

Detecting Large-Scale System Problems by Mining Console Logs

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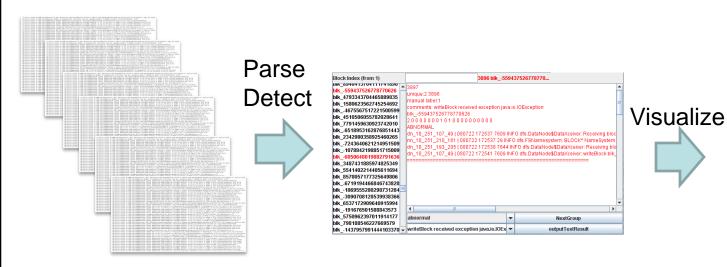
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- Detecting problems in large scale Internet services often requires detailed instrumentation
- Instrumentation can be costly to insert & maintain
 - High code churn
 - Often combine open-source building blocks that are not all instrumented
- Can we use console logs in lieu of instrumentation?
 - Easy for developer, so nearly all software has them
 - Imperfect: not originally intended for instrumentation



Result preview





200 nodes,>24 million lines of logs

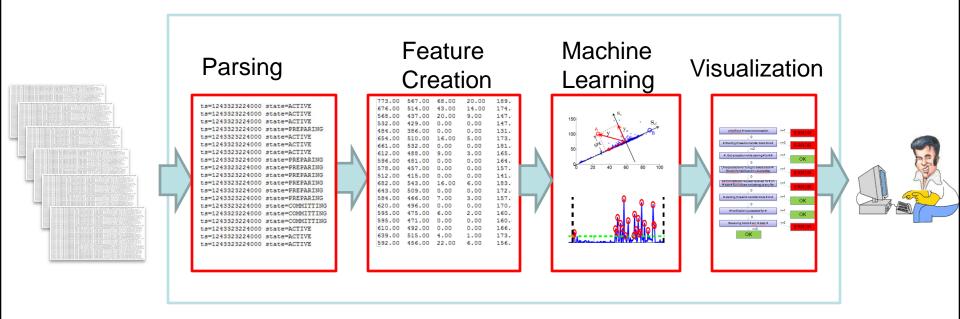
Abnormal log segments

A single page visualization

Fully automatic process without any manual input



Our approach and contribution



- A general methodology for processing console logs automatically
- Validation on two real systems



Key insights for analyzing logs

- The log contains the necessary information to create features
 - Identifiers
 - State variables
 - Correlations among messages

```
receiving blk_1
received blk 1
```

NORMAL

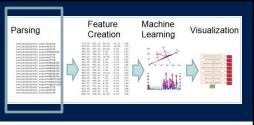
ERROR

receiving blk_2

- Console logs are inherently structured
 - Determined by log printing statement



Step 1: Parsing



- Free text → semi-structured text
- Basic ideas

```
Receiving block blk_1

Log.info("Receiving block " + blockld);

Receiving block (.*) [blockld]
```

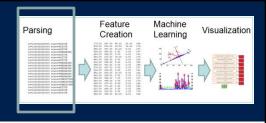
Type: Receiving block

Variables: blockld(String)=blk_1

- Non-trivial in object oriented languages
 - Needs type inference on the entire source tree
- Highly accurate parsing results



Step 2: Feature creation - Message count vector



- Identifiers are widely used in logs
 - Variables that identify objects manipulated by the program
 - file names, object keys, user ids
- · Grouping by identifiers
 - Similar to execution traces

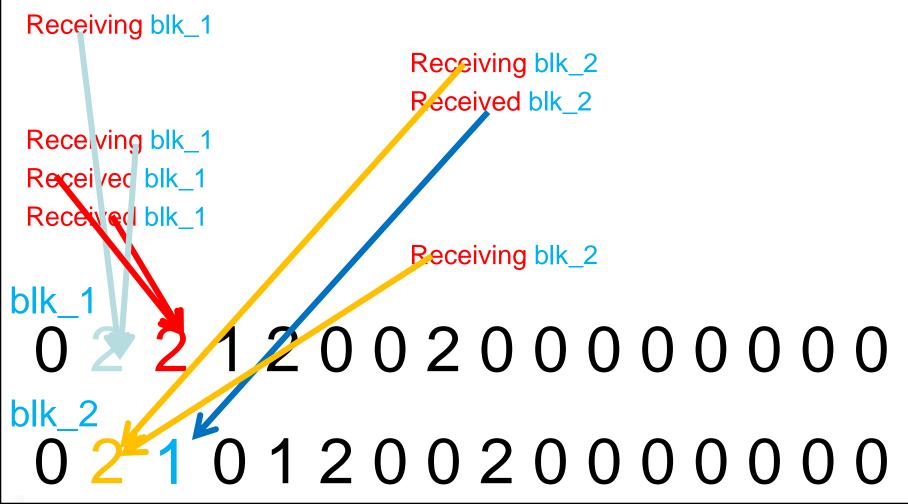
```
receiving blk_1
receiving blk_2
receiving blk_1
received blk_2
received blk_1
received blk_1
received blk_1
receiving blk_2
```

Identifiers can be discovered automatically



Feature creation – Message count vector example

- Numerical representation of these "traces"
 - Similar to bag of words model in information retrieval





Step 3: Machine learning – PCA anomaly detection



- Most of the vectors are normal
- Detecting abnormal vectors
 - Principal Component Analysis (PCA) based detection
 - PCA captures normal patterns in these vectors
- Based on correlations among dimensions of the vectors





receiving blk_2

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Evaluation setup

- Experiment on Amazon's EC2 cloud
 - 203 nodes x 48 hours
 - Running standard map-reduce jobs
 - ~24 million lines of console logs
 - ~575,000 HDFS blocks
- 575,000 vectors
- ~ 680 distinct ones
- Manually labeled each distinct cases
 - Normal/abnormal
 - Tried to learn why it is abnormal
 - For evaluation only



PCA detection results

	Anomaly Description	Actual	Detected
1	Forgot to update namenode for deleted block	4297	4297
2	Write block exception then client give up	3225	3225
3	Failed at beginning, no block written	2950	2950
4	Over-replicate-immediately-deleted	2809	2788
5	Received block that does not belong to any file	1240	1228
6	Redundant addStoredBlock request received	953	953
7	Trying to delete a block, but the block no longer exists on data node	724	650
8	Empty packet for block	476	476
9	Exception in receiveBlock for block	89	89
10	PendingReplicationMonitor timed out	45	45
11	Other anomalies	108	107
	Total anomalies	16916	16808
	Normal blocks	558223	

False Positives

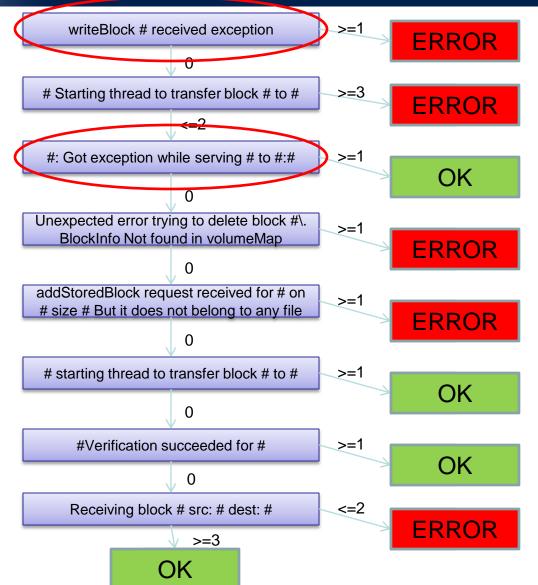
	Description	False Positives
1	Normal background migration	1397
2	Multiple replica (for task / jobdesc files)	349
	Total	1746

How can we make the results easy for operators to understand?



Step 4: Visualizing results with decision tree

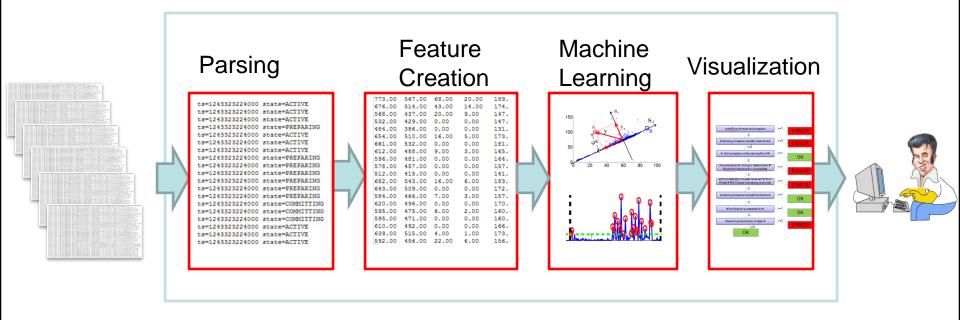






- Parsing
 - Extract templates from program binaries
 - Support more languages
- Feature creation and machine learning
 - Allow online detection
 - Cross application/layers logs





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