Latent Semantic Indexing: A Probabilistic Analysis

C. Papadimitriou, P. Raghavan, H. Tamaki, S. Vempala

Seminar “Theoretical Topics in Data Science”

Vahe Eminyan

vahe.eminyan@rwth-aachen.de

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Overview

Motivation

- Large datasets, often organized in tabular form, represented as matrices
  - Term-document matrix representing word occurrence in documents
  - Movie-user matrix representing watched movies of users

	Doc 1	Doc 2	...	Doc m
Term 1	0	1	...	1
Term 2	1	0	...	1
...	...	...	...	...
Term n	1	0	...	0

$$\longrightarrow \quad \begin{array}{cc} & \text{Documents} \\ \text{Terms} & \begin{pmatrix} 0 & 1 & \dots & 1 \\ 1 & 0 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & 0 \end{pmatrix} \\ & n \times m \end{array}$$

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- Large datasets, often organized in tabular form, represented as matrices
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  - Movie-user matrix representing watched movies of users

- Interesting aspects
  - Find documents semantically associated with a query
  - Recommend a new movie to a user

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- Finds the latent (hidden) semantic structure of textual data. Solves the following problems:
  - Synonymy
  - Polysemy
- Represent term-document matrix as product of three matrices
- Answer queries with help of these matrices
- Based on singular value decomposition of the matrix

LSI Background

Singular Value Decomposition (SVD) [7]

- Any n by m matrix of rank r can be factored into

$$A_{n\times m} = U_{[n\times r]}D_{[r\times r]}(V_{[m\times r]})^T.$$

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- Vector notation

$$A = UDV^T = \sum_{i=1}^{r} \sigma_i u_i v_i^T$$

Singular Value Decomposition (SVD) Example: Matrix A with rank $r = 3$

$$\begin{array}{cc} & \text{Documents} \\ \text{Terms} & \underset{A}{\begin{pmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix}} \end{array} = \overset{\text{Term-Topic similarity}}{\underset{U}{\begin{pmatrix} -0.48 & -0.79 & -0.11 \cdot 10^{-14} \\ -0.58 & 0.16 & 0.71 \\ \mathbf{-0.34} & \mathbf{0.56} & 0.42 \cdot 10^{-15} \\ -0.56 & 0.16 & -0.71 \end{pmatrix}}} \times \overset{\text{Topic "importance"}}{\underset{D}{\begin{pmatrix} 2.1 & 0 & 0 \\ 0 & 1.26 & 0 \\ 0 & 0 & 1 \end{pmatrix}}}$$

$$\times \overset{\text{Topic-Document similarity}}{\underset{V^T}{\begin{pmatrix} -0.5 & \mathbf{-0.71} & -0.5 \\ -0.5 & \mathbf{0.71} & -0.5 \\ 0.71 & 0.67 \cdot 10^{-15} & -0.711 \end{pmatrix}}}$$

LSI Background

Latent Semantic Indexing based on SVD

- LSI considers A_k the rank k approximation of A (I.e. keep only k most relevant topics)

$$A_k = U_k D_k V_k^T = \sum_{i=1}^{k} \sigma_i u_i v_i^T$$

$$\begin{array}{cc} & \text{Documents} \\ \text{Terms} & \underbrace{\begin{pmatrix} 1.0 & 0.01 & 1.0 \\ 0.51 & 1.01 & 0.51 \\ 0.0 & 1.01 & 0.0 \\ 0.49 & 0.98 & 0.49 \end{pmatrix}}_{A_k} \end{array} = \overset{\text{Term-Topic similarity}}{\underbrace{\begin{pmatrix} -0.48 & -0.79 \\ -0.58 & 0.16 \\ \mathbf{-0.34} & \mathbf{0.56} \\ -0.56 & 0.16 \end{pmatrix}}_{U_k}} \times \overset{\text{Topic "importance"}}{\underbrace{\begin{pmatrix} 2.1 & 0 \\ 0 & 1.26 \end{pmatrix}}_{D_k}} \times \overset{\text{Topic-Document similarity}}{\underbrace{\begin{pmatrix} -0.5 & \mathbf{-0.71} & -0.5 \\ -0.5 & \mathbf{0.71} & -0.5 \end{pmatrix}}_{V_k^T}}$$

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- Map a query to k dimensional space with U_k , apply cosine similarity to find similar documents in $D_k V_k^T$

Latent Semantic Indexing based on SVD

Theorem (Eckart and Young [3])

Among all $n \times m$ matrices C of rank at most k, A_k is the one that minimizes $||A - C||_F^2 = \sum_{i,j}(A_{ij} - C_{ij})^2$, where F denotes the Frobenius norm of a matrix.

$$\text{Terms} \underbrace{\overset{\text{Documents}}{\begin{pmatrix} 1.0 & 0.01 & 1.0 \\ 0.51 & 1.01 & 0.51 \\ 0.0 & 1.01 & 0.0 \\ 0.49 & 0.98 & 0.49 \end{pmatrix}}}_{A_k} \approx \text{Terms} \underbrace{\overset{\text{Documents}}{\begin{pmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix}}}_{A}$$

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- Papadimitriou et al. [6] investigated both aspects:
  1. Under certain constraints semantically related documents are mapped to similar vectors
  2. Instead of LSI use LSI by random projection.
     - Map the original term-document matrix into a lower dimensional space
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- We focus on the second aspect

LSI by Random Projection

Random Projection for Dimensionality Reduction

Given a matrix $A \in \mathbb{R}^{n \times m}$ and a matrix $R \in \mathbb{R}^{\ell \times n}$. Use matrix R to reduce the dimensionality of matrix A while preserving pairwise distances between any two points:

$$B = \sqrt{\frac{n}{\ell}} \cdot R^T A \in \mathbb{R}^{\ell \times m}$$

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Lemma (Johnson and Lindenstrauss [4])

Let $v \in \mathbb{R}^n$ be a unit vector, let H be a random ℓ-dimensional subspace through the origin, and let the random variable X denote the square of the length of the projection of v onto H. Suppose $0 < \epsilon < 0.5$, and $24 \log n < \ell < \sqrt{n}$. Then, $E[X] = \frac{\ell}{n}$, and

$$Pr(|X - \frac{\ell}{n}| > \epsilon\frac{\ell}{n}) < 2\sqrt{\ell}e^{-(\ell-1)\epsilon^2/4}$$

LSI by Random Projection

Two-Step LSI

1. Apply a random projection onto ℓ dimensions on A. ($\ell > k$)

$$B = \sqrt{\frac{n}{\ell}} \cdot \begin{pmatrix} | & | & & | \\ r_1 & r_2 & \cdots & r_\ell \\ | & | & & | \end{pmatrix}^T \cdot A$$

2. Apply rank $O(k)$ LSI

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2. Apply rank $O(k)$ LSI

- Improved computational complexity
- With high probability the original matrix A almost as good recovered as by directly using LSI (Formulation and proof of theorem later)

LSI by Random Projection

Comparison of Computational Time

Given the term-document matrix $A \in \mathbb{R}^{n \times m}$.

Time complexity of one-step LSI:

- LSI computation: $O(mnc)$ if A is sparse with about c nonzero entries per column

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Time complexity of LSI by random projection :

- Random projection to ℓ dimensions: $O(mc\ell)$
- LSI computation: $O(m\ell^2)$
- Together: $O(mc\ell + m\ell^2) = O(m(c\ell + \ell^2))$, with $\ell \in \Omega(\frac{\log n}{\epsilon^2})$
- Hence we get a time complexity: $O(m(\log^2 n + c \log n))$

$O(m(\log^2 n + c \log n))$ better than $O(mnc)$

LSI by Random Projection

Comparison of Both Matrices

- A : original term-document matrix
- B : original term-document matrix after random projection and scaling

$$\underset{n \times m}{\overset{\text{A}}{\begin{pmatrix} 0 & 1 & \dots & 1 \\ 1 & 0 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & 0 \end{pmatrix}}} \longrightarrow \underset{\ell \times m}{\overset{\text{B}}{\begin{pmatrix} 0 & 0.47 & \dots & 0.47 \\ \vdots & \vdots & \ddots & \vdots \\ 0.47 & 0 & \dots & 0 \end{pmatrix}}}$$

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Comparison of Both Matrices

- A : original term-document matrix
- B : original term-document matrix after random projection and scaling
- $\ell \in \Omega(\frac{\log n}{\epsilon^2})$, with $\epsilon \in (0, 0.5)$
- Dimensionality reduction for each document $(\ell << n)$

$$\underset{n \times m}{\overset{\text{A}}{\begin{pmatrix} 0 & 1 & \dots & 1 \\ 1 & 0 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \dots & 0 \end{pmatrix}}} \longrightarrow \underset{\ell \times m}{\overset{\text{B}}{\begin{pmatrix} 0 & 0.47 & \dots & 0.47 \\ \vdots & \vdots & \ddots & \vdots \\ 0.47 & 0 & \dots & 0 \end{pmatrix}}}$$

Background and Notation for the Proof

Vector notations of SVD:

$$A = \sum_{i=1}^{n} \sigma_i u_i v_i^T, \qquad A_k = \sum_{i=1}^{k} \sigma_i u_i v_i^T, \qquad B = \sum_{i=1}^{\ell} \lambda_i a_i b_i^T, \qquad B_{2k} = A \sum_{i=1}^{2k} b_i b_i^T.$$

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- B_{2k}: rank $2k$ approximation of A

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Lemma (3)

Let ϵ be an arbitrary positive constant. If $\ell \geq c((\log n)/\epsilon^2)$ for a sufficiently large constant c then, for $p = 1, \ldots, \ell$

$$\lambda_p^2 \geq \frac{1}{k}\left[(1-\epsilon)\sum_{i=1}^{k}\sigma_i^2 - \sum_{j=1}^{p-1}\lambda_j^2\right].$$

LSI by Random Projection

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Corollary (4)

$$\sum_{p=1}^{2k}\lambda_p^2 \geq (1-\epsilon)\|A_k\|_F^2.$$

Background and Notation for the Proof

Lemma (5)

$$\|A - A_k\|_F^2 = \sum_{i=k+1}^{n} \sigma_i^2 .$$

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Theorem (Parsevals identity [2])

Let $b_1, \ldots, b_n$ be an orthonormal basis for a space S. Then for each $s \in S$, $|s|^2 = \sum_{i=1}^{n} (sb_i)^2$.

LSI by Random Projection

Main Theorem

Theorem (Papadimitriou et al. [6])

$$\|A - B_{2k}\|_F^2 \leq \|A - A_k\|_F^2 + 2\epsilon\|A\|_F^2$$

where $\epsilon \in (0, 0.5)$

Informally, the theorem states that the original matrix A after applying random projection and then LSI is with high probability almost as good recovered as by using one-step LSI on the original matrix.

LSI by Random Projection

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Proof

We have

$$A = \sum_{i=1}^{n} \sigma_i u_i v_i^T, \qquad A_k = \sum_{i=1}^{k} \sigma_i u_i v_i^T, \qquad B = \sum_{i=1}^{\ell} \lambda_i a_i b_i^T, \qquad B_{2k} = A \sum_{i=1}^{2k} b_i b_i^T.$$

$b_1, \dots, b_n$ Are orthonormal vectors spanning the row space of A and B_{2k}.
Hence using the Parseval's identity we can write:

$$\|A - B_{2k}\|_F^2 = \sum_{i=1}^{n} |(A - B_{2k})b_i|^2. \tag{1}$$

LSI by Random Projection

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For $i = 1, \dots, 2k$, because $b_i^T b_i = 1$, we have

$$(A - B_{2k})b_i = Ab_i - Ab_i = 0, \tag{2}$$

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and for $i = 2k+1, \ldots, n$, because $b_j^T b_i = 0$, we have

$$(A - B_{2k})b_i = Ab_i. \tag{3}$$

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Proof (continued)

Now we continue from the equation

$$\|A - B_{2k}\|_F^2 = \sum_{i=1}^{n} |(A - B_{2k})b_i|^2 \quad (4)$$

$$= \sum_{i=2k+1}^{n} |Ab_i|^2 \quad (5)$$

(7)

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Proof (continued)

On the other hand, we have

$$\|A - A_k\|_F^2 \overset{\text{Lemma 5}}{=} \sum_{i=k+1}^{n} \sigma_i^2 \tag{8}$$

$$\tag{9}$$

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$$\overset{\text{Frob. norm [5]}}{=} \|A\|_F^2 - \|A_k\|_F^2. \tag{9}$$

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Proof (continued)

Now we consider

$$\|A - B_{2k}\|_F^2 - \|A - A_k\|_F^2 = \|A\|_F^2 - \sum_{i=1}^{2k} |Ab_i|^2 - (\|A\|_F^2 - \|A_k\|_F^2) \tag{10}$$

(11)

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$$\|A - B_{2k}\|_F^2 - \|A - A_k\|_F^2 = \|A\|_F^2 - \sum_{i=1}^{2k} |Ab_i|^2 - (\|A\|_F^2 - \|A_k\|_F^2) \tag{10}$$

$$= \|A_k\|_F^2 - \sum_{i=1}^{2k} |Ab_i|^2, \tag{11}$$

that is equivalent to

$$\|A - B_{2k}\|_F^2 = \|A - A_k\|_F^2 + (\|A_k\|_F^2 - \sum_{i=1}^{2k} |Ab_i|^2) \tag{12}$$

LSI by Random Projection

Theorem (Papadimitriou et al. [6])

$$\|A - B_{2k}\|_F^2 \le \|A - A_k\|_F^2 + 2\epsilon\|A\|_F^2$$

where $\epsilon \in (0, 0.5)$

Proof (continued)

For the next step, we show

$$(1+\epsilon)\sum_{i=1}^{2k} |Ab_i|^2 \ge \sum_{i=1}^{2k} \lambda_i^2. \quad (13)$$

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Hence with a high probability

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$$\iff \|A - B_{2k}\|_F^2 \leq \|A - A_k\|_F^2 + 2\epsilon\|A_k\|_F^2 \tag{24}$$

Due to the formulation of Frobenius norm as in Lemma 5, we have $\|A\|_F^2 \geq \|A_k\|_F^2$. Hence

$$\|A - B_{2k}\|_F^2 \leq \|A - A_k\|_F^2 + 2\epsilon\|A\|_F^2. \tag{25}$$

□

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