# Datenbanksysteme II:
# Cost Estimation for Cost-Based Optimization

Ulf Leser

# Content of this Lecture

- Cost estimation
- Uniform distribution
- Histograms
- Sampling
- Example: Oracle
- Some empirical observations

# Motivation: Cost-based Optimizers

- Find best plan based on estimation of a plan’s cost
- Requires a cost model: How do we compute the cost of an operation, given its input, its output, and its internal computation?
- Most prominent: Size of intermediate results
  - Which are output of some operation and input to other operations
  - This is typically 1:1, for joins 2:1
  - Also called “cardinality estimation”
- In this lecture, we focus on cardinality estimation
  - For good reasons: Probably largest impact

# Other Costs

- Width of tuples
  - Typically easy to estimate – we'll mostly skip this
- Real data access
  - Disk or memory (or network)
  - Blocked / tuple, random / sequential
- Computing the predicate
  - Mostly very cheap: Comparisons
  - But: Aggregations, projections with functions
  - Very expensive: Median
  - Very expensive: Window Functions

# Example

```
SELECT *
FROM    product p, sales S
WHERE   p.id=s.p_id and
        p.price>100
```

- Assume we store for each attribute: (count, min, max)
- Assume 3300 products, prices between 0-1000 Euro, 1M sales, index on sales.p_id and product.id
- Assuming uniform distribution
  - Price range is 0-1000 => selectivity of condition is 9/10
    - Expect 9/10*3300 ~ 3000 products
  - Choose BNL, hash, or sort-merge join
    - Depending on buffer available

# Example

```
SELECT *
FROM    product p, sales S
WHERE   p.id=s.p_id and
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```

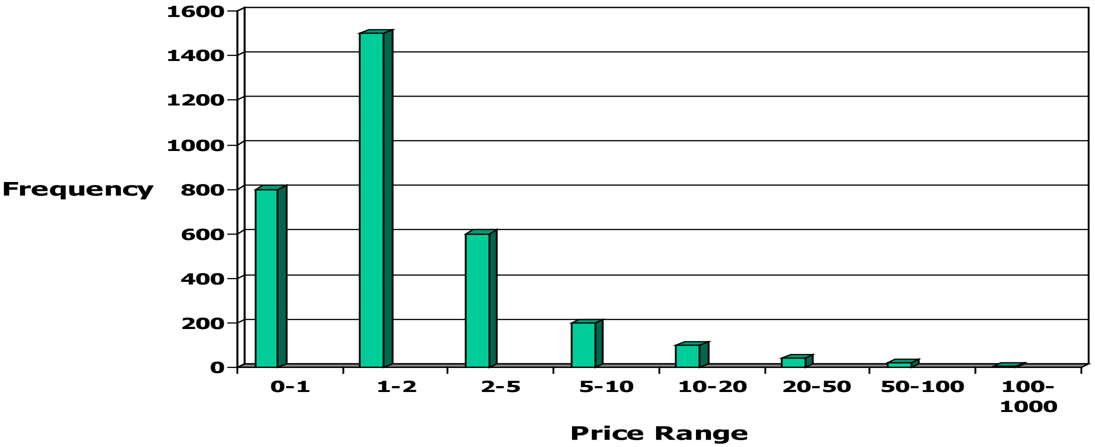

- Approaching real selectivity: Using histograms
  - Assume 10 buckets for price of products
  - We infer: Selectivity of condition is 5/3300 ~ 0,0015
  - Choose index-join: scan p, collect id of selected products, use index on sales.p_id to access sales
- Note: We are making another assumption – which?
  - Maybe people mostly buy expensive goods?

# Cost Estimation

- We approach cost estimation bottom-up
- Start by building a model of individual relations
  - Model should be much smaller than relation
  - Should allow for accurate predictions for all possible operations
    - Selection, projection, group-by, …
    - We will have to make some compromises
  - Should be consistent – same estimates for different ways of implementing the same subquery
  - Should be easy to maintain when data changes
  - Should be generated quickly
  - Needs to be stored and accessed efficiently
  - Should be easily derivable for intermediate relations during query processing

# First Model: Uniform Distribution

- With uniform distribution, we only need (count, min, max):
  - "Smaller": Storing requires only a few bytes per attribute
    - More for string attributes
    - Need not always be exact: "zz" instead of "zweifel", 5 instead of 5,231
  - "Accurate": Let's see (this lecture)
  - "Consistent": No
  - "Maintainable": In constant time for INSERT
    - Update/delete: Exact models may require finding new min / max
    - Alternative: Ignore update/delete, accept errors
  - "Fast generation": Requires only one pass
    - Beware: Count usually cannot be derived from used space
  - "Efficient storage and retrieval": Small is always efficient
  - "Derivable": Let's see (this lecture)

# Other Models

- Recall: Small, accurate, updateable, derivable
- Option 2: Assume one of the standard distributions
  - Normal, Poisson, Zipf, …
    - Weight of persons, number of sales per product, …
  - Small: Very small model
    - Can be characterized by few parameters (mean, stddev, …)
  - Accurate: Very accurate it values follow distribution tightly
    - But: How should the DB know which distribution is the right one?
    - Must be specified by developer
  - Updatable: There are no updates once parameters are known
  - Derivable: Very difficult to impossible
    - Normal distribution after SELECT is not normal anymore
    - We cannot use option 2 everywhere in the plan
  - Only used for special cases

# Other Models II

- Recall: Small, accurate, updateable, derivable
- Option 3: Approximation of distribution by histograms
  - Different types, more or less adequate for different distributions
  - Parameterized size, quite simple to build
  - Accuracy depends on type and size
  - Rather efficient means for updates and derivations
  - Later this lecture
- Option 4: Sampling
  - Maintain a random sample of tuples for each relation
  - Estimate all costs on this sample
  - Configurable size, larger = more accurate
  - Derivation is like simulating a query
  - Even later this lecture

# Important Note

- Derived estimations need not be exact
  - Should only help to discern good transformations from bad ones
  - Only order of alternatives matters, not their concrete cost
  - If 1st/2nd plan have estimated costs 1,1/1,15, although real costs are 10/1000, we nevertheless reach our goal – choosing the best
- Estimates in reality are often very bad
  - Orders of magnitude (see examples at end of this lecture)
  - Especially when data deviates from assumptions of the model
  - Still, resulting plans might be very good
- Trade-off: Accuracy of model-derived estimates versus effort to maintain models

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- Histograms
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# Rules of Thumb

- We discuss impact of each relational operation on parameters of a simple model assuming uniform distributions
  - S will denote the result of a (unary, binary) operation
- For relation R and attribute A, our model consists of
  - v(R, A): Number of distinct values of A
  - max(R, A), min(R, A): Maximal/minimal value of A
    - Values that do exist in R, not maximal / minimal possible values
  - |R|: Number of tuples in R
  - Note: R may be an intermediate result

# Size after a Selection

- Assume min≤const≤max
- Selection of the $S=\sigma_{A=const}(R)$
  - |S| = |R| / v(R,A)
  - v(S,A) = 1; max(S,A)=min(S,A)=const
- Selection of the form "A<const" (or "A ≤ ≥ > const")
  - |S| = |R| / (max-min) * (const-min)
  - v(S,A) = v(R,A) / (max-min) * (const-min)
  - min(S,A) = min; max(S,A)=const
  - Alternative: |S| = |R| / k (e.g. k=10,15,…)
    - Idea: With such queries, one usually searches for outliers
    - k ~ frequency of outliers ("magic constant")
    - Very rough estimate, but requires no knowledge of values in A at all

# Selection II

- Selection of the form "$A \neq const$"
  - $|S| = |R| * (v(R,A)-1)/v(R,A)$
    - We assume that const exists as value in A
  - $v(S,A)=v(R,A)-1$
  - $min(S,A)=min$, $max(S,A)=max$
  - Alternative model: $|S| = |R|$

# Complex Selections

- Conjunction: Selection of the form “$A\theta c_1 \wedge B\theta c_2 \wedge \ldots$”
  - Assumption: Statistical independence of atomic conditions
  - Total selectivity is $sel(c_1) * sel(c_2) * \ldots$
  - v, min, max are adapted iteratively
- Negation: Selection of the form “not $A\theta c$”
  - Selectivity is 1-sel(c)
- Disjunction: Selection of the form “$A\theta c_1 \vee B\theta c_2 \vee \ldots$”
  - Rephrase into $\neg (\neg(A\theta c_1) \wedge \neg(B\theta c_2) \wedge \ldots )$
  - Selectivity is $1- (1-sel(c_1))*(1-sel(c_2))*\ldots)$
- Be careful: “$A<55 \wedge A>55$”

# Distinct and Projection

- Selectivity of DISTINCT
  - |S| = v(R,A)
  - v(S,A)=v(R,A), min(S,A)=min, max(S,A)=max
- Selectivity of projection
  - Projections usually only change the width of a tuple
    - Exception: Window functions
    - Width may increase: Computed attributes
  - Selectivity=1 under BAG semantics
  - Caution
    - In real life, we need to estimate sizes in bytes
    - This requires number of tuples and size of tuples
    - Our current model ignores this issue

# DISTINCT and GROUP-BY

- Selectivity of GROUP-BY
  - Same as selectivity of distinct on group attributes
- But: Selectivity of **`SELECT DISTINCT A,B,C FROM`** …

# Projection and Distinct

- Selectivity of GROUP-BY
  - Same as selectivity of distinct on group attributes
- But: Selectivity of `SELECT DISTINCT A,B,C FROM …`
  - Not easy: We need to know correlations of values
  - Clearly, $\leq < |S| \leq v(R,A) * v(R,B) * v(R,C)$
  - Simple heuristic: $|S| = \min( \frac{1}{2}*|R|, v(R,A)*v(R,B)*v(R,C))$
- Alternative
  - Multi-dimensional histograms (later)

# Selectivity of Cartesian Product

- Consider S=R x T
  - |S| = |R| * |T|
  - For all attributes A of S: max(S,A), min(S,A), v(S,A) are copied from base relation

# Selectivity of Joins

- Consider join: $R \bowtie_A T$ (means $\sigma_{R.A=T.A}(R \times T)$)
- What is the selectivity of the join?
  - Need to know about correlations of values in different relations
  - Similar problem as for … `DISTINCT A,B,C` …,
- Suggestions
  - Option 1: We assume (or know!) joining a PK with a FK
    - Thus, if $v(R,A)<v(T,A)$, T.A is PK in T and R.A is FK
      - Or vice versa
    - Then, each FK "finds" its PK
    - Thus: $|S|=|R|$, $max(S,A)=max(R,A)$, $min(S,A)=min(R,A)$, $v(S,A)=v(R,A)$

# Selectivity of Joins

- Option 2: Assume that value sets are similar
  - Assumption: Users don't join independent attributes
  - Thus, most tuples will find a join partner
  - Thus, each tuple from T will join with app. |R|/v(R,A) tuples from R
  - Symmetrically, each tuple from R will join with app. |T|/v(T,A) tuples from T
  - Thus, we expect |T|*|R|/v(R,A) or |R|*|T|/v(T,A)
  - Typical solution: |S| = |R|*|T| /(max(v(T,A), v(R,A))
  - |R|<|T|: v(S,A)=v(R,A), min(S,A)=min(R,A), max(S,A) = max(R,A)
- What about Theta-Joins: $R \bowtie_{R.A<T.B} T$ ?
  - For each distinct value T.B, estimate which fraction of R has smaller values in R.A, then aggregate

# Remarks

- We did not discuss effects of operations on other attributes
- Simple model: Ignore
  - Operation on R.A does not influence models of other attributes of R
  - Example: “age<19” does not change min(R,name) or max(R,name)
  - Often wrong: “age<19” does change max(R, income)
- In all other cases, we need to have models taking correlations of value sets into account
  - E.g. Multi-Dimensional Histograms
- As far as I know: Nowhere used in practice

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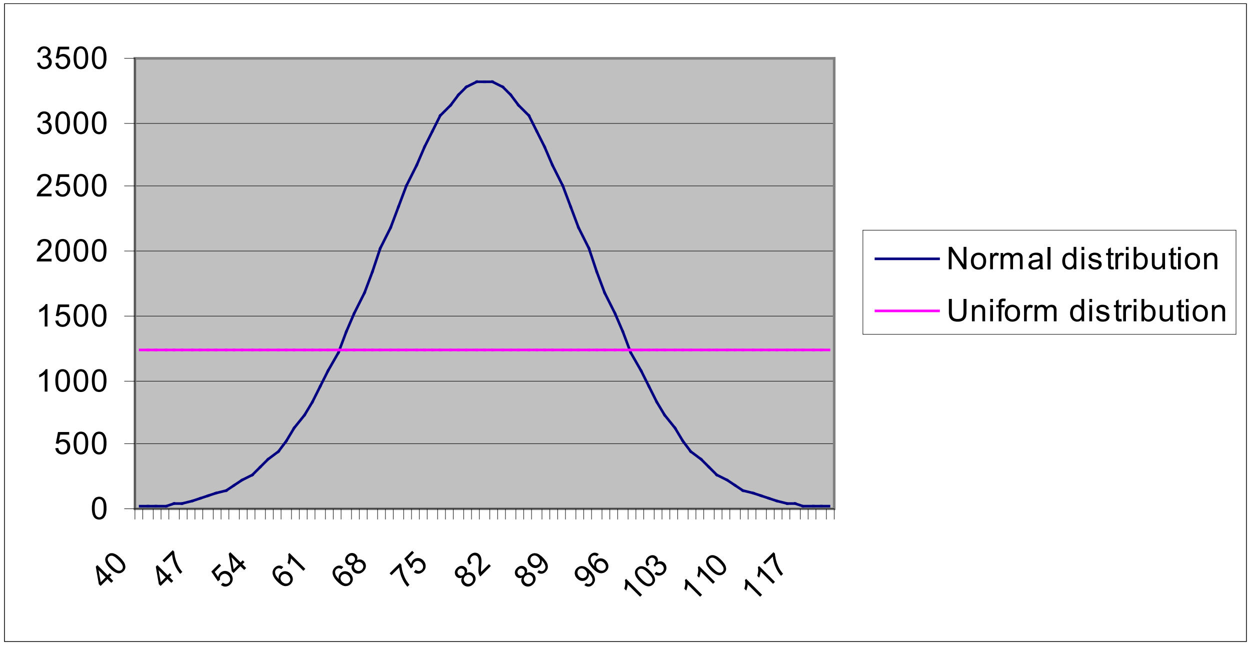
# Histograms

- Real data is rarely uniformly distributed
  - Nor Poisson, normal, Zipf, …
- Solution: Histograms [for single attributes]
  - Partition the (current) value range into buckets
  - Count frequency of tuples in each bucket (i.e. range)
  - During optimization, estimate selectivities from affected buckets
    - Typical: Uniform distribution assumption inside each bucket
- Advantage
  - Hope: Frequencies vary less inside smaller ranges
  - Lower errors due to smaller ranges for uniformity assumption

# Issues

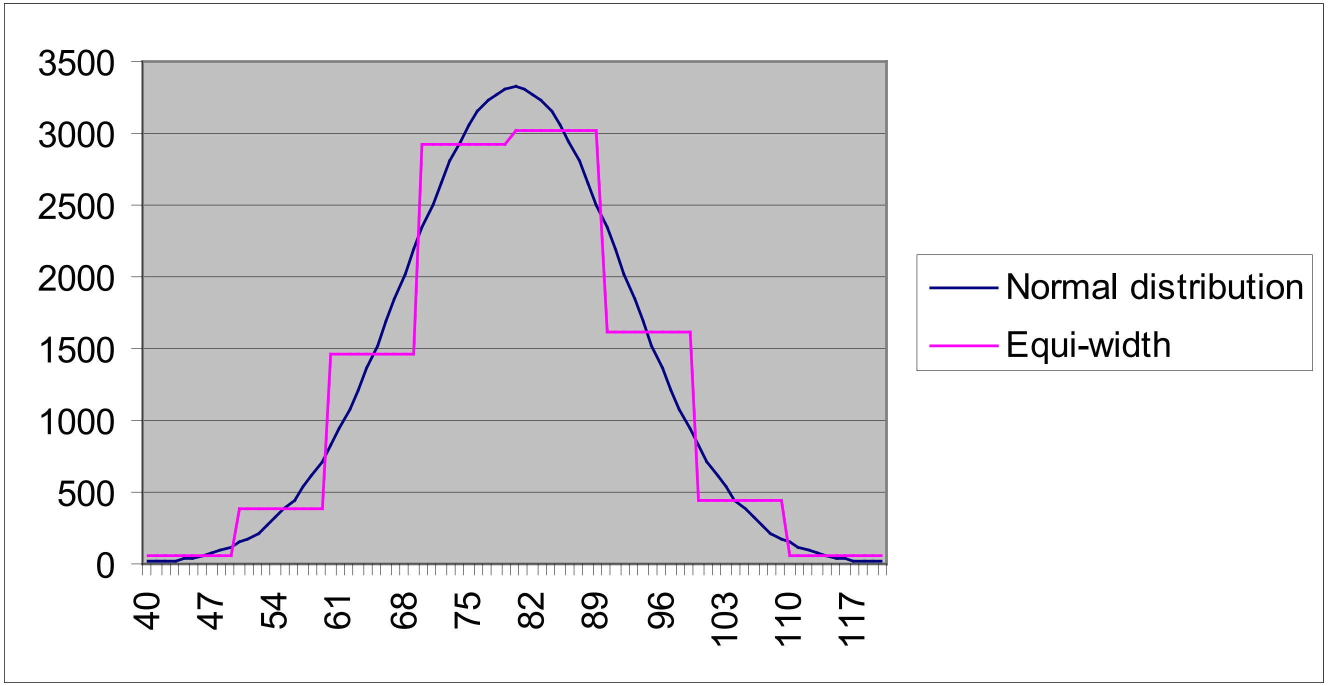
- We must think about
  - How should we chose the borders of buckets?
  - What do we store for each bucket (could be more than count)?
  - How do we keep buckets up-to-date?

# Distribution



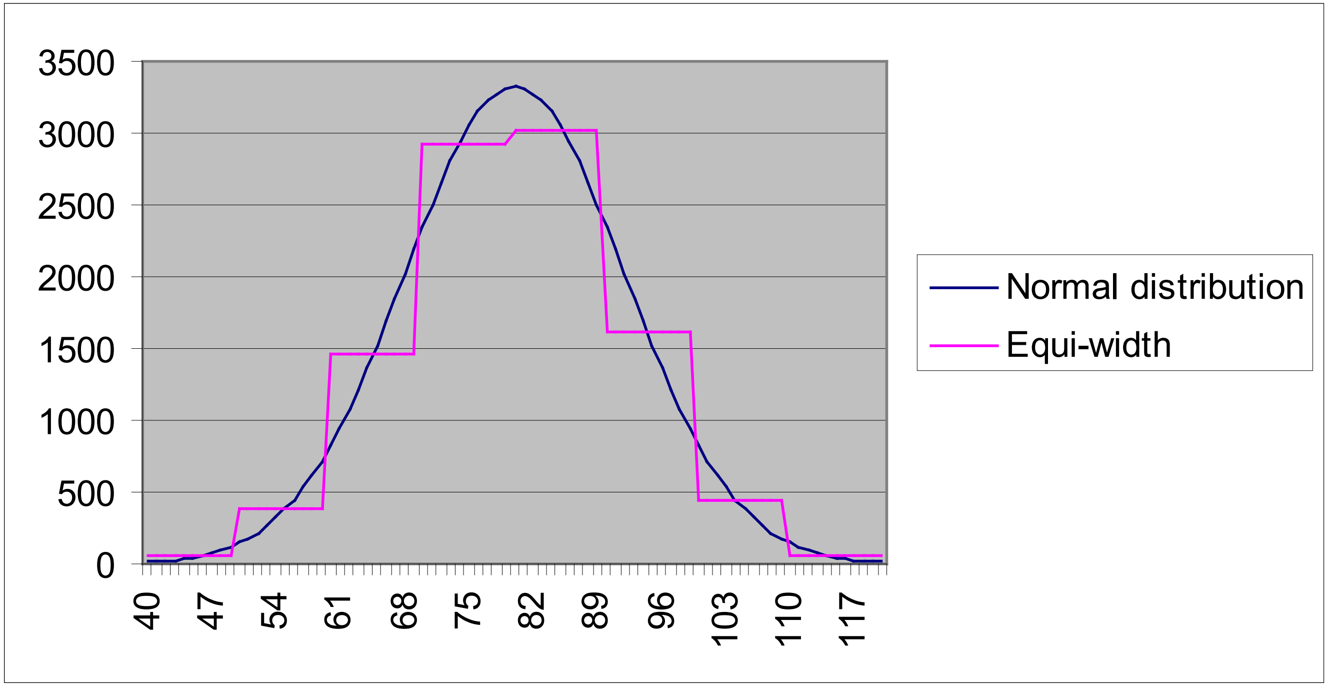
- Assume normal distribution of weights
    - Spread: 120-40=80, mean: 80, stddev: 12; 100.000 people
- Uniform distribution: 100.000/80=1250 for each possible weight
- Leads to large errors in almost all possible query ranges

# Equi-Width Histograms



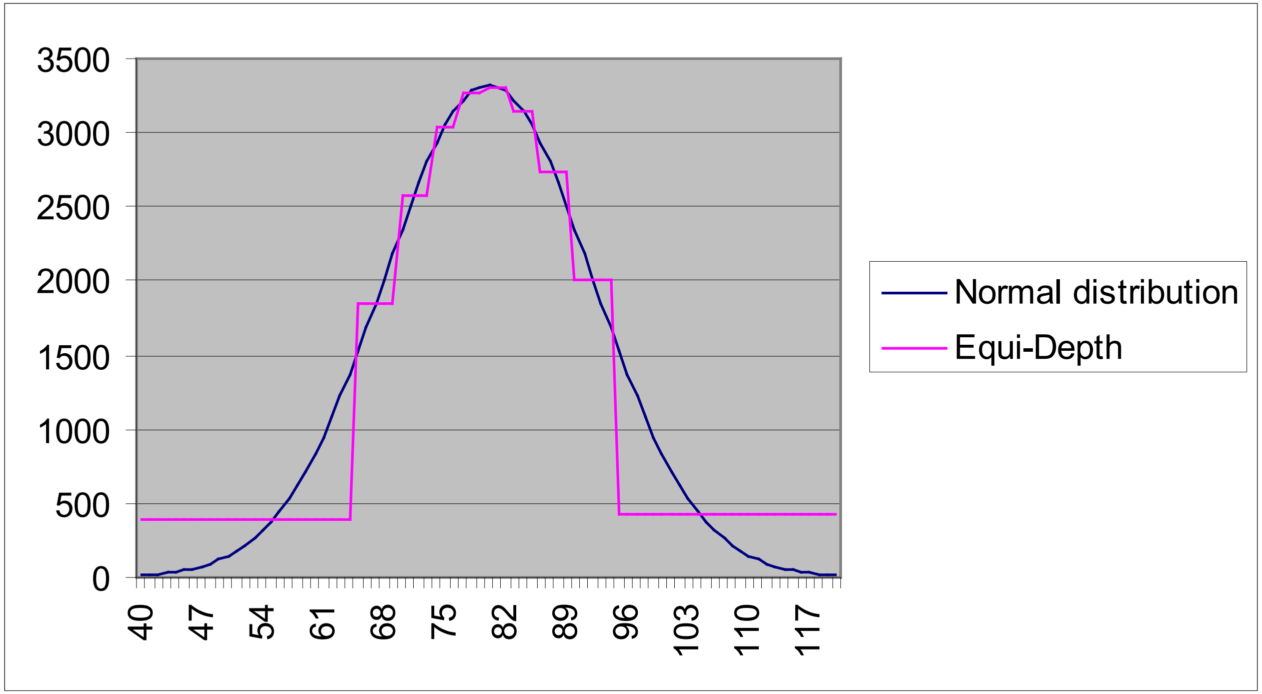
- Fix number b of buckets
- Borders are equi-distant (border values need not be stored)
- In each bucket, assume average frequency inside bucket

# Equi-Width Histograms 2



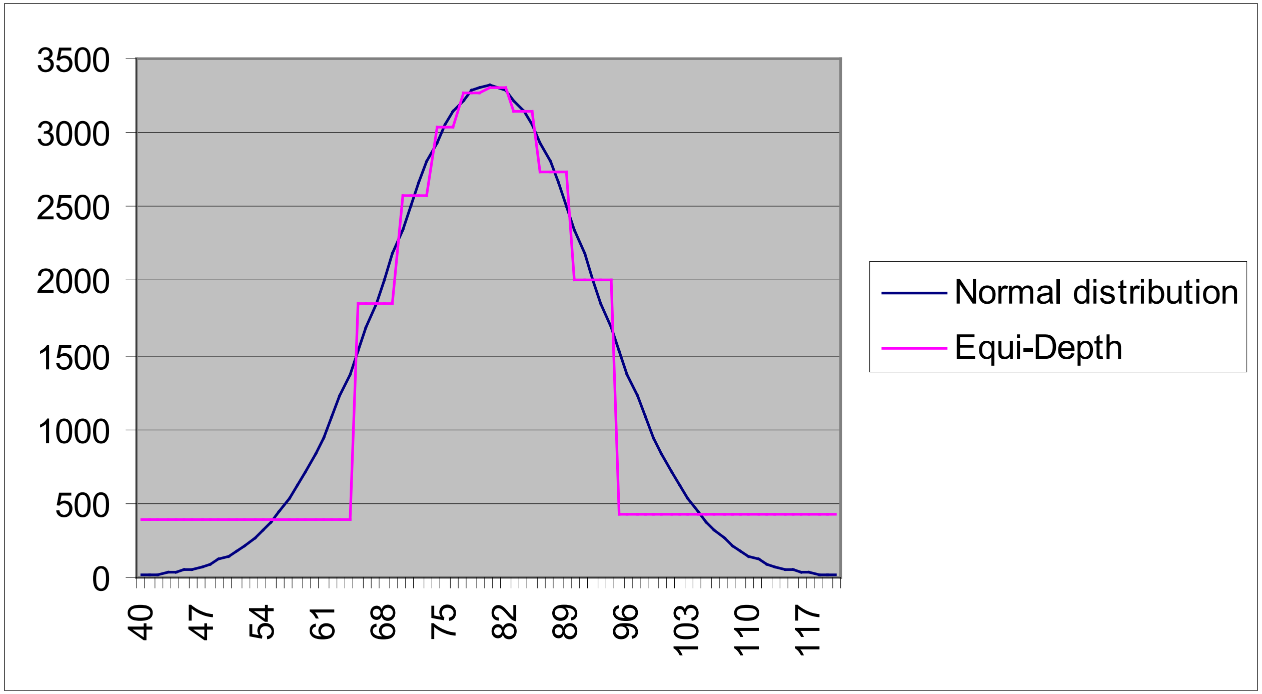
- Bucket counts can be computed by scanning relation once
- Remaining error depends on
  - Number of buckets (more buckets -> less errors, but more space)
  - Distribution of values in each bucket

# Equi-Depth



- Fix number b of buckets
- Chose borders such that frequency of values in each bucket is approximately equal
  - If single value more frequent than |R|/b - use other histograms

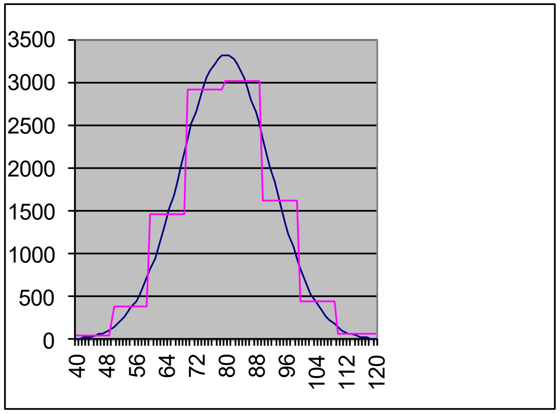
# Equi-Depth



- Buckets have varying sizes (borders need to be stored)
- Better fit to data
- Computation?
  - Sort all values, then jump in equally wide steps

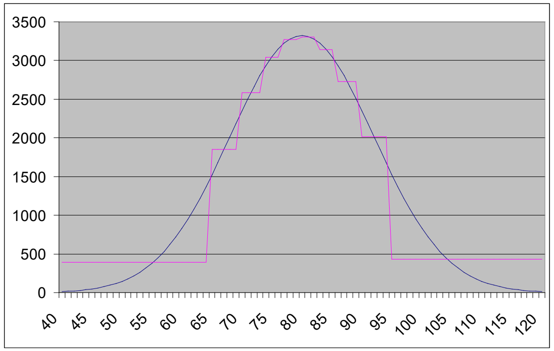
# Example

- Query: Number of people with weight in [65-70]
  - Real value: 11603
  - Uniform distribution: (70-65+1)*1250 = 7500
    - Error: 4103 ~ 35%
  - Equi-width histogram
    - Range 60-69 has average 1469
    - Range 70-79 has average 2926
    - Estimation: 5*1469 + 1*2926 = 10271
      - Error: 1332 ~ 11%



# Example cont'd

- Query: Number of people with weight in [65-70]
  - Real value: 11603
  - Uniform distribution: (70-65+1)*1250 = 7500
    - Error: 4103 ~ 35%
  - Equi-depth histogram
    - Range 65-69 has average 1850
    - Range 70-73 has average 2581
    - Estimation: 5*1850 + 1*2581 = 11831
    - Error: 228 ~ 2%

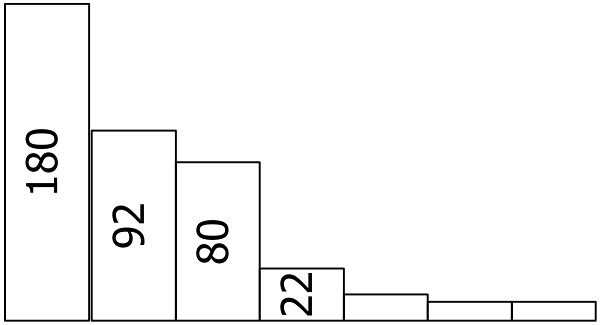


- Error depends on concrete value or range
- In general, equi-depth histograms are considered more accurate than equi-width histograms
  - But more costly to build and maintain

# Other: Serial Histograms

- Sort values by frequency and build buckets as ranges of frequencies (rare values, less rare values, …)
  - Frequency ranges of different buckets do not overlap
- Better fit, but values in buckets must be stored explicitly
  - There are no consecutive ranges any more
  - Not directly applicable for REAL or VARCHAR (discretize!)
- Range queries must find their values in all buckets

| Value | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Cnt | 12 | 92 | 10 | 180 | 22 | 20 | 80 |

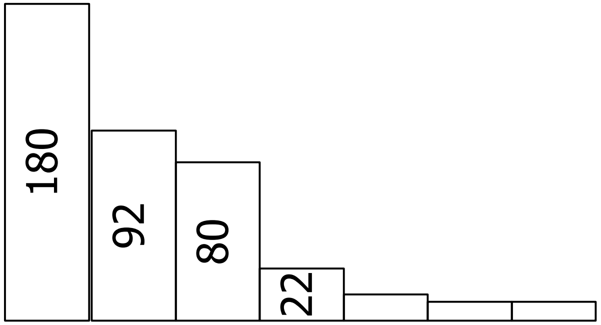


| Bucket | 1 | 2 | 3 |
|---|---|---|---|
| Values | 4 | 2,5,7 | 1,3,6 |
| Total cnt | 180 | 194 | 42 |
| $\sigma^2$ | 0 | ~1400 | ~28 |

# Other: V-Optimal Histograms

- Sort values by frequency and build buckets such that weighted variance is minimized in each bucket
  - Explicitly considers the expected error
- Provably best class of histograms for “average” queries
  - But costly to generate and maintain
  - Best known algorithm is $O(b*n^2)$ (n: |values|, b: |buckets|)

| Value | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Cnt | 12 | 92 | 10 | 180 | 22 | 20 | 80 |



| Bucket | 1 | 2 | 3 |
|---|---|---|---|
| Values | 4 | 2,5 | 1,3,6,7 |
| Total cnt | 180 | 172 | 64 |
| $\sigma^2$ | 0 | ~72 | ~35 |

# Other Types of Histograms

- End-biased histograms
  - Sort values by frequency and build singleton buckets for k largest / smallest frequencies plus one bucket for all other values
  - Simple form of serial histograms, quite effective for many real-world data distributions (e.g. Zipf-like distributions)
- "Commercial systems seem mostly to use equi-depth and compressed histograms (mixture of equi-depth and end-biased histograms)"

Ioannidis, Y. (2003). "The history of histograms (abridged)". VLDB
Ioannidis / Christodoulakis (1993). "Optimal Histograms for Limiting Worst-Case Error Propagation in the Size of Join Results.", TODS
Ioannidis / Poosala (1995). "Balancing Histogram Optimality and Practicality for Query Result Size Estimation." SIGMOD Record

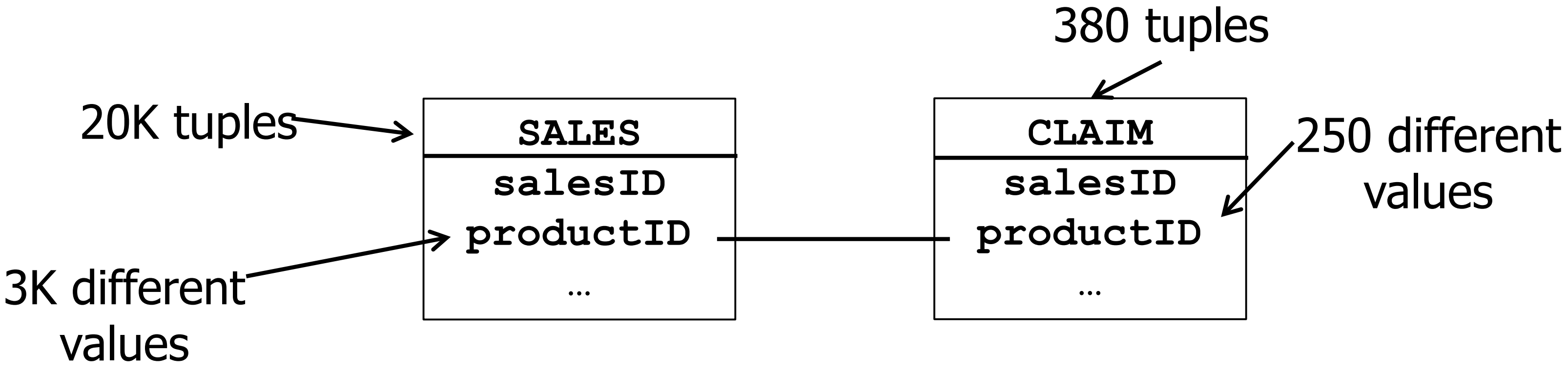
# Content of this Lecture

- Cost estimation
- Uniform distribution
- Histograms
  - Types of histograms
  - Joins, construction, maintenance
- Sampling
- Example: Oracle
- Some empirical observations

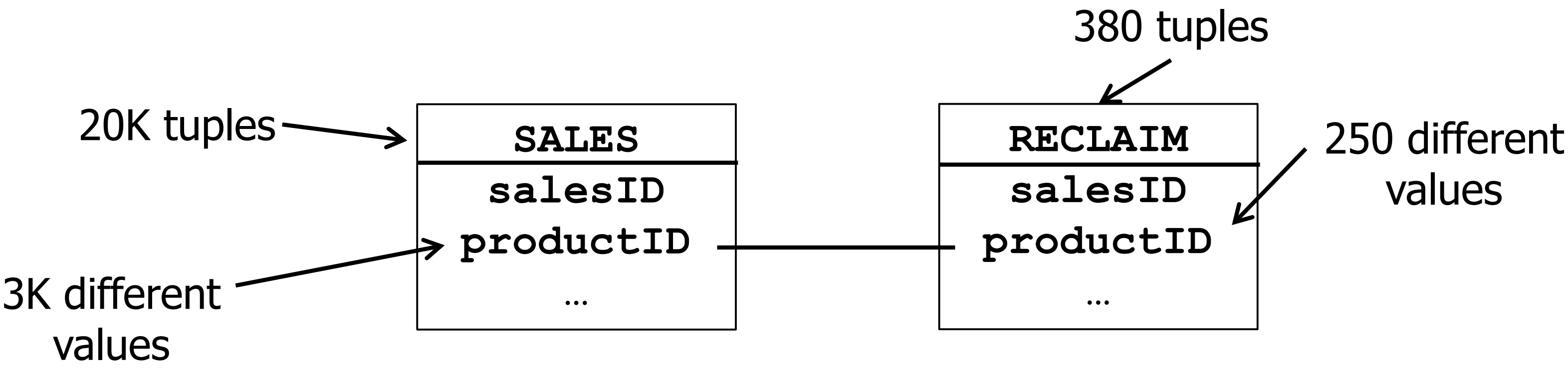
# Histograms for Join Estimation

- Assume sales and reclamations
  - And a slightly strange query, not passing along PK/FK constraints
  - Probably a mistake? But the DB must execute (and optimize) it anyway!

```
SELECT  count(*)
FROM    sales S, reclamation R
WHERE   S.productID=R.productID;
```



# Example without Histograms



380 tuples

20K tuples

**SALES**

**salesID**

**productID**

…

**RECLAIM**

**salesID**

**productID**

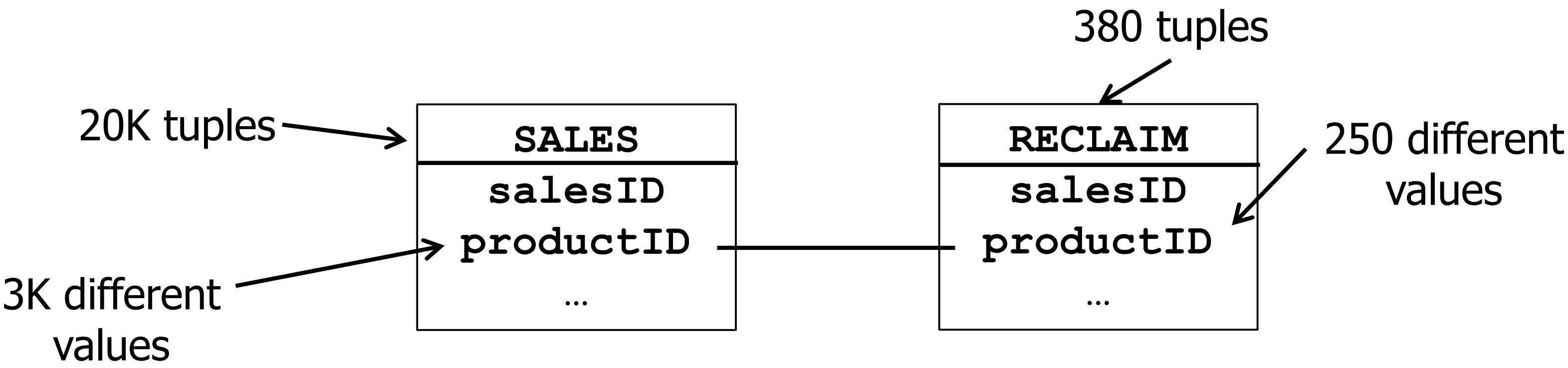
…

250 different values

3K different values

- Without histograms, assuming uniform distribution
  - Recall join-formula (no PK/FK)
  - Gives |S|*|R|/(max (v(R,productID), v(S,productID))) ~ 2500

# Example with Histograms



- Uniform distribution within buckets
  - And uniform distribution of distinct values
    - Better: Store cnt of distinct value per bucket
  - (7000*300/500)+(450*60/500)+…~ 4200
- More complicated if bucket borders of join attributes do not coincide
  - Always the case for equi-depth histograms

| Range | B.pID | R.pID |
|---|---|---|
| 0-499 | 7000 | 300 |
| -999 | 450 | 60 |
| -1499 | 2650 | 0 |
| -1999 | 4900 | 0 |
| -2499 | 100 | 20 |
| -2999 | 4900 | 0 |

# Histograms and Complex Conditions

- We only considered histograms for single attributes
- How to apply histograms for complex conditions?
  - People with weight<30 and age<25 ?
  - People with income>1M and tax depth<100K ?
  - Until now, we assumed statistical independence of attributes
  - Better estimates require conditional distributions
  - But: Combinatorial explosion of the number of combinations
    - Plus: Could be connected by AND, OR, AND NOT, …
- Multidimensional histograms
  - Active research area
  - Need sophisticated storage structures – multidimensional indexes

# Maintaining Equi-Width Histograms

- Building: Two scans
  - One for finding (min, max), one for counting bucket frequencies
    - Borders are regularly distributed over range
  - We can compute histograms for all attributes of a table at once
- Maintaining
  - If min / max does not change: Increase/ decrease frequencies in affected bucket
    - That's the most frequent case: Maintaining EW-histograms is cheap!
    - Finding the bucket is in O(1)
  - If min/max does change: Rebuild histogram
    - Or ignore change and only change frequency in first/last bucket

# Maintaining Equi-Depth Histograms

- Building: Sort
  - We need to sort all values, then partition into b roughly equal-size intervals
  - Requires one scan+sort per attribute
  - That’s rather expensive
    - Alternative: Use sample to estimate border values
- Maintaining
  - Almost all changes influence borders of buckets
    - Only updates of value within ED-range do not
  - Option 1: Accept intermediate inequalities in bucket frequencies
    - … and regularly re-compute entire histogram
  - Option 2: Implement complex bucket merging/ splitting procedures

# Offline Histograms

- Other option: Compute only on request and do not update
  - Administrator needs to trigger re-computation of (all, table-wise, attribute-wise, …) statistics from time to time
  - Otherwise, query performance may degrade
  - Both cases (new or outdated statistics) may lead to unpredictable changes in query behavior
- For long, this was the only available option
- Automatically maintaining statistics is an active research topic
  - General trend: Reduce total cost of ownership
  - Self-optimizing, self-maintaining, zero-administration, …

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# Sampling

- Scanning a table for computing a histogram is expensive, yet accuracy is limited
  - If out-of-date, if conditions don't match bucket borders, …
- Other approach: Use a sample of the data
  - Reservoir sampling: Compute a random sample and maintain
  - If chosen randomly, sample should have same distribution as full data set – and also all correlations
  - Usually, a 1-5% sample suffices
    - The larger |T|, the smaller the percentage
- Also useful for approximate COUNT, AVG, SUM, etc.
  - Approximate query processing: Faster answers with small errors
  - Active research area ("Taming the terabyte")

# Building and Maintaining

- Idea: How to get a random sample of s% of table T?
  - Selecting first s% rows is a bad idea (yet fast)
  - Solution: Scan and pick every tuple with probability s
  - Will create a sample S of size roughly s*|T|
    - Exact size doesn’t matter
    - We just have to make sure that there is no buffer overflow
- Maintain
  - DELETE: If tuple in sample is deleted, choose new tuple at random
  - INSERT: Add new tuple to S with probability s
  - UPDATE: Propagate to sample
  - All this is expensive: Operations always need to check S
  - Alternative: Ignore and rebuild from time to time

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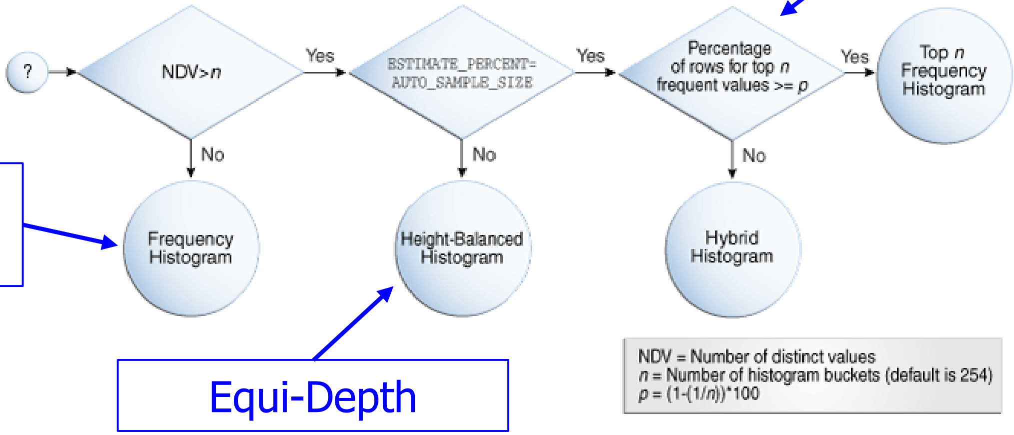
# Example: Oracle Basic Statistics

- Table statistics
  - Number of rows
  - Number of blocks
  - Average row length
- Column statistics
  - Number of distinct values (NDV) in column
  - Number of nulls in column
  - Data distribution (histogram)
- Index statistics
  - Number of leaf blocks
  - Levels
  - Clustering factor
- System statistics
  - I/O performance and utilization
  - CPU performance and utilization

- If activated: “Oracle gathers statistics on all database objects automatically and maintains those statistics in a regularly-scheduled maintenance job.”
- High-frequency tables: “Because the automatic statistics gathering runs during an overnight batch window, the statistics on tables which are significantly modified during the day may become stale”

# Example: Oracle Histograms



Most frequent values are very frequent

Every bucket one value

Equi-Depth

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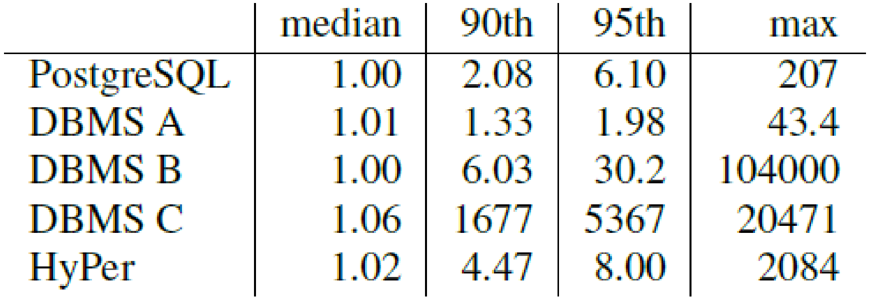
  - Leis, Gubichev, Mirchev, Boncz, Kemper, Neumann (2015): "How good are query optimizers, really?", PVLDB

# Empirical Observations

- Goal: Try to separately measure the relative impact of cardinality estimation, cost model, and join order algorithm
  - Hypothesis: Distribution assumptions (uniform) underlying most cost models are usually wrong
  - How much does this impact plan quality?
- Approach
  - "Real-life" benchmark: IMDB data, 21 tables, ~3GB raw data, many correlations between everything
    - Forget TPC-DS, TPC-H – synthetically generated (uniform) data
  - 33 query types with each ~3 incarnations; 113 queries, 3-16 joins
  - Use optimizers (with hints) to obtain cardinality estimates
  - Execute queries to obtain true cardinalities
  - Compare results from five different database systems
    - PostGreSQL, Hyper, DBMS-A, DBMS-B, DBMS-C

# Selectivity of Selections on Base Tables

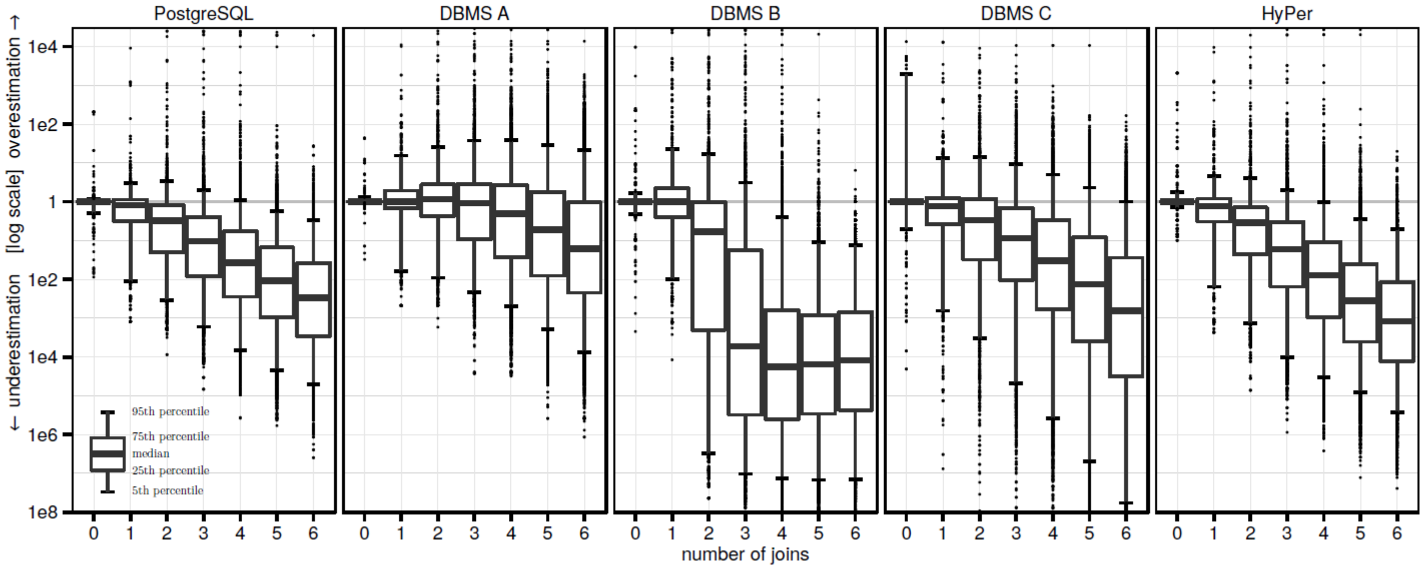


| | median | 90th | 95th | max |
|---|---|---|---|---|
| PostgreSQL | 1.00 | 2.08 | 6.10 | 207 |
| DBMS A | 1.01 | 1.33 | 1.98 | 43.4 |
| DBMS B | 1.00 | 6.03 | 30.2 | 104000 |
| DBMS C | 1.06 | 1677 | 5367 | 20471 |
| HyPer | 1.02 | 4.47 | 8.00 | 2084 |

**Table 1: Q-errors for base table selections**

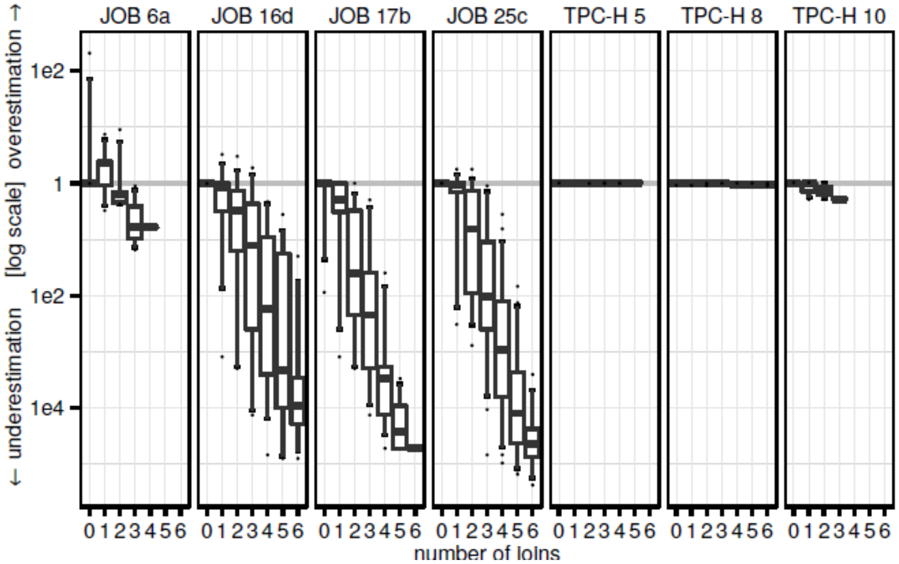
- 50% of estimates are almost perfect, in all systems
- 90% of estimates are wrong by a factor of 6 at most – but much worse in DBMS-C
- Extreme errors go up to factor 100.000
- Simple PostGres model works rather well
  - Min/max, distinct values, histograms

# Cardinality Estimates for Multi-Joins



- All systems work rather well for up to 2 joins
  - With median errors below 10
- In all systems, accuracy decreases quickly with more joins
  - Note the logarithmic scale at y-axis
- Join sizes mostly are heavily underestimated

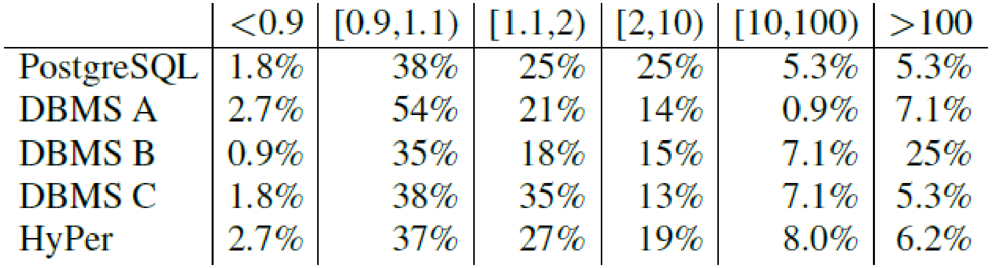
# Do not Use TPC-H!



- Uniform data – perfect estimations

# Impact on Runtime

- Approach: Obtain estimates from system X, inject into PostGres, let PostGres optimize and run the query
  - "Optimal": Same approach using true cardinalities

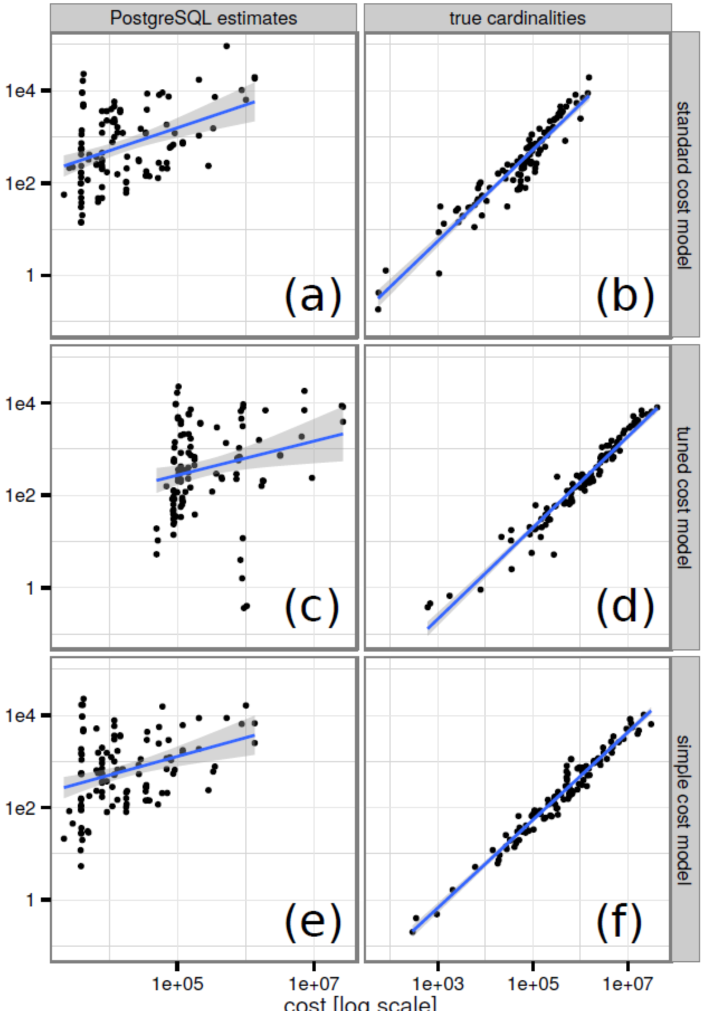


| | <0.9 | [0.9,1.1) | [1.1,2) | [2,10) | [10,100) | >100 |
|---|---|---|---|---|---|---|
| PostgreSQL | 1.8% | 38% | 25% | 25% | 5.3% | 5.3% |
| DBMS A | 2.7% | 54% | 21% | 14% | 0.9% | 7.1% |
| DBMS B | 0.9% | 35% | 18% | 15% | 7.1% | 25% |
| DBMS C | 1.8% | 38% | 35% | 13% | 7.1% | 5.3% |
| HyPer | 2.7% | 37% | 27% | 19% | 8.0% | 6.2% |

- Observations
  - Estimates from DBMS-A (HyPer) lead to near-optimal plans in 54% (37%) of all queries
  - DBMS-B (C, Hyper) estimates lead to plans more than 10 times slower than "optimal" for 32% (12%, 14%) of all queries
  - Overall: Even extremely bad estimates (DBMS-C) do not impact query performance too much too often
    - Wrong estimates sometimes even speed-up queries!

# Quality of Cost Models

- Using true cardinality makes cost estimates much better
  - See different columns
- Changing the concrete cost model has little impact
  - See different rows
  - "Tuned": MainMem-adapted
  - "Simple": Roughly our option 1
- Message: Invest in cardinality estimates, not in performance modelling



# But …

- More interesting results in the paper
  - E.g.: More indexes make estimations harder – larger search space
    - “Harder”, not “worse”
- But
  - A single data set
  - Real data, but synthetic workload
  - Runtimes are all from PostGres, ignoring many special features in the runtime engines of other systems
  - No parallelization
  - Although this data fits in memory, PostGres is not a MM-DBMS
    - Logs are writing to disk all the time
- Solution: Measure, model, and optimize for your workload