Using Message Logs and Resource Use Data for Cluster Failure Diagnosis

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***Abstract*—Failure diagnosis for large compute clusters using only message logs is known to be incomplete. Recent availability of resource use data provides another potentially useful source of data for failure detection and diagnosis. Early work combining message logs and resource use data for failure diagnosis has shown promising results. This paper describes the CRUMEL framework which implements a new approach to combining rationalized message logs and resource use data for failure diagnosis. CRUMEL identifies patterns of errors and resource use and correlates these patterns by time with system failures. Application of CRUMEL to data from the Ranger supercomputer has yielded improved diagnoses over previous research. CRUMEL has: (i) showed that more events correlated with system failures can only be identified by applying different correlation algorithms, (ii) confirmed six groups of errors, (iii) identified Lustre I/O resource use counters which are correlated with occurrence of Lustre faults which are potential flags for online detection of failures, (iv) matched the dates of correlated error events and correlated resource use with the dates of compute node hang-ups and (v) identified two more error groups associated with compute node hang-ups. The pre-processed data will be put on the public domain in September, 2016.**

***Index Terms*—Large cluster system; Cluster log data; Correlation analysis; Failure diagnosis; Lustre file-system;**

I. Introduction

Large clusters and supercomputers suffer from occurrence of faults and failures but generate a massive amount of monitoring data which can be used to analyze these faults and failures. Most of this data has been in the form of message logs. A significant body of research has demonstrated the value of message logs to detect faults [1], [2], diagnose failures [3]–[5] and predict faults/failures [6]–[8]. However, the message logs are incomplete and redundant[1], making failure diagnosis from message logs alone very difficult. Recently, job and processor level resource use data has become available for some systems [9]. A recent body of research has demonstrated the value of performance data to detect faults [10], [11] and predict failures [12]. While use of message logs and performance data separately has provided important tools and methods that help manage the complexity of these systems, there has been little exploration of the diagnostic benefit of combining analyses of message logs and resource use data.

The previous work on failure diagnosis techniques which attempt to combine message logs and resource use data to diagnose and/or predict impending failures [13], [14] have shown increased accuracy over use of message logs alone. In [13], resource use data is used to identify resource anomalies and provide partial diagnosis of system faults and failures, and message log analysis is used to obtain a more specific and precise diagnosis. [14] uses a similar approach to show that combining resource use and message log analyses shows indications of impending failures earlier than message log analyses alone. [15] combines analyses of message logs and resource usage but the focus is on error detection. [16] is focused on detecting patterns in failure logs. This paper builds on and extends the idea. It presents a new workflow for combining message logs and resource use data for failure diagnosis and demonstrates its effectiveness.

The TACC_Stats [9] monitoring system and Rationalized message logging [17] resolve resource usage and system messages by jobs, nodes and time for open-source Linux-based clusters. Previous work [13], [18] has applied only Pearson Correlation, but there is little work which show that more events correlated with system failures can only be identified by applying different correlation algorithms. To address this gap, this paper reports on the implementation and evaluation of a new approach for combining both message logs and resource use data for failure diagnosis. This approach - we call the CRUMEL framework - identifies and links patterns of messages and resource usage with system failures. It evaluates multiple correlation algorithms. CRUMEL implements a two-phase approach where: (i) the message logs patterns are used to categorize errors into groups and diagnose the likely causes of failures, (ii) the resource use data patterns are used to identify specific resource use counters associated with the error group.

The benefit of identifying specific resource use counters which are associated with a group of errors is given as follows: When Lustre I/O counters and Lustre file-system errors are strongly correlated on the same day, it shows that Lustre I/O activity is associated with the generation of Lustre file-system errors. Therefore, the correlated Lustre I/O counters can then be used to monitor Lustre file-system errors that eventually

[1]By incomplete, we mean that the message logs do not contain all the events needed to establish a complete causal trace path to the failure. By redundant, we mean that only a small quantity of the message logs is relevant to the diagnosis of a given failure.

lead to compute node hang-ups. We chose Lustre I/O counters as Lustre file-system errors and network errors make up the majority of errors associated with compute node hang-ups.

The innovations and contributions of the CRUMEL framework and its application include:

- CRUMEL formulates, implements and applies a new workflow for combining rationalized message logs and resource use data for failure diagnosis. CRUMEL identifies patterns of errors and resource use events and correlates these patterns by time with system failures.
- Demonstrated that the CRUMEL workflow extends and improves diagnoses over previous research. CRUMEL shows that more events correlated with system failures can only be identified by applying different correlation algorithms.
- Identified Lustre I/O resource use counters which are correlated with occurrence of Lustre faults which are potential flags for online detection of failures.
- Matched the dates of correlated error events and correlated resource use with dates of compute node hang-ups.
- Identified two previously undiagnosed error groups associated with compute node hang-ups. They are process errors and file-system errors.

The remainder of this paper is structured as follows: We define the fault model and present the problem description and CRUMEL framework in Section II. We evaluate CRUMEL in Section III, review the related work in Section IV and conclude with a summary and future work in Section VI.

II. Models, Problem Specification and CRUMEL

The class of systems to which CRUMEL can be applied is specified in terms of a generic model of cluster systems given in [13]. In this section, we describe the fault model to which our work is applicable. Then, we present the problem specification and the CRUMEL framework.

A. Fault Model

An illustration of the resource usage, error and system failure messages by time is shown in Fig. 1. We observed that soft lockup messages and file-system error messages in the rationalized message logs are correlated. We also observed that messages transmitted in a network, i.e., `tx_msgs` and bytes written to a file-system, i.e., `write_bytes` resource use counters in the resource use data are correlated.

To increase the dependability of such systems, it is important to *tolerate those errors* that lead to a system failure. Knowing the nature of these errors will ease debugging or maintenance. On the other hand, some data centers may decide not to deploy failure recovery mechanisms due to their policies. As such, we do not assume the availability of failure recovery in our fault model.

Understanding the occurrence of an error from message logs alone is challenging. In this paper, we capture the notion of an error when: (i) a message is logged and the message captures a state of the program that deviates from expectation, and (ii) there are message patterns and resource usage patterns as

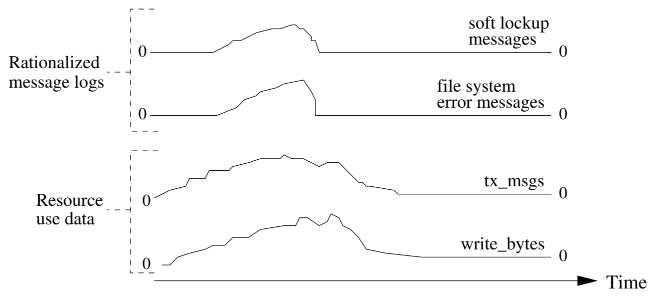


Fig. 1. An illustration of soft lockup and file-system error messages, messages transmitted in a network and bytes written to a file-system.

illustrated in Fig. 1. The CRUMEL framework developed in this paper seeks to determine the occurrence of these patterns for failure diagnosis.

B. Problem Specification and CRUMEL Framework

The problem that our analysis targets can be described as follows: Given (i) a set of resource use data, (ii) message logs that are incomplete and redundant, (iii) keywords of failure events, and (iv) name of resource use counters, then identify the errors which are correlated with the failure and the resource use counters which are correlated on the date of the failure. To achieve this, we develop the CRUMEL (**C**orrelating **R**esource **U**sage data and **ME**ssage **L**ogs) framework shown in Fig. 2.

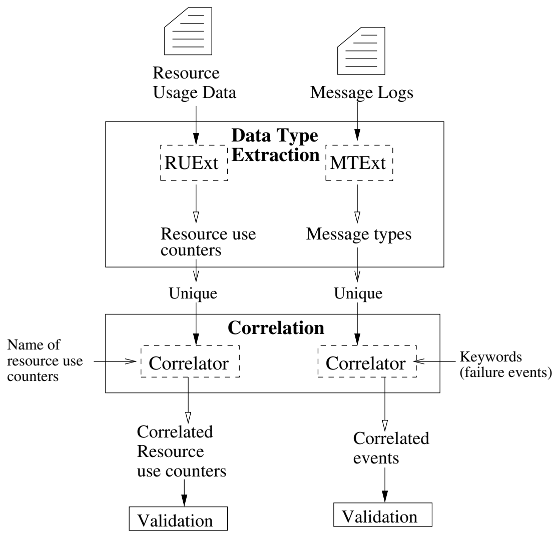


Fig. 2. The workflow of the CRUMEL framework. The CRUMEL framework is composed of two modules: (1) Data Type Extraction, and (2) Correlation. The workflow automatically process the message logs and resource use data through the Data Type Extraction module, followed by the Correlation module. The output of each module are sets of reports which can be used for diagnosis.

Next, we describe in detail, each of the two modules used within the CRUMEL framework.

C. CRUMEL: Data Type Extraction

CRUMEL targets processing of Syslogs [19], Rationalized message logs [17] and TACC_Stats resource use data [9]. The Rationalized message log [17] is a special type of message log that incorporates a logical structure and additional content such as job-identification to the POSIX formatted logs. TACC_Stats [9] is a job-oriented and logically structured version of the conventional Sysstat system performance monitor. We developed a *Data Type Extractor* module that extracts: (i) message types from the message logs, (ii) resource use counters from the resource use data[2].

Message Type Extractor: The Message Type Extractor or *MTExt*, extracts the sources (the nodes and jobs), times and message sequences from the message logs and presents these messages in a form on which standard analysis algorithms can be applied. An example of an error message is given below:

```
1975935 Jun 3 07:25:17 i114-204 kernel X <0>%s.
ECC error  ECC error K8
```

The sources of this error message can be identified from the job (`1975935`) and node (`i114-204`). The time that this error message was recorded can be identified from the timestamp (`Jun 3 07:25:17`). The software associated with this error message can be identified from the word (`kernel`) that follows immediately after the node identifier; in this example, the software is the Linux operating system kernel. The description of the event can be identified from this message *constant* part - it is a sequence of English-only words (`X ECC error  ECC error`) that follow immediately after the software identifier. The message type can be determined from the message constant part; in this example, the message type is an ECC error. The data matrix, $DM_{timebins}$, contains histograms of the message types by time-bins. The steps for extracting the message types and generating the data matrix are given below.

- Step 1: Split the message logs into logs of individual hours by individual days.
- Step 2: For each message log, extract the message *constant* part and store it in a list.
- Step 3: Identify the unique message *constants* in the list and obtain the message types.
- Step 4: Count the number of message types by hour for each day in the logs.

Resource Use Extractor: The Resource Use Extractor or *RUExt*, extracts resource use counters from TACC_Stats resource use data and presents the resource use counters in a form on which standard analysis algorithms can be applied. In addition to the traditional information collected by Sysstat [20], TACC_Stats records hardware performance monitoring data, Lustre file-system operation counts and InfiniBand device usage. An example of a resource use log extracted from TACC_Stats is given below:

```
1975935 Jun 3 00:00:01 i101-101 llite /work
read_bytes 830958447762 write_bytes 337810667092
direct_read 0 direct_write 0 dirty_pages_hits
47079822 dirty_pages_misses 82604275 ...
```

The sources of this resource use log can be identified from the job (`1975935`) and node (`i101-101`). The time that this resource use log was recorded can be identified from the timestamp (`Jun 3 00:00:01`). The software component associated with this resource use log can be identified from the word (`llite`) that follows immediately after the node identifier; in this example, the component is the Lustre file-system. A second-level component can be identified from the word (`/work`) that follows immediately after the first component identifier; in this example, the second-level component is the work directory of the Lustre file-system. The resource use counters can be identified from the key-value pairs (e.g. `read_bytes 830958447762`) that follow after the second component identifier. We define a parameter name, *param-name*, as a triple which comprises of the software component, second-level component and resource use counter key; in this example, the *param-name* is "llite /work read_bytes". A list of resource use counters and their components is given in Table I. The data matrix, $DR_{timebins}$, contains histograms of the param-name types by time-bins. The steps for extracting the resource use counters and generating the data matrix are given below.

TABLE I
RESOURCE USE COUNTERS AND THEIR ASSOCIATED COMPONENTS.

Component	Resource use counters	Qty.
Lustre network	tx_msgs, rx_msgs, rx_msgs_dropped, tx_bytes, rx_bytes, rx_bytes_dropped	6
Lustre /work	read_bytes, write_bytes, direct_read, direct_write, dirty_pages_hits, dirty_pages_misses, ioctl, open, close, mmap, seek, fsync, setattr, truncate, flock, getattr, statfs, alloc_node, setxattr, getxattr, listxattr, removexattr, inode_permission	23
Virtual memory	pgpgin, pgpgout, pswpin, pswpout, pgalloc_normal pgfree, pgactivate, pgdeactivate, pgfault, pgmajfault pgrefill_normal, pgsteal_normal, pgscan_kswapd_normal pgscan_direct_normal, pginodesteal, slabs_scanned, kswapd_steal, kswapd_inodesteal, pageoutrun, allocstall pgrotated	21

- Step 1: Split the resource usage logs into individual hours by individual dates.
- Step 2: For each log entry, extract the *param-name* and store it in a list.
- Step 3: Identify the unique *param-names* in the list and obtain the param-name types.
- Step 4: For each param-name type in a resource use log, if the values associated with the param-name types of two consecutive log entries are different, obtain the difference and add the difference to the value obtained in the preceding operation and store the value.

D. CRUMEL: Correlation

Once the time-bin data matrices have been generated by the Data Type Extraction module, the *Correlation* module generates the correlation matrices by computing: (i) the strength of the relationships between events contained in the time-bin ($DM_{timebins}$) data matrix and extracts a smaller set of message logs for analysis, and (ii) the strength of the relationships between resource use counters contained in the time-bin ($DR_{timebins}$) data matrix and extracts a smaller set of resource use counters for analysis. Our correlation module currently applies two correlation algorithms: (i) Pearson correlation

[2]https://diag-toolkits.github.io/PreprocessedData/

and (ii) Spearman-Rank correlation. We implemented Pearson correlation as the base algorithm to identify linear patterns and Spearman-Rank correlation as the second algorithm to identify patterns that follow a monotonically increasing function.

Pearson correlation [21] draws a line of best fit through the data of two variables, and it indicates how well the data points fit this line of best fit. It assumes a linear relationship between the data of two variables. Spearman-Rank correlation [22] assumes a monotonic relationship between the data of two ranked variables. A monotonic relationship is a relationship that does one of the following: (i) when the value of one variable increases, the value of the other variable increases, or (ii) when the value of one variable remains and does not decrease, the value of the other variable remains and does not decrease. This assumption is less restrictive than the linear relationship assumption that has to be met by Pearson correlation. The possible values for the Pearson and Spearman-Rank correlation coefficients ranges -1 to 1. A correlation coefficient of -1 indicates a perfect negative linear or monotonic relationship, a correlation coefficient of 0 indicates no linear or monotonic relationship, and a correlation coefficient of 1 indicates a perfect positive linear or monotonic relationship.

We apply the Correlation module on the resource use data and message logs separately as shown in Fig. 2. The resource use data and message logs are generated by different open-source software tools which are used in different ways. For example, TACC_Stats can be activated to record resource use on the system node or the application, while the message logging stack logs messages sent by the operating system kernel, system software and user application. As a result, the log entries in the resource use data and message logs may contain different timestamps. Hence, directly correlating the resource use data with message logs by time requires padding the histograms since the correlation algorithms require that, the histograms contain the same number of data points on the x-axis. However, our objective is not to correlate the resource use data with message logs, but to identify patterns in the resource use data and message logs which are strongly correlated.

Once the correlation matrices have been generated, a list containing the strongly correlated events and a list containing the strongly correlated resource use counters are generated. To generate these lists, we use a process that automatically identifies a correlation threshold r_{th} in each correlation matrix and the process is given in [13]. We use the correlation thresholds to extract the strongly correlated events, strongly correlated resource use counters and their correlation coefficients.

Next, we apply Fisher's z-transform, the standard technique, to test the significance of the correlation coefficient [22].

$$F(r) = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right) \tag{1}$$

where r is a correlation coefficient. We define the null hypotheses as: (i) H_{0r} that a pair of resource use counters are independent, and (ii) H_{0e} that a pair of events are independent. We define the alternate hypotheses as: (i) H_{ar} that a pair of resource use counters are *not* independent, and (ii) H_{ae} that a pair of events are *not* independent. Under the null hypothesis H_{0r}, $F(r)$ approximately follows a normal distribution with mean $u_z = F(H_{0r}) = 0$ and standard error $SE = \frac{1}{\sqrt{n_r-3}}$, where n_r is the number of time-bins in the pair of resource use counter-series. Under the null hypothesis H_{0e}, $F(r)$ approximately follows a normal distribution with mean $u_z = F(H_{0e}) = 0$ and standard error $SE = \frac{1}{\sqrt{n_e-3}}$, where n_e is the number of time-bins in the pair of event-series. Then, we obtain the z-score for a given correlation coefficient:

$$z_r = \frac{F(r) - u_z}{SE} = (F(r) - F(H_{0r})) \times \sqrt{n_r - 3} \tag{2}$$

$$z_e = \frac{F(r) - u_z}{SE} = (F(r) - F(H_{0e})) \times \sqrt{n_e - 3} \tag{3}$$

A large absolute value of z_r and z_e, e.g., 2.58 at 99% confidence level, will reject the null hypotheses in favour of the alternate hypotheses that a pair of resource use counters and a pair of events are *not* independent.

III. Case Study: Ranger Supercomputer

Our study of failures is carried out in the context of the decommissioned Ranger supercomputer at the Texas Advanced Computing Center at the University of Texas at Austin. The Ranger supercomputer was in production for five years from 2007 to 2012. It was a Linux-based cluster of 3,936 compute nodes and 112 Lustre file-system, login and visualization nodes. Each node of Ranger generates its own resource use data and messages. The messages were then sent to a centralized logging system where the logs are combined and interleaved in time.. We collected the resource use data and rationalized message logs for the months of June, July and August 2011 and a summary is given in Table II.

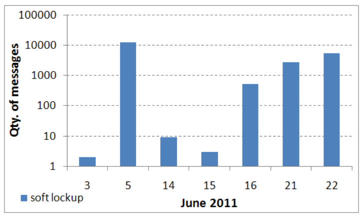
TABLE II
Summary of the data collected on Ranger.

	Resource use data		**Rationalized message logs**	
Month	Size	Qty. lines	Size	Qty. messages
June 2011	29.8 GB	88,821,351	2.7 GB	10,021,516
July 2011	29.3 GB	92,425,427	9.6 GB	64,822,682
August 2011	29.9 GB	91,502,909	14.5 GB	114,745,476

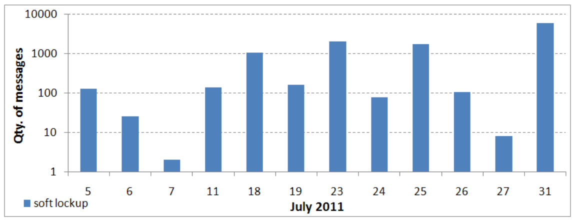
In this section, we present our analysis of the patterns of events and resource use associated with the system failures.

A. Compute Node Hang-ups

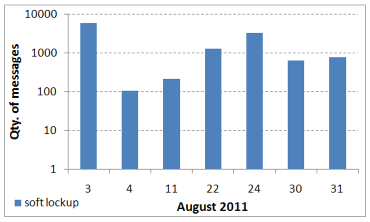
Compute node hang-ups are one of the most frequent source of problems for the systems administrators of the Ranger supercomputer. A compute node hang-up can be identified from a soft lockup event in the rationalized message logs: `BUG: soft lockup stuck for`. In June 2011, node hang-ups occurred on 7 dates. In July 2011, node hang-ups occurred on 12 dates. In August 2011, node hang-ups occurred on 7 dates. The dates and distribution of soft lockup events on Ranger are shown in Fig. 3(a), Fig. 3(b) and Fig. 3(c). We observed that soft lockup messages were recorded more than 21,000 times in June 2011, more than 11,000 times in July 2011 and more than 12,000 times in August 2011.



(a) June 2011.



(b) July 2011.



(c) August 2011.

Fig. 3. Distribution (log-scale) of soft lockup events on Ranger.

B. Phase 1: Identify the Correlated Events

In the first phase of our study, we determine: (i) which events are strongly *positive* correlated to soft lockup events, and (ii) what are the differences in the correlated events dates identified by Pearson correlation and Spearman-Rank correlation. We obtained from the event correlation reports, the events that are strongly correlated to soft lockup events. We presented the list of correlated events to the systems administrators and identify the following errors leading to soft lockups: (1) Process errors, (2) Network errors, (3) Memory errors, (4) File-system errors, (5) Page faults, and (6) Lustre Evict/RPC protocol errors. A summary of the soft lockup dates associated with the error groups and the error groups identified by a CRUMEL-instance is given in Table III.

TABLE III
SUMMARY OF SOFT LOCKUP DATES ASSOCIATED WITH ERROR GROUPS AND ERROR GROUPS IDENTIFIED BY A CRUMEL-INSTANCE.

Error group	**CRUMEL instance**	**No. of dates**	**Error group**	**CRUMEL instance**	**No. of dates**
Process error	Pearson	21	Network error	Pearson + Spearman	11
Memory error	Pearson	9	File-system error	Pearson	11
Page-fault	Pearson	7	Lustre Evict/ RPC error	Pearson	2

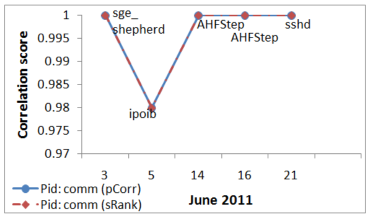
1) Process errors: Information about the name, memory address, running CPU and state of a process is provided by a `Pid: comm` event. From Fig. 4(a), Fig. 4(b) and Fig. 4(c), we observed that `Pid: comm` events are strongly correlated to soft lockup events with scores that range 0.85 to 1 on 21 soft lockup dates. We observed that Pearson correlation identified the correlated events on 21 soft lockup dates. We observed that Spearman-Rank correlation identified the correlated events on 20 soft lockup dates. Our results show that Pearson correlation identified all the dates when process errors and soft lockup events are correlated on Ranger.

We manually scanned the messages and identified the names of the processes associated with the `Pid: comm` events. The names of the processes are: `sge_shepherd`, `ipoib`, `AHFStep`, `sshd`, `ptlrpcd`, `tacc_stats`, `mpmc`, `sge_execd`, `ll_imp_inval` and `sh`. `sge_shepherd` provides the parent process functionality for a single Sun Grid Engine job. `ipoib` is a protocol that defines how to send IP packets over an Infiniband network. `AHFStep` is a program that initiates the Amiga Halo Finder software used for cosmological simulations. `sshd` is a Linux secure shell daemon that provides secure encrypted communication between two clients in an insecure network. `ptlrpcd` is a thread that takes care of sending asynchronous remote procedure calls. `tacc_stats` is a job-oriented and logically structured version of the conventional Sysstat system performance monitor. `mpmc` is an open-source Monte Carlo package used for the simulation of liquids, molecular interfaces and functionalized nanoscale materials. `sge_execd` controls the Sun Grid Engine queues local to the machine on which sge_execd is running and executes the jobs sent from the Sun Grid Engine master to be run on these queues. `ll_imp_inval` is an evictor thread that starts when a client request to connect to a Lustre server is repeatedly refused. `sh` is the Bash shell command-line interpreter used in Linux operating systems. Our results suggest that interactions with these processes have led to compute node hang-ups.

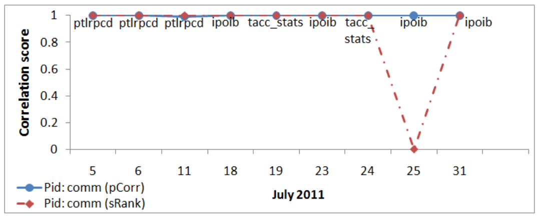
2) Network errors: Errors in communication between the nodes can be identified by `Connection to service was lost` events, `error occurred while communicating with` events, and `failed due to network error` events. From Fig. 5(a), Fig. 5(b) and Fig. 5(c), we observed that network error events are strongly correlated to soft lockup events with scores that range 0.76 to 1 on 11 soft lockup dates. From Fig. 5(b), we observed that only Spearman-Rank correlation identified the network error events on July 26 2011, and only Pearson correlation identified the network error events on July 6, 7 and 19 2011. Our results show that Pearson and Spearman-Rank correlation are required to identify all the dates when network errors and soft lockup events are correlated on Ranger.

The network errors can be caused by high network resource utilization and unresponsive servers. For example, when a client node sends a request to connect to an unresponsive server, the server will refuse the connection. The client then activates its timeout. When the clients timeout expires, it attempts a reconnection to the server. When multiple client reconnection requests are refused by unresponsive servers, it may lead to the client hang-up. Our results suggest that network errors have led to compute node hang-ups.

3) Memory errors: Errors in memory access and usage can be identified from the following log events: `segfault`, `system memory exhausted`, `invoked oom-killer`, `out-of-memory` and `No available memory`. From Fig. 6(a), Fig. 6(b) and Fig. 6(c), we observed that memory error events are strongly correlated to soft lockup events with scores that range 0.8 to 1 on 9 soft lockup dates. We observed that Pearson



(a) June 2011.



(b) July 2011.

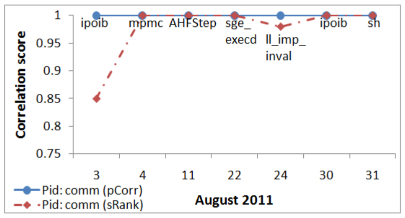


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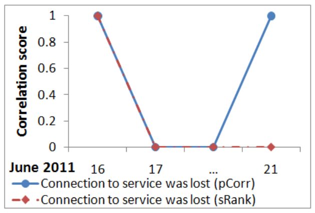
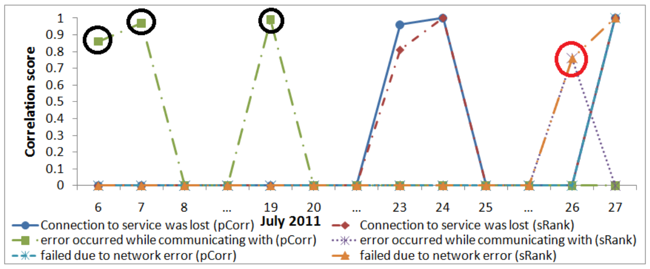
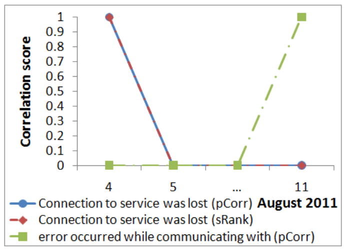
Fig. 4. Correlation of Pid: comm events to soft lockup events.



(a) June 2011.

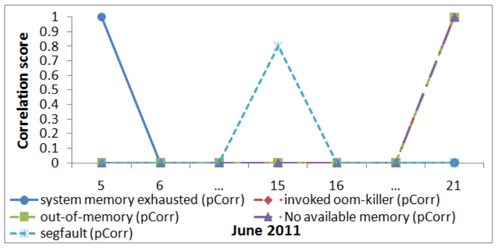


(b) July 2011.

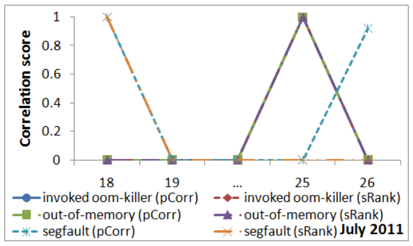


(c) August 2011.

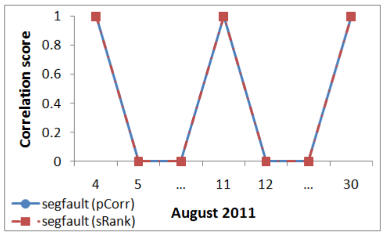
Fig. 5. Correlation of Connection to service was lost, error occurred while communicating with, and failed due to network error events to soft lockup events. The events circled in red were identified by Spearman-Rank correlation only. The events circled in black were identified by Pearson correlation only.



(a) June 2011.



(b) July 2011.



(c) August 2011.

Fig. 6. Correlation of system memory exhausted, invoked oom-killer, out-of-memory, No available memory and segfault events to soft lockup events.

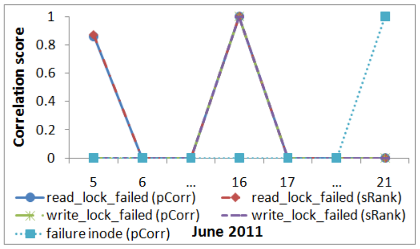
correlation identified the correlated memory error events on 9 soft lockup dates. We observed that Spearman-Rank correlation identified the correlated memory error events on 5 soft lockup dates. Our results show that Pearson correlation identified all the dates when memory errors and soft lockup events are correlated on Ranger.

The memory errors are often caused by memory access violations in buggy software in the Linux operating system. For example, the job of the Linux operating system *oom-killer* is to remove one or more processes in order to free up memory on the node. However, the oom-killer is vulnerable to memory leaks and in some cases, these memory leaks may cause the oom-killer to crash which in turn causes the operating system on the node to crash. Our results suggest that memory errors have led to compute node hang-ups.

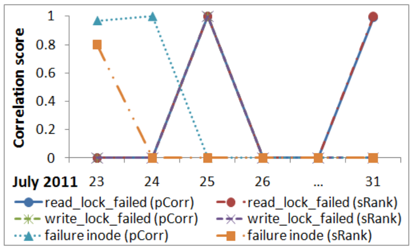
4) File-system errors: Errors in the file-system can be identified from the following log events: `read_lock_failed`, `write_lock_failed` and `failure inode`. From Fig. 7(a), Fig. 7(b) and Fig. 7(c), we observed that file-system error events are strongly correlated to soft lockup events with scores that range 0.8 to 1 on 11 soft lockup dates. We observed that Pearson correlation identified the correlated file-system errors on 11 soft lockup dates. We observed that Spearman-Rank correlation identified the correlated file-system errors on 10 soft lockup dates. Our results show that Pearson correlation identified all the dates when file-system errors and soft lockup events are correlated on Ranger.

A hung client that fails to release a read or write lock on the data it holds can result in a deadlock when another client attempts to access the same data. In another example, an inode provides information that a client needs to access files stored on multiple storage servers. However, when a client attempts to access information it needs on a corrupted inode, this information is lost. Our results suggest that deadlocks and inode failures have led to compute node hang-ups.

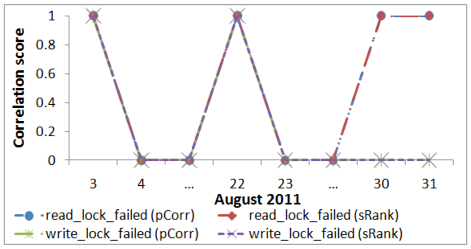
5) Page faults: Errors in the interaction protocol between the operating system's page-fault handler and the rest of the node operating system can be identified from the following log event: `do_page_fault`. From Fig. 8(a), Fig. 8(b) and Fig. 8(c), we observed that page faults are strongly correlated to soft lockup events with scores that range 0.8 to 1 on 7 soft lockup dates. We observed that Pearson correlation



(a) June 2011.

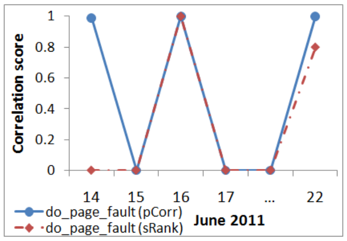


(b) July 2011.

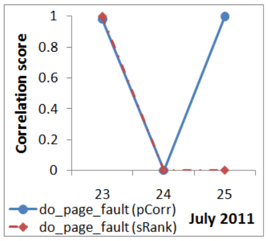


(c) August 2011.

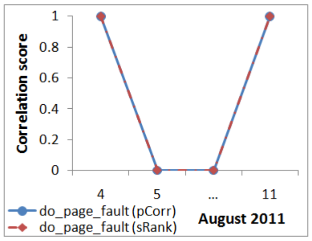
Fig. 7. Correlation of read_lock_failed, write_lock_failed and failure inode events to soft lockup events.



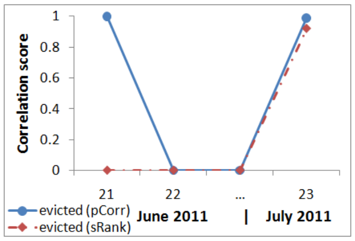
(a) June 2011.



(b) July 2011.



(c) August 2011.



(d) June and July 2011.

Fig. 8. Correlation of page fault events (a - c) and Lustre Evict/RPC events (d) to soft lockup events.

identified the correlated page faults on 7 soft lockup dates. We observed that Spearman-Rank correlation identified the correlated page faults on 5 soft lockup dates. Our results show that Pearson correlation identified all the dates when page faults are correlated to soft lockup events on Ranger.

A page fault is raised by the hardware when a running program accesses a memory page that is mapped into a virtual address space, but not loaded in physical memory. When a page fault occurs, the operating system page fault handler will be invoked. The page fault handler must locate a free space in memory, or choose to free up space in memory for use by the program data. If the latter (also called a major page fault) is chosen, it will incur additional disk latency to an already interrupted program execution. Our results suggest that page faults have led to compute node hang-ups.

6) Lustre Evict/RPC Protocol errors: Errors in the Lustre Evict/RPC protocol can be identified from the following keywords in the log events: `evicted`. From Fig. 8(d), we observed that evicted events are strongly correlated to soft lockup events with scores that range 0.92 to 1 on 2 soft lockup dates. We observed that Pearson correlation identified the correlated evicted events on 2 soft lockup dates. We observed that Spearman-Rank correlation identified the correlated evicted events on 1 soft lockup date. Our results show that Pearson correlation identified all the dates when evicted events are correlated to soft lockup events on Ranger.

The Lustre Evict/RPC protocol is designed to free the file-system resources that are being held by unresponsive clients. However, timing mismatches that result from communication errors between the Lustre clients and servers, a fault that is well-known to the system administrators, could lead to the hang-up of client nodes. Our results suggest that communication errors between the Lustre clients and servers have led to compute node hang-ups.

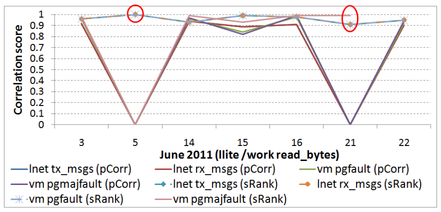
C. Phase 2: Identify the Correlated Resource Use Counters

The first phase of CRUMEL is characterized by the identification of error groups that lead to compute node soft lockups. The existence of related error messages in the log files confirm the presence of errors in the system. However, the objective of this paper is to understand the occurrence of patterns, i.e., correlations that will point to these error messages. To achieve this, we need to identify and understand the link between the resource usage counters and the error groups.

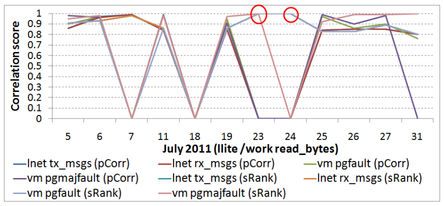
Thus, in the second phase of our study, we determine: (i) which resource use counters are strongly *positive* correlated to the Lustre file-system `read_bytes`, `write_bytes` and `ioctl` resource use counters[3], and (ii) what are the differences in the correlated resource use counters dates identified by Pearson correlation and Spearman-Rank correlation. The Lustre I/O activities are recorded by the `read_bytes`, `write_bytes` and `ioctl` counters. We obtained from the resource use correlation reports, the resource use counters that are strongly correlated to the Lustre file-system `read_bytes`, `write_bytes` and `ioctl` resource use counters. We presented the list of correlated resource use counters to the systems administrators and identify the following components associated with Lustre I/O activity: (1) Lustre network, (2) Linux O/S virtual memory. A summary of the correlated resource use counters identified by a CRUMEL-instance is given in Table IV.

The `lnet tx_msgs` and `lnet rx_msgs` counters record the quantity of messages that were transmitted in the Lus-

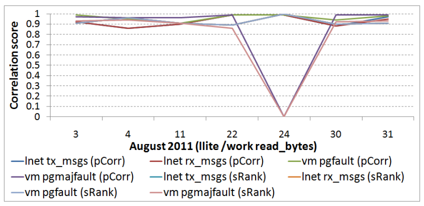
[3]We focus on these counters as there are no counters that are specifically related to process errors, which form the majority of errors identified in Section III-B. Thus, we focused on the next major source of errors, namely network and file system errors.



(a) June 2011.

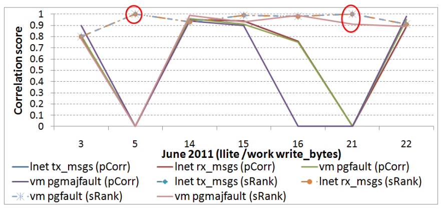


(b) July 2011.

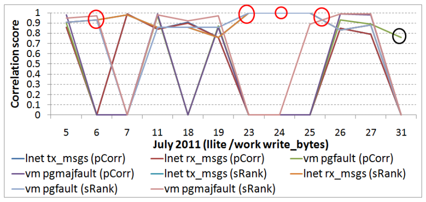


(c) August 2011.

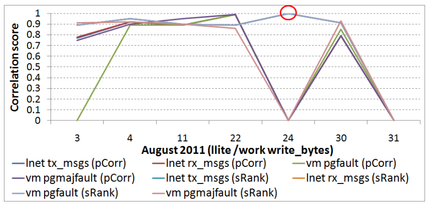
Fig. 9. Correlation of lnet tx_msgs, lnet rx_msgs, vm pgfault and vm majpgfault to llite /work read_bytes on Ranger. The counters circled in red were identified by Spearman-Rank correlation only.



(a) June 2011.

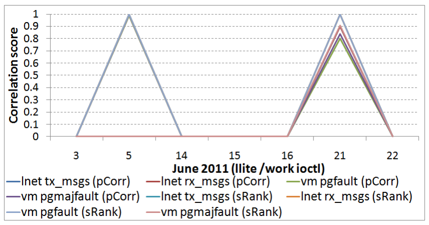


(b) July 2011.

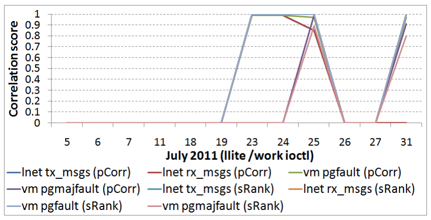


(c) August 2011.

Fig. 10. Correlation of lnet tx_msgs, lnet rx_msgs, vm pgfault and vm majpgfault to llite /work write_bytes on Ranger. The counters circled in red were identified by Spearman-Rank correlation only. The counters circled in black were identified by Pearson correlation only.



(a) June 2011.



(b) July 2011.

Fig. 11. Correlation of lnet tx_msgs, lnet rx_msgs, vm pgfault and vm majpgfault to llite /work ioctl on Ranger.

TABLE IV
SUMMARY OF CORRELATED RESOURCE USE COUNTERS.

Lustre counter	Counter	CRUMEL instance	Lustre counter	Counter	CRUMEL instance
read_ bytes	lnet tx_msgs lnet rx_msgs vm pgfault vm maj- pgfault	Spearman	write_ bytes	lnet tx_msgs lnet rx_msgs vm pgfault vm maj- pgfault	Pearson and Spearman
ioctl	lnet tx_msgs lnet rx_msgs vm pgfault vm majpgfault	Pearson or Spearman			

tre network. The `vm pgfault` and `vm majpgfault` counters record the quantity of page faults in the Linux O/S. From Fig. 9, Fig. 10 and Fig. 11, we observed that the resource use counters `lnet tx_msgs`, `lnet rx_msgs`, `vm pgfault` and `vm majpgfault` are strongly correlated to `read_bytes`, `write_bytes` and `ioctl`. Our results show a strong relationship between: (1) Lustre activity and Lustre network usage, and (2) Lustre activity and Linux page-faults.

Correlation with read_bytes: From Fig. 9(a), Fig. 9(b) and Fig. 9(c), we observed that Pearson correlation identified the correlated resource use counters on 21 soft lockup dates. We observed that Spearman-Rank correlation identified the correlated resource use counters on 25 soft lockup dates. Our results show that Spearman-Rank correlation identified all the dates when `lnet tx_msgs`, `lnet rx_msgs`, `vm pgfault` and `vm majpgfault` are correlated to `read_bytes` on Ranger.

Correlation with write_bytes: From Fig. 10(a), Fig. 10(b) and Fig. 10(c), we observed that Pearson correlation identified the correlated resource use counters on 18 soft lockup dates. We observed that Spearman-Rank correlation identified the correlated resource use counters on 24 soft lockup dates. However, from Fig. 10(b), we observed that only Pearson correlation identified a strong correlation between `vm pgfault` and `write_bytes` on July 31 2011. Our results show that Pearson and Spearman-Rank correlation are required to identify all the dates when `lnet tx_msgs`, `lnet rx_msgs`, `vm pgfault` and `vm majpgfault` are correlated to `write_bytes` on Ranger.

Correlation with ioctl: From Fig. 11(a) and Fig. 11(b), we observed that Pearson correlation identified the strongly correlated resource use counters on 6 soft lockup dates. We also observed that Spearman-Rank correlation identified the strongly correlated resource use counters on 6 soft lockup dates. Our results show that Pearson and Spearman-Rank correlation separately identified all the dates when `lnet tx_msgs`, `lnet rx_msgs`, `vm pgfault` and `vm majpgfault` are correlated to `ioctl` on Ranger.

D. Validation

Next, we test the significance of: (i) the correlation coefficient of the strongly correlated events in each error group, (ii) the correlation coefficient of the strongly correlated resource use counters associated with Lustre activity, Lustre network and Linux virtual memory. We are interested in *positive* correlated events and *positive* correlated resource use counters. We obtained the correlation z-scores and the summaries are given in Tables V and VI.

TABLE V
SUMMARY OF THE CORRELATION Z-SCORES FOR THE ERROR GROUPS. THE SAMPLE SIZE, n, CONTAINS THE NUMBER OF HOURLY TIME-BINS IN ONE DAY'S WORTH OF RATIONALIZED MESSAGE LOGS.

Error group (sample size, n)	**June 2011**	**July 2011**	**August 2011**
Process error ($15 \leq n \leq 24$)	$10.53 \leq z_e \leq 12.13$	$9.17 \leq z_e \leq 12.13$	$9.90 \leq z_e \leq 12.13$
Memory error ($23 \leq n \leq 24$)	$5.03 \leq z_e \leq 12.13$	$7.28 \leq z_e \leq 12.13$	$11.84 \leq z_e \leq 12.13$
Page-fault ($23 \leq n \leq 24$)	$z_e = 12.13$	$z_e = 12.13$	$11.84 \leq z_e \leq 12.13$
Network error ($23 \leq n \leq 24$)	$z_e = 12.13$	$4.57 \leq z_e \leq 12.13$	$11.84 \leq z_e \leq 12.13$
File-system error ($17 \leq n \leq 24$)	$6.11 \leq z_e \leq 12.13$	$9.59 \leq z_e \leq 12.13$	$9.90 \leq z_e \leq 12.13$
Lustre Evict/RPC error ($n = 24$)	$z_e = 12.13$	$z_e = 12.13$	-

From Table V, we observed that the z-scores for all the error groups range from 4.57 to 12.13. At the 99% confidence level, under the null hypothesis, $z_{0e} = 2.58$. Hence, we reject the null hypothesis in favour of the alternate hypothesis.

Next, we determine the probability of rejecting the null hypothesis when it is true. From Table V, we observed the smallest correlation z-score $z_e = 4.57$. We apply a one-sided test and use the significance level, $\alpha = 0.01$ for a given hypothesis test to obtain a P-value. Since this is a one-sided test, the P-value is equal to the probability of observing a value greater than 4.57 in the standard normal distribution, or $P(Z > 4.57) = 1 - P(Z \leq 4.57) = 1 - 0.9999976 = 2.4e^{-06}$. The P-value is less than 0.01, indicating it is highly unlikely this result would be observed under the null hypothesis. The P-values we obtained for all the z-scores in Table V are also less than 0.01, indicating it is highly unlikely these results would be observed under the null hypothesis.

TABLE VI
SUMMARY OF THE CORRELATION Z-SCORES FOR THE CORRELATED RESOURCE USE COUNTERS (CORRRUD) GROUPS. THE SAMPLE SIZE, n, CONTAINS THE NUMBER OF HOURLY TIME-BINS IN ONE DAY'S WORTH OF TACC_STATS RESOURCE USAGE DATA.

CorrRUD group (sample size, n)	**June 2011**	**July 2011**	**August 2011**
Lustre I/O – Lustre network ($n = 24$)	$6.52 \leq z_r \leq 12.13$	$4.56 \leq z_r \leq 12.13$	$4.67 \leq z_r \leq 12.13$
Lustre I/O – Linux O/S VM ($n = 24$)	$4.46 \leq z_r \leq 12.13$	$4.56 \leq z_r \leq 12.13$	$4.45 \leq z_r \leq 12.13$

From Table VI, we observed that the z-scores for all the correlated resource use counters groups range from 4.45 to 12.13. At the 99% confidence level, under the null hypothesis, $z_{0r} = 2.58$. Hence, we reject the null hypothesis in favour of the alternate hypothesis.

Next, we determine the probability of rejecting the null hypothesis when it is true. The P-values for all the z-scores in Table VI are less than 0.01, indicating it is highly unlikely these results would be observed under the null hypothesis.

IV. RELATED WORK

In [23], a method that uses a feature construction scheme to rank system log messages that are important for problem diagnosis was presented. The feature construction scheme evaluates Pearson correlation and Spearman-Rank correlation based clustering for identifying clusters of messages. In contrast, CRUMEL evaluates Pearson correlation and Spearman-Rank correlation to identify patterns of errors and resource use in the message logs and resource use data. In [24], a metric that measures correlations of events and an algorithm called event correlation graphs are proposed. The algorithm was applied on the system message logs of two HPC systems and predicted failure and non-failure events in these systems. In [4], a time-anomaly correlation approach called SIGs was developed to infer influences between interacting components in the system message logs. In [12], the Wilcox Rank-sum correlation method was applied on system performance data to monitor and predict processor failures. CRUMEL complements these approaches by identifying patterns of errors and resource use in the message logs and resource use data.

[18] and [13] which are the predecessors of CRUMEL apply only Pearson Correlation. In Fig. 5(b) in Section III-B, we showed that the network error event correlated with node failure on July 26 2011 was identified by Spearman-Rank correlation only, but network error events correlated with node failures on other dates in July 2011 were identified by Pearson correlation only. If Pearson correlation is used as the only correlation method, the correlated network error event on July 26 2011 would not be identified. CRUMEL has shown that the errors and resource use are linearly and monotonically correlated with compute node hang-ups. It also identified two more error groups associated with compute node hang-ups. They are: (i) process errors, (ii) file-system errors.

Several tools such as IPLOM [25], LoGs [26], SLCT/Loghound [27] and SEC [28] have been developed to automate processing of system message logs. Fluentd[4] is an open-source data collector that process multiple application logs. CRUMEL complements these tools by processing both the Rationalized message logs and TACC_Stats resource use data collected on open-source cluster systems.

A number of works have shown that message logs are useful for classifying log messages into semantic categories that accurately replicated the manual annotation of messages [29], and for establishing six groups of errors associated with compute node hang-ups [30]. In this paper, we confirmed that the six groups of errors are associated with compute node

[4]URL: http://www.fluentd.org/

hang-ups. We also showed that Lustre I/O counters can be used to monitor Lustre file-system and network errors.

V. Discussion

In this section, we discuss one limitation of the CRUMEL diagnosis framework: correlated resource use counters and correlated error events. We do not take into account resource use counters that are not correlated. For example, a popular application may spawn one process which performs only read operations and several processes which perform only write operations to a file-system. When these processes are executed, they may trigger a spike in the file-system `write_bytes` resource use counter which may cause the file-system to slow and eventually hang. We also do not take into account error events that occur on non-failure dates. That being said, we argue that this pertains to the problem described in Section II-B, i.e., *we seek to identify the resource use counters and error events that are correlated on the dates of failures.*.

VI. Conclusion and Future Work

We presented the CRUMEL framework that correlated both the message logs and resource use data to identify errors and resource usage patterns. We showed that the new approach to integration of resource use data and message logs, and the use of multiple correlation algorithms can identify more events associated with system failures. The framework confirmed six groups of errors, identified Lustre I/O resource use counters that are correlated with occurrence of Lustre faults that are potential flags for online detection of failures, matched the dates when correlated errors and correlated resource use counters are associated with the dates of compute node hang-ups, and identified two more error groups - process errors and file-system errors - associated with compute node hang-ups.

In our future work, we plan to extend our analyses of patterns in resource use and message logs to deal with failure types other than Lustre file-system and node failures.

Acknowledgements

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