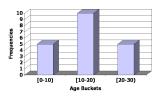
A Comparison of Three Algorithms for Building ST-Histograms

Julián Hernández, Rodrigo Ipince, José Muñiz

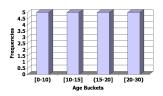
MIT

December 11, 2008

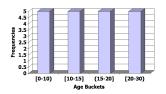
- One dimensional
- Independence assumption between fields in the same and different tables

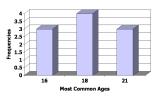


- One dimensional
- Independence assumption between fields in the same and different tables

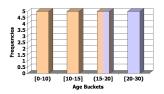


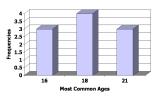
- One dimensional
- Independence assumption between fields in the same and different tables



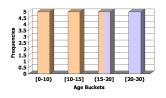


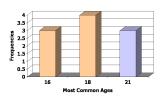
- One dimensional
- Independence assumption between fields in the same and different tables





- One dimensional
- Independence assumption between fields in the same and different tables



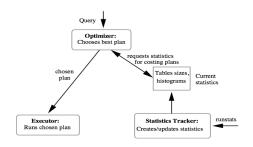


$$\sigma = \alpha \times \sigma_{hist} + \beta \times \sigma_{MCV}$$

Building histograms: Traditional cost-based optimization

Four components:

- Optimizer
- Executor
- Histogram
- Statistics gatherer



No connection between executor and histogram.

Some problems with traditional approach

Key assumptions

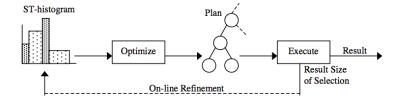
- Uniformity of attribute values
- Uniformity of queries
- Constant number of records per block
- Random placement or full page scan

Problems:

- Tradeoff between performance cost of statistics gatherer versus adaptability to change of conditions
- Tradeoff between number of pages read and adaptability to correlated data
- Postgres suggests turning off autovacuum for large tables and running end-of-day analysis.

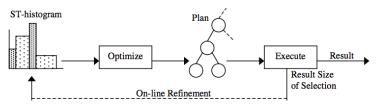
Self Tuning Histograms

Can we do something without needing to implement multidimensional histograms?



Self Tuning Histograms

Can we do something without needing to implement multidimensional histograms?



Interface

- Executor executes emit([a...b], val)
- Histogram builder provides int estimate([a...b])

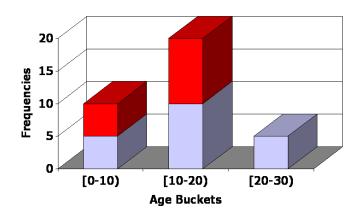


Self Tuning Histograms: Interface and Motivation

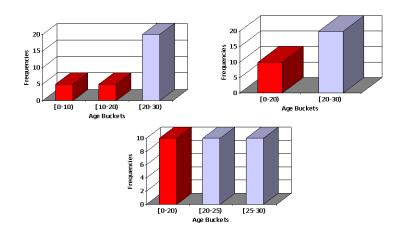
- How do we build the histogram without looking at data?
 - Update frequencies
 - Update buckets
- First idea: Uniform blame
 - Nothing known: assume uniform distribution
 - Update frequencies:
 On emit, calculate percentage error e, multiply all affected intervals by α × p × e, where p is frequency proportion.
 - Update buckets:
 Split buckets with large frequencies.
 Merge buckets with small frequencies.

Updating frequencies

Result from emit([0,19], 30)



Merge and split



Improvements and alternatives

- Occasionally renormalize data to fit to total number of tuples.
 Improves determination of error vs insertion
- Adjust blame proportional to range and frequency
- Split most frequently updated ranges

Experimental Setup

- Middle layer between PostgreSQL and end user
- Process:
 - Relay query to Postgres
 - Obtain query plan via EXPLAIN
 - Simulate query, using results for calling emit
 - Oral Calculate error rate in generated histograms

Results

- Fast to adapt
- Minimal insertion overhead (Small amount of tuples per query)
 - Ideal for large databases with constant insertions and varying ranges.

Caveats:

- Major optimizer misses due to independence assumptions, and not failures in row estimates.
- Not all cases lead to performance gains.
- No solution for LIKE queries.

