

Biathlon: Harnessing Model Resilience for Accelerating ML Inference Pipelines

Chaokun Chang The Chinese University of Hong Kong ckchang@cse.cuhk.edu.hk Eric Lo The Chinese University of Hong Kong ericlo@cse.cuhk.edu.hk Chunxiao Ye The Chinese University of Hong Kong cxye23@cse.cuhk.edu.hk

ABSTRACT

Machine learning inference pipelines commonly encountered in data science and industries often require real-time responsiveness due to their user-facing nature. However, meeting this requirement becomes particularly challenging when certain input features require aggregating a large volume of data online. Recent literature on interpretable machine learning reveals that most machine learning models exhibit a notable degree of resilience to variations in input. This suggests that machine learning models can effectively accommodate approximate input features with minimal discernible impact on accuracy. In this paper, we introduce Biathlon, a novel ML serving system that leverages the inherent resilience of models and determines the optimal degree of approximation for each aggregation feature. This approach enables maximum speedup while ensuring a guaranteed bound on accuracy loss. We evaluate Biathlon on real pipelines from both industry applications and data science competitions, demonstrating its ability to meet real-time latency requirements by achieving 5.3× to 16.6× speedup with almost no accuracy loss.

PVLDB Reference Format:

Chaokun Chang, Eric Lo, and Chunxiao Ye. Biathlon: Harnessing Model Resilience for Accelerating ML Inference Pipelines. PVLDB, 17(10): 2631 -2640, 2024.

doi:10.14778/3675034.3675052

PVLDB Artifact Availability:

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

1 INTRODUCTION

Machine Learning (ML) has gained traction across a diverse array of applications. In the training phase, developers gather data to train their machine learning models. In the serving phase, the trained model is deployed within an *inference pipeline*, which accepts user inputs and carries out real-time model inference.

A typical real-time inference pipeline consists of a series of operations related to *feature preparation*. Generally, there are multiple feature preparation operators responsible for generating features based on runtime inputs. Once all the features are prepared, the model inference operator processes these features as input and produces an inference result that is returned to the user. Despite recent advancements in deep learning, traditional models like Linear Regression, Decision Tree, XGBoost still demonstrate exceptional performance and accuracy on tabular and data science data [36]. In fact, most inference pipelines in Kaggle [38] are using traditional models like random forests and gradient boosting [12, 28, 36, 62]. Traditional models are lightweight in terms of inference cost [44]. The heavy-lifting part of those pipelines, however, often falls on the feature preparation operators when they need to aggregate a large volume of data [10, 86].

Recent literature in the field of machine learning interpretation [52, 63, 64] shows that machine learning models exhibit a notable degree of **resilience** to variations in input. This phenomenon implies that the inference results produced by machine learning models often demonstrate a certain level of stability, even in the presence of imprecise input features. This suggests that machine learning models are capable of accommodating **approximate input features** with **minimal discernible impact on their predictive accuracy**.

Approximately computing input features can yield significant acceleration to an entire inference pipeline by alleviating the data processing burden at its core. Sampling-based approximation query processing (AQP) enables the preparation of aggregation features using a smaller subset of the original dataset [4, 19, 49, 58]. Consequently, this approach offers a powerful means of expediting the feature preparation process within an inference pipeline. However, this endeavor is particularly challenging. First, industrial and data science inference pipelines typically involve multiple input features, each exerting a non-uniform impact on the final inference result. Consequently, determining the appropriate approximation level for each feature becomes a non-trivial task, as their respective influences vary. Second, inference pipelines often comprise a complex flow of inter-dependent operators. Navigating this intricate interplay engenders further complexity when deciding the appropriate approximation level for each feature. The ultimate goal is to strike a delicate balance between maximizing speedup through approximation while maintaining an acceptable level of accuracy loss within permissible bounds.

We propose Biathlon, a new ML real-time serving system that harnesses the resilience of ML models to accelerate the execution of inference pipelines. Biathlon effectively determines the appropriate approximation degree for each feature by considering both its computational cost and its importance in relation to the current inference result. When a feature imposes a high processing burden, Biathlon allocates a higher level of approximation to expedite execution. Conversely, if a feature significantly impacts the inference result, indicating sensitivity to variations in that feature, Biathlon prescribes a lower approximation level to preserve accuracy.

This work is licensed under the Creative Commons BY-NC-ND 4.0 International License. Visit https://creativecommons.org/licenses/by-nc-nd/4.0/ to view a copy of this license. For any use beyond those covered by this license, obtain permission by emailing info@vldb.org. Copyright is held by the owner/author(s). Publication rights licensed to the VLDB Endowment.

Proceedings of the VLDB Endowment, Vol. 17, No. 10 ISSN 2150-8097. doi:10.14778/3675034.3675052



Figure 1: Decision tree example

Figure 2: A (simplified) inference pipeline from Kaggle Fig

Figure 3: System Overview of Biathlon

It is imperative to note the importance of a feature is inputsensitive. Specifically, the importance of a feature fluctuates with different input values. This variability stems from the dynamic interaction between features across varied input values. For instance, consider the decision tree in Figure 1. The importance of feature F_3 depends on the value of feature F_1 . When $F_1 \ge 0.8$, F_3 becomes immaterial. Conversely, when $F_1 < 0.8$, F_3 becomes very important. As the importance of a feature to a specific inference result hinges upon its runtime input value, it is implausible to ascertain an approximation degree for each feature offline. Hence, Biathlon uses an online approach to determine the approximation plan during runtime for each individual inference pipeline execution. Specifically, Biathlon incrementally extracts samples to approximate the feature values and hence the model output. During the process, it also estimates the importance of features using the samples. By utilizing these estimates, Biathlon incrementally refines the approximation plan to draw more samples and early-stops once the model output is statistically guaranteed to be correct.

Biathlon exhibits broad applicability across various ML models. For models with discrete output (e.g., classification), Biathlon provides a probabilistic guarantee that the inference result obtained using its approach is identical to the inference result derived using exact features. For models with continuous output (e.g., regression), Biathlon ensures a probabilistic guarantee that the inference result lies within a bounded error relative to the inference outcome produced with exact features. This characteristic makes Biathlon a versatile solution for enhancing the performance of a wide variety of ML inference pipelines. To demonstrate the efficacy of Biathlon, we conducted a comprehensive evaluation on real inference pipelines, originating from both industry applications and data science competitions. Biathlon successfully harnesses the pipeline model resiliency to offer 5.3× and 16.6× speedup, without noticeable degradation in accuracy.

2 BACKGROUND

A machine learning inference pipeline is often a workflow of operators collective for feature preparation and model inference. Typical operators include:

Datastore Operators: These operators involve external data access such as querying a database. Some datastore operators are lightweight, particularly when suitable indexes are available (e.g., retrieving the gender of a user based on their unique user ID). Some are heavyweight, requiring the retrieval of significant

amounts of data for aggregation (e.g., counting the number of clicks in a user group that shares common interests with the current user).

- (2) Transformation Operators: These operators are responsible for transforming the data. They require no external data access and are lightweight. Examples of such transformations include Standard Scaling, One-Hot Encoding, and N-gram.
- (3) Model Inference Operators: A model inference operator is the terminal operator that ends a pipeline and generates a prediction result. Inferences based on traditional models such as Linear Regression (LR), Support Vector Machines (SVM), and tree-based models like XGBoost and LightGBM are not computationally expensive [44]. Our experiments demonstrate that model inference operations typically execute in milliseconds, falling within the same ballpark as lightweight datastore lookup and data transformations.

Figure 2 shows an inference pipeline from Kaggle [38], simplified for illustration purpose. This example pipeline consists of five feature preparation operators collectively forming three feature preparation sub-pipelines, each yielding a distinct feature utilized in model inference. The data tables in the pipeline have different update frequencies.

To address the aggregation bottleneck in real-time inference pipelines, industries such as Databricks[16], Vertex AI [26], and Tecton [24] often pre-aggregates some features offline. These preaggregated features are stored in specialized databases commonly known as "feature stores" [6, 23, 24, 35] for subsequent online usage. However, the utilization of feature stores inherently introduces space overhead and a certain degree of staleness to the features. This staleness can potentially result in unbounded errors in the inference results.

RALF [82] is an optimized feature store. To reduce errors resulting from potentially stale features, it periodically selects a subset of features to refresh based on a cost budget. RALF assumes the error of each prediction can be promptly obtained and leverages those errors to establish a feedback loop, determining when to reuse a cached feature and when to refresh and recompute a feature. Unfortunately, not many ML pipelines can obtain the error of each prediction promptly. For instance, in the Trip-Fare pipeline we used in our experiments, the error of a trip-fare prediction can only be obtained after the trip has concluded, which may take minutes or even hours. In such cases, RALF often fails to establish an effective feedback loop due to lagged information, resulting in noticeable accuracy loss caused by stale features.

Willump [44] exploits the statistical properties of machine learning models within inference pipelines to reduce the cost of feature preparation. Willump constructs and utilizes an approximate model for simple inputs, and only uses the original model for complex inputs. The approximate model requires fewer features as inputs, directly cutting the cost of feature preparation. However, training the approximation model may pose challenges as it requires access to the training set, which voids all use cases whose training data are not available (e.g., the use of pre-trained models).

Biathlon distinguishes itself as a pioneer in accelerating inference pipelines by taking a different approach from Willump. Instead of approximating the model, Biathlon focuses on approximating the features. Approximating the computation of expensive aggregates belongs to a well-established topic called Approximate Query Processing (AQP). The key, however, lies in determining the appropriate level of approximation for each feature, balancing between maximum speedup and minimal prediction accuracy loss. Biathlon leverages the inherent resilience found in machine learning models to address this challenge.

2.1 Approximate Query Processing

Approximate Query Processing (AQP) is a prominent technique employed to swiftly return approximate responses for queries necessitating the processing of a large volume of data [4, 19, 49, 58].

Sampling has been the most prevalent AQP approach [4, 19, 20, 32, 39, 48, 58], owing to its three pivotal characteristics: (1) *generality*, enabling its broad applicability across a diverse spectrum of aggregation operators encompassing distributive and holistic aggregation; (2) *simple*, requiring solely the specification of a sample size to work; and (3) *theoretical guarantees*, providing bounds to the approximation results.

Sampling-based AQP methods are predominantly dichotomized based on the employed sampling algorithm. AQP based on *uniform sampling* [19, 20, 32, 39, 48, 85] selects samples in a randomized fashion. This method offers several advantages: it is workloadindependent and necessitates no data preprocessing. On the contrary, AQP based on *biased sampling* [4, 58] selects samples based on historical workloads, endowing certain records with a higher likelihood of selection. While biased sampling typically demands a smaller number of samples, it is constrained by its reliance on past workloads and susceptibility to workload shifts.

Online Aggregation [20, 32] incrementally draw samples until the estimated error of the aggregation result attains the specified accuracy target. Online aggregation can support standard statistics like SUM, COUNT, AVG, VAR, STD, MEDIAN, and QUANTILE. However, it cannot support TOP-K, DISTINCT, and extreme statistics MIN and MAX. Conversely, systems that draw (biased) samples offline based on historical workloads do not have an online sampling overhead [4] and support more operators. However, their approximated answers do not necessarily meet the user-specified accuracy target.

Recent advancements in AQP train ML models to replace biased samples, resulting in improved estimation accuracy [34, 51, 59]. However, this approach is still prone to workload shifts and agnostic to user-specified accuracy targets. Biathlon is an ML serving system that utilizes online aggregation to approximate expensive features. Instead of specifying an accuracy target for the aggregation operators, Biathlon specifies the accuracy target for the final prediction result and "back-propagates" this target to determine the accuracy targets for individual upstream aggregate operators by considering their importance and processing costs.

2.2 Feature Importance

In machine learning, Feature Importance plays a significant role in various aspects such as Feature Selection, ML Interpretability, and ML security. For instance, the concept of "permutation importance" [60] is commonly used to measure the importance of a feature. It is defined as the decrease in a model's score when the values of that feature are randomly shuffled. By permuting the feature values, the relationship between the feature and the target is disrupted, and the resulting drop in the model score indicates the extent to which the model relies on that particular feature.

In Feature Selection, models can be built using only features with positive importance scores [8]. In Explainable AI, feature importance scores can be used to interpret specific inference outcomes derived from machine learning models [50, 63, 64, 71]. In Adversarial Machine Learning, evasion attacks [27] involve carefully preparing adversarial examples to cause mis-classification during inference time. Feature importance can guide the search for adversarial examples by identifying critical features [80].

To the best of our knowledge, Biathlon represents a pioneering effort in utilizing feature importance to derive approximation plans for accelerating the execution of inference pipelines.

3 BIATHLON

Given an unoptimized inference pipeline *G*, pipeline inputs (e.g., user ID), an error bound δ , and a confidence level τ , the goal of Biathlon is to execute *G* to obtain an inference result \hat{y} that satisfies the accuracy guarantee specified in Equation 1, with minimal execution cost:

$$Pr(|Y - \hat{y}| \le \delta) \ge \tau \tag{1}$$

where *Y* represents the inference result without Biathlon's optimization (i.e. computing all features exactly).

It is noteworthy that for classification pipelines, the value δ must be 0. Equation 1 intuitively guarantees that the deviation of the inference result obtained using Biathlon from the actual inference result will not exceed δ with at least τ confidence. The execution cost of the inference pipeline is:

$$C^{z} = ||z||_{1} = z_{1} + z_{2} + \dots + z_{k}$$
⁽²⁾

where $z = [z_1, \dots, z_k]$ is the *approximation plan*, a vector that denotes the sample size z_j for each feature, with z_j not exceeding the total number of records N_j for that feature, i.e. $0 \le z_j \le N_j$.

Currently, Biathlon only approximates features that are computed by expensive aggregation operators. We do not approximate other operators (e.g., scaling) because their cost is relatively low compared to aggregation. Inheriting the limitation from online aggregation [3, 19, 20, 32, 39, 48, 85], Biathlon does not approximate TOP-K, DISTINCT, MIN, and MAX. So, k is the number of aggregation features approximated by Biathlon, and C^z is the cost of executing the pipeline according to *z*, measured in terms of the total number of samples across all aggregation features.

The optimal approximation plan z^* in Biathlon is the one that satisfies Equation 1 with the minimal cost C^* . However, similar to many query optimization problems, finding the optimal plan outright without knowing the exact inference result *Y* is infeasible. Consequently, Biathlon adopts an iterative algorithm to progressively approach Equation 1 step by step.

3.1 Workflow of Biathlon

Figure 3 illustrates the workflow of Biathlon. Biathlon comprises two components: (1) The *Planner*, responsible for devising an approximation plan online for the execution of the inference pipeline, and (2) The *Executor*, tasked with executing the inference pipeline approximately in accordance with the plan proposed by the Planner.

Biathlon, when receiving an inference request from a user, begins with the Planner formulating an initial plan z^0 of initial samples for each input feature. The Executor then utilizes this plan for execution.

The execution process within the Executor can be divided into two stages: Approximate Feature Computation (AFC) and Approximate Model Inference (AMI). During the AFC stage, the Executor computes the values of approximate features \hat{x} and estimates their feature uncertainties U_{x} . In the subsequent AMI stage, the Executor performs model inference using the approximate features \hat{x} to obtain the approximate inference result \hat{y} and estimates its inference uncertainty U_{y} . Subsequently, Biathlon performs a validation check to determine whether the current inference result \hat{y} aligns with the specified requirement in Equation 1. Specifically, given the inference uncertainty U_u , we can calculate the cumulative probability that U_u falls within the error interval $(-\delta, \delta)$. If the cumulative probability area within $(-\delta, \delta)$ is greater than or equal to τ , then the condition in Equation 1 is met, and Biathlon would return the approximate inference result \hat{y} to the users. Otherwise, Biathlon initiates a feedback loop and channels (\hat{x}, U_x) and (\hat{y}, U_y) back to the Planner to devise a new approximation plan z^1 for the next iteration of execution. Biathlon continues iterating through the feedback loop and draw more samples until the user obtains an inference result whose inference uncertainty meets Equation 1. In other words, although unlikely, Biathlon may need to draw all samples to compute the exact feature in order to satisfy Equation 1 when confronted with worst-case scenarios (e.g., malicious data distributions).

3.2 Approximate Feature Computation (AFC)

In this stage, Biathlon calculates the values of the features. For non-targeting features, Biathlon computes their exact values. In the case of targeting aggregation feature *j*, Biathlon operates similarly to online aggregation, providing efficient estimations for the aggregation values through a three-step process.

First, Biathlon randomly selects a sample S_j of size z_j for attribute *j* according to the approximation plan *z*. Next, Biathlon estimates the approximate value of feature *j* using sample S_j . This process resembles existing sampling-based AQP techniques. Initially, the aggregation operator θ_j is applied to its input from the

selected sample S_j . The resulting aggregation is then scaled to obtain an estimate of the true aggregation value on the entire dataset, denoted as $\hat{x}_j = \kappa_j(\theta_j(S_j))$. Here, κ_j represents the scaling operator specific to feature *j*. Lastly, Biathlon estimates the uncertainties U_x of the approximated features.

In contrast to traditional AQP systems that employ statistics (e.g., standard deviation) to quantify result uncertainty, Biathlon directly employs the error distribution between the approximate feature and the exact feature to capture the estimation uncertainty U_x . This approach is chosen because, unlike online aggregation, the approximation results here serve as intermediate results rather than final results. Therefore, it aims to preserve as much information as possible for estimating the inference uncertainty U_u later.

In Biathlon, for standard conditional aggregation operators that can be supported by AQP, including SUM, COUNT, AVG, VAR, and STD, we adhere to the approach proposed in [53] by setting the error distribution of the approximate aggregation U_x as a normal distribution. Consequently, estimating U_x involves finding the mean μ and standard deviation σ of the error distribution. The mean μ is 0 since sampling-based AQP can provide unbiased estimation. For holistic measures like MEDIAN and QUANTILE, we use Empirical Bootstrap [22, 61] to obtain an empirical distribution.

Online aggregation eliminates the need for data pre-processing, enabling Biathlon to handle very dynamic data. Furthermore, online aggregation draws samples incrementally, which avoids repeated data access when AFC is triggered multiple times with different approximation plans before Biathlon stops. With this design, if Biathlon is unsatisfied with the inference result and the planner suggests to increase the sample size of a selected feature from from z_j to z'_j , the Executor can incrementally draw $(z'_j - z_j)$ new samples instead of drawing z'_j samples from scratch. This incremental computation mechanism effectively avoids redundant data access and works for most aggregation operators, including both distributive measures and holistic measures [25, 81].

3.3 Approximate Model Inference (AMI)

The AMI stage in Biathlon serves a dual purpose: (1) computing the (approximate) inference result \hat{y} using the approximate features and (2) estimating the uncertainty of the approximate inference result U_{y} .

Computing the approximate inference result \hat{y} is straightforward – Biathlon directly incorporates the approximate feature values \hat{x} into the model inference operator to derive the approximate inference result: $\hat{y} = \mathcal{M}(\hat{x})$, where \mathcal{M} represents the model inference operator. In Biathlon, the error of the inference result refers to the discrepancy between the approximate and the exact inference results. Hence, given the uncertainty of input features U_x , estimating the uncertainty of inference result U_y is actually a problem known as *uncertainty propagation* (UP) [65].

There are two types of methods to solve the UP problem: analytical methods and black-box methods. The former is contingent upon the availability of model-specific closed-form formulas, limiting its applicability to simple models like Linear Regression and rendering it unsuitable for Biathlon's objective of supporting a diverse array of models. Consequently, Biathlon addresses the UP problem through a black-box method based on Monte Carlo simulations (MCS). While alternative black-box methods [46] exist, they lack the flexibility of MCS and often suffer from the curse of dimensionality. Standard Monte Carlo methods, however, are computationally intensive due to sampling inefficiency. Hence, Biathlon employs *quasi-Monte Carlo (QMC)* [9], harnessing low-discrepancy sequences to uniformly cover the input space, thereby achieving comparable estimation accuracy with fewer samples.

Based on QMC, Biathlon estimates the uncertainty of the inference result U_{y} in four steps.

- Generate *m* i.i.d. feature samples x¹,..., x^m, with xⁱ = U_x + x̂. Each xⁱ still follows a normal distribution as U_x. Note that the *m* feature samples are generated using a low-discrepancy sequence [72], also referred to as a quasi-random sequence, to achieve fast convergence.
- (2) Conduct model inference on the generated feature samples, yielding *m* inference samples y¹, · · · , y^m, where yⁱ = M(xⁱ).
- (3) Model the distribution of the true inference result *Y* based on the ensemble of *m* inference samples. In the case of a regression model, the distribution of *Y* follows a normal distribution $N(\bar{y}, \sigma_y^2)$, where $\bar{y} = E(Y) \simeq \frac{1}{m} \sum_{i=1}^m y^i$, and $\sigma_y^2 = E((Y-\bar{y})^2) \simeq \frac{1}{m} \sum_{i=1}^m (y^i - \hat{y})^2$. Alternatively, if the model is a classification model, the distribution of *Y* is a categorical distribution, requiring estimation of the probabilities of all possible classes using their frequencies in the inference samples. The probability of class *j* is estimated as $p_j = \frac{1}{m} \sum_{i=1}^m I_{y^i=j}$, where *I* is an indicator function that $I_{y=j} = 1$ when y = j and $I_{y=j} = 0$ otherwise.
- (4) Compute the uncertainty, i.e. U_y. By definition, U_y = Y − ŷ. Hence, for regression models, U_y follows a normal distribution U_y ~ N(ÿ − ŷ, σ²_y). On the other hand, for classification models,

 $\begin{array}{l} U_y \text{ follows a Bernoulli distribution } U_y \ \sim \ Bernoulli \left(1-p_{\hat{y}}\right), \\ \text{where } p_{\hat{y}} \text{ denotes the probability of class } \hat{y}, \text{i.e., } p_{\hat{y}} = \frac{1}{m} \sum_{i=1}^m I_{y^i = \hat{y}}. \end{array}$

It is worth highlighting that Monte Carlo methods exhibit a high degree of parallelizability in their computation. Biathlon leverages this property by performing the *m* model inferences simultaneously in parallel. This approach effectively enables efficient estimation of U_y with reduced time requirements. As a side note, Biathlon typically employs parametric methods to model the probability distribution of *Y*. However, if *Y* deviates from the distribution assumption of parametric methods, Biathlon resorts to the use of non-parametric Kernel Density Estimation (KDE) instead.

3.4 Planner

The primary responsibility of the Planner in Biathlon is to determine the approximation plan, denoted as z, at the beginning of each iteration. In the beginning, the Planner initializes the initial plan z^0 using a small percentage α of data records within each feature. Therefore, the initial plan is $z^0 = [\alpha N_1, \dots, \alpha N_k]$, where N_j represents the number of records for feature j. For subsequent iterations i > 0, the Planner determines the next plan z^{i+1} in accordance with Equation 3:

$$z^{i+1} = z^i + \gamma d^i \tag{3}$$

where d^i is a vector denoting the direction of the maximum reduction in inference uncertainty based on the current plan z^i , and γ denotes the *step size*, governing the number of additional samples to allocate in each iteration. Similar to any iterative optimization algorithm, the step size is a hyperparameter. An excessively small step size necessitates additional iterations to fulfill Equation 1, leading to increased overhead from more iterations. Conversely, an excessively large step size may result in an overshoot in terms of execution cost, causing Biathlon to fulfill Equation 1 using an excessively large number of unnecessary samples.

The direction characterized by the maximum reduction in inference uncertainty d^i at z^i is as follows:

$$d^{i} = \arg\max_{\Delta z} \frac{Var(Y|z^{i}) - Var(Y|z^{i} + \Delta z)}{\|\Delta z\|_{1}}$$
(4)

where $Var(Y|z^i)$ represents the variance of the inference result when the approximation plan is z^i , serving as a measure of the current level of inference uncertainty, which can be easily obtained given the inference uncertainty U_y in AMI (Section 3.3).

The vector $\Delta z = [\Delta z_1, \dots, \Delta z_k]$ specifies a direction for adjusting the current plan, with each $\Delta z_j \in \{0, 1\}$ indicating how the sample size for feature *j* should be modified. A value of $\Delta z_j = 0$ signifies no change, while $\Delta z_j = 1$ indicates the acquisition of γ samples, considering the multiplication by the step size. It is pertinent to note that decreasing the sample size for a particular feature is not considered, as Biathlon computes features incrementally, and the execution costs associated with a smaller sample size have already been accounted for in previous iterations. In addition, $\|\Delta z\|_1$ is defined as $\|\Delta z\|_1 = \sum_{j=1}^k \Delta z_j$, reflecting the increase of execution cost in that direction. Finally, we note that d^i is not differentiable as z_i is discrete.

Directly computing d^i is not recommended due to the value of $Var(Y|z^i + \Delta z)$ depends on the execution result of the inference pipeline, requiring 2^k pipeline executions that include expensive aggregations and model inference. Fortunately, we have been able to identify a shortcut to estimate d^i with a closed-form solution. Specifically, given a fixed increased sample Δz , the corresponding variance reduction is related to the importance of the feature whose sample size is increased. The more important the feature is, the more the variance is reduced by having more samples. In machine learning, there are many measures to quantify the importance of a feature, including LIME [63], Shapley Value [71], SHAPE [50], and Sobol Indices [73]. Among those, we use Sobol Indices because they define feature importance exactly based on variance reduction.

Sobol Indices comprise a total of $2^k - 1$ indices with different orders ranging from first-order to *k*-th-order, where *k* denotes the number of features. Among these, there are *k* first-order indices $\{I_1, \dots, I_j, \dots, I_k\}$, also known as the *Main Effect indices*, with I_j measuring the importance of feature *j*. There are $\frac{k(k-1)}{2}$ secondorder indices $\{I_{12}, \dots, I_{ij}, \dots\}$, where I_{ij} quantifies the importance of the interaction between features *i* and *j*, and so forth for higherorder indices. In Biathlon, the first-order Main Effect Indices are sufficient. The Main Effect Index for feature *j* is defined as [73]:

$$I_j = \frac{Var_{X_j}(E_{\neg X_j}(Y|X_j))}{Var(Y)}$$

where X_j represents feature j, and $\neg X_j$ denotes all other features except j. The denominator represents the variance of the

inference result, while the numerator represents the variance of the conditional expectation of Y given X_j , quantifying the proportion of variance contributed by feature j. By the law of total variance, the numerator can also be seen as:

$$Var_{X_j}(E_{\neg X_j}(Y|X_j)) = Var(Y) - E_{X_j}(Var_{\neg X_j}(Y|X_j))$$
(5)

In our context, the denominator of the main effect index for feature *j*, i.e., the variance of the inference, is $Var(Y|z^i)$. The term $E_{X_j}(Var_{\neg X_j}(Y|X_j))$ in Equation 5 represents the expectation of conditional inference variance given X_j , i.e., when X_j is based on all N_j records. In our context, the denominator would then be:

$$Var(Y|z^{l}) - E(Var(Y|z^{l}_{i*}))$$

where z_{j*}^i is the plan $[z_1^i, \dots, N_j, \dots, z_k^i]$ with feature *j* computed using all N_j records. Hence, putting it all together, the importance of feature *j* at plan z^i is:

$$I_j^i = \frac{Var(Y|z^i) - E(Var(Y|z^i_{j*}))}{Var(Y|z^i)}$$
(6)

 I_j^i can also be computed efficiently using the Sobol-Satelli method [68], which is also QMC-based like the one in AMI (Section 3.3). With those feature samples and inference results, we can derive I_j^i for all *j*.

Utilizing the Sobol's Main Effect Index, we can estimate the variance reduction by summing the expected variance reduction caused by each feature. Let $I^i = [I_{1}^i, \cdots, I_k^i]$ denote the Sobol's Main Effect Index vector of all features based on the plan z^i . Each individual I_j^i indicates the expected contribution of feature *j* to the inference variance reduction ratio if *j* becomes exact. Hence, the expected variance reduction would be $Var(Y|z^i) \cdot I_j^i$. Therefore, we can compute the unit reduction per future sample as $\frac{Var(Y|z^i) \cdot I_j^i}{N_j - z_j}$, and the variance reduction caused by giving the next iteration of samples to feature *j* as $\frac{Var(Y|z^i) \cdot I_j^i \cdot \Delta z_j}{N_j - z_j}$. Hence, given Δz , we can estimate the overall inference variance reduction as $\sum_{j=1}^k \frac{I_j^i \Delta z_j}{N_j - z_j} Var(Y|z^i)$, i.e.

$$Var(Y|z^{i}) - Var(Y|z^{i} + \Delta z) \simeq \left(\frac{I^{i}}{N-z}\right)^{T} \Delta z Var(Y|z^{i})$$
(7)

Consequently, we can transform Equation 4 into Equation 8:

$$d^{i} \simeq \arg \max_{\Delta z} \left(\frac{I^{i}}{N-z}\right)^{T} \frac{\Delta z}{\|\Delta z\|_{1}} Var(Y|z^{i})$$

$$= \arg \max_{\Delta z} \left(\frac{I^{i}}{N-z}\right)^{T} \frac{\Delta z}{\|\Delta z\|_{1}} \quad //as \, Var(Y|z^{i}) \text{ is a constant}$$
(8)

where d^i can be solved as a linear fractional programming (LFP) problem with a closed-form solution. Equation 8 has already considered to give a higher degree of approximation for a more expensive feature *j*. Specifically, when *j* is "more expensive", it means N_j is a relatively large number. A larger N_j will lead to a smaller $\frac{I_j^i}{N_j-z_j}$, giving it a smaller chance to qualify as argmax in Equation 8. With d^i from Equation 8, Biathlon can derive the next approximation plan by Equation 3 accordingly.

Table 1: Real Inference Pipelines

Pipeline (Description)	DataSet (Num of Records)	Num of Operators				Num of Features		Num of
		Dat AGG	astore Others	Transfor -mation	Model Inference	AGG	Non- AGG	Requests
Trip-Fare [17] (Predict fare of trip)	NYC Taxi [75] (3B)	2	0	5	LGBM (Regression)	3	5	1940
Tick-Price [55] (Forecast price of tick)	Forex Tick [37] (1.1B)	1	6	0	LR (Regression)	1	6	4740
Battery [42] (Predict remaining charging time)	NASA Battery [67] (7.3M)	5	1	0	LGBM (Regression)	10	1	564
Turbofan [43] (Predict RUL of turbofan)	Turbofan [70] (55M)	9	0	0	Random Forest (Regression)	9	0	769
Bearing-Imbalance [15](Detect Imbalance of bearing)	Machinery [77] (95M)	8	0	0	MLP (Classification)	8	0	338
Fraud-Detection [1] (Detect fraudulent click)	TD Click [74] (242M)	3	0	6	XGB (Classification)	3	6	8603
Student-QA [29] (Predict correctness of a question)	Game Log [18] (26M)	13	0	0	Random Forest (Classification)	21	0	471

4 EVALUATION

We conducted an evaluation of Biathlon on seven real inference pipelines sourced from Kaggle and Feast [23], with the aim of demonstrating its ability to reduce inference latency while keeping accuracy loss within acceptable bounds. Our results show that the use of Biathlon leads to a reduction in inference latency of between $5.3 \times$ and $16.6 \times$ times compared to the baseline, which involves executing the inference pipeline without any approximation. Moreover, we find that Biathlon can maintain accuracy levels within 1% relative to the baseline. We also include RALF [82] in the experiments for comparison. For fair comparison, we give RALF an update cost budget no less than the execution time of Biathlon.

Workload. Despite numerous reports about inference pipelines with expensive aggregations (e.g., [1, 7, 15, 17, 30, 55, 76, 78]), very few of them have their corresponding real data available as open source. The ones in FEBench [86] only include feature preparation operators, without any model (i.e., no trained model nor training labels provided). The ones we used in the evaluation are all publicly available. Their characteristics are described in Table 1. The pipelines perform regression or classification tasks and employ different numbers of features and models. Certain aggregation queries can generate multiple aggregate features (e.g., in Trips-Fare, the same datastore query produces two features: COUNT and AVER-AGE). Each pipeline is also associated with a log of real requests, including information such as user IDs. We execute all the requests and calculate the corresponding averages. All inference pipelines were implemented using Python and Scikit-Learn [60].

System Setup. Biathlon is implemented using Python. We used ClickHouse [13], an open-source OLAP DBMS designed for realtime data analytics with support for online sampling, as our datastore. Nonetheless, it is worth noting that Biathlon is not tied to any specific data store solution and may be used with other databases, such as MySQL, or data analytics frameworks, such as Pandas and Dask, without losing its advantages. All the experiments were run on servers with Intel Xeon E5-2620 CPU (2.1 GHz with 8 physical cores), 256 GB of memory, and 745 GB of Intel DC S3610 Series SSD.

Metrics. To provide a comprehensive evaluation of Biathlon, we run the experiments five times and report the average latency of the system when serving all real user requests, as well as its speedup compared to the baseline. Additionally, we report the accuracy. Unless stated otherwise, the accuracy is measured using the true

label in the hold-out set. We use F1-score and r^2 -score to measure the accuracy of classification and regression pipelines, respectively.

Default Configuration. During the evaluation process, we have employed a default configuration that is shared by all workloads for Biathlon. Specifically, we set the sampling ratio for the initial plan as $\alpha = 0.05$. Following typical online aggregation systems [85], we set the step size γ as 1% of the total number of records across all features. The confidence level τ is set to 0.95. For classification tasks, we set the error bound $\delta = 0$ to ensure precise results. For the regression tasks, we set $\delta = MAE$, where MAE is the mean absolute error of the pre-trained model in the test set. Additionally, we set m = 1000 as the number of samples for QMC.

4.1 End to End Performance

Figure 4 presents the performance evaluation of Biathlon on the seven inference pipelines under the default configuration. The top figure illustrates the latency comparison among the baseline, RALF, and Biathlon on the seven workloads. It is evident that feature computation (FC) is the most time-consuming and dominates the latency of the baseline. The baseline incurs a latency of more than a second on most pipelines, which is not ideal for user-facing applications. Despite their distinct characteristics, running the inference pipelines on Biathlon shows a significant speedup, ranging from $5.3 \times$ to $16.6 \times$. More importantly, Biathlon is able to achieve subsecond real-time response latency on all pipelines. The bottom figure shows the accuracy of each workload in Biathlon. It is evident that Biathlon achieves its real-time latency with almost no accuracy loss with respect to the exact baseline.

RALF, in contrast, despite having very low latency, indeed suffers from accuracy loss and unbounded error. Specifically, as a feature store, RALF generally exhibits lower accuracy in pipelines with frequent updates (Tick-Price). In pipelines with slow error feedback (Trip-Fare and Fraud-Detection), RALF also demonstrates lower accuracy due to the inability to update its feedback loop promptly. Furthermore, in pipelines with many new and unseen items (Battery, TurboFan, Bearing Imbalance and Student-QA), RALF has even poorer accuracy because it would never compute the feature value online. Instead, for any compulsory cache miss [33] (i.e., item that has never been in the cache), RALF would assume a default value for that feature and rely solely on the error feedback loop to select those items for pre-computation in the future. Unfortunately, these pre-computed items are seldom seen again in subsequent requests in those workloads.

Figure 5 shows a breakdown of the latency components for each workload in Biathlon. The breakdown comprises three parts: AFC (which measures the cost of feature preparation), AMI (which considers the cost of model inference and the overhead of QMC in estimating the inference result uncertainty U_y), and Planner (which online devises the new plan based on the inference variance reduction via the computation of the Main Effect Indices of individual features).

Within Biathlon, the majority of latency is still dominated by approximated feature computation (AFC), which involves I/O. However, that time has been significantly reduced when compared with the baseline because only a small fraction of data (about 5.4% to 14.4% according to our profiling) is actually touched. Specifically, the average numbers of iterations consumed by each pipeline, as shown in Figure 5, are all less than 5, indicating all pipelines are able to satisfy Equation 1 and early stop. Furthermore, we also empirically measure the percentage of inference requests whose actual error, i.e., $|Y - \hat{y}|$, falls within our given default error bound δ ($\delta = 0$ for classification, $\delta = MAE$ for regression). We found that all pipelines have 95% to 100% of their inference requests with real errors that fall within the required error bound, perfectly aligning with the specified confidence level $\tau = 0.95$.

4.2 Varying the confidence level τ

In this experiment, we aim to study the impact of the confidence level τ in Equation 1. Since Equation 1 defines the guarantee based on the error between the prediction made by the baseline and the prediction made by Biathlon, here we calculate the accuracy based on using the exact value predicted by the baseline as the oracle label. Figure 6 shows the result of varying τ . It can be observed that the speedup of Biathlon decreases as the required confidence level τ increases. This is expected since Biathlon needs to retrieve more data to achieve a higher level of required confidence. When a confidence level of 1.0 is required, Biathlon necessitates exact features as input and does not provide any speedup. However, apart from that, Biathlon maintains a substantial speedup even when the required confidence level is as high as 0.99. Some pipelines maintain near-perfect accuracy while achieving speedup, irrespective of the confidence level value. For these pipelines, the initial approximation plan produces feature computations that yield sufficiently accurate inference results for the majority of requests. Indeed, there are still improvements in accuracy with higher confidence levels but they are not readily apparent in the figures. For instance, in the Turbofan pipeline, the r^2 -score escalates from 0.9943 to 0.9982 as the confidence level rises from 0.0 to 0.99.

4.3 Varying the error bound δ

In this experiment, we aim to study the impact of the error bound δ in Equation 1. Figure 7 presents the results of speedup and accuracy in relation to varying error bound values δ . Same as the above, the accuracy of Biathlon is calculated using the exact value predicted by the baseline as the oracle label. Only the results of regression pipelines are shown since the others involve classification, which cannot tolerate any error.

From the figure, we can observe that the speedup of Biathlon increases as the tolerable error δ increases. This is expected because a higher value of δ allows Biathlon to satisfy Equation 1 more easily, resulting in fewer data being retrieved. As the error bound δ continues to increase, the speedup eventually remains stable. This is because Biathlon can then easily satisfy Equation 1 after the first iteration when given a very large δ . Subsequently, further increasing δ would not reduce the number of iterations any further.

Increasing the error bound would naturally have a negative effect on accuracy because more results with larger errors can satisfy Equation 1. The Tick-Price pipeline is insensitive to this effect because the samples drawn by Biathlon in the first iteration already provide more than enough samples even for the tightest error bound. Therefore, the relaxation of the error is immaterial for this pipeline.



Figure 6: Varying Confidence Level τ



Figure 7: Varying Error Bound δ (Regression Only).

5 RELATED WORK

Many ML serving systems have been proposed to enhance the execution efficiency of inference pipelines. Some systems focus on simplifying the deployment process through containerized execution [14, 79] and in-application execution [5, 66], while others aim to accelerate model inference via resource-sharing [47], compilation [11, 56], scheduling [47, 83], and caching [47]. Some systems [31, 41, 54, 57, 69] propose integrating machine learning and database into unified frameworks for inference pipelines, thereby facilitating cross-optimization [57] between feature computation operators and inference operators. However, these approaches primarily focus on enabling or optimizing ML inference without leveraging the resilience intrinsic to machine learning models, like how Biathlon did. Some recent systems [2, 21, 44] also leverage some other statistical properties besides resilience to expedite inference pipelines, but are limited to Linear models [2] or lack accuracy guarantee [21, 44]. In general, we do not recommend using Biathlon for deep model pipelines. Deep learning models tend to be computationally expensive compared to traditional non-deep models. Since Biathlon conducts multiple model inferences for each inference request during quasi-Monte Carlo (QMC), the resulting overhead can outweigh the benefits gained from feature approximation. However, it is worth noting that accelerating deep learning pipelines is an

important area of research and there are corresponding solutions available [40, 45, 84].

6 CONCLUSION AND FUTURE WORK

This paper presents Biathlon, an innovative ML serving system specifically tailored for data science and industry inference pipelines. Developed to address the stringent user-facing latency demands of real-time inference, Biathlon incorporates several key components: approximate query processing from the database area to compute feature approximately, uncertainty propagation from statistical analysis to estimate inference uncertainty, feature importance based on Sobol Indices from model interpretability to assess the contribution of individual features to the inference uncertainty, and an iterative optimization algorithm for determining the best approximation plan.

Biathlon offers maximum speedup with a probabilistic guarantee of bounded error and achieves a speedup ranging from $5.3 \times$ to $16.6 \times$ on real pipelines without a noticeable loss in accuracy. Inherited from online aggregation, there are operators that Biathlon does not approximate (e.g., Top-K). We believe that, for such cases, the feature store approach, as demonstrated by RALF, can be a viable alternative. However, it is essential to remark that the feature store approach (including RALF) also has its limitations, such as the absence of error bounds or being restricted to a limited set of workloads. Therefore, we believe that the feature store caching methodology of RALF and our AQP approach can complement each other, opening up an intriguing avenue for future research.

ACKNOWLEDGMENTS

This work is partially supported Hong Kong General Research Fund (14208023), Hong Kong AoE/P-404/18, and the Center for Perceptual and Interactive Intelligence (CPII) Ltd under InnoHK supported by the Innovation and Technology Commission. We also thank Professor Yufei Tao for his insightful comment about this work.

REFERENCES

- 4paradigm. 2023. TalkingData AdTracking Fraud Detection. https: //github.com/4paradigm/OpenMLDB/tree/main/demo/talkingdata-adtrackingfraud-detection
- [2] Deepak Agarwal, Bo Long, Jonathan Traupman, Doris Xin, and Liang Zhang. 2014. LASER: a scalable response prediction platform for online advertising. In Proceedings of the 7th ACM international conference on Web search and data mining. https://doi.org/10.1145/2556195.2556252
- [3] Sameer Agarwal, Henry Milner, Ariel Kleiner, Ameet Talwalkar, Michael Jordan, Samuel Madden, Barzan Mozafari, and Ion Stoica. 2014. Knowing when you're wrong: building fast and reliable approximate query processing systems. In Proceedings of the 2014 ACM SIGMOD International Conference on Management of Data (Snowbird, Utah, USA) (SIGMOD '14). Association for Computing Machinery, New York, NY, USA, 481–492. https://doi.org/10.1145/2588555.2593667
- [4] Sameer Agarwal, Aurojit Panda, Barzan Mozafari, Samuel Madden, and Ion Stoica. 2012. BlinkDB: Queries with Bounded Errors and Bounded Response Times on Very Large Data. arXiv: Databases,arXiv: Databases (Mar 2012).
- [5] Zeeshan Ahmed, Saeed Amizadeh, Mikhail Bilenko, Rogan Carr, Wei-Sheng Chin, Yael Dekel, Xavier Dupre, Vadim Eksarevskiy, Senja Filipi, Tom Finley, Abhishek Goswami, Monte Hoover, Scott Inglis, Matteo Interlandi, Najeeb Kazmi, Gleb Krivosheev, Pete Luferenko, Ivan Matantsev, Sergiy Matusevych, Shahab Moradi, Gani Nazirov, Justin Ormont, Gal Oshri, Artiidoro Pagnoni, Ignesh Parmar, Prabhat Roy, Mohammad Zeeshan Siddiqui, Markus Weimer, Shauheen Zahirazami, and Yiwen Zhu. 2019. Machine Learning at Microsoft with ML.NET. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. https://doi.org/10.1145/3292500.3330667
- [6] Alibaba. 2023. FeatHub A stream-batch unified feature store for real-time machine learning. https://github.com/alibaba/feathub
- [7] Alibaba FeatHub. 2023. Fraud Detection. https://github.com/alibaba/feathub/ blob/master/docs/examples/fraud_detection.ipynb
- [8] Leo Breiman. 2001. Random Forests. Machine Learning 45, 1 (Oct. 2001), 5–32. https://doi.org/10.1023/A:1010933404324
- Russel E. Caflisch. 1998. Monte Carlo and Quasi-Monte Carlo Methods. Acta Numerica 7 (Jan. 1998), 1–49. https://doi.org/10.1017/S0962492900002804
- [10] Cheng Chen, Jun Yang, Mian Lu, Taize Wang, Zhao Zheng, Yuqiang Chen, Wenyuan Dai, Bingsheng He, Weng-Fai Wong, Guoan Wu, Yuping Zhao, and Andy Rudoff. 2021. Optimizing In-Memory Database Engine for AI-Powered on-Line Decision Augmentation Using Persistent Memory. Proc. VLDB Endow. 14, 5 (jan 2021), 799–812. https://doi.org/10.14778/3446095.3446102
- [11] Tianqi Chen, Thierry Moreau, Ziheng Jiang, Lianmin Zheng, Eddie Yan, Meghan Cowan, Haichen Shen, Leyuan Wang, Yuwei Hu, Luis Ceze, Carlos Guestrin, and Arvind Krishnamurthy. 2018. TVM: An Automated End-to-End Optimizing Compiler for Deep Learning. Cornell University - arXiv,Cornell University - arXiv (Feb 2018).
- [12] Valerie Chen, Jeffrey Li, Joon Sik Kim, Gregory Plumb, and Ameet Talwalkar. 2021. Interpretable Machine Learning. *Queue* (Dec 2021), 28–56. https://doi.org/ 10.1145/3511299
- [13] ClickHouse. 2023. Fast Open-Source OLAP DBMS ClickHouse. https://clickhouse. com/
- [14] Daniel Crankshaw, Xin Wang, Giulio Zhou, MichaelJ. Franklin, JosephE. Gonzalez, and Ion Stoica. 2016. Clipper: A Low-Latency Online Prediction Serving System. arXiv: Distributed, Parallel, and Cluster Computing, arXiv: Distributed, Parallel, and Cluster Computing (Dec 2016).
- [15] Dasmehdixtr. 2020. Binary Classification of Induction Motor Fault | Kaggle. https://www.kaggle.com/code/dasmehdixtr/binary-classification-ofinduction-motor-fault
- [16] Databricks Inc. 2023. The Data and AI Company Databricks. https://www. databricks.com/
- [17] Databricks Inc. 2023. feature-store-taxi-example Databricks. https://docs.gcp.databricks.com/_extras/notebooks/source/machinelearning/feature-store-taxi-example.html
- [18] etc David Gagnon, Maggie. 2023. Predict Student Performance from Game Play. https://kaggle.com/competitions/predict-student-performance-fromgame-play
- [19] Bolin Ding, Silu Huang, Surajit Chaudhuri, Kaushik Chakrabarti, and Chi Wang. 2016. Sample + Seek: Approximating Aggregates with Distribution Precision Guarantee. In Proceedings of the 2016 International Conference on Management of Data. https://doi.org/10.1145/2882903.2915249
- [20] Alin Dobra, Chris Jermaine, Florin Rusu, and Fei Xu. 2009. Turbo-Charging Estimate Convergence in DBO. Proceedings of the VLDB Endowment 2, 1 (Aug. 2009), 419–430. https://doi.org/10.14778/1687627.1687675
- [21] Kuntai Du, Qizheng Zhang, Anton Arapin, Haodong Wang, Zhengxu Xia, and Junchen Jiang. 2022. AccMPEG: Optimizing Video Encoding for Video Analytics. ArXiv abs/2204.12534 (2022). https://api.semanticscholar.org/CorpusID: 248405608
- [22] Bradley. Efron and Robert. Tibshirani. 1993. An introduction to the bootstrap. Chapman and Hall, New York.

- [23] Feast. 2023. Feature Store for Machine Learning. https://github.com/feast-dev/ feast
- [24] feather-ai. 2023. Feathr A scalable, unified data and AI engineering platform for enterprise. https://github.com/feathr-ai/feathr
- [25] Philippe Flajolet, Éric Fusy, Olivier Gandouet, and Frédéric Meunier. 2007. HyperLogLog: The Analysis of a near-Optimal Cardinality Estimation Algorithm. *Discrete Mathematics & Theoretical Computer Science* DMTCS Proceedings vol. AH,..., Proceedings (Jan. 2007), 3545. https://doi.org/10.46298/dmtcs.3545
- [26] Google Cloud. 2023. Innovate faster with enterprise-ready generative AI. https: //cloud.google.com/vertex-ai
- [27] Gilad Gressel, Niranjan Hegde, Archana Sreekumar, Rishikumar Radhakrishnan, Kalyani Harikumar, Anjali S., and Krishnashree Achuthan. 2023. Feature Importance Guided Attack: A Model Agnostic Adversarial Attack. https: //doi.org/10.48550/arXiv.2106.14815 arXiv:2106.14815 [cs]
- [28] Léo Grinsztajn, Edouard Oyallon, and Gaël Varoquaux. 2022. Why do tree-based models still outperform deep learning on tabular data? arXiv:2207.08815 [cs.LG]
- [29] Gusthema. 2023. Student Performance w/ Random Forests. https://www.kaggle. com/code/cdeotte/random-forest-baseline-0-664/notebook
- [30] Gusthema. 2023. Student Performance w/ TensorFlow Decision Forests. https://www.kaggle.com/code/gusthema/student-performance-w-tensorflowdecision-forests
- [31] Dong He, Supun C Nakandala, Dalitso Banda, Rathijit Sen, Karla Saur, Kwanghyun Park, Carlo Curino, Jesús Camacho-Rodríguez, Konstantinos Karanasos, and Matteo Interlandi. 2022. Query Processing on Tensor Computation Runtimes. Proc. VLDB Endow. 15, 11 (jul 2022), 2811–2825. https://doi.org/10. 14778/3551793.3551833
- [32] Joseph M. Hellerstein, Peter J. Haas, and Helen J. Wang. 1997. Online Aggregation. In Proceedings of the 1997 ACM SIGMOD International Conference on Management of Data (SIGMOD '97). Association for Computing Machinery, New York, NY, USA, 171–182. https://doi.org/10.1145/253260.253291
- [33] John L. Hennessy and David A. Patterson. [n.d.]. Computer Architecture, Fifth Edition: A Quantitative Approach (5 ed.). Morgan Kaufmann Publishers Inc.
- [34] Benjamin Hilprecht, Andreas Schmidt, Moritz Kulessa, Alejandro Molina, Kristian Kersting, and Carsten Binnig. 2019. DeepDB: Learn from Data, not from Queries! arXiv: Databases, arXiv: Databases (Sep 2019).
- [35] Hopsworks. 2023. Hopsworks Batch and Real-time ML Platform. https://www. hopsworks.ai
- [36] Zezhou Huang, Rathijit Sen, Jiaxiang Liu, and Eugene Wu. 2023. JoinBoost: Grow Trees Over Normalized Data Using Only SQL. (Jul 2023).
- [37] JS. 2023. Forex tick data huge database since april 2020 / Kaggle. https://www. kaggle.com/datasets/joseserrat/forex-april-2020-to-june-2021-tick-data
- [38] Kaggle. 2023. Kaggle: Your Machine Learning and Data Science Community. https://www.kaggle.com/
- [39] Srikanth Kandula, Anil Shanbhag, Aleksandar Vitorovic, Matthaios Olma, Robert Grandl, Surajit Chaudhuri, and Bolin Ding. 2016. Quickr: Lazily Approximating Complex AdHoc Queries in BigData Clusters. In Proceedings of the 2016 International Conference on Management of Data. https://doi.org/10.1145/2882903. 2882940
- [40] Daniel Kang, John Emmons, Firas Abuzaid, Peter Bailis, and Matei Zaharia. 2017. NoScope: Optimizing Neural Network Queries over Video at Scale. Proc. VLDB Endow. 10, 11 (aug 2017), 1586–1597. https://doi.org/10.14778/3137628.3137664
- [41] Konstantinos Karanasos, Matteo Interlandi, Doris Xin, Fotis Psallidas, Rathijit Sen, Kwanghyun Park, Ivan Popivanov, Supun Nakandala, Subru Krishnan, Markus Weimer, Yuan Yu, Raghu Ramakrishnan, and Carlo Curino. 2019. Extending Relational Query Processing with ML Inference. Conference on Innovative Data Systems Research, Conference on Innovative Data Systems Research (Jan 2019).
- [42] Kengle. 2023. Predict Charge Time of Battery. https://www.kaggle.com/code/ kenggle/nasa-battery-life-prediction-dataset-cleaning
- [43] Kengle. 2023. RUL Prediction of Turbofan Engine. https://www.kaggle.com/ kenggle/rul-prediction-with-lgbm-on-turbofan-dataset
- [44] Peter Kraft, Daniel Kang, Deepak Narayanan, Shoumik Palkar, Peter Bailis, and Matei Zaharia. 2019. Willump: A Statistically-Aware End-to-end Optimizer for Machine Learning Inference. *Cornell University - arXiv,Cornell University - arXiv* (Jun 2019).
- [45] Ziliang Lai, Chris Liu, Chenxia Han, Pengfei Zhang, Eric Lo, and Ben Kao. [n.d.]. Everest: A Top-K Deep Video Analytics System. In Proceedings of the 2022 International Conference on Management of Data (New York, NY, USA, 2022-06-11) (SIGMOD '22). Association for Computing Machinery, 2357–2360.
- [46] S. H. Lee and W. Chen. 2009. A Comparative Study of Uncertainty Propagation Methods for Black-Box-Type Problems. *Structural and Multidisciplinary Optimization* 37, 3 (Jan. 2009), 239–253. https://doi.org/10.1007/s00158-008-0234-7
- [47] Yunseong Lee, Alberto Scolari, Byung-Gon Chun, MarcoD. Santambrogio, Markus Weimer, and Matteo Interlandi. 2018. Pretzel: opening the black box of machine learning prediction serving systems. Operating Systems Design and Implementation, Operating Systems Design and Implementation (Oct 2018).
- [48] Feifei Li, Bin Wu, Ke Yi, and Zhuoyue Zhao. 2016. Wander Join: Online Aggregation via Random Walks. In Proceedings of the 2016 International Conference on Management of Data. https://doi.org/10.1145/2882903.2915235

- [49] Kaiyu Li and Guoliang Li. 2018. Approximate Query Processing: What is New and Where to Go?: A Survey on Approximate Query Processing. Data Science and Engineering (Dec 2018), 379-397. https://doi.org/10.1007/s41019-018-0074-4
- Scott M. Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting [50] Model Predictions. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 4768-4777
- Qingzhi Ma and Peter Triantafillou. 2019. DBEst: Revisiting Approximate Query [51] Processing Engines with Machine Learning Models. In Proceedings of the 2019 International Conference on Management of Data. https://doi.org/10.1145/3299869. 3324958
- [52] Christoph Molnar. 2023. Interpretable Machine Learning. Online. https:// christophm.github.io/interpretable-ml-book/
- Barzan Mozafari and Ning Niu. 2015. A Handbook for Building an Approximate [53] Query Engine. IEEE Data Eng. Bull. (2015).
- [54] Supun Nakandala, Karla Saur, Gyeong-In Yu, Konstantinos Karanasos, Carlo Curino, Markus Weimer, and Matteo Interlandi. 2020. A tensor compiler for unified machine learning prediction serving. In 14th USENIX Symposium on Operating Systems Design and Implementation (OSDI 20). 899-917.
- [55] Nikhil Kohil. 2020. Stock Prediction using Linear Regression Starter | Kaggle. https://www.kaggle.com/code/nikhilkohli/stock-prediction-using-linearregression-starter
- [56] Shoumik Palkar, James Thomas, Deepak Narayanan, Pratiksha Thaker, Rahul Palamuttam, Parimajan Negi, Anil Shanbhag, Malte Schwarzkopf, Holger Pirk, Saman Amarasinghe, Samuel Madden, and Matei Zaharia. 2018. Evaluating end-to-end optimization for data analytics applications in weld. Proceedings of the VLDB Endowment (May 2018), 1002-1015. https://doi.org/10.14778/3213880. 3213890
- [57] Kwanghyun Park, Karla Saur, Dalitso Banda, Rathijit Sen, Matteo Interlandi, and Konstantinos Karanasos. 2022. End-to-end Optimization of Machine Learning Prediction Queries. In Proceedings of the 2022 International Conference on Management of Data. https://doi.org/10.1145/3514221.3526141
- Yongjoo Park, Barzan Mozafari, Joseph Sorenson, and Junhao Wang. 2018. Ver-[58] dictDB: Universalizing Approximate Query Processing. In Proceedings of the 2018 International Conference on Management of Data. https://doi.org/10.1145/ 3183713.3196905
- Yongjoo Park, Ahmad Shahab Tajik, Michael Cafarella, and Barzan Mozafari. [59] 2017. Database Learning: Toward a Database that Becomes Smarter Every Time. In Proceedings of the 2017 ACM International Conference on Management of Data. https://doi.org/10.1145/3035918.3064013
- [60] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research 12 (2011), 2825-2830.
- [61] A. Pol and C. Jermaine. 2005. Relational confidence bounds are easy with the bootstrap. Proceedings of the 2005 ACM SIGMOD International Conference on Management of Data (2005). https://doi.org/10.1145/1066157.1066224
- [62] Fotis Psallidas, Yiwen Zhu, Bojan Karlas, Matteo Interlandi, Avrilia Floratou, Konstantinos Karanasos, Wentao Wu, Ce Zhang, Subru Krishnan, Carlo Curino, and Markus Weimer. 2019. Data Science through the looking glass and what we found there. arXiv: Learning, arXiv: Learning (Dec 2019).
- [63] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, San Francisco California USA, 1135-1144. https://doi.org/10.1145/ 2939672.2939778
- [64] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2018. Anchors: High-Precision Model-Agnostic Explanations. Proceedings of the AAAI Conference on Artificial Intelligence 32, 1 (April 2018). https://doi.org/10.1609/aaai.v32i1.11491
- [65] Mathieu Rouaud. [n.d.]. Probability, Statistics and Estimation: Propagation of Uncertainties in Experimental Measurement. https://www.lulu.com/shop/mathieurouaud/probability-statistics-and-estimation-propagation-of-uncertainties-inexperimental-measurement/paperback/product-1kwvyjky.html.

- [66] Issac Sacolick. 2020. Amazon, Google, and Microsoft take their clouds to the edge. (2020). https://www.infoworld.com/article/3575071/amazon-google-andmicrosoft-take-their-clouds-to-the-edge.html
- [67] B. Saha and K. Goebel. 2007. Battery Data Set. https://data.nasa.gov/dataset/Liion-Battery-Aging-Datasets/uj5r-zjdb/about_data
- [68] Andrea Saltelli. 2002. Making Best Use of Model Evaluations to Compute Sensitivity Indices. Computer Physics Communications 145, 2 (May 2002), 280-297. https://doi.org/10.1016/S0010-4655(02)00280-1
- Karla Saur, Tara Mirmira, Konstantinos Karanasos, and Jesús Camacho-Rodríguez. [69] 2022. Containerized Execution of UDFs: An Experimental Evaluation. Proc. VLDB Endow. 15, 11 (jul 2022), 3158-3171. https://doi.org/10.14778/3551793.3551860
- [70] Abhinav Saxena, Kai Goebel, Don Simon, and Neil Eklund. 2008. Damage propagation modeling for aircraft engine run-to-failure simulation. In 2008 International Conference on Prognostics and Health Management. 1-9. https: //doi.org/10.1109/PHM.2008.4711414 Lloyd S. Shapley. 1952. A Value for N-Person Games. Technical Report. RAND
- [71] Corporation.
- [72] Ilya M. Sobol. 1967. On the distribution of points in a cube and the approximate evaluation of integrals. Ussr Computational Mathematics and Mathematical Physics 7 (1967), 86–112. https://api.semanticscholar.org/CorpusID:122581245
- [73] I. M Sobol'. 2001. Global Sensitivity Indices for Nonlinear Mathematical Models and Their Monte Carlo Estimates. Mathematics and Computers in Simulation 55. 1 (Feb. 2001), 271–280. https://doi.org/10.1016/S0378-4754(00)00270-6 TalkingData. 2023. TalkingData AdTracking Fraud Detection Challenge /
- [74] Kaggle. https://www.kaggle.com/competitions/talkingdata-adtracking-frauddetection
- NYC Taxi and Limousine Commission. 2023. TLC Trip Record Data TLC. https: [75] //www.nyc.gov/site/tlc/about/tlc-trip-record-data.page
- [76] Tecton. 2023. Real-Time Fraud Detection in the Databricks Lakehouse with Tecton. https://github.com/tecton-ai/blog-sample-code/blob/main/databricks/frauddetection/Real-Time_Fraud_Detection_in_the_Databricks_Lakehouse_with_ Tecton.ipynb
- [77] Serkan Uysal. 2023. Machinery Fault Dataset. https://www.kaggle.com/datasets/ uysalserkan/fault-induction-motor-dataset
- [78] Vivek Khetan. 2016. A linear model on apps and labels. https://www.kaggle.com/ code/vkhetan/a-linear-model-on-apps-and-labels
- [79] Wei Wang, Jinyang Gao, Meihui Zhang, Sheng Wang, Gang Chen, Teck Khim Ng, Beng Chin Ooi, Jie Shao, and Moaz Reyad. 2018. Rafiki: machine learning as an analytics service system. Proceedings of the VLDB Endowment 12, 2 (Oct 2018), 128-140. https://doi.org/10.14778/3282495.3282499
- Zhibo Wang, Hengchang Guo, Zhifei Zhang, Wenxin Liu, Zhan Qin, and Kui [80] Ren. 2022. Feature Importance-aware Transferable Adversarial Attacks. https: //doi.org/10.48550/arXiv.2107.14185 arXiv:2107.14185 [cs]
- [81] Richard Wesley and Fei Xu. 2016. Incremental Computation of Common Windowed Holistic Aggregates. Proceedings of the VLDB Endowment 9, 12 (Aug. 2016), 1221-1232. https://doi.org/10.14778/2994509.2994537
- [82] Sarah Wooders, Xiangxi Mo, Amit Narang, Kevin Lin, Ion Stoica, Joseph M. Hellerstein, Natacha Crooks, and Joseph E. Gonzalez. [n.d.]. RALF: Accuracy-Aware Scheduling for Feature Store Maintenance. 17, 3 ([n.d.]), 563-576.
- [83] Yongji Wu, Matthew Lentz, Danyang Zhuo, and Yao Lu. 2022. Serving and Optimizing Machine Learning Workflows on Heterogeneous Infrastructures. Proc. VLDB Endow. 16 (2022), 406-419. https://api.semanticscholar.org/CorpusID: 248665909
- [84] Minghao Yan, Saurabh Agarwal, and Shivaram Venkataraman. 2024. Decoding Speculative Decoding. arXiv:2402.01528 [cs.LG]
- [85] Kai Zeng, Sameer Agarwal, Ankur Dave, Michael Armbrust, and Ion Stoica. 2015. G-OLA: Generalized On-Line Aggregation for Interactive Analysis on Big Data. In Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data. https://doi.org/10.1145/2723372.2735381
- Xuanhe Zhou, Cheng Chen, Kunyi Li, Bingsheng He, Mian Lu, Qiaosheng Liu, [86] Wei Huang, Guoliang Li, Zhao Zheng, and Yuqiang Chen. 2023. FEBench: A Benchmark for Real-Time Relational Data Feature Extraction. Proc. VLDB Endow. 16, 12 (aug 2023), 3597-3609. https://doi.org/10.14778/3611540.3611550