IMPROVING INFORMATION RETRIEVAL IN SEARCH ENGINE USING AND POSITIVE AND NEGATIVE RELAVANCE FEEDBACK

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Abstract: 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 overcome this limitation is automatic query expansion (AQE), whereby the user’s original query is augmented by new features with a similar meaning. 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. In this paper, 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. These algorithms project the query vector on a subspace spanned by the eigenvector which maximizes the distance between the distribution of quantum probability of relevance and the distribution of quantum probability of non-relevance. The experiments showed that the RF algorithms inspired by quantum detection can outperform the state-of-the-art algorithms.

I. INTRODUCTION

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. Consider topic 329 which is provided with the Text Retrieval Conference (TREC) test collection from which the query is submitted to an IR system based on the Vector Space Model (VSM). Although the number of relevant documents in the top ten document list is quite high, there are some irrelevant documents – for example, LA062790-0048 is irrelevant because it is about a very specific case of river pollution at the Mexican border – and the Mean Average Precision (MAP) is only 15.2 percent.

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 as shown in the previous example.

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. RF has a long history: It was proposed in the 1960s it was implemented in the SMART system in the 1970s in the context of the VSM it was investigated at the theoretical level it eventually attracted interest from other researchers because of the consistent effectiveness improvements observed in many experiments. Fig. 1b shows how RF can improve the retrieval results of Fig. 1a; one additional relevant document was retrieved and the overall document ranking became better; indeed, the MAP increased by 85 percent.

RF can be positive, negative or both. Positive RF only brings relevant documents into play and negative RF makes only use of irrelevant documents; any effective RF algorithms includes a “positive” component. Although positive feedback is a well established technique by now, negative feedback is still problematic and requires further investigation, yet some proposals have already been made such as grouping irrelevant documents before using them for reducing the query. Besides negativeness and positiveness, the RF algorithms can be classified according to the way the relevance assessments are collected. Feedback may be explicit when the user explicitly tells the system what the relevant documents and the irrelevant documents are, it is called pseudo when the system decides what the relevant documents and the irrelevant documents are (e.g., the top-ranked documents are considered as relevant documents), or it is implicit when the system monitors the user’s behaviour and decides what the relevant documents and the irrelevant documents are according to the system’s actions (e.g., a document that is saved in the user’s local disk is likely to be relevant). Although the potential can be large, pseudo RF can be unstable since it may work with some queries and it may not work with others, and therefore a system should learn how and when to apply it or not or to exploit some evidence such as term proximity.

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(a) Before RF

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(b) After RF

Fig 1: Top 10 documents retrieved to answer a query of topic 329. means that the document rank improved, means it worsened, and means it did not change. LA111589-0111 (non-relevant) has been cut off the list and LA061890-0072 (relevant) entered in the list.

Query expansion is not the only means for refining the representation of an information need. An IR system might only re-weight the query terms and apply again the retrieval function using the re-weighted query. Either way, the IR system can re-rank the documents retrieved at the first run. Even supposing query expansion is in general more effective, term re-weighting can be still crucial because: it
does not require disk accesses to the posting lists of the added query terms; it does not introduce noisy terms in the modified query; it can increase recall since the relevant documents ranked at the very lower positions of the retrieved document list can be moved to the highest ranks and made accessible to users; it is also crucial to increase precision since the non-relevant documents placed at the highest ranks after the first run might be moved to the low-est ranks. One major application is contextual search a contextual IR system may re-weight the query terms and then re-rank the documents retrieved in the first run to fit the user’s information needs according to some variables observed from the context such as the end user’s reading level or the document’s complexity.

Although the main root of RF was the VSM, other retrieval models were utilised to incorporate some query expansion or re-weighting algorithms. In the context of the probabilistic models, the Binary Independence Retrieval (BIR) model incorporates RF in a natural way since the statistics of the distribution of term frequency across relevant and irrelevant documents are used in the term weighting schemes and especially in the Best Match No. 25 (BM25) weighting scheme which is perhaps the best known scheme for query term re-weighting. Besides the BIR model and the BM25 weighting, pseudo RF was also investigated in the context of the statistical language models with some success.

We propose to replace the vector-space RF algorithms based on the VSM and the probabilistic algorithms based on the BM25 with algorithms inspired by quantum (signal) detection. We first propose to define signal detection in terms of quantum probability. As quantum probability generalizes classical probability, there are quantum probability distributions that cannot be defined within the usual theory of probability, thus allowing us to find optimal solutions which otherwise could not be found. The use of vectors and matrices in quantum probability allows us to seamlessly integrate our proposal in the VSM. Then, we define the optimal detectors from the setting prepared in terms of quantum probability distributions. The optimal detectors are the eigenvectors – which cannot be found by the theory based on classical probability – of a special matrix prepared from the quantum probability distributions. Finally, we project the query vectors on the eigenvectors found by the quantum probability distributions; the seamless integration of vector spaces and probability within a single quantum probabilistic framework allowed us to define a diverse set of algorithms. We also report on experiments to demonstrate the effectiveness of the RF algorithms inspired by quantum detection.

II. RELATED WORK

2.1 Vector Space Model

The VSM for IR represents both documents and queries as vectors of the k-dimensional real space $\mathbb{R}^k$. This vector space is defined by k basis vectors corresponding to the terms extracted from a document collection; for example, if the document collection stores three documents “orange juice”, “apple juice” and “apple”, the vector space is defined by three canonical basis vectors $e_1 = (1, 0, 0)$, $e_2 = (0, 1, 0)$ corresponding to “apple”, “juice” and “orange”, and the three documents are represented, respectively, by the following vectors $(0, 1, 1)$, $(1, 1, 0)$, $(1, 0, 0)$. Each document vector results from the weighted linear combination of the basis vectors which represents the terms extracted from the document collection. In the example above, the weights are binary, that is, 1 if the term occurs in a document, 0 otherwise. Other weighting schemes that assign vector coordinates are reported. The state-of-the-art is given by the pivoted normalization [36] which defines the following weight:

$$\frac{K_1 tf}{tf + k_1 (1 - b + b \frac{doclen}{avdoclen})} \log \frac{N - df + 0.5}{df + 0.5},$$

(1)
where tf is the frequency of the term in the document, df is the number of documents indexed by the term, N is the number of documents in the collection, doclen is the document length, and avdoclen is the average document length; the parameters b 0:75 and k1 1:2 are constants for each term.

The retrieval function is the inner product between a document vector \( x \) and a query vector \( y \), and it is defined as

\[
x'y \in \mathbb{R}^k \quad y \in \mathbb{R}^k
\]

Where \( x' \) is the transpose of \( x \).

The early formulation of the VSM was reported Salton who later developed the model in the 1970s for describing the statistical methods to measure semantic relationships between words such as synonymy and polysemy and to build networks of terms and documents.

2.2 Relevance Feedback

The RF algorithm is also known as Rocchio’s algorithm and it is designed to compute the new query vector using a linear combination of the original vectors, the relevant document vectors and the non-relevant document vectors, where the labels of relevance are collected in a training set. Suppose \( y \) is the query vector, \( x_1, ..., x_R \) are Relevant document vectors in \( \mathbb{R}^k \). The RF computes the following new query vector

\[
y^* = \frac{\overrightarrow{y}}{\text{modified query}} + \frac{\overrightarrow{y}^+}{\text{positive RF}} - \frac{\overrightarrow{y}^-}{\text{negative RF}}, \quad (3)
\]

Where \( y^+ = \frac{1}{R} \sum_{i=1}^{R} x_i \) \( (4) \)

Involves relevant document vectors and \( y^- = \sum_{i=R+1}^{N} x_i/(N-R) \) involves non-relevant document vectors. After computing the new query vector, the documents \( x's \) are reranked by \( x'y^* \).

2.3 Best Match No. 25

A term weight formula that became one of the most effective weighting schemes of the probabilistic models was proposed. BM25 basically multiplies the Inverse Document Frequency (IDF) by a saturation component, thus obtaining the following weight:

\[
\text{IDF} = \log \frac{N-df+0.5}{df+0.5}, \quad (5)
\]

Where \( k = k_1 (1 - b + b \frac{doclen}{avdoclen}) \), \( k_3 \) is between 7 and 1,000 (usually, qtf = 1 and \( k_3 \) does not impact), qtf is the frequency of the term in the query.

The RF algorithm that is implemented in the BM25 model consists of modifying the IDF component of the term weight. The iterative process of RF begins with the situation in which no relevance data are available and the term weight. At the next steps, the IDF is replaced by \( \log \frac{r+0.5}{R-r+0.5} \frac{N-df-R+r+0.5}{df-r+0.5} \) where \( r \) is the number of training relevant documents indexed by term.
2.4 Quantum Probability
A probability space is given by some observables and by a probability function of these observables. Quantum probability is the theory of probability developed within Quantum Mechanics (QM). In QM, a probability space can be represented as vectors, matrices and operators between them. A tutorial would be out of the scope of this paper, therefore we provide the information instrumental to understanding the rest of this paper.

Consider an observable taking $k$ mutually exclusive values labeled by the natural numbers $1, ..., k$ or $(0, ..., k-1)$; 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 term occurrence when $k = 2$. To each observable value, it is possible to correspond a projector of the $k$-dimensional space. The equivalence relationship between a basis vector $x$ and a projector $A$ is that $A = xx'$. When a probability function is provided, each observable value and then each basis vector corresponds to a probability measure given by the function, thus obtaining a probability distribution. The probability distribution can be arranged along the diagonal of a $k$-dimensional matrix $\rho$ called density matrix, that is $\text{diag}(\rho) = (p_1, ..., p_k)'$. The density matrix corresponding to a classical probability distribution is always diagonal and has unit trace because the sum of the diagonal elements is 1.

When using this algebraic form to represent probability spaces, the function for computing a probability is the trace of the matrix obtained by multiplying the density matrix by the projector corresponding to the event. The usual notation for the probability of the event represented by projector $A$ when the distribution is represented by density matrix $\rho$ is $\text{tr}(\rho A)$.

It should be noted that not all the density matrices corresponding to a distribution need to be diagonal matrices and that the diagonal elements do not necessarily correspond to probability values, although they do have to sum to 1; for example, the density matrix can be

![Fig The general RF algorithm inspired by the principles of quantum detection.](image-url)
\[ \rho = \frac{1}{2} \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}. \]

### III. RELEVANCE FEEDBACK BASED ON QUANTUM DETECTION

In this section, we illustrate the RF algorithms inspired by the principles of quantum detection and tested in this paper. In summary, these algorithms build query vectors as the optimal detectors of a quantum signal detection system. These optimal detectors have to decide the (unknown) relevance state of a document on the basis of the available data, e.g., query term frequency. Technically speaking, these algorithms project the original query vector on a special subspace which is given by the principles of quantum detection. The vector that results from the projection is matched against the vectors of the documents by the inner product function expressed by (2). More precisely, let \( h_1 \) be the vector spanning the subspace given by the principles of quantum detection. The projection of the original query vector can be expressed as \( \eta_1 \eta_1' y \) and it is essentially the query term re-weighting scheme proposed in this paper. If \( x \) is a document vector, ranking is computed by

\[ x' \eta_1 \eta_1' y \text{ -----(6)} \]

The initial query represented as a vector \( y \epsilon \mathbb{R}^k \) is input to the search engine of the IR system. The engine outputs a ranked list of N documents represented by the vectors \( x \). The engine makes use of these document vectors for generating a \( N \times k \) feature matrix to be used to estimate the state vectors \( \phi_0 \) and \( \phi_1 \) according to the relevance assessments \( r \). Then, the matrices \( \rho_0 = \phi_0 \phi_0' \) and \( \rho_1 = \phi_1 \phi_1' \) are calculated and the eigenvectors \( \eta_0 \) and \( \eta_1 \) are extracted. After the projection of the query vector on \( \eta_1 \) the document vectors are re-ranked.

#### 3.1 Quantum Detection

Detection consists of identifying the information concealed in the data which are transmitted by the source placed on one side, through a channel to the detector placed on the other side. The data are only a representation of the “true” information that one side wants to transmit.

A coder is placed between the source and the channel for encoding the signal into a particle which is assigned with a state vector \( \phi \) as depicted in Fig. 3. Each signal of a fixed finite alphabet is assigned a prior probability of emission and the coder does not intervene on the source, therefore, each state has its own prior probability equal to the prior probability of the signal.

![Fig 3. Quantum Communication System](image)

When the particle arrives at the other side, it is measured by the receiver. This measurement is accomplished by an observable. The observed values are utilized to determine the state of the signal (e.g., a document) given by the coder. The outcome of this determination depends on the region of values to which an observed value belongs. If the observed value \( x \) belongs to a certain region of acceptance, the overall system decides that the original signal was, say \( a_0 \), otherwise it was \( a_1 \) as depicted in Fig. 4.
3.2 Detection, Projectors and Probability

Signals, observables and states can algebraically be described using vectors, density matrices and projectors. In particular, the state of a signal (e.g., a document) can be represented as a state vector and some basis vectors correspond to the possible observable values. Suppose the alphabet is binary and consists of only two values. Suppose $\phi_0$ and $\phi_1$ are the state vectors as depicted in Fig. 5.

The probability that the detector receives a symbol given a state can be computed as follows: $P(x \text{ is received when the state is } \phi_j) = |x' \phi_j|^2$ where $x$ is the basis vector of the symbol $x$ measured by the detector.

To obtain the observable used to detect the state of the particle sent through the channel, it is necessary to define the values to be observed, as an observable consists of values. The decision about the state of the particle consists of partitioning the set of observable values and two states, the value $x = 0$ may suggest $\phi_0$ and the value $x = 1$ may suggest $\phi_1$; in the event of a set of four observable values, the values $x \in \{0,1\}$ may suggest $\phi_0$ and the value $x \in \{2,3\}$ may suggest $\phi_1$ as depicted in Fig. 6.

After partitioning the set of observables values, the probability $p(\phi_i|\phi_j)$ that the decision is $\phi_i$ when the state $\phi_j$ can be computed as follows. The channel can be represented by a probability network measuring the degree to which the emitted signals are distributed; when measuring the channel, a symbol $x(e.g., x \in \{0,1,2,3\}$ is observed and used to decide whether the symbol emitted was $a_0$ or $a_1$; to this end, the set of observable values is split into two distinct regions (e.g. $\{0,1\}$ is associated with $a_0$...
and \([2,3]\) is associated with \(\alpha_1\) as depicted in Fig 6. The final decision \(\phi_i\) passes through the observed values \(x\) which are in turn generated in a given state \(\phi_j\) with the probability \(|x'\phi_j|^2\). Suppose \(A_1\) is the region of observable values leading to decide for \(\phi_j\). When the set of observable values is finite and discrete, we have that 
\[ p(\phi_i | \phi_j) = \sum_{x \in A_1} |x'\phi|^2. \]

### 3.3 Optimal Detection

Detection consists of defining the subsets of observable values that correspond to the states in which the signal can be sent through the channel and of minimizing the probability of error or maximize the probability of correct decision. Given two states \(\phi_0\) and \(\phi_1\) the problem is to define one subset of observable values corresponding to \(\phi_1\) (the other subset of observable values is the complement and corresponds to \(\phi_0\)); these subsets are often called “regions”, the subset corresponding to \(\phi_1\) “ is called “region of acceptance” and the subset corresponding to \(\phi_0\) is called “region of rejection”.

In algebraic terms, the projectors of a vector space corresponding to the states have to be defined. Given a partition of the observable values, the collection of projectors form a resolution to unity of the vector space; for example, if two subsets of observable values have to be defined, two projectors \(A_0\) and \(A_1\) such that \(A_0 + A_1 = 1, A_0A_1 = 0\) have to be defined for \(\phi_0\) and \(\phi_1\) respectively.

Suppose the states are represented by two density matrices \(\rho_0\) and \(\rho_1\) respectively. The probability of correct decision is 
\[ Q_d = (1 - \pi) + tr((\pi \rho_1 - (1 - \pi) \rho_0)A_1). \]
Using the same procedure it is found that 
\[ Q_e = 1 - Q_d. \]

It follows that the projectors being sought have to find the projector \(A_1\) that maximizes the trace of \(\pi \rho_1 - (1 - \pi) \rho_0\) \(A_1\). This problem can be solved by the Singular Value Decomposition (SVD) of \(\pi \rho_1 - (1 - \pi) \rho_0\) which yields the following sum: 
\[ \sum_j \lambda_j \eta_j^\prime A_1 \eta_j \]
where the \(\lambda_j^\prime\)'s are the eigenvalues associated with the eigenvectors \(\eta_j\). The probability of a correct decision can be expressed using the eigenvectors and the eigenvalues found by this SVD:

\[ Q_d = (1 - \pi) + \sum_j \lambda_j \eta_j^\prime A_1 \eta_j \quad (7) \]

To find the optimal projector, it should be noted that 
\[ 0 \leq \eta_j^\prime A_1 \eta_j \leq 1 \quad \text{for all } j. \]
Since the eigenvectors are unit vectors and \(A_1\) is Hermitian with trace 1, the maximum of (7) is only obtained when
\[ \lambda_j > 0 \quad \eta_j^{A_1 \eta_j} = 1 \quad (8) \]

The equality of (8) is only obtained when \(A_1 = \eta_j \eta_j^\prime\). Therefore, the solution to the maximization problem and the sought projector is \(A_1 = \sum_{\lambda > 0} \eta_j \eta_j^\prime\). Replacing the latter in (7), We have that
\[ Q_d = (1 - \pi) + \sum_{\lambda > 0} \eta_j \]
Consider two states described by two state vectors \(\phi_0\) and \(\phi_1\). It can be shown that the optimal projectors are the eigenvectors \(\eta_0\) and \(\eta_1\) of
\[ \pi \rho_1 - (1 - \pi) \rho_0, \quad (9) \]
Where $\pi$ is the priori probability of $\rho_1$. Therefore, the projector of the region of acceptance can be written as $A_1 = \eta_1\eta_1'$ since $\eta_1$ has the positive eigenvalue.

The eigenvectors $\eta_0$ and $\eta_1$ “cut” the space of observable values in an “oblique” way to the way in which the space is cut by using classical observable vectors 0 and 1.

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3.4 Detection of Relevance states

It is possible to correspond the theory of quantum detection to the theory of document retrieval – basically, relevance is a document state, a document can be viewed as a particle or signal, and query terms are viewed as observables.

In IR, the information that is relevant to the user’s information need is transmitted by a system to the user by means of a document which is only a representation of the information fulfilling the user’s need. The values observed form a document (e.g., term frequency) can serve to decide about the state of the document. The setting of Section 3.1 corresponds a situation in which documents are emitted by a source and set to a given state of relevance (i.e., relevant or not relevant), transmitted through a channel, and received by a detector which has to decide what the state of document is (i.e., relevant or non-
relevant) using symbols such as index terms; Fig. 8 depicts this setting. The decision taken depends on the range of frequencies to which an observed frequency belongs. If the observed frequency belongs to a certain region of acceptance the retrieval system decides that a document was, say relevant, otherwise it was not relevant. If more index terms are used to decide about relevance as customary when a query is submitted by a user, the IR system computes a score for each document according to a model; then, the score is matched against a region of acceptance used to retrieve or rank the documents.

In IR, the state vectors $\phi_0$ and $\phi_1$ might respectively correspond to “non-relevance” and “relevance” where as $x$ refers to the outcome of a binary variable describing the occurrence of a given index term; one can conceive other states such as topical relevance, authoritativeness or other similar properties. Usually, the symbols used to encode the occurrence of a term are 0 and 1, thus obtaining $\Pr(\text{term occurs in a relevant document}) = |1^\phi_1|^2$ and $\Pr(\text{term occurs in a non-relevant document}) = |1^\phi_0|^2$ For example, each document can be indexed by only one term $x$ such that the observable can yield either 0 or 1. A document may be either relevant (i.e., in state $\phi_1$) or non-relevant (i.e., in state $\phi_0$).

IV. EVALUATION RESULT

USERLIST
Search
Search Result

View User
Add Category

![Add Category screenshot]

Change password

![Change password screenshot]
V. CONCLUSION

Our approach has low complexity and can be used in reality. For each query, the running time of the first document retrieval depends on the number of query terms as usual. The construction of the feature matrix depends on the number of retrieved documents used to estimate the probability distributions – our experiments showed that a few dozens documents can be sufficient. The data that are necessary to compute this feature matrix can be obtained from the snippets or the term arrays of the retrieved documents; these snippets and arrays are usually available from the main memory of the IR system. The complexity of the calculation of the eigenvectors is limited by the small size of the matrix that represents the distance between two quantum probability distributions – the size of this matrix is indeed the number of terms of the original query and it cannot increase since our approach can effectively work for query term reweighting with no query expansion.

VI. FUTURE ENHANCEMENT

In general, RF and in particular the methods inspired by quantum detection can integrate the retrieval functionalities of modern IR systems within a single learning-to-rank framework. These systems do not rely on only one retrieval technology, they rather combine different algorithms and data structures and predict document rankings. The algorithms inspired by quantum detection that are described in this paper can also be integrated. How they perform in a learning-to-rank framework is left to the future work. This paper 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.

REFERENCES