A Data Set for User Request Trace-Oriented Monitoring and its Applications

Jingwen Zhou, Zhenbang Chen, *Member, IEEE*, Ji Wang, *Member, IEEE*, Zibin Zheng, *Member, IEEE*, and Michael R. Lyu, *Fellow, IEEE*

Abstract—User request trace-oriented monitoring is an effective method to improve the reliability of cloud services. However, there are some difficulties in getting useful traces in practice, which hinder the development of trace-oriented monitoring research. In this paper, we release a fine-grained user request-centric open trace data set, called TraceBench, which is collected in a real-world cloud storage service deployed in a real environment. When collecting, we consider different scenarios, involving multiple scales of clusters, different kinds of user requests, various speeds of workloads, many types of injected faults, *etc*. To validate the usability and authenticity, we have employed TraceBench in several trace-oriented monitoring topics, such as anomaly detection, performance problem diagnosis, and temporal invariant mining. The results show that TraceBench well supports these research topics. In addition, we have also carried out an extensive data analysis based on TraceBench, which validates the high quality of the data set.

Index Terms—Data set, end-to-end tracing, trace-oriented monitoring, anomaly detection, cloud services

1 Introduction

Nowadays, cloud systems appear in more and more fields to provide various services that greatly benefit our daily life. However, with the increase in scale and complexity, cloud systems more and more often experience correctness and performance problems, which affect the reliability of cloud services and may bring enormous loss. For example, in August 2013, the services of Apple, Google, Microsoft, and Amazon crashed for different reasons. Google lost 550,000 dollars in 5 minutes, while Amazon lost seven million dollars in less than 100 minutes [1]. Moreover, some of these problems are very hard to detect in the design stage using traditional methods, such as testing, validation, and verification. Therefore, as a complement, the methods at runtime are used to further improve the reliability of cloud services, where monitoring is a most important one.

The monitoring of a system usually contains the activities of collecting the runtime information of the system, analyzing the system behaviors based on the collected information, and adjusting the system according to the analysis results. Therefore, topics like tracing, anomaly detection, and problem diagnosis are all related to the category of monitoring. According to the collected information, the methods of monitoring can mainly be divided into two types: resource-oriented monitoring and trace-oriented monitoring [2]. Resource-oriented monitoring systems [3], [4] record the information of a system from different kinds of system resources, such as CPU speed and available memory. However, sometimes resource information alone is not sufficient for revealing the behaviors of the monitored system, *e.g.*, to tell how a user request is processed. In contrast, trace-oriented monitoring systems [5], [6], [7] track the processes of handling user requests and record the context of each step, such as function name and execution time, in the form of user requests traces, or simply called *traces*. Traces naturally record the execution paths of user requests and contain both the normal and abnormal features of the monitored system, which are more valuable for revealing system behaviors.

In recent years, more and more research topics of improving system reliability are based on traces, such as uncovering bugs [8], diagnosing correctness problems [9] and performance problems [10], [11]. However, there still exist some difficulties in getting useful data of traces, which are essential for these research topics. First, collecting traces manually is a tedious and time-consuming process, which may involves choosing or even implementing a collection system, instrumenting and deploying the monitored system, designing and establishing various scenarios, *etc*. Moreover, these steps may be repeated multiple times if the collected traces are insufficient. For example, the jobs of collecting the trace data in this paper last for more than half a year, showing the difficulties in collecting traces by hand. Second, due to the weakness in authenticity, manually synthesized traces sometimes are not sufficient for the research topics. Finally, in academia and industry, there exist few data sets of traces that can well support these research topics, and companies do not want to release their system traces for safety or other considerations. All the above issues hinder the development of trace-oriented monitoring topics, and also motivate this paper.

• *J. Zhou, Z. Chen, and J. Wang are with the National Laboratory for Parallel and Distributed Processing, National University of Defense Technology, Changsha 410073, China, and the College of Computer, National University of Defense Technology, Changsha 410073, China. E-mail: {jwzhou, zbchen, wj}@nudt.edu.cn.*
• *Z. Zheng and M. R. Lyu are with the Shenzhen Research Institute, Chinese University of Hong Kong, Shenzhen, China, and with the Department of Computer Science and Engineering, Chinese University of Hong Kong, Hong Kong, China. E-mail: {zbzheng, lyu}@cse.cuhk.edu.hk.*

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In this paper,[1] we release TraceBench[2] to support trace-oriented monitoring research. To the best of our knowledge, TraceBench is the first fine-grained user request-centric open trace data set. The collection system is MTracer[3] [13], a trace-oriented monitoring system developed by us. With MTracer, we collected TraceBench among the Hadoop Distributed File System (HDFS) [14], a widely used cloud system that provides storage service. The cluster is deployed in a real environment, which is composed by 50 datanodes, 50 clients, and some other hosts. The whole size of TraceBench is about 3.2 GB. It records more than 370,000 traces stored in 364 files. TraceBench consists of three classes. (1) *Normal*: in this class, the traces are collected when the HDFS runs normally with different cluster sizes and responds to various kinds of user requests in multiple speeds. (2) *Abnormal*: we inject permanent faults into the HDFS during the collection, which result in correctness and performance problems, such as data block missing and network slowdown. (3) *Combination*: we randomly inject faults during HDFS running and then perform the recovery, so that the traces record both the normal and abnormal system behaviors.

TraceBench is a well-designed trace data set, considering multiple scales of clusters, different kinds of user requests, various speeds of workloads, many types of injected faults, and so on, and hence can be used in many trace-oriented monitoring topics as Ref. [15] advises, such as anomaly detection, problem diagnosis, and distributed profiling. For example, the *Normal* class and *Abnormal* class can be treated as knowledge bases for training the algorithms to learn the features of normal behaviors and abnormal behaviors, respectively, and the *Combination* class can be employed as a test set for validating the effectiveness of the algorithms. Since TraceBench is collected in a real environment, other research topics, like system understanding, would also employ this data set.

The remainder of this paper is organized as follows. Section 2 introduces trace-oriented monitoring systems and the system used for collecting TraceBench. Section 3 describes TraceBench, focusing on the details of the data set and the details of the collection. In Section 4, we show several applications of TraceBench. Section 5 discusses the aspects that may threaten the validity of TraceBench. Section 6 reviews the related work and Section 7 concludes the paper.

2 Trace-Oriented Monitoring

In this section, we first describe the trace-oriented monitoring systems, and then introduce MTracer [13], the system we used to collect TraceBench.

2.1 Trace-Oriented Monitoring Systems

Trace-oriented monitoring systems can be mainly divided into two types: black-box-based systems and white-box-based systems [2]. The black-box-based systems, such as lprof [16], PreciseTracer [17], and vpath [18], do not require the source code of the monitored system and apply reasoning methods for reconstructing the trace. In contrast, the white-box-based systems, such as Stardust [19], X-Trace [20], and Fay [21], need to instrument the source code at first for recording traces. In practice, the black-box-based systems are less flexible and less accurate than the white-box-based systems.

1. This paper is an extension to a conference paper [12].
2. Freely available at: http://mtracer.github.io/TraceBench/
3. Freely available at: http://mtracer.github.io/MTracer/

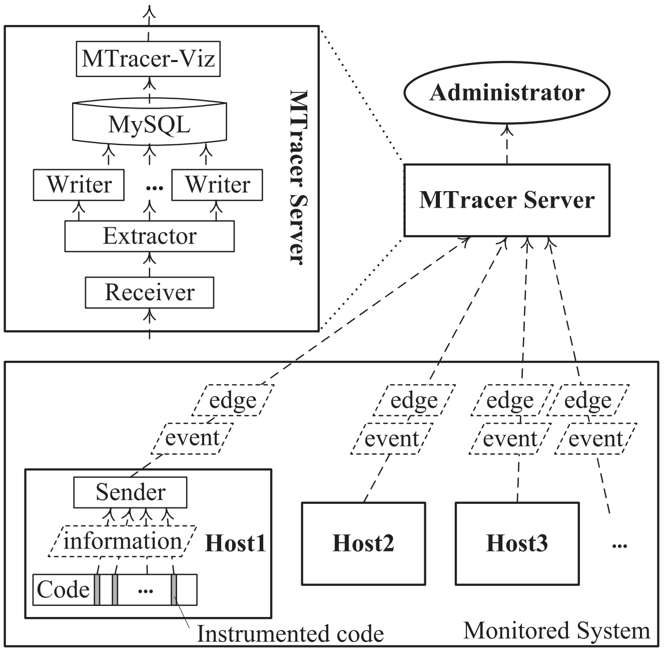


Fig. 1. The architecture of MTracer, where the upper-left box shows the inner structure of MTracer server and the dashed arrows illustrate the data streams in MTracer.

Different monitoring systems record traces in different formats, such as the linear event sequence, the trace tree [20], [22], [26], and the directed acyclic graph (DAG) [10], [23], [24]. The trace that contains more information often employs a more complex format and brings more overheads in monitoring. For example, among the above three formats, the DAG contains the most information and also is the most complex one. A trace with a complex format can be transformed to a simple format. For example, the trace in the format of trace tree can be converted to the format of linear event sequence using the methods like Depth First Search (DFS).

Among many existing trace-oriented monitoring systems, we choose MTracer to collect TraceBench for the following several reasons. 1) *Accuracy*. MTracer is a white-box-based system, which can guarantee that the collected traces exactly record the processes of handling user requests. 2) *Trace format*. MTracer employs the format of trace tree, which balances between recording abundant information and reducing the complexity of the trace format. 3) *Usability*. MTracer is lightweight for deployment and maintenance, and efficient for monitoring and visualization, which is pretty suitable for our collection.

2.2 MTracer

As Fig. 1 shows, MTracer adopts a client/server architecture, in which the hosts of the monitored system are treated as MTracer clients. Since MTracer is a white-box-based system, we need to instrument the source code of the monitored system at first. When the execution crosses these instrumented codes on the MTracer clients, related information is collected and sent to the MTracer server in the form

TABLE 1
Structure of TraceBench

Class	*Type*	*Fault*	*Workload*	*Variable*[a]	*#File*	*Collection Time(min)*	*#Trace*	*#Event*	*#Edge*
Normal (NM)	Clientload (CL)	-	r/w/rw/ rpc/rwrpc	1,5i clients (C)	55	2,761	209,326	3,848,191	1,963,129
	Datanode (DN)	-	r/w/rw	1,5i datanodes (DN)	33	1,980	17,440	2,310,699	941,681
Abnormal (AN)	Process (Proc)	killDN	r/w	0,1,2,3,4,5i FDN	30	600	6,469	682, 595	240,668
		suspendDN	r/w	1,2,3,4,5i FDN	28	515	2,754	317,498	124,630
	Network (Net)	disconnectDN	r/w	1,2,3,4,5i FDN	28	560	5,189	536,810	192,276
		slowHDFS	r/w/rpc	0,10i/2i/100i ms	33	506	41,200	669,692	348,912
		slowDN	r/w	1,2,3,4,5i FDN	28	560	4,395	575,425	232,270
	Data	corruptBlk	r	0,1,2,3,4,5i FDN	15	300	5,354	636,023	244,296
		corruptMeta	r	0,1,2,3,4,5i FDN	15	300	5,285	671,185	214,446
		lossBlk	r	1,2,3,4,5i FDN	14	280	4,920	573,148	186, 554
		lossMeta	r	1,2,3,4,5i FDN	14	280	4,789	590,902	256,211
		cutBlk	r	1,2,3,4,5i FDN	14	280	4,982	619,235	194,904
		cutMeta	r	1,2,3,4,5i FDN	14	280	5,020	595,579	188,863
	System (Sys)	panicDN	r/w	1,2,3,4,5 FDN	10	150	1,977	260,660	103,155
		deadDN	r/w	1,2,3,4,5 FDN	10	150	1,751	228,550	90, 693
		readOnlyDN	w	1,2,3,4,5 FDN	5	75	368	61,944	27,820
Combination (COM)	Single (Sin)	Process (Proc)	rwrpc	1,2,3	3	210	7,037	237,338	111,247
		Network (Net)	rwrpc	1,2,3	3	210	6,539	219,692	103,192
		Data	rwrpc	1,2,3	3	210	7,392	251,902	117,475
		System (Sys)	rwrpc	1,2,3	3	210	7,056	235,379	110,519
		Bug	rwrpc	1,2,3	3	105	3,847	53,011	29,656
	Multiple (Mul)	AnarchyApe (AA)	rwrpc	1,2,3	3	480	17,244	602,512	280,556
Total	**-**	**17 faults**	**5 workloads**	**-**	**364**	**11,002**	**370,334**	**14,777,970**	**6,303,153**

a. $i = 1, 2, \ldots, 10$

of events and edges, which will be introduced in Section 3. The server extracts useful information from the received data and stores the extracted information with MySQL database [25]. A web-based front-end for visualization is provided, called MTracer-Viz[4], to reconstruct the traces, provide various flexible queries, and do some advanced analysis.

By using different mechanisms and optimizations, MTracer requires few additional resources on the clients. For example, MTracer consumes a bandwidth of less than 2 MB/s, which is pretty acceptable comparing to the Gbps-level network in the data center. To improve the efficiency of the server, MTracer adopts a parallel method and several optimizations when storing data. More details about MTracer can be found in Ref. [13].

3 TraceBench

Using MTracer, we collected TraceBench in an environment containing 50 clients for generating user requests, a Hadoop cluster with 50 datanodes and one namenode for processing the requests from clients, and other hosts. When collecting, five workloads and 17 faults in five types are introduced to collect different behaviors of HDFS. As shown in Table 1, the whole size of TraceBench is about 3.2 GB and the total data collection time is $11,002$ minutes. TraceBench consists of $370,334$ traces, $14,777,970$ events, and $6,303,153$ edges in 364 trace files, in which 100 files contain failed user requests.

4. Freely available at: http://mtracer.github.io/MTracer-Viz/

The number of contained events of a trace, or say trace length, in TraceBench spreads from 1 to 420, and the number of involved hosts in a trace spans from 1 to 44. In this section, we first introduce the trace format and the structure of TraceBench, and then give the details about the collection, including the collection environment, the collection process, the employed workloads, and the injected faults.

3.1 Trace Format

In this section, we first introduce the trace tree with a traditional format, and then present the format of the traces in TraceBench, which is a little different from the traditional format. At last, we show some examples in TraceBench.

3.1.1 Trace Tree

Formally, a trace in the form of trace tree can be formalized as (E, R) [2], where E and R are the event set and the set of the relationships between the events, respectively. An event records the context of a request step, where a step stands for the execution of a function or a routine. An event is a triple (tid, eid, I). The first element tid is the identity of the trace, which means that all the events with the same tid belong to the same trace. Each event has a unique eid for distinguishing from each other in a trace. I records the detailed information of the step, such as function name and execution time. A relationship records the causality between two events, and can be expressed in a quadruple $(tid, feid, ceid, T)$, which means the event identified by $feid$ is the father of the event identified by $ceid$, in the trace identified

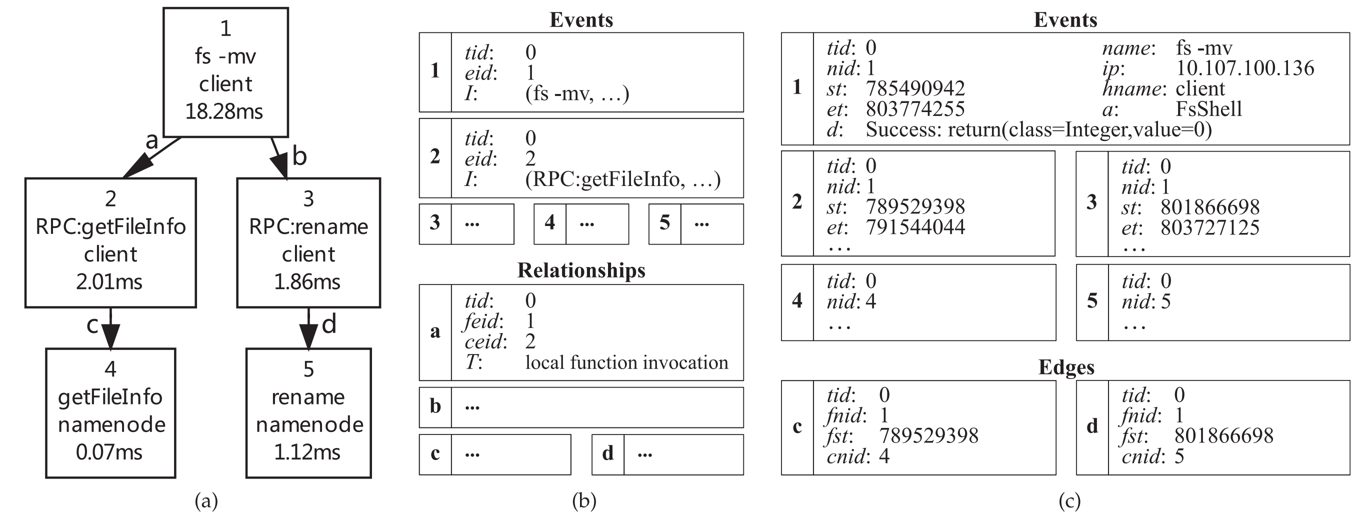

1 fs -mv client 18.28ms
a
b
2 RPC:getFileInfo client 2.01ms
3 RPC:rename client 1.86ms
c
d
4 getFileInfo namenode 0.07ms
5 rename namenode 1.12ms
(a)
Events
1 tid: 0 eid: 1 I: (fs -mv, …)
2 tid: 0 eid: 2 I: (RPC:getFileInfo, …)
3 ···
4 ···
5 ···
Relationships
a tid: 0 feid: 1 ceid: 2 T: local function invocation
b ···
c ···
d ···
(b)
Events
1 tid: 0 nid: 1 st: 785490942 et: 803774255 d: Success: return(class=Integer,value=0) name: fs -mv ip: 10.107.100.136 hname: client a: FsShell
2 tid: 0 nid: 1 st: 789529398 et: 791544044 …
3 tid: 0 nid: 1 st: 801866698 et: 803727125 …
4 tid: 0 nid: 4 …
5 tid: 0 nid: 5 …
Edges
c tid: 0 fnid: 1 fst: 789529398 cnid: 4
d tid: 0 fnid: 1 fst: 801866698 cnid: 5
(c)

Fig. 2. (a) An example of trace tree of a rename request in HDFS, (b) in the form of traditional format with five events and four relationships, and (c) in the form of MTracer format which also contains five events and only two edges. (*tid* = Trace ID, *eid* = Event ID, *I* = Information, *feid* = Father event's *eid*, *ceid* = Child event's *eid*, *T* = Relationship type, *nid* = Temporary thread ID, *name* = Event name, *ip* = Host IP address, *hname* = Host name, *st* = Start time stamp, *et* = End time stamp, *a* = Agent, *d* = Description, *fnid* = Father event's *nid*, *fst* = Father event's *st*, *cnid* = Child events' *nid*).

by tid. And T indicates the type of the relationship, such as a local function invocation or a remote procedure call (RPC). For example, Fig. 2a shows a trace tree of the process of handling a rename request in HDFS. The client first gets the information of the target file from the namenode, like whether the file exists, using the "*RPC: getFileInfo*", and then renames the file with the "*RPC: rename*". In this trace, the event set $E = \{1, 2, 3, 4, 5\}$ and the relationship set $R = \{a, b, c, d\}$, whose contents are shown in Fig. 2b.

Based on the events and the relationships, a trace can be reconstructed to a trace tree, where the nodes in the tree correspond to the events, and the edges correspond to the relationships. In a trace tree, a left node of brother nodes happens earlier than right nodes, e.g., event 2 happens earlier than event 3 in Fig. 2a. And we say a father node *triggers* a child node using the method of T, e.g., edge a represents that the event 1 triggers the event 2 using the method of local function invocation. Naturally, we can convert a trace tree to a linear event sequence with the methods like DFS or using Call (C) and Return (R) to describe a node. For example, the trace tree of Fig. 2a can be expressed as "1,2,4,3,5" using DFS, or "$C_1C_2C_4R_4R_2C_3C_5R_5R_3R_1$" using Call and Return method.

3.1.2 Trace Format in TraceBench

Traces collected by MTracer are organized in the form of the trace tree. The detailed information I of an event is defined as $(name, st, et, ip, hname, a, d)$, representing the event name, start time stamp, end time stamp, host IP address, host name, agent, and description, respectively. The event name is the name of the event, e.g., function name. The start and end time stamps record when the event starts and finishes in nanoseconds, which can be used to calculate the execution time, or say latency, of the corresponding operation. The host IP address and host name denote where the event is from. The agent represents an inner part of the system, like a Java class. The description records the execution results, such as return values and exception information.

For efficiency and overhead consideration, we introduce nid rather than eid for an event [15], [19], [22]. Each time a thread communicates with another thread, a new nid is generated in the second one. So, an nid can be understood as a temporary thread ID, and each event can be identified by nid and st, i.e., $eid = (nid, st)$, since the events with the same nid are generated from the same thread. As an example, the event 1 in Fig. 2c is an intact event in MTracer, corresponding to the node 1 in Fig. 2a.

Correspondingly, we employ a special strategy to record the relationships between events. If a father event and a child event are generated from the same thread, the two events have the same nid, and we do not record their relationship explicitly. Actually, the relationship can be calculated by comparing the time stamps. If a father event and a child event belong to different threads, the relationship is recorded explicitly in the form of an edge, i.e., $(tid, fnid, fst, cnid)$, where $(fnid, fst)$ identifies the father event and $cnid$ indicates the child event. An example of the edge in MTracer is shown as the edge c in Fig. 2c, corresponding to the edge c in Fig. 2a. This strategy saves many times of generating a random ID, which is a time-consuming operation [13], and thus reduces the overhead on the monitored system. For example, Fig. 2c contains only two edges, which is 2 less than the relationships in Fig. 2b.

Using events and edges, we can also reconstruct the trace tree. Fig. 3 illustrates the process of reconstructing the trace tree using the information of Fig. 2c, which contains four steps: (a) select all the events and edges with the same tid identifying the trace; (b) classify the selected events into classes according to their nid, which means all the events in the same class are generated from the same thread; (c) calculate the relationships in each class using the start and end time stamps, e.g., because event 1 starts earlier and finishes later than event 2, and there is no other ancestor of event 2, event 1 is the father of event 2; and (d) construct the relationships between classes using edges, where the event identified by $(fnid, fst)$ is the father of all the root nodes in the classes identified by $cnid$. Regardless of the database querying operation in step (a), the computational complexity of reconstructing a trace tree containing n events and m

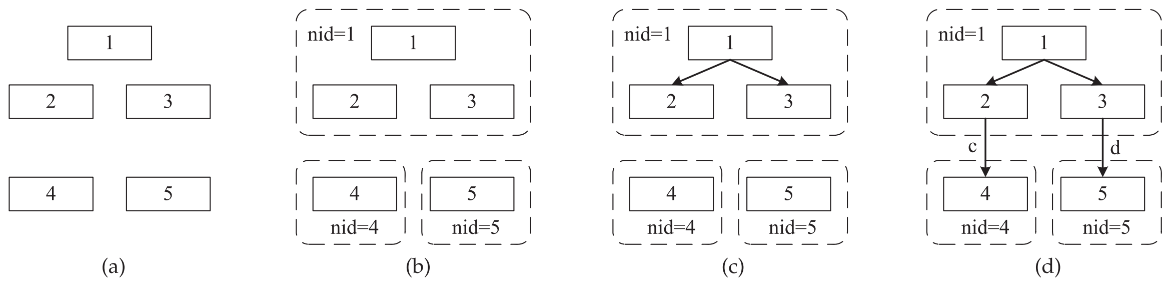


Fig. 3. The process of trace tree reconstruction using the information of Fig. 2c: (a) selecting events and edges, (b) classifying events into classes, (c) constructing the relationships in each class by comparing time stamps, and (d) constructing relationships between classes using edges.

edges is $O(nm + n^2/m)$ on average, and $O(n^2)$ in the worst case. For reasonable traces, the computation is typically not expensive. For example, for a trace with 342 events and 151 edges in TraceBench, the reconstruction requires less than 50 ms on a 3.1 GHz Intel-based computer.

3.1.3 Some Examples

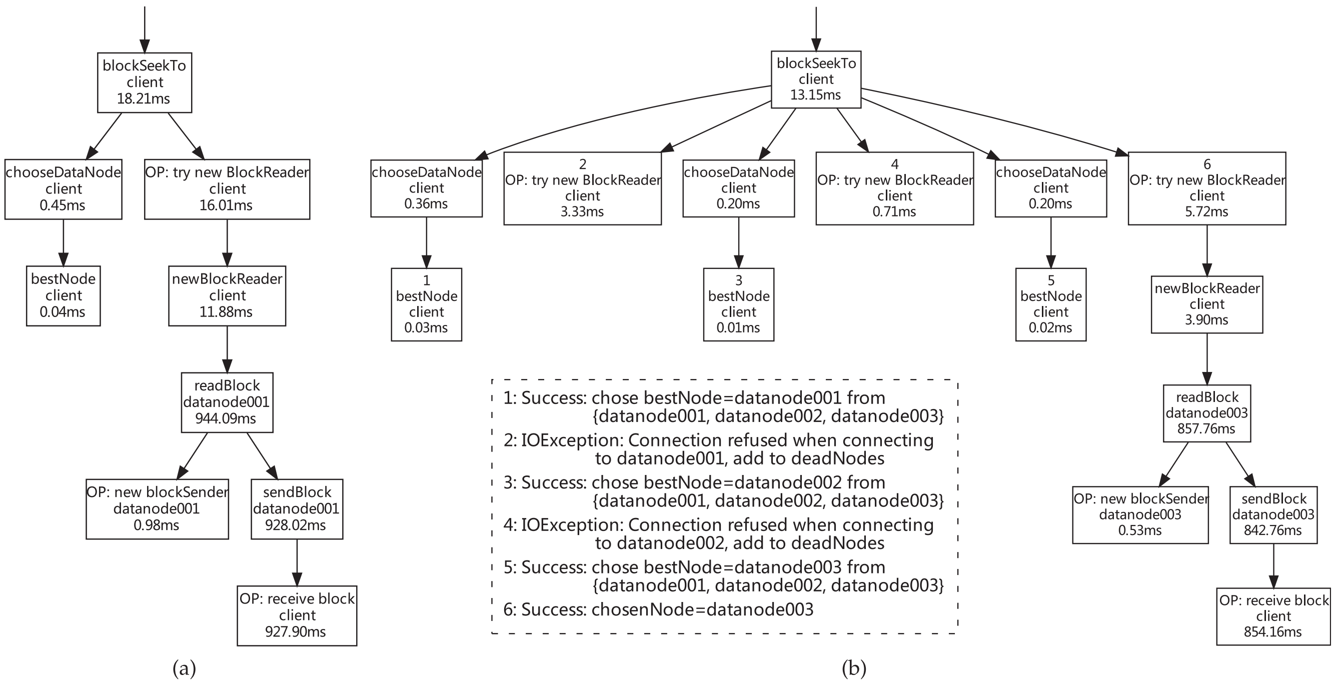
Traces collected by MTracer both record the normal behaviors of the monitored system and the abnormal behaviors when correctness problems or performance problems happen. Following, we give several examples selected from TraceBench.

Fig. 4a illustrates the normal process of reading a data block from HDFS, which is a part of handling a read request. The client first chooses the best datanode from the datanode list informed by the namenode, and then reads the block from the best datanode. However, when the best datanode encounters a *killDN* fault, which kills the HDFS processes on some datanodes, the operation of reading the data block will fail. Then, the client tries other datanodes in the datanode list. At last, the reading operation succeeds on a certain datanode or fails after trying all datanodes in the list. Fig. 4b clearly shows the process of finally succeeding after two failed tries. The content in the dashed box records the description fields of corresponding events, which depict the details of each try.

As another example, when encountering a fault of *slowHDFS*, which slows the whole network of the HDFS cluster, the latencies of some events in the trace tree would increase. For example, when the network slows down by 1 second, the latencies of event 2 and event 3 in Fig. 2a will increase by about 1 second, and thus event 1 by about 2 seconds. And the latencies of event 4 and 5 will not visibly change, since they happen inside a single host and have no relation with the network.

3.2 Structure

As shown in Table 1, TraceBench includes three classes: *Normal*, *Abnormal*, and *Combination*, respectively recording the information when the monitored system runs normally, meets a permanent fault, and encounters temporal faults. Each class consists of several types, which focus on different aspects of each class, e.g., the *Datanode* type mainly considers the aspect when the number of datanodes changes. In each type, we introduce different faults, workloads, and variables to simulate different scenarios. For example, in


blockSeekTo client 18.21ms
chooseDataNode client 0.45ms
OP: try new BlockReader client 16.01ms
bestNode client 0.04ms
newBlockReader client 11.88ms
readBlock datanode001 944.09ms
OP: new blockSender datanode001 0.98ms
sendBlock datanode001 928.02ms
OP: receive block client 927.90ms
(a)
blockSeekTo client 13.15ms
chooseDataNode client 0.36ms
2 OP: try new BlockReader client 3.33ms
chooseDataNode client 0.20ms
4 OP: try new BlockReader client 0.71ms
chooseDataNode client 0.20ms
6 OP: try new BlockReader client 5.72ms
1 bestNode client 0.03ms
3 bestNode client 0.01ms
5 bestNode client 0.02ms
newBlockReader client 3.90ms
readBlock datanode003 857.76ms
OP: new blockSender datanode003 0.53ms
sendBlock datanode003 842.76ms
OP: receive block client 854.16ms
(b)

1: Success: chose bestNode=datanode001 from {datanode001, datanode002, datanode003}
2: IOException: Connection refused when connecting to datanode001, add to deadNodes
3: Success: chose bestNode=datanode002 from {datanode001, datanode002, datanode003}
4: IOException: Connection refused when connecting to datanode002, add to deadNodes
5: Success: chose bestNode=datanode003 from {datanode001, datanode002, datanode003}
6: Success: chosenNode=datanode003

Fig. 4. (a) A normal process of reading a data block in HDFS, and (b) an abnormal reading process when encountering a *killDN* fault, where the content in the dashed box shows the description fields of corresponding events.

```
fault = panicDN
parameter = -R datanode024,datanode033,datanode029
inject time = 2013-11-13 10:11:55
recover time = 2013-11-13 10:17:47 //manual
```

Fig. 5. A fault record in a fault file, where the parameter defines the target datanodes, and the comment "manual" in the last line means the recovery is made by hand rather than automatically.

Datanode type, we introduce three workloads, and with each workload we vary the datanode number to be $1, 5, 10, \ldots, 50$, respectively, to simulate the scenarios with various workloads in different cluster scales. According to the fault, workload, and variable, a trace type contains many trace files, each of which corresponds to a certain scenario. In TraceBench, we name a set of traces according to the items of the first five columns in Table 1, i.e., "[**Class**](_[**Type**](_[**Fault**](_[**Workload**](_[**Variable**])?)?)?)?" in the form of the regular expression, where the bold words means the sets of items appeared in corresponding columns of Table 1. In addition, abbreviations given in the brackets in Table 1 are used for compressing the names. As an example, the trace set named as *Normal_Clientload_-_r*, or *NM_CL_r* for short, contains the traces collected under the workload *r* in the *Clientload* type of *Normal* class. Following, we respectively introduce each trace class of TraceBench.

The traces in the *Normal* class record the behaviors when the HDFS system runs normally, without injecting any faults. The *Normal* class consists of *Clientload* type and *Datanode* type. The *Clientload* type considers different speeds of workloads, and can be used to study the capacities of the HDFS system in dealing with different workloads in a certain scale (i.e., 50 datanodes). Since each client generates the workload in the same speed, we use the number of clients to represent the total workload speed of all valid clients in Table 1, and "1, 5*i* clients" means setting the number of clients to be $1, 5, 10, \ldots, 50$, respectively. In contrast, the *Datanode* type fixes the speed of workload (i.e., 30 clients) and changes the number of datanodes, to study the behaviors with different system scales.

The traces in the *Abnormal* class are collected when a permanent fault is injected into the HDFS system with a fixed scale (i.e., 50 datanodes) and a fixed workload speed (i.e., 30 clients). The traces contain the information about the injected faults, and can be used to study the behaviors when the system runs abnormally. According to the types of faults, the *Abnormal* class can be divided into four types, i.e., *Process*, *Network*, *Data*, and *System*, which will be discussed later. Except the *slowHDFS* affects the whole network, all the faults in this class are injected into datanode(s), e.g., the *lossBlk* means delete all the data blocks in some datanodes. So, the FDN in Table 1 represents the datanodes with a fault injected.

When collecting the traces in *Combination* class, faults are randomly picked and injected into the HDFS system, and later recovered automatically or manually (See column *Recovery* in Table 3). Thus, the *Combination* class contains the traces collected both when the system runs normally and abnormally. In this class, together with a trace file, a fault file is also given, recording the information about the injected faults, including the fault name, injection time, recovery time, *etc*. Fig. 5 shows an example of an injected

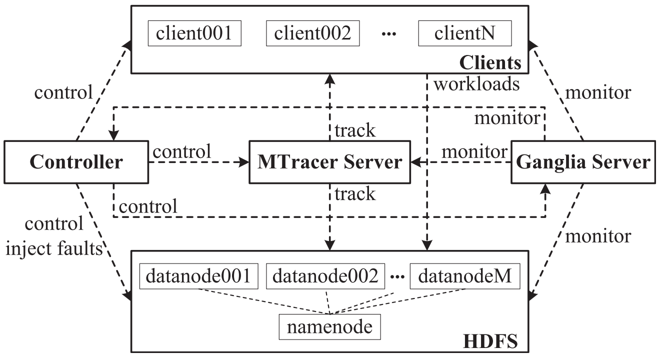


Fig. 6. The collection environment, in which $M = 50$ and $N = 50$.

fault record. The *Combination* class consists of the *Single* type, in which faults are chosen in only one fault type, and the *Multiple* type, in which faults are picked from multiple fault types, e.g., selected from all the faults in AnarchyApe [27]. Note that, besides the faults in *Abnormal* class, we also employ several *Bug* faults in *Single* type, which are real-world bugs selected from Hadoop issues repository [28] and will be introduced later. In addition, in this class, we repeat the collection process of each scenario for three times, which results in three trace files, i.e., "1,2,3" in the column *Variable*. Since the faults are randomly picked and injected, the three trace files of the same scenario contain different faults and a same fault employs different parameters.

3.3 Collection Environment

TraceBench is collected in a real environment, which consists of more than 100 virtual machines (VMs) hosted on our IaaS platform, i.e., CloudStack [29]. Fig. 6 shows the environment, which contains the following components:

- *HDFS*: providing a distributed storage service, containing 50 datanodes and one namenode.
- *Clients*: used to generate workloads to HDFS, to simulate the real usages of HDFS, containing 50 hosts.
- *MTracer server*: receiving, storing, and visualizing traces generated when HDFS processes the requests from clients.
- *Controller*: controlling the whole process of collection, and also being in charge of injecting faults.
- *Ganglia server* [4]: monitoring the whole environment, to help for solving the unexpected issues in collection, like VMs are shut down by accident.

The MTracer Server is deployed on a VM with 4 GB memory and 8×1 GHz CPU, while all the rest hosts are deployed on the VMs with 2 GB memory and 4×1 GHz CPU. The OS that all the VMs use is CentOS 6.3.

3.4 Process of Collection

We take the trace file as the unit of collection. Fig. 7 shows the processes of collecting trace files in each class. When collecting a trace file in the *Normal* class, we first start the MTracer server and the HDFS service with a certain number of datanodes, and then launch the workload on some clients concurrently. When finishing the collection, workload is stopped first. Then, the HDFS service and the MTracer server are shut down after waiting for a few minutes, to guarantee that all requests are finished smoothly and no

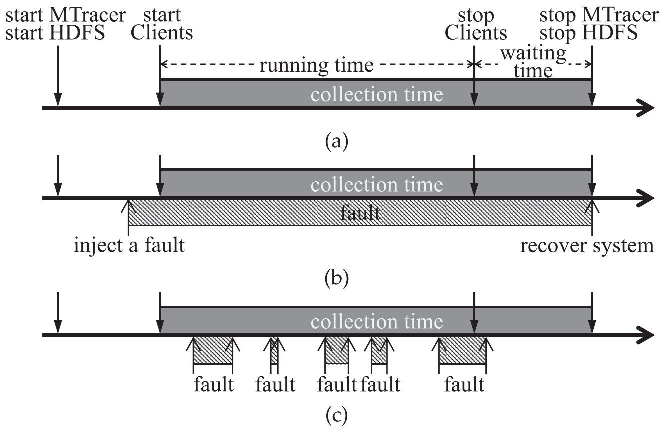


Fig. 7. Collection process of (a) the *Normal* class, (b) the *Abnormal* class, and (c) the *Combination* class.

fragmentary trace is collected. Therefore, in Table 1, the items of the column *Collection Time* are composed of the running time and the waiting time of all contained trace files. When collecting trace files in the *Abnormal* class, faults are injected before starting the workload, and the recovery are done after handling all the requests, to ensure all the traces are collected when the system runs abnormally. In contrast, in the *Combination* class, a randomly chosen fault is injected and the system is later recovered after starting the workload, and the next fault acts in the same way after an interval, to simulate the occasionally occurring faults. In addition, except a few tasks, such as recovering the system from a *System* fault, most jobs of the trace collection are done automatically.

Some parameters used in the collection are described as follows. First, except the *NM_DN* set, the number of datanodes is set to 50 during collecting, corresponding to the maximal capability of the HDFS system in our environment. Except the *NM_CL* set, the number of clients is fixed to 30, producing an appropriate workload, which contains enough requests that can be processed by the HDFS service in time. Second, the collection time of a trace file in the *Normal* class is 60 minutes (50 minutes for running and 10 minutes for waiting), which is enough for collecting plenty of traces to reflect related statistical features. The collection time of an *Abnormal* file is set to 20 minutes (15 minutes for running and 5 minutes for waiting), since HDFS employs some mechanisms to detect and to avoid faults automatically, like the heart-beating protocol, and thus the number of the traces containing exception information may reduce significantly after 20 minutes. Finally, most step sizes of variables are 5, i.e., changing 10 percent each time comparing to 50, which balances between reflecting statistic features of HDFS and controlling the number of trace files, e.g., the numbers of datanodes are set to $5, 10, 15, \ldots, 50$ in *NM_DN* set.

3.5 Workloads

There are about 30 different HDFS requests [14], which can be mainly divided into three kinds: file read request, file write request, and metadata request. A read request downloads files from HDFS to local host, like *copyToLocal*, while a write request uploads files from local host to HDFS, like *copyFromLocal*. Both of them involve communicating with the namenode to get the information about data blocks, and with some datanodes to download or upload data blocks. The metadata requests, such as *rm* and *ls*, operate metadata files, and only communicate with the namenode using RPCs without data block accessing. Table 2 lists the requests contained in TraceBench. The read and write request operates on the files that are automatically generated on HDFS and clients, respectively, with the number of contained data blocks spreading from 1 to 19. Eight most popular requests are considered in metadata kind, involving creating, modifying, querying, and removing of files and directories.

TABLE 2
Chosen Requests

Kind	*Request*
read	*copyToLocal*
write	*copyFromLocal*
metadata	*mkdir*, *touchz*, *mv*, *chmod*, *chown*, *ls*, *count*, *rmr*

The workloads that contain only read, write, and metadata requests are denoted by *r*, *w*, and *rpc*, respectively. Besides, we also introduce two other workloads: *rw*, containing both read and write requests, and *rwrpc*, containing all the three. When collecting the traces in each trace type, we introduce different workloads as needed. For example, since the faults in the *Data* type do not influence the write requests, we do not introduce the *w* workload in the *AN_Data* set.

Bash scripts are employed on each client for generating workloads. Each script takes charge in one kind of workload, e.g., *rpc.sh* produces the *rpc* workload. Using a loop, requests with different parameters are sent to the HDFS service continuously by a client. All the requests from the clients form the global workload. Intervals are introduced between neighbouring requests in a script, i.e., after finishing a request, a script waits for a moment and then starts the next one, to control the speeds of requests.

3.6 Faults

As Table 3 shows, we introduce 17 faults of five types during trace collection. The faults are selected from AnarchyApe [27], a mature injection tool for Hadoop, and from Hadoop issues repository [28], which stores real-world bugs reported by users (Column *Selected From*). Some of these faults bring correctness exceptions when handling requests, e.g., *killDN* may cause a failure of reading a file, while others may introduce performance problems, e.g., *HADOOP-6,502* results in a slow listing operation (Column *Category*).

The faults in AnarchyApe can be categorized into four types. The faults in the *Process* type affect the HDFS processes on HDFS nodes. For example, the fault *killDN* kills the HDFS processes on some datanodes, while *suspendDN* suspends some processes. *Network* faults bring anarchies to the network in the cluster, such as *slowHDFS* slows the whole network by milliseconds, and *slowDN* decreases the speeds of sending and receiving packets on some datanodes. The faults in *Data* introduce errors in the data blocks or the metadata files on some datanodes. For example, *corruptMeta* changes the values of some bits in the metadata files, and *cutBlk* removes parts of bits in the data blocks. The *System* faults introduce problems to the OSs of the HDFS nodes, such as making OSs to be panic, dead or read-only. Besides

TABLE 3
Injected Faults

Type	*Fault*	*Description*	*Category*	*Recovery*	*Selected From*
Process	killDN	Kill the HDFS processes on some datanodes	Correctness	Automatic	AnarchyApe [27]
	suspendDN	Suspend the HDFS processes on some datanodes	Correctness	Automatic	
Network	disconnectDN	Disconnect some datanodes from network	Correctness	Automatic	
	slowHDFS	Slow all the HDFS nodes	Performance	Automatic	
	slowDN	Slow some datanodes	Performance	Automatic	
Data	corruptBlk	Modify all the data blocks on some datanodes	Correctness	Automatic	
	corruptMeta	Modify all the metadata files on some datanodes	Correctness	Automatic	
	lossBlk	Delete all the data blocks on some datanodes	Correctness	Automatic	
	lossMeta	Delete all the metadata files on some datanodes	Correctness	Automatic	
	cutBlk	Remove some bits in all data blocks on some datanodes	Correctness	Automatic	
	cutMeta	Remove some bits in all metadata files on some datanodes	Correctness	Automatic	
System	panicDN	Make the system panic on some datanodes	Correctness	Manual	
	deadDN	Make the system dead on some datanodes	Correctness	Manual	
	readOnlyDN	Make the system read-only on some datanodes	Correctness	Manual	
Bug	HADOOP-3257	The path in HDFS requests is limited by URI semantics	Correctness	Automatic	Hadoop issues repository [28]
	HADOOP-6502	*ls* is very slow when listing a directory with a size of 1,300	Performance	Automatic	
	HADOOP-7064	*rmr* does not properly check the permissions of files	Correctness	Automatic	

AnarchyApe faults, we also selected several real-world bugs from Hadoop issues repository, which can be replayed in our HDFS system and can be captured by MTracer. We categorize them as *Bug* type.

For the faults injected by AnarchyApe, there are some aspects worthwhile to be pointed out. First, except the fault *slowHDFS* making the namenode slowdown, all the other faults only affect the datanodes. The reason is that the whole HDFS system would crash in case some problems happen in the namenode, such as the HDFS process is killed or the OS is panic. In this situation, the collected data is meaningless. Second, injecting *Data* faults should be carried out at datanode level rather than the files inside a datanode, because the exceptions caused by these faults have a probability to happen. For example, if a *lossBlk* fault deletes only one data block rather than all data blocks in a host and the requests do not involve this block, no exception will occur. Finally, as Table 1 shows, most of the variables in the *Abnormal* class are the number of FDNs. The purpose is to make the trace files more usable for studying the states of the HDFS system with different numbers of abnormal datanodes, e.g., to know how many requests will fail when 20 percent of HDFS processes are killed on datanodes.

4 Applications

To validate the usability and authenticity, we have employed TraceBench in several trace-oriented monitoring topics, include anomaly detection, performance problem diagnosis, and temporal invariant mining. We have also carried out an extensive data analysis on TraceBench, which validates the high quality of the data set.

4.1 Anomaly Detection

The same kind of user requests usually result in the traces with similar topologies, which can be extracted as the properties that are useful in anomaly detection, problem diagnosis, and other topics.

For example, when reading a file, the client downloads the data blocks of the target file from HDFS one by one, where a data block downloading starts with invoking the function "*blockSeekTo*" (short for *B*), and ends with calling "*checksumOk*" (*K*) if success. If any data block fails in being downloaded after some retries, the whole request aborts and fails. In other words, in a successfully handled read request, the last data block should be downloaded successfully, which can be expressed by the Linear Temporal Logic (LTL) [30] as the following property:

$$\diamond B \wedge (\Box((B \rightarrow \bigcirc(\Box\neg B)) \rightarrow \bigcirc(\diamond K))),$$

where the operators $\Box$, $\diamond$, $\bigcirc$, $\wedge$, $\rightarrow$, and $\neg$ represent for *All*, *Exist*, *Next*, *And*, *Imply*, and *Not*, respectively. Therefore, $\diamond B$ expresses that at least one reading operation exists, $B \rightarrow \bigcirc(\Box\neg B)$ means no more data blocks are read after current block, i.e., the last reading operation, and $\diamond K$ means there exists a successful reading operation. Thus, the whole property means the request reads at least one data block and succeeds in the last reading, which defines a successful read request. If a trace violates this property, we say a failure happens.

Similarly, we also extracted the properties for write and metadata requests. To validate these properties, we checked the traces in the *AN* set in the form of SQL queries to detect failures. All of the failed requests are picked out correctly. Besides the properties for detecting failures, we have also extracted tens of properties for detecting various problems, such as datanode invalid, data block missing, and operation latency anomaly. All of these properties can be in turn used to monitoring an HDFS system with different methods, e.g., the Monitoring Oriented Programming (MOP) [31] framework in runtime verification (RV) [32], which is part of our future work [33].

4.2 Performance Problem Diagnosis

Principal component analysis (PCA) is widely used in analysing traces for diagnosing performance problems. We implemented a PCA-based diagnosis method [34], [35], which finds the traces with abnormal latencies, and further locates the root causes of the problems. This method performs on trace clusters, where the traces in a cluster contain a

TABLE 4
Results of Performance Problem Diagnosis

Capacity	100	200	300	400	500
Time (ms)	31	65	95	130	154
Results	12,12,0	17,17,0	19,2,0	30,1,0	30,1,0
Length	33	66	99	134	167
Time (ms)	84	1,413	8,359	35,269	100,023
Results	0,0,0	1,1,0	1,1,0	1,1,0	0,0,0

TABLE 5
Results of Temporal Invariant Mining

Log Type	*Trace Set*	$\rightarrow$	$\leftarrow$	$\not\rightarrow$	*Total*
TO	*NM_CL_r_1C*	123	120	42	285
	NM_CL_w_1C	136	120	91	347
	NM_CL_rpc_1C	50	68	697	815
PO	*NM_CL_r_1C*	899	2,103	7,368	10,370
	NM_CL_w_1C	263	1,551	6,002	7,816
	NM_CL_rpc_1C	49	58	688	795

same call sequence, e.g., the call sequence of Fig. 2a is "*fs -mv*"$\rightarrow$"*RPC: getFileInfo*"$\rightarrow$"*getFileInfo*"$\rightarrow$"*RPC: rename*"$\rightarrow$ "*rename*". We call the number of traces contained in a cluster as the cluster capacity, and call the number of events in the corresponding call sequence as the cluster length.

Using the format of linear event sequence, we partitioned traces in *COM_Mul_All_rwrpc* set into clusters according to their call sequences, and then evaluated the method in the aspect of finding abnormal traces with these trace clusters. Table 4 shows the experiment results, which contains two parts: 1) the results of the trace clusters with a same length (i.e., 7) and with different capacities, and 2) the results of the clusters with a same capacity (i.e., 7) and with various lengths. For each cluster, we ran the method for fivetimes and report the average time as the analysis time in row *Time*. The items in row *Results* are expressed in the form of (total abnormal traces), (detected traces), (false alarms). In addition, the experiments are carried out on a VM with 8×1 GHz CPU and 4 GB memory.

As Table 4 shows, this diagnosis method finds all abnormal traces in some cases, and however sometimes only a small parts. Actually, the results depend on the features of data, since the thresholds used for judging the abnormal traces are calculated from the traces. So, when some very abnormal traces exist, some other less abnormal ones would be ignored due to the affected thresholds. For example, only 1 of 30 abnormal traces was found in the trace cluster with the capacity of 400 in Table 4, and after removing this one, another 27 abnormal traces were correctly picked out. In addition, according to the results, this diagnosis method is pretty accurate, with no false alarm in our experiments.

On the other hand, the analysis time increases very fast when the cluster length increases, but pretty slow when the cluster capacity grows, which indicates that this method is more sensitive to the length rather than to the capacity. The primary cause is the process of calculating eigenvalues and eigenvectors of a square matrix for getting principal components, where the calculating time is mainly related to the matrix size that exactly equals to the cluster length and has no relation with the capacity. Therefore, this method seems to be more applicable for short traces. Parallel approaches [36] or a segmentation based method [37] may be helpful for improving the efficiency.

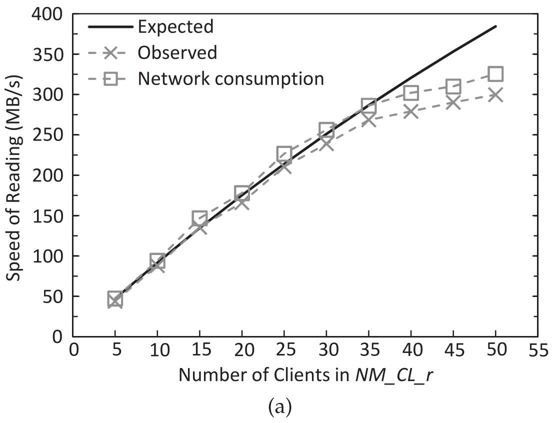
4.3 Temporal Invariant Mining

As an important aspect of system features, temporal invariants record the rules of the orders obeyed by two system operations, which can be obtained by mining system logs and can be used to understand systems, detect abnormal behaviors, diagnose deadlocks, infer higher-level properties, etc. Based on TraceBench, we evaluated a mining algorithm in Ref. [38] with the corresponding tool Synoptic [39] (revision id: cc864f389c71).

After formatting the traces both into the totally ordered (TO) format and the partially ordered (PO) format (refer to [38]), we have mined plenty of invariants in different trace sets with various request kinds in the *NM_CL* set. Table 5 shows the numbers of mined invariants, where $\rightarrow$, $\leftarrow$, and $\not\rightarrow$ respectively means the invariant type of *Always followed by*, *Always precedes of*, and *Never followed by* (refer to [38]). Both TO logs and PO logs imply useful invariants. For example, $INITIAL \rightarrow blockSeekTo$ and $blockSeekTo \rightarrow checksumOk$ mined from the *NM_CL_r_1C* set, respectively mean each read request contains at least one data block reading operation and each successfully handled reading operation invokes the function "*checksumOk*", which coincide to the property introduced in Section 4.1. Actually, many properties can be inferred based on these invariants.

When dealing with PO logs, Synoptic treats the same kind of events generated from different hosts as different events, which makes it possible to mine more useful invariants for concurrent systems. However, this also has several limitations. First, too many invariants are generated due to the massive event types, e.g., more than 10,000 in the *NM_CL_r_1C* set, which makes it difficult to search desirable features. Second, since the occasionally happened or occasionally not happened event combinations between hosts are treated as inherent system features, some false invariants arise. For example, the invariant $receiveBlock_{datanode001} \not\rightarrow receiveBlock_{datanode006}$ mined from the *NM_CL_w_1C* set, (where the function "*receiveBlock*" running on datanodes receives a copy of data block from the client) represents that there does not exist the situation in the *NM_CL_w_1C* set that HDFS stores a data block on datanode006 after storing on datanode001, which is still possible in other executions. Third, many invariants contain the same information, and we call such invariants as identical invariants. For example, the invariants $Conn_{datanode001} \rightarrow receiveBlock_{datanode001}, \ldots, Conn_{datanode050} \rightarrow receiveBlock_{datanode050}$ mined from the *NM_CL_w_1C* set (where "*Conn*" is short for "OP: *connect next Datanode*") all mean that when receiving a copy of data block, the related datanode first builds connection and then receives the copy. To summarize, when mining temporal invariants in PO logs, Synoptic seems to be more suitable for the systems with few hosts.

We consider a postprocess on the generated invariants is helpful for improving Synoptic. For example, using techniques in machine learning and data mining, the identical invariants can be effectively eliminated, like summarizing the 50 identical invariants in above example into one invariant, i.e., $Conn_{host} \rightarrow receiveBlock_{host}$.



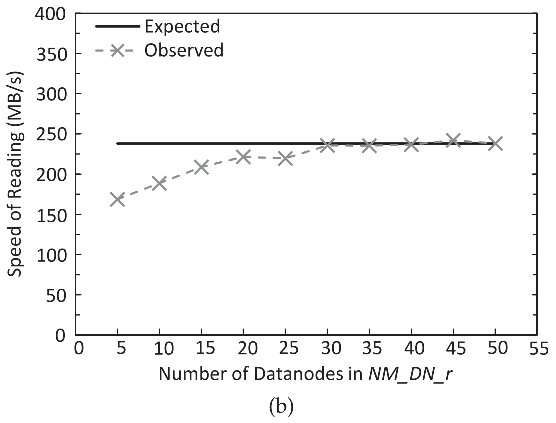


Fig. 8. Analysis of requests handling speeds (a) under different request speeds and (b) with different cluster sizes.

4.4 Data Analysis

We have also carried out an extensive data analysis based on TraceBench and get some characteristics of HDFS in statistics, which can also validate the data set. In this section, we give parts of our analysis results.

4.4.1 Requests Handling

With the traces in the *Normal* class, we have analyzed the relationships between the request handling speed and the request receiving speed of HDFS. Since all the clients take the same speed of sending requests, we use the number of clients to represent the request receiving speed. Because the time of handling a read or write request is related to the size of the file, we use the speed of downloading or uploading instead of the request handling speed. Besides, we use the number of datanodes to represent the scale of the HDFS system.

Theoretically, an HDFS service in a specific environment has a certain upper limit in handling, i.e., the maximal number of the requests that can be processed in a period, which reflects the request handling ability of HDFS. If the request receiving speed is smaller than the handling limit, all the requests can be handled in time. Otherwise, the HDFS service would be overloaded and some requests may be delayed or ignored.

Fig. 8 displays some analysis results. The curve with crosses in Fig. 8a represents the observed reading speeds under different request receiving speeds, where each point corresponds to a trace file in the *NM_CL_r* set. The solid curve is the perfect reading speed without considering the handling limit of HDFS. As the client number increases, the speed of reading increases almost linearly at first, which is close to the expected speed, and then increases slowly when there are more than 30 clients, due to the handling limit. The reading speed in Fig. 8a is calculated with respect to the number of the events with a name of "OP: *receive block*" in a certain period, since we know the size of each block is 64 MB. The curve with squares in Fig. 8a is the network consumption monitored by Ganglia, which is resource-oriented. From Fig. 8a, we can observe that the reading speed is a little smaller than the network consumption. The reason is that other network packets are also counted, such as the events of MTracer and Ganglia. In addition, the match of these two curves implies the viewpoint of that traces also contain some information about resource usages.

The handling limit of HDFS is related to the cluster scale. Fig. 8b is extracted from the *NM_DN_r* set with a fixed reading speed, i.e., 30 clients. The solid line represents the perfect speed of reading with all read requests being processed in time. The curve with crosses displays the actual reading speeds. The reading speed increases first with the increase of datanode number, because the ability of the HDFS service is improved with a larger scale, and then holds steady around the theoretical speed when reaching 30 datanodes, which indicates that the handling limit of the service exceeds the requests receiving speed.

4.4.2 Workload Balancing

Based on the *NM_CL_r* set, Fig. 9 shows the results of analysis of workload balancing in handling read requests, where each point represents the percentage of the data block reading operations happened on a certain datanode in a trace file. For example, the crosses surrounded by the dashed rectangle represent the percentages of reading operations accomplished by datanode021 in each trace file. All points are distributed around the solid line, i.e., 2 percent, which means one of 50 datanodes accomplishes about $1/50$ of the total tasks. This phenomenon also exists in handling write requests, which becomes even more obvious since the number of writing operations in *NM_CL_w* is more than the number of reading operations in *NM_CL_r*. Therefore, HDFS well balances the requests to all datanodes, which improves the resource utilization and avoids overloading.

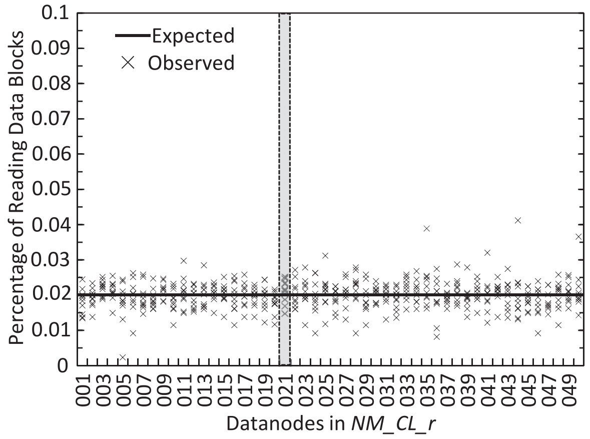


Fig. 9. Analysis of workload balancing in handling read requests.

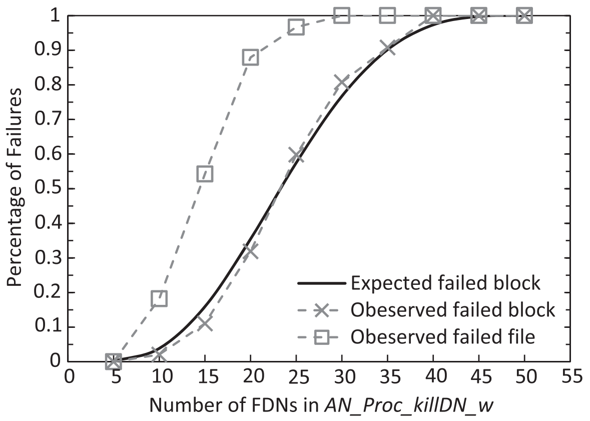


Fig. 10. Analysis of correctness problems.

4.4.3 *Correctness Problems*

Faults may result in correctness errors and even failures in handling user requests. For example, fault *killDN* would cause a failure in uploading a data block, i.e., an error in a write request, and several such errors on the same data block will result a failure of the whole request. We can always judge if a trace in TraceBench contains any correctness errors or failures, by exploring the topology of trace tree and the description fields of contained events, like Fig. 4 shows.

Based on the *AN_Proc_killDN_w* set, Fig. 10 shows the relationships between the number of FDNs and the percentage of errors and failures. The curve with crosses is the percentage of failed block writing operations with different number of FDNs, and the solid curve displays the theoretical percentage values. These two curves are coincident, which validates the authenticity of our data. The curve with squares is the percentages of the failed write requests, from which we can conclude some statistical features, e.g., 80 percent of the datanodes should be valid if we do not want the percentage of the failed write requests to exceed 20 percent.

4.4.4 *Performance Problems*

Besides correctness problems, faults may also lead to performance problems, i.e., increase of the latencies rather than the topological changes of trace trees. Fig. 11 is plotted based on the *AN_Net_slowHDFS* set, and shows the average time of reading a block, writing a block, and RPC invocations, when some slowdowns are introduced into the network of the HDFS cluster. The processing time of each operation increases as the network becomes slower. The slope of each trend line reflects the sensitivity of each operation with this fault. Because requiring plenty of network communications, writing a block is the most sensitive one. According to the trace data, the slowdown of writing operation is about 1,000 times larger than the network slowdown, i.e., 1 millisecond slowdown in network results in about 1 second increase when writing a block. RPC is the least sensitive operation, where 1 millisecond slowdown results in about 1 millisecond increase, since only a few network interactions are required in an RPC invocation.

5 Threats to Validity

Following aspects may threaten the validity of TraceBench.

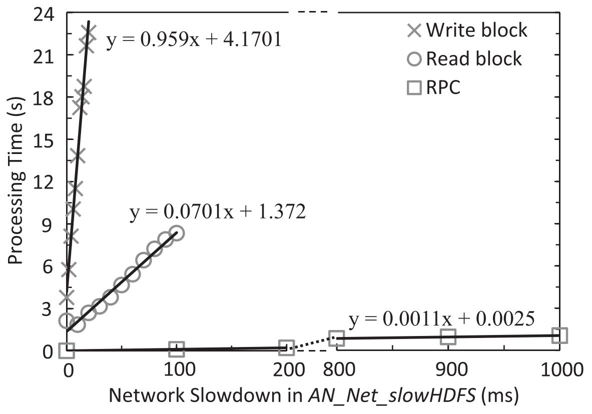


Fig. 11. Analysis of performance problems.

5.1 Collection System

We collected TraceBench with MTracer for the reasons mentioned in Section 2. MTracer stores the trace in the format of the trace tree, which can express sequential, concurrent, and recursive call/reply patterns [15]. However, this format is insufficient for expressing some other behaviors, like a single event causally depends on multiple father events [15], which may make TraceBench invalid in certain applications, e.g., the analysis methods in Pip [7] and Spectroscope [10]. A solution of this limitation is to adopt the format of DAG [15].

For efficiency consideration, MTracer can not perceive the errors and failures in traces. Therefore, there are no explicit tags existing in traces for indicating whether the trace is normal or not. However, like Fig. 4 and Section 4.4 shows, we can always exactly estimate a trace from the recorded information, such as the trace topology, the corresponding fault file which describes the injected faults, and the logged information in events, like the description field and latency field.

5.2 Monitored System

We collected our traces only on HDFS, which is a widely used cloud storage system in academia and industry. Many mechanisms in HDFS, like RPC, are commonly used in other systems. And we consider various scenarios of HDFS during collection. Therefore, TraceBench is representative and we believe TraceBench is helpful for many trace-oriented monitoring topics and other fields.

Our HDFS system is instrumented manually, which leads to record accurate execution paths of user requests. To reduce the monitoring overhead, we only instrument the key steps of requests, which record the main processes of handling HDFS requests. Specifically, we are more interested in the communications between hosts than the actions inside a single host. However, this may make TraceBench unsuitable for certain scenarios, like concerning about the details of operations inside a host.

5.3 Collection Environment

During trace collection, the HDFS cluster contains 50 datanodes, which is smaller than the production systems [40]. However, the cluster size of our HDFS is large enough to exhibit various features of HDFS for research purpose, since a user request in HDFS always involves limited datanodes. Moreover, it is really difficult for academic to deploy a very large-scale cluster in practice. On the other hand, the number of the clients is also set to 50, equalling to the number of datanodes, which should be more in real world. However, the workloads generated from these clients are pretty close to the reality and can make the HDFS system in different states, like reaching the upper limit.

Besides the faults we inject, many others exist in real systems, like dropping packets in network. Nevertheless, the faults we choose are mainly from a mature injection tool created by Yahoo! for Hadoop clusters, and we employ all the fault types in this tool. Hence, we believe that the faults we inject cover the most frequent and representative faults in practice.

5.4 Supported Applications

Our data set can be used in many applications as Section 4 shows, however, also may fail in supporting some others. To help for determining if TraceBench is suitable for a certain application, we give some features of TraceBench as follows:

- Events are totally ordered in each trace;
- Does not assume global clocks;
- Concurrency exists between traces, but no concurrency exists in a single trace;
- No much attentions are paid to the actions inside a single host;
- Traces do not contain synchronization points [15], i.e., each event at most has one father event.

In addition, on the homepage of TraceBench, we list many applications that can or cannot be supported by our data set.

6 Related Work

We have described the monitoring systems in Section 2.1, and in this section, we mainly introduce the related data sets. Currently, there exist some public data sets collected from multiple hosts, just like TraceBench. However, almost all of these data sets are resource-, job- or service-centric, which seldom involve in the details of system running.

Resource-centric data sets record the availability of hosts and components or the usages of resources, focusing on external, rather than internal, information of system programs. For example, the Failure Trace Archive (FTA) [41], [42], collected from parallel and distributed systems, records the information about resource failures; the Computer Failure Data Repository (CFDR) [43] provides the failure data in supercomputers and clusters, e.g., the storage failure data; and the Repository of Availability Traces [44] contains the events that indicate whether and when a host is available.

Job-centric data sets give a coarse-grained view of system running, such as when a job starts and finishes, which hosts are involved, without the details of how a job works. For example, the Grid Observatory (GO) [45], collected on a grid infrastructure, includes many data sets that record the information around jobs, e.g., jobs lifecycle; the Parallel Workloads Archive (PWA) [46] provides job-level usage data and is widely used in the research of job scheduling strategies for parallel systems; the Google Cluster Data [47] describes hundreds of thousands of jobs, composed by lots of tasks, together with the task resource usages.

Service-centric data sets focus on the aspects of services provided by systems for supporting service computing [48] topics. For example, the PW dataset [49], crawled from a service registration center, records implicit feedback of real-world web services; the Web Service QoS Dataset [50], [51] contains plenty of real-world web service Quality of Service (QoS) records by monitoring abundant web services, for validating QoS-based approaches, like Ref. [52]; the CLUS evaluation dataset [53] includes reliability data collected from multiple web services deployed on different geographical locations, which can be used in predicting the reliability of services.

In contrast, TraceBench records the fine-grained information about handling user requests, i.e., the details and casual relations in user requests involving multiple hosts, and hence is user request-centric. To the best of our knowledge, TraceBench is the first fine-grained user request-centric open trace data set. Besides, TraceBench also exceeds some data sets in certain aspects. For example, the CFDR lacks normal data, and the Repository of Availability Traces has limited information besides availability.

7 Conclusion and Future Work

In this paper, we provide a fine-grained user request-centric open trace data set, called TraceBench, collected with a trace-oriented monitoring system we have developed. TraceBench is collected in a real environment considering different scenarios, involving the cluster scale, request type, workload speed, injected fault, etc. We employ TraceBench in several applications to validate the usability and authenticity, and the results show that TraceBench is helpful for the trace-oriented monitoring research topics, such as anomaly detection, performance problem diagnosis, and temporal invariant mining. Moreover, due to the high quality of TraceBench, other related research, like system understanding, can also employ our data set.

In the future, we plan to: 1) accomplish the aforementioned two trace-oriented monitoring techniques, i.e., the runtime verification based anomaly detection method and the segmentation based performance problem diagnosis method; 2) explore more applications on TraceBench to validate our data set and to develop new methods; 3) if needed, collect some more trace sets with a more general trace format, like DAG, and on some other systems, e.g., Map/Reduce.

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REFERENCES

[1] J. Garside. (2013). Nasdaq crash triggers fear of data meltdown [Online]. Available: http://www.theguardian.com/technology/2013/aug/23/nasdaq-crash-data

[2] H. Mi, "Research on key techniques of performance maintenance for cloud services," Ph.D. dissertation, Nat. Univ. Defense Technol., Changsha, China, 2012.

[3] J. Boulon, A. Konwinski, R. Qi, A. Rabkin, E. Yang, and M. Yang, "Chukwa, a large-scale monitoring system," in *Proc. 1st Workshop Cloud Comput. Appl.*, 2008, pp. 1–5.

[4] M. L. Massie, B. N. Chun, and D. E. Culler, "The ganglia distributed monitoring system: Design, implementation, and experience," *Elsevier Parallel Comput.*, vol. 30, no. 7, pp. 817–840, 2004.

[5] P. Barham, A. Donnelly, R. Isaacs, and R. Mortier, "Using magpie for request extraction and workload modelling," in *Proc. 6th USENIX Conf. Symp. Opear. Syst. Des. Implementation*, 2004, pp. 259–272.

[6] M. Y. Chen, E. Kcman, E. Fratkin, A. Fox, and E. Brewer, "Pinpoint: Problem determination in large, dynamic Internet services," in *Proc. Int. Conf. Dependable Syst. Netw.*, 2002, pp. 595–604.

[7] P. Reynolds, C. E. Killian, J. L. Wiener, J. C. Mogul, M. A. Shah, and A. Vahdat, "Pip: Detecting the unexpected in distributed systems," in *Proc. 3rd Conf. Netw. Syst. Des. Implementation*, 2006, pp. 115–128.

[8] L.R. Sivalingam, J. Padhye, S. Agarwal, R. Mahajan, I. Obermiller, and S. Sayandeh, "AppInsight: Mobile app performance monitoring in the wild," in *Proc. 10th USENIX Conf. Oper. Syst. Des.*, 2012, pp. 107–120.

[9] Y. Zhuang, E. Gessiou, S. Portzer, F. Fund, M. Muhammad, I. Beschastnikh, and J. Cappos, "NetCheck: Network diagnoses from blackbox traces," in *Proc. 11th USENIX Symp. Netw. Syst. Des. Implementation*, 2014, pp. 115–128.

[10] R. R. Sambasivan, A. X. Zheng, M. D. Rosa, E. Krevat, S. Whitman, M. Stroucken, W. Wang, L. Xu, and G. R. Ganger, "Diagnosing performance changes by comparing request flows," in *Proc. 8th USENIX Conf. Netw. Syst. Des. Implementation*, 2011, pp. 43–56.

[11] H. Mi, H. Wang, Y. Zhou, M. R. Lyu, and H. Cai, "Toward fine-grained, unsupervised, scalable performance diagnosis for production cloud computing systems," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 6, pp. 1245–1255, Jun. 2013.

[12] J. Zhou, Z. Chen, J. Wang, Z. Zheng, and M. R. Lyu, "Trace bench: An open data set for trace-oriented monitoring," in *Proc. IEEE 6th Int. Conf. Cloud Comput. Technol. Sci.*, 2014, pp. 519–526.

[13] J. Zhou, Z. Chen, H. Mi, and J. Wang, "MTracer: A trace-oriented monitoring framework for medium-scale distributed systems," in *Proc. IEEE 8th Int. Symp. Service Oriented Syst. Eng.*, 2014, pp. 266–271.

[14] Apache. (2015). Hadoop [Online]. Available: http://hadoop.apache.org/

[15] R. R. Sambasivan, R. Fonseca, I. Shafer, and G. R. Ganger, "So, you want to trace your distributed system? Key design insights from years of practical experience," Carnegie Mellon Univ., Pittsburgh, PA, USA, Tech. Rep. CMU-PDL-14-102, 2014.

[16] X. Zhao, Y. Zhang, D. Lion, M. FaizanUllah, Y. Luo, D. Yuan, and M. Stumm, "lprof : A non-intrusive request flow profiler for distributed systems," in *Proc. 11th USENIX Symp. Oper. Syst. Des. Implementation*, 2014, pp. 629–644.

[17] B. Sang, J. Zhan, G. Lu, H. Wang, D. Xu, L. Wang, Z. Zhang, and Z. Jia, "Precise, scalable, and online request tracing for multi-tier services of black boxes," *IEEE Trans Parallel Distrib. Syst.*, vol. 23, no. 6, pp. 1159–1167, Jun. 2012.

[18] B. C. Tak, C. Tang, C. Zhang, S. Govindan, B. Urgaonkar, and R. N. Chang, "vPath: Precise discovery of request processing paths from black-box observations of thread and network activities," in *Proc. Conf. USENIX Annu. Tech. Conf.*, 2009, pp. 19–32.

[19] E. Thereska, B. Salmon, J. D. Strunk, M. Wachs, M. Abd-El-Malek, J. López, and G. R. Ganger, "Stardust: Tracking activity in a distributed storage system," in *Proc. Joint Int. Conf. Meas. Model. Comput. Syst.*, 2006, pp. 3–14.

[20] R. Fonseca, G. Porter, R. H. Katz, S. Shenker, and I. Stoica, "X-trace: A pervasive network tracing framework," in *Proc. 4th USENIX Conf. Netw. Syst. Des. Implementation*, 2007, pp. 271–284.

[21] Ú. Erlingsson, M. Peinado, S. Peter, and M. Budiu, "Fay: Extensible distributed tracing from kernels to clusters," in *Proc. 23rd ACM Symp. Oper. Syst. Principles*, 2011, pp. 23–26.

[22] B. H. Sigelman, L. A. Barroso, M. Burrows, P. Stephenson, M. Plakal, D. Beaver, S. Jaspan, and C. Shanbhag, "Dapper, a large-scale distributed systems tracing infrastructure," Google, Mountain View, CA, USA, Tech. Rep. dapper-2010-1, 2010.

[23] R. Fonseca, M. J. Freedman, and G. Porter, "Experiences with tracing causality in networked services," in *Proc. Internet Netw. Manage. Conf. Res. Enterprise Netw.*, 2010, p. 10.

[24] W. Wang, "End-to-end tracing in HDFS," Master's thesis, Carnegie Mellon Univ., Pittsburgh, PA, USA, 2011.

[25] MySQL. (2015). MySQL: The world's most popular open source database [Online]. Available: http://www.mysql.com/

[26] H. Mi, H. Wang, H. Cai, Y. Zhou, M. R. Lyu, and Z. Chen, "P-Tracer: Path-based performance profiling in cloud computing systems," in *Proc. IEEE 36th Annu. Comput., Softw., Appl. Conf.*, 2012, pp. 509–514.

[27] Yahoo!. (2012). AnarchyApe [Online]. Available: https://github.com/yahoo/anarchyape

[28] Apache. (2015). Hadoop Common-ASF JIRA [Online]. Available: https://issues.apache.org/jira/browse/HADOOP

[29] Apache. (2015). CloudStack [Online]. Available: http://cloudstack.apache.org/

[30] A. Pnueli, "The temporal logic of programs," in *Proc. 18th Annu. Symp. Found. Comput. Sci.*, 1977, pp. 46–57.

[31] P. O. Meredith, D. Jin, D. Griffith, F. Chen, and G. Rosu, "An overview of the MOP runtime verification framework," *Int. J. Softw. Tools Technol. Transfer*, vol. 14, no. 3, pp. 249–289, 2012.

[32] M. Leucker and C. Schallhart, "A brief account of runtime verification," *J. Logic Algebraic Program.*, vol. 78, no. 5, pp. 293–303, 2009.

[33] J. Zhou, Z. Chen, J. Wang, Z. Zheng, and W. Dong, "A runtime verification based trace-oriented monitoring framework for cloud systems," in *Proc. 25th IEEE Int. Symp. Softw. Rel. Eng. Workshops*, 2014, pp. 152–155.

[34] H. Mi, H. Wang, G. Yin, H. Cai, Q. Zhou, and T. Sun, "Performance problems diagnosis in cloud computing systems by mining request trace logs," in *Proc. IEEE Netw. Oper. Manage. Symp.*, 2012, pp. 893–899.

[35] H. Mi, H. Wang, Y. Zhou, M. R. Lyu, and H. Cai, "Localizing root causes of performance anomalies in cloud computing systems by analyzing request trace logs," *Sci. China: Inf. Sci.*, vol. 55, no. 12, pp. 2757–2773, 2012.

[36] J. H. Zheng, L. J. Zhang, R. Zhu, K. Ning, and D. Liu, "Parallel matrix multiplication algorithm based on vector linear combination using mapreduce," in *Proc. IEEE 9th World Congr. Serv.*, 2013, pp. 193–200.

[37] J. Zhou, Z. Chen, and J. Wang, "Segmentation based online performance problem diagnosis," in *Proc. 37th Int. Conf. Softw. Eng.*, 2015, pp. 807–808.

[38] I. Beschastnikh, Y. Brun, M. D. Ernst, A. Krishnamurthy, and T. E. Anderson, "Mining temporal invariants from partially ordered logs," *ACM SIGOPS Oper. Syst. Rev.*, vol. 45, no. 3, pp. 39–46, 2011.

[39] Synoptic. (2011). Studying logged behavior with inferred models [Online]. Available: https://code.google.com/p/synoptic/

[40] Z. Ren, J. Wan, W. Shi, X. Xu, and M. Zhou, "Workload analysis, implications, and optimization on a production hadoop cluster: A case study on taobao," *IEEE Trans. Serv. Comput.*, vol. 7, no. 2, pp. 307–321, Apr.–Jun. 2014.

[41] D. Kondo, B. Javadi, A. Iosup, and D. Epema, "The failure trace archive: Enabling comparative analysis of failures in diverse distributed systems," in *Proc. 10th IEEE/ACM Int. Symp. Cluster, Cloud Grid Comput.*, 2010, pp. 398–407.

[42] B. Javadi, D. Kondo, A. Iosup, and D. Epema, "The failure trace archive: Enabling the comparison of failure measurements and models of distributed systems," *J. Parallel Distrib. Comput.*, vol. 73, no. 8, pp. 1208–1223, 2013.

[43] B. Schroeder and G. Gibson, "The computer failure data repository (CFDR): Collecting, sharing and analyzing failure data," in *Proc. ACM/IEEE Conf. Supercomput.*, 2006, p. 154.

[44] B. Godfrey. (2010). Repository of availability traces [Online]. Available: http://pbg.cs.illinois.edu/availability/

[45] C. Germain-Renaud, A. Cady, P. Gauron, M. Jouvin, C. Loomis, J. Martyniak, J. Nauroy, G. Philippon, and M. Sebag, "The grid observatory," in *Proc. 11th IEEE/ACM Int. Symp. Cluster, Cloud Grid Comput.*, 2011, pp. 114–123.

[46] D. G. Feitelson, et al. (2005). Parallel Workloads Archive [Online]. Available: http://www.cs.huji.ac.il/labs/parallel/workload/

[47] C. Reiss, J. Wilkes, and J. L. Hellerstein, "Google cluster-usage traces: Format + schema," Google, Mountain View, CA, USA, Tech. Rep., Nov. 2011.

[48] L. J. Zhang, J. Zhang, and H. Cai, *Services Computing*. New York, NY, USA: Springer, 2007.

[49] G. Tian, J. Wang, K. He, P. C. K. Hung, and C. Sun, “Time-aware web service recommendations using implicit feedback,” in *Proc. IEEE Int. Conf. Web Serv.*, 2014, pp. 273–280.

[50] Z. Zheng, M. R. Lyu, et al. (2010). WS-DREAM [Online]. Available: http://www.wsdream.net

[51] Z. Zheng, Y. Zhang, and M. R. Lyu, “Investigating QoS of real-world web services,” *IEEE Trans. Serv. Comput.*, vol. 7, no. 1, pp. 32–39, Jan.–Mar. 2014.

[52] Z. Zheng, H. Ma, M. R. Lyu, and I. King, “QoS-aware web service recommendation by collaborative filtering,” *IEEE Trans. Serv. Comput.*, vol. 4, no. 2, pp. 140–152, Apr.–Jun. 2011.

[53] M. Silic, G. Delac, and S. Srbljic, “Prediction of atomic web services reliability based on k-means clustering,” in *Proc. 9th Joint Meeting Found. Softw. Eng.*, 2013, pp. 70–80.

Jingwen Zhou received the bachelor’s degree from the National University of Defense Technology and was recommended admission for the master’s degree in this school in 2009. In 2011, he was again recommended admission for the doctoral degree in this school. He is currently working toward the PhD degree from the College of Computer, National University of Defense Technology, Changsha 410073, China, and works in the National Laboratory for Parallel and Distributed Processing (PDL). His current research interests include cloud computing, distributed systems, and system reliability.

Zhenbang Chen received the PhD degree from the National University of Defense Technology, in 2009. He is an assistant professor in the College of Computer, National University of Defense Technology, Changsha, China. He served as a PC member of conferences such as ICTAC 2014 and FACS 2014, and served as a reviewer for international journals such as *SCP* and *JSS*. His research interests include program analysis, component-based formal modeling and verification, and cloud computing. He is a member of the IEEE.

Ji Wang received the PhD degree from the National University of Defense Technology. He is a professor of the College of Computer, National University of Defense Technology, Changsha, China. He has been awarded National Natural Science Fund for Distinguished Young Scholars of China, and Professorship of Chang Jiang Scholars Program of Ministry of Education of China. He has been an editorial board member of the *Journal of Systems and Software, the Science China* (Information Sciences). He served as a PC member of conferences such as FM, SAS, ATVA, EMSOFT, COMPSAC, APSEC, HASE. His current research interests include formal analysis and verification of software systems, high confidence software development, and distributed computing. He has published more than 80 refereed journal articles and conference papers in these areas. He is a member of the IEEE.

Zibin Zheng received the PhD degree from the Chinese University of Hong Kong, Hong Kong, China, in 2011. He is an associate research fellow in the Shenzhen Research Institute, the Chinese University of Hong Kong, Shenzhen, China. He received the ACM SIGSOFT Distinguished Paper Award at ICSE 2010, the Best Student Paper Award at ICWS 2010, First Runner-up Award at IEEE Hong Kong Postgraduate Research Paper Competition, and the IBM PhD Fellowship Award 2010-2011, etc. He served as a PC member of conferences such as CLOUD 2009, CLOUDCOMPUTING 2011, SCC 2012, ICSOC 2012, and served as a reviewer for international journals such as *TSE, TPDS, TSC, IJCCBS, IJBPIM*. His current research interests include service computing, cloud computing, and software reliability engineering. He is a member of the IEEE.

Michael R. Lyu received the PhD degree from the University of California, Los Angeles, in 1988. He is a professor in the Department of Computer Science and Engineering, the Chinese University of Hong Kong, Hong Kong, China. He initiated the First International Symposium on Software Reliability Engineering (ISSRE) in 1990. He served as a chair or co-chair for many conferences, such as ISSRE 2001, WWW 2010, SCC 2010, DSN 2011. He has been frequently invited as a keynote or tutorial speaker to conferences and workshops in the U.S., Europe, and Asia. His current research interests include software reliability engineering, distributed systems, service computing, information retrieval, social networks, and machine learning, and he has published more than 400 refereed journal articles and conference papers in these areas. He is a fellow of the IEEE and the AAAS for his contributions to software reliability engineering and software fault tolerance.