Approximate Query Processing: Taming the TeraBytes!

A Tutorial

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Outline

- Intro & Approximate Query Answering Overview
  - Synopses, System architecture, Commercial offerings
- One-Dimensional Synopses
  - Histograms, Samples, Wavelets
- Multi-Dimensional Synopses and Joins
  - Multi-D Histograms, Join synopses, Wavelets
- Set-Valued Queries
  - Using Histograms, Samples, Wavelets
- Discussion & Comparisons
- Advanced Techniques & Future Directions
  - Dependency-based, Workload-tuned, Streaming data
- Conclusions

Introduction & Motivation

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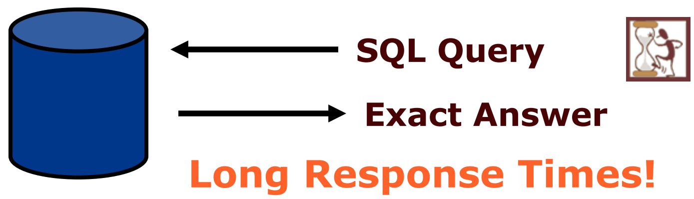
Decision Support Systems (DSS)



Long Response Times!

- Exact answers **NOT** always required
  - DSS applications usually *exploratory:* early feedback to help identify "interesting" regions
  - *Aggregate queries:* precision to "last decimal" not needed
    - e.g., "What percentage of the US sales are in NJ?" (display as bar graph)
  - *Preview* answers while waiting. *Trial* queries
  - Base data can be *remote or unavailable:* approximate processing using locally-cached *data synopses* is the only option

Fast Approximate Answers

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- Primarily for Aggregate queries
- Goal is to quickly report the leading digits of answers
  - In seconds instead of minutes or hours
  - Most useful if can provide error guarantees

E.g., Average salary
$59,000 +/- $500 (with 95% confidence) in 10 seconds
vs. $59,152.25 in 10 minutes

- Achieved by answering the query based on samples or other synopses of the data
- Speed-up obtained because synopses are orders of magnitude smaller than the original data

Approximate Query Answering

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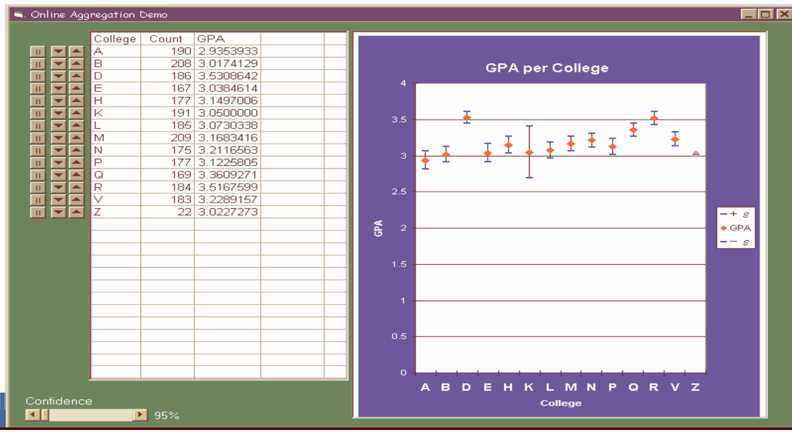
Basic Approach 1: Online Query Processing

- e.g., Control Project [HHW97, HH99, HAR00]
- Sampling at query time
- Answers continually improve, under user control



Approximate Query Answering

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Basic Approach 2: Precomputed Synopses

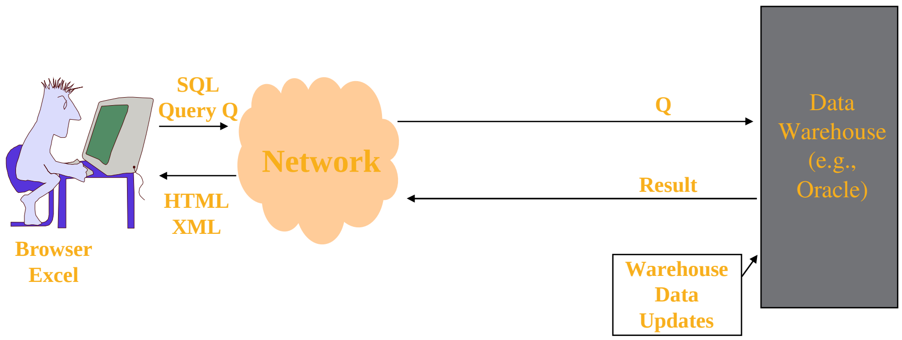
- Construct & store synopses prior to query time
- At query time, use synopses to answer the query

- Like estimation in query optimizers, but
  - reported to the user (need higher accuracy)
  - more general queries

- Need to maintain synopses up-to-date

- Most work in the area based on the precomputed approach
  - e.g., Sample Views [OR92, Olk93], Aqua Project [GMP97a, AGP99,etc]

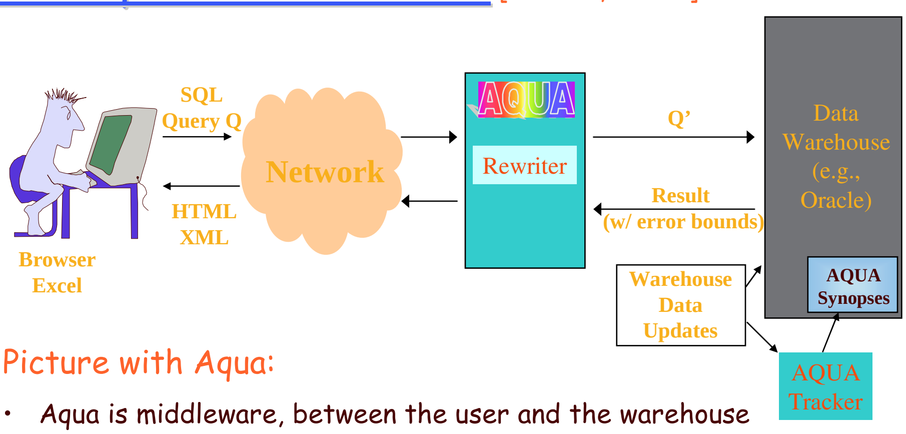
The Aqua Architecture



Picture without Aqua:

- User poses a query Q
- Data Warehouse executes Q and returns result
- Warehouse is periodically updated with new data

The Aqua Architecture [GMP97a, AGP99]



Picture with Aqua:

- Aqua is middleware, between the user and the warehouse
- Aqua Synopses are stored in the warehouse
- Aqua intercepts the user query and rewrites it to be a query Q' on the synopses. Data warehouse returns approximate answer

Online vs. Precomputed

Online:

+ Continuous refinement of answers (online aggregation)
+ User control: what to refine, when to stop
+ Seeing the query is very helpful for fast approximate results
+ No maintenance overheads
+ See [HH01] Online Query Processing tutorial for details

Precomputed:

+ Seeing entire data is very helpful (provably & in practice)
  (But must construct synopses for a family of queries)
+ Often faster: better access patterns,
  small synopses can reside in memory or cache
+ Middleware: Can use with any DBMS, no special index striding
+ Also effective for remote or streaming data

Commercial DBMS

- **Oracle, IBM Informix:** Sampling operator (online)
- **IBM DB2:** "IBM Almaden is working on a prototype version of DB2 that supports sampling. The user specifies a priori the amount of sampling to be done."
- **Microsoft SQL Server:** "New auto statistics extract statistics [e.g., histograms] using fast sampling, enabling the Query Optimizer to use the latest information." The index tuning wizard uses sampling to build statistics.
  - see [CN97, CMN98, CN98]

In summary, not much announced yet

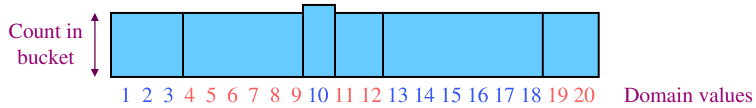
Outline

- Intro & Approximate Query Answering Overview
- One-Dimensional Synopses
  - **Histograms:** Equi-depth, Compressed, V-optimal, Incremental maintenance, Self-tuning
  - **Samples:** Basics, Sampling from DBs, Reservoir Sampling
  - **Wavelets:** 1-D Haar-wavelet histogram construction & maintenance
- Multi-Dimensional Synopses and Joins
- Set-Valued Queries
- Discussion & Comparisons
- Advanced Techniques & Future Directions
- Conclusions

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 [Koo80], [PSC84], etc.
- [PIH96] [Poo97] introduced a taxonomy, algorithms, etc.

1-D Histograms: Equi-Depth

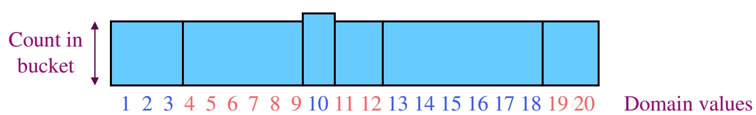


- Goal: Equal number of rows per bucket (B buckets in all)
- Can **construct** by first sorting then taking B-1 equally-spaced splits

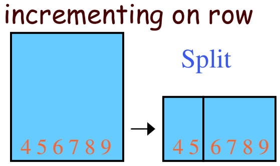
  1 2 2 3 4 7 8 9 10 10 10 10 11 11 12 12 14 16 16 18 19 20 20 20

- **Faster construction:** Sample & take equally-spaced splits in sample
  - Nearly equal buckets
  - Can also use one-pass quantile algorithms (e.g., [GK01])

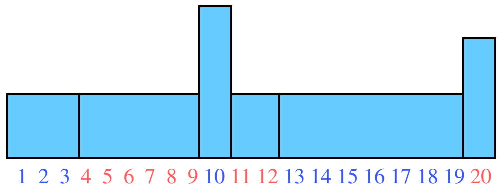
1-D Histograms: Equi-Depth



- Can **maintain** using one-pass algorithms (insertions only), or
- Use a backing sample [GMP97b]: Maintain a larger sample on disk in support of histogram maintenance
  - Keep histogram bucket counts up-to-date by incrementing on row insertion, decrementing on row deletion
  - Merge adjacent buckets with small counts
  - Split any bucket with a large count, using the sample to select a split value, i.e, take median of the sample points in bucket range
    - Keeps counts within a factor of 2; for more equal buckets, can recompute from the sample



1-D Histograms: Compressed



[PIH96]

- Create singleton buckets for largest values, equi-depth over the rest
- Improvement over equi-depth since get exact info on largest values, e.g., join estimation in DB2 compares largest values in the relations

Construction: Sorting + O(B log B) + one pass; can use sample

Maintenance: Split & Merge approach as with equi-depth, but must also decide when to create and remove singleton buckets [GMP97b]

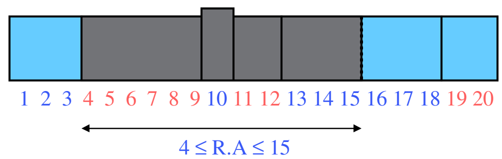
1-D Histograms: V-Optimal

[IP95] defined V-optimal & showed it minimizes the average selectivity estimation error for equality-joins & selections

- Idea: Select buckets to minimize frequency variance within buckets

- [JKM98] gave an O(B*N^2) time dynamic programming algorithm
  - F[k] = freq. of value k; AVGF[i:j] = avg freq for values i..j
  - SSE[i:j] = sum{k=i..j} (F[k]^2 – (j-i+1)*AVGF[i:j]^2)
  - For i=1..N, compute P[i] = sum{k=1..i} F[k] & Q[i] = sum{k=1..i} F[k]^2
  - Then can compute any SSE[i:j] in constant time
  - Let SSEP(i,k) = min SSE for F[1]..F[i] using k buckets
  - Then SSEP(i,k) = min{j=1..i-1} (SSEP(j,k-1) + SSE[j+1:i]), i.e., suffices to consider all possible left boundaries for kth bucket
  - Also gave faster approximation algorithms

Answering Queries: Equi-Depth



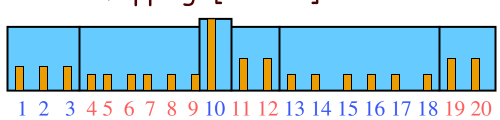
Answering queries:

- 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

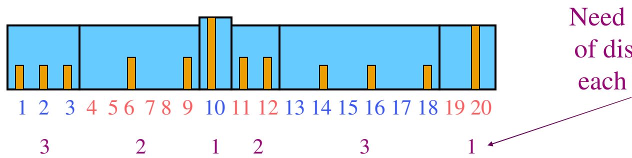
Answering Queries: Histograms

- Answering queries from 1-D histograms (in general):
  - (Implicitly) map the histogram back to an approximate relation, & apply the query to the approximate relation
  - Continuous value mapping [SAC79]:



Count spread evenly among bucket values

  - Uniform spread mapping [PIH96]:

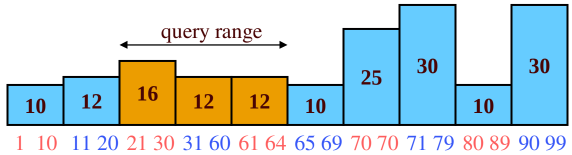


Need number of distinct in each bucket

Self-Tuning 1-D Histograms

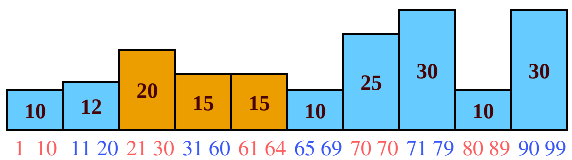
1. Tune Bucket Frequencies: [AC99]

- Compare actual selectivity to histogram estimate
- Use to adjust bucket frequencies



Actual = 60
Estimate = 40
Error = +20

- Divide d*Error proportionately, d=dampening factor



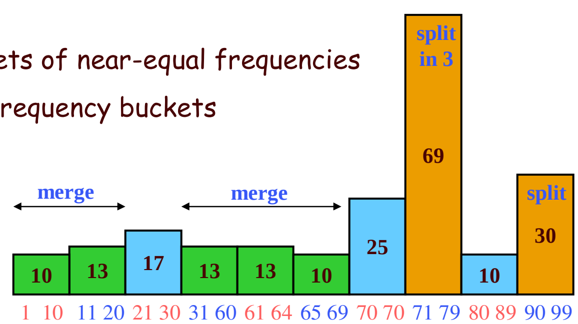
d=½ of Error
= +10
So divide
+4,+3,+3

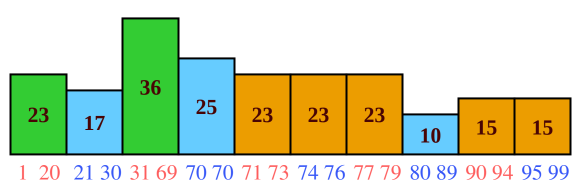
Garofalakis & Gibbons, VLDB 2001 #19

Self-Tuning 1-D Histograms

2. Restructure:

- Merge buckets of near-equal frequencies
- Split large frequency buckets





Also Extends
to Multi-D

Garofalakis & Gibbons, VLDB 2001 #20

Sampling: Basics

Idea: A small random sample S of the data often well-represents all the data

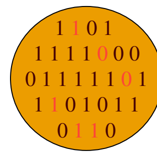
- For a fast approx answer, apply the query to S & "scale" the result
- E.g., R.a is {0,1}, S is a 20% sample

  select count(*) from R where R.a = 0

  ↓

  select 5 * count(*) from S where S.a = 0

  Est. count = 5*2 = 10, Exact count = 10



R.a

Red = in S

Unbiased: For expressions involving count, sum, avg: the estimator is unbiased, i.e., the expected value of the answer is the actual answer, even for (most) queries with predicates!

- 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 prob ≥ 90%

Sampling: Confidence Intervals

Method	90% Confidence Interval (±)	Guarantees?
Central Limit Theorem	1.65 * σ(S) / sqrt(|S|)	as |S| → ∞
Hoeffding	1.22 * (MAX-MIN) / sqrt(|S|)	always
Chebychev (known σ(R))	3.16 * σ(R) / sqrt(|S|)	always
Chebychev (est. σ(R))	3.16 * σ(S) / sqrt(|S|)	as σ(S) → σ(R)

Confidence intervals for Average: select avg(R.A) from R

(Can replace R.A with any arithmetic expression on the attributes in R)

σ(R) = standard deviation of the values of R.A; σ(S) = s.d. for S.A

- If predicates, S above is subset of sample that satisfies the predicate
- Quality of the estimate depends only on the variance in R & |S| after the predicate: So 10K sample may suffice for 10B row relation!
  - Advantage of larger samples: can handle more selective predicates

Sampling from Databases

- Sampling disk-resident data is slow
  - Row-level sampling has high I/O cost:
    - must bring in entire disk block to get the row
  - Block-level sampling: rows may be highly correlated
  - Random access pattern, possibly via an index
  - Need acceptance/rejection sampling to account for the variable number of rows in a page, children in an index node, etc
- Alternatives
  - Random physical clustering: destroys "natural" clustering
  - Precomputed samples: must incrementally maintain (at specified size)
    - Fast to use: packed in disk blocks, can sequentially scan, can store as relation and leverage full DBMS query support, can store in main memory

One-Pass Uniform Sampling

- Best choice for incremental maintenance
  - Low overheads, no random data access
- Reservoir Sampling [Vit85]: Maintains a sample S of a fixed-size M
  - Add each new item to S with probability M/N, where N is the current number of data items
  - If add an item, 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
  - To handle deletions, permit |S| to drop to L < M, e.g., L = M/2
    - remove from S if deleted item is in S, else ignore
    - If |S| = M/2, get a new S using another pass (happens only if delete roughly half the items & cost is fully amortized) [GMP97b]

Biased Sampling

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- Often, advantageous to sample different data at different rates (Stratified Sampling)
  - E.g., outliers can be sampled at a higher rate to ensure they are accounted for; better accuracy for small groups in group-by queries
  - Each tuple j in the relation is selected for the sample S with some probability Pj (can depend on values in tuple j)
  - If selected, it is added to S along with its scale factor sf = 1/Pj
  - **Answering queries from S:** e.g.,

    select sum(R.a) from R where R.b < 5 ➡

    select sum(S.a * S.sf) from S where S.b < 5

    - Unbiased answer. Good choice for Pj's results in tighter confidence intervals

R.a	10	10	10	50	50
Pj	1/3	1/3	1/3	½	½
S.sf	---	3	---	---	2

Sum(R.a) = 130

Sum(S.a*S.sf) = 10*3 + 50*2 = 130

One-Dimensional Haar Wavelets

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- Wavelets: mathematical tool for hierarchical decomposition of functions/signals
- Haar wavelets: simplest wavelet basis, easy to understand and implement
  - *Recursive pairwise averaging and differencing* at different resolutions

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

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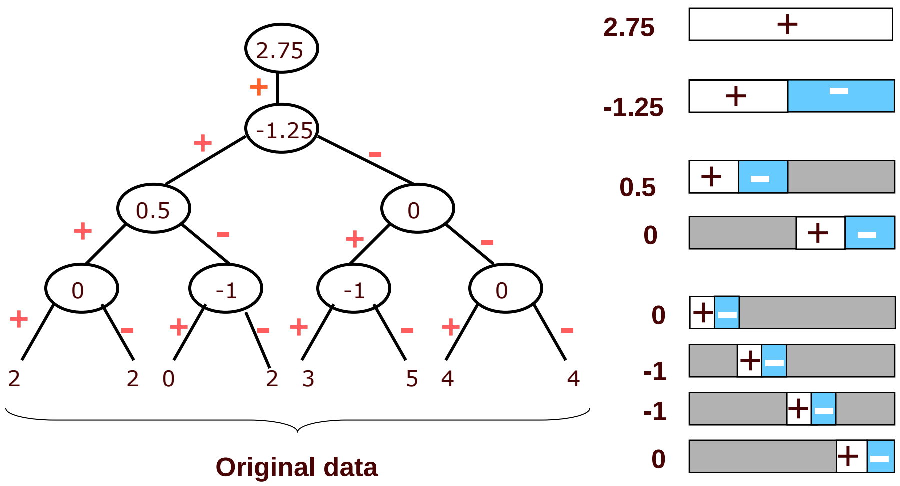
- Hierarchical decomposition structure (a.k.a. "error tree")

Coefficient "Supports"



Wavelet-based Histograms [MVW98]

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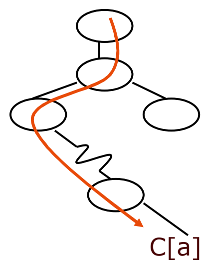
- Problem: range-query selectivity estimation
- Key idea: use a compact subset of Haar/linear wavelet coefficients for approximating the data distribution
- Steps
  - compute cumulative data distribution C
  - compute Haar (or linear) wavelet transform of C
  - coefficient *thresholding* : only b<<|C| coefficients can be kept
    - take largest coefficients in *absolute normalized value*
      - Haar basis: divide coefficients at resolution j by $\sqrt{2^j}$
      - *Optimal* in terms of the overall Mean Squared (L2) Error
    - Greedy heuristic methods
      - Retain coefficients leading to large error reduction
      - Throw away coefficients that give small increase in error

Using Wavelet-based Histograms

- Selectivity estimation: 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 (no. of coefficients), N= size of domain

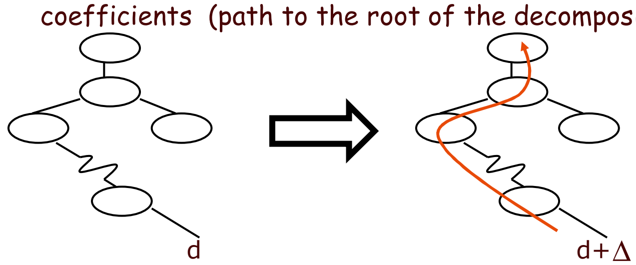


- At most logN+1 coefficients are needed to reconstruct any C value

- Empirical results over synthetic data
  - Improvements over random sampling and histograms (MaxDiff)

Dynamic Maintenance of Wavelet-based Histograms [MVW00]

- Build Haar-wavelet synopses on the original data distribution
  - Similar accuracy with CDF, makes maintenance simpler
- Key issues with dynamic wavelet maintenance
  - Change in single distribution value can affect the values of many coefficients (path to the root of the decomposition tree)

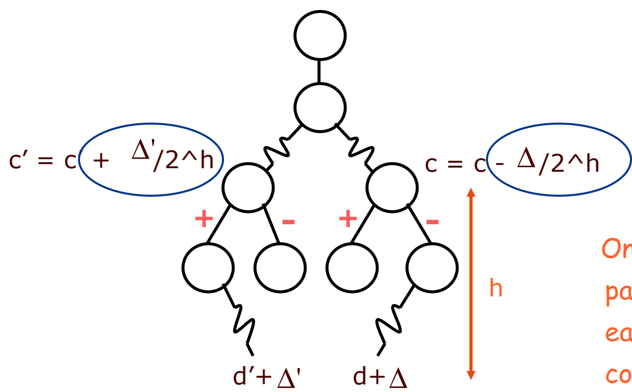


Change propagates up to the root coefficient

  - As distribution changes, "most significant" (e.g., largest) coefficients can also change!
    - Important coefficients can become unimportant, and vice-versa

Effect of Distribution Updates

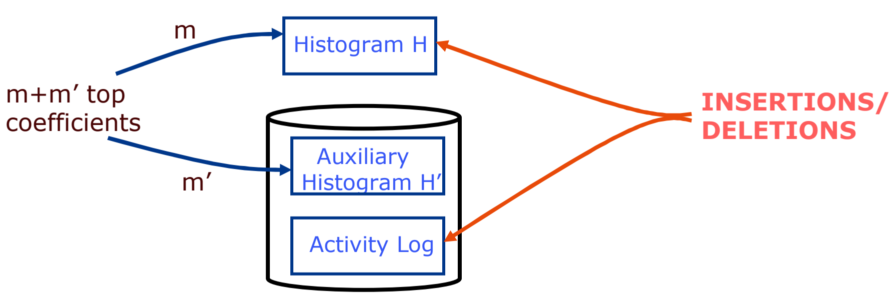
- Key observation: for each coefficient c in the Haar decomposition tree
  - c = (AVG(leftChildSubtree(c)) - AVG(rightChildSubtree(c))) / 2



Only coefficients on path(d) are affected and each can be updated in constant time

Garofalakis & Gibbons, VLDB 2001 #31

Maintenance Architecture



- "Shake up" when log reaches max size: for each insertion at d
  - for each coefficient c on path(d) and in H′ : update c
  - for each coefficient c on path(d) and not in H or H′:
    - insert c into H′ with probability proportional to 1/2^h, where h is the "height" of c (*Probabilistic Counting* [FM85])
  - Adjust H and H′ (move largest coefficients to H)

Garofalakis & Gibbons, VLDB 2001 #32

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- Multi-Dimensional Synopses and Joins
  - Multi-dimensional Histograms
  - Join sampling
  - Multi-dimensional Haar Wavelets
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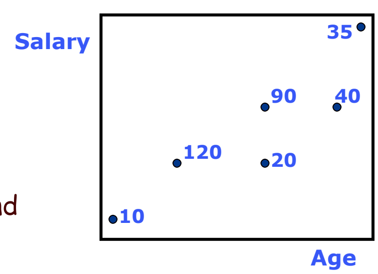
Multi-dimensional Data Synopses

- Problem: Approximate the *joint data distribution* of multiple attributes
  - Motivation
    - Selectivity estimation for queries with multiple predicates
    - Approximating OLAP data cubes and general relations



- Conventional approach: Attribute-Value Independence (AVI) assumption
  - sel(p(A1) & p(A2) & . . .) = sel(p(A1)) * sel(p(A2)) * . . .
  - Simple -- one-dimensional marginals suffice
  - BUT: almost always inaccurate, gross errors in practice (e.g., [Chr84, FK97, Poo97]

Multi-dimensional Histograms

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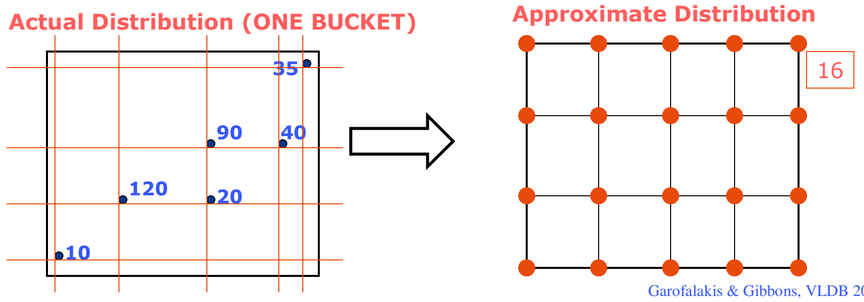
- Use small number of multi-dimensional buckets to *directly* approximate the joint data distribution
- Uniform spread & frequency approximation within buckets
  - n(i) = no. of distinct values along Ai, F = total bucket frequency
  - approximate data points on a n(1)*n(2)*. . . uniform grid, each with frequency F / (n(1)*n(2)*. . .)



Multi-dimensional Histogram Construction

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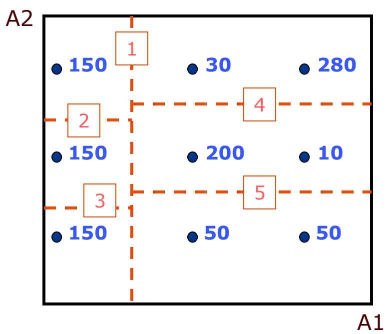
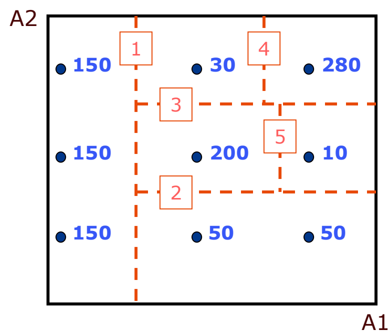
- Construction problem is much harder even for two dimensions [MPS99]
- *Multi-dimensional equi-depth histograms* [MD88]
  - Fix an ordering of the dimensions A1, A2, . . ., Ak, let $\alpha \approx$kth root of desired no. of buckets, initialize B = { data distribution }
  - For i=1, . . ., k: Split each bucket in B in α equi-depth partitions along Ai; return resulting buckets to B
  - Problems: limited set of bucketizations; fixed α and fixed dimension ordering can result in poor partitionings
- *MHIST-p histograms* [PI97]
  - 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

Equi-depth vs. MHIST Histograms

Equi-depth (a1=2,a2=3) [MD88]



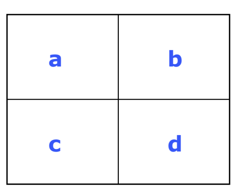
MHIST-2 (MaxDiff) [PI97]

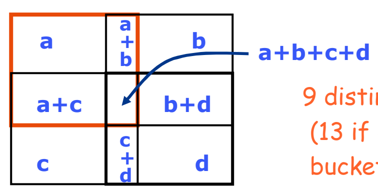


- MHIST: choose bucket/dimension to split based on its *criticality*; allows for much larger class of bucketizations (*hierarchical* space partitioning)
- Experimental results verify superiority over AVI and equi-depth

Other Multi-dimensional Histogram Techniques -- GENHIST [GKT00]

- Key idea: allow for *overlapping* histogram buckets
  - Allows for a much larger no. of distinct frequency regions for a given space budget (= #buckets)



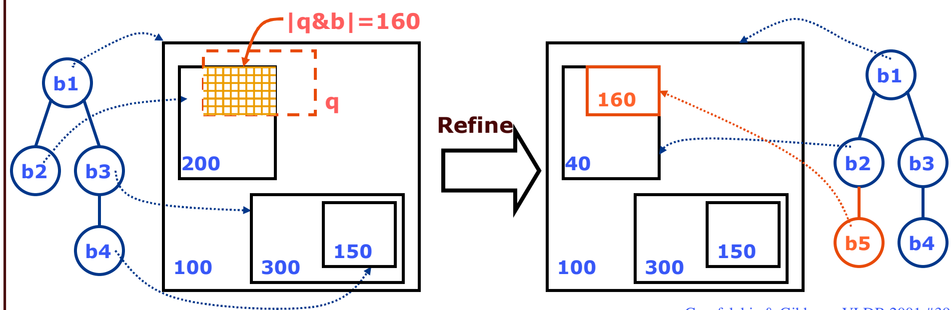


9 distinct frequencies (13 if different-size buckets are used)

- Greedy construction algorithm: Consider increasingly-coarser grids
  - At each step select the cell(s) c of highest density and move enough randomly-selected points from c into a bucket to make c and its neighbors "close-to-uniform"
  - *Truly multi-dimensional* "split decisions" based on *tuple density* -- unlike MHIST

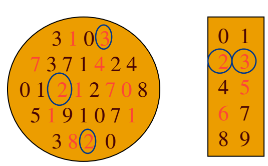
Other Multi-dimensional Histogram Techniques -- STHoles [BCG01]

- Multi-dimensional, workload-based histograms
  - Allow *bucket nesting* -- "bucket tree"
  - Intercept query result stream and count $|q \cap b|$ for each bucket b (< 10% overhead in MS SQL Server 2000)
  - Drill "holes" in b for regions of different *tuple density* and "pull" them out as children of b (first-class buckets)
  - Consolidate/merge buckets of similar densities (keep #buckets constant)



Sampling for Multi-D Synopses

- Taking a sample of the rows of a table captures the attribute correlations in those rows
  - Answers are unbiased & confidence intervals apply
  - Thus guaranteed accuracy for count, sum, and average queries on single tables, as long as the query is not too selective
- Problem with joins [AGP99,CMN99]:
  - Join of two uniform samples is not a uniform sample of the join
  - Join of two samples typically has very few tuples



Foreign Key Join
40% Samples in Red
Size of Actual Join = 30
Size of Join of samples = 3

Join Synopses for Foreign-Key Joins [AGP99]

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- Based on sampling from materialized foreign key joins
  - Typically < 10% added space required
  - Yet, can be used to get a uniform sample of ANY foreign key join
  - Plus, fast to incrementally maintain
- Significant improvement over using just table samples
  - E.g., for TPC-H query Q5 (4 way join)
    - 1%-6% relative error vs. 25%-75% relative error,
      for synopsis size = 1.5%, selectivity ranging from 2% to 10%
    - 10% vs. 100% (no answer!) error, for size = 0.5%, select. = 3%

Multi-dimensional Haar Wavelets

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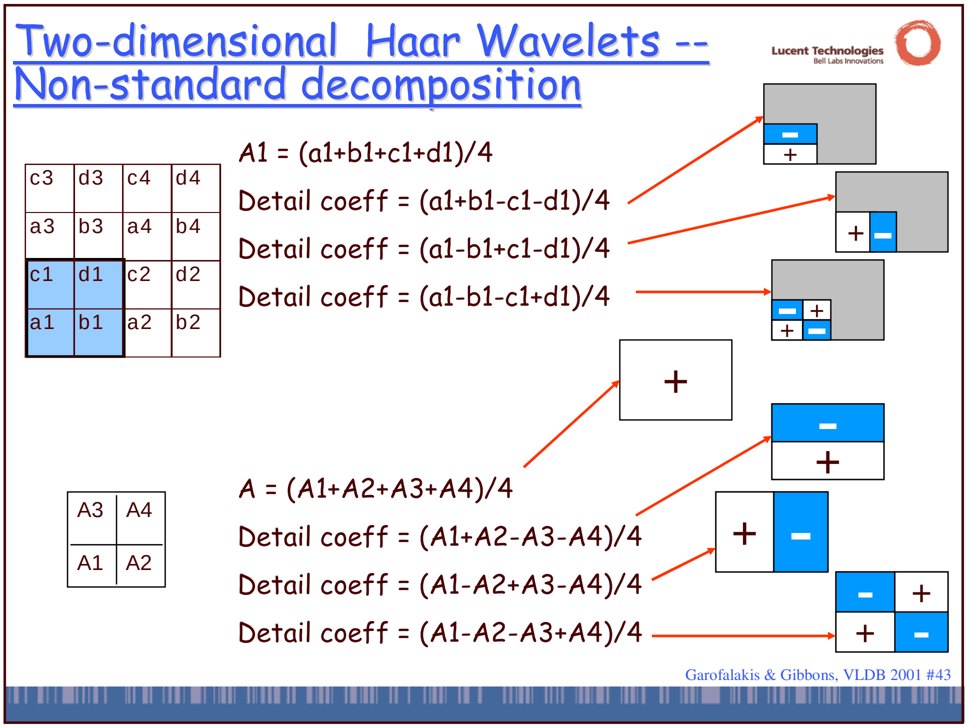
- Basic "pairwise averaging and differencing" ideas carry over to multiple data dimensions
- Two basic methodologies -- no clear winner [SDS96]
  - *Standard* Haar decomposition
  - *Non-standard* Haar decomposition
- Discussion here: focus on *non-standard decomposition*
  - See [SDS96, VW99] for more details on standard Haar decomposition
  - [MVW00] also discusses *dynamic maintenance* of standard multi-dimensional Haar wavelet synopses


Two-dimensional Haar Wavelets --
Non-standard decomposition
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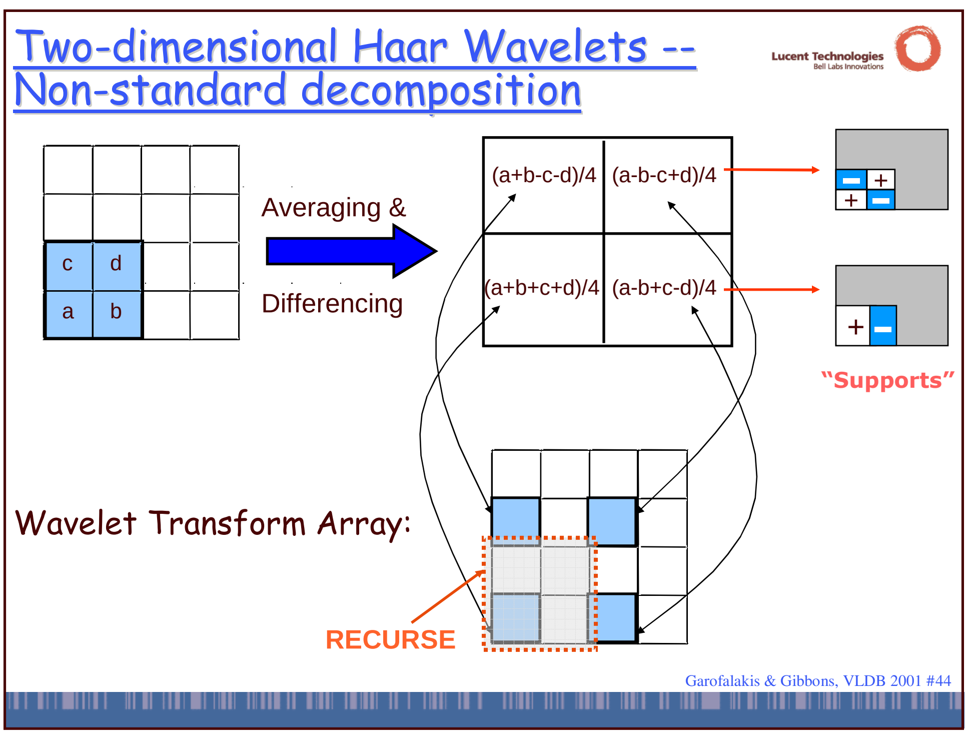
c3 d3 c4 d4
a3 b3 a4 b4
c1 d1 c2 d2
a1 b1 a2 b2
A1 = (a1+b1+c1+d1)/4
Detail coeff = (a1+b1-c1-d1)/4
Detail coeff = (a1-b1+c1-d1)/4
Detail coeff = (a1-b1-c1+d1)/4
A3 A4
A1 A2
A = (A1+A2+A3+A4)/4
Detail coeff = (A1+A2-A3-A4)/4
Detail coeff = (A1-A2+A3-A4)/4
Detail coeff = (A1-A2-A3+A4)/4
Garofalakis & Gibbons, VLDB 2001 #43


Two-dimensional Haar Wavelets --
Non-standard decomposition
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c d
a b
Averaging &
Differencing
(a+b-c-d)/4
(a-b-c+d)/4
(a+b+c+d)/4
(a-b+c-d)/4
"Supports"
Wavelet Transform Array:
RECURSE
Garofalakis & Gibbons, VLDB 2001 #44

Two-dimensional Haar Wavelets -- Non-standard decomposition

Data Array

3	4	3	4
1	2	1	2
3	4	3	4
1	2	1	2

After averaging and differencing

-1	0	-1	0
2.5	-.5	2.5	-.5
-1	0	-1	0
2.5	-.5	2.5	-.5

After distributing results

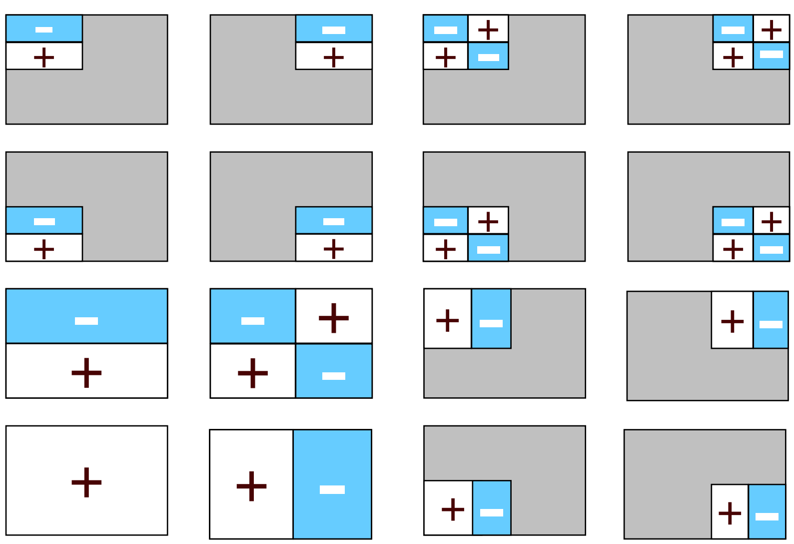
-1	-1	0	0
-1	-1	0	0
2.5	**2.5**	-.5	-.5
2.5	**2.5**	-.5	-.5

RECURSE

Final wavelet transform array

-1	-1	0	0
-1	-1	0	0
0	0	-.5	-.5
2.5	0	-.5	-.5

Non-standard Two-dimensional Haar Basis -- Coefficient Supports



Constructing the Wavelet Decomposition

Joint Data Distribution Array

Attr2 \ Attr1	0	1	2	3
3				
2				
1		6		3
0			4	

Relation (ROLAP) Representation

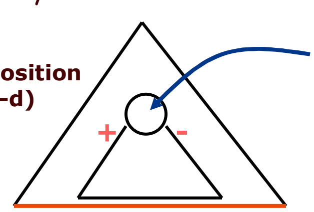
Attr1	Attr2	Count
2	0	4
1	1	6
3	1	3

- Joint data distribution can be very sparse!
- Key to I/O-efficient decomposition algorithms: *Work off the ROLAP representation*
  - Standard decomposition [VW99]
  - Non-standard decomposition [CGR00]
- Typically require a small (logarithmic) number of passes over the data

Range-sum Estimation Using Wavelet Synopses

- Coefficient thresholding
  - As in 1-d case, normalizing by appropriate constants and retaining the largest coefficients minimizes the overall L2 error
- Range-sums: selectivity estimation or OLAP-cube aggregates [VW99] ("measure attribute" as count)
- Only coefficients with support regions intersecting the query hyper-rectangle can contribute
  - Many contributions can *cancel* each other [CGR00, VW99]

Decomposition Tree (1-d)



Query Range

Contribution to range sum = 0

Only nodes on the path to range endpoints can have nonzero contributions (Extends naturally to multi-dimensional range sums)

Outline

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- Intro & Approximate Query Answering Overview
- One-Dimensional Synopses
- Multi-Dimensional Synopses and Joins
- Set-Valued Queries
  - Error Metrics
  - Using Histograms
  - Using Samples
  - Using Wavelets
- Discussion & Comparisons
- Advanced Techniques & Future Directions
- Conclusions

Approximating Set-Valued Queries

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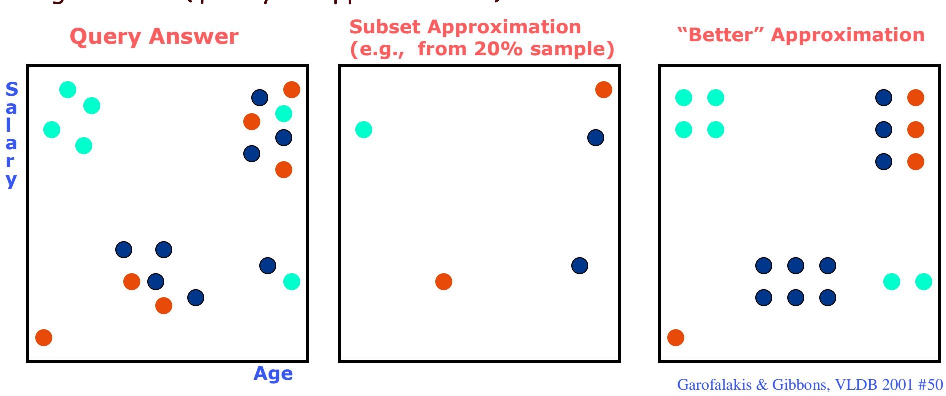
- Problem: Use synopses to produce "good" approximate answers to generic SQL queries -- selections, projections, joins, etc.
  - Remember: synopses try to capture the *joint data distribution*
  - Answer (in general) = *multiset of tuples*
- Unlike aggregate values, NO universally-accepted measures of "goodness" (quality of approximation) exist



Error Metrics for Set-Valued Query Answers

- Need an error metric for (multi)sets that accounts for both
  - differences in element *frequencies*
  - differences in element *values*
- Traditional set-comparison metrics (e.g., symmetric set difference, Hausdorff distance) fail
- Proposed Solutions
  - *MAC (Match-And-Compare) Error [IP99]:* based on perfect bipartite graph matching
  - *EMD (Earth Mover's Distance) Error [CGR00, RTG98]:* based on bipartite network flows

Using Histograms for Approximate Set-Valued Queries [IP99]

- Store histograms as relations in a SQL database and define a *histogram algebra* using simple SQL queries
- Implementation of the algebra operators (select, join, etc.) is fairly straightforward
  - Each multidimensional histogram bucket directly corresponds to a set of approximate data tuples
- Experimental results demonstrate histograms to give much lower MAC errors than random sampling
- Potential problems
  - For high-dimensional data, histogram effectiveness is unclear and construction costs are high [GKT00]
  - Join algorithm requires *expanding* into approximate relations
    - Can be as large (or larger!) than the original data set

Set-Valued Queries via Samples

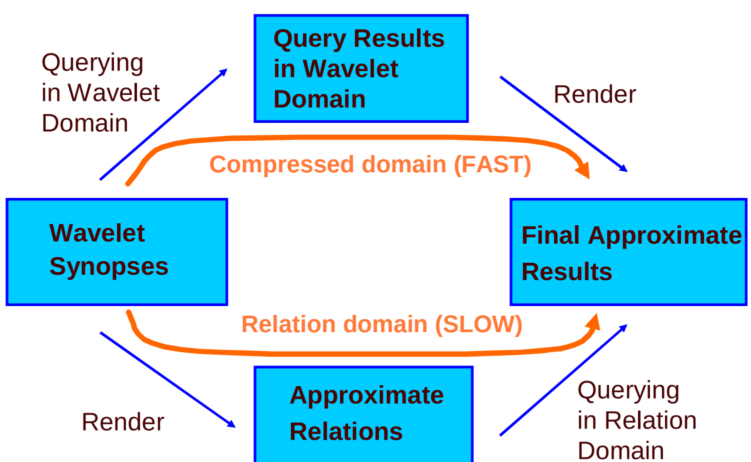
- Applying the set-valued query to the sampled rows, we very often obtain a **subset of the rows in the full answer**
  - E.g., Select all employees with 25+ years of service
  - Exceptions include certain queries with nested subqueries (e.g., select all employees with above average salaries: but the average salary is known only approximately)

- Extrapolating from the sample:
  - Can treat each sample point as the center of a cluster of points (generate approximate points, e.g., using *kernels* [BKS99, GKT00])
  - Alternatively, Aqua [GMP97a, AGP99] returns an approximate count of the number of rows in the answer and a representative subset of the rows (i.e., the sampled points)
    - Keeps result size manageable and fast to display

Approximate Query Processing Using Wavelets [CGR00]

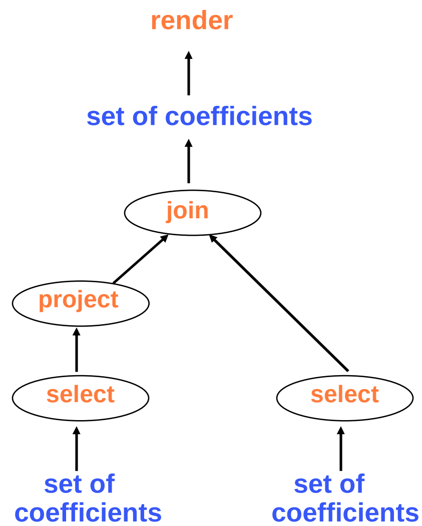
- Reduce relations into compact *wavelet-coefficient synopses*

Entire query processing in the compressed (wavelet) domain



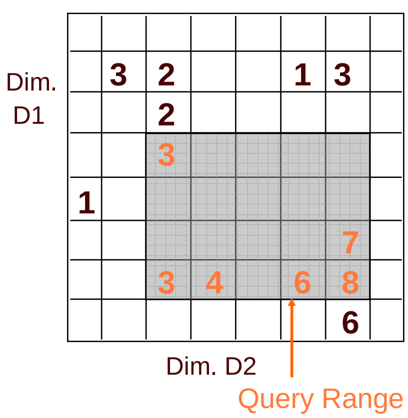
Wavelet Query Processing

- Each operator (e.g., select, project, join, aggregates, etc.)
  - *input:* set of wavelet coefficients
  - *output:* set of wavelet coefficients
- Finally, rendering step
  - *input:* set of wavelet coefficients
  - *output:* (multi)set of tuples



Selection -- Relational Domain

Joint Data Distribution Array

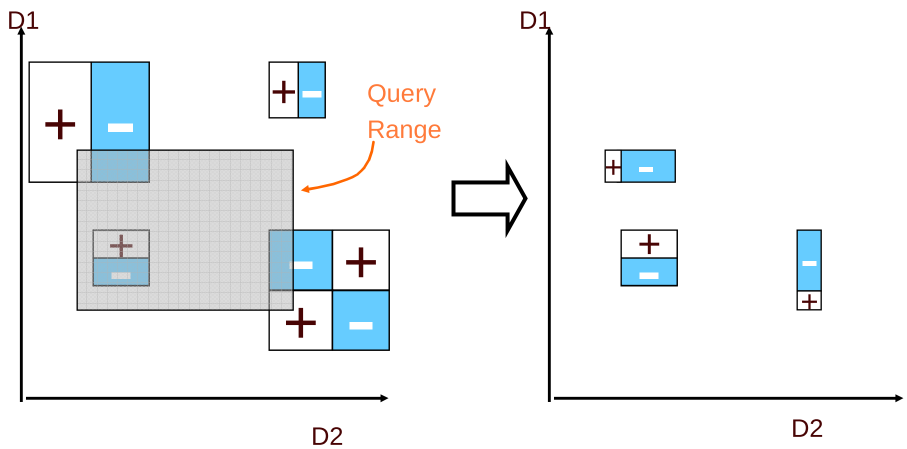


Relation

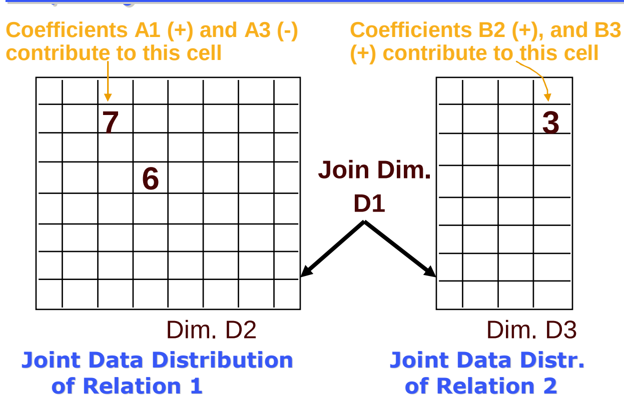
Dim D1 (Attr1)	Dim D2 (Attr2)	Count
0	6	6
1	2	3
1	3	4
1	5	6
1	6	8
2	6	7
3	0	1
4	2	3
5	2	2
6	1	3
6	2	2
6	5	1
6	6	3

- In relational domain, interested in only those cells inside query range
- In wavelet domain, interested in only the coefficients that contribute to those cells

Selection -- Wavelet Domain



Equi-join -- Relational Domain



Relation 1

Dim D1 (Attr1)	Dim D2 (Attr2)	Count
6	2	7
4	3	6

Relation 2

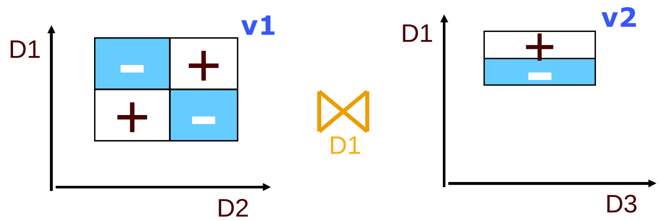
Dim D1 (Attr1)	Dim D3 (Attr3)	Count
6	3	3

Join along D1

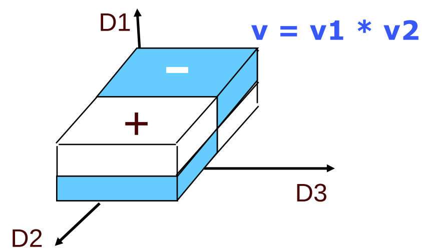
Dim D1 (Attr1)	Dim D2 (Attr2)	Dim D3 (Attr3)	Count
6	2	3	21

- *Relational domain:* Join count= 7*3 = (A1-A3)*(B2+B3)
- *Wavelet domain:* A1*B2 + A1*B3 - A3*B2 - A3*B3
- Consider all pairs of coefficients: (1) check joinability (overlap in join dimension(s)), (2) compute output coefficients

Equi-join -- Wavelet Domain



Join output coefficient:



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Discussion & Comparisons (1)

- *Histograms & Wavelets:* Limited by "curse of dimensionality"
  - Rely on data space partitioning in "regions"
  - Ineffective above 5-6 dimensions
    - Value/frequency uniformity assumptions within buckets break down in medium-to-high dimensionalities!!
- *Sampling:* No such limitations, BUT...
  - Ineffective for ad-hoc relational joins over arbitrary schemas
    - Uniformity property is lost
    - Quality guarantees degrade
  - Effectiveness for *set-valued* approximate queries is unclear
    - Only (very) small subsets of the answer set are returned (especially, when joins are present)

Discussion & Comparisons (2)

- *Histograms & Wavelets:* Compress data by accurately capturing rectangular "regions" in the data space
  - Advantage over sampling for typical, "range-based" relational DB queries
  - BUT, unclear how to effectively handle unordered/non-numeric data sets (no such issues with sampling...)
- *Sampling:* Provides strong probabilistic quality guarantees (unbiased answers) for individual aggregate queries
  - *Histograms & Wavelets:* Can guarantee a bound on the overall error (e.g., L2) for the approximation, BUT answers to individual queries can be heavily biased!!

No clear winner exists!! (Hybrids??)

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  - Dependency-based Synopses
  - Workload-tuned Biased Sampling
  - Distinct-values Queries
  - Streaming Data
- Conclusions

Dependency-based Histogram Synopses [DGR01]

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Attribute Value Independence
*** simplistic**
*** inaccurate**

Multi-dimensional histograms on joint data distribution
*** expensive**
*** ineffective in high dimensions**

Fully independent attributes ⟷ **Fully correlated attributes**

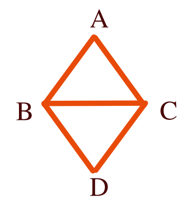
- Extremes in terms of the underlying correlations!!
- Dependency-Based Histograms: explore space between extremes by explicitly identifying data correlations/independences
  - Build a *statistical interaction model* on data attributes
  - Based on the model, build a collection of low-dimensional histograms
  - Use this histogram collection to provide approximate answers
- General methodology, also applicable to other synopsis techniques (e.g., wavelets)

Dependency-based Histograms

- Identify (and exploit) attribute correlation and independence
  - Partial Independence :

    p(salary, height, weight) = p(salary) * p(height, weight)
  - Conditional Independence :

    p(salary, age | YPE) = p(salary| YPE) * p(age | YPE)
- Use forward selection to build a *decomposable statistical model* [BFH75], [Lau96] on the attributes
  - A,D are conditionally independent given B,C
    - p(AD|BC) = p(A|BC) * p(D|BC)
  - Joint distribution
    - p(ABCD) = p(ABC) * p(BCD) / p(BC)
  - ***Build histograms on model cliques***



- Significant accuracy improvements (factor of 5) over pure MHIST
- More details, construction & usage algorithms, etc. in the paper ☺

Workload-tuned Biased Sampling -- Congressional Samples [AGP00]

- 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
  - 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
- Technique: Congressional Samples
  - House: Uniform sample: good for when no group-by
  - Senate: Same size sample per group when use all grouping columns: good for queries with all columns
  - Congress: Combines House & Senate, but considers all subsets of grouping columns, and then scales down

Workload-tuned Biased Sampling -- ICICLES [GLR00]

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- Biased sampling scheme that *dynamically adapts* to query workload
  - Exploit data locality -- more focus (i.e., #sample points) in frequently-queried regions
  - Let Q = {q1, q2, . . .} be a query workload, R(qi) = subset of R used in answering query qi
  - L(R, Q) = Extension of R wrt Q = $R \bigcup_{qi \in Q} R(qi)$ (multiset of tuples)

Icicle: Uniform random sample of L(R,Q)

- Incrementally maintained and adapt ("self-tune") to workload through *Reservoir Sampling* technique [Vit85]
- *Unbiased Icicle estimators:* New formulas to account for duplicates and bias in sample selection
- *Provably better* (smaller variance) than uniform for "focused" queries (that follow the workload model)

Garofalakis & Gibbons, VLDB 2001 #67

Workload-tuned Biased Sampling -- Lifted Workloads [CDN01]

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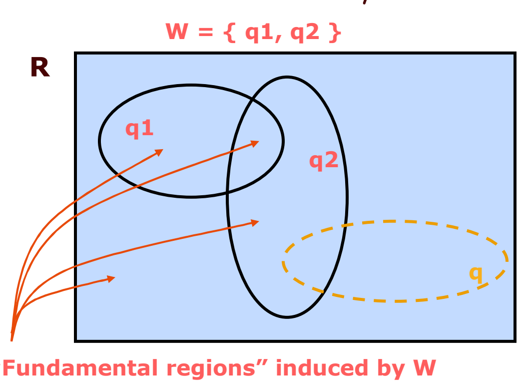
- Formulate sample selection as an *optimization problem*
  - Minimize query-answering error for a given workload model
- Technique for *"lifting a fixed workload W"* to produce a probability distribution over all possible queries
  - Similar to kernel density estimation (queries in W = "sample points")



prob(q|W) = parametric function of q's overlap with queries in W

"Fundamental regions" induced by W

Garofalakis & Gibbons, VLDB 2001 #68

Workload-tuned Biased Sampling -- Lifted Workloads

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- Problem: Find sample of size k that minimizes expected error for a given "lifted" workload
- Solution: *Stratified sampling* [Coc77]
  - Collection of uniform samples (of total size k) over disjoint subsets ("strata") of the population
  - Much better estimates when variance within strata is small [Coc77]
- *Stratification:* Selecting appropriate partitioning of R
  - Using "fundamental regions" as strata is *optimal* for COUNT
  - For SUM, partition "fundamental regions" further to reduce variance of the aggregated attribute (Neymann technique [Coc77])
- *Allocation:* Dividing k among strata
  - Closed form solutions (valid under certain simplifying assumptions)

Distinct Values Queries

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- select count(distinct target-attr)
- from rel
- where P

Template

- select count(distinct o_custkey)
- from orders
- where o_orderdate >= '2001-01-01'

TPCH example

  - How many distinct customers have placed orders this year?

- Includes: column cardinalities, number of species, number of distinct values in a data set / data stream

Distinct Values Queries

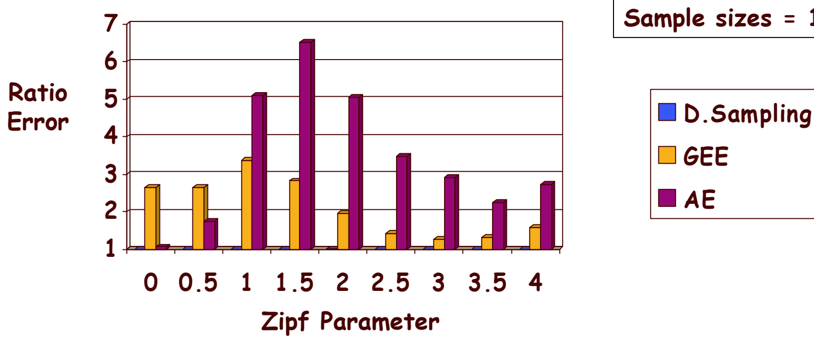
- Uniform Sampling-based approaches
  - Collect and store uniform sample. At query time, apply predicate to sample. Estimate based on a function of the distribution. **Extensive** literature (see, e.g., [CCM00])
    - Many functions proposed, but estimates are often inaccurate
    - [CCM00] proved must examine (sample) almost the entire table to guarantee the estimate is within a factor of 10 with probability > 1/2, regardless of the function used!
- One pass approaches
  - A hash function maps values to bit position according to an exponential distribution [FM85] (cf. [Coh97,AMS96])
    - 00001011111 estimate based on rightmost 0-bit
    - Produces a single count: Does not handle subsequent predicates

Distinct Values Queries

- One pass, sampling approach: Distinct Sampling [Gib01]:
  - A hash function assigns random priorities to domain values
  - Maintains $O(\log(1/\delta)/\varepsilon^2)$ highest priority values observed thus far, and a random sample of the data items for each such value
  - Guaranteed within ε relative error with probability $1 - \delta$
  - Handles ad-hoc predicates: E.g., How many distinct customers today vs. yesterday?
    - To handle q% selectivity predicates, the number of values to be maintained increases inversely with q (see [Gib01] for details)
  - Good for data streams: Can even answer distinct values queries over physically distributed data. E.g., How many distinct IP addresses across an entire subnet? (Each synopsis collected independently!)
  - Experimental results: 0-10% error vs. 50-250% error for previous best approaches, using 0.2% to 10% synopses

Distinct Values Queries

Data set size = 1M
Sample sizes = 1%



Over the entire range of skew :

- Distinct Sampling has 1.00-1.02 ratio error (1.00=no error)
- At least 25 times smaller relative error than best approaches based on uniform sampling (GEE & AE)

Approximate Reports

- Distinct sampling also provides fast, highly-accurate approximate answers for report queries arising in high-volume, session-based event recording environments
- **Environment:** Record events, produce precanned reports
  - Many overlapping sessions: multiple events comprise a session (single IP flow, single call set-up, single customer service call)
  - Events are time-stamped and tagged with session id, and then dumped to append-only databases
  - Logs sent to central data warehouse. Precanned reports executed every minute or hour. TPC-R benchmark
- Must maintain a uniform sample of the sessions & all the events in those sessions in order to produce good approximate reports. Distinct sampling provides this. Improves accuracy by factor of 10+

Data Streams

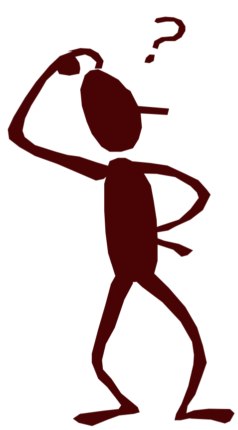
- Data is continually arriving. Collect & maintain synopses on the data. Goal: Highly-accurate approximate answers
  - State-of-the-art: Good techniques for narrow classes of queries
  - E.g., Any one-pass algorithm for collecting & maintaining a synopsis can be used effectively for data streams
- Alternative scenario: A collection of data sets. Compute a compact **sketch** of each data set & then answer queries (approximately) comparing the data sets
  - E.g., detecting near-duplicates in a collection of web pages: Altavista
  - E.g., estimating join sizes among a collection of tables [AGM99]

Looking Forward...

- Optimizing queries for approximation
  - e.g., minimize length of confidence interval at the plan root
- Exploiting mining-based techniques (e.g., decision trees) for data reduction and approximate query processing
  - see, e.g., [BGR01], [GTK01], [JMN99]
- Dynamic maintenance of complex (e.g., dependency-based [DGR01] or mining-based [BGR01]) synopses
- Improved approximate query processing over continuous data streams
  - see, e.g., [GKS01a], [GKS01b], [GKM01b]

Conclusions

- Commercial data warehouses: approaching several 100's TB and continuously growing
  - Demand for high-speed, interactive analysis (click-stream processing, IP traffic analysis) also increasing
- Approximate Query Processing
  - "Tame" these TeraBytes and satisfy the need for interactive processing and exploration
  - Great promise
  - Commercial acceptance still lagging, but will most probably grow in coming years
  - *Still lots of interesting research to be done!!*



http://www.bell-labs.com/user/{minos, pbgibbons}/

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Additional Resources

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