Automated Performance Management for the Big Data Stack

Anastasios Arvanitis, Shivnath Babu, Eric Chu, Adrian Popescu, Alkis Simitsis, Kevin Wilkinson

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Tuning Database Configuration Parameters with iTuned. VLDB’09

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

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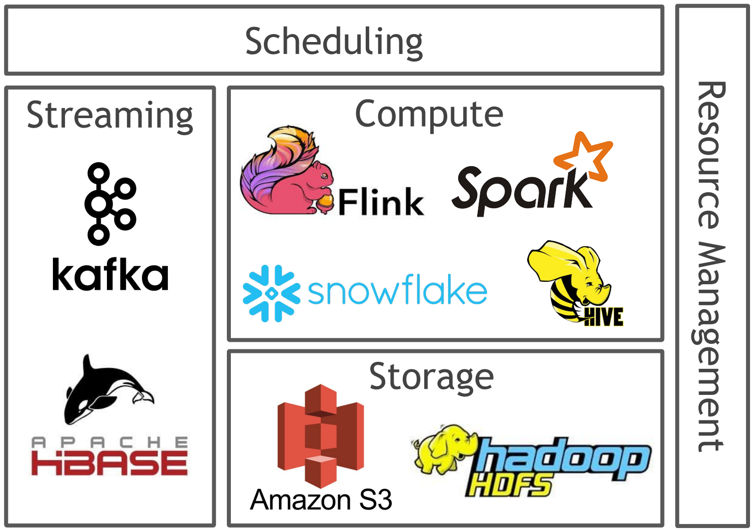
BIG DATA STACK



Roadmap

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

Performance Management Requirements

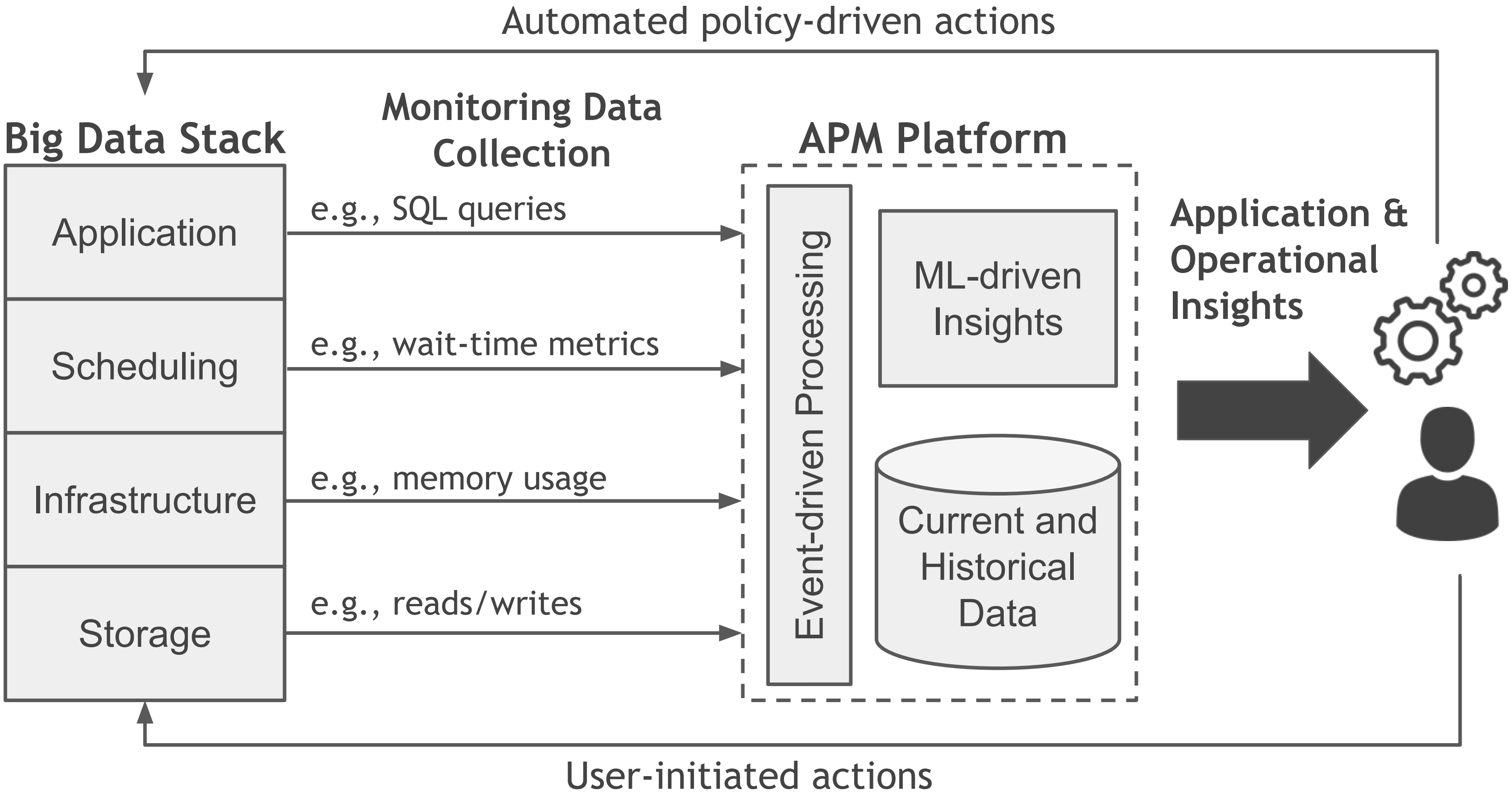
Application:

- 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



Solutions Deep Dive

1. Application failure

2. Cluster optimization

Solution Deep Dive #1: Application Failure

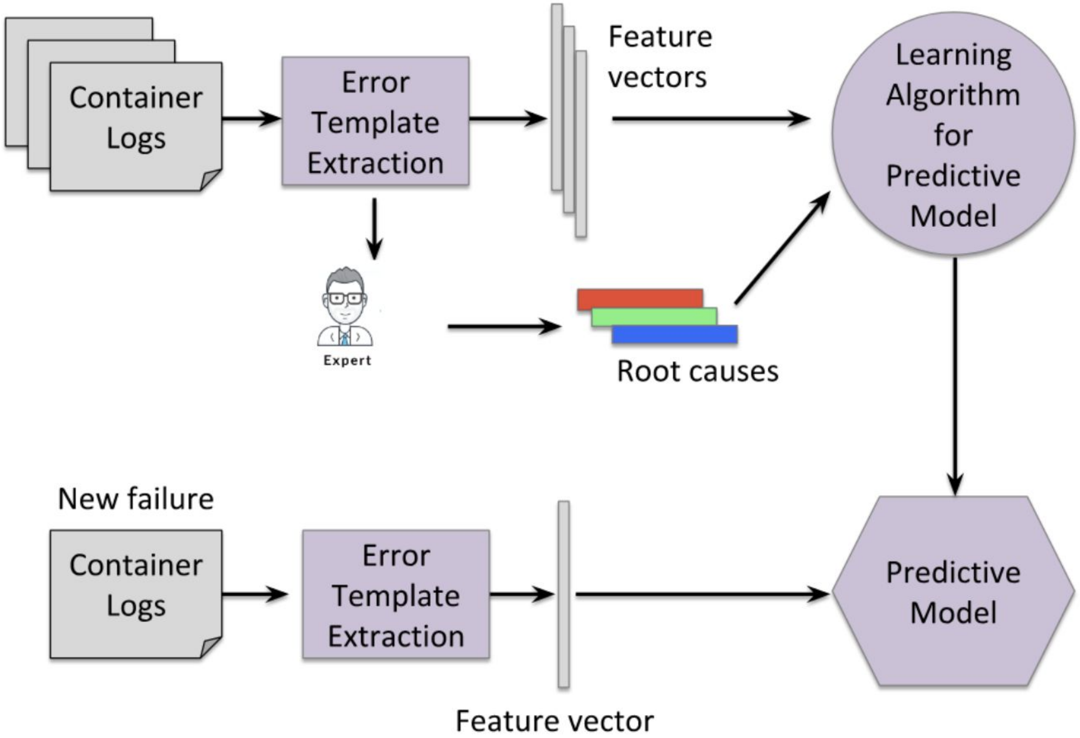
Example: Distributed Spark applications

- 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

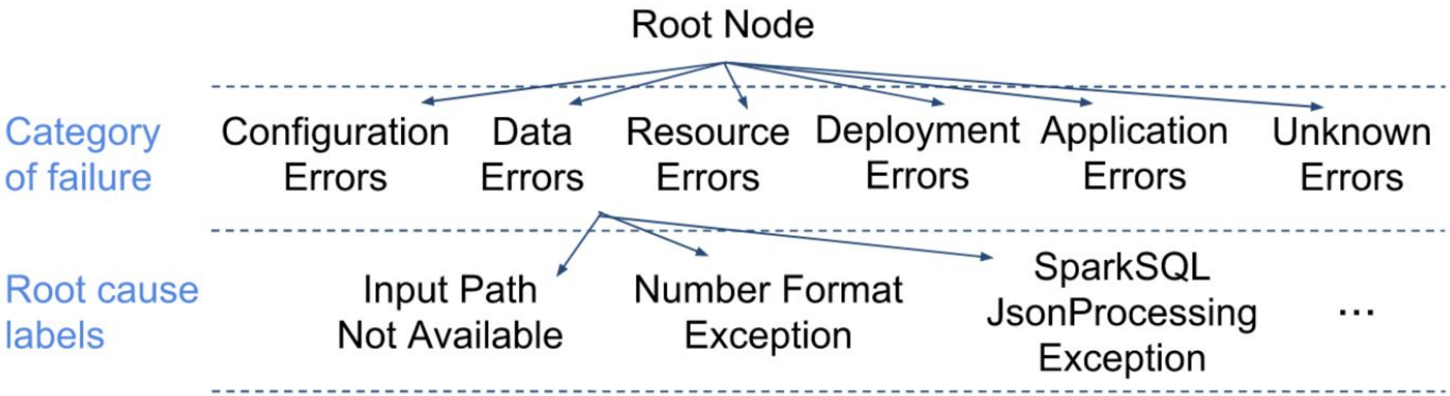
Preprocessing:

- 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



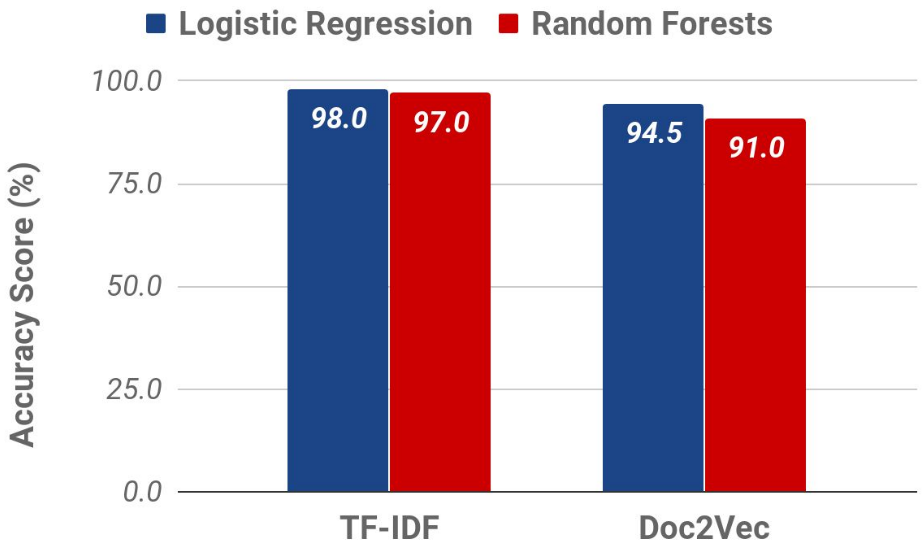
Transforming Logs Into Feature Vectors

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



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 of 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

	TYPE	STATUS	ID	DURATION
☐	SPARK	FAILED	..._1043	15m 34s
☐	SPARK	SUCCESS	..._1044	4m 29s
☐	SPARK	SUCCESS	..._1045	1m 3s
☐	SPARK	SUCCESS	..._1046	1m 5s
☐	SPARK	SUCCESS	..._1047	1m 4s

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

Tune the size of map containers

mapreduce.map.memory.mb

Recommendation: **2048**

Improvement Potential: **High**

Using the recommended default would save 50% of 1,263,087,616 MB from 7275 jobs using the current default, or 97% of total jobs in the workload

Tuning Instructions

Default: **4096**

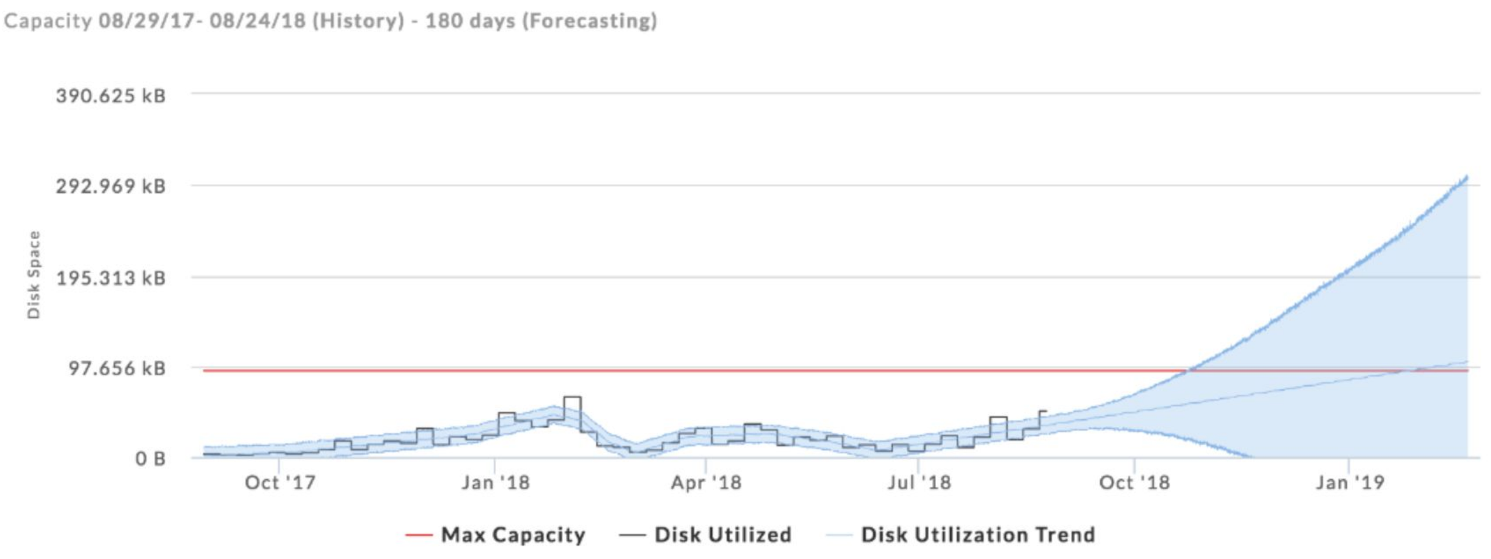
% Apps Default: **97%**

Candidate	% of memor...	% of jobs ...
1792	56%	80%
2048	50%	85%

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