Querying Web Metadata: Native Score Management and Text Support in Databases

GÜLTEKİN ÖZSOYOĞLU[1]
İSMAİL SENGÖR ALTINGÖVDE[2]
ABDULLAH AL-HAMDANI[1]
SELMA AYŞE ÖZEL[2]
ÖZGÜR ULUSOY[2]
and
ZEHRA MERAL ÖZSOYOĞLU[1]
[1]EECS Dept, Case Western Reserve University, Cleveland, Ohio
[2] Computer Engineering Department, Bilkent University, Ankara

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In this paper, we discuss the issues involved in adding a native score management system to object-relational databases, to be used in querying web metadata (that describes the semantic content of web resources). The web metadata model is based on topics (representing entities), relationships among topics (called metalinks), and importance scores (sideway values) of topics and metalinks. We extend database relations with scoring functions and importance scores. We add to SQL score-management clauses with well-defined semantics, and propose the sideway-value algebra (SVA), to evaluate the extended SQL queries. SQL extensions and the SVA algebra are illustrated through two web resources, namely, the DBLP Bibliography and the SIGMOD Anthology.

SQL extensions include clauses for propagating input tuple importance scores to output tuples during query processing, clauses that specify query stopping conditions, threshold predicates—a type of approximate similarity predicates for text comparisons, and user-defined-function-based predicates. The propagated importance scores are then used to rank and return a small number of output tuples. The query stopping conditions are propagated to SVA operators during query processing. We show that our SQL extensions are well-defined, meaning that, given a database and a query Q, under any query processing scheme, the output tuples of Q and their importance scores stay the same.

To process the SQL extensions, we discuss two sideway value algebra operators, namely sideway value algebra join and topic closure, give their implementation algorithms, and report their experimental evaluations.

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Authors' addresses: G. Özsoyoğlu, EECS Department, Case Western Reserve University, Cleveland, Ohio 44106; e-mail: tekin@eecs.cwru.edu; İ. S. Altıngövde, Computer Engineering Department, Bilkent University, Ankara 06800, Turkey; e-mail: ismaila@cs.bilkent.edu.tr; A. Al-Hamdani, EECS Department, Case Western Reserve University, Cleveland, Ohio 44106; e-mail: abd@eecs.cwru.edu; S. A. Özel-Özalp, current address: Industrial Engineering Department, Uludag University, Gorukle, Bursa 16059, Turkey; e-mail: ayseozalp@uludag.edu.tr; Ö. Ulusoy, Computer Engineering Department, Bilkent University, Ankara 06800, Turkey; e-mail: oulusoy@cs.bilkent.edu.tr; and Z. M. Özsoyoğlu, EECS Department, Case Western Reserve University, Cleveland, Ohio 44106; e-mail: ozsoy@eecs.cwru.edu.
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1. INTRODUCTION

This paper proposes SQL and database query engine extensions that add a "score management functionality" to DBMSs, where the "scores" of existing database objects are employed to generate scores for query output objects, and to rank them. Score management appears frequently in web applications. We illustrate with an example.

Example 1.1 Assume that a researcher wants to locate the top-10 most important papers listed at the DBLP Bibliography [Ley] and ACM SIGMOD Anthology [ACM SIGMOD Anthology] sites that are prerequisite papers to understanding the paper "Data Models in Database Management" by E.F. Codd [1980]. Presently, this task is performed manually by retrieving the papers cited by Codd's paper iteratively, attaching importance scores to them, and eliminating those that are not in the top-10 prerequisites to understanding the Codd paper; clearly, a time-inefficient process.

Consider a metadata model for DBLP and Anthology sites where "research paper", "Data Models in Database Management", and "E.F. Codd" are topics with importance scores, *Prerequisites* is a relationship among topics (called *associations* in the topic map standard [Biezunski et al. 1999], and, here, referred to as *topic metalinks*) with importance scores; and for each topic, there are links to web documents containing "occurrences" of that topic, called *topic sources*. Then, the user can formulate and evaluate the above-specified query using the metadata data model.

In this paper, we assume that (i) entities (topics) and relationships (metalinks) (in an object-relational database) have importance scores, and (ii) queries request objects with top-k or above-a-given-threshold importance scores. We propose handling query-based score manipulations *natively* within the database query engine, and discuss, for the target area of web resource querying, a generic (importance) score management component for DBMSs as far as SQL and query processing are concerned.

Score functions appear in the literature in the forms of "scores", "preference values", or "probabilistic values"; we generalize these functions and their evaluations as *sideway functions* and *sideway/importance values*, respectively ("sideway" in the sense that these functions and values are generated not necessarily by web content generators, but by a third party--possibly a data extraction tool). The terms "importance score" and "sideway value" are used interchangeably throughout the paper.

We present the score management extensions in a web database context which we think illustrates best the need for such extensions. We choose as the target area web

resource querying, and, thus, queries have the ability to compare text documents/strings. For web resource modeling, topics and metalinks constitute metadata (i.e., information about web resources) representing the advice of data creators whereas topic sources constitute (URLs to) data, e.g., HTML, XML, ps, pdf, text documents. Topics, metalinks, and sources [Biezunski et al. 1999] can be maintained and queried from an object-relational database; the purpose of maintaining topics and metalinks in a database is to be able to pose complex queries, and to quickly locate and rank the associated topic sources on the web resource

Example 1.2 Consider the web resources DBLP Bibliography and ACM SIGMOD Anthology. Assume that information about papers (e.g., paper titles, index terms, author names, etc.) in these resources are collected as topics, and stored into the Topics relation, as illustrated in Table I (a). As an example, the tuple with topic id T08 is the 1980 paper of E.F. Codd [1980]. And, the importance of the tuple with Tid T01 is 0.9.

Table I Topics, Metalinks and Sources relations in the metadata database

(a) *Topics* relation

Tid	**TName**	**TType**	**TDomain**	**Imp**
T01	Edward F. Codd	author	database	0.9
T08	Data models database management	Paper title	database	0.8

(b) *ResearchPaperOf* metalink relation

Mid	**AuthorId**	**PaperId**
M01	T01	T08

(c) *Sources* relation

Tid	**URL**
T01	http://www.informatik.uni-trier.de/~ley/db/conf/sigmod/Codd80.html

We choose the data model of Table I as our running example for its simplicity; in practice, topics relation is likely to form an inheritance hierarchy with separate authors, papers, etc. relations, each with a large number of additional attributes, etc.. In this paper, we assume the following *minimal* data model of metadata, represented as relations of the object-relational model:

- *One Topics(Tid, TName,TType, TDomain, Imp) relation* having topic id, topic name, topic type, topic domain and topic importance attributes (and possibly other attributes as dictated by the application),
- *One Sources(Tid,URL) relation* with key (Tid, URL) (and possibly other attributes as dictated by the application), and
- *One Metalink relation for each relationship type among topics*, with a metalink id attribute Mid and topic id attributes of topics involved in the relationship (as well as other attributes as dictated by the application). Metalinks may or may not have importance scores. As an example, *ResearchPaperOf* relation of Table I does not have importance scores; however, *RelatedToPapers* relation (discussed later) does have importance scores.

These minimal requirements are sufficient to illustrate our SQL and query engine extensions.

Data extraction techniques [Grishman 1997, Agichtein et al. 2000, Agichtein and Gravano 2000, Agichtein and Gravano 2003, Brin 1998] can be employed to obtain topics and metalinks with importance scores. We have extracted RelatedToPapers and PrerequisitePapers metalinks for the Anthology (about 15,000) papers [Li 2003, Al-Hamdani 2003], and used them in the experiments of this paper. (This paper does not describe the data extraction process, and assumes that the metadata is extracted from web resources, and maintained in a database.)

Querying web metadata stored in a database has two requirements. First, the query language should allow approximate text-similarity comparisons as the web contains text documents. Second, importance scores of the metadata (i.e., input tuples) need to be used to rank query output topics (tuples), and return either the high-ranking topics above a given threshold, or the top-k highest-ranking topics. We refer to the mechanism that propagates the scores of input topics and metalinks to the output topics and metalinks as the score management mechanism. Presently, such mechanisms, if any, are built into applications directly, and outside of database query engines, which is wasteful (each application builds its own score management subsystem) and inefficient (due to the loose coupling between the application and the DBMS as far as the score management is concerned). In this paper, we discuss the issues involved in adding a native score management system to a database query engine that allows top-k and threshold-based SQL queries with approximate text-similarity predicates. In more detail, the main contributions of this paper are, after extending database relations with sideway value functions and importance scores, to (i) add to SQL text-similarity predicates and score-

management clauses with well-defined semantics, (ii) propose an algebra to process the extended SQL queries efficiently, (iii) discuss logical query trees and algebraic optimization for such queries, and, (iv) present and evaluate the implementation algorithms for the algebra operators. Below we elaborate more on our approach.

Topic names in the metadata database are arbitrary phrases, which implies the need for efficient approximate text processing and comparison techniques to be incorporated into SQL query processing. We introduce one type of *approximate similarity predicates* into SQL, namely, *threshold predicates*. A threshold predicate compares the text similarity of two text values, and returns true when the evaluated text similarity is above a given threshold; otherwise, it returns false. In addition, a threshold predicate returns an approximate similarity score, which, when the predicate is True, is used for modifying the score of the involved tuple. Thus, threshold predicates are integrated with the score management system, and used for importance score propagation and modification during query processing.

For web (metadata) databases, the database query engine should return ranked answers to users' queries, necessitating SQL extensions that specify the ranking of output tuples (objects). Our approach is to propagate unambiguously input tuple importance scores of base relations to output tuples, and to use the computed output importance scores in ranking the output tuples. The procedure for importance score propagation and modification within a query is to be specified by the user in the SQL query, and employed by the database system for efficient query processing.

Example 1.3 *(Importance score modification).* Consider the metadata of Table I, and assume that the user asks for all authors of database papers with names similar to "E. Codd". And, the similarity between "Edward F. Codd" and "E. Codd" is judged to be 0.7. Then the tuple T01 is returned to the user with the *revised* importance score of 0.9*0.7=0.63, where 0.9 is the base importance score of the tuple T01.

To return only the "best" answers in a short time, the SQL query output sizes need to be explicitly controlled by users. For this task, we employ the propagated importance scores of input tuples, and provide two approaches:

(a) For the final output size control, users specify a *ranking threshold* k (i.e., output only the top-ranking k (i.e., top-k) tuples [Carey and Kossmann 1997, Carey and Kossmann 1998, Chaudhuri and Gravano 1999, Chang and Hwang 2002]).

(b) For intermediate output size controls during query evaluation, and for final output size controls, users specify a *sideway value threshold* V_t (i.e., output all the tuples with importance scores above the threshold V_t).

We refer to these two conditions as *query stopping conditions,* which constitute a user-guided and system-enforced use of importance scores.

We also provide users with the power to modify importance scores in application-dependent ways. For this purpose, UDF (user-defined-function) predicates are defined where, if the predicate is satisfied, output of the UDF modifies the importance scores of tuples.

The existence of importance score modifications and query stopping conditions necessitate the design and evaluation of new join and selection algorithms. In this paper, we concentrate on the join evaluation algorithms; selection evaluation algorithms are discussed elsewhere [Al-Hamdani and Özsoyoğlu 2003]

Finally, as illustrated in Example 1.1 with the *prerequisite* relationship, a recursive topic closure operator is useful for user queries. Such an operator serves to retrieve topics related to each other via a particular metalink type, or, more generally, via a regular expression of metalink types.

In more detail, the contributions of this paper are as follows:

- Extend SQL with score management and text-similarity-based comparison functionality:
    - Clauses that specify unambiguously the propagation and modifications of importance scores of input relations to query output relations in automated ways.
    - Clauses that specify query stopping conditions.
    - Threshold predicates (in the where clause)–if the threshold predicate is satisfied, the output of the similarity score used in the predicate modifies the importance scores of output tuples.
    - UDF predicates (in the where clause)–if the UDF predicate is satisfied, the output of the UDF modifies the importance scores of output tuples.

  Note that the only relational algebra operators that manipulate scores are selection, join, and cartesian product. SQL queries with aggregate functions and the SQL operator *having* are not discussed here, and constitute future work.
- Show that the above-listed SQL extensions are well-defined, in the sense that, given a database D, the output of a query on D stays the same, regardless of the query processing scheme.

- Present the sideway value algebra (SVA) with two new logical operators, namely SVA join and topic closure, designed to evaluate the extended SQL queries and to support textual approximate similarity comparisons and recursive closure operations.
- Give implementation algorithms for the SVA join and the SVA topic closure operators. In particular, the SVA join employs a nested loops-based evaluation approach where importance scores and textual approximate similarity among tuple components are exploited for early termination. The closure operator adapts a graph traversal algorithm for its evaluation.
- Experimentally evaluate the SVA join and the SVA topic closure algorithms using real data.

In Section 2, we present the basics of the metadata model and web queries with examples, and define new SQL extensions. Section 3 introduces the SVA operators for selection, join and topic closure, and presents logical query trees with these operators. In section 4, we specify the execution semantics of the extended SQL, and prove that the extended SQL queries are well-defined. Section 5 discusses query processing techniques for the SVA join. In Section 6, we present topic closure evaluation algorithms. Sections 7 and 8 report the experimental SVA join and topic closure results. In Section 9, we review the related work in the literature. Section 10 concludes.

2. EXAMPLE QUERIES AND SQL EXTENSIONS

2.1 Metadata-Based Web Queries

Below we illustrate the need for score management and approximate text-similarity support in databases, with examples from research paper digital libraries (DBLP and ACM SIGMOD Anthology) as web resources. However, one can easily envision other web resource metadata for which a database *natively* supporting score management and text-similarity comparisons would be equally useful. Some examples are (a) web-based news articles of news agencies, (b) web-based archeological sites, (c) the Library of Congress web site [Library], (d) disease-specific (e.g., prostate cancer) web sites, etc. Moreover, native score management and text-similarity comparison support would also be useful in non-web-based application frameworks: as mentioned in [Carey and Kossmann 1997], there exist applications posing queries with similarity-based ranking requirements to underlying multimedia or text databases.

Example 2.1 (*Threshold Predicates*). **F**ind the topic ids, topic names and URLs of 20 highest topic-importance-ranked papers having titles (topic names) with similarity above

0.9 to “query processing”. Employ a product-based importance propagation function that uses only topic importance values.

select T.Tid, T.Tname, S.URL

from Topics T, Sources S

where T.TType=“paper title” **and** T.TName $\cong_{(\text{threshold } 0.9)}$ “query processing”

and T.Tid = S.Tid

propagate importance as product **function of** T

stop after 20 most important

Topics relation has attributes Tid, TName, TType, and Imp; Sources relation has attributes Tid and URL, storing URLs for the sources of each topic in the Topics table. The predicate “T.TName $\cong_{(\textbf{threshold } 0.9)}$“query processing”” states that the topic (paper title) name of T is similar to “query processing” with similarity above 0.9. We assume that the similarity between a paper title and the phrase “query processing” is evaluated by information retrieval techniques, e.g., by using the vector space model and the TF-IDF weighting scheme [Salton 1989] (explained in Section 5.1) to represent the topic names. The “propagate importance” clause specifies the importance propagation function for output tuples. In this example, the clause states that the importance scores for output tuples are computed from the importance scores of the base relation Topics, using a “product” function revised with similarities.

Assume that there are three papers with titles “query processing: a survey”, “query processing in a P2P environment with extraordinary network bandwidths” and “string processing for C++ applications”, and with importance scores 0.9, 0.7 and 1, respectively. Also assume that the similarity function returns the results 0.9, 0.2 and 0.1 for these titles. In this case, the first topic will have the highest score (0.9 * 0.9 = 0.81). The second and third topics will have the scores 0.14 (= 0.7*0.2) and 0.1 (= 1*0.1), respectively.

The importance score (sideway) function of base relations (denoted by f_{in}) has the range [0,1]. During SVA operations, for a given output tuple, we materialize the importance score function of the SVA operator, i.e., keep it as a (new) column while processing queries.

Example 2.2 *(Join with a User-Defined Function).* Find titles of pairs of conference and journal papers such that journal paper is an *extension* of the conference paper. The user-defined function Extension(T1, T2) returns the similarity of the papers’ sources, and

we assume that T1 is an extension of T2 if they have at least 50% similarity. Employ a product-based importance propagation function and retrieve top-100 pairs.

select T1.TName, T2.TName
from Topics T1, Topics T2
where T1.TType="conference paper title" **and** T2.TType="journal paper title" **and**
Extension(T1.Tid, T2.Tid) $\geq^{sv}$ 0.5
propagate importance as product **function of** T1, T2
stop after 100 **most important**

Here, the predicate "Extension(T1.Tid, T2.Tid) $\geq^{sv}$ 0.5" constitutes a user-defined (UDF) predicate (distinguished from an ordinary predicate by the superscript sv). We assume that the UDF function Extension(Tid, Tid) is registered to the DBMS beforehand, and its output modifies the importance scores of output tuples by the value v returned by the UDF if v is greater than 0.5. While evaluating this query, the system propagates and/or modifies the importance scores as specified in the importance propagation clause. In particular, importance scores of selected tuples are determined by multiplying them with the score returned by the UDF. The actual implementation method for evaluating the UDF function, i.e., computing content similarity, is "expensive" [Chen 2001, Li 2003], i.e., it may require (a) access to actual information resources, such as the above query that needs to do so to compare the contents of two papers, or (b) submitting additional queries to the database.

Example 2.3 (*Topic Closure Query*)**.** Given the relation *Request*(PaperId) containing user-selected paper ids, the user is interested in finding those ACM SIGMOD Anthology papers that are recursively prerequisites of papers in *Request* with importance values above 0.7. For topic closure, we use a shorthand SQL-like syntax:

select T.TName, S.URL
from Request, Topics T, PrerequisitePapers Prereqs, Sources S
where T.Tid **in** *PrerequisitePapers**(Request,T,{Prereqs}) **and** T.Tid = S.Tid
topic closure importance computation as product **function within a path**
and as max **function among multiple paths**
stop with threshold 0.7

PrerequisitePapers is a metalink type representing the prerequisite paper relationship, and PrerequisitePapers is the relation instance that contains *PrerequisitePapers* metalink instances. ***** is the Kleene's star. We refer to the predicate "T.Tid **in** *PrerequisitePapers**(Request,T,{Prereqs})" as the *topic closure predicate*. Note that a

given paper can have multiple (topic) sources on the web in terms of a pdf file, a postscript file, an HTML document, or an XML document. Finally, another possible query is to request the top 20 highest importance-valued prerequisite papers of *Request*, which is specified by replacing the *stop with threshold* clause with the *stop after 20 most important* clause.

For those database relations that have importance scores (not all may have), we have two ways of specifying tuple (topic/metalink) importance scores: (i) base relation tuples have importance scores explicitly specified as a tuple component (all the examples in this paper use this approach), (ii) base relation has an importance (sideway value) function attached, which, when evaluated using a given tuple from the relation, the function returns the importance score of the tuple. Regardless, once the query processing starts, all importance score functions are materialized, and each (intermediate or final output) tuple (object) gets a new tuple component containing the tuple's importance score.

2.2 SQL Extensions

2.2.1 New Predicates

As observed from examples of section 2.1, we employ new SQL *where* clause predicates which, in addition to holding truth values as typical predicates, are also used for importance score modification as dictated by the score propagation clauses (e.g., see examples 2.1 and 2.2). In this work, we define two particular types of such predicates, namely threshold predicates and UDF predicates.

The *threshold predicate* is illustrated in Example 2.1 by "T.TName $\cong_{\textbf{(threshold 0.9)}}$ "query processing"", and has the syntax "X $\cong_{\textbf{(threshold t)}}$ Y" where X and Y are either text-valued variables instantiated by tuple component values or text-valued constants, and t is a real number within the range [0,1]. The threshold predicate with an instantiation x of X and y of Y is *satisfied* (returns True) if the similarity between x and y (i.e., Sim(x, y) where Sim() is a similarity function) is above the threshold *t*; otherwise it is not satisfied.

Example 2.4. Consider Example 2.1 in which we modify importance scores with a product function. Then, the importance values of the output tuples for the selection operator with the selection formula "T.TName $\cong_{\textbf{(threshold 0.9)}}$ "query processing" is computed as f_{in} * Sim(T.TName, "query processing") where f_{in} denotes the importance values of input tuples, and Sim() denotes the similarity function.

User-defined-function (UDF) predicates in SQL queries are illustrated in Example 2.2 by "Extension(T1.Tid, T2.Tid) $\geq^{sv}$ 0.5". The syntax is "UDF θ c" where UDF is a user defined function that returns a real value in [0,1], θ is a comparison operator from the set $\{<^{sv}, >^{sv}, \leq^{sv}, \geq^{sv}, =^{sv}, \neq^{sv}\}$, and c is a real constant in [0,1]. The superscript symbol sv in the comparison operator states that, the UDF function value, when the associated UDF predicate is true, modifies the importance score of the output tuple during query processing.

2.2.2 New Clauses

We use the following SQL extensions for score management.

(i) The basic importance propagation clause

*"**propagate importance as** <ImpAgg> **function of** <argument list>"*

specifies the formula for propagating importance scores of query input relations to the output relation (see example 2.1). *ImpAgg* is an aggregate function type; in this paper, we use the aggregate function *product*. As discussed later in section 4.3.1 (Rule 4), the function *ImpAgg* is a monotonically decreasing aggregate function, i.e., with an enlarged input, it returns a value less than or equal to its previous value. Another aggregate function with this property is *min;* on the other hand, the functions *max* and *numeric-average* do not satisfy this property. The *argument list* is a sublist of relations listed in the *from* clause of the SQL query. In example 2.1, *ImpAgg* function is product.

(ii) For topic closures, the topic closure (importance computation) clause

"**topic closure importance computation as** <*FPath*> **function within a path and as** <*FPathMerge*> **function among multiple paths**"

specifies how to compute the derived importance scores of topics encountered during topic closures (See example 2.3), where *FPath* and *FPathMerge* are aggregate functions. In this paper, we use *product* as *FPath.* As discussed later in Section 4.2 (Rule 2), *FPath* is a monotonically decreasing aggregate function of its input. The function *FPathMerge*, on the other hand, is an aggregate function that always produces a value upper-bounded by the maximum value in its input (Rule 3). Thus, possible candidates for *FPathMerge* include *product, max, min,* and *numeric-average.*

(iii) The query stopping clause "**stop after** k **most important**" specifies the ranking (top-k) threshold, and

(iv) The query stopping clause "**stop with threshold** V_t" specifies the sideway value threshold.

In this paper, all four new SQL clauses as defined above are also allowed in nonaggregate nested SQL subqueries, and have execution semantics similar to ordinary nested SQL queries (as discussed in Section 4). In particular, if the nested subquery is not correlated to the outer query block, it is separately evaluated and its output can be viewed as a materialized input relation for the outer query block. If the nested subquery is correlated to the outer block, whenever the other formulas in the outer block are satisfied, the occurrences of the correlated variables in the nested subquery are replaced by the corresponding variable instantiations of the outer block, and the nested subquery is evaluated as a standalone SQL query--several times, i.e., once for each correlated variable set instantiations. In the uncorrelated case, the output of the (nonaggregate) nested subquery can be viewed as a materialized relation as far as the outer query evaluation is concerned. In the correlated case, while assigning outer block instantiations to nested subquery variables, the importance scores are also passed to the nested subquery for evaluation. In Section 3.4, we provide an example nested query; and, in section 4.3.2, we discuss the query execution semantics for nested subqueries with the query stopping clause *stop after k most important.*

3. SVA OPERATORS FOR EVALUATING EXTENDED SQL QUERIES

For the RA operators selection and join, there is an SVA counterpart extended with an output sideway value function f_{out} and the *output threshold* β, which is either the integer-valued *ranking threshold*, or the real-valued *sideway value threshold* V_t in the range [0, 1]. And, we introduce a new SVA operator, SVA topic closure. In this section, we define and illustrate the SVA selection, SVA join, and topic closure operators with example queries and their logical query trees.

In the logical query tree examples discussed next, we use the following notation: Operators with superscript * are SVA operators. Operators without superscript * are relational algebra (RA) operators. A unary RA operator without * in its superscript carries (if any) into its output tuples the importance scores of its only operand relation. A binary RA operator without a superscript * carries (if any) into its output tuples the importance scores of either its left (hand side) relation or its right (hand side) relation, indicated (if there is a need) by superscript L or R, respectively.

3.1 SVA Selection Operator

In Example 2.1, we gave a query example where topics with names similar to "query processing" over a specified threshold are selected during the query evaluation. The notation $\cong_{(t)}$ in the SVA operator denotes the threshold predicate with the threshold of t. The logical query tree of Example 2.1 is shown in Figure 1.

Example 3.1 Find the topic ids of the five highest topic-importance-ranked papers having index terms with similarity to "query processing" above 0.9. Employ min as the importance propagation function that uses all involved importance values.

select distinct Indx.PaperId
from Topics T, IndexedBy Indx
where T.TType="Index Term" **and** T.TId **in** Indx.TermIdSet **and**
T.TName $\cong_{\text{(Threshold 0.9)}}$ "query processing"
propagate importance as min **function of** T, Indx
stop after 5 **most important**

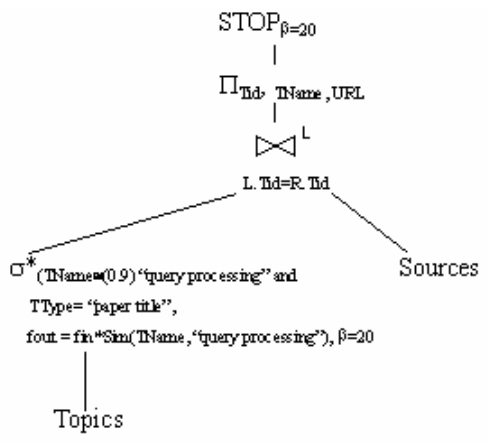


Fig. 1. Logical Query Tree of Example 2.1.

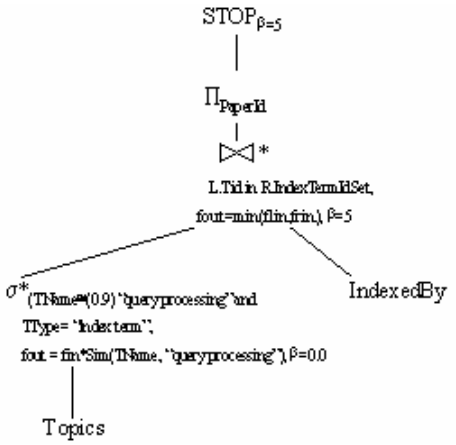


Fig. 2. Logical Query Tree of Example 3.1.

The logical query tree of Example 3.1 is shown in Figure 2. We assume that *IndexedBy* is a metalink type that specifies the relationship between index terms and papers (obtained from keyword/index term list specified in the body of each paper). The signature of the metalink type is *IndexedBy: SetOf IndexTermId* → *PaperId*. Due to the clause "propagate importance", this query chooses paper ids on the basis of the min of the importance values of index terms (topics) and their *IndexedBy* type metalinks.The function Sim() in Figure 1 and 2 computes the text similarity of two strings, and returns a value in the range [0, 1]. Here, Sim() is used to modify the importance scores of output tuples according to their TName similarity to the string "query processing" (see Table I).

The logical query tree shows the SVA selection operator which is denoted as $\sigma^*_{C,\ fout,\ \beta}$ (R).

Definition *(SVA Selection).* The selection operator $\sigma^*_{C,\ fout,\ \beta}$ (R) takes as input a relation R with a sideway value function f_{in}, a selection condition C, an output sideway value propagation function f_{out}, and the output threshold β where β is either a positive integer k as the ranking threshold, or the real-valued sideway value threshold V_t in the range [0, 1]. The operator σ^* returns, in decreasing order of output importance scores, either (i) top k f_{out}-ranking output tuples that satisfy the selection condition C (when β is k), or (ii) all tuples of R with an f_{out}-sideway value greater than V_t and satisfy the selection condition C (when β is V_t). If the output threshold β is 0.0, it is not applied, i.e., the operator is assumed to have no stopping condition and returns all produced tuples.

3.2 SVA Join Operator

Definition *(SVA Join).* The SVA join operator is (L) $\bowtie^*_{A\ \theta\ B,\ fout,\ \beta}$ (R) takes as input two relations L and R with sideway value functions fl_{in} and fr_{in} respectively, a join condition θ on attributes A and B of relations L and R, respectively, a sideway value propagation function f_{out} for the output tuples, and an output threshold β. The join operator produces joined tuples of L and R with importance scores of output tuples computed as specified by f_{out}, and satisfying the output threshold β.

SVA join in Example 3.1 (Figure 2) is exact, i.e., no similarity computations are involved. SVA join in the example below is approximate, with a threshold predicate as a join condition.

Example 3.2 *(join with a threshold predicate).* Assume that topics table allows "journal paper title" and "conference paper title" in topic type field. Find the journal-conference paper pairs with similar titles (i.e., topic name similarity is above 0.98) and return only those pairs that have a derived importance score above 0.95. Employ a product-based importance propagation function that uses all of the involved importance scores.

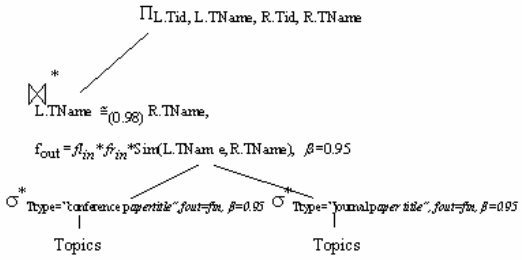


Fig. 3. Logical Query Tree of Example 3.2

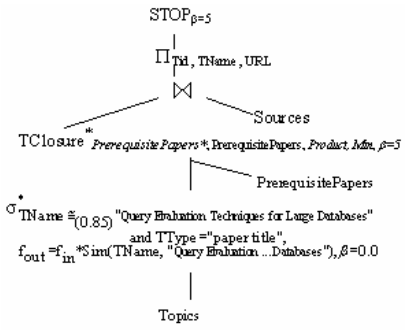


Fig. 4. Logical Query Tree of Example 3.3

select T1.Tid, T1.TName, T2.Tid, T2.Tname

from Topics T1, Topics T2

where T1.TType="journal paper title" **and** T2.TType="conference paper title" **and**

T1.TName $\cong_{(\text{Threshold } 0.98)}$ T2.TName

propagate importance as product **function of** T1, T2

stop with threshold 0.95

Note that, this query may be posed to see the most important works published both at a conference and a journal and with highly similar titles.

In Figure 3, the sideway value threshold of 0.95 is propagated to all of the three operators, namely, the two SVA selections and one SVA join. By employing the semantics of propagation to be discussed in Section 4, the similarity score revises the f_{out} value of the joined tuples.

3.3 SVA Topic Closure Operator

Next we define a recursive operator that takes into account the importance scores of its input tuples. Consider the following query and its logical query tree in Figure 4.

Example 3.3. Find the topic ids, titles and URLs of five highest importance-scored papers such that the selected papers are either (i) papers with titles similar to "Query Evaluation Techniques for Large Databases" with a similarity above 0.85, or (ii) the prerequisites (recursively) of the papers found in (i).

select T2.Tid, T2.TName, S2.URL

from Topics T1, Topics T2, PrerequisitePapers M, Sources S2

where T1.TName $\cong_{(\text{Threshold } 0.85)}$ "Query Evaluation Techniques for Large

Databases" **and** T1.Ttype="PaperTitle" **and**

T2.Tid **in** *PrerequisitePapers**(T1.Tid, T2, {M}) **and** T2.Tid=S2.Tid

propagate importance as product **function of** T1

topic closure importance computation as product **function within a path**
and as min **function among multiple paths**
stop after 5 **most important**

In the above query, prerequisites of the paper "Query Evaluation Techniques for Large Databases" are located recursively by following the metalinks of type *PrerequisitePapers*. For the topic closure predicate evaluation, we introduce the topic closure operator, denoted as $\text{TClosure}^*_{R,\ \{M\},\ FPath,\ FPathMerge,\ \beta}(X)$, which computes the topic closure X^+ of a set X of topics with respect to a regular expression R of metalink types (and, thus, with respect to the set of axioms characterizing the metalink types in R), a set of metalink relations M, and an output threshold β.

Definition *(Topic Closure).* The operator $\text{TClosure}^*_{R,\ \{M\},\ FPath,\ FPathMerge,\ \beta}(X)$ takes as input (1) a topic relation, namely, the relation X of topics with a sideway value function f_X, (2) a set of metalink relations M each with a sideway value function f_M, and (3) four parameters: (a) the regular expression R, (b) a path-based "derived" importance score computation function *FPath* that specifies how to compute the derived importance scores of newly reached topics with respect to a single path, (c) the function *FPathMerge* that specifies how to merge the derived importance scores of a given topic obtained through different paths, and (d) the output threshold β. TClosure^* computes the closure X^+ of X with respect to <R, {M}, f_X, {f_M}, *FPath*, *FPathMerge,* β> where each new topic in the closure is represented as an output tuple, and has a *derived* importance score satisfying the output (ranking or sideway value) threshold β. If the output threshold β is 0.0, it is not applied, i.e., the operator is assumed to have no stopping condition and returns all produced tuples.

R is a regular expression of metalink types. E.g., the regular expression $PrerequisitePapers^*IndexedTerms$ finds the index terms in *all* the prerequisite papers (of a given paper topic). Next we illustrate the notion of paths that satisfy R with an example.

Example 3.4 Let A, B, C, D, and T denote single topics. The metalinks $A \rightarrow^{RelatedTo} B$, $B \rightarrow^{RelatedTo} C$ and $C \rightarrow^{RelatedTo} T$ constitute a path P = {A, M_1, B, M_2, C, M_3, T} where all nodes are single topics and all metalinks M_1, M_2, and M_3 have the type *RelatedTo* (i.e. R = $RelatedTo^*$). As another example, metalinks $AB \rightarrow^{Pre} C$, $C \rightarrow^{Pre} DE$, and $DE \rightarrow^{Pre} T$ form a path P={AB, M_1, C, M_2, DE, M_3, T} that starts with a set of topics AB, followed by a single topic C, then a set of topics DE, and ends with a single topic T. The path P

satisfies R = *Prerequisite** since all of its metalinks M_1, M_2, and M_3 are of type *Prerequisite*.

FPath is the derived importance score computation function with respect to a single path. In this paper, we use the product function as *FPath.* As an example, assume that the topic t is reached from a topic x in X using a path P = <x m1 a m2 t> where a is a topic with importance score v_a, m1 and m2 are metalinks with importance scores v_{m1} and v_{m2}, and the metalink types of m1 and m2 satisfy the regular expression R. Assume *FPath* is Product. Then, the derived importance score of t with respect to P, denoted by $Imp_d(t, P, R)$, is computed as the product of importance scores in P that satisfies R, i.e., $v_x*v_{m1}*v_a*v_{m2}*v_t$, where v_a and v_t are the importance scores of x and t, respectively. The derived importance score of t, denoted by $Imp_d(t, R)$, is the importance score of t with respect to R and *all* paths leading to t.

The intuition for the semantics of derived topic importance scores is as follows: assume topic t is reached through path P. The derived importance score of t in the closure should be a function of the length and the type of path P, and less than or equal to the importance score of t. As the length of P increases, the derived importance score of t should decrease because t is farther away from (and is *less* related to) the topics in X, the original set of topics listed by the user. Thus, $Imp_d(t, P, R)$ with respect to path P should be a monotonically decreasing function of the length of path P (i.e., *path-monotone*).

FPathMerge is one of Product, NumAve, Min, Max, etc., specifying how to compute the derived importance score $Imp_d(t, R)$ of topic t in X^+ in terms of the $Imp_d(t, P, R)$ scores obtained with respect to each path P.

In Example 3.3, the topic closure importance computation clause specifies the use of product function as *FPath,* and min function as *FPathMerge,* as shown in the corresponding query tree.

Finally, we specify the execution semantics of $TClosure^*_{R,\ \{M\},\ FPath,\ FPathMerge,\ \beta}(X)$ procedurally as follows:

(a) Locate metalink paths P from a topic in X to a topic t not in X, where P "satisfies" the regular expression R, and compute $Imp_d(t, P, R)$ scores.

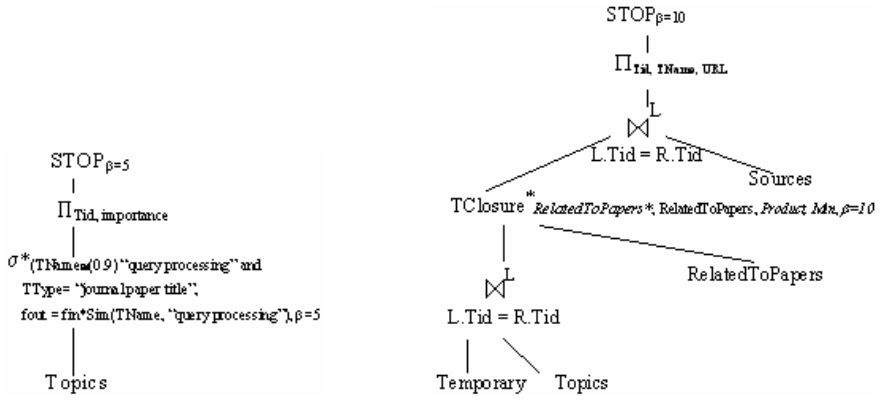
(b) Compute the derived importance score of t as $sv=Imp_d(t, R)$, and, if sv satisfies the sideway value threshold β then add the new topic t to the closure of X. That is, if β is a positive integer k as the ranking threshold, then sv satisfies β when sv is among the top-k output sideway values. If β is the real-valued sideway value threshold V_t in [0, 1], then sv satisfies β when $sv > V_t$.

3.4 SVA Operators in Nested Queries

Consider the nested query example below, and its query tree given in Figure 5.

Example 3.5 Find five highest topic-importance-ranked journal papers having titles similar to "query processing" above 0.9, and then find their ten most important related papers and the associated URLs. Employ a product-based importance propagation function.

select T2.Tid, T2.Tname, S2.URL
from Topics T1, Topics T2, RelatedToPapers M, Sources S2
where T1.Tid **in** (**select** T.Tid
from Topics T
where T.Ttype = "journal paper title" **and**
T.TName $\cong_{(\text{Threshold } 0.9)}$ "query processing"
propagate importance as product **function of** T
stop after 5 **most important**) **and**
T2.Tid **in** *RelatedToPapers**(T1.Tid, T2,{M}, 0.0) **and** T2.Tid = S2.Tid
topic closure importance computation as product **function within a path**
and as min **function among multiple paths**
stop after 10 **most important**



(a) (b)

Fig. 5. Logical Query Tree of Example 3.5: (a) temporary table materialization for inner query, (b) query tree for the outer query.

In this example, first the inner query block is evaluated, and an intermediate relation including topic id's and importance scores (generated automatically) is materialized. Then, this table is used just like base relation with importance scores by the outer query block in a join operation (that implements the set membership), and the final query output

is computed. We assume the execution semantics that intermediate relations generated by inner blocks are *implicitly* included in the "propagate importance" clause of outer query, and their scores are propagated. Thus, the importance scores are always propagated from the inner block to the outer block. In the above example, the join semantics enforce that the importance scores of the intermediate relation are propagated, and T1 and T2 scores are suppressed.

4. EXECUTION SEMANTICS OF THE EXTENDED SQL

Importance score computations (as defined through the SQL extensions of Section 2.2) are functional specifications, superimposed on an SQL query which is logic-based and (mostly) nonprocedural. Therefore, there is a mismatch between functional importance score computations and nonprocedural SQL query specifications. Moreover, importance scores are (a) directly modified by threshold and UDF predicates, and (b) used to choose the final output tuples. Thus, the question arises as to whether SQL extensions of Section 2.2.2 lead to unambiguous query specifications and unique query outputs.

Definition. An SQL query Q is *well-defined* if, for a given database D, the output of Q is unique.

That is, under any query processing scheme, output of Q(D) stays the same. In this section, we show that, with the SQL extensions introduced in Section 2.2.2, SQL queries remain well-defined. In other words, input relation importance scores propagate unambiguously and uniquely to intermediate relations and to the final output of the query, which is also unique. This constitutes the specification of query semantics (of the SQL extensions), pertaining to the propagation of importance scores and stopping conditions.

Next, we enumerate the algebra operators used in logical query trees, and discuss which algebra operators modify and propagate importance scores of their operand relations, and how.

(a) *projection, rename, union, set difference, cartesian product, STOP, GROUP-BY operators:* These operators do not have predicates, and, thus, do not modify input tuple scores. However, depending on the needs of the query plan, they may propagate or suppress importance scores of one of their operand relations. Note that *two tuples that are identical in every tuple component but tuple importances are viewed as two distinct tuples*; if they are unioned, both tuples will be in the output. Similarly, projection will materialize importance scores into its output as

a column (if the user chooses to retain importance scores in the output of the projection); thus, if two projected tuples are identical in all tuple components except their importance scores, both will be retained in the output of the projection.

(b) *aggregation operators:* When an aggregate function, say, summation on relation R over attribute A (e.g., SUM(R, A)) executes, it aggregates multiple tuples into a single output tuple. Then, the question of how to compute the importance score of the aggregated output tuple from the importance scores of input tuples arises. A simple solution is to attach to each aggregation operator a new "importance score computation function". Such a function would have no constraints, other than the fact that its input is defined in terms of the input tuples of R, and its output needs to be in the range [0,1]. In this paper, we do not deal with aggregate operators.

(c) *join and selection operators:* Through the use of the basic importance propagation clause, and threshold and UDF predicates, these two operators may modify and propagate the importance scores of their operand relations; hence the introduction of the SVA selection and the SVA join operators in Sections 3.1 and 3.2, respectively. In Section 4.1, we define the execution semantics of these two operators, and the conditions under which the query engine decides to generate the appropriate operator (RA or SVA), and then discuss their correctness (i.e., that they are well-defined).

(d) *topic closure operators:* This is a new operator. Through the use of the topic closure importance computation clause and topic closure predicates, this operator also modifies the importance scores of its input tuples, and its correctness is discussed in Section 4.2.

The second correctness issue which is orthogonal to the issue of score propagation within a query tree is the propagation of the two query stopping conditions into the SVA operators in the query tree. SVA operators are designed to modify the scores of their input tuples; and, the query processing times will be reduced drastically if the query stopping conditions, which are query-wide, can be correctly propagated to SVA operators, and, hence, become "operator-stopping" (i.e., operator-wide) conditions. This is novel since, with the exception of the STOP operator [Carey and Kossmann 1997], none of the algebra operators in the literature contain operator-stopping conditions. In Section 4.3, we study the conditions for propagating the query-wide sideway value

threshold V_t and the query-wide ranking threshold (i.e., the top-k condition) into the SVA join, the SVA selection, and the topic closure operators.

4.1 Importance Propagation with Threshold and UDF Predicates

In this section, we assume that SQL queries are extended with threshold predicates, UDF predicates, and the basic importance propagation clause, and discuss the query execution semantics.

Threshold predicates are used by the DBMS as follows. Assume that, during query processing, the threshold predicate *P* is part of an SVA selection or join operator *O*, and the evaluation of *P* for a certain output tuple t of *O* generates a similarity value v. Then v is used to modify the importance score of t. That is, the similarity values generated by threshold predicates are used in the computation of importance scores for SVA operator output tuples. Consider the *where* clause of an SQL query with threshold predicates. During query processing, those predicates in the *where* clause that compare a single attribute value to a constant, such as the predicate "T.TName$\cong_{\textbf{(threshold 0.9)}}$"join algorithms"", will be predicates to an SVA selection operator in the logical query tree, and those predicates that compare two attribute values will be predicates to an SVA join operator in the logical query tree. In both cases, the importance score propagation for the output tuples of the selection or the join operator is extended by the application of a function that involves the value of the similarity function employed in the threshold predicate.

Assume that the SQL query Q uses the basic importance propagation clause (but not the topic closure clause), and has regular, threshold, and UDF predicates (but not topic closure predicates, which are discussed in the next section). Consider

Q: **select** ...
from *R, S, T, V*
where ...
propagate importance as *product* **function of** *R, S*

That is, when propagating importance scores of relations R and S for the query at hand, the system will use a product function, and the tuple importance scores of T and V are suppressed, i.e., will not be used. We show below that, given an algebra expression E corresponding to query Q on database D, importance scores for the output tuples of E are unambiguously computed and the output of E is unique.

Next we discuss join and selection operators, and the conditions under which the query engine decides to generate an appropriate version (RA or SVA) of the operator.

Consider the join operator *J* in E, with operands E_1 and E_2 that denote either base or intermediate relations, or equivalently the corresponding algebra expressions in E. We evaluate the alternatives:

(i) Neither E_1 nor E_2 is R or S, and neither has at least one of R or S as an argument: In this case, neither of the operands E_1 and E_2 have tuple importance scores (i.e., they are suppressed). Then, the join is an RA join, and the output tuples of the join operator do not have importance scores.

(ii) Only one of E_1 or E_2 is R or S, or has at least one of R or S as an operand, *and* the join condition involves no score-modifying (i.e., threshold or UDF) predicates : Let E_1 be the operand involving R or S. Then E_1 has tuple importance scores, and E_2 doesn't. And, output tuples of *J* inherit their importance scores from E_1. In this case, the join operator is an RA join with the provision that it propagates the importance scores of E_1 into the output.

(iii) Only one of E_1 or E_2 is R or S, or has at least one of R, S or both as an operand, *and* the join condition involves either a threshold or UDF predicate, or both: Let E_1 be the operand involving R or S (or both). Then E_1 has tuple importance scores, and E_2 doesn't. The output importance scores for the operator *J* are computed as the product of the tuple importance scores of E_1, similarity values generated by those join predicates that are also threshold predicates (if any), and the values of UDFs for the corresponding UDF predicates (if any). In this case, the join operator is an SVA join.

(iv) E_1 and E_2 are either R and S, respectively, or each has at least one of R or S as an argument: If E_i, $1 \leq i \leq 2$, is R (or S) then the tuple importance scores of E_i are the same as R (or S); otherwise they are computed recursively by considering the operators in E_1 and E_2. The output importance scores for the operator *J* are computed as the product (i.e., the *ImpAgg* function) of the tuple importance scores of E_1 and E_2, the similarity values generated by those join predicates that are also threshold predicates (if any), and the UDF values of UDF predicates (if any). In this case, the join operator is an SVA join.

Consider the selection operator *L* in E, with an operand E_1 that denotes either a base or intermediate relation, and a selection condition C applied to E_1. We evaluate the alternatives:

(i) E_1 is either R or S, or has at least one of R or S as an argument, *and* the selection condition C involves either a threshold or UDF predicate, or both: If E_1 is R (or S) then the tuple importance scores of E are the same as R (or S); otherwise they

are computed recursively by considering the operators in E_1. The output of the selection operator *L* contains those tuples that satisfy C. The output tuple importance scores for operator *L* are computed as the product of the tuple importance scores of E_1, the similarity values of threshold predicates, and the UDF values of UDF predicates. In this case, the selection operator is an SVA selection.

(ii) E_1 is either R or S, or has at least one of R or S as an argument, *and* the selection condition C involves no score-modifying (i.e., threshold or UDF) predicates: If E_1 is R (or S) then the output tuple importance scores of E_1 are the same as R (or S); otherwise they are computed recursively by considering the operators in E_1. The output of the selection operator *L* contains those tuples that satisfy C. And, output tuples of S inherit their importance scores from E_1. In this case, the selection operator is an RA selection with the provision that it simply propagates the input tuple importance scores into its output tuples.

(iii) E_1 is neither R nor S, and neither has at least one of R or S as an argument: In this case, E_1 has no tuple importance scores (i.e., they are suppressed). Hence, output tuples of the selection operator *L* do not have importance scores. In this case, the selection operator is an RA selection.

Finally, during the query plan generation for Q, the initial algebra expression E of Q can be transformed into other equivalent algebra expressions. One can specify a set T of algebraic transformations (see Appendix 1) involving RA and SVA operators, and prove that the output of Q stays the same under T. Thus, we have

Lemma 1. Non-aggregate SQL queries extended with the basic importance propagation clause, threshold predicates, and UDF predicates are well-defined.

Hence, we have presented unambiguously the query execution semantics due to a single basic importance propagation clause, and arbitrarily many threshold and UDF predicates.

4.2 Importance Propagation with Topic Closure Predicates

As illustrated in Example 2.3, the topic closure operator is a recursive operator that employs a regular expression (in Example 2.3, the regular expression is "*PrerequisitePapers*"*) to locate new topics with desired importance scores. While different metalink types employ different axioms [Özsoyoğlu et al. 2004, Özsoyoğlu et

al. 2000], the topic closure operator translates into a "transitive closure-like" operator that traverses over paths of metalinks, and computes importance scores of the newly reached topics that are reached over one or more paths. To compute unambiguously the propagated importance scores of the newly reached topics, we employ the *topic closure* (*importance computation*) clause (as defined in Section 2.2.2-(ii)) which is self-explanatory. To have well-defined queries, we use three rules.

Rule 1. Each topic closure predicate is evaluated by a single SVA topic closure operator.

Rule 1 eliminates the use of multiple SVA operators to evaluate a single topic closure predicate, and avoids the specification of topic closure operator interactions within one SQL query.

Definition (*Monotonically decreasing function*). Let f be an aggregate function that takes a set of reals in [0,1] and returns a real in [0,1]. Let S be a nonempty set of reals in [0,1] and v be a real in [0,1]. f is a *monotonically decreasing function* if $f(S \cup \{v\}) \leq f(S)$.

FPath is a (derived) importance score computation function for a topic t reached via a given path.

Rule 2. The function *FPath* defined in the topic closure clause is a monotonically decreasing function.

Rule 2 guarantees that, during the evaluation of the topic closure operator, the search for topics over a metalink path always comes to an end. That is, a topic obtained over a path that includes topic t (and, thus, is "reached" after t is reached) always has a lower propagated importance value than the propagated importance value of t.

FPathMerge function (one of Product, NumAve, Min, Max, etc.) specifies how to compute the (derived) importance score of topic t with respect to multiple paths leading to t.

Rule 3. Assume that the input of *FPathMerge* is the set $S=\{v_1, \ldots, v_n\}$ where v_i is a real in the range [0,1], $1 \leq i \leq n$. Then *FpathMerge*$(S) \leq \text{Max}(S)$.

Rule 3 guarantees that, during topic closure computations, the search for topics over multiple and possibly merging paths comes to an end.

Lemma 2. SQL queries extended with a topic closure importance computation clause and employing rules 1-3 are well-defined.

4.3 Query Stopping Clauses

In Section 2.2.2, we have defined two SQL *query stopping clauses*, namely, threshold and top-k clauses, that specify stopping conditions over the query, whose utility is to

significantly lower the query processing times. These stopping conditions are enforced by SVA operators (selection, join and topic closure) in a query tree via the output threshold β.

Next we discuss how the query stopping conditions (i.e., the sideway value threshold V_t or the top-k condition) are propagated to the SVA operators of the logical query tree (i.e., the query execution semantics of the query stopping clauses). In summary, we show below that (i) for the query threshold stopping clause, all SVA operators in the tree enforce the stopping condition, and (ii) for the top-k query stopping clause, only those SVA operators, for which the "score-conservative top-k propagation policy" holds, enforce the stopping condition.

4.3.1 Stop-With-Threshold Clause

The *stop with threshold* V_t clause directly propagates to all SVA operators of the query *when* the basic importance propagation clause function is a monotonically decreasing aggregate function.

Rule 4. Basic importance propagation clause function f is a monotonically decreasing function.

This rule guarantees that, after propagating $\beta = V_t$ to SVA operators in the query tree, a tuple in the output of a low-level SVA operator and with a score lower than $\beta = V_t$ can be safely eliminated from the output since, if kept in the output of the SVA operator, its score would not increase, and it would not appear in the final query output. Note that the product function used in section 2.2.2 satisfies Rule 4.

Clearly, such a propagation drastically reduces the intermediate output sizes and query evaluation time. Please note that, before propagating the threshold Vt, we assume that the *stop with threshold* V_t clause is enforced with a single STOP operator at the root of the logical query tree with $\beta = V_t$. After propagating β to all SVA operators in the query tree, the STOP operator becomes redundant, and is removed from the query tree.

Lemma 3. Consider an SQL query Q with the *stop with threshold* V_t clause and its query tree with a single STOP operator at the root and having $\beta = V_t$. Then, accompanied with rule 4, the threshold V_t propagates to all the SVA operators in the query, and Q stays well-defined.

Thus, for an extended SQL query with a "*stop with threshold* V_t" clause, all the SVA operators in the corresponding logical query tree inherit the threshold V_t stopping condition, and the query stays well-defined.

4.3.2 Stop-After-k-Most-Important Clause

We first discuss the construction of the initial logical query tree. First, a query tree is constructed with RA and SVA operators in which each SVA operator contains a f_{out} function as discussed in Section 4.1, but with no stopping condition, i.e., each output threshold β is set to zero. Second, a STOP operator with the top-k threshold (i.e., the query stopping condition) is added as the root. In this section, our goal is to propagate the top-k condition of the STOP operator to lower-level SVA operators as β values whenever possible.

The *stop after k most important* clause specifies the size of the *final* query output (i.e., the top-k query), and can not easily propagate to intermediate SVA operators of a logical query tree during query processing. This is because such a propagation can prune away some of the intermediate results too early, that may otherwise be included in the final top-k results [Carey and Kossmann 1997, Carey and Kossmann 1998]. On the other hand, applying the top-k stopping condition only at the uppermost SVA operator would eliminate the opportunity of pruning away intermediate tuples which can never appear in the final output. Here, we revise the conservative strategy proposed by [Carey and Kossmann 1997], and propagate the top-k stopping condition only to those SVA operators that do not over-prune the intermediate results.

Definition *(Nonreductive predicate)* [Carey and Kossmann 1997]. Consider a predicate p of form x=y where x is an expression computable from an input relation R, and y is an expression involving one or more new relations to be added into the logical query tree. Predicate p is called a *nonreductive predicate with respect to* R if it can be inferred that x cannot be null and, for each x, there exists at least one y satisfying p.

Intuitively, given a relation R as an input to an operator, a non-reductive predicate with respect to R is a predicate that, when used in the operator, returns all the tuples of R in the output of the operator.

Definition *(Score-conservative top-k propagation policy).* The top-k condition is propagated to an SVA operator *V* as a stopping condition only when all operators *P* that directly or indirectly consume the output *O(V)* tuples of *V* (i) have non-reductive predicates with respect to *O(V),* and (ii) propagate tuple importance scores of *O(V),* but do not further modify them (i.e., each *P* is either an RA operator, or an SVA operator with $f_{out} = f_{in}$) where f_{in} denotes the scores of *O(V)*).

Condition (i) guarantees that once a tuple is included in the output of an SVA operator *V*, it will not be dropped by any other upper-level operators in the logical query tree. Note that condition (i) alone is not adequate for our query evaluation framework due to the score propagation and modification mechanism: assume that an SVA operator which is an ascendant of *V* revises its input tuple scores by some function *f*, and a tuple t is already pruned away by *V*. In this case, it is still possible that t revised by f could have had a higher revised score than the top-k tuples reported in the output *O(V)* of *V*, causing a false-drop of tuple t. Thus, condition (ii) is also needed in our policy.

Example 4.1. In Figure 1, the top-k stopping condition is propagated to the SVA selection operator (as it has the β value of 20), due to the score-conservative top-k propagation policy. We assume that every topic has at least one source, and, thus, the join operator above the selection is non-reductive. Moreover, the join is an RA join, which does not revise the scores of tuples returned by the selection, but only propagates them. On the other hand, in Figure 2, the top-k condition is only propagated to the SVA join operator, but not the SVA selection, which has the β value of 0.0. In this case, propagating top-k to SVA selection violates the score-conservative policy since SVA join is both reductive and score-revising. Finally, note that, in Figure 4, the top-k condition (i.e., $\beta=5$) is propagated to the topic closure operator, according to the score-conservative top-k propagation policy.

Note that the score-conservative top-k propagation policy does not guarantee the uniqueness of the top-k output, as there may be more than one tuple with the same score that are candidates to occur in the top-k output result. That is, there may be n more tuples in the database having the same score with the k^{th} tuple in the output. In this case, for the sake of providing well-defined query results, we include all of these tuples in the final query output and return (k+n) tuples.

A final subtle issue for propagating top-k stopping condition to SVA operators is the need to re-apply the *top-k output threshold* β after an SVA operator *V* in the query tree: Assume that the top-k stopping condition of a query Q is propagated to an SVA-operator *V* for which the score conservative top-k propagation policy holds. In this case, the operator *V* will produce at most k tuples and stop, during the query evaluation. But, although the reduction in the intermediate output cardinality is disallowed by our policy, the increase is left unspecified, i.e., we have not yet specified the semantics when these k tuples produced by *V*, say, are joined with more than one tuple in a join later in the query tree. To handle this case, we assume that a STOP operator [Carey and Kossmann 1997], which first sorts its input (if necessary) and then returns the top-k (or, $k+n$ as discussed

above) tuples, still remains as the outermost query operator regardless of the top-k propagation to SVA operators [Carey and Kossmann 1997]. This guarantees that only the top-k tuples are retained for the final output, but still allows potential reductions in the intermediate output sizes and query evaluation time.

Example 4.2. In Figure 1, the uppermost RA join operator can increase the number of tuples, if each of the k tuples generated by the SVA selection joins with more than one *Sources* tuples. In this case, the STOP operator at the top of the tree guarantees that only the k (or, k+n) (and no more) tuples are returned as the query output.

We use the following query execution semantics for an extended SQL query with (i) a *stop after k most important* clause, and (ii) no nested subqueries having the new SQL clauses. The query processor first creates all possible query trees (through applicable algebraic transformations) in which no SVA operator contains the top-k stopping condition. In each query tree, a STOP operator is placed as the root due to the reasons discussed above. The query processor then propagates the top-k condition to the lowest possible SVA operator(s) that satisfies the score-conservative top-k propagation policy, in each query tree. As a result, in each query tree, only such SVA operators will be aware of the top-k condition as an operator-wide stopping condition. The query processor then chooses the query tree with the lowest cost to construct the query plan to execute.

In the case of SQL queries having nested subqueries with their own *stop after k most important* clauses, the above construction is revised as follows. Consider each subquery independently and materialize it (for subqueries with correlated variables, instantiate the correlated variables when their instantiations satisfy the outer query block). Thus, each subquery can be considered as an independent query with its own top-k condition propagated down the tree properly. Thus, we have

Lemma 4. In any SQL query Q, the clause *stop after k most important* accompanied with score-conservative top-k propagation policy propagates to SVA operators of Q during query processing, and Q stays well-defined.

From lemmas 1-4, we have

Theorem 1. SQL queries as defined in Section 2.2 and satisfying rules 1-4 are well-defined.

5. SVA JOIN EVALUATION ALGORITHMS

5.1 Text Similarity Metrics

For those functions that require the similarity comparison ≅, we assume that a vector space based similarity model is employed [Salton 1989]. The vector space model first creates a vocabulary (W) of all words (i.e., terms) included in the document collections, and then represents each document with a vector v of |W| terms. The vector entries are real numbers representing term weights. Let v^t denote the vector v element for term t. We use the weighting scheme TF-IDF, which assigns a zero weight for those terms that do not appear in the document, and computes the weights of the other terms using the formula $v^t = (\log (TF_{v,t}) + 1) * \log(IDF_t)$, where $TF_{v,t}$ (term frequency) is the number of occurrences of term t in the document represented by v, and IDF_t is the inverse document frequency that is defined as the ratio of the number of all documents to the number of documents including t. We focus on attributes with short phrases such as topic names. The TF-IDF values are normalized and the similarity of two documents represented with vectors v and u is the cosine of the angle between them, which is defined as Cosine (u, v) $= \sum_{t \text{ in } W} v^t * u^t$.

We assume that term vectors that correspond to string-based attributes of tuples, as well as the vocabulary, are computed a priori. In this section, we assume that vocabulary is small enough to fit in the main memory, whereas all other input and output relations may be arbitrarily large.

Since pipelining is preferable for threshold-based query processing algorithms [Ramakrishnan and Gehrke 2000], and the nested-loop join algorithm does not disrupt pipelining [Graefe 1993], next, we discuss block-nested loops-based SVA join algorithms. Moreover, the nested-loop join is appropriate with arbitrary join conditions. A set of nested-loops based algorithms for processing joins between textual attributes have also been presented in [Meng et al. 1998]. We discuss this in Section 9.

In the algorithms below, we assume input relations are sorted in decreasing order of tuple importance scores, and using sort-merge algorithm might seem like a more reasonable choice than block nested loops join. However, note that our SVA join condition does not only involve equality; rather, in addition to *score-revising* threshold and UDF predicates, it also involves the computation of an f_{out} function and an *inequality comparison* with the threshold value V_t. In this case, each tuple from one relation will be compared with several tuples from the other relation, and sort-merge algorithm will almost degenerate to nested loops. That is, it is very unlikely that there will be a single scan in each relation (unless threshold value is extremely high or tables are very small, in

which case the choice of the join algorithm becomes immaterial) as it is in general sort-merge cases. Thus, the "merge" pointer in the second relation may need to rewind to earlier tuples -perhaps even requiring older blocks to be re-read in some cases-per *tuple* in the first relation. Of course, the simple early-termination heuristics discussed below for the nested loops join are equally applicable to sort-merge; but again, performance will not be drastically different from the nested loops approach.

5.2 Nested-Loops-Based Sideway-Value-Threshold Join Algorithms

We now discuss SVA join algorithms that return joined tuples with derived values above a specified sideway value threshold. We assume that the input relations are sorted in decreasing order of tuple importance scores. We sketch two algorithms for join conditions specifying (i) an arbitrary (user-defined) predicate θ over the join attributes, or (ii) an approximate match in terms of the textual similarity of the join attributes.

Definition. *Monotone f_{out}.* Let sv_t denote the importance score of tuple t. Given relations R and S with tuples r and s respectively, let $f_{out}(r, s)$ denote the importance score of the joined output tuple r.s. Then, $\forall r_1, r_2 \in R$ and $\forall s_1, s_2 \in S$, if $f_{out}(r_1, s_1) \leq f_{out}(r_2, s_2)$ whenever $sv_{r1} \leq sv_{r2}$ and $sv_{s1} \leq sv_{s2}$, the function f_{out} is said to be *monotone* with respect to input importance scores of R and S.

Functions product, numeric average and geometric average are monotone with respect to their input importance scores.

Algorithm NLoop$_{SVT}$
Input: Sorted Relations R and S wrpt sideway values; $f_{out}()$ function; join condition r.A θ s.B; sideway value threshold V_t
Output: {r.s | r∈R **and** s∈S **and** $f_{out}(r, s) \geq V_t$ **and** r.A θ s.B}
{i := 1;
while ($f_{out}(r_i, s_1) \geq V_t$ **and** i ≤ |R|)
{ j := 1;
while ($f_{out}(r_i, s_j) \geq V_t$ **and** j ≤ |S|)
{ **if** r_i.A θ s_j.B **then** append $r_i.s_j$ to the output;
j++ } i++ } }

Fig. 6. NLoop$_{SVT}$ algorithm

Given a query involving a join with a monotone f_{out} function, we improve the nested-loop join algorithm by enforcing new stopping conditions while processing the inner and outer loops, as shown in the NLoop$_{SVT}$ algorithm in Figure 6. In the NLoop$_{SVT}$ algorithm, the inner loop exits whenever the $f_{out}()$ value of the output tuple r.s is below the threshold

V_t, where r is in R and s is in S. Similarly, the outer loop exits at the i^{th} iteration whenever the $f_{out}()$ value of the output tuple $r_i.s_1$ is below the threshold V_t, where r_i is in R and s_1 is the first tuple in S.

In an ordinary block-nested loops (BNL) join [Ramakrishnan and Gehrke 2000], assuming that the size of R is M pages with p tuples per page, the size of S is N pages with q tuples per page, and the memory has B+2 buffer pages, we can read B pages of the outer relation R, and scan the inner relation S by using one of the remaining two buffer pages, leaving the last page to collect the output tuples. In this case, the disk access cost of the BNL algorithm is M + (M*N/B) [Ramakrishnan and Gehrke 2000]. In the worst case, the disk access cost of the $NLoop_{SVT}$ algorithm is the same as the disk access cost of the BNL algorithm. However, in the expected case, the disk access cost of the $NLoop_{SVT}$ algorithm will be reduced depending on how large V_t is. Assume that we revise the allocation of buffer pages as B/2 pages each to the relations R and S; the importance scores in R and S are uniformly distributed; and $f_{out}()$ is the product function, which is monotone. Thus, the tuples in the first B/2 blocks of R have importance scores in the range of [(1 ─ B/(2M)), 1]. Similarly, the tuples in the first B/2 blocks of S have importance scores in the range of [(1 ─ B/(2N)),1]. During the first outer loop iteration, the inner loop will terminate in the j^{th} iteration when the lowest expected importance score of a join tuple in the buffer is equal to (or ε less than) the sideway value threshold V_t. That is, (1 ─ B/(2M)) * (1 ─ j*B/(2N)) = V_t. Rearranging the above equality, we have $j = \frac{N}{B/2} * (1 - V_t) - (\frac{2N - B}{2M})$. Assuming N>>B and M ≈ N, the above equality reduces to $j=(N/(B/2))*(1-V_t)$. That is, in the expected case, for V_t=0.9, the inner loop terminates with 10% of the disk block accesses from S. Since R importance scores are sorted and decreasing in value, for any outerloop tuple of R, S will always be accessed at most for the first $b_S=(N/(B/2))*(1-V_t)$ blocks. And, since the above computations are symmetric for R and S, in the expected case, $NLoops_{SVT}$ algorithm will terminate with $b_R=(M/(B/2))*(1-V_t)$ disk block accesses from R as well. Thus, the expected number E of disk accesses is E = (B/2)* b_S + (B/2)(b_S ─ (B/2)) + (B/2)(b_S ─ 2(B/2))+ … + (B/2)(b_S ─ (b_R ─ 1)* (B/2)). Assuming $b_S = b_R = b$, we have E = (B/2)*b^2 ─ $(B/2)^2$*((b^2 ─b)/2). This, as shown in the experimental results section, is significantly less than the cost of the BNL algorithm.

When the join condition specifies an approximate matching (based on the similarity of the text-valued join attributes being above a given threshold t_{sim}), we cannot directly make use of the similarity function sim(r, s), as it is not monotone, and thus makes f_{out}

non-monotone. However, we can still use the $NLoops_{SVT}$ algorithm of Figure 6 with provisions: (a) the functions $f_{out}(r_i, s_1)$ and $f_{out}(r_i, s_j)$ in the outer and the inner while loop conditions are replaced by $sv_{ri} * sv_{s1}$ and $sv_{ri} * sv_{sj}$, respectively, where sv_{ri}, sv_{s1} and sv_{sj} are the importance scores of tuples r_i, s_1 and s_j. (b) In the inner while loop, we check if $f_{out}(r_i, s_j) = sv_{ri} * sv_{sj} * sim(r_i.A, s_j.B) \geq V_t$ and $sim(r_i.A, s_j.B) \geq t_{sim}$ where A in R and B in S are the join attributes. If so, the tuple $r_i.s_j$ is output.

Note that, so far, the join algorithm has not employed the similarity function in improving its running time. We now summarize an algorithm that uses the vector-space model and the similarity function in improving the efficiency of the join algorithm.

Lemma 5. Let $\mathbf{u_r} = \langle u_1\ u_2\ \ldots\ u_x \rangle$ be the term vector corresponding to the join attribute A of tuple r of R, where u_i represents the weight of the term i in A. Assume that the *filter vector* $\mathbf{f_S} = \langle w_1\ ..\ w_x \rangle$ is created such that each value w_i is the max weight of the corresponding term i among all vectors of S. Then, if $Cosine(\mathbf{u_r}, \mathbf{f_S}) < V_t$ then r can not be similar to any tuple s in S with similarity above V_t.

Algorithm $NLoop_{Sim\text{-}SVT}$
Input: Relations R and S; text-valued join attributes r.A and s.B; Buffers B_S and B_R;
sim function sim()=Cosine(); sim threshold t_{sim}
Output: $\{r.s \mid r \in R$ **and** $s \in S$ **and** $f_{out}(r, s) \geq V_t$ **and** $Cosine(\mathbf{u_r}, \mathbf{u_S}) > t_{sim}\}$
1. Sort R by $sv_r * Cosine(\mathbf{u_r}, \mathbf{f_S})$; Sort S by sv_s;
2. Read tuples from the top of R into a block B_R where, for each r_i in B_R, $sv_{ri} * sv_{s1} * Cosine(\mathbf{u_{ri}}, \mathbf{f_S}) \geq V_t$;
3. Repetitively, read tuples from the top of S into a block B_S, where, for each s_j in B_S, $sv_{r1} * sv_{sj} * Cosine(\mathbf{u_{r1}}, \mathbf{f_S}) \geq V_t$, and compare and join tuples in B_R and B_S:
for each $r \in B_R$ **do for each** $s \in B_S$ **do**
if $(sv_r * sv_s * Cosine(\mathbf{u_r}, \mathbf{u_s}) \geq V_t$ **and** $Cosine(\mathbf{u_r}, \mathbf{u_s}) \geq t_{sim})$ **then**
add r.s into the output;
4. Repeat 2-3 until $sv_{ri} * sv_{s1} * Cosine(\mathbf{u_{ri}}, \mathbf{f_S}) < V_t$

Fig. 7. $NLoop_{Sim\text{-}SVT}$ Algorithm

In this paper, the value $Cosine(\mathbf{u_r}, \mathbf{f_S})$ is called as the *maximal similarity* of a record r in R to any other record s in S. The maximum value of a term for a given relation is determined while creating the vectors for the tuples, and the filter vector for each relation may be formed as a one-time cost. In Figure 7, we summarize the $NLoop_{Sim\text{-}SVT}$ algorithm which makes use of the sorted order of relations R and S by $sv_r * Cosine(\mathbf{u_r}, \mathbf{f_S})$, and sv_s, respectively (also one-time costs). Note that, with both while loop conditions, *false drops* are possible; that is, a tuple r in R and a tuple s in S may satisfy the while loop

conditions, only to be eliminated from the output in the if statement within the inner while loop (the if condition tests the values of the actual $f_{out}()$ and sim() functions). On the other hand, while loop conditions do not allow *false dismissals*; that is, a join tuple that is in the output will be added to the output.

5.3 Nested-Loops-Based Ranking-Threshold (Top-K) Join Algorithms

It is easy to give an SVA join algorithm with top-k output importance scores. Assume that (i) input relations are sorted with respect to importance scores, and (ii) the $f_{out}()$ function is monotone. The algorithm $NLoops_{Top\text{-}k}$ begins in a nested loop like manner, and computes the first k (but not top k yet) joined output tuples, referred to as the "Top-k-Set". And, the importance score of the k^{th} joined tuple becomes the lower bound (minSV); i.e., no tuple with an importance score below this lower bound can be in the top-k output. The algorithm proceeds in a nested-loops manner, and updates the lower bound and the current Top-k-Set whenever it computes a join output with a new importance score larger than the minimum importance score of Top-k-Set.

Similar to the algorithm $NLoop_{Sim\text{-}SVT,}$ the algorithm $NLoop_{Top\text{-}k}$ can be revised for a ranking-threshold algorithm $NLoop_{Sim\text{-}Top\text{-}k}$ with approximate matching conditions; to save space, it is not presented here.

6. SVA TOPIC CLOSURE ALGORITHM

For the sake of simplicity in presentation, we now summarize TClosure algorithms that compute the topic closure X^+ for the simpler case where the regular expression R is a single metalink type M (however, experimental evaluations of Section 8 use arbitrary regular expressions). Each metalink V $\rightarrow^M$ Tid is represented by a tuple in table M, where V is a set of topic identifiers, Tid is a topic identifier, M is a metalink type.

Definition *(LHS-decomposability). A* metalink of type M is *left-hand-side(LHS)-decomposable* if the axioms of M allow replacing any metalink instance of type M having multiple topics on its left-hand-side (LHS) with multiple metalink instances, each having a single topic on its LHS.

As an example, if LHS-decomposibility holds for metalink type M then a metalink instance A,B→C,D of type M can be replaced without loss by A→C,D of type M and B→ C,D of type M. We assume in this section that if a metalink type is LHS-decomposable then each metalink with V in the left-hand-side is decomposed into multiple metalinks with a single topic in the left-hand-side.

Next, we discuss separately the algorithms for sideway value threshold-based and ranking-based topic closures.

6.1 Sideway-Value-Threshold-based Topic Closure

We create an index MIndex for all metalink instances of all metalink types; and the TClosure algorithm uses only MIndex to find the closure of a given set of topics. We assume that all metalinks are right-hand-side decomposed.

MIndex has five attributes: MType, Tid1, Imp(Tid1), ParentList, and ChildList, where MType specifies a metalink type, Tid1 contains the topic identifier of the topic from which the metalink originates, and Imp(Tid1) is the importance score of the topic Tid1. ParentList is a list of topic identifiers of topics from which emanate metalinks of type MType to the topic Tid1. ChildList is a list of triplets <Tid2, Imp(Tid2),Imp(Mid)> where the triplet <Tid2, Imp(Tid2), Imp(Mid)> represents a metalink that has Mid as its metalink identifier, the topic with Tid1 as its antecedent node, the topic with Tid2 as its consequent node, the type MType as its metalink type, Imp(Tid2) as the importance score of the topic with Tid2, and Imp(Mid) as the importance score of the metalink.

The key for MIndex is the two attributes MType and Tid1. Therefore, the MIndex entries with the key (MType, Tid1) contains all metalinks of type MType that have the topic with Tid1 as its antecedent. The entries of MIndex are sorted by (MType, Tid1) so that the metalink of the same type are together within the index.

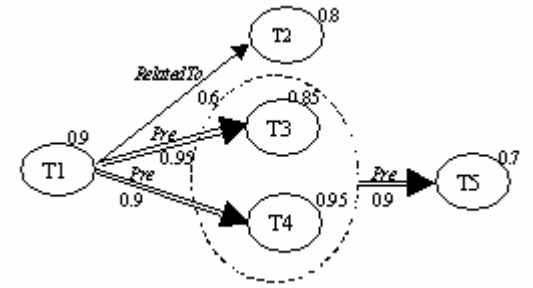


Fig. 8. Graphical representation for non-LHS-decomposable metalink instances in Example 6.2.

Example 6.1. Figure 8 illustrates graphically a Metalinks relation with *RelatedTo* and *Pre(requisite)* metalink instances between five topics. *T1* $\rightarrow^{Pre}$ *T2* denotes that (learning) *T2* is a prerequisite to (learning) *T1* [Özsoyoğlu et al. 2004]. Assume that the only axiom for both *RelatedTo* and *Pre* metalink types is transitivity (thus, none of the metalinks in Figure 8 are redundant). Table II shows the tuples of the index MIndex for the Metalinks relation of Figure 8.

While creating MIndex, for those metalinks that are not LHS-decomposable, we create a second index H(yper)Index, to maintain all nodes that are not decomposable; and the topic closure algorithm uses HIndex to compute the closure of a given set of topics. The HIndex table has two attributes Tid and NodeList, where Tid is the topic identifier of a topic t within the nondecomposable node, and NodeList is a list of pairs <TidSet, Hid> where the pair <TidSet, Hid> represents the Tid's of the nondecomposable (hyper) node (which contains Tid), and Hid is a new topic identifier for the node. Table III illustrates HIndex for a nondecomposable node {T3, T4}. We generate a new entry in MIndex for each nondecomposable node with the identifier Hid as its Tid1 value, and with a set of topic ids that it contains as its "ParentList". For example, in Table II, the entry with Tid1 value of H1 and the ParentList value of {T3, T4} represents the nondecomposable (hyper) node H1 in the HIndex table.

In this section, to simplify the presentation, we assume that the metalink type M has only the transitivity axiom, and may or may not be LHS-decomposable. And, the product function is used to compute *FPath*=$\text{Imp}_d(t, P, R)$.

The topic closure of a set X of topics with respect to R as a single metalink type M and a sideway value threshold V_t is computed as follows. For each topic t in the topic closure X^+, we create a triplet of the form <t.Tid, $\text{Imp}_d(t, R = M)$, {p | p is a path of type M from a topic or topics in X to t}>. We use a set-valued variable DiscoveredTids to contain the topics already in the closure, but not yet checked for paths emanating from them. We construct X^+ by repetitively computing $X^{(0)}$, $X^{(1)}$, …, $X^{(i)}$ where $1 \leq i$. In the first iteration, for each topic t in X, a triplet <t.Tid, $\text{Imp}_d(t, R)$, {t}> is created in $X^{(1)}$ and the topic identifier Tid of t is added into DiscoveredTids.

In each iteration of the closure algorithm, a topic t1 is removed from DiscoveredTids, and all metalinks that emanate from t1 are visited. A triplet <t2,Imp_d(t2,R), t2.paths> for the consequent topic t2 of each visited metalink is added into the currently computed topic closure $X^{(i)}$, if the triplet does not exist in $X^{(i)}$. If the triplet exists then new paths are added into t2.paths, and Imp_d(t,R) is recomputed. The topic t2 is then added into DiscoveredTids. If the metalink type M, for which the topic closure is to be computed, is not LHS-decomposable then the algorithm checks if topic t1 is in the LHS of a metalink of type M. The algorithm uses HIndex to find all HIndex entries that contain topic t1 as a member of their LHS set of topics. For each such HIndex entry, if all of its LHS topics are in the currently computed topic closure $X^{(i)}$ then new (hyper)paths are created and new derived importance scores are computed for every metalink that emanates from the

HIndex entry. When DiscoveredTids is empty, the algorithm stops, and $X^{+}=X^{(i)}$. We refer to this algorithm as the ThresholdTClosure algorithm.

Table II. MIndex Table

MType	Tid1	Imp(Tid1)	ParentList	ChildList <Tid2, Imp(Tid2), Imp(Mid)> triplets
Pre	T1	0.9	{}	<T3,0.85,0.95>, <T4,0.95,0.9>
Pre	H1	Avg(0.9, 0.95)= 0.925	{T3, T4}	<T5,0.7,0.9>
RelatedTo	T1	0.9	{}	<T2,0.8,0.6>

Table III. HIndex Table for the non-LHS-decomposable metalink in Figure 8.

Tid	NodeList <TidList, Hid>
T3	<{T3,T4}, H1>
T4	<{T3,T4}, H1>

Example 6.2 *(Topic Closure Computation for a LHS-Decomposable Metalink Type).* We use the MIndex instance in Table II. Assume that we want to compute the topic closure for the set X={T1} with SV threshold V_t=0.4 using the metalink type M=*RelatedTo*. Also, assume that the average function is used for *FPathMerge.* Since X={T1}, $X^{(1)}$={<T1, 0.9, {T1}>} and DiscoveredTids={T1}. Note that the *RelatedTo* metalink type is LHS decomposable. In the first iteration, topic T1 is removed from DiscoveredTids. Topic T2 has a path T1.T2, obtained using the metalink T1(0.9)$\rightarrow^{RT(0.6)}$ T2 (0.8), and its derived importance score is Imp_d(T2,*RelatedTo*)= 0.9 * 0.6 * 0.8 = 0.43. Therefore, the triplet <T2, 0.43, {T1.T2}> is added into $X^{(1)}$. After the first iteration, $X^{(2)}$ ={<T1, 0.9,{T1}>,<T2, 0.43, {T1.T2}>} and DiscoveredTids = {T2}. Next, the algorithm terminates since there is no *RelatedTo* metalink emanating from topic T2, therefore, DiscoveredTids becomes empty, and the output of the closure operator is {<T1,0.9>, <T2, 0.43>}. Clearly, if we have more axioms (in addition to transitivity) then the output of the closure will have additional tuples. For example, when the axiom "if A $\rightarrow^{Pre}$ B then A $\rightarrow^{RelatedTo}$ B" holds, then all topics will be included into the closure.

Example 6.3 *(Topic Closure Computation for a Non-Left-Hand-Side Decomposable Metalink).* In Figure 8, {(T1$\rightarrow^{Pre}$ T3),(T1$\rightarrow^{Pre}$ T4)}$\rightarrow^{Pre}$ T5 forms a hyperpath of type *Pre*

from topic T1 to topic T5. Assume that we want to compute the topic closure for a set of topics X={T1} with a sideway value threshold V_t=0.7 using the metalink type M=*Pre*, and (a) *FPathMerge* is max, and (b) the geometric average is used to compute the derived importance score of a hypernode. Using the MIndex instance in Table II, we compute X^+ as {<T1, 0.9>, <T3, 0.727>, <T4, 0.769>}. T_5 is not included into the output because its derived importance score is below the threshold.

During closure computations, a metalink instance (i.e., a tuple in MIndex) can be visited more than once if there are multiple paths to the left-hand-side topic node of the metalink. To avoid visiting the same metalink more than once, we use the parent-child relationship between topics. A topic node with Tid1 is in the parent list of another topic node with Tid2 in the metalink M if there is a metalink Tid1 $\rightarrow^M$ Tid2. In the ThresholdTClosure algorithm, we use a set-valued variable PostponedTids to add the restriction that a topic node can not be "processed" until all nodes in its parent list is processed.

The algorithm ThresholdTClosure needs to maintain *all paths* from the set of input topics X to a given topic instance *a* in order to compute the derived importance score of *a* using a generic function. However, some functions, such as max, need to maintain only a single path to compute the derived importance score of a given topic. That is, using the max function, the derived importance score of a topic can be computed by finding the path with the maximum derived importance score. One can give an algorithm ThresholdTClosureMax that does not maintain the path information for any topic, and computes the derived importance score of a topic *x* by comparing its "current" derived importance score with respect to that of the "currently visited" path P. Clearly, ThresholdTClosureMax is much more efficient than ThresholdTClosure.

6.2 Ranking-based Topic Closure

We briefly summarize the RankingTClosureMax algorithm that computes the top k-ranked topic closure using product as *FPath* and max as *FPathMerge.* The algorithm finds the topics with the k highest derived importance scores in the topic closure of a set X of input topics. It first computes the initial candidate top k ranked topics from the input topics X. Then, in each iteration i, it extracts the i^{th} top-ranked topic from the current k-i+1 candidate top-ranked topics and updates the current candidate topics by processing all emanating metalinks from the i^{th} topic. Therefore, the algorithm needs k iterations in order to compute the top-k-ranked topic closure of a set X of input topics.

The RankingTClosureMax algorithm maintains two lists X+ and CandidateTopics of size at most k.The algorithm requires at most Ω(k * |X|) time to compute the initial CandidateTopics list, where |X| is the size of the input topic set X. Then, the algorithm iterates k times in order to compute the top-k-ranked topic closure, and, in each iteration, it finds the next top k topics and updates the CandidateTopics list by applying the metalinks that emanate from a given top-k topic.

7. EXPERIMENTAL RESULTS: EVALUATING THE SVA JOIN OPERATOR

To evaluate the four SVA-Join algorithms discussed in Sections 5.2 and 5.3, we first extracted all the titles of journal and conference papers from the DBLP [Ley] data set into two different files, R and S; R with more than 91,000 journal paper titles (12 Mbytes), and S with more than 132,000 conference paper titles (18 Mbytes). Next, we eliminated the stopwords (i.e., removed words like "the", "a", "of", etc.) from the text in each title, stemmed them and created the word list (vocabulary) for the whole collection (including about 43000 words). The word list was kept in the main memory. Then, we created the vectors for each record of R and S, which were added to paper title records in files R and S.

Topic importance scores for papers are computed based on the rankings of the journals or conferences they appear. For this purpose, we used the ranking list provided at CiteSeer [Citeseer 2003]. We split this list into ten bins, giving the importance score 1 to those venues that are ranked at top 10%, score 0.9 to those at 20% slice, and so on. It turns out that, some of the publication venues encountered in DBLP data set are not found in CiteSeer's list. These are assigned the importance score 0.6, since the average impact estimation score of DBLP venues that appear in CiteSeer list falls into the bin with the score 0.6. Note that, we may perhaps overestimate the importance scores of these venues (and papers published in them), as these unlisted venues are potentially less-known and less-important ones. As a supporting evidence for this claim, we found out that through 210,000 journal/conference papers in our test set, less than 5% are published in those venues. As another observation, a considerable number of the papers listed in DBLP are published in the venues that are ranked in top 10% of CiteSeer, resulting in the score attachment of 1. Thus, our importance score assignment is not uniform, but depends on the properties of real data published at the DBLP site. As a final remark, it could be argued whether all papers published at the same venue have the same importance scores; however, our intention in this section is not to develop a method for measuring paper

importance, but rather provide experimental evaluation on a data set that approximately fits to real life application constraints.

Below, we provide the experimental evaluations of the SVA-join algorithms in terms of the number of comparisons for a given query. The number of comparisons gives an idea about the number of tuples read from each relation. Results involving disk-accesses and execution times are clearly symmetric with the number of comparisons made, and not reported here.

All experiments have been performed on a dual-processor Pentium III PC with 1-GB main memory running WindowsNT 4.0. The input and output buffer sizes hold 10,000 tuples. The algorithms are implemented in C programming language.

A. Evaluating NLoop$_{SVT}$ and NLoop$_{Top\text{-}k}$: These algorithms join tuples of R and S on the basis of an arbitrary join condition (predicate) θ, and return the joined tuples that are over a given threshold V_t or ranked in the top-k results. For the following experiments, $f_{out}()$ is specified as the product of the importance scores of joined tuples. We assume that join condition θ is a user-defined function that requires further (and presumably expensive) processing of the tuples, as illustrated in Section 3.2. For instance, such a function may state that a conference paper tuple is to be joined with a journal paper if they have at least one author in common and the conference paper is published at most 2 years before the journal paper. Clearly, this predicate can be specified as a user defined function (UDF) (syntax omitted to save space).

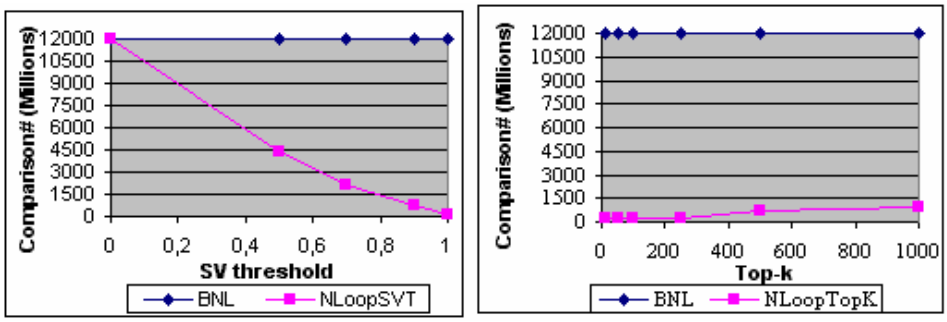


Fig.s 9 and 10. Performance values of BNL vs. NLoop$_{SVT}$ and NLoop$_{Top\text{-}k}$, respectively.

To evaluate a join with an arbitrary condition θ, an ordinary block-nested loops (BNL) algorithm compares each and every tuple, computes the importance scores for those tuples satisfying the user defined function, and finally retrieves the ones that are above the specified threshold or in the specified top-k set. On the other hand, NLoop$_{SVT}$ and NLoop$_{Top\text{-}k}$ evaluate the arbitrary predicate only for those tuples with a derived importance score that satisfies the query constraints. In Figures 9 and 10, we demonstrate

the performance of these algorithms, compared against the "blind" BNL approach. Note that, the savings of the proposed algorithms increase, as the SV threshold value increases or, inversely, as the *k* value decreases. For instance, when the SV threshold value is 0.9, the number of tuple comparisons performed by $NLoop_{SVT}$ is approximately 600 millions, 1/20 of the BNL approach which makes 12 billion comparisons. For this case, $NLoop_{SVT}$ reads only 27% of R and 60% of S from the disk, whereas BNL reads all tuples of the relations. The saving in terms of execution time also matches well with the 1/20 ratio of tuple comparisons, i.e., three minutes vs. an hour. Note that, the percentages of tuple readings from each relation show that tuples with high importance scores dominate DBLP data set, as we have mentioned before, and savings would increase for those cases where only a few tuples can exceed the SV threshold.

B. Evaluating $NLoop_{Sim\text{-}SVT}$ and $NLoop_{Sim\text{-}Top\text{-}k}$: These algorithms perform similarity-based (approximate) joins. In the following experiments, the tuples of R and S are joined if their titles are similar with a similarity value greater than a specified threshold (90%). In this case, $f_{out}()$ is specified as the product of the importance scores of joined tuples and this derived value is further multiplied with the similarity value of tuples, obtained using the cosine similarity measure.

Figures 11 and 12 illustrate the performance superiority of $NLoop_{Sim\text{-}SVT}$ and $NLoop_{Sim\text{-}Top\text{-}k}$ with respect to the BNL. Note that, as discussed before, a blind BNL would compare all pairs, leading to almost 12 billion tuple comparisons. For the special case of similarity based predicates, we employ an inverted index while computing the similarity of the tuples that are read and buffered (in a similar fashion to probing phase of hash-join [Ramakrishnan and Gehrke 2000]). More specifically, we create an in-memory inverted index [Salton 1989] for the tuples of outer relation on the fly, and compare tuples of inner relation that only have common words in their titles. Thus, for all of the algorithms, the results reported in the figures indicate the number of accesses to the in-memory inverted index during the comparison, i.e., BNL accesses to the index 900 million times, also implying the same number of similarity comparison computations, although it reads the blocks of the both relations entirely several times. We observe that SVA algorithms again considerably reduce the cost of join operation. For instance, to retrieve tuple pairs with titles that are 90% similar and have a derived importance score greater than 0.9, BNL achieves a total of 900 million computations, whereas $NLoop_{Sim\text{-}SVT}$ makes only 50 million computations. This improvement is due to the fact that similarity based algorithms are tailored to exploit the vector-space model to its greatest extent.

To summarize, for arbitrary predicates and monotone SV functions, algorithms $NLoop_{SVT}$ and $NLoop_{Top\text{-}k}$ improve the performance of BNL considerably. For the special case of text similarity-based joins, the algorithms are further optimized (e.g., by using the maximal similarity filter heuristic), and more gains are obtained.

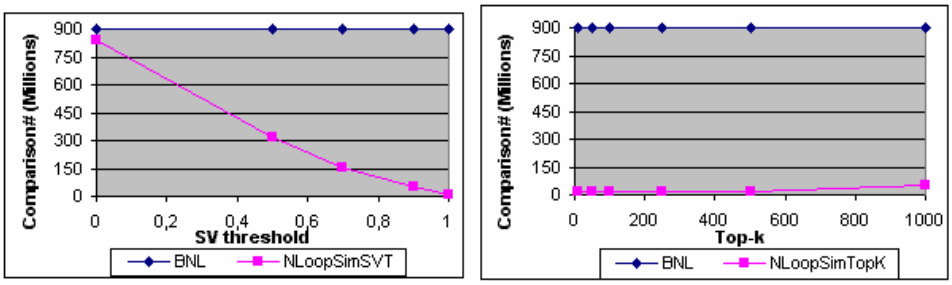


Fig.s 11 and 12. Performance values of BNL vs. $NLoop_{Sim\text{-}SVT}$ and $NLoop_{Sim\text{-}Top\text{-}k}$ algorithms, respectively.

8. EXPERIMENTAL RESULTS: EVALUATING THE SVA TOPIC CLOSURE OPERATOR

We evaluate the performance of the TClosure algorithms using all the articles in the ACM SIGMOD Anthology [ACM SIGMOD Anthology] between 1969 and 2001. All of the articles, available as PDF files, are parsed, indices are constructed and used to extract metalinks between papers, such as the *RelatedTo*, *Prerequisite*, and *WrittenBy* metalinks. In [Al-Hamdani 2003], we provide a more detailed description of the metadata extraction process from the ACM Anthology.

Using topics and metalinks, disk-based index files are constructed. And, in order to efficiently retrieve tuples from two index files (MIndex and HIndex), a memory-based sparse index table is employed. In implementations of topic closure algorithms, we use *max* as the *FPathMerge* function. We evaluate the performances of the Threshold-based and Top-k-based TClosure algorithms in terms of the number of disk accesses and the size of the output result X^+.

We employ a finite state automaton (FSA) that corresponds to a given regular expression R. As an example, the FSA in Figure 13 corresponds to the regular expression $R=PRE^*.RT.RT^*$ (where *PRE* and *RT* are *Prerequisite* and *RelatedTo* metalinks, respectively).

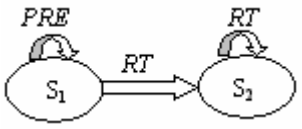


Fig. 13. FSA for regular expression $R=PRE^*.RT.RT^*$

8.1 Data Generation

All ACM Anthology articles (14,891 papers) are converted from PDF files into plain text files. Then, DBLP bibliography information [Ley] is used to extract the titles, authors, publication venue (conference or journal), and the publication year for each paper in the ACM Anthology. We also extract the abstract, index terms, body, and references for each paper using its text file. The TF-IDF vectors are used to represent each component of each paper (i.e., the title, abstract, index terms, and body) and to create the corresponding index files. We also create index files for authors, references, and the publication venue of the papers.

8.1.1 Topic Extraction

We extract two types of topics: papers and authors, and compute their importance scores.

A. Paper Importances: the importance score of a given paper can be computed in multiple ways, such as:

(a) Publications that get referenced by highly "important" papers are more important (residual effect). *PageRank* [Brin and Page 1998] algorithm can be used to recursively compute the importance scores of papers using the importance scores of papers that cite them.

(b) The notion of hubs and authorities (i.e., the HITS algorithm of Kleinberg [1998; 1999]) among papers can be used to compute importances of papers.

(c) Citation count: how many times a paper is cited by other important papers.

(d) Publication venue: e.g., SIGMOD versus CIKM. The importance score of a conference or journal influences the importance of a paper.

(e) Temporal distributions of citations with respect to duration.

(f) Citation venue: e.g., survey journal versus research paper.

(g) Citations by "important" authors' work are more significant.

(h) Importance of an author influences importances of his/her papers.

In this paper, we compute importance scores of papers using (a) citation counts, (b) publication venue, and (c) importance scores of the most important papers that refer to the given paper.

(a) Citation Count: For a given paper P, let *CitationCount*(P) be the number of times paper P is cited by other papers. Using the number of citations, paper P is as important as those papers that have the same number of citations and more important than the papers that have fewer citations. Now, let *PapersWithCitations*(i) be the

number of papers that are cited i times. We compute the importance of a given paper P with respect to its citation count as follows:

$$ImpPaper_{CitationCount}(P) = \sqrt{\frac{\sum_{i=0}^{CitationCount(P)} PapersWithCitations(i)}{No.\ of\ papers}}$$

(b) Publication Venue: the importance score of a given conference or journal is computed using the total number of papers it has and the total number of citations to its papers. We compute the unnormalized conference importance scores using the following formula:

$ImpConf_U$(V)= (# citations of *Conference V*)/ $\sqrt{\#\text{ papers in } Conference\ V}$

Let $ImpConf_{Max}$ be the unnormalized importance score of a conference with the highest unnormalized importance score. By applying the *ConfMinImp factor*, where $0 \leq ConfMinImp \leq$, we have the importance scores for a given conference or a journal as:

$ImpConf$(V)= $ConfMinImp + (1.0 - ConfMinImp) * \sqrt{ImpConf_U(V) / ConfImp_{Max}}$

We use *ConfMinImp*=0.4 in the experiments.

(c) Adding the citation effect of the most important citation: For a given paper P in conference V, let P_{maxcit} be any paper that cites paper P with the highest importance score. We compute the importance score of a paper P using

$ImpPaper$(P) = (1 - *MaxCitFactor*) * [(*ConfFactor* * $ImpConf$(V)) +

(1.0 - *ConfFactor*) * $ImpPaper_{CitationCount}$(P)] + *MaxCitFactor* * $Imp(P_{maxCit})$

where $0 \leq MaxCitFactor \leq 1.0$ and $0 \leq ConfFactor \leq 1.0$. In the experiments, we use *MaxCitFactor* = 0.2 and *ConfFactor* = 0.7.

B. Author Importances: the importance score for an author can be computed in multiple ways:

(a) The most important paper of the author.
(b) Weighted average of the most important k papers of the author.
(c) Weighted average of the most important m% papers of the author
(d) Weighted average of the most-important papers of the author in every y years

We compute the importance score of an author using 20% of his/her most important papers. For the ACM anthology, the importance scores of (a) 106 conferences, journals, and books, (b) 14,891 papers, and (c) 13,208 authors, are computed and stored in files.

The papers are stored in a file of 222KB size, and the authors are stored in a file of 198KB size.

8.1.2 Metalink Extraction

Three types of metalinks and their importance scores are extracted, namely, *RelatedTo*, *Prerequisite*, and *WrittenBy*.

A.RelatedTo Metalink Instance Extraction

A paper P_i is related to a paper P_j if the similarity $Sim(P_i,P_j)$ is above a given threshold value *Vt* (In the experiment, we use *Vt* value of 0.4). We compute the similarity between two papers using a weighted function of their title similarity Sim_{Title}, index terms similarity $Sim_{IndexTerms}$, abstract similarity $Sim_{Abstract}$, body similarity Sim_{Body}, author similarity Sim_{Author}, and the references similarity $Sim_{References}$.

We use the TF-IDF vectors with the *cosine* similarity measure [Salton 1989] to compute the similarities between two paper's titles, abstracts, index terms, and bodies. Each of these similarities is referred to as a "similarity factor". We first remove the stopping words from the terms of a similarity factor, and then use the Porter's algorithm [Porter 1980] to stem the terms.

We compute the author similarity between two papers using the "*Level-0-author-overlap*" relationship (i.e., common authors between two papers) and the "*Level-1-author-overlap*" relationship (i.e., two different authors, each of different papers P_i and P_j, are co-authors in a third paper P_k). We use the following formula to compute the author similarity between two papers:

$Sim_{Author}(P_i, P_j) = L0Weight * Sim_{Level\text{-}0\text{-}Author}(P_i, P_j) + (1 - L0Weight)\, Sim_{Level\text{-}1\text{-}Author}(P_i, P_j)$,

where $0 \leq L0Weight \leq 1$.

The reference similarity between two papers P_i and P_j is computed using the *bibliographic coupling* (the number of common citations between the two papers [Kessler 1963]) and *co-citation* (co-citation frequency with which two papers appear as citations in the same document [Small 1973]) between the two papers. We compute the reference similarity as follows:

$Sim_{References}(P_i, P_j) = BibWeight * Sim_{bib}(P_i, P_j) + (1 - BibWeight)\, Sim_{coc}(P_i, P_j)$,

where $0 \leq BibWeight \leq 1$. In the experiment, we use *L0Weight* and *BibWeight* values of *0.7 and* 0.6, respectively.

Finally, we use the following formula to compute the importance score of the *RelatedTo* metalink instance between two papers P_i and P_j.

$Imp(RelatedTo(P_i, P_j)) = Sim(P_i, P_j)$

$$= W_{Title} * Sim_{Title}(P_i, P_j) + W_{IndexTerms} * Sim_{IndexTerms}(P_i, P_j) + W_{Abstract} * Sim_{Abstract}(P_i, P_j) + W_{Body} * Sim_{Body}(P_i, P_j) + W_{Author} * Sim_{Author}(P_i, P_j) + W_{References} * Sim_{References}(P_i, P_j)$$

where $W_{Title} + W_{IndexTerms} + W_{Abstract} + W_{Body} + W_{Author} + W_{References} = 1.0$

There is also the issue of choosing the right values for weights $W_{IndexTerms}$, $W_{Abstract}$, W_{Body}, W_{Author}, and $W_{References}$. In [Li 2003], an experiment was performed to locate the similarity weights that produce the highest precision queries using 1,000 papers. The experiment shows that the similarity factor weights with the highest precision are W_{Title}=0.143225, $W_{IndexTerms}$=0.0607289, $W_{Abstract}$=0.183921, W_{Body}=0.151375, W_{Author}=0.202429, and $W_{References}$=0.2583211. Therefore, we use these weights in computing the importance scores for *RelatedTo* metalinks.

We normalize the similarity values for each similarity factor, say F (e.g., F=title), using the maximum similarity $Sim_{Fmax}(P_i)$ between a paper P_i and all other papers. *RelatedTo* metalink is reflexive; therefore, for any two papers P_i and P_j, $Imp(RelatedTo(P_i, P_j)) = Imp(RelatedTo(P_j, P_i))$. To maintain the reflexivity property, we normalize the similarity values for a given similarity factor Sim_F between papers P_i and P_j using the minimum of $Sim_{Fmax}(P_i)$ and $Sim_{Fmax}(P_j)$. Thus,

$$Sim_{F_{Normalized}}(P_i, P_j) = Sim_F(P_i, P_j) / min(Sim_{Fmax}(P_i), Sim_{Fmax}(P_j)).$$

B. Prerequisite Metalink Instance Extraction

We use the citation information to extract *Prerequisite* metalinks. A paper P_i is a prerequisite to a paper P_j, written as $Pre(P_i,P_j)$, if paper P_i appears in the references of paper P_j. We use the occurrences of the cited papers to compute the importance scores for their prerequisite metalinks. Let $O_{max}(P_j)$ be the number of occurrences of the most cited reference in the body of a given paper P_j, and $O(P_i,P_j)$ be the number of occurrences of a reference P_i in the body of paper P_j. Then, the importance score for the prerequisite metalink instance $Pre(P_i, P_j)$is computed using the formula

$$Imp(Pre(P_i, P_j)) = (O(P_i,P_j)+1)/ (O_{max}(P_j)+1) \quad (1)$$

We add one to the number of occurrences and to the maximum occurrences so that all the importance scores are greater than zero. Another alternative is to compute the importance scores using the following formula:

$$Imp(Pre(P_i, P_j)) = MinPreFactor + (1 - MinPreFactor) * O(P_i,P_j) / O_{max}(P_j) \quad (2)$$

where $0 \leq MinPreFactor \leq 1$.

In our implementation, we evaluate both formulas (1) and (2).

C. WrittenBy Metalink Instance Extraction

One can construct *WrittenBy* metalink importance scores using the importance scores of the authors of papers. However, in the experiments, we assume that *WrittenBy* metalink type does not have importance scores (Or, more correctly, for each paper P_i and author A_j, *Imp*(*WrittenBy*, P_i, A_j) is assumed to be 1.0).

Using the papers in the ACM Anthology, we have extracted 40,486 *RelatedTo* metalinks, 30,772 *Prerequisite* metalinks, and 34,244 *WrittenBy* metalinks. The total size of the metalink file is 1.8MB.

8.2 Metalink Index Generation

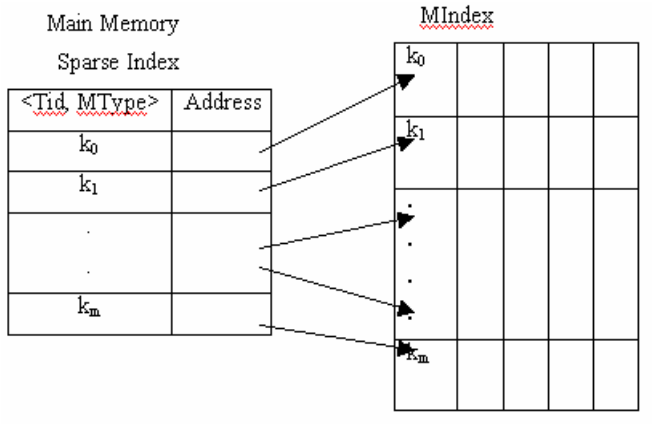


Fig. 14. Disk-based Index Table

We create the index file *MIndex* with the key <Tid, MType> for all metalink types, stored as a paged file on secondary storage. Each *MIndex* page contains data about metalinks of the same type MType (*MIndex* is ordered by topics identifiers Tids), and is of size at most *PageSize* (we use *PageSize* of 1KB). Index entries for the metalinks for a given key <Tid, MType> is maintained in the same page; if there is not enough space in the current page then they are stored in the next page. HIndex to index hypernodes is initialized similarly.

A main memory-based sparse index is created to access any entry <Tid, MType> in *MIndex* (see Figure 14). In the sparse index, we divide <Tid, MType> entries into blocks (we use 1,000 blocks). Each block corresponds to one or more pages in the *MIndex* file. The sparse index file contains the first <Tid, MType> in a given block and its physical address in *MIndex*. In order to retrieve all metalinks of type MType and emanate from Tid, we first use the sparse index to find the physical address of the first page with key <Tid, MType> in the *MIndex* file. If a given block in the sparse index corresponds to

more than one page in the *MIndex* file then we may need to access more than one page in order to retrieve the metalinks for the specified key.

In the implementation, a disk-based metalink index *MIndex* with a page size of 1KB is used to maintain all extracted metalinks. *MIndex* contains 2,768 pages and has the size of 2.785MB. We use a memory-based sparse index of size 1,000; therefore, the first 768 blocks in the sparse index correspond to 3 metalinks pages and the remaining 232 blocks correspond to 2 pages. Thus, 1,000 pages can be accessed using a single disk access; 1,000 pages can be accessed using two disk accesses, and 768 pages require three disk accesses. In order to access the metalinks emanating from a given topic t, we need a single disk access if topic t is in the first page in a given sparse index block, two disk accesses if it is in the second page, and three disk accesses if it is in the third page. Assuming that all pages contain the same number of metalinks and they are uniformly accessed, the expected average number of disk accesses (*avgDA*) to locate metalinks emanating from a given topic t is 1.92.

8.3 Experiments

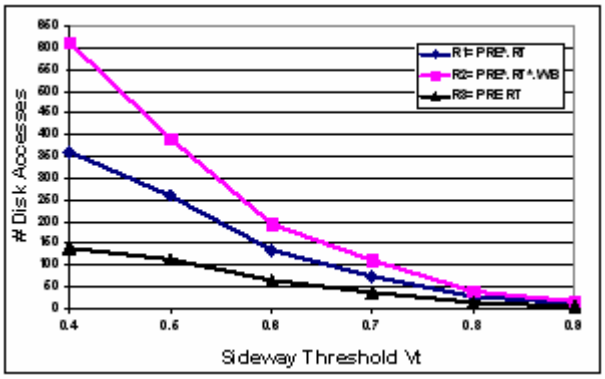
In the experiments of this section, the behavior of TClosure algorithms is evaluated using different values for the regular expression, input topic size, sparse index size, and page size.

(a) Regular Expressions

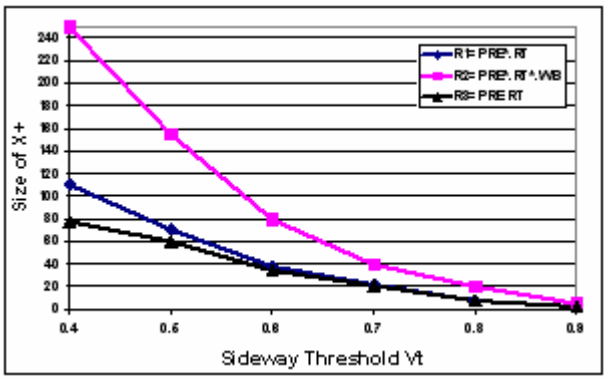
We use three regular expressions, namely, $PRE^*.RT$, $PRE^*.RT^*.WB$, and $PRE.RT$ regular expressions to evaluate the performances of TClosure algorithms.

Observation 1 (Figure 15 and Figure 16): Among the three regular expressions, the regular expression PRE.RT has the lowest number of disk accesses, and the smallest closure (i.e., X+) for both top-k and threshold-based TClosure algorithms.

Observation 2 (Figure 15): For the threshold-based TClosure algorithm, the increase in both the number of disk accesses and the size of output topics X^+ is nonlinear with respect to the decrease in the sideway value threshold V_t. When the sideway importance value V_t is large then there is a small difference between the numbers of disk accesses using different regular expressions. But, the difference becomes very large when V_t is small.



(a) Number of disk Accesses



(b) Size of the output topics X^+

Fig. 15. Threshold-based TClosure algorithm using different regular Expressions

Observation 3 (Figure 16): For all three regular expressions, the increase in the number of disk accesses is linear with respect to the increase in top-k topics for the top-k-based algorithm.

Observation 4 (Figure 15): Among the three regular expressions, the regular expression $PRE^*.RT^*.WB$ has the highest number of disk accesses and the largest closure (i.e., X^+) size for the threshold-based algorithm.

Observation 5 (Figure 16): For the top-k algorithm, the regular expression $PRE^*.RT$ has the highest number of disk accesses when k is less than 250. The reason for such a behavior is that the importance scores for the *WrittenBy* metalinks are 1.0, forcing the algorithm to locate topics with the highest importance using fewer disk accesses.

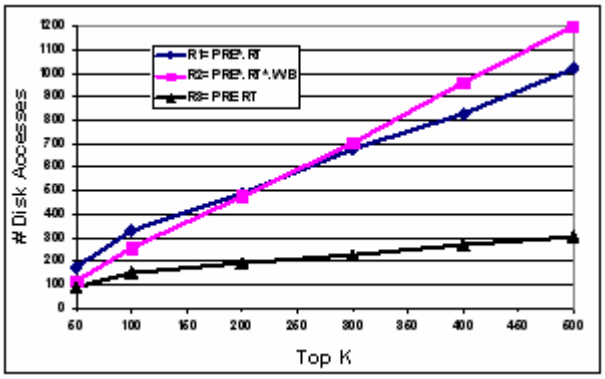


Fig. 16. Top-k-based TClosure algorithm using different regular Expressions

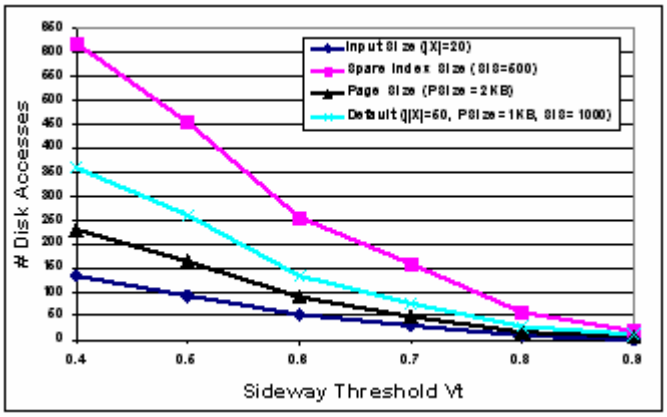
(b) Input size, Page Size and Sparse Index Size

Observation 6 (Figures 17 and 18): When the number of input topics decreases then both the number of disk accesses and the sizes of the output topics are decreased almost linearly.

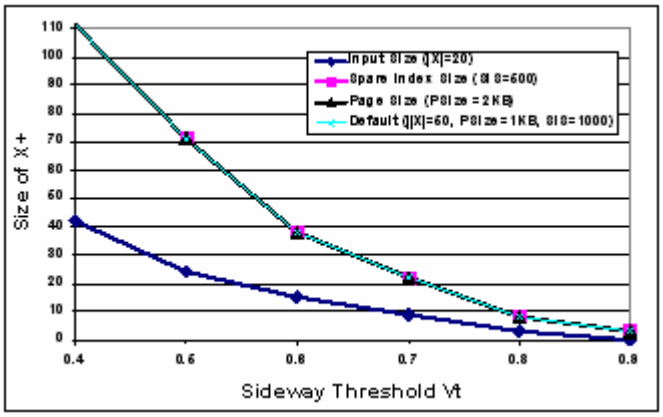
Observation 7 (Figures 17 and 18): When the page size or sparse index size are changed then the number of disk accesses are changed with almost a constant rate for both top-k and threshold-based algorithms.

When the page size is increased from 1KB to 2KB then the number of disk-based pages in the *MIndex* file is decreased from 2,768 to 1,340 pages. Therefore, the expected number of disk accesses per requested metalink is decreased from 1.92 to 1.25 (1,000 pages can be accessed using one disk access and 340 requires two disk accesses). Thus, the expected number of disk accesses per traversed metalink is decreased by the ratio of 1.25/1.92 = 0.65. Figures 17 and 18 illustrate that the number of the disk accesses per metalink instance is decreased by the ratio of 0.55 to 0.67 for threshold-based algorithms and by the ratio of 0.62 to 0.65 for top-k algorithms.

When the size of the sparse index is reduced from 1,000 to 500 blocks then the expected number of disk accesses per traversed metalink instance is changed from 1.92 to 3.29 (since there are 2768 pages; 500 pages require one disk access, 500 pages require two disk accesses, 500 pages require three disk accesses, 500 pages require four disk accesses, 500 pages require five disk accesses, and 268 pages require six disk access). Therefore, the expected rate becomes 3.29/1.92=1.7. As expected, Figure 17 and Figure 18 illustrate that the number of the disk accesses per requested metalink is increased by the ratio of 1.72 to 2.1 for threshold-based algorithms and by the ratio of 1.76 to 1.88 for top-k algorithms.



(a)Number of disk Accesses



(b) Size of the output topics X^{+}

Fig. 17. Threshold TClosure algorithm using different values for the input size, page size, sparse index size

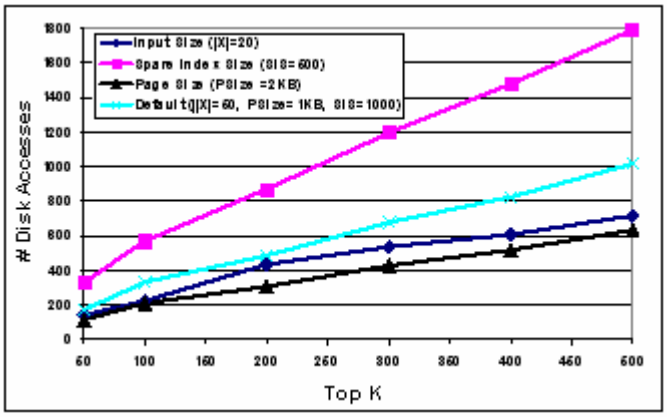


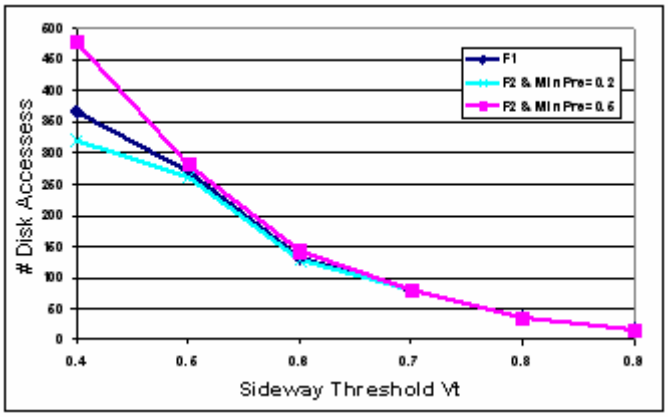
Fig. 18. Top-k TClosure algorithm using different values for the input size, page size, sparse index size

(c) Different Formulas for *Pre* Metalink Importance scores

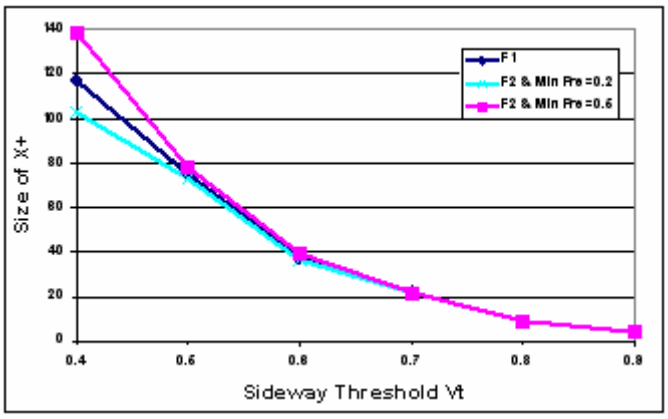
We evaluate the performances of TClosure algorithms using different metalink importance score computations. We use the following two formulas to compute the importance scores of Prerequisite metalinks:

(F1) $Imp(Pre(P_i, P_j)) = (O(P_i,P_j)+1)/ (O_{max}(P_j)+1)$

(F2) $Imp(Pre(P_i, P_j)) = MinPreFactor + (1 - MinPreFactor) * O(P_i,P_j) / O_{max}(P_j)$ where $0 \leq MinPre \leq 1$



(a) Number of disk accesses



(b) Size of the output topics X^+

Fig. 19. Threshold-based TClosure algorithm using different formulas for *Prerequisites* importance scores

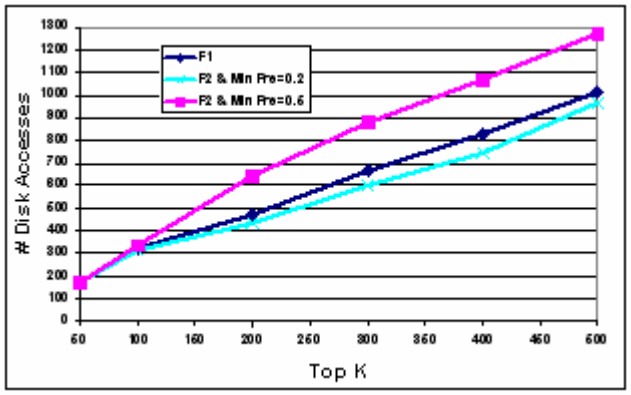


Fig. 20. Top-k TClosure algorithm using different formulas for *Prerequisites* importance scores

Observation 8 (Figures 19 and 20): For both top-k and threshold-based TClosure algorithms, formula F2 with *MinPre* of 0.5 has the highest number of disk accesses and formula F2 with *MinPre* of 0.2 has the lowest number of disk accesses.

Observation 9 (Figures 19 and 20): The differences between the number of disk accesses using different formulas are very small when the sideway threshold V_t is large (or, when k is small).

9. RELATED WORK

A. Web Data Extraction, Web Querying, and Web Metadata Models

Automatically extracting entities and relationships about entities from web documents would be very useful for web resource querying [Özsoyoğlu and Al-Hamdani 2003]. DIPRE [Brin 1998] employs a handful of training tuples of a structured relation R (that represents a specific meta-relationship among entities in the data) to extract all the tuples of R, from a set of HTML documents. DIPRE uses the training tuples to generate new patterns, and uses the newly generated patterns to extract more tuples, and so on. Snowball [Agichtein and Gravano 2000, Agichtein et al. 2000], an extension to DIPRE, improves the quality of the extracted data by including automatic patterns and tuple evaluation. One of the key improvements is that Snowball's patterns include named-entity tags. In addition, Snowball eliminates unreliable tuples and patterns by using strategies to estimate the reliability of the extracted tuples and patterns. The Proteus information extraction system [Grishman 1997, Grishman et al. 2002] divides the extracted text into sentences and into tokens, performs a lexical look-up for each token, and determines its parts-of-speech and features. Next, finite-state patterns are used to recognize names, nouns, verbs, and other special forms. Then, the scenario pattern

matching is used to extract events and relationships for a given relation. Proteus also uses an inference process to locate implicit information and make it explicit, and combines all the information about a single event using event emerging rules. The extracted events and phrases are used to update the database. QXtract [Agichtein and Gravano 2003] uses automated query-based techniques to retrieve documents that are useful for extracting a target relation from a large collection text documents. The field of (meta)data extraction from the web, while promising, has a long way to go at this stage.

There are a number of papers for querying the web via a database-style query language; for a comprehensive survey, see [Florescu et al. 1998]. Our work is distinguished from these works in that our focus is on (i) a metadata model for a web resource (as opposed to the whole web), and (ii) generic SQL extensions, and the associated query processing, for score management and text support. The SQL extensions, the associated query processing, and the proposed SVA operators are not necessarily restricted to metadata databases and web querying; they can also be equally valuable for databases/applications dealing with score manipulations.

There have been extensive research and standardization efforts on information representation models for the web. Two well-publicized metadata standards for web pages are Dublin Core and Warwick framework. As summarized in [Kobayashi and Takeda 2000], Dublin Core specifies a set of 15 metadata elements (e.g., title, creator, subject, etc.) for web pages. More recent and more comprehensive proposals to add semantics to the web include Topic Maps, Resource Description Framework (RDF) and the Semantic Web effort. A Topic Map data model, as described in [Biezunski et al. 1999], is similar to the Entity-Relationship model specialized for the abstract domain of topics and topic-related information. Our metadata model can be seen as a subset and an application of the topic map model, stripped off of many details, stored in an object-relational DBMS, and enriched with the notion of importance scores. Resource Description Framework (RDF) [Lassila and Swick 1999] is a graph-based information model designed to describe web information sources by attaching metadata specified in XML. In [Lacher and Decker 2001], RDF and topic maps are shown to be equivalent in expressive power in that each is able to express the other. Semantic Web [Semantic Web, Berners-Lee 2000] is an RDF schema-based effort to define a semantic-based architecture for web resources, with multiple layers that include a schema layer, a logical layer, and a query language. RQL [Karvounarakis et al. 2001] is a declarative language to query portal catalogs that are created according to the RDF standard in the context of the C-Web project. RQL query engine attempts to optimize a query at the rewriting stage,

and then leaves the job to the underlying ODBMS. In comparison, we propose a set of language extensions and evaluation algorithms that are integrated into the query engine. And, we propose new operators for text similarity joins and topic closure.

B. Function Evaluation, Text Similarity Joins, and IR-style solutions

The notion of user-defined functions (UDF) has been around for quite a long time (i.e., SQL table functions [Reinwald and Pirahesh 1998], etc.), and can perhaps be used for application-based score management. In comparison, we propose a database-centric, native approach to score management: SQL language and a query engine which, together, make use of input tuple scores in an *embedded* manner to answer queries, viewing scores as a native and internal property of a database schema. In this respect, our algebra combines function and score manipulation with traditional query processing in a new and unique way.

As a particular sort of score-generating predicates, we consider IR-style text similarity functions, which we assume to be natively embedded as *threshold predicates* in the system, as opposed to implementing them as user-defined functions. Today's commercial DBMSs provide full-text indexing and relevance ranking features for querying single text attributes (e.g., Oracle 9i Text [Oracle Corp. 2003], IBM DB2 Text Extender [IBM Corp. 2003], SQL Server 2000 Full-text Search [Microsoft Corp. 2003]). In contrast, we allow similarity computations and comparisons not only as selection predicates, but also as join conditions. And, as mentioned before, the scores returned by SVA operators are employed during intermediate stages of query processing to limit the output space, and used to revise final output tuple scores dynamically; this has not been proposed in a commercial DBMS or a research prototype.

An earlier work that makes use of text-similarity as a join condition is presented by Meng et al [1998]. This work describes three nested-loops based algorithms to find top k documents of a relation that are most similar to each document from another relation. These three algorithms are distinguished in their use of an inverted index, i.e., the first algorithm directly compares document vectors from both relations, whereas the second one builds an inverted index for one of the relations, and the third one employs inverted indices for both of the relations. The underlying document representation model is the vector space model as used in our work. Our work differs from Meng et al in that (a) our emphasis is on importance score handling, (b) our threshold predicates join tuples representing metadata (with relatively shorter text fields compared to entire documents), and (c) we make use of a maximal similarity filter as an early termination heuristic.

Additionally, Meng et al algorithms retrieve top-k (most similar) tuples for *each* tuple in the "other" relation whereas our top-k algorithms simply retrieve top-k (most similar) tuple pairs from the (implicit) cartesian product of two relations in a global manner. Note that the inverted index-based approaches are also applicable to our similarity join algorithms; but Meng et al report that these approaches can only be efficient when one of the relations is very small (so that the index can fit into the main memory). In Section 7, we make use of an in-memory inverted index for the blocks of the outer relation (R) read into the memory during the nested-loops-based join processing.

Cohen [1998] describes a new language, called WHIRL, that uses IR-based methods for similarity joins provided as built-in predicates in a data integration system. Our work has benefited from WHIRL, which also makes use of the maximal similarity heuristic (though in the context of the A* search algorithm proposed for query processing). However, our study emphasizes a general framework for handling scores during query processing, and threshold predicates in selection and join conditions are only one particular way of generating such scores, in addition to UDFs or other possible score-generating predicates.

More recently, database solutions that make use of IR techniques (and vice versa) have attracted research interest. A number of works have proposed allowing free-form keyword search over relational databases (e.g., DBXplorer [Agrawal et al. 2002], Discover [Hristidis and Papakonstantinou 2002], BANKS [Bhalotia et al. 2002] and Hristidis et al [2003]). These works fundamentally differ from ours in that they intend to provide a free-form keyword search functionality over databases by automatically identifying and assembling (joining) a set of separate tuples that constitute a query answer as a whole. Other than relying on IR-based similarity computation techniques (employed for evaluating our threshold predicates), our work does not have many common points with the above-listed works. For instance, BANKS provides **b**rowsing **an**d **k**eyword **s**earch for online databases by modeling the database as a graph where nodes are tuples and edges are connections, such as the primary-foreign key relationships. An answer to a keyword query is a subset of this graph, which is modeled as a Steiner tree, with a set of nodes (tuples) including specified keywords and a central informative (root) node. These output tuple trees are also assigned scores according to node weights, edge weights and the notion of prestige (similar to the famous Page-rank). Clearly, BANKS is not a competitive approach with respect to ours, but indeed can be complementary as it can operate on our metadata database just like any other ordinary

database (possibly by turning off our extended SQL and using its own graph-based algorithms).

C. Ranked Query Evaluation

The topic of *top-k queries* has been the subject of extensive research recently. Carey and Kossmann have introduced the **stop after** operator, which is an explicit and declarative way of restricting the cardinality of a query result in SQL [Carey and Kossmann 1997]. If the input stream is sorted, the *scan-stop* operator simply returns the first k tuples arriving as input (in a pipelined manner) and then closes down its input stream. In the case of unsorted input, the input stream must first be sorted to produce the top k tuples. Our work is distinguished from Carey and Kossmann's work in that, instead of using a generic operator that simply reduces the output size of all other operators, SVA operators themselves are *aware* of the cardinality limitation (the SV threshold or the top-k value), and they only produce the requested tuples. SVA operators with top-k stopping conditions can be used in accordance with the conservative and aggressive strategies proposed by Carey and Kossmann [1997] (as top-k can not propagate deeper in the operator tree safely). In this paper we adapt the conservative approach for defining our query semantics with top-k stopping condition. In a follow-up paper [Carey and Kossmann 1998], additional strategies are proposed for processing **stop after** queries. In contrast, SV threshold-based stopping conditions, which are unique to our work, safely propagate to all intermediate operators in the query tree (see Section 4). Thus, SVA operators with threshold-based stopping conditions can be used anywhere in the place of their counterparts in relational algebra.

In a similar fashion to our SVA operators with top-k stopping conditions, top-k selection and join algorithms have been proposed. Two such works for top-k selection are by Chaudhuri and Gravano [1999] and Chang and Hwang [2002], and the latter also supports expensive predicates. We discuss the processing of SVA selection operator elsewhere [Al-Hamdani and Özsoyoğlu 2003]. An early algorithm for top-k join is provided by Fagin [Fagin 1999], and it is further optimized by Güntzer et al [2000]. These algorithms assume equi-join conditions. More recently, join algorithms that support user-defined (arbitrary) join predicates have also been proposed, such as the J* algorithm [Natsev et al. 2001]. In comparison, we give nested-loops-based algorithms for top-k versions of SVA join, and define a max filter heuristic for joins involving textual similarity (threshold) predicates. Our algorithms exploit score distributions and/or the similarity filter, and improve the performance considerably. Optimization of top-k

predicates are also discussed by Mahalingam et al. [Mahalingam and Candan 2001], where the varying query outputs with respect to the different binding order of top-k predicates is taken into account.

Ranked-join operators by Ilyas et al. [2003, 2004] have similarities (and differences) with our work. In an earlier study [Ilyas et al. 2002], the authors proposed to encapsulate two previously-existing rank join algorithms (namely NRA and J*) in a physical join operator, with the focus of providing a ranked-join operator which can be used in pipelining query plans with join hierarchies. To this end, the NRA algorithm was modified to work in an incremental and pipelining manner. In a follow-up work [Ilyas et al. 2003], the authors proposed a new-rank join algorithm and two physical join operators that implement the new algorithm by using variants of the ripple join. Most recently [Ilyas et al. 2004], the authors introduce "interesting rank expressions" , extend dynamic programming-based query optimization to generate candidate plans that employ the rank-join operator, and propose a probabilistic model to estimate the input cardinality (and subsequently, the cost) of rank-join operators for query optimization purposes.

Both our work and the works of Ilyas et al. concentrate on supporting score-aware operators in the query engines; however, the two approaches significantly differ in various aspects: First, we define a general framework for a set of algebraic operators (namely, selection, join and closure) which can (i) modify scores with newly introduced threshold predicates involving textual similarities, (ii) compute and propagate scores with respect to user-defined functions and UDF predicates, (iii) enforce stopping conditions based on either a threshold or a top-k constraint. For our extended-SQL queries, we discuss the semantics of algebraic expressions involving our SVA operators interleaved with ordinary RA operators, and show that the proposed extensions are well-defined. In comparison, Ilyas et al. focus on defining a rank-join operator for pipelining query plans and optimization and cost evaluation issues for queries with a sequence of rank-join operators.

In comparing our SVA join operator and the rank-join operator of Ilyas et al, the most important distinction is our use of the threshold and UDF predicates, which *arbitrarily* change (increase or decrease) the scores of output tuples, making the results of Ilyas et al not directly applicable to our SVA join algorithms. Put another way, output tuple scores of SVA join are dependent on *tuple component values* that are involved in score-modifying predicates, which is not the case in Ilyas et al's rank-join framework. In comparison, the rank-join [Ilyas et al. 2003] applies the *same* output score generation function and *only* to the scores of joining tuples. Another difference is that we allow the

SVA operator itself to be aware of the top-k stopping condition (whenever allowed by our score-conservative policy) to reduce the intermediate output size in complex query trees. In contrast, in Ilyas et al's work, a Scan-Stop(k) [Carey and Kossmann 1997] operator is applied on top of the uppermost rank-join operator, and the join operators themselves do not know the top-k constraint. Having said these, adapting the physical join operators as proposed by Ilyas et al. for our SVA join algorithms is a future research direction.

D. Transitive Closure

SQL/TC is an extension to SQL to express generalized transitive closure queries [Dar and Agrawal 1993]. A directed graph G instance can be represented using a relation R with two columns S and T, where there is a tuple in R with values s and t for S and T if and only if there exists an edge from node s to node t in graph G. The transitive closure TC(G) of the graph G corresponds to the transitive closure TC of relation R with respect to S and T. Each edge in graph G has a value, and the value of an edge in TC(G) is derived from the values of the edges in the corresponding path-set. Dar et al presents polynomial algorithms for transitive closure with restricted paths [Dar et al. 1991]. SQL/TC has a complex syntax, and does not support computing the topic closure with top-k predicates, regular expressions, or hypernodes.

SQL'99 supports recursive queries using "WITH RECURSIVE" statement [Eisenberg and Melton 1999, Lewis et al. 2003]. A recursive query is composed of two parts: the definition of a recursive relation and the query against the definition. The recursive queries employ a complex syntax to express the topic closure operator, and do not deal with closure with top-k predicates, regular expressions, and hypernodes.

E. Other work

In our earlier work, we described the topic-based metadata model in more detail as well as some practical approaches for constructing such databases (e.g., the DBLP metadata database) [Altingövde et al. 2001, Özel et al. 2004]. This paper extends our preliminary results for the SVA framework [Özsoyoğlu et al. 2002] as follows: First, SVA algebra operators are defined more completely, and illustrated with logical query tree examples. Second, threshold and UDF predicates for SQL are introduced. Third, semantics of SQL extensions (correctness notion for "well-defined" queries) are defined, and proven correct. Last, but not least, complete experimental evaluations of the SVA join and topic

closure are reported, for which the importance scores of topics and metalinks are computed from real world data, rather than synthetic data.

Very recently, Al-Khalifa et al. proposed a score-based framework for querying structured text in XML databases [2003]. This work also extends common algebraic operators and defines new ones for score manipulation; however, their focus is on providing IR-style ranked querying facilities for XML documents.

10. CONCLUSIONS

In this paper, we have proposed a native score management and approximate text-similarity support to databases, to be used for web resource querying on metadata extracted from the web resource a priori. To this end, we have proposed SQL language extensions, algebraic extensions, and query processing algorithms that implement the proposed extensions.

Future work includes (i) adding new (e.g., "top-k") predicates to SQL extensions, and (ii) removing the closed world assumption in a controlled manner, and adding focused crawler executions (at the web information resource) during query evaluation time to those SVA operator evaluations that do not have "sufficiently large" number of output tuples.

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APPENDIX 1. SVA EQUIVALENCE RULES

Below, we list the essential algebraic equivalences that either solely involve the SVA operators for selection, join and topic closure, or mix ordinary RA operators with these three SVA operators. Clearly, the following set is not complete; it is provided to give the basic flavor of the algebraic equivalence rules and to illustrate some well-known algebraic equivalences that do not hold for SVA or mixed algebra expressions. We assume that all relations in the expressions below have importance scores, and, unless otherwise indicated, we use

1) *ImpAgg* = product. That is, the basic importance clause function is product. Thus, for SVA selection and join operators, f_{out} is defined as the product of f_{in} of input relations, *Sim()* function values of threshold predicates, and UDF values of UDF predicates.
2) *FPath* = product and *FPathMerge* = max (i.e., the topic closure clause/operator functions).
3) $\beta = V_t$. That is, as the output threshold β, we use the sideway value threshold V_t (not the ranking threshold k).

Therefore, for the sake of readability, in the equivalence transformations listed below, we simplify our notation by *not* specifying f_{out} (*ImpAgg*), *FPath*, *FPathMerge* and β in SVA operator specifications.

I. Transformation rules that only involve SVA operators

- **SVA Selection Cascade Rule:** $\sigma^*_{P1 \wedge P2 \ldots \wedge PN}(R) = \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$

Proof *(by contradiction):* Assume that $\sigma^*_{P1 \wedge P2 \ldots \wedge PN}(R) \neq \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$. Then, $\exists$ at least one tuple t in R such that either $t \in \sigma^*_{P1 \wedge P2 \ldots \wedge PN}(R)$ and $t \notin \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$, or $t \notin \sigma^*_{P1 \wedge P2 \ldots \wedge PN}(R)$ and $t \in \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$.

Case 1. $\exists$ tuple t in R such that $t \in \sigma^*_{P1 \wedge P2 \ldots \wedge PN}(R)$, but $t \notin \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$. As $t \in \sigma^*_{P1 \wedge P2 \ldots \wedge PN}(R)$, t satisfies the formula $P_1 \wedge P_2 \wedge \ldots P_N$ and yields a modified importance score greater than V_t. Assume that each predicate P_i modifies importance score of its input tuple by a real valued factor s_i which is in the range [0.0, 1.0]. Thus, the modified importance score of t is $f_{in} * \prod_{i=1}^{N} s_i$. As $t \notin \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$, t either does not satisfy at least one of the predicates $P_1, P_2, \ldots, P_N$, or modified importance score of t is less than V_t. As t satisfies $P_1 \wedge P_2 \wedge \ldots P_N$, t satisfies all of the selection predicates $P_1, P_2, \ldots, P_N$. For the cascading selection expression $\sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$, the importance score of the input

tuple is modified such that, each of the selection operator multiplies the importance score of its input tuple with a factor s_i in [0.0, 1.0]. Thus, P_N modifies importance score of t as $f_{in}*s_N$, the predicate P_{N-1} modifies as $f_{in}*s_N*s_{N-1}$, …, finally predicate P_1modifies the importance score of t as $f_{in}*s_N*s_{N-1}*s_{N-2}*\ldots*s_1$. So, the modified importance score of t in $\sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$ is equal to $f_{in}*\prod_{i=1}^{N} s_i$ which is greater than V_t, contradiction. Thus $t \in \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$.

Case 2. ∃ tuple t in R such that $t \notin \sigma^*_{P1 \wedge P2\ldots \wedge PN}(R)$ and $t \in \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$. As $t \in \sigma^*_{P1}(\sigma^*_{P2}\ldots(R))$, t satisfies all the selection predicates P_1, P_2, …, P_N and yields a modified importance score $f_{in}*\prod_{i=1}^{N} s_i > V_t$. As t satisfies all the selection predicates P_1, P_2, …, P_N, t also satisfies $P_1 \Lambda P_2 \Lambda \ldots P_N$. Also, as $f_{in}*\prod_{i=1}^{N} s_i > V_t$ for tuple t, $t \in \sigma^*_{P1 \wedge P2\ldots \wedge PN}(R)$, contradiction. Q.E.D.

Note that when β is changed to the ranking threshold k or when *ImpAgg* is not the product function and, say, the average function then the SVA cascade equivalence does not hold.

- **SVA Selection Commutativity Rule:** $\sigma^*_{P1}(\sigma^*_{P2}(R)) = \sigma^*_{P2}(\sigma^*_{P1}(R))$

Proof *(by construction):*

$\sigma^*_{P1}(\sigma^*_{P2}(R)) = \sigma^*_{P1 \wedge P2}(R)$ by the cascade rule of SVA selection operator.

$\sigma^*_{P1 \wedge P2}(R) = \sigma^*_{P2 \wedge P1}(R)$ by the commutativity of conjunction, and by the fact that t in $\sigma^*_{P1 \wedge P2}(R)$ and t in $\sigma^*_{P2 \wedge P1}(R)$ have the same derived importance scores.

$\sigma^*_{P2 \wedge P1}(R) = \sigma^*_{P2}(\sigma^*_{P1}(R))$ by the cascade rule of SVA selection operator. Q.E.D.

- **SVA Join Commutativity Rule:** R *Join** S = S *Join** R where the join condition is commutative.

Proof *(by contradiction):* Assume that (R *Join* * S) ≠ (S *Join* * R). Then ∃ a tuple r in R and a tuple s in S such that r.s ∈ (R *Join* * S), but s.r ∉ (S *Join* * R). As r.s ∈ (R *Join* * S), then r.s satisfies the join condition θ and its importance value is Imp(r)*Imp(s). Note that, the importance score may be further refined by threshold predicates P_{th} (or UDFs) in the join predicate (if any) as $Imp(r)*Imp(s)*P_{th}(r.s)$. Since r.s is in the output of (R *Join* * S), its importance score is greater than V_t. Since θ is a commutative join condition and a

commutative basic importance propagation function (e.g., product) is employed, as r and s satisfy θ, s and r also satisfy θ, and the importance score of s.r in (S *Join* * R) is Imp(s)*Imp(r)* P_{th}(s.r) which is equal to Imp(r)*Imp(s)* P_{th}(r.s), contradiction. Thus, s.r ∈ (S *Join* * R). Q.E.D.

- **SVA Join Associativity Rule:** ((R $Join_{\theta 1}$* S) $Join_{\theta 2}$* T) = (R $Join_{\theta 1}$ * (S $Join_{\theta 2}$* T)) where the join conditions θ1 and θ2 are associative.

Proof *(by contradiction):* Assume that ((R *Join** S) *Join** T) ≠ (R *Join* * (S *Join** T)). Let us call the former join order as Plan-1 and the latter as Plan-2. The join condition between R and S is $\theta_{(R.A,\ S.A)}$, and the join condition between S and T is $\theta_{(S.B,\ T.B)}$. For simplicity, we first consider the case where join conditions do not include a score-modifying predicate (like a threshold predicate or UDF), and later we extend our proof to also cover score-modifying join conditions.

Since the two plans are not equal, then ∃ a tuple r in R, a tuple s in S and a tuple t in T such that r.s.t ∈ (R *Join* * (S *Join** T)), but r.s.t ∉ ((R *Join** S) *Join** T). As r.s.t is produced by Plan-2, then s.t satisfies the join condition $\theta_{(S.B,\ T.B)}$ and its importance value Imp(s)*Imp(t) is greater than V_t. Furthermore, as r.(s.t) is in final output, the join condition $\theta_{(R.A,\ S.A)}$ should also be satisfied and Imp(r)*(Imp(s)*Imp(t)) is greater than V_t. Initially, we have assumed that r.s.t is not produced by Plan 1. To begin, let us assume that the tuple r.s is produced by (R *Join** S), but then discarded during the join operation with T. In this case, since the join condition $\theta_{(S.B,\ T.B)}$ is associative, the join condition $\theta_{(S.B,\ T.B)}$ must be satisfied. Furthermore, since the basic importance propagation function (i.e., product) is also associative, (Imp(r)*Imp(s))*Imp(t) would still be greater than V_t and r.s.t would also be produced by Plan 1, which is a contradiction. Thus, if r.s.t is not in the final output, then r.s should not be produced by (R *Join** S). But, again, we know that for tuples r and s, $\theta_{(R.A,\ S.A)}$ is satisfied. Furthermore, Imp(r)*Imp(s) is guaranteed to be greater than V_t (i.e., follows from the facts that Plan-2 produces r.s.t tuple, Imp(r)*(Imp(s)*Imp(t)) > V_t and Imp(t)<=1, by definition). But then, the tuple r.s would also be in the intermediate result (R *Join** S), and subsequently in the final result. This contradicts the initial assumption, and thus we show that if a tuple is produced by Plan-2, it is also produced by Plan-1. Note that, by a similar argument, we can easily show that if a tuple is not produced by Plan-2, it cannot be produced by Plan-1, either. Thus, the outputs of these two plans are equal.

Now, let us extend the above proof for score-modifying predicates. W.l.o.g., let us assume $\theta_{(R.A,\ S.A)}$ involves one such predicate $P_{R.A,\ S.A}$ with threshold T_1 (e.g., Sim(R.A, S.A) > T_1) and $\theta_{(S.B,\ T.B)}$ involves $P_{S.B,\ T.B}$ with threshold T_2. As in the above, let us assume that then ∃ a tuple r in R, a tuple s in S and a tuple t in T such that r.s.t is produced by Plan-2 but not Plan-1.As r.s.t is produced by Plan-2, then s.t satisfies the join condition $\theta_{(S.B,\ T.B)}$ with $P_{S.B,\ T.B} > T_2$, and its importance score Imp(s)*Imp(t)*$P_{S.B,\ T.B}$ is greater than V_t. Furthermore, as r.(s.t) is in final output, the join condition $\theta_{(R.A,\ S.A)}$ should also be satisfied with $P_{R.A,\ S.A}>T_1$ and Imp(r)* $P_{R.A,\ S.A}$*(Imp(s)*Imp(t)* $P_{S.B,\ T.B}$) is greater than V_t. Along the lines of the above discussion, we can easily realize that tuple r.s must be produced by (R *Join** S) in Plan-1, because, for tuples r and s, join condition will still hold and $P_{R.A,\ S.A}>T_1$ (otherwise, it would not be produced by the join of r and s.t in Plan-2). Again, Imp(r)* $P_{R.A,\ S.A}$*Imp(s) is guaranteed to be greater than V_t (by the same reasoning), and thus r.s is in the intermediate result. Once r.s is produced, it joins with t, as the join condition holds with $P_{S.B,\ T.B}>T_2$, and is included in the final result of Plan-1. Thus, in the presence of score-modifying predicates, the associativity property holds. Q.E.D.

SVA Topic Closure:

- TClosure does not cascade since each topic closure clause in extended SQL corresponds to a single TClosure operator, regardless of its predicates' complexity.
- TClosure is not commutative: $TClosure_{M2}(Tclosure_{M1}(R)) \neq TClosure_{M1}(Tclosure_{M2}(R))$ where M1 and M2 are two different regular expressions (REs).

Proof *(by counterexample)*: Assume that M1 includes PrerequisitePapers* and M2 includes RelatedTo*, and the following metalink instances are specified: A $\rightarrow^{Pre}$ C, C $\rightarrow^{Pre}$ D, D$\rightarrow^{Pre}$ E, B$\rightarrow^{Pre}$ F and A$\rightarrow^{RelatedTo}$ B, B$\rightarrow^{RelatedTo}$ E.

Then, $TClosure_{RelatedTo*}(TClosure_{PrerequisitePapers*}(A)) = TClosure_{RelatedTo*}(A, C, D, E) = \{A, B, C, D, E\}$ whereas $TClosure_{PrerequisitePapers*}(TClosure_{RelatedTo*}(A)) = TClosure_{PrerequisitePapers*}(A, B, E) = \{A, B, C, D, E, F\}$ and thus TClosure operator is not commutative. Q.E.D.

- Topic closure does not distribute over SVA join:

$$TClosure_{M1}\ (R\ Join^*\ S) \neq (TClosure_{M1}\ (R)\ Join^*\ S) \neq (R\ Join^*\ TClosure_{M1}\ (S))$$

Proof *(by counterexample)*: Assume that relation R and S include topics A, B, Q, and A, X, F, respectively, and the following metalink instances hold in the database D: A $\rightarrow^{P1}$ X, A $\rightarrow^{P1}$ Y, F$\rightarrow^{P1}$ Q. Then, $TClosure_{M1}$ (R *Join** S) = $TClosure_{M1}$ (A) = {A, X, Y} whereas $TClosure_{M1}$ (R) *Join** S = $TClosure_{M1}$ (A, B, Q) *Join** S = {A, X, Y, B, Q} *Join** {A, X, F} = {A, X} and (R *Join** $TClosure_{M1}$ (S)) = {A, B, Q} *Join** $TClosure_{M1}$ (A, X, F) = {A, B, Q} *Join** {A, X, F, Y, Q} = {A, Q}, which are all different. Q.E.D.

Note that, in the above example, we assume that the topics with the same name satisfy the join condition. The selection of the notation is just for the sake of simplicity and is not intended to restrict the proof to exact join conditions, as the above proof clearly applies to theta joins as well.

- $TClosure_{M1}$ (R *Join** S) ≠ $TClosure_{M1}$ (R) *Join** $TClosure_{M1}$ (S)

Proof *(by counterexample):* Proof is similar to the one given above, and the same example serves to prove this inequality.

- **SVA Join and selection:** R *Join*$^*_\theta$ S = σ_θ*(R *Join** S)

- **Distributing SVA selection over SVA join:** σ^*_{P1} (R *Join** S) ≠ (σ^*_{P1} (R) *Join** S), where P1 is a formula whose predicates are in Attr(R).

Proof *(by counterexample*): Assume that ∃ a tuple r in R and s in S such that Imp(r) = 0.9, Imp(s) = 0.7, and P_{th}(r) = 0.4 where $P_{th} \subseteq$ P1 denotes the threshold predicate(s) that revise the importance value of tuples selected by the σ* operator. Further assume that selection threshold β_1=0.3 and join threshold β_2=0.1.Now, consider the left-hand-side (LHS) of the above inequality. Since Imp(r.s) = 0.9*0.7= 0.63 > β2, r.s is in the join output. Then, its importance score is further revised by the threshold predicates as 0.63*P_{th}(r) = 0.63*0.4 = 0.252 <β_1=0.3. Thus, r.s is not in the final output of LHS. For the right-hand-side (RHS), however, σ^*_{P1} (R) computes the importance score of r as Imp(r) = 0.9*P_{th}(r) = 0.9*0.4 = 0.36 > β_1=0.3 and Imp(r.s) = 0.36*0.7 = 0.252>β2=0.1. Thus, r.s is in the output of RHS, and we show that the inequality holds. Q.E.D.

- **Distributing SVA selection over SVA join:** σ^*_{P1} (R *Join** S) = (σ^*_{P1} (R) *Join** S), where P1 is a formula whose predicates are in Attr(R) and either β_1=β_2 or P1 does not include any threshold predicates.

Proof *(by contradiction):* First, assume that $\beta_1=\beta_2=\beta$ and the above equality does not hold. Then, ∃ a tuple t such that either t is included in the output of σ^*_{P1} (R *Join** S) but not in the output of σ^*_{P1} (R) *Join** S, or vice versa. For the former case, if t is included in the output of σ^*_{P1} (R *Join** S), then ∃ a tuple r in R and s in S such that their theta join produces the tuple r.s with the importance value $Imp_1(r.s)= Imp(r)*Imp(s) > \beta$ (the join threshold). To be in the final output, r.s satisfies P1 and its revised importance score by the threshold predicates P_{th} is $Imp_2(r.s) = Imp_1(r.s)*P_{th}(r)$ which is greater than β (the selection threshold) . But since P1 only involves attributes from R, the attributes of t that satisfy P1 are the attributes that come from the R tuple r. Similarly, if $Imp_2(r.s)>\beta$, then $Imp(r)* P_{th}(r)$ is also greater than β (since all importance scores are in the range [0, 1]). But then, the expression σ^*_{P1} (R) would select r in its output and its join with s from S would also locate r.s in the output of RHS expression as well. Contradiction.

Now, consider the case that a tuple that is not included in LHS output is included in the RHS output. This means that ∃ a tuple r in R such that $Imp(r)* P_{th}(r) > \beta$ and ∃ a tuple s in S such that $Imp(r)* P_{th}(r)*Imp(s) > \beta$. But then, since Imp(r)*Imp(s) would also be greater than β, the tuple r.s would also be included in the join output of LHS expression and it would also be located in the final output as well. Thus, this contradicts our initial assumption that there may be an extra or missing output tuple in the LHS output when compared with RHS output, and thus the equality holds.

If there are no threshold predicates involved in the selection predicate then trivially the selection predicate cannot modify the importance scores of the selected tuples and thus the equality holds. Q.E.D.

- $\sigma^*_{P1 \wedge P2}$ (R *Join** S) ≠ (σ^*_{P1} (R) *Join** σ^*_{P2} (S)), Attribute(P1) ⊆ R, Attribute(P2) ⊆ S
- $\sigma^*_{P1 \wedge P2}$ (R *Join** S) = (σ^*_{P1} (R) *Join** σ^*_{P2} (S)), Attribute(P1) ⊆ R, Attribute(P2) ⊆ S and either $\beta_1=\beta 2$ or P_1 and P2 do not include any threshold predicates.

Proof: Similar to the preceding proof.

II. Transformation rules that involve both SVA and RA operators:

- **Associativity:** (R *Join** S) *Join* T = R *Join** (S *Join* T)

Distribution of RA selection over SVA join:

- $\sigma_{P1}(R \; Join^{*} \; S) = (\sigma_{P1}(R) \; Join^{*} \; S), \; P1 \subseteq R$
- $\sigma_{P1 \wedge P2}(R \; Join^{*} \; S) = (\sigma_{P1}(R) \; Join^{*} \; \sigma_{P2}(S)), \; P1 \subseteq R, P2 \subseteq S$

TClosure with typical RA operators:

- $TClosure_{M1}(\sigma_{P1}(R)) \neq \sigma_{P1}(Tclosure_{M1}(R))$

Proof *(by counterexample*): Assume that the database D specifies that A $\rightarrow^{M1}$ C, C $\rightarrow^{M1}$ D, D$\rightarrow^{M1}$ E and B$\rightarrow^{M1}$ F. Further assume that only the topics A and B satisfy the selection predicate P1. Then, $TClosure_{M1}(\sigma_{P1}(R)) = TClosure_{M1}(A, B) = \{A, B, C, D, E, F\}$ whereas $\sigma_{P1}(TClosure_{M1}(R)) = \sigma_{P1}(TClosure_{M1}(A, B, C, D, E, F)) = \{A, B\}$. Q.E.D.

- $TClosure_{M1}(R1 \; Join^{*} R2) \neq TClosure_{M1}(R1) \; Join^{*} \; R2 \neq R1 \; Join^{*} \; TClosure_{M1}(R2)$
- $TClosure_{M1}(R1 \; Join^{*} \; R2) \neq TClosure_{M1}(R1) \; Join^{*} \; TClosure_{M1}(R2)$

APPENDIX 2. PROOFS OF THE LEMMAS AND THEOREMS

Lemma 1. SQL queries with the basic importance propagation clause and threshold predicates are well-defined, under the set of transformations **T** (of Appendix 1).

Proof *(by contradiction):* Assume that extended SQL queries with the basic importance propagation clause and threshold predicates are *not* well-defined. Then, there are at least two SQL query executions QE1 and QE2 that process an SQL query under the pre-specified transformation rules **T** and that produce different outputs. This implies that, given a query and its initial logical query tree T1 for query executions QE1 and QE2, the final trees T1' and T1", which are selected as the best plans to be executed (i.e., least costly alternatives), yield different outputs. Then, to produce different outputs, two trees T1' and T1" must differ by at least one transformation applied while alternative trees are being generated, and these transformations invalidate the uniqueness of the output. However, all equivalent transformations that can be performed over a given logical query tree are specified in Appendix 1, and are proven correct. Thus, any such transformation *permitted* in **T** that differ between the trees T1' and T1" are equivalent and must produce a unique output, contradiction. Q.E.D.

Lemma 2. SQL queries having a topic closure clause and employing rules 1-3 are well-defined , under the set of transformations **T** (of Appendix 1).

Proof *(by contradiction):* Assume that SQL queries with topic closure clauses are *not* well-defined. Then, w.l.o.g, there are two SQL query executions QE1 and QE2 that process an SQL query with topic closure under rules 1-3 (of Section 3) and the pre-specified transformation rules **T,** and that produce different outputs. The difference is caused by either different transformations that yield different logical query trees or due to the differing evaluations of the topic closure operator. By Lemma 1, a query tree and its transformations under the equivalent transformation set **T** yield unique output, and the set **T** specifies all and only permissible equivalences for the topic closure operator. Thus, the interaction of topic closure operator with all other operators does not invalidate the uniqueness of the query output. Then, the different evaluations of the topic closure operator leads to different query outputs. Due to Rule 1, each topic closure predicate is processed by a single topic closure operator producing the same output, and, Rules 2 and 3 guarantee that the output is finite, a contradiction. Q.E.D.

Lemma 3. Consider an SQL query Q with the *stop with threshold* V_t clause and its query tree with a single STOP operator at the root and having $\beta = V_t$. Then, accompanied with rule 4, the threshold V_t propagates to all the SVA operators in the query, and Q stays well-defined.

Proof *(by induction):* Assume that, for a given query Q with *stop with threshold* clause, all input relations and the intermediate relations materialize their importance scores and keep them in the column sv. Then, we express the query Q with *stop with threshold* clause and with output attributes, say, A, B as follows:

$$E = \pi\,(STOP_{VT}(E2))$$

where E2 is the SVA expression to evaluate the query Q without the *stop with threshold* clause. We assume that all the operators in E2 keep their sv columns during the query processing, and all projections retain the input relation sv column as well as the projected columns. The outermost projection then simply drops the sv column and keeps the attributes A, B that are specified in the query. Now, we show that the *stop with threshold* condition is propagated to all the operators in the expression E2, and the outermost $STOP_{Vt}$, which becomes redundant, is dropped.

For the basis, assume that the first innermost operator of E2 is Op. Then, Op simply computes its output where the importance value imp_t of an output tuple t is computed by f_{out}. Let us change Op to Op' where Op' employs $\beta = V_t$, and also drop the outermost $STOP_{Vt}$ operator. Then Op' simply compares imp_t with V_t and retains t if $imp_t \geq V_t$. We now show that replacing Op with Op' in E, and thus changing E to E' produces the same query output. If t contributes to the output of E then $imp_t \geq V_t$ and t is in the output of Op', and thus it is in the output of E'. If t does not contribute to the output of E (but produced by E2) then it must be eliminated by the final STOP operator that is applied to E2. Then, $imp_t < V_t$ and t is not in the output of Op', and thus it is also not in the output of E'. Thus E and E' are equivalent.

For the induction step, assume that Lemma 3 holds after replacing the first *k* operators in the expression E, where the output of the expression with the first k operators is the intermediate relation I. Consider the $(k+1)^{th}$ operator Op. Replace the first k operators with their output I, and reconsider the operator Op as if it is a base relation. Clearly, this case becomes identical with the basis case, and the lemma holds. Q.E.D.

Lemma 4. In any SQL query Q, the clause *stop after k most important* accompanied with the score-conservative top-k propagation policy propagates to SVA operators of Q during query processing, and Q stays well-defined.

Proof sketch *(by induction):* Assume that, for a given query Q with *stop after k most important* clause and without any *extended-SQL* subqueries, all input relations and the intermediate relations materialize their importance scores and keep them in the column sv. Then, we express the query Q with *stop after k most important* clause and with output attributes, say, A, B as follows:

$$E = \pi\,(\text{SORT-STOP}_k(E2))$$

where E2 is the SVA expression to evaluate the query Q without the *stop after k most important* clause. The output of E2 is then sorted[1], and the top-k (or, $k+n$, in case of equality) tuples are returned (as SORT-STOP is defined in [Carey and Kossmann 1997]). Note that the SORT-STOP operator is always placed before the final projection operator in the algebraic expression corresponding to a query Q with *stop after k most important* clause, *regardless of* the further propagation of top-k constraint to other SVA operators (as discussed in Section 4.3.2). We further assume that all the operators in E2 keep their sv columns during the query processing, and all projections retain the input relation sv column as well as the projected columns. The outermost projection then simply drops the sv column and keeps the attributes A, B that are specified in the query. Now, we show that the *stop after k most important* condition is propagated to the *deepest* SVA operator(s) in the expression E2 that satisfy the score-conservative top-k propagation policy.

For the basis, assume that the first innermost SVA operator of E2 is Op, for which the score conservative policy holds. That is, all other operators in E2 that succeed Op are guaranteed not to reduce the cardinality of Op's output tuples, or modify their importance scores. Then, Op simply computes its output where the importance value imp_t of an output tuple t is computed by f_{out}. Let us change Op to Op' where Op' employs $\beta = k$. Then, Op' operator returns only the first k tuples with highest scores. We now show that replacing Op with Op' in E, and thus changing E to E' and E2 to E2' produces the same query output: i) If t contributes to the output of E then t is produced by E2 and imp_t is in top-k importance scores (as it satisfies the SORT-STOP operator). Then, since the

[1] In this proof, we assume that the STOP operator is SORT-STOP, for generality. If the input is already sorted, the query processor can simply replace the SORT-STOP with SCAN-STOP, which simply returns its first k input tuples.

importance of this operator is *last modified* by operator Op in E, the tuple t would also be generated by operator Op' in its top-k outputs. Furthermore, since a tuple in the output of Op' is never dropped afterwards, it may never be discarded, and since its score is never modified, t will always remain in the top-k outputs of the final SORT-STOP operator. Subsequently, t would also be generated by E2' and thus it is in the output of E'. ii) If t does not contribute to the output of E then imp_t is not in the top-k scores and must have been pruned by the SORT-STOP operator (as the output of operator Op can not be discarded by any other operator in E2). But, since the tuple score is last computed by the Op, then either one of the following must be true: (a) tuple t is not at all in the output of Op' and thus in the output of E2', or (b) tuple t is included in the output of Op' with some rank *i* (*i*<=*k*), but the first *i*-1 tuples yield more than k tuples after the application of Op' (e.g., by applying a join operation), and tuple t is eliminated by the SORT-STOP operator[2] after E2'. Nevertheless, t is not in the output E', neither. Thus E and E' are equivalent.

For the induction step, assume that Lemma 4 holds after replacing the deepest score-conservative SVA operator Op in the expression E. We provide a proof-sketch to show that we can proceed replacing SVA operators with top-k stopping conditions as long as such score-conservative SVA operators still exist in E.

Let us assume that, after the first replacement the algebraic expression E for query Q can be shown as

$$E = \pi\,(\text{SORT-STOP}_k(E2(Op(E'))))).$$

First, there is no operator in E' which also enforces the top-k stopping condition (i.e., there can be other SVA operators in E' that modify scores, but they don't apply any stopping condition). Suppose an SVA operator Op' exists in E' with the top-k stopping condition. Then, its intermediate result scores will be further modified by Op, which is a contradiction to the score-conservative policy, and thus such an Op' can not exist. That is, Op is the first score-conservative SVA operator encountered in the algebraic expression Op(E').

Now, let us consider the cases for E2.

i) E2 only includes unary operators: In this case, Op is the only SVA operator that enforces the top-k stopping condition in E. This is because, if some SVA operator Op' exists in E2 that enforces top-k condition, the intermediate output scores of Op

[2] Note that, as discussed in Section 4.3.2, this case is only possible if the cardinality of the output of an SVA operator with ranking threshold k is increased by a successive (say, join) operator. And this is why we always enforce an outermost (SORT) STOP operator.

would be modified by Op', which means Op does not satisfy score-conservative policy. This contradicts to the induction hypothesis.

ii) E2 also includes binary operators: In this case, *all binary* operators that involve Op must be typical RA operators (i.e., all binary antecedents of Op are RA operators). Otherwise, they would modify the scores produced by Op, which contradicts with the induction hypothesis. In particular, there must exist *at least one* such outermost RA binary operator B (e.g., union) with inputs E_2Left and E_2Right = E'' (Op(E')). Then, *if* a score conservative SVA operator Op_2 exists in E_2Left, the case becomes identical with the base case and E_2Left will be expressed as E_3Left(Op_2(E_3Right)). The above discussions can then be applied for E_3L recursively as long as another score conservative SVA operators exists, and thus all score-conservative SVA operators will be replaced to enforce the top-k stopping condition.

Thus, we show that for a query Q with no nested subqueries, the output is well-defined. For queries that include subqueries with extended SQL clauses, each sub-query algebra expression is separately considered in the same manner as discussed in above. Q.E.D.

Theorem 1. SQL queries as defined in Section 2.2.2 and satisfying rules 1-4 are well-defined.

Proof: The proof directly follows from Lemmas 1-4.

Lemma 5. Let $\mathbf{u_r} = \langle u_1\ u_2\ \ldots\ u_x \rangle$ be the term vector corresponding to the join attribute A of tuple r of R, where u_i represents the weight of the term i in A. Assume that the *filter vector* $\mathbf{f_S} = \langle w_1\ ..\ w_x \rangle$ is created such that each value w_i is the max weight of the corresponding term i among all vectors of S. Then, if Cosine($\mathbf{u_r}$, $\mathbf{f_S}$) < V_t then r can not be similar to any tuple s in S with similarity above V_t.

Proof *(by contradiction):* Assume that Cosine($\mathbf{u_r}$, $\mathbf{f_S}$) < V_t and ∃ a tuple t in S with the term vector $v = \langle v_1\ v_2\ \ldots\ v_x \rangle$ for join attribute A such that Cosine($\mathbf{u_r}$, v_s) >= V_t. Since Cosine($\mathbf{u_r}$, v_s) >= V_t > Cosine($\mathbf{u_r}$, $\mathbf{f_S}$), ∃ a term *i* in vector v with weight v_i such that v_i> w_i in $\mathbf{f_s}$. But then, v_i is greater than the maximum weight for the term *i* among all vectors of S, which contradicts the definition of filter vector $\mathbf{f_s}$. Thus, we show by contradiction that no such tuple t can exist in S. Q.E.D.

APPENDIX 3. THRESHOLD-BASED CLOSURE ALGORITHM

Threshold-TClosure(R, X, Vt, *MIndex*, *HNode*)

Input: regular expression R, Input topics X, sideway threshold V_t, metalink index table *MIndex*, hypernode table *HNode.*

Output: Topics in X^+ that satisfy the threshold V_t

1. Generate the FSA that corresponds to the regular expression R;
2. $X^+ := \phi$; *PossibleOutput*:= ϕ; S:= The starting state in the FSA;
3. **for** each topic t in X **do**
4. **if**(Imp(t)≥V_t) **then**
   Add the triplet <t.Tid,Imp_d(t):=*Imp*(t), t.state:=S> into *PossibleOutput*;
5. **while** (*PossibleOutput* is not empty) **do**
6. { Remove triplet *tr* := <t_v.Tid, $Imp_d(t_v)$, S_v> with the maximum Imp_d from *PossibleOutput* ;
7. **if**(triplet *tr* $\notin X^+$) **then** add triplet *tr* into X^+;
   //Steps 8-20: Process all metalinks emanating from topic t_v
8. **for** each metalink M:=Expand(S_v) **do**
9. { S_w:=NextState(M,S_v);
10. **for** each metalink t_v.Tid $\rightarrow^M$ t_w.Tid in *MIndex* **do**
11. { $Imp_d(t_w) := Imp_d(t_v) * Imp(M) * Imp(t_w)$;
12. **if** ($Imp_d(t_w) \geq V_t$) **then**
13. { **if** (there exists a triplet tr_w with key <t_w.Tid,S_w> in *PossibleOutput*) **then**
14. { **if**($Imp_d(tr_w) < Imp_d(t_w)$ **then** update triplet tr_w with $Imp_d(tr_w) := Imp_d(t_w)$;}
15. **else** (there does not exists a triplet with key <t_w.Tid,S_w> in X^+)
16. **then** Add triplet <t_w.Tid, $Imp_d(t_w)$, S_w> into *PossibleOutput*;}
    //Handling HyperNodes
17. **for** each pair <TidList, NTid> in *HNode*(t_v.Tid).NodeList **do**
18. **if** (for each topic t with t.Tid ∈TidList, there exists a triplet for topic t in X^+) **then**
19. **for** each metalink NTid$\rightarrow^M$ t_w.Tid in *MIndex* **do**
    //Process metalinks of type M emanating from node NTid
20. {Perform steps 11-16 with t_v.Tid:=NTid and
    $Imp_d(t_v) := GAVG(\{t_n\}: t_n \in TidList);\}\}\}$
21. Return X^+;

Example A3.1. We use the MIndex instance in Table II. Also, assume that we want to compute the topic closure for the set X={T1} with SV threshold V_t=0.5 using the regular expression $R=PRE^*.RelatedTo^*$. Also, assume that the average function is used for *FPathMerge.*

We first generate the FSA that corresponds to the regular expression *R=PRE*.RelatedTo**, see Figure 13. The FSA has two states S1 and S2. The state S1 is the initial state and expands to *Pre* and *RelatedTo* metalinks, therefore, *Expand*(S1)={*Pre*, *RelatedTo*}. The state S2 expands to *RelatedTo* metalink, therefore, *Expand*(S2)={*RelatedTo*}. If the current state S_v is S1 then the next state S_w for *RelatedTo* metalink is S2, S_w=*NextSate*(*RelatedTo*, S1)=S2. The following table shows the next states for the regular expression $R=PRE^*.RelatedTo^*$.

Table A3.1: The next states for the regular expression *R=PRE*.RelatedTo*

Current State S_v	Metalink Type	Next Sate S_w
S1	*Pre*	S1
S1	*RelatedTo*	S2
S2	*RelatedTo*	S2

Since X={T1}, *PossibleOutput*={<T1, 0.9, S1>} and X^+={}. Note that the *RelatedTo* metalink type is LHS decomposable. In the first iteration, topic T1 is removed from *PossibleOuput*.

Expand(T1.State=S1)={*Pre*, *RelatedTo*}, therefore, the algorithm search for <T1, *Pre*> and <T1, *RealtedTo*> in MIndex table. For the *RelatedTo* metalink, Topic T2 has a path T1.T2, obtained using the metalink T1(0.9)$\rightarrow^{RT(0.6)}$ T2 (0.8), and its derived importance value is Imp_d(T2,*RelatedTo*)= 0.9 * 0.6 * 0.8 = 0.43 < Vt. Therefore, the triplet for topic T2 will be not added into *PossibleOutput.* For the *Pre* metalink, Topic T3 and T4 have path T1.T3 and T1.T4, obtained using the metalink T1(0.9)$\rightarrow^{Pre(0.95)}$ T3 (0.85) with Imp_d(T4,*Pre*)= 0.73 > Vt and T1(0.9)$\rightarrow^{Pre(0.9)}$ T4 (0.95) with Imp_d(T4,*Pre*)= 0.77 > Vt, respectively. Therefore, the triplets <T3,0.73, *NextState*(*Pre*,S1)=S1> and <T4,0.77, *NextState*(*Pre*,S1)=S1> will be added into *PossibleOutput.* After the first iteration, X^+={<T1,0.9>} and *PossibleOutput* = {<T3, 0.73, S1 >, <T4, 0.77, S1>}. In the second iteration, the triplet for topic T3 will be removed from *PossibleOuput* and will be added into X^+. There is *Pre* metalink T3T4 $\rightarrow^{Pre}$ T5 but T4 is not in X^+, therefore, it will be not processed. After the second iteration X^+={<T1,0.9>,<T3, 0.73>} and *PossibleOutput* = {<T4, 0.77, S1>}. In the third iteration, the triplet for topic T4 will be

removed from *PossibleOuput* and will be added into X^+. There is *Pre* metalink T3T4(0.75) $\rightarrow^{Pre(0.9)}$ T5(0.7) and both T3 and T4 are in X^+ but with Imp_d(T5,*Pre*)= 0.47 < Vt. Therefore, the triplet for topic T5 will be not added into *PossibleOutput*. After the third iteration X^+={<T1,0.9>,<T3, 0.73>,<T4,0.77>} and *PossibleOutput* is empty. Therefore, the algorithm terminates and the output of the closure operator is {<T1,0.9>, <T3, 0.73>,<T4,0.77>}.

APPENDIX 4. TOP-K-BASED CLOSURE ALGORITHM

Top-k-TClosure(R,X,k, *MIndex, HNode*)

Input: regular expression R, Input topics X, k, metalink index table *MIndex*, hypernode table *HNode*

Output: top-k topics in X^+

1. Generate the FSA that corresponds to the regular expression R;
2. $X^+ := \Phi$; *PossibleOutput*:= Φ; i:=1; S := The starting state in the FSA;
3. Compute the initial top-k topics (those with the k highest Imp_d values) from X **and for** each topic t **do** add the triplet <t.Tid, Imp_d(t):=*Imp*(t), t.state:=S> into *PossibleOutput* ;
4. **while** i < k **do**
5. { Remove triplet *tr* := <t_v.Tid, $Imp_d(t_v)$, S_v> with the maximum Imp_d from *PossibleOutput* ;
6. **if** (triplet *tr* $\notin X^+$) **then {**Add triplet *tr* into X^+; i:=i+1;}
   //*Steps 7-20: Process all metalinks emanating from topic t_v*
7. **for** each metalink type M$\in$Expand(S_v) **do**
8. { S_w := *NextState*(S_v,M);
9. **for** each metalink t_v.Tid $\rightarrow^M$ t_w.Tid in *MIndex* **do**
10. { $Imp_d(t_w) := Imp_d(t_v) * Imp(M) * Imp(t_w)$;
11. Let t_{min} be a topic whose triplet in *PossibleOutput* has the minimum Imp_d;
12. **if** ($Imp_d(t_w) > Imp_d(t_{min})$) **then**
13. { **if** (there exists a triplet tr_w with key <t_w.Tid, S_w> in X^+) **then**
        discard topic t_w;
14. **else if** (there exists a triplet tr_w with key <t_w.Tid, S_w> in *PossibleOutput*) **then**
15. { **if** ($Imp_d(tr_w) < Imp_d(t_w)$) **then**
        update triplet tr_w with $Imp_d(tr_w) := Imp_d(t_w)$;}
16. **else**{ Add triplet <t_w.Tid, $Imp_d(t_w)$, S_w> into *PossibleOutput*;}}}
    //*Handling HyperNodes*
17. **for** each pair <TidList, NTid> in *HNode*(t_v.Tid).NodeList **do**
18. **if** (for each topic t with t.Tid $\in$TidList, there exists a triplet with key <t.Tid,S_v> in X^+)
19. **then for** each metalink NTid$\rightarrow^M$ t_w.Tid in *MIndex* **do**
        //*Process metalinks of type M emanating from node Ntid*
20. {Perform steps 10-16 with t_v.Tid:=NTid and $Imp_d(t_v) := GAVG(\{t_n\}: t_n \in TidList)$;}}}}}

21. Return X^+;

Example A4.1. We use the MIndex instance in Table II. Also, assume that we want to compute the topic closure for the set X={T1} with top-k threshold k=3 using the regular expression $R=PRE^*.RelatedTo^*$. Also, assume that the average function is used for *FPathMerge.*

We first generate the FSA that corresponds to the regular expression *R=PRE*.RelatedTo**, see Figure 13 and Table A3.1. Next, algorithm computes the initial top-k topics from input topics X. Since X={T1}, *PossibleOutput*={<T1, 0.9, S1>} and X^+={}. In the first iteration, topic T1 has the highest Imp_d, therefore, its triplet is removed from *PossibleOuput* and is added into X^+. *Expand*(T1.State=S1) = {*Pre*, *RelatedTo*}, therefore, the algorithm search for <T1, *Pre*> and <T1, *RealtedTo*> in MIndex table. For the *Pre* metalink, Topic T3 and T4 have the metalinks T1(0.9)$\rightarrow^{PRE(0.95)}$ T3 (0.85) with Imp_d(T4,*Pre*)= 0.73 and T1(0.9)$\rightarrow^{PRE(0.9)}$ T4 (0.95) with Imp_d(T4,*Pre*)= 0.77 , respectively. Therefore, the triplets <T3,0.73, *NextState*(*Pre*,S1)=S1> and <T4,0.77, *NextState*(*Pre*,S1)=S1> will be added into *PossibleOutput.* For the *RelatedTo* metalink, Topic T2 has a path T1.T2, obtained using the metalink T1(0.9)$\rightarrow^{RT(0.6)}$ T2 (0.8) with Imp_d(T2,*RelatedTo*)= 0.43. Topic T2 can not be in the top-3 topics because its Imp_d is less that that for T1, T3, and T4. Therefore, its triplet will not be added into *PossibleOutput.* After the first iteration, X^+={<T1,0.9>} and *PossibleOutput* = {<T3, 0.73, S1 >, <T4, 0.77, S1>}. In the second iteration, topic T4 has the highest Imp_d, therefore, the triplet for the topic T4 will be removed from *PossibleOuput* and will be added into X^+. There is *Pre* metalink T3T4 $\rightarrow^{Pre}$ T5 but T3 is not in X^+, therefore, it will be not processed. After the second iteration X^+={<T1,0.9>,<T4, 0.77>} and *PossibleOutput* = {<T3, 0.73, S1>}. In the third iteration, the topic T3 has the highest Imp_d, therefore, its triplet will be removed from *PossibleOuput* and will be added into X^+. In this iteration, all top-k topics are found. Therefore, the algorithm terminates and the output of the closure operator is {<T1,0.9>, <T4, 0.77>,<T3,0.73>}.