CMSC424: Database Design

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Today’s Plan

- Query processing
  - Sorting, then Nested Loops Join, and Hash Joins
  - In class activity on this stuff
  - Make sure to turn that in

- Next week:
  - Wrap up query processing
  - Parallel Databases; Map-Reduce; Apache Spark
    - The last two not covered in the book
    - I don’t have detailed slides, so try not to miss the classes
Overview

query

parser and translator

relational-algebra expression

optimizer

evaluation engine

execution plan

data

query output

statistics about data
Query Processing

- Overview
- Selection operation
- Join operators
- Sorting
- Other operators
- Putting it all together…
Sorting

- Commonly required for many operations
  - Duplicate elimination, group by’s, sort-merge join
  - Queries may have ASC or DSC in the query

- One option:
  - Read the lowest level of the index
    - May be enough in many cases
  - But if relation not sorted, this leads to too many random accesses

- If relation small enough…
  - Read in memory, use quick sort (qsort() in C)

- What if relation too large to fit in memory?
  - External sort-merge
External sort-merge

- Divide and Conquer !!

- Let $M$ denote the memory size (in blocks)

- Phase 1:
  - Read first $M$ blocks of relation, sort, and write it to disk
  - Read the next $M$ blocks, sort, and write to disk …
  - Say we have to do this “$N$” times
  - Result: $N$ sorted runs of size $M$ blocks each

- Phase 2:
  - Merge the $N$ runs ($N$-way merge)
  - Can do it in one shot if $N < M$
External sort-merge

- **Phase 1:**
  - Create sorted runs of size $M$ each
  - Result: $N$ sorted runs of size $M$ blocks each

- **Phase 2:**
  - Merge the $N$ runs (*$N$-way merge*)
  - Can do it in one shot if $N < M$

- **What if $N > M$?**
  - Do it recursively
  - Not expected to happen
  - If $M = 1000$ blocks = 4MB (assuming blocks of 4KB each)
    - Can sort: 4000MB = 4GB of data
Example: External Sorting Using Sort-Merge

Initial relation:
- g 24
- a 24
- d 31
- c 33
- b 14
- e 16
- r 16
- d 21
- m 3
- p 2
- d 7
- a 14

Runs created:
- a 19
- d 31
- g 24
- b 14
- c 33
- d 31
- e 16
- g 24
- d 21
- m 3
- r 16
- a 14
- d 7
- p 2
- r 16

Merge pass 1:
- a 14
- d 7
- m 3
- p 2
- r 16

Merge pass 2:
- a 14
- d 7
- g 24
- m 3
- p 2
- r 16

Sorted output:
- a 14
- a 19
- b 14
- c 33
- d 7
- d 21
- d 31
- e 16
- g 24
- m 3
- p 2
- r 16
Cost analysis:

- Total number of merge passes required: \( \lceil \log_{M-1}(b_r/M) \rceil \).
- Disk accesses for initial run creation as well as in each pass is \( 2b_r \).
  - for final pass, we don’t count write cost
    - we ignore final write cost for all operations since the output of an operation may be sent to the parent operation without being written to disk

Thus total number of disk accesses for external sorting:

\[ b_r \left( 2 \lceil \log_{M-1}(b_r/M) \rceil + 1 \right) \]
Query Processing

- Overview
- Selection operation
- Join operators
- Sorting
- Other operators
- Putting it all together…
Join

- `select * from R, S where R.a = S.a`
  - Called an “equi-join”
- `select * from R, S where |R.a – S.a| < 0.5`
  - Not an “equi-join”

**Option 1:** Nested-loops

```
for each tuple r in R
  for each tuple s in S
    check if r.a = s.a (or whether |r.a – s.a| < 0.5)
```

- Can be used for any join condition
  - As opposed to some algorithms we will see later
- R called *outer relation*
- S called *inner relation*
Nested-loops Join

- Cost? Depends on the actual values of parameters, especially memory
- $b_r, b_s \rightarrow \text{Number of blocks of } R \text{ and } S$
- $n_r, n_s \rightarrow \text{Number of tuples of } R \text{ and } S$
- **Case 1:** Minimum memory required = 3 blocks
  - One to hold the current $R$ block, one for current $S$ block, one for the result being produced
  - Blocks transferred:
    - Must scan $R$ tuples once: $b_r$
    - For each $R$ tuple, must scan $S$: $n_r \times b_s$
  - Seeks?
    - $n_r + b_r$
Nested-loops Join

- **Case 1:** Minimum memory required = 3 blocks
  - Blocks transferred: \( n_r \times b_s + b_r \)
  - Seeks: \( n_r + b_r \)

- **Example:**
  - Number of records -- R: \( n_r = 10,000 \), S: \( n_s = 5000 \)
  - Number of blocks -- R: \( b_r = 400 \), S: \( b_s = 100 \)

- **Then:**
  - blocks transferred: \( 10000 \times 100 + 400 = 1,000,400 \)
  - seeks: 10400

- **What if we were to switch R and S?**
  - 2,000,100 block transfers, 5100 seeks

- **Matters**
Nested-loops Join

- **Case 2: S fits in memory**
  - Blocks transferred: $b_s + b_r$
  - Seeks: 2

- **Example:**
  - Number of records -- $R$: $n_r = 10,000$, $S$: $n_s = 5000$
  - Number of blocks -- $R$: $b_r = 400$, $S$: $b_s = 100$

- Then:
  - blocks transferred: $400 + 100 = 500$
  - seeks: 2

- This is orders of magnitude difference
Block Nested-loops Join

- Simple modification to “nested-loops join”
  - Block at a time
    
    \[
    \text{for each block } B_r \text{ in } R \\
    \text{for each block } B_s \text{ in } S \\
    \text{for each tuple } r \text{ in } B_r \\
    \text{for each tuple } s \text{ in } B_s \\
    \text{check if } r.a = s.a \text{ (or whether } |r.a - s.a| < 0.5)\]

- Case 1: Minimum memory required = 3 blocks
  - Blocks transferred: \(b_r \times b_s + b_r\)
  - Seeks: \(2 \times b_r\)

- For the example:
  - blocks: 40400, seeks: 800
Block Nested-loops Join

- **Case 1: Minimum memory required = 3 blocks**
  - Blocks transferred: $b_r \times b_s + b_r$
  - Seeks: $2 \times b_r$

- **Case 2: S fits in memory**
  - Blocks transferred: $b_s + b_r$
  - Seeks: 2

- **What about in between?**
  - Say there are 50 blocks, but S is 100 blocks
  - Why not use all the memory that we can...
**Block Nested-loops Join**

- **Case 3: 50 blocks (S = 100 blocks)**?
  
  ```plaintext
  for each group of 48 blocks in R
    for each block \( B_s \) in S
      for each tuple \( r \) in the group of 48 blocks
        for each tuple \( s \) in \( B_s \)
          check if \( r.a = s.a \) (or whether \( |r.a - s.a| < 0.5 \))
  ```

- **Why is this good?**
  - We only have to read \( S \) a total of \( b_r/48 \) times *(instead of \( b_r \) times)*
  - Blocks transferred: \( b_r * b_s / 48 + b_r \)
  - Seeks: \( 2 * b_r / 48 \)
Index Nested-loops Join

- `select * from R, S where R.a = S.a`
  - Called an “equi-join”
- Nested-loops
  
  \[
  \text{for each tuple } r \text{ in } R \\
  \hspace{1cm} \text{for each tuple } s \text{ in } S \\
  \hspace{2cm} \text{check if } r.a = s.a \text{ (or whether } |r.a - s.a| < 0.5)\\
  \]
- Suppose there is an index on `S.a`
- **Why not use the index instead of the inner loop?**
  
  \[
  \text{for each tuple } r \text{ in } R \\
  \hspace{1cm} \text{use the index to find } S \text{ tuples with } S.a = r.a \\
  \]
Index Nested-loops Join

- `select * from R, S where R.a = S.a`
  - Called an “equi-join”
- **Why not use the index instead of the inner loop?**
  - `for each tuple r in R`
  - `use the index to find S tuples with S.a = r.a`
- Cost of the join:
  - \( b_r (t_T + t_S) + n_r \cdot c \)
  - \( c == \text{the cost of index access} \)
    - *Computed using the formulas discussed earlier*
Index Nested-loops Join

- Restricted applicability
  - An appropriate index must exist
  - What about $|R.a - S.a| < 5$?

- Great for queries with joins and selections

```
select *
from accounts, customers
where accounts.customer-SSN = customers.customer-SSN and
    accounts.acct-number = "A-101"
```

- Only need to access one SSN from the other relation
So far...

- **Block Nested-loops join**
  - Can always be applied irrespective of the join condition
  - If the smaller relation fits in memory, then cost:
    - $b_r + b_s$
    - This is the best we can hope if we have to read the relations once each
  - CPU cost of the inner loop is high
  - Typically used when the smaller relation is really small (few tuples) and index nested-loops can’t be used

- **Index Nested-loops join**
  - Only applies if an appropriate index exists
  - Very useful when we have selections that return small number of tuples
    - `select balance from customer, accounts where customer.name = "j. s." and customer.SSN = accounts.SSN`
Hash Join

- Case 1: Smaller relation (S) fits in memory
- Nested-loops join:
  
  \[
  \text{for each tuple } r \text{ in } R \\
  \quad \text{for each tuple } s \text{ in } S \\
  \quad \text{check if } r.a = s.a \\
  \]

- Cost: $b_r + b_s$ transfers, 2 seeks
- The inner loop is not exactly cheap (high CPU cost)

- Hash join:
  
  \[
  \text{read } S \text{ in memory and build a hash index on it} \\
  \text{for each tuple } r \text{ in } R \\
  \quad \text{use the hash index on } S \text{ to find tuples such that } S.a = r.a \\
  \]
Hash Join

- Case 1: Smaller relation (S) fits in memory
- Hash join:
  
  \[ \text{read } S \text{ in memory and build a hash index on it} \]
  
  \[ \text{for each tuple } r \text{ in } R \]
  
  \[ \text{use the hash index on } S \text{ to find tuples such that } S.a = r.a \]

- Cost: \( b_r + b_s \) transfers, 2 seeks (unchanged)
- Why good?
  - CPU cost is much better (even though we don’t care about it too much)
  - Performs much better than nested-loops join when \( S \) doesn’t fit in memory (next)
Hash Join

- **Case 2: Smaller relation (S) doesn’t fit in memory**
- Two “phases”
- **Phase 1:**
  - Read the relation $R$ block by block and partition it using a hash function, $h1(a)$
    - Create one partition for each possible value of $h1(a)$
  - Write the partitions to disk
    - $R$ gets partitioned into $R1, R2, \ldots, Rk$
  - Similarly, read and partition $S$, and write partitions $S1, S2, \ldots, Sk$ to disk
  - Only requirement:
    - Each $S$ partition fits in memory
Hash Join

- **Case 2:** Smaller relation \((S)\) doesn’t fit in memory
- Two “phases”
- **Phase 2:**
  - Read \(S1\) into memory, and build a hash index on it \((S1\) fits in memory\)
    - Using a different hash function, \(h_2(a)\)
  - Read \(R1\) block by block, and use the hash index to find matches.
  - Repeat for \(S2, R2,\) and so on.
Hash Join

- **Case 2: Smaller relation \((S)\) doesn’t fit in memory**
- **Two “phases”:**
  - **Phase 1:**
    - Partition the relations using one hash function, \(h_1(a)\)
  - **Phase 2:**
    - Read \(S_i\) into memory, and build a hash index on it (\(S_i\) fits in memory)
    - Read \(R_i\) block by block, and use the hash index to find matches.
- **Cost ?**
  - \(3(b_r + b_s) + 4 \times n_h\) block transfers + \(2(\lfloor b_r/b_b \rfloor + \lfloor b_s/b_b \rfloor)\) seeks
    - Where \(b_b\) is the size of each output buffer
  - Much better than Nested-loops join under the same conditions
Hash Join

![Hash Join Diagram](image-url)
Hash Join: Issues

- How to guarantee that the partitions of S all fit in memory?
  - Say S = 10000 blocks, Memory = M = 100 blocks
  - Use a hash function that hashes to 100 different values?
    - Eg. \( h1(a) = a \mod 100 \) ?
  - Problem: Impossible to guarantee uniform split
    - Some partitions will be larger than 100 blocks, some will be smaller
  - Use a hash function that hashes to \( 100 \times f \) different values
    - \( f \) is called fudge factor, typically around 1.2
    - So we may consider \( h1(a) = a \mod 120 \).
    - This is okay IF \( a \) is uniformly distributed
Hash Join: Issues

- Memory required?
  - Say $S = 10000$ blocks, Memory = $M = 100$ blocks
  - So 120 different partitions
  - During phase 1:
    - Need 1 block for storing $R$
    - Need 120 blocks for storing each partition of $R$
  - So must have at least 121 blocks of memory
  - We only have 100 blocks

- Typically need $\sqrt{|S| \times f}$ blocks of memory

- So if $S$ is 10000 blocks, and $f = 1.2$, need 110 blocks of memory

- If memory = 10000 blocks = $10000 \times 4$ KB = 40MB (not unreasonable)
  - Then, $S$ can be as large as $10000 \times 10000 / 1.2$ blocks = 333 GB
Hash Join: Issues

- What if we don’t have enough memory?
  - Recursive Partitioning
  - Rarely used, but can be done

- What if the hash function turns out to be bad?
  - We used $h_1(a) = a \% 100$
  - Turns out all values of $a$ are multiple of 100
  - So $h_1(a)$ is always = 0
  - Called hash-table overflow

- Overflow avoidance: Use a good hash function
- Overflow resolution: Repartition using a different hash function
Hybrid Hash Join

- **Motivation:**
  - $R = 10000$ blocks, $S = 101$ blocks, $M = 100$ blocks
  - So $S$ doesn’t fit in memory

- **Phase 1:**
  - Use two partitions
    - Read 10000 blocks of $R$, write partitions $R_1$ and $R_2$ to disk
    - Read 101 blocks of $S$, write partitions $S_1$ and $S_2$ to disk
    - Only need 3 blocks for this (so remaining 97 blocks are being wasted)

- **Phase 2:**
  - Read $S_1$, build hash index, read $R_1$ and probe
  - Read $S_2$, build hash index, read $R_2$ and probe

- **Alternative:**
  - Don’t write partition $S_1$ to disk, just keep it memory – there is enough free memory for that
Hybrid Hash Join

- Motivation:
  - $R = 10000$ blocks, $S = 101$ blocks, $M = 100$ blocks
  - So $S$ doesn’t fit in memory

- Alternative:
  - Don’t write partition $S1$ to disk, just keep it in memory – there is enough free memory

- Steps:
  - Use a hash function such that $S1 = 90$ blocks, and $S2 = 10$ blocks
  - Read $S1$, and partition it
    - Write $S2$ to disk
    - Keep $S1$ in memory, and build a hash table on it
  - Read $R1$, and partition it
    - Write $R2$ to disk
    - Probe using $R1$ directly into the hash table
  - Saves huge amounts of I/O
So far...

- **Block Nested-loops join**
  - Can always be applied irrespective of the join condition

- **Index Nested-loops join**
  - Only applies if an appropriate index exists
  - Very useful when we have selections that return small number of tuples
    - `select balance from customer, accounts where customer.name = "j. s." and customer.SSN = accounts.SSN`

- **Hash joins**
  - Join algorithm of choice when the relations are large
  - Only applies to equi-joins (since it is hash-based)

- **Hybrid hash join**
  - An optimization on hash join that is always implemented
Merge-Join (Sort-merge join)

- Pre-condition:
  - The relations must be sorted by the join attribute
  - If not sorted, can sort first, and then use this algorithm
- Called “sort-merge join” sometimes

\[
\begin{align*}
\text{select} & \quad * \\
\text{from} & \quad r, s \\
\text{where} & \quad r.a1 = s.a1
\end{align*}
\]

**Step:**
1. Compare the tuples at pr and ps
2. Move pointers down the list
   - Depending on the join condition
3. Repeat
Merge-Join (Sort-merge join)

- **Cost:**
  - If the relations sorted, then just
    - \( b_r + b_s \) block transfers, some seeks depending on memory size
  - What if not sorted?
    - Then sort the relations first
    - In many cases, still very good performance
    - Typically comparable to hash join

- **Observation:**
  - The final join result will also be sorted on \( a1 \)
  - This might make further operations easier to do
    - E.g. duplicate elimination
Joins: Summary

- **Block Nested-loops join**
  - Can always be applied irrespective of the join condition

- **Index Nested-loops join**
  - Only applies if an appropriate index exists

- **Hash joins – only for equi-joins**
  - Join algorithm of choice when the relations are large

- **Hybrid hash join**
  - An optimization on hash join that is always implemented

- **Sort-merge join**
  - Very commonly used – especially since relations are typically sorted
  - Sorted results commonly desired at the output
    - To answer group by queries, for duplicate elimination, because of ASC/DSC
Query Processing

- Overview
- Selection operation
- Join operators
- Other operators
- Putting it all together…
- Sorting
Group By and Aggregation

```
select a, count(b)
from R
group by a;
```

- Hash-based algorithm
- Steps:
  - Create a hash table on `a`, and keep the `count(b)` so far
  - Read `R` tuples one by one
  - For a new `R` tuple, “r”
    - Check if `r.a` exists in the hash table
    - If yes, increment the count
    - If not, insert a new value
Group By and Aggregation

```sql
select a, count(b)
from R
group by a;
```

- Sort-based algorithm
- Steps:
  - Sort $R$ on $a$
  - Now all tuples in a single group are contiguous
  - Read tuples of $R$ (sorted) one by one and compute the aggregates
Group By and Aggregation

```
select a, AGGR(b) from R group by a;
```

- `sum()`, `count()`, `min()`, `max()`: only need to maintain one value per group
  - Called “distributive”
- `average()`: need to maintain the “sum” and “count” per group
  - Called “algebraic”
- `stddev()`: algebraic, but need to maintain some more state
- `median()`: can do efficiently with sort, but need two passes (called “holistic”)
  - First to find the number of tuples in each group, and then to find the median tuple in each group
- `count(distinct b)`: must do duplicate elimination before the count
Duplicate Elimination

\[
\text{select distinct } a \\
\text{from } R ;
\]

- Best done using sorting – Can also be done using hashing
- Steps:
  - Sort the relation \( R \)
  - Read tuples of \( R \) in sorted order
  - \( \text{prev} = \text{null} \)
  - for each tuple \( r \) in \( R \) (sorted)
    - if \( r \neq \text{prev} \) then
      - Output \( r \)
      - \( \text{prev} = r \)
    - else
      - Skip \( r \)
Set operations

(select * from R) union (select * from S) ;
(select * from R) intersect (select * from S) ;
(select * from R) union all (select * from S) ;
(select * from R) intersect all (select * from S) ;

- Remember the rules about duplicates
- "union all": just append the tuples of \( R \) and \( S \)
- "union": append the tuples of \( R \) and \( S \), and do duplicate elimination
- "intersection": similar to joins
  - Find tuples of \( R \) and \( S \) that are identical on all attributes
  - Can use hash-based or sort-based algorithm
Query Processing

- Overview
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- Sorting
Evaluation of Expressions

Two options:
- Materialization
- Pipelining

select customer-name from account a, customer c where a.SSN = c.SSN and a.balance < 2500
**Evaluation of Expressions**

- **Materialization**
  - Evaluate each expression separately
  - Store its result on disk in *temporary relations*
  - Read it for next operation

- **Pipelining**
  - Evaluate multiple operators simultaneously
  - Skip the step of going to disk
  - Usually faster, but requires more memory
  - Also not always possible..
    - E.g. Sort-Merge Join
  - Harder to reason about
Materialization

- Materialized evaluation is always applicable
- Cost of writing results to disk and reading them back can be quite high
  - Our cost formulas for operations ignore cost of writing results to disk, so
    - Overall cost = Sum of costs of individual operations + cost of writing intermediate results to disk
- **Double buffering**: use two output buffers for each operation, when one is full write it to disk, while the other is getting filled
  - Allows overlap of disk writes with computation and reduces execution time
Pipelining

- Evaluate several operations simultaneously, passing the results of one operation on to the next.
- E.g., in previous expression tree, don’t store result of

  \[ \sigma_{balance<2500}(account) \]

  - instead, pass tuples directly to the join. Similarly, don’t store result of join, pass tuples directly to projection.
- Much cheaper: no need to store a temporary relation to disk.
- Requires higher amount of memory
  - All operations are executing at the same time (say as processes)
- Somewhat limited applicability
- A “blocking” operation: An operation that has to consume entire input before it starts producing output tuples
Pipelining

- Need operators that generate output tuples while receiving tuples from their inputs
  - Selection: Usually yes.
  - Sort: NO. The sort operation is blocking
  - Sort-merge join: The final (merge) phase can be pipelined
  - Hash join: The partitioning phase is blocking; the second phase can be pipelined
  - Aggregates: Typically no. Need to wait for the entire input before producing output
    - However, there are tricks you can play here
  - Duplicate elimination: Since it requires sort, the final merge phase could be pipelined
  - Set operations: see duplicate elimination
Pipelining: Demand-driven

- **Iterator Interface**
  - Each operator implements:
    - `init()`: Initialize the state (sometimes called open())
    - `get_next()`: get the next tuple from the operator
    - `close()`: Finish and clean up

- **Sequential Scan**:
  - `init()`: open the file
  - `get_next()`: get the next tuple from file
  - `close()`: close the file

- Execute by repeatedly calling `get_next()` at the root
  - root calls `get_next()` on its children, the children call `get_next()` on their children etc...

- The operators need to maintain internal state so they know what to do when the parent calls `get_next()`
Hash-Join Iterator Interface

- **open()**:  
  - Call open() on the left and the right children  
  - Decide if partitioning is needed (if size of smaller relation > allotted memory)  
  - Create a hash table

- **get_next()**: ((( assuming no partitioning needed )))
  - First call:  
    - Get all tuples from the right child one by one (using get_next()), and insert them into the hash table  
    - Read the first tuple from the left child (using get_next())
  - All calls:  
    - Probe into the hash table using the “current” tuple from the left child  
      - Read a new tuple from left child if needed  
    - Return exactly “one result”  
      - Must keep track if more results need to be returned for that tuple
Hash-Join Iterator Interface

- close():
  - Call close() on the left and the right children
  - Delete the hash table, other intermediate state etc…

- get_next(): (((partitioning needed )))
  - First call:
    - Get all tuples from both children and create the partitions on disk
    - Read the first partition for the right child and populate the hash table
    - Read the first tuple from the left child from appropriate partition
  - All calls:
    - Once a partition is finished, clear the hash table, read in a new partition from
      the right child, and re-populate the hash table
  - Not that much more complicated

- Take a look at the postgresQL codebase
Pipelining (Cont.)

- In produce-driven or **eager** pipelining
  - Operators produce tuples eagerly and pass them up to their parents
    - Buffer maintained between operators, child puts tuples in buffer, parent removes tuples from buffer
    - if buffer is full, child waits till there is space in the buffer, and then generates more tuples
  - System schedules operations that have space in output buffer and can process more input tuples
Recap: Query Processing

- Many, many ways to implement the relational operations
  - Numerous more used in practice
  - Especially in data warehouses which handles TBs (even PBs) of data
- However, consider how complex SQL is and how much you can do with it
  - Compared to that, this isn’t much
- Most of it is very nicely modular
  - Especially through use of the `iterator()` interface
  - Can plug in new operators quite easily
  - PostgreSQL query processing codebase very easy to read and modify
- Having so many operators does complicate the codebase and the query optimizer though
  - But needed for performance