Query Optimization

CompSci 316

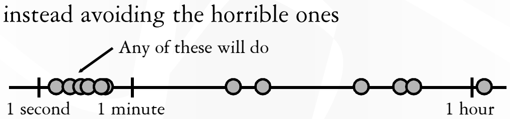
Introduction to Database Systems

Announcements (Thu. Nov. 21)

- Homework #4 due in a week
- Project
  - Milestone #2 feedback will be emailed by this weekend
  - Demo period: Dec. 9-11; you will be contacted by email regarding the sign-up process
  - Public demo slots: Dec. 5; email me if you are interested
- Final exam 9am-12pm Wednesday Dec. 11
  - Open book, open notes
  - Focus on the second half of the course
  - Sample final available soon

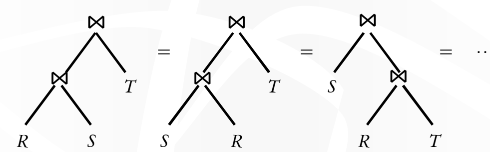
Query optimization

- One logical plan → "best" physical plan
- Questions
  - How to enumerate possible plans
  - How to estimate costs
  - How to pick the "best" one
- Often the goal is not getting the optimum plan, but instead avoiding the horrible ones



Plan enumeration in relational algebra

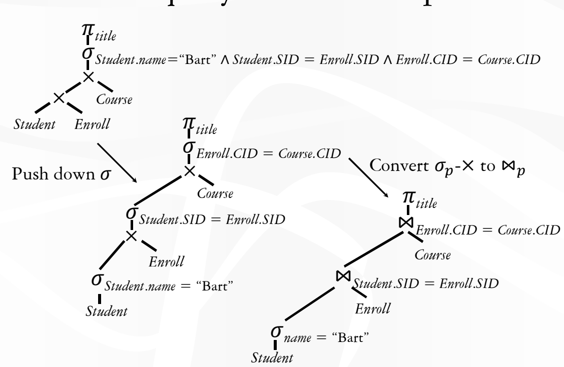
- Apply relational algebra equivalences
- Join reordering: × and ⋈ are associative and commutative (except column ordering, but that is unimportant)



More relational algebra equivalences

- Convert σ_p-× to/from $\bowtie_p$: $\sigma_p(R \times S) = R \bowtie_p S$
- Merge/split σ's: $\sigma_{p_1}(\sigma_{p_2} R) = \sigma_{p_1 \wedge p_2} R$
- Merge/split π's: $\pi_{L_1}(\pi_{L_2} R) = \pi_{L_1} R$, where $L_1 \subseteq L_2$
- Push down/pull up σ: $\sigma_{p \wedge p_r \wedge p_s}(R \bowtie_{p'} S) = (\sigma_{p_r} R) \bowtie_{p \wedge p'} (\sigma_{p_s} S)$, where
  - p_r is a predicate involving only R columns
  - p_s is a predicate involving only S columns
  - p and p' are predicates involving both R and S columns
- Push down π: $\pi_L(\sigma_p R) = \pi_L\left(\sigma_p(\pi_{LL'} R)\right)$, where
  - L' is the set of columns referenced by p that are not in L
- Many more (seemingly trivial) equivalences…
  - Can be systematically used to transform a plan to new ones

Relational query rewrite example



Heuristics-based query optimization

- Start with a logical plan
- Push selections/projections down as much as possible
  - Why? Reduce the size of intermediate results
  - Why not? May be expensive; maybe joins filter better
- Join smaller relations first, and avoid cross product
  - Why? Reduce the size of intermediate results
  - Why not? Size depends on join selectivity too
- Convert the transformed logical plan to a physical plan (by choosing appropriate physical operators)

SQL query rewrite

- More complicated—subqueries and views divide a query into nested "blocks"
  - Processing each block separately forces particular join methods and join order
  - Even if the plan is optimal for each block, it may not be optimal for the entire query
- Unnest query: convert subqueries/views to joins
- ☞ We can just deal with select-project-join queries
  - Where the clean rules of relational algebra apply

SQL query rewrite example

```
SELECT name
FROM Student
WHERE SID = ANY (SELECT SID FROM Enroll);
```

```
SELECT name
FROM Student, Enroll
WHERE Student.SID = Enroll.SID;
```

- Wrong—consider two Bart's, each taking two classes

```
SELECT name
FROM (SELECT DISTINCT Student.SID, name
      FROM Student, Enroll
      WHERE Student.SID = Enroll.SID);
```

- Right—assuming `Student.SID` is a key

Dealing with correlated subqueries

```
SELECT CID FROM Course
WHERE title LIKE 'CPS%'
AND min_enroll > (SELECT COUNT(*) FROM Enroll
                  WHERE Enroll.CID = Course.CID);
```

```
SELECT CID
FROM Course, (SELECT CID, COUNT(*) AS cnt
              FROM Enroll GROUP BY CID) t
WHERE t.CID = Course.CID AND min_enroll > t.cnt
AND title LIKE 'CPS%';
```

- New subquery is inefficient (computes enrollment for *all* courses)
- Suppose a CPS class is empty?

"Magic" decorrelation

```
SELECT CID FROM Course
WHERE title LIKE 'CPS%'
AND min_enroll > (SELECT COUNT(*) FROM Enroll
                  WHERE Enroll.CID = Course.CID);
```

```
CREATE VIEW Supp_Course AS
SELECT * FROM Course WHERE title LIKE 'CPS%';
```

Process the outer query without the subquery

```
CREATE VIEW Magic AS
SELECT DISTINCT CID FROM Supp_Course;
```

Collect bindings

```
CREATE VIEW DS AS
(SELECT Enroll.CID, COUNT(*) AS cnt
 FROM Magic, Enroll WHERE Magic.CID = Enroll.CID
 GROUP BY Enroll.CID) UNION
(SELECT Magic.CID, 0 AS cnt FROM Magic
 WHERE Magic.CID NOT IN (SELECT CID FROM Enroll));
```

Evaluate the subquery with bindings

```
SELECT Supp_Course.CID FROM Supp_Course, DS
WHERE Supp_Course.CID = DS.CID
AND min_enroll > DS.cnt;
```

Finally, refine the outer query

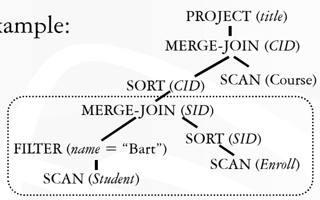
Heuristics- vs. cost-based optimization

- Heuristics-based optimization
  - Apply heuristics to rewrite plans into cheaper ones
- Cost-based optimization
  - Rewrite logical plan to combine "blocks" as much as possible
  - Optimize query block by block
    - Enumerate logical plans (already covered)
    - Estimate the cost of plans
    - Pick a plan with acceptable cost
  - Focus: select-project-join blocks

Cost estimation

Physical plan example:

Input to SORT(CID):



- We have: cost estimation for each operator
  - Example: SORT(CID) takes $O(B(\text{input}) \times \log_M B(\text{input}))$
    - But what is $B(\text{input})$?
- We need: size of intermediate results

Selections with equality predicates

- Q: $\sigma_{A=v} R$
- Suppose the following information is available
  - Size of R: $|R|$
  - Number of distinct A values in R: $|\pi_A R|$
- Assumptions
  - Values of A are uniformly distributed in R
  - Values of v in Q are uniformly distributed over all $R.A$ values
- $|Q| \approx {}^{|R|}/_{|\pi_A R|}$
  - Selectivity factor of $(A = v)$ is ${}^{1}/_{|\pi_A R|}$

Conjunctive predicates

- Q: $\sigma_{A=u \wedge B=v} R$
- Additional assumptions
  - $(A = u)$ and $(B = v)$ are independent
    - Counterexample: major and advisor
  - No "over"-selection
    - Counterexample: A is the key
- $|Q| \approx {}^{|R|}/_{|\pi_A R| \cdot |\pi_B R|}$
  - Reduce total size by all selectivity factors

Negated and disjunctive predicates

- Q: $\sigma_{A \neq v} R$
  - $|Q| \approx |R| \cdot \left(1 - {}^{1}/_{|\pi_A R|}\right)$
    - Selectivity factor of $\neg p$ is $(1 -$ selectivity factor of $p)$
- Q: $\sigma_{A=u \vee B=v} R$
  - $|Q| \approx |R| \cdot \left({}^{1}/_{|\pi_A R|} + {}^{1}/_{|\pi_B R|}\right)$?
    - No! Tuples satisfying $(A = u)$ and $(B = v)$ are counted twice
  - $|Q| \approx |R| \cdot \left(1 - \left(1 - {}^{1}/_{|\pi_A R|}\right) \cdot \left(1 - {}^{1}/_{|\pi_B R|}\right)\right)$
    - Intuition: $(A = u)$ or $(B = v)$ is equivalent to $\neg(\neg(A = u) \wedge \neg(B = v))$
    - Or use inclusion-exclusion principle

Range predicates

- Q: $\sigma_{A>v} R$
- Not enough information!
  - Just pick, say, $|Q| \approx |R| \cdot {}^{1}/_{3}$
- With more information
  - Largest $R.A$ value: $\text{high}(R.A)$
  - Smallest $R.A$ value: $\text{low}(R.A)$
  - $|Q| \approx |R| \cdot \frac{\text{high}(R.A) - v}{\text{high}(R.A) - \text{low}(R.A)}$
  - In practice: sometimes the second highest and lowest are used instead
    - The highest and the lowest are often used by inexperienced database designer to represent invalid values!

Two-way equi-join

- Q: $R(A, B) \bowtie S(A, C)$
- Assumption: containment of value sets
  - Every tuple in the "smaller" relation (one with fewer distinct values for the join attribute) joins with some tuple in the other relation
  - That is, if $|\pi_A R| \leq |\pi_A S|$ then $\pi_A R \subseteq \pi_A S$
  - Certainly not true in general
  - But holds in the common case of foreign key joins
- $|Q| \approx \frac{|R| \cdot |S|}{\max(|\pi_A R|, |\pi_A S|)}$
  - Selectivity factor of $R.A = S.A$ is ${}^{1}/_{\max(|\pi_A R|, |\pi_A S|)}$

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Multiway equi-join

- Q: $R(A,B) \bowtie S(B,C) \bowtie T(C,D)$
- What is the number of distinct C values in the join of R and S?
- Assumption: preservation of value sets
  - A non-join attribute does not lose values from its set of possible values
  - That is, if A is in R but not S, then $\pi_A(R \bowtie S) = \pi_A R$
  - Certainly not true in general
  - But holds in the common case of foreign key joins (for value sets from the referencing table)

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Multiway equi-join (cont'd)

- Q: $R(A,B) \bowtie S(B,C) \bowtie T(C,D)$
- Start with the product of relation sizes
  - $|R| \cdot |S| \cdot |T|$
- Reduce the total size by the selectivity factor of each join predicate
  - $R.B = S.B$: $1/_{\max(|\pi_B R|, |\pi_B S|)}$
  - $S.C = T.C$: $1/_{\max(|\pi_C S|, |\pi_C T|)}$
  - $|Q| \approx \frac{|R| \cdot |S| \cdot |T|}{\max(|\pi_B R|, |\pi_B S|) \cdot \max(|\pi_C S|, |\pi_C T|)}$

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Cost estimation: summary

- Using similar ideas, we can estimate the size of projection, duplicate elimination, union, difference, aggregation (with grouping)
- Lots of assumptions and very rough estimation
  - Accurate estimate is not needed
  - Maybe okay if we overestimate or underestimate consistently
  - May lead to very nasty optimizer "hints"

```
SELECT * FROM Student WHERE GPA > 3.9;
SELECT * FROM Student WHERE GPA > 3.9 AND GPA > 3.9;
```

- Not covered: better estimation using histograms

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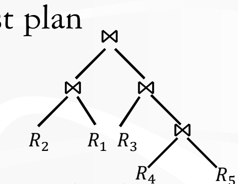
Search for the best plan

- Huge search space
- "Bushy" plan example:



- Just considering different join orders, there are $\frac{(2n-2)!}{(n-1)!}$ bushy plans for $R_1 \bowtie \cdots \bowtie R_n$
  - 30240 for $n = 6$
- And there are more if we consider:
  - Multiway joins
  - Different join methods
  - Placement of selection and projection operators

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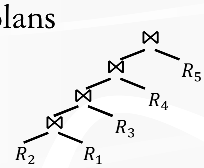
Left-deep plans



- Heuristic: consider only "left-deep" plans, in which only the left child can be a join
  - Tend to be better than plans of other shapes, because many join algorithms scan inner (right) relation multiple times—you will not want it to be a complex subtree
- How many left-deep plans are there for $R_1 \bowtie \cdots \bowtie R_n$?
  - Significantly fewer, but still lots— $n!$ (720 for $n = 6$)

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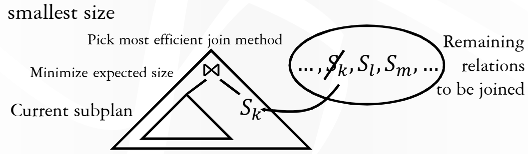
A greedy algorithm

- $S_1, \ldots, S_n$
  - Say selections have been pushed down; i.e., $S_i = \sigma_p(R_i)$
- Start with the pair S_i, S_j with the smallest estimated size for $S_i \bowtie S_j$
- Repeat until no relation is left:
  Pick S_k from the remaining relations such that the join of S_k and the current result yields an intermediate result of the smallest size



A dynamic programming approach

- Generate optimal plans bottom-up
  - Pass 1: Find the best single-table plans (for each table)
  - Pass 2: Find the best two-table plans (for each pair of tables) by combining best single-table plans
  - …
  - Pass k: Find the best k-table plans (for each combination of k tables) by combining two smaller best plans found in previous passes
  - …
- Rationale: Any subplan of an optimal plan must also be optimal (otherwise, just replace the subplan to get a better overall plan)
- ☞ Well, not quite…

The need for "interesting order"

- Example: $R(A,B) \bowtie S(A,C) \bowtie T(A,D)$
- Best plan for $R \bowtie S$: hash join (beats sort-merge join)
- Best overall plan: sort-merge join R and S, and then sort-merge join with T
  - Subplan of the optimal plan is not optimal!
- Why?
  - The result of the sort-merge join of R and S is sorted on A
  - This is an interesting order that can be exploited by later processing (e.g., join, dup elimination, `GROUP BY`, `ORDER BY`, etc.)!

Dealing with interesting orders

- When picking the best plan
  - Comparing their costs is not enough
    - Plans are not totally ordered by cost anymore
  - Comparing interesting orders is also needed
    - Plans are now partially ordered
    - Plan X is better than plan Y if
      - Cost of X is lower than Y, and
      - Interesting orders produced by X "subsume" those produced by Y
- Need to keep a set of optimal plans for joining every combination of k tables
  - At most one for each interesting order

Summary

- Relational algebra equivalence
- SQL rewrite tricks
- Heuristics-based optimization
- Cost-based optimization
  - Need statistics to estimate sizes of intermediate results
  - Greedy approach
  - Dynamic programming approach