Database Implementation For Modern Hardware

Thomas Neumann

Introduction

Database Management Systems (DBMS) are extremely important

- used in nearly all commercial data management
- very large data sets
- valuable data

Key challenges:

- scalability to huge data sets
- reliability
- concurrency

Results in very complex software.

About This Lecture

Goals of this lecture

- learning how to build a modern DBMS
- understanding the internals of existing DBMSs
- understanding the effects of hardware behavior

Rough structure of the lecture

1. the classical DBMS architecture
2. efficient query processing
3. adapting the architecture to hardware trends

Literature

- Theo Härder, Erhard Rahm: *Datenbanksysteme - Konzepte und Techniken der Implementierung*. Springer-Verlag, 2001.
- Hector Garcia-Molina, Jeff Ullman, and Jennifer Widom: *Database Systems: The Complete Book*. Prentice-Hall, 2008.
- Jim Gray, Andreas Reuter: *Transaction Processing: Concepts and Techniques*. Morgan Kaufmann 1993

Unfortunately mainly cover the classical architecture.

Motivational Example

Why is a DBMS different from most other programs?

- many difficult requirements (reliability etc.)
- but a key challenge is **scalability**

Motivational example

Given two lists L_1 and L_2, find all entries that occur on both lists.

Looks simple...

Motivational Example (2)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Simple if both fit in main memory

Motivational Example (2)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Simple if both fit in main memory

- sort both lists and intersect
- or put one in a hash table and probe
- or build index structures
- or ...

Note: pairwise comparison is not an option! $O(n^2)$

Motivational Example (3)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Slightly more complex if only one fits in main memory

Motivational Example (3)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Slightly more complex if only one fits in main memory

- load the smaller list into memory
- build index structure/sort/hash/...
- scan the larger list
- search for matches in main memory

Code still similar to the pure main-memory case.

Motivational Example (4)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Difficult if neither list fits into main memory

Motivational Example (4)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Difficult if neither list fits into main memory

- no direct interaction possible
- sorting works, but already a difficult problem
- or use some kind of partitioning scheme
- breaks the problem into smaller problem
- until main memory size is reached

Code significantly more involved.

Motivational Example (5)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Hard if we make no assumptions about L_1 and L_2.

Motivational Example (5)

Given two lists L_1 and L_2, find all entries that occur on both lists.

Hard if we make no assumptions about L_1 and L_2.

- tons of corner cases
- a list can contain duplicates
- a single duplicate might exceed main memory!
- breaks "simple" external memory logic
- multiple ways to solve this
- but all of them somewhat involved
- and a DBMS must not make assumptions about its data!

Code complexity is very high.

Motivational Example (6)

Designing scalable algorithm is a hard problem

- must cope with very large instances
- hard even in main memory
- billions of data items
- rules out any $O(n^2)$ algorithm
- external algorithms are even harder

This requires a careful software architecture.

Set-Oriented Processing

Small applications often loop over their data

- one for loop accesses all item x,
- for each item, another loop access item y,
- then both items are combined.

This kind of code of code feels "natural", but is bad

- $\Omega(n^2)$ runtime
- does not scale

Instead: **set oriented** processing. Perform operations for large batches of data.

Relational Algebra

Notation:

- $\mathcal{A}(e)$ attributes of the tuples produces by e
- $\mathcal{F}(e)$ free variables of the expression e
- binary operators $e_1 \theta e_2$ usually require $\mathcal{A}(e_1) = \mathcal{A}(e_2)$

$e_1 \cup e_2$	union, $\{x \mid x \in e_1 \vee x \in e_2\}$
$e_1 \cap e_2$	intersection, $\{x \mid x \in e_1 \wedge x \in e_2\}$
$e_1 \setminus e_2$	difference, $\{x \mid x \in e_1 \wedge x \notin e_2\}$
$\rho_{a \to b}(e)$	rename, $\{x \circ (b : x.a) \setminus (a : x.a) \mid x \in e\}$
$\Pi_A(e)$	projection, $\{\circ_{a \in A}(a : x.a) \mid x \in e\}$
$e_1 \times e_2$	product, $\{x \circ y \mid x \in e_1 \wedge y \in e_2\}$
$\sigma_p(e)$	selection, $\{x \mid x \in e \wedge p(x)\}$
$e_1 \bowtie_p e_2$	join, $\{x \circ y \mid x \in e_1 \wedge y \in e_2 \wedge p(x \circ y)\}$

per definition set oriented. Similar operators also used bag oriented (no implicit duplicate removal).

Relational Algebra - Derived Operators

Additional (derived) operators are often useful:

$e_1 \bowtie e_2$	natural join, $\{x \circ y_{\mid \mathcal{A}(e_2) \setminus \mathcal{A}(e_1)} \mid x \in e_1 \wedge y \in e_2 \wedge x =_{\mid \mathcal{A}(e_1) \cap \mathcal{A}(e_2)} y\}$
$e_1 \div e_2$	division, $\{x_{\mid \mathcal{A}(e_1) \setminus \mathcal{A}(e_2)} \mid x \in e_1 \wedge \forall y \in e_2 \exists z \in e_1 : y =_{\mid \mathcal{A}(e_2)} z \wedge x =_{\mid \mathcal{A}(e_1) \setminus \mathcal{A}(e_2)} z\}$
$e_1 \ltimes_p e_2$	semi-join, $\{x \mid x \in e_1 \wedge \exists y \in e_2 : p(x \circ y)\}$
$e_1 \triangleright_p e_2$	anti-join, $\{x \mid x \in e_1 \wedge \nexists y \in e_2 : p(x \circ y)\}$
$e_1 ⟗_p e_2$	outer-join, $(e_1 \bowtie_p e_2) \cup \{x \circ \circ_{a \in \mathcal{A}(e_2)}(a : null) \mid x \in (e_1 \triangleright_p e_2)\}$
$e_1 ⟗_p e_2$	full outer-join, $(e_1 ⟕_p e_2) \cup (e_2 ⟕_p e_1)$

Relational Algebra - Extensions

The algebra needs some extensions for real queries:

- map/function evaluation
  $\chi_{a:f}(e) = \{x \circ (a : f(x)) | x \in e\}$
- group by/aggregation
  $\Gamma_{A;a:f}(e) = \{x \circ (a : f(y)) | x \in \Pi_A(e) \wedge y = \{z | z \in e \wedge \forall a \in A : x.a = z.a\}\}$
- dependent join (djoin). Requires $\mathcal{F}(e_2) \subseteq \mathcal{A}(e_1)$
  $e_1 ⋈\!\!\!\blacktriangleright_p e_2 = \{x \circ y | x \in e_1 \wedge y \in e_2(x) \wedge p(x \circ y)\}$

Set-Oriented Processing (2)

Processing whole batches of tuples is more efficient:

- can prepare index structures
- or re-organize the data
- sorting/hashing
- runtime ideally $O(nlogn)$

Many different algorithms, we will look at them later.

Traditional Assumptions

Historically, DBMS are designed for the following scenario:

- data is much larger than main memory
- I/O costs dominate everything
- random I/O is very expensive

This led to a very **conservative**, but also very **scalable** design.

Hardware Trends

Hardware development changed some of the assumptions

- main memory size is increasing
- servers with 1TB main memory are affordable
- flash storage reduces random I/O costs
- ...

This has consequences for DBMS design

- CPU costs become more important
- often I/O is eliminated or greatly reduced
- the old architecture becomes suboptimal

But this is more evolution than revolution. Many of the old techniques are still required for scalability reasons.

Goals

Ideally, a DBMS

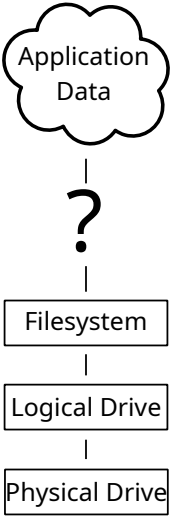
- handles arbitrarily large data sets efficiently
- never loses data
- offers a high-level API to manipulate and retrieve data
- shields the application from the complexity of data management
- offers excellent performance for all kinds of queries and all kinds of data

This is a very ambitious goal!
In many cases indeed reached, but implies complexity.

Overview

Storage

The Problem


Application Data
?
Filesystem
Logical Drive
Physical Drive

Requirements

There are different classes of requirements:

- Data Independence
  - application is shielded from physical storage
  - physical storage can be reorganized
  - hardware can be changed
- Scalability
  - must scale to (nearly) arbitrary data sizes
  - fast retrieval
  - efficient access to individual data items
  - updating arbitrary data
- Reliability
  - data must never be lost
  - must cope with hardware and software failures
- ...

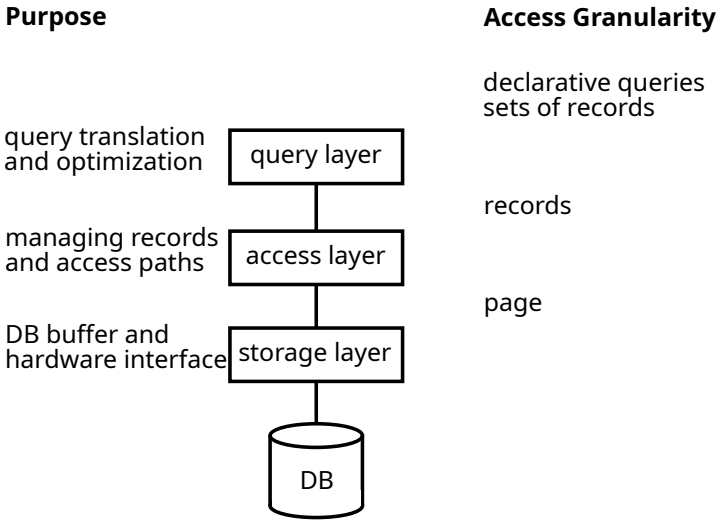
Layer Architecture

- implementing all these requirements on the "bare metal" is hard
- and not desirable
- a DBMS must be maintainable and extensible

Instead: use a **layer** architecture

- the DBMS logic is split into levels of functionality
- each level is implemented by a specific layer
- each layer interacts only with the next lower layer
- simplifies and modularizes the code

A Simple Layer Architecture

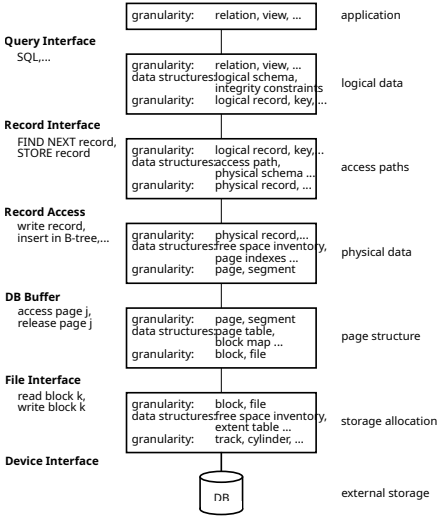


A Simple Layer Architecture (2)

- layers can be characterized by the data items they manipulate
- lower layer offers functionality for the next higher level
- keeps the complexity of individual layers reasonable
- rough structure: physical $\rightarrow$ low level $\rightarrow$ high level

This is a reasonable architecture, but simplified.
A more detailed architecture is needed for a complete DBMS.

A More Detailed Architecture



A More Detailed Architecture (2)

A few pieces are still missing:

- transaction isolation
- recovery

but otherwise it is a reasonable architecture.

Some system deviate slightly from this classical architecture

- most DBMSs nowadays delegate drive access to the OS
- some DBMSs delegate buffer management to the OS (tricky, though)
- a few DBMSs allow for direct logical record access
- ...

Influence of Hardware

Must take hardware into account when designing a storage system.

For a long time dominated by **Moore's Law**:

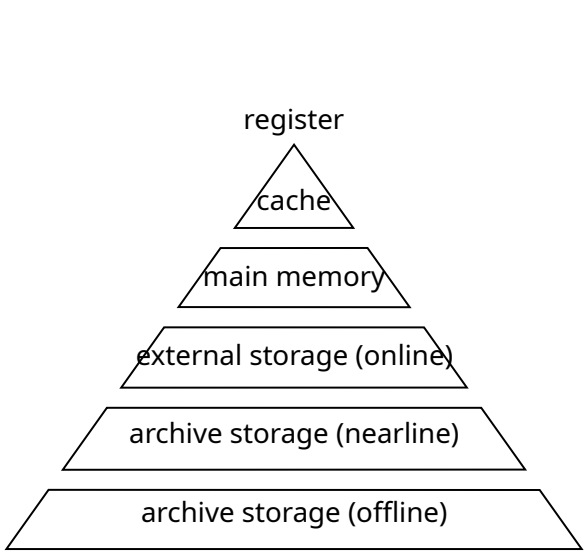
The number of transistors on a chip doubles every 18 month.

Indirectly drove a number of other parameters:

- main memory size
- CPU speed
  - no longer true!
- HD capacity
  - start getting problematic, too. density is very high
  - only capacity, not access time

Later we will look at these again.

Memory Hierarchy



Memory Hierarchy (2)

There are huge gaps between hierarchy levels

- traditionally, main memory vs. disk is most important
- but memory vs. cache etc. also relevant

The DBMS must aim to maximize locality.

Hard Disk Access

Hard Disks are still the dominant external storage:

- rotating platters, mechanical effects
- transfer rate: ca. 150MB/s
- seek time ca. 3ms
- huge imbalance in random vs. sequential I/O!

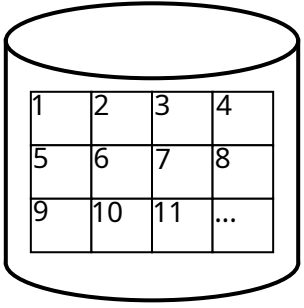
The DBMS must take these effects into account

- sequential access is much more efficient
- gap is growing instead of shrinking
- even SSDs are slightly asymmetric (and have other problems)

Hard Disk Access (2)

Techniques to speed up disk access:

- do not move the head for every single tuple
- instead, load larger chunks
- typical granularity: one **page**
- page size varies. traditionally 4KB, nowadays often 16K and more
- page size is a trade-off



Hard Disk Access (3)

The page structure is very prominent within the DBMS

- granularity of I/O
- granularity of buffering/memory management
- granularity of recovery

Page is still too small to hide random I/O though

- sequential page access is important
- DBMSs use read-ahead techniques
- asynchronous write-back

Buffer Management

Some pages are accessed very frequently

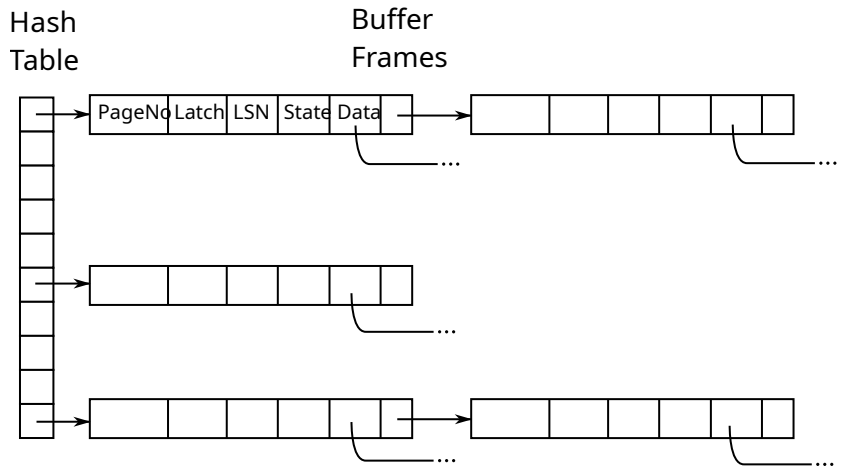
- reduce I/O by buffering/caching
- buffer manager keeps active pages in memory
- limited size, discards/write back when needed
- coupled with recovery, in particular logging

Basic interface:

1. FIX(pageNo,shared)
2. UNFIX(pageNo,dirty)

Pages can only be accessed (or modified) when they are **fixed**.

Buffer Managment



The buffer manager itself is protected by one or more latches.

Buffer Frame

Maintains the state of a certain page within the buffer

pageNo	the page number
latch	a read/writer lock to protect the page (note: must not block unrelated pages!)
LSN	LSN of the last change, for recovery (buffer manager must force the log before writing)
state	clean/dirty/newly created etc.
data	the actual data contained on the page

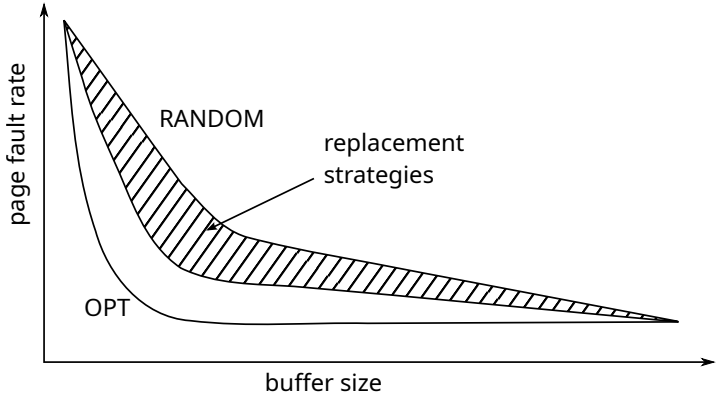
(will usually contain extra information for buffer replacement)

Usually kept in a hash table.

Buffer Replacement

When memory is full, some buffer pages have to be replaced

- clean pages can be simply discarded
- dirty pages have to be written back first
- discarded pages are replaced with new pages



Buffer Replacement - FIFO

First In - First Out

- simple replacement strategy
- buffer frames are kept in a linked list
- inserted at the end, remove from the head
- “old” pages are removed first

Does not take locality into account.

Buffer Replacement - LRU

Least Recently Used

- similar to FIFO, buffer frames are kept in a double-linked list
- remove from the head
- when a frame is unfixed, move it to the end of the list
- "hot" pages are kept in the buffer

A very popular strategy. Latching requires some care.

Buffer Replacement - LFU

Least Frequently Used

- remembers the number of access per page
- in-frequently used pages are remove first
- maintains a priority queue of pages

Sounds plausible, but too expensive in practice.

Buffer Replacement - Second Chance

LRU is nice, but the LRU list is a hot spot.

Idea: use a simpler mechanism to simulate LRU

- one bit per page
- bit is set when page is unfixed
- when replacing, replace pages with unset bit
- set bits are cleared during the process
- strategy is called “second chance” or “clock”

Easy to implement, but a bit crude.

Buffer Replacement - 2Q

Maintain not one queue but two

- many pages are referenced only once
- some pages are hot and reference frequently
- maintain a separate list for those

1. maintain all pages in FIFO queue
2. when a page is references again that is currently in FIFO, move it into an LRU queue
3. prefer evicting from FIFO

Hot pages are in LRU, read-once pages in FIFO. Good strategy for common DBMS operations.

Buffer Replacement - Hints

Application knowledge can help buffer replacement

- 2Q tries to recognize read-once pages
- these occur when scanning over data
- but the DBMS knows this anyway!
- it could therefore give **hints** when unfixing
- e.g., *will-need*, or *will-not-need* (changes placement in queue)

Segments

While page granularity is fine for I/O, it is somewhat unwieldy

- most structures within a DBMS span multiple pages
- relations, indexes, free space management, etc.
- convenient to treat these as one entity
- all DBMS pages are partitioned into sets of pages

Such a set of pages is called a **segment**.

Conceptually similar to a file or virtual memory.

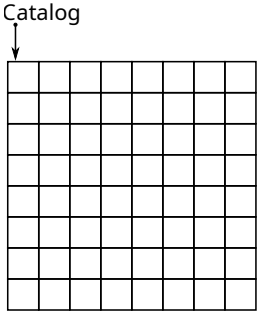
Segments (2)

A segment offers a virtual address space within the DBMS

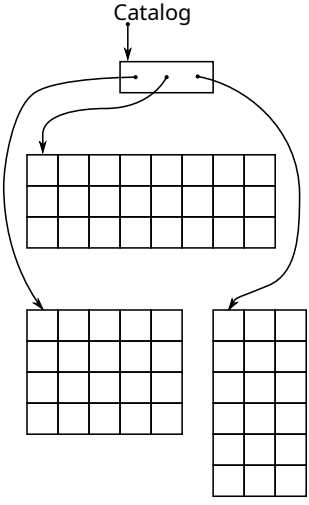
- can allocate and release new pages
- can iterate over all pages
- can drop the whole segment
- optionally offers a linear address space

Greatly simplifies the logic of higher layers.

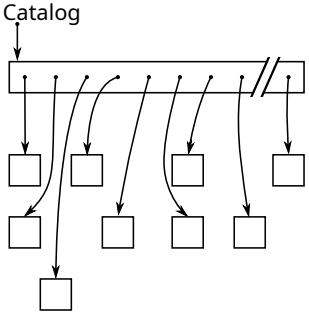
Block Allocation



static file-mapping



dynamic extent-mapping



dynamic block-mapping

Block Allocation

All approaches have pros and cons:

- static file-mapping
  - very simple, low overhead
  - resizing is difficult
- dynamic block-mapping
  - maximum flexibility
  - administrative overhead, additional indirection
- dynamic extent-mapping
  - can handle growth
  - slight overhead

In most cases extent-based mapping is preferable.

Block Allocation (5)

Dynamic extent-mapping:

- grows by adding a new extent
- should grow exponentially (e.g., factor 1.25)
- bounds the number of extents
- reduces both complexity and space consumption
- and helps with sequential I/O!

Segment Types

Segments can be classified into types

- private vs. public
- permanent vs. temporary
- automatic vs. manual
- with recovery vs. without recovery

Differ in complexity and required effort.

Standard Segments

Most DBMS will need at least two low-level segments:

- segment inventory
  - keeps track of all pages allocated to segments
  - keeps extent lists or page tables or ...
- free space inventory
  - keeps track of free pages
  - maintains bitmaps or free extents or ...

High-level segments built upon these.

Common high-level segments:

- schema
- relations
- temp segments (created and discard on demand)
- ...

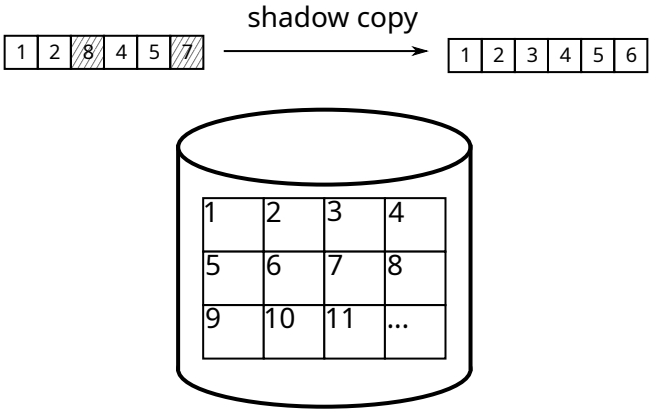
Update Strategies

DBMSs have different update behavior

	steal	¬ steal
force		
¬ force		

- usually one prefers steal, ¬ force
- but then pages contain dirty data
- when using *update-in-place*, dirty data is on on disk
- complicates recovery
- transactions could see dirty data

Shadow Paging



uses a page table, dirty pages are stored in a shadow copy.

Shadow Paging (2)

Advantages:

- the clean data is always available on disk
- greatly simplified recovery
- can be used for transaction isolation, too

Disadvantages:

- complicates the page access logic
- destroys data locality

Nowadays rarely used in disk-based systems.

Delta Files

Similar idea to shadow paging:

- on change pages are copied to a separate file
- a copied page can be changed in-place
- on commit discard the file, on abort copy back

Can be implemented in two flavors:

- store a clean copy in the delta
- store the dirty data in the delta

Both have pros and cons.

Delta Files (2)

Delta files have some advantages over shadow paging:

- preserve data locality
- no mixture of clean and dirty pages

Disadvantages:

- cause more I/O
- abort (or commit) becomes expensive
- keeping track of delta pages is non-trivial

Still, often preferable over shadow paging.

Access Paths

Data Structures

The DBMS needs several separate data structures

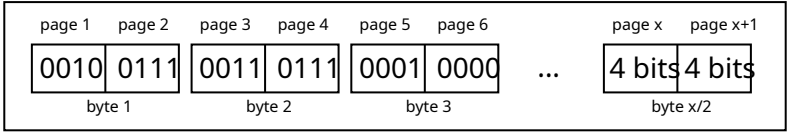
- for the free space management
- for the data itself (storage and retrieval)
- for unusually large data
- for index structures to speed up access

We will look at these in more detail.

Free Space Inventory

Problem: Where do we have space for incoming data?

Traditional solution: free space bitmap



Each nibble indicates the fill status of a given page.

Free Space Inventory (2)

Encode the fill status in 4 bits (some system use only 1 or 2):

- must approximate the status
- one possibility: data size / $\frac{\text{page size}}{2^{bits}}$
- loss of accuracy in the lower range
- logarithmic scale is often better
- $\lceil \log_2(\text{text size}) \rceil$
- or a combination (logarithmic for lower range, linear for upper range)

Encodes the free space (alternative: the used space) in a few bits.

Free Space Inventory (3)

When inserting data,

- compute the required FSI entry (e.g., ≤ 7)
- scan the FSI for a matching entry
- insert the data on this page

Problem:

- linear effort
- FSI is small, for 16KB pages 1 FSI page covers 512MB
- but scan still not free
- only 16 FSI values, cache the next matching page (range)
- most pages will be static (and full anyway)
- segments will mostly grow at the end
- cache avoids scanning most of the FSI entries

Allocation

Allocating pages (or parts of a page) benefits from application knowledge

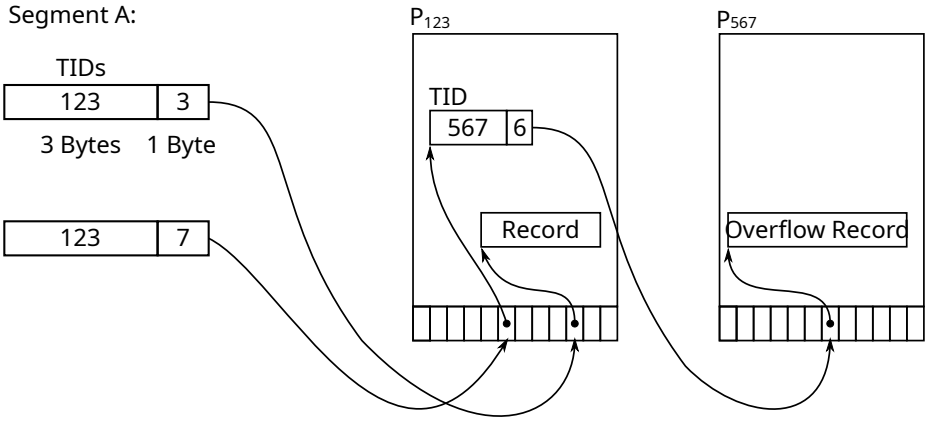
- often larger pieces are inserted soon after each other
- e.g. a set of tuples
- or one very large data item
- should be allocated close to each other

Allocation interface is usually

$$allocate(min, max)$$

- max is a hint to improve data layout
- some interfaces (e.g., segment growth) even implement over-allocation
- reduces fragmentation

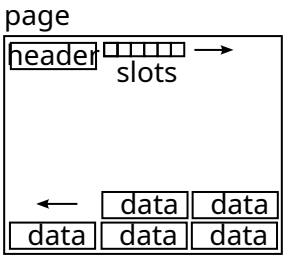
Slotted Pages



(TID size varies, but will most likely be at least 8 bytes on modern systems)

Slotted Pages (2)

Tuples are stored in slotted pages



- data grows from one side, slots from the other
- the page is full when both meet
- updates/deletes complicate issues, though
- might require garbage collection/compactification

Slotted Pages (3)

Header:

LSN	for recovery
slotCount	number of used slots
firstFreeSlot	to speed up locating free slots
dataStart	lower end of the data
freeSpace	space that would be available after compactification

Note: a slotted page can contain hundreds of entries!
Requires some care to get good performance.

Slotted Pages (4)

Slot:

offset	start of the data item
length	length of the data item

Special cases:

- free slot: offset $= 0$, length $= 0$
- zero-length data item: offset > 0, length $= 0$

Slotted Pages (5)

Problem:

1. transaction T_1 updates data item i_1 on page P_1 to a very small size (or deletes i_1)
2. transaction T_2 inserts a new item i_2 on page P_1, filling P_1 up
3. transaction T_2 commits
4. transaction T_1 aborts (or T_3 updates i_1 again to a larger size)

TID concept $\Rightarrow$ create an indirection
but where to put it? Would have to move i_1 and i_2.

Slotted Pages (6)

Logic is much simpler if we can store the TID inside the slot

- borrow a bit from the TID (or have some other way to detect invalid TIDs)
- if the slot contains a valid TID, the entry is redirected
- otherwise, it is a regular slot

Depending on page size size, this wastes a bit space.
But greatly simplifies the slotted page implementation.

Slotted Pages (7)

One possible slot implementation:

T	S	O	O	O	L	L	L

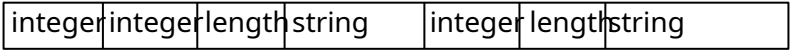
1. if $T \neq 11111111_b$, the slot points to another record
2. otherwise the record is on the current page
   - 2.1 if $S = 0$, the item is at offset O, with length L
   - 2.2 otherwise, the item was moved from another page
     - it is also placed at offset O, with length L
     - but the first 8 bytes contain the original TID

The original TID is important for scanning.

Record Layout

The tuples have to be materialized somehow.

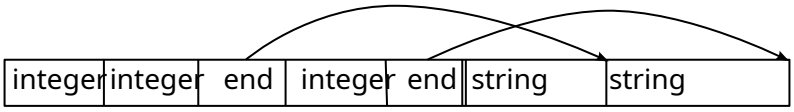
One possibility: serialize the attributes



Problem: accessing an attribute is $O(n)$ in worst case.

Record Layout (2)

It is better to store offset instead of lengths



- splits tuple into two parts
- fixed size header and variable size tail
- header contains pointers into the tail
- allows for accessing any attribute in $O(1)$

Record Layout (3)

For performance reasons one should even reorder the attributes

- split strings into length and data
- re-order attributes by decreasing alignment
- place variable-length data at the end
- variable length has alignment 1

Gives better performance without wasting any space on padding.

NULL Values

What about NULL values?

- represent an unknown/unspecified value
- is a special value outside the regular domain

Multiple ways to store it

- either pick an invalid value (not always possible)
- or use a separate NULL bit

NULL bits allow for omitting NULL values from the tuple

- complicates the access logic
- but saves space
- useful if NULL values are common.

Compression

Some DBMS apply compression techniques to the tuples

- most of the time, compression is **not** added to save space!
- disk is cheap after all
- compression is used to **improve performance**!
- reducing the size reduces the bandwidth consumption

Some people really care about space consumption, of course.
But outside embedded DBMSs it is usually an afterthought.

Compression (2)

What to compress?

- the larger data compressed chunk, the better the compression
- but: DBMS has to handle updates
- usually rules out page-wise compression
- individual tuples can be compressed more easily

How to compress?

- general purpose compression like LZ77 too expensive
- compression is about performance, after all
- most system use special-purpose compression
- byte-wise to keep performance reasonable

Compression (3)

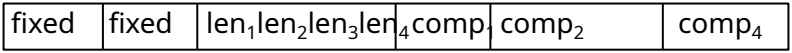
A useful technique for integer: variable length encoding

length (2 bits)	data (0-4 bytes)

	Variant A	Variant B
00	1 byte value	NULL, 0 bytes value
01	2 bytes value	1 byte value
10	3 bytes value	2 bytes value
11	4 bytes value	4 bytes value

Compression (4)

The length is fixed length, the compressed data is variable length



Problem: locating compressed attributes

- depends on preceding compression
- would require decompressing all previous entries
- not too bad, but can be sped up
- use a lookup tuples per length byte

Compression (5)

Another popular technique: dictionary compression

Dictionary:

1	Berlin
2	München
3	Passauerstraße
...	...

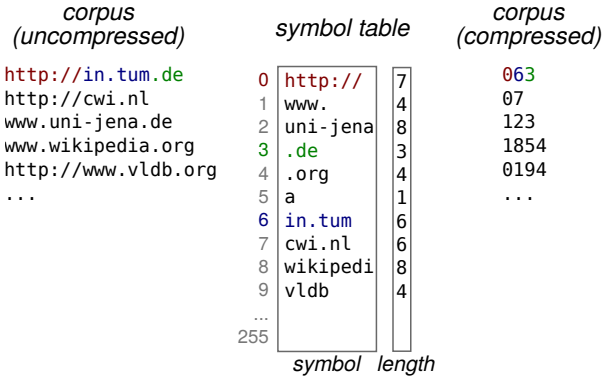
Tuples:

city	street	number
1	3	5
2	3	7
...	...	...

- stores strings in a dictionary
- stores only the string id in the tuple
- factors out common strings
- can greatly reduce the data size
- can be combined with integer compression

Compression (6)

Compressing the strings: FSST



- compresses even short strings
- allow for random access within compressed data
- very fast decompression

Long Records

Data is organized in pages

- many reasons for this, including recovery, buffer management, etc.
- a tuple must fit on a single page
- limits the maximum size of a tuple

What about large tuples?

- sometimes the user wants to store something large
- e.g., embed a document
- SQL supports this via BLOB/CLOB

Requires some mechanism so handle these large records.

Long Records (2)

Simply spanning pages is not a good idea:

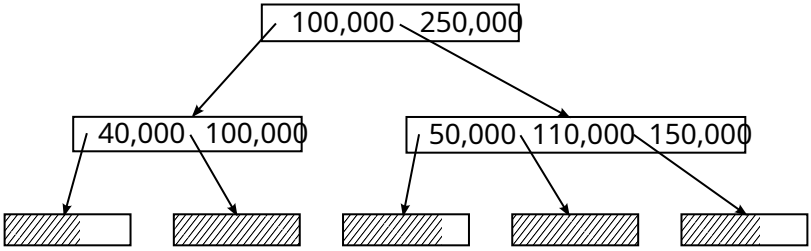
- must read an unbounded number of pages to access a tuple
- greatly complicates buffering
- a tuple might not even fit into main memory!
- updates that change the size are complicated
- intermediate results during query processing

Instead, keep the main tuple size down

- BLOBS/CLOBS are stored separate from the tuple
- tuple only contains a pointer
- increases the costs of accessing the BLOB, but simplifies tuple processing

Long Records (3)

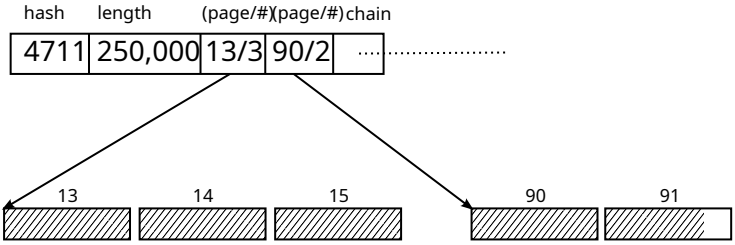
BLOBs can be stored in a B-Tree like fashion



- (relative) offset is search key
- allows for accessing and updating arbitrary parts
- very flexible and powerful
- but might be over-sophisticated
- SQL does not offer this interface anyway

Long Records (4)

Using an extent list is simpler



- real tuple points to BLOB tuple
- BLOB tuple contains a header and an extent list
- in worst case the extent list is chained, but should rarely happen
- extent list only allows for manipulating the BLOB in one piece
- but this is usually good enough
- hash and length to speed up comparisons

Long Records (5)

It makes sense to optimize for short BLOBs/CLOBs

- users misuse BLOBs/CLOBs
- they use CLOB to avoid specifying a maximum length
- but most CLOBs are short in reality
- on the other hand some BLOBs are really huge
- the DBMS cannot know
- so BLOBs can be arbitrary large, but short BLOBs should be more efficient

Approach:

1. BLOBs smaller than TID are encoded in BLOB TID
2. BLOBs smaller than page size are stored in BLOB record
3. only larger BLOBs use the full mechanism

Index Structures

Data is often indexed

- speeds up lookup
- de-facto mandatory for primary keys
- useful for selective queries

Two important access classes:

- point queries
  find all tuples with a given value (might be a compound)
- range queries
  find all tuples within a given value range

Support for more complex predicates is rare.

B-Tree

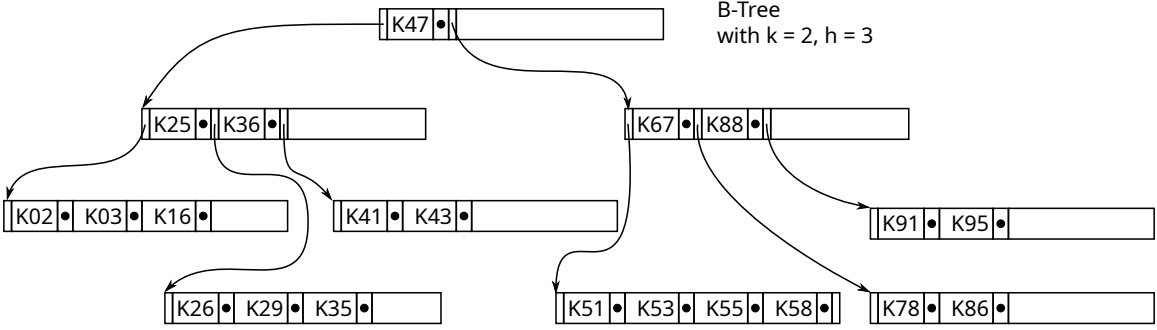
B-Trees (including variants) are the dominant data structure for external storage.

Classical definition:

- a B-Tree has a degree k
- each node except the root has at least k entries
- each node has at most $2k$ entries
- all leaf nodes are at the same depth

B-Tree (2)

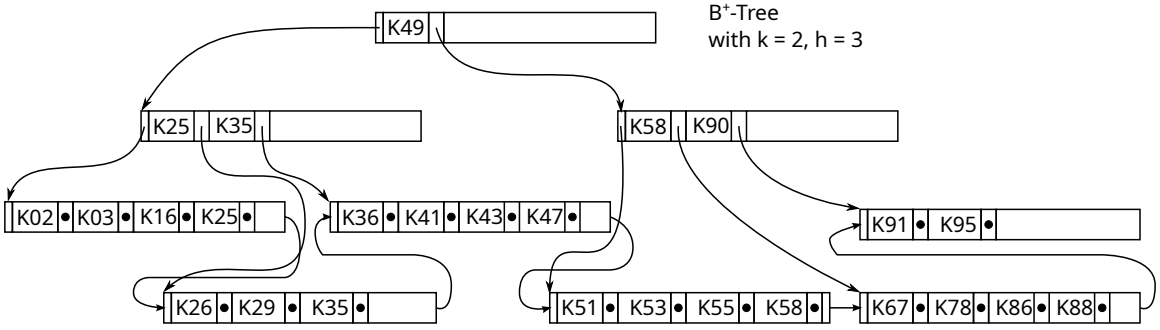
Example:



The ▪ is the TID of the corresponding tuple.

B^+-Tree

Most DBMS use the B^+-Tree variant:



- key+TID only in leaf nodes
- inner nodes contain separators, might or might not occur in the data
- increases the fanout of inner nodes
- simplifies the B-Tree logic

Page Structure

Inner Node:

LSN	for recovery
upper	page of right-most child
count	number of entries
key/child	key/child-page pairs
...	...

Leaf Node:

LSN	for recovery
~0	leaf node marker
next	next leaf node
count	number of entries
key/tid	key/TID pairs
...	...

Similar to slotted pages for variable keys.

Operations - Lookup

Lookup a search key within the B^+-tree:

1. start with the root node
2. is the current node a leaf?
   - if yes, return the current page (locate the entry on it)
3. find the first entry $\geq$ search key (binary search)
4. if no such entry is found, go the *upper*, otherwise go to the corresponding page
5. continue with 2

Lookup can return a concrete entry or just the position on the appropriate leaf page (depends on usage pattern).

Operations - Insert

Insert a new entry into the B^+-tree:

1. *lookup* the appropriate leaf page
2. is there free space on the leaf?
   - if yes, insert entry and stop
3. split the leaf into two, insert entry on proper side
4. insert maximum of left page as separator into parent
5. if the parent overflow, split parent and continue with 4
6. create a new root if needed

Operations - Delete

Remove an entry from the B^+-tree:

1. *lookup* the appropriate leaf page
2. remove the entry from the current page
3. is the current page at least half full?
   - if yes, stop
4. is the neighboring page more than half full?
   - if yes, balance both pages, update separator, and stop
5. merge neighboring page into current page
6. remove the separator from the parent, continue with 3

Most systems simplify the delete logic and accept under-full pages.

Operations - Range Scan

Read all entries within a (start,stop(range

1. *lookup* the *start* value
2. enumerate subsequent entries on the current page
3. use the *next* pointer to find the next page
4. stop once the *stop* value is reached

Very efficient, in particular if leaf nodes are consecutive on disk.

Indexing Multiple Attribute

Compound keys are compared lexicographically:

$$(a_1, a_2) < (b_1, b_2) \Leftrightarrow (a_1 < b_1) \vee (a_1 = b_1 \wedge a_2 < b_2)$$

Otherwise compound keys are quite similar to atomic keys.

- when all attributes are bound, difference is minor
- if only a prefix is bound, the suffix is specified as range

$$a_1 = 5 \Rightarrow (5, -\infty) \leq (a_1, a_2) \leq (5, \infty)$$

Indexing Non-Unique Values

Users can create indexes on any attributes

- not necessarily unique
- in fact might contain millions of duplicates
- main problem: index maintenance
- how to locate a tuple for update/delete?

Solution: only index unique values

- append TID to non-key attributes
- TID works as a tie-breaker
- increases space consumption a bit
- but guarantees $O(\log n)$ access

Concurrent Access

How to handle concurrent access?

- simple page locking/latching is not enough
- will protect against "simple" (single page) changes
- but pages depend upon each other (pointers)

The classical technique is *lock coupling*

- a thread latches both the page and its parent page
- i.e., latch the root, latch the first level, release the root, latch the second level etc.
- prevents conflicts, as pages can only be split when the parent is latched
- no deadlocks, as the latches are ordered

Concurrent Access (2)

But what about inserts?

- when a leaf is split, the separator is propagated up
- might go up to the root
- but we have only locked one parent

Lock coupling up is not an option (deadlocks)

One way around it: “safe” inner pages

- while going down, check if the inner page has enough space for one more entry
- if not, split it
- ensures that we never go up more than one step

Concurrent Access (3)

Alternative: restart

1. first try to insert using simple lock coupling
2. if we do not have to split the inner node everything is fine
3. otherwise release all latches
4. restart the operation, but now keep all latches up to the root
5. all operations can be executed safely now

- greatly reduces concurrency
- but should happen rarely
- simpler to implement, in particular for variable-length keys

B-link Trees

- lock coupling latches two nodes at a time
- seems cheap, but effectively it locks hundreds (all children of the parent node)
- it would be nicer to lock only one page

For pure lookups that is possible when adding *next* pointers to inner nodes:

1. latch a page, find the child page, release the page
2. latch the child page
3. might have been split in between, check neighboring pages

Requires some care when deleting.

Bulkloading

How to build an B-tree for a large amount of data?

- repeated inserts are inefficient
- a lot of random I/O
- pages are touched multiple times

Instead: *sort* the data before inserting

- now inserts become more efficient
- good locality

But we can do even better.

Bulkloading (2)

To construct an initial B^+-Tree:

1. sort the data
2. spool data into leaf pages
   - fill the pages completely
   - remember largest value (separator) in each page in a temp file
3. spool the separators into inner pages
   - fill the pages completely
   - remember largest value (separator) in each page in a temp file
4. repeat 3 until only one inner page remains (root)

Produces a compact, clustered B^+-tree.

Bulkloading (3)

Existing B^+-trees are a bit more problematic, but can still be updated in bulk

1. sort the data
2. merge the data into the existing tree
3. form pages, remember separators, etc.
4. start a new chunk once a page would contain only entries from the original tree
5. merge in the separators as above

Minimizes I/O, but destroys clustering. Usually a good compromise.

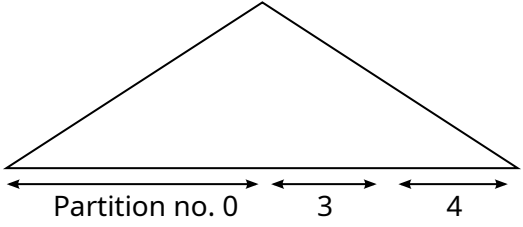
Partitioned B-Tree

Bulk operations are fine if they are rare, but they are disruptive

- usually the B-tree has to be take offline
- the new cannot be queries easily
- existing queries must be halted

Basic idea: *partition* the B-tree

- add an artificial column in front
- creates separate partitions with the B-tree



Partitioned B-Tree (2)

Benefits:

- partitions are largely independent of each other
- one can append to the "rightmost" partition without disrupting the rest
- the index stays always online
- partitions can be merged lazily
- merge only when beneficial

Drawbacks:

- no "global" order any more
- lookups have to access all partitions
- deletion is non-trivial ("anti-matter")

Variable Length Records

So far B-trees are defined for fixed-length keys

- all nodes have between k and $2k$ entries
- simplifies life considerably
- e.g., we "know" if an inner node is full

But in reality, entries can be variable length

- strings
- variable-length encoding, NULL
- compounds of these

Usually keys are *opaque*. The B-tree does not understand the structure. (One could special-case single strings).

Variable Length Records (2)

Variable length keys are problematic. Consider the following example:

a	bbbbbbbb	c	dddddddd	e	ffffffff	g	hhhhhhhh
i	jjjjjjjj	k	llllllll	m	nnnnnnnn	o	

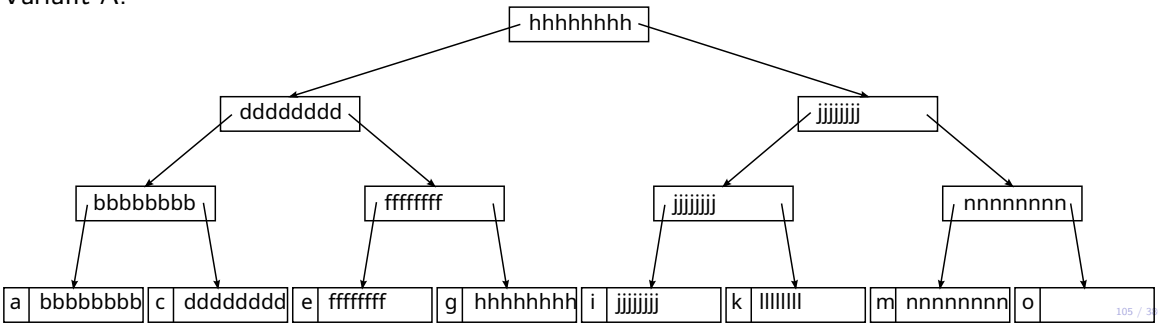
All entries have either length 1 or length 8.

Variable Length Records (2)

Variable length keys are problematic. Consider the following example:

a	bbbbbbbb	c	dddddddd	e	ffffffff	g	hhhhhhhh
i	jjjjjjjj	k	llllllll	m	nnnnnnnn	o	

Variant A:

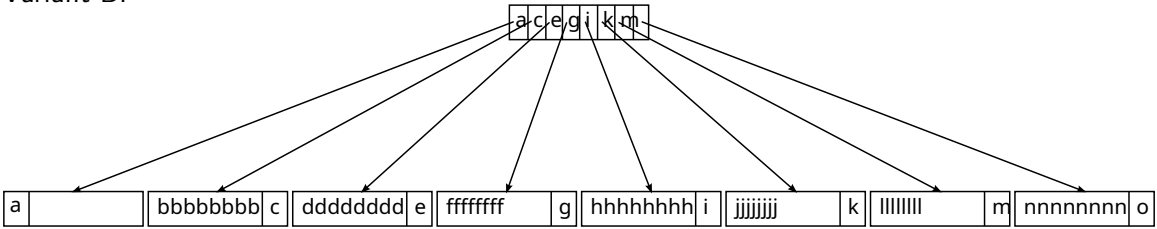


Variable Length Records (2)

Variable length keys are problematic. Consider the following example:

a	bbbbbbbb	c	dddddddd	e	ffffffff	g	hhhhhhhh
i	jjjjjjjj	k	llllllll	m	nnnnnnnn	o	

Variant B:



Height 2 (ignores space consumption for pointers)

Variable Length Records (3)

Separator choice is crucial!

- affects fanout and space consumption
- all standard guarantees are off if normal algorithms are used for variable-length keys

Non-trivial issue

- greedy algorithms exist for the bulkloading case
- idea: recursively pick the smallest value as separator such that the resulting group sizes vary within a constant factor
- can also be extended to the dynamic case (rebuild as need), but non-trivial
- difficult, but gives good amortized bounds

Variable Length Records (4)

Minimal support: modify the split logic

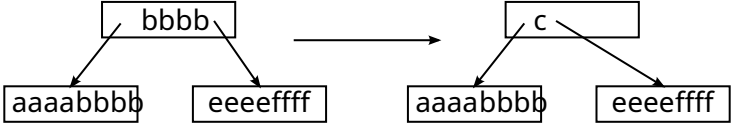
1. when a page overflows, build the sorted list of all values
2. instead of picking the median value as separator, pick the smallest value within 20% around the median
3. for ties, prefer values closer to the median

- pragmatic solution, but not optimal
- can still degenerate
- avoids the worst mistakes

Prefix B$^+$-tree

A B$^+$-tree can contain separators that do not occur in the data

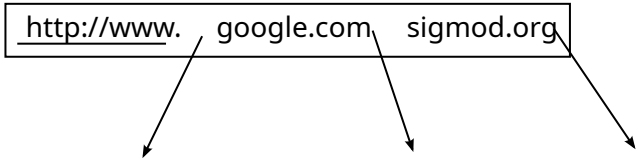
We can use this to save space:



- choose the smallest possible separator.
- no change to the lookup logic required

Prefix B$^+$-tree (2)

We can do even better by factoring out a common prefix:



- only one prefix per page
- the change to the lookup logic is minor
- the lookup key itself is adjusted
- sometimes only inner nodes, to keep scans cheap

Prefix B$^+$-tree (3)

The lexicographic sort order makes prefix compression attractive:

- neighboring entries tend to differ only at the end
- a common prefix occurs very frequently
- not only for strings, also for compound keys etc.
- in particular important if partitioned B-trees
- with big-endian ordering any value might get compressed

Hash-Based Indexes

In main memory a hash table is usually faster than a search tree

- compute a hash-value h, compute a slot (e.g., $s = h \bmod |T|$, access the table $T[s]$
- promises $O(1)$ access
- (if everything works out fine)

A DBMS could profit from this, too. But:

- random I/O is very expensive on disk
- collisions are problematic (e.g., when chaining)
- rehashing is prohibitive

But there are hashing schemes for external storage.

Hash-Based Indexes (2)

Hash indexes are not as versatile as tree indexes:

- only support point query
- range queries are very problematic
- order preserving hashing exists, but is questionable
- quality of the hash function is critical

As a consequence, mainly useful for primary key indexes

- unique keys
- key collisions would be very dangerous
- how to delete a tuple with an indexes attribute of there are 1 million other tuples with the same value?
- can be fixed by separate indexing within duplicate values (complicated)

Extendible Hashing

A central problem of hashing schemes on disk are the table size

- hard to known beforehand
- too small $\Rightarrow$ too many collisions
- chaining is expensive on disk
- too large $\Rightarrow$ waste of space
- would have to grow over time

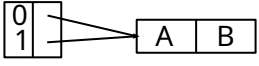
Traditional solution for main memory: *rehashing*

- re-map items to hash table sizes
- involves touching every item
- poor locality, a lot of random I/O
- prohibitive for disk

Idea: Allow for growing the hash table without rehashing by *sharing* table entries.

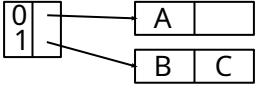
Extendible Hashing (2)

- hash table size is always a power of 2
- hash table points to buckets (pages)
- multiple table entries can point to the same bucket
- but always systematically (buddy systems)
- thus, the “depth” of the buckets varies



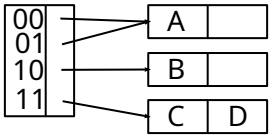
Extendible Hashing (3)

- when a bucket overflows, it is split
- if not a maximum depth, the depth is increased
- achieved by de-sharing slot entries
- one more bit becomes relevant
- items are distributed according to hash values



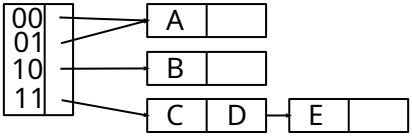
Extendible Hashing (4)

- if the depth cannot be increased, the table is doubled
- other buckets are unaffected
- entries are duplicated, resulting in new sharing
- new buckets are linked as usual



Extendible Hashing (5)

- once a maximum table size is reached start chaining
- ideally occurs rarely, traversing chains is expensive
- optionally one can balance chaining vs. table growth via load factor



Extendible Hashing (6)

Advantages:

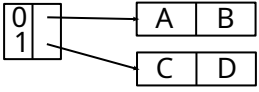
- ideally exactly two page accesses per lookup
- less than in a B-tree
- table can grow independent of existing buckets
- no need for re-hashing

Disadvantages:

- table growth is a very invasive operation
- large steps in space consumption
- what about hash collisions?
- same care is needed to avoid extreme table growth

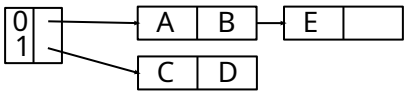
Linear Hashing

- linear hashing avoids the exponential directory growth
- it starts with a regular hash table with buckets



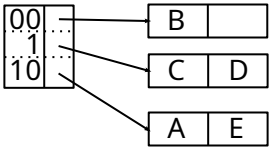
Linear Hashing (2)

- when a bucket overflows it uses chaining
- degrades performance, but ok if the chain is short



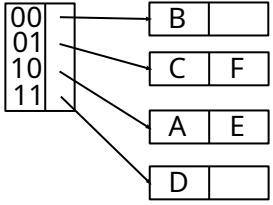
Linear Hashing (3)

- triggered by load factor or chain length a bucket is split
- chains are re-integrated into the bucket
- only one (i.e., the next) bucket is split, the rest remains untouched
- the range of buckets $[1, k[$ has been split, the range $[k, n]$ is unsplit (the range $[n, n + 2k - 2[$ contains the second halves)
- the directory grows page by page



Linear Hashing (3)

- more buckets are split on demand
- at some point all buckets have been split once
- then the cycle starts anew



Linear Hashing (4)

Advantages:

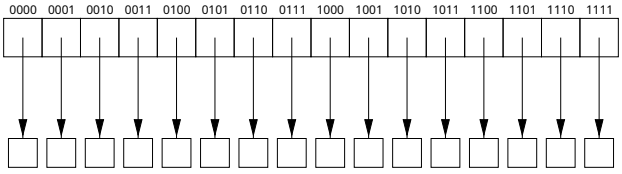
- avoids the disruptive directory growth of EH
- index grows linearly
- amortized the index structure is nice

Disadvantages:

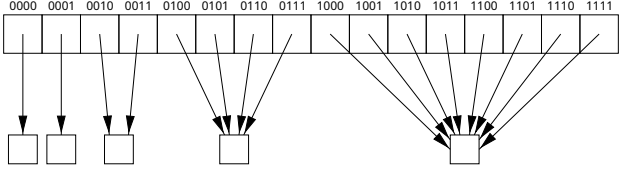
- chaining hurts performance
- it can take a while until chains are re-integrated
- page allocation for the directory problematic

Multi-Level Extendible Hashing

For uniform distributions the EH directory is nice:



But data skew causes poor space utilization

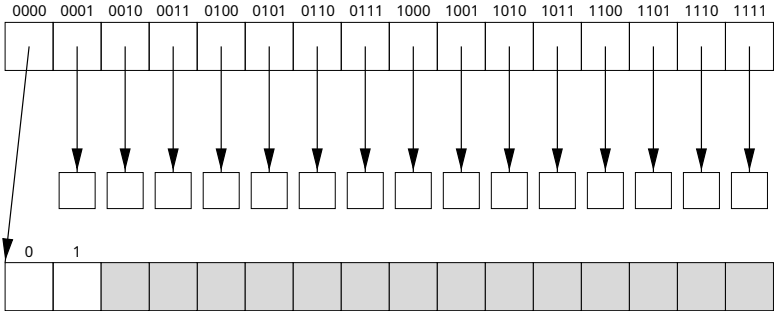


The directory size explodes.

- skew is an unfortunate reality

Multi-Level Extendible Hashing (2)

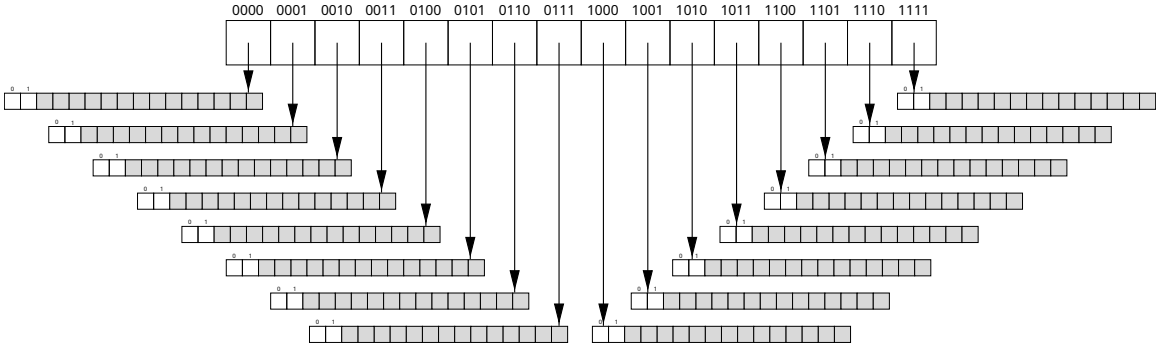
Basic idea: construct a tree of hash tables



- the next level uses the next k bits
- node size is page size
- additional page faults, but fanout is very large
- only the heavily used parts get additional levels

Multi-Level Extendible Hashing (2)

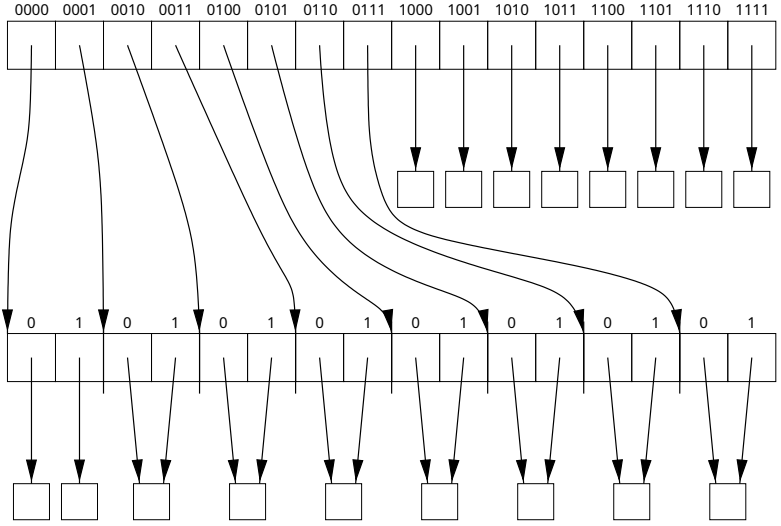
Problem: space utilization



- now uniform is the worst case
- all buckets will overflow at the same time
- second-level hash tables will be nearly empty
- leads to poor space utilization (and poor performance)

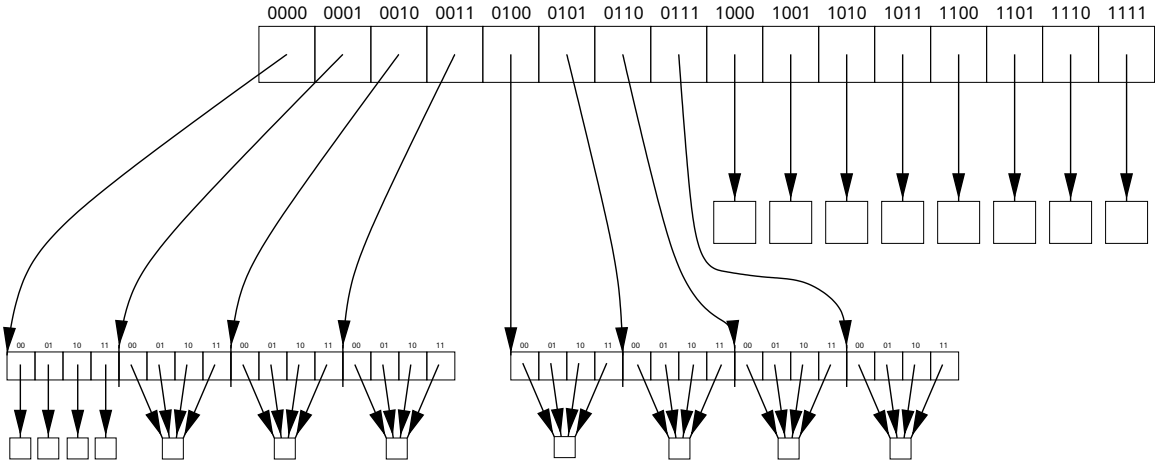
Multi-Level Extendible Hashing (3)

Instead: share inner page between buddies



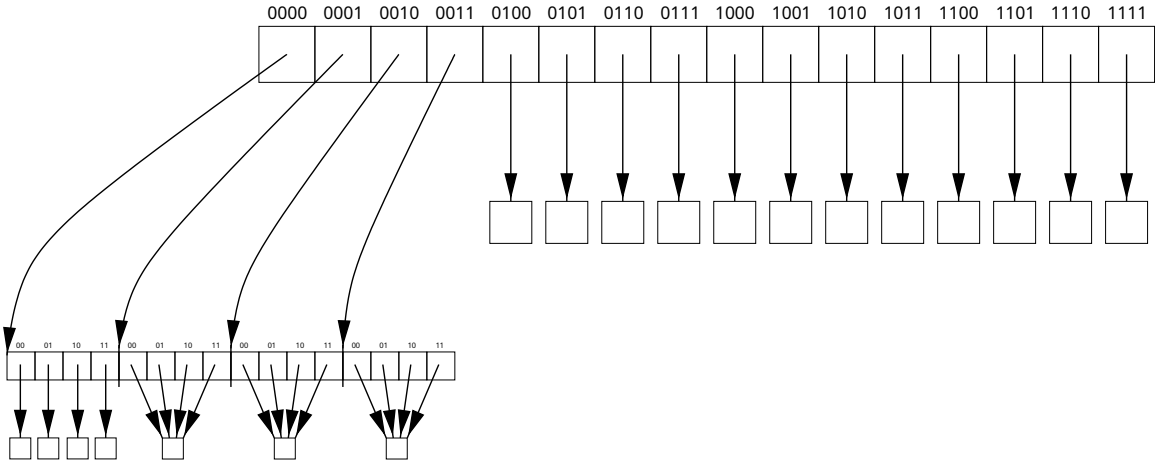
Multi-Level Extendible Hashing (4)

We can get additional bits by splitting the inner page



Multi-Level Extendible Hashing (5)

In fact here we can even move buddies up again



Multi-Level Extendible Hashing (6)

- uses a buddy system (boundaries are powers of 2)
- bit width etc. derived implicitly
- pointer structure contains enough information
- results in large fanout

It has some nice properties

- naturally adapts to data skew
- directory growth is not a problem
- but additional page accesses
- tree is very shallow, however

Bitmap Indexes

Classical indexes do not handle unselective predicates very well

- large fraction of tuples is returned
- index access is more expensive than a table scan
- but a combination of predicates might be selective
- index intersection would help, but is still expensive
- predicates might also contain disjunctions etc.

Expample: $\sigma_{(a=2 \vee b=5) \wedge (c \neq 1)}(R)$

Could be answered by B-trees, but often not very efficient.

Bitmap Indexes (2)

When the attribute domain is small, it can be indexed using **bitmap indexes**

	a=2
tid_1	1
tid_2	0
tid_3	0
tid_4	1
...	...

	a=3
tid_1	0
tid_2	1
tid_3	0
tid_4	0
...	...

...

- one bitmap for every attribute value
- index intersections become bit operations
- very efficient
- remaining ones indicate matching tuples

Bitmap Indexes (3)

- bitmap indexes are compact (one bit per tuple)
- (plus tid directory if needed)
- and are usually sparse
- can be compressed very well
- run-length encoding in particular attractive
- intersection can be performed on the compressed form

Often outperforms other indexes for unselective attributes.

Small Materialized Aggregates

- data is usually stored in physical chunks
- pages, or chunks of pages
- clustering usually insertion order
- older chunks tend to remain static
- we can cheaply pre-computed (i.e., cache) some info

Some useful aggregates:

min	max	sum	count
10	20	1500	1000

Small Materialized Aggregates (2)

Before scanning a chunk, we examine the aggregate

- some predicates can be evaluated on the pure aggregate
- only for the current chunk, of course
- in particular skipping chunks is often possible
- aggregates can be directly re-used
- greatly saves I/O

What about updates?

- small materialized aggregates are like a cache
- can be updated eagerly or lazily
- an invalidation flag is enough

Multi-Dimensional Indexing

- huge field
- R-tree, grid file, pyramid schema, index intersection, ...
- hundreds of approaches
- we do not discuss them here

But: remember the **curse of dimensionality**

- we can only index a relative low number of dimensions
- for higher dimensions, range queries/proximity queries fail
- scan becomes faster than index structures

Transactions and Recovery

Transactions and Recovery

DBMSs offer two important concepts:

1. transaction support
   - a sequence of operations is combined into one compound operation
   - transactions can be execution concurrently with well defined semantics
2. recovery
   - the machine/DBMS/user code can crash at an arbitrary point in time, errors can occur, etc.
   - the recovery component ensures that no (committed) data is lost, instance is consistent

Implementation of both is intermingled, therefore we consider them together.

Why Transactions?

Transfer money from account A to account B

- read the account balance of A into the variable a: **read**(A,a);
- reduce the balance by EURO 50,–: $a := a - 50$;
- write back the new account balance: **write**(A,a);
- read the account balance of B into the variable b: **read**(B,b);
- increase the balance by EURO 50,–: $b := b + 50$;
- write back the new account balance: **write**(B,b);

Many issues here: crashes, correctness, concurrency, ...

Operations

- **begin of transaction** (**BOT**):
  - marks the begin of transaction
  - in SQL: `begin transaction`
  - often implicit
- **commit**:
  - terminates a successful transaction
  - in SQL: `commit [transaction]`
  - all changes are permanent now
- **abort**:
  - terminates an unsuccessful transaction
  - in SQL: `rollback [transaction]`
  - undoes all changes performed by the transaction
  - might be triggered externally

All transactions either commit or abort.

ACID

Transactions should offer ACID properties:

- Atomicity
  - the operations are either executed completely or not at all
- Consistency
  - a transaction brings a database instance from one consistent state into another one
- Isolation
  - currently running transactions are not aware of each other
- Durability
  - once a transaction commits successfully, its changes are never lost

Transactions and Recovery

The concept of *recovery* is related to the *transaction* concept:

- the DBMS must handle a crash at an arbitrary point in time
- first, the DBMS data structures must survive this
- second, transaction guarantees must still hold
- Atomicity
  - in-flight transactions must be rolled back at restart
- Consistency
  - consistency guarantees must still hold
- Durability
  - committed transactions must not be lost, even though data might still be in transient memory

Sometimes the dependency is mutual

- Isolation
  - some DBMS use the recovery component for transaction isolation

Technical Aspects

The logical concept *transactions* and *recovery* can be seen under (largely orthogonal) technical aspects:

- concurrency control
- logging

As we will see, both are relevant for both logical concepts.

Multi User Synchronization

- executing transactions (TA) serialized is safe, but slow
- transactions are frequently delayed (wait for disk, user input, ...)
- in serial execution, would block all other TAs
- concurrent execution is desirable for performance reasons

But: simple concurrent execution causes a number of problems.

Lost Update

T_1	T_2
bot	
$r_1(x)$	
$\hookrightarrow$	bot
	$r_2(x)$
$w_1(x)$	$\hookleftarrow$
$\hookrightarrow$	$w_2(x)$
commit	$\hookleftarrow$
$\hookrightarrow$	commit

The result of transaction T_1 is lost.

Dirty Read

T_1	T_2
bot	
$\hookrightarrow$	bot
	$r_2(x)$
	$w_2(x)$
$r_1(x)$	$\hookleftarrow$
$w_1(y)$	
commit	
$\hookrightarrow$	abort

T_1 reads an invalid value x.

Non-Repeatable Read

T_1	T_2
bot	
$r_1(x)$	
$\hookrightarrow$	bot
	$w_2(x)$
	commit
$r_1(x)$	$\hookleftarrow$
$\ldots$	

T_1 reads the value x twice, with different results.

Phantom Problem

T_1	T_2
bot	
select count(*)	
from R;	
$\hookrightarrow$	
	bot
	insert into R ...;
	commit
select count(*)	$\hookleftarrow$
from R;	
...	

T_1 sees a new tuple during hit second access.

Serial Execution

These problems vanish with *serial* execution

- a transaction always controls the whole DBMS
- no conflicts possible
- but poor performance

Instead: execute transaction as if they were serial

- if they behave as if they were serial they cause no problems
- concept is called *serializable*
- requires some careful bookkeeping

Formal Definition of a Transaction

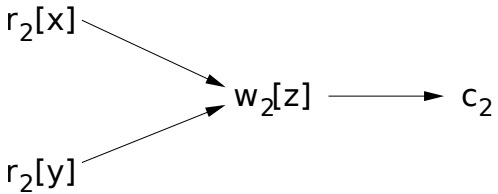
- Possible operations of a TA T_i
  - $r_i(A)$: read the data item A
  - $w_i(A)$: write the data item A
  - a_i: abort
  - c_i: commit successfully
  - *bot*: begin of transaction (implicit)

Formal Definition of a Transaction (2)

- A TA T_i is a partial order of operations with the order relation $<_i$ such that
  - $T_i \subseteq \{r_i[x], w_i[x] \mid x \text{ is a data item}\} \cup \{a_i, c_i\}$
  - $a_i \in T_i$, iff $c_i \notin T_i$
  - Let t be a_i or c_i. Then for all other operations p_i: $p_i <_i t_i$
  - If $r_i[x] \in T_i$ and $w_i[x] \in T_i$, then either $r_i[x] <_i w_i[x]$ or $w_i[x] <_i r_i[x]$

Example

- transactions are often drawn as directed acyclic graphs (DAGs)



- $r_2[x] <_2 w_2[z]$, $w_2[z] <_2 c_2$, $r_2[x] <_2 c_2$, $r_2[y] <_2 w_2[z]$, $r_2[y] <_2 c_2$
- transitive relationships are contained implicitly

Schedules

- multiple transactions can be executed concurrently
- this is captured by a *schedule*
- a schedules orders the operations of the TAs relative to each other
- due to the concurrent execution of operations the schedule defines only partial ordering

Conflicting Operations

- operations that are conflicting must not be executed in parallel
- two operations are in conflict if both operate on the same data item and at least one of the two is a write operation

	T_i	
T_j	$r_i[x]$	$w_i[x]$
$r_j[x]$		$\neg$
$w_j[x]$	$\neg$	$\neg$

Definition of a Schedule

- Let $T = \{T_1, T_2, \ldots, T_n\}$ be a set of transaction
- A schedule H over T is a partial order with order relation $<_H$, such that
  - $H = \bigcup_{i=1}^{n} T_i$
  - $<_H \supseteq \bigcup_{i=1}^{n} <_i$
  - For all conflicting operations $p, q \in H$ the following holds: either $p <_H q$ or $q <_H p$

Example

$$
H = \begin{array}{llllll}
 & & r_2[x] \rightarrow & w_2[y] \rightarrow & w_2[z] \rightarrow & c_2 \\
 & & \uparrow & \uparrow & \uparrow & \\
 & r_3[y] \rightarrow & w_3[x] \rightarrow & w_3[y] \rightarrow & w_3[z] \rightarrow & c_3 \\
 & & \uparrow & & & \\
 & r_1[x] \rightarrow & w_1[x] \rightarrow & c_1 & &
\end{array}
$$

(Conflict-)Equivalence

- The schedules H and H' are *(conflict-)equivalent* ($H \equiv H'$), if:
  - both contain the same set of TAs (including the corresponding operations)
  - both order conflicting operations of non-aborted TAs in the same way
- the general idea is that executing conflicting operations in the same order will produce the same result

Example

$$
\begin{aligned}
& r_1[x] \to w_1[y] \to r_2[z] \to c_1 \to w_2[y] \to c_2 \\
\equiv\ & r_1[x] \to r_2[z] \to w_1[y] \to c_1 \to w_2[y] \to c_2 \\
\equiv\ & r_2[z] \to r_1[x] \to w_1[y] \to w_2[y] \to c_2 \to c_1 \\
\not\equiv\ & r_2[z] \to r_1[x] \to w_2[y] \to w_1[y] \to c_2 \to c_1
\end{aligned}
$$

Serializability

- serial schedules are safe, therefore we are interested in schedules with similar properties
- in particular we want schedules that are equivalent to a serial schedule
- such schedules are called *serializable*

Serializability (2)

- Definition
  - The *committed projections* $C(H)$ of a schedule H contains only the committed TAs
  - A schedule H is *serializable*, if $\exists H_s$ such that H_s is serial and $C(H) \equiv H_s$.

Serializability (3)

- How to check for serializability?
- A schedule H is serializable if and only if the *serializability graph* $SG(H)$ is acyclic.

Serializability Graph

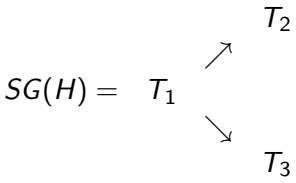
- The serializability graph $SG(H)$ of a schedule $H = \{T_1, \ldots, T_n\}$ is a directed graph with the following properties
  - the nodes are formed by the committed transactions from H
  - two TAs T_i and T_j are connected by an edge from T_i to T_j if there exist two operations $p_i \in T_i$, $q_j \in T_h$ such that p_i and q_j are in conflict and $p_i <_H q_j$.

Example

- Schedule H

$$H = w_1[x] \rightarrow w_1[y] \rightarrow c_1 \rightarrow r_2[x] \rightarrow r_3[y] \rightarrow w_2[x] \rightarrow c_2 \rightarrow w_3[y] \rightarrow c_3$$

- $SG(H)$



Example (2)

- H is serializable
- equivalent serial schedules

$$H_s^1 = T_1 \mid T_2 \mid T_3$$
$$H_s^2 = T_1 \mid T_3 \mid T_2$$
$$H \equiv H_s^1 \equiv H_s^2$$

Example (3)

$$
H = \begin{array}{ccccccc}
r_1[x] & \rightarrow & w_1[x] & \rightarrow & w_1[y] & \rightarrow & c_1 \\
 & & \uparrow & & \uparrow & & \\
 & \swarrow & r_2[x] & \rightarrow & w_2[y] & \rightarrow & c_2 \\
 & & \downarrow & & & & \\
r_3[x] & \rightarrow & w_3[x] & \rightarrow & c_3 & &
\end{array}
$$

$$
SG(H) = \begin{array}{ccc}
 & \nearrow & T_3 \\
T_2 & & \uparrow \\
 & \searrow & T_1
\end{array}
$$

Example (4)

- H is serializable
- equivalent serial schedules

$$H_s^1 = T_2 \mid T_1 \mid T_3$$
$$H \equiv H_s^1$$

Example (5)

$$H = \begin{array}{ccccc} w_1[x] & \rightarrow & w_1[y] & \rightarrow & c_1 \\ \uparrow & & \downarrow & & \\ r_2[x] & \rightarrow & w_2[y] & \rightarrow & c_2 \end{array}$$

$$SG(H) = \quad T_1 \quad \leftrightarrows \quad T_2$$

- H is not serializable

Additional Properties of a Schedule

- Besides serializability, other properties are desirable, too:
  - recoverability
  - avoiding cascading aborts: ACA
  - strictness

Recoverability is required for correctness, the others are more nice to have (but are crucial for some implementations).

Additional Properties of a Schedule (2)

- Before looking at more properties, we define the reads-from relationship
- A TA T_i read (data item x) from TA T_j, if
  - $w_j[x] < r_i[x]$
  - $a_j \not< r_i[x]$
  - if $\exists w_k[x]$ such that $w_j[x] < w_k[x] < r_i[x]$, then $a_k < r_i[x]$
- a TA can read from itself

Recoverability

- A schedule is *recoverable*, if
  - Whenever TA T_i reads from another TA T_j ($i \neq j$) and $c_i \in H$, then $c_j < c_i$
- the TAs must adhere to a certain commit order
- non-recoverable schedules may cause problems with C and/or D of the ACID properties

Recoverability (2)

$$H = w_1[x]\ r_2[x]\ w_2[y]\ c_2\ a_1$$

- H is not recoverable
- this has some unfortunate consequences:
  - if we keep the updates from T_2 then the data is inconsistent (T_2 has read data from an aborted transaction)
  - if we undo T_2, the we change committed data

Cascading Aborts

step	T_1	T_2	T_3	T_4	T_5
0.	$\cdots$				
1.	$w_1[x]$				
2.		$r_2[x]$			
3.		$w_2[y]$			
4.			$r_3[y]$		
5.			$w_3[z]$		
6.				$r_4[z]$	
7.				$w_4[v]$	
8.					$r_5[v]$
9.	a_1 (**abort**)				

Cascading Aborts (2)

- A schdule *avoids cascading aborts*, if the following holds
  - whenever a TA T_i reads from another TA T_j ($i \neq j$), then $c_j < r_i[x]$
- We must only read from transactions that have committed already.

Strictness

- A schedule is *strict*, if the following holds
  - for any two operations $w_j[x] < o_i[x]$ (with $o_i[x] = r_i[x]$ or $w_i[x]$) either $a_j < o_i[x]$ or $c_j < o_i[x]$
- We must only read from committed transactions, and only overwrite changes made by committed transactions.

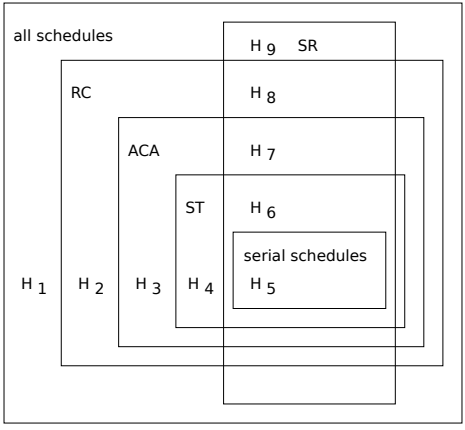
Strictness (2)

- Only strict schedules allow for physical logging during recovery

$$
\begin{array}{ll}
x = 0 & \\
w_1[x, 1] & \text{before image of } T_1\text{: } 0 \\
x = 1 & \\
w_2[x, 2] & \text{before image of } T_2\text{: } 1 \\
x = 2 & \\
a_1 & \\
c_2 &
\end{array}
$$

When aborting T_1 x would incorrectly be set to 0.

Classification of Schedules



SR: serializable, RC: recoverable, ACA: avoids cascading aborts, ST: strict

Scheduler

- the *scheduler* orders incoming operations such that the resulting schedule is serializable and recoverable.
- options:
  - execute (immediately)
  - reject
  - delay
- two main classes of strategies:
  - pessimistic
  - optimistic

Pessimistic Scheduler

- scheduler delays incoming operations
- for concurrent operations, the scheduler picks a safe execution order
- most prominent example: lock-based scheduler (very common)

Optimistic Scheduler

- scheduler executes incoming operations as quickly as possible
- might have to rollback later
- most prominent example: time-stamp based scheduler

Lock-based Scheduling

- The main idea is simple:
  - each data item has an associated lock
  - before a TA T_i accesses a data item, it must acquire the associated lock
  - if another TA T_j holds the lock, T_i has to wait until T_j releases the lock
  - only one TA may hold a lock (and access the corresponding data item)
- how to guarantee serializability?

Two-Phase Locking

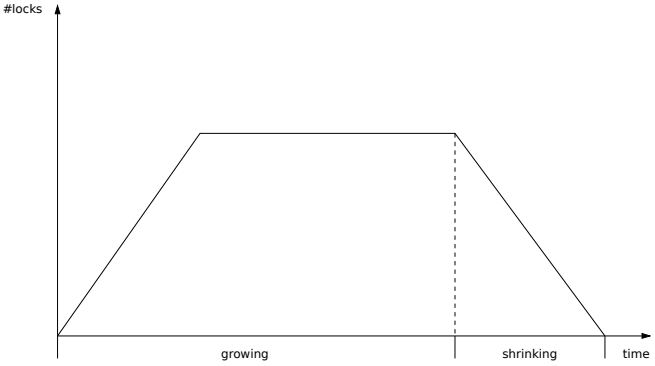
- Abbreviated as 2PL
- Two lock modes:
  - S (shared, read lock)
  - X (exclusive, write lock)
  - compatibility matrix:

	held lock		
acquired lock	none	S	X
S	$\surd$	$\surd$	–
X	$\surd$	–	–

Definition

- before accessing a data item a TA must acquire the corresponding lock
- a TA must not request a lock that it already holds
- if a lock cannot be granted immediately, the TA is put into a wait queue
- a TA most not acquire new locks once it has released a lock (two phases)
- at commit (or abort) all held locks must be released

Two Phases



- growing phase: locks are acquired, but not released
- shrinking phase: locks are released, but not acquired

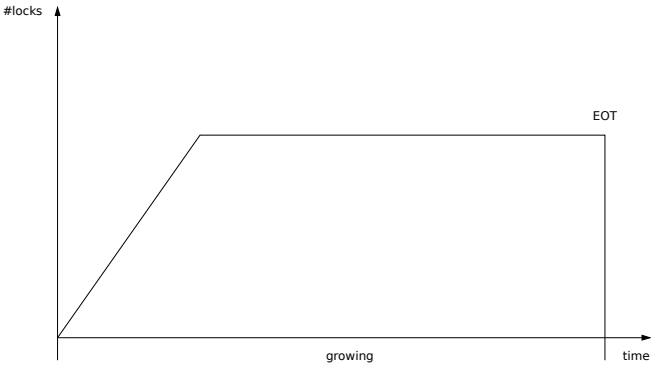
Concurrency with 2PL

Schritt	T_1	T_2	remarks
1.	**BOT**		
2.	**lockX**$[x]$		
3.	$r[x]$		
4.	$w[x]$		
5.		**BOT**	
6.		**lockS**$[x]$	T_2 has to wait
7.	**lockX**$[y]$		
8.	$r[y]$		
9.	**unlockX**$[x]$		T_2 wakes up
10.		$r[x]$	
11.		**lockS**[y]	T_2 has to wait
12.	$w[y]$		
13.	**unlockX**$[y]$		T_2 wakes up
14.		$r[y]$	
15.	**commit**		
16.		**unlockS**$[x]$	
17.		**unlockS**$[y]$	
18.		**commit**	

Strict 2PL

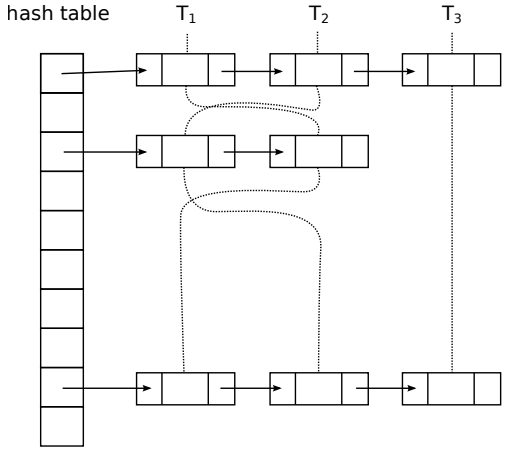
- 2PL does not avoid cascading aborts
- extension to *strict* 2PL:
  - all locks must be held until the end of transaction
  - avoids cascading aborts (the schedule is even strict)

Strict 2PL (2)



Lock Manager

locks are typically organized in a hash table



Lock Manager (2)

Traditional architecture:

- one mutex per lock chain
- within the lock, separate locking/waiting mechanism
- syncing chain mutex/lock latch needs some care to maximize concurrency
- lock includes ownership and lock mode information

Separate per-transaction chaining

- needed for EOT
- no latching required
- but: can only be embedded easily for exclusive locks
- in general: keep the list external

Lock Manager (3)

One problem: EOT

- all locks have to be released
- lock list is available
- but puts a lot of stress on the lock manager
- chains may be scanned and locked repeatedly
- one option: lazy removal of lock entries
- allows for EOT without locking the chains

Reducing the Lock Size

Locks a relatively expensive

- typically 64-256 bytes per lock
- thousands, potentially millions of locks
- space utilization becomes a problem
- commercial DBMS limit the amounts of locks

One solution: use less locks

- space/granularity trade-off
- leads to MGL (as we will see)
- may cause unnecessary aborts

Other option: reduce the size of locks

Reducing the Lock Size (2)

- standard locks contain a wait mechanism
- but when we use strict 2PL, we wait for transactions anyway
- it is sufficient to contain the owner in the lock
- we always wait for the owner
- shared locks are a bit problematic (requires some effort)

64 bit key	32 bit owner	32 bit status

- status include lock mode, pending writes, etc.
- concurrently held require some care (linked list, spurious wakeups, etc.)
- but that is fine if the lists are short

Deadlocks

- Example:

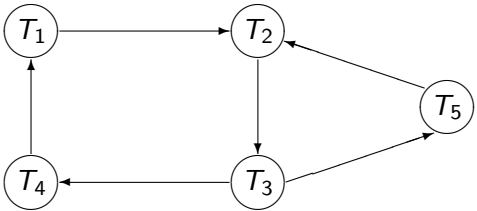
T_1	T_2
bot	
$\text{lockX}_1(a)$	
$w_1(a)$	
$\hookrightarrow$	bot
	$\text{lockS}_2(b)$
	$r_2(b)$
$\text{lockX}_1(b)$	$\hookleftarrow$
$\hookrightarrow$	$\text{lockS}_2(a)$

Deadlock Detection

- no TA should have to wait “forever”
- one strategy to avoid deadlocks are time-outs
  - finding the right time-out is difficult
- a precise method analyzes the waits-for graph
  - TAs form node, edges are induced by waits-for relations
  - if the graph is cyclic we have a deadlock

Waits-for graph

- Example



- the waits-for graph is cyclic, i.e., we have a deadlock
- we can break the cycle by aborting T_2 or T_3

Implementing Deadlock Detection

- timeouts are simple, fast, and crude
- cycle detection is precise but expensive

One alternative: use a hybrid approach

- use a short timeout
- after the timeout triggered, start the graph analysis
- build the wait-for graph on demand

Keeps the common case fast, deadlock detection is only slightly delayed.

Online Cycle Detection

How to find cycles in a directed graph?

- simple solution: depth-first-search and mark
- we have a cycle if we meet a marked node
- problem: $O(n + m)$
- executed at every check

Better: use an online algorithm

- remembers information from last checks
- only re-computes if needed

Observation: a graph is acyclic if and only if there exists a topological ordering.

Online Cycle Detection (2)

- we start with an arbitrary topological ordering $<_T$
- when trying to add a restriction $B < A$, we perform a check

if $B <_T A$
  return true
marker[B]=2
if $\neg$ dfs(A,B)
  for each $V \in [A,B]$
    marker[V]=0
  return false
shift(A,B)

- dynamically updates the ordering

Online Cycle Detection (3)

Depth-first search for contractions. Bounded by N and L.

dsf(N,L)
  marker[N]=1
  for each V outgoing from N
  if $V \leq_T L$
    if marker[V]=2
      return false
    if marker[V]=0
      if $\neg$ dsf(V,L)
        return false
  return true

Online Cycle Detection (4)

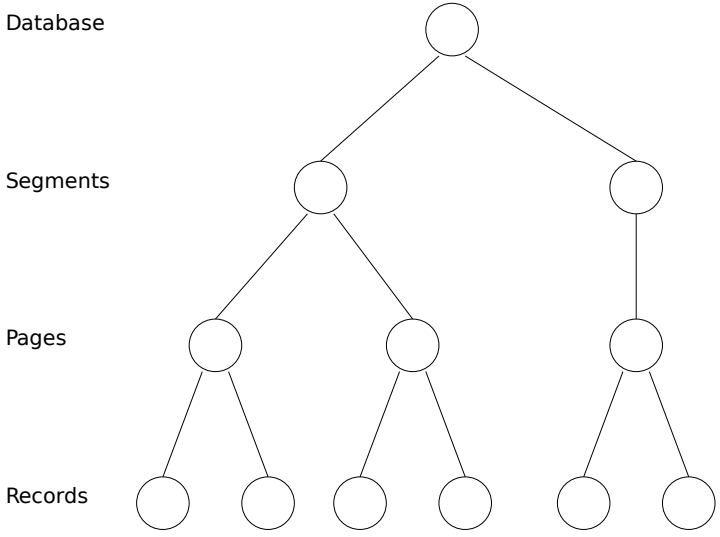
Update the ordering

shift(B,A)
  marker[B]=0
  shift=0
  L=<>
  for each $V \in [A,B]$
    if marker[V]$>$ 0
      L=L$\circ <V>$
      $shift = shift + 1$
      marker[V]=0
    else
      move V *shift* steps to the left
  place the entries in L at $B - shift$

Multi-Granularity Locking

- (strict) 2PL solves the mentioned isolation problems, except the phantom problem
- the phantom-problem cannot be solved by standard locks, as we cannot lock something that does not exist
- we can solve this by using *hierarchical locks* (multi-granularity locking: MGL)

MGL



Additional Lock Modes for MGL

- S (shared): read only
- X (exclusive): read/write
- IS (intention share): intended reads further down
- IX (intention exclusive): intended writes further down the hierarchy

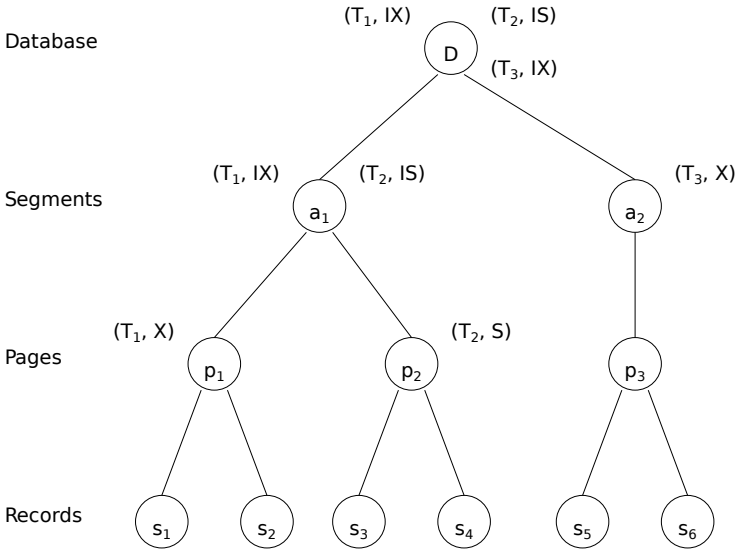
Compatibility Matrix

	current lock				
requested	none	*S*	*X*	*IS*	IX
S	√	√	–	√	–
X	√	–	–	–	–
IS	√	√	–	√	√
IX	√	–	–	√	√

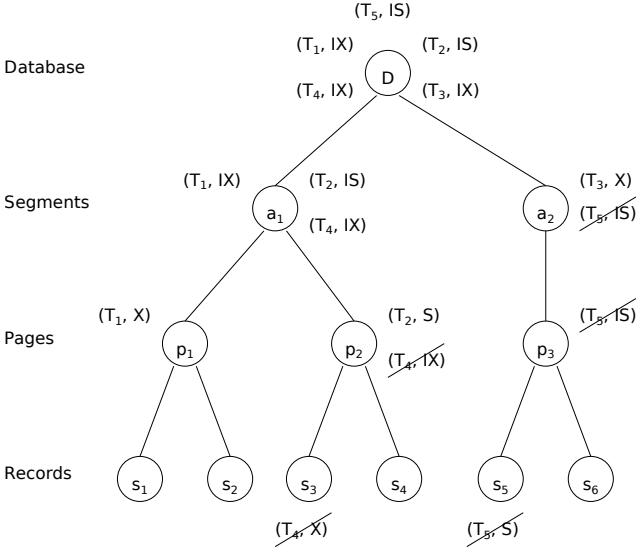
Protocol

- Locks are acquired top-down
  - for a S or IS lock all ancestors must be locked in IS or IX mode
  - for a X or IX lock all ancestors must be locked in IX mode
- locks are released bottom-up (i.e., only if no locks on descendants remain)

Example


Database
Segments
Pages
Records
(T1, IX)
(T2, IS)
D
(T3, IX)
(T1, IX)
(T2, IS)
(T3, X)
a1
a2
(T1, X)
(T2, S)
p1
p2
p3
s1
s2
s3
s4
s5
s6

Example (2)


Database
Segments
Pages
Records
D
a_1
a_2
p_1
p_2
p_3
s_1
s_2
s_3
s_4
s_5
s_6
(T_5, IS)
(T_1, IX)
(T_2, IS)
(T_4, IX)
(T_3, IX)
(T_1, IX)
(T_2, IS)
(T_4, IX)
(T_3, X)
(T_5, IS)
(T_1, X)
(T_2, S)
(T_4, IX)
(T_5, IS)
(T_4, X)
(T_5, S)

Example (3)

- TAs T_4 and T_5 are blocked
- we have no deadlock here, but deadlocks are possible with MGL, too.

Using MGL for Lock Management

Another important use for MGL: lock management

- most DBMSs cannot cope with a huge number of locks
- usually an upper bound on the number of locks
- but MGL can reduce the load
- we can reduce the locks by locking higher hierarchy levels
- and then release the descendant locks
- allows for scaling the number of locks

But: can easily lead to deadlocks/aborted transactions.

Preventing Phantom Problems without MGL

Another way to prevent the phantom problem: add a lock for the "next" tuple

- adds a lock for the "next" pseudo-tuple
- non-PK scans lock this tuple shared
- insert operations lock it exclusive
- prevents phantoms

But: we may want concurrent inserts

- another lock mode just for inserts
- if the TA scans+inserts, we really want exclusive
- gets a bit tricky
- but can be solved

Timestamp Based Approaches

- timestamp based synchronization is an alternative to locking
- each TA is assigned a unique timestamp
- each operation of the TA is uses this timestamp

Assignment of timestamps varies (eager, lazy, ...), the simplest case is order by BOT.

Timestamps

- the scheduler uses the timestamps to order conflicting operations
  - assume that $p_i[x]$ and $q_j[x]$ are conflicting operations
  - $p_i[x]$ is executed before $q_j[x]$, iif the timestamp of T_i is older than the timestamp of T_j

Timestamps (2)

- the scheduler annotates each data item x with the timestamp of the last operations on x
- timestamps are stored separately for each type of operation q: max-q-scheduled(x)
- when the scheduler tries to execute an operator p, the timestamp of p is compared to all max-q-scheduled(x) that conflict with p
- if the timestamp of p is older than any max-q-scheduled(x) the operations is rejected (and the TA aborted)
- otherwise p is executed and max-p-scheduled(x) is updated

Commit Order

- using the basic timestamp approach might produce non-recoverable schedles
- we can guarantee recoverability by commiting TAs in timestamp order
- the commit of a TA T_i is delayed as long as transaction from which T_i has read are still active.

Ideally, timestamps are given out in commit order

- hard to know beforehand
- one alternative: transaction reordering

Limitations

Timestamps are used only relatively rarely

- does not avoid the phantom problem
- aborts TAs if there is any indication of problems
- every read operations is implicitly a write (updating the timestamps)

But it also has some strength

- can synchronize an arbitrary number of items (unlike locks)
- easy to distribute/parallelize

Might become more attractive considering current hardware trends.

Snapshot Isolation

- the DBMS has to keep track of all updates performed by a TA
- needed to undo a TA
- this information is usually available even after a TA committed
- therefore the DBMS can (conceptually) remove the effect of any TA

This can be used to isolate transaction:

- at BOT, the TA is assigned a timepoint T
- all committed changes before are visible
- all changes after T are removed from the data view
- conceptually produces a snapshot of the data

Snapshot Isolation (2)

How to implement SI?

- makes use of the transaction log
- every page contains the LSN
- indicates the last change
- pages with old LSN can be read safely
- for pages with newer LSN the log is checked to eliminate recent changes

Snapshot Isolation (3)

Snapshot isolation has some very nice properties:

- no need for read locks (which could be millions)
- read operations never wait
- serializability (but see below)

Limitations:

- only safe for read-only transactions!
- a read-write transaction must not use snapshot isolation if the schedule has to be serializable
- still, many systems use snapshot isolation even for r/w TAs

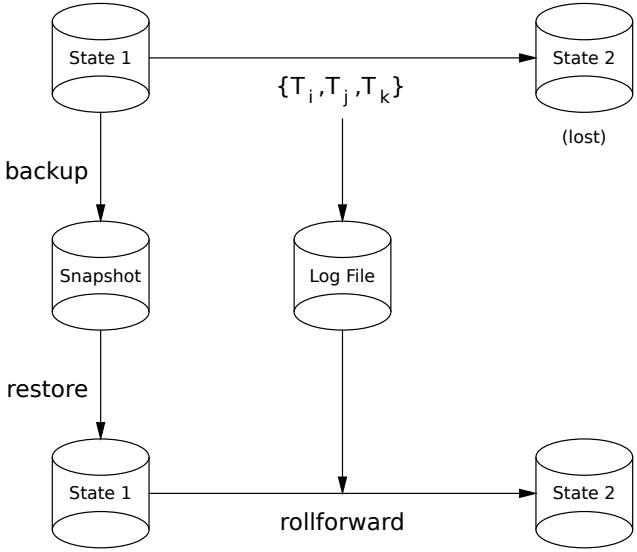
Recovery

- a DBMS must not lose any data in case of a system crash
- main mechanisms of recovery:
  - database snapshots (backups)
  - log files

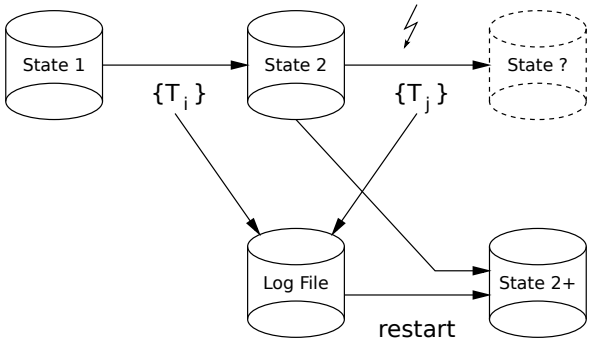
Recovery (2)

- a *database snapshot* is a copy of the database at a certain point in time
- the *log file* is a protocol of all changes performed in the database instance
- obviously the main data, the database snapshots, and the log-files should not be kept on the same machine...

System Failure



Main Memory Loss



- problem: some TAs in $\{T_j\}$ where still active, some committed already
- restart reconstructs state 2 + all changes by comitted TAs in $\{T_j\}$

Aborting a Transaction

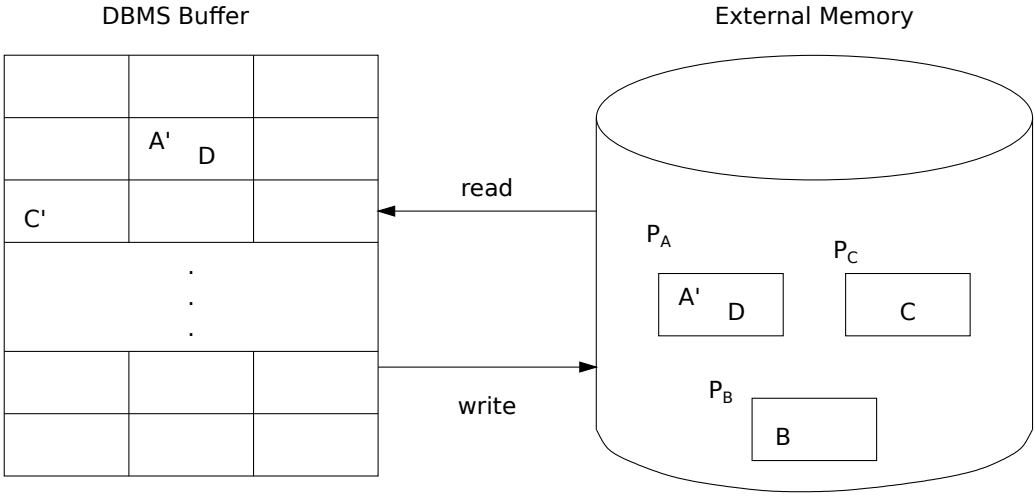
- log files can also be used to undo the changes performed by an aborted TA
- the functionality is needed anyway (system crash)
- can be used for “normal” aborts, too

We now look more closely at the implementation.

Classification of Failures

- local failure within a non-committed transaction
  - effect of TA must undone
  - $R1$ recovery
- failure with loss of main memory
  - all committed TAs must be preserved ($R2$ recovery)
  - all non-committed TAs must be rolled back ($R3$ recovery)
- failure with loss of external memory
  - $R4$ recovery

Storage Hierarchy



Storage Hierarchy (2)

- Replacement strategies for buffer pages
  - $\neg$*steal*: pages that have been modified by active transactions must not be replaces
  - *steal*: any non-fixed pages can be replaced if new pages have to be read in

Storage Hierarchy (3)

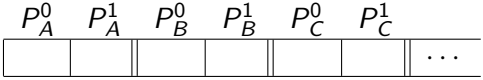
- write strategies for committed TAs
  - *force* strategy: changes are written to disk when a TA commits
  - $\neg$*force* strategy: changed pages may remain in the buffer and are written back at some later point in time

Effects on Recovery

	force	¬force
¬steal	• no redo • no undo	• redo • no undo
steal	• no redo • undo	• redo • undo

Update Strategies

- Update in Place
  - each page corresponds to one fixed position on disk
  - the old state is overwritten
- twin-block approach



- shadow pages
  - only changed pages are replicated
  - less redundancy than with the twin-block approach

System Configuration

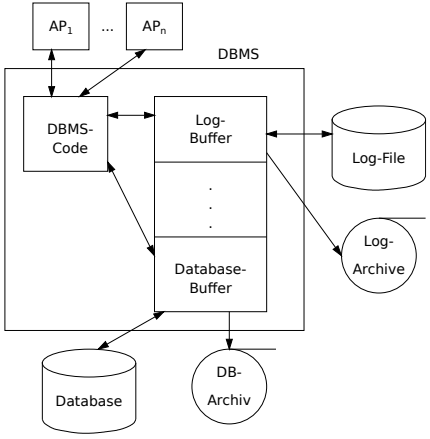
In the following we assume a system with the following configuration

- steal
- ¬force
- update-in-place
- fine-grained locking

ARIES

- The ARIES protocol is a very popular recovery protocol for DBMSs
- The log file contains:
  - Redo Information: contains all information necessary to re-apply changes
  - Undo Information: contains all information necessary to undo changes

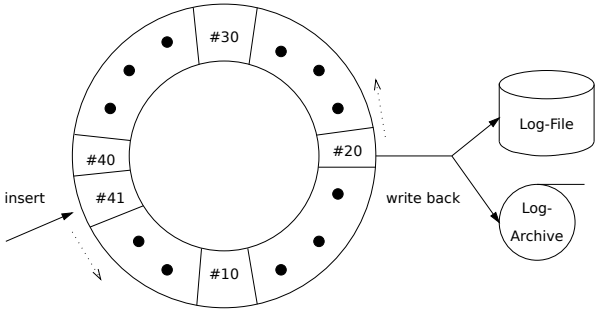
Writing the Log



- The log information stored written two times
  - log file for fast access: R1, R2, and R3 recovery
  - log archive: R4 recovery

Writing the Log (2)

- organization of the log ring-buffer:



Writing the Log (3)

- **W**rite **A**head **L**og Principle
  - before a transaction is **committed**, all corresponding log entries must have been written to disk
  - before a modified page is written back to disk, all log entries involving this page must have been written to disk
- this is called *forcing* the log

Required for Durability.

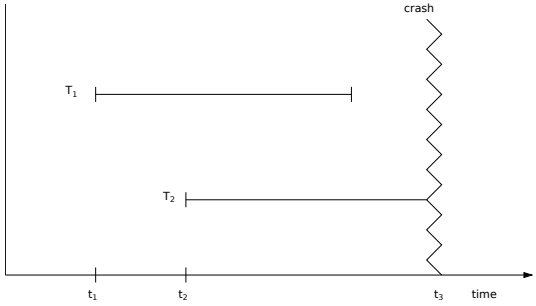
Writing the Log (4)

Some care is needed when writing the log to disk

- disks are not byte addressable
- larger chunks, usually 512 bytes
- remember, the system may crash at any time
- partial writes to the last block are dangerous
- might require additional padding when forcing the log
- related problem: partial page writes

Some of these issues can be solved by hardware.

Restart after Failure

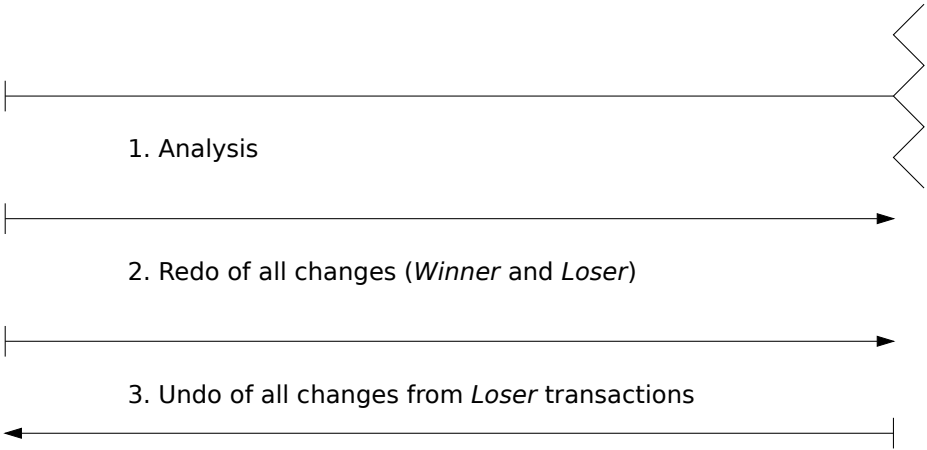


- TAs like T_1 are *winner* transactions: they must be replayed completely
- TAs like T_2 are *loser* transactions: they must be undone

Restart Phases

- *Analysis*:
  - determine the *winner* set of transactions of type T_1
  - determine the *loser* set of transactions of type T_2.
- *Repeating History*:
  - *all* operations contained in the log are applied to the database instance in the original order
- *Undo of Loser Transactions*:
  - the operations of *loser* transactions are undone in the database instance in reverse order

Restart Phases (2)



Structure of Log Entries

[LSN,TA,PageID,Redo,Undo,PrevLSN]

- Redo:
  - physical logging: after image
  - logical logging: code that constructs the after image from the before image
- Undo:
  - physical logging: before image
  - logical logging: code that constructs the before image from the after image

Structure of Log Entries (2)

- *LSN* (*Log Sequence Number*),
  - a unique number identifying a log entry
  - *LSNs* must grow monotonically
  - allows for determining the chronological order of log entries
  - typical choice: offset within log file (i.e., implicit)
- *TA*
  - transaction ID of the transaction that performed the change

Structure of Log Entries (3)

- *PageID*
  - the ID of the page where the update was performed
  - if a change affects multiple pages, multiple log records must be generated
- *PrevLSN*,
  - pointer to the previous log entry of the corresponding transactions
  - needed for performance reasons

Note: often there is a certain asymmetry: physical redo (one page), logical undo (multiple pages)

Example

	T_1	T_2	Log [LSN,TA,PageID,Redo,Undo,PrevLSN]
1.	**BOT**		[#1, T_1,**BOT**, 0]
2.	$r(A, a_1)$		
3.		**BOT**	[#2, T_2, **BOT**, 0]
4.		$r(C, c_2)$	
5.	$a_1 := a_1 - 50$		
6.	$w(A, a_1)$		[#3, T_1, P_A, A–=50, A+=50, #1]
7.		$c_2 := c_2 + 100$	
8.		$w(C, c_2)$	[#4, T_2, P_C, C+=100, C–=100, #2]
9.	$r(B, b_1)$		
10.	$b_1 := b_1 + 50$		
11.	$w(B, b_1)$		[#5, T_1, P_B, B+=50, B–=50, #3]
12.	**commit**		[#6, T_1, **commit**, #5]
13.		$r(A, a_2)$	
14.		$a_2 := a_2 - 100$	
15.		$w(A, a_2)$	[#7, T_2, P_A, A–=100, A+=100, #4]
16.		**commit**	[#8, T_2, **commit**, #7]

The Phases - Analysis

- the log contains BOT, commit, and abort entries
- the log is scanned sequentially to identify all TAs
- when a *commit* is seen, the TA is a *winner*
- when a *abort* is seen, the TA is a *loser*
- TAs that neither commit nor abort are implicitly *loser*

Winner have to be preserved, loser have to be undone

The Phases - Redo

Redo brings the DB into a consistent state

- some changes might still be in main memory at the crash ($\not$force)
- changes can be incomplete (e.g., B-tree split)
- but the log contains everything

Redo is done by one forward pass

- all log entries contain the affected page
- the pages contain LSN entries
- if the LSN of the page is less than the LSN of the entry, the operation must be applied
- the LSN is updated afterwards!
- allows for identifying the current state

Afterwards the DB has a known state.

The Phases - Undo

Eliminates all changes by *loser* transactions.

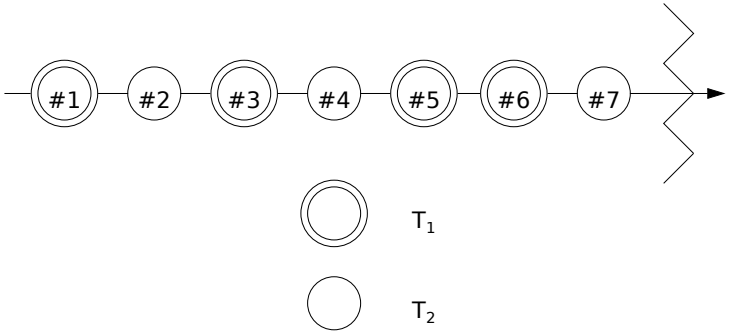
- during analysis, DBMS remembers last LSN of each transaction
- transactions that aborted on their own can be ignored
  (no “last operation”, all undone)
- active TAs have to be rolled back

Log is read backwards

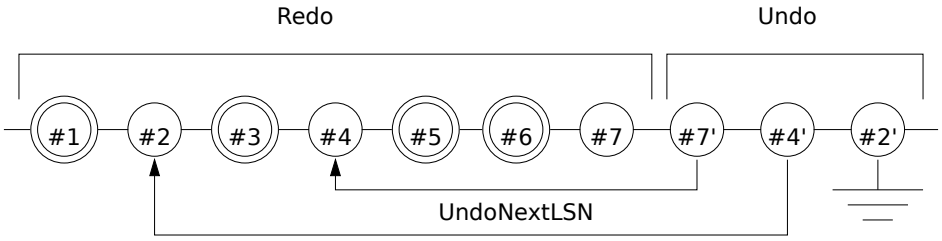
- lastLSN pointers are used for skipping
- all encountered operations are undone
- produces new log entries (redo the undo)

Idempotent Restart

$$undo(undo(\cdots(undo(a))\cdots)) = undo(a)$$
$$redo(redo(\cdots(redo(a))\cdots)) = redo(a)$$



Idempotent Restart (2)



- CLRs (compensating log records) for undone changes
- #7' is a CLR for #7
- #4' is a CLR for #4

Log Entries after Restart

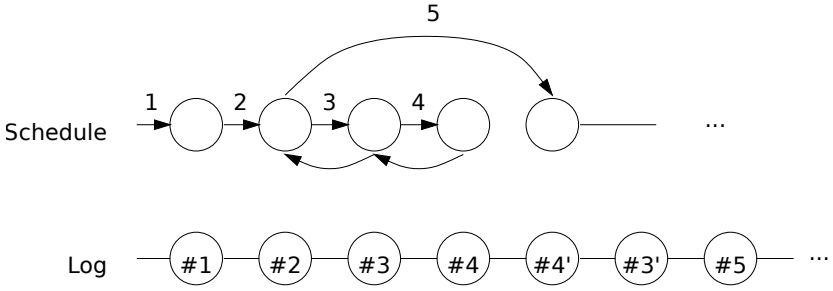
$$[\#1, T_1, \textbf{BOT}, 0]$$
$$[\#2, T_2, \textbf{BOT}, 0]$$
$$[\#3, T_1, P_A, A{-}{=}50, A{+}{=}50, \#1]$$
$$[\#4, T_2, P_C, C{+}{=}100, C{-}{=}100, \#2]$$
$$[\#5, T_1, P_B, B{+}{=}50, B{-}{=}50, \#3]$$
$$[\#6, T_1, \textbf{commit}, \#5]$$
$$[\#7, T_2, P_A, A{-}{=}100, A{+}{=}100, \#4]$$
$$\langle \#7', T_2, P_A, A{+}{=}100, \#7, \#4 \rangle$$
$$\langle \#4', T_2, P_C, C{-}{=}100, \#7', \#2 \rangle$$
$$\langle \#2', T_2, -, -, \#4', 0 \rangle$$

- CLRs are marked by $\langle \ldots \rangle$

CLR

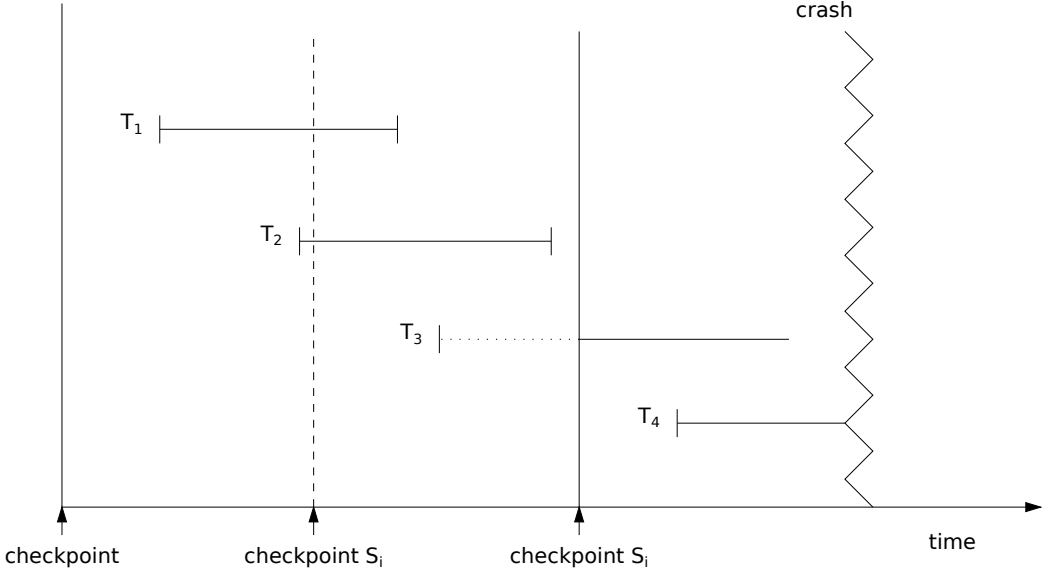
- a CLR is structured as follows
  - LSN
  - TA
  - PageID
  - Redo information
  - PrevLSN
  - UndoNxtLSN (pointer to the next operation to undo)
- no undo information (redo only)
- prevLSN/undoNxtLSN could be combined into one (prevLSN is not really needed)

Partial Rollback



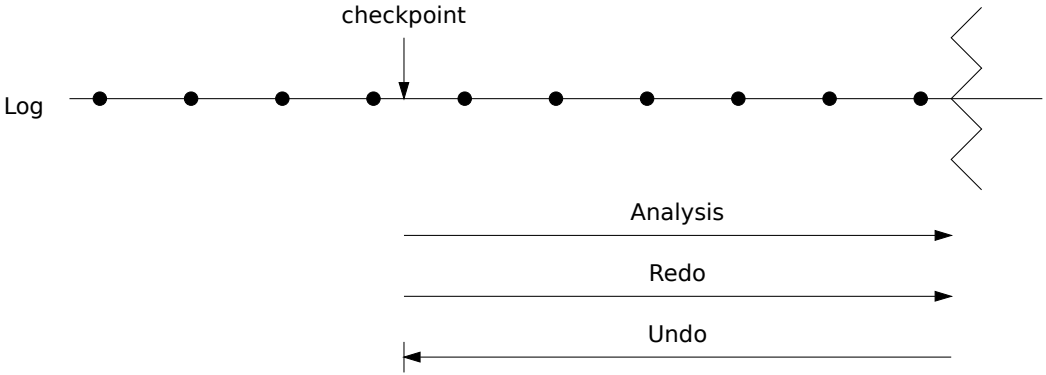
- Steps 3 and 4 are rolled back
- necessary to implement save points within a TA

Checkpoints



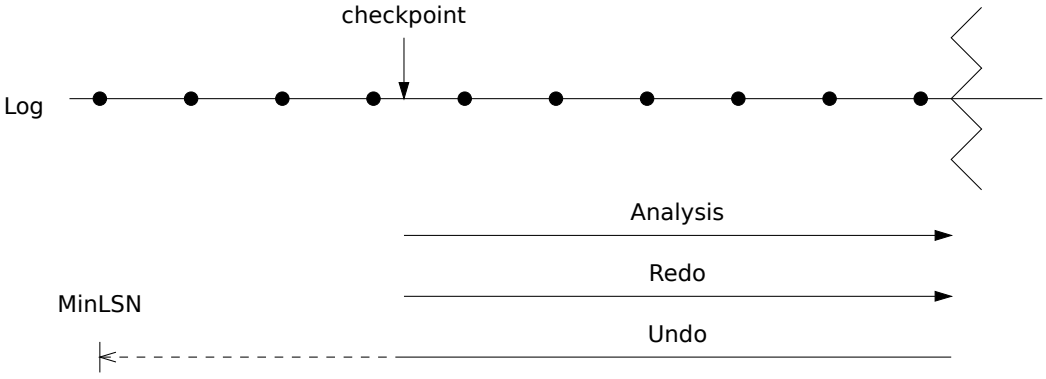
Checkpoints (2)

- transaction consistent:

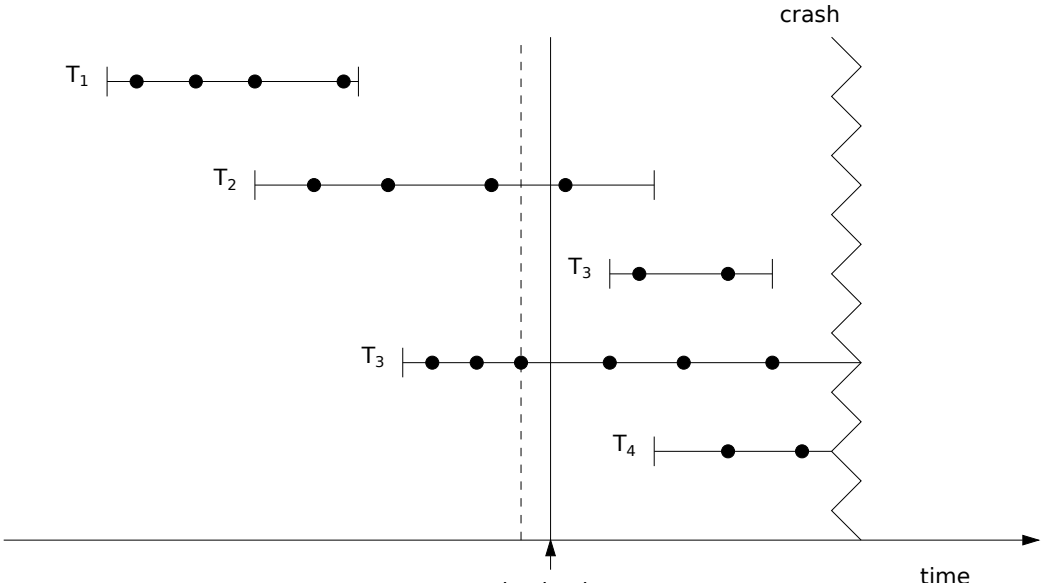


Checkpoints (3)

- action consistent:

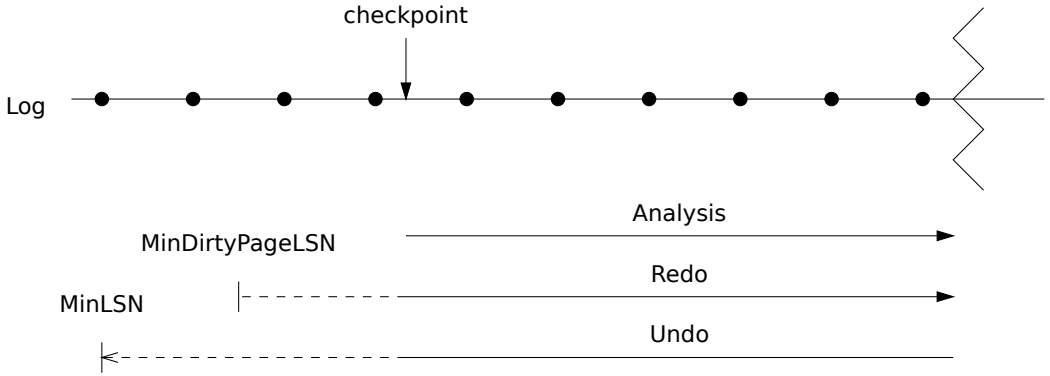


Checkpoints (4)



Checkpoints (5)

- fuzzy checkpoints:



Fuzzy Checkpoints

- modified pages are not forced to disk
- only the page ids are recorded
- *Dirty Pages*=set of all modified pages
- *MinDirtyPageLSN*: the minimum LSN whose changes have not been written to disk yet

Set-Oriented Query Processing

Motivation

During query processing, the DBMS tries to process whole *sets of data items* at a time

- "manual" programming is usually record oriented
- e.g., compare two records
- easy to understand, but this does not scale

Consider: intersecting two lists

- breaking it down into record-level operators is inefficient
- compares each record with each other record
- $O(n^2)$
- considering the complete lists in one step is more efficient
- $O(n \log n)$

Motivation (2)

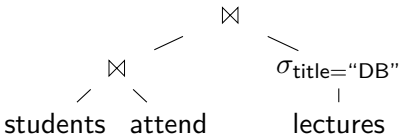
Set-oriented processing has several advantages

- data can be pre-processed before processing
- sorting/hashing/index structures etc.
- amortizes over the set
- leads to more efficient algorithms
- easier to cope with memory limitations etc.
- easier parallelism
- ...

Algorithms tend to become more scalable, but also more involved.

The Algebraic Model

Query processing is usually expressed by relational algebra



- operators consumes zero or more relations, and produce one output relation
- inherently set (or rather: bag) oriented

Implementing the Algebraic Model

Operators are specified in a query agnostic manner:

- intersect
  - left
  - right
  - compare

Operator does not understand the query semantic. It only knows:

- *left* will produce a result set
- *right* will produce a result set
- *compare* compares two elements

Note: a scalable implementation will need more (e.g., *hashLeft*,*hashRight*), we ignore this for now.

Implementing the Algebraic Model (2)

The algebraic operators define the **abstract logic** of query processing primitives. The query specific parts are hidden in **subscripts**.

In particular:

- operators do not "know" the data types or byte size of input tuples
- they do not "understand" the content of a tuple
- they only specify the data flow and the control flow
- all query dependent operations are delegated to helper subscripts
- keeps the operator itself very generic

Note: sometimes operators are hinted with query specific info (e..g, a fixed tuple size) for performance reasons, but this is only a minor variation.

Implementing the Algebraic Model (3)

Example: intersectSorted(left,right,compare)

t_1=next tuple from *left*
n=*right*
while input is not exhausted
  if n=*left*
    t_1=next tuple from *left* **else**
    t_2=next tuple from *right*
  c=*compare*(t_1,t_2)
  if $c = 0$
    store t_1 as result
  else if $c < 0$
    n=*left*
  else
    n=*right*

The code is independent from the concrete query.

Operator Composition

- each operator produces a set (bag/stream) of result tuples
- operators consume zero or more input sets
- usually assume nothing about their input
- therefore can be combined in an arbitrary manner
- very flexible

Operator Interface

Option 1: Full Materialization

Every operator materializes its output. The input is always read from a materialized state.

Advantages:

- easy to implement
- can handle surprises concerning intermediate result sizes (dynamic plans)
- advanced techniques like parallelization, result sharing, etc. are simple

Disadvantages:

- materialization is expensive
- in particular if data is larger than main memory

Few systems use this approach, but some do (MonetDB).

Operator Interface (2)

Option 2: Iterator Model

Each operator produces a tuple stream on demand. The input is iterated over.

Advantages:

- data is pipelined between operators
- avoids unnecessary materialization
- flexible control flow
- easy to implement

Disadvantages:

- millions of virtual function calls
- poor locality

The standard model. Widely used.

Operator Interface (3)

The iterator model usually offers the following interface:

- open
- next
- close

Repeated calls to *next* produce the output stream.

Internally, operators maintain a complex state to offer the iterator interface.

Operator Interface (4)

How to pass data from one operator to the other?

- the data itself is opaque
- as a consequence, it cannot be passed (easily) by value

Alternative 1: pass tuple pointers

- the real data resides on a page/in the buffer
- operators are only passed pointers to the data

Alternative 2: not at all

- there is a global data space ("registers")
- subscript functions operate on these registers
- the operators never touch the data directly

Alternative 2 is more generic, and can cope better with computed columns.

Operator Interface (5)

Option 3: blockwise processing
Each operator produces a tuple stream, but not tuple-by-tuple but as a stream of larger chunks.

Advantages:

- far fewer function calls
- better code and data locality

Disadvantages:

- additional materialization overhead
- consumes memory bandwidth
- control flow not as flexible

Operator Interface (6)

Option 4: pushing tuples up
Each operator pushes produced tuples towards the consuming operators.

Advantages:

- operator logic is concentrated in a few loops
- good code and data locality
- pipelining etc. still possible
- support for DAG-structured plans

Disadvantages:

- some restrictions in control flow
- code generation more involved

Examples - Full Materialization

scan(R)
  // no-op, all operators read their input
  return R
select(R,p)
  R'=new temporary relation
  for each $t \in R$
    if $p(t)$
      append t to R'
  return R'
cross(R_1,R_2)
  R'=new temporary relation
  for each $t_1 \in R_1$
    for each $t_2 \in R_2$
      append $t_1 \circ t_2$ to R'
  return R'

Examples - Iterator Model

class Scan
  $in, tid, limit$

Scan::open(R)
  $in = R$
  $tid = 0$
  $limit = |R|$

Scan::next()
  if $tid \geq limit$
    return false
  load tuple t from in at position tid
  $tid = tid + 1$
  return true

Examples - Iterator Model (2)

```
class Select
  in,p

Select::open(in,p)
  this.in=in
  this.p=p

Select::next(in,p)
  while in.next()
    if p()
      return true
  return false
```

Examples - Iterator Model (3)

```
class Cross
  left,right,step
Cross::open(left,right)
  this.left=left
  this.right=right
  step=true
Cross.next()
  while true
    if step
      if not left.next()
        return false
      right.open()
      step=false
    if right.next()
      return true
    step=true
```

Examples - Blockwise Processing

class Scan
  in,*tid*,*limit*

Scan::open(R)
  in=R
  tid=0
  limit=$|R|$

Scan::next()
  C=min(*limit*-*tid*,1000)
  R'=tuple array of size C
  for i=0...$C-1$
    load tuple $R'[i]$ from *in* at position *tid*+i
  tid=*tid*+C
  return R'

Examples - Blockwise Processing (2)

```
class Select
  in,p
Select::open(in,p)
  this.in=in, this.p=p
Select::next(in,p)
  while true
    R'=in.next()
    if |R'| = 0
      return R'
    w=0
    for i=0...|R'| - 1
      R'[w] = R'[i]
      w = w + p(R'[w])
    R'.length=w
    if |R'| > 0
      return R'
```

Examples - Blockwise Processing (3)

class Cross
  $left, right, c_L, l_L, R_L, c_R, l_R, R_R$

Cross::open($left, right$)
  this.$left$=$left$
  this.$right$=$right$
  $step$=**true**
  $c_L = l_L = c_R = r_R = 0$

Cross.next()
  R'=tuple array of size 1000, w=0

Examples - Blockwise Processing (4)

while true
  while $c_R = l_R$
    if $c_L \geq l_L$
      $R_R = right$.next()
      if $|R_R| = 0$
        $R_L = left$.next()
        if $|R_L| = 0$
          R'.length=w, **return** R'
        $right$.rewind(), $R_R = right$.next()
      $c_L = 0$, $l_L = |R_L|$
    else $c_L = c_L + 1$
    $c_R = 0$, $l_R = |R_R|$
  $R'[w] = R_L[c_L] \circ R_R[c_R]$
  $c_R = c_R + 1$, $w = w + 1$
  if $w = |R'|$
    return R'

Examples - Push

```
class Scan
  consumer,R

Scan::open(consumer,R)
  this.consumer=consumer
  this.R=R

Scan::produce()
  for each t in R
    consumer.consume(t)
```

Examples - Push (2)

```
class Select
  in,consumer, p

Select::open(in,consumer, p)
  this.in=in, this.consumer=consumer, this.p=p

Select::produce()
  in.produce()

Select::consume(t)
  if p(t)
    consumer.consume(p)
```

Examples - Push (3)

class Cross
  $left, right, consumer, t_L$

Cross::open($left$,$right$,$consumer$)
  this.$left$=$left$, **this**.$right$=$right$, **this**.$consumer$=$consumer$

Cross::produce()
  $left$.produce()

Cross::consumeFromLeft(t)
  $t_L = t$
  $right$.produce()

Cross::consumeFromRight(t)
  $consumer$.consume($t_L \circ t$)

Additional Functionality

We ignored the *close* function so far

- releases allocated resources

Other functionality implemented or used by operators:

- rewind/rebind
- memory management
- spooling intermediate results

Implementing Subscripts

The operators are query independent, but the subscripts are not

- cover the query-specific parts of the query
- attribute access (e.g., `x.a`)
- predicates (e.g., `a=b`)
- computations (e.g., `sum(amount*(1+tax))`)
- ...

Must be implemented, too

- different for every query
- but usually relatively simple
- complexity much lower than for operators

Implementing Subscripts (2)

Option 1: interpreter objects

Subscripts are assembled from interpreter objects.

- very flexible
- easy to implement
- widely used
- but: many virtual function calls

```
Val AccessInt::eval(char* ptr)
  return *((int*)(ptr+ofs));

Val CompareEqInt::eval(char* ptr)
  return left->eval(ptr).intValue==right->eval(ptr).intValue
```

Implementing Subscripts (3)

Option 2: virtual machines

Subscripts are compiled into instructions for a virtual machine.

- more efficient than interpreter objects
- but also more complex
- requires a compiler to byte code

```
while (true) switch ((++op)->cmd) {
  case Cmd::AccessInt:
    reg[op->out]=*((*int)(ptr+op->val);
    break;
  case Cmd::CompareEqInt:
    reg[op->out]=reg[op->in1].intValue==reg[op->in2].intValue;
    break;
  ...
}
```

Implementing Subscripts (4)

Option 3: pre-compiled fragments

Subscripts are expressed as combination of pre-compiled fragments.

- each fragment performs a number of operations
- quite efficient (vectorization)
- but usually only applicable for column stores

```
CompareEqInt(unsigned len,int* col1,int* col2,bool* result)
  for (unsigned index=0;index!=len;++index)
    result[index]=col1[index]==col2[index]
```

Implementing Subscripts (5)

Option 4: generated machine code

Subscripts are at runtime compiled into native machine code.

- the most efficient alternative
- but also the most difficulty
- portability is an issue
- we will look at this in the Section Code Generation

```
...
movq  72(%rsp), %rax
movl  (%rax,%r12,4), %r13d
movq  120(%rsp), %rax
movl  (%rax,%r12,4), %edi
cmpl  %r13d,%edi
...
```

Pipelining

As mentioned, most approaches try to avoid copying data between operators

- this is called *pipelining*
- operators that do materialize their input are called *pipeline breakers*
- operators are consume their input completely before processing are called *full pipeline breakers*
- some binary operators are pipeline breakers on only one side

This behavior has implications regarding other operators.

Pipelining (2)

Some effects of different pipeline behavior

- if a pipeline break is between source and sink the original data is no longer accessible
  - relevant for lazy attribute access/TID join/string representations etc.
  - the system must plan defensively
- if a full pipeline breaker is between two operators both are decoupled
  - the full pipeline break breaks the plan into fragments
  - can be executed independent from each other
  - relevant for scheduling
- ...

The code generation must know the pipeline behavior of operators.

Parallelization

How can we exploit multiple cores during query processing?

- inter-query parallelism is simple
- intra-query parallelism is much harder
- independent parts of the query can be executed in parallel (see: full pipeline breaker)
- parallelizing individual operators is more difficult
- usual strategy: partition the input

We will discuss this later in more detail.

Algebraic Operators

Algebraic Operators

Queries are translated into relational algebra

- therefore a DBMS must offer implementations for all algebraic operators
- often more than one implementation
- different implementations are tuned for different usage scenarios

Complexity varies

- a few operators are very simple
- but most are quite complex
- pipelining operators tend to be simple
- pipeline breakers tend to be complex

Table Scan

The most basic operator

- produces all tuples contained in a relation
- conceptually very simple
- implementation complexity varies from simple to complex
- has to navigate the physical representation of the relation
- additional complexity from deferred updates, snapshot isolation, etc.

```
TableScan::produce()
  for each page extent e
    for each page p in e
      fix p
      for each tuple t in p
        consumer.consume(t)
      unfix p
```

Selection

A selection σ_p

- filters out all tuples that do not satisfy p
- a very simple operator
- many systems do not even implement it as separate operator
- instead, piggybacked onto other operators

```
Select::produce()
  input.produce()

Select::consume(t)
  if p(t)
    consumer.consume(t)
```

Map

A map $\chi_{a:f}$

- computes a new column by evaluating f
- another very simple operator
- like selections, often piggybacked

Map::produce()
  input.produce()

Map::consume(t)
  $t' = t \circ [a : f(t)]$
  consumer.consume(t')

Join

A join $e_1 \bowtie_p e_2$

- a very complex operator
- one of the most important operators
- several different implementations exist

Candidate implementations depend on the join itself:

1. if e_2 depends upon e_1, nested loop join must be used
   (i.e. dependent join $e_1 \bowtie e_2$)
2. otherwise, if p has the form $e_1.a = e_2.b$, any join algorithm can be used (equi-join)
3. otherwise, either nest loop or blockwise nested loop can be used

Nested-Loop Join

The nested loop join $\bowtie_p^{NL}$ is the most flexible, but also most simple and inefficient join

- evaluates the right hand side for every tuple of the left side
- pairwise comparison, suitable for any kind of predicate
- the right hand side is evaluated very frequently

NLJoin::produce()
  left.produce()

NLJoin::consumeFromLeft(t)
  $t_L = t$
  right.produce()

NLJoin::consumeFromRight(t)
  $t' = t_L \circ t$
  if $p(t')$
    consumer.consume(t')

Blockwise-Nested-Loop Join

The blockwise nested loop join $\bowtie_p^{BNL}$

- loads as many tuples from the left side as possible
- evaluates the right side and joins
- and repeats this with additional chunks from the left side
- like a NL join, suitable for any predicate (but not for $\ltimes$)
- greatly reduces the number of passes over the right hand side
- potentially speeds up execution by orders of magnitude

```
BNLJoin::produce()
  clear the tuple buffer
  left.produce()
  if tuple buffer is not empty
    right.produce()
```

Blockwise-Nested-Loop Join (2)

BNLJoin::consumeFromLeft(t)
  if not can materialize t
    right.produce()
    clear the tuple buffer
  materialize t in tuple buffer

BNLJoin::consumeFromRight(t)
  for each t_L in the tuple buffer
    $t' = t_L \circ t$
    if $p(t')$
      consumer.consumer(t')

Sort-Merge Join

The sort-merge join $e_1 \bowtie_p^{SM} e_2$

- assumes that p has the form $e_1.a = e_2.b$, that e_1 is sorted on a, and that e_2 is sorted on b
- some implementations actually perform the sort, too, but we consider it as separate operator
- performs a linear pass over the input to find matching entries
- very fast and efficient (after sorting)
- **but:** only simple for the $1 : N$ case!

Note: a SM join is simple in the iterator model, but not in the push model (control flow). We materialize the left hand side here to simplify the code, which is usually not needed.

Sort-Merge Join (2)

SMJoin::produce()
  prepare a temp segment for spooling
  left.produce()
  l_L =first spooled tuple
  right.produce()

SMJoin::consumeFromLeft(t)
  spool t to temp segment

Sort-Merge Join (3)

SMJoin::consumeFromRight(t)
  while $(*l_L).a < t.b$
    advance l_L
  $l_B = l_L$
  while $(*l_B).a = t.b$
    consumer.consume($(*l_B) \circ t$)
    advance l_B

- non-standard, as the left hand side is already materialized
- one usually tries to avoid this
- better: parallel scans through both sides
- materialization only if an $n : m$ match is found

Hash-Join

The hash join $e_1 \bowtie_p^{HJ} e_2$

- assumes that p has the form $e_1.a = e_2.b$
- builds a hash table from e_1, and probes the hash table with e_2
- in-memory case and external memory case
- real implementations offer both in one (first in-memory, external memory when needed)
- we split both cases to simplify the code

HJJoinInMem::produce()
  prepare an in-memory hash table
  left.produce()
  right.produce()

Hash-Join (2)

HJJoinInMem::consumeFromLeft(t)
  store t in hash table[$t.a$]

HJJoinInMem::consumeFromRight(t)
  for each t_L in hash table[$t.b$]
    if $p(t_L \circ t)$
      consumer.consume($t_L \circ t$)

- for the combined case consumeFromLeft would check for overflows
- switch to external memory hash join when memory is full

Hash-Join (3)

HJJoinExternal::produce()
prepare an in-memory spool buffer
prepare a temp segment for spooling
define initial partition boundaries
left.produce()
flush the buffer if needed
repartitionLeft()
right.produce()
flush the buffer if needed
joinPartitions()

- left side and right side are partitioned
- recursive re-partition might be needed
- once partitions fit, partitions can be join in-memory

Hash-Join (4)

HJJoinExternal::consumeFromLeft(t)
  if not can spool t to the buffer
    sort the buffer by hash values
    write entries in corresponding partitions
    update partition statistics
    empty the buffer
  spool t into buffer

- left side is materialized in memory
- when memory is full, data is written to corresponding partitions on disk
- here: sort to produce sequential I/O

Hash-Join (5)

```
HJJoinExternal::repartitionLeft()
  for each partition larger than main memory
    if number of different hash values>1
      derive finer partition bounds within the partition
      load partition piecewise into memory
      write out each piece into finer partitions
      replace large partition with finer partitions
    else
      mark the partition as overflow
```

- breaks large partitions into finer partitions
- until the partition fits into main memory
- overflow partitions are a special case

Hash-Join (6)

HJJoinExternal::consumeFromRight(t)
  if not can spool t to the buffer
    sort the buffer by hash values
    write entries in corresponding partitions
    empty the buffer
  spool t into buffer

- materializes, just like the left side
- but can use the proper partition boundaries now

Hash-Join (7)

```
HJJoinExternal::joinPartitions()
  for each partition P
    if P is an overflow partition
      joinPartitionOverflow(P)
    else
      joinPartition(P)
```

- partitions are joined pair-wise
- due to the equal join, join partners can only be found in corresponding partitions
- the overflow case needs some special care

Hash-Join (8)

HJJoinExternal::joinPartition(P)
  load P for the left side into a hash table
  for each t in the right partition P
    for each t_L in hash table[$t.b$]
      if $p(t_L \circ t)$
        consumer.consume($t_L \circ t$)

- P is known to fit for the left side
- brings it to the in-memory case

Hash-Join (9)

HJJoinExternal::joinPartitionOverflow(P)
  for each memory sized chunk of P from left
    load the chunk into a hash table
    for each t in the right partition P
      for each t_L in hash table[$t.b$]
        if $p(t_L \circ t)$
          consumer.consume($t_L \circ t$)

- partition did not fit (identical values)
- similar to a blockwise-nested-loop join
- but uses a hash-table to speed up finding matches

Singleton Join

A singleton-join is a join $e_1 \bowtie^{1J} e_2$

- where $|e_1|$ is guaranteed to be ≤ 1
- relatively common, e.g., after group-by, scalar subqueries, etc.
- nested loop join would work, of course
- but singleton is even simpler (see following slides)

SingletonJoin::produce()
  left.produce()
  right.produce()

SingletonJoin::consumeFromLeft(t)
  $t_L = t$

SingletonJoin::consumeFromRight(t)
  if $p(t_L \circ t')$
    consumer.consume($t_L \circ t$)

Non-Inner Joins

So far we have only consider inner joins. But:

- $\bowtie$, $\bowtie\!\!\!\!\!\!\subset$, $\bowtie\!\!\!\!\!\!\subset$ have to produce non-matching tuples, too
- $\ltimes$, $\rtimes$ have to produce only matching tuples, without multiplicity
- $\triangleright$, $\triangleleft$ have to produce only non-matching tuples, without multiplicity

Similar mechanism, but requires additional bookkeeping.

Non-Inner Joins (2)

Idea: non-inner joins *mark* tuples with a join partner

- outer joins: additional pass, produce non-marker tuples with NULL values
- semi joins: produce only if not marked yet
- anti joins: additional pass, produce only non-marked tuples

Problem: where to store the marker bit?

Non-Inner Joins (3)

Marking the left side is usually simple:

- left tuples in-memory for potential join partners
- reserve a bit in the memory block/hash table/...
- bit can be examined before flushing the memory

Marking the right side is more problematic:

- ok if a right hand tuple is only considered once
- then, store the marker in a register
- but nested loop joins etc. are difficult
- maintain extra data structure (interval compression)

Sort

Sorting is useful for a number of other operations (sm-join, aggregation, duplicate elimination, etc.)

Basic strategy:

1. load chunks of tuples into memory
2. sort in-memory, write out sorted runs
3. merge sorted runs
4. recurse if needed to handle merge fanout

Implementation varies a bit.

Sort (2)

Sort::produce()
  input.produce()
  flush memory
  merge partitions
  for each t in merged partitions
    consumer.consume(t)

Sort::consume(t)
  if not enough memory to store t
    flush memory
  materialize t in memory

How to implement flush and merge?

Sort (3)

Easy solution for flushing:

- sort the in-memory tuples using quick sort
- write out all of them, release all memory
- fast sort algorithm, simple

More complex solution:

- use heap sort with replacement selection
- write out only when needed
- produces longer runs
- for sorted input: one run
- variable-sized records are difficult to handle

Sort (4)

Merging is usually performed on the fly:

- read all runs in parallel
- retrieve always the smallest element
- tree of losers, or some other priority queue

Problem: what if the number of runs is too large?

- perform a partial merge
- reduces the number of runs
- repeat until merge is feasible

Group By

Aggregation can be implemented in two ways:

Sort based

- input is sorted by group-by attributes
- all tuples within one group are neighboring
- aggregation is largely trivial

Hash based

- aggregate into hash table
- spill to disk if needed
- merge spilled partitions, similar to hash join partitioning

Group By (2)

InMemoryGroupBy::produce()
  initialize an empty hash table
  input.produce()
  for each group t in hash table
    consumer.consume(t)

InMemoryGroupBy::consume(t)
  if hash table[$t_{|A}$] exists
    update the group hash table[$t_{|A}$]
  else
    create a new group in hash table[$t_{|A}$]

Variable-length aggregates require some care.

Set Operations

The DBMS also has to offer set operations

- `union` / `union all`
- `intersect` / `intersect all`
- `except` / `except all`

Somewhat similar to joins, but have a very specific behavior.

Set Operations (2)

`union all`

The only trivial set operations

- concatenates both tuple streams
- attribute rename required
- but otherwise nearly no code

Set Operations (3)

`union`

Like a union, but without duplicates

- can be implemented as `union all` followed by duplicate elimination
- $e_1 \cup e_2 \equiv \Gamma_A(e_1 \bar{\cup} e_2)$
- or: directly write into one hash table
  (slightly more efficient, but nearly identical)

Set Operations (4)

`intersect`

Similar to a semi-join

- $e_1 \cap e_2 \approx e_1 \ltimes e_2$
- only true if e_1 is duplicate free
- can be checked during the build phase
- or: use a strategy like for `intersect all`

Set Operations (5)

`intersect all`

Intersection with bag semantics

- defined via characteristics functions
- group by sides into one hash table
- count occurrences on left and right side
- intersect result is minimum of both
- standard group-by algorithm (including external memory etc.)
- for in-memory case can prune right side

Set Operations (6)

`except`

Similar to a anti-join

- $e_1 \setminus e_2 \approx e_1 \triangleright e_2$
- only true if e_1 is duplicate free
- can be checked during the build phase
- or: use a strategy like for `except all`

Set Operations (7)

`except all`

Set difference with bag semantics

- defined via characteristics functions
- group by sides into one hash table
- count occurrences on left and right side
- except result is $max(0, l_c - r_c)$
- standard group-by algorithm (including external memory etc.)
- for in-memory case can prune right side

Code Generation

Motivation

For good performance, the operator subscripts have to be compiled

- either byte code
- or machine code
- generating machine code is more difficult but also more efficient

Machine code has portability problems

- code generation frameworks hide these
- some well known kits: LLVM, libjit, GNU lightning, ...
- greatly simplify code generation, often offer optimizations

LLVM is one of the more mature choices.

LLVM

Distinct characteristics

- unbounded number of registers
- SSA form
- strongly typed values

```
define i32 @fak(i32 %x) {
     %1 = icmp ugt i32 %x, 1
     br i1 %1, label %L1, label %L2
L1:  %2 = sub i32 %x, 1
     %3 = call i32 @fak(i32 %2)
     %4 = mul i32 %x, %3
     br label %L3
L2:  br label %L3
L3:  %5 = phi i32 [ %4, %L1 ], [ 1, %L2 ]
     ret i32 %5
}
```

Compiling Scalar Expressions

- all scalar values are kept in LLVM registers
- additional register for NULL indicator if needed
- most scalar operations (=, +, -, etc.) compile to a few LLVM instructions
- C++ code can be called for complex operations (`like` etc.)
- goal: minimize branching, minimize function calls

The real challenge is integrating these into set-oriented processing.

Data-Centric Query Execution

Why does the iterator model (and its variants) use the operator structure for execution?

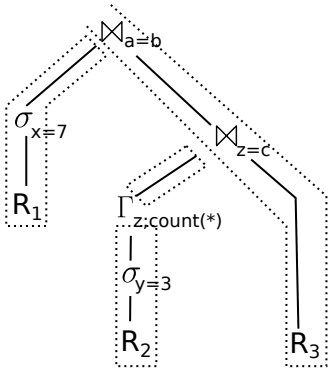
- it is convenient, and feels natural
- the operator structure is there anyway
- but otherwise the operators only describe the data flow
- in particular operator boundaries are somewhat arbitrary

What we really want is **data centric** query execution

- data should be read/written as rarely as possible
- data should be kept in CPU registers as much as possible
- the code should center around the data,
  not the data move according to the code
- increase locality, reduce branching

Data-Centric Query Execution (2)

Example plan with visible pipeline boundaries:



- data is always taken out of a pipeline breaker and materialized into the next
- operators in between are passed through
- the relevant chunks are the pipeline fragments
- instead of iterating, we can push up the pipeline

Data-Centric Query Execution (3)

Corresponding code fragments:

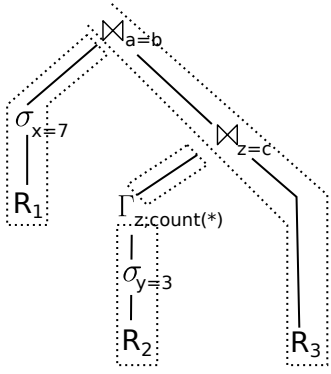
initialize memory of $\bowtie_{a=b}$, $\bowtie_{c=z}$, and Γ_z

for each tuple t in R_1
  if $t.x = 7$
    materialize t in hash table of $\bowtie_{a=b}$

for each tuple t in R_2
  if $t.y = 3$
    aggregate t in hash table of Γ_z

for each tuple t in Γ_z
  materialize t in hash table of $\bowtie_{z=c}$

for each tuple t_3 in R_3
  for each match t_2 in $\bowtie_{z=c}[t_3.c]$
    for each match t_1 in $\bowtie_{a=b}[t_3.b]$
      output $t_1 \circ t_2 \circ t_3$



Data-Centric Query Execution (4)

Basic strategy:

1. the producing operator loops over all materialized tuples
2. the current tuple is loaded into CPU registers
3. all pipelining ancestor operators are applied
4. the tuple is materialized into the next pipeline breaker

- tries to maximize code and data locality
- a tight loops performs a number of operations
- memory access in minimized
- operator boundaries are blurred
- code centers on the data, not the operators

Producing the Code

Code generator mimics the produce/consume interface

- these methods do not really exist, they are conceptual constructs
- the *produce* logic generates the code to produce output tuples
- the *consume* logic generates the code to accept incoming tuples
- not clearly visible within the generated code

Producing the Code (2)

```
void HJTranslatorInner::produce(CodeGen& codegen,Context& context) const
{
  // Construct functions that will be be called from the C++ code
  {
    AddRequired addRequired(context,getCondiution().getUsed().limitTo(left));
    produceLeft=codegen.derivePlanFunction(left,context);
  }
  {
    AddRequired addRequired(context,getCondiution().getUsed().limitTo(right));
    produceRight=codegen.derivePlanFunction(right,context);
  }

  // Call the C++ code
  codegen.call(HashJoinInnerProxy::produce.getFunction(codegen),
    {context.getOperator(this)});
}
void HJTranslatorInner::consume(CodeGen& codegen,Context& context) const
{
```

Producing the Code (3)

```
// Left side
if (source==left) {
  // Collect registers from the left side
  vector<ResultValue> materializedValues;
  matHelperLeft.collectValues(codegen,context,materializedValues);

  // Compute size and hash value
  llvm::Value* size=matHelperLeft.computeSize(codegen,materializedValues);
  llvm::Value* hash=matHelperLeft.computeHash(codegen,materializedValues);

  // Materialize in hash table, spools to disk if needed
  llvm::Value* ptr=codegen.callBase(HashJoinProxy::storeLeftInputTuple,
    {opPtr,size,hash});
  matHelperLeft.materialize(codegen,ptr,materializedValues);
```

Producing the Code (4)

```
  // Right side
  } else {
    // Collect registers from the right side
    vector<ResultValue> materializedValues;
    matHelperRight.collectValues(codegen,context,materializedValues);

    // Compute size and hash value
    llvm::Value* size=matHelperRight.computeSize(codegen,materializedValues);
    llvm::Value* hash=matHelperRight.computeHash(codegen,materializedValues);

    // Materialize in memory, spools to disk if needed, implicitly joins
    llvm::Value* ptr=codegen.callBase(HashJoinProxy::storeRightInputTuple,
      {opPtr,size});
    matHelperRight.materialize(codegen,ptr,materializedValues);
    codegen.call(HashJoinInnerProxy::storeRightInputTupleDone,{opPtr,hash});
  }
}
```

Producing the Code (5)

```
void HJTranslatorInner::join(CodeGen& codegen,Context& context) const
{
  llvm::Value* leftPtr=context.getLeftTuple(),*rightPtr=context.getLeftTuple();
  // Load into registers. Actual load may be delayed by optimizer
  vector<ResultValue> leftValues,rightValues;
  matHelperLeft.dematerialize(codegen,leftPtr,leftValues,context);
  matHelperRight.dematerialize(codegen,rightPtr,rightValues,context);

  // Check the join condition, return false for mismatches
  llvm::BasicBlock* returnFalseBB=constructReturnFalseBB(codegen);
  MaterializationHelper::testValues(codegen,leftValues,rightValues,
    joinPredicateIs,returnFalseBB);
  for (auto iter=residuals.begin(),limit=residuals.end();iter!=limit;++iter) {
    ResultValue v=codegen.deriveValue(**iter,context);
    CodeGen::If checkCondition(codegen,v,0,returnFalseBB);
  }
  // Found a match, propagate up
  getParent()->consume(codegen,context);
```

Parallel Query Execution

Parallelism

Why parallelism

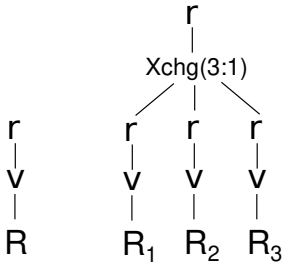
- multiple users at the same time
- modern server CPUs have dozens of CPU cores
- better utilize high-performance IO devices

Forms of parallelism

- inter-query parallelism: execute multiple queries concurrently
  - map each query to one process/thread
  - concurrency control mechanism isolates the queries
  - except for synchronization that parallelism is "for free"
- intra-query parallelism: parallelize a single query
  - horizontal (bushy) parallelism: execute independent sub plans in parallel (not very useful)
  - vertical parallelism: parallelize operators themselves

Vertical Parallelism: Exchange Operator

- optimizer statically determines at query compile-time how many threads should run
- instantiates one query operator plan for each thread
- connects these with "exchange" operators, which encapsulate parallelism, start threads, and buffer data
- relational operator can remain (largely) unchanged
- often (also) used in a distributed setting



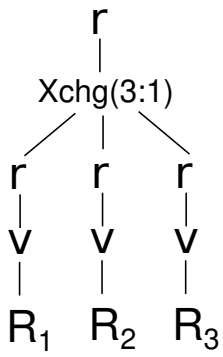
Exchange Operator Variants

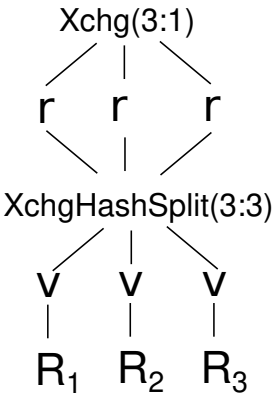
- Xchg(N:M) N input pipelines, M output pipelines

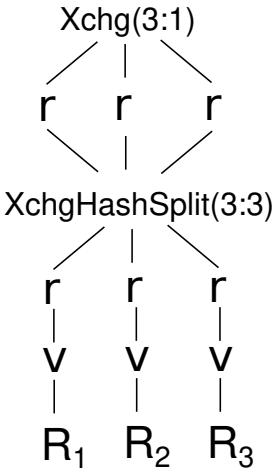
Many useful variants

- XchgUnion(N:1) specialization of Xchg
- XchgDynamicSplit(1:M) specialization of Xchg
- XchgHashSplit(N:M) split by hash values
- XchgBroadcast(N:M) send full input to all consumers
- XchgRangeSplit(N:M) partition by data ranges

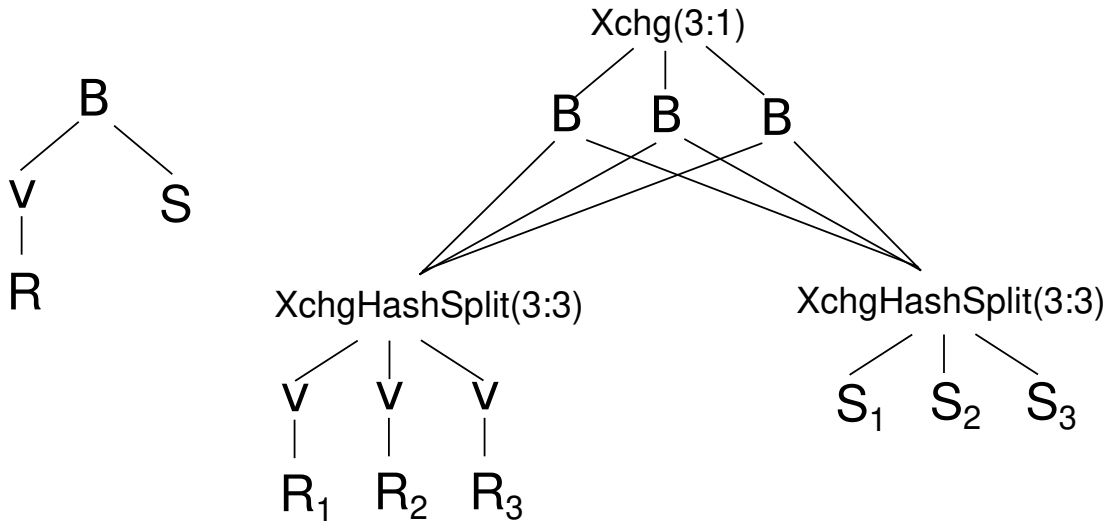
Aggregation with Exchange Operators (3-way parallelism)







Join with Exchange Operators (3-way parallelism)



Disadvantages of Exchange Operators

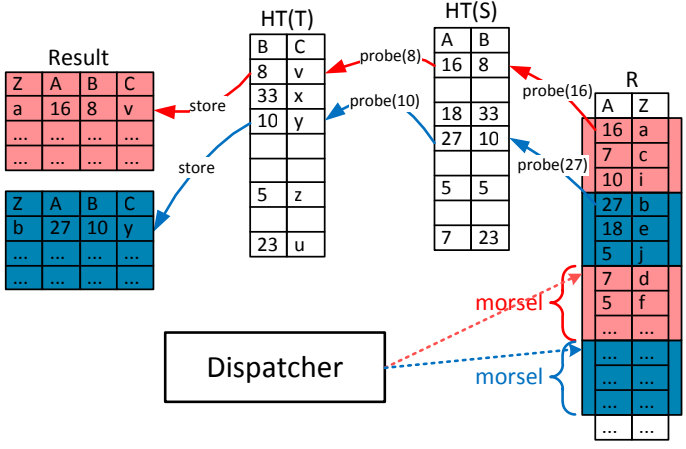
- static work partitioning can cause load imbalances (large problem with many threads)
- degree of parallelism cannot easily be changed mid-query (workload changes)
- overhead:
  - usually implemented using more threads than CPU cores (context switching)
  - hash re-partitioning often does not pay off
  - exchange operators create additional copies of the tuples

Parallel Query Engine

- alternative to Exchange Operators: parallelize operators themselves
- requires synchronization of shared data structures (e.g., hash tables)
- allows for more flexibility in designing parallel algorithms for relational operators

Morsel-Driven Query Execution

- break input into constant-sized work units ("morsels")
- dispatcher assigns morsels to worker threads
- # worker threads = # hardware threads



Dynamic Scheduling

- the total runtime of a query is the runtime of the slowest thread/core/machine
- when dozens of cores are used, often a single straggler is much slower than the others (e.g., due to other processes in the system or non-uniform data distributions)
- solution: don't partition input data at the beginning, but use dynamic work stealing:
  - synchronized queue of small jobs
  - threads grab work from queue
  - the `parallel_for` construct can provide a high-level interface

Parallel In-Memory Hash Join

1. build phase:
   - 1.1 each thread scans part of the input and materializes the tuple
   - 1.2 create table of pointers of appropriate size (tuple count sum of all threads)
   - 1.3 scan materialized input and add pointers from array to materialized tuples using atomic instructions
2. probe phase: can probe the hash table in parallel without any synchronization (as long no marker is needed)

Main-Memory Databases

Motivation

Hardware trends

- Huge main memory capacity
  with complex access characteristics (Caches, NUMA)
- Many-core CPUs
- SIMD support in CPUs
- New CPU features (HTM)
- Also: Graphic cards, FPGAs, low latency networking,...

Database system trends

- Entire database fits into main memory
- New types of database systems
- New algorithms, new data structures

"The End of an Architectural Era.
(It's Time for a Complete Rewrite)."

Recap: Database Workloads

Analytics

- Long-running
- Access large parts of the database
- Often use scans
- Read-only
- Example: "Average order value per year and product group?"

Transaction processing

- Short running
- (Multiple) point queries + simple control flow
- Insert/Update/Delete/Read data
- Example: "Increment account x by 10, decrement account y by 10"

Universal DBMS used for both (but not concurrently).

OLTP

Universal DBMS were optimized for 1970's hardware

- Small fraction of DB in memory buffer
- Hide and avoid disk access at any cost

Today

- Even enterprises can store entire DB in memory
- Transaction are often "one-shot"
- Transactions execute in a few *ms* or even μs

OLTP (2)

Main sources of overhead

- ARIES-style logging
- Locking (2PL)
- Latching
- Buffer Management

Useful work can be as low as $\frac{1}{60}$th of instructions[1].
Modern systems avoid this overhead (see slide 360).

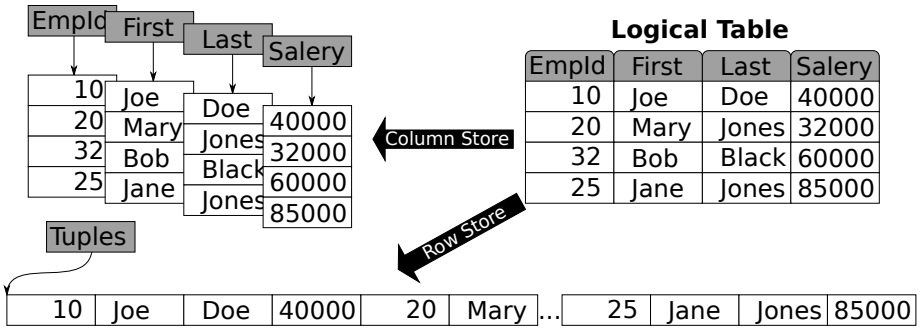
[1] Harizopoulos et al. – *OLTP Through the Looking Glass, and What We Found There*

Physical Data Layout in Main Memory

Lightweight:

- Buffer Manager removed
- No need for segments
- No need for slotted pages

Store data in simple arrays. But: Row-wise or column-wise?



Physical Data Layout in Main Memory (2)

Row Store:

- Beneficial when accessing many attributes
- For OLTP

Column Store:

- Excellent cache utilization
- Sometimes individually sorted
- Compression potential
- Vectorized processing
- For OLAP

Hybrid Row/Column Stores possible

New Systems (Examples)

OLTP-only:

- VoltDB/H-Store
- Microsoft Hekaton

OLAP-only:

- Vectorwise
- MonetDB
- DB2 BLU

Hybrid OLTP *and* OLAP:

- SAP HANA
- HyPer

New Systems: OLTP (Examples)

Challenge:

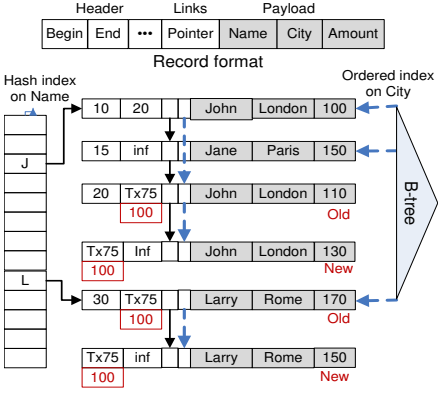
- Avoid overhead
- Guarantee ACID

Approaches:

- Buffer Management: Removed
- Logging
  - H-Store/VoltDB: Log shipping to other nodes
  - Hekaton: Lightweight logging (no index structures)
- Locking:
  - H-Store/VoltDB: Serial execution (on private partitions)
  - Hekaton: Optimistic MVCC
- Latching
  - H-Store/VoltDB: Not necessary
  - Hekaton: Latch-free data structures

New Systems: Hekaton

- Integrated in SQL Server
- Code Generation
- Only access path: Index (Hash or B(w)-Tree)
- Latch-Free Indexes
- MVCC



New Systems: OLAP

- Vectorwise: Vectorized Processing
- HyPer: Query Compilation (cf. Chapter *Code Generation*)

New Systems: Hybrid OLTP and OLAP

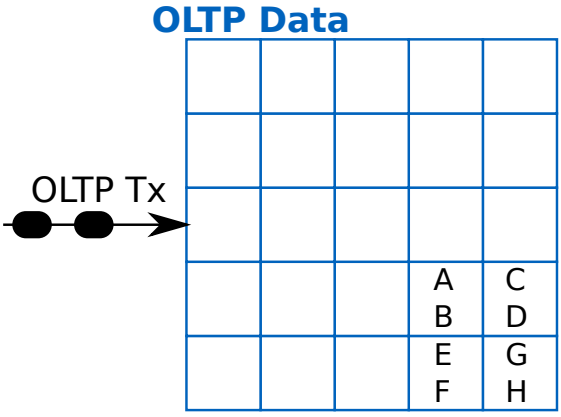
Traditionally:

- Mixing OLTP and OLAP leads to performance decline
- ETL architecture
- 2 systems, stale data

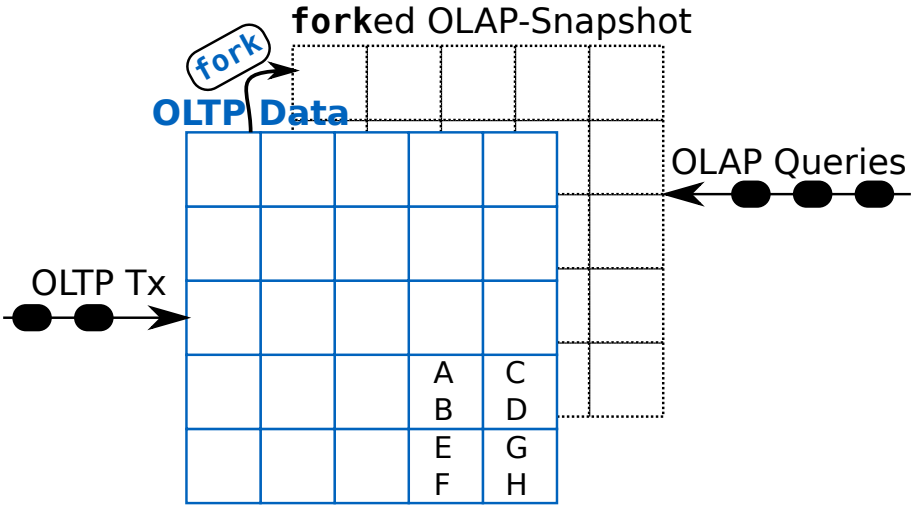
New Systems

- SAP HANA
  - Split DB into read-optimized *main* and update-friendly *delta*
  - OLAP queries read main, OLTP transactions read delta *and* main
  - Periodically merge main and delta
- HyPer: Virtual memory snapshots

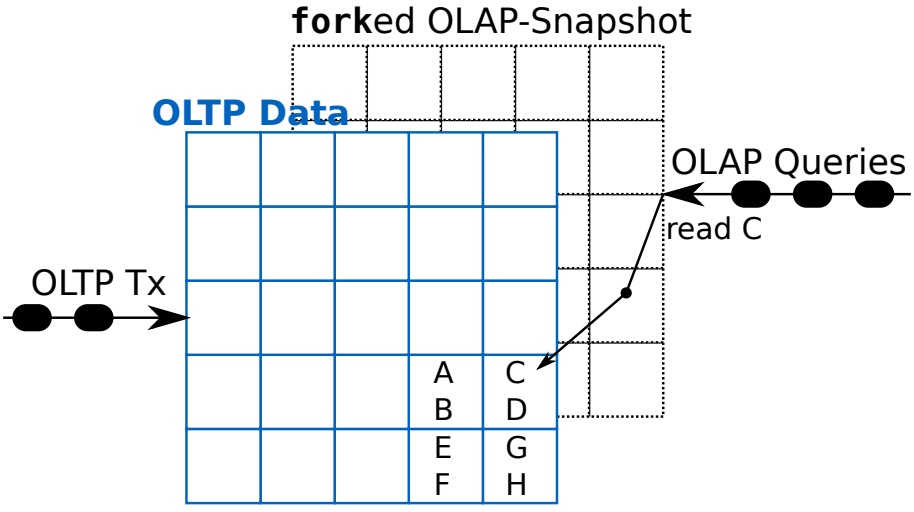
HyPer: Virtual Memory Snapshots



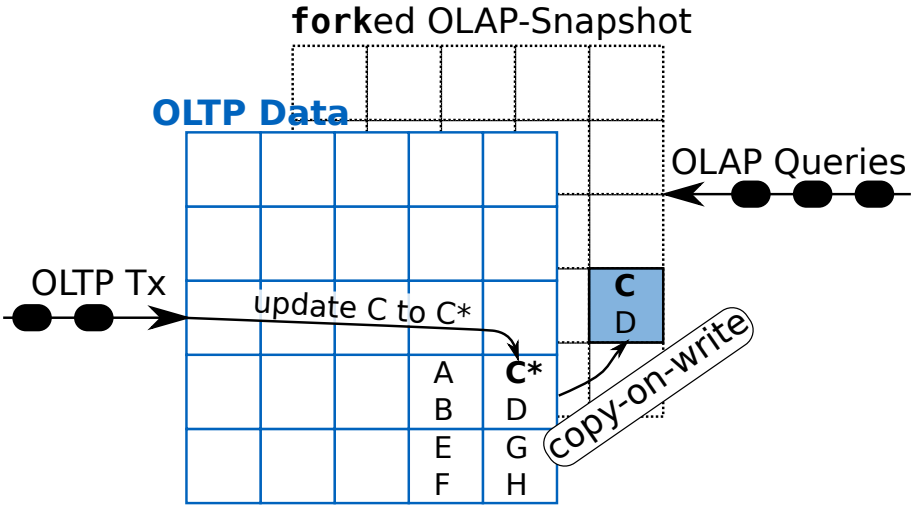
HyPer: Virtual Memory Snapshots



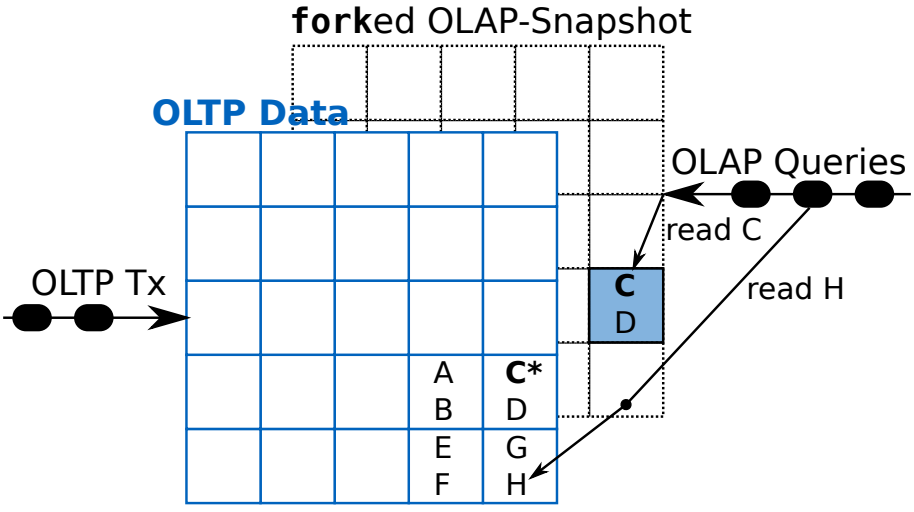
HyPer: Virtual Memory Snapshots



HyPer: Virtual Memory Snapshots



HyPer: Virtual Memory Snapshots



In-Memory Index Structures

- In-memory hash indexes
  - Simple and fast
  - Growing is very expensive
  - Do not support range queries
- Search Trees
  - BSTs are cache unfriendly
  - B-Trees better (even though designed for disk)
- Radix-Trees (“Tries”)
  - Support range queries
  - Height is independent from number of entries

Radix Trees

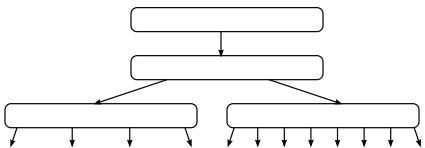
Properties:

- Height depends on key length, not number of entries
- No rebalancing
- All insertion orders yield same tree
- Keys are stored in the tree implicitely

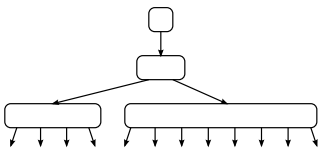
Search:

- Node is array of size 2^s
- s bits (often 8) are used as an index into the array
- s is a trade-off between lookup-performance and memory consuption

Radix Tree



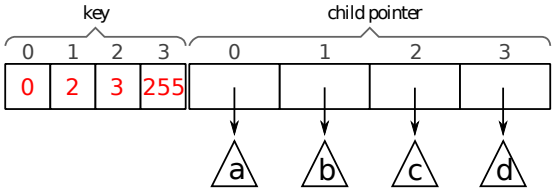
Adaptive Radix Tree



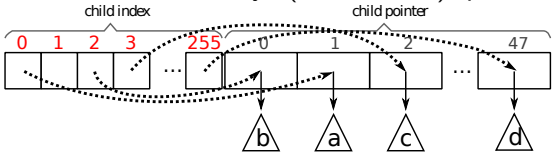
Adaptive Radix Trees

Four node types:

- Node4: 4 keys and 4 pointers at corresponding positions:



- Node16: Like Node4, but with 16 keys. SIMD searchable.
- Node48: Full 256 keys (index offset), point to up to 48 values:

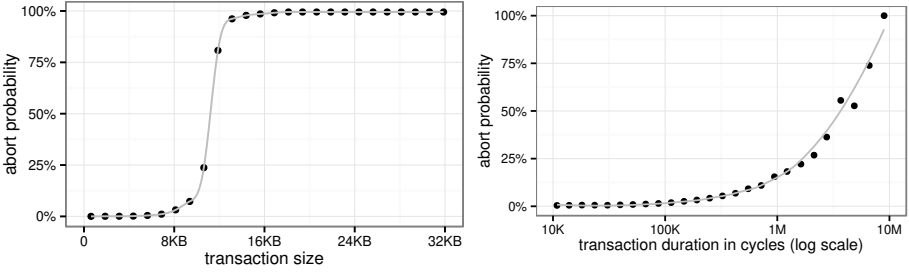


- Node256: Regular trie node, i.e. array of size 256

Additionally: Header with node type, number of entries

Exploiting HTM for OLTP

- Intel's Haswell introduced HTM (via cache coherency protocol)
- Allows to group instructions to transactions
- Can help to implement DB transactions, but
  - Do not guarantee ACID by themselves
  - Limited in size/time



⇒ Use HTM transactions as building blocks for DB transactions

Exploiting HTM for OLTP (2)

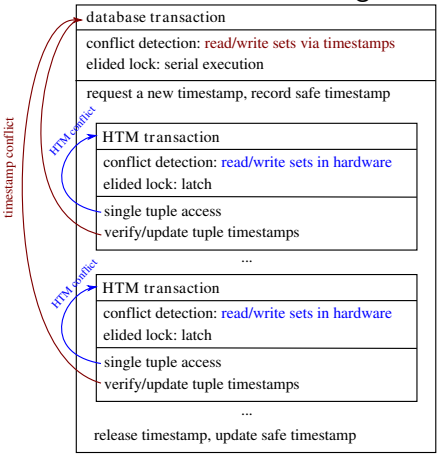
Goals:

- As fine-grained as 2PL, but faster
- As fast as serial execution, but more flexible

```
atomic-elide-lock (lock) {
 account[from]-=amount;
 account[to]+=amount;
}
```

Implementing DB transactions with HTM

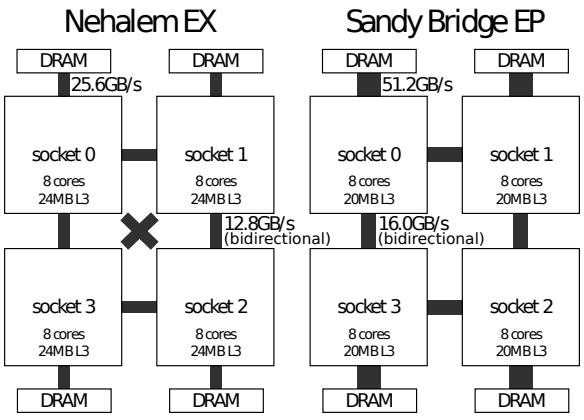
Use TSO + HTM for latching:



- Relation and index structure layout must avoid conflicts

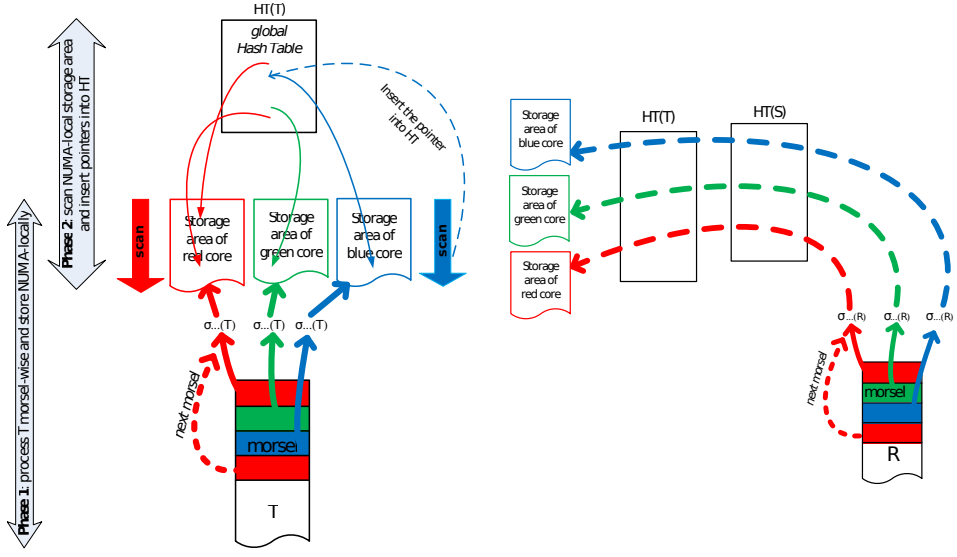
NUMA-Aware Data Processing

NUMA architectures:



- Local access cheap
- Remote access expensive

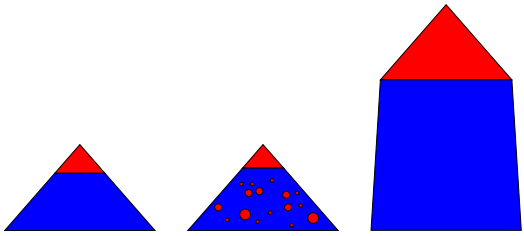
NUMA-Aware Data Processing: Hash Join



Compaction

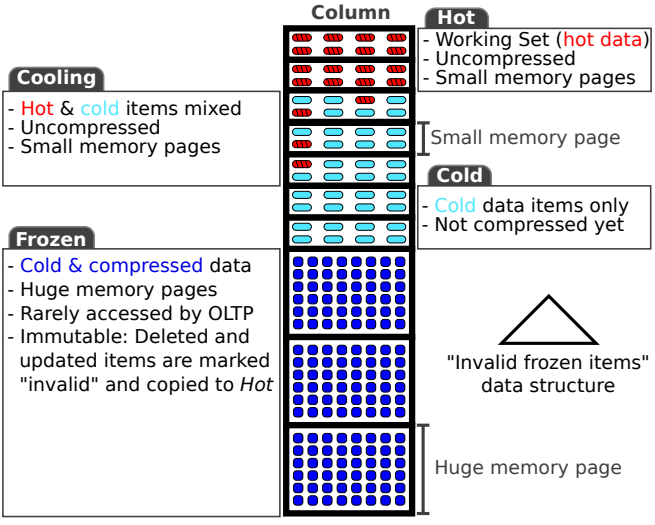
- OLTP & OLAP share the same physical data model
  - Fast modifications vs scan performance
  - Row store vs column store
- Modifications require snapshot maintenance
  - Use more memory
  - Congest memory bus
  - Stall transactions

Compaction: Hot/Cold Clustering



- Compression is applied asynchronously to cold part:
  - Dictionary encoding
  - Run-length encoding
  - Other schemes possible
- Compact snapshots through a mix of regular and huge pages
  - Keeps page table small
  - Clustered updates
  - No huge pages need to be replicated

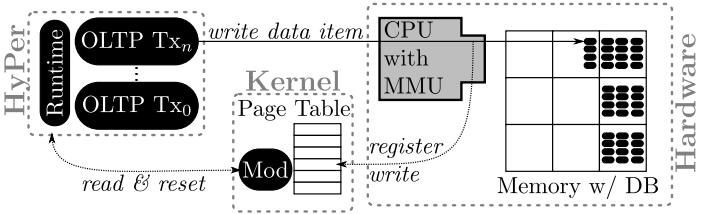
Compaction: Hot/Cold Clustering



Compaction: Hot/Cold Clustering

How to detect temperature without causing overhead?

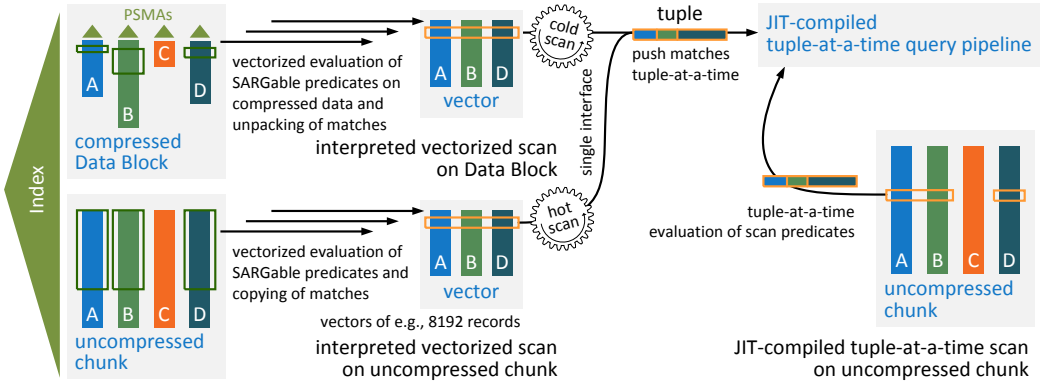
1. Software: LRU lists, counters
2. Hardware: `mprotect`
3. Hardware: `dirty` and `young` flags



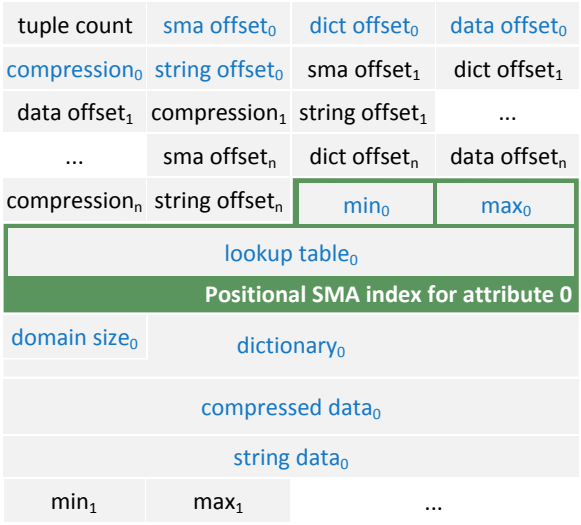
Data Blocks

- most data is cold and rarely / never changes
- it is attrative to compress these aggressively
- and pre-compute SMAs
- helps with skipping data
- fits well with a cloud storage setup

Data Blocks - Scan Types



Data Blocks - Layout



Data Blocks - Vectorized Evaluation