LEAP: A Low-cost Spark SQL Query Optimizer using Pairwise Comparison

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ABSTRACT

Selecting a good execution plan can significantly improve the query efficiency of Spark SQL. Several machine learning-based techniques have been proposed to select good execution plans for DBMS, but none of them perform well on Spark SQL due to the following issues. (1) Limited compatibility with Spark SQL: these approaches rely on physical operator enumeration, while Spark SQL doesn't support it; (2) Unreliable cost estimation: they often select execution plans with poor performance due to inaccurate cost estimation; (3) Time-consuming plan enumeration: they take much time to generate a large number of candidate execution plans in Spark SQL. To overcome these issues, in this paper, we propose LEAP, the first learned query optimizer tailored for Spark SQL, which can be integrated seamlessly into Spark SQL and solves the compatibility issue. Also, to avoid the unreliable cost value estimation, LEAP selects execution plans with an estimation-free method, which directly performs comparisons between the plans. Furthermore, LEAP employs an efficient progressive plan enumeration algorithm with pruning techniques to find better plans with fewer enumerations. Extensive experiments on three public benchmarks show the effectiveness of LEAP. It reduces the end-to-end execution time of the native optimizer by up to 54% and other learned methods by up to 94%.

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The source code, data, and/or other artifacts have been made available at https://github.com/HuashiSCNU0303/LEAP.

1 INTRODUCTION

With the rise of big data, Spark SQL [4] has become increasingly popular for processing and analyzing large-scale data in a distributed environment. For an input query Q, Spark SQL generates an execution plan (or join plan) to specify the sequence in which tables are joined and how data operations are executed. Given the substantial data volumes and extended run times of OLAP workloads, selecting efficient execution plans for queries on Spark SQL is crucial for query optimization. Different execution plans for the same query can vary execution times significantly. Historically, Spark SQL's optimization has relied on its Cost-based Optimization (CBO) module, which utilizes column statistics like the number of distinct values (NDV) and histograms to estimate the cost of various execution plans and select the most cost-effective one. However, these estimates are often inaccurate, leading to the selection of poor plans by Spark SQL's CBO. For example, for TPC-H Q7, enabling CBO leads to a query execution time exceeding 300s, which is much more than 61.2s without CBO, as shown in Figure 1.

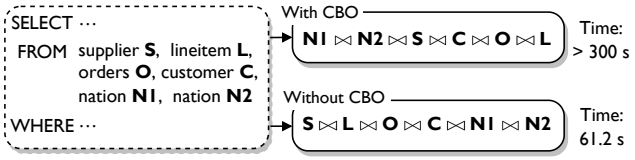

Figure 1: The join plans and their corresponding execution time of TPC-H Q7, with or without CBO.

To further improve query performance, machine-learning-based techniques have become viable approaches in the DBMS field, which mainly focuses on two strategies: learned cardinality estimation [18, 33, 39, 54] and learned optimizer [7, 8, 23, 24, 46, 48, 52, 53]. Learned cardinality estimation methods use machine learning models to predict the output row count (i.e., cardinality) of execution plans, thereby refining the native optimizer's cost estimates to generate better plans. Learned optimizers often use machine learning models to directly estimate costs for entire execution plans, and select the most cost-effective one from a set of promising candidate plans. Notable techniques include plan-constructor methods [7, 24, 46] and plan-steerer methods [8, 23, 48, 53].

However, applying these DBMS-based methods to Spark SQL is challenging due to the following reasons.

Limited compatibility with Spark SQL. Many existing methods can't fully optimize Spark SQL queries due to their limited compatibility with Spark SQL system. For example, hint-set-based methods can optimize physical operator selection but not join orders in Spark SQL, as Spark SQL determines join order based on logical costs related to output cardinalities, unlike traditional DBMSs, which consider physical operators in their plan cost. Thus, disabling physical operators generates candidate plans of the same join order. Also, Lero [53] generates join plans by scaling the cardinality estimation.

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That may lead to join plans with large table broadcasts or shuffles, which significantly increases network costs that are negligible in single-machine DBMSs, causing performance drops or execution failures. Moreover, existing methods often require modifications to Spark SQL's source code, necessitating extensive architectural knowledge and increasing debugging and maintenance costs. A non-intrusive approach could therefore enhance usability.

Unreliable cost estimation. Existing methods often select join plans with poor performance due to inaccurate cardinality or cost estimations from learned estimators. These inaccuracies stem from predicting continuous outputs, making them sensitive to outliers and noise, especially with limited training data. For example, learned cardinality estimators can produce estimates deviating from actual values by tens of times, resulting in join plans with execution times up to 8 to 10 times longer than optimal ones.

Time-consuming plan enumeration. The enumeration space for a query with n tables can reach at least $O(n!)$, making it time-consuming for machine learning models to estimate plan cost or output cardinalities. Additionally, generating an execution plan using Spark SQL's native optimizer is significantly slower compared to DBMS. Creating multiple candidate plans, as required by plan-steerer methods, also demands substantial time.

To overcome these issues, we propose a new learned optimizer tailored for Spark SQL, named LEAP. It introduces the following three modules to tackle the above three challenges respectively:

Optimization framework. To enhance compatibility, we develop an optimization framework to align with Spark SQL system. Spark SQL optimizes queries in two stages: first, it enumerates logical join orders to find the one with the minimum logical cost (related to output cardinality); then, it assigns physical operators based on heuristic rules without enumerating them. Thus, LEAP introduces two modules, Join Plan Enumerator and Join Operator Selector to optimize join order and physical operator selection respectively. For a query Q, Join Plan Enumerator processes it to generate a cost-effective join plan P. Join Operator Selector then assigns physical operators to each join operation in join plan P. These modules can be integrated into existing workflows seamlessly without modifications to Spark SQL's source code, thus improving the usability.

Learned comparator. To avoid unreliable cost estimation, we design a learned comparator $C(P_1, P_2)$ to evaluate two join plans P_1 and P_2. If P_1 is better, $C(P_1, P_2) = 0$, and vice versa. This pairwise comparison approach allows us to identify the best plan among candidates more effectively than regression-based methods, as the optimizer only needs to predict relative costs of join plans to choose one, not their exact costs. Compared to existing comparators [8, 45, 53], our comparator improves accuracy by using predicate information and data features. Also, our comparator uses sequence model to process plans, which may generate better plans than tree models with limited training data [51]. Moreover, our model does not require multiple join plans for the same query as training data; it can be trained directly using accumulated historical query data, significantly reducing computational resource demands.

Enumeration algorithm. To reduce enumeration space, we propose an efficient progressive plan enumeration algorithm to generate a low-cost join plan for a given query Q. The algorithm progressively adds a new table to existing sub-plans to generate a left-deep tree plan. While left-deep plans are simpler, bushy tree plans are preferred in distributed systems like Spark SQL due to their ability to parallelize join operations, though their search space is larger. Thus, we integrate bushy-tree plan enumeration within the search for left-deep tree plans. Specifically, during each iteration, when encountering a sub-plan P_1, the algorithm attempts to generate a bushy tree plan that includes P_1, that is, it recursively generates a join plan P_2 for the remaining tables, and then joins P_1 with P_2. Additionally, the algorithm uses the cost of full join plans to prune the unpromising sub-plans in subsequent searches.

Our contributions are summarized as follows.

- We propose LEAP, the first learned query optimizer tailored for Spark SQL, which is **simple yet effective**. It consists of two modules: Join Plan Enumerator and Join Operator Selector, to optimize join order and physical operator selection, respectively, which can be seamlessly integrated into existing workflows.
- We develop a Learned Comparator to evaluate the relative cost of two join plans rather than their exact cost, which helps to select better join plans. It provides more accurate comparisons with predicate information and data features.
- We propose an efficient progressive plan enumeration algorithm to reduce the enumeration space, which incorporates beam search strategy and pruning techniques.
- We conduct extensive experiments on three public benchmarks. LEAP reduces the native optimizer's end-to-end execution time by up to 54% and other learned methods by up to 94%.

We organize this paper as follows. Section 2 introduces Spark SQL's optimization process. Section 3 presents an overview of LEAP. Sections 4, 5, 6 describe three main components of LEAP respectively. Section 7 analyzes the experimental results. Section 8 displays the related works. Finally, Section 9 concludes the paper.

2 PRELIMINARY

In this section, we provide an introduction to the join plan and the optimization process of Spark SQL.

2.1 Join Plan

Given a query Q composed of n tables $\mathcal{T} = \{T_1, T_2, T_3, \ldots, T_n\}$, a join plan P is a tree consisting of these tables to specify the sequence of join operations. In P, leaf nodes are filter operations on tables, while non-leaf nodes represent logical join operations (e.g., Inner Join ($\bowtie$), Left Join). We denote the number of output rows of P as its output cardinality $Card(P)$, and refer to the tables involved in P as $\mathcal{T}(P)$. Additionally, any subtree within P is defined as a sub-plan.

Join plans can be categorized into left-deep tree plans and bushy tree plans. In a left-deep tree plan, the left child of any join operation is a subtree, and the right child must be a leaf node, as shown in the join plan P_1 in Figure 2. It allows only sequential execution of join operations, with a $O(n!)$ search space. In contrast, bushy tree plans allow both children of any join operation to be subtrees, as shown in the join plan P_2 in Figure 2. This structure enables parallel execution of join operations. However, the complexity of possible join plan trees grows significantly, expanding to $\frac{(2n-2)!}{(n-1)!}$ [29].

2.2 Optimization Process of Spark SQL

In Spark SQL, there are two types of execution plans: LogicalPlan and PhysicalPlan, as shown in Figure 2. LogicalPlan corresponds to

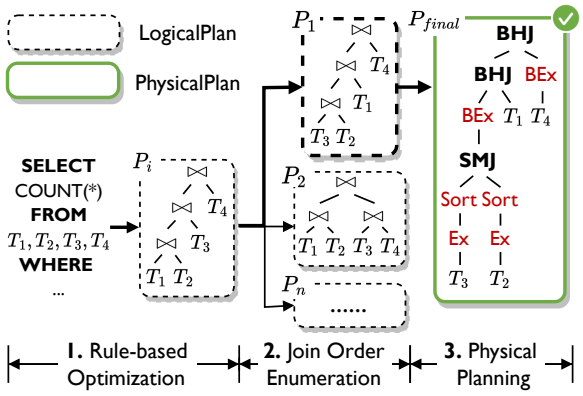


Figure 2: An overview of Spark SQL's optimization process. BHJ and SMJ denote physical join operators, while the red ones are additional physical operators.

the "join plan" in Section 2.1, which only contains logical operations. PhysicalPlan replaces these logical operations with concrete physical operators and adds additional ones (e.g., Exchange). For a query Q, Spark SQL uses the following three stages to first transform Q to an optimized LogicalPlan P_1 and then generate a PhysicalPlan P_{final} for execution, as shown in Figure 2.

2.2.1 Rule-based Optimization. In this stage, native optimizer transforms query Q into an initial LogicalPlan P_i. It converts Q into a LogicalPlan P_i with a parser and an analyzer, and then optimizes P_i using a series of optimization rules (e.g., predicate pushdown).

2.2.2 Join Order Enumeration. In this stage, native optimizer selects a low-cost LogicalPlan P_1 by reordering the Inner Join operations in P_i. The cost of a LogicalPlan is measured by the estimated cardinality and output size, without considering physical operators or resource consumption [5]. Based on the tables $\mathcal{T}$ in query Q, it uses a dynamic programming algorithm to enumerate different join plans from bottom to up. Specifically, the enumeration begins with 1-table sub-plans and incrementally constructs i-table sub-plans from existing j-table sub-plans (where $1 \leq j \leq i-1$). It terminates after sub-plans containing all tables are generated. During the enumeration, native optimizer utilizes the CBO module to estimate the cost of each LogicalPlan, and selects the one P_1 with the lowest cost among candidates P_1, P_2, ..., P_n. The order of join operations significantly impacts query performance. A suitable LogicalPlan can reduce the intermediate tables, thereby reducing the need of time and resource of intermediate join operations.

2.2.3 Physical Planning. In this stage, native optimizer assigns physical operators to each join operation in P_1 based on heuristic rules, and then inserts additional physical operators (e.g., Exchange, Sort) accordingly to generate the PhysicalPlan P_{final} for execution. When assigning physical join operators, native optimizer uses the CBO module to estimate the output size of each sub-plan in P. If the output size of a sub-plan P_s is less than the parameter *spark.sql.autoBroadcastJoinThreshold* (or *BJT* for short), the output of sub-plan P_s is considered suitable for broadcasting. For each join operation, if the output of sub-plan on either side is suitable for broadcasting, a Broadcast Hash Join (BHJ) is used. This operator first broadcasts the smaller table to all workers, and then performs a hash join on the larger table. Otherwise, a Sort Merge Join (SMJ) or Shuffled Hash Join (SHJ) is employed, shuffling both tables to execute the join operation. Using BHJ properly can avoid shuffling large tables and reduce query time. However, using BHJ inappropriately, such as broadcasting excessively large tables due to output size estimation errors, can lead to increased execution times and even query failures.

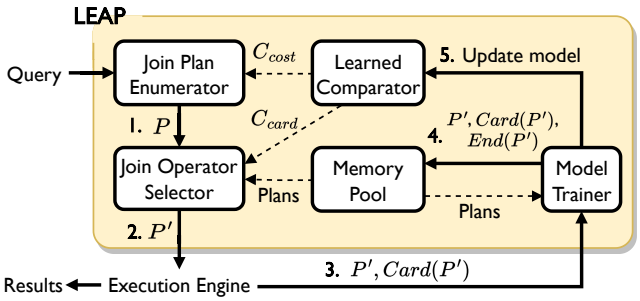


Figure 3: An overview of LEAP.

3 SYSTEM OVERVIEW

In this section, we present an overview of LEAP, and discuss its ability to adapt to different scenarios. It's primarily used for join optimization, as LEAP is designed to replace Spark SQL CBO, which mainly focuses on join order enumeration and join operator selection. It doesn't support physical operator selection of aggregate, indexing, etc, since Spark SQL selects aggregation operators based on rules, and it does not support indexes.

3.1 System Framework

Figure 3 illustrates LEAP's framework, which is mainly composed of five components: **Memory Pool**, **Learned Comparator**, **Join Plan Enumerator**, **Join Operator Selector**, and **Model Trainer**. For a query Q, Join Plan Enumerator generates a join plan P using Learned Comparator C_{cost}. Then, Join Operator Selector assigns physical operators to the join operations in P using Learned Comparator C_{card}, resulting in a final join plan P'. Subsequently, Spark SQL executes the join plan P'. As the execution completed, Model Trainer collects the join plan P' and its output cardinalities $Card(P')$ and saves them to Memory Pool. It also periodically updates the Learned Comparators C_{cost} and C_{card}.

Memory Pool. Memory Pool saves historical join plans in memory for the update of Learned Comparators. It's a key-value storage where the key is $Card(P)$, and the value is a triplet $(P, Card(P), End(P))$, where $P, Card(P), End(P)$ denote the join plan, its output cardinality, and its finish timestamp respectively. Memory Pool is updated after the execution of each query.

Learned Comparator. Learned Comparator $C(P_1, P_2)$ compares two join plans P_1 and P_2 in terms of a performance-related metric $L(P)$ (e.g., latency, cardinality). Formally, $C(P_1, P_2) = 1$ when $L(P_1) \geq L(P_2)$, and 0 otherwise. When $C(P_1, P_2) = 1$, P_1 is worse than P_2. We train two Learned Comparators C_{cost} and C_{card} using different $L(P)$ (i.e., the execution cost and output cardinality).

Join Plan Enumerator. Join Plan Enumerator aims to generate a low-cost join plan for each query Q. It employs an enumeration algorithm to iteratively search for left-deep tree plans, and at each step of the iteration, it attempts to generate bushy tree plans. Finally,

it selects the join plan with the lowest cost from all candidate plans by pairwise comparisons using C_{cost}.

Join Operator Selector. Join Operator Selector assigns appropriate physical operators for each join operation in the join plan P. For simplicity, we only focus on whether to use Broadcast Join (i.e., Broadcast Hash Join or Broadcast Nested Loop Join), which is sufficient for acceptable performance improvement. First, it selects some plans with known cardinalities from Memory Pool. It then compares these plans with each sub-plan P_s in join plan P using C_{card}, to determine whether the output of each sub-plan P_s can be broadcast. After this evaluation, it selects the appropriate physical operator for each join operation.

Model Trainer. Model Trainer periodically updates the Learned Comparators based on the data maintained in Memory Pool. As the query execution completed, it collects the join plan P' and the corresponding output cardinality $Card(P')$, and saves the tuple $(P', Card(P'), End(P'))$ into Memory Pool. Also, it regularly clears old data from Memory Pool and re-trains the Learned Comparators C_{cost} and C_{card} using the accumulated new data.

3.2 Discussion

Here we discuss LEAP's ability to adapt to various scenarios.

Cold-start scenarios. When there is no training plan for a new workload, we can initialize LEAP's Learned Comparator with Spark SQL's native estimates similar to [46, 53]. Specifically, we enumerate sub-plans using Spark SQL's native optimizer for each training query, and train LEAP's comparator using such plans, with native cardinality estimates as labels. Also, as reported in Section 7.2.4, LEAP performs better than native optimizer even with few training queries, which can be quickly collected in production.

Compatibility with other systems. While LEAP is initially designed for Spark SQL, it can support other big data query systems. In other systems, LEAP rewrites SQL queries based on the optimized join order and specifies physical operators using hints, if supported. LEAP first converts the input SQL query into a system-agnostic logical plan P, containing only logical operations (e.g., joins and filters) and regardless of physical operators. It then optimizes join order and physical operators in P to produce an optimized plan P'. Finally, LEAP rewrites the query and organizes the physical operator hints based on P', and sends the rewritten query to the target system for execution. As reported in Section 7.2.3, LEAP also achieves performance improvement in Presto and Apache Doris.

Compatibility with other queries. LEAP can support query types beyond Select-Project-Join (SPJ) queries. It can be extended to handle other operators (e.g., Aggregate, Intersect, Outer Join) by modifying the one-hot encoding of logical operators in Section 4.1.2. Currently, LEAP does not support queries with predicate sub-queries (i.e., sub-queries in IN or EXISTS) as Spark SQL decorrelates them after join order enumeration, preventing us from collecting training labels. We plan to address this limitation in future work.

4 LEARNED COMPARATOR

Learned Comparator $C(P_1, P_2)$ compares the performance-related metric $L(P)$ of join plans P_1 and P_2. If $L(P_1) \geq L(P_2)$, $C(P_1, P_2) = 1$, and 0 otherwise. Our comparator improves the existing learned comparators [8, 53] in the following three aspects. First, we integrate predicate information and data features to increase the accuracy. Second, we use a sequence model to deal with the tree structure. This method is more efficient than tree-based neural networks. Third, our approach eliminates the need to execute multiple different join plans for the same query, and thus speeds up the collection of training data and enhances the usability.

4.1 Model Design

Learned Comparator processes join plan trees P_1 and P_2 by first flattening them into node sequences and transforming each node into a vector representation. These vectors are then aggregated using LSTM to form representations for the entire trees of P_1 and P_2, which are subsequently compared to produce the final result $C(P_1, P_2)$, as shown in Figure 4. Unlike traditional tree-based networks like tree convolutions [23, 24, 53] and Tree-LSTM [35, 48], which often suffer from long inference times due to their complex tree structure processing, our method simplifies the structure by using sequence models to significantly reduce the inference time.

4.1.1 Plan tree linearization. It transforms the join plan tree P into a node sequence $Seq(P)$. Using a direct node traversal sequence would lose structural information. To preserve this, we linearize the tree into a SBT (Structure-based Traversal) node sequence, inspired by code representation techniques [17]. We use a preorder traversal but add a terminal node after each subtree to mark its end. For instance, if a subtree's root node is 'Inner Join', a terminal node labeled ') Inner Join' follows its traversal.

4.1.2 Plan node representation. It converts each join plan tree node $N \in Seq(P)$ into a low-dimensional vector representation $Emb(N)$. As shown in Figure 4, $Emb(N)$ is the concatenation of following four parts: (1) a one-hot encoding of the logical operator on N (e.g., Filter, Inner Join, Left Join), (2) 0/1 encoding of tables touched by N, (3) the row count of chosen tables, and (4) the predicate embedding of the predicates in N. Row counts undergo logarithmic transformation and min-max scaling to scale values within [0, 1], and the details about predicate embeddings are in Section 4.1.3.

4.1.3 Predicate representation. It converts the predicates in join plan tree node N into vector representations. Predicates can also be viewed as a tree, where leaf nodes are atomic predicates f (such as $table.id = 7$), and non-leaf nodes are boolean operators (AND, OR, NOT). We first linearize the predicate tree into a SBT node sequence as in Section 4.1.1. Then, we extract features for each node (atomic predicate f or boolean operator), and finally aggregate the features of all nodes through a LSTM to get the final predicate embedding.

Atomic predicate featurization. An atomic predicate f (such as $table.id = 7$) consists of a column $Col(f)$, an operator $Op(f)$ (e.g., >, <, IN, LIKE), and an operand $Val(f)$. Its feature $Emb(f)$ is the concatenation of the following five parts, as shown in Equation 1,

$$Emb(f) = [Col(f)_{id}\ Op(f)_{id}\ Val(f)\ Hist(f)\ Sel(f)] \quad (1)$$

where $Col(f)_{id}$ and $Op(f)_{id}$ are the one-hot encoding of columns and operators, and $Val(f)$ is the normalized value of the operand. Histogram embedding $Hist(f)$ and selectivity embedding $Sel(f)$ serve as data features, and we discuss their details below.

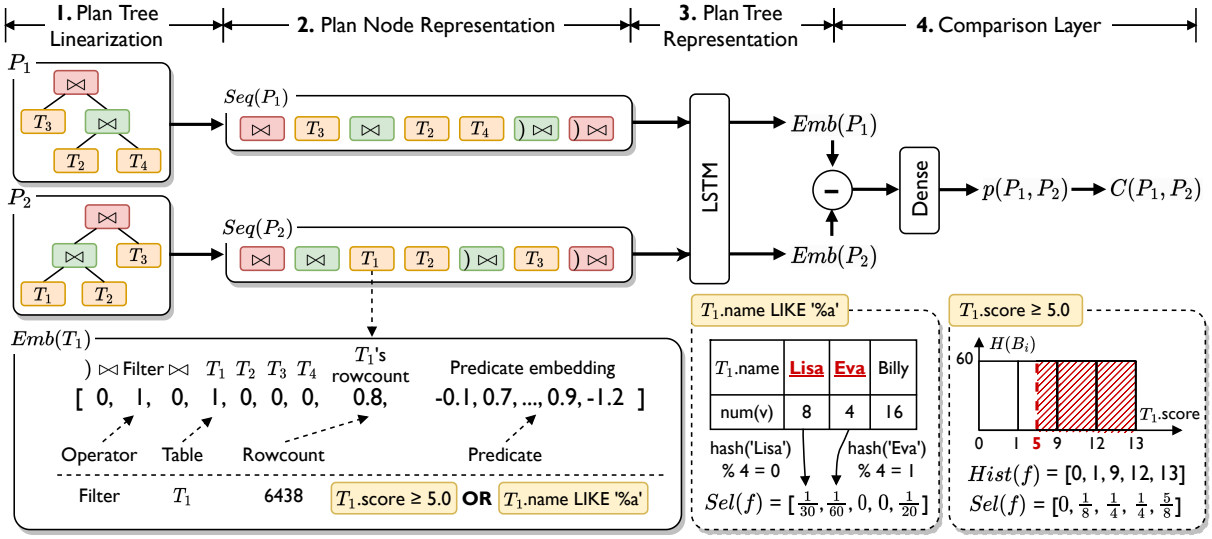


Figure 4: Our comparator model. ⋈ represents Inner Join, while) ⋈ represents the end of the subtree rooted at a ⋈ node.

(1) **Histogram** $Hist(f)$**.** It featurizes the histogram of column $Col(f)$, which represents the data distribution by dividing data into intervals (a.k.a bins). Each bin B_i's width $W(B_i)$ (interval length) may vary while the height $H(B_i)$ (number of elements in B_i) is uniform in Spark SQL's equi-height histograms. For numeric column $Col(f)$, we extract its equi-height histogram from Spark SQL, and $Hist(f)$ is the concatenation of boundary values of each bin. Histogram features help Comparator understand data distributions to handle skewed distributions.

(2) **Selectivity** $Sel(f)$**.** It represents the estimated selectivity of f. We estimate the selectivity by diving the column $Col(f)$ into m bins to estimate the number of qualified elements n_i in the i-th bin, and then summing up n_i as f's overall selectivity ($1 \le i \le m$). Thus, $Sel(f)$ is the concatenation of n_i and f's overall selectivity. We discuss how to compute n_i as below.

- If $Col(f)$ is numeric, we use its histogram as m bins to estimate n_i. For each bin B_i in the histogram, we determine its intersection with f's range $f \cap B_i$, and use the intersect width $|f \cap B_i|$ to calculate n_i as Equation 2,

$$n_i = \frac{|f \cap B_i|}{W(B_i)} \times H(B_i) \tag{2}$$

- If $Col(f)$ is string-based, histograms are not available. Thus, we divide $Col(f)$ into m bins using the hash values of the elements. We build a Most Common Value (MCV) list that identifies the most frequent values v and their counts $num(v)$ in $Col(f)$, using this list to estimate n_i. For predicate f, we identify values $V = \{v_1, v_2, \ldots, v_n\}$ from the MCV list that match the predicate f. For each matching value $v \in V$, we use its hash value $hash(v)$ to allocate it to the i-th bin, and update the corresponding n_i with $num(v)$, as shown in Equation 3. This approach can estimate selectivity for complex string predicates such as IN and LIKE, which are not widely supported in previous works. Note that this approach performs well on string columns with any distribution. For an infrequent or unique value v, we estimate its count $num(v)$ using the number of distinct values (NDV). Our MCV list contains up to 1000 frequent values per column, and NDV estimates are accurate for values outside this list.

$$n_i = \sum_{v \in V:\, hash(v)\%m=i} num(v) \tag{3}$$

We concatenate the n_i and the sum of n_i as the selectivity embedding $Sel(f)$. To normalize the values, we divide each value by the number of total elements $|Col(f)|$ to scale within $[0, 1]$, as shown in Equation 4.

$$Sel(f) = \frac{1}{|Col(f)|}\left[n_1, n_2, ..., n_m, \sum_{1 \le i \le m} n_i\right] \tag{4}$$

For example, for a numeric predicate $f_1 : T_1.score \ge 5.0$ in Figure 4, the histogram of $T_1.score$ has 4 bins, each with a height $H(B_i) = 60$. According to Equation 2, f_1 selects no element in the first bin, half in the second, and all the elements in the third and fourth bins. Thus, $n_i = [0, 30, 60, 60]$, leading to $Sel(f_1) = \frac{1}{240}[0, 30, 60, 60, 150]$. Also, for a string predicate $f_2 : T_1.name$ LIKE '%a' in Figure 4, we set $m = 4$, and the MCV List of $T_1.name$ records three common values 'Lisa', 'Eva' and 'Billy' in this column and their occurrence counts. Since only 'Lisa', 'Eva' end with 'a' in MCV List, we compute n_i based on the two values, and get $n_i = [8, 4, 0, 0]$. Thus, $Sel(f_2) = \frac{1}{240}[8, 4, 0, 0, 12]$.

Boolean operator featurization. We use one-hot encoding for each type of boolean operator as their features.

4.1.4 Plan tree representation. It generates the vector representation $Emb(P)$ of the entire join plan P. It employs a LSTM network to aggregate the representation $Emb(N)$ of each node $N \in Seq(P)$, and the final hidden state of LSTM network is regarded as $Emb(P)$.

4.1.5 Comparison layer. It compares the vector representations of join plans P_1 and P_2 (i.e., $Emb(P_1)$ and $Emb(P_2)$), and outputs a binary label (0 or 1) based on their comparison. We use $Emb(P_1) - Emb(P_2)$ as the final representation of the pair (P_1, P_2), and it's then passed through a linear layer to generate an output logit. The logit

is then transformed by a sigmoid function $\sigma(x) = 1/(1+e^{-x})$ to yield a probability value $p(P_1, P_2) \in (0, 1)$, as shown in Equation 5.

$$p(P_1, P_2) = \sigma(\boldsymbol{W}(Emb(P_1) - Emb(P_2)) + \boldsymbol{b}) \tag{5}$$

where $\boldsymbol{W}$ and $\boldsymbol{b}$ are learnable parameters.

Finally, the binary indicator $C(P_1, P_2)$ is defined as a step function via the probability $p(P_1, P_2)$. Specifically, if $p(P_1, P_2) \geq 0.5$, then $C(P_1, P_2) = 1$, which indicates $L(P_1) \geq L(P_2)$, and vice versa.

4.2 Model Training

Construct training data. We randomly generate some training queries $\mathcal{Q}$, and execute these queries on Spark SQL. Suppose the training query $Q \in \mathcal{Q}$ is executed using join plan P, we collect the corresponding $L(P)$ to form a set of join plans $\mathcal{P}$. Then, we generate plan pairs from $\mathcal{P}$ to build the training data $\mathcal{D}$. For each plan pair $(P_1, P_2) \in \mathcal{P}$, if $L(P_1) \geq L(P_2)$, we assign a label $l(P_1, P_2) = 1$; otherwise, assign $l(P_1, P_2) = 0$. Then, we include the triplet $(P_1, P_2, l(P_1, P_2))$ in the training dataset $\mathcal{D}$. Unlike previous studies [8, 53], we do not need to execute different join plans for the same query $Q \in \mathcal{Q}$. This allows us to construct more training data.

Train the model. We use training data $\mathcal{D}$ to train the comparators using binary cross entropy loss $\mathcal{L}$, as shown in Equation 6.

$$\begin{aligned}\mathcal{L} = -\sum_{(P_1,P_2,l(P_1,P_2))\in\mathcal{D}} & (l(P_1,P_2)\log p(P_1,P_2) \\ & + (1-l(P_1,P_2))\log(1-p(P_1,P_2))),\end{aligned} \tag{6}$$

where $l(P_1, P_2)$ is the binary label of plan pair (P_1, P_2), and $p(P_1, P_2)$ is the output probability of comparator $C(P_1, P_2)$.

4.3 Different Comparators

We train two Learned Comparators C_{cost} and C_{card} with different $L(P)$, to compare the execution cost and output cardinality of two join plans. These two comparators are used in Join Plan Enumerator and Join Operator Selector, as detailed in Sections 5 and 6.

Cost comparator C_{cost}. It compares the execution costs of join plans P_1 and P_2 by using $Cost(P)$ as $L(P)$. Assume that join plan P is a Γ-layer tree, we define its execution cost $Cost(P)$ as the sum of the maximum output cardinality of join nodes at each layer. Formally, $Cost(P) = \sum_{\gamma=0}^{\Gamma} \max\{Card(P_\gamma)\}$, where P_γ is the sub-plan rooted at join nodes in the γ-th layer. We adopt such a cost model since Spark SQL does not provide cost estimation, and this approach accommodates the preference for bushy tree plans in distributed systems. Then, we use $Cost(P)$ to generate labels to train C_{cost}.

Card comparator C_{card}. It compares the output cardinalities of join plans P_1 and P_2 by using $Card(P)$ as $L(P)$, i.e., we use $Card(P)$ to generate labels to train C_{card}.

5 JOIN PLAN ENUMERATOR

Join Plan Enumerator generates a low-cost join plan for query Q using a join plan enumeration algorithm. This algorithm searches for left-deep tree plans progressively, and tries to generate bushy tree plans in each iteration. It then picks the cheapest join plan by pairwise comparison using C_{cost}.

Overview. Algorithm 1 outlines our join plan enumeration method. It starts with table set $\mathcal{T}$ and aims to produce a join plan composed of these tables. The algorithm initializes sub-plans $\mathcal{P}_t$ from $\mathcal{T}$'s pairwise table combinations (line 2). Using a beam search [28], it

Algorithm 1: `findBestPlan`$(\mathcal{T}, k)$

Input : Tables $\mathcal{T}$, beam width k
Output: A cheapest join plan composed of $\mathcal{T}$'s tables

```
1  if |T| ≤ 2 then return a join plan composed of T's tables;
2  P_t ← findTopK({createJoin(T_i, T_j), ∀T_i, T_j ∈ T(i < j)}, k);
3  P_o ← None ;                    /* to store the optimal plan */
4  for i ← 2 to |T| − 1 do
       // Quasi-bushy tree search
5      for P_1 ∈ P_t do
6          if canBeBroadcast(P_1) then
7              P_2 ← findBestPlan(T \ T(P_1), k);
8              P_b ← createJoin(P_1, P_2);
9              if C_cost(P_o, P_b) then P_o ← P_b;
       // Left-deep tree search
10     P_l ← ∅;
11     for P_1 ∈ P_t do
12         for T ∈ T do
13             P_l ← P_l ∪ {createJoin(P_1, T)};
14     P_t ← findTopK(P_l, k);
       // Pruning
15     for P_s ∈ P_t do
16         if C_cost(P_s, P_o) then P_t ← P_t \ {P_s};
17     if |P_t| = 0 then break;
18 return findTopK(P_t ∪ {P_o}, 1);

19 Function createJoin(P_l, P_r)
20 return a new join node with left child P_l and right child P_r;

21 Function findTopK(P, k)
22 return top-k cheapest join plans in P;
```

iteratively extends the sub-plans in $\mathcal{P}_t$ by joining with a new table and keeps the k cheapest new sub-plans for the next iteration, generating left-deep tree plans composed of $\mathcal{T}$'s tables when search terminates. During each beam search iteration, the algorithm first attempts to generate a bushy tree plan that includes all tables (lines 5-9). For each sub-plan P_1, it checks whether a bushy tree plan can be generated based on P_1. If so, it searches for a join plan P_2 using the remaining tables recursively, and joins P_1 and P_2 to generate a full bushy tree plan P_b. After the bushy tree plan search, the algorithm continues to search for the left-deep tree plans (lines 10-17). As bushy tree search can obtain full plans, the algorithm maintains an optimal plan P_o, and uses its cost to prune the unpromising sub-plans. Finally, it combines the bushy tree plans and left-deep tree plans, and selects the join plan with the lowest cost. Overall, in each iteration of Algorithm 1, it first uses **bushy tree search** to generate an optimal full bushy plan based on the left-deep sub-plans generated in the previous iteration (we can generate a full bushy plan for each left-deep sub-plan and select the optimal one), and then uses **left-deep tree search** to generate k left-deep sub-plans with one additional table.

Quasi-bushy tree search. In each beam search iteration, when encountering sub-plan P_1, the algorithm attempts to generate a quasi-bushy tree plan P_b containing all tables. It recursively finds join plan P_2 for the remaining tables and joins P_1 and P_2 to generate P_b. This allows P_1 and P_2 to run in parallel, enhancing performance. However, this method requires time-consuming k recursive

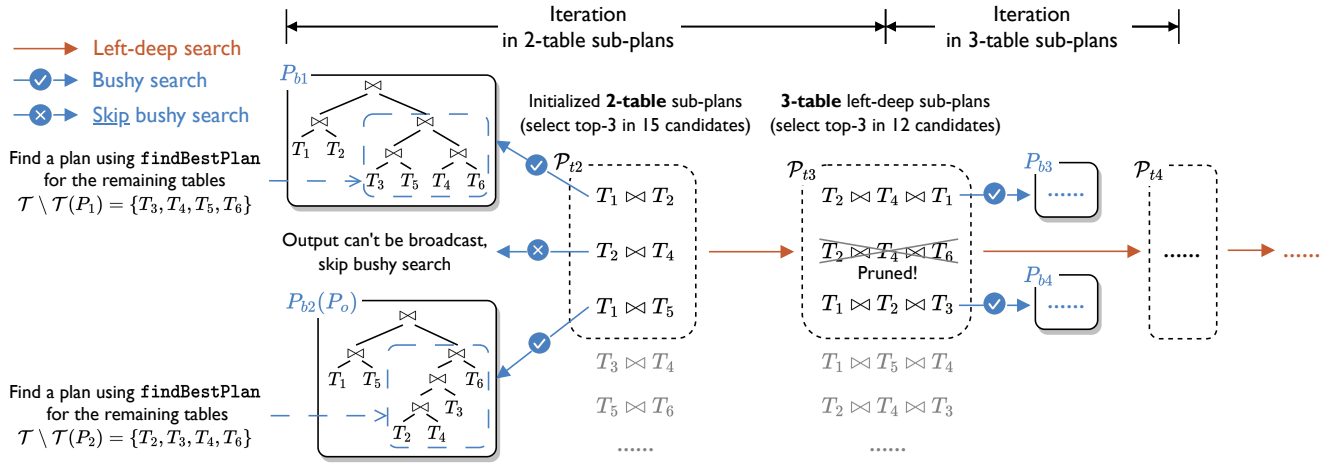


Figure 5: A running example of Algorithm 1 with 6 tables $\mathcal{T} = \{T_1, T_2, \ldots, T_6\}$ and $k = 3$.

searches per iteration. Also, bushy tree plans need to materialize intermediate tables, and the performance degrades if the outputs of P_1 or P_2 are large. To address these issues, we use `canBeBroadcast` to retain the P_1 with output sizes suitable for broadcasting (as detailed in Section 6), and only do the recursive searches based on such P_1. This reduces the number of recursive searches and lowers materialization costs, as P_1 join P_2 can be executed using Broadcast Join, which only materialize the small P_1. When the full plan P_b is generated, the algorithm maintains the optimal full plan P_o to prune the search space. The quasi-bushy tree search method avoids searching in the entire bushy tree space, greatly reducing optimization costs.

Left-deep tree search. After quasi-bushy tree search, the algorithm continues to search for left-deep tree plans. It starts with the sub-plans $\mathcal{P}_t$ from the previous iteration. For each sub-plan $P_1 \in \mathcal{P}_t$ (a d-table sub-plan, $2 \le d < |\mathcal{T}|$), the algorithm joins it with a new table, generating $(d+1)$-table candidate sub-plans $\mathcal{P}_l$. It only retains the k lowest-cost sub-plans of $\mathcal{P}_l$ for the next iteration. Note that, in beam search we only consider left-deep sub-plans, since left-deep sub-plans are partial sets of tables, while the generated bushy plans P_o always include all tables. Thus, left-deep sub-plans consistently have lower costs than full bushy plans, so keeping the top-k plans overall is not meaningful. The search terminates when left-deep plans containing all tables are generated. This reduces the search space while considering multiple search paths to find a better join plan. Moreover, the quasi-bushy tree search yields an optimal join plan P_o. In subsequent iterations of beam search, the algorithm prunes less promising sub-plans based on P_o's cost, further reducing the search space.

Find top-k plans with comparison. Here, we outline how `findTopK` selects the top-k cheapest sub-plans from candidates $\mathcal{P}$. Since C_{cost} doesn't estimate exact costs, it's not straightforward to pick the k lowest-cost sub-plans directly. Thus, we employ the quick select algorithm [16], which uses pairwise comparisons to reorder sub-plans in $\mathcal{P}$ and selects the first k as the cheapest. The process first chooses a pivot sub-plan from $\mathcal{P}$, and compares other sub-plans against this pivot using C_{cost}, and partitions $\mathcal{P}$ into two segments based on these comparisons. It then recursively searches the relevant segment until the k-th sub-plan is identified. While the average number of comparisons is $O(|\mathcal{P}|)$, the actual complexity is often reduced through parallel comparisons within C_{cost}.

Time Complexity Analysis. Assume $n = |\mathcal{T}|$ and the time complexity to process m tables is $T(m)$. In the i-th iteration, we perform at most k recursive searches for the remaining $n-i$ tables, and there are up to $k \cdot (n-i)$ candidate sub-plans in $\mathcal{P}_l$ during left-deep tree search. Consequently, the worst-case time complexity for the i-th iteration is $S(i) = k \cdot T(n-i) + k \cdot (n-i)$. Thus, the worst-case overall time complexity $T(n) = \sum_{2 \le i < n} S(i) = O(k^n \cdot n^2)$. However, the actual time complexity is much lower than $T(n)$. First, the actual number of recursive searches is less than k. In many cases, there is no qualified sub-plan P_1 that can be used to generate a bushy tree plan. Also, in our implementation, we prune the sub-plans with Cartesian Products, thereby reducing the number of candidate sub-plans in $\mathcal{P}_l$ to significantly lower than $k \cdot (n-i)$.

Example 5.1. Figure 5 illustrates a running example of Algorithm 1 involving join of six tables $\mathcal{T} = \{T_1, T_2, \ldots, T_6\}$, with a beam size $k = 3$. We denote $\mathcal{P}_{ti}$ as the set of i-table left-deep sub-plans. It first enumerates all pairwise table combinations, and selects the 3 cheapest ones among $\binom{6}{2} = 15$ candidates, i.e., $\{T_1 \bowtie T_2, T_2 \bowtie T_4, T_1 \bowtie T_5\}$ in $\mathcal{P}_{t2}$. Then, it runs iteratively to expand the sub-plans in $\mathcal{P}_{t2}$, and in this iteration, it works with the following two steps.

- **Bushy search**: Each sub-plan in $\mathcal{P}_{t2}$ generates a full execution plan during bushy search (shown by leftward blue arrows). As the output of sub-plan $P_1 : T_1 \bowtie T_2$ can be broadcast, the remaining tables $\mathcal{T} \setminus \mathcal{T}(P_1) = \{T_3, T_4, T_5, T_6\}$ are used to find a plan composed of the four tables (the blue dashed rectangle in P_{b1}) using Algorithm 1 recursively. This sub-plan is used to join with P_1 using `createJoin`, resulting in a full bushy plan P_{b1}. A bushy plan contains at least one Join operation where both children are also Join operations, as seen in the root nodes of P_{b1} and P_{b2}. This allows the two join operations to be executed in parallel. Similarly, $P_2 : T_1 \bowtie T_5$ generates a bushy plan P_{b2}. However, the algorithm skips the bushy search for sub-plan $P_3 : T_2 \bowtie T_4$, as its output can't be broadcast. Finally, we

maintain the optimal bushy plan P_o among the two bushy candidates P_{b1} and P_{b2}, and set $P_o \leftarrow P_{b2}$.

- **Left-deep search**: After bushy search, sub-plans in $\mathcal{P}_{t2}$ will join with a new table during left-deep search. As shown in the red arrows in Figure 5, each sub-plan in $\mathcal{P}_{t2}$ joins with each new table respectively, generating 3×4 = 12 candidates of 3-table left-deep sub-plans. Then, we select the top-3 cheapest candidates as $\mathcal{P}_{t3}$. Among these, $T_2 \bowtie T_4 \bowtie T_6$ is pruned, as its cost is higher than P_o's cost, and any plan containing $T_2 \bowtie T_4 \bowtie T_6$ will have a higher cost.

The above process is repeated iteratively until $\mathcal{P}_{t6}$, i.e., 6-table left-deep sub-plans are generated. Finally, Algorithm 1 selects a cheapest execution plan in the combination of $\mathcal{P}_{t6}$ and optimal bushy plan P_o.

Comparisons over existing beam-search-based plan enumerators. Beam search is used for plan enumeration in [7, 46]. In these approaches, they use the cost of the entire query containing a specific sub-plan to guide beam search, and thus their beam search operates on search states (each a set of sub-plans for the query). However, in LEAP, beam search differs from previous approaches, since LEAP directly uses the cost of individual sub-plans to guide the beam search. Therefore, LEAP's beam search operates on single sub-plans. As a result, beam search strategies in previous approaches can't be applied in Algorithm 1. LEAP additionally introduces recursive search for bushy plans and pruning techniques to better balance search efficiency and plan quality.

6 JOIN OPERATOR SELECTOR

Join Operator Selector assigns physical operators to each join operation in join plan P. First, it assesses whether the output of each sub-plan in P is suitable for broadcasting. Based on that, it assigns an appropriate physical operator to each join operation in P.

6.1 Assessing Broadcast Suitability

We discuss how to assess if a join plan's output is suitable for broadcasting. As described in Section 2, for a sub-plan P_s, Spark SQL evaluates if P_s's output can be broadcast by comparing its output size to *spark.sql.autoBroadcastJoinThreshold* (or BJT for short). However, that's a user-adjustable parameter. Given the variability of this threshold, assessing broadcast suitability of P_s can be challenging without cardinality value estimations.

To overcome this, we use join plans with known cardinalities from the training data of C_{card} to establish a reference. We can find some join plans $\mathcal{P}_h$ with output size close to BJT, and compare P_s with $\mathcal{P}_h$ using C_{card}. Thus, we can know whether P_s's output size is smaller than the broadcast threshold BJT. If smaller, P_s's output is suitable for broadcasting. The process is outlined in Algorithm 2. For a sub-plan P_s, it first computes a cardinality threshold t_{card} based on the broadcast threshold BJT and P_s's output width estimation from Spark SQL (line 1). Then, it selects some join plans $\mathcal{P}_h$ from Memory Pool that have a cardinality near t_{card} and exhibit high uncertainty (lines 2-3). Finally, it compares P_s with each join plan in $\mathcal{P}_h$ using C_{card}, and generates an output probability p_{card} (line 4). If the average output probability $\overline{p_{card}}$ is < 0.5, it indicates P_s's output size is smaller than that of $\mathcal{P}_h$, and thus smaller than BJT. P_s's output is then considered suitable for broadcasting.

Algorithm 2: `canBeBroadcast`(P_s)

Input : A sub-plan P_s
Output: Whether P_s's output can be broadcast

1 $t_{card} \leftarrow \frac{\text{Broadcast threshold } BJT}{\text{Estimated output width of } P_s}$;
2 $\mathcal{P}_r \leftarrow$ Set of join plans in Memory Pool with cardinality $\in [(1-\epsilon)t_{card}, (1+\epsilon)t_{card}]$;
3 $\mathcal{P}_h \leftarrow$ Join plans in $\mathcal{P}_r$ with top-c highest uncertainty;
4 $\overline{p_{card}} \leftarrow (\sum_{P \in \mathcal{P}_h} p_{card}(P_s, P)) \,/\, |\mathcal{P}_h|$;
5 **return** $\overline{p_{card}} < 0.5$;

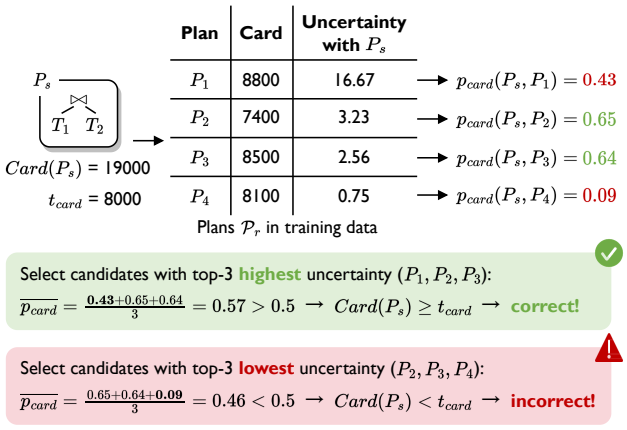


Figure 6: A running example of Algorithm 2 for a sub-plan P_s with $c = 3$ and cardinality threshold $t_{card} = 8000$. Green indicates the correct comparisons, while red indicates incorrect comparisons. The uncertainty of a plan P is measured by the reciprocal of L^2 distance between P and P_s.

Candidate selection. In Algorithm 2, selecting candidate join plans $\mathcal{P}_h$ is critical. Here, we first identify historical plans in Memory Pool with cardinalities that fall within $[(1-\epsilon)t_{card}, (1+\epsilon)t_{card}]$, and then retain c join plans with the highest uncertainty as candidate plans $\mathcal{P}_h$. We select c join plans with cardinality near t_{card} for comparison to avoid the potential inaccuracy of a single comparison. This strategy does not harm the performance, as the default value of BJT is not always optimal. Even if P_s's output size is slightly higher than BJT (for example, within $2 \times BJT$), it can still be considered suitable for broadcasting. In our method, hyperparameters c and ϵ control $|\mathcal{P}_h|$, and thereby affect the comparison accuracy and optimization cost. Their further effects are evaluated in Section 7.5. We prioritize candidate join plans with high uncertainty since they help avoid overly confident incorrect comparisons. Uncertainty is assessed by the L^2 distance between the representations of two join plan trees; a smaller distance indicates higher classification difficulty and uncertainty, as their representations are more similar. The intuition is that, when the embedding vectors of two plans, P_1 and P_2, have a small L^2 distance, $Emb(P_1) - Emb(P_2)$ approaches 0 in Equation 5. After regularization, the bias term $\mathbf{b}$ is also near 0, so $\mathbf{W}(Emb(P_1) - Emb(P_2)) + \mathbf{b}$ is near 0, and the output probability $p_{card} = \sigma(\mathbf{W}(Emb(P_1) - Emb(P_2)) + \mathbf{b})$ tends toward 0.5. Such probability helps to reduce the impact on $\overline{p_{card}}$ when encountering incorrect comparisons, as shown in Example 6.1. This process adds

minimal overhead since representations can be pre-computed for the join plans in Memory Pool.

Example 6.1. In Figure 6, for a sub-plan P_s, we first select $\mathcal{P}_r = \{P_1, P_2, P_3, P_4\}$ with similar cardinality to t_{card} from training data, and we select $c = 3$ candidates from $\mathcal{P}_r$ to evaluate whether P_s's output can be broadcast. Among them, P_1 and P_4 have incorrect comparisons. As P_1 has higher uncertainty, its corresponding output probability $p_{card}(P_s, P_1)$ is closer to 0.5. Thus, selecting P_1 can still lead to a correct decision, as the average probability $\overline{p_{card}}$ doesn't decrease too much. In contrast, selecting P_4 can lead to incorrect final decision, as $\overline{p_{card}}$ is greatly affected by the small value of $p_{card}(P_s, P_4)$.

6.2 Assigning Physical Operator

We assign appropriate physical operators by checking if the output of each sub-plan P_s in P can be broadcast. For each join operation, we use Algorithm 2 to assess whether the output of either child sub-plan can be broadcast. If so, a BROADCAST hint is added to that join, prompting Spark SQL to execute it using Broadcast Join.

7 EXPERIMENTS

In this section, we conduct extensive experiments to validate the effectiveness of our learned Spark SQL optimizer LEAP.

7.1 Experiment Setup

7.1.1 Environment. We conduct the experiments in a 3-node cluster with Spark 3.3.0. Each node is interconnected via a 1Gbps network. We assign a total of 36 executor cores and 60GB executor memory for query execution. We use a NVIDIA RTX-3090 GPU for model training, and use CPU for model inference during optimization.

7.1.2 Benchmarks. We select three typical benchmarks for evaluation by following previous studies [8, 53].

JOB [19]. Join Order Benchmark (JOB) utilizes the real-world IMDB dataset, which includes 21 tables on movies and actors. JOB comprises 113 realistic queries derived from 33 templates, with each query involving between 4 and 17 relations. We expand the IMDB tables tenfold, resulting in a 37GB dataset.

STACK [23]. STACK includes 10 tables about the information from Stack Exchange websites. The benchmark contains queries from 16 templates, with each query involving between 4 and 12 relations. The entire dataset is 100GB. In our evaluation, we exclude templates #4, 7, 9 and 10 because the first two involve arithmetic operations in join conditions, and the last two have predicate subqueries not yet supported by LEAP and all previous related works. We plan to address these limitations in future works.

TPC-H [36]. TPC-H includes 8 tables about the decision support applications in business intelligence. The benchmark contains 22 templates, and we can generate different queries based on them. We produce 100GB data as the dataset. In our evaluation, we only consider the query templates #2, 3, 5, 7, 8, 9, 10 following [53]. We exclude other templates, as they are too simple (only have one or two tables), or contain predicate subqueries.

7.1.3 Baselines. As many competitors can't fully optimize Spark SQL queries, we compare LEAP with three typical methods.

Spark SQL native optimizer employs Cost-Based Optimization (CBO) to estimate the output size of each join plan, and uses these estimations to guide the join plan enumeration and physical operator selection. In CBO module, it uses NDV and histograms for estimation, and we set the number of histogram bins to 64.

Lero [53] is a learned optimizer also using a learned comparator to choose join plans. We adopt the implementation from authors [2].

E2E [33] is a learned query-driven cardinality estimator based on TLSTM model. We implement it on Spark SQL based on its code [1], and replace CBO's cardinality estimation with E2E's estimation. We exclude other query-driven estimators as they lack support for disjunction [18, 20], string predicates [37], or bushy tree plan estimation [26]. We do not consider data-driven cardinality estimators due to their higher inference times according to [37].

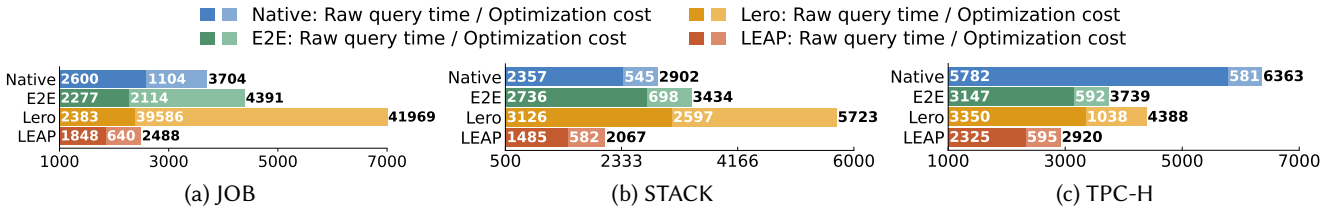
We don't consider another learning-to-rank optimizer LEON [8] as it can't optimize the physical operator selection. The performance drops in this case according to Section 7.4.1. We don't consider learned Spark SQL cost models [21, 22], because they estimate the cost of PhysicalPlans in Spark SQL, not LogicalPlans. As discussed in Section 2.2.2, the optimal join order is determined by the cost of LogicalPlan, so these models cannot be used for join order optimization. Additionally, Spark SQL's native optimizer (Catalyst) does not provide alternative PhysicalPlans for comparison in current implementation [5], making it impossible to select the best plan using a learned cost model without altering the source code.

7.1.4 Settings. We first generate training and test queries as [23, 53], and evaluate the optimizers in a static manner.

Training data generation. For each benchmark, following [23, 53], we generate 1,000 training queries based on its query templates. We randomly choose a query template, retrieve its join conditions, and add some random predicates to generate each training query. To support Lero, we use its plan exploration strategy to generate multiple candidate join plans for each training query. Thus, there are 7,600 distinct plans for JOB, 5,409 distinct plans for STACK and 3,494 distinct plans for TPC-H. This strategy is reasonable, as nearly-identical queries are frequently repeated in some OLAP workloads [23, 44]. For the test set, we employ different strategies. In JOB, we use the 113 realistic queries as test set. In STACK, we randomly select 10 queries from each query template as test set. In TPC-H, we randomly generate 10 queries for each query template.

Evaluation scenarios. All methods are evaluated in a static manner. We first train the optimizers with all training queries until convergence, then use the optimizers to run test queries and report their performance. Thus, we can compare the performance of different methods once they have been stabilized on a workload.

Evaluation metrics. We consider three key metrics in our evaluation. (1) End-to-end query execution time. This is the time a query takes from start to finish to return results. In the following text, we may also call it "query performance". (2) Optimization cost. This is the time required to generate a final join plan for query execution. (3) Raw query time. This is the duration of Spark SQL jobs associated with the query. Simply, end-to-end query execution time is the sum of raw query time and optimization cost.



(a) JOB (b) STACK (c) TPC-H

Figure 7: Query performance on three benchmarks in seconds. Black numbers outside bars represent end-to-end query execution time, while the white numbers in dark and light bars represent raw query time and optimization cost respectively.

7.2 Query Performance

7.2.1 Total execution time. Figure 7 presents the total execution time for all test queries for each method. We set a timeout for raw query time of 300s to reduce the effect of long-running join plans.

End-to-end query execution time. As shown in Figure 7, LEAP outperforms the three baselines in end-to-end query execution time (the sum of dark and light bars in Figure 7). Compared with the native optimizer, LEAP reduces execution time by 32.8%, 28.8%, 54% in JOB, STACK and TPC-H respectively. Compared with E2E, LEAP reduces execution time by 43.3%, 39.8%, 21.9% in JOB, STACK and TPC-H respectively. These results showcase the effectiveness of our learning-to-rank approach over regression-based methods. Compared with Lero, LEAP reduces execution time by 94.1% in JOB, 63.9% in STACK, and 33.5% in TPC-H. Lero's much longer execution time is due to its high optimization cost, as analyzed below.

Optimization cost. We compare the optimization cost (the light bars in Figure 7) of all methods mentioned above. Compared with the native optimizer and E2E, LEAP reduces optimization cost by 42% and 69.7% respectively in JOB. This is because the native optimizer and E2E experience exponential growth in the search space of join plans for queries with more tables, while LEAP's search space maintains stable growth, as reported in Section 7.3.2. While in STACK and TPC-H, LEAP shows similar optimization costs due to the smaller search space with fewer tables and possible join conditions. Compared with Lero, LEAP reduces the optimization cost by 98.4%, 77.6%, 42.7% in JOB, STACK and TPC-H respectively. Lero incurs high optimization costs because it generates $|\alpha| \cdot |\mathcal{T}(Q)|$ candidate join plans with the native optimizer for each test query Q. Here, α is the set of scaling factors, and we adopt $\alpha = \{10^{-2}, 10^{-1}, 1, 10^{1}, 10^{2}\}$ as in [53], resulting in an optimization cost several times higher than that of the native optimizer.

Raw query time. We compare the raw query time without optimization cost (the dark bars in Figure 7) to demonstrate LEAP's effectiveness in finding good join plans. Compared with native optimizer, LEAP reduces raw query time by 28.9%, 37.0%, 59.8% in JOB, STACK and TPC-H respectively. That's because our learning-based approach helps to identify low-cost join plans that the native optimizer may miss due to inaccurate cardinality estimates. Compared with E2E, LEAP reduces raw query time by 18.8%, 45.7%, 26.1% respectively, as E2E still suffers from high cardinality estimation errors, while our approach reduces such errors by an estimation-free pairwise comparison. Compared with Lero, LEAP reduces the raw query time by 22.5%, 52.5%, 30.6% respectively. That's because Learned Comparator in LEAP integrates the predicate information and data features to make more accurate comparisons, instead of relying on Spark SQL CBO's inaccurate estimation. Interestingly, we find that comparison-based Lero performs worse than regression-based E2E in raw query time. The reasons are twofold. First, Lero may generate more sub-optimal candidate plans with its plan exploration strategy in Spark SQL. By scaling up the estimated cardinality of sub-queries, it may convert Broadcast Hash Join to Sort Merge Join, leading to large table shuffles, and conversely, it may trigger large table broadcasts. Both cases will incur very high network transfer costs, causing the execution time to grow faster. Thus, Lero is more likely to choose a sub-optimal plan considering the large amount of sub-optimal candidates. Second, Lero and E2E uses different features to encode the filter information. Lero relies solely on cardinality and width estimates from the native optimizer to encode the data and filter information, which often lack accuracy, especially in Spark SQL. This can reduce the comparator's effectiveness. In contrast, E2E uses predicate information (e.g., column, operator, operand for each predicate) and sample bitmaps to capture fine-grained details of join conditions and filters, which Lero does not support. We also evaluated E2E's raw query time using native cardinality estimates instead of predicate information, as shown in Table 1. The results show that E2E's raw query time is higher than that of Lero when using native cardinality estimates.

Table 1: Total raw query time of E2E using native cardinality estimates to replace predicate information, in seconds.

	JOB	STACK	TPC-H
E2E	2,277.0	2,736.0	3,147.0
E2E with native estimates	2,744.7	3,910.6	6,282.0
Lero	2,383.0	3,126.0	3,350.0

Table 2: The speedup ratio of learned optimizers over native optimizer in training and test queries. The higher, the better.

	JOB (RandSplit)		JOB (SlowSplit)		STACK		TPC-H	
	Train	Test	Train	Test	Train	Test	Train	Test
E2E	1.12	1.3	1.14	1.14	0.81	0.98	1.90	**1.18**
Lero	1.09	1.08	1.08	1.14	0.86	0.61	1.80	1.02
Balsa	0.75	0.58	0.67	0.70	0.35	0.39	2.00	0.89
LEAP	**1.39**	**1.47**	**1.39**	**1.47**	**1.61**	**1.38**	**2.74**	1.00

7.2.2 Comparison with Balsa. We evaluate the speedup ratio of four learned optimizers compared to the native optimizer, measured by the ratio of total raw query time, as shown in Table 2. In JOB and TPC-H, we split the training and test sets as [46], while in STACK,

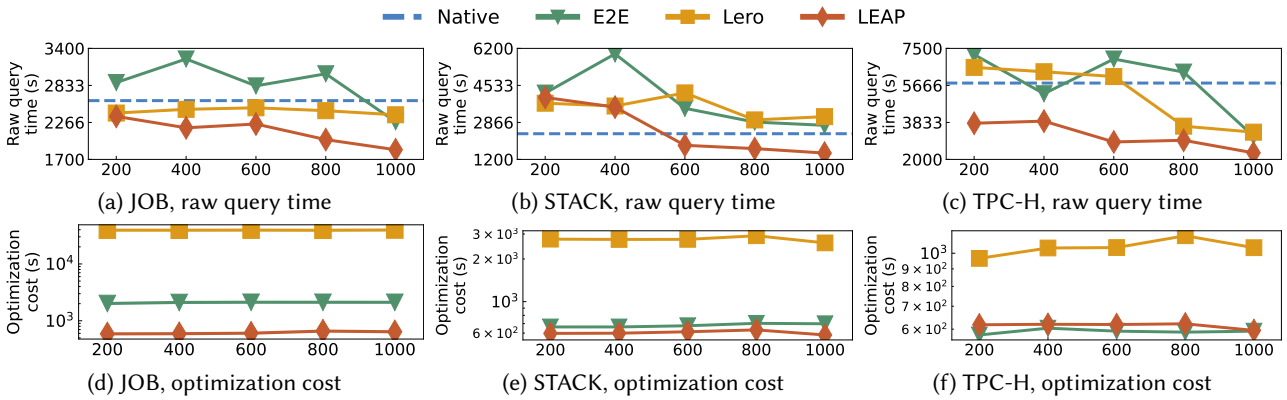


Figure 8: Query performance with varying numbers of training queries of different learning-based methods.

Table 3: Total end-to-end query execution time of LEAP in Presto and Apache Doris, in seconds.

	JOB	STACK	TPC-H
Presto (native)	2,649.4	1,845.7	2,785.6
Presto (with LEAP)	**1,870.6**	**1,404.5**	**2,463.9**
Apache Doris (native)	1,165.9	**271.9**	950.6
Apache Doris (with LEAP)	**508.4**	325.3	**783.8**

we randomly select 18 test queries as the test set, and the remaining queries are the training set. The results across four benchmarks show that LEAP achieves a significantly higher speedup ratio than Balsa for both training and test queries. There are three main reasons for this. First, Balsa relies on a regression model to predict query latency during plan enumeration, which often leads to the selection of inappropriate physical operators due to inaccuracies in the model. Also, Balsa's on-policy learning approach struggles with limited training plans, as it can't efficiently utilize the information from earlier iterations. Lastly, Balsa's search space is more restricted since its beam search expands only one search state per step, making it more prone to missing better plans. In contrast, LEAP expands all candidate sub-plans at each step, allowing it to explore a broader range of possibilities.

7.2.3 Total execution time in other systems. We evaluate LEAP in two additional big data query processing systems, Presto [32] and Apache Doris [3], and compare LEAP's performance with their native cost-based optimizers in Table 3. We select these two systems as they support cost-based exact join order enumeration. We can observe that, although two systems use different strategies for cost estimation, LEAP still significantly outperforms them by up to 29.4% in Presto and 56.4% in Apache Doris, since it can provide more accurate estimations via its learned approach. Note that LEAP performs worse than Apache Doris's native optimizer in STACK since LEAP takes too much time to rewrite the queries, and we will try to fix this issue in our future work.

7.2.4 Training efficiency. We compare the query performance of different learning-based methods (E2E, Lero, LEAP) using varying numbers of training queries. This evaluation simulates the scenario where the model is continuously updated during workload execution, as described in [53]. The raw query times are shown in Figures 8(a)-(c), and the optimization costs are shown in Figures 8(d)-(f). We can observe that, (1) LEAP consistently outperforms E2E and Lero. Compared with E2E, LEAP reduces raw query time by up to 33% in JOB, 47% in STACK, and 59% in TPC-H. Compared with Lero, LEAP reduces raw query time by up to 22% in JOB, 56% in STACK, and 53% in TPC-H. (2) As training data increases, raw query time generally decreases as models can more accurately capture the relations between cost and plans. Notably, in TPC-H, the performance gap between LEAP and baselines shrinks with more training queries, while E2E and Lero exhibit unstable performance in STACK. This is due to the complexity of TPC-H and STACK, where some join plans can produce intermediate tables with up to 10^{12} rows, leading to query timeouts. Baselines may generate such poor plans with insufficient training data. (3) LEAP is able to quickly adapt to new workloads. It outperforms the native optimizer with only 200 training queries (5.4 hours for data collection and training) in JOB, 600 training queries (14 hours) in STACK and 200 training queries (3.5 hours) in TPC-H. The improvement continues to grow with more training queries. Note that LEAP is not specifically designed for dynamic workloads, but it performs better than baselines in this case due to their own limitations. For E2E, LEAP performs better than it due to the superiority of comparison-based approach over regression-based approach. For comparison-based Lero, it tends to generate many sub-optimal candidate plans. With limited training data, the accuracy of plan comparator is affected, and thus a plan with inferior performance is easier to be selected. This issue is particularly pronounced in STACK and TPC-H, where there are numerous poorly performing candidate plans. In contrast, in JOB, where candidate plans generally have acceptable performance, Lero's results remain more stable across different training data sizes. Generally, LEAP avoids the limitation of the above two methods. Also, LEAP has fewer parameters than E2E and Lero, with short input plan node sequence ($3 \times$ num of tables $- 2$). Such data volume makes it less likely to overfit with limited training data and can better generalize to unseen queries. (4) The optimization cost of all methods is relatively stable across varying numbers of training queries, as the number of training queries only affects the accuracy

(a) JOB

		E2E	Lero	LEAP
Improvement		65	10	96
Regression	(-20%, 0)	21	11	12
	(-∞, -20%)	25	92	5
Failure		2	0	0

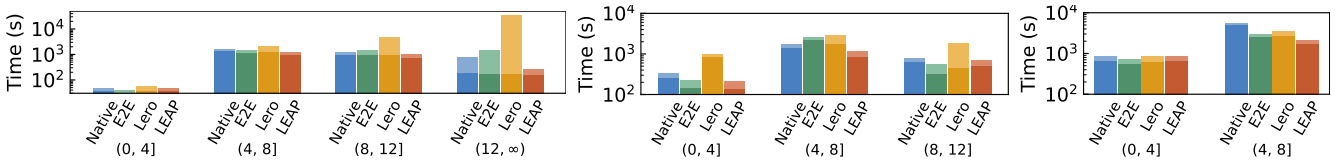
(b) STACK

		E2E	Lero	LEAP
Improvement		94	9	107
Regression	(-20%, 0)	11	18	7
	(-∞, -20%)	7	88	6
Failure		8	5	0

(c) TPC-H

		E2E	Lero	LEAP
Improvement		41	16	56
Regression	(-20%, 0)	4	27	14
	(-∞, -20%)	15	27	0
Failure		10	0	0

Table 4: The number of queries showing performance improvement/regression compared to native optimizer.



(a) JOB (b) STACK (c) TPC-H

Figure 9: Total query execution time for queries with varying number of tables on three benchmarks. The dark and light bars represent raw query time and optimization cost respectively.

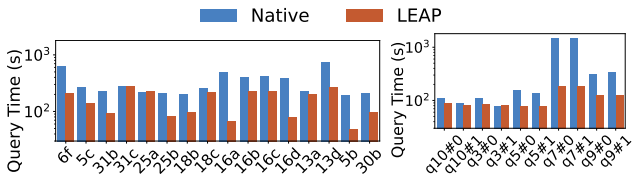
of cardinality estimation or plan comparison, not the plan search space.

7.3 Query Performance on Individual Queries

7.3.1 Performance regression analysis. We compare the end-to-end query execution time of learning-based methods with Spark SQL native optimizer on each test query. For each test query Q executed with a learning-based method $M \in \{\text{E2E, Lero, LEAP}\}$, we compute its performance change as $\Delta(Q, M) = \frac{Time(Q,CBO) - Time(Q,M)}{Time(Q,CBO)}$, where $Time(Q, CBO)$ and $Time(Q, M)$ represent the execution time of Q with native optimizer and method M respectively. $\Delta(Q, M) \geq 0$ indicates improvement, while $\Delta(Q, M) < 0$ indicates regression. Table 4 shows the distribution of $\Delta(Q, M)$ for each method M. LEAP achieves the least performance regression and provides significantly more performance gains compared to E2E and Lero. In JOB, 46 (41%) and 103 (91%) queries show performance regression with E2E and Lero respectively. LEAP outperforms them with only 17 queries (15%) showing regression, 12 of which are minor (<20%). E2E fails on 2 queries due to cardinality underestimation, leading to large table broadcasts, and similar patterns are seen in TPC-H. In STACK, although E2E matches LEAP in the number of improved queries, it has 7 long-running queries and 8 queries that fail after long execution times, leading to much higher overall execution times. We investigate queries where LEAP underperforms compared to the baselines and find that incorrect physical operator selection is the main cause. In STACK q8, LEAP overestimates the output cardinality of two sub-plans, resulting in shuffling two large tables, making it 20% slower than baselines. In TPC-H q7, LEAP underestimates the output cardinality of two sub-plans, leading to inefficient broadcasts of two intermediate tables of 18M rows and making it 150% slower than Lero. These issues stem from the lower accuracy of the cardinality comparator C_{card} which relies heavily on root node labels. We plan to introduce more join features in our future work to improve its accuracy. We also examine queries where LEAP significantly outperforms the baselines, and the improvement is due to better join order selection. For example, in STACK q15, E2E times out (>300s) because it generates a join order that results in an intermediate table with 14.3 billion rows, causing large data shuffling in Spark SQL, whereas LEAP selects a more efficient join order, producing intermediate tables of up to only 479K rows, and finishing the query with only 15s.

7.3.2 Findings on individual queries. On the level of individual queries, we can make the following findings. (1) LEAP's performance improves significantly with queries that involve many tables and join conditions (e.g., JOB's 29a, 29b, 29c and STACK's q2, q3). To validate this, we group the test queries of each benchmark into four categories based on the number of tables: $(0, 4]$, $(4, 8]$, $(8, 12]$, and $(12, \infty)$. We report the total end-to-end query execution time for each group in Figure 9. For queries with more tables, the larger search space makes it difficult for baseline methods to enumerate join plans efficiently, allowing LEAP to reduce optimization costs. For example, for queries with ≥ 8 tables, LEAP is up to 79.5% faster in JOB and 62.8% in STACK. However, with fewer tables and join conditions, the improvement is less pronounced. This is because the search space is smaller, making it easier for baseline methods to match LEAP's recommended execution plans, and in some cases, query time is driven more by reading or shuffling large tables than by join order (e.g., TPC-H q3, q10, where time depends on reading table *lineitem*). In such cases, partition strategies or knob tuning might be more beneficial. (2) LEAP's performance is closely related to the types of filters included in the query. Briefly, the performance improvement of LEAP is more significant in queries with predicates on skewed string columns, or pattern matching predicates. For example, JOB's queries 20b, 5c, and 27c include some predicates of string matching and some from skewed string columns (e.g., *info* in table *movie_info* and *note* in table *movie_companies*). LEAP reduces their raw query time by at least 49% compared to the native optimizer. This is because traditional estimators in Spark SQL do not support these two cases very well, and often produces inaccurate estimations, leading to more inferior plans.

7.3.3 Query performance in large queries. To assess LEAP's effectiveness on larger queries, we execute some long-running queries



(a) JOB (b) TPC-H

Figure 10: The running time of individual large queries in augmented JOB and TPC-H, in seconds.

on augmented JOB and TPC-H datasets in Figure 10. For JOB, we expand the IMDB tables by 100x to create a 400GB dataset and test the top-16 slowest queries. For TPC-H, we generate 200GB data and run two queries per template for time-consuming templates #3, 5, 7, 9, 10. In Figure 10, we can observe that, (1) for JOB, LEAP reduces query time by up to 74.6% compared with native optimizer. However, for some queries like 31c and 25a, LEAP achieves similar performance. For these queries, despite finding better join orders with LEAP, most of the query time is spent on broadcasting the large table *cast_info* due to incorrect size estimation produced by native optimizer. (2) for TPC-H, LEAP significantly reduces the runtime of the two longest-running queries (q7 and q9) by up to 87.8%, as it identifies better join orders that minimize intermediate table sizes. For q10 and q3, LEAP achieves similar or slightly better performance, as these queries involve fewer tables, making it easier for native optimizer to find similar plans as LEAP.

7.3.4 Proportion of bushy plans. Here we discuss the proportion of test queries where the bushy plan P_o is selected. In our experiments, 35 out of 113 queries in JOB, 20 out of 120 queries in STACK, and 10 out of 70 queries in TPC-H adopt the bushy plan P_o. Such a proportion is due to the following two reasons. First, our approach only allows sub-plans with few output rows to be used for generating bushy tree plans, so the number of bushy tree plans is limited. Second, bushy plans are not always more efficient than left-deep plans; for example, in a 4-table query with one small table and three large tables, joining two large tables in a bushy plan may incur higher costs. We use this approach to balance raw query time with optimization cost, exploring only a smaller subset of bushy plans. However, bushy plans are important. To address this, we can retain all generated bushy plans for the final comparison (line 18 in Algorithm 1), rather than only keeping the optimal bushy plan P_o. This prevents us from potentially overlooking better bushy plans, as the comparator model is not always accurate.

7.4 Ablation Study

7.4.1 Effects of each component in LEAP. In this section, we compare the performance of LEAP with some components disabled to understand the benefits of each component. We evaluate LEAP against seven variants: (1) without Join Plan Enumerator, (2) without Join Operator Selector, (3) without bushy tree search in `findBestPlan`, (4) without data features $Hist(f)$ and $Sel(f)$ in Learned Comparator, (5) selecting candidate plans with the closest cardinality to t_{card} in Algorithm 2, (6) selecting candidate plans with lowest uncertainty to P_s in Algorithm 2, and (7) using Spark SQL's native cardinality estimates to replace predicate information and data features in Learned Comparator. The results are shown in Table 5. Without Join Plan Enumerator, performance drops by up to 108% across all benchmarks due to the inferior join orders produced by native optimizer with large intermediate tables. Without Join Operator Selector, query execution time is up to 21.9% higher, as incorrect join operator selection causes large table shuffles and excessive query execution time. Without bushy tree search, performance drops by up to 15.2% because it disallows parallel execution of join operations, limiting performance improvements. Although bushy tree search helps to reduce raw query time by up to 16.1%, the optimization cost is also higher due to larger search space, making the end-to-end execution time slightly improved. Without data features in Learned Comparator, performance drops by up to 38.8% across all benchmarks, as the comparators can't understand the underlying data distributions, thus make inaccurate comparisons. In Algorithm 2, selecting candidate plans with the closest cardinality to t_{card} or the lowest uncertainty reduces LEAP's performance by up to 34% across all benchmarks compared to our high-uncertainty-guided candidate plan selection. This is because choosing high-uncertainty candidate plans helps correct final decisions when faced with single incorrect comparisons, since they decrease the impact on average output probability $\overline{p_{card}}$, as shown in Example 6.1. Lastly, replacing predicate information and data features in Learned Comparator with Spark SQL's native cardinality estimates causes a severe performance drop across all benchmarks. This is due to the high estimation errors in native cardinality estimates, which make it difficult for the Learned Comparator to distinguish between sub-plans accurately. This issue is especially pronounced since Join Plan Enumerator compares sub-plans across different queries.

Table 5: Total end-to-end query execution time of LEAP with different components, in seconds. Each cell shows the end-to-end query execution time (e.g., 2,488.4) on top, with raw query time (e.g., 1,848) and optimization cost (e.g., 640) inside the brackets below.

	JOB	STACK	TPC-H
LEAP	**2,488.4** (1,848+640)	**2,067.7** (1,485+582)	**2,920.4** (2,325+595)
LEAP w/o Join Plan Enumerator	3,380.9 (2,263+1,117)	2,666.1 (2,124+541)	6,090.8 (5,490+600)
LEAP w/o Join Operator Selector	3,034.5 (2,394+640)	2,469.3 (1,895+574)	3,117.3 (2,498+618)
LEAP w/o Bushy tree search	2,607.4 (2,028+579)	2,237.9 (1,694+543)	3,363.1 (2,770+592)
LEAP w/o Data features	2,967.0 (2,358+608)	2,539.9 (1,939+600)	4,053.1 (3,443+609)
LEAP with Cardinality-driven plan selection	2,671.7 (1,953+717)	2,377.0 (1,817+559)	3,298.9 (2,705+593)
LEAP with Low-uncertainty plan selection	2,843.2 (2,097+746)	2,770.3 (2,156+614)	3,798.1 (3,141+657)
LEAP with only Native estimates	4,963.8 (4,281+682)	6,283.9 (5,690+594)	4,672.6 (4,016+657)

Table 6: Query performance of baselines when using `findBestPlan` to generate join plans, in seconds. "(original)" refers to the performance of baselines in Figure 7.

	Native	E2E	Lero	LEAP
JOB	3,291.2 (2,793+497)	2,899.1 (2,223+676)	11,016 (2,483+8,533)	**2,488.4** (1,848+640)
JOB (original)	3,704.9 (2,600+1,104)	4,391.7 (2,277+2,114)	41,969 (2,383+39,586)	
STACK	4,859.4 (4,347+512)	8,892.5 (8,138+753)	6,438.7 (3,417+3,021)	**2,067.7** (1,485+582)
STACK (original)	2,902.6 (2,357+545)	3,434.7 (2,736+698)	5,723.8 (3,126+2,597)	
TPC-H	9,967.7 (9,375+592)	5,798.2 (5,189+609)	4,909.6 (3,766+1,143)	**2,920.4** (2,325+595)
TPC-H (original)	6,363.2 (5,782+581)	3,739.6 (3,147+592)	4,388.2 (3,350+1,038)	

7.4.2 Using `findBestPlan` *in baselines.* Here, we compare the performance of LEAP with baselines, all using `findBestPlan` to generate join plans, to eliminate the differences between LEAP's greedy algorithm and the baseline's exact search algorithm. Table 6 shows that, (1) Compared with the original baselines, the optimization cost of baselines using `findBestPlan` drops significantly in JOB, but remains similar or slightly higher in STACK and TPC-H. This is because `findBestPlan` reduces the search space in all benchmarks, but cardinality underestimation by the baselines can trigger more recursive searches. (2) LEAP still outperforms all baselines in end-to-end query execution time when using `findBestPlan`. LEAP reduces end-to-end execution time by up to 77.4% in JOB, 76.7% in STACK, and 70.7% in TPC-H. This improvement is due to the significant increase in raw query time for baselines, especially in STACK and TPC-H, where incorrect estimations lead to worse join plans in a reduced search space.

7.4.3 Effects of learned comparator and plan enumerator in LEAP. We investigate the effects of LEAP's Learned Comparator and Join Plan Enumerator by using each of them in native optimizer. Table 7 shows that, (1) when using LEAP's Learned Comparator to guide the plan enumeration in native optimizer, across three benchmarks, raw query time decreases by 15.7% in JOB, 13.5% in STACK and 54.3% in TPC-H, as our Learned Comparator helps to find better plans with more accurate plan comparisons. However, optimization costs increases significantly because time-consuming neural network inference replaces simple arithmetic operations in traditional estimators. (2) when using LEAP's Join Plan Enumerator to generate plans with traditional estimators, it shows significant performance degradation compared with native optimizer due to large estimation errors from the traditional estimator, and our enumeration algorithm only explores a limited part of the join plan space.

7.4.4 Different comparator architecture. We further compare the performance of LEAP with different model architectures for Learned Comparator to show the efficiency of our approach. We compare their raw query times, as the search space for each model is influenced by C_{card}, which affects how often Algorithm 1 needs to perform recursive searches. This leads to differences in their optimization costs. As shown in Table 8, with 1000 training queries, our LSTM-based approach outperforms the others across all three benchmarks, reducing raw query time by up to 6.9%, 10% and 26.1% in JOB, STACK and TPC-H respectively. Tree models find worse plans for some queries due to their structural limitations. Tree-LSTM tends to bias toward the root node, placing less emphasis on leaf nodes [40]. As for tree convolution network, it can face challenges in capturing long-distance dependencies between the root and leaf nodes in join plan trees, since its convolution kernels only focus on immediate children. Adding more convolution layers can help, but risks issues like information dilution [6] and gradient vanishing [14]. Also, the pooling mechanism used to aggregate node features can lead to a loss of nuanced information for each node, and is sensitive to outlier features. In fact, join plan trees are simple binary structures with limited height (number of tables - 1), which limits the benefits of tree models and increases complexity, potentially leading to overfitting with limited training data. As a result, tree models underperform in some cases compared to LSTM, which aligns with previous findings in the literature [51]. We also train the tree models with 1500 training queries, and while their performance improve, they can't surpass the performance of LSTM with 1000 training queries in many cases.

Table 7: Total end-to-end query execution time of native optimizer using LEAP's either component, in seconds.

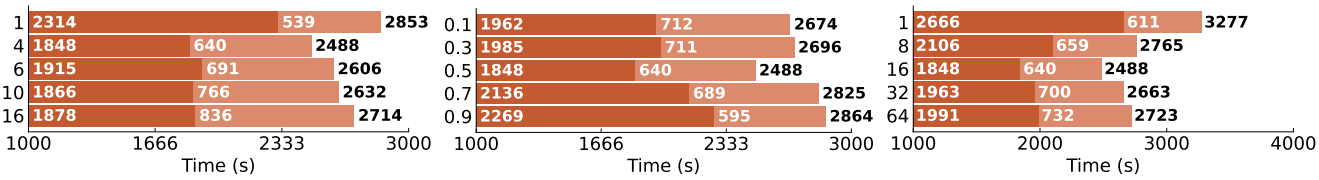
	JOB	STACK	TPC-H
Native	3,704.9 (2,600+1,104)	2,902.6 (2,357+545)	6,363.2 (5,782+581)
Native with Learned Comparator	6,455.4 (2,191+4,264)	2,892.1 (2,038+854)	3,307.1 (2,643+664)
Native with Join Plan Enumerator	3,291.2 (2,793+497)	4,859.4 (4,347+512)	9,967.7 (9,375+592)
LEAP	**2,488.4** (1,848+640)	**2,067.7** (1,485+582)	**2,920.4** (2,325+595)

Table 8: Total raw query time of LEAP using different comparator architecture and different number of training queries, in seconds.

	JOB	STACK	TPC-H
Tree convolution, 1000 queries	1,985.4	1,649.2	3,147.9
Tree convolution, 1500 queries	1,837.0	1,397.3	2,539.1
Tree-LSTM, 1000 queries	1,970.0	1,648.8	2,851.1
Tree-LSTM, 1500 queries	1,902.8	1,545.8	2,608.7
LSTM (ours), 1000 queries	1,848.0	1,485.0	2,325.0

7.5 Parameter Sensitivity Analysis

In LEAP, various hyperparameters can impact query performance. To assess their effects, we evaluate three key hyperparameters: beam width k, cardinality threshold range ϵ, and number of candidate plans c. Due to space constraints, we only report results on the JOB benchmark. We set $k = 4$, $\epsilon = 0.5$ and $c = 16$ by default.



(a) Beam width k (b) Cardinality threshold range ϵ (c) Number of candidate plans c

Figure 11: Total end-to-end query execution time of LEAP by varying k, ϵ and c on JOB.

7.5.1 Beam width k. Beam width k controls the number of plans retained in each iteration in `findBestPlan`, affecting its effectiveness and efficiency [10]. We evaluate query performance with varying k. As shown in Figure 11(a), a balanced beam width of $k = 4$ provides the best query performance, since it strikes a good trade-off between exploration and exploitation, and ensures high-quality plans while managing moderate search space. A larger k can lead to join plans with similar performance as $k = 4$, but their optimization cost is much higher due to the large search space. Conversely, a smaller k may narrow search space and miss globally optimal solutions, resulting in a 14.7% higher execution time.

7.5.2 Cardinality threshold range ϵ. Cardinality threshold range $\epsilon \in (0, 1)$ influences candidate plan selection in Join Operator Selector. Here, we evaluate query performance with varying ϵ. As shown in Figure 11(b), LEAP achieves the best query performance in $\epsilon = 0.5$. With a small ϵ, the query performance slightly drops by 7.5%, as there may be insufficient candidate plans for comparison, leading to inadequate join operator selection. When $\epsilon \geq 0.5$, query performance drops by up to 15% as there are more candidate plans with cardinality much smaller than threshold t_{card}. In this case, LEAP may inaccurately assess some small tables, causing them to avoid Broadcast Join and miss potential performance improvements.

7.5.3 Number of candidate plans c. c controls the number of selected candidate plans in Join Operator Selector, affecting comparison accuracy. Here, we evaluate query performance with varying c. Figure 11(c) shows that the query performance is the best when $c = 16$. With a small c, potential inaccurate single comparisons can lead to the selection of inappropriate join operators, degrading the performance. When $c > 16$, query performance slightly decreases. Although their raw query time remains similar due to sufficient candidate plans for proper join operator selection, their optimization costs are higher due to the increased times of comparisons.

8 RELATED WORK

In this section, we review the related works of cardinality estimation and learned query optimizers.

8.1 Cardinality estimation

Traditional estimators. Native optimizers commonly employ histograms, sketches, and sampling techniques for cardinality estimation. Histogram-based methods [30, 38] create one-dimensional histograms for individual attributes or multi-dimensional histograms for attribute groups. Sketch-based methods [12, 31] represent a column as a vector or matrix to assess static value information. Sampling-based methods [9, 11, 41, 42] sample tuples from multiple tables to effectively discern correlations across different tables. However, traditional estimators fail to capture correlations between tables using histograms or sketches, and face high variance when the sample distribution differs from the real distribution [13, 20, 34]. Thus, their estimations are inaccurate [15]. To address these issues, two types of learned estimators are developed, including learned data-driven estimators that traverse the data in databases to understand the joint distribution of underlying data, and learned query-driven estimators that utilize the query information.

Learned data-driven estimators. Learned data-driven estimators [39, 43, 47, 54] employ machine learning models to better understand the joint distribution of underlying data. NeuroCard [47] uses deep auto-regressive model to decompose the joint distribution of attributes into a series of conditional distributions. FLAT [54] adopts a factorize-split-sum-product network (FSPN) to dynamically decompose the joint distribution based on the level of attribute correlation. FACE [39] leverages the normalizing flow to learn a continuous joint distribution for relational data. However, learned data-driven estimators incur high training and inference costs, which escalate as the data volume increases.

Learned query-driven estimators. Learned query-driven estimators [18, 20–22, 27, 33, 37, 50] collect (query, cardinality) pairs and use various machine learning models to model their relationship, which address cardinality estimation as a regression problem. MSCN [18] uses the multi-set convolutional network to estimate the cardinality of correlated joins. E2E [33] employs a TLSTM model to simultaneously predict cardinality and execution cost. ALECE [20] leverages an attention-based model to uncover hidden relationships between queries and dynamic data. LPCE [37] enhances inference efficiency with a lightweight SRU model and a knowledge distillation-based model compression technique. Despite these advancements, these methods have limited applicability, especially with string predicates and 'OR' conjunctions. In addition, they generally offer less precise estimates than those derived from learned data-driven estimators, due to the lack of underlying data features.

8.2 Learned query optimizers

Instead of estimating the query cardinality to help generate low-cost query plans, learned query optimizers directly optimize the query plans to reduce the query costs. There are primarily plan-constructor and plan-steerer methods, and some learned-comparator-based methods have also emerged recently.

Plan-constructor. Plan-constructor methods [7, 24, 46] create a new learned optimizer that replaces the native optimizer, and generate an execution plan from scratch for each query Q. These methods use deep reinforcement learning (DRL) models trained on historical query data to estimate query cost, and propose various plan search algorithms to generate execution plans. Neo [24] builds a tree convolution network [25] to predict the latency of queries containing a specific sub-plan, and generates plans via best-first search

(BFS) algorithm. Balsa [46] improves it by pre-training the network with native optimizer's cost estimation, and using a beamed BFS algorithm. LOGER [7] utilizes Graph Transformer [49] and ϵ-beam search in Restricted Operator Search Space to generate better plans. However, these methods take high learning costs, requiring substantial computational resources to test multiple execution plans for the same query and a lengthy period to achieve the convergence. Compared with plan-constructor methods (e.g., Balsa), LEAP designs a comparator to compare sub-plan costs instead of estimating overall query costs. Additionally, LEAP introduces a plan enumeration algorithm that separates the search for left-deep and bushy plans, along with a customized physical operator selection mechanism tailored for Spark SQL, rather than relying on operator enumeration in DBMS.

Plan-steerer. Plan-steerer methods [8, 23, 48, 53] leverage the knowledge of the native optimizer to produce improved execution plans. These methods guide the native optimizer to generate multiple candidate plans using techniques like HINT, and select the plan with the lowest estimated cost. BAO [23] utilizes the native optimizer to create a plan for each hint set and employs Thompson Sampling to select one for execution. HybridQO [48] generates candidate plans using leading hints, and then selects a plan with an uncertainty-guided method. Lero [53] adjusts the native optimizer's cardinality estimates to produce plans, choosing the best through pairwise comparison. LEON [8] builds two comparators M^I and M^O to prune the native optimizer's plan enumeration space. While these methods adapt well to changes in data and schema, their dependency on specific DBMS features restricts their use in platforms like Spark SQL. Also, generating execution plans in Spark SQL is slower than in other DBMS, significantly raising optimization costs.

Learned comparators. Learned comparator methods [8, 45, 53] use a comparator to select the best execution plan from a set of candidates. By simplifying the regression task into a binary classification, they enhance model accuracy. While these methods share a similar comparator architecture (tree convolution model, using native cardinality and cost estimation as features), they differ in how they generate candidate plans. COOOL [45] uses the native optimizer to create a plan for each hint set, Lero [53] adjusts the native optimizer's cardinality estimates to produce plans, and LEON [8] enumerates sub-plans with native optimizer. While our LEAP and existing methods (e.g., Lero) share a similar framework of a plan comparator and plan generation strategy, the components differ significantly. For the plan comparator, LEAP incorporates predicate information (e.g., columns, operators, and values of join conditions and filters) and data features (e.g., histograms and selectivity distributions), which previous approaches don't. They rely on cardinality estimates from the native optimizer, which we avoid due to the lower estimation accuracy in Spark SQL. Also, LEAP processes plans using lightweight LSTM model with structure-preserving traversal, which help to produce better plans with limited training data. Additionally, LEAP can train using plans from different queries, while other methods require multiple plans for the same query, increasing their training overhead. As for plan generation strategy, LEAP adopts completely different ways compared with existing methods. LEAP uses a plan-constructor method to build only one plan from scratch without relying on the native optimizer. In contrast, existing methods use plan-steerer methods to produce multiple candidate plans with the help of native optimizer.

9 CONCLUSION

In this paper, we propose LEAP, a learned query optimizer tailored for Spark SQL. To tackle compatibility, LEAP optimizes queries by first enumerating join plans and then assigning physical operators, aligning with Spark SQL and requiring no changes for integration. Also, LEAP enhances the join plan selection with a Learned Comparator to avoid the inaccuracy of exact value estimation, and provides more accurate comparison by using predicate information and data features. Moreover, LEAP adopts a progressive join plan enumeration algorithm with a beam search strategy and pruning techniques, ensuring efficient and effective join plan generation. Extensive experiments on public benchmarks demonstrate that LEAP delivers superior performance in end-to-end execution time, optimization cost, and training efficiency. In the future, we plan to enable LEAP to optimize queries containing predicate subqueries.

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