AIBench Scenario: Scenario-distilling
AI Benchmarking

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AIBench Scenario: Scenario-distilling AI Benchmarking

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Abstract

Modern real-world application scenarios like Internet services consist of a diversity of AI and non-AI modules with huge code sizes and long and complicated execution paths, which raises serious benchmarking or evaluating challenges. Using AI components or micro benchmarks alone can lead to error-prone conclusions. This paper presents a methodology to attack the above challenge. We formalize a real-world application scenario as a Directed Acyclic Graph-based model and propose the rules to distill it into a permutation of essential AI and non-AI tasks, which we call a scenario benchmark. Together with seventeen industry partners, we extract nine typical scenario benchmarks. We design and implement an extensible, configurable, and flexible benchmark framework. We implement two Internet service AI scenario benchmarks based on the framework as proxies to two real-world application scenarios.

We consider scenario, component, and micro benchmarks as three indispensable parts for evaluating. Our evaluation shows the advantage of our methodology against using component or micro AI benchmarks alone. The specifications, source code, testbed, and results are publicly available from \url{https://www.benchcouncil.org/aibench/scenario/}.

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GitHub: \url{https://github.com/BenchCouncil/aibench_scenario}
1 Introduction

Modern real-world application scenarios like Internet services are complex, which raises serious benchmarking and evaluating challenges. First, they often adopt a microservice-based architecture consisting of a diversity of AI and non-AI modules with long and complicated execution paths across different datacenters. Using AI micro or component benchmarks alone can lead to error-prone conclusions.

For Internet services, the overall system tail latency deteriorates even hundreds of times than that of a single AI component. For example, for text classification—an AI component, the gap reaches up to 180× (Section 5.2.1). If we evaluate a new AI model or accelerator with text classification, it reduces the component tail latency. However, it contributes little to the overall system tail latency. Note that tail latency represents the tail performance of a small fraction of requests, e.g., 99th percentile latency, which is significant since these small fractions may exceed the median latency by orders of magnitude [1].

Second, they dwarf the traditional workloads in terms of code sizes and deployment scales. For example, the traditional desktop workloads like data compression [2], image manipulation [2], are about one hundred thousand lines of code, running on a single node. The Web server workloads [3] are hundreds of thousands of lines of code, running on a small-scale cluster, i.e., dozens of nodes. However, the modern AI stacks (e.g., Spark [4], TensorFlow [5]) alone are more than millions of lines of code, and the real-world workloads often run on a large-scale cluster, i.e., tens of thousands of nodes [6]. It is almost impossible to evaluate a real-world application scenario directly. Even it is possible, due to their huge code sizes, it will raise the fairness challenge in assuring the benchmark implementations’ equivalence across different systems and the repeatability challenge in measurement errors.

Third, it is prohibitively costly for porting a real-world application scenario to an innovative system or architecture [7,8]. Especially, the real-world data sets, workloads, and even AI models are treated as first-class confidential issues by their owners [9,10].

While profiling has been applied to various aspects of benchmarking [11,12], we are not aware of evidence demonstrating it can holistically evaluate a large and complex system. For example, for Internet services, a few publicly available performance models or insights observed through profiling [9,10,13,14] do not work across different systems or architectures. As there are no publicly available benchmarks, the state-of-the-art and state-of-the-practice are advanced only by the research staff within various service providers, which poses a considerable obstacle for our communities towards developing an open and mature research field.

This paper proposes a gray-box methodology that accesses no code but
needs the industry’s design input (Fig. 1), to attack the above challenge. We formalize a real-world application scenario as a Directed Acyclic Graph-based model (in short, DAG model) and propose six rules to distill it into a permutation of essential AI and non-AI tasks as a scenario benchmark. We call it a scenario-distilling methodology. Our methodology is to identify the critical path and primary modules of a real-world scenario since they consume the most system resources and are the core focuses for system design and optimization. We will extend to white-box (apply to industry users who can access the code) and black-box (without input) methodologies in the future. In cooperation with seventeen industry partners, we extract nine vital scenario benchmarks. 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. Based on the framework, we implement two scenario benchmarks—E-commerce Search Intelligence and Online Translation Intelligence. With respect to its counterpart real-world application scenario, each scenario benchmark reduces the complexity by one or two orders of magnitude. It is easier to achieve the latter’s efficient implementation to avoid misleading evaluations using a suboptimal implementation. For a real-world application scenario, the complex software evolution also hinders high-performance implementation.

We consider scenario, component, and micro benchmarks as three indispensible parts other than using component or micro benchmark alone. A scenario benchmark lets the software and hardware designers obtain the overall system performance and determine the critical path’s primary components. Furthermore, the system and architecture researchers use the AI component benchmarks that occupy the critical path to evaluate the AI model performance and quality targets. Finally, the code developers can use microbenchmarks obtained through profiling scenario benchmarks and component benchmarks to optimize the hotspot functions. They bridge a considerable gap from real-world application scenario deployment to simulator-based architecture research. The community can tune the system, architecture, and algorithm innovations on a scenario benchmark without disclosing real-world application scenarios’ confidentiality. The developer can test the designs on a scenario benchmark or obtain the trace of a scenario benchmark through sampling, a component benchmark, or a microbenchmark and feed them into simulators for earlier validation. AI Bench Scenario can use SimPoint 15 or Pin 16.

Our evaluations demonstrate how to drill down from a scenario benchmark into the component benchmarks and zoom in on the microbenchmarks’ hotspot functions. The evaluations on two CPU clusters and one GPU cluster show the advantage of our benchmarks against MLPerf and TailBench. We have several observations as follows: (1) The performance characteristic of only one AI component varies from that of a scenario benchmark with a permutation of the previous AI component and other AI and non-
AI components. The benchmark user must understand the implication of benchmarking using only one AI component like MLPerf in the context of a scenario benchmark. In serving the same requests for the online services, different AI components incur different latency. Some AI components contribute little to the overall system performance. (2) The overall system tail latency deteriorates dozens of times or even hundreds of times over a single AI component, which we cannot predict using two state-of-the-art statistical models [17][18]. (3) We argue that on AI benchmarking, systems can benefit from analyzing both online services and offline AI training scenarios. Internet service architects generally attempt to balance the tradeoffs among service quality, input data dimensions, AI model complexity, accuracy, and model update intervals.

We organize the rest of this paper as follows. Section 2 explains the motivation. Section 3 summarizes the related work. Section 4 presents how to distill and implement scenario benchmarks. Section 5 performs the evaluation. Section 6 concludes.
2 Motivation

2.1 Using component benchmarks alone may lead to error-prone conclusions.

Modern Internet services process millions of user queries daily; thus, the tail latency is important in terms of user experience [17]. However, a microservice-based architecture can contain various AI and non-AI modules, and consequently forms long and complicated execution paths. Previous AI benchmarking work provides a few micro or component benchmarks and fails to model an industry-scale application scenario's overall critical paths.

The overall system latency indicates that of the entire execution path, including AI and non-AI components. Our experiments in Section 5.2.1 show the overall system tail latency deteriorates dozens or even hundreds of times than a single component. The gap ranges from 2.2x – 180x between text classification and recommendation, respectively. When we evaluate a new AI model or accelerator using text classification, suppose it reduces the component tail latency. However, it still contributes little to the overall system tail latency.

Another case study is as follows. Model pruning has been shown to be effective in improving inference speed [19]. Evaluating with image-to-text a component of the Translation Intelligence scenario benchmark, a model-pruning implementation [19] decreases the model size from 31MB to 21MB. It reduces the 99th percentile latency by 51% from 4214 to 2081 milliseconds compared to the original model. The accuracy loss is 1%, from 88% decreasing to 87%, which may be considered acceptable considering the vast inference speedup. However, under a scenario benchmark, the overall 99th percentile latency nearly remains the same (about 0.2% reduction), with the same accuracy loss, which may be considered unacceptable as it reduces the service accuracy while providing no non-negligible computational benefit. Thus, scenario benchmarking is essential.

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

The tail latency of many components has been studied by using various profiling-based statistical models. Recent work [20] proposes an algorithm to predict the tail latency of database query systems. However, for complex application scenarios like Internet services, the overall system tail latency prediction is not fully addressed.

In Section 5.2.3, we use two state-of-the-art queueing-based statistical models to estimate the overall system latency and tail latency: a simple queueing model [17] and a sophisticated queueing network model [18]. We find that the gaps between the actual average latency/tail latency and the
theoretical ones are large through the experiments using two scenario benchmarks. For example, for E-commerce Intelligence, the average latency gap is 8.6x and 4.9x using the simple queueing model and the queueing network model, respectively. The 99th percentile latency gap is 3.3x using the simple queueing model. Due to the non-superposition property of the overall system tail latency—being not equal to the sum of each component—the 99th percentile latency is hard to be predicted accurately using a queueing network model [18], so we do not report the 99th percentile latency gap using the queueing network model.

2.3 Why Offline AI Training is also Essential in Scenario Benchmarking

As our many industry partners have witnessed, they have to update the AI models in a real-time manner using an AI model for an online service. 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 of about 3% click-through rate and millions of profits. In Section 5.3 our evaluation shows offline training should be included in scenario benchmarking, as it is essential to balance the tradeoffs among model update intervals, training overheads, and accuracy improvements.
3 Related Work

Several AI benchmark suites only provide component benchmarks, which may lead to error-prone conclusions. Fathom [21] provides eight deep learning component benchmarks implemented with TensorFlow, targeting six AI tasks. DAWNBench [22] is a component benchmark suite, which firstly pays attention to end-to-end performance—the training time to achieve state-of-the-art accuracy. MLPerf [23, 25] is an ML component benchmark suite targeting seven AI tasks and eight AI models for training, and six AI models for inference. Although MLPerf provides the inference for server mode, the server mode only contains one component and fails to cover a real-world industry-scale scenario’s critical path. Our experiments illustrated in Section 2.1 also find that for complex scenarios, containing the execution path with only one component without the entire execution path is insufficient and may even lead to error-prone conclusions. MLPerf Tiny [26] is a deep learning benchmark for embedded and ultra-low-power devices. TBD Suite [27] is a component benchmark suite for DNN training, with eight neural network models for six AI tasks.

Several AI benchmark suites only provide microbenchmarks, ignoring the quality target in benchmarking. DeepBench [28] consists of four operations involved in training deep neural networks. DNNMark [29] is a GPU benchmark suite that consists of a collection of deep neural network primitives.

Additionally, Sirius [30] is an end-to-end IPA web-service application that receives voice and image queries and responds with natural language. TailBench [31] is a benchmark suite that consists of eight latency-critical workloads. CloudSuite [32] provides eight workloads for benchmarking cloud services. MLModelScope [33] proposes a distributed platform for scalable model evaluation. DeathStarBench [34] is a benchmark suite for microservice, including five workloads. They find a single poorly-configured microservice or slow server can degrade end-to-end latency by several orders of magnitude [34, 35].

AIBench distills and abstracts real-world application scenarios into AI Scenario, Training, Inference, Micro and Synthetic Benchmarks across Datacenter, HPC, IoT, and Edge [36]. This paper focuses on scenario benchmark, others include AIBench Training [37], HPC AI500 [38], Edge AIBench [39, 40], and AIoTBench [41].
4 The Design and Implementation

Collaborating with the seventeen industry partners whose domains include search engine, e-commerce, social network, a news feed, video, etc., we distill their products or services into nine representative scenarios, as summarized in Table 1. After identifying their primary components, we design and implement a reusing benchmark framework. Finally, we implement two scenario benchmarks on the reusing framework: E-commerce Search Intelligence (in short, E-commerce Intelligence) and Online Translation Intelligence (Translation Intelligence).

Subsection 4.1 demonstrates how to distill a scenario into a high-level scenario benchmark specification. Subsection 4.2 explains the general steps to implement a scenario benchmark on the reusing benchmark framework and the implementation details of these two scenario benchmarks.

4.1 The Distilling Methodology

We formalize a real-world application scenario as a DAG model, consisting of a series of tasks with dependencies. Fig. 2(a) shows the DAG model of the real-world E-commerce Intelligence derived from one Internet service giant. The formalization requires the domain knowledge, needing input from the primary industry partners. Our partners accept it as it does not expose confidential real-world workloads, data sets, and AI models. After the formalization, the high-level scenario specification is stated in a paper-and-pencil approach and reasonably divorced from individual implementations [8,42].

We distill the scenario’s DAG model into a permutation of essential AI and non-AI tasks and consider it a high-level scenario benchmark specification. Fig. 2 shows the DAG models before and after distilling of E-commerce Intelligence. After distilling, we can reduce the complexity of the scenarios by one or two orders of magnitude. Fig. 3 shows the DAG model of Translation Intelligence after distilling. Due to the page limitations, we only describe how we distill this scenario using text. To capture the essential parts of the original DAG, we propose six distilling rules.

- **R1.** We will keep only one essential branch among the DAG branches that have similar processing logic.

*E-commerce Intelligence.* In the Recommender module, personalized recommendation, product recommendation, and advertising (AD) have similar processing logic though they consider different attributes and having other purposes. For example, personalized and product recommendations think user attributes and product attributes, respectively; recommendation cares about the user experience, while AD mainly concerns the click-through rate.
Table 1: Nine Representative Scenarios Extracted from the Seventeen Industry Partners.

| Application Scenario | Involved AI Task | Involved Non-AI Task | Data | Metrics | Model Update Frequency |
|-----------------------|------------------|----------------------|------|---------|------------------------|
| E-commerce Search Intelligence | Text/Image Classification; Learning to Rank; Recommendation | Query Parsing, Database Operation, Indexing | User Data, Product Data, Query Data | Precision, Recall, Latency | High |
| Online Translation Intelligence | Text-to-Text Translation; Speech Recognition; Image-to-Text | Query Parsing, Audio/Image Preprocessing | Text, Audio, Image | Accuracy, Latency | Low |
| Content-based Image Retrieval | Object Detection; Classification; Spatial Transformer; Image-to-Text | Query Parsing, Indexing | Image | Precision, Recall, Latency | High |
| Web Searching | Text Summarization; Learning to Rank; Recommendation | Query Parsing, Indexing, Crawler | Product Data, Query Data | Precision, Recall, Latency | High |
| Facial Authentication and Payment | Face Embedding; 3D Face Recognition; | Encryption | Face Image | Accuracy, Latency | Low |
| News Feed | Recommendation | Database Operation, Basic Statistics, Filter | Text | Precision, Recall | High |
| Live Streaming | Image Generation; Image-to-Image | Video Codec, Video Capture | Image | Latency | Low |
| Video Services | Image Compression; Video Prediction | Video Codec | Video | Accuracy, Latency | Low |
| Online Gaming | 3D Object Reconstruction; Image Generation; Image-to-Image | Rendering | Image | Latency | Low |
of advertised products. Here we only keep personalized recommendation as one essential branch.

Translation Intelligence. In the Text Translator module, the translation microservices for different languages use a similar AI model while different training data. We only preserve the translation from English to Deutsch.

- R2. We prune the DAG branch that occupies the smallest fraction that less than 1% in the whole scenario.

E-commerce Intelligence. Within Recommender, there are three branches according to the query type—image, audio, and text. The audio query occupies a minuscule fraction and less than 1%, so we prune it.

Translation Intelligence. In the translation scenario, the fractions of text, image, and audio branches are more than 1% according to our industry partner, so we reserve all three branches.

- R3. We remove the components that implement the auxiliary end-user functions.

E-commerce Intelligence. E-commerce Intelligence focuses on the product searching scenario, so we remove the OLAP analyzer that analyzes the product ordering and the supporting systems such as monitoring and logging.

Translation Intelligence. We also remove the supporting systems for tracing, monitoring, logging, etc.

- R4. For each AI component, we provide only one state-of-the-art or state-of-the-practice model for simplicity.
Figure 3: The Distilled DAG Model of Translation Intelligence.

**E-commerce Intelligence.** A scenario usually provides multiple AI models, which different businesses share. For simplicity, we only reserve one state-of-the-art or state-of-the-practice model for each AI component like Ranker.

**Translation Intelligence.** We provide one state-of-the-art or state-of-the-practice model for its three AI components.

- **R5.** We combine the successive steps involved in similar components.

**E-commerce Intelligence.** We combine the entity identification and category classifier within Recommender, as they both include image classifier and text classifier.

**Translation Intelligence.** We combine the Text Translator, since all the three branches, i.e., the image, text, and audio, involve in text-to-text translation.

- **R6.** After performing R1 to R5, we will remove the components related to the pruned ones.

**E-commerce Intelligence.** After pruning the AD branch in the recommender, we remove the AD cluster group in Searcher and AD ranking in Ranker accordingly. Also, we remove the deduplication component in Search Planner since the AD cluster group is removed, and Searcher will return no repeated items. Besides, Indexer only builds the product indexes since Searcher mainly uses the product attributes to search the product item.

**Translation Intelligence.** After removing the translation microservices for the other languages, the related components are removed.
4.2 How to Implement a Scenario Benchmark?

4.2.1 The Summary of Representative AI Tasks

To cover a broad spectrum of AI Tasks, we thoroughly analyze the real-world application scenarios shown in Table 1. We summarize the essential AI tasks and define the AI component specifications. Each AI component specifies an AI task description, a reference AI model, datasets, evaluation metrics, and state-of-the-art quality target [25]. In total, we identify sixteen representative AI tasks illustrated as follows. For each AI task, we implement the AI component benchmarks on both TensorFlow [5] and PyTorch [43].

Classification is to extract different thematic classes within the input data like an image [44] or text file [45]. Image Generation is an unsupervised learning problem to mimic the distribution of data and generate images [46]. Text-to-Text Translation needs to translate a text from one language to another [47]. Image-to-Text is to extract the text information from an image, which is a process of optical character recognition (OCR) [48] or generate the description of an image automatically [49]. Image-to-Image is to convert an image from one representation to another one [50], e.g., season change. Speech Recognition is to recognize and translate a spoken language into text [51]. Face Embedding is to transform a facial image into a vector in an embedding space [52]. 3D Face Recognition is to recognize the 3D facial information from multiple images from different angles [53]. Object Detection is to detect the objects within an image [54]. Recommendation is to provide recommendations [55]. Video Prediction is to predict the future video frames through predicting previous frames transformation [56]. Image Compression is to compress the images and reduce the redundancy [57]. 3D Object Reconstruction is to predict and reconstruct 3D objects [58]. Text Summarization is to generate a text summary [59]. Spatial Transformer is to perform spatial transformations like stretching. Learning to Rank is to learn the attributes of a searched content and rank the scores for the results [61].

Moreover, we profile all implemented component benchmarks and drill down into frequently appearing and time-consuming units of computation. Each of them constitutes a microbenchmark, which is easily portable to a new architecture and system and hence beneficial for fine-grained profiling and tuning.

4.2.2 The Reusing Framework

As shown in Fig. 4, the reusing framework provides loosely coupled modules that are easily configured. It includes the data input, offline training, online inference, non-AI libraries, and deployment tool modules. Based on the reusing framework, we can quickly implement a scenario benchmark. Since there are many other scenarios that we do not investigate, e.g., ma-
chine programming and event prediction, the framework may not suit all the scenarios. We will explore more scenarios and involved AI tasks to achieve broader coverage.

The data input module is responsible for feeding data into the other modules. It collects representative real-world data sets from the authoritative public websites and our industry partners after anonymization. We design the data schema to maintain the real-world data characteristics, alleviating the confidential issues. Our framework covers a broad spectrum of data types and sources, integrates various open-source data storage systems, and supports large-scale data generation and deployment for partial data \[62\].

We provide offline training and online inference modules to implement a scenario benchmark. First, the offline training module chooses one or more component benchmarks by specifying the input data and execution parameters like the 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 \[63\]. 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 scenario, the online inference, non-AI libraries, and offline training modules constitute an overall critical path together.

The framework provides the deployment tools that contain two automated deployment templates using Ansible \[64\] and Kubernetes \[65\] to support large-scale cluster deployments. 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. A user does not need to know how to install and run each module through the deployment tools.
4.2.3 Design and Implementation of Scenario Benchmarks

Based on the reusing framework, we implement two scenario benchmarks—E-commerce Intelligence and Translation Intelligence. They model the complete use cases of a realistic E-commerce search and a real-world online translation scenario augmented with AI.

The implementation steps are as follows.
(a) First, we choose the essential AI and non-AI component benchmarks and corresponding input data from the reusing framework according to Table 1.
(b) Next, the permutation of component benchmarks is specified by the scenario benchmark specification. The permutations of E-commerce Intelligence and Translation Intelligence are shown in Fig. 2(b) and Fig. 3, respectively. They consist of four subsystems: Online Server, Offline Analyzer, Query Generator, and Data Storage. We will provide the permutation specifications of the other seven scenarios listed in Table 1.
(c) Then, we choose the deployment tools, i.e., Ansible and Kubernetes, and modify the reusing framework’s deployment template. The deployment template includes the module-related configurations, i.e., input data, execution parameters, non-AI libraries, and cluster-related configurations, i.e., node, memory, and network information. Note that we have provided the default templates on our open-source website for both Ansible and Kubernetes. Users can change the configurations according to their environments.
(d) Finally, we 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. Note that we also provide pre-trained models for direct use.

Implementation of E-commerce Intelligence. Query generator simulates concurrent users and sends queries to Online Server based on a specific configuration. A query item provides either a text or an image to reflect the different search habits. The configuration designates the parameters like concurrency, query arriving rate, distribution, user thinking time, and ratios of text and image items. The configurations simulate different query characteristics and satisfy multiple generation strategies. Query Generator is based on JMeter [66].

Online Server receives query requests and performs searching and recommendation, integrating AI inference, consisting of four modules.
Search Planner receives and forwards the queries, using the Spring Boot framework [67].
Recommender is to analyze query items and provide a personalized recommendation, according to the user information obtained from User Database. It first conducts query preprocessing and then predicts a query item belongs to which category based on two classification models—FastText [45]...
and ResNet50 [44]. FastText is used to classify a text query, while ResNet50 [44] is used to classify an image query. The Recommender module uses a deep neural network, proposed for e-commerce tasks [68], to provide personalized recommendations. We use TensorFlow Serving [63] to provide text classification, image classification, and online recommendation services.

We deploy Searcher 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, we classify the products into three categories according to 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. We store the indexes of products with different popularity in the other clusters.

The cluster containing high-popularity product data has more nodes and more backups to guarantee searching efficiency. In comparison, the cluster containing low-popularity has the least number of nodes and backups. We use Elasticsearch [69] to set up and manage Searcher deploying on the three clusters.

Ranker uses the weight returned by Recommender as initial weight and ranks the scores of products through a personalized L2R neural network [68]. Ranker uses TensorFlow Serving [63] to implement product ranking.

Offline Analyzer performs job scheduling, AI model training, and updating. Job Scheduler includes batch and streaming-like processing, which updates the models every few hours or seconds accordingly. AI Offline Trainer trains learning models of chosen components or performs real-time model updates for online inference.

**Implementation of Translation Intelligence.** Query generator simulates concurrent users and sends either a text, an image, or audio to Online Server. The configuration information is the same as that of E-commerce Intelligence.

Online Server contains four modules. Search Planner is the entrance of the Online Server, which also uses the Spring Boot framework [67].

**Image Converter** receives an image query and extracts the text information within the image. It first performs image preprocessing using a BASE64 image encoder since a RESTful API requires encoding binary inputs as Base64 [70]. Then it converts the image into text using the Image-to-Text component—optical character recognition (OCR) [48].

**Audio Converter** receives an audio query and recognizes the text information within the audio. It first converts input audio into a WAV format with 16KHz and reuses Speech Recognition [51] component.

**Text Translator** performs translations and reuses Text-to-Text Translation component [47]. It receives text queries directly from Search Planner or the converted text data from Image Converter and Audio Converter.
Offline Analyzer performs job scheduling, which is similar to that of E-commerce Intelligence, except that they use different AI component benchmarks and update intervals.

### 4.2.4 Validation of a Scenario Benchmark

Our methodology provides a two-level mechanism to verify whether a scenario benchmark can represent the real-world application scenario.

**Specification-level Validation.** On the specification level, it is easier to validate whether the scenario benchmark specification captures the essential parts of a scenario, as we can easily reach a consensus about the efficiency of the distilling rules with the industry partners’ feedback. Our methodology and distilling rules only prune the auxiliary modules like the logging system and the non-critical path that occupies little weight; thus, from the specification level, the distilled DAG is close to the original DAG.

**Implementation-level Validation.** On the implementation level, we compare the scenario benchmark with the real-world scenario from the perspectives of both overall system performance and single component performance. From the overall system performance perspective, we compare the overall system latency of the whole execution path under the same deployment. We define their deviation as the ratio of absolute latency difference between a scenario benchmark and a real-world one to the value of the real-world one—the lower the deviation, the closer the benchmark to reality. From the single component performance perspective, we replay the user queries and run the component on the same processor. Finally, we compare the latency of the component, system (e.g., CPU utilization), and micro-architectural (e.g., instructions per cycle) behaviors to check whether the scenario benchmark has similar behaviors with the real-world one.
5 Evaluation

This section summarizes our evaluation using the scenario benchmarks. Through the evaluations in Subsection 5.2 and Subsection 5.3, we demonstrate the advantages of scenario benchmarking in online services and offline training. We gain several insights that cannot be found using MLPerf [23] and TailBench [31]. In Subsection 5.2 and Subsection 5.4, we demonstrate how to drill down from a scenario benchmark into component benchmarks and zoom in on the hotspot functions of the microbenchmarks. The evaluations emphasize the necessity of scenario benchmarking and explain what benefits it can bring for the system and architecture communities.

5.1 Experiment Setup

5.1.1 Node Configurations

Since CPU is widely used for inference in industry [9], 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. Our another paper [37] has evaluated the AI offline training on other platforms like TPU.

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 identical 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.

5.1.2 Benchmark Deployment

**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 Classifier, Image Classifier, Recommendation, and Python 3.6.8 for Preprocessor), six searcher nodes (Elasticsearch 6.5.2 [69]), 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 (Tensor-
Flow 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.

5.1.3 Performance Data Collection

We use the network time protocol (NTP) [71] for synchronizing cluster-wide
clock. We use Perf [72] to collect the CPU micro-architectural data through
the hardware performance monitoring counters (PMCs). For GPU profiling,
we use the Nvidia profiling toolkit—nvprof [73] to track GPU performance.
We run each benchmark three times and report the average numbers.

5.2 Benchmarking Online Services

This subsection demonstrates how to drill down from a scenario bench-
mark into individual modules or even primary components for latency break-
down (Section 5.2.1), explains why a statistical model cannot predict the
overall system tail latency (Section 5.2.3), explores the factors impacting
service quality (Section 5.2.4), and characterizes the micro-architectural be-
haviors (Section 5.2.5).

5.2.1 Latency Breakdown of Different Levels

The latency is an essential metric to evaluate the service quality. This
subsection demonstrates 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.

For E-commerce Intelligence, Product Database contains a hundred thou-
sand products with 32-attribute fields. Query Generator simulates 2000
users with a 30-second warm-up time. A user sends query requests continu-
ously every think time interval, following 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
ten users with a 30-second warm-up time. The think time interval also fol-
lows 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. Also,
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. Simultaneously, 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 various 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 the Recommender occupies the most significant latency proportion: 117.06, 145.73, and 197.63 milliseconds for the average, 90th percentile, 99th percentile latency, respectively. The average, 90th percentile, 99th percentile latency is 50.12, 102.3, 170.21 milliseconds for Searcher, 8.3, 8.9, 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 most considerable 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, 565.8, 815.2, and 1212.1 milliseconds for the average, 90th percentile, and 99th percentile latency. Audio Converter’s high latency is due to its high model complexity, spending thousands of milliseconds processing each audio query. Text Translator needs to process all the queries eventually and results in query queueing, thus becoming the bottleneck of the overall system. We find that different AI components incur different latency for both scenario benchmarks, which their model complexity and dominance in the execution paths determine.

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 recommender’s latency. 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 two milliseconds, one-hundredth of the subsystem’s latency. The overall system tail latency deteriorates dozens of times or even hundreds of times concerning a single component because of the following reasons. First, a single component may not be on the critical path. Second, even an AI component like Recommendation is critical; there are cascading interaction effects with the other AI and non-AI components.

From Fig. 5-2(c), we find that Speech Recognition has a significant 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 AI components’ contributions to the overall system performance vary from different scenarios.

Reproducibility. Reproducibility is significant for a benchmark. We repeat two scenario benchmarks five times to verify their reproducibility. We use the coefficient of variation (CV) as the metric, which is the standard deviation ratio to the mean value. The CV for the average, 90th percentile, and 99th percentile latency is 0.005, 0.007, and 0.014 for E-commerce Intelligence, and 0.006, 0.018, and 0.024 for Translation Intelligence, respectively. The experiments show that our scenario benchmarks have extremely low reproducibility.
5.2.2 Validation of Scenario Benchmarks

To validate how closely our scenario benchmark to real-world application scenarios, we take E-commerce Intelligence as an example to verify the effectiveness.

We compare the E-commerce Intelligence scenario benchmark with the real-world E-commerce scenario from our industry partner. According to Section 4.2.4, we conduct the comparison from the overall system performance and single component performance. We deploy the real-world E-commerce scenario on our 15-node cluster and use the same configurations for the query generator. Fig. 6 shows the overall system latency of the whole execution path. We find that the average, 90th percentile and 99th percentile latency of the real-world scenario are 180.47, 225, and 299 milliseconds, respectively. The values are 178, 238, and 316 milliseconds respectively, for E-commerce Intelligence. The deviations for the average, 90th percentile, and 99th percentile latency are 1.4%, 5.8%, and 5.7%, respectively, within the normal range. Hence, they share the consistent latency behaviors, demonstrating that the scenario benchmark captures the real-world E-commerce scenario’s overall system performance.

We run the Recommendation component both within E-commerce Intelligence and real-world scenarios to compare a single component’s performance. We choose Recommendation as it is the most time-consuming component and impacts the overall system latency. The average latency of Recommendation for E-commerce Intelligence and real-world scenario are 97.03 and 103.68 milliseconds, respectively, and the deviation is 6%. For the CPU utilization and instructions per cycle (IPC), the values are 51% vs. 50%, and 0.59 vs. 0.6, respectively. The deviations are 2% and 1.7% for CPU utilization and IPC. Thus, from a single component level, our bench-
mark still reflects its importance on the critical path and reflects similar workload behaviors within the real-world scenario.

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

As a scenario benchmark is more complicated than a microbenchmark or a component benchmark, we conduct experiments to check whether we can use a statistical model to predict the overall system tail latency.

The state-of-the-art work [17] uses the M/M/1 and M/M/K queueing models to estimate the p’th percentile latency. Since our experiments in Section 5.2.1 only contain one Online Server instance, we adopt the M/M/1 model. The p’th percentile latency \( T_p \) and the average latency \( T_m \) are calculated using the formulas:

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

\( \mu \) is the service rate, following the exponential distribution. \( \lambda \) is the arrival rate, following 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. The average latency theoretical number is 11, 17, and 41 milliseconds for different settings, 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 average latency’s theoretical number 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 vast gap is as follows. It is complex and uncertain about executing a scenario benchmark, and the service rate does not follow the exponential distribution. So, the M/M/1 model is far away from the realistic situation.

We further build a queueing network model [18] for E-commerce Intelligence. The model consists of nine M/M/1 components, each of which corresponds with one component in E-commerce Intelligence, e.g., Text classifier in Fig. 2. We set \( \lambda \) as 3, 33, and 66 requests per second, too. The average gap of the average latency between the theoretical and actual number is 4.9x. We do not report the tail latency gap because the queueing network is hard to accurately predict the overall tail latency due to its non-superposition property.
5.2.4 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 a significant impact on workload behaviors [74,75]. We quantify its effect 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. 7 shows the average latency curve of the 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 rise of data dimension, the IPC increases sharply from 0.34 to 2.37. The cache misses of all levels and pipeline stalls decrease, going down about ten or even dozens of times. Hence, resizing the input data dimension (data quality) to an appropriately larger one is beneficial for improving resource utilization. At the same time, 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 the Image Classifier. The model accuracy improvement is 1.5%, while the overall system 99th percentile latency deteriorates by 10x.

Hence, Internet service architects should attempt to balance tradeoffs among data quality, service quality, model complexity, and model accuracy.
5.2.5 Micro-architectural Characterization

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. 8 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 non-AI components. Thus, they exhibit a larger working set and higher memory bandwidth.

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

5.3 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 input data volume 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 [61]. So, for this AI component, resizing from 60% to 100%, 70% additional training time brings a 1.36% accuracy improvement. Resizing from 80% to 100%, 17% extra training time brings in a 0.12% accuracy improvement.

We conclude that Internet service architects need to 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.

5.4 Zooming in on Hotspot Functions

The evaluations in Section 5.2.1 demonstrate that drilling down from a scenario benchmark into the primary components lets 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 5.2.1 shows the primary five AI components are on the critical path of the two scenario benchmarks and have significant impacts on the overall system latency and tail latency. They are Recommendation, Ranker, Image Classifier for E-commerce Intelligence, and Speech Recognition and Text Translator for Translation Intelligence. To zoom in on these component benchmarks’ hotspot functions, we run both training and inference stages and use nvprof to trace the running time breakdown. To profile accuracy-
ensured performance, we first adjust the parameters, e.g., batch size, 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.

Table 2: Hotspot Functions of Each AI Component.

| Component                         | Function Name                          | Time(%) |
|-----------------------------------|----------------------------------------|---------|
| AI Components of E-commerce Benchmark | Eigen::internal::EigenMetaKernel        | 39.6    |
|                                   | CUDA Memcpy                            | 23.4    |
|                                   | tensorflow::GatherOpKernel             | 8.1     |
|                                   | tensorflow::scatter_op_gpu:ScatterOpCustomKernel | 4       |
| Recommendation                    | Eigen::internal::EigenMetaKernel        | 56.6    |
|                                   | sgemm_32x32x32_NT_vec                  | 9.1     |
|                                   | tensorflow::functor::ColumnReduceSimpleKernel | 8.7     |
|                                   | sgemm_32x32x32_TN_vec                  | 5       |
| Ranker                            | Eigen::internal::EigenMetaKernel        | 56.6    |
|                                   | sgemm_32x32x32_NT_vec                  | 9.1     |
|                                   | tensorflow::functor::ColumnReduceSimpleKernel | 8.7     |
|                                   | sgemm_32x32x32_TN_vec                  | 5       |
| Image Classifier                  | Eigen::internal::EigenMetaKernel        | 18.2    |
|                                   | maxwell_scudnn_128x128_stridedB_splitK_interior_nn | 15.6    |
|                                   | maxwell_scudnn_128x128_relu_interior_nn | 11.5    |
|                                   | maxwell_scudnn_128x128_stridedB_interior_nn | 7.9     |
|                                   | cudnn::detail::bn_bw_1C11_kernel_new    | 7       |
| AI Components of Translation Benchmark | Eigen::internal::EigenMetaKernel        | 26.3    |
| Text Translator                   | sgemm_128x128x8_NT_vec                 | 17.6    |
|                                   | sgemm_128x128x8_NT_vec                 | 15.8    |
|                                   | sgemm_128x128x8_TN_vec                 | 8.3     |
|                                   | cudnn::detail::dgrad2d_alg1_1          | 17.4    |
|                                   | cudnn::detail::dgrad_engine            | 13.4    |
|                                   | sgemm_32x32x32_NT_vec                  | 9.4     |

We find that Eigen::internal::EigenMetaKernel is the most time-consuming function among the five primary AI components. Eigen is a C++ template library for linear algebra [76] used by TensorFlow. Through statistics in Fig. 9, 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, etc. We reveal that these five components and the corresponding hotspot functions are the optimization points for software stack and CUDA library optimizations and microarchitectural optimizations.
Focusing on Eigen::internal::EigenMetaKernel, we further analyze their GPU stalls. We find that the constant memory dependency stall, which immediate constant cache miss incurs, is the top one stall, occupying more than 50% of total stalls on average. The memory dependency stall—a memory operation that cannot be performed due to the required resources not being available or fully utilized—occupies 20% on average. The instruction fetch stall and execution dependency stall, which is due to an unready input required by the instruction, occupies about 14% and 13%, respectively. Possible optimization strategies include storing constants in global memory, improving data placement, and recomputing constant.
6 Conclusion

This paper proposes a scenario-distilling methodology to tackle the challenges of benchmarking modern real-world application scenarios. We formalize a real-world application scenario as a DAG model and present the rules to distill it into the permutation of essential AI and non-AI tasks as a high-level scenario benchmark specification. Concerning the original scenarios, the scenario benchmarks reduce the complexity by one or two orders of magnitude. Together with seventeen industry partners, we extract nine scenarios and identify the primary components. We design and implement an extensible, configurable, and flexible benchmark framework. We implement two Internet service AI scenario benchmarks as proxies to two real-world application scenarios based on the framework. We consider scenario, component, and micro benchmarks as three indispensable parts, and the evaluation shows the advantage of our methodology against using component or micro AI benchmarks alone.
7 Artifact Appendix

7.1 Abstract

The artifact contains AIBench Scenario benchmarks, running and profiling scripts. It can support the characterization results in Chapter V.

7.2 Artifact check-list (meta-information)

- **Program**: AIBench Scenario benchmarks
- **Compilation**: Python 3.6.8, Java 1.8.0
- **Data set**: Anonymous data from industry or open-sourced data sets
- **Run-time environment**: Ubuntu 18.04
- **Hardware**: CPUs and GPUs
- **Run-time state**: Disable Hyper-Threading
- **Execution**: root user or users that can execute sudo without password
- **Experiment**: Deploy the benchmarks and corresponding software stacks; run benchmarks; output the results
- **Publicly available?**: Yes
- **Workflow frameworks used?**: No
- **Archived (provide DOI)**: https://doi.org/10.5281/zenodo.5158715

7.3 Description

7.3.1 How delivered

The artifacts is available on Zenodo: https://doi.org/10.5281/zenodo.5158715, including all the source code scripts, and instructions. The Zenodo DOI is 10.5281/zenodo.5158715. Also, the AIBench scenario benchmarks and framework are open sourced on GitHub:

https://github.com/BenchCouncil/aibench_scenario.
Note that the running or profiling scripts we provide suit for our cluster environment, like the node ip/hostname and port number, if you download and use it in your cluster environment, you need to modify the scripts.

7.3.2 Hardware dependencies
The AI-Bench scenario benchmarks can be run on all processors that can deploy Docker, Jmeter, SpringBoot, TensorFlow Serving, Elasticsearch and Neo4j stacks. However, for cache and pipeline behavior analysis, user need to find the performance counters corresponding to specific processor. We have provided profiling scripts for Xeon E5645 processor.

7.3.3 Software dependencies
Python 3.6.8, Java 1.8.0, Jmeter 5.1.1, SpringBoot 2.1.3, TensorFlow Serving 1.14.0, Elasticsearch 6.5.2, Neo4j 3.5.8, Docker 19.03 and Docker compose 1.29.

7.3.4 Data sets
We provide both anonymous data from industry and open-sourced data sets. Users can find where to download and how to use these data in the README file.

7.4 Installation
User need to install Python, Java, and Docker. For Jmeter, SpringBoot, TensorFlow Serving, Elasticsearch, and Neo4j, user can install them manually or use the deployment templates we provided. The install details can be found in the README file.

7.5 Experiment workflow
Before profiling system and micro-architecture metrics of a scenario benchmark, users should make sure there is no other workload running. Please refer to the README file within the artifacts package for detailed information.

7.5.1 Deploy the benchmarks.
We provide deployment scripts for two scenario benchmarks.

Deploy E-commerce Intelligence:
   i. Under the following directory
      #cd aibench_scenario/benchmarks/e-commerce_search
   ii. Deploy benchmark: #docker-compose up

Deploy Translation Intelligence:
i. Under the following directory
   #cd aibench_scenario/benchmarks/translation
ii. Deploy benchmark: #docker-compose up

7.5.2 Run the benchmarks.

We provide running scripts for two scenario benchmarks.

**Run E-commerce Intelligence:**

i. Load the data
   #cd aibench_scenario/framework/online/non_AI_module/ 
   benchmark-1.0-SNAPSHOT 
   #./create_index.sh 
   #./load_data.sh 
   Note that you need to modify the IP address of the above two shell 
scripts according to your cluster configurations.

ii. Run the benchmark
   #apache-jmeter-5.1.1/bin/jmeter -n -t aibench_scenario/ 
   framework/online/non_AI_module/load_generator/ 
   search_loop_2W.jmx -l result.txt -e -o report 
   Note that you need to modify the search_loop_2W.jmx file. First, use 
docker command to check the IP address of Search Planner; 
   #docker ps 
   #docker inspect $ID 
   The ID is the output of the command ”docker ps” named Search Planner, 
the output will include the IP address of Search Planner. 
   Then change all the IP address of ”172.18.11.91” in the search_loop_2W.jmx 
file to the actual IP address of Search Planner.

iii. Check the results
   After the Step ii, it will generate a directory named ”report”. Within the 
directory, there is a file named ”index.html”, which can show the average 
latency, 90th percentile latency, and 99th percentile latency. We also provide 
”run_search.sh” to run the e-commerce intelligence benchmark. The user 
need to modify the scripts according to their own cluster environment.

**Run Translation Intelligence:**

i. Run the benchmark
   #cd aibench_scenario 
   #apache-jmeter-5.2.1/bin/jmeter -n -t aibench_scenario/ 
   framework/online/translation.jmx 
   -l result.txt -e -o report 
   Note that you need to modify the translation.jmx file. First, use docker 
command to check the IP address of Translation Planner; 
   #docker ps 
   #docker inspect $ID 
   The ID is the output of the command ”docker ps” named Translation 
Planner, the output will include the IP address of Translation Planner.
Then change all the IP address of "172.18.13.26" in the translation.jmx file to the actual IP address of Translation Planner. The result.txt will log the timestamp of all the queries.

ii. Check the results

After the Step i, it will generate a directory named "report". Within the directory, there is a file named "index.html", which can show the average latency, 90th percentile latency, and 99th percentile latency.

7.5.3 Process the metric data and plot the figures

For E-commerce Intelligence, the processing script is log_process.sh in the "aibench_scenario/ecommerce_search" directory. The usage of log_process.sh is .\log_process.sh <log_dir >, for example, .\log_process.sh ../log-0310-1402, the result.csv will be outputted in current directory, and run the command "python e_commerce_search_figure.py" will produce the Fig.5(1).

For Translation Intelligence, in the "aibench_scenario/translation" directory, run the "python translation_intelligence_fig.py" will produce the Fig.5(2).

For the experiment of Fig.7, users have to change the data dimension, recompile the benchmark, and re-run the E-commerce Intelligence benchmark for several times.

i. Change the data dimension

Change the Line #204 of the file "aibench_scenario/framework/online/non_AI_module/recommender/cpu_app.py":

```
img = image.img
to_array(image.load_img(img_path, target_size=(8, 8)))
```

Change (8, 8) to the other dimension you need to test, like (16, 16), (32, 32), (64, 64), (128, 128), or (256, 256).

ii. Recompile the benchmark

```
#cd aibench_scenario/benchmarks/ecommerce_search
#docker-compose up -d
```

After changing the data dimension and recompiling the benchmark, re-run the E-commerce Intelligence benchmark according to the steps of "Run E-commerce Intelligence" and obtain the results.

iii. Use the image_dimension_figure.sh to produce the Fig.7.

```
#./image_dimension_figure.sh <8_logdir><16_logdir><32_logdir><64_logdir>
```

Note that the <x_logdir>are the log directories generated in Step iv when the data dimension is x^x.

For the experiment of Fig.8, lsdata-pact21-fig8.py can produce the corresponding figure, the usage is python lsdata-pact21-fig8.py <input_dir><output_name>, the input_dir refer the hw_log, for example python lsdata-pact21-fig8.py log-0310-1402/hw_log output. This command will produce an excel file named <output_name>.xls and a figure. Note that the use_perf_new1.py we provide only suit for sampling micro-architecture metrics on Intel Xeon E5645
processors. If you need to profile on another processor type, you need to modify the corresponding hardware performance counters.

7.6 Evaluation and expected result

To evaluate the scenario benchmarks, users need to run and profile them. The results should follow the similar trends as reported in the paper. Note that if you download the artifacts and deploy them in your cluster, the results may differ from the values in the paper, due to the differences of cluster scale, node configurations, network configurations, etc.

7.7 Experiment customization

Users can run these scenario benchmarks for different benchmarking purpose, e.g. datacenter deployment strategies. The scenario benchmarks can be deployed on different processors and cluster scales. Also, the AI related TensorFlow serving components can be deployed on different AI chips like GPU and TPU.

7.8 Notes

For the artifact evaluation, it may cost a lot of time to run some benchmarks, we also provide the scripts and the original running logs and profiling data used in our paper, which are suit for our experimental environments and configurations. Since the platform configurations, network configurations, and hardware types (e.g. memory capacity, processing capacity) may be different, so the performance data may be different on another platform.

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