Query Optimization

Introduction to Databases

CompSci 316 Fall 2019

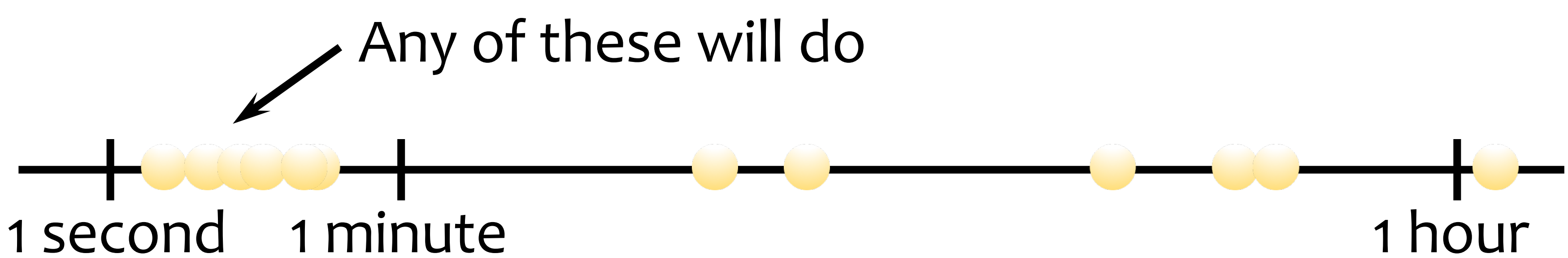
DUKE COMPUTER SCIENCE

Announcements (Mon., Nov. 18)

- Homework 4 due in one week
  - Except Problem X2, which will be due in two weeks
- Homework 3 grades released
  - See Sakai for sample solution
- Project milestone 2 feedback released
  - Weekly piazza update due this Wed.

Query optimization

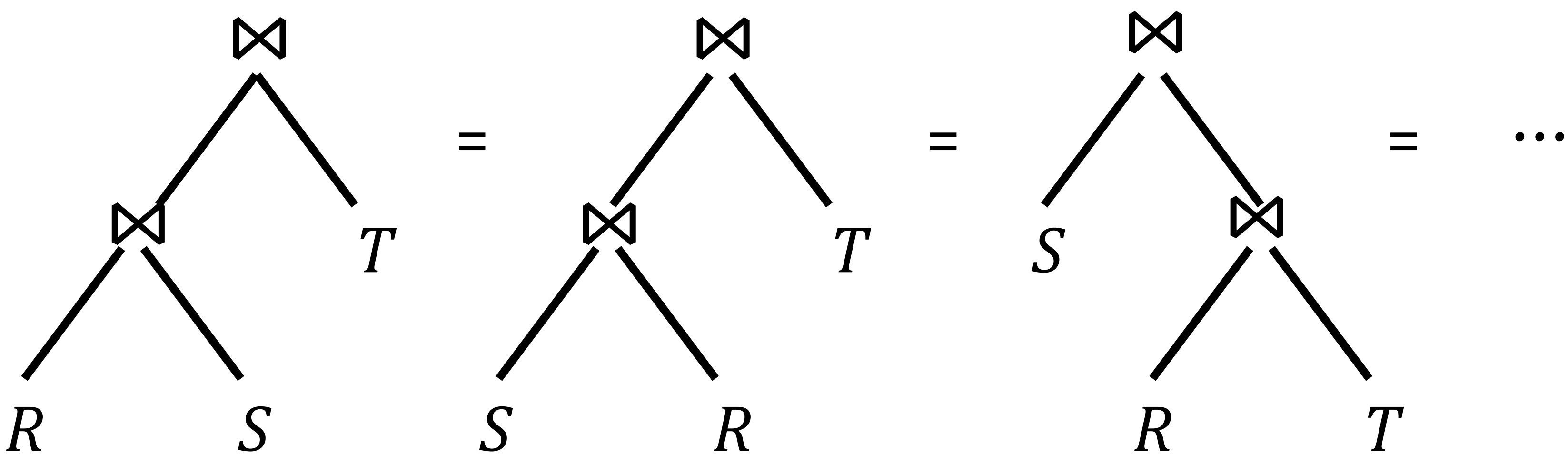
- One logical plan → "best" physical plan
- Questions
  - How to enumerate possible plans
  - How to estimate costs
  - How to pick the "best" one
- Often the goal is not getting the optimum plan, but instead avoiding the horrible ones



Plan enumeration in relational algebra

- Apply relational algebra equivalences

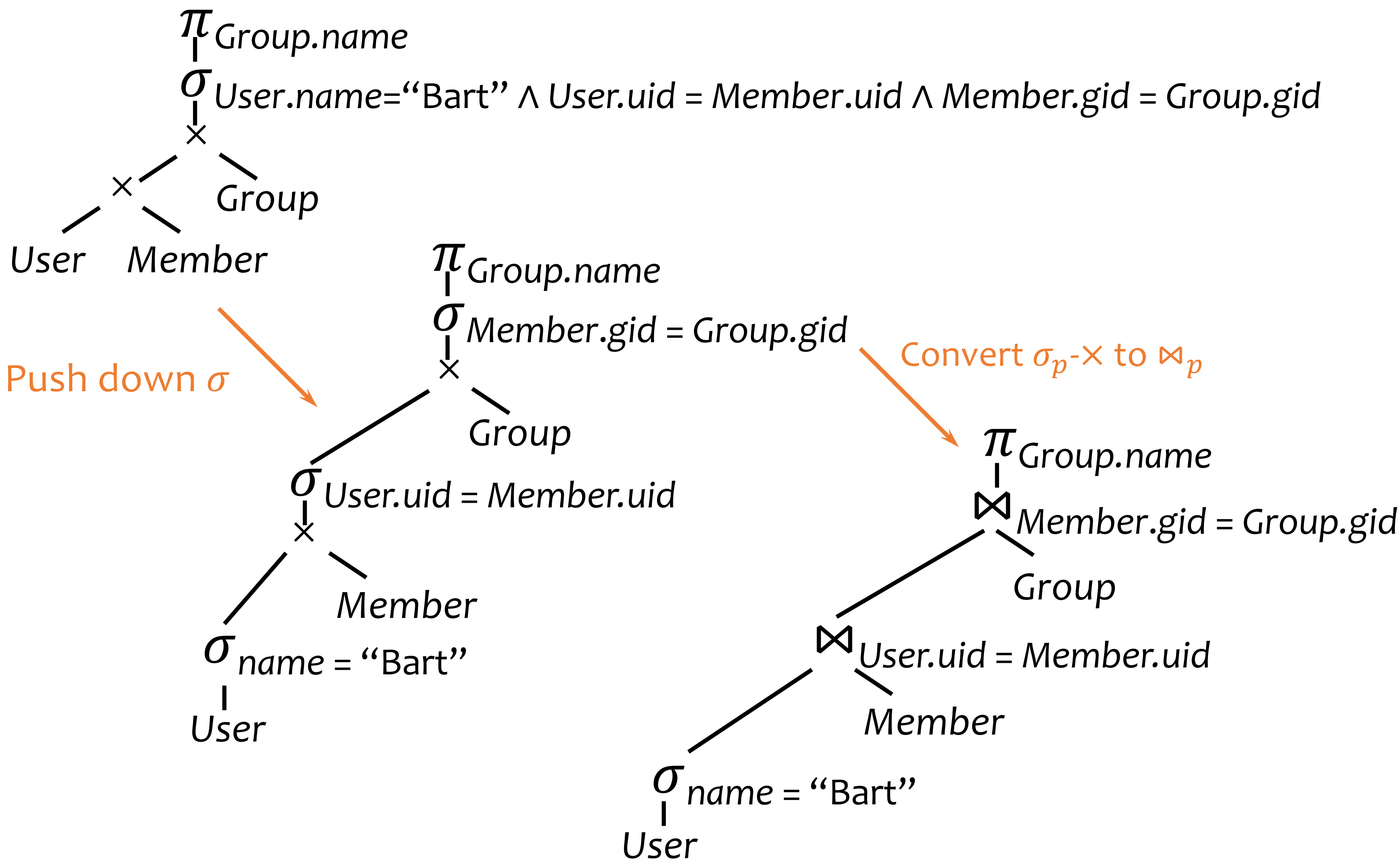
☞ Join reordering: $\times$ and $\bowtie$ are associative and commutative (except column ordering, but that is unimportant)



More relational algebra equivalences

- Convert σ_p-$\times$ to/from $\bowtie_p$: $\sigma_p(R \times S) = R \bowtie_p S$
- Merge/split σ's: $\sigma_{p_1}\left(\sigma_{p_2} R\right) = \sigma_{p_1 \wedge p_2} R$
- Merge/split π's: $\pi_{L_1}\left(\pi_{L_2} R\right) = \pi_{L_1} R$, where $L_1 \subseteq L_2$
- Push down/pull up σ:
  $\sigma_{p \wedge p_r \wedge p_s}\left(R \bowtie_{p'} S\right) = \left(\sigma_{p_r} R\right) \bowtie_{p \wedge p'} \left(\sigma_{p_s} S\right)$, 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: $\pi_L\left(\sigma_p R\right) = \pi_L\left(\sigma_p\left(\pi_{L L'} R\right)\right)$, 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 User
  WHERE uid = ANY (SELECT uid FROM Member);
  ```
- ```
  SELECT name
  FROM User, Member
  WHERE User.uid = Member.uid;
  ```
  - Wrong—consider two Bart's, each joining two groups
- ```
  SELECT name
  FROM (SELECT DISTINCT User.uid, name
        FROM User, Member
        WHERE User.uid = Member.uid);
  ```
  - Right—assuming `User.uid` is a key
  ```

Dealing with correlated subqueries

- ```
  SELECT gid FROM Group
  WHERE name LIKE 'Springfield%'
  AND min_size > (SELECT COUNT(*) FROM Member
                  WHERE Member.gid = Group.gid);
  ```
- ```
  SELECT gid
  FROM Group, (SELECT gid, COUNT(*) AS cnt
               FROM Member GROUP BY gid) t
  WHERE t.gid = Group.gid AND min_size > t.cnt
  AND name LIKE 'Springfield%';
  ```
  - New subquery is inefficient (it computes the size for *every* group)
  - Suppose a group is empty?

"Magic" decorrelation

- ```
  SELECT gid FROM Group
  WHERE name LIKE 'Springfield%'
  AND min_size > (SELECT COUNT(*) FROM Member
                  WHERE Member.gid = Group.gid);
  ```
- ```
  WITH Supp_Group AS
  (SELECT * FROM Group WHERE name LIKE 'Springfield%'),
  ```
  Process the outer query without the subquery
  ```
  Magic AS
  (SELECT DISTINCT gid FROM Supp_Group),
  ```
  Collect bindings
  ```
  DS AS
  ((SELECT Group.gid, COUNT(*) AS cnt
    FROM Magic, Member WHERE Magic.gid = Member.gid
    GROUP BY Member.gid) UNION
   (SELECT gid, 0 AS cnt
    FROM Magic WHERE gid NOT IN (SELECT gid FROM Member)))
  ```
  Evaluate the subquery with bindings
  ```
  SELECT Supp_Group.gid FROM Supp_Group, DS
  WHERE Supp_Group.gid = DS.gid
  AND min_size > DS.cnt;
  ```
  Finally, refine the outer query

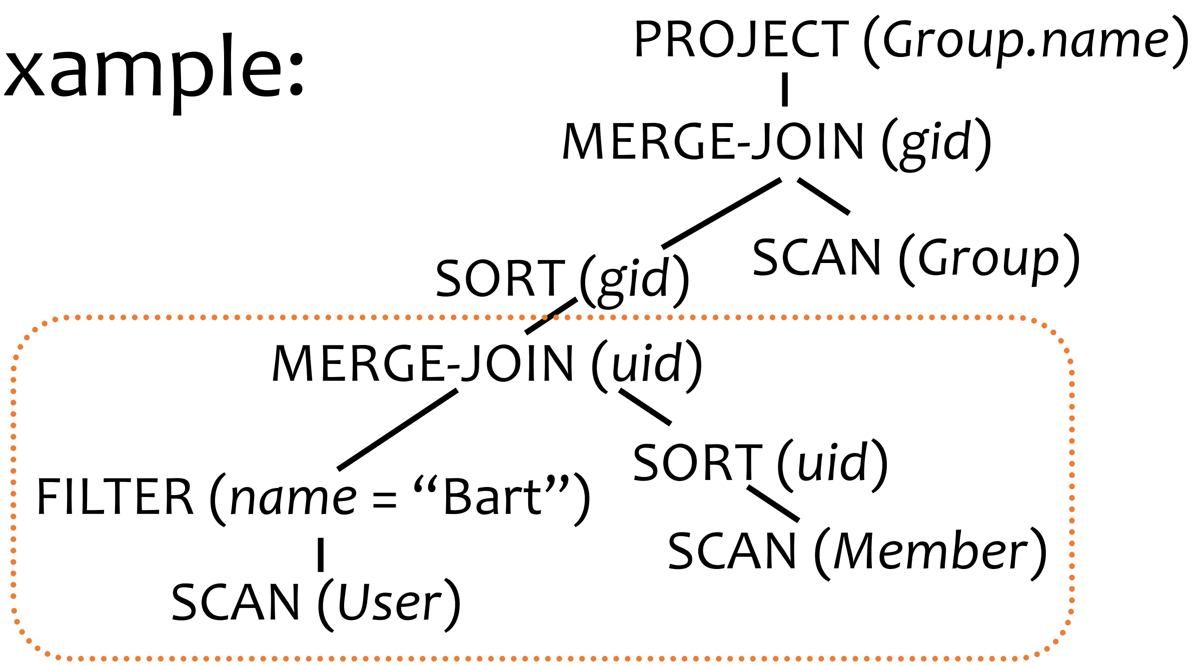
Heuristics- vs. cost-based optimization

- 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(*gid*):



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

Cardinality estimation

http://www.learningresources.com/product/estimation+station.do

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
  - $|Q| \approx |R| \cdot \left({}^{1}/_{|\pi_A R|} + {}^{1}/_{|\pi_B R|} - {}^{1}/_{|\pi_A R||\pi_B R|}\right)$
    - 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 ${}^{1}/_{\max(|\pi_A R|,|\pi_A S|)}$

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)

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
  - $R.B = S.B$: ${}^{1}/_{\max(|\pi_B R|,|\pi_B S|)}$
  - $S.C = T.C$: ${}^{1}/_{\max(|\pi_C S|,|\pi_C T|)}$
  - $|Q| \approx \frac{|R|\cdot|S|\cdot|T|}{\max(|\pi_B R|,|\pi_B S|)\cdot\max(|\pi_C S|,|\pi_C T|)}$

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 User WHERE pop > 0.9;
SELECT * FROM User WHERE pop > 0.9 AND pop > 0.9;
```

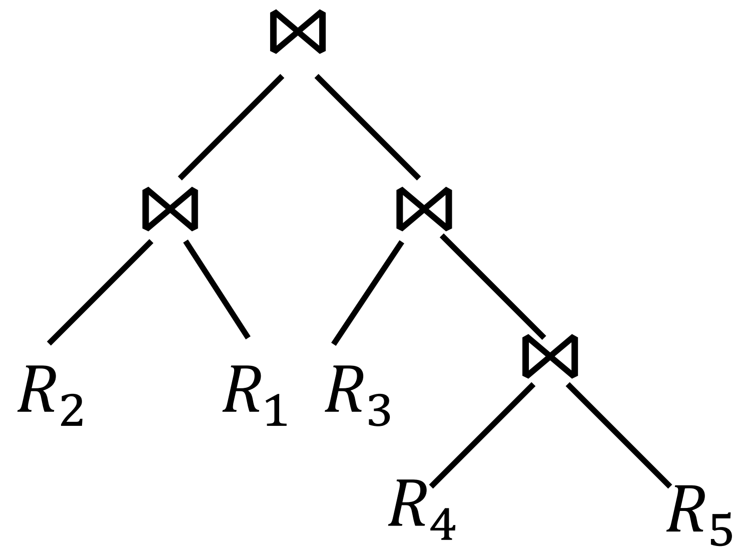
- Not covered: better estimation using histograms

Search strategy

http://1.bp.blogspot.com/-Motdu8reRKs/TgyAi4ki5QI/AAAAAAAAAKE/mi8ejfZ8S7U/s1600/cornMaze.jpg

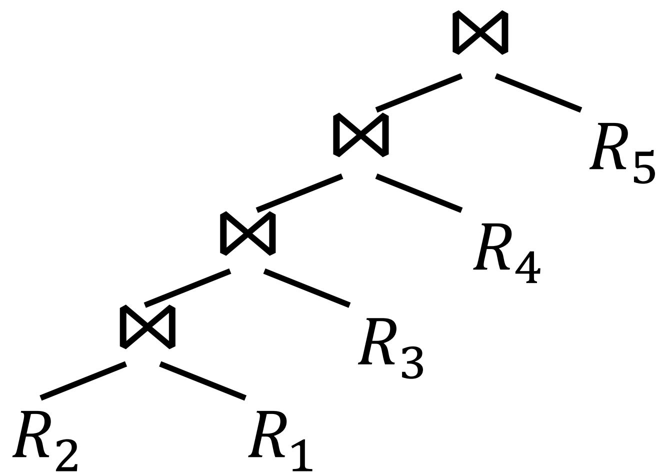
Search space

- Huge!
- "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

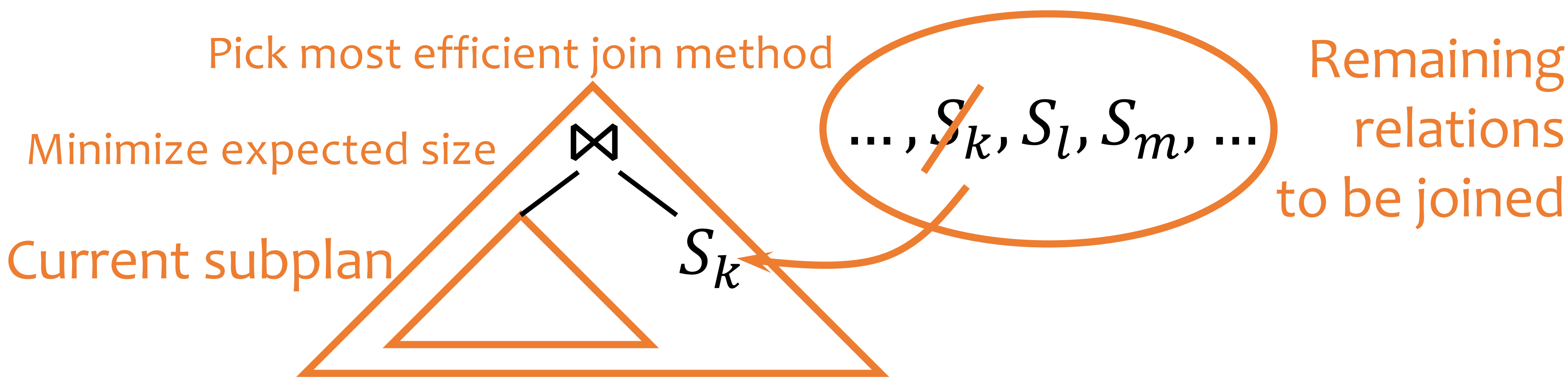
Left-deep plans



- 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 $n = 6$)

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