Introduction to Database Systems

CSE 444

Lecture #16
March 5, 2001

Query Optimization

Required Reading: 7.2, 7.4, 7.5, 7.6

Query Optimization: Phases

- Parsing phase
  - Produces a parse tree
- Query-Rewrite phase
  - Produces a logical tree
- Physical Query plan generation
  - Produces executable (physical) plan

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Query Optimization

- Algebraic laws provide alternative execution plans
- Estimate costs of alternative modes of execution
- Efficiently search the space of alternatives
  - Simplify search by applying heuristics (without costing)
    - apply laws that *seem* to result in cheaper plans

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Converting from SQL to Logical Plans

Select a1, …, an
From R1, …, Rk
Where C

$\Pi_{a1,\dots,an}(\sigma_C(R1 \bowtie R2 \bowtie \dots \bowtie Rk))$

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Converting from SQL to Logical Plans

Select a1, …, an
From R1, …, Rk
Where C
Group by b1, …, bl

$\Pi_{a1,\dots,an}(\gamma_{b1, \dots, bm, aggs}(\sigma_C(R1 \bowtie R2 \bowtie \dots\dots \bowtie Rk)))$

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Algebraic Laws

- Commutative and Associative Laws
  - $R \cup S = S \cup R$, $R \cup (S \cup T) = (R \cup S) \cup T$
  - $R \cap S = S \cap R$, $R \cap (S \cap T) = (R \cap S) \cap T$
  - $R \bowtie S = S \bowtie R$, $R \bowtie (S \bowtie T) = (R \bowtie S) \bowtie T$
- Distributive Laws
  - $R \bowtie (S \cup T) = (R \bowtie S) \cup (R \bowtie T)$

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Algebraic Laws: Selection

- Laws involving selection:
  - $\sigma_{C \text{ AND } C'}(R) = \sigma_C(\sigma_{C'}(R)) = \sigma_C(R) \cap \sigma_{C'}(R)$
  - $\sigma_{C \text{ OR } C'}(R) = \sigma_C(R) \cup \sigma_{C'}(R)$
  - $\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie S$
    - When C involves only attributes of R
  - $\sigma_C(R - S) = \sigma_C(R) - S$
  - $\sigma_C(R \cup S) = \sigma_C(R) \cup \sigma_C(S)$
  - $\sigma_C(R \cap S) = \sigma_C(R) \cap S$

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Algebraic Laws: Selection

- Example: R(A, B, C, D), S(E, F, G)
  - $\sigma_{F=3}(R \bowtie_{D=E} S) =$?
  - $\sigma_{A=5 \text{ AND } G=9}(R \bowtie_{D=E} S) =$?

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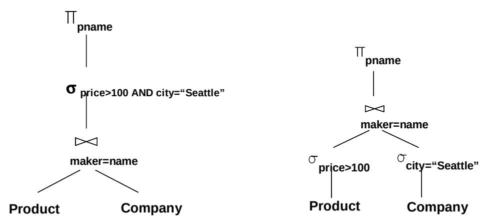
Heuristic: Predicate Pushdown



The earlier we process selections, less tuples we need to manipulate higher up in the tree (but may cause us to lose an important ordering of the tuples).

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Algebraic Laws: Projection

- Laws involving projections
  - $\Pi_M(R \bowtie S) = \Pi_N(\Pi_P(R) \bowtie \Pi_Q(S))$
    - Where N, P, Q are appropriate subsets of attributes of M
  - $\Pi_M(\Pi_N(R)) = \Pi_{M,N}(R)$
- Example R(A,B,C,D), S(E, F, G)
  - $\Pi_{A,B,G}(R \bowtie_{D=E} S) = \Pi_?(\Pi_?(R) \bowtie_{D=E} \Pi_?(S))$

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Other Algebraic Laws

- Duplicate Elimination
  - $\delta(R \bowtie S) = \delta(R) \bowtie \delta(S)$, …
- Grouping
  - $\delta(\gamma_L(R)) = \gamma_{LL}(R)$, …
  - Many transformations depend on aggregate
    - MAX, SUM etc.

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Cost Estimation

- For a given logical plan, there may be many possible physical plans
- We want to choose physical plan with lowest *execution cost*
- Goal: For a given physical plan, estimate cost **without** executing the query

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Cost Estimation

- Ideally should be…
  - Accurate
  - Easy to compute
  - Consistent
    - E.g. cardinality should not depend on join order
- Reality …
  - ?

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Estimating Size of Selection

- How to estimate size of S = $\sigma_{A=20}(R)$?
- Approach 1: Guess!
  - Surprisingly popular method e.g. T(R)/10
- Approach 2: Use *statistics*
  - T(S) = T(R)/V(R,A)

  Where V(R,A) = number of distinct values of A in R
- How about S = $\sigma_{A\leq 20}(R)$?
  - Guess: T(R)/3
  - Statistics: Use *histogram* if available (more later)

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Estimating Size of Projection

- Projection does not change number of tuples
- Size estimate depends on length of columns
- Example: R(a,b,c): a, b are integers, c string of 100 bytes. Tuple header = 12 bytes, Block size = 1024
- $\pi_{a,b,c}(R)$ = ? $\pi_{a,b}(R)$ = ?
- What if c is variable length string?

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Estimating Size of Join

- R(a,b), S(b,c), estimate T(R⋈S)
- Problem: Don’t know how values of R.b and S.b are related
  - May be disjoint sets of values => T (R⋈S) = 0
  - S.b may be *key* of S and R.b may be *foreign key* => T(R⋈S) = T(R)
- Estimate for T(R⋈S)
  - T(R)T(S)/max(V(R,b), V(S,b))

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Estimating Size of Join

- Example: T(R)=1000, T(S)=2000, V(R,b) = 20, V(S,b) = 50
- T(R⋈S) = ?

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Estimating Size of Join

- What happens if query has multiple join attributes?
  - Example: R(a,b,c), S(b,c,d)
  - Estimate = ?
- What happens if query has joins of many relations?
  - Example: R(a,b), S(b,c), U(b,e)
  - Estimate = ?

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Estimating Size of Other Operators

- Union (R,S)
  - Bag Union: T(R) + T(S)
  - Set Union: Max(T(R),T(S)) + Min(T(R),T(S))/2
- Intersection (R,S)
  - Min(T(R),T(S))/2
- Difference (R,S)
  - T(R) - T(S)/2
- Duplicate Elimination

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Cost Based Plan Selection

- Estimates for size parameters
  - Use statistics, e.g. histograms
- Enumerating physical plans

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Histograms

- Popular in commercial DBMSs
- Can give much more accurate cost estimates
- Many types of histograms
  - Equal-width
  - Equal-depth
  - Frequent values
  - …

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Equal-width Histogram

- Each bucket in histogram has same width
- Example: Values = {2,5,23,25,29,31}

Range	Count
1-10	2
11-20	0
21-30	3
31-40	1

- $T(\sigma_{A\leq 20}(R)) = 2$

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Equi-depth Histogram

- Each bucket in histogram has same number of values
- Example: {2,5,33,35,39,41}
  - Bucket Boundary
  - 5
  - 35
  - 41

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Frequent Values

- Keep exact counts of frequent values
- Total count of all other (non-frequent) values
- Example: Values = {1,3,4,4,4,4,4,9}
- Histogram: 4: 5, Others: 3

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Using Histogram for Size Estimation

- Example: R(a,b) S(b,c).
- Histograms:
  - R.b: 1:200, 0:150, 5:100, Others:550
  - S.b: 0:100, 1:80, 2:70, Others:250
- Size of join = ?

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Creating and Maintaining Statistics in a DBMS

- For large tables, creating/refreshing statistics can be expensive
- Alternatives:
  - Refresh statistics only after many changes to data
  - Incremental updating
  - Sampling – need to be careful…

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Enumerating Physical Plans

- Exhaustive – Consider all possible:
  - Join Orders
  - Algorithms for each operator
- Heuristic Search
  - E.g. Greedy approach
  - Pick next relation such that join size is smallest

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Enumerating Physical Plans

- Branch-and-Bound Enumeration
  - Find a good starting plan (having cost C)
  - In subsequent search, eliminate any subquery with cost > C
- Hill Climbing
  - Start with heuristically selected plan
  - Explore plans in the "neighborhood"
    - E.g. replace Nested-Loops join with Hash-Join

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Enumerating Physical Plans

- Dynamic Programming
  - Bottom-up strategy
  - For each subexpression, only keep plan with the least cost
  - Consider possible implementations of each node assuming
  - Extension: also consider *interesting orders*
    - E.g., when subexpression is sorted on a sort attribute at the node
  - More later

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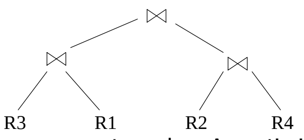
Determining Join Order

- Select-project-join
- Push selections down, pull projections up
- Hence: we need to choose the join order
- This is the main focus of an optimizer

Determining Join Order: Join Trees

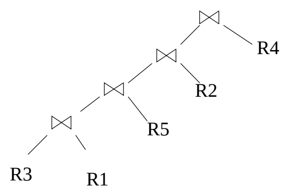
- R1 ⋈ R2 ⋈ …. ⋈ Rn
- Join tree:



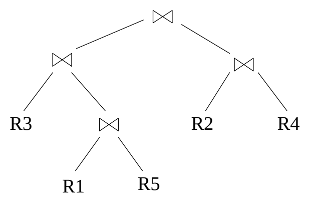
- A join tree represents a plan. An optimizer needs to inspect many (all ?) join trees

Linear Join Trees

- Left deep:



Bushy Join Trees



Join Ordering Problem

- Given: a query R1 ⋈ R2 ⋈ … ⋈ Rn
- Assume we have a function cost() that gives us the cost of every join tree
- Find the best linear join tree for the query

Dynamic Programming

- For each subquery Q□{R1, …, Rn} compute the following:
  - Size(Q)
  - A best plan for Q: Plan(Q)
  - The cost of that plan: Cost(Q)

Dynamic Programming

- Step 1: For each {Ri} do:
  - Size({Ri}) = B(Ri)
  - Plan({Ri}) = Ri
  - Cost({Ri}) = (cost of scanning Ri)

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Dynamic Programming

- Step i: For each Q□{R1, …, Rn} of cardinality i do:
  - Compute Size(Q)
  - For every pair of subqueries Q', Q"
    s.t. Q = Q' U Q"
    compute cost(Plan(Q') ⋈ Plan(Q"))
  - Cost(Q) = the smallest such cost
  - Plan(Q) = the corresponding plan

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Dynamic Programming

- Return Plan({R1, …, Rn})

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Dynamic Programming

To illustrate, we will make the following simplifications:

- Cost(P1 ⋈ P2) = Cost(P1) + Cost(P2) +
  size(intermediate result(s))
- Intermediate results:
  - If P1 = a join, then the size of the intermediate result is size(P1), otherwise the size is 0
  - Similarly for P2
- Cost of a scan = 0

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Dynamic Programming

- Example:
- Cost(R5 ⋈ R7) = 0 (no intermediate results)
- Cost((R2 ⋈ R1) ⋈ R7)
  = Cost(R2 ⋈ R1) + Cost(R7) + size(R2 ⋈ R1)
  = size(R2 ⋈ R1)

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Dynamic Programming

- We used naïve size/cost estimations
- In practice:
  - More realistic size/cost estimations
  - Heuristics for Reducing the Search Space
    - Restrict to left linear trees
    - Restrict to trees "without cartesian product"
  - Need more than just one plan for each subquery:
    - "interesting orders"

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