L9
Query Execution & Optimization

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Steps for a New Application

Requirements

what are you going to build?

Conceptual Database Design

pen-and-pencil description

Logical Design

formal database schema

Schema Refinement:

fix potential problems, normalization

Physical Database Design

optimize for speed/storage

Optimization

App/Security Design

prevent security problems

Recall

Relational algebra

equivalence: multiple stmts for same query

some statements (much) faster than others

Which is faster?

a. $\sigma_{v=1}(R \times T)$

b. $\sigma_{v=1}(\sigma_{v=1}(R) \times T)$

What if

$|R| = |T|$ 10 pages. 100? 1M?

\# unique values of R.v: 1? 100? 1M? ← selectivity!

Overview of Query Optimization

SQL → query plan

How plans are executed

Some implementations of operators

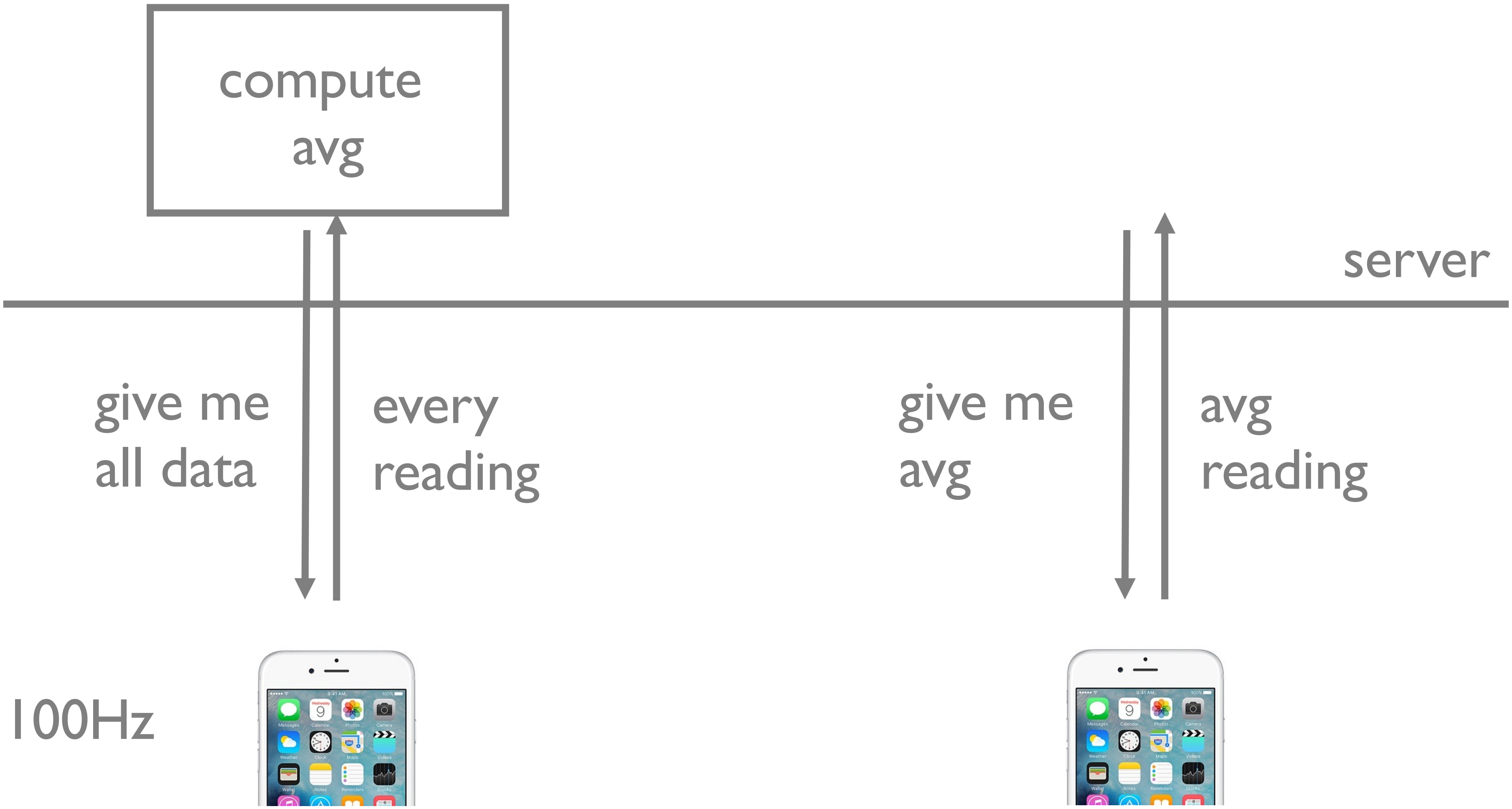
Cost + Selectivity estimation of a plan

System R dynamic programming

All ideas from System R's "Selinger Optimizer" 1979

iPhones as a database

"avg acceleration over the past hour"



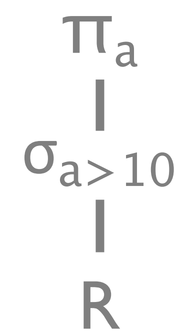
SQL → Query Plan

SELECT a FROM R

$\pi_a(R)$

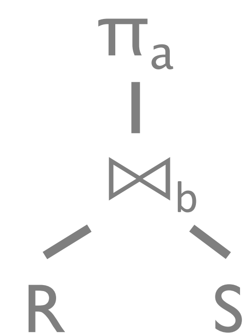
SELECT a FROM R
WHERE a > 10

$\pi_a(\sigma_{a>10}(R))$



SELECT a
FROM R JOIN S
ON R.b = S.b

$\pi_a(\bowtie_b(R,S))$



Query Evaluation

Push vs Pull?

Push

- Operators are input-driven
- As operator (say reading input table) gets data, push it to parent operator.
- Often used in streaming systems

Pull

- Operators are demand-driven
- If parent says "give me next result", then do the work

Are cursors push or pull?

Query Evaluation

Op at a time

- read R
- filter a>10 and write out
- read and project a
- Cost: B + M + M

SELECT a
FROM R
WHERE a > 10

π_a
|
$\sigma_{a>10}$
|
R

B # *data* pages

M # pages matched in WHERE clause

Could we do better?

Query Evaluation

Pipelined exec (at page granularity)

- read first page of R, pass to σ
- filter a > 10 and pass to π
- project a
- (all operators run concurrently)
- Cost: B

Note: can't pipeline some operators!

e.g., sort, some joins, aggregates

why?

SELECT a
FROM R
WHERE a > 10

$$\begin{array}{c} \pi_a \\ | \\ \sigma_{a>10} \\ | \\ R \end{array}$$

B # *data* pages

M # pages matched in WHERE clause

Query Evaluation

What if R is indexed?

- Hash index
  - Not appropriate
- B+Tree index
  - use a>10 to find initial data page
  - scan leaf data pages
  - Cost: $\log_F B + M$

SELECT a
FROM R
WHERE a > 10

$$\pi_a$$
$$|$$
$$\sigma_{a>10}$$
$$|$$
$$R$$

B # *data* pages

M # pages matched in WHERE clause

Push vs Pull?

What are the (typical) tradeoffs?

Pull

easy to pipeline

Push

vectorization, batched computation

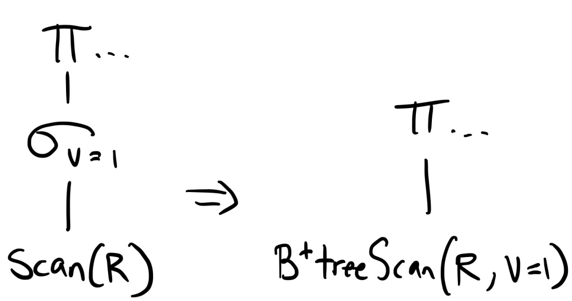
Access Paths

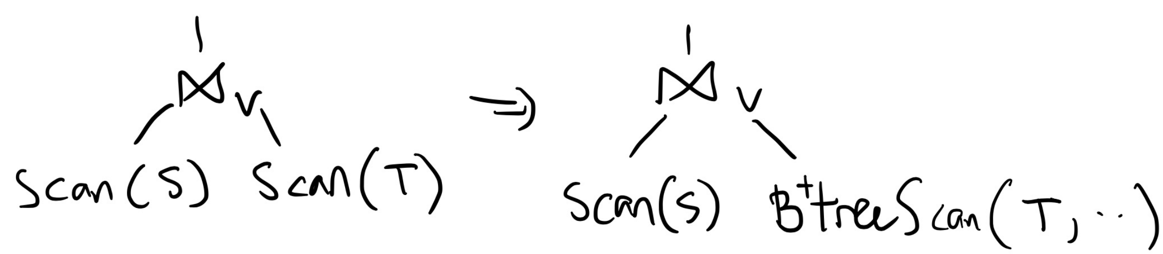
Access Path: how to access input data

file scan or

index + matching condition (e.g., a > 10)

Based on whether there is a "filter" operator **directly above** the Scan operator





Access Paths

Sequential Scan

- doesn't accept any matching conditions

Hash index on <a,b,c>

- accepts conjunction of equality conditions on *all* search keys
- e.g., a=1 and b = 5 and c = 5
- will (a = 1 and b = 5) work?

Tree index on <a,b,c>

- accepts conjunction of terms of *prefix* of search keys
- e.g., a > 1 and b = 5 and c < 5
- will (a > 1 and b = 5) work?
- will (a > 1 and c > 9) work?

How to pick Access Paths?

Selectivity

- ratio of # outputs satisfying predicates vs # inputs
- 0.01 means 1 output tuple for every 100 input tuples

Assume attribute selectivity is independent

Let:

- a=1 has 0.1 selectivity
- b>3 has 0.6 selectivity

What is selectivity of a=1 & b>3

- 0.1* 0.6 = 0.06

How to pick Access Paths?

Hash index on <a, b, c>

a = 1, b = 1, c = 1 how to estimate selectivity?

1. pre-compute attribute statistics by scanning data

   e.g., a has 100 values, b has 200 values, c has 1 value

   selectivity = 1 / (100 * 200 * 1)

2. How many distinct values does hash index have?

   e.g., 1000 distinct values in hash index

3. make a number up

   "default estimate" is the fancy term

System Catalog Keeps Statistics

System R

NCARD	"relation cardinality" # tuples in relation
TCARD	# pages relation occupies
ICARD	# keys (distinct values) in index
NINDX	pages occupied by index

min and max keys in indexes

Statistics were expensive in 1979!

Super elegant: catalog stored in relations too!

What Optimization Options Do We Have?

Access Path ✓

Predicate push-down

Join implementation

Join ordering

In general, depends on operator implementations. So let's take a look

Predicate Push Down

```
SELECT a
FROM R
WHERE a > 10
```

(a)

$$\pi_a$$
$$|$$
$$\sigma_{a>10}$$
$$|$$
$$R$$

(b)

$$\sigma_{a>10}$$
$$|$$
$$\pi_a$$
$$|$$
$$R$$

Access Path selection looks at operator right above the Scan.
Thus, move filters close to Scan (change (b)→(a))

Which is faster if B+ Tree index: (a) or (b)?

(a) $\log_F(B) + M$ pages

(b) B pages

It's a Good Idea, especially when we look at Joins

The Join

Core database operation

- join of 100+ tables common in enterprise apps

Join algorithms is a large area of research

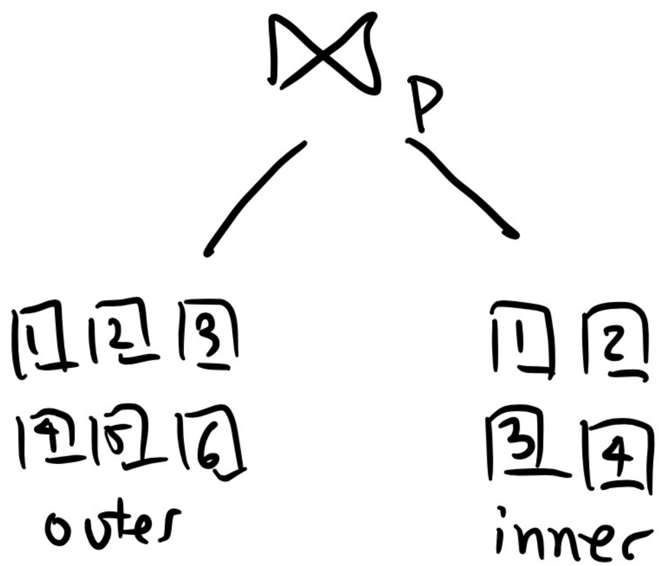
- e.g., distributed, temporal, geographic, multi-dim, range, sensors, graphs, etc
- Discuss three common join impls
  - nested loops, indexed nested loops, hash join

Best join implementation depends on the query, the data, the indices, hardware, etc

Basic Join Algorithms

Costs for: `outer JOIN inner on p`

- Nested Loops Join
- Index Nested Loops Join
- Hash Join

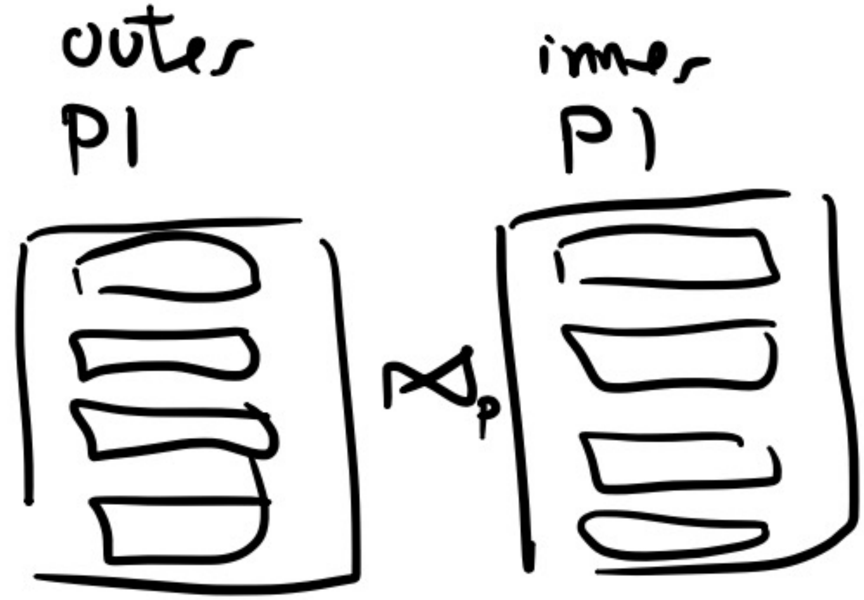


Joins between two pages

Suppose we have one page of records from each join table

opage	outer relation
ipage	inner relation

If both pages in memory, the join itself is "free" in terms of disk costs



Joins between two pages

Suppose we have one page of records from each join table

opage	outer relation
ipage	inner relation

If both pages in memory, the join itself is "free" in terms of disk costs

```
def joinpages(opage, ipage):
    for orow in opage:
        for resulttuple in joinrow(orow, ipage):
            yield resulttuple

def joinrow(orow, ipage):
    for irow in ipage:
        if orow.p == irow.p:
            yield (orow, irow)
```

NLJ: Nested Loops Join

```
for opage in outer:                          # need to read from disk
    for ipage in inner:                      # need to read from disk
        joinpages(opage, ipage)
```

M pages in outer, N pages in inner, T tuples per page

Very flexible

- Equality check can be replaced with any condition
- Incremental algorithm
- Cost: M + MN

Contrast with cross product?

INLJ: Indexed Nested Loops Join

```
for opage in outer:                       # read from disk
   for orow in opage:                     # in memory
      for ipage in index.get(orow.p):     # read from disk
         joinrow(orow, ipage)
```

inner is already indexed on join attribute *p*

M pages in outer, N pages in inner, T tuples/page
Cost of looking up in index is C_I
predicate on outer has 5% selectivity

$M + T * M * 0.05 * C_I$

HJ: Basic Hash Join

```
index = initialize hash index
for ipage in inner:
    for irow in ipage:
        index.insert(irow.p, irow)

for opage in outer:
    for orow in opage:
        for irow in index.get(orow.p):
            yield (row, irow)
```

Build **secondary** hash index in memory

INL Join

Less Flexible

- Equality joins
- M pages in outer, N pages in inner, T tuples/page
- Hash table in mem, assume no overflow pages→1 lookup to get tuple

Cost: $N + M + (T * M) * 1$

Join Cost Summary for S join T

NCARD(S) $= N_s$

NCARD(T) $= N_T$

NPAGES(S) $= P_S$

NPAGES(T) $= P_T$

ICARD(S) $= I_S$

ICARD(T) $= I_T$

Height of index = H

total # data pages depends

on primary vs secondary index

S NLJ T

$P_S + P_S * P_T$

S INLJ T

$P_S + N_S$ * (lookup cost)

S HJ T

$P_T + P_S + N_S$ * (lookup cost)

lookup cost:

H + # data pgs (+ # pointers)

data pgs:

selectivity * total # data pages

Quick Recap

Single relation operator optimizations

- Access paths
- Primary vs secondary index costs
- Predicate (Filter) push downs

2 relation operators aka Joins

- Nested loops, index nested loops, basic hash join

Selectivity estimation

- Statistics and simple models

Next:

- multi-operator plan optimization!

Adaptive Optimization of Very Large Join Queries

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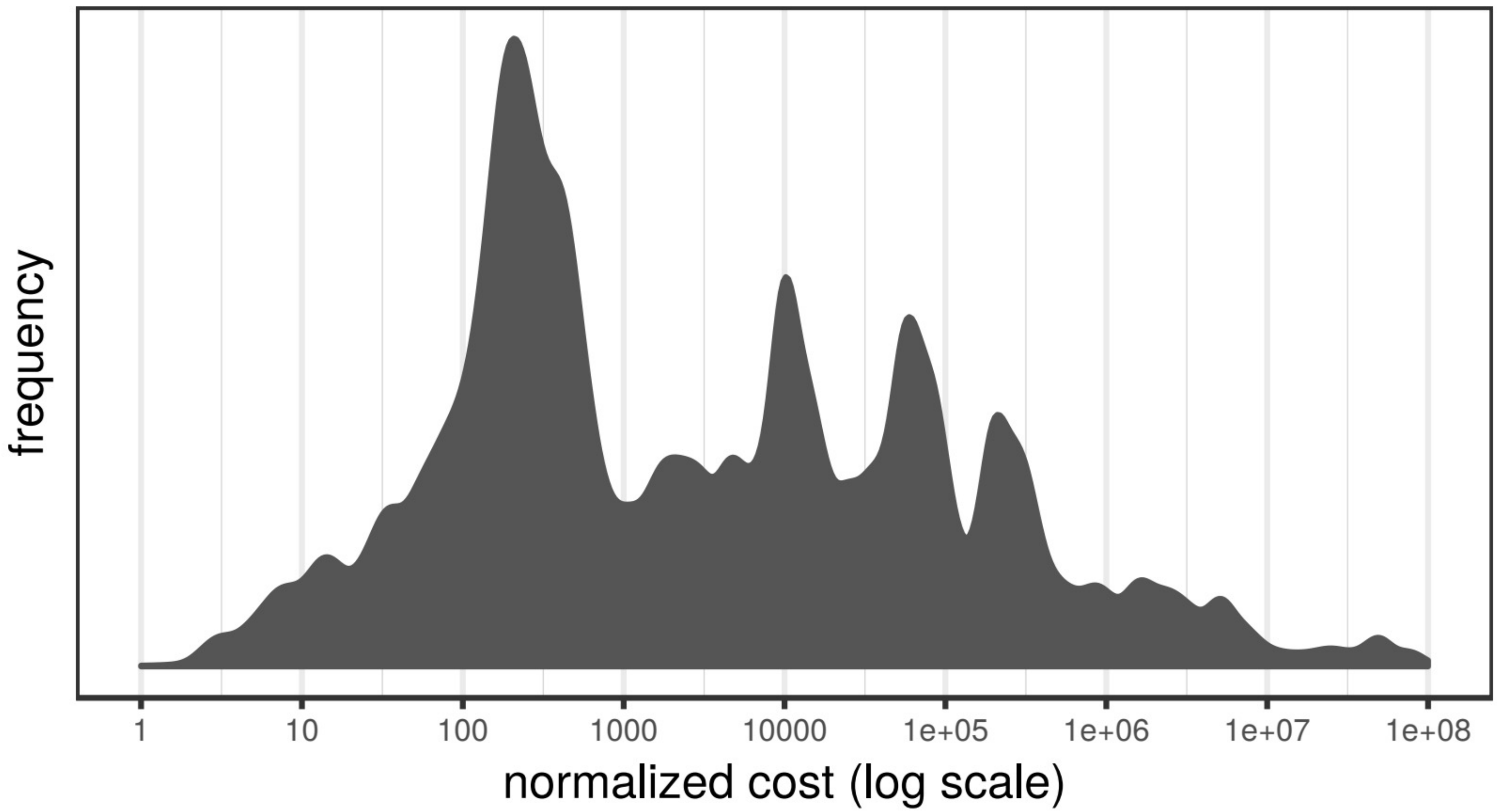

Figure 1: Normalized Cost Distribution of Random Plans for a Data-Warehouse-Style Query with 50 Relations

Selinger Optimizer

Granddaddy of all existing optimizers

- don't go for best plan, go for *least worst plan*

2 Big Ideas

1. Cost Estimator
    - "predict" cost of query from statistics
    - Includes CPU, disk, memory, etc (can get sophisticated!)
    - It's an art
2. Plan Space
    - avoid cross product
    - push selections & projections to leaves as much as possible
    - only join ordering remaining

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2 Big Ideas

1.

2.

Access Path Selection
in a Relational Database Management System

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M. M. Astrahan
D. D. Chamberlin
R. A. Lorie
T. G. Price

IBM Research Division, San Jose, California 95193

ABSTRACT: In a high level query and data manipulation language such as SQL, requests are stated non-procedurally, without reference to access paths. This paper describes how System R chooses access paths for both simple (single relation) and complex queries (such as joins), given a user specification of desired data as a

retrieval. Nor does a user specify in what order joins are to be performed. The System R optimizer chooses both join order and an access path for each table in the SQL statement. Of the many possible choices, the optimizer chooses the one which minimizes "total access cost" for performing the entire statement.

Cost Estimation

estimate(operator, inputs, stats) → cost

estimate **cost** for each operator

  depends on input ***cardinalities*** (# tuples)

  discussed earlier in lecture

estimate **output** size for each operator

  need to call estimate() on inputs!

  use selectivity. assume attributes are independent

Try it in PostgreSQL: `EXPLAIN <query>;`

Estimate Size of Output

```
SELECT    *
FROM      R1, …, Rn
WHERE     term1 AND … AND termm
```

Query input size

$|R1| * \ldots * |Rn|$

Term selectivity

col = v	$1/ICARD_{col}$
col1 = col2	$1/\max(ICARD_{col1}, ICARD_{col2})$
col > v	$(max_{col} - v) / (max_{col} - min_{col})$

Query output size

$|R1| * \ldots * |Rn| * term_1 selectivity * \ldots * term_m selectivity$

Estimate Size of Output

```
Emp:   1000 Cardinality
Dept:  10 Cardinality

 Cost(Emp join Dept)
```

In general

# total records	1000 * 10	= 10,000
Selectivity of Emp	1 / 1000	= 0.001
Selectivity of Dept	1 / 10	= 0.1
Join Selectivity	1 / max(1k, 10)	= 0.001
Output Card:	10,000 * 0.001	= 10

Key, Foreign Key join

Output Card: 1000

note: selectivity defined wrt cross product size

Try it out

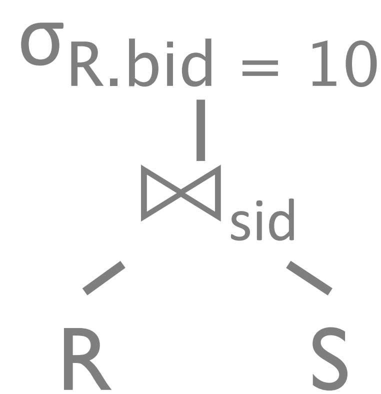
R.sid = S.sid selectivity 0.01
R.bid selectivity 0.05
|R| = M
|S| = N

```
SELECT   *
FROM     R, S
WHERE    R.sid = S.sid
   AND   R.bid = 10
```

Cost: M + MN

selection is pipelined

outputs: 0.0005MN



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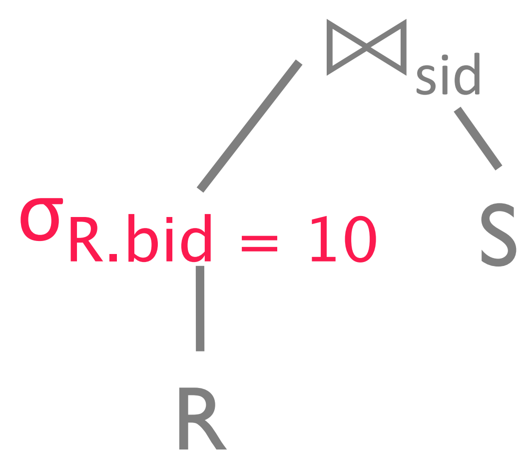
R.bid selectivity 0.05

|R| = M

|S| = N

```
SELECT    *
FROM      R, S
WHERE     R.sid = S.sid
    AND   R.bid = 10
```

Cost: ?????



outputs: 0.0005MN

Try it out

R.sid = S.sid selectivity 0.01

R.bid selectivity 0.05

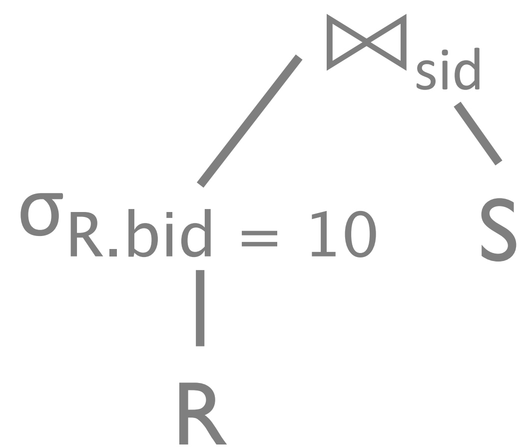
|R| = M

|S| = N

```
SELECT   *
FROM     R, S
WHERE    R.sid = S.sid
   AND   R.bid = 10
```

Cost: M + (0.05MN)

outputs: 0.0005MN



Selinger Optimizer

Granddaddy of all existing optimizers

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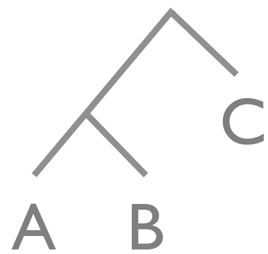
2 Big Ideas

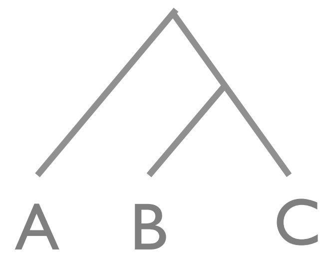
1. Cost Estimator
   - "predict" cost of query from statistics
   - Includes CPU, disk, memory, etc (can get sophisticated!)
   - It's an art
2. Plan Space
   - avoid cross product
   - push selections & projections to leaves as much as possible
   - only join ordering remaining

Join Plan Space

$A \bowtie B \bowtie C$



(AB)C



A(BC)

How many plans?

(AB)C	(AC)B	(BC)A	(BA)C	(CA)B	(CB)A
A(BC)	A(CB)	B(CA)	B(AC)	C(AB)	C(BA)

$\# \text{ parenthetizations} * \underbrace{\#\text{strings}}_{N!}$

Join Plan Space

parenthetizations * #strings

A:	(A)
AB:	(AB)
ABC:	((AB)C), (A(BC))
ABCD:	(((AB)C)D), ((A(BC))D), ((AB)(CD)), (A((BC)D)), (A(B(CD)))
paren(n)	choose(2(N-1), (N-1)) / N

(choose(2(N-1), (N-1)) / N) * N!

N=10 #plans = 17,643,225,600

The Art of Computer Programming, Volume 4A, page 440-450

Selinger Optimizer

Simplify the set of plans so it's tractable and ~ok

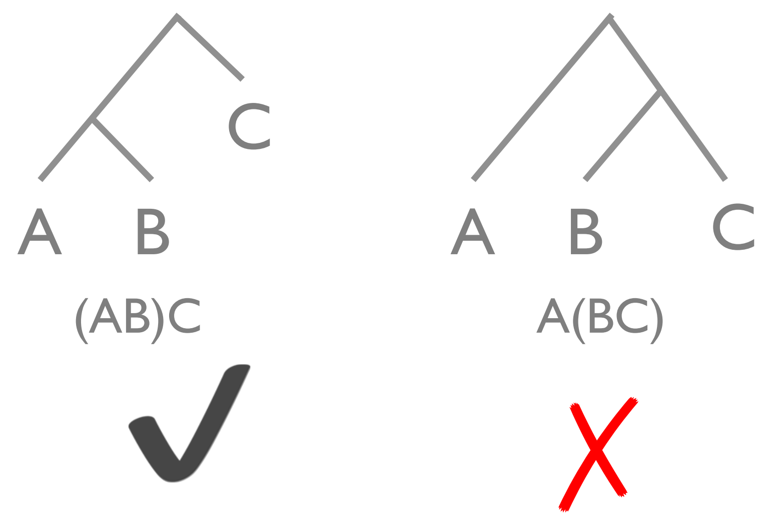
1. Push down selections and projections
2. Ignore cross products (S&T don't share attrs)
3. Left deep plans only
4. Dynamic programming optimization problem
5. Consider interesting sort orders (ignored in this class)

Selinger Optimizer

parens(N) = 1

Only left-deep plans

ensures pipelining



Dynamic Programming

Idea: If considering ((ABC)DE)

compute best (ABC), cache, and reuse

figure out best way to combine with (DE)

```
Dynamic Programming Algorithm
    compute best join size 1, then size 2, …
```

$\sim O(N * 2^N)$

Reducing the Plan Space

```
Dynamic Programming Algorithm
    compute best join size 1, then size 2, …

    R = relations to join
    N = |R|
    for i in {1,… N}
        for S in {all size i subsets of R}
            bestjoin(S) = S-A join A
            where A is relation that minimizes the join cost:
                use bestjoin(S-A) as the outer relation
                min cost join algo of (S-A) with A using
                minimum access cost for A
```

Selinger Algorithm i = 1

bestjoin(ABC), only nested loops join

i = 1

A = best way to access A (assuming single access method)

B = best way to access B

C = best way to access C

cost: N relations

Selinger Algorithm i = 2

bestjoin(ABC)

i = 2

A,B = (A)B or (B)A

A,C = (A)C or (C)A

B,C = (B)C or (C)B

cost: choose(N, 2) * 2

Selinger Algorithm i = 3

bestjoin(ABC)

i = 3

A,B,C = bestjoin(BC)A or
bestjoin(AC)B or
bestjoin(AB)C

cost: choose(N, 3) * 3

Selinger Algorithm Cost

cost = # subsets * # options per subset
set of relations R
N = |R|

#subsets = choose(N, 1) + choose(N,2) + choose(N,3)…
= 2^N

#options = $k<N$ subsets to be inner relation (right side) *
J join algorithms (NL, INL, ...)
$< J*N$

Cost = $J*N*2^N$
N = 12 49152 # if only using INL

Summary

Single operator optimizations

- Access paths
- Primary vs secondary index costs
- Predicate/project push downs

2 operators aka Joins

- Nested loops, index nested loops

Full plan optimizations

- Naïve vs Selinger join ordering

Selectivity estimation

- Statistics and simple models

Summary

Query optimization is a deep, complex topic

Pipelined plan execution

Different types of joins

Cost estimation of single and multiple operators

Join ordering is hard!

You should understand

Estimate query cardinality, selectivity

Apply predicate push down

Given primary/secondary indexes and statistics,

- pick best index for access method + est cost
- pick best index for join + est cost
- pick best join order for 3 tables
- pick cheaper of two execution plans