ASDF : An Automated, Online Framework for Diagnosing Performance Problems ⋆ ⋆⋆

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Abstract.
Performance problems account for a significant percentage of documented failures in large-scale distributed systems, such as Hadoop. Localizing the source of these performance problems can be frustrating due to the overwhelming amount of monitoring information available. We automate problem localization using ASDF an online diagnostic framework that transparently monitors and analyzes different time-varying data sources (e.g., OS performance counters, Hadoop logs) and narrows down performance problems to a specific node or a set of nodes. ASDF's flexible architecture allows system administrators to easily customize data sources and analysis modules for their unique operating environments. We demonstrate the effectiveness of ASDF's diagnostics on documented performance problems in Hadoop; our results indicate that ASDF incurs an average monitoring overhead of 0.38% of CPU time and achieves a balanced accuracy of 80% at localizing problems to the culprit node.

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.

⋆ ASDF stands for Automated System for Diagnosing Failures

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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 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 approach extracts more information to ascertain the underlying root cause of a problem. Hybrid, or *grey-box*, diagnostic approaches leverage the strengths of both *white-box* and *black-box* approaches.

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 [1], an open-source implementation of the MapReduce programming paradigm [2] that supports long-running, parallelized, data-intensive computations over a large cluster of nodes.

This chapter 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 [3]. 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 white-box and black-box data sources 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 Sections 1 and 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. Current online problem-localization frameworks, such as `IBM Tivoli Enterprise Console` [4] and `HP Operations Manager` [5], allow users to augment rules to their existing algorithms but are not geared towards plugging-in new analysis algorithms. As far as we know, `ASDF` is also the first to demonstrate the online diagnosis of problems in Hadoop by analyzing multiple data-sources (black-box and white-box) of varying rates, without requiring modifications to Hadoop or to any applications that Hadoop supports.

1 Online Monitoring and Diagnosis Frameworks

Online monitoring and diagnosis frameworks provide a unified view of the diverse data sources present in distributed systems, and ease the task of detecting and diagnosing problems. These frameworks are designed to: (i) *flexibly* support new data sources and analysis modules; (ii) *scale* gracefully with the number of nodes in the system; (iii) impose *minimal runtime overheads*; and (iv) *ease maintenance* through the automated deployment of monitoring and analysis scripts.

The key components of an online monitoring and diagnosis framework, as illustrated in Figure 1, are:

- Data collectors: Data collectors are daemons which run on each node and collect data from diverse sources such as application logs, and OS performance counters. These data sources can be broadly classified as *time-triggered* sources that are sampled periodically, *event-triggered* sources that are collected whenever an event such as an error occurs, and *request-flow* sources that trace the flow of individual requests across nodes. Data collectors may exploit pre-defined schemas [6–8] to parse data, or they may forgo the need for schemas and store data in a search index [9]. They impose minimal overhead through a combination of data buffering, and sampling.
- Data aggregators: Data aggregators periodically poll a collection of data sources and persist data to file. A primary concern during aggregation is portable transmission of data across heterogeneous nodes. Frameworks achieve portability by using portable data formats such as External Data Representation (XDR) [7], or by leveraging middleware such as ZeroC's ICE (Internet Communications Engine) [10].
- Data analysis: Diagnosis frameworks may schedule analysis modules periodically, or upon the occurrence of pre-defined events. Analysis modules may run locally on each node, or globally at a central node. Local algorithms typically perform simple computations such as data-smoothing, while global algorithms cross-correlate data across multiple nodes. Thresholds for problem detection within the algorithms tradeoff the detection of real problems against the generation of false-positives.
- Persistent storage: Archival of historical data becomes increasingly important as the system scales. Popular archival options are data warehouses [4, 5], round-robin databases [7, 6], and search indices [9]. Companies, such as Google, which process massive amounts of data are opting for distributed databases [11].

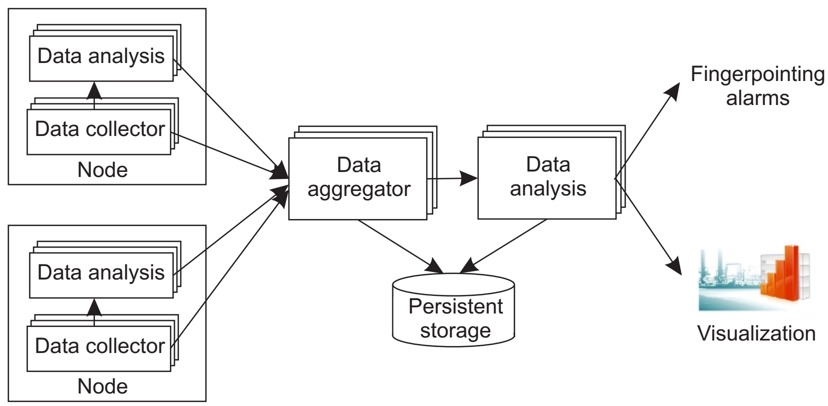


Fig. 1. Key components of online monitoring and diagnosis frameworks.

Category	**Example frameworks**	**Data sources**	**Data analysis**
Event/Time-triggered monitors	Ganglia[7], Nagios[6], Splunk[9], Tivoli[4], Operations Manager [5]	OS performance counters, logs, network data	Rule-based [7, 6, 9], event-correlation [4, 5]
Request-flow monitors	Dapper[11], XTrace [12], Magpie [8], Tivoli[4], Operations Manager [5]	RPC traces, application transactions	Clustering [8], Service-level agreement (SLA) violations [4, 5]

Table 1. Examples of online monitoring and diagnosis frameworks.

– Alarms and visualization: The fingerpointing alarms produced by online diagnosis frameworks range from simple alerts about node crashes and oversubscribed resources [7, 6], to application-specific alerts by sophisticated event-correlation algorithms [4, 5]. The frameworks typically support visualization of the monitored data to allow administrators to spot anomalous trends that might fall outside the scope of the automated diagnosis algorithms. For example, developers at Google used vizualization to pinpoint inefficient queries in their AdWords system [11].

Current online monitoring and diagnosis frameworks can be broadly classified as: (i) coarse-grained event/time-triggered monitors at the node, or process-level; and (ii) fine-grained request-flow monitors that track the progress of individual requests. Table 1 presents examples of these frameworks. The event/time-triggered frameworks [7, 6, 9, 4, 5] rely on event-correlation and human-generated rules for diagnosis, and are more popular than the request-flow frameworks [11, 12, 8]. This popularity stems from the easy-to-develop data collection modules, and the simple rule-based abstractions for diagnosis which shield administrators from complex algorithms. Current frameworks allow administrators to augment rules to their existing algorithms but are not geared towards plugging-in new analysis algorithms. ASDF's support for pluggable algorithms can accelerate testing and deployment of new analysis algorithms, and allow administrators to leverage off-the-shelf analysis techniques.

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 chapter, 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[3]. 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 modifications of, both the hosted applications and any middleware that they

[3] 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.

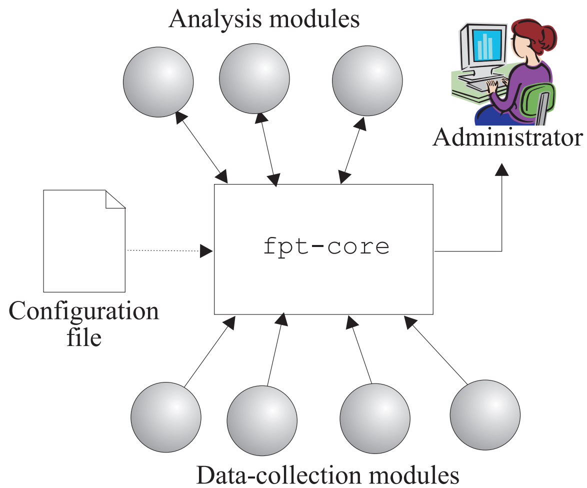


Fig. 2. Logical architecture of ASDF .

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 chapter 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 *sysstat* package [13]. `sadc` is the system activity data collector in the *sysstat* package that monitors system performance and usage activity, such as CPU, disk and memory usage. 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 2 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.

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). Each data-collection module, abc, has 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 periodically calls each of the module instances' *run()* function.

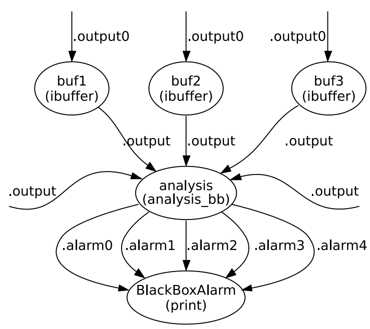
As part of the initialization process, module instances may request to be scheduled perodically, in which case their *run()* functions are called by the `fpt-core`'s scheduler at a fixed frequency. This allows the class of data-collection modules (that typically have no specified inputs) to perodically 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 3.




```
[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] =
   @analysis
```

Fig. 3. A snippet from the `fpt-core` configuration file that we used for Hadoop, along with the corresponding DAG.

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 [13] 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` 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 ZeroC's ICE (Internet Communications Engine) [10] RPC 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, mavgvec, 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, 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 [3]) 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.

4.1 Hadoop

Hadoop [1] is an open-source implementation of Google's MapReduce [2] 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 `tasktracker`s that run on each slave node. Hadoop uses an implementation of the Google Filesystem [14] 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 `datanode`s 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 Injected Faults

We injected one fault on one node in each cluster to validate the ability of our algorithms at diagnosing each fault. The faults cover various classes of representative real-world Hadoop problems as reported by Hadoop users and developers in: (i) the Hadoop issue tracker [3] from October 1, 2006 to December 1, 2007, and (ii) 40 postings from the Hadoop users' mailing list from September to November 2007. We describe our results for the injection of the six specific faults listed in Table 2.

4.3 `ASDF` for Hadoop

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 chapter, we fingerpoint problems only on the slave nodes, as the number of slave nodes in a Hadoop cluster can be arbitrarily many, 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

Fault Type	[Source] Reported Failure	[Fault Name] Fault Injected
Resource contention	[Hadoop mailing list, Sep 13 2007] CPU bottleneck from running master and slave daemons on same node.	[CPUHog] Emulate a CPU-intensive task that consumes 70% CPU utilization.
	[Hadoop mailing list, Sep 26 2007] Excessive messages logged to file.	[DiskHog] Sequential disk workload wrote 20GB of data to filesystem.
	[HADOOP-2956] Degraded network connectivity between `datanode`, s results in long block transfer times.	[PacketLoss] Induce 50% packet loss.
Application bugs	[HADOOP-1036] Infinite loop at slave node due to an unhandled exception from a Hadoop subtask that terminates unexpectedly.	[HADOOP-1036] Manually revert to older version of Hadoop and trigger bug by throwing NullPointerException.
	[HADOOP-1152] Reduce tasks fail while copying map output due to an attempt to rename a deleted file.	[HADOOP-1152] Manually revert to older version of Hadoop and trigger bug by deleting file.
	[HADOOP-2080] Reduce tasks hang due to a miscalculated checksum.	[HADOOP-2080] Simulated by miscomputing checksum to trigger a hang at reducer.

Table 2. Injected faults, and the reported failures that they simulate. HADOOP-xxxx represents a Hadoop JIRA entry.

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 4.

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 `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 [15] for further implementation details. The ASDF `hadoop_log` collection module exposes the log parser counters as FPT outputs for analysis modules. Again, ZeroC's ICE RPC

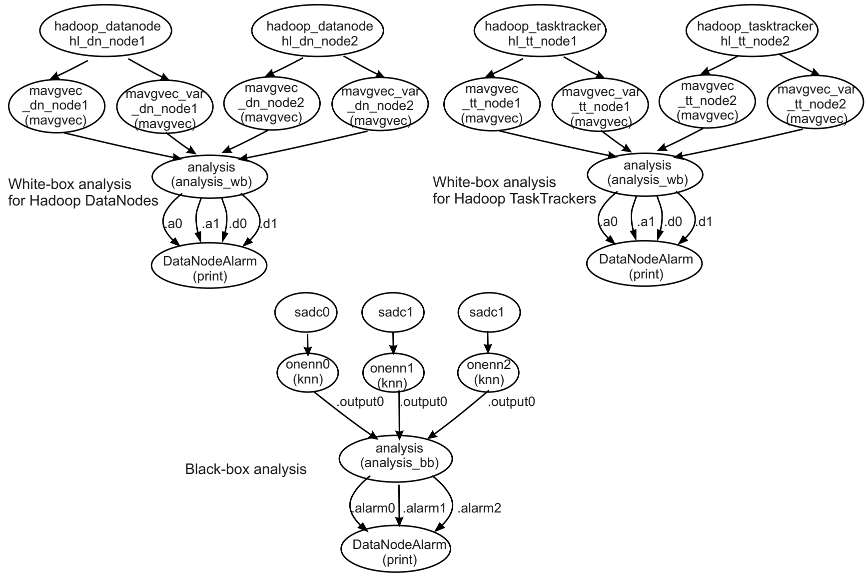


Fig. 4. The DAG constructed by `fpt-core` to fingerpoint Hadoop.

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 [15].

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

```
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
```

Time	...	*MapTask*	*ReduceTask*	...	...	...
2008-04-15 14:23:15	...	1	0	...	...	...
2008-04-15 14:23:16	...	1	1	...	...	...

Fig. 5. A snippet from a TaskTracker Hadoop log showing the log entries that trigger the *StateStartEvent* for the *MapTask* and *ReduceTask* states.

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 [15]. We show, in Figure 5, 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 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 $max1, k \times \sigma_{median}$ 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.

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 $\mathbf{StateVector_j} -$ **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 analyzed system metrics from Hadoop 0.18.3 running on 50-node clusters on Large instances on Amazon's EC2. Each node had the equivalent of 7.5 GB of RAM and two dual-core CPUs, running amd64 Debian/GNU Linux 4.0. Each experiment consisted of one run of the `GridMix` workload, a well-accepted, multi-workload Hadoop benchmark. `GridMix` models the mixture of jobs seen on a typical shared Hadoop cluster by generating random input data and submitting MapReduce jobs in a manner that mimics observed data-access patterns in actual user jobs in enterprise deployments. The `GridMix` workload has been used in the real-world to validate performance across

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

Table 3. 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.

different clusters and Hadoop versions. `GridMix` comprises 5 different job types, ranging from an interactive workload that samples a large dataset, to a large sort of uncompressed data that access an entire dataset. We scaled down the size of the dataset to 200MB for our 50-node clusters to ensure timely completion of experiments.

`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.

4.8 Performance Impact of ASDF

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 3, 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.

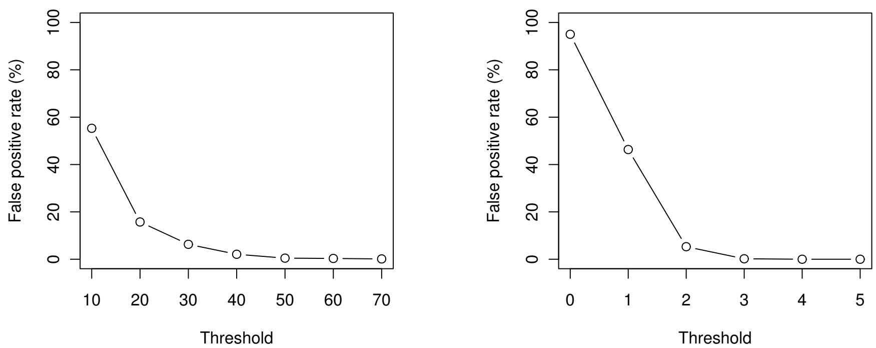
The per-node network bandwidths for both the black-box (`sadc`) and the white-box (`hadoop_log`) data-collection are listed in Table 4. Establishing a TCP RPC client connection with each monitored Hadoop slave node incurs a static overhead of 6 kB per-node, and each iteration of data collection costs 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.

4.9 Results

Black-box Analysis. We conducted two sets of experiments. In the first set, we ran three iterations of the `GridMix` workload without injecting any problems. Black-box data was collected by the `ASDF` for offline analysis. The *windowSize* parameter

RPC Type	Static Ovh. (kB)	Per-iter BW (kB/s)
sadc-tcp	1.98	1.22
hl-dn-tcp	2.04	0.31
hl-tt-tcp	2.04	0.32
TCP Sum	6.06	1.85

Table 4. RPC bandwidth for 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.



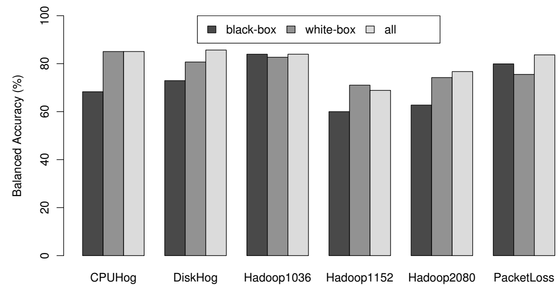
(a) Black-box analysis. (b) White-box analysis.

Fig. 6. False-positive rates for black-box and white-box analysis.

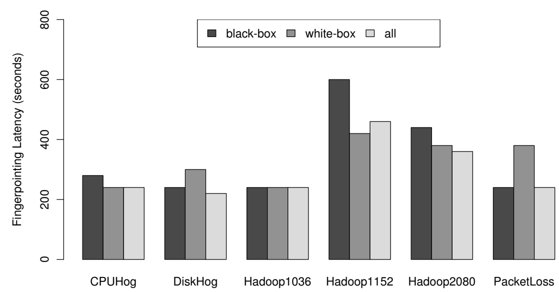
was set to 60 samples. We varied the threshold value from 0 to 70 for the problem-free traces to assess the false-positive rates, and then used the threshold value to that resulted in a low false-positive rate. In the second set of experiments, we ran the `GridMix` workloads, but unlike the first set 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 60 samples.

Figure 6(a) 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 60, any further increases in threshold lead to little improvement in the false-positive rates.

Figure 7(a) displays the balanced accuracy of our black-box diagnostic approach. The balanced accuracy ranges from 0 to 100%, and averages the probability of correctly identifying problematic and problem-free windows. A high balanced accuracy indicates a high true-positive rate and a low false-positive rate. The black-box approach was good at detecting resource-contention and hangs in Map tasks (`Hadoop-1036`)–the balanced accuracy ranged from 68% to 84%. The balanced accuracy for the hangs



(a) Balanced accuracy. A high balanced accuracy indicates a high true positive rate and low false positive rate.



(b) Fingerpointing latency. Delayed manifestation of hangs in reduce tasks (`Hadoop1152` and `Hadoop2080`) led to longer fingerpointing latencies and lower balanced accuracy.

Fig. 7. Fingerpointing results for faults injected.

in the reduce tasks (`Hadoop-1152` and `Hadoop-2080`) was low because the fault remained dormant for several minutes from the time we injected the fault to the time the application executed the faulty code. This delay resulted in longer fingerpointing latencies for hangs in Reduce tasks, as shown in Figure 7(b). The fingerpointing latencies for the other problems was about 200 seconds because it took at least 3 consecutive windows to gain confidence in our detection.

White-box 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 60 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 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 on the data collected during the run. The same *windowSize* of 60 samples was chosen, and k was set to 3. Figure 6(b) 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 3.

Figures 7(a) and 7(b) show that the white-box diagnostic approach had a higher balanced accuracy, and lower fingerpointing latency than the black-box approach. The difference in the two approaches was most pronounced for hangs in Reduce tasks (`Hadoop-1152` and `Hadoop-2080`) which first manifested as slowdowns in the Reduce tasks, before morphing into decreased activity in the OS performance counters. Combining the outputs of the white-box and black-box analysis yielded a modest improvement in the mean balanced accuracy for the set of problems we injected–the mean balanced accuracy was 71% for the black-box approach, 78% for the white-box approach and 80% for the combined approach.

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.

6 Related Work

Our previous work focussed on visualization of performance bottlenecks in Hadoop [16, 17], and offline diagnosis [18–20] of performance problems by comparing the duration of white-box states (Maps and Reduces), and black-box OS performance counters across peers. `ASDF` presents a framework for online monitoring and diagnosis of problems in distributed systems. 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 [6] and Ganglia [7] 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 [12] 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 [21]. 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 [9], 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. [22] 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. Xu et. al [23] diagnosed problems in Hadoop by analyzing source code to automatically discover the structure of messages in the `datanode`, logs, and identifying outlier error messages. Our work leverages both application logs and black-box performance counters for diagnosis.

Problem-Diagnosis Techniques. Current problem-diagnosis work [24, 25] 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 [8] and Pinpoint [26], 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 [27] 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 [28], which relies on detecting anomalous execution paths from many possible ones, will also have limited effectiveness at diagnosing problems in Hadoop.

The idea of correlating system behavior across multiple layers of a system is not new. Hauswirth et al's ”vertical profiling” [29] 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 [30] 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 Future Research Challenges

In our opinion, most of the future research challenges for online monitoring and diagnosis frameworks lie in the development of online diagnosis algorithms that leverage the diverse data sources available in large-scale distributed systems for more accurate diagnosis. There has been considerable research in developing robust, monitoring frameworks which impose minimal overhead [11, 7, 8, 12]. While scalability and the incorporation of new data sources, such as those proffered by virtualized environments, will continue to be a challenge for monitoring, we foresee the following key challenges for online diagnosis:

– Complex failure modes: The complex interactions between components in large-scale distributed systems can result in complex failure modes where cascading failures ripple through multiple nodes in the system. The large-scale of the system also increases the probability of multiple independent failures. Developing tools that can accurately localize the root-cause of these problems is challenging.
– Scalability: Large-scale distributed systems exert pressure on online diagnosis systems to analyze massive amounts of data and produce a diagnosis outcome within minutes. Cohen et al.'s [27] showed how to reduce the number of metrics examined during diagnosis in systems with labeled data. More research is needed on techniques for dealing with large volumes of monitoring data in systems with unlabeled data.
– Adaptation: Diagnosis algorithms need to adapt to new workloads, seasonal trends, and environmental changes such as upgrades. Research is needed to determine the interfaces that online monitoring and diagnosis frameworks should expose to data collection and analysis plugins during adaption.
– Translating diagnosis outcomes into recovery actions: Diagnosis techniques typically rely on problem signatures [27] to identify root-causes that could trigger automated recovery actions. This approach works well for recurrent problems, but more research is needed for novel problems.

8 Conclusion

In this chapter, 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 [3]) 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.

References

1. Foundation, T.A.S.: Hadoop (2007) http://hadoop.apache.org/core.
2. Dean, J., Ghemawat, S.: MapReduce: Simplified data processing on large clusters. In: USENIX Symposium on Operating Systems Design and Implementation, San Francisco, CA (December 2004) 137–150
3. Foundation, T.A.S.: Apache's JIRA issue tracker (2006) https://issues.apache.org/jira.
4. IBM: Tivoli enterprise console (2010) http://www.ibm.com/software/tivoli/products/enterprise-console.
5. Packard, H.: Hp operations manager (2010) http://www.managementsoftware.hp.com.
6. LLC., N.E.: Hagios (2008) http://www.nagios.org.
7. Ganglia: Ganglia monitoring system (2007) http://ganglia.info.
8. Barham, P., Donnelly, A., Isaacs, R., Mortier, R.: Using Magpie for request extraction and workload modelling. In: USENIX Symposium on Operating Systems Design and Implementation, San Francisco, CA (Dec 2004)
9. Inc., S.: Splunk: The it search company (2005) http://www.splunk.com.
10. ZeroC, I.: Internet Communications Engine (ICE) (2010) http://www.zeroc.com/ice.html.
11. Small, C., Ghosh, N., Saleeb, H., Seltzer, M., Smith, K.: Dapper, a large-scale distributed systems tracing infrastructure. Technical Report dapper-2010-1, Google (Apr 2010)
12. Fonseca, R., Porter, G., Katz, R., Shenker, S., Stoica, I.: X-Trace: A pervasive network tracing framework. In: USENIX Symposium on Networked Systems Design and Implementation, Cambridge, MA (Apr 2007)
13. Godard, S.: SYSSTAT (2008) http://pagesperso-orange.fr/sebastien.godard.
14. Ghemawat, S., Gobioff, H., Leung, S.: The Google File System. In: ACM Symposium on Operating Systems Principles, Lake George, NY (Oct 2003) 29 – 43
15. Tan, J., Narasimhan, P.: RAMS and BlackSheep: Inferring white-box application behavior using black-box techniques. Technical Report CMU-PDL-08-103, Carnegie Mellon University PDL (May 2008)
16. Tan, J., Pan, X., Kavulya, S., Gandhi, R., Narasimhan, P.: Mochi: Visual Log-Analysis Based Tools for Debugging Hadoop. In: USENIX Workshop on Hot Topics in Cloud Computing (HotCloud), San Diego, CA (June 2009)

17. Tan, J., Kavulya, S., Gandhi, R., Narasimhan, P.: Visual, log-based causal tracing for performance debugging of MapReduce systems. In: International Conference on Distributed Computing Systems, Genoa, Italy (June 2010)
18. Tan, J., Pan, X., Kavulya, S., Gandhi, R., Narasimhan, P.: SALSA: Analyzing Logs as State Machines. In: USENIX Workshop on Analysis of System Logs, San Diego, CA (December 2008)
19. Pan, X., Tan, J., Kavulya, S., Gandhi, R., Narasimhan, P.: Ganesha: Black-Box Diagnosis of MapReduce Systems. In: Workshop on Hot Topics in Measurement and Modeling of Computer Systems (HotMetrics), Seattle, WA (June 2009)
20. Pan, X., Tan, J., Kavulya, S., Gandhi, R., Narasimhan, P.: Blind Men and the Elephant: Piecing together Hadoop for diagnosis. In: International Symposium on Software Reliability Engineering (ISSRE), Mysuru, India (November 2009)
21. Konwinski, A., Zaharia, M., Katz, R., Stoica, I.: X-tracing Hadoop. Hadoop Summit (Mar 2008)
22. Cohen, I.: Machine learning for automated diagnosis of distributed systems performance. SF Bay ACM Data Mining SIG (Aug 2006)
23. Xu, W., Huang, L., Fox, A., Patterson, D.A., Jordan, M.I.: Detecting large-scale system problems by mining console logs. In: ACM Symposium on Operating Systems Principles, Big Sky, Montana (October 2009) 117–132
24. Aguilera, M.K., Mogul, J.C., Wiener, J.L., Reynolds, P., Muthitacharoen, A.: Performance debugging for distributed system of black boxes. In: ACM Symposium on Operating Systems Principles, Bolton Landing, NY (Oct 2003) 74–89
25. Kiciman, E., Fox, A.: Detecting application-level failures in component-based internet services. IEEE Trans. on Neural Networks: Special Issue on Adaptive Learning Systems in Communication Networks **16**(5) (Sep 2005) 1027– 1041
26. Chen, M.Y., Kiciman, E., Fratkin, E., Fox, A., Brewer, E.: Pinpoint: Problem determination in large, dynamic internet services. In: IEEE Conference on Dependable Systems and Networks, Bethesda, MD (Jun 2002)
27. Cohen, I., Zhang, S., Goldszmidt, M., Symons, J., Kelly, T., Fox, A.: Capturing, indexing, clustering, and retrieving system history. In: ACM Symposium on Operating Systems Principles, Brighton, United Kingdom (Oct 2005) 105–118
28. Kiciman, E., Fox, A.: Detecting application-level failures in component-based internet services. In: USENIX Symposium on Networked Systems Design and Implementation, San Jose, CA (May 2006) 115– 128
29. Hauswirth, M., Diwan, A., Sweeney, P., Hind, M.: Vertical profiling: Understanding the behavior of object-oriented applications. In: ACM Conference on Object-Oriented Programming, Systems, Languages, and Applications, Vancouver, BC, Canada (October 2004) 251 – 269
30. Tucek, J., Lu, S., Huang, C., Xanthos, S., Zhou, Y.: Triage: diagnosing production run failures at the user's site. In: Symposium on Operating Systems Principles (SOSP), Stevenson, WA (October 2007) 131–144