Query Processing

Introduction to Databases
CompSci 316 Fall 2015
Announcements (Tue., Nov. 10)

• **Homework #4** assigned today; due on 12/01
• Project milestone #2 feedback to be emailed by this weekend
Overview

• Many different ways of processing the same query
  • Scan? Sort? Hash? Use an index?
  • All have different performance characteristics and/or make different assumptions about data

• Best choice depends on the situation
  • Implement all alternatives
  • Let the query optimizer choose at run-time
Notation

• Relations: $R, S$
• Tuples: $r, s$
• Number of tuples: $|R|, |S|$
• Number of disk blocks: $B(R), B(S)$
• Number of memory blocks available: $M$
• Cost metric
  • Number of I/O’s
  • Memory requirement
Scanning-based algorithms
Table scan

• Scan table $R$ and process the query
  • Selection over $R$
  • Projection of $R$ without duplicate elimination

• I/O’s: $B(R)$
  • Trick for selection: stop early if it is a lookup by key

• Memory requirement: 2

• Not counting the cost of writing the result out
  • Same for any algorithm!
  • Maybe not needed—results may be pipelined into another operator
Nested-loop join

\[ R \bowtie_p S \]

• For each block of \( R \), and for each \( r \) in the block:
  For each block of \( S \), and for each \( s \) in the block:
    Output \( rs \) if \( p \) evaluates to true over \( r \) and \( s \)
• \( R \) is called the outer table; \( S \) is called the inner table
• I/O’s: \( B(R) + |R| \cdot B(S) \)
• Memory requirement: 3

Improvement: block-based nested-loop join

• For each block of \( R \), for each block of \( S \):
  For each \( r \) in the \( R \) block, for each \( s \) in the \( S \) block: ...
• I/O’s: \( B(R) + B(R) \cdot B(S) \)
• Memory requirement: same as before
More improvements

• Stop early if the key of the inner table is being matched

• Make use of available memory
  • Stuff memory with as much of $R$ as possible, stream $S$ by, and join every $S$ tuple with all $R$ tuples in memory

• I/O’s: $B(R) + \left[ \frac{B(R)}{M-2} \right] \cdot B(S)$
  • Or, roughly: $B(R) \cdot B(S) / M$

• Memory requirement: $M$ (as much as possible)

• Which table would you pick as the outer?
Sorting-based algorithms

http://en.wikipedia.org/wiki/Mail_sorter#mediaviewer/File:Mail_sorting,1951.jpg
External merge sort

Remember (internal-memory) merge sort?
Problem: sort $R$, but $R$ does not fit in memory

- **Pass 0**: read $M$ blocks of $R$ at a time, sort them, and write out a level-0 run

- **Pass 1**: merge $(M - 1)$ level-0 runs at a time, and write out a level-1 run

- **Pass 2**: merge $(M - 1)$ level-1 runs at a time, and write out a level-2 run

...  
- **Final pass** produces one sorted run
Toy example

- 3 memory blocks available; each holds one number
- Input: 1, 7, 4, 5, 2, 8, 3, 6, 9
- Pass 0
  - 1, 7, 4 → 1, 4, 7
  - 5, 2, 8 → 2, 5, 8
  - 9, 6, 3 → 3, 6, 9
- Pass 1
  - 1, 4, 7 + 2, 5, 8 → 1, 2, 4, 5, 7, 8
  - 3, 6, 9
- Pass 2 (final)
  - 1, 2, 4, 5, 7, 8 + 3, 6, 9 → 1, 2, 3, 4, 5, 6, 7, 8, 9
Analysis

• **Pass 0**: read \( M \) blocks of \( R \) at a time, sort them, and write out a level-0 run
  • There are \( \left\lfloor \frac{B(R)}{M} \right\rfloor \) level-0 sorted runs

• **Pass \( i \)**: merge \((M - 1)\) level-(\(i - 1\)) runs at a time, and write out a level-\(i\) run
  • \((M - 1)\) memory blocks for input, 1 to buffer output
  • \# of level-\(i\) runs = \( \left\lfloor \frac{\# \text{ of level-}(i-1) \text{ runs}}{M-1} \right\rfloor \)

• **Final pass** produces one sorted run
Performance of external merge sort

- Number of passes: \[ \log_{M-1} \left( \frac{B(R)}{M} \right) + 1 \]

- I/O’s
  - Multiply by \( 2 \cdot B(R) \): each pass reads the entire relation once and writes it once
  - Subtract \( B(R) \) for the final pass
  - Roughly, this is \( O(B(R) \times \log_M B(R)) \)

- Memory requirement: \( M \) (as much as possible)
Some tricks for sorting

• Double buffering
  • Allocate an additional block for each run
  • Overlap I/O with processing
  • Trade-off: smaller fan-in (more passes)

• Blocked I/O
  • Instead of reading/writing one disk block at time, read/write a bunch (“cluster”)
  • More sequential I/O’s
  • Trade-off: larger cluster → smaller fan-in (more passes)
Sort-merge join

\[ R \bowtie_{R.A=S.B} S \]

• Sort \( R \) and \( S \) by their join attributes; then merge 
  \( r, s \) = the first tuples in sorted \( R \) and \( S \) 
  Repeat until one of \( R \) and \( S \) is exhausted: 
    If \( r.A > s.B \) then \( s = \) next tuple in \( S \) 
    else if \( r.A < s.B \) then \( r = \) next tuple in \( R \) 
    else output all matching tuples, and 
    \( r, s = \) next in \( R \) and \( S \)

• I/O’s: sorting + \( 2B(R) + 2B(S) \)
  • In most cases (e.g., join of key and foreign key)
  • Worst case is \( B(R) \cdot B(S) \): everything joins
Example of merge join

**R:**
- \( r_1.A = 1 \)
- \( r_2.A = 3 \)
- \( r_3.A = 3 \)
- \( r_4.A = 5 \)
- \( r_5.A = 7 \)
- \( r_6.A = 7 \)
- \( r_7.A = 8 \)

**S:**
- \( s_1.B = 1 \)
- \( s_2.B = 2 \)
- \( s_3.B = 3 \)
- \( s_4.B = 3 \)
- \( s_5.B = 8 \)

**R \( \bowtie_{R.A=S.B} \) S:**
- \( r_1s_1 \)
- \( r_2s_3 \)
- \( r_2s_4 \)
- \( r_3s_3 \)
- \( r_3s_4 \)
- \( r_7s_5 \)
Optimization of SMJ

• Idea: combine join with the (last) merge phase of merge sort
• **Sort**: produce sorted runs for $R$ and $S$ such that there are fewer than $M$ of them total
• **Merge and join**: merge the runs of $R$, merge the runs of $S$, and merge-join the result streams as they are generated!

![Diagram of SMJ optimization](image)
Performance of SMJ

• If SMJ completes in two passes:
  • I/O’s: \(3 \cdot (B(R) + B(S))\)
  • Memory requirement
    • We must have enough memory to accommodate one block from each run: \(M > \frac{B(R)}{M} + \frac{B(S)}{M}\)
    • \(M > \sqrt{B(R) + B(S)}\)

• If SMJ cannot complete in two passes:
  • Repeatedly merge to reduce the number of runs as necessary before final merge and join
Other sort-based algorithms

• Union (set), difference, intersection
  • More or less like SMJ

• Duplication elimination
  • External merge sort
    • Eliminate duplicates in sort and merge

• Grouping and aggregation
  • External merge sort, by group-by columns
    • Trick: produce “partial” aggregate values in each run, and combine them during merge
      • This trick doesn’t always work though
        • Examples: SUM(DISTINCT ...), MEDIAN(...)
Hashing-based algorithms

Hash join

\[ R \bowtie_{R.A=S.B} S \]

- **Main idea**
  - Partition \( R \) and \( S \) by hashing their join attributes, and then consider corresponding partitions of \( R \) and \( S \)
  - If \( r.A \) and \( s.B \) get hashed to different partitions, they don’t join

- **Diagram**
  - Nested-loop join considers all slots
  - Hash join considers only those along the diagonal!
Partitioning phase

• Partition $R$ and $S$ according to the same hash function on their join attributes
Probing phase

• Read in each partition of $R$, stream in the corresponding partition of $S$, join
  • Typically build a hash table for the partition of $R$
    • Not the same hash function used for partition, of course!

For each $S$ tuple, probe and join
Performance of (two-pass) hash join

• If hash join completes in two passes:
  • I/O’s: \( 3 \cdot (B(R) + B(S)) \)
  • Memory requirement:
    • In the probing phase, we should have enough memory to fit one partition of \( R \): \( M - 1 > \frac{B(R)}{M-1} \)
    • \( M > \sqrt{B(R)} + 1 \)
    • We can always pick \( R \) to be the smaller relation, so:
      \[ M > \sqrt{\min(B(R), B(S)) + 1} \]
Generalizing for larger inputs

• What if a partition is too large for memory?
  • Read it back in and partition it again!
    • See the duality in multi-pass merge sort here?
Hash join versus SMJ

(Assuming two-pass)
• I/O’s: same
• Memory requirement: hash join is lower
  \[ \sqrt{\min(B(R), B(S))} + 1 < \sqrt{B(R) + B(S)} \]
  • Hash join wins when two relations have very different sizes
• Other factors
  • Hash join performance depends on the quality of the hash
    • Might not get evenly sized buckets
  • SMJ can be adapted for inequality join predicates
  • SMJ wins if \( R \) and/or \( S \) are already sorted
  • SMJ wins if the result needs to be in sorted order
What about nested-loop join?

• May be best if many tuples join
  • Example: non-equality joins that are not very selective

• Necessary for black-box predicates
  • Example: WHERE user_defined_pred(R.A, S.B)
Other hash-based algorithms

• Union (set), difference, intersection
  • More or less like hash join

• Duplicate elimination
  • Check for duplicates within each partition/bucket

• Grouping and aggregation
  • Apply the hash functions to the group-by columns
  • Tuples in the same group must end up in the same partition/bucket
  • Keep a running aggregate value for each group
    • May not always work
Duality of sort and hash

- Divide-and-conquer paradigm
  - Sorting: physical division, logical combination
  - Hashing: logical division, physical combination
- Handling very large inputs
  - Sorting: multi-level merge
  - Hashing: recursive partitioning
- I/O patterns
  - Sorting: sequential write, random read (merge)
  - Hashing: random write, sequential read (partition)
Index-based algorithms

http://il.trekearth.com/photos/28820/p2270994.jpg
Selection using index

• Equality predicate: $\sigma_{A=v}(R)$
  • Use an ISAM, B$^+$-tree, or hash index on $R(A)$

• Range predicate: $\sigma_{A>v}(R)$
  • Use an ordered index (e.g., ISAM or B$^+$-tree) on $R(A)$
  • Hash index is not applicable

• Indexes other than those on $R(A)$ may be useful
  • Example: B$^+$-tree index on $R(A, B)$
  • How about B$^+$-tree index on $R(B, A)$?
Index versus table scan

Situations where index clearly wins:

• **Index-only queries** which do not require retrieving actual tuples
  
  • Example: \( \pi_A(\sigma_{A>v}(R)) \)

• Primary index clustered according to search key
  
  • One lookup leads to all result tuples in their entirety
Index versus table scan (cont’d)

BUT(!):

• Consider $\sigma_{A > \nu}(R)$ and a secondary, non-clustered index on $R(A)$
  • Need to follow pointers to get the actual result tuples
  • Say that 20% of $R$ satisfies $A > \nu$
    • Could happen even for equality predicates
• I/O’s for index-based selection: lookup + 20% $|R|$
• I/O’s for scan-based selection: $B(R)$$\bullet$ Table scan wins if a block contains more than 5 tuples!
Index nested-loop join

\[ R \bowtie_{R.A=S.B} S \]

- Idea: use a value of \( R.A \) to probe the index on \( S(B) \)
- For each block of \( R \), and for each \( r \) in the block:
  Use the index on \( S(B) \) to retrieve \( s \) with \( s.B = r.A \)
  Output \( rs \)
- I/O’s: \( B(R) + |R| \cdot (\text{index lookup}) \)
  - Typically, the cost of an index lookup is 2-4 I/O’s
  - Beats other join methods if \(|R|\) is not too big
  - Better pick \( R \) to be the smaller relation
- Memory requirement: 3
Zig-zag join using ordered indexes

\[ R \bowtie_{R.A=S.B} S \]

- Idea: use the ordering provided by the indexes on \( R(A) \) and \( S(B) \) to eliminate the sorting step of sort-merge join
- Use the larger key to probe the other index
  - Possibly skipping many keys that don’t match
Summary of techniques

• Scan
  • Selection, duplicate-preserving projection, nested-loop join

• Sort
  • External merge sort, sort-merge join, union (set), difference, intersection, duplicate elimination, grouping and aggregation

• Hash
  • Hash join, union (set), difference, intersection, duplicate elimination, grouping and aggregation

• Index
  • Selection, index nested-loop join, zig-zag join