A Comparison of Five Probabilistic View-Size Estimation Techniques in OLAP

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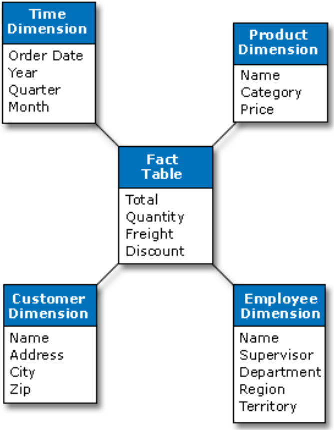
Online Analytical Processing (OLAP)



(Source: dwreview.com)

What is OLAP?

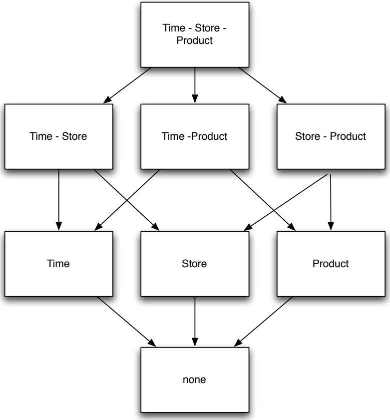
- multidimensional model, several (hierarchical) dimensions
- measures aggregated (SUM, MIN, MAX, AVERAGE,. . .)
- a set of standard operations: drill-down, roll-up, slice, dice
- answers expected in near constant time

The View-Size Materialization problem

Storing the result of a query (a view) is important

- You trade storage for (future) speed.
- Storage is cheap, faster CPUs are expensive.
- Materialized views can be used to compute other views faster.
- From `sales per (time,store)` it is faster to compute `sales per store`, than to go back to transactions!
- For aggressive aggregation (coarse views), materialized views are unbeatable!

The data cube



The Data Cube

- A d dimensional data cube is made of $2^d - 1$ cuboids.
- Typical values for d range from 10 to 20.
- You also have dimensional hierarchies to handle.
- It would take too long to materialize them all **even** if you had enough storage and the data never changed.

View Selection Heuristics

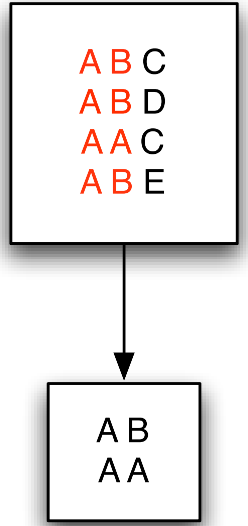
The Data Cube

- given a data warehouse, heuristics can be used to determine which views to aggregate (the problem itself is typically NP-hard);
- many heuristics assume reliable and accurate estimates of the view sizes;
- even if the choice is done by hand, the analyst needs guidance;
- finding optimally fast, accurate and reliable estimates is still an open problem;
- there has been little experimental work to compare the alternatives!

What is view-size estimation?

Algorithmically?

- Views are typically result of `GROUP BY`s;
- The size of the view is the number of distinct elements in the `GROUP BY`;
- thus, in a simplistic sense, view-size estimation is equivalent to **finding the number of distinct elements in a sequence, using little memory**.



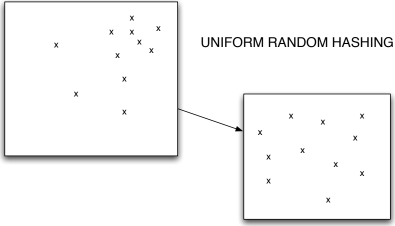
Summary of the methods under review

Sampling Method

- Sampling and Multifractal models [Faloutsos et al., 1996]

Probabilistic Methods

- Adaptive counting [Cai et al., 2005];
- LogLog probabilistic counting [Durand and Flajolet, 2003];
- Gibbons-Tirthapura [Gibbons and Tirthapura, 2001]
- Generalized counting [Bar-Yossef et al., 2002]



What is the big idea?

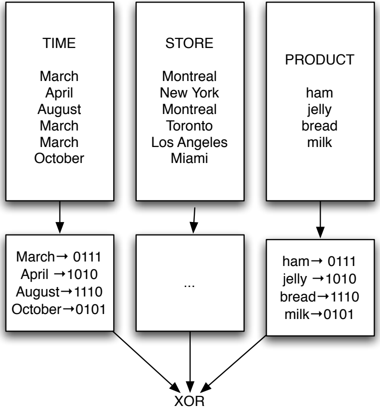
- It is difficult to work with the original data because it has unknown bias.
- Instead of learning the distribution, just hash every element, and work into hashed space.
- Suddenly the data distribution is known: it is uniform!

k-wise independent hashing

What is it?

- hash to $[0, 2^L)$
- uniform hashing: $P(h(x) = y) = 1/2^L$
- pairwise independent hashing: $P(h(x) = y \wedge h(x') = y') = 1/4^L$.
- 3-wise independent hashing: $P(h(x) = y \wedge h(x') = y' \wedge h(x'') = y'') = 1/8^L$
- pairwise independence implies uniformity.

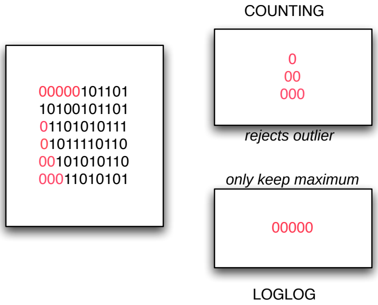
Multidimensional Hashing



How to hash facts?

- Use a random number generator, and generate independent hashed values for each dimensions.
- XOR the hashed values.
- If you have k dimensions, get k-wise independent hashing.
- Scales well if you store the dimension-wise hash functions.

Stochastic (LogLog) Probabilistic Counting



The counting trick

- Hash to $[0, 2^L)$
- Keep track of number of leading zeroes t, estimate $\approx 2^t$
- LogLog variant only seek max leading zero (outliers)
- Stochastic: hash x randomly to one of M intervals $[0, 2^L)$, keep track of M lesser values, do some sort of geometric average of the M estimates

Adaptive counting

[Cai et al., 2005]

- Probablistic counting schemes require the view size to be very large.
- A small view compared to the available memory (M), will leave several of the M counters unused.
- When more than 5% of the counters are unused we return a linear counting estimate [Whang et al., 1990] instead of the LogLog estimate.

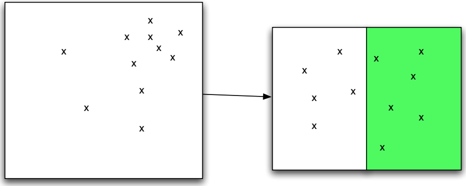
Generalized counting

[Bar-Yossef et al., 2002]

- The tuples and hashed values are stored in an ordered set $\mathcal{M}$.
- For small M with respect to the view size, most tuples are never inserted since their hashed value is larger than the smallest M hashed values.
- Estimate is $2^L \mathrm{size}(\mathcal{M})/\max(\mathcal{M})$ where $\max(\mathcal{M})$ returns an element with the largest hashed value.

[Gibbons and Tirthapura, 2001]

- Keep track of all items hashed to $1/2^t$ of the hashing space
- Estimate is $2^t m$ where m is number of items tracked.



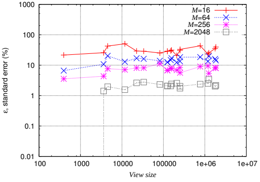
Experimental results

- Benchmark the accuracy and speed for the five algorithms over:
  - synthetic data set (derived by DBGEN)
  - real data set (US Census 1990)

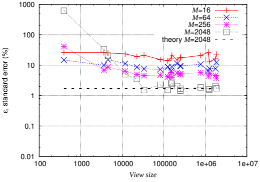
	US Census 1990	**DBGEN**
# of facts	2 458 285	13 977 981
# of views	20	8
# of attributes	69	16
Data size	360 MiB	1.5 GiB

Table: Characteristic of data sets.

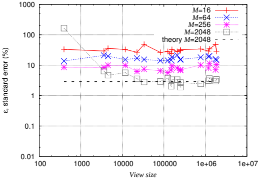
Experimental results: small memory budgets



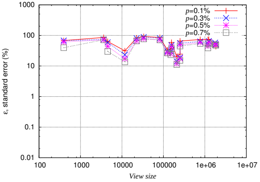
(a) Gibbons-Tirthapura



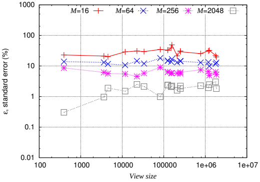
(b) Probabilistic Counting



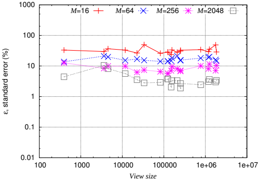
(c) LogLog



(d) Multifractal



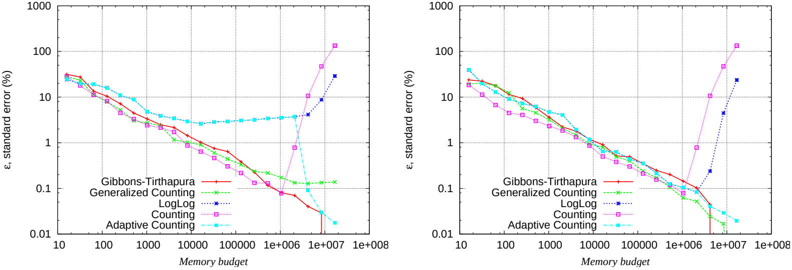
(e) Generalized Counting



(f) Adaptive Counting

Figure: Standard error of estimation as a function of exact view size for increasing values of M (US Census 1990).

Experimental results: large memory budgets



(a) L=32 (b) L=64

Figure: Standard error of estimation for a given view (four dimensions and 1.18×10^7 distinct tuples) as a function of memory budgets M (synthetic data set).

Experimental results: speed

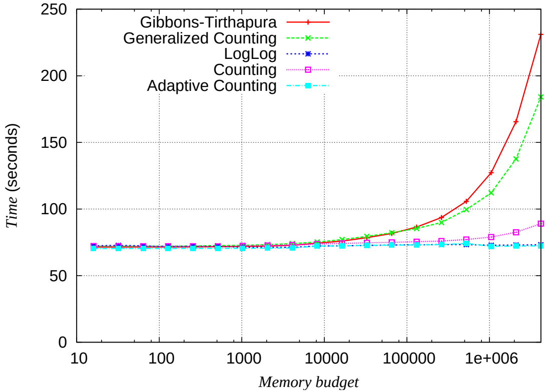


Figure: Estimation time for a given view (four dimensions and 1.18×10^7 distinct tuples) as a function of memory budgets M (synthetic data set).

Conclusion

Main Points

- Sampling can be quite unreliable, but very fast.
- Processing time of probabilistic methods is dominated by hashing.
- For small view-sizes relative to the available memory budget, the accuracy of Probablistic Counting and LogLog can be very low.
- However, as you increase the memory budget, Gibbons-Tirthapura, Generalized Counting and Adaptive counting systematically improve, but they also become slower.
- Adaptive Counting remains constantly fast.

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