Deep Dive Into Apache Spark SQL

with Advanced Performance Tuning

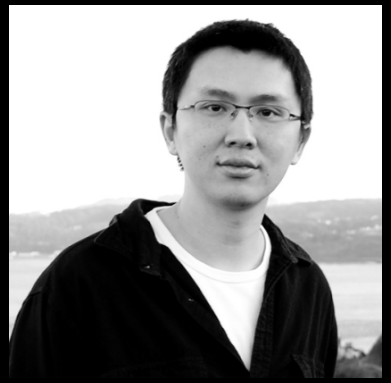
Xiao Li & Wenchen Fan

Spark Summit | SF | Jun 2018

databricks

About US

- Software Engineers at databricks
- Apache Spark Committers and PMC Members



Xiao Li (Github: gatorsmile)

Wenchen Fan (Github: cloud-fan)

Databricks' Unified Analytics Platform

Unifies Data Engineers and Data Scientists

Unifies Data and AI Technologies

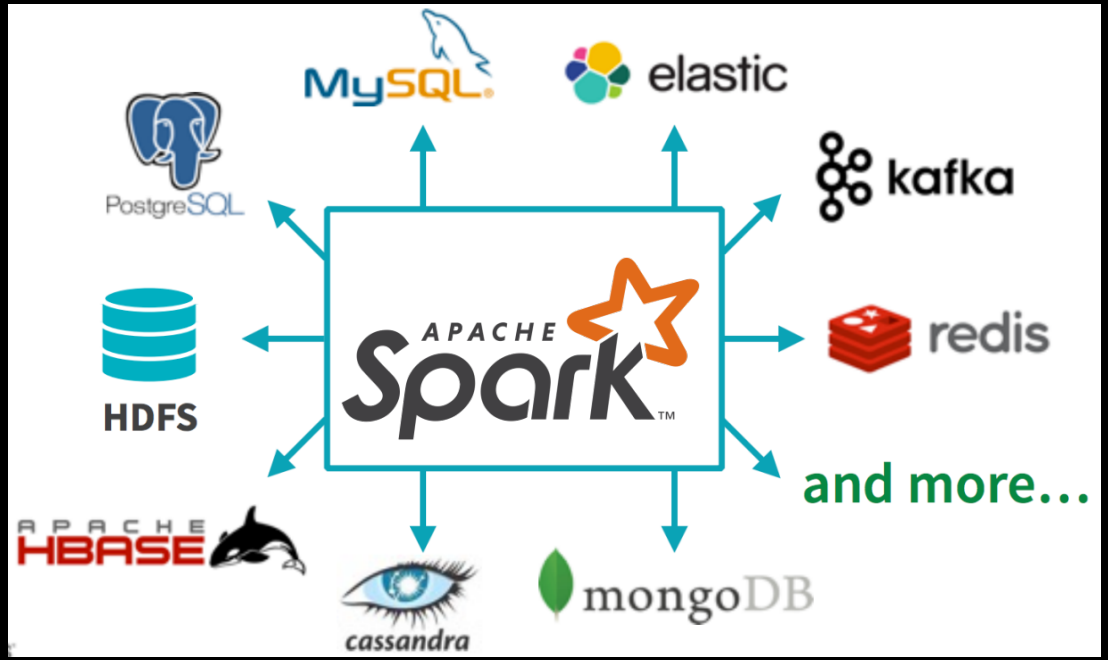
Eliminates infrastructure complexity

Spark SQL

A highly scalable and efficient relational processing engine with ease-to-use APIs and mid-query fault tolerance.

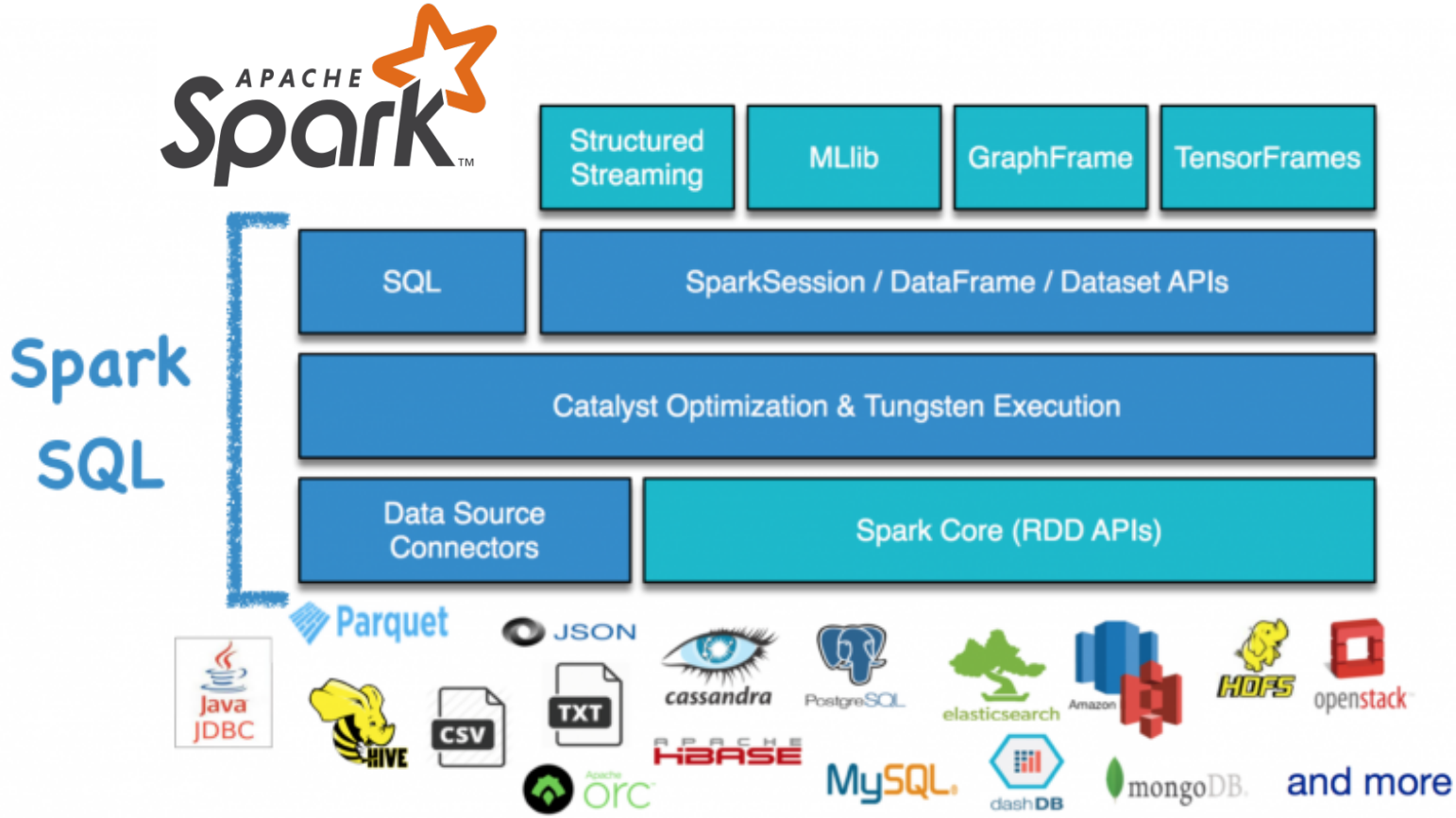
Run Everywhere

Processes, integrates and analyzes the data from diverse data sources (e.g., Cassandra, Kafka and Oracle) and file formats (e.g., Parquet, ORC, CSV, and JSON)



The not-so-secret truth...

is not only SQL.


APACHE Spark
Structured Streaming
MLlib
GraphFrame
TensorFrames
Spark SQL
SQL
SparkSession / DataFrame / Dataset APIs
Catalyst Optimization & Tungsten Execution
Data Source Connectors
Spark Core (RDD APIs)
Parquet
JSON
Java JDBC
HIVE
CSV
TXT
cassandra
PostgreSQL
elasticsearch
Amazon
HDFS
openstack
APACHE HBASE
MySQL
dashDB
mongoDB
and more
Apache orc

Not Only SQL

Powers and optimizes the other Spark applications and libraries:

- Structured streaming for stream processing
- MLlib for machine learning
- GraphFrame for graph-parallel computation
- Your own Spark applications that use SQL, DataFrame and Dataset APIs

Lazy Evaluation

Optimization happens as late as possible, therefore Spark SQL can optimize *across* functions and libraries

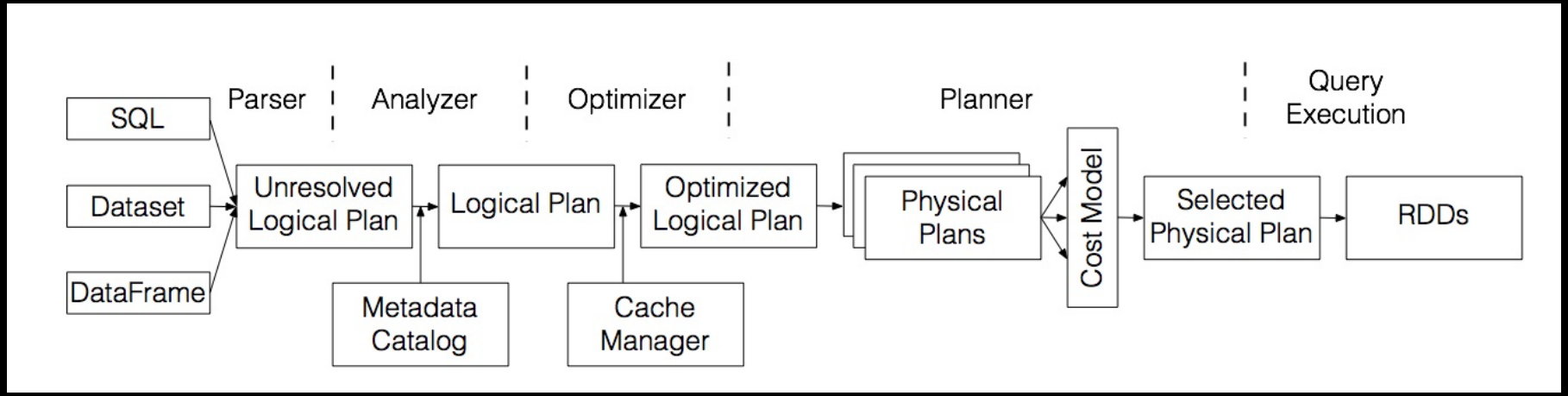
Holistic optimization when using these libraries and SQL/DataFrame/Dataset APIs in the same Spark application.

New Features of Spark SQL in Spark 2.3

- PySpark Pandas UDFs [SPARK-22216] [SPARK-21187]
- Stable Codegen [SPARK-22510] [SPARK-22692]
- Advanced pushdown for partition pruning predicates [SPARK-20331]
- Vectorized ORC reader [SPARK-20682] [SPARK-16060]
- Vectorized cache reader [SPARK-20822]
- Histogram support in cost-based optimizer [SPARK-21975]
- Better Hive compatibility [SPARK-20236] [SPARK-17729] [SPARK-4131]
- More efficient and extensible data source API V2

Spark SQL

A compiler from queries to RDDs.



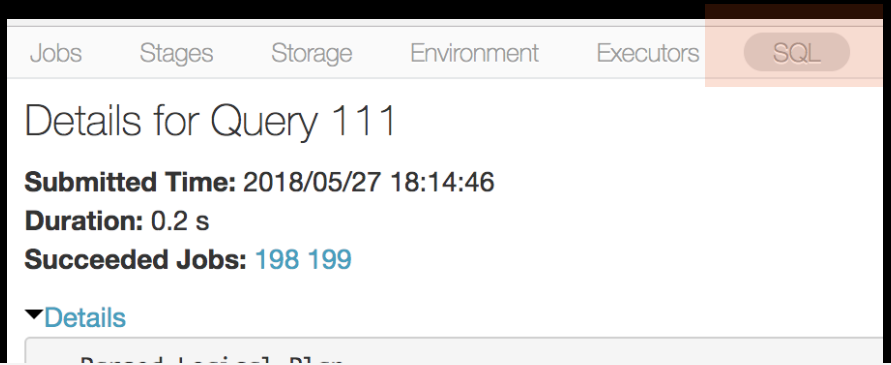
Performance Tuning for Optimal Plans

Run EXPLAIN Plan.

Interpret Plan.

Tune Plan.

Get the plans by running Explain command/APIs, or the SQL tab in either Spark UI or Spark History Server



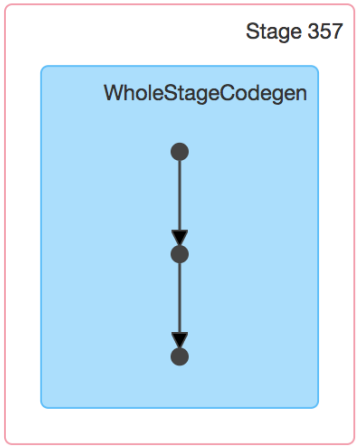

```
== Physical Plan ==
*(3) HashAggregate(keys=[], functions=[finalmerge_count(merge count#2695L) AS count(1)#2691L], output=[count#2692L])
+- Exchange SinglePartition
   +- *(2) HashAggregate(keys=[], functions=[partial_count(1) AS count#2695L], output=[count#2695L])
      +- *(2) Project
         +- *(2) BroadcastNestedLoopJoin BuildRight, LeftSemi, (a1#2679L < b1#2683L)
            :- *(2) Project [id#2677L AS a1#2679L]
            :  +- *(2) Range (0, 20000, step=1, splits=8)
            +- BroadcastExchange IdentityBroadcastMode
               +- *(1) Project [id#2681L AS b1#2683L]
                  +- *(1) Range (0, 10000, step=1, splits=8)
```

More statistics from the Job page

Details for Job 198

Status: SUCCEEDED
Job Group: 864cb5a9-115e-4d69-99a
Completed Stages: 1

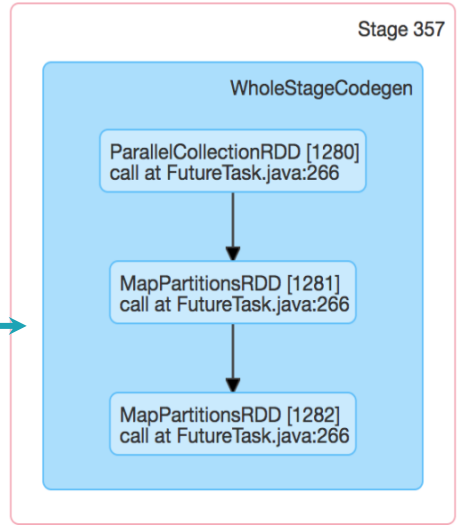
▸ Event Timeline
▾DAG Visualization



Details for Stage 357 (Attempt 0)

Total Time Across All Tasks: 5 ms
Locality Level Summary: Process local: 8

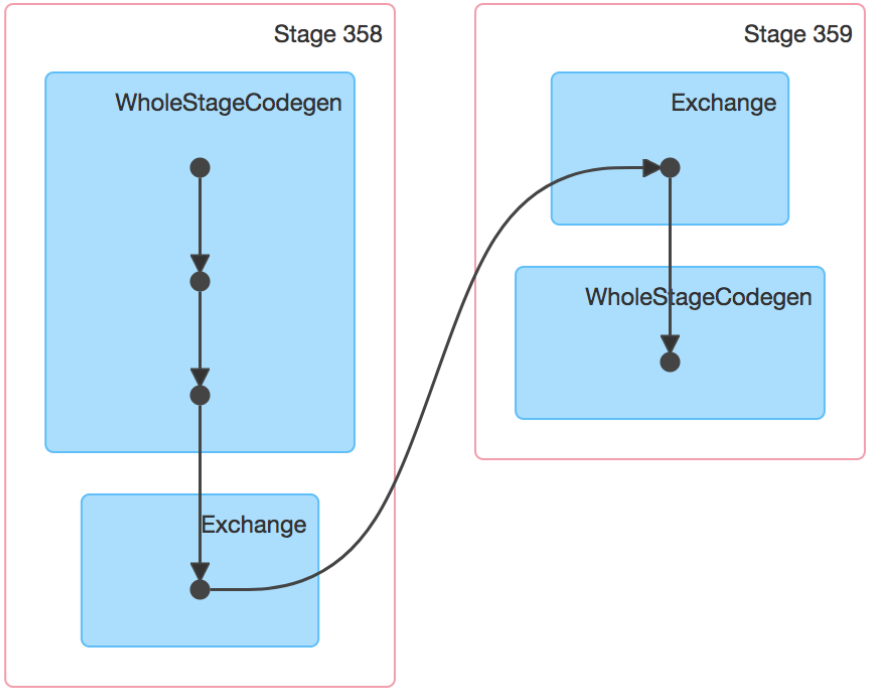
▾DAG Visualization



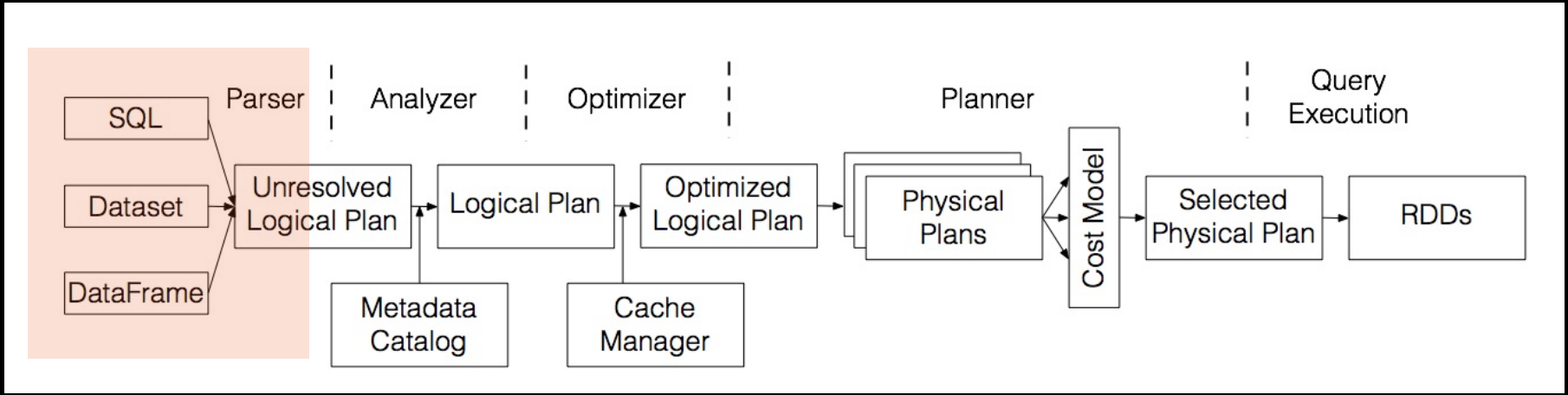
Details for Job 199

Status: SUCCEEDED
Completed Stages: 2

▸ Event Timeline
▾DAG Visualization



Declarative APIs



Declarative APIs

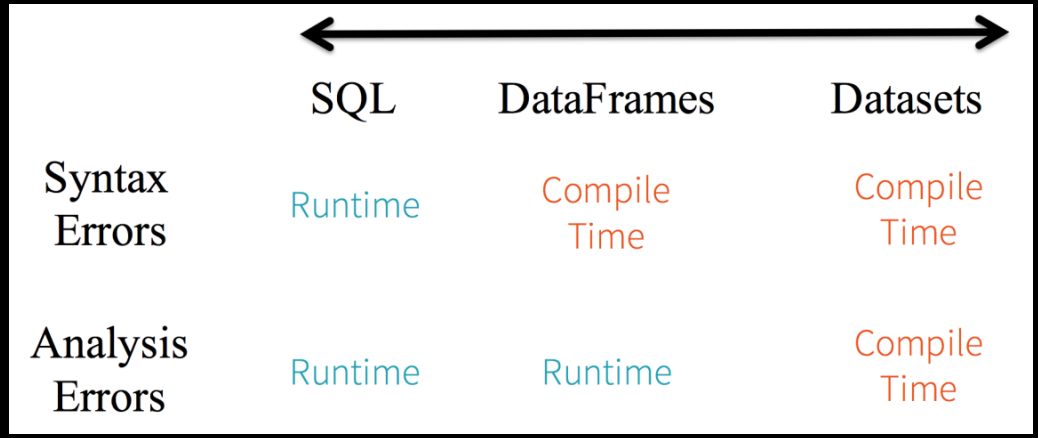
Declare your intentions by

- SQL API: ANSI SQL:2003 and HiveQL.
- Dataset/DataFrame APIs: richer, language-integrated and user-friendly interfaces

Declarative APIs

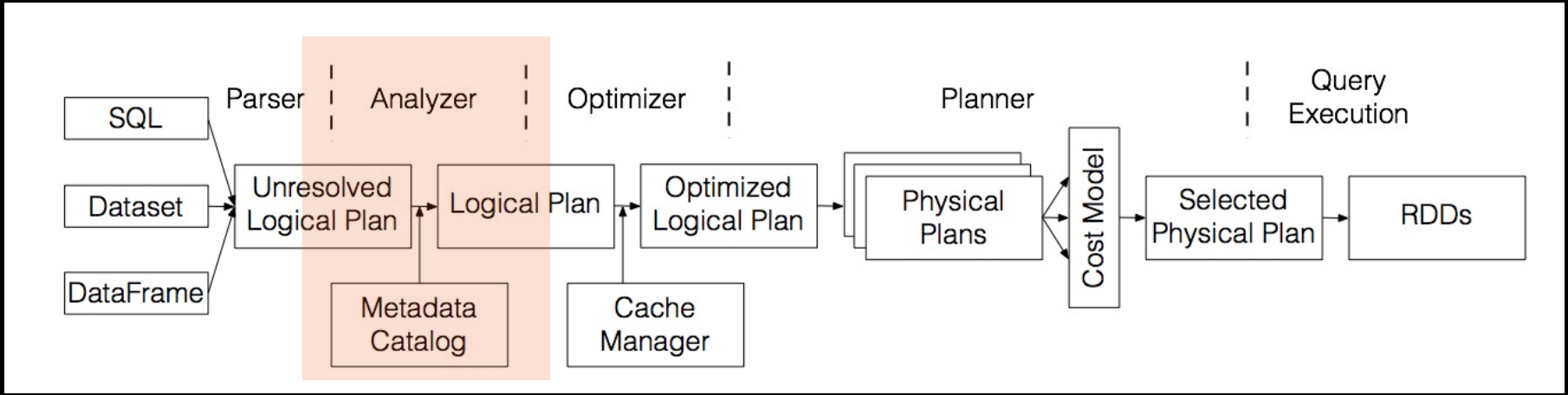
When should I use SQL, DataFrames or Datasets?

- The DataFrame API provides untyped relational operations
- The Dataset API provides a typed version, at the cost of performance due to heavy reliance on user-defined closures/lambdas. [SPARK-14083]
- http://dbricks.co/29xYnqR



	SQL	DataFrames	Datasets
Syntax Errors	Runtime	Compile Time	Compile Time
Analysis Errors	Runtime	Runtime	Compile Time

Metadata Catalog



Metadata Catalog

- Persistent Hive metastore [Hive 0.12 - Hive 2.3.3]
- Session-local temporary view manager
- Cross-session global temporary view manager
- Session-local function registry

Metadata Catalog

Session-local function registry

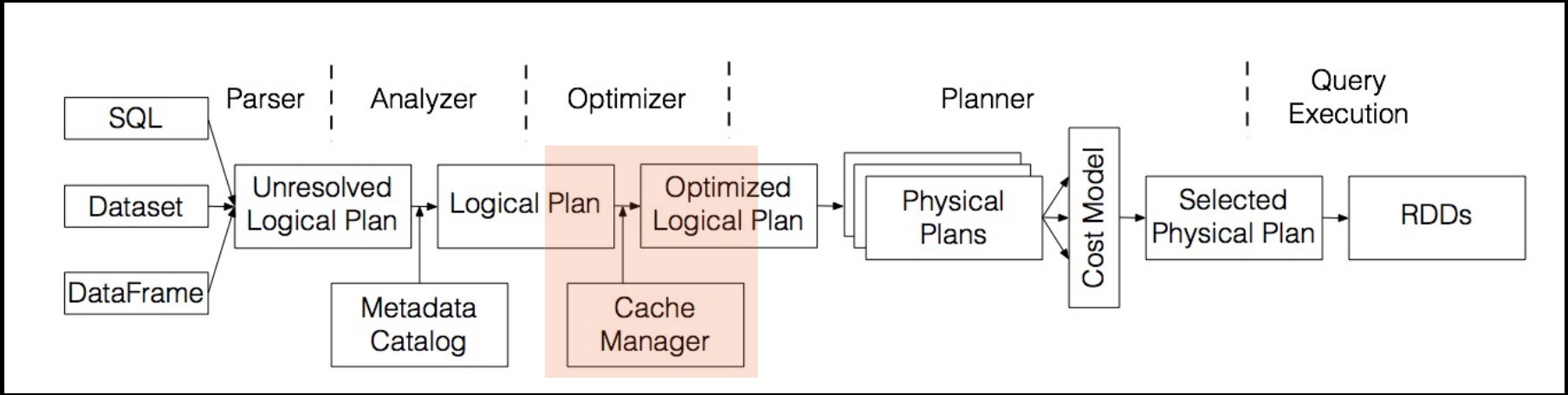
- Easy-to-use lambda UDF
- Vectorized PySpark Pandas UDF
- Native UDAF interface
- Support Hive UDF, UDAF and UDTF
- Almost 300 built-in SQL functions
- Next, SPARK-23899 adds 30+ high-order built-in functions.
- Blog for high-order functions: https://dbricks.co/2rR8vAr

Performance Tips - Catalog

Time costs of partition metadata retrieval:

- Upgrade your Hive metastore
- Avoid very high cardinality of partition columns
- Partition pruning predicates (improved in [SPARK-20331])

Cache Manager



Cache Manager

- Automatically replace by cached data when plan matching
- Cross-session
- Dropping/Inserting tables/views invalidates all the caches that depend on it
- Lazy evaluation

Performance Tips

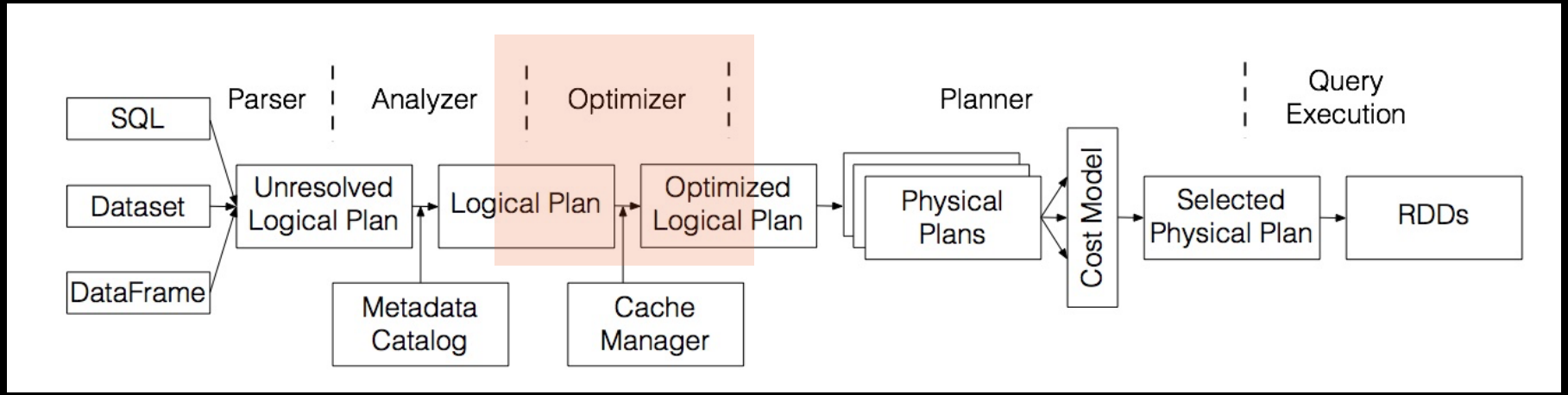
Cache: not always fast if spilled to disk.

- Uncache it, if not needed.

Next releases:

- A new cache mechanism for building the snapshot in cache. Querying stale data. Resolved by names instead of by plans. [SPARK-24461]

Optimizer


SQL
Dataset
DataFrame
Parser
Unresolved Logical Plan
Analyzer
Logical Plan
Metadata Catalog
Optimizer
Optimized Logical Plan
Cache Manager
Planner
Physical Plans
Cost Model
Query Execution
Selected Physical Plan
RDDs

Optimizer

Rewrites the query plans using heuristics and cost.

- Column pruning
- Predicate push down
- Constant folding
- Outer join elimination
- Constraint propagation
- Join reordering

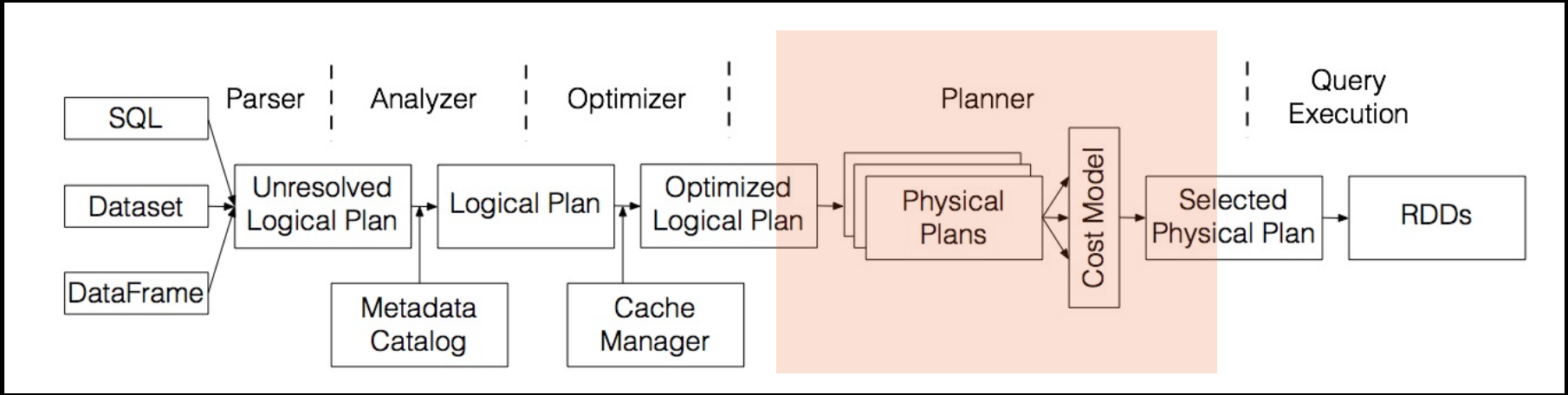
and many more.

Performance Tips

Roll your own Optimizer and Planner Rules

- In class ExperimentalMethods
  - **var** *extraOptimizations*: Seq[Rule[LogicalPlan]] = *Nil*
  - **var** *extraStrategies*: Seq[Strategy] = *Nil*
- Examples in the Herman's talk *Deep Dive into Catalyst Optimizer*
  - Join two intervals: http://dbricks.co/2etjIDY

Planner


Parser
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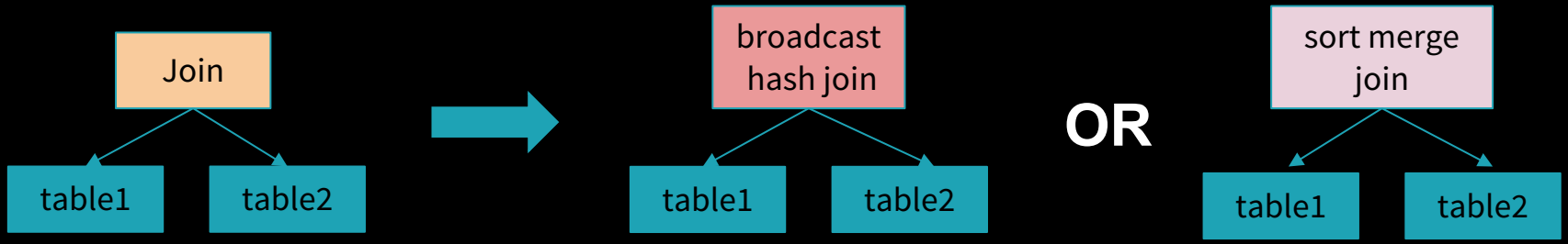
Query Execution
SQL
Dataset
DataFrame
Unresolved Logical Plan
Logical Plan
Optimized Logical Plan
Physical Plans
Cost Model
Selected Physical Plan
RDDs
Metadata Catalog
Cache Manager

Planner

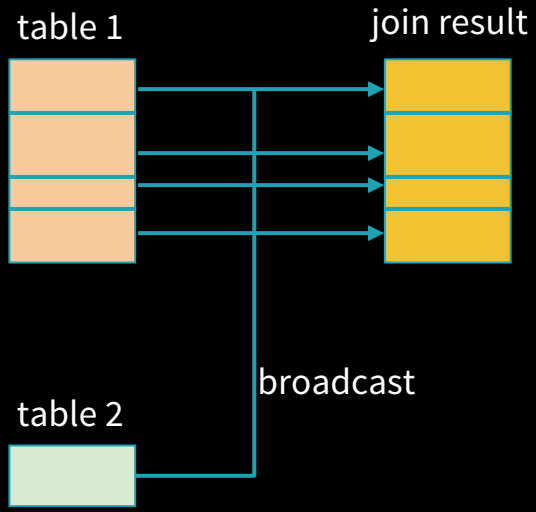
- Turn logical plans to physical plans. (what to how)
- Pick the best physical plan according to the cost



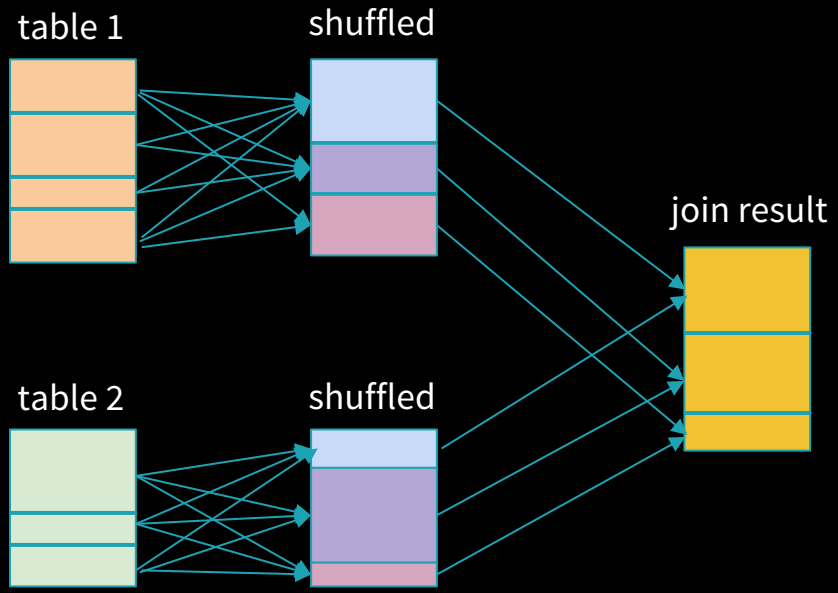
broadcast join has lower cost if one table can fit in memory

Performance Tips - Join Selection

broadcast join



shuffle join



Performance Tips - Join Selection

broadcast join vs shuffle join (broadcast is faster)

- spark.sql.autoBroadcastJoinThreshold
- Keep the statistics updated
- broadcastJoin Hint

Performance Tips - Equal Join

. . . t1 JOIN t2 ON t1.id = t2.id AND t1.value < t2.value

. . . t1 JOIN t2 ON t1.value < t2.value

Put at least one equal predicate in join condition

Performance Tips - Equal Join

... t1 JOIN t2 ON t1.id = t2.id AND t1.value < t2.value

... t1 JOIN t2 ON t1.value < t2.value

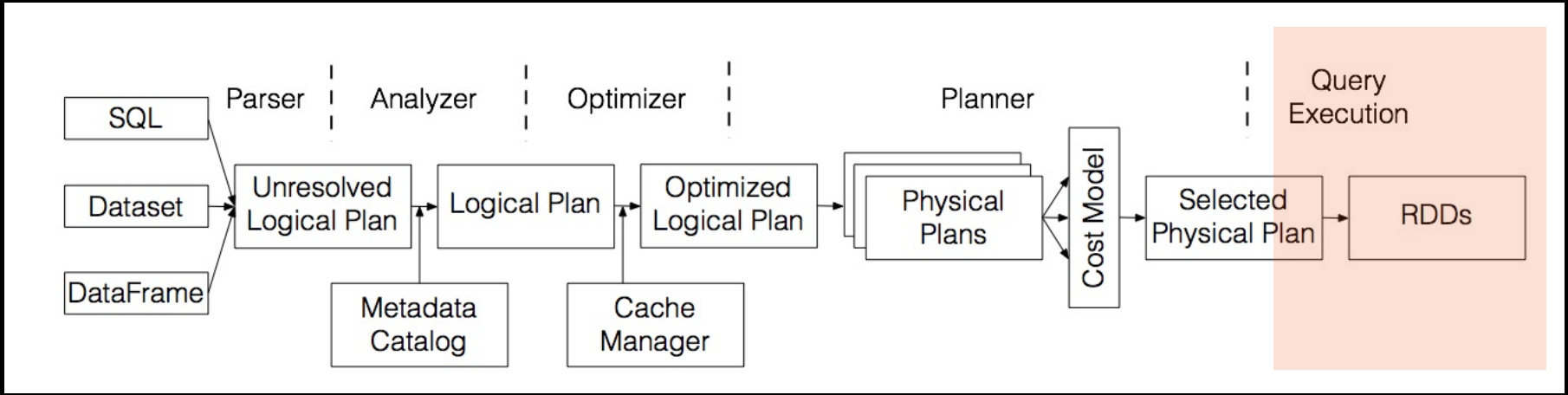
```
for l in left:
  for r in right:
    if (satisfy_join_condition(l, r)):
      yield join(l, r)
```

O(n ^ 2)

```
hash_relation = build_relation(l)
for r in right:
  if (hash_relation.contains(r.joinKey)):
    l = hash_relation.get(r.joinKey)
    if (satisfy_join_condition(l, r)):
      yield join(l, r)
```

O(n)

Query Execution



Query Execution

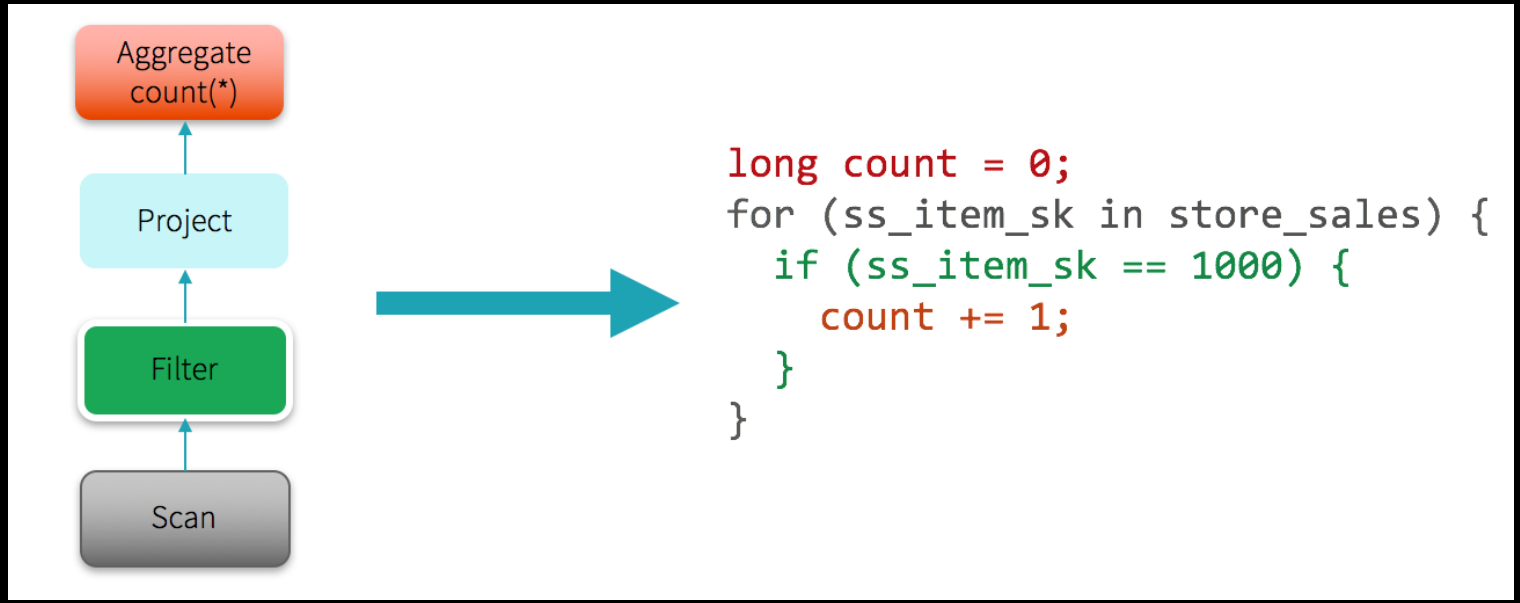
- Memory Manager: tracks the memory usage, efficiently distribute memory between tasks/operators.
- Code Generator: compiles the physical plan to optimal java code.
- Tungsten Engine: efficient binary data format and data structure for CPU and memory efficiency.

Performance Tips - Memory Manager

Tune spark.executor.memory and spark.memory.fraction to leave enough space for unsupervised memory. Some memory usages are NOT tracked by Spark(netty buffer, parquet writer buffer).

Set spark.memory.offHeap.enabled and spark.memory.offHeap.size to enable offheap, and decrease spark.executor.memory accordingly.

Whole Stage Code Generation



Performance Tip - WholeStage codegen

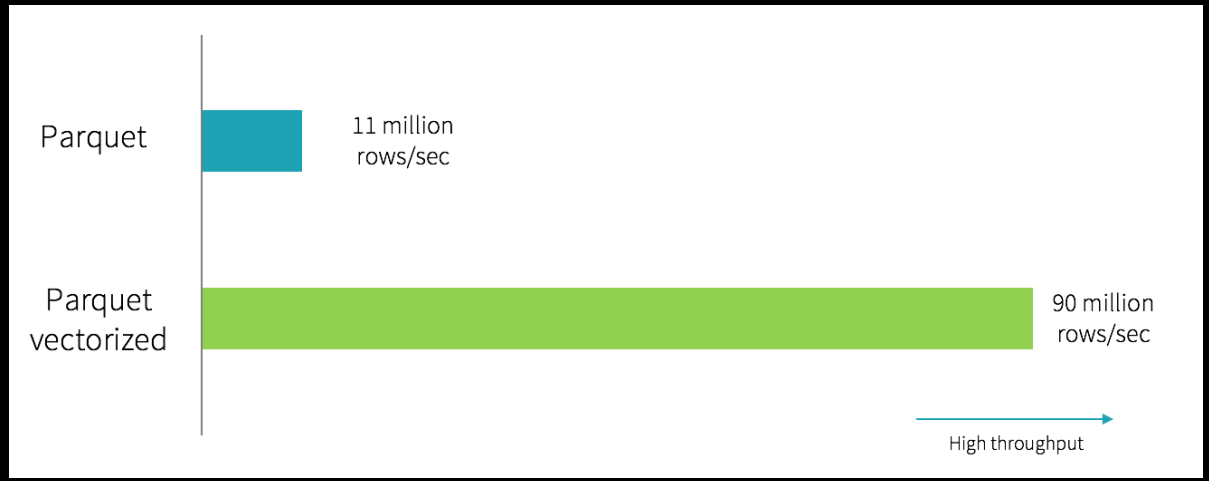
Tune spark.sql.codegen.hugeMethodLimit to avoid big method(> 8k) that can’t be compiled by JIT compiler.

Data Sources

- Spark separates computation and storage.
- Complete data pipeline:
  - External storage feeds data to Spark.
  - Spark processes the data
- Data source can be a bottleneck if Spark processes data very fast.

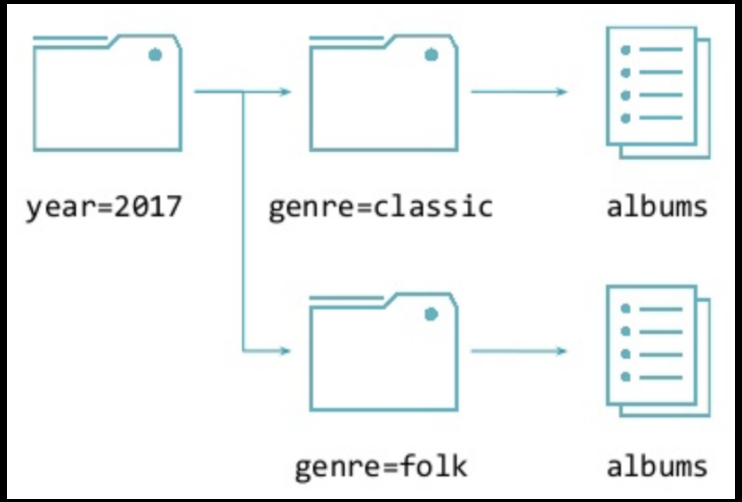
Scan Vectorization

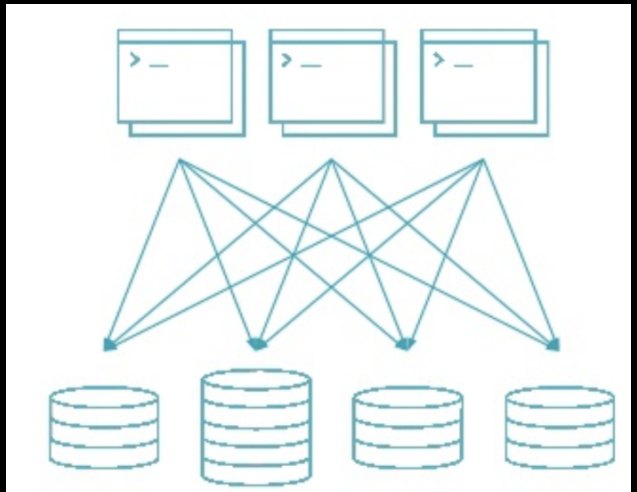
- More efficient to read columnar data with vectorization.
- More likely for JVM to generate SIMD instructions.
- ……



Partitioning and Bucketing

- A special file system layout for data skipping and pre-shuffle.
- Can speed up query a lot by avoid unnecessary IO and shuffle.
- The summit talk: http://dbricks.co/2oG6ZBL

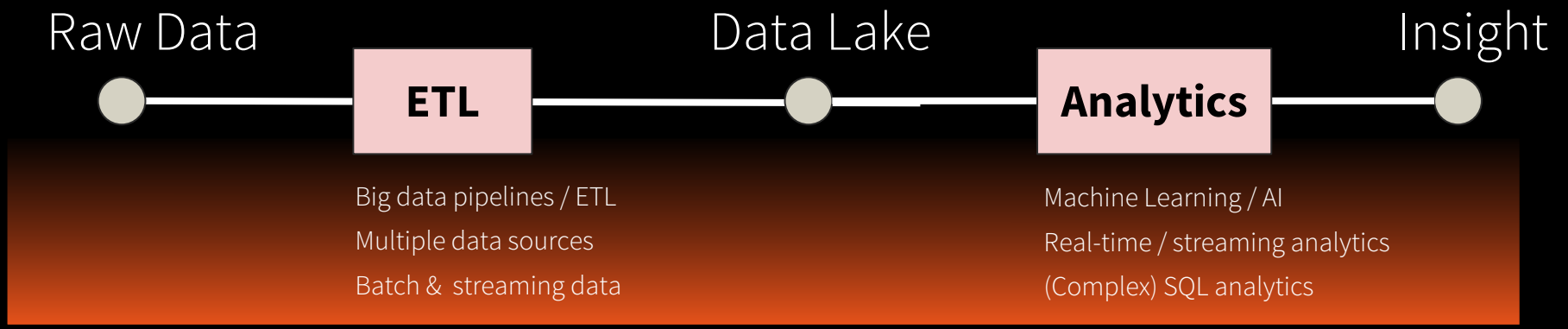




Performance Tips

- Pick data sources that supports vectorized reading. (parquet, orc)
- For file-based data sources, creating partitioning/bucketing if possible.

Yet challenges still remain



Reliability and Complexity

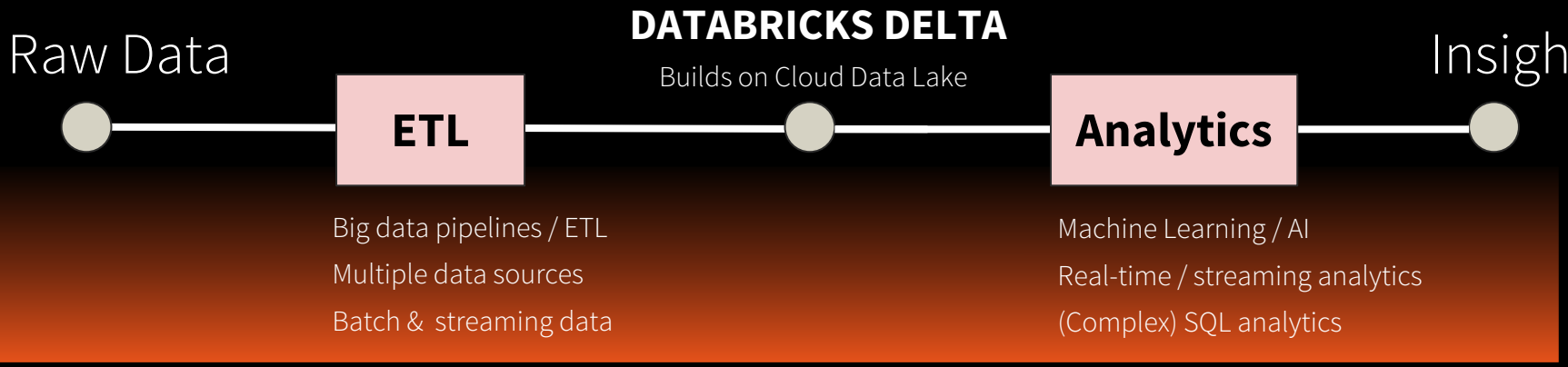
- Data corruption issues and broken pipelines
- Complex workarounds - tedious scheduling and multiple jobs/staging tables
- Many use cases require updates to existing data - not supported by Spark / Data lakes

Reliability & Performance Problems

- Performance degradation at scale for advanced analytics
- Stale and unreliable data slows analytic decisions

Streaming magnifies these challenges

Databricks Delta address these challenges



Reliability & Automation

Transactions guarantees eliminates complexity

Schema enforcement to ensure clean data

Upserts/Updates/Deletes to manage data changes

Seamlessly support streaming and batch

Performance & Reliability

Automatic indexing & caching

Fresh data for advanced analytics

Automated performance tuning

Thank you

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