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BigDataBench: A Dwarf-based Big Data and AI Benchmark Suite

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Abstract

As architecture, system, data management, and machine learning communities pay greater attention to innovative big data and data-driven artificial intelligence (in short, AI) algorithms, architecture, and systems, the pressure of benchmarking rises. However, complexity, diversity, frequently changed workloads, and rapid evolution of big data, especially AI systems raise great challenges in benchmarking. First, for the sake of conciseness, benchmarking scalability, portability cost, reproducibility, and better interpretation of performance data, we need understand what are the abstractions of frequently-appearing units of computation, which we call dwarfs, among big data and AI workloads. Second, for the sake of fairness, the benchmarks must include diversity of data and workloads. Third, for co-design of software and hardware, the benchmarks should be consistent across different communities.

Other than creating a new benchmark or proxy for every possible workload, we propose using dwarf-based benchmarks—the combination of eight dwarfs—to represent diversity of big data and AI workloads. The current version—BigDataBench 4.0 provides 13 representative real-world data sets and 47 big data and AI benchmarks, including seven workload types: online service, offline analytics, graph analytics, AI, data warehouse, NoSQL, and streaming. BigDataBench 4.0 is publicly available from http://prof.ict.ac.cn/BigDataBench.

Also, for the first time, we comprehensively characterize the benchmarks of seven workload types in BigDataBench 4.0 in addition to traditional benchmarks like SPEC CPU, PARSEC and HPCC in a hierarchical manner and drill down on five levels, using the Top-Down analysis from an architecture perspective. We find that the benchmarks of different workload types have different critical bottlenecks. The AI benchmarks have similar pipeline behaviors with the traditional benchmarks from the uppermost-level view. Nevertheless, drilling down on each category of the hierarchy, their pipeline behaviors differ. We also find that the neural network structures of the AI benchmarks have a great impact on pipeline behaviors, while the iteration number has little impact.
1 Introduction

Data explosion is an inevitable trend as the world is connected more than ever. Data are generated faster than ever, and to date about 2.5 quintillion bytes of data are created daily [1]. This speed of data generation will continue in the coming years and is expected to increase at an exponential level, according to IDC’s recent survey. The above fact gives birth to the widely circulated concept Big Data. Recently, the advancement of deep learning—so called data-driven AI has brought breakthroughs in processing images, video, speech and audio [2]. But turning big data into insights or true treasure heavily relies upon and hence boosts deployments of massive big data and AI systems. As architecture, systems, data management, and machine learning communities pay greater attention to innovative big data and AI algorithms, architecture, and systems [3, 4, 5, 6, 7], the pressure of measuring, comparing, and evaluating these systems rises [8]. Benchmarking are the foundation of those efforts [9, 10]. However, the complexity, diversity, frequently changed workloads—so called workload churns [3], and rapid evolution of big data and AI systems impose great challenges in benchmarking.

Table 1: The Summary of Different Big Data Benchmarks.

| Benchmarking Target | Methodology | Application domains | Workload types | Workloads | Scalable data sets abstracting from real data | Software Stacks |
|---------------------|-------------|---------------------|----------------|-----------|---------------------------------------------|-----------------|
| BigDataBench 4.0    | Dwarf-based | Big data and AI systems and architecture | five | seven | forty-seven | 13 real data sets; 6 scalable data sets | sixteen |
| BigDataBench 2.0    | Popularity  | Big data systems and architecture | three | three | nineteen | 6 real data sets; 6 scalable data sets | ten |
| BigBench 2.0        | Proposal    | Big data systems    | one | five | Proposal | Proposal | Proposal |
| CloudSuite 3.0      | Proposal    | Big data analytics | one | one | ten | 3 data generators | three |
| HiBench 6.0         | Proposal    | Cloud services      | N/A | four | eight | 3 data generators | three |
| CALDA [13]          | Popularity  | MapReduce system and parallel DBMSs | N/A | one | five | N/A | three |
| YCSB [14]           | Performance model | Cloud serving systems | N/A | one | six | N/A | four |
| LinkBench [15]      | Application model | Database systems | N/A | one | ten | one data generator | two |
| AMP Benchmarks [16] | Popularity  | Data analytic systems | N/A | one | four | N/A | five |
| Fathom [17]         | Popularity  | AI systems          | N/A | one | eight | N/A | one |

1 The seven workload types are online service, offline analytics, graph analytics, artificial intelligence (AI), data warehouse, NoSQL, and streaming.

First, modern big data and AI workloads are not only complex, but also fast changing and expanding. On one hand, the traditional benchmark methodology that creates a new benchmark for every possible workload is prohibitively costly and hence not scalable [18]. As illustrated in Table 1, most of state-of-the-art and state-of-the-practise benchmarks are put together this way. On the other hand, too complex workloads not only aggravate the cost of porting benchmarks across different architecture and systems, but also raise difficulties in reproducibility and interpretability of performance data. So identifying abstractions of frequently-appearing units of computation, which we call dwarfs, is an important step toward building scalable big data and AI benchmarks [18]. Each dwarf captures the common requirements of each class of unit of computation while being reasonably divorced from individual implementations among a wide variety of big data and AI workloads [18, 19].

Second, the diversity of data sets and workloads is of great significance for fairness of benchmarking. On one hand, there are many classes of big data and AI applications without comprehensive characterization. Even for internet service workloads, there are several important application domains, e.g., search engines, social networks, and e-commerce. Meanwhile, the value of big data and AI drives the emergence of innovative application domains. Moreover, there is no one-size-fits-all solution [9] for big data
and AI software stacks, and hence big data and AI software stacks cover a broad spectrum. On the other hand, data impacts workload behaviors and performance significantly [20], so comprehensive and representative real-world data sets should be included.

Third, the benchmarks should be consistent across different communities for the co-design of software and hardware. On one hand, system and architecture communities should absorb state-of-the-art algorithms from machine learning community. On the other hand, different communities have subtle differences in terms of benchmarking requirements. System communities feel great interest in performance evaluation on large-scale system deployments, while architecture community heavily relies upon simulator-based research, and shorter (simulation) runtime of the benchmarks is a mandatory requirement in addition to micro-architectural data accuracy [18]; AI researchers not only care about the performance data in terms of runtime but also the model’s prediction precision.

This paper presents our joint research efforts on dwarf-based big data and AI benchmarking with several industrial partners. Our previous work [18] notices that a majority of big data workloads are composed of eight dwarfs—including Matrix, Sampling, Transform, Graph, Logic, Set, Sort and Basic statistic computations. Furthermore, we find that the AI workloads we investigated are also composed of the eight dwarfs. We propose using the combination of eight dwarfs to represent the big data and AI benchmarks. Our benchmark suite includes micro benchmarks, each of which is a single dwarf, components benchmarks, which consists of the dwarf combinations, and end-to-end application benchmarks. The current version—BigDataBench 4.0 is significant upgrade to our previous work – BigDataBench 2.0 [10]. BigDataBench 4.0 provides 13 representative real-world data sets and 47 benchmarks. From search engines, social networks, e-commerce, multimedia processing and bioinformatics domains, the benchmarks cover seven workload types including online services, offline analytics, graph analytics, AI, data warehouse, NoSQL, and streaming workloads. Also, for each workload type, we provide diverse implementations using mainstream and state-of-the-art system software stacks. Data varieties are considered with the whole spectrum of data types including structured, semi-structured, and unstructured data. Currently, the included data sources are text, graph, table, and image data. Using real data sets as the seed, the data generators [21] generate synthetic data by scaling the seed data while keeping the data characteristics of raw data.

On a typical state-of-practice processor: Intel Xeon E5-2620 V3, we comprehensively characterize seven workload types in BigDataBench in addition to SPECCPU, PARSEC, and HPCC using the Top-Down method [22]. We classify an issued micro operation (uops) into retiring, bad speculation, frontend bound and backend bound, among which, only retiring represents useful work. In order to explore AI workloads’ characteristics thoroughly, we run them on CPUs instead of GPUs, because the former has comprehensive performance counters.

We have the following observations. First, the ILP (instruction-level parallelism) of the AI benchmarks is 1.26 on average, slightly lower than SPECCPU (1.32). The MLP (memory-level parallelism) of AI is 2.65, similar with HPCC (2.78). Big data has lower ILP (0.85 on average) and MLP (1.86 on average) than AI for almost all types, except that Hive based data warehouse has slightly higher ILP than AI. Further, their performance vary across workload types and software stacks. Second, in terms of uppermost-level breakdown, AI reflect similar pipeline behaviors with the traditional benchmarks, with approximately equal retiring (35% v.s. 39.8%), bad speculation (6.3% v.s. 6.1%), frontend bound (both about 9%), and backend bound percentages (49.7% v.s. 45.1%). Corroborating the observations in previous work [4, 23, 24], the frontend bound of big data is more severe than that of traditional benchmarks (9% on average). However, we notice that the frontend bound varies across different workload types. NoSQL has the highest percentage of 35%, while data warehouse has 25% and the other has only 15% on average. Third, for all seven types of big data and AI, retiring instructions from microcode sequencer (MS) unit are about 10 times larger than that of traditional benchmarks, which incurs notable penalties due to MS switches and further hurts performance. Fourth, Corroborating the previous work [24], the

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1 Graph analytics and AI workloads are two particular types which are widely studied, so we separate them out from offline analytics.
2 To save the space, in the rest of the paper, we use $x$ to represent the $x$ benchmark.
first bottleneck is backend bound for big data and AI. However, different from the previous work [24], we observe that the first backend bottleneck for big data and AI is backend memory bound, except that online service has nearly equal backend core bound and memory bound. Moreover, DRAM latency bound has large impacts on backend memory bound, especially local DRAM latency stalls for a majority of big data and remote cache latency stalls for AI. Fifth, iteration number has little impact on pipeline behaviors of AI.

In a summary, we make the following contributions in this paper.

1) We propose a scalable benchmarking methodology to build micro, component, and end-to-end application benchmarks that center around the dwarfs in big data and AI workloads.
2) Centering around the same eight dwarfs, we present a comprehensive big data and AI benchmark suite—BigDataBench 4.0.
3) For the first time, we thoroughly analyze the pipeline behaviors of seven workload types of big data and AI using the Top-Down method.

The rest of this paper is organized as follows. In Section 2, we present the related work. Section 3 summarizes our benchmarking methodology and decisions—BigDataBench 4.0. Section 4 illustrates the experiment configurations. In Section 5, we present the characterization results. Finally, we draw the conclusion in Section 6.

2 Related Work

Big data and artificial intelligence attract great attention, appealing many research efforts on big data and AI benchmarking, as illustrated in Table 1. Our previous work—BigDataBench 2.0 [10] abstracts three application domains and provides nineteen workloads covering offline analytics, online services and datawarehouse, which targets big data systems and architecture. BigBench 1.0 [8] models a product retailer business model based on TPC-DS [25] and targets big data analytics workloads. BigBench 2.0 [11] is a proposal which still focuses on retail business model and adds four workloads types of streaming, key-value processing, graph processing, and a multimedia data type. CloudSuite 3.0 [4] is a benchmark suite for cloud service, and choose workloads according to popularity, totally including four workload types and eight workloads. It evaluated the server inefficiencies from the frontend and backend, however, the analysis did not drill down on the deeper levels. HiBench 6.0 [12] also chooses workloads according to popularity, containing six workload types and nineteen workloads, including micro, machine learning, sql, graph, websearch and streaming categories. YCSB [14] released by Yahoo! is a benchmark for data storage systems and only includes online service workloads, i.e. Cloud OLTP. The workloads are mixes of read/write operations to cover a wide performance space. CALDA [13] is a benchmarking effort targeting MapReduce systems and parallel DBMSs. Its workloads are from the original MapReduce paper [26] and add four complex analytical tasks. LinkBench [15] is a synthetic benchmark for database systems which models the data scheme and workload patterns according to Facebook. AMP benchmark [16] is a big data benchmark proposed by AMPLab of UC Berkeley, which focuses on real-time analytic applications. The workloads are from CALDA benchmark.

As artificial intelligence inspires more and more interests from both academia and industry, a series of AI benchmarks are proposed. Fathom [17] provides eight deep learning workloads implemented with TensorFlow. DeepBench [27] consists of four operations involved in training deep neural networks, including three basic operations and recurrent layer types. BenchNN [28] develops and evaluates software neural network implementations of 5 (out of 12) high-performance applications from the PARSEC Benchmark Suite. DNNMark [29] is a GPU benchmark suite that consists of a collection of deep neural network primitives. Tonic Suite [30] presents seven neural network workloads that use the DjiNN service.

Our previous work [18] notices that a majority of big data workloads are composed of eight dwarfs—including Matrix, Sampling, Transform, Graph, Logic, Set, Sort and Basic statistic computations. We propose using the combinations of the same eight dwarfs to build a comprehensive big data and AI bench-
mark suite, which is a significant departure from that traditional benchmark methodology. With respect to the other benchmarks, our benchmark suite includes diversity of workloads and real-world data sets, which are comprehensive for fairly measuring and evaluating big data and AI architecture and systems. To achieving the consistency of benchmark across different communities, we absorb state-of-the-art algorithms from machine learning communities that considers the model’s prediction accuracy, and provide not only dwarf-based benchmarks supporting large-scale deployments for system communities, but also dwarf-based simulation benchmarks for architecture communities, which speed up runtime 100 times while preserving system and micro-architectural characteristic accuracy. The simulation benchmarks is illustrated in [18], beyond the scope of this paper.

3 Methodology and Decisions

In this section, we introduce our dwarf-based scalable benchmarking methodology and decisions on BigDataBench 4.0.

3.1 Methodology Principles

Our benchmarking methodology follows three principles.

1) Separating specification from implementation. Benchmark specification is to model relevant domains and define the design decisions in terms of benchmarking requirements and user concerns, which provides an abstract view and a guideline of implementation, and hence the specification should be independent of specific systems.

2) State-of-the-art algorithms and technologies. In big data and AI scenarios, workloads change frequently. Meanwhile, rapid evolution of big data and AI systems brings great opportunities for emerging algorithms. A benchmark suite candidate should absorb the state-of-the-art algorithms. In addition, its implementation should keep in pace with the improvements of the underlying systems.

3) Data impact. Data sets have great impacts on workloads behaviors and running performance [20]. To assure the fairness and comprehensiveness of benchmarking, a benchmark suite candidate should provide representative data sets considering typical types and sources.

3.2 Benchmarking Methodology

3.2.1 Big Data and AI Dwarfs

Each dwarf captures the common requirements of each class of unit of computation while being reasonably divorced from individual implementations [18, 19]. Our previous work identified eight big data dwarfs [18] among a majority of big data workloads, including Matrix, Sampling, Transform, Graph, Logic, Set, Sort and Basic statistic computations. Among them, matrix computation involves vector-vector, vector-matrix and matrix-matrix computations. Sampling is a method to select a subset of origi-
nal data. Transform computation indicates the conversion from the original domain to another domain, such as FFT. Graph computation uses nodes representing entities and edges representing dependencies. Logic computation performs bit manipulation. Set computation means the operations on one or more collections of data. Please note that primitive operators in relation algebra [31] are also classified into set computation in our dwarf taxonomy. Sort and basic statistic computation is fundamental unit of computation in big data and AI. For online services, get, put, post, and delete are identified as basic and abstract operations in previous work [32]. For simplicity, we don’t include those four in our dwarf set.

We analyze the most popular architectures in the deep learning community, ranging from the image recognition, e.g. VGG, Inception, Resnet, to the natural language processing, e.g. Word2vec, Seq2Seq. Also, we study several generative adversarial networks (GANs) which has proven to be hugely successful in unsupervised learning. We find that our eight dwarfs also apply to these AI workloads, and they are also combinations of eight dwarfs.

3.2.2 Dwarf-based Methodology

Fig. 1 summarizes our dwarf-based benchmarking methodology for BigDataBench 4.0, separating the specification from implementation. Circling around the dwarfs, we define the specifications of micro, component, and end-to-end application benchmarks.

**Micro Benchmark Specification** As illustrated in Subsection 3.2.1, dwarfs are fundamental concepts and units of computation among a majority of big data and AI workloads. We design a suite of micro benchmarks, each of which is a single dwarf, as listed in Table 2. We also notice that these micro benchmark implementations have different characteristics, i.e., CPU-intensive, memory-intensive or I/O-intensive.

**Component Benchmark Specification** Dwarf combinations can compose original complex workloads. In addition to micro benchmarks consisting of a single dwarf, we also consider component benchmarks, which are representative workloads in different application domains. Component benchmarks are combinations of one or more dwarfs using a DAG-like structure, as listed in Table 3. For example, SIFT is a combination of five dwarfs, including matrix, sampling, transform, sort and basic statistic computations.

**Application Benchmark Specification** To model an application domain, we define end-to-end application benchmark specification considering user characteristics and processing logic, based on the real process of an application domain. Due to the complexity and difficulty to benchmark a real application domain, we simplify and model the primary process of an application domain, and provide portable and usable end-to-end benchmarks. We use the combination of component benchmarks to represent the processing logic. For example, for online service, we generate queries considering query number, rate, distribution and locality to reflect the user characteristics.

3.3 Benchmark Decisions

On the basis of the specification, we make benchmark decisions and build BigDataBench 4.0, from the perspectives of data characteristics, workloads, and the state-of-the-art techniques. As there are many emerging big data and AI applications, we take an incremental and iterative approach. We first investigate important and emerging application domains using widely acceptable metrics, including search engine, social network, e-commerce from internet service, which occupy 80% page views and daily visitors [33], multimedia processing and bioinformatics as emerging and burgeoning domains [34, 35]. Then we investigate these application domains from workload and data perspectives. From a workload perspective, we investigate the state-of-the-art algorithms in data mining, machine learning, natural language processing, computer vision and artificial intelligence. From the data perspective, we collect diverse and representative real-world data sets and develop corresponding big data generation tools that preserve the original characteristics.
3.3.1 Workloads Diversity

According to benchmark specification, we provide micro benchmarks, each of which is a single dwarf, and component benchmarks, each of which is a combination of one or more dwarfs. Table 2 and Table 3 present the micro benchmarks and component benchmarks of BigDataBench 4.0 respectively, from perspectives of workloads, involved dwarfs, application domains, workload types, data sets and software stacks. In Table 2 and 3, we use SE, SN, EC, MP and BI for short to represent search engine, social network, e-commerce, multimedia processing and bioinformatics domains, respectively. Totally, we provide 47 big data and AI benchmarks, each of which has diverse implementations. Because of the page limitation, we do not report the application benchmarks.

Table 2: The Summary of Micro Benchmarks in BigDataBench 4.0.

| Micro Benchmark    | Involved Dwarf | Application Domain | Workload Type     | Data Set           | Software Stack          |
|--------------------|----------------|--------------------|-------------------|--------------------|-------------------------|
| Sort               | Sort           | SE, SN, EC, MP, BI | Offline analytics | Wikipedia entries  | Hadoop, Spark, Flink, MPI |
| Grep               | Set            | SE, SN, EC, MP, BI | Offline analytics | Wikipedia entries  | Hadoop, Spark, Flink, MPI |
| WordCount          | Basic statistics |                | Offline analytics | Wikipedia entries  | Hadoop, Spark, Flink, MPI |
| MD5                | Logic          |                    | Offline analytics | Wikipedia entries  | Hadoop, Spark, Flink, MPI |
| Connected Component| Graph          | SN                 | Graph analytics   | Facebook social network | Hadoop, Spark, Flink, GraphLab, MPI |
| RandSample         | Sampling       | SE, MP, BI         | Offline analytics | Wikipedia entries  | Hadoop, Spark, MPI |
| FFT                | Transform      | MP                 | Offline analytics | Two-dimensional matrix | Hadoop, Spark, MPI |
| Matrix Multiply    | Matrix         | SE, SN, EC, MP, BI | Offline analytics | Two-dimensional matrix | Hadoop, Spark, MPI |
| Read               | Set            | SE, SN, EC         | NoSQL             | ProfSearch resumes | HBase, MongoDB |
| Write              | Set            | SE, SN, EC         | NoSQL             | ProfSearch resumes | HBase, MongoDB |
| Scan               | Set            | SE, SN, EC         | NoSQL             | ProfSearch resumes | HBase, MongoDB |
| Convolution        | Transform      | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| Fully Connected    | Matrix         | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| Relu               | Logic          | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| Sigmoid            | Matrix         | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| Tanh               | Matrix         | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| MaxPooling         | Sampling       | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| AvgPooling         | Sampling       | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| CosineNorm [36]    | Basic Statistics | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| BatchNorm [37]     | Basic Statistics | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |
| Dropout [38]       | Sampling       | SN, EC, MP, BI     | AI                | Cifar, ImageNet    | TensorFlow, Caffe |

3.3.2 Representative Real-world Data Set

Input data has great impacts on workload behaviors [20]. Data sets should be diverse and representative in terms of both data sources and data types. We collect 13 representative data sets, covering different data sources (text, table, graph, and image), application domains, and data types of structured, un-structured, semi-structured. To support customizable data size, big data generation tools are provided to suit for different cluster scales, including text, table and graph generators.
### Table 3: The Summary of Component Benchmarks in BigDataBench 4.0.

| Component Benchmark | Involved Dwarf | Application Domain | Workload Type | Data Set | Software Stack |
|---------------------|----------------|--------------------|---------------|----------|----------------|
| Xapian Server       | Get, Put, Post | SE                 | Online service | Wikipedia entries | Xapian |
| PageRank            | Matrix, Sort, Basic statistics, Graph | SE | Graph analytics | Google web graph | Hadoop, Spark, Flink, GraphLab, MPI |
| Index               | Logic, Sort, Basic statistics, Set | SE | Offline analytics | Wikipedia entries | Hadoop, Spark |
| Rolling top words   | Sort, Basic statistics | SN | Streaming | Random generate | Spark streaming, JStorm |
| Kmeans              | Matrix, Sort, Basic statistics | SE, SN, EC, MP, BI | Offline analytics | Facebook social network | Hadoop, Spark, Flink, MPI |
| Collaborative Filtering | Graph, Matrix | EC | Offline analytics | Amazon movie review | Hadoop, Spark |
| Naive Bayes         | Basic statistics, Sort | SE, SN, EC | Offline analytics | Amazon movie review | Hadoop, Spark, Flink, MPI |
| SIFT                | Matrix, Sampling, Transform, Sort | MP | Offline analytics | ImageNet | Hadoop, Spark, MPI |
| LDA                 | Matrix, Graph, Sampling | SE | Offline analytics | Wikipedia entries | Hadoop, Spark, MPI |
| OrderBy             | Set, Sort | EC | Data warehouse | E-commerce transaction | Hive, Spark-SQL, Impala |
| Aggregation         | Set, Basic statistics | EC | Data warehouse | E-commerce transaction | Hive, Spark-SQL, Impala |
| Project, Filter     | Set | EC | Data warehouse | E-commerce transaction | Hive, Spark-SQL, Impala |
| Select, Union       | Set | EC | Data warehouse | E-commerce transaction | Hive, Spark-SQL, Impala |
| Alexnet             |                  | SN, MP, BI | AI | Cifar, ImageNet | TensorFlow, Caffe |
| Googlenet           |                  | SN, MP, BI | AI | Cifar, ImageNet | TensorFlow, Caffe |
| Resnet              |                  | SN, MP, BI | AI | Cifar, ImageNet | TensorFlow, Caffe |
| Inception Resnet V2 |                  | SN, MP, BI | AI | Cifar, ImageNet | TensorFlow, Caffe |
| VGG16               |                  | SN, MP, BI | AI | Cifar, ImageNet | TensorFlow, Caffe |
| DCGAN               |                  | SN, MP, BI | AI | LSUN | TensorFlow, Caffe |
| WGAN                |                  | SN, MP, BI | AI | LSUN | TensorFlow, Caffe |
| GAN                 |                  | SN, MP, BI | AI | LSUN | TensorFlow, Caffe |
| Seq2Seq             |                  | SE, EC, BI | AI | TED Talks | TensorFlow, Caffe |
| Word2vec            |                  | SE, SN, EC | AI | Wikipedia entries, Sogou data | TensorFlow, Caffe |
Wikipedia Entries [39]. The Wikipedia data set is unstructured, consisting of 4,300,000 English articles.

Amazon Movie Reviews [40]. This data set is semi-structured, consisting of 7,911,684 reviews on 889,176 movies by 253,059 users.

Google Web Graph (Directed graph) [41]. This data set is unstructured, containing 875713 nodes representing web pages and 5105039 edges representing the links between web pages.

Facebook Social Graph (Undirected graph) [42]. This data set contains 4039 nodes, which represent users, and 88234 edges, which represent friendship between users.

E-commerce Transaction Data. This data set is from an e-commerce web site, which we keep anonymous by request. The data set is structured, consisting of two tables: ORDER and order ITEM.

ProfSearch Person Resumés. This data set is from a vertical search engine for scientists developed by ourselves. The data set is semi-structured, consisting of 278956 resumés automatically extracted from 20,000,000 web pages of about 200 universities and research institutions.

CIFAR-10 [43] This data set is a tiny image data set, which has 60000 color images with the dimension of $32 \times 32$. They are classified into 10 classes and each class has 6000 examples.

ImageNet [44] This data set is an image database organized according to the WordNet hierarchy. We mainly use the Large Scale Visual Recognition Challenge 2014 (ILSVRC2014) [45] data set.

LSUN [46] This data set contains about one million labelled images, classified into 10 scene categories and 20 object categories.

TED Talks [47] This data set comes from translated TED talks, provided by IWSLT evaluation campaign.

SoGou Data [48] This data set is unstructured, including corpus and search query data from Sogou Lab, based on the corpus we gotten the index and segment data which the total data size is 4.98 GB.

MNIST [49] This data set is a database of handwritten digits. It has a training set of 60,000 examples, and a test set of 10,000 examples.

MovieLens Dataset [50] This data set is score data for movies, which has 9,518,231 training examples and 386,835 test examples (semi-structured text).

### 3.3.3 State-of-the-art Techniques

To compare different big data and AI systems, we provide diverse implementations using the state-of-the-art techniques. For offline analytics, we provide Hadoop [51], Spark [52], Flink [53] and MPI [54] implementations. For graph analytics, we provide Hadoop, Spark GraphX [55], Flink Gelly [56] and GraphLab [57] implementations. For AI, we provide TensorFlow [6] and Caffe [7] implementations. For data warehouse, we provide Hive [58], Spark-SQL [59] and Impala [60] implementations. For NoSQL, we provide MongoDB [61] and HBase [62] implementations. For streaming, we provide Spark streaming [63] and JStorm [64] implementations.

The Hadoop version of matrix multiple benchmark is implemented based on Mahout [65], and the Spark version is using Marlin [66]. For AI, we identify representative and widely used dwarfs in a wide variety of deep learning networks (i.e. convolution, relu, sigmoid, tanh, fully connected, max/avg pooling, cosine/batch normalization and dropout) and then implement each single dwarf and dwarf combinations as micro benchmarks and component benchmarks. The AI component benchmarks include Alexnet [67], Googlenet [68], Resnet [69], Inception_Resnet V2 [70], VGG16 [71], DCGAN [72], WGAN [73], Seq2Seq [74] and Word2vec [75], which are important state-of-the-art networks in AI.

### 4 Workload Characterization

In this section, we present our experiment configurations and methodology on characterizing the pipeline efficiency of big data and AI, in comparison to traditional benchmarks including SPEC CPU2006, PARSEC, and HPCC.
Table 4: Configuration Details of Xeon E5-2620 V3

| Hardware Configurations    |       |
|----------------------------|-------|
| CPU Type                   | Intel CPU Core |
| Intel ®Xeon E5-2620 V3     | 12 cores@2.40G |
| L1 DCache                  | 12 × 32 KB |
| L1 ICache                  | 12 × 32 KB |
| L2 Cache                   | 12 × 256 KB |
| L3 Cache                   | 15MB    |
| Memory                     | 64GB,DDR4 |
| Disk                       | SATA@7200RPM |
| Ethernet                   | 1Gb     |
| Hyper-Threading            | Disabled |

| Software Configurations    |       |
|----------------------------|-------|
| Operating System           | CentOS 7.2 |
| Linux Kernel               | 4.1.13 |
| JDK Version                | 1.8.0_65 |
| Hadoop Version             | 2.7.1  |
| Hive Version               | 0.9.0  |
| HBase Version              | 1.0.1  |
| Spark Version              | 1.5.2  |
| Tensorflow Version         | 1.0    |

4.1 Experiment Configurations

We run a series of workload characterization experiments using BigDataBench 4.0 to obtain insights for architectural studies. From BigDataBench 4.0, we test a majority of micro and component benchmarks with all seven workload types.

Our benchmarks support large-scale cluster deployments. For example, our industrial partner Huawei has evaluated the FusionInsight system on 12-node [76] and 200-node [77] clusters. In our experiments, we deploy an one-master-two-slave cluster for architecture evaluation, instead of a much larger cluster because of the following reasons. First, a larger cluster may lead to data skew which results in load unbalance among nodes in the cluster, and lead to the deviation of experimental results. Second, the deployment and running cost is extremely high to collect all hardware events, which always need multiple times running to assure high accuracy of collected data for each benchmark [78]. A larger cluster aggravates the cost. Third, most of previous architecture researches [79, 4, 24] also use a small-scale cluster.

In our experiments, each slave node has two Xeon E5-2620 V3 processors equipped with 64 GB memory and 6 TB disk. The detailed configuration of each node is listed in Table 4. With regard to the input data, we use 100 GB data for offline analytics, except that matrix multiplication uses 10000*10000 matrix data. Data warehouse uses 100 GB E-commerce transaction data. Graph analytics uses 2^26-vertex graph data. For AI, we use CIFAR-10 data set and run 10 epoches for Alexnet, Googlenet and Inception_Resent V2. For Resnet, we run 10000 training steps for each training step takes a short time. Word2vec uses text8 wikipedia corpus. We evaluate HBase with ten million records using NoSQL read and write benchmarks. Online service processes million searching requests. Spark streaming takes 10 seconds streaming data as a batch.

4.2 Experiment Methodology

We adopt a Top-Down methodology [22] to evaluate the pipeline efficiency of big data and AI, which identifies the bottlenecks in a hierarchical manner. At the uppermost level, it classifies an issued micro operation into four categories of retiring, bad speculation, frontend bound and backend bound. Totally, it has five levels, drilling down on the sub-tree of each category. Modern processors provide hardware
performance counters to support micro-architectural level profiling. We use Perf [80], a Linux profiling tool, to collect the hardware events referring to the Intel Developer’s Manual and pmu-tools [81].

4.3 Compared Benchmarks Setup

For comparison, we deploy SPEC CPU2006 [82], PARSEC [83] on one slave node and HPCC [84] on two slave nodes.

**SPEC CPU2006**: We run SPEC CPU 2006 with the reference input, reporting results averaged into two groups, i.e., integer benchmarks (SPECINT) and floating point benchmarks (SPECFP). The gcc version is 4.8.5.

**HPCC**: We run all seven HPCC benchmarks with version 1.4, including HPL, STREAM, PTRANS, RandomAccess, DGEMM, FFT, and COMM.

**PARSEC**: We deploy PARSEC 3.0 Beta Release, which is a benchmark suite composed of multi-threaded programs. We run all the 12 benchmarks with native input data sets and use gcc version 4.8.5 in compilation.

5 Characterization Results

We perform Top-Down analysis on seven types of big data and AI, drilling down on the five levels, and report our characterization results. The seven types and corresponding software stacks include online service (Xapian), offline analytics (Hadoop, Spark), graph analytics (Hadoop, Spark), data warehouse (Hive, Spark sql), AI workloads (TensorFlow), NoSQL (HBase) and streaming (Spark streaming). For each software stack, we also report their average value of all benchmarks listed as AVG bar (e.g. Hadoop-AVG). In the rest of paper, we use Inception to represent Inception_Resnet V2 benchmark. The traditional benchmarks like SPEC CPU, PARSEC and HPCC are listed as SPECCPU-Int, SPECCPU-Float, PARSEC-AVG and HPCC-AVG, respectively. Note that we run all workloads in PARSEC and HPCC, and present their average value.

In the rest of paper, we distinguish the software stacks for the same workload type when they have different behaviors, otherwise we only use the workload type to represent all software stacks when they reflect consistent behaviors. The average execution performance of each workload type is shown in Fig. 2, from the perspectives of ILP (instruction-level parallelism) and MLP (memory-level parallelism). We use IPC (retired instructions per cycle) to reflect the instruction level parallelism. MLP is measured as the average number of memory accesses when there is at least one such access, which indicates the dependencies of missing loads [85]. As seen in Fig. 2, big data and AI, especially Spark sql, NoSQL, online service and streaming, have lower IPC than HPCC. As for memory-level parallelism, big data is lower than the traditional benchmarks like SPECCPU and HPCC. Graph analytics has the lowest MLP while online service has the highest among all big data. AI (2.65 on average) has higher MLP than big data (1.86 on average), close to HPCC (2.78 on average). For the same workload type, different software stacks reflect different execution performance: Hadoop-based one has lower ILP and MLP than that of Spark-based one; Hive-based one has higher ILP but lower MLP than that of Spark sql-based one.

The uppermost-level breakdown of all benchmarks we evaluated are listed in Fig. 3. The retiring percentage of big data is 22.9% on average, lower than traditional benchmarks (39.8% on average), which is also found by previous work [24] on Hadoop-based benchmarks. Specially, NoSQL, online service and streaming have extremely low retiring percentage, approximately 20%. Further, we find that different workload types reflect diverse pipeline behaviors. Corroborating the previous work [24], backend bound is the first bottleneck and frontend bound is the second bottleneck for all big data we investigated. However, the frontend bound percentages vary across different workload types and software stacks. For example, eight out of twelve Spark-based benchmarks have low frontend bound percentages, only occupying less than 8% on average. NoSQL (about 35%) and data warehouse (about 25%) suffer higher frontend bound than the others of big data (15% on average). In addition, software stacks and algorithms both have great impacts on pipeline behaviors. For example, the frontend bound and bad
speculation is 17% and 11% for Hadoop based on average, while 9% and 3% for Spark based. Also, for
the same software stack, the frontend bound percentage is 20% for Spark grep, while 6% for Spark FFT.
AI has higher retiring percentage (35% on average) than big data, approximately equal to the tradi-
tional benchmarks (39.8%). Backend bound is the first bottleneck for AI, however, frontend bound is not
always the second bottleneck. For example, the percentage of frontend bound and bad speculation for
Alexnet is 11% and 14%, respectively. On average, the frontend bound is approximately equal to the tradi-
tional benchmarks (both about 9%). From the uppermost level breakdown, AI reflects similar pipeline
behaviors with the traditional benchmarks. However, neural network structures have a great impact on
pipeline behaviors. For example, the percentage of frontend bound and bad speculation for VGG16 is
about 1%, respectively, while the percentage of frontend bound and bad speculation for Alexnet is more
than 10%, respectively.

Deeper analysis for each category is performed in the following subsections.

5.1 Retiring
Retiring means slots fraction utilized by useful work [22]. Optimizing retiring percentage often increases
the IPC metric and thus improves the execution efficiency. Retiring is composed of retiring regular uops
and retiring uops fetched by the Microcode Sequencer (MS) unit. Among them, retiring regular uops are represented by BASE metric in the Top-Down methodology. Retiring uops fetched by MS is represented by Microcode_Sequencer metric, which means there are CISC instructions not supported by the default decoders, needing switch to MS unit. Even though microcode assists are categorized under retiring, they hurt performance and can often be avoided [81]. Fig. 4 shows retiring breakdown of all benchmarks. We find that the Microcode_Sequencer numbers of big data and AI are about 10 times larger than that of the traditional benchmarks. This result indicates that big data and AI have more CISC instructions and need more microcode assists, which may hurt performance and need to be improved.

5.2 Bad Speculation

Bad speculation means slots fraction wasted due to incorrect speculations, including branch misprediction and machine clears. From our experimental results, we find that machine clears occupy about 0.1% percentage for all benchmarks. So bad speculation mainly occurs due to branch misprediction, and their percentages are nearly equal to Bad_Speculation value in Fig. 3. Overall, big data and AI have a small fraction of bad speculation, about 10% for Hive based and Hadoop based, 3% for Spark sql based, Spark based, NoSQL, online service and streaming. For AI, different neural networks own different percentages of bad speculation, for example, 14% for Alexnet while 1% for VGG16.

5.3 Frontend Bound

Frontend bound occurs when frontend undersupplies the backend in a cycle. It is composed of two categories – frontend latency bound (i.e. delivers no uops) and frontend bandwidth bound (i.e. delivers non-optimal amount of uops). Fig. 5 presents the frontend bound breakdown. Note that the y-axis of the black-bordered box indicates the percentage of frontend latency bound, and the length out of the black-bordered box indicates the percentage of frontend bandwidth bound. Taking Hadoop-Sort as an example, its frontend bound occupies a proportion of 12%, with 7% for latency bound and 5% for bandwidth bound. From Fig. 5 we find that, big data has more severe frontend bound than the traditional benchmarks, especially frontend latency bound, which is also found by previous work [4, 23, 24]. However, the frontend bound percentage varies across different workload types. AI benchmarks suffer approximately equal frontend bound with the traditional benchmarks. Frontend latency bound and bandwidth bound contribute frontend bound equally. Different from previous work [4, 23, 24] that mainly identified frontend inefficiencies due to high instruction miss ratios and long latency introduced by caches, we thoroughly drill down on the sub-tree of frontend latency and bandwidth bound.
5.3.1 Frontend Latency Bound

Frontend latency bound indicates that frontend delivers no uops to backend, which may occur due to six reasons, including ICache misses, ITLB misses, branch resteers, DSB (decoded stream buffer) switches, LCP (length changing prefixes), and MS (microcode sequencer) switches. Among them, ICache misses means stalls due to instruction cache misses. ITLB misses means stalls due to instruction tlb misses. Branch resteers means stalls due to frontend delay when fetching instruction from correct path, which may occur because of branch mispredictions. DSB switches means stalls due to switches from DSB to MITE (Micro-instruction Translation Engine) pipelines. DSB is a decoded ICache used to store uops that have been decoded, so as to avoid penalties of legacy decode pipeline, which is also called MITE. DSB switches are used to measure the penalties of switching from DSB to MITE [81]. LCP means stalls due to length changing prefixes, which can be avoided by using compiler flags. MS switches means stalls due to switches of delivering uops to microcode sequencer. As mentioned in Subsection 5.1, retiring includes retiring regular uops and uops fetched by the MS unit. Generally, uops are coming from DSB or MITE pipeline. For some CISC instructions which cannot be decoded by default decoders, they must be handled by MS unit. However, frequent MS switches hurt performance, so MS switches metric measures this penalties.

The breakdown within the black-bordered box in Fig. 5 shows the proportions of the above six reasons that incur the frontend latency bound. We find that for big data except NoSQL, Branch resteers, ICache misses and MS switches are three main reasons for frontend latency bound, while for NoSQL, the main reasons are ICache misses, ITLB misses and MS switches. The main reason of AI that incurs frontend latency bound is Branch resteers, and the second reason is MS switches, indicating that big data and AI indeed have much larger retiring uops from MS unit.

5.3.2 Frontend Bandwidth Bound

Frontend bandwidth bound indicates that the amount of uops delivering to backend is less than theoretical value, such as 4 for Haswell architecture. The frontend bandwidth bound is occurred mainly by three reasons, including MITE, DSB and LSD. Among them, MITE means stalls due to MITE pipeline, such as the inefficiency of the instruction decoders. DSB means stalls due to DSB fetch pipeline, such as inefficient utilization of DSB. LSD means stalls due to loop stream detector unit, which takes a small proportion generally.

The breakdown of frontend bandwidth bound in Fig. 5 shows the proportions of the above three reasons. DSB and MITE are two main reasons for nearly all listed benchmarks. However, different workload types have different first frontend bandwidth bottleneck. For offline analytics and graph analytics, their
first frontend bandwidth bottleneck is $\text{DSB}$. For data warehouse, NoSQL, online service and streaming, their first frontend bandwidth bottleneck is $\text{MITE}$. For AI, their first bottleneck of frontend bandwidth bound is $\text{DSB}$, except $\text{MITE}$ for Word2Vec benchmark. In order to reduce the frontend bandwidth bound and improve the performance of big data and AI, $\text{DSB}$ utilization and $\text{MITE}$ pipeline efficiency need to be optimized.

5.4 Backend Bound

Backend bound occurs when the backend has not enough required resources to accept new uops, which can be divided into backend core bound and backend memory bound. Among them, backend core bound refers to hardware being lack of out-of-order resources (e.g. Divider unit) or low utilization of execution port. Backend memory bound means the stalls due to load or store instructions.

Fig. 6 lists the backend bound breakdown of all benchmarks. Note that the y-axis of the black-bordered box indicates the percentage of backend core bound, and the length out of the black-bordered box indicates the percentage of backend memory bound. The first bottleneck of big data and AI are backend bound. The previous work [24] found that core bound and memory bound nearly contribute to the backend bound stalls equally. However, we find that memory bound is more severe than core bound for all big data and AI benchmarks, except that online service has nearly equal core bound and memory bound.

5.4.1 Backend Core Bound

Backend core bound can further be split into metric $\text{Divider}$ and $\text{Port utilization}$. $\text{Divider}$ means the cycle fraction that the Divider unit is in use, which has longer latency than other integer or floating-point operations. $\text{Port utilization}$ means the stalls due to low utilization of execution ports. For example, Haswell has eight execution ports, with each port can execute specific uops (4 ports for computation and 4 ports for load/store operations). These execution ports may be under-utilized in a cycle due to data dependency of instructions or non-divider-related resource contention [81].

The breakdown within the black-bordered box in Fig. 6 shows proportions of $\text{Divider}$ and $\text{Port utilization}$ that incur the backend core bound. $\text{Divider}$ occupies a small proportion, except for some computation intensive workloads, such as Hadoop Kmeans. From Fig. 6 we find the utilizations of execution ports are low for big data and AI.
5.4.2 Backend Memory Bound

Backend memory bound can further be divided into $L1$ Bound, $L2$ Bound, $L3$ Bound, DRAM Bound, and Store Bound, which incurs stalls related to memory hierarchy.

Fig. 7 shows the normalized backend memory bound breakdown. Note that $L2$ Bound is negative due to PMU erratum on L1 prefetchers [22]. We find that the main reason for backend memory bound is DRAM Bound for big data and AI, except that online service suffer more store bound than DRAM bound. Different from the traditional benchmarks, big data and AI also suffer more stalls due to $L1$ Bound, $L3$ Bound and Store Bound.

DRAM Bound is the first Backend Memory Bound bottleneck for most benchmarks, and we further analyze two factors that incur DRAM Bound, including DRAM latency and DRAM bandwidth. DRAM latency means the stalls due to the latency from dynamic random access memory. DRAM bandwidth means the stalls due to memory bandwidth limitations. Fig. 8 presents the DRAM bound breakdown. The first DRAM bound bottleneck of big data and AI is DRAM latency bound. They suffer more DRAM latency bound and less DRAM bandwidth bound than the traditional benchmarks. For data warehouse, their DRAM bandwidth bound occupies a small fraction, about 1%. However, AI suffer more DRAM bandwidth bound than big data.

DRAM latency bound includes stalls due to loads from local memory (Local_DRAM), stalls due to loads from remote memory (Remote_DRAM) and stalls due to remote cache (Remote_Cache). Fig. 9 shows their DRAM latency bound breakdown. We find that the main DRAM latency bound bottleneck for the traditional benchmarks is Local_DRAM, except for PARSEC, which has more stalls due to remote
Figure 9: DRAM Latency Bound Breakdown (Level 5) of All Benchmarks.

DRAM. However, for big data, the main DRAM latency bound bottleneck varies with workload types and software stacks. For the same workload type of data warehouse, the DRAM latency bound is mainly due to Local DRAM for Hive-based one, while Remote cache for Spark sql based one. For AI, the main reason is Remote cache.

5.5 Discussion on AI Benchmarks

AI benchmarks always need hundreds of iterations to obtain higher prediction precision and lower training loss. However, for architecture research, AI benchmarks are too time-consuming even if running on GPUs. To evaluate the impact of iteration number on microarchitectural characteristic of AI, we run five neural networks using different number of iterations – Small, Medium, Large. For Alexnet, Googlenet, Inception and VGG16 networks, we run 1 (Small), 10 (Medium), 100 (Large) epoches, respectively. For Resnet networks, we run 2000 (Small), 10000 (Medium), 50000 (Large) training steps. respectively. We use PCA [86] and hierarchical clustering [87] to measure the similarity, using all fifty micro-architectural metrics we collect according to the Top-Down method. Fig. 10 presents the linkage distance of all AI benchmarks, and the smaller distance means the higher similarity. We find that the same neural networks with different iteration numbers are clustered together and have shorter distance, which means a small number of iterations is enough for micro-architectural evaluation of AI benchmarks.

6 Conclusion

In this paper, we propose a dwarf-based scalable benchmarking methodology to build micro, component, and end-to-end application benchmarks. Following this methodology, we release an open source big data and artificial intelligence benchmark suite – BigDataBench 4.0. Finally, we comprehensively characterize seven types of big data and AI benchmarks in BigDataBench 4.0 using the Top-Down methodology, drilling down on five levels of four categories, including retiring, bad speculation, frontend bound and backend bound.

References

[1] http://www-01.ibm.com/software/data/bigdata/.
[2] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015.
[3] 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.
[4] M. Ferdman, A. Adileh, O. Kocberber, S. Volos, M. Alisafaei, D. Jevdjic, C. Kaynak, A. D. Popescu, A. Ailamaki, and B. Falsafi, “Clearing the clouds: A study of emerging workloads on modern hardware,” Architectural Support for Programming Languages and Operating Systems, 2012.

[5] N. P. Jouppi, C. Young, N. Patil, D. Patterson, G. Agrawal, R. Bajwa, S. Bates, S. Bhatia, N. Boden, A. Borchers et al., “In-datacenter performance analysis of a tensor processing unit,” in Proceedings of the 44th Annual International Symposium on Computer Architecture. ACM, 2017, pp. 1–12.

[6] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin et al., “Tensorflow: Large-scale machine learning on heterogeneous distributed systems,” arXiv preprint arXiv:1603.04467, 2016.

[7] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, “Caffe: Convolutional architecture for fast feature embedding,” in Proceedings of the 22nd ACM international conference on Multimedia. ACM, 2014, pp. 675–678.

[8] 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.

[9] P. Wang, D. Meng, J. Han, J. Zhan, B. Tu, X. Shi, and L. Wan, “Transformer: a new paradigm for building data-parallel programming models,” Micro, IEEE, vol. 30, no. 4, pp. 55–64, 2010.

[10] 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.

[11] T. Rabl, M. Frank, M. Danisch, H.-A. Jacobsen, and B. Gowda, “The vision of bigbench 2.0,” in Proceedings of the Fourth Workshop on Data analytics in the Cloud. ACM, 2015, p. 3.
[12] S. Huang, J. Huang, J. Dai, T. Xie, and B. Huang, “The hibench benchmark suite: Characterization of the mapreduce-based data analysis,” in Data Engineering Workshops (ICDEW), 2010 IEEE 26th International Conference on. IEEE, 2010, pp. 41–51.

[13] A. Pavlo, E. Paulson, A. Rasin, D. J. Abadi, D. J. DeWitt, S. Madden, and M. Stonebraker, “A comparison of approaches to large-scale data analysis,” in Proceedings of the 2009 ACM SIGMOD International Conference on Management of data. ACM, 2009, pp. 165–178.

[14] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan, and R. Sears, “Benchmarking cloud servering systems with yeshb,” in Proceedings of the 1st ACM symposium on Cloud computing, ser. SoCC '10, 2010, pp. 143–154.

[15] T. G. Armstrong, V. Ponnekanti, D. Borthakur, and M. Callaghan, “Linkbench: a database benchmark based on the facebook social graph,” in Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data. ACM, 2013, pp. 1185–1196.

[16] https://amplab.cs.berkeley.edu/benchmark/.

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

[18] W. Gao, L. Wang, J. Zhan, C. Luo, D. Zheng, Z. Jia, B. Xie, C. Zheng, Q. Yang, and H. Wang, “A dwarf-based scalable big data benchmarking methodology,” arXiv preprint arXiv:1711.03229, 2017.

[19] K. Asanovic, R. Bodik, B. C. Catanzaro, J. J. Gebis, P. Husbands, K. Keutzer, D. A. Patterson, W. L. Plishker, J. Shalf, S. W. Williams, and Y. Katherine, “The landscape of parallel computing research: A view from berkeley,” Technical Report UCB/EECS-2006-183, EECS Department, University of California, Berkeley, Tech. Rep., 2006.

[20] 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.

[21] 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.

[22] A. Yasin, “A top-down method for performance analysis and counters architecture,” in Performance Analysis of Systems and Software (ISPASS), 2014 IEEE International Symposium on. IEEE, 2014, pp. 35–44.

[23] S. Kanev, J. P. Darago, K. Hazelwood, P. Ranganathan, T. Moseley, G.-Y. Wei, and D. Brooks, “Profiling a warehouse-scale computer,” in Computer Architecture (ISCA), 2015 ACM/IEEE 42nd Annual International Symposium on. IEEE, 2015, pp. 158–169.

[24] Z. Jia, J. Zhan, L. Wang, C. Luo, W. Gao, Y. Jin, R. Han, and L. Zhang, “Understanding big data analytics workloads on modern processors,” IEEE Transactions on Parallel and Distributed Systems, vol. 28, no. 6, pp. 1797–1810, 2017.

[25] “Tpc-ds benchmark,” http://www.tpc.org/tpcds/.

[26] J. Dean and S. Ghemawat, “Mapreduce: simplified data processing on large clusters,” Communications of the ACM, vol. 51, no. 1, pp. 107–113, 2008.

[27] “Deepbench,” https://svail.github.io/DeepBench/.
[28] T. Chen, Y. Chen, M. Duranton, Q. Guo, A. Hashmi, M. Lipasti, A. Nere, S. Qiu, M. Sebag, and O. Temam, “Benchnn: On the broad potential application scope of hardware neural network accelerators,” in Workload Characterization (IISWC), 2012 IEEE International Symposium on. IEEE, 2012, pp. 36–45.

[29] S. Dong and D. Kaeli, “Dnnmark: A deep neural network benchmark suite for gpus,” in Proceedings of the General Purpose GPUs. ACM, 2017, pp. 63–72.

[30] J. Hauswald, Y. Kang, M. A. Laurenzano, Q. Chen, C. Li, T. Mudge, R. G. Dreslinski, J. Mars, and L. Tang, “Djinn and tonic: Dnn as a service and its implications for future warehouse scale computers,” in ACM SIGARCH Computer Architecture News, vol. 43, no. 3. ACM, 2015, pp. 27–40.

[31] E. F. Codd, “A relational model of data for large shared data banks,” Communications of the ACM, vol. 13, no. 6, pp. 377–387, 1970.

[32] D. Guinard, V. Trifa, and E. Wilde, “A resource oriented architecture for the web of things,” in Internet of Things (IOT), 2010. IEEE, 2010, pp. 1–8.

[33] “Alexa topsites,” http://www.alexa.com/topsites/global;0.

[34] “Multimedia,” http://www.oldcolony.us/wp-content/uploads/2014/11/whatisbigdata-DKB-v2.pdf.

[35] “Bioinformatics,” http://www.ddbj.nig.ac.jp/breakdown_stats/dbgrowth-e.html#dbgrowth-graph.

[36] 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.

[37] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in International Conference on Machine Learning, 2015, pp. 448–456.

[38] 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.

[39] “wikipedia,” http://en.wikipedia.org.

[40] http://snap.stanford.edu/data/web-Amazon.html.

[41] “google web graph,” http://snap.stanford.edu/data/web-Google.html.

[42] http://snap.stanford.edu/data/egonets-Facebook.html.

[43] A. Krizhevsky and G. Hinton, “Learning multiple layers of features from tiny images,” 2009.

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

[45] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein et al., “Imagenet large scale visual recognition challenge,” arXiv preprint arXiv:1409.0575, 2014.

[46] 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.
[47] M. Cettolo, C. Girardi, and M. Federico, “Wit3: Web inventory of transcribed and translated talks,” in Proceedings of the 16th Conference of the European Association for Machine Translation (EAMT), vol. 261, 2012, p. 268.

[48] “Sogou labs,” http://www.sogou.com/labs/.

[49] “mnist,” http://yann.lecun.com/exdb/mnist/.

[50] 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.

[51] “Hadoop,” http://hadoop.apache.org/.

[52] M. Zaharia, M. Chowdhury, M. J. Franklin, S. Shenker, and I. Stoica, “Spark: cluster computing with working sets,” in Proceedings of the 2nd USENIX conference on Hot topics in cloud computing, 2010, pp. 10–10.

[53] P. Mika, “Flink: Semantic web technology for the extraction and analysis of social networks,” Web Semantics: Science, Services and Agents on the World Wide Web, vol. 3, no. 2, pp. 211–223, 2005.

[54] “Mpich,” https://www.mpich.org.

[55] R. S. Xin, J. E. Gonzalez, M. J. Franklin, and I. Stoica, “Graphx: A resilient distributed graph system on spark,” in First International Workshop on Graph Data Management Experiences and Systems. ACM, 2013, p. 2.

[56] “Flink gelly,” https://flink.apache.org/news/2015/08/24/introducing-flink-gelly.html.

[57] Y. Low, D. Bickson, J. Gonzalez, C. Guestrin, A. Kyrola, and J. M. Hellerstein, “Distributed graphlab: a framework for machine learning and data mining in the cloud,” Proceedings of the VLDB Endowment, vol. 5, no. 8, pp. 716–727, 2012.

[58] A. Thusoo, J. S. Sarma, N. Jain, Z. Shao, P. Chakka, S. Anthony, H. Liu, P. Wyckoff, and R. Murthy, “Hive: a warehousing solution over a map-reduce framework,” Proceedings of the VLDB Endowment, vol. 2, no. 2, pp. 1626–1629, 2009.

[59] “Spark sql,” https://spark.apache.org/sql/.

[60] M. Bittorf, T. Bobrovitsky, C. C. A. C. Erickson, M. G. D. Hecht, M. J. I. J. L. Kuff, D. K. A. Leblang, N. L. I. P. H. Robinson, D. R. S. Rus, J. R. D. T. S. Wanderman, and M. M. Yoder, “Impala: A modern, open-source sql engine for hadoop,” in Proceedings of the 7th Biennial Conference on Innovative Data Systems Research, 2015.

[61] K. Chodorow, MongoDB: The Definitive Guide: Powerful and Scalable Data Storage. " O’Reilly Media, Inc.", 2013.

[62] L. George, HBase: the definitive guide: random access to your planet-size data. " O’Reilly Media, Inc.", 2011.

[63] “Spark streaming,” https://spark.apache.org/streaming/.

[64] “Jstorm,” https://github.com/alibaba/jstorm.

[65] http://mahout.apache.org.

[66] R. Gu, Y. Tang, Z. Wang, S. Wang, X. Yin, C. Yuan, and Y. Huang, “Efficient large scale distributed matrix computation with spark,” in Big Data (Big Data), 2015 IEEE International Conference on. IEEE, 2015, pp. 2327–2336.
[67] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in neural information processing systems*, 2012, pp. 1097–1105.

[68] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

[69] 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*, 2016, pp. 770–778.

[70] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, “Inception-v4, inception-resnet and the impact of residual connections on learning,” in *AAAI*, 2017, pp. 4278–4284.

[71] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” *arXiv preprint arXiv:1409.1556*, 2014.

[72] A. Radford, L. Metz, and S. Chintala, “Unsupervised representation learning with deep convolutional generative adversarial networks,” *arXiv preprint arXiv:1511.06434*, 2015.

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

[74] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to sequence learning with neural networks,” in *Advances in neural information processing systems*, 2014, pp. 3104–3112.

[75] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” in *Advances in neural information processing systems*, 2013, pp. 3111–3119.

[76] http://e.huawei.com/en/products/cloud-computing-dc/cloud-computing/bigdata/fusioninsight.

[77] http://www.dca.org.cn/content/100190.html.

[78] “Vtune,” https://software.intel.com/en-us/vtune-amplifier-help-allow-multiple-runs-or-multiplex-events.

[79] A. Yasin, Y. Ben-Asher, and A. Mendelson, “Deep-dive analysis of the data analytics workload in cloudsuite,” in *Workload Characterization (IISWC), 2014 IEEE International Symposium on*. IEEE, 2014, pp. 202–211.

[80] “Perf,” https://perf.wiki.kernel.org/index.php/Main_Page.

[81] “Pmu tools,” https://github.com/andikleen/pmu-tools.

[82] “Spec,” “Spec cpu2006,” *Retrieved February*, vol. 23, p. 2015, 2006.

[83] C. Bienia, S. Kumar, J. P. Singh, and K. Li, “The parsec benchmark suite: Characterization and architectural implications,” in *Proceedings of the 17th international conference on Parallel architectures and compilation techniques*. ACM, 2008, pp. 72–81.

[84] P. R. Luszczek, D. H. Bailey, J. J. Dongarra, J. Kepner, R. F. Lucas, R. Rabenseifner, and D. Takahashi, “The hpc challenge (hpcc) benchmark suite,” in *Proceedings of the 2006 ACM/IEEE conference on Supercomputing*. Citeseer, 2006, p. 213.

[85] Y. Chou, B. Fahs, and S. Abraham, “Microarchitecture optimizations for exploiting memory-level parallelism,” in *ACM SIGARCH Computer Architecture News*, vol. 32, no. 2. IEEE Computer Society, 2004, p. 76.
[86] I. T. Jolliffe, “Principal component analysis and factor analysis,” in *Principal component analysis*. Springer, 1986, pp. 115–128.

[87] S. C. Johnson, “Hierarchical clustering schemes,” *Psychometrika*, vol. 32, no. 3, pp. 241–254, 1967.