Lecture 9 10/8/09

Query Optimization

Lab 2 due next Thursday.

M pages memory S and R, with ISI IRI pages respectively; ISI > IRI M > sqrt(ISI)

External Sort Merge

split ISI and IRI into memory sized runs sort each merge all runs simultaneously

total I/O 3 IRI + ISI (read, write, read)

"Simple" hash

given hash function h(x), split h(x) values in N ranges N = ceiling(IRI/M)

```
for (i = 1...N)
for r in R
if h® in range i, put in hash table Hr
o.w. write out
for s in S
if h(s) in range i, lookup in Hr
o.w. write out
```

total I/O

N (IRI + ISI)

Grace hash:

for each of N partitions, allocate one page per partition hash r into partitions, flushing pages as they fill hash s into partitions, flushing pages as they fill for each partition p build a hash table Hr on r tuples in p hash s, lookup on Hr

example:

R = 1, 4, 3, 6, 9, 14, 1, 7, 11 S = 2, 3, 7, 12, 9, 8, 4, 15, 6 $h(x) = x \mod 3$ R1 = 3 6 9 R2 = 1 4 1 7 R3 = 14 11 S1 = 3 12 9 15 6 S2 = 7 4S3 = 2 8 Now, join R1 with S1, R2 with S2, R3 with S3

Note -- need 1 page of memory per partition. Do we have enough memory?

We have IRI / M partitions

 $M \ge sqrt(IRI)$

worst case

IRI / sqrt(IRI) = sqrt(IRI) partitions

Need sqrt(IRI) pages of memory b/c we need at least one page per partition as we write out (note that simple hash doesn't have this requirement)

I/O:

read R+S (seq) write R+S (semi-random) read R+S (seq)

also 3(IRI+ISI) I/OS

What's hard about this?

When does grace outperform simple?

(When there are many partitions, since we avoid the cost of re-reading tuples from disk in building partitions)

When does simple outperform grace? (When there are few partitions, since grace re-reads hash tables from disk)

So what does Hybrid do?

M = sqrt(IRI) + EMake first partition of size E, do it on the fly (as in simple) Do remaining partitions as in grace.



Why does grace/hybrid outperform sort-merge?

CPU Costs! I/O costs are comparable 690 / 1000 seconds in sort merge are due to the costs of sorting 17.4 in the case of CPU for grace/hybrid!

Will this still be true today?

(Yes)

Selinger

Famous paper. Pat Selinger was one of the early System R researchers; still active today.

Lays the foundation for modern query optimization. Some things are weak but have since been improved upon.

Idea behind query optimization:

(Find query plan of minimum cost)

How to do this? (Need a way to measure cost of a plan (a cost model))

single table operations

how do i compute the cost of a particular predicate? compute it's "selectivity" - fraction F of tuples it passes

how does selinger define these? -- based on type of predicate and available statistics

what statistics does system R keep?

- relation cardinalities NCARD
- # pages relation occupies TCARD
- keys in index ICARD
- pages occupied by index NINDX

Estimating selectivity F:

col = val

F = 1/ICARD()F = 1/10 (where does this come from?)

col > val high key - value / high key - low key 1/3 o.w.

col1 = col2 (key-foreign key) 1/MAX(ICARD(col1, col2)) 1/10 o.w.

ex: suppose emp has 10000 records, dept as 1000 records total records is 10000 * 1000, selectivity is 1/10000, so 1000 tuples expected to pass join note that selectivity is defined relative to size of cross product for joins!

p1 and p2

F1 * F2

p1 or p2

1 - (1-F1) * (1-F2)

then, compute access cost for scanning the relation. how is this defined? (in terms of number of pages read)

equal predicate with unique index: 1 [btree lookup] + 1 [heapfile lookup] + W

(W is CPU cost per predicate eval in terms of fraction of a time to read a page)

range scan:

clustered index, boolean factors: F(preds) * (NINDX + TCARD) + W*(tuples read)

unclustered index, boolean factors: F(preds) * (NINDX + NCARD) + W*(tuples read) unless all pages fit in buffer -- why?

seq (segment) scan: TCARD + W*(NCARD)

Is an index always better than a segment scan? (no)

multi-table operations

how do i compute the cost of a particular join?

algorithms:

NL(A,B,pred) C-outer(A) + NCARD(outer) * C-inner(B)

Note that inner is always a relation; cost to access depends on access methods for B; e.g., w/ index -- 1 + 1 + W w/out index -- TCARD(B) + W*NCARD(B)

C-outer is cost of subtree under outer

How to estimate # NCARD(outer)? product of F factors of children, cardinalities of children example:



Image by MIT OpenCourseWare.

Merge_Join_x(P,A,B), equality pred

C-outer + C-inner + sort cost (Saw cost models for these last time)

At time of paper, didn't believe hashing was a good idea

Overall plan cost is just sum of costs of all access methods and join operators Then, need a way to enumerate plans Iterate over plans, pick one of minimum cost

Problem:

Huge number of plans. Example:

suppose I am joining three relations, A, B, C Can order them as:

(AB)C A(BC) (AC)B A(CB) (BA)Ć B(AC) (BC)Á B(AC) (CA)B C(AB) (CB)Á C(BA) Is C(AB) different from (CA)B? Is (AB)C different from C(AB)? yes, inner vs. outer n! strings * # of parenthetizations how many parenthetizations are there? ABCD --> (AB)CD A(BC)D AB(CD) 3 XCD AXD ABX * 2 === 6 --> (n-1)! ==> n! * (n-1)! 6 * 2 == 12 for 3 relations

Ok, so what does Selinger do?

Push down selections and projections to leaves Now left with a bunch of joins to order.

Selinger simplifies using 2 heuristics? What are they?

- only left deep; e.g., $ABCD \Rightarrow (((AB)C)D)$ show
- ignore cross products
- e.g., if A and B don't have a join predicate, doing consider joining them

still n! orderings. can we just enumerate all of them?

10! -- 3million 20! -- 2.4 * 10 ^ 18

so how do we get around this?

Estimate cost by dynamic programming:

idea: if I compute join (ABC)DE -- I can find the best way to combine ABC and then consider all the ways to combine that with DE.

i can remember the best way to compute (ABC), and then I don't have to re-evaluate it. best way to do ABC may be ACB, BCA, etc -- doesn't matter for purposes of this decision.

algorithm: compute optimal way to generate every sub-join of size 1, size 2, ... n (in that order).

```
\begin{array}{l} R <--- \mbox{ set of relations to join} \\ \mbox{for $\partial$ in {1...|Rl}:$} \\ \mbox{ for $S$ in {all length $\partial$ subsets of $R$}:$ \\ \mbox{ optjoin}(S) = a join (S-a), where $a$ is the single relation that minimizes:$ $cost(optjoin(S-a)) +$ $min cost to join (S-a) to $a +$ $min. access cost for $a$ $\end{array}
```

example: ABCD

only look at NL join for this example

A = best way to access A (e.g., sequential scan, or predicate pushdown into index...) " B п н B = " C = " п п " C D = " " п " D $\{A,B\} = AB \text{ or } BA$ $\{A,C\} = AC \text{ or } CA$ $\{B,C\} = BC \text{ or } CB$ {A,D} {B,D} {C,D} $\{A,B,C\}$ = remove A - compare A($\{B,C\}$) to ($\{B,C\}$)A remove B - compare ({A,C})B to B({A,C}) remove C - compare C({A,B}) to ({A,B})C {A,C,D} {A,B,D} {B,C,D} ${A,B,C,D} =$ remove A - compare A({B,C,D}) to ({B,C,D})A remove B remove C remove D Complexity: number of subsets of size 1 * work per subset = W+ number of subsets of size 2 * W + ... number of subsets of size n * W+

n+n+n...n 1 2 3 n number of subsets of set of size $n = power set of n = 2^n$ (string of length n, 0 if element is in, 1 if it is out; clearly, 2ⁿ such strings)

(reduced an n! problem to a 2ⁿ problem)

what's W? (n)

so actual cost is: 2ⁿ * n

So what's the deal with sort orders? Why do we keep interesting sort orders?

Selinger says: although there may be a 'best' way to compute ABC, there may also be ways that produce interesting orderings -- e.g., that make later joins cheaper or that avoid final sorts.

So we need to keep best way to compute ABC for different possible join orders.

so we multiply by "k" -- the number of interesting orders

how are things different in the real world? - real optimizers consider bushy plans (why?)

A D B C E

- selectivity estimation is much more complicated than selinger says and is very important.

how does selinger estimate the size of a join?

- selinger just uses rough heuristics for equality and range predicates.

```
- what can go wrong?
consider ABCD
suppose sel (A join B) = 1
everything else is .1
If I don't leave A join B until last, I'm off by a factor of 10
```

- how can we do a better job? (multi-d) histograms, sampling, etc.

example: 1d hist



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example: 2d hist



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