

Relevance Feedback Algorithm Encouraged By Quantum Detection

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Abstract— Data recovery is concerned with indexing and retrieval documents excluding information related to a user’s information need. Relevance feedback is a class of effective algorithms for improving terms and to re-rank the document retrieved by an information retrieval system. These algorithm projects the query vector on a subspace spanned information recovery, and it consists of gathering further data representing the user’s information need and automatically creating a new query. In this paper, I propose a class of state of being relevant feedback algorithm motivated by quantum detection to re-weight the query by the eigenvector which maximizes the distance among the distribution of quantum probability of bearing and the distribution of quantum probability of non-relevance.

Keywords— Data recovery; Quantum mechanics; quantum detection; relevance feedback; probability.

I. INTRODUCTION

Data recovery is concerned with indexing and recovers documents excluding information related to a user’s information need. Although the end user can express his in order to need using a variety of means queries written in language are the most common means. the query is submitted to an data recovery system base on the vector space model[1]. This system would return to both related documents, and un related documents the number of related documents top ten is quite high, there are some unrelated documents [2]. For example 14551F00La1 is ir-relevant .an information retrieval system address the problems caused by query ambiguity by gathering further evidence that mechanically modify the query.

The automatic process that transforms the user’ queries is known as state of being relevant feedback. Some relevance assessment about the retrieved documents are collected and the query expanded by the terms found in the related documents ,reduced by the terms found in ir-related documents or re-weighted using related and ir-related and documents. Relevance feedback is both positive and negative or both [3]. Positive relevance feedback brings related documents and negative related feedback brings only ir-related documents. State of being relevant algorithm includes only a positive component, negative feedback is still problematic and requires further investigation, and some proposals have already been made such as grouping ir-related s documents before using them for reducing the query [4]. Feedback may be explicit when the user explicitly tells the system what the related documents and un related documents is called pseudo. When the system decides the what the related documents and the unrelated documents are hidden [5].

When the system monitor’s the user behavior and decides what the related documents and unrelated documents are according to the user’s action.

A. Data recovery

Table 1: Before relevance document

Document id	Rank	relevance or related
14551F00La111	1	1
14551F00La222	2	1
14551F00La321	3	1
14551F00La421	4	1
14551F00La521	5	0
14551F00La621	6	1
14551F00La821	7	1
14551F00La921	8	1
14551F00La928	9	0

1. In these data recovery system is a might only re-weight the query terms and apply again recover function using there weighted query. Information retrieval system can re-rank the documents are retrieved[6]. Query expansion is general more than the effective, because it doesn’t require the disk access to the posting lists of the added query terms. An information retrieval system address the problem caused by the query ambiguity by collect additional conformation that can be used automatically modify the query. the relevance algorithms according to the way the bearing assessments are collected. Feedback may implicit when the user implicit tells the system what the relevant documents and the Ir--relevant documents are according to the user action’s, Ir- relevant credentials will be occurred. It provides related documents only to user’s information need [7].
2. Easy to recover the data. It reduces the physical work. IR-relevant credentials will be occurred. When the system decides the related and un related documents it is incurred.
3. Ambiguity of repeatedly change the query.
4. Query not extended for user’s information need.
5. Delay of information to the user’s need.

Table 2: After relevance document

Document id	Rank	relevance or related
14551F00La411	▼	1
14551F00La111	▲	1
14551F00La324	=	1
14551F00La222	▼	0
14551F00La521	=	1
14551F00La621	↑	1
14551F00La921	▲	1
14551F00La821	=	0
14551F00La928	▼	1

In these top 10 documents retrieved to answer a query of topic =means it did not change, means it words end and 14551F00La324 is relevant because it is entered from the list, 14551F00La321 has been cut off the list.

II. RELATED WORKS

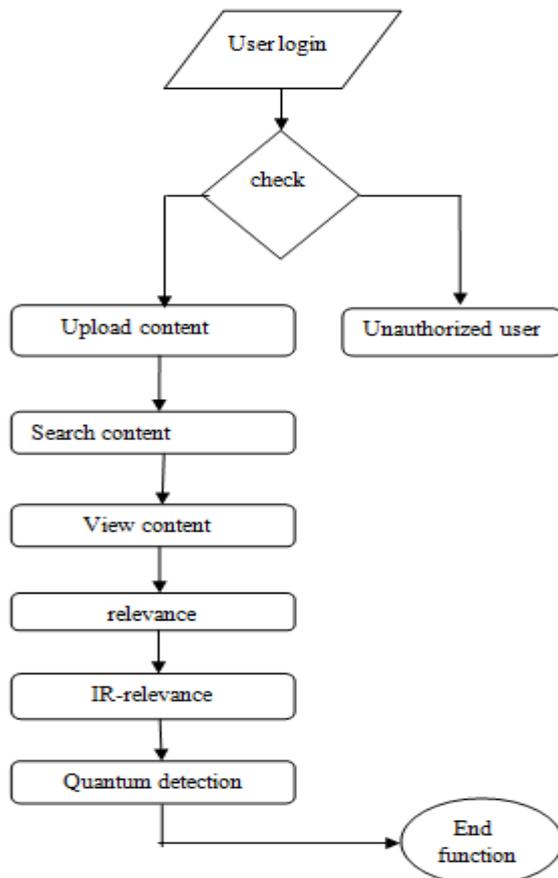
A. Vector space model:

The vector space model document $d_1=(1,0,0)$, $d_2=(0,1,0)$,and $d_3=(0,0,1)$ corresponding to the doc1,doc2,doc3 are represented respectively, by the following vectors (1,1,,),(1,0,0),(1,0,0). Every document for data recovery represents individual credentials and queries as vectors of the k-dimensional real space R_k . this vector space is defined by k-basis vectors corresponding to the conditions extracted from a document set. For example the document collection stores 3 documents are, document1, document2, vector result from the linear combination of the basis vectors.

B. Quantum probability:

A probability space is given by some observables, quantum possibility is the theory of probability developed within quantum mechanics. Quantum possibility can be represented as vectors, matrix, and operators between them. Consider an observable taking k mutually exclusive values labelled by the natural numbers 1; . . . ; k (or0; . . . ; k _ 1); for example, this observable may be the frequency of a term within a document, the number of documents indexed in a collection, or the binary outcome of occurrence when k=2 The equivalence relationship between a basis vector x and a projector A is that $A=xx^1$.

C. Data Flow Diagram



III. PROPOSED SYSTEM

In these proposed system propose a class of state of being relevant feedback algorithm encouraged by quantum detection to re-weight the query terms and to re-rank the document

recover by an information retrieval system. these algorithm project the query vector by the eigenvector which is maximizes the distance among the distribution of bearing and distribution of non relevance probability. It is also out- perform the state of art algorithm I propose to change the vector space state of being relevant algorithms based on the vector space model and the probabilistic algorithms inspired by quantum detection.

Bearing feedback algorithm is also known as rocchio's algorithm. And it is designed to adding the new query vector using a linear combination of the real vectors, related document vector, and un-related vectors. Suppose p is the query vector, s_1, s_2, \dots, s_r are R relevant document vectors in R_k , and s_{r+1}, \dots, s_n are N-R relevant document vectors. After computing the following new query vector.

$$P^* = \frac{q + q^+ - q^-}{\text{Modify query}}$$

Where q is the original query, q^+ is the positive relevant document vector q^- is the negative relevant document vector

Where $q^+ = 1/R \sum_{i=1}^R q_i$ involves relevant document vectors and $q^- = 1/R \sum_{i=R+1}^N q_i / N-R$

IV. RESULT



Figure 1: Relevance document 14551F00La324 is related because it is entered from the list.



Figure 2: IR-relevanceorunrelateddocuments14551F00La321 has been cut off the list.

CONCLUSION

A class of relevance algorithms encouraged by the quantum detection has been projected to re-weight the query conditions by projecting the query vector on the subspace represented by the eigenvector which is the best solution to the problem of finding the maximal distance between two quantum probability distributions. Relevance feedback is then view as a signal finding technique. relevance is the document state to be detected and the queries are the detectors.

First, the document regain by an IR system to answer the original query are used to extract a feature matrix. it has low

complexity and can be used in reality. The constructing of the element matrix depends on the recover documents. The size of the matrix is number of terms of new query and it cannot raise our approach can effectively work for query term re-weighting with no query expansion. The data that are necessary to compute this feature matrix can be obtained from the oddments or the term arrays are usually available from the main memory of the data recovery system. The complexity of the calculation of the eigenvector is limited by the small size of the matrix that represents the space between two quantum probability distributions.

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