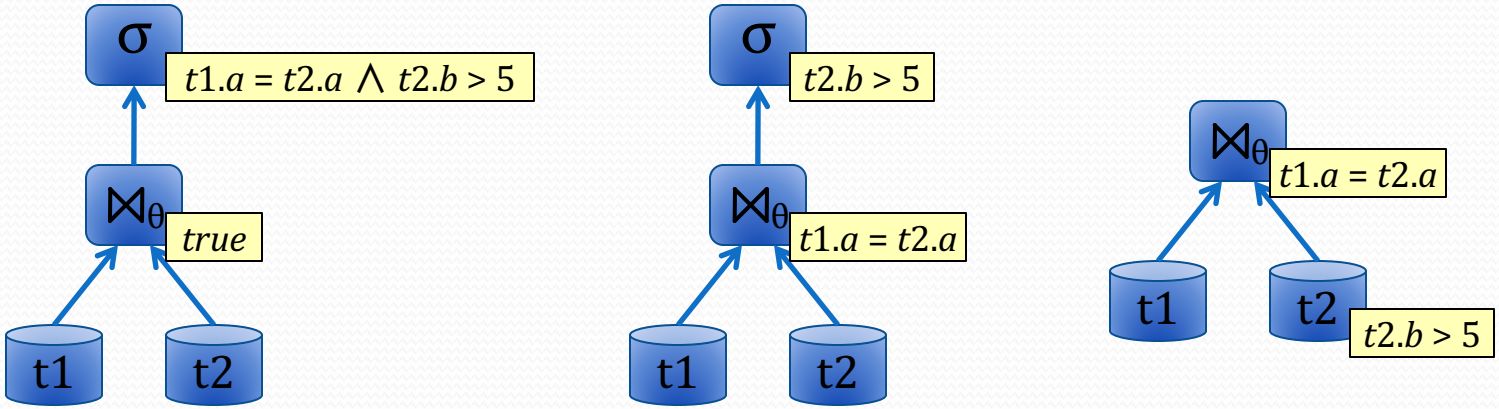
Relational Database System Implementation

CS122 – Lecture 8

Winter Term, 2017-2018

Alternative Plans

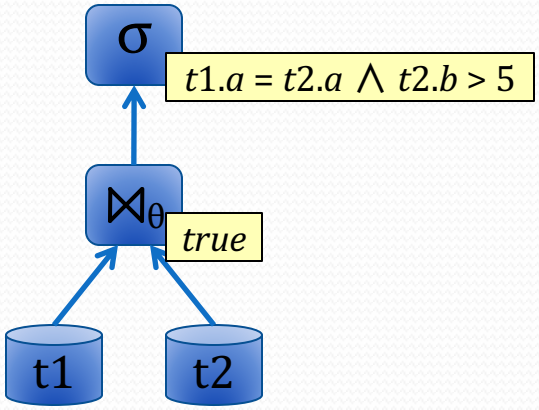
- Earlier, saw three plans for a query:
  - SELECT * FROM t1, t2 WHERE t1.a = t2.a AND t2.b > 5;

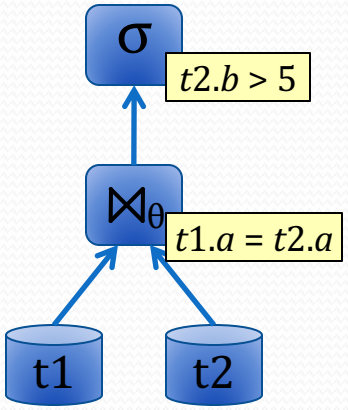


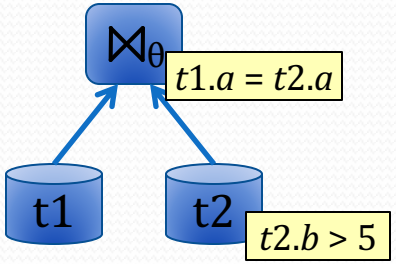
- Two questions:
  - How do we know which plan is best?
  - How do we know the plans are actually equivalent?

Plan Costing

- Can devise ways of measuring costs of different plans
- Basic measurements:
  - Number of rows generated by each plan-node
  - Number of disk-accesses performed by each plan-node
- More advanced measures:
  - CPU/memory usage, avg size of each row in bytes, etc.

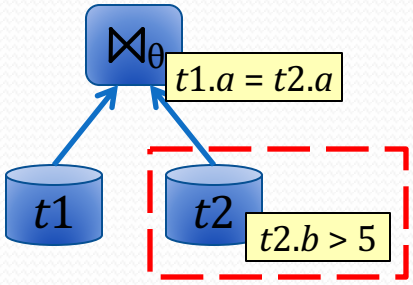






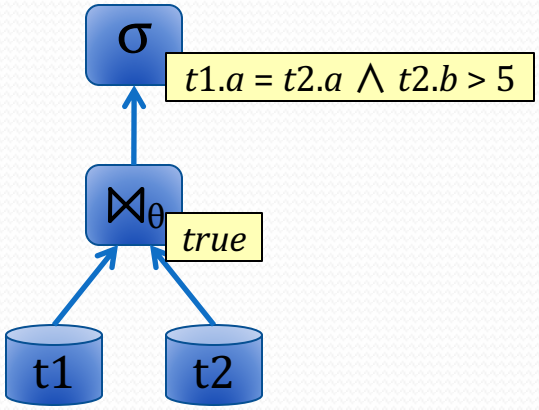
Plan Costing (2)

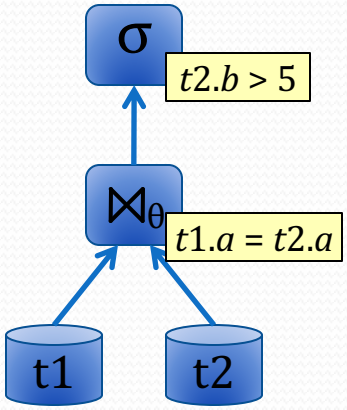
- Example: $\sigma_{b>5}(t2)$
  - Given: $t2$ is a heap file, with no indexes on b
- How many disk blocks are accessed?
  - Every disk block in $t2$
- How many rows will be produced?
  - *???*
- If we knew the minimum and maximum values for $t2.b$:
  - Assume: b is uniformly distributed
  - Guess: # rows in $t2 \times (b_{max} - 5) / (b_{max} - b_{min})$
- If we had a histogram for $t2.b$'s values, could make a *much* better guess!

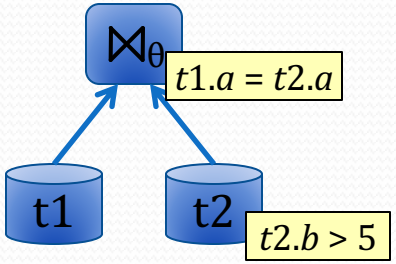


Plan Costing Goals (Ideal)

- Estimates should be as accurate as possible
- Estimates should be easy to compute
- Estimates are logically consistent
  - Estimated statistics for a query shouldn't vary in abnormal ways, based on how the query is computed
  - SELECT * FROM t1, t2 WHERE t1.a = t2.a AND t2.b > 5;
    - Ideally, estimates of how many tuples are produced by each plan will be roughly the same







Plan Costing Goals (Reality)

- Goals of plan costing:
  - Estimates should be as accurate as possible
  - Estimates should be easy to compute
  - Estimates are logically consistent
- Unfortunately, very hard to achieve in practice

- All we *really* require:
  - **Faster plans end up with lower cost than slower ones**

Plan Costing and Statistics

- To make effective cost estimates, the database must keep statistics on values that appear in each table
- Generally, statistics are very expensive to compute…
  - Databases generally don't keep these stats up to date
  - Some update stats when # of rows in a table changes substantially; others require manual updating of stats
- The statistics don't need to be perfect!
  - Just need to be good enough to guide optimization phase
- But, if stats are very different from actual table data, generated plans are likely to be horrible.

Table Statistics

- Some useful statistics to keep per table:
  - n_r – the number of tuples in table r
  - b_r – the number of blocks containing tuples in r
    - For heap files, will be very close to total # of blocks in file
    - For sequential and hashing files, may be very different
  - l_r – the average size of a tuple in r, in bytes
  - f_r – the blocking factor of table r
    - The average number of tuples in r that fit in one block
    - Generally, $b_r \approx \text{ceiling}(n_r / f_r)$

Table Statistics (2)

- More useful statistics:
  - V(A, r) – the number of distinct values of attribute A that appear in table r
  - min(A, r) – the minimum value of attribute A in table r
  - max(A, r) – the maximum value of attribute A in table r

- Provide an operation to compute/update these stats for a given table
  - Expose it as a command, and/or update automatically
  - e.g. **`ANALYZE TABLE t;`**

Select Costs

- $\sigma_\theta(r)$
- Estimate number of rows produced $n_\sigma = n_r \times P(\theta)$
  - $P(\theta)$ is the *selectivity* of the predicate
  - i.e. the likelihood that a tuple will satisfy the predicate
- Simply need to estimate the selectivity of the predicate, then we can estimate the number of rows produced
- For now, assume that *r* is a heap file
  - Select operation will [almost] always read all blocks in *r*
  - *(Other file organizations and indexes change this…)*

Selectivity of Simple Predicates

- $\sigma_{A \le v}(r)$
  - Without a histogram, use minimum/maximum values for A to estimate selectivity
- If $v < \min(A, r)$:
  - $P(A \le v) = 0$
- If $v > \max(A, r)$:
  - $P(A \le v) = 1$
- If $\min(A, r) \le v \le \max(A, r)$:
  - $P(A \le v) = (v - \min(A, r)) / (\max(A, r) - \min(A, r))$
- $\sigma_{A \ge v}(r)$ is similar

Selectivity of Simple Predicates (2)

- $\sigma_{A=v}(r)$
  - Assume uniform distribution of different values of A
  - Estimate $P(A=v)$ to be $1 / V(A, r)$
  - Estimate $n_\sigma = n_r / V(A, r)$
- What if A is a primary key for r ?
  - In that case, $V(A, r)$ will be n_r
  - $P(A=v)$ will be $1 / n_r$, and n_σ will be 1

Selectivity of Simple Predicates (3)

- $\sigma_{A=v}(r)$

- If A is a primary key for r, can also improve file-scan performance:
  - Each value of A can only appear once…
  - Stop scanning r when we find the specified row
  - Average-case block-reads = b_r / 2; worst-case = b_r

Selectivity of Simple Predicates (4)

- For inverse of these predicates: $\sigma_{A>v}(r)$, $\sigma_{A\neq v}(r)$
  - Simply compute selectivity as 1 – P($A \leq v$) or 1 – P($A = v$)
- Boolean negation can be handled in similar way:
  - $\sigma_{\neg\theta}(r)$
  - Simple: $P(\neg\theta) = 1 - P(\theta)$

Complex Selects

- If a predicate includes multiple conditions, estimate selectivities of the components, then combine
- Conjunctive selections: $\sigma_{\theta 1 \wedge \theta 2 \wedge \ldots}(r)$
  - Assumption: conditions are independent of each other
  - $P(\theta 1 \wedge \theta 2 \wedge \ldots) = P(\theta 1) \times P(\theta 2) \times P(\ldots)$
- Disjunctive selections: $\sigma_{\theta 1 \vee \theta 2 \vee \ldots}(r)$
  - Again, compute selectivities of components
  - $P(\theta 1 \vee \theta 2 \vee \ldots)$ = probability that a tuple satisfies at least one condition = 1 – probability it satisfies *none* of them
  - $P(\theta 1 \vee \theta 2 \vee \ldots) = 1 - (1 - P(\theta 1)) \times (1 - P(\theta 2)) \times \ldots$

Estimating Selectivity

- One major assumption here:
  - Conditions involve simple comparisons between an attribute and a constant
- Frequently not true!
  - SELECT * FROM employees WHERE salary * 1.05 > 100000;
  - DELETE FROM employees
    WHERE compute_popularity(emp_id) < 20;
- In simpler cases, can analyze expression to make estimate
- For more difficult situations, use default selectivities, e.g.
  - 1/2 when it's expected to be "common" for tuples to satisfy the condition
  - 1/3 or 1/4 when it's expected to be "uncommon" or "rare"

Selection Against Subplans

- Previous examples were all against a relation r
  - *We had statistics for r!*
- Plans often contain selections against subplans
- Need to estimate the statistics of a plan-node's result as well, if higher-level cost estimates will be useful
- Most difficult are $V(A, r)$, $\min(A, r)$, and $\max(A, r)$
- If selection involves an equality: $\sigma_{A=v}(r)$
  - $V(A, \sigma_{A=v}) = 1$
  - $\min(A, \sigma_{A=v}) = \max(A, \sigma_{A=v}) = v$

Selection Against Subplans (2)

- If selection involves a comparison: $\sigma_{A \le v}(r)$
  - Assume $\min(A, r) \le v \le \max(A, r)$
  - $\min(A, \sigma_{A \le v}) = \min(A, r)$
  - $\max(A, \sigma_{A \le v}) = v$
  - Estimate $V(A, \sigma_{A \le v})$
    $= V(A, r) \times (v - \min(A, r)) / (\max(A, r) - \min(A, r))$
    $= V(A, r) \times P(A \le v)$

- In general, if θ is A *op* v:
  - *op* is some inequality comparison: $< > \le \ge \ne$
  - Estimate $V(A, \sigma_\theta) = V(A, r) \times P(\theta)$

Selection Against Subplans (3)

- If predicate θ forces A to take on a set of values:
  - SELECT * FROM schedule WHERE hour = 3 OR hour = 4;
  - SELECT * FROM shapes
    WHERE color IN ('red', 'orange', 'yellow');
  - $V(A, \sigma_\theta)$ = number of values in the predicate
  - Can compute $\min(A, \sigma_\theta)$, $\max(A, \sigma_\theta)$ from these as well
- If none of these situations occur:
  - Assume $V(A, \sigma_\theta)$, $\min(A, \sigma_\theta)$, $\max(A, \sigma_\theta)$ are independent of selection criteria!
  - Set $V(A, \sigma_\theta)$ to $\min(V(A, r), n_\sigma)$
    - # of distinct values for A is capped by # of rows produced by σ

Join Costs

- Several important costs to estimate for joins
  - Number of rows produced by the join operation
  - Number of disk IOs performed by the join operation
- Second value is harder to estimate, primarily due to the buffer manager, but still critical to estimate
- Example: nested loop join (no optimizations)
  - Worst case (unlikely): $b_r + n_r \times b_s$ block reads
  - Best case (inner table fits in memory): $b_r + b_s$ reads
- Disk IO estimate is very approximate, and depends on the specific join implementation being used

Join Costs (2)

- For now, focus on the number of rows produced
- Cartesian product: $r \times s$
  - Every row in table r is joined to every row in table s
  - $n_{r \times s} = n_r \times n_s$
  - Average tuple length $l_{r \times s} = l_r + l_s$
- Theta join: $r \bowtie_\theta s$
  - Can model as $\sigma_\theta(r \times s)$; compute estimates as for $\sigma_\theta(\ldots)$
  - Big problem: our cost estimates are most accurate when comparing attributes to constants!
  - Join predicates usually compare attributes to attributes

Join Costs (3)

- To compute proper join estimates, need to look at the attributes being compared
- For theta-join $r \bowtie_{r.A=s.A} s$:
  - If $r.A$ is a key for r:
    - Each tuple in s will join with at most one tuple in r
    - Estimate number of tuples in result $n_{r \bowtie s} = n_s$
  - Similarly, if $s.A$ is a key for s:
    - Each tuple in r will join with at most one tuple in s
    - Estimate $n_{r \bowtie s} = n_r$
  - If both are keys for their respective tables:
    - $n_{r \bowtie s} = \min(n_r, n_s)$

Join Costs (4)

- For theta-join $r \bowtie_{r.A=s.A} s$:
  - If neither $r.A$ nor $s.A$ is a key for its respective table:
    - Assume that A is uniformly distributed in both r and s
    - *(Note: ignoring min/max stats for these estimates)*
  - Given a specific tuple t_r in r, estimate that n_s / V(A, s) tuples in s will join with that tuple
    - n_s × probability that a given tuple t_s in s will have value $t_r.A$
    - Suggests that $n_{r \bowtie s} = n_r \times n_s$ / V(A, s)
  - But, given a specific tuple t_s in s, estimate n_r / V(A, r) tuples in r will join with that tuple
    - Suggests that $n_{r \bowtie s} = n_s \times n_r$ / V(A, r)

Join Costs (5)

- For theta-join $r \bowtie_{r.A=s.A} s$:
  - Two estimates for number of rows produced:
    - $n_{r \bowtie s} = n_r \times n_s / \mathrm{V}(A, s)$ *(from perspective of tuples in r)*
    - $n_{r \bowtie s} = n_s \times n_r / \mathrm{V}(A, r)$ *(from perspective of tuples in s)*
  - If $\mathrm{V}(A, r) < \mathrm{V}(A, s)$:
    - Expect that more tuples in s will not join with any tuple in r
    - Use estimate based on r: $n_{r \bowtie s} = n_r \times n_s / \mathrm{V}(A, s)$
    - Similarly, if $\mathrm{V}(A, r) > \mathrm{V}(A, s)$, more tuples in r will be left out
  - If $\mathrm{V}(A, r) \neq \mathrm{V}(A, s)$, choose the larger of $\mathrm{V}(A, r)$, $\mathrm{V}(A, s)$
  - Estimate $n_{r \bowtie s} = n_r \times n_s / \max(\mathrm{V}(A, r), \mathrm{V}(A, s))$

Join Costs (6)

- Can extend these estimates to joins with multiple conjuncts
- For theta-join $r \bowtie_{r.A=s.A \wedge r.B=s.B} s$:
  - Check if $(r.A, r.B)$ or any proper subset is a key for r
  - Check if $(s.A, s.B)$ or any proper subset is a key for s
  - If so, compute estimates as before
- If attributes are *not* keys for r or s:
  - Again, assume the conditions are independent of each other
  - $P(r.A=s.A \wedge r.B=s.B) = P(r.A=s.A) \times P(r.B=s.B)$
    $= 1 / (\max(V(A, r), V(A, s)) \times \max(V(B, r), V(B, s)))$
  - $n_{r \bowtie s} = n_r \times n_s / (\max(V(A, r), V(A, s)) \times \max(V(B, r), V(B, s)))$

Outer Join Costs

- Can use very simple estimates for outer joins
  - Again, only using number of distinct values; not using min/max to further refine statistics
- Left outer join: $n_{r \mathbin{⟕} s} = n_{r \bowtie s} + n_r$
- Right outer join: $n_{r \mathbin{⟖} s} = n_{r \bowtie s} + n_s$
- Full outer join: $n_{r \mathbin{⟗} s} = n_{r \bowtie s} + n_r + n_s$
- These estimates are almost certainly much higher than actual row-counts will be, but they are an upper bound
  - …and they are fast to compute.
  - Could devise a better estimate, but really want to move to better stats (e.g. storing histograms) to make it worthwhile

Other Plan Nodes

- Project: $\Pi_{\ldots}(r)$
- $\Pi_A(r)$, where A is a simple column-reference
  - $n_\Pi = n_r$ (no duplicate-elimination in SQL!)
  - $V(A, \Pi_A) = V(A, r)$
  - Similarly, min/max don't change
- $\Pi_E(r)$, where E is an expression possibly with functions
  - Again, $n_\Pi = n_r$
  - For $V(E, \Pi_E)$/$\min(E, \Pi_E)$/$\max(E, \Pi_E)$, no idea! Either need to guess, or we need more knowledge about E.
    - E.g. just guess $V(E, \Pi_E) = n_\Pi$

Other Plan Nodes (2)

- Grouping/aggregation: $_{G1,G2,\ldots}\mathcal{G}_{E1,E2,\ldots}(r)$
  - Gi can be either column-references or expressions
  - Ei can be simple aggregate function calls, or more advanced expressions involving aggregate functions
    - SELECT SUM(CASE WHEN a < b THEN 1 ELSE 0 END) FROM t;
    - SELECT MIN(a) + MAX(b) FROM t;
- For simple column-references in grouping attributes:
  - $n_{\mathcal{G}} = V(G1, r) \times V(G2, r) \times \ldots$
  - $V(G1, \mathcal{G}) = V(G1, r)$, etc.

Other Plan Nodes (3)

- Grouping/aggregation: $_{G1,G2,\ldots}\mathcal{G}_{E1,E2,\ldots}(r)$
- For simple column-references and simple aggregates:
  - Guess COUNT(A), SUM(A), AVG(A) will produce different values for each group. e.g. $V(\text{COUNT}(A), \mathcal{G}) = n_{\mathcal{G}}$
- Can be a bit more clever with MIN(A) and MAX(A)
  - Could guess $V(\text{MIN}(A), \mathcal{G}) = n_{\mathcal{G}}$ as before
  - Note that MIN(A)/MAX(A) will always select an *existing* value of A from input relation
  - A better guess: $V(\text{MIN}(A), \mathcal{G}) = \min(V(A, r), n_{\mathcal{G}})$

Summary – Plan Costing

- Plan costing is a very imprecise process
  - Almost certainly inaccurate, except in *very* simple cases
  - Hopefully estimates are "good enough" to guide plan selection
  - *(Most databases provide ways to give the optimizer hints about plan optimization.)*
- These estimates are simply one way of estimating costs
  - Different assumptions, or different kinds of statistics, will produce different costing estimates
- Still, an essential part of query planning!
  - Collecting useful table stats, then making reasonably accurate estimates from them, greatly improves DB query performance
  - *(Becomes very obvious when table stats are inaccurate…)*