Lessons From the Field:

Applying Best Practices to Your Apache Spark™ Applications

Silvio Fiorito

Spark Summit Europe, 2017

#EUdev5

databricks

About Databricks

TEAM

Started Spark project (now Apache Spark) at UC Berkeley in 2009

MISSION

Making Big Data Simple

PRODUCT

Unified Analytics Platform

About Me

- Silvio Fiorito
  - silvio@databricks.com
  - @granturing
- Resident Solutions Architect @ Databricks
- Spark developer, trainer, consultant - using Spark since ~v0.6
- Prior to that - application security, cyber analytics, forensics, etc.

Outline

- Speeding Up File Loading & Partition Discovery
- Optimizing File Storage & Layout
- Identifying Bottlenecks In Your Queries

“Why is it taking so long to ‘load’ my DataFrame”

“Loading” DataFrames

Cmd 1

```scala
val df1 = spark.read.load("/tmp/tpcds/store_sales")
  .filter('ss_sold_date_sk isin (2450816,2450835,2450845,2450860))
```

(2) Spark Jobs

Job 0 View (Stages: 1/1)

Stage 0: 1823/1823

Job 1 View (Stages: 1/1)

```
df1: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [ss_sold_time_sk: int, ss_item_sk: int ... 21 more fields]
```

Command took 42.66 seconds -- by silvio@databricks.com at 9/5/2017, 2:00:55 PM on silviotest

“Loading” DataFrames

Spark is lazily executed, right?

Cmd 1

```scala
val df1 = spark.read.load("/tmp/tpcds/store_sales")
  .filter('ss_sold_date_sk isin (2450816,2450835,2450845,2450860))
```

▾ (2) Spark Jobs

▾ Job 0 View (Stages: 1/1)

Stage 0: 1823/1823

▸ Job 1 View (Stages: 1/1)

```
df1: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [ss_sold_time_s
k: int, ss_item_sk: int ... 21 more fields]
```

Command took 42.66 seconds -- by silvio@databricks.com at 9/5/2017, 2:00:55 PM on silviotest

“Loading” DataFrames

Spark is lazily executed, right?

Cmd 1

```
val df1 = spark.read.load("/tmp/tpcds/store_sales")
  .filter('ss_sold_date_sk isin (2450816,2450835,2450845,2450860))
```

▾ (2) Spark Jobs

▾ Job 0 View (Stages: 1/1)

Stage 0: 1823/1823

▸ Job 1 View (Stages: 1/1)

```
df1: org.apache.spark.sql.Dataset[org.apache.spar
k: int, ss_item_sk: int ... 21 more fields]
```

Command took 42.66 seconds -- by silvio@databricks.com at 9/5/2017, 2:00:55 PM on silviotest

Jobs running even though there’s no action, why?

Datasource API

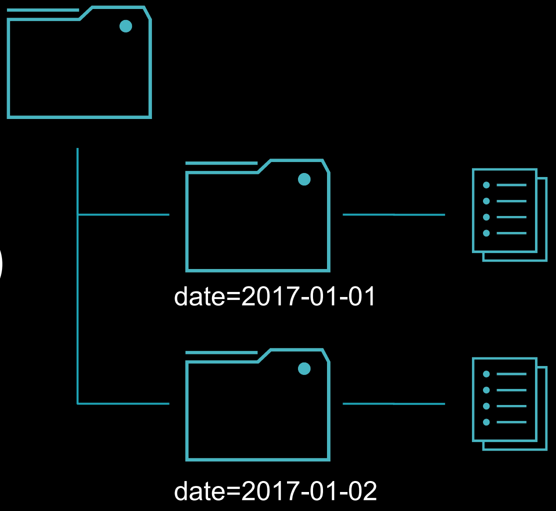
Datasource

- Maps “spark.read.load” command to underlying data source (Parquet, CSV, ORC, JSON, etc.)
- For file sources - Infers schema from files
  - Kicks off Spark job to parallelize
  - Needs file listing first
- Need basic statistics for query planning (file size, partitions, etc.)

Listing Files

InMemoryFileIndex

- Discovers partitions & lists files, using Spark job if needed (spark.sql.sources.parallelPartitionDiscovery.threshold 32 default)
- FileStatusCache to cache file status (250MB default)
- Maps Hive-style partition paths into columns
- Handles partition pruning based on query filters



Partition Discovery

Cmd 1

```
val df1 = spark.read.load("/tmp/tpcds/store_sales")
  .filter('ss_sold_date_sk isin (2450816,2450835,2450845,2450860))
```

(2) Spark Jobs

Job 0 View (Stages: 1/1)

Stage 0: 1823/1823

Job 1 View (Stages: 1/1)

```
df1: org.apache.spark.sql.Dataset[org.apache.spar
k: int, ss_item_sk: int ... 21 more fields]
```

Command took 42.66 seconds -- by silvio@databricks.com at 9/5/2017, 2:00:55 PM on silviotest

1,823 partition paths to index

Partition Pruning

Cmd 2

```
1  df1.explain
```

```
== Physical Plan ==
*FileScan parquet [ss_sold_time_sk#7,ss_item_sk#8,ss_customer_sk#9,     sk
#10,ss_hdemo_sk#11,ss_addr_sk#12,ss_store_sk#13,ss_promo_sk#14,ss_     numbe
r#15L,ss_quantity#16,ss_wholesale_cost#17,ss_list_price#18,ss_sal     ice#19,s
s_ext_discount_amt#20,ss_ext_sales_price#21,ss_ext_wholesale_co     2,ss_ext_li
st_price#23,ss_ext_tax#24,ss_coupon_amt#25,ss_net_paid#26,ss_n     _paid_inc_tax#
27,ss_net_profit#28,ss_sold_date_sk#29] Batched: true, Format: Parquet, Locati
on: InMemoryFileIndex[dbfs:/tmp/tpcds/store_sales], PartitionCount: 4, Partiti
onFilters: [ss_sold_date_sk#29 IN (2450816,2450835,2450845,2450860)], PushedFi
lters: [], ReadSchema: struct<ss_sold_time_sk:int,ss_item_sk:int,ss_customer_s
k:int,ss_cdemo_sk:int,ss_hdemo_sk:int,ss_a...
```

Command took 0.45 seconds -- by silvio@databricks.com at 9/5/2017, 2:14:50 PM on silviotest

We only care about 4 out of 1,823 partitions!!

Dealing With Many Partitions

Option 1:

- If you know exactly what partitions you want
- If you need to use files vs Datasource Tables
- Specify "basePath" option and load specific partition paths
- InMemoryFileIndex "pre-filters" on those paths

Dealing With Many Partitions

Cmd 4

```scala
val df2 = spark.read.option("basePath", "/tmp/tpcds/store_sales")
  .load(
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450816",
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450835",
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450845",
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450860"
  )
```

(1) Spark Jobs

```
df2: org.apache.spark.sql.DataFrame = [ss_sold_time_sk: int, ss_item_sk: int
 ... 21 more fields]
```

Command took 2.10 seconds -- by silvio@databricks.com at 9/5/2017, 2:14:10 PM on silviotest

Dealing With Many Partitions

Cmd 4

```
val df2 = spark.read.option("basePath", "/tmp/tpcds/store_sales")
  .load(
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450816",
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450835",
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450845",
    "/tmp/tpcds/store_sales/ss_sold_date_sk=2450860"
  )
```

~2 seconds vs ~43 seconds

```
spark.sql.DataFrame = [ss_sold_time_sk: int, ss_item_sk: int
... re fields]
```

Command took 2.10 seconds -- by silvio@databricks.com at 9/5/2017, 2:14:10 PM on silviotest

Dealing With Many Partitions

Option 2:

- Use Datasource Tables with Spark 2.1+
- Partitions managed in Hive metastore
- Partition Pruning at logical planning stage
- Scalable Partition Handling for Cloud-Native Architecture in Apach 2.1

Dealing With Many Partitions

Cmd 7

```
val df3 = spark.read.table("tpcds.store_sales")
  .filter('ss_sold_date_sk isin (2450816,2450835,2450845,2450860))
```

```
df3: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [ss_sold_time_s
k: int, ss_item_sk: int ... 21 more fields]
```

Command took 0.29 seconds -- by silvio@databricks.com at 9/5/2017, 2:28:55 PM on silviotest

~0.29 seconds vs ~43 seconds

Using Datasource Tables

Using SQL - External (or Unmanaged) Tables

- Create over existing data
- Partition discovery runs once
- Use “saveAsTable” or “insertInto” to add new partitions

Cmd 3

```
CREATE TABLE IF NOT EXISTS tpcds_temp.store_sales
USING parquet
OPTIONS (path '/tmp/tpcds/store_sales');

MSCK REPAIR TABLE tpcds_temp.store_sales;
```

databricks

Using Datasource Tables

Using SQL - Managed Tables

- SparkSQL manages metadata <u>and underlying files</u>
- Use “saveAsTable” or “insertInto” to add new partitions

Cmd 2

```sql
CREATE TABLE IF NOT EXISTS tpcds_temp.store_sales (
  ss_sold_time_sk int,
  ss_item_sk int,
  ss_customer_sk int,
  ss_sold_date_sk int
)
USING parquet
PARTITIONED BY (ss_sold_date_sk);
```

Using Datasource Tables

Using DataFrame API

- Use “saveAsTable” or “insertInto” to add new partitions

Cmd 10

```
df1.write
  .partitionBy("ss_sold_date_sk")
  .saveAsTable("tpcds_temp.store_sales")
```

Managed Table

Using Datasource Tables

Using DataFrame API

- Use “saveAsTable” or “insertInto” to add new partitions

Cmd 10

```
df1.write
  .partitionBy("ss_sold_date_sk")
  .saveAsTable("tpcds_temp.store_sales")
```

Managed Table

Cmd 10

```
df1.write
  .partitionBy("cs_sold_date_sk")
  .option("path", "/tmp/tpcds_temp/stores_sales")
  .saveAsTable("tpcds_temp.store_sales")
```

Unmanaged Table

Datasource Tables vs Files

TABLES

- Managed, more scalable partition handling
- Schema in metastore
- Faster job startup
- Additional statistics available to Catalyst (e.g. CBO)
- Use SQL or DataFrame API

FILES

- Partition discovery at each DataFrame creation
- Infer schema from files
- Slower job startup time
- Only file-size statistics available
- Only DataFrame API (SQL with temp views)

Reading CSV & JSON Files

Schema Inference

- Runs on whole dataset
- Convenient, but SLOW… delays job startup
- Even worse with poor file layout
  - Large GZIP files
  - Lots of small files

Reading CSV & JSON Files

Avoiding Schema Inference

- Easiest - use Tables!
- Otherwise...If consistent data, infer on subset of files
- Save schema for reuse (e.g. scheduled batch jobs)
- JSON - adjust samplingRatio (default 1.0)

Better Schema Inference

Cmd 2

```
val df = spark.read.format("csv")
  .option("header", true)
  .option("inferSchema", true)
  .load("/tmp/tpcds_csv/store_sales")
```

▸ (3) Spark Jobs

```
df: org.apache.spark.sql.DataFrame = [ss_sold_time_sk: int, ss_item_sk: int ... 21 m
ore fields]
```

Command took 48.10 seconds -- by silvio@databricks.com at 9/15/2017, 3:31:39 PM on silviotest

Better Schema Inference

Cmd 4

```scala
val schemaDF = spark.read.format("csv")
  .option("header", true)
  .option("inferSchema", true)
  .load(sampleFile)

val df = spark.read.format("csv")
  .option("header", true)
  .schema(schemaDF.schema)
  .load("/tmp/tpcds_csv/store_sales")
```

(2) Spark Jobs

```
schemaDF: org.apache.spark.sql.DataFrame = [ss_sold_time_sk: int, ss_item_sk: int
 ... 21 more fields]
df: org.apache.spark.sql.DataFrame = [ss_sold_time_sk: int, ss_item_sk: int ... 21 m
ore fields]
```

Command took 6.60 seconds -- by silvio@databricks.com at 9/15/2017, 3:42:11 PM on silviotest

Better Schema Inference

Cmd 6

```
import org.apache.spark.sql.types._

lazy val useSchema = DataType.fromJson(schemaJSON)
  .asInstanceOf[StructType]

val df = spark.read.format("csv")
  .option("header", true)
  .schema(useSchema)
  .load("/tmp/tpcds_csv/store_sales")
```

```
import org.apache.spark.sql.types._
useSchema: org.apache.spark.sql.types.StructType = <lazy>
df: org.apache.spark.sql.DataFrame = [ss_sold_time_sk: int, ss_item_sk: int ... 21 m
ore fields]
```

Command took 0.59 seconds -- by silvio@databricks.com at 9/15/2017, 3:48:39 PM on silviotest

“What format, compression, and partitioning scheme should I use?”

Managing & Optimizing File Output

File Types

- Prefer columnar over text for analytical queries
- Parquet
  - Column pruning
  - Predicate pushdown
- CSV/JSON
  - Must parse whole row
  - No column pruning
  - No predicate pushdown

Managing & Optimizing File Output

Compression

- Prefer splittable
  - LZ4, BZip2, LZO, etc.
- Parquet + Snappy or GZIP (splittable due to row groups)
  - Snappy is default in Spark 2.2+
- **AVOID** - Large GZIP text files
  - Not splittable
  - GC issues with wide tables
- More - Why You Should Care about Data Layout in the Filesystem

Managing & Optimizing File Output

PARTITIONING

- Coarse-grained filtering of input files
- Avoid over-partitioning (small files), overly nested partitions

```
output.write
  .partitionBy("ss_sold_date_sk")
  .option("path", "/tmp/tpcds_temp/store_sales_temp")
  .saveAsTable("tpcds_temp.store_sales_temp")
```

BUCKETING

- Write data already hash-partitioned
- Good for joins or aggregations (avoids shuffle)
- Must be Datasource table

```
output.write
  .bucketBy(100, "ss_item_sk")
  .sortBy("ss_item_sk")
  .option("path", "/tmp/tpcds_temp/store_sales_temp")
  .saveAsTable("tpcds_temp.store_sales_temp")
```

Partitioning & Bucketing

Writing Partitioned & Bucketed Data

- Each task writes a file per-partition and bucket
- If data is randomly distributed across tasks...lots of small files!
- Coalesce?
  - Doesn’t guarantee colocation of partition/bucket values
  - Reduces parallelization of final stage
- Repartition - incurs a shuffle but results in cleaner files
- Compaction - run job periodically to generate clean files

Managing File Sizes

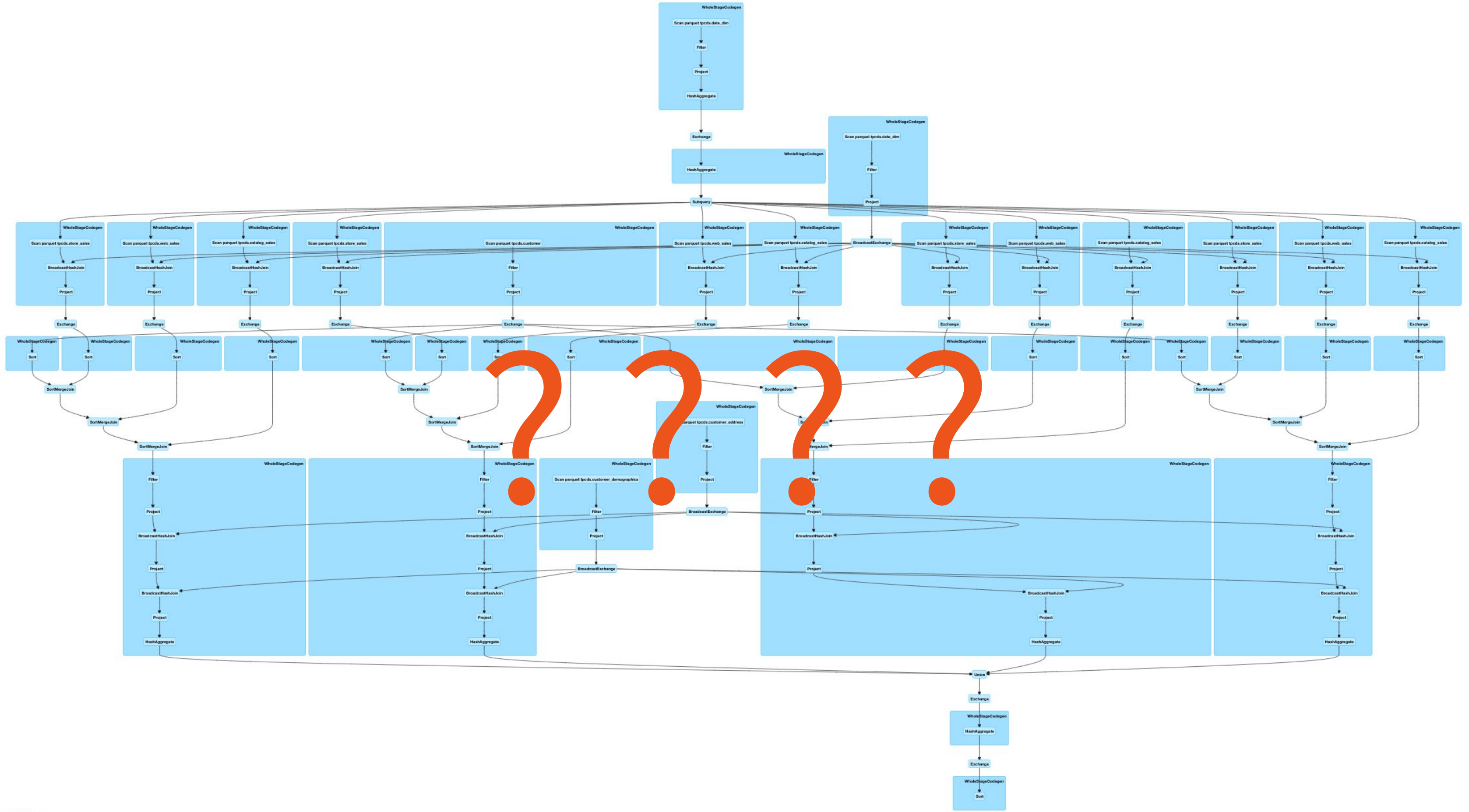
```
output.repartition('ss_sold_date_sk).write
   .partitionBy("ss_sold_date_sk")
   .option("path", "/tmp/tpcds_temp/store_sales_temp")
   .saveAsTable("tpcds_temp.store_sales_temp")
```

Managing File Sizes

What If Partitions Are Too Big

- Spark 2.2 - spark.sql.files.maxRecordsPerFile (default disabled)
- Write task is responsible for splitting records across files
  - WARNING: not parallelized
- If need parallelization - repartition with additional key
  - Use hash+mod to manage # of files

"How can I optimize my query?"

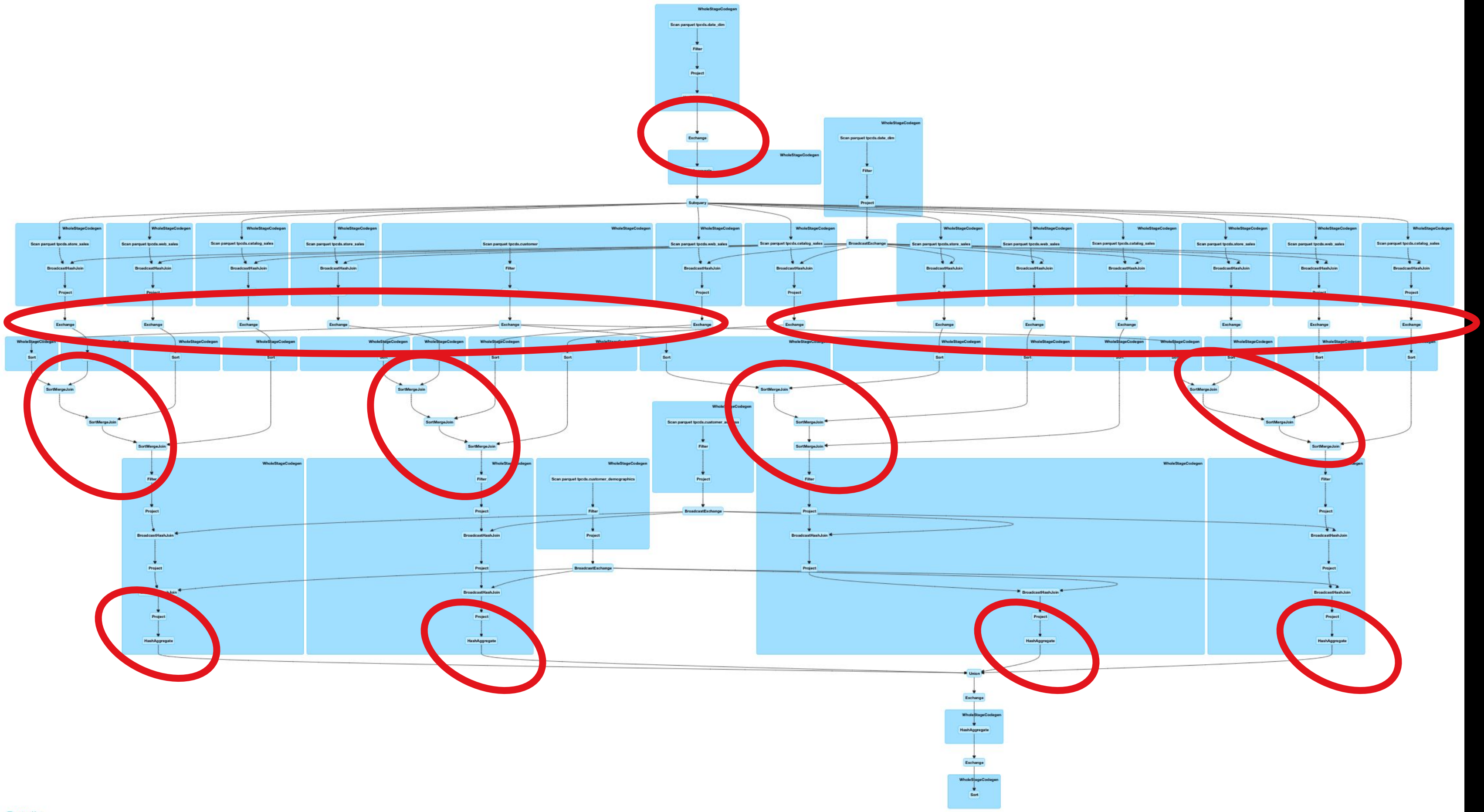

WholeStageCodegen
Scan parquet tpcds.date_dim
Filter
Project
HashAggregate
Exchange
Subquery
BroadcastExchange
Scan parquet tpcds.store_sales
Scan parquet tpcds.web_sales
Scan parquet tpcds.catalog_sales
Scan parquet tpcds.customer
BroadcastHashJoin
Sort
SortMergeJoin
Scan parquet tpcds.customer_address
Scan parquet tpcds.customer_demographics
Union
? ? ? ?

Details

Managing Shuffle Partitions

Spark SQL Shuffle Partitions

- Default to 200, used in shuffle operations
  - groupBy, repartition, join, window
- Depending on your data volume might be too small/large
- Override with conf - spark.sql.shuffle.partitions
  - 1 value for <u>whole query</u>



‣ Details

Managing Shuffle Partitions

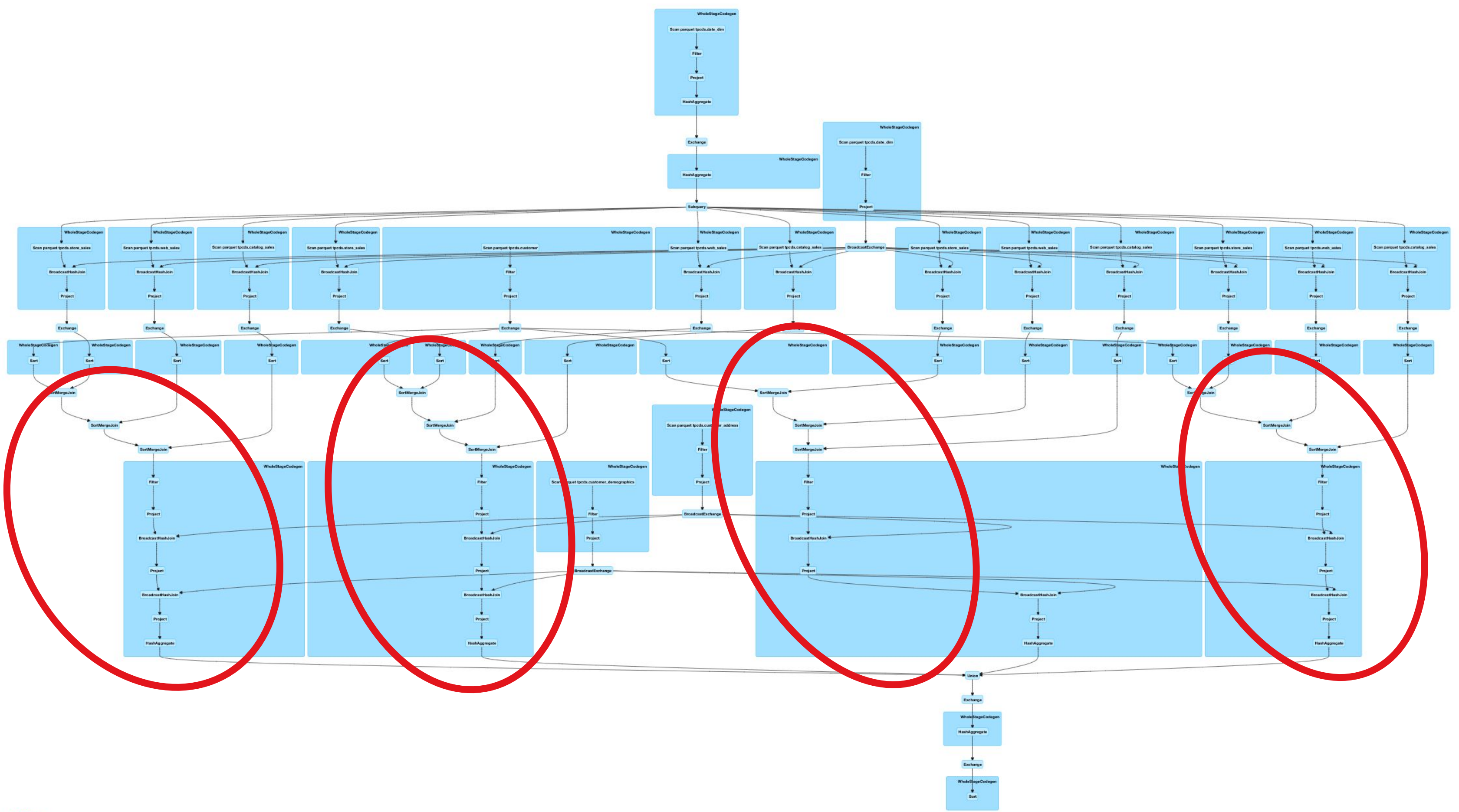
Adaptive Execution

- Introduced in Spark 2.0
- Sets shuffle partitions based on size of shuffle output
- spark.sql.adaptive.enabled (default false)
- spark.sql.adaptive.shuffle.targetPostShuffleInputSize (default 64MB)
- Still in development* - SPARK-9850

Unions

Understanding unions

- Each DataFrame in union runs independently until shuffle
- Self-union - DataFrame read N times (number of unions)
- Alternatives (depends on use case)
  - explode or flatMap
  - persist root DataFrame (read once from storage)



Details

databricks

Optimizing Query Execution

Cost Based Optimizer

- Added in Spark 2.2
- Collects and uses per-column stats for query planning
- Requires Datasource Tables
- [Cost Based Optimizer in Apache Spark 2.2]

Computing Statistics for CBO

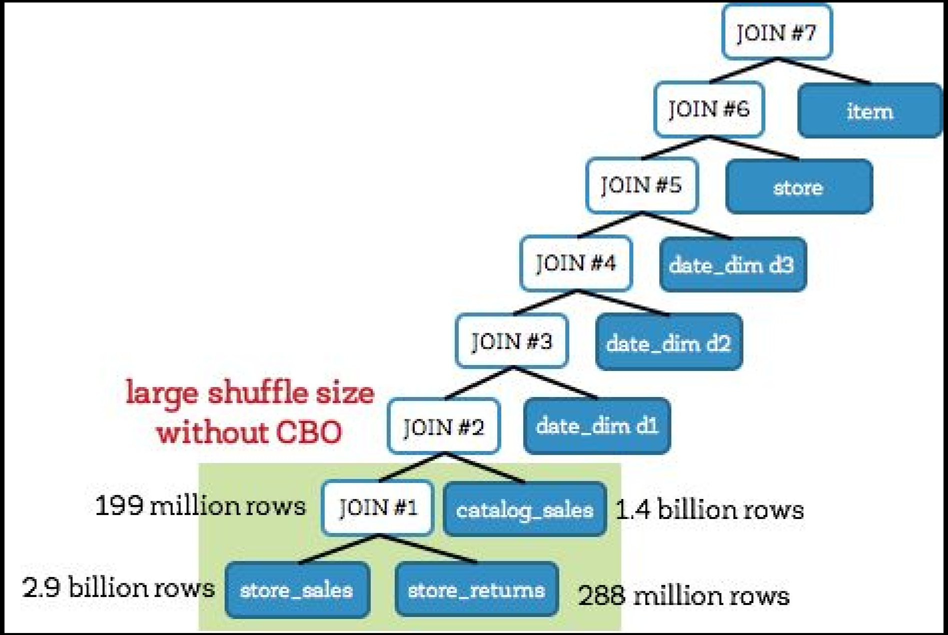
Cmd 9

```sql
--compute table-level statistics (# of rows, size)
ANALYZE TABLE tpcds.store_sales COMPUTE STATISTICS
```

Cmd 10

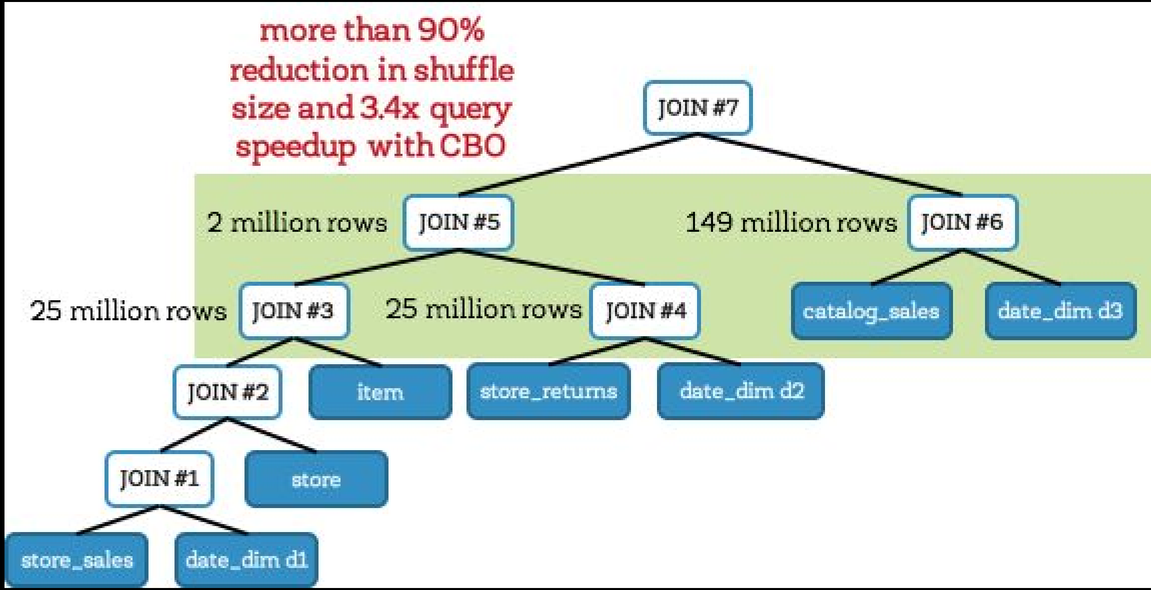
```sql
--compute column-level statistics
ANALYZE TABLE tpcds.store_sales COMPUTE STATISTICS
FOR COLUMNS ss_sales_price, ss_item_sk, ss_quantity
```

TPC-DS Query 25 Without CBO



https://databricks.com/blog/2017/08/31/cost-based-optimizer-in-apache-spark-2-2.html

TPC-DS Query 25 With CBO



https://databricks.com/blog/2017/08/31/cost-based-optimizer-in-apache-spark-2-2.html

Data Skipping Index

- Added in Databricks Runtime 3.0
- Use file-level stats to skip files based on filters
- Requires Datasource Tables
- Opt-in, no code changes
- [Data Skipping Index Docs]

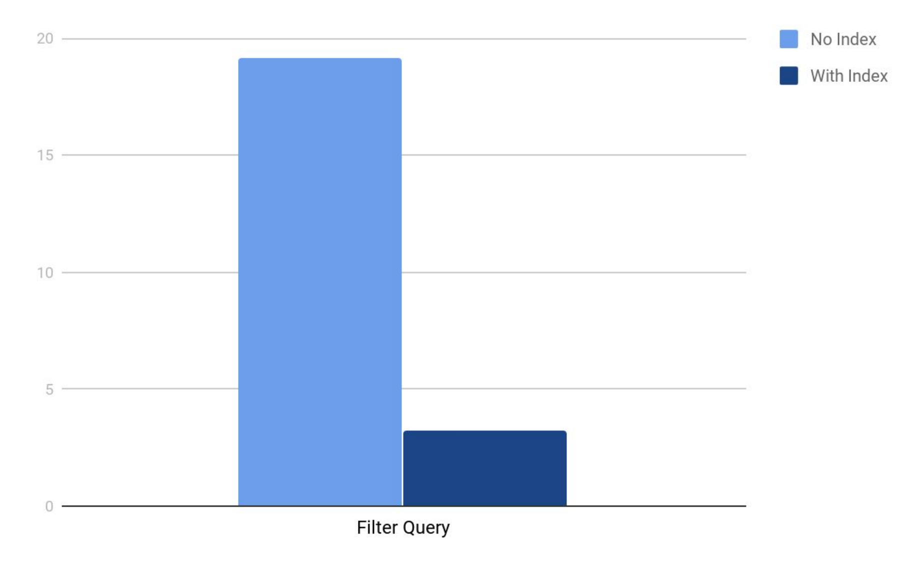
Cmd 11

```
CREATE DATASKIPPING INDEX ON TABLE tpcds.store_sales
```

Data Skipping Index

Cmd 16

```
df1.filter('ss_customer_sk between (1, 10)).foreach { _ => }
```



Try Apache Spark in Databricks!

UNIFIED ANALYTICS PLATFORM

- Collaborative cloud environment
- Free version (community edition)

DATABRICKS RUNTIME 3.3

- Apache Spark - optimized for the cloud
- Caching and optimization layer - DBIO
- Enterprise security - DBES

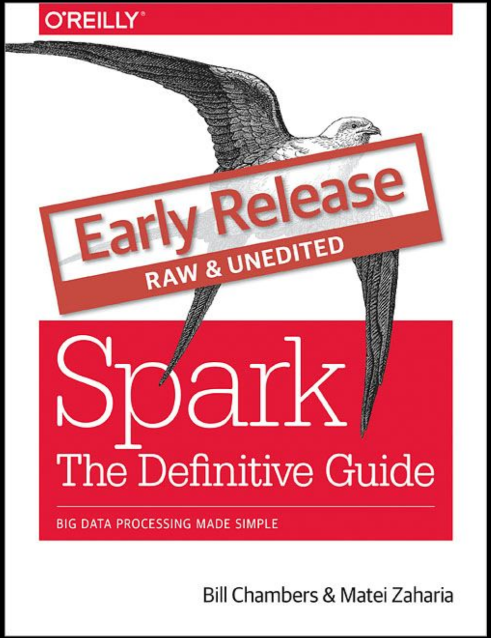
Try for free today.

databricks.com

Spark the Definitive Guide

Early Release

- http://go.databricks.com/definitive-guide-apache-spark
- Blog Post on Preview of Apache Spark: The Definitive Guide



Thank you

Q&A

silvio@databricks.com
@granturing

databricks