

Comparative Performance Evaluation of Hadoop on PaaS Proposals by Leveraging HiBench

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Abstract

The advent of Big Data emerged in any data-driven domain and scaled up the extent as well as the depth of data and its handling. In an ongoing maturing process, new approaches leaning on enhanced distributed storage and computing paradigms are invented helping overcome management and running analytics challenges. In this context Hadoop is embraced in a wide scale by beneficiaries both from industry and academia since its first release in 2005. The commercialization of Cloud Computing started a grand migration movement towards cloud, applying also for Hadoop transferring its presence from on-premises to virtual machines stored and tamed in large data center facilities by global Cloud Service Providers. The CSPs' response to result-focused analytics purposes emerged a service called managed systems where the hard workload of multi node cluster implementation is overtaken by the contractor providing a pre-configured Hadoop package simplifying the installation process to a matter of property selection thus eliminating technical know-how requirements on such an implementation. Converting the concept of cloud based Hadoop from IaaS to PaaS apparently reduced costs commercially presented as pay-as-you-go or pay-per-use. There is a payoff, though, managed Hadoop systems do present a black-box behavior to the end user who cannot be clear on the inner perfor-

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mance dynamics, hence the benefits by leveraging them. In this study we selected three global providers (GCP, Azure, and Alibaba Cloud), activated their Hadoop PaaS services (Dataproc, HDInsight, and e-MapReduce, respectively) within same geographical region and by promise apparently same computing specifications, and executed several Hadoop workloads of the HiBench Benchmark Suite. The results yield that apparently same computation specs among CSPs' services do not necessarily guarantee equal or close performance outputs to each other. Our assumption is that the pre-configuration work of managed systems done by the contractor play a weighing role on their performance.

Keywords: `elsarticle.cls`, Benchmark Hadoop PaaS, HiBench, Performance evaluation

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1. Introduction

Big Data has become an indispensable aspect for enterprises and academia of the information era to deal with. As the global internet access rate covers a weighing majority of the global human population, mobile technology devices
5 become democratized, sensors and IoT devices the more occupy daily life, ongoing scientific researches produce vast amounts of data outputs the Big Data phenomenon gathered itself by means of overwhelming size with Volume, ever accelerating growth rate with Velocity, and splitting into diverse structures with Variety, new approaches were forced to mature in order to ease the maintenance
10 of Big Data and enable extracting valuable insights from it leveraging complex statistical formulae. Distributed frameworks for storage and computation sparked up first by search engines were inherited and furtherly developed by the open source community yielding what is known as Hadoop and its ecosystem today. Considering the complexity of dealing with big data Hadoop represents
15 a modern analytics framework decreasing management efforts and duration of analytics operations to an acceptable level by means of affordable commodity computers.

In parallel, the commercialization of Cloud Computing in the early 2000's delivered utilization of storage and computing resources to the end users saving them high investments on hardware technology that is soon going to be obsolete and is expensive to maintain. As the migration to the cloud is an ongoing process, Hadoop also slips out from its residence on on-prem infrastructure to the cloud by being implemented on virtual machine instances provided as IaaS platforms by many providers. The Cloud Service Providers embraced the need of eliminating Hadoop's complex implementation process on multi-node VMs by providing managed Hadoop systems commercially packaged as PaaS, which are pre-installed and pre-configured Hadoop clusters allowing the installation of tens to hundreds of nodes in a matter of minutes by simply determining some settings like hardware specs and node numbers prior the installation. The Managed Hadoop system is both a blessing and a curse, by leaving the hard implementation part which is not necessarily related with the main analysis objective to a contractor the end user saves time and efforts including a payoff, though: By definition, managed systems are prepackaged solutions provided in black-box nature. CSP apply behind-the-scenes tweaks in terms of reaching better performance results on selected approaches like memory intensive or compute intensive applications.

In this study we put three CSP providers' managed Hadoop services in focus in terms of performance evaluation comparison: GCP Dataproc, Azure HDInsight, and Alibaba Cloud e-MapReduce, each recognized in Gartner's 2020 report in leading or niche section. Bound by availability of their offered hardware and software options we selected by providers' promise apparently same or close settings. Without any performance tweak operation with their settings for any performance optimization on the respective managed systems after installation we immediately executed several workloads from HiBench's micro, sql, ml, and websearch categories. For a more clear understanding of the benchmark outputs, during the benchmark execution we collected system utilization records on each worker node of the cluster. The results yield that Hadoop PaaS offerings by vendor's promise side perform and system utilizations may highly vary among

CSPs.

50 2. Related Work

HiBench is a tool to measure a specific systems performing behaviour during execution. The conceptualization of conducting a benchmark may arise from different soils. Based on the conductors motivation; a benchmarks use case could be an inner evaluation of a systems performance before and after some configuration tweaks are set, comparison of rival / complementary systems, or
55 putting CSPs cloud infrastructure services on scale. Following literature has been searched with finding different use cases of HiBench benchmarking suite in mind.

Poggi et al. [52] Characterizing BigBench

60 Poggi et al. the state of SQL on Hadoop [53]

Samadi et al. conduct an experimental comparison between Spark and Hadoop installed on virtual machines on Amazon EC2 by leveraging nine among the provided HiBench workloads. Accuracy reasons led the conductors run the workloads three times concluding input data scales of 1, 3, and 5 GB respectively. Based on the outputs comprising duration, throughput, speed up, and
65 CPU/memory consumption, the conclusion draws Spark consuming less CPU and performing better on all workload results over Hadoop.

Ahn et al. [54] put Spark on YARNs performance on test with HiBench in terms of handling a deluge of data generated by IoT devices. The experiment is
70 run on a cluster with one master and 3 worker nodes each node possessing Intel Xeon processor with 20 cores and 128GB main memory meaning 60 cores and 384GB memory in total. HiBenchs workloads Micro (comprising Sort, TeraSort, and Wordcount), SQL (comprising Aggregation, Join, and Scan), and Machine Learning (comprising Bayes, Logistic Regression, Gradient Boosting Tree, Random Forest, and Linear Regression) are leveraged by a chosen data scale of 30
75 GB. Spark occupies memory during the whole job execution which in result reduces IOs negative impact on processor performance. For optimizing resource

usage the conductors modified YARNs minimum memory allocation and Spark
executor settings so that the Spark executors overall loads remain below to-
tal system memory. Alongside with HiBenchs duration and throughput report,
CPU / memory utilization and disk throughput are profiled as well. Finding of
this paper points out that Spark guarantees performance when provided with
enough memory.

Han et al. [55] study the impact of memory size on big data processing
by means of Hadoop and Spark performance comparison leveraging HiBenchs
k-Means workload as the only benchmark. For each of the specified memory
sizes of 4, 8, and 12 GB, iterating through a data scale of 1 to 8 GB, with 1GB
increment inbetween, k-Means benchmark for Hadoop and Spark is executed.
The results depict Sparks overperforming Hadoop unless the total input data
size is smaller than 33.5% of the total memory size assigned to worker nodes.
After reaching that ratio Spark suffers with insufficient memory resources and
is led to interoperate with HDFS causing a sharp decrease in its performance
and brings Hadoop in throughput and duration performance to the front. The
conductors make a second experiment to find out if Sparks performance can
be improved by tweaking the allocation setting for storage memory and shuffle
memory while remaining within the specified memory limitations of 4, 8 and
12 GB. Executing HiBenchs k-means benchmark outputs a report interpreted
by the conductors as Spark show a 5-10%, and 15% maximum improvement in
processing time.

Ivanov et al. [56] compare the performances of two enterprise grade applica-
tions, DataStax Enterprise (DSE), a production level implementation of Apache
Cassandra with extended features like in memory computing and advanced secu-
rity to name but two, and Clouderas Distribution of Hadoop (CDH) comprising
core Hadoop elements HDFS and YARN integrated with elements belonging to
the Hadoop ecosystem. DSEs HDFS compatible file system CSF lets Hadoop
applications run without any modification. The conductors installed the latest
stable releases of both softwares on equal CPU, memory and network infras-
tructure configuration. For both installations, default system parameters have

been left with their defaults. HiBenchs three chosen workloads (CPU-bound
110 wordcount, IO-bound dfsioe, and mixed HiveBench) are executed three times,
the average values have been taken for representativeness. Several conclusions of
their study proclaim linearly scaling of both systems by the increase of data size,
while CDH outperforms DSE in read intensive workloads, DSE performs better
in write intensive workloads. Leveraging HiBench is where this study differs
115 in approach related to other studies using YCSB benchmark suite. HiBenchs
results confirm the latters output as well.

3. Method

CSP configurations in Table 1

4. Results

120 Table 2 and Table 3 summarize HiBench benchmark execution outputs.

Analysis. HiBench’s Hadoop related benchmarks in groups micro (Sort, Tera-
sort, Dfsioe, and Wordcount), sql (Scan, Join, and Aggregation), ml (Bayes and
Kmeans), and websearch (Pagerank) have been executed on all three CSPs man-
aged Hadoop services. During benchmark runtime resource utilization on worker
125 nodes have been captured. The resulting multiplots are suggested to be read
as follows: Top-left, top-right, and bottom-left plots represent CPU (user%),
Memory, and IO utilization on each worker node of the respective cluster over
time. CPU utilization lines are given in blue tones, Memory utilization lines
are given in fuchsia tones, IO-read and IO-write tps’ are represented with or-
130 ange tones and green tones, respectively. Even though the coloring convention
might sound confusing, it gives a clear overview in terms of resource utilization
of the total benchmark process over time. The left hand side x-axis measures
CPU/Memory usage in percent, the right hand side x-axis measures IO-read
or IO-write transfers in byte per second. The bottom-right plot represents the
135 comparative benchmark performance outputs of the respective CSP. Duration

	GCP	Azure	Alibaba Cloud
Service	Dataproc	HDInsight	e-MapReduce
Region	europe-west3-a	Germany West Central	eu-central-1
Location	Frankfurt	Frankfurt	Frankfurt
Image	1.4-ubuntu18	HDI 3.6	EMR-3.32.0
OS	ubuntu18.04	ubuntu 16.04	Aliyun Linux 2
Hadoop v.	2.9	2.7.3	2.8.5
Java	1.8.0_275	1.8.0_275	1.8.0_252
MASTER NODE			
Machine Type	e2-highmem-8	A8m v2	ecs.se1.2xlarge
Processors	8 vCPU	8 cores	8 vCPU
Memory	64 GB RAM	64 GB RAM	64 GB RAM
WORKER NODES			
# Nodes	3	3	3
Machine Type	e2-highmem-4	A4m v2	ecs.se1.xlarge
Processors	4 vCPU	4 cores	4 vCPU
Memory	32 GB RAM	32 GB RAM	32 GB RAM
Storage	HDFS 1000 GB	WASB	HDFS 1000 GB
Replication	2	<i>Azure blob storage</i>	2
Block size	128 MB		128 MB

Table 1: Selected configurations on CSPs managed Hadoop services

Data Scale: Huge

Benchmark	IDS	Dataproc		HDInsight		e-MapReduce	
		$D_{(s)}$	$T_{(b/s)}$	$D_{(s)}$	$T_{(b/s)}$	$D_{(s)}$	$T_{(b/s)}$
Sort	3.28 GB	70	47110942	131	25076597	111	29419903
Terasort	32.00 GB	667	47988314	858	37277268	1054	30374710
Wordcount	32.85 GB	978	33594975	1470	22340906	889	36949719
Dfsioe-r	26.99 GB	294	91772636	662	40787869	245	110206431
Dfsioe-w	27.16 GB	379	71733304	658	41296567	281	96488258
Scan	2.01 GB	73	27629405	157	12830581	74 (*)	27193804 (*)
Join	1.92 GB	181	10614143	356	5390513	175 (*)	10950553 (*)
Aggregation	372.38 MB	97	3857328	215	1728400	97 (*)	3849353 (*)
Bayes	1.88 GB	2604	722498	6120	307708	3017	623692
Kmeans	20.08 GB	2321	8652662	2313	8683526	2070	9703348
Pagerank	2.99 GB	1544	1938541	3334	897807	2458	1217764

Data Scale: Gigantic

Benchmark	IDS	Dataproc		HDInsight		e-MapReduce	
		$D_{(s)}$	$T_{(b/s)}$	$D_{(s)}$	$T_{(b/s)}$	$D_{(s)}$	$T_{(b/s)}$
Sort	32.85 GB	715	45939699	787	41721261	896	36680251
Terasort	320.00 GB	9821	32582430	—(**)	—(**)	9660	33126513
Wordcount	328.49 GB	10131	32423997	13596	24159989	8671	37882290
Dfsioe-r	216.03 GB	915	236107099	1886	114538844	660	327294273
Dfsioe-w	217.33 GB	1347	161394226	1914	113574850	1060	205123746
Scan	20.10 GB	457	43964927	514	39085260	407 (*)	49378781 (*)
Join	19.19 GB	595	32268936	761	25240939	594 (*)	32319846 (*)
Aggregation	3.69 GB	523	7051835	594	6203608	565 (*)	6523381 (*)
Bayes	3.77 GB	5350	703332	12589	299143	6363	591341
Kmeans	40.16 GB	4541	8844971	4042	9935665	4034	9956003
Pagerank	19.93 GB	8371	2381276	11779	1692241	13893	1434711

(*) Benchmark execution succeeds after modifying preconfiguration, more on this in Discussion

(**) System failure due to insufficient space on HDFS, more on this in Discussion

Table 2: Use Case 1 benchmark outputs

Benchmark	Dataproc			HDInsight		e-MapReduce	
	IDS	$D_{(s)}$	$T_{(b/s)}$	$D_{(s)}$	$T_{(b/s)}$	$D_{(s)}$	$T_{(b/s)}$
Sort (t)	39.30 KB	36	1077	69	563	32	1173
Wordcount(t)	38.65 KB	38	1005	68	551	31	1242
Sort (s)	3.28 MB	36	90155	70	47090	31	104865
Wordcount (s)	348.29 MB	50	6508975	98	3337158	47	7055759
Sort (l)	328.50 MB	42	7860401	81	4065391	42	7741448
Wordcount (l)	3.28 GB	129	25448586	269	12195273	120	27269866
Sort (h)	3.28 GB	70	47077081	141	23355371	107	30693426
Wordcount (h)	32.85 GB	952	34512554	1487	22093900	888	36991074
Sort (g)	32.85 GB	694	47300549	699	47000056	883	37192377
Wordcount (g)	328.49 GB	9749	33696143	13286	24725537	8622	38100208
(t): tiny, (s): small, (l): large, (h): huge, (g): gigantic							

Table 3: Use Case 2 benchmark outputs

measure in seconds is expected to be perceived as "lower is better" while Throughput which is the amount of processed data per second in bytes is expected to be perceived as "higher is better".

USE CASE 1:

140 *Sort - Huge.* Figure 1; CPU utilization in GCP and Alibaba condenses around 80% to 98% whereas in Azure the range widens up between 50% to 90%. Memory loads in GCP and Alibaba among the worker nodes display a harmonic behavior between 20% to 40% and 90% to 100% respectively, whereas the memory load in Azure's worker nodes vary between 10% and 50%. In the second
145 half of the benchmark execution IO write transfers in GCP and Alibaba show peaks at about 500 tps where in Azure it is limited with 100 tps. Resulting in GCP carrying out the highest Throughput, thus reaching the shortest Duration of 70 seconds.

Sort - Gigantic. Figure 2; switching the data scale for Sort benchmark to gigantic, GCP's processor load condenses around 80% - 95% where its memory load
150 rises to range 80% - 100%; IO write transfers behave at about 500 tps where

Data Scale: Huge					
Benchmark	First	Second	-Perf.%	Third	-Perf.%
Sort	GCP	Alibaba	-58.57%	Azure	-87.14%
Terasort	GCP	Azure	-28.64%	Alibaba	-58.02%
Wordcount	Alibaba	GCP	-10.01%	Azure	-65.35%
Dfsioe-r	Alibaba	GCP	-20.00%	Azure	-170.20%
Dfsioe-w	Alibaba	GCP	-34.88%	Azure	-134.16%
Scan	GCP	Alibaba	-1.37%	Azure	-115.07%
Join	Alibaba	GCP	-3.43%	Azure	-103.43%
Aggregation	GCP-Alibaba	—	—	Azure	-121.65%
Bayes	GCP	Alibaba	-15.86%	Azure	-135.02%
Kmeans	Alibaba	Azure	-11.74%	GCP	-12.13%
Pagerank	GCP	Alibaba	-59.20%	Azure	-115.93%
Data Scale: Gigantic					
Benchmark	First	Second	-Perf.%	Third	-Perf.%
Sort	GCP	Azure	-10.07%	Alibaba	-25.31%
Terasort	Alibaba	GCP	-1.67%	Azure	—
Wordcount	Alibaba	GCP	-16.84%	Azure	-56.80%
Dfsioe-r	Alibaba	GCP	-38.64%	Azure	-185.76%
Dfsioe-w	Alibaba	GCP	-27.08%	Azure	-80.57%
Scan	Alibaba	GCP	-12.29%	Azure	-26.29%
Join	Alibaba	GCP	-0.17%	Azure	-28.11%
Aggregation	GCP	Alibaba	-8.03%	Azure	-13.58%
Bayes	GCP	Alibaba	-18.93%	Azure	-135.31%
Kmeans	Alibaba	Azure	-0.20%	GCP	-12.57%
Pagerank	GCP	Azure	-40.71%	Alibaba	-65.97%

Table 4: Use Case 1 Comparative benchmark outputs

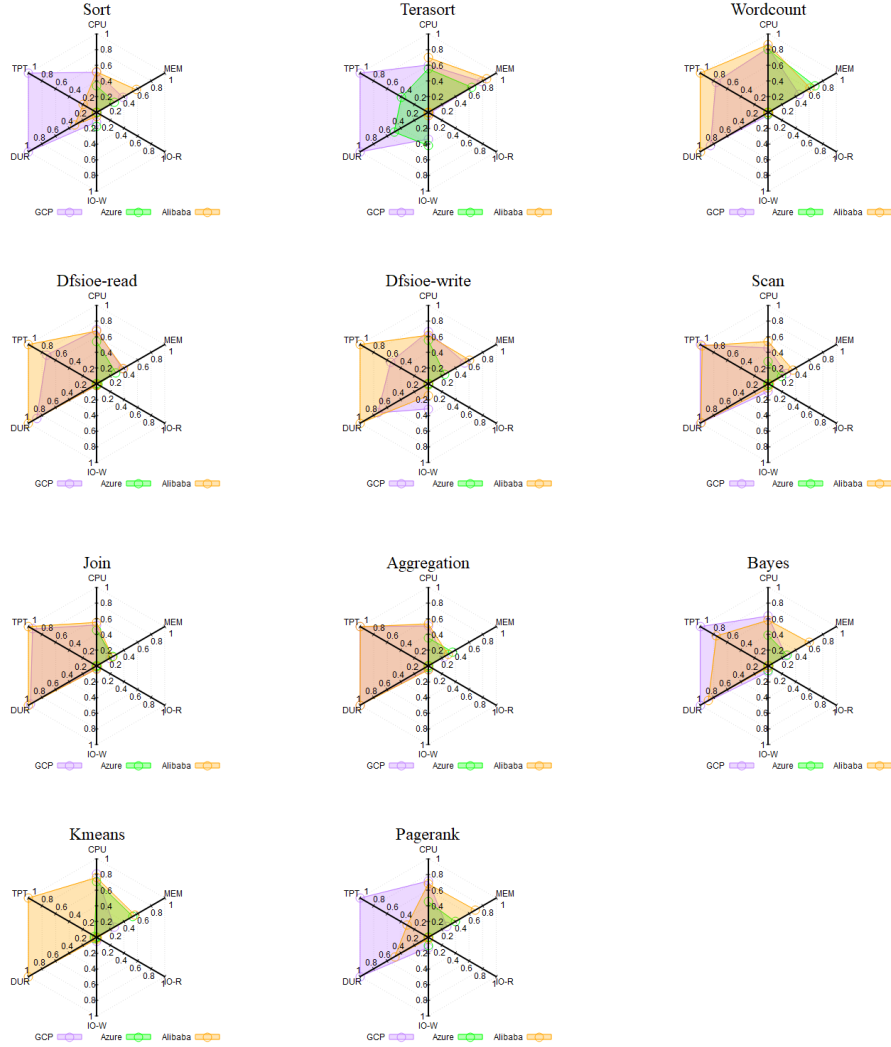


Figure 1: Use Case 1 - Hadoop benchmark comparisons in huge data scale

IO reads reach 1000 tps in the second half of the benchmark process. Azure's processor and memory performances depict a looser behavior not utilizing the maximum potential whereas IO-read and IO-write tps' reach their maximum at 200 and 350, respectively. Alibaba's resource utilization depicts a high memory load of 90% - 100% dropping to 70% and about 83% on partial nodes in the second half. As so with the processor load behaving between 80% and 100% in

the first half dropping to about 50% in the second half where IO write reaches peak at 800 tps. Resulting in GCP embarking highest and Azure the second highest Throughput, respective Durations output in 715 and 758 seconds.

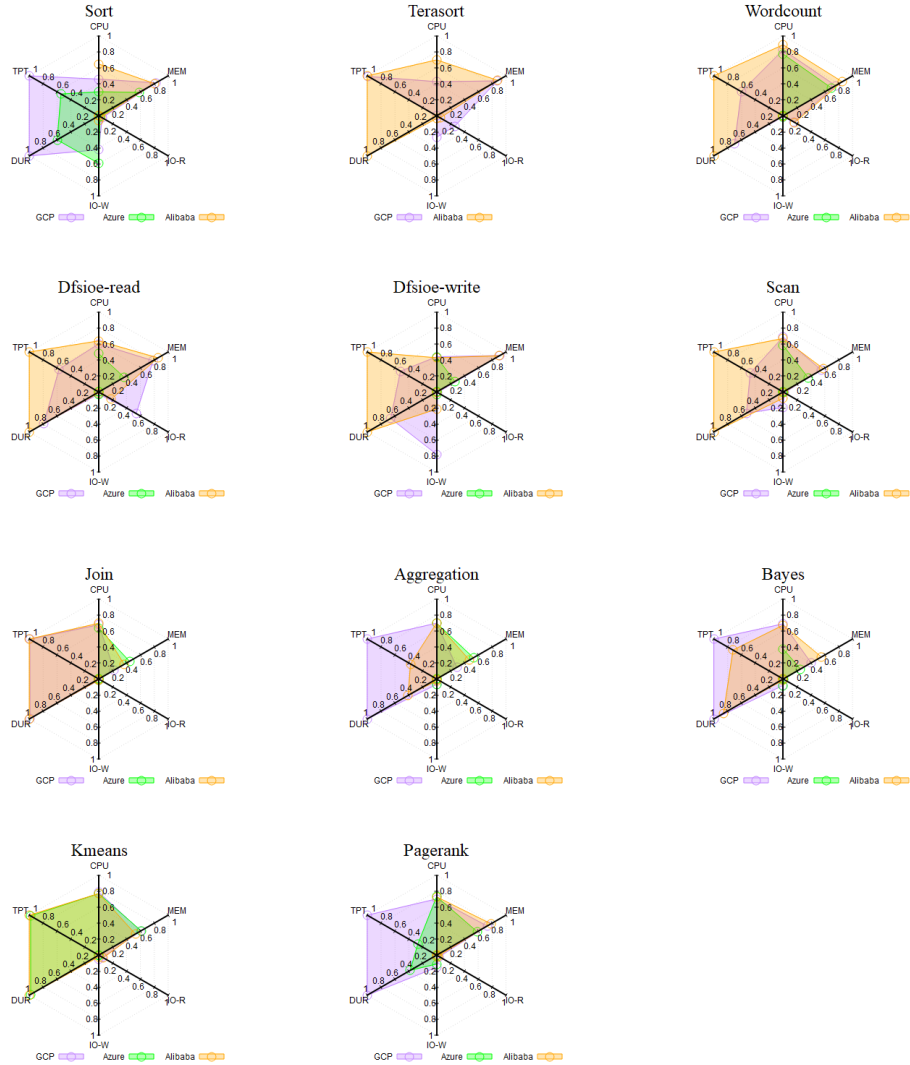


Figure 2: Use Case 1 - Hadoop benchmark comparisons in gigantic data scale

A possible reason for Azure's downperformance in dfsioe over GCP and Alibaba

USE CASE 2:

Sort. Figure 3;

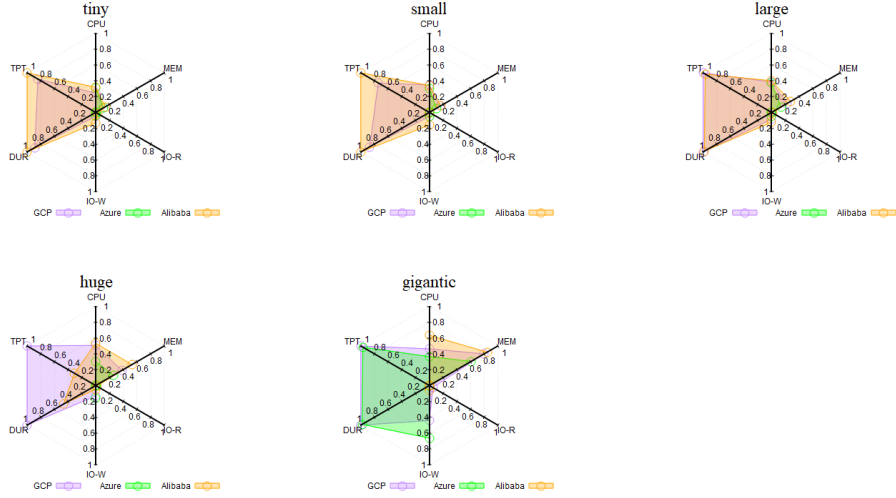


Figure 3: Use Case 2 - Sort performances along data scales

165 *Wordcount.* Figure 4;

Wordcount results in scale

5. Discussion

Limitations, workarounds, failures. One major limitation of this study has been the high-cost of benchmark executions' total running time which is charged in a pay-per-use manner leading the conductors halting benchmarks at only one successful execution for each workload. This is not fitting the best practise, though, where a benchmark would be executed thrice for each workload and the average performance results were taken. Following the best practise would have provided more stable outcomes especially in cases where there occurs very tiny difference between successive performances of respective providers. Hence, we recommend this study to be understood in terms of an attempt trying to

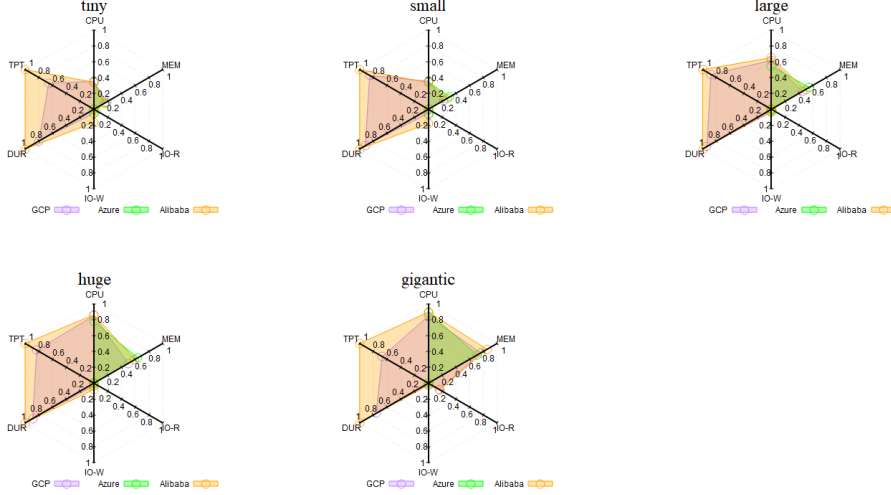


Figure 4: Use Case 2 - Wordcount performances along data scales

bring more clarity to black-box natured managed Hadoop proposals' performance behavior by means of resource utilization dynamics, and as the managed services come out of the box without applying any performance tweaking configurations. We do not recommend this study to be understood as a grading board for the business values provided by respective CSPs.

HiBench comes with dependencies downloaded during its compilation process by Apache Maven. The Hive engine is one of those dependencies leveraged by HiBench for running SQL workloads Scan, Join, and Aggregation. Alibaba's e-Mapreduce comprises a ready made Hive hook triggering a Java file to run post executional transactions for other services within the package. However this preconfiguration prevented HiBench from starting with respective benchmarks' execution since the HiBench based Hive engine does not include the aforementioned jar file defined for e-MapReduce's specific environment. Disabling the predefined Hive hook from Alibaba e-MapReduce's UI management console apparently solved this issue and enabled HiBench's SQL workloads to run, but the impact of this modification on the respective performance values remains unknown, hence the need to annotate it here. With GCP and Azure

issues of this kind did not occur.

195 In Azure environment the Terasort benchmark running in data scale gigantic failed to complete in all three attempts we conducted where about 20% of maps were completed. As distinct from GCP and Alibaba where the end user is liberate to chose HDFS or respective providers storage system as the cluster's file system, Azure obligates the user to go with WASB file system among
200 other Azure storage services with a promise to Peta-scale. However, after inspecting the failure it turned out that the exception is not due the WASB file system. Even though WASB is predefined as the cluster's file system, during the application's run time YARN still leverages the cluster's HDFS file system for storing intermediary results failing to allocate free space on HDFS reaching
205 specific levels of maps operators. The conductors marked this failure as a structural bottleneck, since all end users running Terasort operation at this scale would face the same error, and since resource utilization can be tracked up to the failure point and after, we kept this benchmark as disqualified.

6. Conclusion

210 7. Bibliography styles

There are various bibliography styles available. You can select the style of your choice in the preamble of this document. These styles are Elsevier styles based on standard styles like Harvard and Vancouver. Please use BibTeX to generate your bibliography and include DOIs whenever available.

215 Here are two sample references: [1, 2].

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