Efficient XML Keyword Search based on DAG-Compression

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Abstract—In contrast to XML query languages as e.g. XPath which require knowledge on the query language as well as on the document structure, keyword search is open to anybody. As the size of XML sources grows rapidly, the need for efficient search indices on XML data that support keyword search increases. In this paper, we present an approach of XML keyword search which is based on the DAG of the XML data, where repeated substructures are considered only once, and therefore, have to be searched only once. As our performance evaluation shows, this DAG-based extension of the set intersection search algorithm [1], [2], can lead to search times that are on large documents more than twice as fast as the search times of the XML-based approach. Additionally, we utilize a smaller index, i.e., we consume less main memory to compute the results.

Index Terms—Keyword Search, XML, XML compression, DAG

I. INTRODUCTION

A. Motivation

The majority of the data within the internet is available nowadays in form of tree-structured data (i.e. HTML, XML or 'XML dialects'). When searching for certain information in huge document collections, the user typically (1) has no knowledge of the structure of the document collection itself and (2) is a non-expert user without any technical knowledge of XML or XML query languages. These requirements are met by XML keyword search where the user specifies the searched information in form of a list of keywords (i.e., neither knowledge of the document structure nor of any specific query language is required) and document fragments are returned that contain each keyword of the specified keyword list. For this purpose, the need for efficient keyword search approaches on XML data is high.

B. Contributions

Our paper presents IDCluster, an approach to efficient keyword search within XML data that is based on a DAG representation of the XML data, where repeated substructures exist only once and therefore have to be searched only once. IDCluster combines the following features and advantages:

- Before building the index, IDCluster removes redundant sub-trees and splits the document into a list of so-called redundancy components, such that similar sub-trees have to be indexed and searched only once.
- For keyword search queries where parts of the results are contained partially or completely within repeated sub-trees, the DAG-based keyword search outperforms the XML keyword search by a factor of more than two on large documents, whereas it is comparably fast for keyword search queries where all results occur in sub-trees that exist only once within the document.

To the best of our knowledge, IDCluster is the first approach that shows these advantages.

C. Paper organization

The rest of the paper is organized as follows. Section II introduces the underlying data model and presents the ideas of the set intersection keyword search algorithm [1][2] on which our approach is based. Section III presents our adaptation of the ideas of Zhou et al. to build the index based on the document’s DAG instead of the document’s tree in order to avoid repeated search within identical structures. Section IV contains the performance evaluations, Section V discusses the advantages of our approach to already existing approaches, and finally, section VI concludes the paper with a short summary.

II. PRELIMINARIES

A. Data model

We model XML trees as conventional labeled ordered trees. Each node represents an element or an attribute, while each edge represents a direct nesting relationship between two nodes. We store a list of all keywords \( k_n \) contained in the element name or attribute name respectively, or in any text value for each node \( n \). Thereby, we tokenize each text label into keywords at its white-space characters. E.g., a node with label "name" and text value "Tom Hanks" is split into the three keywords \( name \), \( Tom \) and \( Hanks \). The keywords in \( k_n \) are called directly contained keywords of \( n \). Keywords that are directly contained in a descendant of \( n \) are called indirectly contained keywords of \( n \). Keywords that are either directly or indirectly contained in \( n \) are called contained keywords of \( n \). Furthermore, we assign each node its pre-order traversal number assigned as ID. Fig. I shows a sample XML tree. The ID of each node is written top left next to it. The element or attribute name is given inside the node’s ellipse, while the text values are given below.
B. Query semantics

In the last decade, different search goals for XML keyword search queries have been proposed. These search goals form subsets of the common ancestor (CA) nodes. For a query \( Q \), the set of common ancestors \( \text{CA}(Q) \) contains all nodes that contain every keyword of \( Q \). For the given query \( Q_{ex} = \{ \text{USA}, \text{English} \} \) and the example tree of Fig. 1, the common ancestors are \( \text{CA}(Q_{ex}) = \{ 1, 2, 4, 5, 11, 12 \} \). The two most widely adopted CA subsets are the smallest lowest common ancestor (SLCA) and the exclusive lowest common ancestor (ELCA). All nodes in \( \text{CA}(Q) \) that do not have descendants in \( \text{CA}(Q) \) are in \( \text{SLCA}(Q) \), e.g., \( \text{SLCA}(Q_{ex}) = \{ 5, 12 \} \). A node \( n \) is in \( \text{ELCA}(Q) \), when \( n \) contains each keyword of \( Q \) outside of each subtree of a descending CA node of \( n \), e.g., \( \text{ELCA}(Q_{ex}) = \{ 2, 5, 12 \} \). Node 2 is in \( \text{ELCA}(Q_{ex}) \), because when we would remove node 5 (which is CA) and its descendants, node 2 still contains both keywords: USA in node 9 and English in node 10. Note that the given definitions imply \( \text{SLCA}(Q) \subseteq \text{ELCA}(Q) \subseteq \text{CA}(Q) \).

C. IDLists

This paper’s algorithm is based on the set intersection keyword search algorithm FwdSLCA and its modifications as proposed by Zhou et al. [1], [2].

Zhou et al. use IDLists as an index to efficiently perform keyword search. An IDList is an inverted list of nodes that contain (directly or indirectly) a certain keyword. For each node \( n \) the IDList provides three values: The ID of \( n \), the position of \( n \)'s parent inside the IDList named PIDPos, and the number \( N_{\text{Desc}} \) of nodes within \( n \)'s subtree directly containing the keyword. IDLists are sorted by ID. Fig. 2 shows the IDLists \( L_{USA} \) and \( L_{English} \) of the keywords USA and English respectively. IDLists can be easily generated by a single pass through the document.

D. Search

The general idea is to use set intersection on the IDLists of the query keywords to find CA nodes. The found CA nodes are then checked against the SLCA or ELCA semantics respectively to calculate the result set.

The basic SLCA search algorithm of [1], [2], FwdSLCA, uses the method \textit{fwdGetCA} to efficiently calculate all CA nodes in ascending order. This is done by maintaining pointers to the current position \( C_i \) in each IDList \( L_i \), selecting the highest ID of all \( C_i \), and binary searching for this ID in the remaining IDLists. Due to the ascending order, a CA node \( n \) is SLCA if and only if the next found CA node is not a child of \( n \). This can be checked using the IDList’s PIDPos value.

For checking the ELCA semantics, the algorithm BwdELCA uses an additional stack for storing two arrays for each visited node \( n \): One holds the \( N_{\text{Desc}} \) values of \( n \), the other holds the accumulated \( N_{\text{Desc}} \) values of \( n \)'s CA children. As soon as every CA child of \( n \) has been found, the differences of those two arrays indicate whether \( n \) is ELCA or not.

Beside FwdSLCA, two more SLCA search algorithms based on set intersection are proposed in [1], [2]: The algorithm BwdSLCA finds CA nodes in reversed order, and as a result can efficiently skip ancestors of CA nodes (note that ancestors of CA nodes by definition never can be SLCA). The algorithm BwdSLCA+ additionally improves the binary search required for CA calculation by shrinking the search space. The shrinkage is based on the parent position information given by the PIDPos value.

For FwdELCA, one alternative is proposed: The algorithm BwdELCA finds CA nodes in reversed order and shrinks the binary search space like BwdSLCA+. The ancestor skipping introduced in BwdSLCA cannot be implemented for ELCA search since inner nodes can be an ELCA too.

III. OUR APPROACH

The algorithm described in section II-D is not redundancy-sensitive, i.e., whenever there are repeated occurrences of the same sub-tree, these occurrences are searched repeatedly. However, the goal of our approach is to follow the idea of DAG-based compression approaches and to exploit structural redundancies in order to perform faster keyword search. This is done by splitting the original XML tree into disjoint redundancy components. A redundancy component is a subgraph...
of the original tree which occurs more than once within the tree. We then search each redundancy component only once and combine the results to get the complete result set, i.e., the same result as if we had performed the search based on the tree and not based on the DAG.

A. Index

Our index is called IDCluster. It contains the IDLists for each redundancy component and the redundancy component pointer map (RCPM) which is used for combining the results of redundancy components. The IDCluster is generated in two passes through the document.

The first pass is an extended DAG compression where nodes are considered as being identical when (a) they directly contain the same keywords and (b) all children are identical. When a node \( n' \) is found which is identical to a node \( n \) found earlier, node \( n' \) is deleted and the edge from its parent \( \text{parent}(n') \) to \( n' \) is replaced by a new edge from \( \text{parent}(n') \) to \( n \). This new edge is called an offset edge and contains the difference between the IDs of \( n' \) and \( n \) as an additional integer value. The information contained in offset edges will later be used to recalculate the original node ID of \( n' \). Furthermore, for each node, we store the \( \text{OccurrenceCount} \) which indicates the number of identical occurrences of this node. Fig. 3 shows the XML tree after the first traversal. The nodes with a white background have an \( \text{OccurrenceCount} \) of 1, while nodes with a grey background have an \( \text{OccurrenceCount} \) of 2. E.g., node 5 is identical to node 12 in the original tree. Hence node 12 is deleted and implicitly represented by node 5 and an offset edge on its path with the offset +7. Node 5 has an \( \text{OccurrenceCount} \) of 2, which indicates that node 5 now represents two nodes of the original tree.

![Fig. 3. DAG compressed XML tree after the first traversal.](image)

In the second pass, the \( \text{OccurrenceCount} \) values are used for selecting redundancy components: Each connected component consisting only of nodes with the same \( \text{OccurrenceCount} \) is selected as a redundancy component. (The redundancy component furthermore includes additional dummy nodes which represent nested redundancy components and are introduced below.) Identifying redundancy components and constructing their IDLists can be done easily in a single document traversal utilizing the \( \text{OccurrenceCount} \). For each redundancy component, a distinct set of IDLists is created. Each IDList entry for nodes belonging to a redundancy component \( rc \) is stored in the set of IDLists for \( rc \). The IDLists also include additional entries that represent nested redundancy components. These additional entries, called dummy nodes, have the same ID as the root node of the represented nested redundancy component \( rc_{\text{nested}} \) and are only added to IDLists of keywords contained in \( rc_{\text{nested}} \). Fig. 4 shows the IDLists created for the keywords USA and English. Dummy nodes are the entries at the positions 2 and 4 in \( L^{rc0} \) USA and positions 2 and 4 in \( L^{rc0} \) English.

![Fig. 4. Created IDLists for the keywords USA and English as part of an IDCluster.](image)

The dummy nodes are added to the redundancy component pointer map (RCPM). The key of each entry in the RCPM is the ID of the respective dummy node. Each entry contains the identifier of the redundancy component which the dummy node is representing and an offset. The offset is given by the offset edge between \( rc \) and \( rc_{\text{nested}} \), or +0 if the edge between \( rc \) and \( rc_{\text{nested}} \) is not an offset edge. Fig. 5 shows the RCPM of the IDCluster. Note that only one RCPM is required, no matter how many keywords are indexed.

![Fig. 5. Created redundancy component pointer map (RCPM) as part of an IDCluster.](image)

B. Search

1) SLCA computation: The main idea for SLCA computation is to utilize the base algorithms for searching each redundancy component individually. Due to the additionally added dummy nodes, any SLCA which is found in a redundancy component and is not a dummy node, is also SLCA in the original tree. SLCA, which are dummy nodes, indicate that more SLCA are inside the redundancy component, which the dummy node is representing. This way, all redundancy components containing SLCA can be searched dynamically.
starting at the root redundancy component. The offset values stored in the RCPM are used for recalculating the original ID of SLCA contained in nested redundancy components.

The basic search algorithm for IDCluster is an extension of FwdSLCA [2] and is depicted in Fig. 6. The algorithm starts searching in the redundancy component with the ID 0, which by definition is the redundancy component containing the document’s root node. In lines [14][17] the procedure DagFwdSLCA performs an SLCA search similar to FwdSLCA on one redundancy component. In lines [12][23] the results from this redundancy component are processed. To check whether an SLCA is a dummy node, the SLCA is looked up in the RCPM in line [16]. If the SLCA is a dummy node, the SLCA is looked up in the SLCA list in lines [21][23]. Note that in line 21 the dummy node is deleted from the SLCA list by replacing it with an actual SLCA contained in the nested redundancy component. The only exception to this proceeding is when the SLCA list contains only the root node of the current redundancy component. This is a special case since an RCPM lookup would return dummy node information (the dummy node and the root node of the nested redundancy component have the same ID) and cause an infinite loop.

If we consider our example, a search for the keywords USA and English starts with the call of the main algorithm for the root redundancy component $r_0$. In lines [12][23] node 4 and node 11 are calculated as the SLCA results for this redundancy component. In the first iteration of the loop in lines [14][23] node 4 is identified as a dummy node (line [16]). As there are no results yet for the nested redundancy component, $r_{c_1}$ is searched recursively now. In $r_{c_1}$, the only SLCA result is node 5. Since node 5 is not found in the RCPM (line [16]), the SLCA result list for $r_{c_1}$ remains unchanged and the recursive call terminates. Back in the parenting recursion for $r_{c_0}$, inside the SLCA result list, the dummy node 4 is replaced with the first result of the nested redundancy component, increased by the offset, 5+0=5 in line [21]. Since no more SLCA results exist in $r_{c_1}$, the loop in lines [22][23] is skipped. In the next iteration of the outer loop, node 11 is identified as a dummy node in line [16]. The nested redundancy component is once again $r_{c_1}$, for which at this point results already exist. Therefore, $r_{c_1}$ is not searched again and the dummy node is replaced by the SLCA result from $r_{c_1}$ increased by the offset given by the RCPM, 5+7=12. At this point, the outer loop terminates, and with it, the algorithm terminates, while the SLCA result list for $r_{c_0}$ contains node 5 and node 12 as the final result.

One advantage of this approach is that the algorithm given by Zhou et al. is integrated as unmodified module. This means our approach will benefit from any improvements made to the base algorithm, like the parent skipping introduced in BwdSLCA or the improved binary search introduced in BwdSLCA+.

1: \text{DagFwdSLCA}(IDCluster,0)
2: \text{procedure} \quad \text{DagFwdSLCA}(IDCluster, rc_{cur})
3: \quad IDLists \leftarrow IDCluster.getIDLists(rc_{cur})
4: \quad \text{while } \neg \text{Eol}(IDLists) \text{ do}
5: \quad \quad v \leftarrow \text{FwdGetCA}(IDLists)
6: \quad \quad \text{if } v \neq \text{null} \text{ then}
7: \quad \quad \quad \text{if } u \neq \text{null } \land v.\text{parent} \neq u \text{ then}
8: \quad \quad \quad \quad \text{SLCA}[rc_{cur}].\text{add}(u)
9: \quad \quad \quad u \leftarrow v
10: \quad \quad \quad \text{ADVANCE(IDLists)}
11: \quad \quad \quad \text{if } u \neq \text{null} \text{ then } \text{SLCA}[rc_{cur}].\text{add}(u)
12: \quad \quad \quad \text{if } \text{SLCA}[rc_{cur}][0] = IDLists[0].\text{getId}(0) \text{ then return}
13: \quad \quad \quad \text{size} \leftarrow \text{SLCA}[rc_{cur}].\text{size}
14: \quad \quad \quad \text{for } i = 0, \text{size do}
15: \quad \quad \quad \quad s\text{lca} \leftarrow \text{SLCA}[rc_{cur}][i]
16: \quad \quad \quad \quad \text{if } s\text{lca} \in IDCluster.RCPM \text{ then}
17: \quad \quad \quad \quad rc_{nes} \leftarrow IDCluster.getPointer(slca)
18: \quad \quad \quad \quad os \leftarrow IDCluster.getOffset(slca)
19: \quad \quad \quad \quad \text{if } \neg \text{done}[rc_{nes}] \text{ then}
20: \quad \quad \quad \quad \text{DagFwdSLCA}(IDCluster, rc_{nes})
21: \quad \quad \quad \quad \text{SLCA}[rc_{cur}][i] \leftarrow \text{SLCA}[rc_{nes}][0] + os
22: \quad \quad \quad \quad \text{for each } s\text{lca}_{nes} \in \text{SLCA}[rc_{nes}] \setminus \text{SLCA}[rc_{nes}][0] \text{ do}
23: \quad \quad \quad \quad \text{SLCA}[rc_{cur}].\text{add}(s\text{lca}_{nes} + os)
24: \quad \quad \quad \text{done}[rc_{cur}] \leftarrow \text{true}
25: \quad \quad \text{end procedure}
26: \text{function} \quad \text{Eol(IDLists)}
27: \quad \text{for each } IDList \in IDLists \text{ do}
28: \quad \quad \text{if } IDList.C_i \geq IDList.length \text{ then}
29: \quad \quad \quad \text{return} \text{true}
30: \quad \quad \text{return} \text{false}
31: \text{end function}
32: \text{procedure} \quad \text{ADVANCE(IDLists)}
33: \quad \text{for each } IDList \in IDLists \text{ do}
34: \quad \quad IDList.C_i \leftarrow IDList.C_i + 1
35: \text{end procedure}

Fig. 6. Alternative SLCA search algorithm for redundancy components

2) ELCA computation: ELCA search can be implemented in a similar manner, which is shown in Figure 7. Lines [3][13] are similar to the algorithm given by Zhou et al. [2]. The following lines are adopted from the DagFwdSLCA algorithm. Note that a redundancy component can contain multiple ELCA, even when the root is ELCA. So, if the first ELCA is the root, the first ELCA is just skipped in line [16] instead of aborting the whole function call as in DagFwdSLCA.

In a search for USA and English, the ELCA nodes found in $r_{c_0}$ are 2, 4 and 11. Node 2 is not in the RCPM and therefore a final ELCA. Node 4 is a dummy node and forces a search in $r_{c_1}$. The ELCA list in $r_{c_1}$ contains node 5 only. Therefore, node 4 in the ELCA list of $r_{c_0}$ is replaced with 5 plus the offset 0. Node 11 is also a dummy node pointing to $r_{c_1}$. Since $r_{c_1}$ was already searched, node 11 in the ELCA list of $r_{c_0}$ is replaced with 5 plus the offset 7. Therefore, the final ELCA results are 2, 5, and 12.

IV. Evaluation

To test the performance of this paper’s algorithms, comprehensive experiments were run. The experiments focus on the comparison between the base algorithms and their respective DAG variants introduced in this paper. An evaluation of
the base algorithms showing their superior performance in comparison to other classes of keyword search algorithms can be found in the original papers [1][2].

A. Setup

All experiments were run on a Xeon E5-2670 with 256GB memory and Linux OS. The algorithms were implemented in Java 1.6.0_24 and executed using the OpenJDK 64-Bit Server VM. The time results are the averages of 1,000 runs with warm cache.

The XML version of the music database discogs.com1 is used as testdata. It contains 4.2 million records of music releases of a size of 12.6GB. To evaluate the effects of different database sizes, smaller file sizes are created by successively removing the second half of the set of all remaining records. Thereby, additional databases having the sizes of 0.8GB/1.6GB/3.3GB/6.5GB are created.

For the evaluation, 3 categories of queries are proposed:

• Category 1: Queries consisting of nodes that will not be compressed in a DAG. DAG-based algorithms cannot exploit these kinds of queries. Since the DAG-based algorithms still need time for verifying the absence of RC-Pointers (nodes with entries in the RCPM), they should have worse performance than the base algorithms.

• Category 2: Queries consisting of nodes that will be compressed in a DAG, but having common ancestors (CA) which still cannot be compressed. This means that all results will be in the first redundancy component. DAG-based algorithms can exploit the fact that the IDLists for the first redundancy can be shorter than the IDLists for the base algorithms. On the other hand, the absence of all RC-Pointers still has to be verified. These advantages and disadvantages might cancel each other depending on the situation.

• Category 3: Queries with results that can be compressed in a DAG. This means that there has to be at least a second redundancy component containing all keywords. DAG-based algorithms should have a better performance than the base algorithms for queries from this category.

Queries of different lengths for all categories are selected randomly using the 200 most frequent keywords. The selected queries are shown in Table I. Table II shows the properties of these queries. The columns CA, ELCA and SLCA show the total number of CA-, ELCA- or SLCA-nodes respectively. The columns \(S_{ca}\), \(S_{elca}\) and \(S_{slca}\) show the savings by DAG compression, e.g. a total number of 100 CA and 80% CA savings imply that 20 CA are left in the XML tree after DAG compression. The properties of the used keywords can be found in Table III. The column nodes shows the number of nodes directly containing the respective keyword; the column path shows the number of nodes directly or indirectly containing the keyword. The columns \(S_{nodes}\) and \(S_{path}\) accordingly show the compression savings.

1 http://www.discogs.com/data/

**Table I**

| query | category | length | keywords                  |
|-------|----------|--------|---------------------------|
| Q1    | 1        | 2      | image uri                 |
| Q2    | 3        | 3      | image uri release         |
| Q3    | 4        | 4      | image uri release identifiers |
| Q4    | 2        | 2      | vinyl electronic          |
| Q5    | 3        | 3      | vinyl electronic 12"      |
| Q6    | 4        | 4      | vinyl electronic 12" uk   |
| Q7    | 2        | 2      | description rpm           |
| Q8    | 3        | 3      | description rpm 45        |
| Q9    | 4        | 4      | description rpm 45 /      |

**Table II**

| query | CA   | \(S_{ca}\) | ELCA | \(S_{elca}\) | SLCA | \(S_{slca}\) |
|-------|------|-------------|------|--------------|------|--------------|
| Q1    | 14818739 | 0%        | 7697608 | 0%        | 7697603 | 0%        |
| Q2    | 3560569 | 0%        | 3560568 | 0%        | 3560567 | 0%        |
| Q3    | 1299279 | 0%        | 1299278 | 0%        | 1299277 | 0%        |
| Q4    | 824063 | 0%        | 824062  | 0%        | 824060  | 0%        |
| Q5    | 619691 | 0%        | 619690  | 0%        | 619690  | 0%        |
| Q6    | 207865 | 0%        | 207864  | 0%        | 207863  | 0%        |
| Q7    | 3438507 | 78%       | 709713  | 98%       | 709713  | 98%       |
| Q8    | 2389299 | 78%       | 486003  | 98%       | 486003  | 98%       |
| Q9    | 1307891 | 73%       | 328419  | 99%       | 328419  | 99%       |

**Table III**

| query | CA   | \(S_{ca}\) | ELCA | \(S_{elca}\) | SLCA | \(S_{slca}\) |
|-------|------|-------------|------|--------------|------|--------------|
| Q1    | 14818739 | 0%        | 7697608 | 0%        | 7697603 | 0%        |
| Q2    | 3560569 | 0%        | 3560568 | 0%        | 3560567 | 0%        |
| Q3    | 1299279 | 0%        | 1299278 | 0%        | 1299277 | 0%        |
| Q4    | 824063 | 0%        | 824062  | 0%        | 824060  | 0%        |
| Q5    | 619691 | 0%        | 619690  | 0%        | 619690  | 0%        |
| Q6    | 207865 | 0%        | 207864  | 0%        | 207863  | 0%        |
| Q7    | 3438507 | 78%       | 709713  | 98%       | 709713  | 98%       |
| Q8    | 2389299 | 78%       | 486003  | 98%       | 486003  | 98%       |
| Q9    | 1307891 | 73%       | 328419  | 99%       | 328419  | 99%       |
B. Experiment I: Category

In the first experiment, the performance of the base algorithm FwdSLCA is compared to the DAG-based algorithm DagFwdSLCA. Database size and query length are fixed, while the category is altered. The results are shown in Fig. 8.

The results confirm that in Category 1, the performance of the DAG-based algorithm is a bit worse than the performance of the base algorithm. This is as expected, since there are no redundancies which can be exploited by a DAG-based algorithm, but the DAG-based algorithm has a certain overhead for verifying that no further redundancy components needs to be searched, resulting in a worse performance. In Category 2, the performance of both algorithms is very similar with the base algorithm being slightly faster. The better relative performance of the DAG-based algorithm can be traced back to the IDLists being shorter than the IDLists used in the base algorithm. Finally, in Category 3, the DAG-based algorithm is more than twice as fast as the base algorithm.

C. Experiment II: Query length

In this experiment, the length of the queries is modified. Fig. 9 shows the results for categories 1 and 3 with a fixed database size.

The general tendency is the same: The base algorithm is a bit better for Category 1 queries, while the DAG-based algorithms are better for Category 3 queries. The Category 1 results suggest that the gap between both algorithms get smaller the more keywords are used. This is plausible, since the overhead for the DAG-based algorithms depends on the amount of results. Adding more keywords to a query can reduce the amount of results, but never increase it (see Table III).

D. Experiment III: Database size

The third experiment examines the effects of database size and is shown in Fig. 10 for Category 1 and Category 3 with a fixed query length.

The exponential growth of the database size leads to an exponential growth in the search time for both algorithms. Minor changes in the proportions between both algorithms can be traced back to minor changes in the keyword frequencies and compression savings. Therefore, the database size seems not to have a direct impact on the performance ratio between base algorithm and DAG-based algorithm.

E. Experiment IV: Algorithm

In the last experiment, algorithms FwdSLCA, BwdSLCA+, FwdELCA and BwdELCA as proposed by Zhou et al. are compared to their DAG-based variants. Database size and query length are fixed.

For Category 1, the DAG-based algorithms always have a small overhead independent of the algorithm. In Category 3, the relative difference is smaller for backward algorithms, but still significant. Backward search performs generally better than forward search of the same type. The only exceptions are the DAG-based variants of FwdSLCA and of BwdSLCA+.
in Category 3. The backward algorithm is actually slower. This result suggests that a major part of the speedup in BwdSLCA+ is generated by parent skipping. Due to the DAG compression, every case in which parent skipping provides benefits are already optimized.

F. Index Size

The size of the IDCluster differs from the size of IDLists in two aspects. On the one hand, additional space is required for storing the RCPM. On the other hand, less space is required for storing the IDLists due to DAG compression.

The RCPM can be stored in different ways which affect the required memory space and the time performance. In this evaluation, the RCPM is stored as an array containing the redundancy component identifier and the offset. The node ID is implicitly represented by the position in the array. The size of the array has to be big enough to contain all node IDs. This way of storing the RCPM is optimized for time performance.

The DAG compression strongly depends on the XML database used. The additionally created dummy nodes also have to be considered.

In a typical use case, both effects, additional memory for RCPM and reduced memory due to DAG compression, are likely to cancel each other.

In the Discogs database, the total amount of nodes in the IDLists index is 3.9 billion. Considering the 2 (3) integers per node required for performing an SLCA (ELCA) search and an integer size of 4 byte, the total IDLists index sums up to 28.7GB (43.0GB). The amount of nodes in an IDCluster is only 3.0 billion for the same database. Storing these nodes sums up to 22.5GB (33.7GB) for SLCA (ELCA) search. However, storing the RCPM in an array as described above (with redundancy component identifier and offset both as 4 byte integer) for all 656 million distinct nodes requires an additional 4.9GB. So, the total memory required for the IDCluster is 27.3GB (38.6GB) for SLCA (ELCA) search.

V. RELATED WORK

There exist several approaches that address the problem of keyword search in XML. These approaches can be roughly divided into two categories: approaches that enhance the quality of the search results by considering the semantics of the queries on the one hand, and approaches that enhance the performance of the computation of the set of query results on the other hand.

Within the first category, XSEarch [3] presents a query semantics that returns only those XML fragments, the result nodes of which are meaningfully related, i.e., intuitively belong to the same entity. In order to check this, they examine whether a pair of result nodes has two different ancestor nodes that have the same label (e.g., two nodes with label “author”, s.th. the first keyword belongs to author1 and the second one to author2).

[4] not only focuses on an efficient, stack-based algorithm for keyword search based on inverted element lists of the node’s DeweyIDs, but also aims to rank the search results in such a way, that the user gets the (probably) most interesting results prior to the other results. SUITS [5] is a heuristics-based approach, and the approach presented in [6] uses probabilistic scoring to rank the query results. In order to enhance the usability, [7] and [8] propose an approach on how to group the query results by category.

Within the second category (efficient result computation) most approaches are based on finding a set of SLCA (or ELCA) nodes for all matches of a given keyword list.

Early approaches were computing the LCA for a set of given keywords on the fly. [9] proposes the meet-operator that computes the LCA for a pair of nodes that match two query strings without requiring additional knowledge on the document structure from the user.

In contrast, recent approaches try to enhance the query performance by using a pre-computed index. [10] proposes an extension of the XML query language XML-QL by keyword search. In order to speed-up the keyword search, it computes the so-called “inverted file” for the XML document – a set of inverted element lists – and stores the contents within a relational database.

[11] presents two approaches to compute the Meaningful Lowest Common Ancestor (MLCA), a concept similar to the SLCA considered in our approach. Its first approach allows computing the MLCA with the help of standard XQuery operations, whereas its second approach is a more efficient approach that is based on a stack-based algorithm for structural joins.

Similar to XRank [4] is the stack-based approach presented in [12]. In contrast to the previous stack-based approaches, the authors do not use the DeweyID to identify a node and to calculate the ancestor-descendant or even parent-child relationships, but they propose to use a combination of preorder position, postorder position, and depth of the node.

XKSearch [13] is an indexed-based approach to compute the LCA. They store inverted element lists consisting of DeweyIDs of the nodes. They start searching for the results at node n of the shortest relevant keyword list, and they check for the other keyword lists whether the node l being the next node to the left of n or the node r being the next node to the right of n.
has a smaller distance to \( n \). Then, they use \( n \) and the nearest node (\( i \) or \( r \)) to compute the LCA.

\[\text{IDCluster} \]

presents an anchor-based approach to compute the SLCA. From the set of current nodes of each relevant keyword list, they search the so-called anchor, i.e., that node that is closest to all current nodes. As soon as an anchor is identified, they try to exchange each node \( n_i \) of each other keyword list \( L_i \) by the next node \( \text{next}(n_i) \) of \( L_i \) in order to check, whether \( \text{next}(n_i) \) is closer to the anchor than \( n_i \) and whether \( \text{next}(n_i) \) defines a new anchor. Finally, the set of anchor nodes form the set of LCA candidates that do not have another LCA candidate child is then reduced to the set of SLCA nodes.

\[\text{JDeweyJoin} \]

returns the top-k most relevant results. They compute the results bottom-up by computing a kind of join on the list of DeweyIDs of the nodes in the inverted element list. Whenever they find a prefix that is contained in all relevant element lists, the node with this prefix as ID is a result candidate. In addition, they use a weight function to sort the list entries in such a way, that they can stop the computation after \( k \) results, returning the top-k most relevant results.

\[\text{IDCluster} \]

and \[\text{JDeweyJoin} \]

belong to the intersection-based approaches. They present a more efficient, but more space-consuming approach. The elements of their inverted element lists do not only contain the nodes that have the keyword as label, but also contain all ancestor-nodes of these nodes, and for each node, the inverted element lists contain the ID of the parent node. Therefore, they can compute the SLCA by intersecting the inverted element lists of the keywords and by finally removing each result candidate, the descendant of which is another result candidate.

Like the contributions of the second category, our paper focuses on efficient result computation. It follows the idea of the intersection-based approaches. However, different from all other contributions and similar to a prior approach \[\text{JDeweyJoin} \]

instead of computing an XML-index, we compute a DAG-Index. This helps to compute several keyword search results in parallel, and thereby speeds-up the SLCA computation. To the best of our knowledge, DAG-Index is the first approach that improves keyword search by using XML compression before computing the search index.

\[\text{ONCLUSIONS} \]

VI. CONCLUSIONS

We have presented IDCLCluster, an indexing and search technique that shares common sub-trees in order to index and to search redundant data only once.

As our performance evaluation shows, using the DAG-based index of IDCLCluster, the intersection-based keyword search algorithms can be significantly improved, i.e., gain a speed-up up to a factor of more than 2.

Therefore, we consider the idea to cluster repeated data collections to be a significant contribution to all applications that have to search in large data collections with high amounts of copied, backed-up or redundant data.

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