Query Optimization
Part III

CPS 216
Advanced Database Systems

Announcements (April 21)

- Homework #4 due next Thursday
- Classes on both Tuesday and Thursday next week
- Project demo period: April 28 – May 1
  - Remember to email me to sign up for a 30-minute slot
- Final exam on Monday, May 2, 2-5pm
  - 3 hours—no time pressure!
  - Open book, open notes
  - Comprehensive, but with emphasis on the second half of the course and materials exercised in homework

Review of the bigger picture

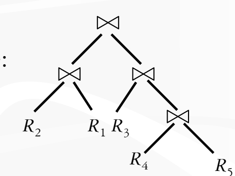
Query optimization

- Consider a space of possible plans
- Estimate costs of plans in the search space
- Search through the space for the "best" plan (today)

☞ Focus on select-project-join query blocks
  - Join ordering is the most important subproblem

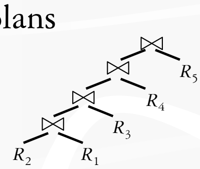
Search space

- "Bushy" plan example:



- Search space is huge: 30240 bushy plans for a six-table join
- More if we consider:
  - Multiway joins
  - Different join methods
  - Placement of selection and projection operators

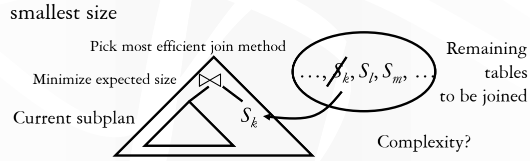
Left-deep plans



- 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) input 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 $n = 6$)

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 table is left:
  Pick S_k from the remaining tables such that the join of S_k and the current result yields an intermediate result of the smallest size



Query optimization in System R

- A.k.a. Selinger-style query optimization
  - The classic paper on query optimization (Selinger et al., *SIGMOD* 1979)
- Basic ideas
  - Left-deep trees only
  - Bottom-up generation of plans using dynamic programming
  - "Interesting orders"

Bottom-up plan generation

- Observation 1: Once we have joined k tables together, the method of joining this result further with another table is independent of the previous join methods
- Observation 2: Any subplan of an optimal plan must also be optimal (otherwise we could replace the subplan to get a better overall plan)
- ☞ Not exactly accurate (next slide)
- Bottom-up generation of optimal left-deep plans
  - Compute the optimal plans for joining k tables together
    - Suboptimal plans are pruned
  - From these plans, derive optimal plans for joining $k+1$ tables

The need for "interesting order"

- Example: $R(A, B) \bowtie S(A, C) \bowtie T(A, D)$
- Best plan for $R \bowtie S$: nested-loop join (beats sort-merge)
- 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, duplicate 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
      - 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

System-R algorithm

- Pass 1: Find the best single-table plans
- Pass 2: Find the best two-table plans by considering each single-table plan (from Pass 1) as the outer input and every other table as the inner input

  …
- Pass k: Find the best k-table plans by considering each (k–1)-table plan (from Pass k–1) as the outer input and every other table as the inner input

  …
- Heuristics
  - Push selections and projections down
  - Process cross products at the end

Reasoning about predicates

- `SELECT * FROM` R, S, T
  `WHERE` $R.A = S.A$ `AND` $S.A = T.A$;
- Looks like a cross product between R and T
  - No join condition
- But there is really a join between R and T
  - $R.A = T.A$ is implied from the other two predicates
- A good optimizer should be able to detect this case and consider the possibility of joining R with T first

System-R algorithm example

- ❖
```
SELECT SID, CID
FROM Student, Enroll, Course
WHERE Student.age < 10
AND Student.SID = Enroll.SID
AND Enroll.CID = Course.CID
AND Course.title LIKE '%data%';
```

- ❖ Primary keys/indexes
  - `Student(SID)`, `Enroll(CID, SID)`, `Course(CID)`
- ❖ Ordered, secondary indexes
  - `Student(age)`, `Course(title)`

Example: pass 1


```
SELECT SID, CID
FROM Student, Enroll, Course
WHERE Student.age < 10
AND Student.SID = Enroll.SID
AND Enroll.CID = Course.CID
AND Course.title LIKE '%data%';
```


- ❖ Plans for {*Student*}
  - ☻ S1: Table scan, then filter (*age* < 10); cost 100; result ordered by *SID* ← interesting order
  - ☻ S2: Index scan using condition (*age* < 10); cost 5; result ordered by *age* ← not an interesting order
- ❖ Plans for {*Enroll*}
  - ☻ E1: Table scan; cost 1000; result ordered by *CID*, *SID* ← interesting order
- ❖ Plans for {*Course*}
  - ☻ C1: Table scan, then filter (*title* `LIKE '%data%'`); cost 40; result ordered by *CID* ← interesting order
  - C2: Index scan with filter (*title* `LIKE '%data%'`); cost 60; result ordered by *title* ← not an interesting order

Example: pass 2


```
SELECT SID, CID
FROM Student, Enroll, Course
WHERE Student.age < 10
AND Student.SID = Enroll.SID
AND Enroll.CID = Course.CID
AND Course.title LIKE '%data%';
```


- ❖ Plans for {*Student*, *Enroll*}
  - Extending best plans for {*Student*}
    - From S1 (table scan, then filter (*age* < 10))
      - Block-based nested loop join with *Enroll*; cost 1100
      - Sort *Enroll* by *SID*, and merge join; cost 3100; ordered by *SID* ← no longer an interesting order
      - … …
    - From S2 (index scan using condition (*age* < 10))
      - ☻ Block-based nested loop join with *Enroll*; cost 1005
      - … …
  - Extending best plans for {*Enroll*} … …

Example: pass 2 continued


```
SELECT SID, CID
FROM Student, Enroll, Course
WHERE Student.age < 10
AND Student.SID = Enroll.SID
AND Enroll.CID = Course.CID
AND Course.title LIKE '%data%';
```


- ❖ Plans for {*Student*, *Course*}
  - Ignore; it is a cross product
- ❖ Plans for {*Enroll*, *Course*}
  - Extending best plans for {*Course*}
    - From C1 (table scan, then filter (title `LIKE '%data%'`))
      - ☻ Merge join; cost 1040
      - … …
  - Extending best plans for {*Enroll*} … …

Example: pass 3


```
SELECT SID, CID
FROM Student, Enroll, Course
WHERE Student.age < 10
AND Student.SID = Enroll.SID
AND Enroll.CID = Course.CID
AND Course.title LIKE '%data%';
```


- ❖ Finally, plans for {*Student*, *Enroll*, *Course*}
  - Extending best plans for {*Student*, *Enroll*}
    - ☻ (INDEX-SCAN(*Student*) NLJ *Enroll*) NLJ FILTER(*Course*); cost …
    - … …
  - Extending best plans for {*Student*, *Course*}
    - None!
  - Extending best plans for {*Enroll*, *Course*}
    - (FILTER(*Course*) SMJ *Enroll*) NLJ (INDEX-SCAN(*Student*)); cost …
    - … …

Considering bushy plans

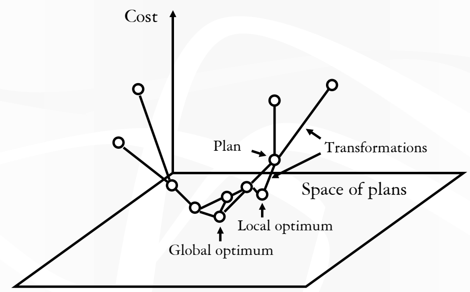
Straightforward generalization:

- ❖ Store all optimal 1-table, 2-table, …, and k-table plans
- ❖ To find the optimal plan for $k+1$ tables
  - For every possible partition of these tables into two groups, find the best ways of joining the optimal plans for the two groups
  - Store the overall optimal plans

Optimizer "blow-up"

- A 20-way join will easily choke an optimizer using the System-R algorithm
- Solutions
  - Heuristics-based query optimization
  - Randomized query optimization (Ioannidis & Kang, *SIGMOD* 1990)
  - Genetic programming (PostgreSQL)

Search space revisited



Transformations

Relational algebra equivalences
(or query rewrite rules in general):

- Join method choice: $R \bowtie_{\text{method1}} S \rightarrow R \bowtie_{\text{method2}} S$
- Join commutativity: $R \bowtie S \rightarrow S \bowtie R$
- Join associativity: $(R \bowtie S) \bowtie T \rightarrow R \bowtie (S \bowtie T)$
- Left join exchange: $(R \bowtie S) \bowtie T \rightarrow R \bowtie (T \bowtie S)$
- Right join exchange: $R \bowtie (S \bowtie T) \rightarrow S \bowtie (R \bowtie T)$
- ☞ Why the last two redundant rules?
  - "Shortcuts" to avoid using the join commutativity rule, which does not change the cost of certain joins (example?)—creating plateaus in the plan space

Iterative improvement

- Repeat until some stopping condition (e.g., time runs out):
  - Start with a random plan
  - Repeatedly go downhill (i.e., pick a neighbor with a lower cost randomly) to get to a local optimum
- Return the smallest local optimum found

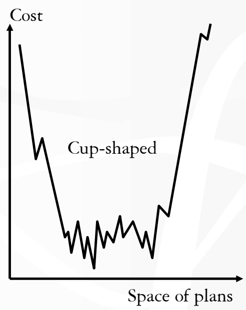
Simulated annealing

- Start with a plan and an initial temperature
- Repeat until temperature is 0:
  - Repeat until some equilibrium (e.g., a fixed number of iterations):
    - Move to a random neighbor of the plan (an uphill move is allowed with probability $e^{-\Delta\text{cost}/\text{temperature}}$)
      - Larger → smaller probability
      - Lower temperature → smaller probability
  - Reduce temperature
- Return the plan visited with the lowest cost

Two-phase optimization

- Phase I: run iterative improvement for a while to find a good local optimum
- Phase II: run simulated annealing with a low initial temperature to get more improvements
- Why does this heuristic tend to work better than both iterative improvement and simulated annealing?

Shape of the cost function



- An average local optimum has a much lower cost than an average plan
- The average distance between a random state and a local optimum is long
- There are lots of local optima
- Many local optima are connected together through low-cost plans within short distances

Comparison of randomized algorithms

- Iterative improvement
  - Too easily trapped in a local optimum
  - Too much work to restart
- Simulated annealing
  - Too much time spent on high-cost plans
- Two-phase
  - Phase I uses iterative improvement to get to the cup bottom quickly
  - Phase II uses simulated annealing to explore the cup bottom further