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# Dynamic Guessing Work for Crucial Access of Keyword Objections over the Databases

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**Summary:** Keyword queries on databases offer easy get right of entry to facts, however frequently suffer from low ranking high-quality, i.e., low precision and/or do not forget, as shown in recent benchmarks. It would be useful to pick out queries which are probable to have low rating fine to enhance the user pleasure. As an example, the system may additionally recommend to the person alternative queries for such difficult queries. In this paper, we examine the traits of tough queries and propose a novel framework to measure the diploma of trouble for a key-word question over a database, considering both the structure and the content material of the database and the query results. We compare our query difficulty prediction version in opposition to two effectiveness benchmarks for popular key-word seek ranking strategies. Our empirical results show that our version predicts the hard queries with excessive accuracy. Similarly, we gift a suite of optimizations to limit the incurred time overhead.

**Index Phrases:** query performance, question effectiveness, keyword question, robustness, databases

## 1. INTRODUCTION

Keyword question interfaces (kqis) for databases have attracted plenty attention inside the last decade because of their flexibility and simplicity of use in looking and exploring the data [1]–[5]. Due to the fact that any entity in a facts set that includes the query keywords is a ability answer, key-word queries normally have many possible solutions. Kqis should discover the facts needs at the back of key-word queries and rank the solutions so that the desired answers seem at the pinnacle of the listing. Unless otherwise mentioned, we confer with keyword query as question inside the the rest of this paper. Databases contain entities, and entities include attributes that take characteristic values. Some of the problems of answering a question are as follows: first, in contrast to queries in languages like sq., customers do not commonly specify the favored schema element(s) for every query time period. As an instance, question q1: godfather at the imdb database does not specify if the user is inquisitive about films whose name is godfather or movies disbursed by way of the godfather enterprise. For this reason, a kqi need to locate the favored attributes related with each term inside the question. 2nd, the schema of the output isn't always specified, i.e., users do now not provide sufficient facts to single out precisely their favored entities. As an instance, q1 can also go back movies or actors or producers. We

present a extra whole analysis of the sources of problem and ambiguity in section 4.2.

These days, there were collaborative efforts to offer general benchmarks and assessment structures for keyword seek methods over databases. One effort is the information-centric song of INEX Workshop in which kqis are evaluated over the well-known IMDB statistics set that carries established facts approximately films and people in display commercial enterprise. Queries have been furnished with the aid of members of the workshop. Another effort is the collection of Semantic search demanding situations (semsearch) at Semantic seek Workshop, where the information set is the Billion Triple undertaking records set at http://vmlion25.deri.de. It is extracted from extraordinary based data resources over the internet together with Wikipedia. The queries are taken from Yahoo! Key-word question log. Users have supplied relevance judgments for both benchmarks. The imply average Precision (MAP) of the great performing method(s) within the remaining information-centric song in INEX Workshop and Semantic seek assignment for queries are approximately zero.36 and 0.2, respectively. These effects imply that regardless of dependent information, locating the preferred solutions to keyword queries remains a hard task. More interestingly, searching closer to the rating first-rate of the best acting methods on both workshops, we be aware that all of them have been appearing very poorly on a subset of queries. For example, take into account the question historical Rome technology over the IMDB records set. Customers would like to look records about movies that communicate approximately ancient Rome. For this question, the country-of the-art XML seek techniques which we implemented return scores of drastically decrease best than their average ranking quality over all queries. Subsequently, some queries are greater difficult than others. Moreover, irrespective of which ranking technique is used, we cannot deliver an affordable rating for these queries. Desk 1 lists a sample of such tough queries from the 2 benchmarks. One of thes trends has been additionally determined for keyword queries over textual content file collections.

## 2. RELATED PAINTINGS

Researchers have proposed methods to expect hard queries over unstructured textual content documents. We can widely categorize these strategies into two groups: pre-retrieval and post-retrieval strategies. Pre-retrieval techniques are expecting the problem of a question without computing its effects. Those methods commonly use the statistical residences of the phrases within the question to measure specificity, ambiguity, or term-relatedness of the question to be expecting its issue. Examples of these statistical traits are common inverse report frequency of the question phrases or the range of files that incorporate at least one query time period. Those techniques typically expect that the greater discriminative the question phrases are, the easier the question might be. Empirical research implies that those strategies have confined prediction accuracies. Submit-retrieval methods make use of the effects of a question to expect its issue and typically fall into one of the following categories.

**Clarity-score-based:** The techniques based totally on the idea of clarity rating count on that users are interested in a very few subjects, in order that

they deem a query easy if its effects belong to only a few topic(s) and therefore, sufficiently distinguishable from other documents inside the collection. Researchers have proven that this method predicts the difficulty of a query extra appropriately than pre-retrieval based methods for text files [10]. A few structures measure the distinguishability of the queries outcomes from the files within the series by way of comparing the probability distribution of terms inside the effects with the possibility distribution of terms within the entire series. If these probability distributions are tremendously comparable, the query outcomes incorporate statistics about almost as many subjects as the whole series, consequently, the query is taken into consideration tough. Several successors advocate methods to improve the efficiency and effectiveness of clarity rating. But, one calls for domain understanding approximately the statistics units to increase idea of clarity score for queries over databases. Every subject matter in a database consists of the entities that are about a similar concern. It's far usually difficult to outline components that walls entities into subjects because it calls for locating an effective similarity feature between entities. Such similarity characteristic depends mainly at the domain knowledge and understanding users' options [21]. For example, distinctive attributes may additionally have exclusive impacts on the diploma of the similarity among entities. Our empirical results will confirm this argument and indicates that the sincere extension of clarity rating predicts problems of queries over databases poorly.

## 3. RECORDS AND QUESTION FASHIONS

We report a database as a hard and fast of entity units. Each entity set S is a collection of entities E. For example, films and those are two entity units in IMDB. Fig. 1 depicts a fraction of a facts set where every sub-tree whose root's label is movie represents an entity. Each entity E has a fixed of attribute each characteristic cost is a bag of terms. Following modern unstructured and (semi-) shape retrieval processes, we forget about stop words that appear in attribute values, although this isn't essential for our techniques. Every attribute value A belongs to an attribute T written as A ∈ T. For example, Godfather and Mafia are characteristic values within the movie entity shown within the subtree rooted at node 1 in Fig. 1. The above is an summary facts model. We forget about the bodily representation of statistics on this paper. This is, an entity will be saved in an XML document or a hard and fast of normalized relational tables. The above model has been broadly utilized in works on entity search [3], [5] and records-centric XML retrieval [8], and has the gain that it could be easily mapped to each XML and relational information. Similarly, if a KQI approach relies at the intricacies of the database design (e.g. Deep syntactic nesting), it'll now not be robust and could have appreciably special ranges of effectiveness over distinctive databases [27]. Therefore, since our aim is to broaden principled formal fashions that cowl reasonably nicely all databases and information formats, we do not recall the intricacies of the database design or records format in our fashions.

A keyword question is a set Q = q1, . . . , q of terms, whereinqwide variety of terms in Q. An entity E is a solution to Q iff at the least one of its attribute values A incorporates a term qi in Q,

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written qi ∈ A1. Given database DB and query Q, retrieval feature g(E,Q,DB) returns a actual range that reflects the relevance of entity E ∈ DB to Q. Given database DB and query Q, a key-word search device returns a ranked listing of entities in DB called L(Q, g,DB) in which entities E are positioned in decreasing order of the cost of g(E,Q,DB).

## 4. RATING ROBUSTNESS PRECEPT FOR DEPENDENT INFORMATION

In this phase we gift the ranking Robustness precept, which argues that there may be a (poor) correlation between the problem of a question and its rating robustness in the presence of noise inside the records. Section four.1 discusses how this principle has been applied to unstructured text records. Phase 4.2 affords the factors that make a key-word query on dependent facts difficult, which provide an explanation for why we cannot follow the strategies evolved for unstructured information. The latter remark is also supported by way of our experiments in phase 8.2 on the Unstructured Robustness approach, which is a direct model of the ranking Robustness principle for unstructured information.

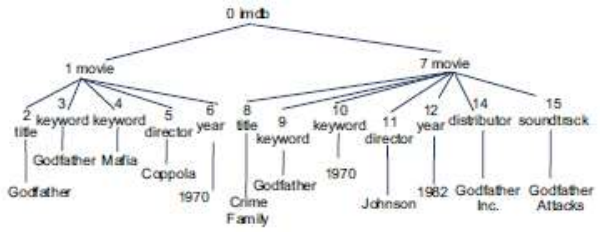


Fig. 1 IMDB database fragment.

### 4.1 Historical past: Unstructured information

Mittendorf has shown that if a textual content retrieval method successfully ranks the answers to a question in a group of textual content documents, it's going to also perform properly for that question over the model of the collection that includes some errors together with repeated phrases [28]. In different words, the degree of the issue of a query is positively correlated with the robustness of its rating over the authentic and the corrupted versions of the gathering. We name this commentary the rating Robustness principle. Zhou and Croft [13] have implemented this principle to predict the diploma of the problem of a query over unfastened textual content documents. They compute the similarity between the scores of the question over the unique and the artificially corrupted versions of a set to predict the issue of the query over the collection. They deem a question to be more difficult if its scores over the authentic and the corrupted versions of the information are much less similar. They have empirically shown their claim to be legitimate. They've additionally proven that this method is usually more powerful than using techniques based at the similarities of possibility distributions that we reviewed in section 2. This end result is special, critical for ranking over databases. As we explained in section 2, it's far generally hard to define an effective and area impartial categorization characteristic for entities in a database. Therefore, we are able to use ranking Robustness principle as a website unbiased proxy metric to measure the degree of the problems of queries.

### 4.2 Houses of difficult Queries on Databases

As discussed in section 2, it is miles well hooked up that the extra various the candidate solutions of a question are, the greater tough the question is over a collection of the textual content files. We extend this concept for queries over databases

and recommend three sources of difficulty for answering a question over a database as follows:

1) The greater entities healthy the terms in a question, the much less specificity of this query and it's miles tougher to answer well. As an example, there are greater than one individual known as Ford within the IMDB records set. If a consumer submits query Q2: Ford, a KQI must clear up the favored Ford that fulfill the user's facts want. As opposed to Q2, Q3: Spielberg matches smaller wide variety of humans in IMDB, so it is simpler for the KQI to go back its applicable effects.

2) Every attribute describes a special thing of an entity and defines the context of terms in characteristic values of it. If a query fits one-of-a-kind attributes in its candidate answers, it will have a extra diverse set of capability solutions in database, and subsequently it has higher characteristic stage ambiguity. As an example, a few candidate solutions for question this autumn: Godfather in IMDB include its time period in their title and some include its time period of their distributor. For the sake of this instance, we ignore different attributes in IMDB. A KQI need to identify the favored matching attribute for Godfather to locate its relevant answers. Rather than this fall, question Q5: taxi driver does not suit any instance of characteristic distributor. As a result, a KQI already knows the preferred matching characteristic for Q5 and has an simpler challenge to carry out.

3) Each entity set contains the statistics about a unique sort of entities and defines some other stage of context (similarly to the context defined by means of attributes) for terms. Hence, if a question suits entities from extra entity units, it will have better entity set degree ambiguity. For example, IMDB contains the information approximately films in an entity set known as film and the statistics approximately the human beings involved in making films in any other entity set called individual. Keep in mind question Q6: divorce over IMDB records set whose candidate solutions come from each entity sets. But, movies approximately divorce and folks who get divorced can't each fulfill statistics want of query Q6. A KQI has a difficult mission to do because it has to discover if the statistics want behind this query is to locate individuals who got divorced or movies about divorce. In contrast to Q6, Q7: romantic comedy divorce suits only entities from film entity set. It's much less difficult for a KQI to answer Q7 than Q6 as Q7 has simplest one viable preferred entity set.

## 5. A FRAMEWORK TO DEGREE DEPENDENT ROBUSTNESS

In segment 4 we presented the ranking Robustness precept and discussed the particular demanding situations in applying this principle to dependent facts. In this segment we present concretely how this principle is quantified in based information.

### 5.1 Dependent Robustness

Corruption of based statistics: The primary venture in the use of the ranking Robustness principle for databases is to outline statistics corruption for structured information. For that, we version a database DB the use of a generative probabilistic version based on its constructing blocks, which might be phrases, characteristic values, attributes, and entity units. A corrupted version of DB can be seen as a random sample of

this kind of probabilistic model. We will further define XT and XS that model the set of attributes T and the set of entity sets S, respectively. The random variable XDB = (XA,XT ,XS) fashions corrupted variations of database DB. In this paper, we conscious most effective at the noise introduced within the content (values) of the database. In other words, we do no longer don't forget other sorts of noise such as changing the characteristic or entity set of an attribute cost in the database. Because the membership of attribute values to their attributes and entity sets stays the identical throughout the unique and the corrupted versions of the database, we can derive XT and XS from XA. Thus, a corrupted model of the database could be a pattern from XA; be aware that the attributes and entity units play a key position in the computation of XA as we talk in section 5.2. Consequently, we use most effective XA to generate the noisy versions of DB, i.e. we count on that XDB = XA. In phase 5.2 we present in element how XDB is computed.

$$f_{Xa}(\vec{x}) = \Pr(X_{a,1}, \ldots\ldots, X_{a,V} = x_{a,V}$$

### 5.2 Noise Generation in Databases

If you want to compute Equation 3, we want to define the noise era model fxdb (M) for database DB. We can display that each attribute value is corrupted through a mixture of three corruption levels: on the price itself, its characteristic and its entity set. Now the information: for the reason that ranking methods for queries over based facts do not usually keep in mind the terms in V that don't belong to question Q, we remember their frequencies to be the equal throughout the authentic and noisy versions of DB. Given query Q, permit x be a vector that carries term frequencies for phrases w ∈ Q ∩ V. In addition, we simplify our model with the aid of assuming the characteristic values in DB and the phrases in Q∩V are unbiased.

$$f_{Xa}(\vec{x}) = \prod_{x_a \in \vec{x}} f_{Xa}(\overrightarrow{x_a})$$

The corruption model should reflect the challenges mentioned in section 4.2 about seek on structured statistics, wherein we confirmed that it's far critical to seize the statistical residences of the question key phrases within the characteristic values, attributes and entity units. We have to introduce content noise (take into account that we do now not corrupt the attributes or entity sets but best the values of characteristic values) to the attributes and entity sets, in order to propagate down to the characteristic values. As an example, if characteristic price of characteristic title consists of key-word Godfather, then Godfather can also appear in any attribute value of attribute identify in a corrupted database instance. Further, if Godfather appears in an attribute value of entity set movie, then Godfather may also seem in any attribute cost of entity set movie in a corrupted example.

## 6 EFFICIENT COMPUTATION OF SR RATING

A key requirement for these paintings to be beneficial in exercise is that the computation of the SR score incurs a minimum time overhead compared to the question execution time. In this section we present green SR rating computation strategies.

### 6.1 Basic Estimation techniques

**Pinnacle-Okay Results:** Generally, the simple records devices in structured datasets attribute

values, are plenty shorter than textual content files. For this reason, a dependent information set consists of a bigger variety of facts gadgets than an unstructured information set of the same length. As an example, each XML document in the INEX records centric series constitutes loads of factors with textual contents. Subsequently, computing Equation three for a large DB is so inefficient as to be impractical. Subsequently, much like, we corrupt simplest the pinnacle-k entity effects of the original information set. We re-rank these results and shift them as much as be the pinnacle-okay solutions for the corrupted versions of DB. In addition to the time financial savings, our empirical outcomes in segment eight.2 display that notably small values for okay expect the issue of queries better than large values. For instance, we discovered that ok = 20 deliver the great overall performance prediction first-class in our datasets. We talk the impact of different values of k within the question issue prediction first-rate more in section 8.2. Variety of corruption iterations (N): Computing the expectation in Equation 3 for all viable values of x may be very inefficient. Therefore, we estimate the expectation the use of N > 0 samples over M (that is, we use N corrupted copies of the statistics. Manifestly, smaller N is favored for the sake of efficiency. However, if we pick very small values for N the corruption version turns into risky. We further analyze how to pick the price of N in phase 8.2. We will restrict the values of okay or N in any of the algorithms defined below.

### 6.2 Structured Robustness Set of Rules

Algorithm 1 suggests the established Robustness set of rules (SR set of rules), which computes the precise SR score primarily based at the pinnacle k end result entities. Each ranking set of rules makes use of little information about query terms or attributes values over the whole content material of DB. A few examples of such statistics are the quantity of occurrences of a question time period in all attributes values of the DB or overall wide variety of characteristic values in every characteristic and entity set. This international information is saved in M (metadata) and i (inverted indexes) inside the SR algorithm pseudocode.

SR set of rules generates the noise inside the DB on-the-fly all through query processing. Because it corrupts handiest the top okay entities, that are anyways lower back by way of the ranking module, it does now not perform any extra I/O get right of entry to to the DB, except to research some records. Furthermore, it uses the statistics that is already computed and stored in inverted indexes and does now not require any greater index.

## 7. APPROXIMATION ALGORITHMS

On this section, we suggest approximation algorithms to enhance the efficiency of SR algorithm. Our methods are independent of the underlying ranking algorithm. Question-particular characteristic values best Approximation (QAO-Approx): QAO-Approx corrupts simplest the characteristic values that match at least one question term. This approximation algorithm leverages the following observations:

**Remark 1:** The noise inside the characteristic values that include query phrases dominates the corruption impact.

**Remark 2:** The quantity of characteristic values that contain at least one question term is a whole

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lot smaller than the quantity of all attribute values in every entity.

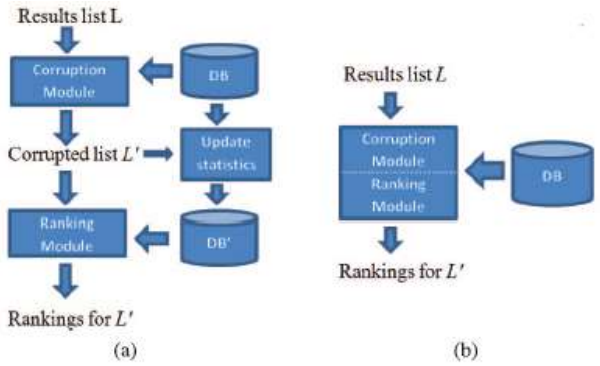


Fig. 2 Execution flows of SR Algorithm and SGS-Approx: (a) SR Algorithm. (b) SGS-Approx.

Hence, we are able to appreciably decrease the time spent on corruption if we corrupt most effective the characteristic values that include question phrases. We upload a test earlier than Line 7 in SR set of rules to test if A incorporates any time period in Q. Hence, we skip the loop in Line 7. The second and third levels of corruption (on attributes, entity units, respectively) corrupt a smaller range of attribute values so the time spent on corruption will become shorter. Static international Stats Approximation (SGS-Approx): sgs approx uses the following commentary:

**Remark 3:** Given that most effective the top-ok result entities are corrupted, the global DB statistics now do not exchange lots. Once we get the ranked listing of pinnacle ok entities for Q, the corruption module produces corrupted entities and updates the worldwide records of DB. Then, SR algorithm passes the corrupted results and updated international facts to the ranking module to compute the corrupted ranking listing. SR algorithm spends a huge part of the robustness calculation time on the loop that re-ranks the corrupted results (Line thirteen in SR set of rules), via taking into consideration the updated international statistics. For the reason that value of k (e.g., 10 or 20) is an awful lot smaller than the quantity of entities in the DB, the top okay entities constitute a very small component of the DB. For this reason, the worldwide information in large part continue to be unchanged or change very little. Hence, we use the global facts of the unique model of the DB to re-rank the corrupted entities. If we refrain from updating the worldwide facts, we will combine the corruption and ranking module collectively. This manner re-ranking is finished on-the-fly for the duration of corruption. SGS-Approx algorithm is illustrated in Fig. 4(b).

## 8 EXPERIMENTS

**8.1 Experimental placing facts sets:** Table 2 indicates the traits of facts units utilized in our experiments. The INEX statistics set is from the INEX 2010 facts Centric song discussed in segment 1. The INEX data set consists of two entity sets: film and man or woman. Each entity inside the film entity set represents one movie with attributes like identify, keywords, and 12 months. The person entity set consists of attributes like name, nickname, and biography. The semsearch information set is a subset of the records set used in Semantic search 2010 task [9]. The unique facts set includes 116 files with approximately one billion RDF triplets. For the reason that length of this records set is extraordinarily huge, it takes a very long term to index and run queries over this data set. Hence, we've got used a subset of the authentic information set in our experiments. We first removed reproduction RDF triplets. Query Workloads: since we use a subset of the dataset from semsearch, a few queries in its question

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workload may also not incorporate sufficient candidate solutions. We picked the 55 queries from the ninety two inside the question workload which have at least 50 candidate answers in our dataset. Due to the fact the number of entries for every query in the relevance judgment record has also been decreased, we discarded some other queries (Q6 and Q92) with none relevant answers in our dataset, according to the relevance judgment report. Subsequently, our experiments is executed the usage of 53 queries from the semsearch question workload. 26 query subjects are provided with relevance judgments inside the INEX 2010 records Centric track. A few query topics contain characters "+" and "–" to signify the conjunctive and specific conditions. In our experiments, we do not use these situations and dispose of the key phrases after man or woman "–". A few searching systems use these operators to enhance search high-quality. Rating Algorithms: to assess the effectiveness of our model for special ranking algorithms, we have evaluated the query performance prediction model with consultant rating algorithms: PRMS [4] and IR-style [1]. Many different algorithms are extensions of those two techniques. PRMS: We explained the concept at the back of PRMS algorithm in segment 6. We alter parameter λ in PRMS in our experiments to get the nice MAP after which use this value of λ for question performance prediction evaluations. Various λ from 0.1 to zero.9 with zero.1 as the take a look at step, we've got discovered that extraordinary values of λ change MAP very slightly on each datasets, and commonly smaller λs supply better MAP. We use λ = zero.1 on INEX and 0.2 on sem search.

**IR-style:** We use a variant of the ranking version proposed in [1] for relational facts model, referred as IR-style ranking. Given a query, IR-fashion returns a minimal be a part of tree that connects the tuples from exclusive tables within the DB that comprise the query terms, called MTNJT. But, our datasets are not in relational layout and the answers in their relevance judgments files are entities and no longer mtnjts. Subsequently, we expand the definition of MTNJT because the minimal subtree that connects the attribute values containing the query keywords in an entity. The foundation of this subtree is the root of the entity in its XML file.

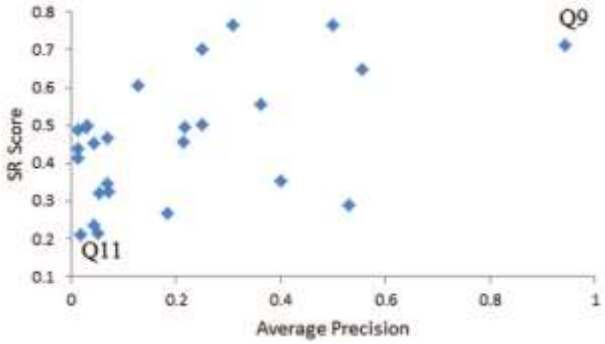


Fig. 3 Average precision versus SR score for queries on INEX using PRMS, $K = 20$ and $(\gamma A, \gamma T, \gamma S) = (1, 0.3, 0.5)$.

## 8.2 High-quality effects

In this segment, we compare the effectiveness of the query great prediction model computed using SR algorithm. We use both Pearson's correlation and Spearman's correlation between the SR score and the average precision of a query to assess the prediction pleasant of SR rating. Placing the cost of N: permit L and L be the unique and corrupted top-k entities for query Q, respectively. The SR score of Q in each corruption new release is the Spearman's correlation between L and L.We corrupt the outcomes N times to get the average

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SR score for Q. On the way to get a strong SR score, the fee of N must be sufficiently large, but this increases the computation time of the SR rating. We chose the subsequent strategy to discover the precise price of N: We step by step corrupt L 50 iterations at a time and calculate the common SR score over all iterations. If the last 50 iterations do now not trade the common SR score over 1%, we terminate. N may additionally vary for distinctive queries in query workloads. Thus, we set it to the most range of iterations over all queries. Consistent with our experiments, the price of N varies very slightly for specific fee of k. Therefore, we set the cost of N to 300 on INEX and 250 on semsearch for all values of okay.

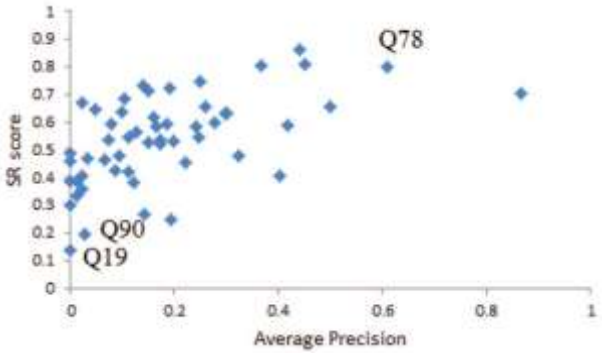


Fig. 4 Average precision versus SR score for queries on SemSearch using PRMS, $K$ = 20 and ($\gamma A$, $\gamma T$ , $\gamma S$) = (1, 0.1, 0.6).

Specific Values for k: The range of exciting consequences for a key-word question is normally small [7]. For instance, the average range of applicable consequences is nine.6 for the semsearch question workload. On this putting, many low ranked solutions might not be relevant and have pretty near ratings, which makes their relative rating positions very touchy to noise. If we use massive values for ok, the SR rating could be ruled by means of the low ranked non-relevant results and the SR rating may deem all queries nearly equally hard.

**IR-style ranking set of rules:** The satisfactory fee of MAP for the IR-style rating algorithm over INEX is 0.134 for okay = 20, which is very low. Notice that we attempted each Equation 12 as well as the vector space version at the beginning used in [1]. As a result, we do no longer have a look at the exceptional performance prediction for IR-fashion rating algorithm over INEX. However, the IR-fashion rating set of rules the usage of Equation 12 grants large MAP value than PRMS on the semsearch dataset. For this reason, we simplest gift outcomes on semsearch. Desk 5 shows Pearson's correlation of SR score with the average precision for exceptional values of ok, for N = 250 and (γa, γt, γs) = (1, zero.1, 0.6). Fig. 7 plots SR rating against the average precision when okay = 20.

## 9. CONCLUSION

We delivered the novel trouble of predicting the effectiveness of key-word queries over dbs. We showed that the present day prediction techniques for queries over unstructured information resources cannot be successfully used to solve this hassle. We set forth a principled framework and proposed novel algorithms to degree the diploma of the difficulty of a query over a DB, the use of the ranking robustness principle. Based on our framework, we propose novel algorithms that correctly expect the effectiveness of a keyword query. Our large experiments show that the algorithms are expecting the issue of a query with fantastically low errors and negligible time overheads.

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