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
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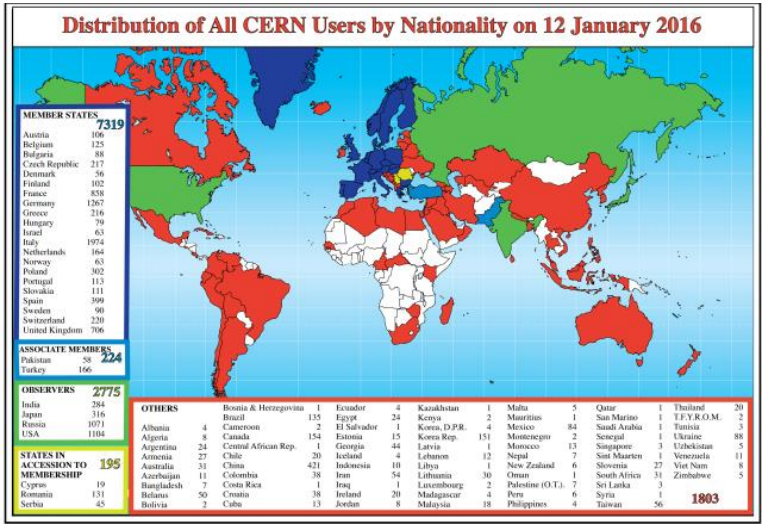
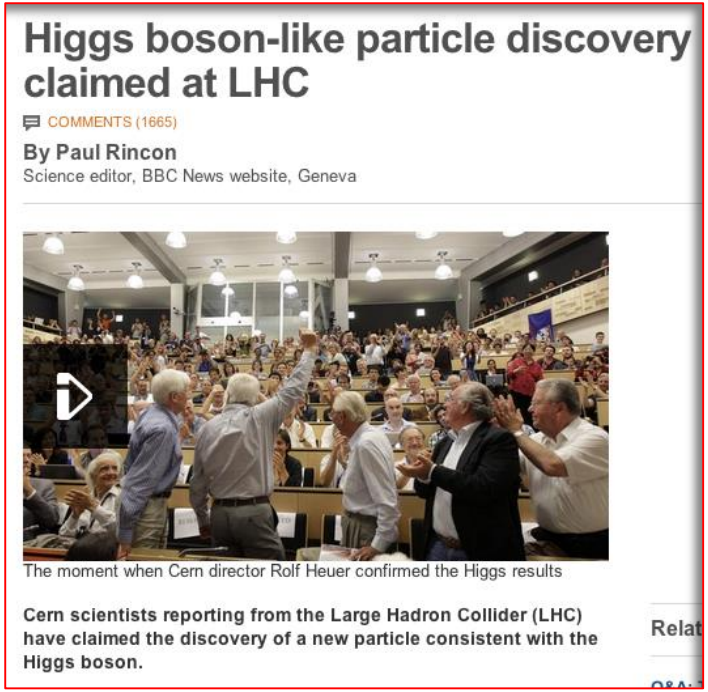
CERN

- 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



Large Hadron Collider

- Largest and most powerful particle accelerator



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

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
```

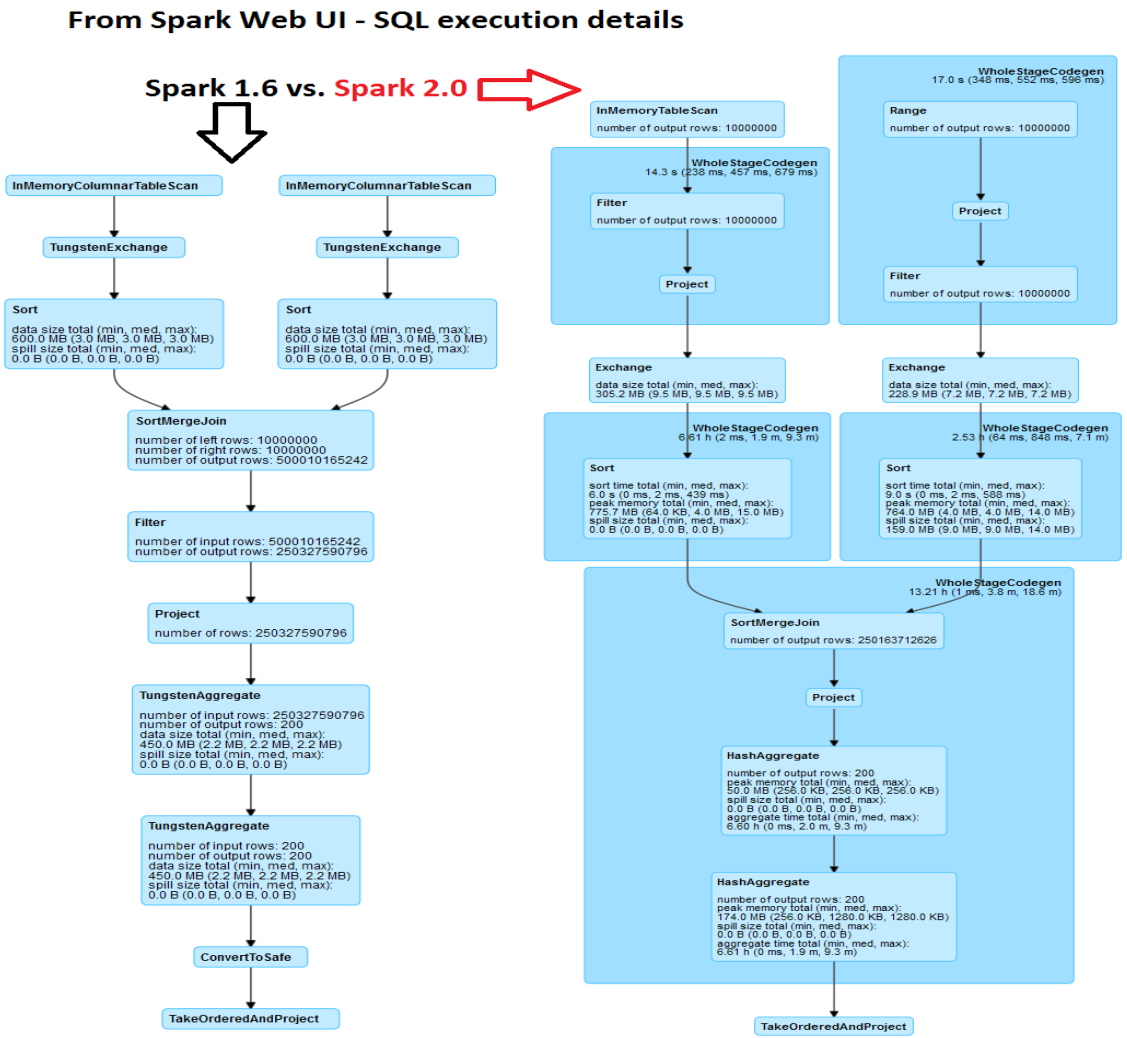
Execution Plan in Spark 2.0

- 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”



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

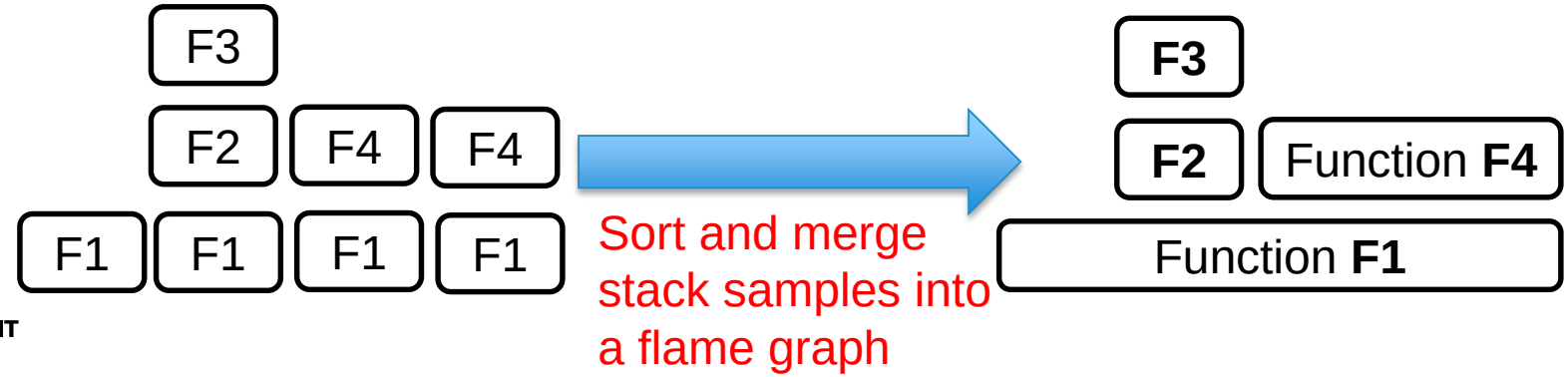
- Flame graph visualization of stack profiles
  - Brain child of Brendan Gregg (Dec 2011)
  - Code: https://github.com/brendangregg/FlameGraph
  - Now very popular, available for many languages, also for JVM
- Shows which parts of the code are hot
  - Very useful to understand where CPU cycles are spent

JVM and Stack Profiling

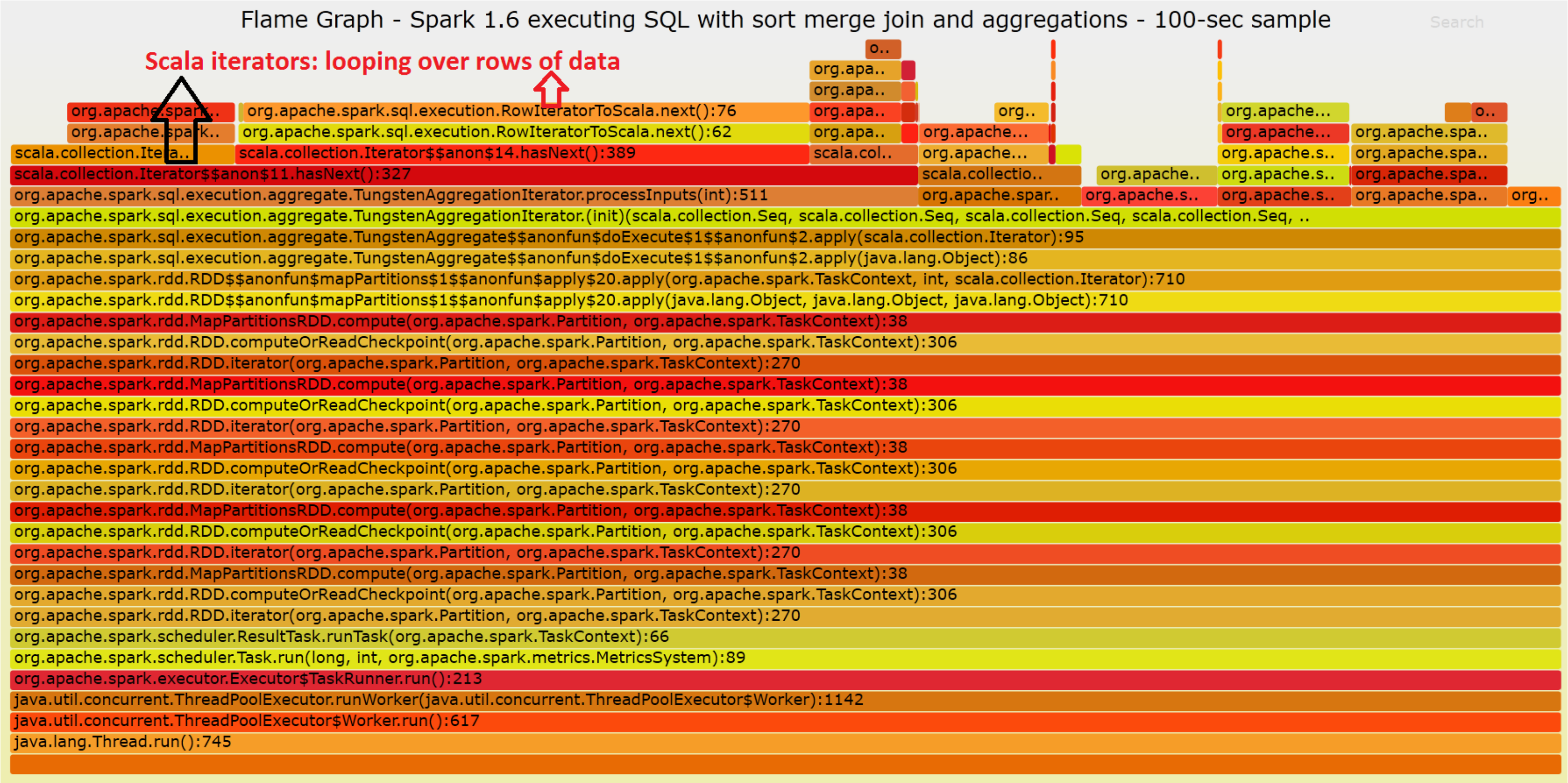
- Jstack <pid>
  - Prints java stack for all threads
  - What you want is a series of stack traces
- Java Flight Recorder
  - Part of the HotSpot JVM (requires license for prod)
- Linux Perf
  - Stack sampling of Java and OS

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



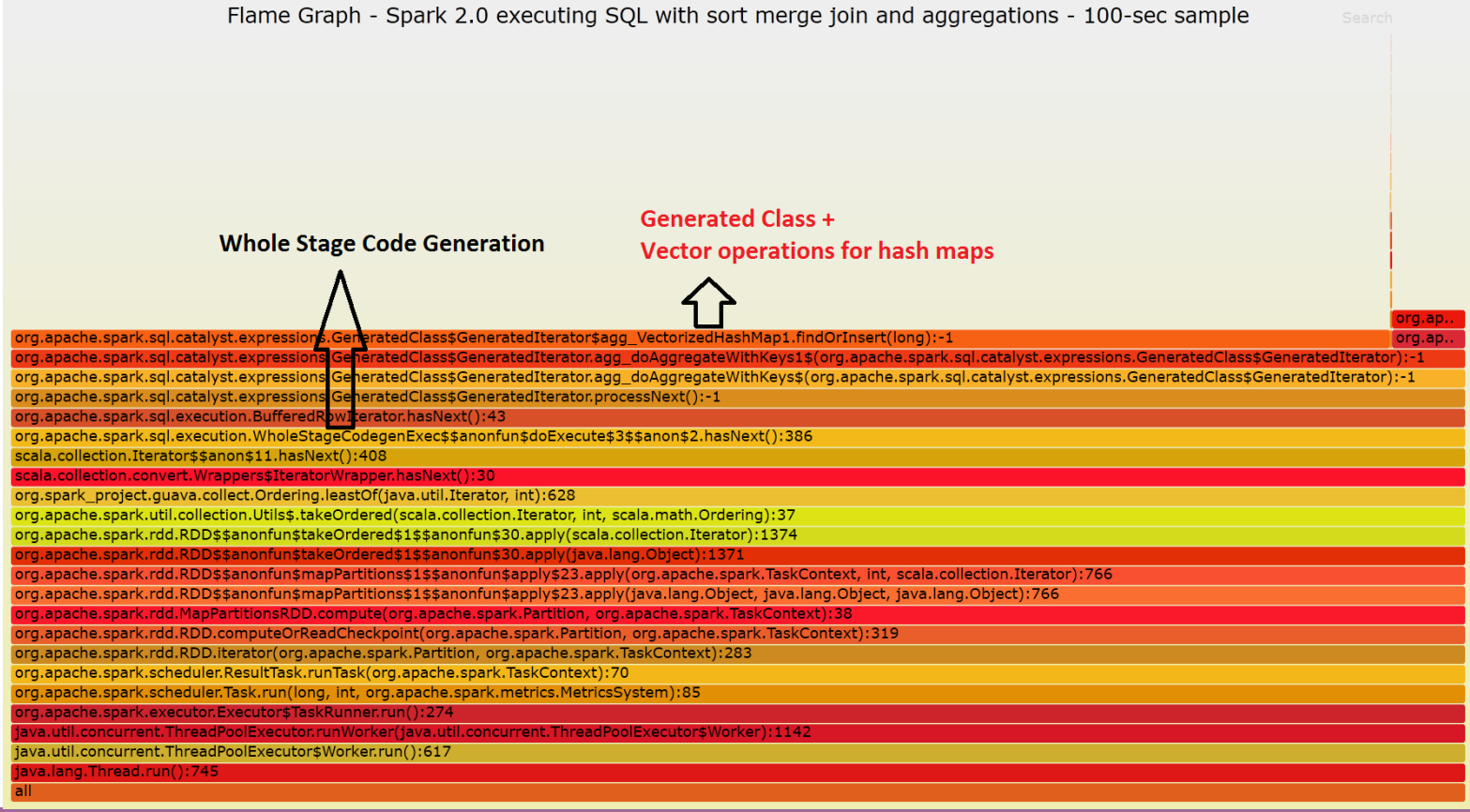
Flame Graph Spark 1.6



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



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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