Automated Performance Management for the Big Data Stack

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Application Performance Management (APM) software: helps with the monitoring and management of the performance and availability of applications.
Roadmap

- Performance management requirements
- Architecture of a performance management solution
- Solutions deep dive
- Conclusion
Performance Management Requirements

Application:
- Failures
- Stalls
- Runaways
- SLA compliance
- Changes over time
- Rogue/victim apps

Operational:
- Resource allocation policies
- Rogue application detection
- Tuning configuration knobs, data partitioning, and storage layout
- Optimizing cloud costs
- Capacity planning
- Efficient ‘chargeback’
Architecture of a Performance Management Solution

Big Data Stack
- Application
- Scheduling
- Infrastructure
- Storage

Monitoring Data Collection
- e.g., SQL queries
- e.g., wait-time metrics
- e.g., memory usage
- e.g., reads/writes

APM Platform
- Event-driven Processing
- ML-driven Insights
- Current and Historical Data

Automated policy-driven actions

User-initiated actions

Application & Operational Insights
Solutions Deep Dive

1. Application failure

2. Cluster optimization
Solution Deep Dive #1: Application Failure

Example: Distributed Spark applications

- 1 driver container, 1+ executor containers
- Many verbose, messy logs are generated each time an application fails

Two parts:

1. Automatic identification of the root cause of the failure
2. Automatic fixes for failed applications
Part 1: Supervised Approach for Automatic Root Cause Analysis (RCA)
Training Data Collection and Preprocessing

Training data:

- Logs from real-life Spark application failures
- Logs generated by their lab framework that artificially injects failures

Preprocessing:

- Extract all possible error message templates from each log
Labeling the Root Cause

- Logs generated from their lab framework: *labels already known*
- Logs from real-life Spark failures: *labeled by a human expert*

Taxonomy of Failures
Transforming Logs Into Feature Vectors

1. Bit vector membership encoding (e.g., 100110)
   a. Each bit represents whether a specific error message template is present in the log

2. Bag of words + TF-IDF
   a. Ignores word order and semantics

3. Doc2Vec
   a. Incorporates word order and semantics information

Ready to train the predictive model.
Accuracy at Predicting the Root Cause

- Training data (failure logs) generated from injecting 14 root causes of failures
- Accuracy calculated using a 75%-25% split of training and test data

![Accuracy Score Graph](chart.png)
Solution Enhancements

- Make the degree of confidence in the predicted root cause easier for users to understand
- Speed up the ability to incorporate new types of application failures
  - Active learning techniques to prioritize failure log labeling tasks
Part 2: Automatic Fixes for Failed Applications

Key findings from analysis of the Spark application failure logs:

- “90-10” rule in the root cause of application failures
- Two most common causes:
  - Running out of memory (OOM) on some component
  - Timeouts while waiting for some resources

Configuring memory allocation and usage:

- Multiple configuration knobs at each component: Driver, Executor, container, JVM, and more...
Automatic Fixes for Failed Applications caused by OOM

Maintain 2 variables for each memory-specific configuration knob \((m)\):

- \(m_{lo}\): max known setting of \(m\) that causes OOM
- \(m_{hi}\): min known setting of \(m\) that does not cause OOM
  - Most resource-efficient setting known to run the application successfully

Let \(m_{curr}\) be the current setting of \(m\) while the application is running and \(m_{obs}\) be the observed usage of \(m\)

On application success:

- \(m_{hi} = \min(m_{hi}, m_{obs})\)

On application failure due to OOM:

- \(m_{lo} = \max(m_{lo}, m_{curr})\)

New run of the application: set \(m = (m_{hi} + m_{lo}) / 2\)
Example: Automatic Tuning of a Failed Spark App (OOM)

- Tuning the amount of memory allocated in an Executor container

<table>
<thead>
<tr>
<th>TYPE</th>
<th>STATUS</th>
<th>ID</th>
<th>DURATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPARK</td>
<td>FAILED</td>
<td>…_1043</td>
<td>15m 34s</td>
</tr>
<tr>
<td>SPARK</td>
<td>SUCCESS</td>
<td>…_1044</td>
<td>4m 29s</td>
</tr>
<tr>
<td>SPARK</td>
<td>SUCCESS</td>
<td>…_1045</td>
<td>1m 3s</td>
</tr>
<tr>
<td>SPARK</td>
<td>SUCCESS</td>
<td>…_1046</td>
<td>1m 5s</td>
</tr>
<tr>
<td>SPARK</td>
<td>SUCCESS</td>
<td>…_1047</td>
<td>1m 4s</td>
</tr>
</tbody>
</table>
Solution Deep Dive #2: Cluster Optimization

Three parts (sort of):

1. Fine-tuning cluster-wide configuration parameters
2. Optimizing resource budget configurations
3. Capacity planning using predictive analysis
Approach for Fine-tuning Cluster-wide Configuration Parameters

- Collect performance data of prior completed applications
- Analyze the applications w.r.t. the cluster’s current configuration
- Generate recommended cluster parameter changes
- Predict/quantify the impact these changes will have on the applications in the future
Example: Fine-tuning Cluster-wide Config Params
Optimizing Resource Budget Configurations

- Track resource utilization
- Compare *pending resource requests* with the *resources currently allocated* to generate insights
- Recommend actions based on the insights
Capacity Planning Using Predictive Analysis

- Cites “Forecasting at Scale” by S. Taylor and B. Letham from Facebook
Conclusion

- Performance management requirements of big data stacks
- Architecture for providing automated solutions to these requirements
- Deep dive into some solutions

Thoughts:

- Wish deep dives went deeper and that there was a larger discussion of the challenges they have encountered along the way
- Glad to see they are still around and making the effort to publish