

Column databases

Chapter content:

2018-2019

- In-memory databases: commercial systems: MariaDB
- In-memory databases: commercial systems: Oracle
- In-memory databases: commercial systems: IBM DB2

Column-oriented DB

Column storage vs Row storage

Idea: modify traditional storage for relation R . In consecutive memory, instead of storing a row we store a column (values of one attribute $R.x$).

Assets:

- ✓ only accesses relevant attributes
- ✓ potentially drastic speedup at query-time, esp. aggregation
- ✓ better compression techniques (values from same domain: many identical)
- ✓ allows vectorization (bitwise, SIMD)

Weaknesses:

- ✗ need fast tuple reconstruction
- ✗ slower on `select *`
- ✗ updates (insertions, deletions...) are harder

⇒ analytical workloads, mostly reads, large data

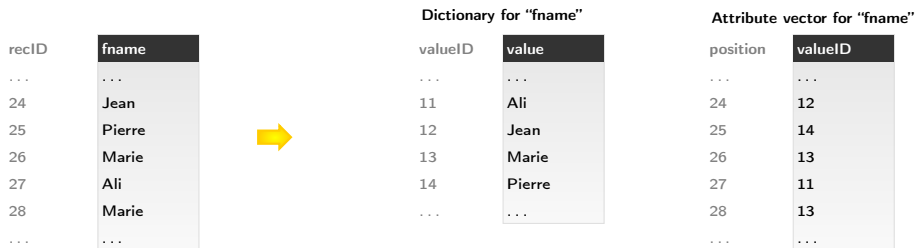
Column-oriented DB

Dictionary encoding



The following slides describe the Sanssouci prototype architecture. Similar ideas (dictionary, buffering updates) apply in other column-oriented DB but with significant variations.

Objective: reduce main memory operations through (lightweight) compression.



[Plattner, in-memory databases course]

The dictionary is sorted \implies fast lookup of id from value, fast range queries.

Column-oriented DB

Compression

valueID is already a “compressed” representation of value. But we can compress attribute vector (e.g.: RLE).

Column	Cardinality	Bits Needed	Item Size	Plain Size	Size with Dictionary (Dictionary + Column)	Compression Factor
First names	5 millions	23 bit	50 Byte	400GB	250MB + 23GB	≈ 17
Last names	8 millions	23 bit	50 Byte	400GB	400MB + 23GB	≈ 17
Gender	2	1 bit	1 Byte	8GB	2b + 1GB	≈ 8
City	1 million	20 bit	50 Byte	400GB	50MB + 20GB	≈ 20
Country	200	8 bit	47 Byte	376GB	9.4kB + 8GB	≈ 47
Birthday	40000	16 bit	2 Byte	16GB	80kB + 16GB	≈ 1
Totals			200 Byte	≈ 1.6TB	≈ 92GB	≈ 17

[Plattner, in-memory databases course]

Dealing with updates

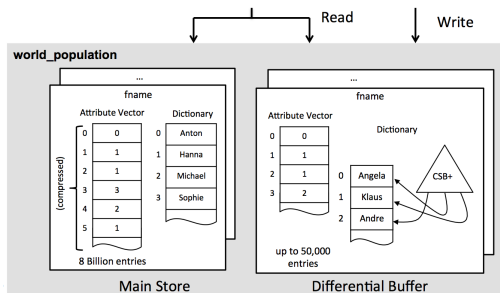
The differential buffer

Inserting a value may:

- have no impact on dictionary
- add a value at the end of dictionary (#bits may change)
- force a dictionary reorganization (sorted dict)

↪ may reorganize the whole attribute vector (same for deletions).

⇒ we keep the main store *read-only*. Perform insert, update, delete on the differential buffer only.



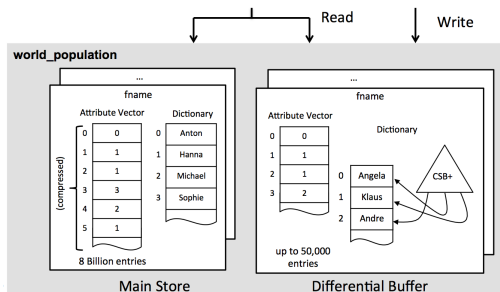
The differential buffer

Queries will check both the *compressed main store* and *differential buffer*.

The differential buffer:

- records updates
- is kept small (periodically merged into the main store and emptied)
- uses column storage but with *unsorted* dictionary
- an index (CSB+-tree) is maintained on the dictionary

A validity attribute is added to tuples (uncompressed bit vector in main store). . .



The differential buffer: updates

Validity attribute: uncompressed bit vector in main store.

Dealing with updates/deletions:

- we update validity attribute in main store
- insert corresponding tuple in differential buffer

recid	fname	lname	gender	country	city	birthday	valid
0	Martin	Albrecht	m	GER	Berlin	08-05-1955	1
1	Michael	Berg	m	GER	Berlin	03-05-1970	0
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968	1
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992	1
4	Ulrike	Schulze	f	GER	Potsdam	09-03-1977	1
5	Sophie	Schulze	f	GER	Rostock	06-20-2012	1
...
8×10^9	Zacharias	Perdopolus	m	GRE	Athen	03-12-1979	1

0	Michael	Berg	m	GER	Potsdam	03-05-1970	1
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Main Store

Michael Berg moves
to Potsdam

Differential
Buffer

[Plattner, in-memory databases course]

One possible way to deal with deletions: do not delete: keep validity interval (like scd type 2) \Rightarrow insert-only approach.

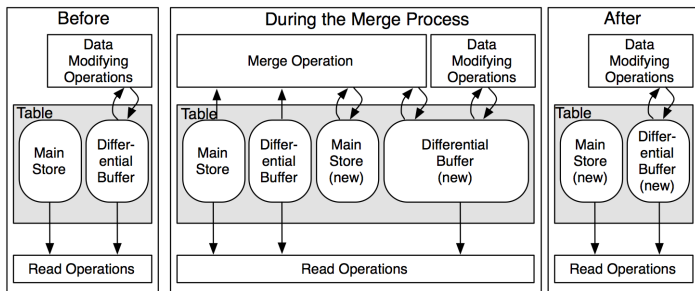
Merging the differential buffer and main store: architecture

Data in main store takes less space (compression) and benefits from faster reads (sorted) \Rightarrow keep differential buffer small \Rightarrow merge process.

We first create a second (empty) differential buffer: updates during (and after) the merge are directed toward that new buffer.

✓ Advantage of working on copies: short lock.

✗ Drawback: needs dedicated resources ($2\times$ space).



[Plattner, in-memory databases course]

Merge process: 1) combine dictionaries 2) compute new attribute vector.

The Merge process

Merge process: 1) combine dictionaries 2) compute new attribute vector.

Main Store

Dictionaries

valueID	fname	city
0	Albert	Berlin
1	Michael	London
2	Nadja	

Attribute vectors

recID	fname	city
0	2	0
1	1	1
2	0	0

Validity vector

recID	valid
0	0
1	0
2	1

Differential Buffer

Dictionaries

valueID	fname	city
0	Michael	Berlin
1	Nadja	Potsdam
2	Hanna	Dresden

Attribute vectors

recID	fname	city
0	0	0
1	1	1
2	0	1
3	2	2

Validity vector

recID	valid
0	0
1	1
2	1
3	1

The Merge process (2)

Merge process: 1) combine dictionaries 2) compute new attribute vector.

Main Store (new)

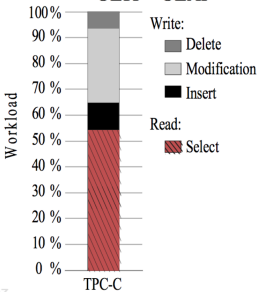
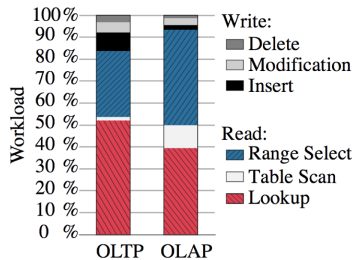
Dictionaries			Attribute vectors			Validity vector	
valueID	fname	city	recID	fname	city	recID	valid
0	Albert	Berlin	0	3	0	0	0
1	Hanna	Dresden	1	2	2	1	0
2	Michael	London	2	0	0	2	1
3	Nadja	Potsdam	3	2	0	3	0
			4	3	3	4	1
			5	2	3	5	1
			6	1	1	6	1

Differential Buffer (new)

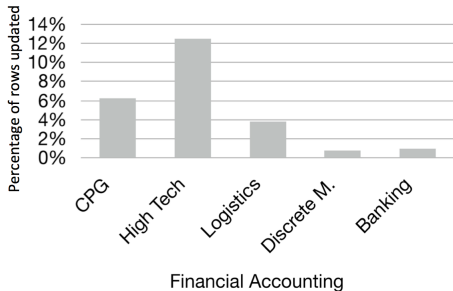
Dictionaries			Attribute vectors			Validity vector	
valueID	fname	city	recID	fname	city	recID	valid

Column-oriented DB

OLTP vs OLAP



Few updates in OLTP



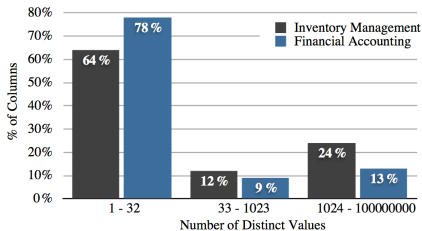
[Plattner, in-memory databases course]

Column-oriented DB

OLTP vs OLAP

55% unused columns per company in average

40% unused columns across all companies



[Plattner, in-memory databases course]

Wide tables with unused columns

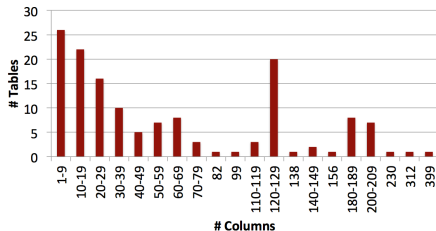


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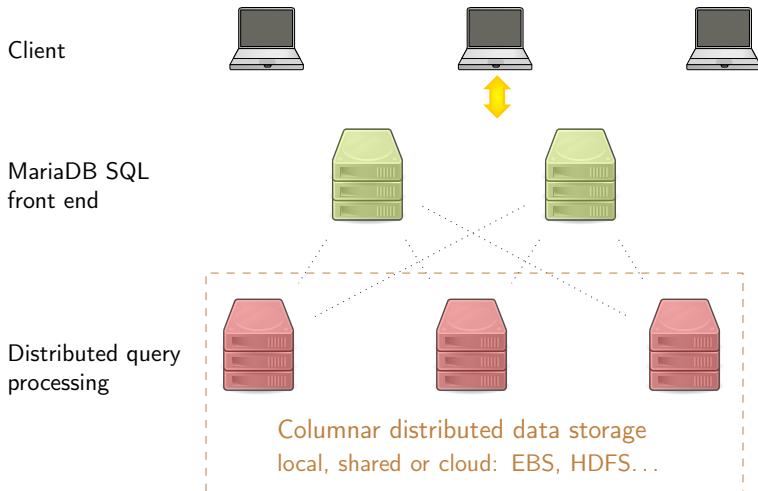
Column databases

- In-memory databases: commercial systems: MariaDB
- In-memory databases: commercial systems: Oracle
- In-memory databases: commercial systems: IBM DB2

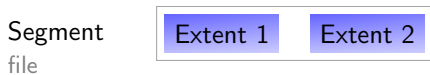
MariaDB ColumnStore

A massively parallel column-storage engine ported from InfiniDB.

Recommended over MariaDB row storage when queries process millions-billions rows from billions-trillions rows tables.



MariaDB ColumnStore: storage architecture



Values are fixed-length datatypes, 1-8bytes.
For larger values: pointer to dictionary entry.

MariaDB

Data is compressed using `snappy` library

≥250MB/s compression, 500MB/s decompression on single Core i7, 64bit.

Extent Map catalogs record the min and max value in each extent.

↔ query engine prunes irrelevant extents.

Block-based MVCC for consistency.

A version buffer records in an in-memory hash table the blocks being modified by a transaction.

Dedicated `cpimport` bulk loader.

```
create table t (  
  id int,  
  Name varchar(20),  
) engine=columnstore;
```



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- In-memory databases: commercial systems: MariaDB
- In-memory databases: commercial systems: Oracle
 - In-memory features
 - IM column store
- In-memory databases: commercial systems: IBM DB2

Oracle 12.2: In-memory features

In-memory aggregation: a query transformation considered by query optimizer, like star transformation, materialized views, or expansion...

For each dimension:

1. compute a dense grouping key for rows satisfying filters
2. compute the vector of grouping keys on the fact table
3. build temporary table mapping grouping keys to attribute values

Then

1. Scan&aggregate the fact table using key vectors: VECTOR GROUP BY
2. join back dimension attributes using temporary tables.

In-memory column store: copy of tables, in column format (detailed later)

In-memory aggregation: example

```
SELECT category, country, state, SUM(amount)
FROM sales s, products p, geography g
WHERE s.g_id = g.geo_id
AND s.p_id = p.prod_id
AND g.state IN ('WA', 'CA')
AND p.manuf = 'ACME'
GROUP BY category, country, state
```

Geography

geo_id	city	state	country
2	Seattle	WA	USA
3	Spokane	WA	USA
7	SF	CA	USA
8	LA	CA	USA
...	France

Products

prod_id	category	manuf
4	sport	Acme
3	sport	Acme
1	food	Acme
8	electric	Acme
...	...	ATOS

dense	gr	key	g	state	country
1				WA	USA
2				CA	USA

dense	gr	key	p	category
1				sport
2				food
3				electric

temporary tables

Sales

p_id	g_id	amount
8	1	100
9	1	150
8	2	100
4	3	110
2	30	130
6	20	400
3	1	100
1	7	120
3	8	130
4	3	200

key vectors

dense	gr	key	p	dense	gr	key	g
3							
3				1			
1				1			
1							
2				2			
1				2			
1				1			

Oracle: IM column store

In-memory column stores. SGA pool that records *copy* of tables, in columnar format. Column store is recorded only in (volatile) memory.

Candidate for column store considered if declared in CREATE or ALTER statement. Once populated, kept consistent with the copy in row format.

```
ALTER TABLE t INMEMORY -- makes t candidate for populating the IM column store
MEMCOMPRESS FOR CAPACITY HIGH
PRIORITY LOW;
```

MEMCOMPRESS FOR

QUERY LOW : best for queries (default)

QUERY HIGH : higher compression

...

CAPACITY HIGH : highest compression

PRIORITY

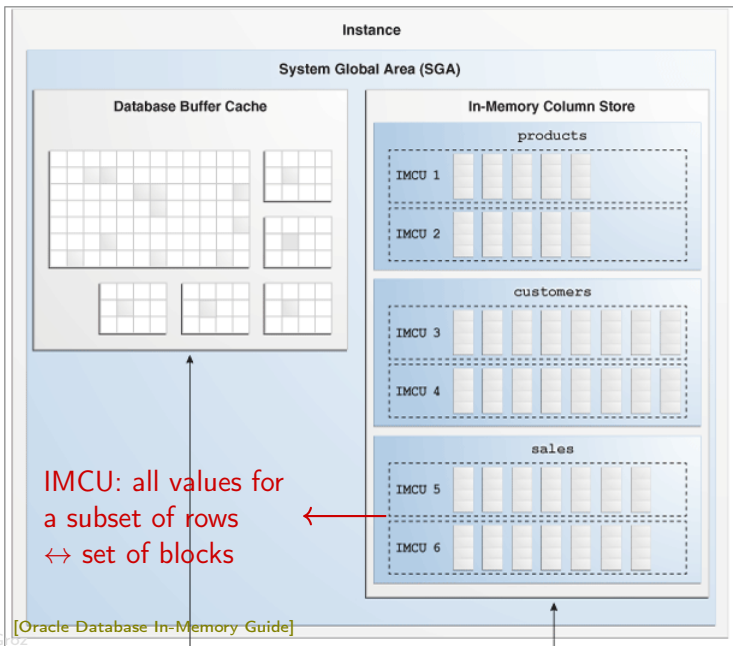
NONE : populates only when object is scanned (default)

LOW : populates after higher priority objects

...

CRITICAL : highest priority

Oracle: IM column store architecture

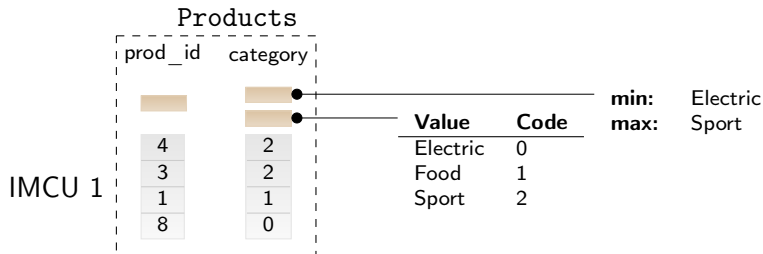


Oracle: IM column store architecture

For each IMCU= set of CU.

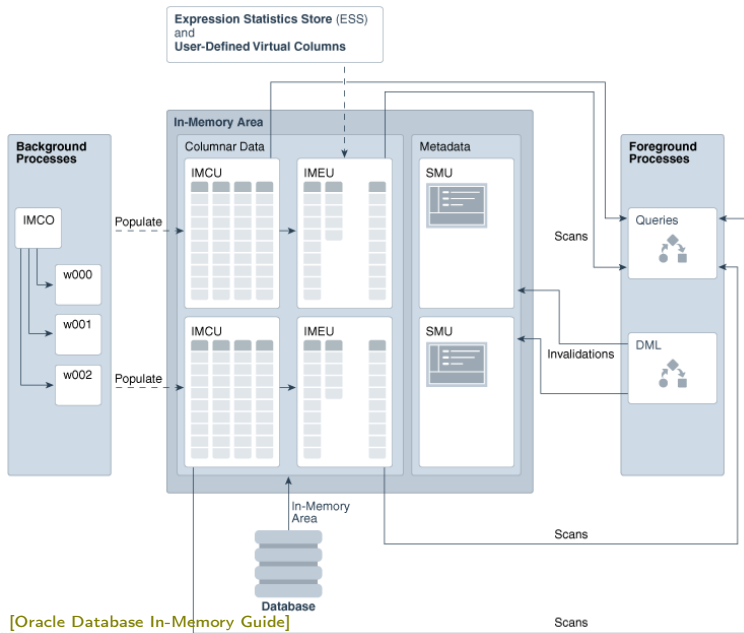
IMCU= In-Memory Compression Unit, CU= Column compression Unit

- header: metadata including
 - min/max value of each local column (*useful for pruning*)
 - (sometimes) local dictionary for local column data, implemented as a sorted list of distinct values with their dictionary code.
- body: the local column data, ordered by ROWID.



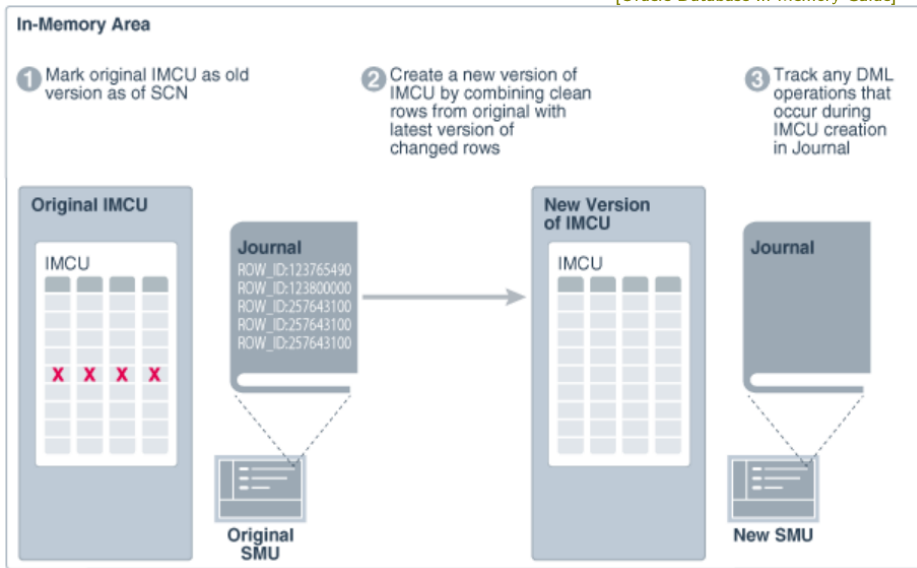
↪ min/max allows IMCU pruning. Ex: `SELECT...WHERE prod_id > 9`

Oracle: IM column store architecture



Oracle: IM column store updates

[Oracle Database In-Memory Guide]



- Threshold-based repopulation (number of changes in journal exceeds threshold)
- Trickle repopulation (periodic, updates all IMCU having some stale data)

Oracle: IM column store: integration on hardware

SQL-on-silicon: SPARC M7 chips:

SIMD on traditional CPU devised for graphics.

So devised chip with 8 Database accelerators with 4 pipelines = 32 engines supporting specialized instructions to process columnar data:

- Extract: uncompress data (byte/bit-packed, Huffman, RLE)
- Scan: filter data w.r.t an interval
- Select: filter data according to bit vector (given data vector and bit vector, return vector of selected items)
- Join

Some claims: 160GB/s bandwidth, 6x speedup on Apache Spark queries.

(Exadata) In-memory format in Exadata smart flash cache. Using additional flash cache to extend main memory (faster than disk): used to record db blocks evicted from SGA buffer cache.

Oracle vs SAP

SAP Hana: prototype around 2008, commercial product end 2011. Industry leader on in-memory techniques (though anteriority sometimes discussed)

2/3 of SAP Business suite customers rely on Oracle database.

By 2015, SAP tried to make ERP customers switch to SAP Hana: integrated stack S/4HANA.

SAP pushing toward cloud-based apps.

2016: Oracle 12 integrates In-memory storage. Special care to support SAP BW.

In 2017, SAP signs with Oracle to support Oracle on their ERP till 2025.

[<http://www.silicon.fr/5-questions-comprendre-guerre-oracle-sap-in-memory-95002.html>]

[<http://www.scmfocus.com/saphana/2017/07/09/saps-change-policy-hana-oracle/>]

As long as we are comparing

Prix des options Oracle (21 juin 2016) « Processor Licence » :

Active Data Guard	11 500 \$
Database In-Memory	23 000 \$
Diagnostics Pack	7 500 \$
Tuning Pack	5 000 \$
Partitionning	11 500 \$
Advanced compression	11 500 \$
OLAP	23 000 \$
Advanced Analytics	23 000 \$
Spatial	17 500 \$
Multitenant	17 500 \$
TOTAL :	139 500 \$

[Source: <https://blog.developpez.com/sqlpro/p13001/ms-sql-server/oracle-vs-sql-server-les-options-payantes-qui-font-la-difference>]

Oracle édition Enterprise : 47 500\$

Pricing of DBMS generally a bit opaque (multiple discounts, what should be counted: license cost only or ROI, etc).

Multiple discussions online about Oracle vs Microsoft SQL Server, MariaDB etc.

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- In-memory databases: commercial systems: MariaDB
- In-memory databases: commercial systems: Oracle
- In-memory databases: commercial systems: IBM DB2
 - In-memory features: DB2 12 for z/OS
 - In-memory Column store: DB2 BLU

IBM DB2 12 for z/OS

DB2 12 (2016) emphasizes in-memory computations. Users must provision large RAM to benefit from enhancements.

In-memory contiguous buffer pool. Unlike versions < 12, makes sure page stealing only occurs in some 10% overflow area, which results in savings on cache page management.

In-memory index optimization. Reserves an in-memory area to speedup lookups in unique indexes.

Speeding up INSERTS. New insertion algorithm for inserts on non-clustered tables (table with MEMBER CLUSTER attribute). Requires more memory be assigned for table space partitions.

DB2 12 also kind of increases pool dedicated to sorting operations so they may fit in-memory. . .



IBM DB2 11.1 LUW with BLU acceleration

DB2 11.1 (2016), but BLU accelerations introduced in DB2 10.5 (2013).
BLU emphasizes processing compressed columnar data, parallelization, SIMD, memory management. . .

For more, see: *DB2 with BLU acceleration*, VLDB'2013

<http://db.disi.unitn.eu/pages/VLDBProgram/pdf/industry/p773-barber.pdf>

```
CREATE TABLE Employee (  
  ID SMALLINT NOT NULL,  
  NAME VARCHAR(9),  
  DEPT SMALLINT,  
  SALARY DECIMAL(7,2)  
)  
ORGANIZE BY COLUMN;
```



References

Column/In-memory databases (general):

- *The Design and Implementation of Modern Column-Oriented Database Systems*, Abadi et al. Foundations and trends in database, 2012

Column/In-memory databases (SAP):

- *In-Memory Data Management*, H.Plattner, livre disponible B.U. Orsay, et MOOC: <https://open.hpi.de/courses/imdb2015>
- *Parallel Replication across Formats in SAP HANA for Scaling Out Mixed OLTP/OLAP Workloads*, VLDB'2017
<http://www.vldb.org/pvldb/vol10/p1598-han.pdf>
- *SAP HANA Adoption of Non-Volatile Memory*, VLDB'2017
<http://www.vldb.org/pvldb/vol10/p1754-andrei.pdf>

Column/In-memory databases (Oracle):

- <https://docs.oracle.com/database/122/INMEM/toc.htm>
- *Query Optimization in Oracle 12c Database In-Memory*, VLDB'15
<http://www.vldb.org/pvldb/vol8/p1770-das.pdf>
- *Distributed Architecture of Oracle Database In-memory*, VLDB'15
<http://www.vldb.org/pvldb/vol8/p1630-mukherjee.pdf>

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Column/In-memory databases (MariaDB):

- <https://mariadb.com/kb/en/library/mariadb-columnstore/>
- <https://mariadb.com/kb/en/library/columnstore-storage-architecture/>

Column/In-memory databases (IBM):

- https://en.wikipedia.org/wiki/IBM_BLU_Acceleration
- *DB2 with BLU acceleration*, VLDB'2013
<http://db.disi.unitn.eu/pages/VLDBProgram/pdf/industry/p773-barber.pdf>
- <http://www.redbooks.ibm.com/redbooks/pdfs/sg248383.pdf> and other redbooks.

Trends in DWH:

- *Vendors white papers (Microsoft, Oracle, etc), Gartner, tdwi, etc. Ex:*
http://download.microsoft.com/download/C/2/D/C2D2D5FA-768A-49AD-8957-1A434C6C8126/The_Microsoft_Modern_Data_Warehouse_White_Paper.pdf

Data processing on modern Hardware:

- <http://www.odbms.org/wp-content/uploads/2014/03/Data-Processing-on-FPGAs.pdf>
- http://edbticdt2016.labri.fr/downloads/gustavo_alonso_slides.pdf

Columnar storage. . .

4 Projects on serialization in column format.

Arrow : *in-memory*

- objective: *standard* for in-memory column storage. More about manipulating (volatile, in RAM) data than about defining a file format
- characteristics: focus on vectorization, zero-copy, random reads

Parquet Parquet : *immutable, on disk*

- characteristics: focus on compression of columnar data

Kudu : *updatable, on disc (+ buffer)*

- characteristics: more like a column store than a format. Format similar to Parquet, but optimized for updates.

ORC

- objective: optimize Hive and MR
- characteristics: compression, indexes, predicate pushdown

References

- A post by McKinney answering a post on Arrow vs Parquet:
<http://wesmckinney.com/blog/arrow-columnar-abadi/>
- and some additional answer to the author:
[http://dbmsmusings.blogspot.fr/2018/03/
an-analysis-of-strengths-and-weaknesses.html](http://dbmsmusings.blogspot.fr/2018/03/an-analysis-of-strengths-and-weaknesses.html)