Datenbanksysteme II: Cost Estimation for Cost-Based Optimization

Ulf Leser

Content of this Lecture

- Cost estimation
- Uniform distribution
- Histograms
- Sampling

Cost Estimation

- Rule-based optimizer
  - Transformations depend only on query and schema information, but not on the actual data
  - No notion of “cost”
    - Cannot differentiate join order
    - Cannot decide on access path selection / index usage ...
- Cost-based optimizer
  - Estimate the cost of each operation in a QEP
  - Approached by estimating size of intermediate results
- Cost estimation required for
  - Choosing best implementation for each operations
  - Finding best plan for entire query
    - Operations have non-local side-effects, especially order

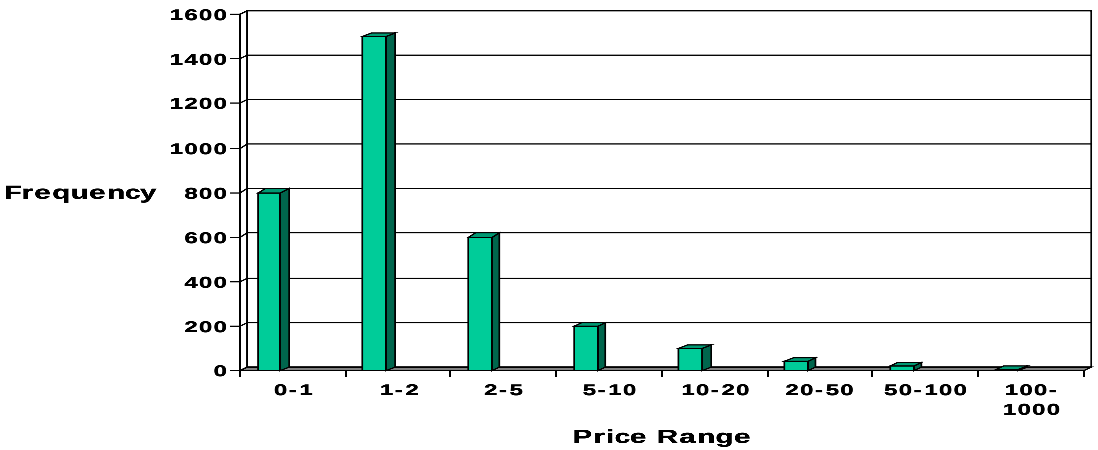
Example

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

- 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
        p.price>100
```



- Using histograms
  - Assume 10 buckets
  - 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 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
  - Model should be easy to maintain when data changes
  - Model should be generated quickly
  - Models need to be stored and accessed efficiently
  - Models must be easily creatable (better: derivable) for intermediate relations during query processing

Example

- Simple approach: count for each relation, (min, max) for each attribute in each relation
  - Generation requires only one pass
    - Beware: Count usually cannot be derived from used space
  - Data inserts possible in constant time
    - Update/delete: Exact models may require finding new min / max
    - Alternative: Ignore update/delete, accept errors
  - Storing requires only a few bytes per attribute
    - More for string attributes
    - Need not always be exact: “zz” instead of “zweifel”, E3 instead of 975
  - Estimating effect of join not easy, other operations are easy

Example

Certainly wrong.
Consider PK/FK constraints

```
SELECT C.name, A.balance
FROM   customer C, account A
WHERE  C.acc# = A.acc# AND
       C.name < "Mater" AND
       C.age > 80
```

Acc#(2, 1, 123456)

Independence assumption: 112*2000/123456~2

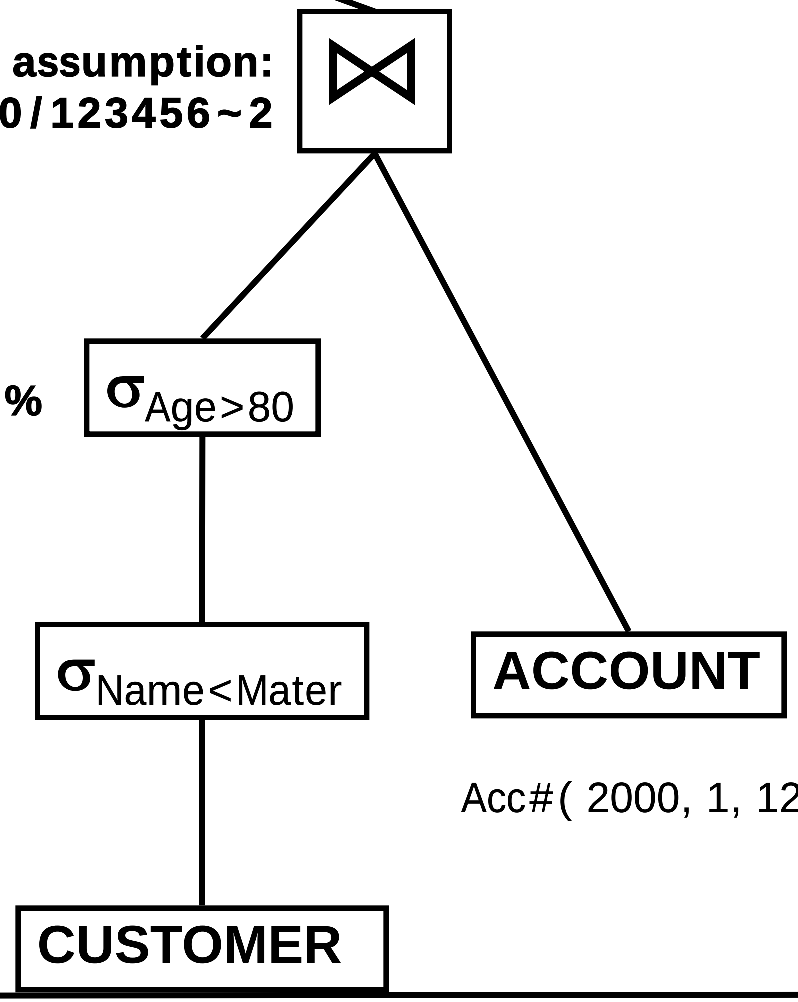
Name(112, Aare, Mater)
Age(112, 80, 98)
Acc#(112, 1, 123456)

Sel: 1/(98-18)*18= 22,5%

Name(500, Aare, Mater)
Age(500, 18, 98)
Acc#(500, 1, 123456)

Sel: 50%

Name(1000, Aare, Zyte)
Age(1000, 18, 98)
Acc#(1000, 1, 123456)



Acc#(2000, 1, 123456)

Types of Models for One Attribute

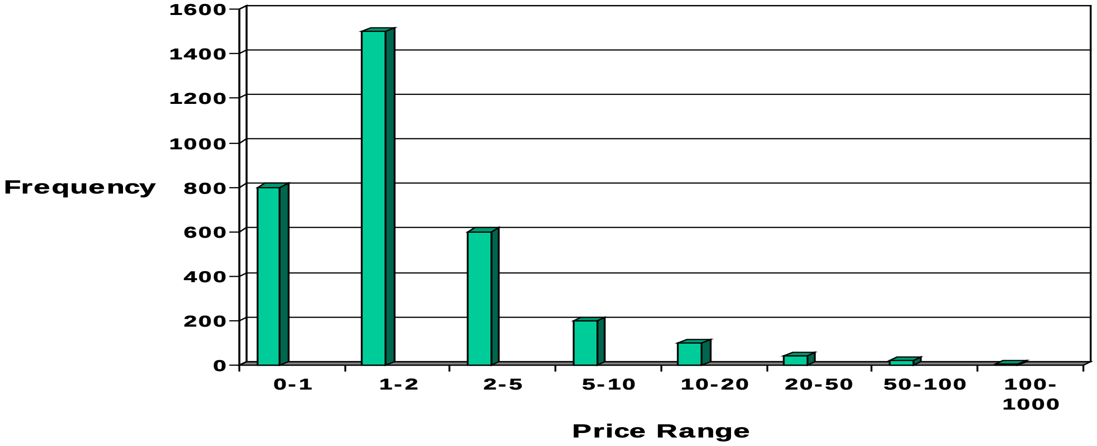
- Option 1: Uniform distribution of values and statistical independence of different attributes
  - Very small model (e.g. count, max, min), simple to build
  - Simple improvement: Also store number of distinct values
  - Arbitrarily bad predictions if assumption violated
  - Cannot capture correlated attributes
    - **SELECT C.name, C.address FROM customer C, account A WHERE C.acc# = A.acc# AND C.age<19 AND A.balance>100.000**

Types of Models II

- Option 2: Known standard distribution
  - Normal, Poisson, Zipf, ...
  - Can be characterized by few parameters (mean, stddev, ...)
  - Very small model, can be very accurate
    - Weight of persons, number of sales per product, ...
  - But: How should the DB know which distribution is the right one?
    - Must be specified by developer
  - Often difficult to propagate through query plans
    - Normal distribution after SELECT is not normal anymore
  - Only used for special cases

Types of Models III

- Option 3: Approximation of concrete distribution by histograms
  - Parameterized size, quite simple to build
  - Independent of underlying distribution
  - Accuracy depends on type and size (and timeliness)



Obtaining Model Parameters

- Exhaustive analysis
  - Even O(|R|) might be too expensive for very large relations
- Sampling
  - Use a representative subset of tuples of a relation
    - Choose subset at random
    - Not so easy to chose a truly random samples
  - Accuracy depends on sampling method and size (and timeliness)
  - Examples later

Important Note

- Derived estimations need not be exact
  - Should only help to discern good transformations from bad ones
  - Order of alternatives matter, not concrete cost
- Estimates are often very bad (orders of magnitude)
  - 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

Content of this Lecture

- Cost estimation
- Uniform distribution
- Histograms
- Sampling

Rules of Thumb

- Definition
  - *The selectivity of a relational operation is the fraction of tuples of the input that will be in the output*
- 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) be number of distinct values of A
  - max(R, A), min(R, A) be the maximal/minimal value of A
    - Values that do exist “now”, not maximal / minimal possible values
  - |R| be the number of tuples in R
  - Note: R may be an intermediate result

Size after a Selection

- We assume $min \leq const \leq max$
- Selection of the form "A=const"
  - |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
    - Very rough estimate, but requires no knowledge of values in A at all

Size of a 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
  - $v(S,A)=v(R,A)$
    - But we don't know! Be careful
  - $min(S,A)=min$, $max(S,A)=max$
  - Alternative: $|S| = |R|$

Complex Selections

- Selection of the form "$A\theta c_1 \wedge B\theta c_2 \wedge ...$"
  - Assumption: Statistical independence of values
  - Total selectivity is $sel(c_1) * sel(c_2) * ...$
  - v, min, max are adapted iteratively for each single condition
- Selection of the form "$A\theta c_1 \vee B\theta c_2 \vee ...$"
  - Rephrase into $\neg (\neg(A\theta c_1) \wedge \neg(B\theta c_2) \wedge ...)$
  - Selectivity is $1- (1-sel(c_1))*(1-sel(c_2))*...)$
- Selectivity of $A=10 \wedge A>10$?

Projection and Distinct

- Selectivity of distinct
  - $|S| = v(R,A)$
  - $v(S,A)=v(R,A)$, $min(S,A)=min$, $max(S,A)=max$
- Selectivity of projection
  - Is 1 under BAG semantics
  - Is same as selectivity of distinct under SET semantics
  - Caution
    - In real life, we need to estimate the size of the intermediate relation in bytes
    - This requires number of tuples and size of tuples
    - We ignore(d) this issue

DISTINCT and GROUP-BY

- Selectivity of grouping
  - Same as selectivity of distinct on group attributes
- Selectivity of `SELECT DISTINCT A,B,C FROM …`

Projection and Distinct

- Selectivity of grouping
  - Same as selectivity of distinct on group attributes
- Selectivity of **`SELECT DISTINCT A,B,C FROM …`**
  - Not easy: We need to know correlations of values
  - Clearly, $0 < |S| < v(R,A) * v(R,B) * v(R,C)$
  - Suggestion: $|S| = \min(½*|R|, v(R,A)*v(R,B)*v(R,C))$
- Alternative
  - Multi-dimensional histograms (later)
  - Note: A, B here may have completely different domains, in a join the domains of the joined attributes must be the same

Selectivity of Joins

- Consider join $R \bowtie_A T$ (or $\sigma_{R.A=T.A}$ (R x T))
- Size of product is |R|*|T|, but 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 join 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
    - 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 (all) 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)
  - Can (and should) be refined by also considering value ranges
- What about $R \bowtie_{R.A<T.B} T$?
  - For each value T.B, estimate which fraction of R has smaller values in R.A

Remarks

- We did not discuss effects on other attributes: Home work
  - For instance: Assuming statistical independence, a condition “age<19” does not change min(R,name) or max(R,name)
  - But: “SELECT name, sum(price) as x FROM products GROUP BY product.name” yields v(S,name)=v(P,name), but introduces a new column x whose model must be estimated

Content of this Lecture

- Cost estimation
- Uniform distribution
- Histograms
- Sampling

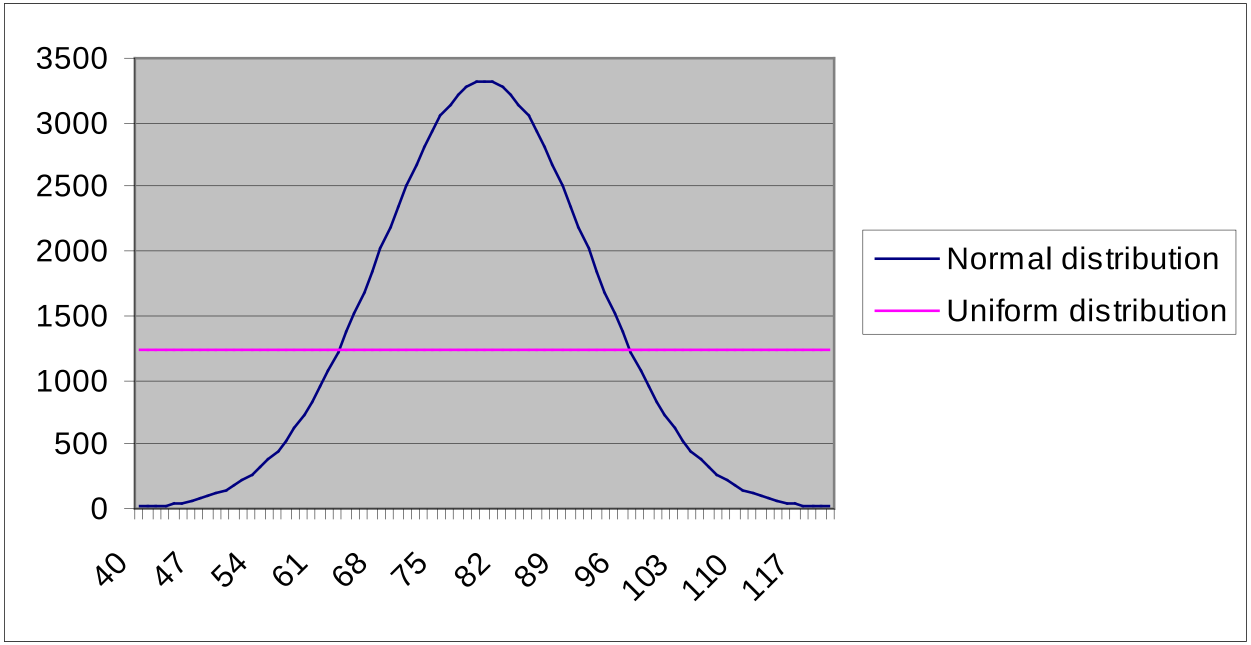
Histograms

- 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 cost estimation, approximate frequency of a single value or a range by averaging over all values in a bucket
    - I.e., make uniform distribution assumption inside each bucket
- Advantage
  – Lower errors due to smaller ranges for uniformity assumption
  – Hope: Frequencies vary less inside smaller ranges
  – Histograms do not help in case of extremely distorted distributions

Issues

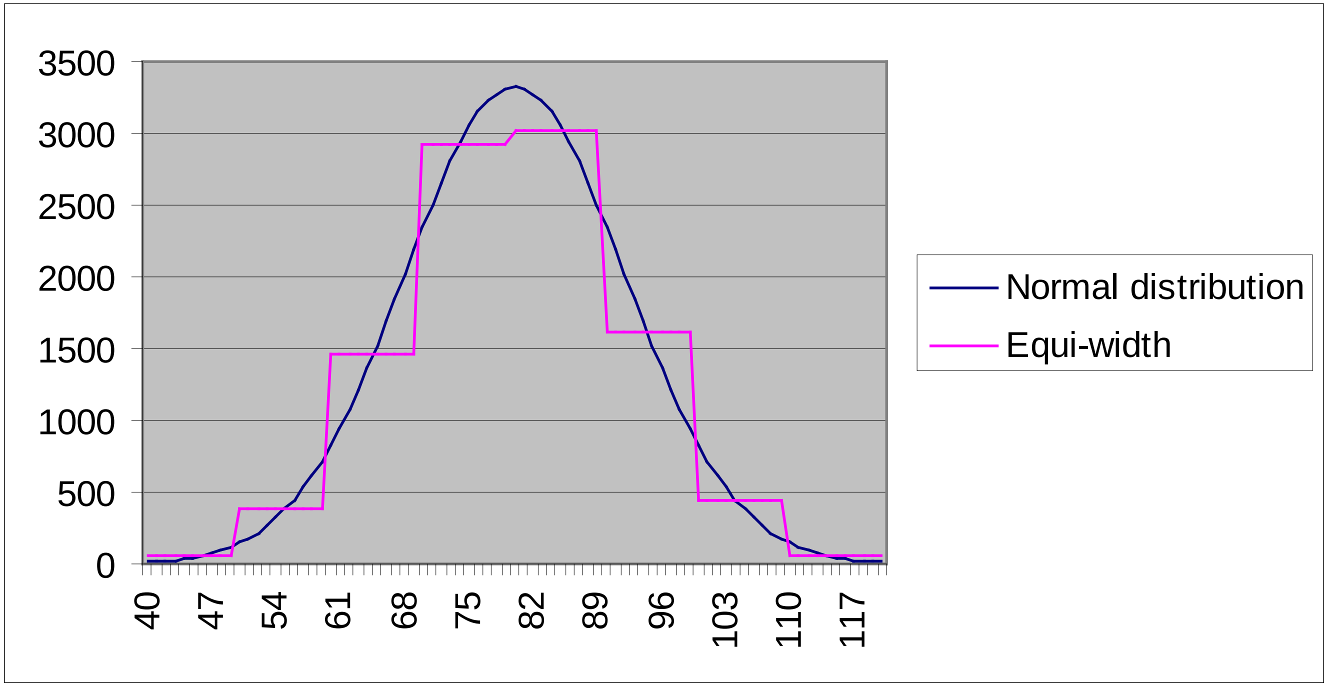
- We must think about
  - How should we chose the borders of buckets?
  - What do we store for each bucket (could be more than count)?
  - How do we keep buckets up-to-date?

Distribution



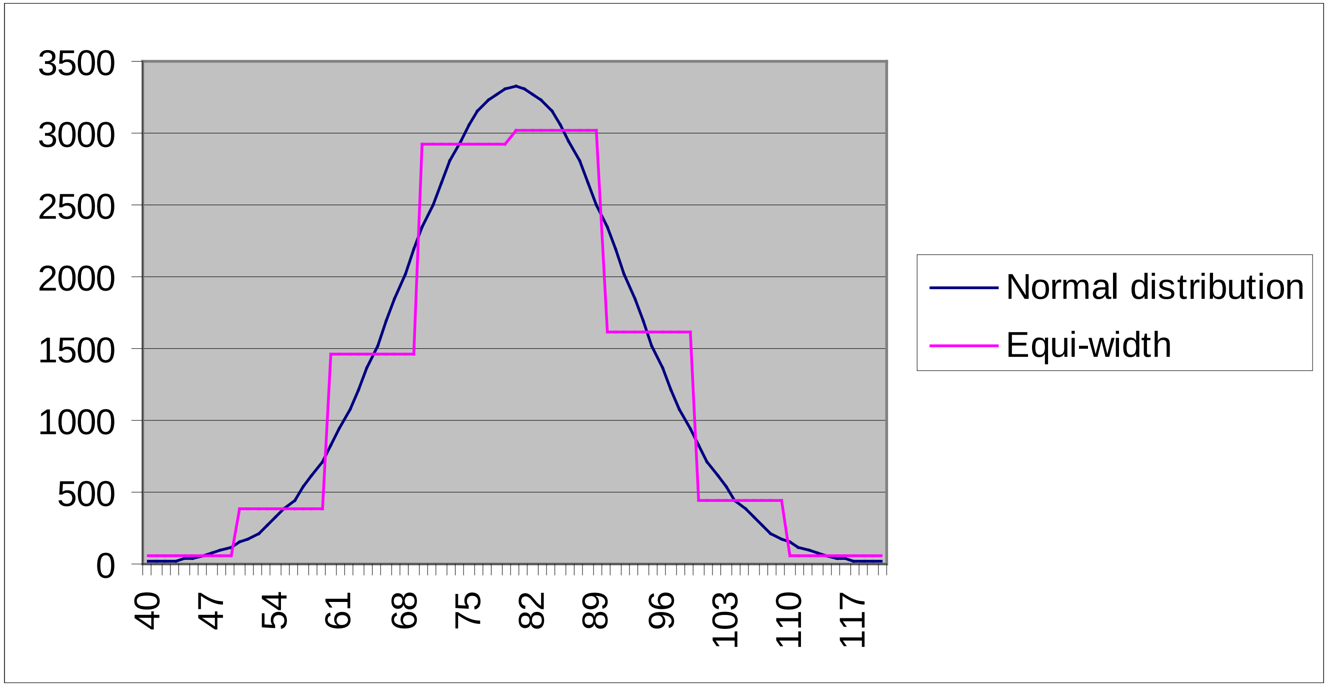
- Assume normal distribution of weights
  - Spread: 120-40=80, mean: 80, stddev: 12; 100000 people
- Uniform distribution: 100000/80=1250 for each possible weight
- Leads to large errors in almost all possible query ranges

Equi-Width Histograms



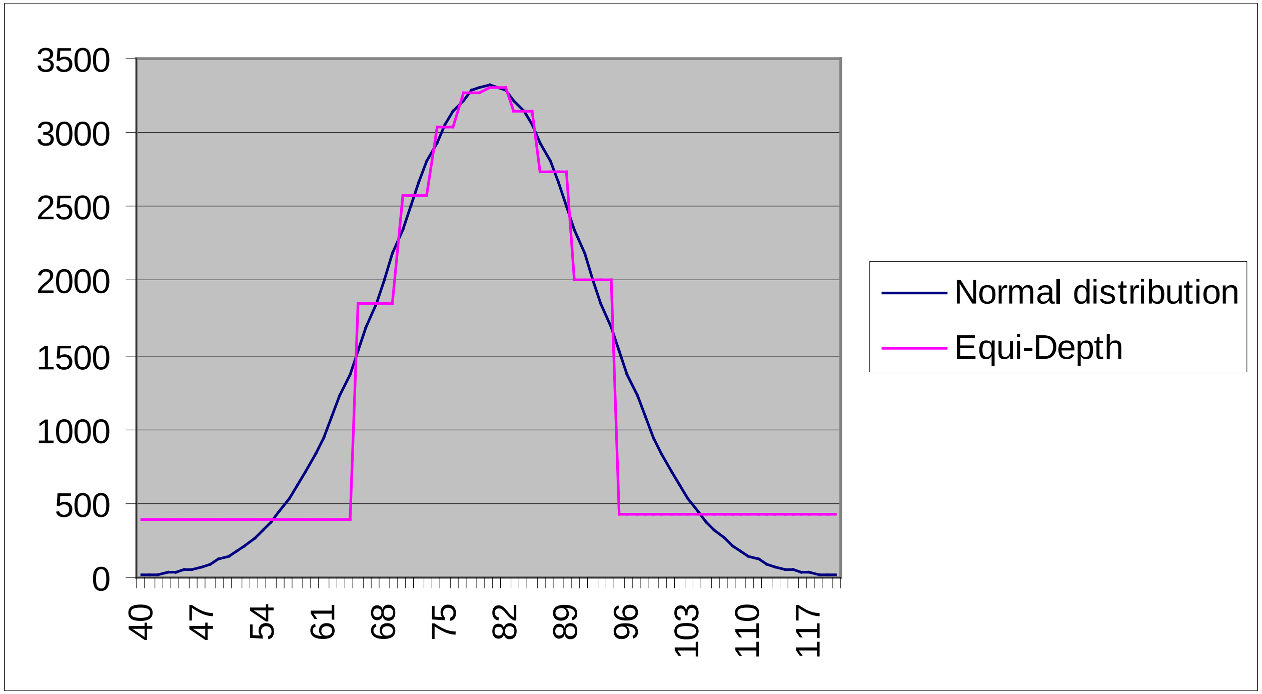
- Fix number of buckets
- Borders are equi-distant (border values need not be stored)
- In each bucket, assume average frequency inside bucket

Equi-Width Histograms 2



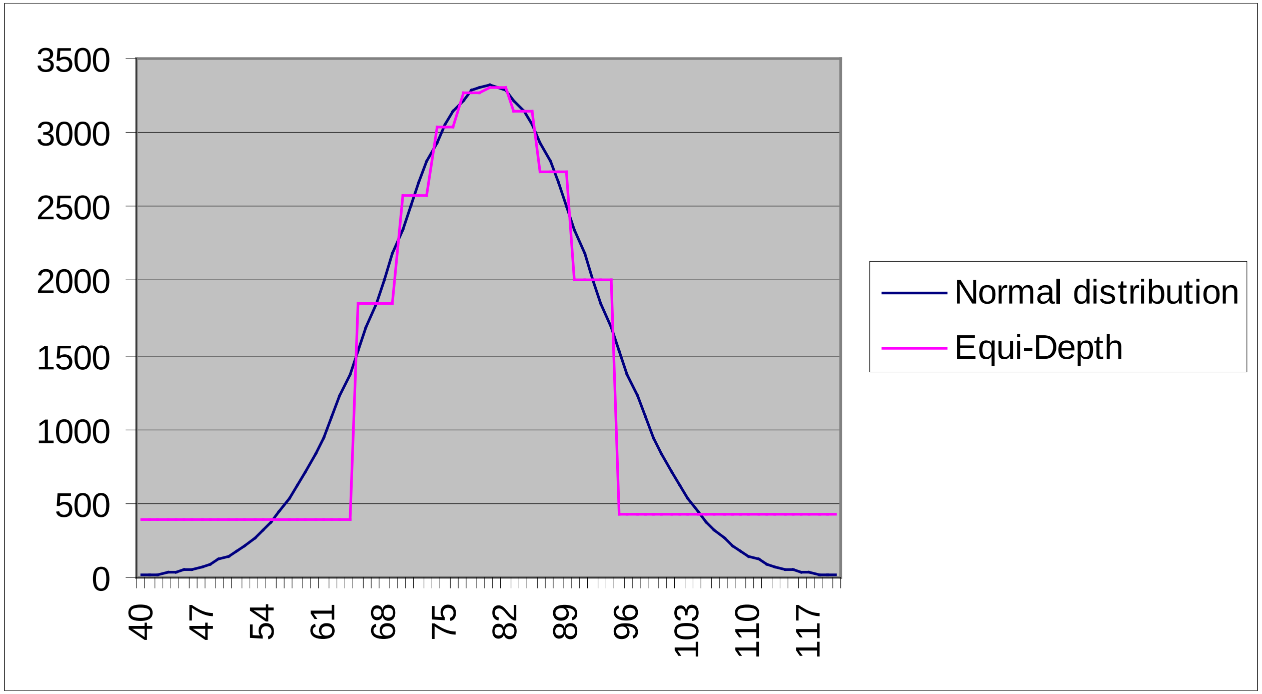
- Bucket counts can be computed by scanning relation once
- Remaining error depends on
  - Number of buckets (more buckets -> less errors, but more space)
  - Distribution of values in each bucket

Equi-Depth



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

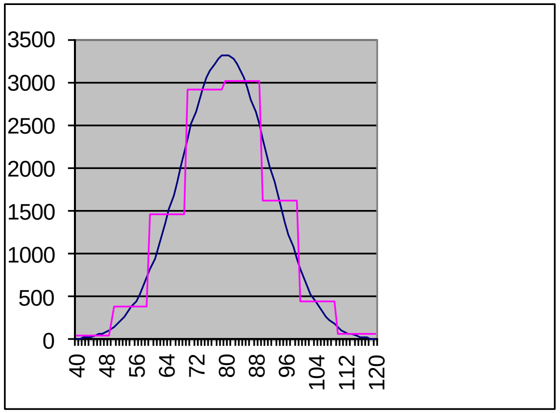
Equi-Depth



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

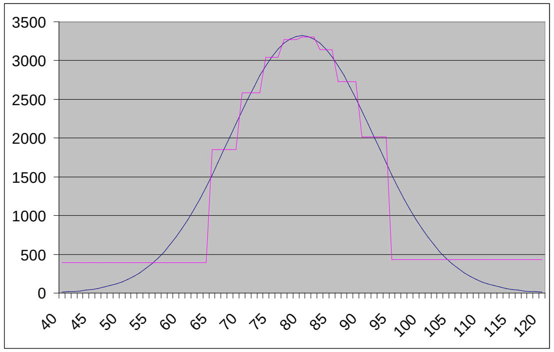
Example

- 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 between 65-70 (incl)
  - 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%

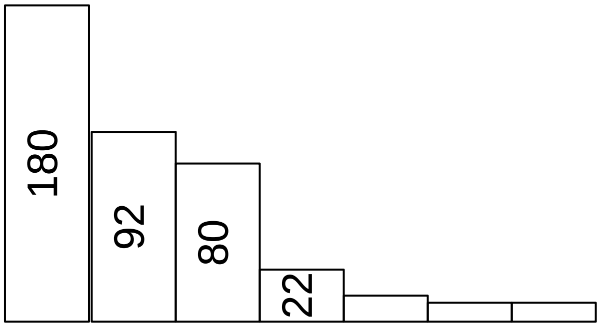


- Error depends on concrete value or range
- In general, equi-depth histograms are considered more accurate than equi-width histograms
  - But more costly to build and maintain

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
- 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

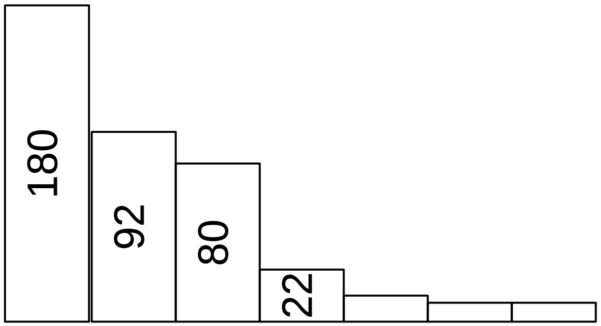


Bucket	1	2	3
Values	4	2,5,7	1,3,6
Total cnt	180	194	42
σ^2	0	~1400	~28

Other: V-Optimal Histograms

- Sort values by frequency and build buckets such that 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: n# values, b: n# 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 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

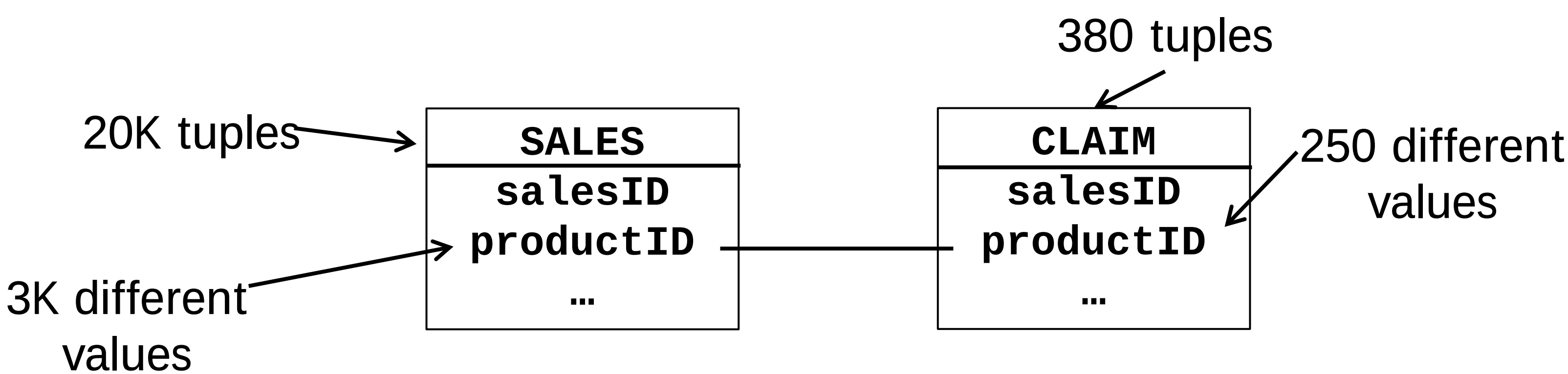
Content of this Lecture

- Cost estimation
- Uniform distribution
- Histograms
  - Types of histograms
  - Joins, construction, maintenance
- Sampling

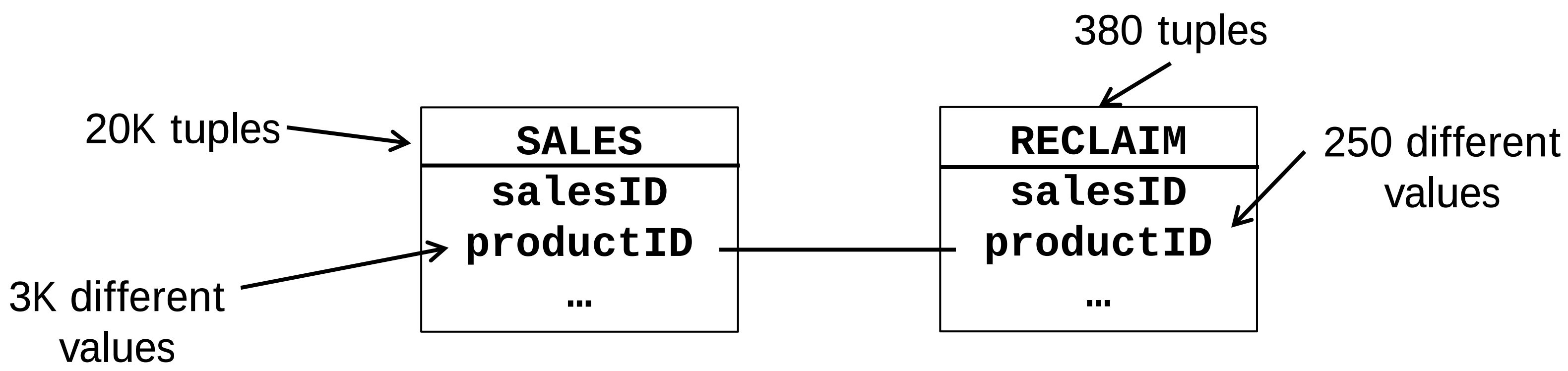
Histograms for Join Estimation

- 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;
```

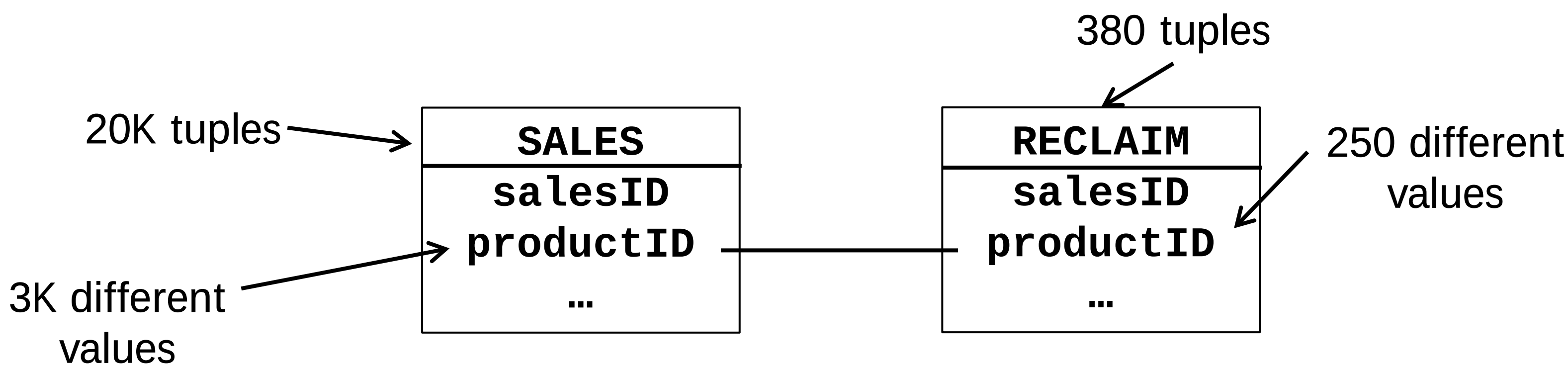


Example without Histograms



- Without histograms, assuming uniform distribution
  - Recall join-formula
  - 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 do not coincide
  - Which usually is 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 for complex conditions?
  - People with weight<30 and age<25 ?
  - People with income>1M and tax depth<500K ?
  - 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

Building Histograms

- Usually, computing histograms requires scanning a table
  - Potentially for each attribute
- Cannot be done before each query – offline statistics
- Indexes can help
  - Statistics such as min, max are directly obtainable from a B+ index
  - Inner nodes of B+ trees ~ equi-depth histograms
  - But we rarely have indexes on all attributes of a relation

Maintaining Histograms

- Idea: Compute once and maintain
- Equi-width histograms
  - Assumption: Number of buckets and min/max does not change
  - Then everything is simple; increase/ decrease frequencies in bucket upon insert/delete/update
  - (Gross) Changes in min/max: Rebuild histogram
- Equi-depth histograms
  - Changes in data may influence borders of buckets
  - Option 1: Proceed as for equi-width, accept intermediate inequalities in bucket frequencies
    - ... and regularly re-compute entire histogram
  - Option 2: Implement complex bucket merging/ splitting procedures

Maintaining Histograms on Request

- Compute only on user 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
    - To prevent, Oracle provides “query outlines”
- Automatically maintaining statistics is a 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
- But we actually only need to estimate the distribution
  - Histograms are estimates anyway
- Solution: Use a sample of the data
  - If chosen randomly, sample should have same distribution as full data set
  - For large data sets, usually, a 1-10% sample suffices
- Also useful for approximate COUNT, AVG, SUM, etc.
  - Approximate query processing: Much faster answers in much less time with minimal error
  - Requires estimation of maximal error (confidence values)
  - Again: Very active research area (“Taming the terabyte”)

Problems with Sampling

- How do we get a random 10% sample?
  – Reading first 10% of rows is a very bad idea
  – Reading a row from 10% of the blocks is about as slow as reading the entire table (sequential reads!)
- Option: Reservoir sampling: Explicitly store and maintain a sample
- Sampling must be a build-in database operator; impossible to emulate efficiently