# PilotScope: Steering Databases with Machine Learning Drivers

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## ABSTRACT

Learned databases, or AI4DB techniques, have rapidly developed in the last decade. Deploying machine learning (ML) and AI4DB algorithms into actual databases is the gold standard to examine their performance in practice. However, due to the complexity of database systems, the difference between ML and DB programming paradigms, and the diversity of ML models, the tasks of developing and deploying AI4DB algorithms into databases are prohibitively difficult. Most previous works focus on specific AI4DB algorithms and ML models whose deployment requires close cooperation between ML and DB developers and heavy engineering cost.

In this paper, we tackle this challenge by designing and implementing PilotScope, an AI4DB middleware with a programming model that largely reduces the difficulties of developing and deploying AI4DB algorithms in databases. With a novel abstraction of AI4DB algorithms for, *e.g.*, knob tuning and query optimization, PilotScope consists of two classes of components, *AI4DB drivers* and *DB interactors*, with different programming paradigms and roles in AI4DB tasks. ML developers focus on designing and implementing AI4DB drivers, which are algorithmic workflows that collect statistics from databases, train ML models, make decisions and optimize databases using learned models. AI4DB drivers interact with databases via DB interactors (*e.g.*, for collecting data and enforcing actions in databases). DB developers focus on implementing these interactors on one or more database engines, with the interaction details hindered from ML developers. PilotScope supports a variety of AI4DB tasks, and the implementations of an AI4DB algorithm on PilotScope can be deployed in different database engines with only minimum modifications. We have made PilotScope publicly available at https://github.com/duoyw/PilotScope, with the implementations of 15 AI4DB algorithms for four representative tasks to steer PostgreSQL and Spark. PilotScope is effective in benchmarking these AI4DB algorithms in real-world scenarios. We hope that PilotScope could significantly accelerate iterating AI4DB research and make AI4DB techniques truly applicable in production.

## 1 INTRODUCTION

Learned databases, or AI4DB techniques, aim at enabling automatic, fine-grained, and data-dependent characterization of the action spaces for various database tasks. To name a few, such AI-aided database tasks (AI4DB tasks) include knob tuning [26, 45, 58], index recommendation [1, 14, 17, 20, 31, 46, 50, 53], query optimization [25, 30, 40, 41, 54–56, 61, 64], index structures [22, 23, 32], monitoring [38, 60], *etc.* A considerable amount of research efforts, ranging from theoretical analysis, model and algorithm design to benchmark evaluation, have been devoted to this field. The superiority of AI4DB algorithms have been witnessed in a number of benchmarks [24, 28, 31, 48, 59] and applications [12, 35, 42].

**Challenges of Deploying AI4DB Algorithms.** We can fairly benchmark various AI4DB algorithms [24, 42, 47] and evaluate their values in production only by deploying them into actual databases. However, due to the complexity of database systems, the different ML and DB programming paradigms, and the diversity of ML algorithms, the tasks of developing and deploying AI4DB algorithms are prohibitively difficult. Most previous works each focus on AI4DB tasks in some specific database engine. For example, [42] deploys the learned query optimizer Bao [40] on SCOPE [16] (the distributed computing system in Microsoft); [35] integrates a number of learned techniques, including query rewriter, cost model, and view advisor, into openGauss [9]; [15, 37, 43] deploy workload forecasting, behavior modeling, data collection and other functions into the NoisePage DBMS [5]. Even for one DB engine, the deployment of AI4DB techniques requires close cooperation between ML and DB developers and heavy engineering cost.

There are some practical challenges and considerations:

- *The ML and DB communities have very different programming paradigms (*e.g.*, PyTorch v.s. C).* Although we expect that the gap is closing, it is rare that one developer masters both. Thus, it is important to have an abstraction of the AI4DB system so that: 1) ML and DB developers can focus their own components; 2) it could be appliable to a wide range of database systems; and 3) their works can be re-used by others in different AI4DB tasks.

  We expect that an AI4DB solution can be easily deployed and extended for different DB engines and tasks. The hope is that, when the solution is transferred from one engine to another (*e.g.*, from PostgreSQL to Spark), only DB developers' work needs to be adapted to the new engine, while ML developers can focus on iterating algorithms and models for various AI4DB tasks.
- *An AI4DB task usually involves a long pipeline (*e.g.*, query optimization) of a number of components (*e.g.*, *cardinality estimator and plan generation). During this pipeline, the AI4DB algorithms may need to interact with the database internal functions multiple times (*e.g.*, *collecting training data and enforcing actions in database).* Any implementation detail may affect the end-to-end performance of a solution significantly. Thus, for a fair benchmark of different solutions, it is better for them to share as many atomic operators as possible (*e.g.*, how data is fetched from and pushed into the database).
- *Existing AI4DB solutions are designed under different technical routines to address different problems. Their requirements are very diversified and complex.* For example, knob tuning algorithms

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are typically applied to optimize the database performance for the entire workload, while a learned query optimizer is designed to speed up each singleton SQL query. Some AI4DB tasks ask for customized functionalities, *e.g.*, periodical model retraining. Therefore, it is very necessary to design a flexible yet easy-to-use framework that accommodates all these diversified requirements of AI4DB algorithms.

In this paper, we design and implement `PilotScope`, a desirable system aiming at resolving the problem of deploying AI4DB tasks into databases. `PilotScope` takes all above practical issues into consideration and resolves these challenges. In the following, we first describe a sample of representative AI4DB tasks and summarize their common elements in Section 1.1 to lay foundation for `PilotScope`. Then, we overview the main features and contributions of `PilotScope` in Section 1.2.

## 1.1 Sample and Elements of AI4DB Tasks

In this paper, we focus on AI4DB tasks for query processing since these methods are growing rapidly and have significant importance to database performance [24, 34, 51, 63]. As shown in Figure 1, for any database, we often tune its configurations, including knobs, indices, views and flags, to make preparations for downstream query processing. Then, for the input query $Q$, it is fed into the *query rewriter* to transform it to an equivalent query $Q'$ with better execution efficiency. The query $Q'$ is then parsed and fed into the *query optimizer* to generate an execution plan $P$. The query optimizer often estimates the cardinality, i.e., number of tuples, of each sub-query of $Q'$, predicts the cost of each candidate plan $P$ and enumerates the join orders of tables to select the plan $P^*$ with the minimum predicted cost for execution. Finally, the *query executor* executes plan $P^*$ and returns a set of tuples $\mathcal{R}$ as the result.

Learned methods have been applied to replace one or more components in this workflow (marked in green in Figure 1) including but not limited to: learned knob tuning, index or view recommendation and query rewriter; learned cardinality estimator, cost model and join search methods; and learned end-to-end query optimizer. We describe the procedures of them as follows.

*1.1.1 Learned Knob Tuning.* This task is required by database users. It targets to automatically tune the values of a set of knobs $K$ to optimize the database performance, which is measured by a metric $M$, on a query workload $W$. The method often works in iterations. Each time it executes all queries $Q \in W$ on the database, collects their execution statistics related to metric $M$ and gradually updates the value of knobs using an ML model, such as a reinforcement learning (RL) model [58] or a Bayesian model [26, 45]. After finishing iterating, the generated value of knobs $K$ are set accordingly into databases. The learned index recommendation and view advisor [27, 57] work in similar ways as knob tuning.

*1.1.2 Learned Cardinality Estimator.* It takes a (sub-)query $Q$ as input and trains an ML model to estimate its cardinality. The ML model could be data-driven [25, 55, 64] or query-driven [30]. The data-driven models are unsupervised models building the joint distribution of all attributes while the query-driven ones are supervised models mapping featurized queries into the estimated cardinality. The models are updated periodically to keep track of data/workload changes. In similar, the learned query rewriter [13, 18, 39], cost model [29, 36] and join order search methods [19, 49] also apply ML models to replace the traditional database components.

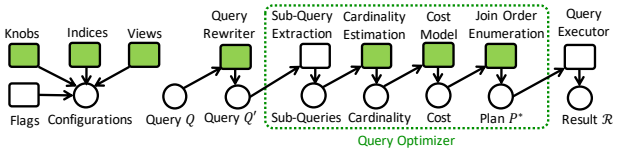



**Figure 1: Workflow of query processing.**

*1.1.3 Learned Query Optimizer.* These methods aim at generating an execution plan $P$ for the input query $Q$ using ML techniques. They often train a model using collected historical data to predicate the execution time (or relative goodness) of a plan. Then, the methods generate a number of candidate plans for $Q$ using different strategies. Specifically, some methods [41, 54] directly search the plan space by themselves and some other ones [40, 56, 61] tune the traditional query optimizer with different flags to produce different plans. The plan with the minimum predicted time is returned for execution. Meanwhile, its execution statistics are collected to update the predication model periodically.

Based on the workflow of these AI4DB tasks, we summarize the following elements required to deploy an AI4DB task:

1) We need a flexible data collection interface to extract different kinds of statistical data, *e.g.*, cardinality, plan cost, execution time, from databases for model training.

2) We require a mechanism to inject the AI4DB task into databases to replace the original component. The injection mechanism is responsible to invoke the AI4DB task when needed, provide the inputs to the AI4DB task and send its output to the databases.

3) We need an ML environment to support the execution of the AI4DB algorithms and the model inference, training and updating.

4) During the execution, we should have an interface to interact with database so that the AI4DB task could operate the databases and exchange data. For example, setting the flags and obtaining the produced plans in learned query optimizer.

## 1.2 Features and Contributions of `PilotScope`

`PilotScope` is a middleware to deploy AI4DB tasks on top of any native database. It provides all required elements to deploy AI4DB tasks and attains a number of attractive features , including: R3W2, R3D2, R3D3

- `PilotScope` is easy-to-use for database users. The database user could access `PilotScope` to start any AI4DB task as needed and operate the database as usual. The execution of any AI4DB algorithm is totally transparent to the database user.
- `PilotScope` enables ML and DB developers to work independently to play their own strengths in developing ML and DB programs. They do not need to learn and care about the details in other side.
- `PilotScope` attains high generality. It could support to deploy a variety of AI4DB tasks on different database systems. More over, it could be easily extended to new tasks and new systems.

Due to space limits, we put the detailed comparison between `PilotScope` and other related work, *i.e.*, composable DBMS [44] and other AI4DB deployment systems [15, 35, 37, 42, 43], in Appendix A of the full paper [62]. Our contributions in `PilotScope`, R1W1 R3W1, R3D1 R3W2, R3D2, R3D3

including design, implementation and applications, are summarized as follows:

1) We propose a comprehensive framework in PilotScope to facilitate the implementation of AI4DB algorithms and their deployment into databases. PilotScope abstracts the requirements of multiple typical AI4DB algorithms and is highly user-friendly to support them in a unified manner.

2) We design a novel mechanism to allow ML and DB developers to work independently in PilotScope. This is achieved by abstracting a DB interactor interface between AI4DB algorithms and databases. The ML developers could focus on writing AI4DB algorithms using this interface without caring about the database details. On the DB side, the DB interactor is implemented as lightweight patches on each steered database by its native DB developers. The DB developers also do not need to know about how the DB interactor is used in the ML side. In different databases, the DB interactor is implemented by DB developers in different ways. This approach enables PilotScope to steer any database with the same copy of an AI4DB algorithm in a unified manner.

3) We highly abstract several simple but robust operators, namely push and pull, for data interaction between ML algorithms and databases. Through these two operators, PilotScope can utilize a simple flow to collect various types of data, inject AI4DB tasks and enforce actions in databases. We have implemented a number of specific push and pull operators, such as sub-query extraction and setting cardinality, in the query optimization workflow.

4) We provide an open-source implementation of PilotScope. In our open-source repository, we implement 15 algorithms on four representative AI4DB tasks, namely knob tuning, index recommendation, cardinality estimation and end-to-end query optimizer, in PilotScope and apply them to steer two well-known databases, *i.e.*, PostgreSQL and Spark. Moreover, we show our system design and implementation in PilotScope are easily extended to support other AI4DB tasks.

5) We conduct a comprehensive evaluation to show the benefits and overheads by deploying AI4DB tasks in databases using PilotScope. The experimental results demonstrate that the overhead brought by PilotScope is negligible. Whereas, the benefits and shortcomings of different AI4DB algorithms are clearly exposed through benchmarking, which could serve as valuable insights for future research iterations.

**Organization.** Section 2 overviews the PilotScope system. Section 3 introduces the detailed programming model in PilotScope. Section 4 exhibits how to apply PilotScope for a number of representative AI4DB tasks. Section 5 describes the implementation details. Section 6 reports the evaluation results on PilotScope. Section 7 concludes the paper and discusses the future work.

# 2 SYSTEM OVERVIEW

## 2.1 A Quick Start

PilotScope is a middleware that largely reduces the difficulties of applying and developing AI4DB tasks in databases. To database users, PilotScope is very easy-to-use by accessing its console and typing several commands (shown in Figure 2). First, the user types a command to ask PilotScope to start an instance to connect and log into the database. After establishing the connection, PilotScope takes control of the database. Then, the user types another command to start an AI4DB task, *e.g.*, learned query optimizer, on the database. After that, the user could operate the database with this connection as usual. PilotScope could identify the commands and send them to databases to execute if needed. Whenever the AI4DB task needs to be invoked, *e.g.*, the user executes a SQL query, the database would automatically apply the learned query optimizer to replace the traditional component. To database users, PilotScope and the underlying AI4DB algorithms are totally transparent. They just need to learn several new commands and experience the benefits of AI4DB algorithms.

In this section, we show the system architecture of PilotScope in Section 2.2. Then, we introduce its detailed workflow and working paradigm in Section 2.3 and Section 2.4, respectively.

## 2.2 System Architecture

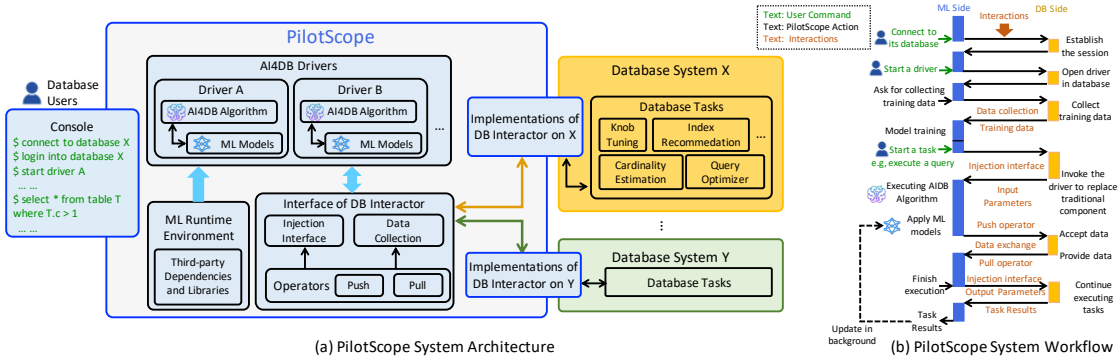
The system architecture of PilotScope is shown in Figure 2(a). PilotScope provides a *console* to operate the whole system. It manages multiple AI4DB *drivers* and the *DB interactor*. The DB interactor contains an *interface* connecting AI4DB drivers with databases. Each database steered by the AI4DB drivers is attached with the *implementations of DB interactor*. The role of each component is described as follows.

*2.2.1 AI4DB Driver.* In PilotScope, each AI4DB task, which targets to replace a database component, is packaged as a *driver*. Each driver contains: 1) an *AI4DB algorithm* describing the algorithmic workflow, *e.g.*, how to learn to generate the execution plan in a learned query optimizer; 2) one or more *ML models* to be consulted in the AI4DB algorithm, *e.g.*, the execution time prediction model in a learned query optimizer; and 3) the *training and inference function* for each ML model. The algorithms and models in the driver are all written in an AI-friendly language, e.g., Python. The PilotScope integrates a *runtime environment* with the third-party dependencies and libraries to support their execution.

*2.2.2 Interface of DB Interactor.* This component shields the underlying details of different databases and serves as a unified bridge for drivers to interact with the databases. We abstract two operators, namely *push* and *pull*, to meet the requirements of AI4DB tasks (see Section 1.1).

The push operator allows AI4DB tasks to send requests to the databases while the pull operator extracts data from the databases. By their cooperation, the AI4DB task could enforce actions in database and exchange data with database. Our push and pull operators are more powerful and general than APIs provided by databases. In our design, we could apply multiple push and pull operators in a logic order, *e.g.*, we could set the database flags using push, execute a query, and then obtain its generated plan and execution time using two pull operators. The details to apply these operators are introduced in Section 3.

The push and pull operators are also applied to inject AI4DB tasks into databases. Based on them, PilotScope abstracts the injection interface as a configurable parameter for AI4DB drivers. The driver only needs to specify the type of injection interface for itself, *e.g.*, a learned knob tuner or a learned cardinality estimator. Then, PilotScope would automatically invoke its AI4DB algorithm to replace the original database component when needed.




(a) PilotScope System Architecture (b) PilotScope System Workflow

**Figure 2: System architecture and workflow of `PilotScope`.**

Besides, we also apply the push/pull operators to collect data, *e.g.*, estimated cardinality, plan cost and query execution time, from databases for model training. We also discuss how to apply them in Section 3 and defer the implementation details to Section 5.

*2.2.3 Implementations of DB Interactor on Databases.* The DB interactor is implemented in different ways on different databases. However, all of them satisfy the same interface of DB interactor and fulfill the required functions. In such way, each driver could apply the interface to steer different databases with minimum modifications. In practice, the implementations are often developed as lightweight patches, *e.g.*, hook functions, to the database codebase so that the changes incurred to the database kennel is minimal.

## 2.3 Workflow of `PilotScope`

As shown in Figure 2(b), after the database user establishes the database connection and starts a driver through `PilotScope` console, the driver starts to collect the pre-defined training data from databases. For example, the query execution time would be collected for training the time prediction model in learned query optimizer. After collecting enough data, the driver would start to train each model using the provided training function. As an option, the users could tune the hyper-parameters before model training.

After finishing model training, the AI4DB algorithm in the driver would wait to be executed. When needed, it would be invoked by `PilotScope` to replace the original database component, *e.g.*, the learned query optimizer is called whenever the database user executes a SQL query. It obtains the inputs from the injection interface (*e.g.*, the query), executes its algorithm in the runtime environment in `PilotScope`, consults the ML models using the provided model inference functions and interacts with the database through push/pull operators to fulfill its job. After it finishes executing, the injection interface sends its result (*e.g.*, the selected execution plan) to the database. For some drivers, the ML models are updated by in background to keep track of database changes.

R1W2 Notably, for all drivers designed for the same task, *e.g.*, different learned cardinality estimation methods, `PilotScope` allows to open at most one driver at any time or else they would make conflicts. For different tasks, `PilotScope` supports to open multiple drivers for them at the same time, *e.g.*, a learned knob tuner and a learned cardinality estimator in Section 6.4. Due to the stability and unpredictable behaviors of ML models [24, 51], `PilotScope` also provides a *validation mode* to safely tune and test AI4DB tasks. In this mode, the AI4DB task could be applied as usual. When quitting this mode, `PilotScope` would automatically recover the databases settings (*e.g.*, knobs or indices) as original.

## 2.4 A Collaborative Working Paradigm

R1W3 The whole working paradigm to integrate an AI4DB program into the codebase of a database includes the designing, developing and maintenance phases. In existing systems [35, 42, 47], ML and DB developers need to work together and know about each other in the whole paradigm. Whereas, `PilotScope` allow ML and DB developers to work more independently and focus on their own fields, especially in the developing phase.

**Designing Phase.** As shown in Figure 3, at the initial stage, the ML researchers design the AI4DB algorithm and ML models to solve the database task. During this phase, they need to learn about the background knowledge of the database task to formulate it into an ML problem and select proper features, models and loss functions to solve it. We note that, the ML researcher often just requires high-level knowledge, *e.g.*, the task inputs, outputs, traditional approaches and constraints, but not need to know about the task implementation details. Thus, the ML researchers could consult the DB developer in a conceptual view or refer to a database seminar book to acquire such knowledge by themselves. The connections between the ML researchers and the DB developers are not too tight.

**Developing Phase.** Then, the ML developers (possible the ML researchers themselves) define the AI4DB driver for the target database task and configure its injection type. After that, they write the AI4DB algorithm, inference and training functions for each model in the AI-friendly language. In this process, existing interface of DB interactor may not meet their requirements. For example, there does not exist an injection interface for such task or a push/pull operator to transfer a new type of data. The ML developers just define the inputs and outputs of these new interfaces and send the requests to the DB developers.

On the DB side, the DB developers for a native database are responsible to implement the requested interfaces on databases. These developers are familiar with the underlying codes of databases, so they could find the best way to implement the interfaces as lightweight patches using the database language. Notably, implementing these patches is much easier than integrating a complete ML program into databases. What they do just likes their ordinary work on developing new features on the native database.

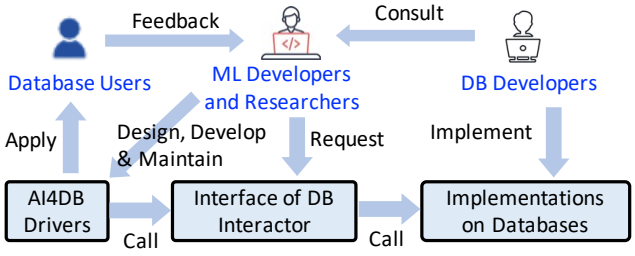



**Figure 3: The collaborative working paradigm in PilotScope w.r.t. different roles.**

In this paradigm, the ML developers are liberated from the database details. The only connection between ML and DB developers is the interface of DB interactor. In our open-source PilotScope, we have defined the interface for some representative tasks (see Section 4) and implemented the interface on PostgreSQL and Spark (see Section 5). In the future, the interface of DB interactor and related implementations could be gradually enriched by the open-source community and commercial database companies.

R1W3 **Maintenance Phase.** After an AI4DB driver is deployed, the ML researchers could also update models and monitor its performance according to user feedbacks through PilotScope. For model updating, we provide commands in PilotScope console to allow researchers (or users) to tune the model hyper-parameters and re-train the model manually. The researchers could also pre-define some events in the AI4DB algorithm to update the model automatically. For example, in Section 4.4, for the learned query optimizer, we apply a timer to re-train the model periodically to keep track of data and workload changes. For performance monitoring, the researchers are required to bury some functions in the AI4DB algorithm to export necessary statistical data. Then, users could access such data for monitoring. In our future work, we would integrate more off-the-shelf tools with PilotScope to improve the convenience of performance monitoring.

## 3 PROGRAMMING MODEL

We introduce the programming APIs for DB interactor operators, ML model and driver. Figure 4 and Figure 5 list all programmable APIs and some examples. We describe the details as follows.

**DB Interactor Operator APIs.** In PilotScope,we use the concept of *session* to define the interaction process between the AI4DB algorithm and the database. In each session, the PilotScope creates and maintains a new connection *e.g.*, a database session, to enforce actions in the database. Each session is created with the API session_start(), which returns a session_id to mark this session, and released by session_end(). In each session, we could enforce the actions to databases, *e.g.*, updating its configurations, sending or acquiring data, using the push() and pull() operators.

The parameters of the two operators include session_id, data_type, data_name and data_value. Here data_type refers to the type of data we send to or acquire from the database. We define a variety of data types to support the AI4DB tasks in the query processing workflow (see details in the comments in Figure 4). The parameter data_name is only appliable for flags, which refers to the specific flag name, *e.g.*, max_memory_size. It is set to null for other data

```
def session_start():
    # create a new session and return its session_id
    ... ...
def session_end(session_id):
    # close the session specified by session_id
    ... ...
def session_exec(session_id):
    # execute all operators registered before it
    ... ...
def push(session_id, data_type, data_name, data_value)
    # send data from ML side to the database side
    # data_type: type of the data, including FLAG, INDEX, VIEW,
    # QUERY, SUB_Q, CARD, COST, PLAN, TIME
    #  FLAG, INDEX, VIEW: database flags, indices and views
    #  QUQEY: SQL query, SUB_Q: sub-queries of input query
    #  CARD, COST, PLAN, TIME: estimated cardinality, plan cost, execution plan
    ↪  and plan execution time of the input query
    # data_name: only appliable for FLAG, null for others
    # data_value: the value of the data
    ... ...
def pull(session_id, data_type, data_name)
    # acquire data from database side to the ML side
    ... ...
def interaction_example(x, y, Q, C)
    sid = session_start()
    push(sid, FLAG, x, y)
    push(sid, QUERY, null, Q)
    push(sid, CARD, null, C)
    P = pull(sid, PLAN, null)
    t = pull(sid, TIME, null) # P and t are placeholder noew
    sesssion_exec(sid) # execute the above push and pull operators
    # The value of P and t are obtained only after sesssion_exec
    Do sth. using P, t
    session_end(sid)
```

**Figure 4: Programming APIs of DB interactor operators.**

```
def collect_data(data_type, data_size, data_addr):
    # collect raw data from database for model training
    # data_type: CARD, COST, PLAN, TIME
    # data_size: the size of data to be collected
    # data_addr: the address to store the collected data
    ... ...
class model(args):
    def model_train(train_data, args): # model training
        ... ...
    def model_inference(inference_data, args): # model inference
        ... ...
class driver(injection_type, args):
    # inference_type: the injection type for the task,
    # including INJ_KNOB, INJ_INDEX, INJ_CARD, INJ_E2EQO
    def init():
        self.injection_type = injection_type
        Collect data to perform model training
        Add customized functions here
        ... ...
    def algo(args):
        Do sth. according to the AI4DB task ... ...
```

**Figure 5: Programming APIs of model and driver.**

types. For push operator, the parameter data_value indicates the value of the data we send to the database.

Notably, in each session, we could apply multiple push() and and pull() operators. However, they are not executed immediately but just define the logic order of the operators. We apply the API session_exec() with a session_id to execute all operators registered in front of it. In such way, we could exchange multiple types of data and/or enfore different actions for the same query.

For example, in the interaction_example() function in Figure 4, we creates a new session sid. We first use push(sid, FLAG, $x$, $y$) to set the database flag $x$ to value $y$. Then we push a query $Q$ to execute and apply push(sid, CARD, null, $C$) to replace its estimated cardinality to $C$. After that, we could acquire the new generated plan $P$ and its execution time $t$ of query $Q$ using two pull() operators. Notably, at this time, $P$ and $t$ are just two placeholders. Their value would be instantiated after invoking the session_exec() API. Finally, we close this session using the session_end() API.

**Model and Driver APIs.** In PilotScope, we define each model and driver by inheriting the base model() and driver() class, respectively. For each new model class, it needs to override two functions, namely model_inference() and model_train() for model training and inference, respectively. Developers could also add other functions, *e.g.*, tuning the hyper-parameters of models.

For each new driver class, it needs to override the init() and algo() functions. The init function initializes the object of this driver. Specifically, we need to do the following necessary jobs in it: 1) specify the injection type, *e.g.*, a member variable, of the driver class; 2) initialize the models to be used in the AI4DB algorithm; and 3) collect training data and train ML models. Developers could also add customized codes to implement other functions,*e.g.*, periodically model updating using a timer. For the injection type, we provide four options for the sample applications in Section 4, namely INJ_KNOB, INJ_INDEX, INJ_CARD and INJ_E2EQO to inject the learned knob tuning, index recommendation, cardinality estimation and end-to-end query optimizer, respectively.

The algo() function, which describes the AI4DB algorithm, applies ML models and DB interactor operators to accomplish the AI4DB task and is called by PilotScope when needed.

For training data collection, we provide the API collect_data() to obtain statistical data from the databases. It has three parameters: 1)data_type for the type of data to be collected. We provide the option CARD, COST PLAN and TIME to obtain estimated cardinality, plan cost, exeuction plan and query execution time, respectively; 2)data_size indicates the size of data to be collected; and 3)data_addr refers to the address to store the collected data. Users could filter or process the collect raw data for model training. Both our injection interface and training data collection are implemented using the DB interactor operators. We discuss the implementation details and the method to extend them to new tasks in Section 5.

## 4 SAMPLE APPLICATIONS

In this section, we exhibit how to apply PilotScope for specific AI4DB tasks. In our open-source repository, we implement 15 ML-based algorithms for four representative tasks mentioned in Section 1.1. Notably, the AI4DB drivers for knob tuning and index recommendation work on the query workload level. They aim at configuring the databases to optimize its overall performance on the workload and are invoked upon user requests, *e.g.*, the query workload characteristics have significant changes. Whereas, the AI4DB drivers for cardinality estimation and query optimizer work on each singleton SQL query. They accept each input SQL query and inject the cardinality or execution plan generated by the AI4DB methods to improve its performance. Except from these well studied problems, we also show PilotScope could support some newly AI4DB tasks. Due to space limits, in Appendix B of the full paper [62], we apply our PilotScope to deploy an AI4DB method, which is recently proposed in [52], to eliminate regressions on learned query optimizers. In the future, PilotScope will be continuously updated to stay aligned with the state-of-the-art literature in AI4DB.

R1W4 R1R4

### 4.1 Knob Tuning

Let $K = \{k_1, k_2, \ldots, k_n\}$ be a set of tuneable system knobs in the databases, e.g., work memory size and maximum connections. For the knob $k_i$, let $S_i$ denote its domain size. Let $S = S_1 \times \cdots \times S_n$. The knob tuning problem asks to find a combination of knob values $(s_1, s_2, \ldots, s_n) \in S$ such that an objective performance metric $M$, e.g., query execution time or system throughput, is maximized.

```
class model_knob():
    model_train(train_data):
        ... ...
    model_inference(X, v, M):
        ... ...
        return predicted_metic # predicting metric M when applying value v of X

class driver_knob(K, S):
    def init():
        self.injection_type = INJ_KNOB
        self.knob_model = model_knob() # pre-trained offline
        ... ...
    def algo(X, W, M): # tune knobs X in K with workload W to optimize metric M
        Set the initial value v of X
        sid = session_start()
        for i in range(MAX_ITER):
            push(sid, FLAG, X, v)
            session_exec(sid)
            for each Q in W:
                push(sid, QUERY, null, Q)
                exec_time = pull(sid, TIME, null) # by metric M
                session_exec(sid)
            Update self.knob_model using W, v, exec_time
            for each new value n_v:
                predict.add(nv, self.knob_model.inference(X, n_v, M))
            v = argmin (nv, predict)  # update the new value to v
        session_end(sid)
        return v
```

**Figure 6: The PilotScope model and driver for knob tuning.**

PilotScope could well support the general workflow of knob tuning algorithms discussed in Section 1.1.1. As shown in Figure 6, we define a driver driver_knob with the parameters $K$ and $S$ on all tuneable knobs and their domain. It applies the injection type INJ_KNOB. In PilotScope, the user could apply a command "auto knob tune -$X$, -$W$ -$M$" to tune knobs $X \subseteq K$ on databases using workload $W$ to optimizer metric $M$. The query workload $W$ could be regarded as the training data for the driver. The injection interface would pass the parameters to the algo() function in driver_knob and execute it immediately. R1W4

In the init() function of driver_knob, it builds an ML model model_knob to predict the metric $M$ when applying value $v$ for knobs $X \subseteq K$. This model is often pre-trained offline and would be gradually updated in executing the algorithm. In the algo() function, it first sets an initial value $v$ for knobs in $X$. Then, we start a database interaction session to set the value of knobs $X$ to $v$, execute each query $Q \in W$ and collect its metric $M$, e.g., the query execution time, by the push() and pull() operators. After finishing execution, we use the exact value of metric $M$ to refine the model parameters, predict the metric value of each candidate new value and update the knob value $v$ to the new value with the minimum predicted number. Finally, the knob value $v$ of $X$ is returned. The injection interface is responsible to set the knob value in databases (see implementation details in Section 5). Notably, such driver are not frequently invoked and the iteration over the training workload $W$ could be done in the background in databases. Therefore, it would not consume too many resources to affect the normal service of the databases. R1W4

This framework could support a variety of advanced knob tuning algorithms mentioned in [28]. We provide two Bayesian optimization methods SMAC [26] and GP-BO [45] and a RL-based method DDPG [58]. They have shown to have better performance on DBMS tuning in recent studies [28, 59].

```
class driver_index():
    def init():
        self.injection_type = INJ_INDEX
        ... ...
    def algo(C, W, B): # select indices from C with workload W under budget B
        Set the initial D of candidate columns
        sid = session_start()
        for i in range(MAX_ITER):
            push(sid, INDEX, null, D)
            session_exec(sid)
            for each Q in W:
                push(sid, QUERY, null, Q)
                plan_cost = pull(sid, COST, null)
                session_exec(sid)
            Update D according to plan cost with some strategies
        session_end(sid)
        return D
```

**Figure 7: The PilotScope driver for index recommendation.**

## 4.2 Index Recommendation

Let $C = \{c_1, c_2, \ldots, c_m\}$ denote a number of columns where we could build index. For column $c_i$, we denote its index size as $s(c_i)$. For any query $Q$, let cost$(Q, D)$ denote the cost of executing $Q$ with indices on all columns in $D \subseteq C$. Given a workload $W$, the index recommendation problem asks to find the $D$ such that: 1) the index size $\sum_{c \in D} s(c) \leq B$ is no greater than the budget $B$; and 2) the cost $\sum_{Q \in W}$ cost$(Q, D)$ of executing $W$ is minimized.

In similar to knob tuning, PilotScope could also build a driver driver_index for index recommendation. It applies the injection type INJ_INDEX. In similar, the user applies the PilotScope command "auto index recom -*C*, -*W* -*B*" to recommend indices on columns *C* using the training workload *W* under budget *B*.

R1W4

As shown in Figure 7, the AI4DB algorithm in driver_index also works in iterations from an initial set $D \subseteq C$. Then, we start a session and use the push() operator to set the database index to $D$ before each loop. We execute all queries $Q \in W$ and collect its estimated cost. After that, the candidate columns $D$ is updated using some strategies and returned in final. We implement multiple algorithms with different index updating strategies in our open-source repository, including: 1) AutoAdmin [17], DB2Advisor [50], DTA [1] and Extend [46] starting with the empty set and adding indices each time; 2) Drop [53] and Relaxation [14] starting with a large set and reducing indices each time; and 3) linear programming, such as CoPhy [20]. AutoAdmin (also DTA) and DB2Advisor have been applied for commercial databases SQL Server and DB2, respectively. Some work [21] also applies learned models to search and update the index in each iteration. We could also deploy the learned view advisor task in PilotScope in a very similar way to index recommendation. We omit the details due to space limits.

## 4.3 Learned Cardinality Estimation

Unlike with knob tuning and index recommendation, which are triggered by user requests, cardinality estimation needs to be called whenever the database executing a SQL query. PilotScope could also support to deploy this type of task.

As shown in Figure 8, in the driver class driver_card, we set its injection type to INJ_CARD in the init() function. We build an ML model model_card for cardinality estimation. For query-driven and data-driven methods, the models are trained using different data. Specifically, for query-driven models, we apply the API collector_data() to collect the estimated cardinality of queries for model training. For data-driven models, we could directly access the data

```
class model_card():
    model_train(train_data):
        ... ...
    model_inference(Q): # return estimated cardinality for query Q
        ... ...
        return est_card

class driver_card():
    def init():
        self.injection_type = INJ_CARD
        train_data = collect_data(CARD, MAX_SIZE, data_addr)
        # for data-driven models, access the tables for train_data
        self.card_model = model_card()
        self.card_model.model_train(train_data)
        Collect train_data when needed
        Set timer to call model_train() periodicallly when needed
        ... ...
    def algo(Q): # input query Q
        sid = session_start()
        push(sid, QUERY, null, Q)
        SQ = pull(sid, SUB_Q, null)
        session_exec(sid)
        new_cards = self.card_model.model_inference(SQ)
        session_end(sid)
        return SQ, new_cards
```

**Figure 8: The PilotScope model and driver for cardinality estimation.**

in database tables to build the unsupervised models. Sometimes, the model needs to be updated. At this time, we could start a background thread to continuously collect training data and set a timer to invoke the model_train() function for updating in periodical.

In the algo() function, for the input query $Q$ (passed by the injection interface), we estimate the cardinality of each sub-query $Q'$ of $Q$. To this end, our pull operator provides the function to obtain all sub-queries $SQ$ of $Q$ in a batch manner. This would save the communication cost but need to adapt the traditional databases a bit. After estimating the cardinality of all queries in $SQ$, we return them together with the new cardinality. Notably, our injection interface also supports to replace the cardinality of all sub-queries in a batch manner. We defer the implementation details in Section 5.

Our driver_card could seamlessly support any learned cardinality estimation method. In our open-source repository, we integrate several representative methods, namely MSCN [30], NeuroCard [55] and DeepDB [25] using supervised deep neural networks, unsupervised auto-regression model and sum-product networks, respectively. They have exhibited superior performance in some benchmark evaluations [24, 48]. Other learned components in query optimizer, such as query rewriter, cost model or join order search method, could also be deployed using PilotScope in a similar way.

## 4.4 Learned Query Optimizer

PilotScope also supports to deploy learned end-to-end query optimizer to directly generate plans for SQL queries. As discussed in Section 1.1.3, different methods apply different strategies for candidate plan search and different models for plan selection. Specifically, Neo [41] and Balsa [54] search the plan search by themselves using (bounded) best-first search strategy and an ML model to predict the execution time of each (partial) plan. Therefore, their training cost and query optimization time is very long. Alternatively, Bao [40], HyperQO [56] and Lero [61] tune the native query optimizer with different knobs to generate a set of candidate plans. Their performance is shown to be much better than others [40, 61]. We present the pseudocodes of Bao in Figure 9. Lero and HyperQO could be implemented in a similar way.

```
class model_prediction():
    model_train(train_data):
        ... ...
    model_inference(P): # return estimated execution time for plan P
        ... ...
        return est_exec_time

class driver_bao(H): # set of hints H for the database
    def init():
        self.injection_type = INJ_E2EQO
        train_data = collect_data(TIME, MAX_SIZE, data_addr)
        self.predict_model = model_prediction()
        self.predict_model.model_train(train_data)
        Collect train_data
        Set timer to call model_train() periodicallly
        ... ...
    def algo(Q): # input query Q
        for each h in H:
            sid = session_start()
            push(sid, FLAG, hint, h)
            push(sid, QUERY, null, Q)
            Ph = pull(sid, PLAN, null)
            session_exec(sid)
            session_end(sid)
            PS.add(Ph)
        plan_time = self.predict_model.model_inference(PS)
        P = argmin(PS, plan_time)
        return P
```

**Figure 9: The PilotScope model and driver for end-to-end query optimizer Bao in [40].**

In our driver_bao class, we set its injection type to INJ_E2EQO. We apply an ML model to predict the execution time of each plan and collect query execution time for model training. According to its requirements, we collect data in background and retrain the model in periodical. For the query $Q$, Bao tunes the native query optimizer with different flags of hints to enable/disable certain operators, *e.g.*, hash_join or index_scan, to generate different candidate plans. By enabling or disabling certain operators, we could enforce the native database to try different code paths and produce possible better plans. To this end, we require to pass the set of all possible hints $H$ as an input parameter for the driver_bao class. This allows us to apply different hints for different databases.

In the algo() function, for each hint $h \in H$, we start a new session to set hint flags to $h$ on databases, send the query $Q$ to database and then obtain the generated candidate plan $Ph$. Notice that, unlike knobs and indices, tuning the flags of hint would only affect the current database session. After obtaining all candidate plans, we consult the time prediction model to find the best plan $P$ and return it as the result. The injection interface is responsible to send $P$ to database for execution.

The HyperQO method applies flags of leading hint on join orders. It could be implemented by just replacing the hint flag $h$ to the leading hint flag. Lero has two difference with Bao. First, it applies a learning-to-rank model to produce the relative order of plans for the same query. We also collect the query execution time but perform model training and inference in different ways (see details in [61]). Second, Lero scales the estimated cardinality of sub-queries with different factors $s$ to produce different candidate plans. To deploy Lero, we just need to pull the estimated cardinality of all sub-queries of $Q$, scale the estimated cardinality and push the new cardinality back to the database to produce different candidate plans. We omit their pseudocodes due to space limits.

# 5 SOME IMPLEMENTATION DETAILS

In this section, we discuss implementation details in PilotScope, including the DB interactor operators (in Section 5.1) and the related injection interface and data collection (in Section 5.2). Based on them, we show how PilotScope could support to simultaneously apply multiple AI4DB tasks in Section 5.3. Finally, we introduce how to implement the validation execution mode and fault tolerance mechanism in PilotScope (in Section 5.4).

## 5.1 DB Interactor Operators

*5.1.1 The General Approach.* We attach the original database with some lightweight patches to enable the interaction with AI4DB algorithms. We describe our approach to support the AI4DB tasks for the query processing workflow (listed in Section 1.1). As shown in Figure 10, we insert a number of blue nodes, called *anchors*, and some new flags, into the original query processing workflow. They represent the new patches added into the database codebase.

Specifically, we add two anchors before and after each database component. When the AI4DB algorithm starts a new database interaction session using session_start(), we prepare an empty *prefix*. This prefix records: 1) all variables in the AI4DB algorithm sent to the database component (in push operators) and 2) all intermediate data produced by database component acquired by the variables in the algorithm (in pull operators). When executing session_exec(), this prefix is sent to the database side. Then, the database starts to invoke the query processing workflow to call each database component, *i.e.*, checking the configurations, query rewriter, query optimizer and executor, one by one. Before each component, the anchor marked with push examines whether there exists a request in the prefix to replace its input. If so, we replace its original input data with the value provided in the prefix. After each component, the anchor marked with pull checks whether we need to pull its output. If so, we fill the value of the corresponding variable into the prefix. After executing all required components, the database returns the prefix to the ML side to instantiate the value of the variables in the AI4DB algorithm. The prefix is reset to be empty.

R1D1, R1D2

For the interaction_example shown in Figure 4, it registers three push and two pull operators before session_exec(). We illustrate the prefix in Figure 10. In execution, the database firstly updates the flag $x$ in configurations to $y$ and then starts executing query $Q$ (see the two dash arrows). Before cardinality estimator, it replaces the estimated cardinality to variable $C$ provided in the prefix. Then, the database generates the query plan and fills the value of variable $P$ (see the dash arrow to $t$). After that, it executes the plan, obtains its execution time and fills the value of variable $t$. $P$ and $t$ are returned to the ML side to instantiate the value of the two variables.

*5.1.2 Our Implementation Strategy on PostgreSQL and Spark.* Later, we could implement the DB interactor interfaces in multiple databases by its developers. The interfaces consist of three modules: the query parser module, the data transmission module, and the anchor module. The query parser module is responsible to add and resolve the prefix before each SQL query. We could simply add its code before the SQL query processing codes in the database. In our implementation, we store all information in the prefix in the common JSON format. The data transmission module receives the prefix from the database to instantiate the value of the variables in the AI4DB algorithm. We implement it using standardized HTTP transmission method. In terms of the code complexity , the query parser and data transmission modules are relatively easy.

R1D1, R1D2, R1D3, R1R1

R3W1, R3D1

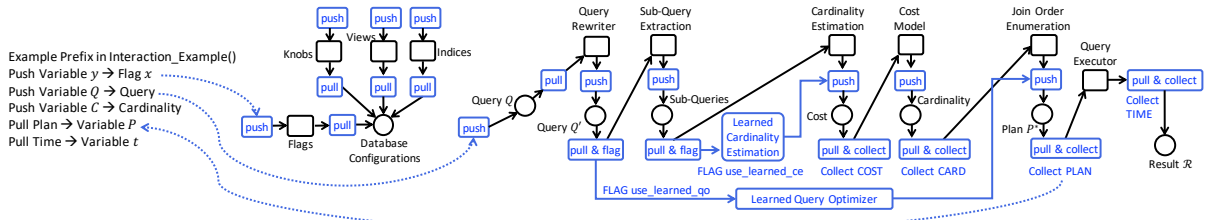



**Figure 10: Workflow of query processing with anchors added by PilotScope.**

The anchor module demands a proficient knowledge of the database codebase. However, in comparison to inject a whole AI4DB algorithm into the database codebase, it is much easier as it just embeds a number of functions into the query execution process. On each specific database, *e.g.*, PostgreSQL and Spark, we could even implement some anchors with off-the-shelf tools provided by the database to incur minimal changes to its kernel.

R1D3, R1R1

First, some anchors could be achieved by directly using database commands. On PostgreSQL, we directly use the "SET" command to set knobs, indices and views and the "EXPLAIN" command to pull the execution plan and its cost. On Spark, for a Spark session, we directly set the values of knobs in "SparkSession.config". For hint flags, we could set it together with the SQL queries in "SparkSession.sql". To get plan, we could apply "DataFrame.explain("plan")".

Second, some anchors are implemented using the database hooks, which are interfaces provided by the database itself to inject codes. In PostgreSQL, we apply its hook mechanism provided by the pg_hint_plan plug-in unit in [7] to set hint flags. We also use the two hook functions ExecutorStart_hook and ExecutorEnd_hook to get plan execution time.

Finally, we write the functions of all remaining anchors, *e.g.*, sub-query extraction, join order setting and other push/pull operators on PostgreSQL and Spark , as patches and insert them into the right place of the database codebase. The code complexity of each anchor depends on the complexity of setting or collecting the specific data. For example, collecting the execution time is relatively easy by deploying timers before and after the execution. However, collecting all sub-queries in a batch manner can be a bit complex. In the query processing workflow, each sub-query is proceeded by the cardinality estimation function one by one. Therefore, the developer needs to embed codes into the cardinality estimation function to collect all sub-queries together.

R1D1, R1D2

R3W1, R3D1

R1D3, R1R1

## 5.2 Injection Interface and Data Collection

The injection interface and data collection are all built upon DB interactor operators. The code complexity to to implement them is very low. We describe the details as follows.

R1D3, R1R1

R3W1, R3D1

*5.2.1 Injection Interface.* Recall that, in PilotScope, we maintain a connection for each user to operate the database (see Section 2.1). Unlike the database sessions that are created by AI4DB algorithms, this database session is created by user. PilotScope automatically records its identifier of this session, denoted as mid. Based on it, we could affect its behaviors using the DB interactor operators to inject AI4DB algorithms.

We divide all AI4DB tasks into two types. First, for tasks like knob tuning and index recommendation, they are invoked upon user request using PilotScope commands. We only need to send their results, *e.g.*, knob value and indices, into the database. This is fairly easy. For knob tuning discussed in Section 4.1, after the user types the command "auto knob tune -$X$, -$W$ -$M$", the AI4DB algorithm in the knob tuning driver is executed. When it finishes, PilotScope obtains the value $v$ for knobs $X$. Then, it executes push(mid, FLAG, $X$, $v$) and session_exec(mid). The knobs in the databases would be tuned according to the AI4DB algorithm. For the index recommendation task in Section 4.1, the injection approach is similar. For similar tasks such as learned view advisor [27, 57], they could be also be supported by PilotScope in this manner.

Second, for tasks like cardinality estimation and query optimizer, they need to be invoked by the database when needed. To this end, we add two flags, namely use_learned_ce and use_learned_qo, as patches in the database (see Figure 10). These flags are closed in default. If the user opens the a driver, PilotScope applies push() and session_exec() with mid to open the corresponding flag in database. Our anchors added before the cardinality estimator and query optimizer (marked as flag in Figure 10) would check the flags. If it is opened, it would ask PilotScope to invoke the AI4DB algorithm and pass the input parameters to it. After the algorithm finishes, PilotScope sends the result, *e.g.*, the new cardinality or plan, to the anchor. The anchor would skip the original component and apply the new result for the downstream procedures. In similar, we could extend PilotScope to support tasks such as learned query rewriter [13, 18, 39], cost model [29, 36], join order search methods [19, 49] and learned index [22, 23, 32].

*5.2.2 Data Collection.* For each type of collected data, *e.g.*, query execution time, we could collect it using the pull operator. Specifically, when we start the collect_data() API, we add a pull() operator on the collected type of data before executing each SQL query. Our anchor (marked as pull & collect in Figure 10) would check the pull() operator in the prefix and send the data to PilotScope if it is opened. PilotScope would write the data into the address specified in the collect_data() API. If the collected data reaches the desired size, the collect_data() API closes the flag. Following this approach, we could extend PilotScope to collect more statistical information from the databases.

## 5.3 Applying Multiple AI4DB Tasks in PilotScope

PilotScope supports to apply multiple AI4DB tasks on one database at the same time. For AI4DB tasks having no overlaps in the execution workflow, PilotScope could execute them in order. For example, we could first apply a learned knob tuning method and then execute a query using learned cardinality estimator. Besides, in query execution, we could apply a learned query rewriter and a learned query optimizer at the same time.

However, for AI4DB tasks having overlapped functions, *e.g.*, cardinality estimator and query optimizer, the situation is a bit complex. In developing each injection interface, PilotScope requires the ML developers to specify whether it has overlaps w.r.t. other injection interfaces. Based on these, PilotScope could identify the conflicts between different drivers. The user could tune the *priority* of each driver in PilotScope. In execution, PilotScope could automatically apply the AI4DB task in the driver with higher priority but ignore the others. In such way, the user could select to apply a learned cardinality estimator or an end-to-end learned query optimizer in databases.

Note that, updating the priority of tasks only affect the database session (marked with mid) where the user operates the database. For tasks running in different sessions, we could apply different priority. We show this by the example on Bao [40], the learned query optimizer discussed in Section 4.4. We could set the learned query optimizer with higher priority in the database user session (with identifier mid), so Bao would be executed for each SQL query. In its algorithm, it iteratively creates a session (with identifier sid) to invoke the traditional query optimizer to generate candidate plans. In this session, we could replace the traditional cardinality estimator to the learned one by opening its flag, *i.e.*, adding push(sid, FLAG, use_learned_ce, true) after session_start() in Figure 9. In this case, the candidate plans are generated using learned cardinality while the execution plan is obtained using Bao.

## 5.4 Validation Mode and Fault Tolerance

PilotScope supports the validation execution mode which could run AI4DB tasks and automatically recover the original settings of databases when quitting it. Meanwhile, it could tolerate faults caused by network failures or system blocks. We apply different strategies to implement them for the two types of AI4DB tasks defined in Section 5.2.1.

For the first type of AI4DB tasks like knob tuning, PilotScope records the original settings, *e.g.*, knobs or indices, when entering the validation mode. When quitting it, PilotScope reset these settings. For fault tolerance, PilotScope sets a pre-defined wait_time for each driver. If the algorithm exceeds its waiting time, PilotScope restarts this job to run once again.

For the second type of AI4DB tasks like cardinality estimation, PilotScope just closes all flags, *e.g.*, use_learned_ce, when quitting the validation mode. For fault tolerance, if the algorithm exceeds the waiting time, the anchors in the database would continue to run this job with the original database component.

# 6 SYSTEM EVALUATION

We conduct extensive experiments to evaluate the performance of PilotScope. We describe our experimental setups in Section 6.1. The conducted experiments target to answer the most crucial questions as follows:

1) How about the performance of AI4DB algorithms when deployed into actual database systems using PilotScope (in Section 6.2);

2) How much overhead of PilotScope brings in the deployment and its impact on the AI4DB algorithms (in Section 6.3);

3) What about the performance of databases when applying multiple AI4DB algorithms together by PilotScope (in Section 6.4).

We emphasize that PilotScope only serves as a middleware to facilitate the implementation of AI4DB algorithms and support to deploy them into databases. Thus, the performance of the AI4DB algorithms is independent of our PilotScope. The problems to analyze their detailed performance and design better methods are beyond the scope of this paper. However, our PilotScope could truly benchmark the actual performance of AI4DB algorithms in real-world scenarios and expose their shortcomings. This would be very helpful to iterate AI4DB research in the future. R1D6, R1D7, R1R2

## 6.1 Experimental Setups

**AI4DB Algorithms and Settings.** We deployed all of the 15 algorithms mentioned in Section 4 on both PostgreSQL and Spark[1] by PilotScope. Due to space limits, we report the evaluation results of the most representative algorithm for each AI4DB task, namely the SMAC [26] for knob tuning, Extend [46] for index recommendation, DeepDB [25] for learned cardinality estimation and Bao [40] for learned query optimizer. The reasons to select these algorithms are described as follows:

1) SMAC is shown to perform better than other algorithms in the benchmark evaluation [28, 59]. For PostgreSQL and Spark, we obtain the set of tuneable knobs in the configuration files, including all numerical (*e.g.*, autovacuum_vacuum_threshold) and Boolean knobs (*e.g.*, enable_indexonlyscan). We tune knobs using the training workload to iterate 50 times to optimize the execution time. R1D4, R1D8

2) Extend is shown to provide the best combination of runtime and solution quality in the benchmark [31]. We use it to build indices on all feasible columns with a budget of 250MB on memory.

3) DeepDB is verified to perform better than the other two algorithms on real-world databases. The benchmark evaluation in [24] shows that, on some datasets, the traditional query optimizer could obtain near optimal plans when applying DeepDB for cardinality estimation.

4) Bao and Lero [61] follow similar technical routines. We select the set of hint flags in the same way as [2]. Its prediction model is updated after executing every 100 queries.

For all algorithms, we use their original implementations in [3, 4, 10, 11] and set all other (hyper-)parameters to the default values.

**Benchmarks.** We apply three benchmarks widely used for query optimization: 1) IMDB dataset on 21 tables of movies and stars with its JOB workload [33] containing 113 realistic queries; 2) STATS dataset on 8 tables of user-contributed content on the Stats Stack Exchange network with its STATS-CEB workload [8, 24] having 146 queries varying in join size and forms; and 3) TPC-DS benchmark [6] on synthetic data. For IMDB and STATS, we apply its JOB and STATS-CEB workload for testing, respectively. We generate a training workload of 1,000 queries where each time we randomly sample a query template from JOB or STATS-CEB, fetch its join template and attach some randomly generated predicates to it. For TPC-DS, we set the scaling factor to 10 and generate a training and testing workload having 4,900 and 490 queries, respectively.

**Environments.** We deploy PilotScope and all databases on a cluster of Linux machines. Each one is equipped with an Intel(R) Xeon(R) Platinum 8163 CPU running at 2.5 GHz, 96 cores, 512GB

[1] All index recommendation algorithms are not deployed on Spark since it does not support index.

DDR4 RAM, 1TB SSD and one NVIDIA RTX-2080TI GPU for model training and inference. We install PostgreSQL 13.1 and Spark 3.3.2.

## 6.2 Performance of AI4DB Algorithms When Deployed using PilotScope

We evaluate the performance of each database with and without each deployed AI4DB algorithm. Specifically, for learned knob tuning (or index recommendation), we record the end-to-end time of executing the test query workload with the knobs (or indices) generated by the AI4DB algorithm and in the default setting, respectively. For knob tuning, the default values of all knobs are provided by the original PostgreSQL in its configuration file. For index recommendation, the default indices are set in the same way to the original benchmark. For learned cardinality estimation (or query optimizer), we record the end-to-end execution time of applying the AI4DB algorithm and traditional component, respectively. Notably, since DeepDB does not support join queries across foreign keys in the JOB workload, we just apply another workload called JOB-light [55, 64] having 70 large queries on IMDB dataset to evaluate its performance. Notice that, JOB-light is not a subset of JOB workload. Their queries are totally different. The results are shown on Figure 11. In each sub-figure, the first red bar and second light blue bar indicate the performance with and the corresponding AI4DB algorithm and the default method, respectively. We observe that:

R1D4

R1D5

R1D4, R1D5, R1D8

1) The generality of PilotScope is verified, which could support to apply different AI4DB algorithms in different databases using one framework.

2) In most cases, the AI4DB algorithms could bring remarkable performance improvement on databases. For example, on STATS dataset, the end-to-end execution time is 2.71×, 1.82×, 1.32× and 1.46× faster than the original PostgreSQL using learned knob tuning, index recommendation, cardinality estimation and query optimizer, respectively. Specifically, for the knob tuning , the SMAC algorithm produces different values for almost all knobs, *e.g.*, set autovacuum_vacuum_scale_factor to 56.86 rather than its default value 0.2. For the index recommendation , the Extend algorithm removes all non-unique indices on 25 columns in the IMDB dataset and recommends to build indices on only four columns. On the STATS dataset, the Extend algorithm removes all non-unique indices on 12 columns and does not recommend database to build any additional indices. Although it builds fewer indices than the original benchmarks, it attains better performance in terms of the query execution time.

R1D4, R1D8

R1D5, R1D8

3) In some cases, the performance of AI4DB algorithms is even worse than the traditional database components. This is due to the shortcomings of the AI4DB algorithms. For example, on PostgreSQL, Bao needs to generate several dozens of candidate plans and predict their execution time through a large model. The DB interaction and model inference time degrade its overall performance, so Bao performs worse than the original database query optimizer on IMDB even its pure plan execution time is better. On Spark, the improvement of learned knobs is not significant due to the large domain size of the knobs.

These results indicate the effectiveness of AI4DB algorithms on different databases and also verify the necessity of developing PilotScope. It could benchmark the actual performance of AI4DB algorithms in real-world scenarios and expose their shortcomings. This would be very helpful to iterate AI4DB research in the future. For example, in learned query optimizer, we need to balance the plan quality and exploration cost to optimize the end-to-end time.

## 6.3 Impact and Overhead of PilotScope

Next, we examine the impact and overhead brought by PilotScope to the databases and AI4DB algorithms.

The third bar in each sub-figure in Figure 11 and Figure **??** reflects the execution time of query workload on PostgreSQL and Spark without installing PilotScope. In comparison to the second bar, where the execution time is recorded on the databases with PilotScope, the two execution time is very close. This indicates that PilotScope makes no difference on the native database systems. This is because all implementations of the DB interactor are developed as lightweight patches into the database codebase. They do not affect the original database behaviors when no AI4DB algorithms are applied.

The right part (corresponding to the right y-axis) in each sub-figure in Figure 11 and Figure **??** represents the overhead brought by PilotScope in executing query workload with each AI4DB algorithm. Specifically, the forth to seventh bars represent the time cost of all pull operators, all push operators, communication and I/O, respectively. We have two observations:

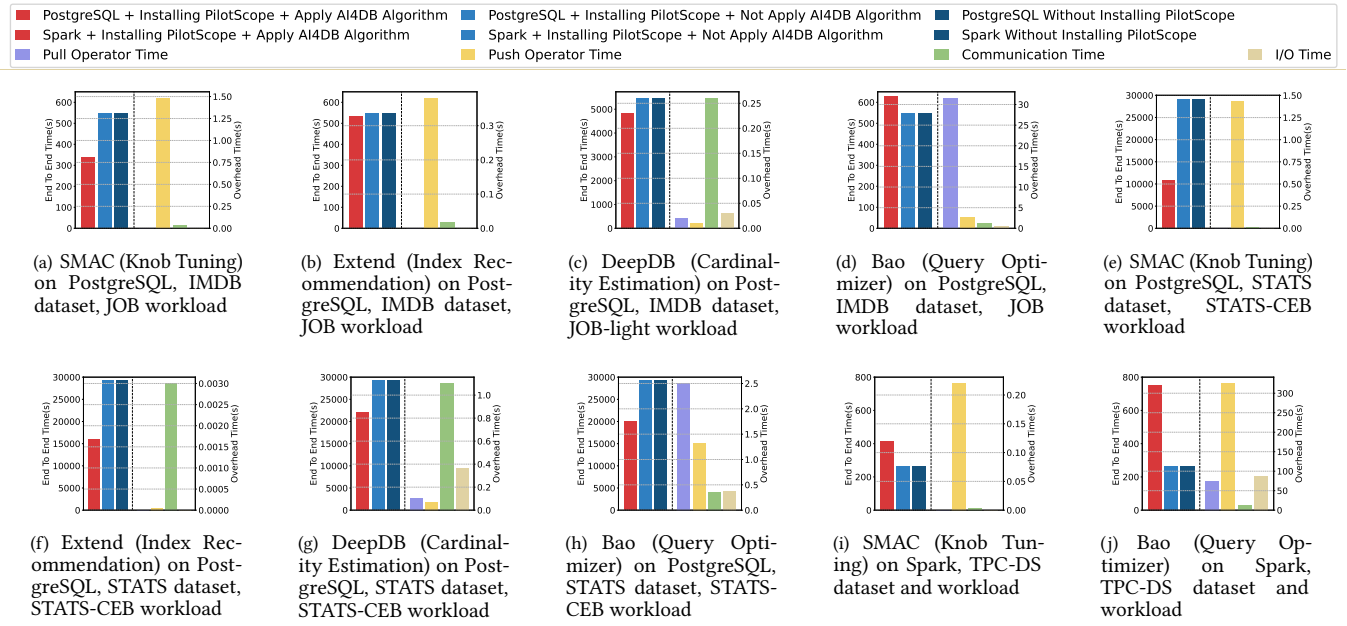
1) In almost all cases, the overall overhead is negligible in comparison to the end-to-end execution time. Specifically, the overhead occupies at most 0.27% and 0.066% for most AI4DB algorithms on PostgreSQL and Spark, respectively. This verifies the success on the design choices of our programming model, which enables the AI4DB algorithms to transfer only a small amount of data to fulfill their jobs. Meanwhile, we adopt some techniques, such as batch of sub-queries, to decrease the data transfer time. The only exception is Bao, whose interaction cost is very high as it needs to fetch a large number of plans from databases.

2) In different AI4DB algorithms, the time cost of each type of overhead is different. For example, DeepDB consumes the most time on communication to pass sub-queries from databases to the AI4DB algorithms and estimated cardinality from AI4DB algorithms to databases. Bao costs large time, especially on IMDB, to invoke traditional query optimizer to pull candidate plans. This detailed analysis could further help us to optimize the bottlenecks of AI4DB algorithms in actual databases. For example, how to decrease the number of generating candidate plans in learned query optimizer while still ensure the plan quality.

## 6.4 Deploying Multiple AI4DB Algorithms using PilotScope

Finally, we exhibit the ability of PilotScope to flexibly deploy multiple AI4DB algorithms on the same database. Notice that, these experiments have never been performed in the literature. The results are shown in Figure 12. We present three settings on PostgreSQL: 1) applying SMAC to tune knobs and then applying Bao to learn to generate execution plans (the left two sub-figures); 2) applying the learned query optimizer Bao, which calls the learned cardinality estimation DeepDB for generating each candidate plan (the middle two sub-figures, the detailed method is discussed in the last paragraph in Section 5.3); 3) applying SMAC to tune knobs and

R1D9, R1R3




(a) SMAC (Knob Tuning) on PostgreSQL, IMDB dataset, JOB workload

(b) Extend (Index Recommendation) on PostgreSQL, IMDB dataset, JOB workload

(c) DeepDB (Cardinality Estimation) on PostgreSQL, IMDB dataset, JOB-light workload

(d) Bao (Query Optimizer) on PostgreSQL, IMDB dataset, JOB workload

(e) SMAC (Knob Tuning) on PostgreSQL, STATS dataset, STATS-CEB workload

(f) Extend (Index Recommendation) on PostgreSQL, STATS dataset, STATS-CEB workload

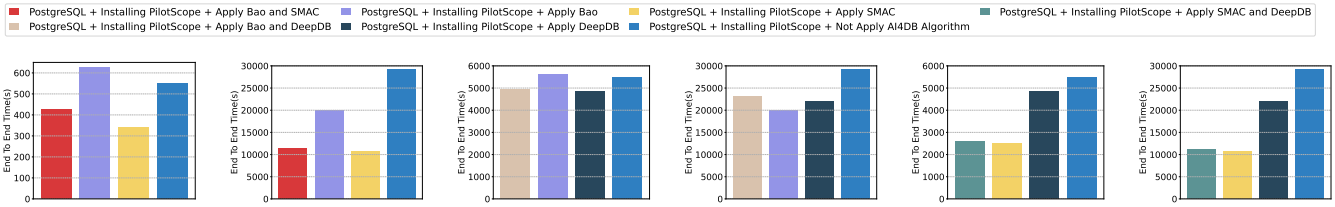
(g) DeepDB (Cardinality Estimation) on PostgreSQL, STATS dataset, STATS-CEB workload

(h) Bao (Query Optimizer) on PostgreSQL, STATS dataset, STATS-CEB workload

(i) SMAC (Knob Tuning) on Spark, TPC-DS dataset and workload

(j) Bao (Query Optimizer) on Spark, TPC-DS dataset and workload

**Figure 11: End-to-end execution time of query workloads and overhead of `PilotScope` on PostgreSQL and Spark.**




(a) SMAC + Bao on IMDB dataset, JOB workload

(b) SMAC + Bao on STATS dataset, STATS-CEB workload

(c) DeepDB + Bao on IMDB dataset, JOB-light workload

(d) DeepDB + Bao on STATS dataset, STATS-CEB workload

(e) DeepDB + SMAC on IMDB dataset, JOB-light workload

(f) DeepDB + SMAC on STATS dataset, STATS-CEB workload

**Figure 12: End-to-end execution time of multiple AI4DB algorithms on PostgreSQL.**

DeepDB to estimate cardinality since these two methods provide the most benefits by Figure 11 (the right two sub-figures)

We observe that, the effect of applying multiple AI4DB algorithms is complex. In some cases, such as Figure 12(b), (c) (e) and (f), the performance of applying two algorithms is comparable to applying only one. In other cases, such as Figure 12(a) and (d), the performance of applying two algorithms is even worse than applying any single algorithm. We predict that it is possible due to the turned knob value (or new estimated cardinality) affects the behaviors of the learned query optimizer so it explores bad plans. However, it still needs more in-depth analysis on their correlations. Note that, until now, there exists very little research on the impact of applying multiple AI4DB algorithms together. `PilotScope` could serve as a powerful tool to conduct research towards this direction. It is very attractive to design AI4DB algorithms that could work together to optimize the overall performance of databases.

## 7 CONCLUSIONS AND FUTURE WORK

We propose `PilotScope`, an AI4DB middleware with a programming model to deploy and develop AI4DB algorithms in databases. `PilotScope` abstracts the interactions between typical AI4DB algorithms and databases into purely simple interface that hinders the underlying details of databases. With such abstraction, the same AI4DB algorithm in `PilotScope` could be applied to steer multiple different databases. Meanwhile, ML and DB developers could work more independently and play to their own strengths on developing AI4DB tasks in databases. The abstract interface is shown to be enough expressive and general. It has been applied to support a variety of AI4DB tasks and algorithms and could be easily extended to new AI4DB tasks. Extensive experiments have verified the effectiveness of `PilotScope` in terms of research and applications in the AI4DB field.

In the future, we hope to inspire and iterate AI4DB research with `PilotScope`. We target to build an open-source community for `PilotScope` to attract developers to: 1) develop and evaluate more AI4DB tasks and algorithms, *e.g.*, learned index, database monitor and diagnosis; and 2) implement the DB interactor to steer more databases, *e.g.*, MySQL and MongoDB. More over, we would try to push forward to set up the standard on the interface of DB interactor and deploy `PilotScope` in real-world production scenarios.

R1R4

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# A COMPARING PILOTSCOPE WITH RELATED WORKS

## A.1 PilotScope vs. Composable DBMS

R1W1

In this subsection, we briefly review the goals of composable DBMS and analyze the difference, as well as relations, between our work *w.r.t.* composable DBMS [44]. Our DB interactors are much more lightweight and easier than the composable DBMS in terms of both conceptual and implementation view. We elaborate on the details as follows.

**Goals of Composable DBMS.** In the last several decades, the data processing requirements become more and more diversified. As a result, a proliferation of specialized data management systems, where each one targeted to a narrow class of applications, have been developed. Certainly, this paradigm is not efficient for developers and not friendly to users as there exists very limited reuse across different systems. It enforces developers to reinvent the wheels to do duplicate engineering works and users to learn the idiosyncrasies of different systems.

To tackle with this problem, the concept of the composable DBMS has been proposed in the literature. It aims at standardizing different data processing systems into a unified and composable architecture. Each component and interface in this architecture is well-defined and is able to process any kind of data in a general manner. As a result, the components and interfaces in the composable DBMS could be reused across different data processing systems as off-the-shelf tools. By applying this new paradigm, the engineering burden of developers and the learning curves of users could be largely reduced.

**Difference and Relations with Our Work.** Until now, there still does not exist an actual composable DBMS system. The most difficult work is how to abstract each component and interface in the composable DBMS such that: 1) each of them could hinder the difference incurred by different data processing tasks. For example, the language frontend and intermediate representation form should be able to support both SQL and non-SQL queries. 2) each of them could be implemented in a universal manner to fulfill its job. For example, the execution engine should support different data access methods and storage formats. and 3) each of them could be easily extended to meet specialized functions.

The very recent work [44] advocates the vision of the composable DBMS, proposes a reference architecture with the responsibility of each component and interface, discusses how recent popular open source projects fit this model but also highlights a number of open questions where additional researches are still needed.

In comparison to building a monolithic composable DBMS system, the goal of our DB interactors is much more lightweight and easier.

First, from the conceptual view, the DB interactors are actually a number of well-defined interfaces to replace certain functions (*e.g.*, index recommendation, cardinality estimation) in DBMS. Unlike with the composable DBMS, we do not need to consider how to abstract any high-level architecture in terms of data processing and how to decompose it into smaller components and interfaces. The abstracted interfaces applied for the interactions between ML drivers and database components are very straightforward and clear. Specifically, for the knob tuning or index recommendation, we just need to consider how to configure the resulting value of the knobs or indices in the databases. For learned cardinality estimation or query optimizer, we just consider how to extract the query from the database and replace the generated cardinality or plan to the database.

Second, implementing these interfaces in DB interactors on specific databases is much easier. Unlike with composable DBMS with each component or interface needs to be generally implemented to cover specialized requirements, our DB interactors are implemented using specific database properties to fulfill the general functional requirements of each interface. Specifically, for non-inclusive components such as the knob tuning and index recommendation, the resulting knobs and indices could be set by external database commands. For inclusive components such as learned cardinality estimation or query optimizer, we also provide the general approach (in Section 5.1.1) to implement the interfaces by adding some well-defined anchor functions in the database codebase. By our experience on implementing these anchor functions in PostgreSQL and Spark, this work does not require a deep understanding and analysis of the whole codebase. Some anchors can be directly implemented using the database hooks, which are interfaces provided by the database itself to inject codes. The remaining ones just require to add some patches in certain positions in the database codebase.

**Future Work between Composable DBMS and Our Work.** Finally, we advocate that the development of the composable DBMS would contribute to our work. Given an actual composable DBMS system, we could also implement our DB interactors on it. Since its components could be reused for different data processing tasks, our PilotScope could also support these data processing tasks with the same DB interactor.

## A.2 PilotScope vs. Other AI4DB Deployment Systems

R3W1, R3D1

In comparison with other solutions on deploying AI4DB algorithms into DBMS, e.g., openGauss [35] and NoisyPage [15, 37, 43] which incursively integrate multiple learned methods and SCOPE with customized learned query optimizer Bao [42], our PilotScope system has more advantages. We summarize the comparison results in the following table.

On one hand, for each role in the workflow, PilotScope is superior in terms of usability:

- To researchers, PilotScope liberates them from the underlying details of the DBMS to focus on designing the logic of the ML algorithms. This could largely accelerates the iteration of learned database methods.
- To ML and DB developers, PilotScope reduces the engineering burden and allows them to play their own strengths: The ML developers only need to write the logic of ML algorithms without knowing the details of the DBMS. They could directly apply the DB interactor interface. For each DBMS, the native DB developers are responsible for implementing the interfaces. They are required to be only familiar with the underlying database codes to implement the interfaces as patches.

**Table 1: Comparison between PilotScope and other systems on deploying AI4DB algorithms into databases.**

| Comparison Item | PilotScope (Our Work) | OpenGauss [35] / NoisyPage [15, 37, 43] | SCOPE with Bao [42] |
|---|---|---|---|
| Iteration speed | Fast (Researchers do not consider DB details) | Slow (Researchers must know DB details) | |
| Develop cost | Low (ML and DB sides are separate) | High (ML and DB sides are coupled) | |
| DBA/User experience | Smooth (Totally transparent) | Not Smooth (Switch to a new system) | |
| Supported tasks | Multiple methods on multiple databases | Multiple methods on one database | One method on one database |
| Generality | High (One ML algorithm to all databases) | Low (One ML algorithm to one database) | |
| Extend to new tasks | Easy (Plug-in components) | Hard (Incursive integration from scratch) | |
| Extend to new databases | Easy (Only implement interfaces) | Hard (Incursive Integration from scratch) | |

- To DBAs and database users, PilotScope is more flexible. The ML algorithms deployed by PilotScope are totally transparent to them. Each ML algorithm could be started or stopped at any time according to user requirements. Meanwhile, they could operate and apply the databases using commands as usual (as stated in Section 2.1). They do not need to interpret any normal service and afford the cost and risk of switching to a new database. The user experience is much smoother.

However, in existing AI4DB deployment works, the ML and DB developers are coupled. They need to work together to integrate the ML codes into the database codebase (as we stated above). This requires the developers on each side to know about the details on another side. This requires close cooperation between ML and DB developers and heavy engineering costs. Meanwhile, for DBAs and database users, the databases with incursively integrated ML algorithms may have different behaviors. They need to adapt and learn to operate these new algorithms.

On the other hand, from the system perspective, PilotScope also brings more benefits:

- PilotScope allows one implementation of an ML algorithm to be applied to steer different databases in the same manner. However, in existing AI4DB deployment works, the ML algorithm needs to be integrated individually for each database.
- PilotScope is easy to extend to support new ML algorithms and databases. All ML algorithms are plug-in components in PilotScope. To support new databases, we only need to implement the DB interactor interface. However, in existing AI4DB deployment works, for any new ML algorithm and database, the deployment work needs to be done from scratch.

## B DEPLOYING COMPLEX AI4DB TASKS BY PILOTSCOPE

R1R4

Except for the four typical types of AI4DB tasks stated in Section 4, namely knob tuning, index recommendation, cardinality estimation and query optimizer, our PilotScope could also be applied to more complex tasks. In the following, we show an example to apply our PilotScope to deploy a regression elimination method on query optimizer, which was proposed in very recent time in [52]. In the future, PilotScope will be continuously updated to stay aligned with the state-of-the-art literature and be motivated to explore new requirements in the field of AI4DB.

We introduce a new framework called Eraser in [52]. Each learned query optimizer would generate plans whose performance is worse than the plans generated by the traditional query optimizer on some queries. For example, in Section 6.1, the learned

```
class model_lero():
    model_train(train_data):
        ... ...
    model_inference(P): # return the estimated rank score of plan P
        ... ...
        return est_plan_rankscore

class model_eraser():
    model_train(train_data):
        ... ...
    model_inference(P): # return the estimated risk of plan P
        ... ...
        return est_plan_risk

class driver_lero_eraser(C, theta):
# parameter C: set of factors for scaling cardinality in Lero to generate
↪  candidate plans
# parameter theta: the threshold for filtering risky plans in Eraser
    def init():
        self.injection_type = INJ_E2EQO
        train_data = collect_data(TIME, MAX_SIZE, data_addr)
        self.lero_model = model_lero()
        self.lero_model.model_train(train_data)
        self.eraser_model = model_eraser()
        self.eraser_model.model_train(train_data)
        Set timer to call self.lero_model. model_train() periodicallly
        Set timer to call self.eraser_model. model_train() periodicallly
        ... ...
    def algo(Q): # input query Q
        sid = session_start() # obtain the basic plan and its cardinality
        push(sid, QUERY, null, Q)
        Cards = pull(sid, CARD, null)
        Pb = pull(sid, PLAN, null)
        session_exec(sid)
        session_end(sid)
        PS.add(Pb) # the basic plan generated by the original database is added
        ↪  into the candidate set
        for each c in C: # generate all plans using Lero's enumeration method and
        ↪  filter each using Eraser's model
            cid = session_start()
            push(cid, QUERY, null, Q)
            push(cid, CARD, null, Cards*c)
            Pc = pull(cid, PLAN, null)
            session_exec(cid)
            session_end(cid)
            if self.eraser_model.model_inference(Pc) <= theta: # only plans with
            ↪  low risky are reserved
                PS.add(Pc)
        plan_rank = self.lero_model.model_inference(PS)
        P = argmin(PS, plan_time)
        return P
```

**Figure 13: The PilotScope model and driver for the performance elimination method Eraser in [52].**

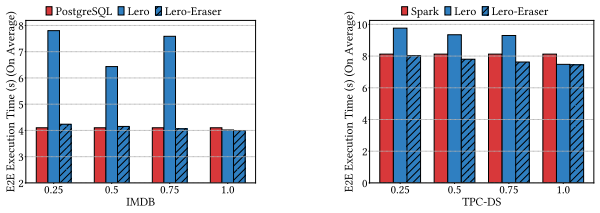
query optimizer Bao [40] performs worse than PostgreSQL. Eraser aims to eliminate the performance regression of any learned query optimizer to balance the performance benefits and regressions. Eraser is a plugin deployed on top of the ML model of existing ML algorithms. It receives all candidate plans generated by the plan enumeration method in the learned query optimizer, *e.g.*, plans generated by different hints in Bao [40] or generated with different cardinality in Lero [61], and applies a decision model to filter out

risky plans where the learned query optimizer is likely to make inaccurate predictions. To train its decision model, Eraser needs to collect the actual execution times of some SQL queries. PilotScope could accelerate the implementation and deployment of Eraser.

Figure 13 illustrates a complete example where Eraser is deployed on top of the Lero method to eliminate its performance regression. We set two classes model_lero for the model used in the Lero method to predict the rank score of each plan and model_eraser for the model used in Eraser to predict the risk of each plan. In the driver_lero_eraser class, we set its injection type to INJ_E2EQO. We apply an ML model to predict the rank score of each plan and another model to predict the risk of each plan. We collect query execution time to train these two models. The two models are retrained in the background periodically.

In the algo() function, we first push the input query $Q$ and obtain its estimated cardinality and the basic plan $Pb$ produced by the original query optimizer. Then, for each scaling factor $c \in C$, we start a new session to scale the cardinality of all sub-queries of $Q$ and obtain the generated candidate plan $Pc$. The plan $Pc$ is filtered by the risky model of Eraser if its risk score exceeds the threshold. After examining all candidate plans, we consult the rank score prediction model to find the best plan $P$ and return it as the result. The injection interface is responsible for sending $P$ to the database for execution.

Figure 14 shows the performance of the Lero algorithm with or without Eraser. Following the original Eraser paper, the Lero algorithm is trained on 25%, 50%, 75% and 100% training data of the IMDB and TPC-DS benchmarks, and is tested on the complete test set. The experiment results show that Eraser can eliminate most of the performance regression when Lero exhibits worse performance than the baseline PostgreSQL. When Lero has better performance than PostgreSQL, Eraser brings little impact on the benefits.




(a) Performance on IMDB (b) Performance on TPC-DS

**Figure 14: Performance of the Lero algorithm with and without Eraser.**