

Alert Detection in System Logs

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Abstract

We present Nodeinfo, an unsupervised algorithm for anomaly detection in system logs. We demonstrate Nodeinfo’s effectiveness on data from four of the world’s most powerful supercomputers: using logs representing over 746 million processor-hours, in which anomalous events called alerts were manually tagged for scoring, we aim to automatically identify the regions of the log containing those alerts. We formalize the alert detection task in these terms, describe how Nodeinfo uses the information entropy of message terms to identify alerts, and present an online version of this algorithm, which is now in production use. This is the first work to investigate alert detection on (several) publicly-available supercomputer system logs, thereby providing a reproducible performance baseline.

1 Introduction

For a large production computer system, like a supercomputer, unscheduled downtime carries a huge cost: the equipment and personnel required to find and fix the causes of downtime are a major contributor to the total cost of owning such a system. The data that these systems generate, typically in the form of system logs, are the primary avenue by which system administrators gain insight into the behavior of production systems. There is an increasing need for better tools for wading through the plethora of data that large systems generate.

In particular, logs are used to detect and localize faults. The manifestation of a fault in the log is an *alert*; every line in a log has an associated *alert* category, which may be *null*. Lines with a non-null alert category (henceforth *alerts*) are messages that merit the attention of a system administrator,

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either because immediate action must be taken or because there is an indication of an underlying problem. Many alerts may be symptomatic of the same *failure*. Failures may be anything from a major filesystem malfunction to a transient connection loss that kills a job (see Oliner [8] for examples). The task of *alert detection* is to automatically separate both new and known alerts from innocuous messages (noise).

In this paper, we formalize the alert detection task and propose a metric called *binary scoring* that we found to appropriately quantify operational value (Section 3). We then present *Nodeinfo*, an unsupervised alert detection algorithm that considers the information entropy of message terms (Section 4). Nodeinfo may be applied to any timestamped and tokenizable text log, it requires no system-specific information. Using nearly 750 million supercomputer log messages (81 GB) from a public data repository [8], we demonstrate Nodeinfo’s effectiveness on four separate systems (Sections 5 and 6).

The analysis gives us deeper insight into the logs that even months of prior study did not provide. First, we identify and confirm ten new alert categories, yielding new alert messages on all four systems (Section 5.1). Second, we observe that similar computers, correctly executing similar workloads, tend to generate similar logs (Section 5.3), and demonstrate how statistical algorithms can exploit this fact to obtain substantial performance improvements (Section 6). Specifically, our algorithm ultimately achieves up to seven times baseline performance on some workloads.

Nodeinfo is currently in production use on at least three supercomputers. The data sets and code are public [13, 14], so the results in this paper are verifiable and reproducible; this work provides a performance baseline for alert detection. These first steps have already improved the system administration task for the machines under study, and we are confident that further efforts will be similarly rewarded.

2 Related Work

System logs are generally readily available and often contain critical clues to causes of failure, so many tech-

niques for detecting alerts in logs have been proposed. Most prior works focus on logs with dependable structure (easily tokenizable into message-type-ID’s), and identify alerts according to a *severity* field. These attempts include pattern-learning [2], data mining techniques to discover trends and correlations [7, 12, 17, 19], and message timing [4]. However, system logs are notoriously unstructured and “severity” is not a dependable alert indicator [8].

Less work has been done in the area of unstructured message content. Attempts to apply techniques from genomic sequence mining to logs [12, 18] have run up against scaling problems. Vaarandi has applied clustering [16] and Apriori data mining [17], and was the first to encode word positions in his analyses (e.g., the first word of the message, the second, etc.), thereby effectively capturing a simple form of message context. This paper extends the understanding of how valuable such position encoding can be.

Reuning [9] and Liao [5] have each applied simple term weighting schemes to intrusion detection in logs, but Reuning concludes that his false positive rate renders the approach unusable in practice. We apply the more complex “log.entropy” weighting scheme that has been shown to be highly effective for information retrieval tasks [1].

Schroeder and Gibson conduct a long-term study of faults on clusters at Los Alamos National Labs [11]. They use a *remedy database*, a data set of failures (no noise) derived from system logs using a combination of automated scripts and manual effort, rather than the raw logs.

In this paper, we analyze system logs as they actually are: huge, unstructured, time-varying, ambiguous, and rich with information. Our algorithm makes few assumptions about what data the logs contain (and in what form), and we evaluate our method quantitatively on a large, public data set from several of the world’s most powerful supercomputing systems. As logs of this kind have only recently become available [8], we believe ours is the first such work.

3 The Challenge

Let a *log* be a sequence L of lines l_1 through l_N , where N is the total number of *messages*: $L = (l_1, l_2, \dots, l_N)$. Each line l_i consists of a sequence of characters broken up into tokens s_1 through s_M according to some delimiting sequence of characters (we use whitespace): $l_i = (s_1, s_2, \dots, s_M)$. Let $s_{i,m}$ denote the m^{th} token of line i . M may be different from line to line, and s_m need not have the same semantic interpretation throughout the log. We calculate and prepend certain important tokens. Let t be the `time` (universal time in seconds) for the line, and so let t_i be the time of line i . In addition, let c_i be the computer (hereafter *node*) that generated the line.

We decompose logs into *nodehours*: all lines from a single node c in one hour intervals corresponding to wall clock

time. Such lines are said to be *contained* by (or *in*) their corresponding nodehour; the *count* of a nodehour is the number of messages it contains. We define H_j^c , the j^{th} nodehour for node c , to be $H_j^c = \{l_i \mid c_i = c \wedge j \leq t_i/3600 < j + 1\}$.

Decomposing logs into documents by source and time reflects how many system administrators divide and conquer logs, as learned through the trial-and-error of experience. Individual lines lack the context to sufficiently characterize a message, whereas huge log dumps with interleaved node output can be difficult to mentally parse. A nodehour provides a happy medium between these extremes, and we found it to be a useful abstraction for detecting alerts. Implicitly, nodehours are chunks of data that we expect to be relatively uniform in content over time—anomalous nodehours are noteworthy events. Space constraints prevent us from discussing alternative log decompositions.

3.1 Objective

Ultimately, the goal of reliability research is to minimize unscheduled downtime. An alert detector can facilitate this goal by accurately identifying when and where alerts are generated, so that remedial or preventive action may be taken. Every log line is categorically either an alert or not, so nodehours, which consist of lines, can also be categorized by whether they contain alerts or not. A natural objective is to automatically rank nodehours by the probability that they contain alerts.

In the original data sets, every line is *tagged* with an alert category using a combination of expert rules and manual labeling [8]. In this paper, we extend that tagging, due in part to the results from our alert detection methods (Section 5.1). The message tags are used exclusively for quantifying the effectiveness of our alert detection methods: the methods themselves ignore the tags entirely.

3.2 Metrics

Call H_j^c an *alert nodehour* if it contains at least one alert. An alert detection algorithm outputs a list of nodehours, sorted in decreasing order of the probability that each is an alert nodehour. Let R_k be the union of nodehours formed by taking the top k nodehours from this output list.

Scoring a ranking of nodehours depends on the definition of what constitutes a true positive (TP), false positive (FP), true negative (TN), and false negative (FN). We experimented with several such definitions before determining that *binary scoring*, described below, is most useful in practice. This conclusion is related to the fact that some faults are *bursty*, meaning they produce numerous alert messages in a short period of time. Although the majority of fault types are not bursty [8], our alternative metrics disproportionately reward discovery of bursty alerts. (Many naïve

algorithms seemed excellent, often near-optimal.)

The *binary scoring* metric treats nodehours as atomic, considering only whether or not each nodehour H_j^c is an alert nodehour. Nodehours are categorized as follows:

$$\begin{aligned} TP &= \{H_j^c \in R_k \mid \exists l_i \in H_j^c \text{ s.t. } l_i \text{ is an alert}\} \\ FP &= \{H_j^c \in R_k \mid \forall l_i \in H_j^c, l_i \text{ is not an alert}\} \\ TN &= \{H_j^c \notin R_k \mid \forall l_i \in H_j^c, l_i \text{ is not an alert}\} \\ FN &= \{H_j^c \notin R_k \mid \exists l_i \in H_j^c \text{ s.t. } l_i \text{ is an alert}\} \end{aligned}$$

A set of nodehours, R_k , yields a single value each for precision ($\frac{TP}{TP+FP}$), recall ($\frac{TP}{TP+FN}$), and the standard F1 measure ($\frac{2*TP}{2*TP+FP+FN}$). Binary scoring spurred us to investigate false positives, thereby finding new alert types that other metrics had obscured; some of these alerts were previously unknown even to the system administrators.

Solutions are driven by the metrics used to assess them. For alert detection, the scoring method must be chosen carefully to prevent bursty alerts from eclipsing the more elusive ones. In addition to accurately reflecting the true value of an algorithm, binary scoring accomplishes what per-alert category threshold filtering [4, 10] does not: captures and filters cross-category temporal correlations. Based on our experience in this study, and following the lead of previous work [15], we recommend using binary scoring on nodehours.

3.3 Optimal and Baseline

OPT outputs exactly the list of alert nodehours and appears implicitly in all precision-recall plots as a horizontal line at a precision of one. In addition to OPT, we compute scores for a baseline that represents the predominant practice of system administrators. This Bytes baseline simply ranks nodehours by the number of bytes of message data they contain, from largest to smallest. This practice is based on the fact that some alert categories are bursty, and thus the highest-byte nodehours often do contain alerts.

4 Nodeinfo

The motivating premise of Nodeinfo is that similar computers correctly executing similar work should produce similar logs, in terms of content (i.e., line tokens). Nodeinfo is universally applicable, in the sense that it can be computed on any tokenizable log with timestamps. Nodeinfo does not train on labeled data; it is unsupervised. The results represent a performance baseline for alert detection without incorporating system-specific information. The development of Nodeinfo, as well as its performance on a small subset of the data considered in this paper, is detailed elsewhere [15]. The current work contributes examination of its effectiveness on multiple systems, larger systems, and over longer time ranges (together resulting in nearly two orders of magnitude more data). In addition, it examines the effects of using different sized sliding windows, as done in practice.

The first step is to compute how much information each token conveys regarding the computer that produced it. Let W be the set of unique *terms* formed by concatenating each line token with its position m in the line ($w_m = m, s_{i,m}$), and let C be the total number of nodes. Let \mathbf{X} be a $|W| \times C$ matrix such that $x_{w,c}$ is the number of times term w appears in messages generated by node c . Towards understanding how unevenly each term is distributed among nodes, let G be a vector of $|W|$ weights where g_w is equal to 1 plus term w 's Shannon information entropy [1]. Specifically, $g_w = 1 + \frac{1}{\log_2(C)} \sum_{c=1}^C p_{w,c} \log_2(p_{w,c})$, where $p_{w,c}$ is the number of times term w occurs on node c divided by the number of times it occurs on *any* node ($p_{w,c} = \frac{x_{w,c}}{\sum_{c=1}^C x_{w,c}}$). Thus, a term appearing on only a single node receives a weight of 1, and a term appearing the same number of times on all nodes receives a weight of 0.

The second step ranks nodehours according to how many high-information terms each contains. Let H be the set of all nodehours and let \mathbf{Y} be the $|W| \times |H|$ matrix where $y_{w,c,j}$ is the number of times term w occurs in nodehour H_j^c . The Nodeinfo value for each nodehour is then calculated as

$$\text{Nodeinfo}(H_j^c) = \sqrt{\sum_{w=1}^{|W|} (g_w \log_2(y_{w,c,j}))^2}.$$

Nodehours are then ranked by decreasing Nodeinfo value. Those containing high-information terms will be ranked high, and those containing low-information terms (even a great number of them) will be ranked low. These calculations are modeled after the ‘‘log.entropy’’ weighting scheme [1], where term entropy is calculated over node documents and then applied to all nodehour documents in the corpus.

We now describe two practical considerations important for reproducibility of our results. First, we exclude all $m = 1$ terms in order to decrease the false positive rate [15]. Second, we institute a minimum support threshold of 2. Most terms are infrequent, so this significantly reduces memory overhead and has little impact on the outcome. For instance, terms with a support of 1 must each have a weight of 1, but can contribute no more than the square root of their total number to a nodehour’s Nodeinfo(H_j^c) magnitude. One class of terms eliminated in this manner is hexadecimal addresses, which rarely facilitate alert detection. We do not evaluate the actual impact of this threshold on the results due to computational limitations.

5 Results

Using previously released supercomputer system logs [8, 15], we ran Nodeinfo offline on data from four systems: Liberty, Spirit, Thunderbird, and Blue Gene/L (BG/L). In these initial tests, the algorithm did not significantly outperform Bytes; moreover, it was far from optimal. We now

Alert Type/Cat.	Count	Nodehours	Example Message Body (Anonymized)
Affected Systems: Thunderbird, Spirit, and Liberty			
H / CHK_COND	3,948,364	66	kernel: [hex] has CHECK CONDITION, sense key = 0x3
S / EXT_INODE	1,299,603	47	kernel: EXT3-fs error [...] unable to read inode block - [...]
H / HDA_NR	883,399	1846	kernel: hda: drive not ready for command
H / HDA_STAT	883,398	1846	kernel: hda: status error: status=[...]
S / PBS_U09	437,776	199	pbs_mom: Unknown error 15009 (15009) in job_start_error from node [IP:port], [job]
S / PBS_EPI	53,647	1192	pbs_mom: scan_for_exiting, system epilog failed
S / CALL_TR	40,810	839	kernel: Call Trace: [<[...]>] net_rx_action [kernel] [...]
S / PBS_U23	5177	8	pbs_mom: Unknown error 15023 (15023) in job_start_error from node [IP:port], [job]
Affected System: Blue Gene/L			
H / DDR_STR	243	241	ddr: Unable to steer [...]consider replacing the card
H / DDR_EXC	41	41	ddr: excessive soft failures, consider replacing the card

Table 1. Additional actionable alert messages discovered via our algorithms.

describe the insights that allow us, in Section 6, to improve performance several-fold.

5.1 Data Refinement

We investigated this mediocre performance by scanning the output nodehour lists for false positives, starting with the most highly-ranked nodehours that ostensibly contained no alerts. In these nodehours, we discovered several new alert types that had been incorrectly assigned null alert tags. Using the same rigorous verification process as was employed to tag the original alerts, we updated the data sets with these new alert types. This process involves discussions with the system administrators and a characterization of the alerts that allows us to identify them elsewhere in the log. We also discovered 80 lines erroneously tagged as alerts in the original data [8]. Two were test scripts run on Spirit by an administrator, and the other 78 (on Thunderbird) appear to have been the result of a buggy tagging script. The new alerts are summarized in Table 1, similar to Table 4 in Oliner et al [8]. “Cat.” is the alert category. Types are H (Hardware) and S (Software). Bracketed text indicates omitted information; a bracketed ellipsis indicates sundry text. In all, we discovered ten alert categories, containing 7,552,458 new alert messages across 6325 nodehours.

One might speculate whether such alerts could have been discovered via inspection, such as by selecting and reading random nodehours. Years of intense scrutiny by the system administrators, and later by Oliner and Stearley, failed to elucidate the alerts discovered via our automated method. Thus, we believe such speculation is idle; our information-theoretic algorithm revealed new alert categories with great efficiency, and the administrators have since incorporated these alerts into their production detection infrastructure.

5.2 Tagging Limitations

In addition to the ten alert categories enumerated in Table 1, our analysis revealed dozens of other alert categories

System	Counts	C %	A/IO %	O %
Blue Gene/L (8.48% alerts)	Total: 1,816,627	87.08	12.10	0.8200
	Alert: 154,014	45.42	54.52	0.0600
Thunderbird (0.163% alerts)	Total: 15,255,833	89.50	0.6603	9.840
	Alert: 24,877	85.81	0.0764	14.11
Spirit (0.207% alerts)	Total: 6,731,957	98.76	0.3894	0.8506
	Alert: 13,933	93.12	5.828	1.052
Liberty (0.282% alerts)	Total: 1,820,433	96.07	1.492	2.438
	Alert: 5139	97.90	0.1946	1.905

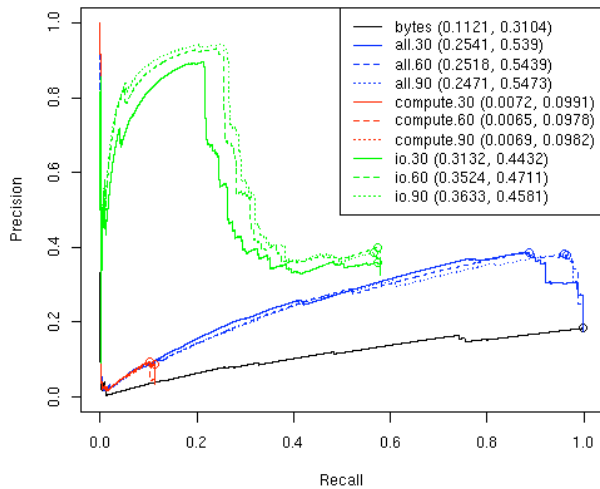
Table 2. Distribution of total and alert node-hours across node types. ‘C’ is Compute, ‘A/IO’ is Admin and IO, and ‘O’ is Other.

that were more challenging to incorporate into our current tagging framework. Whether or not certain messages are alerts may depend on (i) the rate at which the messages were generated (rate-sensitive), (ii) proximate messages or the operational status [8] of the node (context-sensitive), or (iii) whether the corresponding remedy is actually known or elected (non-actionable).

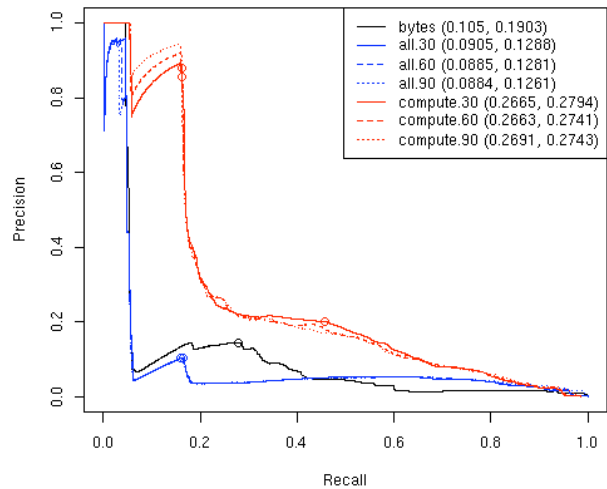
Per-message alert tagging is straightforward (linewise regular expressions) and precise (exact time and source of an alert). Furthermore, the use of linewise tagging in this paper is consistent with prior work [3, 6, 8]. Nevertheless, limitations of our tagging tools and a poor understanding of rate thresholds obliged us to exclude rate- and context-sensitive messages as alerts. There is reason to expect that including them would improve the performance of our techniques. System administrators have advised us that non-actionable alerts still merit their attention, and so we treat them on par with actionable alerts for scoring.

5.3 Similar Nodes

Statistical anomaly detection algorithms compare a sample against a reference distribution and measure the variation from “normal”; such algorithms perform better when the reference distribution is from the same homogenous population as the sample. In the context of large clusters



(a) Blue Gene/L. Detection performance on the IO nodes in isolation exceeds that of detection over the log as a whole, even when dropping alerts from every other functional group on the floor.



(b) Spirit. For comparison, the compute nodes group on Spirit yielded area under the curve more than twice that of both Bytes and Nodeinfo run on the entire log, even without considering the remainder of the data.

Figure 1. Precision-recall curves for the online Nodeinfo detector. The legend indicates the functional group, window size, area under the curve, and maximal F1: group.window (area, F1).

and supercomputers, different nodes serve different functions: computation, administration, communication, etc.

We ran Nodeinfo on logs from all nodes, and on functionally similar subsets independently, but scored all results using the full number of alerts in all the logs. When considering only compute nodes on Liberty, the Nodeinfo algorithm achieves a maximal F1 score that is seven times better than when non-compute nodes are included. In other words, even when we cripple Nodeinfo by showing it only logs from the compute nodes, its score against the entire data set improves. Although we omit these offline results, the online experiments show similar improvements (Section 6).

Table 2 shows the distribution of nodehours from each functional group: compute nodes, administrative nodes (Thunderbird, Spirit, and Liberty), IO nodes (BG/L), and other nodes. Columns 4–6 give the percent contribution of that functional group to the total number of nodehours (first row) and the number of alert nodehours (second row). For example, only 12.1% of the nodehours on BG/L were from I/O nodes, but this functional group contributed 54.52% of the alert nodehours. Considering that only 3.9% of Liberty’s nodehours were from non-compute nodes, the significant impact of their exclusion on Nodeinfo is particularly impressive. These data support our claim that similar computers (compute nodes) tend to generate similar logs.

6 Online Detection

The offline techniques are valuable for exploring the data, but a production setting requires online detection with low latency. In this section, we modify Nodeinfo to oper-

ate using a sliding bounded history window. Furthermore, we try running on major functional groups individually, to evaluate the impact of leveraging our observation regarding similar nodes.

We use a “sticky” sliding window to compute the Nodeinfo score for the current nodehours: for reasons of efficiency, this window is not of fixed size; it always starts at midnight $W - 1$ days prior, for a window size of W days. For example, if $W = 30$, then all nodehours on January 30th will use data generated since January 1st at 12:00 AM. Thus, W is an upper bound on the amount of history considered in the computation. We consider windows of 30, 60, and 90 days. For consistency, the first 90 days of data are omitted from scoring all online experiments.

To evaluate our similar nodes hypothesis, we divide the logs into functional groups (see Table 2) and run Nodeinfo on each group; the resulting lists of ranked nodehours are then scored against *all* functional groups. (Alerts in other groups are automatically false negatives.) Results from BG/L and Spirit are plotted in Figure 1, and these are representative. For example, Nodeinfo on Spirit (Figure 1(b)) performs slightly worse than Bytes when run on logs from all nodes, but beats it by more than twice (area under the curve) when considering functional groups individually. For comparison, consider the area under the curve metric when the results in Figure 1 are scored against only their respective functional groups: on the BG/L IO nodes, Nodeinfo achieves 0.63 of OPT; on the compute nodes, the metric improves nearly ten-fold. The critical conclusion is that we can leverage the homogeneity of large systems to dramatically improve the quality of alert detection.

Our results show that (i) Nodeinfo is an improvement over Bytes, (ii) Nodeinfo performs better on homogenous functional groups than on all the log at once, and (iii) larger window sizes yield marginal improvements, suggesting both that the logs are changing slowly enough for the past few months to reflect the future and that the computationally inexpensive parameters yield competitive results.

7 Contributions

The central goal of reliability research for high performance computing is to minimize unscheduled downtime. In order to do so, we must reduce the time that system administrators spend investigating new fault types and performing root cause analysis. Better techniques for alert detection are an important step toward more efficient system management, automatic fault prediction and response, and greater overall reliability.

In this paper, we formalized the alert detection problem; presented Nodeinfo, a general, unsupervised alert detection algorithm; and quantitatively demonstrated its effectiveness on 81 GB of public supercomputer system logs. Our most salient insight into the alert detection problem is that similar nodes running similar workloads tend to generate similar logs—we can better identify anomalous behavior when normal behavior appears more uniform. The most compelling evidence of our success is that we discovered several new alert categories that had eluded experts for years and that our online implementation of Nodeinfo [14] is in production use on Red Storm, Thunderbird, and Liberty. According to the administrators of these systems, “[our method] has automatically detected, and more importantly isolated, a wide range of problems,” and they have found it to be “a useful diagnostic tool.” Thus, our work has already had a positive operational impact on the systems we studied.

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