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

“Loading” DataFrames

Spark is lazily executed, right?

“Loading” DataFrames

Spark is lazily executed, right?

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

Datasource API

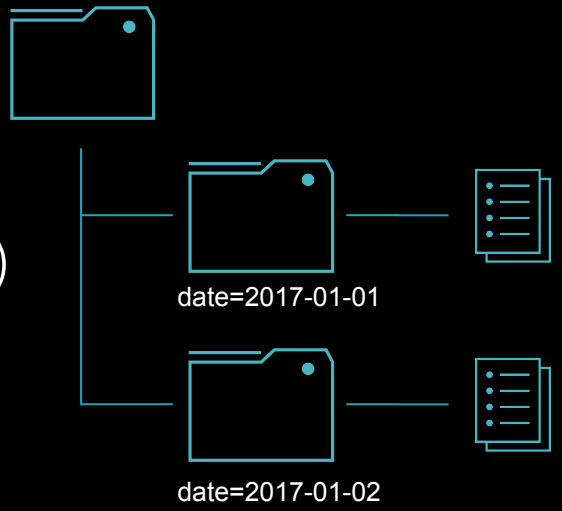
Datasource

- 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.)

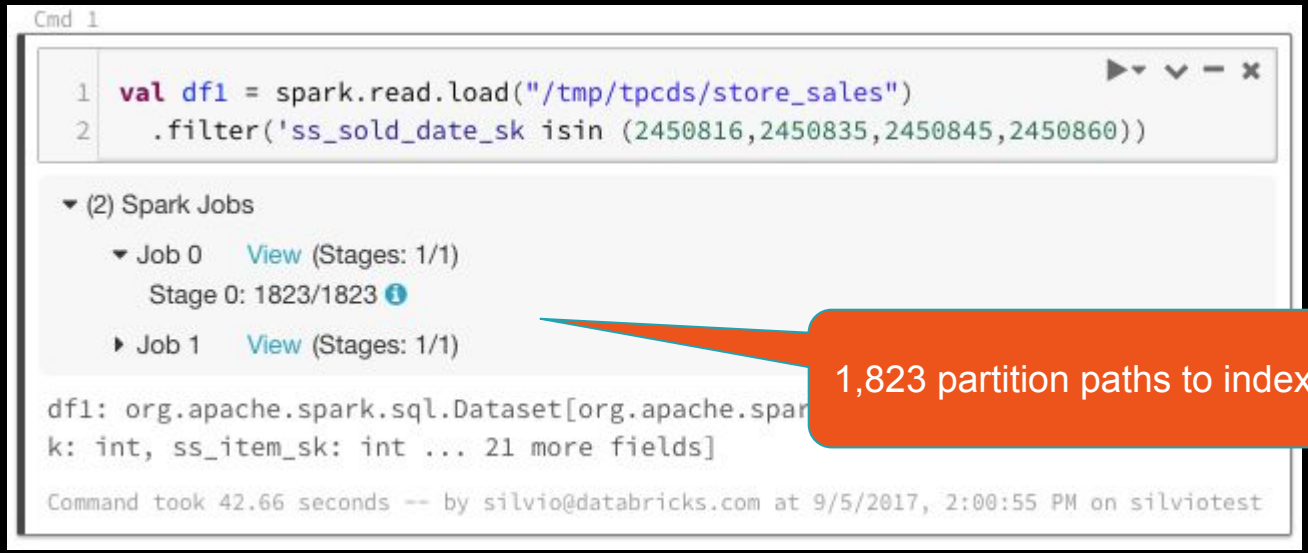
Listing Files

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



Partition Pruning

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

Dealing With Many Partitions

~2 seconds vs ~43 seconds

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

```
1  val df3 = spark.read.table("tpcds.store_sales")
2    .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

```
1  CREATE TABLE IF NOT EXISTS tpcds_temp.store_sales
2  USING parquet
3  OPTIONS (path '/tmp/tpcds/store_sales');
4
5  MSCK REPAIR TABLE tpcds_temp.store_sales;
```

Using Datasource Tables

Using SQL - Managed Tables

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

Cmd 2

```
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

Using Datasource Tables

Using DataFrame API

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

Cmd 10

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

Managed Table

Cmd 10

```
1  df1.write
2    .partitionBy("cs_sold_date_sk")
3    .option("path", "/tmp/tpcds_temp/stores_sales")
4    .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

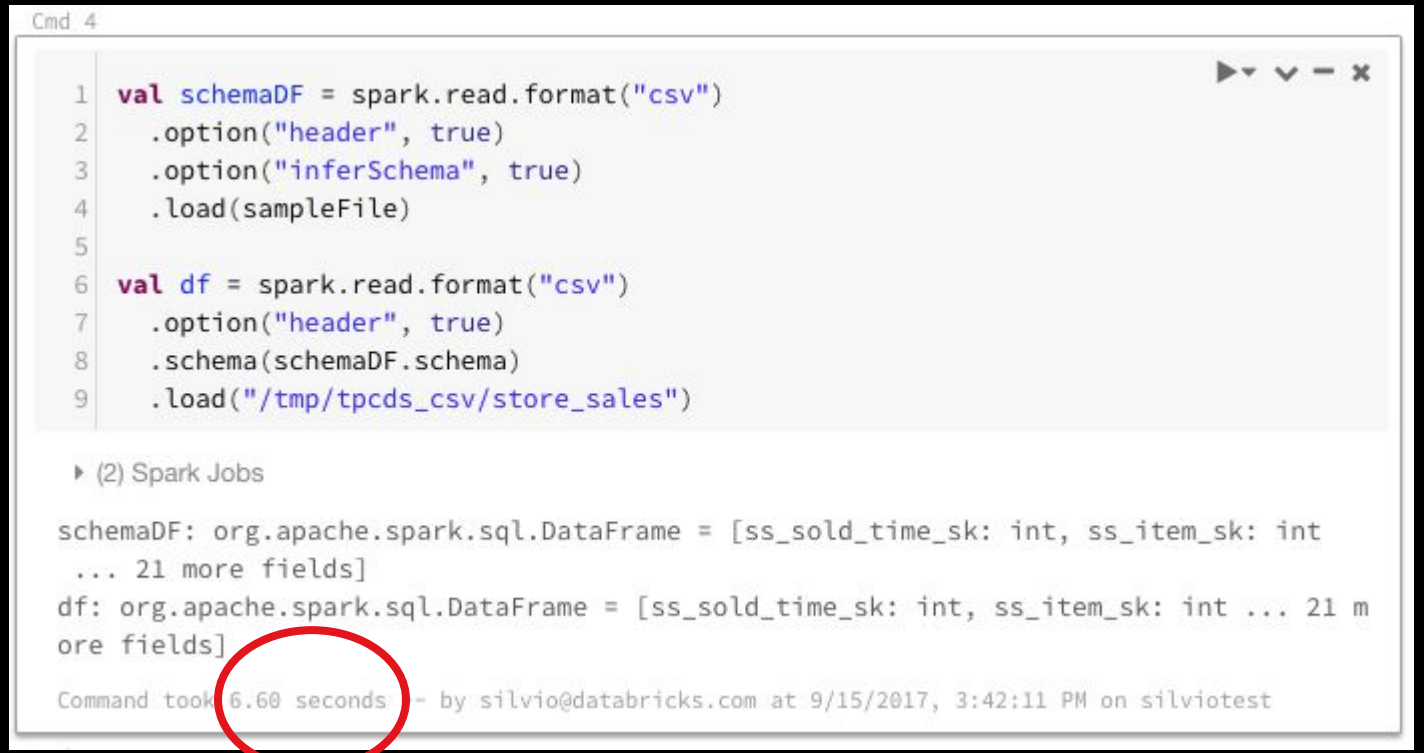
Reading CSV & JSON Files

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

Better Schema Inference



Better Schema Inference

Cmd 6

```
1  import org.apache.spark.sql.types._
2
3  lazy val useSchema = DataType.fromJson(schemaJSON)
4    .asInstanceOf[StructType]
5
6  val df = spark.read.format("csv")
7    .option("header", true)
8    .schema(useSchema)
9    .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

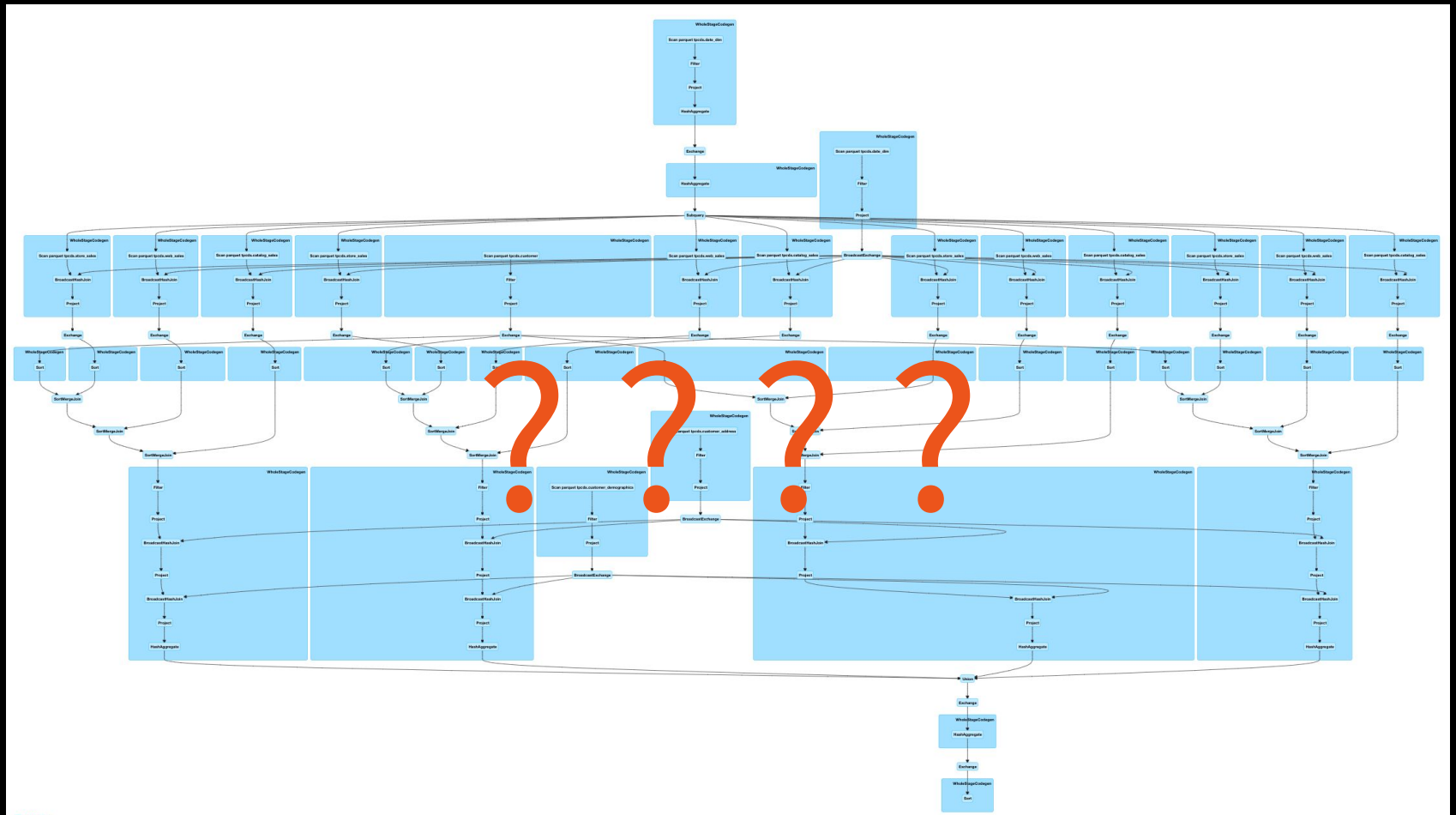
```
output.repartition('ss_sold_date_sk).write
  .partitionBy("ss_sold_date_sk")
  .option("path", "/tmp/tpcds_temp/store_sales_temp")
  .saveAsTable("tpcds_temp.store_sales_temp")
```

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

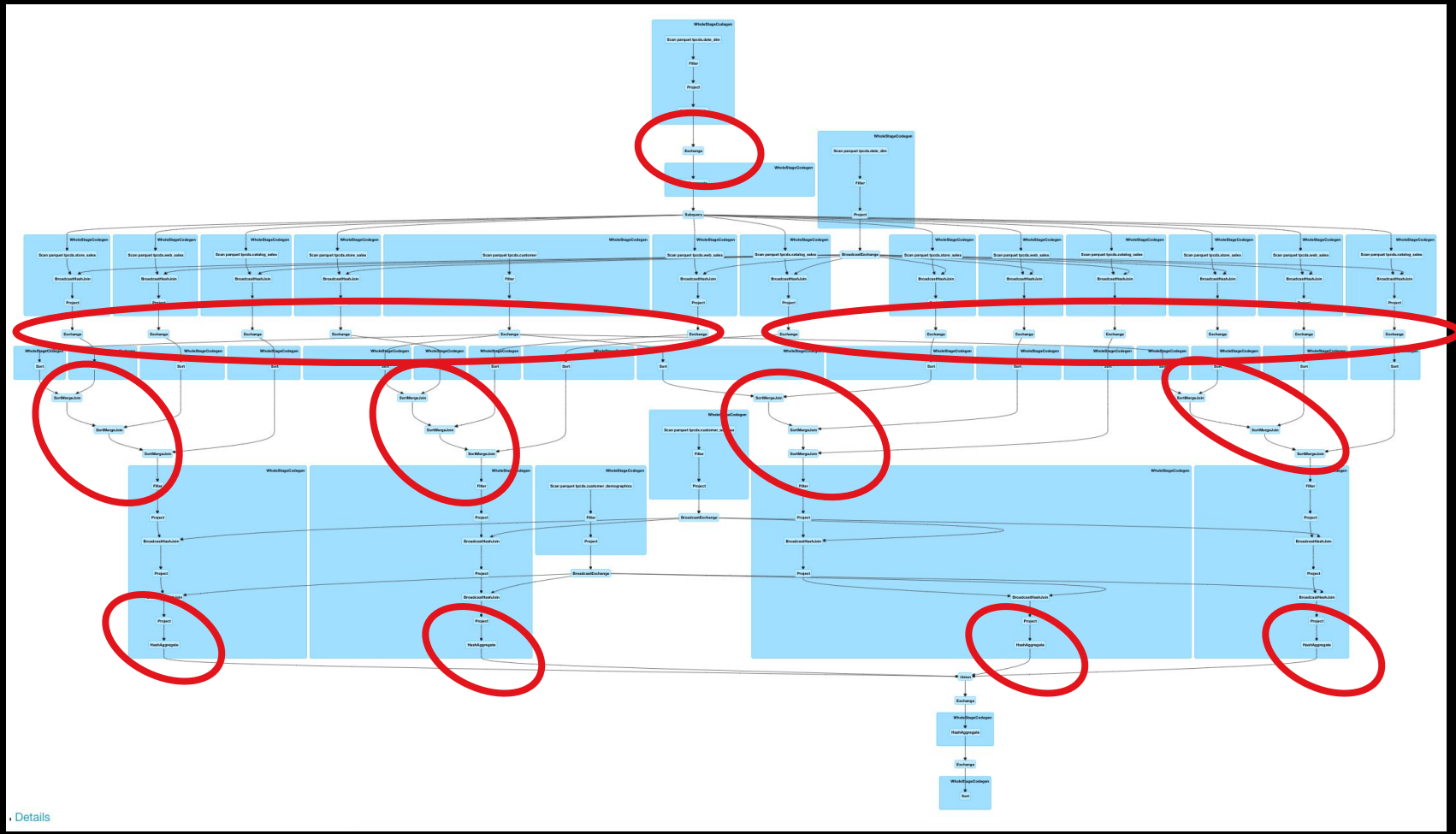
“How can I optimize my query?”


? ? ? ?
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 whole query


Details

Managing Shuffle Partitions

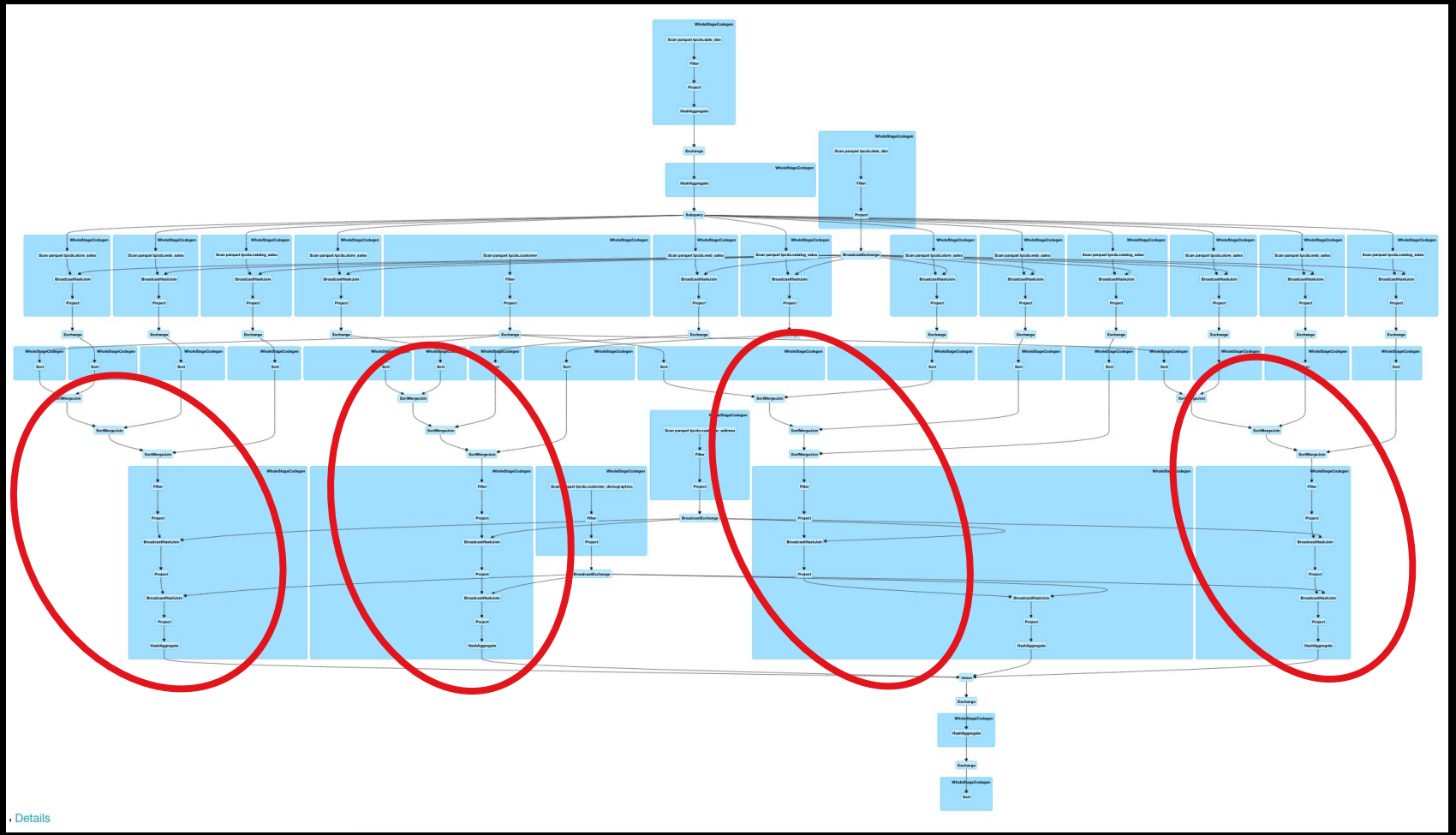
Adaptive Execution

- 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

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

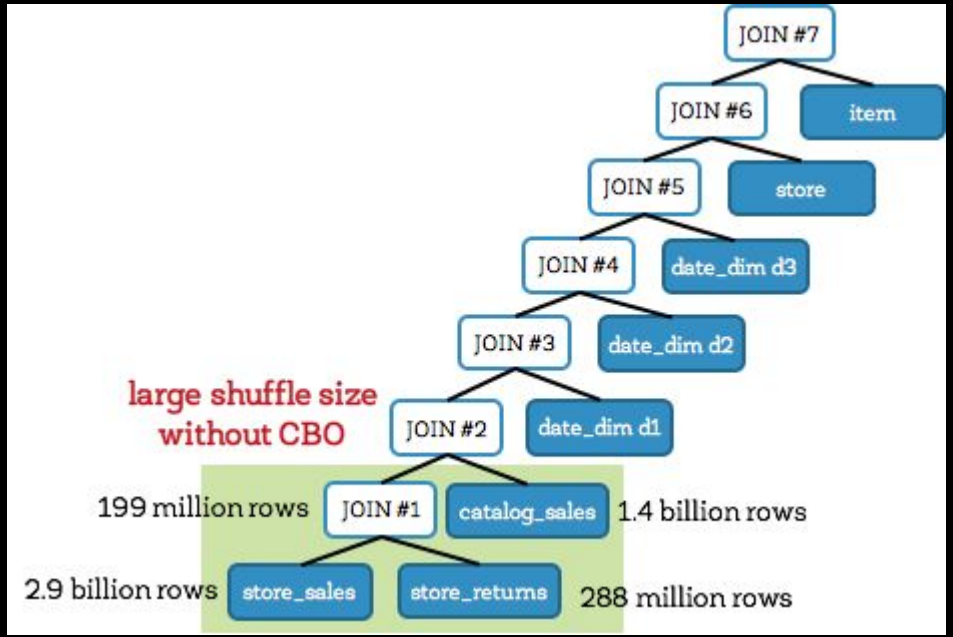
Cmd 9

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

Cmd 10

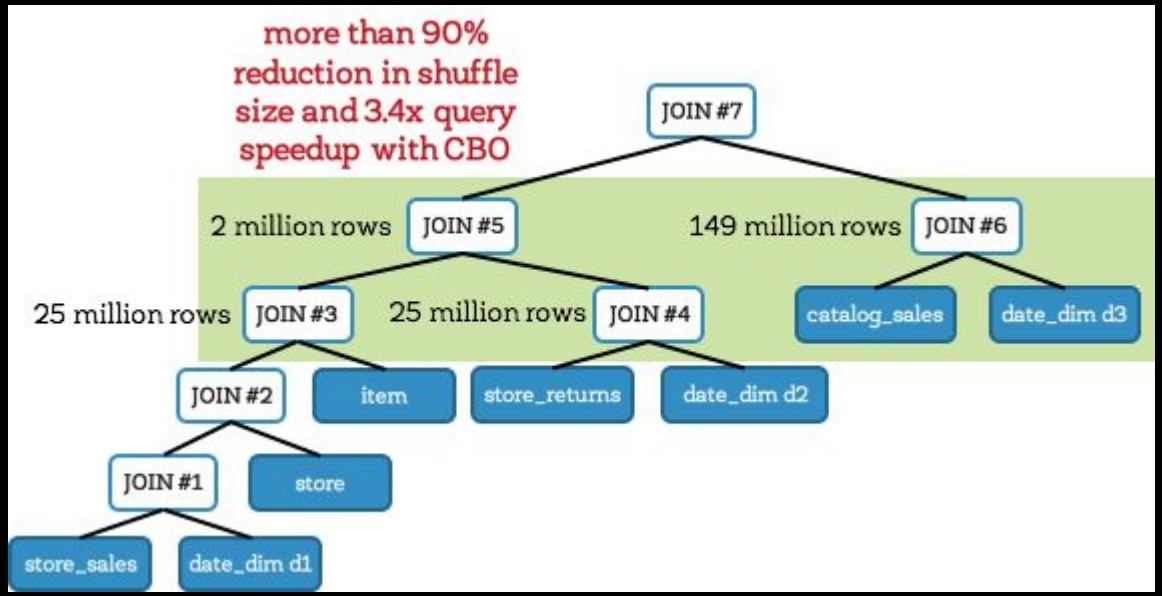
```
--compute column-level statistics
ANALYZE TABLE tpcds.store_sales COMPUTE STATISTICS
FOR COLUMNS ss_sales_price, ss_item_sk, ss_quantity
```

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

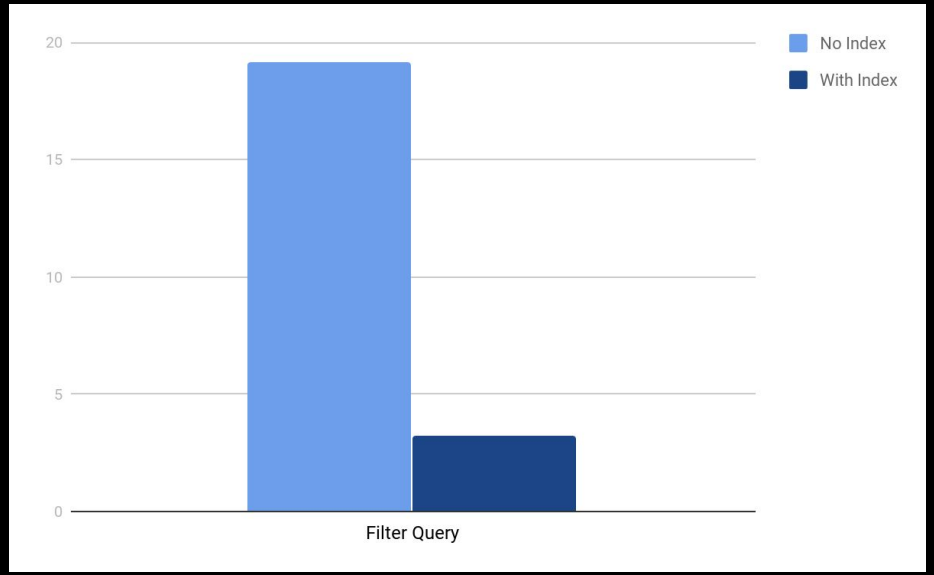
```
Cmd 11

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

Data Skipping Index

```
Cmd 16

1  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.
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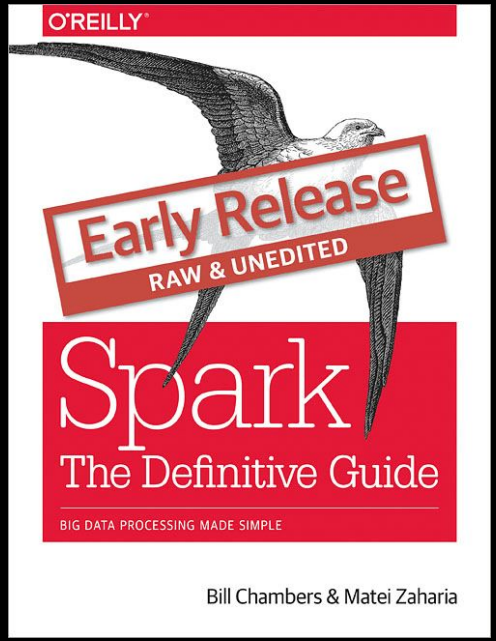
Spark the Definitive Guide

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

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