Eraser: Eliminating Performance Regression on Learned Query Optimizer

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ABSTRACT

Efficient query optimization is crucial for database management systems. Recently, machine learning models are applied in query optimizers to generate better plans. Despite such learned query optimizers have shown superiority in some benchmarks, unpredictable performance regressions prevent them from being truly applicable. To be more specific, while a learned query optimizer commonly outperforms the traditional query optimizer on average for a workload of queries, its performance regression seems inevitable for some queries due to model under-fitting and difficulty in generalization. In this paper, we propose a system called `Eraser` to resolve this problem. `Eraser` aims at eliminating performance regressions while still attaining considerable overall performance improvement. To this end, `Eraser` applies a two-stage strategy to estimate the model accuracy for each candidate plan, and helps the learned query optimizer select more reliable plans. The first stage serves as a coarse-grained filter that removes all highly risky plans with features that are seen for the first time. The second stage clusters plans in a more fine-grained manner and evaluates each cluster according to the estimation quality of plans for selecting the final execution plan. `Eraser` could be deployed as a plugin on top of any learned query optimizer. We implement `Eraser` and demonstrate its superiority on PostgreSQL and Spark. In our experiments, `Eraser` eliminates most of the regressions while brings very little negative impact on the overall performance of learned query optimizers, no matter whether they perform better or worse than the traditional query optimizer. Meanwhile, it is adaptive to dynamic settings and generally applicable to different database systems.

R4D14

1 INTRODUCTION

Query optimization plays a crucial role in database management systems. The goal of query optimizer is to find an optimal execution plan that minimizes a user-specified cost metric, e.g., the query execution time or resource usage. Traditional query optimizers rely on a cost-based model that estimates the cost of execution plans based on simple statistics and experience-driven rules [34]. However, the estimated costs are often shown to have large errors [11, 15, 21, 37], due to unrealistic independence assumptions or over-simplified models, which heavily degrade the generated plan quality.

R4D14

Recently, there has been an active line of works using learned optimizers to improve query optimization [13, 26, 28, 29, 43, 44, 47]. These optimizers apply (deep) models to learn from data and/or queries to generate better execution plans. The pipeline of a learned query optimizer often includes two main steps. First, it generates a number of candidate plans $\mathcal{P}_Q$ by some exploration strategy. Second, all candidate plans $P \in \mathcal{P}_Q$ are fed into a learned deep model to predict its cost $C(P)$. The plan $P_r \in \mathcal{P}_Q$ that minimizes the predicted cost is selected to execute.

The first two authors contribute equally to this paper.

Challenges of Learned Query Optimizer. Despite the promising results of learned query optimizers have been shown in the literature [10, 26, 47], they still suffer inevitable drawbacks that prevent them from being truly applicable. Specifically, the executed plans selected by the learned query optimizer may be worse, sometimes even seriously worse, than the traditional native query optimizer. This phenomenon is called *performance regression*, and has been observed in all learned query optimizers [13, 26, 28, 29, 43, 44, 47].

The learned models can not accurately predict the exact cost of some data due to numerous reasons, such as the inherent difficulty of the learning problem [22, 27, 47], the low generalization ability of the prediction model on new data, the under-fitting on training data due to insufficient training data, loss of features, noisy labels and inappropriate model training methods. Due to such intrinsic drawbacks, the performance regressions of learned query optimizers seem inevitable, no matter how we improve the models in learned query optimizers. This is very harmful, or even unacceptable, to database systems which require high stability.

R4W1, R4W2

In the literature, there exists very little work on eliminating the performance regression, especially on learned query optimizer [48]. [23] and [19] propose methods to enhance the robustness in dynamic settings by updating models in the proper time. They are post-processing methods but do not detect and eliminate regression before query execution. [44] tries to reduce the regression using the ensemble methods [3, 14, 20, 38, 41], but it is time costly and often falsely filters some truly good plans. As far as we know, until now, this problem has not been well solved.

Our Contributions. In this paper, we try to tackle this problem in a novel way. Notably, the benefits and risks of the learned models always come together. Our goal is not to eliminate any possible regression (which degenerates to the traditional query optimizer), but to eliminate it to a low level while still attaining considerable performance improvement. To this end, we design a system called `Eraser`, which could be deployed as an external plugin on top of any existing learned query optimizer. `Eraser` could be tuned to eliminate its performance regression while brings minimal impact on its performance benefit.

The key to eliminate the performance regression is to identify whether the predicted cost is accurate for each candidate plan. Based on this, we could filter out all unpromising candidate plans but reserve other ones with high learning accuracy for plan selection. However, learning the exact estimation accuracy is very challenging, which is as difficult as learning the accurate cost of each plan [11, 15, 21, 27, 37]. In `Eraser`, we try to simplify the learning tasks while still preserve enough knowledge for plan identification.

R4W1, R4W2

Specifically, Eraser adopts a two-stage strategy for plan identification. (R4D14) The first stage serves as a coarse-grained filter that qualitatively removes all highly risky plans. We observe that the prediction models are very likely to perform worse on plans with feature values not occurring in the training data, due to their low generalization ability. These plans are called *unexpected plans*. To detect how the model behaves w.r.t. each feature value, we design an *unexpected plan explorer* to divide the unexpected plan space into a number of subspaces, each with one or more unseen feature values. Then, we generate plans in a small number of representative subspaces. Based on the model evaluation results on these plans, we could classify all subspaces into precise and imprecise. All candidate plans fall into the imprecise subspace would be filtered.

In the second stage, we learn a *segment model* to process the remaining plans in a more fine-grained manner. We observe that the performance of the prediction model is highly skewed, since it is under-fitting for some plans. To this end, the segment model groups plans into a number of clusters and associates each cluster with a reliability interval reflecting the quality of the estimation results. Based on the reliability interval, we design a plan selection method to balance the risk of regressions and the loss of benefits. Both the unexpected plan explorer and the segment model are lightweight.

By comprehensive evaluations, we find that: When the learned query optimizer performs worse, i.e., even 1.1× to 2.9× than the traditional query optimizer, Eraser could help to improve its performance to be comparable with the traditional query optimizer. When the learned query optimizer performs better than the traditional query optimizer, Eraser makes little difference on its performance. Eraser is adaptive to balance regression risks and improvement impacts to attain the best overall performance in both static and dynamic settings. Meanwhile, Eraser exhibits good generality to different underlying learned query optimizers in [13, 44, 47] and different DBMSes, i.e., PostgreSQL and Spark [45].

Our main contributions are summarized as follows:

1) We propose a general framework subsuming existing learned query optimizers. Based on this, we rigorously define the performance regression elimination problem on the learned query optimizer.

2) We design Eraser, a system that could be deployed on top of any learned query optimizer to eliminate its performance regression while preserving its performance benefit.

3) We conduct extensive experiments to evaluate the performance of Eraser in different settings.

2 PRELIMINARIES

In the traditional query optimizer, such as the one in PostgreSQL, for any input SQL query Q, all candidate plans are often enumerated using dynamic programming. Then, a basic cost model is applied for plan selection. It relies on estimated cardinality, which is often generated by simple statistical methods such as histogram or sampling, and experience-driven rules to predict the cost of each candidate plan. (R4D7) Let $C(P)$ and $\widehat{C}(P)$ denote the exact and estimated cost of query plan P, respectively. The cost $C(P)$ is a user-specified metric, e.g., execution time or I/O throughput, regarding the efficiency of executing P. Finally, the plan P_b with the minimum estimated cost is returned for execution.

Recently, a number of learned query optimizers [13, 26, 28, 43, 44, 47] are proposed to provide instance-level query optimization. Their procedures could be generalized into a unified framework with two main steps. For the input query Q, a learned query optimizer first generates a set of candidate plans $\mathcal{P}_Q = \{P_0, P_1, \ldots, P_k\}$ using some plan exploration strategies. Then, a learned risk model M_r, i.e., a complex ML-based model, is applied for plan selection. M_r could predict the goodness of each plan in $\mathcal{P}_Q$ in terms of $C(P)$. The best plan $P_r \in \mathcal{P}_Q$ minimizing $\widehat{C}(P)$ is selected for execution. We note that, different learned query optimizers, including Neo [28], Balsa [43], Bao [26], HyperQO [44], Lero [47], PerfGuard [13] and some other works [12, 17, 27, 30, 35, 49], apply different plan exploration strategies and risk models, but they could all be subsumed under this framework. Due to space limits, we defer the details to Appendix A in the full version [42].

Problem Statement The plan P_r selected by the above learned query optimizer is often shown to have a better performance than P_b. However, it may also suffer a heavy performance regression on some queries due to numerous reasons: 1) the candidate set $\mathcal{P}_Q$ does not contain plans better than P_b; 2) the risk model can not generalize well on new data/workload, especially in dynamic settings; and 3) the risk model is under-fitting on the training data owing to loss of features, noisy labels, insufficient training data, bad hyper-parameters or inappropriate training optimizers.

Let $\Pr_Q$ be the distribution of all SQL queries occurring for a database. Let $\mathcal{Q}$ be a workload where each query $Q \in \mathcal{Q}$ occurs with the probability $\Pr_Q$. Formally, a learned query optimizer learned_opt in our framework generates an execution plan P_r for a query $Q \in \mathcal{Q}$

$$P_r \leftarrow \text{learned\_opt}(\mathcal{P}_Q, M_r)$$

by enumerating candidate plans $\mathcal{P}_Q$ and selecting the best one based on a learned risk model M_r. In practice, the risk model M_r is often trained on a workload $\mathcal{W} \subseteq \mathcal{Q}$, so the regression is often more serious for query $Q \in \mathcal{Q} - \mathcal{W}$.

Our goal is to find other plans to replace P_r with less or no regressions before execution. Here, we assume the plan P_b output by the native traditional query optimizer is in $\mathcal{P}_Q$. A performance elimination method perf_elim can be interpreted as a plugin function (in any learned optimizer learned_opt) which filters out unreliable candidates and selects a different plan P'_r

$$P'_r \leftarrow \text{perf\_elim}(\text{learned\_opt}(\cdot), \mathcal{P}_Q, M_r).$$

Let $\mathcal{R}$ and $\mathcal{B}$ denote the overall performance regression and benefit over all queries in $\mathcal{Q}$, respectively. They are computed as

$$\mathcal{R} = \sum_{Q \in \mathcal{Q}:\, C(P_r) > C(P_b)} (C(P_r) - C(P_b)) \tag{1}$$

and

$$\mathcal{B} = \sum_{Q \in \mathcal{Q}:\, C(P_r) \le C(P_b)} (C(P_b) - C(P_r)). \tag{2}$$

Let $\mathcal{R}'$ and $\mathcal{B}'$ denote the overall performance regression and benefit by replacing all selected plans P_r with P'_r in Eq. (1) and Eq. (2), respectively. After the replacement, there may exist a positive impact on the performance regression and simultaneously a negative impact on the performance benefit. Obviously, $\mathcal{R} - \mathcal{R}'$ and $\mathcal{B} - \mathcal{B}'$ represent the decline in the performance regression and benefit, respectively. We aim at finding a performance elimination method

perf_elim that is able to eliminate regressions but brings little impact on the benefits. Formally, our problem is stated as follows:

Performance Regression Elimination Problem

Input: a learned query optimizer learned_opt with its risk model M_r trained on a workload $\mathcal{W} \subseteq \mathcal{Q}$ and a parameter $\lambda \geq 0$;

Output: a performance elimination method perf_elim such that $\mathcal{R}' - \mathcal{R} + \lambda(\mathcal{B} - \mathcal{B}')$ is minimized.

R2D1

R2D3

Here λ balances the decline on the regression ($\mathcal{R} - \mathcal{R}'$) and the loss of the benefit ($\mathcal{B} - \mathcal{B}'$). A small value of λ, e.g., $\lambda = 0.8$ in our experiments, emphasizes filtering out risky plans, even at the expense of removing some good plans. It could be applied when the learned risky models are not very accurate on scare training data or varied workload. Whereas, a large value of λ encourages perf_elim to improve the benefit by reserving more plans. We recommend to use it when the learned models is more accurate with sufficient training data and stable workload. Due to space limits, we reserve the discussion on tuning hyper-parameter λ in Appendix B and the analysis on existing solutions for eliminating performance regressions in Appendix C in the full version [42].

3 SYSTEM OVERVIEW

The fundamental reason arising the performance regression is that the risk model can not accurately predict the cost of some plans, due to the lack of generalization ability and/or model under-fitting. Thus, the key to eliminate the performance regression is to identify the learning accuracy for each plan, so that we can filter out all unpromising plans and only reserve other ones with high learning accuracy for plan selection. However, existing learned query optimizers often provide very little knowledge on the learning accuracy of plans. Meanwhile, it is very difficult (or even impossible) to learn the exact estimation accuracy of each plan, which is as challenging as learning the accurate cost of each plan [26, 27, 44].

To this end, we design other tasks which are much easier but still preserve enough information to identify truly good plans. We design a system, called `Eraser`, to eliminate regression of learned query optimizer. The architecture, as well as its pipeline, is shown in Figure 1.

Notably, `Eraser` could be deployed on top of any learned optimizer, as long as it satisfies our proposed framework in Section 2, to eliminate its performance regression while reserving the performance improvement. Given a query Q, we first collect the plan P_b generated by the traditional query optimizer and candidate plans $\mathcal{P}_Q$ produced by the plan exploration strategy in the learned query optimizer. Later, `Eraser` adopts a two-stage strategy to identify another plan P'_r to execute. Its main idea is discussed as follows.

Main Idea of the Strategy in `Eraser`. We have some basic observations on the estimation quality of risk models in learned query optimizers. We illustrate them by an example in Figure 2. Specifically, we employ the t-SNE [39] method to map plans in the the TPC-H benchmark [6] onto a two-dimensional space. Each dimension is a snapshot of some dimensions in the plan feature space. Then, we mark all plans whose reliability (a metric of the estimation quality, see details in Section 5.3) is larger than or no more than the threshold 0.7 (selected by our expert knowledge) in red and green color, respectively. Notice that, the phenomenon shown in

R4D2

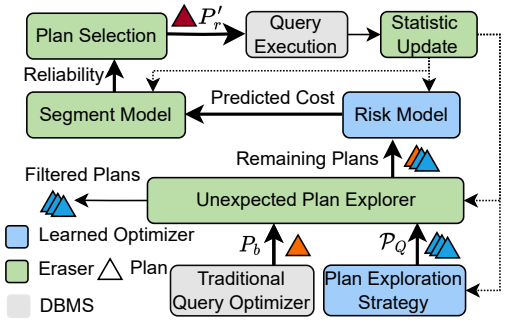
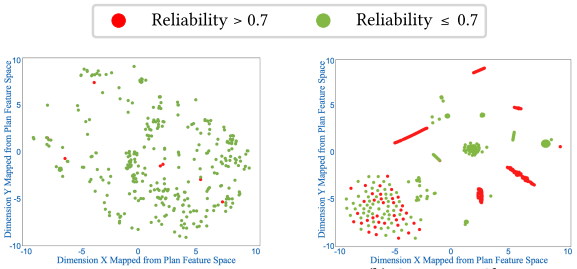


Figure 1: The system architecture and pipeline of `Eraser`.



(a) Unexpected Plans (b) Remaining Plans

Figure 2: Estimation quality (reliability) of the risk model in Lero on plans of the TPC-H benchmark. All plans in the high-dimensional feature space are mapped onto the two-dimensional space using the t-SNE method in [39].

Figure 2 is arisen by the intrinsic limitations of deep models. It is also applicable on other learned query optimizers and benchmarks. We find that:

1) Figure 2(a) shows the performance on plans for queries $Q \in \mathcal{Q} - \mathcal{W}$. We call these plans *unexpected plans* as they contain feature values not occurring in the training data. Obviously, the risk model performs badly on most of the unexpected plans, due to its low generalization ability. Therefore, in the first stage, we design an ***unexpected plan explorer*** to systematically investigate the space of all unexpected plans to quantitatively evaluate the performance of the risk model. Based on it, we could filter all highly risky plans in $\mathcal{P}_r$ at the front in a coarse-grained manner, which largely reduces the burden of downstream procedures.

2) Figure 2(b) illustrates the performance on remaining plans for queries Q falls into $\mathcal{W}$ and a small portion of unexpected plans where the risk model could generalize well. At this time, the performance of the risk model is highly *skewed*. The plans naturally form different clusters. Some of them contain purely accurate or inaccurate plans, but some clusters, e.g., the cluster in the left bottom, contain a mixture of both accurate and inaccurate plans. This is because the risk model does not have enough capacity to fit well on all plans. It is under-fitting for some subspaces of plans. To distinguish them, we apply a ***segment model*** to cluster plans in a more fine-grained manner. Meanwhile, we associate each cluster of plans with an interval of *reliability*, which reflects the range of the estimation quality of the risk model on these plans.

Based on the reliability interval, we could further filter some unpromising plans with low learning accuracy. We design a plan selection method in `Eraser` to select the final execution plan P'_r. This method could balance the benefit of improvements and the risk

of regressions. For example, in a conservation scenario, we only reserve plans with high reliability, which may miss some improvement opportunities but could reduce the performance regression to a very low level. On the contrary, in an aggressive scenario, we could relax the risk constraint to pursue more possible improvements. After the plan P'_r is executed by the query execution engine, we collect its execution statistics to periodically update the plan exploration strategy and risk model in the original learned query optimizer, and simultaneously the unexpected plan explorer and segment model in `Eraser`.

In the following content, we introduce the technical details of the unexpected plan and the segment model (together with the plan selection method) in Section 4 and Section 5, respectively.

4 UNEXPECTED PLAN EXPLORER

In this section, we present the details on investigating the space of unexpected plans. We propose a method that hierarchically divides these unexpected plans into a number of subspaces according to the domain of features. Then, we select a small number of unexpected plan subspaces and generate some plans in each subspace. Based on these plans, we know how well the risk model performs in any unexpected plan subspace. In the following, Section 4.1 introduces the basic plan encoding method. Section 4.2 describes the main framework of our space division method. Then, Section 4.3 and Section 4.4 discuss two key techniques applied in our framework.

4.1 Plan Encoding Method

In this paper, we consider the SQL query Q in the following form:

SELECT $*$ FROM $T_1, \ldots, T_m$ WHERE $J_1, \ldots J_{m-1}$ AND $E_1, \ldots, E_n$.

Here, each $T_{1 \le i \le m}$ refers to a table in the database, and each $J_{1 \le j \le m-1}$ stands for a join relation, e.g., equal or non-equal join, between any two columns in tables, and each $E_{1 \le \ell \le n}$ represents a filtering predicate on a column. Notice that we do not consider any feature related to the projection columns and nested SQL queries. However, our proposed encoding and division methods could be easily extended to support these queries.

A physical plan P of Q can be represented as a binary tree structure, as the example shown in Figure 3. In the plan tree, each leaf node has a scan operation on a column C in a table with its filtering predicate, and each inner node has a join operation with the join relation across two tables. Notably, the information of query Q is losslessly contained in the plan P.

R2W2 R4W3, R4D3, R4D4

Feature Selection. In the literature work on learned query optimizer [26, 28, 43, 44, 47], the query plans are featured as vectors and fed into the risk model for cost prediction. We could conceptually divide frequently-used features into two types: the plan-level features and the data-level features. The plan-level features, such as the join relations, filtering predicates and operator types, affect the execution behaviors of plans on the database execution engine. The data-level features, such as the estimated cardinality and data distribution, provide additional statistical information to measure the execution cost. The learned query optimizers require sufficient information to predict the plan execution time. Therefore, they apply both plan-level and data-level features to characterize the execution behavior and cost of plans.

However, the goal of `Eraser` is different. It aims at clustering the plans and then evaluating the estimation accuracy of the learned models on each cluster of plans. (refer details in Section 4.2 and Section 5). At this time, the plan-level features are more important as they are more comprehensive to distinguish different plans in a macro-view. Since `Eraser` does not require predicting the execution cost, the data-level features are not very necessary. By our expert knowledge, we consider the following widely used features:

- *join and scan type*: two categorical features indicating the types of all join and scan operators used in the query plan. For example, assume that the DBMS supports three types of join operators, namely merge_join (MJ), hash_join (HJ) and nested_loop_join (LJ), then the value of the join type has seven different values, where each corresponds to a non-empty subset of {MJ, HJ, LJ }. For the plan shown in Figure 3, the value of join type is {MJ, HJ}. Notice that, we only consider the scan type and could support scan operator on any number of columns. R4D4
- *join relations*: a vector encoding the existence of join relations occurred in the query plan. The set of all possible join relations across any two tables are provided by users or found by an auto-exploration method proposed in [46]. We use a binary variable to encode the existence of each join relation in the vector.
- *filtering predicate*: a vector encoding the filtering condition on each column (attribute). Specifically, we represent the predicate on each column C in a canonical form $l \le C \le u$ and record the two endpoints l and u in the vector. Let lb and ub denote the lower and upper bound of C, respectively. Other forms of the predicates could be equivalently converted into this form as
  $(C \le u) \rightarrow (lb \le C \le u), (C \ge l) \rightarrow (l \le C \le ub)$,
  $(C < u) \rightarrow (lb \le C \le u - \epsilon), (C > l) \rightarrow (l + \epsilon \le C \le ub)$,
  $(l < C < u) \rightarrow (l + \epsilon \le C \le u - \epsilon)$, where $\epsilon \rightarrow 0^+$.
  In our implementation, we divide the domain of each continuous attribute to a number of small intervals, so ϵ could be set to a value smaller than the range of each divided interval. R3W2, R3D2
- *structure*: a categorical variable indicating the shape of the plan tree. Each value corresponds to a specific form of the plan ignoring the physical operator type and filtering predicates on all nodes (as they have been encoded in other features). For example, Figure 3 lists several possible structures, e.g., bushy tree, left-deep and right-deep, on plans joining 4 tables.

A complete example of our plan encoding is shown in Figure 3. Notice that, our plan encoding method is independent of the risk model. Meanwhile, it is flexible enough to be extended to support other new features to enhance the capability of `Eraser`. R2W2 Specifically, for each new feature related to statistical or structural property of queries plans, we could model it as a categorical or continuous variable. Then, we process all categorical features, such as GROUP BY and ORDER BY operators, in a similar way to the join type feature. For all features with continuous values, we process them in a similar way to the filtering predicate. It is important to highlight that the features of `Eraser` is independent of the learned query optimizer. Thus, even if certain features cannot be covered by `Eraser`, it still has the capability to effectively eliminate regressions.

The effectiveness of our selected features is verified by the experimental results in Section 6. We also note that the impact of each

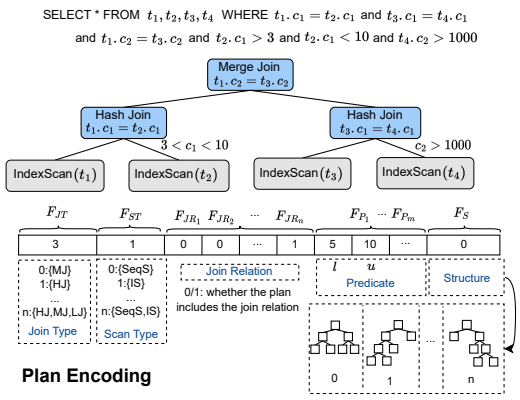


Figure 3: An example of plan encoding.

plan-level feature may be different to `Eraser`. It is worth investigating which subset of features plays the most important roles in distinguishing plans. However, this topic falls within the realm of feature engineering and goes beyond the scope of this paper. We reserve it as an important direction in our future work.

4.2 Division Method Framework

Next, we consider how to investigate the performance of the risk model over unexpected plans. To balance efficiency and accuracy, we propose a very general framework. It hierarchically divides the plan space into a number of subspaces and generates plans in some representative subspaces to evaluate the model performance.

Without loss of generality, let $F_1, F_2, \ldots, F_n$ denote a number of features of query plans encoded by us. For each feature F_i, we denote its domain as D_i. Let S_i and U_i denote all values of F_i occurring and unseen in the training workload $\mathcal{W}$, respectively. For a plan P, if P contains any unseen value $d_i \in U_i$ of any feature F_i, we call P an unexpected plan. Obviously, the feature space $\mathcal{U}$ of all unexpected plans is $\mathcal{U} = (D_1 \times D_2 \times \cdots \times D_n) - (S_1 \times S_2 \times \cdots \times S_n)$.

Each point $p = (d_1, d_2, \ldots, d_n) \in \mathcal{U}$ refers to all plans having value d_i for feature F_i. Note that, these plans share the same encoding vector, so they are difficult to distinguish for the learned risk model. To investigate the model performance on any unexpected plan, we need to evaluate the performance of the risk model on each point. However, this is very costly and unrealistic as the unexpected plan space contains $|\mathcal{U}| = \prod_i |D_i| - \prod_i |S_i|$ points. For continuous features such as the filtering predicate, their domains are divided into a number of small intervals, and $|D_i|$ refers to the number of divided intervals. This size grows exponentially w.r.t. the number of features and $|D_i - S_i|$ is very large for some attributes, i.e., filtering predicates.

R3W2, R3D2

To address this problem, we design a new algorithm by selecting a small number of representative unexpected plans. Our method arises from two fundamental observations:

- First, we observe that if the risk model in the learned query optimizer can not perform well on plans with only one single unseen value $d_i \in U_i$ of feature F_i, it is highly likely to perform worse on plans with unseen values on more features. This is reasonable as the bad performance implies that the model does not acquire enough knowledge to process value d_i on F_i, even with the help of other features F_j where $j \neq i$. At this time, providing other unseen values d_j to the model would certainly not contribute, but degrade its performance.
- Second, as illustrated in Figure 2(a), the risk model is likely to have similar performance for nearby value $d_i, d_i' \in D_i$ of feature F_i, especially for the continuous feature. This is because similar plans may have similar execution time, so as the outputs of the prediction model. This implies that we could group nearby unseen values together to further reduce the evaluation cost.

Algorithm Description. Based on these observations, we present our method in the Algorithm Plan_Space_Division. Notably, our splitting method is independent of the feature. For each feature F_i with its unseen domain U_i, we split U_i into a number of smaller and disjoint subset $U_i^1, U_i^2, \ldots, U_i^k$ and call the Procedure Recur_Split to recursively divide each subset (line 5 in the Algorithm). In general, we apply three methods for division (line 10 in the Procedure). For domain U_i with categorical value, if $|U_i|$ is smaller than a threshold, we set each subset U_i^j to contain a singleton value in U_i; otherwise, we randomly split each value U_i to two subsets U_i^1 and U_i^2. For domain U_i with (discretized) continuous value, we binary split U_i into two subsets U_i^1 and U_i^2 with equal size. Obviously, the division of U_i forms a hierarchical structure. We could control the splitting granularity to balance the evaluation efficiency and accuracy.

R4D6

The Recur_Split process terminates if $|U_i^j|$ is smaller enough than a user-specified threshold (line 1). For each U_i^j without further splitting, we then generate a number of plans falling into this subspace, namely $S_1 \times \cdots \times S_{i-1} \times U_i^j \times S_{i+1} \times \cdots \times S_n$. Then, we evaluate the risk model performance using these plans (lines 2–3). If the model can not perform well, we mark all points p in the unexpected plan space $\mathcal{U}$ whose feature value of F_i falling into U_i^j, namely $p \in D_1 \times \cdots \times D_{i-1} \times U_i^j \times D_{i+1} \times \cdots \times D_n$, as imprecise (line 5 by our first observation). Otherwise, we mark all points p in the evaluated subspace as precise (line 7).

R4D9

Note that, for each U_i^j, we examine all points in the subspace $S_1 \times \cdots \times S_{i-1} \times U_i^j \times S_{i+1} \times \cdots \times S_n$ altogether. Since each U_i^j contains at least one element in U_i, the number of the subspace is at most $\sum_i |U_i|$, which is much less than the number of all points $(\prod_i |D_i| - \prod_i |S_i|)$ in the space. Meanwhile, as we only need to examine the performance of risk models on each subspace, we do not need to generate a large number of plans. In our experiments, we show that we only need to generate a small number (e.g., several tens) of queries to evaluate model performance. In the following, we introduce our implementations on generating plans for evaluation in each subspace (in Section 4.3) and evaluating the model performance (in Section 4.4).

R2D2

4.3 Plan Generation Method

We design a method to manually generate a number of new plans having unseen value on one feature in four steps. Remarkably, we use the *hints* on DBMS to control the join/scan operators used in the plan and the join order between tables. They are supported by popular DBMS such as PostgreSQL, MySQL and SQL Server. We could set the hint command to enable/disable certain operators, e.g., enable only merge_join and hash_join, or specify the join order, e.g., join T_a with T_b then T_a with T_c, before the plan generation. The process is as follows:

Algorithm Plan_Space_Division($F_1, \ldots, F_n, D_1, \ldots, D_n, U_1, \ldots, U_n$)
1: **for** each $1 \le i \le n$ **do**
2: $S_i \leftarrow D_i - U_i$
3: **end for**
4: **for** each feature F_i **do**
5: Recur_Split($F_i, U_i, D_1, \ldots, D_n, S_1, \ldots, S_n$)
6: **end for**

Procedure Recur_Split($F_i, U_i, D_1, \ldots, D_n, S_1, \ldots, S_n$)
1: **if** $|U_i|$ is smaller enough according to feature F_i **then**
2: generate plans falling into $S_1 \times \cdots \times S_{i-1} \times U_i^j \times S_{i+1} \times \cdots \times S_n$
3: evaluate model performance using generated plans
4: **if** the model perform bad **then**
5: mark all points $p \in D_1 \times \cdots \times D_{i-1} \times U_i^j \times D_{i+1} \times \cdots \times D_n$ as imprecise
6: **else**
7: mark all points $p \in S_1 \times \cdots \times S_{i-1} \times U_i^j \times S_{i+1} \times \cdots \times S_n$ as precise
8: **end if**
9: **else**
10: divide U_i into disjoint subset $U_i^1, U_i^2, \ldots, U_i^k$
11: **for** each U_i^j where $1 \le j \le k$ **do**
12: Recur_Split($F_i, U_i^j, D_1, \ldots, D_n, S_1, \ldots, S_n$)
13: **end for**
14: **end if**

- First, we obtain a join form as the template for query generation. For each join relation F_i, if the generated unexpected plan space requires the only unseen value occurring in d_i of F_i, we pick its value d_i from U_i. Otherwise, the value d_i of F_i must contain seen values, so we randomly sample $d_i \in S_i$. We continue the following steps if the obtained join form is valid across tables.
- Second, we attach filtering predicates on each column (attribute). For each filtering predicate F_i, we also pick d_i from U_i if F_i is the required unseen value. Otherwise, we randomly sample $d_i \in S_i$ such that the two endpoints l and u satisfy $l \le u$. Then, we obtain a valid query Q for further plan generation.
- Third, we specify the structure of the generated plan P of Q. Similarly, we pick a possible structure shape d_i from U_i if the structure F_i is the required unseen value. Otherwise, we randomly sample a seen structure shape $d_i \in S_i$ for Q. Then, we randomly select a join order between tables in Q according to d_i and set the hint according to the join orders into DBMS.
- Forth, we restrict the set of available join/scan types. If the join/scan type F_i is required to be unseen, we pick d_i from U_i. Otherwise, we randomly select a seen set $d_i \in S_i$ of join/scan types for P. Then, we set the hint on available operators into DBMS based on d_i.

After that, we ask the native query optimizer to generate the plan P for query Q and collect such plans for model evaluation.

4.4 Model Performance Evaluation

After obtaining a number of generated unexpected plans in each subspace, we then consider how to evaluate the performance of the risk model. In the literature work, the risk model could be either a pointwise regression model [26, 44] or pairwise a classification model [13, 47]. We process it in different ways.

If the risk model is pointwise, it takes a plan P as input and predicts its estimated time $\widehat{C}(P)$ to approach the exact time $C(P)$. At this time, we define the accuracy metric $e(P)$ of the plan P as R4D7

$$e(P) = \min(|\frac{\widehat{C}(P)}{C(P)} - 1|,\ \text{UB}) \quad (3)$$

Here, the UB is an upper bound to prevent severe prediction bias of a part of plans to dominate the average error ratio. We set it to 2 by our expert knowledge in our experiments. We compute the average ratio $\overline{e}(P)$ of all unexpected plans generated for the subspace. We always have $\overline{e}(P) \in [0, \text{UB}]$. We mark the subspace as precise if $\overline{e}(P)$ is less than a threshold α and imprecise otherwise. Notice that, the hyper-parameter α is tuned to be proportional to the input parameter λ, as large α could filter out more risky plans.

When the risk model is a pairwise model, it takes a pair of plans P, P' and outputs a binary label to indicate which plan is better. For such models, we could directly apply the pairwise accuracy w.r.t. the relative order to measure the model performance. Specifically, for each plan P in the subspace, we consider all other plans P' and collect pairs of plans (P, P'). We then compute $e(P)$ as the proportion of pairs where the risk model could accurately find the better plan. We mark the subspace using a threshold α on the average value $\overline{e}(P)$ in the same way. R4D7

5 SEGMENT MODEL AND PLAN SELECTION

After filtering all unexpected plans where the risk model is highly likely to perform badly, we next discuss how to process the remaining plans in the whole place space in this section. At this time, we need to process each plan in a more fine-grained manner to filter unpromising plans. By our observations, the performance of the risk model is different for different regions in the plan space. Therefore, we design a segment model to cluster plans according to model performance and associate each cluster with the reliability interval for plan selection. We introduce the segment model design and training details in Section 5.1 and Section 5.2, respectively. Then, Section 5.3 presents the method for plan selection.

5.1 Segment Model Design

We discuss how to design the segment model in this subsection, including the loss function and the model structure.

Loss Function. Formally, let s be a possible segment model that divides the plan space into multiple non-overlapping subspaces $\mathcal{G} = \{G_1, G_2, \ldots, G_k\}$. Recall that $\mathcal{R}$ and $\mathcal{B}$ (or $\mathcal{R}'$ and $\mathcal{B}'$) denote the regression and benefit before (or after) applying our segment model and plan selection method (discussed in Section 5.3). By Section 2, our goal is, after clustering the remaining plans, to balance the risk of regressions and the benefit of improvements in the plan selection stage. To this end, we train the segment model with the following loss function.

$$L(s) = \log(\mathcal{R}' - \mathcal{R}) + \lambda(\mathcal{B} - \mathcal{B}')) + \lambda_1 |\mathcal{G}| + \lambda_2 \sum_i \max(\sigma - |G_i|, 0). \quad (4)$$

Here, the first term is our goal on minimizing the performance regression elimination problem (see Section **??**). The second term penalizes the clustering granularity on the number of groups. The third term penalizes the number of plans in each group where $\sigma > 0$ is a hyper-parameter to restrict the minimum number of plans in each group. We do not encourage too many clusters and too few plans in each group to avoid over-fitting.

Model Structure. We have several fundamental requirements for the segment model. First, it should be lightweight as the segment model would be frequently retrained when the risk model is updated. Second, the behavior of the segment model should be deterministic and better to be explainable. This is because the behavior

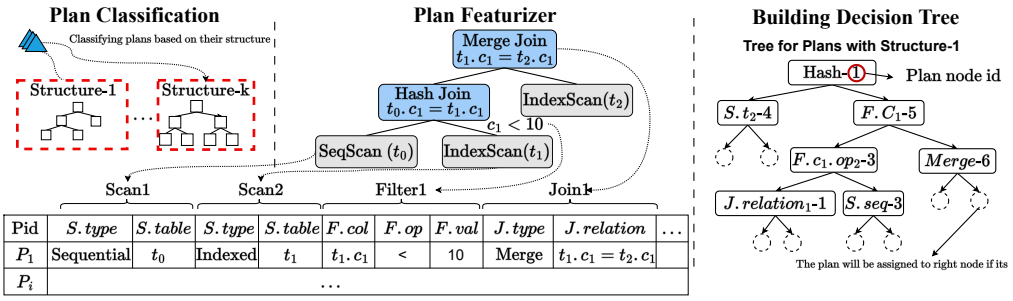


Figure 4: The example of the segment model.The left part is the plan classification process based on their structure. The middle part is the plan featurizer. The right part is a forest, where each tree represents the clustering model for a specific structure.

of the risk deep model is often uncertain [40]. As we try to eliminate its performance regression, it is better not to bring additional uncertainty w.r.t. downstream models. Otherwise, it is difficult to analyze whether the additional error of the segment model would reduce or enlarge the regression. To this end, we pursue a traditional statistical model rather than a deep model, whose training cost is often higher and behavior is often highly uncertain.

Our learning task resembles the classification process of the decision tree, which recursively splits the training data according to their labels using different features. We borrow this idea to design our segment model with two critical differences.

First, training our segment model is an unsupervised task. The decision tree is split to minimize the classification error. Whereas, our splitting criteria is to minimize the loss function in Eq. (4). The details are elaborated in the following Section 5.2.

Second, the structure of the plan tree is very diversified, which is difficult to be encoded as a vector having a fixed length. To address this problem, existing deep models [26, 28, 47] encode the feature of each node and then generate the tree-level encoding using a convolution operation [29]. Obviously, this method is not applicable to our segment model. Another possible way is to compress all node-level vectors into a tree-level vector using bitwise sum or mean value [7]. However, this would lose the structural information. In our design, we maintain a forest where each tree focuses on clustering plans having a specific form of structure. This structure is defined as the simplified logical plan tree, which consists of logical operators (e.g., join and scan), while ignoring the specific physical operator type (e.g., hash join or seq scan), filtering predicates, and other details. It is important to note that the "ignoring" is only applied to define the plan structure. We will apply these features to build our segment model.

Figure 4 illustrates an example of our segment model, where we list several possible plan structures in the left part. The feature vector of each plan shown in the middle part is obtained by concatenating the encoding vector on all nodes. Specifically, for all inner node with join operation, we encode the join operator type and the join relation as categorical variables. For all leaf nodes with scan operation, we encode the scan operator type and the scanned table as categorical variables. Meanwhile, we also encode the filtering predicate, which includes the column, the operator type and the filtering value. For each type of tree structure, we build the decision tree model using the featurized plans as shown in the right part.

5.2 Model Training

We train the segment model using the set of plans $\mathcal{P}_S$. It contains all candidate plans for the queries Q in the training workload $\mathcal{W}$, i.e., $\bigcup_{Q \in \mathcal{W}} (\mathcal{P}_Q \cup \{P_b\})$. Thus, $\mathcal{P}_S$ is a snapshot of the remaining plans filtered by the unexpected plan explorer. For each kind of plan structure, the tree-based segment model is constructed in the same manner. We present the model training method in the Algorithm Model_Construction. First, we collect all plans $\mathcal{P}_N \subseteq \mathcal{P}_S$ with this kind of structure (line 2) and maintain it in the root node (line 3). Then, the algorithm calls the Procedure Model_Train() to build the decision tree in a recursive manner (line 4).

Specifically, in the Procedure Model_Train(), let f_i denote the i-th feature in the plan's encoding vector. Let $f_{i,j}$ denote the j-th value of the feature f_i. For each possible $f_{i,j}$, we split $\mathcal{P}_N$ into $\mathcal{P}_L$ and $\mathcal{P}_R$ on the left and right child according to $f_{i,j}$ and compute the loss (lines 2–3). That is, we select another execution plan P'_r to replace the original execution plan P_r using the plan selection method (discussed in Section 5.3) based on this tree structure. Then, we compute the new regression $\mathcal{R}'$ and the new benefit $\mathcal{B}'$ using all plans P'_r. We select the best splitting feature value $f^*_{i,j}$ that minimizes the loss function defined in Eq. (4) (line 5). It is applied to split the set of plans $\mathcal{P}_N$ (lines 6–7). If f_i is a categorical variable, $\mathcal{P}_L$ contains all plans having value $f^*_{i,j}$ on feature f_i. Otherwise when f_i is a continuous variable, $\mathcal{P}_L$ contains all plans whose feature value of f_i is no more than $f^*_{i,j}$. Then we set $\mathcal{P}_R = \mathcal{P}_N - \mathcal{P}_L$. After that, the procedure works in a recursive manner. It splits all plans in the parent node into two children each time using the best splitting feature value (line 11 and 16). To avoid over-fitting, we terminate the splitting process when the number of plans on the current node is less than a pre-defined threshold (line 8 and 13), typically, 5% of the training data size.

Remarkably, the three features, i.e., column, operator and filtering predicate, are dependent. That is, different columns (attributes) would have different filtering operators and predicates. We add a constraint that the filtering operators and predicate can only be selected as the splitting condition if the corresponding column has been applied for the split in the ancestors.

5.3 Plan Selection Method

Based on the segment tree model, we introduce how to select plans in this subsection. According to how the risk model is designed in existing learned query optimizer [13, 26, 28, 43, 44, 47], we process it in different ways.

Algorithm Model_Construction($\mathcal{P}_S$)
1: **for** each kind of structure **do**
2: collect $\mathcal{P}_N \subseteq \mathcal{P}_S$ with this kind of structure
3: set $\mathcal{P}_N$ to be the root node of the decision tree
4: Model_Train($f_1, f_2, \ldots, f_t, \mathcal{P}_N$)
5: **end for**

Procedure Model_Train($f_1, f_2, \ldots, f_t, \mathcal{P}_N$)
1: **for** each $f_{i,j}$ **do**
2: split $\mathcal{P}_N$ into $\mathcal{P}_L$ and $\mathcal{P}_R$ by $f_{i,j}$
3: compute the loss using the current tree structure
4: **end for**
5: find the feature value $f^*_{i,j}$ with the minimum loss
6: get $\mathcal{P}_L$ and $\mathcal{P}_R$ by $f^*_{i,j}$
7: set $\mathcal{P}_L$ and $\mathcal{P}_R$ to be the left and right child of $\mathcal{P}_N$
8: **if** $|\mathcal{P}_L|$ is less than the pre-defined threshold **then**
9: set $\mathcal{P}_L$ to be a leaf node
10: **else**
11: Model_Train($f_1, f_2, \ldots, f_t, \mathcal{P}_L$)
12: **end if**
13: **if** $|\mathcal{P}_R|$ is less than the pre-defined threshold **then**
14: set $\mathcal{P}_R$ to be a leaf node
15: **else**
16: Model_Train($f_1, f_2, \ldots, f_t, \mathcal{P}_R$)
17: **end if**

When the risk model is a pointwise regression model, for each candidate plan P, we try to find the corresponding tree model for P according to its plan structure. If we have not trained a model for such a structure, it implies we have very limited knowledge of it, so we safely skip plan P to avoid risk or accept plan P to attain potential benefit. Otherwise, in this model, there must exist a leaf node having plans $\mathcal{P}_L$ such that P is assigned into $\mathcal{P}_L$. We define a reliability value $r(P)$ for each plan P. Obviously, the error ratio could reflect the quality of the estimation results. Therefore, we directly define $r(P) = \widehat{C}(P)/C(P)$. Then, we filter plans according to the reliability interval of plans in $\mathcal{P}_L$.

R4D7

Specifically, let $d(\mathcal{P}_L) = \max_{P \in \mathcal{P}_L} r(P) - \min_{P \in \mathcal{P}_L} r(P)$ denote the width of the reliability interval of plans in $\mathcal{P}_L$. If $d(\mathcal{P}_L)$ is smaller than a user-specified threshold β, it indicates the reliability of plans in $\mathcal{P}_L$ are very similar. By our observations in Figure 2(b), at this time, plans in $\mathcal{P}_L$ have similar levels of accuracy, i.e., they may all be accurately or inaccurately learned together. Therefore, we trust this reliability value. Let $\overline{r}(\mathcal{P}_L)$ be the average reliability value of plans in $\mathcal{P}_L$. We correct the predicted cost $C(P)$ to $C'(P) = C(P)/\overline{r}(P)$. Otherwise, when $d(\mathcal{P}_L)$ is larger than β, it indicates the range of the reliability value is not tight. At this time, it implies that this group of plans may not have similar accuracy levels, such as the cluster in the left bottom in Figure 2(b). Therefore, we filter this candidate plan P as we do not have confidential information to correct its estimated cost. After the correction, we select all remaining plans P with the minimum $C'(P)$ to execute. Users could adjust the threshold β to balance the potential benefit and regression risk.

When the risk model is a pairwise classification model, it takes a pair of plans P, P' and outputs which plan is better in terms of their cost. At this time, if we can not find the trained model for any of them, we also skip comparing P and P' to avoid risk. Otherwise, we find the segment model, as well as the leaf node $\mathcal{P}_L$ and $\mathcal{P}'_L$ for plans P and P', respectively. Then, we collect all pair of plans (P_1, P_2) such that $P_1 \in \mathcal{P}_L$ and $P_2 \in \mathcal{P}'_L$. Let $r(\mathcal{P}_L, \mathcal{P}'_L)$ denote the portion of pairs that the risk model can accurately find the better plan. $r(\mathcal{P}_L, \mathcal{P}'_L)$ could also indicate the confidence of the risk model on these plans. Similarly, we trust the risk model if $l(P, P')$ is larger than a user-specified threshold β. At this time, we think plan P surpasses P' if the risk model predicts plan P to be better and vice versa. Otherwise, we do not trust the risk model and ignore the comparison results between P and P'. Finally, the plan P that surpasses the most number of other plans is selected to execute.

6 EVALUATION RESULTS

In this section, we conduct experiments to comprehensively investigate the performance of our `Eraser` system. We make our implementation of `Eraser` open-source[1]. Specifically, our experiments aim to answer the most crucial questions as follows:

- When `Eraser` is deployed on top of the existing learned query optimizer, how much performance regression could it eliminate, and how much impact it may cause to the benefit? (in Section 6.2)
- Could `Eraser` adapt well in dynamic settings? (in Section 6.3)
- How much contribution does each component in `Eraser` make in eliminating performance regression? (in Section 6.4)
- What is the impact of the parameters λ, α and β? (in Section 6.5 and Section 6.6)
- What is the impact of splitting granularity? (in Section 6.7)

6.1 Experimental Setup

Baselines. We use three representative learned query optimizers in our experiments. Specifically, **HyperQO** [44] and **Lero** [47] are two learned query optimizers using pointwise and pairwise risk models, respectively. HyperQO applies the ensemble method to eliminate regression. They have been shown to perform better than Bao [26]. Besides, Lero is shown to perform better than Balsa [43]. Therefore, we do not apply Bao, Balsa and Neo [28] (which performs even worse than Bao) in our experiments. **PerfGuard** [13] is a learned query optimizer that supports any plan generation strategy. We also use Lero's plan exploration strategy to generate plans for PerfGuard. We implement HyperQO and Lero using their source code in [1] and [2], respectively and implement PerfGuard by ourselves. Notably, all of these learned query optimizers are primarily designed for **PostgreSQL**. Therefore, we deploy all of them on the native query optimizer of PostgreSQL. Its original query optimizer serves as a baseline for the traditional query optimizer. For each learned query optimizer, we deploy `Eraser` on top of it. We denote the resulting query optimizer as **HyperQO-`Eraser`**, **Lero-`Eraser`** and **PerfGuard-`Eraser`**, respectively.

R4D1

Benchmarks. We evaluate the performance of all query optimizers on four benchmarks widely used in the literature [26, 28, 44, 47]. We summarize their statistical information in Appendix D [42] due to space limitations. Each benchmark contains a number of tables and query templates with various types of joins. We generate a training and testing workload for each benchmark. In each workload, each time we randomly pick a query template, and then attach some randomly generated predicates to it. Notably, for TPC-H and TPC-DS, we select 14 and 49 templates in all the templates for query generation. The other templates contain complex features such as nested SQL queries or views that are not supported by HyperQO or Lero. The TPC-DS benchmark is mainly used for experiments on a distributed database (in Section E.2). The remaining ones are used for experiments on PostgreSQL (in Section 6.2 to Section 6.5).

[1] https://github.com/duoyw/Eraser

R4D12 R3D3, R3W3

In addition, to demonstrate the effectiveness of Eraser for eliminating performance regression in a more fine-grained manner. We have introduced two new test sets, FAST-IMDB and SLOW-IMDB, which consist of the top 30% and last 30% SQL queries, respectively, obtained by sorting the full test set based on the execution time of plans generated by PostgreSQL.

Evaluation Methods and Metrics. Following [26, 47], we evaluate all learned query optimizers in two scenarios. In the first scenario, we evaluate their stable performance. At this time, the learned query optimizers are trained on a number of training queries. Then, we investigate their performance on the test workload with the stable learned models. In the second scenario, we simulate a real-world environment to test its online performance. At this time, all learned query optimizer starts with randomly initialized models. Then, the learned query optimizer processes each training query online one by one and retrains its model using all observed queries after seeing every 100 queries. In our experiments, we report the average end-to-end (e2e) plan execution time of each query, which includes the plan generation and selection time of the original learned query optimizer, the plan examination and selection time of Eraser and the physical plan execution time.

R2W1

Parameters. For HyperQO, Lero and PerfGuard, we use the same default hyper-parameters in the original paper. For our Eraser, we set the input parameter $\lambda = 0.8$ on all benchmarks. This choice makes the best trade-off between regression and improvement to attain the lowest overall execution time. In each benchmark, we generate 200 queries to evaluate model performance to filter unexpected plans. We tune the hyper-parameters α for filtering unexpected plans and β for filtering unreliable plans in Eraser using grid search to attain the best overall performance.

Environments. All experiments are conducted on a Linux machine with an Intel(R) Xeon(R) Platinum 8163 CPU running at 2.5 GHz, 96 cores, 768GB DDR4 RAM and 2TB SSD. Eight NVIDIA Tesla V100-SXM2 GPUs are equipped for model training and inference. The version of PostgreSQL is 12.1, which is configured with 4GB shared buffers.

6.2 Performance of Eraser

6.2.1 Performance with Stable Models. We train each learned query optimizer on the 25%, 50%, 75% and 100% data of each training workload and then test it on the test workload, respectively. This could reflect the generalization ability of learned query optimizers on queries with unseen feature values. Figure 5 shows the average execution time of all queries in the test workloads in three benchmarks. We have the following observations:

1) Performance regressions commonly occur in learned query optimizers, especially when the test workloads contain queries with unseen feature values. For example, Lero, HyperQO and PerfGuard all perform much worse than PostgreSQL unless they witness 100% of the training data on IMDB. This indicates that eliminating the performance regression is crucially important to improve the stability of the learned query optimizer. Meanwhile, the ensemble method in HyperQO can not ensure to eliminate regression. The reasons are analyzed in Appendix B in the full version [42]

2) By deploying our Eraser, almost all of the performance regressions are eliminated. In all cases when the original learned query optimizer performs worse than PostgreSQL, Eraser could help to improve its performance to be comparable, or slightly better than PostgreSQL. This indicates that Eraser could filter most of the unpromising plans that are falsely predicted and selected by the risk models in learned query optimizers.

Table 1: The cost of Eraser and learned query optimizers.

Metric	Learned Query Optimizer	IMDB		STATS		TPC-H	
		w. Eraser	w.o. Eraser	w. Eraser	w.o. Eraser	w. Eraser	w.o. Eraser
E2E Execution Time (ms) (On Average)	Lero	4,237	7,802	12,228	13,421	3,469	3,500
	HyperQO	4,101	5,858	11,271	12,917	4,495	4,500
	Perfguard	4,198	4,699	12,240	19,783	3,429	3,428

Metric	Learned Query Optimizer	IMDB		STATS		TPC-H	
		Eraser	Original	Eraser	Original	Eraser	Original
Extra Time Cost (ms) (On Average)	Lero	24	201	4.5	28.8	4.1	16.5
	HyperQO	2.4	34.2	0.9	12.2	0.17	21.9
	Perfguard	2.0	176.8	15.3	37.9	11.1	27.3
Training Time (s)	Lero	14.8	199	5.9	118	3.46	132
	HyperQO	14.3	3157	3.45	1467	2.5	2550
	Perfguard	13.2	147	4.6	89	3.4	87
Data Collection Time (Min)	Lero	26	260	34	1,343	63	2,106
	HyperQO	26	733	34	300	63	685
	Perfguard	26	/	34	/	63	/
Model Size (MB)	Lero	0.27	1.35	0.13	1.22	0.02	1.23
	HyperQO	0.28	16.7	0.14	16.29	0.01	6.5
	Perfguard	0.27	16	0.08	1.3	0.02	1.3

3) When the learned query optimizers perform well, Eraser brings very little negative impact on the performance. In all cases when the original learned query optimizer performs better than PostgreSQL, its execution time makes little difference, sometimes even better, when deployed with Eraser. This indicates that Eraser could learn enough information to match our desired goal.

6.2.2 Extra Cost of Eraser. Table 1 shows the extra cost of Eraser and original learned query optimizers. Specifically, the extra cost incurred by the original learned query optimizers include the time to generate candidate plans and select the best one using ML models. The extra cost incurred by Eraser include the time to examine and select plans using unexpected plan explorer and segment model components. We could see that Eraser only consumes very little extra time, i.e., 0.17*ms* to 15.3*ms* per query. In comparison to the end-to-end plan execution time, the percentage is less than 0.001% (on TPC-H) to 0.5% (on IMDB), which is negligible. The model training time and training data collection time of Eraser is much smaller than the original learned query optimizers. The training data collection time of Eraser is used to collect the execution time of the generated plans for the unexpected plan explorer component. It is important to note that this data collection is only performed once for each benchmark and is independent of the learned query optimizers. Meanwhile, the training data collection and model training are performed offline in the background using idle resources. This makes little impact on the online query performance. The memory cost of Eraser is less than 0.3MB, which is totally affordable for the DBMS. Therefore, the time and space cost to apply Eraser is very small.

R2W1 R3W1, R3D1 R4W5, R4D11

6.2.3 Performance Analysis for Fast and Slow Queries . We demonstrate the effectiveness of Eraser for eliminating performance regression in a more fine-grained manner by evaluating the performance of these optimizers on the FAST-IMDB and SLOW-IMDB test sets. Each learned query optimizers is trained with different proportions of the IMDB training data, and the results are presented in Figure 6. We have the following observations:

R4D12

1) Performance regression often occurs when the learned query optimizer is not trained on the full 100% training set. This suggests

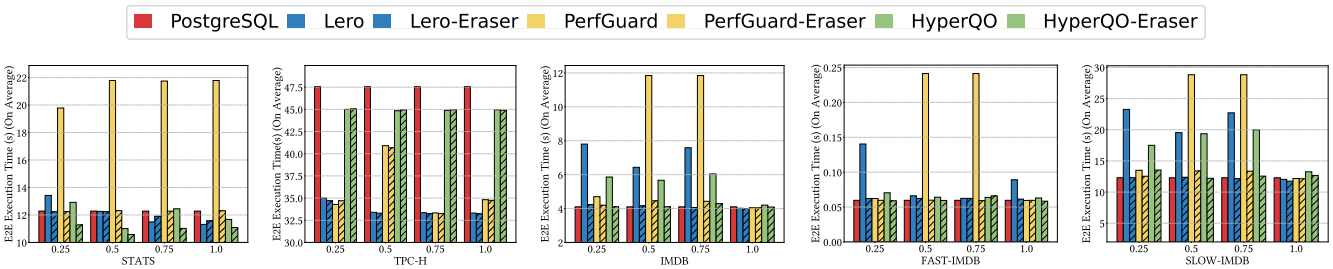
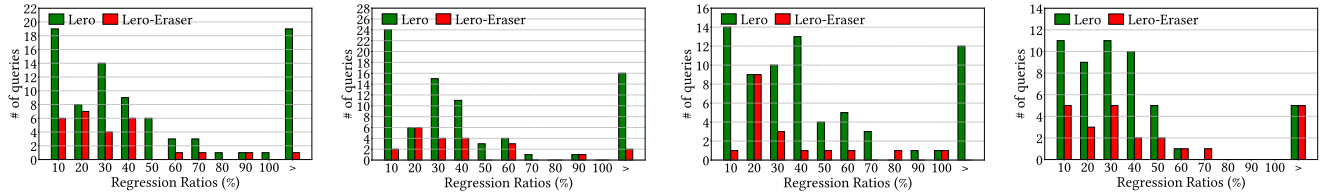


Figure 5: Performance of learned query optimizer with stable models.

Figure 6: Performance on fast and slow queries.



(a) IMDB with 25% training data (b) IMDB with 50% training data (c) IMDB with 75% training data (d) IMDB with 100% training data

Figure 7: Performance of Lero-Eraser on queries with different levels of regression.

that the ML model is easy to make imprecise predictions when the test and training sets are not from the same distribution. Consequently, an approach that can effectively eliminate performance regression is crucial.

2) Eraser demonstrates its ability to eliminate a significant portion of performance regression in both FAST-IMDB and SLOW-IMDB test sets. These results indicate that Eraser is not sensitive to the complexity of SQL queries and is suitable for a wide range of diverse SQL workloads.

By showcasing these fine-grained experiments, we provide strong evidence of the effectiveness of Eraser in mitigating performance regression and its suitability for optimizing various SQL queries.

6.2.4 Analysis of Regression Elimination. To present more details, we present the effects of Eraser on queries with different levels of regression. On the IMDB benchmark, we divide all test queries Q with regressions according to the ratio of the regression time, i.e., $(C(P_r) - C(P_b))/C(P_b)$. The results of Lero and Lero-Eraser that are trained on 25%, 50%, 75% and 100% of the IMDB training data are shown in Figure 7. Notice that the goal of Eraser is to balance the regression and the improvement to attain the best overall performance on all queries. Therefore, when models are trained using different volumes of data, Eraser will automatically adapt and exhibit varying behaviors:

R2W4

R3W3, R3D3

1) In Figure 7 (a) (b) and (c), the risk models are trained on the part of the training data. Since the models witness a number of queries having unseen feature values, they select a large number of plans with heavy regression. The overall performance of the learned query optimizer is worse than the baseline PostgreSQL. At this time, Eraser would focus more on filtering these unexpected plans with high risks to ensure the learned query optimizer keeps comparable performance with the baseline. The number of filtered plans is 57, 59 and 54 in Figure 7 (a), (b) and (c), respectively.

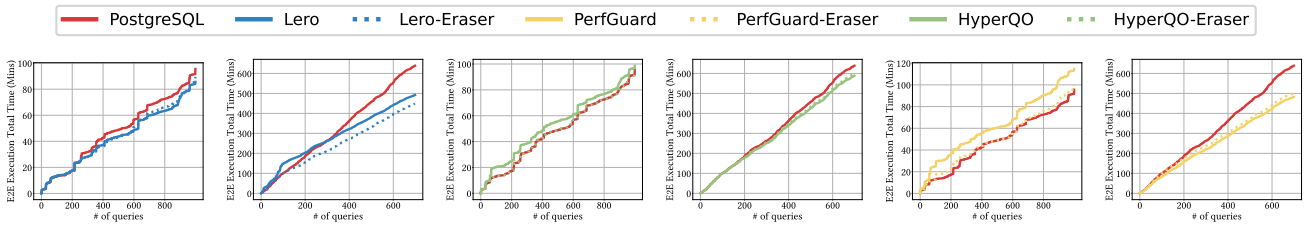
2) In Figure 7 (d), the model is trained on all data, and the overall performance of the learned query optimizer is already better than the baseline. At this time, Eraser would be more concerned with balancing the regression elimination and impact on the improvement. Therefore, it only filters a small number of queries, i.e., only 28 in Figure 7 (d), to avoid affecting the overall performance. As a result, more queries with large regression ratios are likely to be kept. For example, in Figure 7 (d), Eraser chooses to retain all plans that have a regression ratio exceeding 100%. Notably, in our Eraser method, we remove all plans with similar feature values in a subspace together (see technical details of the unexpected plan explorer in Section 4 and segment model in Section 5). Therefore, removing these plans with significant regressions may also result in the removal of other more plans in the same subspace with substantial performance benefits. As a result, Eraser prefers to retain all plans. Notably, although Eraser keeps more queries with large regression ratios, the overall performance of the learned query optimizer becomes better.

This adaptiveness ensures Eraser to make the best trade-off between regression and improvement to attain better overall performance.

6.2.5 Performance Curve since Deployment. We show the performance curve since deployment in the online evaluation scenario. Figure 8 shows the performance of all learned query optimizers on IMDB and TPC-H. The results on STATS are similar. We make the following observations:

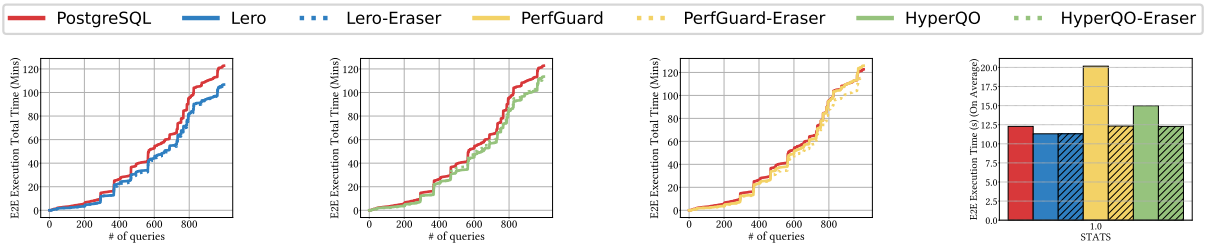
1) When the learned query optimizer consistently performs worse than PostgreSQL, e.g., HyperQO and PerfGuard on IMDB, Eraser could help to eliminate the regressions and attain comparable performance w.r.t. PostgreSQL. On the contrary, when the learned query optimizer consistently performs better than PostgreSQL, e.g., PerfGuard on TPC-H, Eraser makes very little impact on its performance. Once again, this verifies its effectiveness.

2) In other cases, the learned query optimizer could perform better than PostgreSQL after only seeing enough training queries, e.g., Lero on TPC-H and IMDB. Eraser could still eliminate the regression at the very early stage and bring non-negative, even possible good (e.g. Lero on TPC-H), impact at the later stage. This



(a) Lero and Lero-Eraser on IMDB (b) Lero and Lero-Eraser on TPC-H (c) HyperQO and HyperQO-Eraser on IMDB (d) HyperQO and HyperQO-Eraser on TPC-H (e) PerfGuard and PerfGuard-Eraser on IMDB (f) PerfGuard and PerfGuard-Eraser on TPC-H

Figure 8: Performance curve of learned query optimizer since deployment.



(a) Lero and Lero-Eraser (b) HyperQO and HyperQO-Eraser (c) PerfGuard and PerfGuard-Eraser (d) Performance of Stable Models

Figure 9: Performance of learned query optimizer on dynamic data.

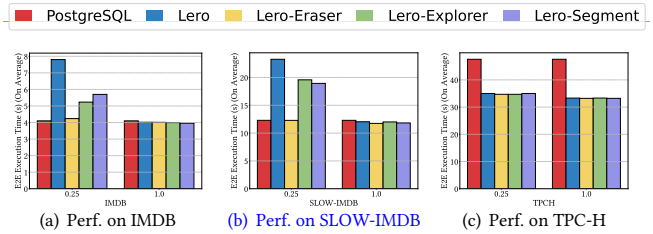
once again verifies the adaptiveness of Eraser to risk models with different performances in different stages.

Meanwhile, we find that in both evaluation scenarios, Eraser could work well on different learned query optimizers with different plan exploration strategies and risk models. This is due to the models in Eraser are totally independent of the underlying systems, so they are applicable to any learned query optimizer. Whereas, the other methods, such as the ensemble method in HyperQO, can not be easily extended to other learned query optimizers.

We put more experiments in terms of Eraser into the Appendix E in the full version [42] due to space limits. First, we compare the performance of Eraser with another technical routine to eliminate regression by enlarging the training workload in Appendix E.1. We find that the performance regressions can not be resolved by simply applying more training data owing to the inherent drawbacks of the learned models. Second, we investigate the performance of Eraser on distributed databases, i.e., Spark 3.3 [45], in Appendix E.2. The results verify the effectiveness and generality of Eraser to be applicable to different DBMSes with different query optimization mechanisms.

6.3 Performance on Dynamic Data

In this experiment, we evaluate the performance of Eraser in the setting of dynamic data. To this end, we insert 50% of the data into the database at the beginning and insert 12.5% of the data after receiving every 25% of training queries. Figure 9(a-c) shows the performance curve of several learned query optimizers since deployment on the training workload of the STATS benchmark. Figure 9(d) illustrates the performance of the stable models on test workload. We observe that Eraser could still help to eliminate the regression with very little impact on the improvement. This is because both the unexpected plan explorer and segment model in Eraser work on the space of plan features, which are totally independent of the data distributions. As a result, Eraser is robust to data changes.



(a) Perf. on IMDB (b) Perf. on SLOW-IMDB (c) Perf. on TPC-H

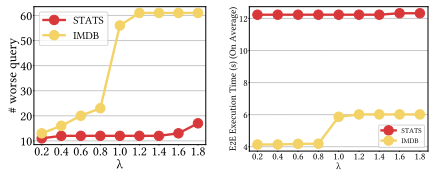
Figure 10: Ablation analysis for two components.

Meanwhile, Eraser could eliminate the regression at the very early stage. This is because the unexpected plan explorer in Eraser has been trained on the plan space using generated queries, so the initial performance of Eraser does not rely on training queries. In the later stage, the segment model in Eraser is gradually updated with the information of training queries. Therefore, Eraser could bring a non-negative, even possibly good, impact. This verifies the success of our design in Eraser.

6.4 Ablation Analysis

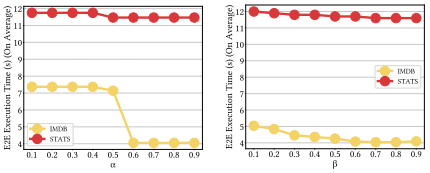
We conduct an ablation analysis to investigate the effects of each component, namely unexpected plan explorer and segment model, in Eraser. We attach Lero with only each component and compare their performance. The results of stable models on test workloads of the IMDB and TPC-H benchmarks are shown in Figure 10. We have the following findings:

1) Each component could contribute to eliminating the performance regression, but the effect is worse than combining them together. For example, on the IMDB benchmark with 25% training data, the unexpected plan explorer and segment model could eliminate 68% and 57% regression of Lero, respectively. However, by using both components, Lero-Eraser could eliminate 96% of the regression. This is because the two components filter plans with regressions caused by different reasons. Unexpected plan explorer



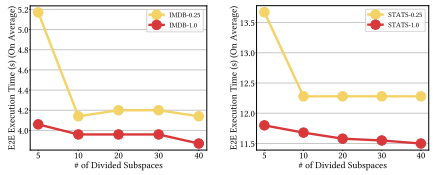
(a) # of Regression Queries (b) Average Execution Time

Figure 11: Effects of parameter λ.



(a) Effect of parameter α (b) Effect of parameter β

Figure 12: Effects of parameter α and β.



(a) Results on IMDB (b) Results on STATS

Figure 13: Effect of splitting granularity.

eliminates plans with unseen features that the model can not generalize well, while the segment model eliminates remaining plans with low learning accuracy.

2) Each component has little impact on the improvement of Lero. This is because the candidate plans with benefits are often not unexpected plans (see Figure 2(a)), which would often not be filtered by the unexpected plan explorer. Meanwhile, the learning difficulty of the segment model is much smaller than the risk model's. Thus, it is easier to attain our desired goal in loss function to balance the regressions and benefits.

R3W3, R3D3

3) Figure 10(b) reports the ablation study results of `Eraser` on top-30% slowest queries. We find that the observations on slow queries are the same as other workloads. That is, the unexpected plan explorer eliminates plans with unseen features that the model can not generalize well, while the segment model eliminates remaining plans with low learning accuracy. This once again verifies the effectiveness of `Eraser` on processing slow queries.

6.5 Effects of Parameter λ

We study the effects of λ on balancing the elimination of regression and the impact on improvement. We vary λ from 0.2 to 1.8 on IMDB and STATS benchmarks. Figure 11 illustrates the number of regression queries (in the left part) and average execution time (in the right part) of the stable models in Lero-`Eraser` on the test workloads. We find that:

1) By increasing λ, the number of regression queries also increases. This is simply because a larger λ encourages to improve the benefits, so the segment model reserves more candidate plans.

2) For different λ, the execution time may vary. By filtering different plans, the total benefit $\mathcal{B}'$ and the total regression $\mathcal{R}'$ varies, so the time variance, i.e., $\mathcal{B}' - \mathcal{R}'$ may be different. On different datasets, the volume of $\mathcal{B}'$ and $\mathcal{R}'$ differs, so the varying speed is also different. In our dataset, the execution time increases on IMDB but tends to keep stable on STATS.

R4W4

6.6 Effects of Parameters β and α

We study the effects of α and β on balancing the elimination of regression and the impact on improvement. Specifically, we vary the parameter α or β from 0.1 to 0.9 and examine the average time of Lero on the IMDB and STATS benchmarks. Figure 12 illustrates the results. We have the following observations:

1) Increasing the value of α leads to an improvement of the overall performance. This is because the learned query optimizer tends to make imprecise predictions on unexpected plans. By pruning more subspaces of such unexpected plans, we can achieve a higher performance improvement. It is worth noting that the performance stabilizes after α reaches 0.7. At this time, the unexpected plan explorer has already filtered almost all risky plans.

2) Similarly, increasing the value of parameter β also results in a slight improvement in performance. This phenomenon reflects the fact that the ML models exhibit poor performance on a subset of the data. By setting a reasonable value for β to filter out such risky plans, we can also eliminate some performance regressions.

It is worth noting that determining the optimal value for parameters α and β is data-dependent and can be determined through a grid search on a validation set.

6.7 Effect of the Splitting Granularity

R4D6

Here, we investigate the effects of the splitting granularity in the unexpected plan explorer on the performance of `Eraser`. We gradually decrease the splitting threshold in the division method (in Section 4.2) such that the number of divided subspaces increases from 5 to 40. We then generate 10 plans in each subspace to evaluate the model performance. From Figure 13, we find that: by decreasing the threshold, the overall performance of `Eraser` continuously improves. However, the performance becomes stable after the number of divided subspaces exceeds 10. This indicates that a deep hierarchical structure could help us to examine the effects of each feature value in a more fine-grained manner. However, when the number of divided subspaces is small enough, the feature values within it have a similar effect on damaging the prediction accuracy of the ML models. Thus, this implies that `Eraser` can offer valuable insights on the impact of unseen feature values even with limited budgets.

7 CONCLUSIONS AND FUTURE WORK

Performance regression commonly occurs in learned query optimizers and has a serious impact on their applicability and stability. In this paper, we design a system called `Eraser` to resolve this challenging problem. `Eraser` could be deployed on top of any existing learned query optimizer to eliminate the performance regression while preserving the performance improvement. `Eraser` adopts a two-stage strategy to identify the estimation accuracy of each plan, where the first stage qualitatively filters all unpromising plans with high risks, and the second stage quantitatively evaluates the estimation quality of remaining plans. The final plan is selected to make the best trade-off between benefit and risk. Extensive experiments on different learned query optimizers in PostgreSQL and Spark exhibit the effectiveness and generality of `Eraser`.

In future work, we try to internally integrate `Eraser` into the plan exploration strategy and prediction models in learned query optimizers. Meanwhile, we consider extending `Eraser` to other tasks in learned databases, such as knob tuning [18, 24, 36], index recommendation [4, 7, 25, 31–33] and view advisor [8, 16, 50].

REFERENCES

[1] 2022. HyperQO Implementation. https://github.com/yxfish13/HyperQO.

[2] 2022. Lero Implementation. https://github.com/Blondig/Lero-on-PostgreSQL.

[3] Omer Achrack, Raizy Kellerman, and Ouriel Barzilay. 2020. Multi-loss sub-ensembles for accurate classification with uncertainty estimation. *arXiv preprint arXiv:2010.01917* (2020).

[4] Surajit Chaudhuri and Vivek R Narasayya. 1997. An efficient, cost-driven index selection tool for Microsoft SQL server. In *VLDB*, Vol. 97. San Francisco, 146–155.

[5] Transaction Processing Performance Council(TPC). 2021. TPC-DS Vesion 2 and Version 3. http://www.tpc.org/tpcds/.

[6] Transaction Processing Performance Council(TPC). 2021. TPC-H Vesion 2 and Version 3. http://www.tpc.org/tpch/.

[7] Bailu Ding, Sudipto Das, Ryan Marcus, Wentao Wu, Surajit Chaudhuri, and Vivek R. Narasayya. 2019. AI Meets AI: Leveraging Query Executions to Improve Index Recommendations. In *SIGMOD Conference*. ACM, 1241–1258.

[8] Tansel Dokeroglu, Murat Ali Bayir, and Ahmet Cosar. 2015. Robust heuristic algorithms for exploiting the common tasks of relational cloud database queries. *Applied Soft Computing* 30 (2015), 72–82.

[9] Yuxing Han. 2021. Github repository: STATS End-to-End CardEst Benchmark. https://github.com/Nathaniel-Han/End-to-End-CardEst-Benchmark.

[10] Yuxing Han, Ziniu Wu, Peizhi Wu, Rong Zhu, Jingyi Yang, Tan Wei Liang, Kai Zeng, Gao Cong, Yanzhao Qin, Andreas Pfadler, Zhengping Qian, Jingren Zhou, Jiangneng Li, and Bin Cui. 2021. Cardinality Estimation in DBMS: A Comprehensive Benchmark Evaluation. *PVLDB* 15, 4 (2021), 752–765.

[11] Yuxing Han, Ziniu Wu, Peizhi Wu, Rong Zhu, Jingyi Yang, Liang Wei Tan, Kai Zeng, Gao Cong, Yanzhao Qin, Andreas Pfadler, et al. 2021. Cardinality estimation in dbms: A comprehensive benchmark evaluation. *arXiv preprint arXiv:2109.05877* (2021).

[12] Benjamin Hilprecht, Andreas Schmidt, Moritz Kulessa, Alejandro Molina, Kristian Kersting, and Carsten Binnig. 2020. DeepDB: learn from data, not from queries! *PVLDB* 13, 7, 992–1005.

[13] H. M. Sajjad Hossain, Marc T. Friedman, Hiren Patel, Shi Qiao, Soundar Srinivasan, Markus Weimer, Remmelt Ammerlaan, Lucas Rosenblatt, Gilbert Antonius, Peter Orenberg, Vijay Ramani, Abhishek Roy, Irene Shaffer, and Alekh Jindal. 2021. PerfGuard: Deploying ML-for-Systems without Performance Regressions, Almost! *Proc. VLDB Endow.* 14, 13 (2021), 3362–3375.

[14] Gao Huang, Yixuan Li, Geoff Pleiss, Zhuang Liu, John E Hopcroft, and Kilian Q Weinberger. 2017. Snapshot ensembles: Train 1, get m for free. *arXiv preprint arXiv:1704.00109* (2017).

[15] Harish D Pooja N Darera Jayant and R Haritsa. 2008. Identifying robust plans through plan diagram reduction. In *VLDB*, Vol. 24. Citeseer, 25.

[16] Alekh Jindal, Konstantinos Karanasos, Sriram Rao, and Hiren Patel. 2018. Selecting subexpressions to materialize at datacenter scale. *Proceedings of the VLDB Endowment* 11, 7 (2018), 800–812.

[17] Andreas Kipf, Thomas Kipf, Bernhard Radke, Viktor Leis, Peter Boncz, and Alfons Kemper. 2018. Learned cardinalities: Estimating correlated joins with deep learning. *arXiv preprint arXiv:1809.00677* (2018).

[18] Mayuresh Kunjir and Shivnath Babu. 2020. Black or white? how to develop an autotuner for memory-based analytics. In *Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data*. 1667–1683.

[19] Meghdad Kurmanji and Peter Triantafillou. 2022. Detect, Distill and Update: Learned DB Systems Facing Out of Distribution Data. *CoRR* abs/2210.05508 (2022).

[20] Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. 2017. Simple and scalable predictive uncertainty estimation using deep ensembles. *Advances in neural information processing systems* 30 (2017).

[21] Viktor Leis, Andrey Gubichev, Atanas Mirchev, Peter Boncz, Alfons Kemper, and Thomas Neumann. 2015. How good are query optimizers, really? *Proceedings of the VLDB Endowment* 9, 3 (2015), 204–215.

[22] Viktor Leis, Andrey Gubichev, Atanas Mirchev, Peter A. Boncz, Alfons Kemper, and Thomas Neumann. 2015. How Good Are Query Optimizers, Really? *Proc. VLDB Endow.* 9, 3 (2015), 204–215.

[23] Beibin Li, Yao Lu, and Srikanth Kandula. 2022. Warper: Efficiently Adapting Learned Cardinality Estimators to Data and Workload Drifts. In *SIGMOD Conference*. ACM, 1920–1933.

[24] Guoliang Li, Xuanhe Zhou, Shifu Li, and Bo Gao. 2019. Qtune: A query-aware database tuning system with deep reinforcement learning. *Proceedings of the VLDB Endowment* 12, 12 (2019), 2118–2130.

[25] Martin Luhring, Kai-Uwe Sattler, Karsten Schmidt, and Eike Schallehn. 2007. Autonomous management of soft indexes. In *2007 IEEE 23rd International Conference on Data Engineering Workshop*. IEEE, 450–458.

[26] Ryan Marcus, Parimarjan Negi, Hongzi Mao, Nesime Tatbul, Mohammad Alizadeh, and Tim Kraska. 2021. Bao: Making learned query optimization practical. In *SIGMOD*. 1275–1288.

[27] Ryan Marcus and Olga Papaemmanouil. 2019. Plan-structured deep neural network models for query performance prediction. *arXiv preprint arXiv:1902.00132* (2019).

[28] Ryan C. Marcus, Parimarjan Negi, Hongzi Mao, Chi Zhang, Mohammad Alizadeh, Tim Kraska, Olga Papaemmanouil, and Nesime Tatbul. 2019. Neo: A Learned Query Optimizer. *Proc. VLDB Endow.* 12, 11 (2019), 1705–1718.

[29] Lili Mou, Ge Li, Lu Zhang, Tao Wang, and Zhi Jin. 2016. Convolutional Neural Networks over Tree Structures for Programming Language Processing. In *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, February 12-17, 2016, Phoenix, Arizona, USA*, Dale Schuurmans and Michael P. Wellman (Eds.). AAAI Press, 1287–1293. http://www.aaai.org/ocs/index.php/AAAI/AAAI16/paper/view/11775

[30] Jennifer Ortiz, Magdalena Balazinska, Johannes Gehrke, and S Sathiya Keerthi. 2019. An empirical analysis of deep learning for cardinality estimation. *arXiv preprint arXiv:1905.06425* (2019).

[31] Wendel Góes Pedrozo, Júlio Cesar Nievola, and Deborah Carvalho Ribeiro. 2018. An adaptive approach for index tuning with learning classifier systems on hybrid storage environments. In *Hybrid Artificial Intelligent Systems: 13th International Conference, HAIS 2018, Oviedo, Spain, June 20-22, 2018, Proceedings 13*. Springer, 716–729.

[32] Zahra Sadri, Le Gruenwald, and Eleazar Leal. 2020. Online Index Selection Using Deep Reinforcement Learning for a Cluster Database. In *ICDE Workshops*. IEEE, 158–161.

[33] Karl Schnaitter, Serge Abiteboul, Tova Milo, and Neoklis Polyzotis. 2007. On-line index selection for shifting workloads. In *2007 IEEE 23rd International Conference on Data Engineering Workshop*. IEEE, 459–468.

[34] P Griffiths Selinger, Morton M Astrahan, Donald D Chamberlin, Raymond A Lorie, and Thomas G Price. 1979. Access path selection in a relational database management system. In *Proceedings of the 1979 ACM SIGMOD international conference on Management of data*. 23–34.

[35] Ji Sun and Guoliang Li. 2019. An end-to-end learning-based cost estimator. *arXiv preprint arXiv:1906.02560* (2019).

[36] Jian Tan, Tieying Zhang, Feifei Li, Jie Chen, Qixing Zheng, Ping Zhang, Honglin Qiao, Yue Shi, Wei Cao, and Rui Zhang. 2019. ibtune: Individualized buffer tuning for large-scale cloud databases. *Proceedings of the VLDB Endowment* 12, 10 (2019), 1221–1234.

[37] Kostas Tzoumas, Amol Deshpande, and Christian S Jensen. 2011. Lightweight graphical models for selectivity estimation without independence assumptions. *Proceedings of the VLDB Endowment* 4, 11 (2011), 852–863.

[38] Matias Valdenegro-Toro. 2019. Deep sub-ensembles for fast uncertainty estimation in image classification. *arXiv preprint arXiv:1910.08168* (2019).

[39] Laurens Van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-SNE. *Journal of machine learning research* 9, 11 (2008).

[40] Xiaoying Wang, Changbo Qu, Weiyuan Wu, Jiannan Wang, and Qingqing Zhou. 2021. Are We Ready For Learned Cardinality Estimation? *PVLDB* 14, 9 (2021), 1640–1654.

[41] Yeming Wen, Dustin Tran, and Jimmy Ba. 2020. Batchensemble: an alternative approach to efficient ensemble and lifelong learning. *arXiv preprint arXiv:2002.06715* (2020).

[42] Lianggui Weng, Rong Zhu, Di Wu, Bolin Ding, Bolong Zheng, and Jingren Zhou. 2023. Eraser: Eliminating Performance Regression on Learned Query Optimizer. *https://github.com/duoyw/Eraser/tree/main/paper* (2023).

[43] Zongheng Yang, Wei-Lin Chiang, Sifei Luan, Gautam Mittal, Michael Luo, and Ion Stoica. 2022. Balsa: Learning a Query Optimizer Without Expert Demonstrations. In *SIGMOD Conference*. ACM, 931–944.

[44] Xiang Yu, Chengliang Chai, Guoliang Li, and Jiabin Liu. 2022. Cost-based or Learning-based? A Hybrid Query Optimizer for Query Plan Selection. *Proc. VLDB Endow.* 15, 13 (2022), 3924–3936.

[45] Matei Zaharia, Mosharaf Chowdhury, Michael J Franklin, Scott Shenker, Ion Stoica, et al. 2010. Spark: Cluster computing with working sets. *HotCloud* 10, 10-10 (2010), 95.

[46] Erkang Zhu, Dong Deng, Fatemeh Nargesian, and Renée J. Miller. 2019. JOSIE: Overlap Set Similarity Search for Finding Joinable Tables in Data Lakes. In *SIGMOD Conference*. ACM, 847–864.

[47] Rong Zhu, Wei Chen, Bolin Ding, Xingguang Chen, Andreas Pfadler, Ziniu Wu, and Jingren Zhou. 2022. Lero: A Learning-to-Rank Query Optimizer. *Proc. VLDB Endow.* 16, 6 (2022), 1466–1479.

[48] Rong Zhu, Ziniu Wu, Chengliang Chai, Andreas Pfadler, Bolin Ding, Guoliang Li, and Jingren Zhou. 2022. Learned Query Optimizer: At the Forefront of AI-Driven Databases.. In *EDBT*. 1–4.

[49] Rong Zhu, Ziniu Wu, Yuxing Han, Kai Zeng, Andreas Pfadler, Zhengping Qian, Jingren Zhou, and Bin Cui. 2021. FLAT: Fast, Lightweight and Accurate Method for Cardinality Estimation. *PVLDB* 14, 9 (2021), 1489–1502.

[50] Daniel C Zilio, Calisto Zuzarte, Sam Lightstone, Wenbin Ma, Guy M Lohman, Roberta J Cochrane, Hamid Pirahesh, Latha Colby, Jarek Gryz, Eric Alton, et al. 2004. Recommending materialized views and indexes with the IBM DB2 design advisor. In *International Conference on Autonomic Computing, 2004. Proceedings.* IEEE, 180–187.

A FRAMEWORK OF LEARNED QUERY OPTIMIZER

We elaborate on how existing learned query optimizers are subsumed under our framework presented in Section 2.

- **Neo** [28] and **Balsa** [43] generate the candidate plans $\mathcal{P}_Q$ from scratch by best-first and beam search strategy, respectively. Then, their risk models apply the tree convolution network [29] to predict the execution time of each plan $P \in \mathcal{P}_Q$.
- **Bao** [26] steers the native traditional query optimizer with different hints to enable or prohibit certain physical operators to generate different candidate plans. Its risk model is also based on a tree convolution network with simpler features.
- **HyperQO** [44] uses different leading hints to control the join order of tables to collect candidate plans. Its risk model relies on the multi-head LSTM structure for predicting execution time.
- **Lero** [47] applies the estimated cardinality as the tuning knob for generating candidate plans. It scales the estimated cardinality by some factors to produce different (possibly better) plans. Unlike other works, Lero trains a pairwise classification model. For each pair of plans $P, P' \in \mathcal{P}_Q$, the model learns to predict which plan is better in terms of cost. The plan surpassing the most number of other plans is then selected to execute.
- **PerfGuard** [13] could support any method to generate candidate plans. It also applies the pairwise model, which incorporates graph convolution networks, for plan selection.
- Some other works replace the cardinality estimation [12, 17, 30, 49] or cost model [27, 35] in query optimizer to learned models. They apply the same plan exploration method as the traditional query optimizer but could predict more accurate cost.

R2W3

B PARAMETER SELECTION OF λ

As discussed in Section 2, the parameter λ plays a crucial role in controlling the optimization goal of `Eraser`. A larger value of λ encourages `Eraser` to prioritize improving benefits, while a smaller value of λ is expected to filter out more risky plans to eliminate regression. Thus, the most appropriate value of λ depends on the user's requirements and usage scenario. Although the value of λ is subjective and user-dependent, we can share some insights on the effects of different values of λ in various scenarios. Specifically, when the training data is scarce or the workload varies frequently, we recommend setting λ slightly less than 1, for instance, $\lambda = 0.8$. In such a scenario, the learned query optimizer often provides inaccurate predictions, and a smaller value of λ can filter out more risky plans without a significant impact on benefits. Otherwise, if the training data is sufficient or the workload is stable, setting a larger $\lambda = 1$ or larger than 1 is more preferable. At this time, the learned query optimizer is more accurate, so we could filter less plans but reserve more to obtain more improvement benefits. In practice, the most appropriate value for λ can be influenced by various factors, including the structure of the model and the training method employed. Different learned query optimizers may require different values for λ to achieve the optimal performance. The database users could also conduct an evaluation on the validation set with different λ to select the best value periodically.

C ANALYSIS OF EXISTING SOLUTIONS

In recent times, there has been a significant shift towards enhancing the robustness of learned-based models. For instance, Warper [23] enhances the cardinality estimation model by generating additional queries to update it when data or workload drift is detected. DDUp [19] uses a two-stage sampling procedure to test whether the model should be updated w.r.t. dynamic data. Although these methods are effective, they are post-processing techniques used for model updating. Whereas, our goal is to detect and eliminate regression before query execution.

An intuitive way to eliminate regression is to add more training data. However, this can not be guarantee to work well for two reasons: 1) The plan space size is very large. Adding more training data can not guarantee the model will generalize well on any plan. 2) Some regressions are caused by the limited capacity of models. This under-fitting problem can not be resolved by using more training data. Our experimental results in Section E.1 verify that this method is ineffective.

The literature work [44] tries to apply the ensemble method. It deploys a multi-head LSTM model to learn multiple prediction results for each plan $P \in \mathcal{P}_Q$. All candidate plans P with a large variance in the prediction results are filtered before plan selection. Then, they select the remaining plans with the best average estimated cost to execute. When all candidate plans are filtered, it prefers to execute the plan P_b generated by the traditional optimizer.

The ensemble method has two main drawbacks. First, to improve accuracy, it requires training a large number of models, which is not efficient. Second, its plan filtering strategy can not always reflect the performance of models. A small variance only indicates all models learn similar results for the same plans, but does not ensure the accuracy of the prediction results. A bad plan P may be reserved if all models make the same mistake, while a good plan P may be filtered if its cost is only accurately learned by a small number of models. Therefore, the ensemble method can not fundamentally distinguish the models' performance over different plans. By our experiments in Section 6.2, HyperQO has poor performance in eliminating regression. This motivates us to pursue new solutions to resolve the performance regression elimination problem.

D BENCHMARK STATISTICS

We show the detailed statistical information of the benchmarks used in our experiments in Table 2.

Table 2: Statistics of benchmarks used in experiments.

Statistic	IMDB	STATS	TPC-H	TPC-DS
Source	[22]	[9]	[6]	[5]
# of tables	21	8	8	24
# of query templates	113	146	14	49
# of training queries	1,000	1,000	700	4,900
# of testing queries	113	146	140	490

E ADDITIONAL EXPERIMENTS

We provide more experimental results in this section.

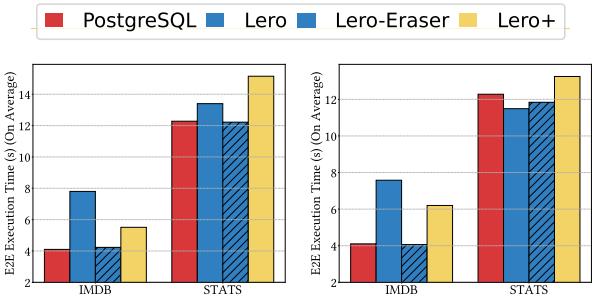
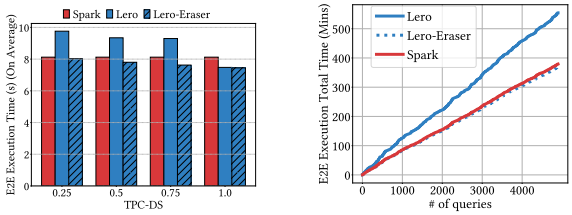


Figure 14: Performance when training model with more data.



(a) Performance of Stable Models (b) Online Performance

Figure 15: Performance of learned query optimizer on Spark.

E.1 Regression Elimination by More Training Data.

Another possible way to eliminate regression is to enlarge the training workload of the learned query optimizer. For fair of comparison, we add the queries generated in unexpected plan explorer into the training workload and compare the performance of Lero with more training queries (denoted as Lero+). Their results of the stable models on IMDB and STATS benchmarks are shown in Figure 14.

We find that Lero+ still has a severe performance regression while `Eraser` could eliminate all regression. This is because a small volume of additional training data can not guarantee that the risk models will generalize well on all unexpected plans. However, they are enough to qualitatively evaluate the performance of risk models for each coarse-grained subspace of unexpected plans, as we do in `Eraser`. Meanwhile, some regressions are caused due to the limited capacity of the risk model. This intrinsic under-fitting problem may not be resolved by only using more training data. Due to the same reason, adding more training queries can not ensure a positive impact on the performance. For example, Lero+'s performance is worse than Lero's on STATS with more training data. A similar phenomenon is also observed for PerfGuard on the STATS benchmark (see the middle figure in Figure 5).

E.2 Performance of `Eraser` on Spark

In this set of experiments, we test the performance of `Eraser` on the distributed database. We deploy `Eraser` on Lero on Spark and apply the TPC-DS benchmark for evaluation. Figure 15 shows the execution time of Lero and Lero-`Eraser` in the two evaluation scenarios. We find that, for the stable models of Lero (in Figure 15(a)), it only performs better than the original query optimizer in Spark when trained on 100% of data. In the online evaluation scenario (in Figure 15(b)), Lero consistently performs worse than Spark. Fortunately, `Eraser` could help to eliminate regressions of Lero in all cases to attain comparable, or slightly better, performance of Spark. This indicates the generality on the design choices of our `Eraser`, which is applicable to different DBMSes with different query optimization mechanisms.