Polynomial Heuristics for Query Optimization

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***Abstract*— Research on query optimization has traditionally focused on exhaustive enumeration of an exponential number of candidate plans. Alternatively, heuristics for query optimization are restricted in several ways, such as by either focusing on join predicates only, ignoring the availability of indexes, or in general having high-degree polynomial complexity. In this paper we propose a heuristic approach to very efficiently obtain execution plans for complex queries, which takes into account the presence of indexes and goes beyond simple join reordering. We also introduce a realistic workload generator and validate our approach using both synthetic and real data.**

I. Introduction

Research in query optimization has quickly acknowledged the exponential nature of the problem. While certain special cases can be solved in polynomial time (e.g., chain queries with no cross-products [1] or acyclic join queries under ASI cost models [2]), the general case is NP-hard (see [3], [2]).

Despite the inherent complexity of query optimization, algorithmic research has traditionally focused on exhaustive enumeration of alternatives (see [4] for the classical dynamic programming approach and [5], [6] for a transformation-based approach). As queries become more complex, exhaustive algorithms simply cannot enumerate all alternatives in any reasonable amount of time. For instance, enumerating all join orders for a 15-table star query takes several minutes in commercial systems (but we have seen scenarios with queries that join more than 50 tables together).

To be able to cope with such complex queries, several heuristics have been proposed in the literature (see Section II for more details). However, previous work is limited to joins operators (i.e., they do not consider other relational operators like group-by clauses), do not consider the presence of indexes (which, as we will see, can drastically change the landscape of optimal plans), and can still be inefficient or inadequate in certain scenarios. This is illustrated by the following examples:

Language integrated queries: New advances in programming languages [7] allow expressing declarative queries (similar to those using SQL) in procedural languages like C#. Extensions to compilers and the language themselves make possible to optimize such queries at runtime. In contrast to traditional DBMSs, such declarative queries might be executed in main-memory, are dynamically generated, and usually operate on relatively small amounts of data. For that reason, the latency for optimizing such queries needs to be minimal, and only very efficient optimization strategies are allowed. In fact, any heuristic with more than a quadratic complexity factor risks being longer than a naïve execution of an un-optimized query! At the same time, availability of indexes and large join graphs present the opportunity for some amount of optimization.

Transformation-based optimization: Some optimization frameworks, like Volcano [6] and Cascades [5], perform a significant amount of exploration, where logical alternatives are discovered, before obtaining physical execution plans that could be evaluated. Note that if we decide to abort optimization (due to time limits or memory pressure) before implementation is well underway, we might not have a single plan to evaluate. To mitigate this problem with complex queries, some implementations of Cascades (e.g., Microsoft SQL Server) use optimization stages, which are performed sequentially. In a first stage, a heuristic join reordering is done, followed by very restricted exploration and implementation phases (e.g., the exploration phase does not consider join reordering, or only uses it in a very restricted manner). A later stage performs the exhaustive enumeration. In this case, if the later (and time-consuming) stage is aborted, the optimizer can always return the result of an earlier phase (which would always be available). It is therefore crucial that the plan found by the first phase is of reasonably good quality (since it will be returned if later phases are aborted), but also very quickly produced (since it is just an initial component of the whole optimization process).

As illustrated in the previous examples, new applications require efficient optimization heuristics that go beyond the traditional scenario that exclusively handles join predicates with no indexes. The main contributions of the paper are:

- We introduce the *Enumerate-Rank-Merge* framework (or *ERM* for short), that generalizes and extends previous join reordering heuristics in the literature (Section III).
- We extend previous work on heuristic join reordering to take into account other operators (Section IV).
- We design a workload generator that goes beyond previous proposals, and use it to comprehensively evaluate our techniques on synthetic as well as real data (Section V).

II. Related Work

There has been significant research on techniques to exhaustively enumerate search spaces for relational query optimization. The pioneering work in [4] presents a dynamic programming algorithm to enumerate joins of a given query. This result was extended several times, culminating in a technique in [8] that efficiently enumerates all bushy trees with no cross products, and additionally considers outer-joins. A different approach is considered in [9], which presents

a top-down approach to exhaustively enumerate bushy trees with no cross-products. Finally, reference [10] introduces an exhaustive algorithm to enumerate all bushy trees including cross-products. Reference [11] extends the dynamic programming technique to additionally consider group-by operators. A different line of work in [6], [5] exhaustively enumerates joins by using transformations, and can be more easily extended to explore other relational operators.

Whenever certain query properties hold, there are polynomial algorithms that guarantee optimality. For instance, for chain queries, it is known that the classical dynamic programming algorithm works in polynomial time [1]. Also, if the join graph is acyclic and the cost model satisfies the ASI property [2], the IKKBZ technique in [12] returns the optimal plan in $O(N^2)$ where N is the number of tables.

The join reordering problem has also received significant attention in the context of heuristic algorithms. One line of work adapts randomized techniques and combinatorial heuristics to address this problem. These techniques consider the space of plans as points in a high-dimensional space, that can be "traversed" via transformations (e.g., join commutativity and associativity). Reference [13] surveys different such strategies, including iterative improvement, simulated annealing, and genetic algorithms. These techniques can be seen as heuristic variations of transformation-based exhaustive enumeration algorithms. Another line of work implements heuristic variations of dynamic programming. These approaches include reference [14] (which performs dynamic programming for a subset of tables, picks the best k-table join, replaces it with a new "virtual" table, and repeats the procedure until all tables are part of the final plan), reference [15] (which simplifies an initial join graph by disallowing non-promising join edges and then exhaustively searches the resulting, simpler problem using [8]), and references [16], [17] (which greedily build join trees one table at a time).

Except for [16], [17], the above heuristics do not naturally fit the scenarios described in the introduction. Although more efficient than exhaustive search, these approaches are still expensive for low-latency scenarios, do not consider other relational operators beyond joins, and are unaware of indexes.

III. Enumerate-Rank-Merge Approach

In this section we introduce our main approach, which can be seen as a generalization of earlier greedy techniques (e.g., see [17], [16]). When trying to understand the different heuristics, it is useful to refer to Figure 1, which presents a generic pseudocode that is used, in one form or another, by virtually all greedy approaches. The input to the algorithm is a set of tables T and a join graph J. Each table is associated with a base cardinality and, optionally, a selectivity of all single-table predicates applied to it. The join graph J has associated a selectivity value to each join edge. In line 1 we initialize a pool of plans P, which consists of a `Scan` operator for each table $t \in T$. We then modify the pool of plans P in lines 2-6, until there is a single plan remaining, which we return in line 7. Each iteration of the main loop starts by enumerating all

```
ERM (T: set of tables, J: join graph)
01 P = { Scan(t) | t ∈ T }
02 while |P| ≥ 1
03   E = {(P1, P2) ∈ P × P : valid(P1, P2)}
04   find (P1, P2)∈ E that maximizes R(P1, P2)
05   Pn = merge(P1, P2)
06   P = P − {P1, P2} ∪ {Pn}
07 return p ∈ P
```

Fig. 1. Generic greedy technique to enumerate joins.

valid ways to combine two plans in P (*enumerate* step). Line 4 chooses the pair with the best ranking value (*ranking* step). Line 5 then combines the highest ranked pair of plans into a new plan P_n (*merge* step). Finally, line 6 removes the original plans in the highest ranked pair from P and adds the new plan P_n into the pool. The invariant at all times is that any plan p in P is valid for the sub-query that contains all tables of the plans that were merged to obtain p. Therefore, at the end, when $|P| = 1$, the only plan in P is valid for the original query.

The generic algorithm *ERM* is parameterized by three components. First, we need to determine which pairs of plans in P are valid (*enumerate*). Second, we need to rank each valid pair of plans (*rank*). Third, we need to combine a pair of plans into a new plan (*merge*). The complexity of *ERM* is then $O(N^2R + NM)$, where N is the number of tables, and R and M are, respectively, the complexities of a assigning a score to a single alternative, and merging a pair of plans (if R is constant and M is at most linear, the complexity of *ERM* is quadratic in the number of tables). Ranking has a factor N^2 because we can arrange the computation so that the first time we evaluate N^2 pairs, and then at each iteration we only compute the rank of each element in P and the newly added P_n (other ranks stay the same), which is linear per iteration[1]. The following sections explain the components of *ERM* in detail.

A. Enumerate Step

The enumeration step determines the fundamental characteristics of plans that we consider. If we are only interested in linear trees, the *valid* function in line 3 only allows a pair (P_1, P_2) if, after merging, there will be exactly one plan in the pool defined over more than one table. It is easy to see that this condition always results in linear trees. Similarly, if we do not want to consider cross products, the *valid* function would reject any pair (P_1, P_2) for which there is no join predicate in J between a table in P_1 and a table in P_2. If the *valid* function succeeds for every possible combination, we end up considering bushy trees with cross products. Previously proposed approaches use different versions of *Enumerate*: *minSel* [16] considers linear trees with no cross products, and *Goo* [17] considers bushy trees and cross products.

Linear vs. Bushy Trees

Since bushy trees include linear trees, the optimal bushy tree is never worse than the optimal linear tree. However,

[1]In this analysis we assume that the ranking of pairs is done by assigning a score to each pair, and then sorting by such score.

exhaustively enumerating all bushy trees is significantly more expensive than doing so for just the subset of linear trees. For that reason, query engines commonly restrict the search space to consider only linear trees. In the context of our greedy heuristics, the real advantage of bushy trees comes from the additional flexibility and potential to recover from mistakes. A problem with greedy techniques that only consider linear trees is that they are fragile with respect to initial bad choices.

Example 1: Suppose that we have a chain query $R_1 \bowtie R_2 \bowtie R_3 \bowtie \ldots \bowtie R_k$, and suppose that $R_1 \bowtie R_2$ is the highest ranked join. Furthermore, suppose that $R_2 \bowtie R_3$ is a really bad choice, since it increases 100x the number of tuples in R_3. Suppose that we initially choose $R_1 \bowtie R_2$. Next, we have no choice but choosing $(R_1 \bowtie R_2) \bowtie R_3$ to respect linear trees and no cross products (even though $(R_1 \bowtie R_2, R_3)$ is ranked badly, it is the only valid pair). The net effect is an explosion of intermediate results. Alternatively, if bushy trees are allowed, we can still first join R_1 and R_2, but we would have the option to choose other join sub-trees before joining the plans containing R_2 and R_3 (the final plan could be something like $(R_1 \bowtie R_2) \bowtie (R_3 \bowtie \ldots \bowtie R_k)$, therefore delaying the "bad join" as much as possible. ∎

As we show experimentally, including bushy trees in a greedy search strategy greatly improves the quality of results.

B. Ranking Step

Consider a pair of plans (P_1, P_2), and denote $T(P)$ the set of tables referenced in plan P. Further assume that J is the set of join predicates in the query. There are several ways to assign a score to (P_1, P_2) to enable ranking of pairs. In this section we review some alternatives (we assume that smaller scores are better ranked), and in the next section we refine the ranking function so that it is aware of merging. We first present the rationale behind a good ranking function. The total cost of an execution plan p is the sum of costs of all operators in p. Consider for simplicity a join tree composed exclusively of hash-based algorithms. Under a simple cost model, the cost of each hash join is proportional to the sizes of both its inputs and output. Since all plans would read the same amount of data from base tables, minimizing the cost of the query is very well aligned with minimizing the total sizes of intermediate results. The different metrics discussed below try to minimize the sum of intermediate results in different ways:

- *MinSel*: The score of pair (P_1, P_2) is defined as $\frac{|P_1 \bowtie P_2|}{|P_1| \times |P_2|}$, where the join predicate is the conjunction of all join predicates in J for which one table is in $T(P_1)$ and the other table in $T(P_2)$. In other words, it is the selectivity of the join predicates between $T(P_1)$ and $T(P_2)$. This ranking function is used in *minSel* [16].
- *MinCard*: The score of pair (P_1, P_2) is defined as $|P_1 \bowtie P_2|$, where the join predicate is the same as above. In other words, it is the cardinality of the intermediate result that joins all tables in $T(P_1) \cup T(P_2)$. This ranking function is used in *Goo* [17].
- *MinSize*: The score of pair (P_1, P_2) is defined as $|P_1 \bowtie P_2| \cdot rowLen(P_1 \bowtie P_2)$, where the join predicate is defined as before, and *rowLen*(P) is the size, in bytes, of a row produced by plan P. We slightly generalized *MinCard* into *MinSize*, which additionally takes into account the width of tuples produced by different operators, and more closely satisfies the original intent of minimizing intermediate result sizes.

We experimentally validated that *MinSize* is consistently better and more robust than the alternatives, and this is the ranking function we assume for the rest of the paper. It is important to note, though, that we can construct scenarios for which MinSel results in better results (but this rarely happens in practice, especially when considering bushy trees). The following example illustrates this fact.

Example 2: Consider a chain query $A \bowtie B \bowtie C \bowtie D$, where $|A| = |B| = 1\text{K}$, $|C| = |D| = 100$, $|A \bowtie B| = 1\text{K}$ (selectivity is $1/1\text{K}$), $|B \bowtie C| = x$ (selectivity is $x/100\text{K}$), and $|C \bowtie D| = 200$ (selectivity is $1/50$). Further assume, for simplicity, that all tuples have the same size. For $x = 300$ (selectivity is $3/1\text{K}$), *minSel* would choose the join order $((A \bowtie B) \bowtie C) \bowtie D$, and the sum of intermediate results would be $1\text{K}+300+600 = 1.9\text{K}$. In turn *minSize* would choose the order $((D \bowtie C) \bowtie B) \bowtie A$, and the sum of intermediate results would be smaller at $200+600+600 = 1.4\text{K}$. Now, if we change $x = 900$ (selectivity is $9/1\text{K}$), *minSel* would still choose the same join order, and the sum of intermediate results would be $1\text{K}+900 + 1.8\text{K} = 3.7\text{K}$. When considering *minSize*, it will first choose $C \bowtie D$ as before. After the first iteration, we have $|C \bowtie D| = 200$ and thus $|(C \bowtie D) \bowtie B| = 1.8\text{K}$, which is larger than $|A \bowtie B| = 900$. If we are restricted to linear trees, *minSize* would still end up choosing the same plan as before, and the sum of intermediate results would be $200+1.8\text{K}+1.8K = 3.8\text{K}$ (which is worse than that of *minSel*). If bushy trees are allowed, however, *minSize* would choose $A \bowtie B$ in the second iteration, and would return the final plan $(D \bowtie C) \bowtie (B \bowtie A)$, with a sum of intermediate results of $200 + 1\text{K}+1.8\text{K} = 3\text{K}$ (better than *minSel*, which returns the same plan for either linear or bushy trees). ∎

C. Merging Step

Once we decide in line 4 in Figure 1 the highest ranked pair of plans (P_1, P_2), we have to merge them together in line 5 and replace the P_1 and P_2 with the merged plan P_n in line 6. Traditionally, the merge operation simply combines both execution sub-plans with a join alternative (i.e., P_n=$P_1 \bowtie P_2$), which always results in a valid plan. Note however that we can consider alternative execution plans, as long as we do it efficiently (as we discussed earlier, since there is a quadratic number of -constant time- ranking invocations, and a linear number of merges, we have a linear budget to implement better versions of merging without increasing the complexity of the algorithm). An interesting aspect of merging is that it is very flexible. If we think of a new way of merging two execution plans, we can add the new alternative and pick the best option

overall. We next introduce our merging alternatives, assuming that the ranking function is *minSize*.

Switch-HJ

This is a very simple merge, motivated by our ranking functions not distinguishing between left and right inputs. In reality, it is better to have the smaller relation in the build side of a hash join. So when merging P_1 and P_2, we choose the alternative that uses the smaller input as the build side.

Switch-Idx

If we are about to merge P_1 and P_2, where P_2 refers to a single table T_2, and there is an index on T_2 that enables an index-join strategy between P_1 and T_2, we consider this alternative in addition to the one that does not use indexes, and pick the one expected to be cheaper.

While this is an interesting merge that consider indexes, it still depends on the ranking function to choose the appropriate pair P_1 and P_2. In other words, we would only use an index alternative "reactively," if by chance there was an available index for the highest ranked pair. A more robust alternative would be to bias the ranking function so that it takes into account the presence of indexes "natively". At the same time, since ranking is done for each pair of plans, this modification to the ranking function needs to be very cheap to compute.

Suppose that we are considering a pair of plans (P_1, P_2) where P_2 covers a single table T_2. Further suppose that P_1 has cardinality C. An index-join alternative needs to perform an index lookup for each of the C outer tuples, and seek the index for matches (if the index is not covering, for each one of these matches there should be a clustered index lookup to obtain the remaining columns)[2]. Suppose that each index lookup fetches LT_2 tuples that fit in LP_2 pages from T_2. Then, the index-join would read $C \cdot LP_2$ pages (plus $C \cdot LT_2$ pages from the clustered index if the index is not covering), for the benefit of not reading T_2 altogether. The value $\mathcal{P}_I$, defined as:

$$\mathcal{P}_I = \max\left(0, \text{pages}(T_2) - C \cdot (LP_2 + \delta_{cov(I)} \cdot F \cdot LT_2)\right)$$

approximates the number of pages we would save (if any) by using an index-join alternative with index I, where $pages(T_2)$ is the number of pages of table T_2, $\delta_{cov(I)}$ is zero if the index is covering (and one otherwise), and F is the ratio of a random page read versus a sequential page read (to normalize $\mathcal{P}_I$ values to "sequential page reads"). The value of F can be obtained by either using the optimizer's cost model (which we did) or by a calibration phase. We then refine the *minSize* ranking function as follows:

$$minSize'(P_1, P_2) = minSize(P_1, P_2) - \text{pageSize} \cdot \mathcal{P}_I$$

This function is still an approximation based on some simplifying assumptions, such as not modeling duplicate outer values or buffer pool effects. While all these could be accommodated by further refining the ranking function, our simple metric already provides good quality results.

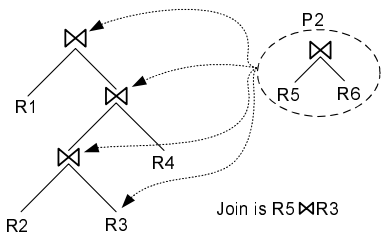
[2]The details are slightly more complex since we need to take into account the single-table predicates on table T_2, which could be applied before the clustered index lookup. We omit such details for simplicity.

Push

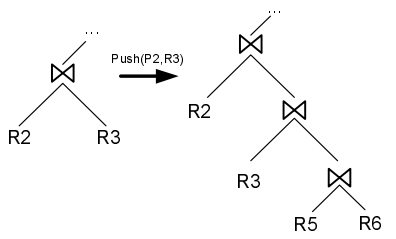
The previous merging alternatives are simple and can be implemented in constant time (they only change the root of the merged tree). *Push* is a merging alternative that sometimes is able to correct early "mistakes" that result from using a greedy heuristic. Consider merging (P_1, P_2) and suppose that J is the set of join predicates between tables in P_1 and tables in P_2. As hinted by its name, the *Push* alternative tries to *push* one plan inside the other. Consider pushing P_2 into P_1. Without considering cross products, we can push P_2 to any subtree in P_1 that has a non-empty join predicate between the subtree and P_2 (Figure 2(a) shows the positions where we could push $P_2 = R_5 \bowtie R_6$ if the join predicate between P_1 and P_2 is $J = R_3 \bowtie R_5$). For each such sub-tree p of P_1, we replace p with an additional join operator that joins p and P_2 (see Figure 2(b) for an example).

Once we determine all subtrees for pushing P_2, we select the one with the highest aggregated rank (i.e., the sum of sizes for all intermediate results). Note that pushing P_2 into a subtree p in P_1 only changes the result size of all ancestors of p in P_1. This enables strategies that share most of the work for calculating aggregated ranks of all push alternatives. For instance, if we assume independence among join predicates, each pushing of P_2 into a subtree can be calculated in constant time, by precomputing cardinality information on each plan in the pool incrementally. There are two extensions to this basic approach. First, note that for each push, we can apply the *Switch-HJ* and *Switch-Idx* merges to each intermediate join in the path from the root to the pushed element. This is useful as changes in cardinality might make a index-join alternative much more useful than before the push. Note that, since P_2 into the root of P_1 is the same as joining both trees, the *Push* strategy is effectively a generalization of the previous *Switch-HJ* and *Switch-Idx*. At the same time, the complexity of this alternative is larger than that of the original approach.

The benefit of the *Push* technique is twofold. First, it might help correct early mistakes done by the greedy technique. For instance, suppose that $(A \bowtie B) \bowtie C$ is better than $(A \bowtie C) \bowtie B$ overall, but $A \bowtie B$ is more expensive than $A \bowtie C$ (this is the canonical adversarial scenario for a greedy technique). Our greedy heuristic would pick $A \bowtie C$ first, obtaining a suboptimal plan. However, when later joining with B, we can push B towards A and obtain the better plan again. The second (related) benefit of *Push* has to do with join cycles, or residual predicates that operate over a subset of tables. Greedy heuristics are not aware that certain joins are beneficial because they are part of a larger join cycle (or a multi-table predicate) that would significantly reduce cardinality values. Therefore, greedy heuristics sometimes do not close cycles early enough. Whenever the join cycle is eventually closed, the *Push* heuristic will attempt to push it down into the tree, possibly making a substantial reduction in intermediate cardinality appear earlier.



(a) Candidate subtrees for pushing P_2.



(b) Applying a specific push operation.

Fig. 2. Merging two plans using *Push*.

Pull

This strategy tries to correct missed opportunities of index-based joins. After merging P_1 and P_2, the resulting cardinality can decrease significantly (either as a result of the join or because of an additional residual predicate or join cycle). Then, some early decisions that discarded index joins because of large outer cardinalities can become interesting again. The *Pull* strategy operates on $P_1 \bowtie P_2$ as follows. It first considers each leaf node in the plan that is not already the inner side of an index-join alternative, and tries to "pull" the leaf node all the way up to the root of the plan to be used as the inner of an index join. Figure 3 illustrates how R_3 is pulled up to the root of the tree (it also shows that sometimes earlier joins that involve the pulled table must be converted in cross products). As before, every pull operation of node p changes the cardinality of all operators in the path from root to p. By carefully maintaining cardinality information for all leaf nodes in the pool of plans, the pulling of each node can be done in constant time, and thus the Pull strategy is linear in the size of the tree (we omit details due to space constraints).

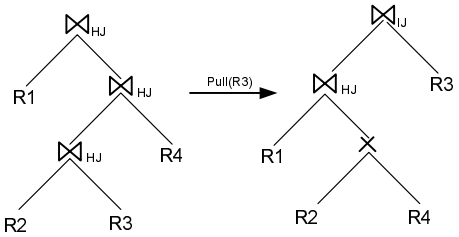


Fig. 3. Pulling table R_3.

D. BSizePP: Heuristic join reordering

Figure 4 shows an instance of the ERM algorithm of Figure 1 (the name *BSizePP* is explained in Section V). We consider bushy trees and cross products, use the *minSize* ranking function with the extensions in Section III-C to natively consider indexes, considers all valid pull and push merges and picks the one that minimizes the aggregated *minSize* value. We will validate each of this choices experimentally in Section V.

IV. Beyond Join Reordering

In this section we extend our strategies, which heuristically reorder join graphs, to additionally handle other operators.

```
BSizePP (T: set of tables, J: join graph)
01 P = { Scan(t) | t ∈ T }
02 while |P| ≥ 1
03   E = { (P1, P2) ∈ P × P }   // consider bushy trees
04   find (P1, P2) ∈ E minimizing minSize(P1, P2)
05   Pn = best of Push(P1, P2) and Pull(P1, P2)
           // Includes Switch-HJ and Switch-Idx
06   P = P − {P1, P2} ∪ {Pn}
07 return p ∈ P
```

Fig. 4. Generic greedy technique to enumerate joins.

A. Group-by Clauses

After joins, group-by clauses are the most commonly used operator in SQL. A group-by clause is defined by (i) a set of grouping columns c, (ii) a set of aggregate functions a, and (iii) the relational input expression R. We concisely write a group-by expression as GB(c,a,R), or simply GB(c,R) if the aggregate functions are not relevant for the discussion.

Group-by clauses can be done before or after joins in certain situations. Specifically, a group-by clause can be pulled up above a join, as long as (i) we add a key of the other join relational input to the set of grouping columns, and (ii) the join predicate is not defined over an aggregated column (otherwise the resulting join is not well-formed). Figure 5 illustrates this transformation (note that b_2 must include b_1 so that the original join is well-formed). A group-by clause can be pushed below a join $R \bowtie S$ (down to S) whenever (i) the grouping columns include a key of R, (ii) the columns from S in the join predicate are included in the grouping columns or derived from them via functional dependencies, and (iii) all aggregates are defined in terms of columns in S [11], [18].

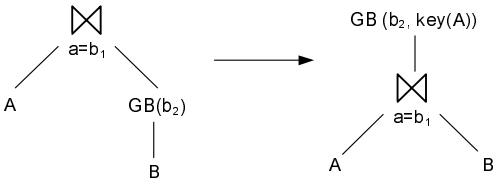


Fig. 5. Pulling a group-by clause above a join.

Canonical representation

Join graphs are well-known canonical representations of *SPJ* queries. We now describe how to extend this concept for queries that additionally contain group-by clauses. The canonical representation of a generic query with joins and group-by

clauses is a join graph augmented with a set of *canonical group-by clauses*. Each canonical group-by clause is obtained from an original group-by in the query, and consists of (i) a set of grouping columns, (ii) a set of aggregate functions, and (iii) an *input signature* (instead of the relational input expression in regular group-by clauses). An input signature consists of a set of tables and optionally other canonical group-by clauses. Consider a logical operator tree representing a query with joins and group-by clauses. We first push all group-by clauses down joins as much as possible (reordering joins below group-by clauses if required). Since group-by clauses in the same query are either defined over disjoint relational inputs or else one is part of the other's input, the result of this step is always unique and well defined. We then consider each group-by clause in the resulting tree, and convert it into a canonical group-by. The grouping columns and aggregate functions in the canonical group-by clause are identical to those in the original group-by clause. The input signature contains all tables and group-by clauses that are descendants of the original group-by clause and can be reached from it using a path in the query tree that does not go through another group-by clause. The join graph, in turn, is constructed as if no group-by clauses were present (for simplicity, cases which define joins between aggregated columns are discussed later in this section).

Example 3: Consider the query in Figure 6(a) and the corresponding operator tree representation in Figure 6(b). The inner group-by clause initially is defined by (i) columns key(A), B.1, D.3, (ii) the `COUNT(*)` aggregate, and (iii) the input relation $A \bowtie B \bowtie C \bowtie D$. Note that we can push the group-by below $A \bowtie_{A.1=B.1} (B \bowtie C \bowtie D)$ since k(A) and B.1 are part of the grouping columns. Then, the group-by is canonically defined as (i) the set of grouping columns {B.1, D.3}, (ii) the aggregate, and (iii) the input signature {B, C, D}. We concisely write this as GB_1 = GB({B.1,D.3},{B,C,D}). Using a similar argument, the canonical representation of the outer group-by clause is GB_2 = GB({E.3},{A, GB_1,E}). Figure 6(c) shows the canonical representation of the query above. ∎

It is important to note that we were able to obtain a single join graph even though the original query had two join components "separated" by a group-by clause. This would allow to reorder joins *across* group-by clauses, which is not possible in previous approaches.

The canonical representation of a query allows identifying the locations in a join tree where each group-by clause can be inserted. Specifically, we can insert a group-by G on top of a sub-tree T whenever T contains *at least* all tables and group-by clauses in G's input signature. In such case, the set of grouping columns in the resulting group-by clause would additionally include keys for any table or group-by clause in T that is not present in the "transitive closure" of the input signature of G (i.e., not present in G's input signature, in input signatures in G's input signature, and so on).

Example 3: (continued) Consider a sub-tree $T = A \bowtie B \bowtie C \bowtie D \bowtie E$. We can insert a root group-by G_1 (see Figure 6) on top of T because T includes all tables in G_1's input signature. We have to include in G_1's grouping columns a key for A and E (which are not in the input signature of G_1). Group-by G_2 can now be placed on top of the resulting sub-tree because G_1, A and E are present in the sub-tree. The grouping columns in G_2 do not need to be augmented, since all tables and group-by clauses in the sub-tree appear in either G_2's input signature, or in G_1's input signature (which belongs to G_2's input signature). ∎

Selectivity Estimation of Group-By Clauses

When considering a query that only contains joins, we can associate a selectivity value with each join because this value is independent of the order of the join in an execution tree. No matter where a join is positioned in an execution plan, the selectivity of the join would always be the same[3]. We now extend this idea to queries that also contain group-by clauses.

We define the selectivity of a group-by G as the number of output tuples divided by the number of input tuples. In this work we do not take a position on how to calculate this selectivity value (in general it would involve using statistical formulas and exploiting histogram information). Instead, we show that the selectivity of a group-by clause is independent to its position in an execution plan.

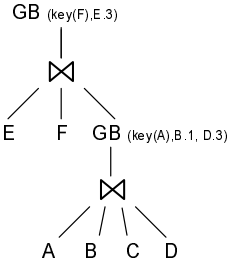
Suppose that there are $|A|$ tuples in A and $|B|$ tuples in B. Furthermore, assume that there are dv_A distinct values of a in A, each one repeating D_A times, so $|A| = dv_A * D_A$ (this is a simplification, but is the information that we have per histogram bucket on $A.a$, and we can extend the discussion to hold over all buckets). Similarly, there are dv_B distinct values of b in B, each one repeating D_B times, so $|B| = dv_B * D_B$. Additionally, each distinct value of b in B (i.e., these D_B tuples) contain distinct values for b' (recall that the columns in b' includes those in b, so it tuples that share b values generally vary in columns $b' - b$). Let's say that there are dv'_B distinct values of b' in these D_B tuples, each one repeating D'_B times, so $D_B = dv'_B * D'_B$ (again, there is an implicit assumption about independence of column distributions here, which is typically used during cardinality estimation). With this notation, we can calculate cardinality and selectivity values in presence of both joins and group-by clauses. Specifically:

1) $|\text{GB}(b', B)| = dv_B \cdot dv'_B$ (the group-by clause removes all D_B' copies).
2) $Sel(\text{GB}(b', B)) = |\text{GB}(b', B)|/|B| = 1/D'_B$.
3) $|A \bowtie B| = \min(dv_A, dv_B) \cdot D_A \cdot D_B$ (using the containment assumption for joins).
4) $|A \bowtie (\text{GB}(b', B))| = \min(dv_A, dv_B) \cdot D_A \cdot dv'_B$ (using the containment assumption again, but now each group of D_B tuples was reduced to only dv_B' tuples due to the group-by clause).
5) $|A \bowtie (\text{GB}(b', B))| = |\text{GB}(b', key(A), A \bowtie B)|$ (since both expressions are the same when pulling up a group-by).
6) $Sel(\text{GB}(b', key(A), A \bowtie B) = |\text{GB}(b', key(A), A \bowtie B)|/|A \bowtie B| = 1/D'_B$.

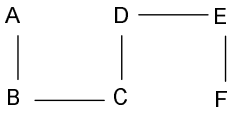
[3]This statement leverages the standard independence assumption commonly used for cardinality estimation.

```
SELECT E.3, COUNT(*)
FROM E, F,
     (SELECT A.1, B.1, D.3, COUNT(*)
      FROM A,B,C,D
      WHERE A.1=B.1 AND
            B.2=C.2 AND
            C.3=D.3
      GROUP BY key(A), B.1, D.3) T1
WHERE E.1=F.1 AND E.2=T1.A.1
GROUP BY key(F), E.3
```

(a) Original Query.



(b) Operator tree representation.



GB_1 = GB({B.1, D.3}, {B, C, D})
GB_2 = GB({E.3}, {A, GB_1, E})

(c) Canonical Representation.

Fig. 6. Canonical representation of joins and group-by clauses.

By 2 and 6 above, the selectivity of the group-by is the same independent of placement of additional joins. Join selectivities are also unaffected by additional group-by clauses, since:

7) $Sel(A \bowtie B) = \min(dv_A, dv_B) \cdot D_A \cdot D_B/|A| \cdot |B| = \min(dv_A, dv_B)/(dv_A \cdot dv_B) = 1/\max(dv_A, dv_B)$.
8) $Sel(A \bowtie \text{GB}(b', B)) = |A \bowtie \text{GB}(b', B)|/(|A| \cdot |\text{GB}(b', B)|) =_{\text{(by 4 and 1)}} \min(dv_A, dv_B) \cdot D_A \cdot dv'_B/(|A| \cdot dv_B \cdot dv'_B) = \min(dv_A, dv_B)/(dv_A \cdot dv_B) = 1/\max(dv_A, dv_B)$.

This means that joins and group-by clauses, considered together, are not that different from joins alone in terms of having a single selectivity value that is independent of the position of the operator in the final tree. The main difference is that group-by clauses cannot be placed arbitrarily in an execution plan, but can only be placed on top of a plan that contains all elements in its input signature.

Reordering Joins and Group-by Clauses

To summarize the previous discussion, we showed (i) how to extend canonical representations of queries so that they also handle group-by clauses (which allows us to understand when a group-by clause can be "merged" with an existing sub-tree), and (ii) how to assign a selectivity value to a group-by clause independent on the position in the execution tree. An interesting consequence of these properties is that group-by clauses can now be naturally incorporated into the *Enumerate-Rank-Merge* approach. We now describe the extensions to the approach in Section III by explaining how each component in the main algorithm of Figure 1 needs to be extended.

Initial pool of plans *P (line 1):* In addition to one `Scan` operator for each table in the query, we include one *virtual group-by* node for each canonical group-by in the query. These virtual group-by nodes are not executable leaf-nodes (as `Scan` nodes are), but instead only make sense when they are put on top of a valid execution sub-plan.

Enumerate *(line 3):* We disallow pairing two virtual group-by nodes together (as explained before, it does not result in a well-formed execution plan). Additionally, we only consider pairing a virtual group-by G with a non virtual group-by plan P_2 if this would results in a valid placement of the group-by as per definition of canonical representation (i.e., if the tables and group-by clauses in P_2 include those in the signature of G). All other pairings of non-virtual group-by nodes are handled as before (note that these input plans can have a group-by operator as the root node, but the pairing would result, as before, in a join or cross product).

Ranking *(line 4):* The ranking functions introduced in Section III-B are easily extended to deal with group-by clauses. For instance, the value *minSize*(G, P_1) is the output size of applying the group-by operator G on top of P_1. This value can easily be computed based on the cardinality of P_1 and the selectivity of G, which, as we saw earlier, does not depend on the operator placement in the tree.

Merging *(line 5):* The naïve merging operation is trivially extended so that when combining a virtual group-by G with a non-virtual plan P, the generated plan consists of the group-by G (augmenting the grouping columns appropriately) on top of P. *Switch-HJ* and *Switch-Idx* only operate on the root of the tree, so they are not applicable when one of the plans in the pair is a virtual group-by operator. Push and Pull operations require a bit more care, but are also simple to extend. The main challenge is to prevent invalid trees from being generated through merges. Consider the *pull* operation of a table T that is in the input signature of some intermediate group-by. In this case, simply pulling the table to the root of the tree would generate an invalid plan with a group-by that does not operate on its input signature. Instead, when the pulled table appears in the input signature of an intermediate group-by G, we pull, along with the table, any dependent group-by operator as well to the top of the tree. Similarly, consider the push operation when applied to a virtual group-by node G. In addition to generating the group-by at the root of the new tree, we try to push the group-by down whenever possible, and pick the best alternative. At a high level, the main extensions require us to re-evaluate the ranking function of alternative plans, and pick the one with the best ranking as the resulting merging plan.

Additional Details

For simplicity, we have not discussed a special case when handling join predicates defined on aggregate columns of group-by clauses, as illustrated in the example below:

```
SELECT *
FROM T1, (SELECT SUM(x) AS SX FROM TX) T2
WHERE T1.X = T2.SX
```

We cannot join $T1$ and $T2$ until after doing the aggregation on $T2$ (otherwise, the join is not well-defined). In general, this situation results in a dependency graph between joins and

group-by nodes, where the application of some operator is blocked until other operators unlock it. Earlier in this section, we discussed the case of group-by operators being blocked by their input signatures. The same ideas and solutions can be applied in this case, where group-by clauses block joins. A suitable extension of the *enumerate* step in line 3 of Figure 1 is required, but we omit such details due to space constraints.

B. Semi-join operators

Although semi-joins ($\ltimes$) are not directly specified in SQL queries, they are very useful relational operators because (i) semi-joins can be used to handle nested sub-queries with optional correlation, (ii) there exist efficient set- and tuple-oriented implementations of semi-joins, and (iii) algebraically they can be expressed as group-by clauses and joins, which enables additional optimization alternatives. To make the last item concrete, the traditional algebraic equivalence that relates semi-joins with joins and group-by clauses is as follows:

$$A \ltimes B = \text{GB}(key(A), A \bowtie B)$$

We use this equivalence to produce a canonical representation of a query that contains joins, group-by clauses and semi-joins. Suppose that the semi-join predicate in the equality above is $A \ltimes_{a=b} B$. This equality results in the functional dependency ($key(A) \rightarrow b$) and thus in $\text{GB}(\{key(A), b\}, A \bowtie B)$, which can then be rewritten by pushing the group-by clause down the join as in $A \bowtie_{a=b} (GB(b, B))$. Now consider a slightly different example without an equi-join, namely $A \ltimes_{a<b} B$. This is equivalent to the expression $\text{GB}(key(A), A \bowtie_{a<b} B)$ but we cannot push the group-by down the join since column b in the join predicate is not a grouping column. As a more complex example, consider $A \ltimes_{a=b} (B \bowtie_{b2=c2} C)$. In this case, the transformation results in $\text{GB}(key(A), A \bowtie B \bowtie C)$, which, by a similar reasoning as in the first case above, can be pushed down through the first join into $A \bowtie_{a=b} GB(b, B \bowtie_{b2=c2} C)$.

In general, to obtain a canonical representation for a subplan like $R \ltimes T$ we replace the $\ltimes$ with a $\bowtie$ and add a group-by with key(R) as the grouping columns. We then proceed as before, by pushing the group-by as much as possible and obtaining the join graph and canonical group-by clauses. As a final example consider expression $A \ltimes_{a=key(B)} (B \bowtie_{b=c} C)$. We translate it to $\text{GB}(key(A), A \bowtie B \bowtie C)$, but $key(A) \rightarrow a$, which is equal to $key(B)$, and $key(B) \rightarrow b$ which is equal to c, so this is actually $\text{GB}(\{key(A), key(B), c\}, A \bowtie B \bowtie C)$, and now we can push the group-by below joins to result in $A \bowtie B \bowtie GB(c, C)$. The canonical representation contains the join graph $A \bowtie B \bowtie C$ and the canonical group-by clause $\text{GB}(c, C)$.

Integrating Semi-joins

Since we transform semi-joins into joins and group-by clauses, our algorithms can handle semi-joins with no modifications. While this approach is correct, it has a drawback: group-by clauses obtained from semi-joins have sometimes special properties. For instance, often there is a single table in the right side of the semi-join, and if there are indexes, we can use efficient index-based execution plans without actually performing the group-by and join. Below we outline some suggestions to address this issue.

Leveraging that a semi-join results into a join plus a group-by, the ranking function can have certain limited look-ahead capabilities. In general, if there are no aggregate functions defined on a group-by clause over a join, we can attempt to apply the join *and* the corresponding group-by together using an index-based strategy when ranking the pair that contains the join. Of course, merging should be made aware of the look-ahead mechanism and implement the optimized plans whenever possible. The main challenge in this approach is that the merge operators (e.g., Pull and Push) need to be aware of new physical operators that we might introduce in specialized plans. We believe that this is not a straightforward task, and we consider this form of tighter integration of semi-joins with our *Enumerate-Rank-Merge* framework as part of future work.

C. Other operators

In addition to joins, semi-joins and group-by clauses, there are other operators in SQL that need to be handled. In this section we briefly comment on how we can approach such operators[4]. In general, these operators are handled independently of the join/semi-join/group-by components, either using pre- or post-processing, as explained next.

Anti-Joins: As far as we know, we cannot freely reorder left and right children of anti-joins as we did for joins and semi-joins. Conceptually, $R \triangleright_{a=b} S$ is evaluated by considering each row in R and processing it according to S (in the example, it would return the tuple from R if there is no tuple in S that satisfies predicate a=b). This procedure can be seen as evaluating an expensive predicate for each row of R. In fact, the cost per tuple in R depends on S and, according to cardinality estimation, only a fraction of tuples from R would pass the anti-join. To deal with queries that include anti-joins, we first obtain a heuristic execution plan for the query that omits the anti-join. We then identify the most specific point in the query plan in which the anti-join can be evaluated, and use the heuristic techniques in [20], [21] to obtain the most appropriate place to position the anti-join in the tree.

Outer-Joins: We pre-process a query with outer-joins (denoted as $\rightarrow$) by delaying them as much as possible (and therefore obtaining larger join components). We do this using the algebraic equivalence $R \bowtie (S \rightarrow T) = (R \bowtie S) \rightarrow T$ and pull outer-joins above joins as much as possible *before* applying the *ERM* approach to the join component. A full integration of outer-join reordering is part of future work.

Other operators: We do not specifically handle other operators (such as unions or full outer-joins), and leave them as in the original query.

D. Putting it All Together

Out technique to heuristically optimize queries is as follows:

[4]An alternative, more systematic approach that adapts work on anti-join and outer-join reordering (e.g., [8], [19]) is part of future work.

1) Analyze the query and transform it into a set of join/semi-join/group-by canonical components (with associated anti-join expensive predicates), and connected among each other via (delayed) outer-joins, unions, and any other un-handled operators.
2) Apply *ERM* to each component.
3) Greedily place anti-joins in each component.
4) Use default implementations for outer-joins, unions, and other un-handled operators.

V. Experimental Evaluation

We now report an experimental evaluation of the techniques described in this paper. We implemented a C# prototype that enables us to compare different optimization variants. Each experiment is specified by three components: a query workload, an index configuration, and a set of optimizers to evaluate. We next detail each component in detail.

A. Query Workloads

A query is specified by a set of tables (with selectivity values given by single-table predicates), a join graph with associated selectivity values, and a set of group-by clauses.

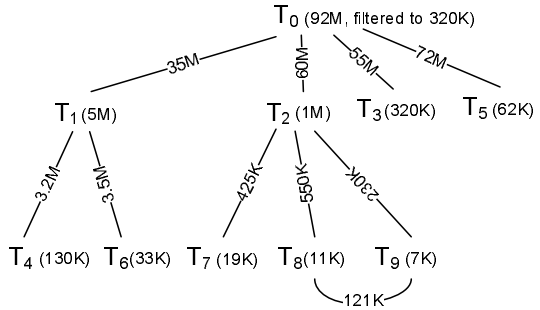
Tables: We generate table cardinalities by following Zipfian distributions. The parameters of the table generation routine are number of tables NT and the Zipfian parameter Z. A value $Z = 0$ generates tables with the same cardinality, while a value $Z = 5$ generates 10 tables with the following cardinalities (for a total 100M tuples): {96440632, 3013770, 396875, 94180, 30861, 12403, 5738, 2943, 1633, 964} Alternatively, we used two additional data generation routines: *random* (which generates tables with random cardinality) and *stratified* (which was previously proposed in the literature [13] and generates tables of size 10-100 with 15% probability, size 100-1K with 30% probability, size 1K-10K with 25% probability, and size 10K-100K with 30% probability). Finally, a boolean parameter, *sorted*, specifies whether the tables are sorted by cardinality or are instead shuffled during query construction (this is important due to join and filter generation, explained next).

Join Graphs: These are generated using the following parameters:

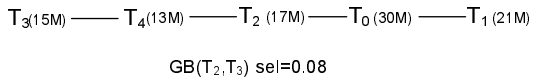
- J: Number of joins. The first $NT-1$ joins form a spanning tree, and remaining joins introduce cycles.
- $0 \le JL \le JR \le 1$, which control the graph topology. The *i-th* join (for $i < NT$) is done between the *i-th* table (in the order produced during table generation) and a random table between JL*(i-1) and JR*(i-1). This procedure generalizes previous approaches in the literature to generate interesting join topologies. For instance, for JL=JR=0 we obtain star topologies, for JL=JR=1 we obtain chain topologies, and for other values, such as JL=0 and JR=0.3 we obtain snowflake-like topologies. After $NT - 1$ joins, we randomly join pairs of tables generating cycles.
- JoinType, which is a categorical variable which determines the cardinality of the join. It could be *random* (which assigns a random selectivity value to the join), *Min/Max/MinMax* (which assigns the cardinality of the smallest/largest table, or a number in between), or *N-M* (which models n-m joins by picking a number of distinct values in each table and having the join selectivity be 1/max(dv1, dv2) as in [13]). We can specify a different distribution for the first $NT - 1$ joins and the rest.

Table filters: So far each table is joined without applying any filter on it, which is fine if no indexes are present (since we always need to read the full table). When indexes are present, tables with filters can result in big differences. We specify table filters by a pair of values ($0 \ge lo \ge hi \ge 1$) specifying the selectivity of the filter, and a choice of tables to filter, which could be either a random fraction of the tables, the value *First* (which filters the fact table in a snowflake topology), or *Leaves* (which filters dimension tables in snowflake topologies).

Group-by clauses: Group-by clauses are generated by parameters G (the number of group-by clauses) and T (the number of random tables that are required in the group-by input signature).



(a) Snowflake topology.



(b) Chain topology.

Fig. 7. Synthetically generated queries.

An Example

The generation procedure described above is rather flexible, and many combinations are possible. We can produce star, linear, and snowflake topologies respecting foreign key constraints, as well as cycles simulating M-N joins. Figure 7 shows examples generated with this approach. We generated the snowflake query in Figure 7(a) using $NT = 10$ tables with $Z = 4$ tuple distribution (sorted by cardinality), a join graph with 10 joins (the first 9 using $JL = 0$, $JR = 0.5$ and *MinMax* selectivity values, and the last one introducing a cycle with *N-M* selectivity), and filter predicates on the fact table. Figure 7(b) shows a chain query generated with $NT = 5$ tables with $Z = 0.5$ tuple distribution (shuffled tables), a join graph with 4 joins using $JL = JR = 1$ and *Max* selectivity values, and a group-by clause over two tables.

B. Index Configurations

A configuration is defined a set of indexes. Each index consists of a leading column and a boolean value which specifies whether the index is covering during an index lookup. A configuration is generated by two parameters: *ProbIndex* (which gives the probability that an join column or single table predicate has a backing index) and *ProbCover* (which gives the probability of an index being covering).

C. Optimizers

To simplify the presentation, we encode an optimizer by a three-part name *E-R-M*, where:

- *E* identifies the search space, which can be *L* (linear trees with no cross products) or *B* (bushy trees with cross products).
- *R* identifies the ranking function and can be *Sel* (rank by *minSel*), *Size* (rank by *minSize*), and *ST* (rank by *smallestTable*[5]).
- *M* identifies the merging approach. It could be empty if only the trivial merge is used, + if *Switch-HJ* and *Switch-Idx* are used, and *PP* if additionally *Pull/Push* is used.

Using this notation, our experiments use subsets of the following optimizers: *LSel, LSel+, LST, LST+, BSel, BSel+, BSize, BSize+, BSizePP*. We additionally implemented the following exhaustive optimizers:

- *LEx*: Exhaustive optimizer that considers linear trees and no cross products.
- *BEx*: Exhaustive optimizer that considers bushy trees and cross products.
- *LIKKBZ, LIKKBZ+*: Optimizer that returns optimal linear trees for acyclic queries and no indexes, augmented with minimum spanning trees for cyclic queries [12].

D. Metrics

For a given workload, index configuration, and set of optimizers, we proceed as follows. We optimize each query by all optimizers. We cost each resulting execution plan using Microsoft SQL Server's cost model. We then divide the cost of each plan by the cost of the best plan found by any optimizer in our set. The value that we assign to a given optimizer is this ratio, which goes from one (optimal) upwards, and quantifies how much worse the solution is compared to the optimal one. After repeating this procedure for all queries in a workload, we report the minimum, maximum, average, median, and the 95%-quantile of the ratio for each optimizer. These quality numbers are precise if an exhaustive optimizer is in the mix, since the optimal execution plan would be found. While we can evaluate exhaustively for small number of tables (<15), it is not possible to do so for a large number of tables. In that case we do not know what the optimal plan is, but we always include *LIKKBZ* in the set of optimizers (which is guaranteed to produce optimal linear trees for acyclic queries, and thus is a baseline).

[5]This is another heuristic found in the literature [16], where at each iteration we choose that smallest table that can be joined.

E. Summary of Results

The sections below show a sample of experiments performed on a 3GHz dual core machine. We focused on general trends and insights, and omit several additional variants that we tried due to space constraints.

Execution times

We first report execution times for the techniques discussed in this paper. Note that our prototype is not optimized for speed (instead, we tried to reuse as much code as possible to implement all variants, which results in performance limitations). Therefore, performance numbers should be interpreted as trends rather than in absolute terms. Figure 8 shows elapsed times for all techniques (note the logarithmic scale). All heuristic implementations show the same trend and finish in less than 200 milliseconds for 60 tables, and in tens of milliseconds for up to 30 tables (query graphs were generated randomly in this experiment, as we just wanted to measure average performance). In contrast, exhaustive techniques quickly become too slow over 10 seconds for as little as 13 tables. Also note that exhaustively exploring bushy trees can be an order of magnitude slower than just exploring linear trees. The results in Figure 8 do not consider indexes. We ran the experiment again but adding 50% of relevant indexes to the physical design, and the results (while slower than the ones reported in the figure) showed the same trends.

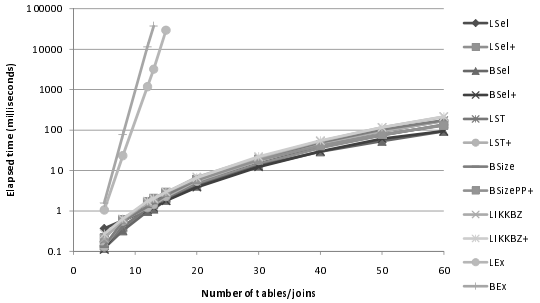


Fig. 8. Performance of different optimization alternatives.

Quality results

We first generated a workload with $NT = 10$ tables with $Z = 4$ cardinalities (not sorted by cardinality), and a chain join topology ($JL = JR = 1$) where each join has a cardinality given by *MinMax*. We did not consider any index. Figure 9 shows the quality metrics for all optimizers (ordered by average ratio). We make the following observations:

1) *BEx* is (obviously) the best strategy in all cases.
2) With the exception of *BSel*, all bushy strategies are better than linear strategies. This is a direct consequence of the join topology, which is very restrictive and does not give flexibility to recover from large intermediate results.
3) *LEx* is on average 4.2 times (up to 35.2 times) worse than *BEx*, which shows that bushy trees can be substantially better than optimal linear trees. It is interesting to note that most bushy heuristics result in better plans than that of the exhaustive linear tree.

4) *LIKKBZ+* has almost the same quality as *LEx* (the slight difference comes from small variations in the cost model used by IKKBZ [12]).
5) Simple merging variants (+) generally pay off, resulting in better quality than the corresponding technique with naïve merging..
6) Our technique *BSizePP* performs on average 6% worse than the optimal bushy strategy (and 32% worse in 95% of cases). The advanced merging operations *Push* and *Pull* did not additionally improve quality over *BSize+*.

	Avg	Min	Median	95%	Max
BEx	1.000	1.000	1.000	1.000	1.000
BSizePP+	1.060	1.000	1.001	1.328	1.880
BSize+	1.060	1.000	1.002	1.328	1.880
BSize	1.367	1.000	1.131	2.462	4.096
BSel+	3.764	1.006	1.509	15.184	69.812
LEx	4.288	1.000	1.533	17.345	35.278
LIKKBZ	4.295	1.000	1.533	17.345	35.278
LIKKBZ+	4.295	1.000	1.533	17.345	35.278
BSel	11.241	1.033	3.156	51.432	234.573
LSel+	12.074	1.005	4.169	43.504	129.153
LST+	12.331	1.001	3.797	50.236	193.288
LST	13.061	1.037	4.779	50.371	193.604
LSel	45.256	1.012	12.420	177.877	536.407

Fig. 9. 10-table chain queries with no indexes.

We repeated the experiment increasing the number of tables from 10 to 50. In this case, we could not obtain results for *LEx* or *BEx*. However, *LIKKBZ* (which for acyclic queries and no indexes is almost the same as *LEx*) was included in the set of optimizers. The results are shown in Figure 10. We see that results are amplified, and *LIKKBZ+* (which would be almost the same as an exhaustive optimizer considering linear trees) is, on average, 62 times worse than *BSizePP* (and up to 477 times worse overall). We also see that *BSizePP* consistently returns the best quality among the heuristics.

	Avg	Min	Median	95%	Max
BSizePP	1.000	1.000	1.000	1.000	1.000
BSize+	1.004	1.000	1.000	1.003	1.320
LIKKBZ+	62.615	1.000	20.991	279.523	477.828
LST+	203.410	1.000	73.013	1056.145	2596.727
LSel+	218.113	1.000	74.098	814.333	4295.878

Fig. 10. 50-table chain queries with no indexes.

Indexes

We repeated the previous experiments with three variations. First, we added covering indexes for 25% of all join predicates. Second, we added single-table predicates with 1% to 10% selectivity to half the tables in the query. Finally, we added 2 additional join predicates (resulting in join cycles). The results of this experiment, with $NT = 10$ tables, is shown in Figure 11. In this case, we observe:

1) *BEx* is optimal, and *LEx* is a close second. This shows that the presence of indexes changes the landscape of optimal plans in subtle ways.
2) In general, non-trivial merges (+) result in better quality than when using naïve merges due to indexes.
3) Our proposed technique *BSizePP* results in 25% average degradation compared to the optimal exhaustive optimizer, and is 2.7 times worse for 95% of the queries.

	Avg	Min	Median	95%	Max
BEx	1.000	1.000	1.000	1.000	1.000
LEx	1.019	1.000	1.000	1.061	1.960
BSizePP	1.258	1.000	1.005	2.779	6.968
BSize+	5.083	1.000	1.034	31.531	75.319
LIKKBZ+	5.647	1.000	1.011	31.349	89.143
LSel+	32.317	1.000	1.325	122.621	1689.996
LIKKBZ	34.782	1.000	1.159	148.631	928.081
LSel	76.965	1.000	3.613	262.510	3416.043
BSize	91.763	1.000	1.358	421.005	2640.823
BSel+	107.132	1.002	1.504	122.950	7522.576
LST+	180.787	1.000	1.033	72.599	16854.665
LST	269.542	1.069	3.351	645.925	16859.123
BSel	328.761	1.005	3.256	395.120	24734.621

Fig. 11. 10-table chain queries with 50% indexes and join cycles.

4) Previous techniques proposed in the literature (*LSel*, *LST*, and *BSize* can be hundred times worse (and even thousands in the worst case) than our approach.

As in the previous experiment, we increased the number of tables from 10 to 50. The results are summarized in Figure 12. The two main observations from this figure is (i) *BSizePP* consistently ranks the best among polynomial heuristics (including those that return optimal plans for acyclic join trees), and (ii) the quality of the other heuristics is not consistent across workloads (contrast *LST+* and *BSize+* in Figures 10 and 12). As additional supporting evidence for these two claims, Figure 13 shows the results of changing the join topology to snowflake ($JL = 0$, $JR = 0.3$) and introducing filter predicates (with selectivity between 1% and 50%) to all dimension tables. In this case, *BSizePP* is still the overall winner, while *LST* performs really poorly for the bottom 5-percentile (note that *LST* was the second-best in Figure 12).

	Avg	Min	Median	95%	Max
BSizePP	1.336	1.000	1.000	2.452	16.551
LST+	1.757	1.000	1.001	2.571	56.198
BSize+	7.275	1.000	1.030	20.250	287.116
LIKKBZ+	16.600	1.000	1.011	73.224	504.403
LSel+	3477149.692	1.000	1.853	11348.939	347519317.250

Fig. 12. 50-table chain queries with 50% indexes.

	Avg	Min	Median	95%	Max
BSizePP+	1.011	1.000	1.000	1.042	1.785
BSize+	1.913	1.000	1.071	6.622	24.941
LIKKBZ+	8.571	1.000	1.030	18.617	570.039
LSel+	53993.686	1.001	2.131	6481.553	4954352.880
LST+	3.6E18	1.156	70.655	9.6E13	3.6E20

Fig. 13. 50-table snowflake queries with 25% indexes.

Group-by Clauses

To evaluate group-by clauses we generated $NT = 10$ table queries ($Z = 4$, not sorted by cardinality) with a join cycle ($JL = JR = 1$ for the first 9 joins, and the last join closing the loop). Additionally, we randomly chose a connected component of size 3, and use it as the group-by clause with a selectivity value between 5% and 95%. Figure 14 shows the result of this experiment comparing *LEx*, *BEx*, *BSizePP*, and two new optimizers: *LExNoGB* and *BExNoGB*. These last two versions do not attempt to reorder group-by clauses. Instead, they perform exhaustive join reordering of the connected join

components (separated by group-by clauses) in the query. This represents the best possible behavior of a heuristic that does not consider group-by clauses. *BSizePP* results in execution plans that are 15% worse than the optimal on average (up to 6 times worse in the worst case), which coincidentally is almost the same performance that the exhaustive *LEx*. The alternatives that do not handle group-by clauses are not robust. While for 50% of the queries they perform very well (6% and 33% degradation with respect to the optimal plan), there are situations in the bottom 5-percentile where the techniques are tens of thousands of times worse than the optimal. The reason for this behavior is that in some situations, the 3-way join that covers the group-by tables results in a very big intermediate result. By pulling the group-by above other joins, and then reordering a larger join sub-graph, we can significantly reduce the cardinality of intermediate results. This can be seen as a group-by clause artificially restricting the search space of join orders to be forced to go through a specific intermediate result (the subset of tables in the group-by clause), which in general can be a very bad choice. This behavior for *LExNoGB* and *BExNoGB* is common for the cycle join topology that we chose, but happens in a much lest extreme way for other workloads (we omit these results due to space constraints).

	Avg	Min	Median	95%	Max
BEx	1.000	1.000	1.000	1.000	1.000
LEx	1.147	1.000	1.005	2.083	5.893
BSizePP	1.155	1.000	1.004	1.733	6.021
BExNoGB	17282.120	1.000	1.064	16875.686	1408364.416
LExNoGB	18290.878	1.000	1.332	17793.046	1415005.930

Fig. 14. 10-table join cycle with a group-by clause.

Real Data

We also experimented on real data and workloads. As an example, Figure 15 shows the estimated cost of different techniques for a data warehouse query that joins 15 tables together using a shallow snowflake schema, and two different index configurations (C_{lo} and C_{hi} correspond to lightly and heavily indexed configurations, respectively). We see that *BSizePP* is very close to the optimal plans returned by *BEx* and *LEx* in both cases, and improves over the basic *BSize+* that does not consider *Pull* and *Push* operations. We also see that other heuristics are not robust (e.g., both *LSel+* and *LST+* range from close to *BSizePP* to being the worst alternative for some index configuration.

	C_{lo} (opt. time)	C_{hi} (opt. time)
BEx	7.86	1.04
LEx	7.86	1.09
BSizePP	7.89	1.14
BSize+	7.91	3.08
LIKKBZ+	7.90	3.34
LSel+	7.89	3.68
LST+	908.72	1.58

Fig. 15. 15-table snowflake for using real data.

VI. Conclusions

Motivated by new requirements for query processing techniques, in this paper we introduced polynomial-time heuristics to optimize SQL queries. Our techniques generalize previous approaches in the literature in a number of aspects. First, we introduce the notion of *merging*, which can be seen as a corrective action that helps recovering from early mistakes in the greedy techniques. Second, we extend our techniques to handle group-by clauses, semi-joins, and the availability of indexes. Finally, we designed a realistic workload generator and validated our hypothesis on both synthetic and real data.

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