

# **A RECOMMENDER SYSTEM FOR SOCIAL BOOK SEARCH**

A thesis

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by

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## **Dedication**

This thesis is dedicated to my family for their love, endless support and encouragement.

## **Abstract**

Information retrieval (IR) is a field of computing which deals with storing and retrieving document information. The World Wide Web (WWW) contains a vast amount of information. Storage and retrieval of this information is a huge task. Extensible Markup Language (XML) is used to represent documents so that portions (or elements) may be effectively retrieved. INEX (Initiative for the Evaluation of XML retrieval) is a forum for experimental XML retrieval. It is used to evaluate XML retrieval systems and provides a number of tracks (e.g., Social Book Search, Linked Data, and Tweet Contextualization) and evaluation strategies for the systems designed by competing teams. It also provides a set of XML documents and queries that can be used as a test bed.

This thesis focuses on the 2014 INEX Social Book Search (SBS) Suggestion task. The goal of this track is to provide support to users in searching and navigating a large set of books using professional and metadata and user-generated content. In this task, given book requests from LibraryThing discussion forums and a collection of 2.8 million book descriptions from Amazon and LibraryThing, a ranked list of book suggestions is returned to the user. The methodology (based on traditional retrieval and recommendation), the experimental results, and conclusions are described herein.

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## **1. Introduction**

Information retrieval (IR) is a field of computing which deals primarily with storing and retrieving document information. The World Wide Web (WWW) contains a vast amount of information. Storage and retrieval of this information is a huge task. Extensible Markup Language (XML) is used to represent documents so that portions (or elements) may be effectively retrieved.

INEX (Initiative for the Evaluation of XML retrieval) [1] is a forum for experimental XML retrieval. It is used to evaluate XML retrieval systems and provides a large set of tracks (e.g., Social Book Search, Linked Data, and Tweet Contextualization) and evaluation strategies for the systems designed by competing teams. It also provides a set of XML documents and queries that can be used as a test bed.

This research focuses on the 2014 INEX Social Book Search (SBS) Track [2]. The goal of this track is to provide support to users in searching and navigating a large set of books (2.8 million, in this case) using professional metadata and user-generated content. This track consists of two tasks: the suggestion task and the interactive task. The former task is the focus of interest of this research, wherein using book requests from LibraryThing [3] discussion forums and a collection of 2.8 million book descriptions from Amazon and LibraryThing, a ranked list of book suggestions are returned to the user.

Chapter 2 describes the background for this research and in Chapter 3, the methodology supporting the Suggestion task is described. Chapter 4 describes the experiments and experimental results. Conclusions and suggestions for future research are contained in Chapter 5.

## 2. Background

This chapter provides an overview of Salton's Vector Space Model [4] and the Smart [5] retrieval system. An overview of INEX and the INEX Social Book Search Track in 2011-2014 is also provided.

### 2.1 Vector Space Model and Smart

The Vector Space Model (VSM) is the model most used in information retrieval. In this model, documents and queries are represented as vectors. Every document and query is represented by an  $n$ -dimensional vector, where  $n$  is the number of unique terms in the document. Each dimension in a vector corresponds to a term. If a term occurs in the document, its value in the vector is non-zero.

There are three basic steps in creating a vector. The first step is document indexing, where content-bearing words are extracted from the document which is then represented as a vector of terms. The second step is the weighting of terms in the vector, based on a function of frequency. The last step is retrieval: finding the similarity between the document vector and the query vector by calculating the similarity between the vectors.

Smart is a retrieval system based on the Vector Space Model. It is used for indexing, term weighting, and retrieval. Generally, extreme variation in vector length does not occur across document collections; this occurs often when dealing with element retrieval. To help equalize the chances of retrieval across vectors which vary greatly in length, an appropriate weighting scheme (such as *Lnu-ltu* [6, 7]) must be used. Smart produces a ranked list of documents that closely correlate with the query.

## **2.2 INEX and the Social Book Track**

INEX is an evaluation forum for experimentation, design and evaluation of systems for XML retrieval. It provides a set of tasks and evaluation metrics for use by participant teams. It also provides a set of XML documents and queries that can be used as a test bed. Our focus in 2014 is the Social Book Search Track.

### **The INEX 2011 Social Book Search Track [8]**

The goal of this track is to evaluate the relative value of user-generated metadata, such as reviews and tags, versus publisher-supplied and library catalogue metadata in retrieving the most relevant books for a given user request. A list of these "recommended" books is returned as a reply to a user's request that has been posted on the LibraryThing forums. The 2011 Social Book Search track document collection consists of 211 topics (user requests) and 2.8 million book descriptions, with each description combining information from Amazon and LibraryThing.

### **The INEX 2012 Social Book Search Track [9]**

In this track, the number of topics is increased to 300, and the document collection is extended with library catalogue records from the Library of Congress and the British Library. In addition, user profile information such as the location of the user, books read and favorite books is provided to facilitate the search process.

### **The INEX 2013 Social Book Search Track [10]**

This track is similar to the previous year's track except that the number of topics is increased to 386. In addition, INEX provides a mediated query field for each topic that aims to be both a concise and comprehensive expression of the information need.

## **The INEX 2014 Social Book Search Track [2]**

The goal of this track is to provide support to users in searching and navigating books, using both professional metadata and user-generated content. This track consists of two tasks: Suggestion task and Interactive task. Our focus in 2014 is the former task, wherein using book requests from the LibraryThing discussion forums and a collection of 2.8 million book descriptions from Amazon and LibraryThing, a ranked list of book suggestions is returned to the user. A sample document from the collection is shown in Figure 1.

In this track, the number of topics increased to 680. A topic represents the information need of a user. It contains the title and message of a LibraryThing member who requested book suggestions, as well as the name of the discussion in which the message is posted. Topics are enriched with a user profile of the topic creator, which contains information about the books catalogued, including tags and ratings. A sample topic is shown in Figure 2.

In addition, INEX also provides a large set of 94,000 anonymous user profiles from LibraryThing. A sample user profile is shown in Figure 3.

The official evaluation measure for this task is  $nDCG@10$ . It takes graded relevance values into account and concentrates on the top-ranked results.

```

<?xml version="1.0" encoding="UTF-8"?>
<!-- version 1.0 / 2009-11-10T06:20:02+01:00 -->
<!DOCTYPE book SYSTEM "books.dtd">
<book>
  <isbn>0684141000</isbn>
  <title>The young man who wrote soap operas</title>
  <ean>9780684141008</ean>
  <binding>Unknown Binding</binding>
  <label>Scribner</label>
  <listprice/>
  <manufacturer>Scribner</manufacturer>
  <publisher>Scribner</publisher>
  <readinglevel/>
  <releasedate/>
  <publicationdate>1975</publicationdate>
  <studio>Scribner</studio>
  <edition/>
  <dewey/>
  <numberofpages>180</numberofpages>
  + <dimensions>
  <reviews/>
  <editorialreviews/>
  <images/>
  + <creators>
  <blurbers/>
  <dedications/>
  <epigraphs/>
  <firstwords/>
  <lastwords/>
  <quotations/>
  <series/>
  <awards/>
  <characters/>
  <places/>
  <subjects/>
  <tags/>
  <similarproducts/>
  + <browseNodes>
</book>

```

Figure 1: Excerpt of INEX Document

```

<?xml version="1.0"?>
- <topics>
  - <topic id="1220">
    <title>Best George book?</title>
    <mediated_query>George Harrison</mediated_query>
    <group>LibraryThings We Said Today</group>
    <narrative> I'm looking for the best book on George Harrison. </narrative>
  - <catalog>
    - <book>
      <LT_id>11412</LT_id>
      <entry_date>2005-12</entry_date>
      <rating>0.0</rating>
      <tags>occult, biography</tags>
    </book>
    - <book>
      <LT_id>1390944</LT_id>
      <entry_date>2006-08</entry_date>
      <rating>0.0</rating>
      <tags>bukowski, letters</tags>
    </book>
  </catalog>
</topic>
</topics>

```

**Figure 2: A Sample Topic**

user id	LT_id	entry_date	Rating	Tags
.....	.....	.....	.....	.....
.....	.....	.....	.....	.....
u8218518	4900952	2012-02	6.0	
u8218518	6172473	2012-02	8.0	
u8780837	542201	2009-05	10.0	tarot
u9054475	5403381	2010-11	10.0	Fun, joy
u9054475	5145202	2010-11	9.0	
.....	.....	.....	.....	.....
.....	.....	.....	.....	.....

**Figure 3: A Sample User Profile**

### **3. Implementation**

In this chapter, Indri [11] and the methodology underlying the SBS Suggestion task are explained.

#### **3.1 Indri Search Engine**

Indri is a text search engine developed at the University of Massachusetts. It is a part of the Lemur project. Indri provides a powerful indexer capable of indexing a variety of document formats such as HTML, XML, PDF, plain text and TREC documents. This tool is used as the primary indexing tool in this research.

#### **3.2 Methodology**

The methodology used for the Suggestion task combines the two aspects of retrieval and recommendation. Retrieval and recommendation are performed using the traditional and recommendation systems, respectively. Figure 4 shows the architecture of both systems.

##### **3.2.1 Traditional System**

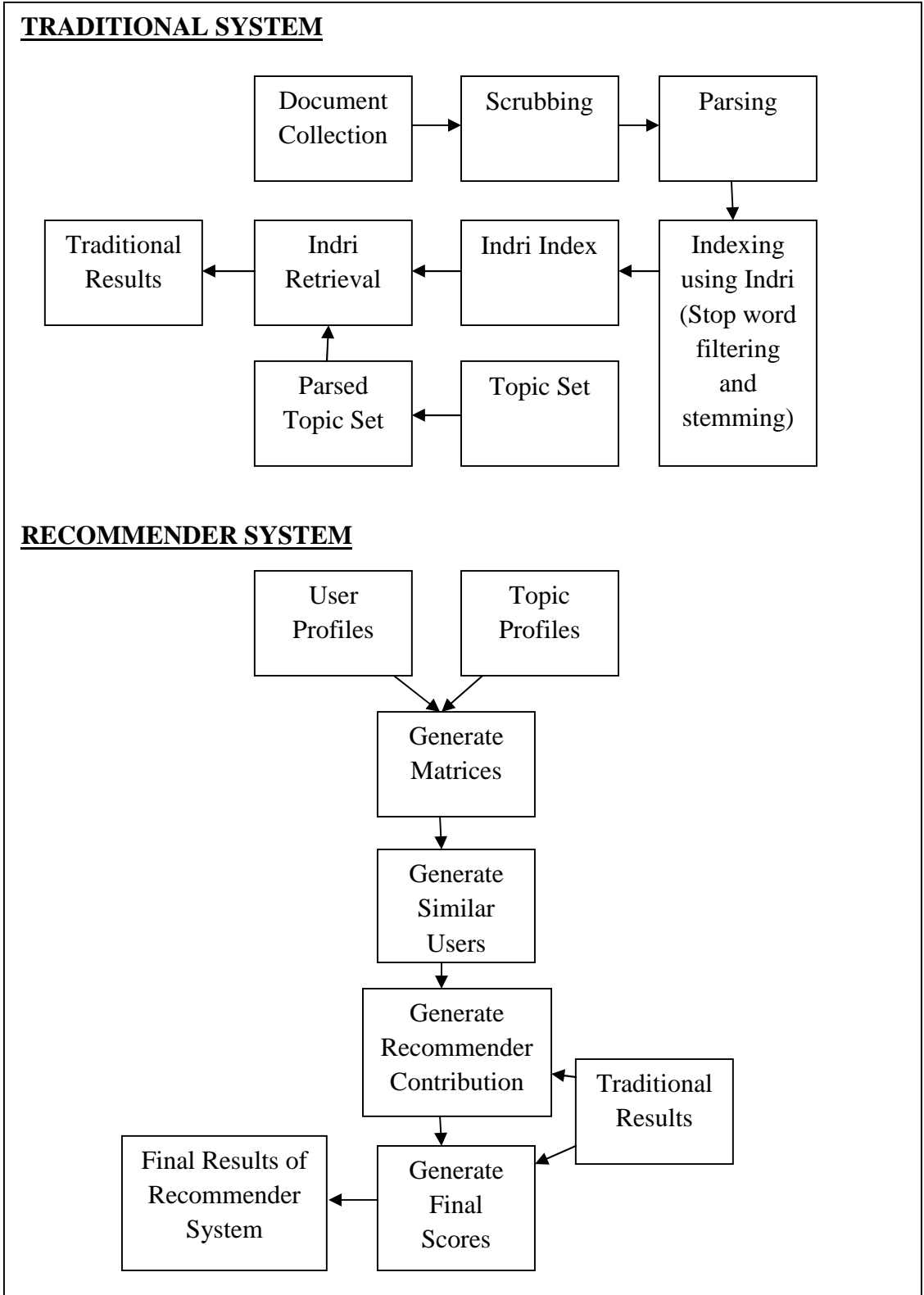
This system is responsible for document retrieval, including scrubbing, parsing, and indexing using Indri.

##### **Scrubbing**

The first step in the traditional system is the scrubbing of the document collection. Scrubbing is the process of removing unwanted tags and text, i.e., tags and text that do not aid in retrieval.

##### **Parsing**

The second step is parsing of scrubbed document collection based on specified tags present in the XML documents. The six parses produced are: Amazon, Full, Library-



**Figure 4: Traditional and Recommender Systems Architecture**



Thing, Professional, Social and Title.

### **Indexing**

In the third step, we index the six parse files using Indri. Indri takes two files as input parameters, namely, the path of the parse file to be indexed, stemmer (Krovetz), and a list of stop-words. Indri creates an index from the parse file. These six indices (Amazon, Full, LibraryThing, Professional, Social and Title) are used as the primary indices for document retrieval.

### **Topic Parsing**

In the fourth step, topics are parsed based on the various combinations of the title, query, group and narrative XML tags that are present in the topics file into six parses. The six topic parses are Title (T), Query (Q), Title-Query (TQ), Title-Query-Group (TQG), Title- Query-Narrative (TQN) and Title-Query-Group-Narrative (TQGN).

### **Indri Retrieval**

Using a combination of each index and topic parse, Indri retrieval was performed both with and without pseudo-feedback to produce an initial, ranked list of documents which constitutes the traditional results.

### **3.2.2 Recommender System:**

This system re-ranks the results produced by the traditional system by making use of the information from users “similar to” the user who posted the topic. Here we assume that similar users tend to have similar preferences and tastes in books.

### **Generate Matrices**

The first step in the recommender system is to generate a matrix for each of the 680 topics. These matrices consist of work IDs and tags, and the values in the matrices

are combinations of numeric and binary values. Here we require that users must have a minimum of 5 work IDs in common before they are considered similar. The matrix representations are shown in Table 1.

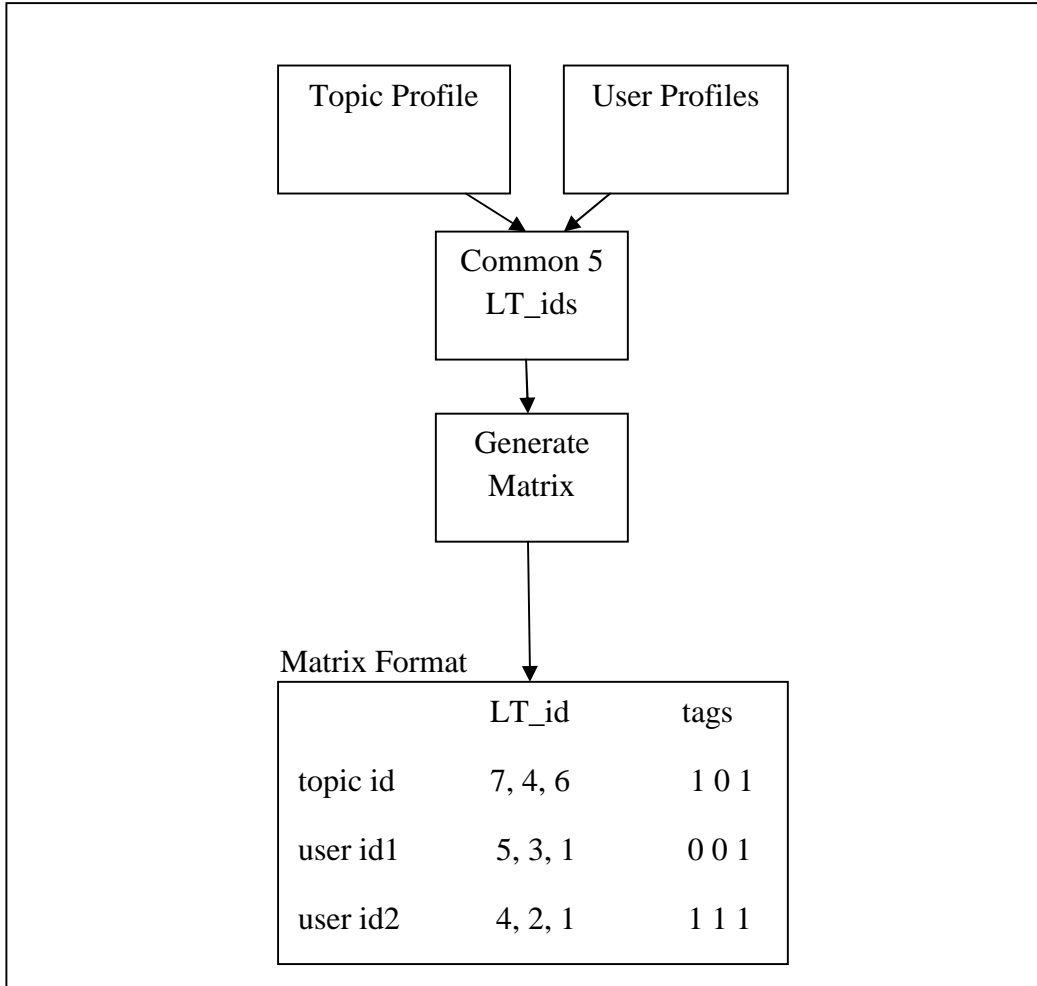
<b>Matrix Representation</b>	<b>Work ID Value</b>	<b>Tag Value</b>
bin_bin	binary 1 = work ID exists 0 = otherwise	binary 1 = tag exists 0 = otherwise
num_bin	numeric rating for work ID	binary 1 = tag exists 0 = otherwise

**Table 1: Matrix Representation**

For each of the 680 topics there exists a "topic profile" contained between <catalog> and </catalog> tags. This tag gives information regarding the books present in the user's catalog. Information regarding a book consists of LibraryThing id (LT\_id), entry date of the book in the catalog, rating given to the book and tags given to the book. Using this topic profile and anonymous user profiles, matrices are constructed as explained in Figure 5.

**Generate Similar Users**

In the second step, a list of similar users along with their similarity scores is generated for each topic based on the context vectors of the matrix generated in the previous step. Pairwise cosine similarity is used as the similarity measure, and the top-ranked 50 and 100 "similar users" are considered the sets of interest.



**Figure 5: Matrix Construction**

**Generate Recommender Contribution**

In the third step, we now generate  $\mathcal{C}$ , the contribution of recommender system, using as input, for each primary user: (1) the rank ordered list of similar users, (2) the similarity score of each such user, (3) the rating for each LT\_id identified by document retrieval using the traditional system, and (4) the count of similar users having that same LT\_id in their catalogs. Here we use 2 metrics to calculate  $\mathcal{C}$ . One metric is a DCG-style metric, and the other uses an MRR approach. These metrics are defined in Figure 6.

Metric	Binary Score	Numeric Score
Metric 1 (DCG-style)	$R_{ij} = \sum_{k=1}^{50/100} \frac{S_{ik} + 1}{\log_2(\text{rank}) + 1}$	$R_{ij} = \sum_{k=1}^{50/100} \frac{S_{ik} + r_{jk}}{\log_2(\text{rank}) + 1}$
Metric 2 (MRR- style)	$R_{ij} = \sum_{k=1}^{50/100} \frac{S_{ik} + 1}{\text{rank}}$	$R_{ij} = \sum_{k=1}^{50/100} \frac{S_{ik} + r_{jk}}{\text{rank}}$
<p>i = topic id</p> <p>j = work ID</p> <p>k = similar user for topic 'i' (50/100)</p> <p><math>R_{ij}</math> = Recommended score for topic 'i' work ID 'j'</p> <p><math>S_{ik}</math> = Similarity score for user 'k'</p> <p><math>r_{jk}</math> = Rating given by user 'k' for work ID 'j'</p>		

**Figure 6: Metrics for Calculating (the Contribution of the Recommender System)**

### Generate Final Scores

In the fourth step, a linear combination of the scores produced by traditional system and , the contribution of the recommender system is calculated. As a result, the re-ranked list of "recommended" scores is produced, which constitutes the final results.

## 4. Experiments and Results

This chapter describes the experiments performed for the 2014 INEX SBS Suggestion task both for traditional and recommender systems.

### 4.1 Traditional System Experiments

Pseudo-feedback is a feature of information retrieval systems. In this feedback, a normal retrieval is performed to find an initial set of the highest correlating documents. It is then assumed that the top "k" ranked documents are relevant and the top "n" terms from these documents are selected based on a function of their tf-idf weights. The query is expanded by adding these terms to it and then used to retrieve another document set.

In experiment 1, we perform document retrieval without pseudo-feedback. The experiments performed for the 2011 and 2013 INEX SBS suggestion tasks without pseudo-feedback [12, 13] yielded best results for the Full-TQG combination. So only this combination was chosen for 2014 experiments.

#### Experiment 1

In this experiment, Indri retrieval is performed without pseudo-feedback on the Full-TQG combination. Results are found in Table 2.

	<b>nDCG@10</b>	<b>R@1000</b>	<b>MAP</b>	<b>MRR</b>
<b>Full-TQG</b>	0.0847	0.3169	0.0579	0.1656

**Table 2: Indri Retrieval (Base Case)**

#### Experiment 2

In this experiment, to improve document retrieval, pseudo-feedback is used. From an initial retrieval, the top-ranked 5, 10 and 15 documents, respectively, are chosen and sets of 5, 15, 20, 25 and 40 terms are selected from these documents for expansion.

Results obtained are shown in Table 3.

#docs	#terms	nDCG@10	R@1000	MAP	MRR
5	5	0.0885	0.3675	0.0587	0.1792
5	20	0.0900	0.3809	0.0629	0.1761
10	15	<b>0.0908</b>	<b>0.3801</b>	0.0641	0.1777
10	25	0.0931	0.3774	<b>0.0650</b>	<b>0.1804</b>
15	40	0.0915	0.3761	0.0631	0.1766

**Table 3: Indri Retrieval With Pseudo-Feedback**

As seen in Table 3, the best results were obtained for 10 documents and 15 terms combination (by considering the corresponding nDCG@10 and R@1000 values).

### **Experiment 3**

A book is represented by an ISBN number in the INEX 2014 SBS Suggestion task. But in general, a single book can have different editions, thus leading to different ISBNs for that book. In 2014, INEX provided the participants of the SBS Suggestion task with a mapping of different ISBNs of a book to a single LT\_ID. Using this information, data from different ISBNs (ISBN1, ISBN2, ... , ISBNn) is merged into a single LT\_ID and the experiment is performed. Results obtained are seen in Table 4.

#docs	#terms	nDCG@10	R@1000	MAP	MRR
5	5	0.0558	0.3875	0.0449	0.1016
10	15	<b>0.0575</b>	<b>0.3953</b>	<b>0.0473</b>	<b>0.1056</b>

**Table 4: Indri Retrieval With Pseudo-Feedback and Merged ISBNs**

As seen in Table 4, best results were obtained for 10 documents and 15 terms combination (by considering the corresponding nDCG@10 and R@1000 values).

From Tables 3 and 4, it can be observed that 10 documents and 15 terms yield best results. So this combination is used for the rest of the experiments performed.

#### **Experiment 4**

In this experiment, to further improve the results of Experiment 2 for the 10 documents and 15 terms combination, weighted pseudo-feedback [14] is considered. Results are seen in Table 5.

<b>Weight</b>	<b>nDCG@10</b>	<b>R@1000</b>	<b>MAP</b>	<b>MRR</b>
0.70	<b>0.0935</b>	<b>0.3819</b>	0.0647	<b>0.1786</b>
0.75	0.0923	0.3804	0.0641	0.1768
0.80	<b>0.0934</b>	<b>0.3811</b>	0.0638	0.1777
0.85	0.0940	0.3809	<b>0.0652</b>	0.1753
0.90	0.0912	0.3754	0.647	0.1743
0.95	0.0889	0.3655	0.0618	0.1710

**Table 5: Indri Retrieval With Weighted Pseudo-Feedback**

Best results are obtained for weights 0.7 and 0.8 (in terms of nDCG@10 and R@1000 values). So the results produced by the traditional system for these weights are now input to and re-ranked by the recommender system in Experiment 6.

#### **Experiment 5**

To further improve the results of Experiment 3, weighted pseudo-feedback is utilized. Results obtained are presented in Table 6.

Best results are obtained for weight 0.7 (by considering R@1000 value). So the results produced by the traditional system for these weights are now input to and re-ranked by recommender system in Experiment 7.

<b>Weight</b>	<b>nDCG@10</b>	<b>R@1000</b>	<b>MAP</b>	<b>MRR</b>
0.70	0.0593	<b>0.3953</b>	0.0485	0.1111
0.75	0.0589	0.3883	0.0478	0.1092
0.80	0.0598	0.3827	0.0481	0.1124
0.85	0.0616	0.3730	0.0491	0.1140
0.90	0.0621	0.3669	0.0495	0.1151
0.95	<b>0.0636</b>	0.3629	<b>0.0506</b>	<b>0.1184</b>

**Table 6: Indri Retrieval With Weighted Pseudo-Feedback of Merged ISBNs**

## 4.2 Recommender System Experiments

The recommender system re-ranks the results produced by the traditional system. The recommender system is designed to make use of information from users "similar to" the user who posted the topic. Here we assume that similar users tend to have similar preferences and tastes in books.

### Experiment 6

In this experiment, bin\_bin and num\_bin matrix representations (as presented in Chapter 3) are chosen; 50 and 100 "similar users" are the sets of interest. Metric 1 (DGC-style) and Metric 2 (MRR-style) (defined in Chapter 3) are used with  $\alpha$  set to 0.00001. (Experiments performed to fine tune  $\alpha$  for the 2011 and 2013 INEX SBS suggestion tasks [12, 13] yield best results for 0.00001). Results are recorded in Table 7.

From Table 7, it can be observed that the best results are achieved when Metric 2 is used on bin\_bin matrix representation (by considering nDCG@10 value). The value of nDCG@10 is greater when 50 rather than 100 similar users are sets of interest and 0.7 is chosen for weighted pseudo-feedback.



Metric	Feature	Users		Weight	nDCG@10	R@1000	MAP	MRR	
Metric 1	bin_bin	50	0.00001	0.7	0.0954	<b>0.3819</b>	0.0651	0.1963	
				0.8	0.0868	0.3811	0.0579	0.1880	
		100	0.00001	0.7	0.0911	<b>0.3819</b>	0.0623	0.1898	
				0.8	0.0848	0.3811	0.0562	0.1861	
	num_bin	50	0.00001	0.7	0.0929	<b>0.3819</b>	0.0630	0.1859	
				0.8	0.0853	0.3811	0.0565	0.1798	
		100	0.00001	0.7	0.0928	<b>0.3819</b>	0.0628	0.1889	
				0.8	0.0878	0.3811	0.0579	0.1861	
	Metric 2	bin_bin	50	0.00001	0.7	<b>0.1008</b>	<b>0.3819</b>	0.0692	0.1966
					0.8	0.0914	0.3811	0.0625	0.1880
			100	0.00001	0.7	0.1005	<b>0.3819</b>	<b>0.0701</b>	<b>0.1968</b>
					0.8	0.0920	0.3811	0.0632	0.1858
num_bin		50	0.00001	0.7	0.0961	<b>0.3819</b>	0.0666	0.1901	
				0.8	0.0872	0.3811	0.0588	0.1816	
		100	0.00001	0.7	0.0984	<b>0.3819</b>	0.0684	0.1942	
				0.8	0.0906	0.3811	0.0625	0.1898	

**Table 7: Final Results of the Recommender System**

## **Experiment 7**

In this experiment, `bin_bin` and `num_bin` matrix representations (defined in Chapter 3) are chosen; 50 and 100 "similar users" are the sets of interest. Metric 1 (DGC-style) and Metric 2 (MRR-style), defined in Chapter 3, are used with `weight` set to 0.00001 (Experiments to fine tune `weight` for the 2011 and 2013 INEX SBS suggestion tasks [12, 13] yield best results for 0.00001). Results are shown in Table 8.

From Table 8, it can be observed that the best results are achieved when Metric 1 is used on `bin_bin` matrix representation (by considering `nDCG@10` value). The value of `nDCG@10` is greater when 100 rather than 50 similar users are sets of interest and 0.7 is chosen as weighted pseudo-feedback.

### **4.3 Analysis of Results**

From Tables 7 and 8, it can be observed that the best results are achieved when Metric 2 is used on `bin_bin` matrix representation (`nDCG@10` value). The value of `nDCG@10` is greater when 50 rather than 100 similar users are sets of interest and 0.7 is chosen as weighted pseudo-feedback. It can also be observed that `num_bin` matrix representation didn't produce the best results in either of the Tables 7 and 7. Moreover, merging ISBNs was also not successful.

According to the six runs [12, 13] submitted to the INEX 2014 competition, our current best result (0.1058) would rank at 17 in terms of `nDCG@10` and 13 in terms of `R@1000` when compared to the INEX 14 official results. Many of these results exhibit small differences; significance results are not available and thus we do not know how meaningful the disparity in the results is.

Metric	Feature	Users		Weight	nDCG@10	R@1000	MAP	MRR
Metric 1	bin_bin	50	0.00001	-	0.0715	0.3953	0.0559	0.1327
				0.7	0.0820	0.3953	0.0623	0.1586
	100	0.00001	-	0.0740	0.3953	0.0566	0.1365	
			0.7	<b>0.0856</b>	<b>0.3953</b>	0.0636	<b>0.1672</b>	
	num_bin	50	0.00001	-	0.0657	0.3953	0.0519	0.1225
				0.7	0.0781	0.3953	0.0596	0.1507
		100	0.00001	-	0.0689	0.3953	0.0533	0.1285
				0.7	0.0835	0.3953	0.0616	0.1632
Metric 2	bin_bin	50	0.00001	-	0.0692	0.3953	0.0553	0.1278
				0.7	0.0807	0.3953	0.0624	0.1572
	100	0.00001	-	0.0710	0.3953	0.0562	0.1286	
			0.7	0.0833	0.3953	<b>0.0642</b>	0.1604	
	num_bin	50	0.00001	-	0.0650	0.3953	0.0531	0.1200
				0.7	0.0765	0.3953	0.0591	0.1495
		100	0.00001	-	0.0674	0.3953	0.0542	0.1232
				0.7	0.0804	0.3953	0.0620	0.1578

**Table 8: Final Results of the Recommender System with Merged ISBNs**

## 5. Conclusions and Future Work

The results of the 2014 INEX SBS Suggestion task suggest that the best features for the matrices are bin\_bin, where both work IDs and tags are represented as binary values. The value of nDCG@10 is greater when 50 rather than 100 similar users are considered. Metric 2 produces a higher nDCG@10 result when weighted pseudo-feedback is used.

From R@1000 we observe that few relevant documents are retrieved in the top 1000 during document retrieval. One reason may be because QRels are retrieved from answers in the LibraryThing forum and the users might not have knowledge of all books, whereas document retrieval retrieves all correlating books. Increasing recall at this stage may be expected to produce improvement in the final scores.

It is evident that the methodology supporting the Suggestion task in this work is restricted by the recall of Indri. Use of a thesaurus for query expansion is a possible solution to this problem.

We experimented with only one distance function (cosine similarity) to calculate the similarity between users. There is a scope in the future to experiment with other distance functions to calculate the similarity.

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