Physical Data Organization and Indexing

Introduction to Databases

CompSci 316 Fall 2017

DUKE COMPUTER SCIENCE

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Announcements (Wed., Mar. 8)

- Homework #3
  - follow piazza posts for updates after each lecture
- Project
  - Comments on milestone-1 tomorrow
  - Keep working on it

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Today:

- Finish B+ tree and index
- Start query processing

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Index

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Recall: What are indexes for?

- Given a value (search key), locate the record(s) with this value, or range search
  - SELECT * FROM *R* WHERE *A* = *value*;
  - SELECT * FROM *R*, *S* WHERE *R.A* = *S.B*;
  - SELECT * FROM *R* WHERE *A* > *value*;
- Search key ≠ key in a relation (unique attributes)
  - "Key" is highly overloaded in databases
- Recap: index structure on whiteboard

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Recall: Index classification

- Dense vs. Sparse
- Clustered vs. unclustered
- Primary vs. Secondary
- Tree-based vs. Hash-based
  - we will only do tree indexes in 316

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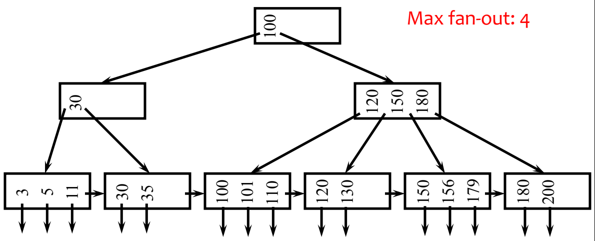
Recall: B+-tree

- A hierarchy of nodes with intervals
- Balanced (more or less): good performance guarantee
- Disk-based: one node per block; large fan-out



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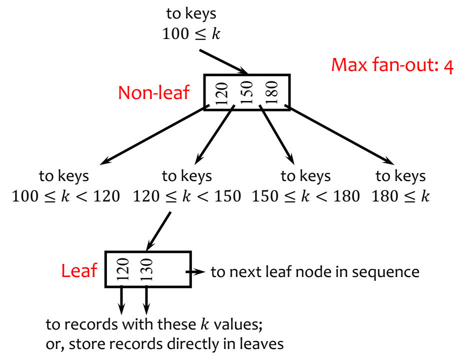
Recall: Sample B+-tree nodes



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Recall: B+-tree balancing properties

- Height constraint: all leaves at the same lowest level
- Fan-out constraint: all nodes at least half full (except root)

	Max # pointers	Max # keys	Min # active pointers	Min # keys
Non-leaf	f	$f-1$	$\lceil f/2 \rceil$	$\lceil f/2 \rceil - 1$
Root	f	$f-1$	2	1
Leaf	f	$f-1$	$\lfloor f/2 \rfloor$	$\lfloor f/2 \rfloor$

End of lecture 14

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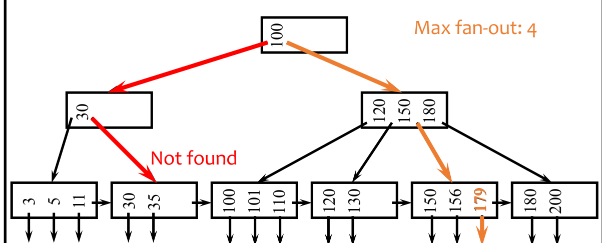
Lookups

- SELECT * FROM R WHERE $k = 179$;
- SELECT * FROM R WHERE $k = 32$;



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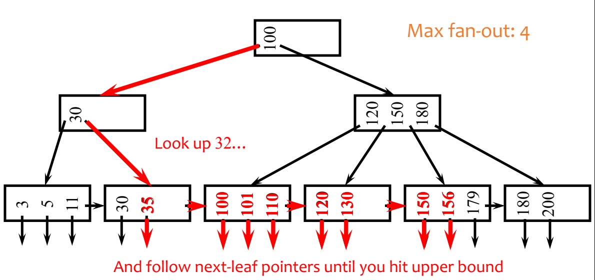
Range query

- SELECT * FROM R WHERE $k > 32$ AND $k < 179$;



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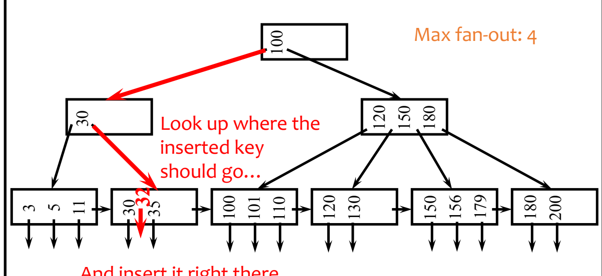
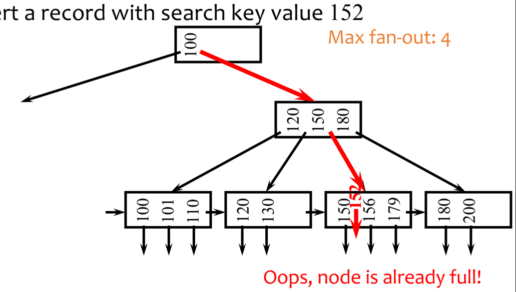
Insertion

- Insert a record with search key value 32

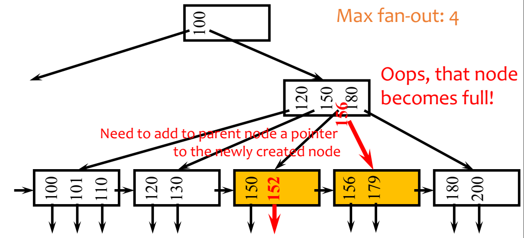


Another insertion example

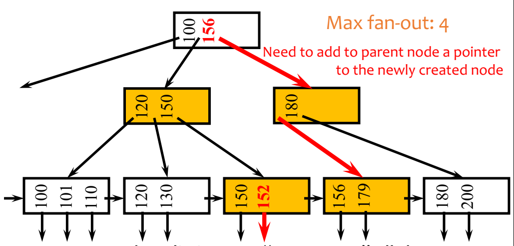
- Insert a record with search key value 152



Node splitting



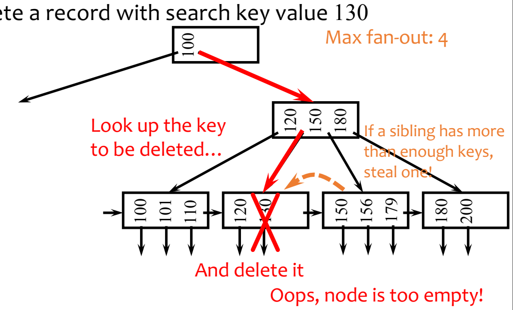
More node splitting



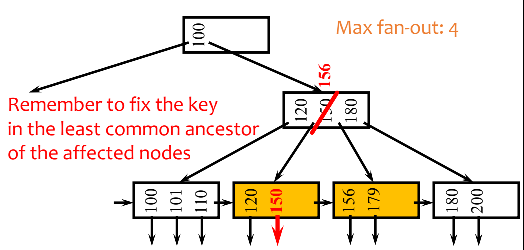
- In the worst case, node splitting can "propagate" all the way up to the root of the tree (not illustrated here)
  - Splitting the root introduces a new root of fan-out 2 and causes the tree to grow "up" by one level

Deletion

- Delete a record with search key value 130

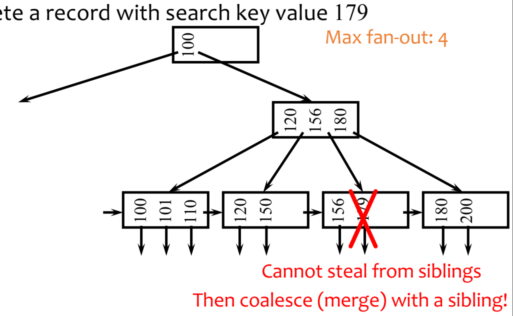


Stealing from a sibling



Another deletion example

- Delete a record with search key value 179



Coalescing

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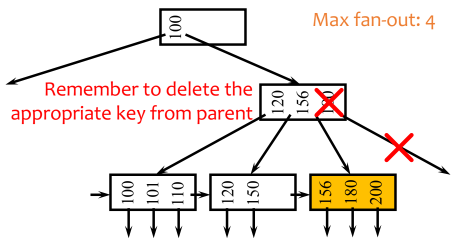

- Deletion can "propagate" all the way up to the root of the tree (not illustrated here)
  - When the root becomes empty, the tree "shrinks" by one level

Performance analysis

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- How many I/O's are required for each operation?
  - h, the height of the tree (more or less)
  - Plus one or two to manipulate actual records
  - Plus $O(h)$ for reorganization (rare if f is large)
  - Minus one if we cache the root in memory
- How big is h?
  - Roughly $\log_{\text{fanout}} N$, where N is the number of records
  - B⁺-tree properties guarantee that fan-out is least $f/2$ for all non-root nodes
  - Fan-out is typically large (in hundreds)—many keys and pointers can fit into one block
  - A 4-level B⁺-tree is enough for "typical" tables

B⁺-tree in practice

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- Complex reorganization for deletion often is not implemented (e.g., Oracle)
  - Leave nodes less than half full and periodically reorganize
- Most commercial DBMS use B⁺-tree instead of hashing-based indexes because B⁺-tree handles range queries

The Halloween Problem

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- Story from the early days of System R…

```
UPDATE Payroll
SET salary = salary * 1.1
WHERE salary <= 25000;
```

  - There is a B⁺-tree index on *Payroll*(*salary*)
  - The update never stopped until all employees earned 25k (why?)
- Solutions?

https://en.wikipedia.org/wiki/Halloween_Problem

B⁺-tree versus ISAM

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- ISAM is more static; B⁺-tree is more dynamic
- ISAM can be more compact (at least initially)
  - Fewer levels and I/O's than B⁺-tree
- Overtime, ISAM may not be balanced
  - Cannot provide guaranteed performance as B⁺-tree does

B⁺-tree versus B-tree

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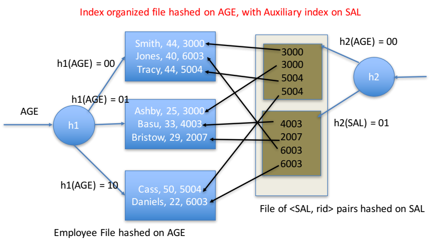
- B-tree: why not store records (or record pointers) in non-leaf nodes?
  - These records can be accessed with fewer I/O's
- Problems?
  - Storing more data in a node decreases fan-out and increases h
  - Records in leaves require more I/O's to access
  - Vast majority of the records live in leaves!

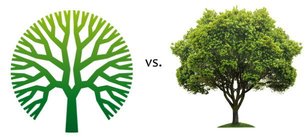
B+ tree vs. Hash-based indexes

- Extensible hashing, linear hashing, etc.
- Can only handle "=" in join or selection
  - Cannot handle range predicates >, ≥, <, ≤



Beyond ISAM, B-, and B⁺-trees, and hash

- Other tree-based indexes: R-trees and variants, GiST, etc.
  - How about binary tree?



- Text indexes: inverted-list index, suffix arrays, etc.
- Other tricks: bitmap index, bit-sliced index, etc.

Query Processing

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

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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

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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

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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: $B(R) + \left\lceil \frac{B(R)}{M-2} \right\rceil \cdot B(S)$
    - Or, roughly: $B(R) \cdot B(S)/M$
  - Memory requirement: M (as much as possible)
- Which table would you pick as the outer?

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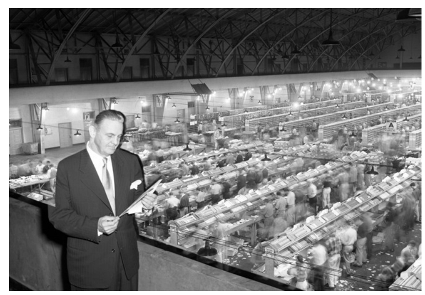
Sorting-based algorithms



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

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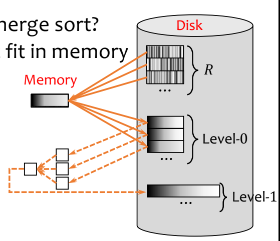
External merge sort

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

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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

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- Pass 0: read M blocks of R at a time, sort them, and write out a level-0 run
  - There are $\left\lceil \frac{B(R)}{M} \right\rceil$ 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 = $\left\lceil \frac{\text{\# of level-}(i-1)\text{ runs}}{M-1} \right\rceil$
- Final pass produces one sorted run

Performance of external merge sort

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- Number of passes: $\left\lceil \log_{M-1} \left\lceil \frac{B(R)}{M} \right\rceil \right\rceil + 1$
- 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

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- 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

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$R \bowtie_{R.A=S.B} S$

- 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

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R:	S:	$R \bowtie_{R.A=S.B} S$:
$r_1.A = 1$	$s_1.B = 1$	$r_1 s_1$
$r_2.A = 3$	$s_2.B = 2$	$r_2 s_3$
$r_3.A = 3$	$s_3.B = 3$	$r_2 s_4$
$r_4.A = 5$	$s_4.B = 3$	$r_3 s_3$
$r_5.A = 7$	$s_5.B = 8$	$r_3 s_4$
$r_6.A = 7$		$r_7 s_5$
$r_7.A = 8$		

Optimization of SMJ

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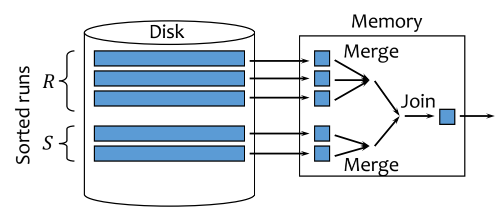
- Idea: combine join with the (last) merge phase of merge sort
- Sort: produce sorted runs for R and S such that there are fewer than M of them total
- Merge and join: merge the runs of R, merge the runs of S, and merge-join the result streams as they are generated!



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(…)

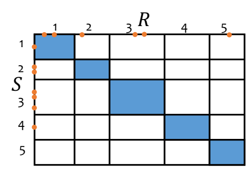
Hashing-based algorithms

http://global.rakuten.com/en/store/citygas/item/041233/

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

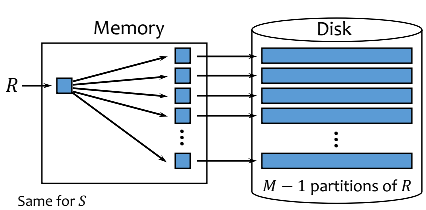


Nested-loop join considers all slots

Hash join considers only those along the diagonal!

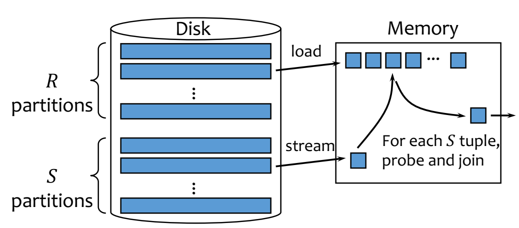
Partitioning phase

- 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!



Performance of (two-pass) hash join

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- If hash join completes in two passes:
  - I/O's: $3 \cdot \big(B(R) + B(S)\big)$
  - 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: $M > \sqrt{\min\big(B(R), B(S)\big)} + 1$

Generalizing for larger inputs

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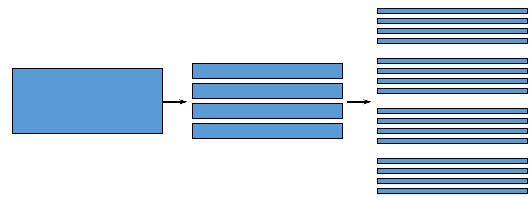
- What if a partition is too large for memory?
  - Read it back in and partition it again!
    - See the duality in multi-pass merge sort here?



Hash join versus SMJ

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(Assuming two-pass)

- I/O's: same
- Memory requirement: hash join is lower
  - $\sqrt{\min\big(B(R), B(S)\big)} + 1 < \sqrt{B(R) + B(S)}$
  - 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?

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- 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

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- 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

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- 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://i1.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 $\sigma_{A>v}(R)$ 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 $A > v$
    - Could happen even for equality predicates
  - I/O's for index-based selection: lookup + 20% $|R|$
  - I/O's for scan-based selection: $B(R)$
  - Table scan wins if a block contains more than 5 tuples!

Index nested-loop join

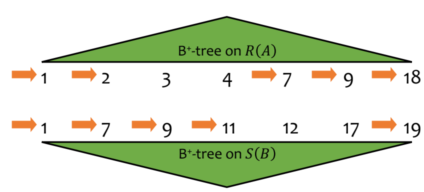
$R \bowtie_{R.A=S.B} S$

- 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



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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