Information Retrieval Based On Relevance Feedback Algorithm

Dipalee S. Hirde
Student of M.E, Department of Computer Science & Engineering,
HVPM's College of engineering & technology, Amravati.

Prof. R. R. Keole
Asst. Professor , Department of Information Technology & Engineering,
HVPM's College of engineering & technology, Amravati.

ABSTRACT: Information Retrieval (IR) is concerned with indexing and retrieving documents including information relevant to a user's information need. Relevance Feedback (RF) is a class of effective algorithms for improving Information Retrieval (IR) and it consists of gathering further data representing the user's information need and automatically creating a new query. Relevance Feedback consists in automatically formulating a new query according to the relevance judgments provided by the user after evaluating a set of retrieved documents. Finding relevant document is one of the hard tasks. we propose a class of RF algorithms inspired by quantum detection to re-weight the query terms and to re-rank the document retrieved by an IR system. Information retrieval (IR) is the activity of obtaining information resources relevant to an information need from a collection of information resources. Searches can be based on full-text or other content-based indexing. Automated information retrieval systems are used to reduce what has been called "information overload". Most IR systems compute a numeric score on how well each object in the database matches the query, and rank the objects according to this value. The top ranking objects are then shown and IR system return relevant document to the user. The process may then be iterated if the user wishes to refine the query.

KEYWORDS: Information retrieval, quantum mechanics, relevance feedback, quantum detection.

I. INTRODUCTION

Information Retrieval (IR) is concerned with indexing and retrieving documents including information relevant to a user's information need. Although the end user can express his information need using a variety of means, queries written in natural language are the most common means. However, a query can be very problematic because of the richness of natural language. Indeed, a query is usually ambiguous; a query may express two or more distinct information needs or one information need may be expressed by two or more distinct queries. Text Retrieval Conference(TREC) test collection from which the query is submitted to an IR system based on the Vector Space Model (VSM). This system would return both relevant documents and irrelevant documents. Finding relevant document is one of the hard tasks. Information retrieval (IR) is the activity of obtaining information resources relevant to an information need from a collection of information resources. Searches can be based on full-text or other content-based indexing. Automated information retrieval systems are used to reduce what has been called "information overload". Many universities and public libraries use IR systems to provide access to books, journals and other documents. web search engine are the most visible IR application .An information retrieval process begins when a user enters a query into the system. Queries are formal statements of information needs, for example search strings in web search engines. In information retrieval a query does not uniquely identify a single object in the collection. Instead, several objects may match the query, perhaps with different degrees of relevancy.

Information retrieval (IR) has experienced huge growth in the past decade as increasing numbers and types of information systems are being developed for end-users. The incorporation of users into IR system evaluation and the study of users information search behaviors and interactions have been identified as important concerns for IR researchers .The proposition that IR systems are fundamentally interactive and should be evaluated from the perspective of users is not new. Relevance feedback is the retrieval task where the system is given not only a user query, but also user feedback on some of the top ranked results. Feedback gives the retrieval system a chance to improve its results by exploiting the extra information through more elaborate techniques. This can be helpful in cases where the users want as many relevant results as possible.

An IR system addresses the problems caused by query ambiguity by gathering additional evidence that can be used to automatically modify the query . Usually a query is expanded because the queries are short and it cannot exhaustively describe every aspect of the user's information need; however, some irrelevant documents may be retrieved or relevant documents may also be missed when a query is not short .The automatic procedure that modify the user's queries is known as Relevance Feedback (RF); some relevance assessments about the retrieved documents are collected and the query is expanded by the terms found in the relevant documents, reduced by the terms found in the irrelevant documents or reweighted using relevant or irrelevant documents.

II. LITERATURE REVIEW

Buckley and Voorhees [1] introduced a new evaluation metric, which allows to overlook non-judged documents and does not require to consider them to be irrelevant (the metric is computed by analyzing the relative rankings of the relevant and irrelevant documents). Second, we compute the standard metrics such as Mean Average Precision (MAP), Normalized Discounted Cumulative Gain (NDCG) only for the documents for which we have judgments.

Ingo Frommholz [2] present how a geometrical retrieval framework inspired by quantum mechanics can be extended to support polyrepresentation. We show by example how different representations of a document can be modelled in a Hilbert space, similar to physical systems known from quantum mechanics. We further illustrate how these representations are combined by means of the tensor product to support polyrepresentation, and discuss the case that representations of documents are not independent from a user point of view.

M. Shanmugham [3] Present a class of RF algorithms inspired by the quantum detection has been proposed to re-weight query terms by projecting the query vector on the subspace represented by the eigenvector which is the optimal solution to the problem of finding the maximal distance between two quantum probability distributions. The complexity of the calculation of the eigenvector is limited by the small size of the matrix that represents the distance between two quantum probability distributions.

AblimitAji [4] evaluate an approach that relies on a novel source of such knowledge, namely, the revision history of a document. Many information retrieval models, notably statistical language models, assume a generative process of document creation, whereas the terms are chosen to be included in the document according to their importance to the chosen document topic(s), previously chosen terms, and other factors that vary by model. Yet these models only examine one (final) version of the document to be retrieved, effectively ignoring the actual document generation process, even when it is available.

Shuqin Liu [5] present a weighted coefficients of image retrieval algorithm based on relevance feedback are determined in advance, which is lack of flexibility. In order to obtain satisfactory retrieval results, this algorithm requires a large amount of feedback calculation and efficiency of the algorithm is low. Aiming at the faults of relevance feedback, the adaptive adjustment algorithm of weighted coefficients based on quantum particle swarm optimization is presented, which is composed of user feedback process and particle evolution process..

Diane Kelly [6] present a foundation around which others can discuss methods for studying IIR. This includes the creation of more detailed reviews of some of the topics discussed in this paper such as IIR history, measures and ethics. People have varying opinions about how IIR evaluation should be conducted. The content of this paper represents one such opinion that is informed heavily by the literature, the author's research experiences and an academic background that is rooted in the behavioral sciences.

Luis M. de Campos [7] present an approach for relevance feedback in the Bayesian Network Retrieval (BNR) model. Our proposal is based on the propagation of partial evidences in the Bayesian network, representing the new information obtained from the user's relevance judgments to compute the posterior relevance probabilities of the documents.

Pang et al. [8] introduced the relevance degree information into a spectral embedding framework, and proposed a novel Ranking Graph Embedding (RANGE) algorithm by modeling the global structure and the local relationships in and between different relevance degree sets, respectively.

Tian et al. [9] investigated the reranking problem from the probabilistic perspective and derived an optimal reranking function based on Bayesian analysis. In their methods, textual information is modeled as a likelihood to reflect the disagreement between the reranked results and the text-based search results, and the visual information is modeled as a conditional prior to indicate the ranking score consistency among visually similar samples.

Liu et al. [10] proposed a novel unsupervised one-class learning method by jointly learning a large margin one-class classifier and a soft label assignment for targets and outliers. Extensive experiments have shown its effectiveness in outlier image removal and ISR. These approaches have been successfully employed in CBIR and ISR, however, the selection of appropriate kernel is still an open problem. Moreover, the idea of hypersphere in SVDD has not been employed.

K. Collins-Thompson [11] present traditionally, the search engines have ignored the reading difficulty of documents and the reading proficiency of users in computing a document ranking. This is one reason why Web search engines do a poor job of serving an important segment of the population: children. While there are many important problems in interface design, content altering, and results presentation related to addressing children's search needs.

Y. Lv, C. Zhai [12] present the pseudo-relevance feedback has proven effective for improving the average retrieval performance. Unfortunately, many experiments have shown that although pseudo-relevance feedback helps many queries, it also often hurts many other queries, limiting its usefulness in real retrieval applications. Thus an important, yet difficult challenge is to improve the overall effectiveness of pseudo-relevance feedback without sacrificing the performance of individual queries too much.

Claudio Carpineto [13] present the relative ineffectiveness of information retrieval systems is largely caused by the inaccuracy with which a query formed by a few keywords models the actual user information need. One well known method to over- come this limitation is automatic query expansion (AQE), This survey presents a unified view of a large number of recent approaches to AQE that leverage various data sources and employ very different principles and techniques.

J. Kamps [14] present, during retrieval, our system initially operates just like a regular information retrieval system: given a query, our system will retrieve potential list of documents from the latest revisions index for scoring, and passes this initial list to the RHA module. In the future, we plan to further optimize the retrieval efficiency by precomputing the RHA term weights for all documents, instead of performing RHA analysis and re-ranking at retrieval time.

Massimo Melucci [15] present a class of RF algorithms inspired by quantum detection to re-weight the query terms and to re-rank the document retrieved by an IR system. Focuses on explicit RF and on pseudo RF. Implicit RF is based on observations (e.g., click-through data) that are proxies of relevance. The main problem with proxies is that they are not necessarily reliable indicators of relevance and thus should be considered noisy. How quantum detection can help "absorbe" noise can also be investigated in the future work.

Le Zhao [16] we try to develop a feedback algorithm that works well on all levels of feedback by extending the relevance model for pseudo relevance feedback to include judged relevant documents when scoring feedback terms. Within these different levels of feedback, it is more difficult for the feedback algorithm to perform well when given minimal amount of feedback. Experiments show that our algorithm performs well in those difficult cases.

Croft and Harper [17] first suggested a technique by as a means of estimating probabilities within the probabilistic model for an initial search. It has since been widely investigated as a technique for improving document rankings. Croft and Harper also pointed to the fact that this method of improving a document ranking can suffer from one major flaw query drift. Query drift occurs when the documents used for RF contain few or no relevant documents. In this case, RF will add terms to the query that are poor at detecting relevance, and hence in retrieving relevant documents.

Mitra et al. [18] have attempted, with some success, to rectify query drift by improving the precision at the top of the documents ranking, increasing the likelihood of actual relevant material being contained within the set of pseudo-relevant documents, and hence decreasing the likelihood of query drift. Their experiments used two approaches: a set of Boolean filters and term correlation information to priorities retrieval of documents that covers all aspects of a query. They found that their approaches work well for manually and automatically created filters, however around 25% of the queries still suffer from query drift.

III. PROPOSED WORK

We are going to propose a IR system using which the user can easily get the relevant document. When the user enter the query for search the document, then it directly compare within the data of the document file. So the relevant document will found by the system. We are also working to add feature, the system will recommend the keyword to the user for getting the best result or document. The basic procedure is:

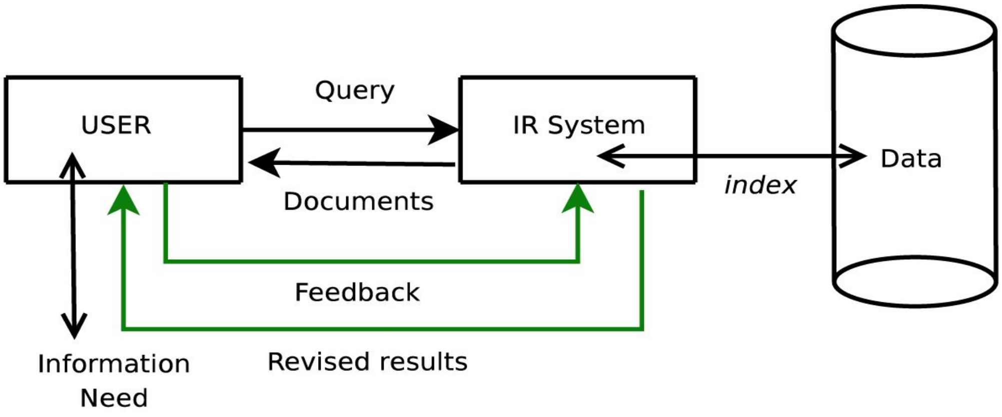


Fig No 1: Data flow diagram

1. The user issues a (short, simple) query
2. The system returns an initial set of retrieval results.
3. The user marks some returned documents as relevant or nonrelevant.
4. The system computes a better representation of the information need based on the user feedback.
5. The system displays a revised set of retrieval results.
6. It provides relevant documents only to user‘s information need.
7. Easy to retrieve the data.
8. It reduces the manual work.
9. Explicit Relevance Feedback also called as Term relevance feedback. The system will suggest the term which types of term the user should add in search.
10. Implicit Relevance Feedback will find out the frequently search document easily.

Pattern matching is the act of checking a given sequence of tokens for the presence of the constituents of some pattern. The pattern matching include,

1. User enter a query into IR system which represent data inside the document.
2. IR system extract document from the database .
3. IR system return relevant document that user want.

Relevance Feedback Algorithm.

Relevance feedback (RF) is the retrieval task where the system is given not only a user query, but also user feedback on some of the top ranked results. Feedback gives the retrieval system a chance to improve its results by exploiting the extra information through more elaborate techniques. This can be helpful in cases where the users want as many relevant results as possible. RF is one of the most useful Query Modification techniques in the field of Information Retrieval (IR). This method is put into practice when the user needs to improve the query formulated to the IR system, because the documents initially retrieved do not completely fulfill the user's information need. Relevance feedback works in the following way: a user submits a query representing his/her information need to the IR system, which then ranks the documents according to their corresponding degrees of relevance to the query (with the documents most closely matching the query ranked first). The user then inspects this list,1 and determines which documents are relevant and which are not relevant to his/her information need (the relevance judgments). Using this information, the IR system updates the initial query, modifying the importance of the terms it contains 2 (term reweighting), and adding new terms that are considered useful to retrieve more relevant documents (query expansion). This process is repeated until the user is completely satisfied with the set of retrieved relevant documents. Relevance feedback has been successfully applied in a great variety of IR models.

VI. SIMULATION AND RESULTS

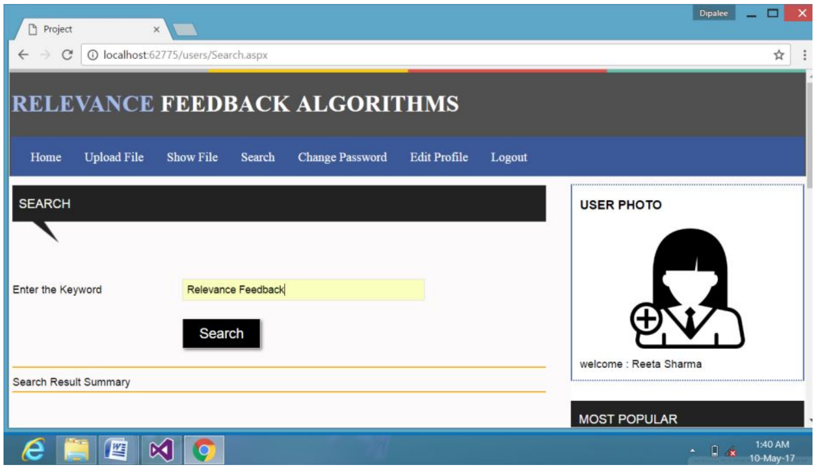
Interactive Query Expansion

- Several of the reasons given by users for not using Automatic Query Expansion(AQE) are also applicable to IQE, e.g. these are time-consuming actions, the relation between cause and effect is not clear and on what principles the selection of terms should be made is not obvious.
- The general intuition that some increased control for the user in selecting query expansion terms would be beneficial seems to be valid. Although systems have access to internal statistical information that allows them to select good discriminatory terms, users can make more informed relevance decision. The question is how this process of query modification should be constructed to translate the potential benefits of IQE into actual increases in retrieval performance.
- There are several issues involved in this problem. The first is to decide what is the actual role of the user: should we ask the user to interactively create queries or perform an editing role on system- generated queries? How much of the query-generating process should be interactive and at what stages should we expect and desire user involvement?
- Several of the reasons given by users for not using AQE are also applicable to IQE, e.g. these are time-consuming actions, the relation between cause and effect is not clear and on what principles the selection of terms should be made is not obvious.

Relevance Feedback

- In this study we explore the effectiveness of relevance feedback methods in assisting the user to access a predefined target document through searching or browsing.
- We devise an innovative approach to study this problem by exploiting the fact that the display processing time and total word count.
- It is then feasible to generate and study the complete space of a user's interactions and obtain the upper bound on the effectiveness of relevance feedback. This bound represents the actions of an "ideal user" who at every step makes choices that enable the system to reach the target in the minimum number of iterations.
- We believe that analysis of the complete search space is a novel experimental paradigm and can lead to interesting insights into the behavior of relevance feedback algorithms.
- This approach has the further advantage of permitting the study of relevance feedback and display strategies without the need for time-consuming user studies. This, in turn, allows a far greater number of experiments to be performed and we are optimistic that the statistical evidence gathered in this way can be used to predict actual user performance. This will be verified in future work.

Fig 1 shows user enter quary into Information retrieval (IR) system for searching document.



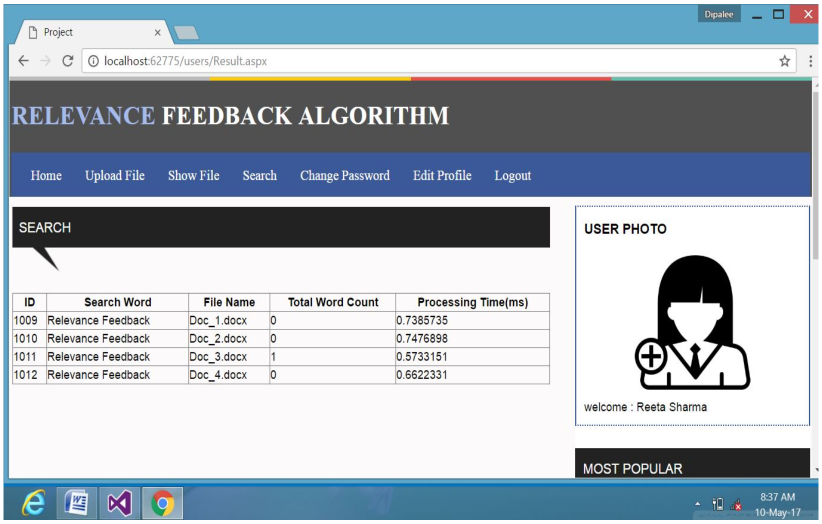
Enter the Keyword Relevance Feedback

Search Result Summary

welcome : Reeta Sharma

Fig1: User search document.

In Fig 2: shows relevant document that user want. Relevant document is one whose total word count is 1 means word relevance feedback is found only in one document that is Doc_3 and display processing time require for each document.



ID	Search Word	File Name	Total Word Count	Processing Time(ms)
1009	Relevance Feedback	Doc_1.docx	0	0.7385735
1010	Relevance Feedback	Doc_2.docx	0	0.7476898
1011	Relevance Feedback	Doc_3.docx	1	0.5733151
1012	Relevance Feedback	Doc_4.docx	0	0.6622331

welcome : Reeta Sharma

Fig 2:IR system display result.

V. CONCLUSION

Relevance feedback can go through one or more iterations of this sort. The process exploits the idea that it may be difficult to formulate a good query when you don't know the collection well, but it is easy to judge particular documents, and so it makes sense to engage in iterative query refinement of this sort. In such a scenario, relevance feedback can also be effective in tracking a user's evolving information need: seeing some documents may lead users to refine their understanding of the information they are seeking. The user submit a query into IR system. IR system return both relevant and irrelevant documents so the automatic procedure that modify the user's queries is known as RF; some relevance assessments about the retrieved documents are collected and the query is expanded by the terms found in the relevant documents, reduced by the terms found in the irrelevant documents or reweighted using relevant or irrelevant documents.

REFERENCES

[1] C. Buckley and E. M. Voorhees,"*Retrieval evaluation with incomplete information*".In SIGIR'04, 2004.

[2] Ingo Frommholz, Birger Larsen, Benjamin Piwowarski,MouniaLalmas, Peter Ingwersen ,Keith van Rijsbergen, "*Supporting Polyrepresentation in a Quantum-inspired Geometrical Retrieval Framework"*.IIiX 2010, August 18– 21, 2010.

[3] M. Shanmugham1, P. Logaiyan2, S. Annapoorana3, "*Bearing Stimulated algorithms inspired by quantum detection"*, International Journal of Current Trends in Engineering &Research (IJCTER) e-ISSN 2455–1392 Volume 2 Issue 7, July 2016.

[4] AblimitAji, Yu Wang ,Eugene Agichtein, EvgeniyGabrilovich,"*Using the Past To Score the Present: Extending Term Weighting Models Through Revision History Analysis".*CIKM'10, October 26–30, 2010.

[5] Shuqin Liu,JinyePeng,*"A Novel Image Retrieval Algorithm Based on Adaptive Weight Adjustment and Relevance Feedback "*,JOURNAL OF COMPUTERS, VOL. 9, NO.11, NOVEMBER 2014.

[6] Diane Kelly*, "Methods for Evaluating Interactive Information Retrieval Systems with Users "*, Foundations and Trendsin Information Retrieval Vol. 3, Nos. 1–2 (2009) 1–224 c 2009.

[7] Luis M. de Campos, Juan M. Fernańdez-Luna ,Juan F. Huete*"Implementing Relevance Feedback in the Bayesian Network Retrieval Model",JOURNAL OF THE AMERICAN SOCIETY FOR INFORMATION SCIENCE AND TECHNOLOGY, 54(4):302–313, 2003.*

[8] Y. Pang, Z. Ji, P. Jing, and X. Li, "*Ranking graph embedding for learning to rerank",* IEEE Trans. Neural Netw. Learn. Syst., vol. 24, no. 8, pp. 1292–1303, 2013.

[9] X. Tian, L. Yang, J. Wang, X. Wu, and X. Hua, "*Bayesian visual reranking*," IEEE Trans. Multimedia, vol. 13, no. 4, pp. 639–652, 2011.

[10] W. Liu, G. Hua, and J. Smith, *"Unsupervised One-Class Learning for Automatic Outlier Removal",*in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., 2014, pp. 3826–3833

[11] K. Collins-Thompson, P. N. Bennett, R. W. White, S. de la Chica, and D. Sontag, "*Personalizing web search results by reading level*", in Proc. 20th ACM Int. Conf. Inf. Knowl. Manage., 2011, pp. 403–412.

[12] Y. Lv, C. Zhai, and W. Chen,"*A boosting approach to improving pseudo-relevance feedback"*, in Proc. 34th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2011, pp.165–174.

[13] C. Carpineto and G. Romano, "*A survey of automatic query expansion in information retrieval*", ACM Comput.Surv., vol. 44, no. 1, pp. 1–50, Jan. 2012.

[14] J. Kamps, S. Geva, and A. Trotman."*Analysis of the inex 2009 ad hoc track results*".In INEX, 2009.

[15] Massimo Melucci, *"Relevance Feedback Algorithms Inspired By Quantum Detection",IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, VOL. 28, NO. 4, APRIL 2016.*

[16] Le Zhao, Chenmin Liang and Jamie Callan, "*Extending Relevance Model for Relevance Feedback".* CMU participation in Relevance Feedback track TREC 2008.

[17] W. Croft and D. Harper, "*Using probabilistic models of information retrieval without relevance information*". Journal of Documentation. 35. 4. pp 285-295. 1979.

[18] M. Mitra, A. Singhal and C. Buckley, "*Improving automatic query expansion*". Proceedings of the Twenty-First Annual International ACM SIGIR Conference on Research and Development in Information Retrieval. pp 206-214. Melbourne. 1998.

BIOGRAPHY

Dipalee S. Hirde is a Student of M.E Computer Science & Engineering Department, H.V.P.M'S College of Engineering & Technology, Amravati, Maharashtra , India. She received Bachelor of Engineering Degree in 2015 from SGBAU Amravati, Maharashtra, India. Her research interests are Education technology and Data Mining.

Prof. R. R. Keole is a Asst. Professor in Department of Information Technology & Engineering, H.V.P.M'S College of Engineering & Technology, Amravati , Maharashtra , India.