USING SEMANTICS IN XML QUERY PROCESSING

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CONTENTS

ABSTRACT

XML has become a standard data format for information representation and exchange. As more and more information is stored in XML format, how to query XML data efficiently becomes increasingly important.

In this thesis, we try to make use of semantics information, e.g., value, property, object and relationship among objects, to improve the efficiency of XML query processing. We focus on matching a twig pattern, which is considered the core pattern of XML queries, to an XML tree. We also show that our approach can be extended to handle queries with ID references and queries across multiple twig patterns in one or multiple documents. The main idea of our research is to capture such semantic information as value, property, object and relationship among objects, and incorporate relational tables as indexes to reflect the semantic information. During query processing, both proposed semantic tables and inverted lists that are adopted in existing twig pattern matching algorithms are used to achieve better performance.

In the first part of this thesis, we propose a novel twig pattern matching algorithm *VERT*, which solves the problems regarding values in existing twig pattern matching algorithms. In VERT we model a twig pattern query as two parts, structural search and content search, and use property-based relational tables and inverted lists to perform two types of searches separately during query processing. We show that our approach not only handles the problems in value management and content search (e.g., range search *price<50*) in other twig pattern matching approaches, but also improves query processing performance. Later, we propose three optimizations to further integrate object-based semantic information into the tables, to reduce the number of structural joins required to process a query. In these optimizations, we replace property tables by object/property or object tables, and introduce relationship tables to improve query processing. We demonstrate that using these optimizations, VERT can perform relevant queries even faster. Furthermore, our approach can efficiently process general queries joining several twig patterns and queries with ID references. This is because the semantic tables can easily link different twig patterns by value-based joins. Finally, after twig pattern matching, VERT can return actual values, instead of node labels as in other twig pattern matching approaches. Then we can remove duplicate answers under different labels, to make returned result more meaningful and readable.

Based on VERT, we propose two extensions to twig pattern query to enhance its expressivity and to support grouping and aggregation in queries.

The second part of the thesis studies the characteristics, i.e., the purpose (predicate or output), the optionality (required or optional) and the occurrence (one or many) of query nodes in a twig pattern query, based on which the query nodes are classified into six types. We focus on output information, and propose the *TP+Output* to extend the existing twig pattern query to explicitly express each type of output nodes. Using TP+Output, a query with complex output information can be expressed by fewer tree-structured query patterns, compared to the

number of query patterns in the original twig pattern query. By extending VERT to efficiently match TP+Output queries, naturally a query with a complex output can be solved by performing less structural joins than the exiting approaches using the original twig pattern query. As a result, the query processing performance can be improved. Furthermore, all advantages of VERT, e.g., efficiently processing content search and returning more meaningful and readable answers, can be inherited.

In the third part of the thesis, we propose an algorithm to physically perform grouping and aggregation in XML queries. Existing twig pattern query processing approaches can hardly be extended to support grouping and aggregation, because they normally return node labels rather than actual values as result. In our approach, we model such a query by separating its core query pattern from the grouping and aggregation operations. We use VERT algorithm to match query patterns to documents first. Since VERT can return value answers directly using semantic tables, the matching result is ready for any post-processing, e.g., grouping and aggregation computing. Finally, we design a recursive method to analyze nested and parallel grouping operations in the query, and perform grouping and aggregation over the intermediate result returned by VERT. Moreover, if the query pattern has complex output information, we can use TP+Output to model the query pattern and process, to improve performance.

After all, this thesis theoretically and experimentally demonstrates that using semantic information to process XML queries one can gain a lot of benefit in terms of efficiency. This result should be useful for future research and applications in XML query processing.

LIST OF PUBLICATIONS

The contents of this thesis are adapted from the following list of our publications:

- **Huayu Wu**, Tok Wang Ling, Bo Chen. "VERT: A Semantic Approach for Content Search and Content Extraction in XML Query Processing". *The 26th International Conference on Conceptual Modeling (ER), 2007* [137][1].

- Zhifeng Bao, **Huayu Wu**, Bo Chen, Tok Wang Ling. "Using Semantics in XML Query Processing". *The 2nd International Conference on Ubiquitous Information Management and Communication (ICUIMC), 2008* [7].

- **Huayu Wu**, Tok Wang Ling, Gillian Dobbie, Zhifeng Bao, Liang Xu. "Reducing Graph Matching to Tree Matching for XML Queries with ID References". *The 21th International Conference on Database and Expert Systems Applications (DEXA), 2010* [140]

- **Huayu Wu**, Tok Wang Ling, Bo Chen, and Liang Xu. "TwigTable: Using Semantics in XML Twig Pattern Query Processing". *Journal of Data Semantics (JoDS) XV, 2011* [138].

[1] The citation appears in the bibliography at the end of this thesis.

- **Huayu Wu**, Tok Wang Ling, Liang Xu, Zhifeng Bao. "Performing Grouping and Aggregate Functions in XML Queries". *The 18th International World Wide Web Conference (WWW), 2009* [141].

- **Huayu Wu**, Tok Wang Ling, Gillian Dobbie. "TP+Output: Modeling Complex Output Information in XML Twig Pattern Query". *The 7th International XML Database Symposium (XSym), 2010* [139].

Our other publications related to XML query processing and data semantics, but not included in this thesis, are listed as follows:

- Liang Xu, Tok Wang Ling, **Huayu Wu**, Zhifeng Bao. "DDE: From Dewey to a Fully Dynamic XML Labeling Scheme". *The ACM SIGMOD International Conference on Management of Data (SIGMOD) 2009* [150].

- Zhifeng Bao, Jiaheng Lu, Tok Wang Ling, Liang Xu, **Huayu Wu**. "An Effective Object-Level XML Keyword Search". *The 15th International Conference on Database Systems for Advanced Applications (DASFAA), 2010* [5]

- Liang Xu, Tok Wang Ling, Zhifeng Bao, **Huayu Wu**. "Efficient Label Encoding for Range-Based Dynamic XML Labeling Schemes". *The 15th International Conference on Database Systems for Advanced Applications (DASFAA), 2010* [148]

- **Huayu Wu**, Hideaki Takeda, Masahiro Hamasaki, Tok Wang Ling, Liang Xu. "An Adaptive Ontology-based Approach to Identify Correlation between Publications". *The 20th International World Wide Web Conference (WWW), 2011* [143].

- **Huayu Wu**, Tok Wang Ling, Zhifeng Bao, Liang Xu. "Object-Oriented

XML Keyword Search". *The 30th International Conference on Conceptual Modeling (ER), 2011* [136].

- Liang Xu, Tok Wang Ling, **Huayu Wu**. "Labeling Dynamic XML Documents: An Order-Centric Approach". *IEEE Transactions on Knowledge and Data Engineering (TKDE), 2011* [149].

- Ruiming Tang, **Huayu Wu**, Sadegh Nobari, Stephane Bressan. "Edit Distance between XML and Probabilistic XML Documents". *The 22th International Conference on Database and Expert Systems Applications (DEXA), 2011* [120].

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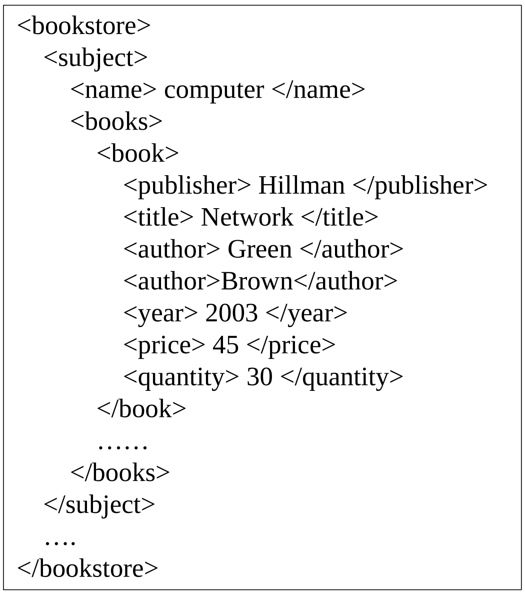
CHAPTER 1

INTRODUCTION

XML (eXtensible Markup Language) already becomes an important standard for data storage and exchange over the Internet. Similar to HTML (Hypertext Markup Language), XML has a tag-based structure; however, different from HTML, in an XML document, each start tag must have a corresponding end tag to enclose other nested tags and texts. Moreover, tags in HTML are predefined and only for formatting purpose, but XML tags are user-defined and also provide information. Consider a portion of an example XML document shown in Fig. 1.1. In this document, the tags not only form a hierarchical structure, but also describe the content of the document with meaningful tag labels. This property of XML data helps applications search for relevant XML documents or relevant content within an XML document more accurately.



```
<bookstore>
  <subject>
    <name> computer </name>
    <books>
      <book>
        <publisher> Hillman </publisher>
        <title> Network </title>
        <author> Green </author>
        <author>Brown</author>
        <year> 2003 </year>
        <price> 45 </price>
        <quantity> 30 </quantity>
      </book>
      ……
    </books>
  </subject>
  ….
</bookstore>
```

Figure 1.1: A portion of a *bookstore* XML document

1.1 Data Model

Normally an XML document is modeled as an ordered tree, due to the hierarchy formed by the nested tags in the document. Fig. 1.2 shows the tree structure representation of the bookstore document in Fig. 1.1. In an XML tree, the internal nodes represent the elements and attributes in the document, and the leaf nodes represent the data values. Thus a node name[1] is a tag label, an attribute name or a value. Edges in an XML tree reflect element-subelement, element-attribute, element-value, and attribute-value pairs. Two nodes connected by a tree edge are in parent-child (PC) relationship, and the two nodes on the same path are in ancestor-descendant (AD) relationship.

ID and IDREF are two important attribute types in XML. They can be likened to primary key and foreign key constraints in relational databases. Using ID/IDREF, an element can be stored with a unique ID, and be referred by other elements with

[1] It is also referred as node label. To distinguish from the structural label (discussed in Section 1.3) of each node, we use *node name* instead of *node label* to describe each document tree node.

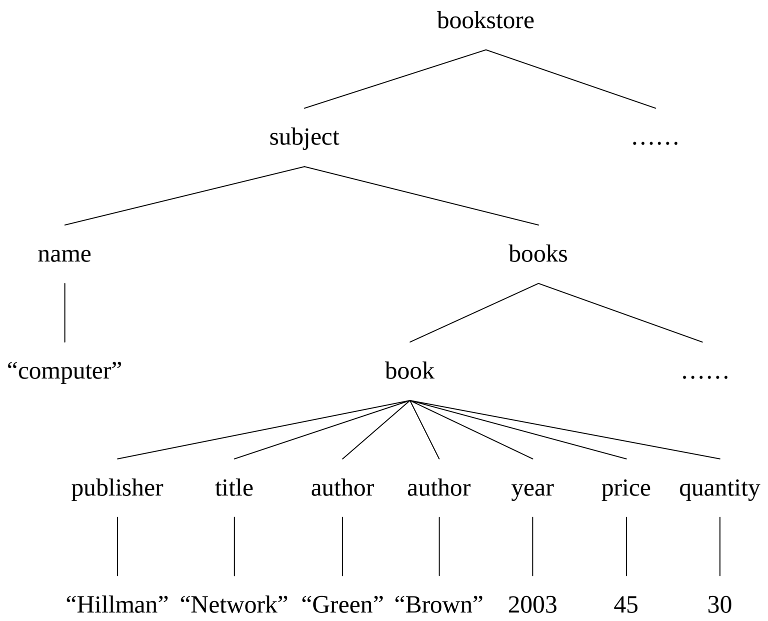


Figure 1.2: Tree structure representation of the *bookstore* document in Fig. 1.1

the same IDREF value. The use of ID/IDREF an effective way to reduce redundancy in XML data [93]. When we consider the references between ID values and IDREF values, an XML document is not in a tree structure any more, but in a special directed graph structure.

1.2 XML query

XML queries are classified into *structured queries* and *keyword queries*. Structured queries require a user to know the underlying structure of an XML database, to specify structural constraints (e.g., PC or AD constraints between query nodes, as introduced later) in a query. They are similar to SQL queries in relational databases. When a user is unaware of the structure of an XML database, he can only issue keyword queries to search for fuzzy result. This is similar to keyword search in IR area. In this thesis, we focus on structured XML query processing.

XPath [128] and XQuery [129] are two XML query languages developed and recommended by W3C Consortium, to compose structured queries. The core pattern of XPath and XQuery queries is called *twig pattern*, which is a small tree structure. How to efficiently match a twig pattern query to an XML document is considered a main operation for XML query processing. Now we describe how XML queries in XPath and XQuery are related to twig pattern matching.

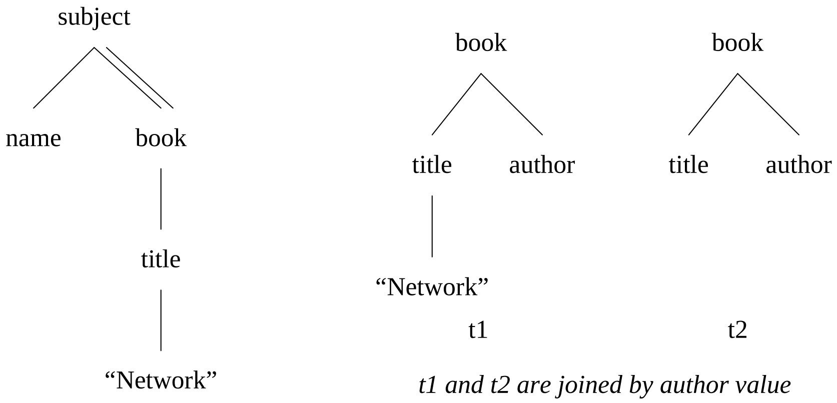
1.2.1 From XPath and XQuery query to twig pattern query

XPath is used to navigate through an XML document to find all substructures satisfying the constraints specified in the query expression, and return the value under or the subtree rooted at the output node. There are 13 axes in the XPath specification, among which *child* ("/") and *descendant* ("//") are most commonly used. An expression A/B (or A//B) denotes finding all nodes with name of B which is a child (or descendant) of a node with name of A, in an XML tree[2]. In other words, A and B must be in parent-child (or ancestor-descendant) relationship in the document tree.

The graphic representation of an XPath expression is normally a twig pattern. Consider an XPath query //subject[//book/title="Network"]/name to find to which subject the book with the title of "Network" belongs in the bookstore document shown in Fig. 1.2. This query can be represented as a twig pattern query shown in Fig. 1.3(a). As we see, similar to a document tree, a twig pattern query is also in a tree-like structure with all query nodes. However, different from the edges in a document tree, the edges in a twig pattern query can be either single-lined or double-lined, which correspond to the "/" and "//" (i.e., PC and AD) axes in the XPath expression.

Twig pattern can be used to model XPath queries with only child and descen-

[2] When we explain twig pattern queries in this section, we assume the tree model of XML data. This is because twig pattern query only works for tree-modeled XML documents.



(a) Twig pattern for XPath query

(b) Twig pattern for XQuery query

Figure 1.3: Twig patterns for example XPath and XQuery queries

dant axes. XPath queries with other reversible axes, i.e. *parent* and *ancestor* axes, can be transformed to an expression with child and descendant axes only [98, 8], and then be expressed as twig pattern queries. In this thesis, we focus on the structured XML queries that can be represented as twig pattern queries.

XQuery builds on XPath by introducing FLWOR (For-Let-Where-Order by-Return) constructs to make XML query more expressive for different purposes. For example, a query to find the title of all books written by some author of the book “Network” can be expressed by an XQuery expression as shown below:

```
FOR $a IN distinct-values(doc(“bookstore.xml”)//book[title=“Network”]/author)
RETURN
    <book>
    {
        FOR $b IN doc(“bookstore.xml”)//book
        WHERE $b/author = $a
        RETURN <title>$b/title</title>
    }
    </book>
```

To process this XQuery query, actually we need to match two twig patterns, which correspond to the two XPath expressions in the FOR clauses, to the bookstore document; and join the matching results from the two patterns as shown in Fig. 1.3(b). Generally, most XQuery expressions are decomposed into several path expressions, which can be viewed as twig patterns, during query processing. After matching each twig pattern to the document, the results are post-processed by sorting, grouping, joining and so on, to get final answer to the XQuery query. This process also leads a lot of research efforts to rewrite XQuery expression to a set of effective twig patterns, and to develop efficient XQuery optimizer to assemble multiple similar twigs or select good pattern matching order. For example, [63, 30, 102] invent tree algebras to rewrite XQuery expressions, [3] identifies twig patterns in XQuery expressions, [91] uses an algebraic framework to decide when twig pattern matching algorithms should be used during XQuery query processing.

As we see, twig pattern is a core pattern for XML queries. Thus how to efficiently match a twig pattern to XML documents to find all matches is essential to XML query processing.

1.2.2 Twig pattern matching

Fig. 1.3(a) shows an example twig pattern query, in which query nodes correspond to elements or values in the bookstore document and edges specify the structural constraints between relevant nodes. Since a twig pattern normally represents an XPath expression, it is reasonable to allow a leaf node of a twig pattern query to also be a range value comparison or even a conjunction/disjunction of several value comparisons, if the corresponding XPath expression contains such predicates. For example, the XPath query //book[price>40 and price<50]/title, which aims to find the title of the book with price between 40 and 50, contains a conjunction of value comparison “>40 and <50” under the query node *price*. Thus in the corresponding twig pattern representation, the conjunction appears as a leaf node. Compared to most existing algorithms, our algorithm proposed in this thesis can also efficiently handle the case that a twig pattern query contains advanced content search, such as range search and conjunction/disjunction of value comparisons.

The process to find all the occurrences of a twig pattern in an XML document is called *twig pattern matching*. A match of a twig pattern Q in a document tree T is identified by a mapping from the query nodes in Q to the document nodes in T, such that: (i) each query node either has the same string name as or is evaluated true based on the corresponding document node, depending on whether the query node is an element/attribute node or a value comparison; (ii) the relationship between the query nodes at the ends of each “/” or “//” (PC or AD) edge in Q is satisfied by the relationship between the corresponding document nodes. Matching Q to T returns a list of n-ary tuples, where n is the number of nodes in Q and each tuple (a_1, a_2,..., a_n,) consists of the document nodes that identify a distinct match of Q in T, in terms of node labels.

A twig pattern query consists of two parts: structural search and content search. Take the query in Fig. 1.3(a), whose path expression is //subject[//book/title= “Network”]/name, as an example. In this query, //subject[//book/title]/name is a structural search, aiming to find patterns in the document satisfying this structural constraint; whereas, title=“Network” is a content search, which filtering the patterns found by this value comparison. Most research efforts only focus on how to efficiently perform structural search, as discussed in Chapter 3.

1.3 Document labeling and inverted list

Discovering structural relationship between document nodes is necessary for twig pattern query processing. Concretely, a twig pattern query processing algorithm needs to check whether two document nodes satisfy the parent-child (PC or "/") or ancestor-descendant (AD or "//") constraint specified in the query, when it processes a query.

To facilitate structural relationship checking, we normally assign a structural label (*label* for short, if no confusion arises) to each document node, so that PC or AD relationship between any pair of document nodes can be determined during twig pattern query processing.

There are multiple labeling schemes proposed for XML documents. The containment labeling scheme, which is first proposed by Dietz [38] and introduced to XML applications by Zhang et al. [156], assigns each document node a label containing three numbers: (pre : $post$, $level$)[3]. *Pre* and *post* are the pre-order and post-order traversal position of the corresponding node in the document tree, and *level* is the depth of the corresponding node in the document tree. The document order, and the PC and AD relationships between two nodes can be determined by checking their labels based on the following properties:

- Node u precedes node v in document order, if and only if

$$u.pre < v.pre$$

- Node u is an ancestor of node v in an XML tree, if and only if the interval ($u.pre$, $u.post$) contains the interval ($v.pre$, $v.post$), or say

[3] Other works may also use the notation of ($start$: end, $level$), where *start* and *end* indicate an interval.

$$u.pre < v.pre < v.post < u.post$$

- Node u is the parent of node v in an XML tree, if and only if the interval ($u.pre$, $u.post$) contains the interval ($v.pre$, $v.post$) and u is one level higher than v, or say

$$u.pre < v.pre < v.post < u.post \text{ and } u.level + 1 = v.level$$

The labeled document tree for the bookstore document shown in Fig. 1.2 using containment labeling scheme is shown in Fig. 1.4. In this labeled tree, *subject (2:269,2)* is an ancestor of *book (8:37,4)* because the interval *(2,269)* contains the interval *(8,37)*, and *book (8:37,4)* is the parent of *title (13:16,5)* because the interval *(8,37)* contains the interval *(13,16)* and the level difference between the two nodes is 1.

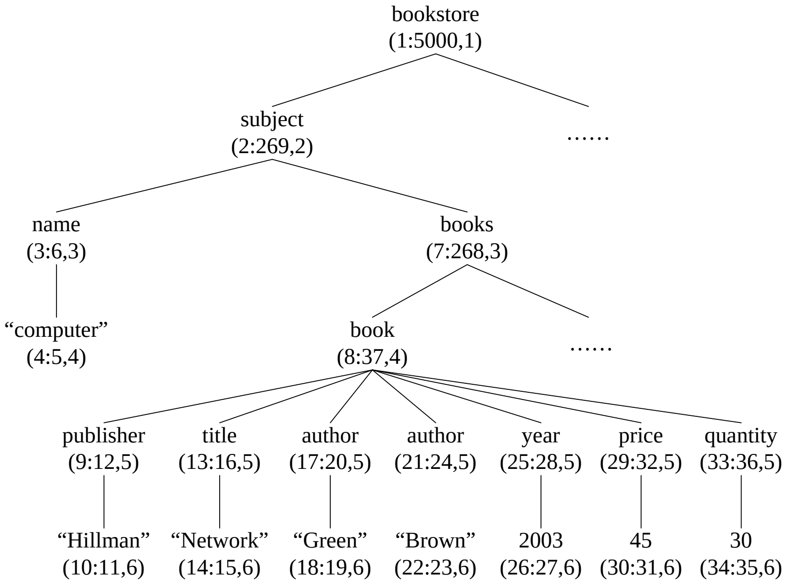


Figure 1.4: The bookstore document tree with containment labels

Another frequently used XML labeling scheme is the Dewey labeling scheme [121], which is also referred as the prefix labeling scheme. Compared to the containment labeling scheme, the Dewey labeling scheme has advantage in finding the lowest common ancestor of a few document nodes, which is a core operation for XML keyword query processing. Thus the Dewey labeling scheme is widely adopted in XML keyword search algorithms.

In the Dewey labeling scheme, the document root is assigned an initial ID, e.g. 1, and for any non-root node u, its Dewey ID is assigned by *Dewey(u)=Dewey(v).x*, where u is the x-th child of node v. In other words, the Dewey ID of any document node is its parent node's Dewey ID appending a new component to indicate its position among all siblings under the same parent node. Thus the level information of each Dewey ID is implicitly represented by the number of components in it. The document order, and PC and AD relationships are checked by Dewey IDs in such a way that:

- Node u precedes node v in document order, if and only if *Dewey(u)* is lexicographically precedes *Dewey(v)*.
- Node u is an ancestor of node v in an XML tree, if and only if *Dewey(u)* is a prefix of *Dewey(v)*.
- Node u is a parent of node v in an XML tree, if and only if *Dewey(u)* is a prefix of *Dewey(v)* and the number of components in u is one less than that of v.

Fig. 1.5 shows the bookstore document tree with nodes labeled by the Dewey labeling scheme. In this labeled tree, *subject (1.1)* is an ancestor of *book (1.1.2.1)* because the Dewey ID *1.1* is a prefix of the Dewey ID *1.1.2.1*; *book (1.1.2.1)* is the parent of *title (1.1.2.1.2)* because *1.1.2.1* is a prefix of *1.1.2.1.2* and the difference of number of components in the two Dewey IDs is 1; *subject (1.1)* is the LCA of

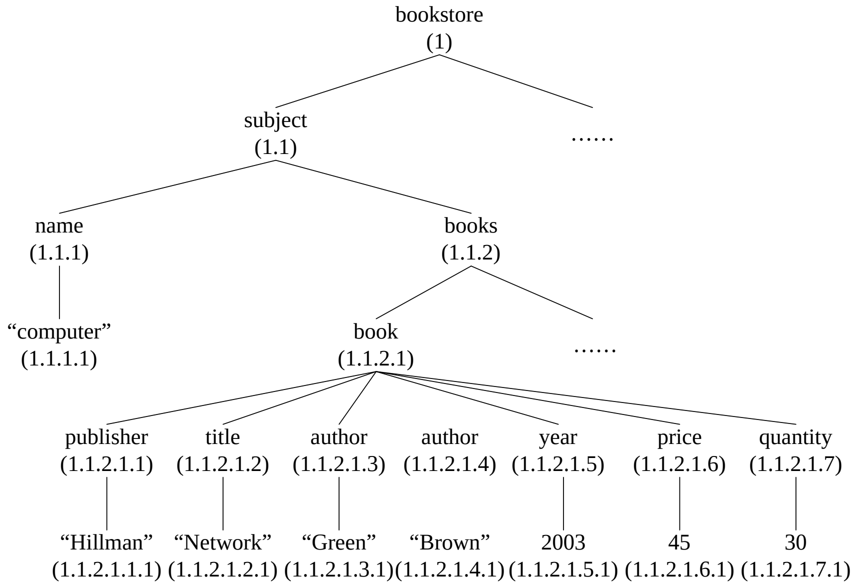


Figure 1.5: The bookstore document tree with Dewey labels

computer (1.1.1.1) and *book (1.1.2.1)* because *1.1* is the longest common prefix of *1.1.1.1* and *1.1.2.1*.

The Dewey labeling scheme has an advantage over the containment labeling scheme in checking the LCA (lowest common ancestor) relationship between two document nodes, which is widely used in XML keyword search. Since in this thesis we focus on structured XML query, we do not illustrate how the labeling schemes work for XML keyword search. Although both the two labeling schemes can be used for twig pattern query processing, we choose to use the containment labeling scheme in our demonstrations and experiments. This is because in the containment labeling scheme, each label has a fixed size, which brings convenience in inverted list management.

The containment labeling scheme and the Dewey labeling scheme are suitable for static XML documents which are not updated. When the document is more dynamic with updates, both schemes suffer from high cost of re-labeling. Recently, several encoding schemes are proposed to transform the label format in each labeling scheme to a dynamic format, which is adaptive to updates. Such encoding schemes include QED [78], Vector label [147] and DDE [150]. Apparently, the containment labeling scheme used in this thesis can be enhanced by any dynamic encoding schemes.

Labels are usually organized by inverted lists. Inverted list is an important data structure widely adopted in XML twig pattern matching, XML keyword search, as well as IR search. During XML twig pattern query processing, for each type of document node (i.e., tag name or value), there is a corresponding inverted list to store the labels of all nodes of this type in document order. To process a query, only relevant inverted lists that correspond to the query nodes are scanned. Because in most algorithms, each relevant inverted list is scanned in a streaming fashion during query processing, inverted list in XML twig pattern query processing is also referred as *label stream*, or simply *stream*. The update of the inverted list is discussed in [15, 125, 19, 41].

1.4 Our research scope and contributions

Our research focuses on applying semantic information, such as value, property, object and relationship among objects, to perform content search in structured XML query processing. We put more focus on twig pattern query which is the core pattern for structured queries as discussed in Section 1.2. Since we do not emphasize on structural search, we use the basic twig pattern queries without special structural predicates, e.g., OR predicate between edges, negation on edges and wildcard nodes, for illustration. Those algorithms that perform structural joins for these special predicates can be used for structural search in our approach, when we extend our approach to support such special predicates.

Our contributions are summarized as:

1. We propose the *VERT* algorithm to efficiently perform both content search and structural search during twig pattern query processing. The novelty of *VERT* is to make use of the semantic information on object and property to organize and query data values in XML documents. We observe that the parent node of each value in an XML tree must be a property node, and value predicate in queries is normally in form of *property <operator> "value"*. Thus we introduce property-based relational tables to index each property node by its value, and perform content search by selection in property tables. After performing content search, a twig pattern query can be simplified by removing value predicates, and some relevant inverted lists are reduced by the result of content search. Then performing structural search on a simpler query pattern with smaller inverted lists significantly improves the overall query processing performance. In the last step, the relational tables can be used to extract actual values based on returned labels, to answer queries. In this way, we can eliminate redundant value answers though they may correspond to different node labels. We also propose three optimizations when more semantic information on object and relationship between objects is known. Those semantic optimizations can further improve query processing efficiency. Furthermore, we discuss how to use *VERT* to process queries across different parts of an XML document by ID references or value-based joins, and queries across multiple documents. Such a query is a bottleneck for many other existing twig pattern matching algorithms, because they cannot link different twig patterns by node labels.

2. We analyze the characteristics of each node in twig pattern query, i.e., the purpose, optionality and occurrence, and classify the nodes in a twig pattern

query into six types. Then we propose the *TP+Output* expression to extend twig pattern queries, to model complex output information based on the semantics of different node types. With *TP+Output*, many queries with a complex output centered at a unique object can be expressed in one twig using *TP+Output* expression, rather than multiple twigs in the original twig pattern query expression. Thus we will use less structural joins to match a TP+Output query. We extend *VERT* to *VERT*^{O}, to process the *TP+Output* query, and demonstrate the performance improvement of using *TP+Output* to represent queries.

3. We observe that one more advantage of using relational tables to store values in XML data is the convenience to perform value grouping and aggregation. This operation, however, cannot be efficiently achieved in other existing structural join algorithms, because they only return labels as pattern matching result. Based on this observation, we propose an algorithm *VERT*^{G} to perform grouping and aggregate functions in XML queries. Generally, a query with grouping and aggregation has two parts, pattern matching part and grouping operation part. We process the two parts separately. The query pattern plays as a selection predicate, and is processed by *VERT*. Then we model the multi-level grouping operations in a query as a grouping tree. By traversing the grouping tree, we compute the aggregate functions for each level of grouping using the relational-like result from pattern matching of the query.

1.5 Thesis organization

The rest of this thesis is organized as follows. We review related work to XML twig pattern query processing and XML keyword search in Chapter 2. Chapter 3 presents the algorithm VERT, which use semantics-based tables to solve different content problems in existing approaches, and to process twig pattern queries more efficiently. We propose the twig pattern query extension, TP+Output, in Chapter 4, using which a subset of queries with complex output information centered at one object can be easily expressed. An extended algorithm VERT^O to process TP+Output queries is also presented. In Chapter 5, we propose an algorithm VERT^G to physically perform grouping and aggregation in XML queries. Finally, Chapter 6 concludes this thesis, and discusses some future research work.

CHAPTER 2

LITERATURE REVIEW

XML query processing has been studied for more than a decade. In this chapter, we revisit existing research work on XML query processing. As mentioned in Chapter 1, XML data can be modeled as tree or graph, depending on whether the ID reference is considered. We organize this chapter based on the tree model and graph model of XML databases.

2.1 Query processing over XML tree

Twig pattern matching over tree-modeled XML data attracts the most research interests in XML query processing. Generally, twig pattern matching algorithms are categorized into two classes, the relational approach and the native approach. They essentially differ on whether relational databases are used to store and query XML data.

2.1.1 The relational approach

Relational model is a dominant model for structured data management. Over decades, relational database management systems (RDBMS) have been well developed to store and to query structured data. As XML becomes more and more popular, many researchers and organizations put more efforts into designing algorithms to store and query semi-structured XML data using the mature RDBMS. Generally, those relational approaches shred XML documents into relational tables and transform XML queries into SQL statements to query the database. The advantage of the relational approach is that the existing query optimizer in the RDBMS can be directly used to optimize the transformed XML queries. Especially for the queries with content search, the RDBMS can not only process the value comparisons efficiently, but also push the value predicates ahead of table joins using the optimizer. There are multiple shredding methods proposed for the relational approach, which are classified into schemaless methods and schema-based methods. The schemaless methods assume there is no schematic information available, and decompose the XML document tree purely based on different tree components. Typical schemaless methods include the node approach, the edge approach and the path approach. The schema-based methods decompose the XML document tree based on schematic information, e.g., DTD. This kind of methods require schema available alongside the document. Now we review the two kinds of document decomposition methods and the corresponding query transformations in more details.

Schemaless decomposition

Zhang et al. [156] proposed a node-based approach, which stores each document node with its positional label into relational tables. The relationship between each pair of nodes that are connected by an edge can be checked by the labels. Fig. 2.1(a) shows an example node table for the labeled bookstore document tree in Fig. 1.4. A twig pattern query, under the node-based approach, is decomposed into separate nodes, and the structural joins between nodes in the twig pattern query are transformed into θ-joins on labels between tables in SQL. The twig pattern query shown in Fig. 1.3(a) is transformed as:

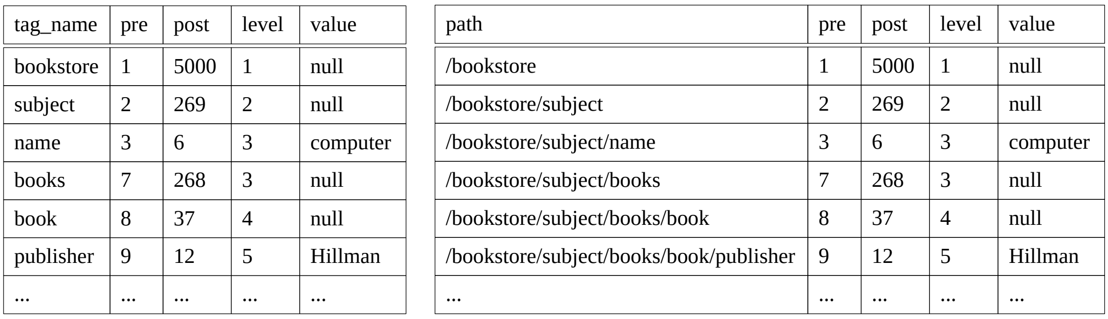
select *name.value*

from *Node subject, Node name, Node book, Node title*

where *subject.pre<name.pre and subject.post>name.post and*
subject.level=name.level-1 and subject.pre<book.pre and
subject.post>book.post and book.pre<title.pre and
book.post>title.post and book.level=title.level-1 and
title.value="Network"

The node table can be horizontally partitioned based on tag names. Furthermore the works by Grust et al. [55, 56, 57] can optimize joins in the node-based approach by introducing index to skip nodes which are proven useless for each query. We can see the major problem of the node-based approach is that when the query structure is complex there will be too many θ-joins between tables involved for structural search, which is not as efficient as equi-join to process using most RDBMS.

The edge-based approach [44] is quite similar to the node-based approach, except the edge-based approach puts each edge into tables. Thus it suffers the same efficiency problem as the node-based approach for structural search. The path-based approach [153] is another kind of schemaless method in the relational ap-



tag_name	pre	post	level	value
bookstore	1	5000	1	null
subject	2	269	2	null
name	3	6	3	computer
books	7	268	3	null
book	8	37	4	null
publisher	9	12	5	Hillman
...	...	...	...	...

(a) A node table

path	pre	post	level	value
/bookstore	1	5000	1	null
/bookstore/subject	2	269	2	null
/bookstore/subject/name	3	6	3	computer
/bookstore/subject/books	7	268	3	null
/bookstore/subject/books/book	8	37	4	null
/bookstore/subject/books/book/publisher	9	12	5	Hillman
...	...	...	...	...

(b) A path table

Figure 2.1: Example tables in node-based and path-based relational approaches

proach, which stores each path wholly without decomposition. One example path table is shown in Fig. 2.1(b). The path-based approach saves table joins between different nodes or edges along the same path, however, to perform a structural search involving AD edge ("//"-axis), the path-based approach has to do a string pattern matching ("*LIKE*" in *SQL*) on the path column, which is also an expensive operation for relational database systems. Pal et al. [100] modified the path-based approach by reversing the node positions in each path. By doing this, a twig pattern query with AD edges can be decomposed into components beginning with "//", and "*LIKE*" pattern matching can be replaced by string prefix matching in reversed paths, which is generally less expensive. There are also several works focus on performing string prefix matching to improve efficiency, e.g., *BLAS* [28]. In the last step, different components can be joined by the ORDPATH [99] label of each path. This XML storage based on reversed path is used in Microsoft SQL Server.

Schema-based decomposition

When the schema of an XML document is known, the document can be shredded based on the schematic information. Different from the schemaless methods, the design of relational tables in the schema-based methods may vary for documents with different schemas. Shanmugasundaram et al. [114, 113] proposed a DTD-based approach to decompose XML documents. Consider the example shown in Fig. 2.2. Based on the DTD, we can get a hierarchical structure between elements. Then from the hierarchical structure, a set of relational tables are built. The automatically generated attributes *self_id* and *parent_id* are the primary key and foreign key of each table, which play as join attributes during query processing.

```
<!ELEMENT bookstore (subject*)>
<!ELEMENT subject (name, books)>
<!ELEMENT name (#PCDATA)>
<!ELEMENT books (book*)>
<!ELEMENT book (publisher, title, author*,
year, price, quantity)>
<!ELEMENT publisher (#PCDATA)>
<!ELEMENT title (#PCDATA)>
<!ELEMENT author (#PCDATA)>
<!ELEMENT year (#PCDATA)>
<!ELEMENT price (#PCDATA)>
<!ELEMENT quantity (#PCDATA)>
```

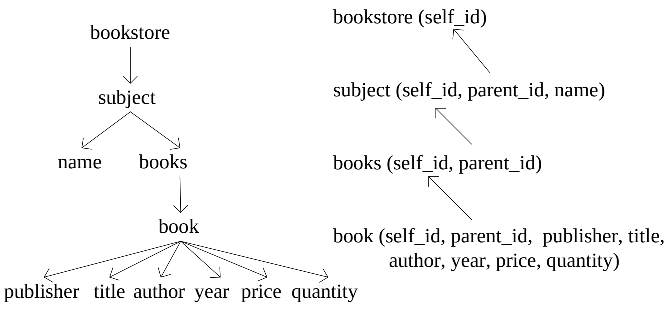

bookstore
subject
name
books
book
publisher
title
author
year
price
quantity
bookstore (self_id)
subject (self_id, parent_id, name)
books (self_id, parent_id)
book (self_id, parent_id, publisher, title, author, year, price, quantity)

Figure 2.2: Example DTD, hierarchical structural between DTD elements, and the relations

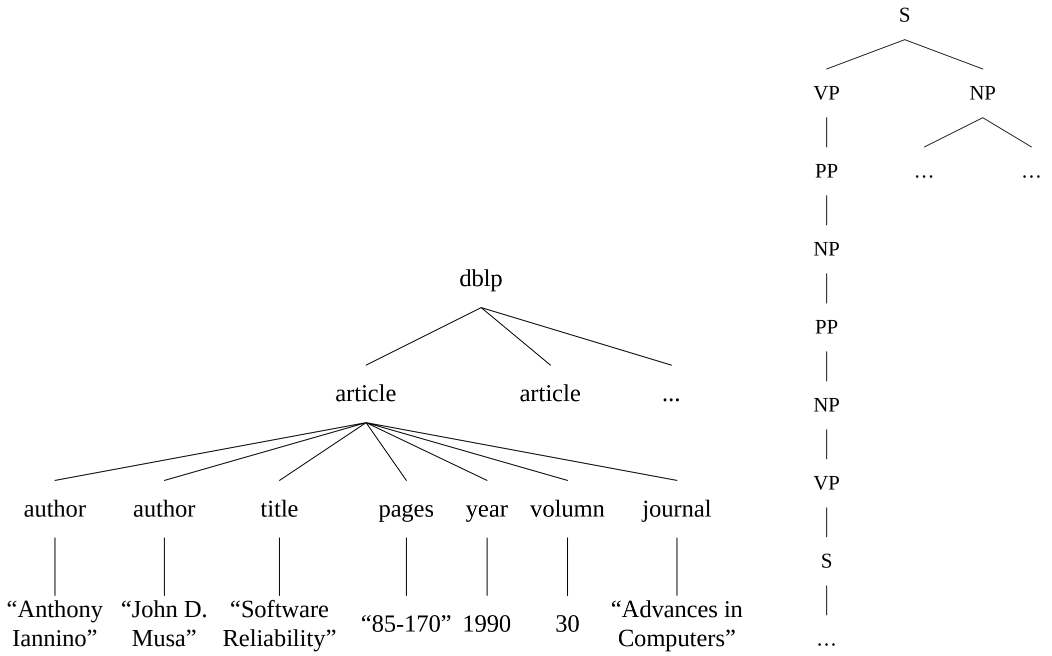
Georgiadis et al. [48] enhanced the DTD-based approach by introducing an additional relation to store path information, and proposed optimization [49] to improve the efficiency of relational processor, as well as to accelerate XML reconstruction from relational format. Some other similar schema-based decomposition approach include [12, 36]. In particular, [36] discovers the schematic information, i.e., the correlation between elements, by mining XML data.

A summary

Most relational approaches make use of existing relational query optimizers and tune the system settings to get better performance for XML query processing. Compared to the schemaless approaches, the schema-based relational approaches is generally more efficient, as reported by [124].

Now we use to two real-life XML data, as shown in Fig. 2.3 to show the advantage and the disadvantage of the relational approach. One major advantage of the relational approach is the efficiency for content search in a query. All value comparisons in query predicates are eventually transformed into table selection, which can be efficiently evaluated under the help of B^+ tree index of the RDBMS. Thus, the relational approach is suitable for regular XML data, such as DBLP [35] data which is partially shown in Fig. 2.3(a). Queries over such data normally have simple structural constraints, but focus more on content search.

However, some XML data are rather deep and complex in structure. For example, the TreeBank [97] data (a partial document is shown in Fig. 2.3(b)) has a maximum depth of 36 and an average depth of 8, and contains a lot of recursive tags. Queries to such a deep and complex document may also contains complex structures, which require many steps of expensive table joins for structural search. Furthermore, the schema-based approach cannot efficiently handle AD edges ("//") in queries to such a document with recursive tags. Consider a query edge *VP//PP* to be matched in the TreeBank data. The schema-based approach can hardly decide what tables to be joined between *VP* and *PP* and how many times to join them. Krishnamurthy et al. [76] proposed to use structural labels (e.g., containment labels) as keys of each table, which can handle AD edges. In more details, for each "//"-axis join, they join the two tables based on labels to check AD relationship, which is the same as what the node approach does. However, transforming equi-join based on primary key and foreign key to θ-join on labels seriously affects the performance because most RDBMS cannot perform θ-join as efficiently as equi-join. There are also some other work to handle recursive elements during query transformation, e.g., [75]. Similarly, they also suffer from efficiency problems during query processing. Structural join based native approach is much more efficient than the relational approach for such queries and data, which will be reviewed in the next section.



(a) DBLP data (b) TreeBank data

Figure 2.3: Two real-life (partial) documents with different characteristics

2.1.2 The native approach

To improve the performance of structural search in XML queries, many native approaches are proposed. In the native approach, documents are not stored using relational tables, thus the overhead on table join to perform structural search can be avoided.

Structural join approach

The structural join approach is a very important class of native approach that attracts most research interest. In this sort of approach, a document is pre-parsed by assigning a label to each document node. Then the labels for each type of document node are organized using an inverted list (or called stream), in document order. The details of document labeling and inverted lists were discussed in Section 1.3. A twig pattern query is processed by scanning the relevant inverted lists to find the matched documents nodes.

Binary join

In the early work, Zhang et al. [156] proposed the multi-predicate merge join algorithm. In their approach, the twig pattern query is decomposed into multiple binary joins. The query is processed by finding all matched node pairs to each binary join, and combining these binary matches. When they match a binary join, e.g., A/B (or $A//B$), they scan the inverted lists for the node type A and B. For each pair of labels in the two inverted lists they check whether they are satisfied with parent-child (or ancestor-descendant) relationship. Because the labels in each inverted list are sorted by the document order, this process can be implemented efficiently, which is quite similar to the merge-join in relational systems. However, this technique suffers from the efficiency problem of unnecessary checking of labels in inverted lists, as pointed out by Al-Khalifa et al [1]. Then in [1] they improved the binary join approach by adding a stack to cache the nested nodes so that the unnecessary label checking can be avoided. This stack-based binary join algorithm is also adopted by the native XML database, *TIMBER* [62]. There are also several indices built on inverted list to accelerate label scans for structural join processing [33, 65].

The major problem of the binary join approach is the large size of useless intermediate results produced by binary joins, when the query plan is not well chosen. Once we perform the binary join with very low selectivity first, many intermediate matches may be useless for final result. This also motivated some work on structural join order selection [145].

Holistic join

Bruno et al. proposed *TwigStack* [16], which is a holistic join approach to avoid producing too many useless intermediate results. Comparing to the binary join approach, the major difference is that *TwigStack* introduces multiple stacks for all the query nodes and scanning multiple inverted lists at one time, to find the matched patterns. *TwigStack* first produces the matched paths that contribute to the final result, and then merges the matched paths to twigs. They introduce a *getNext* function to ensure that each matched path is useful in later merging pass, when the path contains only AD relationships. In this point of view, *TwigStack* is optimal for twig pattern queries with only AD relationships.

There are many subsequent works [83, 66, 45, 26, 85, 64, 155] to optimize *TwigStack* in terms of I/O, or extend *TwigStack* to solve different kinds of problems. In particular, Lu et al. [83] introduced a *list* structure to make it optimal for queries containing parent-child relationships between non-branching nodes. *TSGeneric* [66] improved the query performance based on indexing each inverted list and skipping labels within one inverted list. Fontoura et al. [45] further optimize the cursor move in inverted lists to reduce cost. Chen et al. [26] divided one inverted list into several sub-lists associated to each prefix path or each (tag, level) pair and pruned some sub-lists before evaluating the twig pattern. Lu et al. [85] used Extended Dewey labeling scheme and scanned only the labels of leaf nodes in a twig query. [64] and [155] extended twig pattern query to support OR-predicate and NOT-predicate respectively.

Besides, *Twig*^{2}*Stack* [25] proposed a bottom-up strategy to evaluate twig pattern queries using nested stacks. It is worst-case optimal, and is also capable to process queries with optional edges. Some later work [67, 104, 79] use improved evaluation strategy and data structure to achieve better performance for practical queries, though they are not optimal for the worst cases. Recently, Grimsmo et al.

[54] proposed to use a similar data structure to those in [104, 79] to achieve worse-case optimal time without scarifying performance for practical queries. Shalem et al. [112] discussed the space usage of twig pattern matching, and proposed a query-driven technique to avoid some overhead. The optimality of twig pattern matching is theoretically studied in [84].

Graphic index

Graphic index is a useful tool to accelerate query processing with the structural join based approaches. A graph index normally covers all path or twig patterns in an XML document, so that when a query is contained in a graphic index, the query processor could return the matching results directly, without performing (or performing less) structural joins. The graphic indexes are categorized into two classes: path index and twig index.

Strong DataGuides [51] is an early path index which could cover all path information. However, *Strong DataGuides* is too large comparing with the target document. Later *1-index* [92], *A(k)-index* [71] are proposed to reduce the index size based on backward bisimilarity and k-bisimilarity. To process a twig pattern query using a path index, the twig pattern is first decomposed into paths. After finding the intermediate results for each path, the final result is generated by joining these intermediate results based on the positional relationships of paths.

Twig index is the other class of graphic index, which covers all twig patterns in the given XML document. One famous twig index is the *F&B index* [69, 105], which is also proven the smallest index to cover all twig patterns for any XML document [69]. Using *F&B index*, the twig pattern queries with only PC relationships can be processed by searching the index to return the answers, instead of performing structural joins. However, sometimes *F&B index* is still too large to fit in memory.

Wang et al. proposed a disk-based organization [133] for *F&B index*. Intuitively, to process a twig pattern query using *F&B index* involves the traversal of the *F&B index*, which is non-deterministic as pointed by [133]. When the query also contains "//"-axis, the searching becomes more complex. In [133], they combine the *F&B index* with other structural join based native approach, e.g., *TwigStack*, to process queries. They decomposed the twig pattern query by "//"-axis. For each part that contains only "/"-axis, they use the disk-based *F&B index* to find the intermediate results in terms of node labels, and then use *TwigStack* with the intermediate node label streams to handle the "//"-axis. In this way, the structural search becomes more efficient. Recently, Tang et al. [118] proposed an indexing technique that can cover twig patterns containing both "/"-axis and "//"-axis.

Other native approaches

The subsequence matching approach is another class of native approach. *PRIX* [106] and *ViST* [132] transform both XML documents and queries into sequences and perform subsequence matching between query sequence (as subsequence) and document sequence. In particular, *ViST* derives document sequence based on pre-order document traversal, while *PRIX* makes use of Prüfer sequences which are derived from post-order traversal. Tatikonda et al. [122] employed a dynamic programming based technique to perform subsequence matching. Moro et al. [124] conducted experiments to show that the subsequence matching approach is normally not efficient and robust as the structural join approach.

Besides the structural join approach and the subsequence matching approach, there are also a number of algorithms which scan an XML document to find the occurrences of queries. We name this sort of approach navigational approach. A direct navigational approach is to read an XML document with a certain API, e.g., SAX parser [110], and check the events generated by SAX based on query constraints. Some applications, e.g., [50], use this direct approach to match a query pattern to a document. However, this naive approach can only process simple twig pattern queries without recursive nodes. When a query involves recursive nodes, they have to use stacks to store SAX events [11], which is similar to the structural join approach.

The navigational approach for query processing is widely adopted by different native XML storages. In some early native XML database systems [90, 43], documents are normally partitioned into pieces to store on disk, and queries are processed by navigating relevant disk pages. Buneman et al. [17] summarized an XML document as a skeleton (similar to the *DataGuides* index), and clustered the values under each kind of document path together. They traversed the skeleton and load relevant values to process queries. In [59] and [158], the authors argued that navigating a proper XML storage is more efficient than structural join to process "/" axis in queries. Motivated on this, they proposed to decompose a twig pattern query based on "//" axis, so that every component only contains edges of "/" axis. Each component is matched by navigating the native XML storage, and structural join is used to solve the "//" axis between components. Wong et al. [135] proposed a compact XML storage and a way to perform relevant navigational operations over their storage. The navigational approach is also used in querying XML streams [103, 68, 29, 8].

Generally, both the subsequence matching approach and the navigational approach need to scan a large portion of (or whole) XML document during query processing. This attempt leads a high I/O cost. In contrast, the structural join approach only reads the inverted lists which are relevant to the query nodes to process a query. Thus it normally introduces lower I/O cost. Also, there are several techniques, e.g., selective index [60] and materialized view [4, 87, 151, 2, 119, 23], to maintain cache for frequently asked (sub-)query pattern in the structural join approach. All these factors make the structural join approach a representative native approach.

2.1.3 Comparison between the relational approach and the native approach

Both the relational approach and the native approach to process XML queries have their own advantages and disadvantages. In relational approach, the values in an XML document can be efficiently managed using relational tables. Also both the content search and the value extraction for final answer can be easily performed by SQL selection. However, though there are different methods to shred XML data into tables, all of them suffer from problems in performing structural search, especially for handling "//" axis. The native approach is a good choice for structural search. However, the native approach cannot perform content search efficiently, and cannot extract values to answer the query using the inverted list index. The details of these problems regarding values in the native approach are discussed in Section 3.1.

It is not easy to generally comment on which kind of approach is better in query processing performance, because both approaches have a number of variants, and both approaches may employ different indexes to speed up query processing. In some preliminary reports, Zhang et al. [156] conducted experiments to show a binary join based native approach is better than a node based relational approach. Kurt et al. [77] showed the relational approach is faster than the native approach for data-centric XML documents. Chaudhri et al. [22] concluded that the native approach is suitable for large data sets and the relational approach is good for smaller data sets (though they did not mention the concrete size). However, all the comparisons are done by particular implementations of the relational approach and the native approach and conducted under particular environments (hardware, database parameter, indexing, etc). As mentioned by Serna et al. [111], actually there is no tool feasible to analyze whether XML data should be queried natively or using RDBMS, to get a better performance.

Although it is hard to compare the two approaches, the advantages and limitations of the two approaches are obvious. It will be interesting to find a way to combine the advantages of the relational approach and the native approach, and avoid the limitations.

2.1.4 Hybrid management of relational data and XML data

In the early stage, most XML-enabled relational database systems used the relational approach to process XML queries, and most native XML database systems used the native approach. As both the relational format and the XML format have become very important in data storage and exchange, many database vendors extended their systems to be hybrid for both relational data and XML data. We take Oracle 11g, Microsoft SQL Server, and IBM DB2 to show how these database systems manage XML data in a hybrid platform.

In the prior versions of Oracle database systems, XML data is either stored as a CLOB column or shredded into object-relational tables based on their schema. In Oracle 11g [82, 157], a new binary storage is introduced. This is a native storage for XML data. When they process an XML query, the query is first rewritten to their SQL-like syntax with Oracle operators. Then the processor scan the binary XML input stream to find the query answers. The whole process of query processing is a navigational native approach.

Microsoft SQL Server 2000 [108] shredded XML data into relational tables to manage and query. Later, in SQL Server 2005 [109], they developed a native BLOB storage for XML data. However, besides the native XML storage, they also use relational tables to index each path. During XML query processing, they actually searched the relational tables [100, 99]. Thus with respect to query processing, the technique in Microsoft SQL Server is actually a relational approach.

IBM DB2 used the System RX [11] to store and query relational data and XML data separately. For XML storage, they invented a column type of XML, which is similar to the Oracle database. An XML document is stored natively as a tree model under each XML-typed entry. During query processing, they traversed the XML document to find query matches, under the help of different indexes. Actually this attempt is also a navigational native approach.

The concept of "hybrid" in Oracle, SQL Server and DB2 means they manage both relational and XML data in a single system. However, when they process XML queries, they adopt either a pure relational approach or a pure native approach. Our approach, which is presented later, incorporates both relational tables and native inverted lists to aid query processing. This is a hybrid attempt w.r.t. query processing, to effectively inherit the advantages of the relational approach and the native approach, and avoid the problems of these two kinds of approaches.

2.2 Query processing over XML graph

When we consider the ID references in an XML document, the document should be modeled as a graph, rather than a tree. Similarly, when a query involves ID references, it is not in a twig pattern, but in a graph pattern. How to match a graph pattern query to an XML graph is essential to XML query processing with

ID references. The relational approach for twig pattern matching, reviewed in the previous section, can be used for XML graph matching. However, as indicated previously, the efficiency problem caused by the overhead on table joins becomes a major concern for the relational approach. In this section, we focus on the existing works of native graph matching, without using RDBMS.

The initial attempt for XML graph matching is to check subgraph isomorphism, which is a classic mathematical problem and is widely adopted in graph databases. For example, the approach proposed in [115] generated all possible mappings between each pair of nodes in two graphs and check for correctness. Generally, this sort of graph matching problem is NP-complete [47]. There are also many indices proposed on graph database to reduce the complexity of subgraph isomorphism checking [152, 159, 31, 134, 160, 61]. However, subgraph isomorphism checking is only suitable for matching a graph pattern XML query without AD relationships. There is another class of research problems in graph databases that focus on connectivity-based pattern matching [32, 126, 161]. Theoretically, they can be modified to match a graph pattern query to an XML graph by setting a distance constraint between the two nodes connected by a PC or AD edge in the query. However, all these attempts focused on random graph databases and did not capture the characteristics of XML queries. In an XML query, the edge between two adjacent nodes can only be “/” or “//”, which specify the distance between them is either 1 or unlimited. Applying the general subgraph matching algorithms to XML graph matching may not be efficient as expected. There is a need to design specific algorithms based on the characteristics of XML data, to perform XML queries involving ID references.

Chen et al. [24] extended *TwigStack*, which is used for twig pattern matching, to process graph matching for XML data and queries involving ID references. They assumed the XML data to be DAGs (Directed Acyclic Graphs), and maintain an index to store positional relationships between nodes. Each time they process a query, partial solutions are expanded based on the index. Although they showed that their approach was more efficient than a traditional graph matching algorithm [115], compared with other structural join based algorithms for XML query processing, their algorithm was still very slow. Similarly, Vagena et al. [127] proposed another algorithm to match graph pattern queries on XML DAGs. The major problem of these DAG-based matching algorithms is that an XML document with ID references may form cycles. When they handle such cyclic XML documents, they may generate a large number of results that contribute to the same valuable information [74]. Recently, Wang et al. [131] proposed a new labeling scheme for document graph so that PC and AD relationships between two graph nodes can be identified based on their labeling scheme, and then queries can be processed by structural joins. However, this approach, as well as the DAG-based approaches, only paid attention to the characteristics of XML queries, but did not notice the semantics of ID references in both data and queries, which is that an ID reference always starts from an IDREF attribute and points to an object with the same ID value. In Chapter 3, we will demonstrate that our semantic approach can reduce graph matching to less complex tree matching by using the semantics of ID reference.

2.3 Summary of related work

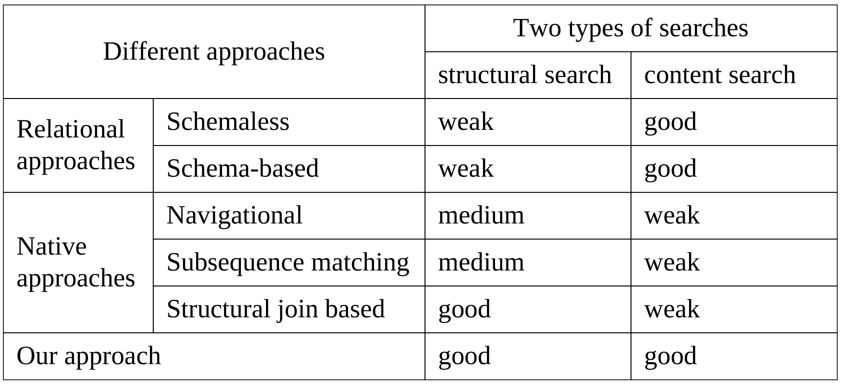
In this chapter, we review the related work on XML query processing. We start from the case that queries are issued over tree-modeled XML data. In this case, we can model the queries as twig patterns, which is also a tree structure. There are two classes of approaches to match a twig pattern query to an XML document, namely the relational approach and the native approaches.

The relational approach use the RDBMS to store XML documents, and convert queries into SQL statements to query the tables. There are two types of decomposition methods to shred an XML document into relational tables. The first type is the schemaless decomposition, which creates tables and shreds documents based on structural components of a document tree, i.e. node, edge or path. The second type is the schema-based decomposition, which shreds documents based on schematic information, e.g., DTD. Generally, the schema-based decomposition is more efficient than the schemaless decomposition to process queries, but it requires schematic information that may not be available for any XML documents.

The native approach to process XML twig pattern queries attracts more interest in recent research. The native approach can be divided into the navigational approach, the subsequence matching approach and the structural join approach. The structural join approach uses inverted lists to organize document nodes (in terms of labels), thus avoids the high I/O cost to scan irrelevant parts of a document. This makes the structural join approach more efficient than the other two approaches generally. The state-of-the-art structural join approach is based on holistic structural join, which performs structural joins in a holistic view. This attempt controls the size of useless intermediate result, thus results in a better query performance.

The comparison of different approaches to process XML twig pattern queries, w.r.t. the efficiency in structural search and content search, is shown in Fig. 2.4. We can see different existing approaches suffer from efficiency problems in either structural search and content search. Our approach can perform both types of searches efficiently.

Last, we review the research works on the XML query processing over graph-



Different approaches		Two types of searches	
		structural search	content search
Relational approaches	Schemaless	weak	good
	Schema-based	weak	good
Native approaches	Navigational	medium	weak
	Subsequence matching	medium	weak
	Structural join based	good	weak
Our approach		good	good

Figure 2.4: Comparison of approaches to process twig pattern query processing

modeled XML data, i.e., the data with ID references under consideration. Generally, the relational approach can be adopted to process graph pattern matching, however, the inefficiency of multiple rounds of table joins becomes a main limitation. There are two ways to perform pattern matching natively in graph-modeled XML data. The first way is to modify the graph isomorphism checking or graph pattern matching algorithms in general graph databases to process XML queries. However, an XML graph is not as complex as a random graph and an XML queries only contains edges of two types (i.e., PC edge and AD edge). Using the algorithms in general graph matching may not be efficient as expected to process XML queries. The second way to perform XML graph pattern matching is to extend the structural join algorithms in twig pattern matching. The relevant approaches either maintain index to record additional edges on top of tree structure (to form a graph) for the XML data, or invent new labeling scheme for XML graphs. We argue that graph pattern matching is generally more complex than twig (tree) pattern matching. If we can capture the semantics of ID reference, we may reduce graph matching to tree matching to process queries over XML data with ID references.

CHAPTER 3

A SEMANTIC APPROACH FOR TWIG PATTERN QUERY PROCESSING

As introduced in Chapter 1, a twig pattern query includes structural search and content search. Existing approaches to process XML twig pattern queries suffer from problems in either structural search or content search. In this chapter, we present our work which adopts a semantic approach to process XML twig pattern queries. Briefly, our approach introduces both semantics-based relational tables and inverted lists to aid query processing. The structural search and the content search in a twig pattern query are performed with inverted lists and relational tables separately. We show that this hybrid approach can achieve better performance in both searches. Moreover, using relational tables to store values and perform content search, our algorithm can easily process queries involving ID reference and more general queries containing multiple twig patterns linked by value-based joins.

Furthermore, relational tables in our approach are initially constructed based on the default semantics, i.e., the relationship between property and value, which can be discovered in any XML documents. Later, as more semantics on object and relationship between objects is known, we further optimize the tables accordingly. We demonstrate that using the optimized tables, we can process twig pattern queries more efficiently.

Last, we conduct experiments to show the benefit of our approach, by comparing with existing approaches.

3.1 Introduction and motivation

Twig pattern is the core pattern for XML queries, as introduced in Chapter 1. Existing twig pattern query processing approaches are classified into relational approaches and native approaches. Both approaches have their own advantages and disadvantages in performing the structural search and the content search in a twig pattern query. In Chapter 2, we illustrate the problems of relational approaches to handle structural search. In this section, we discuss the problems of a representative native approach in dealing with values in XML documents, which motivate our research in this chapter.

The structural join based approach is the state-of-the-art approach in XML twig pattern query processing. It is proven more efficient than relational approaches and other native approaches generally. However, because they do not differentiate the semantics of value and other types of document nodes (i.e., elements and attributes), they suffer from several problems related to values during query processing. Now we illustrate the problems caused by ignoring value semantics.

1. **Inverted list management.** In most structural join based approaches, all the nodes including elements, attributes and values in an XML tree are labeled

and the labels of each type of nodes are organized in an inverted list. When we build inverted lists for values, the management is a problem. Consider the bookstore document with every node labeled as shown in Fig. 1.1. There are a large number of books and each of them probably has a different title. In this case we have to maintain an inverted list for each different title value, e.g., ‘Network’, ‘Database’ and so on. Based on our investigation, a 100MB XML document contains around 4 million different values, which correspond to 4 million inverted lists[1]. This number will linearly increase according to the document size. To manage the tremendous number of inverted lists becomes a problem.

2. **Advanced content search.** Twig pattern queries normally models XPath expressions. Thus the advanced content search, such as numeric range search, containment search or even conjunction/disjunction of several value comparisons, which often appear in XPath query predicates, may also appear as a leaf node in a twig pattern query. Without handling values specially, existing approaches have difficulty in supporting these advanced content search. For example, to process a query to find the books with price less than 50, it is time consuming to get all the inverted lists with numeric names which are less than 50, and combine labels in them by document order, to perform this range search. Also for the query //book[contains(@title, ‘XML query’)]/price to find the price of the book that contains ‘XML query’ in its title, using inverted lists to index title values can hardly support such containment search efficiently.

[1] Different from the inverted lists used in IR search and XML keyword search which index every single keyword, inverted list used in existing twig pattern query processing algorithms indexes a whole value so that the structural join between this value and other types of nodes can be performed with the corresponding inverted lists.

3. **Redundant search in inverted lists.** Inverted lists for values do not have semantic meanings. This may cause redundant search during inverted list scanning. For example, When a query is interested in the books with price of 35 in the bookstore document, structural search scans the inverted list for value node '35' (denoted by T_{35}). Since in T_{35} we do not differentiate whether a label corresponds to *price* or *quantity*, we need check all the labels in this inverted list though many of them stand for *quantity* equals to 35, and definitely do not contribute to the query result.

4. **Actual value extraction.** When we issue a query to an XML document, what we need is not all the twig pattern occurrences represented as tuples of labels, but the value results of that query. For example, after finding a number of occurrences of the twig pattern query in Fig. 1.3(a), we need to know the value under each *name* node. One major advantage of the structural join based approaches is that they only need to load the relevant inverted lists to process the query, instead of scanning the whole document with high I/O cost in other approaches. However, after getting a set of resulting labels from pattern matching, they cannot find the child value under each label using inverted lists. To extract actual values, they have to read the document again, which violates the initial will in I/O saving.

Motivated on solving all these problems, we propose a semantic approach that uses both inverted lists and relational tables to perform twig pattern matching. In particular, relational tables are used to store values, while inverted lists are used to index internal document nodes, including property nodes and object nodes. We propose the *VERT* algorithm to perform content search and structural search separately with the two kinds of indexes in twig pattern matching. Content search is performed by table selection before structural search. Because content search is always a predicate between a property and a value, after performing content search the size of the inverted list of the relevant property node is reduced due to the selectivity of the predicate, and the twig pattern query can be simplified by removing value comparisons. Matching a simplified twig pattern with reduced inverted lists for several query nodes will reduce the complexity of structural search, and thus improve the twig pattern matching performance. Finally, the semantic table can help to extract actual values to answer the query, if the query output is a property node (*property node* is discussed below) which appears in most practical XML queries. Whereas, it is not efficient to extract child values of node labels in other structural join based approaches.

We also need to highlight that the relational tables are constructed based on semantic information such as value, property, object and relationship among objects. The semantics of property is apparent for any XML document, i.e., the parent node of each value must be the property of that value. Based on this default semantic information, we initially store each value with the label of its property in the corresponding relational table. With more semantics on object, we propose three optimization techniques to change the tables to be object based. We will show that using object-based tables, a query can be processed even more efficiently.

The rest of this chapter is organized as follows. We present the main algorithm of *VERT* in Section 3.2. In Section 3.3 we describe how we optimize tables, as well as query processing with more semantic information. We discuss how to extend *VERT* to process general XML queries across multiple twig patterns in Section 3.4. We present the experimental results in Section 3.5 and summarize this work in Section 3.6.

3.2 VERT algorithm

In this section, we present our algorithm *VERT*, to efficiently process XML twig pattern queries. We introduce relational tables as an index to help to perform content search and value extraction. Our approach is a semantic approach because the relational tables are built based on semantic information such as property, object, and relationship among objects. We first discuss the semantics of object and property, and then move to our main algorithm.

3.2.1 Object-related semantics in XML data

Object (or entity) is an important information unit in database management, such as the ER approach to design a relational database. In XML databases, object also plays an important role, as most XML queries ask about information of certain objects. An object may have several properties to describe the object from different aspects. The property is also referred as attribute. To differentiate it from attribute type in document schema (e.g., DTD), we use the term *property* in this thesis.

The semantics of object and property in XML data is actually apparent. If a user does not know how objects are organized in an XML document, he cannot compose any structured query, e.g., XPath or XQuery query to search the database. For example, a user wants to find the title of the book written by "White" in the two documents designed differently in Fig. 3.1 (partially shown). No matter how the document is designed, the user has to know that the book node is the object he wants to find, though the book node is not directly connecting the author node in the two documents. Knowing this, he will issue the query //book[authors/author="White"]/title to the first document and the query //book/basicInfo[author="White"]/title to the second document. Although semantics is important in query composing, very few work paid attention to use such semantic information to improve query processing performance.

In our approach, we make use of such semantics as object and property to aid twig pattern query processing. In an XML document tree, *value* nodes must appear as tree leaves. The parent node of each value node must be a *property* node with the corresponding value. For example, publisher, title, author, price and quantity are all properties in the bookstore document, because they are parent nodes of values. An object node sometimes appears as the parent node of some property nodes. For example, in the document in Fig. 3.3, every *subject* and every *book* are all objects, and they are parent nodes of properties such as name, publisher, title, etc. However, in some documents, the properties do not directly follow their objects. For example, if the document further groups the properties of a book as shown in the two examples in Fig. 3.1, the parent node of a property, i.e., authors, basicInfo or saleInfo, is not an object.

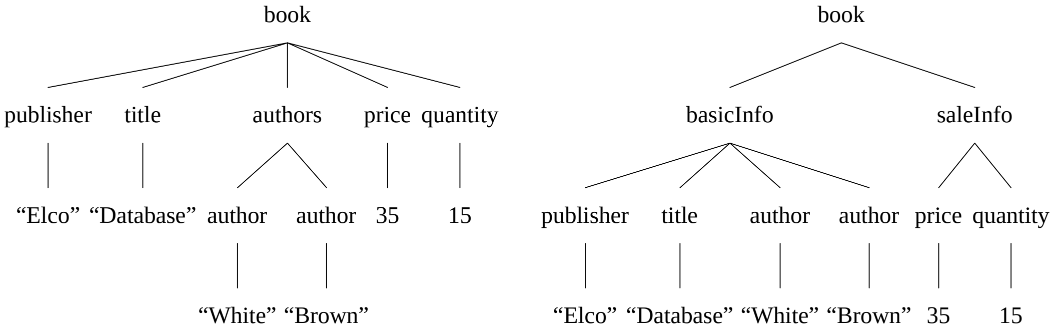


Figure 3.1: Two alternative design of book in the bookstore document

Two or more objects that are related to each other normally reside along the same path in an XML tree. However, the properties of a relationship may be misunderstood with object properties, due to the hierarchical structure of XML data. Consider the document design in Fig. 3.10. *Quantity* is a property of the relationship between *branch* and *book*, but this property appears as a child node of *book*, in the same way as other book properties. Although simply from the document tree (or even DTD or XML Schema) we cannot tell the difference between relationship property and object property, in fact, this information must be known beforehand. Actually, a user's awareness of the semantic meaning of each document node is not bound to the structure of the document. As mentioned above, a user must always be aware of such semantics in order to compose a correct XPath or XQuery query based on his search intention.

In case such semantic information is not available, there are also many attempts to discover the semantics such as object and relationship between objects in an XML document. Generally, there are categorized into three classes.

1. Using available tools and information. There are semantic rich models that work as a schema for XML documents. For example, ORA-SS [80] model can distinguish between properties, objects and relationships, as well as specify the degree of n-ary relationships and indicate if a property belongs to an object or a relationship. If such model is available alongside an XML document, we can easily discover useful semantic information. Also as semantic web is rapidly developed, there are many ontologies available for different domains. By exploring the ontology of relevant domains, we can have desired semantic information of an XML document.

2. Mining schema or document. Liu et al. [81] infer objects by analyzing DTD, though it is not very precise. [27] and [154] propose algorithms to discover the semantics such as keys and functional dependencies in XML documents, which can help to identify objects and relationships. There are also many data mining techniques, such as decision tree, can be adopted to infer semantic information.

3. User interaction. In many web-based information management systems [39][116], they use mass collaboration to seek for feedback from users to improve semantics identification.

In our work, we use known semantics on value, property, object and relationship among objects to design our algorithms.

3.2.2 An overview of VERT

In *VERT*, we pay attention to values during index construction. We maintain inverted list index only for structural nodes (non-valued nodes). For each value node, we store it into the relational table index[2] with the label of its property node, instead of labeling it and putting its label into an inverted list as other approaches do. Now, the number of inverted lists is limited to the number of different element/attribute types in the document.

Query processing in *VERT* includes three steps. In the first step, we perform content search for the value comparisons in query predicates, using relational tables. After that, the query is rewritten by removing all value comparisons. In the second step, we perform structural search for the simplified query pattern, using any structural join algorithms, e.g., *TwigStack* [16]. The last step is to extract values to answer the query from the relational tables. Fig. 3.2 shows the general process of query processing with *VERT*.

[2] To avoid the overhead on maintaining relational tables, the relational table index can also be replaced by other types of index to bidirectional map values and their properties. However, the trade-off is the inconvenience to support advanced content search and to meet the requirements in our object-related optimizations.

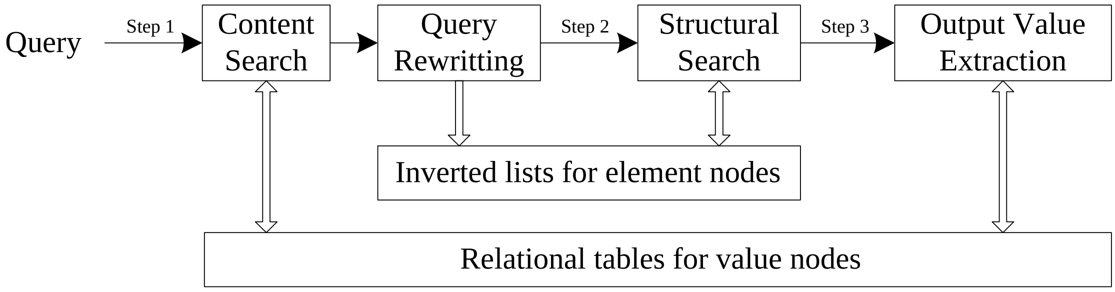


Figure 3.2: Overview of *VERT*

3.2.3 Document parsing in VERT

When we parse an XML document, we only label elements and attributes, and put the labels into corresponding inverted lists in document order. Values in the document are not labeled, instead we put them into relational tables together with labels of their parent *property* nodes. Normally this parsing step is only executed once for an XML document, and after all relevant indexes are properly built during the parsing step, the system is ready to process any twig pattern queries over the given document. The detailed algorithm *Parser* is presented in Algorithm 3.1.

We use the *SAX* to read the input document and transform each tag and value into events. Line 3 captures the next event if there are more events in the SAX stream. Based on different types of events, different operations are performed accordingly. Line 4-16 are executed if the event e is a start tag. In this case, the first two steps are triggered. The system first constructs an object for this element and assigns a label to it. It then puts the label into the inverted list for that tag. A stack S is used to temporarily store the object so that when an end tag is reached, the system can easily tell on which object the operation will be executed. At line 9-14, the system analyzes the attributes for an element if any. Based on the same operating steps, it labels the attributes and puts labels into inverted lists. The attribute values are treated in the same way as element values. Line 17-18 is the

Algorithm 3.1 Parser

Input: A *SAX* stream of the given XML document

Output: A set of inverted lists and a set of relational tables

```
 1: initialize Stack $S$
 2: while there are more events in SAX stream do
 3:    let $e$ = next event
 4:    if $e$ is a start tag then
 5:       //step 1: label elements
 6:       create an object $o$ for $e$
 7:       assign label to $o$
 8:       push $o$ onto $S$
 9:       for all attributes $attr$ of $e$ do
10:          //attributes are parsed in the same way as elements.
11:          assign label to $attr$
12:          put label of $attr$ into the inverted list $T_{attr}$
13:          insert the label of $attr$ and the value of $attr$ into the table $R_{attr}$
14:       end for
15:       //step 2: put labels of elements into inverted lists
16:       put label of $o$ into the inverted list $T_e$
17:    else if $e$ is a value then
18:       set $e$ to be the child value of the top object in $S$
19:    else if $e$ is an end tag then
20:       // step 3: Insert values with their parent element into tables
21:       pop $o$ from $S$
22:       if $o$ contains a child value then
23:          insert label of $o$ together with its child value into table $R_e$
24:       end if
25:    end if
26: end while
```

case that the event is a value type. Then the value is simply bound to the top object in S for further table insertion. When the event is an end tag in line 19-25, the last step is performed, which is popping the top object o from S and inserting the label of o together with its value into the relational table for o, if it has a value.

Example 3.1. *When we parse the bookstore document, the new labeled document tree under the containment labeling scheme is shown in Fig. 3.3. For convenience to illustrate our algorithms, we modify some data in Fig. 3.3. Comparing to the document tree in Fig. 1.4, we can see that* VERT *does not label value nodes. This* *attempt will save the number of labeled nodes in memory and reduce the number of node types (i.e., the number of inverted lists to manage). Detailed advantages of document parsing in* VERT *are reported in Section 3.4.*

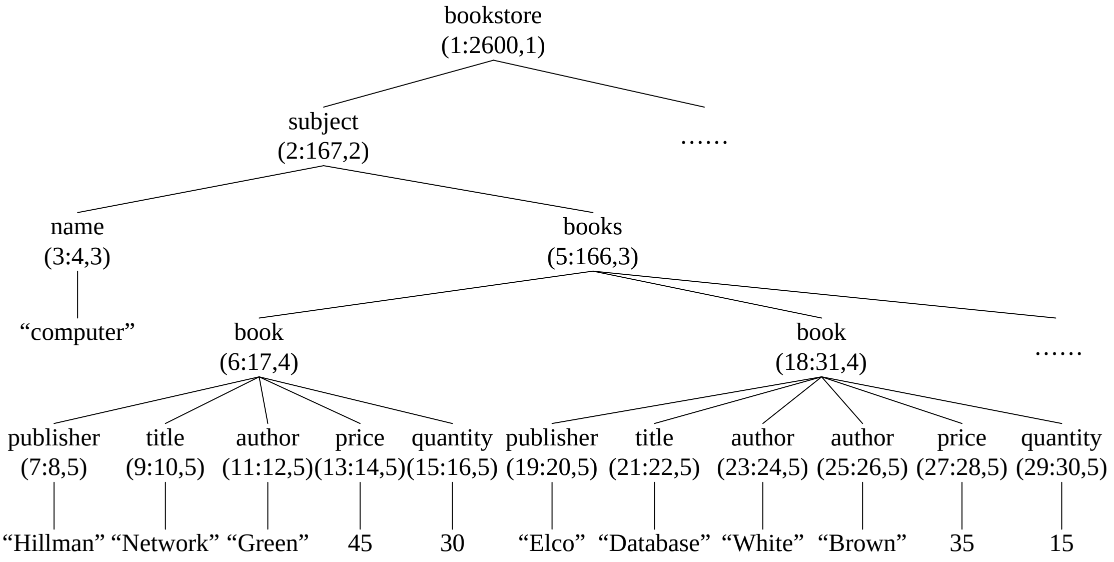


Figure 3.3: The bookstore document with only internal nodes labeled, during *VERT* parsing

Some example relational tables which store data values are shown in Fig. 3.4. The name of each table is a property name, and each table contains two fields, the label of the property node and the corresponding child value. We call these tables property *tables.*

$R_{publisher}$

label	value
(7:8,5)	Hillman
(19:20,5)	Elco
…	…

R_{title}

label	value
(9:10,5)	Network
(21:22,5)	Database
…	…

R_{author}

label	value
(11:12,5)	Green
(23:24,5)	White
(25:26,5)	Brown
...	...

Figure 3.4: Example property tables

Compared to other structural join based approaches, which use inverted list to index values, our approach to use relational tables for values has the following advantages:

- Relational tables can support advanced search, such as numeric range search and containment search for values. These advanced search is highly expected by users in XPath expressions. Other approach cannot perform advanced search easily when they employ inverted lists to index both structural nodes and value nodes.

- Using relational table, we can both select the property labels based on a given value and selection child value based on a given property table. This feature is very important because when we perform content search we need to extract labels based on values for further structural join, whereas to answer the query we need to extract values based on property labels. However, in other approaches, inverted list can only be used to get a list of labels for structural join. To answer the query, they have to access the document again to fetch the values based on property labels. This violates the purpose of using inverted lists to save I/O cost in these approaches.

Similar to inverted list, relational table also plays an index role to aid twig pattern query processing, which is presented in the next section. As a result, how to cope with document updates is an important issue for both inverted lists and relational tables. Inverted list is widely used to process different forms of queries for years, e.g., twig pattern query and keyword query. There are different ways to maintain an inverted list for updates, e.g., employing a B-tree for each list. Here we focus on the maintenance of relational tables when the XML document is updated. Actually relational tables are easy to maintain. If the document is dynamic, which means there are frequent updates to the document, we can adopt a dynamic labeling scheme to label the document so that the update will not cause re-labeling for remaining document nodes. Thus, when some document nodes are deleted, we simply delete the corresponding tuples in the relational tables; while when some new nodes are added, we assign them new labels, and put them into corresponding relational tables without affecting the existence of other tuples.

3.2.4 Query processing in VERT

As shown in Fig. 3.2, query processing in *VERT* contains three steps: content search and query rewriting, structural search, and value extraction. Theoretically, the first two steps, i.e., content search and structural search, can be reordered. The reason that we perform content search before structural search is that content search normally results high selectivity. By performing content search first, we can significantly reduce the inverted list size of relevant query nodes. This is similar to selection push-ahead in relational query optimizers. The pseudo-code of *VERT* query processing is presented in Algorithm 3.2.

We first perform content search in Line 2-8. The algorithm recursively handles all value comparisons in two phases: creating new inverted lists based on the predicates and rewriting the query to remove the processed value comparisons. In more details, Line 3-6 execute *SQL* selection in the corresponding property tables based on the value comparison, and then put all the selected labels, which satisfy the value comparison, into the new inverted lists for the corresponding property node. Line 7 rewrites the query in such a way that every value comparison and its parent property are replaced by a new query node which has an identical name as the corresponding new inverted list. The second step is using *TwigStack* or other efficient structural join algorithms to process the simplified query with new inverted lists in Line 10-11. Last in line 13, we can extract actual values based on

Algorithm 3.2 VERT query processing

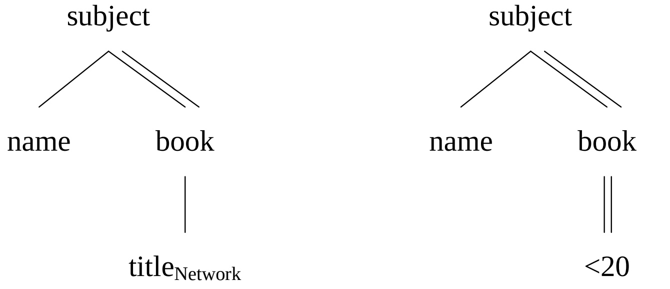
Input: A query Q and necessary inverted lists and relational tables

Output: A set of value results answering Q

```
//step 1: perform content search, construct new inverted lists and rewrite the query
while there are more value comparisons in predicates of $Q$ do
    let $c$ be the next value comparison, and $p$ be its property (parent element or attribute)
    create a new inverted list $T_{p'}$ for $p$
    select the labels based on $c$ from the table $R_p$
    put the selected labels into $T_{p'}$
    rewrite the query to replace the sub-structure $p/c$ by $p'$
end while
//step 2: perform structural search on the rewritten query with new inverted lists
process the rewritten pattern of $Q$ using any existing efficient structural join algorithm like TwigStack, to get labels for output nodes
delete newly created inverted lists
//step 3: extract query answer
extract and refine actual values with labels from corresponding tables, if the output node is a property node; otherwise access the document to return sub-trees
```

node labels from the corresponding table, if the output node is a property node. When different node labels contribute to the same value answer, we can refine the result by removing the duplicates.

Example 3.2. *Now we use the twig pattern query in Fig. 1.3(a) to illustrate how* VERT *works. In the first step,* VERT *identifies the only predicate with value comparison is* title="Network"*. During content search,* VERT *executes an* SQL *selection in the table R_{title} to get all the labels of element* title *which have a value of "Network". Then we put the selected labels into the new inverted list for* title*, $T_{title'}$. After that we rewrite the twig pattern query to replace the sub-structure of the node* title *and its child node* "Network" *by* title'*. The rewritten query is shown in Fig. 3.5(a). Now the query node* title' *corresponds to the newly created inverted list $T_{title'}$, in which all the labels satisfy the constraint* title="Network"*. To clearly* *explain* title’ *in the rewritten query, we use* $title_{Network}$ *in Fig. 3.5(a). Finally we use a twig pattern matching algorithm, e.g.,* TwigStack *to process the rewritten query in Fig. 3.5(a), with the inverted list* $T_{title'}$ *for the node* $title_{Network}$*.*



(a) Rewritten query example (b) Invalid query example

Figure 3.5: A rewritten query example and an invalid twig pattern query example

As described in Section 1.2.1, twig pattern query is an intermediate query representation for some formal XML query languages, e.g., XPath and XQuery. Since in the predicate of an XPath or XQuery query, a value must link to a property through an operator, e.g., price<20, the value comparison in the corresponding twig pattern representation must be a child (‘/’), instead of a descendant (“//”) of an internal query node. A twig pattern expression shown in Fig. 3.5(b) is invalid, as the value comparison follows a “//” edge. Semantically, this query cannot be well interpreted; and practically, this query will never appear in XPath or XQuery expressions. We do not consider such invalid twig patterns, thus our algorithm can perform any content search using property tables.

Note that *VERT* saves I/O cost in value extraction when the output node is a property node, because we do not need to visit the original document, but only access relevant relational tables to find values. However, if the output node matches some internal nodes with subelements in the document, the result should be the whole subtree rooted at each matched node, instead of a single value. In this case, *VERT* has no advantage in result return over other approaches.

3.2.5 Analysis of VERT

In this section, we analyze our algorithm in five points of view: the management of labeled nodes and inverted lists, content search for predicates and value extraction for final results, the size of inverted lists to be searched, the number of structural joins required during query processing, and the support for advanced search.

Label and inverted list management. Normally in a large XML document, value nodes take a high proportion to all document nodes. *VERT* combines values to their parent elements, and avoids labeling value nodes separately. Then the number of labeled nodes in memory will be greatly reduced. Moreover, *VERT* also has advantage in inverted list management. Since the high variety of values is ignored during inverted list construction in *VERT*, the number of inverted lists is limited to the number of element or attribute types. In this point of view, the problem of managing tremendous number of inverted lists in previous work can be solved.

Content search and value extraction. Consider the previous example that a query aims to find the books with price of 35 and output their titles. As mentioned earlier, when we perform content search for this query using existing approaches we have to read the inverted list for '35', which contains labels with different semantics like the *price* of a book and the *quantity* of a book. To mix them together will cause unnecessary search. Instead of searching in inverted lists, *VERT* handles content search in semantic tables. In this case, we just move into the property table for *price* and avoid searching for the value '35' under *quantity*. Furthermore, after getting all the satisfied occurrences of the output node *title* in terms of labels, we aim to find the actual value under each title. Previous approaches have to refer to the document again to fetch values because the inverted lists cannot help to extract values based on parent node labels. *VERT* can efficiently get the desired values without considering the document storage because all the values are stored in tables and we can directly extract them using the labels of their associated property by *SQL* selections. Also, if different node labels contribute to the same value answer, we can refine the returned answer by removing duplicates. In a word, relational tables are not only helpful for content search, but also usable to extract desired values.

Inverted list searching reduction. Performing content search before structural join in *VERT* can significantly reduce the size of relevant inverted lists. Consider the query in Fig. 1.3(a). Assume there is only one book called "Network". If the number of different books is b, the size of the inverted list for the element *title* is also b in previous approaches. Then we need *O(b)* to scan all the labels in the inverted list for *title*. *VERT* processes selection in advance, so that the new inverted list for *title* is created based on the value "Network". In this case the new inverted list has only 1 label inside based on our assumption. Normally, when the selectivity of an element is high, like in this example, *VERT* can be very efficient in structural search because it significantly reduces the searching in inverted lists for the relevant nodes. This is similar to the selection push-ahead in *SQL* query processing in relational databases.

Query nodes and structural joins reduction. There are two factors driving a high performance of structural search in *VERT*. One is inverted list searching reduction as mentioned above and the other factor is query nodes and structural joins reduction in the rewritten query. Still consider the original and rewritten query in Fig. 1.3(a) and 2.1. The rewritten query has only three edges which need structural joins, while the original query has four. Also when we rewrite the query, we remove the query nodes of value comparison. This naturally simplifies the query. Optimizations to further reduce the size of inverted lists and the number of both query nodes and structural joins will be discussed in the next section.

Advanced search support. Advanced search is quite common in real life queries. For example, in an XPath expression, numeric range search and the *contains* function are usually issued in predicates. Since *VERT* can use any existing RDBMS to manage property tables, all the advanced search which are supported by the relational system are also supported in *VERT*. Also *VERT* permits conjunction or disjunction of value comparisons appearing as a leaf node in a twig pattern query.

We can observe that sequential scans and structural joins for labels of both property node and value node in previous work are replaced by selections in semantic tables in *VERT*. Actually in any relational database system, such table selection can be done very efficiently. It is not surprising that replacing structural join by selection for content search will improve the overall performance.

Generally, *VERT* gains benefit from performing content search ahead of structural search, and then reduce the complexity of structural search. Thus most advantages discussed in this section hold only for queries with value predicates, which are commonly seen in real life. When a query does not have value comparison as predicate, the first part in our algorithm, i.e., the content search part will be ignored. Then we just follow any existing structural join algorithm to perform structural search directly. In this case, our algorithm is the same as other existing algorithms.

3.3 Semantic optimizations

Tables in *VERT* are built based on the semantic relationship between property and value. That is why we call them property tables. Using property tables to perform content search may still not efficient enough in some cases. We notice that object is an important information unit for most queries. In this section, we optimize the property tables to be object based, to further improve the query processing efficiency.

3.3.1 Optimization 1: object/property table

Motivation:

We identify two efficiency problems with property table to process twig pattern queries. The first problem is that the property table may produce redundant labels during content search. Consider a query to find the title of all books with price less than 35. To process this query, we need to find all *price* labels in the price table with value less than 35. However, if the bookstore document also contains magazine or other products with the property *price*, many of the selected labels may stand for price of other products and it is redundant to use them to construct the new inverted list for *book price*. The second problem is the redundant search on other relevant inverted lists. Generally, by specifying conditions on certain properties, most queries aim to find the associated object and then get some other property values of that object. Consider the query in Fig. 1.3(a). Suppose there are b books in the bookstore and only one of them is called "Network". After *VERT* rewrites the query in Fig. 3.5(a), the size of the inverted list for *title* is reduced to 1. However the size of the inverted list for *book* is still b, which means we need to search all the b labels though we know only one of them matches the label in the *title* inverted list. To solve these two efficiency problems, we propose an optimization scheme based on the relationship between object and property.

Optimization:

Instead of storing each value with the label of its associated property node, we can put the property value and the label of the corresponding object node into relational tables. For example, in the bookstore document we put values for *publisher*, *title* and so forth with labels of the corresponding object *book* into *object/property* tables as shown in Fig. 3.6(a). The 'label' field of each table stores the label of the object and the following 'value' corresponds the value of different properties in different tables. When we perform a content search, we can directly select the object labels in the corresponding object/property tables and construct a new inverted list for the object. Then to process the query in Fig. 1.3(a), we perform the content search using $R_{book/title}$ to restrict the book labels based on the condition on title value. After that the query can be further rewritten accordingly, as shown in Fig. 3.6(b), where $T_{book'}$ is the new inverted list for the element *book* and we use $book_{title=\text{“}Network\text{”}}$ is to explicitly explain *book'*. Now we not only reduce the size of T_{book}, but also further reduce the number of structural joins and the number of query nodes by one. Then we can get a higher performance when we execute the simplified query.

Discussion:

Ordinal Column: This optimization may lose order information for multi-valued properties. Such information may be important in some cases. For example, the order of authors is important, but from the book/author table we cannot tell which author comes first for a certain book. To solve this limitation, we can simply add

$R_{book/publisher}$

label	value
(6:17,4)	Hillman
(18:31,4)	Elco
…	…

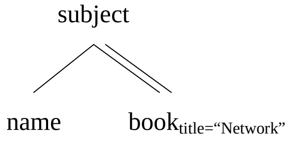
$R_{book/title}$

label	value
(6:17,4)	Network
(18:31,4)	Database
…	…

$R_{book/author}$

label	value
(6:17,4)	Green
(18:31,4)	White
(18:31,4)	Brown
…	…

(a) Tables in *VERT* Optimization 1



(b) Rewritten query for Fig 1.3(a) with inverted list size of $book_{title=\text{“}Network\text{”}}$= $|T_{book'}|$=1

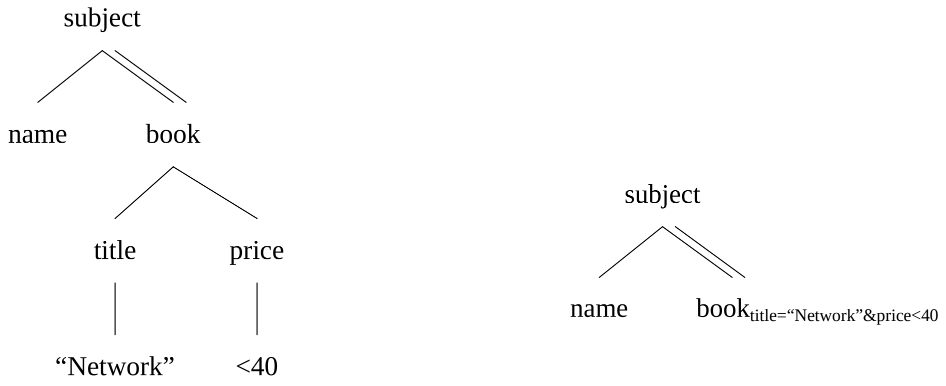
Figure 3.6: Tables and rewritten query under *VERT* Optimization 1

an additional column in the object/property tables for multi-valued properties, to indicate the ordinal information.

3.3.2 Optimization 2: object table

Motivation:

It is quite normal that some queries contain multiple predicates on a common object. Consider the query shown in Fig. 3.7(a), which aims to find the subject of the book with title of "Network" and price less than 40. To answer this query, Optimization 1 needs to find the labels of books with title of "Network" and labels of books with price less than 40 separately using the object/property tables, and intersect the two sets of labels. With semantic information, we know that *title* and *price* are both properties of the object *book*. If we have one table for this object that contains the both properties, books satisfying these two constraints can be found directly with one *SQL* selection, and then the intermediate results can be avoided.



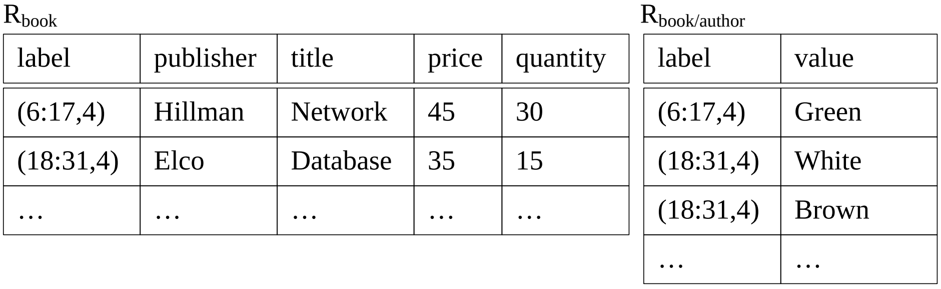
(a) Query with multiple value predicates under the same object

(b) Rewritten query for Fig 3.7(a) under Optimization 2

Figure 3.7: Example query with multiple value predicates under the same object and its rewritten query in Optimization 2

Optimization:

A simple idea is to merge the object/property tables in Optimization 1 based on the same objects. For multi-valued properties, such as *author* in our example, it is not practical to merge it with other properties. In this case, we can merge all the single-valued properties of an object into one object table and keep the object/property tables for multi-valued properties. The resulting tables for the object *book* in the bookstore document under this optimization are shown in Fig. 3.8. In R_{book}, each label of book is stored with all the single-valued property values of that book. When we process queries with multiple predicates on single-valued properties of an object, we can do selection in that object table based on multiple constraints in one time. For example, to process the query in Fig. 3.7(a), we can select book labels based on the two predicates in R_{book} with one SQL selection. Then the original query can be rewritten as shown in Fig. 3.7(b). Comparing with the Optimization 1 approach, we further simplify the query and prune intermediate results for the two predicates.



R_{book}

label	publisher	title	price	quantity
(6:17,4)	Hillman	Network	45	30
(18:31,4)	Elco	Database	35	15
…	…	…	…	…

$R_{book/author}$

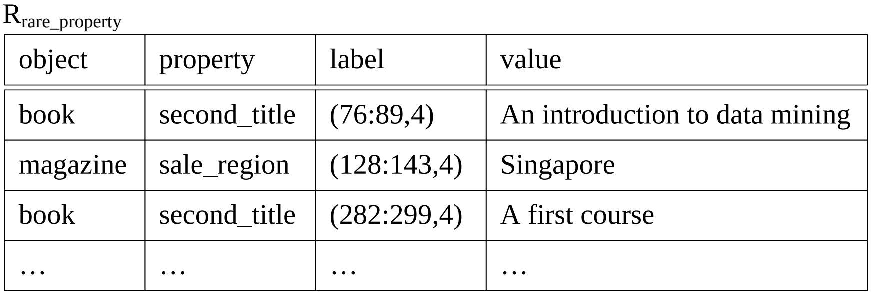
label	value
(6:17,4)	Green
(18:31,4)	White
(18:31,4)	Brown
…	…

Figure 3.8: Tables for *book* in the bookstore document under *VERT* Optimization 2

Discussion:

Mixed table selection: If the multiple predicates involve both single-valued properties and multi-valued properties, we can perform selection for all single-valued properties in the object table, and then intersect the result with the selection result from the object/property tables for the multi-valued properties.

Rare property: Properties may optionally appear under the associated objects. In some cases, the occurrence of certain properties may be rare. We call such properties *rare properties*. Suppose in the bookstore document, only a few books have a *second_title*, then *second_title* is a rare property. If we put this rare property as a column in the book table, there will be too many NULL entries.



$R_{rare\_property}$

object	property	label	value
book	second_title	(76:89,4)	An introduction to data mining
magazine	sale_region	(128:143,4)	Singapore
book	second_title	(282:299,4)	A first course
…	…	…	…

Figure 3.9: Table for rare properties

Some relational database systems can deal with the case of sparse attribute in the physical storage. In case some other systems do not have this function, we can maintain a rare property table to store all such rare properties. The rare property table contains: the object name, the rare property name, the object label and the property value. Suppose in the bookstore document, *second_title* is a rare property of *book* and *sale_region* is a rare property of *magazine*, the rare property table for this document is shown in Fig. 3.9. Queries involving rare properties are processed by accessing the rare property table with the object name and the property name.

Vertical partitioning: Object table is obtained by merging the object/property tables for all the single-valued property under the same object. When there are many single-valued properties under a certain object, the tuple size of the corresponding object table will be too large. When we perform a selection based on only a few properties, all other properties are also loaded. This results a high I/O cost.

A common way in RDBMS design to reduce such I/O cost is the vertical partitioning of a table ([95]). We can refer to the query history to see which properties often appear together in the same query, and then split the original object table into several partitions according to such information. Since vertical partitioning is not a new technique, we do not discuss it any more.

3.3.3 Optimization 3: relationship table

Motivation:

Unlike the ER model for relational data, the hierarchical structure of an XML document cannot reflect the relationships between objects explicitly. However, such relationships do exist usually. Consider another design of the bookstore document as shown in Fig. 3.10, in which the books under each subject are also grouped by different branches.

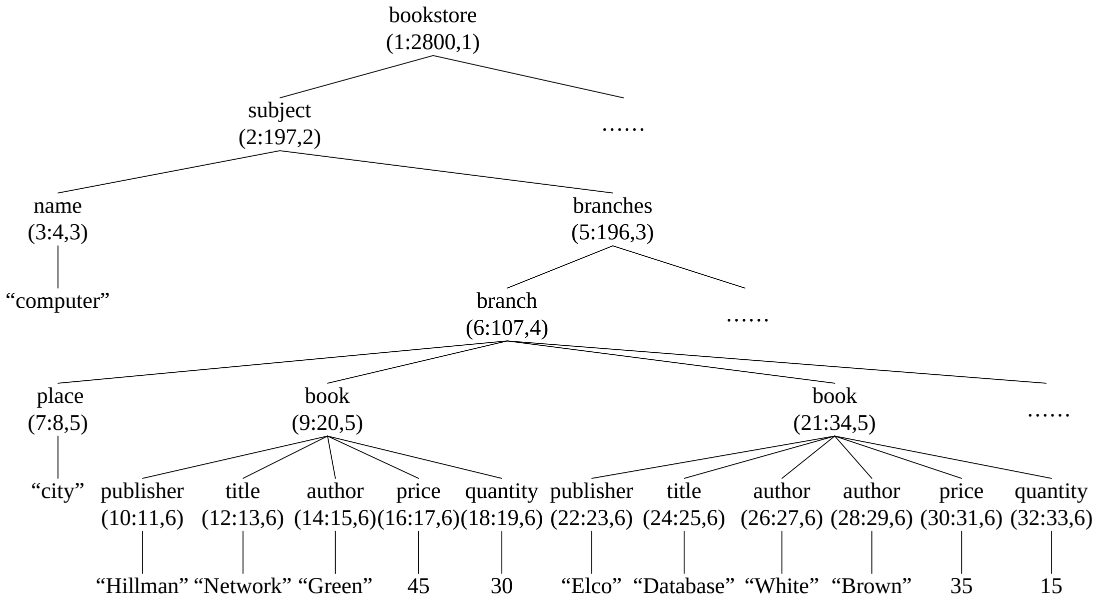
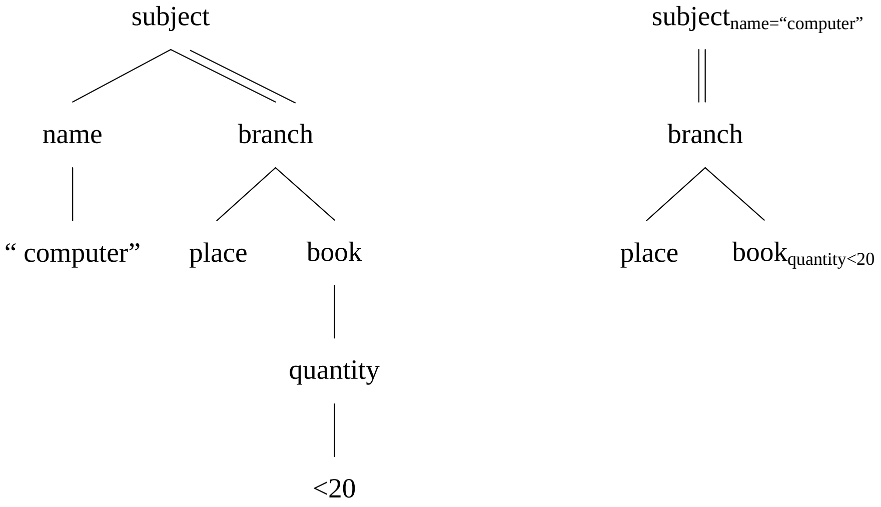


Figure 3.10: Another design of the bookstore document

In Fig. 3.10, the *quantity* is not a property of book, but a property of the relationship between *branch* and *book*. In other words, only given a branch of the bookstore and a book we can determine the quantity. Putting a relationship property into the object table of the property's nearest object does not affect the accuracy of query processing. Consider a query to find the place of the branch that has some computer book with a low quantity, i.e., less than 20. A twig pattern expression of this query is shown in Fig. 3.11(a). Suppose we have no idea on the relationship between *branch* and *book*, but store the property *quantity* in the object table for *book*. Then to process this query, Optimization 2 will rewrite it as in Fig. 3.11(b) for further matching, and return precise result. However, in this example, we aim to find some qualified branch. Matching the *book* node seems redundant. If we know the predicate is on the relationship between *branch* and *book*, we may ignore *book* during pattern matching, and thus improve matching efficiency.



(a) Example twig pattern query

(b) Rewritten query for Fig 3.5(a) under Optimization 2

Figure 3.11: Example query with predicate on relationship property and its rewritten query in Optimization 2

Optimization:

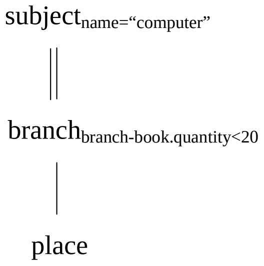
If we have the semantic information that *quantity* is actually a property of the relationship between *branch* and *book*, we can include this information in table construction, i.e., introducing a relationship table. A relationship table stores the property value and the label of the participating objects of each relationship instance. The example relationship table for the document in Fig. 3.10 is shown in Fig. 3.12(a). Actually the relationship table is similar to the relationship table in ER design for structured data. When a relationship involves more than two objects, the corresponding relationship table will include the labels of all the objects. Using the knowledge on relationship and the relationship table, the query in Fig. 3.11(a) can be rewritten as in Fig. 3.12(b).

Compared to Optimization 2, the query is further simplified with the semantic information on relationship. Then the query processing performance will be further improved.

$R_{\text{branch-book}}$

$\text{label}_{\text{branch}}$	$\text{label}_{\text{book}}$	quantity
(6:107,4)	(9:20,5)	30
(6:107,4)	(21:34,5)	15
…	…	…

(a) Relationship table



(b) Rewritten query for Fig 3.11(a) under Optimization 3

Figure 3.12: Example relationship table and rewritten query in *VERT* Optimization 3

Discussion:

Overlapping predicate: When a query node is involved in both an object predicate and a relationship predicate, we call this case overlapping predicate. For example, if the query in Fig. 3.11(a) has an additional predicate on book price, then the query node *book* will have an overlapping predicate, i.e., one predicate on the relationship between book and branch, and one predicate on the book itself. To handle the overlapping predicate, we can perform the content search based on different predicates separately, and then intersect the two sets of label results to construct the temporary inverted list for the involved object.

Merging object table and relationship table: If the semantics of participation constraint between two object classes is known, we can merge the object table(s) and the relationship table when the constraint is many-to-one or one-to-one. This is similar to the translation from ER diagram to tables with the consideration of participation constraints in relational database design. However, similar to the vertical partitioning, how to physically maintain relational tables is generally bound to the performance analysis for practical queries.

3.4 Query across multiple twig patterns

A twig pattern can be used to model a simple query. When a query is more complex, we need to model it with multiple twig patterns and value-based join is used to connect these twig patterns. One example is shown in Fig. 3.13, which finds the titles of all books written by some author of the book "Network". Moreover, different twig patterns from a query may target at different documents. As pointed by [16], structural join based algorithms can only efficiently process single-patterned queries. When a complex queries involves several twig patterns, either from a same document or across different documents, those structural join based algorithms will fail to work.

The reason why the structural join based twig pattern matching algorithms cannot process queries involving several twig patterns is that those algorithms cannot perform value-based join between twig patterns using their inverted list indexes that store node labels. One naive approach is to match different twig patterns in such a complex query separately. By considering each query node that are involved in value-based join as an output node, they can then access the original document to retrieve the child values for these query nodes. Lastly, they perform joins based on retrieved values. Obviously this attempt is I/O costly, and also may produce a large size of useless intermediate result.

One special case is that a query is issued to an XML document with ID references. As reviewed in Section 2.2, most existing approaches will consider both the document and the query as graphs, and perform graph pattern matching. Generally, matching two graphs is much more complex than matching two trees. Actually, a query with an ID reference can be considered as two twig pattern queries with a value-based join based on the equation between the ID value and the IDREF value. If we can design an efficient algorithm to process queries involving multiple twig patterns, we can also reduce the graph matching problem to the tree matching problem to process queries with ID references.

In *VERT*, we introduce relational tables to store values. This structure can effectively bridge the gap between twig pattern matching and value-based joins between twig patterns. We observe that a join operation between two twig patterns is based on a value comparison between two properties in the two twigs. Actually, by performing joins between property tables, we can easily handle the value-based join between multiple twig patterns, even across multiple XML documents.

Example 3.3. *Consider a query given in Chapter 1, i.e., the query to find the title of all books written by some author of the book "Network". The two twig patterns used to process this query are shown in Fig. 3.13.* VERT *starts from either one of them to process this query. For example,* VERT *matches (t1) to the document first, to get the value result of query node* author*. Then* VERT *joins the value result to the* author *table which corresponds to the joining node in (t2). Finally, we put the selected labels into a new inverted list for the* author *node in (t2), and match (t2) to the document.*

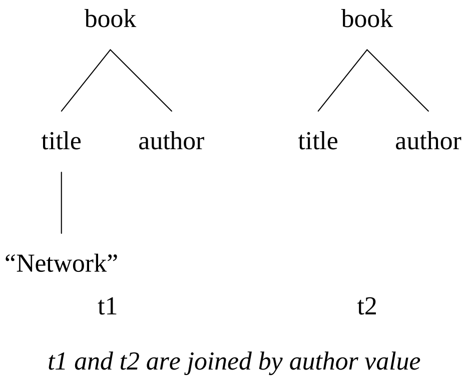


Figure 3.13: Example query with multiple twig patterns

Another query plan to solve the query in Fig. 1.3(b) is to match (t2) first, and then using the matching result to get *author* labels to match (t1). Obviously, the query plan used in Example 3.3 is more efficiently because (t1) is much more selective than (t2) and matching matching (t1) before (t2) will have smaller intermediate result size. Thus, one important issue to extend *VERT* to process a general query modeled by multiple twig patterns with joins is how to choose a good query plan.

3.4.1 Query plan selection

A twig pattern matching is considered as a series of structural joins between query nodes. The value-based join linking different twig patterns is quite similar to the table join in RDBMS. How to arrange the order of structural joins during twig pattern matching [145] and how to arrange the order of different kinds of value-based joins in RDBMS [46] have been studied. Actually, in a general XML query involving pattern matchings and value-based inner joins, different join operations (structural joins and value-based joins) are also reorderable. When a value-based join between two twig patterns is an outer join, the approach in [46] can be extended to make join operations reorderable for this case. The reorderability of structural join and value-based join in general XML queries is investigated in our another work [142]. We do not show the details in this thesis. Because joins are reorderable, we can generate different query plans to process a general XML query. With an effective cost model of each operation, i.e., pattern matching and value-based join, and an efficient method to estimate result size after each step, we can choose a good query plan to proceed.

Cost models

Twig Pattern Matching: The holistic structural join approach is the state-of-the-art approach to process a twig pattern query. Thus we estimate the cost of the holistic join based approach. It is proven in [16] that in the worst case, the I/O and CPU time for the holistic join based twig pattern matching algorithm is linear to the size of input inverted lists and the size of results. The cost of pattern matching is $f_{in}*sum(|T_1|, ..., |T_n|)+f_{out}*|RS_{p\_out}|$, where f_{in} and f_{out} are the factors for input size and output size, $|T_m|$ is the size of m-th inverted list and $|RS_{p\_out}|$ is the size of output result set.

Value-based Join: We adopt the cost model for table join in relational query optimizer for value-based join. Take the inner join as an example. Suppose the sizes of the two sets are t_1*n_1 and t_2*n_2, where t_i is the size of each tuple and n_i is the number of tuples (i=1 or 2). If we adopt the nested loops join, the cost is $f_{outer}*t_1*n_1+f_{inner}*t_1*n_1*t_2*n_2$, or $f_{outer}*t_2*n_2+f_{inner}*t_1*n_1*t_2*n_2$, depending on which set is chosen as the outer set. f_{outer} and f_{inner} are factors for outer set I/O cost, and inner set I/O and join cost. The final join result should be sorted as the input stream for pattern matching. The cost on result sorting is $f_{sort}*|RS_{v\_out}|$, where f_{sort} is the sort factor and $|RS_{v\_out}|$ is the size of join result.

After tuning and normalizing the factors, the cost models can be used to estimate the cost for each operation.

Result Size Estimation

There are many approaches to estimate the result size of a value-based join in RDBMS. Those approaches can also be used to estimate the result size of a value-based join. Estimating result size of structural joins is also studied in many previous research works, e.g., [144]. We can use them in our approach.

Using the cost models and the estimated result size, we can easily extend the query optimizer in RDBMS to generate and select good query plans for general XML queries.

3.5 Experiments

In this section, we conduct experiments to show the advantage of our sematic approach, *VERT*, in twig pattern query processing. We focus on matching a single twig pattern query to an XML document. We first compare our approach to a schema-aware relational approach [114], which is considered more efficient than other relational approaches. Then we compare *VERT* and its two optimizations to *TwigStack*, a typical structural join based twig pattern matching algorithm. Note that in this experiment, our algorithms take *TwigStack* to perform structural search, thus we compare to *TwigStack* to show the benefit gained. We can also take any other structural join algorithm to perform structural search. We do not compare with them because the comparison with *TwigStack* is sufficient to show the advantage of our approach.

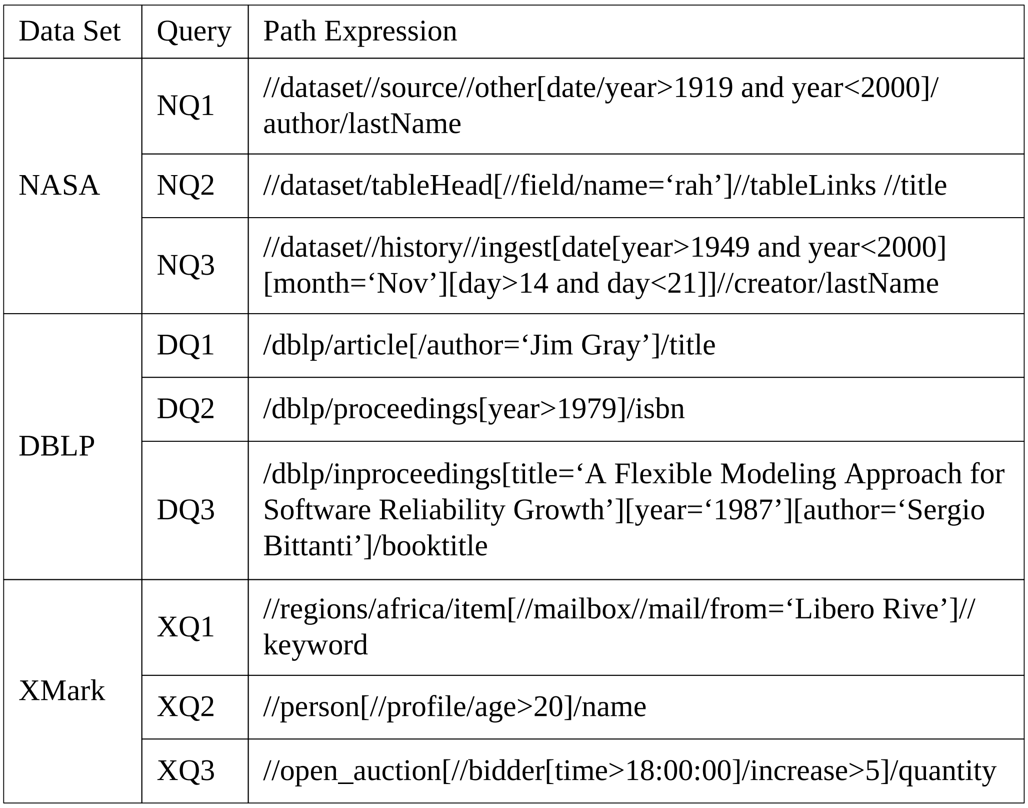
3.5.1 Settings

We implemented all algorithms in Java. The experiments were performed on a dual-core 2.33GHz CPU and a 4GB RAM under Windows XP.

We used three types of real-world and synthetic data sets to compare the performance of *TwigStack* and our approaches: NASA [94], DBLP [35] and XMark [146]. NASA is a 25MB document with deep and complex schema. DBLP data set is a 127MB fragment of DBLP database. It is rather regular with a simple DTD schema but a large amount of data values. We also used 10 sets of XMark benchmark data with size from 11MB to 110MB for our experiments.

We randomly selected three meaningful queries for each data set. All the queries chosen contain predicates with value comparisons, as value predicates appear in most practical queries. Generally, there are three types of queries: queries with predicates of equality comparison, queries with predicates of range comparison and queries with multiple predicates of different comparisons. The queries are shown in Fig. 3.14.

In VERT, we use the Sybase SQL Anywhere [117] to manage relational tables, and inherit the default database parameters. In all the compared approaches, no additional index is built on inverted lists or tables.



Data Set	Query	Path Expression
NASA	NQ1	//dataset//source//other[date/year>1919 and year<2000]/author/lastName
	NQ2	//dataset/tableHead[//field/name='rah']//tableLinks //title
	NQ3	//dataset//history//ingest[date[year>1949 and year<2000][month='Nov'][day>14 and day<21]]//creator/lastName
DBLP	DQ1	/dblp/article[/author='Jim Gray']/title
	DQ2	/dblp/proceedings[year>1979]/isbn
	DQ3	/dblp/inproceedings[title='A Flexible Modeling Approach for Software Reliability Growth'][year='1987'][author='Sergio Bittanti']/booktitle
XMark	XQ1	//regions/africa/item[//mailbox//mail/from='Libero Rive']//keyword
	XQ2	//person[//profile/age>20]/name
	XQ3	//open_auction[//bidder[time>18:00:00]/increase>5]/quantity

Figure 3.14: Experimental queries

3.5.2 Comparison with Schema-based Relational Approach

In this section, we compare *VERT* with a Schema-based Relational Approach proposed in [114]. We name it *SRA* for short. We also use the Sybase SQL Anywhere as a database for *SRA*. Since this approach is weak in dealing with "//"-axis, we adopt the proposal in [52] to augment it. In particular, [52] uses containment labels as primary key of each table, so that the "//"-axis join can be efficiently performed with the property of containment labeling scheme. *SRA* is proven more efficient than other schemaless relational approach to process XML queries. The execution time for both *SRA* and *VERT* to process the queries in NASA, DBLP and a 110MB XMark data is shown in Fig. 3.15. Note that the Y-axis is log scaled.

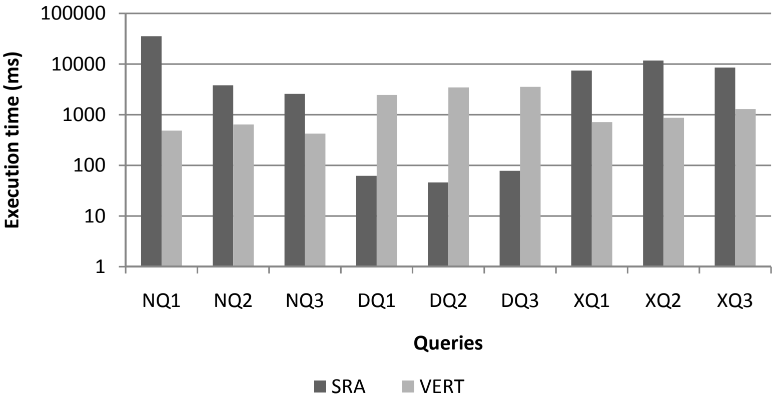


Figure 3.15: Comparison result between *SRA* and *VERT*

From Fig. 3.15 we can see that for NASA and XMark data (NQ1-3, XQ1-3) *VERT* is more efficient, but for DBLP data (DQ1-3) *SRA* is more efficient. DBLP data is rather regular and flat, thus the values in DBLP data can be perfectly shredded into relational tables. The maximum height of DBLP is 4, which means using *SRA* shredding method, there is at most one table join required for all queries and this join is between the table for root (containing only one tuple) and another table. For such a relational-like document, the relational approach is much more efficient, because table selection dominates the overall performance and this operation can be performed very efficiently in all relational databases.

However, most real life XML data is not as regular as DBLP, otherwise, it violates the advantage of the semi-structured format. As we see for NQ1-3 and XQ1-3, when the document is deeper and more complex, i.e., requires more table joins for *SRA*, the performance of *SRA* is badly affected.

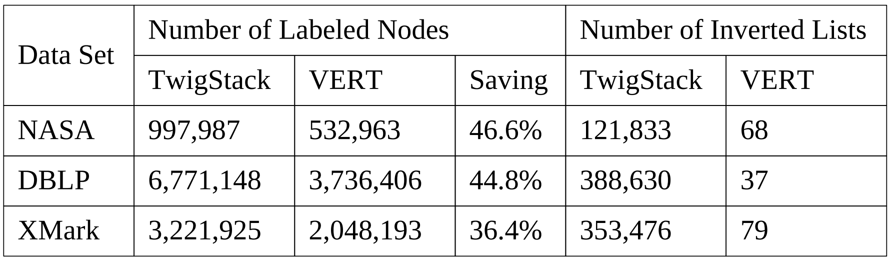
In a word, the relational approach to process XML queries is only suitable for regular XML documents, but not as good as structural join based approaches for complex XML structures.

3.5.3 Comparison with TwigStack

Now we compare *VERT* with *TwigStack*, which is a typical structural join based twig pattern matching algorithm. We test on two aspects, space management and query performance.

Space management

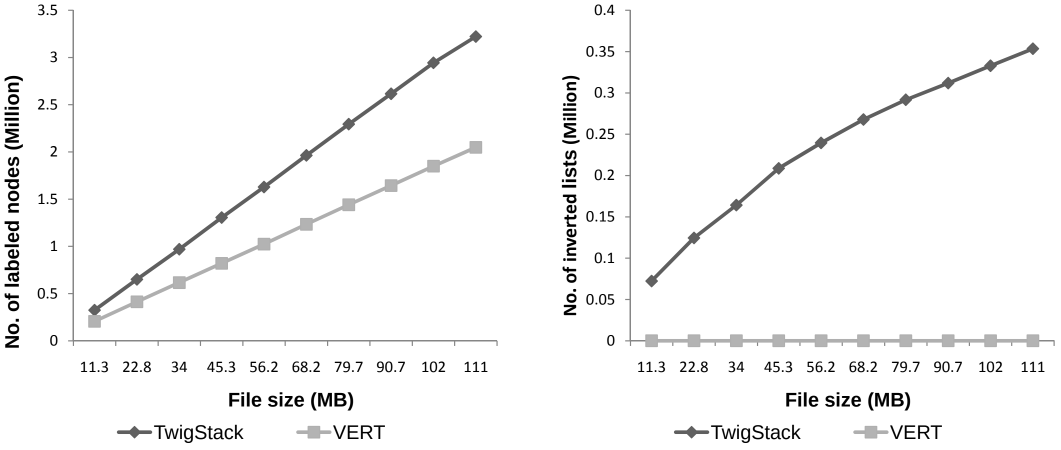
As mentioned earlier, *TwigStack* does not specially handle value nodes during document parsing and query processing, but treat them the same as other internal nodes. There may be too many inverted lists, most of which contain very few labels. In this part, we test the required space in document parsing, including the number of labeled nodes in memory, and the number of inverted lists to be managed. We parse the two real-world data sets, NASA and DBLP, and a 110MB XMark data using *TwigStack* and *VERT* separately. The number of labeled nodes and the number of inverted lists in the two approaches are shown in Fig. 3.16.



Data Set	Number of Labeled Nodes			Number of Inverted Lists	
	TwigStack	VERT	Saving	TwigStack	VERT
NASA	997,987	532,963	46.6%	121,833	68
DBLP	6,771,148	3,736,406	44.8%	388,630	37
XMark	3,221,925	2,048,193	36.4%	353,476	79

Figure 3.16: Number of labeled nodes and inverted lists in *TwigStack* and *VERT*

This result validates our analysis in Section 3.2.5 about the reduction of labeled nodes in memory and the reduction of inverted lists. In *VERT*, values are stored in relational tables and the relational tables are built based on different types of properties, so the number of tables is limited to the number of different property types. There is no problem to manage the tables. We also use 10 sets of Xmark data, whose sizes vary between 11MB and 110MB, to further prove the superiority of *VERT* in space management. The experimental result is shown in Fig. 3.17. We can see from the result that the number of labeled nodes is scaled to the document size for both approaches, and *VERT* always manages less labeled nodes. Furthermore, the number of inverted lists is scaled to the size of document in *TwigStack*, whereas this number is a constant in *VERT*. For a large data set it is not practical to handle the tremendous number of inverted lists using *TwigStack*.



(a) Number of labeled nodes

(b) Number of inverted lists

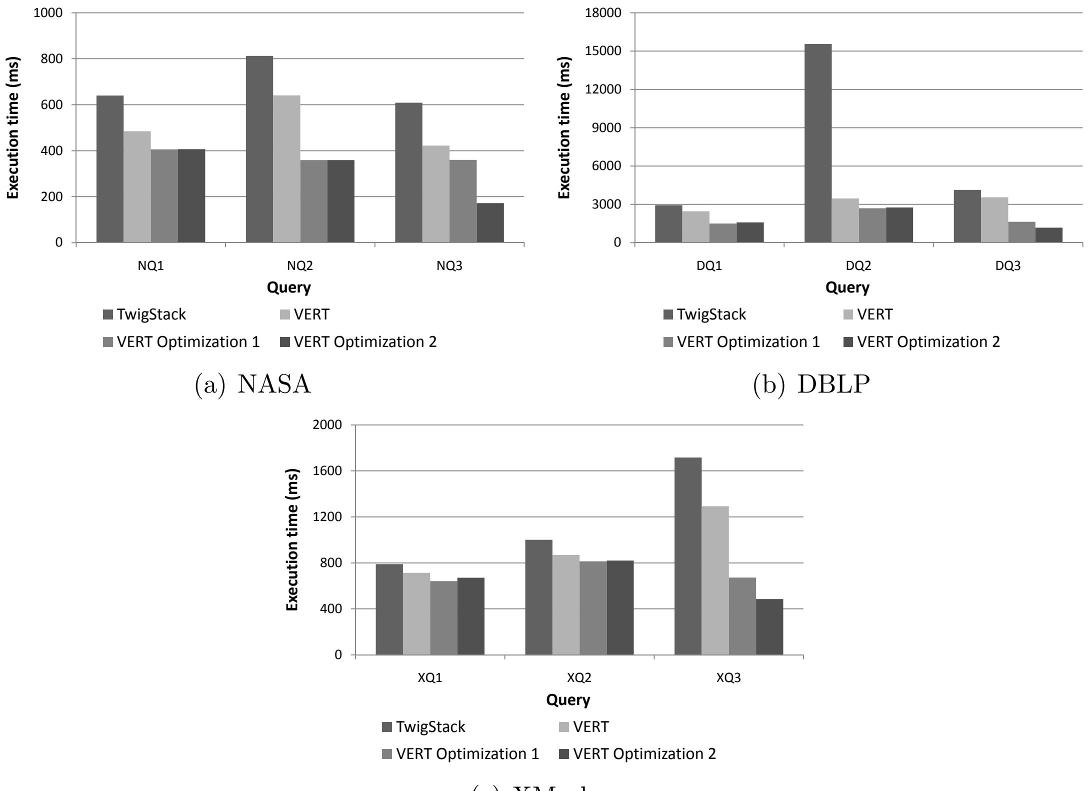
Figure 3.17: Space management comparisons

Query performance

We used NASA, DBLP and a 110MB XMark data set to compare the query processing performance between *TwigStack* and our algorithms. The implementation of *TwigStack* adopts B^+ tree to index inverted lists, which ensures a high performance of inverted list access for different values. We compare *TwigStack* with our original *VERT* algorithm, as well as *VERT* Optimization 1 and Optimization 2. As mentioned earlier, we can infer the object information in an XML document. Although the inference may not be semantically correct, it will not affect the correctness of the result. In the two optimizations, we use such inference to construct object/property tables and object tables. Since relationship information is not easy to discovered without designer's declaration, we do not test Optimization 3. The execution time of *VERT* and its optimizations includes the I/O and CPU costs to access relational tables to perform content search, the cost to construct temporary inverted lists, and the cost on structural search. The comparison result is shown in Fig. 3.18.

From the result we can see that for all queries, *VERT* outperforms *TwigStack*. The reason is *VERT* performs content search first to simplify the query pattern before structural joins, thus gains better overall performance. The result also proves that the overhead on table selection will not affect the benefit gained from twig pattern simplification. *TwigStack* performs very badly on DQ2. In the DBLP data, there are a lot of numeric values. To process DQ2, *TwigStack* has to combine the labels in all the inverted lists with a number name greater than 1979, based on document order. To load and merge these inverted lists is costly. However, in *VERT* this step is replaced by table selection, thus it is more efficient. We can see, though for small document (e.g., NASA), *TwigStack* is not very slow to perform range search, when the amount of labels in numeric inverted lists is large, *TwigStack* will be inefficient to load and merge the labels.

For all the queries, Optimization 1 works better than *VERT*. The reason is that Optimization 1 reduces one more level up to the original twig pattern query.



(a) NASA

(b) DBLP

(c) XMark

Figure 3.18: Execution time by *TwigStack* and *VERT* without optimizations, with Optimization 1 and with Optimization 2 in the three XML documents

Similarly, the query processing performance is further improved.

Comparing Optimization 1 with Optimization 2, we can see that for single-predicated queries there is no obvious difference. For some queries, Optimization 2 is even slightly worse than Optimization 1. The reason is that the combined object table is larger than object/property table, and then there may be more I/Os to load tuples for object table. However, for multi-predicated queries, e.g., the queries Q3, Q6 and Q9, Optimization 2 has a better performance, because Optimization 2 performs content search for all the value comparisons on the same object at the same time. This again proves our analysis in Section 3.2.5.

3.6 Summary

In this chapter, we propose a semantic approach *VERT* to solve different kinds of content problems raised in existing approaches for twig pattern query processing. Unlike *TwigStack* and its subsequent algorithms, our approach uses semantic tables to store values in XML document and avoids the management of tremendous number inverted lists for different values. Query processing in our approach is done by performing content search first to reduce the size of relevant inverted lists, rewriting twig pattern queries to reduce the number of structural nodes and the number of structural joins for structural search, and matching the simplified pattern with reduced inverted lists to the document.

Our approach is a semantic approach because the relational tables are initially built based on the semantics of property. With more semantics on objects and relationships, we propose three optimizations to further improve the tables and enhance efficiency of query processing. In particular, if the relationship between object and property is known, we can optimize the property table to object/property table; if we know certain properties belong to the same object, we can combine the object/property tables to be object table; if the relationship between objects is known, we can introduce relationship tables to precisely store the property values of relationships. Furthermore, after finding an occurrence of a twig pattern in the document in terms of labels, our algorithm can easily extract actual value to answer the query from relational tables if the output node is a property node; whereas the previous approaches need more work to convert labels into values by accessing documents again. Due to this advantage, our approach can easily bridge the gap between pattern matching and value-based join for general XML queries involving ID references and other types of value-based joins.

CHAPTER 4

ENHANCING TWIG PATTERN SEMANTICS FOR COMPLEX OUTPUT INFORMATION

Due to the limited expressivity of twig pattern expressions, many queries that aim to find complex output information under one object have to be expressed in several twig patterns linked by joins. Although our *VERT* algorithm proposed in Chapter 3 can match and join multiple twig patterns for such a query, intuitively it is redundant to do so because all the twig patterns for such a query are centered on the same object and we may perform the same structural join multiple times when matching different twig patterns.

In this chapter we analyze the characteristics of each query node, i.e., the purpose, optionality and occurrence, and classify the nodes in a twig pattern query into six types, namely, *predicate node*, *optional-predicate node*, *output node*, *optional-*

output node, *predicated-output node*, and *optional-predicated-output node*. Then we propose the *TP+Output* expression to extend twig pattern queries, to model complex output information based on the semantics of different node types. With TP+Output, queries with a complex output can be expressed in fewer twig expressions and processed by fewer structural joins in pattern matching. Last, we extend the *VERT* algorithm as $VERT^O$, to process the TP+Output query, and demonstrate the performance improvement of using TP+Output to represent queries.

4.1 Introduction

As mentioned in Chapter 1, an XML document is normally modeled as a tree, without considering ID references. Fig. 4.1 shows an example XML document modeled as a tree with positional labels under the containment labeling scheme. We refer to this document as the *Company* document in later examples. Also, the core query pattern for a general XML query is a twig pattern or multiple twig patterns linked by joins. Matching a twig pattern query to an XML document tree is considered the main operation for XML query processing. In this chapter, we focus on how the rich semantics of a query pattern impacts on the efficiency of query processing.

There is a class of queries, which finds a particular object based on certain predicates, and outputs complex information about that object. Such queries cannot be expressed by a single twig pattern expression, because of the complexity of the output. This class of queries have to be expressed using XQuery expressions which match with more than one twig patterns. Fig. 4.2 shows some example queries with complex output information from a unique object. All of them have simple, or in some cases no predicate applied to the target object, but none of these queries

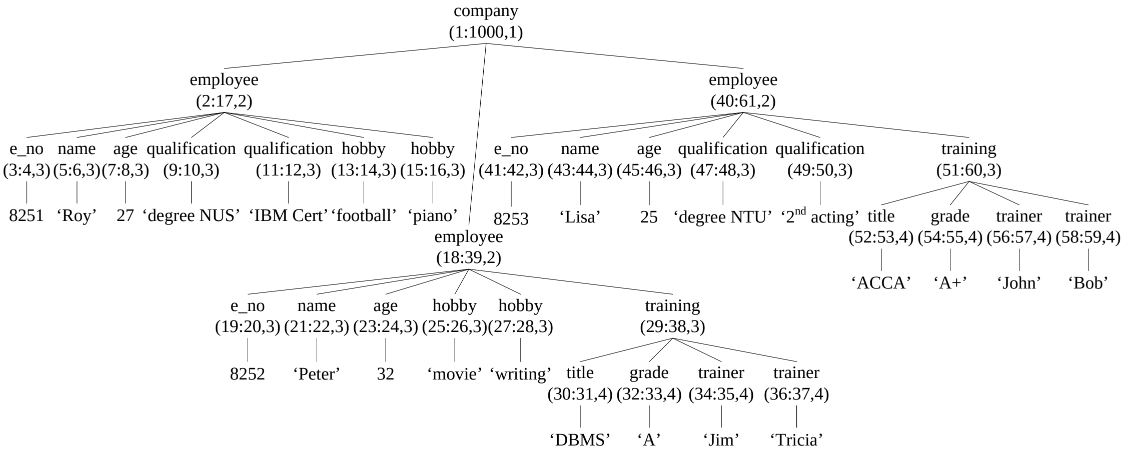


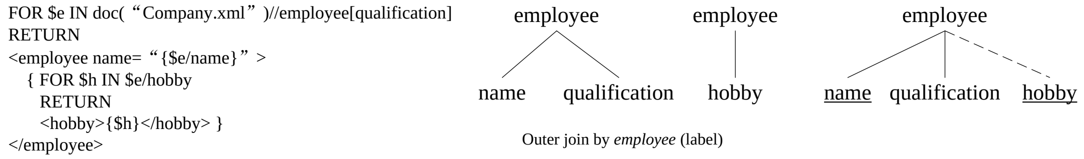
Figure 4.1: The *Company* document in tree representation

Q1: Find the employees who have at least one qualification, and output their name, as well as hobbies if they have any.
Q2: Find the employees who have football as a hobby, and output their name, and this hobby.
Q3: Find the employees who have football as a hobby, and output their name, and all their hobbies.
Q4: Find all the employees, and output their name, as well as their hobby if it is football.
Q5: Find all the employees, and output their name, and all their hobbies if one of them is football.

Figure 4.2: Example queries

can be expressed in a single twig pattern. Take Q1 as an example, in which *hobby* is optional. Although some employees may not have a hobby, we still output their name. If we attempt to write this query as a single twig pattern expression, *hobby* will be a required node to qualify employee, which violates the query purpose. Instead to express this query we have to use an XQuery expression, which is shown in Fig. 4.3(a). To process this query, we need to match two twig patterns and perform an outer join, as shown in Fig. 4.3(b). However, intuitively matching one pattern should be enough because both the predicate and the output information are centered around the same object.

The generalized tree pattern (GTP) [30] is an important extension to twig pattern that enhances expressivity, which explicitly marks all output nodes in the twig structure, and introduces a dotted edge to represent optional output nodes.



```
FOR $e IN doc( “Company.xml” )//employee[qualification]
RETURN
<employee name= “{$e/name}” >
   { FOR $h IN $e/hobby
      RETURN
      <hobby>{$h}</hobby> }
</employee>
```

(a) XQuery expression (b) Twig patterns (c) GTP

Figure 4.3: Query expressions for Q1 in Fig. 4.2

Q1 can be expressed by GTP as one twig pattern with output nodes underlined and optional edges dotted, as shown in Fig. 4.3(c). Using certain algorithms (e.g., [25]), matching a single GTP pattern is naturally more efficient than matching several twig patterns and joining results, to process queries like Q1.

Although optional output can be expressed by GTP, some other output information can be even more complex and neither GTP nor other twig pattern extensions (e.g., [123] and its subsequent works) can express them. For example, the queries Q3 and Q5 are similar to Q2 and Q4 respectively in Fig. 4.2. They only differ in the occurrence of the output node *hobby*, i.e., Q2 and Q4 return one hobby, but Q3 and Q5 return all hobbies. Unfortunately, neither twig pattern nor GTP can express Q3 and Q5 precisely. We have to use XQuery to express them, and again as a consequence match different twig patterns even though they are all centered at *employee*.

As we can see, although twig pattern query is an intermediate query representation for general queries, the limited expressivity of twig pattern query may seriously affect the query processing efficiency. In this work we aim to extend the expressivity of twig pattern queries so that a class of queries which involves complex output information under the same output object can be modeled with fewer twig patterns, and thus be processed by fewer structural joins during pattern matching. We first investigate different types of nodes in an XML query, and then extend twig pattern query by introducing additional notation to model different output types.

The contributions of this chapter can be summarized as follows:

- Analyze the characteristics of query nodes, which leads to the classification of query nodes: *predicate nodes*, *optional-predicate nodes*, *output nodes*, *optional-output nodes*, *predicated-output nodes* and *optional-predicated-output nodes*.

- Extend twig pattern queries with notation to explicitly mark different types of output nodes. We call the extended twig pattern *TP+Output*.

- Extend our previous query processing algorithm, *VERT* to $VERT^O$, to process TP+Output queries.

- Conduct experiments to compare the query processing performance between TP+Output, the original twig pattern representation, and two typical XQuery processors, to verify the performance improvement of using TP+Output.

The rest of this chapter is arranged as follows. Section 4.2 analyzes the characteristics of query nodes and Section 4.3 presents TP+Output, our extension to the twig pattern query. Section 4.4 provides our extension $VERT^O$, to process TP+Output queries. Finally, Section 4.5 describes our experimental results and Section 4.6 summarizes this chapter.

4.2 Query node characteristics

In this section, we analyze the characteristics of each node in a twig pattern query in three aspects: the purpose, the optionality and the occurrence.

4.2.1 Purpose of query nodes

Normally an XML query aims to return some information based on certain conditions. As a result, in an XML twig pattern query, some nodes represent conditions, while some nodes represent information to be returned. In a twig pattern query, if a query node specifies some constraints to filter the results, we say this node is for predicate purpose. Contrarily, if a query node specifies what information the query needs to return, we say this node is for output purpose.

Consider the query Q1 in the GTP representation in Fig. 4.3(c). Nodes *employee* and *qualification* are used to specify the structural constraint of the query, so they are for predicate purpose, while nodes *name* and *hobby* are for output purpose. However, there is a case that some query nodes are for both predicate and output purposes. Consider a query to find the names of all employees with age greater than 30, and also output the age. In this query, *age* plays a predicate role, as it specifies a selection condition; and it also plays an output role, as we need to return its value. Finally, we classify the purpose of nodes in a twig pattern query into *predicate*, *output* and *predicated-output.*

4.2.2 Optionality of query nodes

The existence of a query node can be either *required* or *optional.* We start from the optionality of predicate node. A predicate node specifying selection condition of a query is normally *required.* For example in Q1, the predicate node *qualification* must be matched in every qualified answer. In some cases, predicate node can also be optional. Suppose we change the condition of Q1 to be the employee whose qualification is “IBM Cert” if he has any (i.e., either have no qualification or have qualification of “IBM Cert”). Then the qualification node becomes an optional predicate node.

Now we focus on the output information. Output node and predicated-output node in twig pattern query can be either *required* or *optional.* In Q1 *name* is required output information, but *hobby* is optional. If a qualified employee has certain hobbies, we output them alongside his name; otherwise, we just output his name with an empty set of hobbies.

Similarly, the predicated-output node is either required or optional. The query Q2 and Q4 in Fig. 4.2 both involve predicated-output nodes, but differ on the optionality of the predicated-output node. In Q2, *hobby* is required to qualify an employee. However in Q4, *hobby* is optional, i.e., we do not qualify an employee based on *hobby.* If the *hobby* football exists for a qualified employee, we will output it; otherwise no hobby is output for the qualified employee.

4.2.3 Occurrence of output information

Predicate node is not constrained by the occurrence of the node. In other words, as long as one document node matches a predicate node, the predicate is satisfied. However, the occurrence of output information may vary with query purpose, when the node corresponds to a multi-valued element. We discuss the occurrence of output node and predicated-output node as follows.

In an XML document, an element or attribute can be either single-valued or multi-valued with respect to its parent element. For example, in the *Company* document, *e_no*, *name* and *age* are single-valued with respect to *employee*, but *qualification* and *hobby* are multi-valued with respect to *employee.*

The occurrence of an output node is always *many.* When the corresponding document node is single-valued, the target value is outputted; while when the corresponding document node is multi-valued, all values must be outputted. For example, if both *name* and *hobby* are output nodes in a twig pattern query, for each qualified employee the single name and all hobbies he/she has are returned. However, the occurrence of a predicated-output node is not as trivial. Comparing the query Q2 and Q3 in Fig. 4.2, we notice that *hobby* corresponds to a multi-valued element; but unlike Q3, Q2 does not return all the hobbies under a qualified employee. It only returns the satisfied hobby. To summarize, if a predicated-output node corresponds to a multi-valued element, the occurrence of the output information can be either *one* or *many*.

4.3 TP+Output: an extension of twig pattern

Now we integrate all the analysis in the previous section, i.e., the purpose of query node, the optionlity of query node and the occurrence of output information. We define six types of query nodes based on these characteristics. The classification is shown in Fig. 4.4.

Purpose	**Optionality**	**Node Type**	**Occurrence**
predicate	required	**predicate node**	——
predicate	optional	**optional-predicate node**	——
output	required	**output node**	many
output	optional	**optional-output node**	many
predicated-output	required	**predicated-output node**	one or many
predicated-output	optional	**optional-predicated-output node**	one or many

Figure 4.4: Query node classification

The six types of query nodes include *predicate node*, *optional-predicate node*, *output node*, *optional-output node*, *predicated-output node* and *optional-predicated-output node*. As discussed in the previous section, the occurrence of *output node* and *optional-output node* is always many in twig pattern queries, but the occurrence of *predicated-output node* and *optional-predicated-output node* can be either one or many.

We first define the TP+Output query, which is an extension of twig pattern query.

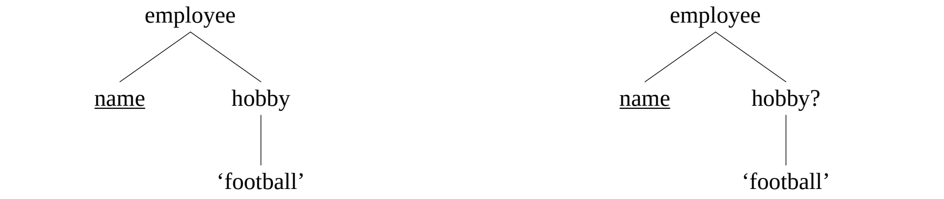
Definition 4.1. *A TP+Output query is* TPO = *((*n, L*)*, (*e_s | e_d*)*).* n *is a query node with the same semantics as that in the original twig pattern query.* L *is a set of labels associated to the query node* n*, where* L ⊆ {*?, __, →*$\underline{\text{n}}$}*. In particular, a query node* n *may be marked as optional ("?"), output ("__"), and the occurrence of* many *("→*$\underline{\text{n}}$*").* e_s *and* e_d *stand for solid edge and dotted edge respectively.*

Now we formally define each type of query node, and present how to use the TP+Output to express queries with these node types.

4.3.1 Predicate node

Definition 4.2. In a twig pattern query, if certain nodes specify either a structural constraint or a value constraint, and the existence of these nodes is required, then these nodes are called *predicate nodes*.

It is quite often that an XML query involves value comparisons on certain query nodes. Obviously those value comparisons, together with their parent query nodes, are predicate nodes. The node hobby and 'football' in the query in Fig. 4.5(a) are both predicate node. Now we show another case of predicate node, where no value comparison is involved. Consider the twig pattern representation for Q1 in Fig. 4.6(a) (ignoring additional notation). In this query, *qualification* is not for output purpose, but specifies a selection constraint. Although it does not have any child value comparison, we still consider it as a predicate node. In TP+Output extension, the nodes without any special labels are all predicate nodes.



(a) Query with predicate node (b) Query with optional-predicate node

Figure 4.5: Example of predicate node and optional-predicate node

4.3.2 Optional-predicate node

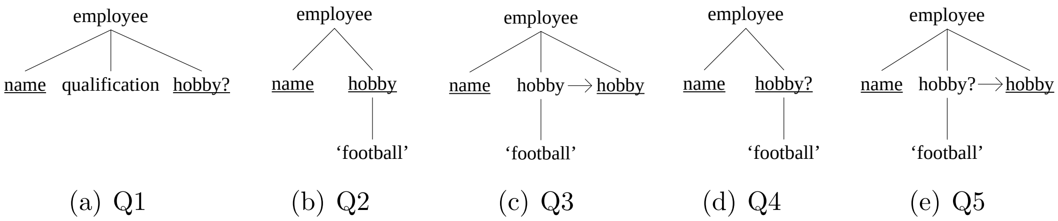
Definition 4.3. In a twig pattern query, if certain nodes specify selection constraint, but the existence of these nodes is not required, then these nodes are called *optional-predicate nodes.*

The query in Fig. 4.5(b) contains an optional-predicate node, *hobby.* We can compare this query with the query in Fig. 4.5(a). The query in Fig. 4.5(a) requires every qualified employee having a hobby, but this query does not. In this query, if an employee does not have any hobby, he is still qualified; but if he has some hobbies, one of them must be football. Then in this query, hobby is an optional-predicate node. We append a "?" to a predicate node to indicate that it is optional.

4.3.3 Output node

Definition 4.4. In a twig pattern query, if the purpose of certain nodes is for output, and the existence of these nodes is required to qualify an answer, then these query nodes are called *output nodes.*

In Q1 in Fig. 4.6(a), node *name* is an output node because its purpose is for output and it must exist in each matching answer. We underline ("__") the output nodes in a TP+Output query.



(a) Q1 (b) Q2 (c) Q3 (d) Q4 (e) Q5

Figure 4.6: TP+Output expressions for the examples queries in Fig. 4.2

4.3.4 Optional-output node

Definition 4.5. In a twig pattern query, if the purpose of certain nodes is for output, but the existence of these nodes is not required to qualify an answer, then these query nodes are called *optional-output nodes*.

Consider again the query Q1 in Fig. 4.6(a). *Hobby* is an optional-output node, because it will be outputted, and although some employee may not have a hobby, he/she still qualifies as a solution. We underline ("__") the node and append a "?" to represent optional-output nodes.

4.3.5 Predicated-output node

Definition 4.6. In a twig pattern query, if certain nodes are for both predicate and output purposes, and the existence of these nodes is required to qualify an answer, then these query nodes are called *predicated-output nodes*.

There are two cases for predicated-output node: (1) the node corresponds to a single-valued element, and (2) the node corresponds to a multi-valued element in the document. We illustrate why we need to distinguish the occurrence of a predicated-output node.

Recall the example given in Section 4.2.1, which finds the names of all employees with age greater than 30, and also output their age. In this query, *age* acts as both a predicate and an output role, so this node is a predicated-output node. From the document, we can see *age* is a single-valued property for each *employee.* In our extension, such single-valued predicated-output nodes are simply underlined ("__"), and the child value comparison can be used to differentiate predicated-output nodes from output nodes.

However, as mentioned earlier, a predicated-output node may correspond to a multi-valued element in the XML document. In such a case, this notation is insufficient to differentiate some query intentions. Consider the query Q2 and Q3 in Fig. 4.2. The two queries have exactly the same query predicate, but differ on the occurrence of the predicated-output node *hobby*, i.e., Q2 outputs the employee's name together with his/her hobby that satisfies the predicate, while Q3 outputs the employee's name with ALL his/her hobbies as long as one of them satisfies the predicate. Nevertheless, the notation introduced above for predicated-output node is not able to differentiate the two query purposes. To differentiate the two queries, we introduce an additional query node with the same name as the multi-valued predicated-output node, and an arrow ("→") starting from the original node, to indicate the case in which the output occurrence is *many.* The → can be interpreted as "if then" (i.e., in Q3 if one hobby satisfies the predicate, all hobbies are output), so the additional query node pointed to by → is not matched during pattern matching. Now the query Q2 is represented as in Fig. 4.6(b), and Q3 is represented as in Fig. 4.6(c).

4.3.6 Optional-predicated-output node

Definition 4.7. In a twig pattern query, if certain nodes are for both predicate and output purposes, but the existence of these nodes is not required to qualify an answer, then these query nodes are called *optional-predicated-output nodes.*

Predicated-output node can also be optional, and this leads to the optional-predicated-output node. In the TP+Output extension, we simply append a "?" to the predicated-output node to indicate its optionality. Similarly, if the node corresponds to a multi-valued element, we express the different output occurrences by introducing additional node and arrow ("→"). The queries Q4 and Q5 in Fig. 4.6(d) and 4.6(e) demonstrate this concept.

Original twig pattern queries cannot express complex output information. If a query contains, e.g., optional-output nodes, predicated-output nodes or optional-predicated-output nodes, the original twig pattern query has to rely on XQuery semantics to translate the complex output information into several twigs linked by joins. Using our extension, such queries can be expressed in a single twig. In Section 4.4, we will introduce how we extend the *VERT* algorithm, to evaluate the TP+Output queries.

4.3.7 Discussion

We define six types of query node based on the characteristics analyzed in Section 4.2. However, with these six node types we still cannot express any query using a single TP+Output expression. For example, a general XQuery query may involve different TP+Output expressions linked by joins, which is similar to the join-linked twig pattern representations for XQuery queries discussed in Section 1.2.1. In this case, after matching several TP+Output queries, we still need to join them. The advantage of TP+Output is that we can avoid expressing queries with complex output fitting our analysis with several twigs, and thus avoid redundant structural joins to process different twig patterns with common edges in such queries.

4.4 VERT^O to process TP+Output queries

In this section we extend the *VERT* algorithm, which is proposed in Chapter 3, to support the TP+Output query. We name our extended algorithm *VERT*^{O}. Note that, most structural join based pattern matching algorithms are compatible with *VERT*, thus they are compatible with our extension as well. Because our TP+Output query extension is proposed for object-aware queries, our *VERT*^{O} is built on the second optimization of the *VERT* algorithm, which uses object-based tables to aid query processing.

The general idea of *VERT*^{O} is to simplify a TP+Output query by differentiating the query nodes that requires structural join from the query nodes that can be solved by table operations. In particular, the property-based (optional-)predicate node can be solved by table selection during pattern matching, and the values of all optional output-related query nodes can be retrieved from tables after pattern matching. Thus we do not need to perform structural join for these types of query nodes. The algorithm of *VERT*^{O} is shown in Algorithm 4.1.

Predicate node and optional-predicate node: All the query nodes in a TP+Output query which are not underlined are either predicate nodes or optional-predicate node, depending whether a '?' is appended. Similar to *VERT*, *VERT*^{O} processes non-property (optional-)predicate nodes by structural joins, using any feasible structural join algorithms. For example, [25] proposes an efficient structural join technique for matching both predicate nodes and optional-predicate nodes. We discuss how the queries involving property-based (optional-)predicate node can be processed more efficiently.

The original *VERT* can deal with value comparison in predicates efficiently, as described in Chapter 3. This attempt can be easily extended to handle optional-predicate node, because when we perform table selection for content search, we

Algorithm 4.1 *$VERT^O$* to process TP+Output queries

Input: A TP+Output query Q with different types of nodes marked ,and necessary inverted lists and object tables

Output: A set of value results answering Q

```
for each object query node $o$ do
    initiate a predicate list $P$
    for each property-based predicate node or optional-predicate node $p$ under $o$ do
        append the predicate to $P$
        remove $/p$
    end for
    for each property-based output node $p$ under $o$ do
        append $o/p$ to the output list $L$
    end for
    for each property-based optional-output node $p$ under $o$ do
        append $o/p$ to the optional-output list $OL$
        remove $/p$
    end for
    for each property-based predicated-output node $p$ under $o$ do
        append the predicate to $P$
        append $o/p$ and a flag (self or all) to the predicated-output list $PL$
    end for
    for each property-based optional-predicated-output node $p$ under $o$ do
        append the predicate to $P$
        append $o/p$ and a flag (self or all) to the optional-predicated-output list $OPL$
        remove $/p$
    end for
    select the labels based on $P$ from the table $R_o$ or $R_{o/p}$ if $p$ is a multi-valued property
    put the selected labels into $T_{o'}$
    rewrite the query to replace $o$ by $o$'
end for
match the rewritten query using any existing efficient structural join algorithm, to get labels for relevant object nodes
extract answers for the nodes in $L$, $OL$, $PL$ and $OPL$ from object tables
```

can also qualify the object nodes which have no values for the optional property predicate. For example, to process the query in Fig. 4.5(b), we perform the content search for the optional predicate by selecting the labels of *employees* who either have no hobby or have a hobby of football.

Especially to be mentioned is that $VERT^O$ can solve the predicate nodes without value comparison, which appear as a leaf in a TP+Output query, in a more efficient way rather than pattern matching. Once we encounter such a predicate node p, we create a new inverted list for its parent object node o, whose content is a selection of labels from the object table R_o based on the condition that p is not null. If p is a multi-valued property of o, values for p are stored in object/property table $R_{o/p}$, as shown in Section 3.3.2. Hence, the selection is done in $R_{o/p}$ and *distinct* labels are returned. After that this predicate node can be removed from the TP+Output query.

Output node: Output nodes in a TP+Output query are underlined and appear as a leaf query node. We maintain an output list L for all output nodes, together with the objects to which they belong in the query, so that after pattern matching we know the values of which nodes should be extracted. However, we need to keep output nodes for pattern matching, as they are used to qualify matching result.

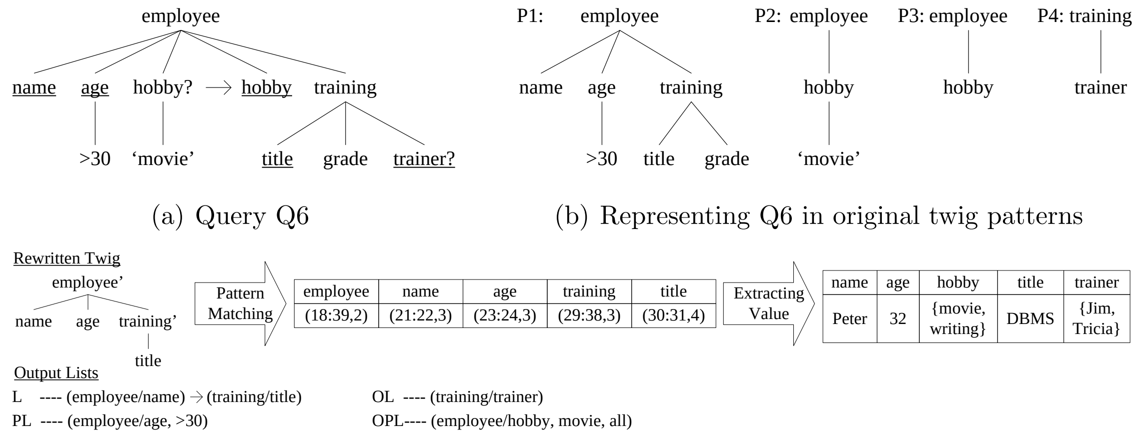
Optional-output node: When we encounter an underlined leaf query node with "?" in the TP+Output query, we know that it is an optional-output node. We use a list OL to store all the optional-output nodes. Concretely, for each optional-output node p, we identify the object o to which it belongs, and store o/p in OL. Since optional-output nodes are not required to qualify each solution in the document, these nodes can be omitted during pattern matching.

Predicated-output node: Predicated-output nodes are also underlined in the TP+Output query. The constraint to differentiate between predicated-output node and output node is that predicated-output node has a child value comparison whereas the output node is a leaf node. We maintain a predicated-output node list *PL* to store predicate-output nodes. If the predicated-output node is a single-valued property, we put it along with the object to which it belongs and the value predicate into *PL*. When the predicated-output node is a multi-valued property, we have two cases as mentioned in Section 4.3. In the first case we only need to return the value of the property satisfying the predicate, and in the second case, we need to find all values of the multi-valued property, as long as one of them satisfies the predicate. If we have the first case of a predicated-output node p with the associated object o, we store o/p and the value predicate in *PL*. If it is in the second case, we store o/p, the value predicate and a flag of *all*. Then when we extract values after pattern matching, we can know what kind of occurrence that answers should be returned, by checking whether the flag of *all* is there.

Optional-predicated-output node: Optional-predicated-output nodes are marked by "?" and underlined, and contain child value comparisons. Similar to optional-output nodes, optional-predicated-output nodes are not involved in pattern matching as they are not required to qualify solutions. We use an optional-predicated-output list *OPL* to store such query nodes. Similarly for multi-valued properties, we have two cases: one is outputting the values satisfying the predicate only, while the other one is outputting all values as long as one of them satisfies the predicate. So in *OPL*, for each optional-predicated-output node p we store the o/p pair with its object o, the associated predicate, and also a flag of *all* to indicate the existence of → for this node. Optional-predicated-output nodes are removed during pattern matching.

After handling all the enhanced notations, the TP+Output query is rewritten as a normal twig pattern by removing notations and relevant query nodes as described above, and is matched using *VERT*. Using the output of pattern matching, which is in terms of node labels, we can extract values for the property nodes in *L*, *OL*, *PL* and *OPL* in relevant tables separately. In more detail, for each *o/p* in *L*, we do a selection in object table R_o based on *o*'s labels that are returned by pattern matching. The optional-output nodes in *OL* are also extracted in a similar way. For the nodes in *PL* and *OPL*, when we extract the values from relevant tables, we also have to note that if the property is multi-valued, whether only the satisfied values are required or all values are required.

Example 4.1. *Consider the TP+Output query Q6 shown in Fig. 4.7(a). This query aims to find the employees who have age greater than 30, and have completed some training (thus given a grade), and output the employee's name, age, all the hobbies he/she has if one of them is 'movie', the title of the training he/she completed, and the trainers if any. In this query, all four types of output information are involved. If we use the original twig patterns to represent Q6, we need to match four sub-patterns, as shown in Fig. 4.7(b), and post-process matching results with inner and outer joins. In* VERT^O*, the predicate node* grade*, as well as the predicate on* age*, are solved by table selection before pattern matching, and then removed from the twig pattern. Output nodes, optional-output nodes, predicated-output nodes and optional-predicated-output nodes are inserted into corresponding lists based on the description above. Particularly,* hobby *is a optional-predicated-output node with* →*, so it is inserted into* OPL *with the predicate and flag of* all*. After solving the enhanced notations, the twig pattern query is rewritten by removing optional-*



(a) Query Q6

(b) Representing Q6 in original twig patterns

(c) Processing Q6 using extended twig pattern and $VERT^O$

Figure 4.7: Example query and query processing using original and extended twig pattern

output node trainer *and optional-predicated-output node* hobby*, because they are not required to qualify a result during pattern matching. The rewritten query is processed by pattern matching, and then the values for the property nodes in* L, PL, OL *and* OPL *are extracted using the relational tables. The whole process is shown in Fig. 4.7(c). Notice in particular that the columns* hobby *and* trainer *in the final result contain two values respectively. This is because we get answers for such multi-valued property in the object/property tables using a unique employee label. If we process this query by matching multiple original twig patterns and joining the results, we will get four tuples of answers with the same employee name and different hobby-trainer combinations in a cross product manner. Obviously the output format generated by our approach is more readable.*

4.4.1 Analysis

Putting predicate nodes and optional nodes in lists, instead of the twig pattern, significantly simplifies the twig pattern query by reducing the number of query nodes and the number of structural joins. Also the inverted list size for relevant query nodes is reduced by table selection. Thus the twig pattern matching efficiency will be improved. Furthermore, when a query involves a multi-valued property as a predicate node, existing matching methods may return many matched patterns contributing to the same object node. Using $VERT^O$, for such cases the object node is matched only once, because the multi-valued predicate is processed by table selection before pattern matching.

Note that, *VERT* complements pattern matching algorithms to handle values. Thus though $VERT^O$ is bound to *VERT*, it is not limited to a particular pattern matching algorithm to perform a structural search in a *TP+Output* query. In other words, any pattern matching algorithm can be extended to process *TP+Output* queries.

4.5 Experiments

In this section, we compare our algorithm $VERT^O$ to process TP+Output queries with several other approaches.

4.5.1 Experimental settings

In our experiments, all algorithms are implemented in Java, and executed with a dual-core 2.33GHz CPU and a 4GB RAM under Windows XP. Similar to the experiments in Chapter 3, we use two real-life data sets and one benchmark data set for our experiments: a 25MB NASA data, a 91MB DBLP data, and a 80MB XMark benchmark data. We randomly choose 5 queries for each data set to execute. The queries contain different types of output nodes for different query purposes. They are shown in Fig. 4.8, as TP+Output expressions. Similar to the experiment section in Chapter 3, we use the Sybase SQL Anywhere [117] to manage relational tables, and inherit the default database parameters.

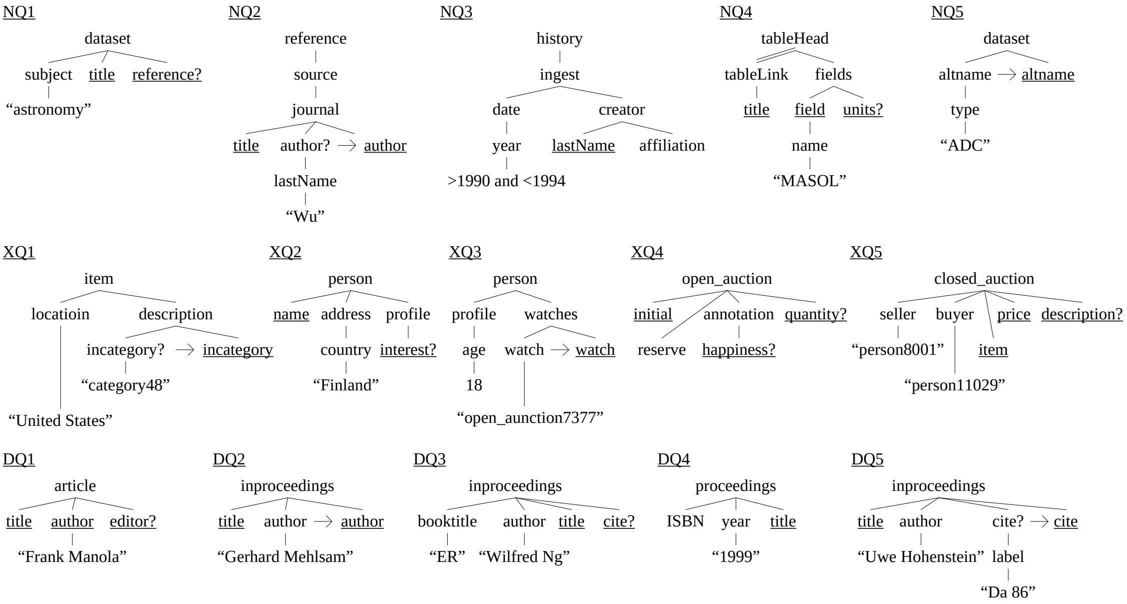
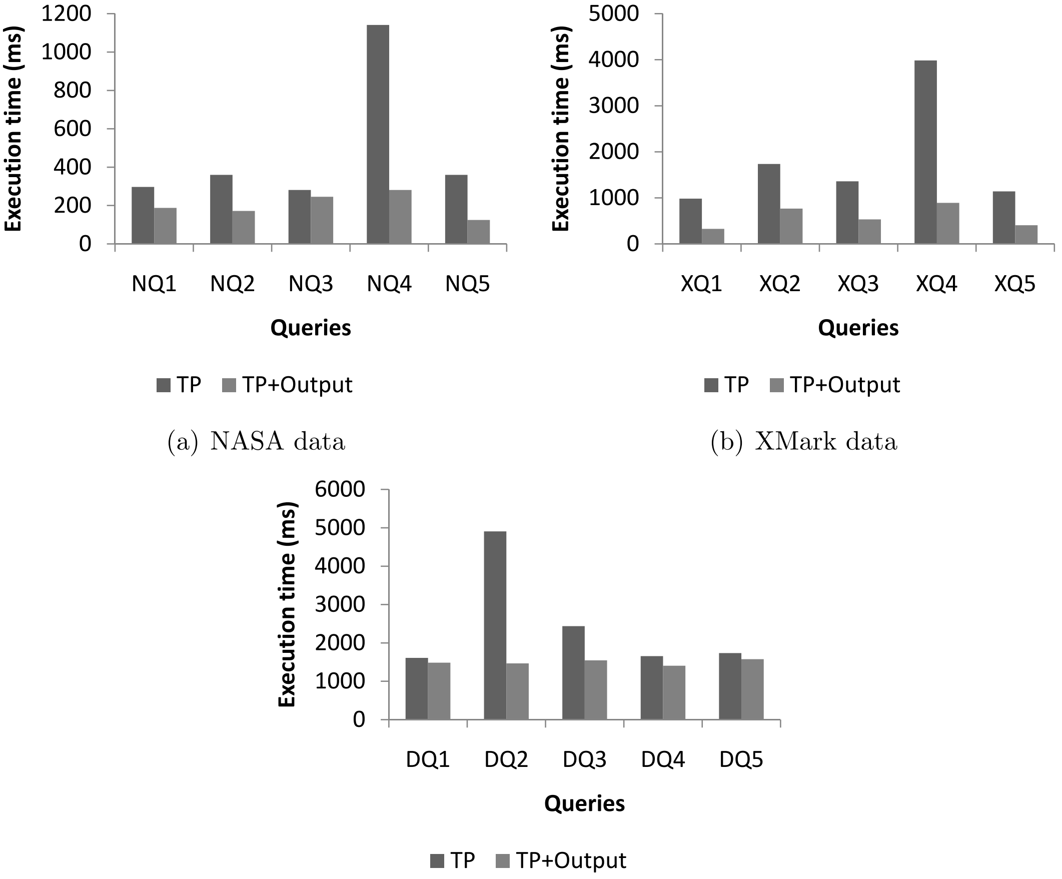


Figure 4.8: Experimental queries in TP+Output expressions

4.5.2 Compare TP+Output with TP and GTP

We first test query processing efficiency using the original twig pattern (TP), the general tree pattern (GTP) and our TP+Output to represent queries. The TP+Output representations for each query are shown in Fig. 4.8. We transform each query into TP representation in such a way that (1) for each optional edge, we break the TP+Output expression into two TPs with outer join, and (2) for each multi-valued (optional-)predicated-output node that outputs ALL values, we use a separate twig pattern query to get all values for the multi-valued node. The GTP queries is formed by adding in optional edges for relevant TP queries. We do not show the TP and GTP expressions for the queries. We use the same pattern matching technique to match each TP, GTP and TP+Output pattern to the corresponding document. In particular, we use *TwigStack* for structural search (joins), and use *VERT* for content search. Thus the only factor that affects the performance is the query representation, instead of the efficiency of pattern matching. The experimental results are shown in Fig. 4.9. Note that the execution time only includes the time of pattern matching and we ignore other costs such as that to output results.



(a) NASA data

(b) XMark data

(c) DBLP data

Figure 4.9: Performance comparison between TP and TP+Output representations

We can see that for all the queries, TP+Output has better performance. We will look more closely at two cases. The first case is where the query involves optional output nodes, or involves multi-valued output nodes requiring all values to be output. In this case, TP cannot express the query using a single pattern. To perform such a query, we need to match more than one query pattern and outer join the results. Thus the query processing performance is seriously affected. For example, for query NQ1, we first match the pattern without *reference* to select all the satisfied *title*s, and then match all the *reference*s and outer join the results with previously selected labels. When the twig pattern for the optional output leads a large size of intermediate result, the overall performance will be significantly affected, like in NQ4 and XQ4. GTP performs well if the query only contains optional output nodes, but if the query also contains multi-valued output nodes, GTP still has expressive problems, and thus has bad performance.

In the second case, the query does not involve optional-output nodes or multi-valued nodes requiring all values to be output, so like TP+Output, TP requires only a single pattern to represent the query. Queries NQ3 and DQ4 are examples of such queries that only contain predicate nodes and output nodes. In this case, TP+Output still demonstrates better performance, though not as significant as that in the first case. The reason is $VERT^O$ rewrites TP+Output expression by reducing the predicate property nodes and the inverted list size of the object nodes, instead of performing a structural join for such predicates; whereas in TP representation, every edge requires a structural join, because it cannot differentiate leaf predicate nodes from output nodes.

4.5.3 Scalability of VERT^O

We test the scalability of $VERT^O$ to process TP+Output queries. We execute queries XQ1-XQ5 on four XMark data sets of differing sizes. The experimental result in Fig. 4.10 shows that all queries scale well.

4.5.4 Comparison with XQuery processors

Last, we compare $VERT^O$ with two XQuery processors, to further validate the efficiency advantage of our TP+Output representation and TP+Output query pro-

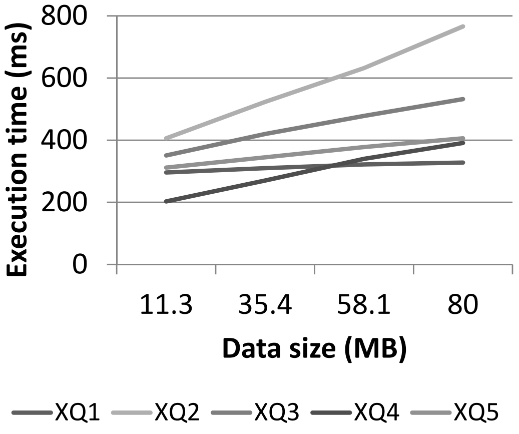
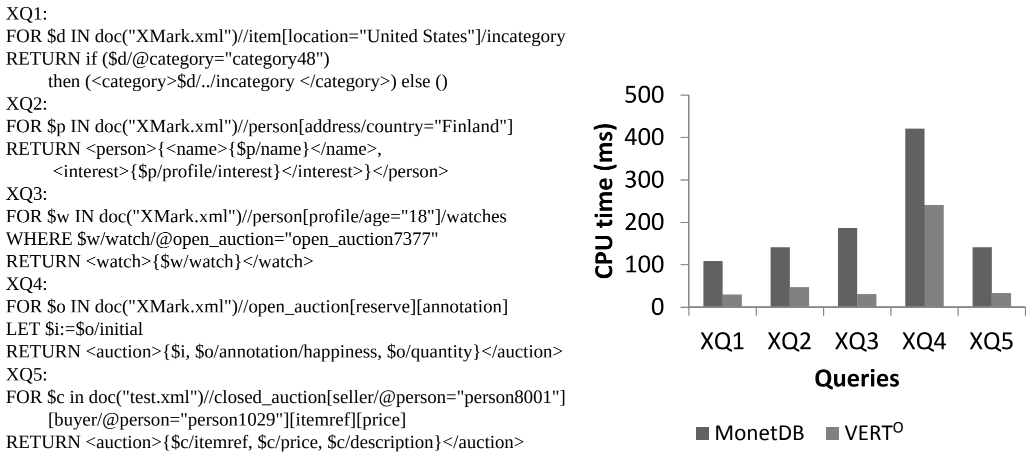


Figure 4.10: Scalability test of VERT^O

cessing algorithm. We use two XQuery processors: MonetDB [13] and IBM DB2 [34]. MonetDB adopts relational approach to process queries, while DB2 is native based. These are two representative approaches to process XML queries.

Since MonetDB is a memory-based XQuery processor which cannot accept large XML data files, we use a small XMark data set (11MB) for the queries XQ1-XQ5, and only compare CPU time in this test. We show the XQuery expressions for the tested queries as in Fig. 4.11(a), which are executed by MonetDB. The testing result is shown in Fig. 4.11(b). We can see for all the queries $VERT^O$ is more efficient than MonetDB.

Next we use DB2 to execute all the queries in the three documents as mentioned in Section 4.5.1, to compare with $VERT^O$. Similar to the expressions in Fig. 4.11(a), the XQuery expressions for the queries of the other two documents can also be simply composed. In this test, the execution time in $VERT^O$ includes index loading, pattern matching and result outputting, thus it is slower than the time shown in Fig. 4.9 in our first test. The comparison result is shown in Fig. 4.12. We can see that for all queries, our approach is more efficient than DB2, which adopts a navigational approach to evaluate each XQuery expression.



```
XQ1:
FOR $d IN doc("XMark.xml")//item[location="United States"]/incategory
RETURN if ($d/@category="category48")
        then (<category>$d/../incategory </category>) else ()
XQ2:
FOR $p IN doc("XMark.xml")//person[address/country="Finland"]
RETURN <person>{<name>{$p/name}</name>,
        <interest>{$p/profile/interest}</interest>}</person>
XQ3:
FOR $w IN doc("XMark.xml")//person[profile/age="18"]/watches
WHERE $w/watch/@open_auction="open_auction7377"
RETURN <watch>{$w/watch}</watch>
XQ4:
FOR $o IN doc("XMark.xml")//open_auction[reserve][annotation]
LET $i:=$o/initial
RETURN <auction>{$i, $o/annotation/happiness, $o/quantity}</auction>
XQ5:
FOR $c in doc("test.xml")//closed_auction[seller/@person="person8001"]
        [buyer/@person="person1029"][itemref][price]
RETURN <auction>{$c/itemref, $c/price, $c/description}</auction>
```

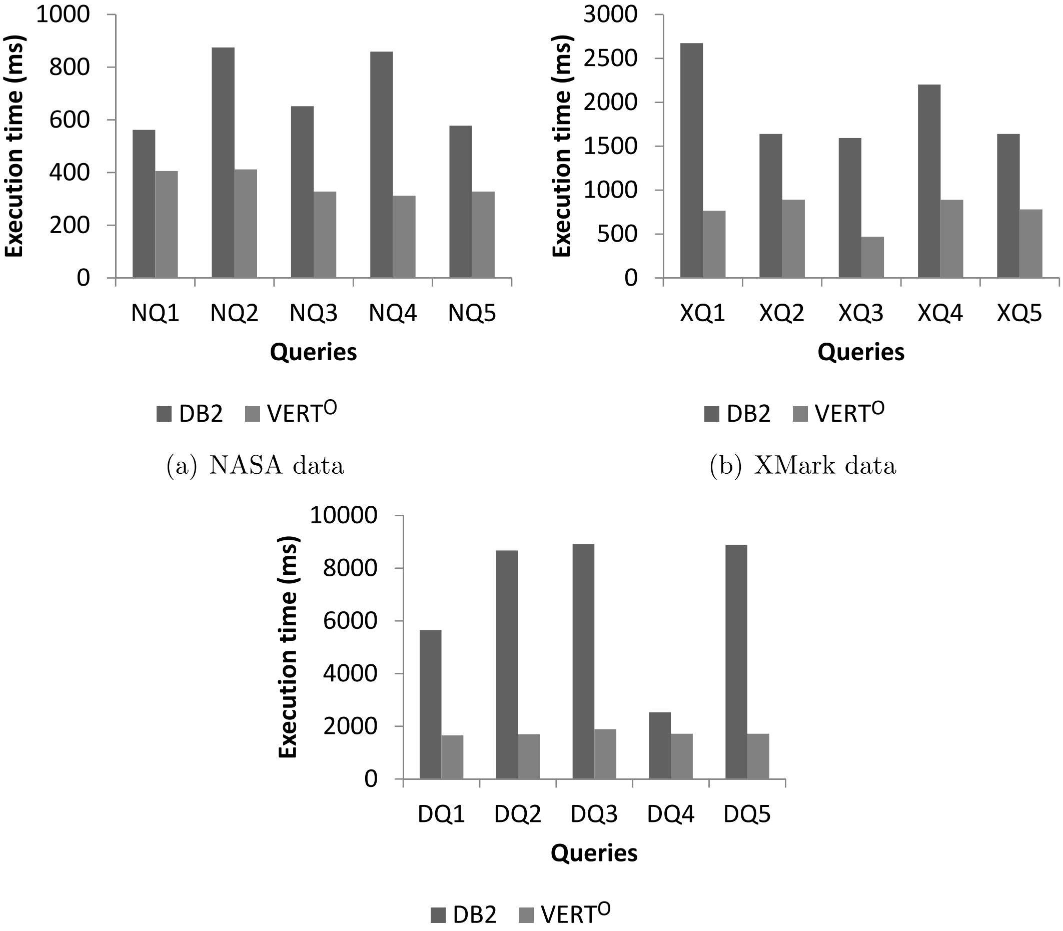
(a) XQuery expression

(b) Compare with MonetDB

Figure 4.11: Figures for scalability test and comparison with MonetDB

4.6 Summary

In this chapter we extend the expressive power of twig pattern queries so that queries with complex output under a single object query node can be expressed easily with fewer twig patterns. We first analyze the purpose and the optionality of each query node, and the occurrence of the output information. Based on these characteristics, we define six types of query node in a twig pattern query, namely *predicate node*, *optional-predicate node*, *output node*, *optional-output node*, *predicated-output node* and *optional-predicated-output node*. After that we propose a more expressive twig pattern, TP+Output, by introducing a set of notations to distinguish different types of query nodes. With these notations, many queries can be expressed by fewer TP+Output expressions than the original twig pattern expressions, thus require less structural joins during pattern matching. We also extend our previously proposed algorithm, *VERT* to efficiently process TP+Output queries, and show experimentally the advantage of our approach.



(a) NASA data

(b) XMark data

(c) DBLP data

Figure 4.12: Performance comparison between $VERT^O$ and DB2

CHAPTER 5

PERFORMING GROUPING AND AGGREGATION IN XML QUERIES

Since more and more business data are represented in XML format, there is a compelling need of supporting analytical operations in XML queries. Particularly, the latest version of XQuery proposed by W3C, XQuery 1.1, introduces a new construct to explicitly express grouping operation in FLWOR expression. Existing works in XML query processing mainly focus on physically matching query structure to XML document. Given the explicit grouping operation in a query, how to efficiently compute grouping and aggregate functions over XML document is not well studied yet. In this chapter, we extend the *VERT* algorithm proposed in Chapter 3, to efficiently perform grouping and aggregate function in XML queries. We present experimental results to validate the efficiency of our approach, over other existing approaches.

5.1 Introduction

As introduced in previous sections, existing works on XML query processing mainly focus on how to efficiently match the query pattern to XML document, which is considered a core operation to process queries in most standard XML query languages. As more and more business data are represented in XML format, analytical queries involving grouping and aggregate operations have become more popular. To process an analytical query with grouping, existing pattern matching techniques are no longer effective. A new technique is required to handle the grouping operation in queries.

Similar to relational databases, most analytical queries over XML documents contain a main operator *group-by* and a set of aggregate functions such as max( ), min( ), sum( ), count( ), avg( ), etc. In most XML query languages, aggregate functions are syntactically supported; however, the common shortcoming of many XML query languages is the lack of explicit support for grouping. For example, XQuery 1.0 is the widely adopted version of XQuery in most XQuery engines, however, grouping in XQuery 1.0 can only be expressed implicitly using nesting. This nested expression for representing the grouping operation can be neither well understood and composed by users, nor easily detected by a query optimizer, as pointed out by [10].

There are many efforts [14, 9, 72] on extending the expressive power for XQuery to support grouping, until W3C publishes the latest version of XQuery, XQuery 1.1 [40], to introduce a new construct to explicitly express grouping in FLWOR expressions. For example, consider the bookstore document shown in Fig. 5.1, and a query to find the average book price for each publisher in each year. This query can be expressed in XQuery 1.1 as follows:

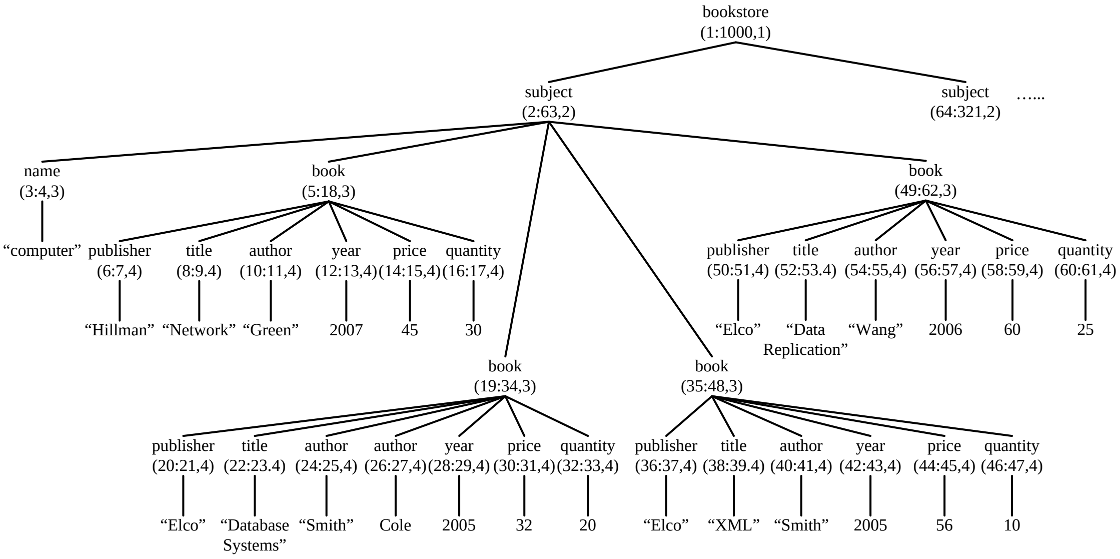


Figure 5.1: An example document *bookstore.xml*

```
FOR $p IN distinct-values(doc("bookstore.xml")//book/publisher),
        $y IN distinct-values(doc("bookstore.xml")//book/year),
LET $pr := doc("bookstore.xml")//book[publisher=$p and year=$y]/price
GROUP BY $p, $y
ORDER BY $p, $y
RETURN
    <book publisher="{$p}" year="{$y}">
        <average_price>{avg($pr)}</average_price>
    </book>
```

Although the work of XQuery 1.1 has just started, it reflects the importance of grouping operations in XML queries. As a result, how to efficiently process XML queries with grouping becomes a new research direction.

There are many relational approaches to process XML queries, as introduced in Chapter 2. In these relational approaches, they normally shred XML documents into tables and convert XML queries into *SQL* statements to query the database.

This sort of approaches can handle grouping in XML queries with the group-by function in *SQL*. However, *SQL* has difficulty supporting multi-level (nested) grouping, which often appears in analytical XML queries. Also the primeval drawbacks of relational approaches in query structural search are a big concern. A recent work [50] proposed an algorithm to compute *group-by* queries natively over XML document. They scan the document for each query and prune out irrelevant nodes. For the relevant nodes, they merge and count the analytical attributes for each group so that aggregate function can be easily performed. The major problem is that their navigational approach is only suitable for queries with a simple predicate. They find the relevant nodes in documents by scanning the document for each query. However, if a query contains complex predicates as selection conditions and the document schema is complex (e.g., "//"-axis query and documents with recursively appearing tags), file scan is neither efficient, nor effective to return correct answers. That also explains why many twig pattern matching techniques, e.g., *TwigStack* [16], attract lots of research attention.

To solve the problem in structural search in existing work for XML query processing with grouping, we extend our algorithm *VERT* proposed in Chapter 3, to efficiently compute *group-by* operators in XML queries with complex predicates. Given a group-by query, we match the query pattern to the document based on query predicates using *VERT*. *VERT* can handle both structural search and content search in an XML query efficiently, thus it is suitable for queries with complex predicates. After that, we use the table indexes to get the values of relevant properties and compute the aggregate functions in different levels of nested grouping by scanning the resulting tuples.

The rest of this chapter is organized as follows. Related work on XML grouping is presented in Section 5.2. In Section 5.3 and 5.4 we describe a format of queries with grouping and aggregation, which is used in our system, and design the algorithm *VERT*^{G} to efficiently process queries. We present experimental results in Section 5.5 and summarize this chapter in Section 5.6.

5.2 Related work on XML grouping

Grouping and aggregation is well supported by SQL in relational databases. There are also research works [53, 73] to generalize or optimize such analytical operations in RDBMS. Since XQuery 1.0 lacks functions to explicitly support grouping, processing queries with grouping in XML is addressed by researchers in recent years. Intuitively, the relational approaches to store and query XML data can support grouping and aggregation because of the powerful SQL. However, these sort of approaches have limitations in structural search, as reviewed in Chapter 2.

The research in XML grouping in native XML databases mainly focuses on three directions. The first direction is on how to support grouping by either providing logical grouping operators [43, 20, 96], or detecting grouping in nested queries and rewriting queries [37, 42, 88, 101, 107]. Particularly, in [43] they provide algebraic operators for grouping, and achieve efficient construction of XML elements using their algebra. [20, 96] focus on designing a graphical query language supporting grouping, and eventually the query will be translated to XQuery expression to process. The works [37, 42, 88, 101, 107] detect the potential grouping from nested queries and using different rewriting rules to transform the queries into a new structure with explicit *group-by* operator. However, this approach has a bottleneck, which is the difficulty of detecting grouping in nested queries. Sometimes it is even not possible to detect such potential grouping [9].

Due to the limitation of detecting grouping in nested queries, some researchers focus on a second direction, which is extending XQuery 1.0 to explicitly support grouping in queries. In [14, 9, 72] they defined extra operator to complement FLWOR expression in XQuery for grouping. In this case, the query optimizer does not need to detect potential grouping in an XQuery expression. Based on these research efforts, W3C published the new version of XQuery, XQuery 1.1 [40], in which a grouping construct is introduced as a core requirement, though the work has just started.

Since none of the works mentioned above focuses on physically computing *group-by* and aggregate function over XML documents, a new research direction works on algorithmic support for processing grouping and aggregation. [50] proposes an algorithm to directly compute *group-bys*. However their method did not consider the case that an XML query may contain complex predicate and the document may also have a complex schema such as containing recursively appearing elements. For such documents and queries, the file scan to select relevant nodes in [50] may fail to work, and this motivates many pattern matching techniques ([52]). There are also works ([89]) to eliminate duplicates during grouping computation so that better performance can be retrieved.

5.3 Query expression

In this section, we describe the general form of XML queries with grouping, which is used in our $VERT^G$ algorithm. The general query form is shown in Fig. 5.2.

The reason why we introduce this query form is that we want to separate the query pattern from the grouping and aggregate functions. The main components in our query form are:

Pattern: The grouping operation and aggregate function is built on twig pattern

```
Expr         ::= "PATTERN:" XPath_expression
                 Group-by*
Group-by     ::= "GROUP BY:" group-by_attribute+
                 ("ORDER BY:" group-by_attribute+)?
                 ("HAVING:" condition+ )?
                 "RETURN: {" aggregate_function+
                              Group-by* "}"
Occurrence Indicator: + 1 or more  * 0 or more  ? 0 or 1
```

Figure 5.2: Query form used by $VERT^G$

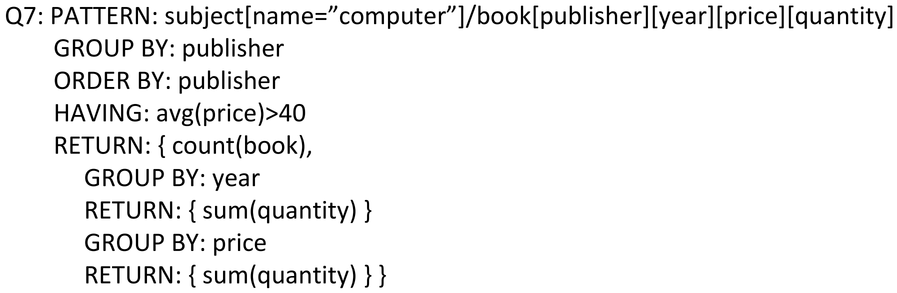
queries because twig pattern is the core pattern for general XML queries. We use XPath expressions to represent twig patterns. The nodes in a twig pattern should include all the predicate nodes, group-by nodes and output nodes in the given query[1].

Grouping: Grouping is explicitly expressed in the *group by* clause. *Group by* indicates the query nodes by which the results are grouped, and an optional *order by* clause indicates the order to output each group. Without indicating the grouping order, we will output the result based on the ascending order of the group-by nodes by default. Grouping often comes with optional *having* clause, which is used to specify the aggregate conditions. Grouping can be parallel, which means the results are grouped in multiple ways by different properties. Grouping can also be nested, which means the results within each *return* clause can be further grouped.

Return: The *return* clause specifies the aggregate functions in each group. As mentioned above, grouping can recursively appear in a query, so the output information following the *return* clause can be the value of an aggregate function, or a nested grouping operation with another *return* clause.

[1] Note that, if the query pattern is complex, we will use multiple twig patterns with joins or the TP+Output expression introduced in Chapter 4, to represent the query pattern. Details are discussed in Section 5.4.6

Example 5.1. *Consider a query to find first all the computer books grouped by publisher to output the total number of books of each publisher whose average book price is greater than 40, and then group all books under each of these publishers by year and price separately to find the total quantity of books in each subgroup. This query can be expressed as Q7 in Fig. 5.3. Note that the pattern in Q7 is an XPath expression in which all relevant nodes to the query are included.*



```
Q7: PATTERN: subject[name="computer"]/book[publisher][year][price][quantity]
      GROUP BY: publisher
      ORDER BY: publisher
      HAVING: avg(price)>40
      RETURN: { count(book),
          GROUP BY: year
          RETURN: { sum(quantity) }
          GROUP BY: price
          RETURN: { sum(quantity) } }
```

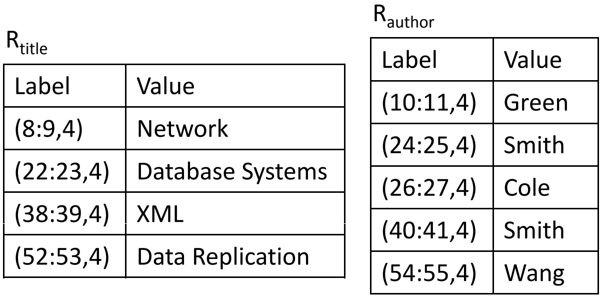
Figure 5.3: Example query Q7

5.4 VERT^G algorithm

In this section, we introduce the algorithm *VERT^G* to perform grouping as well as aggregate functions in XML queries with complex predicate. Our algorithm contains two phases. In the first phase, we perform pattern matching to find all the relevant nodes that satisfy the query predicates in XML document. In our implementation we use the algorithm *VERT*, which is presented in Chapter 3, to match query pattern, because: (1) *VERT* solves content problems existing in many other algorithms, such as the inefficiency of content management, content search and content extraction, and (2) *VERT* makes use of relational tables to index values, which is more compatible with the algorithm proposed in this chapter. After that, in the second phase we use the table indexes on values, together with the result from pattern matching, to perform grouping and compute aggregate functions. Multi-level grouping can be efficiently supported in $VERT^G$.

5.4.1 Data structures and output format

We define the query format in Section 5.3. In this section, we discuss how we store document information and query information into relevant data structures, which will be used during query processing with $VERT^G$. Since we adopt *VERT* to process pattern matching for queries, we need to maintain inverted lists and relational tables, as mentioned in Chapter 3. We do not repeat the process to construct these data structures. Take the document in Fig. 5.1 as an example, the relational tables for the property *title* and *author* are shown in Fig. 5.4.



R_{title}

Label	Value
(8:9,4)	Network
(22:23,4)	Database Systems
(38:39,4)	XML
(52:53,4)	Data Replication

R_{author}

Label	Value
(10:11,4)	Green
(24:25,4)	Smith
(26:27,4)	Cole
(40:41,4)	Smith
(54:55,4)	Wang

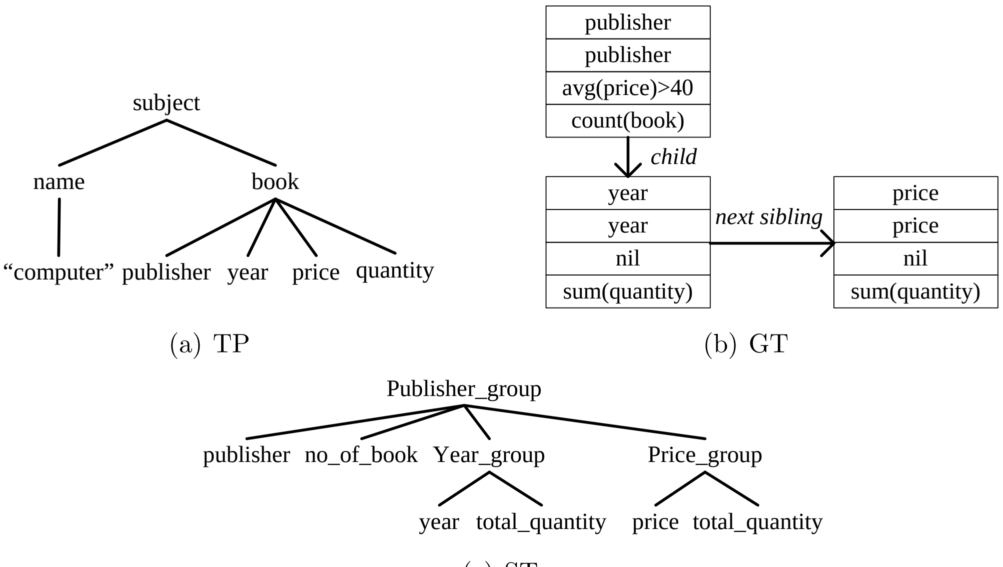
Figure 5.4: Relational tables for “title” and “author”

Besides the table indexes, we also need three tree structures for queries in $VERT^G$. The first one is a twig pattern, named *TP*, to represent the XPath expression in a query. The second one is a grouping tree, named *GT*, to reflect the structure of the complex grouping operations in a query. The last one is a skeleton tree, named *ST*, to summarize the structural information of output. *TP* is used to match to the document. This pattern matching process can be considered as a selection based on predicates. In *GT*, each node stands for a grouping operation. Thus within a *GT* node we record the group-by property[2], the order-by property,

[2] To simplify the explanation, we assume there is one group-by property in each grouping

the grouping constraint and the output aggregate function. Each *GT* node has two pointers: *child* and *next sibling.* The *child* points to a nested grouping operation, and the *next sibling* points to a parallel grouping operation in the same grouping level as the current node.

Example 5.2. *Consider Q7 in Fig. 5.3. The structures* TP*,* GT *and* ST *for Q7 are shown in Fig. 5.5. In* GT*, the four entries in each node stand for group-by property, order-by property, grouping constraint and output aggregate function in order. The* child *pointer reflects the nested relationship between the two levels of grouping, and the* next sibling *pointer reflects the parallel relationship between the two grouping operations in the same level.* ST *is constructed based on* GT*. It summarizes the structure of the output.*



(a) TP

(b) GT

(c) ST

Figure 5.5: Data structures for Q7: TP, GT and ST

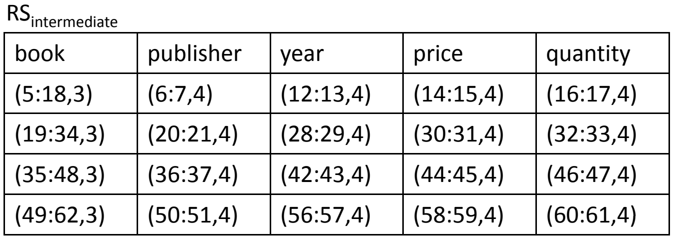
operation. The data structures can be easily extended to support multiple group-by properties. The same assumption is made for grouping constraint and output aggregate function.

5.4.2 Query processing

To process a query with grouping using $VERT^G$, we first perform a pattern matching to the XML document. After that in the second phase we perform grouping and aggregation based on the matching results.

Pattern matching:

As mentioned previously, we adopt $VERT$ for pattern matching. At the beginning, pattern matching returns tuples of labels for relevant matched nodes, which is considered as intermediate result set, named as $RS_{intermediate}$. The relevant nodes means the nodes which are searched by the query, used as group-by properties, or involved in aggregate functions. For example, to process Q7, we match the path expression following PATTERN to the document. Since nodes "book", "publisher", "year", "price" and "quantity" appear in GROUP BY, HAVING and RETURN clauses, pattern matching will output the labels for these nodes in each matched segment. The intermediate result set for Q7 is shown in Fig. 5.6, where each tuple contains the node labels in each twig pattern occurrence in document.



$RS_{intermediate}$

book	publisher	year	price	quantity
(5:18,3)	(6:7,4)	(12:13,4)	(14:15,4)	(16:17,4)
(19:34,3)	(20:21,4)	(28:29,4)	(30:31,4)	(32:33,4)
(35:48,3)	(36:37,4)	(42:43,4)	(44:45,4)	(46:47,4)
(49:62,3)	(50:51,4)	(56:57,4)	(58:59,4)	(60:61,4)

Figure 5.6: Pattern matching result for Q7

Performing grouping:

In the second phase, we perform grouping, as well as aggregate functions. We first construct RS_{final} by extracting actual values for the properties in the intermediate result set $RS_{intermediate}$ using table indexes for each property. After that we traverse the GT for the query according to a child-first fashion. The recursive method for GT traversal is shown in Algorithm 5.1. We start with **traverse** ($GT.root$) and the global variable *level*, which indicates the grouping level that we start performing grouping with, is initialized to be 1. When we visit a node, we attach the group-by property, order-by property, grouping constraint and aggregate function in that node to the end of the corresponding global lists GL, OL, CL and AL. If a node does not have a child, we begin to perform grouping in RS_{final} with current GL, OL, CL, AL and *level*. We also consider the parallel grouping within the same level by checking the next sibling of each GT node. The *level* value is set to be the level of the node which has a next sibling.

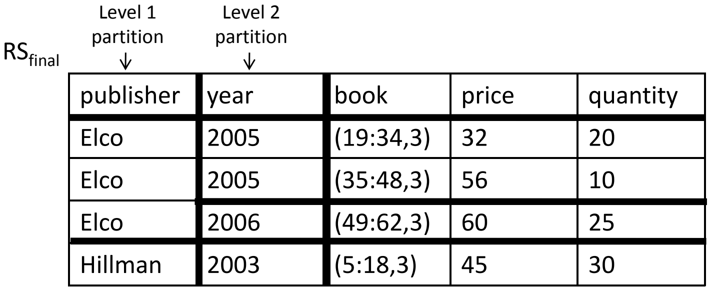
Algorithm 5.1 traverse (*node*)

```
attach the group-by property, order-by property, grouping constraint and aggregate function in node to the end of the lists GL, OL, CL and AL separately
if node.getChild == null then
    perform ($RS_{final}$, GL, OL, CL, AL, level)
else
    traverse (node.getChild)
end if
delete the last entry of GL, OL, CL and AL
if node.getNextSibling != null then
    level=node.getLevel
    traverse (node.getNextSibling)
end if
```

To process the query Q7, we traverse the GT in Fig. 5.5(b). By Algorithm 5.1, we perform grouping twice for Q7: one is for properties “publisher” and “year” with *level*=1, and the other one is for “publisher” and “price” with *level*=2. Now we move to the algorithm to perform grouping, which is shown in Algorithm 5.2. Note that although the RS_{final} is in relational table format, we cannot use SQL to compute all the group-by clauses, because SQL cannot support nested grouping due to the flat format of relational table.

We partition RS_{final} in line 1. The function $partition(RS_{final}, GL, OL)$ sorts the table RS_{final} based on all the properties in GL, following the order by which the properties appear in OL if it is different from that in GL. Sorting by multiple properties works in the way that the system sorts tuples by the first property, and if two or more tuples have the same value on the first property, then it sorts them by the second property, and so forth. Now the tuples can be partitioned into different groups for different levels.

Example 5.3. *Consider Q7 in Fig. 5.3 with the intermediate result set shown in Fig. 5.6. Using the index tables $R_{publisher}$, R_{year}, R_{price} and $R_{quantity}$ we can get the exact values for each field. When the* **perform** *function is first called in Algorithm 5.1, we partition the RS_{final} based on properties "publisher" and "year". The result is shown in Fig. 5.7. The bold lines in the RS_{final} show the partition.*


RS$_{final}$
Level 1 partition
Level 2 partition

publisher	year	book	price	quantity
Elco	2005	(19:34,3)	32	20
Elco	2005	(35:48,3)	56	10
Elco	2006	(49:62,3)	60	25
Hillman	2003	(5:18,3)	45	30

Figure 5.7: Example RS_{final} with partition for Q7

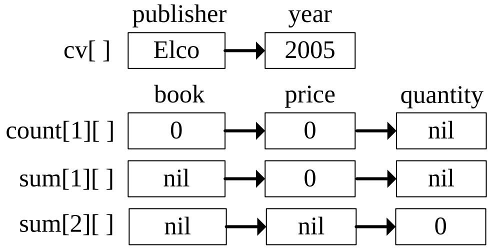
In lines 2-6, we initialize the lists used in this algorithm. Particularly, cv[i] stores the current value of the group-by property in the ith level group, while statistic lists count[i][ ], sum[i][ ], max[i][ ] and min[i][ ] store the corresponding current statistic values for the ith level group. In lines 7-31, we update these lists to get aggregate results. We check each tuple in RS_{final} to see whether any new partition in the different levels begins at this tuple. This is done by checking whether the value

Algorithm 5.2 perform (RS_{final}, GL, OL, CL, AL, $level$)

```
partition($RS_{final}$, $GL$, $OL$)
let $n$ = $GL$.length
for each $i = level$ to $n$ do
    initialize $cv$[i] = $RS_{final}[GL$[i]]
    initialize lists count[i][ ], sum[i][ ], max[i][ ], min[i][ ] for relevant properties
        in $RS_{final}$, which are used to compute aggregate functions
end for
for each tuple $t$ in $RS_{final}$ do
    for each $i = level$ to $n$ do
        if $t$[GL[i]] != cv[i] then
            for each $j = i$ to $n$ do
                check the constraints in $CL$[j]
                if CL[j] holds then
                    compute aggregate functions in $AL$[j]
                    put $cv$[j] and the aggregate results into the appropriate position in
                        result tree
                end if
                $cv$[j] = $t[GL$[i]]
                reset count[j][ ], sum[j][ ], max[j][ ], min[j][ ]
            end for
            break
        else
            update count[j][ ], sum[j][ ], max[j][ ], min[j][ ]
        end if
    end for
end for
for each $i = level$ to $n$ do
    check the constraints in $CL$[i]
    if CL[i] holds then
        compute aggregate functions in $AL$[i]
        put $cv$[i] and the aggregate results into the appropriate position in result
            tree
    end if
end for
```

of the group-by property in each level is changed in line 9. If any new partition begins in a certain grouping level, for every lower level a new partition also begins. Then we check the HAVING constraint in these levels and compute the aggregate functions using the corresponding statistic lists, as shown in lines 11-15. After that we reset the current group-by property value and the statistic lists for each of these levels, in lines 16-17. If in a tuple, some grouping level does not end, we simply update the statistic lists in line 21. In many cases, we do not need to maintain all the statistic lists as the query may be only interested in some of them. To simplify the presentation, we use all the statistic lists in the pseudo-code. Lines 25-31 finalize the query processing by outputting the result for the last group in each grouping level.

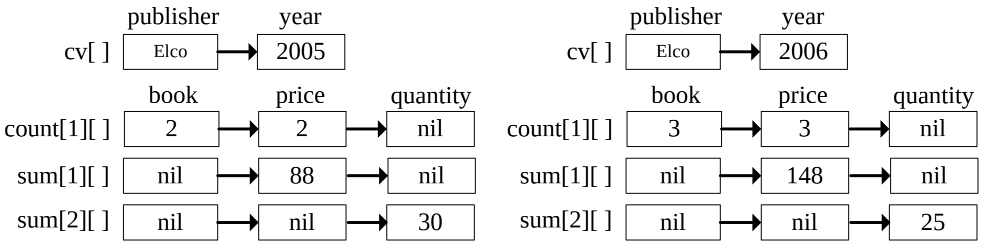
Example 5.4. *When the* **perform** *function is first called during* GT *traverse for Q7, the RS_{final} with partition is shown in Fig. 5.7. We start with* level=*1, and initialize the current value and the necessary statistic lists for each grouping level, as shown in Fig. 5.8. The list cv[ ] contains two entries since there are two levels of grouping. The statistical list, saying count[1][ ], stores the total number of each target property in the first level, e.g., count[1][2] is the count of the second property "price" in level 1 grouping.* Nil *in some entries of each list means the corresponding statistic value is not asked by the query and we do not need to maintain it.*



Note: In count[i][j] and sum[i][j], i is the grouping level and j is the position in the list.

Figure 5.8: Example initial lists for Q7

When the system reads the third tuple in RS_{final}, the value in cv[1] is the same as the "publisher" value in the third tuple. That means the current level 1 group does not end at this tuple. Thus it updates the lists count[1][ ] and sum[1][ ]. However, the value "2005" in cv[2] is different from the "year" value "2006" in the third tuple, which means current level 2 group ends. It then follows lines 11-15 in Algorithm 5.2 to compute the aggregate function in level 2 grouping based on current statistic list for this level, e.g., sum[2][ ], and puts the value "2005" for the group-by property "year" and the result "30" for aggregate function sum(quantity) *into appropriate position in the resulting tree based on the* ST *shown in Fig. 5.5(c). After that the system resets cv[2] and the statistic list sum[2][ ] for level 2 grouping and continues reading the next tuple. The relevant lists before and after reading the third tuple is shown in Fig. 5.9.*



(a) Before the third tuple

(b) After the third tuple

Figure 5.9: Example lists before and after reading the third tuple in RS_{final} for Q7 processing

5.4.3 Early pruning

Anti-monotonic constraint is defined as the constraint which will never be true once it becomes false. Some aggregate constraints that appear in HAVING clauses, such as count( ) $\leq$ *num*, max( ) $\leq$ *num*, min( ) $\geq$ *num* or sum( ) $\leq$ *num* (*num* is a numeric value), are anti-monotonic constraints. For example, for the constraint max(price) $\leq$ 100, once we get a price greater than 100 in a group, we can never turn the constraint to be true, no matter how many more prices are checked in the same group. Motivated by anti-monotonic constraints, some early pruning can be done to enhance the query performance. When we read tuples in RS_{final}, we can check the anti-monotonic constraint first, rather than checking all constraints after meeting the end tuple of the group. If any anti-monotonic constraint is violated by a certain tuple, all other tuples in the same group can be skipped.

5.4.4 Extension flexibility

The query form and query processing algorithms presented in Section 5.3 and Section 5.4.1 are built on basic aggregation. Sometimes the user may issue queries involving keyword constraints *distinct*, or some other aggregate functions, or even moving windows following the group-by properties. In this section, we explain briefly how our algorithm is flexible to be extended to support these advanced features.

Distinct:

Some aggregate function aims to find aggregate results on distinct values in a group. In this case, we need to introduce keyword *distinct*. There are two types of parameters that can be used by *distinct* constraint. The first type is property. For example, count(*distinct* name) counts the number of different names distinguished by name values. To support this type of *distinct*, we can maintain a sorted list to store different values for the corresponding properties. When a value comes, we can know whether it is a *distinct* value by checking the sorted list.

The second type of parameter following *distinct* constraint is object, e.g., count(*distinct* book). This function is not easy to compute as "book" is an object class rather than property, and there is no child value for "book" to explicitly distinguish each "book" object. One way to distinguish objects under the same class is to discover more semantics on object ID [18]. As long as the ID of an object class is clear, we can easily perform aggregate functions on distinct objects by introducing ID to RS_{final} for the relevant object.

Other aggregate functions:

We discuss four more aggregate functions that are frequently asked, namely, *maxN( )*, *minN( )*, *median( )* and *mode( )*. The function *maxN( )* and *minN( )* are top N functions to find the N maximum or minimum values. *Median( )* returns the value that separates the higher half of a set of values from the lower half, and *mode( )* is used to find the value that occurs most often in a set. In the discussion about *distinct* keyword above, we mentioned that we can maintain an additional sorted list to store different values for particular property. To compute *maxN( )*, *minN( )*, *median( )* and *mode( )*, we not only need the sorted list for the distinct values for relevant properties, but also need a frequency list in which each entry stores the number of occurrences of the value in the corresponding entry in the sorted list. Using these two lists, these aggregate functions can be easily computed.

Moving windows:

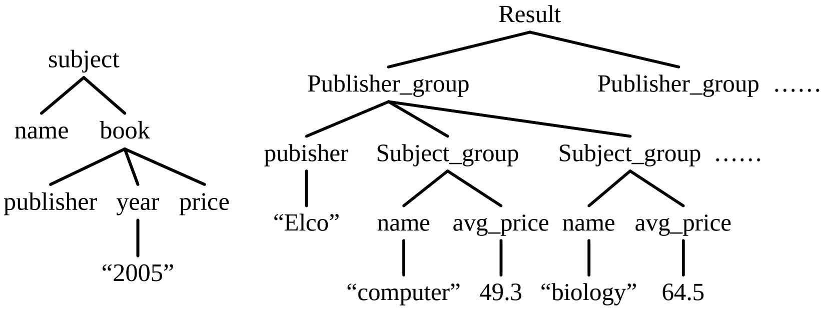
Moving windows are used to group answers by ranges of values on a certain property. For example, a query needs to find the total quantity of books group by range of 5 years with a moving step of 3 years, beginning at 2008. In this query, we need to put books with year in [2008, 2012] together, with year in [2011, 2015] together and so on. The general approach to handle moving windows is, we first do grouping and aggregation as usual for each distinct value, and after that we perform a post-aggregation that aggregates the results from the previous step based on each window range. Consider the query mentioned above. First we get the sum(quantity) for each year, and then in the post-aggregation step, we just sum up the quantity for years from 2008 to 2012, and from 2011 to 2015, etc. If there are nested grouping operations inside each window group, the post-aggregation is also effective. For example, continuing with the above query, suppose for each year window, we need to find the number of books grouped by publisher. In the first step, we group books by each different year, and then in each group, we do a secondary grouping on publisher and count the books in each subgroup. The post-aggregation will integrate all subgroups in the five groups with year value from 2008 to 2012, from 2011 to 2015, etc, by summing up the results under the same publisher.

5.4.5 Discussion on semantic optimization

In Q7, we group "book" by its own properties. Actually our algorithm also supports grouping by the properties appearing in other places in document, rather than descendant properties of a given object. Example 5.5 shows such a case.

Example 5.5. *Consider the query Q8 to find the average price of books published in 2005, group by publisher first and then group by subject name. In this query, subject name appears as a property of another object, instead of "book". To answer this query, we just match the twig pattern shown in Fig. 5.10(a) to the document tree, and extract values for each property using the table index for both "book" and "subject", to form* RS_{final}*. Then grouping operation and aggregate functions can be processed as normal in* RS_{final}*. The result structure is shown in Fig. 5.10(b).*

However, by investigating analytical queries, we find many of them group objects by their own properties. For example in Q7, we group books by publisher and then by year and price. *Publisher*, *year* and *price* are all properties of *book*.



(a) Twig pattern (b) Result tree

Figure 5.10: Query Q8 and result tree

Naturally, we can adopt the semantic optimizations proposed in *VERT* in Chapter 3 to match query patterns to documents in $VERT^G$.

We take the second optimization of *VERT*, which is using object tables to aid twig pattern matching, to explain the advantages. The first advantage is the complexity reduction of twig patterns during pattern matching with *VERT*. This is illustrated in Section 3.3.2. The second advantage is when we generate RS_{final} from $RS_{intermediate}$, we do not need to join with multiple property tables as in the original *VERT*. Instead, we only need to join with one object table (and relevant object/property tables for multi-valued properties, possibly), if the grouping properties are centered at one object. Thus, the performance can be improved. The details of *VERT* optimizations are discussed in Chapter 3, so we do not repeat it in this chapter.

5.4.6 Combining VERT^O and VERT^G

We proposed TP+Output expression to extend the existing twig pattern expression to enhance the expressivity, and proposed $VERT^O$ to match a TP+Output pattern query to an XML document, in Chapter 4. We discuss how to combine $VERT^O$ and $VERT^G$ to serve queries with grouping and aggregation.

Actually $VERT^O$ and $VERT^G$ have different focuses for XML query processing. *VERT*^{O} focuses on the query structure, i.e., it models query predicates and output information in a more expressive way, and match the query pattern to the document. Whereas, *VERT*^{G} focuses post-processing the pattern matching result to support grouping and aggregation. In *VERT*^{G} proposed in this chapter, we still use the original twig pattern query to represent the structure of the a query involving grouping operations. If a query is complex in its output, we may need multiple twig patterns to represent it. After matching all twig patterns to the document and joining the results, we will post-process it for grouping and aggregation computation. Since TP+Output expression proposed in Chapter 4 is used to model complex query output, we can adopt TP+Output to represent the query pattern in *VERT*^{G} so that complex output nodes can be easily expressed in one or fewer patterns. In this case, we will use *VERT*^{O} to match the TP+Output query pattern before performing grouping on the matching results, instead of using *VERT* to match the original twig pattern as stated previously in this chapter.

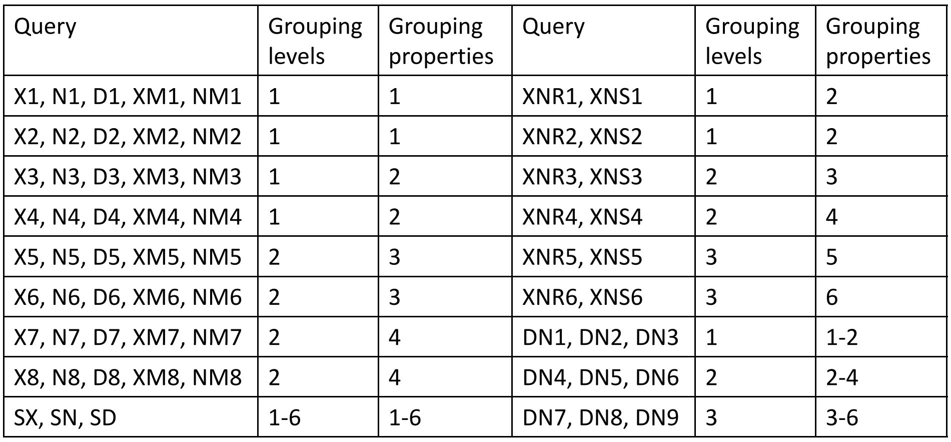
Since *VERT*^{G} emphasizes on its ability to perform grouping and aggregation, for simplicity, we do not consider complex query pattern. Thus in this chapter we still use *VERT* in illustrations.

5.5 Experiments

In this section we present experimental results. First we conduct experiments to compare the performance of using *VERT* without optimization, with Optimization 1 and with Optimization 2 to perform pattern matching in *VERT*^{G}. Consequently, we name the three algorithms *VERT*^{G}, *VERT*^{G}-opt1 and *VERT*^{G}-opt2. We show that *VERT*^{G}-opt2 has the best overall performance. Then we use *VERT*^{G}-opt2 to compare with other approaches including an XQuery processor, MonetDB [13], and a recently proposed algorithm N-GB [50] on group-by query processing.

5.5.1 Experimental settings

We implemented all algorithms in Java. The experiments were performed on a dual-core 2.33GHz processor with 4G RAM. We still used the real-world data sets DBLP (91MB) and NASA (23MB), and the well known synthetic data set XMark in our experiments. The characteristics of the queries used is shown in Fig. 5.11.



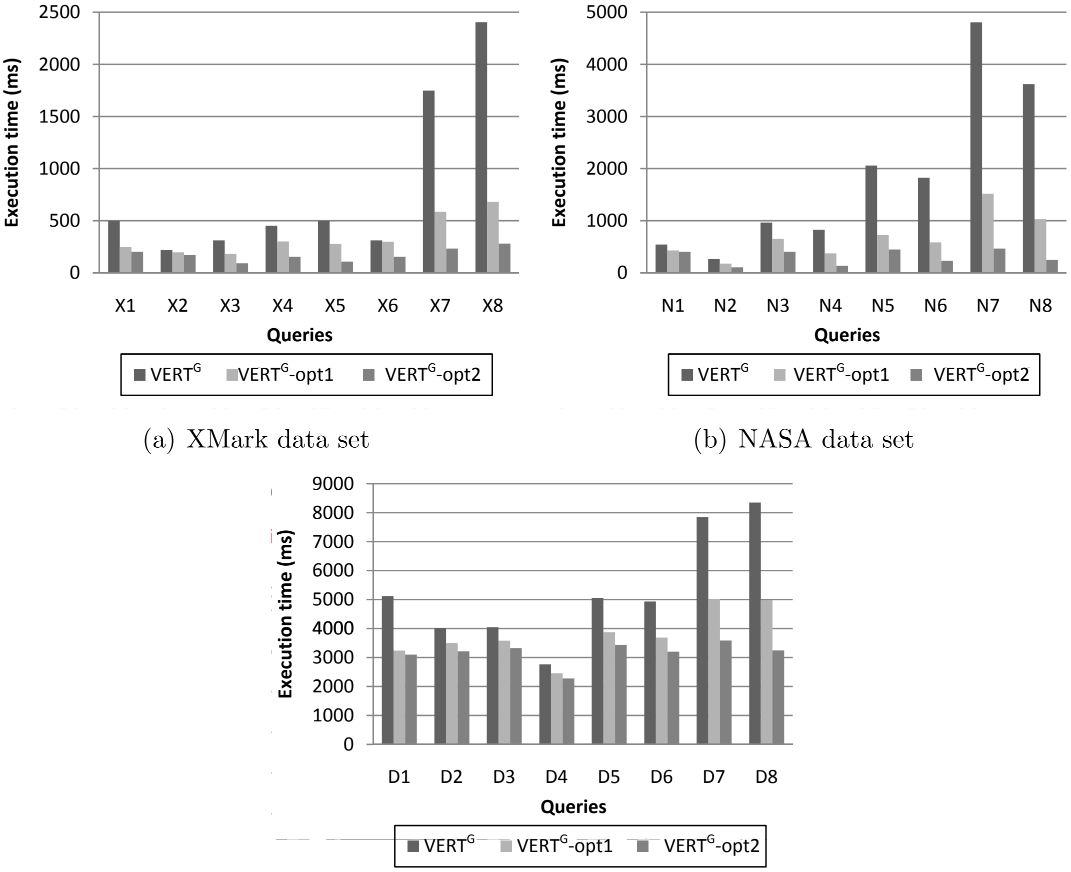
Query	Grouping levels	Grouping properties	Query	Grouping levels	Grouping properties
X1, N1, D1, XM1, NM1	1	1	XNR1, XNS1	1	2
X2, N2, D2, XM2, NM2	1	1	XNR2, XNS2	1	2
X3, N3, D3, XM3, NM3	1	2	XNR3, XNS3	2	3
X4, N4, D4, XM4, NM4	1	2	XNR4, XNS4	2	4
X5, N5, D5, XM5, NM5	2	3	XNR5, XNS5	3	5
X6, N6, D6, XM6, NM6	2	3	XNR6, XNS6	3	6
X7, N7, D7, XM7, NM7	2	4	DN1, DN2, DN3	1	1-2
X8, N8, D8, XM8, NM8	2	4	DN4, DN5, DN6	2	2-4
SX, SN, SD	1-6	1-6	DN7, DN8, DN9	3	3-6

Figure 5.11: Experimental queries with No. of grouping levels and No. of grouping properties

5.5.2 Comparison between VERT^G without and with optimizations

Query performance

We process 8 queries in each document to compare the query performance between *VERT*^{G} and two optimizations, *VERT*^{G}-opt1 and *VERT*^{G}-opt2. Queries X1-X8 are issued to the XMark document, N1-N8 to the NASA document and D1-D8 to the DBLP document. The experimental results on execution time are shown in Fig. 5.12.



(a) XMark data set

(b) NASA data set

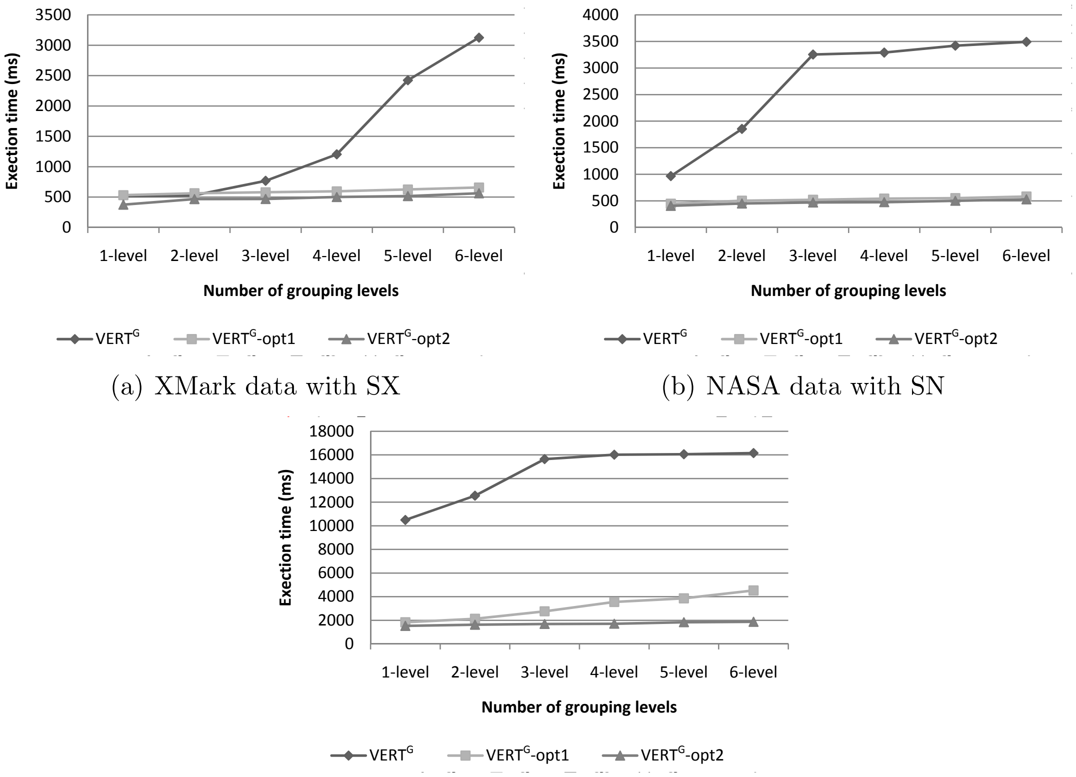
(c) DBLP data set

Figure 5.12: Query performance comparison for $VERT^G$, $VERT^G$-opt1 and $VERT^G$-opt2

We can see that for all the queries $VERT^G$-opt2 outperforms $VERT^G$-opt1, and $VERT^G$-opt1 outperforms $VERT^G$ without optimization. This again validates the analysis in Chapter 3 that using semantic optimizations can improve query processing performance.

Scalability as grouping levels increase

It is natural that the user issues a query with nested grouping. In this section we measure the time trend of $VERT^G$ and the optimizations when the grouping levels increase. For each document, we select one type of query with predicates fixed and grouping levels varied. The result on the scalability is shown in Fig. 5.13.



(a) XMark data with SX

(b) NASA data with SN

(c) DBLP data with SD

Figure 5.13: Scalability for $VERT^G$, $VERT^G$-opt1 and $VERT^G$-opt2

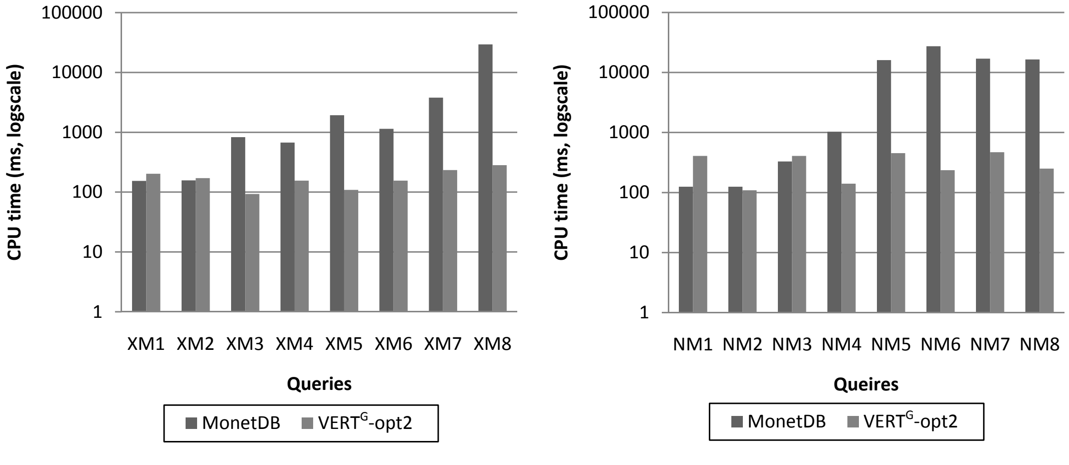
From the result we can see that running time for $VERT^G$ increases as the number of grouping levels increases. The reason is, if we group a set of objects by a new property, we have to include that property for pattern matching, which is time consuming. However, if we adopt $VERT^G$ with either $VERT^G$-opt1 or $VERT^G$-opt2, we only match the relevant objects, instead of each property node. As a result, the execution time increases slowly when more grouping levels are involved. $VERT^G$-opt2 is better than $VERT^G$-opt1 because we access less tables in $VERT^G$-opt2.

5.5.3 Comparison with other approaches

In this section, we compare our approach with other approaches including an XQuery processor MonetDB, and N-GB. We use $VERT^G$-opt2 in our approach for the comparison. There is no additional index built for all approaches.

Comparison with XQuery

We take MonetDB [13], which is a well known efficient memory-based XQuery processor, for comparison. To be fair, we only compare the CPU time, ignoring the time to load the document or relevant indices into the memory. Since MonetDB is memory based, we used two smaller data sets, XMark (11MB) and NASA (23MB), and conducted experiments on 8 queries in each data set (XM1-XM8 and NM1-NM8). All the queries contain grouping operation, and the group-by properties may not necessarily be the children or descendants of the object to be grouped. For example in NM8 for NASA data, we group journals by subject, which is the ancestor node of "journal" in the document. The experimental results are shown in Fig. 5.14 (Y-axis is in logarithmic scale).



(a) XMark data set

(b) NASA data set

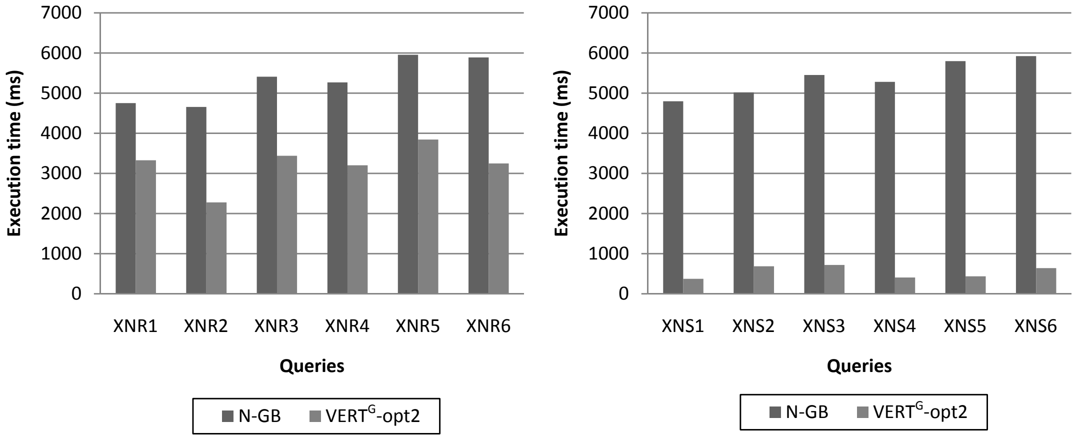
Figure 5.14: CPU time comparison between *MonetDB* and $VERT^G$-opt2

For both data sets, we can see that for 1-level grouping with one property, MonetDB performs well. However, when the number of group-by properties and the number of grouping levels increases, since XQuery needs to express such queries using nesting with multiple document retrievals and joins, the performance of MonetDB is affected. In XMark data set, the CPU time for MonetDB increases fast on XM3-XM8. In NASA data set, though the CPU time on NM3-NM4 is still relatively low, when we increase the number of grouping levels in NM5-NM8, the efficiency of MonetDB is significantly affected. Our approach, $VERT^G$-opt2, outperforms MonetDB for those queries with multi-level groupings.

Comparison with N-GB

We also compare our work with a recently proposed algorithm N-GB ([50]) to process queries with grouping and aggregation. We take two larger data sets, XMark (111MB) and DBLP (91MB) for the comparison. For XMark data, we perform two sets of queries. The first set contains queries in which group-by properties appear in any positional relationship with the object to be grouped. For example, we group journals by either its child property "year" or its ancestor property "subject". For this set of queries, our optimization can reduce the complexity during query processing, but we still need pattern matching to get query node occurrences in document. The second set of queries have group-by properties, output nodes and aggregate properties under the same object. In this case, we do not need to perform pattern matching, and the efficiency will be enhanced. For each query set, we have 6 queries with grouping levels varying among 1, 2 and 3. Fig. 5.15 shows the experimental results for XMark data.

From the figure above we can see $VERT^G$-opt2 always outperforms N-GB. For the first set of queries (Fig. 5.15(a)), $VERT^G$-opt2 saves 30%-51% in running time,



(a) Group-by properties in random position (b) Group-by properties in the same object as outputs

Figure 5.15: Execution time comparison between *N-GB* and *VERT*^{G}-opt2 for XMark data

and for the second query set (Fig. 5.15(b), this saving becomes 86%-93%.

We also used the real-world data DBLP to compare our approach and N-GB. We used 9 queries for DBLP data, which are DN1-DN9. Since N-GB assumes the answer tree can fit in memory, we allocated 1GB memory for JVM during experiments. The results are shown in Fig. 5.16. We can see from the figure, *VERT*^{G}-opt2 outperforms N-GB for all kinds of queries. This result shows that our approach is efficient not only for complex documents (e.g., XMark), but also for flat documents (e.g., DBLP).

5.6 Summary

In this chapter we analyzed the drawbacks of different existing approaches to process XML queries with grouping and aggregation, and proposed a novel algorithm, *VERT*^{G}, which can perform both parallel and nested grouping operations and compute aggregate functions efficiently in XML queries with complex predicate. *VERT*^{G} extends the *VERT* algorithm which introduces table index during XML

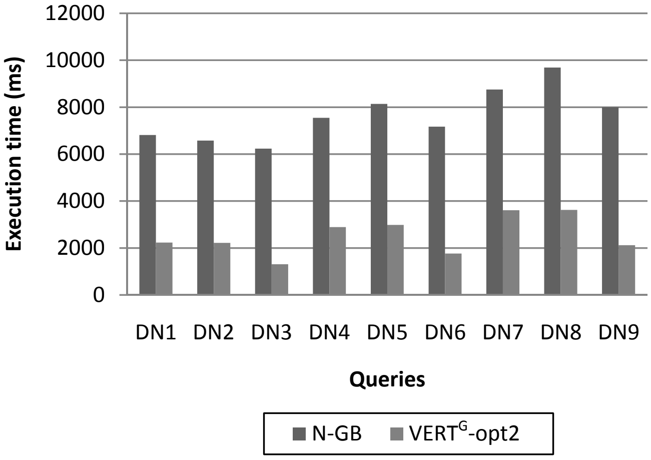


Figure 5.16: Execution time comparison between *N-GB* and *VERT*^{G}-opt2 for DBLP data

query processing. After matching the pattern of an XML query to the document natively using *VERT*, *VERT*^{G} extracts actual values for relevant nodes with table indexes and then performs different levels of grouping and aggregation. Furthermore, we can also adopt the semantic optimizations in *VERT* to significantly enhance the query processing performance. We conducted experiments to compare our approach with a well known XQuery processor, MonetDB and a recently proposed algorithm, N-GB to show the advantages of our approach.

CHAPTER 6

CONCLUSION

6.1 Conclusion

In this thesis, we propose to use semantic information such as value, property, object and relationship among objects, to improve the efficiency of XML query processing. The core technique of our research is to integrate semantic relational tables into native XML query processing approaches, which use inverted lists to process twig pattern queries. With relational tables, for the first time, one can separately process content search to reduce the relevant inverted lists and the number of structural joins for structural search, and thus improve search efficiency. Also using relational tables one can effectively extract values based on node labels to return to users. We theoretically and experimentally demonstrate that our semantic approach can achieve better performance in twig pattern query processing than existing approaches.

In Chapter 3, we propose the *VERT* algorithm to process XML twig pattern queries. We first analyze the shortcomings in the structural join based native XML twig pattern query processing approach, which is the state-of-the-art approach and considered more efficient than other twig pattern query processing approaches in general. In particular, the structural join based approach has difficulties in (1) managing tremendous number of inverted lists for different values, (2) performing content search for value predicates (e.g., range search $price{<}50$), and (3) extracting values to answer a query. To solve these limitations, we introduce semantics-based relational tables as an index to manage values in XML data. Using relational tables, we can easily manage the tremendous number of data values in an XML document as tuples. Also we can efficiently perform content search for query predicates and return value answers to users. Especially to be mentioned is our relational tables are constructed based on semantic information. Initially we use the default semantics in XML documents, which is the parent node of each value must be its associated property, to build property tables. A property table stores the label of each document node that in this property type, and its corresponding value. Content search in a query is performed by SQL selection in relevant property tables, and the selected property labels are used to construct new inverted lists for the related property query nodes. After performing content search, the query can be simplified by removing the value predicates to reduce the number of structural joins, and the structural search can be performed by any existing efficient structural join algorithms, with the new inverted lists for related query nodes. Later we use more semantics on relationship between object and property and relationship among objects, to further optimize the relational tables to be object based. We propose three optimizations which introduce object/property tables, object tables and relationship tables respectively, to make twig pattern query processing more efficient. Such semantic information is actually available in XML data, otherwise, uses cannot compose, e.g., XQuery expressions to query XML data correctly. We also show that our approach can be easily extended to process queries with ID references and more general queries joining different twig patterns in one or several documents.

Later, in Chapter 4 and 5 we extend twig pattern query to express complex output information and to support grouping and aggregation respectively.

In Chapter 4, we explain the limitation of the existing twig pattern representation to express a subset of queries with complex output information centered at one object. Normally such a query needs to be represented by multiple twig patterns with joins to link them. Consequently, we have to match multiple twig patterns and join the matching results. In our research, we analyze the characteristics of query nodes, i.e., the purpose (predicate or output), the optionality (required or optional) and the occurrence (one or many), and based on our analysis, we extend the existing twig pattern query to express complex output information, such as optional output, predicated output and optional-predicated output. Using our extension, which is named *TP+Output*, we can express the queries with complex output information under a same object by fewer query patterns, compared to the original twig pattern representation, and thus perform less structural joins to process the query. Last, we extend the second optimization, which uses object tables, of *VERT* to match *TP+Output* queries. We call the extended algorithm $VERT^O$.

In Chapter 5 we present how we extend the *VERT* algorithm to perform grouping and aggregations (e.g., sum, avg, max, min, etc.) in XML queries, to meet the compelling needs of analytical queries in business data. We model the query pattern part and the grouping operation part in an XML query separately. Then our extended algorithm, $VERT^G$, adopts *VERT* to match the query pattern part to document first, and then traverse the grouping tree, which is constructed to reflect the complex grouping operations in the query, to perform grouping and compute aggregate functions. Our approach can effectively link the efficient twig pattern matching algorithms to grouping and aggregation computation, which is not well studied in existing twig pattern query processing works. We also show that the semantic optimizations in *VERT* and the extended algorithm $VERT^O$ can also be used in $VERT^G$ to model and process query patterns, to achieve better overall performance.

6.2 Future work

Our research opens a new direction to use semantic information and to integrate the data structures and indexes for both structured data and unstructured data, to improve query processing in semistructured XML data. We demonstrate how our approach solves the problems in value management and content search and meets some practical functions that are not supported in existing XML query processing approaches. In this section, we discuss the future research directions following our semantic approach.

Twig pattern query processing has attracted considerable research attention. However, many queries cannot be expressed with a single twig pattern. We proposed TP+Output to extend the expressivity of twig pattern query for complex output information. Although TP+Output effectively represents queries with complex output centered at a unique object by one enhanced twig pattern, it still cannot model any complex query, probably expressed in XQuery, using a single twig. For example, some queries require value-based joins to link multiple twigs and each of them can be represented by a TP+Output expression. Thus one future research direction is to translate a general XQuery expression into one or several join-linked

TP+Output expressions, so that our TP+Output and its corresponding query processing algorithm can be used to process general queries.

Our work focuses on handling content search in twig pattern queries with basic PC and AD edges. There are research works performing structural joins in twig pattern queries with OR-predicate, NOT-predicate, wildcards, etc, as these predicates may appear in general XPath and XQuery expressions. Thus how to extend our algorithms to solve the queries with these predicates can be another future research direction. Also though in our algorithms we can extract actual values to answer a twig pattern query, the format of returned result is still in tuples. How to correctly and efficiently transform tuple result into XML format to output to users needs to be studied.

Last, this thesis focuses on using semantics, e.g., object information, to process structured XML query. Actually, by noticing such semantics, we can also improve the search quality and efficiency in XML keyword search. Some of our research works studied how to utilize object-based semantics in XML keyword query processing, e.g., [6]. More continuous work is required to achieve better search quality and efficiency in XML keyword search.

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