Query Optimization

Query Optimization

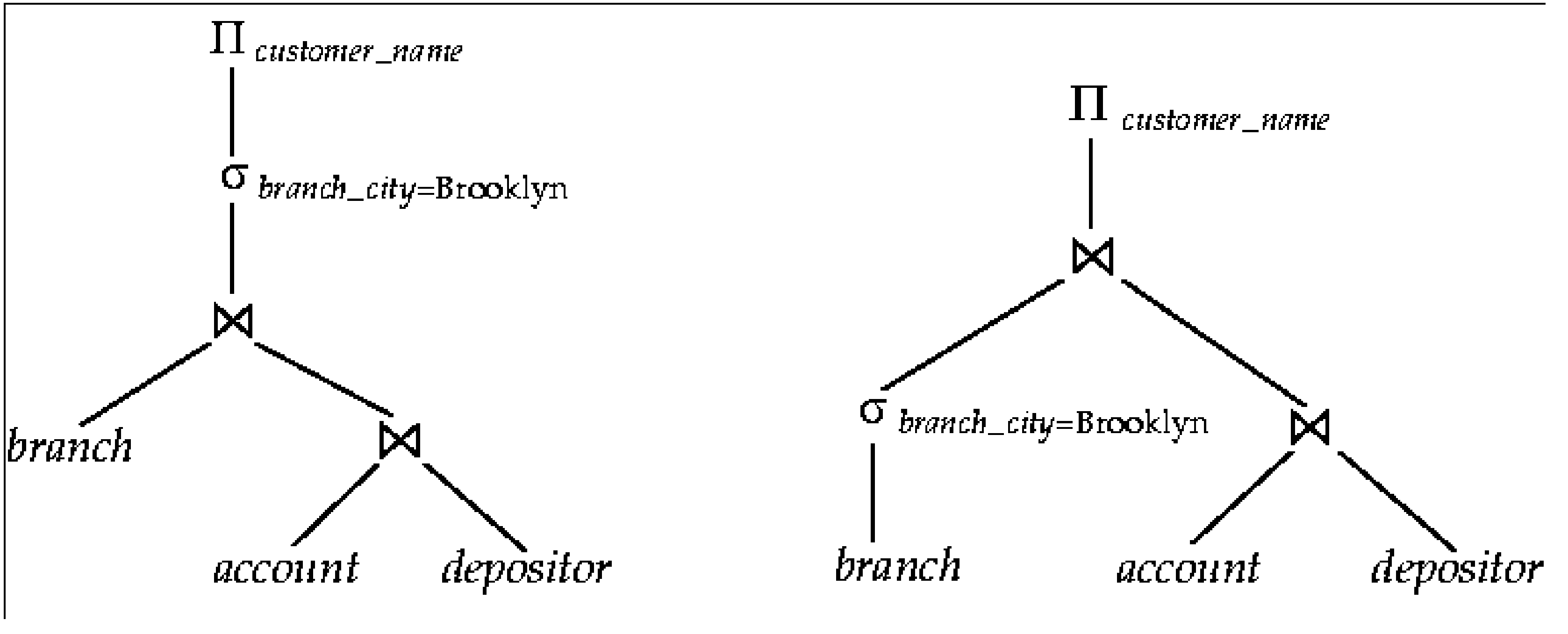
- Why ?
  - Many different ways of executing a given query
  - Huge differences in cost
- Example:
  - select * from person where ssn = “123”
  - Size of person = 1GB
  - Sequential Scan:
    - Takes 1GB / (100MB/s) = 10s
  - Use an index on SSN (assuming one exists):
    - Approx 4 Random I/Os = 20ms

Query Optimization

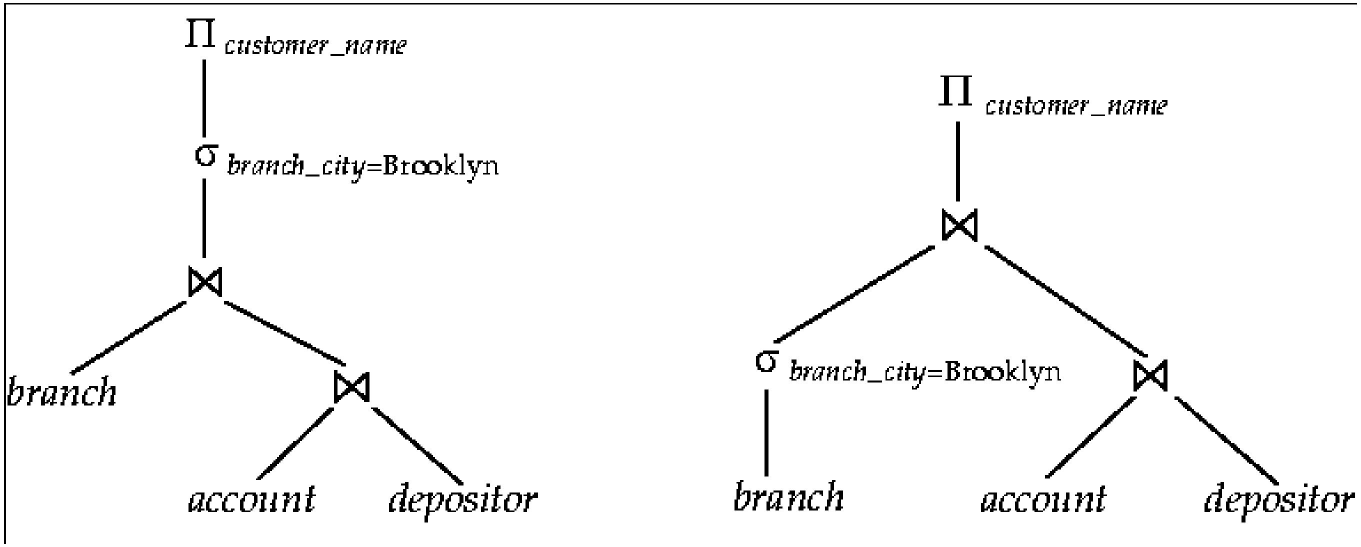
- Many choices
  - Using indexes or not, which join method (hash, vs merge, vs NL)
  - What join order ?
    - Given a join query on R, S, T, should I join R with S first, or S with T first ?
- This is an optimization problem
  - Number of different choices is very very large
  - Step 1: Figuring out the solution space
  - Step 2: Finding algorithms/heuristics to search through the solution space

Query Optimization

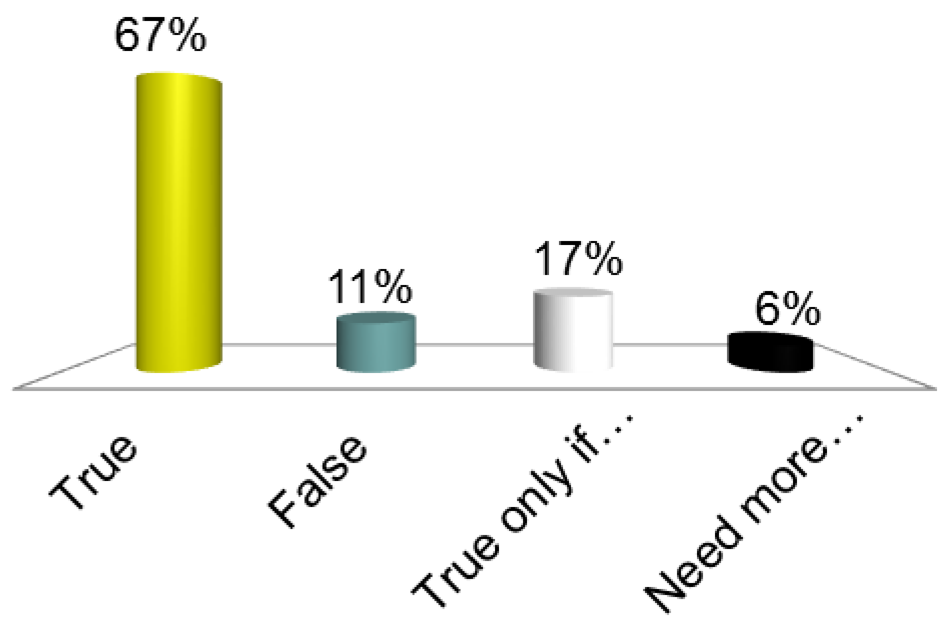
- Relational expressions
  - Drawn as a tree
  - List the operations and the order



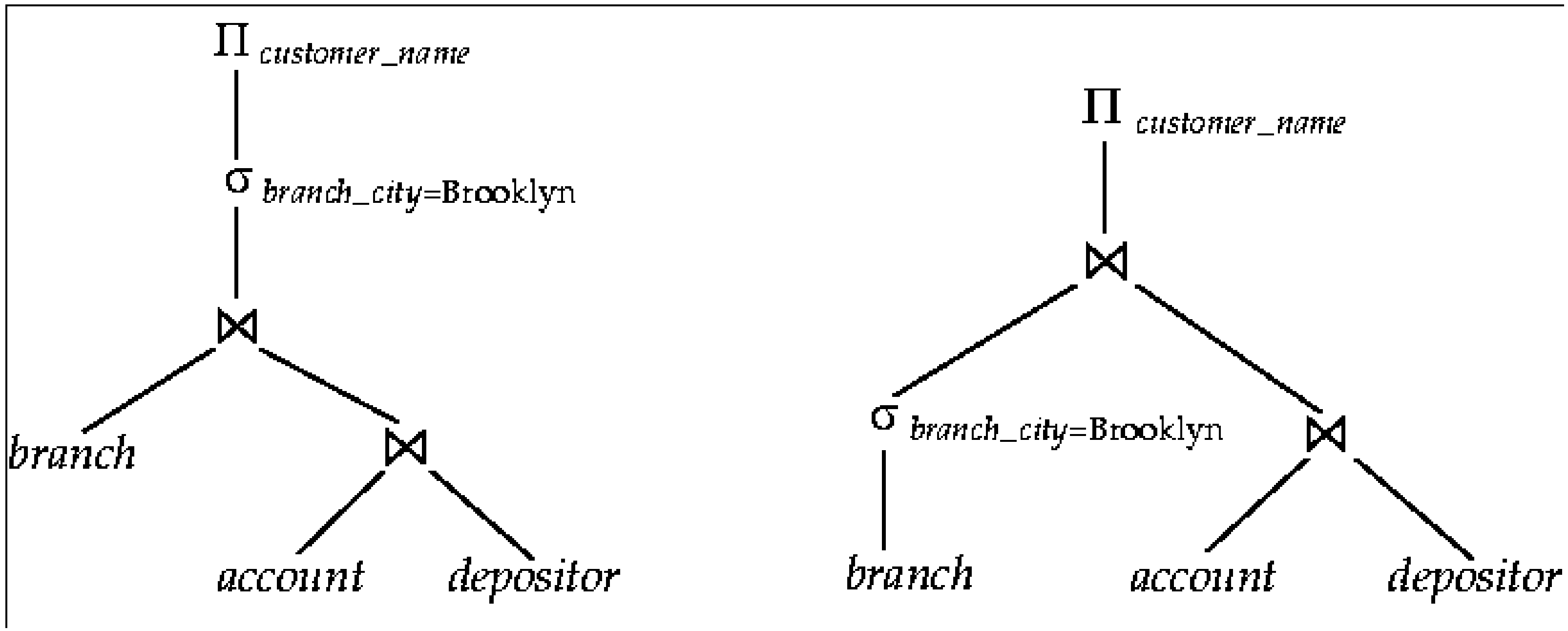
These query plans produce the same final result



A. True
B. False
C. True only if branch_city cannot be NULL
D. Need more information



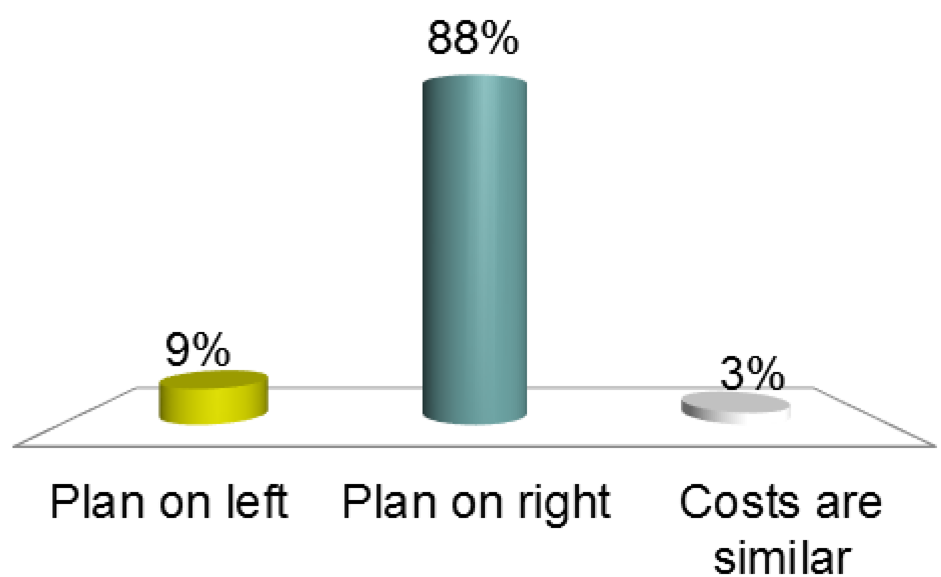
Which query plan is probably faster?



A. Plan on left

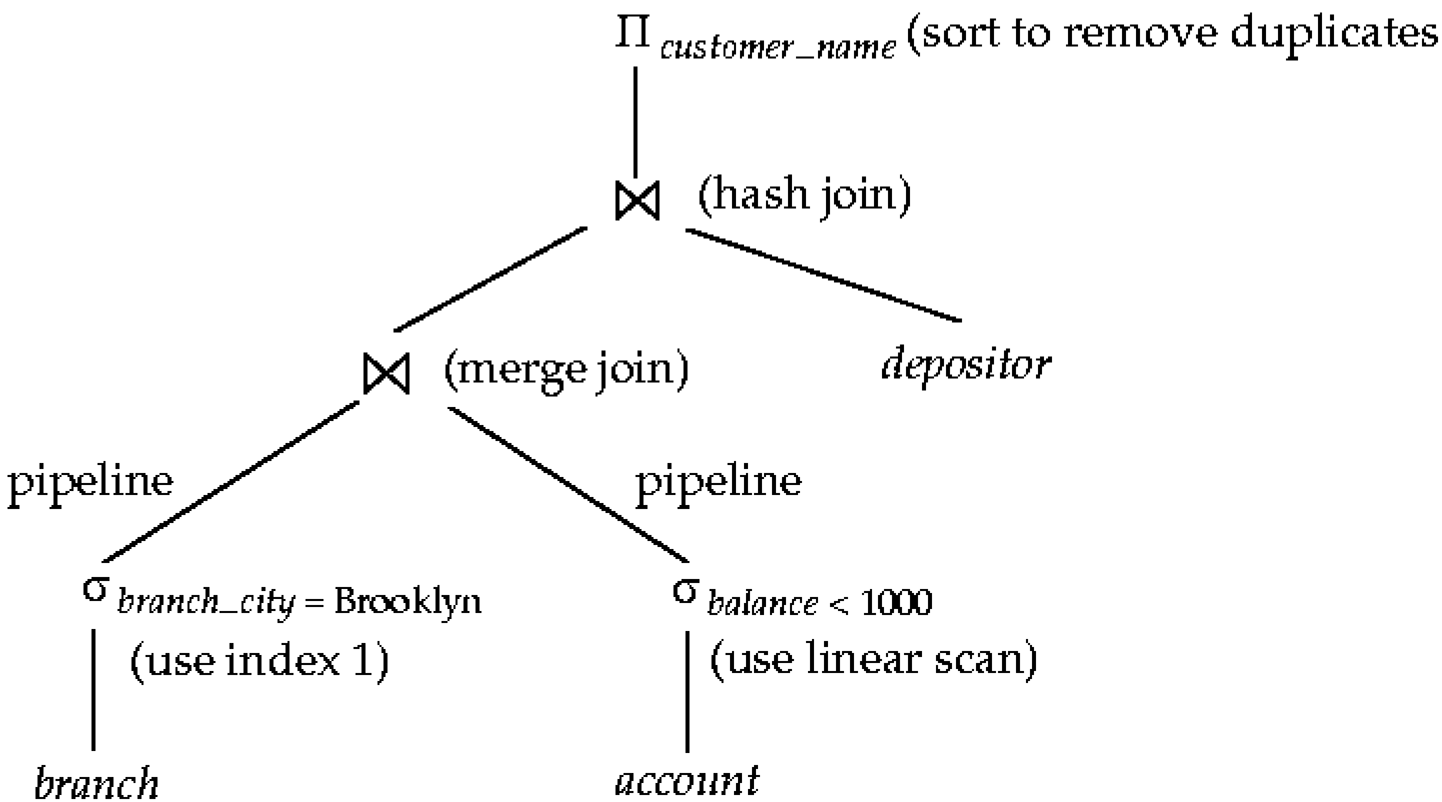
B. Plan on right

C. Costs are similar



Query Optimization

- Execution plans
  - Evaluation expressions annotated with the methods used



Query Optimization

- Steps:
  - Generate all possible execution plans for the query
  - Figure out the cost for each of them
  - Choose the best

- Not done exactly as listed above
  - Too many different execution plans for that
  - Typically interleave all of these into a single efficient search algorithm

Query Optimization

- Steps (detail):
  - Generate all possible execution plans for the query
    - First generate all equivalent expressions
    - Then consider all annotations for the operations
  - Figure out the cost for each of them
    - Compute cost for each operation
      - Using the formulas discussed in prior weeks
      - One problem: How do we know the number of result tuples for, say, $\sigma_{balance<2500}(account)$
        - Count them or estimate…
  - Choose the best

Cost estimation

- Computing operator costs requires information like:
  - Primary key ?
  - Sorted or not, which attribute
    - So we can decide whether need to sort again
  - How many tuples in the relation, how many blocks ?
  - How many tuples match a predicate like “age > 40” ?
    - E.g. Need to know how many index pages need to be read
  - Intermediate result sizes
    - E.g. (R JOIN S) is input to another join operation – need to know if it fits in memory
  - And so on…

Cost estimation

- Some info is static and maintained in the metadata
    - Primary key ?
    - Sorted or not, which attribute
        - So we can decide whether need to sort again
    - How many tuples in the relation, how many blocks ?
- Typically kept in special “catalog” table in the DB
    - E.g., “all_tab_columns” in Oracle
    - E.g., “pg_database” in Postgres

Cost estimation

- Others need to be estimated:
  - How many tuples match a predicate like “age > 40” ?
  - Intermediate result sizes
- The problem variously called:
  - “intermediate result size estimation”
  - “selectivity estimation”

- Very important to estimate reasonably well
  - e.g. consider “SELECT * FROM R WHERE zipcode = 20742”
  - We estimate that there are 10 matches, and choose to use a secondary index (remember: random I/Os)
  - Turns out there are 10000 matches
  - Using a secondary index very bad idea
  - Optimizer often chooses nested-loop joins if one relation very small… underestimation can be very bad

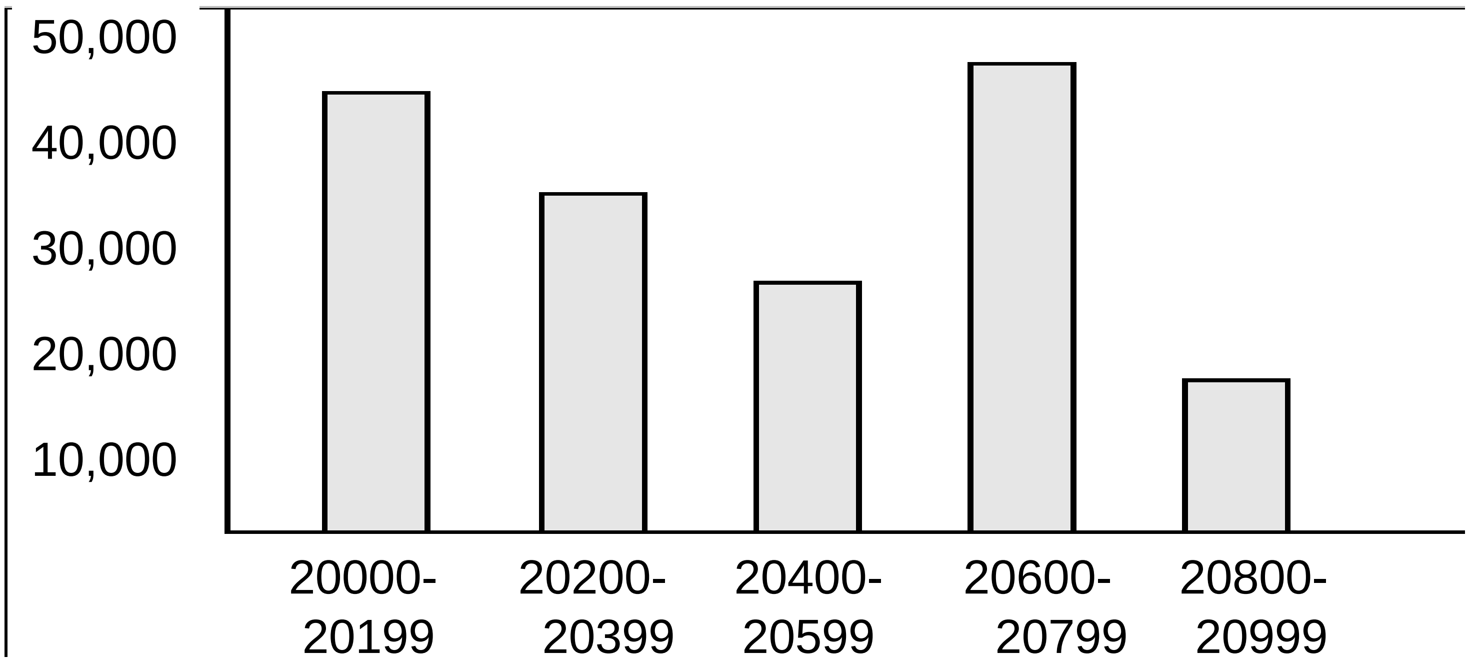
Selectivity Estimation

- Basic idea:
  - Maintain some information about the tables
    - More information → more accurate estimation
    - More information → higher storage cost, higher update cost
  - Make uniformity and randomness assumptions to fill in the gaps

- Example:
  - For a relation “people”, we keep:
    - Total number of tuples = 100,000
    - Distinct “zipcode” values that appear in it = 100
  - Given a query: “zipcode = 20742”
    - We estimated the number of matching tuples as: 100,000/100 = 1000
  - What if I wanted more accurate information ?
    - Keep histograms…

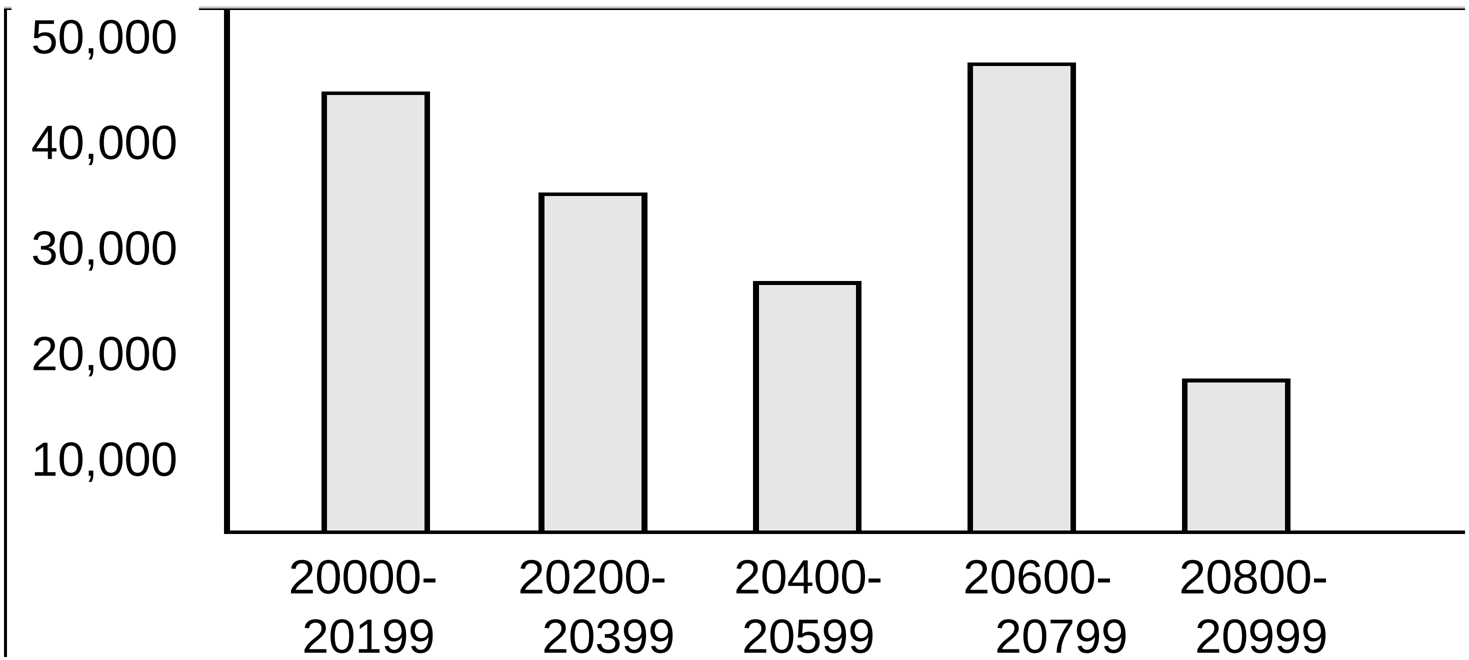
Histograms

- A condensed, approximate version of the “frequency distribution”
  - Divide the range of the attribute value in “buckets”
  - For each bucket, keep the total count
  - Assume uniformity within a bucket



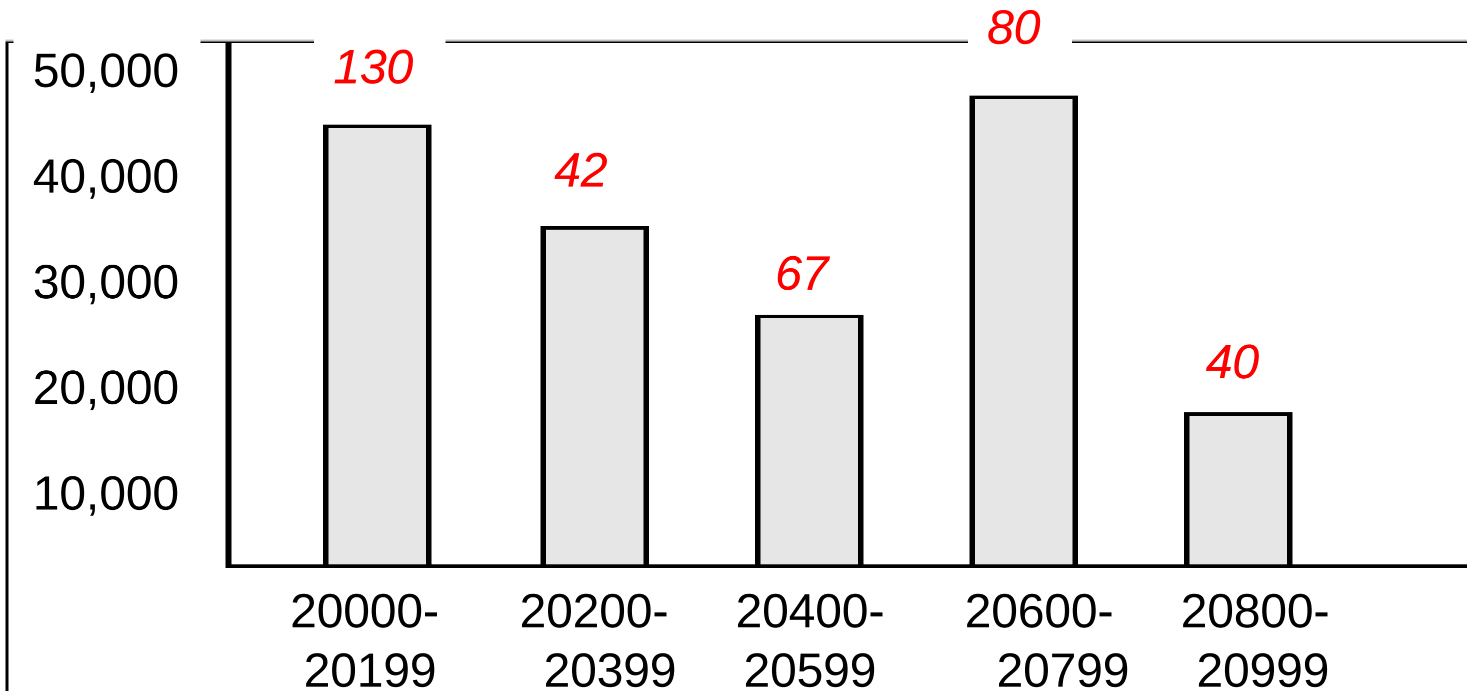
Histograms

- Given a query: zipcode = “ 20742”
  - Find the bucket (Number 3)
  - Say the associated count = 45000
  - Assume uniform distribution within the bucket: 45,000/200 = 225



Histograms

- What if the ranges are typically not full ?
  - ie., only a few of the zipcodes are actually in use ?
- With each bucket, also keep the number of zipcodes that are valid
- Now the estimate would be: 45,000/80 = 562.50
- More Information → Better estimation



Histograms

- Very widely used in practice
  - One-dimensional histograms kept on almost all columns of interest
    - ie., the columns that are commonly referenced in queries
  - Sometimes: multi-dimensional histograms also make sense
    - Less commonly used as of now
- Two common types of histograms:
  - Equi-depth
    - The attribute value range partitioned such that each bucket contains about the same number of values
  - Equi-width
    - The attribute value range partitioned in equal-sized buckets
  - others…

Estimating sizes of the results of various operations

- Guiding principle:
  - Use all the information available
  - Make uniformity and randomness assumptions otherwise
  - Many formulas, but not very complicated…
    - In most cases, your initial intuition is probably correct

Basic statistics

- Basic information stored for all relations
  - n_r = $|r|$ = number of tuples in a relation *r.*
  - b_r: number of blocks containing tuples of *r.*
  - l_r: size of a tuple of *r.*
  - f_r*:* blocking factor of *r* — i.e., the number of tuples of *r* that fit into one block.
  - *V(A, r):* number of distinct values that appear in *r* for attribute *A;* same as the size of $\prod_A(r)$.
  - *MAX(A, r):* th maximum value of *A* that appears in *r*
  - *MIN(A, r)*
  - If tuples of *r* are stored together physically in a file, then:

$$b_r = \left\lceil \frac{n_r}{f_r} \right\rceil$$

Selection Size Estimation

- $\sigma_{A=v}(r)$
  - $n_r / V(A,r)$: number of records that will satisfy the selection
  - equality condition on a key attribute: *size estimate* = 1

- $\sigma_{A \leq V}(r)$ (case of $\sigma_{A \geq V}(r)$ is symmetric)
  - Let c denote the estimated number of tuples satisfying the condition.
  - If min(A,r) and max(A,r) are available in catalog
    - c = 0 if v < min(A,r)
    - c = $n_r \cdot \frac{v - \min(A,r)}{\max(A,r) - \min(A,r)}$
  - If histograms available, can refine above estimate
  - In absence of statistical information *c* is assumed to be $n_r / 2$.

Size Estimation of Complex Selections

- selectivity(θ_i) = the probability that a tuple in r satisfies θ_i .
  - If s_i is the number of satisfying tuples in r, then selectivity (θ_i) = s_i / n_r.

- conjunction: $\sigma_{\theta 1 \wedge \theta 2 \wedge \ldots \wedge \theta n}(r)$. *Assuming independence,* estimate of tuples in the result is:

$$n_r * \frac{s_1 * s_2 * \ldots * s_n}{n_r^n}$$

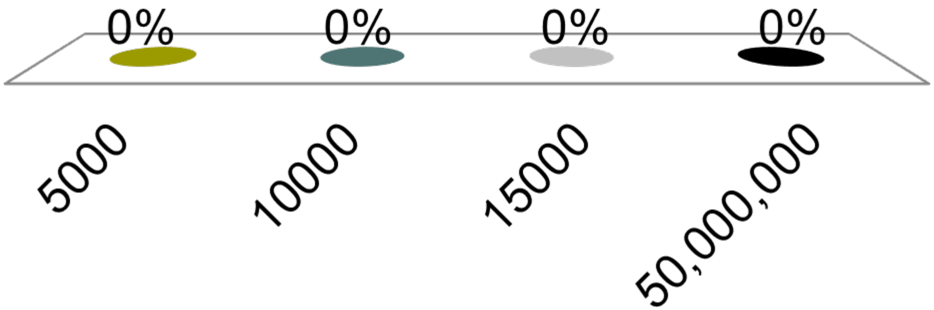
- disjunction: $\sigma_{\theta 1 \vee \theta 2 \vee \ldots \vee \theta n}(r)$. Estimated number of tuples:

$$n_r * \left(1 - (1 - \frac{s_1}{n_r}) * (1 - \frac{s_2}{n_r}) * \ldots * (1 - \frac{s_n}{n_r})\right)$$

- negation: $\sigma_{\neg\theta}(r)$. Estimated number of tuples: $n_r - size(\sigma_\theta(r))$

# of tuples produced in **worst case**:
R JOIN S: R.a = S.a
a is primary key of S
|R| = 10,000; |S| = 5000

A. 5000
B. 10000
C. 15000
D. 50,000,000



Joins

- R JOIN S: R.a = S.a
  - |R| = 10,000; |S| = 5000
- CASE 1: *a* is key for S
  - *Worst case: each tuple of R joins with exactly one tuple of S*
  - So: |R JOIN S| = |R| = 10,000
- CASE 2: *a* is key for R
  - Similar --- so |S| = 5,000

Joins

- R JOIN S: R.a = S.a
  - |R| = 10,000; |S| = 5000

- CASE 3: *a* is not a key for either
  - Reason with the distributions on *a*
  - Say: the domain of *a: V(A, R)* = 100 (the number of distinct values *a* can take)
  - THEN, *assuming uniformity*
    - For each value of *a*
      - We have 10,000/100 = 100 tuples of R with that value of a
      - We have 5000/100 = 50 tuples of S with that value of a
      - All of these will join with each other, and produce 100 *50 = 5000
    - So total number of results in the join:
      - 5000 * 100 (distinct values) = 500,000
  - We can improve the accuracy if we know the distributions on *a* better
    - Say using a histogram

Equivalence of Expressions

- Two relational expressions equivalent iff:
  - Their result is identical on all legal databases
- Equivalence rules:
  - Allow replacing one expression with another
- Examples:

1. $\sigma_{\theta_1 \wedge \theta_2}(E) = \sigma_{\theta_1}(\sigma_{\theta_2}(E))$

2. Selections are commutative

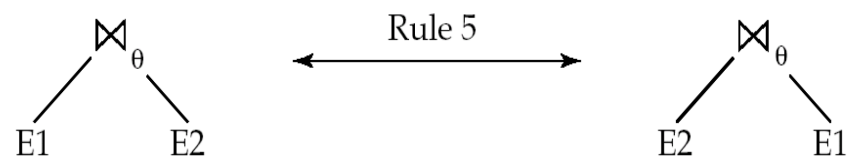
$$\sigma_{\theta_1}(\sigma_{\theta_2}(E)) = \sigma_{\theta_2}(\sigma_{\theta_1}(E))$$

Equivalence Rules

- Examples:

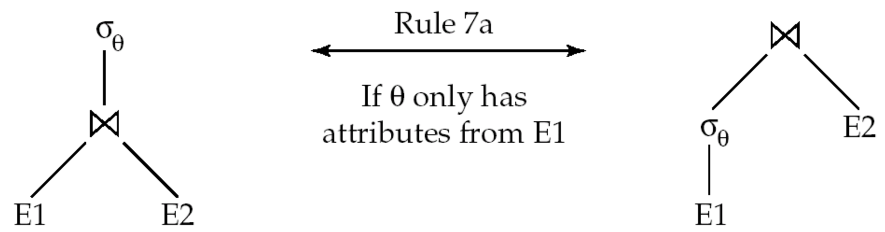
  3. $\Pi_{L_1}(\Pi_{L_2}(\ldots(\Pi_{Ln}(E))\ldots)) = \Pi_{L_1}(E)$

  5. $E_1 \bowtie_\theta E_2 = E_2 \bowtie_\theta E_1$



  7(a). If *θ_0 only involves attributes from E_1*

  $$\sigma_{\theta 0}(E_1 \bowtie_\theta E_2) = (\sigma_{\theta 0}(E_1)) \bowtie_\theta E_2$$



- And so on…
  - Many rules of this type
  - See textbook for more examples

Example

- Find the names of all customers with an account at a Brooklyn branch whose account balance is over $1000.

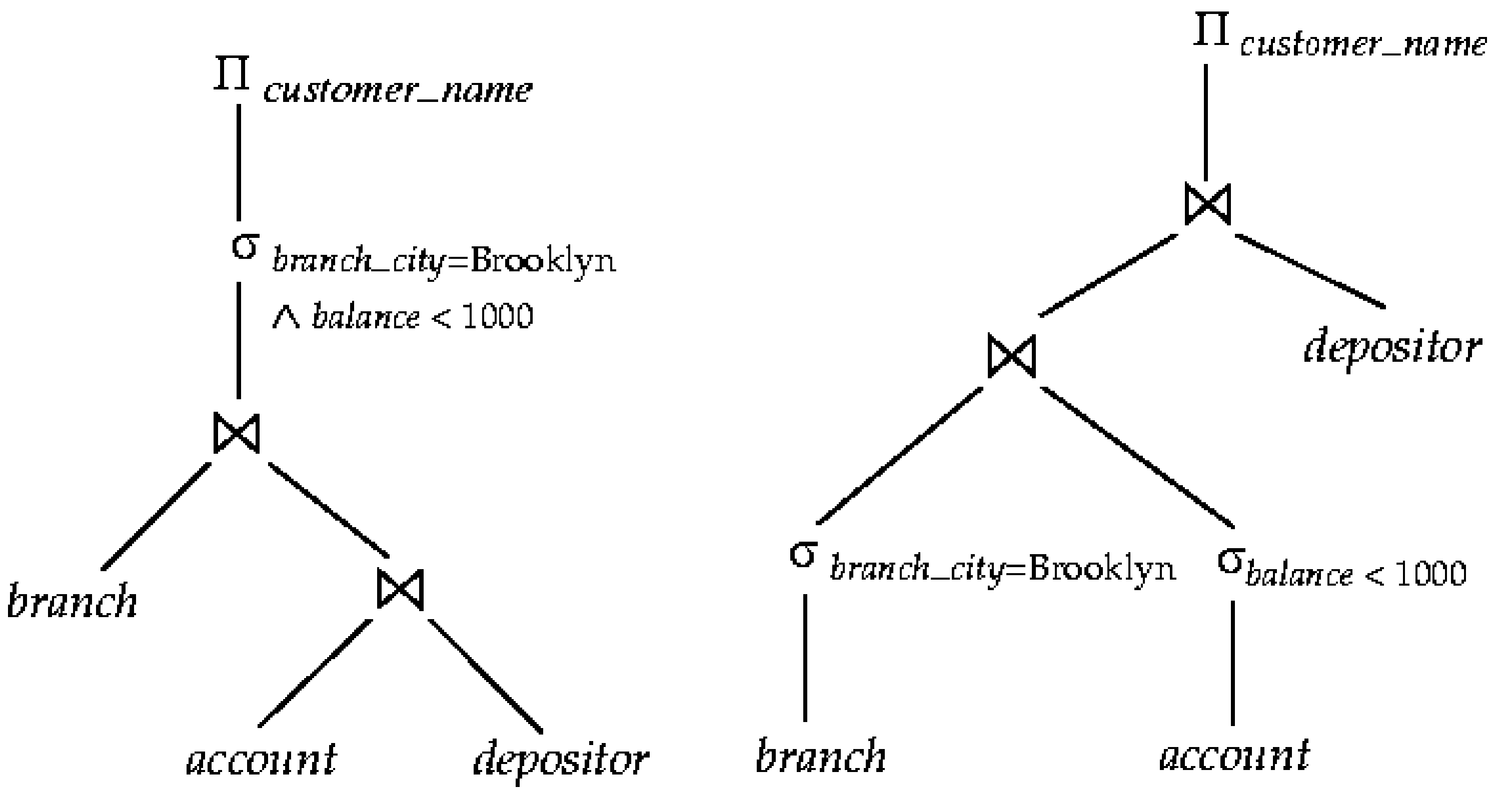
$$\Pi_{customer\_name}(\sigma_{branch\_city\ =\ \text{“Brooklyn”}\ \wedge\ balance\ >\ 1000}$$
$$(branch \bowtie (account \bowtie depositor)))$$

- Apply the rules one by one

$$\Pi_{customer\_name}((\sigma_{branch\_city\ =\ \text{“Brooklyn”}\ \wedge\ balance\ >\ 1000}$$
$$(branch \bowtie account)) \bowtie depositor)$$

$$\Pi_{customer\_name}(((\sigma_{branch\_city\ =\ \text{“Brooklyn”}}(branch)) \bowtie (\sigma_{balance\ >\ 1000}$$
$$(account))) \bowtie depositor)$$

Example



(a) Initial expression tree (b) Tree after multiple transformations

Equivalence of Expressions

- The rules give us a way to enumerate all equivalent expressions
  - Note that the expressions don't contain physical access methods, join methods etc…
- Simple Algorithm:
  - Start with the original expression
  - Apply all possible applicable rules to get a new set of expressions
  - Repeat with this new set of expressions
  - Till no new expressions are generated

Equivalence of Expressions

- Works, but is not feasible
- Consider a simple case:
  - $R1 \bowtie (R2 \bowtie (R3 \bowtie (\ldots \bowtie Rn)))\ldots.)$
- Just join commutativity and associativity can give us up to $n! * 2^n$ plans to consider
  - Typically enumeration combined with the search process

Evaluation Plans

- We still need to choose the join methods etc..
  - Option 1: Choose for each operation separately
    - Usually okay, but sometimes the operators interact
    - Consider joining three relations on the same attribute:
      - $R1 \bowtie_a (R2 \bowtie_a R3)$
    - Best option for R2 join R3 might be hash-join
      - But if *R1* is sorted on *a,* then *sort-merge join* is preferable
      - Because it produces the result in sorted order by *a*
- Also, pipelining or materialization
- Such issues typically arise when doing the optimization

Query Optimization

- Integral component of query processing
- One of the most complex pieces of code in a database system
- Active area of research
  - E.g. JSON Query Optimization
  - What if you don't know anything about the statistics
  - Better statistics
  - How to prune search space
  - How good is good enough?