ASDF: Automated, Online Fingerpointing for Hadoop (CMU-PDL-08-104)

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Abstract

Localizing performance problems (or fingerpointing) is essential for distributed systems such as Hadoop that support long-running, parallelized, data-intensive computations over a large cluster of nodes. Manual fingerpointing does not scale in such environments because of the number of nodes and the number of performance metrics to be analyzed on each node. `ASDF` *is an automated, online fingerpointing framework that transparently extracts and parses different time-varying data sources (e.g.,* `sysstat`*, Hadoop logs) on each node, and implements multiple techniques (e.g., log analysis, correlation, clustering) to analyze these data sources jointly or in isolation. We demonstrate* `ASDF`*'s online fingerpointing for documented performance problems in Hadoop, under different workloads; our results indicate that* `ASDF` *incurs an average monitoring overhead of 0.38% of CPU time, and exhibits average online fingerpointing latencies of less than 1 minute with false-positive rates of less than 1%.*

[1] `ASDF` stands for Automated System for Diagnosing Failures

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Keywords: problem diagnosis, hadoop

1 Introduction

Distributed systems are typically composed of communicating components that are spatially distributed across nodes in the system. Performance problems in such systems can be hard to diagnose and to localize to a specific node or a set of nodes. There are many challenges in problem localization (i.e., tracing the problem back to the original culprit node or nodes) and root-cause analysis (i.e., tracing the problem further to the underlying code-level fault or bug, e.g., memory leak, deadlock). First, performance problems can originate at one node in the system and then start to manifest at other nodes as well, due to the inherent communication across components–this can make it hard to discover the original culprit node. Second, performance problems can change in their manifestation over time–what originally manifests as a memory-exhaustion problem can ultimately escalate to resemble a node crash, making it hard to discover the underlying root-cause of the problem. Obviously, the larger the system and the more complex and distributed the interactions, the more difficult it is to diagnose the origin and root-cause of a problem.

Problem-diagnosis techniques tend to gather data about the system and/or the application to develop *a priori* templates of normal, problem-free system behavior; the techniques then detect performance problems by looking for anomalies in runtime data, as compared to the templates. Typically, these analysis techniques for anomaly detection and diagnosis are run offline and post-process the data gathered from the system. The data used to develop the models and to perform the diagnosis can be collected in different ways.

A *white-box* diagnostic approach extracts application-level data directly and requires instrumenting the application and possibly understanding the application's internal structure or semantics. A *black-box* diagnostic approach aims to infer application behavior by extracting data transparently from the operating system or network without needing to instrument the application or to understand its internal structure or semantics. Obviously, it might not be scalable (in effort, time and cost) or even possible to employ a white-box approach in production environments that contain many third-party services, applications and users. A black-box approach also has its drawbacks–while such an approach can infer application behavior to some extent, it might not always be able to pinpoint the root cause of a performance problem. Typically, a black-box approach is more effective at problem localization, while a white-box strategy can be implemented to extract more information to ascertain the underlying root cause of a problem.

There are two distinct problems that we pursued. First, we sought to address support for problem localization (what we call *fingerpointing*) online, in an automated manner, even as the system under diagnosis is running. Second, we sought to address the problem of automated fingerpointing for Hadoop [9], an open-source implementation of the MapReduce programming paradigm [6] that supports long-running, parallelized, data-intensive computations over a large cluster of nodes.

This paper describes `ASDF`, a flexible, online framework for fingerpointing that addresses the two problems outlined above. `ASDF` has API support to plug in different time-varying data sources, and to plug in various analysis modules to process this data. Both the data-collection and the data-analyses can proceed concurrently, while the system under diagnosis is executing. The data sources can be gathered in either a black-box or white-box manner, and can be diverse, coming from application logs, system-call traces, system logs, performance counters, etc. The analysis modules can be equally diverse, involving time-series analysis, machine learning, etc.

We demonstrate how `ASDF` automatically fingerpoints some of the performance problems in Hadoop that are documented in Apache's JIRA issue tracker [8]. Manual fingerpointing does not scale in Hadoop environments because of the number of nodes and the number of performance metrics to be analyzed on each node. Our current implementation of `ASDF` for Hadoop automatically extracts time-varying black-box data sources (`sysstat`: `sadc` and `pidstat`) and specific white-box data sources (Hadoop logs) on every node in a Hadoop cluster. `ASDF` then feeds these data sources into different analysis modules (that respectively perform clustering, peer-comparison or Hadoop-log analysis), to identify the culprit node(s), in real time. A unique aspect of our Hadoop-centric fingerpointing is our ability to infer Hadoop states (as we chose to define them) by parsing the logs that are natively auto-generated by Hadoop. We then leverage the information about the states and the time-varying state-transition sequence to localize performance problems.

There is considerable related work in the area of both instrumentation/monitoring as well as in problem-diagnosis techniques, as described in Section 6. To the best of our knowledge, ASDF is the first automated, online problem-localization framework that is designed to be flexible in its architecture by supporting the plugging-in of data sources and analysis techniques. As far as we know, ASDF is also the first to demonstrate the online diagnosis of problems in Hadoop, without requiring modifications to Hadoop or to any applications that Hadoop supports. Specifically, for Hadoop, ASDF addresses the operational challenges of performing the analysis online, while dealing with multiple data-sources (black-box and white-box) of varying rates.

2 Problem Statement

The aim of ASDF is to assist system administrators in identifying the culprit node(s) when the system experiences a performance problem. The research questions center around whether ASDF can localize performance problems quickly, accurately and non-invasively. In addition, performing online fingerpointing in the context of Hadoop presents its own unique challenges. While we choose to demonstrate ASDF's capabilities for Hadoop in this paper, we emphasize that (with the appropriate combination of data sources and analysis modules) ASDF is generally applicable to problem localization in any distributed system.

2.1 Goals

We impose the following requirements for ASDF to meet its stated objectives.

Runtime data collection. ASDF should allow system administrators to leverage any available data source (black-box or white-box) in the system. No restrictions should be placed on the rate at which data can be collected from a specific data-source.

Runtime data analysis. ASDF should allow system administrators to leverage custom or off-the-shelf analysis techniques. The data-analysis techniques should process the incoming, real-time data to determine whether the system is experiencing a performance problem, and if so, to produce a list of possible culprit node(s). No restrictions should be placed on the type of analysis technique that can be plugged in.

Performance. ASDF should produce *low false-positive rates*, in the face of a variety of workloads for the system under diagnosis, and more importantly, even in the face of workload changes at runtime[1]. The ASDF framework's data-collection should impose *minimal runtime overheads* on the system under diagnosis. In addition, ASDF's data-analysis should result in *low fingerpointing latencies* (where we define fingerpointing latency as a measure of how quickly the framework identifies the culprit node(s) at runtime, once the problem is present in the system).

We impose the additional requirements below to make ASDF more practical to use and deploy.

Flexibility. ASDF should have the flexibility to attach or detach any data source (white-box or black-box) that is available in the system, and similarly, the flexibility to incorporate any off-the-shelf or custom analysis module.

Operation in production environments. ASDF should run transparently to, and not require any modifica-

[1] The issue of false positives due to workload changes arises because workload changes can often be mistaken for anomalous behavior, if the system's behavior is characterized in terms of performance data such as CPU usage, network traffic, response times, etc. Without additional semantic information about the application's actual execution or behavior, it can be difficult for a black-box approach, or even a white-box one, to distinguish legitimate workload changes from anomalous behavior.

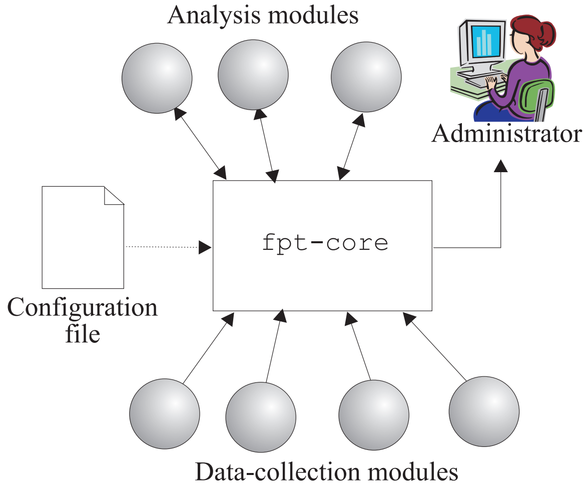


Figure 1: Logical architecture of ASDF.

tions of, both the hosted applications and any middleware that they might use. ASDF should be deployable in production environments, where administrators might not have the luxury of instrumenting applications but could instead leverage other (black-box) data. In cases where applications are already instrumented to produce logs of white-box data (as in Hadoop's case) even in production environments, ASDF should exploit such data sources.

Offline and online analyses. While our primary goal is to support online automated fingerpointing, ASDF should support offline analyses (for those users wishing to post-process the gathered data), effectively turning itself into a data-collection and data-logging engine in this scenario.

2.2 Non-Goals

It is important to delineate the research results in this paper from possible extensions of this work. In its current incarnation, ASDF is intentionally *not* focused on:

- Root-cause analysis: ASDF currently aims for (coarse-grained) problem localization by identifying the culprit node(s). Clearly, this differs from (fine-grained) root-cause analysis, which would aim to identify the underlying fault or bug, possibly even down to the offending line of code.
- Performance tuning: ASDF does not currently attempt to develop performance models of the system under diagnosis, although ASDF does collect the data that could enable this capability.

3 Approach & Implementation

The central idea behind the ASDF framework is the ability to incorporate any number of different data sources in a distributed system and the ability to use any number of analysis techniques to process these data sources. We encapsulate distinct data sources and analysis techniques into *modules*. Modules can have both inputs and outputs. Most data-collection modules will tend to have only outputs, and no inputs because they collect/sample data and supply it to other modules. On the other hand, analysis modules are likely to have both inputs (the data they are to analyze) and outputs (the fingerpointing outcome).

As an example on the data-collection side, ASDF currently supports a sadc module to collect data through the sysstatpackage, which contains various utilities to monitor system performance and usage activity. There can be multiple *module instances* to handle multiple data sources of the same type. On the analysis side, an example of a currently implemented module is `mavgvec`, which computes arithmetic mean and variance of a vector input over a sliding window of samples from multiple given input data streams.

3.1 Architecture

The key `ASDF` component, called the `fpt-core` (the "fingerpointing core"), serves as a multiplexer and provides a plug-in API for which modules can be easily developed and integrated into the system. `fpt-core` uses a directed acyclic graph (DAG) to model the flow of data between modules. Figure 1 shows the high-level logical architecture with `ASDF`'s different architectural elements–the `fpt-core`, its configuration file and its attached data-collection and analysis modules. `fpt-core` incorporates a scheduler that dispatches events to the various modules that are attached to it.

Effectively, a specific *configuration* of the `fpt-core` (as defined in its configuration file) represents a specific way of wiring the data-collection modules to the analysis modules to produce a specific online fingerpointing tool. This is advantageous relative to a monolithic data-collection and analysis framework because `fpt-core` can be easily reconfigured to serve different purposes, e.g., to target the online diagnosis of a specific set of problems, to incorporate a new set of data sources, to leverage a new analysis technique, or to serve purely as a data-collection framework for post-processing of the data.

As described below, `ASDF` already incorporates a number of data-collection and analysis modules that we have implemented for reuse in other applications and systems. We believe that some of these modules (e.g., the `sadc` module) will be useful in many systems. It is possible for an `ASDF` user to leverage or extend these existing modules to create a version of `ASDF` to suit his/her system under diagnosis. In addition, `ASDF`'s flexibility allows users to develop, and plug in, custom data-collection or analysis modules, to generate a completely new online fingerpointing tool. For instance, an `ASDF` user can reconfigure the `fpt-core` and its modules to produce different instantiations of `ASDF`, e.g., a black-box version, a white-box version, or even a hybrid version that leverages both black- and white-box data for fingerpointing.

Because `ASDF` is intended to be deployed to diagnose problems in distributed systems, `ASDF` needs a way to extract data remotely from the data-collection modules on the nodes in the system and then to route that data to the analysis modules. In the current incarnation of `ASDF`, we simplify this by running the `fpt-core` and the analysis modules on a single dedicated machine (called the `ASDF` control-node), and we perform the remote data collection using ONC RPC with protocol stubs generated by `rpcgen` [17]. For each data-collection module, `abc`, there exists a corresponding `abc_rpcd` counterpart that runs on the remote node to gather the data that forms that module's output.

3.2 Plug-in API for Implementing Modules

The `fpt-core`'s plug-in API was designed to be simple, yet generic. The API is used to create a module, which, when instantiated, will become a vertex in the DAG mentioned above. All types of modules–data-collection or analysis–use the same plug-in API, simplifying the implementation of the `fpt-core`.

A module's *init()* function is called once each time that an instance of the module is created. This is where a module can perform any necessary per-instance initialization. Typical actions performed in a module's *init()* function include:

- Allocating module-specific instance data
- Reading configuration values from the section for the module instance
- Verifying that the number and type of input connections are appropriate
- Creating output connections for the module instance

- Setting origin information for the output connections
- Adding hooks that allow for the `fpt-core`'s scheduling of that module instance's execution
- Performing any other module-specific initialization that is necessary.

A module's *run()* function is called when the `fpt-core`'s scheduler determines that a module instance should run. One of the arguments to this function describes the reason why the module instance was run. If a module instance has inputs, it should read any data available on the inputs, and perform any necessary processing. If a module instance has outputs, it should perform any necessary processing, and then write data to the outputs.

3.3 Implementation of `fpt-core`

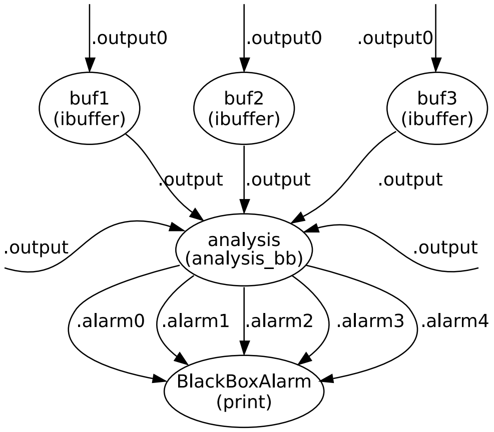
An `ASDF` user, typically a system administrator, would specify instances of modules in the `fpt-core`'s configuration file, along with module-specific configuration parameters (e.g., sampling interval for the data source, threshold value for an analysis module's anomaly-detection algorithm) along with a list of data inputs for each module. The `fpt-core` then uses the information in this configuration file to construct a DAG, with module instances as the graph's vertices, and the graph's edges represent the data flow from a module's outputs to another module's inputs. Effectively, the DAG captures the "wiring diagram" between the modules of the `fpt-core` at runtime.

The `fpt-core`'s runtime consists of two main phases, initialization and execution. As mentioned above, the `fpt-core`'s inialization phase is responsible for parsing the `fpt-core`'s configuration file and constructing the DAG of module instances. The DAG construction is perhaps the most critical aspect of the `ASDF` online fingerpointing framework since it captures how data sources are routed to analysis techniques at runtime.

1. In the first step of the DAG construction, `fpt-core` assigns a vertex in the DAG to each module instance represented in the `fpt-core`'s configuration file.
2. Next, `fpt-core` annotates each module instance with its number of unsatisfied inputs. Those modules with fully satisfied inputs (i.e., output-only modules that specify no inputs) are added to a module-initialization queue.
3. For each module instance on the module-initialization queue, a new thread is spawned and the module's *init()* function is called. The *init()* function verifies the module's inputs, the modules's configuration parameters, and specifies its outputs. A module's outputs, which are dynamically created at initialization time, are then used to satisfy other module instances' inputs. Whenever a new output causes all of the inputs of some other module instance to be satisfied, that module instance is placed on the queue.
4. The previous step is repeated until all of the modules' inputs are satisfied, all of the threads are created, and all of the module instances are initalized. This should result in a successfully constructed DAG. If this (desirable) outcome is not achieved, then, it is likely that the `fpt-core`'s configuration was incorrectly specified or that the right data-collection or analysis modules were not available. If this occurs, the `fpt-core` (and consequently, the `ASDF`) terminates.

Once the DAG is successfully constructed, the `fpt-core` enters its execution phase where it frequently calls each of the module instances' *run()* function.

As part of the initialization process, module instances may request to be scheduled perodically, in which case their *run()* functions are called by the `fpt-core`'s scheduler at a fixed frequency. This allows the class



```
[ibuffer]
id = buf1
input[input] =
  onenn0.output0
size = 10

[ibuffer]
id = buf2
input[input] =
  onenn0.output0
size = 10

[ibuffer]
id = buf3
input[input] =
  onenn0.output0
size = 10
```

```
[analysis_bb]
id = analysis
threshold = 5
window = 15
slide = 5
input[l0] = @buf0
input[l1] = @buf1
input[l2] = @buf2
input[l3] = @buf3
input[l4] = @buf4

[print]
id = BlackBoxAlarm
input[a] = @anal
```

Figure 2: A snippet from the `fpt-core` configuration file that we used for Hadoop, along with the corresponding DAG.

of data-collection modules (that typically have no specified inputs) to perodically poll external data sources and import their data values into the `fpt-core`.

For module instances with specified inputs (such as data-analysis modules), `fpt-core` automatically executes their *run()* functions each time that a configurable number of their inputs are updated with new data values. This enables data-analysis modules to perform any analysis immediately when the necessary data is available.

3.4 Configuring the `fpt-core`

Configuration files for the `fpt-core` have two purposes: they define the DAG that is used to perform problem diagnosis and they specify any parameters processing modules may use. The format is straightforward.

A module is instantiated by specifying its name in square brackets. Following the name, parameter values are assigned. The resulting module instance's id can be specified with an assignment of the form "id = *instance-id*". To build the graph, all of a module instance's inputs must be specified as paremeters. This is done with assignments of the form "input[*inputname*] = *instance-id.outputname*" or "input[*inputname*] = @*instance-id*". The former connects a single output, while the latter connects all outputs of the specified module instance. All other assignments are provided to the module instance for its own interpretation. A snippet from the `fpt-core` configuration file that we used in our experiments with Hadoop, along with the corresponding `fpt-core` DAG, are displayed in Figure 2.

3.5 Data-Collection Modules

Given the plug-in API described in Section 3.2, `ASDF` can support the inclusion of multiple data sources. Currently, `ASDF` supports the following data-collection modules: `sadc` and `hadoop_log`. We describe the `sadc` module below and the `hadoop_log` module in Section 4.4 (in order to explain its operation in the context of Hadoop).

The `sadc` Module. The `sysstat` package [20] comprises utilities (one of which is `sadc`) to monitor system performance and usage activity. System-wide metrics, such as CPU usage, context-switch rate, paging activity, I/O activity, file usage, network activity (for specific protocols), memory usage, etc., are traditionally logged in the /proc pseudo-filesystem and collected by /proc-parsing tools such as `sadc` and `pidstat` from the `sysstat` package. `ASDF` uses a modified version of the `sysstat` code in the form of a library, `libsadc`, which is capable of collecting system-wide and per-process statistics in the form of `C` data structures.

The `ASDF` `sadc` data-collection module exposes these /proc black-box metrics as `fpt-core` outputs and makes them available to the `fpt-core`'s analysis modules. We use Open Network Computing Remote Procedure Call (ONC RPC) `rpcgen` to generate the RPC stubs that facilitate the collection of remote statistics from a `sadc_rpcd` daemon that uses `libsadc` internally. Each node on which we aim to diagnose problems using `sadc` runs an instance of the `sadc_rpcd`daemon. In all, there are 64 node-level metrics, 18 network-interface-specific metrics and 19 process-level metrics that can be gathered via the `sadc` module. Our black-box online fingerpointing strategy leverages the `sadc` module.

3.6 Analysis Modules

White-box and black-box data might reveal very different things about the system–white-box reveals application-level states and the application's behavior, while black-box reveals the performance characteristics of the application on a specific machine. Although `ASDF` aims to operate in production environments, `ASDF` allows its user to incorporate any and all (either black-box or white-box) data-sources that are already available in the system. If a data-source can be encapsulated in the form of an `fpt-core` data-collection module, then, it can be made available to the `fpt-core` analysis modules. In this spirit, as we show later, `ASDF` supports both black-box and white-box fingerpointing for Hadoop.

We discuss some of the basic analysis modules that `ASDF` supports. Currently, the `ASDF` supports the following analysis modules: `knn`, `mavg`, `mavgvec`, `simple_correl_test` and `hadoop_log`. We describe some of these implemented modules below and the `hadoop_log` module in Section 4.4 (in order to explain its operation in the context of Hadoop).

The `mavgvec` module. The `mavgvec` module calculates arithmetic mean and variance of a moving window of sample vectors. The sample vector size and window width are configurable, as is the number of samples to slide the window before generating new outputs.

The `knn` module. The `knn` (*k*-nearest neighbors) module is used to match sample points with centroids corresponding to known system states. It takes as configuration parameters k, a list of centroids, and a standard deviation vector with each element of the vector corresponding to each input statistic. For each input sample $\mathbf{s}$, a vector $\mathbf{s}'$ is computed as

$$s'_i = \frac{\log(1+s_i)}{\sigma_i}$$

and the Euclidean distance between $\mathbf{s}'$ and each centroid is computed. The indices of the k nearest centroids to $\mathbf{s}'$ in the configuration are output.

3.7 Design & Implementation Choices

Throughout the development of `ASDF`, a number of design choices have been made to bound the complexity of the architecture, but which have resulted in some limitation on the means by which analysis may be performed.

1. Since `ASDF` uses a directed acyclic graph (DAG) to model the flow of data, data flows are inherently undirectional with no provision for cross-instance data feedback. Such feedback may be useful for certain methods of analysis, for example, if one were to use the output of the black-box analysis to provide hints of anomalous conditions to the white-box analysis, or vice-versa.

2. Although the fpt-core API does have some provisions for propagating alert conditions on inputs, or back-propagating enable/disable state changes on outputs, there is no explicit mechanism for cross-instance data synchronization.
3. Since fpt-core operates in the context of a single node, there is no builtin provision for starting RPC daemons on remote nodes or synchronizing remote clocks. Thus, RPC daemons must be started either manually, or at boot time on all monitored nodes. In addition, clocks on all nodes must be sychronized at all times, as either time skews, or their abrupt correction thereof, may alter the interpretation of cross-node time series data.

We should also note that while the above requirements apply to ASDF as a whole, they don't necessarily apply equally to both the black-box and white-box data collection and analysis components. In general, the black-box instrumentation technique of polling for system metrics in /proc generally requires less cross-node coordination than the white-box technique. For example, since black-box system metrics are polled in realtime, they are timestamped directly on the ASDF control node and passed immediately to the next analysis module—thus, the wallclock time on other nodes is irrelevant to black-box analysis. In contrast, the white-box technique of parsing recently written log files requires clock synchronization across all monitored nodes so that written timestamps in the log files match events as they happen.

Additionally, the white-box technique faces an additional data synchronization issue that is not present in the realtime black-box data collection. Internal buffering in Hadoop results in log data being written at slightly different times on different Hadoop nodes. Additionally, the hadoop-log-parser is unable to compute all statistics in real time, and occasionally needs to delay one or two iterations to resolve values for recent log entries. Since the data analysis must operate on data at the same time points, cross-instance sychronization is needed within the hadoop_log module to ensure that data outputs for each node is updated with Hadoop log data from the same time point.

Since fpt-core has limited control flow, such data synchronization is implemented within the scope of the hadoop_log module itself. Since each module instance shares the same address space, global timestamps are maintained for the most recently seen and most recently outputted timestamps. The hadoop_log module waits for all nodes to reveal data with the same timestamp before updating its outputs, or, if one or more nodes does not contain data for a particular timestamp, this data is dropped.

A more general point concerning online fingerpointing is that data collection may potentially be faster than data analysis. Since some heavyweight analysis algorithms may take many seconds to complete, multiple data collection iterations are likely to occur during ths computation time. Normally, since the analysis algorithms cannot absorb the incoming data flow in a timely fashion, many of these data points are likely to be dropped. To handle this rate mismatch, a buffer module (ibuffer) has been written to collect individual data points from a data collection module output, and present the data as an array of data points to an analysis module, which can then process a larger data set more slowly.

4 Applying ASDF to Hadoop

One of our objectives is to show the ASDF framework in action for Hadoop, effectively demonstrating that we can localize performance problems (that have been reported in Apache's JIRA issue tracker [8]) using both black-box and white-box approaches, for a variety of workloads and even in the face of workload changes. This section provides a brief background of Hadoop, a description of the reported Hadoop problems that we pursued for fingerpointing, the ASDF data and analysis modules that are relevant to Hadoop, and concludes with experimental results for fingerpointing problems in Hadoop.

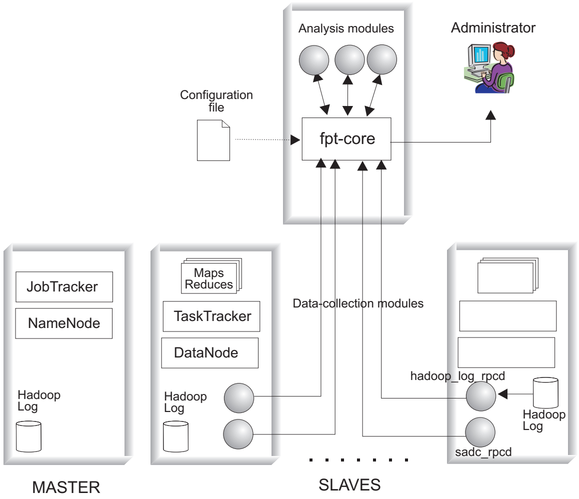


Figure 3: Deploying ASDF and its modules for a Hadoop cluster. The `fpt-core` runs on the ASDF control node.

4.1 Hadoop

Hadoop [9] is an open-source implementation of Google's MapReduce [6] framework. MapReduce eases the task of writing parallel applications by partitioning large blocks of work into smaller chunks that can run in parallel on commodity clusters (effectively, this achieves high performance with brute-force, operating under the assumption that computation is cheap). The main abstractions in MapReduce are (i) Map tasks that process the smaller chunks of the large dataset using key/value pairs to generate a set of intermediate results, and (ii) Reduce functions that merge all intermediate values associated with the same intermediate key.

Hadoop uses a master/slave architecture to implement the MapReduce programming paradigm. Each MapReduce job is coordinated by a single JobTracker that is responsible for scheduling tasks on slave nodes and for tracking the progress of these tasks in conjunction with slave TaskTrackers that run on each slave node. Hadoop uses an implementation of the Google Filesystem [18] known as the Hadoop Distributed File System (HDFS) for data storage. HDFS also uses a master/slave architecture that consists of a designated node, the NameNode, to manage the file-system namespace and to regulate access to files by clients, along with multiple DataNodes to store the data.

Due to the large scale of the commodity clusters, Hadoop assumes that failures can be fairly common and incorporates multiple fault-tolerance mechanisms, including heartbeats, re-execution of failed tasks and data replication, to increase the system's resilience to failures.

4.2 Problems of Interest

We sought to discover which types of problems were prevalent in Hadoop and examined a survey of 41 resolved bugs in Apache's JIRA issue tracker for Hadoop [8] over the 14-month period from October 1, 2006 to December 1, 2007. We limited our investigations to bugs that affected either HDFS or MapReduce.

We also scanned the Hadoop users' mailing list for similar information. However, due to the large volume of postings to the mailing list, we sampled 40 postings over the 3-month period from September–November 2007.

Examining these 81 incidents, we classified the reported problems according to their manifestation, namely, into the following distinct categories:

Manifestation	[Source] Reported Problem	Problem-Injection for Validation
Hang	[Hadoop 1036] Infinite loop at TaskTracker due to an unhandled exception. The process hang is not detected by the JobTracker heartbeats due to an error in handling task cleanup.	Induce by reverting patch and triggering bug by throwing NULL exception.
	[Hadoop 1255] Infinite loop at NameNode if a DataNode registers twice then subsequently dies. The NameNode hangs when attempting to clear the duplicate registration from the queue.	Registered the DataNode with the NameNode twice and, then, crashed the DataNode.
Limp	[Hadoop users' mailing list, Sep 13, 2007] CPU bottleneck caused by running the NameNode and the DataNode on the same machine.	Emulated by running a CPU-intensive task that uses 70% of the CPU.
	[Hadoop users' mailing list, Sep 26, 2007] Excessive messages logged to file during the JobTracker's startup.	Launch a sequential disk workload that writes 20GB of data to the file system.

Figure 4: Reported Hadoop performance problems that we chose to diagnose.

- Crash/abort–the job/task terminates abnormally;
- Hang–the job/task fails to make any progress;
- Limp–the job makes progress but is abnormally slow;
- Error–the execution of the job/task generates exception messages in the logs;
- Incorrect–the job/task produces an incorrect value as its result.

The performance problems that we elected to diagnose in Hadoop are listed in Table 4. We also indicate whether these problems were reported in the JIRA (denoted by "Hadoop ####", where #### represents the bug/issue number in JIRA) or the Hadoop users' mailing list. Also included in this table is the problem-injection methodology that we used to validate ASDF's fingerpointing capabilities. In our validation experiments, described in Section 4.7, we artificially induce these problems, one problem at a time on one node at a time, in a Hadoop cluster that is under monitoring by ASDF.

4.3 ASDF for Hadoop

As Figure 3 shows, we deploy ASDF to fingerpoint the performance problems of interest listed in Section 4.2. The Hadoop cluster consists of a master node and a number of slave nodes. In the experiments described in this paper, we fingerpoint problems only on the slave nodes, as the number of slave nodes in a Hadoop cluster can be arbitrarily many in the order of master nodes, so it appears most profitable to begin problem diagnosis from the slave nodes. Nonetheless, there is nothing inherently in ASDF's architecture that would prevent us from fingerpointing problems on the master node as well.

On each slave node, we run two daemons (sadc_rpcd and hadoop_log_rpcd) that interface with the fpt-core running on the ASDF control node shown in the figure. The sadc_rpcd modules on each node support black-box fingerpointing, while the hadoop_log_rpcd modules on each node support white-box fingerpointing. In fact, the ASDF framework supports both the black-box and the white-box analyses in parallel, as shown in the data-flow diagrams in Figure 5.

Each node runs a sadc daemon and/or a hadoop_log daemon, depending on whether black-box and/or white-box analysis is being performed. These RPC daemons expose procedures that return system statistics in the case of sadc and Hadoop state information in the case of the hadoop_log module. A single ASDF instance is run on a dedicated machine (the ASDF control node) in the cluster which runs a small number of

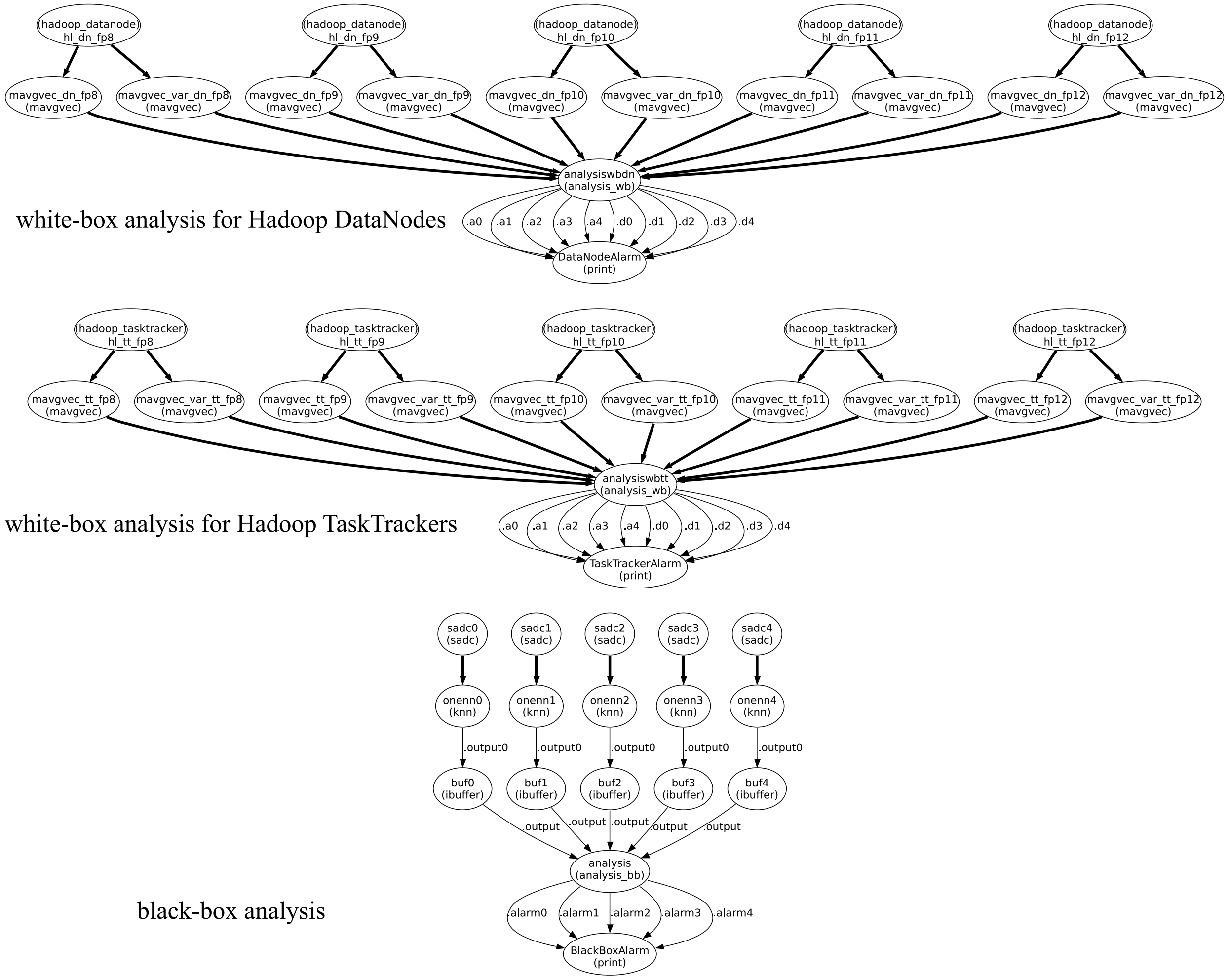

(hadoop_datanode) hl_dn_fp8
(hadoop_datanode) hl_dn_fp9
(hadoop_datanode) hl_dn_fp10
(hadoop_datanode) hl_dn_fp11
(hadoop_datanode) hl_dn_fp12
mavgvec_dn_fp8 (mavgvec)
mavgvec_var_dn_fp8 (mavgvec)
mavgvec_dn_fp9 (mavgvec)
mavgvec_var_dn_fp9 (mavgvec)
mavgvec_dn_fp10 (mavgvec)
mavgvec_var_dn_fp10 (mavgvec)
mavgvec_dn_fp11 (mavgvec)
mavgvec_var_dn_fp11 (mavgvec)
mavgvec_dn_fp12 (mavgvec)
mavgvec_var_dn_fp12 (mavgvec)
analysiswbdn (analysis_wb)
white-box analysis for Hadoop DataNodes
.a0 .a1 .a2 .a3 .a4 .d0 .d1 .d2 .d3 .d4
DataNodeAlarm (print)
(hadoop_tasktracker) hl_tt_fp8
(hadoop_tasktracker) hl_tt_fp9
(hadoop_tasktracker) hl_tt_fp10
(hadoop_tasktracker) hl_tt_fp11
(hadoop_tasktracker) hl_tt_fp12
mavgvec_tt_fp8 (mavgvec)
mavgvec_var_tt_fp8 (mavgvec)
mavgvec_tt_fp9 (mavgvec)
mavgvec_var_tt_fp9 (mavgvec)
mavgvec_tt_fp10 (mavgvec)
mavgvec_var_tt_fp10 (mavgvec)
mavgvec_tt_fp11 (mavgvec)
mavgvec_var_tt_fp11 (mavgvec)
mavgvec_tt_fp12 (mavgvec)
mavgvec_var_tt_fp12 (mavgvec)
analysiswbtt (analysis_wb)
white-box analysis for Hadoop TaskTrackers
.a0 .a1 .a2 .a3 .a4 .d0 .d1 .d2 .d3 .d4
TaskTrackerAlarm (print)
sadc0 (sadc)
sadc1 (sadc)
sadc2 (sadc)
sadc3 (sadc)
sadc4 (sadc)
onenn0 (knn)
onenn1 (knn)
onenn2 (knn)
onenn3 (knn)
onenn4 (knn)
.output0
.output0
.output0
.output0
.output0
buf0 (ibuffer)
buf1 (ibuffer)
buf2 (ibuffer)
buf3 (ibuffer)
buf4 (ibuffer)
.output
.output
.output
.output
.output
analysis (analysis_bb)
black-box analysis
.alarm0 .alarm1 .alarm2 .alarm3 .alarm4
BlackBoxAlarm (print)

Figure 5: The DAG constructed by `fpt-core` to fingerpoint Hadoop.

ASDF modules for each machine, each of which makes requests to the RPC daemons of a particular slave node.

We decided to collect state data from Hadoop's logs instead of instrumenting Hadoop itself, in keeping with our original goal of supporting problem diagnosis in production environments. This has the added advantage that we do not need to stay up-to-date with changes to the Hadoop source code and can confine ourselves to the format of the Hadoop logs alone.

The hadoop_log parser provides on-demand, lazy parsing of the logs generated by each of the Hadoop DataNode and TaskTracker instances to generate counts of *event* and *state* occurrences (as defined in Section 4.4). All information from prior log entries is summarized and stored in compact internal representations for just sufficiently long durations to infer the states in Hadoop. We refer interested readers to [19] for further implementation details. The ASDF hadoop_log collection module exposes the log parser counters as FPT outputs for analysis modules. Again, ONC RPC is used to collect remote statistics from a hadoop_log_rpcd daemon which provides an interface to the log parser library.

4.4 Hadoop: White-Box Log Analysis

We have devised a novel method to extract white-box metrics which characterize Hadoop's high-level modes of execution (e.g. Map task, Reduce task taking place) from its textual application logs. Instead of text-mining logs to automatically identify features, we construct an *a priori* view of the relationship between Hadoop's mode of execution and its emitted log entries. This *a priori* view enabled us to produce structured numerical data, in the form of a numerical vector, about Hadoop's mode of execution.

Consider each thread of execution in Hadoop as being approximated by a deterministic finite automaton (DFA), with DFA **states** corresponding to the different modes of execution. Next, we define **events** to be the entrance and exit of states, from which we derive DFA transitions as a composition of one state-entrance and one state-exit event. Since Hadoop is multi-threaded, its aggregate high-level mode of execution comprises multiple DFAs representing the execution modes in simultaneously executing threads. This aggregate mode is represented by a vector of states for each time instance, showing the number of simultaneously executing instances of each state. A full list of states that characterize the high-level behavior of Hadoop is in [19].

Each entry in a Hadoop log corresponds to one event–a state-entrance or state-exit event, or an "instant" event (a special case which denotes the immediate entrance to and subsequent exit from a state for short-lived processing, e.g. a block deletion in the Hadoop DataNode). Then, we parse the text entries of the Hadoop logs to extract events. By maintaining a minimal amount of state across log entries, we then infer the vector of states at each time instance by counting the number of entrance and exit events for each state (taking care to include counts of short-lived states, for which entrance and exit events, or instant events, occurred within the same time instance). Some important states for the TaskTracker are Map and Reduce tasks, while some important states for the DataNode are those for the data-block reads and writes. Details of the log parser implementation and architecture are in [19]. We show, in Figure 6, a snippet of a TaskTracker log, and the interpretations that we place on the log entries in order to extract the corresponding Hadoop states, as we have defined them.

We have currently implemented a log-parser library for the logs gathered from the DataNode and the TaskTracker. This library maintains state that has constant memory use in the order of the duration for which it is run. In addition, we have implemented an RPC daemon that returns a time series of state vectors from each running Hadoop slave, and an ASDF module which harvests state vectors from RPC daemons for use in diagnosis.

To fingerpoint using the white-box metrics, we compute the mean of the samples for a white-box metric *metric* over the window for all the nodes (denoted by $mean\_metric_i$ for node i) and use the mean values for peer comparison. One way to do the peer comparison is to compute the difference (called $diff\_mean\_metric_{i,j}$) of $mean\_metric_i$ at node i with $mean\_metric_j$ at the other nodes. A node i is classified

```
2008-04-15 14:23:15,324 INFO org.apache.hadoop.mapred.TaskTracker:  LaunchTaskAction:
task_0001_m_000096_0
2008-04-15 14:23:16,375 INFO org.apache.hadoop.mapred.TaskTracker:  LaunchTaskAction:
task_0001_r_000003_0
2008-04-15 14:23:26,755 INFO org.apache.hadoop.mapred.TaskRunner:  task_0001_r_000003_0 Copying
task_0001_m_000128_0 output from pc73.emulab.net.
2008-04-15 14:23:31,595 INFO org.apache.hadoop.mapred.TaskRunner:  task_0001_r_000003_0 done
copying task_0001_m_000128_0 output from pc73.emulab.net.
```

Time	…	*MapTask*	*ReduceTask*	…	*ReduceCopy_Remote*	…
2008-04-15 14:23:15	…	1	0	…	0	…
2008-04-15 14:23:16	…	1	1	…	0	…
⋮						
2008-04-15 14:23:26	…	1	1	…	1	…
2008-04-15 14:23:27	…	1	1	…	1	…
⋮						
2008-04-15 14:23:31	…	1	1	…	0	…

Figure 6: A snippet from a TaskTracker Hadoop log showing the log entries that trigger *StateStartEvent*s and *StateStopEvent*s for the *ReduceCopyTask_Remote* states, along with the log entries that trigger the *StateStartEvent* for the *MapTask* and *ReduceTask* states.

as anomalous if $diff\_mean\_metric_{i,j}$ for $j = 1,2,\ldots,N$ is greater than a threshold value for more than $\frac{N}{2}$ nodes. This process can be repeated for all the nodes in the system leading to N^2 comparison operations. To reduce the number of comparisons, we use an alternate method: we compute the median of the $mean\_metric_i$ for $i = 1,2,\ldots,N$ (i.e., across all the nodes in the system). Denote the median value $median\_mean\_metric$. Since more than $\frac{N}{2}$ nodes are fault-free the $median\_mean\_metric$ will correctly represent the metric mean for fault-free nodes. We then compare $mean\_metric_i$ for each node i with $median\_mean\_metric$ value and flag a node as anomalous if the difference is more than a threshold value. A node is fingerpointed during a window if one or more of its white-box metrics show an anomaly. To determine the threshold values for a white-box metric we first compute the standard deviations of the metric for all the slave nodes over the window.

We chose the threshold value for all the metrics to be of the form $max\{1, k \times sigma_{median}\}$ where k is a constant (for all the metrics) whose value is chosen to minimize the false positive rate over fault-free training data (as explained in Section 4.9). The intuition behind the choice of $k \times \sigma_{median}$ in the threshold is that if the metric has a large standard deviation over the window then it is likely that the difference in the mean value of the metric across the peers will be larger requiring a larger threshold value to reduce false positives and vice versa. The reason for choosing the threshold value to be of the form $max 1, k \times \sigma_{median}$ is that several white-box metrics tend to be constant in several nodes and vary by a small amount (typically 1) in one node. The fact that the white-box metric is a constant over the window for a node implies that the standard deviation for that metric will be zero for that node. If several nodes have zero standard deviation, the median standard deviation will also turn out to be zero and will cause significant false positives for the node on which the metric varies by as small as 1.

4.5 Hadoop: Black-Box Analysis

Our hypothesis for fingerpointing slave nodes in the Hadoop system is that we can use peer comparison across the slave nodes to localize the specific node with performance problems. The intuition behind the hypothesis is that on average, the slave nodes will be doing similar processing (map tasks or reduce tasks) and as a result the black-box and white-box metrics would have similar behavior across the nodes in fault free conditions. The black-box and white-box metrics of the slave nodes will behave similarly even if there are changes in the workload since a workload change may cause more (or fewer) maps or reduces to be launched on all the slave nodes. However, when there is a fault in one of the slave nodes, the black-box and white-box metrics of the faulty node will show significant departure from that of the other (non-faulty) slave nodes. We can therefore use peer comparison of averaged metrics to detect faulty nodes in the system. Our hypothesis rests on the following two assumptions i) all the slave nodes are homogeneous and ii) more than half of the nodes in the system are fault-free (otherwise, we may end up fingerpointing the non-faulty nodes since their behavior will differ from the faulty nodes).

Our analysis algorithm gathers black-box as well as white-box metrics from all the slave nodes. We collect samples of white-box and black-box metric samples from all the nodes over a window of size *windowSize*. For each node we collect one sample of each white-box and black-box metric per second over the window. Consecutive windows over which the metrics are collected can overlap with each other by an amount equal to *windowOverlap*.

In our black-box fingerpointer, we first characterize the workload perceived at each node by using all the black-box metrics from it. We classify the workload perceived at the node by considering the similarity of its metric vector to a pre-determined set of centroid vectors. Its closest centroid vector is then determined using the one Nearest Neighbor (1-NN) approach. The pre-determined set of centroid vectors are generated by using offline k-Means clustering using fault-free training data consisting different workloads (the random writer and sort sample applications, and the Nutch web crawler).

Instead of using raw metric values to characterize workloads, we use the logarithm of every metric sample (we used $\log(x+1)$ for a metric value, x to ensure positive values for logarithms). We used logarithms to reduce the dynamic range of metric samples since many black-box metrics have a large dynamic range. Furthermore, we scaled the resulting logarithmic metric samples by the standard deviation of the logarithm computed over the fault-free training data. We use these vectors of scaled logarithmic metric values (denoted by $\mathbf{X}_i$ for node i) for comparison against the pre-determined centroid vectors using the 1-NN approach. The outcome of the 1-NN is the assignment of a "state" to each $\mathbf{X}_i$ (the index of the centroid vector closest to $\mathbf{X}_i$).

For each state we determine the number of vectors $\mathbf{X_i}$ that were assigned to it over a window of size *windowSize*. This generates, for a node j, a vector ($\mathbf{StateVector_j}$) whose dimensions are equal to the number of centroids, and whose k-th component represents the number of times the centroid k was associated with $\mathbf{X_i}$ for that node in the window. The $\mathbf{StateVector_j}$ for $j = 1,2,3,\ldots,N$ are used for peer comparison to detect the anomalous nodes. This is done by first computing a component-wise median vector (denoted by **medianStateVector**) and then comparing $\mathbf{StateVector_j}$ with **medianStateVector**. We use the $\mathscr{L}_1$ distance of $\mathbf{StateVector_j} - \mathbf{medianStateVector}$ for $j = 1,2,3,\ldots,N$ and flag a node j as anomalous if the $\mathscr{L}_1$ distance of $\mathbf{StateVector_j} - \mathbf{medianStateVector}$ is greater than a pre-determined threshold.

4.6 Metrics

False-positive rate. A false positive occurs when ASDF wrongly fingerpoints a node as a culprit when there are no faults on that node. Because alarms demand attention, false alarms divert resources that could otherwise be utilized for dealing with actual faults. We measured the false-positive rates of our analyses on data traces where no problems were injected; we can be confident that any alarm raised by ASDF in these traces are false positives. By tuning the threshold values for each of our analysis modules, we were able to observe different average false-positive rates on the problem-free traces.

Fingerpointing latency. An online fingerpointing framework should be able to quickly detect problems in the system. The fingerpointing latency is the amount of time that elapses from the occurrence of a problem to the corresponding alarm identifying the culprit node. It would be relevant to measure the time interval between the first manifestation of the problem and the raising of the corresponding alarm; however, doing so assumes the ability to tell when the fault first manifested. However, the detection of a fault's manifestation is precisely the problem that we are attempting to solve. We instead measure the time interval between the injection of the problem by us and the raising of the corresponding alarm.

4.7 Empirical Validation

We performed our experiments on Hadoop version 0.12.4 running on the amd64 version of Debian GNU/Linux 4.0. We verified that the computational usage of `ASDF` would be constant and small compared to the that of Hadoop. We assumed that each node's primary responsibility was to run Hadoop jobs. Each DataNode and TaskTracker instance ran on its own node. The NameNode and JobTracker instances also ran on their own node. We employed a dedicated `ASDF` control node to run the `fpt-core`.

Our experiments were conducted on a 38-node dedicated cluster. Each node consists of an AMD Opteron 1220 dual-core CPU with 4GB of memory, Gigabit Ethernet and a dedicated 320GB disk for HDFS storage.

`ASDF` is not dependent on a particular hardware configuration, though the relative overhead of our instrumentation is dependent on the amount of memory and processing power available. Although `ASDF` assumes the use of Linux and /proc, it is hardware-architecture-agnostic. For our white-box analysis, we make reasonable assumptions about the format of the Hadoop logs, but our Hadoop-log parser was designed so that changes to the log format could be accounted for.

We ran 10 fault-free workloads on a 6-node Hadoop cluster for each of the following workloads

- RandomWriter (4 Maps, where each Map writes 25GB to HDFS)
- Sort (sorts 6GB of data per node from HDFS)

We selected the parameters for the workloads so that each job ran for about 50 minutes on our cluster.

4.8 Performance Impact of `ASDF`

There are two concerns when considering the performance impact of `ASDF`. The first is the impact of data collection on the running Hadoop applications on the fingerpointee nodes, and the second is the cost of the analysis on the `ASDF` control node.

For data collection, it is preferred that the RPC daemons have minimal CPU time, memory, and network bandwidth overheads so as to minimally alter the runtime performance of the monitored system. In contrast, the cost of analysis on the `ASDF` control node is of a lesser concern since the `fpt-core` may run on a dedicated or otherwise idle cycle server. However, the cost of this analysis is still important as it dictates the size of the server needed, or alternatively for a given serrver, determines the number of monitored nodes to which the fingerpointer may scale.

As depicted in Table 1, for our white-box analysis, the `hadoop_log_rpcd`uses, on average, less than 0.02% of CPU time on a single core on cluster nodes, and less than 2.4 MB of resident memory. For our black-box analysis, the `sadc_rpcd` uses less than 0.36% of CPU time, and less than 0.77 MB of resident memory. Thus, the `ASDF` data collection has negligible impact on application performance.

For simultaneous black-box and white-box analysis, the `fpt-core`process on the `ASDF` control node uses, on average, less than 0.81% of CPU time on a single core, and less than 5.1 MB of resident memory, to monitor five nodes. Since the computation cost of the fingerpointing algorithms used in our analysis agents scales linearly with the number of monitored nodes, we expect to scale to hundreds of monitored nodes by running `fpt-core` on a single cycle server.

The per-node network bandwidths for both the black-box (`sadc`) and the white-box (`hadoop_log`) data-collection are listed in Table 2. Establishing a TCP RPC client connection with each monitored Hadoop slave

Process	% CPU	Memory (MB)
hadoop_log_rpcd	0.0245	2.36
sadc_rpcd	0.3553	0.77
fpt-core	0.8063	5.11

Table 1: CPU usage (% CPU time on a single core) and memory usage (RSS) for the data collection processes and the combined black-box & white-box analysis process.

node incurs a static overhead of 6 kB per-node, and each iteration of data collection costs less than 2 kB/s. Thus, the network bandwith cost of monitoring a single node is negligible, and the aggregate bandwith is on the order of 1 MB/s even when monitoring hundreds of nodes.

RPC Type	Static Ovh. (kB)	Per-iter BW (kB/s)
sadc-udp	0.80	0.74
sadc-tcp	1.98	1.22
hl-dn-udp	0.87	0.19
hl-dn-tcp	2.04	0.31
hl-tt-udp	0.87	0.20
hl-tt-tcp	2.04	0.32
UDP Sum	2.55	1.13
TCP Sum	6.06	1.85

Table 2: RPC bandwidth for both UDP and TCP transports for the three ASDF RPC types: sadc, hadoop_log-datanode, hadoop_log-tasktracker. Static overheads include per-node traffic to create/destroy connections, and the per-iteration bandwidth includes per-node traffic for each iteration (one second) of data collection.

4.9 Results

Black-box Offline Analysis. We conducted two sets of experiments. In the first set, we ran three different Hadoop jobs (and different workloads, RandomWriter and sort) without injecting any problems. Black-box data was collected by the ASDF for offline analysis. The *windowSize* parameter was set to 30 samples. We varied the threshold value from 0 to 60 for the problem-free traces to assess the false-positive rates, and then used the threshold value that resulted in a low false-positive rate.

In the second set of experiments, we ran the RandomWriter and sort workloads, but unlike the first set of experiments, we injected performance problems from Section 4.2 into the runs. Black-box data was again collected, and the black-box analysis module was used to fingerpointings problems. The *windowSize* parameter was set to 30 samples, and we measured the false-positive rates for a threshold value of 25.

Figure 7 shows the false-positive rates for the different threshold levels. As the threshold is initially increased from 0, false-positive rates drop rapidly. However, beyond a threshold of 20, any further increases in threshold lead to little improvement in the false-positive rates.

Table 9 shows that our black-box analysis detects most of the problems injected on the RandomWriter and sort workloads, with the exception of the CPU-hog and disk-hog problems on the RandomWriter. This is because disk activity in all slave nodes dominate all other activity, so little difference is observed in the black-box metrics of the peer slave nodes.

White-box Offline Analysis. To validate our white-box analysis module, we ran similar sets of experiments as those for the black-box analysis. We again chose a *windowSize* of 30 samples. We varied the value of *k* from 0 to 5 for the problem-free traces to assess the false-positive rates, and then used the value of *k* that

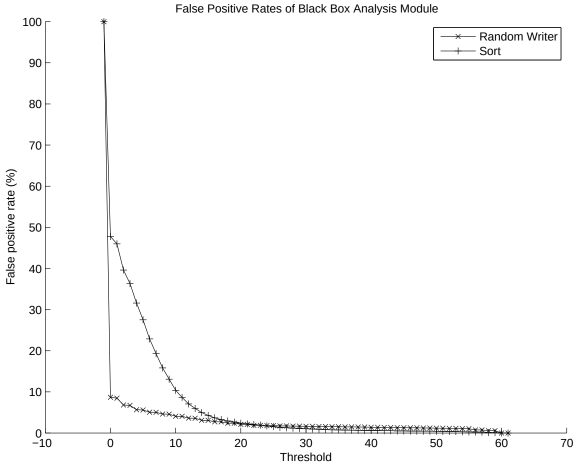


Figure 7: False-positive rates for black-box analysis.

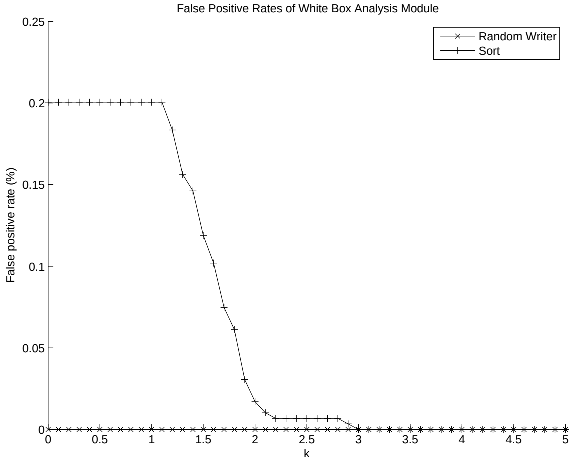


Figure 8: False-positive rates for white-box analysis.

resulted in a low false-positive rate.

For the second set of experiments, we induced the performance problems listed in Section 4.2, and ran the white-box analysis module offline on the data collected during the run. The same *windowSize* of 30 samples was chosen, and *k* was set to 2.

Figure 8 shows the false-positive rates for the different values of *k*. False-positive rates are under 0.2%, and we observe little improvement when the value of *k* is increased beyond 2.

Table 9 shows that we were able to detect the Hadoop problem 1036. However, the resource hogs and Hadoop problem 1255 were not detected. Since Hadoop is unaware of activity outside of itself, the white-box analysis module is unable to detect the resource hogs. The culprit node in Hadoop problem 1255 crashes, and thus, no further log events are produced, resulting in the white-box module being able to detect the problem.

White- and Black-box Online Analysis. In addition to the above two experiments, we also used our online fingerpointing framework with both black- and white-box metrics to successfully fingerpoint process-hangs (Hadoop problem 1036 running the RandomWriter workload) in one of the slave nodes.

The latency for fingerpointing the culprit node was less than 1 minute for the online version of our

		Diagnosable	Diagnosable
Workload	Bug	using Black-box?	White-box?
Random-writer	CPU-hog	No	No
	Disk-hog	No	No
	HADOOP-1036	Yes	Yes
	HADOOP-1255	Yes	No
Workload	Bug	using Black-box?	White-box?
Sort	CPU-hog	Yes	No
	Disk-hog	Yes	No
	HADOOP-1036	Yes	Yes
	HADOOP-1255	Yes	No

Figure 9: Outcome of offline black- and white-box fingerpointing.

white-box analysis module, as well as the black-box analysis module. The white-box analysis was marginally faster, by about 5 seconds.

5 Future Work

In its current implementation, `fpt-core` provides for unidirectional data flow between data collection and analysis modules with no cycles or data feedback. `fpt-core` however, does not yet allow module instances to run remotely on different nodes, nor does it allow for explicit data synchronization or other control flow between module instances.

We believe these features are necessary to support a robust framework, however, it was unclear until after our experience with fingerpointing in Hadoop exactly how to implement these features in a general, extensible fashion. From our experience in implementing cross-node RPC and cross-instance data synchronization in the context of the `hadoop_log` module, we are now evaluating plans to implement a cross-node communications layer within `fpt-core` itself.

We are currently developing new `ASDF` modules, including a `strace` module that tracks all of the system calls made by a given process. We envision using this module to detect and diagnose anomalies by building a probabilistic model of the order and timing of system calls and checking for patterns that correspond to problems.

We also plan to equip `ASDF` with the ability to actively mitigate the consequences of a performance problem once it is detected. Upon detecting a failure, an `ASDF` euthanizer module would kill the process and notify other Hadoop nodes.

6 Related Work

Since our work on `ASDF` involves two complementary aspects–monitoring/instrumentation and problem-diagnosis techniques–we cover the related work in both those aspects.

Monitoring Tools. Numerous tools exist for the performance monitoring of distributed systems of networked computers. Nagios [16] and Ganglia [10] are monitoring systems that coordinate the collection of performance indicators on each networked node in a distributed system. Ganglia focuses on keeping the gathered data compact for storage and visualization, while Nagios, in addition to metric collection, allows rudimentary "state flapping" checks to identify excessively frequent changes in service availability. X-Trace [7] is a network-level tracing tool that aggregates trace messages generated by custom network-level or application-level instrumentation. These tools produce coordinated views of a distributed system of communicating components. More recently, X-Trace has been applied to Hadoop [15]. Our work differs from these tools by building an automated, online problem-diagnosis framework that can certainly leverage Ganglia, Nagios and X-Trace output as its data sources, if these data sources are already available in production environments.

Application-Log Analysis. Splunk [12], a commercial log-analyzer, treats logs as searchable text indexes and generates views of system anomalies. Our use of application logs, specifically those of Hadoop, differs from Splunk by converting logs into numerical data sources that then become immediately comparable with other numerical system metrics.

Cohen et. al. [4] have also examined application logs, but they used feature selection over text-mining of logs to identify co-occurring error messages, and extracted unstructured data from application logs that limited the extent to which typical machine learning techniques could be used to synthesize the application views from the application logs and system metrics.

Problem-Diagnosis Techniques. Current problem-diagnosis work [1, 13] focuses mostly on collecting traces of system metrics for offline processing, in order to determine the location and the root-cause of problems in distributed systems. While various approaches, such as Magpie [2] and Pinpoint [3], have explored the possibility of online implementations (and can arguably be implemented to run in an online manner), they have not been used in an online fashion for live problem localization even as the system under diagnosis is executing. Our ASDF framework was intentionally designed for the automated online localization of problems in a distributed system; this required us to address not just the attendant analytic challenges, but also the operational issues posed by the requirement of online problem-diagnosis. Cohen et al.'s [5] work continuously builds ensembles of models in an online fashion and attemtps to perform diagnosis online. Our work differs from that of Cohen et al. by building a pluggable architecture, into which arbitrary data sources can be fed to synthesize information across nodes. This enables us to utilize information from multiple data sources simultaneously to present a unified system view as well as to support automated problem-diagnosis.

In addition, Pinpoint, Magpie, and Cohen et al.'s work rely on large numbers of requests to use as labeled training data *a priori* for characterizing the system's normal behavior via clustering. However, Hadoop has a workload of long-running jobs, with users initiating jobs at a low frequency, rendering these techniques unsuitable. Pip [14], which relies on detecting anomalous execution paths from many possible ones, will also have limited effectiveness at diagnosing problems in Hadoop. Execution paths in Hadoop are generally uninteresting for problem-diagnosis, as these paths are homogeneous within any given job, and offer limited opportunities for clustering to infer other types of possible normal paths.

The idea of correlating system behavior across multiple layers of a system is not new. Hauswirth et al's "vertical profiling" [11] aims to understand the behavior of object-oriented applications by correlating metrics collected at various abstraction levels in the system. Vertical profiling was used to diagnose performance problems in applications in a debugging context at development time, requiring access to source code while our approach diagnoses performance problems in production systems without using application knowledge.

Triage [21] uses a check-point/reexecution framework to diagnose software failures on a single machine in a production environment. They leverage an ensemble of program analysis (white-box) techniques to localize the root-cause of problems. ASDF is designed to flexibly integrate both black-box and white-box data sources, providing the opportunity to diagnose problems both within the application, and due to external factors in the environment. Triage targeted single-host systems whereas ASDF targets distributed systems.

7 Conclusion

In this paper, we described our experience in designing and implementing the ASDF online problem-localization framework. The architecture is intentionally designed for flexibility in adding or removing multiple, different data-sources and multiple, different data-analysis techniques. This flexibility allows us to attach a number of data-sources for analysis, as needed, and then to detach any specific data-sources if they are no longer needed.

We also applied this Hadoop, effectively demonstrating that we can localize performance problems (that have been reported in Apache's JIRA issue tracker [8]) using both black-box and white-box approaches, for a variety of workloads and even in the face of workload changes. We demonstrate that we can perform online fingerpointing in real time, that our framework incurs reasonable overheads and that our false-positive rates are low.

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