Don’t Trash your Intermediate Results, Cache ’em*

Prasan Roy †1  Krithi Ramamritham†1
S. Seshadri§2  Pradeep Shenoy2  S. Sudarshan1
1 IIT Bombay
{prasan,krithi,sudarsha}@cse.iitb.ernet.in
2 Bell Laboratories, Murray Hill
{seshadri,pshenoy}@research.bell-labs.com

Abstract

In data warehouse and data mart systems, queries often take a long time to execute due to their complex nature. Query response times can be greatly improved by caching final/intermediate results of previous queries, and using them to answer later queries. An automatic caching system that makes intelligent decisions on what results to cache would be an important step towards knobs-free operation of a database system, essentially a step towards a database system that auto-tunes itself.

In this paper we describe an automatic query caching system called Exchequer which is closely coupled with the optimizer to ensure that the caching system and the optimizer make mutually consistent decisions. In contrast, in existing work, such a close coupling is absent. We present a cache management/replacement algorithm which we call Incremental. Furthermore, existing approaches are either restricted to cube (slice/point) queries, or to caching just the final query results. On the other hand, our work is extensible and in fact presents a data-model independent framework and algorithm. Our experimental results attest to the efficacy of our cache management techniques and show that over a wide range of parameters (a) Exchequer’s query response times are lower by more than 30% compared to the best performing competitor, and (b) Exchequer can deliver the same response time as its competitor with just one tenth of the cache size.

1 Introduction

Data warehouses and On-Line Analytical Processing (OLAP) systems are becoming increasingly important parts of data analysis. The typical processing time of decision support and OLAP queries range from minutes to hours. This is due to the nature of complex queries used for decision making. Data warehouses act as mediators between data sources and data consumers.

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‡Also affiliated with Univ. of Mass. Amherst.
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Various OLAP, data mining, querying and reporting tools access data at the central warehouse. The aim of our work is to improve the query response time by caching the (final as well as intermediate) results produced during query processing.

In a traditional database engine, every query is processed independently. In decision support applications, the query workload, consisting of a sequence of queries, often has overlapping expressions between queries. A natural way to improve performance is to cache and reuse results of previous query results when evaluating later queries. The unit of caching need not just be final results of queries — intermediate results of queries may also be cached.

We use the term query caching in this paper to mean caching of final and/or intermediate results of queries. Query caching differs from standard page caching in three major ways.

1. In contrast with page replacement schemes, where recency of usage is often sufficient, other factors such as size and cost of computation of results must be considered.

2. The query optimizer must be extended to consider the possibility of using cached results of previous queries.

3. In traditional page caching, the pages cached are independent of each other in that the presence (or absence) of a page in the cache does not affect the benefit of caching another page for a given workload. In contrast, a given query may be computable from any one of several query results (or intermediate query results). Therefore, the benefit (to the given query) of caching a particular query result depends on what else is present in the cache.

There has been some work on caching of query results in the recent past. We discuss related work in more detail in Section 5, but outline the main differences of our approach from directly related prior work here. Earlier work on caching has been for specialized applications (e.g. data cubes [DRSN98, KR99, SSV99], or just selections [DFJ+96, KB96]), or does not take caching of intermediate results into account ([SSV96]), or has relatively simple cache replacement algorithms, which do not take into account the fact that the benefit of a cached result may depend on what else is in the cache ([CR94, which handles only select-project-join queries]).

There has been work on the related area of materialized view/index selection, which can be viewed as a static version of caching, where the cache contents do not vary (e.g., see [RSS97, LQA97, Sup97] for general views, [HRU96, GHRU97, SDN98] for data cubes, and [CN97] for index selection). Techniques for materialized view/index selection use sophisticated ways of deciding what to materialize, where the computation of the benefit of materializing a view takes into account what other views are materialized. However, this body of work does not consider dynamic changes, and ignores the cost of materializing the selected views. The major disadvantage of static cache contents is that it cannot cater to changing workloads. The data access patterns of the queries cannot be expected to be static. To answer all types of queries efficiently, we need to dynamically change the cache contents. Another related area is multiquery optimization, where, e.g., the work of [RSSB00] takes the cost of materializing the selected
views, but still makes a static decision on what to materialize based on a fixed workload. In this paper, we study how to adapt the sophisticated techniques proposed for materialized view selection, to solve the problem of query caching. A first cut approach could be to simply run a view selection algorithm periodically. However, doing so naively (a) could increase the cost of materializing the selected views, and (b) would not be able to react quickly to changes in the query load. Hence we propose and evaluate more sophisticated alternatives, and show that dealing with the dynamics of query workloads is not only possible but also necessary for improved performance. The techniques presented in this paper form part of the Exchequer® query caching system, which we are currently implementing.

The contributions of this paper are as follows:

- We show how to use materialized view/index selection techniques for short to medium term caching. To achieve this we have developed efficient techniques for exploiting sharing opportunities that arise when several related queries follow one another, and it is useful to cache their results even if they are not part of a long-term trend.

- In general we have to interleave query execution with materializing selected results. Doing this efficiently requires a careful analysis of the costs and benefits of forcing a query to execute in such a way as to materialize a selected result.

- We cache intermediate as well as final results. Intermediate results, in particular, require sophisticated handling, since caching decisions are typically made based on usage rates; usage rates of intermediate results are dependent on what is in the cache, and techniques based only on usage rates would be biased against results that happen not to be currently in the cache.

  Our caching algorithms exploit sophisticated techniques for deciding what to cache, taking into account what other results are cached. Specifically, using incremental techniques developed by us in [RSSB00], we are able to efficiently compute benefits of final/intermediate results that are candidates for caching.

- We use an AND-OR DAG representation of queries and cached results, as in Volcano [GM91]:
  - The representation is extensible to new operations, unlike much of the prior work on caching, and efficiently encodes alternative ways of evaluating queries. In particular, therefore, our algorithms can handle any SQL query including nested queries. To the best of our knowledge, no other caching technique is capable of handling such a general class of queries.
  - The representation allows the optimizer to efficiently take into consideration the use of cached results.

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1Efficiently eXploiting caCHEd QUery Results
– Our DAG representation also includes physical properties such as sort orders, and the presence of indexes. Thus we are able to consider caching indices constructed on the fly in the same way as we consider caching of intermediate query results.

• We present an implementation-based performance study that clearly demonstrates the benefits of our approach over earlier approaches. Our study shows that

– intelligent caching can be done fast enough to be practical, and leads to huge overall savings, and

– our approach performs better than previously proposed algorithms. For a given cache size, our response times are at least 30% lower than the nearest competitor. Furthermore, we can deliver the same response times as our nearest competitor with just one tenth of the cache size.

Overall, our experimental results indicate that storing intermediate results is important, and using sophisticated caching techniques (which invest extra effort in careful transient view selection) is well worth it.

The rest of the paper is organized as follows. We start with a brief description of the architecture of the Exchequer query caching system, and an overview of our dynamic query caching algorithms in Section 2. Section 3 covers background material regarding the DAG (directed acyclic graph) representations that underlie our algorithm implementations. Details of the adaptive caching strategies, including when to materialize a result chosen for caching are presented in Section 4. Results of experimental evaluation of the proposed algorithms are discussed in Section 5. Related work is covered in detail in Section 6, and conclusions and future work are outlined in Section 7.

2 Overview of Exchequer’s Query Caching Architecture and Algorithms

The caching algorithms presented in this paper form part of the Exchequer query caching system. The architecture of the Exchequer system is portrayed in Figure 1.

As shown, the optimizer optimizes an incoming query based on the current cache state. We have integrated the cache manager and the optimizer and this tight coupling is demonstrated in Figure 1. The cache manager decides which intermediate results to cache and which cached results to evict based on the workload (which depends on the sequence of queries in the past). Conceptually, as the architecture shows, for each query, the optimizer cum cache manager produces the query execution plan as well as the cache management plan (which describes changes to the cache state if any). A query execution plan may refer to cached relations (since the optimizer is cache-aware) which are obtained from the query cache by the execution engine when required. In addition, new intermediate results produced by the query may be cached on the advise of the cache manager.
In addition to the above functionality, a caching system should also support invalidation or refresh of cached results in the face of updates to the underlying database. Exchequer does support this functionality. In this paper, however, we will confine our attention only to the issue of efficient query processing, ignoring updates. Data Warehouses are an example of an application where the cache replacement algorithm can ignore updates, since updates happen only periodically (once a day or even once a week).

The techniques needed (a) for managing the cache contents intelligently as queries arrive and (b) for performing query optimization exploiting the cache contents, form the crux of this paper. The main question related to intelligent cache management and cache-aware optimization is:

1. How do we dynamically characterize a changing workload and accordingly decide the caching and query optimization strategies so as to minimize the overall response time for all the queries?

Answering this question presents several subproblems:

- Characterizing the dynamically changing query workload so as to construct a representative set of queries, denoted, henceforth, by repset, to make dynamic caching decisions with.

Our model for changing workloads is based on a representative set of the past N distinct queries with attached weights which are related to their recency of occurrence. The cache manager (incrementally) maintains the consolidated DAG of these queries. We explain this model in more detail in Section 4.

- Given the dynamic characteristics of the workload, dynamically adapting the contents of the cache to suit the needs of the workload.
The decisions concerning what to cache are based on the computation of the benefits accruing from caching a particular set of materialized views (specifically, final query results as well as intermediate results). The cache manager adapts the cache contents to both long term variations in the workload and short term variations in the workload.

One of the goals of using a multi-query optimizer is to reuse a set of intermediate results (across queries) so as to reduce the overall response time for a set of queries. If these intermediate results are cached, this is precisely what is needed for the caching problem also, at a certain point in time. Hence we adapt a multi-query optimizer developed earlier \cite{RSSB00} to decide what should be cached.

- Optimizing the execution of a set of queries in a cache-cognizant fashion.

A by-product of the multi-query optimizer is an optimal plan for a set of queries given a set of materialized views. This proves useful for cache-cognizant optimization as well.

In the next section we discuss the AND–OR DAG representation of queries and then show how this representation aids in solving the above subproblems.

3 DAG Representation of Queries

An AND–OR DAG is a directed acyclic graph whose nodes can be divided into AND-nodes and OR-nodes; the AND-nodes have only OR-nodes as children and OR-nodes have only AND-nodes as children.

An AND-node in the AND-OR DAG corresponds to an algebraic operation, such as the join operation $(\bowtie)$ or a select operation $(\sigma)$. It represents the expression defined by the operation and its inputs. Hereafter, we refer to the AND-nodes as operation nodes. An OR-node in the AND-OR DAG represents a set of logical expressions that generate the same result set; the set of such expressions is defined by the children AND nodes of the OR node, and their inputs. We shall refer to the OR-nodes as equivalence nodes henceforth.
3.1 Representing a Single Query

The given query tree is initially represented directly in the AND-OR DAG formulation. For example, the query tree of Figure 2(a) is initially represented in the AND-OR DAG formulation, as shown in Figure 2(b). Equivalence nodes (OR-nodes) are shown as boxes, while operation nodes (AND-nodes) are shown as circles.

The initial AND-OR DAG is then expanded by applying all possible transformations on every node of the initial query DAG representing the given set of queries. Suppose the only transformations possible are join associativity and commutativity. Then the plans \((A \bowtie (B \bowtie C))\) and \((A \bowtie C) \bowtie B\), as well as several plans equivalent to these modulo commutativity can be obtained by transformations on the initial AND-OR-DAG of Figure 2(b). These are represented in the DAG shown in Figure 2(c). We shall refer to the DAG after all transformations have been applied as the expanded DAG. Note that the expanded DAG has exactly one equivalence node for every subset of \(\{A, B, C\}\); the node represents all ways of computing the joins of the relations in that subset.

3.2 Representing Sets of Queries in a DAG

Given a repset, the representative set of queries used to make dynamic caching decisions (how repset is chosen is described later, in Section 3), we represent the queries in repset in a single consolidated DAG structure. Since repset evolves with time, we need to insert and delete queries from the DAG. Since parts of the DAG may be shared by multiple queries, deletion of intermediate nodes of the DAG is done by a reference counting mechanism.

Queries are inserted into the DAG structure one at a time. When a query is inserted, equivalence nodes and operation nodes are created for each of the operations in its initial query tree. Some of the subexpressions of the initial query tree may be equivalent to expressions already in the DAG. Further, subexpressions of a query may be equivalent to each other, even if syntactically different. For example, suppose a query contains a subexpression that is logically equivalent to, but syntactically different from another subexpression (e.g., \((A \bowtie B) \bowtie C\), and \(A \bowtie (B \bowtie C)\)). Before the second subexpression is expanded, the DAG would contain two different equivalence nodes representing the two subexpressions. We modify the Volcano DAG generation algorithm so that whenever it finds nodes to be equivalent (in the above example, after applying join associativity) it unifies the nodes, replacing them by a single equivalence node. The Volcano optimizer [GM91] already has a hashing-based scheme to efficiently detect repeated expressions, thereby avoiding creation of new nodes that are equivalent to existing nodes. Our extension additionally unifies existing equivalent nodes.

Another extension is to detect and handle subsumption derivations. For example, suppose two subexpressions \(e_1: \sigma_{A<5}(E)\) and \(e_2: \sigma_{A<10}(E)\) appear in the query. The result of \(e_1\) can be obtained from the result of \(e_2\) by an additional selection, i.e., \(\sigma_{A<5}(E) \equiv \sigma_{A<5}(\sigma_{A<10}(E))\). To represent this possibility we add an extra operation node \(\sigma_{A<5}\) in the DAG, between \(e_1\) and \(e_2\). Similarly, given \(e_3: \sigma_{A=5}(E)\) and \(e_4: \sigma_{A=10}(E)\), we can introduce a new equivalence node \(e_5: \sigma_{A=5} \lor A=10(E)\) and add new derivations of \(e_3\) and \(e_4\) from \(e_5\). The new node
represents the sharing of accesses between the two selection. In general, given a number of selections on an expression \( E \), we create a single new node representing the disjunction of all the selection conditions. Similar derivations also help with aggregations. For example, if we have \( e6: \text{dno} \sum\text{(Sal)}(E) \) and \( e7: \text{age} \sum\text{(Sal)}(E) \), we can introduce a new equivalence node \( e8: \text{dno,age} \sum\text{(Sal)}(E) \) and add derivations of \( e6 \) and \( e7 \) from equivalence node \( e8 \) by further groupbys on \( \text{dno} \) and \( \text{age} \).

More details of unification and subsumption derivations, which we developed and used initially for multi-query optimization, can be found in \([RSB00]\).

### 3.3 Physical Properties

It is straightforward to refine the above AND-OR DAG representation to represent physical properties \([GM91]\), such as sort order, that do not form part of the logical data model, and obtain a physical AND-OR DAG \(^2\). We also model the presence of an index on a result as a physical property of the result. Physical properties of intermediate results are important, since e.g., if an intermediate result is sorted on a join attribute, the join cost can potentially be reduced by using a merge join. This also holds true of intermediate results that are materialized and shared. Our implementation of the AND-OR DAG model for caching purposes and our search algorithms indeed handle physical properties. However, for pedagogical reasons, we do not explicitly consider physical properties further.

### 4 Details of the Exchequer System

We first discuss how optimization of a query is carried out in a cache cognizant fashion. To select results for caching, we need to be able to predict the future, based on the past. We therefore describe a model based on representative sets of queries, which permits us to select final and intermediate results. We then describe a greedy algorithm for selecting results for caching, and consider optimizations of the algorithm.

#### 4.1 Cache-Aware Query Optimization

We now consider how to perform cache-aware optimization. We first describe the basic Volcano optimization algorithm, and then extend it to handle cached results.

The Volcano optimization algorithm finds the best plan for each node of the expanded DAG by performing a depth first traversal of the DAG. Costs are defined for operation and equivalence nodes. The cost of an operation node is \( o \) is defined as follows:

\[
\text{cost}(o) = \text{cost of executing } (o) + \sum_{e_i \in \text{children}(o)} \text{cost}(e_i)
\]

The children of \( o \) (if any) are equivalence nodes. The cost of an equivalence node \( e \) is given as

\[
\text{cost}(e) = \min\{\text{cost}(o_i) | o_i \in \text{children}(e)\}
\]

and is 0 if the node has no children (i.e., it represents a relation). Note that the cost of executing an operation \( o \) also takes into account the cost of reading the inputs, if they are not pipelined.

\(^2\)For example, an equivalence node is refined to multiple physical equivalence nodes, one per required physical property, in the physical AND-OR DAG.
Volcano also caches the best plan it finds for each equivalence node, in case the node is re-visited during the depth first search of the DAG.

A simple extension of the Volcano algorithm to find best plans given a set of materialized views (in our context, cached results) is described in [RSSB 00]. We outline this extension below.

The first step is to identify those equivalence nodes in the query DAG which correspond to cached results. This is carried out by treating the cached results as a set of queries, and creating a DAG structure for the cached results. The query to be optimized is inserted into this DAG structure as discussed earlier in Section 3.2. Also, as part of this step, subsumption derivations are introduced as required. Thus, given a view \( v : \sigma_{A>5}(r) \) and a node (query) \( n : \sigma_{A>10}(r) \), a selection operation is inserted to represent the alternative of computing node \( n \) from view \( v \).

Let \( \text{reusecost}(m) \) denote the cost of reusing the materialized result of \( m \), and let \( M \) denote the set of materialized nodes.

To find the cost of a node given a set of nodes \( M \) have been materialized, we simply use the Volcano cost formulae above for the query, with the following change. When computing the cost of an operation node \( o \), if an input equivalence node \( e \) is materialized (i.e., in \( M \)), the minimum of \( \text{reusecost}(e) \) and \( \text{cost}(e) \) is used for \( \text{cost}(o) \). Thus, we use the following expression instead:

\[
\text{cost}(o) = \text{cost of executing (o)} + \sum_{e_i \in \text{children}(o)} C(e_i)
\]

where \( C(e_i) = \text{cost}(e_i) \) if \( e_i \notin M \)

\[
= \min(\text{cost}(e_i), \text{reusecost}(e_i)) \text{ if } e_i \in M.
\]

Thus, the extended optimizer computes best plans for the query in the presence of cached results. The extra optimization overhead is quite small.

4.2 Representative Set of Queries

To characterize the dynamic workload, the cache manager keeps a window of the most recent \( N \) distinct queries as representative of the workload at instant \( t \), and (incrementally) maintains the consolidated query DAG of these queries. \( N \) is a parameter of the algorithm. This set of \( N \) queries is termed the representative set and the consolidated query DAG is termed the representative query DAG (for the workload) at the instant \( t \).

A query may occur more than once in the representative set. Each query in the representative set is weighted by its age – we use a weight of \( \delta^i \) for an occurrence of the query \( i \) queries behind the current occurrence, where \( \delta \in (0, 1] \) is a decay parameter. The overall weight of a query, denoted by \( \text{weight}(q) \), is then the sum of the weights of all its occurrences in the repset.

We shall equate (for description purposes) a final/intermediate result with the equivalence node in the DAG that represents that result. Also, for brevity, we shall use the term \( \text{node} \) in the rest of the paper to mean an equivalence node, unless otherwise indicated.

4.3 Incremental Greedy Algorithm

We now consider how to decide what results to keep in the cache. When a query arrives, it is optimized using the current cache contents, as described in Section 4.1.
Procedure Greedy

**Input:** Expanded DAG for \( R \), the representative set of queries, and the set of candidate equivalence nodes for caching

**Output:** Set of nodes to be cached

\( X = \emptyset \)

\( Y = \) set of candidates equivalence nodes for caching

while \( (Y \neq \emptyset) \)

L1: Among nodes \( y \in Y \) such that \( \text{size}(\{y\} \cup X) < \text{CacheSize} \)

Pick the node \( x \) with the highest \( \text{benefit}(R, x, X) / \text{size}(x) \)

/* i.e., highest benefit per unit space */

if (\( \text{benefit}(R, x, X) < 0 \))

break; /* No further benefits to be had, stop */

\( Y = Y - x; \quad X = X \cup \{x\} \)

return \( X \)

Figure 3: The Greedy Algorithm

The Incremental algorithm then attempts to find out if any of the nodes of the chosen query plan are worth caching. These nodes are available for free, but their benefit must be compared with the benefit of other nodes. Specifically, the algorithm described below compares their benefits only with nodes that were selected (for caching) when previous queries in the representative set were considered.

To make the incremental decision, the representative set is updated with the new query, and the selection algorithm is applied with the candidate nodes being

1. nodes selected when the previous query was considered, and
2. all nodes of the chosen query plan.

Suppose a set of nodes \( S \) has been selected to be cached. Given a query \( q \), let \( \text{cost}(q, S) \) denote the cost of computing \( q \) given that \( S \) is in the cache. Let \( \text{cost}(R, S) \) be defined as

\[
\text{cost}(R, S) = \Sigma_{q \in R} (\text{cost}(q, S) * \text{weight}(q))
\]

i.e., the weighted sum of the costs of all queries in the representative set \( R \), given nodes in \( S \) are cached.

Given a set of nodes \( S \) already chosen to be cached, and a node \( x \), let \( \text{benefit}(R, x, S) \) be defined as

\[
\text{benefit}(R, x, S) = \text{cost}(R, S) - (\text{cost}(R, \{x\} \cup S) + \text{cost}(x, S))
\]

i.e., given nodes in \( S \) are already cached, the above formula measures the additional benefit of caching node \( x \). (In some cases, if \( x \) is known to have been computed already, we will assume \( \text{cost}(x, S) \) to be 0; we return to this issue in later sections.)

Figure 3 outlines a greedy algorithm for static caching, which iteratively picks nodes to be cached. Nodes are selected for caching in order of maximum-benefit-first. It takes as input the
set of candidate results (equivalence nodes) for caching. At each iteration, among nodes that will fit in the remaining cache space, the node $x$ that gives the maximum benefit per unit space, if it is cached, is chosen to be added to $X$. The algorithm terminates when benefit becomes zero/negative, or the cache size is exceeded, whichever is earlier.

The output of greedy is a set of nodes that are marked for caching and the best plan for the current query. When the query is executed, any nodes in its best plan that are marked are added to the cache, replacing unmarked nodes that are in the cache.

At the end of the incremental greedy selection algorithm, the set of nodes selected must fit in cache, but the set may be much smaller than the cache size.

Unmarked nodes already in the cache are chosen for replacement on the basis of LCS/LRU, i.e. the largest results are preferentially evicted, and amongst all results of the same size, the least recently used one is evicted. This policy has been shown to be good by ADMS [CR94].

A variant of the above procedure is to admit even unmarked nodes in the best plan of the current query in the cache. We LCS/LRU replacement as before for these unmarked nodes. Our performance experiments study the effect of such admission, and show that it does not provide very large benefits and may be harmful on the workloads we studied.

We note that results are cached without any projections, to maximize the number of queries that can benefit from a cached result. Extensions to avoid caching very large attributes are possible.

Note that because a query is optimized before fresh caching decisions are made (see Section 4.1) the chosen best plan for each query is optimal for that query, given the current cache contents. Plans that increase the cost of a query are not chosen, even if it generates a node that is beneficial to multiple queries.

4.4 Optimizations of Greedy Algorithm

The greedy algorithm as described above can be expensive due to the potentially large number of nodes in the set $Y$, and the large number of times the function benefit is called, (which in turn calls the expensive function cost()). Three important optimizations to a greedy algorithm for multi-query optimization, presented in [RSSB00], can be adapted for the purpose of selecting the cachable nodes efficiently:

1. Consider for caching only nodes that are shared in some plan for the query, i.e., nodes that appear as subexpression of two queries, or appear more than once in some plan for a single query. (The variable $Y$ in Figure 3 is set to the set of such nodes.) We call such nodes sharable nodes, and for multiquery optimization, these are the only nodes worth considering for materialization.

Additionally, we may consider nodes for caching even if they are not shared, if they are available for free. For instance, a final/intermediate result of a query can be considered for caching, since it is available for free, even if it is not shared with any other query. Since some queries may get repeated, it is worth caching final/intermediate results of
such queries. That is, if a query is repeated in the repset, every equivalence node that can form part of a plan for the query is a candidate (considering only the root of the query is an alternative, which corresponds, for example, to [SSV96]).

2. Since there are many calls to \textit{benefit} (and thereby to \textit{cost()}) at line L1 of Figure 3, with different parameters, a simple option is to process each call to \textit{cost} independent of other calls. However, observe that the set of cached nodes, which is the second argument of \textit{cost}, changes minimally in successive calls — successive calls take parameters of the form \textit{cost}(R, \{x\} \cup X), where only \(x\) varies. That is, instead of considering \(x_1 \cup X\) for storing in the cache, we are now considering storing \(x_2 \cup X\) for storing in the cache. The best plans computed earlier does not change for nodes that are not ancestors of either \(x_1\) or \(x_2\). It makes sense for a call to leverage the work done by a previous call by recomputing best plans only for ancestors of \(x_1\) and \(x_2\).

Our incremental cost update algorithm maintains the state of the DAG (which includes previously computed best plans for the equivalence nodes) across calls to \textit{cost}, and may even avoid visiting many of the ancestors of \(x_1\) and \(x_2\).

3. With the greedy algorithm as presented above, in each iteration the benefit of every candidate node that is not yet cached is recomputed since it may have changed. If we can assume that the benefit of a node cannot increase as other nodes are chosen to be cached (while this is not always true, it is often true in practise) there is no need to recompute the benefit of a node \(x\) if the new benefit of some node \(y\) is higher than the previously computed benefit of \(x\). It is clearly preferable to cache \(y\) at this stage, rather than \(x\) — under the above assumption, the benefit of \(x\) could not have increased since it was last computed.

4.5 Discussion

In addition to the above incremental algorithm, we considered a cache management strategy that periodically runs the greedy algorithm with all nodes in the expanded DAG of all queries in the representative set. However, we found the performance of this algorithm to depend heavily on the correlation between its period and the periodicity of queries, leading in many cases to poor gains at a high cost. We then abandoned this strategy. In contrast, the \textit{Incremental} algorithm has a period of 1, but considers a smaller set of nodes for caching.

5 Related Work

The closest work related to Exchequer include ADMS [CR94], Dynamat [KR99] and Watchman [SSV96]. A very recent extension to Watchman [SSV99] allows results to be used by other queries, but (a) restricts the class of queries to select-project-join-aggregate queries, and (b) caches only selection-free select-project-join-aggregate queries, i.e., cube queries.
In contrast to ADMS, Dynamat and Watchman, our techniques are applicable to any class of queries, including cube queries. While cube queries are important, general purpose decision support systems must support more general queries as well. Moreover our techniques are extensible in that new operators can be added easily, due to the use of the AND-OR DAG framework.

Query caching systems proposed earlier [DFJ+96, SSV96, CR94, DRSN98, KR99, SSV99], maintain statistics for each cached result, which is used to compute a replacement metric for the same; the replacement metric is variously taken as the cached results last use, its frequency of use in a given window, its rate of use, etc. Of the above systems, [SSV99] and [KR99] use more sophisticated techniques, specifically computing benefits of cached results taking other cache contents into account. However, their techniques are restricted to the case where each result can be derived directly from exactly one parent (and indirectly from any ancestor). Our techniques do not have this restriction.

Moreover, our techniques can find benefits even if the results are not currently in the cache, and decide to materialize them if they give an overall benefit, which the other caching techniques are unable to achieve.

6 Experimental Evaluation of the Algorithms

In this section we describe our experimental setup and the results obtained.

6.1 System Model

Our algorithms were implemented on top of the multi-query optimization code [RSSB00] that we have integrated into our Volcano-based query optimizer. The basic optimizer took approx. 17,000 lines of C++ code, with MQO and caching code taking about 3,000 lines.

The block size was taken as 4KB and our cost functions assume 6MB is available to each operator during execution (we also conducted experiments with memory sizes up to 128 MB, with similar results). Standard techniques were used for estimating costs, using statistics about relations. The cost estimates contain an I/O component and a CPU component, with seek time as 10 msec, transfer time of 2 msec/block for read and 4 msec/block for write, and CPU cost of 0.2 msec/block of data processed. We assume that intermediate results are pipelined to the next input, using an iterator model as in Volcano; they are saved to disk only if the result is to be materialized for sharing. The materialization cost is the cost of writing out the result sequentially.

All our cost numbers are estimates from the optimizer. We validated our estimates for a few of the queries against actual execution times on Microsoft SQL-Server 7.0 (SQL queries with hints on execution plan) and found a good match (within 20 percent).

The tests were performed on a Sun workstation with UltraSparc 10 333Mhz processor, 256MB, and a 9GB EIDE disk, running Solaris 5.7.
6.2 Test Query Sequences

We test our algorithms with streams of 1000 randomly generated queries on a TPCD-based star schema similar to the one proposed by [SSV99]. The schema has a central *Orders* fact table, and four dimension tables *Part*, *Supplier*, *Customer* and *Time*. The size of each of these tables is the same as that of the TPCD-1 database. This corresponds to base data size of approximately 1 GB. Each generated query was of the form:

```sql
SELECT SUM(QUANTITY)
FROM ORDERS, SUPPLIER, PART, CUSTOMER, TIME
WHERE join-list AND select-list
GROUP BY groupby-list;
```

The `join-list` enforces equality between attributes of the order fact table and primary keys of the dimension tables. The `select-list` i.e., the predicates for the selects were generated by selecting 0 to 3 attributes at random from the join result, and creating equality or inequality predicates on the attributes. The `groupby-list` was generated by picking a subset of `{suppkey, partkey, custkey, month, year}` at random. A query is defined uniquely by the pair `(select-list, groupby-list)`. Even though our algorithms can handle a more general class of queries, the above class of cube queries was chosen so that we can have a fair comparison with DynaMat [KR99] and Watchman [SSV96].

There are two independent criteria based on which the pair `(select-list, groupby-list)` was generated:

- Whether the queries are:
  - *CubePoints*: that is, predicates are restricted to equalities, or
  - *CubeSlices*: that is, predicates are a random mix of equalities and inequalities.

- The distribution from which the attributes and values are picked up in order to form the `groupby-list` and the predicates in the `select-list`.
  - *Uniform Workload*: Uses uniform distribution. All `groupby` combinations and selections are equally likely to occur.
  - *Skewed Workload*: Uses Zipfian distribution with parameter of 0.5. The `groupby` distribution additionally rotates after every interval of 32 queries, i.e. the most frequent subset of `groupbys` becomes the least frequent, and all the rest shift up one position. Thus, within each block of 32 queries, some `groupby` combinations and selection constants are more likely to occur than others.

Based on the four combinations that result from the above criteria, the following four workloads are considered in the experiments: uniform workload of *CubeSlices* (termed *CubeSlices/Uniform*), skewed workload of *CubeSlices* (termed *CubeSlices/Zipf*), uniform workload of *CubePoints* (termed *CubePoints/Uniform*), and skewed workload of *CubePoints* (termed *CubePoints/Zipf*).
Due to lack of space, we present the results only on CubePoints/Uniform and CubePoints/Zipf. We did run all our experiments on CubeSlices/Uniform and CubeSlices/Zipf, and found their performance is similar to the corresponding CubePoint queries.

6.3 Metric

The metric used to compare the goodness of caching algorithms is the total response time of a set of queries. We report the total response time for a sequence of 900 queries that enter the system after a sequence of 100 queries warm up the cache. This total response time is as estimated by the optimizer and hence denoted as estimated cost in the graphs of Section 6.5.1. The estimations are validated by the results of experiments reported in Section 6.5.3.

6.4 List of algorithms compared

We compare Incremental with the following baselines, prior approaches, and variants.

We consider the following baseline approaches.

- **NoCache**: Queries are run assuming that there is no cache. This gives an upper bound on the performance of any well-behaved caching algorithm.

- **InfCache**: The purpose of this simulation is to give a lower bound on the performance of any caching algorithm. We assume an infinite cache and do not include the materialization cost. Each new result is computed and cached the first time it occurs, and reused whenever it occurs later.

Experiments are conducted on these two extremes to evaluate the absolute benefits and competitiveness of the algorithms considered.

We evaluate the Incremental algorithm against the following prior approaches.

- **LCS/LRU**: We experiment with the caching policy found to be the best in ADMS [CR94], namely replacing the result occupying largest cache space (LCS), picking the least recently used (LRU) result in case of a tie. The incoming query is optimized taking the cache contents into account. The final as well as intermediate results in the best plan are considered for admission into the cache based on LCS. It should be pointed out that LCS/LRU is not aware of the workload since each result is assumed independent when caching decisions are made.

- **DynaMat**: We simulate DynaMat [KR99] by considering only the top-level query results (in order to be fair to DynaMat, our benchmark queries have either no selection or only single value selections). The original DynaMat performs matching of cube slices using R-trees on the dimension space. In our implementation, query matching is performed semantically, using our unification algorithm, rather than syntactically. We use our algorithms to optimize the query taking into account the current cache contents; this covers the subsumption dependency relationships explicitly maintained in [KR99]. The replacement metric is computed as
(number-of-accesses * cost-of-computation)/(query-result-size)
where the number of accesses are from the entire history (observed so far).

- **WatchMan:** Watchman [SSV96] also considers caching only the top level query results. The original Watchman does syntactic matching of queries, with semantic matching left for future work. We improve on that by considering semantic matching. Our Watchman implementation is similar to the Dynamat implementation described above. The difference is in the replacement metric: instead of using the number of accesses as in the Dynamat implementation, we use the rate of use on a window of last ten accesses for each query. The replacement metric for Watchman is thus

\[(\text{rate-of-use} \times \text{cost-of-computation})/(\text{query-result-size})\]

where the cost of computation is with respect to the current cache contents. The original algorithms did not consider subsumption dependencies between the queries; our implementation considers aggregation subsumption among the cube queries considered.

Given the enhancements mentioned above, the performance of our implementations of DynaMat and Watchman will be better than the originally proposed versions. Still, as we will see, the Exchequer algorithms significantly outperform them.

We consider the following variants of the **Incremental** algorithm.

- **Incremental/FinalQuery:** In this variant of **Incremental**, the caching of intermediate results is turned off; that is, only the final query result is admitted for each query in the workload. If the cache is full, a previous unmarked query result is picked for replacement using LCS/LRU.

- **Incremental/NoFullCache:** In this variant of **Incremental**, only marked nodes that have been selected from the candidate set are admitted into the cache. If the cache is full, a previous unmarked cached result is picked for replacement using LCS/LRU.

- **Incremental/FullCache:** In this variant of **Incremental**, apart from the marked nodes selected from the candidate set, the unmarked nodes of the query are also considered for admission into the cache. The marked nodes always get admitted. If the cache is full, a previous unmarked result is picked for replacement using LCS/LRU. Unmarked nodes are admitted based on LCS/LRU in the space beyond that used by marked nodes. The idea is to keep the cache full as much as possible at all times.

The variant that only stores the full query results, but fills up the cache based on LCS/LRU is not considered. This is because the size of marked results at any point is expected to be small for our workloads, and therefore the performance of this variant is expected to be identical to the LCS/LRU algorithm described above.

As a part of the experimental study below, we evaluate these variants against each other as well as against the prior approaches.
6.5 Experimental Results

The size of the representative set is set to 10 for the experiments. We experiment with different cache sizes, corresponding to roughly 0%, 5%, 16%, 32% and 50% of the total database size of approximately 1GB.

6.5.1 Experiment 1: Comparison of Estimated Response Times

In our first experiment, we compare the performance of Incremental/FinalQuery, Incremental/NoFullCache and Incremental/FullCache against each other and against LCS/LRU, WatchMan and Dynamat. NoCache and InfCache are also included as baselines in order to compare with the worst and best case performance bounds respectively. The experiments were carried out on the workloads described in Section 6.2. Figure 4 and Figure 5 show the results of this experiment for CubePoints/Uniform and CubePoints/Zipf respectively.

Incremental/FullCache and Incremental/NoFullCache perform the best among the algorithms considered, followed by DynaMat, WatchMan, Incremental/FinalQuery and finally LCS/LRU, which performed the worst of all.

In all of the considered workloads, Incremental/FullCache and Incremental/NoFullCache were both much better than the competition for small cache sizes. As the cache size was increased from 0 to 5% of the database size, these algorithms displayed major performance benefits, almost reaching the performance of WatchMan with much higher cache sizes. The better performance of these algorithms can be attributed to their ability to identify intermediate results that benefit the workload as a whole. This is crucial at low cache sizes, where maintaining intermediate results that benefit most of the queries in the workload turns out to be a better idea than maintaining a set of overall query results that can benefit fewer number of queries in
the workload due to recurrence or subsumption.

DynaMat, WatchMan and Incremental/FinalQuery made good improvements as the cache is enlarged. However, the performance of Incremental/FinalQuery does not improve further; marked and cached results get unmarked after some time and then replacement becomes LCS/LRU, which is not very effective. For low cache sizes, the rate of improvement for DynaMat was much higher than the other two. This can be attributed to DynaMat having a superior replacement policy which takes the dependency among the cached results into account. However, the rate of improvement for DynaMat decreased for larger cache sizes, and the relative improvement over WatchMan diminished. This is because there is a lower bound on the response times delivered by algorithms that cache only the top level results: in case a query cannot be computed from the result of a previous query, the algorithm pays the full cost for computing the query (cost of computing from the base relations).

In Figure 5, observe that as the cache size is enlarged beyond 32%, the estimated cost for Incremental/FullCache increases. This anomaly can be explained as follows: after a given cache size (that depends on the workload), the investment made by the system (in terms of the materialization cost) in caching the extra results that can be accommodated given the increased cache size does not pay off in terms of benefits of maintaining these results in the cache. This behavior for large cache sizes is also displayed by DynaMat on CubeSlices/Zipf.

Thus, at high cache sizes, the admissibility decisions must be made on cost-benefit criteria rather than just space availability. Incremental/NoFullCache scores over Incremental/FullCache in this respect. Incremental/NoFullCache admits a result into the cache only if it has a benefit, irrespective of whether there is enough space in the cache; in contrast, Incremental/FullCache admits a result if there is enough space in the cache irrespective of its benefit. Thus, as ex-
pected, Incremental/NoFullCache makes more judicious choice for high cache sizes. In fact, even for small cache sizes, the exclusive cost-benefit criterion can make an appreciable difference, as is apparent in Figure 4, where Incremental/NoFullCache performs better than Incremental/FullCache even for small cache size.

To summarize, these results clearly show the need to cache intermediate results in addition to the final results of queries. Also, even though keeping the cache as full as possible at all points seems to be a good idea, it is potentially counterproductive. Overall, they attest to the effectiveness of the techniques utilized by the Exchequer approach.

6.5.2 Experiment 2: Space and Time Overheads

The Incremental algorithm is heavily dependent on a multi-query optimization framework developed in [RSSB00]. This raises issues about the algorithm's overheads and efficacy in an online environment. In this section, we address these issues by showing that the Incremental algorithm has small space and time overheads.

As an estimate of the memory overhead the Incremental algorithm, we determined the space taken by the AND/OR DAG during the execution of the Incremental algorithm. For the run of Incremental/NoCache on the CubeSlices/Uniform workload, the DAG took approximately 18M of memory, and was independent of the cache size.

In terms of the execution time, the optimization of the 1000 queries comprising the workload took about 20 minutes at cache size of 5% and about 48 minutes at cache size of 50%. The optimization time depends on the cache size since the greedy algorithm chooses nodes only till their size does not exceed the cache size. Volcano took about 4 minutes to optimize these 1000 queries. This difference in optimization time is negligible to the total running cost of the 1000 queries which is of the order of tens of hours as shown by our cost estimates, as well as by extrapolation from actual runtimes of 100 queries on MS SQL Server 7.

6.5.3 Experiment 3: Validation of the Estimated Response Times

In this experiment, we study actual run-times of a sequence of 100 Cubepoint/Uniform queries on Microsoft SQL-Server, with caching decisions made externally.

The workload was analyzed offline using (a) Incremental/NoFullCache, and (b) DynaMat (chosen because it is the closest competitor in Experiment 1). The algorithms were instrumented to emit SQL for dynamic materialization (in the form of temporary tables), indexing and usage of intermediate results selected for caching by the algorithm. The temporary tables were created on the tempdb database in order to prevent any logging overheads. The generated SQL script was then executed as a batch on SQL-Server 7.0 running on Windows NT 4.0 on a 233 MHz Pentium II machine with 128MB of memory. The database size was about 100MB, and the cache size was 4MB.

The following table shows the results of the experiment, as well as the estimate of the execution cost obtained by Incremental. These results attest to the efficacy of Incremental, and
also verify our cost model.

DynaMat performs badly in this experiment, since there were not many repetitions of the queries within the stream of 100 queries. Incremental is able to exploit the sharing of intermediate results.

| Algorithm                      | Time on SQL-Server 7.0 | Estimated Response Time |
|-------------------------------|------------------------|-------------------------|
| NoCache                       | 46 min                 | 53 min                  |
| DynaMat                       | 46 min                 | 51 min                  |
| Incremental/NoFullCache       | 32 min                 | 31 min                  |

7 Conclusions and Future Work

In this paper we have presented new techniques for query result caching, which can help speed up query processing in data warehouses. The novel features incorporated in our Exchequer system include optimization aware cache maintenance and the use of a cache aware optimizer. In contrast, in existing work, the module that makes cost-benefit decisions is part of the cache manager and works independent of the optimizer which essentially reconsiders these decisions while finding the best plan for a query. In our work, the optimizer takes the decisions for the cache manager. Whereas existing approaches are either restricted to cube (slice/point) queries, or cache just the query results, our work presents a data-model independent framework and algorithm. Our experimental results attest to the efficacy of our cache management techniques and show that over a wide range of parameters lower query response times (more than 30% reduction compared to the best performing competitor) can be achieved. Said differently, a much smaller cache size (around one tenth) is sufficient for Exchequer to achieve the same performance as its best competitor.

We have developed several extensions of our techniques, which we outline below, along with directions for future work. The first extension is, when we run short of cache space, instead of discarding a stored result in its entirety, we can discard only parts of the result. We can implement this by partitioning selection nodes into smaller selects and replacing the original select by a union of the other selects. Two issues in introducing these partitioned nodes are: (i) What partition should we choose? and (ii) If the top level is not a select, we can still choose an attribute to partition on, but which should this be? The second extension is, instead of discarding a cached result completely, we can replace it by a summarization. An important direction of future work is to take updates into account. We need to develop techniques for (a) taking update frequencies into account when deciding whether to cache a particular result, and (b) decide when and whether to discard or refresh cached results. We could refresh cached results eagerly as updates happen, or update them lazily, when they are accessed.

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