T \cdot A = V \cdot \Sigma \cdot \underbrace{U^T \cdot U}_{=I} \cdot \Sigma \cdot V^T = V \cdot \Sigma^2 \cdot V^T$$



# Latent Semantic Indexing 8/9

---

- With the SVD, rank- $k$  approximation becomes easy
  - For a given  $m \times n$  matrix  $A$ , compute SVD  $A = U \cdot \Sigma \cdot V^T$
  - Let  $U_k$  = the first  $k$  columns of  $U$
  - Let  $\Sigma_k$  = the upper  $k \times k$  part of  $\Sigma$
  - Let  $V_k$  = the first  $k$  columns of  $V$
  - Then  $AA = U_k \cdot \Sigma_k \cdot V_k^T$  is the desired approximation  
that is, that rank- $k$  matrix  $A_k$  which minimizes  $\|A - A_k\|$
  - Let's look at our example in Octave ...

# Latent Semantic Indexing 9/9

■ LSI can be viewed as **document expansion**

- LSI "replaces"  $A = U \cdot \Sigma \cdot V^T$  by  $AA = U_k \cdot \Sigma_k \cdot V_k^T$
- Observe:  $U_k \cdot U_k^T \cdot U = [U_k \ 0]$  ... let's check in Octave
- Hence  $AA = T \cdot A$ , where  $T = U_k \cdot U_k^T$  ( $m \times m$  matrix)
- **Exercise Sheet 9:** on our Wikipedia collection, see which term pairs get a high value in  $T$  (for various values of  $k$ )

*Use with zeroes padded on the right*

*internet*  
*web*

$$\begin{pmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} 0 \\ 1 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 0 \end{pmatrix}$$

*example T*

*his entry says: if there is "web" add "internet"*

## ■ Script language for numerical computation

- GNU's open source version of the proprietary Matlab
- Makes numerical computations easy, which would otherwise be a pain to use in Java / C++

In particular: comp. involving matrices and vectors

- Also comes with an interactive shell ... see next slide
- Language has C-like commands (`printf`, `fopen`, ...)
- Still it's a **script language**, and correspondingly slow
- The built-in functions (like `svd`) are fast though
- Download and Doc.: <http://www.gnu.org/software/octave>

- Use the Octave shell pretty much like a Bash shell
  - Arrow ↑ : previous command
  - Arrow ↓ : next command
  - CTRL+R : search in history
  - CTRL+A : go to beginning of line
  - CTRL+E : go to end of line
  - CTRL+K : delete from cursor position to end of line

- Here are some commands useful for ES#8

- Create a vector or matrix

```
A = [1 1 1 0 0; 0 0 1 2 0; 1 0 0 1 1]; // 3 x 5 matrix.
```

- Compute part of SVD pertaining to  $k$  top singular values

```
[U, S, V] = svd(A); // For dense matrices, k = rank(A)
```

```
[U, S, V] = svds(A, k); // For sparse matrices, must spec. k
```

- Get a portion of a matrix or vector

```
UU = U(:, 1:k); // First k columns of U.
```

- Multiply a matrix with its transpose

```
T = UU * UU';
```

- Note: if you omit the semicolon or write a comma, the result will be printed on the screen

## ■ Sparse matrices

- Our term-document matrices are very sparse, that is  $nnz \ll \#rows \cdot \#cols$  where  $nnz = \#non-zero$  values
- Therefore write in following format, one entry per line  
`<row-index> <column-index> <value>`
- Read such a sparse matrix into Octave with

```
tmp = load("A.matrix");  
A = spconvert(tmp);  
clear tmp;
```

## ■ Vectors of strings

- Read file with one string per line into Octave like this

```
A = {};  
file = fopen("words.txt");  
i = 1;  
while true  
    line = fgetl(file);  
    if line == -1, break; endif;  
    A(1, i) = line;  
    i++;  
endwhile
```

- With Octave version  $\geq 3.4$ , easier with `textread` ...

# References

---

## ■ Further reading

- Textbook Chapter 18: Matrix decompositions & LSI  
<http://nlp.stanford.edu/IR-book/pdf/18lsi.pdf>
- Deerwester, Dumais, Landauer, Furnas, Harshman  
[Indexing by Latent Semantic Analysis](#), JASIS 41(6), 1990

## ■ Wikipedia

- [http://en.wikipedia.org/wiki/Latent\\_semantic\\_indexing](http://en.wikipedia.org/wiki/Latent_semantic_indexing)
- [http://en.wikipedia.org/wiki/Singular\\_value\\_decomposition](http://en.wikipedia.org/wiki/Singular_value_decomposition)
- <http://www.gnu.org/software/octave>
- [http://en.wikipedia.org/wiki/GNU\\_Octave](http://en.wikipedia.org/wiki/GNU_Octave)



