CMSC424: Database Design

Instructor: Amol Deshpande
amol@cs.umd.edu

Databases

- Data Models
  - Conceptual representation of the data
- Data Retrieval
  - How to ask questions of the database
  - How to answer those questions
- Data Storage
  - How/where to store data, how to access it
- Data Integrity
  - Manage crashes, concurrency
  - Manage semantic inconsistencies

Query Optimization

- Overview
- Statistics Estimation
- Transformation of Relational Expressions
- Optimization Algorithms

Query Optimization

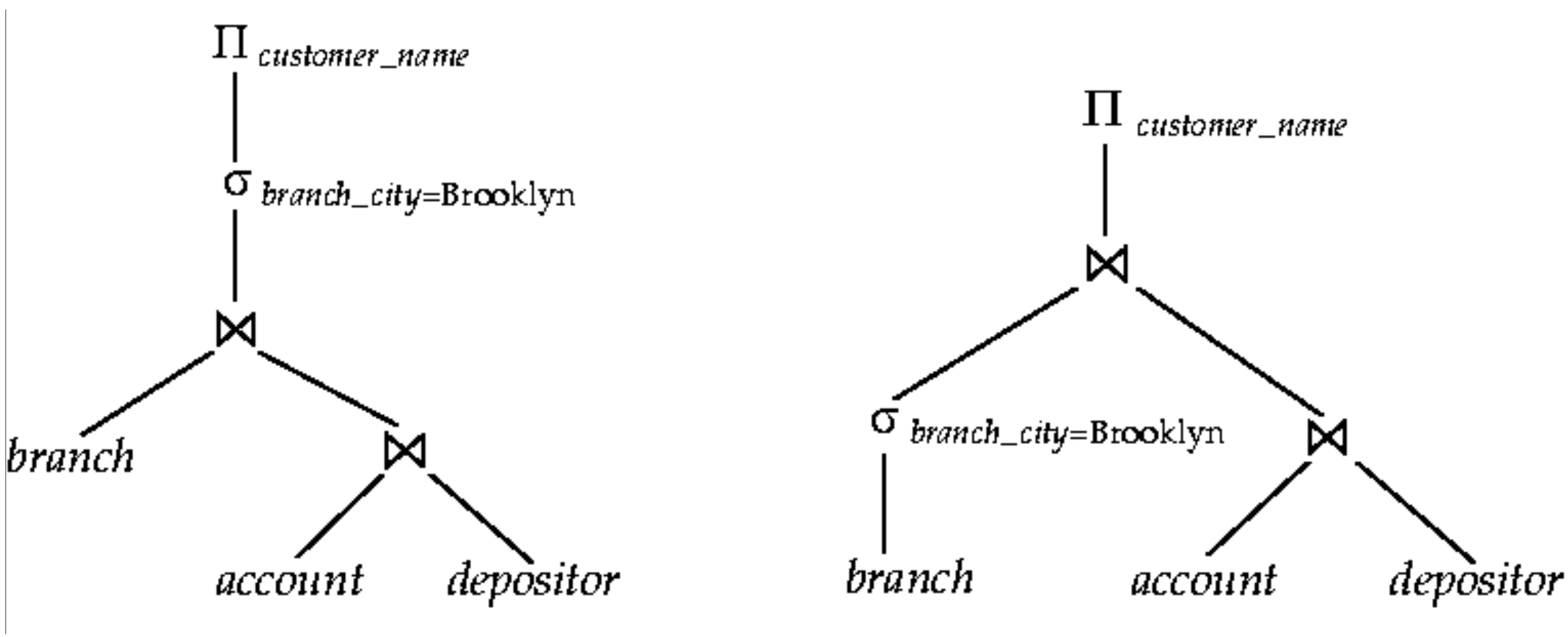
- Why ?
  - Many different ways of executing a given query
  - Huge differences in cost
- Example:
  - select * from person where ssn = “123”
  - Size of *person* = 1GB
  - Sequential Scan:
    - Takes 1GB / (20MB/s) = 50s
  - Use an index on SSN (assuming one exists):
    - Approx 4 Random I/Os = 40ms

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
  - Similar to say *traveling salesman 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

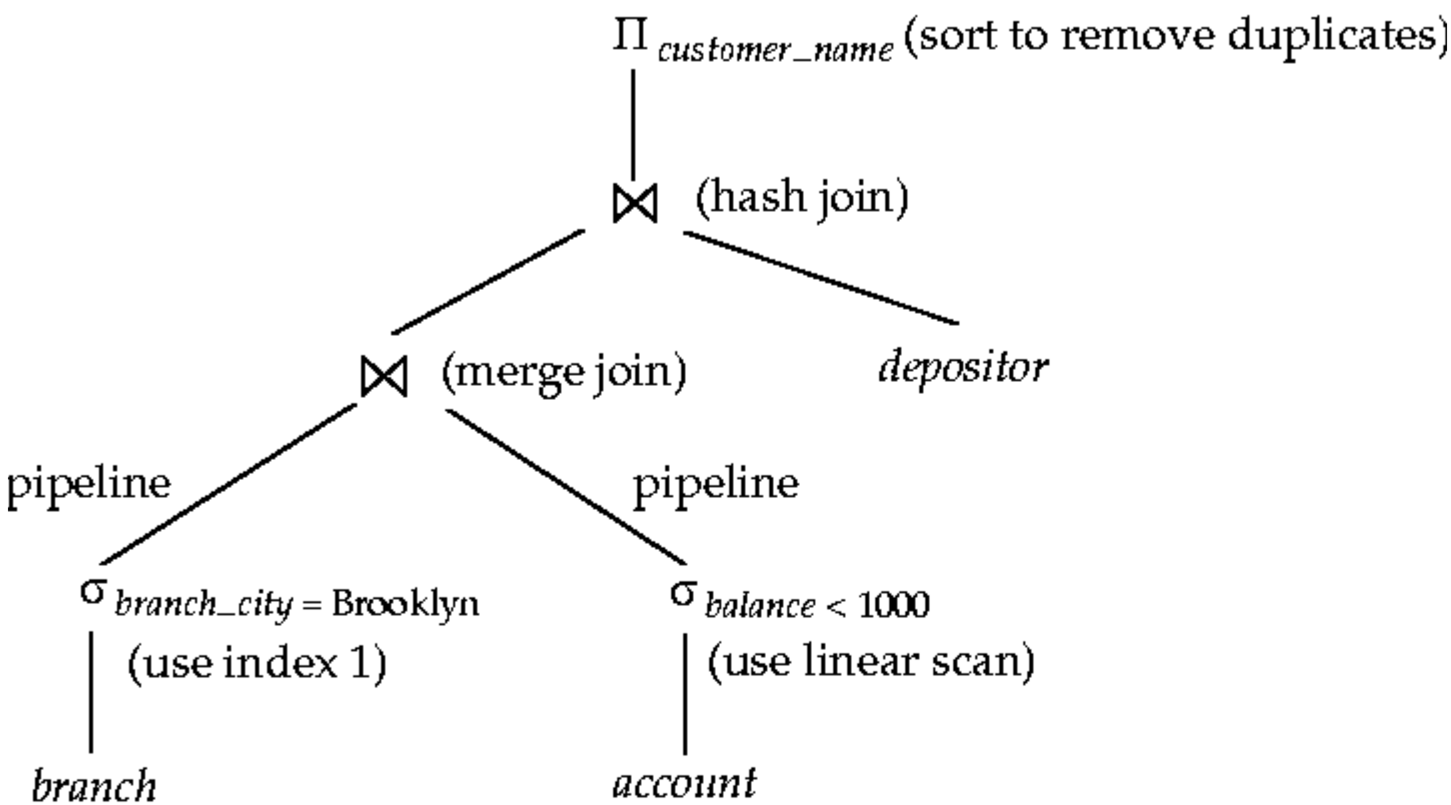
Query Optimization

- Equivalent relational expressions
  - Drawn as a tree
  - List the operations and the order



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:
  - 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 before
      - One problem: How do we know the number of result tuples for, say, $\sigma_{balance<2500}(account)$
    - Add them !
  - Choose the best

Query Optimization

- Introduction
- Example of a Simple Type of Query
- Transformation of Relational Expressions
- Optimization Algorithms
- Statistics Estimation

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 ?
  - RAID ?? Which one ?
    - Read/write costs are quite different
  - 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 information is static and is 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 ?
  - RAID ?? Which one ?
    - Read/write costs are quite different

- Typically kept in some tables in the database
  - "all_tab_columns" in Oracle
- Most systems have commands for updating them

Cost estimation

- However, others need to be estimated somehow
  - 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
- 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 also often choose Nested-loop joins if one relation very small… underestimation can result in very bad

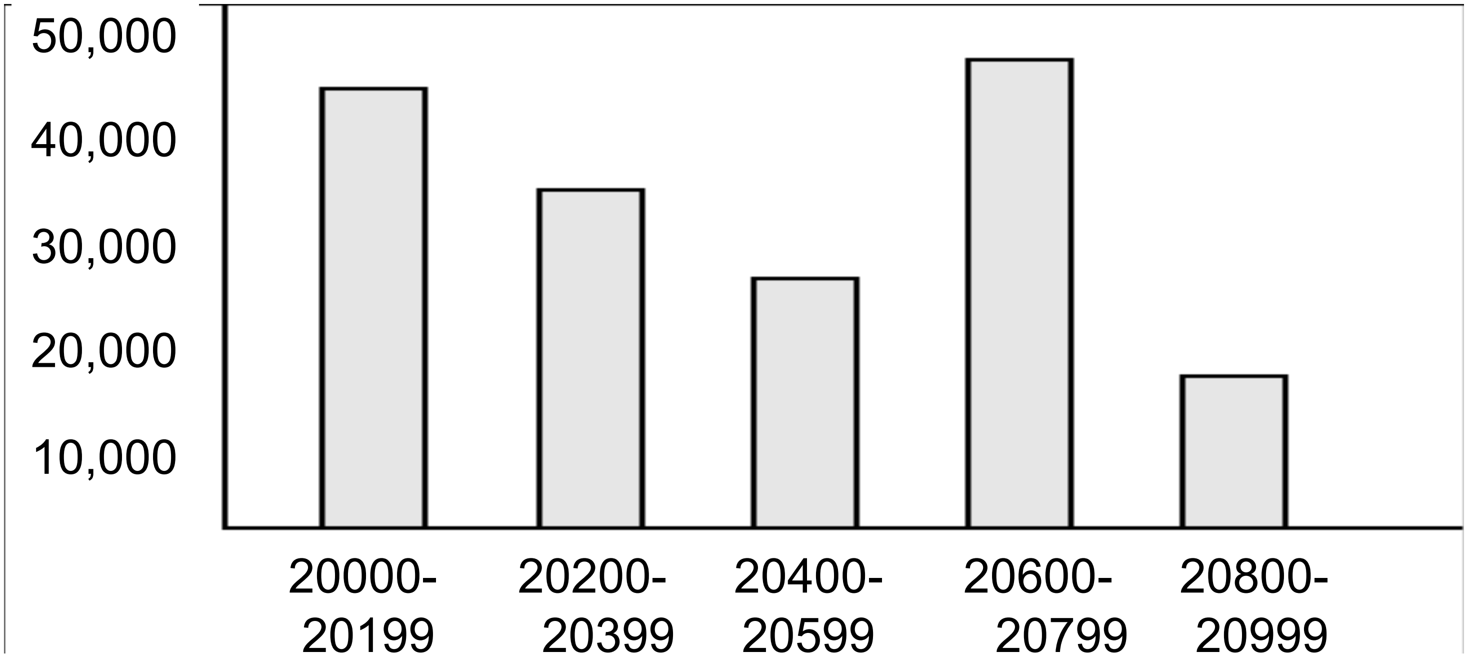
Selectivity Estimation

- 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…

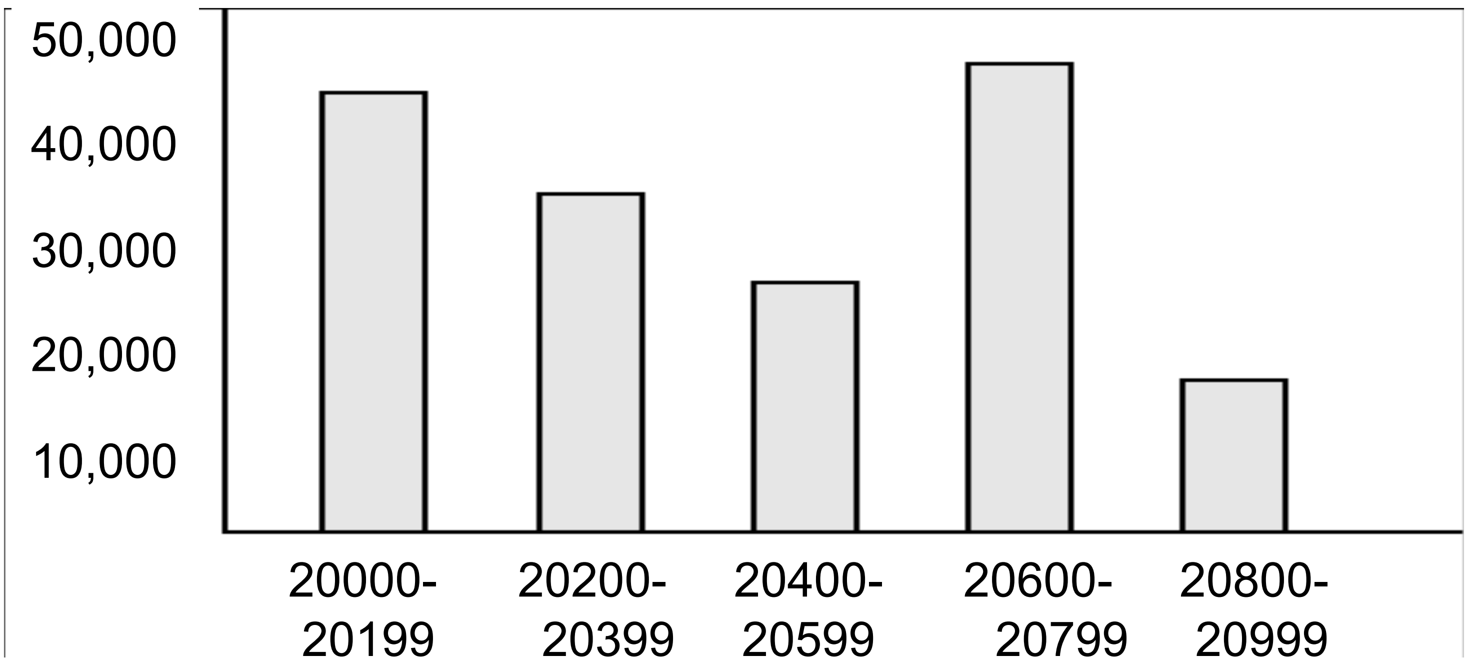
Histograms

- 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



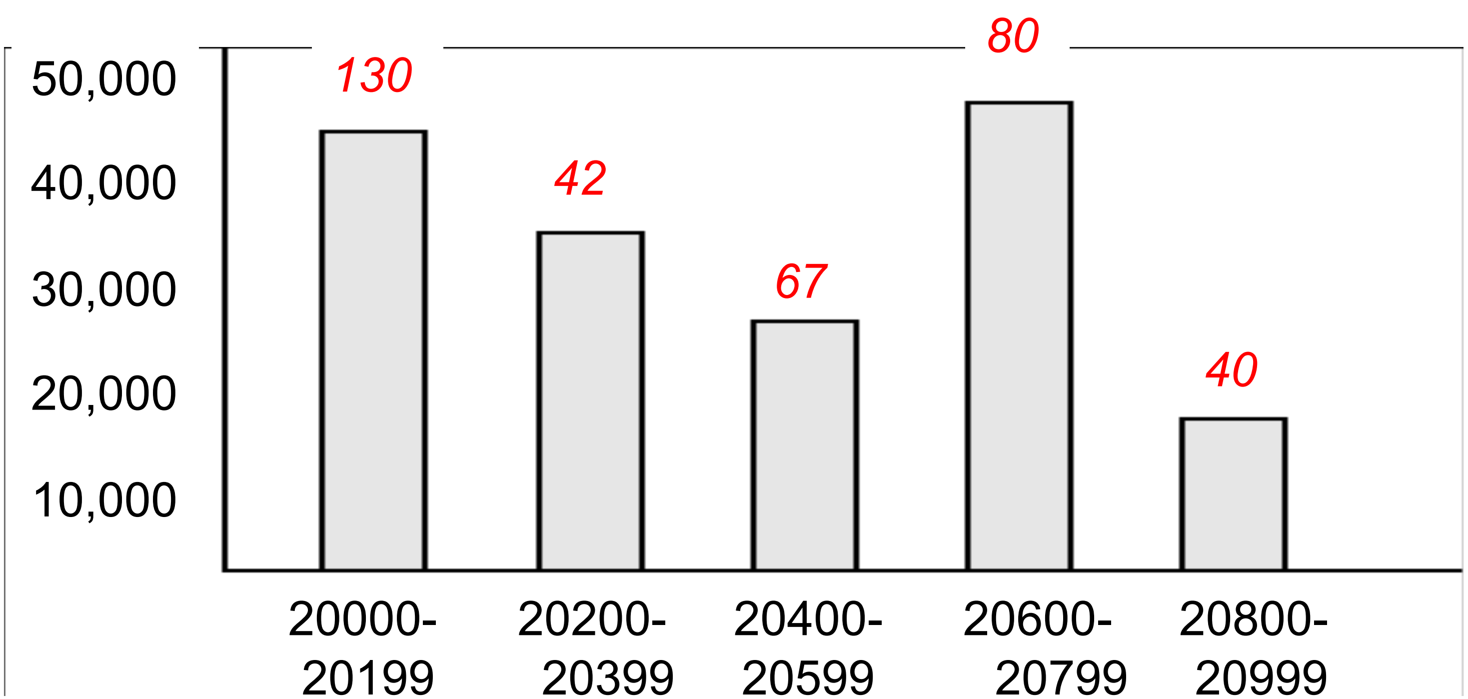
Histograms

- Given a query: zipcode = " 20742"
  - Find the bucket (Number 3)
  - Say the associated cound = 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 tuples
  - Equi-width
    - The attribute value range partitioned in equal-sized buckets
  - VOptimal histograms
    - No such restrictions
    - More accurate, but harder to use or update

Next…

- 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, the first thing you think of

Basic statistics

- Basic information stored for all relations
  - n_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: $n_r - size(\sigma_\theta(r))$

Joins

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

- CASE 1: *a* is key for S
  - *Each tuple of R joins with exactly one tuple of S*
  - So: |R JOIN S| = |R| = 10,000
  - Assumption: Referential integrity holds

  - What if there is a selection on R or S
    - Adjust accordingly
    - Say: S.b = 100, with selectivity 0.1
    - THEN: |R JOIN S| = |R| * 0.1 = 100

- CASE 2: *a* is key for R
  - Similar

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)* = 1000 (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 = 500000
  - We can improve the accuracy if we know the distributions on *a* better
    - Say using a histogram

Other Operations

- Projection: $\prod_A(R)$
  - If no duplicate elimination, THEN $|\prod_A(R)| = |R|$
  - If *distinct* used (duplicate elimination performed): $|\prod_A(R)| = V(A, R)$
- Set operations:
  - Union ALL: $|R \cup S| = |R| + |S|$
  - Intersect ALL: $|R \cap S| = \min\{|R|, |S|\}$
  - Except ALL: $|R - S| = |R|$ (a good upper bound)
  - Union, Intersection, Except (with duplicate elimination)
    - Somewhat more complex reasoning based on the frequency distributions etc…
- And so on …

Query Optimization

- Introduction
- Transformation of Relational Expressions
- Statistics Estimation
- Optimization Algorithms

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

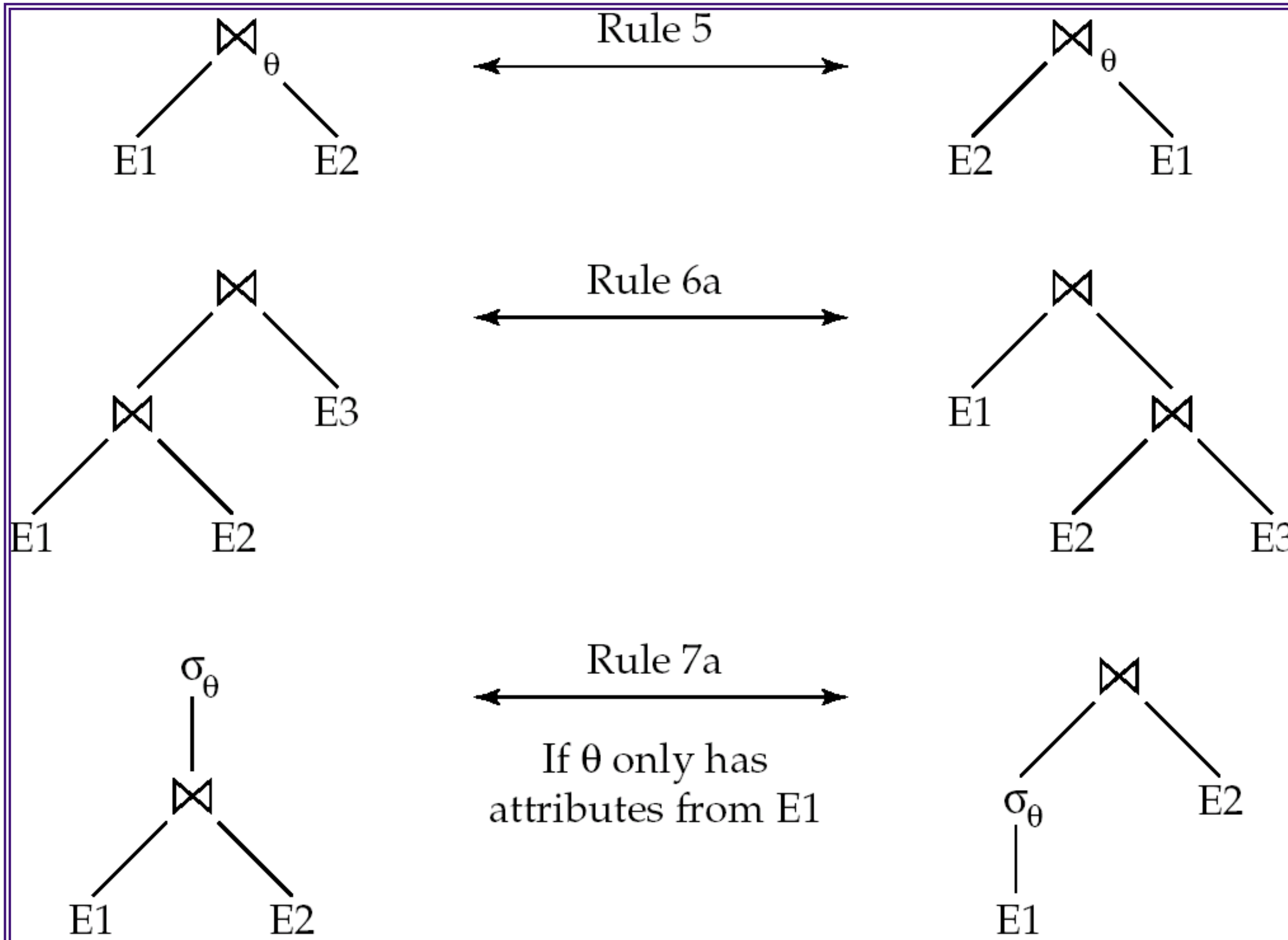
  5. $E_1 \bowtie_\theta E_2 = E_2 \bowtie_\theta E_1$

  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

Pictorial Depiction



Example

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

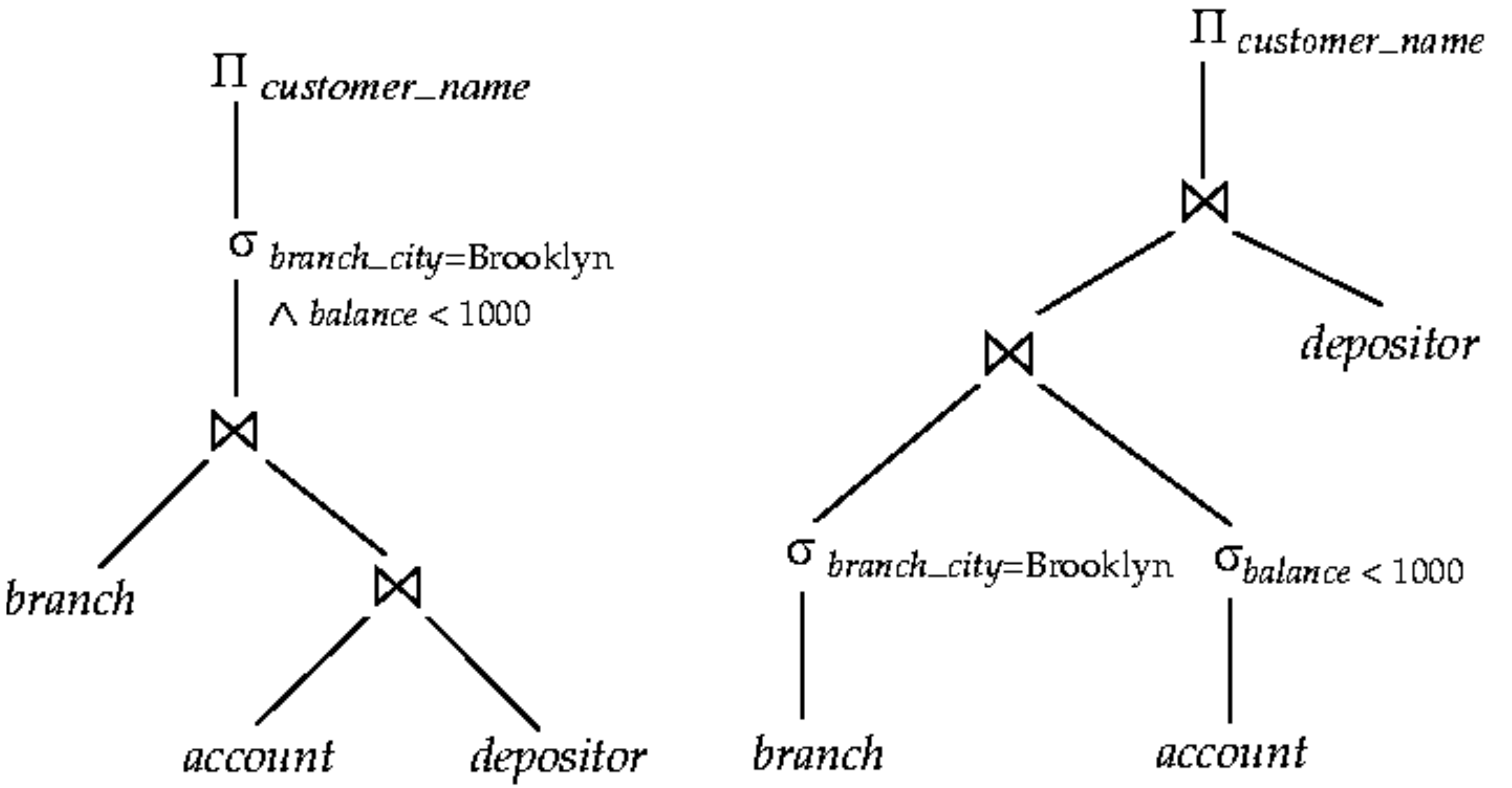
$$\Pi_{customer\_name}(\sigma_{branch\_city = \text{“Brooklyn”} \wedge \; balance > 1000}(branch \bowtie (account \bowtie depositor)))$$

- 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 will give us:
  - At least:
    - n^2 * 2^n
  - At worst:
    - n! * 2^n
- Typically the process of enumeration is 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, we need to decide whether to use pipelining or materialization
- Such issues are typically taken into account when doing the optimization

Query Optimization

- Introduction
- Example of a Simple Type of Query
- Transformation of Relational Expressions
- Optimization Algorithms
- Statistics Estimation

Optimization Algorithms

- Two types:
  - Exhaustive: That attempt to find the best plan
  - Heuristical: That are simpler, but are not guaranteed to find the optimal plan

- Consider a simple case
  - Join of the relations *R1, …, Rn*
  - No selections, no projections
- Still very large plan space

Searching for the best plan

- Option 1:
  - Enumerate all equivalent expressions for the original query expression
    - Using the rules outlined earlier
  - Estimate cost for each and choose the lowest

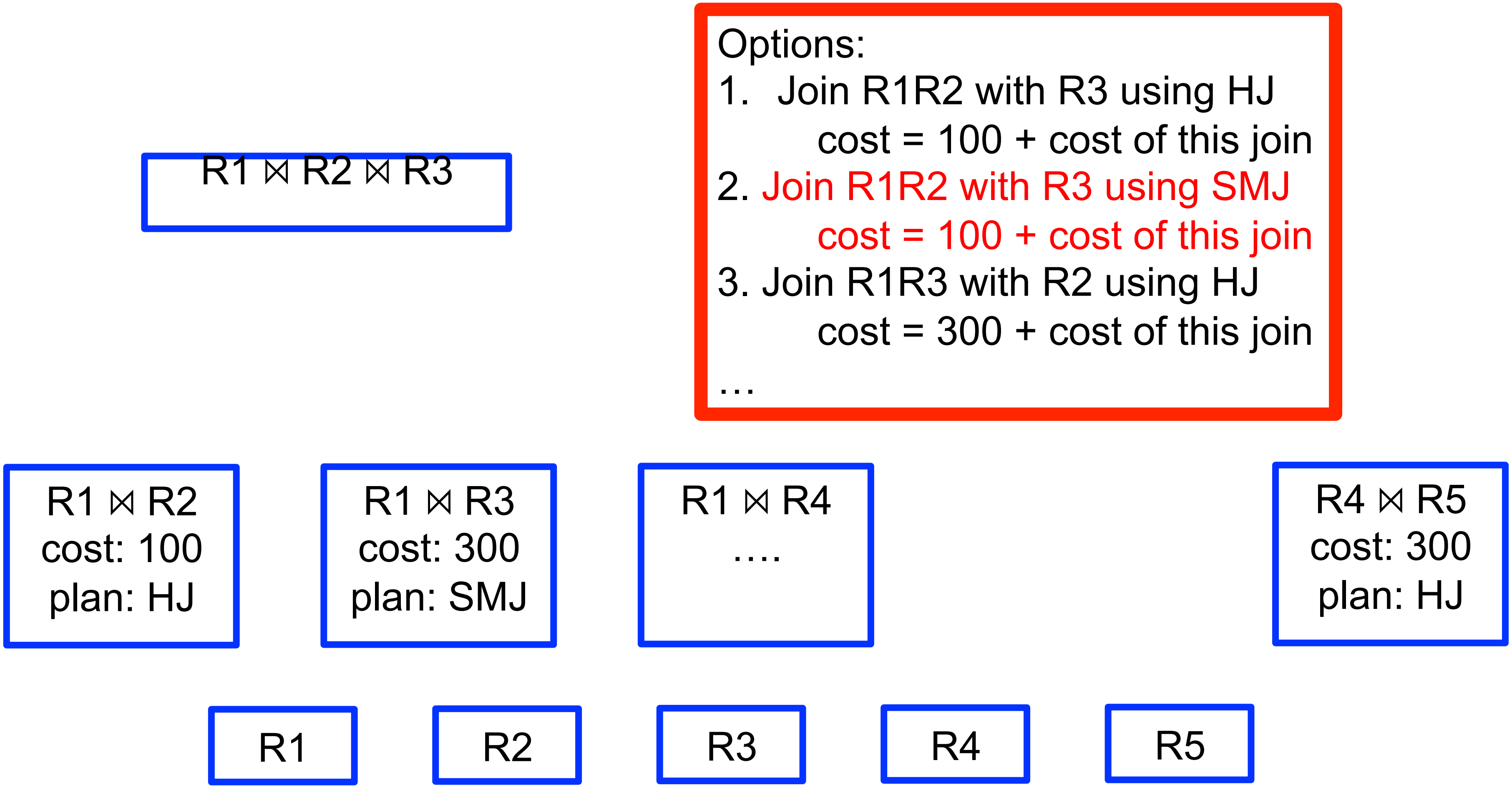
- Too expensive !
  - Consider finding the best join-order for $r_1 \bowtie r_2 \bowtie \ldots r_n$.
  - There are $(2(n-1))!/(n-1)!$ different join orders for above expression. With $n = 7$, the number is 665280, with $n = 10$, the number is greater than 176 billion!

Searching for the best plan

- Option 2:
  - Dynamic programming
    - There is too much commonality between the plans
    - Also, costs are additive
      - Caveat: Sort orders (also called “interesting orders”)
  - Reduces the cost down to O(n3^n) or O(n2^n) in most cases
    - Interesting orders increase this a little bit
  - Considered acceptable
    - Typically n < 10.
  - Switch to heuristic if not acceptable

Dynamic Programming Algo.

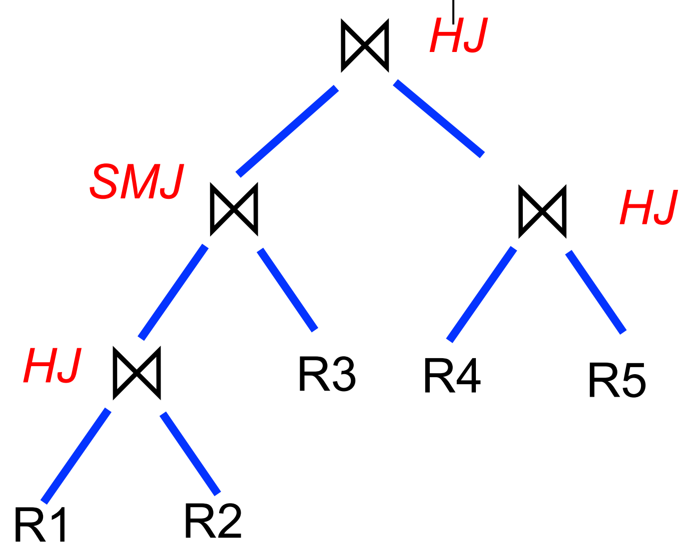
- Join R1, R2, R3, R4, R5



R1 ⋈ R2 ⋈ R3 ⋈ R4 ⋈ R5
cost: 1200
plan: *HJ(R1R2R3, R4R5)*

R1 ⋈ R2 ⋈ R3 ⋈ R4
cost: 700
plan: *HJ(R1R2R3, R4)*

....



R1 ⋈ R2 ⋈ R3
cost: 400
plan: *SMJ(R1R2, R3)*

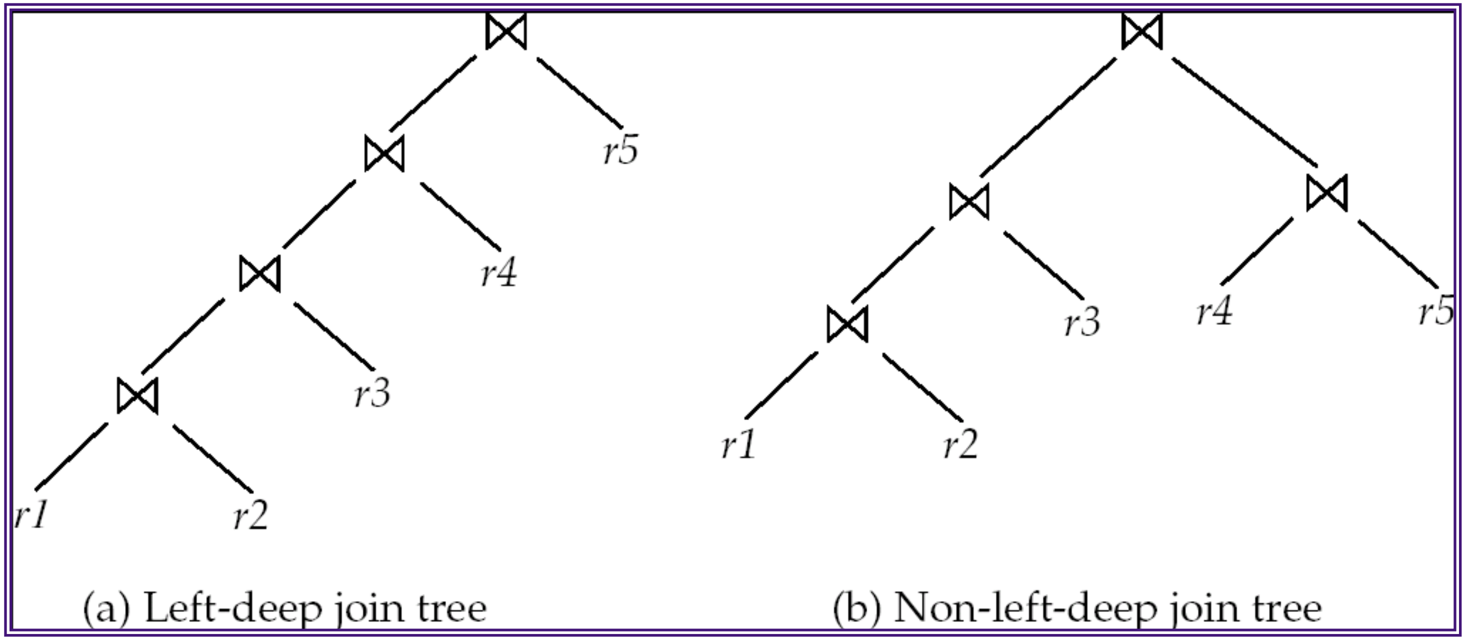
....

R1 ⋈ R2	R1 ⋈ R3	R1 ⋈ R4	....	R4 ⋈ R5
cost: 100	cost: 300	....		cost: 300
plan: HJ	plan: SMJ			plan: HJ

R1 R2 R3 R4 R5

Left Deep Join Trees

- In **left-deep join trees,** the right-hand-side input for each join is a relation, not the result of an intermediate join
- Early systems only considered these types of plans
  - Easier to pipeline



Heuristic Optimization

- Dynamic programming is expensive
- Use *heuristics* to reduce the number of choices
- Typically rule-based:
  - Perform selection early (reduces the number of tuples)
  - Perform projection early (reduces the number of attributes)
  - Perform most restrictive selection and join operations before other similar operations.
- Some systems use only heuristics, others combine heuristics with partial cost-based optimization.

Steps in Typical Heuristic Optimization

1. Deconstruct conjunctive selections into a sequence of single selection operations (Equiv. rule 1.).
2. Move selection operations down the query tree for the earliest possible execution (Equiv. rules 2, 7a, 7b, 11).
3. Execute first those selection and join operations that will produce the smallest relations (Equiv. rule 6).
4. Replace Cartesian product operations that are followed by a selection condition by join operations (Equiv. rule 4a).
5. Deconstruct and move as far down the tree as possible lists of projection attributes, creating new projections where needed (Equiv. rules 3, 8a, 8b, 12).
6. Identify those subtrees whose operations can be pipelined, and execute them using pipelining).

Query Optimization

- Introduction
- Example of a Simple Type of Query
- Transformation of Relational Expressions
- Optimization Algorithms
- Statistics Estimation
- Summary

Query Optimization

- Integral component of query processing
  - Why ?
- One of the most complex pieces of code in a database system
- Active area of research
  - E.g. XML Query Optimization ?
  - What if you don't know anything about the statistics
  - Better statistics
  - Etc …