Building an Apache Spark Performance Lab: Tools and Techniques for Optimization

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About Luca



- Data Engineer at CERN
 - Data analytics and Spark service, database services
 - 20+ years with databases and data engineering
 - Passionate about performance engineering

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Motivations and Scope

- Apache Spark is great at large-scale data processing
 - Distributed computing is hard
 - Getting optimal execution plans is hard
- Data-driven troubleshooting and tuning of Spark jobs
 - Beyond just measuring execution time
 - Collect and analyze Spark Metrics, Spark-Dashboard
 - Workload generator instrumented with sparkMeasure: TPCDS-PySpark
- Not a goal
 - A guide to Spark performance troubleshooting and tuning



Build a Lab!

- The key idea of this presentation:
 - Build a Spark Performance Lab
 - Run Spark jobs at scale
 - Start small (GB) and scale to TBs
 - Use instrumentation
 - Monitor the workload execution
 - Understand using data: use Spark metrics
 - Learn by running experiments: change configuration, scale, SW version, HW, etc.





Tools



1. Workload Generation

- Start by deploying TPCDS_PySpark.
 - It's a workload generator that runs TPC-DS queries on Spark, allowing for performance studies across different configurations and Spark versions.
 - Execute TPC-DS queries, a well-known suite of complex SQL, representative of many OLAP environments
 - Run at scale, from local mode and a few GB to cluster and 10s of TBs
 - Collect and analyze Spark performance metrics thanks to the integration with sparkMeasure (see discussion on sparkMeasure).



TPCDS_PySpark – getting started

• Run this getting-started example from the command line:

```
# Install the tool and dependencies
pip install pyspark
pip install sparkmeasure
pip install tpcds_pyspark
```

```
# Download the test data
wget
https://sparkdltrigger.web.cern.ch/sparkdltrigger/TPCDS/tpcds_10.zip
unzip -q tpcds_10.zip
```

1. Run the tool for a minimal test
tpcds_pyspark_run.py -d tpcds_10 -n 1 -r 1 --queries q1,q2

2. run all queries with default options
tpcds pyspark run.py -d tpcds 10



2. Explore: WebUI

- Spark WebUI is the official Spark instrumentation a starting point for performance investigations. Use it to explore the SQL, jobs, and configurations while the workload is running.
- <u>https://spark.apache.org/docs/latest/web-ui.html</u>



3. Detailed Analysis with sparkMeasure

- For a more detailed analysis, integrate SparkMeasure into your applications
- This tool is invaluable for identifying performance bottlenecks, understanding resource utilization, and comparing different Spark configurations or code changes.
- Modes of operation
 - Interactive use, analyze the metrics as you go. Use it with Notebooks or CLI.
 - Batch mode for post-execution analysis. Use it to instrument your code and/or use it for CI/CD jobs.
 - Flight-recorder mode: collect metrics without any code change.

SparkMeasure – getting started

• Run these getting started examples from the command line:

```
from sparkmeasure import StageMetrics
stagemetrics = StageMetrics(spark)
stagemetrics.runandmeasure(globals(), 'spark.sql("select count(*) from
range(1000) cross join range(1000) cross join range(1000)").show()')
```



SparkMeasures' architecture

Spark Listener Bus, Task Metrics, and SparkMeasure Architecture





4. Monitor execution with Spark-Dashboard

- Use Spark-Dashboard to monitor the Spark jobs execution in real time.
 - This involves collecting metrics from your Spark jobs and visualizing them with a Grafana dashboard.
- The dashboard displays metric related to CPU usage, I/O, Shuffle, Memory usage.
 - Time-series to follow the evolution and find bottlenecks
- The setup process is straightforward, thanks to pre-configured Docker container images.



Spark-Dashboard's architecture

Spark-Dashboard, a Monitoring Pipeline

Spark Metrics System + Telegraf + VictoriaMetrics + Grafana = Monitoring





Spark-Dashboard – getting started

1. Start the container image

docker run -p 3000:3000 -p 2003:2003 -d lucacanali/spark-dashboard

2. Run Spark

bin/spark-shell (or spark-submit or pyspark)

- --conf "spark.metrics.conf.*.sink.graphite.class"="org.apache.spark.metrics.sink.GraphiteSink" \
- --conf "spark.metrics.conf.*.sink.graphite.host"="localhost" \
- --conf "spark.metrics.conf.*.sink.graphite.port"=2003 \
- --conf "spark.metrics.conf.*.sink.graphite.period"=10 \
- --conf "spark.metrics.conf.*.sink.graphite.unit"=seconds \
- --conf "spark.metrics.conf.*.sink.graphite.prefix"="lucatest" \
- --conf "spark.metrics.conf.*.source.jvm.class"="org.apache.spark.metrics.source.JvmSource" \
- --conf "spark.metrics.staticSources.enabled"=true \
- --conf "spark.metrics.appStatusSource.enabled"=true

3. Go to the dashboard: http://localhost:3000



Example Dashboard

Partial view of the dashboard

<u> </u>			🗚 Add 🗸 🛱 🐵 < 🕐 2024-03-01 19:15:25 to 2024-03-02 11:08:58 × > Q 🕻 × 🧍		
User luca ~ Spark Application Id application_1709030796221_6947 ~ Task metrics time average 10s ~					
~ Summary metrics					
Task Run Time	Executors CPU time ①	Task CPU Usage 🕕	Task GC Time 💿	N# of Completed Tasks ①	Current N# of Running Staç 🛈
97.0 days	87.0 days	81.4 days	13.7 hours	5617544	
Heap memory Used (% of n \odot	Bytes read	Bytes written	Shuffle bytes written ①	N# of Failed Tasks ①	Failed Stages 🕕
64.2%	64.6 тів	0в	21.5 тів	8	0
N# of Active Tasks - latest ③	CPU Application Total - Exe 🛈	N# Tasks Application Total ①	Succeeded Jobs Count ③		
N/A	87.0 days	5623879	8283		
~ Spark workload metrics					
Number of Active Tasks ③			Executors JVM CPU Utilization (N# cores-equivalent) ①		
300	11 107 L 0001 1000 00 1 10 10 10		300 (tr		
200 - yeg 200 - 100 - 50 - 0			CPU Utilization (N# cores equivalence of the cores equivalence of the cores equivalence of the cores equivalence of the cores of the co		
20:00 22:00 0	00:00 02:00 04:00 0	6:00 08:00 10:00	20:00 22:00 0	00:00 02:00 04:00 0	6:00 08:00 10:00



Tutorials and Demos

Demos and tutorials of the tools for a Spark Performance Lab.

- SparkMeasure metrics collection
 - Watch the video sparkMeasure's getting started demo and tutorial
- TPCDS_PySpark workload generator
 - Watch the video Watch <u>TPCDS-PySpark demo and tutorial</u>
- Spark-Dashboard real-time dashboards
 Watch the video <u>Spark-Dashboard demo and tutorial</u>



Metrics Drill Down

- Metrics provide insights
 - They take us beyond simple timing, revealing details about task execution, resource utilization, and bottlenecks.
- Execution Time is Not Enough
 - Measuring the execution time of a job is useful but it doesn't show the whole picture.
 - Say the job ran in 10 seconds. It's crucial to understand why it took 10 seconds instead of 100 seconds or just 1 second. What was slowing things down? Was it the CPU, data input/output, or something else, like data shuffling?
 - This helps us identify the root causes of performance issues.



Make the Best of Spark Metrics

Documentation: Spark Task Metrics docs

Key Metrics to Collect and Monitor:

- **Executor Run Time:** Total time executors spend processing tasks.
- Executor CPU Time: Direct CPU time consumed by tasks.
- JVM GC Time: Time spent in garbage collection, affecting performance.
- Shuffle and I/O Metrics: Critical for understanding data movement and disk interactions.
- Memory Metrics: Key for performance and troubleshooting Out Of Memory errors



Metric Analysis, What to Look For

- Look for bottlenecks:
 - Are there resources that are the bottleneck? Are the jobs running mostly on CPU or waiting for I/O or Garbage Collection, or..?
- USE method:
 - Utilization Saturation and Errors (USE) Method
 - It is a methodology for analyzing the performance of any system.
 - The tools described here can help you to measure and understand Utilization and Saturation.



Cluster CPU Utilization

- Are you getting all allocated cores to work for you?
 - Check the number of active tasks vs. time
 - Figure: during TPCDS 10TB on a YARN cluster with 256 cores
 - Spikes and troughs. Drill down on root cause:
 - Resource allocation, partition skew, straggler tasks, stage boundaries, etc





Which Tools Should I Use?

- Start with using the Spark Web UI
- Instrument your jobs with sparkMesure.
 - This is recommended early in the application development, testing, and for Continuous Integration (CI) pipelines.
- Observe your Spark application execution with Spark-Dashboard
- Use OS-tools
 - See also Spark-Dashboard extended instrumentation: it collects and visualizes OS metrics (from cgroup statistics) like network stats, etc
- An example of "offline" Spark metrics analysis
 - TPCDS run at scale 10 TB



Lessons Learned

- **Collect, Analyze and Visualize Metrics:** Go beyond just measuring jobs' executions time, to troubleshoot and fine-tune Spark performance effectively.
- Use the Right Tools: Familiarize yourself with tools for performance measurement and monitoring.
- Start Small, Scale Up: Begin with smaller datasets and configurations, then gradually scale to test larger, more complex scenarios.
- **Tuning is an Iterative Process:** Experiment with different configurations, parallelism levels, and data partitioning strategies to find the best setup for your workload.



Conclusions

- Establishing a Spark Performance Lab is a fundamental step for any developer and data engineer aiming to master Spark's performance.
- By integrating tools like Web UI, TPCDS_PySpark, sparkMeasure, and Spark-Dashboard, developers and data engineers can gain unprecedented insights into Spark operations and optimizations.
- Learn by doing and experimentation!



Resources

- Blog: Building an Apache Spark Performance Lab: Tools and Techniques for Spark Optimization
- TPCDS_PySpark
- SparkMeasure
- Spark-Dashboard and Dashboard Notes
- Flame Graphs for Spark and Grafana Pyroscope with Spark
- Tools for <u>OS performance monitoring</u>

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