Platform-independent Robust Query Processing

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***Abstract*—To address the classical selectivity estimation problem in databases, a radically different approach called `PlanBouquet` was recently proposed in [3], wherein the estimation process is completely abandoned and replaced with a calibrated discovery mechanism. The beneficial outcome of this new construction is that, for the first time, provable guarantees are obtained on worst-case performance, thereby facilitating robust query processing.**

The `PlanBouquet` formulation suffers, however, from a systemic drawback – the performance bound is a function of not only the query, but also the optimizer's behavioral profile over the underlying database platform. As a result, there are adverse consequences: (i) the bound value becomes highly variable, depending on the specifics of the current operating environment, and (ii) it becomes infeasible to compute the value without substantial investments in preprocessing overheads.

In this paper, we present `SpillBound`, a new query processing algorithm that retains the core strength of the `PlanBouquet` discovery process, but reduces the bound dependency to only the query. Specifically, `SpillBound` delivers a worst-case multiplicative bound of $D^2 + 3D$, where D is simply the number of error-prone predicates in the user query. Consequently, the bound value becomes independent of the optimizer and the database platform, and the guarantee can be issued just by inspecting the query, without incurring any additional computational effort.

We go on to prove that `SpillBound` is within an $O(D)$ factor of the *best possible* deterministic selectivity discovery algorithm in its class. Further, a detailed empirical evaluation over the standard TPC-H and TPC-DS benchmarks indicates that `SpillBound` provides markedly superior worst-case performance as compared to `PlanBouquet` in practice. Therefore, in an overall sense, `SpillBound` offers a substantive step forward in the quest for robust query processing.

I. Introduction

A long-standing problem plaguing database systems is that the predicate selectivity estimates used for optimizing declarative SQL queries are often significantly in error [11], [10]. This results in highly sub-optimal choices of execution plans, and corresponding blowups in query response times. The reasons for such substantial deviations are well documented [16], and include outdated statistics, coarse summaries, attribute-value independence (AVI) assumptions, complex user-defined predicates, and error propagations in the query execution tree. It is therefore of immediate practical relevance to design query processing techniques that limit the deleterious impact of these errors, and thereby provide robust query processing.

We use the notion of Maximum Sub-Optimality (**MSO**), introduced in [3], as a measure of the robustness provided by a query processing technique to errors in selectivity estimation. Specifically, given a query, the MSO of the processing algorithm is the worst-case ratio, over the entire selectivity space, of its execution cost with respect to the optimal cost incurred by an oracular system that magically knows the correct selectivities. It has been empirically determined that MSOs can reach very large values on current database engines [3] – for instance, with Query 19 of the TPC-DS benchmark, it goes as high as a million![1] More importantly, worrisomely large sub-optimalities are *not rare* – for the same Q19, the sub-optimalities for as many as 40% of the locations in the selectivity space were higher than 1000.

As explained in [3], most of the previous approaches to robust query processing (e.g. [11], [1], [13], [8]), including the influential POP and Rio frameworks, are based on heuristics that are not amenable to bounded guarantees on the MSO measure. A notable exception to this trend is the `PlanBouquet` algorithm, recently proposed in [3], which provides, for the first time, a provable MSO guarantee. Here, the selectivities are not estimated, but instead, systematically *discovered* at run-time through a calibrated sequence of cost-limited executions from a carefully chosen set of plans, called the "plan bouquet". The search space for the bouquet plans is the *Parametric Optimal Set of Plans* (POSP) [6] over the selectivity space. The `PlanBouquet` technique guarantees $MSO \leq 4 * |PlanBouquet|$. [2]

A. `PlanBouquet`

We describe the working of `PlanBouquet` with the help of the example query EQ shown in Figure 1, which enumerates orders for cheap parts costing less than 1000. To process this query, current database engines typically estimate three selectivities, corresponding to the two join predicates ($part \bowtie lineitem$) and ($lineitem \bowtie orders$), and the filter predicate ($p\_retailprice < 1000$). While it is conceivable that the filter selectivity may be estimated reliably, it is often difficult to ensure similarly accurate estimates for the join predicates. We refer to such predicates as error-prone predicates, or epp in short (shown bold-faced in Figure 1).

Example Execution: Given the above query, `PlanBouquet` constructs a two-dimensional space corresponding to the epps, covering their entire selectivity range ($[0,1] * [0,1]$), as shown in Figure 2(a).[3] A location (x, y) in the 2D space corresponds to a scenario in which the selectivities of ($part \bowtie lineitem$) and ($lineitem \bowtie orders$)

[1] Assuming that estimation errors can range over the entire selectivity space.
[2] A more precise bound is given later in this section.
[3] Please view the diagrams from a *color copy* to ensure clarity of contents.

select * from lineitem, orders, part where
p_partkey = l_partkey and **o_orderkey = l_orderkey**
and p_retailprice $<$ 1000

Fig. 1: Example Query (EQ)

are x and y, respectively. Further, associated with each location in the space are the optimal plan for the location and its execution cost. On this selectivity space, a series of *iso-cost* contours, $\mathcal{IC}_1$ through $\mathcal{IC}_m$, are drawn – each iso-cost contour $\mathcal{IC}_i$ has an associated cost $\texttt{CC}_\texttt{i}$, and represents the connected selectivity curve along which the cost of the optimal plan(s), as determined by the optimizer, is equal to $\texttt{CC}_\texttt{i}$. Further, the contours are selected such that the cost of the first contour $\mathcal{IC}_1$ corresponds to the minimum query cost C at the origin of the space, and in the following intermediate contours, the cost of each contour is *double* that of the previous contour. That is, $\texttt{CC}_\texttt{i} = 2^{(i-1)}C$ for $1 < i < m$. The last contour's cost, $\texttt{CC}_\texttt{m}$, is capped to the maximum query execution cost at the top-right corner of the space.

As a case in point, in Figure 2(a), there are five hyperbolic-shaped contours, $\mathcal{IC}_1$ through $\mathcal{IC}_5$, with their costs ranging from C to $16C$. Each contour has a set of optimal plans covering disjoint segments of the contour – for instance, contour $\mathcal{IC}_2$ is covered by plans P_2, P_3 and P_4.

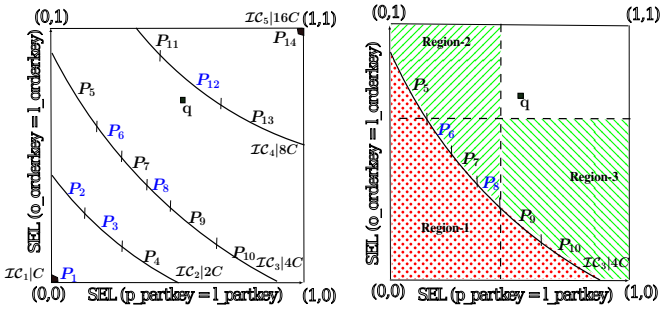
The *union* of the optimal plans appearing on all the contours constitutes the "plan bouquet" – so, in Figure 2(a), plans P_1 through P_{14} form the bouquet. Given this set, the `PlanBouquet` algorithm operates as follows: Starting with the cheapest contour $\mathcal{IC}_1$, the plans on each contour are sequentially executed *with a time limit equal to the contour's budget*.[4] If a plan fully completes its execution within the assigned time limit, then the results are returned to the user, and the algorithm finishes. Otherwise, as soon as the time limit of the ongoing execution expires, the plan is forcibly terminated and the partially computed results (if any) are discarded. It then moves on to the next plan in the contour and starts all over again. In the event that the entire set of plans in a contour have been tried out without any reaching completion, it *jumps* to the next contour and the cycle repeats.

The basic idea underlying `PlanBouquet` is that it can be shown, under certain mild assumptions, that the first time the (unknown) query location falls within the *hypograph* of a contour, the execution of some plan on the contour is guaranteed to complete the query within the assigned budget. [5] By hypograph we mean the search region *below* the contour curve (after extending, if need be, the corner points of the contour to meet the axes of the search space). A pictorial view is shown in Figure 2(b), which focuses on contour $\mathcal{IC}_3$ – here, the hypograph of $\mathcal{IC}_3$ is the Region-1 marked with red dots.

Now consider the case where the query is located at q, in the intermediate region between contours $\mathcal{IC}_3$ and $\mathcal{IC}_4$, as shown in Figure 2(a). To process this query, `PlanBouquet`

[4]We assume a *perfect* cost model, an issue discussed later in this section.

[5]All points in the ESS fall within the hypograph of at least one contour, and the algorithm is therefore guaranteed to complete the query.



(a) Selectivity Discovery (b) Pruned Regions - $\mathcal{IC}_3$

Fig. 2: `PlanBouquet` and `SpillBound`

would invoke the following budgeted execution sequence:

$$P_1|C, P_2|2C, P_3|2C, P_4|2C, P_5|4C, \ldots, P_{10}|4C, P_{11}|8C, P_{12}|8C$$

with the execution of the final P_{12} plan completing the query.

Performance Guarantees: By sequencing the plan executions and their time limits in the calibrated manner described above, the overheads entailed by this "trial-and-error" exercise can be *bounded*, *irrespective of the query location in the space*. In particular, it is shown that $MSO \leq 4*\rho$, where ρ is the plan cardinality on the "maximum density" contour. The density of a contour refers to the *number* of plans present on it – for instance, in Figure 2(a), the maximum density contour is $\mathcal{IC}_3$ which features 6 plans.

Limitations: The `PlanBouquet` formulation, while breaking new ground, suffers from a systemic drawback – the specific value of ρ, and therefore the bound, is a function of not only the query, but also the optimizer's behavioral profile over the underlying database platform (including data contents, physical schema, hardware configuration, etc.). As a result, there are adverse consequences: (i) The bound value becomes highly variable, depending on the specifics of the current operating environment – for instance, with TPC-DS Query 25, `PlanBouquet`'s MSO guarantee of 24 under PostgreSQL shot up, under an identical computing environment, to 36 for a commercial engine, due to the change in ρ; (ii) It becomes infeasible to compute the value without substantial investments in preprocessing overheads; and (iii) Ensuring a bound that is small enough to be of practical value, is contingent on the heuristic of "anorexic reduction" [5] holding true.

B. SpillBound

The goal of our work is to develop a robust query processing approach that offers an MSO bound which is *solely query-dependent*, irrespective of the underlying database platform. That is, we desire a "structural bound" instead of a "behavioral bound". In this paper, we present a new query processing algorithm, called `SpillBound`, that materially achieves this objective. Specifically, it delivers an MSO bound that is only a function of D, the *number* of predicates in the query that are prone to selectivity estimation errors. Moreover, the dependency is in the form of a low-order polynomial, with MSO expressed as $(D^2 + 3D)$. Consequently, the bound value becomes: (i) independent of the underlying database

platform [6], (ii) known upfront by merely inspecting the query, and not incurring any preprocessing overhead, (iii) indifferent to the anorexic reduction heuristic, and (iv) certifiably low in value for practical values of D.

Example Execution: SpillBound shares the core contour-wise discovery approach of PlanBouquet, but its execution strategy differs markedly. Specifically, it achieves a significant reduction in the cost of the sequence of budgeted executions employed during the selectivity discovery process. For instance, in the example scenario of Figure 2(a), the sequence of budgeted executions correspond to the plans highlighted in blue:

$$P_1|C, P_2|2C, P_3|2C, P_6|4C, P_8|4C, P_{12}|8C$$

with P_{12} again completing the query. Note that the reduced executions result in cost savings of more than 50% over PlanBouquet.

The advantages offered by SpillBound are achieved by the following key properties – Half-space Pruning and Contour Density Independent execution – of the algorithm.

Half-space Pruning: PlanBouquet's *hypograph*-based pruning of the selectivity discovery space is extended to a much stronger *half-space*-based pruning. This is vividly highlighted in Figure 2(b), where the half-space corresponding to Region-2 is pruned by the (budget-limited) execution of P_8, while the half-space corresponding to Region-3 is pruned by the (budget-limited) execution of P_6. Note that Region-2 and Region-3 together subsume the entire Region-1 that is covered by PlanBouquet when it crosses $\mathcal{IC}_3$. Our half-space pruning property is achieved by leveraging the notion of *"spilling"*, whereby operator pipelines are prematurely terminated at chosen locations in the plan tree, in conjunction with run-time monitoring of operator selectivities.

Contour Density Independent Execution: In the example scenario, while advancing through the various contours in the discovery process, SpillBound executes at most *two plans* on each contour. In general, when there are D error-prone predicates in the user query, SpillBound is guaranteed to make a *quantum progress* in its discovery process, based on cost-budgeted execution of at most D carefully chosen plans on the contour. Here, a quantum progress refers to a step in which the algorithm either (a) jumps to the next contour, or (b) fully learns the selectivity of some epp (thus reducing the effective number of epps).

Specifically, in each contour, for each dimension, one plan is chosen to be executed in spill-mode (therefore at most D in the contour). The plan chosen for spill-mode execution is the one that provides the *maximal* guaranteed learning of the selectivity along that dimension. In our example, P_8 and P_6 are the two plans chosen for contour $\mathcal{IC}_3$ along the X and Y dimensions, respectively.

C. Performance Results

A natural question to ask is whether there might exist some alternative selectivity discovery algorithm, based on half-space pruning, that could provide a much better MSO than SpillBound. In this regard, we theoretically show that *no* deterministic technique in this class can provide an MSO less than D. This result establishes that the SpillBound guarantee is no worse than a factor $O(D)$ in comparison to the best possible algorithm in its class.

The bounds delivered by PlanBouquet and SpillBound are, in principle, *uncomparable*, due to the inherently different nature of their parametric dependencies. However, in order to assess whether the platform-independent feature of SpillBound is procured through a deterioration of the numerical bound, we have carried out a detailed experimental evaluation of both the approaches on standard benchmark queries, operating on the PostgreSQL engine. Moreover, we have empirically evaluated the MSO obtained for each query through an exhaustive enumeration of the selectivity space.

Our experiments indicate that for the most part, SpillBound provides similar guarantees to PlanBouquet, and occasionally, much tighter bounds. As a case in point, for TPC-DS Query 91 with 4 error-prone predicates, the MSO bound is 52.8 with PlanBouquet, but comes down to 28 with SpillBound. More pertinently, the *empirical* MSO of SpillBound is significantly better than that of PlanBouquet for *all* the queries. For instance, the empirical MSO for Q91 decreases drastically from PlanBouquet's 34 to just 7 for SpillBound.

Caveats: While arbitrary selectivity estimation errors are permitted in our study, we have assumed the optimizer's *cost model* to be *perfect* – that is, only optimizer costs are used in the evaluations, and not actual run times. While this assumption is certainly not valid in practice, improving the model quality is, in principle, an orthogonal problem to that of cardinality estimation errors. Dealing with imprecise cost models, and other such practical deployment considerations, are discussed in Section VII.

We hasten to also add that SpillBound is *not* a substitute for a conventional query optimizer. Instead, it is intended to complementarily co-exist with the traditional setup, leaving to the user's discretion, the specific approach to employ for a query instance. When small estimation errors are expected, the native optimizer could be sufficient, but if larger errors are anticipated, SpillBound is likely to be the preferred choice.

Organization: The remainder of this paper is organized as follows: In Section II, a precise description of the robust execution problem is provided, along with the associated notations. The building blocks of SpillBound are presented in Section III. The SpillBound algorithm and the proof of its MSO bound are presented in Section IV. The lower bound analysis is carried out in Section V, while the experimental framework and performance results are enumerated in Section VI. Pragmatic deployment aspects are discussed in Section VII, and the related literature is reviewed in Section VIII. Finally, our conclusions are summarized in Section IX.

II. Problem Framework

In this section, we present the key concepts, notations, and the formal problem definition. For ease of presentation, we assume that the error-prone selectivity predicates (epps) for a given user query are known apriori, and defer the issue of identifying these epps to Section VII.

[6]Under the assumption that D remains constant across the platforms.

A. Error-prone Selectivity Space (ESS)

Consider a query with D epps. The set of all epps is denoted by $\texttt{EPP} = \{e_1, \ldots, e_D\}$ where e_j denotes the jth epp. The selectivities of the D epps are mapped to a D-dimensional space, with the selectivity of e_j corresponding to the jth dimension. Since the selectivity of each predicate ranges over $[0, 1]$, a D-dimensional hypercube $[0, 1]^D$ results, henceforth referred to as the *error-prone selectivity space*, or ESS. In practice, an appropriately discretized grid version of $[0, 1]^D$ is considered as the ESS. Note that each location $q \in [0, 1]^D$ in the ESS represents a specific instance where the epps of the user query happen to have selectivities corresponding to q. Accordingly, the selectivity value on the jth dimension is denoted by $q.j$. We call the location at which the selectivity value in each dimension is 1, i.e, $q.j = 1, \forall j$, as the *terminus*.

The notion of a location q_1 *dominating* a location q_2 in the ESS plays a central role in our framework. Formally, given two distinct locations $q_1, q_2 \in \texttt{ESS}$, q_1 dominates q_2, denoted by $q_1 \succeq q_2$, if $q_1.j \geq q_2.j$ for all $j \in 1, \ldots, D$. In an analogous fashion, other relations, such as $\not\succ$, $\preceq$, and $\not\prec$ can be defined to capture relative positions of pairs of locations.

B. Search Space for Robust Query Processing

We assume that the query optimizer can identify the *optimal* query execution plan if the selectivities of all the epps are correctly known.[7] Therefore, given an input query and its epps, the optimal plans for *all* locations in the ESS grid can be identified through repeated invocations of the optimizer with different epp values. The optimal plan for a generic selectivity location $q \in \texttt{ESS}$ is denoted by P_q, and the set of such optimal plans over the complete ESS constitutes the Parametric Optimal Set of Plans (POSP) [6].[8]

We denote the cost of executing an *arbitrary* plan P at a selectivity location $q \in \texttt{ESS}$ by $Cost(P, q)$. Thus, $Cost(P_q, q)$ represents the *optimal* execution cost for the selectivity instance located at q. In this framework, our search space for robust query processing is simply the set of tuples $< q, P_q, Cost(P_q, q) >$ corresponding to all locations $q \in \texttt{ESS}$.

Throughout the paper, we adopt the convention of using q_a to denote the actual selectivities of the user query epps – note that this location is unknown at compile-time, and needs to be explicitly discovered. For traditional optimizers, we use q_e to denote the *estimated* selectivity location based on which the execution plan P_{q_e} is chosen to execute the query. However, this characterization is not applicable to plan switching approaches like PlanBouquet and SpillBound because they explore a *sequence* of locations during their discovery process. So, we denote the deterministic sequence pursued for a query instance corresponding to q_a by $\texttt{Seq}_{q_a}$.

C. Maximum Sub-Optimality (MSO) [3]

We now present the performance metrics proposed in [3] to quantify the robustness of query processing.

A traditional query optimizer will first estimate q_e, and then use P_{q_e} to execute a query which may actually be located at q_a. The sub-optimality of this plan choice, relative to an oracle that magically knows the correct location, and therefore uses the ideal plan P_{q_a}, is defined as:

$$SubOpt(q_e, q_a) = \frac{Cost(P_{q_e}, q_a)}{Cost(P_{q_a}, q_a)} \tag{1}$$

The quantity $SubOpt(q_e, q_a)$ ranges over $[1, \infty)$.

With this characterization of a specific (q_e, q_a) combination, the *maximum* sub-optimality that can potentially arise over the entire ESS is given by

$$MSO = \max_{(q_e, q_a) \in \texttt{ESS}} (SubOpt(q_e, q_a)) \tag{2}$$

The above definition for a traditional optimizer can be generalized to selectivity discovery algorithms like PlanBouquet and SpillBound. Specifically, suppose the discovery algorithm is currently exploring a location $q \in \texttt{Seq}_{q_a}$ – it will choose P_q as the plan and $Cost(P_q, q)$ as the associated budget. Extending this to the whole sequence, the analogue of Equation 1 is defined as follows:

$$SubOpt(\texttt{Seq}_{q_a}, q_a) = \frac{\sum_{q \in \texttt{Seq}_{q_a}} Cost(P_q, q)}{Cost(P_{q_a}, q_a)} \tag{3}$$

leading to

$$MSO = \max_{q_a \in \texttt{ESS}} SubOpt(\texttt{Seq}_{q_a}, q_a) \tag{4}$$

D. Problem Definition

With the above framework, the problem of robust query processing is defined as follows:

For a given input query Q with its EPP, and the search space consisting of tuples $< q, P_q, Cost(P_q, q) >$ for all $q \in$ ESS, develop a query processing approach that minimizes the MSO guarantee.

As in [3], the primary assumptions made in this paper that allow for systematic construction and exploration of the ESS are those of *plan cost monotonicity* (PCM) and *selectivity independence* (SI). PCM may be stated as: For any two locations $q_b, q_c \in \texttt{ESS}$, and for any plan P,

$$q_b \succ q_c \Rightarrow Cost(P, q_b) > Cost(P, q_c) \tag{5}$$

That is, it encodes the intuitive notion that when more data is processed by a query, signified by the larger selectivities for the predicates, the cost of the query processing also increases. On the other hand, SI assumes that the selectivities of the epps are all independent – while this is a common assumption in much of the query optimization literature, it often does not hold in practice. In our future work, we intend to look into extending SpillBound to handle the more general case of dependent selectivities.

E. Geometric View and Notations

We now present a geometric view of the discovery space and some important notations. Consider the special case of a query with two epps, resulting in an ESS with X and Y dimensions. Now, incorporate a third Z dimension to capture the *cost* of the POSP plans on the ESS, i.e, for $q \in \texttt{ESS}$, the

[7] For example, through the classical DP-based search of the plan space [15].

[8] Letter subscripts for plans denote locations, whereas numeric subscripts denote identifiers.

value of the Z-axis is $Cost(P_q, q)$. This 3D surface, which captures the cost of the POSP plans on the ESS, is called the *Optimal Cost Surface* (OCS). Associated with each point on the OCS is the POSP plan for the underlying location in the ESS. A sample OCS corresponding to the example query **EQ** in the Introduction is shown in Figure 3, which provides a perspective view of this surface. In this figure, the optimality region of each POSP plan is denoted by a unique color. So, for example, the region with blue points corresponds to those locations where the "blue plan" is the optimal plan.[9]

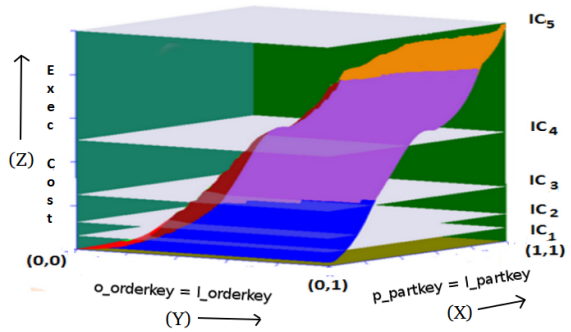


Fig. 3: 3D Cost Surface on ESS

Discretization of OCS: Let C_{min} and C_{max} denote the minimum and maximum costs on the OCS, corresponding to the origin and the terminus of the 3D space, respectively (an outcome of the PCM assumption). We define $m = \lceil \log_2(\frac{C_{max}}{C_{min}}) \rceil + 1$ hyperplanes that are parallel to the XY plane as follows. The first hyperplane is drawn at C_{min}. For $i = 2, \ldots, m-1$, the i^{th} hyperplane is drawn at $C_{min} \cdot 2^{i-1}$. The last hyperplane is drawn at C_{max}. These hyperplanes correspond to the m isocost contours $\mathcal{IC}_1, \ldots \mathcal{IC}_m$. The isocost contour $\mathcal{IC}_i$ is essentially the 2D curve obtained by intersecting the OCS with the i^{th} hyperplane. We denote the cost of $\mathcal{IC}_i$ by $\texttt{CC}_\texttt{i}$. The set of plans that are on the 2D curve of $\mathcal{IC}_i$ are referred to as $\texttt{PL}_\texttt{i}$. For example, in Figure 3, $\texttt{PL}_\texttt{4}$ includes the purple and maroon plans (in addition to plans that are not visible in this perspective). The *hypograph* of an isocost contour $\mathcal{IC}_i$ is the set of all locations $q \in \texttt{ESS}$ such that $Cost(P_q, q) \leq \texttt{CC}_\texttt{i}$.

The above geometric intuition and the formal notations readily extend to the general case of D epps, and these notations are summarized in Table I for easy reference.

III. Building Blocks of SpillBound

The platform-independent nature of the MSO bound of the SpillBound is enabled by the key properties of half-space pruning and contour density independent execution. In this section, we present these two building blocks of our approach.

A. Half-space Pruning

Half-space pruning is the ability to prune half-spaces from the search space based on a single cost-budgeted execution of a contour plan. We now present how half-space pruning is achieved by executing query plans in *spilling mode*. While the use of spilling to accelerate selectivity discovery had been mooted in [3], they did not consider its exploitation for obtaining guaranteed search properties.

[9]Since Figure 3 is only a perspective view of the OCS, it does not capture all the POSP plans.

TABLE I: Notations

Notation	Meaning
epp (EPP)	Error-prone predicate (its collection)
ESS	Error-prone selectivity space
D	Number of dimensions of ESS
$e_1, \ldots, e_D$	The D epps in the query
$q \in [0,1]^D$	A location in the ESS space
$q.j$	Selectivity of q in the jth dimension of ESS
P_q	Optimal Plan at $q \in$ ESS
q_a	Actual run-time selectivity
$Cost(P, q)$	Cost of plan P at location q
$\mathcal{IC}_i$	Isocost Contour i
$\texttt{CC}_\texttt{i}$	Cost of an isocost contour $\mathcal{IC}_i$
$\texttt{PL}_\texttt{i}$	Set of plans on contour $\mathcal{IC}_i$

We use spilling as the mechanism for modifying the execution of a selected plan – the objective here is to utilize the assigned execution budget to extract increased selectivity information of a specific epp. Since spilling requires modification of plan executions, we shall first describe the query execution model.

1) Execution Model: We assume the demand driven iterator model, commonly seen in database engines, for the execution of operators in the plan tree [4]. Specifically, the execution takes place in a bottom up fashion with the base relations at the leaves of the tree.

In conventional database query processing, the execution of a query plan can be partitioned into a sequence of *pipelines* [2]. Intuitively, a pipeline can be defined as the maximal concurrently executing subtree of the execution plan. The entire execution plan can therefore be viewed as an ordering on its constituent pipelines. We assume that only one pipeline is executed at a time in the database system, i.e, there is no inter-pipeline concurrency – this appears to be the case in current engines. To make these notions concrete, consider the plan tree shown in Figure 4 – here, the constituent pipelines are highlighted with ovals, and are executed in the sequence $\{L_1, L_2, L_3, L_4\}$.

Finally, we assume a standard plan costing model that estimates the individual costs of the internal nodes, and then aggregates the costs of all internal nodes to represent the estimated cost of the complete plan tree.

2) Spilling Mode of Execution: We now discuss how to execute plans in spilling mode. For expository convenience, given an internal node of the plan tree, we refer to the set of nodes that are in the subtree rooted at the node as its *upstream* nodes, and the set of nodes on its path to the root as its *downstream* nodes.

Suppose we are interested in learning about the selectivity of an epp e_j. Let the internal node corresponding to e_j in plan P be N_j. The key observation here is that the execution cost incurred on N_j's downstream nodes in P is *not useful* for learning about N_j's selectivity. So, discarding the output of N_j without forwarding to its downstream nodes, and devoting the entire budget to the subtree rooted at N_j, helps to use the

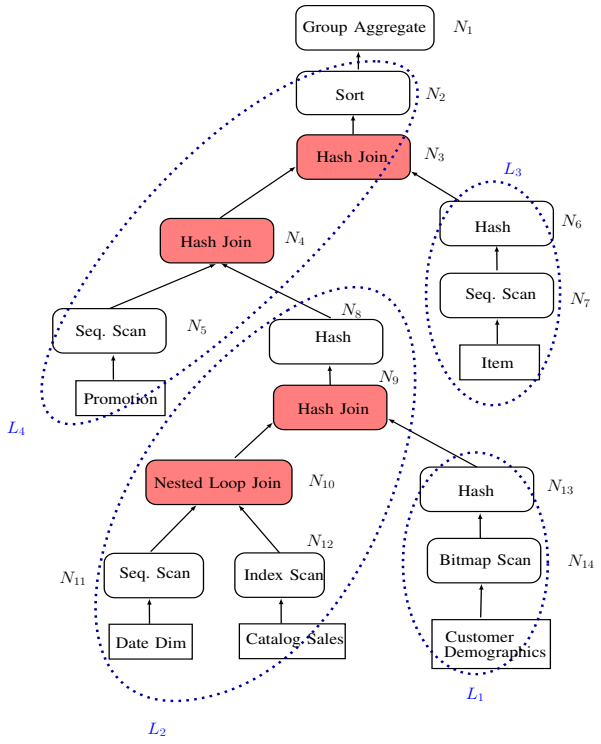


Fig. 4: Execution Plan Tree of TPC-DS Query 26

budget effectively to learn e_j's selectivity. Specifically, given plan P with cost budget B, and epp e_j chosen for spilling, the spill-mode execution of P is simply the following: Create a modified plan comprised of only the subtree of P rooted at N_j, and execute it with cost budget B.

Since a plan could consist of multiple epps (red coloured nodes in Figure 4), the sequence of spill node choices should be made carefully to ensure guaranteed learning on the selectivity of the chosen node – this procedure is described next.

3) Spill Node Identification: Given a plan and an ordering of the pipelines in the plan, we consider an ordering of epps based on the following two rules:

> *Inter-Pipeline Ordering:* Order the epps as per the execution order of their respective pipelines; in Figure 4, since L_4 is ordered after L_2, the epp nodes N_3 and N_4 are ordered after N_9 and N_{10}.
>
> *Intra-Pipeline Ordering:* Order the epps by their upstream-downstream relationship, i.e., if an epp node N_a is downstream of another epp node N_b within the same pipeline, then N_a is ordered after N_b; in the example, N_3 is ordered after N_4.

It is easy to see that the above rules produce a total-ordering on the epps in a plan – in Figure 4, it is N_{10}, N_9, N_4, N_3. Given this ordering, we always choose to spill on the node corresponding to the *first* epp in the total-order. The selectivity of a spilled epp node is fully learnt when the corresponding execution goes to completion within its assigned budget. When this happens, we remove the epp from EPP and it is no longer considered as a candidate for spilling in the rest of the discovery process.

As a result of this procedure, note that the selectivities of all predicates located *upstream* of the currently spilling epp will be known *exactly* – either because they were never epps, or because they have already been fully learnt in the ongoing discovery process. Therefore, their cost estimates are accurate, leading to the following half-space pruning property.

Lemma 3.1: Consider a location $q \in$ ESS and the corresponding contour plan P_q. Let epp e_j be selected by the spill node identification mechanism. When P_q is executed with budget $Cost(P_q, q)$ and spilling on e_j, then we either learn (a) the exact selectivity of e_j, or (b) that $q_a.j > q.j$.

Proof: For an internal node N of a plan tree, we use $N.cost$ to refer to the execution cost of the node. Let N_j denote the internal node corresponding to e_j in plan P_q. Partition the internal nodes of P_q into the following: $Upstream(N_j)$, $\{N_j\}$, and $Residual(N_j)$, where $Upstream(N_j)$ denotes the set of internal nodes of P_q that appear before node N_j in the execution order, while $Residual(N_j)$ contains all the nodes in the plan tree excluding $Upstream(N_j)$ and $\{N_j\}$. Therefore, $Cost(P_q, q) = \sum_{N \in Upstream(N_j)} N.cost + N_j.cost + \sum_{N \in Residual(N_j)} N.cost$. The value of the first term in the summation is known with certainty because $Upstream(N_j)$ does not contain any epp. Further, the quantity $N_j.cost$ is computed assuming that the selectivity of N_j is $q.j$. Since the output of N_j is discarded and not passed to downstream nodes, the nodes in $Residual(N_j)$ incur zero cost. Thus, when P_q is executed in spill-mode, the budget is sufficiently large to either learn the exact selectivity of e_j (if the spill-mode execution goes to completion) or to conclude that $q_a.j$ is greater than $q.j$. ■

Remark. During the entire discovery process of SpillBound, only contour plans are considered for spill-mode executions. Moreover, when we mention the spill-mode execution of a particular plan on a contour, it implicitly means that the budget assigned is equal to the cost of the contour. For ease of exposition, if the epp chosen to spill on is e_j for a plan P, we shall hereafter highlight this information with the notation P^j.

B. Contour Density Independent Execution

We now show how the half-space pruning property can be exploited to achieve the contour density independent (CDI) execution property of the SpillBound algorithm. For this purpose, we employ the term "quantum progress" to refer to a step in which the algorithm either jumps to the next contour, or fully discovers the selectivity of some epp. Informally, the CDI property ensures that each quantum progress in the discovery process is achieved by expending no more than $|$EPP$|$ number of plan executions.

For ease of understanding, we present here the technique for the special case of two epps referred to by X and Y, deferring the generalization for D epps to the next section.

Consider the 2D ESS shown in Figure 5, and assume that we are currently exploring contour $\mathcal{IC}_3$. The two plans for spill-mode execution in this contour are identified as follows: We first identify the subset of plans on the contour that spill on

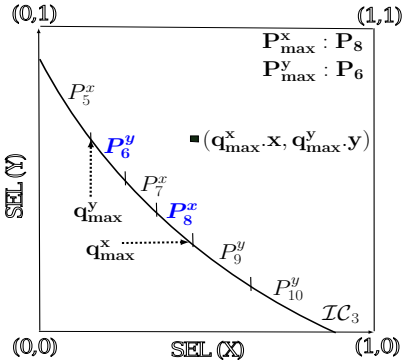


Fig. 5: Choice of Contour Crossing Plans

X using the spill node identification algorithm – these plans are identified as P^x_5, P^x_7, P^x_8 in Figure 5. The next step is to enumerate the subset of locations on the contour where these X-spilling plans are optimal. From this subset, we identify the location with the *maximum* X coordinate, referred to as q^x_{max}, and its corresponding contour plan, which is denoted as P^x_{max}. The P^x_{max} plan is the one chosen to learn the selectivity of X – in Figure 5, this choice is P^x_8.

By repeating the same process for the Y dimension, we identify the location q^y_{max}, and plan P^y_{max}, for learning the selectivity of Y – in Figure 5, the plan choice is P^y_6. Note that the location $(q^x_{max}.x, q^y_{max}.y)$ is guaranteed to be either on or beyond the $\mathcal{IC}_3$ contour.

The following lemma shows that the above plan identification procedure satisfies the CDI property.

Lemma 3.2: In contour $\mathcal{IC}_i$, if plans P^x_{max} and P^y_{max} are executed in spill-mode, and both do not reach completion, then $Cost(P_{q_a}, q_a) > \texttt{CC}_\texttt{i}$, triggering a jump to the next contour $\mathcal{IC}_{i+1}$.

Proof: Since the executions of both P^x_{max} and P^y_{max} do not reach completion, we infer that $q^x_{max}.x < q_a.x$ and $q^y_{max}.y < q_a.y$. Therefore, q_a strictly dominates the location $(q^x_{max}.x, q^y_{max}.y)$ whose cost, by PCM, is greater than $\texttt{CC}_\texttt{i}$. Thus $Cost(P_{q_a}, q_a) > \texttt{CC}_\texttt{i}$. ■

IV. SpillBound Algorithm

In this section, we present our new robust query processing algorithm, `SpillBound`, which leverages the properties of half-space pruning and CDI execution. We begin by introducing an important notation: Our search for the actual query location, q_a, begins at the origin, and with each spill-mode execution of a contour plan, we monotonically move closer towards the actual location. The running selectivity location, as progressively learnt by `SpillBound`, is denoted by q_{run}.

For ease of exposition, we first present a version, called `2D-SpillBound`, for the special case of two epps, and then extend the algorithm to the general case of several epps.

A. The `2D-SpillBound` Algorithm

To provide a geometric insight into the working of `2D-SpillBound`, we will refer to the two epps, e_1 and e_2, as X and Y, respectively. `2D-SpillBound` explores the doubling isocost contours $\mathcal{IC}_1, \ldots, \mathcal{IC}_m$, starting with the minimum cost contour $\mathcal{IC}_1$. During the exploration of a contour, two plans P^x_{max} and P^y_{max} are identified, as described in Section III-B, and executed in spill-mode. The order of execution between these two plans can be chosen arbitrarily, and the selectivity information learnt through their execution is used to update the running location q_{run}. This process continues until one of the spill-mode executions reaches completion, which implies that the selectivity of the corresponding epp has been completely learnt.

Without loss of generality, assume that the learnt selectivity is X. At this stage, we know that q_a lies on the line $X = q_a.x$. Further, the discovery problem is reduced to the 1D case, which has a unique characteristic – each isocost contour of the new ESS (i.e. line $X = q_a.x$) contains only *one* plan, and this plan alone needs to be executed to cross the contour, until eventually some plan finishes its execution within the assigned budget. In this special 1D scenario, there is no operational difference between `PlanBouquet` and `2D-SpillBound`, so we simply invoke the standard `PlanBouquet` with only the Y epp, starting from the contour currently being explored. Note that plans are *not* executed in spill-mode in this terminal 1D phase because spilling in the 1D case weakens the bound, as explained in [9].

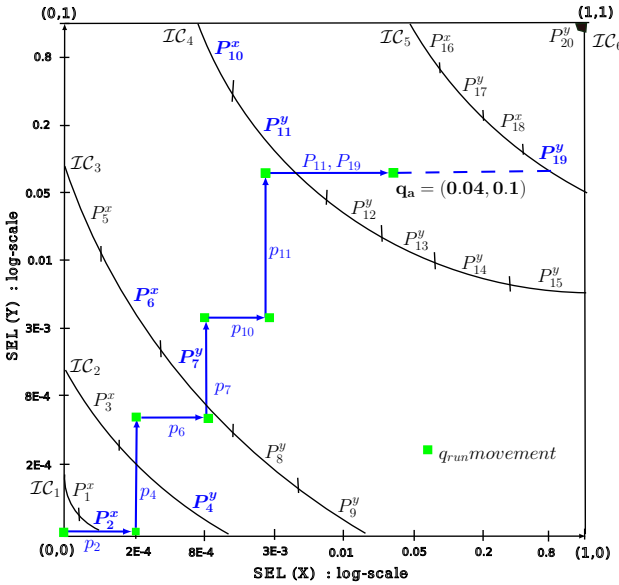


Fig. 6: Execution trace for TPC-DS Query 91

1) Execution Trace: An illustration of the execution of `2D-SpillBound` on TPC-DS Query 91 with two epps is shown in Figure 6. In this example, the join predicate *Catalog Sales* ⋈ *Date Dim*, denoted by X, and the join predicate *Customer* ⋈ *Customer Address*, denoted by Y, are the two epps (both selectivities are shown on a log scale).

We observe here that there are six doubling isocost contours $\mathcal{IC}_1, \ldots, \mathcal{IC}_6$. The execution trace of `2D-SpillBound` (blue line) corresponds to the selectivity scenario where the user's query is located at $q_a = (0.04, 0.1)$.

On each contour, the plans executed by 2D−SpillBound in spill-mode are marked in blue – for example, on $\mathcal{IC}_2$, plan P_4 is executed in spill-mode for the epp Y. Further, upon each execution of a plan, an axis-parallel line is drawn from the previous q_{run} to the newly discovered q_{run}, leading to the Manhattan profile shown in Figure 6. For example, when plan P_6 is executed in spill-mode for X, the q_{run} moves from (2E-4,6E-4) to (8E-4,6E-4). To make the execution sequence unambiguously clear, the trace joining successive q_{run}s is also annotated with the plan execution responsible for the move – to highlight the spill-mode execution, we use p_i to denote the spilled execution of P_i. So, for instance, the move from (2E-4,6E-4) to (8E-4,6E-4) is annotated with p_6.

With the above framework, it is now easy to see that the algorithm executes the sequence $p_2, p_4, p_6, p_7, p_{10}, p_{11}$, which culminates in the discovery of the actual selectivity of the Y epp. After this, the 1D PlanBouquet takes over and the selectivity of X is learnt by executing P_{11} and P_{19} in regular (non-spill) mode.

This example trace of 2D−SpillBound exemplifies how the benefits of half-space pruning and CDI execution are realized. It is important to note that 2D−SpillBound may execute a few plans *twice* – for example, plan P_{11} – once in spill-mode (i.e., p_{11}) and once as part of the 1D PlanBouquet exploration phase. In fact, this notion of repeating a plan execution during the search process substantially contributes to the MSO bound in the general case of D epps.

2) Performance Bounds: Consider the situation where q_a is located in the region between $\mathcal{IC}_k$ and $\mathcal{IC}_{k+1}$, or is directly on $\mathcal{IC}_{k+1}$. Then, the 2D−SpillBound algorithm explores the contours from 1 to $k+1$ before discovering q_a. In this process,

Lemma 4.1: The 2D−SpillBound algorithm ensures that at most two plans are executed from each of the contours $\mathcal{IC}_1, \ldots, \mathcal{IC}_{k+1}$, except for one contour in which at most three plans are executed.

Proof: Let the exact selectivity of one of the epps be learnt in contour $\mathcal{IC}_h$, where $1 \leq h \leq k+1$. From CDI execution, we know that 2D−SpillBound ensures that at most two plans are executed in each of the contours $\mathcal{IC}_1, \cdots, \mathcal{IC}_h$. Subsequently, PlanBouquet begins operating from contour $\mathcal{IC}_h$, resulting in three plans being executed in $\mathcal{IC}_h$, and one plan each in contours $\mathcal{IC}_{h+1}$ through $\mathcal{IC}_{k+1}$. ■

We now analyze the worst-case cost incurred by 2D−SpillBound. For this, we assume that the contour with three plan executions is the *costliest* contour $\mathcal{IC}_{k+1}$. Since the ratio of costs between two consecutive contours is 2, the total cost incurred by 2D−SpillBound is bounded as follows:

$$\begin{aligned} TotalCost &\leq 2 * \mathtt{CC}_1 + \ldots + 2 * \mathtt{CC}_k + 3 * \mathtt{CC}_{k+1} \\ &= 2 * \mathtt{CC}_1 + \ldots + 2 * 2^{k-1} * \mathtt{CC}_1 + 3 * 2^k * \mathtt{CC}_1 \\ &= 2 * \mathtt{CC}_1 \left(1 + \ldots + 2^k\right) + 2^k * \mathtt{CC}_1 \\ &= 2 * \mathtt{CC}_1 \left(2^{k+1} - 1\right) + 2^k * \mathtt{CC}_1 \\ &\leq 2^{k+2} * \mathtt{CC}_1 + 2^k * \mathtt{CC}_1 \\ &= 5 * 2^k * \mathtt{CC}_1 \end{aligned} \quad (6)$$

From the PCM assumption, we know that the cost for an oracle algorithm (that apriori knows the location of q_a) is lower bounded by $\mathtt{CC}_k$. By definition, $\mathtt{CC}_k = 2^{k-1} * \mathtt{CC}_1$. Hence,

$$MSO \leq \frac{5 * 2^k * \mathtt{CC}_1}{2^{k-1} * \mathtt{CC}_1} = 10 \quad (7)$$

leading to the theorem:

Theorem 4.2: The MSO bound of 2D−SpillBound for queries with two error-prone predicates is bounded by **10**.

Remark: Note that even for a ρ value as low as 3, the MSO bound of 2D−SpillBound is better than the $4 * 3 = 12$ offered by PlanBouquet.

B. Extending to Higher Dimensions

We now present SpillBound, the generalization of the 2D−SpillBound algorithm to handle D error-prone predicates $e_1, \ldots, e_D$. Before doing so, we hasten to add that the EPP set, as mentioned earlier, is constantly updated during the execution, and epps are removed from this set as and when their selectivities become fully learnt.

The primary generalization that needs to be achieved is to select, prior to exploration of a contour $\mathcal{IC}_i$, the best set (wrt selectivity learning) of $|\mathtt{EPP}|$ plans that satisfy the half-space pruning property and ensure complete coverage of the contour. To do so, similar to the 2D case, the plan P^j_{max} corresponding to $e_j \in \mathtt{EPP}$ is identified as follows: Among the contour locations for which the corresponding plan spills on e_j, the location with the *maximum* value on the jth coordinate is chosen, and the contour plan at the chosen location is assigned to be P^j_{max}. In essence, among all plans that could provide a guaranteed learning of e_j's selectivity through spill-mode execution, the plan that provides the highest guaranteed learning is chosen.

A subtle but important point to note here is that, *during* the exploration of $\mathcal{IC}_i$, the identity of P^j_{max} *may change* as the contour processing progresses. This is because some of the plans that were assigned to spill on other epps, may switch to spilling on e_j due to their original epps being completely learnt during the ongoing exploration. Accordingly, we term the first execution of a P^j_{max} in contour $\mathcal{IC}_i$ as a *fresh execution*, and subsequent executions on the same epp as *repeat executions*.

Finally, it is possible that a specific epp may have *no* plan on $\mathcal{IC}_i$ on which it can be spilled – this situation is handled by simply skipping the epp. The complete pseudocode for SpillBound is presented in Algorithm 1 – here, Spill-Mode-Execution(P^j_{max},e_j,$\mathtt{CC_i}$) refers to the execution of plan P^j_{max} spilling on e_j with budget $\mathtt{CC_i}$.

With the above construction, the following lemma can be proved in a manner analogous to that of Lemma 3.2:

Lemma 4.3: In contour $\mathcal{IC}_i$, if no plan in the set $\{P^j_{max} | e_j \in \mathtt{EPP}\}$ reaches completion when executed in spill-mode, then $Cost(P_{q_a}, q_a) > \mathtt{CC_i}$, triggering a jump to the next contour $\mathcal{IC}_{i+1}$.

1) Performance Bounds: We now present an overview of how the MSO bound is obtained for SpillBound – the full proof is available in [9].

In the worst-case analysis of 2D−SpillBound, the exploration cost of every intermediate contour is bounded by

Algorithm 1 The SpillBound Algorithm

```
Init: i=1, EPP = {e_1, ..., e_D};
while i ≤ m do                                  ▷ for each contour
  if |EPP| = 1 then                             ▷ only one epp left
    Run PlanBouquet to discover the selectivity of the
    remaining epp starting from the present contour;
    Exit;
  end if
  Run the spill node identification procedure on each plan in
  the contour IC_i, i.e, plans in PL_i, and use this information
  to choose plan P^j_max for each epp e_j;
  exec-complete = false;
  for each epp e_j do
    exec-complete = Spill-Mode-Execution(P^j_max, e_j, CC_i);
    Update q_run.j based on selectivity learnt for e_j;
    if exec-complete then
      /*learnt the actual selectivity for e_j*/
      Remove e_j from the set EPP;
      Break;
    end if
  end for
  if ! exec-complete then
    i = i+1; /* Jump to next contour */
  end if
  Update ESS based on learnt selectivities;
end while
```

twice the cost of the contour. Whereas the exploration cost of the last contour (i.e., $\mathcal{IC}_{k+1}$) is bounded by three times the contour cost because of the possible execution of a third plan during the PlanBouquet phase. We now present how this effect is accounted for in the general case.

Repeat Executions: As explained before, the identity of plan P^j_{max} may dynamically change during the exploration of a contour $\mathcal{IC}_i$, resulting in repeat executions. If this phenomenon occurs, the new P^j_{max} plan would have to be executed to ensure compliance with Lemma 4.3. We observe that each repeat execution of an epp is preceded by an event of fully learning the selectivity of some other epp, leading to the following lemma (proof in [9]):

Lemma 4.4: The SpillBound algorithm executes at most D fresh executions in each contour, and the total number of repeat executions across contours is bounded by $\frac{D(D-1)}{2}$.

Suppose that the actual selectivity location q_a is located in the region between $\mathcal{IC}_k$ and $\mathcal{IC}_{k+1}$, or is directly on $\mathcal{IC}_{k+1}$. Then, the total cost incurred by the SpillBound algorithm in discovering q_a is the sum of costs from fresh and repeat executions in each of the contours $\mathcal{IC}_1$ through $\mathcal{IC}_{k+1}$. Further, the worst-case cost is incurred when all the repeat executions happen at the costliest contour, namely $\mathcal{IC}_{k+1}$. Hence, the total cost of SpillBound is given by

$$\sum_{i=1}^{k+1} (\#\text{fresh executions}(\mathcal{IC}_i)) * \mathtt{CC_i} + \tfrac{D(D-1)}{2} * \mathtt{CC_{k+1}}$$

Since the number of fresh executions on any contour is bounded by D, we obtain the following theorem (proof on similar lines to the 2D scenario):

Theorem 4.5: The MSO bound of the SpillBound algorithm for any query with D error-prone predicates is bounded by $D^2 + 3D$.

V. Lower Bound

In this section, we present a lower bound on MSO for a class of deterministic half-space pruning algorithms denoted by $\mathcal{E}$, that includes SpillBound in its ambit. Consider an algorithm $\mathcal{A} \in \mathcal{E}$. For any potential plan P, $\mathcal{A}$ is assumed to have the following information for any instance of the triple $< q, e_j, l >$ where $q \in$ ESS, $j \in \{1, \ldots, D\}$, and $0 \leq l \leq 1$: (i) $Cost(P, q)$ and (ii) $PredCost(P, e_j, l)$ which denotes the cost budget required by an execution of P that allows $\mathcal{A}$ to infer that $q_a.j \geq l$. Since, SpillBound requires $PredCost(P, e_j, l)$ information for only one epp combination, the algorithms in the class $\mathcal{E}$ are given access to even more information than SpillBound. Thus the lower bound result on MSO for algorithms in class $\mathcal{E}$ applies to SpillBound as well.

The goal of $\mathcal{A}$ is to discover the unknown query location q_a. The actions and outcomes of a generic step of $\mathcal{A}$ can be one of the following: (i) a plan P is executed to completion incurring $Cost(P, q_a)$, (ii) a plan P is executed with budget $Cost(P, q)$ for a $q \in$ ESS and $\mathcal{A}$ infers that $q \not\succ q_a$, (iii) a plan P is executed with budget $PredCost(P, e_j, q.j)$ (for example in spill mode) and learns (a) that $q_a.j \geq q.j$, or (b) $q_a.j$ exactly.

Notion of Separation: At any stage of the execution of $\mathcal{A}$, it maintains a partition of the ESS into two sets: a set which is guaranteed not to contain q_a and its complement which contains q_a. We say that these two sets are *separated*. Formally, for two disjoint subsets of ESS, U_1 and U_2, we say that $\mathcal{A}$ *separates* the set $U_1 \cup U_2$ into U_1 and U_2, if in a single step we infer that $q_a \notin U_1$ and $q_a \in U_2$.

Consequence of Deterministic Behavior: Since $\mathcal{A}$ is deterministic, its sequence of steps for two different q_as is identical till a step wherein their respective sets for possible locations of q_a differs. We let $\mathcal{A}(q)$ denote the sequence of steps that $\mathcal{A}$ takes when $q_a = q$. Since $\mathcal{A}$ is deterministic, its action at a step is determined completely by the actions and outcomes of previous steps. Suppose, for $q_1, q_2 \in U$, both $\mathcal{A}(q_1)$ and $\mathcal{A}(q_2)$ separate a set $U \subseteq$ ESS. Then, the consequence of deterministic behavior is that the steps in both $\mathcal{A}(q_1)$ and $\mathcal{A}(q_2)$ are identical at least till they separate U.

Construction of ESS: We construct a special D-dimensional ESS which is used in our proof. Our construction is such there will be exactly D plans $P_1, P_2, \ldots, P_D$ and their cost structure is as follows:

$$\begin{aligned} Cost(P_i, q) &= D * q.i \\ Cost(P_i, e_j, q.j) &= D * q.j \ \forall q \in \text{ESS}, \text{epp } j \end{aligned}$$

It can be verified that our construction satisfies the PCM property for all D plans.[10] Further, we are interested in a set of locations $V = \{q_1, \ldots, q_D\}$ given by $q_i.j = 1/D$ if $j = i$, else $q_i.j = 1$. Finally, the POSP plan at q_i is P_i and has a cost of 1.

[10]More precisely, a relaxed version of PCM wherein the relation "$>$" in Equation 5 is replaced by "$\geq$". The analysis for strict PCM is deferred to [9].

Using the above notion of separation, we can prove the following claim for the specially constructed ESS.

Claim 5.1: Let $q_a \in V$. Let V_1, V_2 be such that $V_1 \cap V_2 = \phi$ and $V_1 \cup V_2 = V_3 \subseteq V$. If $\mathcal{A}$ separates V_3 into V_1 and V_2, then either $|V_1| = 1$ or $|V_2| = 1$.

This claim can be leveraged to establish Theorem 5.1.

Theorem 5.1: For any algorithm $\mathcal{A} \in \mathcal{E}$ and $D \geq 2$, there exists a D-dimensional ESS where MSO of $\mathcal{A}$ is at least D.

The proofs of Claim 5.1 and Theorem 5.1 are deferred to [9].

VI. Experimental Evaluation

As mentioned earlier, the MSO guarantees delivered by PlanBouquet and SpillBound are not directly comparable, due to the inherently different nature of their dependencies on the ρ and D parameters, respectively. However, we need to assess whether the platform-independent feature of SpillBound is procured at the expense of a deterioration in the numerical bounds. Accordingly, we present in this section an evaluation of SpillBound on a representative set of complex OLAP queries, and compare its MSO performance with that of PlanBouquet. The experimental framework, which is similar to that used in [3], is described first, followed by an analysis of the results.

A. Database and System Framework

Our test workload is comprised of representative SPJ queries from the TPC-DS and TPC-H benchmarks, operating at their base sizes of 100GB and 1GB, respectively. The number of relations in these queries range from 4 to 10, and a spectrum of join-graph geometries are modeled, including *chain*, *star*, *branch*, etc. The number of epps range from 2 to 6, all corresponding to join predicates, giving rise to challenging multi-dimensional ESS spaces. Due to space limitations, we present only the results for TPC-DS queries here – the corresponding results for the TPC-H queries are available in [9].[11]

To succinctly characterize the queries, the nomenclature xD_Qz is employed, where x specifies the number of epps, and z the query number in the TPC-DS benchmark. For example, 3D_Q15 indicates TPC-DS Query 15 with three of its join predicates considered to be error-prone.

The database engine used in our experiments is a modified version of PostgreSQL 8.4 [14] engine, with the primary changes being the incorporation of spilling and time-limited execution of plans. Due to the intrusive nature of spilling, we are not in a position to provide experimental results on commercial database engines.

The MSO guarantee for PlanBouquet on the original ESS typically turns out to be very high due to the large values of ρ. Therefore, as in [3], we conduct the experiments for PlanBouquet only after carrying out the *anorexic reduction* transformation [5] at the default $\lambda = 0.2$ replacement threshold – we use ρ_{RED} to refer to this reduced value.

In the remainder of this section, for ease of exposition, we use the abbreviations PB and SB to refer to PlanBouquet and SpillBound, respectively. Further, we use MSO_g (MSO guarantee) and MSO_e (MSO empirical) to distinguish between the MSO guarantee and the empirically evaluated MSO obtained on our suite of queries.

[11]Results for additional performance metrics such as *average sub-optimality* and *sub-optimality distributions* are also available in [9].

B. Comparison of MSO guarantees (MSO_g)

A summary comparison of MSO_g for PB and SB over almost a dozen TPC-DS queries of varying dimensionality is shown in Figure 7 – for PB, they are computed as $4(1+\lambda)\rho_{RED}$, whereas for SB, they are computed as D^2+3D.

We observe here that in a few instances, specifically 4D_Q26 and 4D_Q91, SB's guarantee is noticeably *tighter* than that of PB – for instance, the values are 28 and 52.8, respectively, for 4D_Q91. In the remaining queries, the bound quality is roughly similar between the two algorithms. Therefore, contrary to our fears, the MSO guarantee is not found to have suffered due to incorporating platform independence.

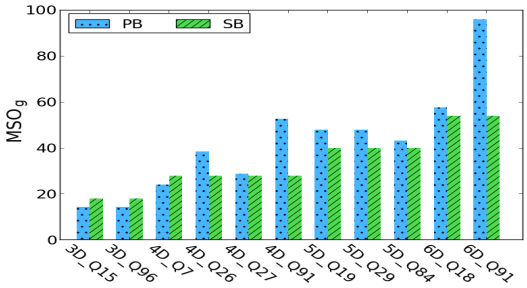


Fig. 7: Comparison of MSO Guarantees (MSO_g)

C. Variation of MSO Guarantee with Dimensionality

In our next experiment, we investigated the behavior of MSO_g as a function of ESS dimensionality for a given query. We present results here for an example TPC-DS query, namely Query 91, wherein the number of epps were varied from 2 upto 6 – the corresponding performance profile is shown in Figure 8. We observe here that while SB is marginally worse at the lowest dimensionality of 2, it becomes appreciably better than PB with increasing dimensionality – in fact, at 6D, the values are 96 and 54 for PB and SB, respectively.

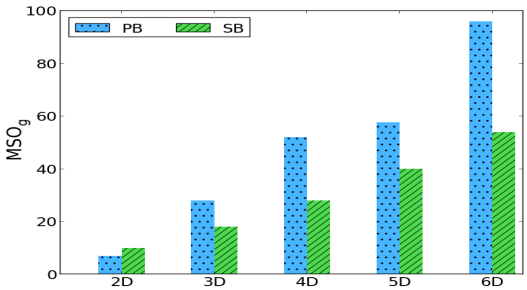


Fig. 8: Variation of MSO_g with Dimensionality (Q91)

D. Comparison of Empirical MSO (MSO_e)

We now turn our attention to evaluating the empirical MSO, MSO_e, incurred by the two algorithms. There are two reasons

that it is important to carry out this exercise: Firstly, to evaluate the looseness of the guarantees. Secondly, to evaluate whether PB, although having weaker bounds in theory, provides better performance in practice, as compared to SB.

The assessment was accomplished by explicitly and exhaustively considering each and every location in the ESS to be q_a, and then evaluating the sub-optimality incurred for this location by PB and SB. Finally, the maximum of these values was taken to represent the MSO_e of the algorithm.

The MSO_e results are shown in Figure 9 for the entire suite of test queries. Our first observation is that the empirical performance of SB is far better than the corresponding guarantees in Figure 7. In contrast, while PB also shows improvement, it is not as dramatic. For instance, considering 6D_Q18, PB reduces its MSO from 57.6 to 35.2, whereas SB goes down from 54 to just 16.

The second observation is that the gap between SB and PB is *accentuated* here, with SB performing substantially better over a larger set of queries. For instance, consider query 5D_Q29, where the MSO_g values for PB and SB were 52.8 and 40, respectively – the corresponding empirical values are 42.3 and 15.1 in Figure 9.

Finally, even for a query such as 4D_Q7, where PB had a marginally *better* bound (24 for PB and 28 for SB in Figure 7), we find that it is SB which behaves better in practice (16.1 for PB and 13.9 for SB in Figure 9).

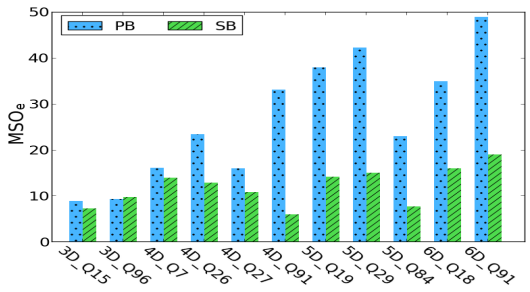


Fig. 9: Comparison of Empirical MSO (MSO_e)

E. Analysis of Looseness of SB's MSO_g

We now profile the execution of the queries to investigate the significant gap between SB's MSO_g and MSO_e values. Recall that the analysis (Section IV-B1) bounded the cost of repeat executions by attributing *all of them* to the last contour, i.e., $\mathcal{IC}_{k+1}$. Moreover, the number of fresh executions in all the contours, including $\mathcal{IC}_{k+1}$, was assumed to be D. This results in the execution cost over $\mathcal{IC}_{k+1}$ being the dominant contributor to MSO_g. To quantitatively assess this contribution, we present in Table II the drilled-down information of: (i) the number of fresh executions of plans on $\mathcal{IC}_{k+1}$, and (ii) the number of repeat executions of plans on $\mathcal{IC}_{k+1}$. For each of these factors, we present both the theoretical and empirical values. Note that the specific q_a locations used for obtaining these numbers corresponds to the locations where the MSO was empirically observed.

Armed with the statistics of Table II, we conclude that the main reasons for the gap are the following: Firstly, while

TABLE II: SUB-OPTIMALITY CONTRIBUTION OF IC_{k+1}

Query	Fresh Executions in $\mathcal{IC}_{k+1}$		Repeat Executions in $\mathcal{IC}_{k+1}$	
	Bound	Empirical	Bound	Empirical
3D_Q15	3	2	3	1
3D_Q96	3	2	3	0
4D_Q7	4	3	6	0
4D_Q26	4	4	6	4
4D_Q27	4	4	6	0
4D_Q91	4	3	6	0
5D_Q19	5	2	10	0
5D_Q29	5	4	10	2
5D_Q84	5	3	10	1
6D_Q18	6	4	15	1
6D_Q91	6	6	15	7

the number of repeat executions in contour $\mathcal{IC}_{k+1}$, as per the analysis, is $D(D-1)/2$, the empirical count is far fewer – in fact there are *no* repeat executions in queries such as 3D_Q96, 4D_Q7, 4D_Q27, 4D_Q91 and 5D_Q19. While it is possible that repeat executions did occur in the earlier lower cost contours, their collective contributions to sub-optimality are not significant.

Secondly, by the time the execution reaches the $\mathcal{IC}_{k+1}$ contour, it is likely that the selectivities of some of the epps have *already been learnt*. The bound however assumes that *all* selectivities are learnt only in the last contour. As a case in point, for 5D_Q19, the selectivities of three of the five epps had been learnt prior to reaching the last contour.

VII. DEPLOYMENT ASPECTS

Over the preceding sections, we have conducted a theoretical characterization and empirical evaluation of the SpillBound algorithm. We now discuss some pragmatic aspects of its usage in real-world contexts. Most of these issues have already been previously discussed in [3], in the context of the PlanBouquet algorithm, and we summarize the salient points here for easy reference.

First, our assumption of a perfect cost model. If we were to be assured that the cost modeling errors, while non-zero, are *bounded* within a δ error factor, then the MSO guarantees in this paper will carry through modulo an inflation by a factor of $(1+\delta)^2$ [9]. That is, the MSO guarantee of SpillBound would be $(D^2+3D)(1+\delta)^2$.

Second, with regard to identification of the epps that constitute the ESS, we could leverage application domain knowledge and query logs to make this selection, or simply be conservative and assign all uncertain predicates to be epps.

Third, the construction of the contours in the ESS is certainly a computationally intensive task since it is predicated on repeated calls to the optimizer, and the overheads increase exponentially with ESS dimensionality. However, for canned queries, it may be feasible to carry out an offline enumeration; alternatively, when a multiplicity of hardware is available, the contour constructions can be carried out in parallel since they do not have any dependence on each other.

Fourth, while PlanBouquet can directly work off the API of existing query optimizers, SpillBound is *intrusive* since it requires changes in the core engine to support plan spilling and monitoring of operator selectivities. However,

our experience with PostgreSQL is that these facilities can be incorporated relatively easily – the full implementation required only a few hundred lines of code.

Finally, while PlanBouquet is dependent on the highly variable parameter ρ, it is possible that ρ itself is a weak function of D. Therefore, when D becomes really large, SpillBound's quadratic dependency on D may make its bounds weaker than those of PlanBouquet. However, our experience suggests that this transition does not happen for the D settings that are typically seen in current applications.

VIII. Related Work

Our work materially extends the PlanBouquet approach presented in [3], which is the first work to provide worst-case guarantees for query processing performance. As already highlighted, the primary new contribution is the provision of a structural bound with SpillBound, whereas PlanBouquet delivered a behavioral bound. Further, the performance characteristics of SpillBound are substantively superior to those of PlanBouquet, as illustrated in the experimental study.

A detailed comparison to the prior literature on selectivity estimation issues is provided in [3]. For completeness, we summarize the salient features here. The prior work can be classified into the following three categories:

Improving Estimation Accuracy: A comprehensive survey on the standard estimation techniques is available in [7]. Typically, histograms are used in current systems for storing statistical summaries of attribute value distributions, and their use is based on untenable assumptions such as Attribute Value Independence (AVI). Recently [17] took a step towards removing the independence assumption, but their work is restricted to handling two-dimensional histograms, and is inefficient for databases subject to frequent updates.

Bounding Estimation Error Impact: Techniques to minimize the adverse impact of errors in selectivity estimations are proposed in [12]. However, they do not address of recovering from large errors, which are quite common in practice, and also do not provide any guarantees.

Plan-switching Approaches: Plan-switching techniques have been considered for over two decades, and include influential systems such as POP [11] and Rio [1]. The key difference of SpillBound and PlanBouquet with regard to this prior work is the provision of performance guarantees. Further, they use the optimizer's plan choice as the starting point, and re-optimize at run-time if the estimates are found to be significantly in error. In contrast, SpillBound (and PlanBouquet) always start executing plans from the *origin* of the selectivity space, ensuring both repeatability of the query execution strategy as well as controlled switching overheads.

IX. Conclusions and Future Work

We presented SpillBound, a query processing algorithm that delivers a worst-case performance guarantee dependent solely on the dimensionality of the selectivity space ($D^2 + 3D$). This substantive improvement over PlanBouquet is achieved through a potent pair of conceptual enhancements: half-space pruning of the ESS thanks to a spill-based execution model, and bounded number of executions for jumping from one contour to the next. The new approach facilitates porting of the bound across database platforms, easy knowledge of the bound value, low magnitudes of the bound, and indifference to the efficacy of the anorexic reduction heuristic. Further, our experimental evaluation on complex high-dimensional OLAP queries demonstrated that SpillBound provides competitive guarantees to its PlanBouquet counterpart, while the empirical performance is significantly superior.

In our future work, we intend to look into developing automated assistants for guiding users in deciding whether to use the native query optimizer or SpillBound for executing their queries. We also plan to work on extending SpillBound to handle the case of dependent predicate selectivities. Finally, we wish to leverage the empirical observation that plan cost functions are typically concave across the selectivity space, to further tighten the MSO guarantees of SpillBound.

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