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Data lineage and observability for ensemble Machine Learning serving in the edge

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Abstract

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1. Introduction

Recently, Machine Learning (ML) has been applied extensively to many problems, including customer journey optimization in marketing [19], particle identification in Physics [8], and mental health problems prediction in healthcare [18]. Then, with the increasing number of ML applications and their proven performance, several organizations are seeking third-party ML service providers to improve their operations, creating a new business model — ML as a Service (MLaaS). As with other kinds of service, MLaaS requires a contract which is usually called a Service Level Agreement (SLA) that sets the expectations and describes the delivered service to preserve the benefits of both stakeholders. However, the current SLA has yet to fulfill its preservation job because ML-specific attributes, such as data quality, inference accuracy, and explainability, have created new challenges. For instance, in Internet of Things (IoT) applications, many issues of the ML models have their root causes in the quality of data, which is impacted by many factors such as erroneous measurement, environmental noise, and discrete observations [15]. Moreover, because of the relationship between data quality and inference accuracy, ML models can produce false predictions when data quality problems exist, causing ML providers to be penalized based on the SLA. Another issue is that in MLaaS, the customers only submit the data and does not cooperate with the ML provider in the prediction task. Thus, from their perspective, ML models are considered like a black box, which is insufficient in human life-related applications such as e-health and autonomous vehicles where uncertain decisions cannot be tolerated.

One approach to resolve these two challenges is increasing model explainability by explaining the inference result to the customer [12]. However, explainability aspects of ML models have been researched mostly in the training task [15], making it unclear about the appropriate utilization and implementation of ML-specific attributes and constraints. As an approach to support ML-specific service contracts, Linh et al., proposed QoA4ML framework which outlines the essential components of such contracts, the definition of ML attributes and constraints, and the guidance on how these elements should be monitored and assessed [20]. Although QoA4ML has created a foundation for robust ML monitoring, current implementation focuses on a general ML model such as the final confidence of the ensemble model instead of the base models' confidence. This can be inefficient for some sophisticated applications such as digital assistants where a complex chain of models are used for inference task. Additionally, with the increasing number of research in autoscaler for inference serving system [16] and automated ensemble [2], it requires monitoring all underlying base models to ensure dynamic and robust inference capabilities of ML solutions.

In this research, I perform an analysis of data lineage monitoring and its implementation in edge environment. From that, I propose an approach to improve QoA4ML framework with data lineage, which can be combined with other techniques to improve the current MLaaS. I provide a prototype with QoA4ML as the foundation so that ML developer and provider can integrate it with their deployed service.

The rest of this paper is organized as follows. Section 2 discusses the background of the research, and section 3 explains data lineage implementation in the QoA4ML framework. Section 4 describes the experiment and its result, while section 5 concludes the research.

2. Background

This section presents the background on data quality in the edge and discusses the data lineage definition, characteristic and its relationship with data quality. We then identify the challenges of monitoring data lineage for ML serving.

2.1 Data quality and Data dimensions

In [13], Liu et al. defines data quality as the suitability of the data for the application and data dimension as metrics that describe the level of data quality. As the definitions are pretty general, data dimensions depend highly on the application, and different organizations value data dimensions differently [5]. For example, although completeness is valuable when working with tabular data, it is not as relevant in computer vision. Instead, attributes such as sharpness, noise, or dynamic range, are more significant and can affect the inference accuracy heavily. In edge computing and IoT applications, data characteristics are uncertain, erroneous, and noisy [13], so the requirements will focus on recognizing methods for capturing data quality and the causal relationship between data quality and the performance of machine learning services for dynamic inferences. [15].

2.2 Data lineage

Data lineage or provenance describes the origin of data, its derivation and changes over time [11]. Based on which questions it can answer, Ikeda and Widom [11] classify data lineage into two types: *where*-lineage and *how*-lineage. Then for each class, there are two *granularities*:

- Schema-level (coarse-grained) answers data lineage questions at the general level. It can be which datasets our current data originate from for where-lineage and which transformations have been applied for how-lineage

- Instance-level (fine-grained), on the other hand, clarifies the origin of a specific data point and how different data points are combined to achieve such results.

The answers that data lineage can provide will shine in edge computing because the complicated data pipeline makes it very time-consuming and costly for ML providers to trace down the root cause of the problems manually. However, with data lineage, they can immediately identify the data input's origin and derivation and then confirm the data quality based on them, helping reduce the required work [17]. Although data lineage is precious in MLaaS, there are some challenges requires considering in this research:

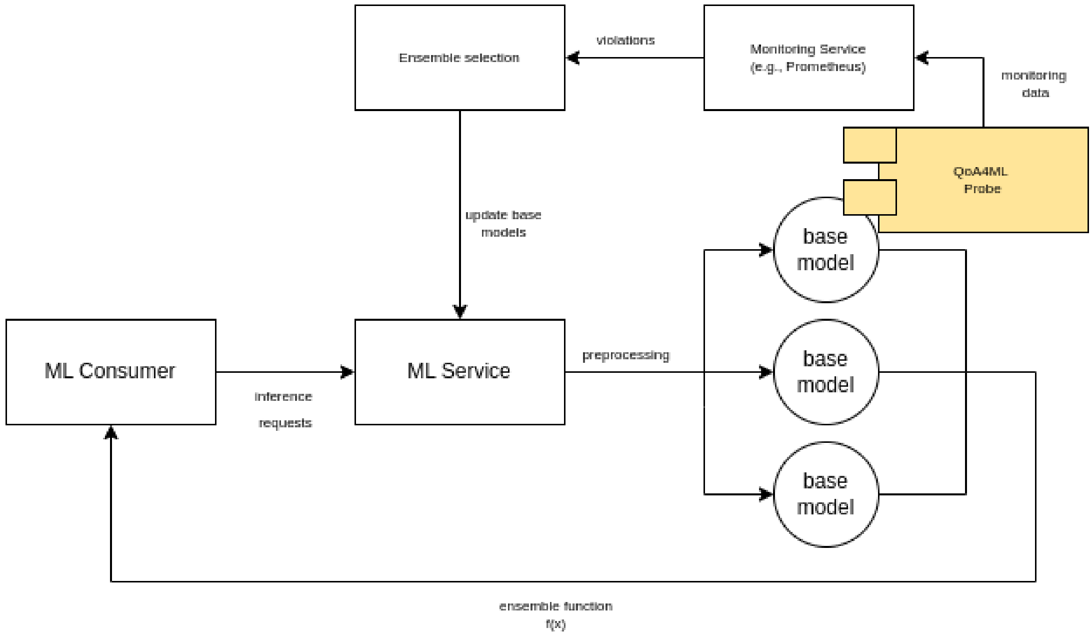
- Storing and querying lineage can be expensive when the number of IoT devices and the complexity of the pipeline increase[11]. Additionally, a resource-constrained environment like the edge demands an even more efficient processes.

- Current ML solution adopts many open source application and library that can be considered as a black box, so how can we accurately capture data provenance for black box operations and many others [17]

2.3 Related work

Data lineage/provenance: Data provenance research has been active for three decades with the first paper dated back to 1990 [21]. Since then, data lineage has been applied in scientific database[22] [3] [1] [10], datawarehouse [6] [7], and recently big data platform [14] [9] and IoT. Although data lineage can be used for ML interpretability as their goals are clearly similar [4], the number of papers about this application is moderate. In this research, I analyzes the application of data lineage in increasing data interpretability which can be utilized in optimizing ensemble ML model for dynamic inference.

3. Data lineage for ensemble ML serving



4. Experiment and Results

5. Conclusion

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