Advanced Databases

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Course logistics

- *Lecturer*: Stratis Viglas
  - *email*: `sviglas@inf.ed.ac.uk`
- *Days/Times*: Mon & Thu, 11:10-12:00
- *Office hours*: Mon, Thu 12:00-13:00 (or, by appointment)
  - *Room*: IF, 5.11
- *Course webpage*: `www.inf.ed.ac.uk/teaching/courses/adbs`
- *Mailing list*: `adbs-students@inf.ed.ac.uk`

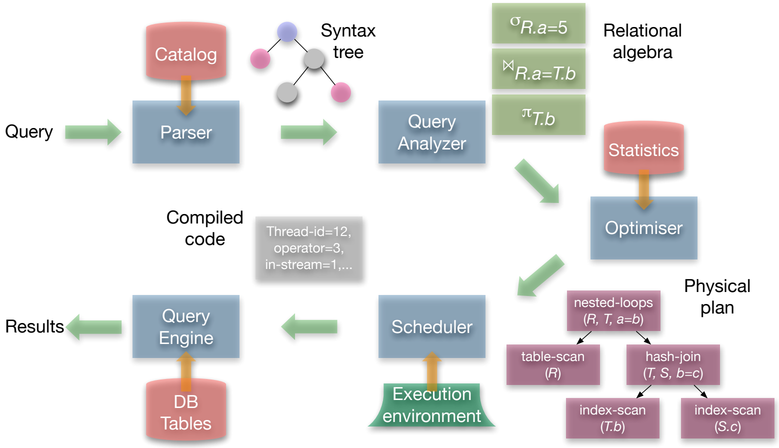
Syllabus

- Introduction
- Relational databases *overview*
  - *Data* model, *evaluation* model
- *Storage*
  - *Indexes*, *multidimensional* data
- Query *evaluation*
  - *Join* evaluation *algorithms*, *execution* models
- Query *optimisation*
  - *Cost* models, search space *exploration*, *randomised* optimisation
- *Concurrency* control and *recovery*
  - *Locking* and *transaction* processing
- *Parallel* databases

Assignments and software

- *Programming* assignments
- The *attica* database system
  - Home-grown *RDBMS*, written in Java
  - Visit `inf.ed.ac.uk/teaching/courses/adbs/attica` to download the system and the API documentation
  - *All* programming assignments will be using the *attica* front-end and code-base
- *Plagiarism policy*: You cheat, you're caught, you fail
  - *No* discussion

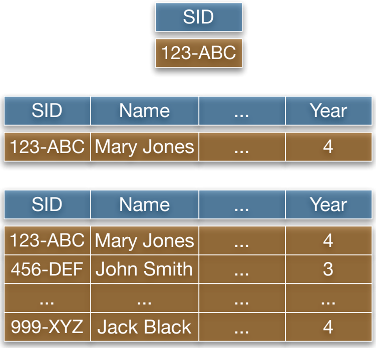
Query cycle



Query
Catalog
Parser
Syntax tree
Query Analyzer
$\sigma_{R.a=5}$
$\bowtie_{R.a=T.b}$
$\pi_{T.b}$
Relational algebra
Statistics
Optimiser
Physical plan
nested-loops (R, T, a=b)
table-scan (R)
hash-join (T, S, b=c)
index-scan (T.b)
index-scan (S.c)
Scheduler
Execution environment
Compiled code
Thread-id=12, operator=3, in-stream=1,...
Query Engine
DB Tables
Results

Three basic building blocks

- *Attribute*
  - A (name, value) *pair*
- *Tuple*
  - A *set* of attributes
- *Relation*
  - A *set* of tuples with the same schema



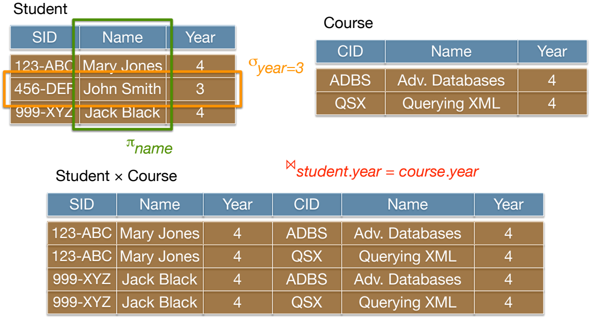
SID
123-ABC

SID	Name	...	Year
123-ABC	Mary Jones	...	4

SID	Name	...	Year
123-ABC	Mary Jones	...	4
456-DEF	John Smith	...	3
...	...	...	...
999-XYZ	Jack Black	...	4

Data manipulation

- Operations to *isolate* a *subset* of a *single relation*: Selection (σ), Projection (π)
- All *set operations*: Intersection, union, Cartesian product, set difference
- More *complex* operations: *Joins* ($\bowtie$), semi-joins, . . .



Student

SID	Name	Year
123-ABC	Mary Jones	4
456-DEF	John Smith	3
999-XYZ	Jack Black	4

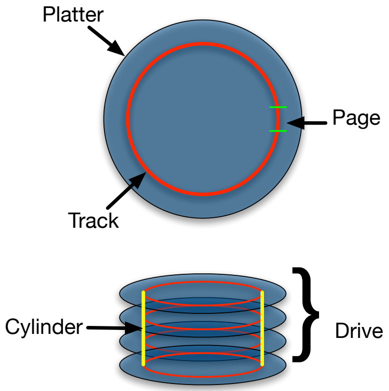
Course

CID	Name	Year
ADBS	Adv. Databases	4
QSX	Querying XML	4

Student × Course

SID	Name	Year	CID	Name	Year
123-ABC	Mary Jones	4	ADBS	Adv. Databases	4
123-ABC	Mary Jones	4	QSX	Querying XML	4
999-XYZ	Jack Black	4	ADBS	Adv. Databases	4
999-XYZ	Jack Black	4	QSX	Querying XML	4

Data storage



- *Disk drives* are *organised* in *records* of *512 bytes*
- The DB (and the OS) *I/O unit* is a *disk page* (typically, 4,096 bytes long)
- *Pages* (and records) are *stored* on *tracks*
- *Tracks* make up a *platter* (or a disk)
- *Platters* make up a *drive*
- The *same tracks* across all *platters* make up a *cylinder*
- The *disk head* (arm) reads the *same block* of *all tracks* on *all platters*

A bit of perspective

- The *dimensions* of the *head* are *impressive*[1]. With a *width* of less than a *hundred nanometers* and a *thickness* of about *ten*, it flies above the platter at a *speed* of up to *15,000 RPM*, at a *height* that is the equivalent of *40 atoms*. If you start multiplying these infinitesimally small numbers, you begin to get an idea of their significance.
- Consider this little *comparison*: if the *read/write head* were a *Boeing 747*, and the *hard-disk platter* were the *surface of the Earth*
  - The *head* would *fly* at *Mach 800*
  - At less than *one centimeter* from the *ground*
  - And *count every blade of grass*
  - Making *fewer than 10* unrecoverable counting *errors* in an *area* equivalent to all of *Ireland*

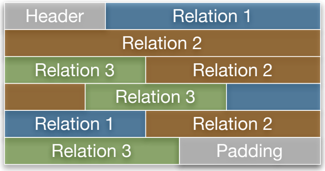
[1]Source: Matthieu Lamelot, Tom's Hardware.

What about flash memory and solid state?

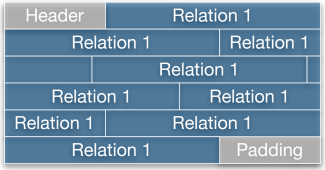
- The *geometry* is different
  - There are no tracks, or platters, or cylinders or anything of the sort
- But the *issues* are *similar*
  - Data is still accessed in *blocks*
  - Blocks are still organised in *pages*
  - *Sequential vs. random* I/O is still a *problem*
- Most of the things we say in this course are *applicable* to solid state as well
  - Added *complexity*: *write/read asymmetry*

Storing tuples

- Every *disk block* contains
  - A *header*
  - *Data* (*i.e.*, tuples)
  - *Padding* (maybe)
- *Two ways* of storing tuples
  - Either *interleave tuples* of multiple relations, or
  - Keep the tuples of the *same relation clustered*



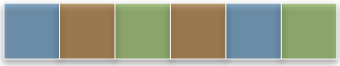
Interleaved tuples

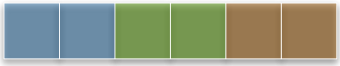


Clustered tuples

Advantages of clustering

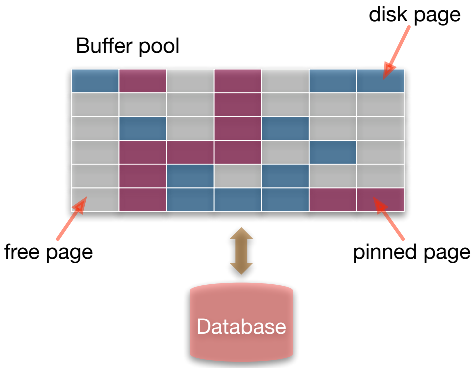
- *Scan* a relation of *X tuples*, *Y tuples per block*
  - If *unclustered*, worst case scenario: *read X blocks*
  - *Clustered*: *read X/Y blocks*
- How about *clustering* disk *blocks*?
  - *Reduces* unnecessary arm *movement*


Unclustered storage

Clustered storage


The buffer manager

- Though the *data* is *on disk*, real *processing* is in *main memory*
- Disk blocks are read and put into the *buffer pool*
  - A collection of *memory pages*
- The *buffer manager* manages the buffer pool
  - Keeping track of *page references*, *replacing pages* if full, . . .



What does the buffer manager do?

- When a *page is requested* it:
  - Checks to see *if the page is in* the buffer pool; if so *it returns it*
  - If not, it *checks whether there is room* in the buffer pool; if so *it reads it in and places it in the available room*
  - If not, it *picks a page for replacement*; if the page has been "touched" it *writes the page to disk and replaces it*
  - In all three cases, it *updates the reference count* for the requested page
  - If necessary, it *pins the new page*
  - It *returns* a *handle to the new page*

Page replacement

- *Least recently used* (LRU): check the number of references for each page; replace a page from the group with the lowest count (usually implemented with a priority queue)
  - Variant: *clock replacement*
- *First In First Out* (FIFO)
- *Most recently used* (MRU): the inverse of LRU
- *Random*!

Why not use the OS

- The OS implements virtual memory, so why not use it?
  - *Page reference patterns* and *pre-fetching*: the RDBMS in most cases *knows which page will be accessed later* (think of a clustered sequential scan)
  - Different *page replacement policies* according to the *reference pattern* (check p. 322 of your book)
  - *Page pinning*: certain *pages should not be replaced*
  - *Control* over *when a page is written to disk*: at times, pages need to be *forced to disk* (we'll revisit that when discussing crash recovery)

Indexing and sorting

- Can be summarised as:
  - *Forget whatever you've learned about indexing, searching and sorting in main memory* (well, almost ...)
- Remember, we are *operating over disk files*
  - The main idea is to *minimise disk I/O* and *not number of comparisons* (*i.e.*, complexity)
  - Just an idea: *comparing two values* in *memory* costs $4.91 \cdot 10^{-8}$ *seconds*; Comparing two values on *disk* costs $18.2 \cdot 10^{-5}$ seconds (3 orders of magnitude more expensive.)

Indexing functionality

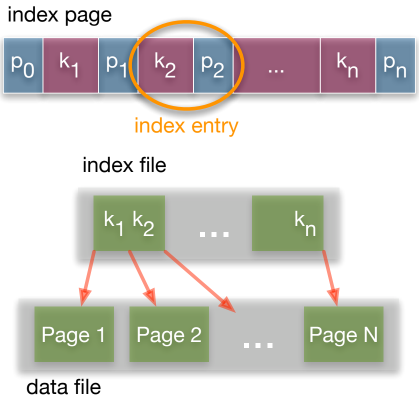
- Indexes can be used for:
  - *Lookup* queries (*e.g.*, [...] `where value = ‘‘foo’’`)
  - *Range* queries (*e.g.*, [...] `where value between 20 and 45`)
  - *Join processing* (after all, predicates are value-based, aren't they?)
- The above uses, and much more, are what we call *access methods*

Two main classes

- *Tree-structured* indexes
  - Much like you would use a binary tree to search, but with a *higher key-per-node cardinality*
  - Retains *order*
  - Great for *range queries*
  - Both *one*-dimensional and *multi*-dimensional
- *Hash-based* indexes
  - Fully *randomized* (*i.e.*, no order)
  - Great for single *lookup queries*

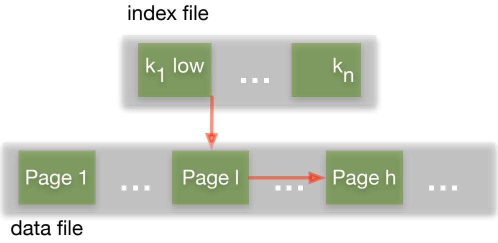
Sorted indexes

- The basic idea:
  - An *index* is on *an (collection of) attribute(s)* of a relation (called the *index key*)
  - It is *much smaller* than the relation
  - Index pages contain *(key, pointer) pairs*
    - ★ *key* of the *index*
    - ★ *pointer* to the *data page*
  - Plus one additional pointer (*low key*)



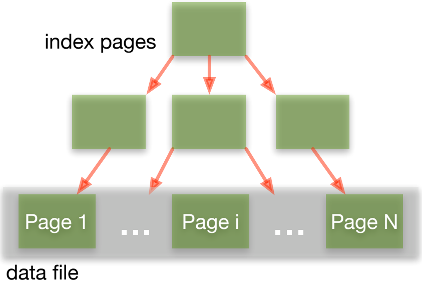
How does it answer range queries?

- Query is
  low ≤ value ≤ high
- Do a *binary search* on the *index file* to identify the *page containing the low key*
- *Keep scanning* the data file until the *high key* is *found*
- All *done*!

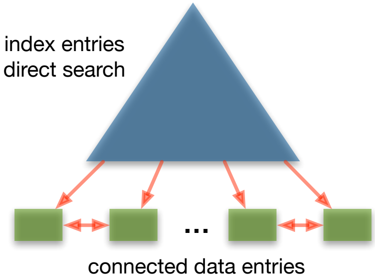


Potential problem (and the solution)

- The *index* is *much smaller* than the *relation*, but it's *still big*
- *Binary search* on it is *still expensive*
  - Remember, *data* is *on disk*
  - Have to access *half the index file pages*, *plus the pages satisfying the predicate*, all doing *random I/O*
- Why not build an *index on the index*?
  - *Tree*!

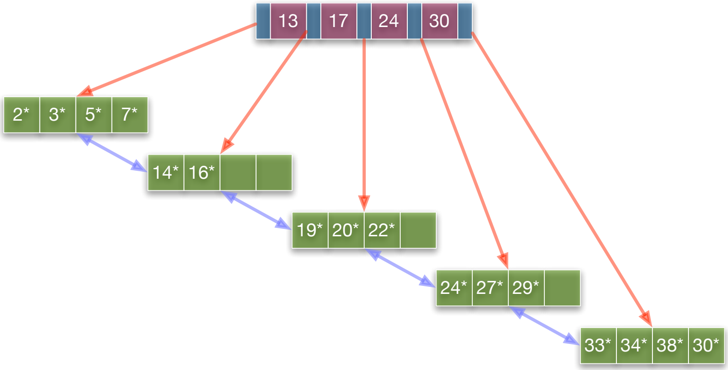


B+trees: the most widely used indexes



- *Insertion/deletion* at $\log_f N$ *cost* (f = fanout, N = # leaf pages)
- Tree is *height-balanced*
- Minimum *50% occupancy* (except for root)
- Characterised by its *order d*; *each node* contains $d \leq m \leq 2d$ *entries*
- *Equality* and *range* searches are *efficient*

B+tree example



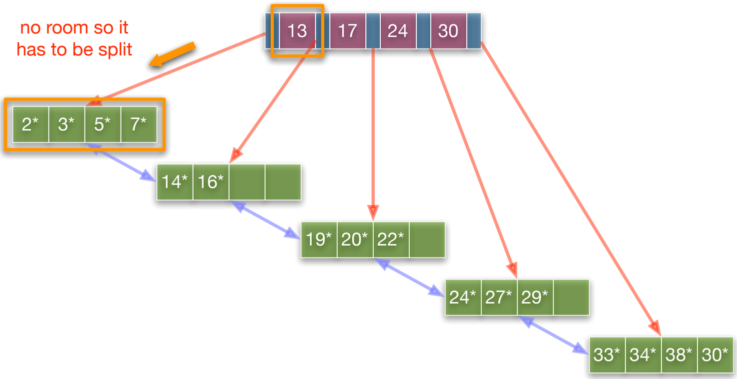
B+trees in practice

- Typical *order*: *100*, typical *fill-factor*: *67%*
  - Average *fan-out*: *133*
- Typical capacities
  - Height *3*: *2,532,637*
  - Height *4*: *312,900,700* (!)
- The *top levels* can often be kept *in memory*
  - 1st level: 4,096, or 8,192 bytes (1 page)
  - 2nd level: 0.5, or 1MB (133 pages)
  - 3rd level: 62, or 133MB

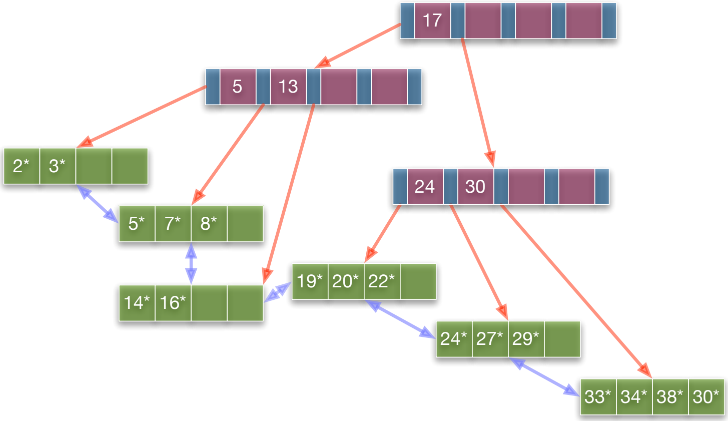
B+tree insertion

- *Find* correct *leaf L*
- *Put* data entry into L
  - *If* there is *enough space* in L, *done*!
  - *If* there is *no space*, L needs to be *split* into L and L'
  - *Redistribute* entries evenly in L and L'
  - *Insert index entry* pointing to L' into the *parent of L*
- *Ascend* the tree *recursively*, *splitting* and *redistributing* as needed
- *Tree tries to grow horizontally*; *worst case* scenario: a *root split* increases the height of the tree

B+tree insertion: 8*



B+tree insertion: 8*



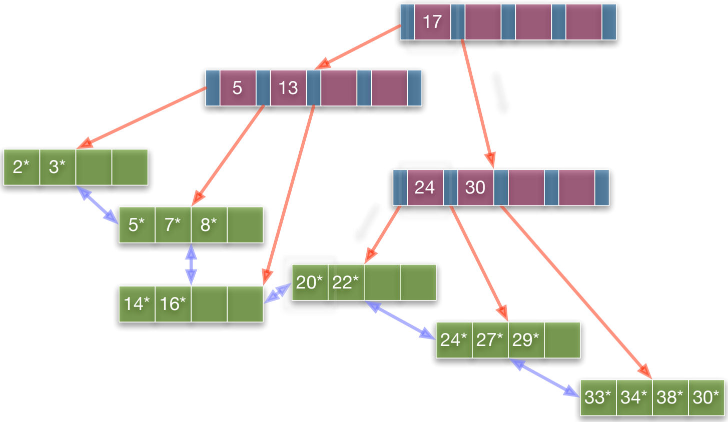
Insertion observations

- *Minimum occupancy* is *guaranteed* at both *leaf and non-leaf* pages
- A *leaf split* leads to *copying* the key; a *non-leaf* split leads into *pushing up* the key (*why?*)
- The tree tries to *first grow horizontally* and if this is not possible, *then vertically*
  - In the example we could have *avoided* the *extra level* by *redistributing*
  - But *in practice* this is *hardly ever done* (why?)

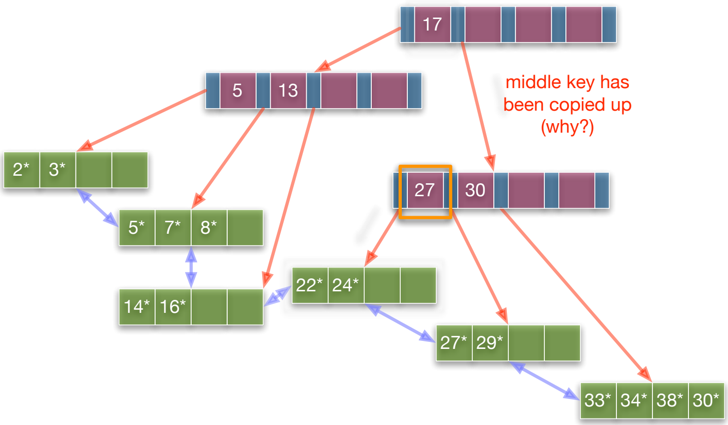
B+tree deletion

- *Find leaf L* where entry belongs
  - *Remove* the entry
  - If *L is half-full*, *done*!
  - If *L only has $d - 1$* entries
    - ⋆ Try to *redistribute* entries, *borrowing* from an *adjacent sibling* of *L*
    - ⋆ If *redistribution fails*, *merge L* and its *sibling*
    - ⋆ If *merge has occurred*, *delete* the *entry* for the *merged page* from the *parent of L*
- *Ascend* the tree *recursively*, performing the same algorithm
- *Merge* could *propagate to the root*, *decreasing* the trees *height*

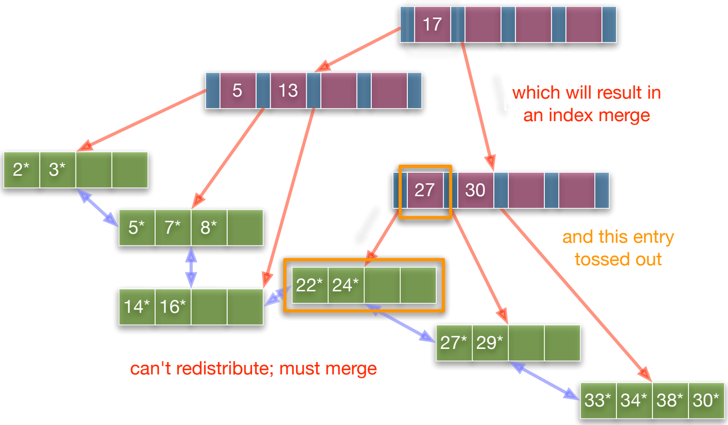
B+tree deletion: 19*



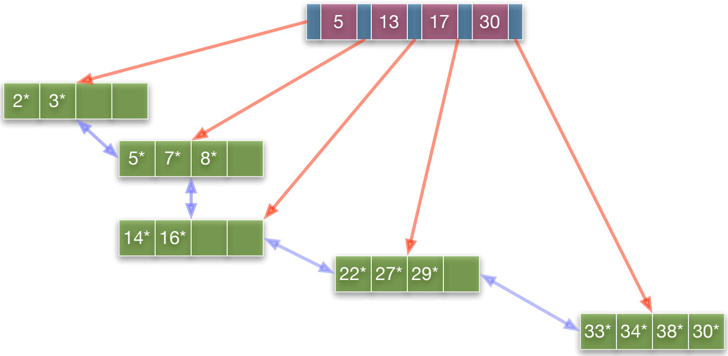
B+tree deletion: 20*



B+tree deletion: 24*


17
5
13
27
30
2*
3*
5*
7*
8*
14*
16*
22*
24*
27*
29*
33*
34*
38*
30*
which will result in an index merge
and this entry tossed out
can't redistribute; must merge

B+tree after deletion of 24*



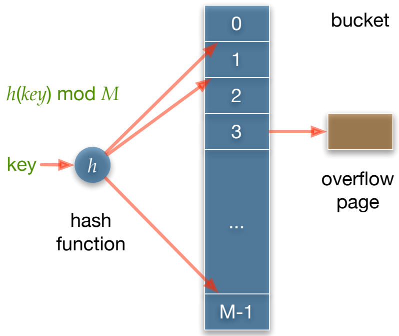
Summary of B+tree indexes

- *Ideal* for *range searches*, *good* for *equality searches*
- Highly *dynamic* structure
  - *Insertions* and *deletions* leave tree *height-balanced*, $\log_f N$ *cost*
  - For most *typical implementations*, *height* is *rarely greater* than *3 or 4*, occupancy at 67%
  - Which means that the *index is almost always in memory*! (remember the buffer pool?)
  - Almost always *better than* maintaining a *sorted file*
  - The *most optimised RDBMS structure*

Hash indexes

- *Hash-based indexes* are *good* for *equality* selections, *not* for *range* selections
  - In fact, they *cannot support range* selections (why?)
- *Static* and *dynamic techniques* exist here as well
  - *Trade-offs* similar to those between ISAM and B+trees

Static hashing



- *Number of primary pages fixed*
  - *Allocated sequentially*, never de-allocated
  - *Overflow pages* if needed
- $h(k) \mod M =$ bucket to which *data entry* with *key k* belongs ($M =$ number of buckets)

Static hashing observations

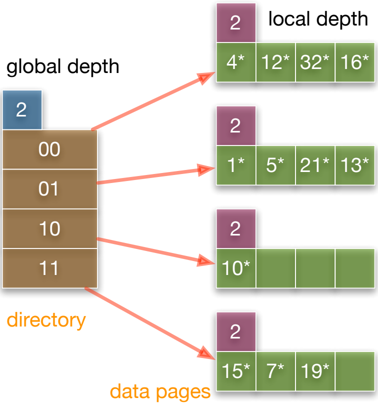
- The *buckets contain* the *actual data*!
  - But *only* the *key* is *hashed*
  - *No secondary index* like in the tree case
- The *hash function must uniformly distribute* the *keys* across all buckets
  - Lots of ways to *tune* the hash function
- Again, *long overflow chains* of pages will develop, and pretty soon we're doing *random I/O*
  - *Need* a *dynamic* technique (big surprise here...)
  - *Extendible hashing* to the rescue

Extendible hashing

- *Problem*: *bucket* (*i.e.*, primary page) becomes *full*
- *Solution*: *re-organize* the file by *doubling the number of buckets*
    - *Are you crazy*? Reading and writing out everything is *expensive*!
    - Why not *keep a directory of buckets* and *double only* the *directory*? Only *read* the *bucket* that *overflowed*
    - *Directory* much *smaller*; *operation* much *cheaper*

Extendible hashing example

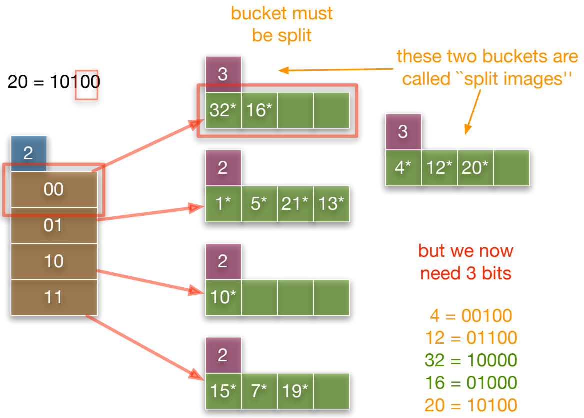
- *Directory*: *array* of *size 4*
- *Key k*, apply *hash function $h(k)$* and *translate* the result to *binary*
  - *e.g.*, $h(k) = 5 = 101$
- Last *global depth number of bits* identify the *bucket*



Global, local depth and doubling

- *Global depth* (pertains to *directory*): maximum *number of bits* needed to tell which *bucket an entry belongs to*
- *Local depth* (pertains to *bucket*): maximum *number of bits* needed to tell whether an *entry belongs to this bucket*
- *Before* insertion ($local = global$) holds; *if insertion causes* ($local > global$) then *directory* needs to be *doubled*

Insertion example: $h(k) = 20$

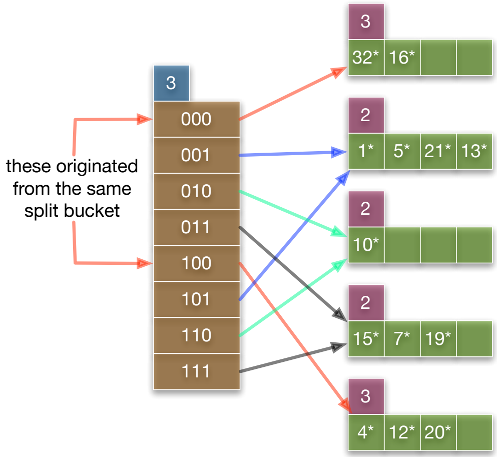


but we now need 3 bits

4 = 00100
12 = 01100
32 = 10000
16 = 01000
20 = 10100

so we must double the directory

Doubling the directory



Extendible hashing observations

- *Directory fits in memory*: *equality search* answered with only *one disk I/O* (two in the worst case!)
  - 100MB file, 100 bytes/tuple, 4kB pages, *1,000,000 data entries*, *25,000 directory entries*: *fits in memory*!
  - If the *value distribution* is *skewed*, *directory grows large*
  - *Same hash-value entries* are a *problem* (why?)
- *Deletion*: if removal *empties bucket*, then it can be *merged* with *split image*; if *each directory entry points* to the *same bucket as its split image*, the *directory is halved*

Linear hashing

- *Extendible hashing directory*: even if it is small, it is still a *materialised level of indirection*
- Though the *number of buckets grows linearly*, the size of the *directory* grows *exponentially*
- Objective: *no directory*, *linear growth*
- *Linear* hashing gets the job done

Why one, when you can have many?

- Key idea: *instead* of having a *single* hash function and using a *set of bits*, have *multiple hash functions*
  - *Multiple* hash functions implement the *progressive doubling* of the directory
- *Allocate* buckets *not* when they become *full*, *but* whenever we reach some *pretetermined load factor*
- *Single* bucket *allocation*
- *Each* bucket *allocation* results in *another hash function* to be used
- *Keep track* of the number of *buckets* and the number of *times* the number of buckets has *doubled*
- *Discard unused* hash functions

In more detail

- Use a *family* of *hash functions* $h_0, h_1, h_2, \ldots$
  - $h_i(key) = g(key) \mod (2^i M)$
  - M = *initial* number of *buckets*
  - g is some *hash function* (*range* is *not* $[0, \ldots, N-1]$)
  - If $M = 2^{d_0}$, for *some* d_0, h_i consists of *applying* g and *looking* at the *last* d_i *bits*, where $d_i = d_0 + i$.
  - h_{i+1} *doubles* the *range* of h_i (similar to *directory doubling*)

Bookkeeping

- Two variables: *N*ext, and *L*evel
  - *N* points to the *bucket* to be *split next*
  - *L* keeps track of the number of *times* the *range* of the *hash function* has *doubled*
- *Splitting* proceeds in *'rounds*
  - *Round ends* when *all* M_R *initial* (for *round R*) buckets are *split*
  - Buckets *0* to $N - 1$ have *been split*
  - Buckets N to M_R have yet *to be split*
- *Current round* is L

Search and insert

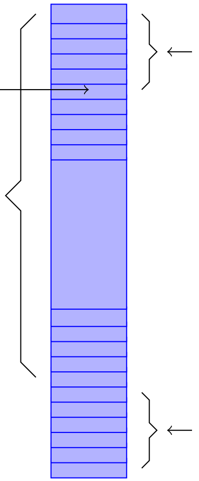
Search

- To *find* bucket for *key* K, find $h_L(K))$
  - If $h_L(K) \in [N, \dots M_R]$, r *belongs here*
  - Else, r *could belong* to bucket $h_L(K)$ *or* bucket $h_L(r) + M_R$; we *must apply* $h_{L+1}(K)$ to find out.

Insert

- *Find bucket* as above, by *applying* h_L or h_{L+1}
- If *bucket* to insert is *full*
  - Add *overflow page* and *insert* entry
  - (*Maybe*) *Split* bucket N and increment N

Linear hashing file



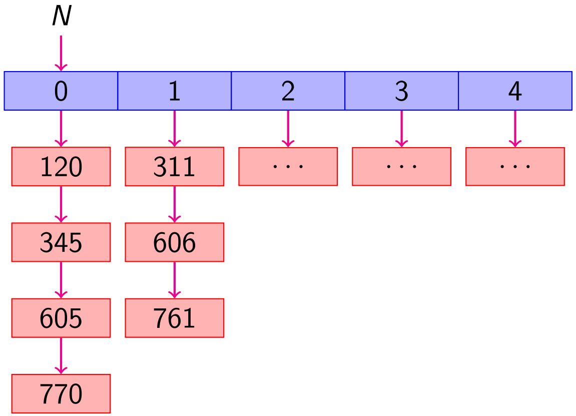
Bucket to be *split* *N*ext

Buckets that *existed* at *beginning* of round; *range of h_L*

Buckets split in *this round*; if h_L falls *here*, must *use h_{L+1}*

Split image buckets created thourgh *splitting* of *other buckets* in *this round*

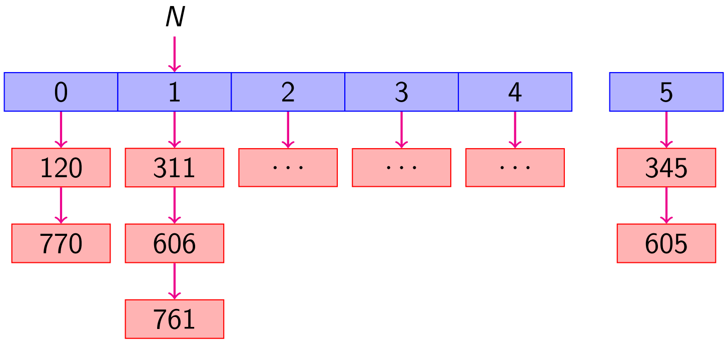
Splitting a bucket (0 in this case)



Hash functions

- $h_0(K) = K \mod 5$

Splitting a bucket (0 in this case)



Hash functions

- $h_1(K) = K \mod 10$

Algorithms in more detail

Lookup for key K

```
$bucket := h_L(K);$
if $bucket < N$ then $bucket = h_{L+1}(K)$
```

Expansion

```
$N := N + 1;$
if $N = M2^L$ then
  $L := L + 1;$   $N := 0;$
```

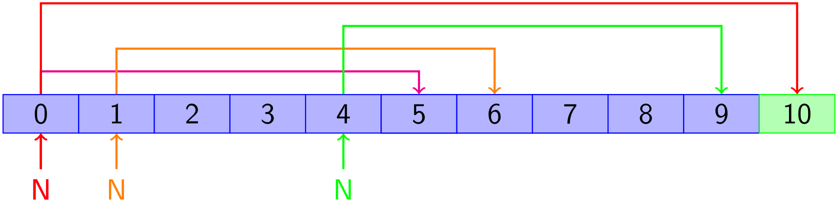
Contraction

```
$N := N - 1;$
if $N < 0$ then
  $L := L - 1;$   $N := M2^L - 1;$
```

The expansion process (round 0)

Expansion

```
$N := N + 1$;
if $N = M2^L$ then
  $L := L + 1$;    $N := 0$;
```

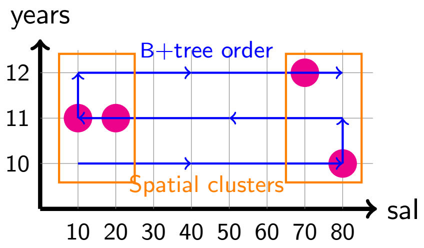


Linear hashing observations

- Can choose *any criterion* to *trigger split*
  - *Typically*, we want to maintain some *load factor*
- Since *buckets* are *split round-robin*, *long* overflow *chains do not develop!*
- *Doubling* of *directory* in *extendible hashing* is *similar*
  - *Switching* of *hash functions* is *implicit* in how the *number of bits* examined is *increased*

Why more than one dimensions?

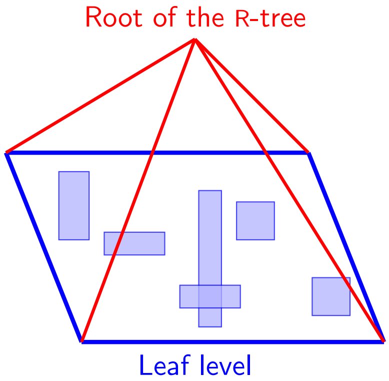
- *Single-dimensional* indexes are *not enough*
  - Consider a *composite search* key *e.g.*, an index on $\langle sal, years \rangle$
  - The *2-dimensional* space is *linearised*
  - We *sort* entries *first* by *sal* and *then* by *years*
- A *multidimensional index clusters entries*
  - *Exploits nearness* in *multidimensional* space.
  - *Balanced* index structures in *multiple dimensions* are *challenging*



$\langle 10, 11 \rangle$, $\langle 20, 11 \rangle$
$\langle 70, 12 \rangle$, $\langle 80, 10 \rangle$

The R-tree

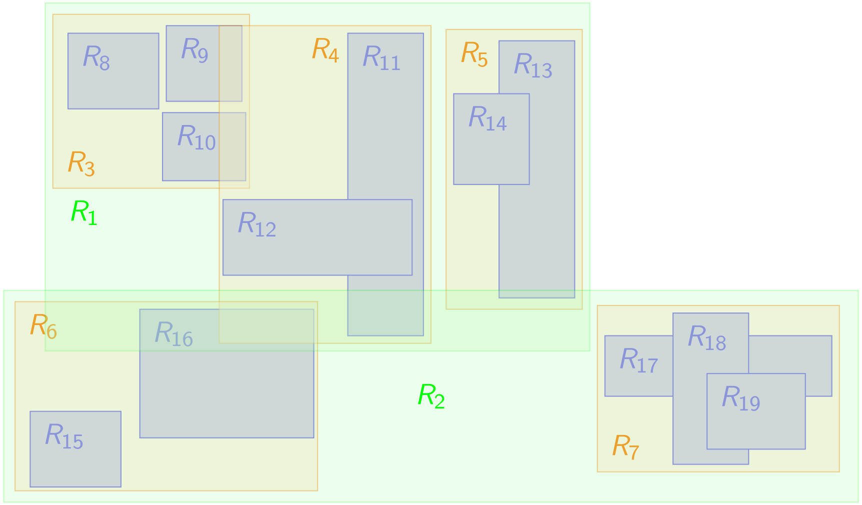
- The *R-tree* is a *tree-structured* index that remains *balanced* on *insertions* and *deletions*
- Each *key* stored in a *leaf entry* is intuitively a *box*, or collection of *intervals*, with *one* interval *per dimension*



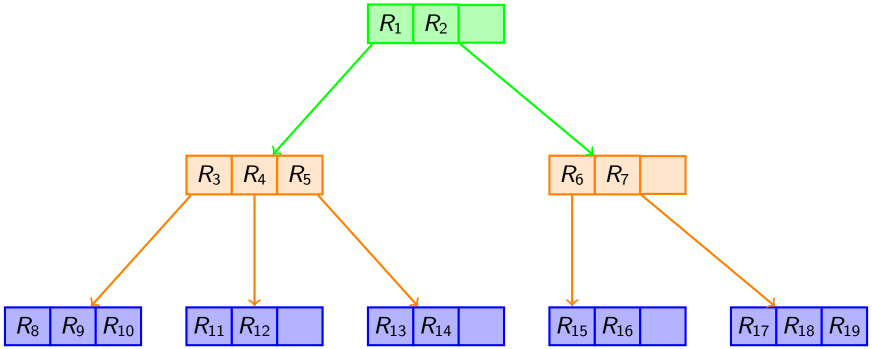
R-tree properties

- *Leaf entry* format: ⟨ *n-dimensional bounding box, pointer to record* ⟩
  - *Bounding box* is the *tightest bounding box* for a data object
- *Non-leaf entry* format: ⟨ *n-dim box, pointer to child node* ⟩
  - The *box covers all boxes* in *child* node (in fact, subtree)
- *All leaves* at *same distance* from *root*
- *Nodes* can be kept *50% full* (except root)
  - Can *choose* some *parameter m* that is $\leq 50\%$, and *ensure* that *every node* is at *least m% full*

R-tree example



R-tree example (cont.)



Search for objects overlapping box Q

```
Start at *root*
  If *current node* is *non-leaf*
    *For each* entry $\langle E, ptr\rangle$, if *box E overlaps Q*, *search subtree* identified by *ptr*
  If *current node* is *leaf*
    *For each* entry $\langle E, rid\rangle$, if *E overlaps Q*, *rid* identifies an *object* that *might overlap Q*
```

Note

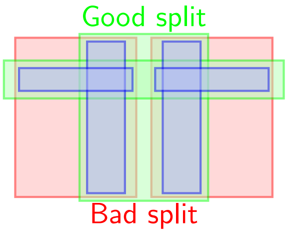
May have to *search several subtrees* at each node! (In *contrast*, a *B+tree* equality search goes to *just one leaf*.)

Insert entry $\langle B, ptr \rangle$

- Start at *root* and *go down* to *"best-fit" leaf L*
  - Go to *child* whose *box* needs *least enlargement* to *cover B*; *resolve ties* by going to *smallest area child*
- If *best-fit leaf L has space*, *insert* entry and *stop*. *Otherwise*, *split L* into L_1 and L_2
  - *Adjust* entry for *L* in its *parent* so that the *box* now *covers (only)* L_1
  - *Add* an entry (in the *parent* node of *L*) for L_2. (This *could cause* the parent node to *recursively split*.)

Splitting a node

- The *entries* in *node L* plus the *newly inserted* entry must be *distributed* between L_1 and L_2
- *Goal* is to *reduce likelihood* of *both L_1 and L_2* being *searched* on subsequent queries
- *Redistribute* so as to *minimize area* of L_1 *plus* area of L_2



Redistribution

Exhaustive algorithm is *too slow*; *quadratic* and *linear heuristics* are used in practice

Comments on R-trees

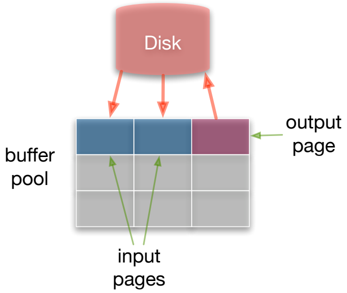
- *Deletion* consists of *searching for the entry* to be *deleted*, *removing* it, and *if* the *node* becomes *under-full*, *deleting* the *node* and then *re-inserting* the remaining *entries*
- Overall, *works* quite *well* for *2-* and *3-D datasets*
- Several *variants* (notably, *R+* and *R* trees*) have been *proposed*; *widely used*
- Can *improve search performance* by using a *convex polygon* to *approximate query shape* (*instead* of a *bounding* box) and testing for *polygon-box intersection*.

Overview

- *Sorting* is probably the most *classic problem* in CS
  - *Simple* idea: impose a *total order* on a *set of values*
- It is a *classic problem* in *databases* too
  - Remember *ISAM*? First step is to sort the file
  - In fact, if you're *bulk loading a B+tree*, you're better off sorting the file first
- *Useful* as well for *duplicate elimination*
- Useful for *join evaluation* (*sort-merge* algorithm)
- But what if I have a *1GB relation* and *1MB of physical memory*?
  - Remember, its all about *minimising I/O*
  - (Or, why your algorithms class didn't tell you the whole truth)

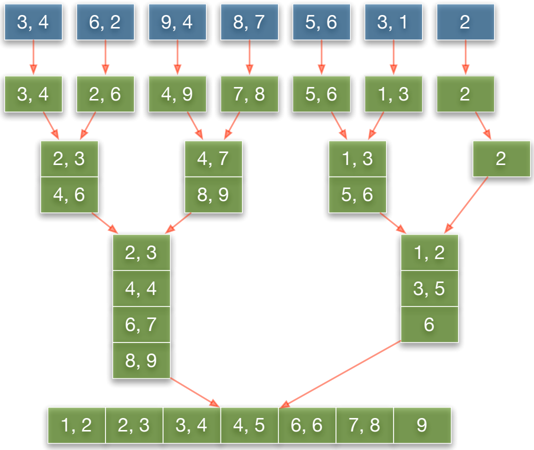
Two-way external merge sort

- Requires a *maximum of three buffer pages* and *multiple passes over the data*
- *First pass*: *read one* page, *sort* it, *write* it out
- *Subsequent passes*: *read two* pages, *merge* them, *write* out the result



How it works

- *Each pass* will *read and write each page* in the file
- *N pages*, so the number of passes is $\lceil \log_2 N \rceil + 1$
- So, the *total I/O cost* is $2N(\lceil \log_2 N \rceil + 1)$



But why only three pages?

- We have an *entire buffer pool* of *more than three pages*, can we utilise it?
  - *Yes*: *N-way merge sort*
- To sort a *file of N pages* using *B buffer pool pages*:
  - *First pass*: sorted runs of *B pages each* ($\lceil \frac{N}{B} \rceil$)
  - *Subsequent passes*: *merge $B - 1$ runs* (why?)

What is the I/O cost?

- *Number of passes*: $1 + \lceil \log_{B-1} \lceil \frac{N}{B} \rceil \rceil$
- *I/O cost*: $2N\cdot$ *(Number of passes)*
- *For example*: *108 pages* in the file, *5 buffer pool pages*
  - *Pass 0*: $\lceil \frac{108}{5} \rceil = 22$ *sorted runs of 5* pages each
  - *Pass 1*: $\lceil \frac{22}{4} \rceil = 6$ *sorted runs of 20* pages each
  - *Pass 2*: *2 sorted runs*, *80* pages and *28* pages
  - *Pass 3*: *final merge*, *done*!

A bit of perspective

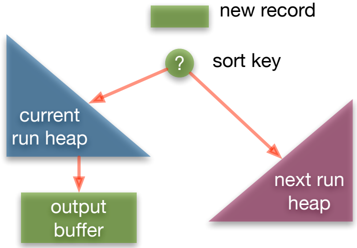
257 * 4,096 = 1,052,672

N	B=3	B=5	B=9	B=17	B=129	B=257
100	7	4	3	2	1	1
1,000	10	5	4	3	2	2
10,000	13	7	5	4	2	2
100,000	17	9	6	5	3	3
1,000,000	20	9	7	5	3	3
10,000,000	23	12	8	6	4	3
100,000,000	26	14	9	7	4	4
1,000,000,000	30	15	10	8	5	4

Are we done?

- *No*! We can actually *do much better* than this
- *Key observation*: we are using *main memory algorithm* (*e.g.*, quicksort) to sort pages in memory
  - But that *doesn't minimise I/O*, does it?
  - Wouldn't it be nice if we could *generate sorted runs longer than memory*?
  - *Solution*: *heapsort* (a.k.a. *tournament* or *replacement sort*)

How does heapsort work?



- Keep *two heaps* in memory, *one for each run* (the *current* and the *next* one)
- *Sum of memory* needed for the two heaps *equals the buffer size*
- *Keep adding* to the *current* run *until* we are *out of buffer space*
- When *buffer is full*, *swap* heaps and *iterate*

The algorithm

```
Initialisation: read B pages into the current heap
while (not finished) do {
 while ($r$ = lowest key from current heap) {
  write $r$ to the current run
  max = $r$
  get $k$ from input
  if ($k >$ max) insert $k$ into current heap
  else insert $k$ into next heap
 }
 swap current and next heaps, max = 0
}
```

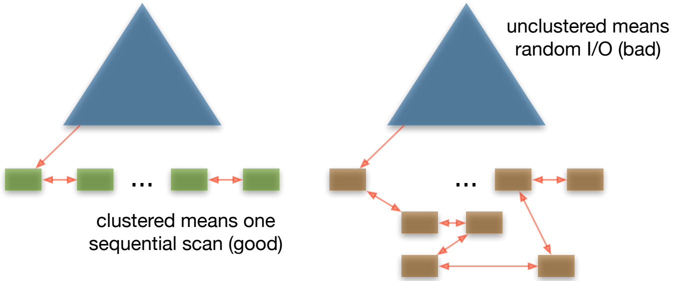
Heapsort observations

- What is *the average length* of a run?
  - Proven to be $2B$ (!)
- *Quicksort* is *computationally cheaper*
- But *heapsort* produces *longer runs*
  - *Minimises I/O*
  - *Remember*, you should *"forget" main memory* methods when it comes to databases!

Good-old B+trees

- What if the *table to be sorted* has a *B+tree index on sort field*?
- *Traverse* the *leaf pages* and *we're done*!
  - Follow the *left-most pointers*, find the *low key*, *scan forward*
- Is this *always a good idea?*
  - If the *B+tree is clustered*, it's a *great idea*
  - *Otherwise*, it could lead to *random I/O*

Clustered *vs.* unclustered storage


...
clustered means one sequential scan (good)
...
unclustered means random I/O (bad)

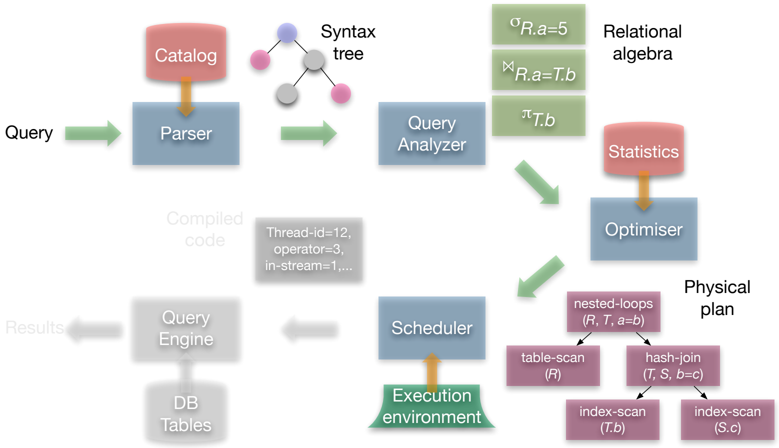
Summary of sorting

- *Databases* spend *a lot of their time sorting*
- In fact, they might *dedicate part of their buffer pool* for sorting data
    - Remember *pinning buffer pool pages*?
- *External sorting minimises I/O* cost
    - *First* you produce *sorted runs*, *then* you *merge* them
- The *choice of internal sort matters* as well
    - Yes, *quicksort* is *computationally cheap*
    - Though *heapsort* is *computationally more expensive*, it *produces longer runs*, which means *less I/O*
- Finally, *clustered B+trees* (when they exist) are a good way of *sorting in one sequential scan*

Overview

- A *physical plan* is what the *query engine* uses in order to *evaluate queries*
- In most cases, it is a *tree of physical operators*
  - *Physical* in the sense that they *access and manipulate* the *raw, physical data*
- *Plenty of ways* to *formulate this tree*
  - Identifying the *"best" tree* is the job of the *query optimiser*

Query cycle


Query
Catalog
Parser
Syntax tree
Query Analyzer
$\sigma_{R.a=5}$
$\bowtie_{R.a=T.b}$
$\pi_{T.b}$
Relational algebra
Statistics
Optimiser
Physical plan
nested-loops (R, T, a=b)
table-scan (R)
hash-join (T, S, b=c)
index-scan (T.b)
index-scan (S.c)
Scheduler
Execution environment
Compiled code
Thread-id=12, operator=3, in-stream=1,...
Query Engine
DB Tables
Results

Algebraic operators *vs.* physical operators

- A *relational algebraic operator* is a *procedural abstraction* of *what should be retrieved*
- The *physical operator* specifies *how the retrieval will take place*
- The *same algebraic operator* may map to multiple *physical operators*
- *Physical operators* for the *same algebraic operator* may be implemented using *different algorithms*
  - For instance: *join* $\rightarrow$ *physical join* $\rightarrow$ *sort-merge join*

Example

SQL query

```
select   student.id, student.name
from     student, course
where    student.cid = course.cid and
         course.name = 'ADBS'
```

Algebraic expression

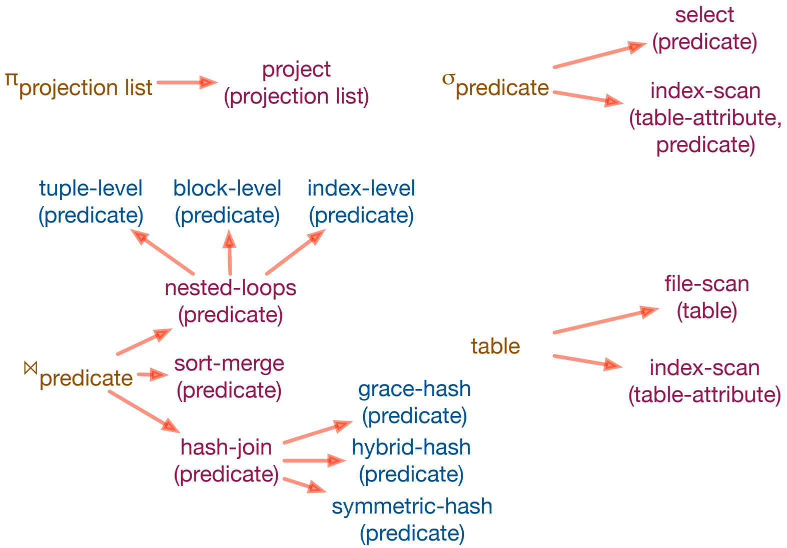
$\pi_{student.id,student.name}$

$(student \bowtie_{student.cid=course.cid}$
$\sigma_{course.name='ADBS'}(course))$

Algebraic operations

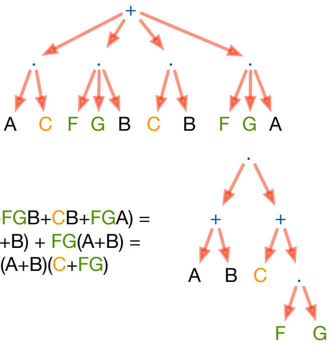
- $\pi_{student.id,\ student.name}$
- $\bowtie_{student.cid\ =\ course.cid}$
- $\sigma_{course.name\ =\ 'ADBS'}$

Mappings to/of various physical operators



Math analogy

- Remember *factoring*?
- Same *arithmetic expression* can be *evaluated in different ways*
- If you map arithmetic expressions to *infix notation*, you have *different "plans"*



(AC+FGB+CB+FGA) =
C(A+B) + FG(A+B) =
(A+B)(C+FG)

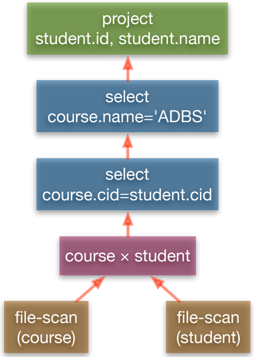
Physical plans

- *Physical plans* are *trees of physical operators over* the *physical data*
  - Just as *arithmetic expressions* are *trees of arithmetic operators* over *numbers*
- There are *different ways* of *organising trees* of *physical operators*
  - Just as there are *different ways* to *organise* a *mathematical expression*
- *Physical plans* are what *produce query results*

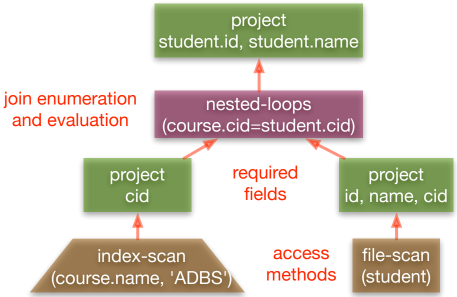
Here's a plan

SQL query

```
select   student.id, student.name
from     student, course
where    student.cid = course.cid and
         course.name = ‘ADBS’
```



Here's a better plan



SQL query

```
select   student.id, student.name
from     student, course
where    student.cid = course.cid and
         course.name = ‘ADBS’
```

Observations

- Certain *selection predicates* can be *incorporated* into the *access method*
- If a *field* is *not needed*, it is *thrown out* (why?)
- *More than two sources* need to be *combined* (even through a Cartesian product)
- The *query plan* includes *operators not present* in the *original query*
- Yes, the *query specifies what should be retrieved*
  - But *how it is retrieved* is an *entirely different* business

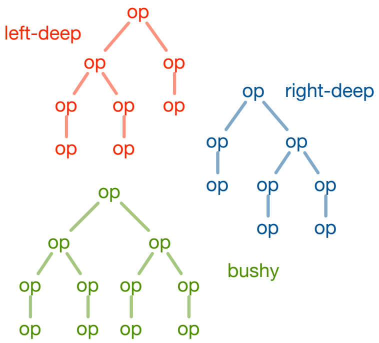
Issues

- *Choice of* order in which *the physical operators are executed*
  - Heuristics, access methods, *optimisation*
- *Choice of algorithms* whenever there are more than one
  - Again, *optimisation* (*join enumeration*, mainly)
- How are *physical operators connected*?
  - Different *execution models*
- What does a *connection* actually *imply*?
  - *Pipelining* (sometimes)
- What about *multiple readers* or even *concurrent updates* of the data?
  - *Concurrency control* (be patient . . .)
- Finally, *how is it all executed*?
  - *Query engine*

A note on duplicates

- The *relational model* calls for *sets of tuples*
- The *query language* (SQL) *does not*
  - Remember "*distinct*"?
- *Sets* can be *guaranteed on base relations* by specifying *key (integrity) constraints*
- But what happens with *intermediate results*?
  - *Set semantics are lost*, intermediate results have *bag semantics*
  - But *set semantics* can always *be imposed*; they are just more *expensive to ensure*

Types of plan



- There are *two types of plan*, *according to their shape*
  - *Deep* (*left or right*)
  - *Bushy*
- *Different shapes* for *different objectives*

Plan objectives

- A *deep plan* is better for *pipelining*
  - Because, let's face it, *it's a line*!
- A *bushy plan* is better for *parallel computation*
  - *Different branches* can be *executed concurrently*
- But all of these *depend* on the *algorithms chosen*
  - And on the *execution model*

Summary

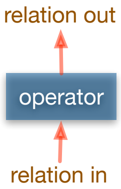
- A *plan* is what the *query engine* accepts as *input*
  - . . . and what *produces* the *query results*
- The *same algebraic expression* can produce *multiple plans*
  - Because the *same algebraic operator* maps to *multiple physical operators*
- A *physical operator* implements an *evaluation algorithm*
- A *physical plan* does *not necessarily contain all* the *algebraic operators* of the query
  - *More or fewer, depending* on the *available physical operators*
- The *optimiser chooses* the *best physical plan*
- *Types* of plans are *classified* according to their *shape* and *evaluation objectives*

Overview

- *Physical plans* are *trees* of *connected physical operators*
- The *execution model* defines the *interface of the connections*
  - And *how data* is *propagated* from one operator to the next
- It also defines *how operators* are *scheduled* by the query engine
  - Different *execution models* map to different *process execution paradigms*

Operator connections

- Operator *functionality*: *relation in*, *relation out*
- The *connections* are the *interface* through which the *input* is *read* and *propagated*
- In fact, there is a *producer/consumer* analogy



Pipelining

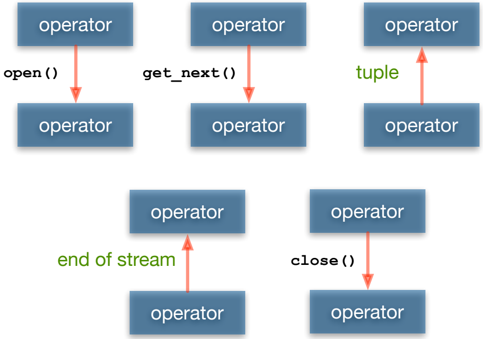
- *Pipelining* is the following process: *read*, *process*, *propagate*
- The *opposite* is to *materialise intermediate results*
- Pipelining *works in theory*, but *in practice* certain *intermediate relations* need to be *materialised*
  - This is called *blocking* (*e.g.*, sorting)
- The benefits of pipelining include
  - *No buffering*
    - *No intermediate relation* is *materialised*
  - *Faster evaluation*
    - Since nothing is materialised, *no disk I/O*
  - *Better resource utilisation*
    - No disk I/O means more *in-memory operation*

What happens in practice

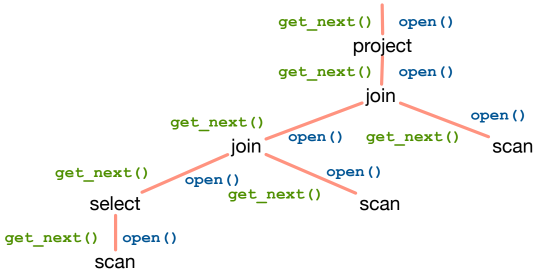
- *Pipelining* is *simulated* through the *operator interface*
- But *different operations* have *different evaluation times*
  - So there will be *some need for buffering*
- If we have *joins*, chances are the *plan will block*
  - We will see *why* that happens when talking about *join algorithms*

The iterator model

- *Also* known as a *cursor*
- *Three* basic *calls*
  - `open()`
  - `get_next()`
  - `close()`
- Have you ever accessed a database through external code?
  - For example: `exec sql declare cursor` in embedded `SQL`, `ResultSet`s in Java/JDBC, *etc.*



Call propagation



- All *calls* are *propagated downstream*
- The *query engine* makes the *calls* to the *topmost operator only*

Pure implementation

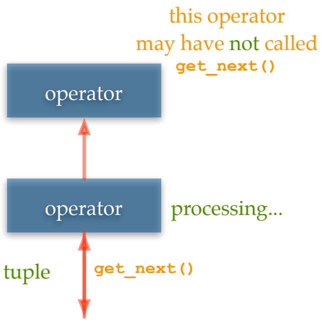
- The *iterator interface*, as described, is a *completely synchronous* interface
- A *pure implementation* means that all *operators reside in the same process space*
  - So *calls* can be *propagated downstream*
- But *certain operators* are *"faster"* than others
  - It *could be* the case that an *asynchronous implementation* could be *more beneficial*

Different implementations

- The *iterator interface* is what *operators* use to *communicate*
- But *how it is implemented*, can be *entirely different*
  - The *reason* is that there might be *need for buffering*
  - *Three possibilities*
    - ⋆ *Push model* (buffering in the *operator making the calls*)
    - ⋆ *Pull* model (buffering in the *operator accepting the calls*)
    - ⋆ *Streams* (buffering in the *connections*)

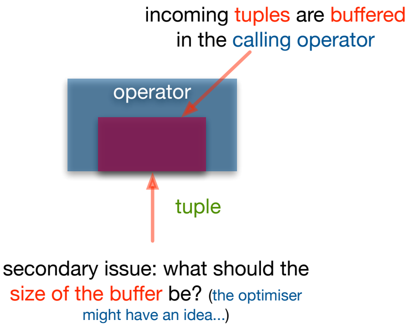
The push model

- Tuple *propagation begins* at the *lower levels* of the evaluation tree
- A *lower operator propagates* a tuple *as soon as it is done* with it
  - *Does not "care"* if the *receiving operator* has called `get_next()`

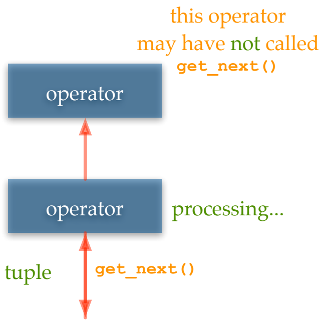


Buffering

- The main issue: *what happens* if the *lower operator* has *propagated* the tuple *before* the *operator above* it has called `get_next()`?

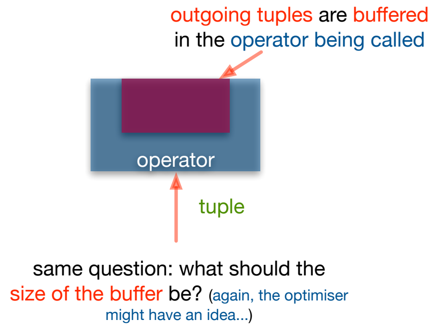

incoming tuples are buffered in the calling operator
operator
tuple
secondary issue: what should the size of the buffer be? (the optimiser might have an idea...)

The pull model



- The *inverse* of the *push model*
- If the *lower operator* is *done processing* a *tuple* it *does not propagate* it
  - It *waits* until the *operator above it makes* a `get_next()` call

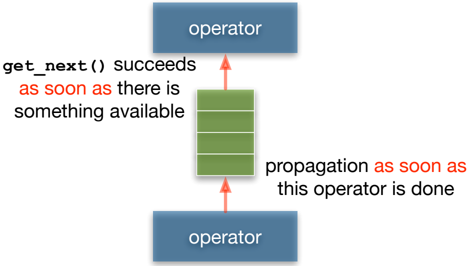
Buffering — again


outgoing tuples are buffered
in the operator being called
operator
tuple
same question: what should the
size of the buffer be? (again, the optimiser
might have an idea...)

- The question this time: *what happens* if the *lower operator* is *done processing* the tuple *before* the *operator above it* calls `get_next()`?

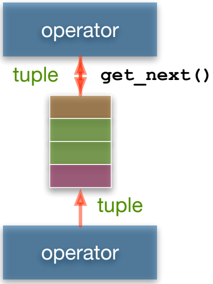
The stream model

- The *connections* become *first-class citizens*
- *Streams* are *queues of tuples* connecting the operators
- *Propagations* and `get_next()` calls are *synchronised* on *each stream*


operator
get_next() succeeds as soon as there is something available
propagation as soon as this operator is done
operator

Buffering — third time

- *This time*, there is *no question*!
- When the *lower operator* is *done*, it *propagates* the tuple
- When the *top operator* is *ready*, it calls `get_next()` on the incoming stream



Why all this?

- *Pure iterator* implementation
  - If an *operator receives* `get_next()` and is *not ready*, it *blocks*
  - In fact, the *entire plan blocks* (why?)
  - Assume there is a *sort operation somewhere* in the plan
    - ⋆ Congratulations, *your plan is officially blocked*
- *Non-pure* implementations
  - *Operators act* (almost) *independently* of *one another*
  - *Depending on the implementation* of the interface (push-, pull-, stream-based) there are *different benefits*
    - ⋆ There *could still be blocking*, but the *time during* which a *plan* is *blocked* is *minimised*
  - It could lead to a *each operator* running in its own *process thread*
    - ⋆ Though this is *not always* a *good idea*

Benefits of each model

- Push model
  - *Minimises idle time* of the operators (why?)
  - *Great* for *pipelining*
- Pull model
  - *Closest* to a *pure implementation*
  - But *still on-demand*
- Streams model
  - Fully *asynchronous* to the operators, the *synchronisation* is *on* the *streams*
  - Highly *parallelisable*

Summary

- A *physical plan* is a tree of *connected operators*
- *Operators* need to *communicate data* to one another
- The *iterator interface* is the *means* of this *communication*
  - `open()`, `close()`, `get_next()`
- As with any *interface* there are *different ways of implementing* it, known as *execution models*
  - Push model
    - ★ *Data propagated as soon as* they are *available*
  - Pull model
    - ★ *Data retrieved on demand*
  - Stream model
    - ★ *Asynchronous communication* on the *connections* between operators

Overview

- The *join operation* is *everywhere*
  - Any *single query* with *two or more sources* will *need* to have a *join* (even in the form of a Cartesian product)
  - So *common* that certain *DBMSs implement join indexes*
- As a *consequence*, a DBMS spends *a lot of time* evaluating *joins*
- Probably the *most optimised physical operator*
- A *physical operator* can be mapped to *different algorithms*
- As is *always the case*, a *good join algorithm minimises I/O*
- *Choosing* a *join algorithm* is *not as straightforward*; the *choice* might *depend* on
  - The *cardinality* of the input, its *properties* (clustered, sorted, *etc.*) and any available *indexes*
  - Available *memory*

Overview (cont.)

- *Choosing* how to *evaluate* a *single join* is *different* than *choosing* the *order* in which *joins* should be *evaluated*
- The *query optimiser* spends *most of its time enumerating* (*ordering*) the *joins* in a query
  - In fact, the *order* in which *joins* are *evaluated affects* the *choice* of *algorithm*
  - The *two* are *largely interconnected* (more on that when discussing *query optimisation*)

Three classes of algorithms

- *Iteration-based*
  - Namely, *nested loops join* (in three flavours)
- *Order-based*
  - *Sort-merge join* (essentially, merging two sorted relations)
- *Partition-based*
  - *Hash join* (again, in three flavours)

Terminology

- We want to *evaluate* $R \bowtie S$, *shorthand for* $R.a = S.b$
  - Also known as an *equi-join*
- In *algebra*: $R \bowtie S = S \bowtie R$
  - *Not true* for the *physical join*: $cost(R \bowtie S) \neq cost(S \bowtie R)$
- *Three factors* to take into account
  - *Input cardinality* in *tuples* T_R and *pages* P_R
  - *Selectivity factor* of the predicate
    - ⋆ Think of it as the *percentage of the Cartesian product propagated*
  - *Available memory*

Nested loops join

- The *simplest way* to *evaluate a join*
- But it can *still be optimised* so that it *minimises I/O*
- *Very useful* for *non-equi joins* (the other two approaches will not work)
- *Three variations*
  - *Tuple-level* nested loops
  - *Block-level* nested loops
  - *Index* nested loops

It doesn't get simpler than this...

Tuple-level nested loops

```
*for each* tuple $r \in R$ *do*
  *for each* tuple $s \in S$ *do*
    *if* $r.a == s.b$ *then add* $\langle r, s \rangle$ to the result
```

- *R* is the *outer relation*
- *S* is the *inner relation*

What is the cost?

- *One scan* over the *outer relation*
- *For every tuple* in the *outer relation*, *one scan* over the *inner relation*
- If relations are *not clustered*, then
  - $cost(R \bowtie S) = T_R + T_R \cdot T_S$
    - ⋆ Assume $T_R = 100,000$, $T_S = 50,000$, then $cost = 5,000,100,000$ *I/Os*
    - ⋆ At 10ms an I/O, that is *50,001,000 seconds*, or, *14,000 hours*

What about clustered storage?

- *Much, much better*; I/O is at a *page level*
- So, the *total cost* will be
  - $cost(R \bowtie S) = P_R + P_R \cdot P_S$
  - In the previous example, for 100 tuples per page, then $P_R = 1,000$, $P_S = 500$, $cost = 501,000$ *I/Os*
  - At 10ms an I/O, that is *5010 seconds*, or *about an hour and a half*
- But we can *improve* that *even more*!
  - *Block-level I/O* and the *buffer pool* will *work wonders*

Here's an idea

- Assume we have *B pages available* in the buffer pool
- *Read as many outer relation pages as possible*; this constitutes a *block*
    - Put the *pages of the block* in the *buffer pool*, *pin* them
- *Read* the *inner relation* in *pages*
- *Block size* is $B - 2$ *pages* (why?)
- Even more *I/O savings*

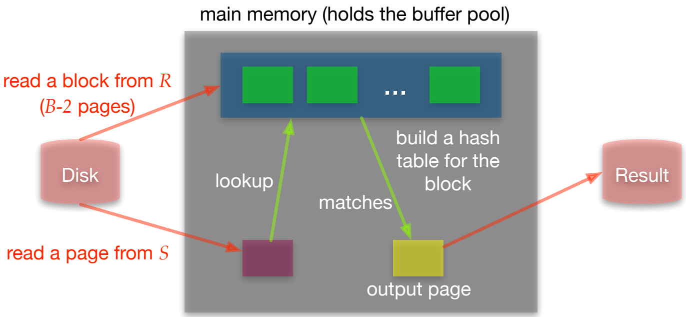
The Algorithm

Block-level nested loops

Assumption: B dedicated pages in the buffer pool, block size is $B - 2$ pages

```
for each block of $B-2$ pages of $R$ do
  for each page of $S$ do {
    for all matching in-memory tuples $r \in R$-block and $s \in S$-page
      add $\langle r, s \rangle$ to result
  }
```

How it works


main memory (holds the buffer pool)
read a block from R (B-2 pages)
Disk
read a page from S
...
lookup
build a hash table for the block
matches
output page
Result

How much does it cost?

- The *outer relation* is *still scanned once* (P_R pages)
- The *inner relation* is *scanned* $\lceil \frac{P_R}{B-2} \rceil$ *times*
  - *Each scan* costs P_S *I/Os*
  - So, $cost(R \bowtie S) = P_R + P_S \cdot \lceil \frac{P_R}{B-2} \rceil$
  - Same example, $P_R = 1,000$, $P_S = 500$, assume a block size of 100 pages, then *number of I/Os is 6,500*
  - At 10ms per I/O, it will take *65 seconds*

Key observation

- The *inner relation* is *scanned* a number of *times* that is *dependent on* the *size* of the *outer relation*
- So, the *outer relation* should be the *smaller one*
- Let's *forget the ceilings* and assume two relations: *big* and *small*
- Then we are *comparing*
  - $\mathit{big} + \mathit{small} \cdot \frac{\mathit{big}}{B-2}$
  - $\mathit{small} + \mathit{big} \cdot \frac{\mathit{small}}{B-2}$
- And $\mathit{big} > \mathit{small}$
- *Remember*, $cost(R \bowtie S) \neq cost(S \bowtie R)$ when it comes to *physical operators*

What if there is an index?

- Suppose the *inner relation* has an *index on the join attribute*
- We can *use the index* to *evaluate the join*
  - Remember, the *join predicate*, if we fix one of the join attribute values, is *just a selection*
- *Scan* the *outer relation*
  - Look at the *join attribute's value* and use it to *perform* an *index lookup* on the *inner relation*

The algorithm

Index nested loops

Assumption: there is an index on $S.b$

```
for each tuple $r \in R$ do
  for each tuple $s \in S$ where $r.a == s.b$
    add $\langle r, s \rangle$ to the result
```

- Predicate evaluation is an *index lookup* in the *index* over $S.b$

What is the cost?

- *Depending* on whether the *outer relation* is *clustered or not*, P_R *or* T_R *I/Os* to scan it
- *Selectivity factor* f: *percentage* of the *Cartesian product propagated*; this means that *every outer tuple joins with* $f \cdot T_S$ tuples
  - *Depending on the index*, each *lookup* will be, say, *avg_lookup* I/Os
- If R is *clustered*
  - $cost(R \bowtie S) = P_R + T_R \cdot f \cdot T_S \cdot avg\_lookup$
- If R is *not clustered*
  - $cost(R \bowtie S) = T_R + T_R \cdot f \cdot T_S \cdot avg\_lookup$

Index nested loops

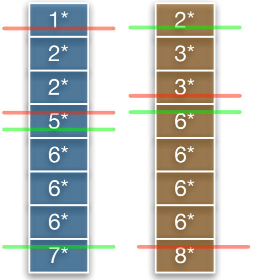
- If the *selectivity factor* and the *average lookup cost* are *small*, then the *cost* is *essentially a (few) scan(s)* of the *outer relation*
- If the *outer relation* is the *smaller one*, it leads to *significant I/O savings*
- Again, it is the *job* of the *query optimiser* to *figure out if this is the case*

Sort-merge join

- Really *simple idea*
- The *join* is *evaluated* in *two phases*
  - *First*, the two *input relations* are *sorted* on the *join attribute*
  - *Then*, they are *merged* and join *results* are *propagated*
- *External sorting* can be used to *sort* the *input relations*
- The *merging phase* is a *straightforward generalisation* of the *merging phase* used in *merge-sort*

How it works

- Key idea: there *exist groups* in the *sorted relations* with the *same value* for the *join attribute*
- We need to *take that into account* when *merging*
  - The *reason* is that we will have to *do some backtracking* when *generating* the *complete result*



The algorithm

Merge-join

```
$r \in R, s \in S, gs \in S$

while (more tuples in inputs) do {

  while ($r.a < gs.b$) do advance r
  while ($r.a > gs.b$) do advance gs        // a group might begin here
  while ($r.a == gs.b$) do {
    $s = gs$        // mark group beginning
    while ($r.a == s.b$) do        // while in group
        add $\langle r, s \rangle$ to the result; advance s        // produce result
    advance r        // move forward
  }
  $gs = s$        // candidate to begin next group

}
```

What is the cost?

- We know the *cost* of *externally sorting* either *relation*: $2 \cdot P_R \cdot \log P_R$, or $2 \cdot P_S \cdot \log P_S$
- The *merge phase* is essentially *one scan* of *each sorted input*: P_R or P_S (these scans are always clustered)
- $cost(R \bowtie S) = P_R \cdot (2 \cdot \log P_R + 1) + P_S \cdot (2 \cdot \log P_S + 1)$
  - Running example: $P_R = 1,000$, $P_S = 500$, 100 buffer pool pages to sort, the *number of I/Os is 7,500*
  - At 10ms an I/O, this is *one minute and fifteen seconds* (about the same as block nested loops)

A few issues

- If there are *large groups* in the *two relations*, then we *may* have to *do a lot of backtracking*
  - *Performance will suffer* due to *possible extra I/O*
  - *Hopefully*, *pages* will be in the *buffer pool*
- *Most relations* can be *sorted* in *2-3 passes*
  - Which *means* that we can *compute the join* in *4 passes max (almost regardless of input size!)*
  - In fact, we can *combine* the *final merge of external sorting* with the *merging phase* of the *join* and save even *more I/Os*

Hash join

- *Partition-based* join algorithms
- Key idea: *partition R and S* into *m partitions*, R_i and S_i, so that *every R_i fits in memory*
  - Observation: *joining tuples* will fall into the *same partition*
- Then, *for every R_i load* it *in memory*, *scan S_i* and *produce* the *join results*
- Three flavours: *Simple* hash join, *grace* hash join, *hybrid* hash join

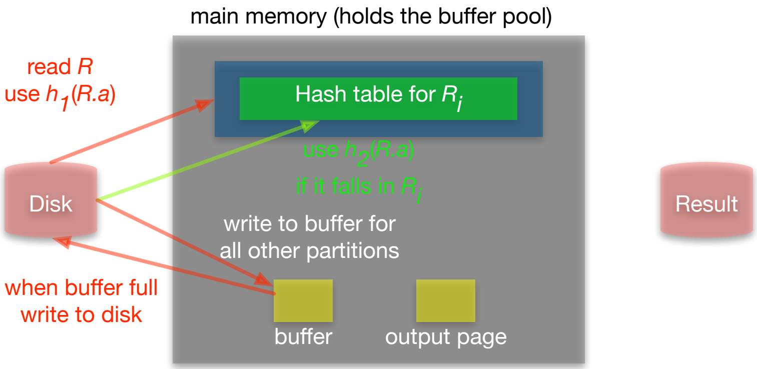
The simple algorithm

Simple hash join

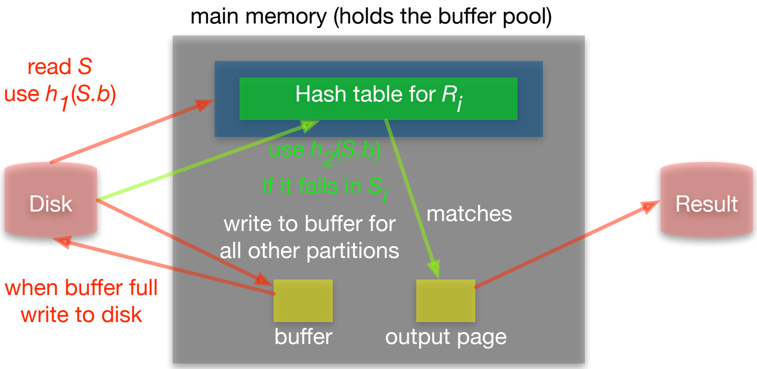
Assumption: m partitions, each partition P_i fits in main memory

```
for all partitions $P_i, i \in [1, m]$
  for each $r \in R$ read $r$ and apply hash function $h_1(r.a)$
    if $r$ falls into $P_i$ apply hash function $h_2(r.a)$ and put it in an in-memory hash table for $P_i$
    otherwise, write it back out to disk
  for each $s \in S$ read $s$ and apply hash function $h_1(s.b)$
    if $s$ falls into $P_i$ apply hash function $h_2(s.b)$ and for all matching tuples $r \in P_i$, add $\langle r, s \rangle$ to the result
    otherwise, write it back out to disk
```

How it works — partitioning R, iteration i



How it works — paritioning and joining S, iteration i



What is the cost?

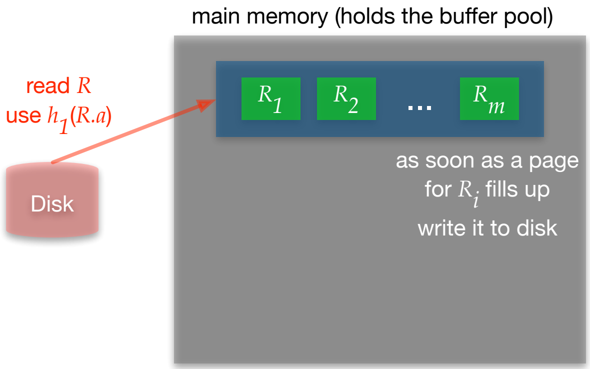
- *Assume equal partition* sizes, input T, P_T *pages*
- For *m partitions*, we will make *m passes* over each input
  - For the first pass:
    - *Read* P_T pages, *write* $P_T - \frac{P_T}{m}$ pages: $2P_T - \frac{P_T}{m}$ I/Os
  - For the second pass:
    - *Read* $P_T - \frac{P_T}{m}$, *write* $P_T - \frac{P_T}{m} + P_T - 2\frac{P_T}{m}$ pages: $2P_T - 3\frac{P_T}{m}$ I/Os
  - Pass i: $2P_T - (2i-1)\frac{P_T}{m}$ I/Os
- In the end, $m(m+1)P_T$ I/Os
- For two relations R and S, *total cost* is $m(m+1)(P_R + P_S)$
- Makes sense if *m is small*, or we have *a lot of memory*
- Effectively, this is nested loops join
  - *But* the number of *iterations* is decided by the *number of partitions, not the input sizes*!

The "grace" algorithm

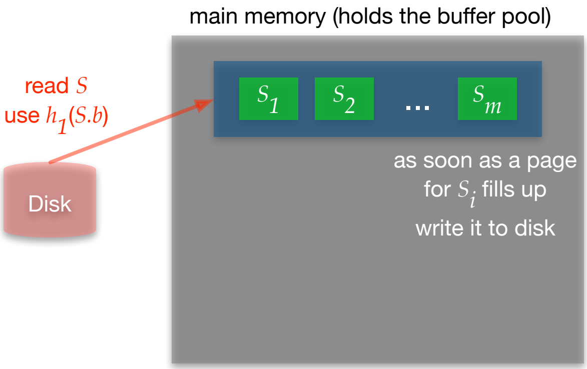
Grace hash join

```
for each $r \in R$ read $r$ and add it to the buffer page for $h_1(r.a)$
for each $s \in S$ read $s$ and add it to the buffer page for $h_1(s.b)$
for $i = 1, \ldots, m$ do {
  for each $r \in R_i$ read $r$ and insert it into a hash table using $h_2(r.a)$
  for each $s \in S_i$ do {
    read $s$, probe the hash table using $h_2(s.b)$
    for all matching tuples $r \in R_i$ add $\langle r, s \rangle$ to the result
  }
clear hash table
}
```

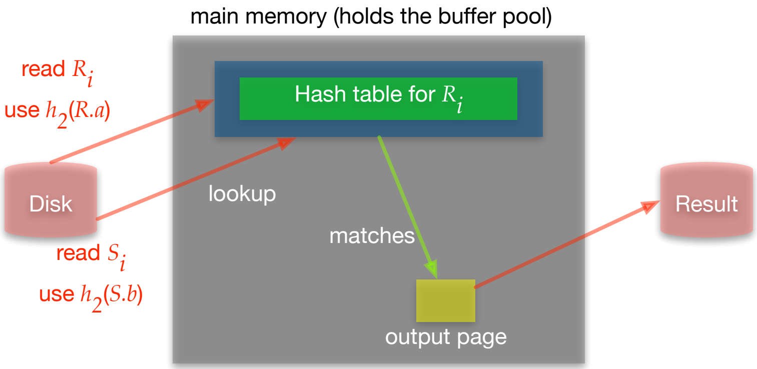
How it works — partitioning *R*


main memory (holds the buffer pool)
read R
use $h_1(R.a)$
Disk
R_1
R_2
...
R_m
as soon as a page for R_i fills up
write it to disk

How it works — partitioning S


main memory (holds the buffer pool)
read S
use $h_1(S.b)$
Disk
S_1
S_2
...
S_m
as soon as a page for S_i fills up
write it to disk

How it works — joining



What is the cost?

- *Scan R* and *write* it to disk, so $2 \cdot P_R$
- Do the *same for S*, so $2 \cdot P_S$
- *Read R* in *partition-by-partition*, so P_R
- *Scan S partition-by-partition* and *probe* for matches, so P_S
- $cost(R \bowtie S) = 3 \cdot (P_R + P_S)$
  - Same example, $P_R = 1,000$, $P_S = 500$, cost is *4,500 I/Os*
  - At 10ms an I/O the join will take *45 seconds* to evaluate

Memory requirements

- *Objective*: the *hash table* for a *partition* must *fit in memory*
  - *Minimise partition size by maximising number of partitions*
- What are the *optimum sizes*?
  - For *B buffer pool pages*, maximum number of partitions $m = B - 1$ (why?)
- *Size* of each *partition* is $\lceil \frac{P_R}{B-1} \rceil$
- *Size* of the *hash table* is $\lceil \frac{f \cdot P_R}{B-1} \rceil$ ($f =$ *fudge factor* to capture the *increase* in *partition size due to the hash table*)
- During the *probing phase*, in addition to the hash table, we need *one page to read S*, plus *one page for output*
  - So, $B > \lceil \frac{f \cdot P_R}{B-1} \rceil + 2 \Rightarrow B > \sqrt{f \cdot P_R}$

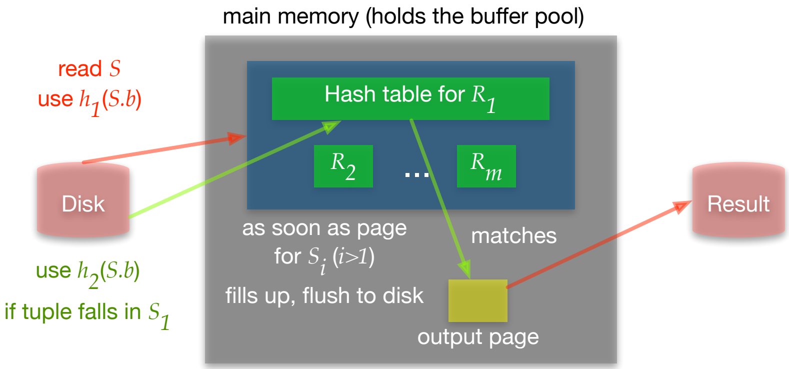
Hybrid hash join

- An *improvement over hash join* if there is *extra memory*
  - *Minimum amount* of *memory* for *hash join* $B > \sqrt{f \cdot P_R}$
  - *Suppose* that $B > \frac{f \cdot P_R}{k}$, for some *integer* k
  - *Divide* R into k *partitions* of *size* $\frac{P_R}{k}$ ($k + 1$ *buffer pool pages* needed)
  - This leaves $B - (k + 1)$ *extra buffer pool pages*

How it works

- *Suppose* that $B - (k+1) > \frac{f \cdot P_R}{k}$
  - We have *enough memory* during partitioning to *hold* an *in-memory hash table* of *size* $B - (k+1)$ *pages*
- Idea: *keep* R_1 in *memory* at *all times*
- *While partitioning* S, if a *tuple falls* into S_1, *don't write* it to disk; instead *probe* the *hash table for* R_1 for matches
- For all *partitions* $R_i, S_i, i > 2$, *continue as in hash join*

How it works — partitioning and joining



Savings over grace hash join

- Essentially, *reduces* the *number* of *full passes*
- Running example, $P_R = 1,000$, $P_S = 500$, assume 300 pages in the buffer pool
- *Choose* the *smaller relation, S*
- *Two partitions* for it, *each 250 pages*
  - But *one* will *stay in memory*; so, cost is 500+250=750 I/Os
- *Scan R*, use *two partitions*, *each 500 pages*
  - But the *first one* is *not written* to disk; so cost is 1,000+500=1500 I/Os
- *Join* the *two on-disk partitions*, cost 250+500=750 I/Os
- Total cost *750+1500+750=300 I/Os*
- At 10ms an I/O, this is *half a minute*

On predicates

- The *algorithms* we talked about *will work on equi-join predicates*
  - If there are *no equi-join predicates* (inequality joins) the *only algorithm* that will work is *nested loops* (why?)
  - If there are *indexes* on the *inequality join predicate's attributes*, we can *use index nested loops* and *revert* the *join* to *multiple scans*
    - ★ *Hoping* that we will have *buffer pool hits*
    - ★ Remember *access patterns* and *page replacement policy*?
  - Luckily, in a *typical query workload* there will *mostly be equi-join predicates*

On pipelining

- *Pipelining* is *great*, but it *cannot always be achieved*
- *All* three *algorithms* will essentially *block* at some point
    - In the *best case*, *between matches*
    - In the *worst case*, *until after a few scans* of the input relations
- This is *not necessarily bad*; in fact, *even* if the *algorithms block*, the *time needed* to compute the complete join result *might be less*
- *In reality*, *more than two stages* of pipelining can *rarely be obtained* in a single plan

Summary

- The *physical join* is the *most optimised physical evaluation operator*
  - Because a *DBMS spends most of its time evaluating joins*
- *Three main classes* of algorithms
  - *Iteration-based*, *order-based*, *partition-based*
- Three main *choice criteria*
  - *Physical layout*, *indexes*, *available memory*

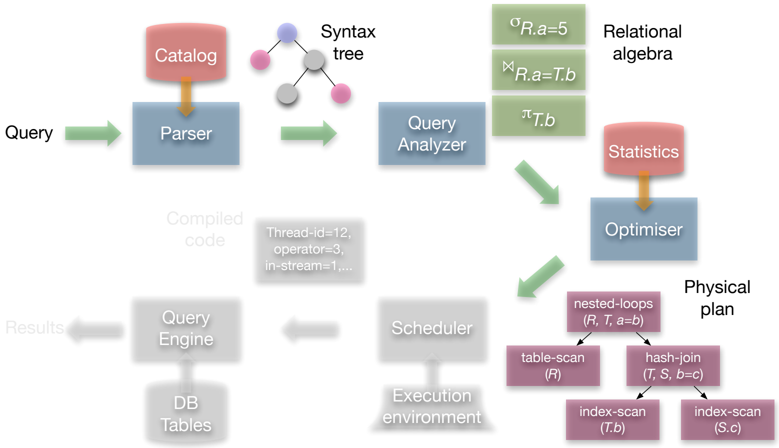
Summary (cont.)

- *Iteration-based* methods
  - Essentially, *nested loops*
  - Very *simple to implement*, but if *implemented poorly* very *inefficient*
  - But also *very useful* because they *evaluate non-equi-join predicates*
- *Order-based* methods
  - *Sort* the inputs, *merge* them afterwards
  - *Well-behaved cost* — 3-4 passes over the data will do the trick

Summary (cont.)

- *Partition-based* methods
  - *Simple hash join*, *Grace hash join*, and *hybrid hash join*
  - If there is *extra memory*, *hybrid hash join*'s behaviour is *excellent*
- *Figuring out* the *best join algorithm* for a *particular pair* of inputs is the *job* of the *query optimiser*
- Which, along with *good implementations*, will *choose the one* that *evaluates a join in 30 seconds and not in 14,000 hours*

Query cycle


Catalog
Syntax tree
σ R.a=5
⋈ R.a=T.b
π T.b
Relational algebra
Query
Parser
Query Analyzer
Statistics
Optimiser
Compiled code
Thread-id=12, operator=3, in-stream=1,...
Physical plan
nested-loops (R, T, a=b)
table-scan (R)
hash-join (T, S, b=c)
index-scan (T.b)
index-scan (S.c)
Results
Query Engine
Scheduler
DB Tables
Execution environment

Query optimiser

- The *query optimiser* is the *heart* of the *evaluation engine*
    - Yes, the *physical operators* get the *job done*
    - Yes, the *execution model* makes sure the *operators* actually *run*
    - But, unless the *query optimiser decides on those things*, the query will never run
    - And the *decision* needs to be a *good one*

Decisions

- Two *crucial decisions* the *optimiser makes*
  - The *order* in which the *physical operators* are applied on the inputs (*i.e.*, *the plan employed*)
  - The *algorithms* that *implement* the *physical operators*
- These *two decisions* are *not independent*
  - In fact, *one affects the other* in *more ways than one*

Cost-based query optimisation

- The *paradigm* employed is *cost-based query optimisation*
  - Simply put: *enumerate* alternative *plans*, *estimate* the *cost* of *each plan*, *pick* the *plan* with the *minimum cost*
- For *cost-based optimisation*, we need a *cost model*
  - Since *what "hurts"* performance *is I/O*, the *cost model* should *use I/O* as its *basis*
  - Hence, the *cardinality-based cost model*
    - ⋆ *Cardinality* is the *number* of *tuples* in a *relation*

Plan enumeration

- *Plan enumeration* consists of *two parts* (again, *not necessarily independent* from one another)
  - *Access method selection* (*i.e.*, what is the *best way* to *access a relation* that appears in the query?)
  - *Join enumeration* (*i.e.*, what is the *best algorithm* to *join* two relations, and *when should we apply it*?)
- *Access methods*, *join algorithms* and their various *combinations* define a *search space*
  - The *search space* can be *huge*
  - *Plan enumeration* is the *exploration* of this *search space*

Search space exploration

- As was stated, the *search space* is *huge*
  - *Exhaustive exploration* is *out of the question*
  - Because it *could be the case* that *exploring* the search space might *take longer than* actually *evaluating* the query
  - The *way* in which we *explore* the *search space* describes a *query optimisation method*
    - ⋆ *Dynamic programming*, *rule-based* optimisation, *randomised* exploration, . . .

Just an idea . . .

- A query over *five relations*, only *one access method*, only *one join algorithm*, only *left-deep plans*
    - Remember, $cost(R \bowtie S) \neq cost(S \bowtie R)$
    - So, the number of *possible plans* is $5! = 120$
    - If we add *one extra access method*, the number of *possible plans* becomes $2^5 \cdot 5! = 3840$
    - If we add one *extra join algorithm*, the number of *possible plans* becomes $2^4 \cdot 2^5 \cdot 5! = 61440$

Cardinality-based cost model

- A *cardinality-based cost model* means we need *good ways of* doing the following
  - *Using cardinalities* to *estimate costs* (*e.g.*, accurate cost functions)
  - *Estimating output cardinalities after* we apply *certain operations* (*e.g.*, after a selection the cardinality will change; it will not change after a projection)
    - ⋆ *Because* these *output cardinalities will be used as inputs* to the *cost functions* of *other operations*

Cardinality estimation

- An *entire area* of *query optimisation*
- Largely a *matter of statistics*
- It has *triggered* the "*percentage wars*"
  - "This estimation technique is within x% of the true value with a y% probability"
- *Fact*: the *better* the *statistics*, the *better* the *decisions*
- *Another fact*: *errors* in statistics *propagate exponentially*; after 4 or 5 joins, you might as well flip a coin
- *Third fact*: *cost functions* are *discontinuous*, so in certain scenarios *only perfect statistics will help*

Are we done?

- The *previous issues* were only a *subset* of the *problems* an *optimiser solves*
    - We also need to *worry* about *certain properties* of the data
        - ★ For instance, if we *use a B+tree* as an access method, then *we won't have to sort* (*e.g.*, interesting orders in System R)
        - ★ If we use a *hash join later on* the *order is spoiled*
        - ★ So we will *have to sort again*
    - *Depending* on the *algorithm* and the *environment*, we need to *allocate memory*
- And as if *all these were not enough*, *optimisation time assumptions* do *not necessarily hold* at *run time*

The final nail . . .

- These are *all* for *one query*
- Now, imagine a *system* doing that for *1000 queries*
    - *Simultaneously*
- And it *all* has to be *done fast*
    - Once a *decision* is *made*, it *cannot be undone*

Conclusion

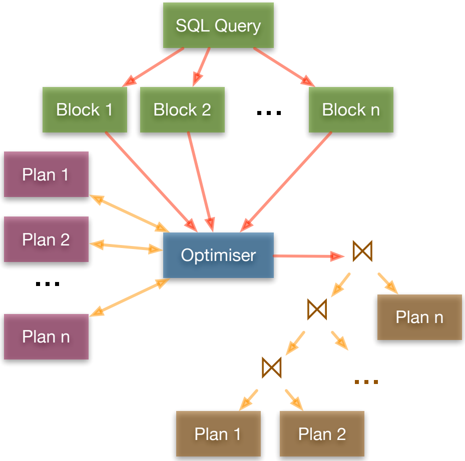
- *Query optimisation* is a *very, very hard problem*
- But *without it* a DBMS is *doomed* to *seriously sub-optimal performance*
- The *problem* is *not nearly solved*
  - All we *have* is *decent optimisation strategies*
  - And *decent sub-problem solutions*
- *Fact*: *rarely* will an *optimiser pick* the *"best"* plan
  - But it will *almost always pick* a *plan* with *good performance* and *stay away* from *bad choices*
  - At the end of the day, thats what counts

The agenda

- *Mapping SQL queries* to *relational algebra*
  - Query blocks, uncorrelated *vs.* correlated queries
- *Optimisation* of a *single query block*
- *Equivalence rules*
- *Statistics* and *cardinality estimation*
- *Search space exploration*
  - *Dynamic programming* (System-R)

SQL decomposition

- *SQL queries* are *optimised* by *decomposing* them into a *collection* of *query blocks*
- A *block* is *optimised* in *isolation*, *resulting* in a *plan* for a *block*
- *Plans* for *blocks* are *combined* to form the *complete plan* for the query



What is a block?

- An *SQL query* with *no nesting*
- Exactly *one select-clause*
- Exactly *one from-clause*
- *At most one*
  - *Where-clause* in *conjunctive normal form*
  - *Group by-/sort by-*clause
  - *Having-*clause

Example

Sample schema

- *Sailors* (*sid*, *sname*, *rating*, *age*)
- *Boats* (*bid*, *bname*, *color*
- *Reserves* (*sid*, *bid*, *day*, *rname*)

Example

For each sailor with the highest rating over all sailors, and at least two reservations for red boats, find the sailor id and the earliest date on which the sailor has a reservation for a red boat.

SQL query

```
select      s.sid, min(r.day)
from        sailors s, reserves r, boats b
where       s.sid = r.sid and r.bid = b.bid and
            b.color = 'red' and
            s.rating = ( select  max(s2.rating) from sailors s2)
group by    s.sid
having      count(*) > 1
```

Two blocks in the query

```
select   s.sid, min(r.day)
from     sailors s, reserves r, boats b
where    s.sid = r.sid and r.bid = b.bid and
         b.color = 'red' and
         s.rating = ( )
group by s.sid
having   count(*) > 1
```

reference

```
select max(s2.rating)
from   sailors s2
```

outer
block

nested
block

```
select   s.sid, min(r.day)
from     sailors s, reserves r, boats b
where    s.sid = r.sid and r.bid = b.bid and
         b.color = 'red' and
         s.rating = (select max(s2.rating)
                     from   sailors s2)
group by s.sid
having   count(*) > 1
```

Single block optimisation — step 1

SQL query

```
select      s.sid, min(r.day)
from        sailors s, reserves r, boats b
where       s.sid = r.sid and r.bid = b.bid and
            b.color = 'red' and
            s.rating = ( select  max(s2.rating) from sailors s2)
group by    s.sid
having      count(*) > 1
```

Relational algebra

$\pi_{s.sid,\min(r.day)}($

$having_{count(*)>2}($

$group\ by_{s.sid}($

$\sigma_{s.sid=r.sid \wedge r.bid=b.bid \wedge b.color=red \wedge s.rating=nested-value}($

$sailors \times reserves \times boats))))$

- *Express* the query in *relational algebra*
- More specifically, *extended relational algebra*

Single block optimisation — step 2

Relational algebra — before

$\pi_{s.sid, \min(r.day)}($
$having_{count(*)>2}($
$group\ by_{s.sid}($
$\sigma_{s.sid=r.sid \wedge r.bid=b.bid \wedge b.color=red \wedge s.rating=nested-value}($
$sailors \times reserves \times boats))))$

Relational algebra — after

$\pi_{s.sid}($
$\sigma_{s.sid=r.sid \wedge r.bid=b.bid \wedge b.color=red \wedge s.rating=nested-value}($
$sailors \times reserves \times boats))$

- *Ignore* the *aggregate operations*
  - They *only have meaning* for the *complete result*
  - *Convert* the *query* into a *subset* of *relational algebra* called $\sigma\pi\times$

Single block optimisation — step 3

- Use *equivalence rules* to identify *alternative ways* of *formulating the query*
- “*Plug in*” *algorithms*
- *Enumerate plans*
- *Estimate* the *cost* of each *plan*
- *Pick* the *one* with the *minimum cost*

Equivalence rules

- Essentially, *every query block* consists of *three things*
  - *Cartesian product* of all *relations* in the *from-clause*
  - *Selection predicates* of the *where-clause*
  - *Projections* of the *select-clause*
- The *equivalence rules define* the *space* of *alternative plans* considered by an optimiser
  - In other words, the *search space of a query*

Selection and projections

- Cascading of selections
  - $\sigma_{c_1 \wedge c_2 \wedge \ldots \wedge c_n}(R) \equiv \sigma_{c_1}(\sigma_{c_2}(\ldots(\sigma_{c_n}(R))))$
- Commutativity
  - $\sigma_{c_1}(\sigma_{c_2}(R)) \equiv \sigma_{c_2}(\sigma_{c_1}(R))$
- Cascading of projections
  - $\pi_{a_1}(R) \equiv \pi_{a_1}(\pi_{a_2}(\ldots(\pi_{a_n}(R))\ldots)$
  - iff $a_i \subseteq a_{i+1}$, $i = 1, 2, \ldots n-1$

Cartesian products and joins

- Commutativity
  - $R \times S \equiv S \times R$
  - $R \bowtie S \equiv S \bowtie R$
- Assosiativity
  - $R \times (S \times T) \equiv (R \times S) \times T$
  - $R \bowtie (S \bowtie T) \equiv (R \bowtie S) \bowtie T$
- Their combination
  - $R \bowtie (S \bowtie T) \equiv R \bowtie (T \bowtie S) \equiv (R \bowtie T) \bowtie S$
    $\equiv (T \bowtie R) \bowtie S$

Among operations

- Selection-projection commutativity
  - $\pi_a (\sigma_c (R)) \equiv \sigma_c (\pi_a (R))$
  - iff *every attribute in c* is *included* in the *set of attributes a*
- Combination (join definition)
  - $\sigma_c (R \times S) \equiv R \bowtie_c S$
- Selection-Cartesian/join commutativity
  - $\sigma_c (R \times S) \equiv \sigma_c(R) \bowtie S$
  - iff the *attributes in c* appear *only in R* and *not in S*
- Selection distribution/replacement
  - $\sigma_c(R \bowtie S) \equiv \sigma_{c_1 \wedge c_2} (R \bowtie S) \equiv \sigma_{c_1} (\sigma_{c_2} (R \bowtie S)) \equiv \sigma_{c_1}(R) \bowtie \sigma_{c_2}(S)$
  - iff c_1 *is relevant only to R* and c_2 *is relevant only to S*

Among operations (cont.)

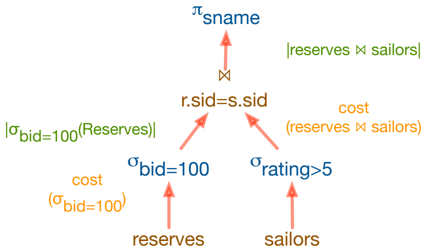
- Projection-Cartesian product commutativity
  - $\pi_a (R \times S) \equiv \pi_{a_1}(R) \times \pi_{a_2}(R)$
  - iff a_1 *is the subset of attributes in a appearing in R* and a_2 *is the subset of attributes in a appearing in S*
- Projection-join commutativity
  - $\pi_a (R \bowtie_c S) \equiv \pi_{a_1}(R) \bowtie_c \pi_{a_2}(R)$
  - iff *same as before* and *every attribute in c appears in a*
- Attribute elimination
  - $\pi_a(R \bowtie_c S) \equiv \pi_a(\pi_{a_1}(R) \bowtie_c \pi_{a_2}(S))$
  - iff a_1 *subset of attributes in R appearing in either a or c* and a_2 *is the subset of attributes in S appearing in either a or c*

What do we have and what do we need?

- We have
  - A way to *decompose SQL queries* into *multiple query blocks*
  - A way to *map a block* to *relational algebra*
  - *Equivalence rules* between different *algebraic expressions*, *i.e.*, a search space
- We need
  - A way to *estimate the cost* of *each alternative* expression
    - ⋆ *Depending* on the *algorithms* used
  - A way to *explore* the *search space*

Cost estimation

- A *plan* is a tree of operators
- *Two parts* to *estimating* the *cost* of a plan
  - For *each node*, estimate the *cost* of *performing* the corresponding *operation*
  - For *each node*, *estimate* the *size* of the *result* and any *properties* it might have (*e.g.*, sorted)
- *Combine* the *estimates* and *produce* an *estimate* for the *entire plan*



Cost and cardinality

- We have seen *various storage methods* and *algorithms*
  - And *know the cost* of *using each* one, *depending* on the *input cardinality*
- The *problem* is *estimating* the *output cardinality* of the *operations*
  - Namely, *selections* and *joins*

Selectivity factor

- The *maximum number of tuples* in the *result* of any *query* is the *product* of the *cardinalities* of the *participating relations*
- Every *predicate* in the *where-clause eliminates some* of these *potential results*
- *Selectivity factor* of a *single predicate* is the *ratio* of the *expected result size* to the *maximum result size*
- *Total result size* is *estimated* as the *maximum size times* the *product* of the *selectivity factors*
- *Key assumption*: the *predicates* are statistically *independent*

How it works

SQL query

```
select   $a_1, a_2, \ldots a_k$
from     $R_1, R_2, \ldots R_n$
where    $P_1$ and $P_2$ and ... and $P_m$
```

Maximum output cardinality

$|R_1| \cdot |R_2| \cdot \ldots \cdot |R_n|$

Selectivity factor product

$f_{P_1} \cdot f_{P_2} \cdot \ldots \cdot f_{P_m}$

Estimated output cardinality

$(f_{P_1} \cdot f_{P_2} \cdot \ldots \cdot f_{P_m}) \cdot |R_1| \cdot |R_2| \cdot \ldots \cdot |R_n|$

Various selectivity factors

- $column = value \rightarrow \frac{1}{\#keys(column)}$
  - Assumes *uniform distribution* in the values
  - Is itself an *approximation*
- $column_1 = column_2 \rightarrow \frac{1}{\max(\#keys(column_1), \#keys(column_2))}$
  - *Each value* in *column*$_1$ has a *matching value* in *column*$_2$; *given* a *value* in *column*$_1$, the *predicate* is just a *selection*
  - Again, an *approximation*

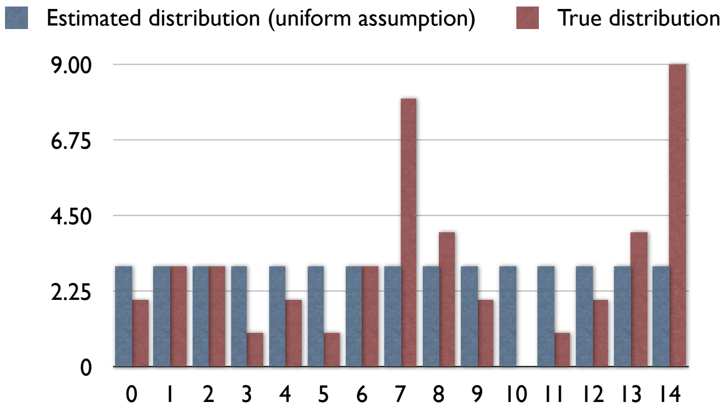
Various selectivity factors (cont.)

- *column* $>$ *value* $\rightarrow \frac{(high(column) - value)}{(high(column) - low(column))}$
- $value_1 < column < value_2 \rightarrow \frac{(value2 - value1)}{(high(column) - low(column))}$
- *column in list* $\rightarrow$ *number of items in list times s.f. of column* $=$ *value*
- *column in sub-query* $\rightarrow$ *ratio* of *subquery's estimated size* to the *number of keys* in column
- *not (predicate)* $\rightarrow$ *1 - (s.f. of predicate)*
- $P_1 \vee P_2 \rightarrow f_{P_1} + f_{P_2} - f_{P_1} \cdot f_{P_2}$

Key assumptions made

- The *values across columns* are *uncorrelated*
- The *values* in a *single column* follow a *uniform distribution*
- *Both* of these assumptions *rarely hold*
- The *first assumption* is *hard to lift*
  - Only recently have researchers started tackling the problem
- The *uniform distribution* assumption can be *lifted* with *better statistical methods*
  - In our case, *histograms*

What we would like



Lifting the uniform distribution assumption

- At the *basic level*, all we *need* is a *collection* of *(value, frequency) pairs*
- Which is *just a relation*!
  - So, *scan* the *input* and *build* it
- But this is *unacceptable*
  - Because the *size* might be *comparable* to the *size* of the *relation*
  - And we *need* to *answer queries* about the *value distribution fast*

parts

name	color	stock
bolt	red	10
bolt	green	5
nut	blue	4
nut	black	10
nut	red	5
nut	green	10
cam	blue	5
cam	green	10
cam	black	10

parts.color

value	freq
red	2
green	3
blue	2
black	2

parts.stock

value	freq
10	4
5	3
4	1

Histograms

- *Elegant data structures* to *capture value distributions*
  - *Not affected* by the *uniform distribution* assumption (though this is *not entirely true*)
- They offer *trade-offs* between *size* and *accuracy*
  - The *more memory* that is dedicated to a histogram, the *more accurate* it is
  - But also, the *more expensive* to manipulate
- *Two* basic classes: *equi-width* and *equi-depth*

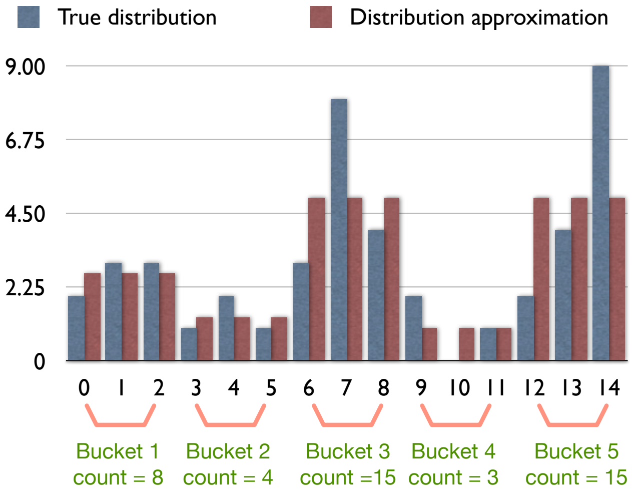
Desirable histogram properties

- *Small*
  - Typically, a DBMS will allocate a *single page* for a histogram!
- *Accurate*
  - Typically, less than *5% error*
- *Fast access*
  - *Single lookup* access and *simple algorithms*

Mathematical properties

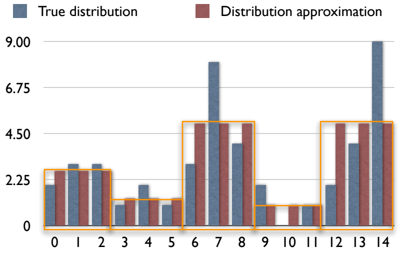
- A *histogram approximates* the *value distribution* for *attribute X* of *table T*
- The *value distribution* is *partitioned* into a number of *b subsets*, called *buckets*
- There is a *partitioning constraint* that *identifies how* the *partitioning* takes place
  - *Different constraints*, lead to *different classes* of histograms
- The *values* and *frequencies* in *each bucket* are *approximated* in some *common fashion*

Equi-width histogram



Equi-width histogram construction

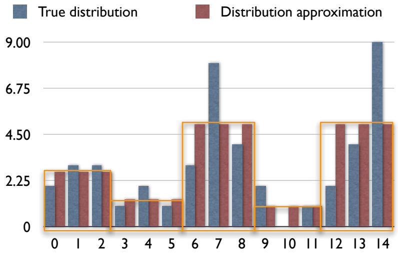
- The *total range* is *divided* into *sub-ranges* of *equal width*
- Each *sub-range* becomes a *bucket*
- The *total number of tuples* in *each bucket* is *stored*



min	max	count
0	2	8
3	5	4
6	8	15
9	11	3
12	14	15

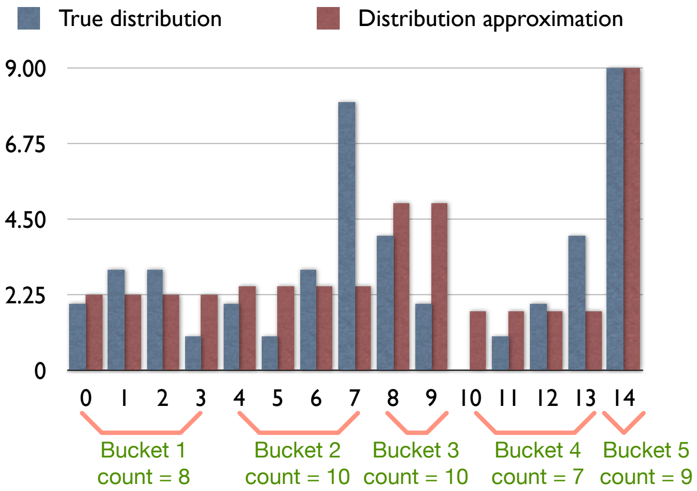
Equi-width histogram estimation

- To *estimate* the output cardinality of a range query
  - The *starting bucket* is *identified*
  - The *histogram* is then *scanned forward* until the *ending bucket* is *identified*
  - The *numbers of tuples* in the *buckets* of the range are *summed*
  - *Within each bucket* the *uniform distribution assumption* is made
- $6 \leq v \leq 10$: $\frac{3}{3} \cdot 15 + \frac{2}{3} \cdot 3 = 17$



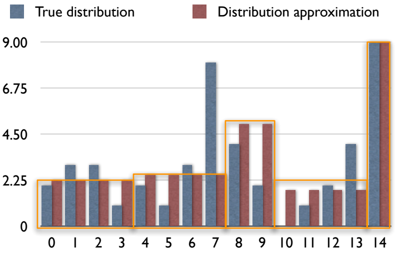
min	max	count
0	2	8
3	5	4
6	8	15
9	11	3
12	14	15

Equi-depth histogram



Equi-depth histogram construction and estimation

- The *total range* is *divided* into *sub-ranges* so that the *number of tuples* in *each range* is (approximately) *equal*
- Each *sub-range* becomes a *bucket*
- The *same schema* as in *equi-width* histograms is used
- In fact, the *same algorithm* is used for *estimation* (!)
- $6 \leq v \leq 10$: $\frac{2}{4} \cdot 10 + \frac{2}{2} \cdot 10 + \frac{1}{4} \cdot 7 \approx 17$



min	max	count
0	3	8
4	7	10
8	9	10
10	13	7
14	14	9

Comparison

- *Equi-depth* histograms are *generally better* than *equi-width*
  - *Buckets* with *frequently occurring values* contain *fewer values*
  - *Infrequently occurring values* are approximated *less accurately (but the error is less significant)*
  - So the *uniform distribution assumption within* each *bucket* leads to *better approximation*

What do we have and what do we need?

- *We have*
  - A way to *decompose* a *query*
  - A way to *identify* equivalent, *alternative representations* of it (*i.e.*, a *search space*)
  - A *statistical framework* to *estimate cardinalities*
  - A *cost model* to *estimate* the *cost* of an alternative
- *We need*
  - A way to *explore* the *search space*
  - *Dynamic programming*

Dynamic programming

- In the beginning, there was *System R*, which had an *optimiser*
- *System R's optimiser* was using *dynamic programming*
  - An *efficient way* of *exploring* the search space
- *Heuristics*: use the *equivalence rules* to *push down selections* and *projections*, *delay Cartesian products*
  - *Minimise input cardinality* to, and *memory* requirements of the *joins*
- *Constraints*: *left-deep plans*, *nested loops* and *sort-merge join* only
  - *Left-deep plans* took better *advantage of pipelining*
  - *Hash-join* had *not* been *developed* back then

Interesting orders

- If there is an *order by* or *group by* clause on an *attribute*, we say that this *attribute* has an *interesting order* associated with it
  - *Interesting*, because *depending* on the *access method* we can get away with *fewer physical operations* (*e.g.*, sorting)
- The *same holds* for *attributes* participating in a *join*
  - Again, *interesting* because we can *use* the *access method* in *evaluating* the join

Dynamic programming steps

- *Identify* the *cheapest* way to *access every* single *relation* in the query, *applying local predicates*
  - For *every relation*, *keep* the *cheapest access method overall* and the *cheapest access method* for an *interesting order*
- For *every access method*, and for *every join predicate*, find the *cheapest way* to *join* in a *second relation*
  - For *every join result keep* the *cheapest plan overall* and the *cheapest plan* in an *interesting order*
- *Join* in the *rest* of the *relations* using the *same principle*

An example

emp

name	dno	job	salary
Smith	50	12	8500
Jones	50	5	15000
Doe	51	5	9500

dept

dno	dname	location
50	MFG	Edinburgh
51	Billing	London
52	Shipping	Glasgow

job

job	title
5	clerk
6	typist
8	sales
12	mechanic

name, salary, job title, department name of employees who are clerks and work in departments in Edinburgh

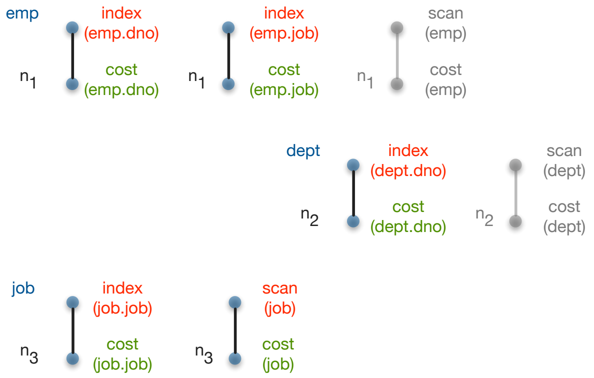
local predicates

```
select name, title, salary, dname
from   emp, dept, job
where  job.title='Clerk' and
       dept.location = 'Edinburgh' and
       emp.dno = dept.dno and
       emp.job = job.job
```

join predicates

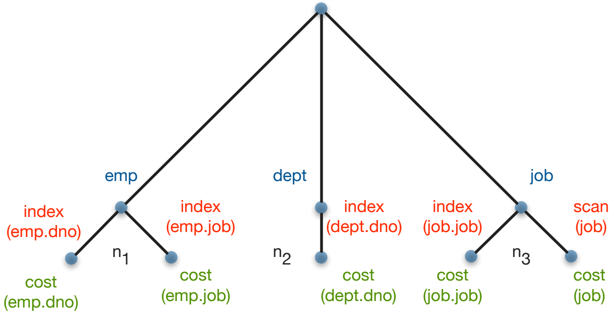
interesting orders

Access methods and local predicates

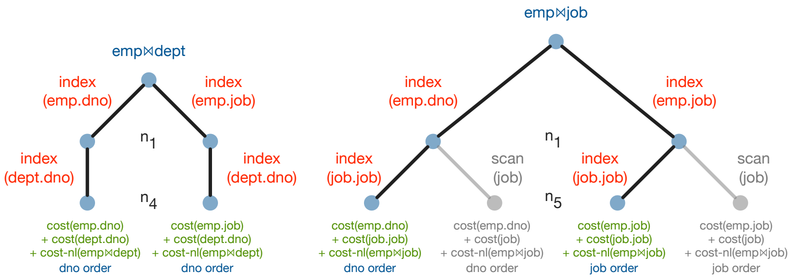


- *Scanning emp* is the *most expensive* method for *emp*; *emp.dno* and *emp.job* are *interesting orders*
- *Scanning dept* is the *most expensive* method for *dept*; *dept.dno* is an *interesting order*
- *Scanning job* is the *cheapest* method for *job*; but, *job.job* is an *interesting order*

Search tree for access methods

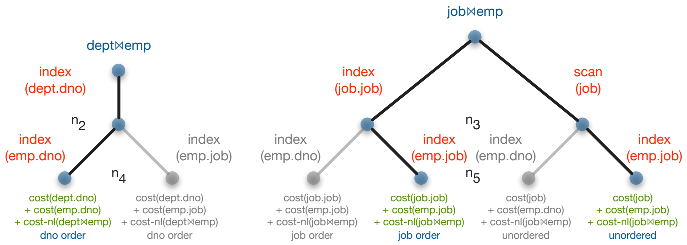


Join enumeration for relation *emp* (nested loops join)


emp⋈dept
index (emp.dno)
index (emp.job)
n1
index (dept.dno)
index (dept.dno)
n4
cost(emp.dno) + cost(dept.dno) + cost-nl(emp⋈dept) dno order
cost(emp.job) + cost(dept.dno) + cost-nl(emp⋈dept) dno order
emp⋈job
index (emp.dno)
index (emp.job)
n1
index (job.job)
scan (job)
index (job.job)
scan (job)
n5
cost(emp.dno) + cost(job.job) + cost-nl(emp⋈job) dno order
cost(emp.dno) + cost(job) + cost-nl(emp⋈job) dno order
cost(emp.job) + cost(job.job) + cost-nl(emp⋈job) job order
cost(emp.job) + cost(job) + cost-nl(emp⋈job) job order

- Both *emp ⋈ dept results* are *in different interesting orders* so they are propagated
- Only the *cheapest result* in any *interesting order* is propagated for *each pair of inputs*

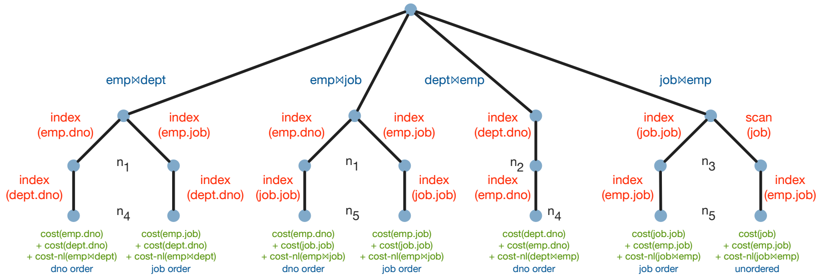
Join enumeration for relations *dept*, *job* (nested loops)



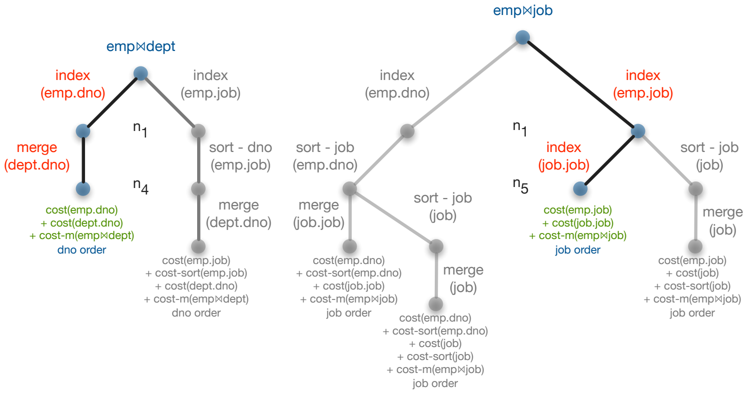
dept⋈emp
index (dept.dno)
n2
index (emp.dno)
index (emp.job)
n4
cost(dept.dno) + cost(emp.dno) + cost-nl(dept⋈emp) dno order
cost(dept.dno) + cost(emp.job) + cost-nl(dept⋈emp) dno order
job⋈emp
index (job.job)
scan (job)
n3
index (emp.dno)
index (emp.job)
index (emp.dno)
index (emp.job)
n5
cost(job.job) + cost(emp.job) + cost-nl(job⋈emp) job order
cost(job.job) + cost(emp.job) + cost-nl(job⋈emp) job order
cost(job) + cost(emp.dno) + cost-nl(job⋈emp) unordered
cost(job) + cost(emp.job) + cost-nl(job⋈emp) unordered

- *cost(emp ⋈ dept) ≠ cost(dept ⋈ emp)* so we will *enumerate dept's joins* even though we have an alternative for generating the same result (same for *job* ⋈ *emp*)
- Both *dept ⋈ emp results* in the same order, *only* one propagated
- Since there is *no dept ⋈ job predicate* in the query, that join is *not enumerated* (same for *job* ⋈ *dept*)
- The *unordered* result for *job ⋈ emp* is propagated because it is the *cheapest overall*

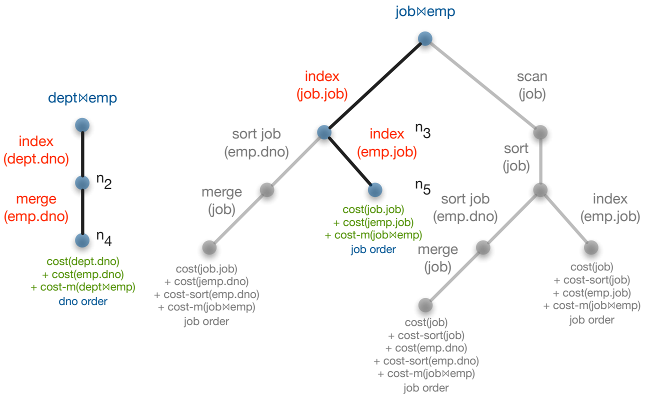
Search tree — 2 relations, nested loops join


emp⋈dept
emp⋈job
dept⋈emp
job⋈emp
index (emp.dno)
index (emp.job)
index (emp.dno)
index (emp.job)
index (dept.dno)
index (job.job)
scan (job)
n1
n1
n2
n3
index (dept.dno)
index (dept.dno)
index (job.job)
index (job.job)
index (emp.dno)
index (emp.job)
index (emp.job)
n4
n5
n4
n5
cost(emp.dno) + cost(dept.dno) + cost-nl(emp⋈dept) dno order
cost(emp.job) + cost(dept.dno) + cost-nl(emp⋈dept) job order
cost(emp.dno) + cost(job.job) + cost-nl(emp⋈job) dno order
cost(emp.job) + cost(job.job) + cost-nl(emp⋈job) job order
cost(dept.dno) + cost(emp.dno) + cost-nl(dept⋈emp) dno order
cost(job.job) + cost(emp.job) + cost-nl(job⋈emp) job order
cost(job) + cost(emp.job) + cost-nl(job⋈emp) unordered

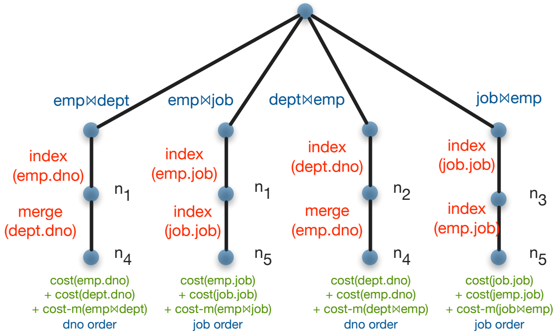
Join enumeration for relation *emp* (sort-merge)


emp⋈dept
index (emp.dno)
index (emp.job)
n1
merge (dept.dno)
n4
sort - dno (emp.job)
merge (dept.dno)
cost(emp.dno) + cost(dept.dno) + cost-m(emp⋈dept) dno order
cost(emp.job) + cost-sort(emp.job) + cost(dept.dno) + cost-m(emp⋈dept) dno order
emp⋈job
index (emp.dno)
index (emp.job)
n1
sort - job (emp.dno)
index (job.job)
sort - job (job)
n5
merge (job.job)
sort - job (job)
merge (job)
merge (job)
cost(emp.dno) + cost-sort(emp.dno) + cost(job.job) + cost-m(emp⋈job) job order
cost(emp.dno) + cost-sort(emp.dno) + cost(job) + cost-sort(job) + cost-m(emp⋈job) job order
cost(emp.job) + cost(job.job) + cost-m(emp⋈job) job order
cost(emp.job) + cost(job) + cost-sort(job) + cost-m(emp⋈job) job order

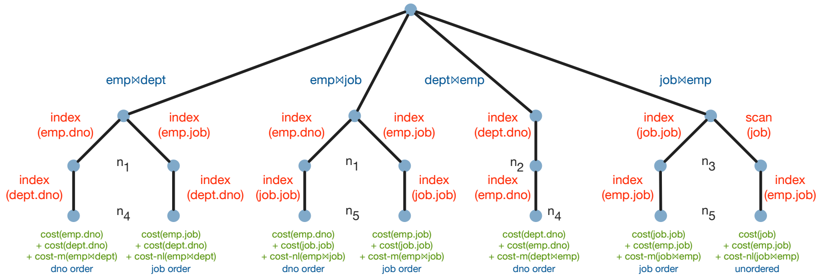
Join enumeration for relations *dept*, *job* (sort-merge)



Search tree — 2 relations, sort-merge join



Search tree — 2 relations, both join methods


emp⋈dept
emp⋈job
dept⋈emp
job⋈emp
index (emp.dno)
index (emp.job)
index (emp.dno)
index (emp.job)
index (dept.dno)
index (job.job)
scan (job)
n1
n1
n2
n3
index (dept.dno)
index (dept.dno)
index (job.job)
index (job.job)
index (emp.dno)
index (emp.job)
index (emp.job)
n4
n5
n4
n5
cost(emp.dno) + cost(dept.dno) + cost-m(emp⋈dept) dno order
cost(emp.job) + cost(dept.dno) + cost-nl(emp⋈dept) job order
cost(emp.dno) + cost(job.job) + cost-nl(emp⋈job) dno order
cost(emp.job) + cost(job.job) + cost-m(emp⋈job) job order
cost(dept.dno) + cost(emp.dno) + cost-m(dept⋈emp) dno order
cost(job.job) + cost(emp.job) + cost-m(job⋈emp) job order
cost(job) + cost(emp.job) + cost-nl(job⋈emp) unordered

- For *each pair or relations*, for *each different join order* and *for each interesting order for that pair one plan* is propagated
- An *unordered result* is *only* propagated if it is the *cheapest overall* for a *pair* in a *given join order*

Three relations

- *Repeat* the process
  - For *every pair* of two relations
  - For *every join* method
  - For *every access method* of the *remaining relation*
  - *Find* the *cheapest way* to *join* the *third relation* with the *pair*
    - ⋆ *Estimate cardinalities*
    - ⋆ *Estimate* the *cost* of computing the *join*
  - *Keep* the *cheapest choice* for *every interesting order* and the *cheapest* for the *unordered* case *if* it is the *cheapest overall*

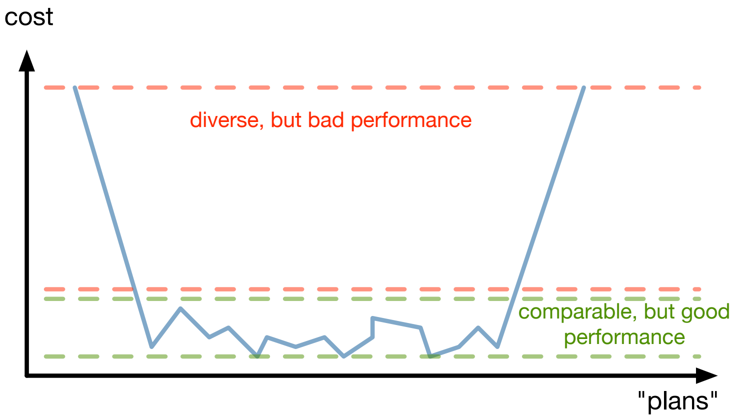
Rule-based optimisation

- *Basically* an issue of *if-then rules*
  - *If* (*condition list*) *then apply some transformation* to the plan constructed so far
    - ⋆ *Estimate* the *cost* of the *new plan*, *keep* it *only if* it is *cheaper than* the *original*
  - The *order* in which the *rules are applied* is *significant*
  - As a *consequence*, rules are applied *by precedence*
    - ⋆ For instance, *pushing down selections* is given *high precedence*
    - ⋆ Combining two relations with a *Cartesian product* is given *low precedence*

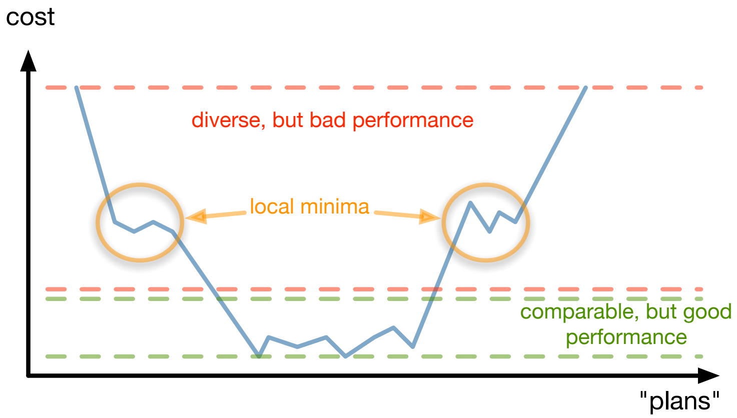
Randomised exploration

- *Mostly useful* in *big queries* (more than 15 joins or so)
- The *problem* is one of *exploring a bigger portion* of the search space
    - So, *every once in a while* the *optimiser "jumps"* to some *other part* of the search space *with some probability*
- As a *consequence*, it gets to *explore parts* of the search space it would *not have explored otherwise*

The “well”


cost
diverse, but bad performance
comparable, but good performance
"plans"

The “well” and local minima


cost
diverse, but bad performance
local minima
comparable, but good performance
"plans"

Final step — the entire plan

- The *optimiser* has produced *plans* for *each query block*
- The *question* is now one of *combining* the *sub-plans* to *formulate* the *entire query plan*
- The *strategy* used *depends* on *whether* the *outer* and *nested* queries are *correlated or not*
  - *If they are*, then in all probability the *two sub-plans* will be *combined through a join*

Uncorrelated queries

- *Usually*, they can be *executed in isolation*
- The *nested query feeds* the *outer query with results*

```
select s.sname
from   sailors s
where  s.rating = (select max(s2.rating)
                   from sailors s2)
```

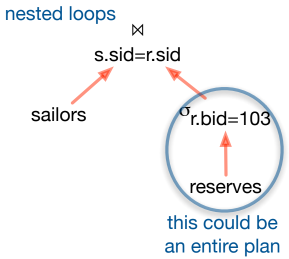
executed first

once the nested query is executed,
the outer is simply a selection

Correlated queries

- Sometimes, it is *not possible* to *execute* the *nested query just once*
- In those cases the *optimiser reverts* to a *nested loops* approach
    - The *nested query* is *executed* once for *every tuple* of the *outer query*

```
select s.sname
from   sailors s
where  exists (select *
               from reserves r
               where r.bid = 103 and
                     s.sid = r.sid)
```



In practice

- *Before* breaking up the *query into blocks*, most systems *try* to *rewrite* the *query* in some *other way* (*de-correlation*)
  - The idea is that *there will probably be a join*, so it will be *better* if the *query* is *optimised in its entirety*
- If *de-correlation* is *not possible*, then it is *nested loops all the way*
  - Usually, *compute* the *nested query*, *store* it in a temporary relation and *do nested loops* with the *outer*

What do we have and what do we need?

- *We have*
  - A way to *decompose* a *query*
  - A way to *identify* equivalent, *alternative representations* of it (*i.e.*, a *search space*)
  - A *statistical framework* to *estimate cardinalities*
  - A *cost model* to *estimate* the *cost* of an alternative
  - Ways of *exploring* the *search space*
- *We need*
  - *Nothing*!

Summary

- The *query optimiser* is the *heart* of the *query engine*
  - If it does *not* do a *good job*, the engine is doomed to *sub-optimal performance*
- *Two* key, closely related *decisions*
  - *Order* in which *operations* are performed
  - *Algorithms* that *perform* the *operations*
- The *paradigm* used is *cost-based optimisation*
  - *Three steps*: *generate* alternative plans, *estimate* the cost of each plan, *pick* the cheapest
- The *cost model* used is the *cardinality-based* cost model
  - Because *cardinality* is a *good I/O metric*
  - As a *consequence*, we need *good ways of doing* two things
    - ⋆ *Estimating* the *cost* of an *algorithm*
    - ⋆ *Estimating* the *output cardinality* of *operations*

Summary (cont.)

- *Cardinality estimation* is *50%* of the *problem*
  - Two *approaches*: *uniform distribution assumption*, or *histograms*
  - The *uniform distribution* assumption essentially does *not "care"* about the *values* themselves, they all have an *equal probability of appearing*
  - *Histograms* are a *better* and *more elegant* distribution *approximation technique*
    - ⋆ *Equi-width* and *equi-depth* histograms are the two dominant classes

Summary (cont.)

- The *remaining 50%* is *search space exploration*
  - Largely *based* on the *equivalence rules* of *relational algebra*
  - *Dynamic programming* is the *dominant approach*
    - ⋆ Find the *cheapest way* to *access single relations*
    - ⋆ Find the *cheapest way* to *join two relations*
    - ⋆ *For each pair*, find the *cheapest way* to *join* in a *third relation*
    - ⋆ Keep going . . .

Summary (cont.)

- *Other approaches* include *rule-based optimisation*, *randomised exploration*, ...
- *All* approaches *aim* at one thing
  - *Picking* a *good* evaluation *plan*
  - It *might not be* the *cheapest overall*, but it *usually* is of *comparable cost*
- *Query optimisation* is *still* an *open issue*
  - We have *good ways* of *solving sub-problems*, but the *entire problem* remains *largely unsolved*

Overview

- So far, we have *focussed* on *query processing*
  - In other words, *reading* and *manipulating* data
- A *database system*, however, *not only reads*, *but also stores* data
  - *At the same time* as others are *querying* it
- We *need* a way to *ensure concurrent access* to the data
  - *Without compromising* system *performance*

Overview (cont.)

- The *basic concept* is *transaction processing*
- *Every transaction* needs to satisfy *four basic properties*
  - *Atomicity*, *consistency*, *isolation*, *durability*
- *How* does the system *guarantee* these *properties*?
  - Remember, *without compromising performance*
  - *Solution*: by *interleaving transactions*

Overview (cont.)

- *How* can we *decide* if, after we have interleaved transactions, the *result is correct*?
  - *Interleaving transactions* actually *causes* certain *anomalies*
  - *Solution*: the system uses *locks* to *ensure correctness*
- *How* are *locks used*?
  - *Lock granularity*, *degrees of consistency* and *two-phase locking*
- What *impact* do *locks* have on *performance*?

Overview (cont.)

- *Locking* poses significant *overhead*
  - *Luckily*, however, this *overhead* can be *"tuned" by the user*
  - *Transaction isolation* levels
- But what if the *worse comes to worst*?
  - *System crashes*
  - *Transactional semantics* and *recovery*
  - *Write-ahead logging* and the *ARIES algorithms*

Transactions

- A *DBMS spends* a lot of *time waiting* on *I/O*
    - It is *important* to *keep* the *CPU busy while waiting*
    - In other words, *execute* other *operations concurrently*
- *Fact*: the *DBMS* does *not "care" what* the *user does* with the *data* that is *being read* or *written*
    - All *it cares about* is that *data* is *being read* or *written*
- A *transaction* is the *DBMS's abstract view* of *user programs*: a *sequence* of *reads* and *writes*

Concurrent execution

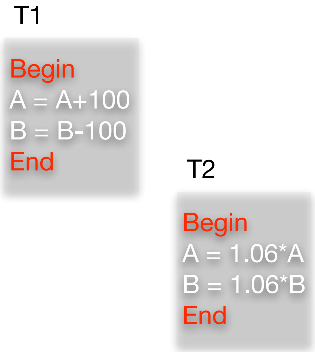
- The *transaction user abstraction*: when a *user submits* a *transaction* it is *as if* the *transaction* is *executing by itself*
  - The *DBMS achieves concurrency* by *interleaving transactions*
  - If the *transaction begins* with the *DB* in a *consistent state*, it *must leave* the *DB* in a *consistent state* after it *finishes*
- The *semantics* of the *transactions* are *unknown* to the *system*
  - Whether the transaction updates a bank account or it fires a rocket missile, the DBMS will never know!

ACID properties

- *Atomicity*: *all* the *actions* in a transaction are *executed* as a *single atomic operation*; either they are all carried out or none are
- *Consistency*: if a *transaction begins* with the *DB* in a *consistent state*, it must *finish* with the *DB* in a *consistent state*
- *Isolation*: a transaction should *execute as if* it is the *only one executing*; it is *protected* (*isolated*) from the *effects* of *concurrently running transactions*
- *Durability*: if a *transaction* has been *successfully completed*, its *effects* should be *permanent*

Example

- Consider *two transactions*
  - *First* transaction *transfers funds*, *second* transaction *pays* 6% *interest*
- *If* they are *submitted* at the *same time*, there is *no guarantee* as to *which* is *executed first*
  - But the *end effect* should be *equivalent* to the *transactions running serially*



```
T1
Begin
A = A+100
B = B-100
End
```

```
T2
Begin
A = 1.06*A
B = 1.06*B
End
```

Example (cont.)

Acceptable schedule

T1	A = A+100		B = B-100	
T2		A = 1.06*A		B = 1.06*B

Problematic schedule

T1	A = A+100			B = B-100
T2		A = 1.06*A	B = 1.06*B	

DBMS's view

T1	R(A), W(A)			R(B), W(B)
T2		R(A), W(A)	R(B), W(B)	

Scheduling

- A *schedule* is a *sequence* of *reads* and *writes* for some *transaction workload* *incorporating all actions* of the *workload's transactions*
  - *Serial schedule*: the *actions* of *different transactions* are *not interleaved*
  - *Equivalent schedules*: for *any database state*, the *effect* of *executing* the *first schedule* is *identical* to the *effect* of *executing* the *second schedule*
  - *Serialisable schedule*: a *schedule* that is *equivalent* to a *serial schedule*

Conflicts

Reading uncommitted data (WR conflicts, or "dirty reads")

T1	R(A), W(A)			R(B), W(B), A
T2		R(A), W(A)	R(B), W(B), C	

Unrepeatable reads (RW conflicts)

T1	R(A)			R(A), W(A), C
T2		R(A)	W(A), C	

Overwriting uncommitted data (WW conflicts, or "lost updates")

T1	W(A)			W(B), C
T2		W(A)	W(B), C	

The solution: locks

- *Before* a *transaction "touches"* a *DB object* it has to *obtain a lock* for it
  - *S (Shared)* lock for *reading*
  - *X (eXclusive)* lock for *writing*
- *Strict two-phase locking* (Strict 2PL)
  - Each *transaction* must obtain an *S lock* for *everything it reads before* it *starts reading* it and an *X lock* for *everything it writes before* it *starts writing*
  - *All locks* held by a transaction are *released only when* the *transaction commits*
  - Once a *transaction obtains* an *X lock for a DB object no other transaction* can *obtain* an *X or* an *S lock* for *that object*
- *Strict 2PL* produces *only serialisable schedules*

What can go wrong?

- If a *transaction* T_i is *aborted*, then *all its actions* have to be *undone*; not only that, but *if* T_j *reads* an *object written by* T_i, T_j needs to be *aborted* as well (*cascading aborts*)
- Most systems *avoid cascading aborts* with the following rule:
  - *If* T_i *writes* an object T_j *can read* this object only *after* T_i *commits*
- *In order to know what* needs to be *undone*, the *system keeps a log*, *recording all writes*
- The *log* is also *helpful* when *recovering* from *system crashes*

The log

- The *following actions* are *recorded* in the *log*
  - Whenever a *transaction writes* an *object*
    - The *log record must* be *on disk before* the *data record* reaches the disk
  - Whenever a *transaction commits/aborts*
- *Log records* are *chained* by *transaction ID* (why?)
- All *log-related activities* (in fact, all *concurrency control related activities*) are *handled by the DBMS*
  - The *user does not know anything*

Crash recovery

- *Three phases* to *recovery* (ARIES)
  - *Analysis*: *scan* log *forward*, *identifying* *committed* and *aborted/unfinished* transactions
  - *Redo*: all *committed transactions* are *made durable*
  - *Undo*: the *actions* of all *aborted* and/or *unfinished transactions* are *undone*

Concurrency control

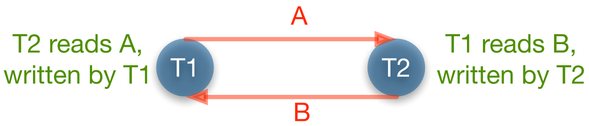
- *Serial schedule*: the *actions* of *different transactions* are not *interleaved*
- *Equivalent schedules*: for *any database state*, the *effect* of *executing* the *first schedule* is *identical* to the *effect* of *executing* the *second schedule*
- *Serialisable schedule*: a *schedule* that is *equivalent* to a *serial schedule*
- Two *schedules* are *conflict equivalent* if:
  - They *involve* the *same actions* of the *same transactions*
  - *Every pair* of *conflicting actions* is *ordered* the *same way*
- *Schedule S* is *conflict serialisable* if *S* is *conflict equivalent* to *some serial schedule*

Dependency graphs

- *Given* a *schedule S*
  - One *node* per *transaction*
  - An *edge* from T_i *to* T_j, if T_j *reads or writes* an *object written by* T_i
- *Theorem*: a *schedule S* is *conflict serialisable if and only if* its *dependency graph* is *acyclic*

Example: not conflict serialisable schedule

T1	R(A), W(A)			R(B), W(B)
T2		R(A), W(A)	R(B), W(B)	



Review: Strict 2PL

- *Strict two-phase locking (Strict 2PL)*
  - Each *transaction* must obtain an *S (Shared) lock* for *everything it reads before* it *starts reading* it and an *X (eXclusive) lock* for *everything it writes before* it *starts writing*
  - *All locks* held by a transaction are *released only when* the *transaction commits*
  - Once a *transaction obtains* an *X lock for a DB object no other transaction* can *obtain* an *X or* an *S lock* for *that object*
- *Strict 2PL* produces *only serialisable schedules*
  - In other words: *schedules* with *acyclic dependency graphs*

Simple 2PL

- *Two-phase locking (2PL)*
  - Each *transaction* must obtain an *S (Shared) lock* for *everything it reads* *before* it *starts reading* it and an *X (eXclusive) lock* for *everything it writes* *before* it *starts writing*
  - A *transaction cannot request additional locks* *once it releases any locks*
  - Once a *transaction obtains* an *X lock for a DB object* *no other transaction* can *obtain* an *X or* an *S lock* for *that object*

Lock management

- *Lock* and *unlock requests* are *handled by* the *lock manager* that maintains a *lock table*
- *Lock table entry*:
  - *Number of transactions* currently *holding a lock*
  - *Type of lock* held (*shared* or *exclusive*)
  - *Pointer* to *queue* of *lock requests*
- *Locking* and *unlocking* have to be *atomic operations*
- *Lock upgrade*: *transaction* that *holds* a *shared lock* can be *upgraded* to hold an *exclusive lock*

Deadlocks

- As *always*, where *there are locks*, *there are deadlocks*
- *Deadlocks*: *cycle* of *transactions* *waiting for locks* to be *released* by *each other*
- *Two ways* of *dealing* with *deadlocks*
  - Deadlock *prevention*
  - Deadlock *detection*

Deadlock prevention

- The *solution* involves *timestamps*; a *timestamp* is the *transaction's priority*
- If T_i *wants* a *lock* that T_j *holds*, there are *two possible policies*
  - *Wait-Die*: if T_i has *higher priority*, T_i *waits for* T_j; *otherwise* T_i *aborts*
  - *Wound-Wait*: if T_i has *higher priority*, T_j *aborts*; *otherwise* T_i *waits*
- If a *transaction re-starts*, it has its *original timestamp*

Deadlock detection

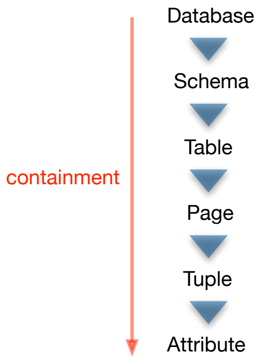
- *Create* a *waits-for graph*
  - *Nodes* are *transactions*
  - There is an *edge* from *T_i to T_j* if *T_i* is *waiting for T_j* to *release a lock*
- *Periodically check* for *cycles* in the *waits-for graph*

T1	S(A)	R(A)			S(B)					
T2			X(B)	W(B)				X(C)		
T3						S(C)	R(C)			X(A)
T4									X(B)	

$$\begin{tikzcd}
T1 \arrow[r] & T2 \arrow[d] \\
T4 \arrow[ur] & T3 \arrow[ul]
\end{tikzcd}$$

Multiple granularity locks

- *What* should we *lock*?
  Tuples, pages, tables, ...
- But there is an *implicit containment*
- *Idea*: *lock* DB objects *hierarchically*



Hierarchical locks and new locking modes

- *Allow transactions* to *lock* at *each level* of the *hierarchy*
- Introduce *"intention" locks*: *IS* and *IX*
  - *Before locking* an item, a *transaction must introduce intention locks* on *all* the *item's ancestors* in the *hierarchy*
  - *Release locks* in *reverse order*
- One *extra lock*: *SIX* — "share, with intention to write"

Compatibility matrix

held lock

wanted lock

	NL	IS	IX	SIX	S	X
NL	Y	Y	Y	Y	Y	Y
IS	Y	Y	Y	Y	Y	N
IX	Y	Y	Y	N	N	N
SIX	Y	Y	N	N	N	N
S	Y	Y	N	N	Y	N
X	Y	N	N	N	N	N

In more detail

- *Each transaction starts* from the *root* of the *hierarchy*
- To *obtain S* or *IS lock on* a *node*, *must hold IS* or *IX* on *parent node*
    - What if a transaction holds SIX on parent? S on parent?
- To *obtain X* or *IX* or *SIX* on a *node*, *must hold IX* or *SIX* on *parent node*
- *Must release* locks in *bottom-up order*

A few examples

- *T1 scans R*, and *updates* a few *tuples*
  - *T1* gets an *SIX lock* on *R*, then *repeatedly* gets an *S lock* on *tuples of R*, and *occasionally upgrades* to *X* on the *tuples*
- *T2 uses an index* to *read* only *part of R*
  - *T2* gets an *IS lock* on *R*, and *repeatedly* gets an *S lock* on *tuples of R*
- *T3 reads all of R*
  - *T3* gets an *S lock* on the *entire relation*
  - *Or*, it gets an *IS lock* on *R*, *escalating* to *S lock* on every tuple

Here's the catch (the phantom problem)

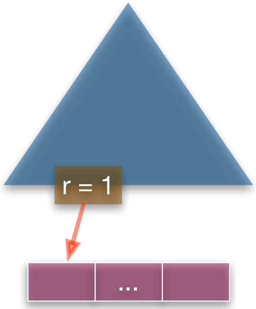
- If we *relax* the *assumption* that the *DB* is a *fixed collection* of objects, *even Strict 2PL* will *not assure serialisability*!
  - *T1 locks all pages* containing *sailor records* with $rating = 1$, and *finds oldest sailor* (say, $age = 71$)
  - Next, *T2 inserts* a *new sailor*: $rating = 1$, $age = 96$
  - *T2* also *deletes oldest sailor* with $rating = 2$ (and, say, age=80), and *commits*
  - *T1* now *locks all pages* containing *sailor records* with $rating = 2$, and *finds oldest* (say, age=63)
- *No lock conflicts*, *but also no consistent DB state* where T1 is "correct"!

The problem

- *T1 implicitly assumes* that it has *locked the* set of *all sailor* records with *rating* $= 1$
  - The *assumption* only *holds if no sailor* records are *added while T1* is *executing*!
  - We *need* some *mechanism* to *enforce* this *assumption*
    - ⋆ *Index locking*
    - ⋆ *Predicate locking*
- The *example shows* that *conflict serialisability guarantees serialisability* only *if* the set of *objects* is *fixed*!

Index locking

- *If* there is an *index* on the *rating field*, *T1* should *lock* the *index page* containing the *data entries* with $rating = 1$
  - *If* there are *no records* with $rating = 1$, *T1 must lock* the *index page* where such a *data entry would be*, *if* it *existed*!
- *If* there is *no suitable index*, *T1 must lock all pages*, and *lock* the *file/table* to *prevent* new *pages* from being *added*, to *ensure* that *no* new *records* with $rating = 1$ are *added*



Predicate locking

- *Grant lock* on all *records* that *satisfy* some *logical predicate*, *e.g.*, $\textit{salary} > 2 \cdot \textit{salary}$
    - *Index locking* is a *special case* of *predicate locking* for which an *index supports* efficient *implementation* of the *predicate lock*
    - What is the *predicate* in the *sailor example*?
- *In general*, *predicate locking* imposes a *lot of locking overhead*

B+tree locking

- *How* can we *efficiently lock* a *particular node*?
  - This is *entirely different* than *multiple granularity locking* (why?)
- One *solution*: *ignore* the *tree structure*, just *lock pages* while *traversing* the tree, following *2PL*
  - *Terrible performance*
  - *Root* node (and many *higher level nodes*) become *bottlenecks* because *every tree access* begins at the *root*

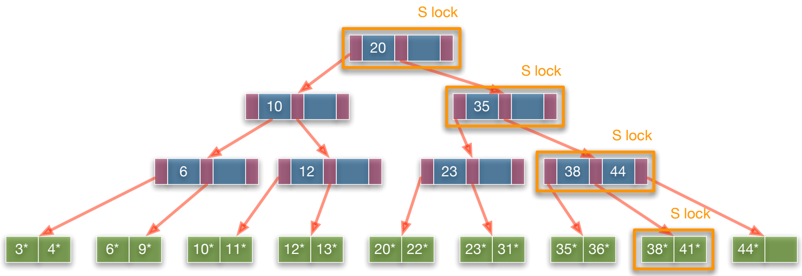
Key observations

- *Higher levels* of the tree *only direct searches* to leaf pages
- For *insertions*, a *node* on a *path* from the *root* to a modified *leaf* must be *locked* (in *X mode*, of course), *only if* a *split* can *propagate up* to it *from* the *modified leaf* (similar point holds for deletions)
- We can *exploit* these *observations* to design *efficient locking protocols* that *guarantee serialisability* even though they *violate 2PL*

The basic algorithm

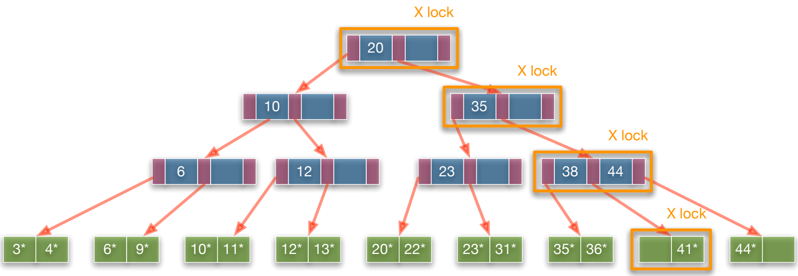
- *Search*: *start* at *root* and *descend*; repeatedly, *S lock child* then *unlock parent*
- *Insert/Delete*: *start* at *root* and *descend*, obtaining *X locks as needed*; once *child* is *locked*, *check* if it is *safe*:
  - *Safe node*: a *node* such that *changes* will *not propagate* up *beyond* this *node*
    - ⋆ *Insertion*: *node* is *not full*
    - ⋆ *Deletion*: *node* is *not half-empty*
  - If *child* is *safe*, *release* all *locks* on *ancestors*

Example: search 38*



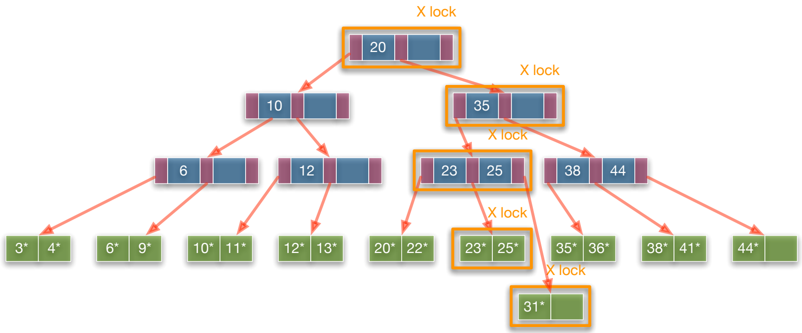
Obtain and *release* *S-locks level-by-level*

Example: delete 38*



Obtain X-locks while *descending*; *release them top-down* once the node is *designated safe*

Example: insert 25*

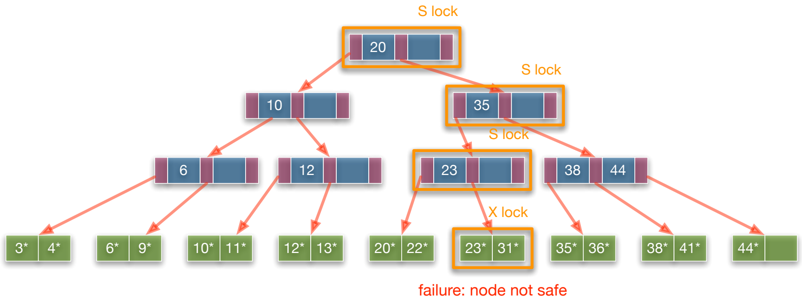


Obtain X-locks while *descending*; *leaf-node is not safe* so *create* a *new* one and *lock it in X-mode*; first release *locks on leaves* and then the rest *top-down*

Optimistic B+tree locking

- *Search*: *as before*
- *Insert/delete*: set *locks as* if for *search*, get to the leaf, and *set X lock on the leaf*
    - *If* the *leaf is not safe*, *release* all locks, and *restart* transaction, *using previous insert/delete protocol*
- *"Gambles"* that only *leaf node* will be *modified*; *if not*, *S locks* set on the first pass to leaf are *wasteful*
    - *In practice*, *better* than previous algorithm

Example: insert 25*

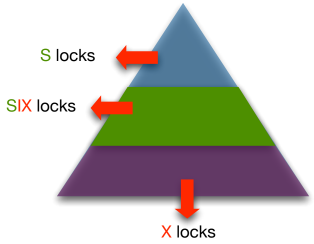


Obtain S-locks while *descending*, and *X-lock* at leaf; the leaf is *not safe*, so *abort*, *release all locks* and *restart* using the *previous algorithm*

Even better algorithm

- *Search*: *as before*
- *Insert/delete*: use *original insert/delete* protocol, but *set IX locks instead of X* locks at all nodes
  - *Once leaf* is *locked*, *convert* all *IX locks to X locks top-down*: *i.e.*, starting from the unsafe node nearest to root
  - *Top-down reduces* chances of *deadlock*
    - ⋆ Remember, this is *not the same* as *multiple granularity locking*!

Hybrid approach



- The *likelihood* that we will *need* an *X lock decreases* as we *move up* the *tree*
- Set *S locks* at *high levels*, *SIX locks* at *middle levels*, *X locks* at *low levels*

Transaction isolation

Isolation level	Dirty read	Unrepeatable read	Phantoms
Read uncommitted	Maybe	Maybe	Maybe
Read committed	No	Maybe	Maybe
Repeatable reads	No	No	Maybe
Serialisable	No	No	No

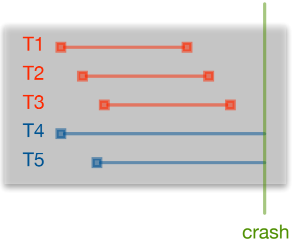
Review: ACID properties

- *Atomicity*: *all* the *actions* in a transaction are *executed* as a *single atomic operation*; either they are all carried out or none are
- *Consistency*: if a *transaction begins* with the *DB* in a *consistent state*, it must *finish* with the *DB* in a *consistent state*
- *Isolation*: a transaction should *execute as if* it is the *only one executing*; it is *protected* (*isolated*) from the *effects* of *concurrently running transactions*
- *Durability*: if a *transaction* has been *successfully completed*, its *effects* should be *permanent*

Atomicity and durability are ensured by the recovery algorithms

What can go wrong?

- *Atomicity*
  - *Transactions* may *abort*; their *effects* need to be *undone*
- *Durability*
  - What if the *system stops running*?



Transactional semantics

- *T1, T2, T3 should be durable*
- *T4, T5 should be aborted*

Problem statement

- *Updates* are happening *in place*
  - There is a *buffer pool*
    - *Data pages* are *read from disk*
    - *Data pages* are *modified in memory*
    - *Overwritten on*, or *deleted from disk*
- We need a *simple scheme* to *guarantee atomicity* and *durability*

More on the buffer pool

- Two issues: *force* and *steal*
- *Force*: when a *data page* is *modified* it is *written* straight to *disk*
  - *Poor response time*
  - *But durable*
- *Steal*: effects of *uncommitted transactions* reach the *disk*
  - *Higher throughput*
  - *But not atomic*

	No steal	Steal
Force	Trivial	
No force		Desired

The problems

- *Steal*'s problems are all about *atomicity*
  - What if a *transaction modifying a page aborts*?
  - If we *steal a page*, we need to *remember its old value* so it can be *restored* (*UNDO*)
- *No force*'s problems are all about *durability*
  - What if a *system crashes before a modified page* is *written to disk*?
  - We need to *record enough information* to make the *changes permanent* (*REDO*)

The solution: logging

- *Record* *REDO* and *UNDO* information in a record of a *separate structure*: the *log*
  - *Sequential writes* for *every update*
  - *Minimal information* written (more efficient!)
  - *Keep* it on a *separate disk*!
- *Log*: a *list* of *REDO* and *UNDO actions*
  - Each *log record* contains *at least*:
    - ⋆ *Transaction id*, *modified page*, *old data*, *new data*

Write-ahead logging

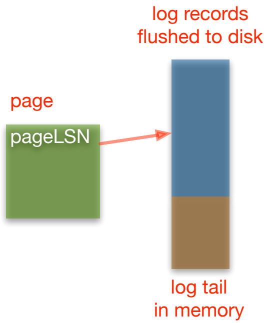
- The *log adheres* to the *write-ahead protocol* (WAL)
    1. *Must force* the *log record* for an *update* before the *corresponding data page* gets to *disk*
    2. *Must force* all *log records* for a *transaction before it commits*
- *#1* guarantees *atomicity*
- *#2* guarantees *durability*

Normal execution

- *Series* of *reads* and *writes*
- *Followed* by a *commit* (success) or *abort* (failure)
- *Steal, No-force* management
- *Adherence* to the *WAL protocol*
- *Checkpoints*: *periodically*, the *system creates a checkpoint* to *minimise* the *time* taken to *recover*
  - *Assume* the *DB* is *consistent after* a *checkpoint*

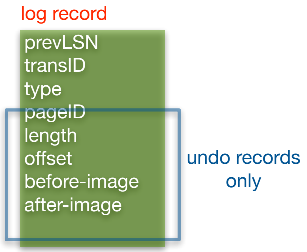
WAL and the log

- Each *log record* has a unique *log sequence number* (LSN)
  - *LSNs* are *always increasing*
- Each *data page* contains a *pageLSN*
  - The *LSN* of the *most recent log record* for an *update to that page*
- The *system keeps track of flushedLSN*
  - The max *LSN flushed so far*
- *WAL*: *before* a *page* is *written*, *pageLSN* $\leq$ *flushedLSN*



Log records

- Possible *log records types*
  - *Update*
  - *Commit*
  - *Abort*
  - *End* (signifies commit or abort!)
  - *Compensation Log Records* (CLR)
    - ★ *Logging UNDO actions*!
    - ★ But we will not talk about them in more detail



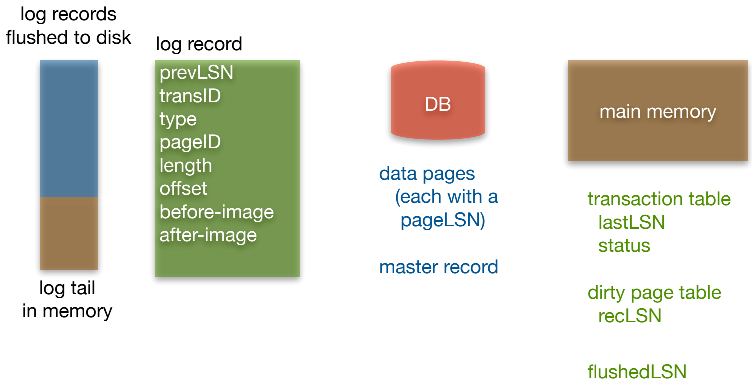
Other log-related state

- *Transaction table*: one *entry per active transaction*
  - Contains *transaction id*, *status* (running/commited/aborted) and *lastLSN* — *log sequence number* of the *last log record* for that *transaction*
- *Dirty page table*: one *entry per dirty page* in *buffer pool*
  - Contains *recLSN* — the *LSN* of the *log record* which *first caused the page to be dirty*

Checkpoint records

- `begin_checkpoint` record: indicates *when checkpoint began*
- `end_checkpoint` record: contains *current transaction table* and *dirty page table*
- This is a *"fuzzy checkpoint"*
  - Other *transactions continue to run*; so these *tables accurate* only *as* of the *time* of the `begin_checkpoint` *record*
  - *No attempt* to *force dirty pages* to disk; *effectiveness* of *checkpoint limited* by *oldest unwritten change* to a *dirty page*
  - So it's a *good idea* to *periodically flush dirty pages* to disk
- Store *LSN* of *checkpoint record* in a *safe place* (master record)

What’s stored where



Simple transaction abort

- For now, consider an *explicit abort* of a transaction
  - *No crash* involved
- We want to "*play back*" the log in *reverse order*, *UNDO ing updates*
  - Get *lastLSN* of *transaction* from *transaction table*
  - *Follow chain* of *log records backward* via the *prevLSN* field
  - *Before starting UNDO*, write an *Abort log record*
    - For *recovering* from crash *during UNDO*!

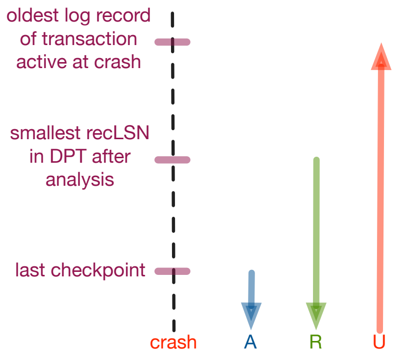
Abort (cont.)

- To *perform UNDO*, must have a *lock on data*
  - No problem
- *Before restoring old value* of a page, *write a CLR*
  - *Continue logging* while you *UNDO*!
  - *CLR* has one *extra field*: *undonextLSN*
    - ⋆ Points to the *next LSN to undo* (*i.e.*, the *prevLSN* of the *record we're currently undoing*)
  - *CLRs are never undone* (but they *might be redone* when repeating history: *guarantees atomicity*)
- At the *end of UNDO*, write an *"end" log record*

Transaction commit

- Write *commit record* to *log*
- All *log records* up to the *transaction's lastLSN* are *flushed*
    - *Guarantees* that *flushedLSN* $\geq$ *lastLSN*
    - Note that *log flushes* are *sequential*, *synchronous writes* to disk
    - *Many log records per log page*
- `Commit()` *returns*
- Write *end record* to *log*

Recovery: big picture


oldest log record of transaction active at crash
smallest recLSN in DPT after analysis
last checkpoint
crash
A
R
U

- *Start* from a *checkpoint* (found via *master record*)
- *Three phases*
  - *Analysis*: *figure out* which *transactions committed* since the checkpoint, and which *failed*
  - *REDO* all actions
    - ★ *Repeat history*
  - *UNDO* effects of *failed transactions*

Additional issues

- *What happens* if the *system crashes* during the *analysis phase*? During *REDO phase*?
- How can the *amount of work* during *REDO* be *limited*?
  - *Flush asynchronously* in the background
- How can the *amount of work* during *UNDO* be *limited*?
  - *Avoid long-running transactions*

Summary

- *Concurrency control* and *recovery* are *key concepts* of a DBMS
- *Both* are *ensured* by the *system itself*; the user does not (and should not!) know of their existence
- The *key abstraction* is the *transaction*
  - The *processing unit* of the *system*
  - *Four* key *properties*
    - *Atomicity*, *consistency*, *isolation*, *durability*

Summary (cont.)

- A *transaction* is *viewed by the system* as a *series* of *reads* and *writes*
- To *improve throughput*, the *system interleaves* the *actions* of the *transactions* (*i.e.*, a schedule)
  - At all times, *ensuring serialisability* of the *produced schedules*
- *Locks* are the *mechanism* that *ensures serialisability*
  - *Before reading*, obtain a *Shared lock*
  - *Before writing*, obtain an *eXclusive lock*

Summary (cont.)

- *Multiple granularity* of *locks*
    - *Leads* to an *escalation of locks*, as we are *descending the hierarchy*
- *Special protocols* for *indexes* and *predicates*
- *Transactions* help *after recovering* from a *crash*
    - As the *processing unit*, we know *what needs to be repeated or deleted*

Summary (cont.)

- *Steal*, *no-force* buffer pool management
  - *Higher response time* (steal)
  - *Higher throughput* (no-force)
- Need to *use it*, *without satisfying correctness*
- *Use a log* to *record all actions*
  - *Employ* the *Write-Ahead Logging protocol*

Summary (cont.)

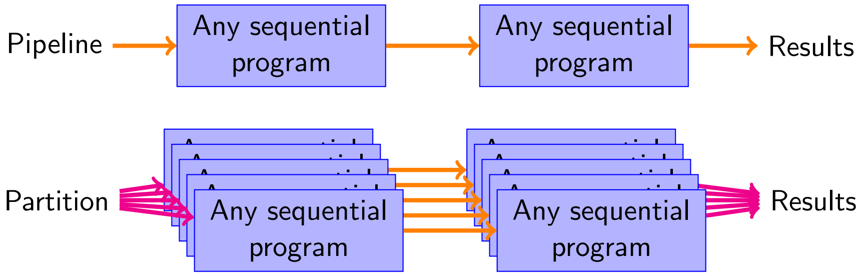
- Use *checkpoints* to *periodically record consistent states* and *limit* the amount of the *log* that needs to be *scanned during recovery*
- *Recovery* in *three phases*
  - *Analysis*: from checkpoint, *figure out REDO and UNDO extents*
  - *REDO*: *repeat entire history*
  - *UNDO*: *delete effects of failed transactions*
- *Repeating history simplifies the logic*

Why parallelism?

- The very *definition* of *parallelism*: *divide* a big *problem* into many *smaller* ones to be *solved in parallel*
- Consider we have a *terabyte* of data to *scan*
    - With *one pipe* of $10MB/s$, we need 1.2 *days*
    - By *partitioning* the data in *disjoint subsets* and having $1,000$ *parallel pipes* of the same bandwidth, we need $90s$

Parallelism and DBMSs

- *Parallelism* is *natural* to *DBMS* processing
  - *Pipeline* parallelism: *many machines* each doing *one step* in a *multi-step* process
  - *Partition* parallelism: *many machines* doing the *same thing* to *different pieces* of data.
  - *Both* are *natural* in a DBMS



Partitioning: *split* inputs, *merge* outputs

The parallelism success story

- *DBMSs* are the *most (only?) successful application* of *parallelism*
  - Teradata, Tandem vs. Thinking Machines, KSR, ...
  - Every *major DBMS vendor* has some *parallel server*
  - *Workstation manufacturers* now depend on *parallel DB server* sales
- *Reasons* for success
  - Bulk-processing (*partition parallelism*)
  - Natural *pipelining*
  - *Inexpensive hardware* can do the trick
  - Users/app-programmers do *not* need to *think in parallel*

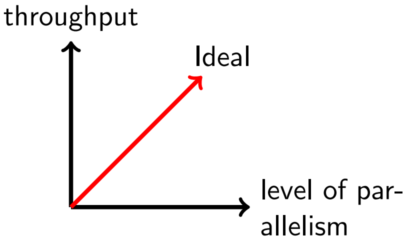
Terminology

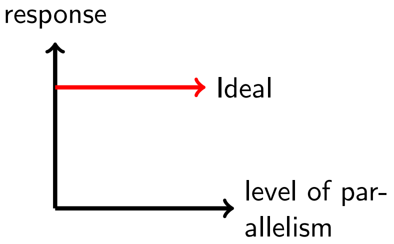
Speed-up

More resources means *proportionally less time* for *given* amount of *data* (throughput)

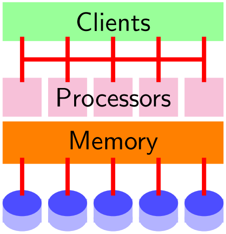
Scale-up

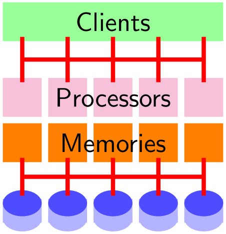
If *resources increased* in *proportion* to *increase* in *data* size, *time* is *constant*

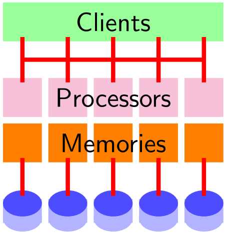




Architecture: what to share?







Shared memory

- *Easy* to *program*
- *Expensive* to build
- *Difficult* to *scale* up

Shared disk

- *Middle* of the road
- *Distributed* file system
- *Cluster* computing

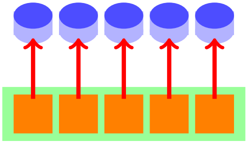
Shared nothing

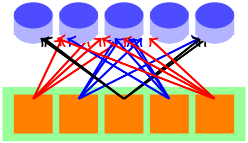
- *Hard* to *program*
- *Cheap* to build
- *Easy* and *ideal* to *speed/scale* up

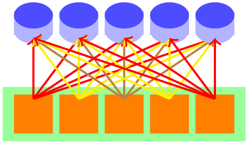
Different types of parallelism

- *Intra*-*operator* parallelism
  - *All machines* working to compute a *single operation* (scan, sort, join)
- *Inter*-*operator* parallelism
  - *Each operator* may run *concurrently* on a *different site* (exploits pipelining)
- *Inter*-*query* parallelism
  - *Different queries* run on *different sites*
- We shall*focus* on *intra-operator* parallelism

Automatic data partitioning







Range

- *Good* for *equi-joins*
- *Range-queries*
- *Good* for *aggregation*

Hash

- *Good* for *equi-joins*
- *No range-queries*
- *Problematic* with *skew*

Round-robin

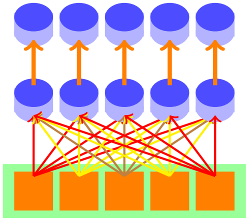
- *Indifferent* for *equi-joins*
- *Range-queries complicated*
- *Load-balanced*

Parallel scans

- *Scan* in *parallel*, and *merge*
- *Selections* may *not require all* sites for *range* or *hash* partitioning
- *Indexes* can be built at *each partition*
- *Question*: how do *indexes differ* in the different *schemes*?
  - Think about *both lookups* and *inserts*!
  - What about *key* indexes?

Parallel sorting

- Key idea: sorting *phases* are intrinsically *parallelisable*
  - *Scan* in parallel, *range-partition* as you go
  - As *tuples come in*, begin *"local" sorting* using standard algorithm
  - *Resulting data* is *sorted*, and *range-partitioned*
- Problem: *skew*
  - Solution: *sample* the data to determine *partition points*



Parallel aggregation

- For *each aggregate* function, need a *decomposition*
  - *count*(S) $= \sum_i$ *count*(s(i)), ditto for *sum*()
  - *avg*(S) $= (\sum_i$ *sum*(s(i))) / $\sum_i$ *count*(s(i))
  - and so on . . .
- For *groups*
  - *Sub-aggregate* groups *close* to the *source*
  - *Pass* each *sub-aggregate* to its *group's site*
    - ⋆ Chosen via a *hash function*

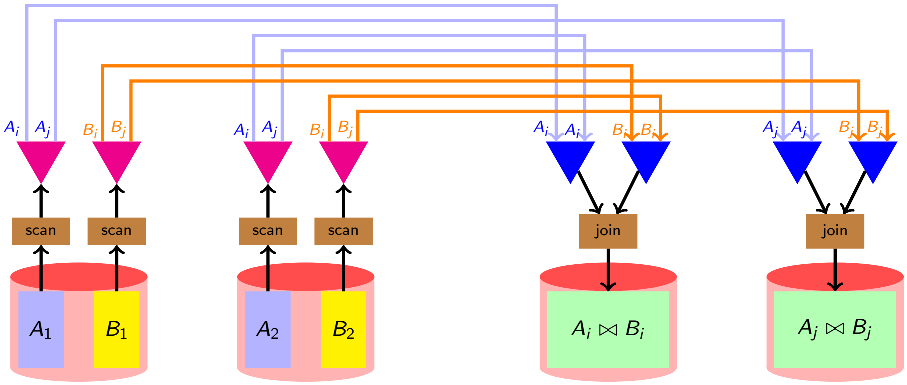
Parallel joins

- *Nested loops*
  - *Each outer* tuple must be *compared* with *each inner* tuple that might join
  - *Easy* for *range partitioning* on *join columns*, *hard otherwise*
- *Sort-merge* (or plain *merge-*) *join*
  - *Sorting* gives *range-partitioning*
  - *Merging* partitioned tables is *local*

Parallel hash join

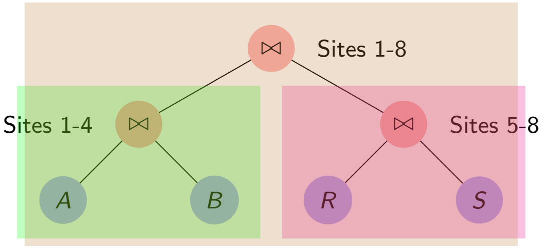
- During the *first phase*, *partitions* are *distributed* to *different sites*
  - A good *hash function automatically* distributes work *evenly*
- *Second phase* is *local* at each *site*
  - Almost *always* the *winner* for *equi-join*
- *Good use* of *split/merge* makes it *easier* to build *parallel versions* of *sequential join* code

Dataflow network for parallel join



Complex parallel query plans

- *Complex* queries: *inter-operator* parallelism
  - *Pipelining* between operators
    - Note that *sorting* and *phase one* of *hash-join* *block* the pipeline (yet again!)
  - *Bushy* execution trees



Observations

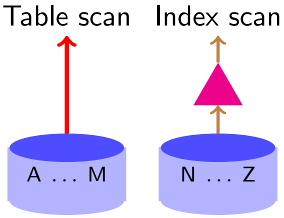
- It is *relatively easy* to build a *fast parallel query executor*
- It is *hard* to write a robust and world-class *parallel query optimizer*
    - There are many *tricks*
    - One quickly hits the *complexity barrier*
    - Still *open research*

Parallel query optimization

- *Common* approach: *two phases*
  - Pick *best sequential* plan (System R algorithm)
  - Pick *degree of parallelism* based on current system parameters
- *Allocate operators* to processors
  - Take *query tree*, *decorate* as in previous example

What can go wrong?

- *Best sequential* plan $\neq$ *best parallel* plan
- Trivial *counter-example*
  - *Table partitioned* with *local secondary index* at *two nodes*
  - *Range query*: *all* of *node 1* and 1% of *node 2*
    - ★ *e.g.*, **select** * **from** telephone_book **where** name < "NoGood"
  - *Node 1 should* do a *scan* of its partition
  - *Node 2 should* use secondary *index*



Parallel databases summary

- *Parallelism* natural to *query processing*
  - Both *pipeline* and *partition parallelism*
- *Shared-nothing vs. Shared-memory*
  - *Shared-disk* too, but *less standard*
  - *Shared-mem easy*, *costly*; does *not scaleup*
  - *Shared-nothing cheap*, *scales* well, *harder* to implement
- *Intra-operator*, *inter-operator*, and *inter-query* parallelism all possible.

Parallel database summary (cont.)

- *Data layout* choices *important*
- *Most* database *operations* can be done using *partition-parallelism*
  - Sort
  - Sort-merge join, hash-join
- *Complex plans*
  - Allow for *pipeline-parallelism*, but sorts, hashes *block* the *pipeline*
  - *Partition-parallelism* achieved through *bushy trees*

Parallel database summary (cont.)

- *Hardest* part: *optimization*
  - *Two-phase* optimization *simplest*, but can be *ineffective*
  - More *complex schemes* still at the *research* stage
- We have not discussed transactions, logging
  - *Easy* in *shared-memory/shared-disk* architecture
  - Takes *some care* in *shared-nothing*
  - Some ideas from *distributed transactions* are *handy*