How we test correctness and performance

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About me



BOGDAN GHIT

Databricks, Software Engineer



• Query performance optimizations

IBM T.J. Watson, Research Intern

Bid advisor for cloud spot markets

Delft University of Technology, PhD in Computer Science

- Resource management in datacenters
- Performance of Spark, Hadoop



About Databricks Amsterdam

We are hiring!

https://databricks.com/company/careers bogdan.ghit@databricks.com

Company mission: make Databricks Runtime a unified analytics platform to accelerate innovation

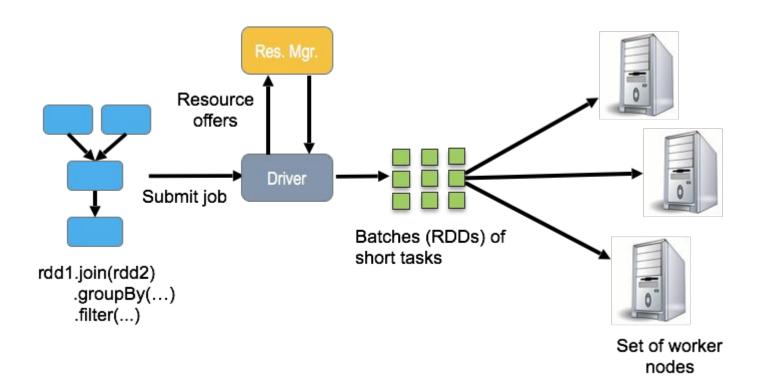
Team mission: make the Databricks Runtime the fastest execution engine for Apache Spark

Teams in Amsterdam:

- 1. Query Performance
- 2. Storage and IO
- 3. Spark Benchmarking
- 4. Databricks UIs
- 5. Billing Infrastructure (new)

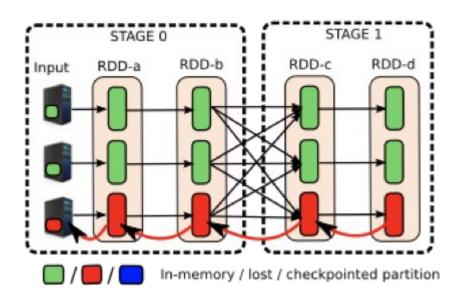


How Spark works

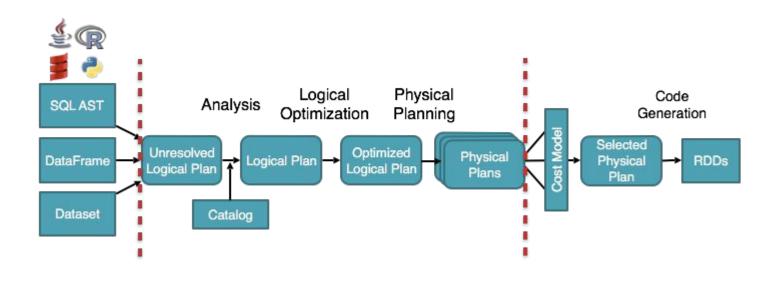


RDD abstraction

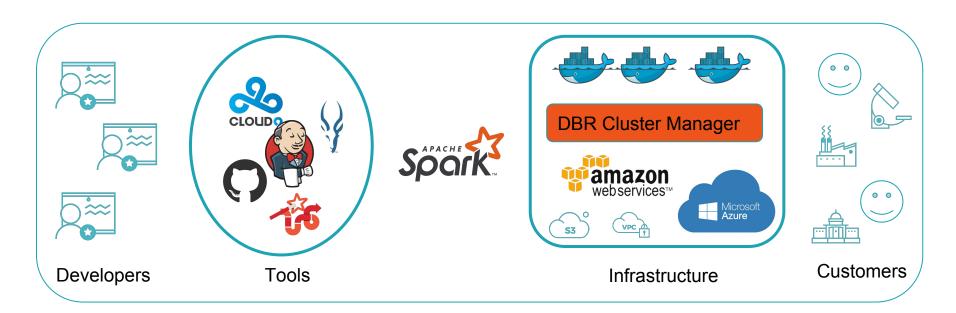
Main abstraction: resilient distributed datasets (RDDs)
Collection of data partitions distributed across multiple machines.
Rich set of coarse-grained transformations.



Spark SQL behind the scenes



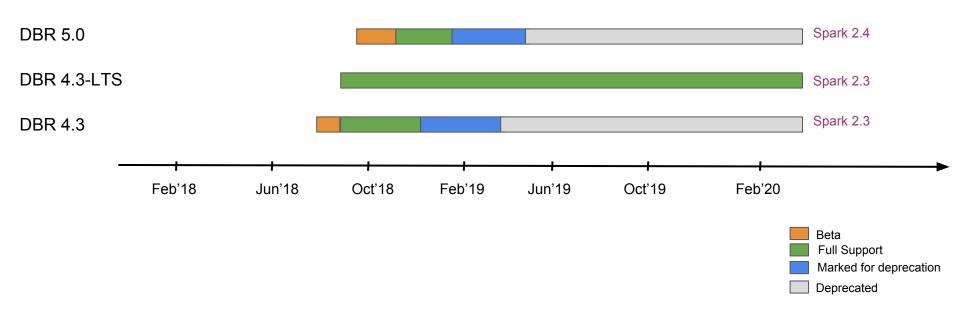
Databricks ecosystem







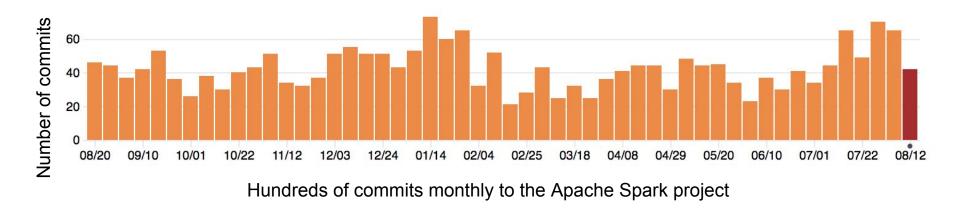
Databricks runtime (DBR) releases



Our goal is to make releases automatic and frequent



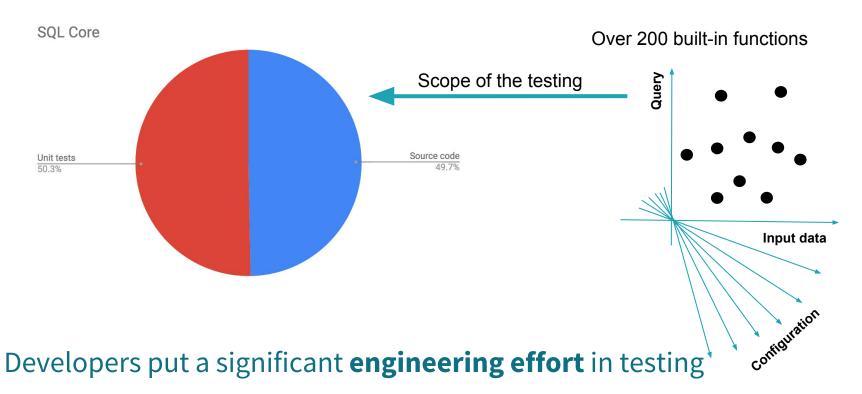
Apache Spark contributions



At this pace of development, **mistakes** are bound to happen

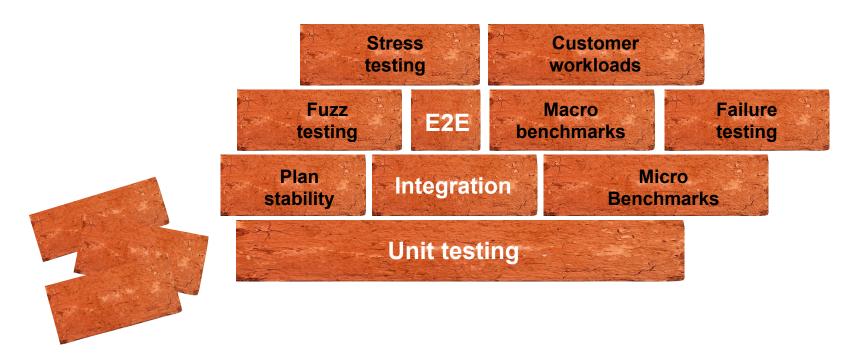


Where do these contributions go?



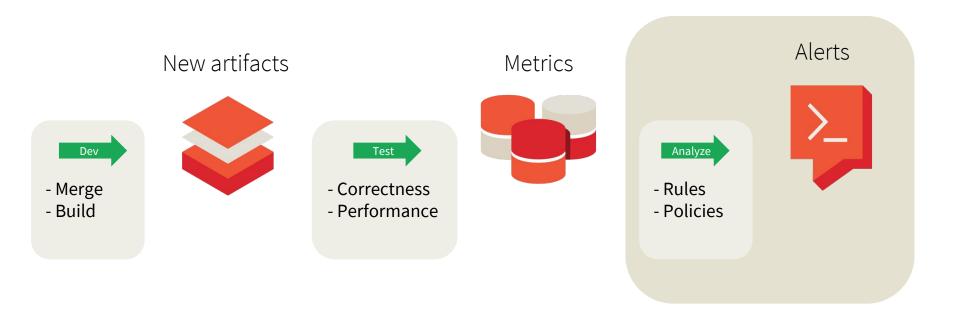


Yet another brick in the wall



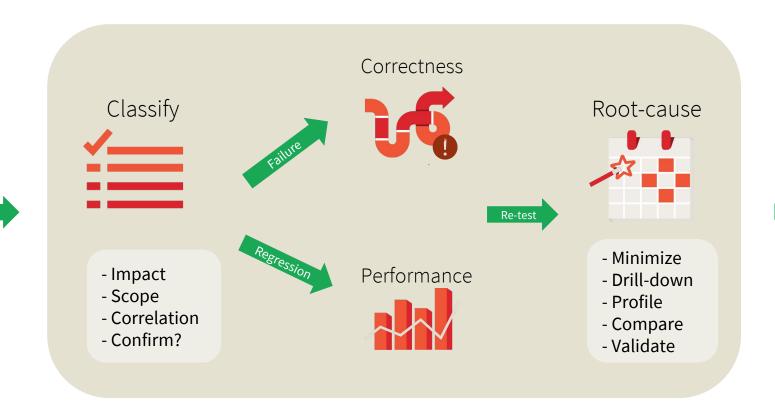
Unit testing is not enough to guarantee correctness and performance

Continuous Integration pipeline





Classification and alerting

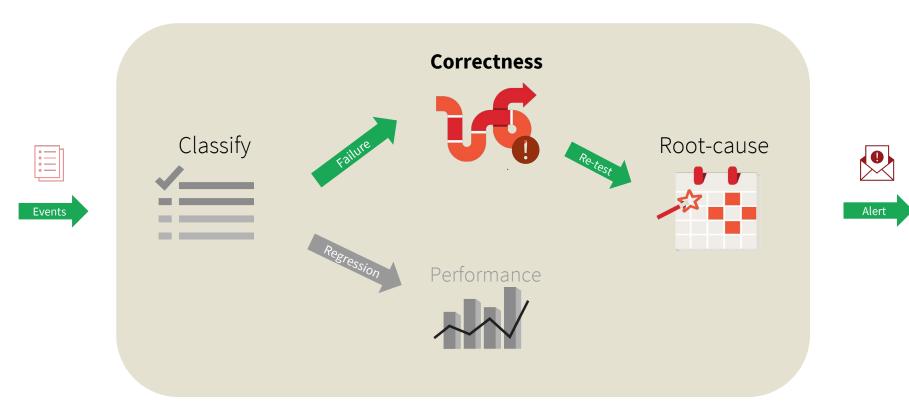




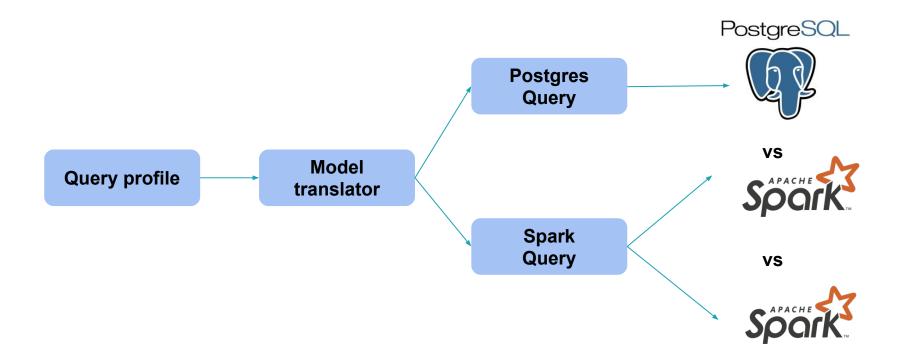
Events

Alert

Correctness



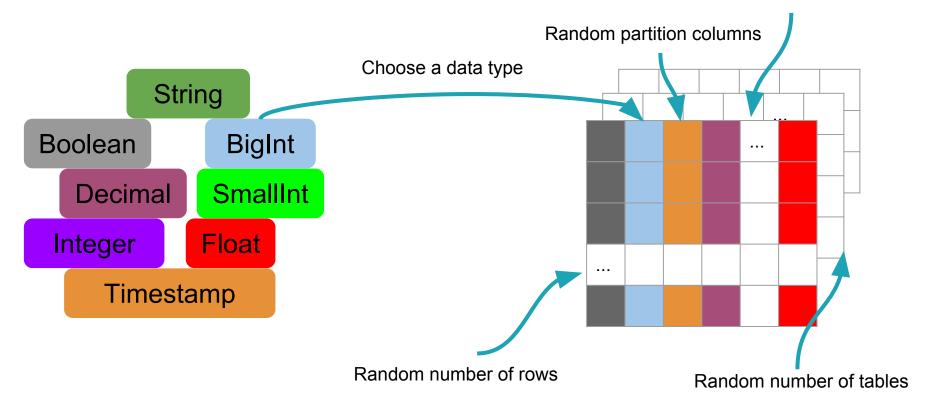
Random query generation



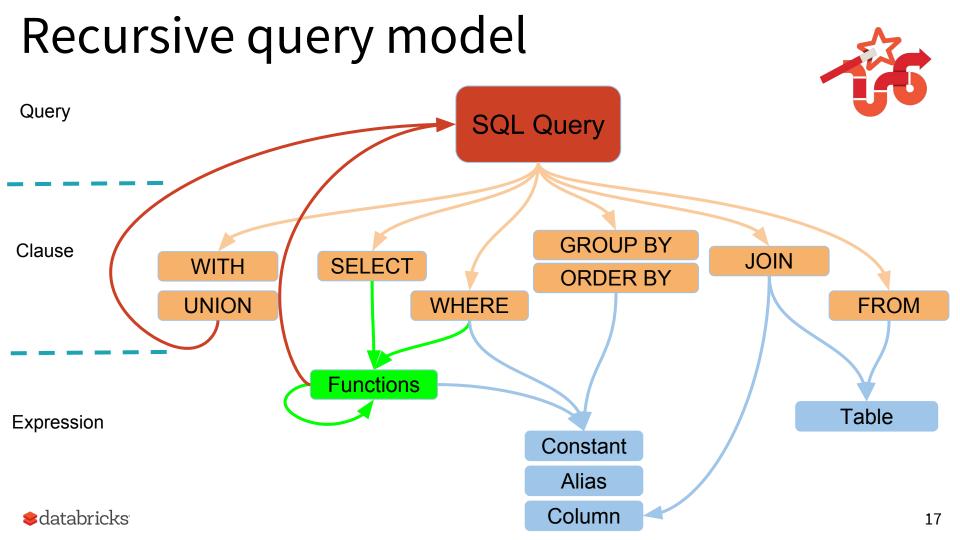


DDL and datagen

Random number of columns



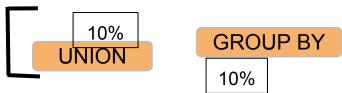


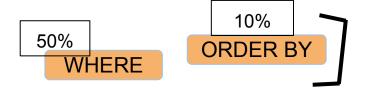


Probabilistic query profile

Independent weights

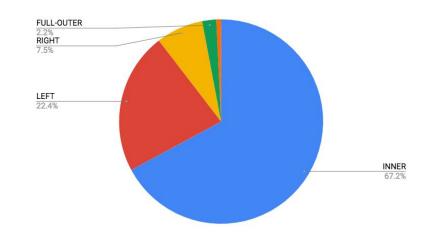
Optional query clauses





Inter-dependent weights

- Join types
- Select functions





Coalesce flattening (1/4)

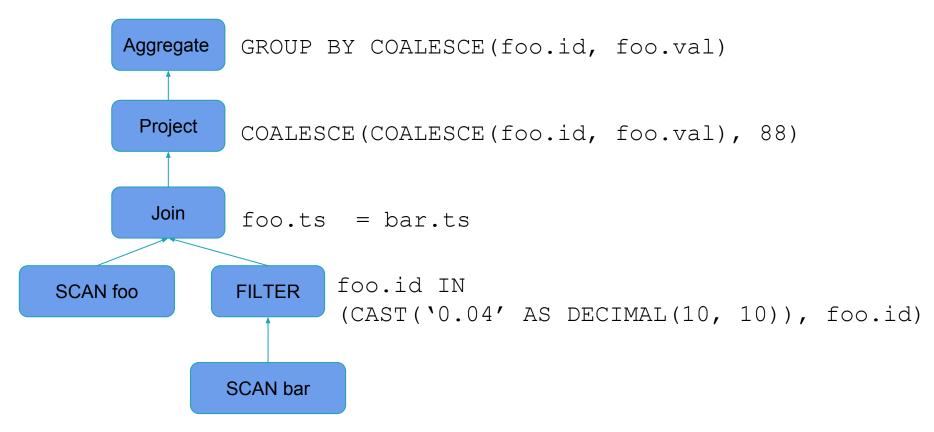
```
SELECT COALESCE(t2.smallint_col_3, t1.smallint_col_3, t2.smallint_col_3) AS int_col,
    IF(NULL, VARIANCE(COALESCE(t2.smallint_col_3, t1.smallint_col_3, t2.smallint_col_3)),
    COALESCE(t2.smallint_col_3, t1.smallint_col_3, t2.smallint_col_3)) AS int_col_1,
    STDDEV(t2.double_col_2) AS float_col,
    COALESCE(MIN((t1.smallint_col_3) - (COALESCE(t2.smallint_col_3, t1.smallint_col_3, t2.smallint_col_3))), COALESCE(t2.smallint_col_3, t1.smallint_col_3, t2.smallint_col_3),
    COALESCE(t2.smallint_col_3, t1.smallint_col_3, t2.smallint_col_3)) AS int_col_2
FROM table_4 t1
INNER JOIN table_4 t2 ON (t2.timestamp_col_7) = (t1.timestamp_col_7)
WHERE (t1.smallint_col_3) IN (CAST('0.04' AS DECIMAL(10,10)), t1.smallint_col_3)
GROUP BY COALESCE(t2.smallint_col_3, t1.smallint_col_3, t2.smallint_col_3)
```

Small dataset with 2 tables of 5x5 size Within 10 randomly generated queries

Error: Operation is in ERROR_STATE

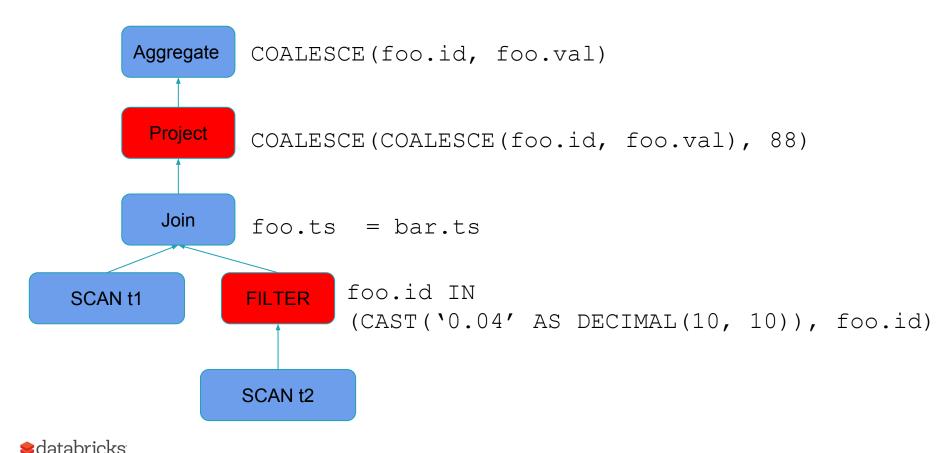


Coalesce flattening (2/3)

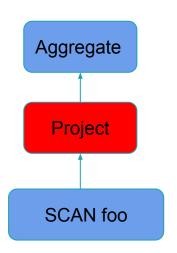




Coalesce flattening (3/4)



Coalesce flattening (4/4)



Minimized query:

```
SELECT

COALESCE(COALESCE(foo.id, foo.val), 88)

FROM foo

GROUP BY

COALESCE(foo.id, foo.val)
```

Analyzing the error

- The optimizer flattens the nested coalesce calls
- The SELECT clause doesn't contain the GROUP BY expression
- Possibly a problem with any GROUP BY expression that can be optimized



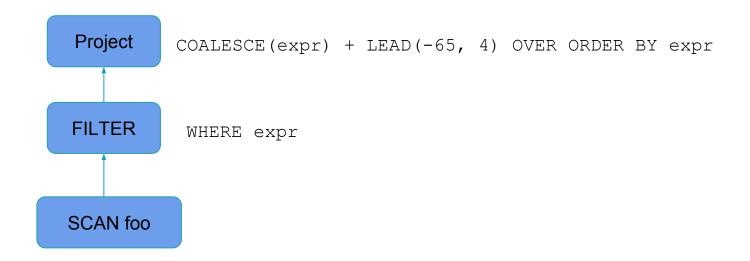
Lead function (1/3)

Error: Column 4 in row 10 does not match:

```
[1.0, 696, -871.81, <<-64.98>>, -349] SPARK row [1.0, 696, -871.81, <<None>>, -349] POSTGRESQL row
```

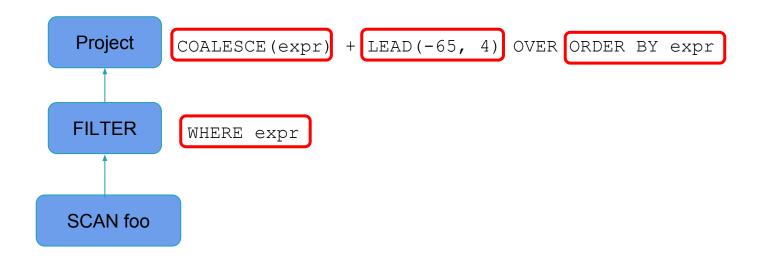


Lead function (2/3)





Lead function (3/3)

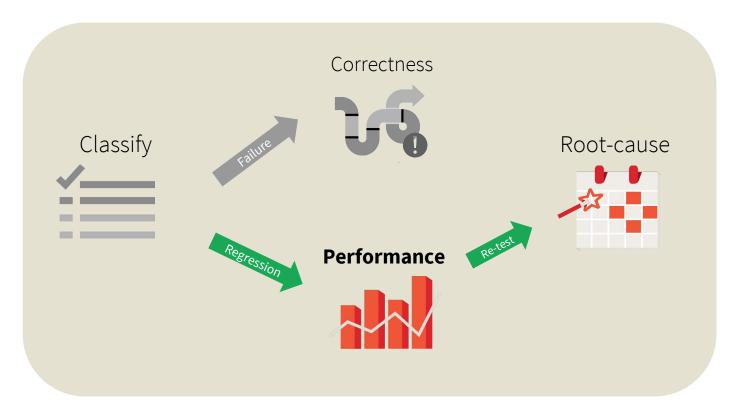


Analyzing the error

- Using constant input values breaks the behaviour of the LEAD function
- SC-16633: https://github.com/apache/spark/pull/14284



Performance

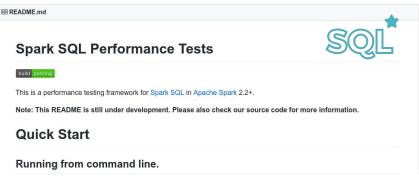




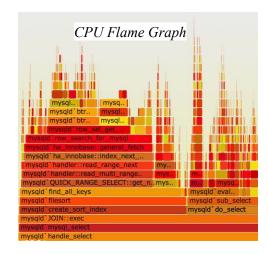
Events

Benchmarking tools

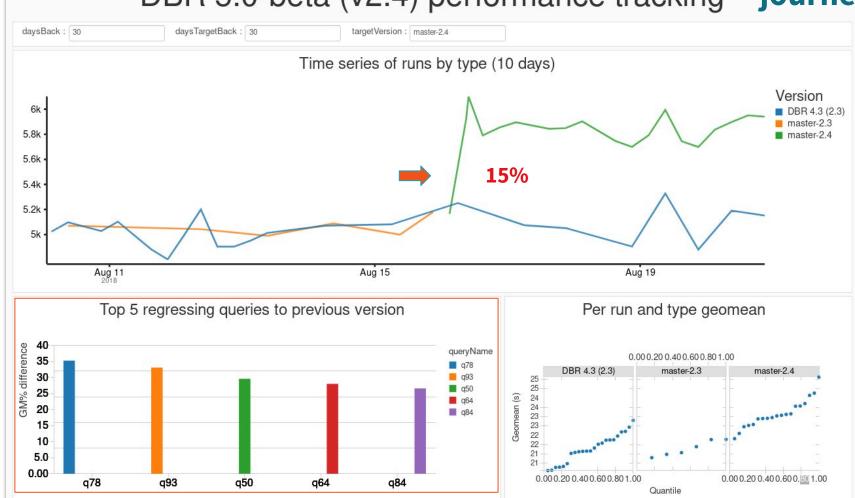
- spark-sql-perf public library for TPC workloads
- datagen and import scripts local, cluster, S3
- dashboards for analyzing results
- Spark micro benchmarks
- Async-profiler to produce flamegraphs



https://github.com/databricks/spark-sql-perf



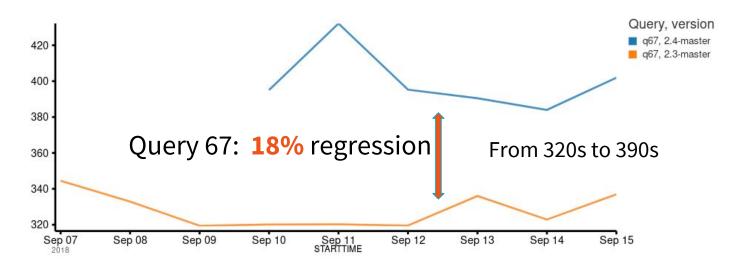
DBR 5.0-beta (v2.4) performance tracking -- journey targetVersion: master-2.4



Per query drill-down: 67

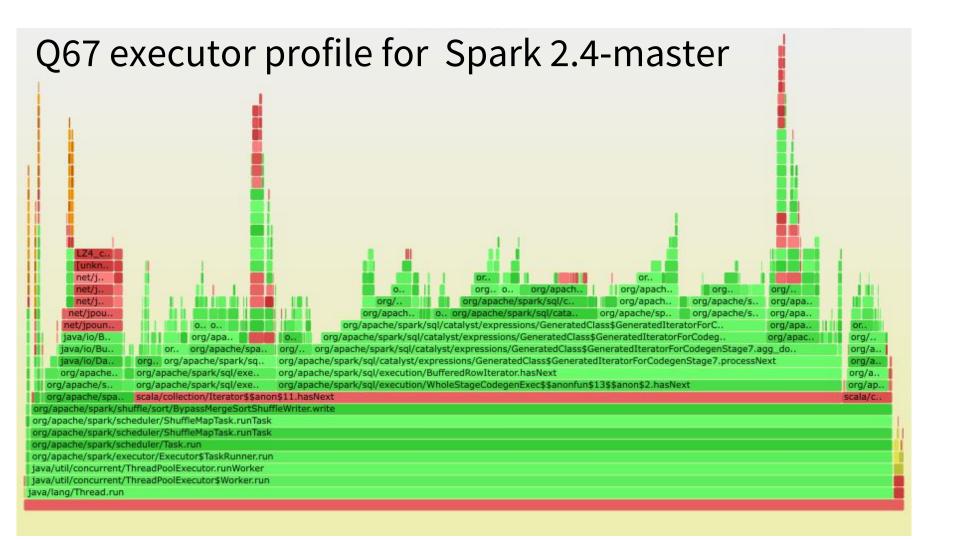


First, scope and validate



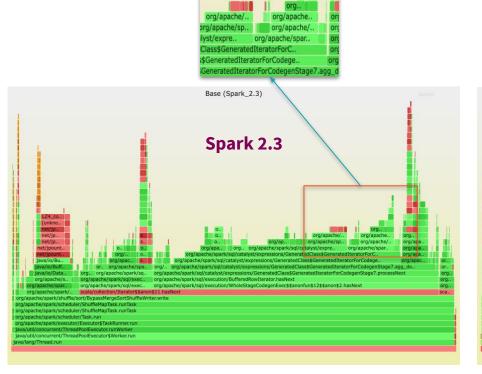
- in 2.4-master (dev) compared
- to 2.3 in DBR 4.3 (prod)

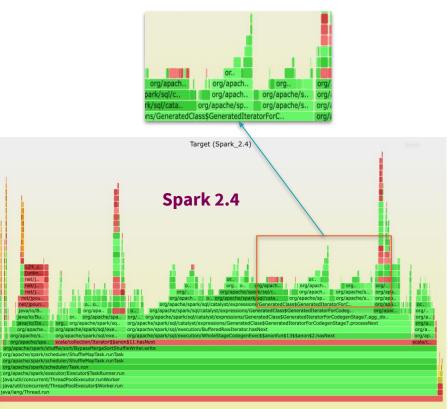




Side-by-side 2.3 vs 2.4: find the differences





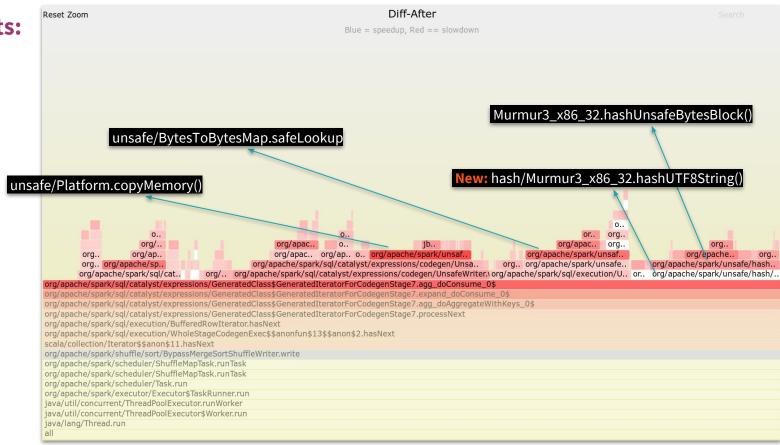


Framegraph diff zoom



Look for hints:

- Mem mgmt
- Hashing
- unsafe





Root-causing

Microbenchmark for UTF8String

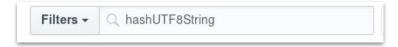
```
test("hashing") {
   import org.apache.spark.unsafe.hash.Murmur3_x86_32
   import org.apache.spark.unsafe.types.UTF8String
   val hasher = new Murmur3_x86_32(0)
   val str = UTF8String.fromString("b" * 10001)
   val numIter = 100000
   val start = System.nanoTime
   for(i <- 0 until numIter) {
      Murmur3_x86_32.hashUTF8String(str, 0)</pre>
```

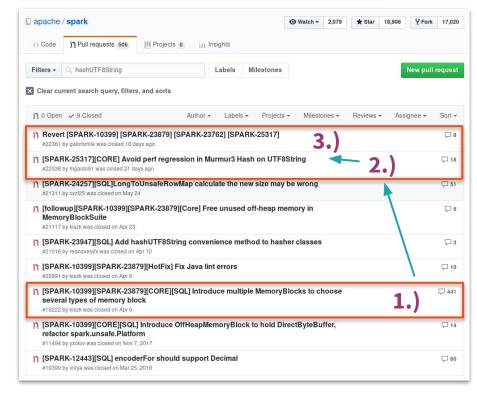
Results:

- Spark 2.3: hashUnsafeBytes() -> 40μs
- Spark 2.4 hashUnsafeBytesBlock() -> 140μs
- also slower UTF8String.getBytes()

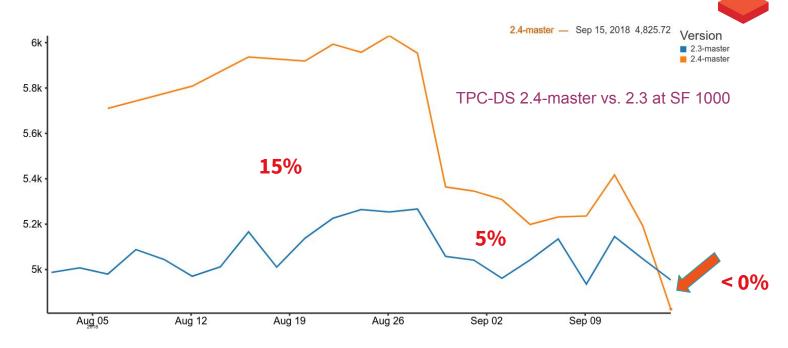


GIT BISECT





It is a journey to get a release out



DBR and Spark testing and performance are a continuous effort

Over a month effort to bring performance to improving

Conclusion

Spark in production is *not just the framework*Unit and integration testing are not enough

We need Spark specific tools to automate the process to ensure both correctness and performance



Thanks! Analyze