A Quick Introduction to Approximate Query Processing

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Outline

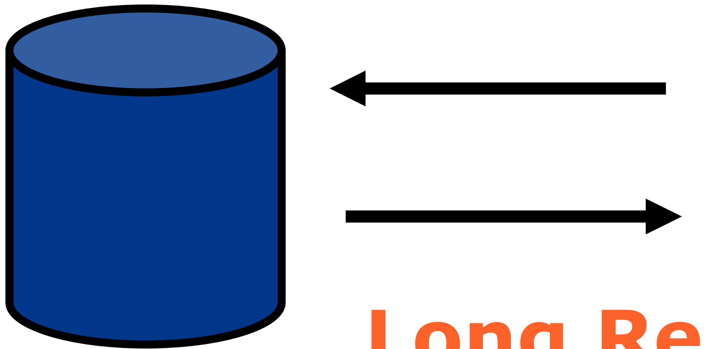
- Intro & Approximate Query Answering Overview
  - Synopses, System architectures, Commercial offerings
- One-Dimensional Synopses
  - Histograms, Samples, Wavelets
- Multi-Dimensional Synopses and Joins
  - Multi-D Histograms, Join synopses, Wavelets
- Set-Valued Queries
  - Using Histograms, Samples,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

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!)

Introduction & Motivation

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

- 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

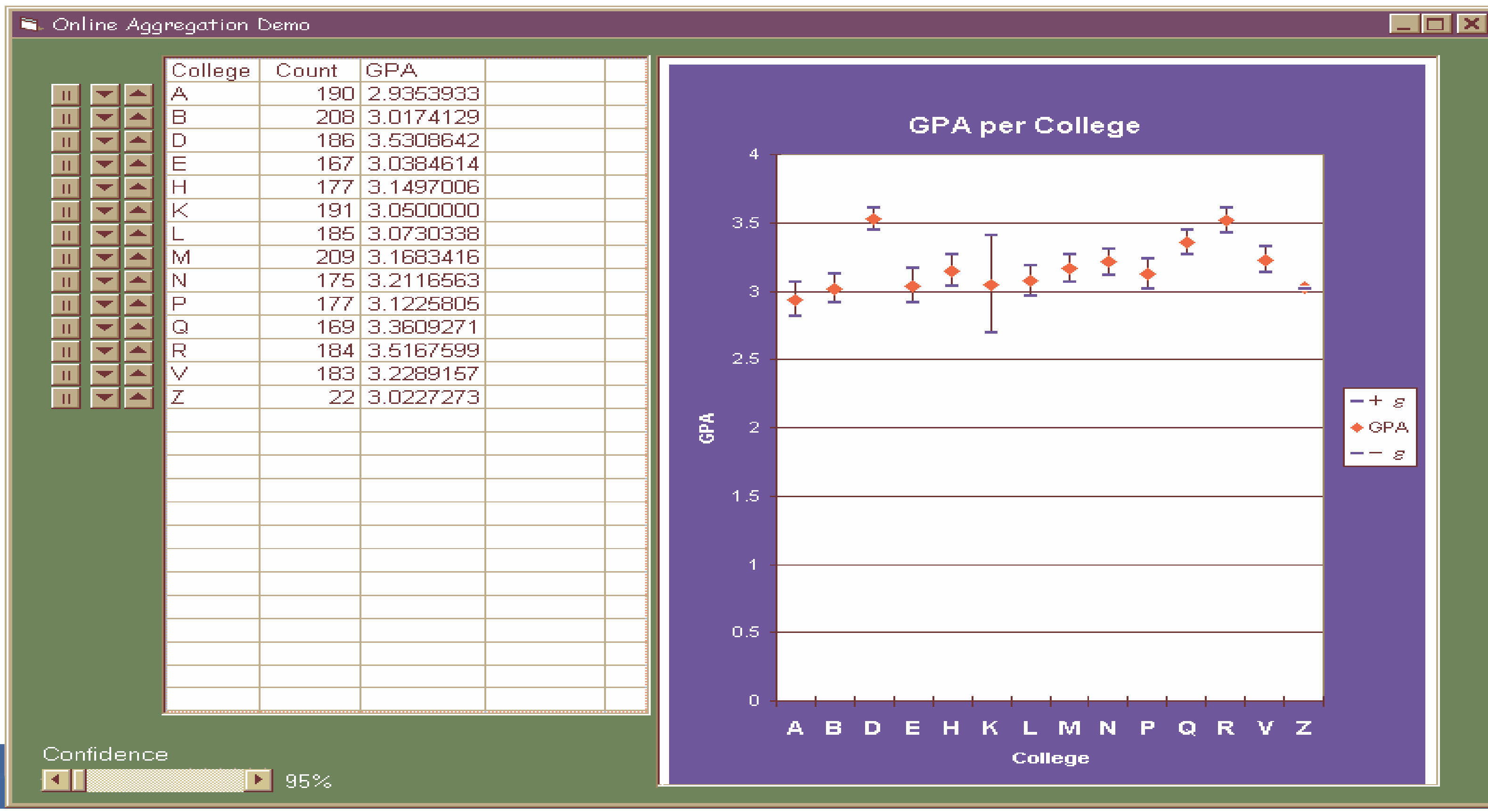
> E.g., Average salary
> $59,000 +/- $500 (with 95% confidence) in 10 seconds
> vs. $59,152.25 in 10 minutes

- 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

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

Basic Approach 2: Precomputed Synopses

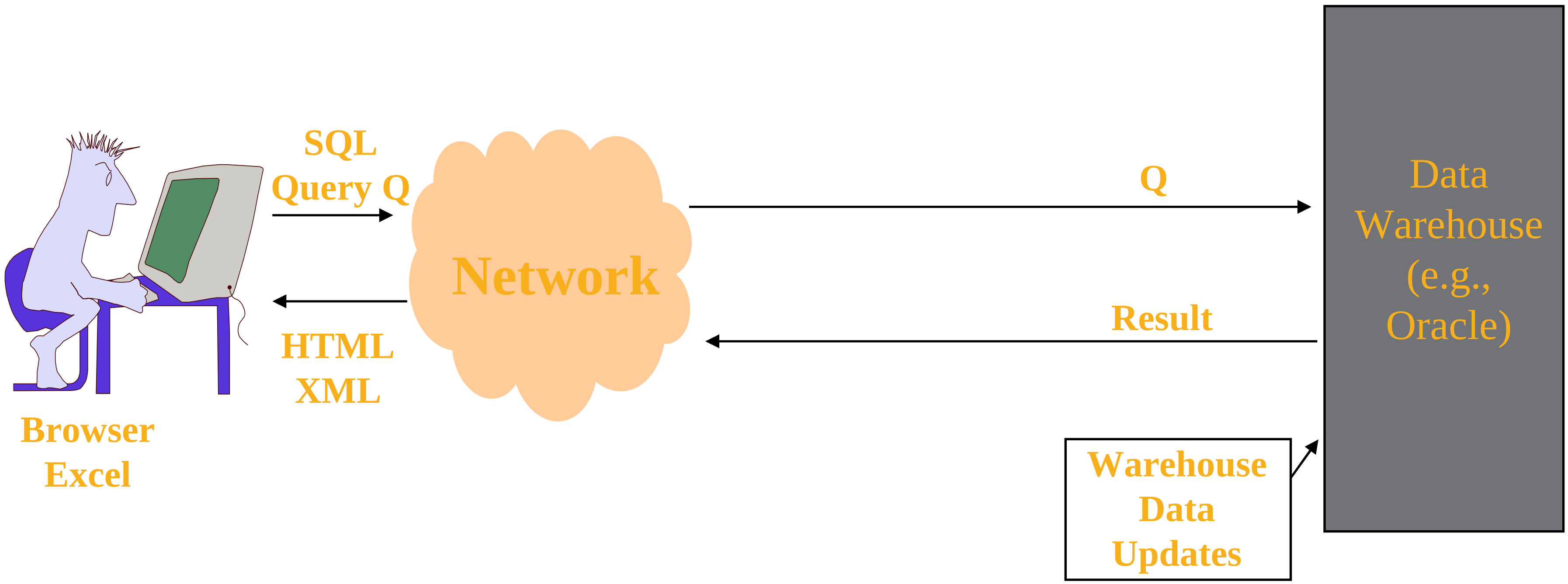
- Construct & store synopses prior to query time
- At query time, use synopses to answer the query

- 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]

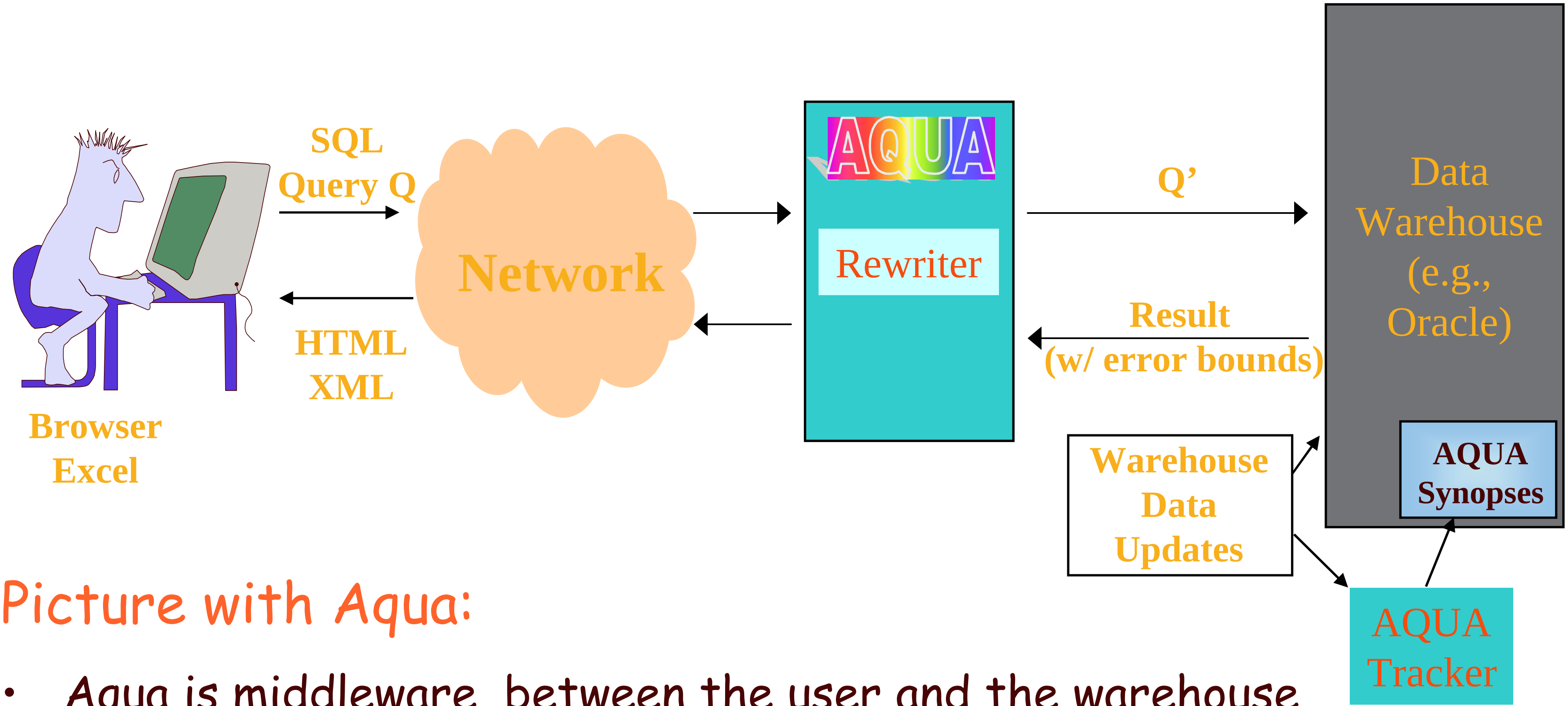
The Aqua Architecture



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:

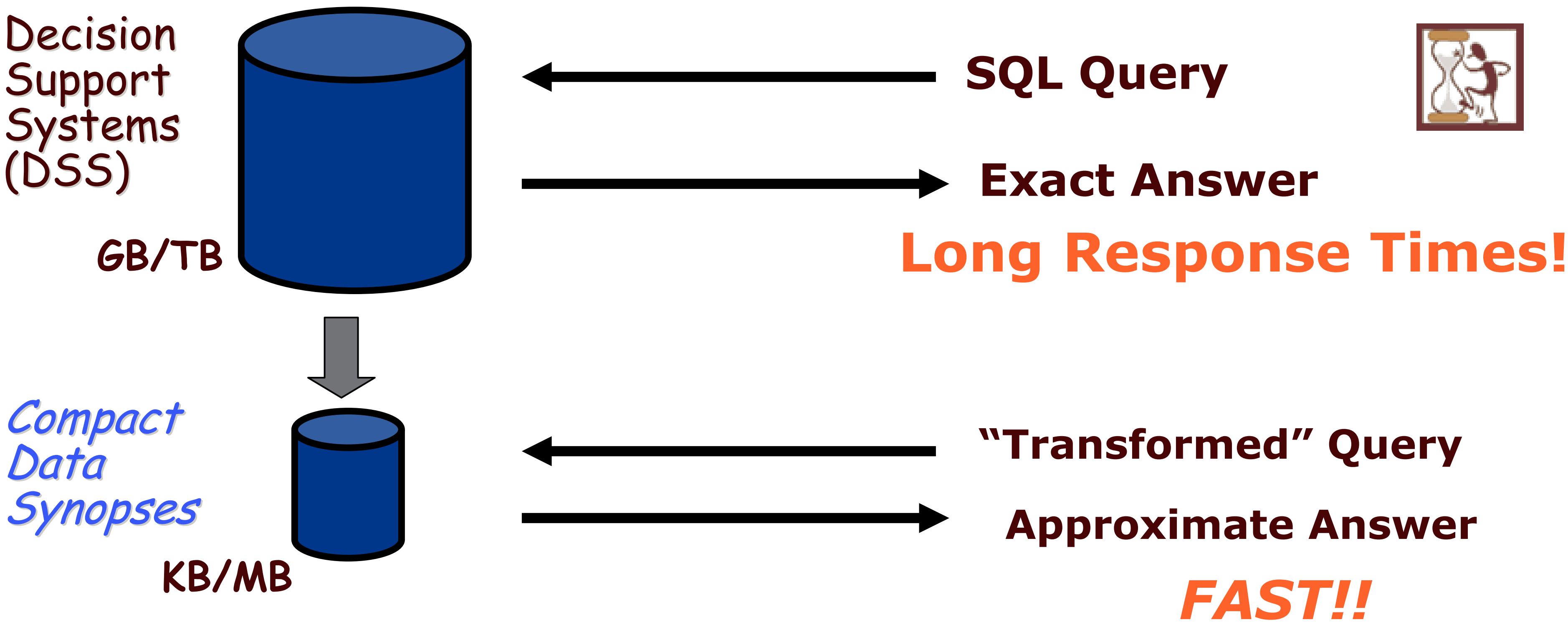
+ Seeing entire data is very helpful (provably & in practice)
  (But must construct synopses for a family of queries)
+ Often faster: better access patterns,
  small synopses can reside in memory or cache
+ Middleware: Can use with any DBMS, no special index striding
+ Also effective for remote or streaming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

Approximate Query Processing using Data Synopses



- How to construct effective *data synopses* ??

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
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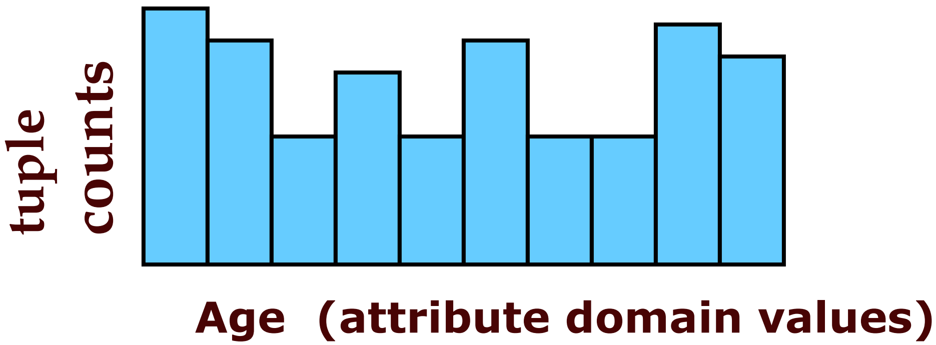
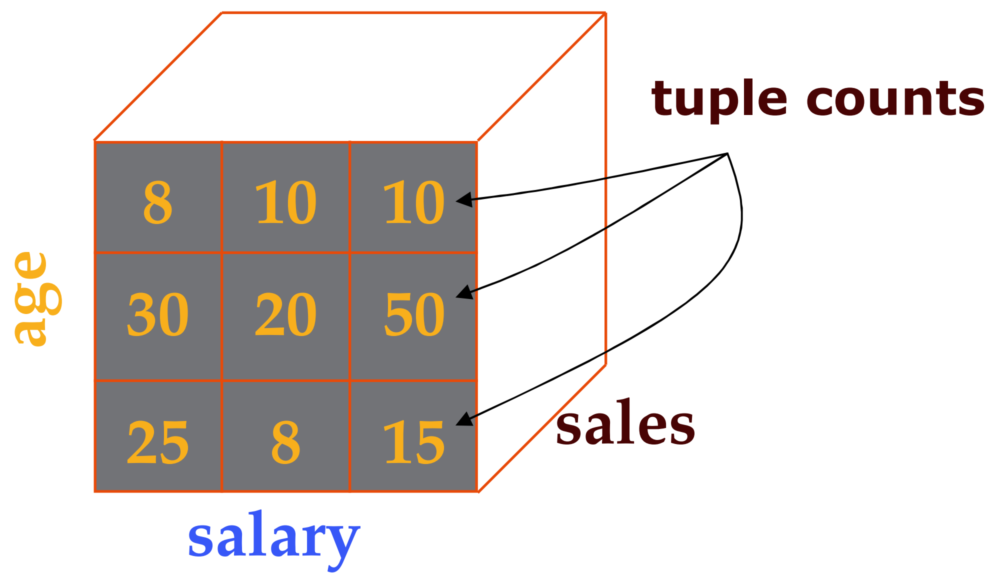
Relations as Frequency Distributions

One-dimensional distribution



Three-dimensional distribution

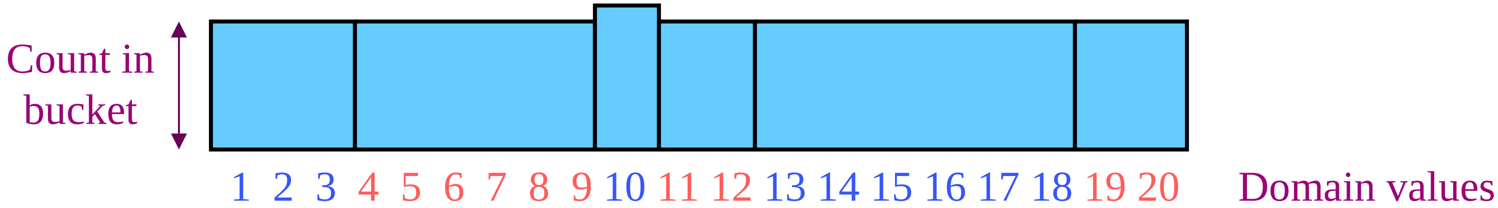


name	age	salary	sales
MG	34	100K	25K
JG	33	90K	30K
RR	40	190K	55K
JH	36	110K	45K
MF	39	150K	50K
DD	45	150K	50K
JN	43	140K	45K
AP	32	70K	20K
EM	24	50K	18K
DW	24	50K	28K

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



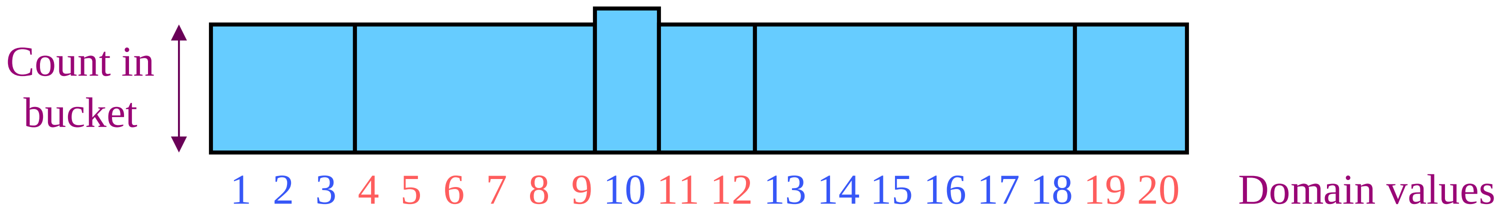
- Goal: Equal number of rows per bucket (B buckets in all)

- Can **construct** by first sorting then taking B-1 equally-spaced splits

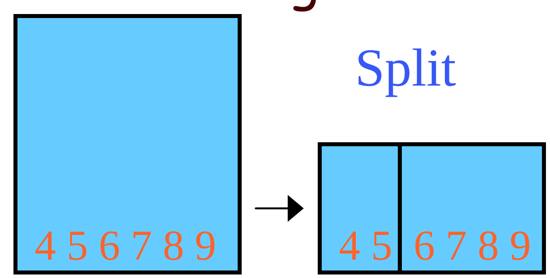
1 2 2 3 4 7 8 9 10 10 10 10 11 11 12 12 14 16 16 18 19 20 20 20

- **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

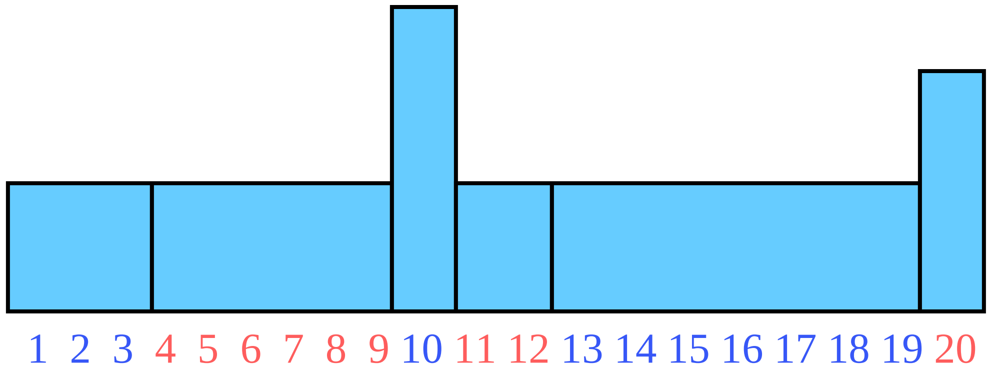


- Can **maintain** using one-pass algorithms (insertions only), or
- Use a backing sample [GMP97b]: Maintain a larger sample on disk in support of histogram maintenance
  - Keep histogram bucket counts up-to-date by incrementing on row insertion, decrementing on row deletion
  - Merge adjacent buckets 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]

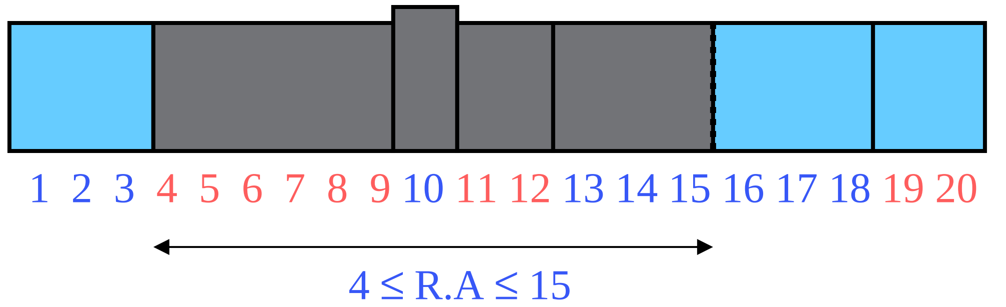
1-D Histograms: V-Optimal

[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



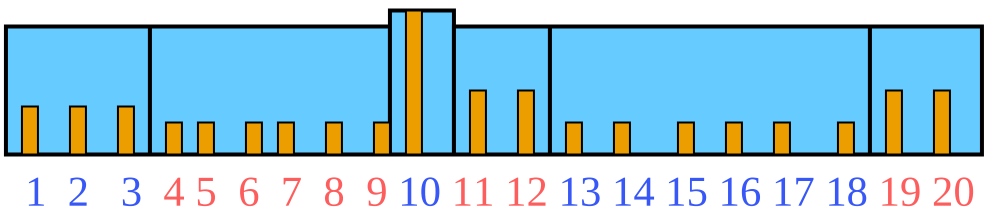
Answering queries:

- 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

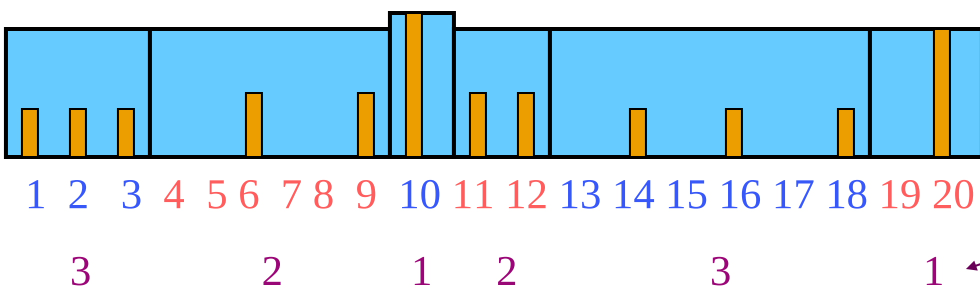
Answering Queries: Histograms

- 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]:

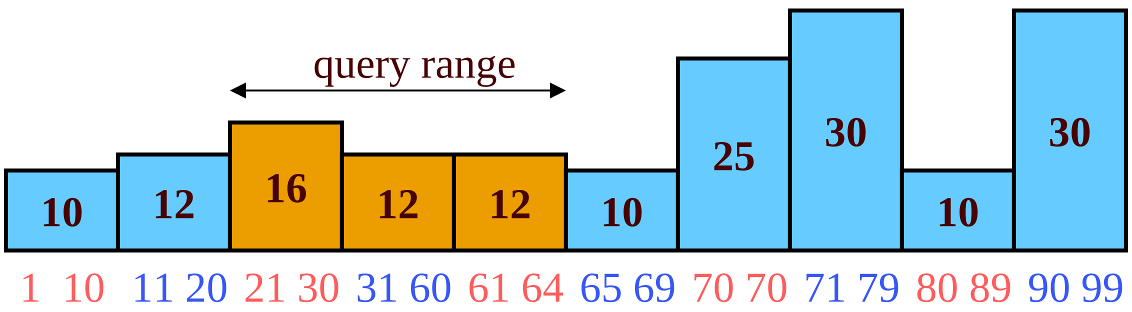


Need number of distinct in each bucket

Self-Tuning 1-D Histograms

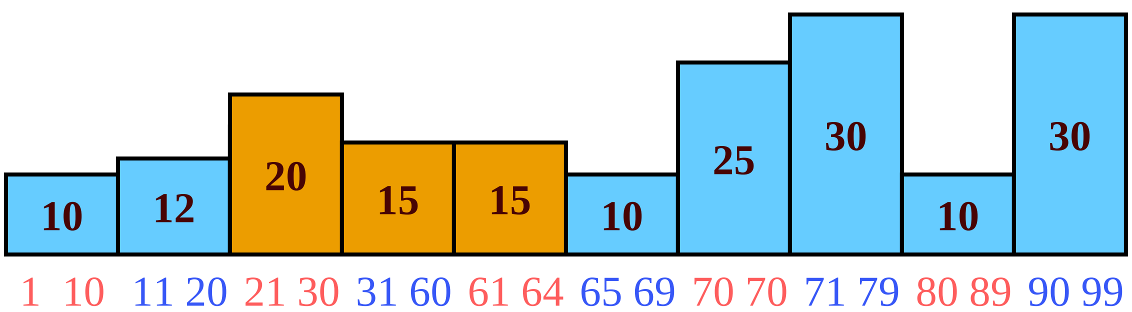
1. Tune Bucket Frequencies: [AC99]

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



Actual = 60
Estimate = 40
Error = +20

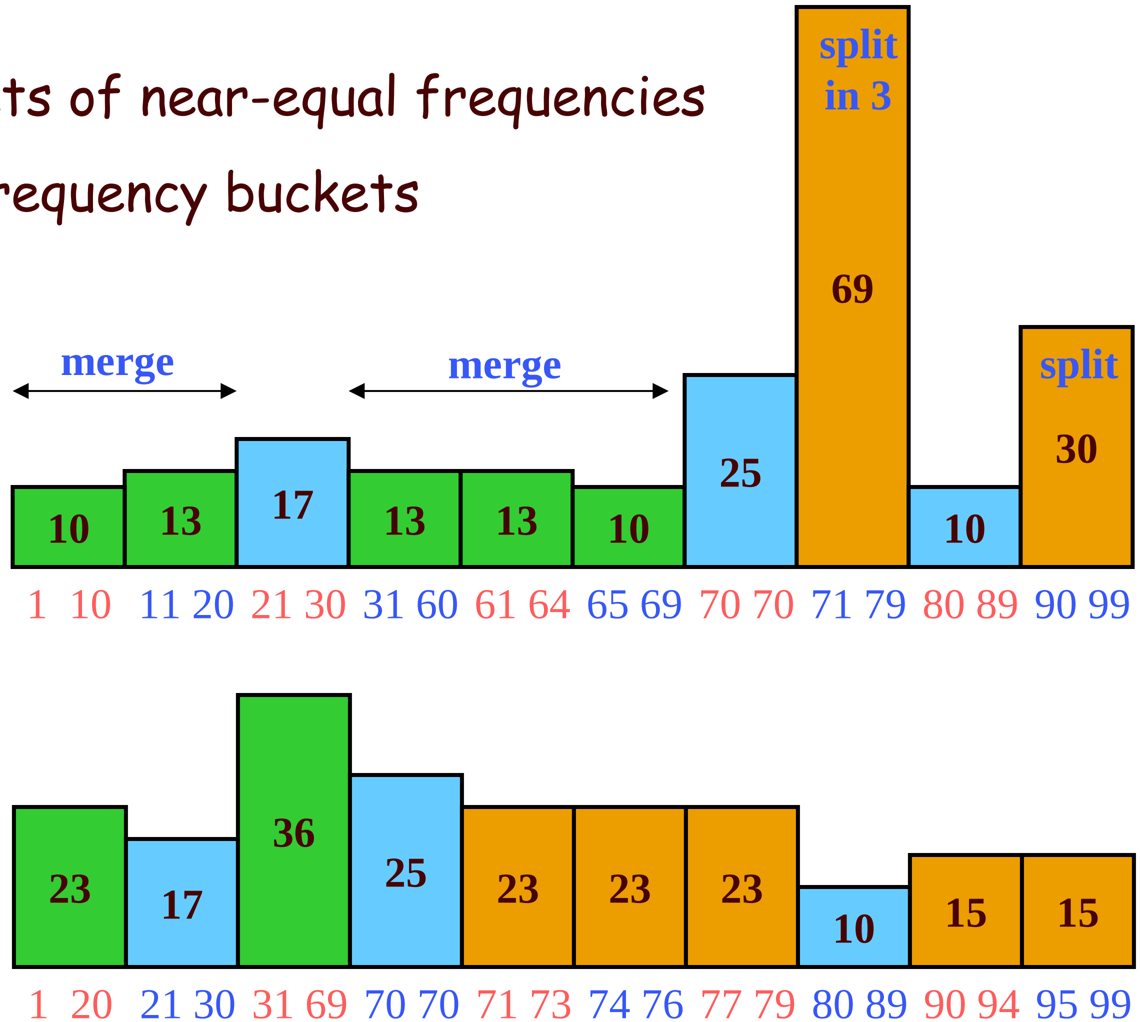
- Divide d*Error proportionately, d=dampening factor



d=½ of Error
= +10
So divide
+4,+3,+3

Self-Tuning 1-D Histograms

2. Restructure:
   - Merge buckets of near-equal frequencies
   - Split large frequency buckets



Also Extends to Multi-D

Sampling: Basics

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

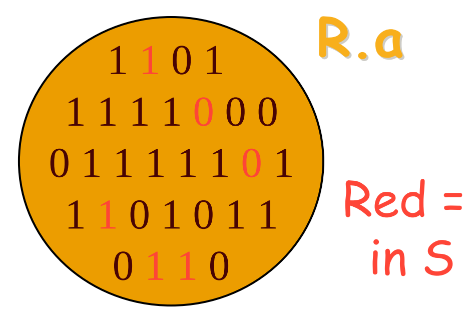
- For a fast approx answer, apply the query to S & "scale" the result
- E.g., R.a is {0,1}, S is a 20% sample

  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



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

- 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