Using Random Indexing to improve Singular Value Decomposition for Latent Semantic Analysis

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Abstract

We present results from using Random Indexing for Latent Semantic Analysis to handle Singular Value Decomposition tractability issues. We compare Latent Semantic Analysis, Random Indexing and Latent Semantic Analysis on Random Indexing reduced matrices. In this study we use a corpus comprising 1003 documents from the MEDLINE-corpus. Our results show that Latent Semantic Analysis on Random Indexing reduced matrices provide better results on Precision and Recall than Random Indexing only. Furthermore, computation time for Singular Value Decomposition on a Random Indexing reduced matrix is almost halved compared to Latent Semantic Analysis.

1. Introduction

We are developing an FAQ-system called ACC (Automatic Contact Center) were clients requests for guidance, help or contact information are handled without human intervention, c.f. (Åberg, 2002). We use a two-step approach for our development of ACC. First, we collect human-human call center conversations and build a database that can be searched in various ways. This database will be used to suggest responses to the call center agent continuously. The database will be extended when new requests arise. Once the database is large enough we will use it to automatically answer requests from the clients.

In this paper we present improvements to techniques for identifying “similar” requests from a collection of FAQ-items. Such techniques differ from techniques utilised in traditional QA systems, such as FALCON (Harabagiu et al., 2000), where a collection of documents are used to retrieve an answer. Typically QA-systems first utilise information retrieval techniques to select documents corresponding to the question type and keywords from the question. Then the answer is extracted from this subset of documents, for instance, through pattern matching.

FAQ-systems are instead based on previously recorded FAQ-items and utilise various techniques to identify the FAQ-item(s) that best resembles the current question and present a matching answer. For instance, the FAQFinder system (Mlynarczyk and Lytinen, 2005), which uses existing FAQ knowledge bases to retrieve answers to natural language questions. FAQFinder utilises a mixture of semantic and statistical methods for determining question similarities. Another technique is to use a frequency-based analysis from an ordinary FAQ with given/static questions and answers (Ng’Ambi, 2002). Linguistic based automatic FAQ systems often starts with finding the question word, keywords, keyword heuristics, named entity recognition, and so forth (Moldovan et al., 1999). Knowledge based systems can also utilise dialogue to ask the user to guide the search (Kurohashi and Higasa, 2000). Their knowledge base has a dictionary-like structure based on domain concepts.

One issue for automatic help-desk systems is that we have often many-to-many mappings between requests and responses. A question is stated in many ways and, as humans answer the requests, the response to a question can be stated in many ways. The propositional content can also vary, although operators re-use sentences, at least in e-mail help desk-systems (Zukerman and Marom, 2006).

Help-desk e-mail conversations are further characterised by: (1) having many requests raising multiple issues, (2) having high language variability and (3) with many answers utilising non-technical terms not matching technical terms in the requests (Marom and Zukerman, 2007). In this paper we will not consider (1), i.e. we will not present answers comprising multiple issues.

2. Vector space models

To handle (2) and (3) above, it is natural to investigate techniques that in various ways reduce the linguistic variability and better capture semantically related concepts. One prominent such technique is vector space models (Eldén, 2007). The basic idea is to formulate the problem in a matrix terminology, usually by constructing a matrix using text units as columns and letting the words in all text units each have a row in the matrix. Then a certain entry in the matrix is nonzero iff the word corresponding to the row exists in the text unit represented by the column. There are also other ways of representing text in a matrix but those will not be discussed further here.

2.1. Latent Semantic Analysis

Latent Semantic Analysis (LSA) (Landauer and Dumais, 1997) is one of the most well-known vector space models and has, among other things, been used on a limited help-desk data set with promising results (Caron, 2000). When using questions in an FAQ to compute a vector space model, LSA uses Singular Value Decomposition(SVD) to find a reduced vector space that fits the original as well as possible using a lower ranked matrix. The SVD factorizes a matrix $A$ into $A = USV^T$ where $U$ is the new orthonormal basis for $A$, $S$ is a diagonal matrix denoting how prevalent each column is in the basis while $V^T$ is the coordinates of the original documents using the new basis.
It turns out that results are often improved when dimensions that correspond to the lower values of $S$ are removed from the basis. This removes the orthogonality restraint between the different word vectors, and words that appear in similar contexts will have a scalar product $\neq 0$. The product of the $l$ biggest values of $S$, $S_1$ and the corresponding columns and rows of $U_1$ and $V_1^T$ makes the closest possible approximation of $A$ of rank $l$ (Eldén, 2007).

One way to look at this is that the dimensionality reduction is reducing the amount of noise in the data. An additional bonus of reducing the rank of the SVD is that the result is faster to compare with queries, due to fewer elements to multiply. It is also less computationally demanding to compute a partial SVD consisting of only the $l$ biggest singular values and the corresponding singular vectors than it takes to compute a complete SVD factorization.

Answers to questions are retrieved based on how similar they are to previous questions in the vector space, by changing the basis of the query to $U$ and then compare likeness with the coordinates in $V^T$, often based on the cosine between the two (Caron, 2000).

For larger data sets SVD can be computationally demanding. One way to improve scalability of LSA is by using Generalised Hebbian Learning (GHA) for SVD (Gorrell, 2006). This allows for incremental SVD and handles very large data sets. When applied to a situation with continuously added FAQs, the GHA approach may well be preferred. For our current application the frequency of novel requests is small, and simpler methods may suffice. One such possibility is to reduce the dimensionality of the matrix on which SVD is calculated using Random Indexing (Gorrell, 2006; Kanerva et al., 2000).

2.2. Random Indexing

Random Indexing is an incremental vector space model that is computationally less demanding (Karlgren and Sahlgren, 2001). The Random Indexing model reduces dimensionality by, instead of giving each word a whole dimension, it gives them a random vector by a much lesser dimensional vector. This removes the orthogonality restraint between each word and the k-dimensional random vectors are distributed evenly in the unit sphere of dimension $k$ (Sahlgren, 2005). An even distribution will ensure that every pair of vectors have a high probability to be orthogonal.

Information is lost during this process (pigeonhole principle, the fact that the rank of the reduced matrix is lower). However, if used on a matrix with very few nonzero elements, the induced error will decrease as the likelihood of a conflict in each document, and between documents, will decrease.

Using Random Indexing on a matrix will introduce a certain error to the results. These errors will be introduced by words that match with other words, i.e. the scalar product between the corresponding vectors will be $\neq 0$. In the matrix this will show either that false positive matches are created for every word that have a nonzero scalar product of any vector in the vector room of the matrix. False negatives can also be created by words that have corresponding vectors that cancel each other out.

Random Indexing has been used and compared to LSA on the TOEFL test giving similar results on the tests, but with a much reduced matrix (Kanerva et al., 2000).

3. Experiment

We will investigate the performance of these three techniques, i.e. (1) standard Latent Semantic Analysis, (2) Random Indexing and (3) Latent Semantic Analysis on a matrix where Random Indexing is used to reduce the dimensionality of the matrix before singular value decomposition. Performance will be measured as calculation time as well as precision and recall.

We have used a subset of the MEDLINE-corpus\(^1\). The subset comprise 1003 documents and 30 test queries. The corpus and test queries are parsed, stemmed and have stop words removed. Stemming and removal of stop words are performed since the information contained in them doesn’t matter for the problem area and these actions will be very likely to increase performance. The results are inserted into a word-document matrix with words representing rows and documents representing columns, resulting in a matrix with 3020 rows and 1063 columns.

MEDLINE is, admittedly, a small corpus, but it is publicly available and sufficient to show if Random Indexing applied prior to computing SVD is more efficient. It should also be sufficient to show what effects the usage of Random Indexing have on precision and recall compared to LSA with SVD on a Random Indexing reduced matrix.

To investigate how Random Indexing affects the computation time of the SVD we make two Random Indexing transformations, one with half the size of the original matrix, i.e. 1500 rows, and one with a quarter of the original size, 750 rows. After this we run SVD on the original matrix and also on both matrices reduced with Random Indexing. These reduced matrices contain a lot more nonzero values than the original matrix, and our aim is to see how this trade off between more nonzero values versus fewer rows behave performance wise.

We do this by first performing SVD for matrices with just a few columns for all three alternatives, and then increasing

\(^1\)www.dcs.gla.ac.uk/idom/ir_resources/test_collections
the amount of columns incrementally while measuring the
time it takes to perform the SVD.
We use precision and recall to compare the tech-
niques (Eldén, 2007). Precision measures how exact the
retrieval process is and is defined as the number of doc-
uments correctly retrieved divided by the total number of
documents Recall is a measure of how complete the re-
trieval process is and it is defined as the number of doc-
uments correctly retrieved divided by the total number of
correct documents.
To measure precision and recall we run tests with the 30
MEDLINE query entries and then compare the results to a
handmade set of correct answers, also publicly available.
We do this for the pure vector model sans LSA, for pure
LSA, for pure Random Indexing and lastly for LSA applied
on a matrix that have been reduced with Random Indexing.

4. Results
Our results show that SVD on a Random Indexing reduced
matrix with 1500 rows is about twice as fast as SVD on our
non-reduced matrix. Furthermore, the difference is more or
less independent on the number of columns used, see Fig-
ure 1. Using the more reduced matrix on 750 rows provides
even shorter running time, but the reduction is not as dra-
matic as the reduction from the original 3000 rows matrix
to the 1500 rows matrix.
Precision and Recall for LSA on Random Indexing reduced
matrices compared to Random Indexing and LSA show that
LSA on Random Indexing reduced matrices provides far
better results, for precision above 0.2, than Random Index-
ing, but slightly worse results than pure LSA, Figure 2. We
also see a loss in Precision and Recall for Random Index-
ing compared to not only our two versions of LSA, but also
to the pure vector space model. This seemingly contradict
(Karlgren and Sahlgren, 2001) who report similar perfor-
mance as for LSA (although for a different problem).

5. Summary
In this paper we have presented results from using Random
Indexing to reduce the dimensionality of the matrix used to
perform Singular Value Decomposition for Latent Seman-
tic Analysis. Our results show that Precision and Recall
are far better than using only Random Indexing and that
computation time for the Singular Value Decomposition is
almost halved compared to non-reduced matrices.
The presented results used a rather small data set, 1003 doc-
uments from the MEDLINE corpus, as it is readily available.
Consequently our original matrix has few rows. We be-
lieve, however, that the gain is most likely to increase sig-
nificantly if this test would have been conducted on a larger
matrix. Here we only used reductions of a half and a quar-
ter of the size, while on a real big problem it would be more
likely to be somewhere along the lines of two to three magn-
itudes of change (Kanerva et al., 2000).

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Figure 2: Precision as a function of Recall for LSA, Random Indexing and LSA with Random Indexing reduced matrices

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