Lecture #7

Query Optimization

May 16th, 2002

Agenda/Administration

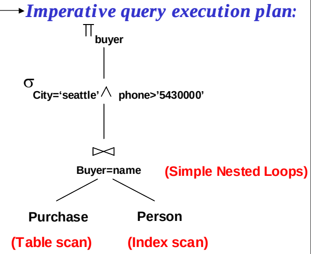
- Last homework handed out by the weekend.
- Projects status?
- Trip Report
- Query optimization

Query Optimization

Goal:

Declarative SQL query → ***Imperative query execution plan:***

```
SELECT S.buyer
FROM Purchase P, Person Q
WHERE P.buyer=Q.name AND
      Q.city='seattle' AND
      Q.phone > '5430000'
```



Inputs:
- the query
- statistics about the data (indexes, cardinalities, selectivity factors)
- available memory

Ideally: Want to find best plan. Practically: Avoid worst plans!

How are we going to build one?

- What kind of optimizations can we do?
- What are the issues?
- How would we architect a query optimizer?

Discussion

How Would You Do It?

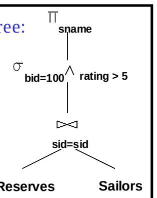
Schema for Some Examples

Sailors (<u>*sid*: integer</u>, *sname*: string, *rating*: integer, *age*: real)
Reserves (<u>*sid*: integer, *bid*: integer, *day*: dates</u>, *rname*: string)

- Reserves:
  - Each tuple is 40 bytes long, 100 tuples per page, 1000 pages (4000 tuples)
- Sailors:
  - Each tuple is 50 bytes long, 80 tuples per page, 500 pages (4000 tuples).

Motivating Example

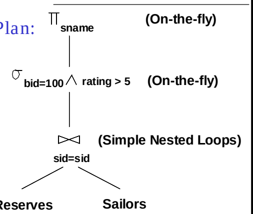
RA Tree:



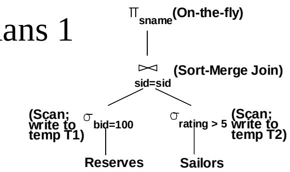

```
SELECT S.sname
FROM  Reserves R, Sailors S
WHERE  R.sid=S.sid AND
   R.bid=100 AND S.rating>5
```

- Cost: 500+500*1000 I/Os
- By no means the worst plan!
- Misses several opportunities: selections could have been `pushed' earlier, no use is made of any available indexes, etc.
- *Goal of optimization:* To find more efficient plans that compute the same answer.

Plan:



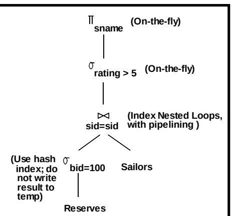
Alternative Plans 1



- ***Main difference:*** *push selects.*
- With 5 buffers, cost of plan:
  - Scan Reserves (1000) + write temp T1

  (10 pages, if we have 100 boats, uniform distribution).
  - Scan Sailors (500) + write temp T2 (250 pages, if we have 10 ratings).
  - Sort T1 (2*2*10), sort T2 (2*3*250), merge (10+250), total=1800
  - Total: 3560 page I/Os.
- If we used BNL join, join cost = 10+4*250, total cost = 2770.
- If we `push' projections, T1 has only *sid*, T2 only *sid* and *sname*:
  - T1 fits in 3 pages, cost of BNL drops to under 250 pages, total < 2000.

Alternative Plans 2 With Indexes



- With clustered index on *bid* of Reserves, we get 100,000/100 = 1000 tuples on 1000/100 = 10 pages.
- INL with ***pipelining*** (outer is not materialized).
  - Join column *sid* is a key for Sailors.
    - At most one matching tuple, unclustered index on *sid* OK.
  - Decision not to push *rating>5* before the join is based on availability of *sid* index on Sailors.
  - Cost: Selection of Reserves tuples (10 I/Os); for each, must get matching Sailors tuple (1000*1.2); total 1210 I/Os.

Building Blocks

- Algebraic transformations (many and wacky).
- Statistical model: estimating costs and sizes.
- Finding the best join trees:
  - Bottom-up (dynamic programming): System-R
- *Newer* architectures:
  - Starburst: rewrite and then tree find
  - Volcano: all at once, top-down.

Query Optimization Process (simplified a bit)

- Parse the SQL query into a logical tree:
  - identify distinct blocks (corresponding to nested sub-queries or views).
- Query rewrite phase:
  - apply algebraic transformations to yield a cheaper plan.
  - Merge blocks and move predicates between blocks.
- Optimize each block: join ordering.
- Complete the optimization: select scheduling (pipelining strategy).

Key Lessons in Optimization

- There are many approaches and many details to consider in query optimization
  - Classic search/optimization problem!
  - Not completely solved yet!
- Main points to take away are:
  - Algebraic rules and their use in transformations of queries.
  - Deciding on join ordering: System-R style (Selinger style) optimization.
  - Estimating cost of plans and sizes of intermediate results.

Operations (revisited)

- Scan ([index], table, predicate):
  - Either index scan or table scan.
  - Try to push down **sargable** predicates.
- Selection (filter)
- Projection (always need to go to the data?)
- Joins: nested loop (indexed), sort-merge, hash, outer join.
- Grouping and aggregation (usually the last).

Algebraic Laws

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

Algebraic Laws

- 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
  - $\sigma_C(R - S) = \sigma_C(R) - S$
  - $\sigma_C(R \cup S) = \sigma_C(R) \cup \sigma_C(S)$
  - $\sigma_C(R \cap S) = \sigma_C(R) \cap S$

Algebraic Laws

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

Algebraic Laws

- 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)
  - $\Pi_{A,B,G}(R \bowtie_{D=E} S) = \Pi_?(\Pi_?(R) \bowtie_{D=E} \Pi_?(S))$

Query Rewrites: Sub-queries

```
SELECT Emp.Name
FROM Emp
WHERE Emp.Age < 30
        AND   Emp.Dept# IN
          (SELECT Dept.Dept#
           FROM Dept
           WHERE  Dept.Loc = "Seattle"
            AND      Emp.Emp#=Dept.Mgr)
```

The Un-Nested Query

```
SELECT Emp.Name
FROM Emp, Dept
WHERE    Emp.Age < 30
     AND  Emp.Dept#=Dept.Dept#
     AND  Dept.Loc = "Seattle"
     AND  Emp.Emp#=Dept.Mgr
```

Converting Nested Queries

```
Select distinct x.name, x.maker
From product x
Where x.color= "blue"
  AND x.price >= ALL (Select y.price
                      From  product y
                      Where x.maker = y.maker
                        AND y.color="blue")
```

How do we convert this one to logical plan ?

Converting Nested Queries

Let's compute the complement first:

```
Select distinct x.name, x.maker
From product x
Where x.color= "blue"
  AND x.price < SOME (Select y.price
                      From  product y
                      Where x.maker = y.maker
                        AND y.color="blue")
```

Converting Nested Queries

This one becomes a SFW query:

```
Select distinct x.name, x.maker
From product x, product y
Where x.color= "blue" AND x.maker = y.maker
  AND y.color="blue"  AND x.price < y.price
```

This returns exactly the products we DON'T want, so…

Converting Nested Queries

```
(Select x.name, x.maker
 From product x
 Where x.color = "blue")

EXCEPT

(Select x.name, x.maker
 From product x, product y
 Where x.color= "blue" AND x.maker = y.maker
  AND y.color="blue"  AND x.price < y.price)
```

Semi-Joins, Magic Sets

- You can't always un-nest sub-queries (it's tricky).
- But you can often use a semi-join to reduce the computation cost of the inner query.
- A magic set is a superset of the possible bindings in the result of the sub-query.
- Also called "sideways information passing".
- ***Great idea; reinvented every few years on a regular basis.***

Rewrites: Magic Sets

Create View DepAvgSal AS
(Select E.did, Avg(E.sal) as avgsal
From Emp E
Group By E.did)

Select E.eid, E.sal
From Emp E, Dept D, DepAvgSal V
Where E.did=D.did AND D.did=V.did
And E.age < 30 and D.budget > 100k
And E.sal > V.avgsal

Rewrites: SIPs

Select E.eid, E.sal
From Emp E, Dept D, DepAvgSal V
Where E.did=D.did AND D.did=V.did
And E.age < 30 and D.budget > 100k
And E.sal > V.avgsal

- DepAvgsal needs to be evaluated only for departments where V.did IN

Select E.did
From Emp E, Dept D
Where E.did=D.did
And E.age < 30 and D.budget > 100K

Supporting Views

1. Create View PartialResult as
(Select E.eid, E.sal, E.did
From Emp E, Dept D
Where E.did=D.did
And E.age < 30 and D.budget > 100K)
2. Create View Filter AS
Select DISTINCT P.did FROM PartialResult P.
2. Create View LimitedAvgSal as
(Select F.did Avg(E.Sal) as avgSal
From Emp E, Filter F
Where E.did=F.did
Group By F.did)

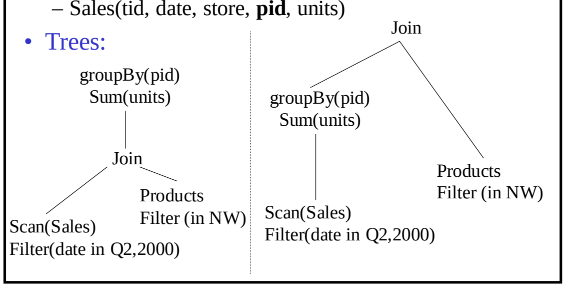
And Finally…

Transformed query:

Select P.eid, P.sal
From PartialResult P, LimitedAvgSal V
Where P.did=V.did
And P.sal > V.avgsal

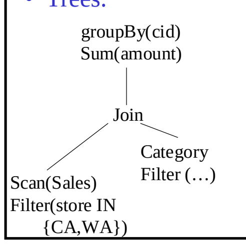
Rewrites: Group By and Join

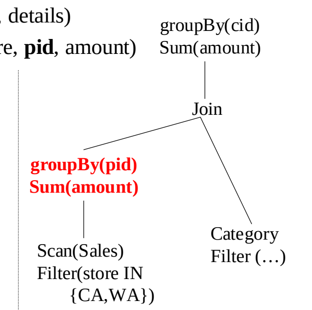
- Schema:
  - Product (**pid**, unitprice,…)
  - Sales(tid, date, store, **pid**, units)
- Trees:



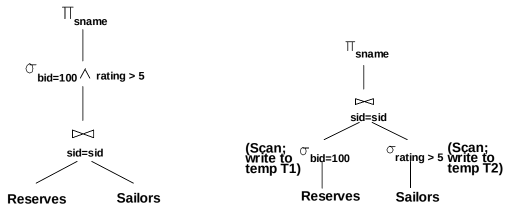
Rewrites:Operation Introduction

- Schema: (pid determines cid)
  - Category (**pid**, cid, details)
  - Sales(tid, date, store, **pid**, amount)
- Trees:





Query Rewriting: Predicate Pushdown



The earlier we process selections, less tuples we need to manipulate higher up in the tree.

Disadvantages?

Query Rewrites: Predicate Pushdown (through grouping)

```
Select   bid, Max(age)
From     Reserves R, Sailors S
Where    R.sid=S.sid
GroupBy  bid
Having Max(age) > 40
```

```
Select   bid, Max(age)
From     Reserves R, Sailors S
Where    R.sid=S.sid  and
         S.age > 40
GroupBy  bid
```

- *For each boat, find the maximal age of sailors who've reserved it.*
- Advantage: the size of the join will be smaller.
- Requires transformation rules specific to the grouping/aggregation operators.
- **Will it work work if we replace Max by Min?**

Query Rewrite: Predicate Movearound

Sailing wiz dates: when did the youngest of each sailor level rent boats?

```
Select   sid, date
From     V1, V2
Where    V1.rating = V2.rating  and
         V1.age = V2.age
```

```
Create View V1 AS
Select   rating, Min(age)
From     Sailors S
Where    S.age < 20
Group By  rating
```

```
Create View V2 AS
Select   sid, rating, age, date
From     Sailors S, Reserves R
Where    R.sid=S.sid
```

Query Rewrite: Predicate Movearound

Sailing wiz dates: when did the youngest of each sailor level rent boats?

First, move predicates up the tree.

```
Select   sid, date
From     V1, V2
Where    V1.rating = V2.rating  and
         V1.age = V2.age, age < 20
```

```
Create View V1 AS
Select   rating, Min(age)
From     Sailors S
Where    S.age < 20
Group By  rating
```

```
Create View V2 AS
Select   sid, rating, age, date
From     Sailors S, Reserves R
Where    R.sid=S.sid
```

Query Rewrite: Predicate Movearound

Sailing wiz dates: when did the youngest of each sailor level rent boats?

First, move predicates up the tree.

```
Select   sid, date
From     V1, V2
Where    V1.rating = V2.rating  and
         V1.age = V2.age, and age < 20
```

Then, move them down.

```
Create View V1 AS
Select   rating, Min(age)
From     Sailors S
Where    S.age < 20
Group By  rating
```

```
Create View V2 AS
Select   sid, rating, age, date
From     Sailors S, Reserves R
Where    R.sid=S.sid, and
         S.age < 20.
```

Query Rewrite Summary

- The optimizer can use any *semantically correct* rule to transform one query to another.
- Rules try to:
  - move constraints between blocks (because each will be optimized separately)
  - Unnest blocks
- Especially important in decision support applications where queries are very complex.
- In a few minutes of thought, you'll come up with your own rewrite. Some query, somewhere, will benefit from it.
- Theorems?

Cost Estimation

- For each plan considered, must estimate cost:
  - Must estimate *cost* of each operation in plan tree.
    - Depends on input cardinalities.
  - Must estimate *size of result* for each operation in tree!
    - Use information about the input relations.
    - For selections and joins, assume independence of predicates.
- We'll discuss the System R cost estimation approach.
  - Very inexact, but works ok in practice.
  - More sophisticated techniques known now.

Statistics and Catalogs

- Need information about the relations and indexes involved. ***Catalogs*** typically contain at least:
  - # tuples (NTuples) and # pages (NPages) for each relation.
  - # distinct key values (NKeys) and NPages for each index.
  - Index height, low/high key values (Low/High) for each tree index.
- Catalogs updated periodically.
  - Updating whenever data changes is too expensive; lots of approximation anyway, so slight inconsistency ok.
- More detailed information (e.g., histograms of the values in some field) are sometimes stored.

Cost Model for Our Analysis

* As a good approximation, we ignore CPU costs:
  - **B:** The number of data pages
  - **P:** Number of tuples per page
  - **D:** (Average) time to read or write disk page
  - Measuring number of page I/O's ignores gains of pre-fetching blocks of pages; thus, even I/O cost is only approximated.

Simple Nested Loops Join

For each tuple r in R do
    for each tuple s in S do
        if r_i == s_j then add <r, s> to result

- For each tuple in the *outer* relation R, we scan the entire *inner* relation S.
  - Cost: M + (P_R * M) * N.
- Page-oriented Nested Loops join: For each *page* of R, get each *page* of S, and write out matching pairs of tuples <r, s>, where r is in R-page and S is in S-page.
  - Cost: M + M*N.

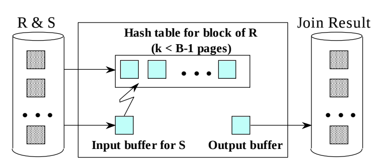
Index Nested Loops Join

foreach tuple r in R do
    foreach tuple s in S where r_i == s_j do
        add <r, s> to result

- If there is an index on the join column of one relation (say S), can make it the inner.
  - Cost: M + ((M*P_R) * cost of finding matching S tuples)
- For each R tuple, cost of probing S index is about 1.2 for hash index, 2-4 for B+ tree. Cost of then finding S tuples depends on clustering.
  - Clustered index: 1 I/O (typical), unclustered: up to 1 I/O per matching S tuple.

Block Nested Loops Join

- Use one page as an input buffer for scanning the inner S, one page as the output buffer, and use all remaining pages to hold "block'' of outer R.
  - For each matching tuple r in R-block, s in S-page, add <r, s> to result. Then read next R-block, scan S, etc.



Sort-Merge Join $(R \bowtie_{i=j} S)$

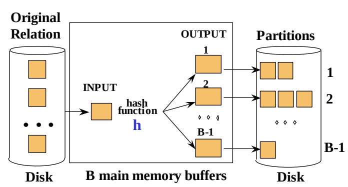
- Sort R and S on the join column, then scan them to do a ``merge'' on the join column.
  - Advance scan of R until current R-tuple >= current S tuple, then advance scan of S until current S-tuple >= current R tuple; do this until current R tuple = current S tuple.
  - At this point, all R tuples with same value and all S tuples with same value *match*; output <r, s> for all pairs of such tuples.
  - Then resume scanning R and S.

Cost of Sort-Merge Join

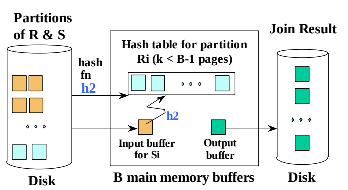
- R is scanned once; each S group is scanned once per matching R tuple.
- Cost: M log M + N log N + (M+N)
  - The cost of scanning, M+N, could be M*N (unlikely!)

Hash-Join

- Partition both relations using hash fn **h**: R tuples in partition i will only match S tuples in partition i.



- Read in a partition of R, hash it using **h2 (<> h!)**. Scan matching partition of S, search for matches.



Cost of Hash-Join

- In partitioning phase, read+write both relations; 2(M+N). In matching phase, read both relations; M+N I/Os.
- Sort-Merge Join vs. Hash Join:
  - Given a minimum amount of memory both have a cost of 3(M+N) I/Os. Hash Join superior on this count if relation sizes differ greatly. Also, Hash Join shown to be highly parallelizable.
  - Sort-Merge less sensitive to data skew; result is sorted.

Size Estimation and Reduction Factors

- Consider a query block:

```
SELECT attribute list
FROM relation list
WHERE term_1 AND ... AND term_k
```

- Maximum # tuples in result is the product of the cardinalities of relations in the FROM clause.
- *Reduction factor (RF)* associated with each *term* reflects the impact of the *term* in reducing result size. *Result cardinality* = Max # tuples * product of all RF's.
  - Implicit assumption that *terms* are independent!
  - Term *col=value* has RF *1/NKeys(I)*, given index I on *col*
  - Term *col1=col2* has RF *1/MAX(NKeys(I1), NKeys(I2))*
  - Term *col>value* has RF *(High(I)-value)/(High(I)-Low(I))*

Histograms

- Key to obtaining good cost and size estimates.
- Come in several flavors:
  - Equi-depth
  - Equi-width
- Which is better?
- Compressed histograms: special treatment of frequent values.

Histograms

- Statistics on data maintained by the RDBMS
- Makes size estimation much more accurate (hence, cost estimations are more accurate)

Histograms

Employee(ssn, name, salary, phone)

- Maintain a histogram on salary:

Salary:	0..20k	20k..40k	40k..60k	60k..80k	80k..100k	> 100k
Tuples	200	800	5000	12000	6500	500

- T(Employee) = 25000, but now we know the distribution

Histograms

Ranks(rankName, salary)

- Estimate the size of Employee $\bowtie_{Salary}$ Ranks

Employee	0..20k	20k..40k	40k..60k	60k..80k	80k..100k	> 100k
	200	800	5000	12000	6500	500

Ranks	0..20k	20k..40k	40k..60k	60k..80k	80k..100k	> 100k
	8	20	40	80	100	2

Histograms

- Assume:
  - V(Employee, Salary) = 200
  - V(Ranks, Salary) = 250
- Then T(Employee $\bowtie_{Salary}$ Ranks) =
  $= \Sigma_{i=1,6} T_i T_i' / 250$
  $= (200x8 + 800x20 + 5000x40 + 12000x80 + 6500x100 + 500x2)/250$
  = ….

Plans for Single-Relation Queries (Prep for Join ordering)

- **Task:** create a query execution plan for a single Select-project-group-by block.
- **Key idea**: consider each possible ***access path*** to the relevant tuples of the relation. Choose the cheapest one.
- The different operations are essentially carried out together (e.g., if an index is used for a selection, projection is done for each retrieved tuple, and the resulting tuples are *pipelined* into the aggregate computation).

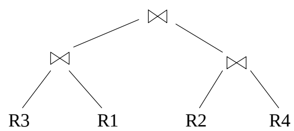
Example

```
SELECT S.sid
FROM Sailors S
WHERE S.rating=8
```

- If we have an Index on *rating*:
  - (1/NKeys(I)) * NTuples(R) = (1/10) * 40000 tuples retrieved.
  - Clustered index: (1/NKeys(I)) * (NPages(I)+NPages(R)) = (1/10) * (50+500) pages are retrieved (= 55).
  - Unclustered index: (1/NKeys(I)) * (NPages(I)+NTuples(R)) = (1/10) * (50+40000) pages are retrieved.
- If we have an index on *sid*:
  - Would have to retrieve all tuples/pages. With a clustered index, the cost is 50+500.
- Doing a file scan: we retrieve all file pages (500).

Determining Join Ordering

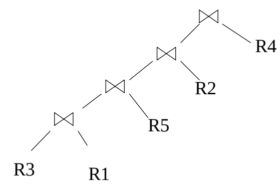
- R1 $\bowtie$ R2 $\bowtie$ …. $\bowtie$ Rn
- Join tree:



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

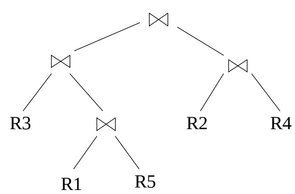
Types of Join Trees

- Left deep:



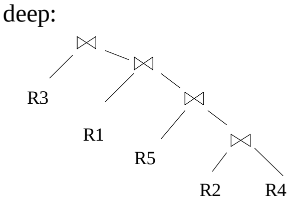
Types of Join Trees

- Bushy:



Types of Join Trees

- Right deep:



Problem

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

Dynamic Programming

- Idea: for each subset of {R1, …, Rn}, compute the best plan for that subset
- In increasing order of set cardinality:
  - Step 1: for {R1}, {R2}, …, {Rn}
  - Step 2: for {R1,R2}, {R1,R3}, …, {Rn-1, Rn}
  - …
  - Step n: for {R1, …, Rn}
- A subset of {R1, …, Rn} is also called a *subquery*

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)

Dynamic Programming

- **Step i**: For each Q ⊆ {R1, …, Rn} of cardinality i do:
  - Compute Size(Q) (later…)
  - 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

Dynamic Programming

- Return Plan({R1, …, Rn})

Dynamic Programming

- Summary: computes optimal plans for subqueries:
  - Step 1: {R1}, {R2}, …, {Rn}
  - Step 2: {R1, R2}, {R1, R3}, …, {Rn-1, Rn}
  - …
  - Step n: {R1, …, Rn}
- We used naïve size/cost estimations
- In practice:
  - more realistic size/cost estimations (next)
  - 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"

Completing the Physical Query Plan

- Choose algorithm to implement each operator
  - Need to account for more than cost:
    - How much memory do we have ?
    - Are the input operand(s) sorted ?
- Decide for each intermediate result:
  - To materialize
  - To pipeline