Apache Spark 2.0 Performance Improvements Investigated With Flame Graphs

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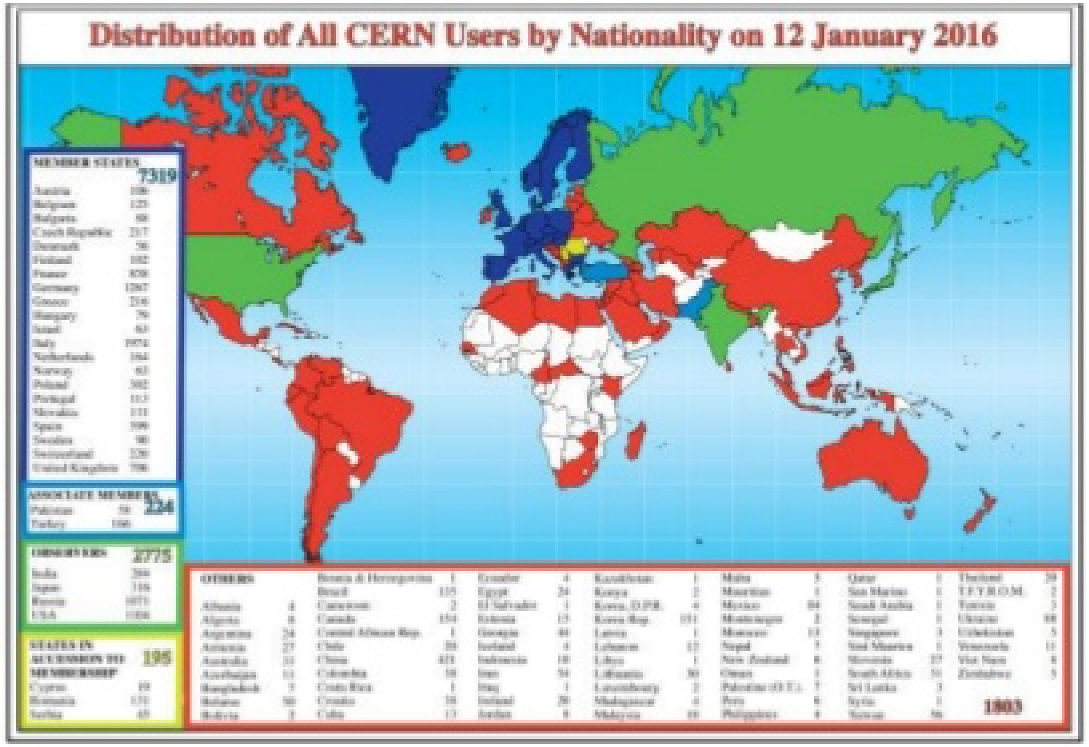
Speaker Intro

- Database engineer and team lead at CERN IT
  - Hadoop and Spark service
  - Database services
- Joined CERN in 2005
- 16 years of experience with database services
  - Performance, instrumentation, tools, Linux
- @LucaCanaliDB – http://cern.ch/canali

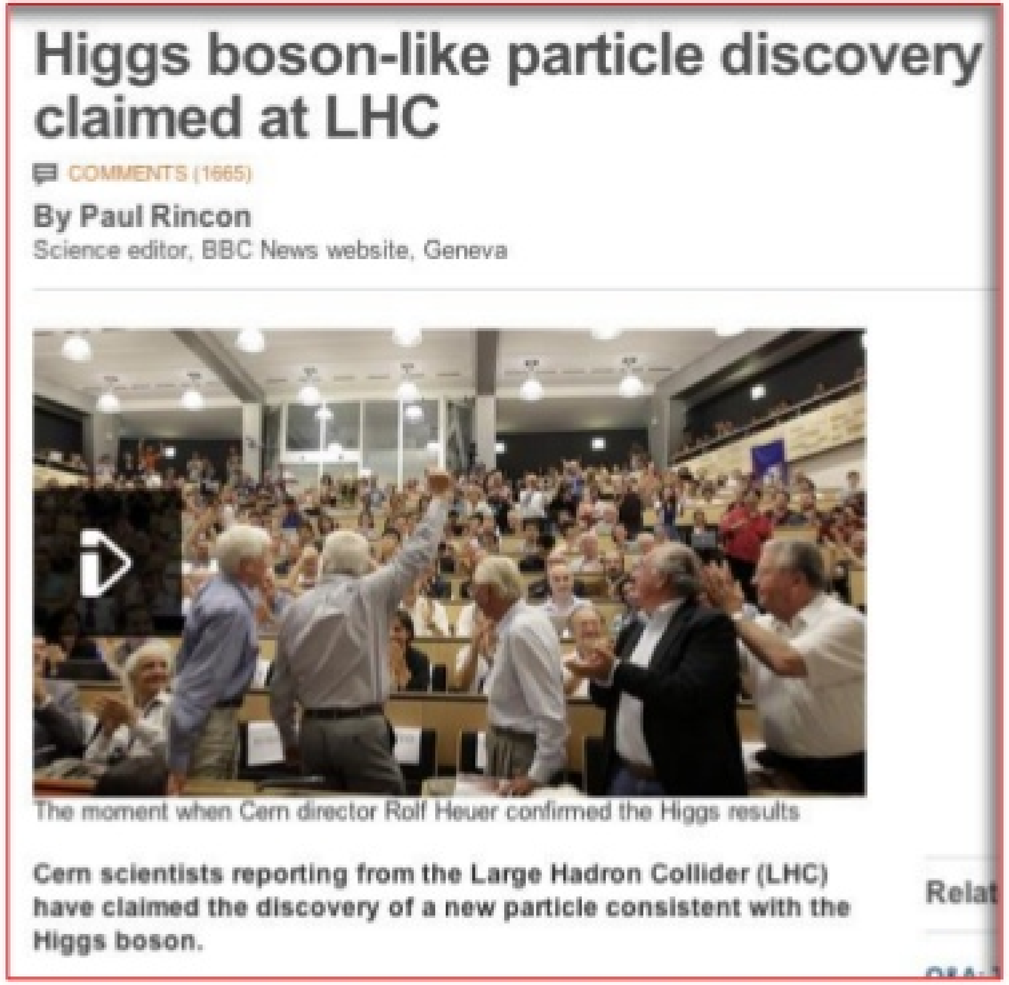
CERN

- CERN - European Laboratory for Particle Physics
- Founded in 1954 by 12 countries for fundamental research in physics
- Today 22 member states + world-wide collaborations
- About ~1000 MCHF yearly budget
- 2’300 CERN personnel, 10’000 users from 110 countries


Distribution of All CERN Users by Nationality on 12 January 2016
MEMBER STATES 7319
ASSOCIATE MEMBERS 224
OBSERVERS 2775
STATES IN ACCESSION TO MEMBERSHIP 195
OTHERS
1803

Large Hadron Collider

- Largest and most powerful particle accelerator



Higgs boson-like particle discovery claimed at LHC

COMMENTS (1665)

By Paul Rincon

Science editor, BBC News website, Geneva

The moment when Cern director Rolf Heuer confirmed the Higgs results

Cern scientists reporting from the Large Hadron Collider (LHC) have claimed the discovery of a new particle consistent with the Higgs boson.

Relat

LHC Physics and Data

- LHC physics is data- and compute- intensive
  - Oct 2016: ~160 PB archive on tape at CERN
    - Current rate of data acquisition: ~ 50 PB/year
  - Distributed computing effort (WLCG)
    - Computing: utilize ~ 300K cores
  - Technology
    - Custom data formats, applications and frameworks: ROOT

WLCG
Worldwide LHC Computing Grid

Apache Spark @ CERN

- Spark is a key component of the CERN Hadoop Service
  - Three production Hadoop/YARN clusters
    - Aggregated capacity: ~1000 cores, 3 TB RAM, 1.2 PB used space on HDFS
  - Projects involving Spark:
    - Analytics for accelerator controls and logging
    - Monitoring use cases, this includes use of Spark streaming
    - Analytics on aggregated logs
    - Explorations on the use of Spark for physics analysis

A Case from Production

- Slow query in a relational database
  - Ad-hoc report for network experts
  - Query runs in >12 hours, CPU-bound, single-threaded
- Run using Spark on a Hadoop cluster
  - Data exported with Apache Sqoop to HDFS
  - The now query runs in ~20 minutes, unchanged
  - Throw hardware to solve the problem -> cost effective

Spark 1.6 vs. Spark 2.0

- Additional tests using Spark 2.0
  - The query execution time goes down further
    - One order of magnitude: from 20 min to 2 min
  - How to explain this?
    - Optimizations in Spark 2.0 for CPU-intensive workloads
    - Whole stage code generation, vector operations

Main Takeaways

- Spark SQL
  - Provides parallelism, affordable at scale
  - Scale out on storage for big data volumes
  - Scale out on CPU for memory-intensive queries
  - Offloading reports from RDBMS becomes attractive
- Spark 2.0 optimizations
  - Considerable speedup of CPU-intensive queries

Root Cause Analysis

- Active benchmarking
  - – Run the workload and measure it with the relevant diagnostic tools
  - – Goals: understand the bottleneck(s) and find root causes
  - – Limitations:
    - Our tools, ability to run and understand them and time available for analysis are limiting factors

Test Case 1/2

- Preparation of source data:
  - Generate a DataFrame with 10M rows, and three columns randomly generated
  - Cache it in memory and register it as a temporary table

```
$ pyspark --driver-memory 2g

sqlContext.range(0, 1e7,1).registerTempTable("t0")

sqlContext.sql("select id, floor(200*rand()) bucket, floor(1000*rand())
val1, floor(10*rand()) val2 from t0").cache().registerTempTable("t1")
```

Test Case 2/2

- Test SQL:
  - Complex and resource-intensive select statement
    - With non-equijoin predicate and aggregations

```
sqlContext.sql("""
select a.bucket, sum(a.val2) tot
from t1 a, t1 b
where a.bucket=b.bucket
        and a.val1+b.val1<1000
group by a.bucket order by a.bucket""").show()
```

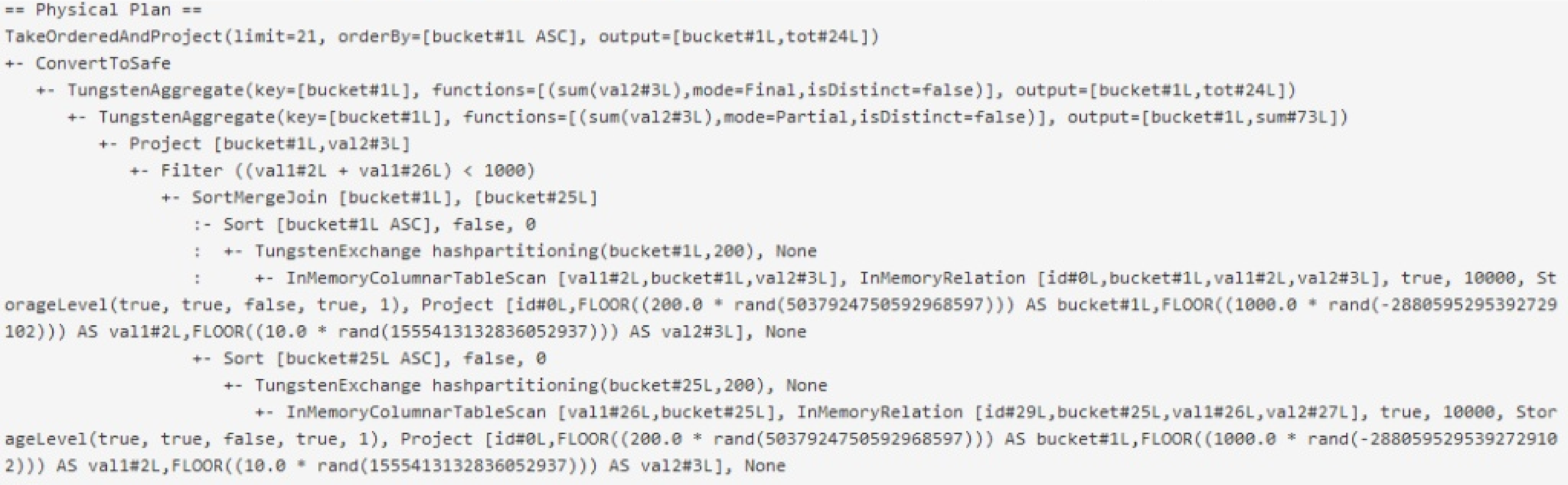
Execution Plan

- The execution plan:
  - First instrumentation point for SQL tuning
  - Shows how Spark wants to execute the query

- Main players:
  - Catalyst, the optimizer
  - Tungsten the execution engine

Execution Plan in Spark 1.6

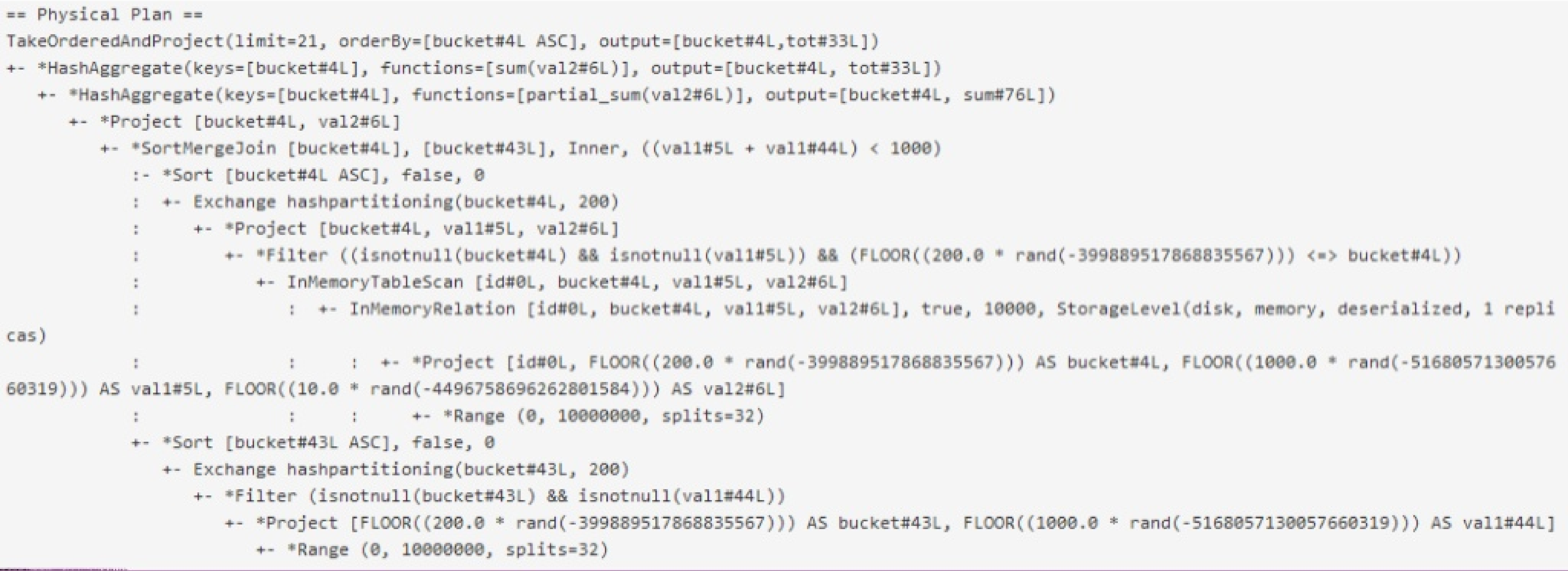
- Note: Sort Merge Join and In Memory Scan



```
== Physical Plan ==
TakeOrderedAndProject(limit=21, orderBy=[bucket#1L ASC], output=[bucket#1L,tot#24L])
+- ConvertToSafe
   +- TungstenAggregate(key=[bucket#1L], functions=[(sum(val2#3L),mode=Final,isDistinct=false)], output=[bucket#1L,tot#24L])
      +- TungstenAggregate(key=[bucket#1L], functions=[(sum(val2#3L),mode=Partial,isDistinct=false)], output=[bucket#1L,sum#73L])
         +- Project [bucket#1L,val2#3L]
            +- Filter ((val1#2L + val1#26L) < 1000)
               +- SortMergeJoin [bucket#1L], [bucket#25L]
                  :- Sort [bucket#1L ASC], false, 0
                  :  +- TungstenExchange hashpartitioning(bucket#1L,200), None
                  :     +- InMemoryColumnarTableScan [val1#2L,bucket#1L,val2#3L], InMemoryRelation [id#0L,bucket#1L,val1#2L,val2#3L], true, 10000, St
orageLevel(true, true, false, true, 1), Project [id#0L,FLOOR((200.0 * rand(5037924750592968597))) AS bucket#1L,FLOOR((1000.0 * rand(-2880595295392729
102))) AS val1#2L,FLOOR((10.0 * rand(1555413132836052937))) AS val2#3L], None
                  +- Sort [bucket#25L ASC], false, 0
                     +- TungstenExchange hashpartitioning(bucket#25L,200), None
                        +- InMemoryColumnarTableScan [val1#26L,bucket#25L], InMemoryRelation [id#29L,bucket#25L,val1#26L,val2#27L], true, 10000, Stor
ageLevel(true, true, false, true, 1), Project [id#0L,FLOOR((200.0 * rand(5037924750592968597))) AS bucket#1L,FLOOR((1000.0 * rand(-288059529539272910
2))) AS val1#2L,FLOOR((10.0 * rand(1555413132836052937))) AS val2#3L], None
```

Execution Plan in Spark 2.0

- Note: steps marked with (*) -> Code generation



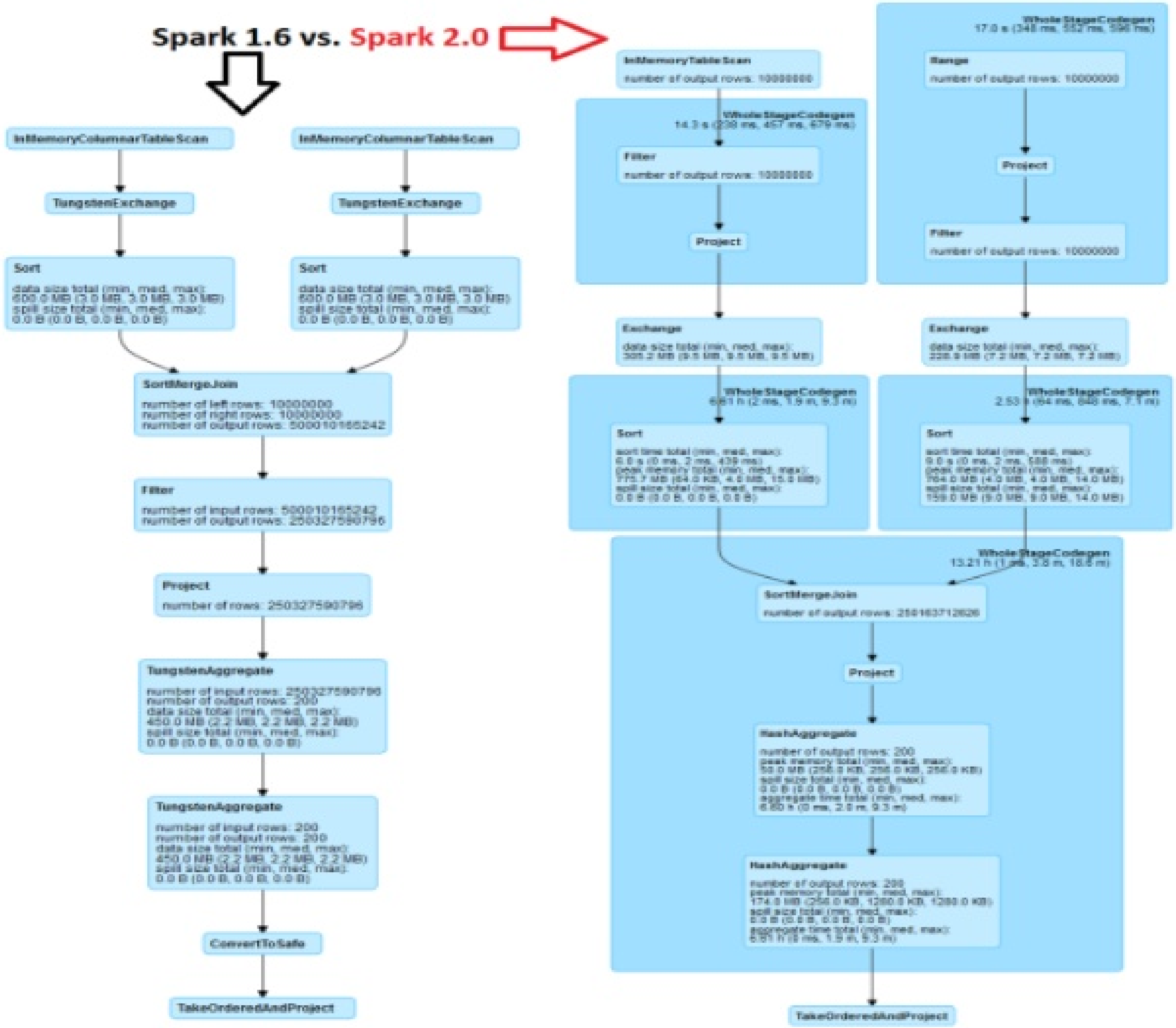
```
== Physical Plan ==
TakeOrderedAndProject(limit=21, orderBy=[bucket#4L ASC], output=[bucket#4L,tot#33L])
+- *HashAggregate(keys=[bucket#4L], functions=[sum(val2#6L)], output=[bucket#4L, tot#33L])
   +- *HashAggregate(keys=[bucket#4L], functions=[partial_sum(val2#6L)], output=[bucket#4L, sum#76L])
      +- *Project [bucket#4L, val2#6L]
         +- *SortMergeJoin [bucket#4L], [bucket#43L], Inner, ((val1#5L + val1#44L) < 1000)
            :- *Sort [bucket#4L ASC], false, 0
            :  +- Exchange hashpartitioning(bucket#4L, 200)
            :     +- *Project [bucket#4L, val1#5L, val2#6L]
            :        +- *Filter ((isnotnull(bucket#4L) && isnotnull(val1#5L)) && (FLOOR((200.0 * rand(-399889517868835567))) <=> bucket#4L))
            :           +- InMemoryTableScan [id#0L, bucket#4L, val1#5L, val2#6L]
            :              :  +- InMemoryRelation [id#0L, bucket#4L, val1#5L, val2#6L], true, 10000, StorageLevel(disk, memory, deserialized, 1 repli
cas)
            :              :     :  +- *Project [id#0L, FLOOR((200.0 * rand(-399889517868835567))) AS bucket#4L, FLOOR((1000.0 * rand(-51680571300576
60319))) AS val1#5L, FLOOR((10.0 * rand(-4496758696262801584))) AS val2#6L]
            :              :     :     +- *Range (0, 10000000, splits=32)
            +- *Sort [bucket#43L ASC], false, 0
               +- Exchange hashpartitioning(bucket#43L, 200)
                  +- *Filter (isnotnull(bucket#43L) && isnotnull(val1#44L))
                     +- *Project [FLOOR((200.0 * rand(-399889517868835567))) AS bucket#43L, FLOOR((1000.0 * rand(-5168057130057660319))) AS val1#44L]
                        +- *Range (0, 10000000, splits=32)
```

Web UI: plan comparison

Note in Spark 2.0 steps with “Whole Stage CodeGen”

From Spark Web UI - SQL execution details

Spark 1.6 vs. Spark 2.0


InMemoryColumnarTableScan
InMemoryColumnarTableScan
TungstenExchange
TungstenExchange
Sort
data size total (min, med, max):
600.0 MB (3.0 MB, 3.0 MB, 3.0 MB)
spill size total (min, med, max):
0.0 B (0.0 B, 0.0 B, 0.0 B)
Sort
data size total (min, med, max):
600.0 MB (3.0 MB, 3.0 MB, 3.0 MB)
spill size total (min, med, max):
0.0 B (0.0 B, 0.0 B, 0.0 B)
SortMergeJoin
number of left rows: 10000000
number of right rows: 10000000
number of output rows: 500010165242
Filter
number of input rows: 500010165242
number of output rows: 250327590796
Project
number of rows: 250327590796
TungstenAggregate
number of input rows: 250327590796
number of output rows: 200
data size total (min, med, max):
450.0 MB (2.2 MB, 2.2 MB, 2.2 MB)
spill size total (min, med, max):
0.0 B (0.0 B, 0.0 B, 0.0 B)
TungstenAggregate
number of input rows: 200
number of output rows: 200
data size total (min, med, max):
450.0 MB (2.2 MB, 2.2 MB, 2.2 MB)
spill size total (min, med, max):
0.0 B (0.0 B, 0.0 B, 0.0 B)
ConvertToSafe
TakeOrderedAndProject
InMemoryTableScan
number of output rows: 10000000
WholeStageCodegen
14.3 s (239 ms, 457 ms, 679 ms)
Filter
number of output rows: 10000000
Project
WholeStageCodegen
17.0 s (348 ms, 552 ms, 596 ms)
Range
number of output rows: 10000000
Project
Filter
number of output rows: 10000000
Exchange
data size total (min, med, max):
305.2 MB (9.5 MB, 9.5 MB, 9.5 MB)
Exchange
data size total (min, med, max):
228.9 MB (7.2 MB, 7.2 MB, 7.2 MB)
WholeStageCodegen
6.81 h (2 ms, 1.9 m, 9.3 m)
Sort
sort time total (min, med, max):
6.0 s (0 ms, 2 ms, 439 ms)
peak memory total (min, med, max):
775.7 MB (64.0 KB, 4.0 MB, 15.0 MB)
spill size total (min, med, max):
0.0 B (0.0 B, 0.0 B, 0.0 B)
WholeStageCodegen
2.53 s (64 ms, 840 ms, 7.1 m)
Sort
sort time total (min, med, max):
9.0 s (0 ms, 2 ms, 588 ms)
peak memory total (min, med, max):
764.0 MB (4.0 MB, 4.0 MB, 14.0 MB)
spill size total (min, med, max):
159.0 MB (9.0 MB, 9.0 MB, 14.0 MB)
WholeStageCodegen
13.21 h (1 ms, 2.8 m, 18.8 m)
SortMergeJoin
number of output rows: 250163712626
Project
HashAggregate
number of output rows: 200
peak memory total (min, med, max):
50.0 MB (256.0 KB, 256.0 KB, 256.0 KB)
spill size total (min, med, max):
0.0 B (0.0 B, 0.0 B, 0.0 B)
aggregate time total (min, med, max):
6.80 h (0 ms, 2.8 m, 9.3 m)
HashAggregate
number of output rows: 200
peak memory total (min, med, max):
174.0 MB (256.0 KB, 1280.0 KB, 1280.0 KB)
spill size total (min, med, max):
0.0 B (0.0 B, 0.0 B, 0.0 B)
aggregate time total (min, med, max):
6.81 h (0 ms, 1.9 m, 9.3 m)
TakeOrderedAndProject

Additional Checks at OS Level

- Observation: the test workload is CPU-bound
  - OS tools confirm this
  - Spark used in local mode
    - One multi-threaded java process
    - Takes all available CPU resources in the machine
- Specs of the machine for testing:
  - 16 cores (2 x E5-2650) and 128 GB of RAM (virtual memory allocated ~ 16 GB)

Profiling CPU-Bound Workloads

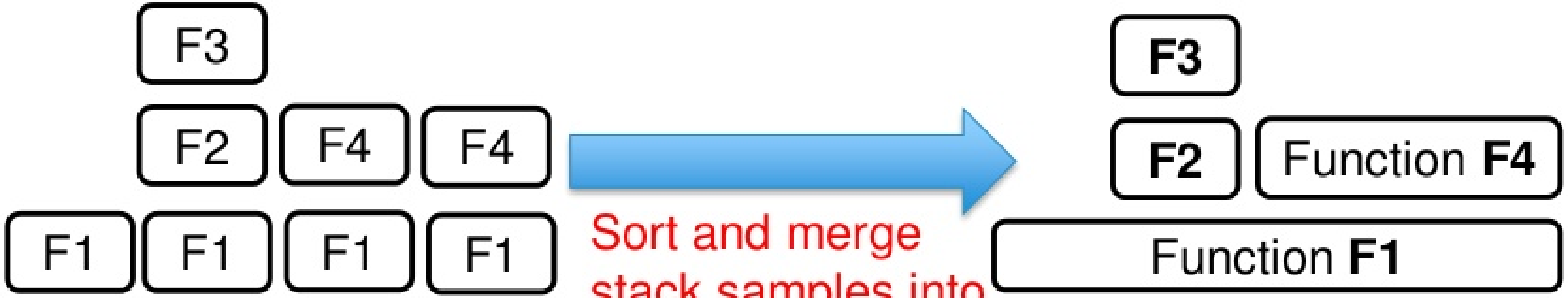
- Flame graph visualization of stack profiles
  - Brain child of Brendan Gregg (Dec 2011)
  - Code: https://github.com/brendangregg/FlameGraph
  - Now very popular, available for many languages, also for JVM
- Shows which parts of the code are hot
  - Very useful to understand where CPU cycles are spent

JVM and Stack Profiling

- Jstack <pid>
  - Prints java stack for all threads
  - What you want is a series of stack traces
- Java Flight Recorder
  - Part of the HotSpot JVM (requires license for prod)
- Linux Perf
  - Stack sampling of Java and OS

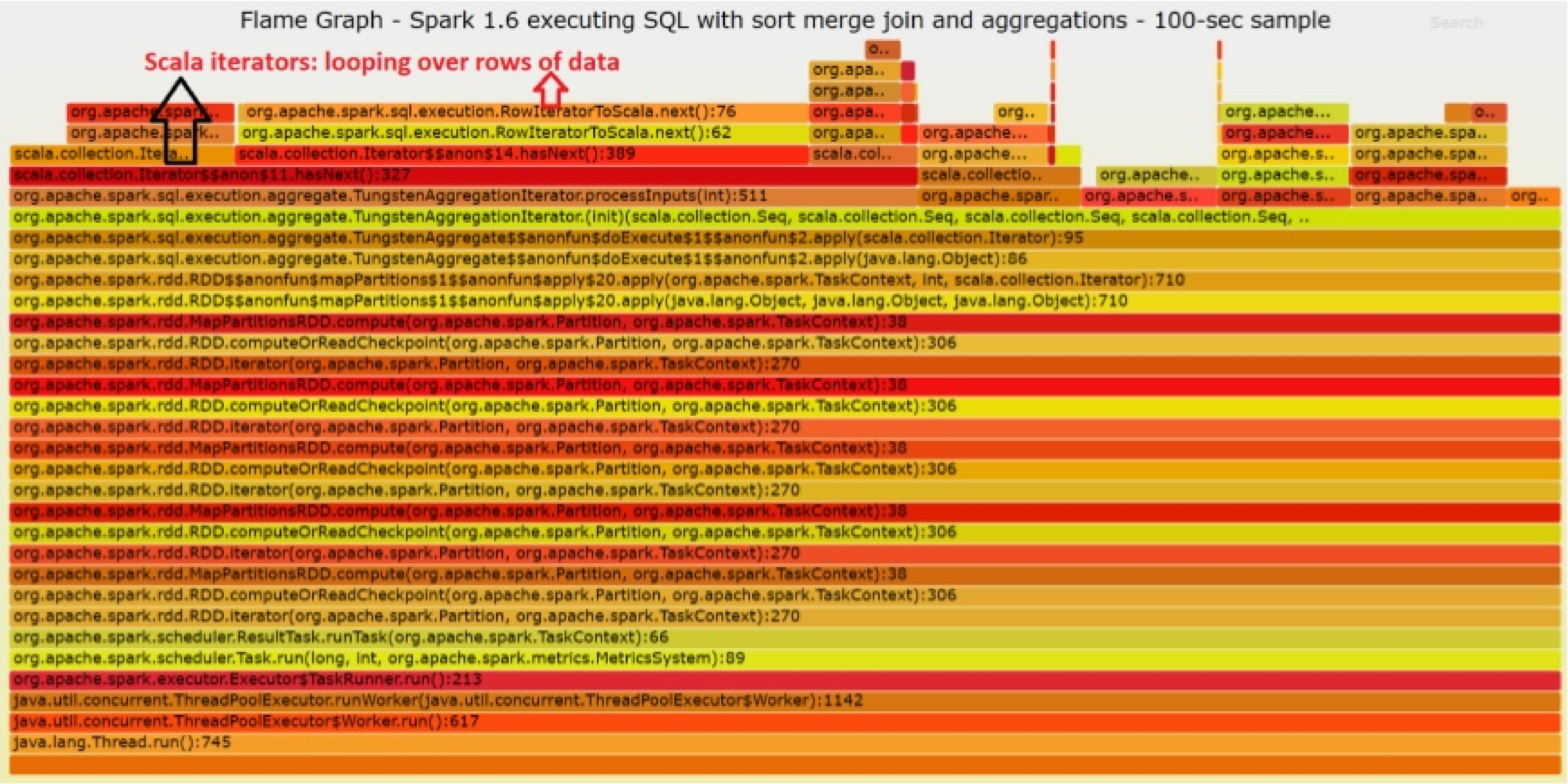
Flame Graph Visualization

- Recipe:
  - Gather multiple stack traces
  - Aggregate them by sorting alphabetically by function/method name
  - Visualization using stacked colored boxes
  - Length of the box proportional to time spent there



Sort and merge stack samples into a flame graph

Flame Graph Spark 1.6



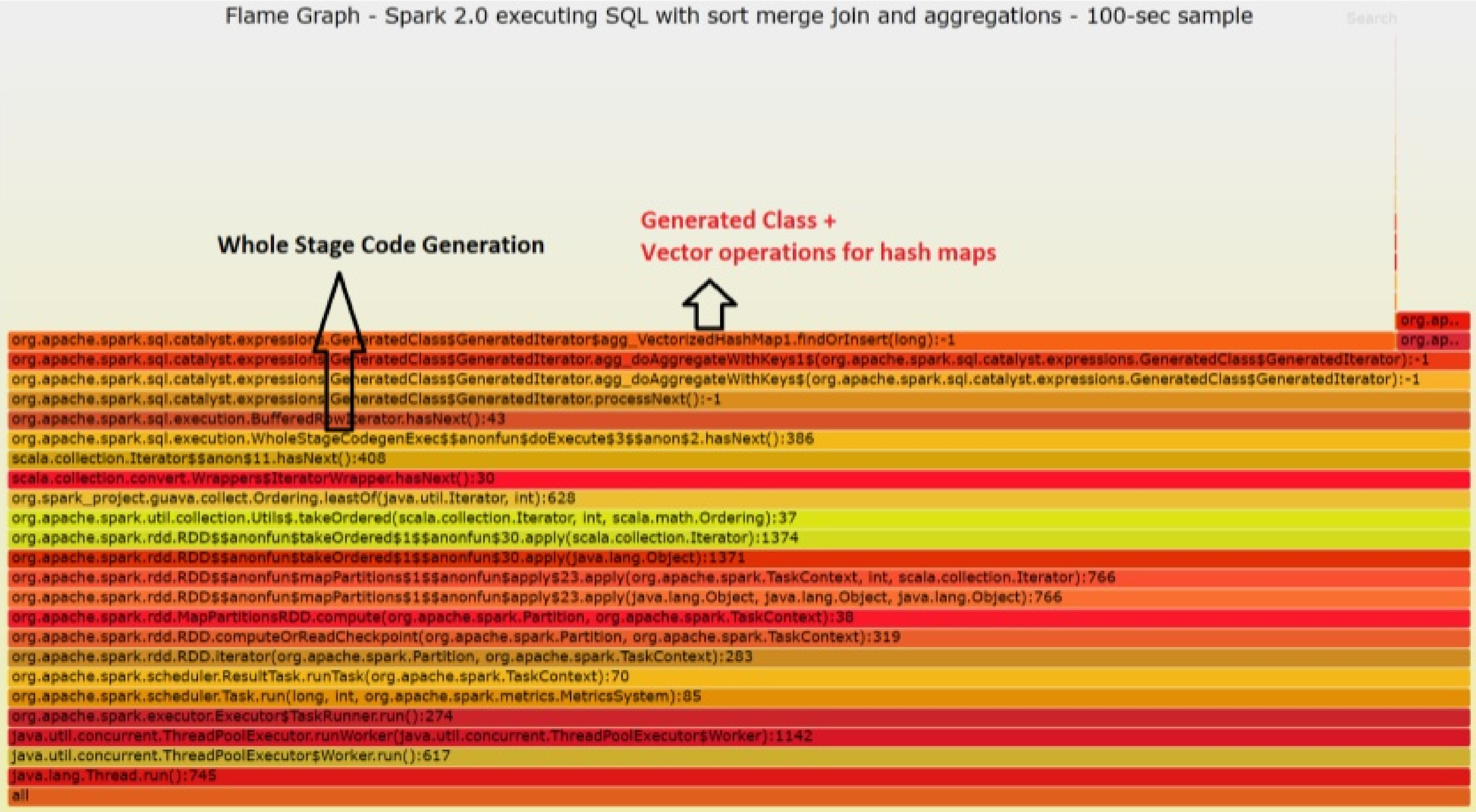
Flame Graph - Spark 1.6 executing SQL with sort merge join and aggregations - 100-sec sample

Scala iterators: looping over rows of data

Spark CodeGen vs. Volcano

- Code generation improves CPU-intensive workloads
  - Replaces loops and virtual function calls (volcano model) with code generated for the query
  - The use of vector operations (e.g. SIMD) also beneficial
  - Codegen is crucial for modern in-memory DBs
- Commercial RDBMS engines
  - Typically use the slower volcano model (with loops and virtual function calls)
  - In the past optimizing for I/O latency was more important, now CPU cycles matter more

Flame Graph Spark 2.0



Flame Graph - Spark 2.0 executing SQL with sort merge join and aggregations - 100-sec sample

Whole Stage Code Generation

Generated Class +
Vector operations for hash maps

```
org.apache.spark.sql.catalyst.expressions.GeneratedClass$GeneratedIterator$agg_VectorizedHashMap1.findOrInsert(long):-1
org.apache.spark.sql.catalyst.expressions.GeneratedClass$GeneratedIterator.agg_doAggregateWithKeys1$(org.apache.spark.sql.catalyst.expressions.GeneratedClass$GeneratedIterator):-1
org.apache.spark.sql.catalyst.expressions.GeneratedClass$GeneratedIterator.agg_doAggregateWithKeys$(org.apache.spark.sql.catalyst.expressions.GeneratedClass$GeneratedIterator):-1
org.apache.spark.sql.catalyst.expressions.GeneratedClass$GeneratedIterator.processNext():-1
org.apache.spark.sql.execution.BufferedRowIterator.hasNext():43
org.apache.spark.sql.execution.WholeStageCodegenExec$$anonfun$doExecute$3$$anon$2.hasNext():386
scala.collection.Iterator$$anon$11.hasNext():408
scala.collection.convert.Wrappers$IteratorWrapper.hasNext():30
org.spark_project.guava.collect.Ordering.leastOf(java.util.Iterator, int):628
org.apache.spark.util.collection.Utils$.takeOrdered(scala.collection.Iterator, int, scala.math.Ordering):37
org.apache.spark.rdd.RDD$$anonfun$takeOrdered$1$$anonfun$30.apply(scala.collection.Iterator):1374
org.apache.spark.rdd.RDD$$anonfun$takeOrdered$1$$anonfun$30.apply(java.lang.Object):1371
org.apache.spark.rdd.RDD$$anonfun$mapPartitions$1$$anonfun$apply$23.apply(org.apache.spark.TaskContext, int, scala.collection.Iterator):766
org.apache.spark.rdd.RDD$$anonfun$mapPartitions$1$$anonfun$apply$23.apply(java.lang.Object, java.lang.Object, java.lang.Object):766
org.apache.spark.rdd.MapPartitionsRDD.compute(org.apache.spark.Partition, org.apache.spark.TaskContext):38
org.apache.spark.rdd.RDD.computeOrReadCheckpoint(org.apache.spark.Partition, org.apache.spark.TaskContext):319
org.apache.spark.rdd.RDD.iterator(org.apache.spark.Partition, org.apache.spark.TaskContext):283
org.apache.spark.scheduler.ResultTask.runTask(org.apache.spark.TaskContext):70
org.apache.spark.scheduler.Task.run(long, int, org.apache.spark.metrics.MetricsSystem):85
org.apache.spark.executor.Executor$TaskRunner.run():274
java.util.concurrent.ThreadPoolExecutor.runWorker(java.util.concurrent.ThreadPoolExecutor$Worker):1142
java.util.concurrent.ThreadPoolExecutor$Worker.run():617
java.lang.Thread.run():745
all
```

How-To: Flame Graph 1/2

- Enable Java Flight Recorder
  - Extra options in spark-defaults.conf or CLI. Example:

```
$ pyspark --conf "spark.driver.extraJavaOptions"="-XX:+UnlockCommercialFeatures -
XX:+FlightRecorder" --conf "spark.executor.extraJavaOptions"="-XX:+UnlockCommercialFeatures
-XX:+FlightRecorder"
```

- Collect data with jcmd.
    - Example, sampling for 10 sec:

```
$ jcmd <pid> JFR.start duration=10s filename=$PWD/myoutput.jfr
```

How-To: Flame Graph 2/2

- Process the jfr file:
  - From .jfr to merged stacks

```
$ jfr-flame-graph/run.sh -f myoutput.jfr -o myoutput.txt
```

  - Produce the .svg file with the flame graph

```
$ FlameGraph/flamegraph.pl myoutput.txt > myflamegraph.svg
```

- Find details in Kay Ousterhout’s article:
  - https://gist.github.com/kayousterhout/7008a8ebf2babeedc7ce6f8723fd1bf4

Linux Perf Sampling 1/2

- Java mixed-mode flame graphs with Linux Perf_events
  - Profiles CPU cycles spent on JVM and outside (e.g. Kernel)
    - Additional complexity to work around Java-specific dtails
  - Additional options for JVM are needed
    - Issue with preserving frame pointers
    - Fixed in Java8 update 60 build 19 or higher

```
$ pyspark --conf "spark.driver.extraJavaOptions"="-XX:+PreserveFramePointer” --conf
"spark.executor.extraJavaOptions"= "="-XX:+PreserveFramePointer”
```

- Another issue is with inlined functions:
  - fixed adding option: -XX:MaxInlineSize=0

Linux Perf Sampling 2/2

- Collect stack samples with perf:

```
# perf record –F 99 –g –a –p <pid> sleep 10
```

- Additional step: dump symbols. See
  - https://github.com/jrudolph/perf-map-agent
  - https://github.com/brendangregg/Misc/blob/master/java/jmaps
- Create flame graph from stack samples:

```
$ perf script > myoutput.txt
$ ./stackcollapse-perf.pl myoutput.txt | ./flamegraph.pl --color=java --hash > myoutput.svg
```

HProfiler

- Hprofiler is a home-built tool
  - Automates collection and aggregation of stack traces into flame graphs for distributed applications
  - Integrates with YARN to identify the processes to trace across the cluster
  - Based on Linux perf_events stack sampling
- Experimental tool
  - Author Joeri Hermans @ CERN
  - https://github.com/cerndb/Hadoop-Profiler
  - https://db-blog.web.cern.ch/blog/joeri-hermans/2016-04-hadoop-performance-troubleshooting-stack-tracing-introduction

Recap on Flame Graphs

- Pros: good to understand where CPU cycles are spent
  - Useful for performance troubleshooting and internals investigations
  - Functions at the top of the graph are the ones using CPU
  - Parent methods/functions provide context

- Limitations:
  - Off-CPU and wait time not charted
    - Off-CPU flame graphs exist, but still experimental
  - Aggregation at the function/method level
    - Does not necessarily highlight the critical path in the code
  - Interpretation of flame graphs requires experience/knowledge

Further Drill Down, the Source Code

- Further drill down on the source code
  - Search on Github for the method names as found in the flame graph
  - Examples:
    - "org.apache.sql.execution.WholeStageCodegenExec“
    - "org.apache.spark.sql.executio.aggregate.VectorizedHashMapGenerator.scala"

Linux Perf Stat

- Perf stat counters to further understand
  - Access to memory is key
  - Much higher memory throughput in Spark 2.0 vs 1.6
    - See LLC-LOAD, LLC-load-misses

```
# perf stat -e task-clock,cycles,instructions,branches,branch-misses \
        -e stalled-cycles-frontend,stalled-cycles-backend \
        -e cache-references,cache-misses \
        -e LLC-loads,LLC-load-misses,LLC-stores,LLC-store-misses \
        -e L1-dcache-loads,L1-dcache-load-misses,L1-dcache-stores,L1-dcache-store-misses \
        -p <pid_spark_process> sleep 100
```

Conclusions

- Apache Spark
  - Scalability and performance on commodity HW
  - For I/O intensive and compute-intensive queries
  - Spark SQL useful for offloading queries from RDBMS

- Spark 2.0, code generation and vector operations
  - Important improvements for CPU-bound workloads
  - Speedup close to one order of magnitude
    - Spark 2.0 vs. Spark 1.6 for the tested workload
  - Diagnostic tools and instrumentation are important:
    - Execution plans, Linux perf events, flame graphs

Acknowledgements and Links

- This work has been made possible thanks to the colleagues at CERN IT and Hadoop service
  - In particular Zbigniew Baranowski and Joeri Hermans
  - See also blog - http://db-blog.web.cern.ch/

- Brendan Gregg – Resources on flame graphs:
  - http://www.brendangregg.com/flamegraphs.html

THANK YOU.

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