SPARK+AI
SUMMIT EUROPE

Lessons from the Field, Episode II:

Applying Best Practices to Your Apache Spark™ Applications

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#SAISExp9

About Me

Resident Solutions Architect @ Databricks

Developer, application security engineer, consultant, instructor

Using Spark since ~2012

Work with Databricks customers in banking, manufacturing, info-sec, new & experienced Spark users

SSE17: [Lessons from the Field]

To build more reliable,
& better performing Spark
applications we should
understand...

File Formats & Data Types

Partitioning, Shuffling, & Parallelization

Using Query Plans to Debug & Tune

CSV, JSON, Parquet, Avro, ORC,...

File formats have different benefits and tradeoffs that we need to be aware of...

Reading CSV Files

Raw text

1000,user1,”2010-01-23”,123.34,............
2002,user2,”2008-02-14”,349.02,............

Read each
line as String

“1000,user1,2010-01-23,123.34,............”,
“2002,user2,2008-02-14,349.02,............”,

Tokenize

Array(“1000”,”user1”,”2010-01-23”,”123.34”,..........),
Array(“2002”,”user2”,”2008-02-14”,”349.02”,..........),

Convert to types
& create rows

1000	user1	14632	123.34	
2002	user2	13923	349.02	

Common Issues with CSV

- Slow startup on large datasets
- Poor parallelization due to non-splittable files
- Be mindful of "wide" files
  - GC issues
  - Spark 2.4 column pruning (SPARK-24244)

GC Time	Min	25th percentile	Median	75th percentile	Max
Column Pruning **Off**	0.5 s	0.5 s	0.6 s	0.6 s	0.6 s
Column Pruning **On**	9 ms	31 ms	61 ms	64 ms	70 ms

Selecting 2 out of 200 columns from 3.6GB compressed dataset

Schema Inference

- CSV
  - `inferSchema` causes full scan of data
  - Specify schema or use tables
  - Be precise, use the right types!
- JSON
  - Full scan of data
  - Specify schema or use tables

	Shuffle Write
strings	217.0 MB
doubles	159.0 MB
decimals	145.3 MB

Aggregate query on 2 columns & 10 million rows

Schema Inference

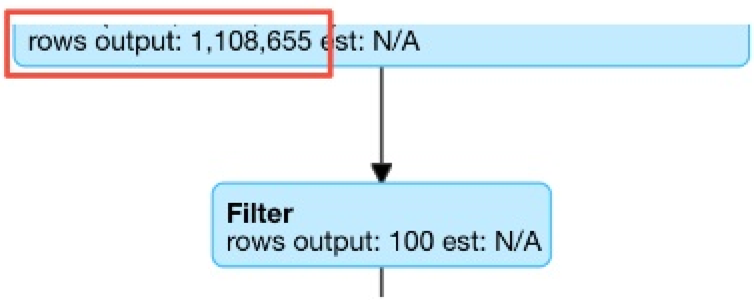
- Parquet
  - If no `_metadata`, use schema from first file
  - If `mergeSchema` read footers from <u>all files</u>
  - Specify schema or use tables
- ORC
  - Reads first file for schema
  - Specify schema or use tables

Optimizing Parquet Storage

- Embedded column statistics
  - min, max, count
  - Useful for filtering
- Most effective on sorted data
  - Order by filter column when writing
  - Reduce data reads by skipping files

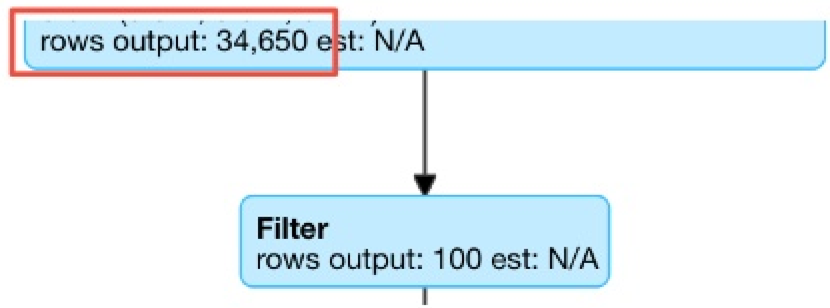
```
select * from mytable
where id between 1 and 100
```

UNSORTED



Duration	Tasks: Succeeded/Total	Input
12 s	32/32	209.3 MB

SORTED



Duration	Tasks: Succeeded/Total	Input
2 s	32/32	12.8 MB

Challenges with Parquet Data Skipping

- Really most effective on single sort key
- Need to be careful with data skew
- How to maintain performance as new data appended?
- Data Skipping and ZORDER clustering
  - [Processing Petabytes of Data in Seconds with Databricks Delta]

Parallelization with File Formats

- Spark 2.0 default split 128MB
  - `spark.sql.files.maxPartitionBytes`
- Bin packing of smaller files
  - Auto-compaction, avoids coalesce
- Based on file-size
  - High compression ratio may result in smaller files
  - Data is decoded & uncompressed when reading

Parallelization & File Sizes

- Controlling file sizes during ETL
- Generating more rows in queries (`explode`, `flatMap`, broadcast joins)
- Solution - `repartition?`
  - Adds shuffle boundary, memory & I/O constraints
- Consider instead
  - `maxPartitionBytes` (for splittable input)
  - `maxRecordsPerFile` (for controlling output)

Using Spark UI & Query Plans

- SQL UI is invaluable to understanding execution
- Identify stage boundaries (shuffles)
- Use metrics for diagnosing your query
  - Are filters and column pruning applied?
  - How large are your shuffles?
  - How much memory usage and spilling?

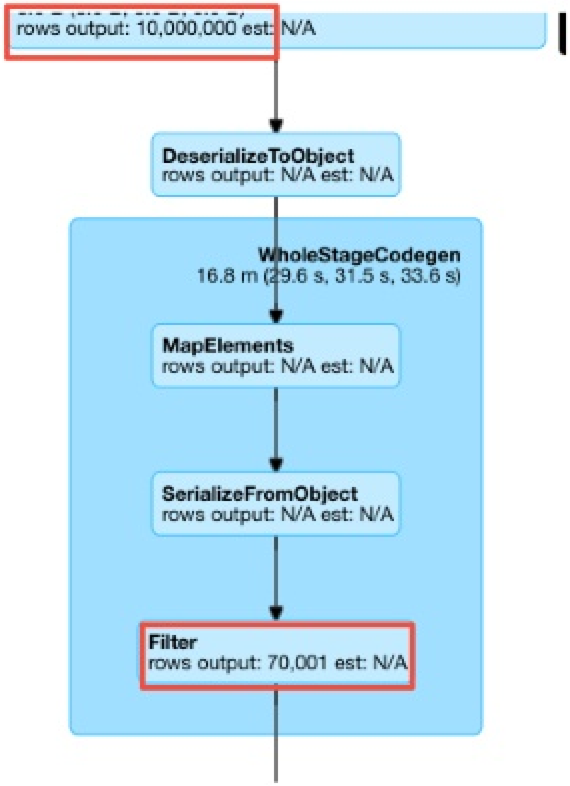
Datasets & Order of Operations

```scala
case class Input(id: Long, col1: String)

case class Output(id: Long, col1: String, col2: String)

def transformToOutput(input: Input): Output = {
  ...
}


val query = basedata.as[Input]
  .map(i => transformToOutput(i))
  .filter('id <= 700000)
```



Datasets & Order of Operations

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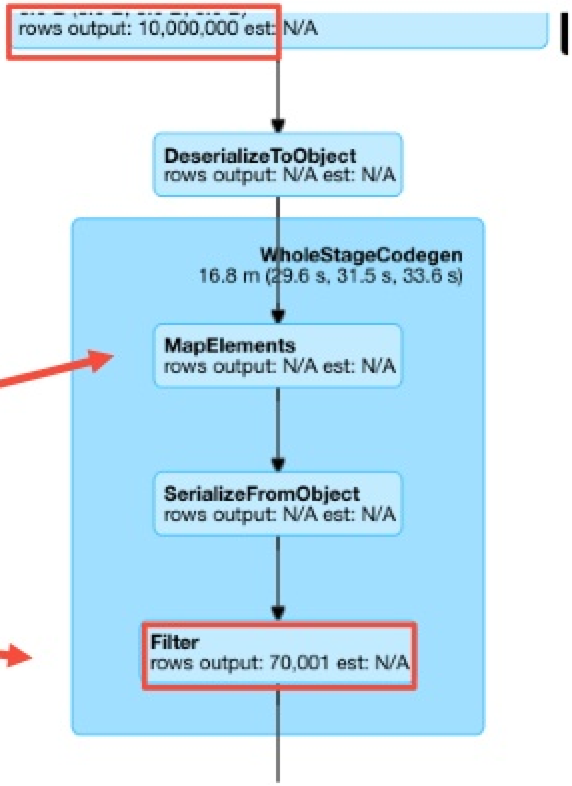
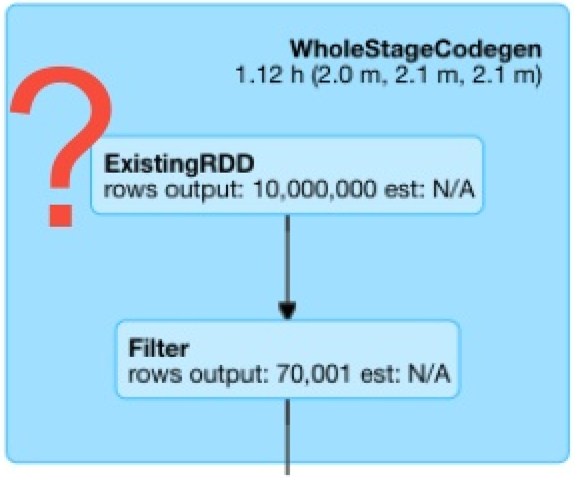


Dataset `map` breaks lineage of "id" column, no predicate pushdown!

Moving Between DataFrames & RDDs

```
output = df.rdd.map(myPythonFunc)

outputDF = spark.createDataFrame(
  output,
  ["id", "col1", "col2"]
).where("id <= 700000")
```



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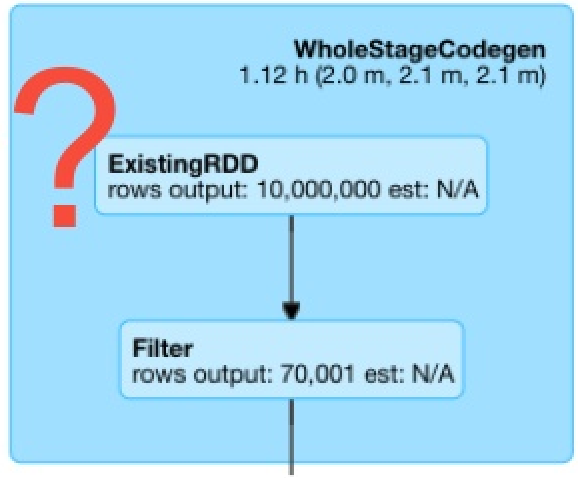
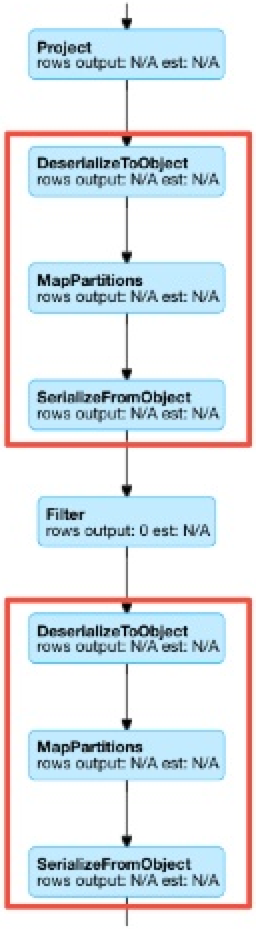


Converting to RDD breaks DataFrame lineage, no predicate pushdown, no column pruning, no SQL plan, and less efficient PySpark RDD transformations...

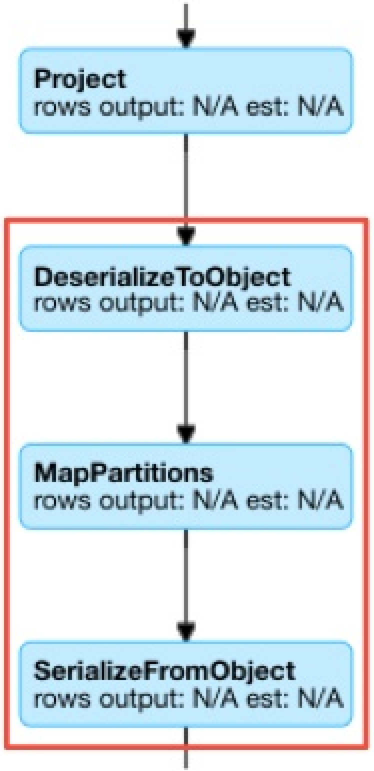
Using SparkR UDFs

```
step1 = dapply(input, firstUDF, step1Schema) # UDF

step2 = filter(step1, step1$id2 >= 5000000) # Spark filter

step3 = dapply(step2, secondUDF, step3Schema) # UDF
```



Using SparkR UDFs

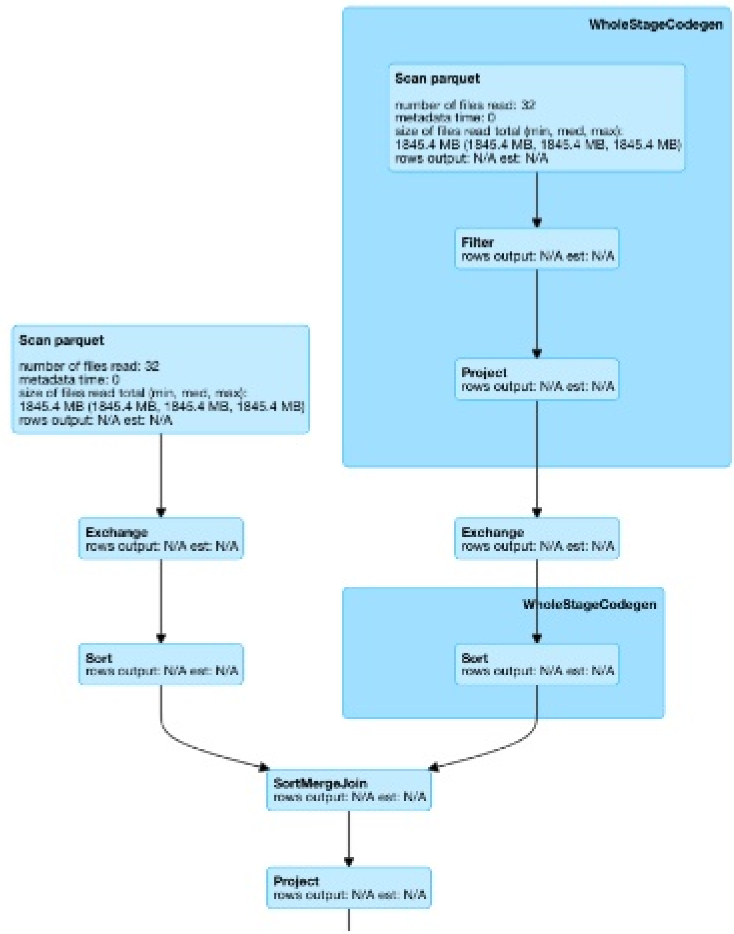
```
bothUDFs <- function(input) {
  step1 <- firstUDF(input)
  step2 <- subset(step1, id2 >= 5000000)
  step3 <- secondUDF(step2)

  return(step3)
}

singleStep = dapply(input, bothUDFs, step3Schema)
```



Self-Joins

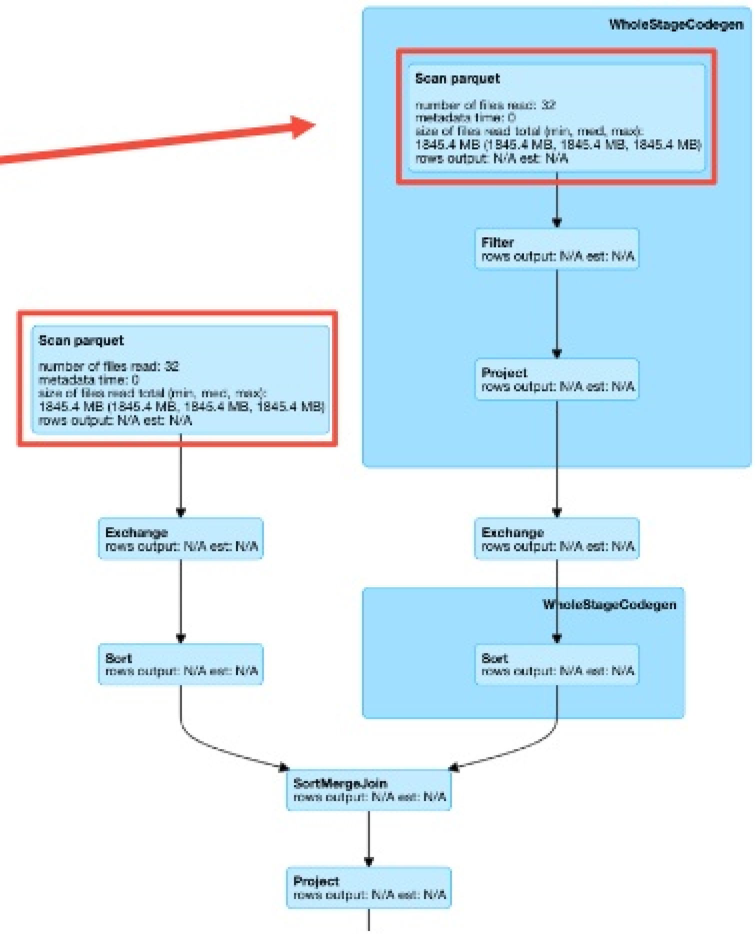
```scala
val basedata_ex = basedata
  .withColumn("id", ...)
  .withColumn("mycol", ...)

val joined = basedata
  .join(basedata_ex, Seq("id"), "left")
```

- Two DataFrames referring to same data
- Typically, some transformation applied to original DF
- Join second DF to original DF (look ahead/behind, shifting rows, self reference, etc)



Self-Joins

Reading the SAME data twice!

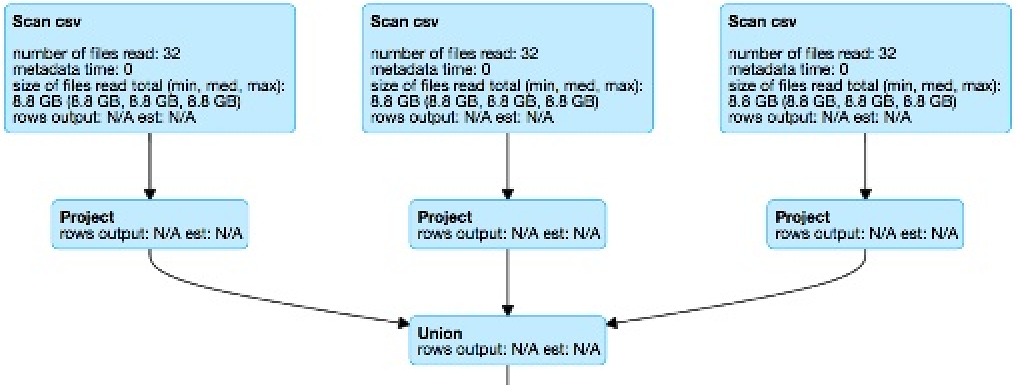


Instead consider window functions, `flatMap`, `explode`

If absolutely necessary then try caching, checkpointing, or [local checkpointing]()

Repetitive Unions

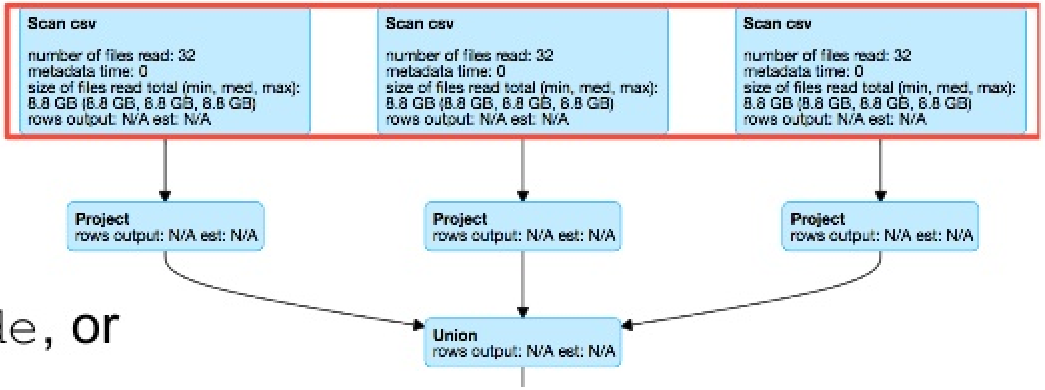
```
for config in configs:
  temp = computeDF(input, config)
  unioned_dfs = unioned_dfs.union(temp)
```



- Typically for different transformations to same record
- Sometimes used for Python distributed Cross Validation

Repetitive Unions

Reading the SAME data!



Increases number of tasks and Catalyst complexity with each union

Instead consider `flatMap`, `explode`, or broadcast join (dep. on data size)

If absolutely necessary then try caching, checkpointing, or local checkpointing

UDFs and Datasets

- PLEASE – Learn the built-in functions!
  - Prefer Pandas UDFs to PySpark UDFs
- Filter and project early
  - UDFs, lambdas are opaque to Catalyst
- Prefer DataFrames & Datasets
- SparkR – 100x Faster UDFs

How Can You Learn More?

- Spend the time to understand your query plan
  - Is Spark doing what you expect?
- Understand how different transformations, UDFs, and configs impact execution
- If you're not sure...go to the source!
  - Apache Spark GitHub

QUESTIONS?