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A New Modified Collection Selection Algorithm using Optimal Term Weight for Web based Applications

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7 Abstract

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As the number of electronic data collections available on the internet increases, so does the difficulty of finding the right collection for a given query. Often the first time user will be 9 overwhelmed by the array of options available, and will waste time hunting through pages of 10 collection names, followed by time reading results pages after doing an adhoc search. 11 Collection selection using optimal weight methods try to solve this problem by suggesting the 12 best subset of collections to search based on a query. This is of importance to fields containing 13 large number of electronic collections which undergo frequent change, and collections that 14 cannot be fully indexed using traditional methods such as spiders. This paper presents a 15 solution to these problems of selecting the best collections and reducing the number of 16

- ¹⁷ collections needing to be searched.
- 19 Index terms—singular value matrix(s), term matrix (u), collection matrix (v).

40 1 Modified Collection Selection

41 Modified Collection Selection using optimal term is the selection of an optimal set of information sources from a

42 large set of information sources. An information source can be a Web interface, a standard relational collection,

 a_3 a file, a search engine, or any other textual representation of information. Collection Selection aims to be efficient

Introduction he 21st century is the age of Internet and World Wide Web. The Web revolutionizes the way we gather, process, and use information. At the same time, it also redefines the meanings and processes of business, merce, marketing, finance, publishing, education, research, development, as well as other aspects of our daily life [1].

Modified Collection selection is the selection of an optimal weight subset of collections from a large set of 24 collections for the purpose of reducing costs associated with Distributed Information Retrieval. The goal of 25 modified collection selection is to make searching multiple collections appear as seamless as searching a single 26 collection. Another requirement of a modified collection selection using optimal term weighting system is to learn 27 which collections contain relevant information and which collections contain no relevant information. This reduces 28 the number of overall search requests needed. If only a small high quality subset of the available collections is 29 searched then savings can be made in time, bandwidth, and computation [4]. Web based collection selection is 30 significant because as the internet grows the number of internet based collections grows. It is now impossible 31 to anually track and index all collections as they number in the thousands. This method will enable users 32 to choose the best collections for their needs without having to sift through irrelevant collections. Collection 33 selection optimal term method reduces expenses, increasing search speed, learning to adapt to change in the 34 search environment, using ontology to increase precision, and learning to adapt to the users preferences. 35

The paper is organized as follows. Section 2 discusses main difference between traditional method in web based collection and optimal term weight method for collection selection Section 3 presents application of the approach. Conclusion presents main features of the system that help fulfill fundamental demands of the intelligent Web's design and development II.

with respect to bandwidth and computation, and decreases both resource usage and time taken to return a set
of results for a query. Well planned collection selection can have a large influence on the efficiency of a query.
Collection selection is significantly different to document selection in a number of areas. Collection selection
uses different methods to document selection for scoring items relevance [3]. Document selection commonly uses
a binary relevance value, which collection selection cannot use. Instead collection selection must use a floating
point number to represent relevance.

Collection selection also differs from document selection in that it uses different ways of calculating term weighting. (terms distributed across all documents in a collection are worth more than terms clustered in one document of a collection) Another difference between collection selection and document selection is that different

53 content selection methods are needed, with Web based collection selection commonly using partial collection

sampling, and document selection using full document indexing. These differences mean that collection selection

using optimal term requires a significantly different approach to document selection III.

⁵⁶ 2 Modified Collection Selection Algorithm

In this section, we give the details of our collection selection algorithm. The inputs of the algorithms include a
query, a selected set of terms (key words), and a set of sample documents from each collection. a) Algorithm 1.
Calculate the term-collection matrix A where we view the query as a new collection.

2. Use singular value decomposition. U ?V T = A 3. Sort the collections according to the values in the query 60 row in the matrix V T 4. Use the threshold to calculate a rank of collections. 5. After ranking the collection 61 we need to find the optimal term weight to find the relevant pages which are more appropriate. Term-collection 62 matrix is created, adding the query to the matrix in the form of a new (small) document column. Negative 63 weights can be given to terms that are not to be returned in the query. Applying Singular Value Decomposition 64 to the matrix returns a term matrix (U), a Singular Value matrix(S), and a collection matrix (V). For every 65 search performed, the user will give the top n collections (n is currently 10) a floating point precision ranking in 66 the range of 0 to 1. 67

The higher the ranking the more precise the results. After training run of (say) twenty searches collection matrix and the latent statistical relationships between collections computed [5]. The returned values are a score for each collection, with zero being not relevant and one being most relevant. This will find relationships existing between collections that are not immediately obvious, and will result in a more personalized search which will over time learn the user's preferences.

73 IV.

74 **3** Conclusions

A solution to the Web Based Collection Selection problem has been presented, and preliminary results indicate that the technique is suited to the task of selecting the most relevant collections and learning user preferences in collections. The approach uses short queries and is thus suitable for use on the Web. This approach also reduces the need for ontologies and thesaurus. With some modification, this collection selection method is suitable for traditional information retrieval systems across servers and databases. A problem is that these systems do not rank the data before returning it. This could be solved using simple sampling techniques that would grab a

81 representative sample of the collection, rank it, then compare it across collections. As the number of collections 82 indexed grows, so does the number of terms and the size of the matrix.

However in this research, only the top n most representative documents from each collection are sampled so it is possible to compare hundreds of collections in a reasonable time if n is small. Due to the time expense of writing screen scraping applications for web based collections and comparing the results to human rankings of the documents in the collections, the researchers were unable to perform large scale tests of the methods presented

in this research. Work still needs to be done to on the optimal sample size taken from each collection.

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