Probabilistic Latent Semantic Indexing

Thomas Hofmann

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Presentation by Jonathan Ultis
Computer Science and Engineering Department
University of California, San Diego
jultis@cs.ucsd.edu

1

Outline

I. Latent Semantic Analysis
II. Singular Value Decomposition
III. Probabilistic Latent Semantic Analysis
IV. Experiments
V. The PLSA Advantage

2

Issues in Information Retrieval

- **Synonyms are separate words that have the same meaning. They tend to reduce recall.**
- **Polysemy refers to words that have multiple meanings. This problem tends to reduce precision.**
- **Both issues point to a more general problem. There is a disconnect between topics and keywords.**

3

Latent Semantic Analysis (LSA)

- **LSA attempts to discover information about the meaning behind words.**
- **Highly correlated words usually indicate the existence of a topic.**
- **LSA is proposed as an automated solution to the problems of synonymy and polysemy.**

4

Indexing by Latent Semantic Analysis[1]

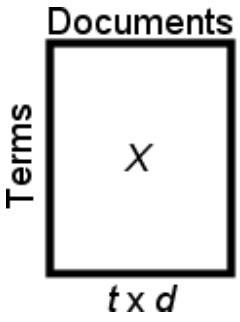
- **Once LSA has been performed, documents can be written as vectors in latent semantic space rather than as word vectors. This is known as Latent Semantic Indexing (LSI).**
- **This paper proposed Singular Value Decomposition (SVD) as an appropriate technique for LSA.**
- **SVD is still the most commonly used technique for LSA.**

1) Scott Deerwester, Susan T. Dumais, George W. Furnas, Thomas K. Landauer, Richard Harshman (1990)

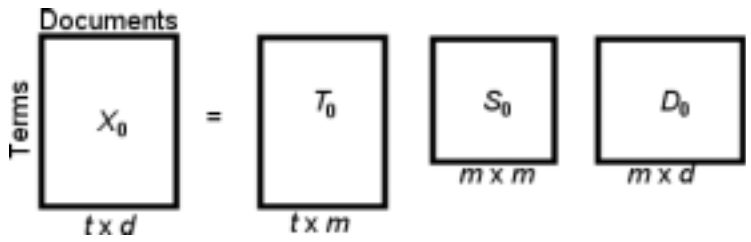
5

SVD Overview

- **Documents are commonly represented as vectors of term frequencies.**
- **Multiple documents can be represented as a matrix *X* of terms by documents.**

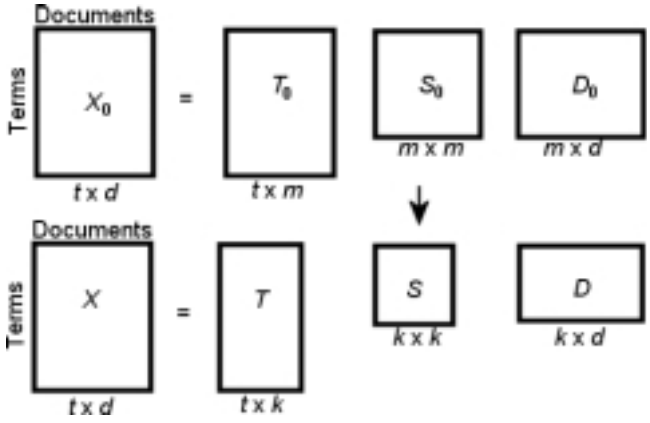


6



- **SVD is a standard technique for breaking a matrix into orthogonal components.**
- ***m* is the rank of the original matrix. *m* is usually much smaller than either *t* or *d*.**
- **The matrix S_0 is a diagonal matrix of singular values.**
- **T_0 and D_0 are matrices of orthonormal columns and rows respectively.**

7



- **The largest entries in S_0 represent the dimensions of greatest variance. These represent strong divisions in term usage.**
- **LSA is performed by removing small entries in S_0.**
- ***X* will be as close to X_0 as possible for a rank *k* matrix (least-squares-fit).**

8

Least Squares Fit

- **The least-squares-fit error has the minimum sum squared error for a matrix of its rank.**
- **Example:**

  Given the vector {1, 5, 1}

  The vector {2, 5, 2} has a sum squared error of 2.

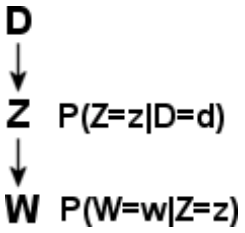
  The vector {1, 8, 1} has a sum squared error of 9.

  Therefore {1, 5, 1} is closer to {2, 5, 2} in a least-squares sense.

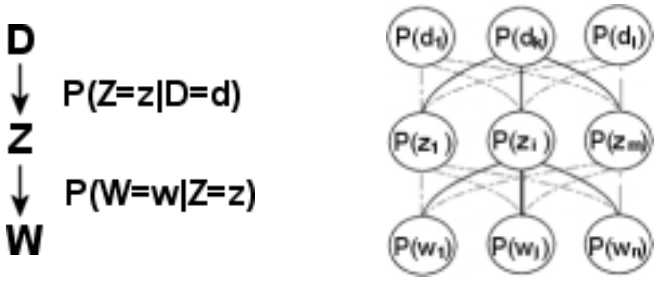
9

Probabilistic Latent Semantic Analysis

- **PLSA is based on a generative probabilistic model.**
- **Documents generate a particular distribution of aspects (topics).**
- **Aspects generate a particular distribution of word usage.**



10



Visualizations of equation 2

$$P(w|d) = \sum_{z \in Z} P(w|z)P(z|d)$$

- **The probability of each document and the probability of each word are known.**
- **The probability of an aspect given a document is unknown.**
- **The probability of a word given an aspect is unknown.**

11

Maximum Likelihood

- **The EM algorithm is used to estimate the unknowns by maximizing the log likelihood of the training data.**

$$\mathcal{L} = \sum_{d \in \mathcal{D}} \sum_{w \in \mathcal{W}} n(d, w) \log P(d, w)$$

- **Example:**

  Given the vector {1, 5, 1} and a perfectly trained model of one document *P*(*w*) = {0.14, 0.71, 0.14}

  The vector {2, 5, 2} has a likelihood of –4.16.

  The vector {1, 8, 1} has a likelihood of –2.90.

  Therefore {1, 5, 1} is closer to {1, 8, 1} in a log likelihood sense.

12

"plane"	"space shuttle"	"family"	"Hollywood"
plane	space	home	film
airport	shuttle	family	movie
crash	mission	like	music
flight	astronauts	love	new
safety	launch	kids	best
aircraft	station	mother	hollywood
air	crew	life	love
passenger	nasa	happy	actor
board	satellite	friends	entertainment
airline	earth	cnn	star

Each column holds the 10 words that a particular aspect is most likely to generate. Column headings were assigned by a human.

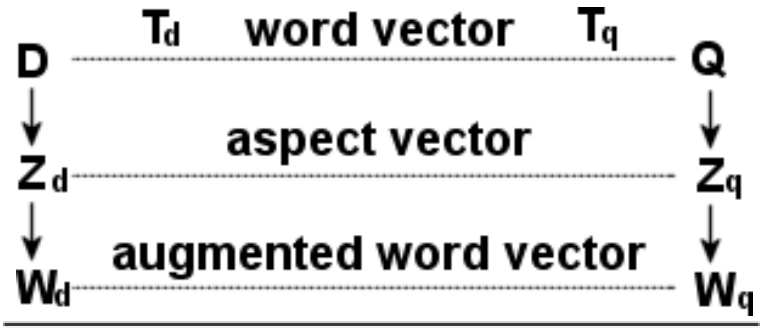
- **The EM algorithm performs an implicit clustering of words into aspects.**

13

Effectiveness of PLSA

- **The effectiveness of PLSA is tested by using the aspects to perform queries (PLSI).**
- **Two basic query techniques for PLSI are tested against the normal query technique for LSI.**
- **All queries use the cosine similarity metric to find the similarity between vectors.**

14



PLSI-U

$$sim(D, Q) = \lambda\, sim(T_d, T_q) + (1 - \lambda)\, sim(W_d, T_q)$$

PLSI-Q

$$sim(D, Q) = \lambda\, sim(T_d, T_q) + (1 - \lambda)\, sim(Z_d, Z_q)$$

15

- **PLSI-U incorporates TF-IDF weighting by directly modifying the word vectors of the document and query before performing the comparison.**
- **PLSI-Q uses a weighted average of the TF-IDF scores of the words that affect each aspect.**
- **The aspect vector for a query is generated by treating the query as a new document. The query is added to the model and the weights for the query are trained with the EM algorithm.**

16

PLSI-Q* and PLSI-U*

- **The two basic query techniques are also tested using combinations of models.**
- **PLSI-U* combines the augmented word vectors predicted by models with different numbers of aspects.**
- **PLSI-Q* combines the cosine similarities of the aspect vectors predicted by models with different numbers of aspects.**

17

Experiments

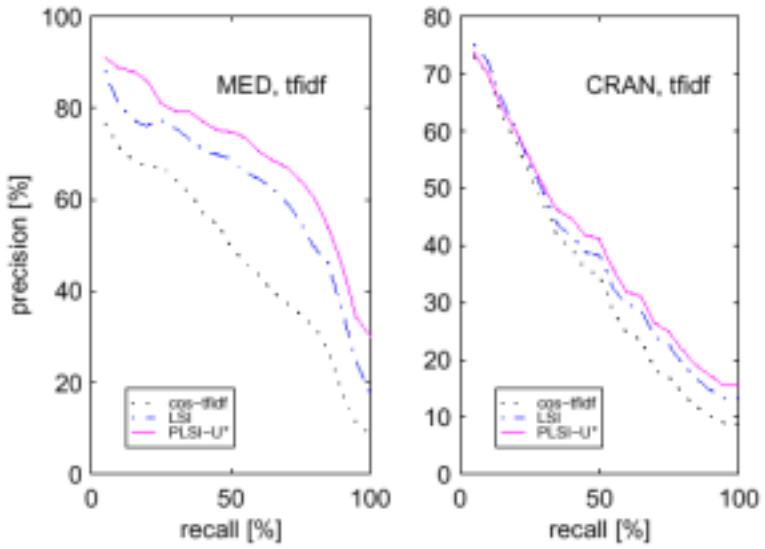
- **4 document collections provide a test bed.**
  - **MED – 1033 abstracts from the National Library of Medicine**
  - **CRAN – 1400 documents on aeronautics**
  - **CACM – 3204 abstracts from the CACM journals**
  - **CISI – 1460 abstracts in library science**
- **Average precision across 9 recall levels is reported (10, 20, …, 90%).**
- **Average relative improvement over the baseline at each recall level is reported.**

18

	MED		CRAN		CACM		CISI	
	precision	improvement	precision	improvement	precision	improvement	precision	improvement
cos+tfidf	49.0	-	35.2	-	21.9	-	20.2	-
LSI	64.6	+31.8	38.7	+9.9	23.8	+8.7	21.9	+8.4
PLSI-U	69.5	+41.8	38.9	+10.5	25.3	+15.5	23.3	+15.3
PLSI-Q	63.2	+29.0	38.6	+9.7	26.6	+21.5	23.1	+14.4
PLSI-U*	72.1	+47.1	40.4	+14.8	27.6	+26.0	24.6	+21.8
PLSI-Q*	66.3	+35.3	40.1	+13.9	28.3	+29.2	24.4	+20.8

- **PLSI-U is better than LSI in every case.**
- **PLSI-U* is the champion in almost every case**
- **The author speculates that PLSI-Q* could do much better if tf-idf weighting were incorporated more effectively.**

19



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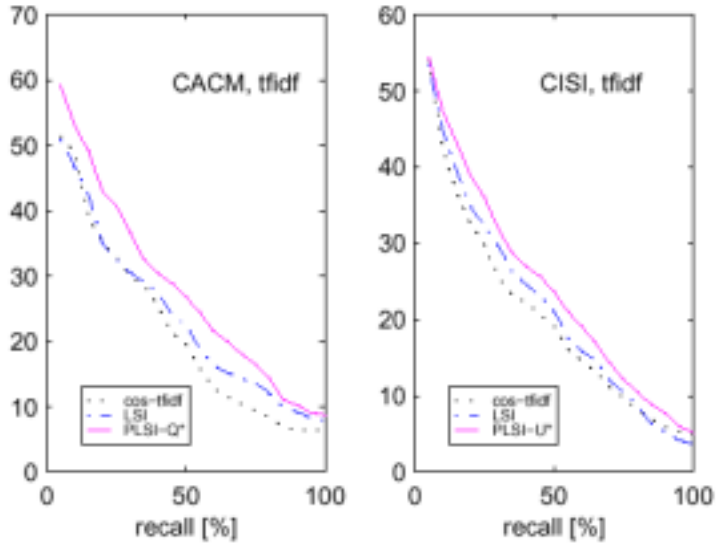

21

The PLSA Advantage

- **PLSA has several advantages over traditional SVD based LSA.**
- **PLSA attempts to maximize the likelihood of the data rather than minimizing the sum squared error.**
- **PLSA can use the usual methods to prevent overfitting, which can lead to more general models.**

22

- **Models can be combined productively with PLSA.**
- **PLSA provides a “more intuitive” definition for aspects.**
- **Empirical results bear out these advantages.**

23