A Quick Introduction to Approximate Query Processing Part II

CS286, Spring'2007

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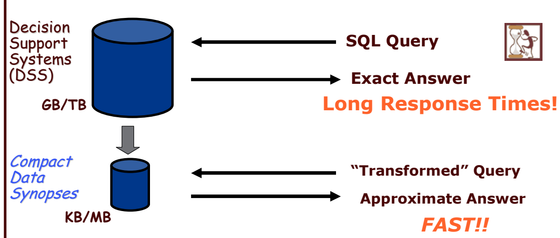
Decision Support Systems

- Data Warehousing: Consolidate data from many sources in one large repository.
  - Loading, periodic synchronization of replicas.
  - Semantic integration.
- OLAP:
  - Complex SQL queries and views.
  - Queries based on spreadsheet-style operations and "multidimensional" view of data.
  - Interactive and "online" queries.
- Data Mining:
  - Exploratory search for interesting trends and anomalies. (Another lecture!)

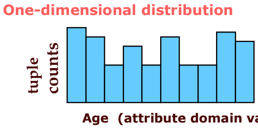
Approximate Query Processing using Data Synopses



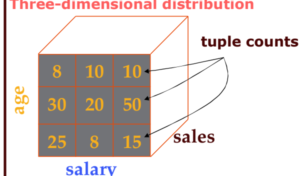
- How to construct effective *data synopses* ??

Relations as Frequency Distributions

One-dimensional distribution



Three-dimensional distribution



name	age	salary	sales
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Outline

- Intro & Approximate Query Answering Overview
  - Synopses, System architectures, Commercial offerings
- 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

One-Dimensional Haar Wavelets

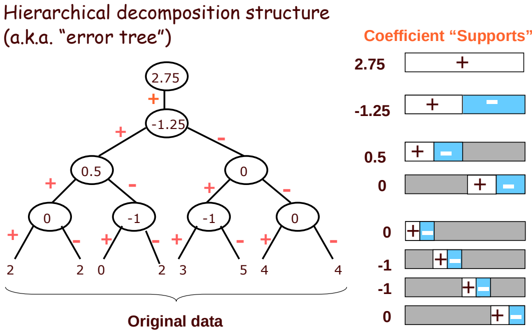
- Wavelets: mathematical tool for hierarchical decomposition of functions/signals
- Haar wavelets: simplest wavelet basis, easy to understand and implement
  - *Recursive pairwise averaging and differencing* at different resolutions

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

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

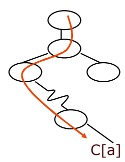


Wavelet-based Histograms [MVW98]

- 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

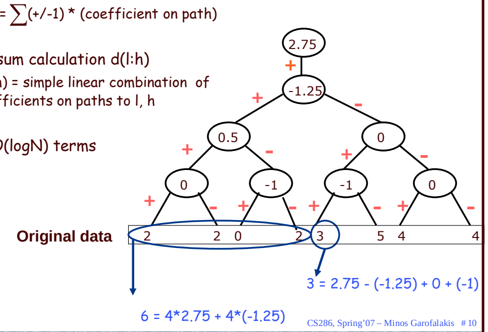
- Selectivity estimation: sel(a<= X<= b) = C'[b] - C'[a-1]
  - C' is the (approximate) "reconstructed" cumulative distribution
  - Time: O(min{b, logN}), where b = size of wavelet synopsis (no. of coefficients), N= size of domain



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

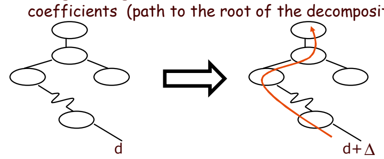
Haar Wavelet Coefficients

- Reconstruct data values d(i)
  - d(i) = $\sum$(+/-1) * (coefficient on path)
- Range sum calculation d(l:h)
  - d(l:h) = simple linear combination of coefficients on paths to l, h
- Only O(logN) terms



Dynamic Maintenance of Wavelet-based Histograms [MVW00]

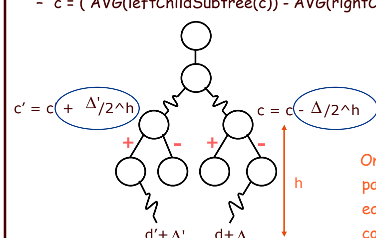
- Build Haar-wavelet synopses on the original data distribution
- Key issues with dynamic wavelet maintenance
  - Change in single distribution value can affect the values of many coefficients (path to the root of the decomposition tree)



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

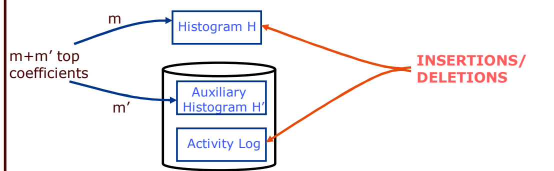
Effect of Distribution Updates

- 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

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)

Problems with Conventional Wavelet Synopses

- An example data vector and wavelet synopsis (|D|=16, B=8 largest coefficients retained)

Over 2,000% relative error! — Always accurate!

Original Data Values	127	71	87	31	59	3	43	99	100	42	0	58	30	88	72	130
Wavelet Answers	65	65	65	65	65	65	65	65	100	42	0	58	30	88	72	130

Estimate = 195, actual values: d(0:2)=285, d(3:5)=93!

- Large variation in answer quality
  - Within the same data set, when synopsis is *large*, when data values are about the same, when actual answers are about the same
  - Heavily-biased approximate answers!
- Root causes
  - Thresholding for aggregate L2 error metric
  - Independent, greedy thresholding (⇒ large regions without any coefficient!)
  - Heavy bias from dropping coefficients without compensating for loss

Approach: Optimize for Maximum-Error Metrics

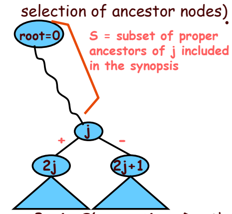
- Key metric for effective approximate answers: *Relative error with sanity bound* $\frac{|\hat{d}_i - d_i|}{\max\{|d_i|, s\}}$
  - Sanity bound "s" to avoid domination by small data values
- To provide tight error guarantees for *all* reconstructed data values

  Minimize $\max_i \{\frac{|\hat{d}_i - d_i|}{\max\{|d_i|, s\}}\}$

  - Minimize *maximum relative error* in the data reconstruction
- Another option: Minimize *maximum absolute error* $\max_i \{|\hat{d}_i - d_i|\}$
- Algorithms can be extended to general *"distributive" metrics* (e.g., average relative error)

Our Approach: Deterministic Wavelet Thresholding for Maximum Error

- ***Key Idea:*** Dynamic-Programming formulation that *conditions the optimal solution on the error that "enters" the subtree* (through the selection of ancestor nodes)



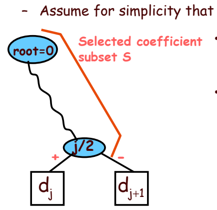
- Our DP table:

  M[j, b, S] = optimal maximum relative (or, absolute) error in T(j) with space budget of b coefficients (chosen in T(j)), *assuming subset S of j's proper ancestors have already been selected for the synopsis*

  - Clearly, |S| $\le$ min{B-b, logN+1}
  - Want to compute M[0, B, ϕ]
- ***Basic Observation:*** Depth of the error tree is only logN+1 ⇒ we can explore and tabulate all S-subsets for a given node at a space/time cost of only O(N) !

Base Case for DP Recurrence: Leaf (Data) Nodes

- Base case in the bottom-up DP computation: Leaf (i.e., data) node d_j
  - Assume for simplicity that data values are numbered N, …, 2N-1



- M[j, b, S] is not defined for b>0
  - Never allocate space to leaves
- For b=0

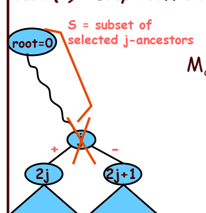
  $$M[j,0,S] = \frac{|d_j - \sum_{c\in S} sign(c,d_j)\cdot c|}{\max\{|d_j|, s\}}$$

  for each coefficient subset $S \subseteq path(d_j)$ with $|S| \le$ min{B, logN+1}
  - *Similarly for absolute error*
- Again, time/space complexity per leaf node is only O(N)

DP Recurrence: Internal (Coefficient) Nodes

- Two basic cases when examining node/coefficient j for inclusion in the synopsis: (1) Drop j; (2) Keep j

Case (1): Drop Coefficient j



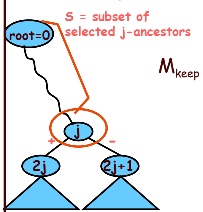
- In this case, the minimum possible maximum relative error in T(j) is

  $$M_{drop}[j,b,S] = \min_{0\le b'\le b} \max\{ M[2j,b',S], M[2j+1,b-b',S]\}$$

  - Optimally distribute space b between j's two child subtrees
- Note that the RHS of the recurrence is well-defined
  - Ancestors of j are obviously ancestors of 2j and 2j+1

DP Recurrence: Internal (Coefficient) Nodes (cont.)

Case (2): Keep Coefficient j



- In this case, the minimum possible maximum relative error in T(j) is

$$M_{keep}[j,b,S] = \min_{0\le b'\le b-1} \max\{ M[2j,b',S\cup\{c_j\}],\ M[2j+1,b-b'-1,S\cup\{c_j\}]\}$$

  - Take 1 unit of space for coefficient j, and optimally distribute remaining space
  - Selected subsets in RHS change, since we choose to retain j
- Again, the recurrence RHS is well-defined
- Finally, define $M[j,b,S] = \min\{ M_{drop}[j,b,S],\ M_{keep}[j,b,S]\}$
- Overall complexity: $O(N^2)$ time, $O(N \min\{B,\log N\})$ space

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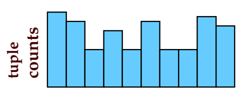
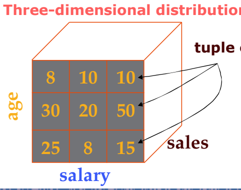
- Intro & Approximate Query Answering Overview
- One-Dimensional Synopses
- Multi-Dimensional Synopses and Joins
  - Multi-dimensional Histograms
  - Join sampling
  - Multi-dimensional Haar Wavelets
- Set-Valued Queries
- Discussion & Comparisons
- Advanced Techniques & Future Directions
- Conclusions

Relations as Frequency Distributions

One-dimensional distribution



Three-dimensional distribution



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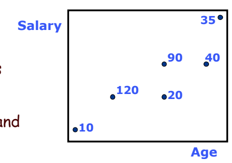
Multi-dimensional Data Synopses

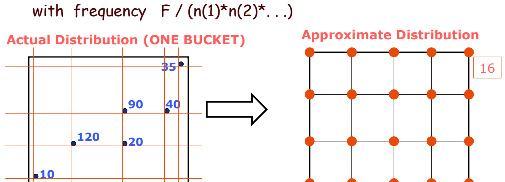
- Problem: Approximate the *joint data distribution* of multiple attributes
  - Motivation
    - Selectivity estimation for queries with multiple predicates
    - Approximating OLAP data cubes and general relations



- 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

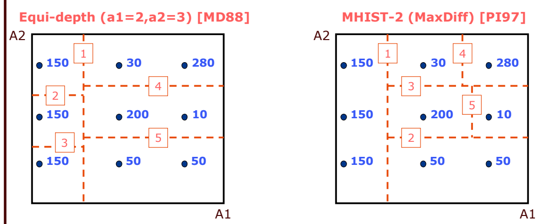
- Use small number of multi-dimensional buckets to *directly* approximate the joint data distribution
- Uniform spread & frequency approximation within buckets
  - n(i) = no. of distinct values along Ai, F = total bucket frequency
  - approximate data points on a n(1)*n(2)*. . . uniform grid, each with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



Multi-dimensional Histogram Construction

- 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

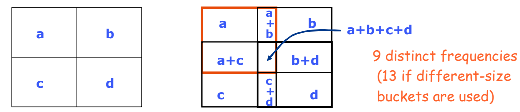
Equi-depth vs. MHIST Histograms



- 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]

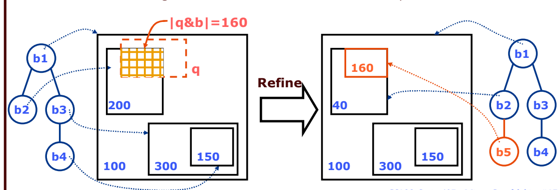
- Key idea: allow for *overlapping* histogram buckets
  - Allows for a much larger no. of distinct frequency regions for a given space budget (= #buckets)



- 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

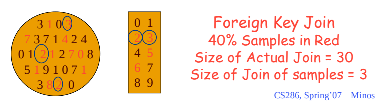
Other Multi-dimensional Histogram Techniques -- STHoles [BCG01]

- Multi-dimensional, workload-based histograms
  - Allow *bucket nesting* -- "bucket tree"
  - Intercept query result stream and count |q ∩ 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



Join Synopses for Foreign-Key Joins [AGP99]

- 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%