A Capable Forecasting of Complex Keyword Queries over Database

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Abstract—*Keyword queries on informationbases offer easy accessibility to data, however usually suffer from low ranking quality, i.e., low exactitude and/or recall, as shown in recent benchmarks. It'd be helpful to spot queries that square measure probably to own low ranking quality toimprove the user satisfaction. For example, the system could recommend to the user different queries for such onerous queries.We set forth a high-principled framework and proposed novel algorithms to live the degree of the issueof a question over a dB, exploitation the ranking strengthprinciple. Supported our framework, we tend to propose novel algorithms that with efficiency predict the effectiveness of akeyword question. Our intensive experiments show that thealgorithms predict the issue of a question with comparativelylow errors and negligible time overheads.*

Index Terms-*Query performance, query effectiveness, keyword query, robustness, databases.*

I. INTRODUCTION

KEYWORD question interfaces (KQIs) for databases haveattracted a lot of attention within the last decade because of theirflexibility and easy use in looking and exploring thedata.Since any entity in an exceedingly information set that containsthe question keywords may be a potential answer, keyword queriestypically have several potential answers. KQIs should determinethe information desires behind keyword queries and rankthe answers so the required answers seem at the highest ofthe list [3]. Unless otherwise noted, we tend to ask keywordquery as question within the remainder of this paper.

Some of the difficulties of answeringa query are as follows: First, unlike queries in languageslike SQL, users do not normally specify the desired schemaelement(s) for each query term. For instance, query $Q1$:*Godfather* on the IMDB database (http://www.imdb.com)does not specify if the user is interested in movies whose*title* is *Godfather* or movies distributed by the *Godfather*Company. Thus, a KQI must find the desired attributes associatedwith each term in the query. Second, the schema ofthe output is not specified, i.e., users do not give enoughinformation to single out exactly their desired entities [4].For example, $Q1$ may return movies or actors or producers.We present a more complete analysis of the sources ofdifficulty and ambiguity

There are cooperative efforts to producestandard benchmarks and analysis platforms forkeyword search strategies over databases. One effort is that thedata-centric Track of INEX Workshop [5] wherever KQIs square measureevaluated over the well-known IMDB information set that containsstructured info regarding movies and other people in showbusiness. Queries were provided by participants of theworkshop. Another effort is that the series of linguistics SearchChallenges (SemSearch) at linguistics Search Workshop,where {the information theinfo the information} set is that the Billion Triple Challenge data set athttp://vmlion25.deri.de. It's extracted from completely different structureddata sources over the online like Wikipedia. Thequeries square measure taken from Yahoo! keyword question log. Usershave provided relevancy judgments for each benchmark.

These results indicate thateven with structured information, finding the specified answers tokeyword queries remains a tough task. additional apparently,looking nearer to the ranking quality of the most effective playactingmethods on each workshops, we tend to notice that all of them havebeen playacting terribly poorly on a set of queries. Forinstance, take into account the question ancient Rome era over the IMDBdata set. Users would really like to check data regarding moviesthat state ancient Rome. For this question , the state-of the-art XML search ways that we tend to enforced comerankings of significantly lower quality than their averageranking quality over all queries. Hence, some queries area unitmore difficult than others. Moreover, regardless of that rankingmethod is employed, we tend to cannot deliver an inexpensive rankingfor these queries. Table one lists a sample of such arduous queriesfrom the 2 benchmarks. Such a trend has been additionallyobserved for keyword queries over text document collections.

It is necessary for a KQI to acknowledge such queries andwarn the user or use various techniques like questionreformulation or question suggestions. It's going to additionally usetechniques like question results

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diversification. To the most effective of our data, there has not been anywork on predicting or analysing the difficulties of queriesover databases. Researchers have projected some waysto sight tough queries over plain text documentcollections. However, these techniques aren'tapplicable to our drawback since they ignore the structureof the information. Above all, as mentioned earlier,a KQI should assign every question term to a schema element(s) within the information. It should additionally distinguish the specifiedresult type(s). We tend to through empirical observation show that direct diversificationsof these techniques area unit ineffective for structureddata.

II.   LITERATURE SURVEY

Y. Luo, X. Lin, W. Wang, and X. Zhou, [2],in this paper, we study the effectiveness and the efficiency issues of answering top-k keyword query in relational database systems. We propose a new ranking formula by adapting existing IR techniques based on a natural notion of virtual document. Compared with previous approaches, our new ranking method is simple yet effective, and agrees with human perceptions. We also study efficient query processing methods for the new ranking method, and propose algorithms that have minimal accesses to the database. We have conducted extensive experiments on large-scale real databases using two popular RDBMSs. The experimental results demonstrate significant improvement to the alternative approaches in terms of retrieval effectiveness and efficiency.

 V. Ganti, Y. He, and D. Xin, [3], Keyword search over entity databases (e.g., product, movie databases) is an important problem. Current techniques for keyword search on databases may often return incomplete and imprecise results. On the one hand, they either require that relevant entities contain all (or most) of the query keywords, or that relevant entities and the query keywords occur together in several documents from a known collection. Neither of these requirements may be satisfied for a number of user queries. Hence results for such queries are likely to be incomplete in that highly relevant entities may not be returned. On the other hand, although some returned entities contain all (or most) of the query keywords, the intention of the keywords in the query could be different from that in the entities. Therefore, the results could also be imprecise. To remedy this problem, in this paper, we propose a general framework that can improve an existing search interface by translating a keyword query to a structured query. Specifically, we leverage the keyword to attribute value associations discovered in the results returned by the original search interface

G. Bhalotia, A. Hulgeri, C. Nakhe, S. Chakrabarti, and S. Sudarshan[4], With the growth of the Web, there has been a rapid increase in the number of users who need to access online databases without having a detailed knowledge of the Schema or of query languages; even relatively simple query languages designed for non-experts are too complicated for them. We describe BANKS, a system which enables keyword-based search on relational databases, together with data and schema browsing. BANKS enables users to extract information in a simple manner without any knowledge of the schema or any need for writing complex queries. A user can get information by typing a few keywords, following hyperlinks, and interacting with controls on the displayed results.

A. Trotman and Q. Wang [5] this paper presents an overview of the INEX 2011 Data-Centric Track. Having the ad hoc search task running its second year, we introduced a New task, faceted search task, which goal is to provide the infrastructure to investigate and evaluate different techniques and strategies of recommending facet-values to aid the user to navigate through a large set of query results and quickly identify the results of interest. The same IMDB collection as last year was used for both tasks. A total of 9 active participants contributed a total of 60 topics for both tasks and submitted 35 ad hoc search runs and 13 faceted search runs. A total of 38 ad hoc search topics were assessed, which include 18 subtopics for 13 faceted search topics. We discuss the setup for both tasks and the results obtained by their participants.

S. C. Townsend, Y. Zhou, and B. Croft, [6] we develop a method for predicting query performance by computing the relative entropy between a query language model and the corresponding collection language model. The resulting *clarity score* measures the coherence of the language usage in documents whose models are likely to generate the query. We suggest that clarity scores measure the ambiguity of a query with respect to a collection of documents and show that they correlate positively with average precision in a variety of TREC test sets. Thus, the clarity score may be used to identify ineffective queries, on average, without relevance information. We develop an algorithm for automatically setting the clarity score threshold between predicted poorly-performing queries and acceptable queries and validate it using TREC data. In particular, we compare the automatic thresholds to optimum thresholds and also check how frequently results as good are achieved in sampling experiments that randomly assign queries to the two classes.

Clarity-score-based: The methods based on the conceptof *clarity score* assume that users are interested in a veryfew topics, so they deem a query easy if its results belongto very few topic(s) and therefore, sufficiently distinguishablefrom other documents in the collection [6], [7], [8],[9]. Researchers have shown that this approach predictsthe difficulty of a query more accurately than pre-retrievalbased methods for text documents [6]. Some systems measurethe distinguishability of the queries results from the Documents in the collection by comparing the probabilitydistribution of terms in the results with the probabilitydistribution of terms in the whole collection. If theseprobability distributions are relatively similar, the queryresults contain information about almost as many topicsas the whole collection, thus, the query is considered difficult. Several successors propose methods to improvethe efficiency and effectiveness of clarity score [7], [8].

However, one requires domain knowledge about thedata sets to extend idea of clarity score for queries overdatabases. Each topic in a database contains the entities thatare about a similar subject. It is generally hard to definea formula that partitions entities into topics as it requiresfinding an effective similarity function between entities.Such similarity function depends mainly on the domainknowledge and understanding users' preferences. Forinstance, different attributes may have different impacts onthe degree of the similarity between entities.

III. IMPLEMENTATION DETAILS

3.1 Basic Estimation Techniques:

Data sets: The INEX data set is from the INEX 2010 Data Centric Track [14]. The INEX data set contains two entity sets: movie and person.Each entity in the movie entity set represents one moviewith attributes like title, keywords, and year. The person entityset contains attributes like name, nickname, and biography.The SemSearch data set is a subset of the data set usedin Semantic Search 2010 challenge [15]. The original dataset contains 116 files with about one billion RDF triplets.Since the size of this data set is extremely large, it takes avery long time to index and run queries over this data set.Hence, we have used a subset of the original data set inour experiments. We first removed duplicate RDF triplets.Then, for each file in SemSearch data set, we calculated thetotal number of distinct query terms in SemSearch queryworkload in the file. We selected the 20, out of the 116,files that contain the largest number of query keywords forour experiments. We converted each distinct RDF subject in this data set to an entity whose identifier is the subjectidentifier. The RDF properties are mapped to attributesin our model. The values of RDF properties that end withsubstring "#type" indicates the type of a subject. Hence,we set the entity set of each entity to the concatenation ofthe values of RDF properties of its RDF subject that endwith substring "#type". If the subject of an entity does nothave any property that ends with substring "#type", weset its entity set to "Undefined Type". We have added thevalues of other RDF properties for the subject as attributesof its entity. We stored the information about each entityin a separate XML file. We have removed the relevancejudgment information for the subjects that do not reside inthese 20 files. The sizes of the two data sets are quite close;however, SemSearch is more heterogeneous than INEX asit contains a larger number of attributes and entity sets.

Query Workloads: Since we use a subset of the datasetfrom SemSearch, some queries in its query workload maynot contain enough candidate answers. We picked the 55queries from the 92 in the query workload that have atleast 50 candidate answers in our dataset. Because thenumber of entries for each query in the relevance judgmentfile has also been reduced, we discarded another twoqueries (Q6 and Q92) without any relevant answers in ourdataset, according to the relevance judgment file. Hence,our experiments is done using 53 queries (2, 4, 5, 11-12,14-17, 19-29, 31, 33-34, 37-39, 41-42, 45, 47, 49, 52-54, 56-58, 60, 65, 68, 71, 73-74, 76, 78, 80-83, 88-91) from theSemSearch query workload. 26 query topics are providedwith relevance judgments in the INEX 2010 Data CentricTrack. Some query topics contain characters "+" and "−"to indicate the conjunctive and exclusive conditions. In ourexperiments, we do not use these conditions and removethe keywords after character "−". Some searching systemsuse these operators to improve search quality.

Top-K results: Generally, the basic information units in structured data sets, attribute values, are much shorter than text documents. Thus, a structured data set contains a larger number of information units than an unstructured data set of the same size. For instance, each XML document in the INEX data centric collection constitutes hundreds of elements with textual contents. Hence, computing Equation 3 for a large DB is so inefficient as to be impractical. Hence, similar to [13], we corrupt only the top-K entity results of the original data set. We re-rank these results and shift them up to be the top-K answers for the corrupted versions of DB. In addition to the time savings, our empirical results in Section 8.2 show that relatively small values for K predict the difficulty of queries better than large values. For instance, we found that $K = 20$ delivers the best performance prediction quality in our datasets.

Number of corruption iterations (*N*)**:** Computing theexpectation in Equation 3 for all possible values of _x is veryinefficient. Hence, we estimate the expectation using $N > 0$ samples over M $(|A| \times V)$. That is, we use N corruptedcopies of the data. Obviously, smaller N is preferred forthe sake of efficiency. However, if we choose very smallvalues for N the corruption model becomes unstable.

3.2 Existing Work

As per our recent literature reviews, there has not been any work on predicting or analyzing the difficulties of queries over databases. Researchers have proposed some methods to detect difficult queries over plain text document collections recently. But techniques are not applicable to our problem since they ignore the structure of the database.

There are two categories of existing methods, pre-retrieval and post-retrieval for predicting the difficulties of query. But below are limitations of this method:
- Pre-retrieval methods are having less prediction accuracies.
- Post-retrieval methods are having better prediction accuracies but one requires domain knowledge about the data sets to extend idea of clarity score for queries over databases.
- Each topic in a database contains the entities that are about a similar subject.
- Some Post-retrieval methods success only depends on the amount and quality of their available training data

3.2 Proposed Work

To address the issues of scalability and processing time under large datasets, we proposed new extended framework in which before going to calculate SR scores we are applying the k-means clustering to divide input dataset into number of clusters those having legitimate information's. Due to this, time required for predicting the difficult keywords over large dataset is minimized and process becomes robust and accurate (figer shown in fig.1).

3.3 Algorithm:

SR(Structured Robustness) Algorithm:
The Structured Robustness Algorithm (SR Algorithm), which computes the exact SR score based on the top K result entities. Each ranking algorithm uses some statistics about
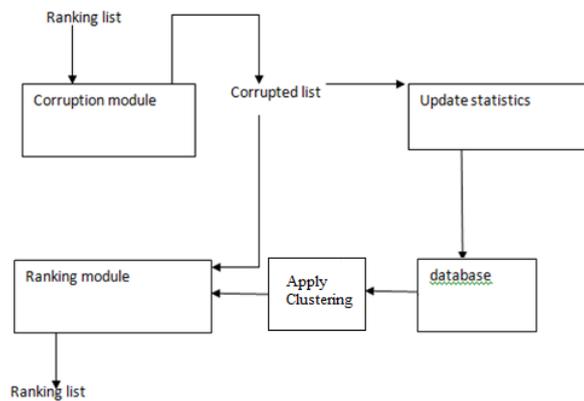
Fig.1 System architecture

query terms or attributes values over the whole content of DB.

Input: -Query Q, Top-K result list L of Q by ranking function g, Metadata M, Inverted indexes I, Number of corruption iteration N.

Output: -SR score for Q.

1. SR ← 0; C← {}; //C catches t_P , s
2. **FOR**i =1 → N **Do**
3. I' ← I; M' ← M ; L' ← L; // Corrupted copy of I ,M and L
4. **For** each result R in L **DO**
5. **FOR** each attribute value A in R **DO**
6. A' ← A; //Corrupted versions of A
7. **For** each keyword w in Q **Do**
8. Compute # of w in A' by Equation // If $\lambda_{T,w}$, $\lambda_{S,we}$needed but not in C, calculate and cache them
9. **IF** # of w varies in A' and A **THEN**
10. Update A' , M' and entry of w in I' ;
11. Add A' to R';
12. Add R' to L'**;**
13. Rank L' using g, which returns L based on I' ,M'
14. SR+= Sim(L,L') ; //Sim computers Spersman correlation
15. **RETURN** SR ← SR / N ; //AVG score over N rounds

Each ranking algorithm usessome statistics about query terms or attributes values overthe whole content of DB. Some examples of such statisticsare the number of occurrences of a query term in allattributes values of the DB or total number of attribute valuesin each attribute and entity set. These global statistics are stored in *M* (metadata) and *I* (inverted indexes) in theSR Algorithm pseudo code.

SR Algorithm generates the noise in the DB on-the-flyduring query processing. Since it corrupts only the top *K*entities, which are anyways returned by the ranking module,it does not perform any extra I/O access to the DB,except to lookup some statistics. Moreover, it uses the informationwhich is already computed and stored in invertedindexes and does not require any extra index.

3.4 Performance Study:

SR Algorithm: We report the common computation timeof SR score (SR-time) victimization SR rule and compare itto the common question time interval (Q-time) victimization PRMSfor the queries in our question workloads. These Times Square measurepresented in Table half-dozen for K = twenty. SR-time chiefly consists oftwo parts: the time spent on corrupting K results and therefore thetime to re-rank the K corrupted results. We've rumoredSR-time victimization (corruption time + re-rank time) format. Wesee that SR rule incurs a substantial time overheadon the question process. This overhead is higher forqueries over the INEX dataset, as a result of their square measure solely 2entity sets, (person and movie), within the INEX dataset, and allquery keywords within the question load occur in each entity sets.

Hence, consistent with Equation ten, each attribute worth intop K entities are going to be corrupted as a result of the third level ofcorruption. Since SemSearch contains much more entity setsand attributes than INEX, this method doesn't happen forSemSearch.

3.5 K-means Algorithm:

1. Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the K centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated

QAO-Approx.:QAO-Approx. on INEX and SemSearch, severally.We live the prediction effectiveness for smaller valuesof N exploitation average correlation score. The QAO-Approx. rule delivers acceptable correlation scores and also thecorruption times of regarding two seconds for N = ten on INEXand N = twenty on SemSearch. Examination to the results ofSR rule for N = 250 on SemSearch and N = three hundredon INEX, the Pearson's correlation score drops, becauseless noise is else by second and third level corruption.These results show the importance of those 2 levels ofcorruption.

3.6 Mathematical Model:

Structured Robustness: Let *V* be the number of distinct terms in database *DB*. Each attribute value $Aa \in A$, $1 \leq a \leq |A|$, can be modeled using a V-dimensional multivariate distribution $X_a = (X_a, 1, \ldots, X_a, V)$, where $X_a, j \in X_A$ is a random variable that represents the frequency of term *wj* in *Aa*. The probability mass function of *Xa* is:

$$F_{Xa}(\overrightarrow{X_a}) = Pr(X_a, 1 = X_a, 1, \ldots, X_a, V = X_a, V),$$

Where$\overrightarrow{X_a} = xa, 1, \ldots, X_a, V$ and $X_a, j \in \overrightarrow{X_a}$are non-negative integers.

$$fX_A(\overrightarrow{X}) = f\overrightarrow{X_A}(\overrightarrow{X_1}, \ldots, \overrightarrow{X_{|A|}})$$
$$= Pr(\overrightarrow{X_1} = \overrightarrow{X_1}, \ldots, X_{|A|} = \overrightarrow{X_{|A|}}),$$

where $\overrightarrow{X_a} \in \overrightarrow{X}$ are vectors of size *V* that contain non-negative integers. The domain of $\overrightarrow{X}$ is all $|A| \times V$ matrices that contain non-negative integers, i.e. $M(|A| \times V)$.
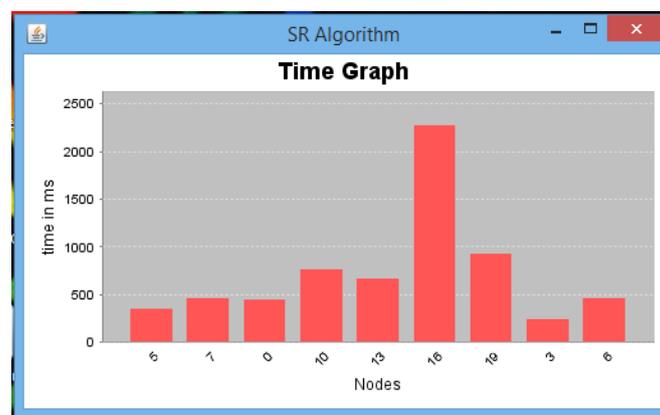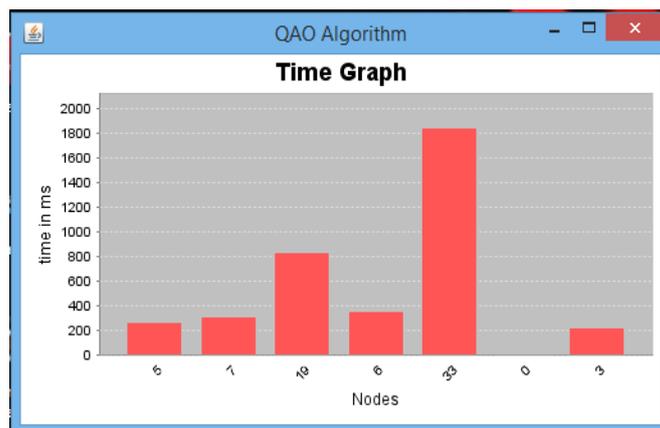
Structured Robustness calculation:It ranges between 1 and −1, where 1, −1, and 0 indicate perfect positive correlation, perfect negative correlation, and almost no correlation, respectively.

   SR(Q, g,DB,XDB)
   $= E\{Sim(L(Q, g,DB), L(Q, g,XDB))\}$
   $= \sum_x Sim(L(Q, g, DB), L(Q, g, \_x)) fXDB(\_x),$

where $X \in M(|A| \times V)$ and *Sim* denotes the Spearman rank correlation between the ranked answer lists.

IV.   RESULTS

Graphs:-

V.   CONCLUSION

In this paper,we analyse the characteristics of laborious queries and propose a unique framework to live the degree of issue for akeyword question over an information, considering each the structure and also the content of the information and also the question results. We have a tendency to assessour question issue prediction model against 2 effectiveness benchmarks for widespread keyword search ranking strategies. Ourempirical results show that our model predicts the laborious queries with high accuracy. Further, we have a tendency to gift a set of optimizations to

Minimize the incurred time overhead. We have a tendency to propose novel algorithms that expeditiously predict the effectiveness of akeyword question. Our in depth experiments show that thealgorithms predict the problem of a question with comparativelylow errors and negligible time overheads.To address the issues of scalability and processing time under large datasets is difficult, so we proposed new extended framework in which before going to calculate SR scores we are applying the k-means clustering to divide input dataset into number of clusters those having legitimate information's. Due to this, time required for predicting the difficult keywords over large dataset is minimized and process becomes robust and accurate.

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