AIBench: An Industry Standard Internet Service AI Benchmark Suite

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AIBench: An Industry Standard Internet Service AI Benchmark Suite

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Abstract

Today’s Internet Services are undergoing fundamental changes and shifting to an intelligent computing era where AI is widely employed to augment services. In this context, many innovative AI algorithms, systems, and architectures are proposed, and thus the importance of benchmarking and evaluating them rises. However, modern Internet services adopt a microservice-based architecture and consist of various modules. The diversity of these modules and complexity of execution paths, the massive scale and complex hierarchy of datacenter infrastructure, the confidential issues of data sets and workloads pose great challenges to benchmarking.

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In this paper, we present the first industry-standard Internet service AI benchmark suite—AIBench with seventeen industry partners, including several top Internet service providers. AIBench provides a highly extensible, configurable, and flexible benchmark framework that contains loosely coupled modules. We identify sixteen prominent AI problem domains like learning to rank, each of which forms an AI component benchmark, from three most important Internet service domains: search engine, social network, and e-commerce, which is by far the most comprehensive AI benchmarking effort. On the basis of the AIBench framework, abstracting the real-world data sets and workloads from one of the top e-commerce providers, we design and implement the first end-to-end Internet service AI benchmark, which contains the primary modules in the critical paths of an industry scale application and is scalable to deploy on different cluster scales. The preliminary evaluation has shown the value of our benchmark suite with respect to the previous documented performance models and insights without the publicly available ensemble of Internet service data sets, workloads and user logs. The specifications, source code, and performance numbers are publicly available from the benchmark council web site http://www.benchcouncil.org/AIBench/index.html.
1 Introduction

Modern Internet service providers pervasively employ AI to augment their services, as the advancement of AI technology has brought breakthroughs in processing images, video, speech, and audio [1], and hence boost the deployments of massive AI algorithms, systems and architectures. For example, Alibaba proposes a new DUPN network for more effective personalization [2]. Facebook integrates AI into many essential products and services like news feed [3]. Google proposes the TensorFlow [4] system and the tensor processing unit (TPU) [5] to accelerate the service performance. Amazon adopts AI for intelligent product recommendation [6].

Consequently, the pressures of measuring and evaluating these algorithms, systems, and architectures rise. First, the real world data sets and workloads from Internet services are treated as first-class confidential issues by their providers, and they are isolated between academia and industry, or even among different providers. However, there are only a few publicly available performance model or observed insights [3, 7] about industry-scale Internet services that can be leveraged for further research. As there is no publicly available industry-scale Internet service benchmark, the state-of-the-art and state-of-the-practice are advanced only by the research staffs inside Internet service providers, which is not sustainable and poses a huge obstacle for our communities towards developing an open and mature research field.

Second, AI has infiltrated into almost all aspects of Internet services, ranging from offline analytics to online service. Thus, to cover the critical paths and characterize prominent characteristics of a realistic AI scenario, end-to-end application benchmarks should be provided [8, 9]. Meanwhile, there are many classes of Internet services. Modern Internet services workloads expand and change very fast, and it is not scalable or even impossible to create a new benchmark or proxy for every possible workload [10]. Moreover, data sets have great impacts on system and microarchitectural characteristics [11, 10], so diverse data inputs should be considered. So we need identify representative data sets, abstract the prominent AI problem domains (component benchmarks), and further understand what are the most intensive units of computation (micro benchmarks), on the basis of which, we can build a concise and comprehensive AI benchmark framework.

Finally but not least, from an architectural perspective, porting a full-scale AI applications to a new architecture at an earlier stage is difficult and even impossible [12], while using micro or component benchmarks alone are insufficient to discover the time breakdown of different modules and locate the bottleneck within a realistic AI application scenario at a later stage [12]. Hence, a realistic AI benchmark suite should have the ability to run not only collectively as a whole end-to-end application to discover the time breakdown of different modules but also individually as a micro or component benchmark for fine tuning hot spot functions or kernels. The state-of-the-art or state-of-the-practice [13, 14, 15, 16, 17] AI benchmarks only provide a few micro or component benchmarks, and none of them is able to cover the full use cases of an industry-scale Internet service. So an industry standard Internet service AI benchmark suite consisting of a full spectrum of micro or component benchmarks and an end-to-end application benchmark is of great significance to bridge this huge gap.

To the best of our knowledge, this paper presents the first industry scale AI benchmark suite, AIBench, joint with seventeen industry partners. First, we present a highly extensible, configurable, and flexible benchmark framework, containing multiple loosely coupled modules like data input, prominent AI problem domains, online inference, offline training and automatic deployment tool modules. We analyze typical AI application scenarios from three most important Internet services domains, including search engine, social network, and e-commerce, and then we abstract and identify sixteen prominent AI problem domains, including classification, image generation, text-to-text translation, image-to-image, speech-to-text, face embedding, 3D face recognition, object detection, video prediction, image compression, recommendation, 3D object reconstruction, text summarization, spatial transformer, and learning to rank. We implement sixteen component benchmarks for those AI problem domains, and further profile and implement twelve fundamental units of computation across different component benchmarks as the micro benchmarks. On the basis of the AIBench framework, we design and implement the first end-to-end Internet service AI benchmark with an underlying e-commerce searching business model. As a whole, it covers the major modules and critical paths of an industry scale e-commerce provider.
application benchmark reuses ten component benchmarks from the AIBench framework, receives the query requests and performs personalized searching, recommendation and advertising, integrated with AI inference and training. The data maintains the real-world data characteristics through anonymization. Data generators are also provided to generate specified data scale, using several configurable parameters.

In summary, our contributions are four-fold as follows.

• We propose and implement a highly extensible, configurable, and flexible AI benchmark framework.
• We identify sixteen prominent AI problem domains with seventeen industry partners, and implement sixteen component benchmarks targeting those domains accordingly.
• We design and implement the first industry scale end-to-end Internet service AI benchmark suite, with an underlying e-commerce searching model.
• On the CPU and GPU clusters, we perform workload characterizations of the end-to-end Internet service AI benchmark. We found that AI-related components significantly change the critical paths of the online service and deteriorate the average and tail latency, and the architects must perform a serious trade-off between the service quality and the complexity of neural network model. For offline training, we identify six kernels, consistent with our micro benchmarks\(^1\) and the corresponding function calls that takes up the most percentages of running time, and analyze the GPU execution stalls that influence the performance, which provide the guide for further optimizations.

The rest of this paper is organized as follows. In Section 2, we present the related work. Section 3 summarizes the AIBench framework. Section 4 illustrates the design and implementation of an end-to-end application benchmark. Section 5 illustrates the experiment configurations. In Section 6, we present the characterization results on GPUs and CPUs. Finally, we draw the conclusion in Section 7.

2 Related Work

AI attracts great attention, appealing many research efforts on benchmarks. Table 1 compares AIBench with respect to the state-of-the-art or state-of-the-practice AI benchmark suites, from the perspectives of end-to-end application benchmarks, component benchmarks, micro benchmarks, real-world data sets and software stacks.

MLPerf [13] is an ML benchmark suite targeting five AI problem domains, including image classification, object detection, translation, recommendation, and reinforcement learning. For several problem domains, it provides both light-weight and heavy-weight implementations. Totally, it includes seven benchmarks for training and five benchmarks for inference.

Fathom [14] provides eight deep learning component benchmarks implemented with TensorFlow, among which, three of them use different models to solve image classification problem. The Autoencoder workload provides a variational autoencoder and can be used to reduce the dimension and compress images. This benchmark suite also lacks of the micro and application benchmarks.

DeepBench [15] consists of four operations involved in training deep neural networks, including three basic operations and recurrent layer types. Although the recurrent layer is the combination of several basic operations like convolution, while it is still simpler comparing to our component benchmarks. In total, this benchmark suite only provides micro benchmarks, and lacks of the component and application benchmarks.

DNNMark [16] is a GPU benchmark suite that consists of a collection of deep neural network primitives. It provides eight micro benchmarks while lacking of component and application benchmarks.

DAWNBench [17] is a benchmark and competition focusing on end-to-end performance, which means the training or inference time to achieve a state-of-the-art accuracy. It only focuses on two component benchmarks.

\(^1\)The six kernels are named based on CUDA functions and they are a subset of our micro benchmarks.
Table 1: AI Benchmark Comparison.

| End-to-End Application Benchmark | AI Bench | MLPerf | Fathom | DeepBench | DNNMark | DAWNBench | TBD |
|----------------------------------|----------|--------|--------|-----------|---------|-----------|-----|
| Online module                    | ✔        | ✗      | ✗      | ✔         | ✔       | ✔         | ✗   |
| Offline module                   | ✔        | ✗      | ✗      | ✔         | ✔       | ✔         | ✗   |
| Component Benchmark              |          |        |        |           |         |           |     |
| Image classification             | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Image generation                 | Train    | ✔      | ✗      | ✗         | ✗       | ✗         | ✗   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Text-to-Text                     | Train    | ✔      | ✔      | ✗         | ✗       | ✗         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Image-to-Text                    | Train    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Image-to-Image                   | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Speech recognition               | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Face embedding                   | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| 3D Face Recognition              | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Object detection                 | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Recommendation                   | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Video prediction                 | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Image compression                | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| 3D object reconstruction         | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Text summarization               | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Spatial transformer              | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Learning to rank                 | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Games                            | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Memory network                   | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Question answering               | Train    | ✔      | ✔      | ✔         | ✔       | ✔         | ✔   |
|                                  | Infer    | ✗      | ✗      | ✗         | ✗       | ✗         | ✗   |
| Micro Benchmark                  |          |        |        |           |         |           |     |
| Convolution                      | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Fully connected                  | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Element-wise op                  | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Activation                       | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Pooling                          | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Normalization                    | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Dropout                          | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Softmax                          | ✔        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| AllReduce                        | ✗        | ✗      | ✗      | ✗         | ✔       | ✔         | ✗   |
| Real-world Data sets and Software Stack |        |        |        |           |         |           |     |
| Text data                        | 3        | 1      | 2      | N/A       | N/A     | 1         | 1   |
| Image data                       | 8        | 2      | 2      | N/A       | N/A     | 2         | 4   |
| 3D data                          | 2        | 0      | 0      | N/A       | N/A     | 0         | 0   |
| Audio data                       | 1        | 0      | 1      | N/A       | N/A     | 0         | 1   |
| Video data                       | 1        | 0      | 1      | N/A       | N/A     | 0         | 0   |
| Software Stack                   | 3        | 2      | 1      | 1         | 1       | 2         | 4   |
benchmarks including image classification on CIFAR10 and ImageNet, and question answering on SQuAD, and lacks of the micro and application benchmarks.

TBD Suite [18] is a benchmark suite for DNN training. It provides eight neural network models that covers six application domains. Analogously, it only contains component-level benchmarks, and lacks of an end-to-end application benchmark that can depict the entire execution paths of industry scale application.

Additionally, for machine learning and deep learning evaluation, MLModelScope [26] proposes a specification for repeatable model evaluation and a runtime to measure experiments.

In conclusion, the state-of-the-art and state-of-the-practise AI benchmarks only provide a few micro or component benchmarks, and none of them is able to characterize an industry-scale Internet service. AIBench provides a benchmark framework that all benchmarks collectively constitute an end-to-end application benchmark with an underlying industry scale Internet service model, while each individually forms a micro or component benchmark that supports fine-grained benchmarking for AI systems, architectures, and algorithms. Meanwhile, the HPC AI benchmarks [19], IoT AI benchmarks [20], Edge AI benchmarks [21], the previous version of AIBench for datacenter [22], and big data benchmarks [23, 24, 25] are also released on the BenchCouncil web site.

3 AIBench Framework

In this section, we introduce the AIBench framework from the perspectives of framework architecture, metrics, prominent AI problem domains we identified, implemented micro and component benchmarks, and framework scalability on large-scale clusters.

3.1 Framework Architecture

The AIBench framework provides an universal AI benchmark framework that is flexible and configurable, which is shown in Fig. 1. It provides loosely coupled modules that can be easily configured and extended to compose an end-to-end application, including the data input, AI problem domain, online inference, offline training, and deployment tool modules.

The data input module is responsible to feed data into the other modules. It collects representative real-world data sets 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, so as to alleviate the confidential issue. Based on the data schema, a series of data generators are further provided to support large-scale data generation, like the user or product information. To cover a wide spectrum of data characteristics, we take diverse data types, e.g., structured, semi-structured, un-structured, 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 [27].

To achieve diversity and representativeness of our framework, we first identify prominent AI problem domains that play important roles in most important Internet services domains. And then we provide the concrete implementation of the AI algorithms targeting those AI problem domains as component benchmarks. Also, we profile the most intensive units of computation across those component benchmarks, and implement them as a set of micro benchmarks. Both micro and component benchmarks are implemented with the concern for composability, each of which can run collectively and individually.

The offline training and online inference modules are provided to construct an end-to-end application benchmark. First, the offline training module chooses one or more component benchmarks from the AI problem domain module, through specifying the required benchmark ID, 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. Collaborating with the other non AI-related modules in the critical paths, an end-to-end application benchmark is built.
To be easily deployed on a large-scale cluster, the framework provides deployment tools that contain two automated deployment templates using Ansible and Kubernetes, respectively. Among them, the Ansible templates support scalable deployment on physical machines or virtual machines, while the Kubernetes templates are used to deploy on container clusters. A configuration file needs to be specified for installation and deployment, including module parameters like the chosen benchmark ID, input data, and the cluster parameters like nodes, memory, and network information.

3.2 The Prominent AI Problem Domains

To cover a wide spectrum of prominent AI problem domains among Internet services, we thoroughly analyze the core scenarios among three primary Internet services, including search engine, social network, and e-commerce, as shown in Table 2. In total, we identify sixteen representative AI problem domains as follows.

**Classification.** This problem domain is to extract different thematic classes within the input data like an image or a text file, which is a supervised learning problem to define a set of target classes and train a model to recognize. It is a typical task in Internet services or other application domains, and widely used in multiple scenarios, like category prediction and spam detection.

**Image Generation.** This problem domain aims to provide an unsupervised learning problem to mimic the distribution of data and generate images. The typical scenario of this task includes image resolution enhancement, which can be used to generate high-resolution image.

**Text-to-Text Translation.** This problem domain need to translate text from one language to another, which is the most important field of computational linguistics. It can be used to translate the search query intelligently and translate dialogue.

**Image-to-Text.** This problem domain is to generate the description of an image automatically. It can
Table 2: Prominent AI Problem Domains in Internet Service.

| Internet Service | Core Scenario | Involved AI Problem Domain |
|------------------|---------------|-----------------------------|
| Search Engine    | Content-based image retrieval (e.g., face, scene) | Object detection; Classification; Spatial transformer; Face embedding; 3D face recognition |
|                  | Advertising and recommendation | Recommendation |
|                  | Maps search and translation | 3D object reconstruction; Text-to-Text translation; Speech recognition |
|                  | Data annotation and caption (e.g., text, image) | Text summarization; Image-to-Text |
|                  | Search result ranking | Learning to rank |
|                  | Image resolution enhancement | Image generation; Image-to-Image |
|                  | Data storage space and transfer optimization | Image compression; Video prediction |
| Social Network   | Friend or community recommendation | Recommendation; Face embedding; 3D face recognition; |
|                  | Vertical search (e.g., image, people) | Classification; Spatial transformer; Object detection; |
|                  | Language translation | Text-to-Text translation |
|                  | Automated data annotation and caption | Text summarization; Image-to-Text; Speech recognition |
|                  | Anomaly detection (e.g., spam image detection) | Classification |
|                  | Image resolution enhancement | Image generation; Image-to-Image |
|                  | Photogrammetry (3D scanning) | 3D object reconstruction |
|                  | Data storage space and transfer optimization | Image compression; Video prediction |
|                  | News feed ranking | Learning to rank |
| E-commerce       | Product searching | Classification; Spatial transformer; Object detection |
|                  | Product recommendation and advertising | Recommendation |
|                  | Language and dialogue translation | Text-to-Text translation; Speech recognition |
|                  | Automated data annotation and caption | Text summarization; Image-to-Text |
|                  | Virtual reality (e.g., virtual fitting) | 3D object reconstruction; Image generation; Image-to-Image |
|                  | Data storage space and transfer optimization | Image compression; Video prediction |
|                  | Product ranking | Learning to rank |
|                  | Facial authentication and payment | Face embedding; 3D face recognition; |

be used to generate image caption and recognize optical character within an image.

**Image-to-Image.** This problem domain is to convert an image from one representation of an image to another representation. It can be used to synthesize the images with different facial ages and simulate virtual makeup. Face aging can help search the facial images ranging different age stages.

**Speech recognition.** This problem domain is to recognize and translate the spoken language to text. This task is beneficial for voice search and voice dialogue translation.

**Face embedding.** This problem domain is to transform a facial image to a vector in embedding space. The typical scenarios of this task are facial similarity analysis and face recognition.

**3D face recognition.** This problem domain is to recognize the 3D facial information from multiple images from different angles. This task mainly focuses on three-dimensional images and is beneficial to the facial similarity and facial authentication scenario.

**Object detection.** This problem domain is to detect the objects within an image. The typical scenarios are vertical search like contented-based image retrieval and video object detection.

**Recommendation.** This problem domain is to provide recommendations. This task is widely used for advertise recommendation, community recommendation, or product recommendation.

**Video prediction.** This problem domain is to predict the future video frames through predicting previous frames transformation. The typical scenarios are video compression and video encoding, for efficient video storage and transmission.

**Image compression.** This problem domain is to compress the images and reduce the redundancy [28]. The task is important for Internet service in terms of data storage overhead and data transmission efficiency.

**3D object reconstruction.** This problem domain is to predict and reconstruct 3D objects [29]. The typical scenarios are maps search, light field rendering and virtual reality.

**Text summarization.** This problem domain is to generate the text summary, which is important for search results preview, headline generation, and keyword discovery.

**Spatial transformer.** This problem domain is to perform spatial transformations [30]. An typical scenario of this task is space invariance image retrieval, so that the image can be retrieved even if the
Learning to rank. This problem domain is to learn the attributes of searched content and rank the scores for the results, which is the key for searching service.

3.3 Micro and Component Benchmarks

Targeting the major AI problem domains abstracted in Section 3.2, we provide the concrete implementation of the AI algorithms. Individually, these algorithm implementations form a series of micro and component benchmarks for fine-grained evaluation. Table 3 and Table 4 list the component and micro benchmarks in AIBench. In total, AIBench includes sixteen component benchmarks for AI problem domains and twelve micro benchmarks that extract unit of computation from the typical AI algorithms [10].

### Table 3: Component Benchmarks in AIBench.

| No. | Component Benchmark       | Algorithm                                  | Data Set                |
|-----|---------------------------|--------------------------------------------|-------------------------|
| DC-AI-C1 | Image classification    | ResNet50 [31]                             | ImageNet                |
| DC-AI-C2 | Image generation         | WassersteinGAN [32]                       | LSUN                    |
| DC-AI-C3 | Text-to-Text translation | Recurrent neural networks [33]            | WMT English-German      |
| DC-AI-C4 | Image-to-Text            | Neural Image Caption Model [34]           | Microsoft COCO          |
| DC-AI-C5 | Image-to-Image           | CycleGAN [35]                             | Cityscapes              |
| DC-AI-C6 | Speech recognition       | DeepSpeech2 [36]                          | Librispeech             |
| DC-AI-C7 | Face embedding           | Facenet [37]                              | LFW, VGGFace2           |
| DC-AI-C8 | 3D Face Recognition      | 3D face models [38]                       | 77,715 samples from 253 face IDs |
| DC-AI-C9 | Object detection         | Faster R-CNN [39]                         | Microsoft COCO          |
| DC-AI-C10| Recommendation           | Neural collaborative filtering [40]       | MovieLens               |
| DC-AI-C11| Video prediction         | Motion-Focused predictive models [41]    | Robot pushing data set  |
| DC-AI-C12| Image compression        | Recurrent neural network [23]             | ImageNet                |
| DC-AI-C13| 3D object reconstruction | Convolutional encoder-decoder network [29] | ShapeNet Data set       |
| DC-AI-C14| Text summarization       | Sequence-to-sequence model [42]          | Gigaword data set       |
| DC-AI-C15| Spatial transformer      | Spatial transformer networks [30]         | MNIST                   |
| DC-AI-C16| Learning to rank         | Ranking distillation [43]                 | Gowalla                 |

### Table 4: Micro Benchmarks in AIBench.

| No. | Micro Benchmark      | Data Set                |
|-----|----------------------|-------------------------|
| DC-AI-M1 | Convolution        | ImageNet, Cifar         |
| DC-AI-M2 | Fully Connected     | ImageNet, Cifar         |
| DC-AI-M3 | Relu                | ImageNet, Cifar         |
| DC-AI-M4 | Sigmoid             | ImageNet, Cifar         |
| DC-AI-M5 | Tanh                | ImageNet, Cifar         |
| DC-AI-M6 | MaxPooling          | ImageNet, Cifar         |
| DC-AI-M7 | AvgPooling          | ImageNet, Cifar         |
| DC-AI-M8 | CosineNorm          | ImageNet, Cifar         |
| DC-AI-M9 | BatchNorm           | ImageNet, Cifar         |
| DC-AI-M10| Dropout             | ImageNet, Cifar         |
| DC-AI-M11| Element-wise multiply| ImageNet, Cifar         |
| DC-AI-M12| Softmax             | ImageNet, Cifar         |
3.4 Data Model

To cover a diversity of data sets from various applications, we collect 15 representative data sets, including ImageNet [47], Cifar [48], LSUN [49], WMT English-German [50], Cityscapes [51], LibriSpeech [52], Microsoft COCO data set [53], LFW [54], VGGFace2 [55], Robot pushing data set [41], MovieLens data set [56], ShapeNet data set [57], Gigaword data set [58], MNIST data set [59], Gowalla data set [60] and the 3D face recognition data set from our industry partner.

3.5 Metrics

AIBench focuses on a series of metrics covering accuracy, performance, and energy consumption, which are major industry concerns.

The metrics for online inference contains query response latency, tail latency, and throughput from performance aspect, inference accuracy, and inference energy consumption.

The metrics for offline training contains the samples processed per second, the wall clock time to train the specific epochs, the wall clock time to train a model achieving a target accuracy [17], and the energy consumption to train a model achieving a target accuracy [17].

4 The Design and Implementation of Application Benchmark

On the basis of the AIBench framework illustrated in Section 3, we implement the first end-to-end AI application benchmark, modelling the complete use-cases of a realistic E-commerce search intelligence.

4.1 The Design and Implementation

The end-to-end application benchmark consists of four modules: online server, offline analyzer, query generator, and data storage, as shown in Fig. 2. Among them, online server receives the query requests...
and performs personalized searching and recommendation, integrated with AI inference.

Offline analyzer chooses the appropriate AI algorithm implementations and performs a training stage to generate a learning model. Also, the offline analyzer is responsible to build 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. The configuration designates parameters like concurrency, query arriving rate, distribution, and user thinking time, to simulate different query characteristics and satisfy multiple generation strategies. We implement our query generator based on JMeter [61].

Data storage module stores all kinds of data, including the user database that saves all the attributes of user information, the product database that holds all the attributes of product information, logs that record the complete query histories, text data that contains the product description text or the user comments, image and video data that depict the appearance and usage of product vividly, and audio data that stores the voice search data and voice chat data. Overall, the data storage covers various data types including structured, un-structured, and semi-structured data, and diverse data sources, including table, text, image, audio and video.

To support scalable deployment on the clusters with different scales, each module is able to deploy on multiple nodes. Also, a series of data generators are provided to generate the 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.

4.1.1 Online Server

Online server provides personalized searching and recommendations combining traditional machine learning and deep learning technologies. Online server consists of four submodules including search planer, recommender, searcher, and ranker.

**Search Planer** is the entrance of online server. It is responsible for receiving the query requests from query generator, and sending the request to the other online components and receiving the return results. We use the Spring Boot framework [62] to implement the search planer.

**Recommender** is to analyze the query item and provides personalized recommendation, according to the user information obtained from the user database. It first conducts query spelling correction and query rewrite, then it predicts the belonged category of the query item based on a classification model—FastText [63]. Using a deep neural network proposed by Alibaba [2], the query planer then conducts an inference process and uses the offline trained model to provide personalized recommendation. It returns two vectors—the probability vector of the predicted categories and the user preference score vector of product attribute, such as the user preference for brand, color, etc. We use the Flask Web framework [64] and Nginx [65] to build our recommender for category prediction, and adopt TensorFlow serving [66] to implement online recommendation.

To guarantee scalability and service efficiency, Searcher follows an industry scale architecture. **Searcher** is deployed on several different, i.e., three clusters, that hold the inverted indexes of product information in memory to guarantee high concurrency and low latency. In view of the click-through rate and purchase rate, the products belong to three categories according to the popularity—high, medium, and low, occupying the proportion of 15%, 50%, and 50%, respectively. Note that the high popularity category is the top 15% popular products chosen from the medium popularity category. The indexes of products with different popularities are stored into different clusters. Given a searching request, the searcher searches these three clusters one by one, until reaching a specific amount. Generally, the cluster that holds low popularity products is rarely searched in a realistic scenario. So for each category, searcher adopts different deployment strategies. The cluster for high popularity contains more nodes and more backups to guarantee the searching efficiency. While the cluster for low popularity deploys the least number of nodes and backups. We use the Elasticsearch [67] to set up and manage the three clusters of searcher.

**Ranker** uses the weight returned by **Recommender** as initial weight, and ranks the scores of products through a personalized L2R neural network [2]. The ranker also uses the Elasticsearch [67] to implement
product ranking.

The online serving process is as follows.
(1) *Query Generator* simulates concurrent users and sends query requests to *Search Planer*;
(2) *Search Planer* receives the query request and sends the query item to *Recommender*;
(3) *Recommender* analyzes the query and returns the category prediction results and personalized attribute weights to *Search Planer*;
(4) *Search Planer* sends the initial query item and predicted category results to *Searcher*;
(5) *Searcher* searches the inverted indexes and returns the product ID to *Search Planer*;
(6) *Search Planer* sends the product ID and personalized attribute weights to *Ranker*;
(7) *Ranker* ranks the product according to the initial weights and returns the ranking scores to *Search Planer*;
(8) *Search Planer* sends a product database access request according to the product ID and obtains the product information;
(9) *Search Planer* returns the searched product information to *Query Generator*.

### 4.1.2 Offline Analyzer

Offline analyzer is responsible for training models and building indexes to improve the online serving performance. It consists of three parts—AI trainer, job scheduler, and indexer.

AI trainer is to train models using related data stored in database. To dig the features within product data, e.g., text, image, audio, video, and power the efficiency of online server, the AI trainer chooses ten AI algorithms (component benchmarks) from the AIBench framework currently, including classification for category prediction, recommendation for personalized recommendation, learning to ranking for result scoring and ranking, image-to-text for image caption, image-to-image and image generation for image resolution enhancement, face embedding for face detection within an image, spatial transformer for image rotating and resizing, object detection for detecting video data, speech recognition for audio data recognition.

Job schedule provides two kinds of training mechanisms: batch processing and streaming-like processing. In a realistic scenario, some models need to be updated frequently. For example, when we search an item and click one product showed in the first page, the application will immediately train a new model based on the product that we just clicked, and make new recommendations shown in the second page. Our benchmark implementation considers this situation, and adopts a streaming-like approach to update the model every several seconds. For batch processing, the trainer will update the models every several hours. The indexer is to build indexes for product information. In total, the indexer provides three kinds of indexes, including the inverted indexes with a few fields of products for searching, forward indexes with a few fields for ranking, and forward indexes with a majority of fields for summary generation.

### 4.2 Extensibility for Other Industry Applications

Taking medicine AI scenario as an example—which is one of the most representative scenario for AI, we illustrate how we use the AIBench framework to construct an end-to-end benchmark for clinical diagnosis application. The AI-related critical path of clinical diagnosis contains the following steps. 1) train a series of diagnosis models according to history data offline, e.g., detection model, classification model, recommendation model, etc; 2) detect the abnormal information within patient’s physical examination data, such as the tumour detection of a CT image; 3) classify and predict the potential disease which is an online inference stage; 4) recommend an optimal treatment plan.

To construct an end-to-end clinical diagnosis application benchmark, the AIBench framework is flexible to provide an AI-related offline module and online module. Within the offline module, component benchmarks of object detection, classification, and recommendation are chosen for training models. Within the online module, these models are loaded for online inference as a service.

In conclusion, the AIBench framework is extensible for building other industry applications.
5 Experiment Setup

In this section, we describe the experimental setting and methodology.

5.1 Node Configurations

We deploy a 16-node CPU and GPU cluster. For the CPU cluster, all the nodes are connected with a 1 Gb ethernet network. Each node is equipped with two Xeon E5645 processors and 32 GB memory. Each processor contains six physical out-of-order cores. The OS version of each node is Linux CentOS 6.9 with the Linux kernel version 3.11.10. The software versions are JDK 1.8.0, Python 3.6.8, and GCC 5.4, respectively. The GPU node is equipped with four Nvidia Titan XP GPUs. Every Titan XP owns 3840 Nvidia Cuda cores and 12 GB memory. The detailed hardware configuration of each node is listed in Table 5.

5.2 The Benchmark Deployment

We deploy the end-to-end AI application benchmark, introduced in Section 4 on the above mentioned clusters, for online server and offline trainer.

Online Server Setting. Online server is deployed on the 16-node CPU cluster, containing one query generator node, one search planer node, two recommender nodes, nine searcher nodes, one ranker node, and two nodes for data storage. The detailed module setup information and involved software information are listed in Table 6.

Offline Trainer Settings. Offline trainer is deployed on the GPUs. The CUDA and Nvidia driver versions are 10.0 and 410.78, respectively. We evaluate the PyTorch implementations with the version of 1.1.0. The data sets for each benchmark are ImageNet for image classification (137 GB), LSUN for image generation (42.8 GB), VGGFace2 for face embedding (36 GB), Microsoft COCO (13 GB) for Image-to-Text and object detection, MNIST (9.5 MB) for spatial transformer, Cityscapes (267 MB)
for Image-to-Image, MovieLens (190 MB) for recommendation, Librispeech (59.3 GB) for speech recognition, and Gowalla (107 MB) for learning to rank, respectively.

5.3 Performance Data Collection

We use network time protocol (NTP) \[68\] to perform clock synchronization in all cluster nodes and obtain the latency and tail latency metrics of online server. We use a profiling tool—Perf \[69\] to collect the CPU micro-architectural data through hardware performance monitoring counters (PMCs). For GPU profiling, we use Nvidia profiling toolkit—nvprof \[70\] to track the running performance of GPU. To obtain more accurate metric numbers, we run each benchmark three times and report the average value.

6 Evaluation

In this section, we evaluate the end-to-end AI application benchmarks introduced in Section 4, including online server and ten AI component benchmarks included in offline analyzer.

6.1 Evaluation of Online Server

We evaluate the online server performance on the 16-node CPU cluster. The product database contains a hundred thousand products with 32 attribute fields. The query generator simulates 1000 users with 30-second warm up time. The users send query requests continuously every think time interval, which follows a poisson distribution. In total, we collect the performance numbers when 20,000 query requests finish.

Latency is an important metric to evaluate the service quality. Fig. 3 shows the latencies of online server. We find that the overall latencies of the entire execution paths of the current baseline implementation are 161.13, 392, and 956 milliseconds for the average, 90th percentile and 99th percentile latencies respectively, as listed in Fig. 3(a)\[2\]. We further deeply analyze the latency of each module, including recommender, searcher, and ranker, as shown in Fig. 3(b). The latency of search planer is negligible, so we do not report it in Fig. 3(b). We find that the recommender occupies the largest latency: 75.7 milliseconds, 209.4 milliseconds, and 557.7 milliseconds for the average, 90th percentile, 99th percentile latencies, respectively. In comparison, the latencies of searcher and ranker are both within 4 milliseconds. Although

\[2\]With respect to the real numbers in our industry partner, the number is quite high. They have taken many measures to decrease the overall latency. However, this baseline implementation indeed confirm the importance of the AI components in the critical paths as the data access and communication overhead can be further decreased.
recommender and ranker both contain AI-related components, they incur different latencies. The average communication latency between the modules is also high, nearly equal to that of recommender.

Furthermore, Fig. 3(c) presents the latency breakdown of recommender in terms of query parsing, user database access, category prediction, and TensorFlow serving. We find that database access and TensorFlow serving latencies are the top two factors that impact the service performance. The user information is represented as graph data that contains entities and relationships. The sophisticated data structure and frequent garbage collection may influence the data access speed largely. While TensorFlow serving needs to run a forward inference using the recommendation model, and thus incurs larger latency. In order to measure the impact of the AI component on service performance and find the bottlenecks, we make a discussion from the following aspects.

**The weights of AI-related components on service performance.** AI components change the critical path significantly. In our evaluation, the time spent on AI-related and non AI-related components is 34.29 and 49.07 milliseconds for the average latency, 74.8 and 135.7 milliseconds for the 90th percentile latency, 152.2 and 466.5 milliseconds for the 99th percentile latency, except for the data preprocessing and communication latency, which indicates that an industry scale AI application benchmark suite is essential to depict the characteristics of a modern Internet service.

**The limitations for AI to ensure a good service.** The online inference module needs to load the trained model and conducts a forward computation to obtain the result. However, the depth or the size of a neural network model may largely affect the inference time. For comparison, we train a more complicated neural network for TensorFlow serving with the size of the model increasing from 184 MB to 253 MB. We find that the latency of TensorFlow serving increases sharply, with the average latency increasing from 30.78 to 125.71 milliseconds, and the 99th percentile latency increasing from 149.12 to 5335.12 milliseconds. Hence, the Internet service architects must perform a trade-off between the service quality and the depth or size of a neural network model.

**The difference of micro-architectural behaviors.** We characterize the changes of micro-architectural behaviors from the following two aspects.

- **The difference between non AI-related and AI-related components.** We use perf to sample the cache behaviors of AI-related and non AI-related components. We find that comparing to the non AI-related components, the AI-related components suffer from more cache misses in memory hierarchy, especially L2 cache misses per Kilo instructions. TensorFlow serving suffers from 61 L2 cache misses per Kilo instructions, while the average number of non AI-related components is 37.

- **The changes from a small neural network model to a large one.** We compare two neural network models for TensorFlow serving, with a smaller one 184 MB, and a larger one 253 MB. We also sample their cache behaviors. We find that with a larger model, the L3 cache misses per Kilo instructions increase extremely sharply, from 1.38 to 8.9, which incurs large memory backend stalls to fetch data from memory. And thus the 99th percentile latency increases more than thirty times.

6.2 Evaluation of Offline Training

GPU architecture contains multiple streaming multiprocessors (SM), each of which has a certain number of CUDA cores, memory registers, memory caches, warp schedulers, etc. The GPU efficiencies of running AI benchmarks are significantly important for both the GPU architecture design and AI system optimization. In this subsection, we mainly explore the GPU execution efficiency and evaluate the ten component benchmarks used in offline analyzer of the end-to-end AI application benchmark on Titan XP GPU. We choose the PyTorch implementations with the version of 1.1.0 for evaluation.

We comprehensively characterize the GPU efficiency, drilling down to functional-level running time breakdown and execution stall analysis. The overall execution performance of these ten component benchmarks are varying in terms of SM efficiency, which measures the percentage of time that the SM has one or more warps are active. Fig. 4 shows the SM efficiency of each benchmark, with the value ranging from 29% (Learning to rank) to 95% (Recommendation). We find that some benchmarks like
learning_to_rank have extremely low SM efficiency comparing to the other benchmarks. To discover the factors that impact the performance greatly, we first conduct running time breakdown analysis and decompose the benchmarks to the hotspot kernels or functions, then we find the GPU execution efficiency in terms of different percentage of stalls.

### 6.2.1 Running Time Breakdown

We use nvprof to trace the running time breakdown and find the hotspot functions that occupy more than 80% of running time in total. Since each run involves dozens of function calls, we single out the functions that occupy large proportions of running time and classify them into several categories of kernels according to their computation logics. Through statistics, we find that the most time-consuming functions among all the ten component benchmarks have much in common, and they are classified into six categories of kernels: convolution, general matrix multiply (gemm), batch normalization, relu activation, element-wise operation and gradient calculation, which is consistent with our micro benchmarks and further indicates the decision of including them is correct. Note that each kernel contains a bunch of functions that solve the similar problem. For example, gemm kernel includes single or double precision
floating general matrix multiply, etc. Fig. 5 shows the running time breakdown of the above six kernels, using the average value of all involved functions within each kernel. Note that the remaining 20% functions are not considered in this figure. Further, for each kernel, we summarize the typical functions that occupy a large proportion of running time among the ten component benchmarks, as shown in Table 7. We find that learning to rank spends too much time on convolution from Fig. 5, and the corresponding function call is maxwell_scudnn_128x32_stridedB_splitK_interior_nn with the SM efficiency of 18.5%, so this is the reason why leaning to rank has the lowest SM efficiency of 29%. We believe that the six kernels and these corresponding functions are the optimization directions not only for CUDA library optimizations but also for micro-architectural optimizations.

Table 7: Hotspot Functions for Each Kernel.

| Kernel    | Function Name                                                                                     |
|-----------|--------------------------------------------------------------------------------------------------|
| Convolution | maxwell_scudnn_128x128_stridedB_splitK_interior_nn                                                  |
| GEMM      | maxwell_sgemm_128x64_at                                                                            |
| GEMM      | maxwell_sgemm_128x64_nn                                                                           |
| GEMM      | sgemm_32x32x32_NN_vec                                                                           |
| BatchNorm | cudnn::detail::bn_fw_tr_1C11_kernel_NCHW                                                        |
| Relu      | maxwell_scudnn_128x128_relu_small_nn                                                             |
| Relu      | maxwell_scudnn_128x128_relu_small_nn                                                             |
| Relu      | maxwell_scudnn_128x32_relu_interior_nn                                                           |
| Element-wise | element-wise add kernel                                                                         |
| Gradient  | cudnn::detail::dgrad_engine                                                                        |
| Gradient  | cudnn::detail::dgrad_alg1_engine                                                                   |

6.2.2 GPU Execution Efficiency Analysis

Focusing on the above six most time-consuming kernels, we evaluate the stalls of these kernels, including instruction fetch stall (Inst_fetch), which indicates the percentage of stalls because the next assembly instruction has not yet been fetched, execution dependency stall (Exe_depend), which is the percentage of stalls because an input required by the instruction is not yet available, memory dependency stall (Mem_depend), which is the percentage of stalls because a memory operation cannot be performed due to the required resources not being available or fully utilized, texture stall (Texture), which is the percentage of stalls because of the under-utilization of the texture sub-system, synchronization stall (Sync), which is the percentage of stalls due to a syncthreads call, constant memory dependency stall (Const_mem_depend), which is the percentage of stalls because of immediate constant cache miss, pipe busy stall (Pipi_busy), which is percentage of stalls because a compute operation cannot be performed because the compute pipeline is busy, and memory throttle stall (Mem_throttle), which is the percentage of stalls due to large pending memory operations.

The breakdown of eight kinds of stalls of each kernel is shown in Fig. 6. We find that the top two GPU execution stalls are memory dependency stalls, and execution dependency stalls. For example, for Element-Wise kernels, the memory dependency stalls occupy a very large proportion of 68%, thus resulting low SM efficiency of about 50%. The memory dependency stalls may occur due to the high cache misses and thus the load/store resources are not available. The optimization strategies include optimizing date alignment, data locality, and data access pattern. The execution dependency stalls may occur due to the low instruction-level parallelism, so exploiting ILP may alleviate partial execution dependency stalls to a certain degree.
We also identify the functional level stalls, including the hotspot functions illustrated in Table 7, to provide potential optimization guidelines for function calls. We find that performing analytics of stalls on a function level in addition to a kernel level is helpful. For example, the memory dependency stall percentage of maxwell_scudnn_128x32_stridedB_splitK_interior_nn function in “convolution” category achieves 61%, however, the percentage of maxwell_sgemm_128x64_nn function in “GEMM” category is 18%, indicating that different optimization strategies are needed to achieve maximum performance improvement.

7 Conclusion

This paper presents the first industry standard Internet service AI benchmark suite with seventeen industry partners. We propose and implement a highly extensible, configurable, and flexible AI benchmark framework, and identify sixteen prominent AI problem domains from three most important Internet services domains: search engine, social network, and e-commerce. On the basis of the AIBench framework, we design and implement the first end-to-end Internet service AI benchmark suite, with an underlying e-commerce searching model. On the CPU and GPU clusters, we perform a preliminary evaluation of the end-to-end application benchmark. We observe that the AI-related components significantly change the critical paths and workload characterization of the Internet service, which justifies the end-to-end AI application benchmark.

References

[1] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[2] Y. Ni, D. Ou, S. Liu, X. Li, W. Ou, A. Zeng, and L. Si, “Perceive your users in depth: Learning universal user representations from multiple e-commerce tasks,” in Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 596–605, ACM, 2018.

[3] K. Hazelwood, S. Bird, D. Brooks, S. Chintala, U. Diril, D. Dzhulgakov, M. Fawzy, B. Jia, Y. Jia, A. Kalro, J. Law, K. Lee, J. Lu, P. Noordhuis, M. Smelyanskiy, L. Xiong, and X. Wang, “Applied
machine learning at facebook: A datacenter infrastructure perspective,” in 2018 IEEE International Symposium on High Performance Computer Architecture (HPCA), pp. 620–629, IEEE, 2018.

[4] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mane, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, “Tensorflow: Large-scale machine learning on heterogeneous distributed systems,” arXiv preprint arXiv:1603.04467, 2016.

[5] N. P. Jouppi, C. Young, N. Patil, D. Patterson, G. Agrawal, R. Bajwa, S. Bates, S. Bhatia, N. Boden, A. Borchers, R. Boyle, P.-l. Cantin, C. Chao, J. Coriell, M. Daley, M. Dau, J. Dean, B. Gelb, T. V. Ghaemmaghami, R. Gottipati, W. Gulland, R. Hagmann, C. Ho, D. Hogberg, J. Hu, R. Hundt, D. Hurt, J. Ibarz, A. Jaffey, A. Jaworski, A. Kaplan, H. Khaitan, D. Killebrew, A. Koch, N. Kumar, S. Lacy, J. Laudon, J. Law, D. Le, C. Leary, Z. Liu, K. Lucke, A. Lundin, G. Mackeck, A. Maggiore, M. Mahony, K. Miller, R. Nagarajan, R. Narayanaswami, R. Ni, K. Nix, T. Norrie, M. Omernick, N. Penukonda, A. Philips, J. Ross, M. Ross, A. Salek, E. Samadiani, C. Severn, G. Sizikov, M. Snelham, J. Souter, D. Steinberg, A. Swing, M. Tan, G. Thorson, B. Tian, H. Toma, E. Tuttle, V. Vasudevan, R. Walter, W. Wang, E. Wilcox, and D. H. Yoon, “In-datacenter performance analysis of a tensor processing unit,” in Proceedings of the 44th Annual International Symposium on Computer Architecture, pp. 1–12, ACM, 2017.

[6] B. Smith and G. Linden, “Two decades of recommender systems at amazon.com,” Ieee internet computing, vol. 21, no. 3, pp. 12–18, 2017.

[7] G. Ayers, J. H. Ahn, C. Kozyrakis, and P. Ranganathan, “Memory hierarchy for web search,” in 2018 IEEE International Symposium on High Performance Computer Architecture (HPCA), pp. 643–656, IEEE, 2018.

[8] L. A. Barroso and U. Hölzle, “The datacenter as a computer: An introduction to the design of warehouse-scale machines,” Synthesis Lectures on Computer Architecture, vol. 4, no. 1, pp. 1–108, 2009.

[9] A. Ghazal, M. Hu, T. Rabl, F. Raab, M. Poess, A. Crolotte, and H.-A. Jacobsen, “Bigbench: Towards an industry standard benchmark for big data analytics,” in SIGMOD 2013, 2013.

[10] W. Gao, J. Zhan, L. Wang, C. Luo, D. Zheng, F. Tang, B. Xie, C. Zheng, X. Wen, X. He, H. Ye, and R. Ren, “Data motifs: A lens towards fully understanding big data and AI workloads,” Parallel Architectures and Compilation Techniques (PACT), 2018 27th International Conference on, 2018.

[11] B. Xie, J. Zhan, X. Liu, W. Gao, Z. Jia, X. He, and L. Zhang, “Cvr: Efficient vectorization of spmv on x86 processors,” in 2018 IEEE/ACM International Symposium on Code Generation and Optimization (CGO), 2018.

[12] D. H. Bailey, E. Barszcz, J. T. Barton, D. S. Browning, R. L. Carter, L. Dagum, R. A. Fatoohi, P. O. Frederickson, T. A. Lasinski, R. S. Schreiber, H. Simon, V. Venkatakrishnan, and S. Weeratunga, “The nas parallel benchmarks,” The International Journal of Supercomputing Applications, vol. 5, no. 3, pp. 63–73, 1991.

[13] “Mlperf.” https://mlperf.org.

[14] R. Adolf, S. Rama, B. Reagen, G.-Y. Wei, and D. Brooks, “Fathom: reference workloads for modern deep learning methods,” in Workload Characterization (IISWC), pp. 1–10, IEEE, 2016.

[15] “Deepbench.” https://svail.github.io/DeepBench/.
[16] S. Dong and D. Kaeli, “Dnnmark: A deep neural network benchmark suite for gpus,” in Proceedings of the General Purpose GPUs, pp. 63–72, ACM, 2017.

[17] C. Coleman, D. Narayanan, D. Kang, T. Zhao, J. Zhang, L. Nardi, P. Bailis, K. Olukotun, C. Ré, and M. Zaharia, “Dawnbench: An end-to-end deep learning benchmark and competition,” Training, vol. 100, no. 101, p. 102, 2017.

[18] H. Zhu, M. Akrout, B. Zheng, A. Pelegris, A. Phanishayee, B. Schroeder, and G. Pekhimenko, “Tbd: Benchmarking and analyzing deep neural network training,” arXiv preprint arXiv:1803.06905, 2018.

[19] Z. Jiang, W. Gao, L. Wang, X. Xiong, Y. Zhang, X. Wen, C. Luo, H. Ye, X. Lu, Y. Zhang, S. Feng, K. Li, W. Xu, and J. Zhan, “HPC AI500: A Benchmark Suite for HPC AI systems,” 2018 BenchCouncil International Symposium on Benchmarking, Measuring and Optimizing (Bench18), 2018.

[20] C. Luo, F. Zhang, C. Huang, X. Xiong, J. Chen, L. Wang, W. Gao, H. Ye, T. Wu, R. Zhou, and J. Zhan, “AloT Bench: Towards Comprehensive Benchmarking Mobile and Embedded Device Intelligence,” 2018 BenchCouncil International Symposium on Benchmarking, Measuring and Optimizing (Bench18), 2018.

[21] T. Hao, Y. Huang, X. Wen, W. Gao, F. Zhang, C. Zheng, L. Wang, H. Ye, K. Hwang, Z. Ren, and J. Zhan, “Edge AI Bench: Towards Comprehensive End-to-end Edge Computing Benchmarking,” 2018 BenchCouncil International Symposium on Benchmarking, Measuring and Optimizing (Bench18), 2018.

[22] Gao W, Luo C, Wang L, Xiong X, Chen J, Hao T, Jiang Z, Fan F, Du M, Huang Y, Zhang F, Wen X, Zheng C, He X, Dai J, Ye H, Cao Z, Jia Z, Zhan K, Tang H, Zheng D, Xie B, Li W, Wang X, Zhan J.: AI Bench: Towards Scalable and Comprehensive Datacenter AI Benchmarking. In BenchCouncil International Symposium on Benchmarking, Measuring and Optimizing (Bench18), 2018.

[23] W. Gao, J. Zhan, L. Wang, C. Luo, D. Zheng, X. Wen, R. Ren, C. Zheng, X. He, H. Ye et al., “BigDataBench: A scalable and unified big data and ai benchmark suite,” arXiv preprint arXiv:1802.08254, 2018.

[24] L. Wang, J. Zhan, C. Luo, Y. Zhu, Q. Yang, Y. He, W. Gao, Z. Jia, Y. Shi, S. Zhang et al., “BigDataBench: A big data benchmark suite from internet services,” IEEE International Symposium On High Performance Computer Architecture (HPCA), 2014.

[25] Z. Jia, L. Wang, J. Zhan, L. Zhang, and C. Luo, “Characterizing data analysis workloads in data centers,” in 2013 IEEE International Symposium on Workload Characterization (IISWC). IEEE, 2013, pp. 66–76.

[26] A. Dakkak, C. Li, J. Xiong, and W.-m. Hwu, “Frustrated with replicating claims of a shared model? a solution,” arXiv preprint arXiv:1811.09737, 2019.

[27] Z. Ming, C. Luo, W. Gao, R. Han, Q. Yang, L. Wang, and J. Zhan, “Bdgs: A scalable big data generator suite in big data benchmarking,” arXiv preprint arXiv:1401.5465, 2014.

[28] G. Toderici, D. Vincent, N. Johnston, S. Jin Hwang, D. Minnen, J. Shor, and M. Covell, “Full resolution image compression with recurrent neural networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 5306–5314, 2017.

[29] X. Yan, J. Yang, E. Yumer, Y. Guo, and H. Lee, “Perspective transformer nets: Learning single-view 3d object reconstruction without 3d supervision,” in Advances in Neural Information Processing Systems, pp. 1696–1704, 2016.
[30] M. Jaderberg, K. Simonyan, A. Zisserman, and K. Kavukcuoglu, “Spatial transformer networks,” in Advances in neural information processing systems, pp. 2017–2025, 2015.

[31] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778, 2016.

[32] M. Arjovsky, S. Chintala, and L. Bottou, “Wasserstein gan,” arXiv preprint arXiv:1701.07875, 2017.

[33] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, pp. 5998–6008, 2017.

[34] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, “Show and tell: Lessons learned from the 2015 mscoco image captioning challenge,” IEEE transactions on pattern analysis and machine intelligence, vol. 39, no. 4, pp. 652–663, 2017.

[35] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in Proceedings of the IEEE international conference on computer vision, pp. 2223–2232, 2017.

[36] D. Amodei, S. Ananthanarayan, R. Anubhai, J. Bai, E. Battenberg, C. Case, J. Casper, B. Catanzaro, Q. Cheng, G. Chen, J. Chen, J. Chen, Z. Chen, M. Chrzanowski, A. Coates, G. Diamos, K. Ding, N. Du, E. Elsen, J. Engel, W. Fang, L. Fan, C. Fougner, L. Gao, C. Gong, A. Hannun, T. Han, L. V. Johannes, B. Jiang, C. Ju, B. Jun, P. LeGresley, L. Lin, J. Liu, Y. Liu, W. Li, X. Li, D. Ma, S. Narang, A. Ng, S. Ozair, Y. Peng, R. Prenger, S. Qian, Z. Quan, J. Raiman, V. Rao, S. Sarthesh, D. Seetapun, S. Sengupta, K. Srinet, A. Sriram, H. Tang, L. Tang, C. Wang, J. Wang, K. Wang, Y. Wang, Z. Wang, Z. Wang, S. Wu, L. Wei, B. Xiao, W. Xie, Y. Xie, D. Yogatama, B. Yuan, J. Zhan, and Z. Zhu, “Deep speech 2: End-to-end speech recognition in English and Mandarin,” in International conference on machine learning, pp. 173–182, 2016.

[37] F. Schroff, D. Kalenichenko, and J. Philbin, “Facenet: A unified embedding for face recognition and clustering,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 815–823, 2015.

[38] R.-L. Vieriu, S. Tulyakov, S. Semeniuta, E. Sangineto, and N. Sebe, “Facial expression recognition under a wide range of head poses,” in 2015 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG), vol. 1, pp. 1–7, IEEE, 2015.

[39] S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” in Advances in neural information processing systems, pp. 91–99, 2015.

[40] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T.-S. Chua, “Neural collaborative filtering,” in Proceedings of the 26th international conference on world wide web, pp. 173–182, International World Wide Web Conferences Steering Committee, 2017.

[41] C. Finn, I. Goodfellow, and S. Levine, “Unsupervised learning for physical interaction through video prediction,” in Advances in neural information processing systems, pp. 64–72, 2016.

[42] R. Nallapati, B. Zhou, C. Gulcehre, and B. Xiang, “Abstractive text summarization using sequence-to-sequence rnns and beyond,” arXiv preprint arXiv:1602.06023, 2016.

[43] J. Tang and K. Wang, “Ranking distillation: Learning compact ranking models with high performance for recommender system,” in ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2018.

[44] C. Luo, J. Zhan, L. Wang, and Q. Yang, “Cosine normalization: Using cosine similarity instead of dot product in neural networks,” arXiv preprint arXiv:1702.05870, 2017.
[45] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in International Conference on Machine Learning, pp. 448–456, 2015.

[46] N. Srivastava, G. E. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: a simple way to prevent neural networks from overfitting,” Journal of machine learning research, vol. 15, no. 1, pp. 1929–1958, 2014.

[47] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and F.-F. Li, “Imagenet: A large-scale hierarchical image database,” in Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pp. 248–255, IEEE, 2009.

[48] A. Krizhevsky, V. Nair, and G. Hinton, “The cifar-10 dataset,” online: http://www.cs.toronto.edu/kriz/cifar.html, vol. 55, 2014.

[49] F. Yu, A. Seff, Y. Zhang, S. Song, T. Funkhouser, and J. Xiao, “Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop,” arXiv preprint arXiv:1506.03365, 2015.

[50] https://nlp.stanford.edu/projects/nmt/.

[51] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele, “The cityscapes dataset for semantic urban scene understanding,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3213–3223, 2016.

[52] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: an asr corpus based on public domain audio books,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 5206–5210, IEEE, 2015.

[53] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, “Microsoft coco: Common objects in context,” in European conference on computer vision, pp. 740–755, Springer, 2014.

[54] G. B. Huang, M. Mattar, T. Berg, and E. Learned-Miller, “Labeled faces in the wild: A database for studying face recognition in unconstrained environments,” in Workshop on faces in ’Real-Life’ Images: detection, alignment, and recognition, 2008.

[55] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, “Vggface2: A dataset for recognising faces across pose and age,” in 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018), pp. 67–74, IEEE, 2018.

[56] F. M. Harper and J. A. Konstan, “The movielens datasets: History and context,” ACM Transactions on Interactive Intelligent Systems (TiiS), vol. 5, no. 4, p. 19, 2016.

[57] A. X. Chang, T. Funkhouser, L. Guibas, P. Hanrahan, Q. Huang, Z. Li, S. Savarese, M. Savva, S. Song, H. Su, J. Xiao, L. Yi, and F. Yu, “Shapenet: An information-rich 3d model repository,” arXiv preprint arXiv:1512.03012, 2015.

[58] A. M. Rush, S. Harvard, S. Chopra, and J. Weston, “A neural attention model for sentence summarization,” in ACLWeb. Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, 2017.

[59] Y. LeCun, C. Cortes, and C. Burges, “Mnist handwritten digit database,” AT&T Labs [Online]. Available: http://yann.lecun.com/exdb/mnist, vol. 2, p. 18, 2010.

[60] E. Cho, S. A. Myers, and J. Leskovec, “Friendship and mobility: user movement in location-based social networks,” in Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 1082–1090, ACM, 2011.
[61] A. JMeter, “Apache jmeter,” Online.(2016). [http://jmeter.apache.org/-Visited, pp. 04–25, 2017.

[62] P. Webb, D. Syer, J. Long, S. Nicoll, R. Winch, A. Wilkinson, M. Overdijk, C. Dupuis, and S. Deleuze, “Spring boot reference guide,” Part IV. Spring Boot features, vol. 24, 2013.

[63] A. Joulin, E. Grave, P. Bojanowski, M. Douze, H. Jégou, and T. Mikolov, “Fasttext.zip: Compressing text classification models,” arXiv preprint arXiv:1612.03657, 2016.

[64] M. Grinberg, Flask web development: developing web applications with python. ” O’Reilly Media, Inc.”, 2018.

[65] W. Reese, “Nginx: the high-performance web server and reverse proxy,” Linux Journal, vol. 2008, no. 173, p. 2, 2008.

[66] C. Olston, N. Fiedel, K. Gorovoy, J. Harmsen, L. Lao, F. Li, V. Rajashekhar, S. Ramesh, and J. Soyke, “Tensorflow-serving: Flexible, high-performance ml serving,” arXiv preprint arXiv:1712.06139, 2017.

[67] C. Gormley and Z. Tong, Elasticsearch: the definitive guide: a distributed real-time search and analytics engine. ” O’Reilly Media, Inc.”, 2015.

[68] D. L. Mills, “Network time protocol (ntp),” Network, 1985.

[69] A. C. De Melo, “The new linux perf tools,” in Slides from Linux Kongress, vol. 18, 2010.

[70] “Nvidia profiling toolkit.” https://docs.nvidia.com/cuda/profiler-users-guide/index.html.