Tag Cloud Control by Latent Semantic Analysis

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Declaration

I declare that:
this work has been prepared by myself,
all literal or content based quotations are clearly pointed out,
and no other sources or aids than the declared ones have been used.

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Chapter 1

Introduction

Identifying the main concepts in texts is the subject of many research studies in the field of information retrieval and data mining.

This work investigates the implementation of Latent Semantic Analysis (LSA) for discovering the main concepts in texts, in order to present an overview of the text content in the form of a tag cloud.

1. introductory words, why is this work being written
2. mention information retrieval, lsa, tag clouds - generally
3. mention cms ? document collections ? content ?
4. mention the work of david mugo

During the last decade there have been constant optimizations in information retrieval effectiveness, making web search the preferred source of finding information. A substantial part of information retrieval deals with providing access to unstructured information in various domains. Information Retrieval (IR) refers to finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers) [1]. Many people today use methods from the field of IR when they use a search engine online, or search through their emails. In this context "unstructured data" refers to data which does not have a clear structure.

IR technologies find wide application - in search engines, for browsing or filtering document collections, for further processing a set of retrieved documents. Before retrieval the documents are indexed, otherwise at each search, they would have to be scanned through for each query. The index maps the words or terms back to the documents where they occur. A method for document indexing, which is applied in this work, is called Latent Semantic Analysis (LSA). It indexes the document collection by

representing it as a reduced matrix of words and documents. LSA representation improves IR performance with respect to a basic problem of word-matching search - synonymy, or the case when more than one term describe the same concept.

While IR deals with retrieval of documents, other systems manage content, such as documents. Content management includes a set of technologies and processes that support the creation, management and publication of content in any form or medium. Content may be documents, multi-media files, or any other file types that follow content lifecycle and require management. Content Management Systems (CMS) vary depending on their purpose and target environments - there are CMS for the web, for enterprise, for mobile devices, as well as CMS for managing collection of documents.

1.1 Motivation and objective

A drawback of the classical LSA implementation as an IR method is the low precision of the returned results. A previous work by David Mugo [2] has investigated the improvement of LSA precision performance by annotating the document collection and including the anotations used in LSA. In his work, Mugo constructs a concept-document matrix from the annotations used, and concatenates it with the word-document matrix normally generated in LSA process. The proposed solution, however, results in a slow speed of LSA, and has left Mugo's hypothesis open.

Taking into consideration the results from Mugo's work, the current project has several objectives to reach. It will investigate the implementation of LSA method for improving information retrieval in a domain-specific document management system with respect to context-based search. A further investigation will be made on improving the precision performance of LSA method by using semantic annotations, and on finding an adequate way to present the results of LSA as a tag cloud. And finally, it will be investigated how to use the tag cloud as a form of a relevance feedback to control LSA method.

In the context of the stated objectives, semantic annotations are meta data annotations used to add information to unstructured data, or to the document collection. Semantic annotations are based on an ontology in our case, specifically developed for the domain of interest CoreMedia CMS. Ontologies are used to capture some knowledge about a certain

domain, by describing the concepts of the domain and the relationships between them. To further clarify the objectives, relevance feedback is an IR technique, used to influence the retrieved results based on the user's preference. It allows the user to modify the initial tag cloud by selecting the most relevant words. The tag cloud is then re-generated from LSA results with the relevance feedback posted as a query.

1.2 Outline

The reminder of this work is organized as follows. Chapter **??** describes in more detail what a document management system is, and provides an overview of the general structure of DocMachine 2.0, the CMS deployed at CoreMedia AG. Chapter **??** presents the basic concepts of ontologies and document annotations based on ontologies. In Chapter 2 an overview of latent semantic analysis method is given, as well as an approach for improving LSA's precision by including semantic annotations in the method. Chapter **??** presents the prototype implementation and makes an evaluation of the results achieved in this work. And finally, conclusions are drawn in Chapter **??**, along with some limitations of the current study and outlook for a future research.

Chapter 2

Latent Semantic Analysis

Summary. *The chapter gives a theoretical overview of LSA in the context of its use in this work.*

2.1 Overview

LSA was first introduced in [3] and [4] as a technique for improving information retrieval. Most search engines work by matching words in a user's query with words in documents. Such information retrieval systems that depend on lexical matching have to deal with two problems: synonymy and polysemy. Due to the many meanings which the same word can have, also called polysemy, irrelevant information is retrieved when searching. And as there are different ways to describe the same concept, or synonymy, important information can be missed. LSA has been proposed to address these fundamental retrieval problems, having as a key idea dimension reduction technique, which maps documents and terms into a lower dimensional semantic space. LSA models the relationships among documents based on their constituent words, and the relationships between words based on their occurrence in documents. By using fewer dimensions that there are unique words, LSA induces similarities among words including ones that have never occurred together [5]. There are three basic steps to using LSA: text pre-processing, computing Singular Value Decomposition (SVD) and dimensionality reduction, and querying the constructed semantic space.

2.2 Text pre-processing

If we have a document collection or a text corpus, on which we want to apply LSA, the initial step is to pre-process the texts into a suitable form for running LSA. Pre-processing can include a number of techniques, depending on the application requirements. The process of parsing, also called tokenization, is breaking the input text stream into useable tokens. During tokenization, filtering can be applied, i.e. removing HTML tags or other markup, as well as stop-wording, and removing punctuation marks. Stop words don't convey information specific to the text corpus, but occur frequently, such as: $a, an, and, any, some, that, this, to$.

A distinction has to be made between words or terms, and tokens. A term is the class which is used as a unit during parsing, and a token is each occurence of this class. For example, in the sentence:

> *CoreMedia CMS is shipped with an installation program for interactive graphical installation and configuration of the software.*

the term *installation* is represented by two tokens.

There is no universal way in which to parse a text, and the parsing decisions to address depend on the application in which the text collection will be used. Text parsing will influence all posterior processing in the following stages of LSA.

After tokenization, one has to construct a term-document matrix (2.1). Having as rows the terms, and as columns the documents, its elements are the occurrences of each term in a particular document, where a_{ij} denotes the frequency with which term i occurs in document j. The size of the matrix is **m x n**, where **m** is the number of terms, and **n** is the number of documents in the text collection. Since every term doesn't appear in each document, the matrix is usually sparse.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \tag{2.1}$$

Local and global weightings are applied to increase or decrease the importance of terms within documents. We can write

$$a_{ij} = L(i,j) \times G(i), \tag{2.2}$$

where $L(i, j)$ is the local weighting of the term i in document j, and $G(i)$ is the global weighting for term i. The choice of a weight function has impact on LSA performance, therefore in Section 2.5 we give an overview of the most common weight functions.

2.3 Singular Value Decomposition

After the initial pre-processing, the term-document matrix is decomposed into three matrices (2.3) by applying Singular Value Decomposition (SVD). It is a unique decomposition of a matrix into the product of three matrices - U and V are ortonormal matrices, and Σ is a diagonal matrix having singular values on its diagonal.

$$A = U\Sigma V^T \tag{2.3}$$

After the initial matrix A is decomposed, all but the highest k valued of S are set to 0. The resulting reduced matrix is the semantic space of the text collection. A classical example presenting the truncated SVD [3] can be used for displaying dimensionality reduction, and how it affects all three matrices.

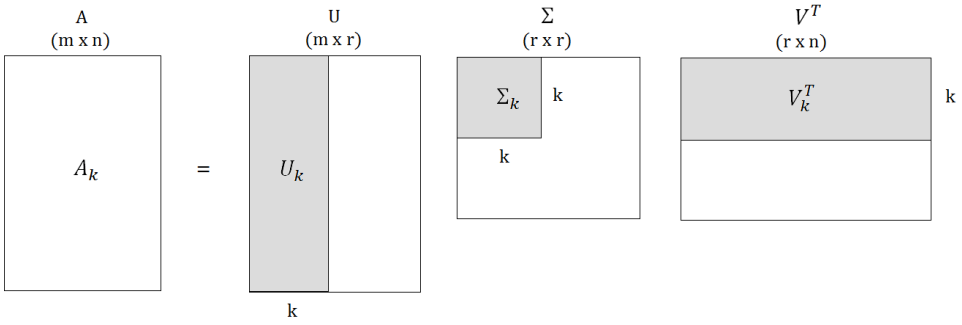

Figure 2.1: Diagram of truncated SVD

A_k - best rank-k approximation of A	m - number of terms
U - term vectors	n - number of documents
Σ - singular values	k - number of factors
V^T - document vectors	r - rank of A

Figure 2.1 is a visual representation of SVD as defined in equation (2.3). U and V are considered as containing the term and document vectors

respectively, and Σ is constructed by the singular values of A. An imporant property of SVD is that the singular values placed on the diagonal of Σ are in decreasing order. Hence, if all but the first k singular values are set to 0, the semantic meaning in the resulting space is preserved to some approximation k, while noise or variability in word usage, is filtered out. Noise in this case are the terms with lowest weights which carry little meaning. By using fewer dimensions k, LSA induces similarities amont terms including ones that have never occured together. Terms which occur in similar documents, for example, will be near each other in the k-dimensional space even if they never co-occur in the same document. This means that some documents which do not share any words with a users query may be near it in k-space.

A factor to be considered when computing SVD is the run-time complexity of the algorithm. For decomposition of very large matrices, it is $O(n^2k^3)$, where n is the number of terms in the text corpus, and k is the number of dimensions in semantic space after dimensionality reduction. Note that k is typically a small number between 50 and 350.

A more detailed description of SVD can be found in [6] and [7].

2.4 Querying the semantic space

In this work we are using LSA for IR purpose. Therefore, the final step of applying the technique is to pose queries on the constructed semantic space. A query q is a set of words which must be represented as a document in the k-dimensional space, in order to be compared to other documents. The user's query can be represented by

$$q = q^T U_k \Sigma_k^{-1} \tag{2.4}$$

where q is the set of words in the query, multiplied by the reduced term and singular values matrices. Using the transformation in (2.4), the query is "mapped" onto the reduced k-space. After the mapping, the resulting query vector can be compared to the documents in the k-space, and the results ranked by their similarity or nearness to the query. A common similarity measure is the cosine between the query and the document vector. From the resulting document set, the documents closest to the query above certain treshold are returned.

2.5 Factors influencing LSA performance

The effective usage of LSA is a process of a sophisticated tuning. Several factors can influence the performance of the technique. These factors are pre-processing of texts (removal of stop-words, filtering, stemming), frequency matrix transformations, choice of dimensionality k, choice of similarity measure.

Dumais et al. [8] and Nakov et al. [9] have carried research on LSA performance depending on the choice of factors such as frequency matrix transformations, similarity measures, and choice of dimension reduction parameter k. They conclude that performance based on the choice of these factors depends on the particular text corpus, as well as on the purpose of LSA application. However, in the case of matrix transform, log-entropy performs better as compared to other matrix transform function combinations, including the popular term frequency - inverse document frequency ($tf \times idf$). Therefore, we implement the former in this work.

Local function: logarithm	$L(i,j) = \log(tf(i,j) + 1)$
Global function: entropy	$G(i) = 1 + \frac{\Sigma_j p(i,j)}{\log n}$

where n is the number of documents in the collection.

Further, it has been stated ([8],[10]) that with respect to similarity measures used, LSA performs optimal when cosine similarity measure is implemented to calculate the distance between vectors in the semantic space. We have therefore used it to measure the relevance between queries and documents. The cosine measure between two vectors d_1 and d_2 is given by:

$$sim(d1, d2) = \frac{\overrightarrow{V}(d_1).\overrightarrow{V}(d_2)}{\left|\overrightarrow{V}(d_1)\right| . \left|\overrightarrow{V}(d_2)\right|} \tag{2.5}$$

Dimensionality reduction parameter k is defined empirically based on the experimentation results presented in Chapter **??**.

Acronyms

CMS Content Management Systems.

IR Information Retrieval.

LSA Latent Semantic Analysis.

SVD Singular Value Decomposition.

Appendix A

Appendix

TODO: insert important source code parts here.

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