Tradeoffs in Processing Complex Join Queries via Hashing in Multiprocessor Database Machines

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ABSTRACT — In this paper we examine the problem of processing multi-way join queries (on the order of 10 joins) through hash-based join methods in a shared-nothing database machine. We first discuss how the choice of a format for a complex query can significantly affect performance in a multiprocessor database machine. Several query processing algorithms are then proposed and experimental results obtained from a simulation study are presented to demonstrate the tradeoffs of left-deep and right-deep scheduling strategies for complex join query evaluation. These results demonstrate that right-deep scheduling strategies can provide significant performance advantages in large multiprocessor database machines under many circumstances, even when memory is limited.

1. Introduction

Several important trends have occurred in the last ten years which have combined to change the traditional view of database technology. First, microprocessors have become much faster while simultaneously becoming much cheaper. Next, memory capacities have risen while the cost of memory has declined. Finally, high-speed communication networks have enabled the efficient interconnection of multiple processors. All these technological changes have combined to make feasible the construction of high performance multiprocessor database machines.

Of course, as with any new technology, there are many open questions regarding the best ways to exploit the capabilities of these multiprocessor database machines in order to achieve the highest possible performance. Because the join operator is critical to the operation of any relational DBMS, a number of papers have addressed parallel implementations of the join operation including [BARU87, BRAT87, DEWI85, DEWI88, KITS88, LU85, SCHN89a]. However, these papers have not addressed the processing of queries with more than one or two joins. Also, the performance impact of alternative formats for representing multi-way join queries has received little attention in the context of this new environment. The related work that has been done is discussed in Section 2.

In this paper we examine the tradeoffs imposed by left-deep, right-deep and bushy query trees in a multiprocessor environment when queries contain on the order of ten joins. We focus on hash-based join methods because their performance has been demonstrated bo be superior in systems with large memories [BRAT87, DEWI84, SCHN89a, SHAP86], although we include a brief discussion of the sort-merge join algorithm. The tradeoffs we consider include the potential for exploiting intra-query parallelism (and its corresponding effect on performance), resource consumption (primarily memory), support for dataflow processing, and the cost of optimization. The examination of these tradeoffs demonstrated the feasibility of the right-deep representation strategy and resulted in several new algorithms for processing query trees in this format. As well as providing superior opportunities for exploiting parallelism within a query tree, a right-deep representation strategy can also reduce the importance of correctly estimating join selectivities. This analysis of the tradeoffs of the alternative query tree representation strategies and a description of several new algorithms for processing right-deep query trees is presented in Section 3.

Because left-deep and right-deep representation strategies present the extreme cases among the alternative query representation strategies, we were interested in quantitatively examining the performance tradeoffs between these two strategies. To perform this analysis, we constructed a multiprocessor database machine simulator and implemented scheduling algorithms for both of these tree formats. The description of the simulation model, its validation, and the experimental results obtained are contained in Section 4. Results from this experimental analysis confirm the more qualitative results which indicate that right-deep trees can indeed provide substantial performance improvements under many different experimental conditions but that this strategy is not optimal under all circumstances. Our conclusions and plans for future work are presented in Section 5.

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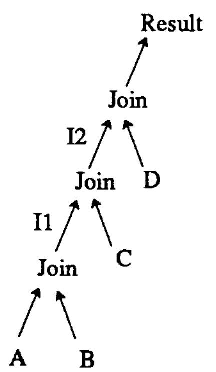
Degrees of Parallelism

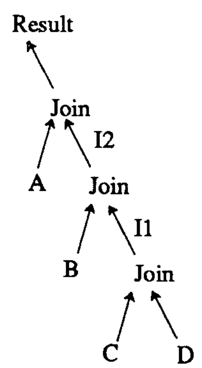
There are three possible ways of utilizing parallelism in a multiprocessor database machine. First, parallelism can be applied to each operator within a query. For example, ten processors can work in parallel to compute a single join or select operation. This form of parallelism is termed **intra-operator** parallelism and has been studied extensively by previous researchers. Second, **inter-operator** parallelism can be employed to execute several operators within the same query concurrently. Finally, **inter-query** parallelism refers to executing several queries simultaneously. In this paper, we specifically address only those issues involved with exploiting inter-operator parallelism for queries composed of many joins. We defer issues of inter-query parallelism to future work.

Query Tree Representations

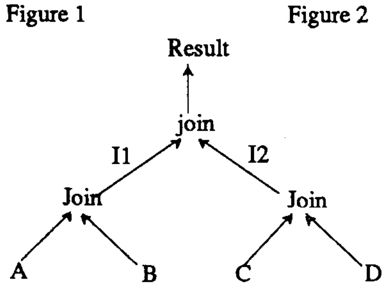
Instrumental to understanding how to process complex queries is understanding how query plans are generated. A query is compiled into a tree of operators and several different formats exist for structuring this tree of operators. As will be shown, the different formats offer different tradeoffs, both during query optimization and query execution.



(((A * B) * C) * D)
Left-Deep Query Tree
Figure 1



(A * (B * (C * D)))
Right-Deep Query Tree
Figure 2



((A * B) * (C * D))

Bushy Query Tree
Figure 3

The different formats that exist for query tree construction range from simple to complex. A ''simple'' query tree format is one in which the format of the tree is restricted in some manner. There are several reasons for wanting to restrict the design of a query tree. For example, during optimization, the space of alternative query plans is searched in order to find the "optimal" query plan. If the format of a query plan is restricted in some manner, this search space will be reduced and optimization will be less expensive. Of course, there is the danger that a restricted query plan will not be capable of representing the optimal query plan.

Query tree formats also offer tradeoffs at runtime. For instance, some tree formats facilitate the use of dataflow scheduling techniques. This improves performance by simplifying scheduling and eliminating the need to store temporary results. Also, different formats dictate different maximum memory requirements. This is important because the performance of hash-based join algorithms depends heavily on the amount of available memory [DEWI84, SCHN89a, SHAP86]. Finally, the format of the query plan is one determinant of the amount of parallelism that can be applied to the query.

Left-deep trees and right-deep trees represent the two extreme options of restricted format query trees. Bushy trees, on the other hand, have no restrictions placed on their construction. Since they comprise the design space between left-deep and right-deep query trees, they have some of the benefits and drawbacks of both strategies. They do have their own problems, though. For instance, it is likely to be harder to synchronize the activity of join operators within an arbitrarily complex bushy tree. We will examine the tradeoffs associated with each of these query tree formats more closely in the following sections. Refer to Figures 1, 2 and 3 for examples of left-deep, right-deep, and bushy query trees, respectively, for the query A join B join C join D. (Note that the character * is used to denote the relational join operator.)

2. Survey of Related Work

[GERB86] describes many of the issues involved in processing hash-based join operations in multiprocessor database machines. Both inter-operator and intra-operator concurrency issues are discussed. In the discussion of inter-operator parallelism, the tradeoffs of left-deep, right-deep and bushy query tree representations with regard to parallelism, pipelined data flow, and resource utilization (primarily memory) are addressed. However, while [GERB86] discusses the basic issues involved in processing complex queries in a multiprocessor environment, it does not explore the tradeoffs between the alternative query tree representation strategies in great depth. [GRAE90] also supports the three alternative query tree formats in the shared-memory database machine Volcano, but the tradeoffs are not discussed in detail. [GRAE87] considers some of the tradeoffs between left-deep and bushy query trees in a single processor environment. Analytic cost functions for hash-join, index join, nested loops join, and sort-merge join are developed and used to compare the average plan execution costs for the different query tree formats.

[STON89] describes how the XPRS project plans on utilizing parallelism in a shared-memory database machine. Optimization during query compilation assumes the entire buffer pool is available, but in order to aid optimization at runtime, the query tree is divided into fragments. At runtime, the desired amount of parallelism for each fragment is weighed against the amount of available memory. If insufficient memory is available, three techniques are described that can be used to reduce memory requirements. First, a fragment can be decomposed into sequential fragments. This requires the spooling of data to temporary files. If further decomposition is not possible, the number of batches used for the Hybrid join algorithm [DEWI84] can be increased. Finally, the level of parallelism applied to the fragment can be reduced.

3. Tradeoffs of Alternative Query Tree Representations

In this section we discuss how each of the alternative query tree formats affects memory consumption, dataflow scheduling, and the ability to exploit parallelism in a multi-way join query. The discussion includes processing queries in the best case (unlimited resources) to more realistic situations where memory is limited.

A good way of comparing the tradeoffs between the alternative query tree representations is through the construction of **operator dependency graphs** for each representation strategy. In the dependency graph for a particular query tree, a subgraph of nodes enclosed by a dashed line represent operators that should be scheduled together for efficient pipelining. The directed lines within these subgraphs indicate the producer/consumer relationship between the operators. The bold directed arcs between subgraphs show which sets of operators must be executed before other sets of operators are executed, thereby determining the maximum level of parallelism and resource requirements (e.g. memory) for the query. Either not scheduling the set of operators enclosed in the subgraphs together or failing to schedule sets of operators according to the dependencies will result in having to spool tuples from the intermediate relations to disk.

The operator dependency graphs presented in this section are based on the use of a hash-join algorithm as the join method. In this paper, we consider two different hash-join methods, Simple hash-join and Hybrid hash-join [DEWI84]. It is assumed that the reader is familiar with these join methods although a brief description of them is included here. For this description, consider the join of relations R and S, where R is the smaller joining relation.

The Simple hash-join method is an optimistic algorithm that assumes that all the tuples from the **smaller**[1] joining relation R (termed the **Building** relation) can be staged into a main memory hash table. If this assumption fails, overflowing tuples from R are dynamically staged to a temporary file on disk. Once all the tuples from R have been processed, the tuples from the **larger** relation S (the **Probing** relation) are processed. As each tuple from S is read from disk, the tuple is either used to probe the hash table containing tuples from R or is written back to disk, if hash-table overflow occurred while building the hash table with R (see [SCHN89a] for more details). If hash-table overflow has occurred, the overflow partitions of R and S are recursively joined using this same procedure.

The Hybrid hash-join algorithm was developed in order to prevent the overflow processing discussed above while utilizing as much memory as is available. The key idea is to recognize a priori that the join will exceed the memory capacity and partition each joining relation into enough disjoint buckets such that each bucket will fit into the available memory. As an enhancement, a portion of the join result is computed while the two joining relations are being partitioned into buckets.

With hash-join algorithms, the computation of the join operation can be viewed as consisting of two phases. First, a hash table is constructed from tuples produced from the left input stream (relation R, in the above examples). In the second phase, tuples from the right input stream (relation S) are used to probe the hash table for matches in order to compute the join. Since the first operation must completely precede the second, the join operator can be viewed as consisting of two separate operators, a **build** operator and a **probe** operator. The dependency graphs model this two phase computation for hash-joins by representing $Join_i$ as consisting of the operators B_i and P_i. The base relations to be joined are represented in the operator dependency graphs as S_i, signifying the scan of relation i.

The reader should keep in mind that intra-operator parallelism issues are being ignored in this paper. That is, when we discuss executing two operators concurrently, we have assumed implicitly that **each** operator will be computed using multiple processors as described in [SCHN89a].

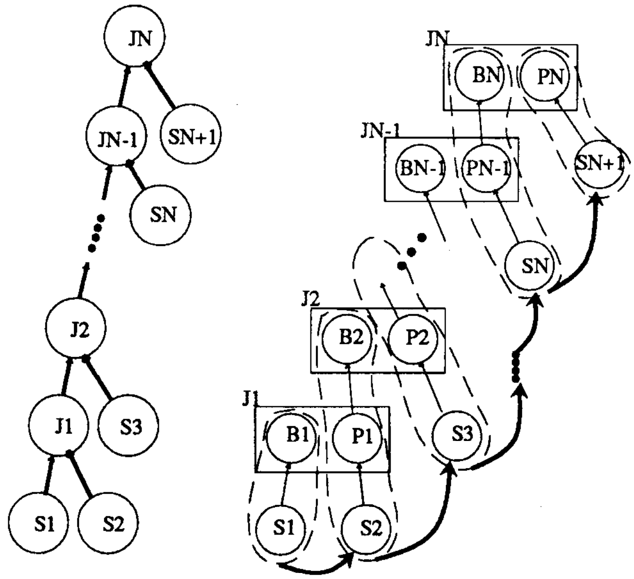
3.1. Left-Deep Query Trees

Figure 4 shows a generic N-join query represented as a left-deep query tree and its associated operator dependency graph. From the dependency graph it is obvious that no scan operators can be executed concurrently. It also follows that the dependencies force the following unique query execution plan:

1) Scan S1 - Build J1
2) Scan S2 - Probe J1 - Build J2
3) Scan S3 - Probe J2 - Build J3
•
•
N) Scan SN - Probe JN-1 - Build JN
N+1) Scan SN+1 - Probe JN

The above schedule demonstrates that at most one scan and two join operators can be active at any point in time. Consider Step N in the above schedule. Prior to the initiation of Scan SN, a hash table was constructed from the output of Join N-1. When

[1] The smaller relation is always used as the building or inner relation in a hash join algorithm in order to minimize the number of times the outer relation must be read from disk. Also by using the smaller relation as the inner or building relation, one maximizes the probability that the outer relation will only have to be read once.



Left-Deep Query Tree and Dependency Graph
Figure 4

the Scan SN is initiated, tuples produced from the scan will immediately probe this hash table to produce join output tuples for Join N. These output tuples will be immediately streamed into a hash table constructed for Join N. The hash table space for Join N-1 can only be reclaimed after all the tuples from scan SN have probed the hash table, computed Join N, and stored the join computation in a new hash table. Thus, the maximum memory requirements of the query at any point in its execution consist of the space needed for the hash tables of any two adjacent join operators.

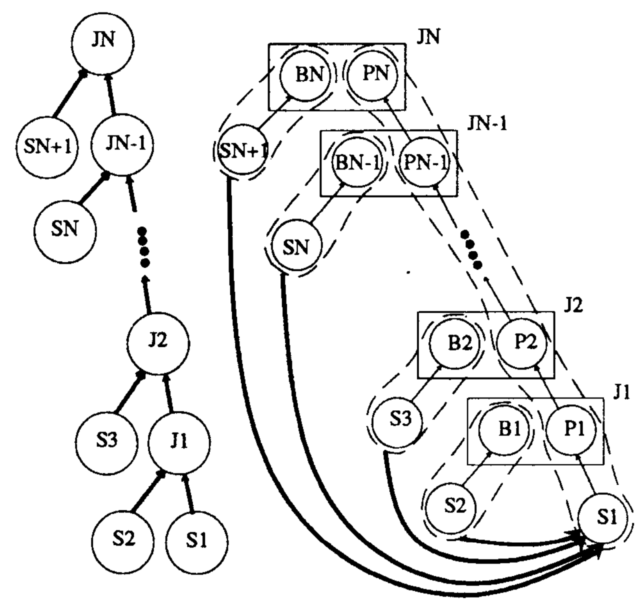
Limited Memory

Although left-deep query trees require that only the hash tables corresponding to two adjacent join operators be memory resident at any point during the execution of any complex query, the relations staged into the hash tables are the result of intermediate join computations, and hence it is likely to be difficult to predict their size. Furthermore, even if the size of the intermediate relations can be accurately predicted, in a multi-user environment it can not be expected that the optimizer will know the exact amount of memory that will be available when the query is executed. If memory is extremely scarce, sufficient memory may not exist to hold even one of these hash tables. Thus, even though only two join operators are active at any point in time, many issues must be addressed in order to achieve optimal performance.

[GRAE89] proposes a solution to this general problem by having the optimizer generate multiple query plans and then having the runtime system choose the plan most appropriate to the current system environment. A similar mechanism was proposed for Starburst [HAAS89]. One problem with this strategy is that the number of feasible plans may be quite large for the complex join queries we envision. Besides having to generate plans which incorporate the memory requirements of each individual join operator, an optimizer must recognize the consequences of intra-query parallelism. For example, if a join operator is optimized to use most of the memory in the system, the next higher join operator in the query tree will be starved for memory. If it is not possible to modify the query plan at runtime, performance will suffer.

A simpler strategy may be to have the runtime query scheduler adjust the number of buckets for the Hybrid join algorithm in order to react to changes in the amount of memory available. An enhancement to this strategy would be to keep statistics on the size of the intermediate join computations stored in the hash tables and use this information to adjust the number of buckets for join operators higher in the query tree.

3.2. Right-Deep Query Trees



Right-Deep Query Tree and Dependency Graph
Figure 5

Figure 5 shows a generic right-deep query tree for an N-join query and its associated dependency graph. From the dependency graph it can easily be determined which operators can be executed concurrently and the following execution plan can be devised to exploit the highest possible levels of concurrency:

1) Scan S2-Build J1, Scan S3-Build J2, ...,Scan Sn+1-Build Jn
2) Scan S1-Probe J1-Probe J2-...-Probe Jn

From this schedule it is obvious that all the scan operators but S1, and all the build operators can be processed in parallel. After this phase has been completed, the scan S1 is initiated and the resulting tuples will probe the first hash table. All output tuples will then percolate up the tree. As demonstrated, very high levels of parallelism are possible with this strategy (especially since every operator will also generally have intra-operator parallelism applied to it). However, the query will require enough memory to hold the hash tables of **all** N join operators throughout the duration of the query.

A question arises as to the performance implications of scheduling scans S2 through SN+1 concurrently. If these operators access relations which are declustered over the same set of storage sites, initiating all the scans concurrently may be detrimental because of the increased contention at each disk [GHAN89]. However, in a large database machine, it is **not** likely that relations will be declustered over all available storage sites. Further declustering eventually becomes detrimental to performance because the costs of controlling the execution of a query eventually outweigh the benefits of adding additional disk resources [GERB87, COPE88, DEWI88]. In Section 4 we present experimental results which illustrate the performance implications of the data declustering strategy.

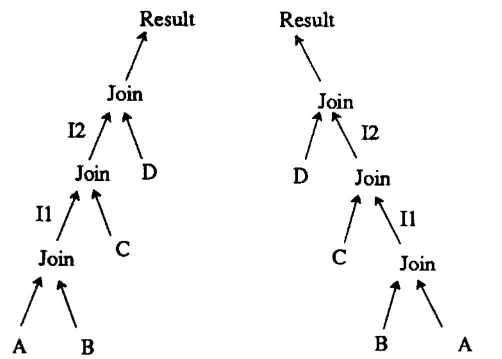
Limited Memory

Dealing with limited memory is expected to be a bigger problem with right-deep trees than with left-deep trees because more hash tables must be co-resident in memory. Also, there is little opportunity for runtime query modifications since once the scan on S1 is initiated the data flows through the query tree to completion. However, it is expected that more accurate estimates of memory requirements will be available for a right-deep query tree since the left children (the building relations) will always be base relations (or the result of applying selection predicates to a base relation), while with a left-deep tree the building input to each join is always the result of the preceding join operations.

Several alternative techniques exist for exploiting the potential performance advantages of right-deep query trees when memory is limited. One strategy (similar to that proposed in [STONE89]) involves having the optimizer or runtime scheduler *break* the query tree into disjoint pieces such that the sum of the hash tables for all the joins within each piece are expected to fit into memory. This splitting of the query tree will, of course, require that temporary results be spooled to disk. When the join has been computed up to the boundary between the two pieces, the hash table space currently in use can be reclaimed. The query can then continue execution, this time taking its right-child input from the temporary relation. This scheduling strategy is termed **static right-deep scheduling**.

A more dynamic strategy, called **dynamic bottom-up scheduling**, schedules the scans S2 to SN+1 (Figure 5) in a strict bottom-up manner. The scan S2 is first initiated and the resulting tuples are used to construct a hash table for the join operator J1. After this scan completes the memory manager is queried to check if enough memory exists to stage the tuples expected as a result of the scan S3. If sufficient space exists, scan S3 is initiated. This same procedure is followed for all scans in the query tree until memory is exhausted. If all the scans have been processed, all that remains is for the scan S1 to be initiated to start the process of probing the hash tables. However, in the case that only the scans through S_i can be processed in this first pass, the scan S1 is initiated but now the results of the join computation through join J_{i-1} are stored into a temporary file S1′. Further processing of the query tree proceeds in an identical manner only the first scan to be scheduled is S_{i+1}. Also, the scan to start the generation of the probing tuples is initiated from the temporary file S1′. Although this strategy sacrifices parallelism in scanning the "building" relations, it has some interesting properties when certain filtering techniques are applied [GERB90]. This tradeoff will be analyzed in future work.

Both of these strategies share a common feature of dealing with limited memory by "breaking" the query tree at one or more points. Breaking the query tree has a significant impact on performance because the benefits of data flow processing are lost when the results of the temporary join computation must be spooled to disk. Although, we have assumed that enough memory is available to hold at least each relation individually and, hopefully, several relations simultaneously, this may not always be the case. An alternative approach is to preprocess the input relations in order to reduce memory requirements. This is what the Hybrid join algorithm attempts to do. Below, we discuss the use of the Hybrid join algorithm for processing complex query trees represented as right-deep query trees. We refer to the resulting algorithm as **Right-Deep Hybrid Scheduling**.



Left-Deep Query Tree Right-Deep Query Tree

Figure 6

Consider the right-deep join query in Figure 6 and assume that each join will be broken into two buckets, with the first being staged immediately into memory. The first bucket of A (denoted A_{b1}) will join with the first bucket of B to compute the first half of A*B. Since this is a right-deep tree the first inclination would be to probe the hash table for C (actually C_{b1}) with all these output tuples. However, this cannot be done immediately because the join attribute may be different between C and B, in which case the output tuples corresponding to A*B (I1) must be rehashed before they can join with the first bucket of C. Since I1 must use the same hash function as C, I1 must be composed of two buckets (one of which will directly map to memory as a probing segment). Thus, the tuples corresponding to B_{b1}*A_{b1} will be rehashed to $I1_{b1}$ and $I1_{b2}$, with the tuples corresponding to the first bucket (about half the A*B tuples assuming uniformity) immediately probing the hash table built from C_{b1}. Again, the output tuples of this first portion of A*B*C will be written to the buckets $I2_{b1}$ and $I2_{b2}$. Output tuples will thus keep percolating up the tree, but their number will be reduced at each succeeding level based on the number of buckets used by the respective building relation. Query execution will then continue with the join B_{b2}*A_{b2}. After all the respective buckets for A*B have been joined, the remaining buckets for C*I1 will be joined. Processing of the entire query tree will proceed in this manner.

With Right-Deep Hybrid Scheduling (RDHS), some tuples will be delivered to the host as a result of joining the first buckets of the two relations at the lowest level of the query tree. This is not possible with an analogous left-deep or bushy query tree. If a user is submitting the query, the quicker feedback will result in a faster response time (even though the time to compute the entire result may be identical). And, in the case of an application program submitting the query, it may be very beneficial to provide the result data sooner and in a more "even" stream as opposed to producing the entire result in one step because the computation of the application can be overlapped with the processing of the join.

Several questions arise as how to best allocate memory for right-deep query trees with the RDHS join algorithm. For correctness it is necessary that the first bucket of EACH of the building relations be resident in memory. However, it is NOT a requirement that all relations be distributed into the same number of buckets. For example, if relation B and D are very large but relation C is small, it would be possible to use only one bucket for relation C while using additional buckets for relations B and D. Hence, the intermediate relation I1 would never be staged to disk in any form, rather it would exist solely as a stream of tuples to the next level in the query tree.

As can be seen, RDHS provides an alternative to the static and dynamic bottom-up scheduling algorithms described above. Whereas these algorithms assumed that enough memory was available to hold at least each relation individually and hopefully several relations simultaneously, the use of the RDHS algorithm potentially reduces the memory requirements while still retaining some dataflow throughout the **entire** query tree. If RDHS can use a single bucket for every relation, it becomes equivalent to the static right-deep scheduling algorithm. It remains an open question as to when one scheduling strategy will outperform the other.

The Case for Right-Deep Query Trees

(1) Right-deep query trees provide the best potential for exploiting parallelism.

(2) In the best case, intermediate join results exist only as a stream of tuples flowing through the query tree.

(3) The size of the "building" relations can be more accurately predicted since the cardinality estimates are based on predicates applied to a base relation as opposed to estimates of the size of intermediate join computations.

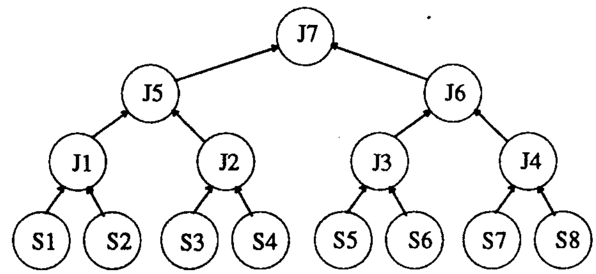
(4) Even though bushy trees can potentially re-arrange joins to minimize the size of intermediate relations, a best-case right-deep tree will never store its larger intermediate relations on disk.

(5) Several strategies exist to deal with limited memory situations. "Breaking" the query tree represents a static approach while the dynamic bottom-up scheduling algorithm reacts better to the amount of memory available at run-time. The RDHS strategy can deliver tuples **sooner** and in a more constant stream to the user/application than a similar left-deep query tree can.

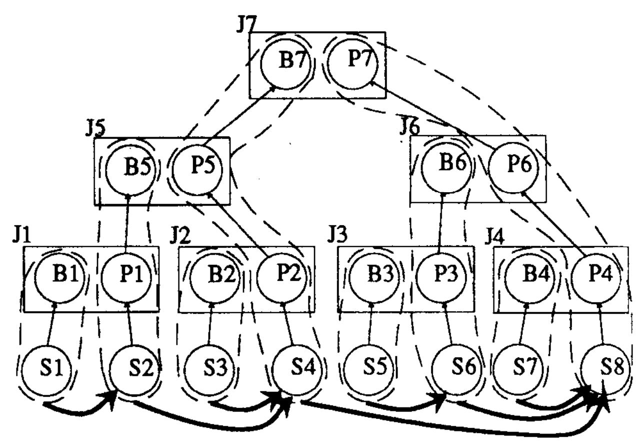
(6) Right-deep trees are generally assumed to be the most memory intensive query tree format but this is not always the case. Consider the join of relations A, B, C, and D as shown in Figure 6 for both a left-deep and a right-deep query tree format. Assume the size of all the relations is 10 pages. Furthermore, assume that the size of A*B is 20 pages and the size of A*B*C is 40 pages. At some point during the execution of the left-deep query tree, the results of A*B and A*B*C will simultaneously reside in memory. Thus, 60 pages of memory will be required in order to execute this query. With a right-deep query tree, however, relations B, C and D must reside in memory, but these relations will only consume 30 pages of memory.

(7) The size of intermediate relations may grow with left-deep trees in the case where attributes are added as the result of each additional join. Since the intermediates are stored in memory hash tables, memory requirements will increase. Note that although the width of tuples in the intermediate relations will also increase with right-deep trees, these tuples are only used to probe the hash tables and hence they don't consume memory for the duration of the join.

3.3. Bushy Query Trees



Bushy Query Tree
Figure 7



Dependency Graph for a Bushy Query Tree
Figure 8

With more complex query tree representations such as the bushy query tree for the eight-way join shown in Figure 7, several different schedules can be devised to execute the query. A useful way of clarifying the possibilities is again through the construction of an operator dependency graph. Figure 8 contains the dependency graph corresponding to the join query shown in Figure 7. By following the directed arcs it can be shown that the longest path through the graph is comprised of the subgraphs containing the scan operators S1, S2, S4 and S8. Since the subgraphs containing these operators must be executed serially in order to maximize dataflow processing (i.e., to prevent writing tuples to temporary storage), it follows that every execution plan must consist of at least four steps. One possible schedule is:

1) Scan S1-Build J1, Scan S3-Build J2, Scan S5-Build J3, Scan S7-Build J4.
2) Scan S2-Probe J1-Build J5, Scan S6-Probe J3-Build J6.
3) Scan S4-Probe J2-Probe J5-Build J7.
4) Scan S8-Probe J4-Probe J6-Probe J7.

However, notice that non-critical-path operations like Scan S7 and Build J4 could be delayed until Step 3 without violating the dependency requirements. The fact that scheduling options such as the above exist, demonstrates that runtime scheduling is more complicated for bushy trees than for the other two tree formats. As was the case with the other query tree designs, if the order in which operators are scheduled does not obey the dependency constraints, tuples from intermediate relations must be spooled to disk and re-read at the appropriate time.

Limited Memory

By intelligently scheduling operators it is possible to reduce the memory demands of a query represented as a bushy tree. Consider again the previous schedule for executing the 7 join query. After the execution of Step 1, four hash tables will be resident in memory. After Step 2 completes, memory can be reclaimed from the hash tables corresponding to join operators J1 and J3 but new hash tables for join operators J5 and J6 will have been constructed. Only after the execution of Step 3 can the memory requirements be reduced to three hash tables (J7, J6, and J4). However, it may be possible to reduce the memory consumption of the query by constructing a different schedule. Consider the following execution schedule in which we have noted when hash table space can be reclaimed:

1) Scan S1-Build J1.
2) Scan S2-Probe J1-Build J5-Release J1, Scan S3-Build J2.
3) Scan S4-Probe J2-Probe J5-Build J7-Release J2 and J5.
4) Scan S5-Build J3.
5) Scan S6-Probe J3-Build J6-Release J3, Scan S7-Build J4.
6) Scan S8-Probe J4-Probe J6-Probe J7-Release J4, J6 and J7.

Although this execution plan requires six steps instead of four, the maximum memory requirements have been reduced throughout the execution of the query from a maximum of 4 hash tables to a maximum of 3 hash tables. If these types of execution plan modifications are insufficient in reducing memory demands, the techniques described in the last two subsections for left-deep and right-deep query trees can also be employed.

3.4. Issues When Using the Sort-Merge Join Algorithm

The use of hash-join methods affects the preceding discussion on the achievable levels of parallelism associated with the alternative query tree designs. For example, reconsider the left-deep query tree and its associated operator dependency graph in Figure 4. With the sort-merge algorithm as the join method, the scan S1 does not necessarily have to precede the scan S2. For example, the scan and sort of S1 could be scheduled in parallel with the scan and sort of S2. The final merge phase of the join can proceed only when the slower of these two operations is completed. This is in contrast to the strictly serial execution of the two scans in order for a hash join algorithm to work properly.

The modifications to the operator dependency graphs required to support the sort-merge join method can be found in [SCHN89b]. These modifications are very simple but are not presented here due to space limitations. One interesting point to note about using the sort-merge join algorithm is that the left-deep and right-deep query tree representations become equivalent because all the base relations (S1 through SN+1) can be scanned/sorted concurrently in either strategy, whereas with the hash-join algorithm there is an ordering dependency which specifies that the left-child input must be completely consumed before the right-child input can be initiated.

4. An Initial Performance Evaluation of Left-Deep vs. Right-Deep Query Trees

The preceding discussion indicated that a multi-way join query represented in a right-deep query tree can potentially offer significant performance advantages over the same query represented in a left-deep tree. In this section we focus on quantitatively measuring the extent of this performance advantage. The reader should note that the goal of the performance evaluation is to determine the range of possible performance tradeoffs between left-deep and right-deep query trees and does not purport to encompass all possible situations. Rather, the analysis will serve to show the feasibility of the strategies proposed for processing multi-way join queries.

As the experimental vehicle for our analysis we chose the shared-nothing database machine Gamma [DEWI86, DEWI90]. Gamma currently runs on a 32 processor iPSC/2 Intel hypercube [INTE88] with one 330 megabyte MAXTOR 4380 (5 1/4") disk directly attached to each Intel 80386 processor. One deficiency of the iPSC/2's I/O system is that it does not provide DMA support for disk transfers. Rather, disk blocks are instead transferred by the disk controller into a FIFO buffer, from which the CPU must copy the block into memory.[2] A high-speed hypercube connected network topology using specially designed hardware routers is used for communication between processors.

[2]Intel was forced to use such a design because the I/O system was added after the system had been completed and the only way of doing I/O was by using an empty socket on the board which did not have DMA access to memory.

Instead of implementing the scheduling algorithms directly on Gamma and measuring their performance, we chose to build a simulation model of Gamma. There were two reasons for this decision. First, we felt it would be simpler and faster to construct new scheduling algorithms in a simulator than in the actual system. Second, a simulation model allows us to study the different algorithms in hardware configurations much larger than Gamma currently provides.

4.1. Simulation Model

The simulation model of Gamma is constructed as follows. Each node in the multiprocessor system consists of a Disk module, a CPU module, a Query Scheduler module, and multiple instances of an Operator module. Additionally, three stand-alone modules are provided: a Network module, a File Manager module, and a Terminal module. The DeNet simulation language [LIVN88] was used to construct the simulator.

The Disk module schedules disk requests according to an elevator algorithm. In order to accurately reflect the hardware currently being used by Gamma, the disk module interrupts the CPU when there are bytes to be transferred from the I/O channel's FIFO buffer to memory or vice versa. The CPU module enforces a FCFS non-preemptive scheduling paradigm on all requests, with the exception of these byte transfers to/from the disk's FIFO buffer. Operator modules are responsible for modeling the relational operators select and join. These modules repeatedly make requests to the CPU, Disk and Network modules in order to perform their particular operation. The Query Scheduler module implements the algorithms to process left-deep and right-deep query trees. The Network module currently models a fully connected network and the Terminal module provides the entry point of new queries. Finally, the File manager keeps track of how many files are defined, what disks each file is declustered over, and the number of pages of each file on each disk. An assignment of each page in a file to a physical disk address is maintained. This physical assignment of file pages allows for more accurate modeling of sequential as well as random disk accesses.

4.2. Simulation Model Validation

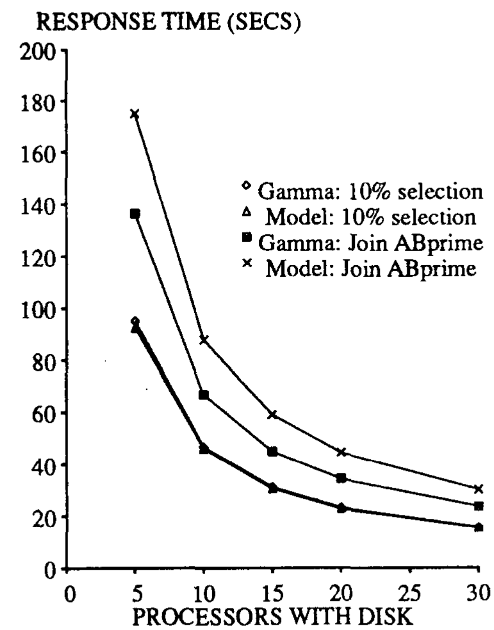
In order to provide more faith in the results from the multiprocessor database machine simulator, we validated the simulator against results produced by Gamma. For the validation procedure, the system was configured to use 18 KByte disk pages and 8 KByte network pages. Costs associated with basic operations on this machine and relevant system parameters are summarized in Table 1.

To validate the simulation model we present the performance of both a 10% selection query and a join query in a system with 5-30 processors with disks. Expanded versions of the Wisconsin Benchmark relations [BITT83] serve as the test database. The selection query retrieves 100,000 tuples from a 1,000,000 tuple relation and stores the resulting tuples back into the database. As shown in Figure 9, the simulation model matches with observed Gamma performance very closely for this query. However, the actual error is greater than implied because Gamma uses a one page readahead mechanism when reading pages from a file sequentially. The performance implications of this mechanism are discussed in more detail below.

Disk Parameters	
Average Seek Time	16 msec
Average Settle Time	2 msec
Average Latency	0-16.67 msec (Unif)
Transfer Rate	1.8 MBytes/sec
Disk Page Size	18 KBytes
Xfer Disk Page from SCSI to mem	9000 instructions
Network Parameters	
Maximum Packet Size	8 KBytes
Send 100 bytes	0.6 msec
Send 8192 bytes	5.6 msec
Cpu Parameters	
Instructions/Second	4,000,000
Read 18K Disk Page	32,800 instructions
Write 18K Disk Page	61,500 instructions
Miscellaneous	
Tuples/Network Packet	36
Tuples/Disk Page	82
Number of Sites	5-30

Simulation Parameters for Model Validation
Table 1

In order to validate join performance in the model, we joined a 1,000,000 tuple relation (200 megabytes) with a 100,000 tuple relation (20 megabytes) to produce a 100,000 tuple result relation (40 megabytes). As illustrated by Figure 9, the simulation model



Validation of Selection and Join Performance
Figure 9

overestimates the response time for this query by a constant factor of 20% over the range of 5 to 30 processors with disk. We attribute much of this modeling inaccuracy to be related to Gamma's use of a one page readahead mechanism when scanning a file sequentially. Since join queries are very CPU intensive operations, Gamma can effectively overlap most of the CPU costs of constructing and probing the hash table with the disk I/O necessary for reading the joining relations. This should not imply, though, that the model is overpredicting performance by 20% for the selection query presented in Figure 9. The CPU requirements of this query are much lower and thus the extent of the overlap of CPU and disk processing is much more limited. This claim is further supported by the fact that the simulation model accurately predicts execution times for selection queries which use a non-clustered B-tree access. These queries generate a series of random disk requests and hence readahead is not employed.

4.3. Experimental Design

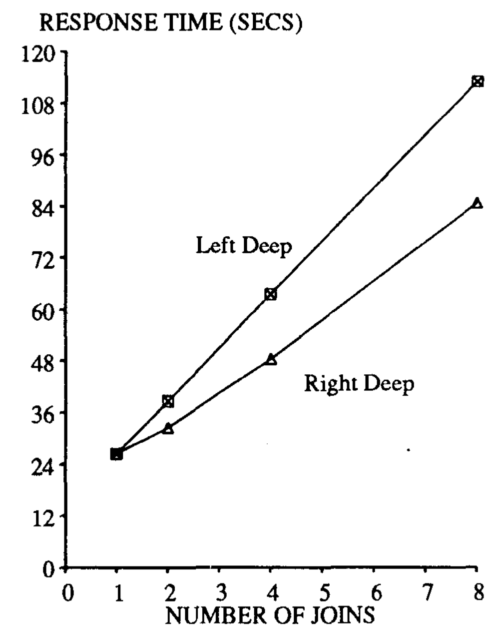
As stated in the beginning of the section, the experiments were designed to present the range of performance differences between left-deep and right-deep query trees. For the experiments conducted, the query suite consisted of join queries composed of 1, 2, 4, and 8 joins. In order to simplify the analysis, though, the queries were highly constrained. For example, the queries were designed such that the size of the result relation is constant regardless of the number of joins in the query or the query tree representation. This was accomplished by making all relations the same size and by setting the join "probe-ability" factor to 1 for every join in the query tree. That is, each probing tuple joins with exactly one building tuple. Constraining queries in this manner allowed for a direct comparison between a query represented as a left-deep tree and its analogous right-deep tree. Comparing randomly generated queries could be misleading because an optimizer would most certainly produce different plans for the same query given the different query tree formats.

The database was composed of nine 1,000,000 tuple relations and each relation has a selection predicate applied to it which reduces the output cardinality to 500,000 tuples. Since input tuples are 208 bytes wide and attributes are not added with each successive join, the result cardinality of ALL the joins was 500,000 tuples, each 208 bytes wide. All result relations were written back into the database. A parallel version of the Simple hash-join algorithm [DEWI84, SCHN89a] was used as the join method and, unless otherwise stated, enough main memory existed to guarantee that hash table overflow would never occur, regardless of the number of concurrent join operations. In order to more accurately predict performance for "typical" database machines, a 25% buffer pool hit ratio was specified in order to model a disk prefetch mechanism. Response time for the queries is measured from the time the query plan is submitted to the database machine until the query is fully computed.

Four major experiments are reported here. The first experiment considers performance differences in an environment where the declustering of the joining relations forces a high level of resource contention. In the second experiment, the environment is changed to ensure a low level of resource contention. In the third and fourth experiments, the first two experiments are repeated in an environment where memory for joining is limited.

4.3.1. High Resource Contention Environment

In a database machine with a relatively small number of processors, it is likely that large relations will be declustered over all the available nodes. Thus, executing multiple scan and join operators concurrently will result in a high degree of resource contention. For these experiments, the system was configured such that each relation was declustered over 50 nodes. Each join in the query tree was also processed on all 50 nodes.



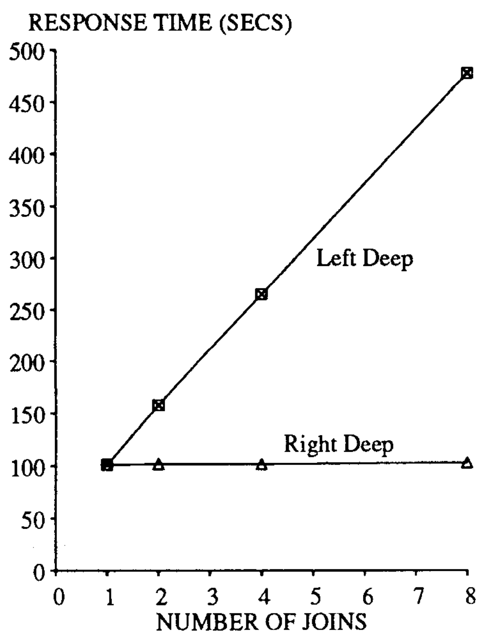
Full Declustering - 50 nodes
Figure 10

The results of these full declustering experiments are shown in Figure 10. For each join query, the performance of the right-deep query tree is approximately 15-20% faster than for its analogous left-deep query tree (left-deep and right-deep query trees are identical for single join queries). This performance improvement occurs because the disks are not fully utilized, and thus executing the scans in parallel for the right-deep trees provides a performance advantage. Note, that the maximal memory requirements for left-deep and right-deep query trees is identical for 1 and 2 join queries, but is twice as high for right-deep queries with 4 joins and four times as high with 8 joins. Thus, when all the relations to be joined are declustered over the same set of nodes, the benefits provided by using right-deep query trees cannot be maintained relative to the amount of memory consumed as the number of joins in the query increases.

4.3.2. Low Resource Contention Environment

In this next set of experiments we repeated the previous experiments in a machine with more processors and where relations are declustered over a subset of nodes and hence, resource contention is reduced when executing several operators concurrently. The system was configured as follows. Each of the nine 1,000,000 tuple relations was declustered over 10 distinct, non-overlapping nodes. Each join was also processed on the 10 processors on which its "building" relation was declustered. Given these conditions, the number of processors actively participating in each query during the scanning of relations and the building/probing of hash tables increased as the number of joins in the query increased. For example, in the 2-join query 30 nodes were used, and in the 8-join query 90 nodes were used. Regardless of the number of joins in the query, each **result** relation was declustered over all 90 nodes.

As illustrated by Figure 11, left-deep query trees are unable to take advantage of the hardware resources that become available as additional joins are added to the query. This is to be expected because relations must be scanned one at a time when a left-deep query tree is employed. However, for right-deep query trees, a nearly constant response time is maintained as the number of joins is increased from one to eight. This may appear startling but can be easily explained given the experimental parameters. Consider the first step in executing the query - scanning the "building" relations and constructing the corresponding hash tables. Since all relations are the same size and have the same selectivity factor applied, and since all the relations are declustered over distinct nodes and the join nodes correspond to the base relation declustering nodes, each scan can be executed completely in parallel and without interference. Thus, the cost of this operation is constant regardless of the number of joins (disregarding the small overhead necessary for initiating the operators).



Partial Declustering - 90 nodes
Figure 11

The second phase (the "probing" phase) can scale with the number of joins due to the effect of pipelining. As tuples are produced from a lower join they are immediately sent across the network to participate in the next level of the join. Thus, processing of tuples in different levels of the tree are overlapped. Viewed another way, the throughput of the pipeline is constant regardless of the depth of the join tree and the difference in response time as the number of join levels increases is due to the increased latency to initiate and terminate the pipeline.

The results contained in Figure 11 represent the best-case performance improvements of right-deep query trees. All experimental parameters were set to allow the parallelism potential of the right-deep strategy to be exploited to its fullest. Under more realistic conditions, the performance improvements of right-deep query trees will fall between the extremes presented in Figures 10 and 11. However, it should be noted that the right-deep query with eight joins required four times more memory than any of the left-deep join queries. The results do demonstrate, though, the extreme performance benefits that can be obtained with a right-deep strategy.

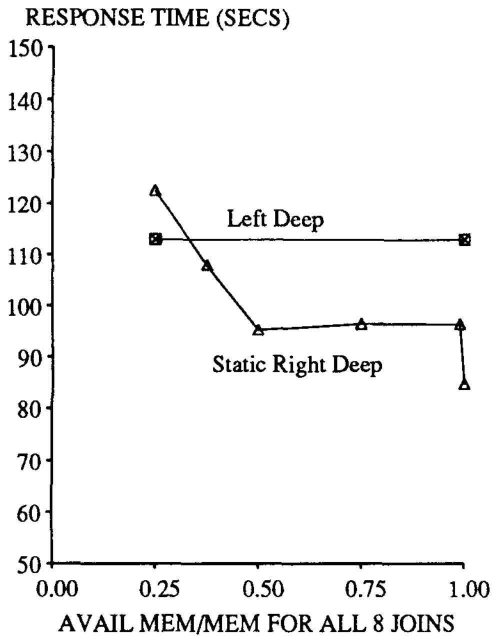
4.3.3. Limited Memory Experiments

In this set of experiments we relaxed the assumption that an unlimited amount of memory exists. All query and model parameters are identical to those reported in the previous section with the exception that we only considered the query with 8 joins. High resource and low resource contention (full declustering and disjoint declustering) experiments were again conducted. The static right-deep scheduling strategy (see Section 3.2) was used for processing right-deep query trees.

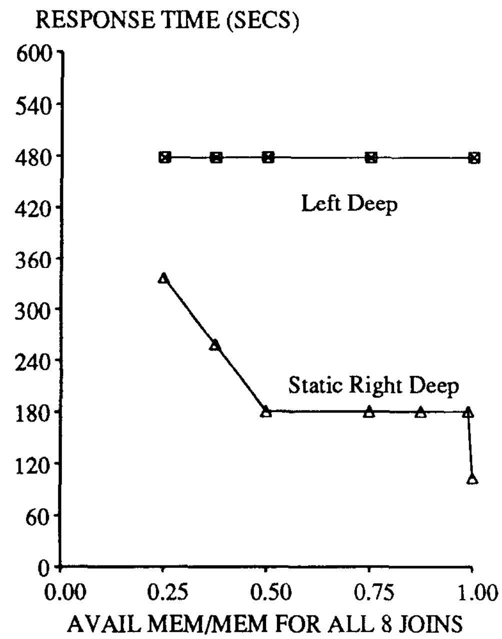
In order to model a limited memory environment, we modified the aggregate amount of memory available for joining relative to the memory required to stage all eight "building" relations into memory simultaneously. Response time was plotted for left-deep and right-deep strategies for x-axis values ranging from a value of 0.25, where only 2 of the 8 building relations could co-reside in memory, to a value of 1.00, where all 8 building relations can fit in memory simultaneously. X-axis values less than 0.25 would have required resolution of memory overflow for left-deep query trees and are not reported. For the static right-deep strategy it was assumed that the optimizer could perfectly predict scan selectivities and thus could always choose the optimal places to "break" the query tree.

4.3.3.1. Limited Memory - High Resource Contention

In Figure 12, the performance of the left-deep and static right-deep scheduling algorithms are shown as the amount of available memory is varied in an environment where all base relations are declustered across all 50 sites. Three observations should be noted from this figure. First, it is obvious that the left-deep scheduling algorithm is not able to take advantage of memory as it is added. In contrast, the static right-deep scheduling algorithm demonstrates significant performance improvements with additional memory. Next, the cross-over point in the graphs demonstrates the fact that "breaking" the query tree into too many pieces can be detrimental to the performance of right-



Limited Memory - Full Declustering
Figure 12



Limited Memory - Partial Declustering
Figure 13

deep scheduling algorithms. For example, at the x-axis value 0.25, the tree had to be broken into three pieces to ensure that the right-deep strategy did not experience memory overflow (requiring the writing and subsequent reading of temporary join computations to and from the disk at three points during query execution). The last point to note is the flatness of the right-deep scheduling graph from 0.5 to just before 1.0. Over this range, the query tree had to be broken into only two pieces. Since the queries produced intermediate relations of a constant size regardless of the number of joins in the query, the placement of the "break" has no effect on performance because the same number of tuples are temporarily staged to disk. Under more likely conditions of growing or diminishing temporary join size results, the selection of the break points for a query will almost certainly have some effect on the execution time of the query. This will be explored in a future performance analysis.

4.3.3.2. Limited Memory - Low Resource Contention

In Figure 13, we present the execution time of the left-deep and right-deep scheduling strategies for the 8-join query when the relations to be joined are declustered over mutually disjoint processors with disks. The simulation parameters are identical to those reported in Section 4.3.2.

The results are very similar to those shown in Figure 12, i.e., the shape of the curves is identical. It is obvious though, that the partial declustering environment offers additional performance advantages for right-deep scheduling strategies even when memory is not unlimited. This is very encouraging because, as stated earlier, it is likely that relations will be partially declustered in database machines with large numbers of processors/disks.

5. Conclusions

In this paper, we have described many of the problems and tradeoffs associated with the task of processing queries composed of many joins in a multiprocessor database machine. In particular, we focused on how the strategy chosen to represent a query tree affects the degree to which parallelism can be applied within a query and the corresponding effects on performance, the resource consumption of the query, and the extent that dataflow processing techniques can be applied. Hash based join methods were assumed for much of this analysis although the sort-merge join method was discussed briefly.

Results obtained from this analysis indicate that the right-deep query representation strategy is well suited to exploit the parallelism inherent in large multiprocessor database machines. As an added benefit, the importance of accurately estimating join selectivities is potentially reduced when using right-deep query trees. These results encouraged us to develop several algorithms for processing queries represented in this query tree format.

In order to quantitatively measure the performance benefits that right-deep query trees can provide over their corresponding left-deep query trees, we constructed a simulation model of a parallel database machine and implemented scheduling algorithms for processing queries represented in these formats. Experimental results from the analysis of these algorithms confirmed that right-deep query trees can offer very significant performance advantages in large database machines. However, the extent of the performance improvement is strongly dictated by the physical placement of the base relations and comes at the cost of increased resource consumption. Furthermore, when memory is limited the performance difference between the scheduling algorithms diminishes.

Our future work includes extending the current study to include a much richer mix of queries, selectivity factors, and base relation cardinalities. We are also interested in studying the performance of the alternative query processing algorithms under multiuser workloads and with skewed data distributions. Although multiuser performance comparisons were beyond the scope of this paper, the memory requirements of a query will serve as a good indicator of potential throughput because memory is so crucial to high performance query processing, especially with the hash-join algorithms. We hope to apply the technique of Adaptive Sampling [LIPT90a, LIPT90b] to help tackle the problem of skew.

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