Survey of Approximate Query Processing Techniques

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Outline

- Introduction
- Non-Sampling Based Methods
  - Histograms
  - Wavelets
- Sampling Based Methods
  - Uniform Random Sampling
  - Biased/Non-Uniform Random Sampling
  - Distinct Value Estimation
- Conclusions

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Introduction

- Approximate Query Processing (AQP) in Relational Databases
- Focus on answering *Aggregate* queries
  - Aggregation queries often arise in OLAP and Data-Mining for large Databases

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Motivation for AQP

- Answering complex aggregation queries over large data warehouses **exactly** can be time consuming
- If **approximate** answers are acceptable, can we answer these queries much faster?
  - Along with approximate answers, an **estimate of the error** in the approximation is important
    - Confidence Intervals

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Examples of Aggregate Queries

- SPJ queries with
  - aggregation operators such as
    - Count, Sum, Count(Distinct), Avg
  - Group By

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Example

SELECT State, COUNT (*) as ItemCount
FROM SalesData
WHERE ProductID = 5437
GROUP BY State
ORDER BY ItemCount **DESC**

Exact Answer

State	ItemCount
WA	3425
CA	1065
WY	432
TN	235
KY	56

Approximate Answer

State	EstItemCount	EstError
WA	3400	50
CA	1150	100
WY	400	50

Estimates may have errors
Small groups may be missing

Quantifying Error

- Consider a simple aggregation query
  - Answer is a single number
  - Relative error of query Q

$$Error(Q) = \left| \frac{ExactAnswer - ApproxAnswer}{ExactAnswer} \right|$$

- For GROUP-BY query
  - Error of query = average error per group

Basic Approach

- Synopsis of data
  - Computed online
  - Pre-computed
- Rewrite query to run against synopsis
- Give error estimate

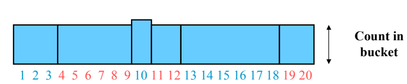
Different Synopses

- Histograms, Wavelets, Samples
- Comparing different methods
  - Changes necessary to the SQL engine
  - Accuracy and confidence intervals
  - Resilience to high dimensional data
  - Maintenance over updates
    - not the focus of this talk

Histograms

- Partition attribute value(s) domain into a set of buckets
- Issues:
  - How to partition
  - What to store for each bucket
  - How to estimate an answer using the histogram
- Long history of use for selectivity estimation within a query optimizer

1-D Histograms: Equi-Depth



- Goal: Equal number of rows per bucket
  - B buckets in all

Equi-Depth Histogram Construction

- First sort, then taking B-1 equally-spaced splits
- Faster construction: Sample, take equally-spaced splits in sample
  - Nearly equal buckets
- Can also use one-pass quantile algorithms

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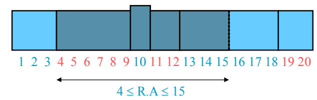
Answering Queries



- select count(*) from R where 4 <= R.A <= 15
- approximate answer: F * |R|/B, where
  - F = number of buckets, including fractions, that overlap the range
  - error guarantee: ± 2 * |R|/B

answer: 3.5 * |R|/6 ± 0.5 * |R|/6

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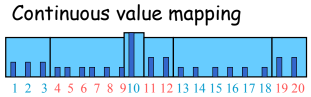
Answering Queries

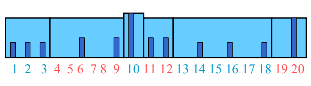
(Implicitly) map the histogram back to an approximate relation, apply the query to the approximate relation

Continuous value mapping



Count spread evenly among bucket values

Uniform spread mapping



Need number of distinct in each bucket

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1-D Histograms: V-Optimal

- Select buckets to minimize frequency variance within buckets [Ioannidis, Poosala 95]
- O(B*N^2) time dynamic programming algorithm [Jagadish et al, 98]

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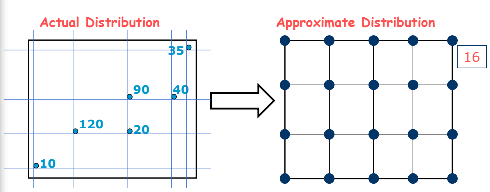
Multi-Dimensional Histograms

- Use small number of multi-dimensional buckets to *directly* approximate the joint data distribution
- Uniform spread & frequency approximation within buckets



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Multi-Dimensional Histogram Construction

- Construction problem is much harder even for two dimensions [Muthukrishnan et al 99]
- *Multi-dimensional equi-depth histograms* [Muralikrishna, DeWitt 88]
  - Fix an ordering of the dimensions A1, A2, . . ., Ak
  - Let *a* = kth root of desired no. of buckets
  - initialize B = data distribution
  - For i = 1, . . ., k
    - Split each bucket in B into *a* equi-depth partitions along Ai
  - return resulting buckets
- Problems: limited set of bucketizations; fixed *a* and fixed dimension ordering can result in poor partitioning

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Multi-Dimensional Histogram Construction

- *MHIST histograms* [Poosala, Ioannidis 97]
  - At each step
    - Choose the bucket b in B containing the attribute Ai whose marginal *is the most in need of partitioning*
    - Split b along Ai into p (e.g., p=2) buckets
- *MHIST* chooses bucket/dimension to split based on its *criticality, thus* allows for much larger class of bucketizations (*hierarchical* space partitioning)
- Experimental results verify superiority over equi-depth

Other Multi-Dimensional histograms

- GenHist [Gunopulos et al 90]
  - Allows for overlapping buckets
- STHoles [Bruno et al 01]
  - Workload based
  - Considers nested buckets

Histograms: Summary

- 1-Dimensional histograms very useful in selectivity estimation
- Multi-dimensional histograms suffer from the curse of dimensionality
  - Model of the joint distribution becomes inaccurate as dimensions increase
- Histograms as AQP systems require substantial changes to the QP engine

Wavelets

- Mathematical tool for hierarchical decomposition of functions/signals
- Popular in the speech/signal/image processing domains

One-Dimensional Haar Wavelets

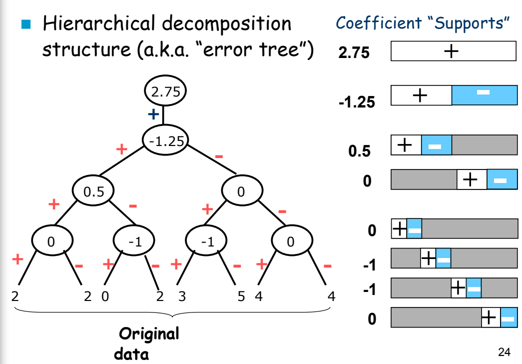
- Simplest wavelet basis, easy to understand and implement

Resolution	Averages	Detail Coefficients
3	[2, 2, 0, 2, 3, 5, 4, 4]	----
2	[2, 1, 4, 4]	[0, -1, -1, 0]
1	[1.5, 4]	[0.5, 0]
0	[2.75]	[-1.25]

Haar wavelet decomposition: [2.75, -1.25, 0.5, 0, 0, -1, -1, 0]

Haar Wavelet Coefficients

- Hierarchical decomposition structure (a.k.a. "error tree")



Wavelet-based Synopsis

- Key idea: use a compact subset of wavelet coefficients [Matias et al 98]
- Steps
  - Compute wavelet transform of ***cumulative data distribution***
  - Coefficient ***thresholding*** : only b<<|C| coefficients can be kept
    - Take largest coefficients in ***absolute normalized value***
      - Divide coefficients at resolution j by $\sqrt{2^j}$
      - *Optimal* in overall Mean Squared (L2) Error
    - Greedy heuristic methods
      - Retain coefficients leading to large error reduction

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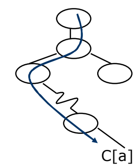
Estimating Selectivity

- Range Queries: sel(a<= X<= b) = *C'*[b] - *C'*[a-1]
  - *C'* is the (approximate) "reconstructed" cumulative distribution
  - Time: O(min{b, logN}), where b = size of wavelet synopsis N= size of domain



- At most logN+1 coefficients are needed to reconstruct any *C* value

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Multi-Dimensional Haar Wavelets

- Basic pairwise averaging and differencing ideas carry over to multiple data dimensions
- Two basic methodologies -- no clear "winner"
  - *Standard* Haar decomposition [Stollnitz et al 96]
  - *Non-standard* Haar decomposition [Chakrabarti et al 00]

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Wavelets: Summary

- Suitable for multi-resolution data analysis
- Experimentally seem to perform better than histograms
- Multi-dimensional wavelets need to be studied more
- As with histograms, wavelets as AQP systems require substantial changes to the QP engine

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Sampling

- Basic Idea: A small random sample S of the data R often well-represents the entire data
  - For a fast approx answer, apply the query to S & "scale" the result
  - Use a small random sample of rows of the original database table to answer queries approximately

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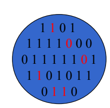
Sampling: Basics

- E.g., S is a 20% sample of R



Original Query:
Select count(*) from R where R.a = 0
Count = 10

Rewritten Query:
Select 5 * count(*) from S where S.a = 0
Est. count = 5*2 = 10

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Non-Uniform/Biased Sampling

- Different data sampled at different rates
  - E.g., outliers sampled at a higher rate for better accuracy
- Each tuple j is selected for the sample S with some probability Pj
  - If selected, it is added to S along with its *scale factor* = 1/Pj

R.a	10	10	10	50	50
Pj	⅓	⅓	⅓	½	½
Sf	---	3	---	---	2

Original Query:
Select sum(R.a) from R
from S
where R.b < 5
Sum(R.a) = 130

Rewritten Query:
Select sum(S.a * S.sf)

where S.b < 5
Sum(S.a*S.sf) = 10*3 + 50*2 = 130

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Error Estimation

- Unbiased estimation for *count, sum, avg* queries
  - I.e., the expected value of the answer is the actual answer
- Error in the answer depends on
  - Sample size
  - Variance in the data
- Error can be estimated with high probability
  - Leverage extensive literature on confidence intervals for sampling
  - Actual answer is within the interval [a,b] with a given probability
    - E.g., 54,000 ± 600 with probability ≥ 90

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Error Estimation

- Let R = {y_1, y_2, …, y_n} be a set of numbers. Let sum(R) = Y
- Let S be an uniform sample of size k from R. Let sum(S) = y

$$Expected\ \ Error\ = Expected\left[\left(\frac{\left(\frac{n}{k}\right)y - Y}{Y}\right)^2\right] \approx \frac{n^2 Var}{Y^2 k}$$

- Even confidence intervals can be estimated using *Central Limit Theorem*
  - E.g., 54,000 ± 600 with probability ≥ 95%

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Online vs. Pre-computed Sampling

- Online:
  - Continuous refinement of answers (online aggregation)
  - Online sampling is expensive in practice, unless data is randomly clustered on disk
    - Online Query Processing tutorial [Haas, Hellerstein 01]
- Pre-computed:
  - Seeing entire data is very helpful (provably & in practice)
    - (But must construct synopses for a family of queries)
  - Often faster: pre-computed synopses can reside in memory
  - Middleware: Can use with any DBMS, no special index

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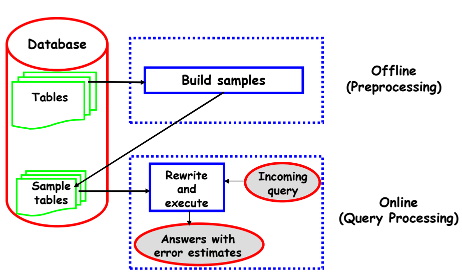
Precomputed Sampling Based Architecture for AQP



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Uniform Random Sampling

- Pre-computation using *Bernoulli Sampling*
  - Expected sample size is f*N, where f is the sampling fraction
  - Add each tuple in R to sample S with probability f
  - Low overheads, no random data access
- Pre-Computation using *Reservoir Sampling* [Vitter 85]
  - Maintains a sample S of fixed-size f*N
  - Add each new item to S with appropriate probability
  - If overfull, evict a random item from S
  - Instead of flipping a coin for each item, determine the number of items to skip before the next to be added to S

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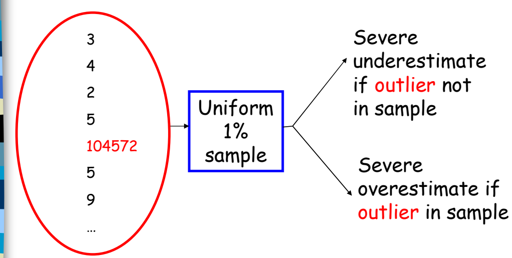
Advantages/Disadvantages of Uniform Random Sampling

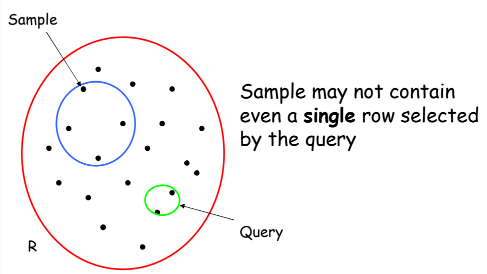
Advantages
- Simplicity
- Efficient preprocessing

Disadvantages
- Large errors due to
  - Large data variance
  - Low selectivity queries

Large Data Variance



Low Selectivity

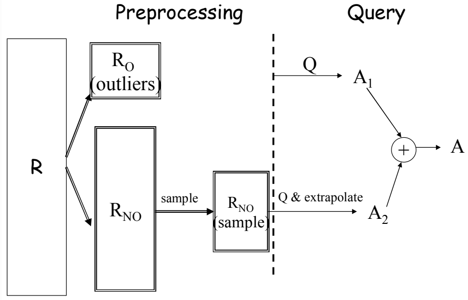


Sample may not contain even a **single** row selected by the query

Biased Sampling Techniques: Outlier Indexing

- Basic Idea [Chaudhuri et al 01]
  - Separate the outliers from the rest of the data into an *outlier index*
  - Keep a *uniform random sample* of the data
  - Use *outlier index* as well as *random sample* to answer queries

Outlier Indexing Scheme



Selection of Outlier Index.

- Select outliers (subject to space restriction) such that the rest of the relation has least variance.

$\boxed{1},\ \boxed{4},\ 6,\ \boxed{7},\ \boxed{10}$

Theorem: Given a sorted set of values the set that reduces the variation looks like:

$\boxed{\ldots, v_k}, v_{k+1}, v_{k+2}, \ldots, v_{m-1}, v_m, \boxed{v_{m+1}, \ldots}$

Algorithm Outlier Index

4, 6, 1, 10, 7

↓ sort

1, 4, 6, 7, 10

↓

1, 4, 6, 7, 10

Outliers = {1,10}

Var = 1.55

Var = 2.88 | Var = 1.55 | Var = 4.22

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Algorithm Implementation

- Requires a single pass over the relation.
- Main memory required = 2 * size of outlier index.

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Discussion

- How to allocate storage between samples and outlier index?
- Outlier index useful for *Sum, Avg*
  - Not useful for *Count, Max, Min*
- *Global Outliers* versus *Local Outliers*

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Biased Sampling Techniques: ICICLES [Ganti et al 00]

- Let W = {q1, q2, . . .} be a query workload
- Biased sampling scheme exploits data locality
  - more focus (i.e., #sample points) in frequently-queried regions
- Biased sample incrementally maintained and adapts ("self-tune") to changing workload

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Drawback with Static Uniform Random Samples

- In practice, queries exhibit locality
- Consequence: sample wastes precious real estate
- Example
  - Consider the relation recording sales in all Walmart outlets across United States
  - An analyst based in Madison may only be interested in sales in and around Wisconsin
  - In such cases, uniformly sampling the relation wastes space

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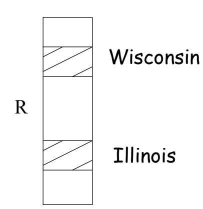
Locality in Query Workload

Workload W: $Q_1,\ldots,Q_n$

W exhibits locality if, say, Wisconsin and Illinois tuples are accessed more often



A query Q follows W if tuples required to answer Q are accessed *more frequently* by queries in W

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Problem

- Given
  - Relation R
  - Workload W: $Q_1,\dots,Q_n$
  - A fixed amount of space
- Goal: Maintain a "*sample $S_W(R)$ of R tuned w.r.t. W*" to improve accuracy for queries following W

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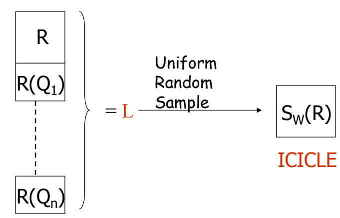
ICICLES

- R(Q): set of tuples in R *required* to answer Q
- Icicle $S_W(R)$: Random sample of $R \cup^{+} R(Q_1) \cup^{+} \dots \cup^{+} R(Q_n)$
  - Tuples required often are *more likely* to be in $S_W(R)$



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Maintaining Icicles

- Current workload W: $Q_1,\dots,Q_n$
- L: $R \cup^{+} R(Q_1) \cup^{+} \dots \cup^{+} R(Q_n)$
- Current icicle $S_W(R)$: random sample of L
- New query: Q
- Update $S_W(R)$ to be the sample of $L \cup^{+} R(Q)$
  - Reservoir sampling technique to update
- Note: L is not materialized

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Restricting the Workload

- Maintaining icicles requires queries to be answered exactly!
- Which queries to include in the workload?
  - Tradeoff between precision versus overhead
- Restrict the workload to such queries
  - Avoids extra overhead
  - Represents the most relevant set of queries

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ICICLES: Discussion

- Quality Guarantee : The number of tuples in $S_W(R)$ satisfying a query Q is higher (than a static sample) if Q follows W

  Theorem: If a query Avg(Q) follows the workload W, then the icicle $S_W(R)$ is expected to yield a better estimate for Avg(Q) than a static sample

- Queries with different counts have different errors
- Does not claim optimality
- Does not handle data variance

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Biased Sampling Techniques: Congressorial Sampling

- Approximating Group By queries: [Acharya et al 00]
  - Decision support queries routinely segment data into groups & then aggregate the information within each group
    - Each table has a set of "grouping columns": queries can group by any subset of these columns
- Goal: Maximize the accuracy for all groups (large or small) in each group-by query

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Congressorial Sampling

- E.g., census DB with state (s), gender(g), and income (i)
  - Q: Avg(i) group-by s : seek good accuracy for all 50 states
  - Q: Avg(i) group-by s,g : seek good accuracy for all 100 groups
- Congress Algorithm: Considers a "workload" of all subsets of grouping columns, and attempts to design a sample such that all groups get equal importance

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Congress: Discussion

- Basically uses a form of *stratified sampling*
- Allocation of samples not necessarily optimal
- Does not consider data variance

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Biased Sampling Techniques: STRAT

- Generalization of *Outlier Indexing*, *ICICLES*, and *Congressorial Sampling*
- [Chaudhuri, Das, Narasayya 01]
- Based on *stratified sampling*

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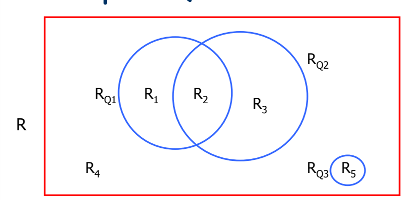
Balancing Errors Across Multiple Queries



- Pay attention to:
  - "Hot spots" e.g., R_2
  - Small regions e.g., R_5

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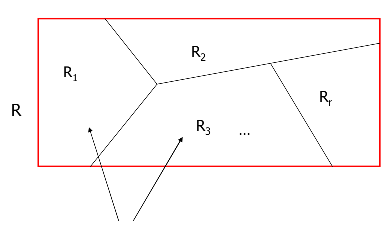
STRAT: an algorithm based on **stratified sampling**



Different strata sampled at different rates

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Intuition

- Stratification reduces data variance
- Allows "hot spots" in relation to be given more importance
  - **Workload** provides necessary information
  - Don't take workload literally

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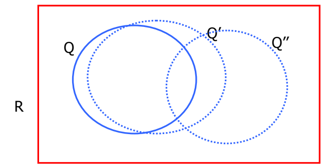
Lifting Workload to a Query Distribution

- Motivation – Resilience to variations in workload
- Let **W** = $\{Q_1, \ldots, Q_q\}$ be the given workload
- We assume that **W** is a sample from a *query distribution* p_W
- Lifting => deriving p_W from **W**

Modeling Query Distribution

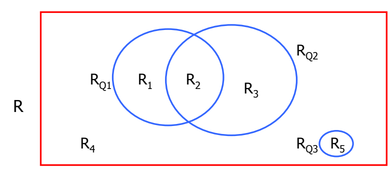


- Probability of Q' > Probability of Q''
- prob(Q|W) = parametric function of Q's overlap with queries in W
  - Similar to *kernel density estimation* (queries in W = "sample points")

Steps in STRAT

- **Stratification**
  - R is partitioned into strata: $\{R_1, \ldots, R_r\}$
- **Allocation**
  - Total of k samples
  - Stratum R_j contributes k_j samples such that error for lifted workload is minimized
  - $k_1 + \ldots k_r = k$

Stratification Step



- $R_1, \ldots R_5$ are called **fundamental regions**

Allocation Step

- Assume r unknowns: $k_1, \ldots, k_r$
- Express error for lifted workload in terms of unknowns
- For e.g., for Mean Squared Error, MSE($p_{\{Q\}}$):

$$\frac{\sum_{R_j \subseteq R_Q} \frac{n_j^2}{k_j}\delta(1-\delta) + \sum_{Rj \subseteq R \setminus R_Q} \frac{n_j^2}{k_j}\gamma(1-\gamma)}{\left(\sum_{R_j \subseteq R_Q} \delta n_j + \sum_{R_j \subseteq R \setminus R_Q} \gamma n_j\right)^2}$$

- Minimize MSE(p_W) subject to $k_1+k_2+\ldots+k_r = k$

$$MSE(p_{\{Q\}}) \approx \frac{\sum_{R_j \subseteq R_Q} \frac{n_j^2}{k_j}\delta(1-\delta) + \sum_{Rj \subseteq R \setminus R_Q} \frac{n_j^2}{k_j}\gamma(1-\gamma)}{\left(\sum_{R_j \subseteq R_Q} \delta n_j + \sum_{R_j \subseteq R \setminus R_Q} \gamma n_j\right)^2}$$

I.e.

$$MSE(p_{\{Q\}}) \approx \frac{\alpha_1}{k_1} + \frac{\alpha_2}{k_2} \ldots + \frac{\alpha_r}{k_r}$$

I.e.

$$MSE(p_w) \approx \frac{\beta_1}{k_1} + \frac{\beta_2}{k_2} \ldots + \frac{\beta_r}{k_r}$$

Minimizing MSE(p_W)

- Minimize MSE(p_W) subject to $k_1+k_2+\ldots k_r = k$
- Using calculus

$$k_j = k\left(\frac{\sqrt{\beta_j}}{\sum\sqrt{\beta_j}}\right)$$

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STRAT: Summary

- Formal framework
  - Quantify errors for lifted workload
  - Frame it as an *optimization* problem
- Principled, pragmatic solution
  - Provide error estimates
- Unifies key ideas from past work
  - Weighted sampling, outlier indexing, congressional sampling
- *Lifting* workload to query distributions
  - Motivation: resilience to variations in workload

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Dynamic Sample Selection

- Basic Idea [Babcock, Chaudhuri, Das 03]
  - Optimal bias differs from query to query
  - Past work: carefully select biased sample to give good answers for many queries
  - Instead, pre-compute *many* samples, and only use *appropriate* samples at run time

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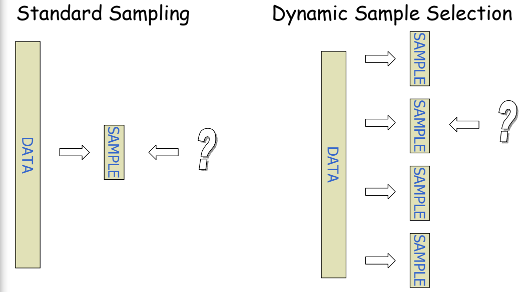
Dynamic Sample Selection

Standard Sampling

Dynamic Sample Selection



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Dynamic Sample Selection

- Improved accuracy, no change to query time
  - Query time is the scarce resource
  - OK to use extra pre-processing, disk space

How to pick a good set of samples?

- Construct many differently-biased samples
- For each query, use the best sample and ignore the others

Given a query, what's the best sample?

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Small vs. Large Groups

- In a group-by query, small groups are difficult to approximate
- ***Small Group Sampling***
  - A specific example of dynamic sample selection for handling group by queries

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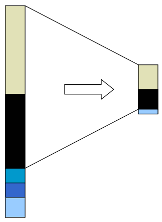
Small Group Sampling

Main idea: Treat small and large groups differently



Large Groups: Use uniform random sample

- Well-represented in sample
- Good quality of approximation

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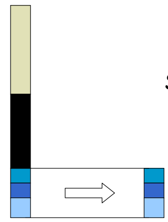
Small Group Sampling

Main idea: Treat small and large groups differently



Small Groups: Use Original Data

- Contain few records, by definition
- Thus can be scanned very quickly

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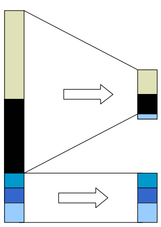
Small Group Sampling

Main idea: Treat small and large groups differently



- Small groups are query-dependent
  - Depend on grouping attributes
  - Depend on selection predicates
- How do we know which rows to scan to find the small groups?

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Finding the Small Groups

- Heuristic idea:
  - Most small groups in most queries have a rare value for at least one grouping attribute
- Small group in this query → rare value in entire DB
  - Not always true (snowblower sales in California)
- Summary of Small Group Sampling:
  - Identify rare values during pre-processing
  - Store rows with rare values in a different (small) table for each attribute: the small groups tables
  - At query time, scan small groups table for each grouping attribute

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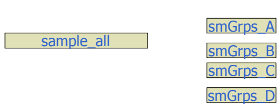
Pre-Processing Steps

- Create a table sample_all containing a uniform random sample of all data
- For each attribute A in the schema:
  - Identify rare values for attribute A
  - Create a table smGrps_A containing all records with rare A values
  - Size of smGrps_A table limited by threshold



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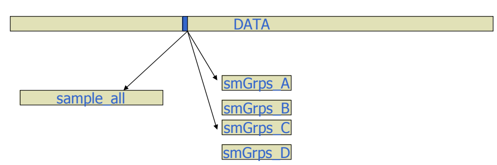
Pre-Processing Steps

- Augment rows in sample_all, smGrps_* with table membership information
  - Some rows may be added to multiple tables
  - One extra bitmask column: which small group tables contain this row?
  - Used to avoid double-counting during query processing



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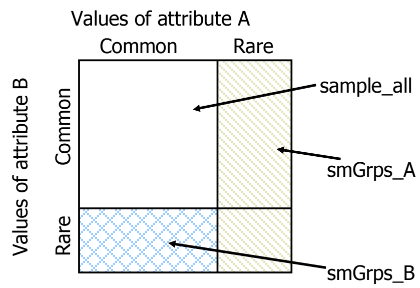
Answering Queries Using Small Group Sampling



Query Answering Example

- Run query on small group table for each grouping attribute
- Run scaled query on sample_all
- Combine answers

```
SELECT A,B,COUNT(*)
FROM FACT_TBL
WHERE C=10
GROUP BY A,B
```

```
SELECT A,B,COUNT(*) as cnt
FROM smGrps_A
WHERE C=10
GROUP BY A,B UNION ALL
SELECT A,B,COUNT(*) as cnt
FROM smGrps_B
WHERE C=10 AND bitmask & 1 = 0
GROUP BY A,B UNION ALL
SELECT A,B,100 * COUNT(*) as cnt
FROM sample_all
WHERE C=10  AND bitmask & 3 = 0
GROUP BY A,B
```


Dynamic Sample Selection: Summary

- Dynamic Sample Selection
  - Gain accuracy at the cost of disk space.
  - Non-uniform samples are good, but different ones are good for different queries.
  - Build lots of different non-uniform samples.
  - For each query, pick the best sample.
- Small Group Sampling
  - Treat large and small groups differently.
  - Uniform sampling works well for large groups.
  - Small groups are cheap to scan in their entirety.

Sampling over multi-table databases

- Sampling over the joins of tables is difficult [Chaudhuri et al 99]
  - Not possible to push the sampling operator below the join
- However, sampling over foreign-key joins is ok
  - In *star schemas*, F-K joins represent a "widening" of the fact table

Sampling over F-K Joins

- Two approaches
  - Only pre-sample the fact table, and at run time join with the dimension tables
  - Join synopses, where we pre-sample from materialized F-K joins

Join Synopses for F-K Joins

- Based on sampling from materialized foreign key joins [Acharya et al 99]
  - Typically < 10% added space required
  - Yet, can be used to get a uniform sample of ANY foreign key join
  - Plus, fast to incrementally maintain

Distinct Value Estimation

- Example of distinct value query

```
select count(distinct target-attr)
from T
where P
```

- Uniform Sampling-based approaches
  - Collect and store uniform sample. At query time, apply predicate to sample. Estimate based on a function of the distribution. **Extensive** literature.

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Distinct Value Estimation

- Pessimistic lower bound [Chaudhuri et al 00]

For any $p > e^{-r}$ there exists a relation such that with probability at least p,

$$error(d') > \sqrt{\left(\frac{n \ln \frac{1}{p}}{r}\right)}$$

I.e., any estimator must examine (sample) almost the entire table to guarantee the estimate is within a factor of 10 with probability > 1/2!

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"Proof" of Lower Bound

- Consider two distributions, one with all identical values, and another with x+1 distinct values, of which x are singleton and the x+1st occurs n-x times

- A small sample will miss the singleton values with high probability, and hence cannot distinguish between the two distributions

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Example of a DV Estimator

- Let r be the sample size from n tuples
- Let f_i $1 <= i <= r$ denote the number of distinct values that occur exactly i times. (Clearly $\sum f_i = r$)

- Estimator is

$$d' = \sqrt{\frac{n}{r}} f_1 + \sum_{2<=i<=r} f_i$$

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Sampling-Based Distinct Value Estimation: Summary

- Very difficult to solve using sampling
  - Often, some data distribution information needs to be used for good results
- One pass hash-based approaches more successful
  - AQP over data streams
  - Not topic of this tutorial

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Sampling for AQP: Summary

- Resilient to high dimensional data
- Easy to give probabilistic error guarantees
- Can be implemented with minimal changes to QP

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AQP topics not covered in this tutorial

- Other synopses models for joint distributions
  - Kernel Density models, Bayes Nets
- AQP over data streams
- Beyond aggregations
  - How to return approximations to set-valued results

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AQP Systems in the Industry

- AQP internally used by query optimizers for selectivity estimation
- AQP not yet externalized by major vendors
  - Although sampling operators are appearing in commercial DBMS
- Research prototypes, e.g.
  - AQP from MSR
  - AQUA from Bell Labs

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Conclusions

- Much theoretical advance in AQP algorithms
- Big gap between algorithms and actual systems
  - future work should focus on this aspect
- But, likely to catch on as data repositories are ever increasing

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