AIBench: An Industry Standard AI Benchmark Suite from Internet Services

Authors’ contributions

Section 1 was contributed by Jianfeng Zhan and Wanling Gao. Section 2 was contributed by Wanling Gao. Section 3 was contributed by Jianfeng Zhan and Lei Wang. Section 4 was contributed by Wanling Gao, Fei Tang, Chuanxin Lan, Chunjie Luo, Jiahui Dai, Zheng Cao, Xingwang Xiong, Zihan Jiang, Tianshu Hao, Fanda Fan, Fan Zhang, Yunyou Huang, Jianan Chen, Mengjia Du, Rui Ren, Chen Zheng, Daoyi Zheng, Haoning Tang, Kunlin Zhan, Biao Wang, Defei Kong, Tong Wu, Minghe Yu, Chongkang Tan, Huan Li, Xinhui Tian, Yatao Li, Gang Lu, Junchao Shao, Zhenyu Wang, Xiaoyu Wang, and Hainan Ye. Section 5 was contributed by Fei Tang, Wanling Gao, Chuanxin Lan, and Xu Wen. Section 6 was contributed by Jianfeng Zhan.

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AIBench: An Industry Standard AI Benchmark Suite from Internet Services

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Abstract

The booming successes of machine learning in different domains boost industry-scale deployments of innovative AI algorithms, systems, and architectures, and thus the importance of benchmarking grows. However, the confidential nature of the workloads, the paramount importance of the representativeness and diversity of benchmarks, and the prohibitive cost of training a state-of-the-art model mutually aggravate the AI benchmarking challenges.

In this paper, we present a balanced AI benchmarking methodology for meeting the subtly different requirements of different stages in developing a new system/architecture and ranking/purchasing

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commercial off-the-shelf ones. Performing an exhaustive survey on the most important AI domain—Internet services with seventeen industry partners, we identify and include seventeen representative AI tasks to guarantee the representativeness and diversity of the benchmarks. Meanwhile, for reducing the benchmarking cost, we select a benchmark subset to a minimum—three tasks—according to the criteria: diversity of model complexity, computational cost, and convergence rate, repeatability, and having widely-accepted metrics or not. We contribute by far the most comprehensive AI benchmark suite—AIBench.

The evaluations show AIBench outperforms MLPerf in terms of the diversity and representativeness of model complexity, computational cost, convergent rate, computation and memory access patterns, and hotspot functions. With respect to the AIBench full benchmarks, its subset shortens the benchmarking cost by 41%, while maintaining the primary workload characteristics. The specifications, source code, and performance numbers are publicly available from the web site http://www.benchcouncil.org/AIBench/index.html
1 Introduction

The AI advancements have brought breakthroughs in processing images, video, speech, and audio [1, 2, 3, 4, 5, 6], and hence boost industry-scale deployments of massive AI algorithms, systems and architectures. Consequently, the importance of benchmarking grows.

The benchmarks accelerate the process [7], as they provides not only the design inputs, but also the evaluation methodology and metrics [8]. Their relevancy, representativeness, and diversity are of paramount importance as no single benchmark or metric can measure the performance of computer systems on all applications [9]. Unfortunately, there are many factors mutually aggravating the challenges of AI benchmarking.

First, AI has infiltrated into many domains with a huge number of AI workloads–including data sets–being treated as first-class confidential issues. They are isolated between the academia and industry, or even among different owners. Even for the most visible AI domain–Internet services, there are only a few publicly available performance model or observed insights [5, 10] that can be leveraged for further research. This situation is not sustainable and poses a huge obstacle for our communities towards developing an open and mature research field.

Second, even we can cover a full spectrum of AI tasks, models, and data sets, running an entire training session–train an AI model to achieve a state-of-the-art quality target–is prohibitively costly, and it often takes several weeks. For AI tasks, some mixed-precision optimizations immediately improve traditional performance metrics like throughput, while adversely affect the quality of the final model, which can only be observed by running an entire training session [11, 12]. The architecture community heavily relies upon simulations with slowdowns varying wildly from 10X to 1000X, which further exaggerates this situation.

Third, through profiling massive AI tasks with different models and data sets, we can obtain frequently-appearing primitive operations or units of computation as micro benchmarks. The micro benchmarks like DeepBench [13] are affordable and repeatable to perform a fair comparison of competing systems, but it overlooks statistical optimizations [12], which is the essential of AI benchmarking. Different from a micro benchmark, an AI component benchmark performs a independent AI task with a specified quality target–an end-to-end performance [11].

Fourth, using a few AI component benchmarks like MLPerf [14] alone may lead to error-prone design–over-optimization for some specific workloads or benchmarketing [9]. Figure 1 shows with respect to AlBench, presented in this paper, MLPerf has a significantly smaller coverage in terms of AI model complexity, computational cost (FLOPs–floating-point operations), and convergent rate–the epochs to training a model to achieve a convergent quality (Figure 1(a)), computation and memory access patterns (Figure 1(b)).

Finally but not least, there are subtly different benchmarking requirements of different stages in developing a new system/architecture and ranking/purchasing commercial off-the-shelf ones. For example, the initial design input needs considering diverse computation and memory access patterns. Earlier-stage evaluations of a new architecture or system need more lightweight and portable benchmarks, while later-stage evaluations or purchasing needs detailed evaluation using comprehensive benchmarks.

To tackle the above challenges, we present a balanced AI benchmarking methodology for meeting the subtly different requirements of different stages. On one hand, with seventeen prominent industry partners, we identify and include seventeen representative AI tasks from the most important domain–Internet Services to guarantee the representativeness and diversity of the benchmarks. On the other hand, we select a minimum benchmark subset (three tasks) for affordability according to the criteria: diversity of model complexity, computational cost, convergence rate, repeatability, and having widely-accepted metrics or not.

Our contributions are as follows:

- We present a balanced AI benchmarking methodology that considers subtly different requirements in developing a new system/architecture and ranking/purchasing commercial off-the-shelf ones.
Figure 1: The comparisons of 17 benchmarks in AIBench against 7 benchmarks in MLPerf from the perspectives of AI model complexity (parameters), computational cost (FLOPs), convergent rate (epochs) (Figure 1(a)), computation and memory access patterns (Figure 1(b)). The raw data and the details are reported in Section 5.2.

- We identify seventeen prominent AI tasks from the most important and visible AI domain with seventeen industry partners, and contribute by far the most comprehensive AI benchmark suite–AIBench.

- We perform by far the most comprehensive workload characterization on AIBench and MLPerf from the perspectives of model complexity, computational cost, and convergent rate, computation and memory access patterns, hotspot functions, and other micro-architecture characteristics.

- For the first time, we systematically quantify the run-to-run variation of the seventeen benchmarks of AIBench in terms of the ratio of the standard deviation to the mean of the training epochs to achieve a convergent quality. We found the variation varies wildly from 0% to 38.46%.

- To achieve affordability, we select a minimum AI component benchmark subset–three tasks–Image Classification, Object Detection, and Learning to Rank. Our experiments demonstrate the subset maintain the primary workload characteristics of seventeen benchmarks of AIBench while reducing the benchmarking cost by 41%.

- We found AIBench covers a much broader range (1.3X to 6.4X) against MLPerf in terms of the ratios of peak numbers of model complexity, computational cost, and convergent rate. The seventeen benchmarks of AIBench reflect distinct and different computation and memory access patterns from that of MLPerf. AIBench outperforms MLPerf in terms of the diversity and representativeness of models complexity, computation and memory access patterns, and hotspot functions. With respect to MLPerf, AIBench reduces the benchmarking cost while avoiding error-prone design or benchmarketing.

The rest of this paper is organized as follows. Section 2 summaries the related work. Section 3 proposes our balanced methodology. Section 4 presents the AIBench design and implementation. In Section 5, we present the detailed workload characterization and evaluations on GPUs and CPUs. Finally, we draw the conclusion in Section 6.

2 Related Work

AI attracts great attention, appealing many research efforts on benchmarking. Table 1 compares AIBench with respect to the state-of-the-art or state-of-the-practice AI benchmark suites, from the perspectives
of the component benchmarks, subset, real-world data sets and software stacks. AIBench is the only benchmark suite that provides not only the most comprehensive AI component benchmarks but also an affordable subset.

MLPerf [14] is an ML benchmark suite containing five AI tasks, including image classification, object detection, translation, recommendation, and reinforcement learning. For several tasks, it provides both light-weight and heavy-weight implementations. Totally, it includes seven benchmarks for training and five benchmarks for inference.

Fathom [15] consists of eight deep learning benchmarks, each of which is implemented with TensorFlow. The Autoenc workload provides a variational autoencoder and can be used to reduce the dimension and compress images.

DeepBench [13] provides three basic operations and recurrent layer operations (micro benchmarks) that are frequently appeared in training deep neural networks.

DNNMark [16] provides eight micro benchmarks which are a suite of deep neural network primitives.

DAWNBench [11] 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 including image classification on CIFAR10 and ImageNet, and question answering on SQuAD.

TBD Suite [17] focuses on training performance evaluation and provides eight neural network models that covers six application domains.

In conclusion, the state-of-the-art and state-of-the-practise AI benchmarks can not meet the subtly different benchmarking requirements of different stages in developing a new system/architecture and ranking/purchasing commercial off-the-shelf ones.

3 The Methodology

Our balanced AI benchmarking methodology consists of four essential parts as follows.

3.1 Performing a detailed survey of the most important domain rather than a rough survey of a variety of domains

As it is impossible to investigate all AI domains, we single out the most important AI domain–Internet services for the detailed survey with seventeen prominent industry partners.

3.2 Include as most as possible representative benchmarks

We believe the prohibitive cost of training a model to a state-of-the-art quality cannot justify including only a few AI benchmarks. Instead, using only a few AI component benchmarks may lead to error-prone design: over-optimization for some specific workloads or Benchmarketing.

For Internet services, we identify and include as most as possible representative AI tasks, models and data sets into the benchmark suite, so as to guarantee the representativeness and diversity of the benchmarks. For each benchmark, we propose the benchmarking rule to assure the fairness across different systems.

This strategy is also witnessed by the past successful benchmark practice. Actually, the cost of execution time for other benchmarks like HPC [18], SPECCPU [19] on simulators, is also prohibitively costly. However, the representativeness and coverage of a widely accepted benchmark suite are paramount important. For example, SPECCPU 2017 [20] contains 43 benchmarks. The other examples include PARSEC3.0 (30) [21], TPC-DS (99) [22].

3.3 Keep the benchmark subset to a minimum

We choose a minimum AI component benchmark subset (less than MLPerf) according to the criteria: diversity of model complexity, computational cost, convergence rate, repeatability, and having the
Table 1: AI Component Benchmarks Comparison. ✅ ✅ indicates a benchmark is also included into the subset.

| Seventeen Component Benchmarks          | AI Bench | MLPerf | Fathom | DeepBench DNN Mark | DAWN Bench | TBD |
|-----------------------------------------|----------|--------|--------|--------------------|------------|-----|
| Image classification                    | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Image generation                        | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Text-to-Text                            | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Image-to-Text                           | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Speech recognition                      | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Face embedding                          | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| 3D Face Recognition                     | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Object detection                        | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Recommendation                         | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Video prediction                        | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Image compression                       | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| 3D object reconstruction                | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Text summarization                      | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Spatial transformer                     | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Learning to rank                        | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Neural architecture search              | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Games                                   | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Memory network                          | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |
| Question answering                      | Train    | ✅      | ✅      | ✅                  | ✅          | ✅   |

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 |
widely-accepted metrics or not. Meanwhile, we quantify the performance relationships between the full benchmark suite and its subset.

Using the subset for ranking is also witnessed by the past practice. For example, Top500 [23], a super computer ranking—only reports HPL [18] and HPCG [24]—two benchmarks out of 20+ representative HPC benchmarks like HPCC [25], NPB [26].

3.4 Consider the comprehensive benchmarks and its subset as two indispensable parts

Different stages have subtly different benchmarking requirements. The initial design inputs of a new system/architecture need comprehensive workload characterization. For earlier-stage evaluations of a new system or architecture, which usually adopts simulation-based methods, heavy benchmarking is a big burden, thus, concise, portable, and lightweight benchmarks are of great significance. While later-stage evaluations of a new architecture or system or purchasing a commercial off-the-shelf ones needs detailed evaluation using comprehensive benchmarks to avoid error-prone design or benchmarking.

Previous work [17, 27] find that each iteration of an AI task has the same computation logic and the iteration number has little impact on micro-architectural behaviors. We train the AI models of the seventeen benchmarks to a convergent quality, most of which are close to the state-of-the-art ones. We call each training a quasi-entire training session.

Considering subtly different benchmarking requirements of different stages, we run entire training sessions of the subset and/or selectively run quasi-entire training sessions from the full benchmarks to avoid over-optimization or benchmarking.

For initial design inputs, we perform detailed workload characterization. For earlier-stage evaluations of a new system or architecture, we run a subset, as it is portable and lightweight.

For later-stage evaluation of a new system or architecture, we run entire training session or selectively run quasi-entire training session from the full benchmarks to help quickly locate the bottlenecks.

For purchasing or ranking commercial off-the-shelf systems or architecture, running an entire training session of the subset provides valuable performance implications. Meanwhile, we also run quasi-entire or entire training session of the full benchmark suites to avoid benchmarketing.

4 The Benchmark Design and Implementation

In this section, we illustrate the benchmark design and implementation, including selection of workloads and quality targets (Section 4.1), metric, implementations and reimplementation rules (Section 4.2).

4.1 The Benchmark Decisions

To cover a wide spectrum of prominent AI problem domains among Internet services, we thoroughly analyze the essential applications scenarios among three primary Internet services, including search engine, social network, and e-commerce, as shown in Table 2. In total, we identify seventeen representative AI tasks, and implement each task with the state-of-the-art model as a component benchmark, as shown in Table 3. Due to the space limitation, we give a brief introduction.

4.1.1 Image Classification

Image classification is to classify an image into multiple categories.

**ResNet-50** [28]: ResNet-50 [28] is a convolutional neural network with 50 layers. The main module in ResNet-50 is the bottleneck, consisting of three convolutional layers and a identity mapping.

**ImageNet Dataset** [29]: This dataset contains more than 14 million images, and the data size is more than 100 GB.

**Reference Quality**: The reference implementation on the ImageNet dataset achieves Top-1 accuracy 74.9%.
4.1.2 Object Detection

Object detection aims to find objects of certain target classes with precise localization in a given image.

**Faster R-CNN Model [30]**: For object detection, we use the Faster R-CNN model, with the backbone network of ResNet-50 to extract the features of an input image.

**VOC2007 [31]**: The dataset has 9,963 images, containing 24,640 annotated objects. Each image has an annotation file giving a bounding box and object class label for each object in one of the twenty classes present in the image [31].

**Reference Quality**: The model achieves 75% mAP on the VOC2007 test data.

4.1.3 Learning to Rank

Learning to rank is to train models for ranking tasks using machine learning methods.

**Ranking Distillation Model [32]**: Ranking distillation is a technique that uses knowledge distillation to train a smaller student model for ranking under the supervision of a larger teacher model, and this student model has similar performance to the teacher model but has better online inference performance.

**Gowalla Dataset [33]**: The dataset contains the geographical location shared by users and user relationship network, including 196591 nodes, 950327 edges, and 6442890 location sharing records.

**Reference Quality**: The target accuracy of the model is 14.58% on the Gowalla dataset.

| 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; Neural architecture search            |
|                  | 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; Neural architecture search                                                          |
|                  | 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; Neural architecture search                                        |
|                  | 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                                                                             |

4.1.4 Image Generation

Image generation is to generate similar images with the input image.
Wasserstein Generative Adversarial Networks (WGAN) Model [34]: This model consists of a generator and a discriminator, which are 4-layer RELU-MLP with 512 hidden units.

LSUN Dataset [35]: This task uses the LSUN-Bedrooms dataset [35]. The generated samples are 3-channel images of 64x64 pixels in size.

Reference Quality: This task has no widely accepted evaluation metric. We use the estimated Earth-Mover (EM) distance as loss function in training, which needs to reach $0.5 \pm 0.005$.

4.1.5 Text-to-Text Translation

Text-to-Text translation is to translate a sequence of words into another language.

Transformer [36]: Transformer is combined of self-attention and Feed Forward Neural Network.

WMT English-German Dataset [37]: The training dataset is the WMT’14 English-German data, which has 4.5 million sentence pairs. The inference dataset is newstest2014, which has 2737 sentence pairs.

Reference Quality: The target accuracy is 55%.

4.1.6 Image-to-Text

Image-to-text is to generate the description of an image automatically.

Neural Image Caption Model [38]: This model consists of a vision convolution neural network (CNN) followed by a language generating recurrent neural network (RNN).

MSCOCO 2014 Dataset [39]: The dataset has more than 82,000 images with caption annotations, and the testing set is separated from the training set.

Reference Quality: The model achieves 4.2 perplexity on the MSCOCO 2014 dataset.

4.1.7 Image-to-Image Translation

Image-to-image translation is to learn image mapping of two different domains.

CycleGAN Model [40]: CycleGAN has two generators and two discriminators. Following [40], our generator adopts the network structure in [41], and the discriminator adopts 70x70 PatchGANs [42].

Cityscapes Dataset [43]: Image-to-image translation task uses the Cityscapes dataset [43], which contains more than 50 cities street scenes.

Reference Quality: This task has no widely accepted evaluation metric, we adopt per-pixel accuracy ($0.52 \pm 0.005$), per-class accuracy ($0.17 \pm 0.001$), and Class IOU ($0.11 \pm 0.001$) referring to the Cityscapes benchmark [43].

4.1.8 Speech Recognition

Speech recognition is to recognize the speech audio and translate it into a text format.

DeepSpeech2 Model [44]: the Deep Speech 2 model is a recurrent neural network (RNN) with one or more convolutional input layers, followed by multiple recurrent layers and one fully connected layer before a softmax layer [44].

LibriSpeech Dataset [45]: The dataset contains 1000 hours of speech sampled at 16 kHz [45].

Reference Quality: The word error rate (WER) of the reference implementation of DeepSpeech2 model on LibriSpeech test-cleans data is 5.33%.

4.1.9 Face Embedding

Face embedding is to verify the face by learning an embedding into the Euclidean space.

FaceNet [46]: FaceNet model is based on the GoogleNet style Inception model, which has about 24 million parameters.

VGGFace2 Dataset [47]: This dataset includes 9000+ identities, and 3.3 million+ faces.

Reference Quality: The target quality is an accuracy of 98.97%.
4.1.10 3D Face Recognition

3D face recognition performs identification of 3D face images.

**3D Face Model** [48]: The model uses ResNet-50 network as backbone network and adjusts the first convolutional layer and the fully connect layer so that RGB-D images can be fed into the RGB-D ResNet-50 model.

**Intellifusion Dataset**: The dataset is a RGB-D dataset, provided by Intellifusion.

**Reference Quality**: The reference implementation achieves an accuracy of 94.64% on the Intellifusion dataset.

4.1.11 Recommendation

This task is widely used for advertisement recommendation, community recommendation, and etc.

**Neural collaborative filtering** [49]: A probabilistic approach using Gaussian assumptions on the known data and the factor matrices.

**MovieLens Dataset** [50]: The MovieLens 100K movie ratings dataset contains 100,000 ratings from 1000 users on 1700 movies.

**Reference Quality**: The quality metric is HR@10, which means whether the correct item is on the top-10 list. The target quality is 63.5% HR@10.

4.1.12 Video Prediction

Video prediction is to predict how its actions affect objects in its environment.

**Motion-Focused Predictive Model** [51]: This model predicts how to transform the last image into the next image.

**Robot Pushing Dataset** [51]: This dataset contains 59,000 robot interactions involving pushing motions.

**Reference Quality**: This task achieves 72 MSE on the test data.

4.1.13 Image Compression

Image compression aims to reduce the cost for storage or transmission.

**Recurrent Neural Network** [52]: This model consists of a recurrent neural network (RNN)-based encoder and decoder, a binarizer, and a neural network for entropy coding.

**ImageNet Dataset** [29]: The dataset used for this task is the same with that of Image Classification.

**Reference Quality**: The metric is 0.99 MS-SSIM (Multi-Scale-Structural Similarity Index [53]).

4.1.14 3D Object Reconstruction

3D reconstruction is to capture the shape and appearance of real objects.

**Convolutional Encoder-decoder Network** [54]: This model combines image encoder, volume decoder, and perspective transformer.

**ShapeNet Dataset** [55]: ShapeNetCore contains about 51,300 unique 3D models from 55 common object categories.

**Reference Quality**: The metric is the average IU (intersection-over-union) score. The target average IU is 45.83% on ShapeNetCore.

4.1.15 Text Summarization

Text summarization is the task of generating a headline or a short summary.

**Sequence-to-sequence Model** [56]: This model consists of the off-the-shelf attentional encoder-decoder RNN.
**Gigaword Dataset** [57]: The dataset contains about 3.8M training examples, and 400K validation and test examples.

**Reference Quality**: The model achieves 41 Rouge-L on the Gigaword dataset.

### 4.1.16 Spatial Transformer

Spatial Transformer is to provide spatial transformation capabilities.

**Spatial Transformer Network** [58]: The model includes a localisation network, a grid generator, and a sampler.

**MINST Dataset** [59]: The MNIST dataset consists of 60,000 training images and 10,000 test images.

**Reference Quality**: This task achieves an accuracy of 99%.

### 4.1.17 Neural architecture search [60]

Neural network search is to automatically design neural networks.

**Neural Architecture Search**: Neural Architecture Search is to maximize the accuracy of the searched neural network.

**Reinforcement learning** [61]: This model finds efficient neural networks by sharing parameters in child models to find an optimal neural architecture.

**PTB Dataset** [62]: The dataset contains 2,499 stories from a three-year Wall Street Journal collection of 98,732 stories for syntactic annotation.

**Reference Quality**: The target quality is 100 perplexity.

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**Table 3: Component Benchmarks in AI Bench**

| No. | Component Benchmark | Algorithm | Data Set | Target Quality |
|-----|---------------------|-----------|----------|----------------|
| DC-AI-C1 | Image classification | ResNet50 [28] | ImageNet | 74.9% (accuracy) |
| DC-AI-C2 | Image generation | WassersteinGAN [31] | LSUN | N/A |
| DC-AI-C3 | Text-to-Text translation | Recurrent neural networks [29] | WMT English-German | 55% (accuracy) |
| DC-AI-C4 | Image-to-Text | Neural Image Caption Model [38] | Microsoft COCO | 4.2 (perplexity) |
| DC-AI-C5 | Image-to-Image | CycleGAN [40] | Cityscapes | N/A |
| DC-AI-C6 | Speech recognition | DeepSpeech2 [34] | Librispeech | 5.33% (WER) |
| DC-AI-C7 | Face embedding | Facenet [46] | LFW, VGGFace2 | 98.97% (accuracy) |
| DC-AI-C8 | 3D Face Recognition | 3D face models [18] | 77,715 samples from 253 face IDs | 94.64% (accuracy) |
| DC-AI-C9 | Object detection | Faster R-CNN [39] | VOC2007 | 75% (mAP) |
| DC-AI-C10 | Recommendation | Neural collaborative filtering [49] | MovieLens | 63.5% (HR@10) |
| DC-AI-C11 | Video prediction | Motion-Focused predictive models [51] | Robot pushing data set | 72 (MSE) |
| DC-AI-C12 | Image compression | Recurrent neural network [52] | ImageNet | 0.99 (MS-SSIM) |
| DC-AI-C13 | 3D object reconstruction | Convolutional encoder-decoder network [54] | ShapeNet Data set | 45.83% (IU) |
| DC-AI-C14 | Text summarization | Sequence-to-sequence model [50] | Gigaword data set | 41 (Rouge-L) |
| DC-AI-C15 | Spatial transformer | Spatial transformer networks [53] | MNIST | 99% (accuracy) |
| DC-AI-C16 | Learning to rank | Ranking distillation [32] | Gowalla | 14.58% (accuracy) |
| DC-AI-C17 | Neural architecture search | Efficient neural architecture search [61] | PTB [62] | 100 (perplexity) |
4.2 Metrics, Implementations, and Reimplementation Rules

This section briefly presents the metrics, implementations and reimplementation rules.

4.2.1 Metrics

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

The metrics for online inference contains query response latency, tail latency, throughput, 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 [11], and the energy consumption to train a model achieving a target accuracy [11].

4.2.2 The Implementations and Reimplementation Rules

AIBench provide reference implementations and corresponding running scripts, dataset, and monitoring tools for each component benchmark. We provide two implementations on both TensorFlow [2] and PyTorch [63] frameworks.

The benchmark reimplementation are allowed to adjust the hyper parameters to suit for the system under test and maximize the execution performance, e.g., learning rate, batch size. However, the reimplementation disallows retraining of the model, model pruning, and reducing the input data size.

5 Evaluation

In this section, we compare AIBench against MLPerf from the perspectives of model and micro-architectural characteristics (Section 5.2), quantify the run-to-run variation and measure their benchmarking cost (Section 5.3), propose a minimum subset to achieve affordability and representativeness (Section 5.4), and characterize micro-architectural behaviors from the perspectives of runtime breakdown, hotspot functions and stall analysis (Section 5.5).

5.1 Experimental Configuration

We conducted experiments on two type servers equipped with different GPUs: one is TITAN XP, and the other is TITAN RTX. The other configurations of the servers are the same. The experiments for workload characterization are based on the TITAN XP GPUs, while the experiments running training sessions are based on TITAN RTX GPUs. The configurations of GPUs and other servers are shown in Table 4. The operating system we use is ubuntu 16.04 with the kernel version of Linux 4.4, and the other software is CUDA 10, python 3.7, and PyTorch 1.10. In the rest of this section, we only evaluate the reference PyTorch implementations of AIBench because of the prohibitive training cost explained in Section 5.3.2.

5.2 The Comparison of AIBench against MLPerf

5.2.1 Model Characteristics

In this subsection, we characterize the model characteristics of the AIBench and MLPerf benchmarks from the perspectives of model complexity, computational cost, and convergent rate.

The characterization approach is similar to that of [64]. The differences have two points: they only evaluate different AI models of the same image classification task, while we evaluate twenty-two AI tasks (17 of AIBench and 5 of MLPerf) with different state-of-the models; They report Top-1 accuracy, while we report the convergent rate—the cost of training a model.
Table 4: Hardware Configuration Details.

| CPU Configurations | Intel CPU Core |
|--------------------|----------------|
| CPU Type           | Intel Xeon E5-2620 v3 |
| L1 DCache          | 12 × 32 KB |
| L1 ICache          | 12 × 32 KB |
| L2 Cache           | 12 × 256 KB |
| L3 Cache           | 15MB |
| Memory             | 64GB, DDR3 |
| Ethernet           | 1G |
| Hyper-Threading    | Disabled |

| GPU Configurations v1 | Nvidia Titan XP |
|-----------------------|-----------------|
| GPU Type              | Nvidia Cuda Cores |
|                       | 3840 cores |
| GPU Memory            | 12GB, GDDR5X |

| GPU Configurations v2 | Nvidia Titan RTX |
|-----------------------|-----------------|
| GPU Type              | Nvidia Cuda Cores |
|                       | 4608 cores |
| GPU Memory            | 24GB, GDDR6 |

We use the total amount of learnable parameters, FLOPs of a single forward computation, and the number of epochs to achieve a convergent quality (e.g., accuracy, BLEU) to characterize the above three characteristics, respectively. We use the OpCounter tool [65] to estimate the FLOPs and learnable parameters for both AIBench and MLPerf benchmarks. Since some operations cannot be counted by the tool, the reported numbers may be smaller than the actual one. We do not report the numbers of the reinforcement learning model for both AIBench (Neural Architecture Search) and MLPerf (Game) shown in Table 1, because the FLOPs and learnable parameters vary significantly from different epochs.

For each benchmark of AIBench and MLPerf, we train the model to achieve a convergent quality. Specifically, the convergent quality is 73.7% (accuracy) for Image Classification, 55% (accuracy) for Text-to-Text translation, 4.2 (perplexity—the smaller is the better) for Image-to-Text, 23.5% (WER—the smaller is the better) for Speech Recognition, 89% (accuracy) for Face Embedding, 94.59% (accuracy) for 3D Face Recognition, 74% (mAP) for Object Detection, 60% (HR@10) for Recommendation, 72 (MSE—the smaller is the better) for Video Prediction, 0.99 (MS-SSIM) for Image Compression, 45% (IU) for 3D Object Reconstruction, 41 (Rouge-L) for Text Summarization, 99% (accuracy) for Spatial Transformer, 13.9% (accuracy) for Learning-to-Rank, and 100 (perplexity) for Neural Architecture Search. For the MLPerf benchmarks, the convergent quality is 37.7 (BBOX) for Object Detection (heavy), 22.47 (mAP) for Object Detection (light), 22.21 (BLEU) for Translation (recurrent), 25.25 (BLEU) for Translation (nonrecurrent). Note that AIBench and MLPerf use the same model and dataset for Image Classification and Recommendation, so their numbers are consistent in the rest of this paper.

Fig. 2 shows the model characteristics. We find that from the perspective of computation cost, the FLOPs of the AIBench benchmarks range from 0.09 to 157802 M-FLOPs, while that of MLPerf vary from 0.213248 to 24500 M-FLOPs—a much narrower range. From the perspective of model complexity, the amount of learnable parameters of AIBench range from 0.03 million to 68.4 million, while MLPerf only cover a range of 5.2 to 49.53 million. From the perspective of convergent rate, the required epochs of AIBench range from 6 to 96, while MLPerf only cover a range of 3 to 49. Thus, only using MLPerf cannot cover the diversities of different AI models.

We find that Object Detection and 3D Object Reconstruction have approximate amounts in terms of both FLOPs and learnable parameters. They have the largest FLOPs among all benchmarks. Learning-to-Rank has the smallest number of FLOPs. Image-to-Text has the most complex model, while Spatial Transformer has the least complex model. Text-to-text translation requires the most largest epochs to converge, while the remaining models converge within 60 epochs.
5.2.2 Micro-architectural Characteristics

GPU architecture contains multiple streaming multiprocessors (SM), each of which has a certain number of CUDA cores, memory registers, memory caches, warp schedulers and etc. To compare the AIBench and MLPerf from a perspectives of computation and memory access patterns, We choose five micro-architectural metrics, including achieved occupancy, ipc efficiency, gld_efficiency, gst_efficiency, and dram_utilization. Achieved occupancy represents the ratio of the average active warps per active cycle to the maximum number of warps provided by a multiprocessor [66]. Ipc_efficiency indicates the ratio of the executed instructions per cycle to the theoretical number [66]. Gld_efficiency means the ratio of the requested global memory load throughput to the required global memory load throughput [66]. Gst_efficiency means the ratio of the requested global memory store throughput to the required global memory store throughput [66]. Dram_utilization means the utilization level of the device memory relative to the peak utilization [66].

Fig. 3 presents the computation and memory access patterns of the twenty four AI benchmarks (17 of AIBench, 7 of MLPerf). We find that they have distinct computation and memory patterns not only under different scenarios, e.g., processing text, image, audio, video, but also under different tasks of the same scenario, e.g., image classification and image generation.

Performing further analytics on Fig. 2 and Fig. 3, Figure 1 shows with respect to AIBench, MLPerf has a significantly smaller coverage in terms of AI model complexity, computational cost, convergent rate (Figure 1(a)), computation and memory access patterns (Figure 1(b)). AIBench outperforms MLPerf in terms of representativeness and diversity.

5.3 Repeatability and Benchmarking Cost Evaluation

In this subsection, we quantify the run-to-run variation and measure the benchmarking cost of AIBench against MLPerf.

5.3.1 Run-to-run Variation

Repeatability [67] refers to the variation in repeat measurements (different runs of the same benchmark implementation under the identical configurations) made on the same system under test. A good benchmark must be repeatable. However, most of the AI benchmarks exhibit run-to-run variation even using the same benchmark implementation on the same system.
For each benchmark, we fix the hyperparameters, i.e., batch size, learning rate, optimizer, weight
decays, and repeat at least four times (maximally 10 times) for each benchmark, to measure the run-to-run
variation. Note that our evaluation uses the random seed and does not fix the initial seed except for speech
recognition. We use the coefficient of variation—the ratio of the standard deviation to the mean—of the
training epochs to achieve a convergent quality, to represent the run-to-run variation. Table 5 shows the
results. We find that the run-to-run variation of different AI benchmarks vary wildly. The run-to-run
variation of 3D face recognition is the largest (38.46%). While object detection, image classification and
learning to rank are the smallest, which are 0%, 1.12% and 1.9%, respectively. The run-to-run variations
of Image-to-Image and Image generation are not reported due to a lack of a widely accepted metric to
determine the termination condition for a run. For speech recognition, even sharing the same initial seed,
the run-to-run variation still reaches to 12.08%.
Table 5: Run-to-run Variation of Seventeen Benchmarks.

| No.   | Component Benchmark       | Variation | Repeat Times |
|-------|---------------------------|-----------|--------------|
| DC-AI-C1 | Image classification      | 1.12%     | 5            |
| DC-AI-C2 | Image generation          | Not available | N/A         |
| DC-AI-C3 | Text-to-Text translation  | 9.38%     | 6            |
| DC-AI-C4 | Image-to-Text             | 23.53%    | 5            |
| DC-AI-C5 | Image-to-Image            | Not available | N/A         |
| DC-AI-C6 | Speech recognition        | 12.08%    | 4            |
| DC-AI-C7 | Face embedding            | 5.73%     | 8            |
| DC-AI-C8 | 3D Face Recognition       | 38.46%    | 4            |
| DC-AI-C9 | Object detection          | 0         | 10           |
| DC-AI-C10| Recommendation            | 9.95%     | 5            |
| DC-AI-C11| Video prediction          | 11.83%    | 4            |
| DC-AI-C12| Image compression         | 22.49%    | 4            |
| DC-AI-C13| 3D object reconstruction  | 16.07%    | 4            |
| DC-AI-C14| Text summarization        | 24.72%    | 5            |
| DC-AI-C15| Spatial transformer       | 7.29%     | 4            |
| DC-AI-C16| Learning to rank          | 1.90%     | 4            |
| DC-AI-C17| Neural Architecture Search| 6.15%     | 6            |

5.3.2 Evaluate Benchmarking Cost

Running entire training sessions of all AIBench benchmarks is prohibitively costly. Table 6 lists the elapsed time for both an epoch and the total time for a training session. We find that Image Classification, Speech Recognition, and 3D Face Recognition are the top-three most time-consuming benchmarks, which take about 184.8 hours in total. Supposing that we run each of the above three benchmarks five times, the time consumption reaches up to 38.5 days. If we do these for all seventeen benchmarks, the time consumption will reach up to 47 days, which is not affordable for most of industry and academia. So a concise, portable, and lightweight subset is of great significance.

In addition, we also evaluate the benchmarking cost of running a training session for MLPerf. To achieve a convergent quality, the time costs for MLPerf are: 130 hours for Image Classification, 0.16 hours for Recommendation, 73.34 hours for Object Detection (Heavy), 23.7 hours for Object detection (light), 16.52 hours for Translation (recurrent), and 22 hours for Translation (nonrecurrent). For Reinforcement Learning in MLPerf, we train the model more than 96 hours, and the pro move prediction reaches to 34%, while the target is 40%. Hence, running all seven benchmarks in MLPerf to achieve a convergent quality one time, the time cost reaches to more than 362 hours, even larger than running all benchmarks in AIBench. If we repeat MLPerf benchmarks for five times, the time cost will be more than 75 days.

5.4 The AIBench Subset and its Implications

In this subsection, we illustrate how to choose a subset and the subset’s implications.

5.4.1 How to Choose a subset?

To achieve the fairness and affordability, we keep the subset to a minimum from the following perspectives.

Reflecting Diversity of model complexity, computational cost, and convergent rate. To be specific, we intend to choose the benchmarks that cover different aspects of Fig. 2 as much as possible. For example, the subset should cover a wide range of the number of FLOPs, learnable parameters, convergent rate.

Run-to-run Variation. The repeatability is an important selection criteria of the subset. To avoid two much run-to-run variation, we choose the benchmarks with variance under 2%.

Widely accepted evaluation metrics. A benchmark should have widely accepted performance metrics, so that runs from different users have consistent termination conditions. So we exclude the
Table 6: Training Costs of Seventeen Benchmarks in AIBench.

| No.   | Component Benchmark            | Time Per Epoch (second) | Total Time (hour) |
|-------|--------------------------------|-------------------------|-------------------|
| DC-AI-C1 | Image Classification          | 10516.91                | 130               |
| DC-AI-C2 | Image Generation              | 3935.75                 | N/A               |
| DC-AI-C3 | Text-to-Text Translation      | 64.83                   | 1.72              |
| DC-AI-C4 | Image-to-Text                 | 845.02                  | 10.21             |
| DC-AI-C5 | Image-to-Image                | 251.67                  | N/A               |
| DC-AI-C6 | Speech Recognition            | 14326.86                | 42.78             |
| DC-AI-C7 | Face Embedding                | 214.73                  | 3.43              |
| DC-AI-C8 | 3D Face Recognition           | 36.99                   | 12.02             |
| DC-AI-C9 | Object Detection              | 1627.39                 | 2.52              |
| DC-AI-C10 | Recommendation                | 36.72                   | 0.16              |
| DC-AI-C11 | Video Prediction              | 24.99                   | 2.11              |
| DC-AI-C12 | Image Compression             | 763.44                  | 3.67              |
| DC-AI-C13 | 3D Object Reconstruction      | 28.41                   | 0.38              |
| DC-AI-C14 | Text Summarization            | 1923.33                 | 6.41              |
| DC-AI-C15 | Spatial Transformer           | 6.38                    | 0.06              |
| DC-AI-C16 | Learning-to-Rank              | 74.16                   | 0.47              |
| DC-AI-C17 | Neural Architecture Search    | 932.79                  | 7.47              |

GAN-based models.

5.4.2 The Subset Decision

We include three benchmarks into the subset: Image Classification, Object Detection, and Learning-to-Rank. To satisfy the first criterion, they cover different ranges of numbers in terms of FLOPs and learnable parameters (both small for Learning-to-Rank, medium for Image Classification, and large for Object Detection), and different convergent rates (small epochs for Object Detection, medium for Learning-to-Rank, and large for Image Classification). As for the second criterion, three benchmarks have the least run-to-run variation, 1.12% for Image Classification, 1.9% for Learning-to-Rank, and 0% for Object Detection. In addition, they have widely accepted evaluation metrics—accuracy for Image Classification, precision for Learning-to-Rank, and mAP for Object Detection.

Comparing to the full benchmark of AIBench and MLPerf, the AIBench subset shortens the training time by 41% and 63%, respectively.

5.4.3 The Subset’s Implication

Using the metrics reflecting computation and memory access patterns illustrated in Section 5.2.2, we conduct a cluster analysis on all seventeen component benchmarks and subset of AIBench, to explore their similarities. Fig. 4 shows the cluster result using t-Distributed Stochastic Neighbor Embedding (t-SNE) [68], which is a dimensionality reduction technique to embed high-dimensional data in a low-dimensional space for visualization [69]. We find that these seventeen benchmarks are clustered into three classes, and the subset—Image Classification, Learning-to-Rank, and Object Detection—are in three different clusters. The result further demonstrates that our subset is a minimum set to achieve the maximum representativeness and diversity of seventeen component benchmarks. To a certain degree, the performance of a benchmark in the subset has the ability to estimate the performance of the other benchmarks within in the same cluster. However, from Fig. 4, we also find that even the benchmarks in the same cluster may have a large distance. Hence, to obtain more accurate performance data and detailed characterization, the full benchmarks are indispensable.
5.5 Micro-architectural Behaviors

This subsection characterizes the micro-architectural behaviors from the perspectives of runtime breakdown, hotspot function analysis, and stall analysis.

5.5.1 Runtime Breakdown

We evaluate the PyTorch implementations with the version of 1.1.0. The data set for each benchmark is as follows: ImageNet (137 GB) for Image Classification and Image Compression; LSUN (42.8 GB) for Image Generation; VGGFace2 (36 GB) for Face Embedding; Microsoft COCO (13 GB) for Image-to-Text; VOC2007 (439 MB) for 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; Gowalla (107 MB) for Learning-to-Rank; WMT English-German (1.2 MB) for Text-to-Text translation; Robot pushing data set (137 GB) for Video Prediction; ShapeNet data set (6.8 GB) for 3D Object Reconstruction; Gigaword data set (277 MB) for Text summarization; 3D face data (37 GB) for 3D Face Recognition; PTB data set (4.9 MB) for Neural Architecture Search, respectively.

The overall execution performance of these component benchmarks vary in terms of IPC, which measures the executed instructions per cycle. From Fig. 3, we find that the IPC efficiency ranges from 0.25 (Learning-to-Rank) to 0.77 (Text-to-Text translation). Some benchmarks like learning-to-rank have extremely low IPC comparing to the other benchmarks. To reveal the factors that impact the performance greatly, we first conduct runtime breakdown analysis and decompose the benchmarks into the hotspot functions, then we characterize the GPU execution efficiency in terms of different percentage of stalls.

We use nvprof to trace the runtime breakdown and find the hotspot functions that occupy more than 80% of runtime in total. Since each run involves dozens of function calls, we single out the functions that occupy large proportions of runtime and classify them into several categories of kernels according to their computation logic. Through statistics, we find that the most time-consuming functions among all component benchmarks have much in common, and they are classified into eight categories of kernels: data arrangement, convolution, general matrix multiply (gemm), batch normalization, element-wise operation, relu activation, pooling, and memory copy, spanning from computation kernels to memory access kernels. Note that each kernel contains a bunch of functions that solve the similar issue. For example, a gemm kernel includes single or double precision floating general matrix multiply. Fig. 5 shows the runtime breakdown of seventeen benchmarks of AIBench, using the average number of all involved functions within each category of kernels. Note that the remaining 20% functions are not considered.

1Relu activation is an element-wise operation, here we use a separate category of Relu considering its large proportion and diverse CUDA functions.
in this figure. Further, for each each category of kernels, we summarize typical functions that occupy a large proportion of runtime among the component benchmarks, as shown in Table 7. We find that learning_to_rank spends too much time on data arrangement operations from Fig. 5, and the corresponding function call is maxwell_scdn128x32_stridedB_splitK_interior_nn with an IPC of 0.98. This is the reason why leaning_to_rank has the lowest IPC of 0.99. We believe that the eight categories of kernels and these corresponding functions are the optimization points not only for CUDA library optimizations but also for micro-architectural optimizations.

5.5.2 Hotspot Function Analysis

Hotspot function identification is of great significance for bottleneck locating and code optimization. We compare the important hotspot functions identified by AIBench and MLPerf.

Fig. 6 shows the numbers of hotspot functions within each category of occupying different time percentages identified by AIBench and MLPerf. We find that MLPerf only covers a fraction of hotspot functions with respect to that of AIBench. For example, within the category that occupies more than 10% of runtime, the number of hotspot functions profiled from AIBench is 30, while only 9 for MLPerf. Thus, MLPerf omits a large number of hotspot functions occurred in a wide spectrum of AI tasks.

We further profile the AIBench subset, to find whether they can capture the primary hotspot functions. Our evaluation result shows that even though the subset captures the least number of hotspot functions comparing to the seventeen benchmarks of AIBench and MLPerf, however, it covers the most time-consuming and frequently-appearing functions like maxwell_scdn128x128_stridedB_splitK_interior_nn (e.g., occupying 17.28% running time for 3D object reconstruction).

In conclusion, for AIBench, the full benchmarks and the subset are two indispensable parts. With respect to MLPerf, the full benchmarks of AIBench provide comprehensive workload characterization and detailed evaluation while reducing the training time by 37%. With respect to the AIBench full benchmarks, its subset further shortens the benchmarking cost by 41%, while maintaining the primary workload characteristics.

5.5.3 Stall Analysis

Focusing on the above eight most time-consuming categories of kernels, we analyze the following stalls of these kernels. Instruction fetch stall (Inst_fetch) indicates the percentage of stalls because the next assembly instruction has not yet been fetched; Execution dependency stall (Exe_depend) is the percentage
Table 7: Hotspot Functions.

| Micro Benchmark | Function Name |
|-----------------|---------------|
| Data Arrangement | maxwell_scudnn_128x128_stridedB_splitK_interior.nn |
|                 | maxwell_scudnn_128x32_stridedB_splitK_interior.nn |
|                 | maxwell_scudnn_128x128_stridedB_interior.nn |
| Convolution     | maxwell_scudnn_winograd_128x128_lgd1_lgd4_tile148n_nt |
|                 | wgrad_algo_engine |
|                 | fft2d_j2c_32x32 |
| GEMM            | maxwell_sgemm_128x64_nt |
|                 | maxwell_sgemm_128x64_nn |
|                 | sgemm_32x32x32_NN_vec |
| BatchNorm       | cudnn::detail::bn_fw_ir_1C11_kernel_NCHW |
|                 | cudnn::detail::bn_bw_1C11_kernel_new |
|                 | batch_norm_backward_kernel |
|                 | at::native::batch_norm_backward_kernel |
| Relu            | maxwell_scudnn_128x128_relu_small_nn |
|                 | maxwell_scudnn_128x128_relu_interior_nn |
|                 | maxwell_scudnn_128x32_relu_interior_nn |
| Element-wise    | element-wise add kernel |
|                 | element-wise threshold kernel |
|                 | element-wise mul kernel |
| Pooling         | MaxPoolBackward |
|                 | AvePoolForward |
|Memcpy           | CUDA memcpy HtoD |
|                 | CUDA memcpy DtoD |

of stalls because an input required by the instruction is not yet available; Memory dependency stall (Mem_depend) 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) is the percentage of stalls because of the under-utilization of the texture sub-system; Synchronization stall (Sync) is the percentage of stalls due to a syncthreads call; Constant memory dependency stall (Const_mem_depend) is the percentage of stalls because of immediate constant cache miss; Pipe busy stall (Pipi_busy) is percentage of stalls because a compute operation cannot be performed because the compute pipeline is busy; Memory throttle stall (Mem_throttle) is the percentage of stalls due to large pending memory operations [66].

The breakdown of eight stalls of the hotspot functions is shown in Fig. 7. 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 70%, thus resulting in a low IPC.
The memory dependency stalls may occur due to high cache misses, and thus the load/store resources are not available. Possible optimization strategies include optimizing date alignment, data locality, and data access patterns. The execution dependency stalls may occur due to low instruction-level parallelism, and exploiting ILP may alleviate partial execution dependency stalls to a certain degree.

6 Conclusion

This paper presents a balanced AI benchmarking methodology that considers the comprehensive component AI benchmarks and its subset as two indispensable parts. We contribute by far the most comprehensive open-source industry-standard AI benchmark suite—AIBench. We perform by far the most comprehensive workload characterization on AIBench and/or MLPerf from the perspectives of model complexity, computational cost, and convergent rate, computation and memory access patterns, repeatability, hotspot functions, and other micro-architecture characteristics. Our evaluations show AIBench outperforms MLPerf in terms of the diversity and representativeness of model complexity, computational cost, convergent rate, computation and memory access patterns, and hotspot functions. With respect to MLPerf, AIBench reduces the benchmarking cost while avoiding error-prone design or benchmarking. With respect to the AIBench full benchmarks, its subset shortens the benchmarking cost by 41%, while maintaining the primary workload characteristics.

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