Edge AIBench: Towards Comprehensive End-to-end Edge Computing Benchmarking

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Abstract. In edge computing scenarios, the distribution of data and collaboration of workloads on different layers are serious concerns for performance, privacy, and security issues. So for edge computing benchmarking, we must take an end-to-end view, considering all three layers: client-side devices, edge computing layer, and cloud servers. Unfortunately, the previous work ignores this most important point. This paper presents the BenchCouncil's coordinated effort on edge AI benchmarks, named Edge AIBench. In total, Edge AIBench models four typical application scenarios: ICU Patient Monitor, Surveillance Camera, Smart Home, and Autonomous Vehicle with the focus on data distribution and workload collaboration on three layers. Edge AIBench is publicly available from http://www.benchcouncil.org/EdgeAIBench/index.html. We also build an edge computing testbed with a federated learning framework to resolve performance, privacy, and security issues.

Keywords: Edge Computing · AI Benchmarks · Testbed · Federated Learning.

1 Introduction

Cloud computing is a mature model to share computing resources by providing network access to users [1]. In cloud computing models, users communicate with the data center to get hardware, software and other computing resources and store data. However, In recent years, the number of client-side devices (e.g. smart devices and monitors) grows rapidly. IoT Analytics [2] has reported the number of connected devices reached 17 billion in 2018 and Gartner says the IoT

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devices will install 26 billion units by 2020 [3]. These client-side devices produce a large amount of data to process. The overhead of data transmission and data encryption among devices and data centers becomes significant bottlenecks for many IoT scenarios, and hence it raises a daunting challenge for throughput, latency, and security guarantee.

Edge computing emerges as a promising technical framework to overcome the challenges in cloud computing. The edge computing framework adds a new layer, named the edge computing layer, on the basis of the traditional cloud computing framework. In the edge computing framework, only the real-time data processing is transferred to the edge computing layer, while other complicated data processing is still executed on the cloud server. Figure 1 shows a general edge computing framework, which includes three layers: cloud server, edge computing layer, and client-side devices.

In the edge computing scenarios, the distribution of data and collaboration of workloads on different layers are serious concerns for performance, security, and privacy issues. So for benchmarking, designing, and implementing edge computing systems or applications, we shall take an end-to-end view, considering all three layers. Unfortunately, the previous work, especially the previous benchmarking efforts [4, 6, 7, 14] ignore this most important point.

In edge computing scenarios, AI techniques are widely used to augment device, edge and cloud intelligence, and they are most demanding in terms of computing power, data storage, and network. Typical application scenarios include smart city, smart home, autonomous vehicle, surveillance camera, smart medical, wearable devices and so on. These scenarios are complicated because of different kinds of client-side devices, a large quantity of heterogeneous data, privacy and security issues. Most of these scenarios have a high requirement for latency and network bandwidth. However, edge computing is in the initial stage and doesn't have a uniform standard for these scenarios. Therefore, a comprehensive end-to-end edge computing benchmark suite is needed to measure and optimize the systems and applications.

Meanwhile, edge computing is still in the initial stage with a lack of testbed. Because of the privacy issue, there is no incentive to share data. Because of the complexity, there is no end-to-end application scenario to validate the architectures, systems, or specific algorithms in certain settings.

Above all, it's necessary to develop a benchmark suite and testbed for edge computing. This paper reports the BenchCouncil's coordinated effort on edge AI benchmarks, named Edge AIBench, which is publicly available from `http://www.benchcouncil.org/EdgeAIBench/index.html`. Edge AIBench includes four typical application scenarios: ICU Patient Monitor, Surveillance Camera, Smart Home, and Autonomous Vehicle, which consider the complexity of all edge computing AI scenarios. Coordinated by BenchCouncil (http://www.benchcouncil.org), we are also building an edge computing testbed with a federated learning framework to resolve security and privacy issue, which can be accessed from `http://www.benchcouncil.org/testbed/index.php`. BenchCouncil also release datacenter AI benchmarks [8, 9], HPC AI benchmarks [10], IoT AI benchmarks [11], and big data benchmarks [12, 13], publicly available from the BenchCouncil website.

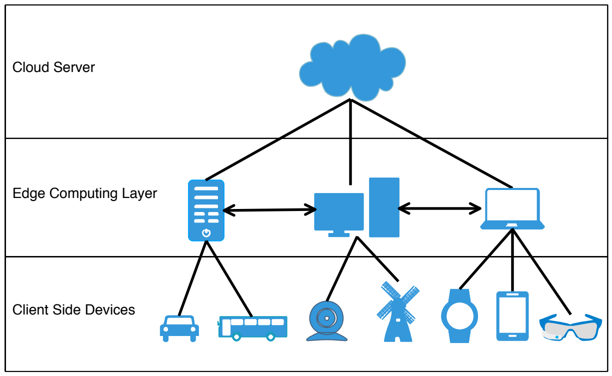

Fig. 1. A General Edge Computing Framework.

2 Related Work

Since the edge computing AI applications have become more and more popular these years, benchmarks are needed to measure and optimize the systems and applications. There are several related benchmark suites. We summarize the state-of-the-art and state-of-the-practice work on edge AI benchmarking.

MLPerf [4] is a benchmark suite focusing on measuring Machine Learning(ML) performance. It provides the edge inference benchmarks, including eight ML tasks: image classification, object detection and so on [5]. But this benchmark suite just evaluates the edge computing layer with the lack of an end-to-end view.

EEMBC [6] develops an ML benchmark suite, named MLMark on embedded edge computing platforms. MLMark includes four AI applications: image classification, object detection, language translation, and speech recognition. However, only the licensees and members of EEMBC have the right to access these benchmarks and this benchmark suite is still in "beta" state now.

EdgeBench [14] compares two edge computing platforms–Amazon AWS Greengrass and Microsoft Azure IoT Edge. And it includes two AI applications: speech-to-text and image recognition. EdgeBench fails to provide an end-to-end application benchmarking framework.

AI Benchmark [7] is a benchmark suite for AI applications on smartphones, and it includes nine AI applications. It's an IoT benchmark suite and only focuses on the client-side devices (smartphones)' performance.

Table 2 compares the state-of-the-art and state-of-the-practice edge computing AI benchmarks. It shows many of them only focus on the edge computing layer instead of the whole edge computing framework. Our benchmark suite Edge AIBench provides an end-to-end application benchmarking framework, including train, validate and inference stages. Moreover, Edge AIBench includes four typical edge computing AI scenarios and measures the whole three-layer edge computing framework.

Table 1. Comparison among Edge Computing AI benchmarks

Benchmark Name	End-to-end Application Scenarios	Components on Cloud Server	Components on Edge Computing Layer	Components on Client-side Devices	Open-Source
Edge AIBench	ICU Patient Monitor Surveillance Camera Smart Home Autonomous Vehicle	√	√	√	√
MLPerf	N/A	×	√	×	√
EEMBC MLMark	Not Clear	Not Clear	Not Clear	Not Clear	×
EdgeBench	N/A	√	√	√	√
AI Benchmark	N/A	×	×	√	√

3 The summary of Edge AIBench

Edge AIBench includes four typical scenarios: Intensive care unit(ICU) patient monitor, surveillance camera, smart home, and autonomous vehicle. These four AI scenarios can present the complexity of edge computing AI scenarios from different perspectives.

3.1 ICU Patient Monitor

ICU is the treatment place for critical patients. Therefore immediacy is significant for ICU patient monitor scenario to notify doctors of the patients' status as soon as possible. The dataset we use is MIMIC-III [15]. MIMIC-III provides many kinds of patients data such as vital signs, fluid balance and so on. Moreover, we choose heart failure prediction [16] and endpoint prediction [17] as the AI benchmarks.

Heart failure prediction uses the MIMIC-III dataset and a two-level neural attention model. It collects the patients' data on the virtual client-side devices, trains on the cloud server (the data will be sent from the edge) and predicts the heart failure on the edge computing layer.

Endpoint prediction benchmark also uses the MIMIC-III dataset, and it uses an LSTM model. This benchmark collects patients' data on the virtual patient device generator and then transmit it to the edge to make the inference. Then the data will be sent to the cloud server to do more training.

3.2 Surveillance Camera

There are many surveillance cameras all over the world nowadays, and these cameras will produce a large quantity of video data at all times. If we transmit all of the data to cloud servers, the network transmission bandwidth will be very high. Therefore, this scenario focus on edge data preprocesses and data compression.

We choose the person re-identification application as the component benchmark. It collects data from the virtual camera devices and pre-process and infer these video data on the edge computing layer. Then the edge computing layer will send the compressed data to the cloud server. Moreover, the decompression and training process are on the cloud server.

3.3 Smart Home

Smart home includes a lot of smart home devices such as automatic controller, alarm system, audio equipment and so on. Thus, the uniqueness of the smart home includes different kinds of edge devices and heterogeneous data. We will choose two AI applications as the component benchmarks: speech recognition and face recognition. These two components have heterogeneous data and different collecting devices. These two component benchmarks both collect data on the client side devices(e.g. camera and smartphone), infer on the edge computing layer and train on the cloud server.

Speech recognition uses the DeepSpeech2 [18] model and the LibriSpeech dataset [19].

Face recognition uses the FaceNet [20] model and uses the LFW(Labeled Faces in the Wild) [21] dataset.

3.4 Autonomous Vehicle

The uniqueness of the autonomous vehicle scenario is that the high demand for validity. That is to say, it takes absolute correct action even without human intervention. This feature represents the demand of some edge computing AI scenarios. The automatic control system will analyze the current road conditions and make a corresponding reaction at once. We will choose the road sign recognition as the component benchmark.

The road sign recognition will collect the road signs data from the camera, train these data on the cloud and infer on the edge computing layer.

Table 2 shows the component benchmarks of Edge AIBench. Edge AIBench provides an end-to-end application benchmarking, consisting of train, inference, data collection and other parts using a general three-layer edge computing framework.

Table 2. The Summary of Edge AIBench

End-to-end Application Scenarios	AI Component Benchmarks	Cloud Server	Edge Computing Layer	Client Side Device
ICU Patient Monitor	Heart Failure Prediction	Train	Infer Send Alarm	Generate Data
ICU Patient Monitor	Endpoint Prediction	Train	Infer	Generate Data
Surveillance Camera	Person Re-Identification	Decompress Data Train	Compress Data Infer	Generate Data
Smart Home	Speech Recognition	Train	Infer	Generate Data
Smart Home	Face Recognition	Train	Infer	Generate Data
Autonomous Vehicle	Road Sign Recognition	Train	Infer	Generate Data

3.5 A Federated Learning Framework Testbed

We have developed an edge computing AI testbed to provide support for researchers and common users, which is publicly available from `http://www.benchcouncil.org/testbed.html`. Security and privacy issues become significant focuses in the age of big data, as well as edge computing. Federated learning is a distributed collaborative machine learning technology whose main target is to preserve the privacy [22]. Our testbed system will combine the federated learning framework.

At present, we are implementing the ICU scenario on the testbed. We are developing a "virtual patient" data generator and a federated machine learning training model. Doctors can train the model on the local server and transmit the encrypting parameter to the cloud server. Then the cloud server computes the overall parameter on the basis of these encrypting parameter from different hospitals. After all, the cloud server will send the overall parameter to the local server and the local server will decrypt it to update their models. Figure 2 shows our federated learning testbed framework.

4 Conclusion

This paper presents an edge computing AI benchmark, named Edge AIBench, which consists of four end-to-end application benchmarking framework and six component benchmarks. These scenarios we choose can present the complexity of edge computing scenarios from different perspectives. Also, we build an edge computing AI testbed with a federated learning framework.

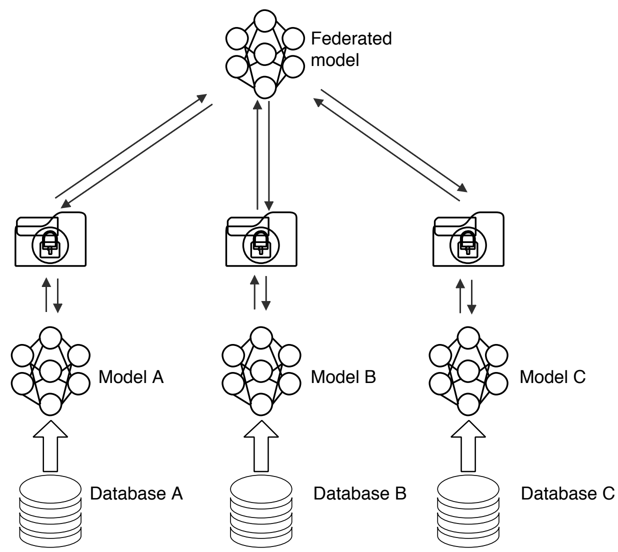

Fig. 2. An Edge Computing AI Testbed with a Federated Learning Framework

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