

Advanced Databases

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Outline

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

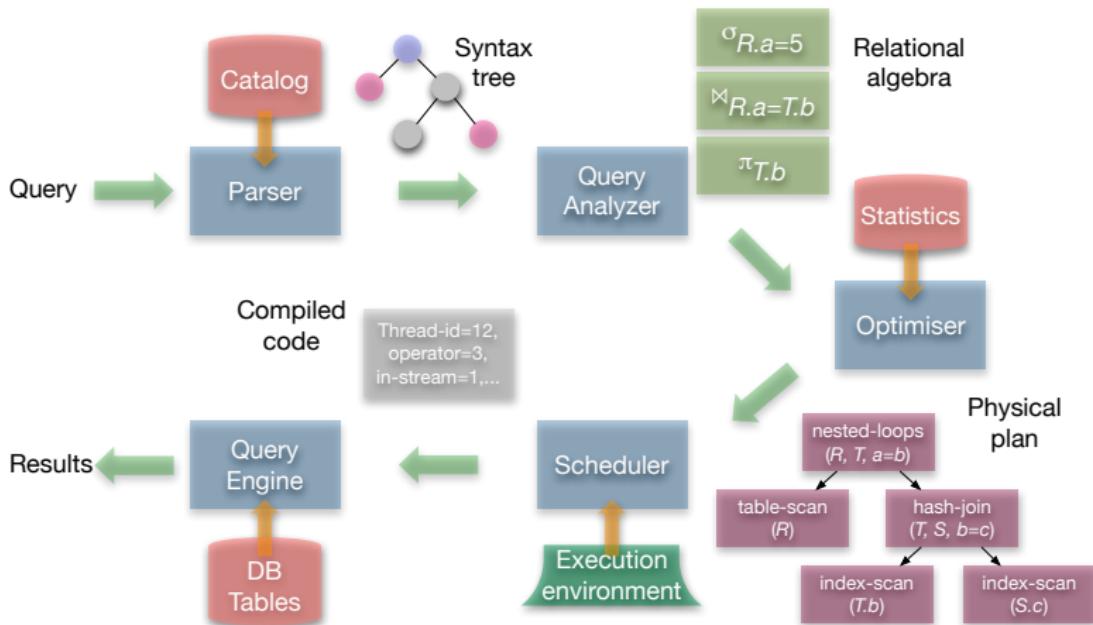
Syllabus

- 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



Outline

Three basic building blocks

- **Attribute**

- **Attribute**
 - ▶ A (name, value) *pair*

SID
123-ABC

- **Tuple**

- **Tuple**
 - ▶ A *set* of attributes

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

- **Relation**

- **Relation**
 - ▶ A *set* of tuples with the same schema

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

 $\sigma_{\text{year}=3}$

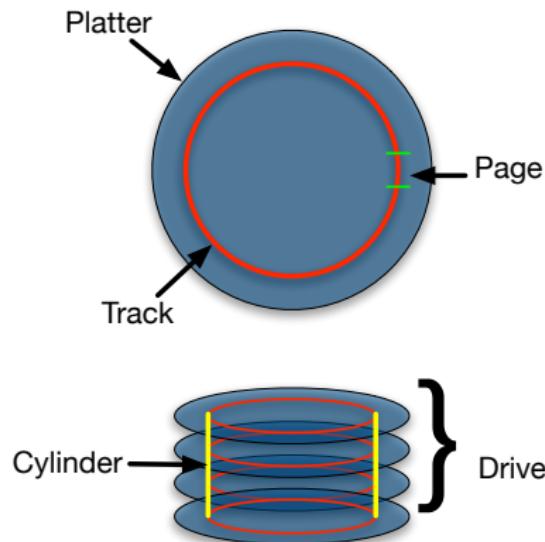
Course

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

 π_{name} Student \times Course $\bowtie_{\text{student.year} = \text{course.year}}$

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*

¹Source: 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*

Header	Relation 1	
	Relation 2	
Relation 3	Relation 2	
	Relation 3	
Relation 1	Relation 2	
Relation 3	Padding	

Interleaved tuples

Header	Relation 1	
	Relation 1	
	Relation 1	
Relation 1	Relation 1	
Relation 1	Relation 1	
Relation 1	Padding	

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



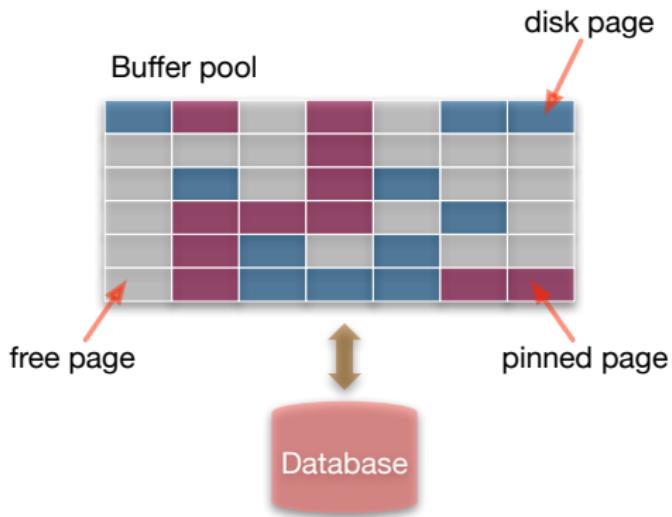
Unclustered storage



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)

Outline

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.)

Outline

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

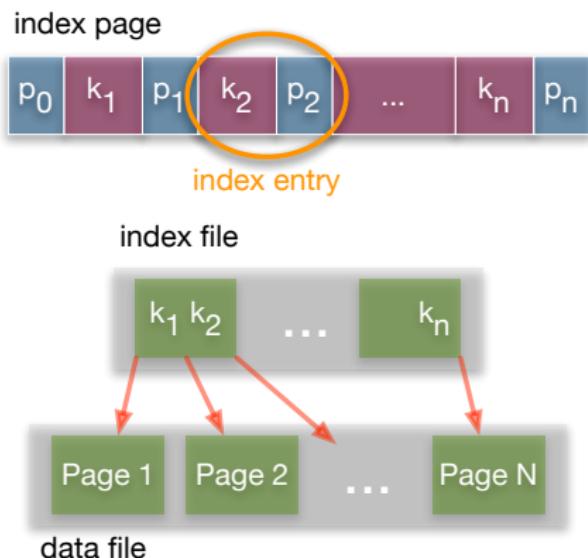
- ▶ Fully *randomized* (i.e., no order)
- ▶ Great for single *lookup queries*

Outline

Sorted indexes

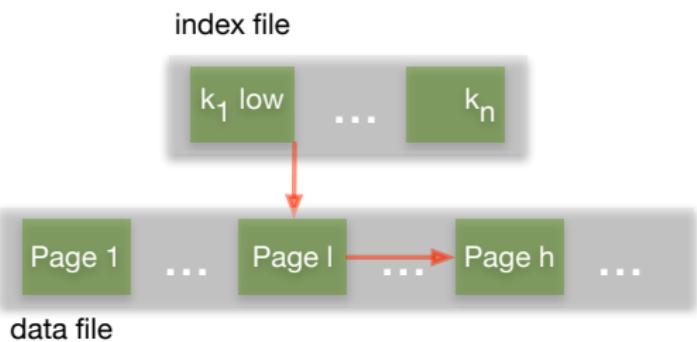
- The basic idea:

- 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*)



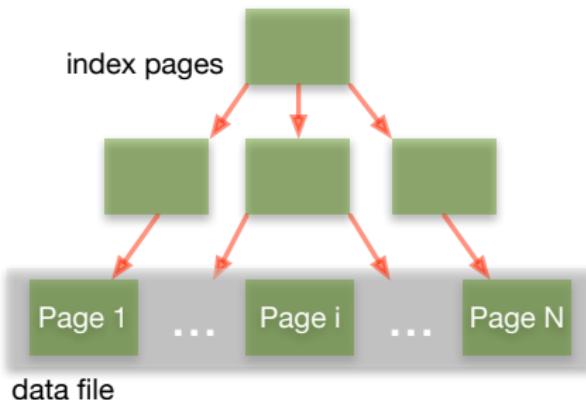
How does it answer range queries?

- Query is
 $low \leq value \leq high$
- 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!*

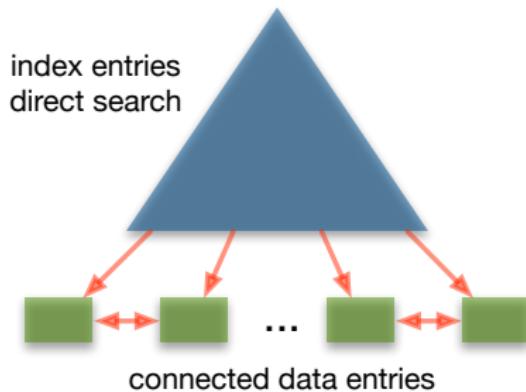


Potential problem (and the solution)

- 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!*

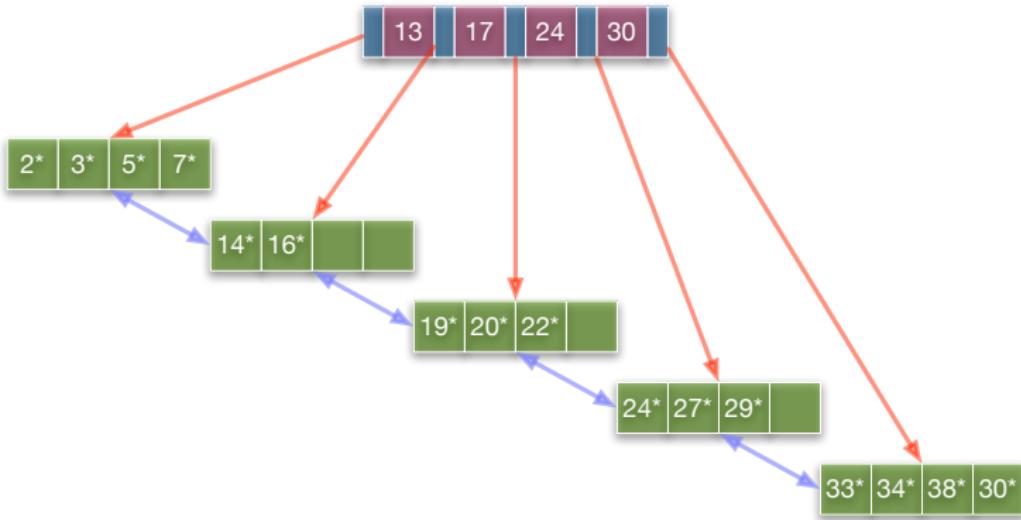


B+trees: the most widely used indexes



- *Insertion/deletion* at $\log_f N$ cost ($f = \text{fanout}$, $N = \# \text{ leaf pages}$)
- 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



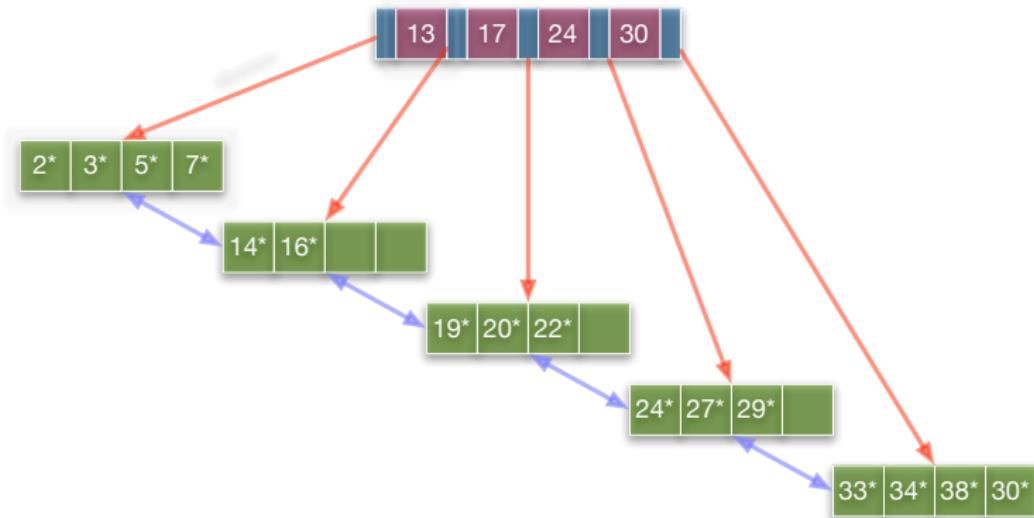
B+trees in practice

- 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

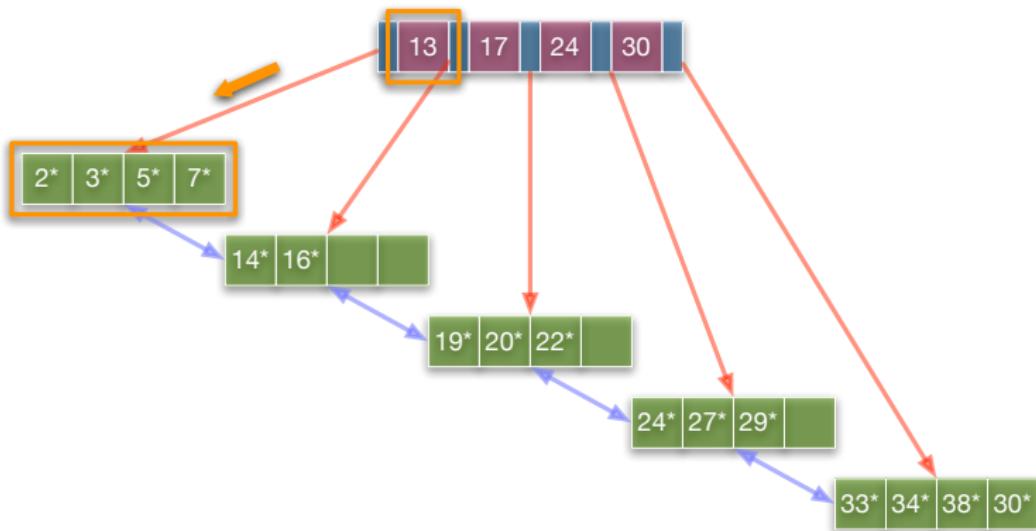
B+tree insertion

- *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

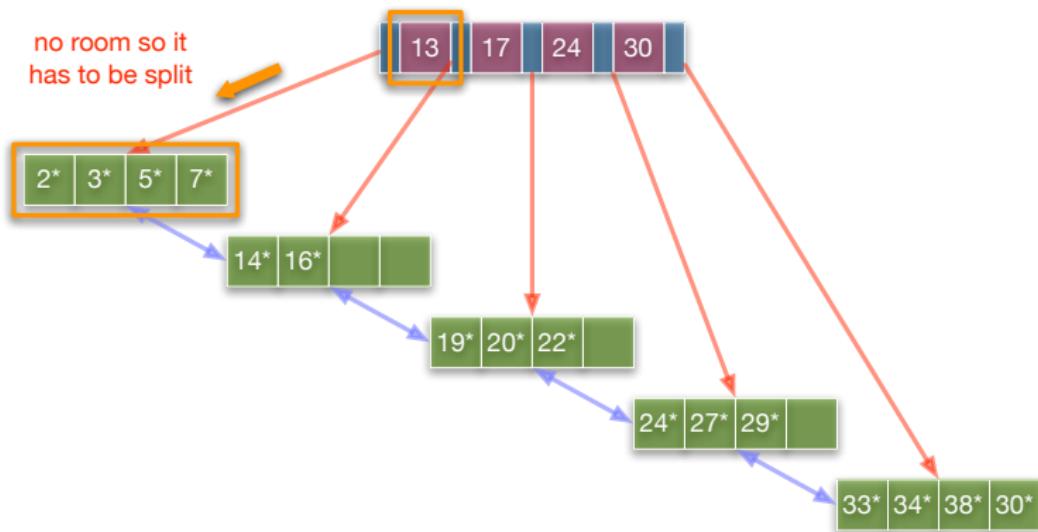
B+tree insertion: 8*



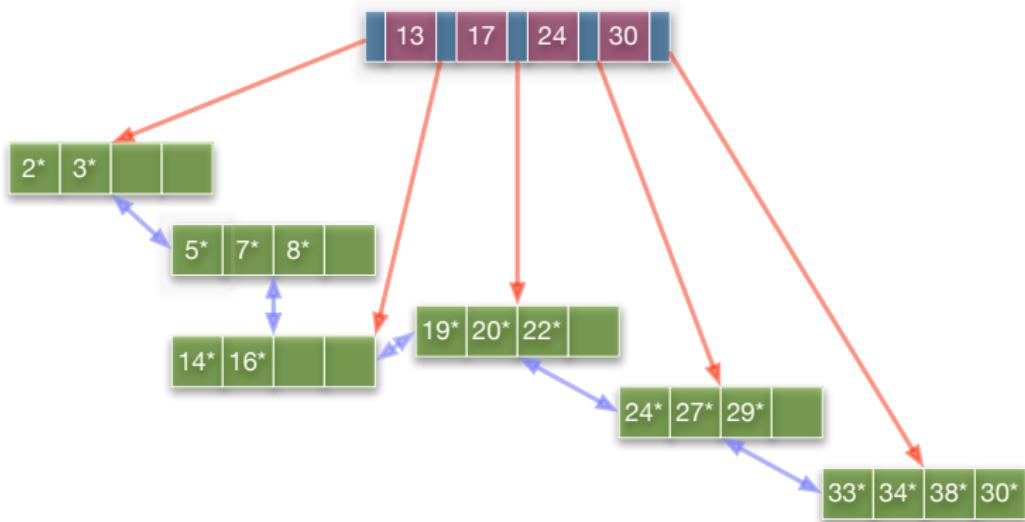
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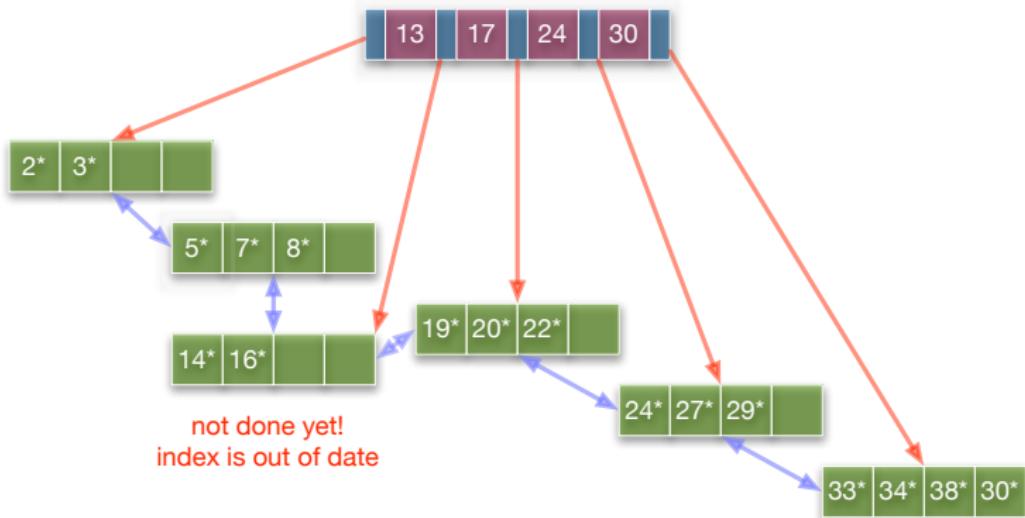
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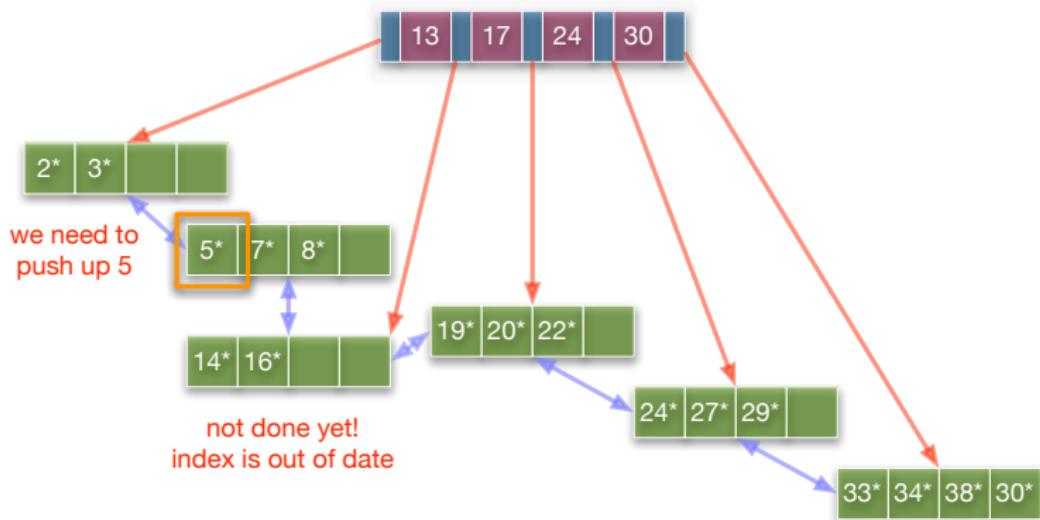
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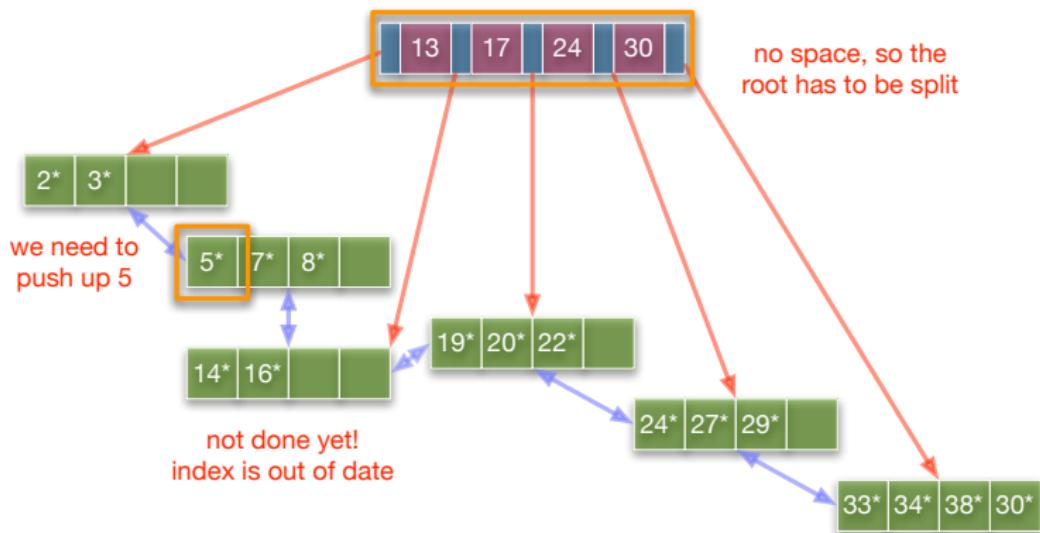
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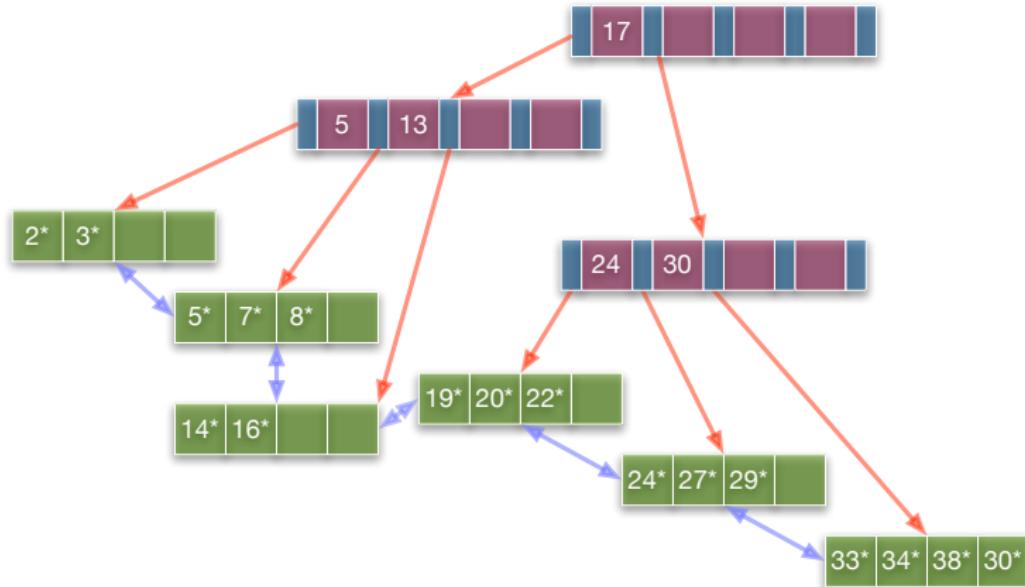
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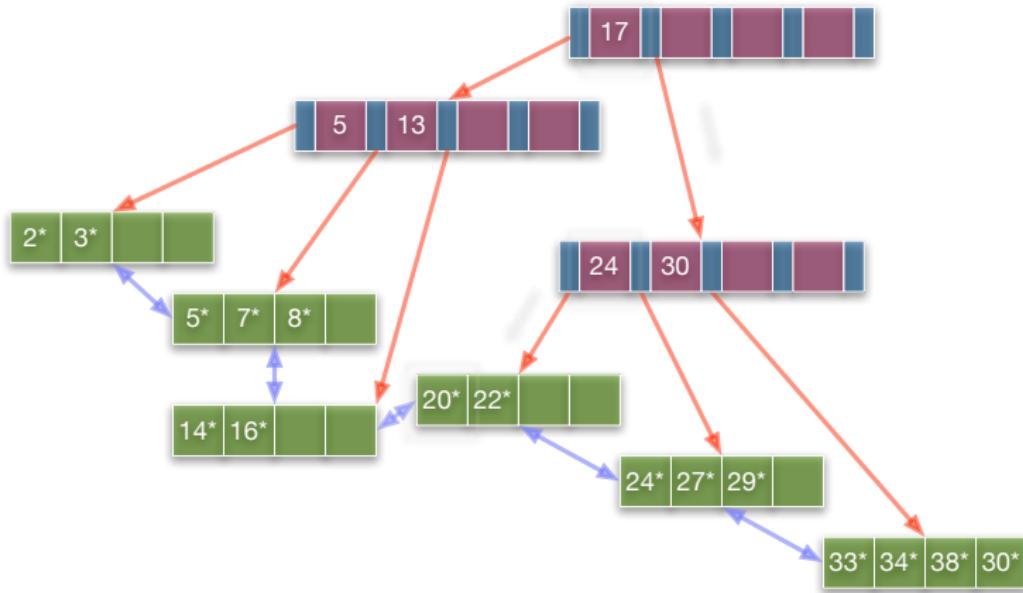
Insertion observations

- *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?*)

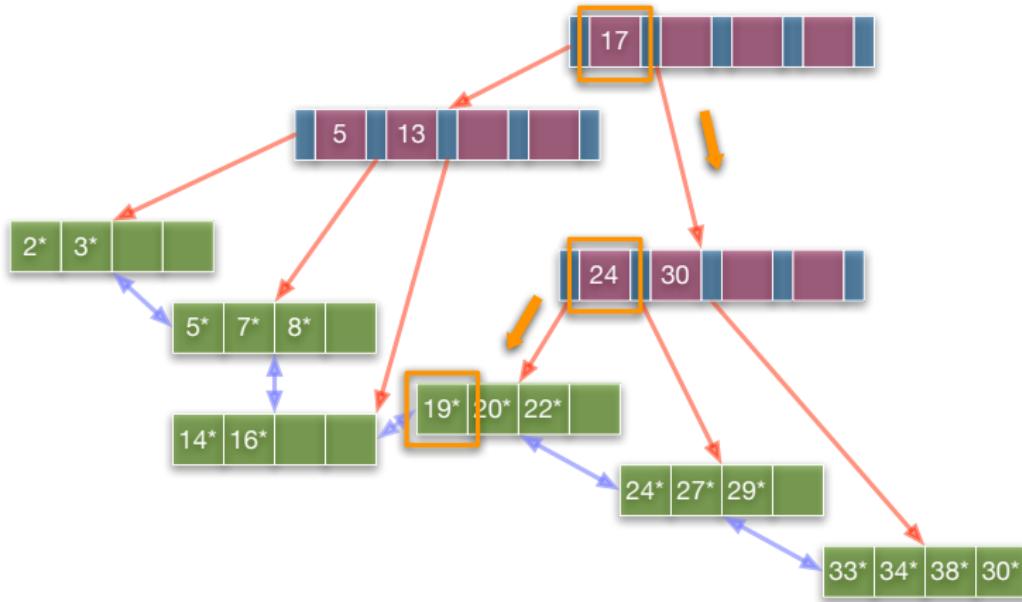
B+tree deletion

- *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*

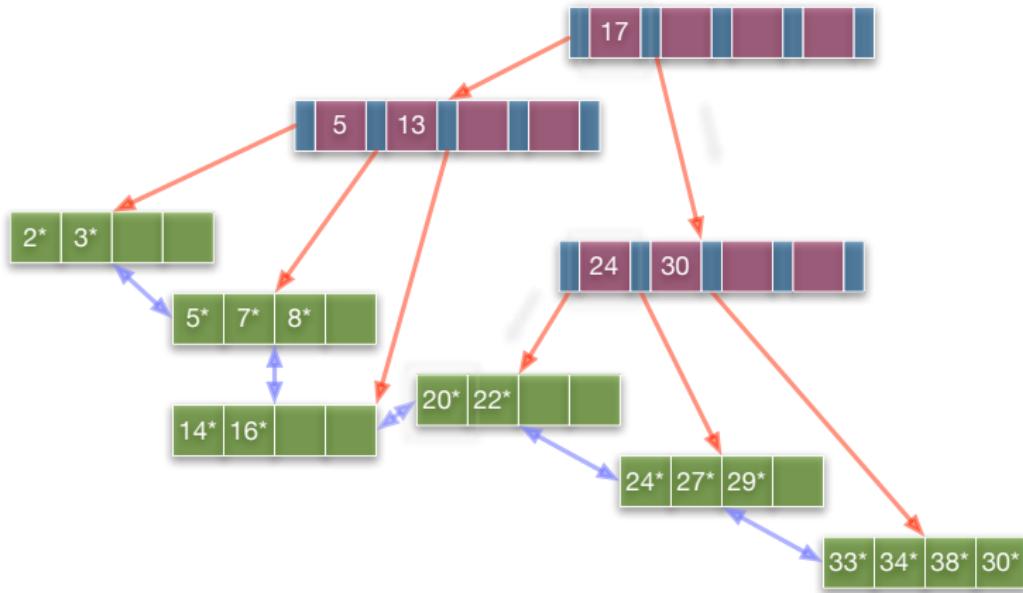
B+tree deletion: 19*



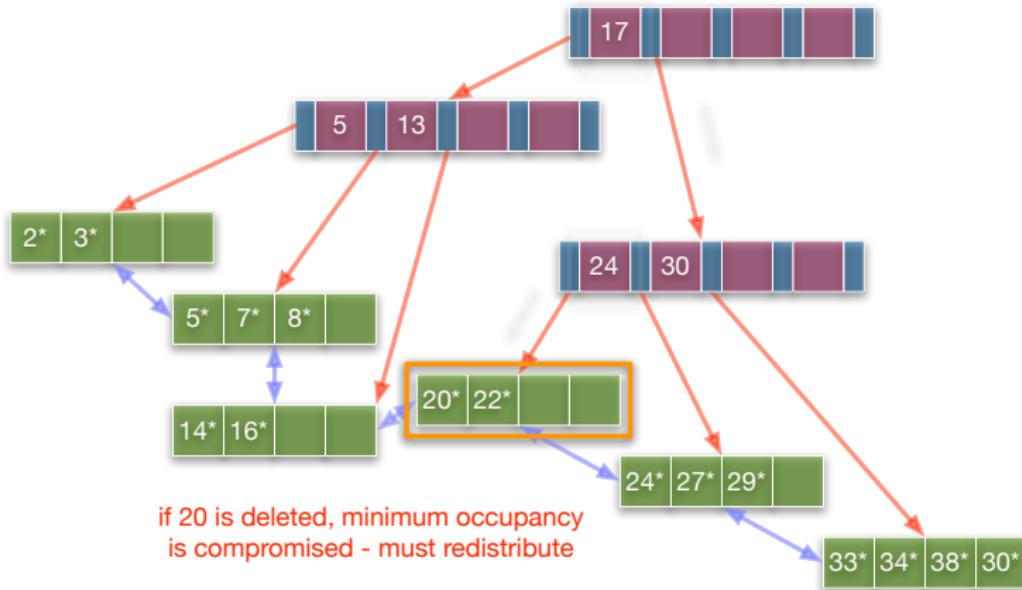
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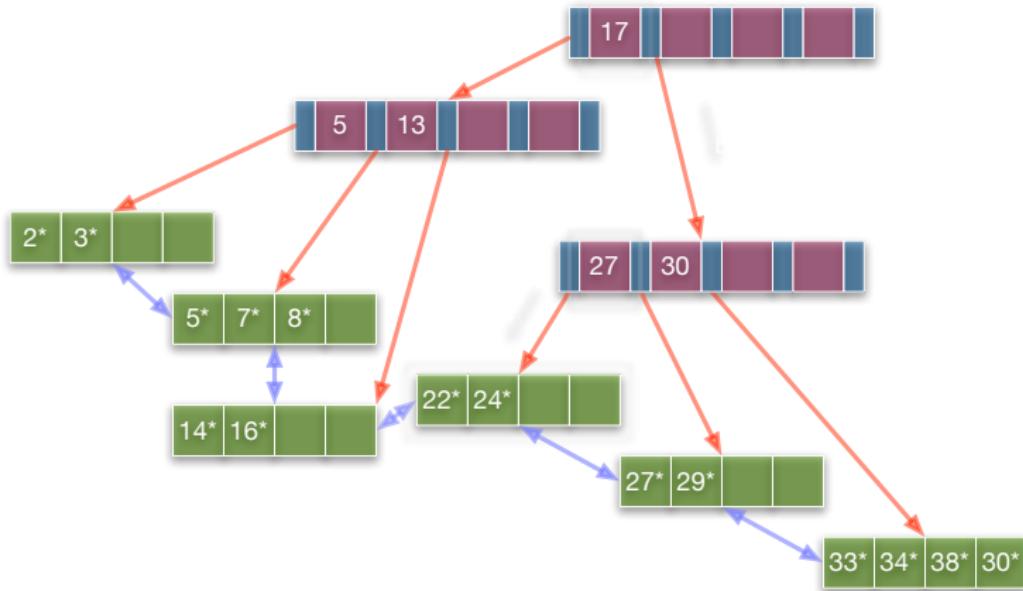
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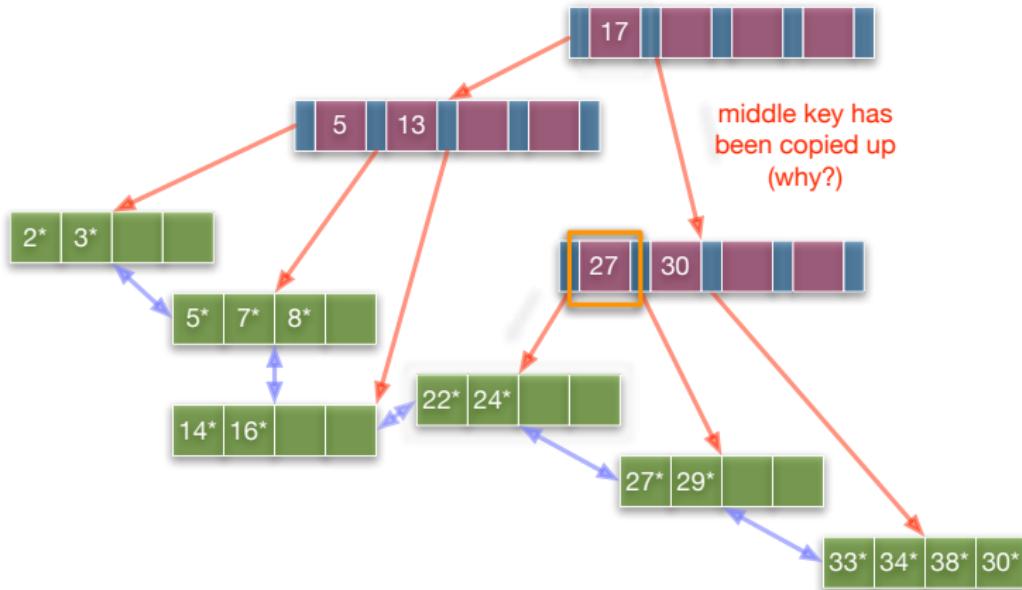
B+tree deletion: 20*



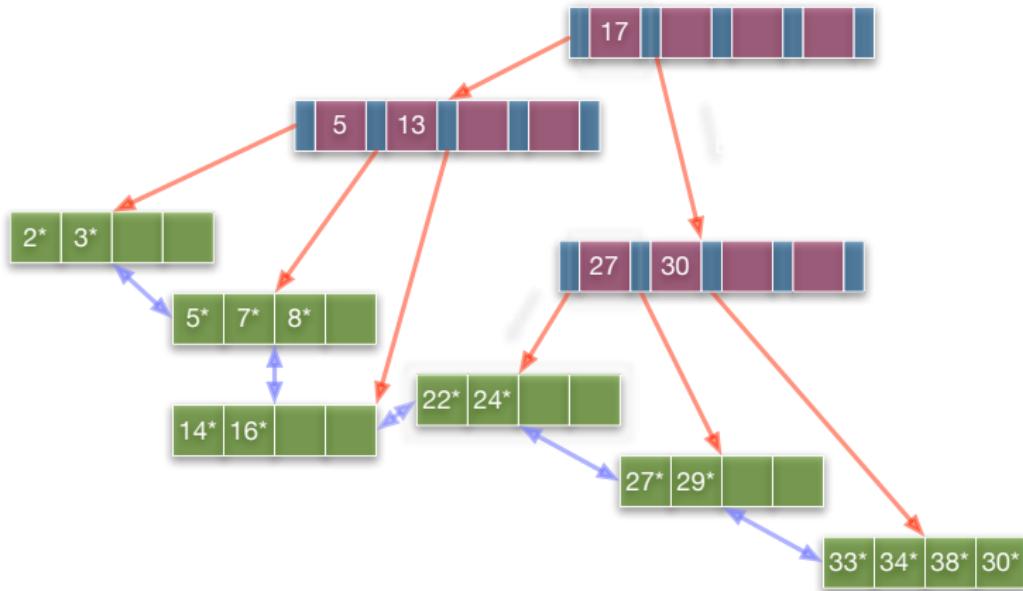
B+tree deletion: 20*



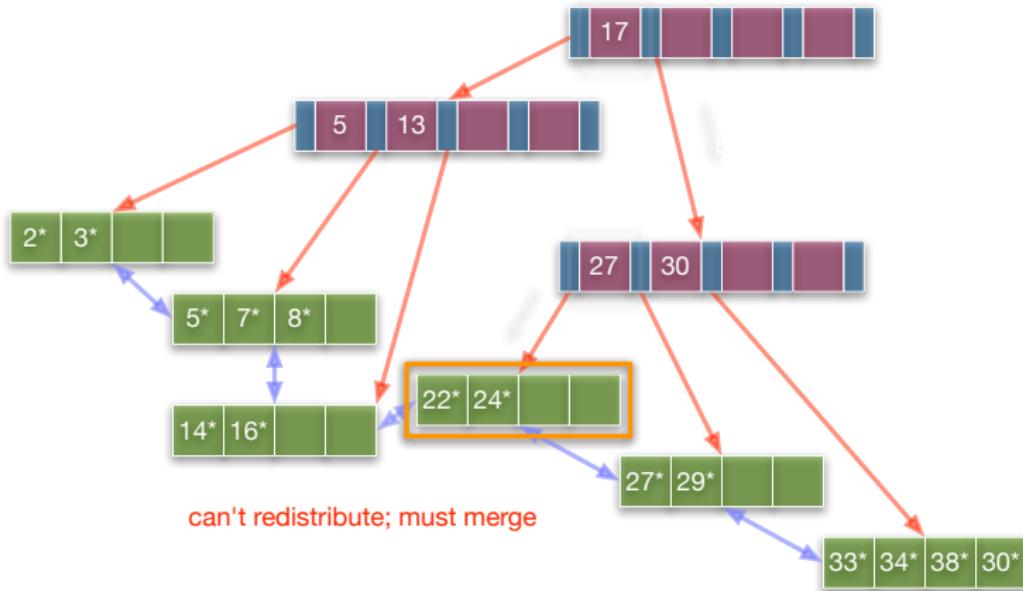
B+tree deletion: 20*



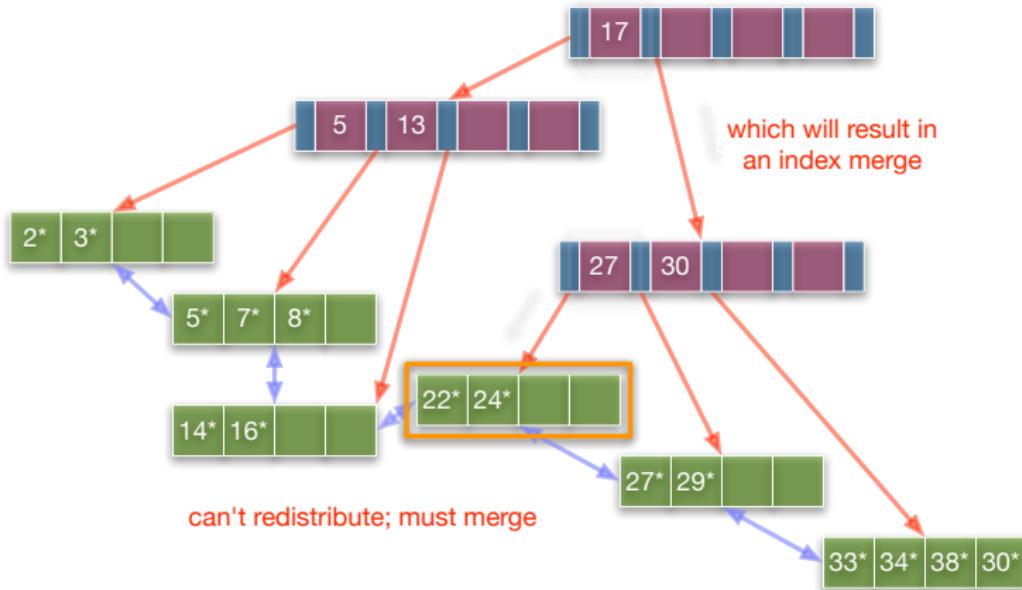
B+tree deletion: 24*



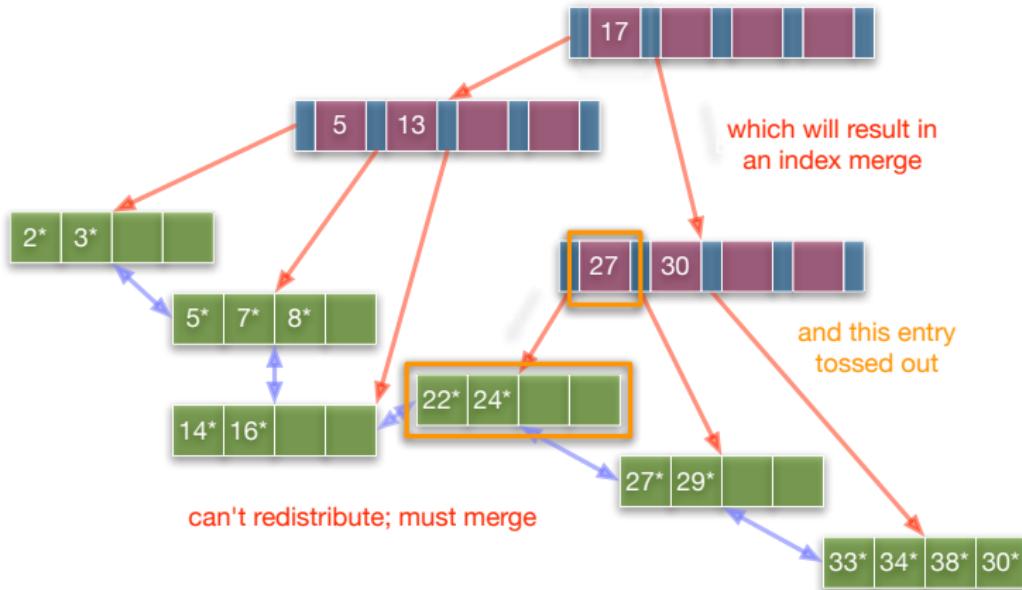
B+tree deletion: 24*



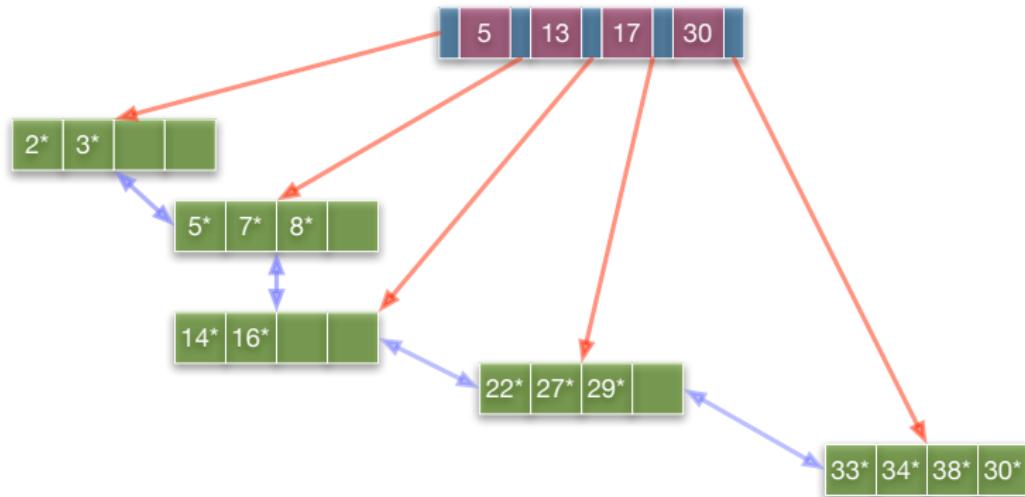
B+tree deletion: 24*



B+tree deletion: 24*



B+tree after deletion of 24*



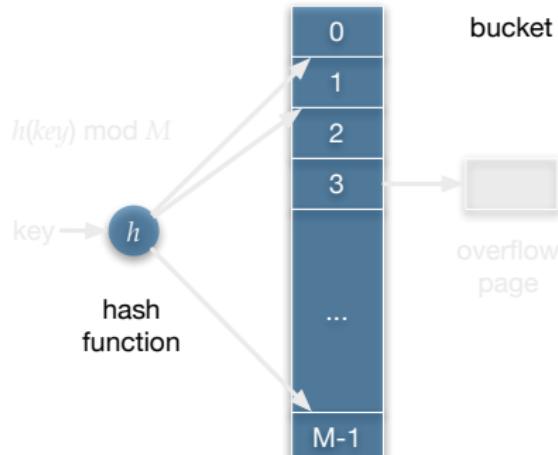
Summary of B+tree indexes

- *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

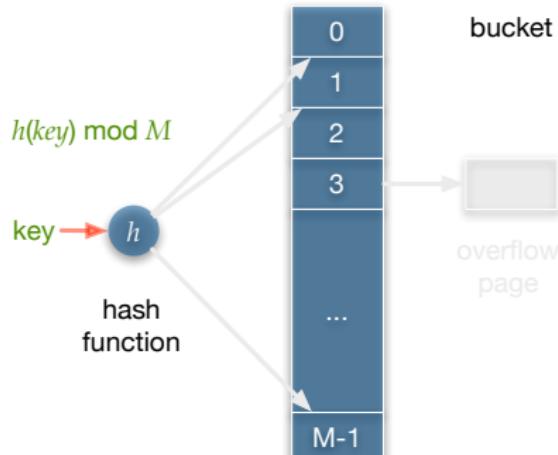
- *Hash-based indexes* are *good* for *equality* selections, *not* for *range* selections
 - ▶ In fact, they *cannot support range* selections (why?)
- *Static* and *dynamic techniques* exist here as well
 - ▶ *Trade-offs* similar to those between ISAM and B+trees

Static hashing



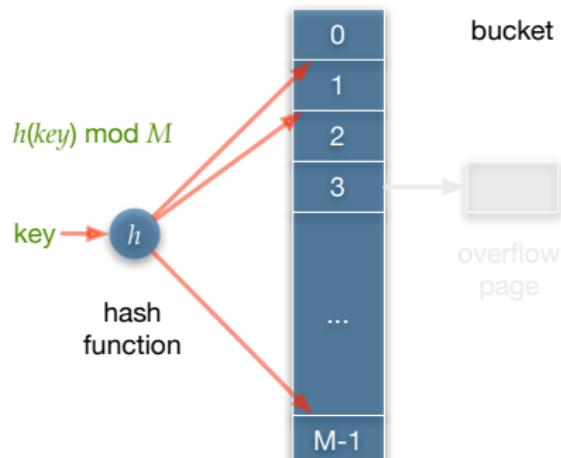
- *Number of primary pages fixed*
 - ▶ Allocated sequentially, never de-allocated
 - ▶ Overflow pages if needed
- $h(k) \bmod M = \text{bucket}$ to which *data entry* with *key k* belongs ($M =$ number of buckets)

Static hashing



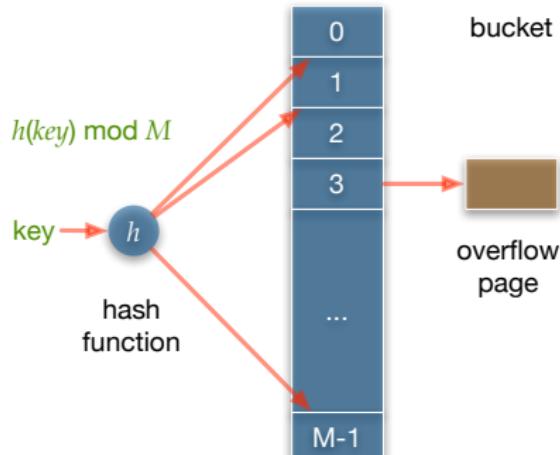
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Static hashing observations

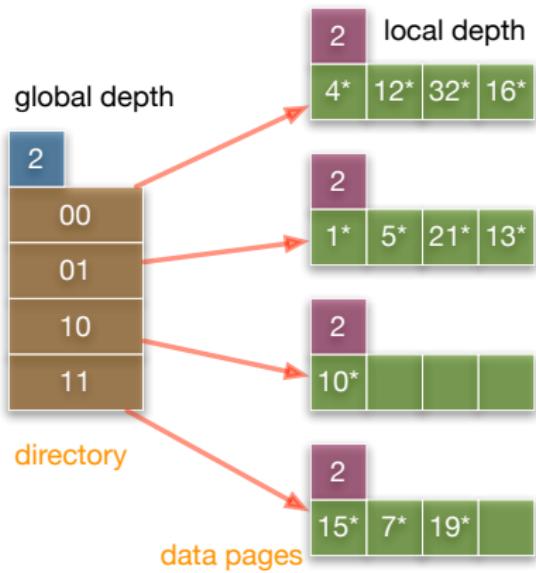
- The *buckets contain* the *actual data!*
 - ▶ But *only* the *key* is *hashed*
 - ▶ *No secondary index* like in the tree case
- The *hash function must uniformly distribute* the *keys* across all buckets
 - ▶ Lots of ways to *tune* the hash function
- Again, *long overflow chains* of pages will develop, 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

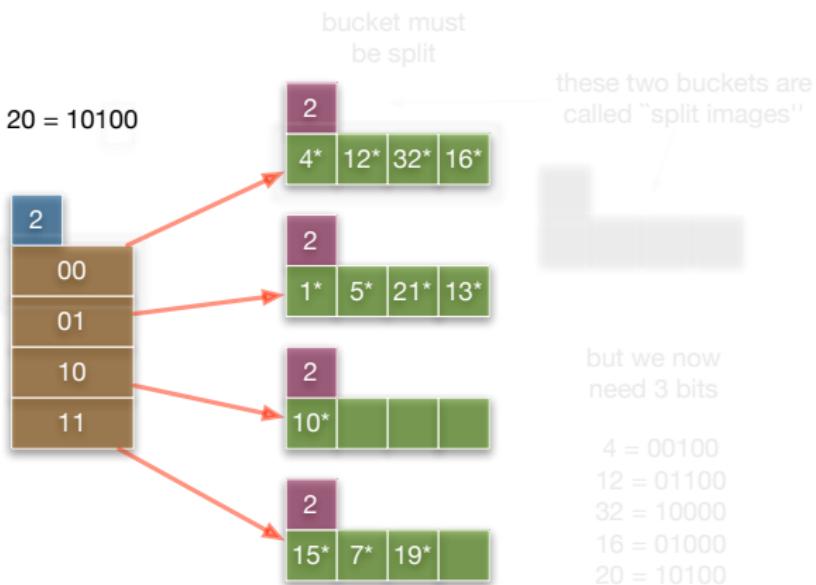
- *Directory*: array of size 4
- *Key k*, apply hash function $h(k)$ and translate the result to binary
 - ▶ e.g., $h(k) = 5 = 101$
- Last *global depth number of bits* identify the *bucket*



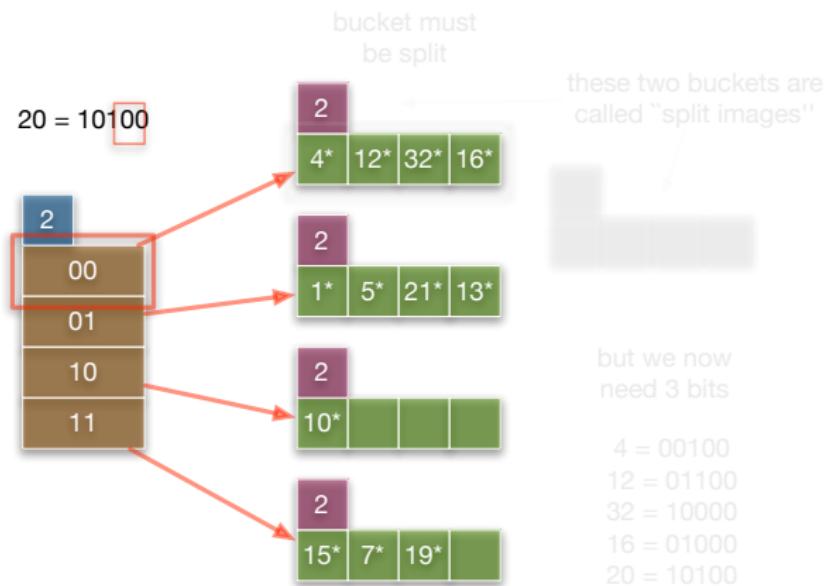
Global, local depth and doubling

- *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: $h(k) = 20$

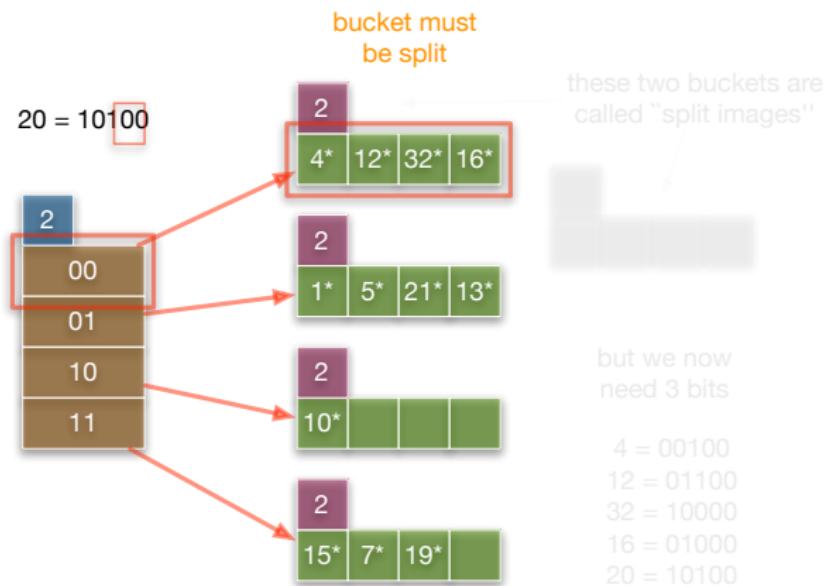


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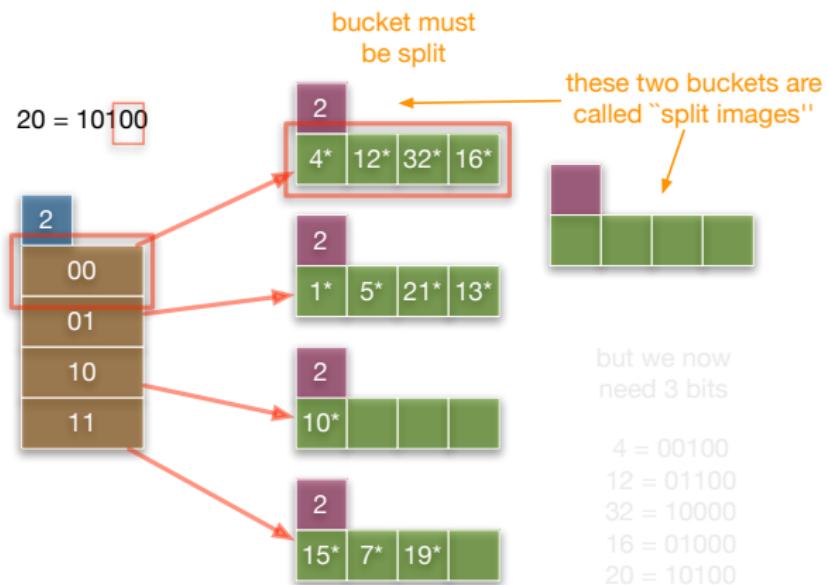


so we must double
the directory

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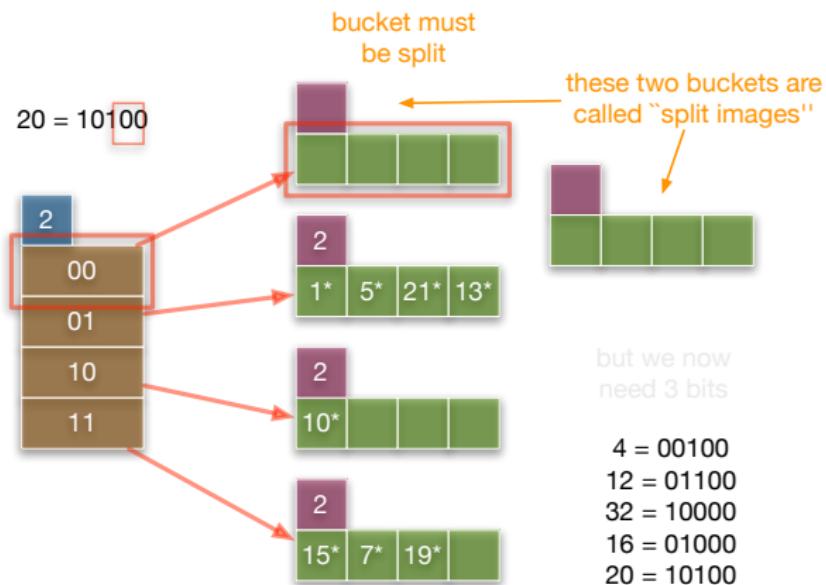


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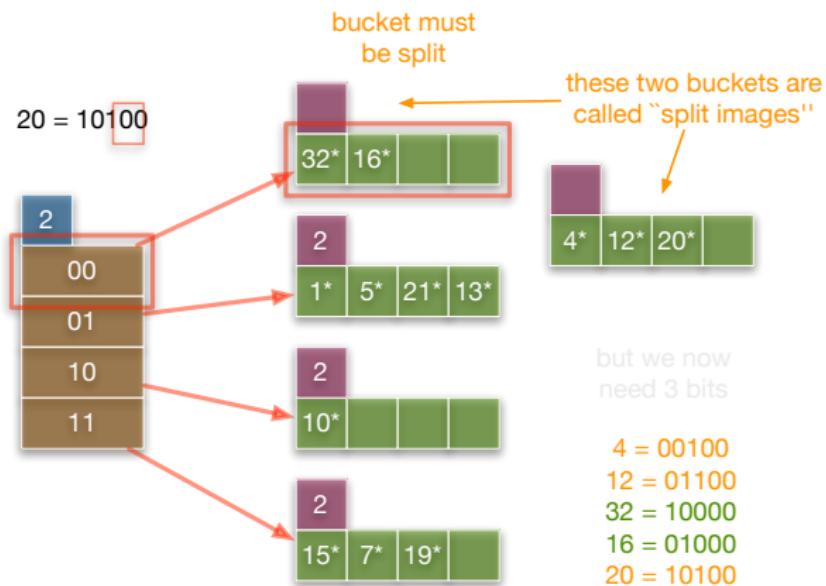
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Insertion example: $h(k) = 20$



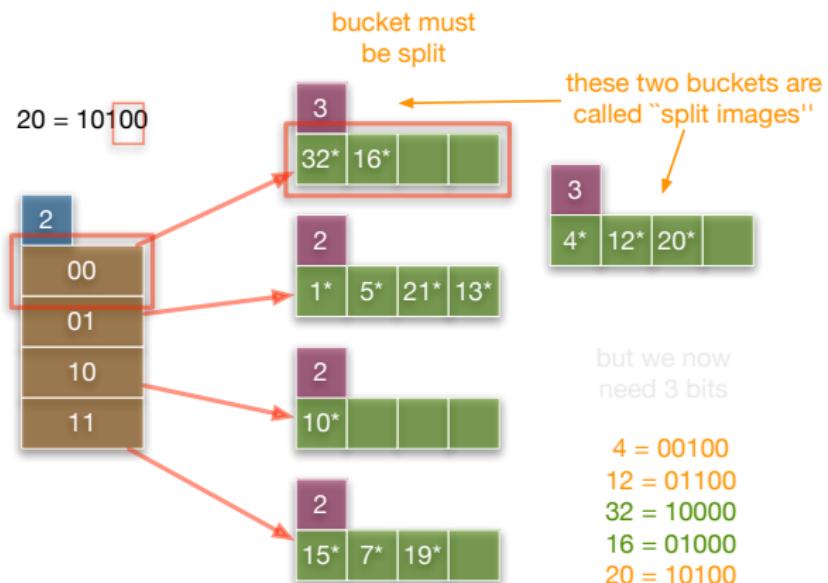
so we must double
the directory

Insertion example: $h(k) = 20$

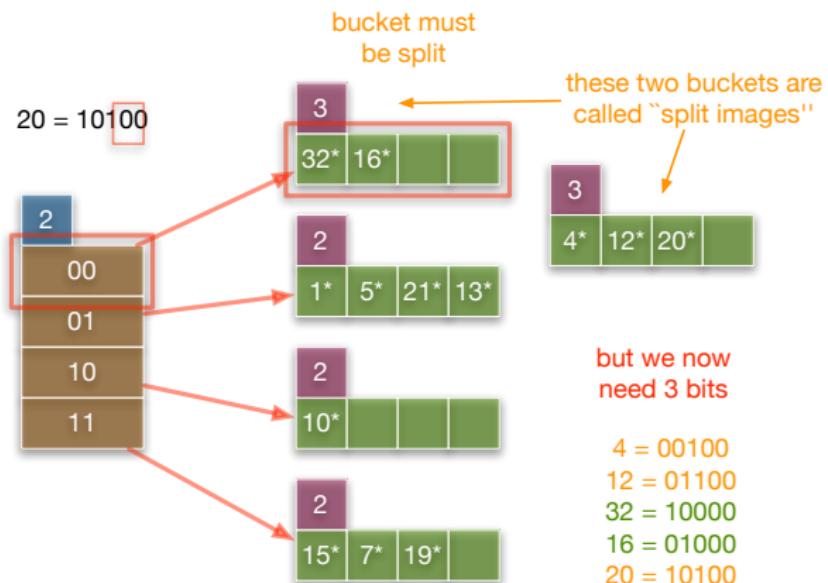


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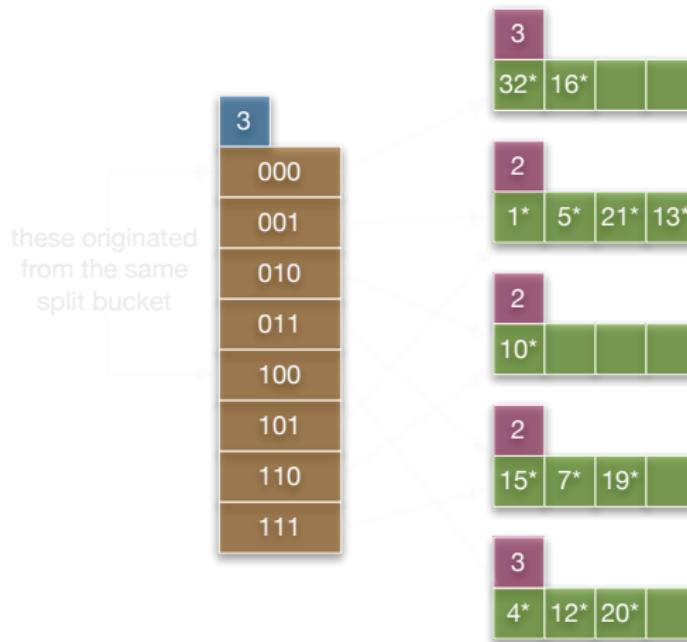


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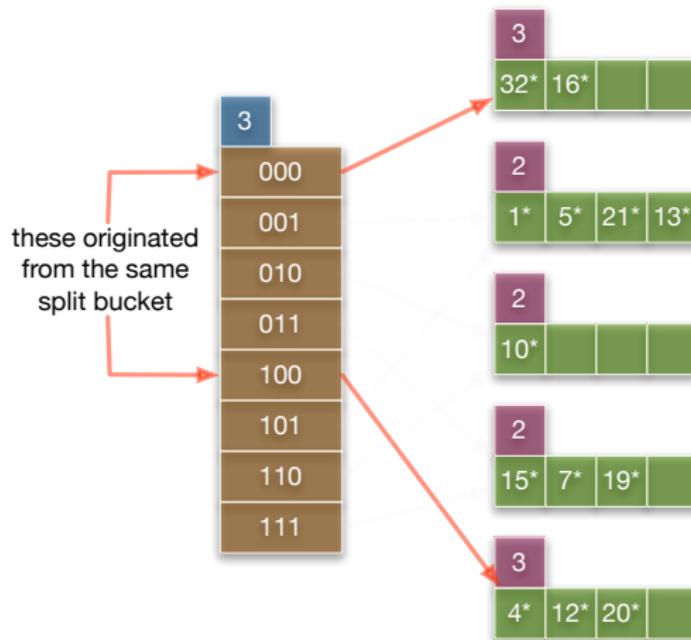


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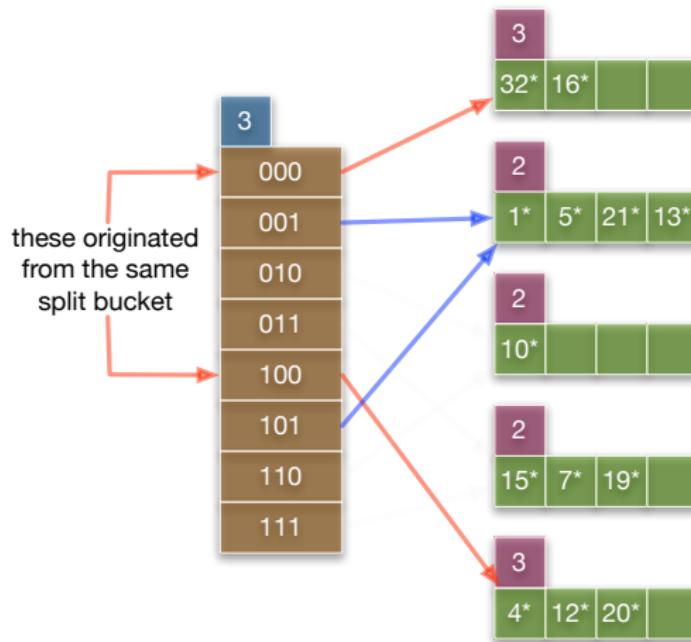
Doubling the directory



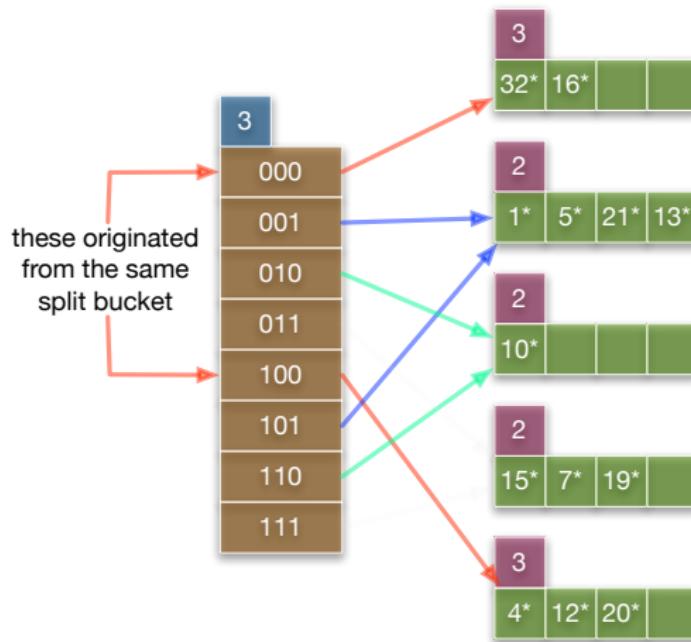
Doubling the directory



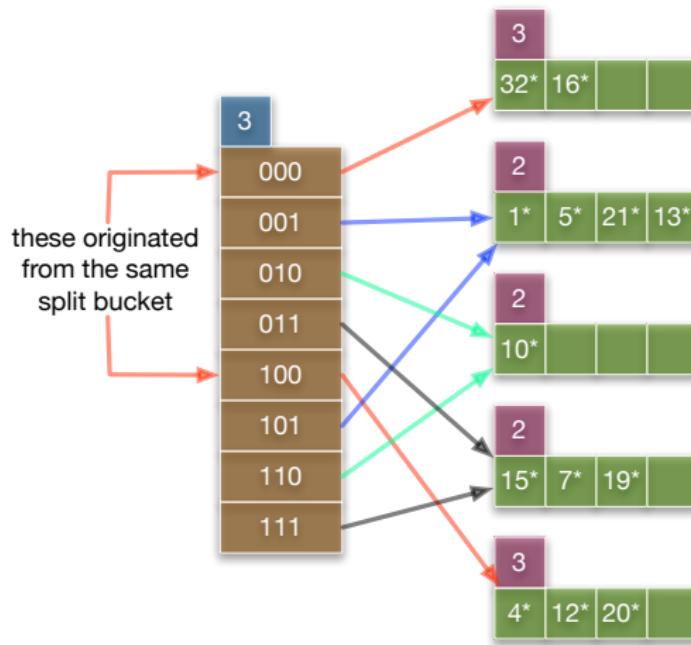
Doubling the directory



Doubling 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 *preetermined 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, \dots
 - ▶ $h_i(\text{key}) = g(\text{key}) \bmod (2^i M)$
 - ▶ M = *initial number of buckets*
 - ▶ g is some *hash function* (*range is not* $[0, \dots, N - 1]$)
 - ▶ 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 , and L
 - ▶ 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.

Search and insert

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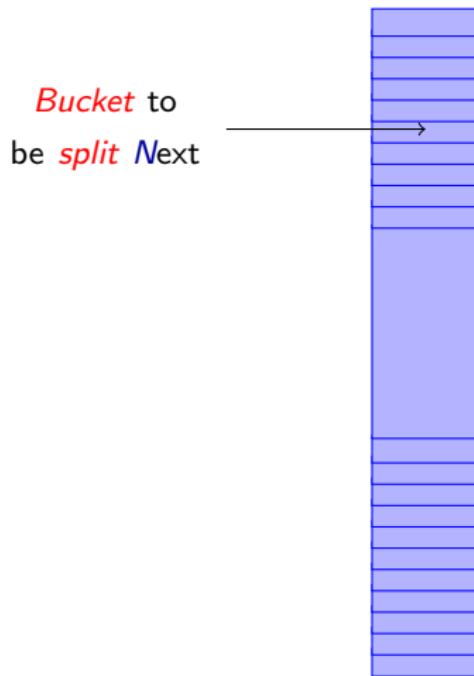
Insert

- 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

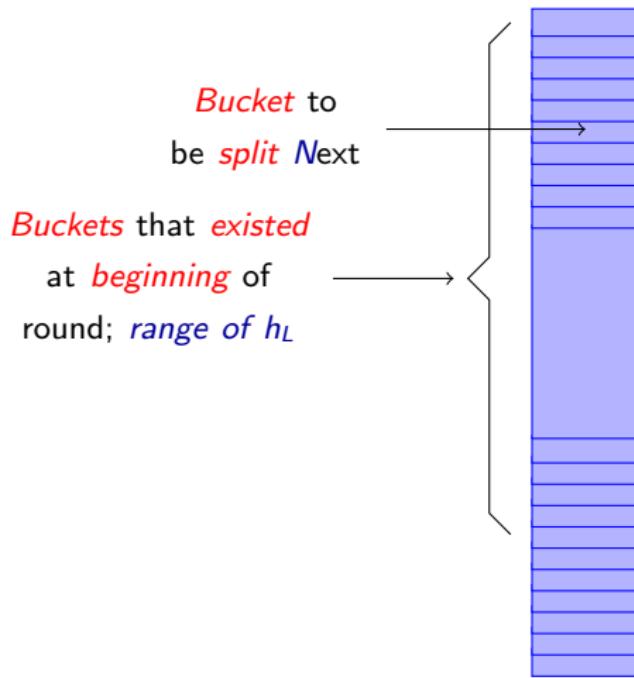
Linear hashing file



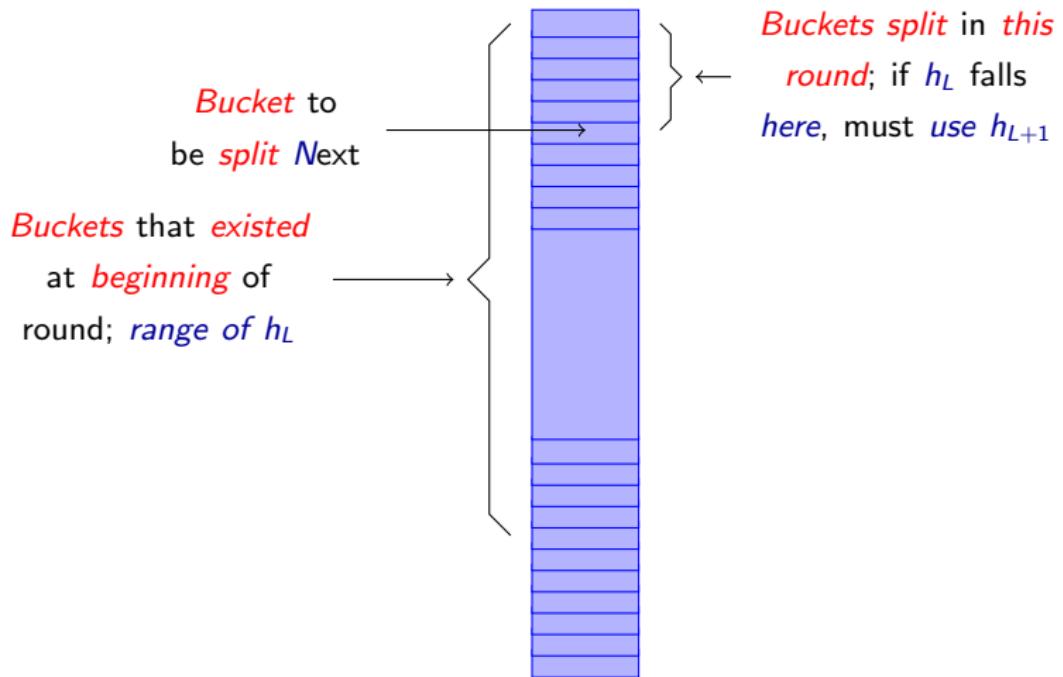
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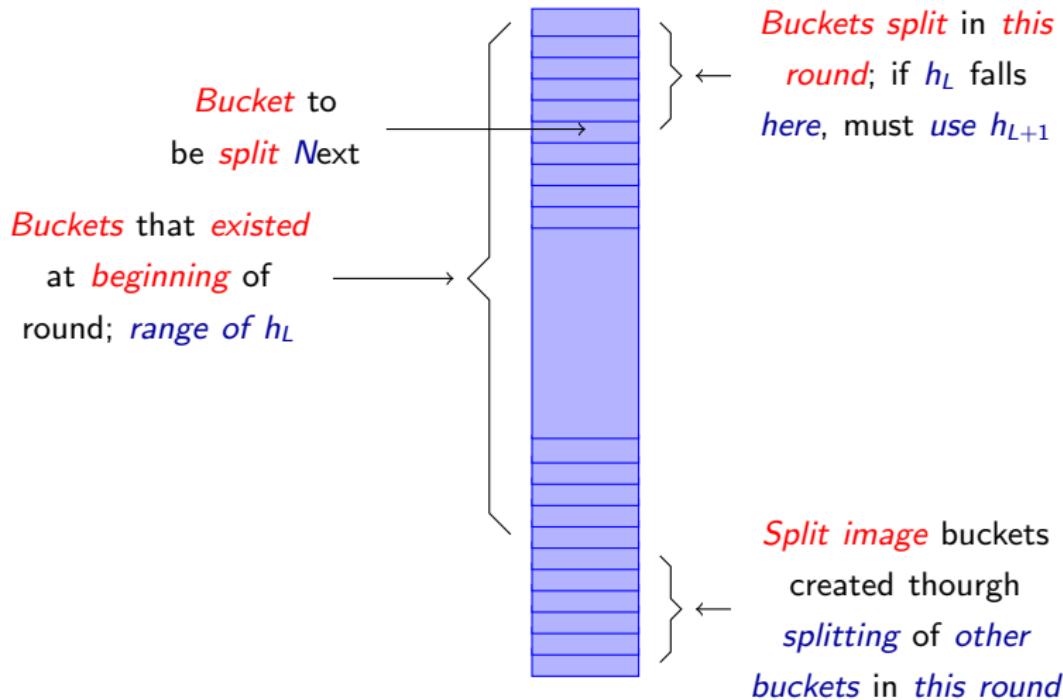
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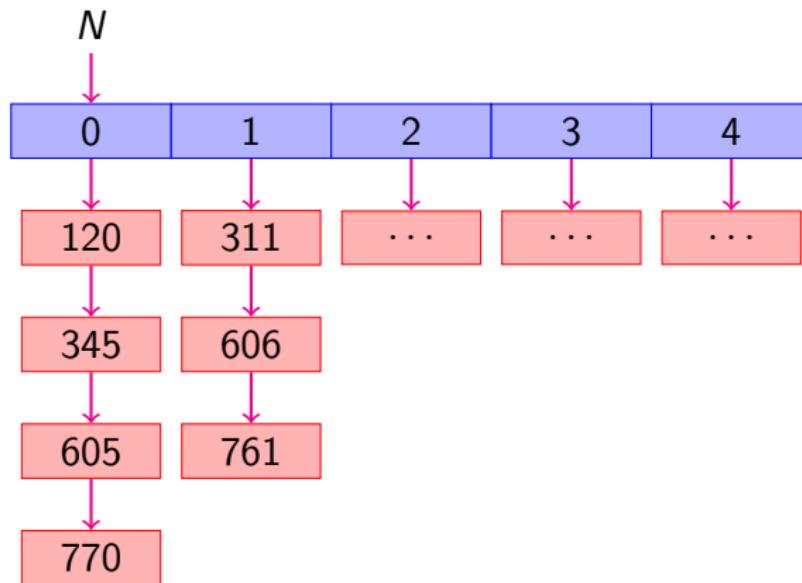
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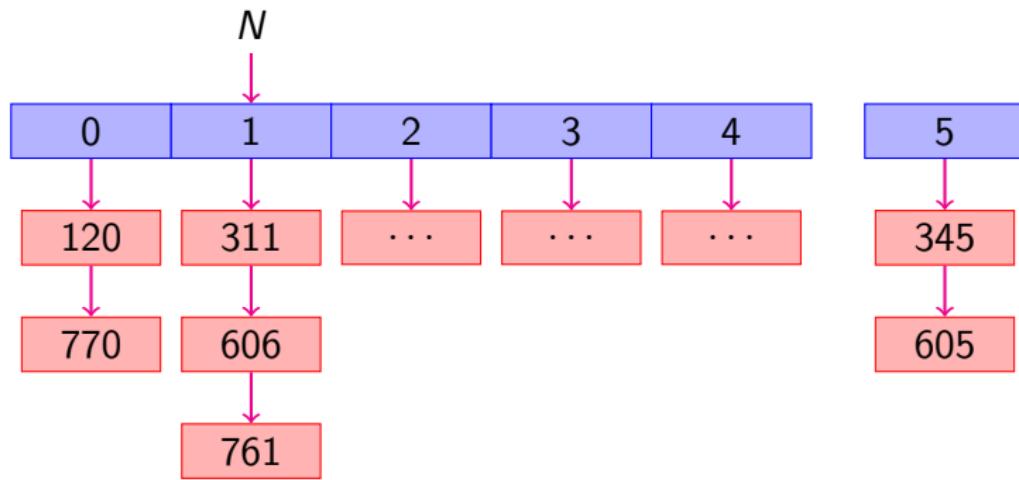
Splitting a bucket (0 in this case)



Hash functions

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

Splitting a bucket (0 in this case)



Hash functions

- $h_0(K) = K \bmod 5$
- $h_1(K) = K \bmod 10$

Algorithms in more detail

Lookup for key K

$\text{bucket} := h_L(K);$

if $\text{bucket} < N$ then $\text{bucket} = h_{L+1}(K)$

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  
 $L := L + 1$ ;     $N := 0$ ;
```

Algorithms in more detail

Lookup for key K

$\text{bucket} := h_L(K);$

if $\text{bucket} < N$ then $\text{bucket} = h_{L+1}(K)$

Expansion

$N := N + 1;$

if $N = M2^L$ then

$L := L + 1;$ $N := 0;$

Contraction

$N := N - 1;$

if $N < 0$ then

$L := L - 1;$ $N := M2^L - 1;$

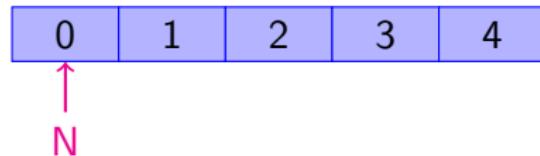
The expansion process (round 0)

Expansion

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if $N = M2^L$ then

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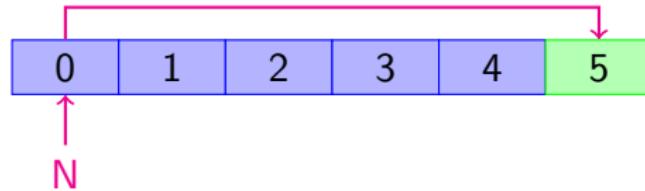
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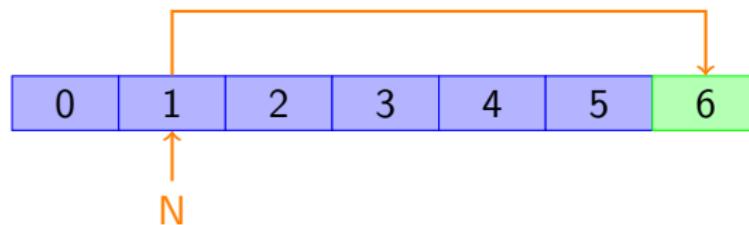
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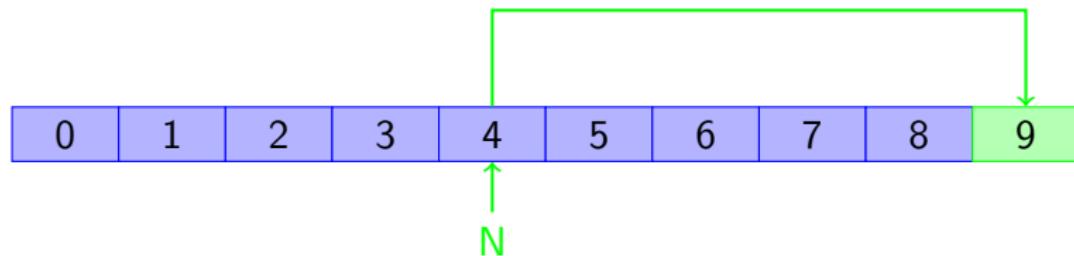
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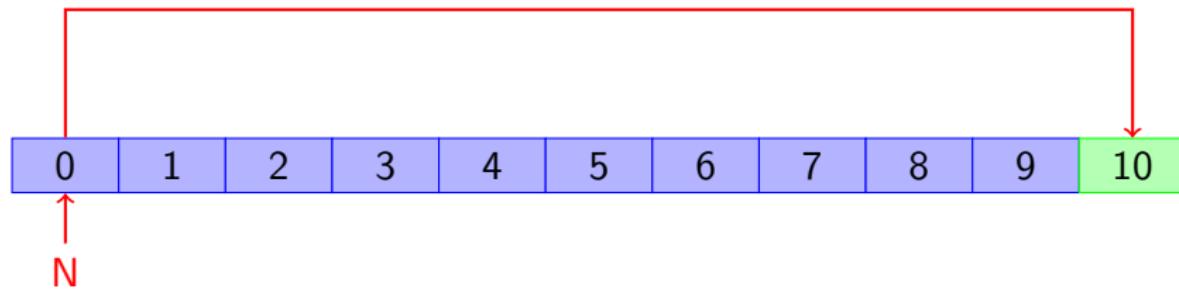
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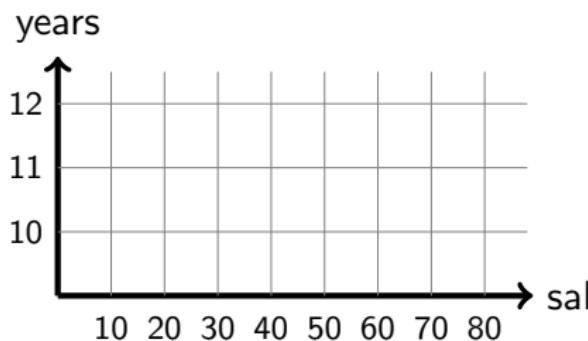
Linear hashing observations

- 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*

Outline

Why more than one dimensions?

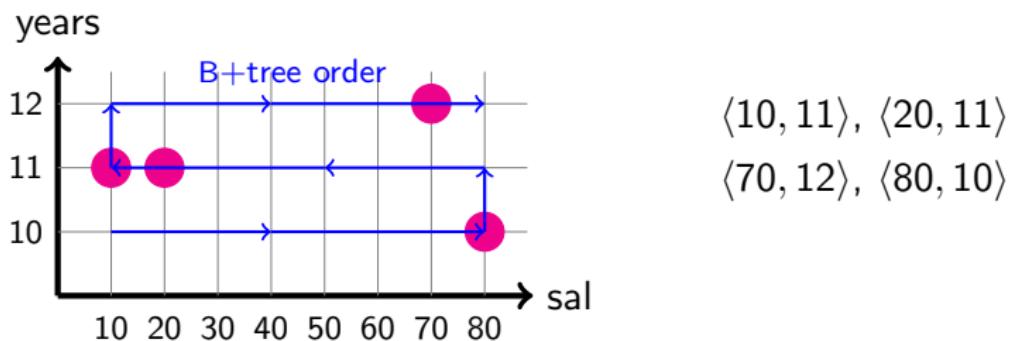
- *Single-dimensional* indexes are *not enough*
 - ▶ Consider a *composite search* key e.g., an index on $\langle \text{sal}, \text{years} \rangle$



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

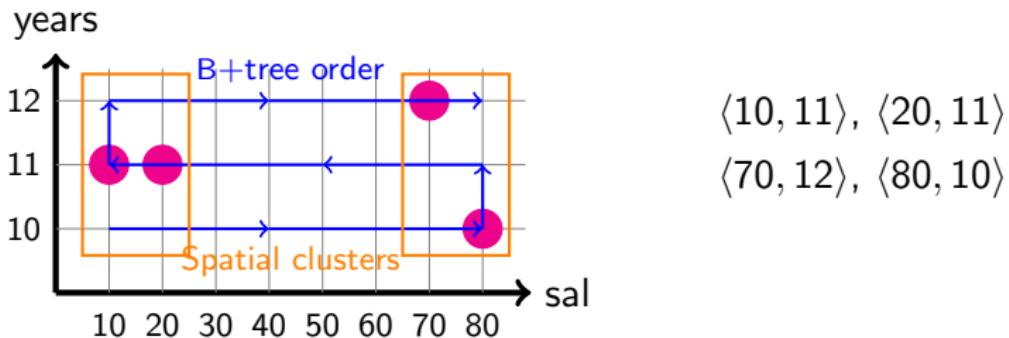
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 - ▶ Consider a *composite search* key e.g., an index on $\langle \text{sal}, \text{years} \rangle$
 - ▶ The *2-dimensional* space is *linearised*
 - ▶ We *sort* entries *first* by *sal* and *then* by *years*



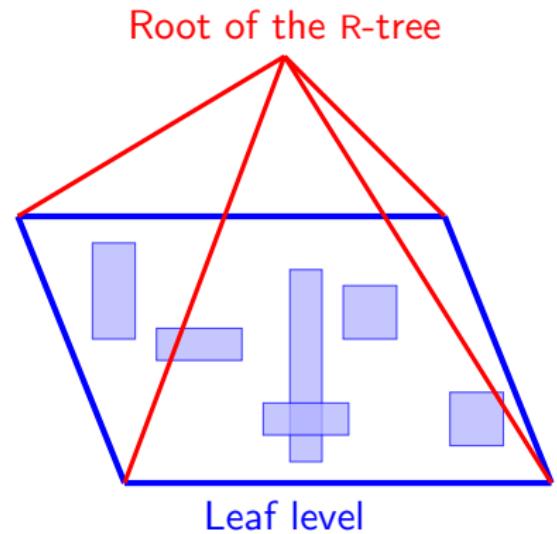
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 - ▶ Consider a *composite search* key e.g., an index on $\langle \text{sal}, \text{years} \rangle$
 - ▶ The *2-dimensional* space is *linearised*
 - ▶ We *sort* entries *first* by *sal* and *then* by *years*
- A *multidimensional index* *clusters* entries
 - ▶ *Exploits nearness* in *multidimensional* space.
 - ▶ *Balanced* index structures in *multiple dimensions* are *challenging*



The R-tree

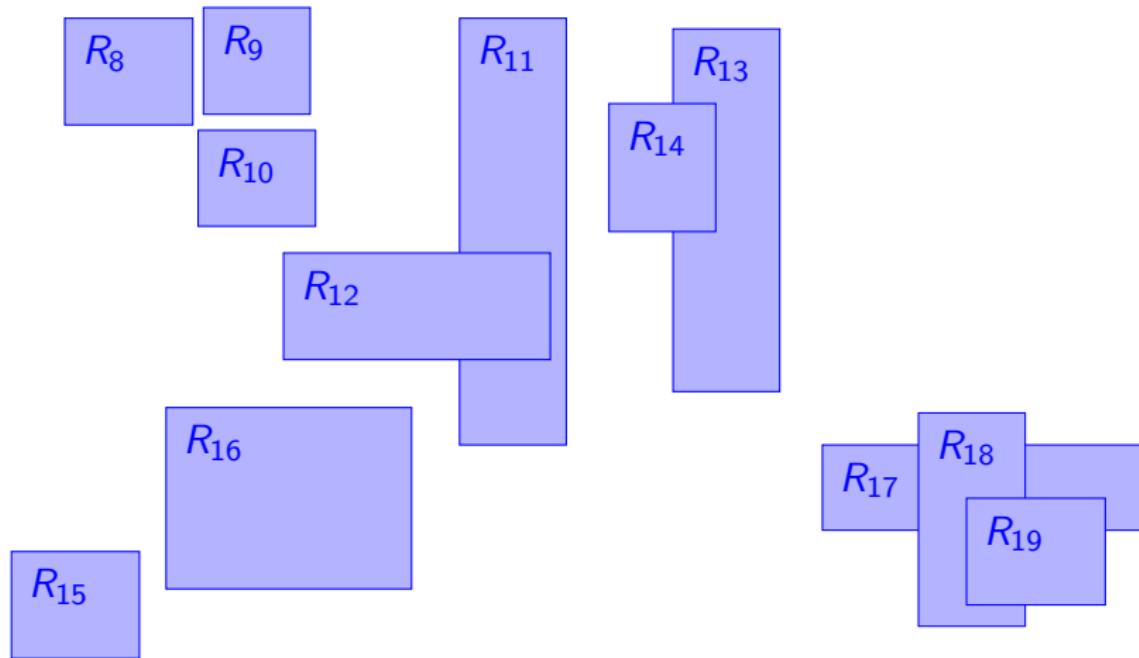
- The *R-tree* is a *tree-structured* index that remains *balanced* on *insertions* and *deletions*
- Each *key* stored in a *leaf entry* is intuitively a *box*, or collection of *intervals*, with *one interval per dimension*



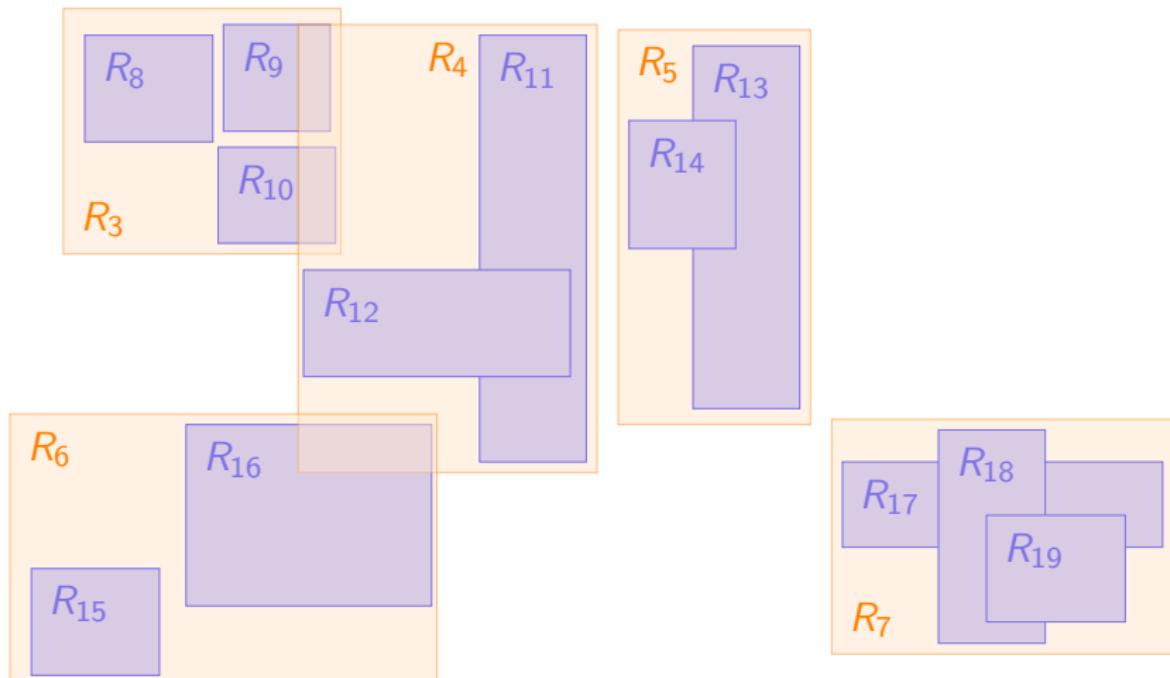
R-tree properties

- *Leaf entry* format: $\langle n\text{-dimensional bounding box, pointer to record} \rangle$
 - ▶ *Bounding box* is the *tightest bounding box* for a data object
- *Non-leaf entry* format: $\langle n\text{-dim box, pointer to child node} \rangle$
 - ▶ 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*

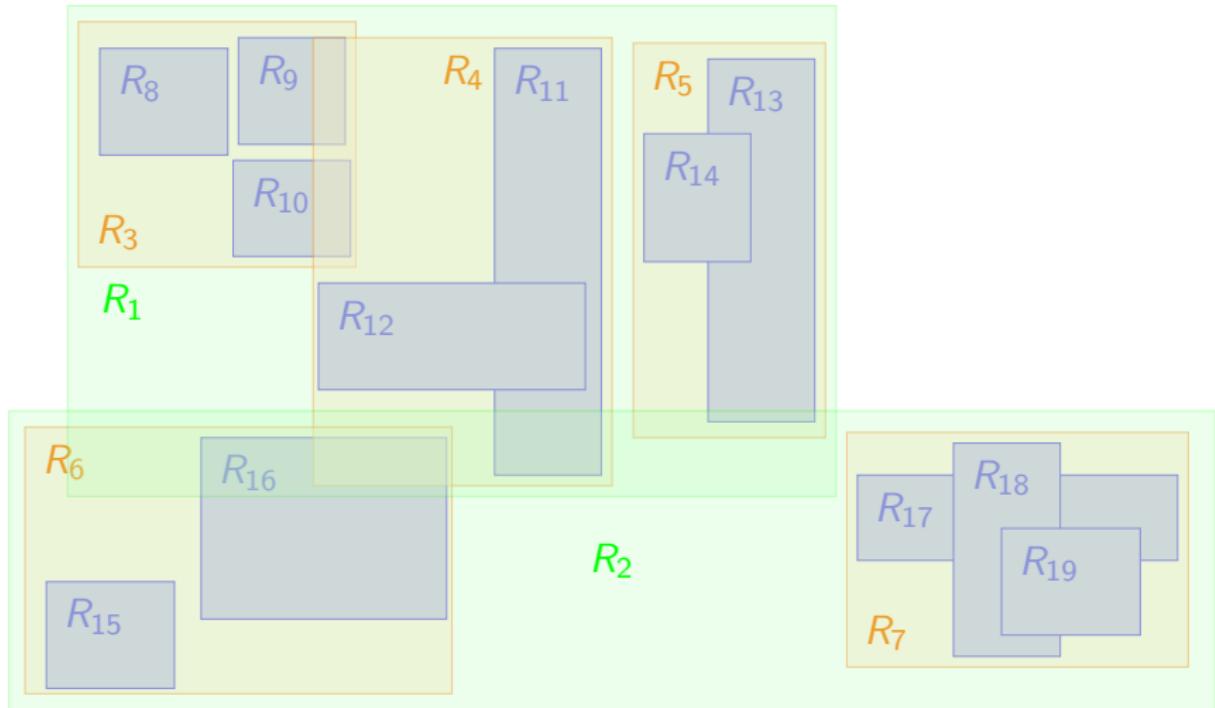
R-tree example



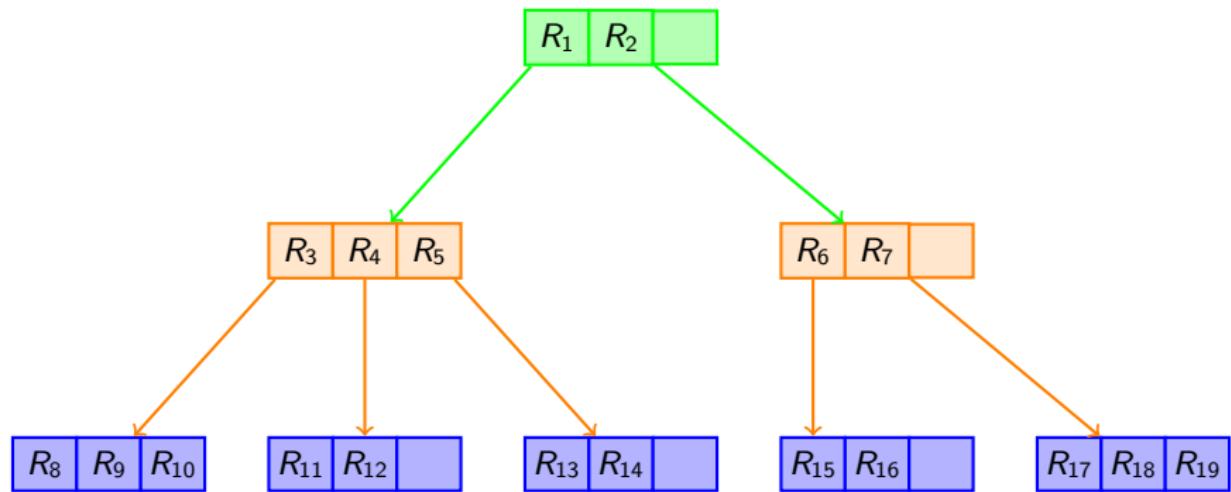
R-tree example



R-tree example



R-tree example (cont.)



Search for objects overlapping box Q

Start at *root*

Search for objects overlapping box Q

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If *current node* is *non-leaf*

For each entry $\langle E, \text{ptr} \rangle$, if *box E overlaps Q* , search *subtree* identified by *ptr*

Search for objects overlapping box Q

Start at *root*

If *current node* is *non-leaf*

For each entry $\langle E, \text{ptr} \rangle$, if *box E overlaps Q* , search *subtree* identified by *ptr*

If *current node* is *leaf*

For each entry $\langle E, \text{rid} \rangle$, if *E overlaps Q* , *rid* identifies an *object* that *might overlap Q*

Search for objects overlapping box Q

Start at *root*

If *current node* is *non-leaf*

For each entry $\langle E, \text{ptr} \rangle$, if *box E overlaps Q* , search subtree identified by *ptr*

If *current node* is *leaf*

For each entry $\langle E, \text{rid} \rangle$, 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 $\langle B, \text{ptr} \rangle$

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*

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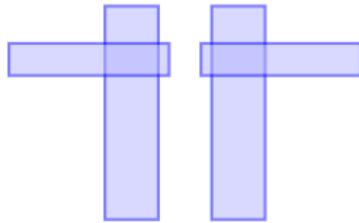
If *best-fit leaf L has space*, *insert* entry and *stop*. *Otherwise*, *split L into L_1 and L_2*

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*.)

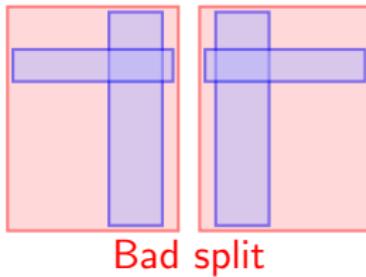
Splitting a node

- 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



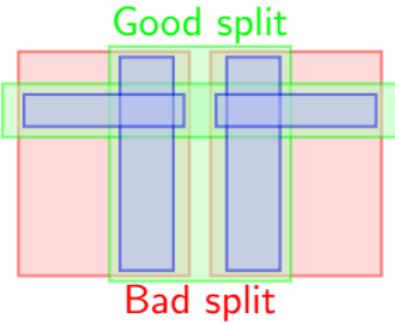
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Splitting a node

- 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*.

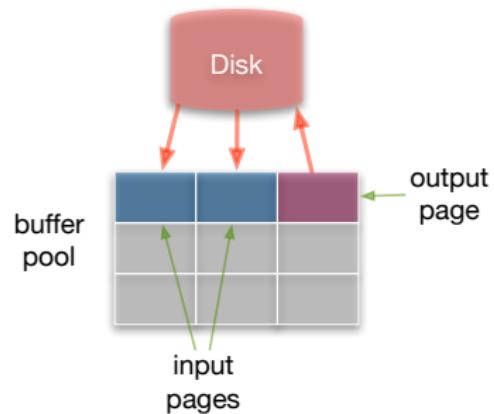
Outline

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)

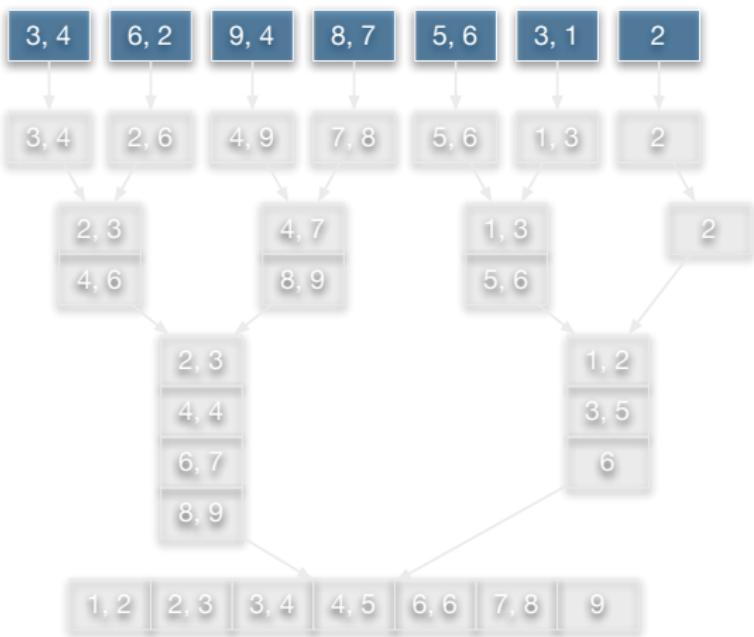
Two-way external merge sort

- 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*



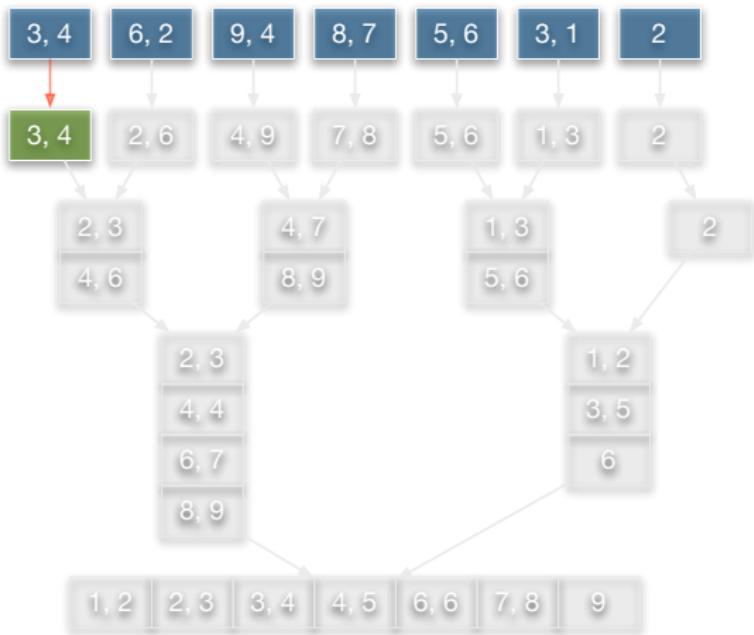
How it works

- *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 $2N(\lceil \log_2 N \rceil + 1)$



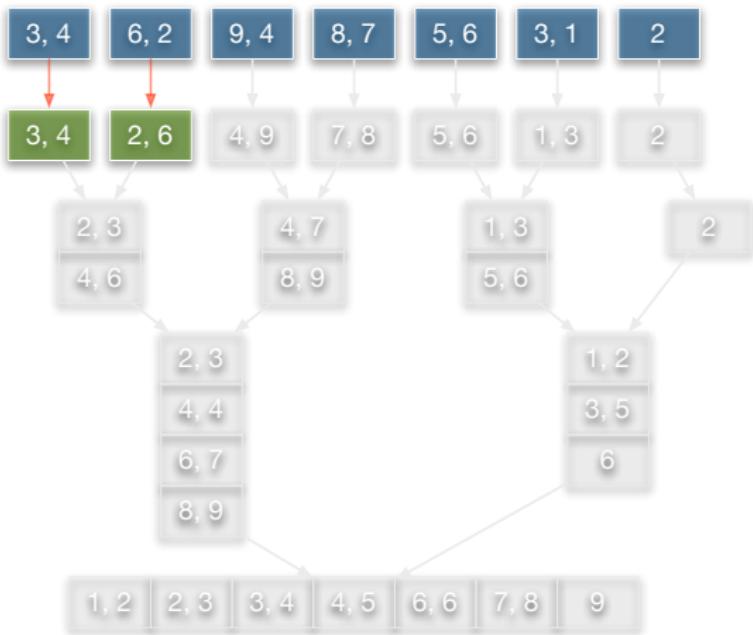
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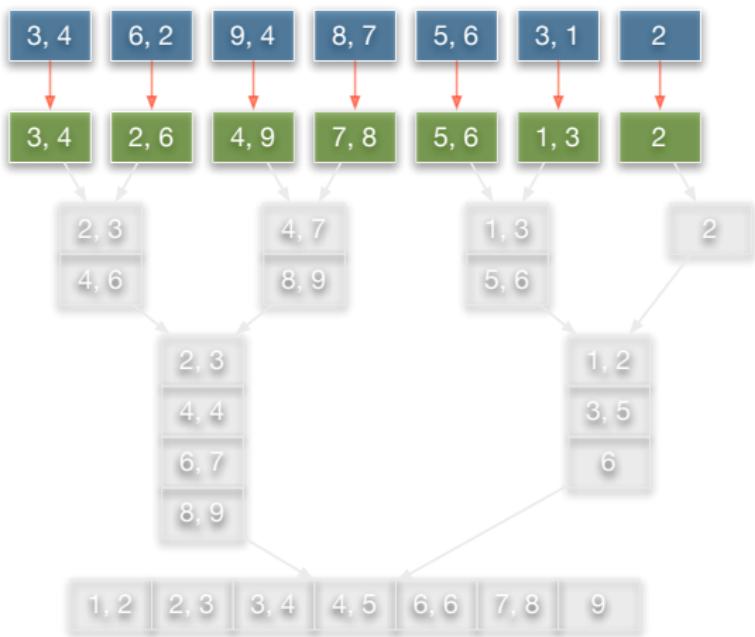
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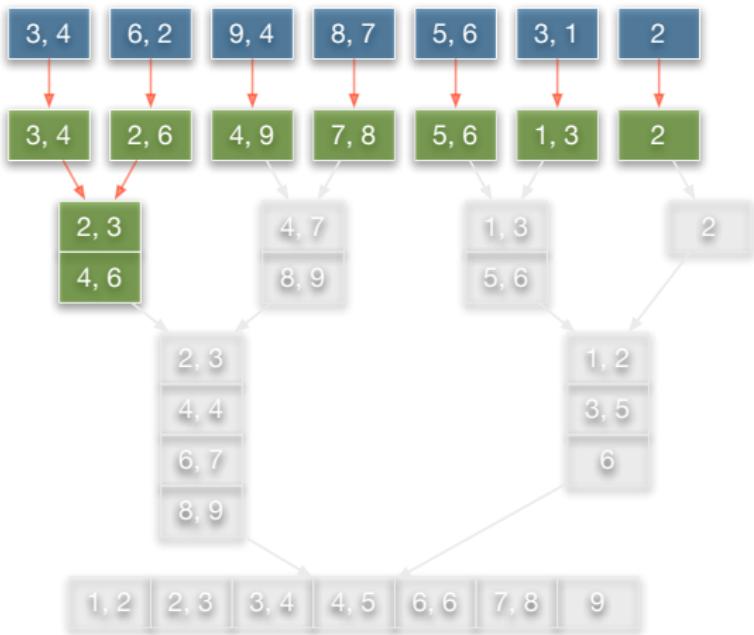
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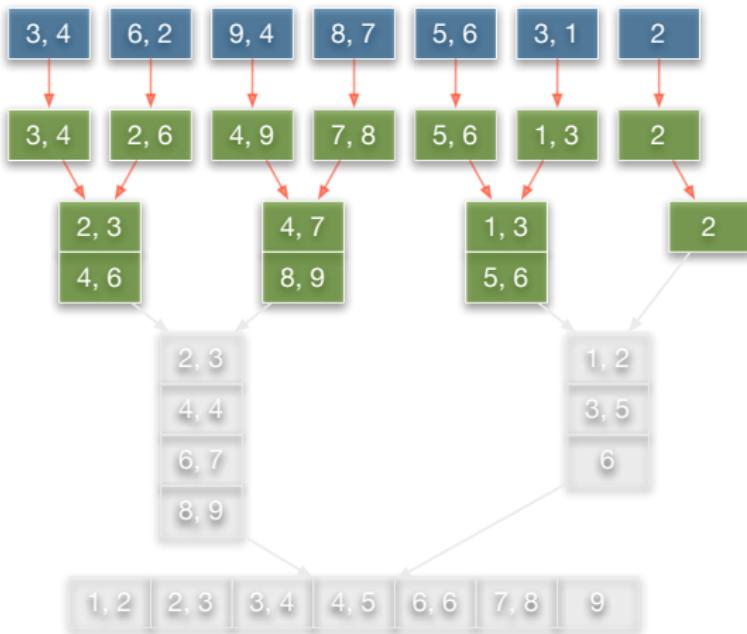
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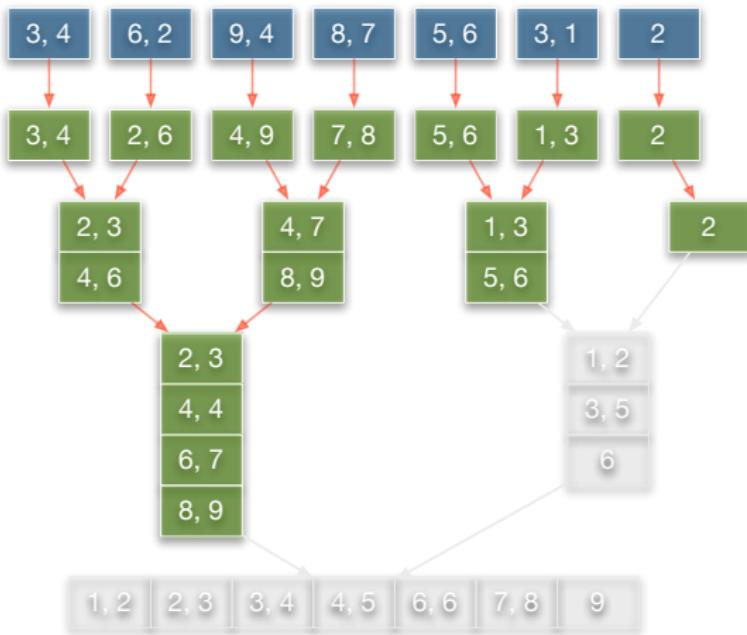
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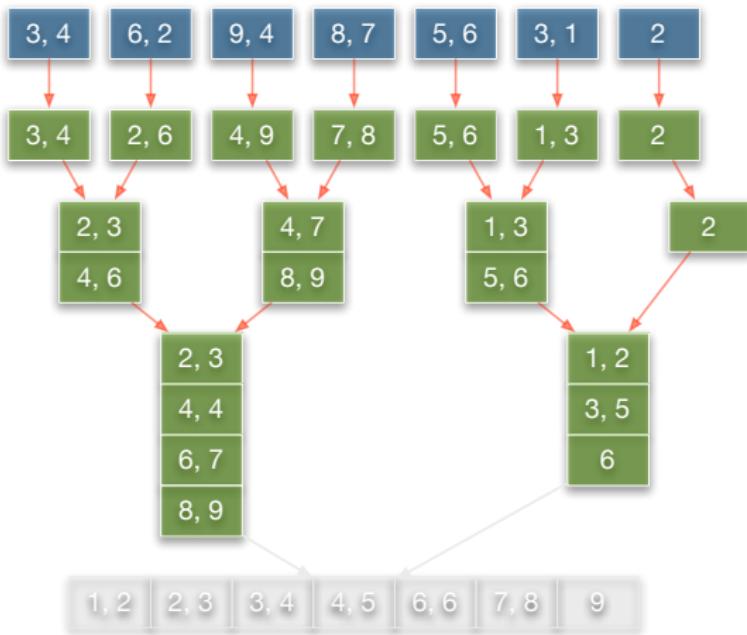
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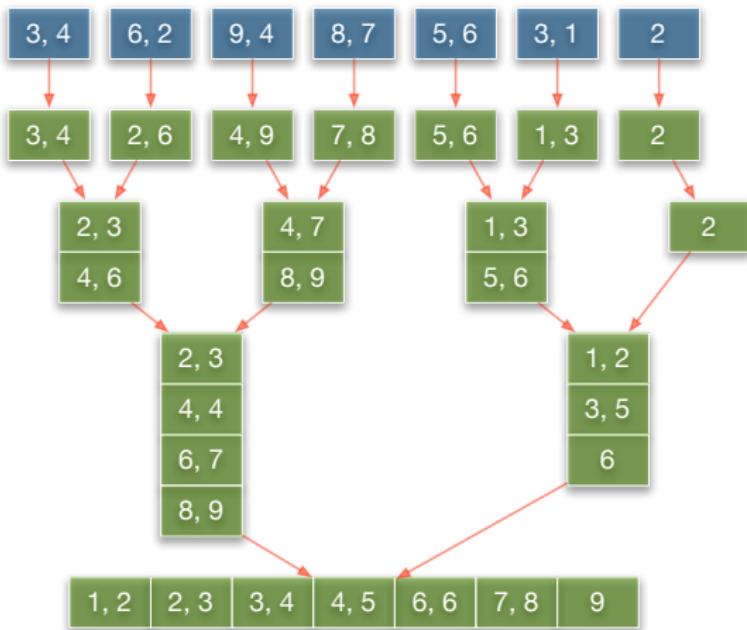
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But why only three pages?

- 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:* $1 + \lceil \log_{B-1} \lceil \frac{N}{B} \rceil \rceil$

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- *For example:* 108 pages in the file, 5 buffer pool pages

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 - ▶ *Pass 3:* final merge, done!

A bit of perspective

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

A bit of perspective

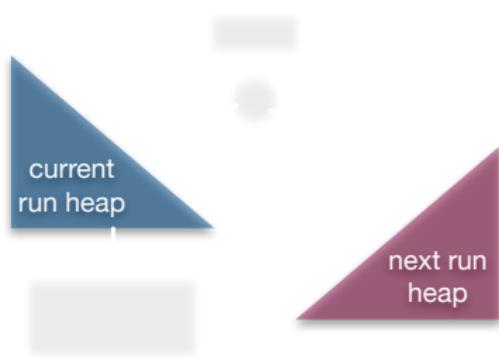
$$257 * 4,096 = 1,052,672$$

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
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10,000,000	23	12	8	6	4	3
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Are we done?

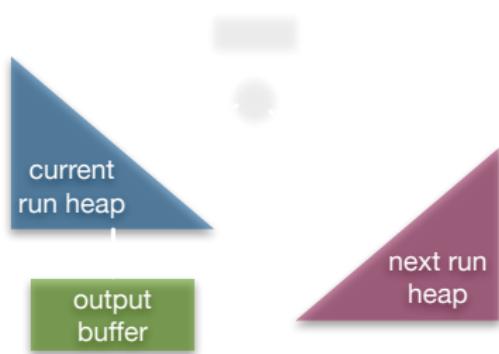
- **No!** We can actually *do much better* than this
- **Key observation:** we are using *main memory algorithm* (e.g., quicksort) to sort pages in memory
 - ▶ But that *doesn't minimise I/O*, does it?
 - ▶ Wouldn't it be nice if we could *generate sorted runs longer than memory*?
 - ▶ **Solution:**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

How does heapsort work?



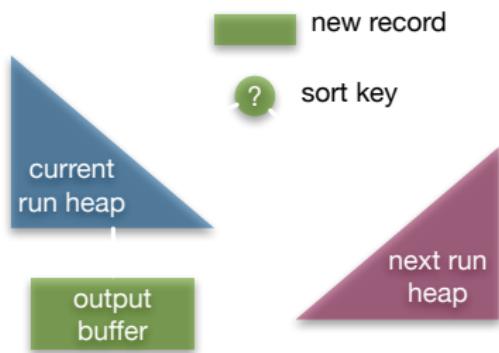
- Keep *two heaps* in memory, *one for each run* (the *current* and the *next* one)
- *Sum of memory* needed for the two heaps *equals the buffer size*
- *Keep adding* to the *current* run *until* we are *out of buffer space*
- When *buffer is full*, *swap* heaps and *iterate*

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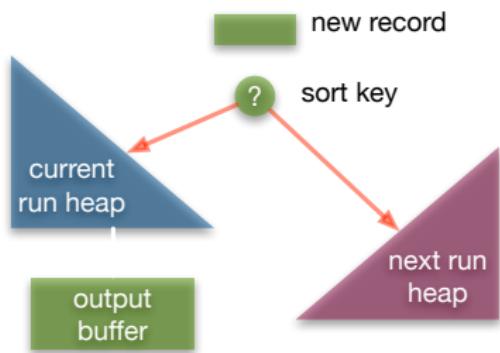
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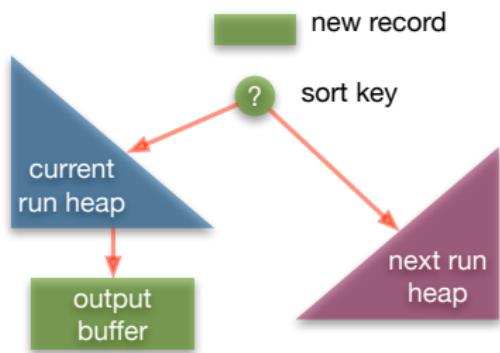
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The algorithm

Initialisation: read B pages into the *current heap*

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get k from input

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while ($r = \text{lowest key from current heap}$) {

*write r to the *current run**

max = r

get k from input

if ($k > \text{max}$) insert k into current heap

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while (not finished) do {
    while ( $r = \text{lowest key from current heap}$ ) {
        write  $r$  to the current run
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*swap *current* and *next* heaps, max = 0*

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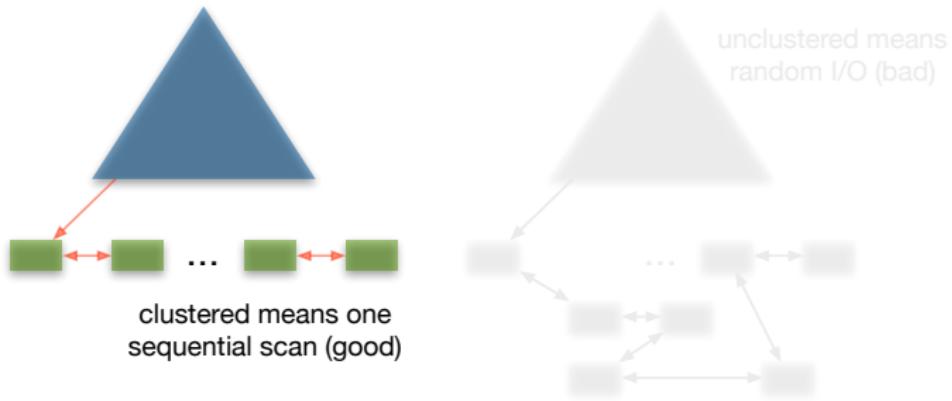
Heapsort observations

- 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!

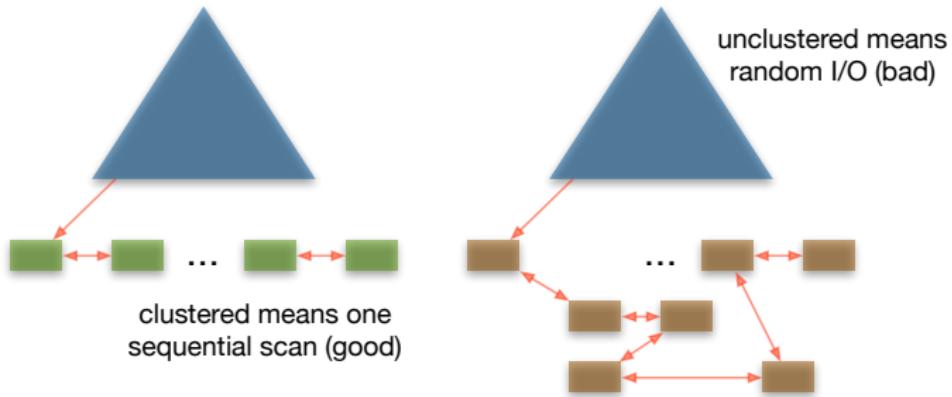
Good-old B+trees

- 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 vs. unclustered storage



Summary of sorting

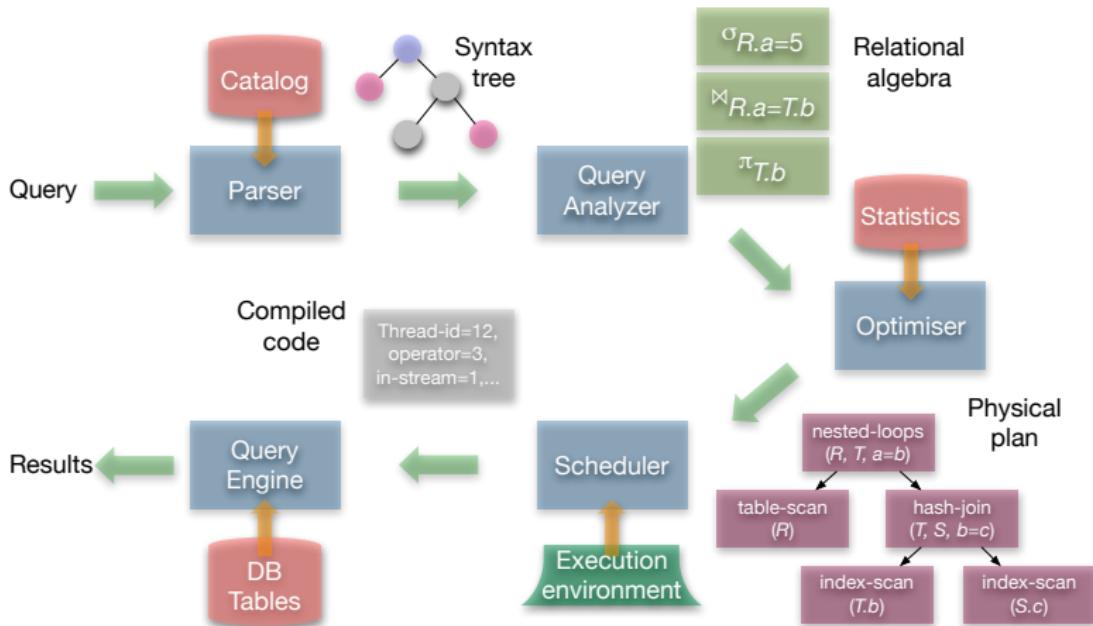
- Databases spend *a lot of their time sorting*
- In fact, they might *dedicate part of their buffer pool* for sorting data
 - ▶ Remember *pinning buffer pool pages*?
- External sorting minimises I/O cost
 - ▶ First you produce *sorted runs*, then you merge them
- The choice of internal sort matters 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*

Outline

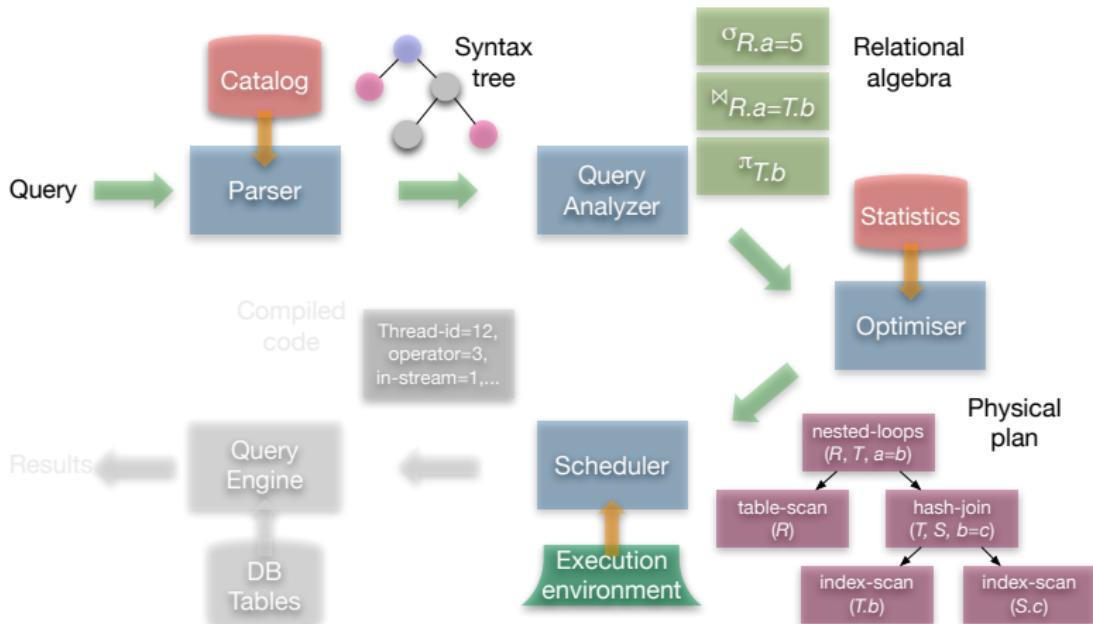
Overview

- 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 cycle



Outline

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* → *physical join* → *sort-merge join*

Example

SQL query

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

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Algebraic expression

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

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Algebraic expression

$$\begin{aligned} & \pi_{student.id, student.name} \\ & (student \bowtie_{student.cid=course.cid} \\ & \sigma_{course.name='ADBS'} (course)) \end{aligned}$$

Algebraic operations

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

Mappings to/of various physical operators

π projection list

σ predicate

\bowtie predicate

table

Mappings to/of various physical operators

$\pi_{\text{projection list}}$ → project
(projection list)

$\sigma_{\text{predicate}}$

$\bowtie_{\text{predicate}}$

table

Mappings to/of various physical operators

$\pi_{\text{projection list}}$ → project
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$\sigma_{\text{predicate}}$ →
select
(predicate)
index-scan
(table-attribute,
predicate)

$\bowtie_{\text{predicate}}$

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Mappings to/of various physical operators

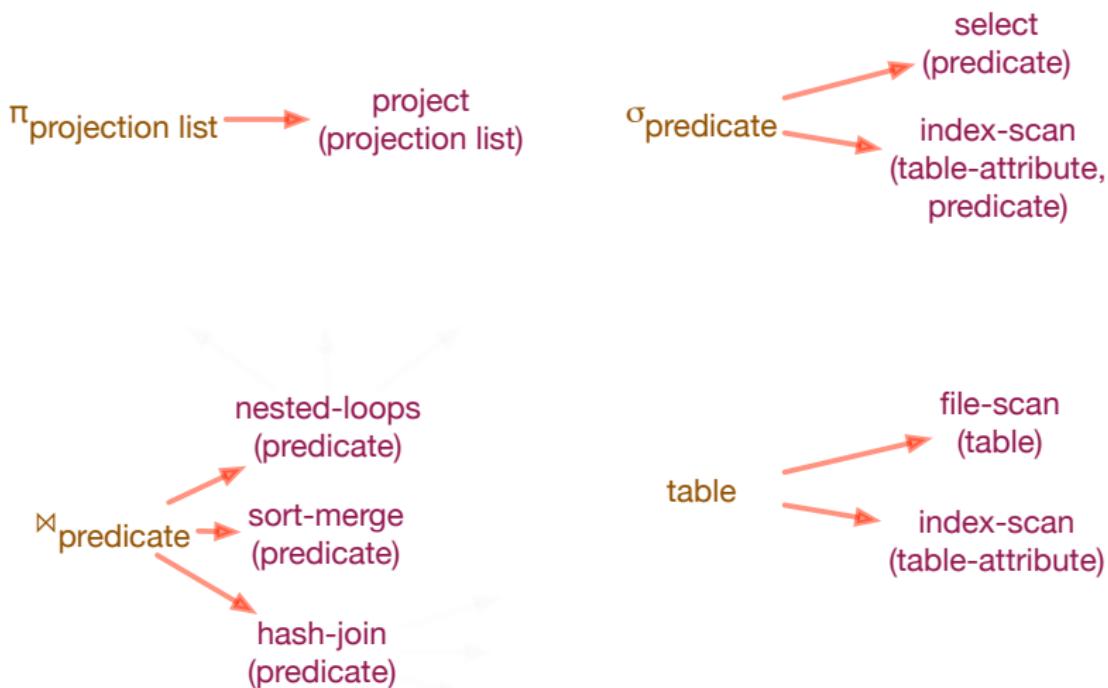
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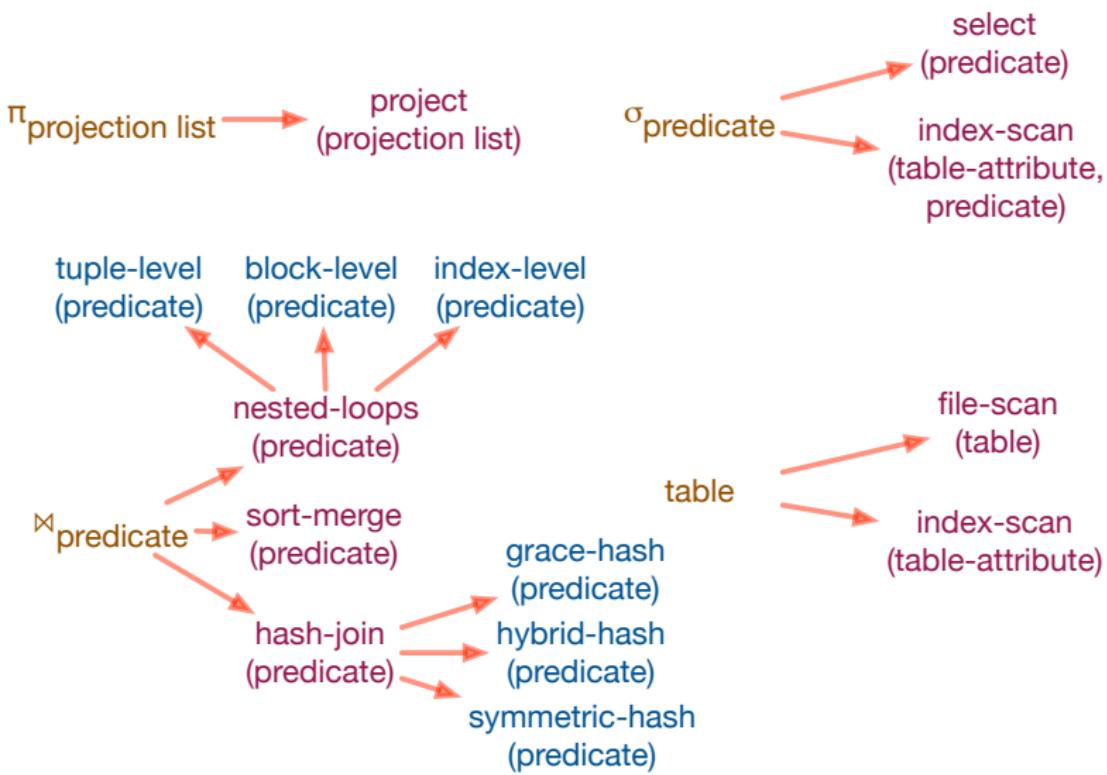
$\bowtie_{\text{predicate}}$

table → file-scan
(table)
→ index-scan
(table-attribute)

Mappings to/of various physical operators

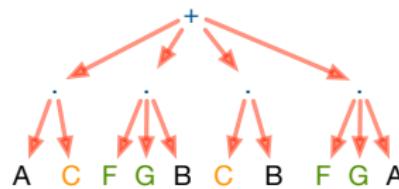


Mappings to/of various physical operators

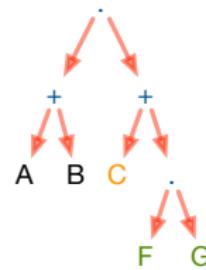


Math analogy

- 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

```
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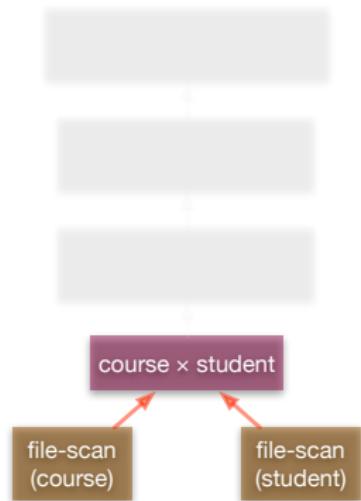
file-scan
(course)

file-scan
(student)

Here's a plan

SQL query

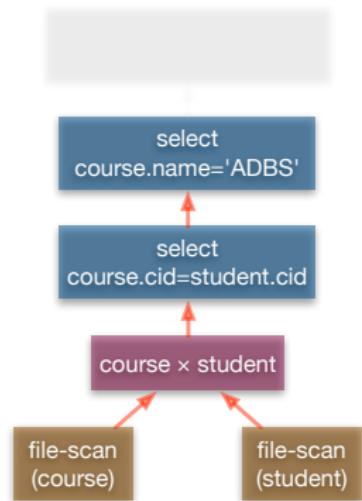
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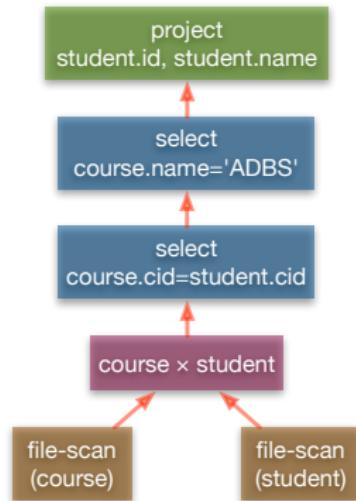
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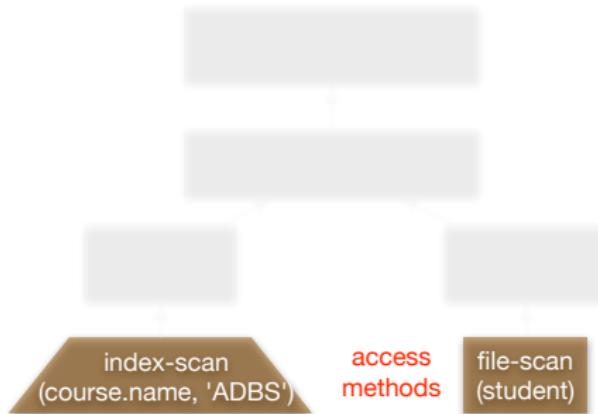
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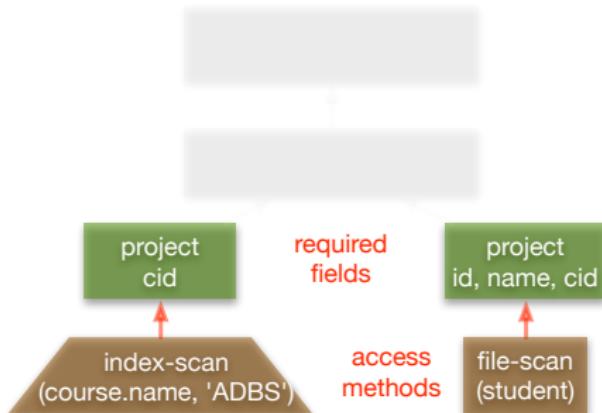
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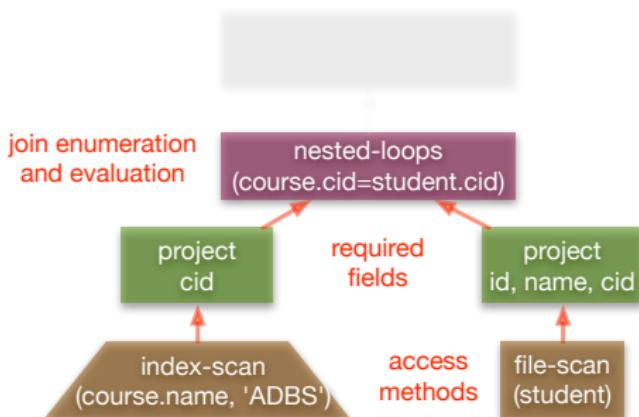
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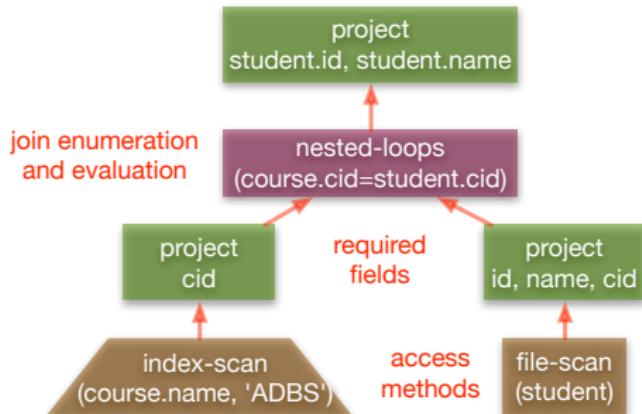
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Here's a better plan



SQL query

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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*

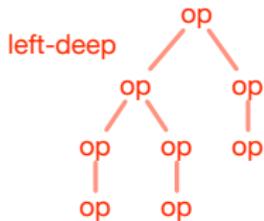
A note on duplicates

- 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

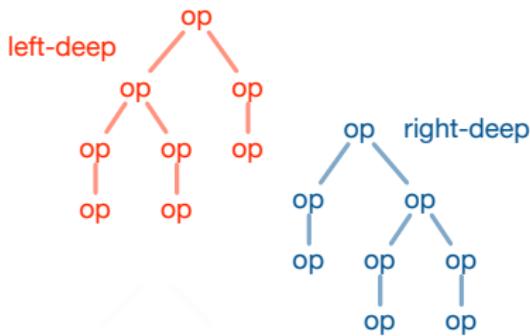
- There are *two types of plan*, according to their shape
 - ▶ *Deep* (left or right)
 - ▶ *Bushy*
- *Different shapes* for different objectives

Types of plan



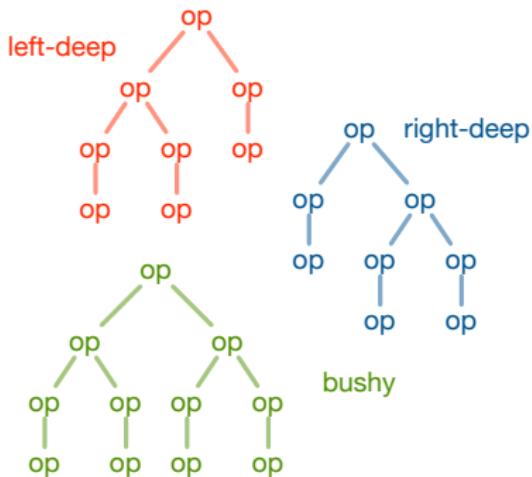
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Types of plan



- There are *two types of plan*, according to their *shape*
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 - ▶ 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*

Outline

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,`
`ResultSets in`
`Java/JDBC, etc.`

operator

The iterator model

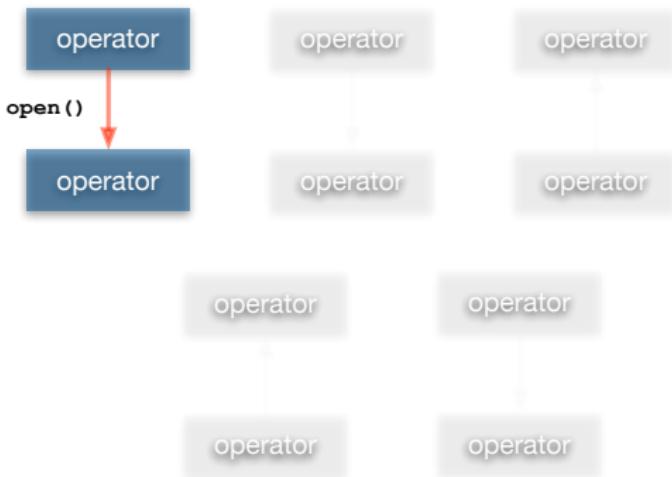
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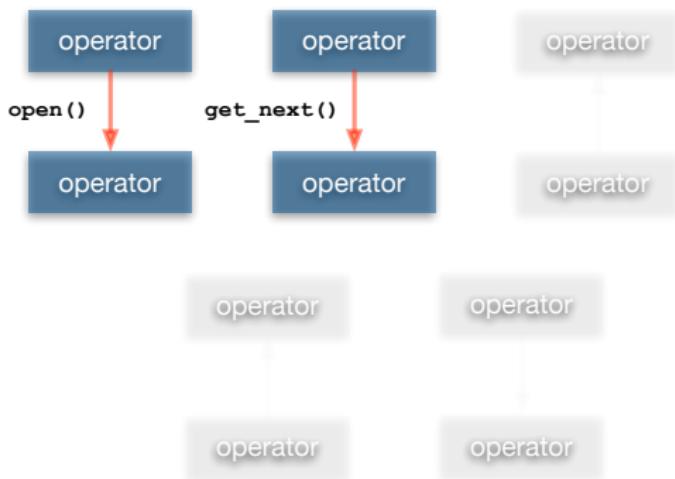
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The iterator model

- *Also* known as a *cursor*
- *Three* basic *calls*
 - ▶ `open()`
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 - ▶ `close()`



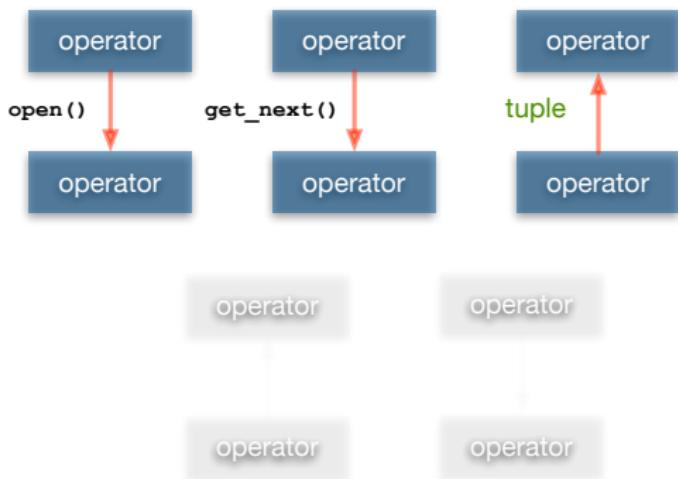
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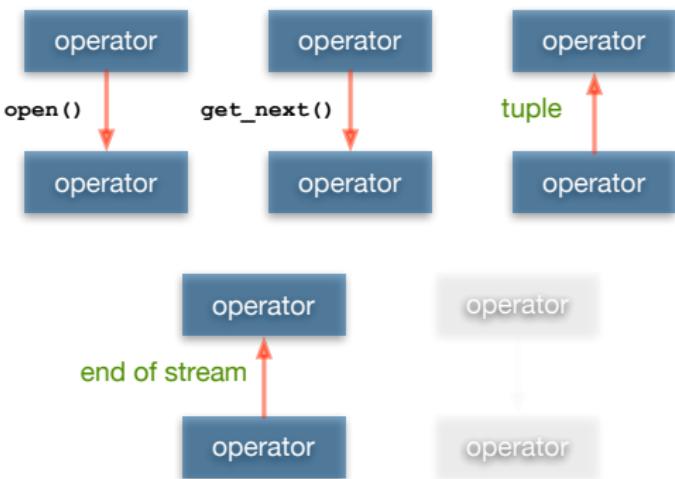
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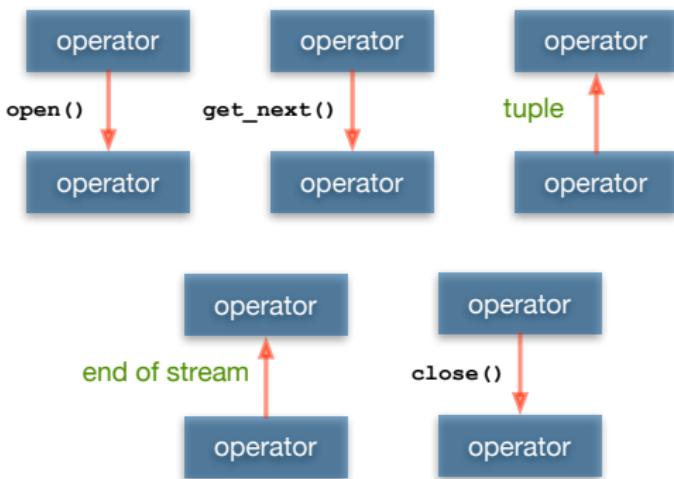
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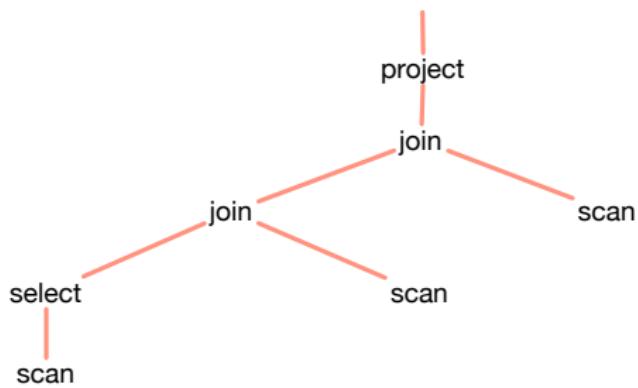


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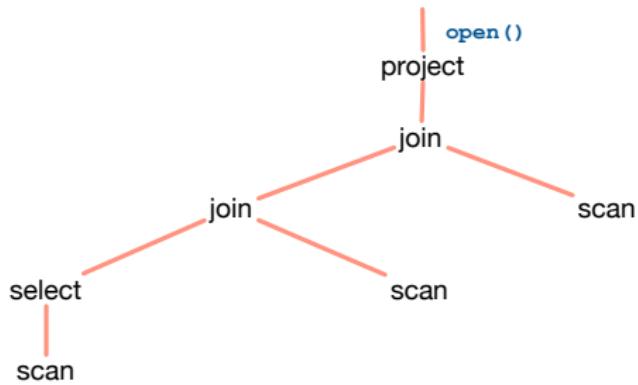
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Call propagation



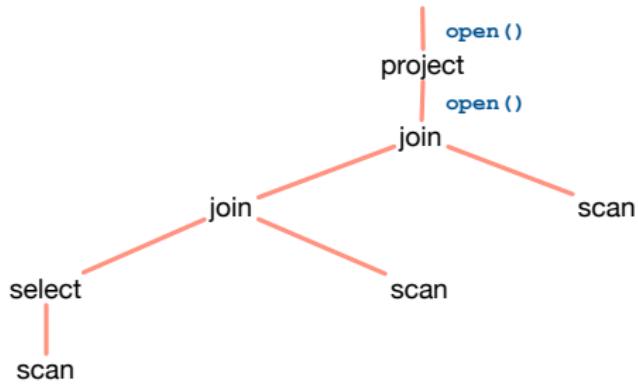
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- The *query engine* makes the *calls* to the *topmost operator only*

Call propagation



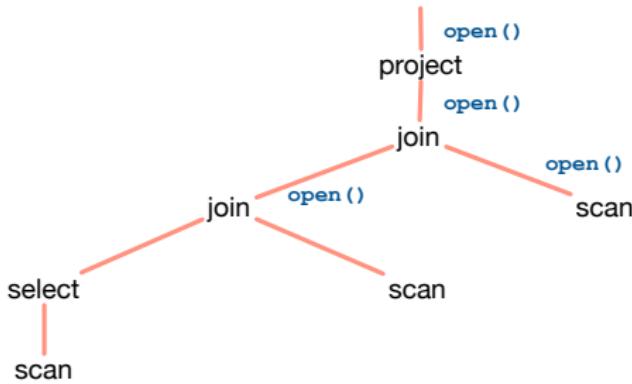
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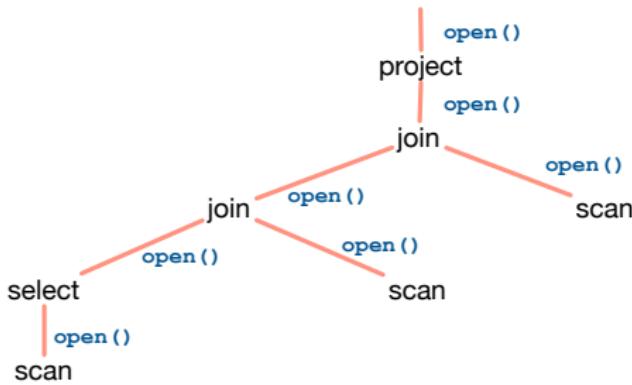
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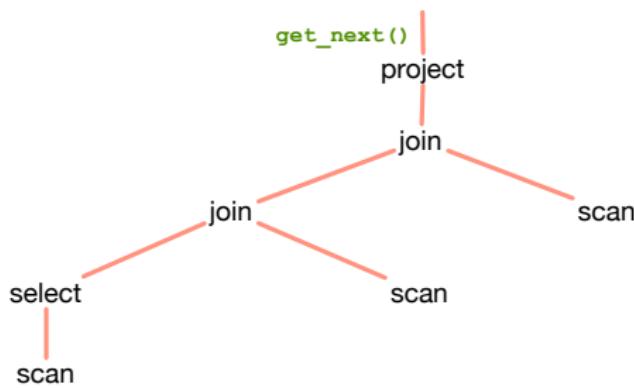
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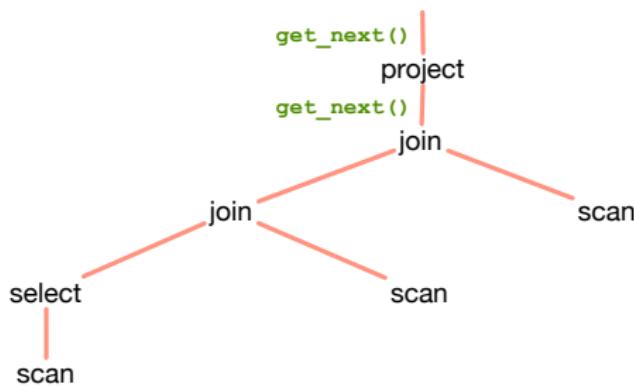
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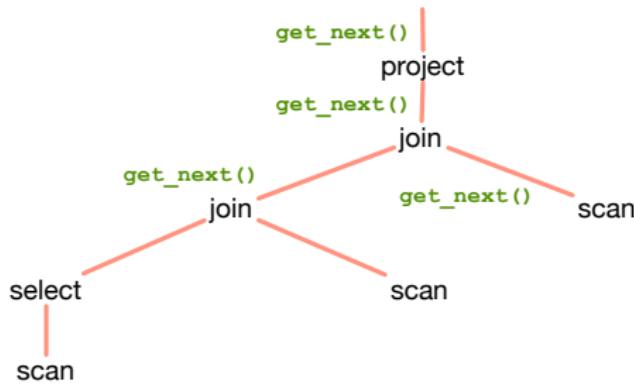
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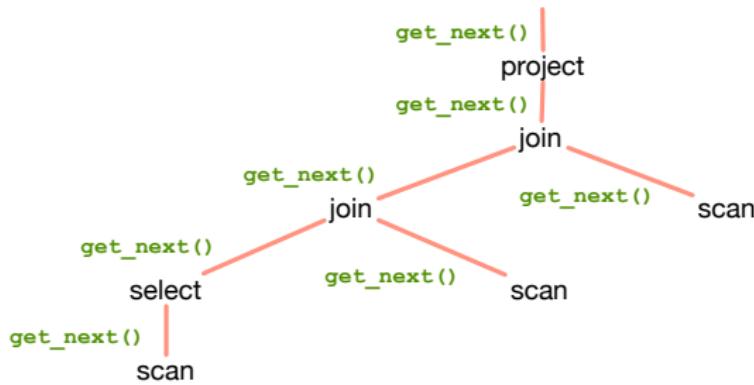
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Pure implementation

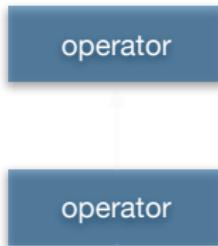
- The *iterator interface*, as described, is a *completely synchronous* interface
- A *pure implementation* means that all *operators reside in the same process space*
 - ▶ So *calls* can be *propagated downstream*
- But *certain operators* are “*faster*” than others
 - ▶ It *could be* the case that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

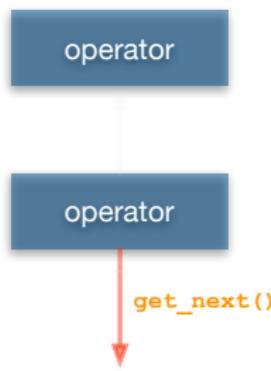


operator

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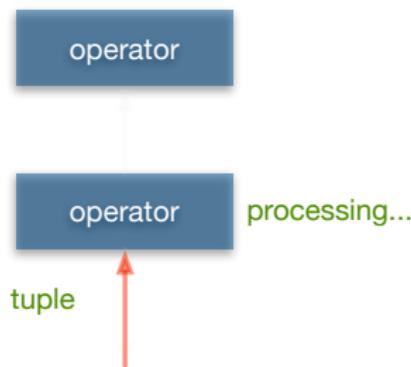
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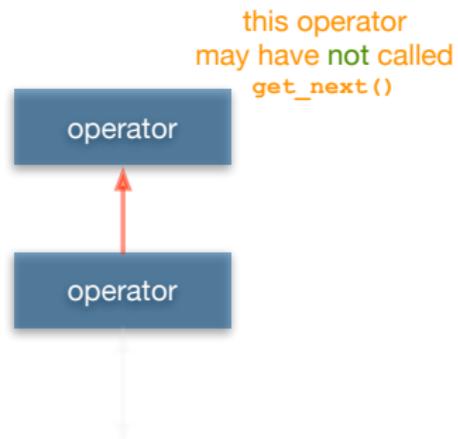
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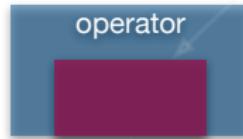
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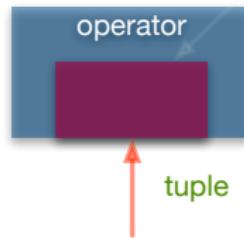
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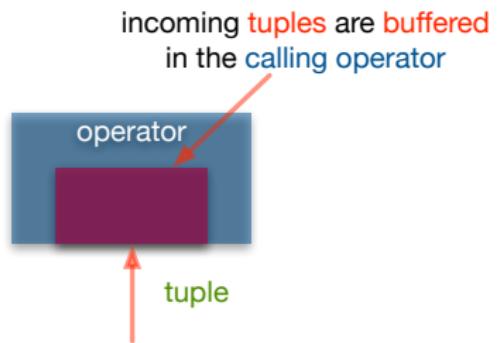
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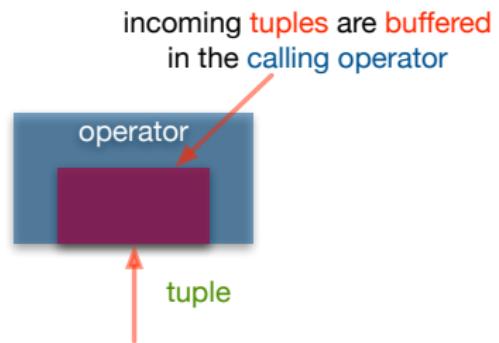
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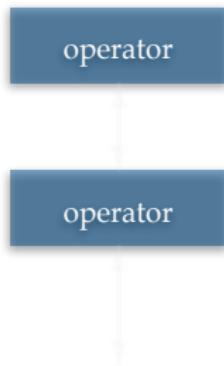
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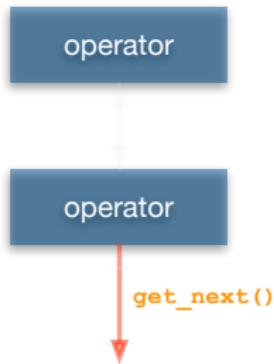
secondary issue: what should the size of the buffer be? (the optimiser might have an idea...)

The pull model



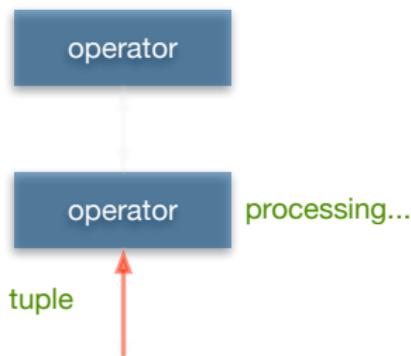
- The *inverse* of the *push model*
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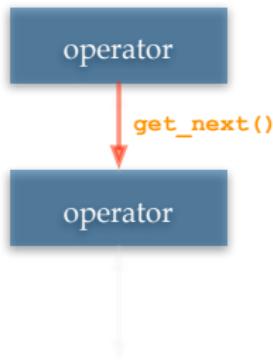
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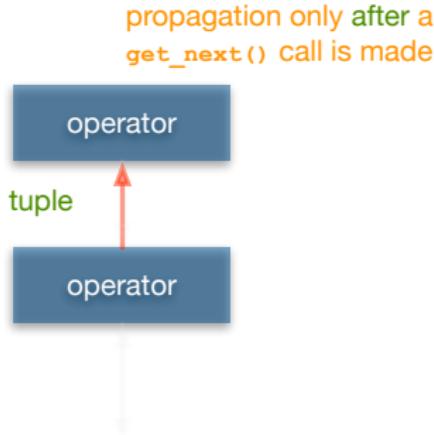
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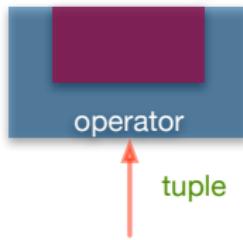
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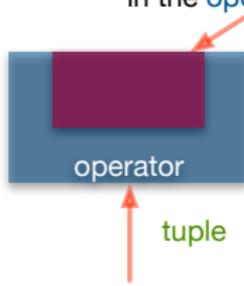
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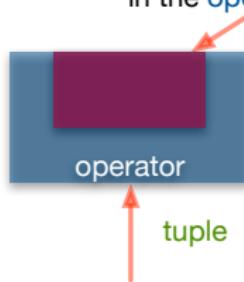
Buffering — again



outgoing tuples are buffered
in the operator being called

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

Buffering — again



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

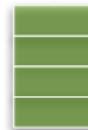


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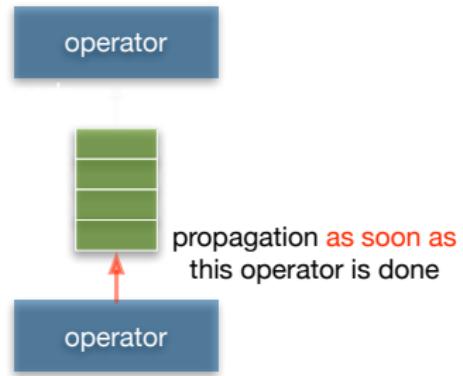
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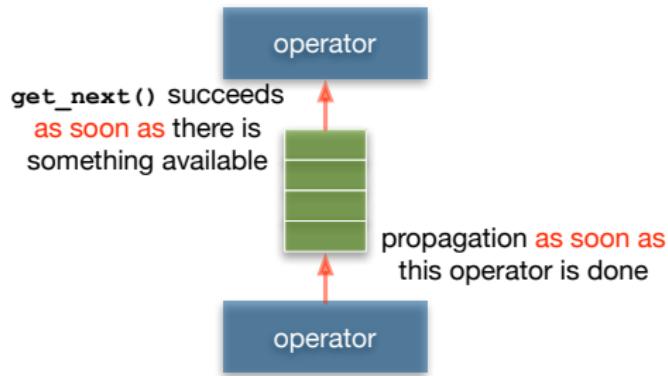
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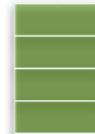
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Buffering — third time

- *This time*, there is *no question!*
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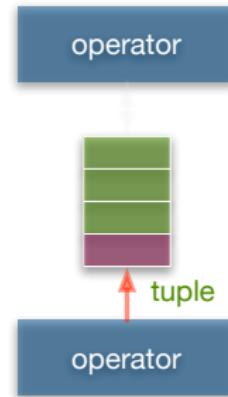
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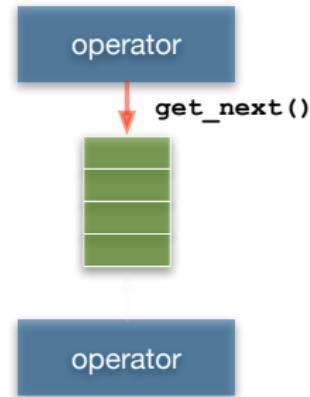
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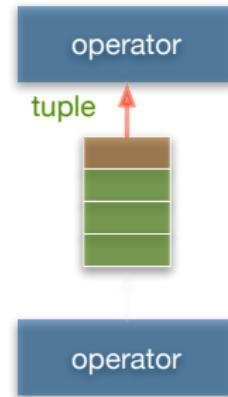
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Why all this?

- *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

Outline

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*: $\text{cost}(R \bowtie S) \neq \text{cost}(S \bowtie R)$
- *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

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for each tuple $r \in R$ do
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Tuple-level nested loops

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

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Tuple-level nested loops

*for each tuple $r \in R$ do
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- R is the *outer relation*

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Tuple-level nested loops

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for each tuple  $r \in R$  do  
  for each tuple  $s \in S$  do  
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```

- 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
 - ▶ $\text{cost}(R \bowtie S) = T_R + T_R \cdot T_S$
 - ★ Assume $T_R = 100,000$, $T_S = 50,000$, then $\text{cost} = 5,000,100,000 \text{ I/Os}$
 - ★ 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
 - ▶ $\text{cost}(R \bowtie S) = P_R + P_R \cdot P_S$
 - ▶ 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

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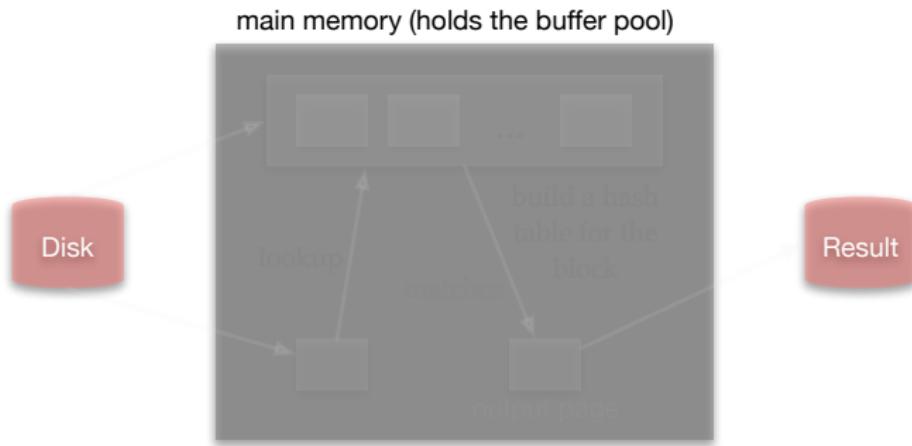
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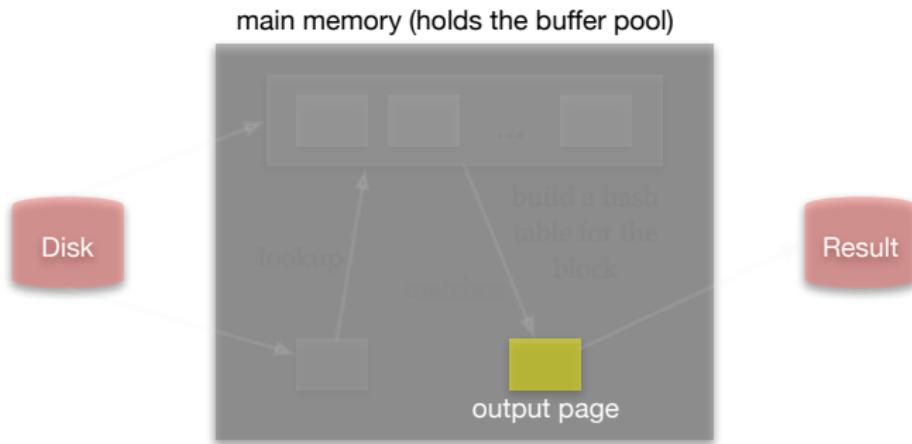
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for each block of  $B - 2$  pages of  $R$  do
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        for all matching in-memory tuples  $r \in R\text{-block}$  and  $s \in S\text{-page}$ 
            add  $\langle r, s \rangle$  to result
  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

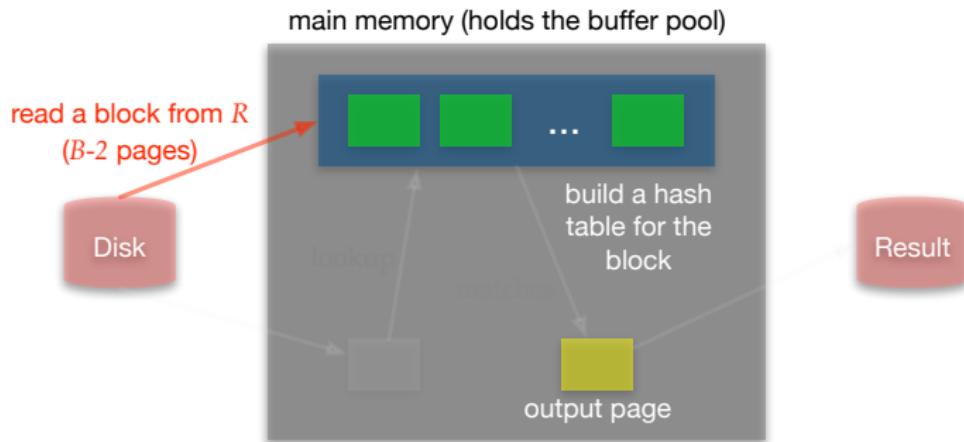
How it works



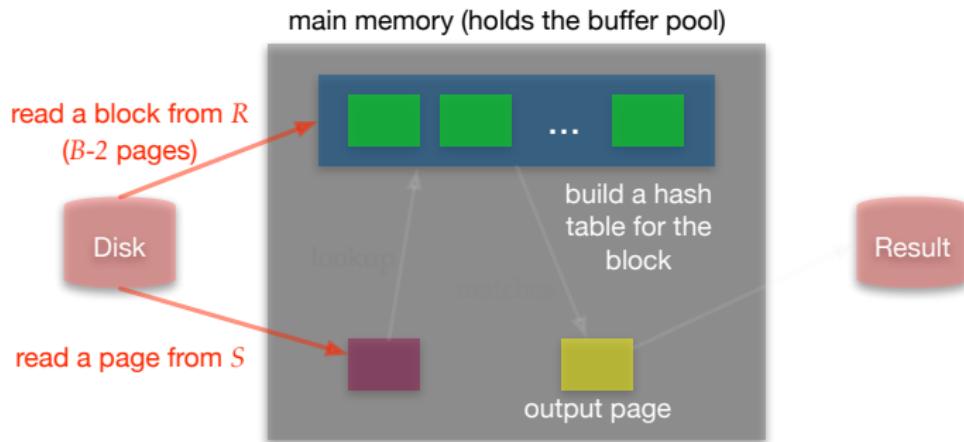
How it works



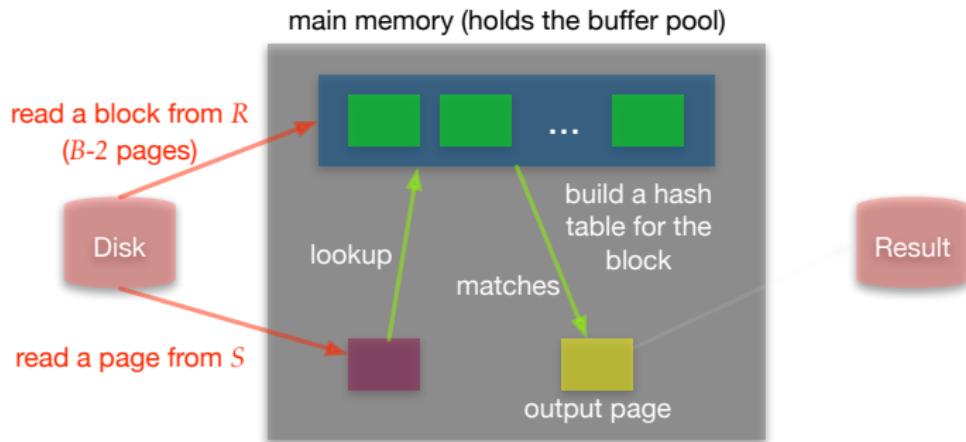
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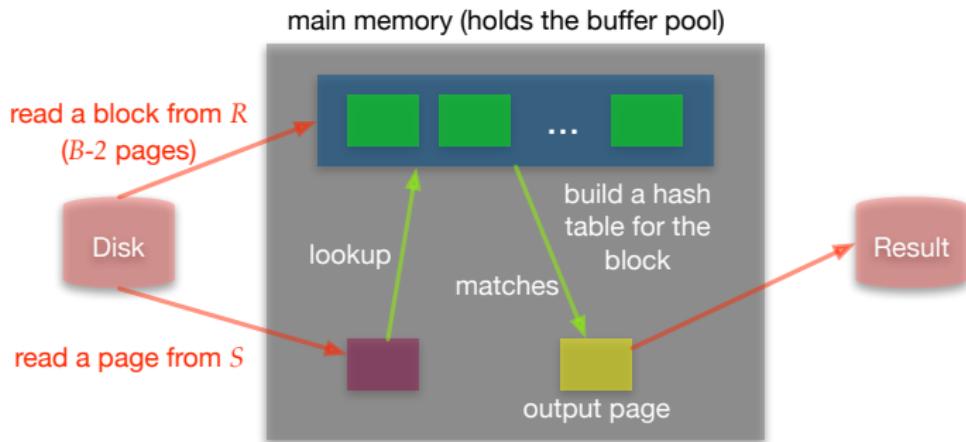
How it works



How it works



How it works



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, $\text{cost}(R \bowtie S) = P_R + P_S \cdot \lceil \frac{P_R}{B-2} \rceil$
 - ▶ 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*
 - ▶ $\text{big} + \text{small} \cdot \frac{\text{big}}{B-2}$
 - ▶ $\text{small} + \text{big} \cdot \frac{\text{small}}{B-2}$
- And $\text{big} > \text{small}$
- *Remember*, $\text{cost}(R \bowtie S) \neq \text{cost}(S \bowtie R)$ 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

The algorithm

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add $\langle r, s \rangle$ to the result

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*
 - ▶ $\text{cost}(R \bowtie S) = P_R + T_R \cdot f \cdot T_S \cdot \text{avg_lookup}$
- If R is *not clustered*
 - ▶ $\text{cost}(R \bowtie S) = T_R + T_R \cdot f \cdot T_S \cdot \text{avg_lookup}$

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*

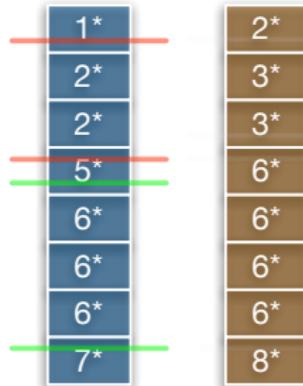
How it works

- 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*

1*	2*
2*	3*
2*	3*
5*	6*
6*	6*
6*	6*
6*	6*
7*	8*

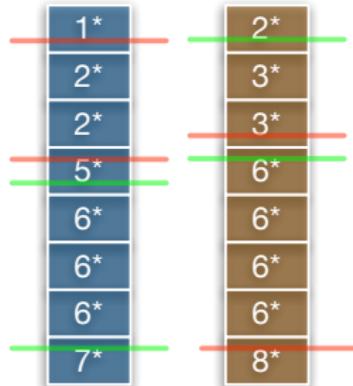
How it works

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How it works

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The algorithm

Merge-join

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

The algorithm

Merge-join

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

while (*more tuples in inputs*) **do** {

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*

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
```

The algorithm

Merge-join

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

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while (more tuples in inputs) do {
    while ( $r.a < gs.b$ ) do advance r
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```

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        s = gs      // mark group beginning
```

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        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
    }
}
```

The algorithm

Merge-join

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while (more tuples in inputs) do {
    while ( $r.a < gs.b$ ) do advance r
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        advance r      // move forward
    }
}
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The algorithm

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

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    while ( $r.a < gs.b$ ) do advance r
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    }
    gs = s      // candidate to begin next group
}
```

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
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        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 s      // 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)
- $\text{cost}(R \bowtie S) = P_R \cdot (2 \cdot \log P_R + 1) + P_S \cdot (2 \cdot \log P_S + 1)$
 - ▶ 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 $P_i, i \in [1, m]$*

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

The simple algorithm

Simple hash join

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

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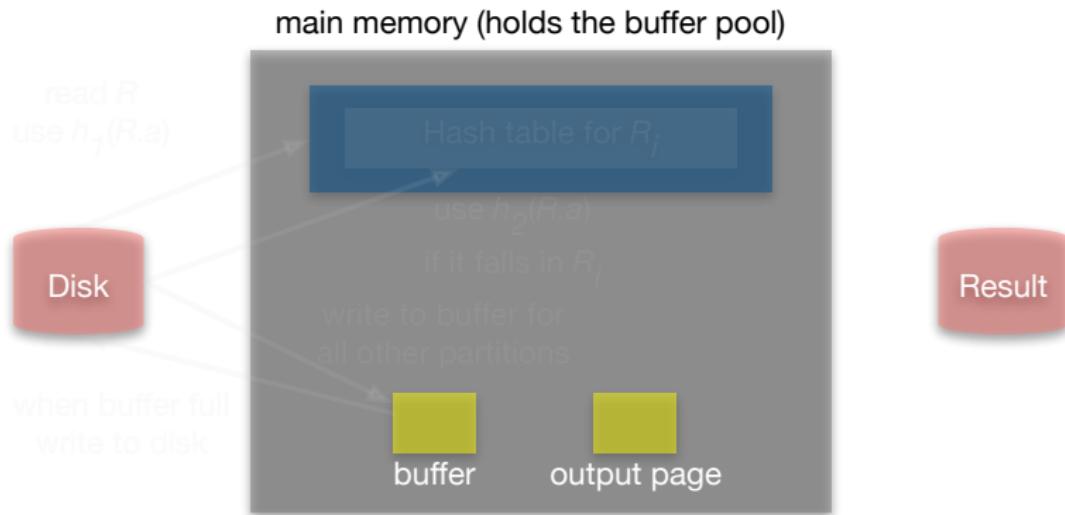
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for each $s \in S$ read s and apply hash function $h_1(s.b)$

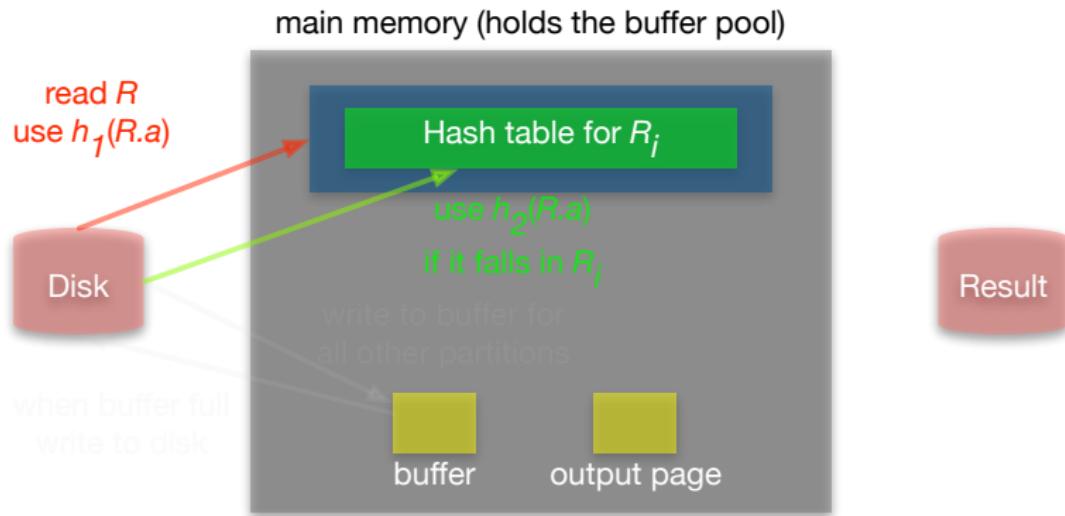
if s falls into P_i apply hash function $h_2(s.b)$ and for all matching tuples $r \in P_i$, add $\langle r, s \rangle$ to the result

otherwise, write it back out to disk

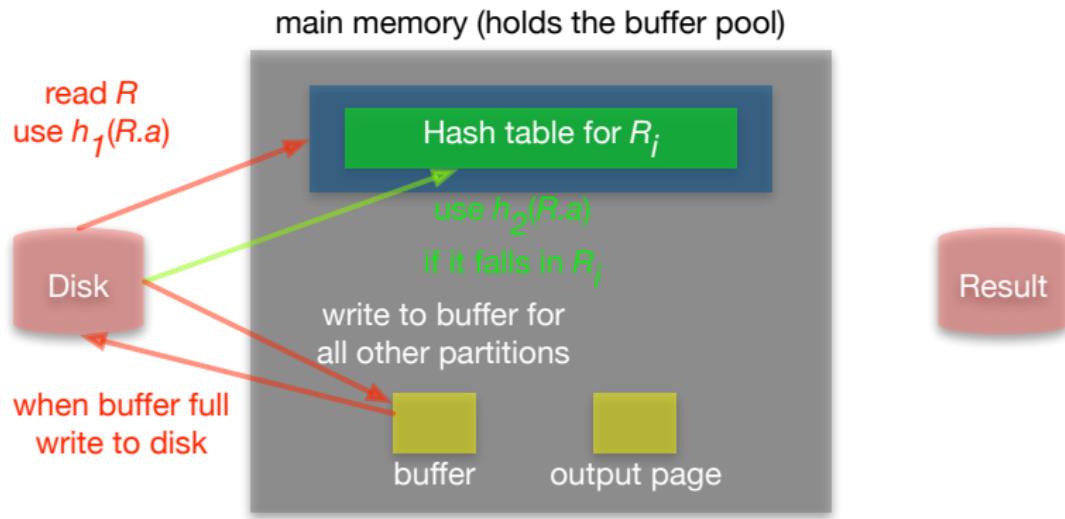
How it works — partitioning R , iteration i



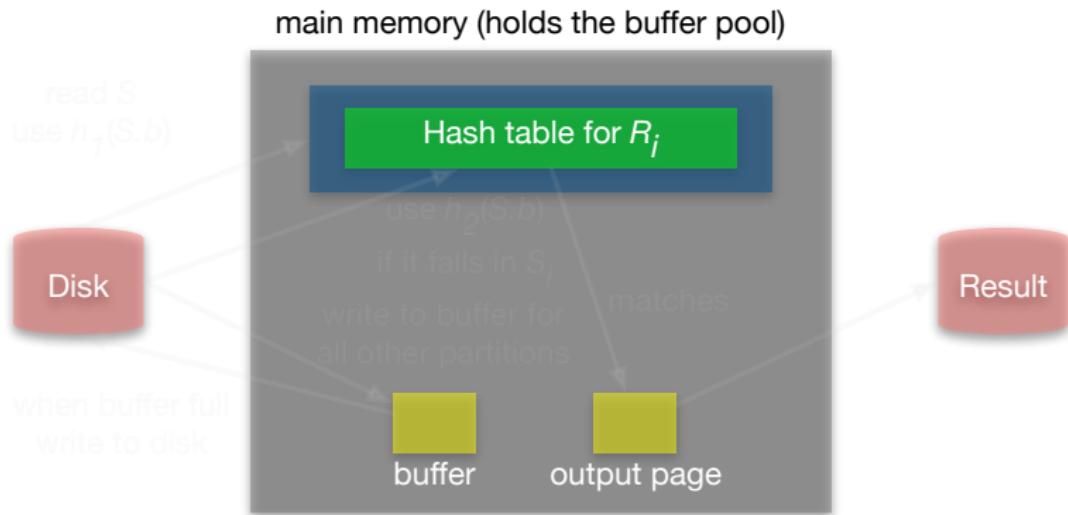
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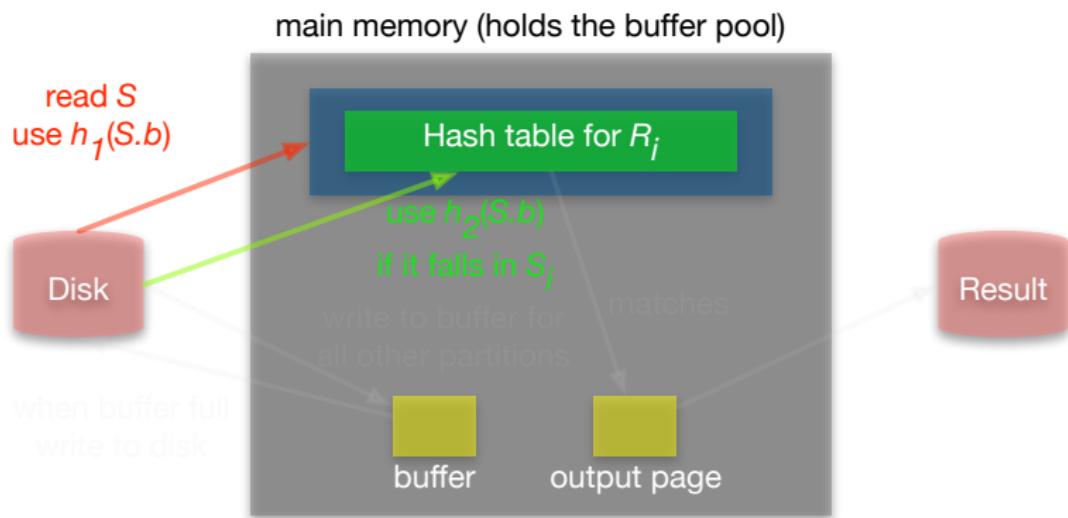
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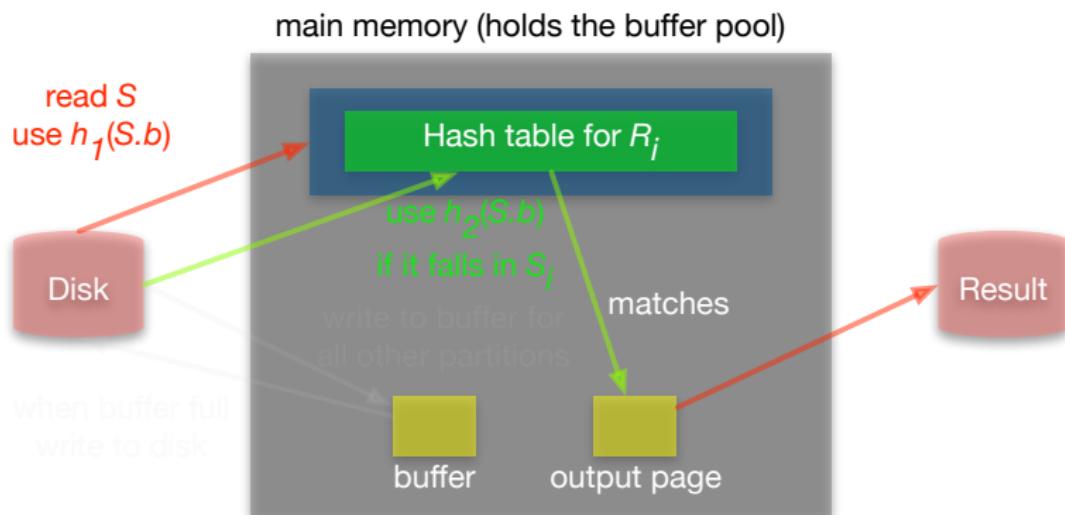
How it works — partitioning and joining S , iteration i



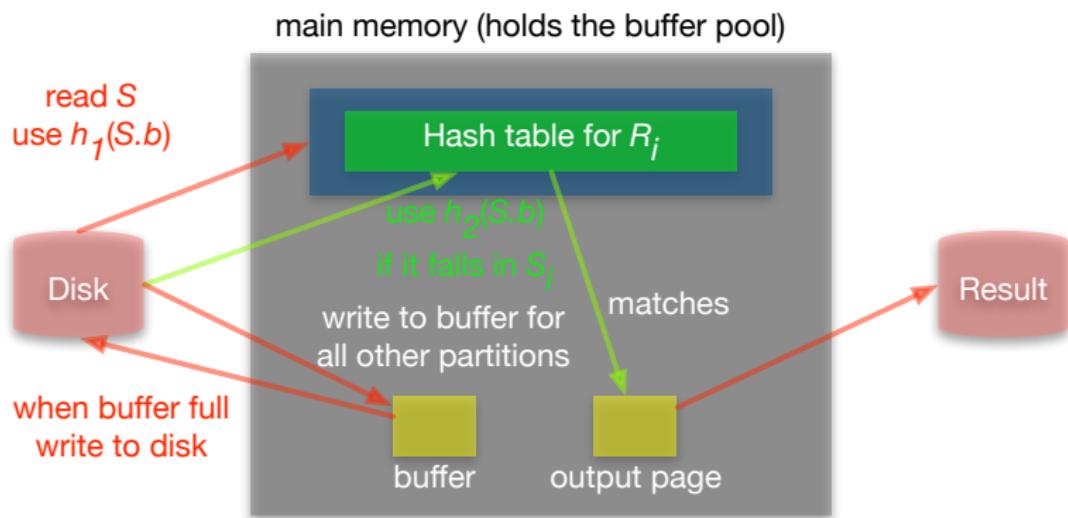
How it works — partitioning and joining S , iteration i



How it works — partitioning and joining S , iteration i



How it works — partitioning 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 $h_1(r.a)$

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for each $r \in R$ read r and add it to the buffer page for $h_1(r.a)$

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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  $i = 1, \dots, m$  do {
```

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for each  $r \in R$  read  $r$  and add it to the buffer page for  $h_1(r.a)$ 
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for  $i = 1, \dots, m$  do {
    for each  $r \in R_i$  read  $r$  and insert it into a hash table using  $h_2(r.a)$ 
```

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    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  $h_2(s.b)$ 
```

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        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
    }
}
```

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Grace hash join

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for  $i = 1, \dots, m$  do {
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    for each  $s \in S_i$  do {
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    }
}
```

The “grace” algorithm

Grace hash join

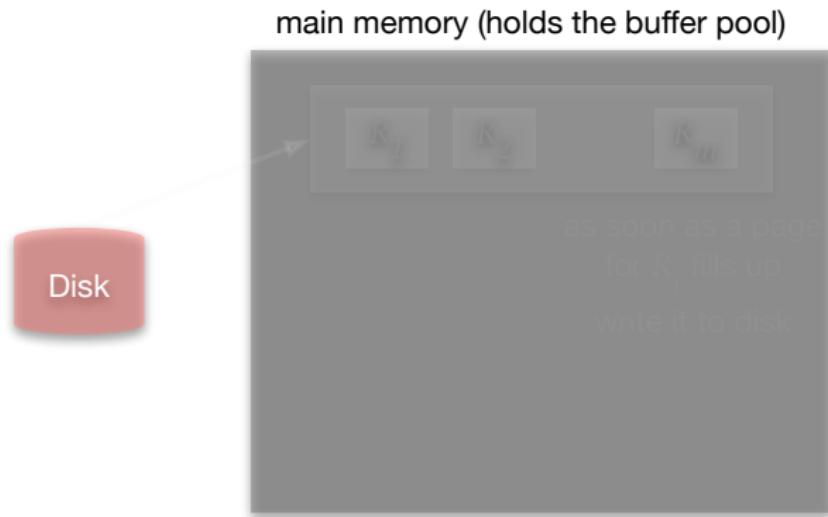
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}
clear hash table
```

The “grace” algorithm

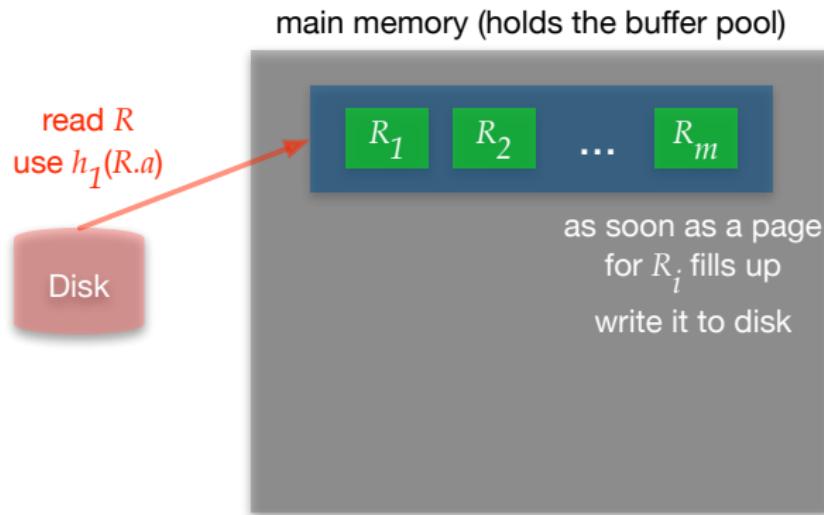
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        for all matching tuples  $r \in R_i$  add  $\langle r, s \rangle$  to the result
    }
    clear hash table
}
```

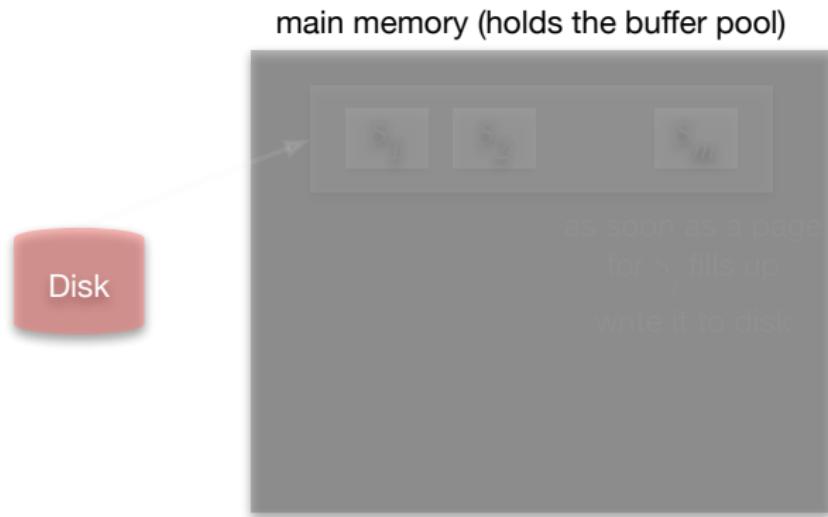
How it works — partitioning R



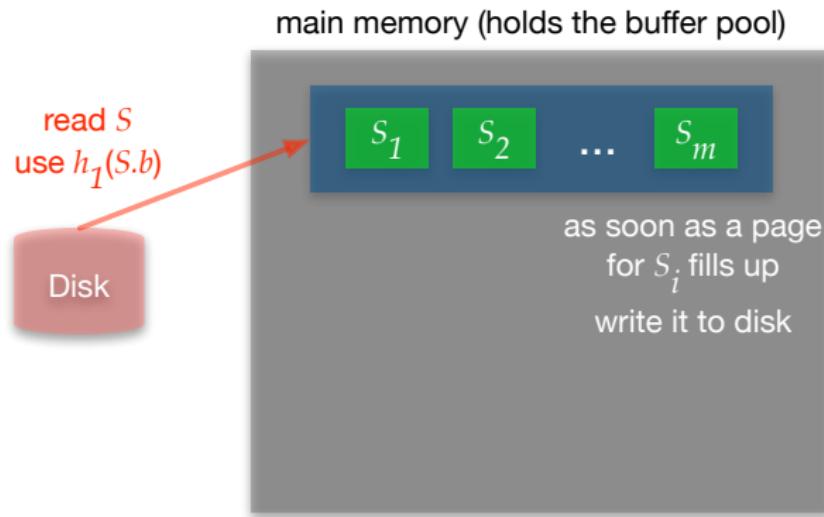
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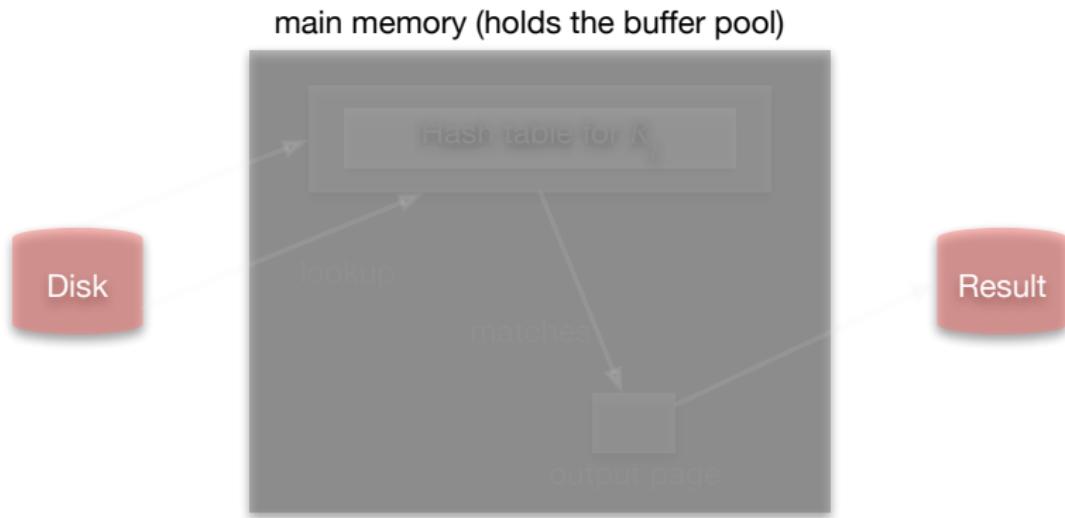
How it works — partitioning S



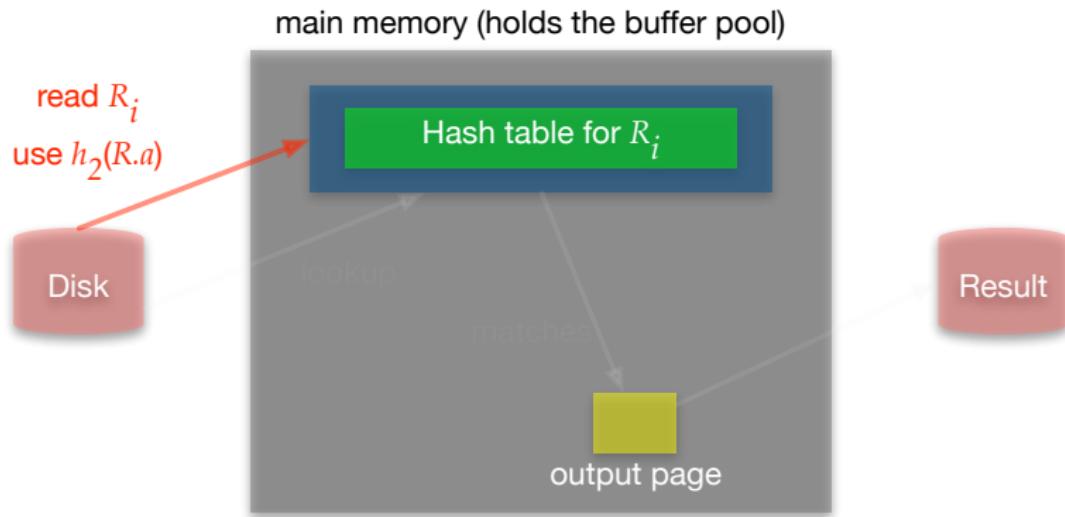
How it works — partitioning S



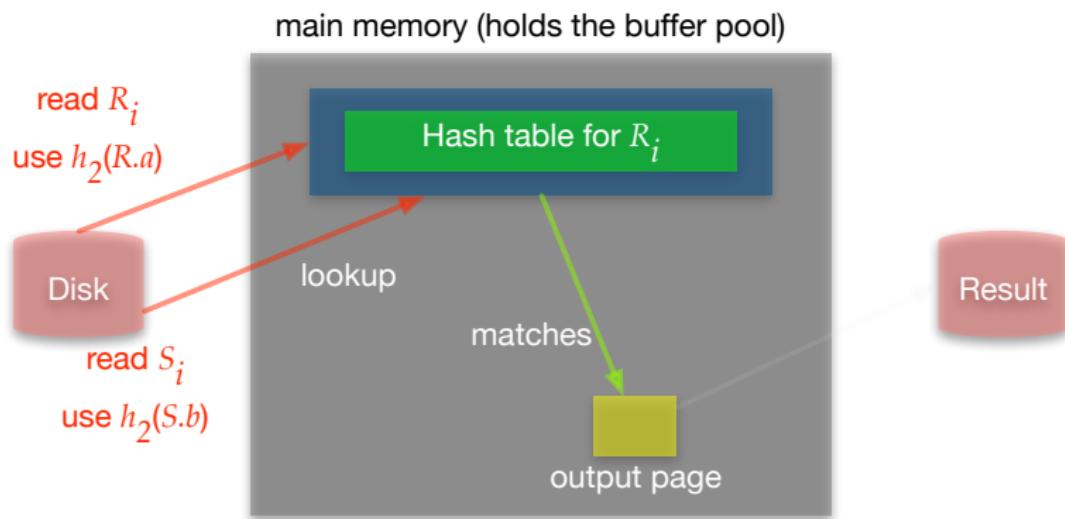
How it works — joining



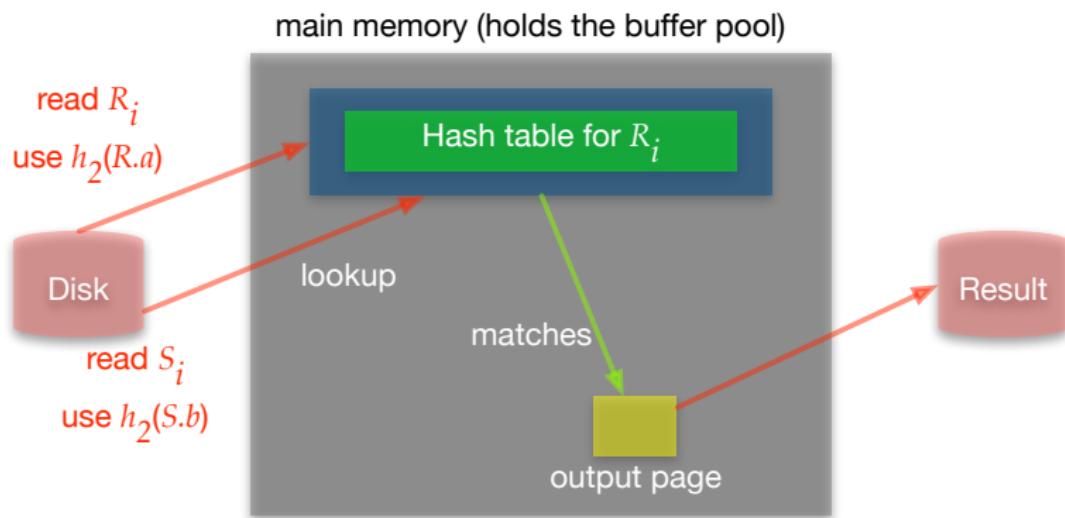
How it works — joining



How it works — joining



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
- $\text{cost}(R \bowtie S) = 3 \cdot (P_R + P_S)$
 - ▶ 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*

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- **Objective:** the *hash table* for a *partition* must *fit in memory*
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- What are the *optimum sizes*?
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- During the *probing phase*, in addition to the hash table, we need *one page to read S*, plus *one page for output*
 - ▶ So, $B > \lceil \frac{f \cdot P_R}{B-1} \rceil + 2 \Rightarrow B > \sqrt{f \cdot P_R}$

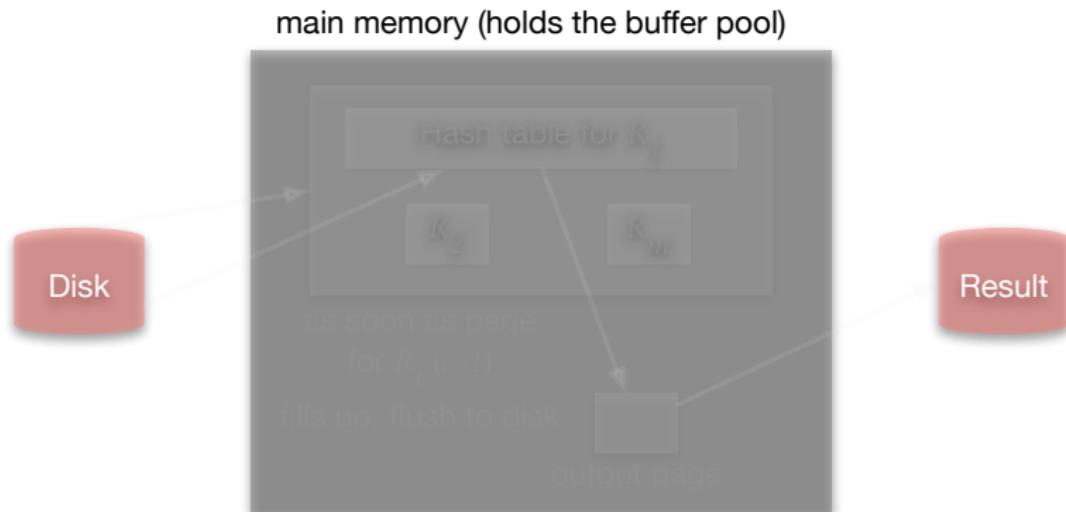
Hybrid hash join

- 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*

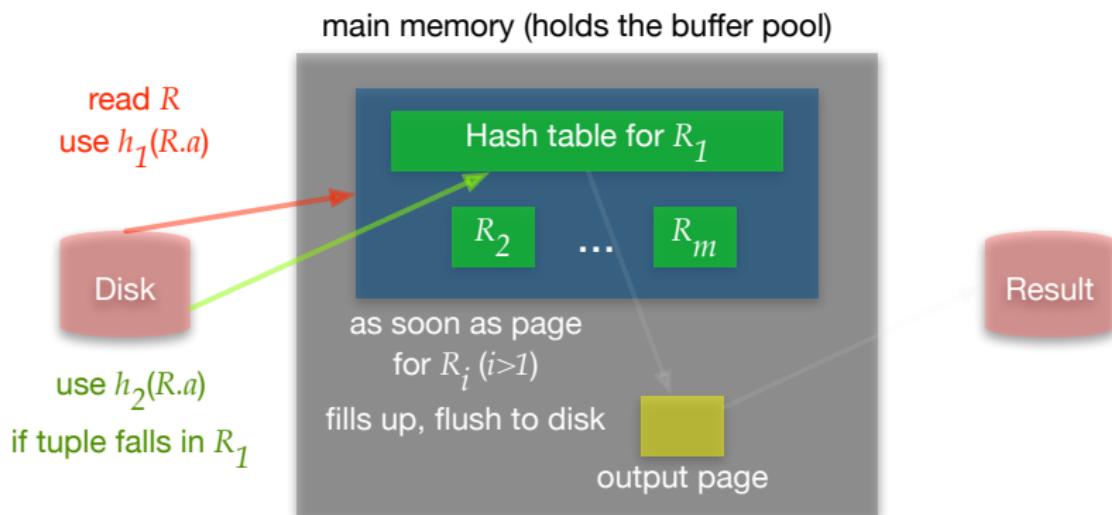
How it works

- 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*

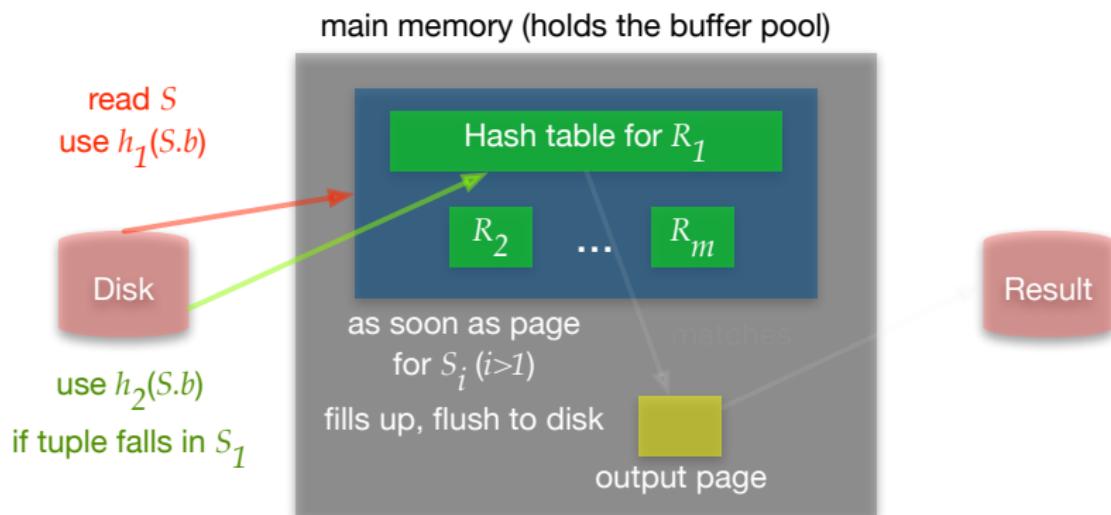
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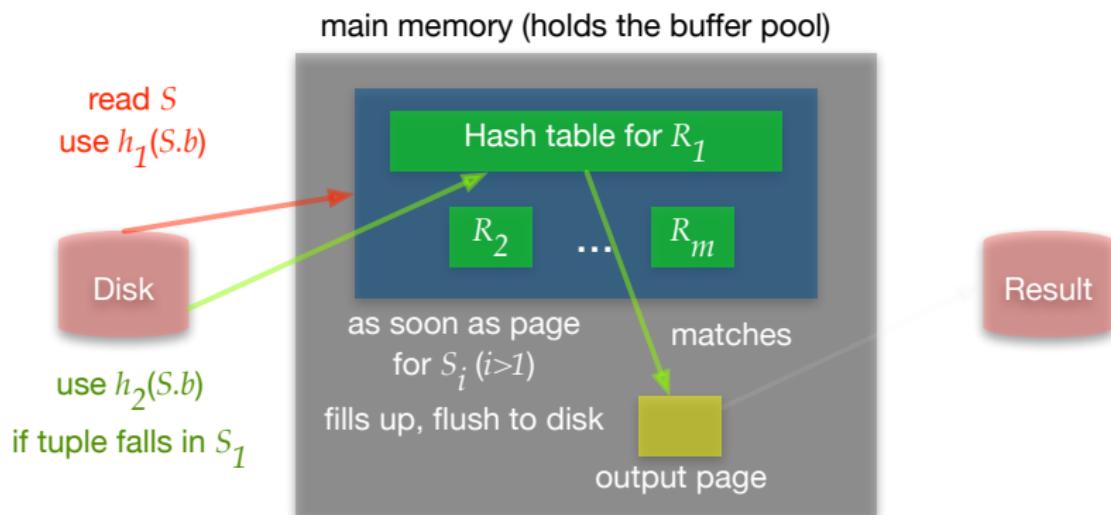
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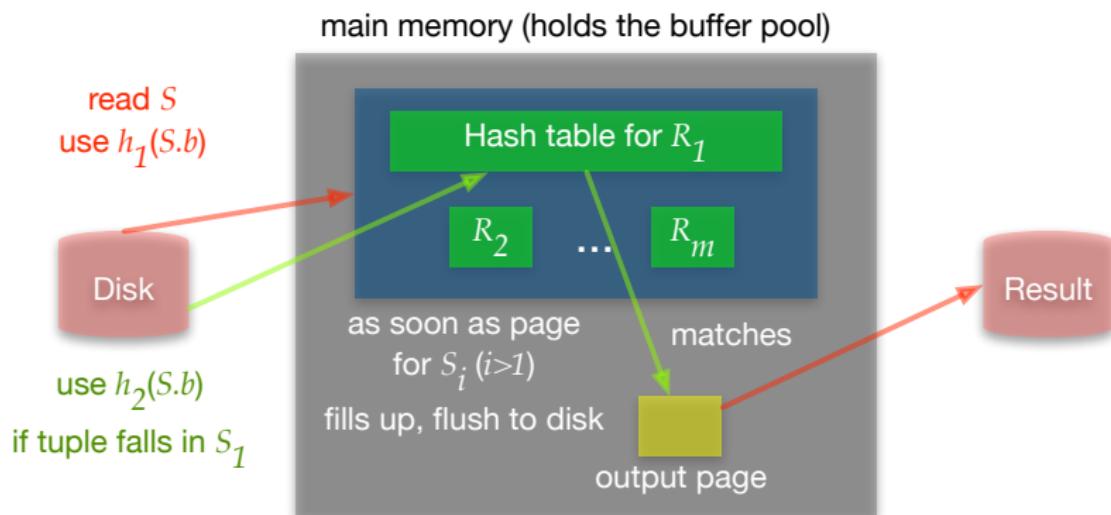
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How it works — partitioning and joining



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.)

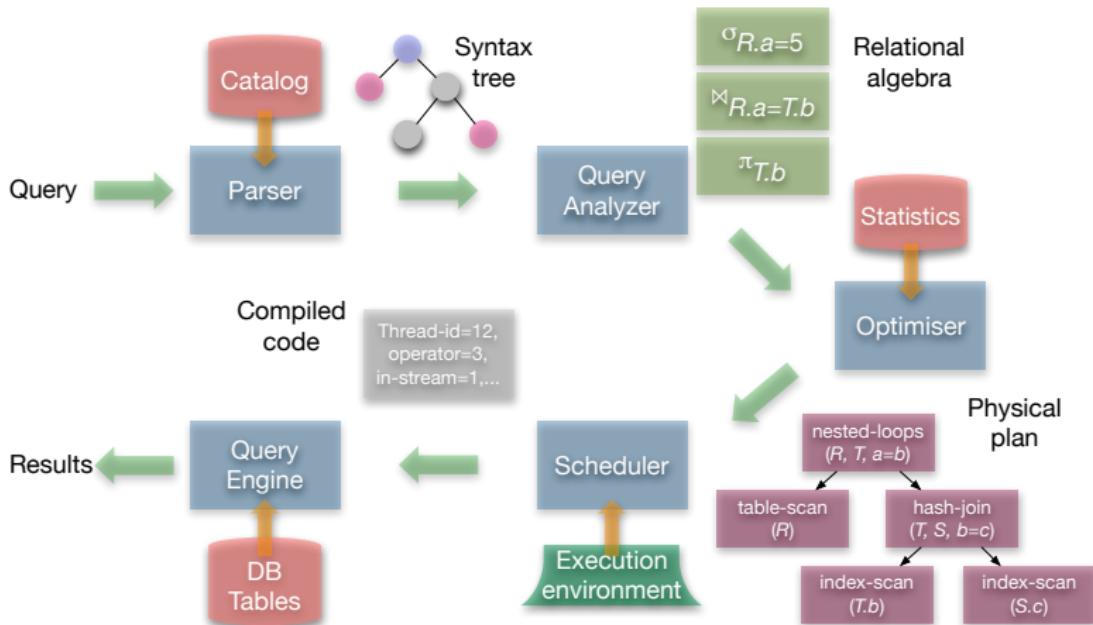
- *Iteration-based* methods
 - ▶ Essentially, *nested loops*
 - ▶ Very *simple to implement*, but if *implemented poorly* very *inefficient*
 - ▶ But also *very useful* because they *evaluate non-equi-join predicates*
- *Order-based* methods
 - ▶ *Sort* the inputs, *merge* them afterwards
 - ▶ *Well-behaved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

Summary (cont.)

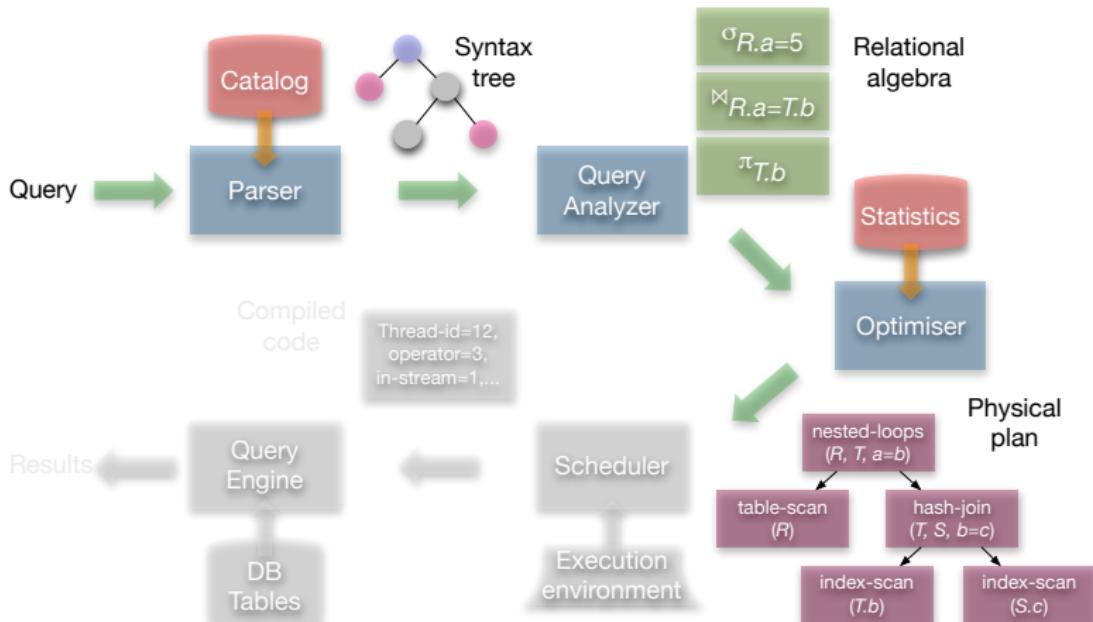
- *Partition-based* methods
 - ▶ *Simple hash join*, *Grace hash join*, and *hybrid hash join*
 - ▶ If there is *extra memory*, *hybrid hash join*'s behaviour is *excellent*
- *Figuring out* the *best join algorithm* for a *particular pair* of inputs is the *job* of the *query optimiser*
- Which, along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

Outline

Query cycle



Query cycle



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, $\text{cost}(R \bowtie S) \neq \text{cost}(S \bowtie R)$
 - ▶ 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, that's 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)

Outline

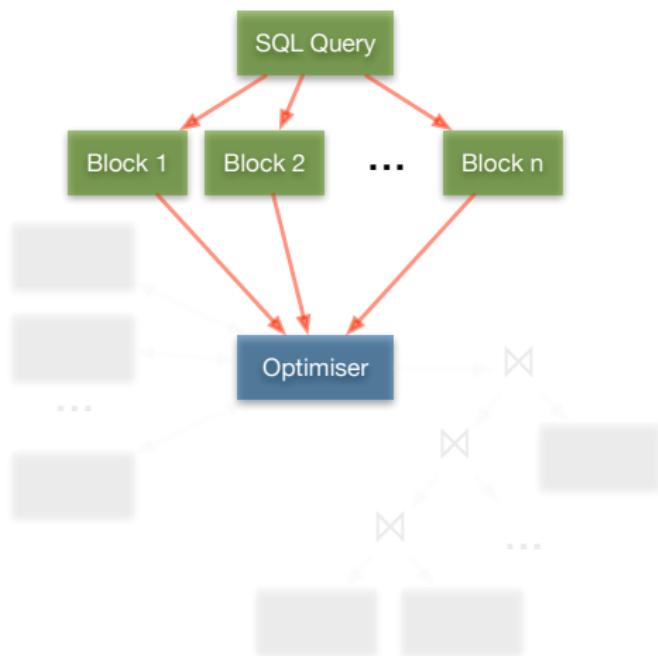
SQL decomposition

- *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



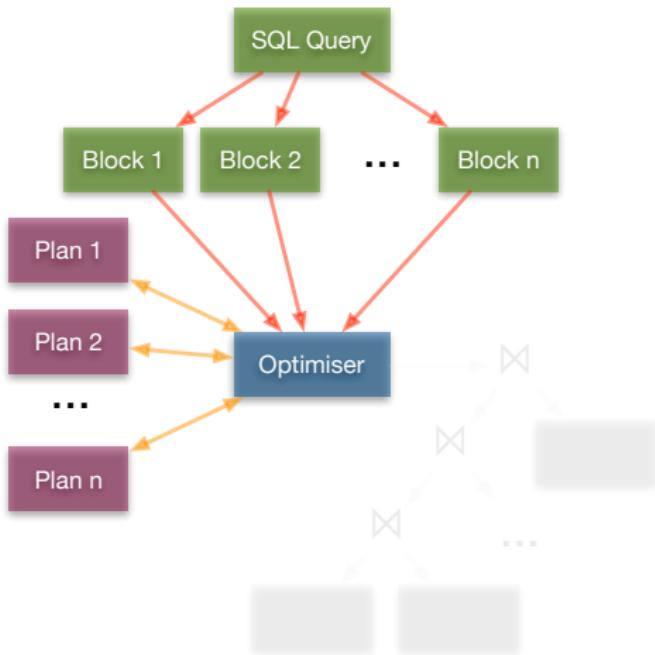
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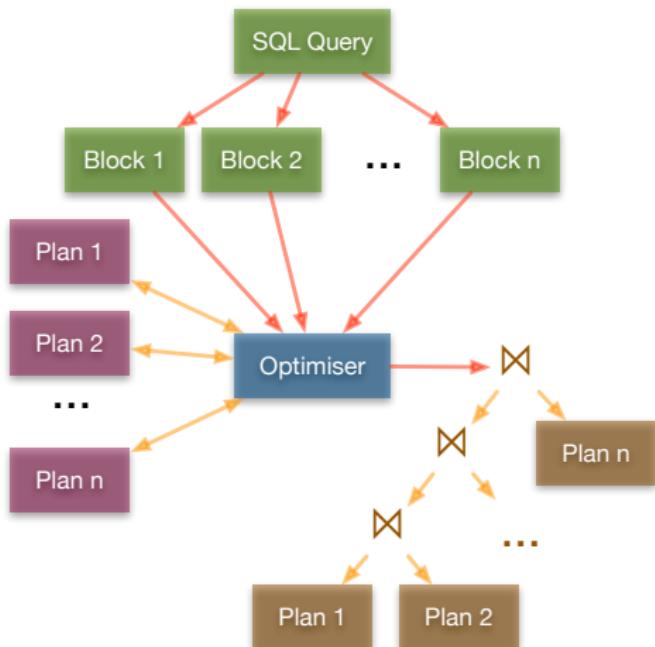
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What is a block?

- 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*)

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SQL query

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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)
           s.sid
group by    count(*) > 1
```

Two blocks in the query

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```

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

nested
block

Two blocks in the query

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    group by    s.sid
    having      count(*) > 1
  
```

reference

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Single block optimisation — step 1

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

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Relational algebra

$$\begin{aligned} &\pi_{s.sid, \min(r.day)}(\\ &\text{having}_{\text{count}(<*)>2}(\\ &\text{group by}_{s.sid}(\\ &\sigma_{s.sid=r.sid \wedge r.bid=b.bid \wedge b.color=red \wedge s.rating=\text{nested-value}}(\\ &\text{sailors} \times \text{reserves} \times \text{boats})))) \end{aligned}$$

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

Single block optimisation — step 2

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

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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

- ▶ $\sigma_{c_1 \wedge c_2 \wedge \dots \wedge c_n} (R) \equiv \sigma_{c_1} (\sigma_{c_2} (\dots (\sigma_{c_n} (R))))$

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 - ▶ $\pi_{a_1} (R) \equiv \pi_{a_1} (\pi_{a_2} (\dots (\pi_{a_n} (R)) \dots))$
 - ▶ iff $a_i \subseteq a_{i+1}$, $i = 1, 2, \dots, n - 1$

Cartesian products and joins

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- ▶ $R \times S \equiv S \times R$
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- Their combination

- ▶ $R \bowtie (S \bowtie T) \equiv R \bowtie (T \bowtie S) \equiv (R \bowtie T) \bowtie S$
 $\equiv (T \bowtie R) \bowtie S$

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- 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*

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 *c₁ is relevant only to R and c₂ is relevant only to S*

Among operations (cont.)

- Projection-Cartesian product commutativity

- ▶ $\pi_a (R \times S) \equiv \pi_{a_1}(R) \times \pi_{a_2}(S)$

- ▶ iff a_1 is the subset of attributes in R and a_2 is the subset of attributes in S

Among operations (cont.)

- Projection-Cartesian product commutativity
 - ▶ $\pi_a (R \times S) \equiv \pi_{a_1}(R) \times \pi_{a_2}(S)$
 - ▶ iff *a₁ is the subset of attributes in a appearing in R and a₂ is the subset of attributes in a appearing in S*
- Projection-join commutativity
 - ▶ $\pi_a (R \bowtie_c S) \equiv \pi_{a_1}(R) \bowtie_c \pi_{a_2}(S)$
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Among operations (cont.)

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 - ▶ 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 *a₁ subset of attributes in R appearing in either a or c and a₂ is the subset of attributes in S appearing in either a or c*

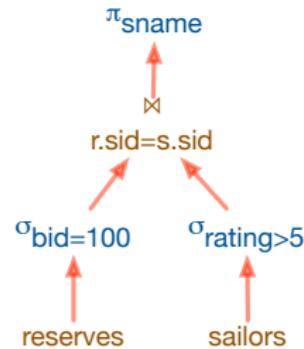
What do we have and what do we need?

- 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*

Outline

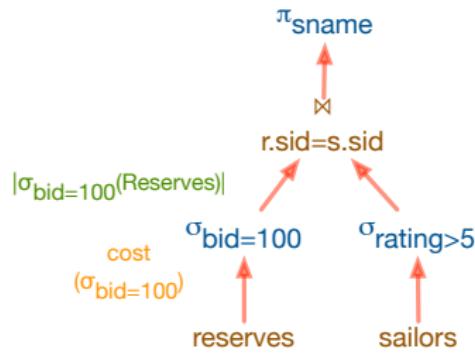
Cost estimation

- 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*



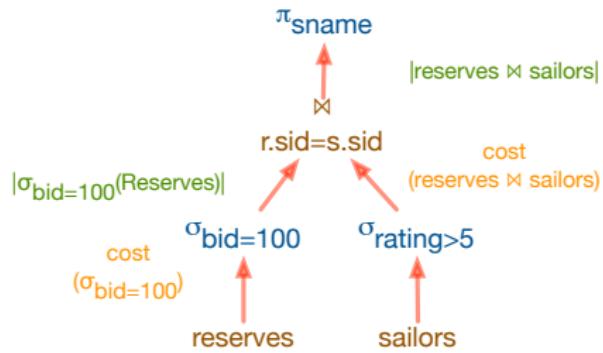
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Cost and cardinality

- 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  a1, a2, ... ak
from    R1, R2, ... Rn
where   P1 and P2 and ... and Pm
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Selectivity factor product

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

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$$|R_1| \cdot |R_2| \cdot \dots \cdot |R_n|$$

Selectivity factor product

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

Estimated output cardinality

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

Various selectivity factors

- $\text{column} = \text{value} \rightarrow \frac{1}{\#\text{keys}(\text{column})}$
 - ▶ Assumes *uniform distribution* in the values
 - ▶ Is itself an *approximation*

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- $\text{column}_1 = \text{column}_2 \rightarrow \frac{1}{\max(\#\text{keys}(\text{column}_1), \#\text{keys}(\text{column}_2))}$
 - ▶ *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.)

- $\text{column} > \text{value}$ →
$$\frac{(\text{high}(\text{column}) - \text{value})}{(\text{high}(\text{column}) - \text{low}(\text{column}))}$$

Various selectivity factors (cont.)

- $column > value \rightarrow \frac{(high(column) - value)}{(high(column) - low(column))}$
- $value_1 < column < value_2 \rightarrow \frac{(value_2 - value_1)}{(high(column) - low(column))}$

Various selectivity factors (cont.)

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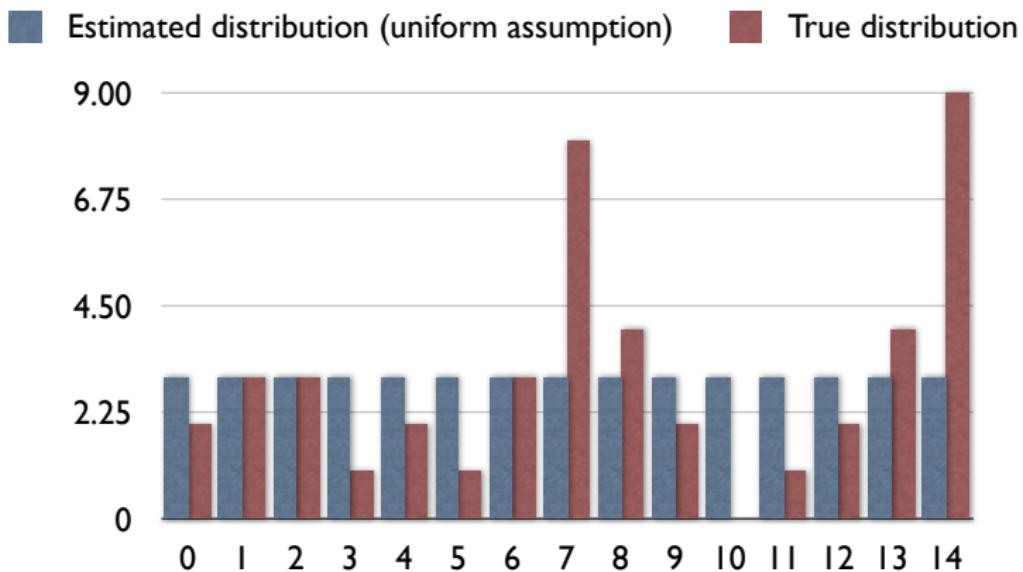
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- $P_1 \vee P_2 \rightarrow f_{P_1} + f_{P_2} - f_{P_1} \cdot f_{P_2}$

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

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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*

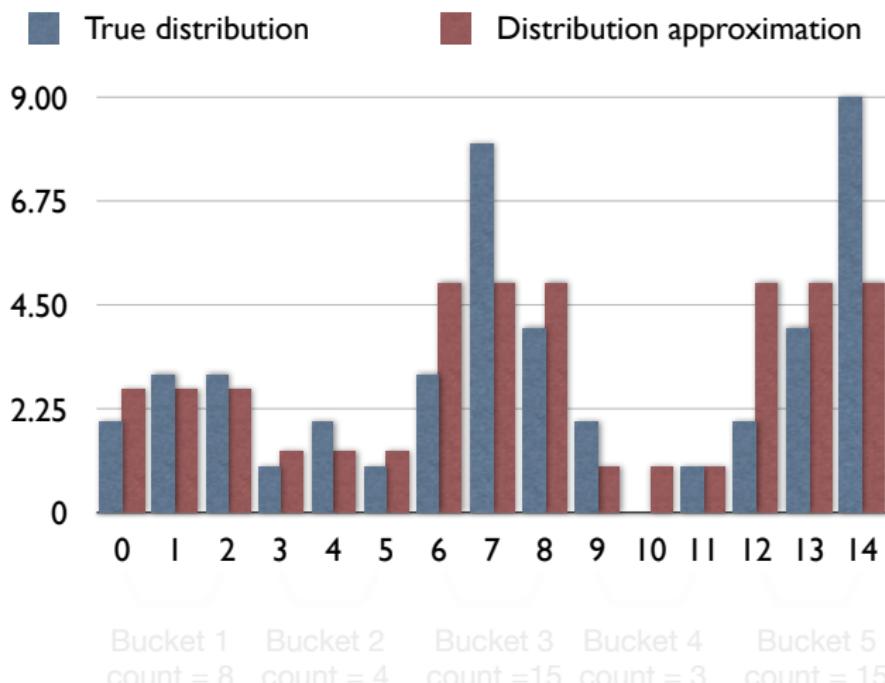
Desirable histogram properties

- *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*

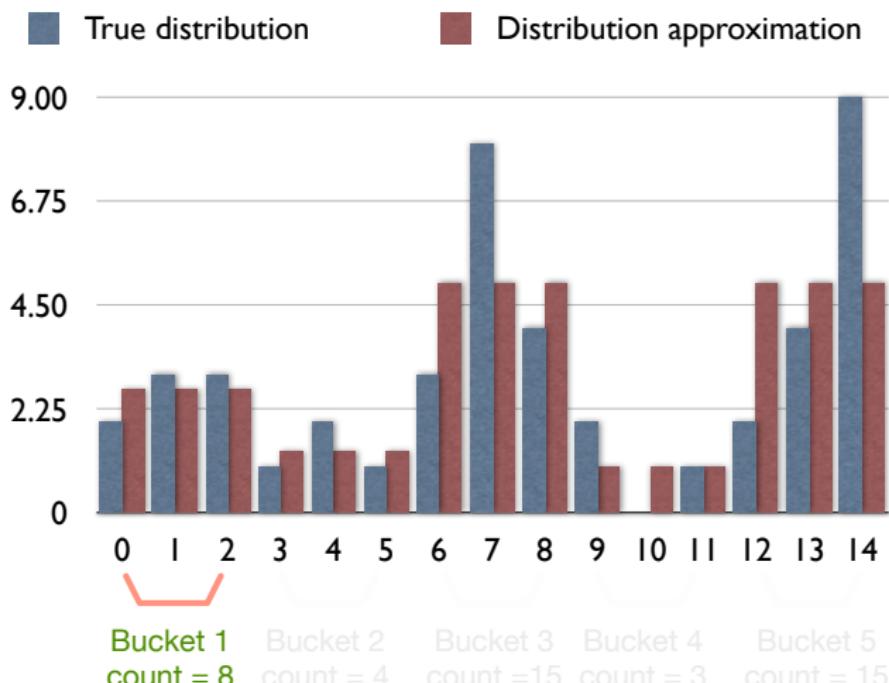
Mathematical properties

- 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*

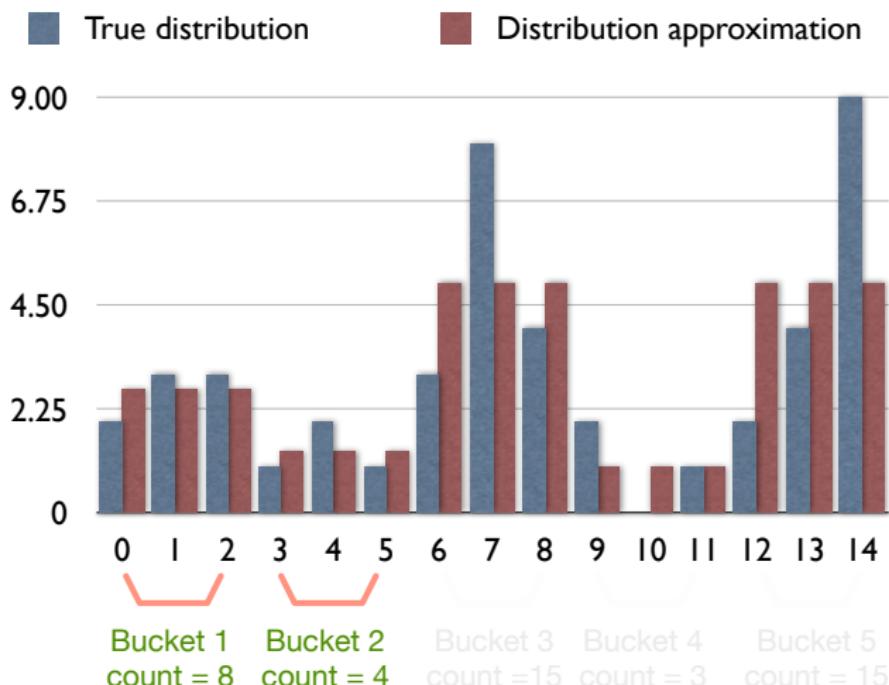
Equi-width histogram



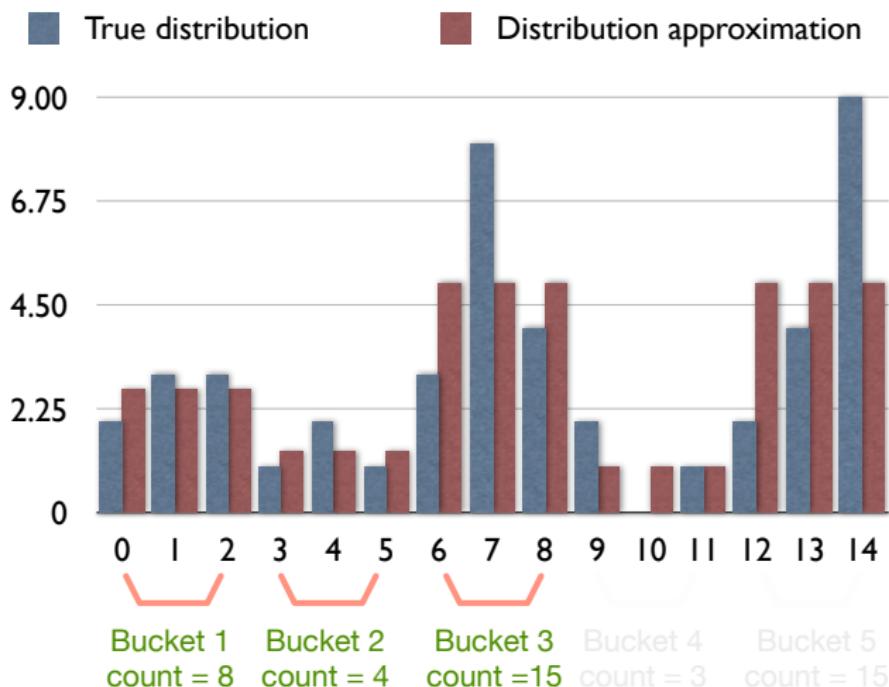
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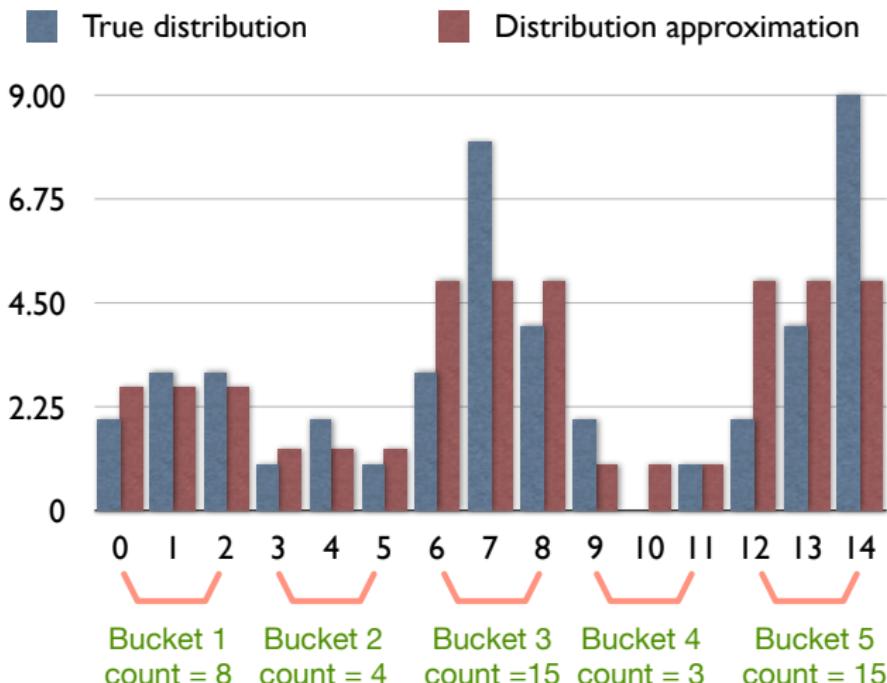
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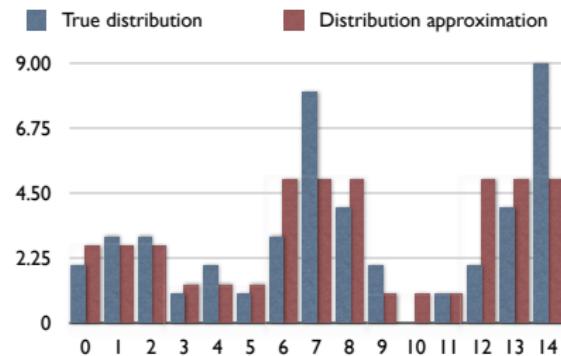


Equi-width histogram



Equi-width histogram construction

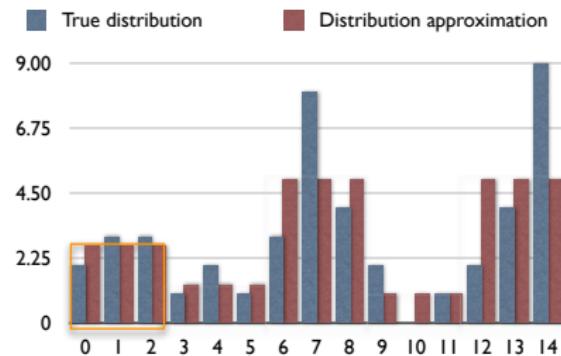
- The *total range* is *divided* into *sub-ranges* of *equal width*
- Each *sub-range* becomes a *bucket*
- The *total number of tuples* in *each bucket* is *stored*



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

Equi-width histogram construction

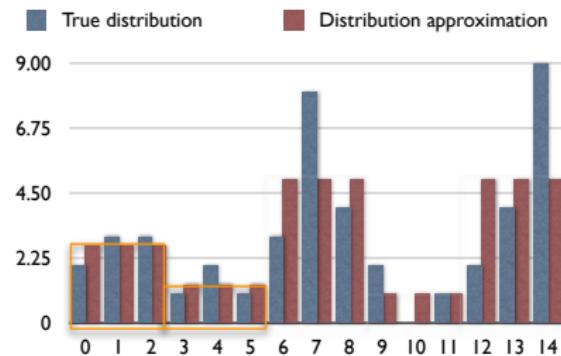
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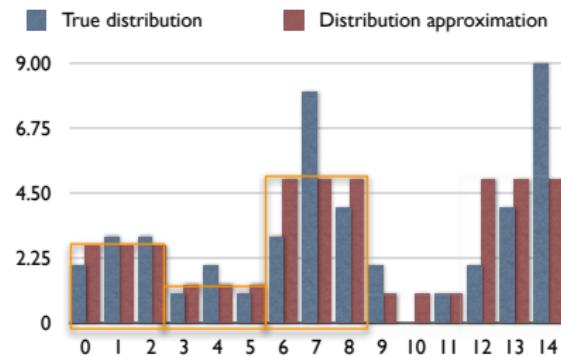
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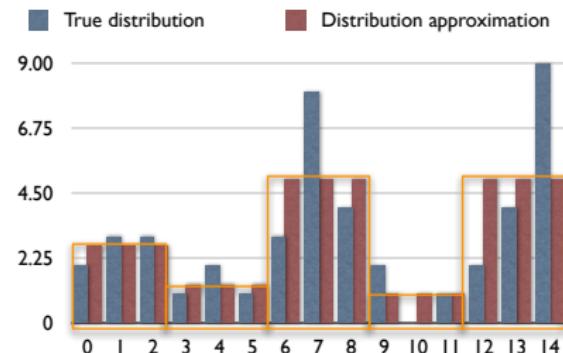
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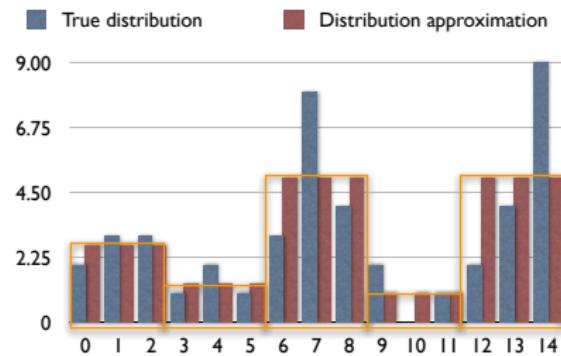
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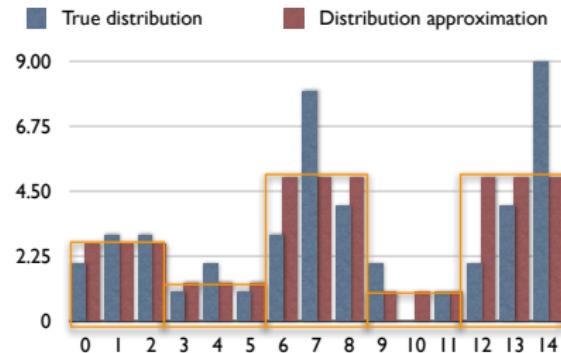
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Equi-width histogram estimation

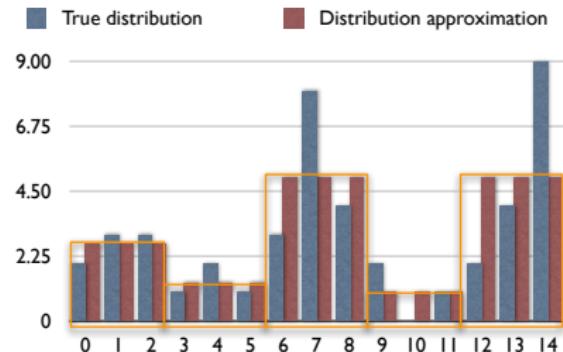
- To *estimate* the output cardinality of a range query
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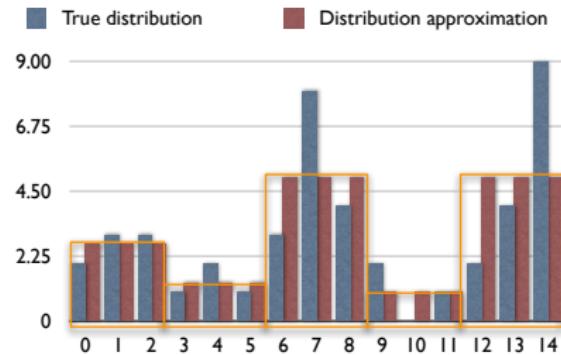
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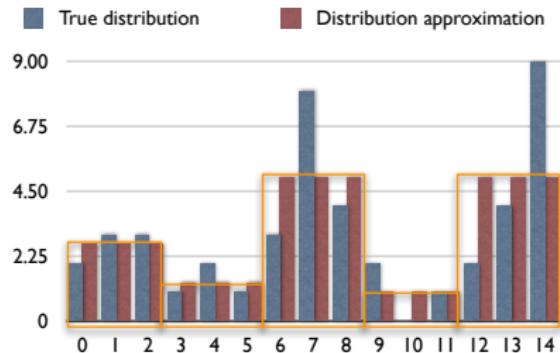
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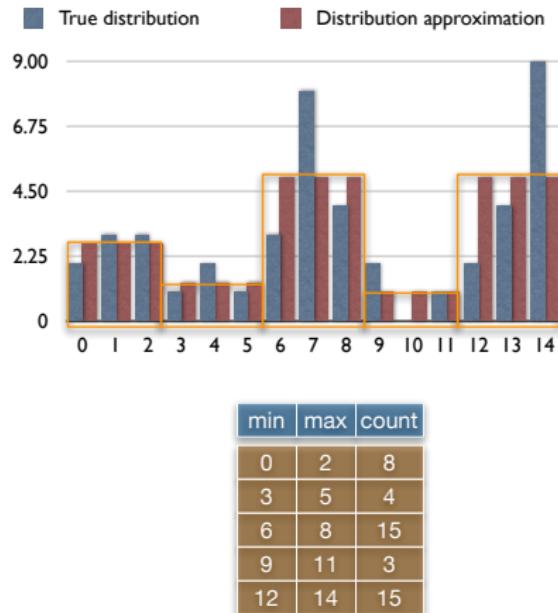
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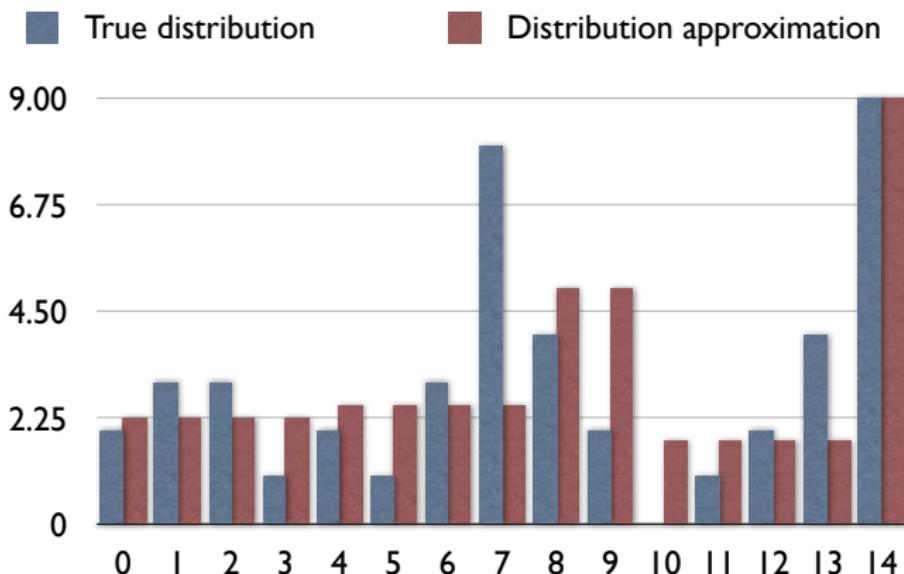
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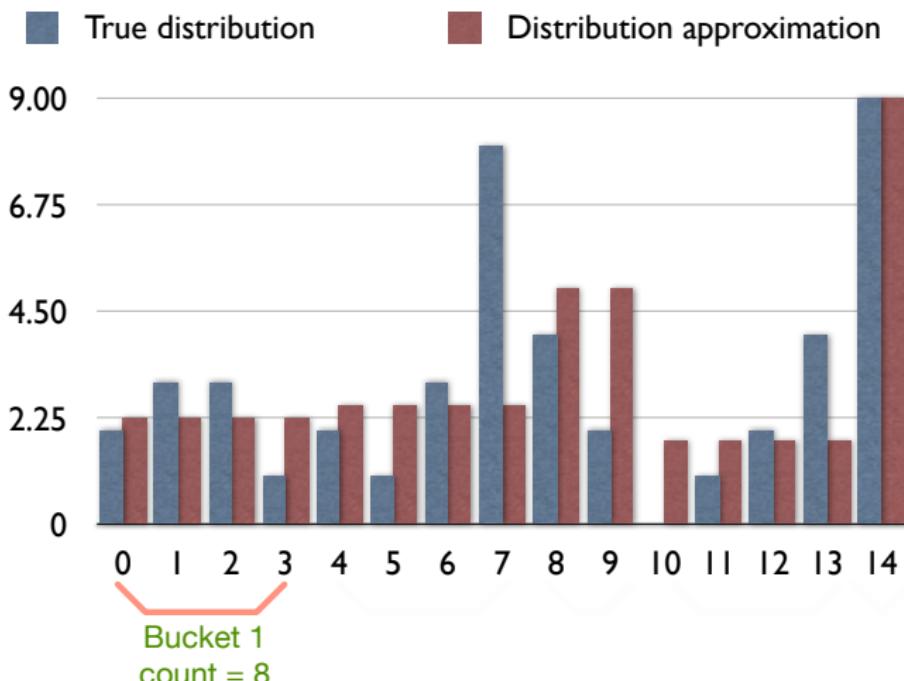
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- $6 \leq v \leq 10: \frac{3}{3} \cdot 15 + \frac{2}{3} \cdot 3 = 17$



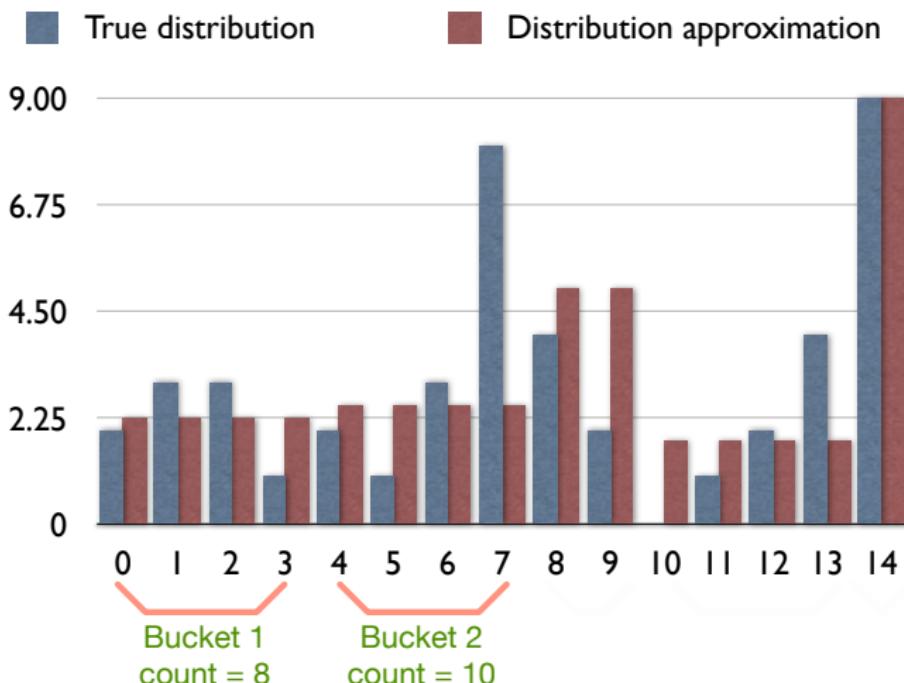
Equi-depth histogram



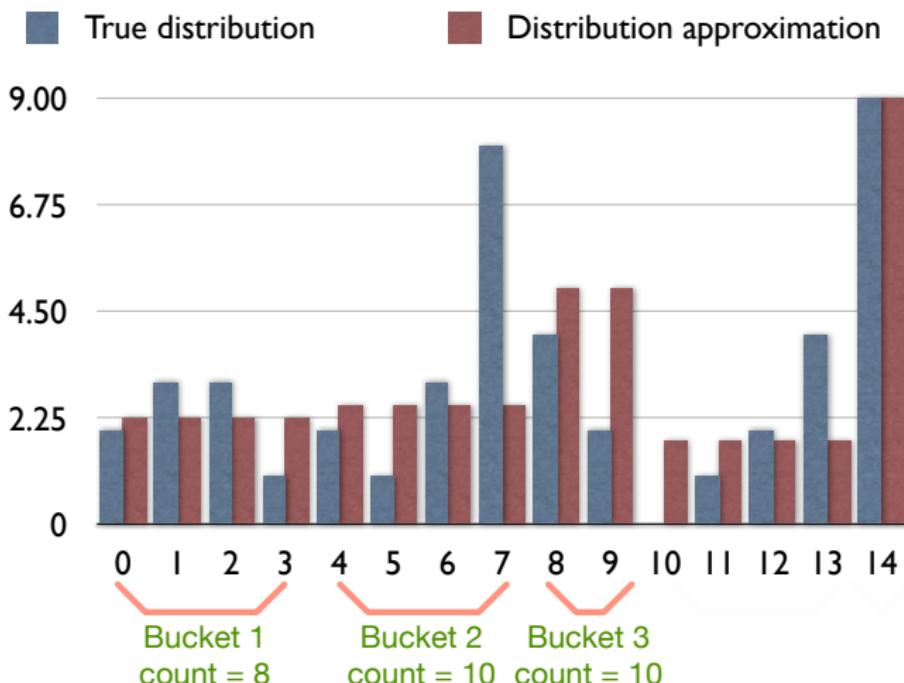
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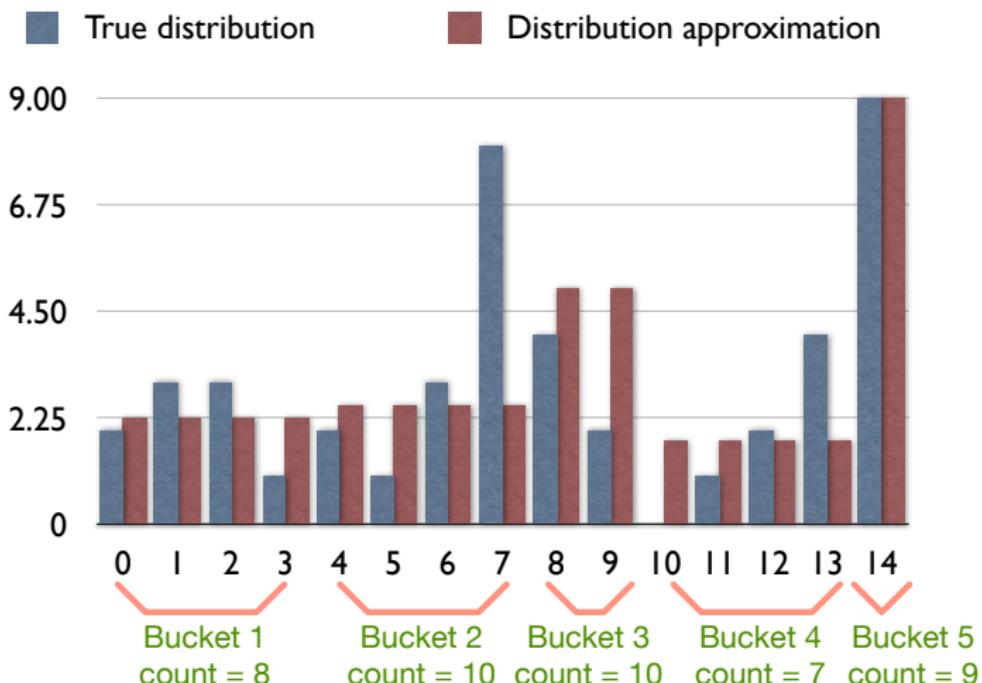
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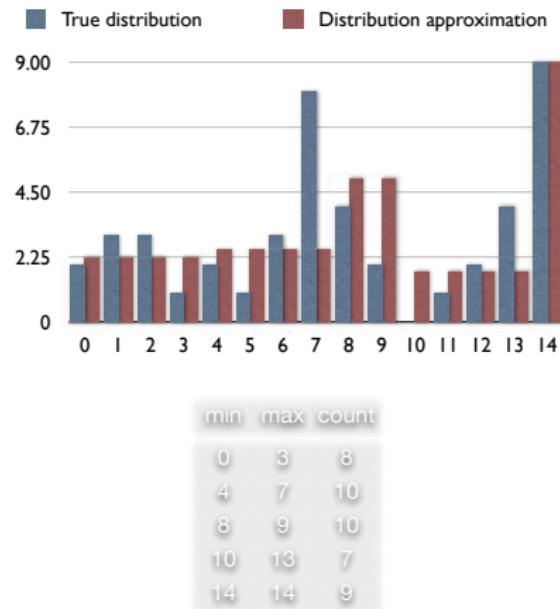


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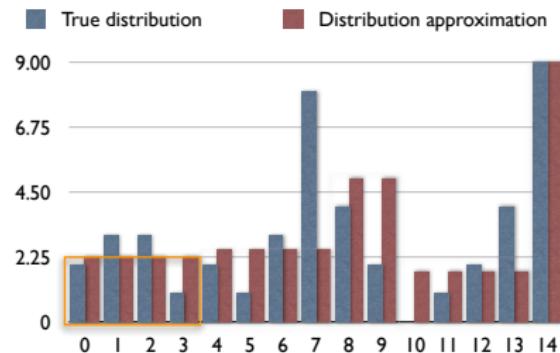
Equi-depth histogram construction and estimation

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



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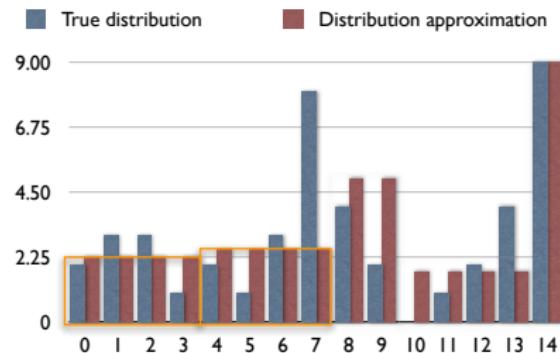
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Equi-depth histogram construction and estimation

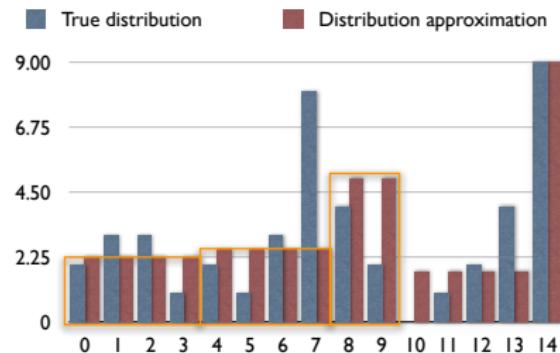
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- In fact, the *same algorithm* is used for *estimation* (!)
- $6 \leq v \leq 10$:
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min	max	count
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4	7	10
8	9	10
10	13	7
14	14	9

Equi-depth histogram construction and estimation

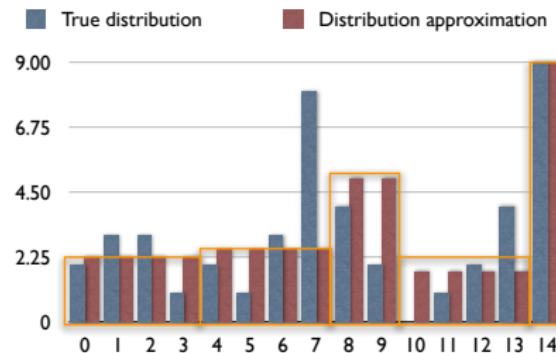
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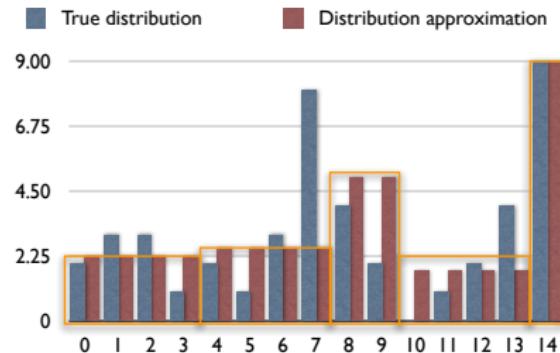
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Comparison

- *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*

Outline

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

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 - ▶ 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

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select name, title, salary, dname
from   emp, dept, job
where  job.title='Clerk' and
       dept.location = 'Edinburgh' and
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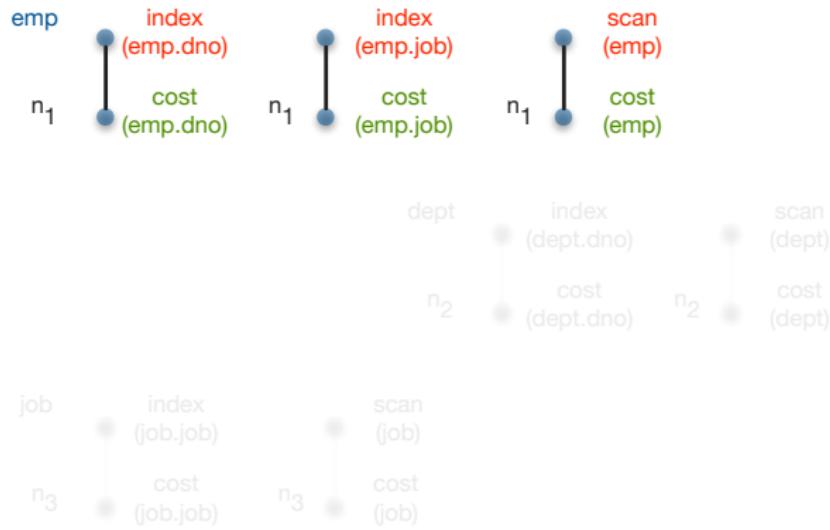
Access methods and local predicates



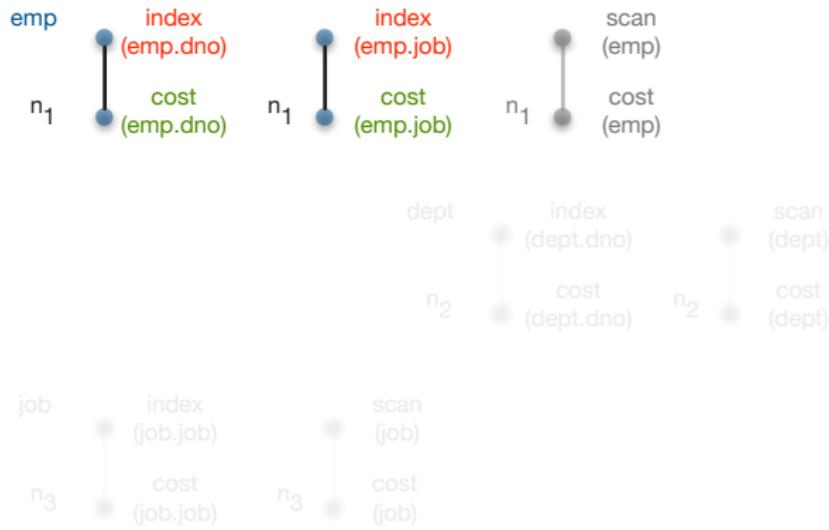
Access methods and local predicates



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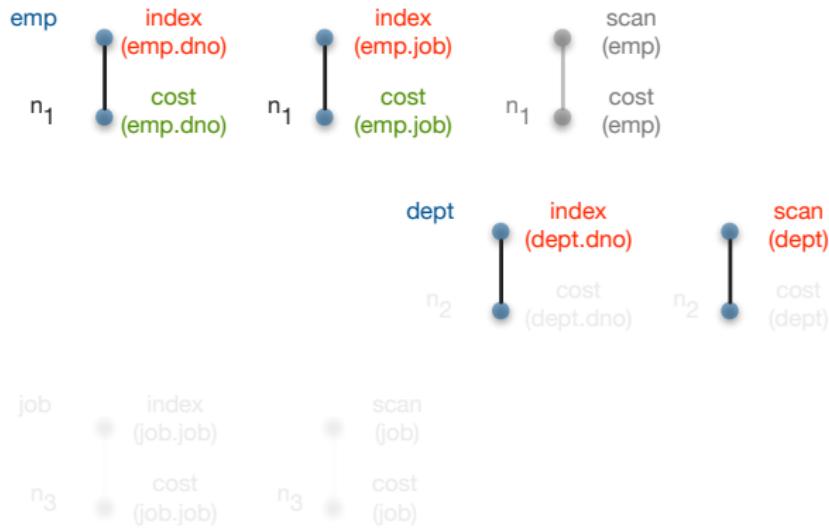


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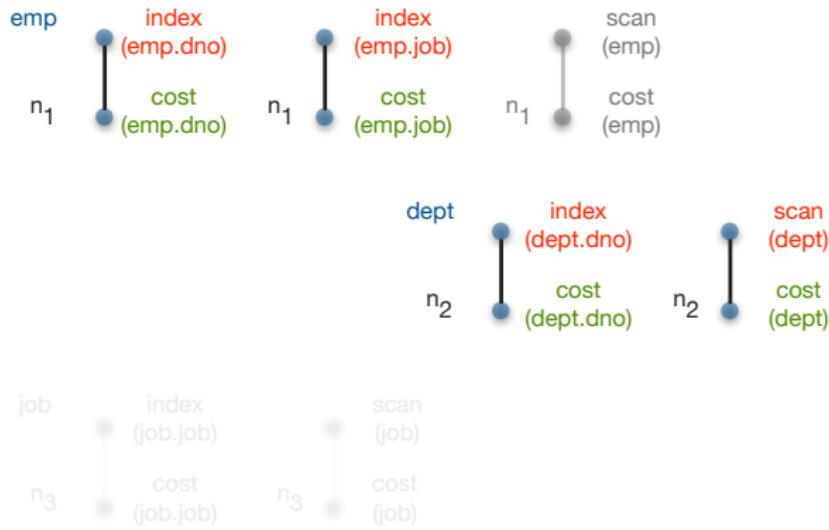
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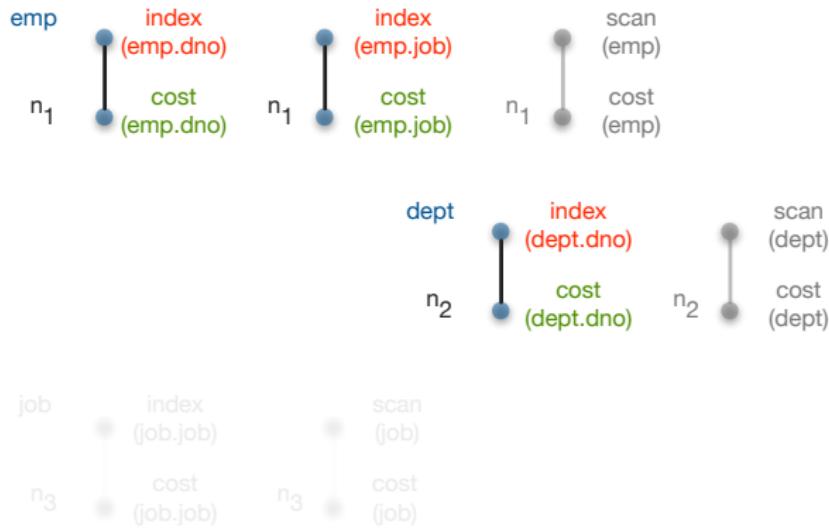
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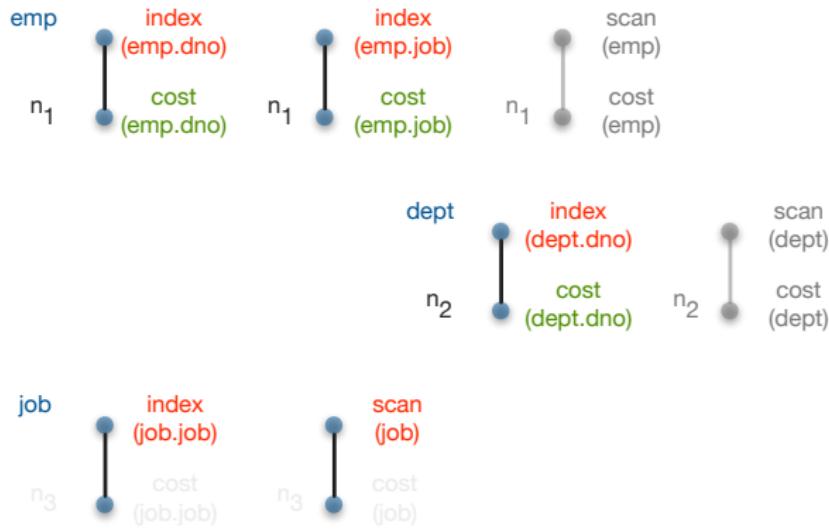
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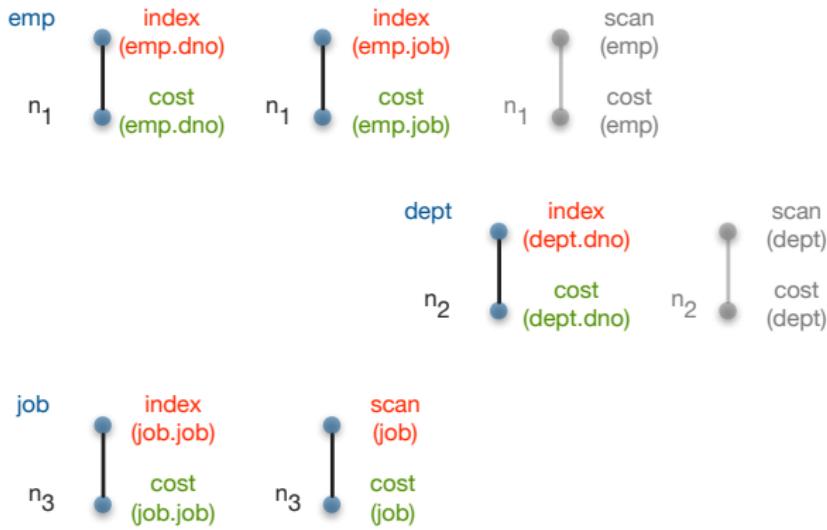
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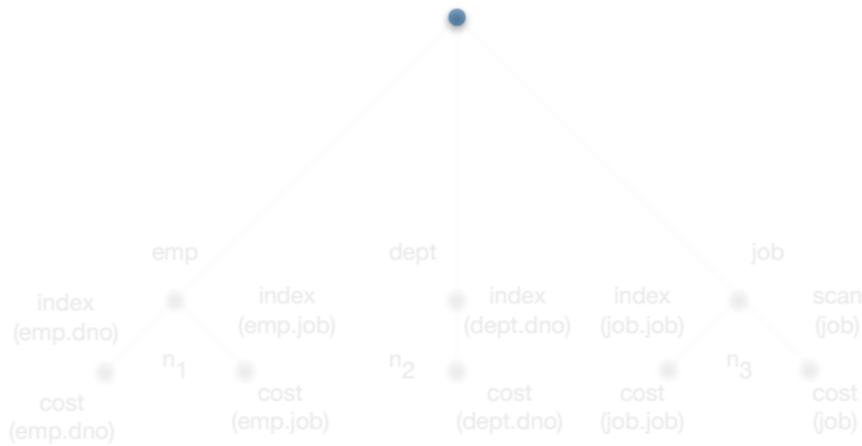
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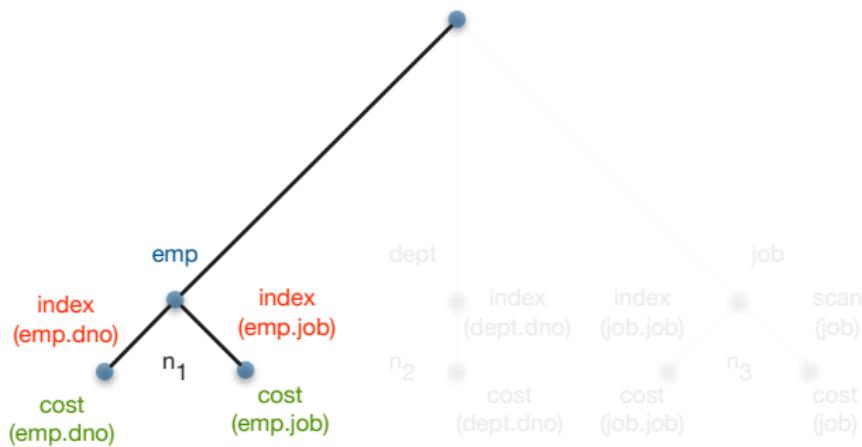


- Scanning *emp* is the *most expensive* method for *emp*; *emp.dno* and *emp.job* are *interesting orders*
- Scanning *dept* is the *most expensive* method for *dept*; *dept.dno* is an *interesting order*
- Scanning *job* is the *cheapest* method for *job*; but, *job.job* is an *interesting order*

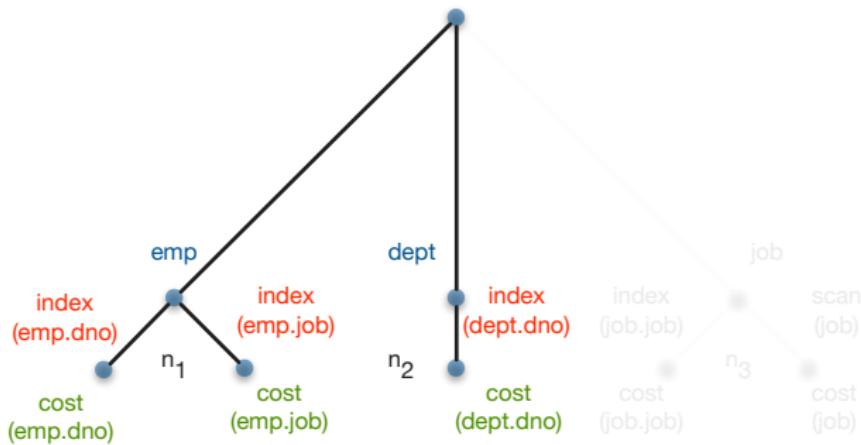
Search tree for access methods



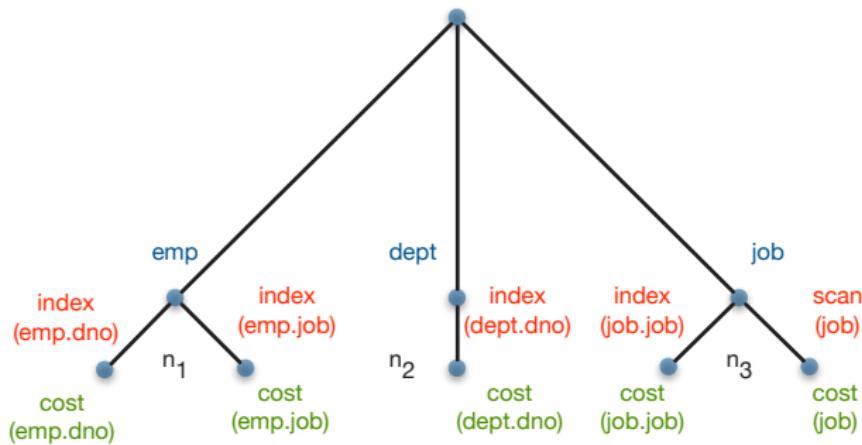
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Join enumeration for relation *emp* (nested loops join)



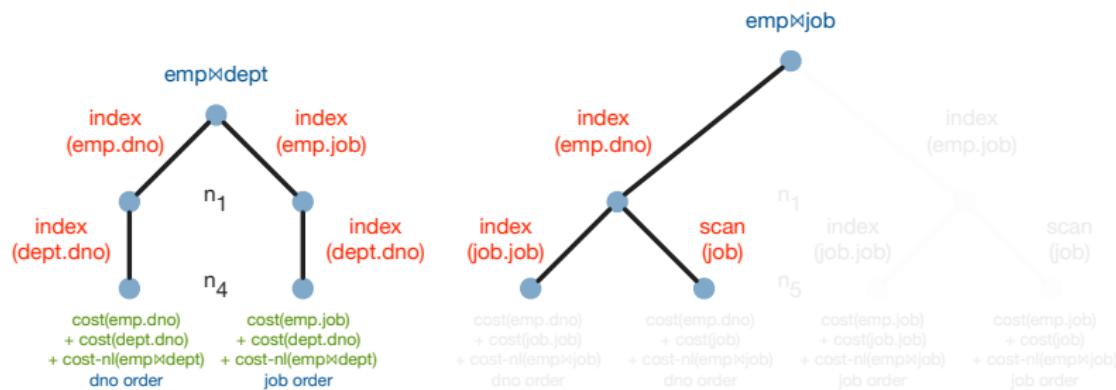
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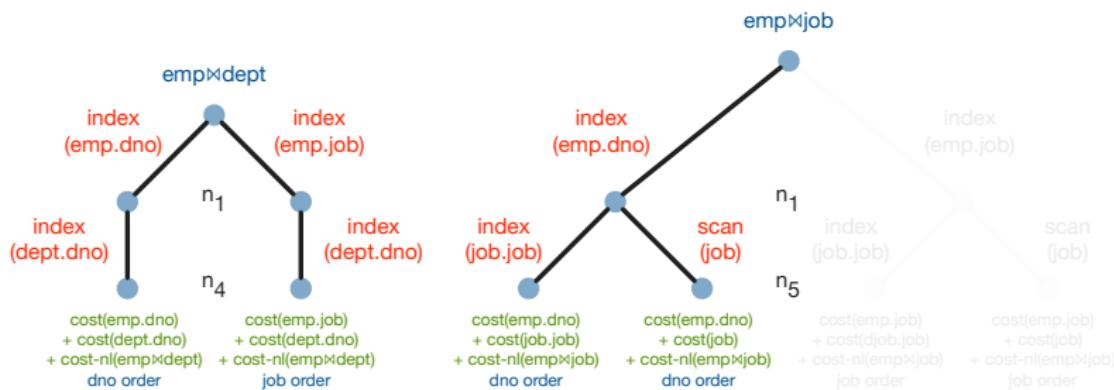


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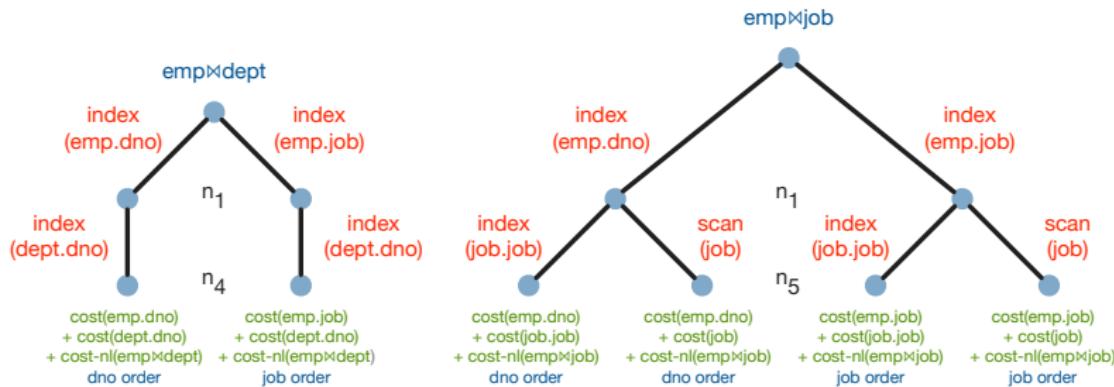
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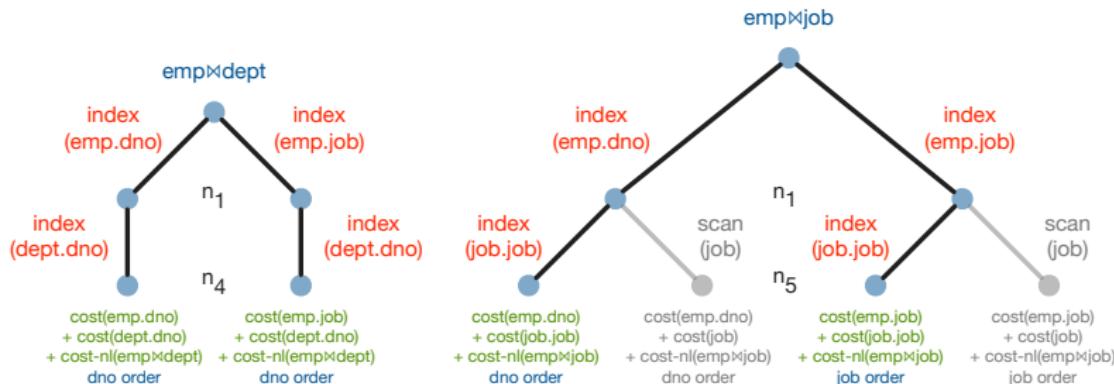
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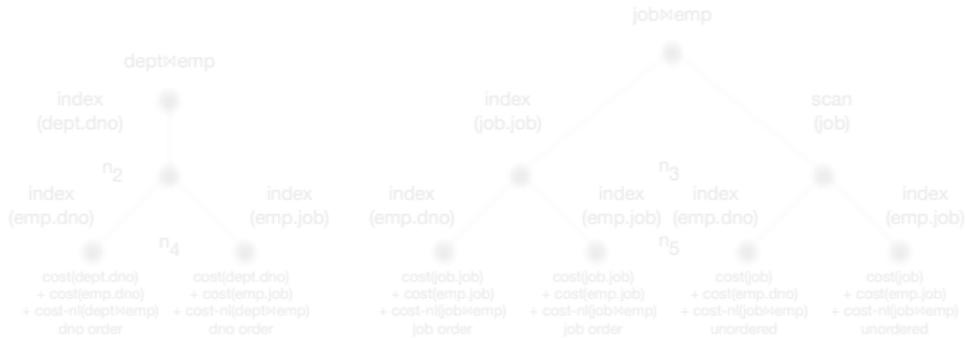
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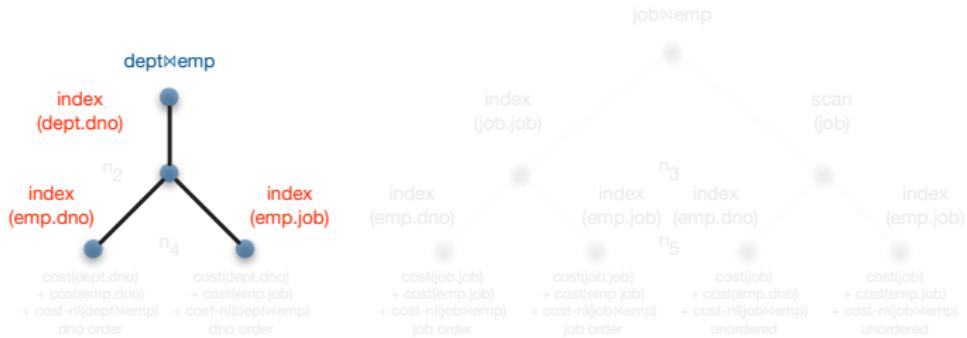
- Both $emp \bowtie dept$ results are *in different interesting orders* so they are propagated
- Only the *cheapest result* in any *interesting order* is propagated for *each pair of inputs*

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



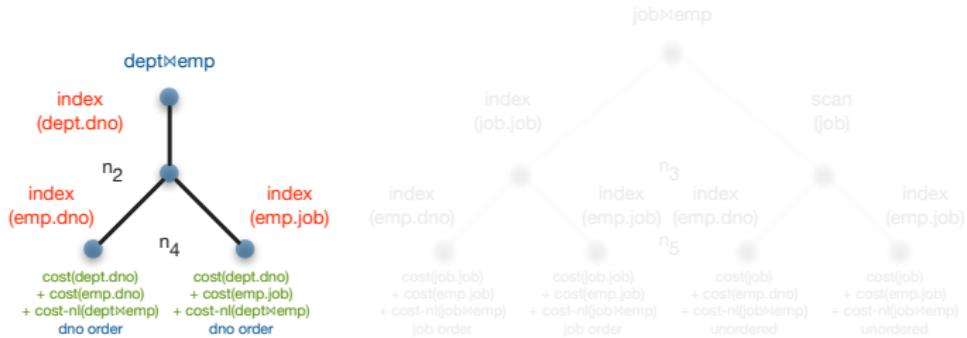
- $\text{cost}(emp \bowtie dept) \neq \text{cost}(dept \bowtie emp)$ so we will *enumerate dept's joins* even though we have an alternative for generating the same result (same for $job \bowtie emp$)

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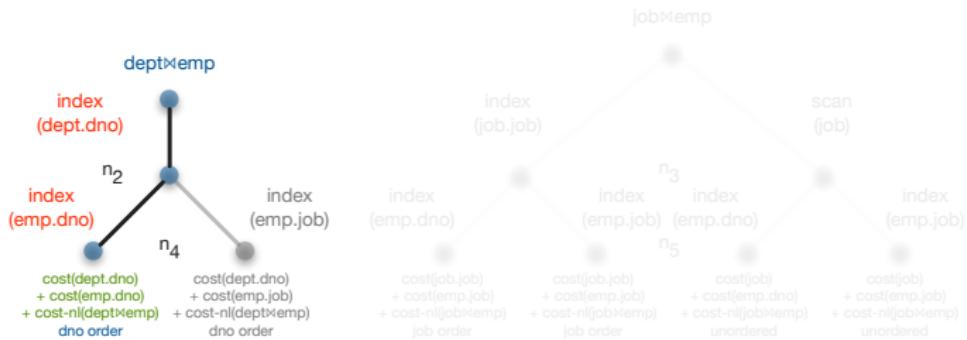
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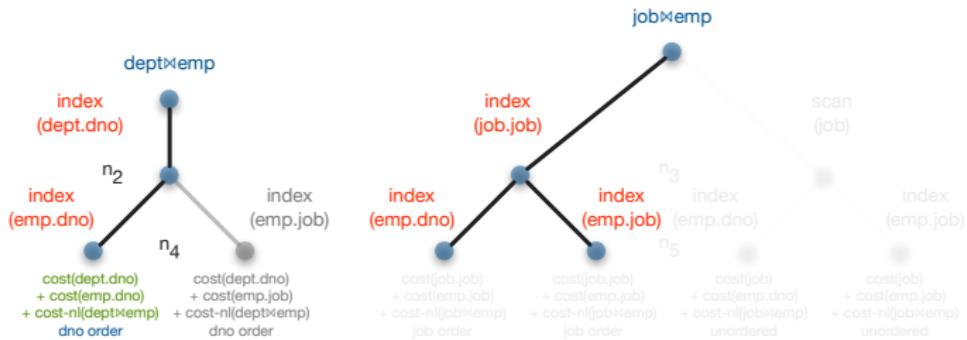
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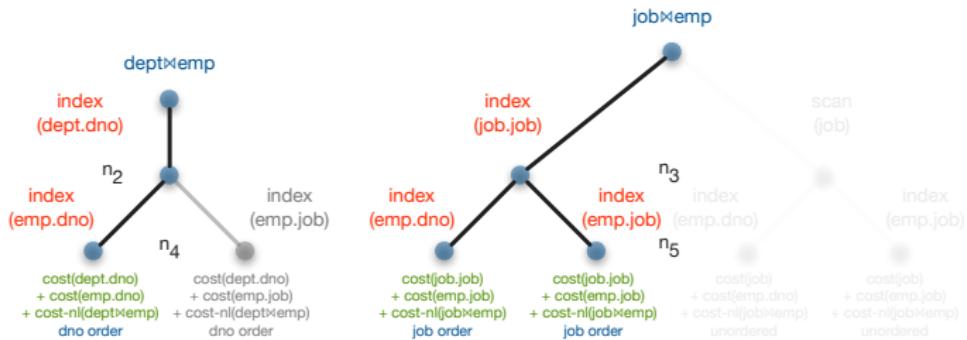
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- Both $dept \bowtie emp$ results in the same order, *only* one propagated
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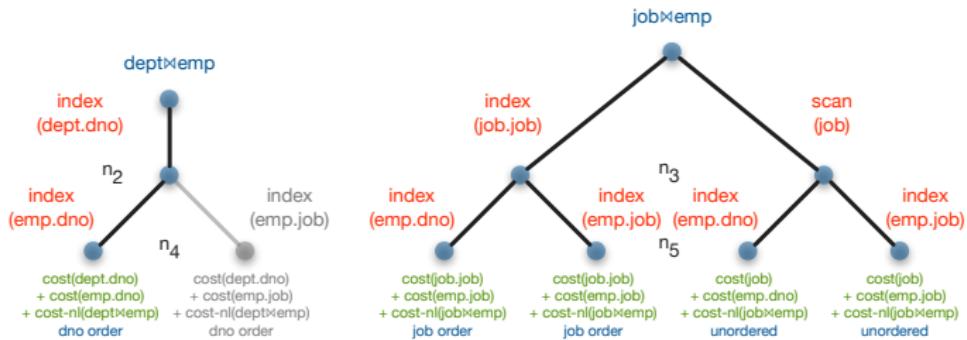
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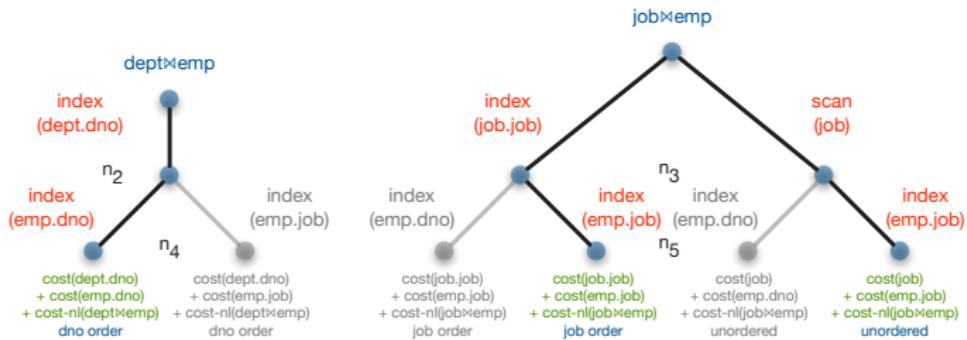
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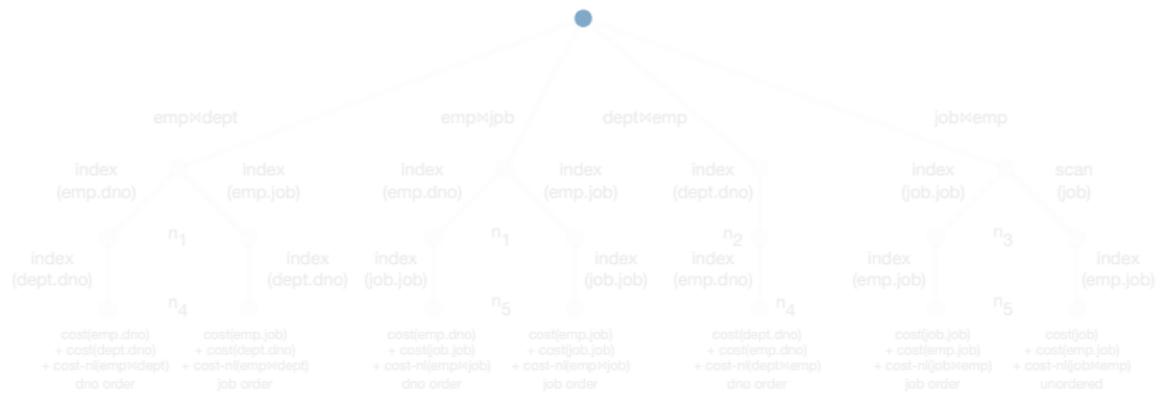
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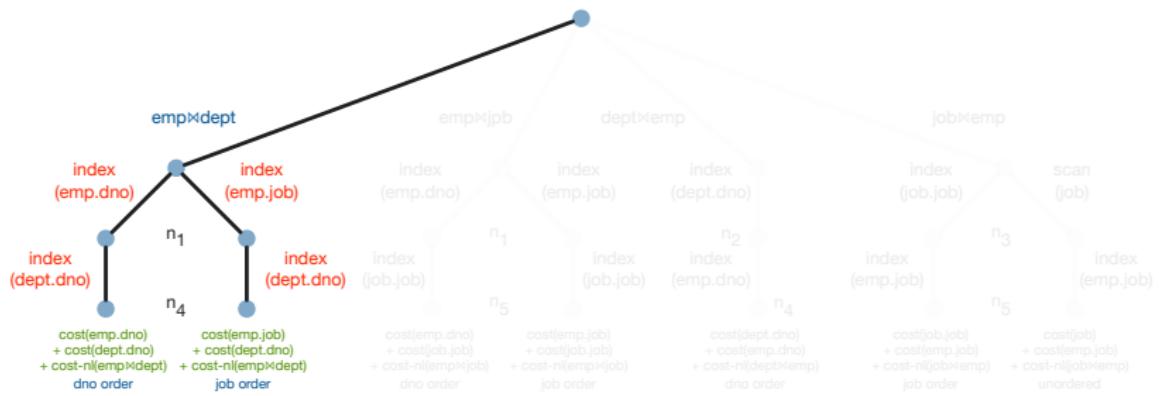


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- Since there is *no dept ⊲ job predicate* in the query, that join is *not enumerated* (same for $\text{job} \bowtie \text{dept}$)
- The *unordered* result for $\text{job} \bowtie \text{emp}$ is propagated because it is the *cheapest overall*

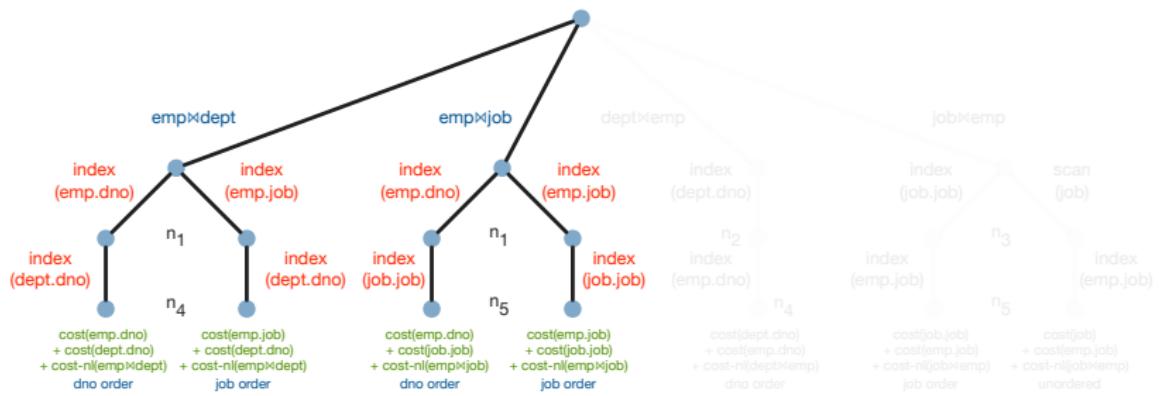
Search tree — 2 relations, nested loops join



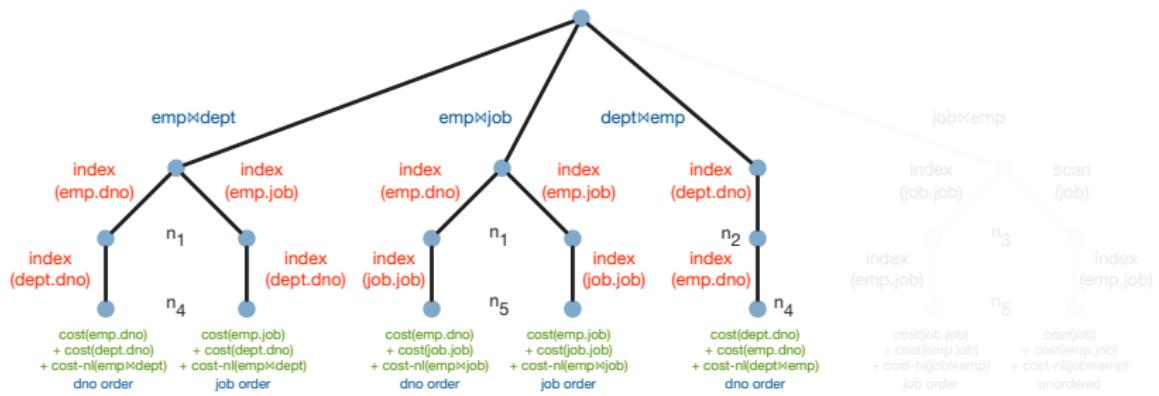
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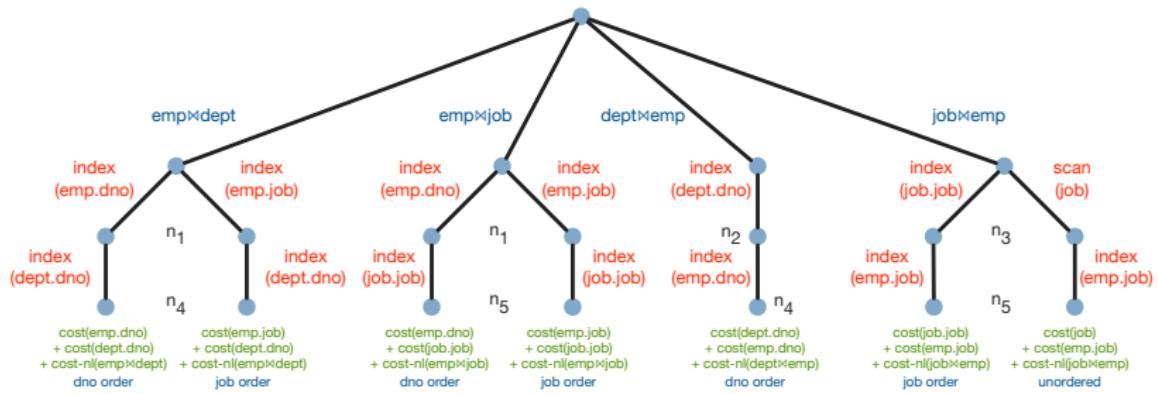
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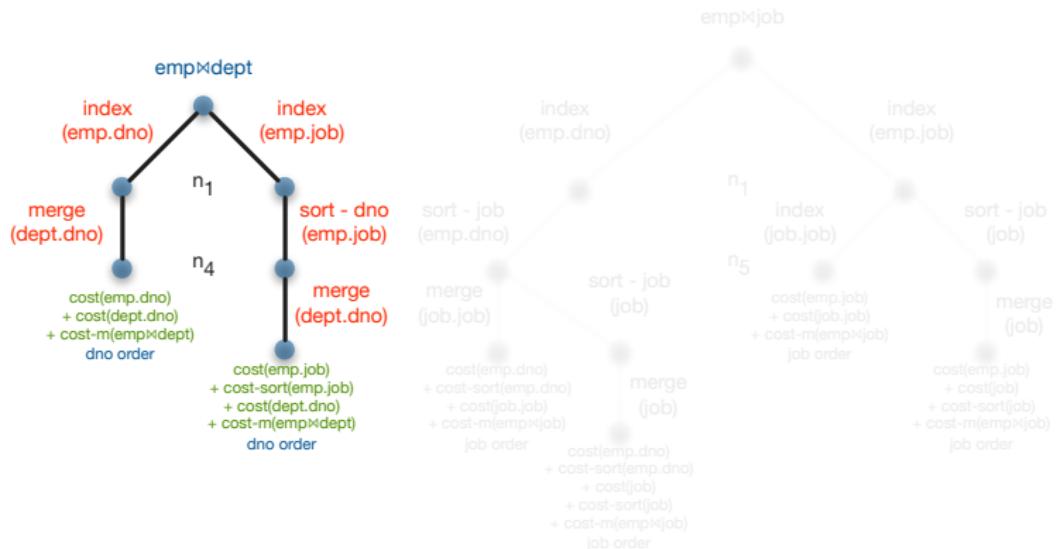
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Join enumeration for relation *emp* (sort-merge)



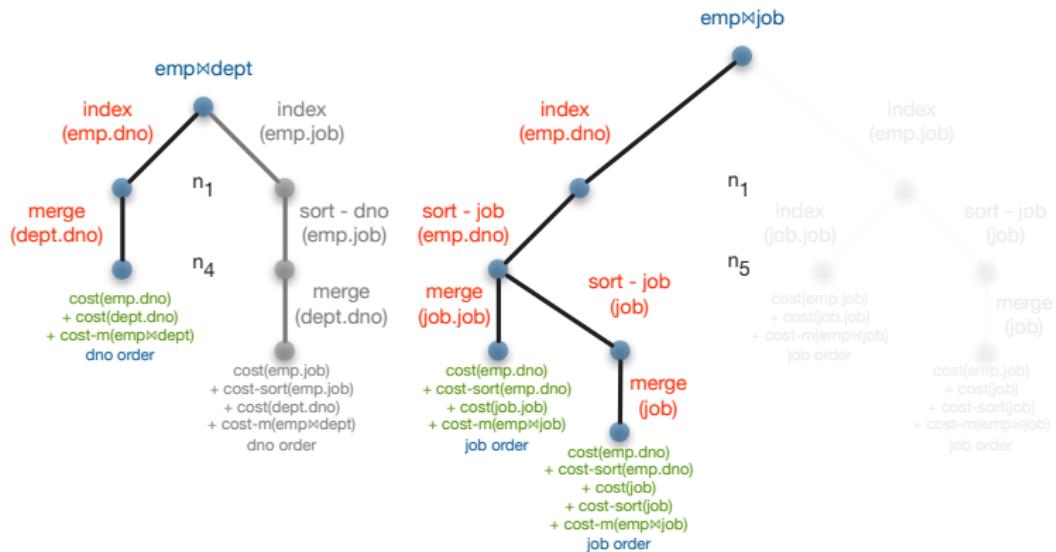
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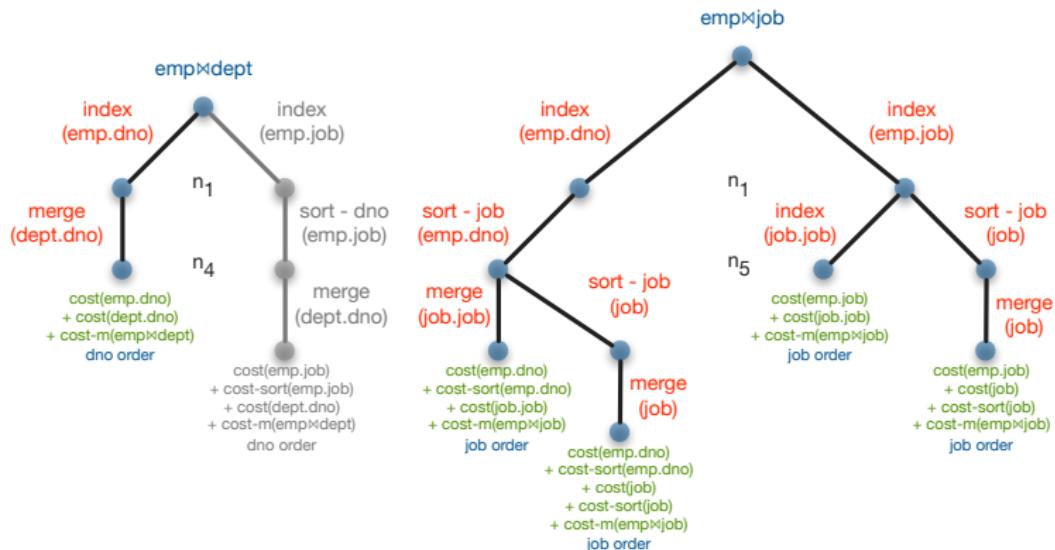
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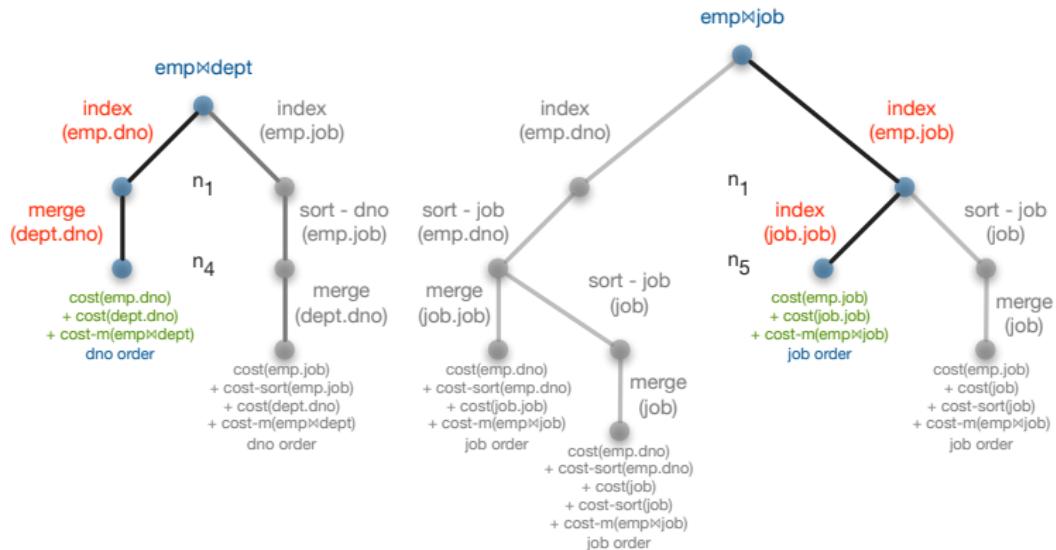
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Join enumeration for relation *emp* (sort-merge)



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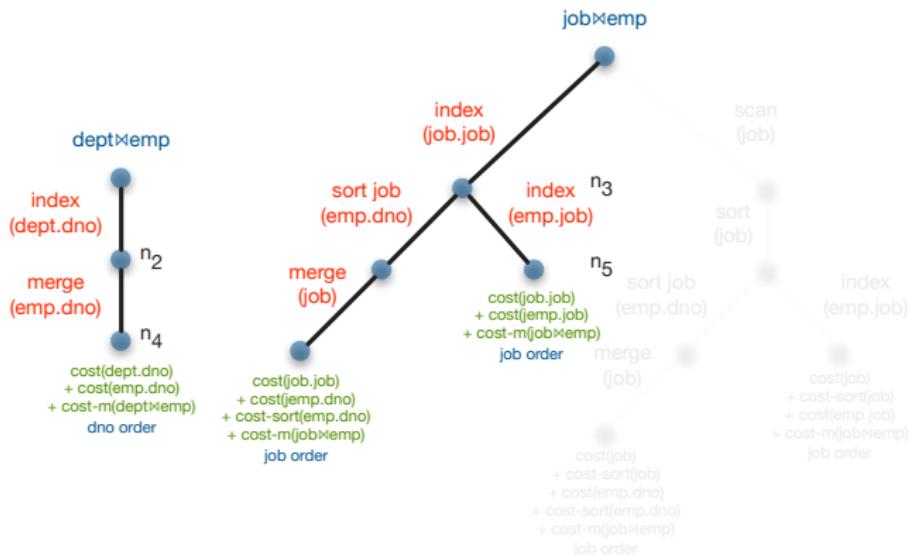
Join enumeration for relations *dept*, *job* (sort-merge)



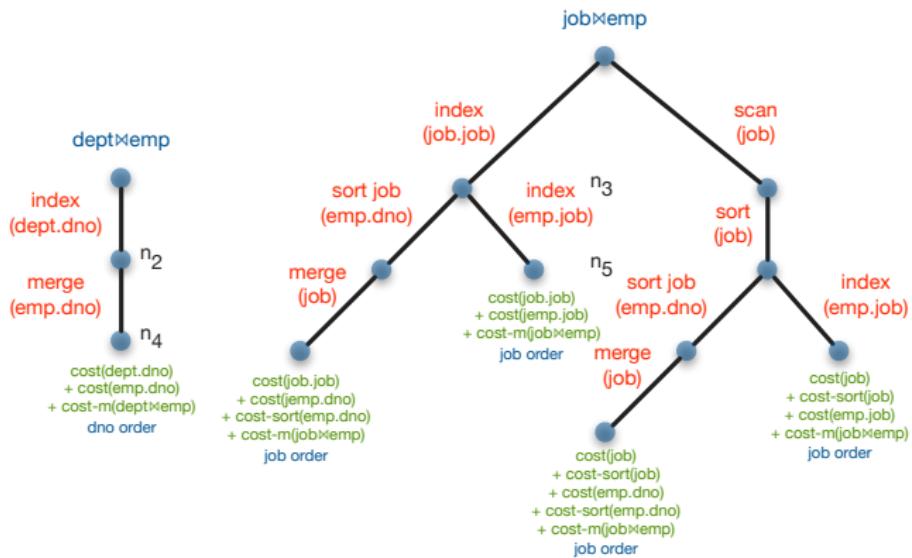
Join enumeration for relations *dept*, *job* (sort-merge)



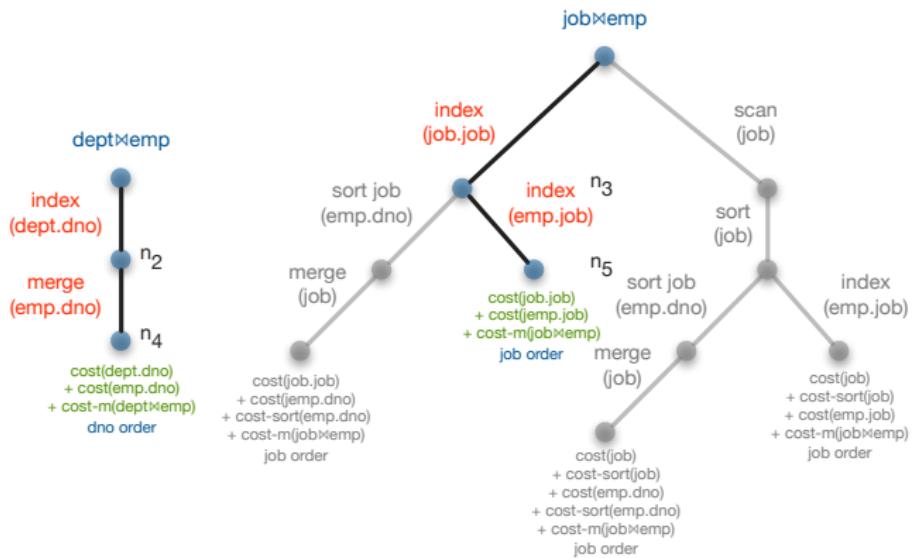
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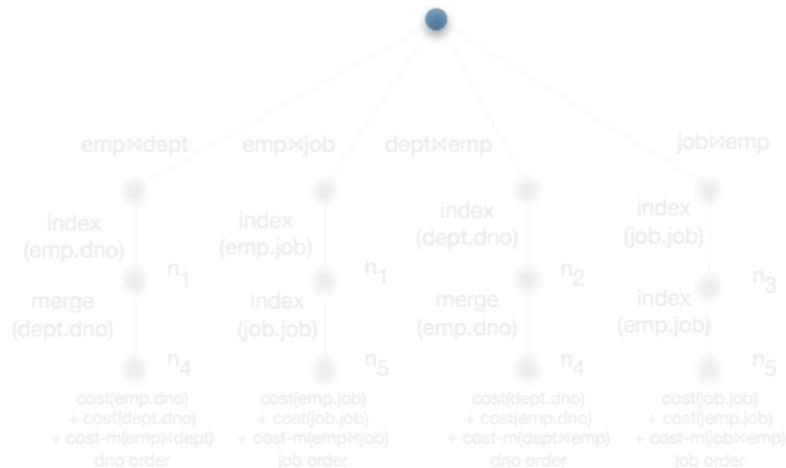
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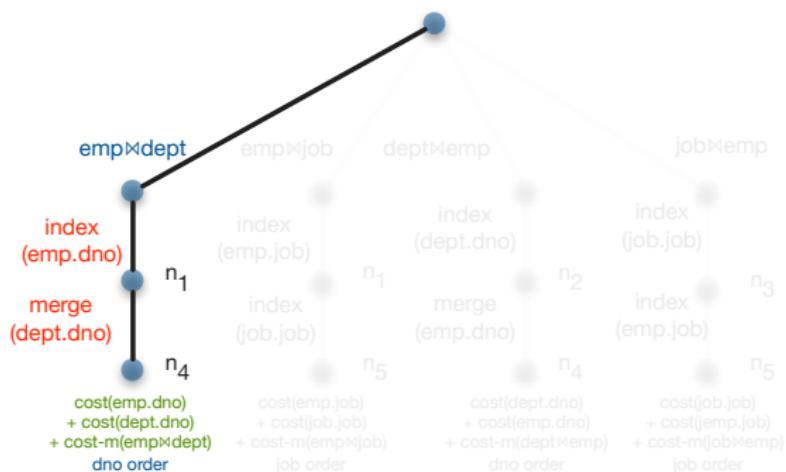
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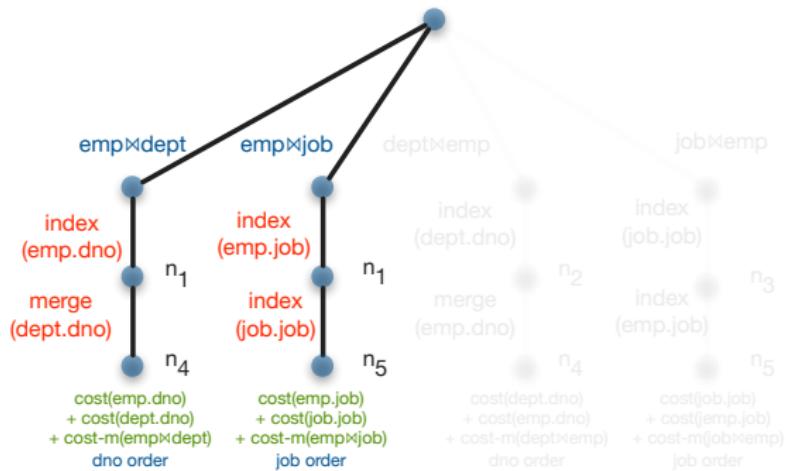
Search tree — 2 relations, sort-merge join



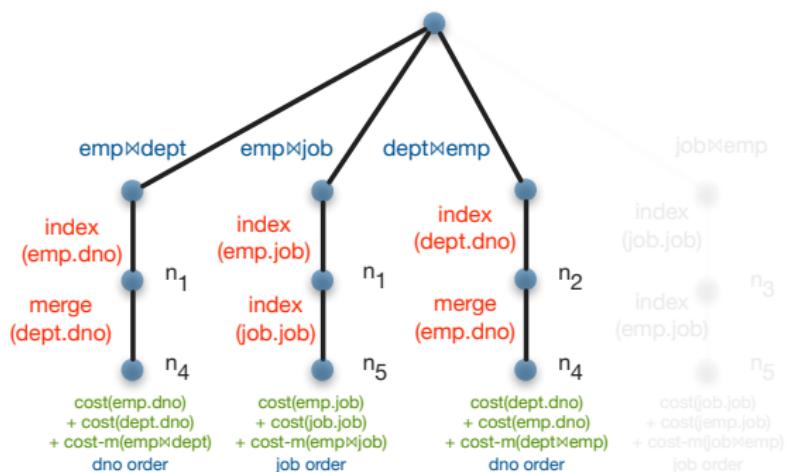
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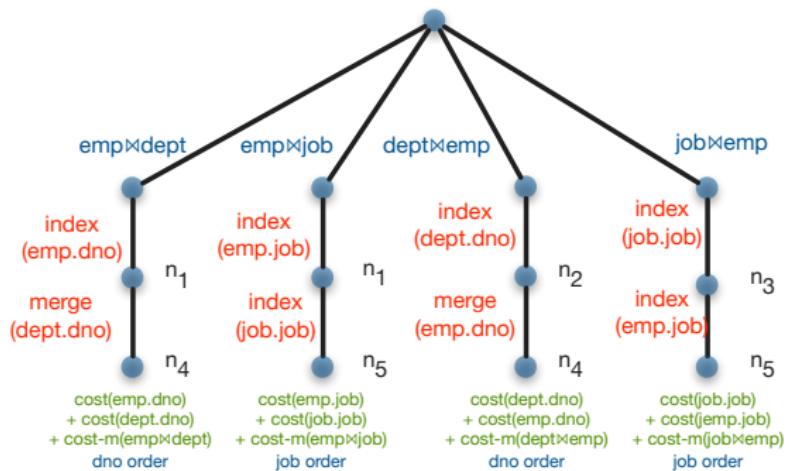
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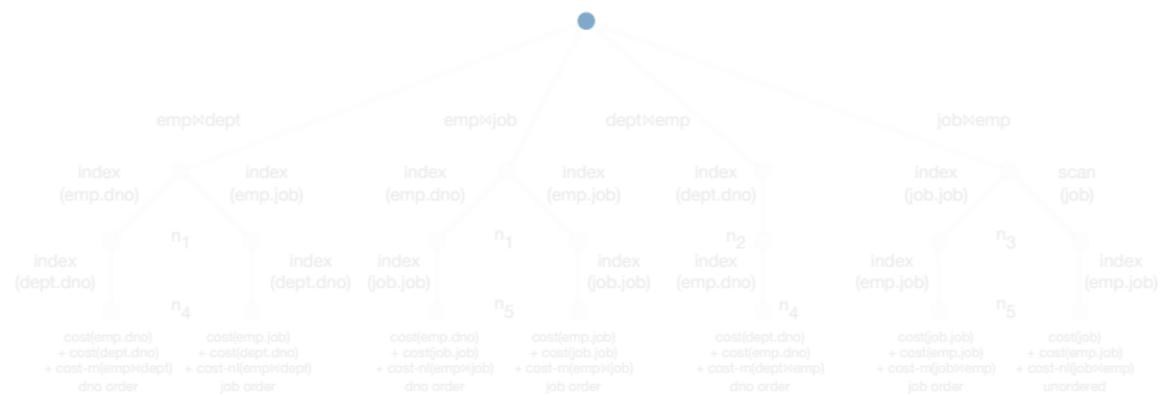
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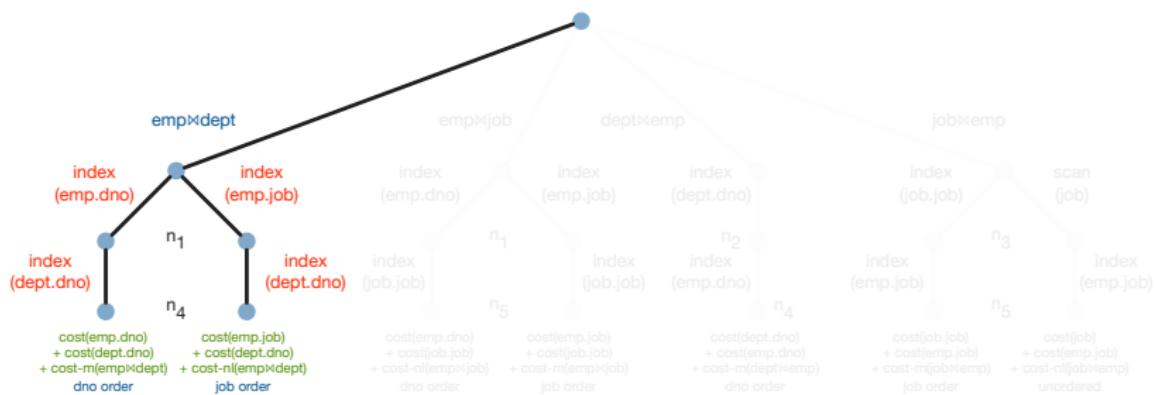
Search tree — 2 relations, sort-merge join



Search tree — 2 relations, both join methods

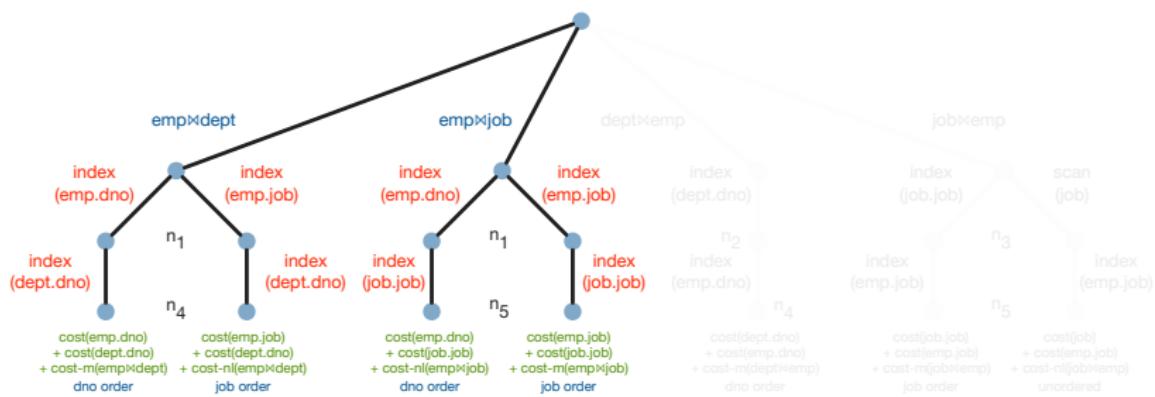


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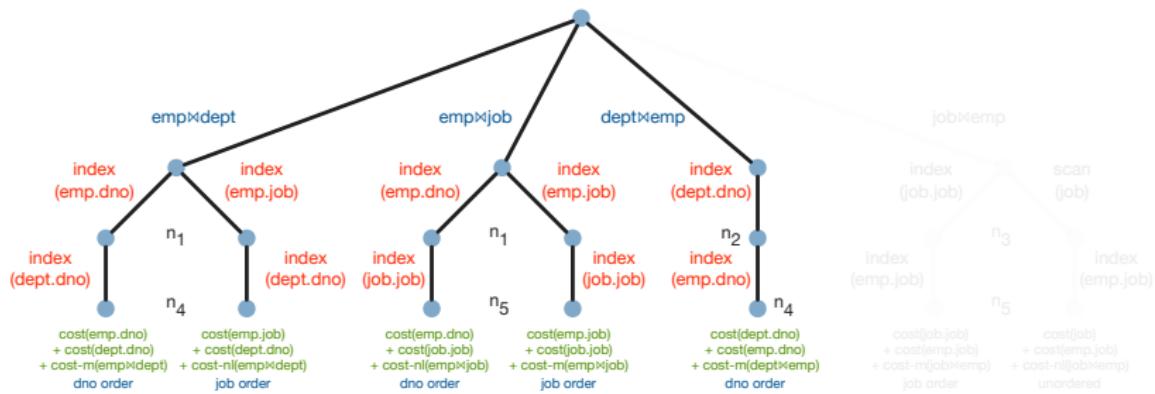
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Search tree — 2 relations, both join methods



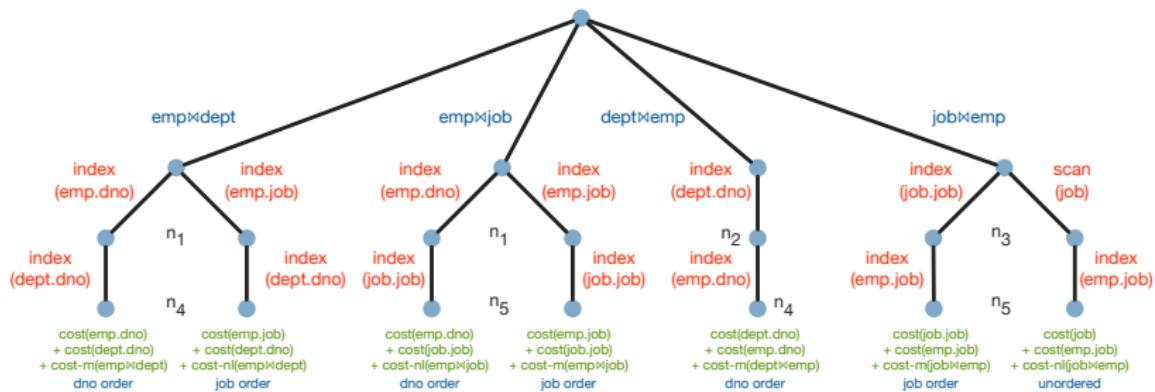
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Search tree — 2 relations, both join methods



- For each pair of 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*

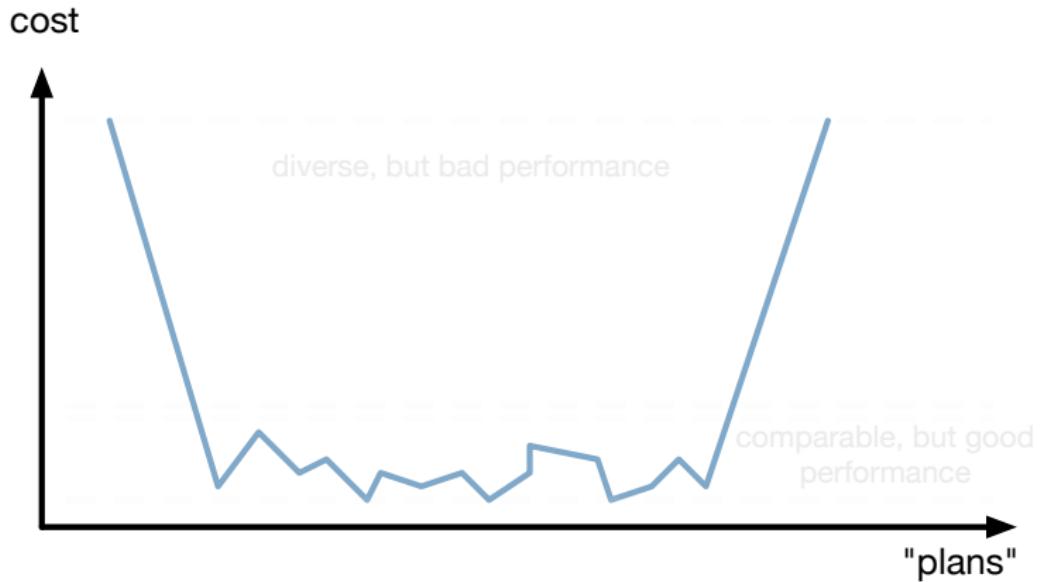
Randomised exploration

- *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*

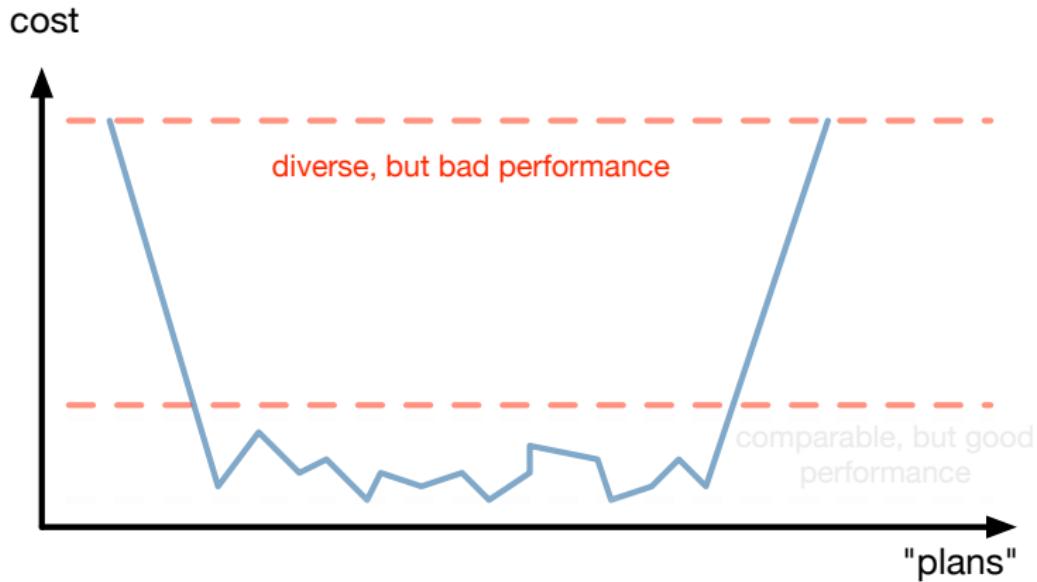
The “well”



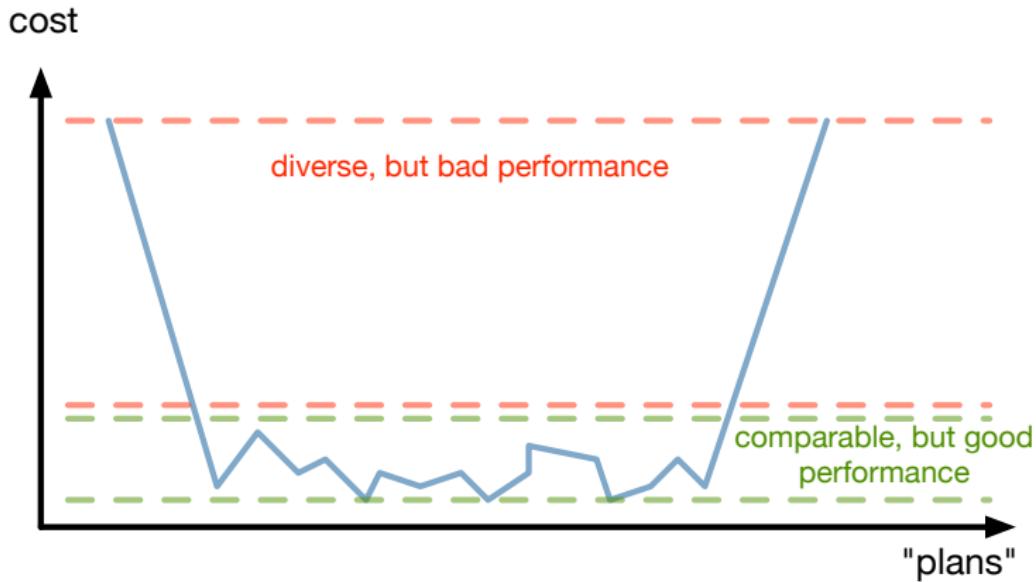
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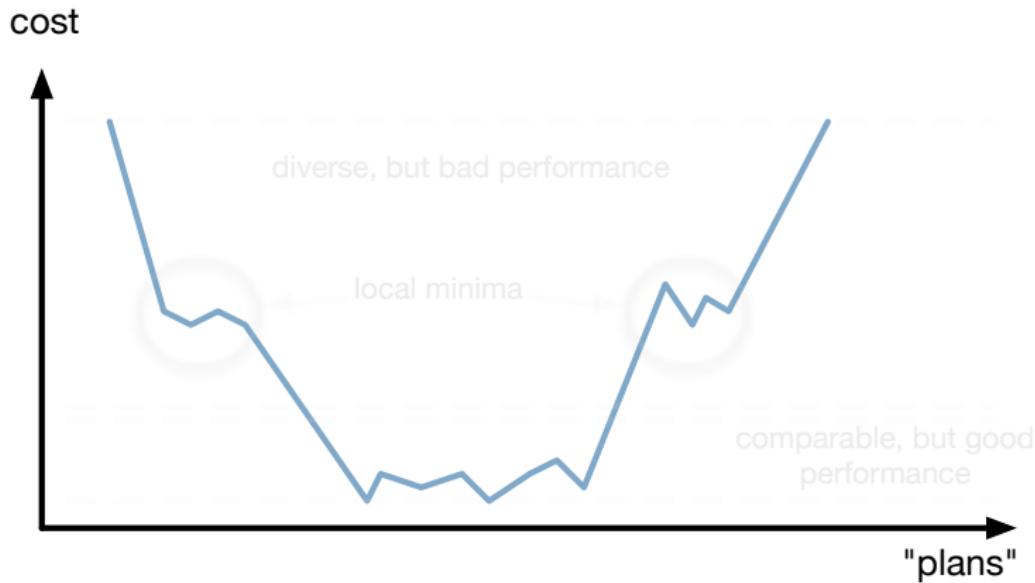
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The “well” and local minima



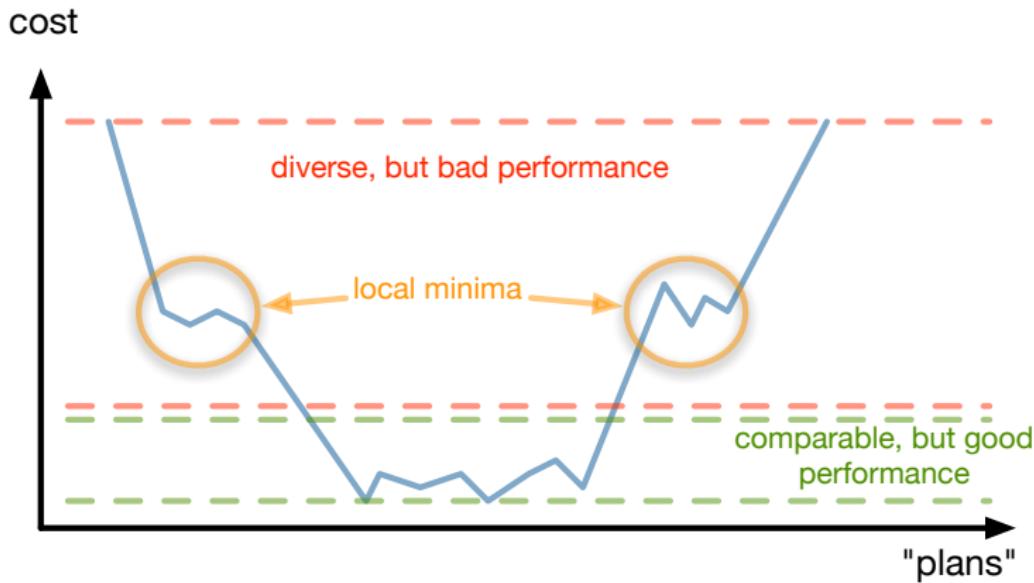
The “well” and local minima



The “well” and local minima



The “well” and local minima



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)
```

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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)
```

nested loops



s.sid=r.sid

sailors

$\sigma_{r.bid=103}$

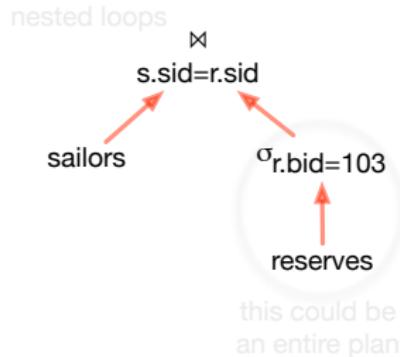
reserves

this could be
an entire plan

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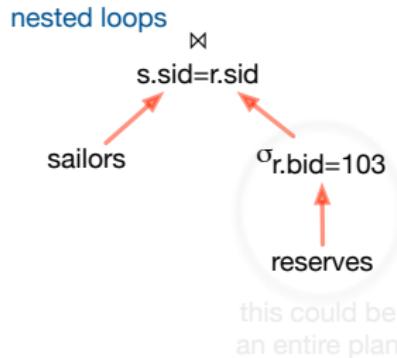
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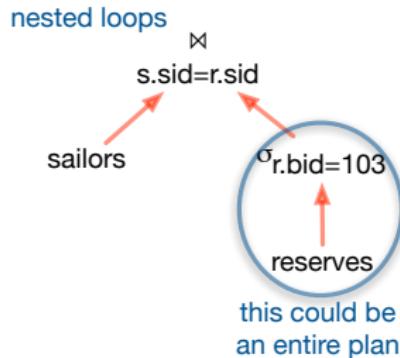
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In practice

- 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!*

Outline

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*

Outline

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*

Outline

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

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- **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)	

Example (cont.)

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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*
 - ▶ *Serializable 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
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 - ▶ 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*

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- 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*

The solution: locks

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- *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*

Outline

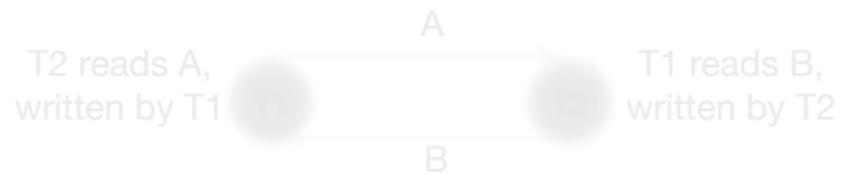
Concurrency control

- **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*
- **Serializable 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

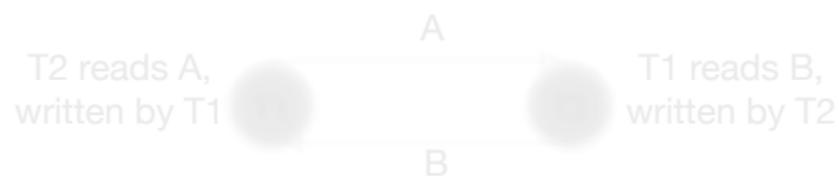
- Given a *schedule S*
 - ▶ One *node* per *transaction*
 - ▶ An *edge* from T_i to T_j , if T_j reads or writes an *object* written by T_i
- *Theorem:* a *schedule S* is *conflict serialisable* if and only if its *dependency graph* is *acyclic*

Example: not conflict serialisable schedule



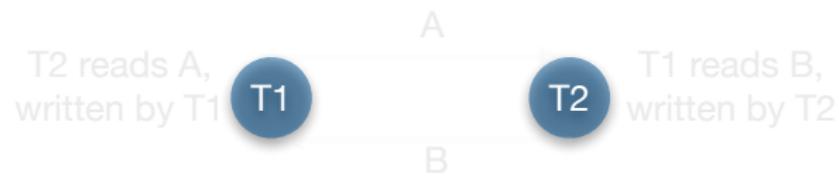
Example: not conflict serialisable schedule

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



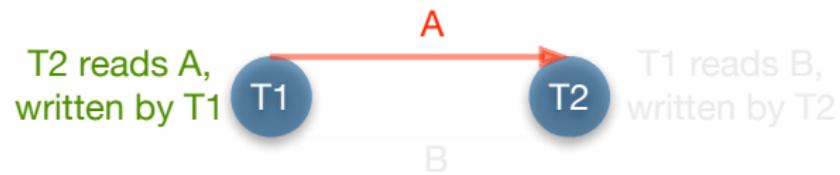
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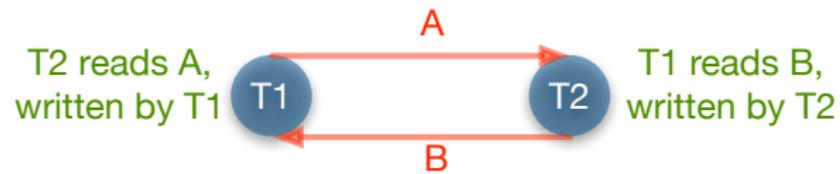
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Review: Strict 2PL

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

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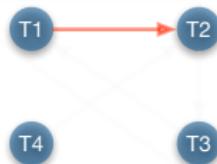
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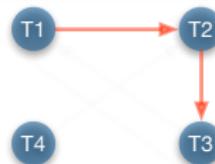
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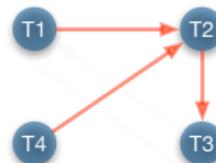
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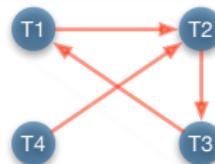
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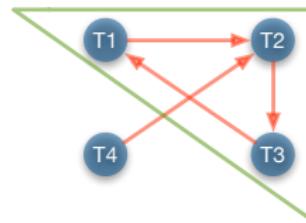
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Multiple granularity locks

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

containment



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

	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

- T_1 scans R , and updates a few tuples

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 - ▶ T_1 gets an *SIX lock* on R , then repeatedly gets an *S lock* on tuples of R , and occasionally upgrades to *X* on the tuples

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 - ▶ *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*
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 - ▶ *T2 gets an IS lock on R, and repeatedly gets an S lock on tuples of R*
- *T3 reads all of R*

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- *T1 scans R, and updates a few tuples*
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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)

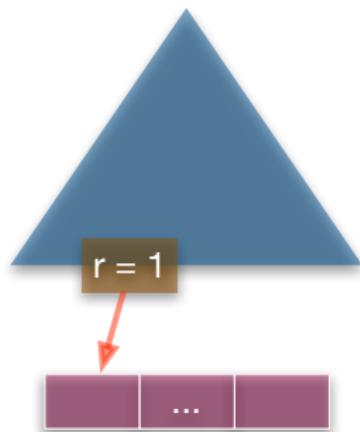
- If we *relax* the *assumption* that the *DB* is a *fixed collection* of objects, even *Strict 2PL* will *not assure serialisability*!
 - ▶ *T1 locks all pages* containing *sailor records* with *rating = 1*, and *finds oldest sailor* (say, *age = 71*)
 - ▶ Next, *T2 inserts* a *new sailor*: *rating = 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.,
 $\text{salary} > 2 \cdot \text{salary}$
 - ▶ *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

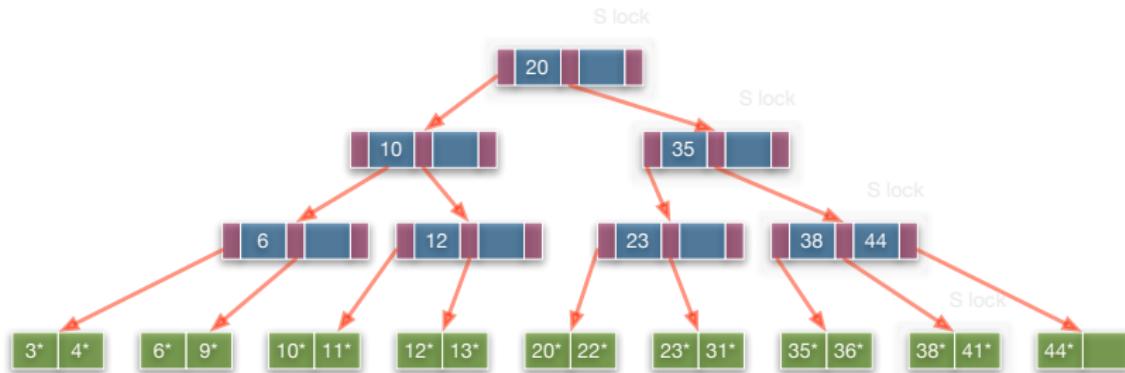
Key observations

- *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

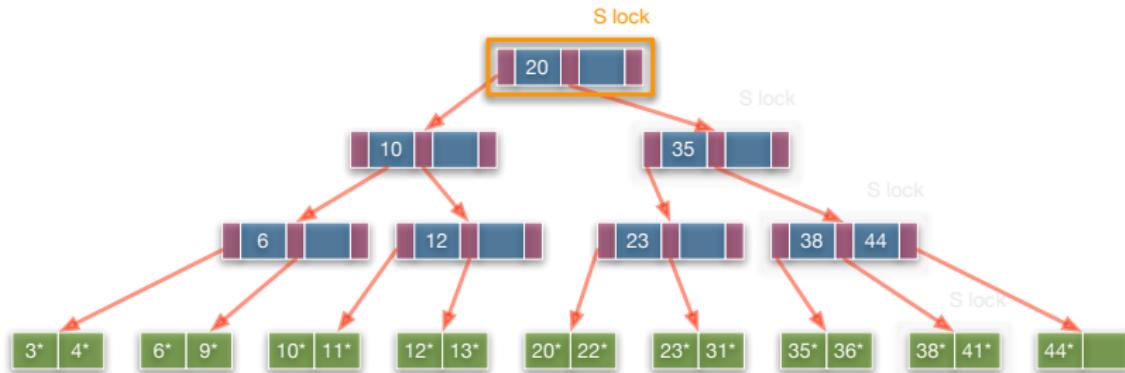
- **Search:** *start* at *root* and *descend*; repeatedly, *S lock child* then *unlock parent*
- **Insert/Delete:** *start* at *root* and *descend*, obtaining *X locks as needed*; once *child* is *locked*, *check* if it is *safe*:
 - ▶ *Safe node*: a *node* such that *changes* will *not propagate up 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*



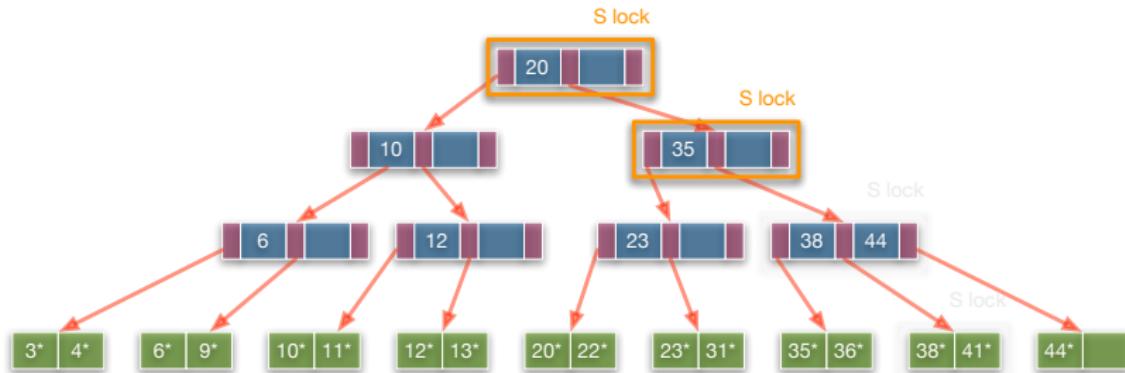
Obtain and release S-locks level-by-level

Example: search 38*



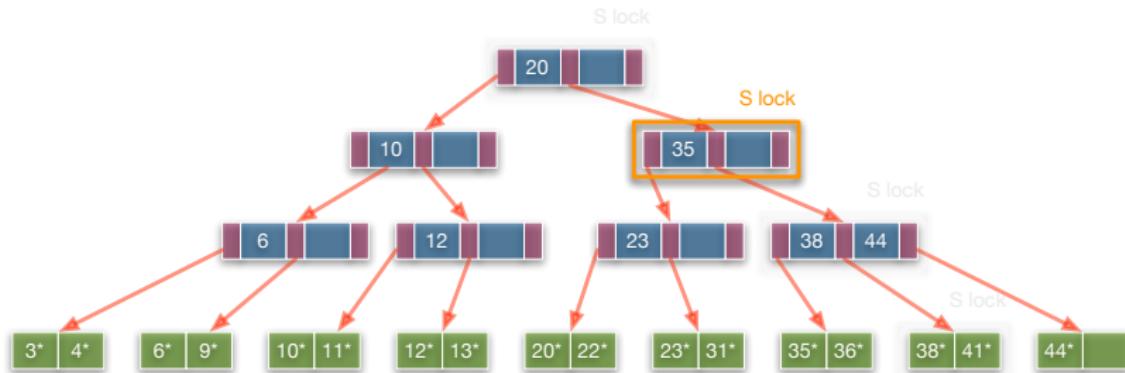
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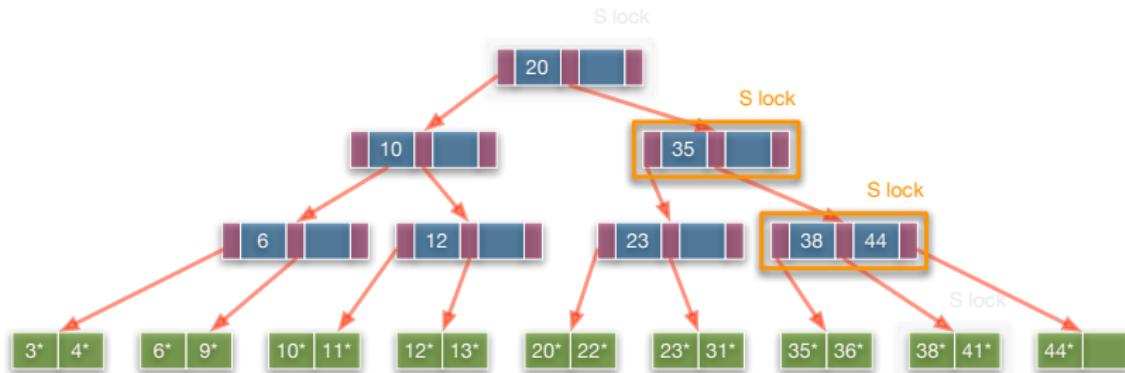
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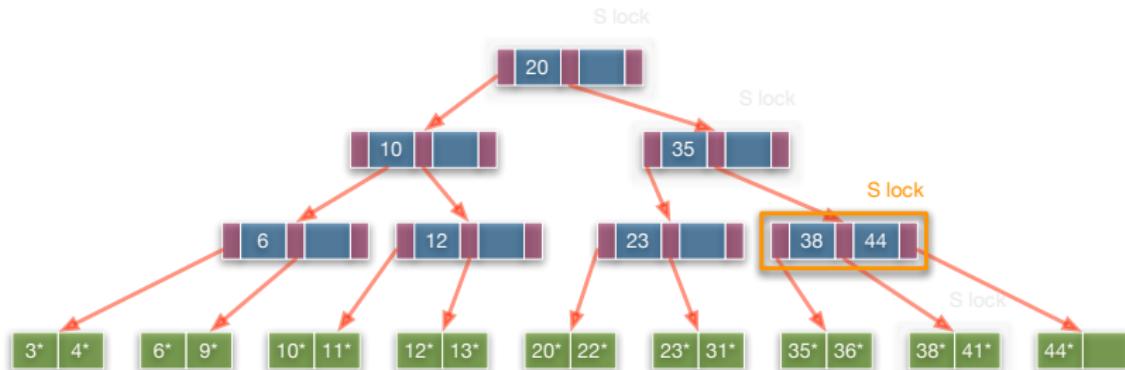
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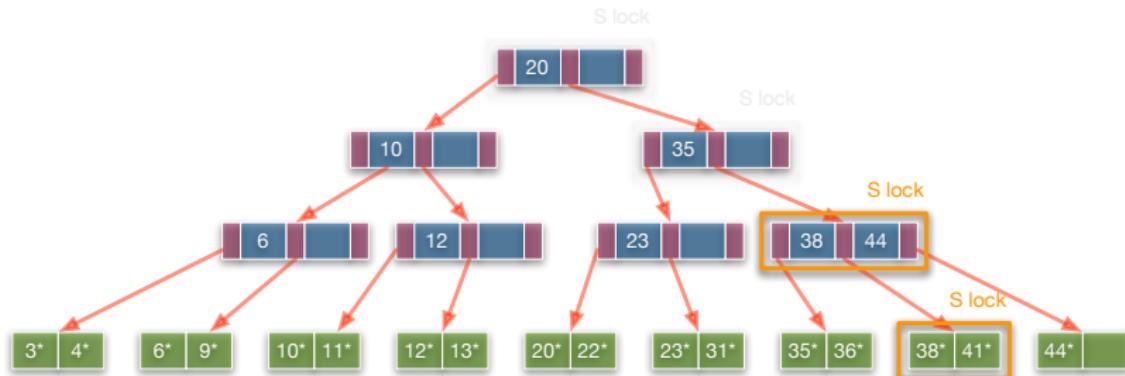
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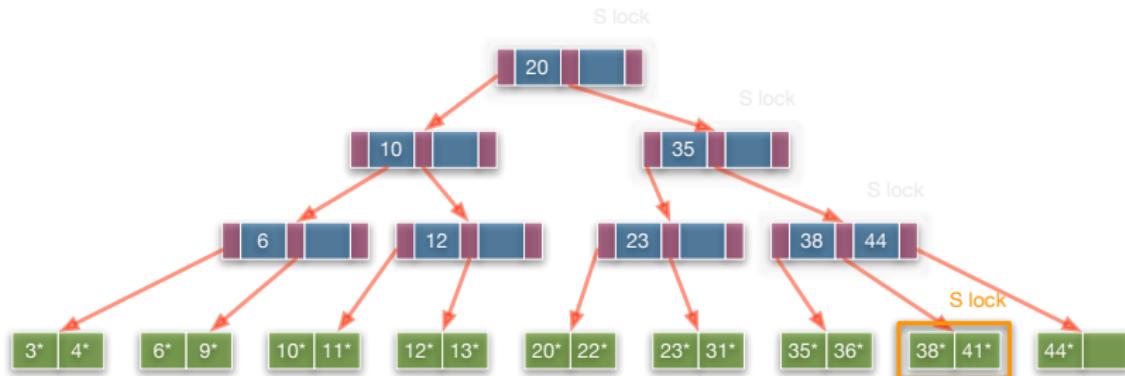
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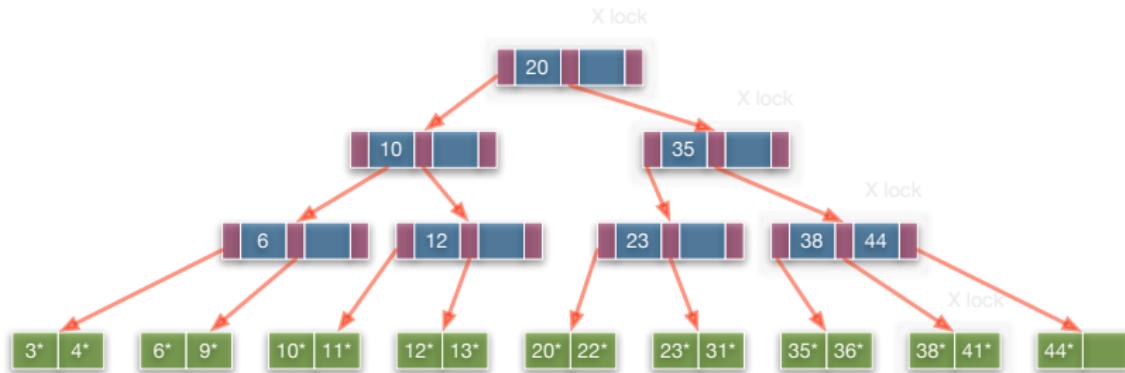
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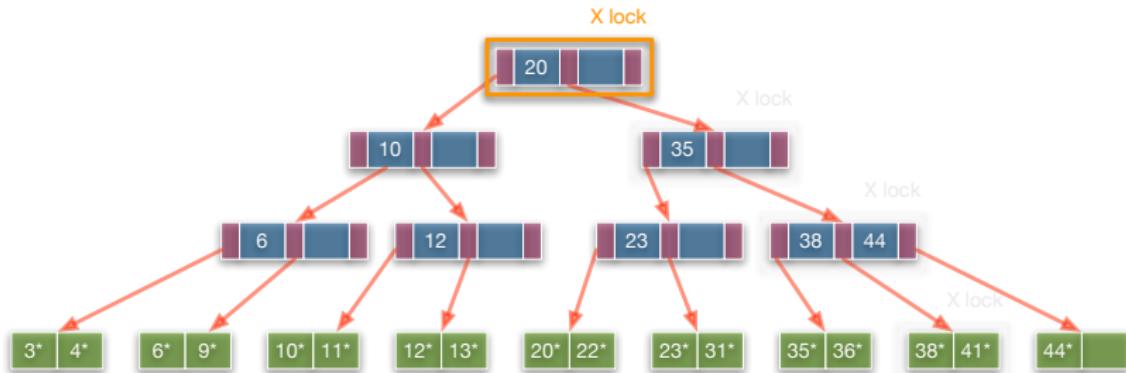
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Example: delete 38*



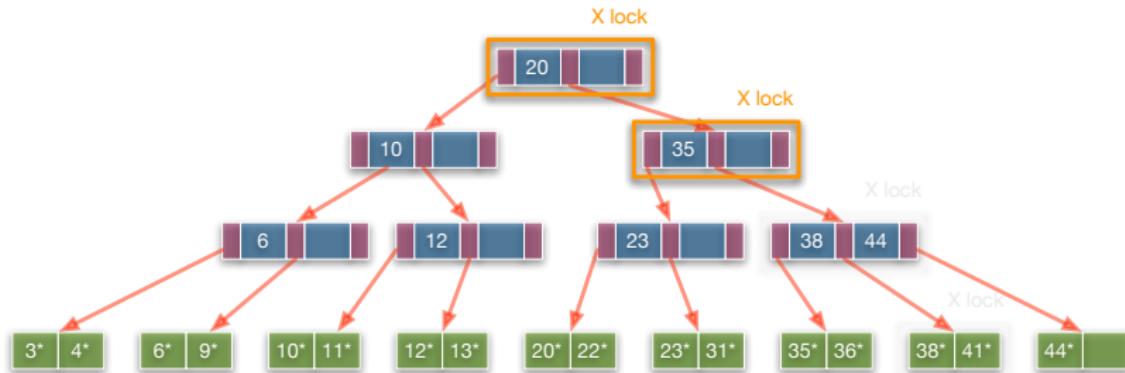
Obtain X-locks while descending; release them top-down once the node is designated safe

Example: delete 38*



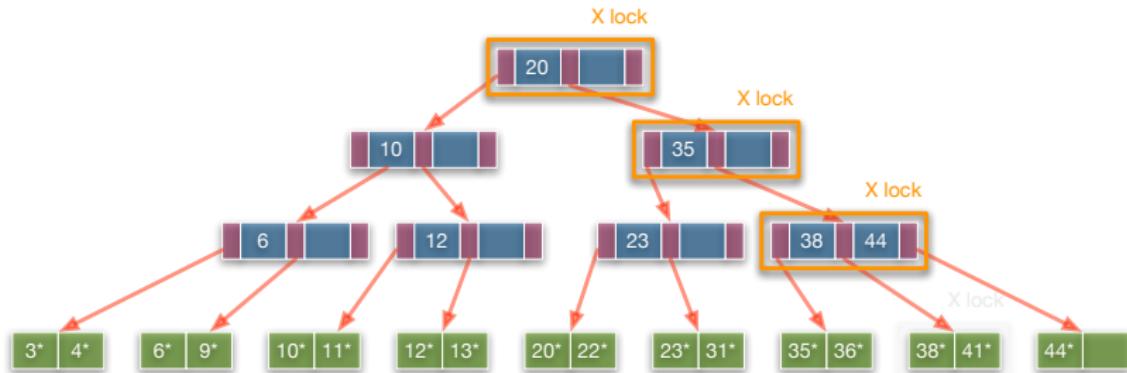
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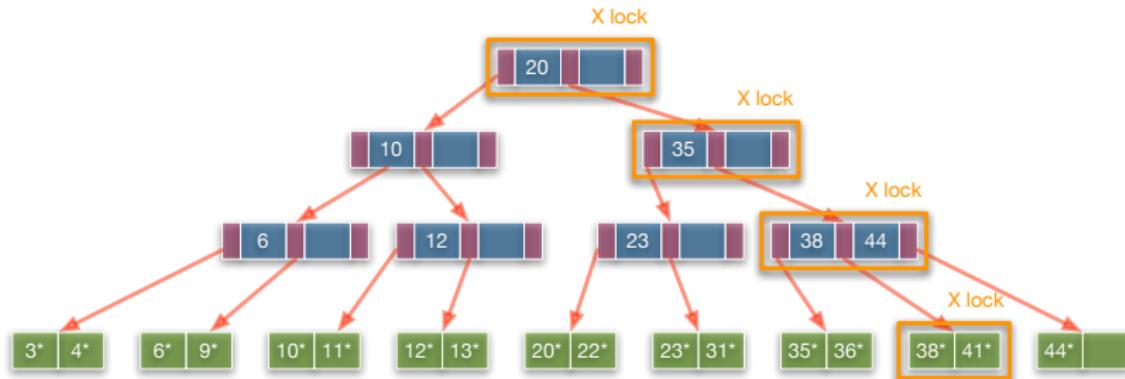
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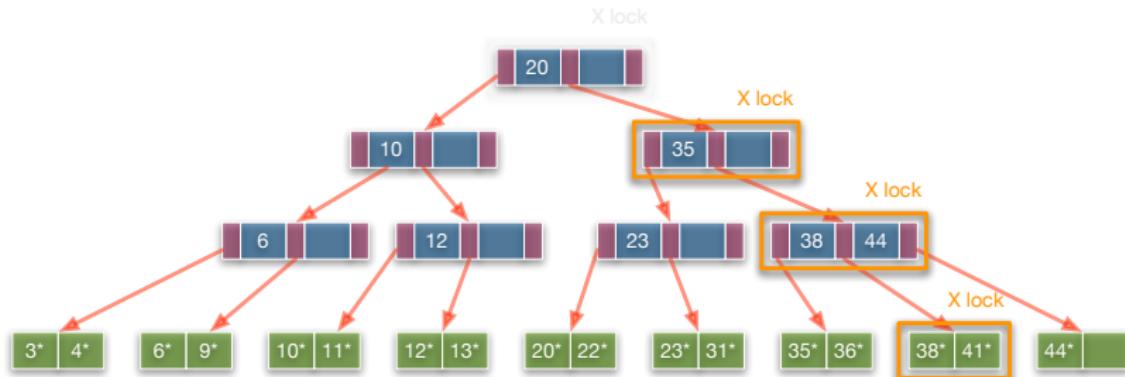
Obtain X-locks while *descending*; release them *top-down* once the node is *designated safe*

Example: delete 38*



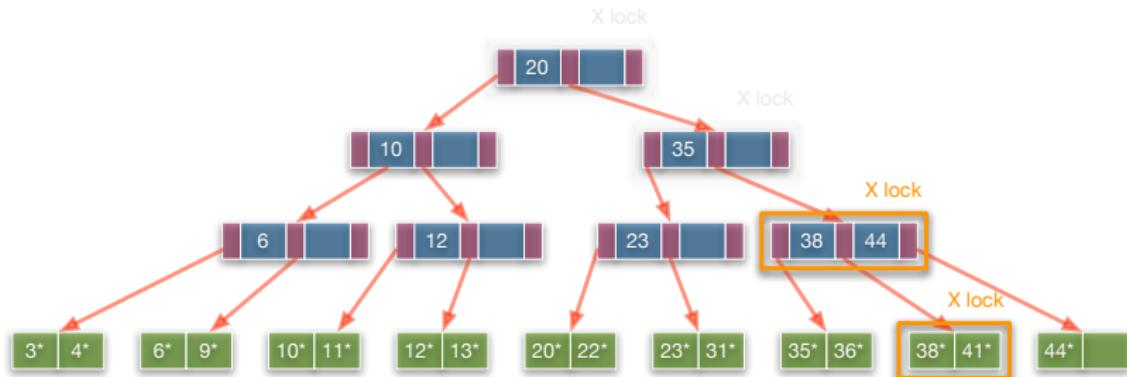
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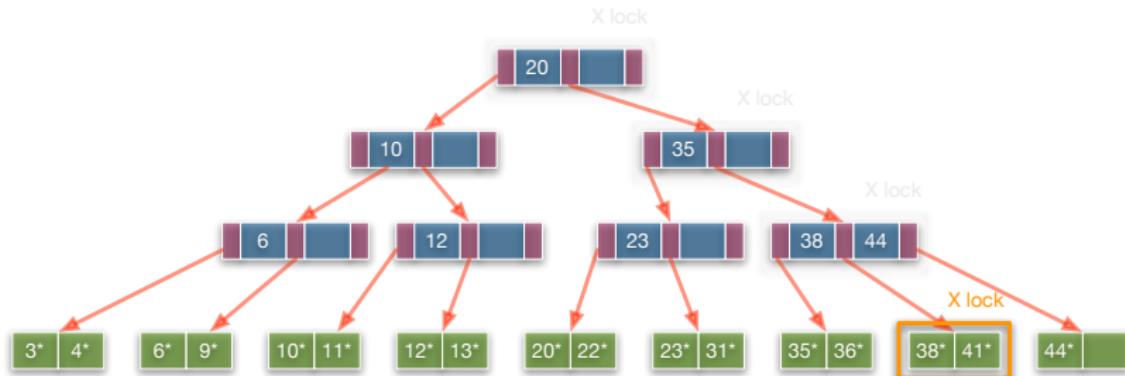
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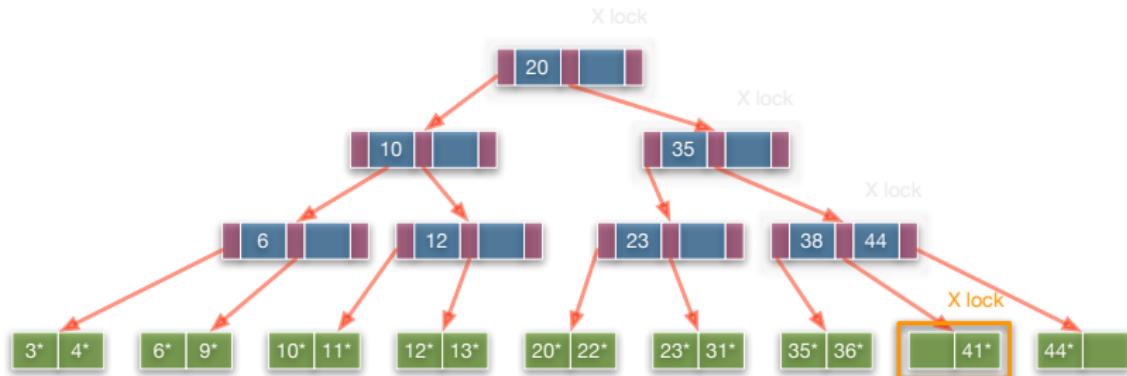
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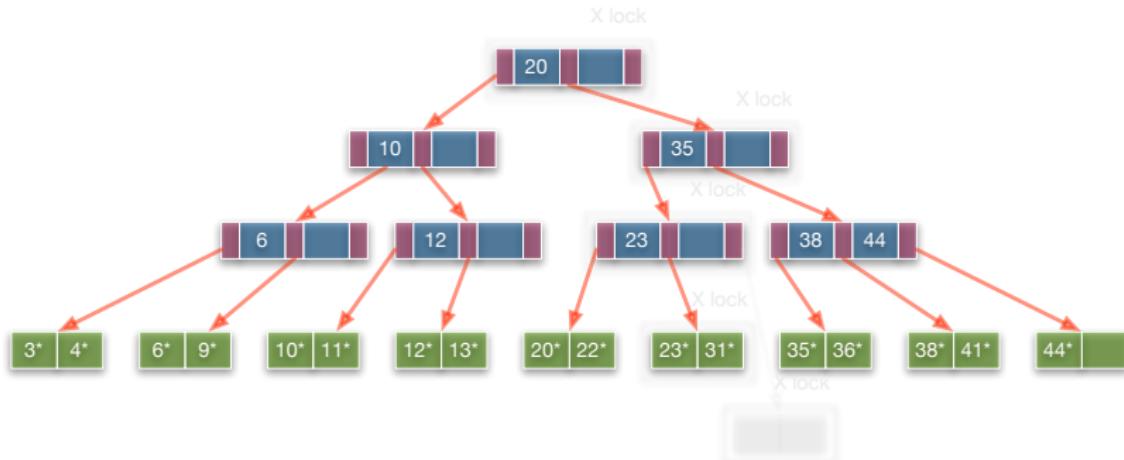
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Example: delete 38*



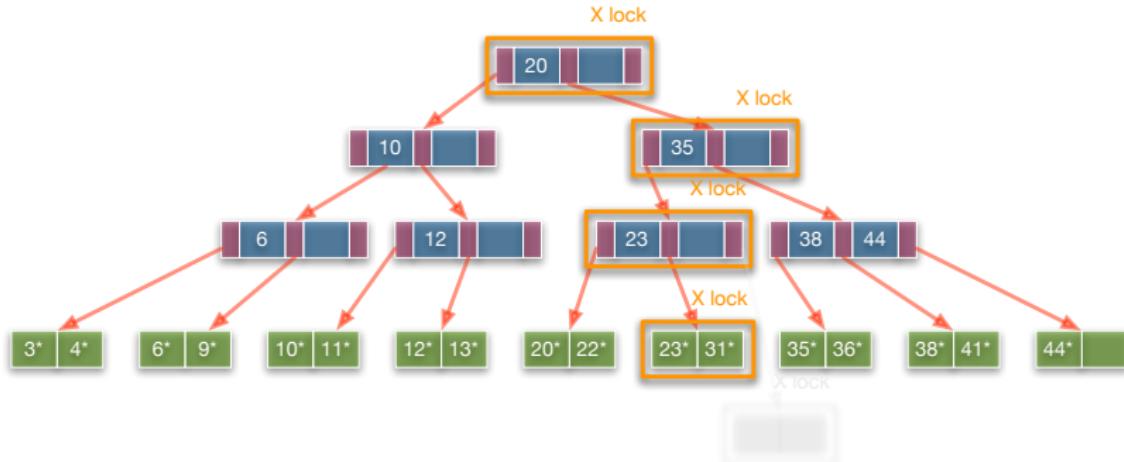
Obtain X-locks while descending; release them top-down once the node is designated safe

Example: insert 25*



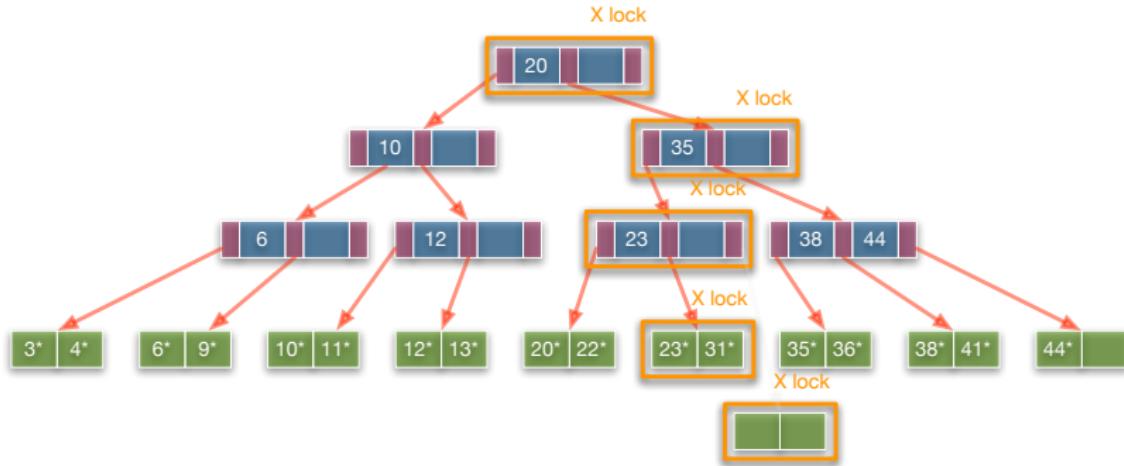
Obtain **X-locks** while *descending*; *leaf-node is not safe* so *create* a *new* one and *lock it in X-mode*; first release *locks on leaves* and then the rest *top-down*

Example: insert 25*



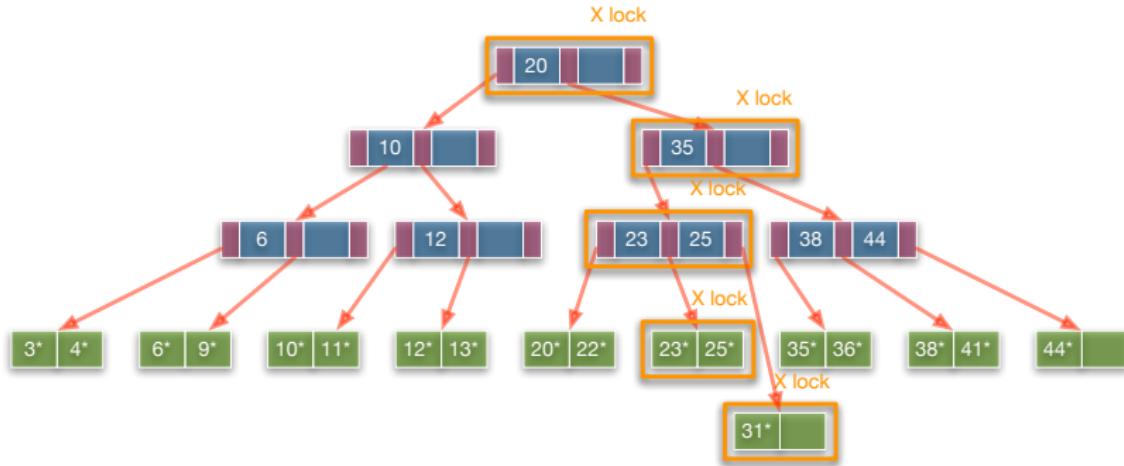
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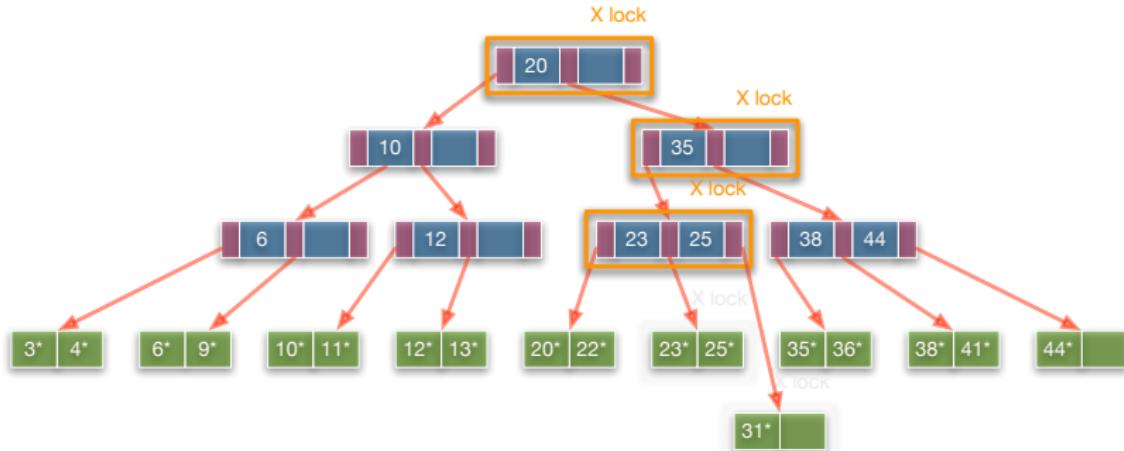
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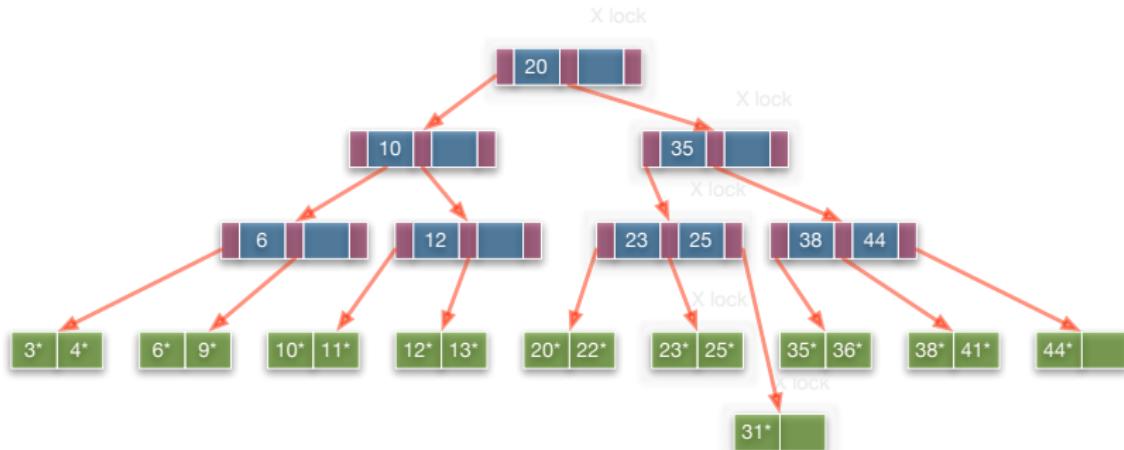
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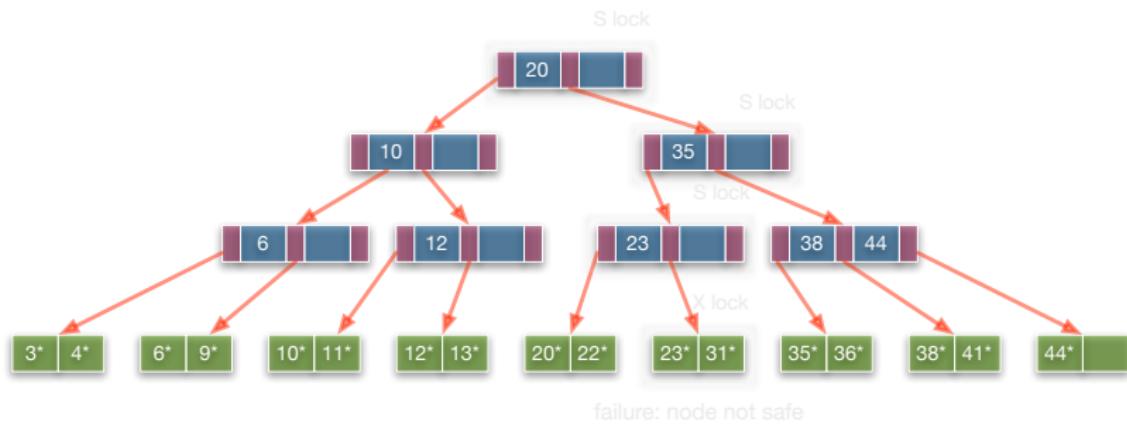


Obtain **X-locks** while *descending*; leaf-node is not safe so *create* a new one and *lock it in X-mode*; first release *locks on leaves* and then the rest *top-down*

Optimistic B+tree locking

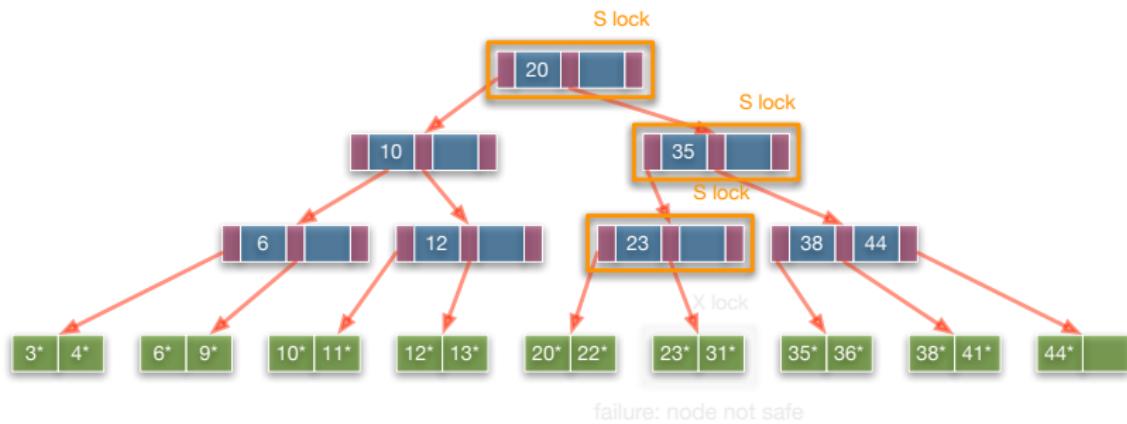
- *Search*: as before
- *Insert/delete*: set *locks as* if for *search*, get to the leaf, and *set X lock on the leaf*
 - ▶ If the *leaf is not safe*, *release all locks*, and *restart transaction, using previous insert/delete protocol*
- “*Gambles*” that only *leaf node* will be *modified*; if not,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

Example: insert 25*



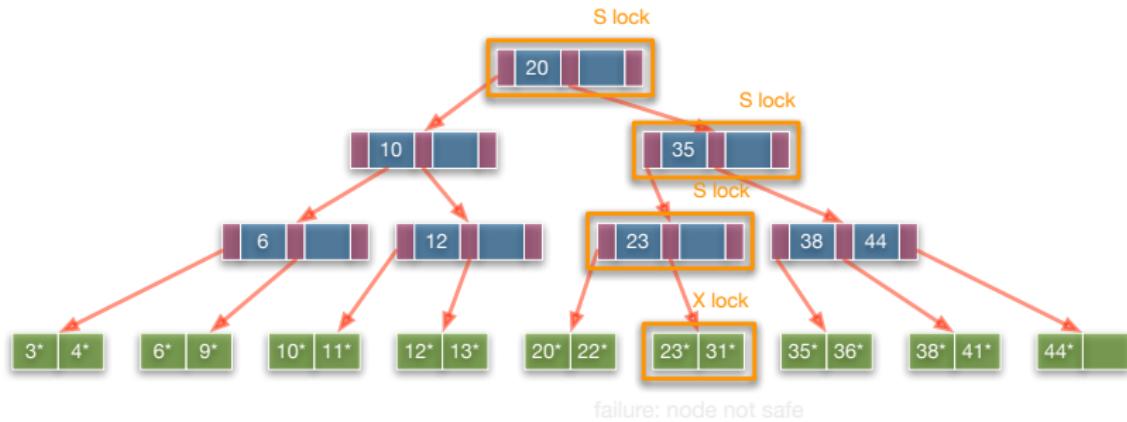
Obtain **S-locks** while *descending*, and **X-lock** at leaf; the leaf is *not safe*, so *abort*, *release all locks* and *restart* using the *previous algorithm*

Example: insert 25*



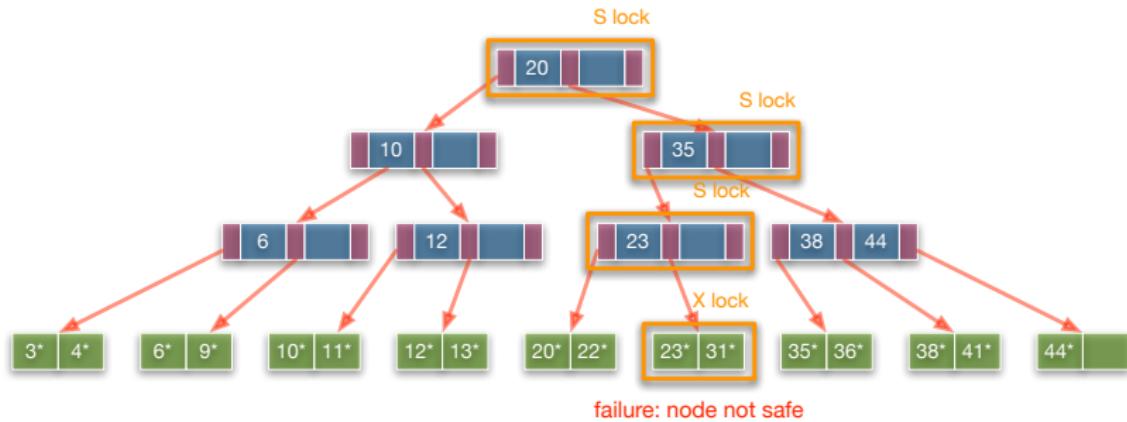
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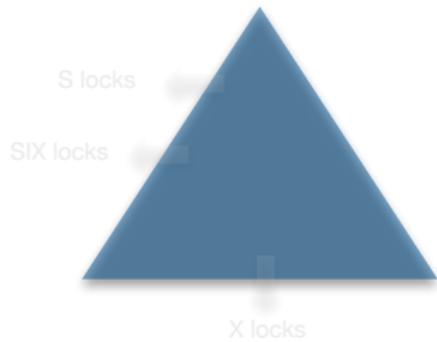


Obtain **S-locks** while *descending*, and **X-lock** at leaf; the leaf is *not safe*, so **abort**, **release all locks** and **restart** using the *previous algorithm*

Even better algorithm

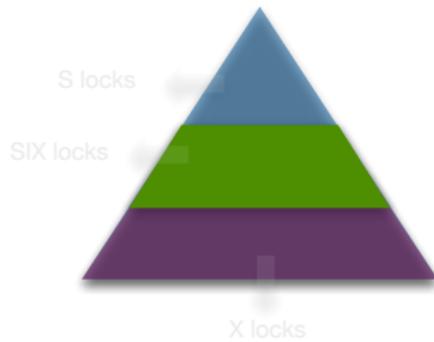
- *Search*: as before
- *Insert/delete*: use *original insert/delete protocol*, but *set IX locks instead of X locks at all nodes*
 - ▶ Once leaf is *locked*, convert all *IX locks to X locks top-down*: i.e., starting from the unsafe node nearest to root
 - ▶ *Top-down reduces chances of deadlock*
 -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

Hybrid approach



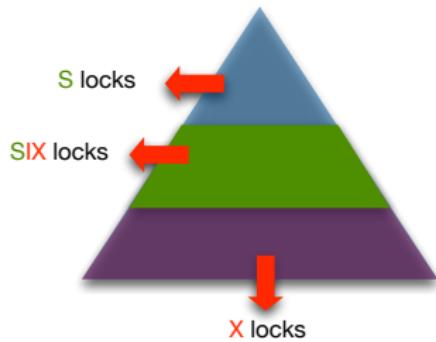
- The *likelihood* that we will *need* an *X lock* decreases as we *move up* the *tree*
- Set *S locks* at *high levels*, *SIX locks* at *middle levels*, *X locks* at *low levels*

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Transaction isolation

Transaction isolation

Isolation level	Dirty read	Unrepeatable read	Phantoms
Read uncommitted			
Read committed			
Repeatable reads			
Serialisable			

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Serialisable	No	No	No

Outline

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*

Review: ACID properties

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Atomicity and durability are ensured by the recovery algorithms

What can go wrong?

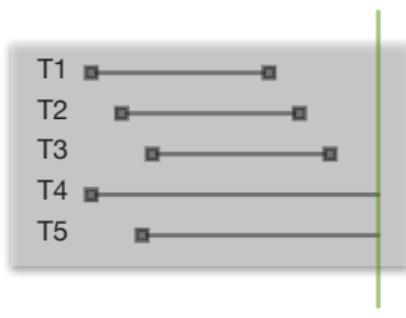
- *Atomicity*
 - ▶ *Transactions* may *abort*; their *effects* need to be *undone*
- *Durability*
 - ▶ What if the *system stops running*?



Transactional semantics

What can go wrong?

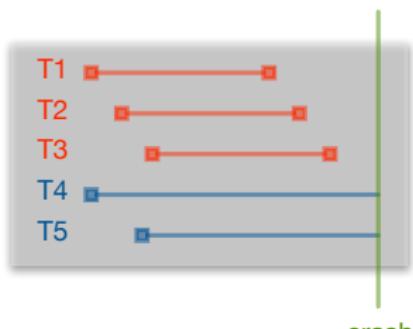
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Transactional semantics

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*



More on the buffer pool

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 - ▶ *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

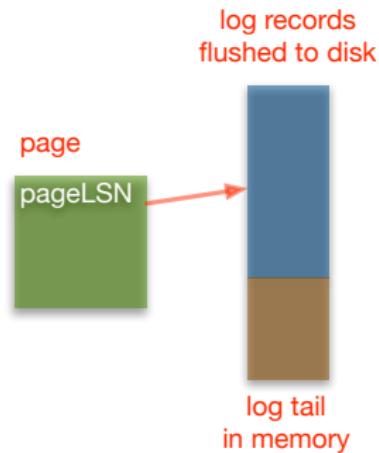
- The *log adheres* to the *write-ahead protocol* (WAL)
 - ① *Must force* the *log record* for an *update* before the *corresponding data page* gets to *disk*
 - ② *Must force* all *log records* for a *transaction* before it *commits*
- #1 guarantees *atomicity*
- #2 guarantees *durability*

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, $\text{pageLSN} \leq \text{flushedLSN}$*



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

log record

prevLSN
transID
type
pageID
length
offset
before-image
after-image

undo records
only

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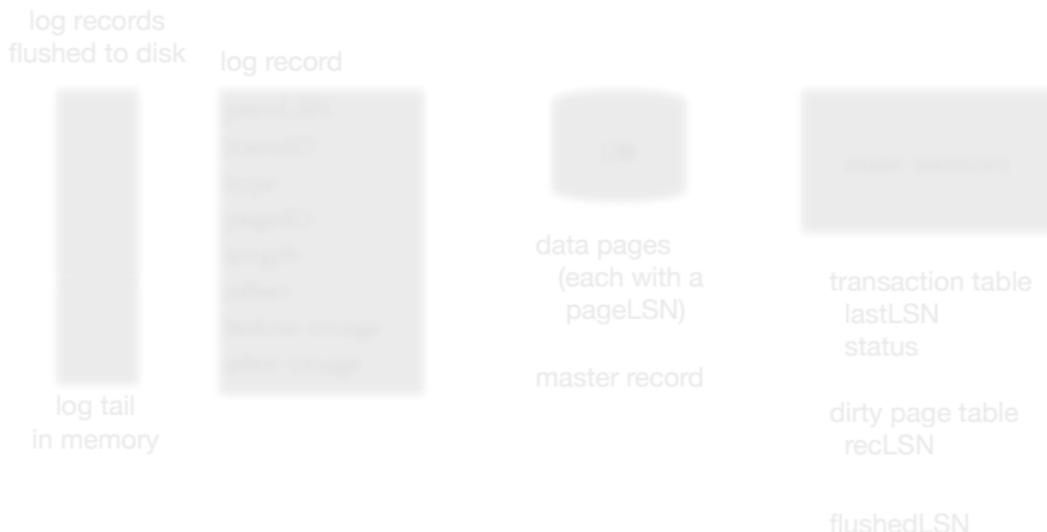
Other log-related state

- **Transaction table:** one *entry per active transaction*
 - ▶ Contains *transaction id*, *status* (running/committed/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*

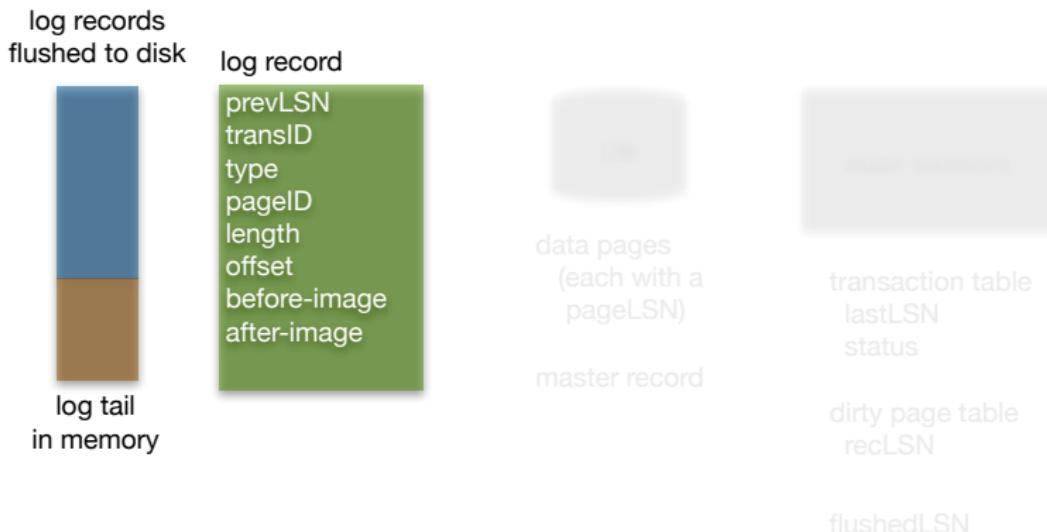
Checkpoint records

- **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)

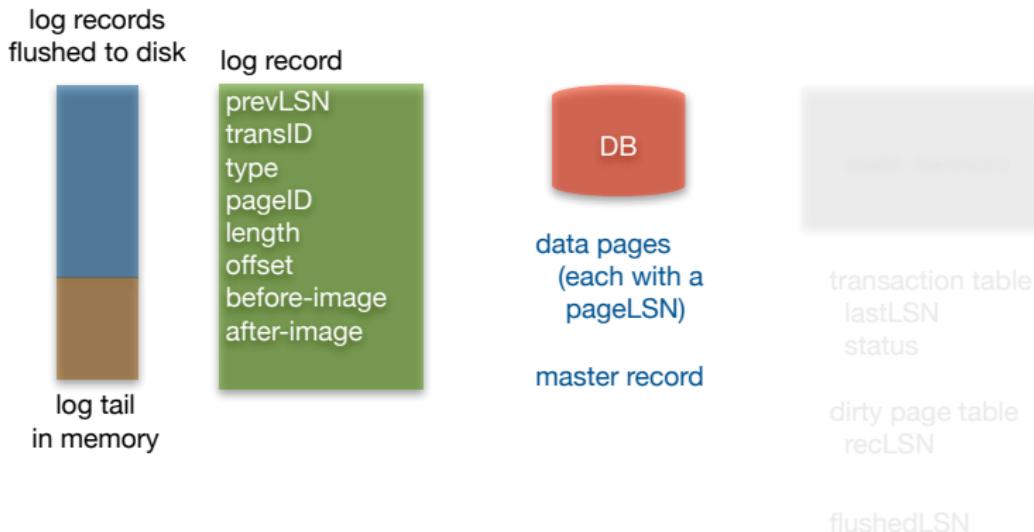
What's stored where



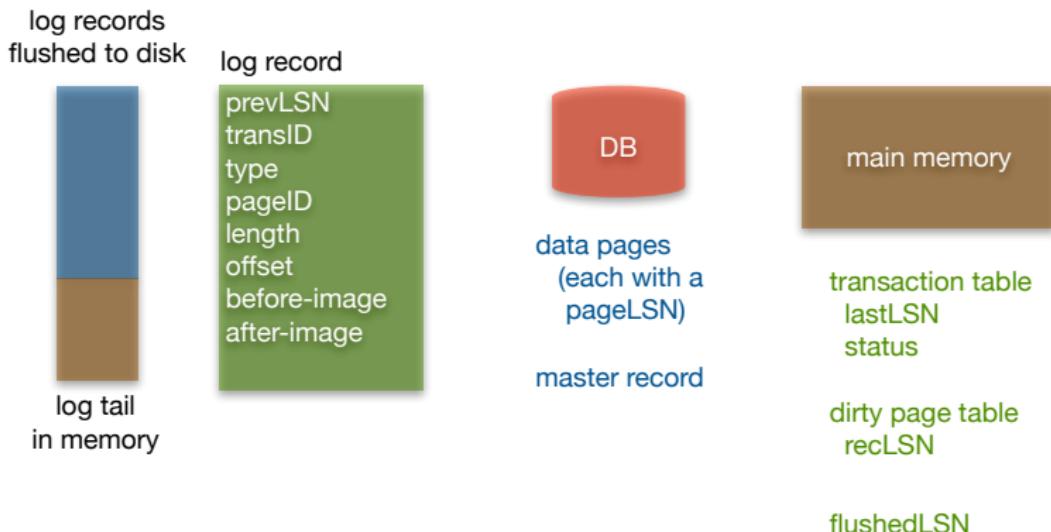
What's stored where



What's stored where



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 $\text{flushedLSN} \geq \text{lastLSN}$
 - ▶ 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

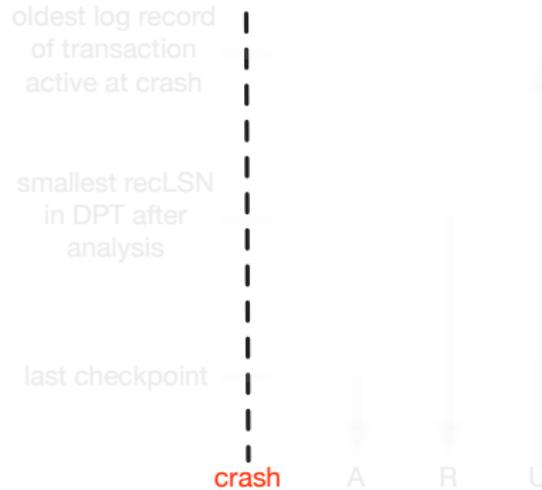
A

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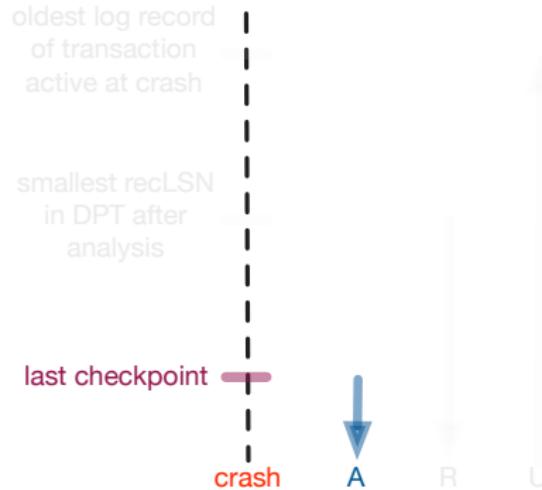
- **Start** from a *checkpoint* (found via *master record*)
- **Three phases**
 - ▶ **Analysis:** figure out which *transactions committed* since the checkpoint, and which *failed*
 - ▶ **REDO** all actions
 - ★ *Repeat history*
 - ▶ **UNDO** effects of *failed transactions*

Recovery: big picture



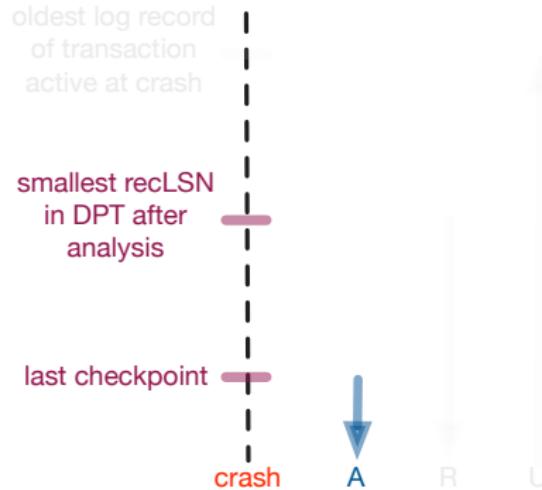
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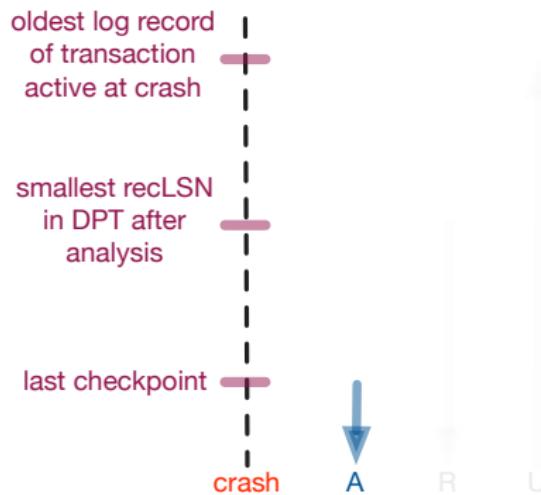
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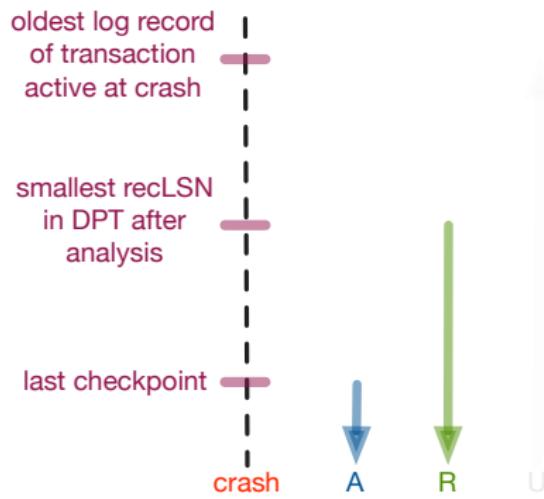
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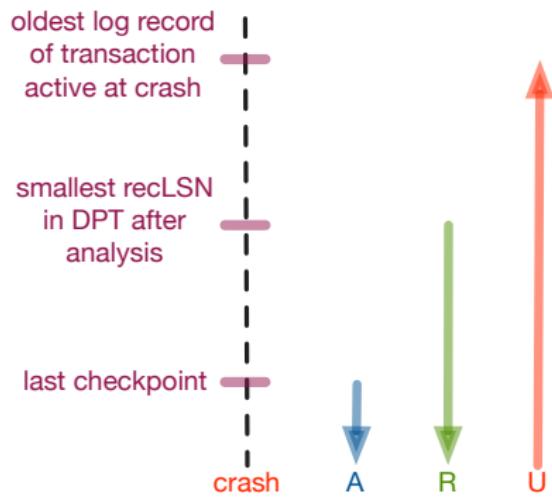
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Recovery: big picture



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 - ▶ **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*

Outline

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.)

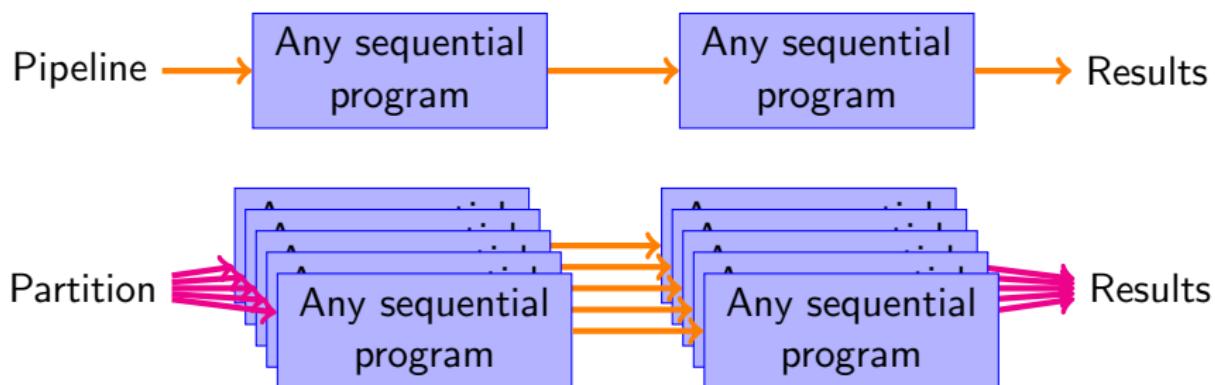
- Use *checkpoints* to *periodically record consistent states* and *limit* the amount of the *log* that needs to be *scanned during recovery*
- *Recovery* in *three phases*
 - ▶ *Analysis*: from checkpoint, *figure out REDO and UNDO extents*
 - ▶ *REDO*: *repeat entire history*
 - ▶ *UNDO*: *delete effects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

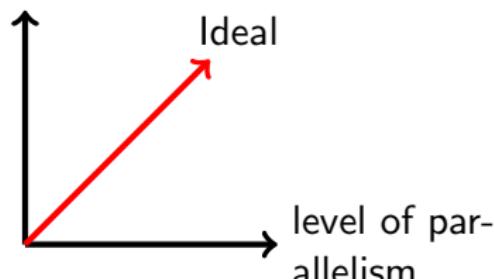
Speed-up

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

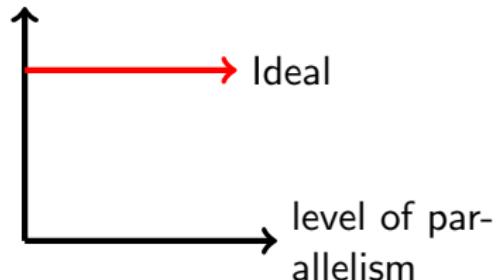
Scale-up

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

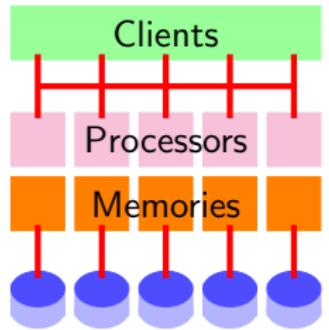
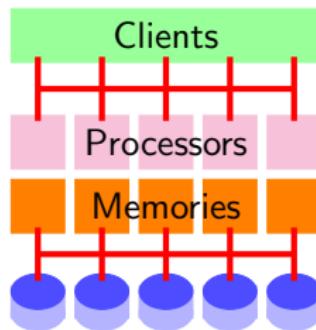
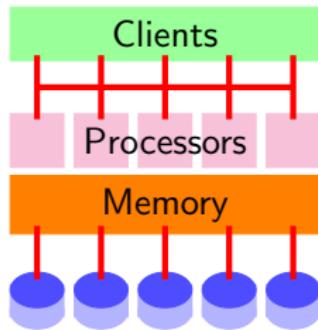
throughput



response



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*

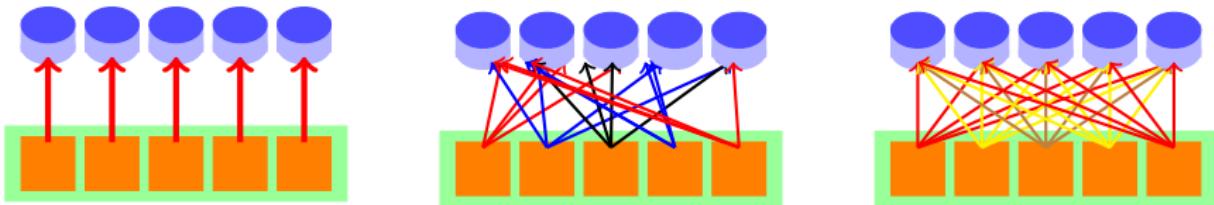
Shared nothing

- *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

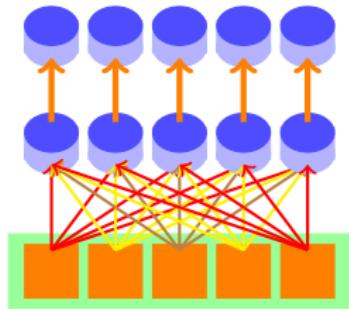
- *Indifferent* for *equi-joins*
- *Range-queries complicated*
- *Load-balanced*

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*
 - ▶ $\text{count}(S) = \sum_i \text{count}(s(i))$, ditto for *sum()*
 - ▶ $\text{avg}(S) = (\sum_i \text{sum}(s(i))) / \sum_i \text{count}(s(i))$
 - ▶ 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*

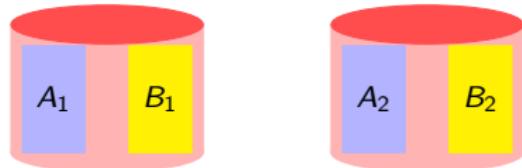
Parallel joins

- *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*

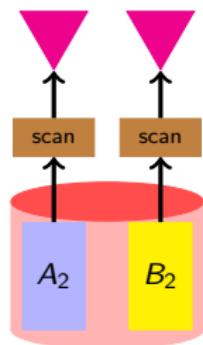
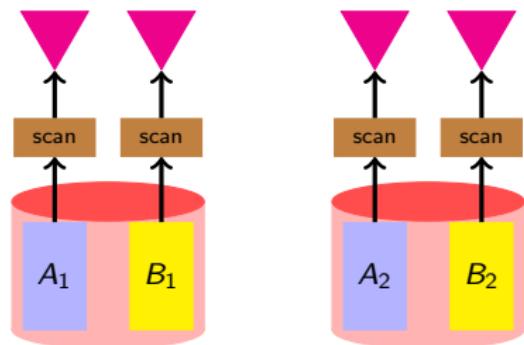
Parallel hash join

- 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

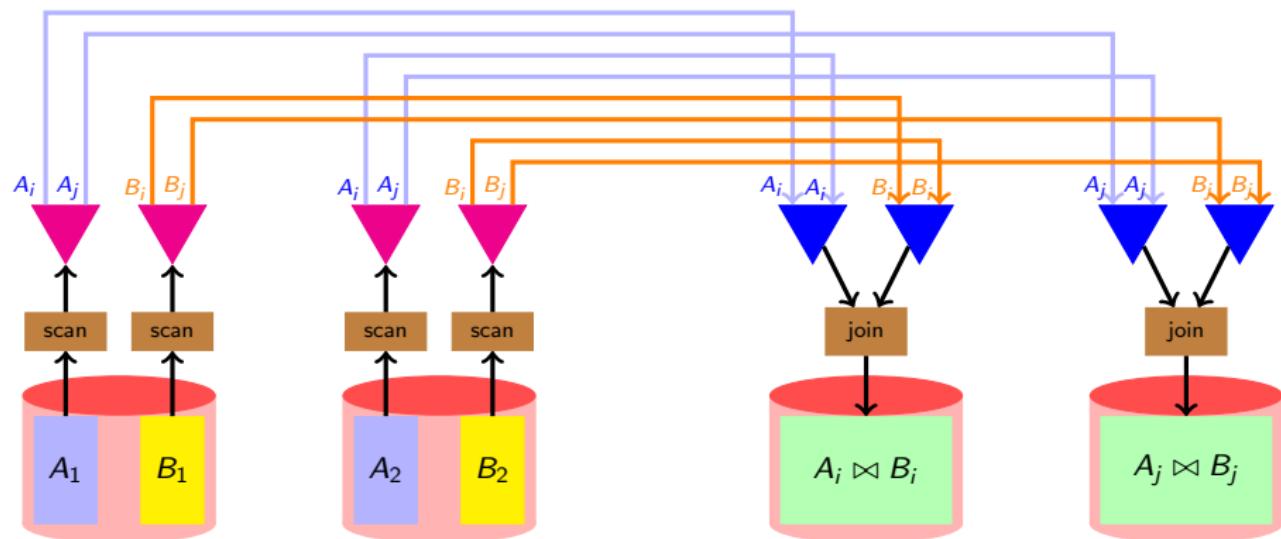
Dataflow network for parallel join



Dataflow network for parallel join

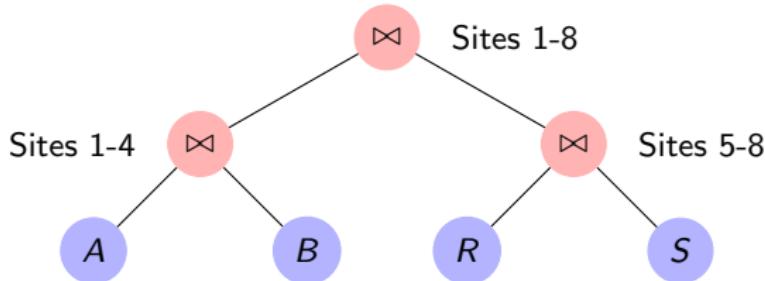


Dataflow network for parallel join



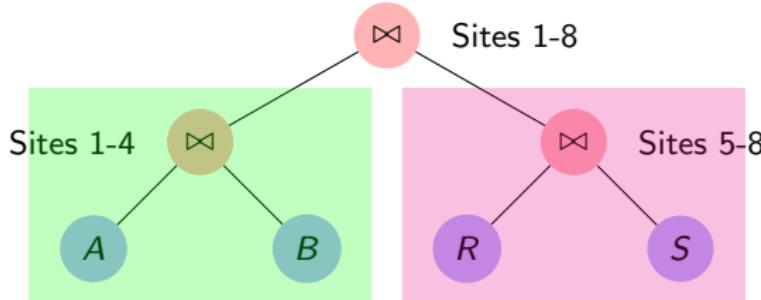
Complex parallel query plans

- **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



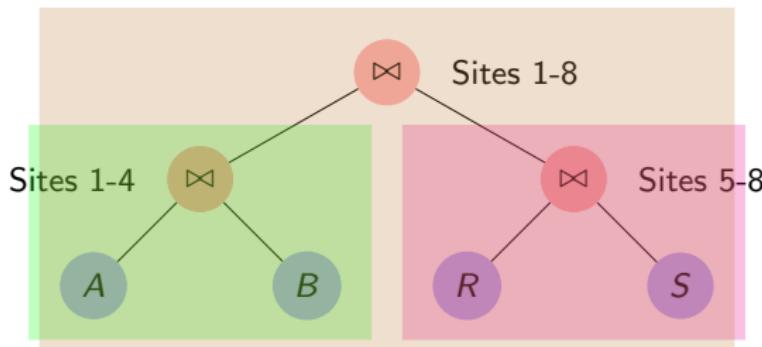
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Observations

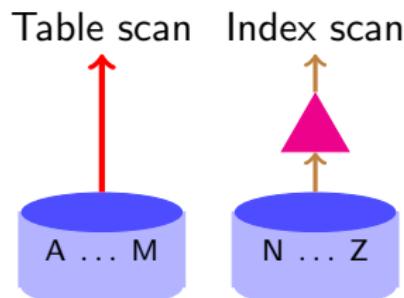
- It is *relatively easy* to build a *fast parallel query executor*
- It is *hard* to write a robust and world-class *parallel query optimizer*
 - ▶ There are many *tricks*
 - ▶ One quickly hits the *complexity barrier*
 - ▶ Still *open research*

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*