

# Profiling and optimizing a Spark job with Babar

**BENOIT HANOTTE, BERLIN BUZZWORDS 2018** 



criteo.



500TB
INGESTED DAILY

15PB
READ DAILY

4000+

HADOOP NODES

















presto



#### Context

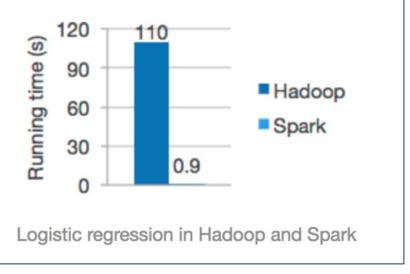
Teams moving from MapReduce-based frameworks to newer alternatives

**Spark** very popular, advertises faster & more efficient processing

# **Speed**

Run workloads 100x faster.

Apache Spark achieves high performance for both batch and streaming data, using a state-of-the-art DAG scheduler, a query optimizer, and a physical execution engine.



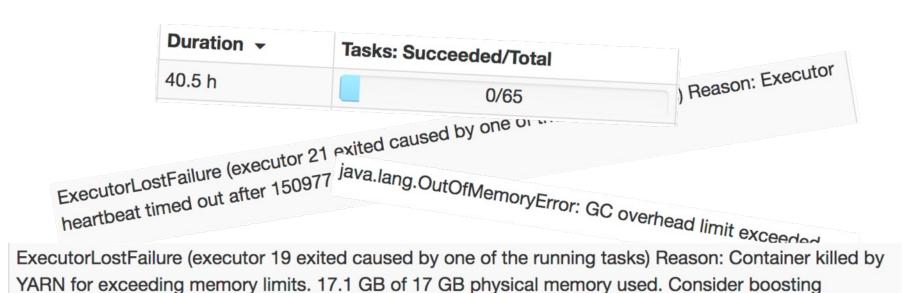
Source: <a href="http://spark.apache.org">http://spark.apache.org</a> (June 2018)



#### Context

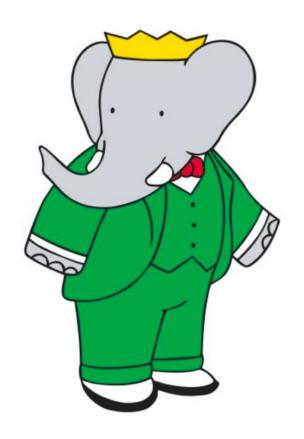
But this is not what we experienced...

spark.yarn.executor.memoryOverhead.



Jobs were unstable, teams were solving it by allocating too much resources to their jobs.





## Profiler for distributed applications on Hadoop

Works with any JVM framework





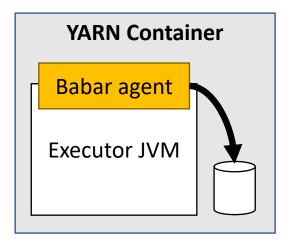


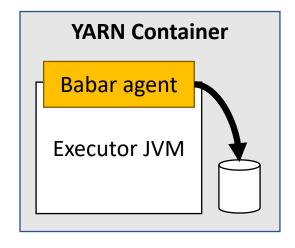
- Easy to get started, no infrastructure required
- Made for distributed applications
- Works on 10000+ containers apps
- Exports ready-to-use graphs as HTML file

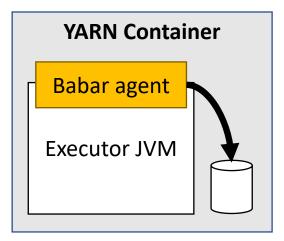


https://github.com/criteo/babar









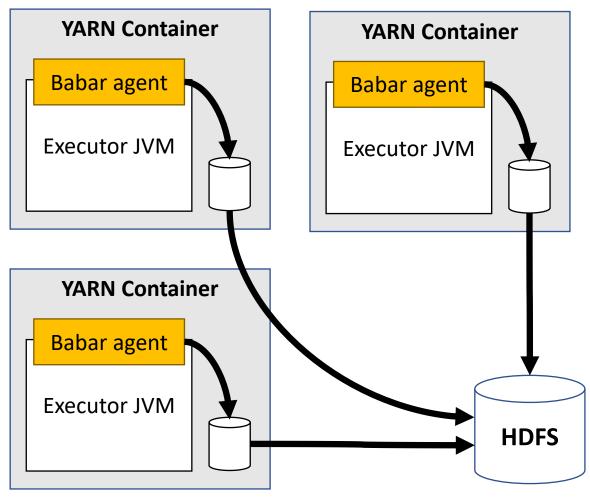
Babar agent instruments the executor JVM, logs metrics to local FS.

Agent can be distributed with spark-submit (no installation).

#### **Metrics from:**

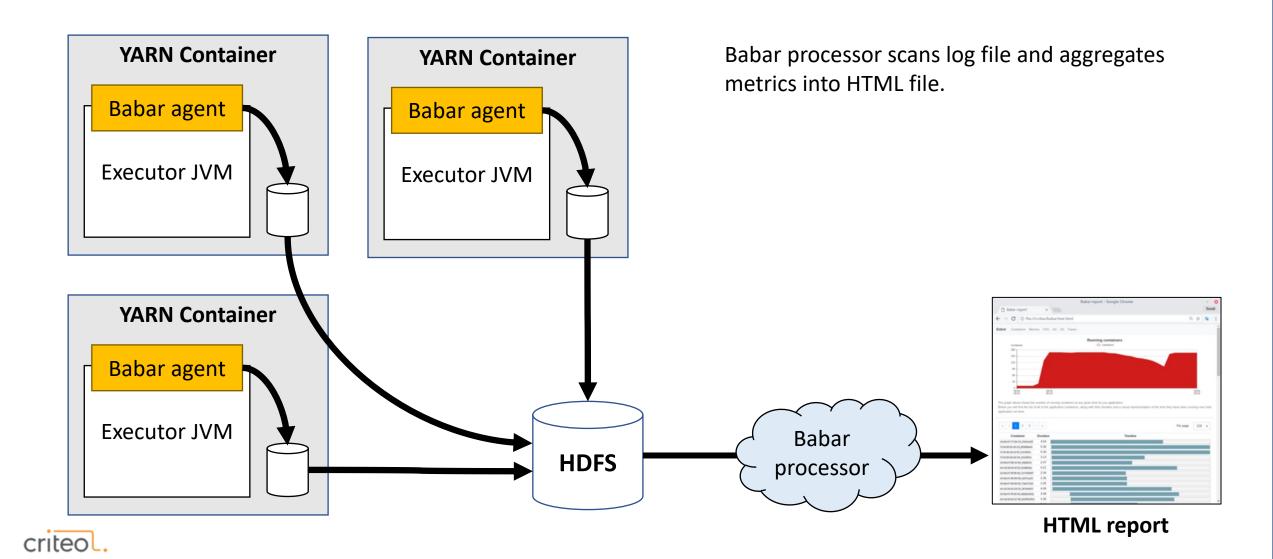
- JVM
- Stack traces
- /proc/

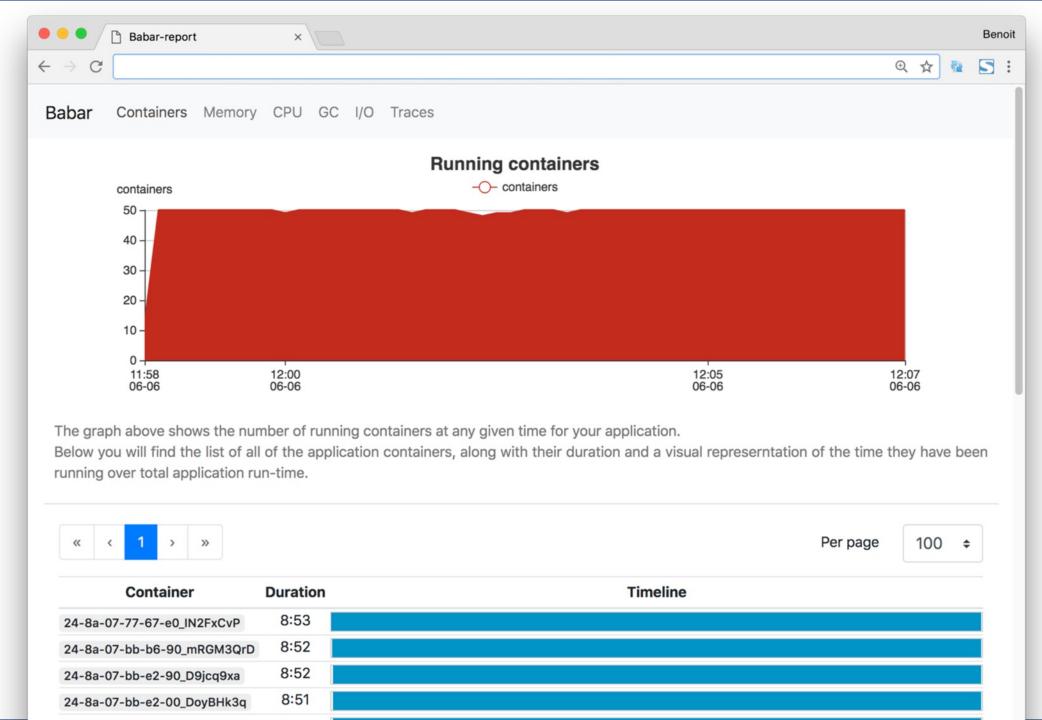




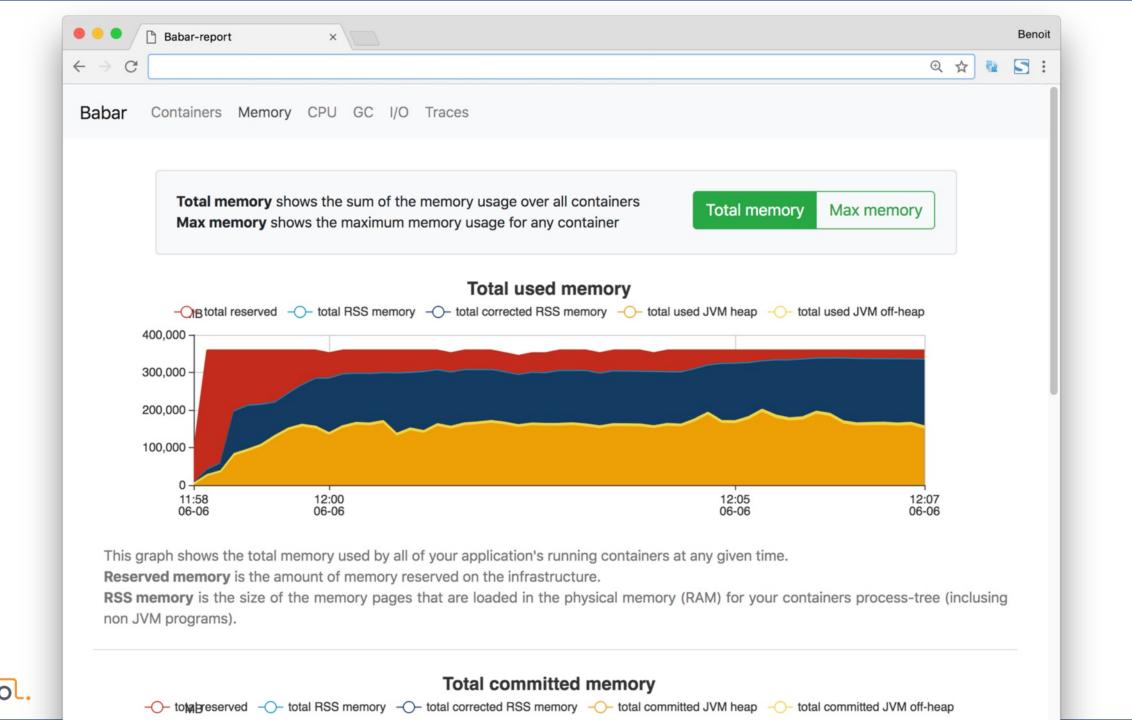
On job complete, YARN aggregates logs from all executors into single file on HDFS.

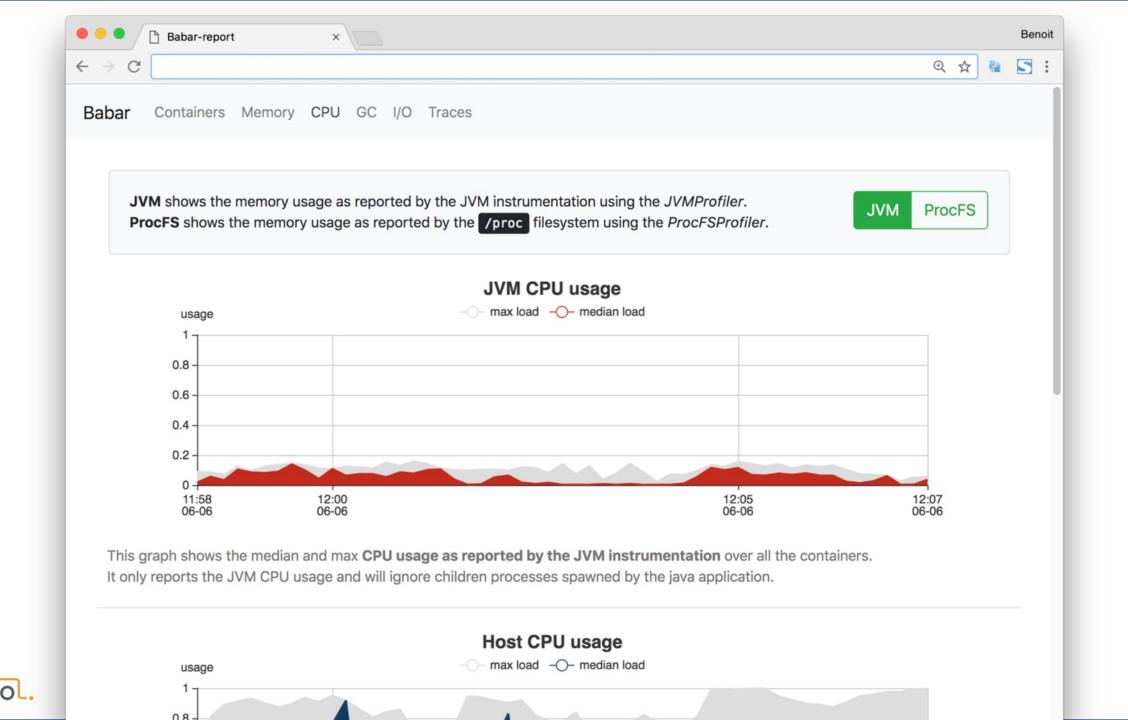


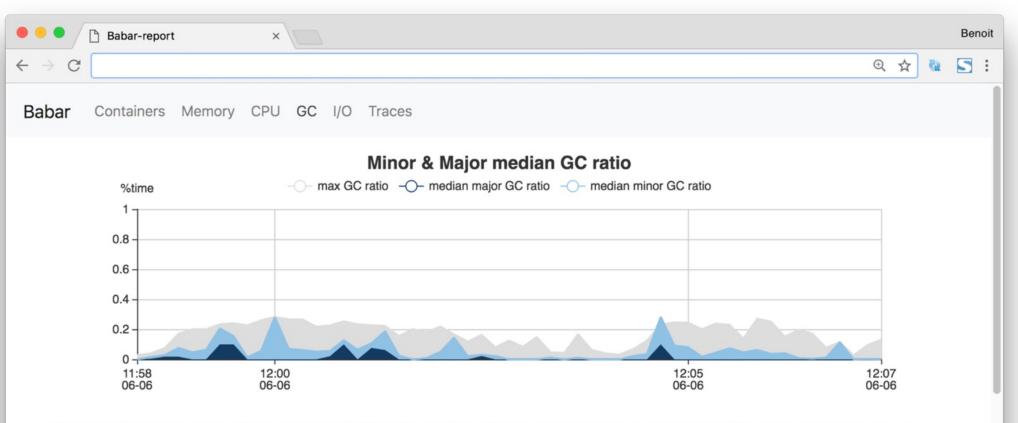












This graph shows the median ratio of wall-clock time spent doing minor and major garbage collections in the JVMs over all containers.

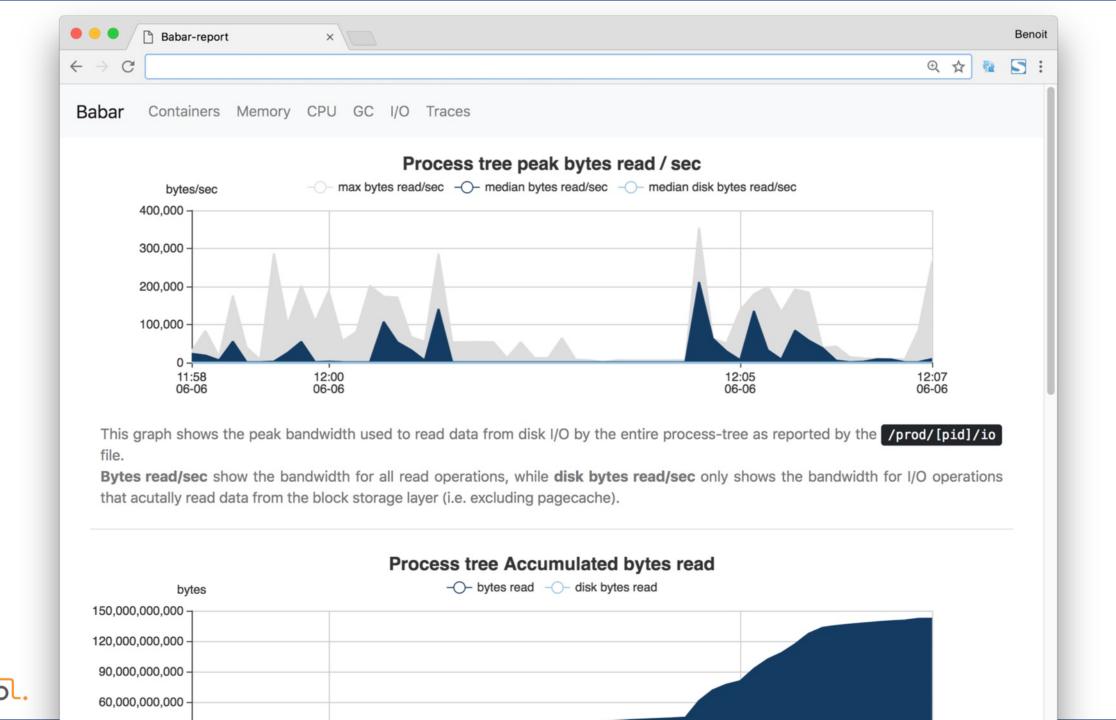
Minor GC only clean the young generation, while Major GC cleans both the young and old ones. The major GC should be much less frequent that the minor one, otherwise it could indicate that too many short lived-objects are promototed to the old generation. If this is the case, you may want to resize the generations and make sure that no humongous object uses most of the old generation (which could trigger frequent major GC).

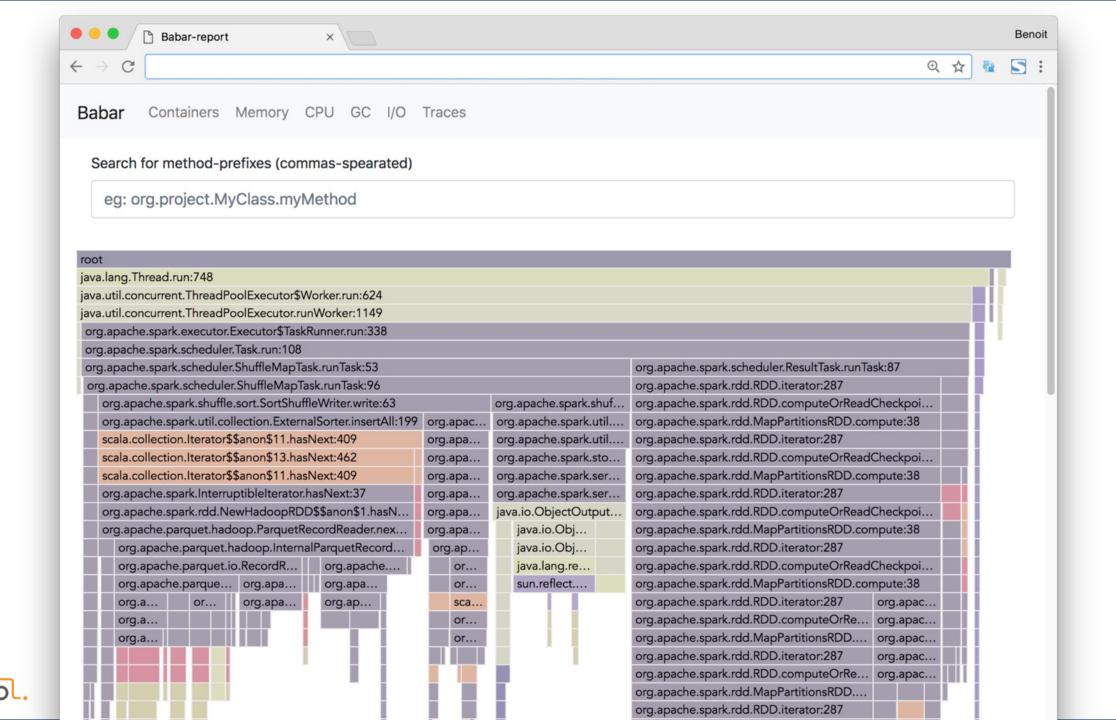
You can tune the size of the generations either by specifying the -XX:NewRatio (integer value only) parameter or with the -XX:NewSize and -XX:MaxNewSize parameters for finer-grained tuning.

#### Accumulated JVM CPU time and GC CPU time





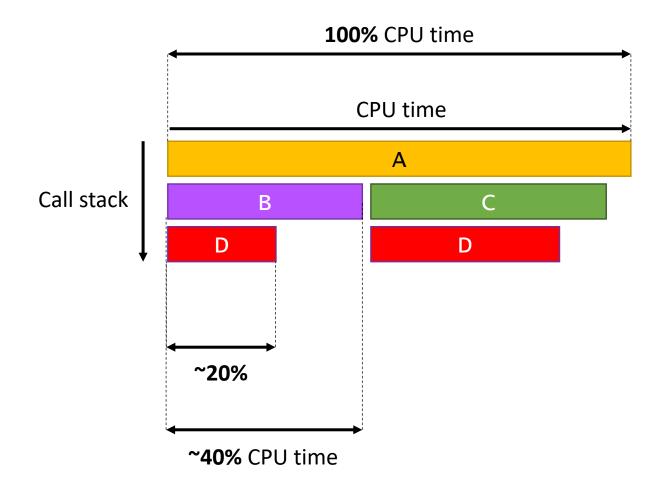




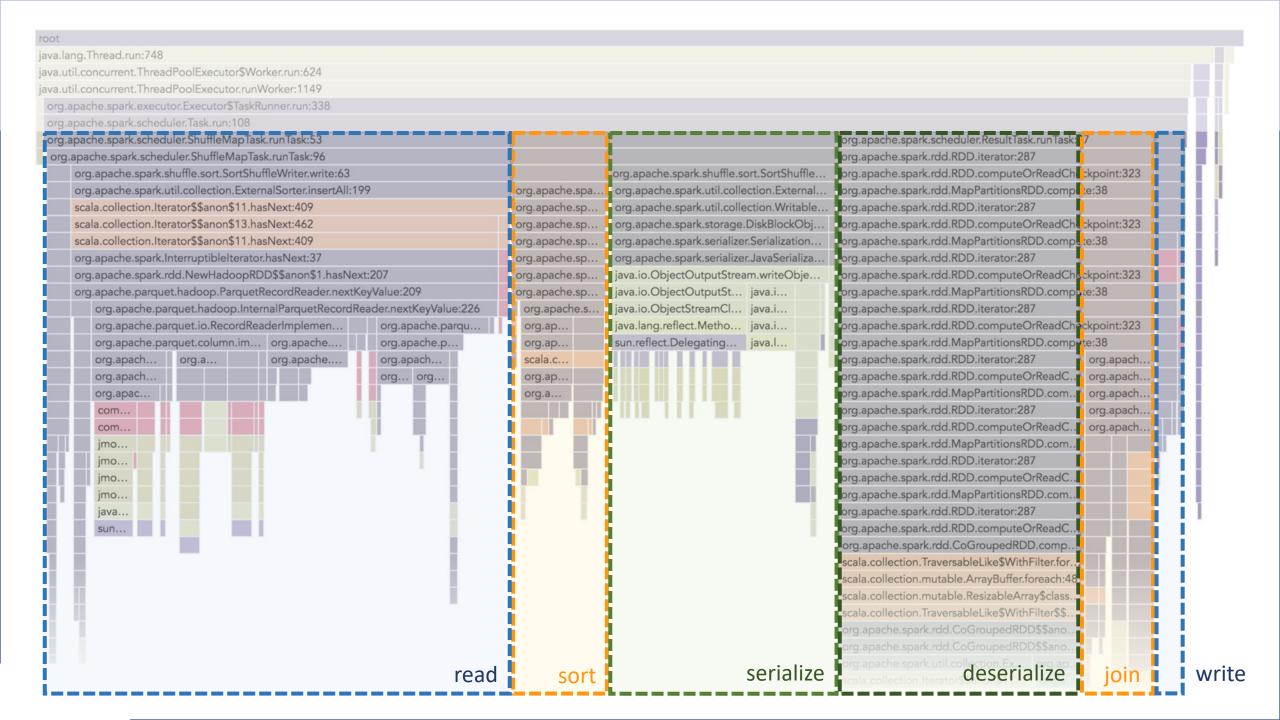
# In practice: Flame Graphs & CPU time

Visualize expensive code paths from sampled stack traces

```
A(){
    B(){
```



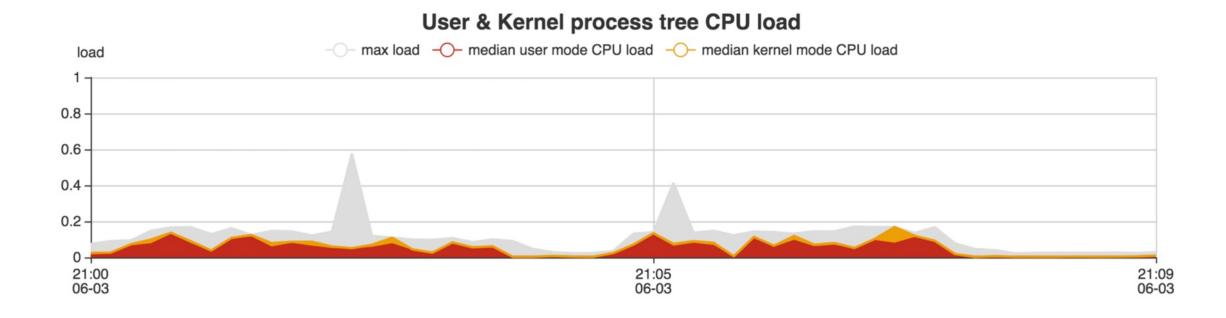




## In practice: Flame Graphs & CPU time

Shuffle is expensive

Not network, not IO, but serialization!





## In practice: Flame Graphs & CPU time

### Pick models accordingly

- Serialization/deserialization efficiency often more important than memory footprint
- **Use specialized serializers** (can allow further optimizations by Spark)

In this example join: -40% CPU time!

Models also impact cost of **size estimation**Can be very expensive (we have seen up to 30% CPU time)

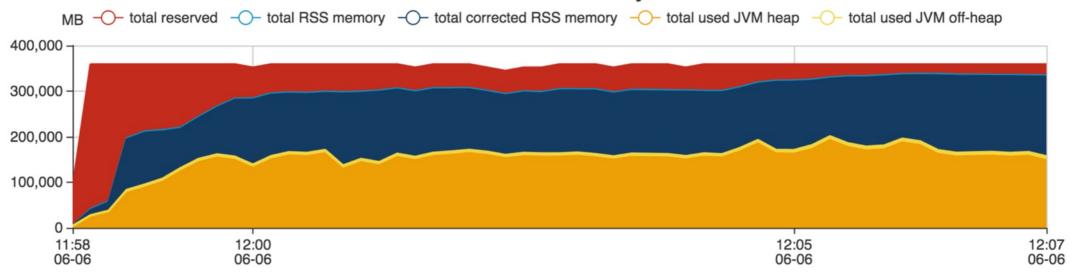
		org.apache.spark.util.collection		org.apache.spark.stora
org.apache.spark.util.SizeEstimator\$.estimate:69 (samples: 34162, 18.3%)				
org.apache.spark.util.collection			cutil.collection	org.apache.spark.seria
org.apache.spark.util.SizeEstimat.			java.io.ObjectOutputS	
		org.apache.spark.util.SizeEstimat		java.io.ObjectOutputS
		org.apache.spark.util.SizeEstim		java.io.ObjectOutputS
ext:62		org.apache.s	org.apache.s	java.io.ObjectOutputS
rapper.ne	ext:14	org.apache.s	org.apache.s	java.io.ObjectOutputS



#### Understanding the memory usage

- JVM heap & off-heap memory used
- Physical memory used (RSS memory)
- Reserved memory

#### **Total used memory**



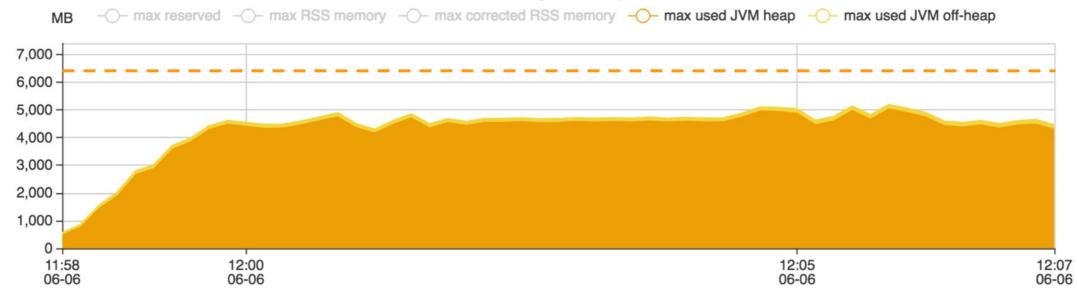


#### Dimensioning and tuning memory

Setting executor & container memory to accommodate the largest executor:

Avoiding OutOfMemoryErrors (spark.executor.memory)

#### Max used memory for any container



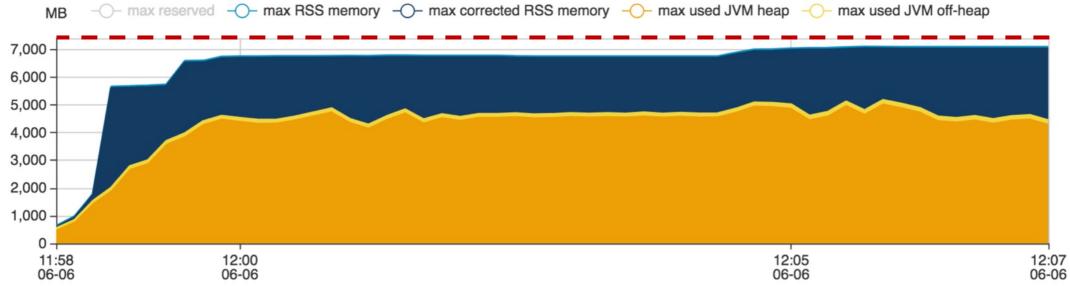


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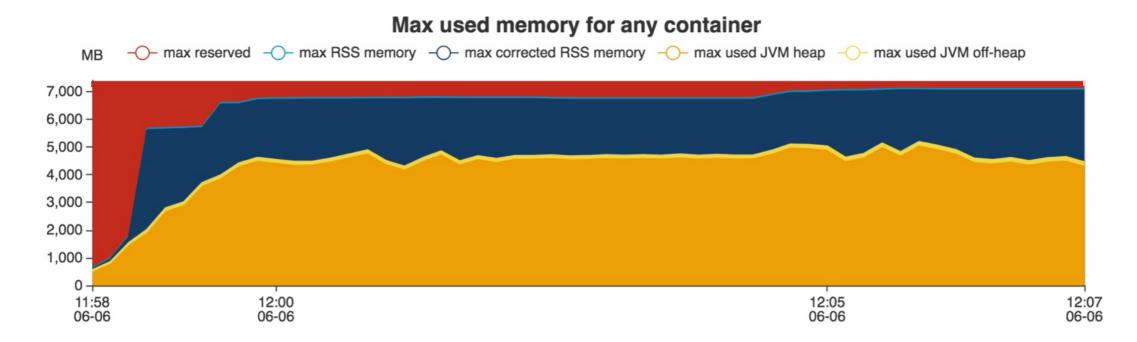




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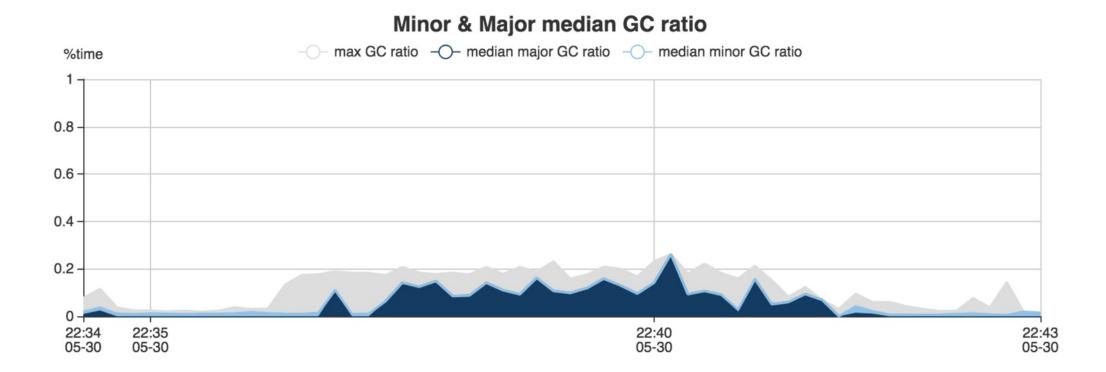
- Avoiding OutOfMemoryErrors (spark.executor.memory)
- Avoiding YARN killing containers for exceeding reserved memory (spark.yarn.executor.memoryOverhead)





## Dimensioning and tuning memory

Keeping Garbage Collection under control





## Recap

Babar helped us a lot, we hope it can help you too!





# **THANK YOU!**

