L9
Query Execution & Optimization

Eugene Wu
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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
App/Security Design
  prevent security problems

$\boxed{\text{Physical Database Design – optimize for speed/storage}}$ Optimization

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

  $|R| = |T| =$ 10 pages. 100? 1M?
  # unique values in R = 1. 100? 1M? ← selectivity!

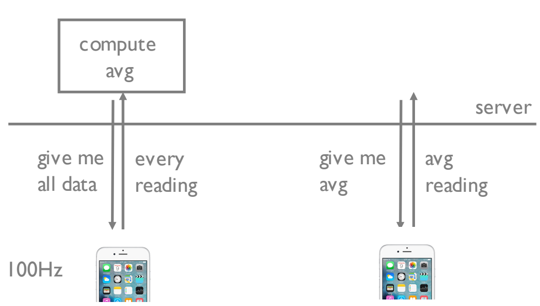
Overview of Query Optimization

SQL → query plan
How plans are executed
Some implementations of operators
Cost estimation of a plan
  Selectivity
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	$\pi_a(R)$	π_a – R
SELECT a FROM R WHERE a > 10	$\pi_a(\sigma_{a>10}(R))$	π_a – $\sigma_{a>10}$ – R
SELECT a FROM R JOIN S ON R.b = S.b	$\pi_a(\bowtie_b(R,S))$	π_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.

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

Are cursors push or pull?

Query Evaluation

Naïve execution (operator 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 (tuple/page at a time)
- read first page of R, pass to σ
- filter a > 10 and pass to π
- project a
- (all operators run concurrently)
- Cost: B

SELECT a
FROM R
WHERE a > 10

π_a
|
$\sigma_{a>10}$
|
R

B # *data* pages
M # pages matched in WHERE clause

Note: can't pipeline some operators!
e.g., sort, some joins, aggregates
why?

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

π_a
|
$\sigma_{a>10}$
|
R

B # *data* pages
M # pages matched in WHERE clause

Access Paths

Choice of how to access input data is called the Access Path
- file scan or
- index + matching condition (e.g., a > 10)

Access Paths

Sequential Scan
- doesn't accept any matching conditions

Hash index search key <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? why?

Tree index search key <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?

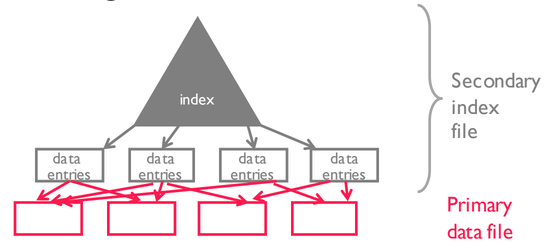
Selectivity

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

Assume

- attribute selectivity is independent
  - if selectivity(a=1) = 0.1, selectivity(b>3) = 0.6
  - selectivity(a=1 and b>3) = 0.1*0.6 = 0.06

High level index structure



What is a data entry?

- actual data record
- <search key value, rid>
- <search key value, rid_list>

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

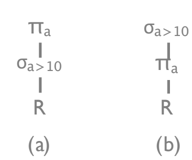
Join implementation

Join ordering

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

Predicate Push Down

SELECT a
FROM R
WHERE a > 10



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

Projection with DISTINCT clause

need to deduplicate e.g., π_{rating}Sailors

Two basic approaches
- Sort: fundamental database operation
  - sort on rating, remove dups on scan of sorted data
- Hash:
  - partition into N buckets
  - sort each bucket and remove dups

Index on projected fields
- scan the index pages, avoid reading data

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 basic joins
  - nested loops, indexed nested loops, hash join

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

Datasets

```
from collections import defaultdict
from random import randint

M = 10000
N = 1000
outer = [ [randint(0, 1000), randint(0, 1000)]
          for i in xrange(M)]
inner = [ [randint(0, 1000), randint(0, 1000)]
          for i in xrange(N)]

# outer ⋈1 inner
# outer JOIN inner ON outer.1 = inner.1
```

Nested Loops Join

```
for row in outer:
   for irow in inner:
      if row[0] == irow[0]:    # could be any check
         yield (row, irow)
```

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

Is this the same as a cross product?

Nested Loops Join

What this means in terms of disk IO

outer join inner
M pages in outer, N pages in inner, 2 tuples per page

M + 2 * M * N

for each tuple *t* in the outer, (M pages, 2M tuples)
- scan through each page *pi* in the inner (N pages)
  - compare all the tuples in *pi* with *t*

Indexed Nested Loops Join

```
for row in outer:
   for irow in index.get(row[0], []):
      yield (row, irow)
```

Slightly less flexible
- Only supports conditions that the index supports

Indexed Nested Loops Join

What this means in terms of disk IO

outer join inner on sid
M pages in outer, N pages in inner, 50 tuples/page
inner is indexed on sid
predicate on outer has 5% selectivity

M + 50 * M * 0.05 * 1

for each tuple t in the outer: (M pages, 50M tuples)
  if predicate(t): (5% of tuples satisfy pred)
    lookup_in_index(t.sid) (1 disk IO)

Sort Merge Join

Sort outer and inner tables on join key
  Cost: 2-3 scans of each table
Merge the tables and compute the join
  Cost: 1 scan of each table

Overall Properties
  cost: 3(M+N) to 4(M+N)
  results are sorted
  highly sequential access
  (weapon of choice for very large datasets)

Sort Merge Join

What does this mean in terms of disk IO?

R join T on sid
R has M pages, T has N pages, 50 tuples/page
Assume sort takes 3 scans, merge takes 1 scan

3 * M + 1 * M + 3 * N + 1 * N

(note, tuples/page didn't matter)

Quick Recap

Single relation operator optimizations
  Access paths
  Primary vs secondary index costs
  Projection/distinct
  Predicate/project push downs
2 relation operators aka Joins
  Nested loops, index nested loops, sort merge
Selectivity estimation
  Statistics and simple models

Where we are

We've discussed
  Optimizations for a single operator
  Different types of access paths, join operators
  Simple optimizations e.g., predicate push-down

What about for multiple operators?
  System R Optimizer

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

Selinger Optimizer

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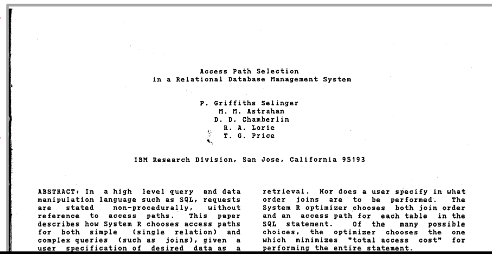
2 Big Ideas

1.

2.


Access Path Selection
in a Relational Database Management System

P. Griffiths Selinger
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.

ble

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)
```

Naïve

# 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

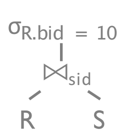
- Output Card: 1000

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

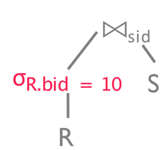
\# outputs: 0.0005MN

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: ?????



\# outputs: 0.0005MN

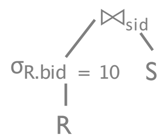
Try it out

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

Cost: M + (0.05MN)

outputs: 0.0005MN

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



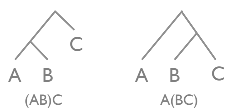
Selinger Optimizer

Granddaddy of all existing optimizers
don't go for best plan, go for *least worst plan*

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

Join Plan Space

A⋈B⋈C



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

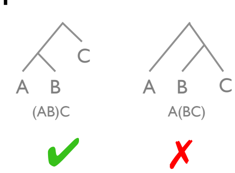
Selinger Optimizer

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

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, …
```
~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 single relation that minimizes:
                    cost(bestjoin(S-A)) +
                    min cost to join A to (S-A) +
                    min access cost for A
```

Selinger Algorithm i = 1

bestjoin(ABC), only nested loops join

i = 1
A = best way to access A
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 ways to remove a relation A +
1 way to join A with R-A (if only NLJ)
< N

Cost = $N*2^N$
N = 12 49152

Summary

Single operator optimizations
- Access paths
- Primary vs secondary index costs
- Projection/distinct
- Predicate/project push downs

2 operators aka Joins
- Nested loops, index nested loops, sort merge

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