Cardinality Estimation through Histogram in Apache Spark 2.3

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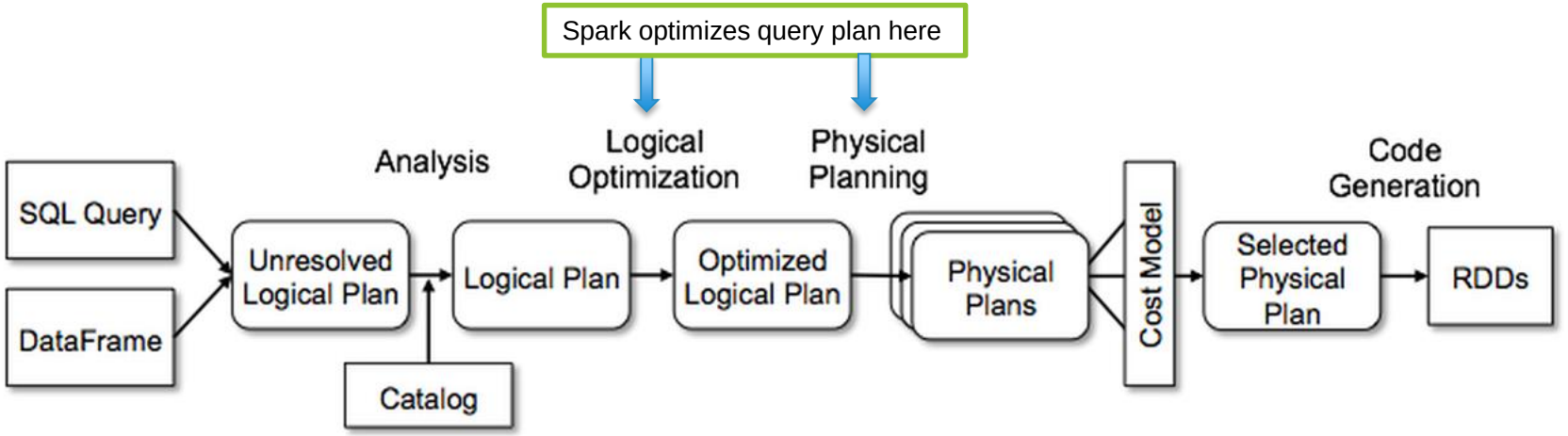
Agenda

- Catalyst Architecture
- Cost Based Optimizer in Spark 2.2
- Statistics Collected
- Histogram Support in Spark 2.3
- Configuration Parameters
- Q & A

Catalyst Architecture



Reference:Deep Dive into Spark SQL's Catalyst Optimizer, a databricks engineering blog

Query Optimizer in Spark SQL

- Spark SQL's query optimizer is based on both rules and cost.
- Most of Spark SQL optimizer's rules are heuristics rules.
  - PushDownPredicate, ColumnPruning, ConstantFolding,….
- Cost based optimization (CBO) was added in Spark 2.2.

Cost Based Optimizer in Spark 2.2

- It was a good and working CBO framework to start with.
- Focused on
  - Statistics collection,
  - Cardinality estimation,
  - Build side selection, broadcast vs. shuffled join, join reordering, etc.
- Used heuristics formula for cost function in terms of cardinality and data size of each operator.

Statistics Collected

- Collect Table Statistics information
- Collect Column Statistics information
- Goal:
  - Calculate the cost for each operator in terms of number of output rows, size of output, etc.
  - Based on the cost calculation, adjust the query execution plan

Table Statistics Collected

- Command to collect statistics of a table.
  - Ex: `ANALYZE TABLE table-name COMPUTE STATISTICS`
- It collects table level statistics and saves into metastore.
  - Number of rows
  - Table size in bytes

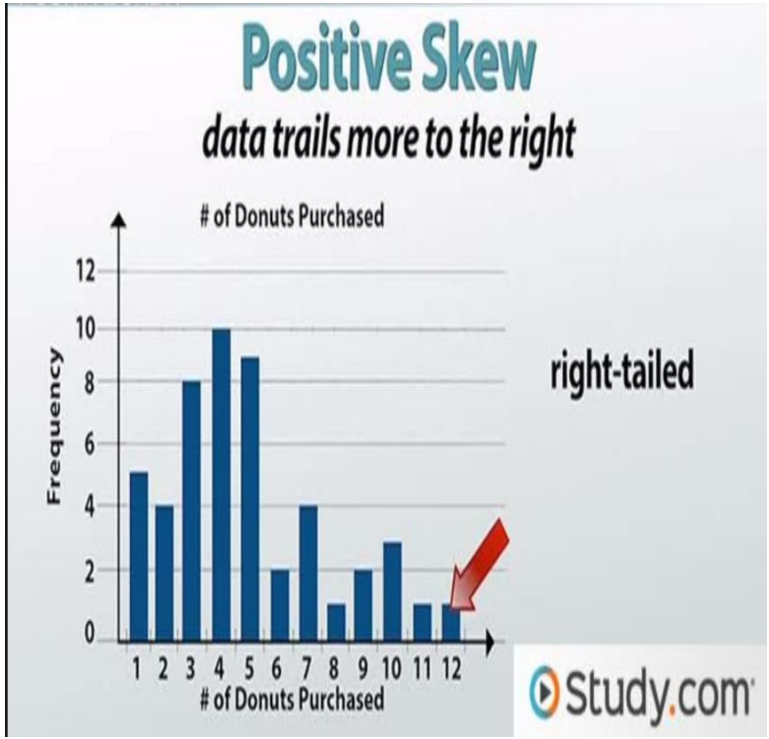
Column Statistics Collected

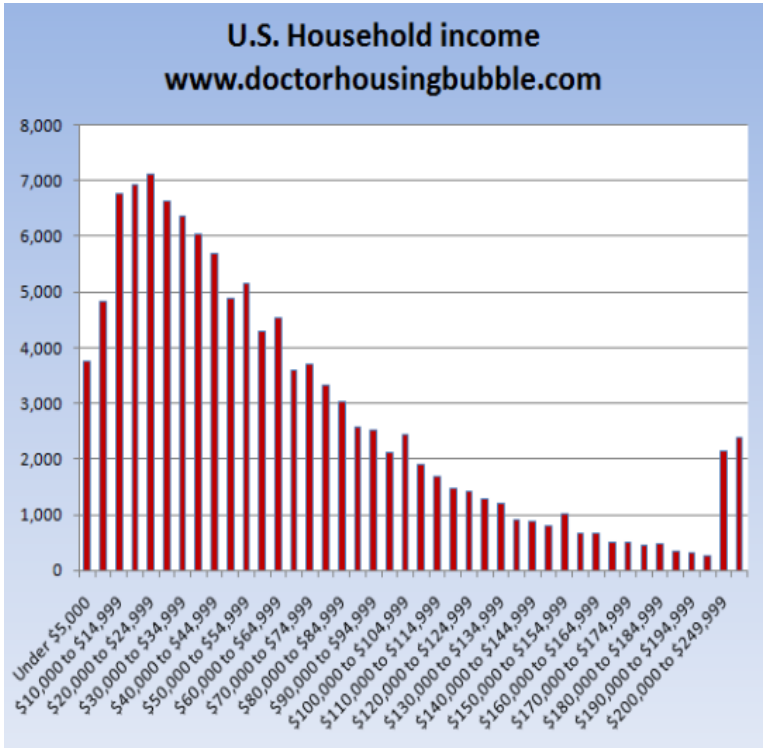
- Command to collect column level statistics of individual columns.
  - Ex: `ANALYZE TABLE table-name COMPUTE STATISTICS FOR COLUMNS column-name1, column-name2, ….`
- It collects column level statistics and saves into meta-store.

Numeric/Date/Timestamp type
- ✓ Distinct count
- ✓ Max
- ✓ Min
- ✓ Null count
- ✓ Average length (fixed length)
- ✓ Max length (fixed length)

String/Binary type
- ✓ Distinct count
- ✓ Null count
- ✓ Average length
- ✓ Max length

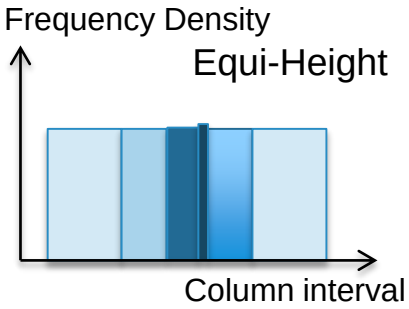
Real World Data Are Often Skewed

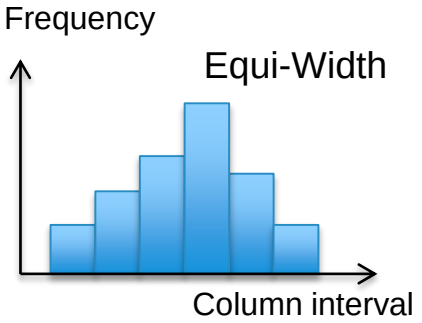




Histogram Support in Spark 2.3

- Histogram is effective in handling skewed distribution.
- We developed equi-height histogram in Spark 2.3.
- Equi-Height histogram is better than equi-width histogram
  - Equi-height histogram can use multiple buckets to show a very skewed value.
  - Equi-width histogram cannot give right frequency when a skewed value falls in same bucket with other values.





Histogram Algorithm

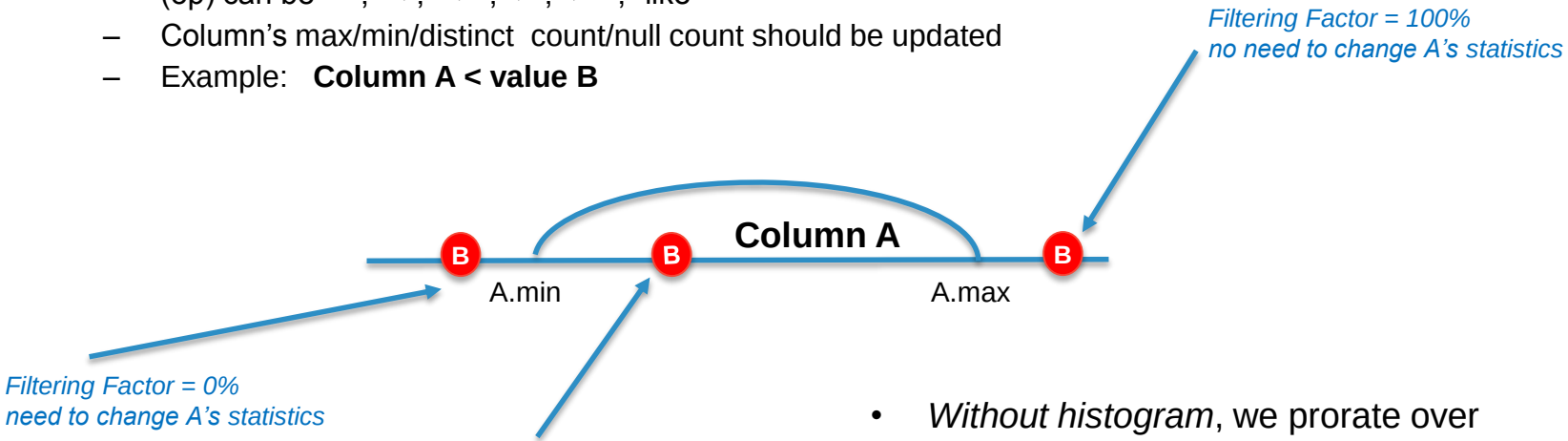
- Each histogram has a default of 254 buckets.
  - The height of a histogram is number of non-null values divided by number of buckets.
- Each histogram bucket contains
  - Range values of a bucket
  - Number of distinct values in a bucket
- We use two table scans to generate the equi-height histograms for all columns specified in `analyze` command.
  - Use ApproximatePercentile class to get end points of all histogram buckets
  - Use HyperLogLog++ algorithm to compute the *number of distinct values* in each bucket.

Filter Cardinality Estimation

- Between Logical expressions: AND, OR, NOT
- In each logical expression: =, <, <=, >, >=, in, etc
- Current support type in Expression
  - For <, <=, >, >=, <=>: Integer, Double, Date, Timestamp, etc
  - For = , <=>: String, Integer, Double, Date, Timestamp, etc.
- Example: A <= B
  - Based on A, B's min/max/distinct count/null count values, decide the relationships between A and B. After completing this expression, we set the new min/max/distinct count/null count
  - Assume all the data is evenly distributed if no histogram information.

Filter Operator without Histogram

- ***Column A (op) literal B***
  - (op) can be “=“, “<”, “<=”, “>”, “>=”, “like”
  - Column’s max/min/distinct count/null count should be updated
  - Example: **Column A < value B**



Filtering Factor = (B.value – A.min) / (A.max – A.min)
A.min = no change
A.max = B.value
*A.ndv = A.ndv * Filtering Factor*

- *Without histogram*, we prorate over the entire column range.
- It works only if it is evenly distributed.

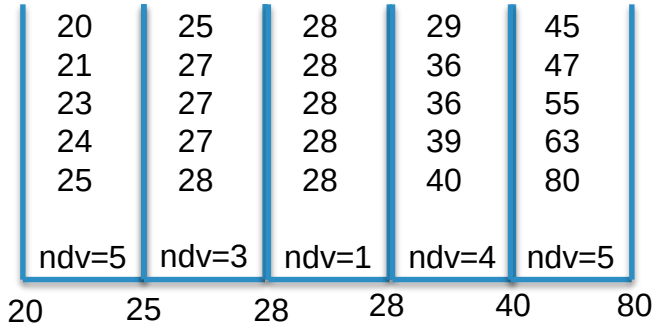
Filter Operator with Histogram

- With histogram, we check the range values of a bucket to see if it should be included in estimation.
- We prorate only the boundary bucket.
- This way can enhance the accuracy of estimation since we prorate (or guess) only a much smaller set of records in a bucket only.

Histogram for Filter Example 1

Age distribution of a restaurant:

Total row count: 25
age min = 20
age max = 80
age ndv = 17

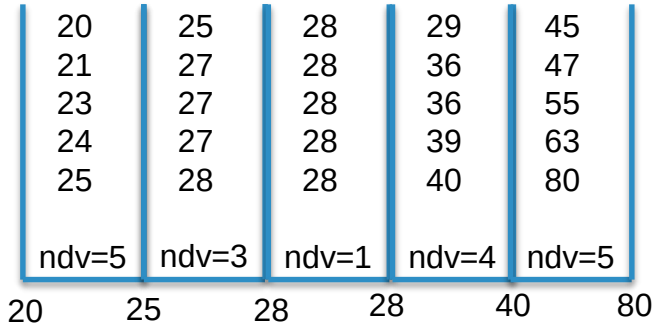


- Estimate row count for predicate “age > 40”. Correct answer is 5.
- Without histogram, estimate:
  25 * (80 – 40)/(80 – 20) = 16.7
- With histogram, estimate:
  1.0 * // only 5th bucket
  5 // 5 records per bucket
  = 5

Histogram for Filter Example 2

Age distribution of a restaurant:

Total row count: 25
age min = 20
age max = 80
age ndv = 17



- Estimate row count for predicate “age = 28”. Correct answer is 6.
- Without histogram, estimate:
  25 * 1 / 17 = 1.47
- With histogram, estimate:
  (1/3 // prorate the 2nd bucket
  + 1.0 // for 3rd bucket
) * 5 // 5 records per bucket
  = 6.67

Join Cardinality without Histogram

- *Inner-Join:* The number of rows of "A join B on A.k1 = B.k1" is estimated as:

  $num(A \bowtie B) = num(A) * num(B) / max(distinct(A.k1), distinct(B.k1))$,

  - where num(A) is the number of records in table A, distinct is the number of distinct values of that column.
  - The underlying assumption for this formula is that each value of the smaller domain is included in the larger domain.
  - *Assuming uniform distribution for entire range of both join columns.*

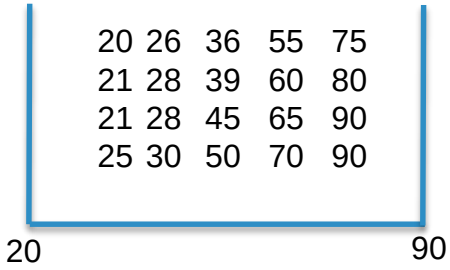
- We similarly estimate cardinalities for Left-Outer Join, Right-Outer Join and Full-Outer Join

Join Cardinality without Histogram

Table A, join column k1

Total row count: 25
k1 min = 20
k1 max = 80
k1 ndv = 17

Table B, join column k1



Total row count: 20
k1 min = 20
k1 max = 90
k1 ndv = 17

Without histogram, join cardinality estimate is 25 * 20 / 17 = 29.4
The correct answer is 20.

Join Cardinality with Histogram

- The number of rows of “A join B on A.k1 = B.k1” is estimated as:

  $\text{num}(A \bowtie B) = \sum_{i,j} \text{num}(Ai) * \text{num}(B_j)$ / *max (ndv(A_i.k1), ndv(B_j.k1))*

  – where $\text{num}(A_i)$ is the number of records in bucket *i* of table A, ndv is the number of distinct values of that column in the corresponding bucket.

  – We compute the join cardinality bucket by bucket, and then add up the total count.

- If the buckets of two join tables do not align,

  – We split the bucket on the boundary values into more than 1 bucket.

  – In the split buckets, we prorate *ndv* and bucket height based on the boundary values of the newly split buckets by *assuming uniform distribution within a given bucket*.

Aligning Histogram Buckets for Join

- Form new buckets to align buckets properly

Table A, join column k1,
Histogram buckets

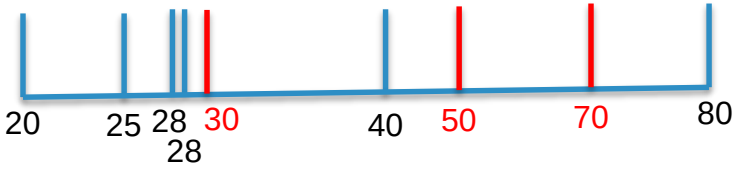
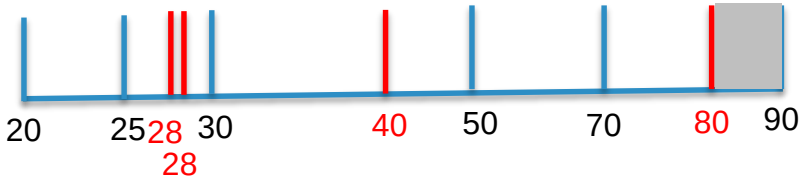


Table B, join column k1,
Histogram buckets



Original bucket boundary

Extra new bucket boundary
To form additional buckets

This bucket is excluded
In computation

Table A, join column k1,
Histogram buckets:
Total row count: 25
min = 20, max = 80
ndv = 17

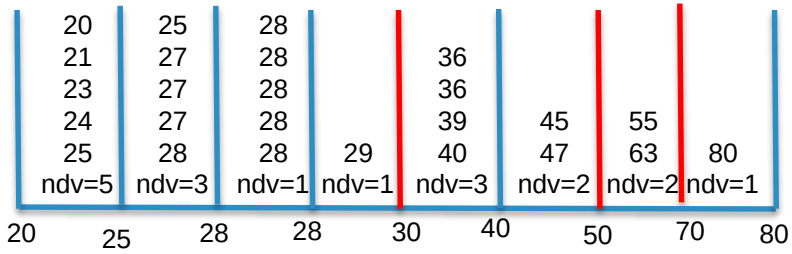
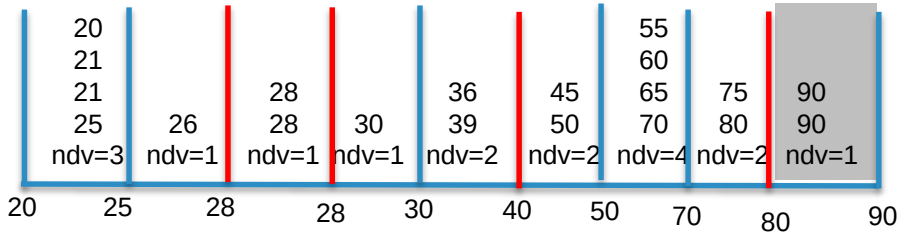


Table B, join column k1,
Histogram buckets:
Total row count: 20
min = 20, max = 90
ndv = 17

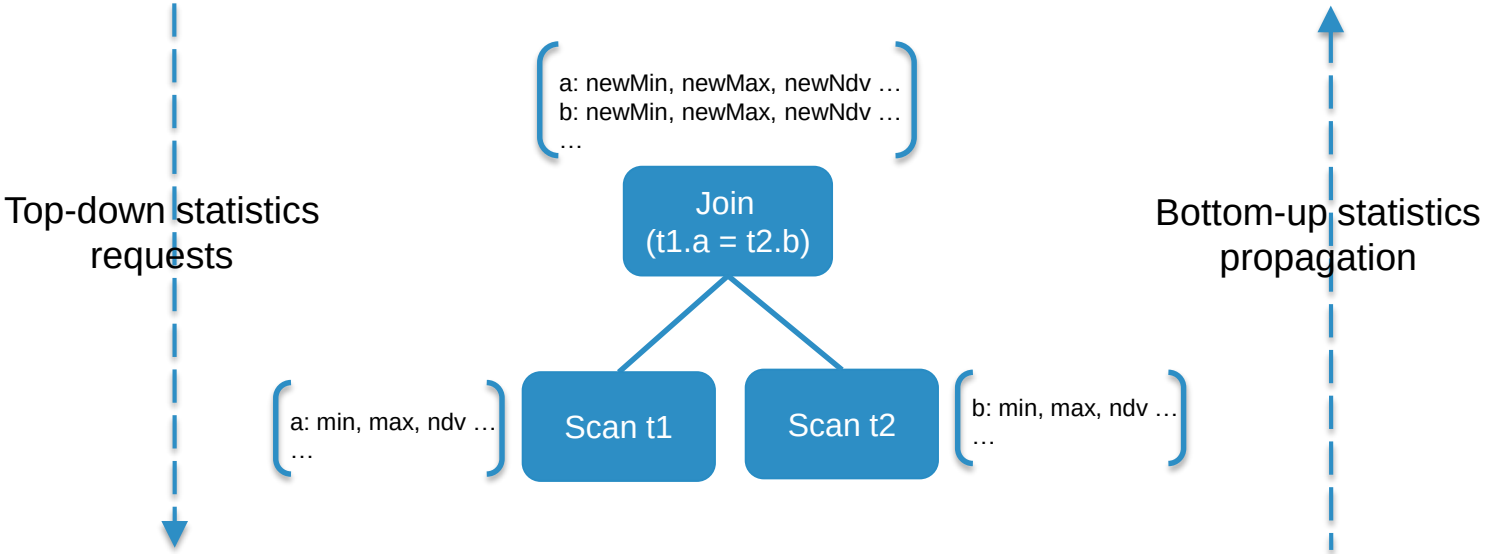


- With histogram, join cardinality estimate is 21.8 by computing the aligned bucket's cardinality one-by-one.
- Without histogram, join cardinality estimate is 29.4
- The correct answer is 20.

Other Operator Estimation

- Project: does not change row count
- Aggregate: consider uniqueness of group-by columns
- Limit, Sample, etc.

Statistics Propagation



Statistics inference

- Statistics collected:
  - Number of records for a table
  - Number of distinct values for a column
- Can make these inferences:
  - If the above two numbers are close, we can determine if a column is a unique key.
  - Can infer if it is a primary-key to foreign-key join.
  - Can detect if a star schema exists.
  - Can help determine the output size of group-by operator if multiple columns of same tables appear in group-by expression.

Configuration Parameters

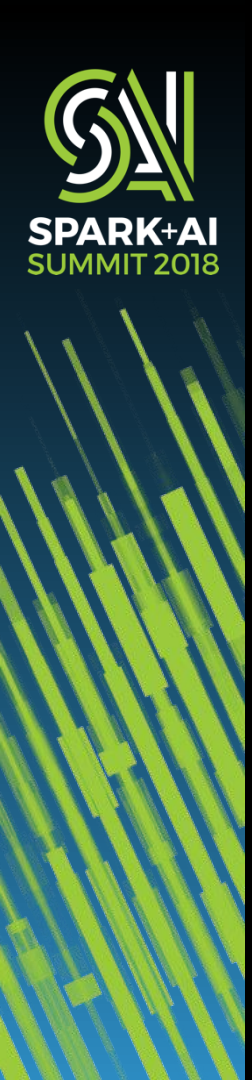
Configuration Parameters	Default Value	Suggested Value
spark.sql.cbo.enabled	False	True
spark.sql.cbo.joinReorder.enabled	False	True
spark.sql.cbo.joinReorder.dp.threshold	12	12
spark.sql.cbo.joinReorder.card.weight	0.7	0.7
spark.sql.statistics.size.autoUpdate.enabled	False	True
spark.sql.statistics.histogram.enabled	False	True
spark.sql.statistics.histogram.numBins	254	254
spark.sql.statistics.ndv.maxError	0.05	0.05
spark.sql.statistics.percentile.accuracy	10000	10000

Reference

- SPARK-16026: Cost-Based Optimizer Framework
  - https://issues.apache.org/jira/browse/SPARK-16026
  - It has 45 sub-tasks.
- SPARK-21975: Histogram support in cost-based optimizer
  - https://issues.apache.org/jira/browse/SPARK-21975
  - It has 10 sub-tasks.

Summary

- Cost Based Optimizer in Spark 2.2
- Statistics Collected
- Histogram Support in Spark 2.3
  - *Skewed data distributions are intrinsic in real world data.*
  - *Turn on histogram configuration parameter “spark.sql.statistics.histogram.enabled” to deal with skew.*



Q & A

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