Datenbanksysteme II: Cost Estimation for Cost-Based Optimization

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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?
  - And: How do we aggregate operator cost to query cost?
- Most prominent: Size of intermediate results
  - Output of some operation and input to other operations
  - This is typically 1:1, for joins 2:1
  - Requires accurate cardinality estimation

Other Costs

- Width of tuples
  - Typically easy to estimate – we'll mostly skip this
- Real data access
  - Disk or cache (which cache?)
  - Random / sequential read?
  - Access by index?
- Computing the relational operation itself
  - Mostly cheap: Comparisons
  - But: Aggregations, projections with functions
    - E.g. Median
    - E.g. Window Functions

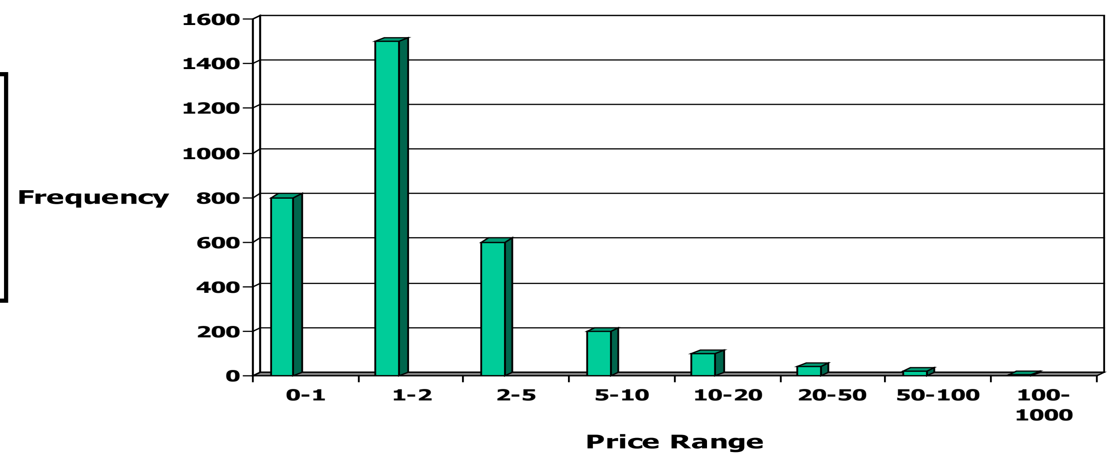
Example

```
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 = 0,9
    - 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
        p.price>100
```



- More accurate selectivity: Histograms
  - Assume 10 buckets for price of products
  - Real 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 Model

- A cost model characterizes (base or intermediate) relations
  - Relation = set of attributes + number of tuples (count)
- Encompasses methods to derive model of the result of a relational operation from the input(s)
- Requirements
  - Model should be much smaller than relation
  - Should allow for accurate predictions for all relational operations
    - We will have to make some compromises
  - 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 in Each Attribute

- With uniform distribution, we may try min, max:
  - "Smaller": 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)
  - "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
  - "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: Yes, only a 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: No updates necessary once parameters are known
  - Derivable: Very difficult to impossible
    - Normal distribution after SELECT is not normal anymore

Other Models II

- Recall: Small, accurate, updateable, derivable
- Option 3: Approximation of distribution by histograms
  - Different types, more or less accurate for different distributions
  - Parameterized size, simple to build
  - Accuracy depends on type and size
  - 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

- 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: Impact of higher accuracy of more complex models versus effort to maintain models

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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
  - Count = |R|: Number of tuples in R
- Task: Given those values for input relations, estimate them for output relation S
- Recall: Selectivity is the fraction of tuples after a selection

Selectivity of a Selection

- Assume min≤const≤max
- Selection of the form $S=\sigma_{A=const}(R)$
  - sel(query) = 1/ v(R,A)
    - And hence |S| = |R| / v(R,A); will be skipped from now on
  - v(S,A) = 1; max(S,A)=min(S,A)=const
- Selection of the form "A<const" (or ≤, ≥, >)
  - sel(query) = (const-min) / (max-min)
  - v(S,A) = v(R,A) *sel(query)
  - 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≠const"
  – Sel(query) = (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: sel(query)=1

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 $sel(A\theta c_1) * sel(B\theta c_2) * \ldots$
  - v, min, max are adapted iteratively
- Negation: Selection of the form "not $A\theta c$"
  - Selectivity is $1\text{-}sel(A\theta c)$
- 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 $1 - (1-sel(c_1))*(1-sel(c_2))*\ldots)$

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
  - Only change the width of a tuple
  - Selectivity=1
  - 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 with single attribute
  - 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, $|S| \leq v(R,A) * v(R,B) * v(R,C)$
  - Simple heuristic: $|S| = \min(½*|R|, v(R,A)*v(R,B)*v(R,C))$
- 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 correlation of values in different relations
- 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

- Careful: When we select a tuples by condition on attribute A, also value ranges of all other attributes change
  - Because many tuples are filtered away from the input
- We did not discuss these effects yet
- 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)
- Otherwise, we need a model taking correlations of values into account
  - E.g. Multi-dimensional Histograms

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- Histograms
  - Types of histograms
  - Building and maintenance
  - Derivation on intermediate results
- Sampling
- Example: Oracle
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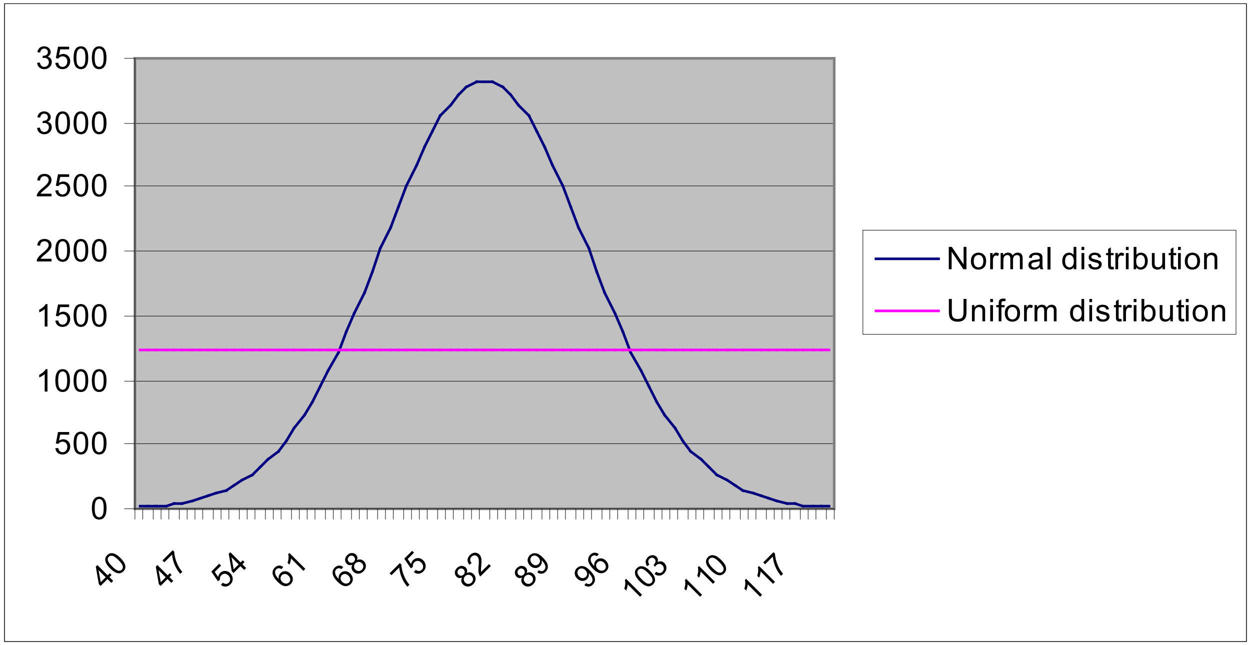
Histograms

- Real data is rarely uniformly distributed
  - Nor Poisson, normal, Zipf, …
- Solution: Histograms [for single attributes]
  - Partition the (current) value range into b buckets
  - Count number of tuples in each bucket
  - During optimization, estimate selectivities from affected buckets
    - Typical: Assume uniform distribution within each bucket
- Advantage
  - Frequencies usually vary less inside smaller ranges
  - Lower errors due to smaller ranges for uniformity assumption
  - b is a parameter tuning the accuracy / effort trade-off

Issues

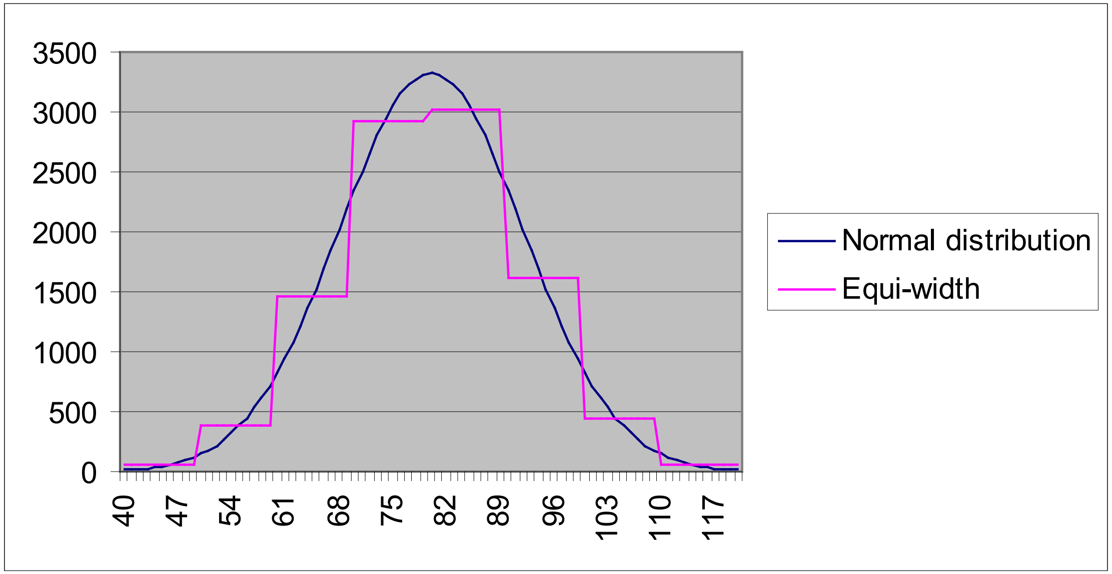
- We must think about
  - How should we choose the borders of buckets?
  - What do we store for each bucket (could be more than count)?
  - How do we keep buckets up-to-date?

Example: Assuming Uniform Distribution



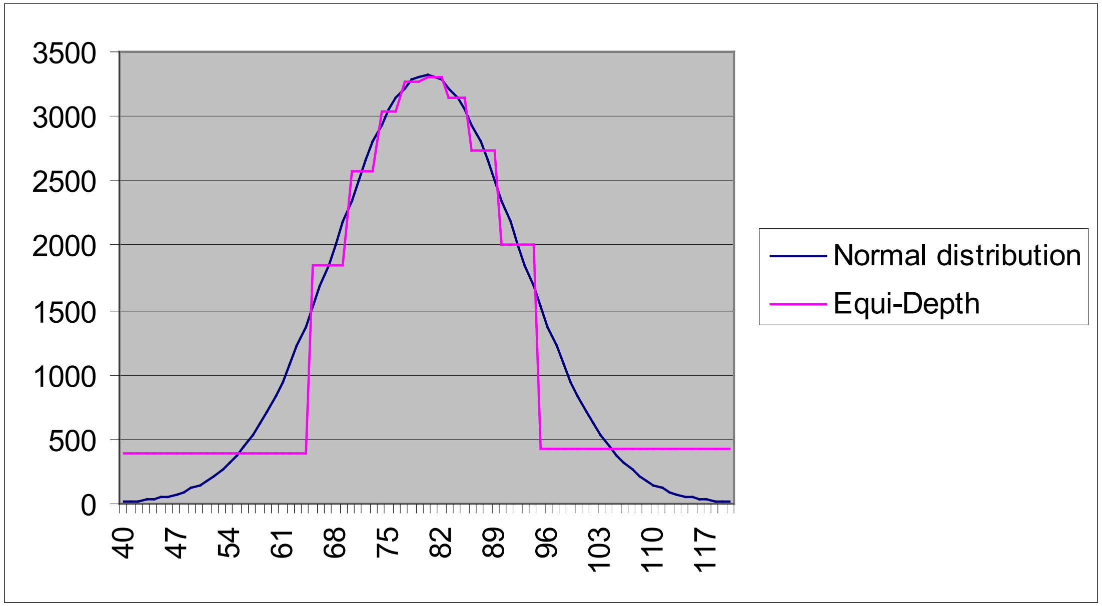
- Assume normal distribution of weights
  - Spread: 120-40=80, mean: 80, stddev: 12; 100.000 people
- Uniform distribution: 100.000/80=1250 for each possible weight
- Leads to large errors in almost all possible query ranges

Equi-Width Histograms



- Borders are equi-distant (distance: value range / b)
  - Advantage: Border values need not be stored
- Remaining error depends on
  - Number of buckets (large b -> less errors, but more space)
  - Distribution of values in each bucket

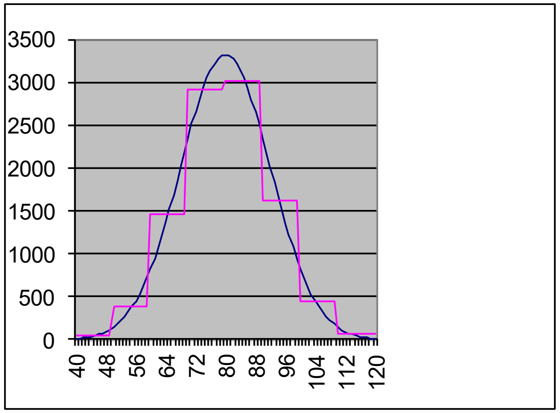
Equi-Depth



- Choose borders such that frequency of values in each bucket is approximately equal
  - If single value more frequent than |R|/b - use other type of histograms
  - Buckets have varying sizes - borders need to be stored
- Better fit to data in dense areas

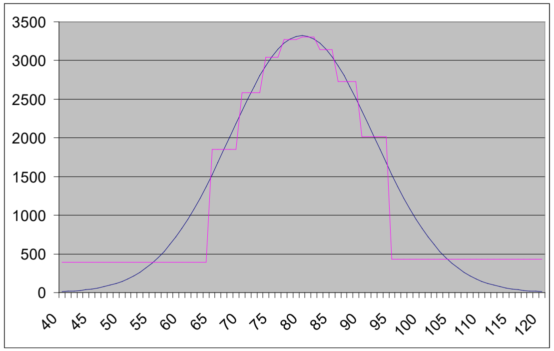
Example

- 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
    - Average frequency in range 60-69 is 1469
    - Average frequency in range 70-79 is 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
    - Average frequency in range 65-69 is 1850
    - Average frequency in range 70-73 is 2581
    - Estimation: 5*1850 + 1*2581 = 11831
    - Error: 228 ~ 2%

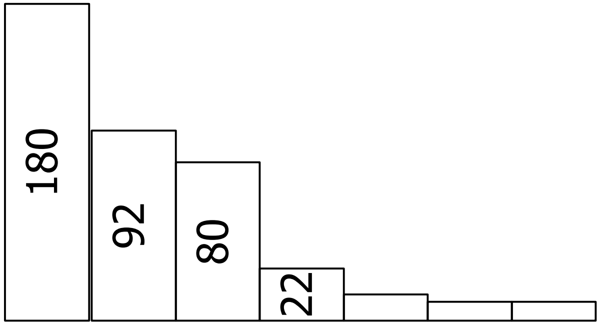


- In general, equi-depth histograms are considered more accurate than equi-width histograms
  - But more costly to build and maintain

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

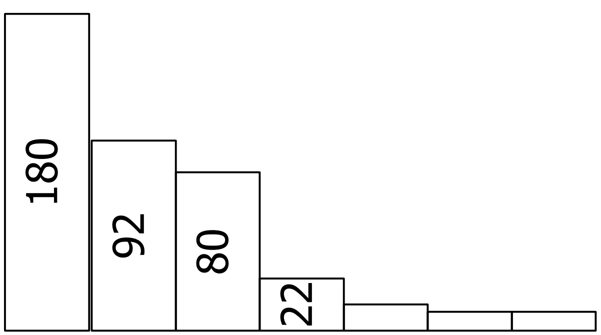


Bucket	1	2	3
Values	4	2,5,7	1,3,6
Total cnt	180	194	42
σ^2	0	~1400	~28

Other: V-Optimal Histograms

- Sort values by frequency and build buckets such that sum of 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
σ^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

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  - Types of histograms
  - Building and maintenance
  - Derivation and cardinality estimation
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- Example: Oracle
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Building and 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

Building and Maintaining Equi-Depth Histograms

- Building: Scanning and sorting
  - 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; sort on few 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

- We assumed histograms to be updated with every data update
- Other option: (Re-)compute only on request
  - 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
- Today: Automatically maintained statistics
  - General trend: Reduce cost of ownership
  - Self-optimizing, self-maintaining, zero-administration, …

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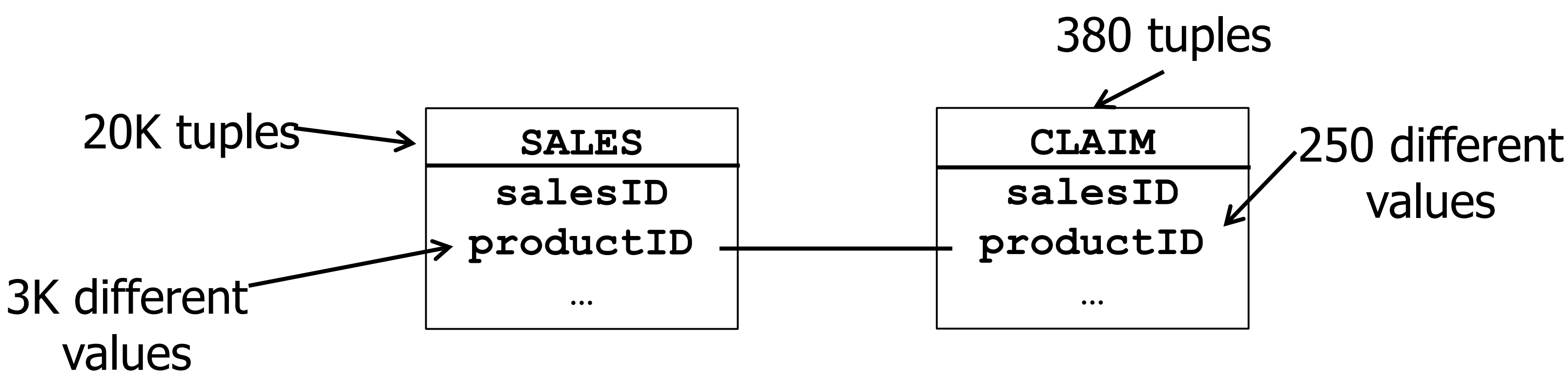
Estimation - Selection

- A=const: Find enclosing bucket, assume uniform distribution within bucket
- A<const: Find matching buckets and aggregate counts
  - When const does not coincide with bucket border, assume uniform distribution in bucket
- DISTINCT
  - No support
  - Solution: Also keep v(R,A)
    - Plus COUNT plus histograms

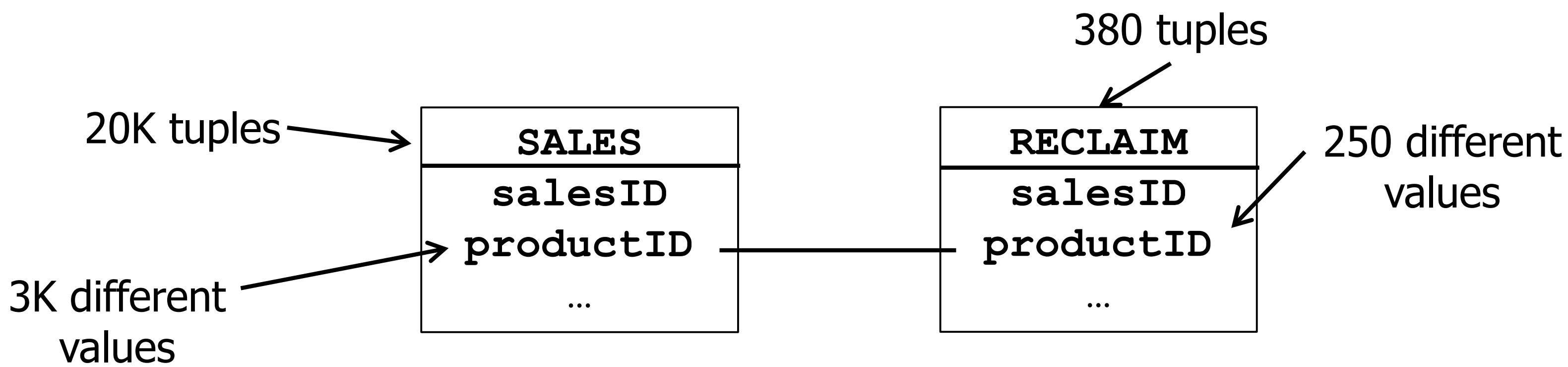
Histograms for Join Estimation

- Assume sales and reclamations
  - And a slightly strange query, not joining a PK/FK pair

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

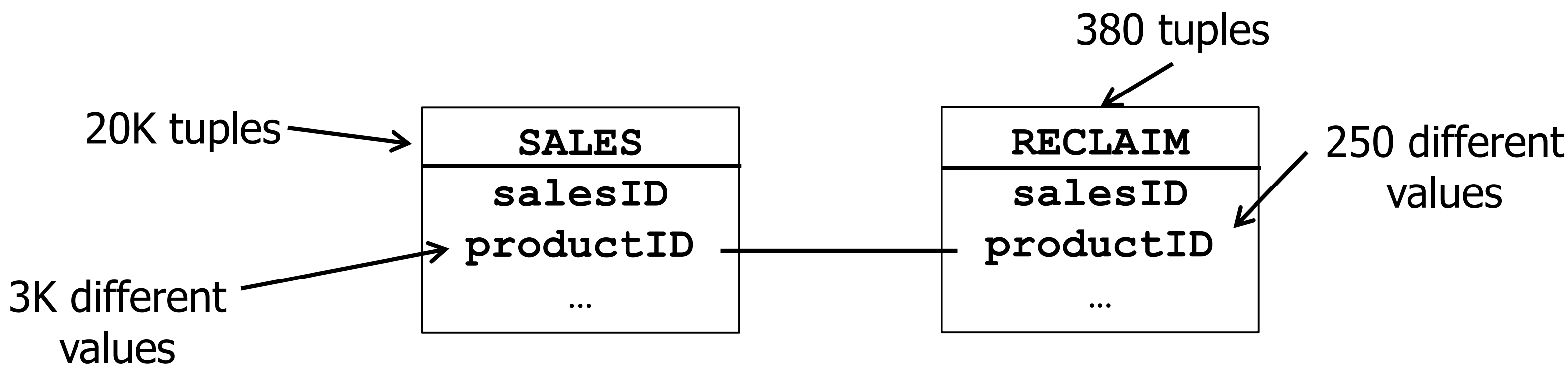


Example without Histograms



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

Complex Selections

- 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
  - Build histograms on combinations of value ranges
  - Need sophisticated storage structures – multidimensional indexes

Derivation - Selection

- A=const: Histogram degenerates to a singleton bucket
- A<const: Histogram is cut into two pieces
  - Keeping number of buckets / same depth of buckets would require recreating the histogram
  - Other option: Go on with "partial" histogram
- DISTINCT
  - Equi-Width: No change
    - We do not record distinct values, min / max does not change
  - Equi-Depth: Recreate or ignore

Derivation - Joins

- Assume histograms on both join keys
- Histogram needs to be build during join execution
  - Equi-Width:
    - Find min/max from both input histograms (larger min, smaller max)
    - Fix bucket borders depending on b
    - While generating join results, always increment corresponding bucket
    - On-the-fly computation
  - Equi-Depth
    - Compute all join results, then sort and compute buckets
      - Sort can be skipped when sort-merge is used
      - But on-the-fly computation is impossible: Size of join result is unknown

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???

Sampling

- Alternative to histograms: 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 contain all correlations
  - Usually, a 1-5% sample suffices
  - Statistics give the methods to estimate sample size depending on error probabilities
- 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 S of s% of a 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 a 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 updates and rebuild from time to time

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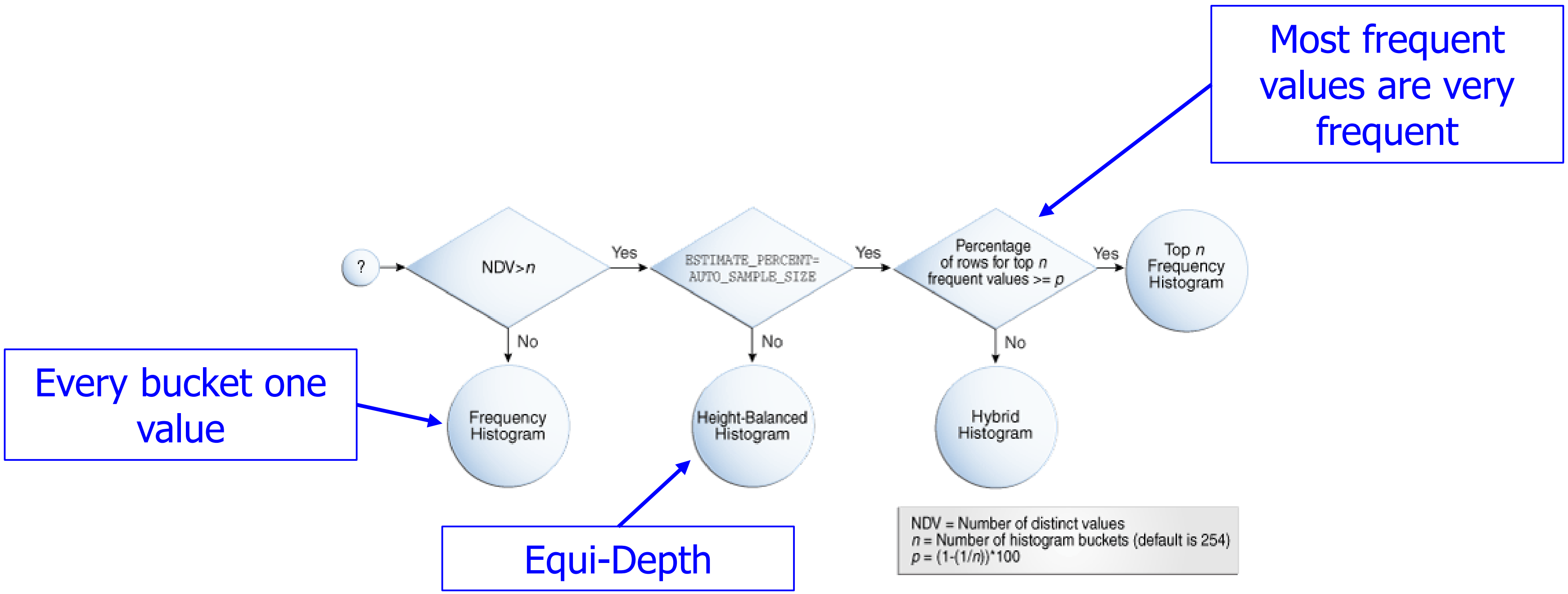
Example: Oracle Basic Statistics

- 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



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- Some empirical observations
  - 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

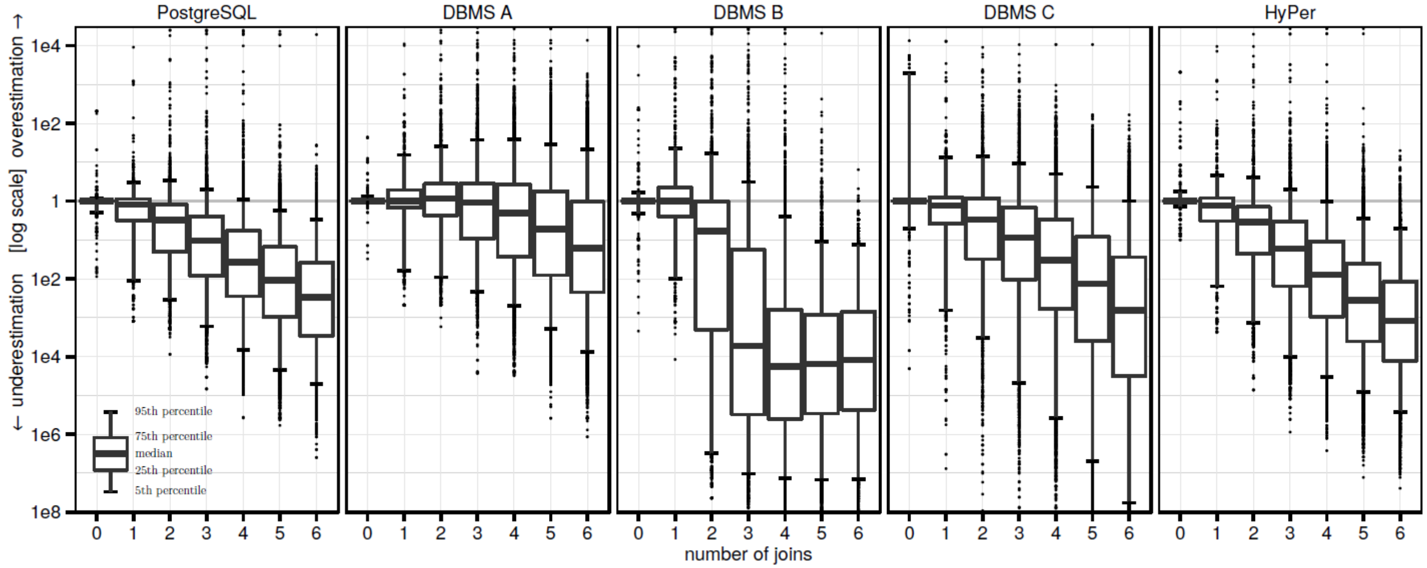
Selectivity of Selections on Base Tables

	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

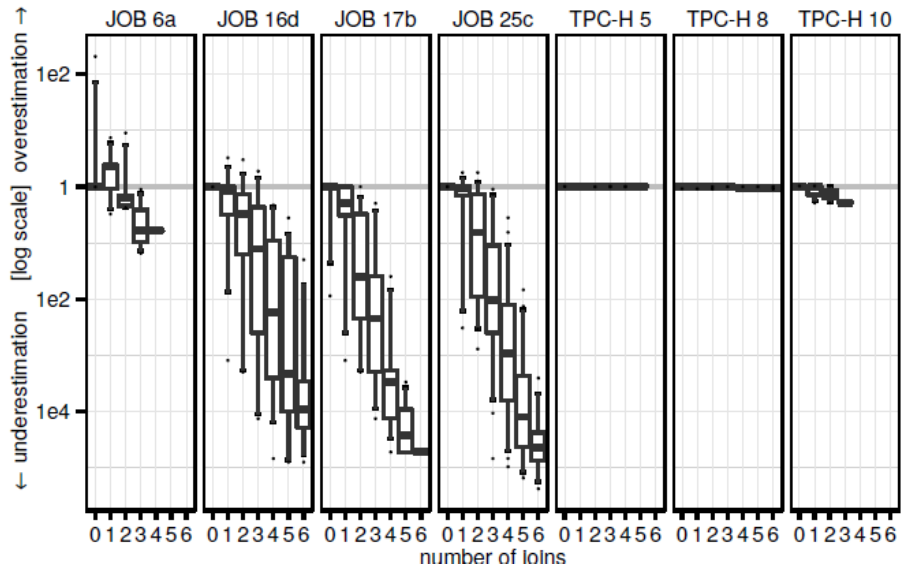
- 50% of estimates are almost perfect, in all systems
- 90% of estimates are wrong by a factor of 6 at most – but much worse in DBMS-C
- Extreme errors go up to factor 100.000
- Simple PostGres model works rather well
  - Min/max, distinct values, histograms

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

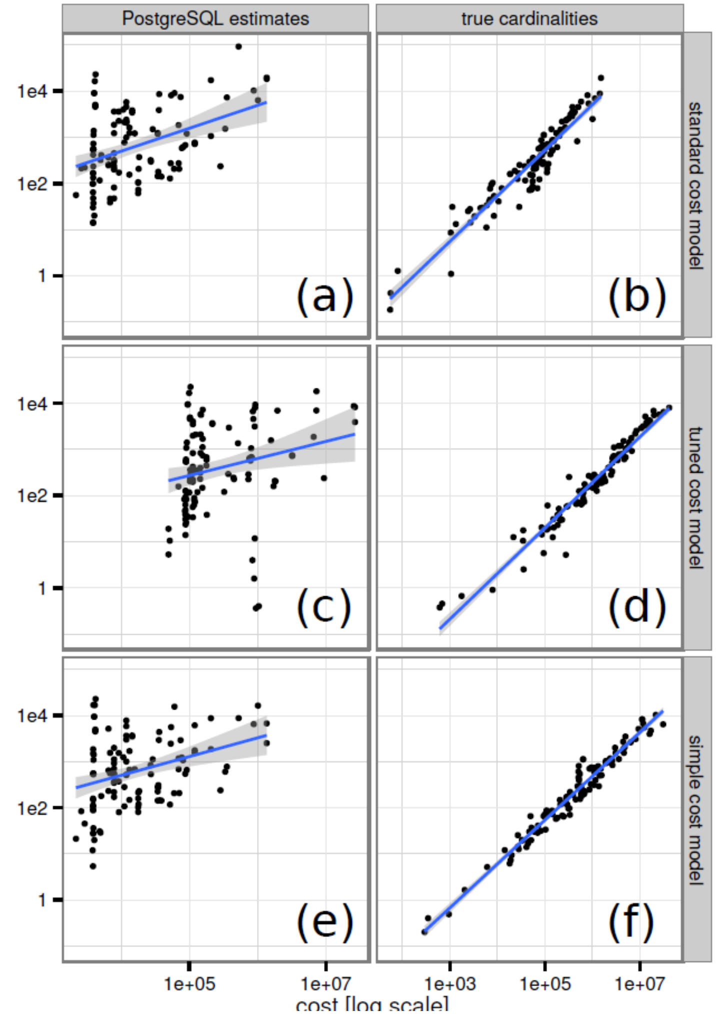
- Approach: Obtain estimates from system X, inject into PostGres, let PostGres optimize and run the query
  - "Optimal": Same approach using true cardinalities

	<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