AIBench: Scenario-distilling AI Benchmarking

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AIBench: Scenario-distilling AI Benchmarking

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Abstract

Real-world application scenarios like modern Internet services consist of diversity of AI and non-AI modules with very long and complex execution paths. Using component or micro AI benchmarks alone can lead to error-prone conclusions. This paper proposes a scenario-distilling AI benchmarking methodology. Instead of using real-world applications, we propose the permutations of essential AI and non-AI tasks as a scenario-distilling benchmark. We consider scenario-distilling benchmarks, component and micro benchmarks as three indispensable parts of a benchmark suite.

Together with seventeen industry partners, we identify nine important real-world application scenarios. We design and implement a highly extensible, configurable, and flexible benchmark framework. On the basis of the framework, we propose the guideline for building scenario-distilling benchmarks, and present two Internet service AI ones.

The preliminary evaluation shows the advantage of scenario-distilling AI benchmarking against using component or micro AI benchmarks alone. The specifications, source code, testbed, and results are publicly available from the web site \url{http://www.benchcouncil.org/AIBench/index.html}.

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1 Introduction

Gartner analysts report that the AI trend impacts the infrastructure significantly, and predict AI will be introduced in almost every products or service by 2020 [25, 26]. Benefiting from AI technologies, many Internet service giants have made significant strides towards improving serving efficiency, and hence boost the industry-scale deployments of massive AI algorithms, systems and architectures. For example, Google proposes the TensorFlow [10] system and the tensor processing unit (TPU) [35] to accelerate the service performance. Amazon adopts AI for intelligent product recommendation [45]. Alibaba proposes a new DUPN network for more effective personalization [40]. Facebook integrates AI into many essential products and services like news feed [29].

Modern Internet services adopt a microservice-based architecture, consisting of diversity of AI and non-AI modules with very long and complex execution paths across different datacenters. Worst of all, the real-world data sets, workloads or even AI models are hidden within the Internet service giant’ datacenters [29, 14], which further exaggerates the benchmarking challenges. In addition, modern Internet service workloads dwarf the traditional ones in terms of code size, deployment scale, and execution path, and hence raise serious benchmarking challenges. For example, the traditional desktop workloads, e.g., data compression [9], image manipulation [9], are about one hundred thousand lines of code, and run on a single node; The Web server workloads [4] are hundreds of thousands of lines of code, and run on a small scale cluster, i.e., dozens of nodes. However, for modern AI workloads, their runtime environment stacks (e.g., Spark [8], TensorFlow [10]) alone are more than millions of lines of code, and these workloads often run on a large-scale cluster, i.e., tens of thousands of nodes [16].

On one hand, the hardware and software designers should consider the overall system effects from the perspective of an application scenario. Using component or micro AI benchmarks alone can lead to error-prone conclusions. For example, in Section 7.2.1 we found that the overall system tail latency deteriorates even hundreds times comparing to a single AI component tail latency, which can not be predicted by a state-of-the-art statistical model [20] as discussed in Section 7.2.2. The previous work also demonstrates that using a micro AI component alone is misleading [37], as some mixed precision optimizations may improve the throughput while significantly increase time-to-quality. For many application scenarios shown in Table 1 the overall critical paths also cover offline AI training in addition to online services, as it is essential to update an AI model for the services in a real time manner, as discussed in Section 7.3.

On the other hand, it is usually difficult to justify porting a real-world application to a new computer system or architecture simply to obtain a benchmark number [24, 15]. For hardware designers, a real-world application is too huge to run on the simulators, even if we can build it from scratch. Moreover, as a benchmark, a full-scale real-world application raises the repeatability challenge in terms of measurement errors and the fairness challenge in terms of assuring the equivalence of the benchmark implementations across different systems. After gaining full knowledge of overall critical information, micro and component benchmarks are still a necessary part of the evaluation.

This paper proposes a scenario-distilling benchmarking (in short, scenario benchmarking or benchmark under different contexts) methodology as shown in Fig. 1. Instead of using real-world applications, we propose the permutations of essential AI and non-AI tasks as a scenario benchmark. Each scenario benchmark is a distillation of the essential attributes of an industry-scale application, and hence reduces the side effect of the latter’s complexity in terms of huge code size, extreme deployment scale, and complex execution paths. We consider scenario, component and micro benchmarks as three indispensable parts of a benchmark suite. A scenario benchmark lets software and hardware designers learn about the overall system information, and locates the primary component benchmarks—representative tasks with specified targets—which provide diverse computation and memory access patterns for the micro-architectural researchers. Finally, the code developers can zoom in on the hotspot functions of the micro benchmarks—frequently-appearing units of computation among diverse component benchmarks—for performance optimization.

Without losing its generality, we apply it in characterizing typical Internet services scenarios. In cooperation with seventeen industry partners, we extract nine important real-world application scenarios. Then we present a highly extensible, configurable, and flexible benchmark framework, allowing researchers to
create scenario benchmarks by reusing the components commonly found in major application scenarios. On the basis of the framework, we propose guidelines on how to build scenario benchmarks, and design and implement two benchmarks–E-commerce Search Intelligence and Online Translation Intelligence.

The evaluations on two CPU clusters and one GPU cluster show the value of AIBench against MLPerf and TailBench. Our evaluations demonstrate how to drill down from scenario benchmarks into components benchmarks and zoom in on the hotspot functions of micro benchmarks. We have several important observations as follows: (1) The contributions of the AI components to the overall system performance vary significantly from the scenario benchmarks; In serving the same requests for the online services, the AI components incur significantly different latency. (2) The overall system tail latency deteriorates dozens times or even hundreds times with respect to a single AI component, which can not be predicted by a state-of-the-art statistical model \[20\]. (3) Both online services and offline AI training should be considered in scenario benchmarking. Internet service architects must balance the tradeoffs among service quality, input data dimensions, AI model complexity, accuracy, and model update intervals.

The rest of this paper is organized as follows. Section 2 explains the motivation. Section 3 summarizes the related work. Section 4 proposes the methodology. Section 5 describes the design and implementation of the framework. Section 6 illustrates how to build scenario benchmarks. Section 7 performs evaluation. Section 8 draws a conclusion.

2 Motivation

2.1 Why Scenario Benchmarking Is Necessary

Modern Internet services process millions of user queries daily, thus the tail latency is of paramount importance in terms of user experience \[20\]. However, a microservice-based architecture contains various AI and non-AI modules, and consequently forms long and complex execution paths. Existing AI benchmarking efforts provide a few micro or component benchmarks, and thus fail to model the overall critical paths of an industry-scale application.

The overall system tail latency deteriorates even 100X comparing to a single component tail latency. The overall system latency indicates that of the entire execution path, including AI and non-AI components. Our experiments in Section 7.2.1 show that the overall system tail latency deteriorates dozens
or even hundreds times comparing to that of a single component. With respect to Recommendation—an AI component—the gap is 2.2X, while for Text Classification, the gap reaches up to 180X.

Debugging the performance of a single component benchmark alone without considering the overall system information may lead to error-prone conclusions. For example, considering a 90th percentile latency, we found that among the four AI-related components of E-commerce Search Intelligence, Recommendation and Image Classification occupy 54% and 17% of the execution time, respectively, while the least one—Text Classification—only occupies 1%. If we benchmark the system using Text Classification alone, the conclusion will be misleading.

2.2 Can a Statistical Model Predict the Overall System Tail Latency?

Someone may argue after profiling the tail latency of many components, a statistical model can predict the overall system tail latency. Our answer is NO!

In Section 7.2.2, We use a state-of-the-art queuing theory [20] to estimate the overall system latency and tail latency. Through the experiments, we find that the gap between the actual average latency or tail latency and the theoretical one is large for two scenario benchmarks. For example, the average latency gap is 8.6 times and the 99th percentile latency gap is 3.3 times for E-commerce Intelligence. Furthermore, the state-of-art queuing model [20] for tail latency takes the system as a whole, and not suits for the real-world application that needs to characterize the permutations of several or dozens of components.

2.3 Why Offline AI Training is also Essential in Scenario Benchmarking

As witnessed by our many industry partners, when an AI model is used for online service, it has to be updated in a real time manner. For example, one E-commerce giant demands that the AI models are updated every one hour, and the updated model will bring in the award about 3% click-through rate and millions of profits. In Section 7.3, our evaluation shows offline training should be included into scenario benchmarking, as it is essential to balance the tradeoffs among model update intervals, training overheads, and accuracy improvements.

3 Related Work

AIBench considers scenario, component, and micro benchmarks as three indispensable parts of a benchmark suite. Several previous or concurrent work only provides component benchmarks. Using a component benchmark alone without considering the overall system effect may lead to error-prone conclusions. Fathom [11] provides eight deep learning component benchmarks implemented with TensorFlow, targeting at six AI tasks. DAWNbench [17] is a component benchmark suite, which firstly pays attention to end-to-end performance—the training time to achieve a state-of-the-art accuracy. MLPerf [3, 42, 37] is an ML component benchmark suite targeting at six AI tasks, including image classification, object detection, translation, speech recognition, recommendation, and reinforcement learning. The MLPerf training benchmark [37] proposes a series of benchmarking rules to eliminate the side effect of the stochastic nature of AI. TBD Suite [55] is a component benchmark suite for DNN training, with eight neural network models for six AI tasks.

Several AI benchmark suites only provide micro benchmarks, ignoring the quality target in benchmarking. DeepBench [1] consists of four operations involved in training deep neural networks, including three basic operations and recurrent layer operations. DNNMark [21] is a GPU benchmark suite that consists of a collection of deep neural network primitives (micro benchmarks).

Additionally, Sirius [28] is an end-to-end IPA web-service application that receives voice and images queries, and responds with natural language. TailBench [36] is a benchmark suite that consists of eight latency-critical workloads. MLModelScope [18] proposes a specification for repeatable model evaluation and a runtime to measure experiments. DeathStarBench [22] is a benchmark suite for microservice, including five workloads.
4 The Methodology

As modern workloads like Internet services are not only diverse, but also fast changing and expanding, the traditional benchmark methodology that creates a new benchmark or proxy for every possible workload is prohibitively costly and even impossible [24]. Hence, an agile scenario benchmarking methodology is extremely essential. Fig. 1 summarizes our methodology.

Step One. We investigate the important benchmarking requirements with the primary industry partners. The input of this step is a candidate list of industry-scale real-world applications. Just copying the real-world applications is impossible for two reasons. First, they treat the real-world workloads, data sets, or models are confidential issues. Second, the massive code size, extreme deployment scale, and complex execution path raise the repeatability and fairness challenges of benchmarking. So the purpose of this step is to understand their essential components and the permutations of different components.

Step Two. According to the output from Step One, this step abstracts representative AI and non-AI tasks. Different from a traditional task, each AI task like Image Classification has both performance and quality targets. Generally, a component benchmark specification defines a task in a high level language [54]–algorithmically in a paper-and-pencil approach [15]. We implement each task as a component benchmark. The AI component benchmark also provides a reference AI model, evaluation metrics, and state-of-the-art quality target [37]. Meanwhile, for each benchmark, a detailed benchmarking rule like that in [37] is mandated to assure fairness across different systems.

Step Three. According to the output of Step Two, we profile the full component benchmarks and drill down into frequently-appearing and time-consuming units of computation. We implement each of those units of computation as a micro benchmark. A micro benchmark is easily portable to a new architecture and system, and hence beneficial to fine-grained profiling and tuning.

Step Four. According to the outputs of Steps One and Two, we design and implement a reusing benchmark framework, including the AI and non-AI component libraries, data input, online inference, offline training, and deployment tool modules.

Step Five. On the basis of the benchmark framework, we build scenario benchmarks. Each scenario benchmark models the permutation of several or tens of essential AI or non-AI components. For each scenario benchmark, we propose the specific evaluation metrics from the perspective of the corresponding industry partner.

5 The Design and Implementation

We first give a summary of the seventeen Industry Partners’ benchmarking requirements, abstract nine important application scenarios, and then identify the representative AI tasks (component benchmarks) among those scenarios. Finally, we propose the reusing benchmark framework.

5.1 The Benchmarking Requirements

Collaborating with the seventeen industry partners whose domains include search engine, e-commerce, social network, news feed, video and etc, we extract typical real-world application scenarios from their products or services.

A real-world application is complex, and we only distill the permutations of primary AI and non-AI tasks. Table 1 summarizes the list of important application scenarios.

For example, the first scenario in Table 1–E-commerce Search Intelligence (in short, E-commerce Intelligence)–is extracted from an E-commerce giant. When a user searches a product, him or her will be classified into different groups. For each group, a personalized service is provided. The search results are ranked according to the relations between the queries and the products. And the ranking is adjusted by learning from the history queries and hitting logs. The recommended products are also returned with the search results to the users. We extract this industry-scale real-world application into several AI tasks like Classification, Learning to Rank, Recommendation, and non-AI tasks like Query Parsing, Database
Table 1: Nine Application Scenarios Extracted from the Seventeen Industry Partners.

<table>
<thead>
<tr>
<th>Important Application Scenario</th>
<th>Involved AI Task</th>
<th>Involved Non-AI Task</th>
<th>Data</th>
<th>Metrics</th>
<th>Model Update Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-commerce Search Intelligence</td>
<td>Text/Image Classification; Learning to Rank; Recommendation</td>
<td>Query Parsing, Database Operation, Indexing</td>
<td>User Data, Product Data, Query Data</td>
<td>Precision, Recall, Latency</td>
<td>High</td>
</tr>
<tr>
<td>Online Translation Intelligence</td>
<td>Text-to-Text Translation; Speech Recognition; Image-to-Text</td>
<td>Query Parsing; Audio/Image Preprocessing</td>
<td>Text, Audio, Image</td>
<td>Accuracy, Latency</td>
<td>Low</td>
</tr>
<tr>
<td>Content-based Image Retrieval</td>
<td>Object Detection; Classification; Spatial Transformer; Image-to-Text</td>
<td>Query Parsing, Indexing</td>
<td>Image</td>
<td>Precision, Recall, Latency</td>
<td>High</td>
</tr>
<tr>
<td>Web Searching</td>
<td>Text Summarization; Learning to Rank; Recommendation</td>
<td>Query Parsing, Indexing, Crawler</td>
<td>Product Data, Query Data</td>
<td>Precision, Recall, Latency</td>
<td>High</td>
</tr>
<tr>
<td>Facial Authentication and Payment</td>
<td>Face Embedding; 3D Face Recognition;</td>
<td>Encryption</td>
<td>Face Image</td>
<td>Accuracy, Latency</td>
<td>Low</td>
</tr>
<tr>
<td>News Feed</td>
<td>Recommendation</td>
<td>Database Operation, Basic Statistics, Filter</td>
<td>Text</td>
<td>Precision, Recall</td>
<td>High</td>
</tr>
<tr>
<td>Live Streaming</td>
<td>Image Generation; Image-to-Image</td>
<td>Video Codec, Video Capture</td>
<td>Image</td>
<td>Latency</td>
<td>Low</td>
</tr>
<tr>
<td>Video Services</td>
<td>Image Compression; Video Prediction</td>
<td>Video Codec</td>
<td>Video</td>
<td>Accuracy, Latency</td>
<td>Low</td>
</tr>
<tr>
<td>Online Gaming</td>
<td>3D Object Reconstruction; Image Generation; Image-to-Image</td>
<td>Rendering</td>
<td>Image</td>
<td>Latency</td>
<td>Low</td>
</tr>
</tbody>
</table>

Operations, and Indexing. Section[6.1] describes how to implement this scenario benchmark on the basis of the reusing framework described in Section[5].

In general, a scenario benchmark concerns the overall system’s effects, including quality-ensured response latency, tail latency, and latency-bounded throughput. A quality-ensured performance example is a quality (e.g., accuracy) deviation from the target being within 2%. In general, each application scenario has its specific performance concerns. For example, several real-world applications require that the AI model is updated in a real time manner.

5.2 The Summary of Representative AI Tasks

To cover a wide spectrum of AI Tasks, we thoroughly analyze the real-world application scenarios shown in Table[1]. In total, we identify sixteen representative AI tasks. For each AI task, we implement it on both TensorFlow[10] and PyTorch[6] as the AI component benchmarks.

Classification is to extract different thematic classes within the input data like an image or text file.

Image Generation is an unsupervised learning problem to mimic the distribution of data and generate images.

Text-to-Text Translation needs to translate a text from one language to another.

Image-to-Text is to extract the text information from an image, which is a process of optical character recognition (OCR) or generate the description of an image automatically.

Image-to-Image is to convert an image from one representation to another one, e.g., season change.

Speech Recognition is to recognize and translate a spoken language into text.

Face Embedding is to transform a facial image into a vector in an embedding space.

3D Face Recognition is to recognize the 3D facial information from multiple images from different angles.

Object Detection is to detect the objects within an image.
**Recommendation** is to provide recommendations.

**Video Prediction** is to predict the future video frames through predicting previous frames transformation.

**Image Compression** is to compress the images and reduce the redundancy [47].

**3D Object Reconstruction** is to predict and reconstruct 3D objects [53].

**Text Summarization** is to generate a text summary.

**Spatial Transformer** is to perform spatial transformations [32] like stretching.

**Learning to Rank** is to learn the attributes of a searched content and rank the scores for the results.

### 5.3 The AIBench Framework

As shown in Fig. 2, the framework provides the loosely coupled modules that can be easily configured. Currently, the AIBench framework includes the data input, offline training, online inference, non-AI libraries, and deployment tool modules. On the basis of the AIBench framework, we can easily build a scenario benchmark.

The data input module is responsible for feeding data into the other modules. It collects representative real-world data sets, which are from not only the authoritative public websites but also our industry partners after anonymization. The data schema is designed to maintain the real-world data characteristics, alleviating the confidential issues. Based on the data schema, a series of data generators are further provided to support large-scale generation of user or product information. To cover a wide spectrum of data characteristics, we take diverse data types (e.g., structured, semi-structured, unstructured), and different data sources (e.g., table, graph, text, image, audio, video) into account. Our framework integrates various open-source data storage systems, and supports large-scale data generation and deployment [39].

The offline training and online inference modules are provided to build a scenario benchmark. First, the offline training module chooses one or more component benchmarks, through specifying the input data, and execution parameters like batch size. Then the offline training module trains a model and provides the trained model to the online inference module. The online inference module loads the trained model onto the serving system, i.e., TensorFlow Serving [41]. The non-AI library module provides non-AI computation and database access, including Query Parsing, Database Operations, Image and
audio Preprocessing, Indexing, Crawler, Encryption, Basic Statistics, Filter, Video Codec, Video Capture, Rendering. For a complex application, the online inference, non-AI libraries, and offline training modules constitute an overall critical path together.

To support large-scale cluster deployments, the framework provides the deployment tools that contain two automated deployment templates using Ansible and Kubernetes. The Ansible templates support scalable deployment on physical or virtual machines, while the Kubernetes templates are used to deploy on a container cluster. A configuration file needs to be specified for installation and deployment, including the module parameters like input data, and the cluster parameters like nodes, memory, and network information. Through the deployment tools, a user doesn’t need to know how to install and run each individual module.

6 Building Scenario Benchmarks

In this section, we illustrate how to build a scenario benchmark in detail, and later discuss the general guideline.

6.1 Design and Implementation of E-commerce Intelligence

On the basis of the reusing framework, we implement E-commerce Intelligence. This benchmark models the complete use case of a realistic E-commerce search augmented with AI, covering both text and image searching.

E-commerce Intelligence consists of four subsystems: Online Server, Offline Analyzer, Query Generator, and Data Storage, as shown in Fig. 3. Among them, Online Server receives query requests and performs personalized searching and recommendation, integrating AI inference.

Offline Analyzer chooses the appropriate AI component benchmarks and performs training to generate a learning model. Also, Offline Analyzer is responsible for building data indexes to accelerate data access.

Query Generator is to simulate concurrent users and send query requests to Online Server based on a specific configuration. Note that a query item provides either a text or an image to reflect different

Figure 3: The E-commerce Intelligence Implementation.
search habits of a user. The configuration designates the parameters like concurrency, query arriving rate, distribution, user thinking time, and ratio of text items to image items. The configurations simulate different query characteristics and satisfy multiple generation strategies. We implement Query Generator based on JMeter [33].

The Data Storage module stores all kinds of data. User Database saves all the attributes of the user information. Product Database holds all the attributes of the product information. The logs record the complete query histories. The text data contain the product description text or user comments. The image and video data depict the appearance and usage of a product vividly. The audio data contain the voice search data and voice chat data.

To support scalable cluster deployments, each module is scalable and can be deployed on multiple nodes. Also, a series of data generators are provided to generate E-commerce data with different scales, through setting several parameters, e.g., the number of products and product attribute fields, the number of users and user attribute fields.

6.1.1 Online Server

Online Server provides personalized searching and recommendations. Online Server consists of four modules: Search Planner, Recommender, Searcher, and Ranker.

Search Planner is the entrance of Online Server. It receives query requests from Query Generator, sends the requests to the other modules, and receives the return results. We use the Spring Boot framework [50] for Search Planner.

Recommender is to analyze query items and provide personalized recommendation, according to the user information obtained from User Database. It first conducts query spelling correction and query rewriting, and then predicts a query item belongs to which category based on two classification models—FastText [34] and ResNet50 [30]. FastText is used to classify a text query, while ResNet50 [30] is used to classify an image query. Using a deep neural network proposed by Alibaba [40], the Recommender module provides personalized recommendation. It returns two vectors: the probability vector of the predicted categories, and the user preference score vector of the product attributes, such as the user preferences for brand, color and etc. We use TensorFlow Serving [41] to provide text classification, image classification, and online recommendation services.

To guarantee scalability and service efficiency, Searcher is deployed on three different clusters on default, which follows an industry-scale deployment. The clusters hold the inverted indexes of product information in the memory to guarantee high concurrency and low latency. According to the click-through rate and purchase rate, the products are classified into three categories according to the popularity: high, medium, and low, and the proportion of data volume is 15%, 50%, and 50%, respectively. Note that the high-popularity category is a subset of the medium-popularity one. The indexes of products with different popularity are stored into the different clusters. Given a request, Searcher searches these three clusters one by one until the searched product data reach a threshold amount. Generally, the cluster that holds low-popularity products is rarely searched. So for each category, Searcher adopts different deployment strategies. The cluster containing high-popularity product data has more nodes and more backups to guarantee the searching efficiency. While the cluster containing low-popularity has the least number of nodes and backups. We use Elasticsearch [27] to set up and manage Searcher deploying on the three clusters.

Ranker uses the weight returned by Recommender as an initial weight, and ranks the scores of products through a personalized L2R neural network [40]. Ranker uses TensorFlow Serving [41] to implement product ranking.

6.1.2 Offline Analyzer

Offline Analyzer is responsible for training models to augment online services. It consists of three modules—AI Offline Trainer, Job Scheduler, and Indexer.

Job Scheduler provides two training mechanisms: batch processing and streaming-like processing. According to the experience from our industry partner, some models need to be updated frequently, as shown in Table 1. When a user searches an item and clicks one product showed in the first page, a new model will be trained immediately based on the product the users just clicked. Finally, a new recommendation will be made and shown in the second page. Our benchmark implementations consider this situation, and adopt a streaming-like approach to updating the models every few seconds. For batch processing, AI Offline Trainer will update the models every few hours.

Indexer is to build the indexes for product information. Indexer provides three kinds of indexes: the inverted indexes with a few fields of products for searching, the forward indexes with a few fields for ranking, and the forward indexes with a majority of fields for summary generation.

6.2 Design and Implementation of Translation Intelligence

To illustrate the usability and composability of our reusing framework, we build another scenario benchmark—Online Translation Intelligence (in short, Translation Intelligence). This benchmark models the complete use case of a realistic online translation scenario, including not only text-to-text translation but also audio translation and image-to-text conversion and translation.

Translation Intelligence consists of four subsystems: Online Server, Offline Analyzer, Query Generator, and Data Storage, shown in Fig. 4. Among them, Online Server receives query requests and performs translation. Offline Analyzer chooses the corresponding AI component benchmarks and trains a learning model. Query Generator simulates concurrent users and send text, audio, or image queries to Online Server according to specific configurations. The configuration information is the same with that of E-commerce Intelligence, which is based on JMeter [33]. The Data Storage module stores the query histories, training data and validation data used for the translation of text, audio, and image queries.
6.2.1 Online Server

Online Server is responsible for providing translation services. It consists of four modules, including Search Planner, Image Converter, Audio Converter, and Text Translator.

**Search Planner** receives the query request and determines which modules should be delivered to. The text, audio, and image queries are delivered to Text Translator, Audio Converter, and Image Converter, respectively. Search Planner uses the Spring Boot framework [50].

**Image Converter** receives an image query and extracts the text information within the image. It first loads the image data and performs image preprocessing through a BASE64 image encoder, since a RESTful API requires binary inputs to be encoded as Base64 [7]. Then it converts the image into text using an offline trained model—optical character recognition (OCR) [51]. After that, the extracted text information is sent to Text Translator for text translation. We reuse the Image-to-Text component.

**Audio Converter** receives an audio query and performs speech recognition to recognize the text information within an audio. It first loads the audio data and performs audio preprocessing, which converts an input audio into a WAV format with 16KHz. And then the Speech Recognition [12] component is reused to recognize the text information.

**Text Translator** performs text-to-text translations [48]. It receives text queries directly from the Search Planner or the converted text data from Image Converter and Audio Converter. We reuse the Text-to-Text Translation component. We use TensorFlow Serving [41] to provide OCR, speech recognition, and translation services.

6.2.2 Offline Analyzer

Offline Analyzer is responsible for job scheduling, and AI model training and updating. Among them, Job Scheduler includes batch processing and streaming-like processing, which are the same like that of E-commerce Intelligence. AI Offline Trainer is to train learning models or perform real-time model updates for online inference. For Translation Intelligence, AI Offline Trainer chooses three AI components from the AIBench framework, including Speech Recognition, Image-to-Text (OCR), and Text-to-Text translation.

6.3 Guidelines

We are implementing other scenario benchmarks listed in Table 1. There are several guidelines.

1. Determine the essential AI and non-AI component benchmarks.
2. For each component benchmark, find the valid input data from the data input module.
3. Determine the valid permutation of AI and non-AI components.
4. Specify the module-related configurations, i.e., input data, execution parameters, Non-AI libraries, and cluster-related configurations, i.e., node, memory, and network information.
5. Specify the deployment strategy and write the scripts for the automated deployment tool.
6. Train the AI models of the selected AI component benchmarks using the offline training module, and transfer the trained models to the online inference module.

7 Evaluation

This section summarizes our evaluation using the AIBench scenario benchmarks. Through the evaluations in Subsection 7.2 and Subsection 7.3, we demonstrate the advantages of scenario benchmarking in both online services and offline training, and gain several insights that can not be found using MLPerf [3] and TailBench [36]. In Subsection 7.2 and Subsection 7.4, we demonstrate how to drill down from a scenario benchmark into component benchmarks, and zoom in on the hotspot functions of the micro benchmarks. The evaluations not only emphasize the necessity of scenario benchmarking, but also explains what benefits can it bring for the system and architecture communities.
7.1 Experiment Setup

7.1.1 Node Configurations

The online server of E-commerce Intelligence and Translation Intelligence is deployed on a 15-node CPU cluster and a 5-node CPU cluster, respectively. Their offline trainers are deployed on GPUs.

For the 15-node CPU cluster, each node is equipped with two Xeon E5645 processors and 32 GB memory. For the 5-node CPU cluster, each node is equipped with two Xeon E5-2620 V3 (Haswell) processors and 64 GB memory. Each processor of the above two CPU clusters contains six physical out-of-order cores and disables Hyper-threading. They use the same OS version: Linux Ubuntu 18.04 with the Linux kernel version 4.15.0-91-generic, and the same software versions: Python 3.6.8 and GCC 5.4. All the nodes are connected with a 1 Gb Ethernet network.

Each GPU node is equipped with Nvidia Titan XP GPU. Every Titan XP owns 3840 Nvidia Cuda cores and 12 GB memory. The CUDA and Nvidia driver versions are 10.0 and 410.78, respectively.

7.1.2 Benchmark Deployment

The deployments of two AI scenario benchmarks introduced in Section 6 are as follows.

**Online Server Settings of E-commerce Intelligence.** We deploy E-commerce Intelligence on the 15-node CPU cluster, containing one Query Generator node (Jmeter 5.1.1), one Search Planner node (SpringBoot 2.1.3), four Recommender nodes (TensorFlow Serving 1.14.0 for Text Classier, Image Classier, Recommendation, and Python 3.6.8 for Preprocessor), six searcher nodes (Elasticsearch 6.5.2), one Ranker node (TensorFlow Serving 1.14.0), and two nodes for Data Storage (Neo4j 3.5.8 for User Database, Elasticsearch 6.5.2 for Product Database).

**Online Server Settings of Translation Intelligence.** We deploy Translation Intelligence on the 5-node CPU cluster, containing one Query Generator node (Jmeter 5.1.1), one Search Planner node (SpringBoot 2.1.3), one Image Converter node (TensorFlow Serving 1.14.0 for Image-to-Text and Python 3.6.8 for Image Preprocessing), one Audio Converter node (TensorFlow Serving 1.14.0 for Speech Recognition and Python 3.6.8 for Audio Preprocessing), and one Text Translator node (TensorFlow Serving 1.14.0).

**Offline AI Trainer Settings.** We deploy offline AI Trainers on 4-node GPUs for E-commerce Intelligence and on 3-node GPUs for Translation Intelligence, to train AI models or update AI models in a real-time manner.

7.1.3 Performance Data Collection

We use the network time protocol (NTP) [38] for synchronizing cluster-wide clock. A profiling tool—Perf [19] is used to collect the CPU micro-architectural data through the hardware performance monitoring counters (PMCs). For GPU profiling, we use the Nvidia profiling toolkit—nvprof [5] to track the running performance on GPU. We run each benchmark three times and report the average numbers.

7.2 Benchmarking Online Services

This subsection demonstrates how to drill down from scenario benchmarks into individual modules and further primary components for latency breakdown (Section 7.2.1), explains why a statistical model cannot predict the overall system tail latency (Section 7.2.2), explores the factors impacting service quality (Section 7.2.3), and characterizes the micro-architectural behaviors (Section 7.2.4).

7.2.1 Latency Breakdown of Different Levels

The latency is an important metric to evaluate the service quality. This subsection demonstrate how to drill down into different levels for a detailed latency breakdown using two scenario benchmarks on the two CPU clusters. The scenario benchmark configurations are as follows:
Figure 5: Overall System, Modules, and Components Latency Breakdown of Two Scenario Benchmarks.

For E-commerce Intelligence, Product Database contains a hundred thousand products with 32-attribute fields. Query Generator simulates 2000 users with 30-second warm up time. A user sends query requests continuously every think time interval, which follows a Poisson distribution. According to history logs, we set the proportion of text and image queries as 99% and 1%, respectively. For Translation Intelligence, Query Generator simulates 10 users with 30-second warm up time. The think time interval also follows a Poisson distribution. The proportion of text, image, and audio queries is 90%, 5%, and 5%, respectively. We collect the performance numbers until 20,000 query requests have finished for both two scenario benchmarks. In addition, we train each AI task to achieve the quality target of the referenced paper.

Fig. 5 shows the overall-system and individual-module latency of two scenario benchmarks, respectively. From Fig. 5-1(a) and Fig. 5-2(a), we find the average, 90th percentile, and 99th percentile latency of the overall system of E-commerce Intelligence is 178, 238, and 316 milliseconds, respectively, while for Translation Intelligence, the number is 778.7, 934.4, and 5919.7 milliseconds, respectively. The two scenario benchmarks reflect different latency characteristics because of different permutations of AI and non-AI tasks.

We further give a latency breakdown of each module to identify the critical paths. Fig. 5-1(b) shows the latency of the Recommender, Searcher, Search planner, and Ranker modules within E-commerce Intelligence. The latency of Search Planner is negligible, so we do not report it. We find that Recommender
occupies the largest proportion of latency: 117.06, 145.73, and 197.63 milliseconds for the average, 90th percentile, 99th percentile latency, respectively. In comparison, the average, 90th percentile, 99th percentile latency is 50.12, 102.3, and 170.21 milliseconds for Searcher, and 8.3, 8.9, and 11.5 milliseconds for Ranker, respectively. Fig. 5.2(b) shows the latency of Image Converter, Audio Converter, and Text Translator modules within Translation Intelligence. Among them, Audio Converter incurs the largest latency: 3897.4, 5431.4, and 6613.3 milliseconds for the average, 90th percentile, 99th percentile latency, respectively. Text Translator also has a large proportion of latency, which is 565.8, 815.2, and 1212.1 milliseconds for the average, 90th percentile, 99th percentile latency, respectively. The high latency of Audio Converter is due to its high model complexity, spending much time for processing each audio query. While for Text Translator, it needs to process all the queries eventually and results in query queuing, and thus becomes the bottleneck of the overall system. For both two scenario benchmarks, we find that different AI components incur significantly different latency, which is determined by their model complexity and dominance in the execution paths.

Furthermore, Fig. 5.1(c) and Fig. 5.2(c) shows the latency breakdown of the most time-consuming modules: Recommender for E-commerce Intelligence, Audio Converter and Image Converter for Translation Intelligence. Recommender includes Query Parsing, Preprocessor, User DB Access, Image Classifier, Text Classifier, and Recommendation, as shown in Fig. 5.1(c). We find that Recommendation, Image Classifier (two AI components) and User DB Access (non-AI component) are the top three key components that impact the latency of Recommender. Especially, the average latency of Recommendation (component) takes up 80% of the average latency of Recommender (module), and occupies 54% of the total latency of Online Server (overall system). The 99th percentile latency of Recommendation is 149.9 milliseconds, while the number of Recommender and Online Server is 197.63 and 316 milliseconds, respectively. For Text Classifier, its average latency and tail latency is less than 2 milliseconds, which is one hundredth of the latency of the subsystem. The reason for the overall system tail latency deteriorates dozens times or even hundreds times with respect to a single component are 1) a single component may be not in the critical path; 2) even an AI component like Recommendation is in the critical path, there exists cascading interaction effects with the other AI and non-AI components. From Fig. 5.2(c), we find that Speech Recognition has a great impact on the latency, more than thousands of milliseconds both for the average and tail latency, due to its high model complexity.

We also analyze the execution time ratio of the AI components vs. non-AI components of the overall system latency. If we exclude the communication latency, the average time spent on the AI and the non-AI components is 137.12 and 58.16 milliseconds for E-commerce Intelligence. While for Translation Intelligence, nearly 99% execution time is spent on the AI components. This observation indicates that the contributions of the AI components to the overall system performance vary from different scenarios.

7.2.2 Can a Statistical Model Predict the Overall System Tail latency?

As a scenario benchmark is much complex than a component or a micro benchmark, an intuition is that can we use a statistical model to predict the overall system tail latency? The answer is NO!

The state-of-the-art work [20] uses the M/M/1 and M/M/K queuing models to calculate the p’th percentile latency. We repeat their work, and choose the M/M/1 model to predict the latency as we only deploy one instance of Online Server for two scenario benchmarks. In the M/M/1 model, the p’th percentile latency ($T_p$) and the average latency ($T_m$) can be calculated using the following formula:

\[ T_p = -\ln(1 - \frac{p}{100}) \frac{1}{\mu - \lambda}, \]

\[ T_m = \frac{1}{\mu - \lambda}, \]

$\mu$ is the service rate, which follows the exponential distribution. $\lambda$ is the arrival rate, which follows the Poisson distribution.

For E-commerce Intelligence, we obtain $\mu$ as 90 requests per second through experiments. Then we set $\lambda$ as 3, 33, and 66 requests per second, respectively, to estimate 100, 1000, and 2000 concurrent users. For different settings, the theoretical number of the average latency is 11, 17, and 41 milliseconds, while the actual number is 141, 148, and 178 milliseconds, respectively. The average gap is 8.6X. The theoretical number of the 99th percentile latency is 52, 80, and 191 milliseconds, while the actual number is 261, 267, and 316 milliseconds, respectively. The average gap is 3.3X. For Translation Intelligence, we
get $\mu$ as 5.5 requests per second through experiments. Then we set $\lambda$ as 0.3, 0.8, and 1.5 requests per second, respectively, to estimate 5, 10, and 20 concurrent users. For different settings, the theoretical number of the average latency is 192, 212, and 250 milliseconds, while the actual number is 788, 799, and 821 milliseconds, respectively. The average gap is 3.7X. The theoretical number of the 99th percentile latency is 885, 979, and 1151 milliseconds, while the actual number is 4283, 5354, and 5362 milliseconds, respectively. The average gap is 5.0X.

The main reason for this huge gap is as follows. It is complex and uncertain to execute a scenario benchmark, and the service rate doesn’t follow the exponential distribution. So, the M/M/1 model is far away from the realistic situation. However, the more generalized model (e.g., G/G/1 model) is difficult to be used to calculate the tail latency. Furthermore, if we try to characterize the permutations of dozens of components in a scenario benchmark, we need a more sophisticated analytical model such as a queuing network model, which is much infeasible to perform a calculation of tail latency.

### 7.2.3 Factors Impacting Service Quality

We explore the impacts of the data dimension and model complexity on the service quality.

#### Impact of Data Dimension

The data input has great impact on workload behaviors [23, 52]. We quantify its impact on the service quality through resizing the dimensions of input image data for Image Classifier in E-commerce Intelligence, including 8*8, 16*16, 32*32, 64*64, 128*128, and 256*256 dimensions. Fig. 6 shows the average latency curve of Image Classifier. We find that with the data complexity increases, the average latency deteriorates, but its slope gradually decreases. For example, the data dimension changes from 128*128 to 256*256, while the average latency deteriorates three times. The reason is that with the enlargement of the data dimension, the increase of continuous data accesses brings in better data locality. From the micro-architectural perspective, we notice that with the increase of data dimension, the IPC increases sharply from 0.34 to 2.37, and the cache misses of all levels and pipeline stalls decrease significantly, going down about ten or even dozens of times. Hence, resizing the input data dimension (data quality) to a properly larger one is beneficial to improve the resource utilization, while there is a tradeoff between good service quality and enlarged data dimensions.

#### Impact of Model Complexity

The online inference module needs to load the trained model and conducts a forward computation to obtain the result. Usually, increasing the depth of a neural network model may improve the model accuracy, but the side effect is that a larger model size results in longer inference time. For comparison, we replace ResNet50 with ResNet152 in Image Classifier. The model accuracy improvement is 1.5%, while the overall system 99th percentile latency deteriorates by 10X.

Hence, Internet service architects must balance tradeoffs among data quality, service quality, model complexity, and model accuracy.
We characterize the micro-architectural behaviors of both AI and non-AI components of two scenario benchmarks using Perf. To compare AI and non-AI behaviors as a whole, we first report their average numbers of all AI and non-AI components. In our experiments, the AI components have lower IPC (instructions per cycle) (0.35) than that of the non-AI components (0.99) on average, since they suffer from more cache misses, TLB misses, and execution stalls, even up to a dozen times. Fig. 7 shows the cache and pipeline behavior differences between AI and non-AI components. The reason is that the AI components serving the services have more random memory accesses and worse data locality than that of the non-AI components. Thus, they exhibit a larger working set and higher memory bandwidth.

As for different AI components, we find that in E-commerce Intelligence, the two components with higher latency, i.e., Image Classifier and Recommendation, suffer from higher backend bound while lower frontend bound than Text Classifier and Ranker. The higher backend bound is mainly due to higher L1 data cache misses (more than 1.7 times) for Image Classifier, and more DRAM accesses (more than 1.4 times) for Recommendation. The higher frontend bound for Text Classifier and Ranker is mainly due to higher frontend latency bound caused by large L1 instruction cache misses (more than 2.5 times) and instruction TLB misses (more than 3.9 times). For Translation Intelligence, Image Converter and Audio Converter suffer from higher backend bound while lower frontend bound than that of Text Translator. The higher backend bound for Image Converter and Audio Converter is mainly due to higher L1 data cache misses (more than 2 times) and more DRAM accesses (more than 1.5 times). The lower frontend bound, incurred by inefficient utilization of the Decoded Stream Buffer (DSB), attributes to lower frontend bandwidth bound (about 2 times lower).

### 7.2.4 Micro-architectural Characterization.

### 7.3 Benchmarking Offline Training

Updating AI models in a real time manner is a significant industrial concern in many scenarios shown in Table 1. We evaluate how to balance the tradeoffs among model update intervals, training overheads and accuracy improvements using AI Offline Trainer of E-commerce Intelligence on the Titan XP GPUs.

We resize the volume of the input data to investigate how to balance tradeoffs among model update intervals, training overheads and accuracy improvements. For Image Classifier, using 60% of training images, the training time is 2096.8 seconds to achieve the highest accuracy of 68.7%. When using 80% and 100% of training images, the time spent is 2347.8 and 3170.7 seconds to achieve the highest accuracy of 71.8% and 73.7%, respectively. Hence, resizing the volume from 60% to 100%, 51% additional training time brings in a 4.96% accuracy improvement; From 80% to 100%, 35% additional training time brings
in a 1.9% accuracy improvement. For Ranker, using 60%, 80%, and 100% of training data, the training time is 839.3, 1222.8, and 1430.7 seconds, respectively. The highest accuracy is 12.4%, 13.6%, and 13.72%, respectively, which is close to [46]. So for this AI component, resizing from 60% to 100%, 70% additional training time brings in a 1.36% accuracy improvement. Resizing from 80% to 100%, 17% additional training time brings in a 0.12% accuracy improvement.

We conclude that Internet service architects need balance the tradeoffs among model update intervals, training overheads and accuracy improvements. Moreover, for different AI components, the tradeoffs have subtle differences, and the evaluation should be performed using a scenario benchmarking methodology.

Table 2: Hotspot Functions of Each AI Component.

<table>
<thead>
<tr>
<th>Component</th>
<th>Function Name</th>
<th>Time(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI Components of E-commerce Benchmark</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recommendation</td>
<td>Eigen::internal::EigenMetaKernel</td>
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<tr>
<td></td>
<td>CUDA Memcpy</td>
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<td></td>
<td>tensorflow::GatherOpKernel</td>
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<td></td>
<td>tensorflow::scatter_op_gpu::ScatterOpCustomKernel</td>
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<tr>
<td></td>
<td>cub::DeviceSelectSweepKernel</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>cub::DeviceReduceSingleTileKernel</td>
<td>2.7</td>
</tr>
<tr>
<td>Ranker</td>
<td>Eigen::internal::EigenMetaKernel</td>
<td>56.6</td>
</tr>
<tr>
<td></td>
<td>sgemm_32x32x32_NT_vec</td>
<td>9.1</td>
</tr>
<tr>
<td></td>
<td>tensorflow::functor::ColumnReduceSimpleKernel</td>
<td>8.7</td>
</tr>
<tr>
<td></td>
<td>sgemm_32x32x32_TN_vec</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>gemmk1_kernel</td>
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<tr>
<td></td>
<td>tensorflow::BiasGradNHWC_SharedAtomics</td>
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</tr>
<tr>
<td>Image Classifier</td>
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<td></td>
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<td>cudnn::detail::bn_jw_tr_IC11_kernel_new</td>
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<tr>
<td>AI Components of Translation Benchmark</td>
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</tr>
<tr>
<td>Text Translator</td>
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<td></td>
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</table>

7.4 Zooming in on Hotspot Functions

The evaluations in Section 7.2.1 demonstrate that drilling down from a scenario benchmark into the primary components let us focus on the component benchmarks without losing the overall critical path. This subsection will further demonstrate how to zoom in on the hotspot functions of these primary component benchmarks. Section 7.2.1 shows the primary five AI components are on the critical path of the two scenario benchmarks and have great impacts on the overall system latency and tail latency. They are Recommendation, Ranker, and Image Classifier for E-commerce Intelligence, and Speech Recognition and Text Translator for Translation Intelligence. To zoom in on the hotspot functions of these component benchmarks, we run both training and inference stages and use nvprof to trace the running time breakdown.
Figure 8: Running time breakdown of Eigen::internal::EigenMetaKernel—the most time-consuming function among the five AI components.

To profile accuracy-ensured performance, we first adjust the parameters, e.g., batch size, to achieve the state-of-the-art quality target of that model on a given dataset, and then sample 1,000 epochs of the training using the same parameter settings.

Table 2 shows the hotspot functions of the five primary components of the two scenario benchmarks. Note that we merge the time percentages of the same function and report the total sum. For example, the time percentage of Eigen::internal::EigenMetaKernel merges all the functions that call Eigen::internal::EigenMetaKernel with different parameters, like scalar_sum_op and scalar_max_op.

We find that Eigen::internal::EigenMetaKernel is the most time-consuming functions among the five primary AI components. Eigen is a C++ template library for linear algebra [2] used by TensorFlow. Through statistics in Fig. 8 we further find that within Eigen::internal::EigenMetaKernel, the most commonly used kernels are matrix multiplication, sqrt, compare, sum, quotient, argmax, max, and data_format computations. Here data_format means variable assignment, data slice, data resize, and etc. We reveal that these five components and the corresponding hotspot functions are the optimization points not only for software stack and CUDA library optimizations but also for micro-architectural optimizations.

8 Conclusion

This paper proposes a scenario benchmarking methodology. We propose the permutations of essential AI and non-AI components as a scenario benchmarks—a proxy for a real-world application scenario; We considers scenario, component, and micro benchmarks as three indispensable parts of a benchmark suite. Together with seventeen industry partners, we identify nine important application scenarios. We design and implement a reusable benchmark framework, on the basis of which, we build two scenario benchmarks to model two realistic scenarios: E-commerce Intelligence and Translation Intelligence. Our evaluation shows the advantage of the scenario benchmarking methodology against using component or micro benchmarks alone.

References


