



# ByteCard: Enhancing ByteDance's Data Warehouse with Learned Cardinality Estimation

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## ABSTRACT

Cardinality estimation is a critical component and a longstanding challenge in modern data warehouses. ByteHouse, ByteDance's cloud-native engine for extensive data analysis in exabyte-scale environments, serves numerous internal decision-making business scenarios. With the increasing demand for ByteHouse, cardinality estimation becomes the bottleneck for efficiently processing queries. Specifically, the existing query optimizer of ByteHouse uses the traditional Selinger-like cardinality estimator, which can produce substantial estimation errors, resulting in sub-optimal query plans.

To improve cardinality estimation accuracy while maintaining a practical inference overhead, we develop a framework ByteCard that enables efficient training and integration of learned cardinality estimators. Furthermore, ByteCard adapts recent advances in cardinality estimation to build models that can balance accuracy and practicality (e.g., inference latency, model size, training overhead). We observe significant query processing speed-up in ByteHouse after replacing the existing cardinality estimator with ByteCard for several optimization scenarios. Evaluations on real-world datasets show the integration of ByteCard leads to an improvement of up to 30% in the 99th quantile of latency. At last, we share our valuable experience in engineering advanced cardinality estimators. This experience can help ByteHouse integrate more learning-based solutions on the critical query execution path in the future.

## CCS CONCEPTS

• **Information systems** → **Data management systems**; • **Computing methodologies** → **Machine learning**.

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*SIGMOD-Companion '24, June 9–15, 2024, Santiago, AA, Chile*  
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ACM ISBN 979-8-4007-0422-2/24/06...\$15.00  
<https://doi.org/10.1145/3626246.3653376>

## KEYWORDS

Learned Cardinality Estimators, Query Optimization, ModelForge Service, Inference Engine, ByteHouse, ByteCard

### ACM Reference Format:

Yuxing Han\*, Haoyu Wang, Lixiang Chen, Yifeng Dong, Xing Chen, Benquan Yu, Chengcheng Yang\*, and Weining Qian. 2024. ByteCard: Enhancing ByteDance's Data Warehouse with Learned Cardinality Estimation. In *Companion of the 2024 International Conference on Management of Data (SIGMOD-Companion '24)*, June 9–15, 2024, Santiago, AA, Chile. ACM, New York, NY, USA, 14 pages. <https://doi.org/10.1145/3626246.3653376>

## 1 INTRODUCTION

ByteHouse, ByteDance's internal data warehouse, is crucial for handling analytics at an exabyte scale, underpinning various business decisions through applications that include risk management and strategic marketing. Building on the collective research insights and engineering endeavors of predecessors [1, 3, 11, 25, 29, 48], ByteHouse has demonstrated robust performance across a range of business workloads. In its consistent pursuit of excellence, ByteHouse continually seeks to evolve and improve, particularly in addressing the cardinality estimation (CardEst) challenge—a critical aspect of query optimization that has received extensive attention from academia and industry. Cardinality estimation aims to estimate query operator results size without actual execution, consisting of COUNT and COUNT-DISTINCT (NDV) estimation. Accurate estimation approaches are important for enhancing query plans' quality, which is one of ByteHouse's most notable performance bottlenecks.

In its initial stages, ByteHouse employed traditional CardEst approaches like other modern data warehouses. However, the inherent data skewness in real-world datasets, coupled with the simplified assumptions of these approaches, hindering ByteHouse from achieving reliable estimates. This problem is further exacerbated when encountering large volumes of customer data and rapid data updates. Traditional sketch-based approaches [16, 41] often require

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**Table 1: Estimation Errors of Traditional CardEst Approaches in ByteHouse**

CardEst	IMDB			STATS			AEOLUS		
	50%	90%	99%	50%	90%	99%	50%	90%	99%
COUNT Est.	3.06	1145	$1 \cdot 10^6$	493	$3 \cdot 10^4$	$3 \cdot 10^7$	7.45	$3 \cdot 10^6$	$8 \cdot 10^6$
NDV Est.	15	984	$3 \cdot 10^4$	134	$1 \cdot 10^4$	$6 \cdot 10^4$	598	4912	$2 \cdot 10^4$

full data scans, creating considerable pressure on ByteHouse’s storage layer. Meanwhile, the sample-based approaches face inherent challenges in balancing accuracy with the sampling rate.

The evaluation report in Table 1 shows the inadequacy of traditional CardEst approaches in handling current analytical workloads. This report evaluates various quantiles of the Q-Error, a widely used metric in evaluating CardEst approach [31, 32], known for its theoretical lower bound of 1. Specifically, the datasets under consideration include two benchmarks, IMDB [27] and STATS [20], as well as AEOLUS, an internal business workload from ByteHouse that comprises 200 complex queries from customers. The evaluation results indicate that for both COUNT and COUNT-DISTINCT estimation, the errors of traditional approaches deviate far from the theoretical optimal lower bound across various quantiles, often by several orders of magnitude. This discrepancy highlights a significant potential for improving the estimation methodology.

Recently, learning-based CardEst approaches [10, 15, 24, 27, 35, 37, 54–59, 63] have drawn much attention due to their superior accuracy [20, 47, 50]. The prosperity of these CardEst research work naturally raises a question: Could we replace traditional approaches in ByteHouse with learning-based ones to get more accurate cardinality estimates, thereby enhancing query optimization? After a deep survey of the learned approaches, we identify three challenges of integrating learning-based estimators into the ByteHouse’s existing architecture: (1) *How to discern the appropriate estimation models that balance accuracy and practicability?* Although the existing studies have proposed numerous learned estimators, most focus on improving accuracy. The goal of ByteCard is to achieve accurate estimation and improve ByteHouse’s overall query performance in a resource-efficient manner. (2) *How to manage the training process and integrate the inference algorithms of these models in the query processing?* Due to the necessity of not disrupting customers’ active online queries, training directly on large-scale data volumes stored in ByteHouse is impractical. Furthermore, deploying existing inference algorithms within multi-threaded execution environments poses another challenge. (3) *How to utilize the models’ estimates to enable enhanced query optimization for ByteHouse?* Identifying optimization scenarios in ByteHouse that suffer from poor estimation approaches and applying accurate estimates from ByteCard for enhanced query optimization presents a non-trivial challenge.

In this paper, we present ByteCard, an enhanced CardEst framework designed to integrate learning-based approaches into ByteHouse seamlessly. To strike a balance between accuracy and practicality, we first select models by carefully evaluating inference latency, model size, and the training/updating overhead for optimization scenarios in ByteHouse. Then, ByteCard introduces an abstraction engine to ease the integration of inference algorithms for different models. Besides, the engine could also help identify immutable data structures, which would further avoid data races and enable high-concurrency inference executions in the multi-threaded environment. In addition, ByteCard also proposes a dedicated service for isolated training to ensure no disruption on the

online queries. Moreover, ByteCard employs auxiliary modules for model loading and accuracy monitoring to sustain its effectiveness. As a result, applying ByteCard’s estimation in ByteHouse’s optimization scenarios has significantly accelerated query processing. For now, ByteCard is responsible for millions of cardinality estimations within ByteHouse’s online clusters, providing substantial benefits to various analytical workloads. As a pioneer in integrating learning-based approaches into a production-scale data warehouse, ByteCard demonstrates the significant potential of machine learning to enhance query optimization in large-scale systems.

In summary, our main contributions are listed as follows:

- We make careful model choices for learned cardinality estimators by evaluating factors such as inference latency and training overhead for effective integration into ByteHouse.
- We introduce ByteCard, a framework designed to integrate learning-based cardinality estimators in ByteDance’s internal data warehouse, ByteHouse. The framework features an inference abstraction engine and a dedicated training service, which facilitate the integration of chosen models.
- The accurate cardinality estimates provided by ByteCard are applied in several optimization scenarios and have demonstrated their effectiveness in enhancing ByteHouse’s query performance in subsequent evaluations.
- We share lessons derived from the design, development, and deployment experience of ByteCard, along with our future efforts to integrate more learning-based approaches to further enhance ByteHouse’s query optimization.

## 2 RELATED WORK

**Learning-Based CardEst Methods:** The research community has proposed a diverse set of learned models [10, 15, 24, 35, 54–56, 58, 63] for both COUNT and COUNT-DISTINCT estimation. Based on recent studies [20, 63], they can be broadly classified into query-driven and data-driven methods. The query-driven methods [15, 27, 35, 46] aim to map each featurized query to its COUNT or COUNT-DISTINCT cardinality, utilizing advanced models like gradient boosted trees [15] and DNNs [10, 27]. In contrast, the data-driven methods [24, 52, 56, 58, 63] treat table tuples as samples from a joint distribution, applying ML-based models such as deep auto-regression [58, 59], Bayesian Networks [56], and Sum-Product Networks [24, 63]. Another model, RBX (named after the initials of its first three authors’ surnames) [54], offers a workload-independent approach for NDV estimation. Selecting the most suitable models for ByteCard’s requirements is a crucial priority.

**ML-enhanced Components of Databases:** Recent efforts in both academia and industry have focused on harnessing machine learning to boost database system performance. SageDB [13] is a data analytics prototype that utilizes learned components to self-tune for optimal performance across various datasets and queries, focusing on machine learning techniques like partial materialized views and global optimization algorithms. Bourbon [12], a learned index

for LSM trees, uses piecewise linear regression for key distribution learning to enhance the lookup efficiency. It also offers guidance for integrating learned indexes into LSM trees tailored to specific levels and workloads. Xindex [49] is a concurrent ordered index optimized for quick queries, employing a hierarchical structure that adapts to real-time workloads, outperforming traditional index structures in efficiency. OpenGauss [33] integrates machine learning for various self-management tasks, including query rewriting, cost estimation, and plan generation. Auto-WLM [39] is a machine learning-based workload management system employed in Amazon Redshift [3], which dynamically schedules workloads and adjusts to changes, using local query performance models to enhance overall cluster performance. We posit that ByteCard represents the first instance of integrating learning-based cardinality estimation models into an industrial data warehouse system.

### 3 BACKGROUND AND MODEL CHOICES

This section begins with an overview of ByteHouse, followed by an analysis of several optimization scenarios hindered by the poor cardinality estimation approaches. At last, we thoroughly discuss our selection process for ByteCard’s learned CardEst models.

#### 3.1 Overview of ByteHouse

The high-level architecture of ByteHouse is shown in 1. ByteHouse employs an architecture that separates storage from computation, consisting of three discrete layers: service, computing, and storage. This modular structure facilitates a clear division of responsibilities, enhancing scalability and efficiency within the system. The service layer parses queries, optimizes execution plans, and dispatches tasks to computing nodes. The computing layer dynamically allocates resources and executes query operators. The storage layer consists of a distributed key-value store for managing metadata and a distributed file system for storing business data. Core components include the Resource Manager, which orchestrates the allocation of computing resources; the Time Oracle, which ensures synchronized computation operations; the Data Ingestor, which manages data flow from multiple sources; and the Daemon Manager, which manages the lifecycle of background tasks. In addition, ByteHouse utilizes other widely adopted techniques in modern data warehouses, such as columnar storage, and vectorized execution.

**3.1.1 Optimization Scenarios Hindered by Inaccurate Cardinality Estimation.** Many optimization scenarios have been developed across ByteHouse’s three layers to ensure good performance for its users. These scenarios include sideways information passing [26], magic set rewriting [42], and late materialization [2, 44]. However, their effectiveness is limited by the inaccuracies of traditional CardEst approaches. We explore two examples in the following discussions. **Materialization Strategies:** During query processing in column-based systems like ByteHouse, materialization involves converting data from a columnar format to a row-based tuple. Regarding materialization strategies, ByteHouse adopts the method of early materialization, where tuples are generated early in the query plan, owing to its simplicity and common use [44, 48]. Initially, ByteHouse adopted a one-stage reader approach for early materialization, which involves scanning and processing queried columns in one pass, applying all necessary predicates simultaneously. The

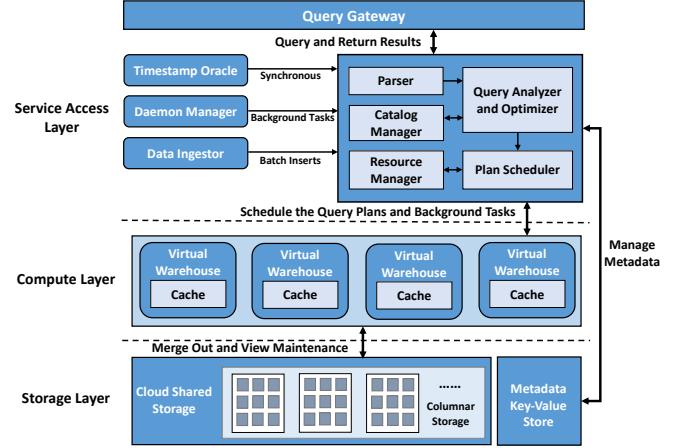


Figure 1: The Architecture of ByteHouse

method is effective for non-selective predicates as it reduces per-tuple processing by handling entire column blocks. However, the current method becomes less efficient with highly selective predicates, where it constructs many unnecessary tuples, even though only a small subset of tuples require further processing. Therefore, accurate selectivity estimation becomes crucial in optimizing the materialization strategies. Traditional CardEst approaches often struggle to provide accurate cardinality/selectivity due to their limited capability in identifying cross-column correlations compared to learned ones, especially with small sample sizes.

**Aggregation Processing:** The common practice of aggregation processing in data warehouses usually involves employing an in-memory hash table to record the distinct values of aggregation keys. Effectively managing this hash table often involves addressing the issue of handling the increasing values of aggregation keys. The *resizing* operation, which requires allocating larger memory blocks and rehashing entries, is resource-intensive due to the consumption of significant CPU and memory. We observe that frequent early-stage *resizings* incur notable overhead, adversely affecting ByteHouse’s performance of aggregation processing. To address this issue, the current strategy employed by ByteHouse is to cache the size of hash tables of previous queries. However, this method is effective only for identical repeat queries and quickly loses its effectiveness due to data updates. An alternative method is to reduce the frequency of *resizing* by accurately estimating the initial size of the required hash table. Therefore, a highly accurate NDV estimator is pivotal in minimizing the frequent *resizings* operations.

#### 3.2 CardEst Model Choice

Selecting the most suitable estimation models from the various options available is a crucial challenge for ByteCard, considering their practical integration into ByteHouse’s existing architecture. The ideal models for the integration must fulfill the following criteria: 1) They should offer higher accuracy in cardinality estimates than traditional approaches in most cases; 2) Given the limited resources for cardinality estimation in query optimization, the training process should be resource-efficient; 3) The inference algorithm needs to be efficient enough to avoid heavily influencing the query execution time. After careful analysis and evaluation, ByteCard selects three



**Table 2: Estimation Errors of Learned CardEst Approaches in ByteCard**

CardEst	IMDB			STATS			AEOLUS		
	50%	90%	99%	50%	90%	99%	50%	90%	99%
COUNT Est.	1.14	4.82	425	1.47	8.03	4026	1.3	3.57	7491
NDV Est.	3.67	191	392	2.93	362	517	3.8	133	934

learned CardEst models, each optimized for specific optimization scenarios in ByteHouse.

**3.2.1 Choice for COUNT CardEst Models.** Query-driven models like MSCN [27], which necessitate extensive query logs and computation of true cardinality for training, are resource-intensive. Besides, these models may diminish effectiveness with data changes as they are specific to certain workloads. Therefore, query-driven methods are considered impractical for ByteCard’s requirements. Alternatively, data-driven methods focus on learning data distributions through unsupervised ML models. For example, BayesCard [56] offers a solution with its tree-structured Bayesian Networks (BNs), addressing single-table COUNT estimations. These networks stand out for their advantages of high accuracy, efficient training, small model size, quick inference, and adaptability to data changes [20].

However, to handle join-size estimation, most of the data-driven methods [24, 52, 56, 58, 63], including BayesCard, hold the design philosophy to understand the joint distribution of the joined tables, imposing a non-trivial overhead for model training. Besides, these methods usually employ the denormalizing strategy, which will add extra columns to facilitate later inference. The number of extra columns will expand rapidly as the number of join relationships increases. This is not affordable inside ByteHouse as the system often needs to handle numerous complex join relationships between different tables. Therefore, we decide to adopt a recent approach FactorJoin [55] for join queries. It naturally supports using the Bayesian Networks as simple-table cardinality estimation and requires almost no additional training overhead. Specifically, in the offline training phase, FactorJoin creates specialized buckets on the join key values (i.e., join-buckets), and builds Bayesian Networks to understand the correlations among filter columns and join keys within a single table. In the online inference phase, FactorJoin first dynamically constructs a factor graph [36], which is derived from the join relationships specified in the query. Then, it utilizes the related simple-table Bayesian Networks and applies inference on the graph with join-buckets to estimate the cardinality bounds accurately. FactorJoin is feasible for integration in ByteCard due to its efficient training process and proven advantage in estimation accuracy and inference speed over alternative methods [55].

**3.2.2 Choice for COUNT-DISTINCT CardEst Models.** The traditional COUNT-DISTINCT (NDV) CardEst approaches can be classified into sketch-based and sampling-based categories. However, both of them face challenges when dealing with small samples. The commonly used sketch-based estimator HyperLogLog (HLL) [16, 21] has no theoretical guarantees for sampled data and usually requires a full dataset scan for accurate estimation. Moreover, frequent data updates reduce the effectiveness of old sketches. Meanwhile, the sample-based estimators [6, 7] often rely on specific heuristics or data assumptions, which might not generally apply to diverse datasets. Their robustness is compromised as the foundational assumptions are prone to breakdown.

The learning-based NDV estimator proposed in [10] adopts a supervised learning framework, requiring the collection of true NDV from a significant number of online queries for each workload. Alternatively, RBX [54] adopts a one-model-fits-all approach that treats NDV as a standard data property akin to standard deviation in statistics, and aims to derive a “closed”-formula of NDV calculation. This approach opts for a neural network to learn this formula with the belief it can approximate any continuous function. This estimator exhibits robust performance across a spectrum of workloads and maintains effectiveness across different sampling rates, fulfilling the accuracy criterion. The workload-independent nature guarantees one training process can serve a wide range of workloads, aligning with the resource-efficiency criterion. Moreover, the neural network designed by RBX has an acceptable number of network layers, enabling ByteCard to conduct efficient inference within ByteHouse’s query processing. Therefore, ByteCard chooses RBX as its learning-based NDV estimator.

**3.2.3 Evaluation & Summary for Model Choices.** To ascertain the effectiveness of our model choices for ByteCard, we translate ByteHouse’s cardinality estimation into SQL queries when processing the workloads from the IMDB, STATS, and AEOLUS datasets. Next, we train different models on the three datasets offline. The performance of these models is evaluated by comparing their Q-Error results, as shown in Table 2, against those of traditional approaches shown in Table 1. This comparison showcases the effectiveness of selected models, especially notable at the 99% quantile, where learning-based approaches demonstrate significant improvements.

Then, we investigate the training time and model size across different datasets for different estimation models. Given that RBX follows a one-model-fits-all approach, its training algorithm is not evaluated here. We select MSCN as the representative query-driven model alongside three data-driven models: DeepDB, BayesCard, and FactorJoin. The training configurations for all models follow the default specifications. Specifically, for FactorJoin’s bucket strategy, we opt for equi-height buckets with a total count of 200. From the results in Table 3, we can see that the training time of MSCN consistently exceeds that of other models across various datasets. Note that this time does not include the computation time of true cardinalities as training objectives. This observation underscores the impracticality of query-driven models for integration in ByteCard. Among data-driven models, DeepDB [24] and BayesCard [56] exhibit longer training times and larger model sizes, which is attributed to their denormalization strategy for join-size estimation. In contrast, FactorJoin effectively reduces training overhead and model size while preserving high-accuracy estimations, because it leverages simple-table models and captures join-key distributions using join-buckets and factor graphs.

**Summary:** ByteCard employs a lightweight Bayesian Network per table for estimating single-table COUNT cardinalities and combines these models through FactorJoin to accurately estimate join sizes.

**Table 3: The Training Time and Model Size between Different CardEst Models**

Measure	MSCN			DeepDB			BayesCard			FactorJoin		
	IMDB	STATS	AEOLUS	IMDB	STATS	AEOLUS	IMDB	STATS	AEOLUS	IMDB	STATS	AEOLUS
Training Time (Min)	41	34	45	78	113	145	33	27	31	7	13	11
Model Size (MB)	3.9	2.8	7.3	43	162	201	2.4	6.1	6.5	4.3	2.3	3.2

For NDV estimation, ByteCard leverages the workload-independent RBX approach, where one model from the offline training process is adequate for the majority of estimation scenarios.

## 4 SYSTEM ARCHITECTURE OF BYTECARD

In this section, we first outline the design principles of ByteCard. Then, we give a detailed description of ByteCard’s each module.

### 4.1 Design Principles

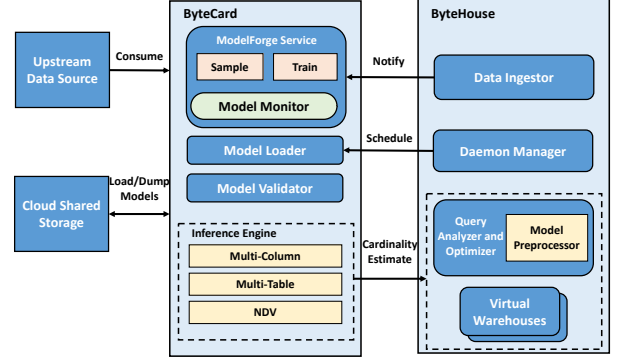
When developing ByteCard to optimize ByteHouse’s query processing, we emphasize its practicability, which requires reducing computational overhead and ensuring efficient use of learned CardEst models. Moreover, we preserve ByteCard’s flexibility to facilitate the integration of new CardEst models and broaden the framework to include more learning-based query optimization techniques. The architecture of ByteCard is shown in Figure 2. To fulfill the goals described above, ByteCard introduces two core modules, i.e., a high-level program abstraction known as Inference Engine and a standalone service called ModelForge Service, alongside auxiliary modules, to keep ByteCard’s efficiency and effectiveness while safeguarding ByteHouse’s stability.

The Inference Engine is the central hub for deploying inference algorithms of CardEst models. It aims to simplify the integration process for inference algorithms in multi-threaded query processing environments. The ModelForge Service is designed to focus on the iterative integration for training and the models’ management, ensuring their accuracy. In addition to the core modules, auxiliary modules are developed, including the Model Loader and Model Monitor. The Model Loader is responsible for efficiently loading and updating models across the large-scale cluster. Meanwhile, the Model Monitor takes care of the model quality, triggering models’ fine-tuning if necessary. The auxiliary modules collectively guarantee the efficient functioning of the Inference Engine and ModelForge Service, which further provide strong support for the effectiveness of the ByteCard framework and the stability of ByteHouse.

### 4.2 Inference Engine

As shown in Figure 3, the Inference Engine provides a high-level abstraction for communication with ByteCard’s other modules and the integration with ByteHouse’s query processing. With this engine, ByteHouse can enhance its query optimization by leveraging the accurate estimations provided by the advanced learning-based cardinality estimation models.

**4.2.1 Interact with other modules.** As each selected model in ByteCard has different structures and serialization methods, the load-Model interface is crafted to encapsulate the deserialization process for different models. This interface is usually invoked by Model Loader, a background process responsible for loading CardEst models from the cloud-based storage. From the perspective of ByteHouse’s Daemon Manager, the Model Loader operates similarly

**Figure 2: The Architecture of ByteCard**

to other background tasks, such as the LSM-tree’s compaction task [8, 38] in ByteHouse’s storage layer. Then, the Daemon Manager assigns resources to these loading tasks similarly, except for the strategy of task triggering. In contrast to the complex strategies utilized for LSM-tree’s compaction, our approach employs a timestamp-based approach for loading the up-to-date model. Consequently, ByteCard guarantees only models with the most recent timestamp are considered for loading and updating. In the current configuration, models are scheduled for loading at a default interval of one hour unless Model Monitor detects that the performance of models is decreased due to the shift of data distribution.

Upon loading a model into memory, the Model Validator employs its validate interface to evaluate the model’s validity. This step is crucial for preventing potential crashes during actual inference (i.e., executing the estimate interface) in ByteHouse’s query processing. The validation process involves two primary checks: the *size checker* and the *health detector*. The *size checker* regulates the size of individual models and the total size of all the loaded models to prevent excessive memory usage in ByteHouse. To avoid the case in which one table’s model occupies too much memory, ByteCard will refuse to load a model if its size is too large. Moreover, when the cumulative size exceeds a predetermined threshold, ByteCard employs a Least Recently Used (LRU) strategy to prioritize and retain the most frequently used models. The *health detector* is responsible for maintaining the models’ healthy state. For example, in the case of Bayesian Networks, the detector employs a cyclic detection method to verify the structural legitimacy of the model, ensuring its structure conforms to a directed acyclic graph (DAG).

After the model is validated successfully, the subsequent step involves employing `initContext` to establish the programming context for inference algorithms, thereby preparing the model for estimation in the query processing. This interface enables the initialization of immutable data structures extracted from the inference algorithms, ensuring these structures remain read-only within each query thread. This approach allows the algorithms to be executed lock-free, thereby achieving high-concurrency inference.

```

1  template <typename T>
2  class CardEstInferenceEngine {
3  // Load a CardEst model
4      bool loadModel(String modelPath);
5
6  // Validate model legitimacy
7      bool validate();
8
9  // Initialize inference context
10     void initContext();
11
12 // Featurize a SQL query into a vector
13     FeatureVector featurizeSQLQuery(String sqlQuery);
14
15 // Featurize an abstract syntax tree into a vector
16     FeatureVector featurizeAST(AbstractSyntaxTree ast);
17
18 // Perform CardEst inference using a feature vector
19     double estimate(FeatureVector featVec);
20 };

```

**Figure 3: The APIs of Inference Engine**

**4.2.2 APIs for Integration with ByteHouse’s Query Processing.** The Inference Engine offers two kinds of APIs for integration with ByteHouse: one for final estimation (via the estimate interface) and the other for featurization (via the featurizeSQLQuery and featurizeAST interfaces). The final estimation is contingent upon the feature vector from the featurization phase. The specific inference algorithm of each CardEst model can be implemented by their own probability calculations or matrix operations in this interface.

The featurization interface is orthogonal to the inference algorithms. Its primary role is to capture the features of ByteHouse’s query-related data structures. To facilitate this, two APIs are provided for ByteHouse: One for featurization of SQL queries and the other for featurization of the abstract syntax tree (AST) produced by the ByteHouse’s analyzer. SQL-based featurization is designed for easy integration with emerging inference algorithms developed by the research community, as these algorithms usually develop featurization methods directly based on SQL queries. This interface is handy for rapid proof-of-concept evaluation. Alternative featurization, which leverages AST structures, is more effective in extracting richer features, including syntactic structures. Notably, modern database systems often utilize non-standard in-memory AST structures, leading to a lack of portability. Therefore, to harness the advantages of learned cardinality estimation using AST-based featurization in different systems, specialized inference algorithm implementations aligned with their specific AST structures must be developed. This customization would greatly help maximize the utility of the learning-based cardinality estimators, facilitating more accurate estimation for the system.

### 4.3 ModelForge Service

The ModelForge Service is designed to encapsulate the training algorithms of learning-based CardEst models into a standalone service, which facilitates the automatic training process for different models. The decision to develop a standalone service for model update on upstream data is driven by two factors: 1) Continuous sampling and training directly on the data stored in the storage layer would be resource-intensive and might risk impairing the performance of online customer queries. 2) This dedicated

service enables ByteCard to easily incorporate the latest training algorithms of CardEst models from the research community.

Within ModelForge Service, there are two main tasks: routine training for COUNT CardEst models and occasional fine-tuning for COUNT-DISTINCT CardEst models. The regular training of COUNT CardEst models per table involves structural learning of Bayesian Networks using the Chow-Liu tree algorithm [9], followed by parameter learning based on the Expectation Maximization (EM) [14] applied to the discovered structure. In addition, the fine-tuning of COUNT-DISTINCT CardEst models for individual columns is designed to adjust the pre-trained RBX model to some specific columns where the original parameters are less effective. This process allows the model to learn the unique features of the specific columns and improve the estimation of their NDVs.

The initial COUNT models for existing database tables in ByteHouse are trained on the online sampled data, with the sampling process scheduled during low-activity periods of the ByteHouse cluster. Whenever the data updates come, ByteHouse’s Data Ingestor signals the service with related information on data consumption, which is essential for model updates. The information for Apache Hive includes table schema, data format, and location, while for Apache Kafka, it contains topic names, data formats, and offset details. The retraining process begins after gathering sufficient data from upstream sources. The updated model is then saved in a specific location in the cloud storage, making it accessible later for Model Loader. The data used for training is automatically deleted after a set period. To further improve the effectiveness of learned estimators, ModelForge Service supports training for individual table shards, particularly when there is significant variation in data distribution across different shards. This process involves obtaining the shard keys and functions for the training service, segmenting the training data accordingly, and then training local models for each shard.

### 4.4 Auxiliary Modules

This subsection introduces ByteCard’s auxiliary modules, including Model Preprocessor and Model Monitor.

**4.4.1 Model Preprocessor.** This module performs data preprocessing in ByteHouse’s query analyzer and optimizer, facilitating the training and inference processes of different CardEst models. The key steps consist of column selection, type mapping, and join collection. The first step, column selection, involves excluding columns with complex types such as Array and Map, which are beyond the processing capabilities of current models. The second step of type mapping is developed to convert the database type of each selected column into compatible types with machine learning algorithms. For example, machine learning typically uses types like Binary, Categorical, and Continuous. The results after the above two steps are recorded in a system table named model\_preprocessor\_info. The ModelForge Service then accesses this table to retrieve essential information (such as which columns to read) and uses the type mapping to conduct the actual training.

The final step, join collection, involves gathering join patterns with ByteHouse’s analyzer. This process is critical because data warehouses’ customers are not required to define the relationships of the primary key to the foreign key (PK-FK) during the table



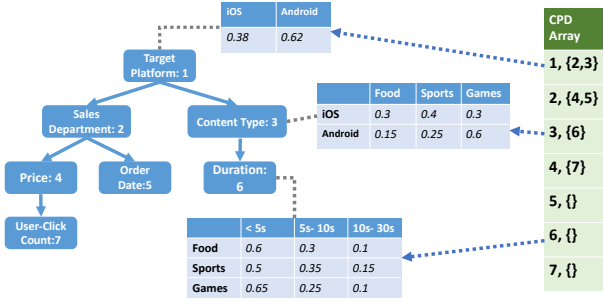


Figure 4: The Single-Table BN Model with its CPDs

creation. For multi-table CardEst models, the join pattern serves as an essential input for the training process, as these models are required to capture the joint distribution of the join keys.

**4.4.2 Model Monitor.** To ensure stability, ByteCard includes a Model Monitor to oversee the quality of CardEst models trained by ModelForge Service, ensuring that inferior models do not hinder the query processing of ByteHouse. Following the evaluation method from [20], Model Monitor automatically generates queries for COUNT and COUNT-DISTINCT estimation with multiple predicates. These queries are then executed by ByteHouse to obtain true cardinalities, enabling the Model Monitor to make estimations and compute Q-Errors for CardEst models. Models are retained only if their Q-Error is below a certain threshold. If the models cannot meet this threshold after several trials, ByteCard reverts to traditional methods for estimating the cardinality of the affected tables, ensuring consistent performance and reliability.

Note, Model Monitor is configured to monitor only the single-table COUNT and COUNT-DISTINCT models, and the multi-table COUNT models are excluded. This is because ByteHouse can’t afford the substantial computational resources that are needed to calculate true join sizes in Q-Error computation. Given that the multi-table model (i.e., FactorJoin) used by ByteCard relies on single-table models for join-size estimation, monitoring the performance of single-table models (i.e., Bayesian Networks) indirectly contributes to the oversight of multi-table models. This approach ensures efficient resource utilization while maintaining the accuracy and reliability of the learned estimators in ByteCard.

## 5 MODEL INTEGRATION

The training algorithms of all CardEst models are deployed with ModelForge Service without disrupting ByteHouse’s query processing. This section focuses on the integration of model inference. Given the constraints of Python in multi-threading, especially due to the Global Interpreter Lock (GIL) [4], ByteCard implemented inference algorithms with C++ to enhance system efficiency.

### 5.1 The Single-Table COUNT Model

We employ the tree-based Bayesian Networks (BNs) [17] as our single-table model for COUNT estimation. A tree-based BN is a probabilistic graphical model representing a set of variables and their conditional dependencies via a tree structure. ByteCard utilizes this model to capture the joint probability distributions across table columns. In this model, each node represents a random variable (corresponding to a table column in the context of CardEst).

Each edge denotes the conditional dependencies between these variables (corresponding to the correlation across table columns), which are captured by structures known as the conditional probability distributions (CPDs). In ByteCard, the CPDs are represented as one-dimensional (1D) vectors or two-dimensional (2D) matrices.

Figure 4 illustrates a distilled BN model trained from a business table in an online ByteHouse cluster for analyzing the advertising placement strategy. The columns of the table are structured as a tree, with Target Platform as the root node and Content Type as a dependent child node. The adjacent CPDs depicts the dependence between those columns. The CPD of Target Platform is a 1D vector, while the CPD of Content Type and Target Platform are 2D matrices to capture the probabilistic relationships between the columns.

The inference algorithm for single-table cardinality estimation is based on the method of variable elimination (VE) [28]. Applying VE for BNs should avoid potential data races in multi-threaded environments. To address this issue, ByteCard proposes two key techniques to the initContext interface, which are:

- (1) **Root Identification:** The VE algorithm initiates at the root node and moves towards the leaves, involving a probability message passing down the tree to update distributions at each level. In order to prevent data races between query threads and enable high-concurrency inference invocations in multi-threaded query processing environments, we can achieve this by identifying the root of each model and making it immutable in the initContext interface, instead of using a global lock for the entire model.
- (2) **CPD Indexing:** The execution of single-table model inference, conducted via the estimate interface, requires frequent accesses to the values of probabilities in the CPDs. The CPDs are often located in the tree structure’s nodes. However, it is inefficient to perform repeated traversal of the tree to access CPDs during inference. To address the issue, the tree structures with CPDs are transformed into an array indexed according to the topological order of nodes. This array also records the information of nodes’ children for convenient reference. As illustrated in Figure 4, the root node Target Platform is assigned an index of 1, with subsequent numbers reflecting the topological order of its children. Meanwhile, the leaf node Duration is assigned an index of 6 without any children. This indexing mechanism, integrated within the initContext interface, enables direct access to any CPD by its index, thereby eliminating the need for repeated traversal through the tree structure.

### 5.2 The Multi-Table COUNT Model

ByteCard selects the FactorJoin model for multi-table join estimation. FactorJoin employs an approach that integrates single-table models to analyze join key distributions, which subsequently partitions the joint domain of these keys into discrete buckets (i.e., join-buckets). It effectively utilizes a factor graph model to encapsulate these keys within a probabilistic graphical paradigm, which further facilitates the computation of an upper bound on the join sizes. To effectively integrate FactorJoin’s inference algorithm, it is important to invoke the initContext interface of each related

single-table model during the initialization phase. Besides, ByteCard develops two key techniques to facilitate the inference of FactorJoin:

- (1) **Join-Bucket Construction:** Model Preprocessor plays a crucial role in creating join-buckets for FactorJoin, essential for join-size inference on the factor graph. This process relies on two facilities: One is the join schema collected by the step of join collection, as mentioned in Section 4.4. The other one is the equi-height histograms that are built within the optimizer of ByteHouse. Leveraging these resources, Model Preprocessor can construct join-buckets based on the joint value domain of all join keys.
- (2) **Distribution-Dimension Reduction:** A standard fact table with several join keys is common in business scenarios. Inference on the factor graph needs to maintain the joint distribution of these join-keys. However, excessive join-keys in a single table can lead to high distribution dimensionality and increase inference complexity. The solution of FactorJoin is to explore the causality patterns between these join-keys with a tree probabilistic structure, such that the dimensionality of the joint distribution can be effectively reduced. To apply this method, ByteCard leverages the same training procedure of the Chow-Liu algorithm in ModelForge Service. This approach greatly reduces the inference complexity of join-size estimation of fact tables by reducing the distribution dimension.

### 5.3 The COUNT-DISTINCT CardEst Model

ByteCard has chosen RBX as its NDV estimator, which employs a seven-network layer training on the general feature called “frequency profile” of NDV estimation. The “frequency profile” is a compact representation of the frequency distribution of distinct values calculated based on a sample of column data. Although training RBX from the ground up is time-consuming, it usually does not require retraining when facing new workloads. Upon completion of the training, the model weights can be stored in the cloud storage.

To integrate RBX into our framework, ByteCard loads the neural network architecture of RBX into memory during the startup of ByteHouse. Meanwhile, the Model Monitor is responsible for loading the RBX model parameters through the initContext interface. Unlike the frequent loading of Bayesian Networks’ parameters, the RBX model weights are loaded with a relatively lower frequency because of the models’ workload-independent properties.

The featurization process of RBX involves computing an important feature called the “frequency profile”. This task is computationally intensive and can significantly impact the overall inference performance of RBX. In optimization scenarios where real-time NDV estimation is necessary, it is critical to create the “frequency profile” to provide accurate NDV estimates to ByteHouse efficiently. Section 6.2 provides insights into a specific estimation scenario where we apply RBX’s estimation and refine the computation of the “frequency profile”. Once the feature extraction is complete, the main inference computation within the estimate interface involves matrix multiplication operations on the neural network.

## 6 ENHANCED QUERY OPTIMIZATION

This section shows how ByteHouse leverages the accurate cardinality estimates from ByteCard to enhance its query optimization. While the discussion is limited to only two optimization scenarios, ByteCard has the potential to offer broader benefits.

### 6.1 The Cases for Materialization Strategy

We enhance ByteHouse’s previous strategy by introducing a multi-stage reader approach. In contrast to the single-stage reader that retrieves columns and applies predicate filtering in one pass, this approach incrementally constructs tuples through sequential filtering and appending columns. To support different workloads, ByteHouse utilizes different strategies. This approach, together with the integration with ByteCard, enables the materialization strategies to reduce I/O costs during query processing significantly. At last, we will discuss how join-order selection affects the efficiency of materialization strategies.

**6.1.1 Column-Order Selection in Multi-Stage Reader.** In the multi-stage reader, the order to access the required columns is crucial. Specifically, it is beneficial to prioritize highly selective columns to minimize I/O overhead in subsequent stages. The strength of learned CardEst models is their capability to capture cross-column correlations, which is challenging for traditional histogram-based approaches. Although the independent storage of each column in ByteHouse might suggest that cross-column correlations are negligible, this assumption is incorrect in certain cases.

**Example.** Assume, for contradiction, that the selection order of columns, despite their cross-column correlations, has no substantial effect on I/O overhead. Consider an instance where filters are set as  $col1 > 0$  AND  $col2 > 0$  AND  $col3 > 0$ , with  $col1$  independent of  $col2$  and  $col3$ , which are strongly correlated ( $col2 = col3 + 2$ ). This assumption leads to  $prob(col2 > 0) \leq prob(col2 > -2) = prob(col3 > 0)$ . Assuming  $prob(col1 > 0) = 0.7$ ,  $prob(col2 > 0) = 0.6$  and  $prob(col3 > 0) = 0.8$ , a straightforward selectivity estimation would prioritize  $col2 \rightarrow col1 \rightarrow col3$ . However,  $prob(col2 > 0 \text{ AND } col3 > 0) = prob(col2 > 0) < prob(col1 > 0)$ , suggesting that reading  $col2$  and  $col3$  before  $col1$  would minimize I/Os. This contradicts our initial assumption, proving that the order of column access, especially considering cross-column correlations, critically impacts I/O overhead. Therefore, accounting for these correlations and optimizing the access order of columns is essential to maximize the effectiveness of learned CardEst models.

To exploit the power of learned CardEst, it is necessary to estimate the selectivity of column combinations along with their corresponding predicates. This incurs additional overhead due to the need to enumerate all possible orders of read columns. To mitigate this overhead, we impose the constraints on the enumeration process. Specifically, we early-stop the enumeration if the selectivity of the current generated combination exceeds a predefined threshold. This practice allows us to simplify the enumeration process while leveraging the benefits of learned CardEst models.

**6.1.2 Dynamical Decision of Reader Selection.** No single materialization strategy is universally optimal due to the diversity of analytical workloads. While the multi-stage reader effectively reduces unnecessary reading? I/Os and performs well in most cases,



it has been observed that for some queries, the multi-stage reader might incur more I/Os than its single-stage alternative. These cases often occur when the query predicates are non-selective, requiring the multi-stage reader to go through a significant part of the dataset. This often leads to increased maintenance overhead, as the multi-stage needs to maintain essential processing information across the stages. To select the best materialization strategy for a query, ByteHouse utilizes ByteCard’s cardinality estimates to calculate the query’s overall selectivity. If the overall selectivity of the query is high, ByteHouse will choose the single-stage reader approach. Alternatively, if the overall selectivity is low, ByteHouse will default to the multi-stage reader approach. The single-table CardEst model (i.e., tree-based BN) that we employ proves rather efficient for queries with multiple AND-ed predicates, due to its inherent modeling of joint probability distributions across columns. In practice, ByteCard uses the *inclusion-exclusion* principle to transform OR-ed queries to AND-ed formats before calculating selectivities.

**6.1.3 Join-Size Estimation.** The effectiveness of materialization strategies for multi-table join queries is heavily influenced by two factors: the size of the join and the order in which the joins are performed. The size of the join affects the performance-critical decision of whether to materialize tuples before or after applying the join operation in the query plan [2]. On the other hand, the join order significantly impacts the materialization overhead that occurs during join processing, especially when large tables are involved in early join operations. Therefore, it is crucial to estimate the join size and infer the join order to minimize materialization overhead and improve efficiency. In Section 3, we discussed how ByteCard effectively estimates join size by utilizing FactorJoin, which ensures that the assumption of join-uniformity is avoided, allowing for more accurate estimates. With FactorJoin, ByteCard has already shown considerable promise in reducing materialization overhead and enhancing ByteHouse’s join processing efficiency. Notably, the enhanced accuracy in join size estimation enables ByteHouse to optimize join order, significantly reducing the amount of intermediate results that need to be materialized.

## 6.2 The Cases for Aggregation Processing

This subsection discusses how ByteCard utilizes RBX estimator to optimize the aggregation processing in ByteHouse and how to deal with the cases where the estimator may underperform.

**6.2.1 How RBX can help?** During query processing, *resizing* the aggregation hash table can have an impact on query performance, especially regarding memory management. Therefore, it is essential to have an accurate estimate of the initial size for the hash table. Underestimating the initial size can lead to frequent resizing due to rapid saturation, which can degrade performance. Overestimating the initial size can lead to unnecessary disk spillover or sub-optimal memory utilization.

The estimation of hash table size can benefit from ByteCard’s learned NDV estimator (i.e., RBX), which adapts to the diverse data distributions in different scenarios. This approach differs fundamentally from traditional approaches that use statistics collection in optimizers to calculate NDV estimations for different columns

beforehand. A notable challenge in hash-table size prediction for aggregation processing is that the data amount of aggregated columns can be heavily influenced by ad-hoc predicates, making the pre-computation of NDVs impractical. To estimate the hash table size using RBX, ByteCard needs to construct a key feature (i.e., “frequency profile”) in the featurization interface as mentioned in Section 5. To build this feature, Model Loader loads a small sample (nearly 10 million rows) for each table and converts them into a DataFrame format with a high-performance C++ library. The DataFrame is a mutable two-dimensional table supporting different data types and labeled axes for in-memory computation. This structure enables efficient filtering and calculation of the “frequency profile”. Once the “frequency profile” has been calculated, ByteCard facilitates RBX’s actual inference through the estimate interface.

**6.2.2 Calibration.** While the RBX estimator offers ByteHouse high-accuracy estimation in most cases, it may underestimate NDV when the true number of distinct values in a column is exceptionally high. To address this issue, ByteCard has developed a calibration protocol to fine-tune the estimation of the RBX model. If the Model Monitor detects poor NDV estimates with large Q-Errors of some columns, it will initiate a fine-tuning procedure for the columns that have been identified as problematic in the ModelForge Service. Technically, this procedure augments the original RBX’s training dataset with sampled data from the problematic columns, alongside additional synthetic data characterized by high NDVs. The model is then retrained from the last checkpoint, which is applied in general use cases. For scenarios with exceptionally high NDVs, the retraining process uses a relatively small learning rate and imposes more penalties for underestimation cases. Once the fine-tuning is completed, the refined neural network parameters are saved in the cloud. Later, Model Loader makes use of these parameters to build a calibrated model. It is worth mentioning that these updated parameters are specifically trained to adjust and calibrate only the problematic columns.

## 7 PERFORMANCE EVALUATION

This section evaluates ByteCard’s effectiveness with workloads from academic and industrial datasets. We begin our evaluation by analyzing how ByteCard enhances the query processing of ByteHouse across different workloads. This end-to-end evaluation proves the practical benefits of the proposed framework. Then, we analyze this improvement from the system’s perspective, focusing on metrics like reading I/Os. Finally, we examine the accuracy of ByteCard’s cardinality estimates from the algorithm’s perspective and provide further observations on ByteCard’s models.

### 7.1 Experimental Setup

All experiments are conducted on a large-scale ByteHouse cluster with the specifications detailed in Table 4.

**Datasets.** We utilize three datasets: IMDB [31], STATS [20] from the academic community, and AEOLUS from our internal business scenario. The original sizes of the two academic datasets are relatively small, so we scale them to 1TB using the method proposed in [23]. This scaling method preserves the original data distribution, making it easy to calculate the actual cardinality.

**Table 4: Machine and Cluster setup.**

CPU	Intel(R) Xeon(R) Gold 6230 (CPU @ 2.10GHz and 75 cores)
Memory	300 G
Network	10Gbps Ethernet
OS	Debian 9 (Linux Kernel Version 5.4.56)
Cache	55M shared L3 cache
Server	1
Compute-Worker	8
Ingestor-Worker	8

**Table 5: Workload Statistics.**

	JOB-Hybrid	STATS-Hybrid	AEOLUS-Online
# of queries	100	200	200
# of join templates	23	70	-
# of joined tables	2-5	2-8	2-5
# of group-by keys	1-2	1-2	2-4
range of true cardinality	$9 \cdot 10^3 - 9 \cdot 10^{12}$	$5.2 \cdot 10^4 - 4.4 \cdot 10^{12}$	$7 \cdot 10^3 - 4.7 \cdot 10^{11}$
# of queries hit the max joined-table	31	6	7
# of queries hit the max group-by key	11	13	50

**Workloads.** We choose the JOB-LIGHT [27] and STATS-CEB [20] workloads for the IMDB and STATS dataset as they are the latest benchmark sufficiently complex to evaluate CardEst methods. To evaluate the performance of aggregation processing, we manually extend the original workloads by adding queries that reflect practical analytical usage. These queries, together with the original ones, created new workloads called JOB-Hybrid and STATS-Hybrid. For instance, the aggregation queries for the STATS dataset include an average score of user posts and several comments per post by year. For the AEOLUS dataset, we use a workload called AEOLUS-Online from an online business scenario. The workload includes five business tables and features a mix of various join and aggregation queries. The statistical information of the three workloads is presented in Table 5.

## 7.2 Query Latency

We compare end-to-end query performance between two traditional CardEst methods and ByteCard on the three workloads. The first method leverages sketch-based algorithms (Histogram and HyperLogLog) with pre-computed sketches for each dataset. The second is sample-based, akin to AnalyticDB’s approach [60]. We standardize sample rates and the degree of parallelisms across methods for a fair comparison and disable query caching in all experiments to ensure unbiased results. The results are plotted in Figure 6, with latency normalized against the highest value in each plot. The figure illustrates the 50th, 75th, 90th, and 99th percentile query latency across three workloads. For each workload, ByteCard demonstrates the optimal latency almost at all quantiles. This efficiency is due to its accurate cardinality estimates, which are applied in performance-critical execution paths in ByteHouse, particularly in materialization strategies and join-order selection.

At the lower latency quantiles, the sketch-based method performs better than the sample-based method, while ByteCard exhibits comparable efficiency. The sample-based approach shows sub-optimal performance due to the need for predicate computation

during real-time sampling. This process incurs significant overhead in the cardinality estimation stage, a limitation not present in the other two methods. At higher quantiles of latency, ByteCard outperforms traditional methods, especially in terms of the P99 latency of the STATS-Hybrid workload, improving it by at least 30%. This improvement is attributed to ByteCard’s selection of lightweight models, which provide high-accuracy cardinality estimation and benefit from efficient inference procedures. The STATS workload presents a complex data distribution, which poses a challenge for traditional methods to deliver accurate cardinality estimates. Therefore, the marked enhancement of the STATS workload is due to ByteCard’s ability to overcome this challenge.

## 7.3 System Analysis

We examine the system’s perspective to see how ByteCard improves query latency across different workloads. In our experiment, we split the STATS and AEOLUS datasets, train models at each scale, and evaluate ByteCard’s impact on reducing reading I/Os and hash table resizing during aggregation processing.

**Reading I/Os.** Figure 6(a) illustrates the reading I/Os for processing the STATS-Hybrid workload across STATS’ different scales, with the results normalized to the observed largest size. In smaller data scales, the sketch-based method aids ByteHouse’s materialization strategy in reducing reading I/Os more effectively than the sample-based method, owing to its relatively accurate estimates. However, as the data scale enlarges, the sketch-based method’s performance deteriorates due to its reliance on simplified assumptions. In contrast, the sample-based method delivers more accurate estimations in larger data scales, benefiting from its flexibility and adaptability to changing data patterns. Despite these advantages, both traditional methods are surpassed by ByteCard. ByteCard’s superiority is attributed to its ability to capture cross-column and cross-table correlations, utilizing Bayesian Networks and FactorJoin. Thus, ByteCard guides the materialization strategy for ByteHouse to minimize reading I/Os more effectively.

**Resizing Frequency.** Figure 6(b) displays the frequency of hash table resizing during the aggregation processing of the AEOLUS dataset at different scales. The sketch-based method, specifically HyperLogLog, fails to provide NDV estimation effectively in such a dynamic scenario; the sample-based method has significant overhead due to its real-time requirement to evaluate query predicates. Considering the given limitations, neither of the methods is considered appropriate for scenarios involving aggregation processing. As a result, our analysis is limited to evaluating whether enabling ByteCard in ByteHouse would reduce resizing frequency. The results revealed by Figure 6(b) emphasize the efficiency of RBX’s integration in significantly reducing the necessity for hash table resizing during the aggregation processing of ByteHouse, showcasing its superior performance and adaptability.

Note, RBX’s workload-independent nature eliminates the requirement of separate model training for each dataset scale. As the data scale enlarges, resizing frequency rapidly increases in the absence of ByteCard. In contrast, by utilizing RBX’s estimates, ByteHouse shows remarkable effectiveness in significantly reducing the frequency of hash table resizing, even amidst escalating data scales. This highlights the effectiveness of RBX in dynamically adjusting to

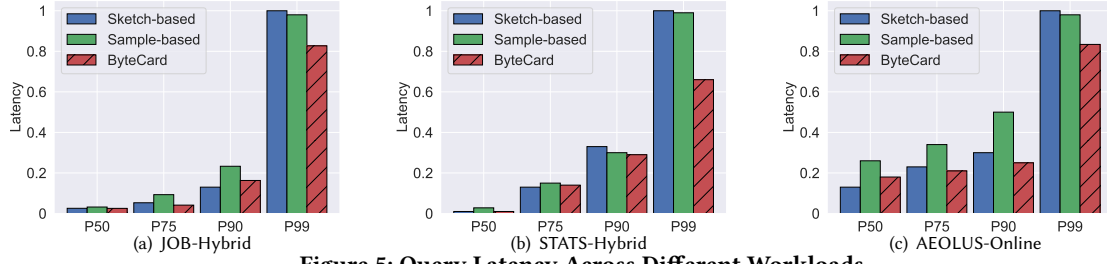


Figure 5: Query Latency Across Different Workloads

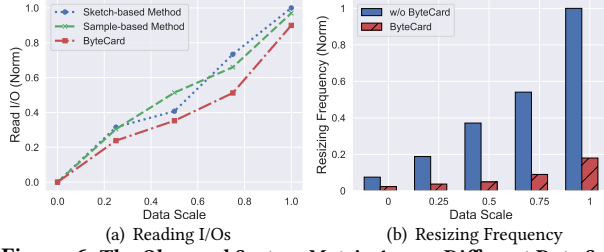


Figure 6: The Observed System Metric Across Different Data Scales

various data volumes, thereby enhancing ByteCard’s effectiveness in memory management during aggregation processing.

#### 7.4 Algorithmic Observations

In this set of experiments, we delve into an algorithmic perspective to evaluate the estimation accuracy of ByteCard. Then, we examine the resource consumption of the models employed by ByteCard, focusing on model size and training time.

**Q-Error.** Figure 7 presents the Q-Errors using violin plots. For all the distributions of Q-Errors, we can see that most are concentrated on smaller values indicated by the width of the violin. The white line in the middle of the box inside each violin represents the median of Q-Error, while the black rectangle shows the interquartile range (the middle 50% of the values). When it comes to the critical aspects of the plots, such as the median of Q-Errors and interquartile range, traditional methods and ByteCard exhibit different characteristics.

The median Q-Error of ByteCard across all the workloads achieves the lowest value among the three evaluated methods. Its interquartile range is also relatively lower than the two traditional methods. For JOB-Hybrid, the sketch-based method’s median Q-Error is comparable to that of the sample-based method but exhibits poorer performance at higher quantiles. For STATS-Hybrid, the sketch-based method’s performance deteriorates further, attributable to STATS’s more complex data distribution and the larger query space of STATS-Hybrid. In the case of AEOLUS-Online, the sample-based method demonstrates limited robustness, primarily due to the complexity of business queries, which hinders accurate estimates from small samples. Interestingly, in some cases, the sample-based method demonstrates better Q-Errors than the sketch-based method. Yet, it does not translate into superior end-to-end query performance. This paradox arises because the improved cardinality estimation of the sample-based method comes at the expense of increased estimation overhead. This result emphasizes why ByteCard prioritizes models that offer high-accuracy estimation and efficient inference. Owing

Table 6: Details of ByteCard’s Models Per Table

Dataset	Method	Model Size	Training Time
IMDB	BN	3.6 Mb	2.5 min
	FactorJoin	2.9 Mb	1.9 min
	RBX	256 Kb	-
STATS	BN	4.2 Mb	3.1 min
	FactorJoin	2.3 Mb	0.8 min
	RBX	256 Kb	-
AEOLUS	BN	4.3 Mb	2.2 min
	FactorJoin	3.6 Mb	1.7 min
	RBX	534Kb	57 min

to this strategy of model selection and the Inference Engine abstraction for efficiently integrating the inference algorithms, ByteCard consistently achieves the best Q-Errors across all workloads.

**Model Details.** Table 6 contains information on the average size and training time of ByteCard’s models, including Bayesian Networks extracted from the ModelForge Service. The table also shows details about FactorJoin, including the size of the *join-buckets* and their construction time as the training time. We can see both models maintain a compact size, below 5 Mb. When integrated into ByteHouse, these models result in a moderate increase in memory footprint, but this expansion does not impose a substantial resource burden on the system. The RBX model doesn’t require recording of training time for IMDB and STATS datasets as it’s workload-independent and needs only a single offline training session. Thus, the model size remains consistent across these datasets. While RBX is generally effective, it faces challenges with columns in AEOLUS’s tables with exceptionally high NDVs. To mitigate this, a calibration protocol involving model fine-tuning is developed. During the fine-tuning process in ModelForge Service, the learning rate is reduced which leads to slower convergence. Fine-tuning for a single problematic column can take up to an hour. Note, this does not compromise ByteHouse’s stability. This is because the fine-tuning process is executed in ModelForge Service, which does not impact ByteHouse’s query processing. Besides, if Model Monitor identifies poor NDV estimates from RBX models for specific columns, it instructs ByteHouse to switch to a traditional NDV estimator. ByteCard only integrates a new RBX model for estimating these problematic columns once Model Monitor has validated the calibrated parameters.

## 8 LESSONS AND FUTURE DIRECTIONS

**Limitations of Learned CardEst Methods:** While learned cardinality estimators have considerable promise in improving ByteHouse, their deployment can sometimes lead to sub-optimal performance owing to several factors. Firstly, the complexity of data

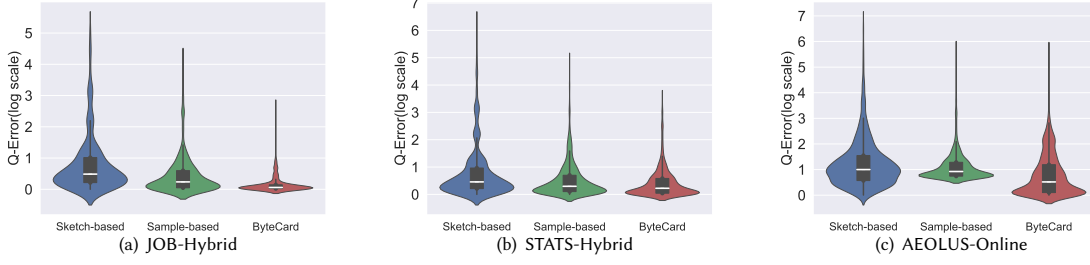


Figure 7: The Observed Algorithm Metric Across Different Workloads

distributions and the diversity of query workloads across different scenarios pose substantial challenges to achieving accurate cardinality estimates. This means that no single model can perform well in all scenarios. For example, BayesCard, which is one of the models adopted by FactorJoin, is prone to underestimate large true cardinalities in comparison to its alternatives [20]. Therefore, we plan to further explore emerging approaches such as meta-learning [22, 23, 57] to tackle the challenge. Secondly, current estimators are limited by their focus on base tables, requiring research that synergizes ML with the Cascades framework [18], which is foundational in modern query optimizers. The Cascades framework typically employs the memogroup [30], a base abstraction for organizing logically equivalent query plans or expressions. We recommend constructing CardEst models around the memogroup, which plays an essential role in exploring potential query plans. Thirdly, achieving accurate cardinality estimation does not ensure optimal system performance. Other critical factors, like cost estimation, also influence the overall system efficiency. The intricacy of systems and the fluctuating nature of cloud environments [40, 45] render accurate cost modeling of query plans difficult despite having accurate cardinality estimates. Our future work will explore more opportunities for ML to enhance ByteHouse’s query processing [45, 46].

**Model Preference for ML-enhanced Components:** Unlike approaches like knob tuning [43, 51, 61, 62], materialized view recommendations [19, 34], and others that apply ML for external logical tuning [43, 51, 61], ByteCard is an ML-enhanced component embedded in the core of system, aiming at the physical (in-kernel) optimization. When it comes to physical optimization, it is important to establish different criteria for model selection than those used in learning-based logical tuning approaches. Unlike logical tuning where ML serves mainly as an intelligent advisor, physical optimization demands direct integration into the system core, necessitating different considerations for model selection. For model selection in physical optimization tasks, we suggest prioritizing models that can perform fast inference. This means preferring models that are both compact and accurate over more complex options, such as large language models (LLMs) [5, 53]. Large models require extensive training and resources, which make them impractical for physical optimization tasks where efficiency and speed are crucial.

**Future Integration of More ML-Enhanced Components:** Integrating ML-enhanced components into database systems requires a thoughtful design, as different models have their unique characteristics. In a tightly coupled architecture, both model training and

inference processes should work in the kernel. However, this approach limits the framework’s ability to evaluate emerging learned approaches. Besides, developing both training and inference algorithms using the same native language of system development requires significant engineering effort. In this work, we showcase an engineering example of deploying learned cardinality estimators with ByteCard by integrating the training algorithms in a standalone service and embedding the inference algorithms in the system kernel. Our ongoing work aims to deploy more ML-enhanced components, such as learned cost estimators, into our system. Unlike cardinality estimators, cost estimators usually employ query-driven approaches to improve their estimate performance. These models, such as XGBoost [39] and Elastic Net [45], require runtime traces or query plan statistics for training. To integrate the training algorithms for the learned cost estimators, ModelForge Service can trigger the training process after retrieving query logs collected from ByteHouse. To integrate inference algorithms into our system, we need to avoid Python implementations that may negatively affect query performance. Fortunately, the interface provided by Inference Engine standardizes the integration process of inference algorithms. When loading cost models, we can follow the existing process for CardEst models. However, the initialization and validation stages require customized developments for each model. It’s important to identify immutable data structures to prevent any potential data race during query processing.

## 9 CONCLUSIONS

ByteCard is a novel framework that aims to integrate learned cardinality estimators into ByteDance’s data warehouse system, ByteHouse. The framework’s design comprises Inference Engine and ModelForge Service, which enable efficient model training and inference, thus improving query processing without overburdening ByteHouse’s computational resources. This work paves the way for ByteHouse’s future integration of more ML-enhanced components.

## ACKNOWLEDGMENTS

Thanks to anonymous reviewers for feedback and to former colleague Duc Canh Le for contributing to early development of ByteCard prototype. This work is supported by NSFC 62202171, Fundamental Research Funds for the Central Universities, Shanghai Pujiang Program (21PJ1403200), and ByteDance-ECNU joint program (PJ20240202900021).



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