BlueGene/L Failure Analysis and Prediction Models

Liang, Y.; Zhang, Y.; Jette, M.; Anand Sivasubramaniam; Sahoo, R.;

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Presented by:
Ignacio Laguna
Dependable Computing Systems Lab (DCSL)

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The Complexity of Today's Supercomputers

IBM BlueGene/L at Lawrence Livermore National Laboratory (LLNL)

The fastest supercomputer (The Top500 Supercomputers list by Ago, 05)

- 64 racks of 128K PowerPC 440 700MHz processors
- Each rack consists of 2 midplanes
- Each midplane has
  - * 1024 processors
  - * 16 node cards
  - * 4 I/O cards
  - * 24 midplane switches
- Huge amount of event logs collected at a centralized point (1,318,137 entries)

- Challenge: How to analyze and (possibly anticipate) failures in such a complex environment?

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Key Contributions of the Paper

- Presented a careful study of collected event logs from BlueGene/L over > 100 days
- Developed three prediction algorithms based on:
  - * Failure characteristics
  - * Correlation between fatal events and non-fatal events
- Evaluated the effectiveness of the algorithms to anticipate failures

Outline

- Motivation for Failure Prediction
- Description of Event Logs
- Data Processing mechanisms
- Failure Prediction Algorithms
  - * Based on failure characteristics
  - * Based on the occurrence of non-fatal events
- Summary

Motivation for Failure Prediction in BlueGene/L

- Different applications may span several thousand processors
  * Hydrodynamics, quantum chemistry, climate modeling
- Failures are becoming a norm rather than an exception
  * Transient hardware failure increasing (from memory to combinational circuits)
  * Permanent hardware device failures leading to immense heat dissipation
  * In addition, software bugs may increase application crashes
- Applications running for a long time may be aborted because of failures → waste of effort

Motivation for Failure Prediction in BlueGene/L

- Low availability impacts response time
  * A real example:
    - LLNL has found frequent L1 cache failures for long running jobs
    - To finish these jobs, L1 cache has been disable for jobs > 4 hours
    - Results → much prolonged execution times for jobs
- Checkpointing techniques are not effective
  * Much overhead compared to the gain
  * Checkpointing a job of tens of thousands tasks may take at least ½ hour
- Failure prediction is considered challenging
  * One reason is the lack of suitable data from real systems

Event Logs Description

- Event logs have been collected for more than 100 days (~1,3 millions of entries)

- Attributes in each record of the logs:
  * RECID — sequence number of an entry
  * EVENT_TYPE — mechanism through which the event is recorded
  * FACILITY — The component where the event is flagged:
    - LINKCARD, APP, KERNEL, HARDWARE, DISCOVERY, CMCS, BGLMASTER, SERV_NET
  * SEVERITY — denotes increasing order of severity:
    - INFO, WARNING, SEVERE, ERROR, FATAL, or FAILURE (these two ones usually lead to application crashes)
  * EVENT_TIME — timestamp
  * JOB_ID — the job that detect this event
  * LOCATION — a combination of job ID, processor, node, and block (or a separate field)
  * ENTRY_DATA — gives a short description of the event

Data Processing Schemes

- Log entries may be repeated or redundant
  * Filtering tools have been developed in previous work (*DSN 2005*)

- Steps on filtering data:
  1. *Extracting and Categorizing Failure Events*
     * Extract all the events with severity levels of FATAL or FAILURE (called failures).
       * These events will lead to application crashes
  2. *Temporal Compression at a Single Location*
     * Clusters—failure events from the same location that often occur in bursts
  3. *Spatial Compression Across Multiple Locations*
     * A failure can be detected or reported by multiple locations.
     * For example, a network failure is likely detected by multiple locations
     * It removes failures that are close to each other (from the same job) but from different locations

* After these steps, unique failures can be identified

Filtering Thresholds for Clustering

Log size with T_{th} =	Memory	Network	APP-IO	Midplane Switch	Node Cards
0	8,206	10,554	178,292	166	96
30 sec	267	9,418	178,015	83	6
1 min	251	9,418	173,491	52	6
5 min	246	9,415	102,442	30	4
30 min	241	9,219	89,333	22	4
1 hour	237	8,705	81,834	17	4

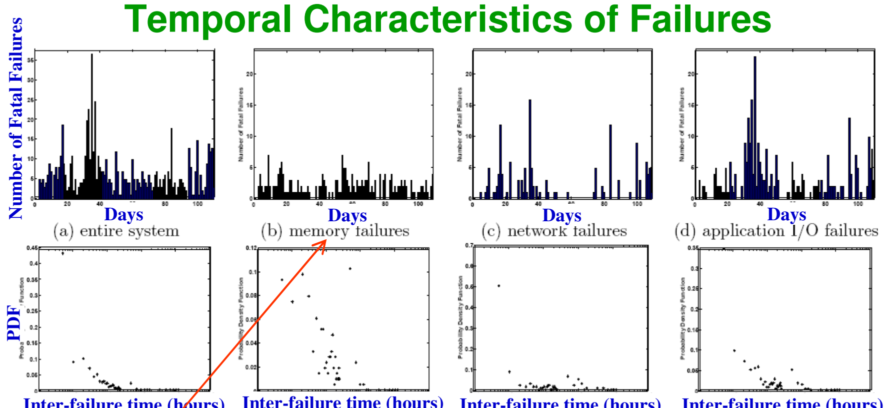
(a) Number of failure events after temporal filtering using different T_{th}

Log size with S_{th} =	Memory	Network	APP-IO	Midplane Switch	Node Cards
0	246	9,415	101,196	30	4
30 sec	217	139	331	30	4
1 min	217	139	318	30	4
5 min	215	139	299	30	4
30 min	208	114	237	22	4
1 hour	199	105	225	17	4

(b) Number of failure events after spatial filtering using different S_{th}

Table 1. Filtering thresholds

Temporal Characteristics of Failures



(a) entire system (b) memory failures (c) network failures (d) application I/O failures

(e) entire system (f) memory failures (g) network failures (h) application I/O failures

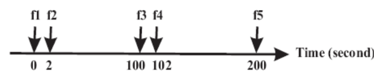
- Memory failures occur everyday
- Many TBF values have comparable likelihood (not a single value dominates)

- Network and application I/O failures occur in burst
- Small TBF values are more popular than larger ones
- For example, 50% of the network failures occur within half an hour after the previous failure

Failure Prediction Based on TBF

- Failure Prediction Strategy for network and application I/O failures:
  * When a failure is reported, the system is monitored closely for a period of time, since more failures are likely to occur

- Predicting too close failure is not very useful



- This prediction algorithm was run for application I/O and network failures
  * A failure can be predicted by another failure in a window of 5 min ~ 2 hours
    - Rationale: < 5 min is not useful, and > 2 hours incurs in high overhead
  * 52 network failures predicted out of 139 (37%)
  * 143 application I/O failure predicted out of 299 (48%)

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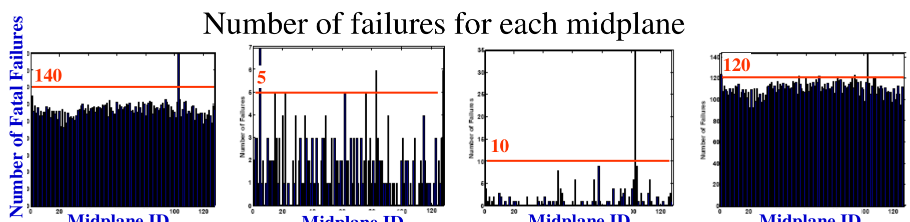
Spatial Characteristics of Failures

Number of failures for each midplane



(a) entire system (b) memory failures (c) network failures (d) application I/O failures

- Memory failures are evenly distributed across all the midplanes
  * 104 out 128 midplanes have reported failures
- All the midplanes have similar probabilities of having memory failures
  * It is hard to predictic memory failures based on spatial characteristics
- Network failures show more pronounced skewness
  * 61 out of 128 midplanes have network failures
  * Midplane 103 alone experiences 35 failures (26% of the total)

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Failure Prediction Based on Spatial Skewness

- For network failures, the focus is for midplanes that has reported more failures than others

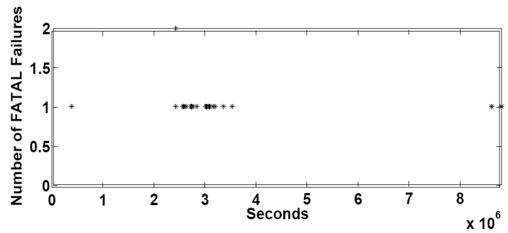

Figure 5. The time series of failure occurrence on midplane 103

- Most of the failures on midplane 103 are close to each other
  * A simple prediction strategy is very promising (most of the failures are clustered together)

Predicting Failures Using the Occurrence of Non-Fatal Events

- Correlation between fatal events and non-fatal events is studied

- Conducted a quick experiment to evaluate the likelihood of such correlation
  * Filter all fatal events (by JOB_ID), and see whether the same job has reported non-fatal events before
  * Results of the experiment:

Type of Fatal Failure	Number of Jobs Terminated by the Fatal Failure	Number of Jobs that Reported One or More Non-Fatal Events Before
Memory	134	82
Network	34	15

- It is promising to predict fatal failures by the use of the occurrence of non-fatal failures!

Predicting Failures Using the Occurrence of Non-Fatal Events (Cont'd)

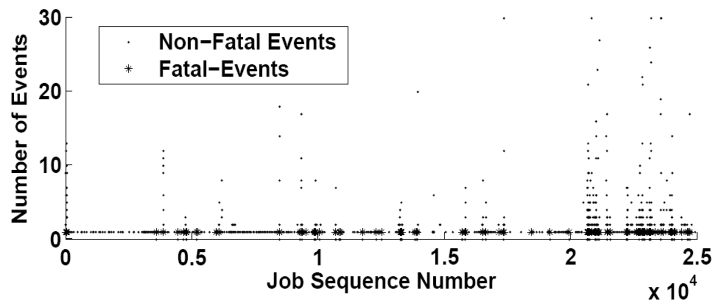

Figure 6. The number of non-fatal and fatal events for each job. On the x-axis, we obtain the job sequence number by subtracting the minimum JOB_ID from the original JOB_ID field of the raw log.

- Counted the number of events each job has encountered (a job has at most one fatal event)
- Large burst of non-fatal events are likely to occur followed by fatal failures

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Exploring the Correlation Between Non-Fatal Events and Fatal Events

n	no. of jobs with n non-fatal events (x)	no. of failures within a window of 5 jobs after these jobs (y)	y/x (%)
$[40, \infty)$	4	1	25
$[20, 40)$	9	2	22.22
$[10, 20)$	30	8	26.67
$[2, 10)$	257	53	20.62
1	1543	74	4.70

(a) The correlation between non-fatal events and fatal events

If a job reports more than 40 non-fatal events, there is a chance of 25% that a fatal failure will occur (in a windows of 5 jobs after it)

- On average, if a job experiences 2 or more non-fatal events, there is a change of 21.33% that a fatal failure will follow
- Prediction Strategy:
  - If a job has observed two non-fatal events, a fatal failure may occur to this job or the following four jobs
  - Results: predicted 65 out of 168 fatal failures

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Summary

- This paper has tackled the challenges of predicting failures at the level of very complex supercomputing systems such as the IBM BlueGene/L

- It has been collected event logs from BlueGene/L over a period of 100 days

- The paper finds strong correlations between the occurrence of a failure and factors such as:
  * Timestamps of other failures
  * Location of other failures
  * The occurrence of non-fatal events

- Three simple predictions schemmes has been proposed for failure prediction
  * Because of their simplicity, this schemes can be implemented a at low runtime cost