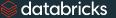


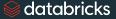
Top 5 Tuning Tips for Delta Lake and Spark 3.0 on Databricks

Joe Widen, Solutions Architect Chris Hoshino-Fish, Solutions Architect Denny Lee, Developer Advocate



Top 5 Tuning Tips

- Use the latest version of DBR
- 2. Pick the best join for your workload
- 3. Use Spark 3.0 with AQE
- 4. Partitions, File Sizes, Zorder, Stats and Merges
- 5. Pick the right machines





Keeping up with the Databricks Runtime

 The latest Databricks runtime is almost always faster than the one before it.

- We constantly work with some of the largest users of Apache Spark and Delta Lake to make it easier, faster, and better.
 - DBR 7.3 significantly reduced delta metadata overhead time
 - DBR 7.2 added cloning, upgraded cloud connectors, upgraded AQE
 - DBR 7.1 added convert to delta, MERGE INTO performance improvements
 - DBR 7.0 upgraded to Spark 3.0, Delta Lake Auto Loader and COPY INTO and Dynamic Subquery Reuse



Picking the best join strategy **a** databricks

Physical Join Types - A review in performance

BroadcastHashJoin

BroadcastNestedLoopJoin

ShuffledHashJoin: One side is smaller (3x or more) and a partition of it can fit in memory (off by default, enable by 'spark.sql.join.preferSortMergeJoin = false')

SortMergeJoin: Scalable - just works

Cartesian: Try not to do this

databricks

Physical Join Types - A review in performance

Broadcast Hash Join / Nested Loop

SELECT /*+ BROADCAST(a) */ id FROM a JOIN b ON a.key = b.key

Shuffle Hash Join

SELECT /*+ SHUFFLE_HASH(a, b) */ id FROM a JOIN b ON a.key = b.key

Sort-Merge Join

SELECT /*+ MERGE(a, b) */ id FROM a JOIN b ON a.key = b.key

Shuffle Nested Loop Join (Cartesian)
 SELECT /*+ SHUFFLE_REPLICATE_NL(a, b) */ id
 FROM a JOIN b

Requires one side to be small. No shuffle, no sort, very fast.

Needs to shuffle data but no sort. Can handle large tables, but will 00M too if data is skewed. One side is smaller (3x or more) and a partition of it can fit in memory (enable by `spark.sql.join.preferSortMergeJoin = false`)

Robust. Can handle any data size. Needs to shuffle and sort data, slower in most cases when the table size is small.

Does not require join keys as it is a cartesian product of the tables. Avoid doing this if you can



Lets use hints!

SELECT /*+ BROADCAST(t1) */ * from t1... - Broadcast hint SELECT /*+ SHUFFLE_HASH(t1) */* from t1... - Shuffle Hash Join SELECT /*+ SHUFFLE_MERGE(t1) */* from t1... - Sort Merge Join

Use multiple hints?

SELECT /*+ BROADCAST(t1), SHUFFLE_HASH(t2)*/* - Broadcast t1, shuffle hash t2



Help Catalyst choose the right Joins

At the cluster level, set these configs:

spark.sql.autoBroadcastJoinThreshold 100*1024*1024 spark.sql.join.preferSortMergeJoin false

Why do I need the slide before?

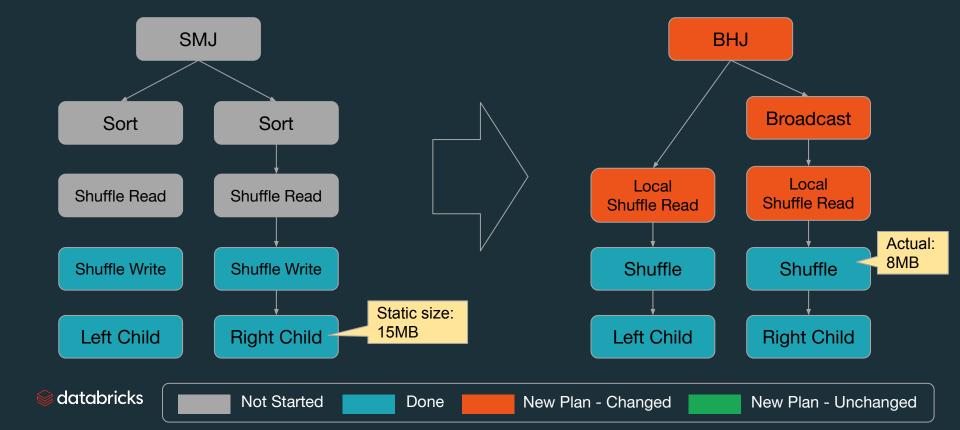
You know your data best. For example, you're joining two tables on a partitioned column and a couple others, a sort merge join would make more sense then a full shuffle

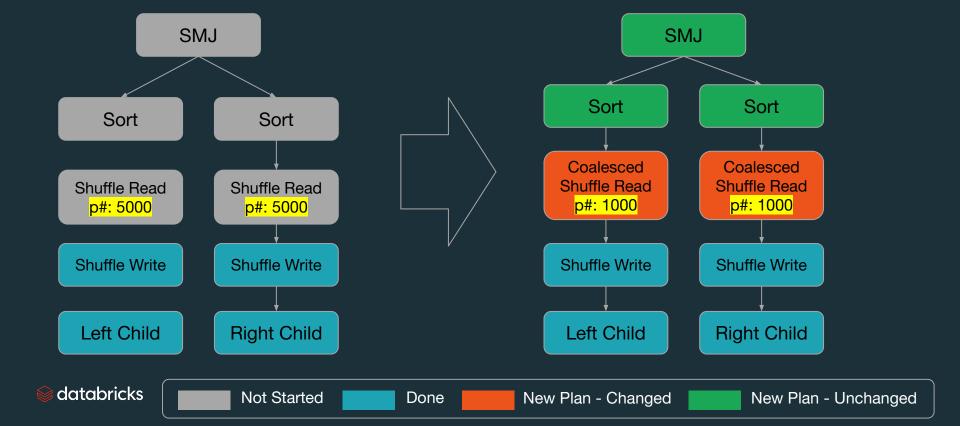


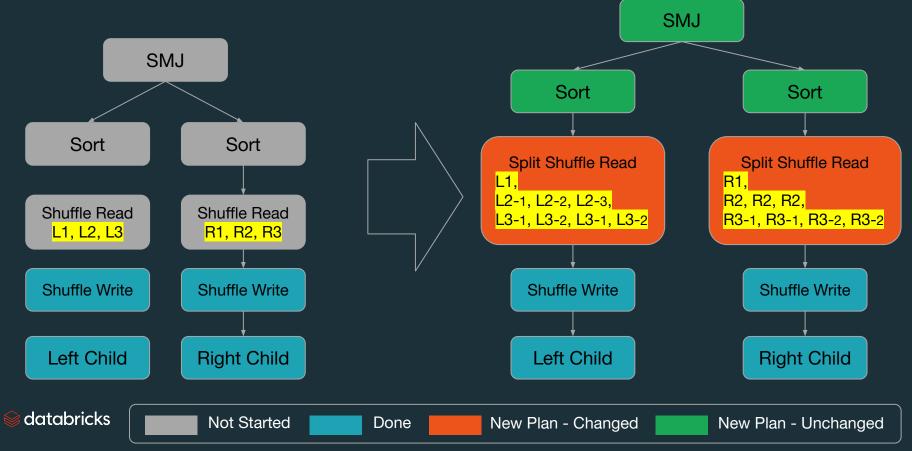
Use Apache Spark 3.0 and AQE

- What is it? [#SPARK-23128] A new approach to do adaptive execution in Spark SQL ASF JIRA
- What does it do?
 - Adapts a query plan <u>automatically</u> at runtime based on <u>accurate</u> metrics (<u>no hint needed</u>)
 - Capabilities in release
 - Sort Merge Join (SMJ) → Broadcast Hash Join (BHJ)
 - Coalesce shuffle partitions
 - Skew Join

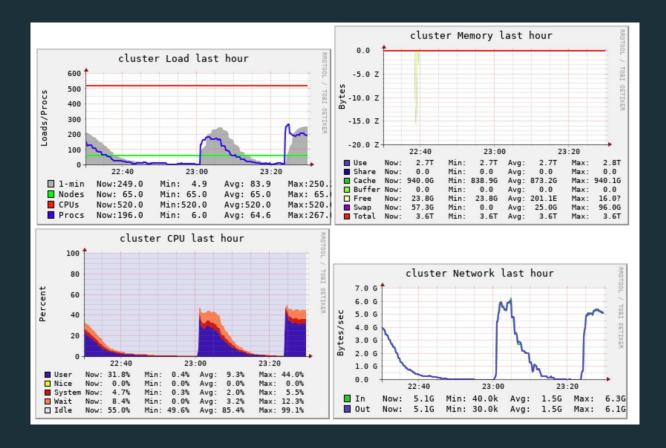






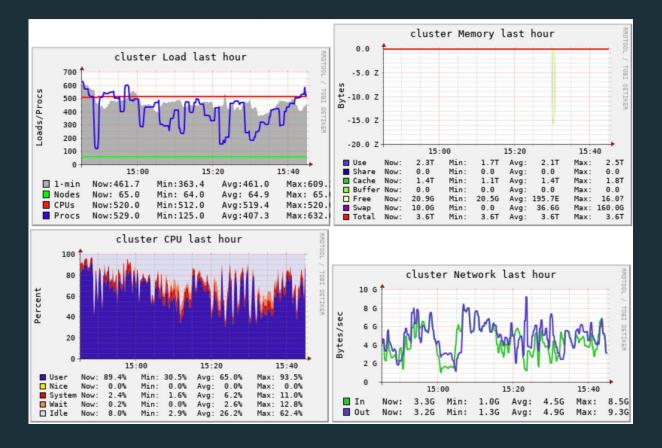


Does it work? This ran in 6h 47m





You tell me. This ran in 2h 28m







Partition Pruning



Partition Pruning

Select * from deltalake_table where part = 2



Data Skipping

Simple, well-known I/O pruning technique

- Track file-level stats like min & max
- Leverage them to avoid scanning irrelevant files

file_name	col_min	col_max
1.parquet	6	8
2.parquet	3	10
3.parquet	1	4



Data Skipping

Simple, well-known I/O pruning technique

- Track file-level stats like min & max
- Leverage them to avoid scanning irrelevant files

```
SELECT * FROM TABLE WHERE col < 5

SELECT file_name FROM index

WHERE col_min < 5
```

file_name	col_min	col_max
1.parquet	6	8
2.parquet	3	10
3.parquet	1	4



Data Skipping

Simple, well-known I/O pruning technique

- Track file-level stats like min & max
- Leverage them to avoid scanning irrelevant files

```
SELECT * FROM TABLE WHERE col < 5

SELECT file_name FROM index

WHERE col_min < 5 AND col_max >= 5
```

file_name	col_min	col_max
1.parquet	6	8
2.parquet	3	10
3.parquet	1	4



Z-Ordering

optimize table zorder by col

Old Layout

file_name	col_min	col_max
1.parquet	6	8
2.parquet	3	10
3.parquet	1	4

New Layout

file_name	col_min	col_max
1.parquet	1	3
2.parquet	4	7
3.parquet	8	10



Z-Ordering

Select * from table where col = 7

Old Layout

file_name	col_min	col_max
1.parquet	6	8
2.parquet	3	10
3.parquet	1	4

New Layout

file_name	col_min	col_max
1.parquet	1	3
2.parquet	4	7
3.parquet	8	10



Z-Ordering Tips

- Z-Ordering is pretty effective on up to 3-4 columns
 - New Hilbert based Z-Ordering will allow for 5-6 in the future
- Z-Ordering creates 1 GB files (by default)
 - If your partitions are less than 1 GB, default Z-Ordering won't help
 - You can change the zorder file size
 - 16MB -> 128MB seem to be ideal, choose based on your average partition size
 - The file size will be auto-tuned in the not so distant future
 - Delta doesn't care about the number of partitions, only the number of files
- Z-Order on columns commonly used in filters/where predicates



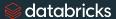
Databricks Delta Lake and Stats

- Databricks Delta Lake collects stats about the first N columns
 - o dataSkippingNumIndexedCols = 32
- These stats are used in queries
 - Metadata only queries: select max(col) from table
 - Queries just the Delta Log, doesn't need to look at the files if col has stats
 - Allows us to skip files
 - Partition Pruning, **Data Filters**, Pushed Filters apply in that order
 - TimeStamp and String types aren't always very useful
 - Precision/Truncation prevent exact matches, have to fall back to files sometimes
- Avoid collecting stats on long strings
 - Put them outside first 32 columns or collect stats on fewer columns
 - alter table change column col after col32
 - set spark.databricks.delta.properties.defaults.dataSkippingNumIndexedCols = 3



Easy Patterns you can follow

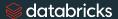
- Don't collect stats on your Bronze tables
 - o alter table bronze set TBLPROPERTIES(delta.dataSkippingNumIndexedCols = 0)
- Only collect stats on useful columns in Silver and Gold level tables
 - Join keys
 - Common WHERE clauses
 - INSERT/UPDATE/DELETE/MERGE predicates
 - Don't collect stats on long strings
 - If using lots of equals filters on TimeStamps, stats are useful, not so much for greater or less than
 - Z-Order on join keys, and commonly used columns in where clauses



MERGE Basics

```
MERGE INTO my_table d USING my_view s ON condition
WHEN MATCHED AND d.status = 'CLOSED' THEN DELETE
WHEN MATCHED THEN UPDATE SET d.status = 'CLOSED'
WHEN NOT MATCHED THEN INSERT *
```

- Leverage data skipping (partition + stats) and figure out which files may match *predicate*
- Perform inner join and collect input_file_name for all rows that match condition. Ensure 1-1 mapping
- Rewrite files found above by updating the rows that match the conditions using a full outer join



FYI on Merge Functionality

Merges rewrite EVERY file that have a matching record in the ON clause, regardless of what is in the WHEN [NOT] MATCHED

```
MERGE INTO myTable
USING myChanges
ON table.id = myChanges.id
WHEN MATCHED AND 1=2
THEN UPDATE *
```

WHEN MATCHED AND 1=2 is never true, so it shouldn't do anything, merge still scans the entire table myTable, and rewrites every file with matching id



Optimizing Merges - Reduce the scan

 Addition additional information into the ON clause will reduce the amount of data to be scanned

```
MERGE INTO myTable
USING myChanges
ON myTable.id = myChanges.id AND myTable.date > current_day() -
interval 7 days
THEN UPDATE *
```

This leverages <u>partition pruning</u> on the destination table, resulting in smaller data to be scanned during the join of table.id = myChanges.id



Optimizing Merges - Rewrite less data

- Use smaller files for merges that can rewrite a large number of files
 - set spark.databricks.delta.optimize.maxFileSize = 32mb
 - File sizes between 16mb and 128mb are good

Z-Order on the columns in your ON predicate

Use the Hilbert Curve Z-Order (in beta in DBR 7.3, see Tip #1!)



Optimizing Merges - Write fewer files

 Use optimized writes (aka auto optimize) to prevent writing a lot of small files after the merge

```
alter table tablename set tblproperties
(delta.autoOptimize.optimizeWrite = true)
```



Pick good instance types



What happens when you only change the instance type?

Example:

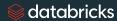
Select * from table where partCol = this and otherCol = 1

- Dataset was in Delta Lake, 2.2TB, 3k files
- Cluster configs:
 - 6 nodes, 16 cores/node, 32GB ram
 - 6 nodes, 16 cores/node, 128GB ram
 - 3 nodes, 32 cores/node, 256GB ram



What happens when you only change the instance type?

DBR Version	Cache	VM	Duration
6.6	cold	16 core 32 GB RAM	1.82 minutes
6.6	cold	16 core, 128 GB RAM	2.29 minutes
6.6	warm	16 core, 128 GB RAM	1.95 minutes
5.5 LTS	cold	16 core, 128 GB RAM	2.46 minutes
5.5 LTS	warm	16 core, 128 GB RAM	1.92 minutes
6.6	cold	32 cores, 256 GB RAM	4.18 minutes
6.6	warm	32 cores, 256GB RAM	3.72 minutes



Instance Types

- Rules of thumb
 - Use 32 to 128GB machines
 - Cores are cheap, you and your employee's time aren't
 - Not all processors/cores are created equal
- Doing ETL?
 - Use a compute optimized instance
- Running interactive queries?
 - Use an instance with a NVMe SSD
- Building machine learning models?
 - Use an instance with a NVMe SSD



Thank you for attending
For more information go to delta.io and join the
Delta Lake slack channels

