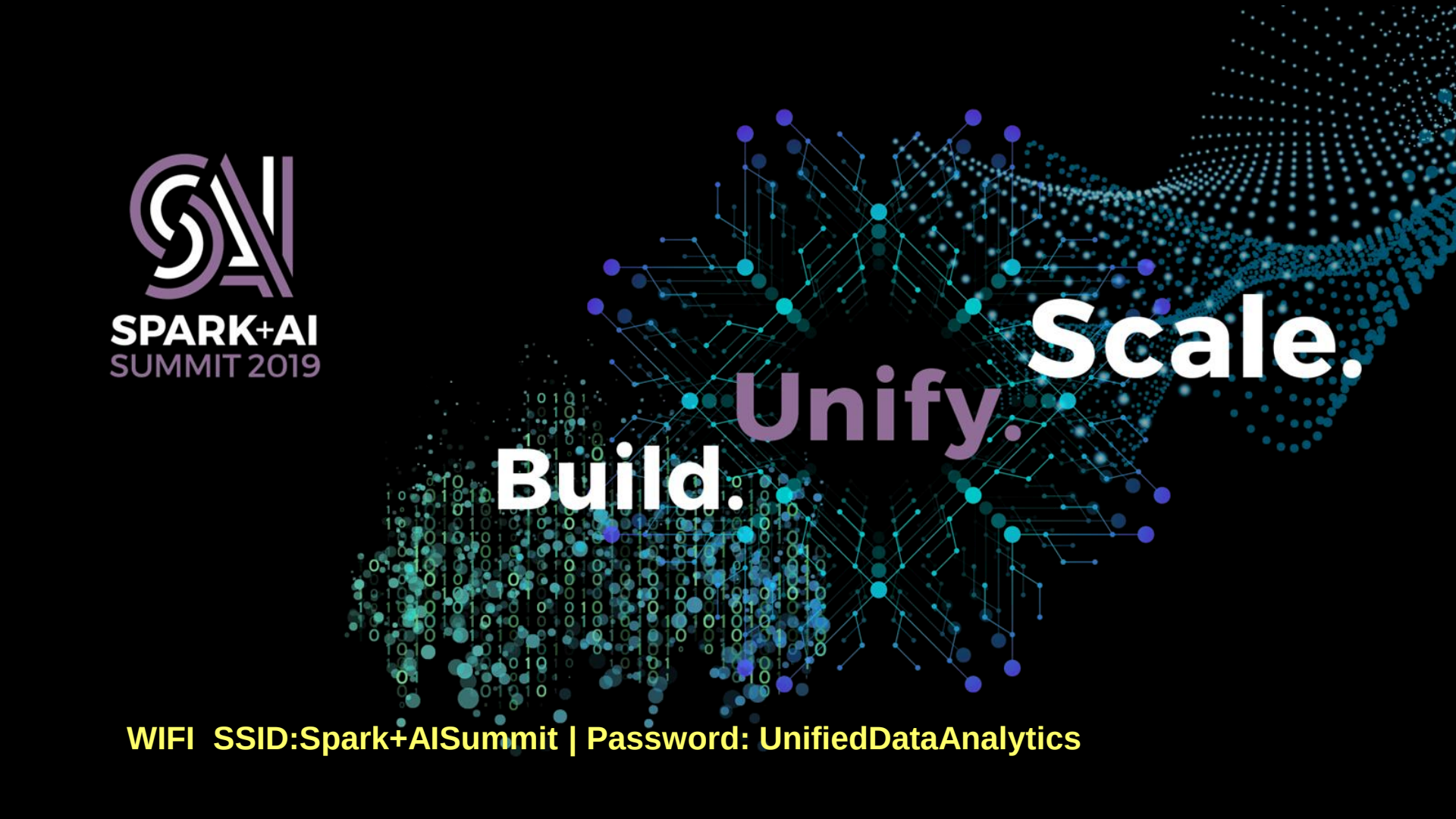


WIFI SSID:Spark+AISummit | Password: UnifiedDataAnalytics

Performance Troubleshooting Using Apache Spark Metrics

Luca Canali, CERN

#UnifiedDataAnalytics #SparkAISummit

About Luca

- Data Engineer at CERN
  - Hadoop and Spark service, database services
  - 19+ years of experience with data engineering
- Sharing and community
  - Blog, notes, tools, contributions to Apache Spark

 @LucaCanaliDB – http://cern.ch/canali

CERN: founded in 1954: 12 European States

Science for Peace and Development

Today: 23 Member States

~ 2600 staff
~ 1800 other paid personnel
~ 14000 scientific users

Budget (2019) ~ 1200 MCHF

Member States: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Israel, Italy, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovak Republic, Spain, Sweden, Switzerland and United Kingdom

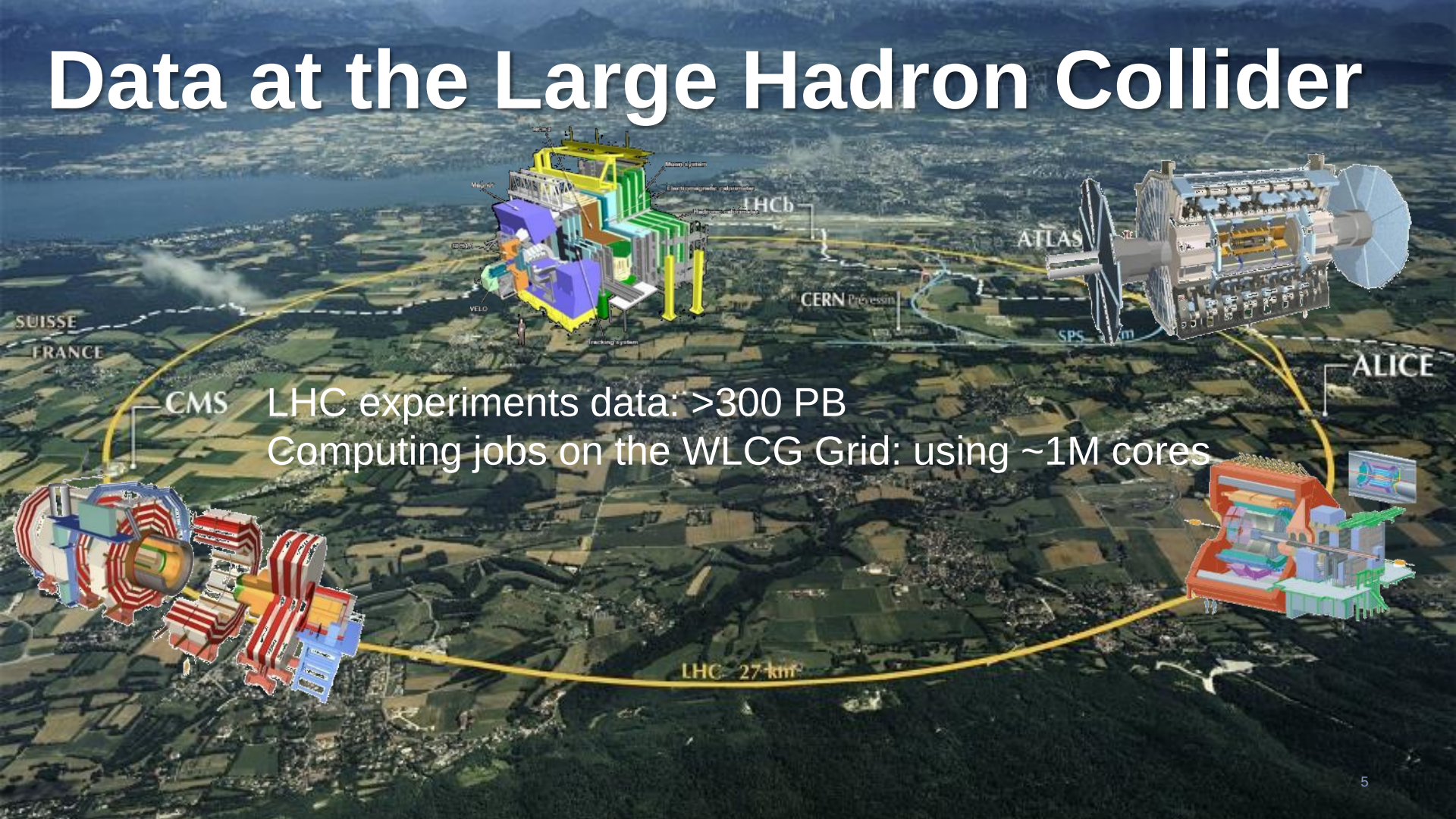
Associate Members in the Pre-Stage to Membership: Cyprus, Slovenia

Associate Member States: India, Lithuania, Pakistan, Turkey, Ukraine

Applications for Membership or Associate Membership: Brazil, Croatia, Estonia

Observers to Council: Japan, Russia, United States of America; European Union, JINR and UNESCO

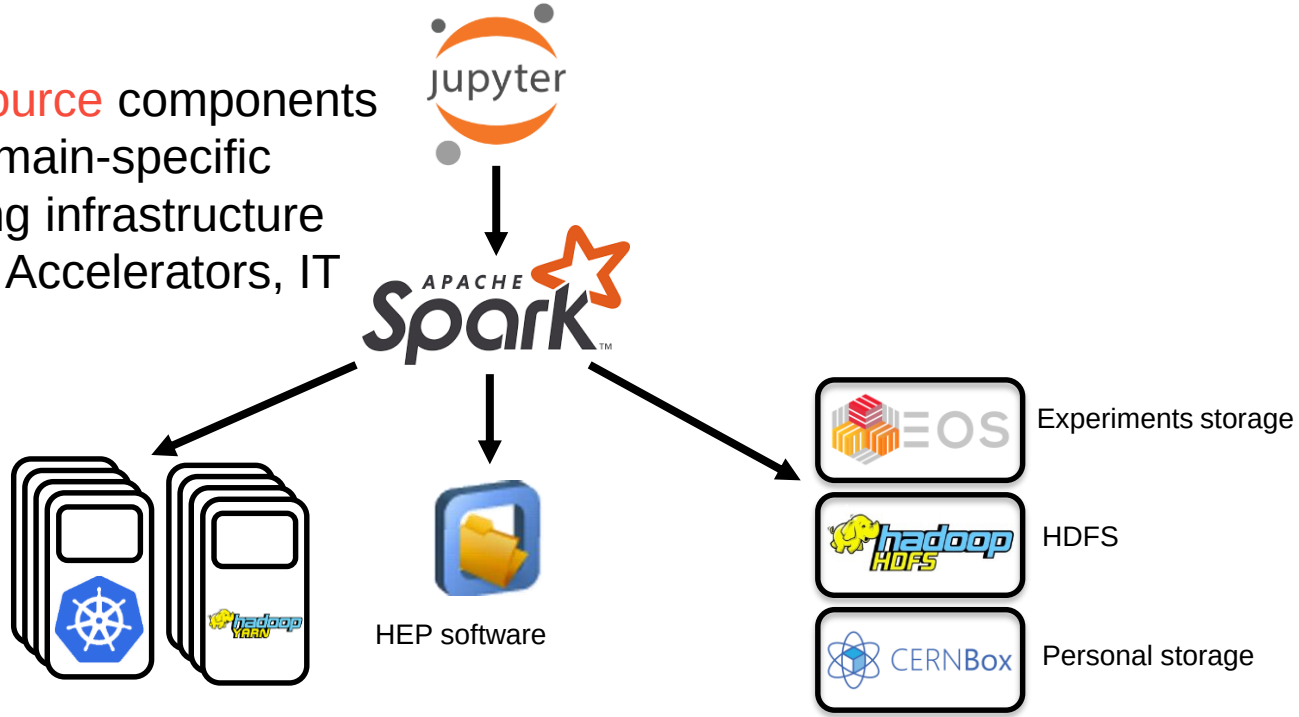
Data at the Large Hadron Collider



LHC experiments data: >300 PB
Computing jobs on the WLCG Grid: using ~1M cores

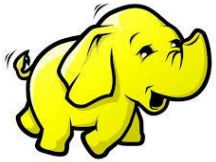
Analytics Platform @CERN

- “Big Data” open source components
- Integrated with domain-specific software and existing infrastructure
- Users in: Physics, Accelerators, IT



Hadoop and Spark Clusters at CERN

- Spark running on clusters:
  - YARN/Hadoop
  - Spark on Kubernetes



Accelerator logging (part of LHC infrastructure)	Hadoop - YARN - 30 nodes (Cores - 1200, Mem - 13 TB, Storage – 7.5 PB)
General Purpose	Hadoop - YARN, 65 nodes (Cores – 2.2k, Mem – 20 TB, Storage – 12.5 PB)
Cloud containers	Kubernetes on Openstack VMs, Cores - 250, Mem – 2 TB Storage: remote HDFS or EOS (for physics data)

FILE EDIT VIEW INSERT CELL KERNEL HELP Trusted Python 2

Code

Do the heavylifting in spark and collect aggregated view to panda DF

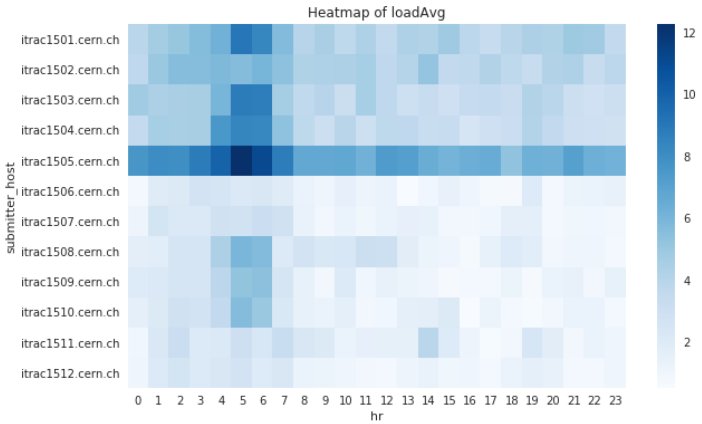
```
In [11]: df_loadAvg_pandas = spark.sql("SELECT submitter_host, \
                                        avg(body.LoadAvg) as avg, \
                                        hour(from_unixtime(timestamp / 1000, 'yyyy-MM-dd HH:mm:ss')) as hr \
                                FROM loadAvg \
                                WHERE submitter_hostgroup = 'hadoop/itdb/datanode' \
                                AND dayofmonth(from_unixtime(timestamp / 1000, 'yyyy-MM-dd HH:mm:ss')) = 15 \
                                GROUP BY hour(from_unixtime(timestamp / 1000, 'yyyy-MM-dd HH:mm:ss')), submitter_host")\
                        .toPandas()
```

Apache Spark: 90 EXECUTORS 180 CORES Jobs: 1 COMPLETED

Job ID	Job Name	Status	Stages	Tasks	Submission Time	Duration
3	toPandas	COMPLETED	2/2	388 / 388	4 minutes ago	36s

Visualize with seaborn

```
In [19]: # heatmap of service availability
plt.figure(figsize=(10, 6))
ax = sns.heatmap(df_loadAvg_pandas.pivot(index='submitter_host', columns='hr', values='avg'), cmap="Blues")
ax.set_title("Heatmap of loadAvg")

Out[19]: Text(0.5,1,u'Heatmap of loadAvg')
```



Text

Code

Monitoring

Sparkmonitor -> Jupyter extension for Spark monitoring, developed as a GSoC project with CERN. https://medium.com/@krishnanr/sparkmonitor-big-data-tools-for-physics-analysis-bbcdef68b35a

Visualizations

CERN

Performance Troubleshooting

Goals:

- Improving productivity
- Reducing resource usage and cost

- Metrics: latency, throughput, cost

How:

- Practice and methodologies
- Gather performance and workload data

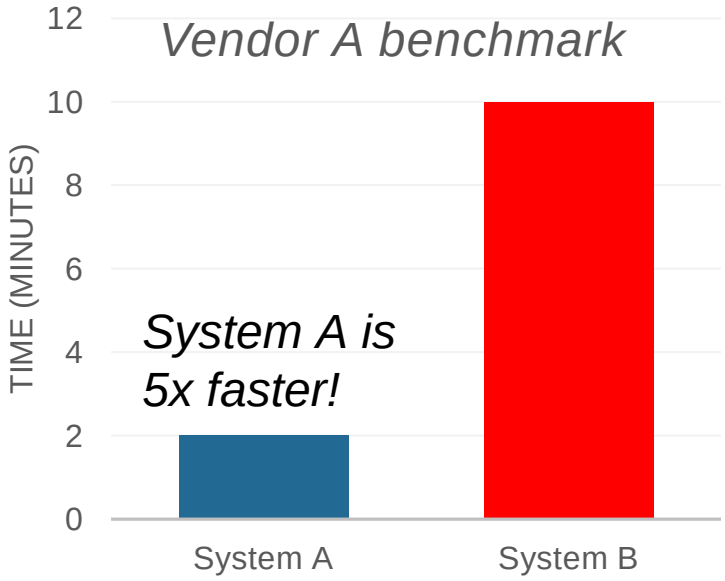
Performance Methodologies and Anti-Patterns

Typical benchmark graph

- Just a simple measurement
- No root-cause analysis
- Guesses and generalization

Sound methodologies:

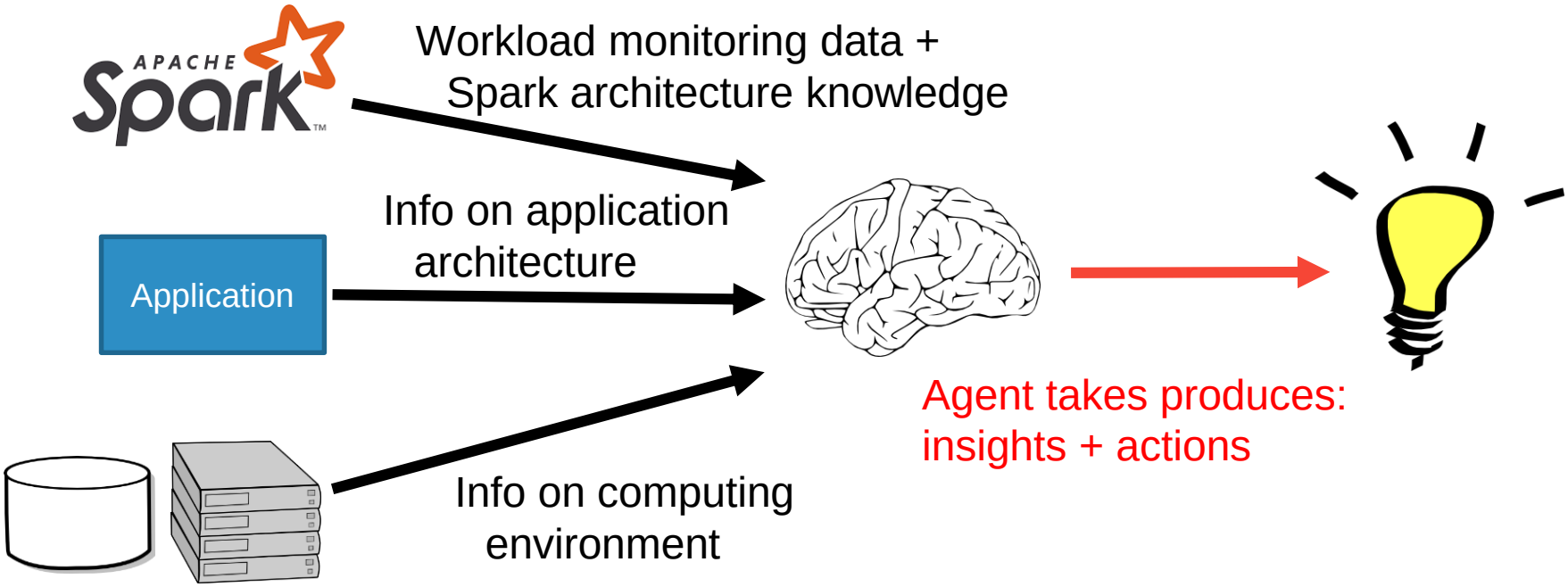
http://www.brendangregg.com/methodology.html



Workload and Performance Data

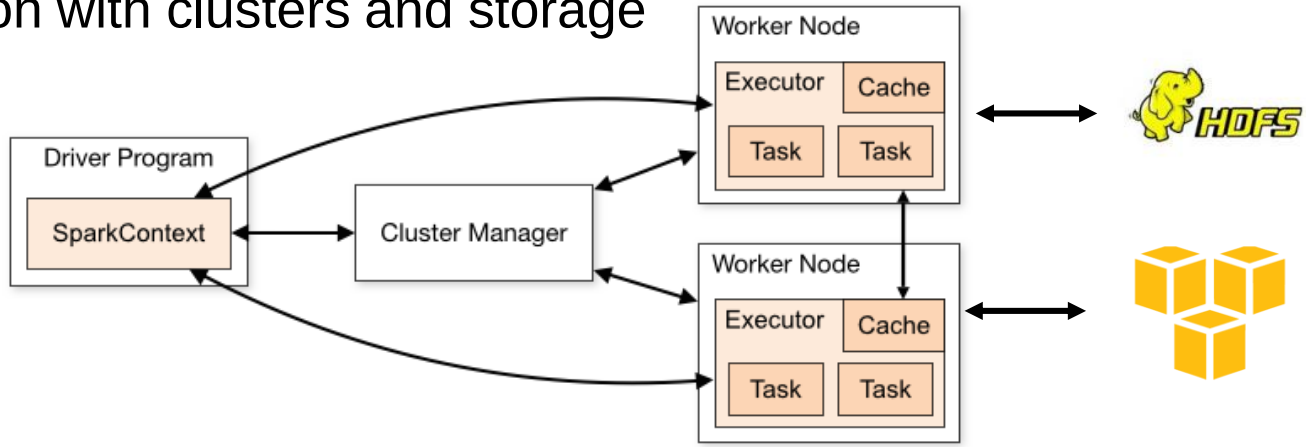
- You want data to find answers to questions like
  - What is my workload doing?
  - Where is it spending time?
  - What are the bottlenecks (CPU, I/O)?
  - How are systems resources used?
  - Why do I measure the {latency/throughput} that I measure?
    - Why is not 10x better?

Data + Context => Insights



Measuring Spark

- Distributed system, parallel architecture
  - Many components, complexity increases when running at scale
  - Execution hierarchy: SQL -> Jobs -> Stages -> Tasks
  - Interaction with clusters and storage



Spark Instrumentation - WebUI

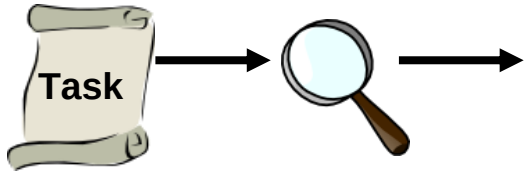
WebUI and History server: standard instrumentation

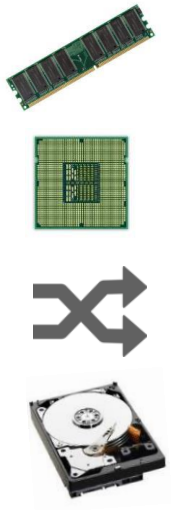
- Details on jobs, stages, tasks
- Default: http://driver_host:4040
- Details on SQL execution and execution plans
- https://github.com/apache/spark/blob/master/docs/web-ui.md

Spark Instrumentation – Metrics

Task metrics:

- Instrument resource usage by executor tasks:
  - Time spent executing tasks,
  - CPU used, I/O metrics,
  - Shuffle read/write details, ..
  - SPARK-25170: https://spark.apache.org/docs/latest/monitoring.html





SQL metrics:

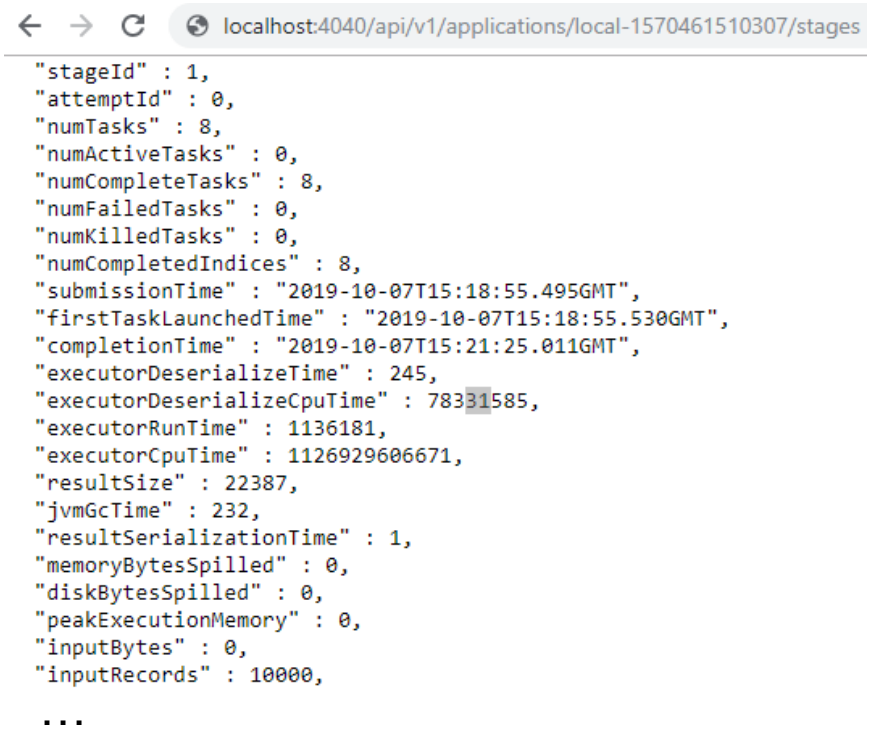
- DataFrame/SQL operations. Mostly used by Web UI SQL tab. See SPARK-28935 + Web-UI documentation

How to Gather Spark Task Metrics

- Web UI exposes REST API
  Example: http://localhost:4040/api/v1/applications
  History server reads from Event Log (JSON file)
  - `spark.eventLog.enabled=true`
  - `spark.eventLog.dir = <path>`

- Programmatic interface via "Spark Listeners"
  sparkMeasure -> a tool and working example code of how to collect metrics with Spark Listeners

Spark Metrics in REST API



Task Metrics in the Event Log

```
val df = spark.read.json("/var/log/spark-history/application_1567507314781_..")
df.filter("Event='SparkListenerTaskEnd'").select("Task Metrics.*").printSchema
```

```
|-- Disk Bytes Spilled: long (nullable = true)
 |-- Executor CPU Time: long (nullable = true)
 |-- Executor Deserialize CPU Time: long (nullable = true)
 |-- Executor Deserialize Time: long (nullable = true)
 |-- Executor Run Time: long (nullable = true)
 |-- Input Metrics: struct (nullable = true)
 |    |-- Bytes Read: long (nullable = true)
 |    |-- Records Read: long (nullable = true)
 |-- JVM GC Time: long (nullable = true)
 |-- Memory Bytes Spilled: long (nullable = true)
 |-- Output Metrics: struct (nullable = true)
 |    |-- Bytes Written: long (nullable = true)
 |    |-- Records Written: long (nullable = true)
 |-- Result Serialization Time: long (nullable = true)
 |-- Result Size: long (nullable = true)
 |-- Shuffle Read Metrics: struct (nullable = true)
 |    |-- Fetch Wait Time: long (nullable = true)
 |    |-- Local Blocks Fetched: long (nullable = true)
 |    |-- Local Bytes Read: long (nullable = true)
 |    |-- Remote Blocks Fetched: long (nullable = true)
 |    |-- Remote Bytes Read: long (nullable = true)
 |    |-- Remote Bytes Read To Disk: long (nullable = true)
 |    |-- Total Records Read: long (nullable = true)
 |-- Shuffle Write Metrics: struct (nullable = true)
 |    |-- Shuffle Bytes Written: long (nullable = true)
 |    |-- Shuffle Records Written: long (nullable = true)
 |    |-- Shuffle Write Time: long (nullable = true)
 |-- Updated Blocks: array (nullable = true)
 |    |-- element: string (containsNull = true)
```

Spark Internal Task metrics:
Provide info on executors' activity:
Run time, CPU time used, I/O metrics, JVM Garbage Collection, Shuffle activity, etc.

Spark Listeners, @DeveloperApi

- Custom class, extends SparkListener

```
class StageInfoRecorderListener extends SparkListener {
```

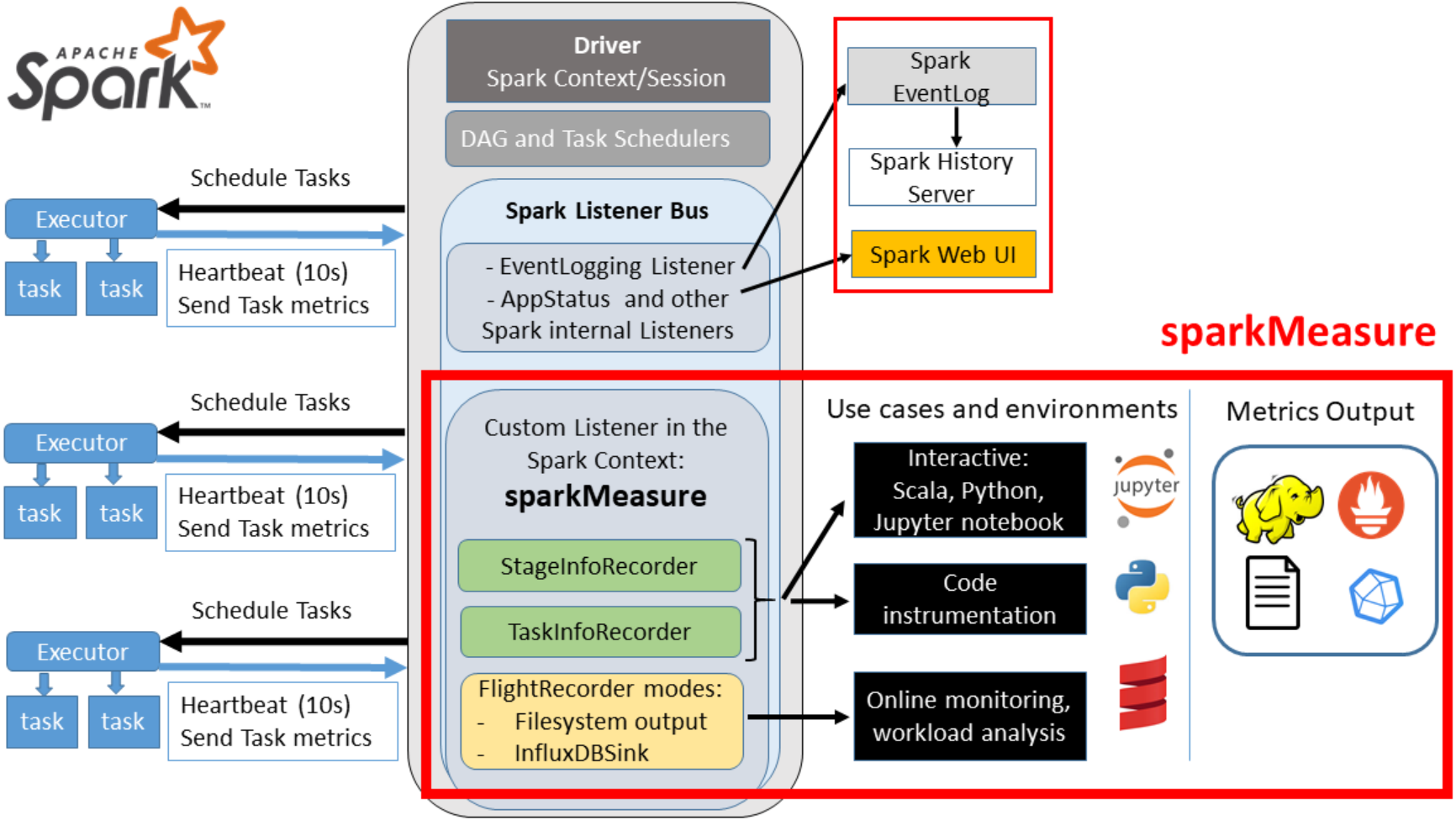
- Methods react on events to collect data, example:

```
override def onStageCompleted(stageCompleted: SparkListenerStageCompleted): Unit = {
  val stageInfo = stageCompleted.stageInfo
  val taskMetrics = stageInfo.taskMetrics
  val jobId = StageIdtoJobId(stageInfo.stageId)
```

- Attach custom Lister class to Spark Session

```
--conf spark.extraListeners=..
```

Spark Task Metrics, the Listener Bus and SparkMeasure Architecture



SparkMeasure – Getting Started

```
bin/spark-shell --packages ch.cern.sparkmeasure:spark-measure_2.11:0.15

val stageMetrics = ch.cern.sparkmeasure.StageMetrics(spark)

val myQuery = "select count(*) from range(1000) cross join range(1000) cross join range(1000)"

stageMetrics.runAndMeasure(spark.sql(myQuery).show())
```

SparkMeasure Output Example

```
Scheduling mode = FIFO
Spark Context default degree of parallelism = 8
Aggregated Spark stage metrics:
numStages => 3
sum(numTasks) => 17
elapsedTime => 9103 (9 s)
sum(stageDuration) => 9027 (9 s)
sum(executorRunTime) => 69238 (1.2 min)
sum(executorCpuTime) => 68004 (1.1 min)
sum(executorDeserializeTime) => 1031 (1 s)
sum(executorDeserializeCpuTime) => 151 (0.2 s)
sum(resultSerializationTime) => 5 (5 ms)
sum(jvmGCTime) => 64 (64 ms)
sum(shuffleFetchWaitTime) => 0 (0 ms)
sum(shuffleWriteTime) => 26 (26 ms)
max(resultSize) => 17934 (17.0 KB)
sum(numUpdatedBlockStatuses) => 0
sum(diskBytesSpilled) => 0 (0 Bytes)
sum(memoryBytesSpilled) => 0 (0 Bytes)
max(peakExecutionMemory) => 0
sum(recordsRead) => 2000
sum(bytesRead) => 0 (0 Bytes)
sum(recordsWritten) => 0
sum(bytesWritten) => 0 (0 Bytes)
sum(shuffleTotalBytesRead) => 472 (472 Bytes)
sum(shuffleTotalBlocksFetched) => 8
sum(shuffleLocalBlocksFetched) => 8
sum(shuffleRemoteBlocksFetched) => 0
sum(shuffleBytesWritten) => 472 (472 Bytes)
sum(shuffleRecordsWritten) => 8
```

SparkMeasure, Usage Modes

- Interactive: use from shell or notebooks
  - Works with Jupyter notebooks, Azure, Colab, Databricks, etc.
- Use to instrument your code
- Flight recorder mode
  - No changes needed to the code
  - For Troubleshooting, for CI/CD pipelines, …
- Use with Scala, Python, Java

https://github.com/LucaCanali/sparkMeasure

Instrument Code with SparkMeasure

```
from sparkmeasure import StageMetrics
stagemetrics = StageMetrics(spark)

stagemetrics.begin()
spark.sql("select count(*) from range(1000) cross join range(1000) cross join range(1000)").show()
stagemetrics.end()

# print report to standard output
stagemetrics.print_report()

# save session metrics data in json format (default)
df = stagemetrics.create_stagemetrics_DF("PerfStageMetrics")
stagemetrics.save_data(df.orderBy("jobId", "stageId"), "/tmp/stagemetrics_test1")

aggregatedDF = stagemetrics.aggregate_stagemetrics_DF("PerfStageMetrics")
stagemetrics.save_data(aggregatedDF, "/tmp/stagemetrics_report_test2")
```

https://github.com/LucaCanali/sparkMeasure/blob/master/docs/Instrument_Python_code.md

SparkMeasure on Notebooks: Local Jupyter and Cloud Services

In [ ]:
```
spark = SparkSession \
 .builder \
 .master("local[*]") \
 .appName("Test sparkmeasure instrumentation of Python/PySpark code") \
 .config("spark.jars.packages","ch.cern.sparkmeasure:spark-measure_2.11:0.15") \
 .getOrCreate()
```

In [1]:
```
# Install the Python wrapper package
!pip install sparkmeasure
```

In [2]:
```
# Load the Python API for sparkmeasure package
# and attach the sparkMeasure Listener for stagemetrics to the active Spark session

from sparkmeasure import StageMetrics
stagemetrics = StageMetrics(spark)
```

https://github.com/LucaCanali/sparkMeasure/tree/master/examples

SparkMeasure on Notebooks: Jupyter Magic: %%sparkmeasure

In [3]:
```
# Define cell and line magic to wrap the instrumentation
from IPython.core.magic import (register_line_magic, register_cell_magic, register_line_cell_magic)

@register_line_cell_magic
def sparkmeasure(line, cell=None):
    "run and measure spark workload. Use: %sparkmeasure or %%sparkmeasure"
    val = cell if cell is not None else line
    stagemetrics.begin()
    eval(val)
    stagemetrics.end()
    stagemetrics.print_report()
```

```
+----------+
|  count(1)|
+----------+
|1000000000|
+----------+
```

In [4]:
```
%%sparkmeasure
spark.sql( "select count(*) from range(1000) cross join range(1000) cross join range(1000)").show()
```

```
Scheduling mode = FIFO
Spark Context default degree of parallelism = 8
Aggregated Spark stage metrics:
numStages => 3
sum(numTasks) => 17
elapsedTime => 13962 (14 s)
sum(stageDuration) => 13928 (14 s)
sum(executorRunTime) => 110345 (1.8 min)
sum(executorCpuTime) => 109816 (1.8 min)
```

… (note, output truncated to fit in slide

SparkMeasure as Flight Recorder

Capture metrics and write to files when finished:

```
bin/spark-submit --master local[*] --packages ch.cern.sparkmeasure:spark-measure_2.11:0.15 \
--class org.apache.spark.examples.SparkPi \
--conf spark.extraListeners=ch.cern.sparkmeasure.FlightRecorderStageMetrics \
--conf spark.sparkmeasure.printToStdout=true \
--conf spark.sparkmeasure.outputFilename="/tmp/myoutput_$(date +%s).json" \
examples/jars/spark-examples_2.11-2.4.3.jar 10
```

Monitoring option: write to InfluxDB on the fly:

```
bin/spark-shell --master local[*] --packages ch.cern.sparkmeasure:spark-measure_2.11:0.15 \
--conf spark.sparkmeasure.influxdbURL="http://myInfluxDB:8086"
--conf spark.extraListeners=ch.cern.sparkmeasure.InfluxDBSink
```

Spark Metrics System

- Spark is also instrumented using the Dropwizard/Codahale metrics library
- Multiple sources (data providers)
  - Various instrumentation points in Spark code
  - Including task metrics, scheduler, etc
  - Instrumentation from the JVM
- Multiple sinks
  - Graphite (InfluxDB), JMX, HTTP, CSV, etc…

Ingredients for a Spark Performance Dashboard

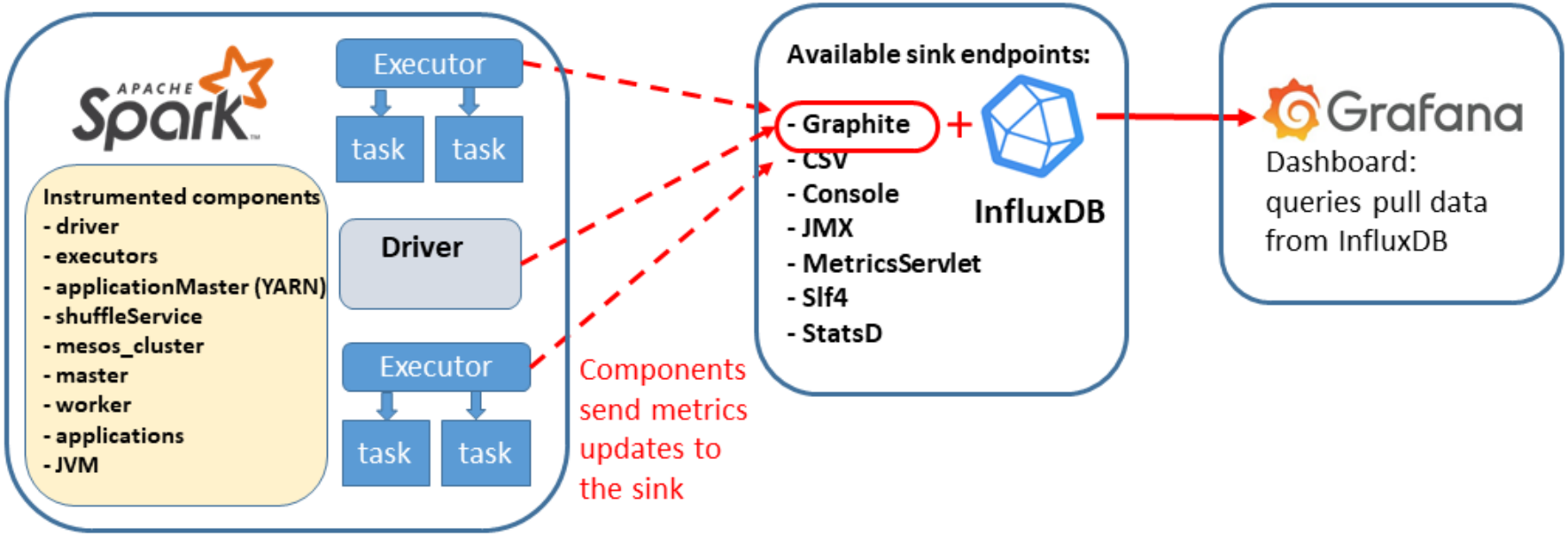
- Architecture
  - Know how the “Dropwizard metrics system” works
  - Which Spark components are instrumented
- Configure backend components
  - InfluxDB and Grafana
- Relevant Spark configuration parameters
- Dashboard graphs
  - familiarize with available metrics
  - InfluxDB query building for dashboard graphs

Apache Spark Metrics System + InfluxDB + Grafana => Dashboard

Source: Spark components instrumented with dropwizard library metrics

Sink: collect and store the metrics using InfluxDB

Visualize: using Grafana dashboards



Send Spark Metrics to InfluxDB

- Edit $SPARK_HOME/conf/metrics.properties
- Alternative: use the config parameters spark.metrics.conf.*

```
$ SPARK_HOME/bin/spark-shell \
--conf "spark.metrics.conf.driver.sink.graphite.class"="org.apache.spark.metrics.sink.GraphiteSink"\
--conf
"spark.metrics.conf.executor.sink.graphite.class"="org.apache.spark.metrics.sink.GraphiteSink"
--conf "spark.metrics.conf.*.sink.graphite.host"="graphiteEndPoint_influxDB_hostName>" \
--conf "spark.metrics.conf.*.sink.graphite.port"=<graphite_listening_port> \
--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"
```

Assemble Dashboard Components

Metrics written from Spark to InfluxDB

- Configuration of a Graphite endpoint in *influxdb.conf*
- Templates: how to ingest Spark metrics into InfluxDB series

https://github.com/LucaCanali/Miscellaneous/tree/master/Spark_Dashboard

Grafana graphs built using data queried from InfluxDB

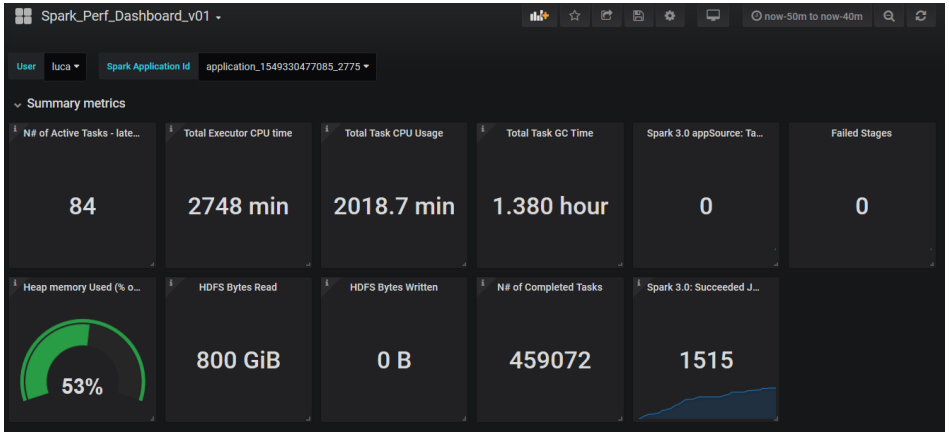
- Get started: Import an example dashboard definition

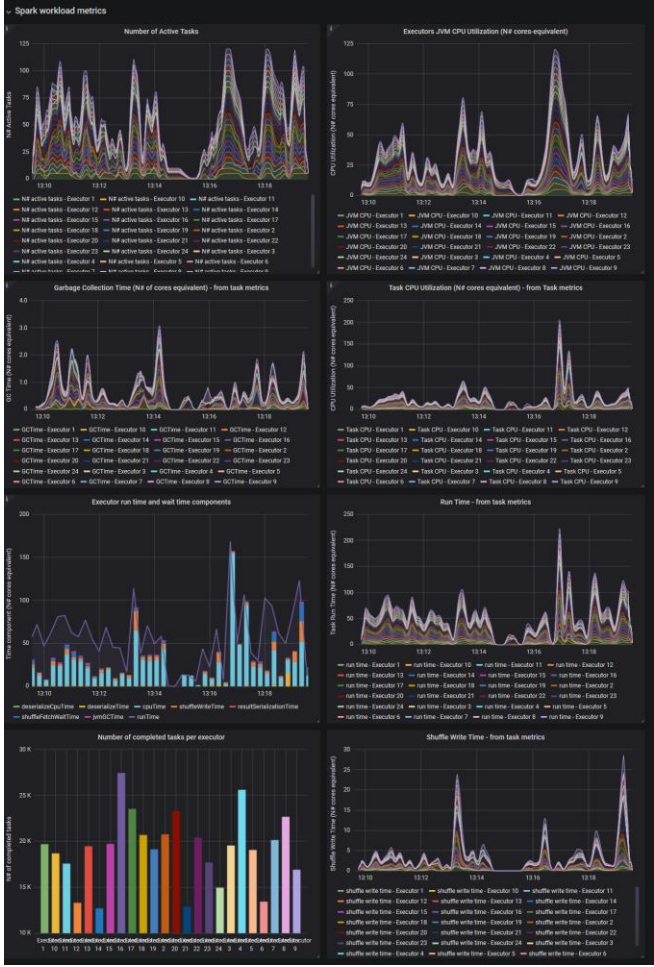
Kubernetes users: a helm chart to automate config at:

- https://github.com/cerndb/spark-dashboard

Grafana Dashboard

- Summaries
- Key metrics
- Graphs for drill-down analysis





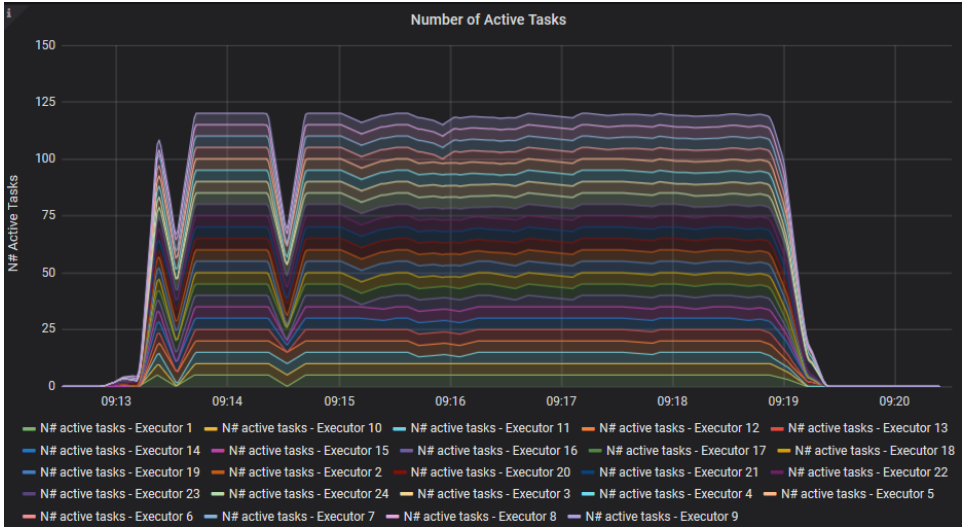
Spark Dashboard - Examples

Graph: “number of active tasks” vs. time

- Is Spark using all the available resources/cores?
- Are there time ranges with significant gaps?

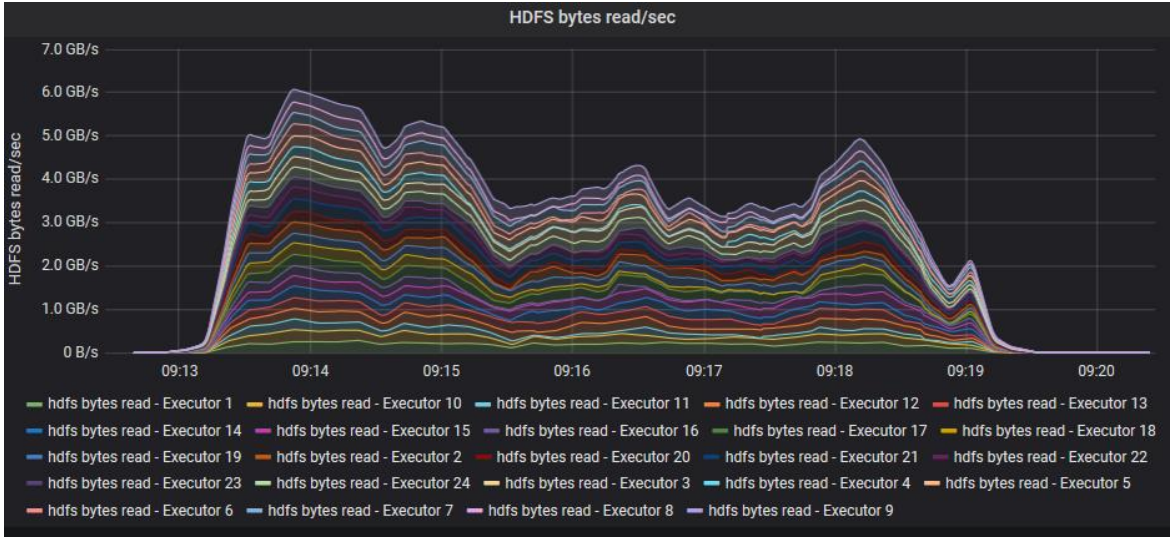
Identify possible issues:

- Long tails
- Stragglers
- Data skew



Dashboard – I/O metrics

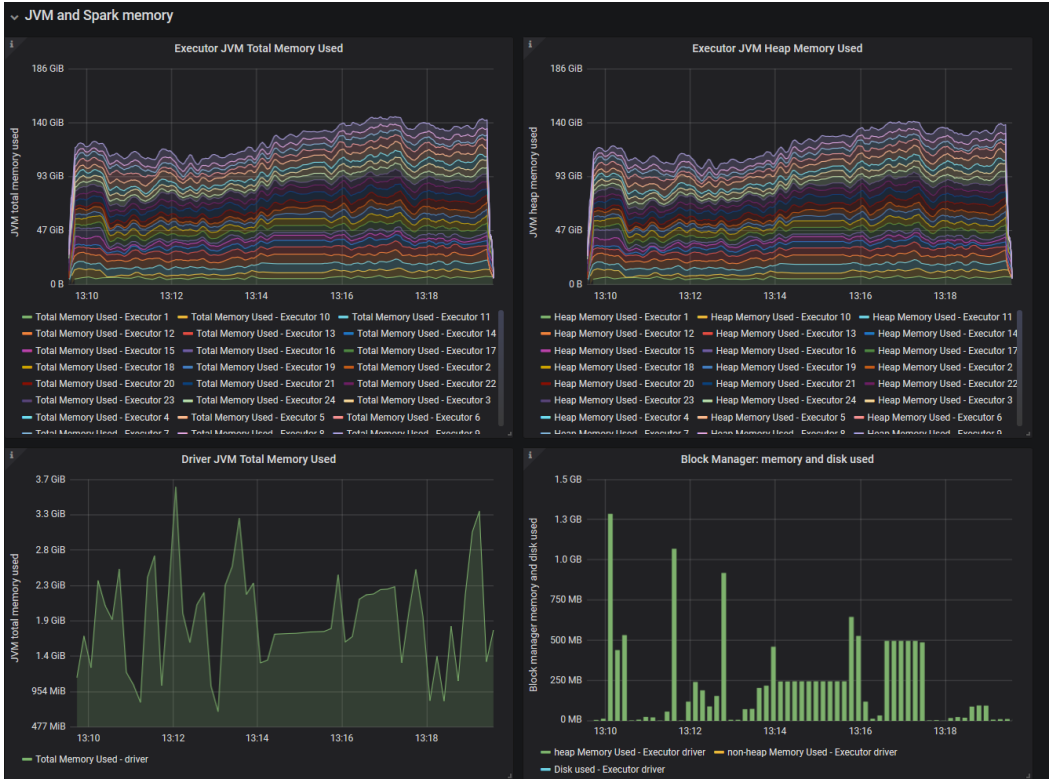
Graph: “HDFS Read Throughput” vs. time



Dashboard – Memory

Graphs of JVM memory usage

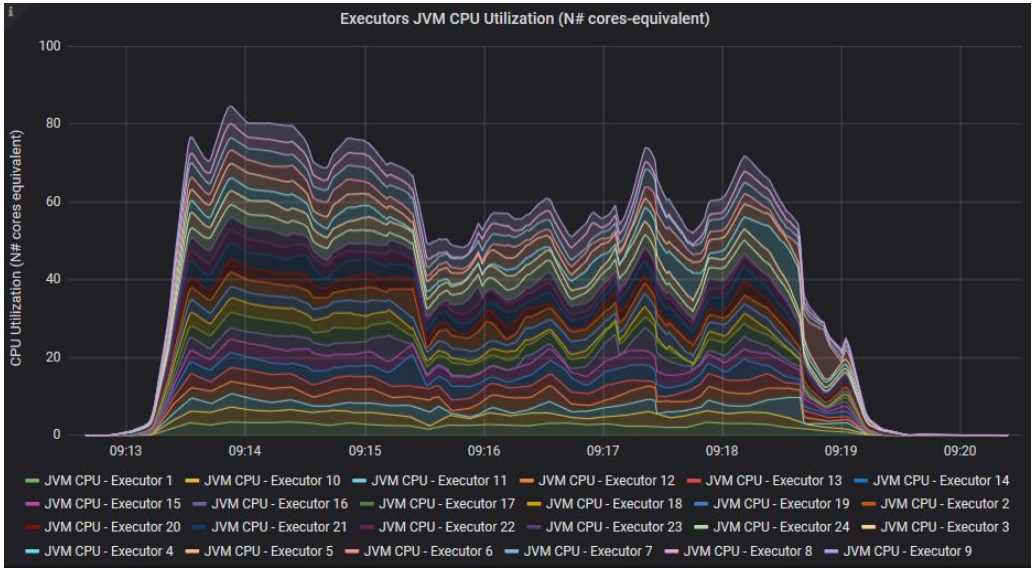
- Heap
- Off-heap
- Executors and driver



Dashboard – Executor CPU Utilization

Graph: “CPU utilization by executors’ JVM” vs. time

- Total JVM CPU:
- CPU used by tasks
- CPU used by GC



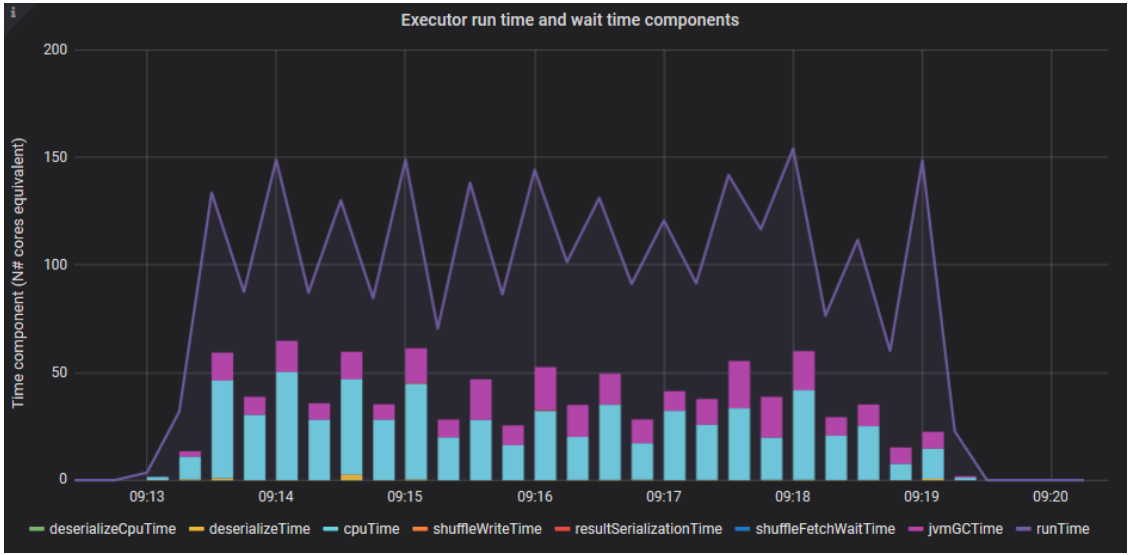
Task Time Drill Down, by Activity

Graph: Task total run time + drill down by component:

- CPU, Wait time, Garbage collection, etc

Investigation:

- CPU bound?
- Impact of GC
- I/O time?
- Other time?



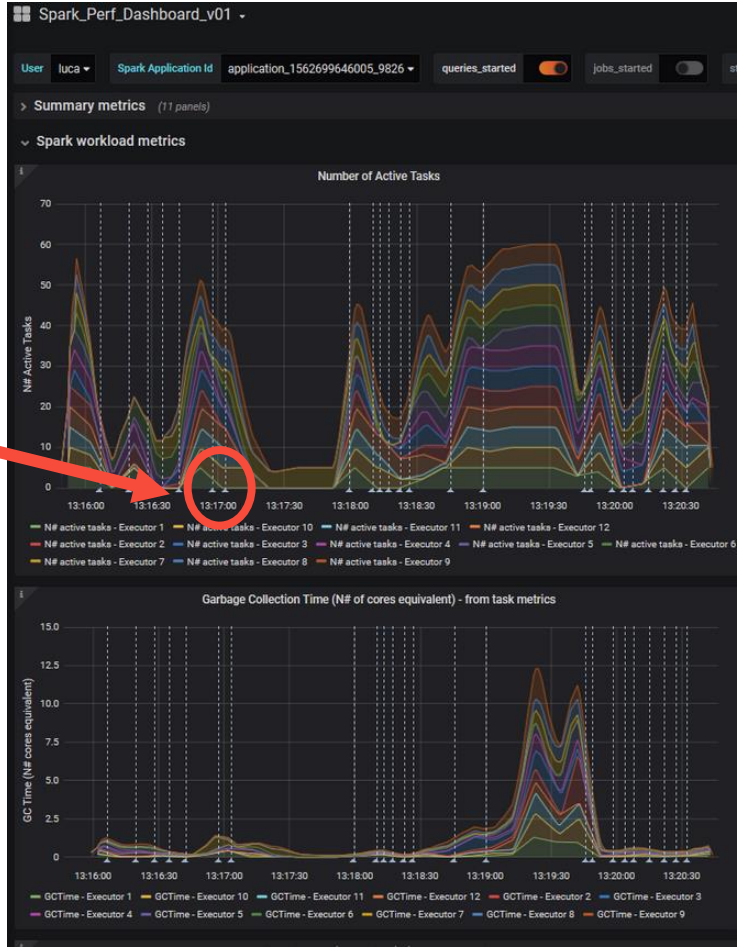
Graph Annotations

Improvement:

- Mark SQL/job/stage begin and end timestamps

Implementation:

- SparkMeasure collects and writes query/jobs begin and end timestamps data to InfluxDB
- Grafana implements annotations



Spark Dashboard, Lessons Learned

- Very useful to search for bottlenecks
  - Many instrumented components
  - Drilldown where time is spent
  - Time evolution details
    - Time series of N# active tasks, CPU, I/O, memory, etc

- Effort: you have to understand the root causes
  - Use data to make and prove or disprove models
  - The instrumentation is still evolving
    - example: I/O time is not measured directly, Python UDF, etc

WIP: How to Measure I/O Time?

Goal:

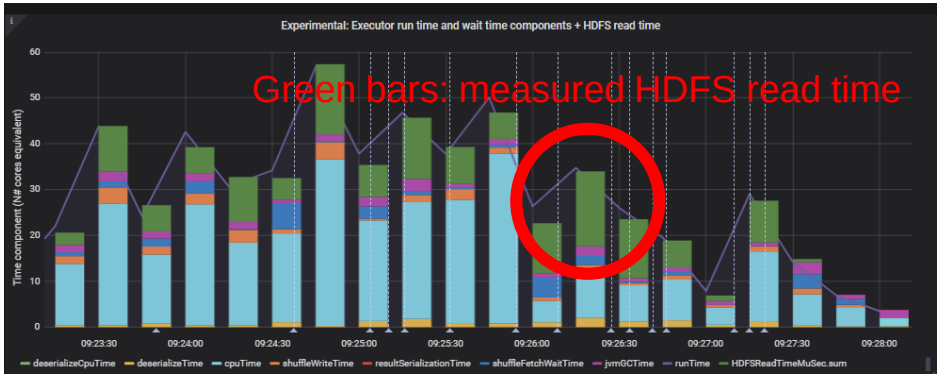
- How much of the workload time is spent doing I/O (reading)?

Apache Spark does not instrument I/O time

- Apache Hadoop Filesystem API does not measure I/O time

Experimenting

- Added I/O read time instrumentation for HDFS and S3A to sandbox Hadoop fork
- Exported the metrics using Spark Executor Plugins SPARK-28091



Executor Plugins Extend Metrics

- User-defined executor metrics, SPARK-28091, target Spark 3.0.0
  - Example: add I/O metrics for s3a filesystem:

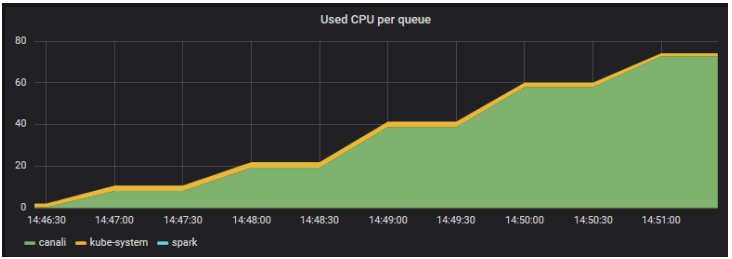
```
/bin/spark-shell --jars <path>/sparkexecutorplugins_2.12-0.1.jar \
 --conf spark.executor.plugins=ch.cern.ExecutorPluginScala.S3AMetrics27
```

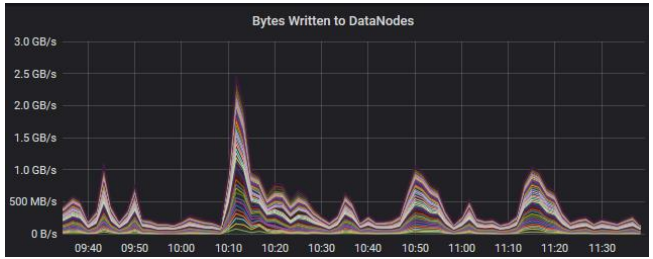
https://github.com/cerndb/SparkExecutorPlugins

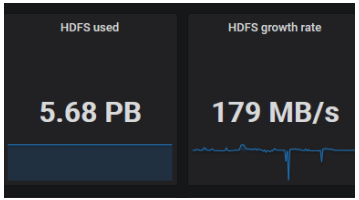
```
class S3AMetrics27 extends org.apache.spark.ExecutorPlugin {

  override def init(myContext:ExecutorPluginContext)  = {

    val metricRegistry = myContext.metricRegistry

    metricRegistry.register(MetricRegistry.name("s3BytesRead"), new Gauge[Long] {
      override def getValue: Long = {
        val hdfsStats = FileSystem.getAllStatistics().asScala.find(s => s.getScheme.equals("s3a"))
        hdfsStats.map(_.getBytesRead).getOrElse(0L)
      }
    })
```

Metrics from OS Monitoring

- Very useful also to collect OS-based metrics
  - Hadoop: dashboard with HDFS and YARN metrics
  - OS host metrics: Collectd, Ganglia
  - Kubernetes: Prometheus-based monitoring and dashboard





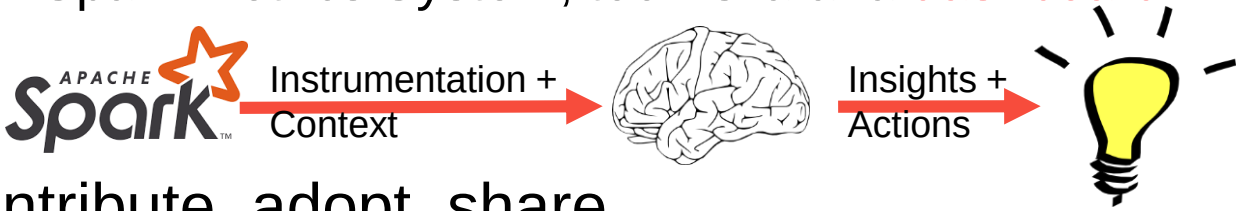


Notable JIRAs about Metrics

- Documentation improvements “Spark monitoring”
  - Master, SPARK-26890, Add Dropwizard metrics list and configuration details
  - Spark 2.4.0, SPARK-25170: Add Task Metrics description to the documentation
- Master, SPARK-23206 Additional Memory Tuning Metrics
  - Master, SPARK-29064 Add Prometheus endpoint for executor metrics
  - WIP, SPARK-27189 Add memory usage metrics to the metrics system
- Master, SPARK-28091 Extend Spark metrics system with user-defined metrics using executor plugins
- Master, SPARK-28475 Add regex MetricFilter to GraphiteSink
- CPU time used by JVM:
  - Spark 2.4.0: SPARK-25228 Add executor CPU Time metric
  - Master: SPARK-26928, Add driver CPU Time to the metrics system,
- Spark 2.3.0: SPARK-22190 Add Spark executor task metrics to Dropwizard metrics

Conclusions

- Performance troubleshooting by understanding
  - Spark architecture + Spark instrumentation, Web UI
  - Spark Task metrics + Listeners, tool: sparkMeasure
  - Spark Metrics System, tool: Grafana dashboard



- Contribute, adopt, share
  - Instrumentation in Spark ecosystem keeps improving
  - Solid methodologies and tools are key
  - Share your results, tools, issues, dashboards..

Acknowledgements

- Colleagues at CERN
  - Hadoop and Spark service, in particular Prasanth Kothuri and Riccardo Castellotti
- Thanks to Apache Spark committers and community
  - Help with JIRAs and PRs

- References:
  - https://github.com/LucaCanali/sparkmeasure
  - https://db-blog.web.cern.ch/blog/luca-canali/2019-02-performance-dashboard-apache-spark

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