

Introduction to In-memory Column-based Databases

Radim Benek, SAP April 24, 2024

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Introduction

Achievements of column store in-memory database:

- 150 sensors
- 2GB of data in one lap
- **3TB** in a single race
- "SAP HANA enables McLaren existing systems to process these data 14 000 times faster then before."
- "Analysis that previously took almost a week to process, can be completed in a span of a pit stop."



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Development

Localization

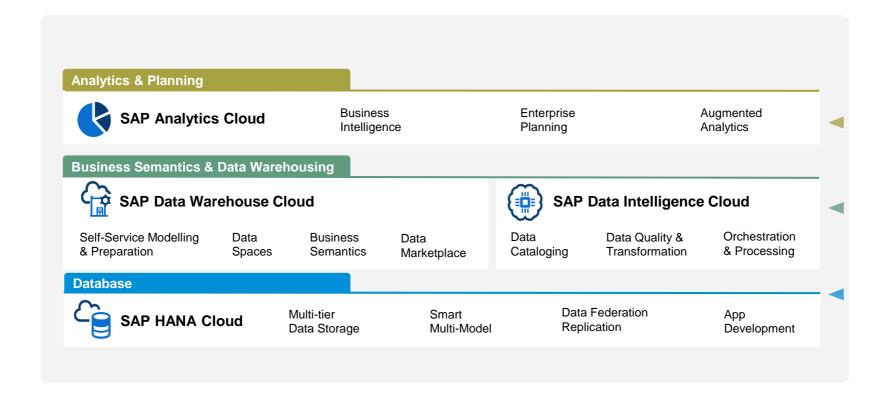
Maintenance





SAP Data & Analytics Capabilities Today

Covering the entire lifecycle of data-to-value

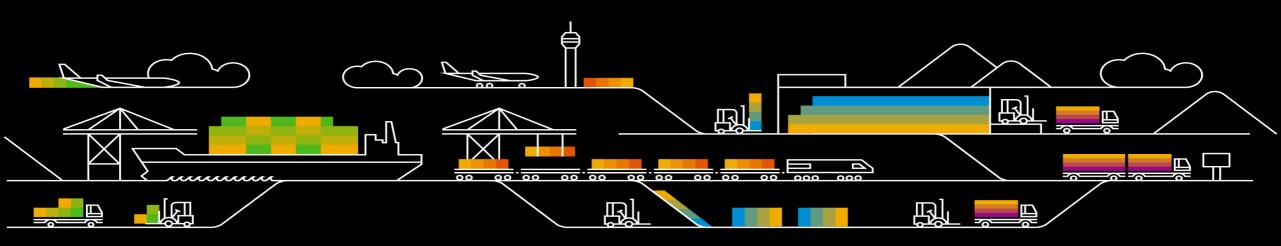




SAP HANA CLOUD

Agenda

- Introduction
- Changes in Hardware
- Data Layout
- Dictionary Encoding
- Compression
- Delete, Insert, Update
- Tuple Reconstruction
- Scan Performance
- Demo



Evolution



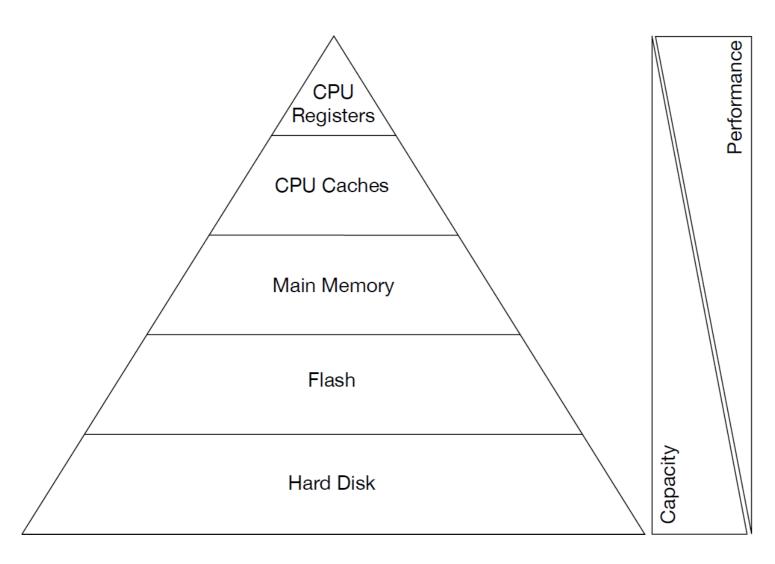
- Multi-core CPU introduction (32 cores/CPU)
- Multi-CPU boards massively used (8 CPUs/board)
- CPU cache grows
- RAM capacity grows
- RAM speed grows
- New interfaces (QPI, HT)

→ Enormous bandwidth and performance potential

HDDs still dominated overall performance and design mindset

Latency Overview

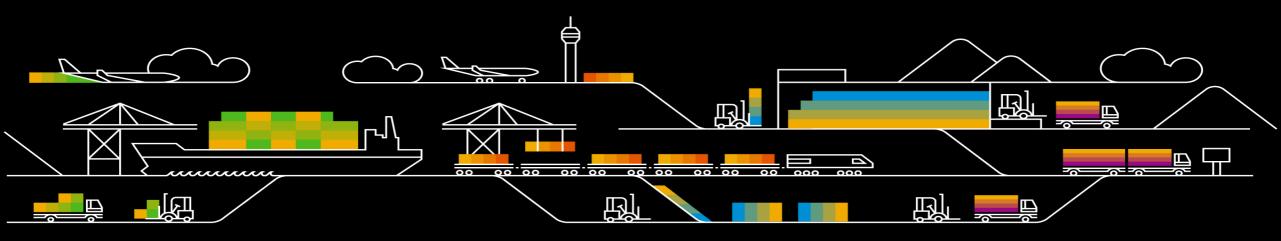




Latency Overview



Action	Time in nanoseconds	Time
L1 cache reference (cached data word)	0.5 ns	
Branch mispredict	5 ns	
L2 cache reference	7 ns	
Mutex lock / unlock	25 ns	
Main memory reference	100 ns	$0.1~\mu s$
Send 2,000 byte over 1 Gb/s network	20,000 ns	$20 \mu s$
SSD random read	150,000 ns	$150 \mu s$
Read 1 MB sequentially from memory	250,000 ns	$250~\mu s$
Disk seek	10,000,000 ns	10 ms
Send packet CA to Netherlands to CA	150,000,000 ns	150 ms



Database Data Layouts



- What are the most common layouts of relational data in main memory?
 - For each layout we present the pros and cons of their approach

	Col ₁	Col ₂	Col ₃
Row ₁	Α	В	С
Row ₂	Α	В	С
Row ₃	Α	В	С
Row ₃	Α	В	С

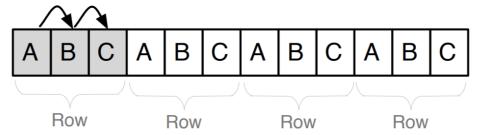
Row Data Layouts



- Data is stored tuple-wise
- Leverage co-location of attributes for a single tuple
- Low cost for reconstruction, but higher cost for sequential scan of a single attribute

Column Operation A B C A B C A B C Row Row Row

Row Operation

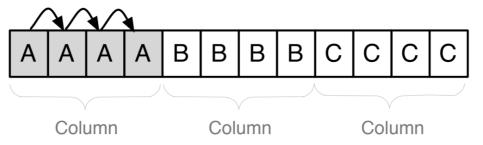


Columnar Data Layouts

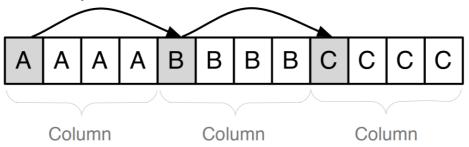


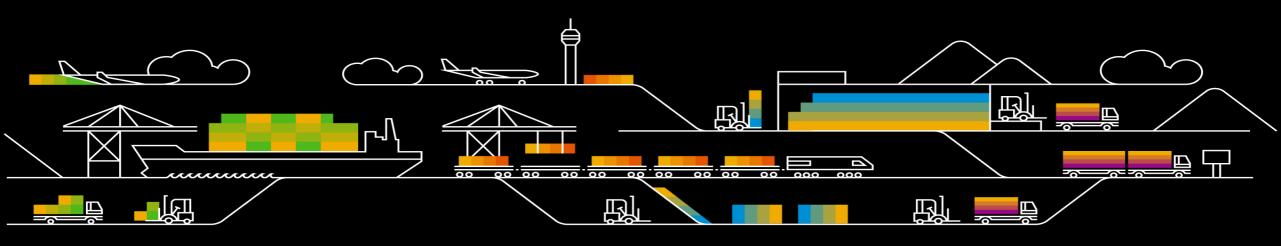
- Data is stored attribute-wise
- Leverage sequential scan speed in main memory
- Tuple reconstruction is expensive

Column Operation



Row Operation





Example

HPI Hasso Plattner Institut

IT Systems Engineering | Universität Potsdam

- 8 billion humans
- Attributes:
 - first name
 - last name
 - gender
 - country
 - city
 - birthday
 - → 200 byte per tuple
- Each attribute is dictionary encoded



Motivation



- Main memory access is the new bottleneck
- Compression reduces number of I/O operations to main memory
- Operation directly on compressed data
- Offsetting with bit-encoded fixed-length data types
- Based on limited value domain

Sample Data



Table: world_population

recID	fname	Iname	gender	city	country	birthday
39	John	Smith	m	Chicago	USA	12.03.1964
40	Mary	Brown	f	London	UK	12.05.1964
41	Jane	Doe	f	Palo Alto	USA	23.04.1976
42	John	Doe	m	Palo Alto	USA	17.06.1952
43	Peter	Schmidt	m	Potsdam	GER	11.11.1975
•••			•••			

Dictionary Encoding a Column



- A column is split into a dictionary and an attribute vector
- Dictionary stores all distinct values with implicit valueID
- Attribute vector stores valueIDs for all entries in the column.
- Position is stored implicitly
- Enables offsetting with bit-encoded fixed-length data types

recID	fname	Dictionary for "fname" Attribute Vector for "f					
			valueID	Value	position	valueID	
39	John		•••		•••		
40	Mary		23	John	39	23	
41	Jane		24	Mary	40	24	
42	John		25	Jane	41	25	
43	Peter		26	Peter	42	23	
					43	26	
		•					

Querying Data using Dictionaries



Search for Attribute Value (i.e. retrieve all persons with fname "Mary")

- Search valueIDs for requested value ("Mary")
- Scan Attribute Vector for valueID ("24")
- 3. Replace valueIDs in result with corresponding dictionary value

Sorted Dictionary

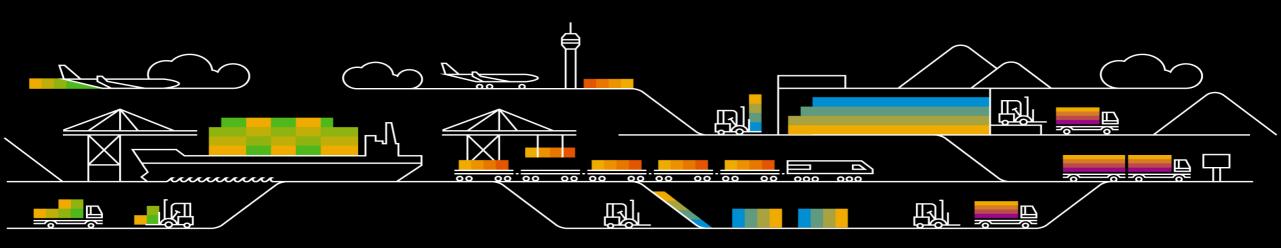


- Dictionary entries are sorted either by their numeric value or lexicographically
 - Dictionary lookup complexity: O(log(n)) instead of O(n)
- Dictionary entries can be compressed to reduce the amount of required storage

Data Size Examples



Column	Cardi-nality	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



Compression Techniques



- Heavy weight vs. light weight techniques
- Focus on light weight techniques for databases
- For attribute vector
 - Prefix encoding
 - Run length encoding
 - Cluster encoding
 - Sparse encoding
 - Indirect encoding
- For dictionary
 - Delta compression for strings
 - Other data types are stored as sorted arrays

Example Table



recID	fname	Iname	gender	country	city	birthday	2nd_nationality
0	Martin	Albrecht	m	GER	Berlin	08-05-1955	n/a
1	Michael	Berg	m	GER	Berlin	03-05-1970	n/a
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968	n/a
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992	US
4	Ulrike	Schulze	f	GER	Potsdam	09-03-1977	n/a
5	Martin	Schulz	m	GER	Mainz	06-04-1980	GER
6	Sushi	Pao	f	CN	Peking	09-12-1954	n/a
7	Chen	Su Wong	m	CN	Shanghai	27-06-1999	n/a
				•••			

200 countries = 8 bit

■ 1 million cities = 20 bit

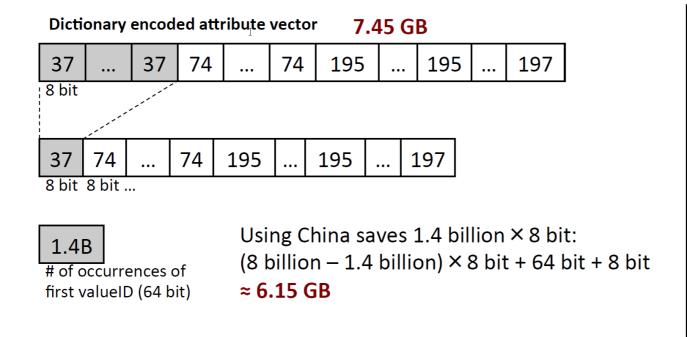
100 different 2nd nationalities = 7 bit

• 5 million first names = 23 bit

Prefix Encoding



- Used if the column starts with a long sequence of the same value
- One predominant value in a column and the remaining values are mostly unique or have low redundancy Example: country column, table sorted by population of country



Dictionary

valueID	value
37	CN
68	GER
74	IN
195	US
197	VA

Direct access!

Run Length Encoding



- Replace sequence of the same value with a single instance of the value and
 - a. Its number of occurrences
 - b. Its start position (shown below)
- Variant b) speeds up access compared to a)

Direct access!

Dictionary

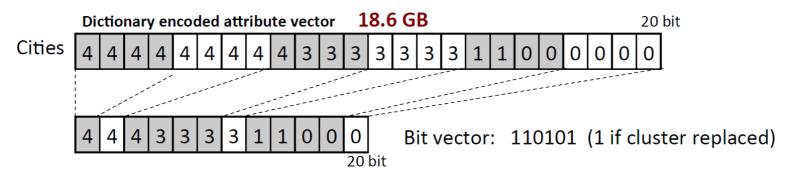
	Dicti	onary	encod	ed att _r i	ibute v	vector	7. 45	GB			
	37		37	74	:	74	195	:	195	:	
	\ 8 bit					·	<u>-</u>	Run l	ength	end	coded
Value		37	74	195			2	200 >	< (33 b	it +	8 bit) + 33 bit
Start positio	8 k	oit O	1.4B	2.6E	3		=	≈ 1 K	В		occurrences est field
positio	33	bit	1	Re	cord	— with	ID 1.5	billic	on via b	ina	ry search

valueID	value
37	CN
68	GER
74	IN
195	US

Cluster Encoding



- Attribute vector is partitioned into N blocks of fixed size (typically 1024)
- If a cluster contains only a single value, it is replaced by a single occurrence of this value
- A bit vector of length N indicates which clusters were replaced by a single value



Example: city column, table sorted by country, city

– Cluster size: 1024 elements →7.8 mio blocks

Worst case assumption: 1 uncompressible block per city

- Uncompressible blocks: 1 mio \times 1024 \times 20 bit

- Compressible blocks: $(7.8 - 1) \text{ mio} \times 20 \text{ bit}$

- Bit vector: 7.8 million × 1 bit

No direct access!

Compute position via bit vector.

+ 1 MB ≈2.4 GB

2441 MB

+ 16 MB

Sparse Encoding

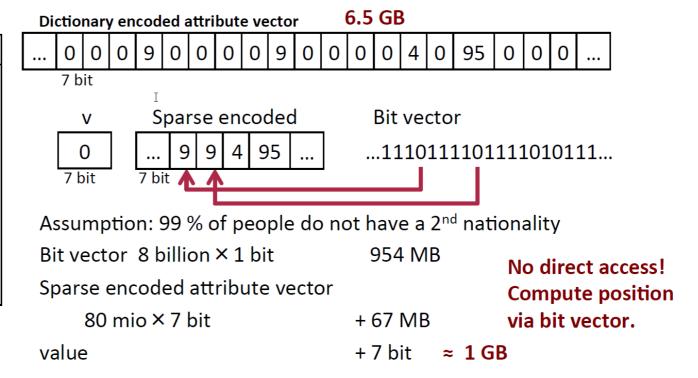


- Remove the value v that appears most often
- A bit vector indicates at which positions v was removed from the original sequence

Example: 2nd nationality column, regardless of sorting order of table

Dictionary						
valueID	value					
0	n/a					
4	CO					
9	GER					
95	US					

Dictionary



Indirect Encoding



- Sequence is partitioned into N blocks of size S (typically 1024)
- If a block contains only a few distinct values an additional dictionary is used to encode the values in that block
- Additionally: links to the new dictionaries + blocks that have a dictionary

Example: fname column, table sorted by country Direct access! block size = 1024Dictionary encoded attribute vector ≈ 21.4GB 23 bit 212 | 3 | 19 126 | 576 | 55 | 126 | 2 | 2 55 881 461 792 45 13 23 bit 8 bit 792 881 19 461 45 13 Block 2 is not compressed 55 Assumption: each set of 1024 people of the same country 126 contains on average 200 different names Dictionary Dictionaries: $(200 \times 23 \text{ bit+64 bit}) \times \#blocks$ 4.2 GB 576 for Address of dictionary Block 1 Compressed vector: 8 billion × 8 bit $7.6 \text{ GB} \approx 11.8 \text{ GB}$ 199

Delta Encoding for Dictionary



35

For sorted string values

Block--wise compression (typically 16 strings per block)

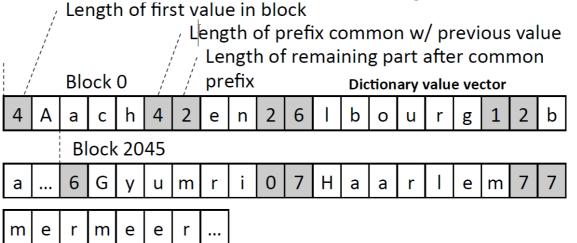
Dictionary

Dictionary:

1 million cities à 49 byte

≈ 46.7 MB

	וט	Cuonary
	valueID	value
< 0	0	Aach
Block 0	1	Aachen
В	2	Aalbourg
	3	Aba
45	32720	Gyumri
Block 2045	32721	Haarlem
ock	32722	Haarlemmer-
B		meer



Assumptions: average length of city names 7 average overlap of 3 letters

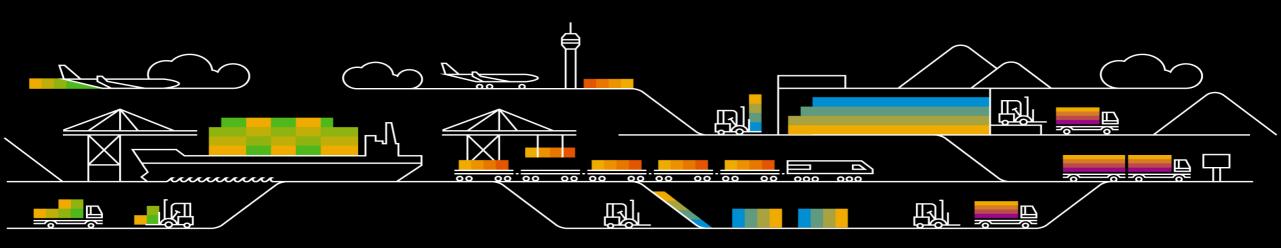
For the "numbers": longest city name 49 letters = 6 bit Size of block × #blocks (encoding numbers + 1^{st} city + 15 other cities) × #blocks ($(1+15\times2)\times6$ bit + 7×1 byte + $15\times(7-3)\times1$ byte) × 62500

≈ 5.4 MB

Keep in Mind

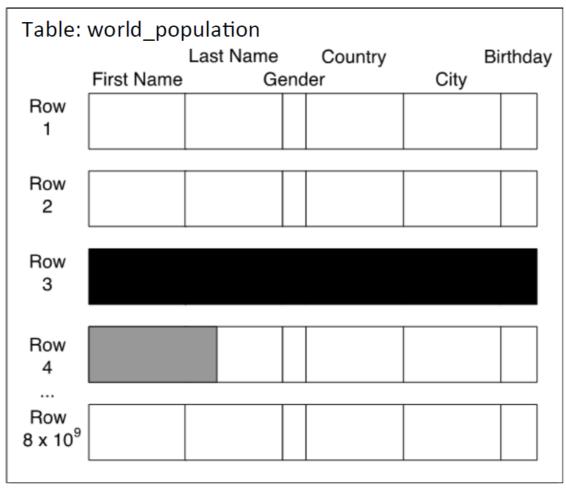


- Most compression techniques require sorted sets, but a table can only be sorted by one column or cascading
- No direct access to rows in some cases, but offset has to be computed





Accessing a record in a row store

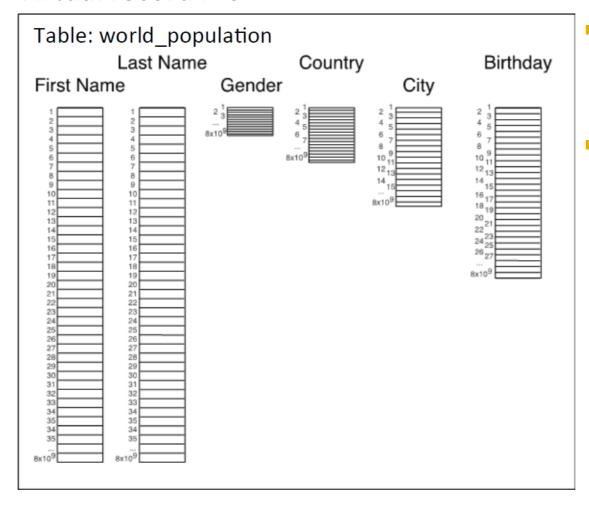


- All attributes are stored consecutively
- 200 byte

 4 cache accesses à 64 byte
 - → 256 byte
- Read with 4MB/ms/core
- $\rightarrow \approx 0.064 \, \mu s$ with 1 core



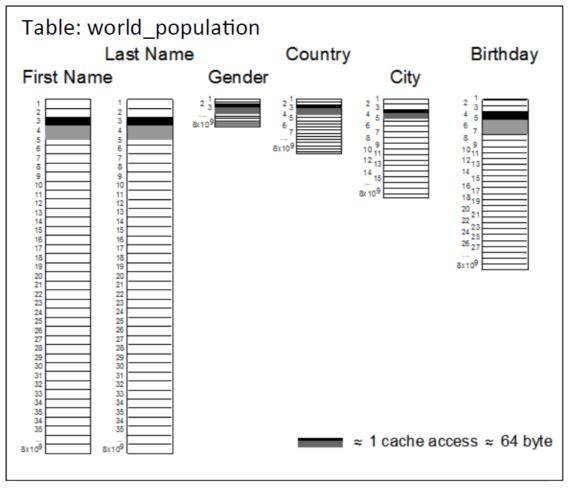
Virtual record IDs



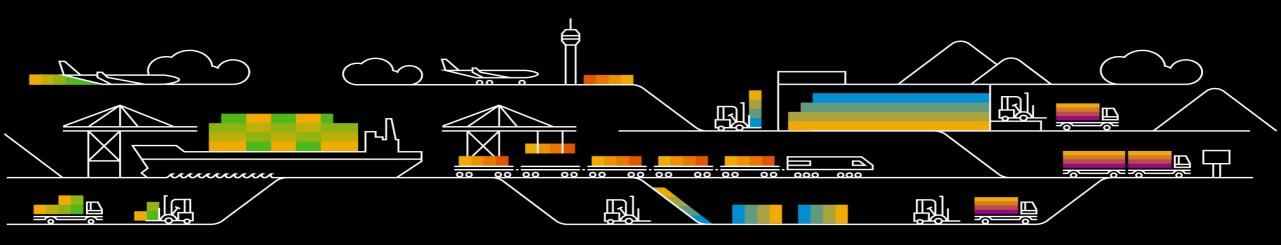
- All attributes are stored in separate columns
- Implicit record Ids are used to reconstruct rows



Virtual record IDs



- 1 cache access for each attribute
- 6 cache accessesà 64 byte
 - → 384 byte
- Read with 4MB/ms/core
- $\rightarrow \approx 0.096 \,\mu s$ with 1 core





- 8 billion humans
- Attributes:
 - first name
 - last name
 - gender
 - country
 - city
 - birthday
 - → 200 byte per tuple
- Question: How many women, how many men?
- Assumed scan speed: 4MB/ms/core





Row Store – Layout

Table: world_population					
		Last Name	Country		Birthday
	First Name	Ger	nder	City	
Row 1					
Row 2					
Row 3					
Row 8 x 10 ⁹					



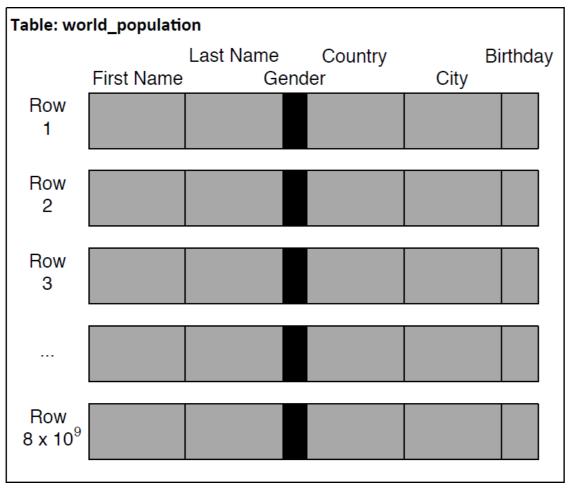
Row Store – Layout

Table: world_population						
		Last Name		Country		Birthday
	First Name	Ge	enc	der	City	
Row 1						
Row 2						
Row 3						
Row 8 x 10 ⁹						

Table size:8 billion tuples ×200 bytes pertuple ≈ 1.6 TB



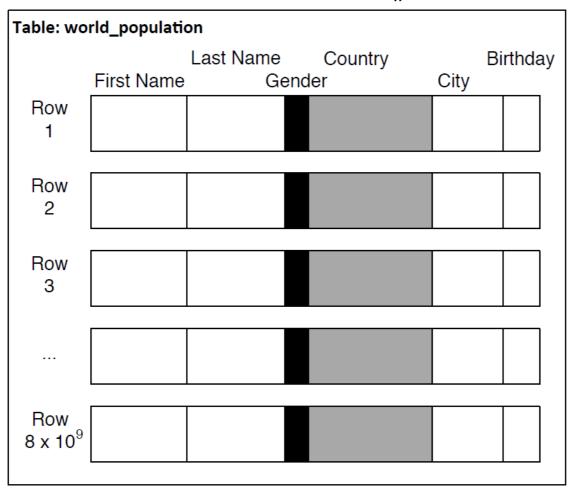
Row Store - Full Table Scan



- Table size:
 8 billion tuples ×
 200 bytes per
 tuple ≈ 1.6 TB
- Scan through all rows with 4MB/ms/core
 - → 400 s
 with 1 core



Row Store – Stride Access "Gender"



 8 billion cache accesses à 64 byte

≈ 512 GB

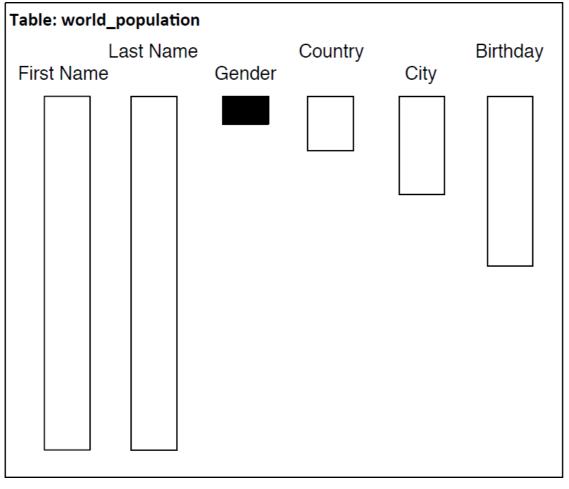
Read with 4MB/ms/core

→ 128 s

with 1 core



Column Store – Full Column Scan "Gender"



- Size of attribute vector "Gender":8 billion tuples ×1 bit per tuple
 - ≈ 1 GB
- Scan through column with 4MB/ms/core

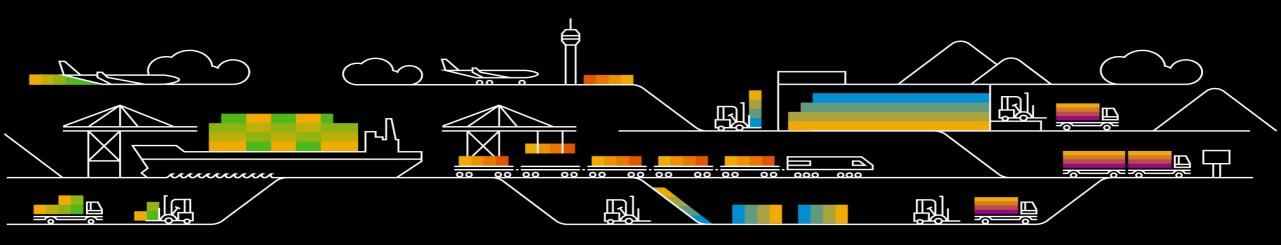
 \rightarrow 0.25 s with 1 core



How many women, how many men?

	Row Store		Column Store	
	Full table scan	Stride access	Column Store	
Time in seconds	400	128	0.25	

Delete, Insert, Update



DELETE

DELETE



- Physical DELETE
 - Removed tuple is removed from database and you cannot access it anymore
- Logical DELETE
 - Validity of this tuple is set to non-valid and this tuple can be accessed in historic queries or reporting
- Operation DELETE is very expensive to perform
- SQL-Syntax:

DELETE FROM table_name
WHERE attribute_name = some_value

DELETE - example



Remove Jane Doe from the database table

Dictionary "fname"		Attribute V	ector "fname"
valueID	value	recID	valueID

22	Andrew	38	22
23	Jane	39	24
24	John	40	25
25	Mary	41	23
26	Peter	42	24
	ı	I	

recID	valueID
•••	
38	22
39	24
40	25
41	23
42	24
43	26
	•

Dictionary "Iname"		Attribute Ve	ctor "Iname"
valueID	value	recID	valueID
•••		***	
17	Brown	38	19
18	Doe	39	21
19	Miller	40	17
20	Schmidt	41	18
21	Smith	42	18
		43	20
,		•••	

DELETE - example



Remove Jane Doe from the database table

Dictionary "fname"

Dictional	y illallie	A1
valueID	value	
22	Andrew	
23	Jane	
24	John	
25	Mary	
26	Peter	

Attribute Vector "fname"		
recID	valueID	
•••		
38	22	
39	24	
40	25	
41	23	
42	24	
43	26	
•••		

Dictionary "Iname"		Attribute Ve	ctor "Iname"
valueID	value	recID	valueID
17	Brown	38	19
18	Doe	39	21
19	Miller	40	17
20	Schmidt	41	18
21	Smith	42	18
		43	20

Dictional	y ilialile	Attribute ve	ctor mame
valueID	value	recID	valueID
17	Brown	38	19
18	Doe	39	21
19	Miller	40	17
20	Schmidt	41	18
21	Smith	42	18
		43	20
'			
		'	•

DELETE - example



Remove Jane Doe from the database table

	Dictio	nary	"fnam	ıe"
--	--------	------	-------	-----

valueID	value
22	Andrew
23	Jane
24	John
25	Mary
26	Peter

Attribute Vector "fname"

recID	valueID
38	22
39	24
40	25
41	23
42	24
43	26

Dictionary "Iname"

valueID	value
17	Brown
18	Doe
19	Miller
20	Schmidt
21	Smith
•••	

Attribute Vector "Iname"

recID	valueID
38	19
39	21
40	17
41	18
42	18
43	20
•••	

DELETE - example



Remove Jane Doe from the database table

Dictionary "fname"			Attribute	V	ector "fname"	_
valueID	value		recID		valueID	
22	Andrew		38		22	
23	Jane		39		24	
24	John	John			25	
25	Mary		41		23	1
26	Peter		41		24	2
			42		26	2
			•	,		

Dictionary "Iname"		_	Attribute Ve	ector "Iname"
valueID	value		recID	valueID
17	Brown		38	19
18	Doe		39	21
19	Miller		40	17
20	Schmidt		41	18
21	Smith		41	18
			42	20
		- '		

INSERT

INSERT



- INSERT without new dictionary entry
 - New entry is already in dictionary, new valueID is appended to the attribute vector
- INSERT with new dictionary entry
 - New entry is added to the dictionary, dictionary is sorted, valueIDs are updated in attribute vector, new valueID is appended to the attribute vector

SQL-Syntax:

INSERT INTO table_name
VALUES (value1,value2)

INSERT – example (Without New Dictionary Entry)



INSERT INTO world_population **VALUES** (Karen, <u>Schulze</u>, f, GER, Rostock, 06-20-2014)

D	V	Α	
Albrecht	0	0	0
Berg	1	1	1
Meyer	2	3	2
Schulze	3	2	3
	·	3	4

	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Sophie	Schulze	f	GER	Potsdam	09-03-1977

AV – Attribute Vector

D - Dictionary

INSERT – example (Without New Dictionary Entry)



INSERT INTO world_population **VALUES** (Karen, <u>Schulze</u>, f, GER, Rostock, 06-20-2014)

A'	V		D
0	0	0	Albrecht
1	1	1	Berg
2	3	2	Meyer
3	2	3	Schulze
4	3	· '	

	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
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3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Sophie	Schulze	f	GER	Potsdam	09-03-1977

Look-up on dictionary → entry found

AV – Attribute Vector

D - Dictionary

INSERT – example (Without New Dictionary Entry)



INSERT INTO world_population **VALUES** (Karen, <u>Schulze</u>, f, GER, Rostock, 06-20-2014)

A <u>V</u> D			
0	0	0	Albrecht
1	1	1	Berg
2	3	2	Meyer
3	2	3	Schulze
4	3	·	
5	3		

fname	Iname	gender	country	city	birthday
Martin	Albrecht	m	GER	Berlin	08-05-1955
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Anton	Meyer	m	AUT	Innsbruck	10-20-1992
Sophie	Schulze	f	GER	Potsdam	09-03-1977
	Schulze				

- Look-up on dictionary → entry found
- 2. Append valueID to attribute vector

AV – Attribute Vector

D – Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (Karen, Schulze, f, GER, Rostock, 06-20-2014)

A'	V		D
0	0	0	Berlin
1	0	1	Hamburg
2	1	2	Innsbruck
3	2	3	Potsdam
4	3		

	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
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4	Sophie	Schulze	f	GER	Potsdam	09-03-1977
5		Schulze				

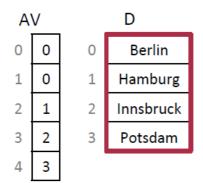
AV - Attribute Vector

D - Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (Karen, Schulze, f, GER, Rostock, 06-20-2014)



	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Sophie	Schulze	f	GER	Potsdam	09-03-1977
5		Schulze				

Look-up on dictionary → no entry found

AV – Attribute Vector

D - Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (Karen, Schulze, f, GER, Rostock, 06-20-2014)

Α	V		D
0	0	0	Berlin
1	0	1	Hamburg
2	1	2	Innsbruck
3	2	3	Potsdam
4	3	4	Rostock

	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Sophie	Schulze	f	GER	Potsdam	09-03-1977
5		Schulze				

- 1. Look-up on dictionary → no entry found
- 2. Append new value to dictionary

AV – Attribute Vector

D – Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (Karen, Schulze, f, GER, Rostock, 06-20-2014)

Α	V		D
0	0	0	Berlin
1	0	1	Hamburg
2	1	2	Innsbruck
3	2	3	Potsdam
4	3	4	Rostock
5	4		

					_	_
	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Sophie	Schulze	f	GER	Potsdam	09-03-1977
5		Schulze			Rostock	
						,

1. Look-up on dictionary → no entry found

AV – Attribute Vector

2. Append new value to dictionary

D - Dictionary

3. Append valueID to attribute vector

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (<u>Karen</u>, Schulze, f, GER, Rostock, 06-20-2014)

A۱	V		D
0	2	0	Anton
1	თ	1	Hanna
2	1	2	Martin
3	0	3	Michael
4	4	4	Sophie

·	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Sophie	Schulze	f	GER	Potsdam	09-03-1977
5		Schulze			Rostock	

AV - Attribute Vector

D - Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (<u>Karen</u>, Schulze, f, GER, Rostock, 06-20-2014)

Α	V		D
0	2	0	Anton
1	თ	1	Hanna
2	1	2	Martin
3	0	3	Michael
4	4	4	Sophie

		_				
	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Sophie	Schulze	f	GER	Potsdam	09-03-1977
5		Schulze			Rostock	

1. Look-up on dictionary → no entry found

AV – Attribute Vector

D – Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (<u>Karen</u>, Schulze, f, GER, Rostock, 06-20-2014)

0	Anton
1	Hanna
2	Martin
3	Michael
4	Sophie
5	Karen
	1 2 3 4

fname	Iname	gender	country	city	birthday
Martin	Albrecht	m	GER	Berlin	08-05-1955
Michael	Berg	m	GER	Berlin	03-05-1970
Hanna	Schulze	f	GER	Hamburg	04-04-1968
Anton	Meyer	m	AUT	Innsbruck	10-20-1992
Sophie	Schulze	f	GER	Potsdam	09-03-1977
	Schulze			Rostock	

1. Look-up on dictionary → no entry found

Append new value to dictionary

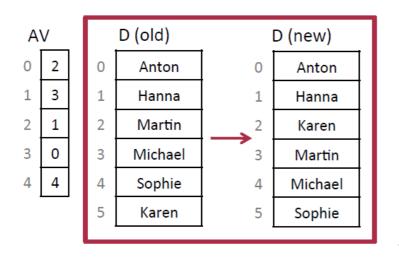
AV – Attribute Vector

D – Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (<u>Karen</u>, Schulze, f, GER, Rostock, 06-20-2014)



fname	Iname	gender	country	city	birthday	
Martin	Albrecht	m	GER	Berlin	08-05-1955	
Michael	Berg m Schulze f		GER	Berlin	03-05-1970	
Hanna			GER	Hamburg	04-04-1968	
Anton	Meyer	er m AUT		Innsbruck	10-20-1992	
Sophie	Schulze	f	GER Potsdam		09-03-1977	
	Schulze			Rostock		

1. Look-up on dictionary → no entry found

AV – Attribute Vector

2. Append new value to dictionary

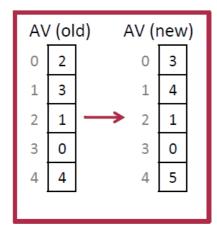
D – Dictionary

3. Sort Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (<u>Karen</u>, Schulze, f, GER, Rostock, 06-20-2014)



D (new)						
0	Anton					
1	Hanna					
2	Karen					
3	Martin					
4	Michael					
5	Sophie					

fname	Iname	gender	country	city	birthday	
Martin	Albrecht	m	GER	Berlin	08-05-1955	
Michael	Berg	m	GER Berlin		03-05-1970	
Hanna	Schulze	f	GER	Hamburg	04-04-1968	
Anton	Meyer	Meyer m AUT Innsbruck		10-20-1992		
Sophie	Schulze	f	GER	Potsdam	09-03-1977	
	Schulze			Rostock		

- 1. Look-up on dictionary → no entry found
- 2. Append new value to dictionary
- 3. Sort Dictionary
- 4. Change valueIDs in attribute vector

AV - Attribute Vector

D – Dictionary

INSERT – example (With New Dictionary Entry)



INSERT INTO world_population **VALUES** (<u>Karen</u>, Schulze, f, GER, Rostock, 06-20-2014)

Α	V	D			
0	თ	0	Anton		
1	4	1	Hanna		
2	1	2	Karen		
3	0	3	Martin		
4	5	4	Michael		
5	2	5	Sophie		

·	fname	Iname	gender	country	city	birthday
	Martin	Albrecht	m	GER	Berlin	08-05-1955
	Michael	Berg	m	GER	Berlin	03-05-1970
	Hanna	Schulze	f	GER	Hamburg	04-04-1968
·	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
·	Sophie	Schulze	f	GER	Potsdam	09-03-1977
	Karen	Schulze			Rostock	

1. Look-up on dictionary → no entry found

AV – Attribute Vector

2. Append new value to dictionary

D - Dictionary

- 3. Sort Dictionary
- 4. Change valueIDs in attribute vector
- 5. Append new valueID to attribute vector

UPDATE

UPDATE



Combination of DELETE and INSERT operation

SQL-Syntax:

UPDATE world_population

SET city = "Bamberg"

WHERE fname = "Hanna" AND Iname = "Schulze"

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

UPDATE – example



UPDATE world_population SET city = "Bamberg" WHERE Iname = "Schulze"

Dictionary old						
1	Berlin					
2	Hamburg					
3	Innsbruck					
4	Potsdam					
5	Rostock					

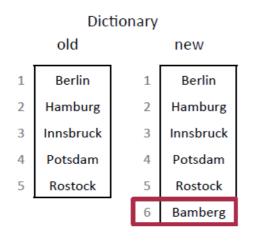
recID	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Ulrike	Schulze	f	GER	Potsdam	09-03-1977
5	Sophie	Schulze	f	GER	Rostock	06-20-2012
6						

1. Look-up "Bamberg" in dictionary → entry not found

UPDATE – example



UPDATE world_population SET city = "Bamberg" WHERE Iname = "Schulze"



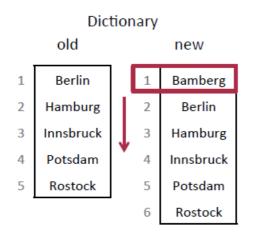
recID	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Ulrike	Schulze	f	GER	Potsdam	09-03-1977
5	Sophie	Schulze	f	GER	Rostock	06-20-2012
6						

- 1. Look-up "Bamberg" in dictionary → entry not found
- 2. Append new value "Bamberg" to dictionary

UPDATE – example



UPDATE world_population SET city = "Bamberg" WHERE Iname = "Schulze"



recID	fname	Iname	gender	country	city	birthday
0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hanna	Schulze	f	GER	Hamburg	04-04-1968
3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Ulrike	Schulze	f	GER	Potsdam	09-03-1977
5	Sophie	Schulze	f	GER	Rostock	06-20-2012
6						

- 1. Look-up "Bamberg" in dictionary → entry not found
- 2. Append new value "Bamberg" to dictionary
- 3. Reorganize dictionary

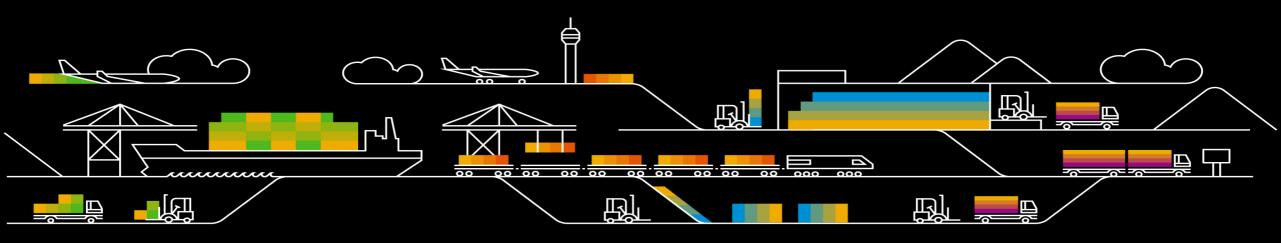
UPDATE – example



UPDATE world_population SET city = "Bamberg" WHERE Iname = "Schulze"

	Dict	tionary	А	ttribu	te V	ector							
	old		new	olo	1 n	ew	recID	fname	Iname	gender	country	city	birthday
	Old	ı	TICW .		- "	CVV	0	Martin	Albrecht	m	GER	Berlin	08-05-1955
1	Berlin	1	Bamberg	1	Ш	2	1	Michael	Berg	m	GER	Berlin	03-05-1970
2	Hamburg	2	Berlin	1	Ш	2	2	Hanna	Schulze	f	GER	Bamberg	04-04-1968
3	Innsbruck	3	Hamburg	2	Ш	1	3	Anton	Meyer	m	AUT	Innsbruck	10-20-1992
4	Potsdam	4	Innsbruck	3	Ш	4	4	Ulrike	Schulze	f	GER	Potsdam	09-03-1977
5	Rostock	5	Potsdam	4	Ш	5	5	Sophie	Schulze	f	GER	Rostock	06-20-2012
		6	Rostock	5	JL	6	6						

- 1. Look-up "Bamberg" in dictionary → entry not found
- 2. Append new value "Bamberg" to dictionary
- 3. Reorganize dictionary
- 4. Replace old values with new values in attribute vector (expensive)



Performance

- System QM0 48 TB / 1100 CPUs
- System HANA Express edition (VM) 16 GB / 4 CPUs

```
SELECT rbukrs, ryear, SUM( hsl ) AS hsl, COUNT (*) AS c
FROM "ACDOCA"
WHERE rrcty = '0'
AND ryear BETWEEN 2017 AND 2018
AND poper BETWEEN 000 AND 012
AND rldnr = '0L'
AND (bstat = '' OR bstat = 'L' OR bstat = 'U' OR bstat = 'J' OR bstat = 'C')
GROUP BY rbukrs, ryear
ORDER BY c DESC;
```

Performance

System QM0 – 48 TB / 1100 CPUs

Table	Store	Rows	Size	Time
ACDOCA_C	Column	110 million	5 GB	

System HANA Express edition (VM) – 16 GB / 4 CPUs

Table	Store	Rows	Size	Time

Performance

System QM0 – 48 TB / 1100 CPUs

Table	Store	Rows	Size	Time
ACDOCA_C	Column	110 million	5 GB	1,8 s

System HANA Express edition (VM) – 16 GB / 4 CPUs

Table	Store	Rows	Size	Time

Performance

System QM0 – 48 TB / 1100 CPUs

Table	Store	Rows	Size	Time
ACDOCA_C	Column	110 million	5 GB	1,8 s
ACDOCA_R	Row	110 million	240 GB	

System HANA Express edition (VM) – 16 GB / 4 CPUs

Table	Store	Rows	Size	Time

Performance

System QM0 – 48 TB / 1100 CPUs

Table	Store	Rows	Size	Time
ACDOCA_C	Column	110 million	5 GB	1,8 s
ACDOCA_R	Row	110 million	240 GB	22,5 s

System HANA Express edition (VM) – 16 GB / 4 CPUs

Table	Store	Rows	Size	Time

Performance

System QM0 – 48 TB / 1100 CPUs

Table	Store	Rows	Size	Time
ACDOCA_C	Column	110 million	5 GB	1,8 s
ACDOCA_R	Row	110 million	240 GB	22,5 s
ACDOCA	Column	19,5 billion	1,3 TB	

System HANA Express edition (VM) – 16 GB / 4 CPUs

Table	Store	Rows	Size	Time

Performance

System QM0 – 48 TB / 1100 CPUs

Table	Store	Rows	Size	Time
ACDOCA_C	Column	110 million	5 GB	1,8 s
ACDOCA_R	Row	110 million	240 GB	22,5 s
ACDOCA	Column	19,5 billion	1,3 TB	139 s

System HANA Express edition (VM) – 16 GB / 4 CPUs

Table	Store	Rows	Size	Time

Performance

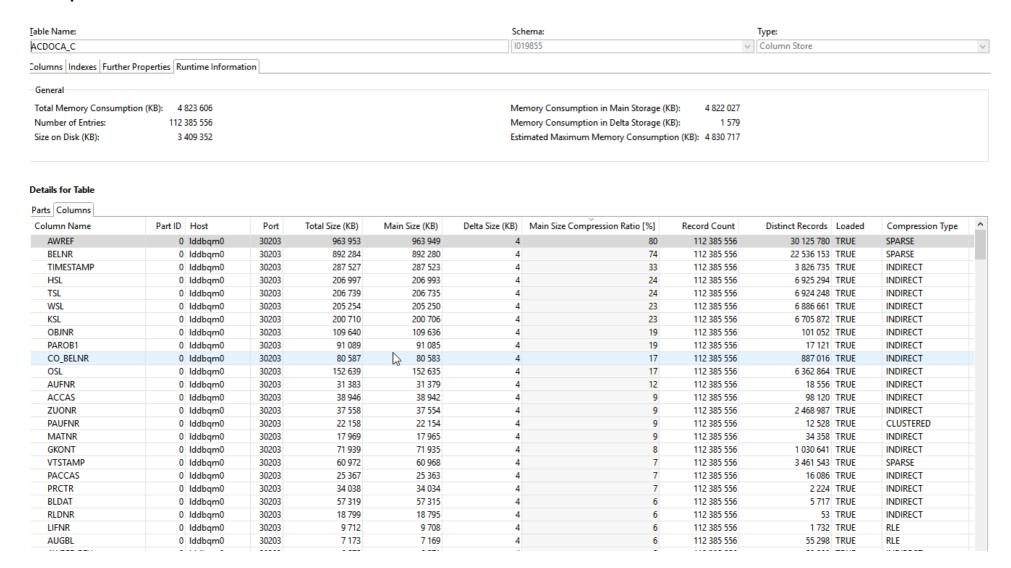
System QM0 – 48 TB / 1100 CPUs

Table	Store	Rows	Size	Time
ACDOCA_C	Column	110 million	5 GB	1,8 s
ACDOCA_R	Row	110 million	240 GB	22,5 s
ACDOCA	Column	19,5 billion	1,3 TB	139 s
ACDOCA_sm	Column	5 million	140 MB	0,5 s
CDHR	Column	31 million	1,3 GB	12,4 s
CDPOS	Column	730 million	44 GB	

System HANA Express edition (VM) – 16 GB / 4 CPUs

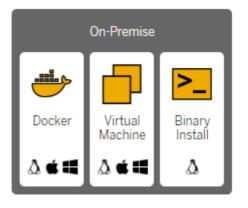
Table	Store	Rows	Size	Time
ACDOCA_sm	Column	5 million	140 MB	0,9 s

Columns compression



SAP HANA, Express Edition

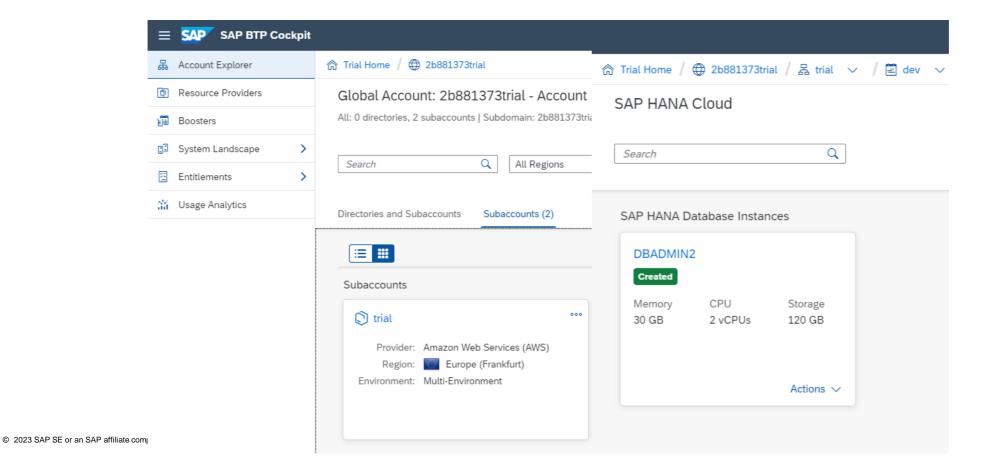
<u>SAP HANA, express edition</u> is a database and application development platform. You can run it for free (up to 32GB of RAM) on your laptop and start building new apps.





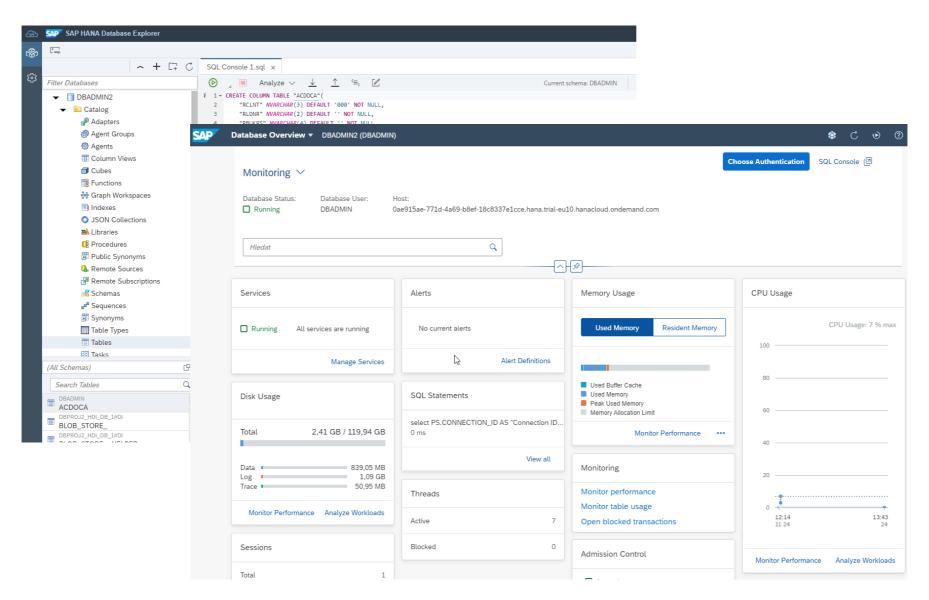
SAP HANA Cloud

SAP HANA Cloud trial is a trial version of HANA DB. You can run it for free with following resources: 32GB of RAM, 120GB Storage, 2vCPU.

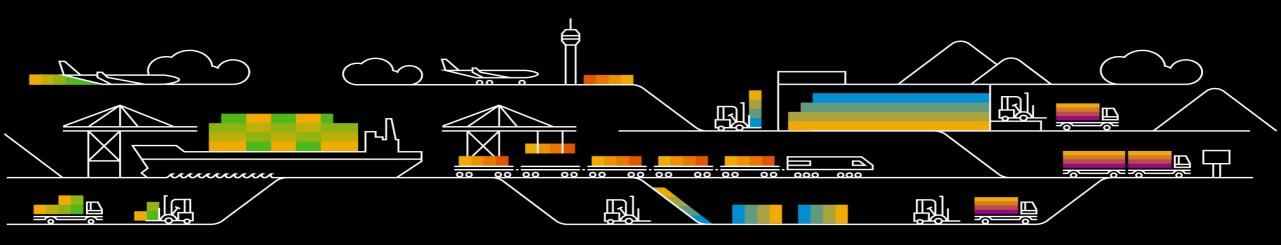


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SAP HANA Cloud



Resources



Resources

- Plattner, Hasso. "In-Memory Data Management 2015" OpenHPI. Hasso-Plattner-Institute, 07 Sept. 2015.
 Web. 13 July 2017. https://open.hpi.de/courses/imdb2017
- SAP HANA Cloud https://developers.sap.com/topics/hana.html
- SAP HANA Cloud Trial https://www.sap.com/products/technology-platform/hana/cloud-trial.html
- SAP HANA trial: https://www.sap.com/products/hana/express-trial.html
- SAP HANA Academy Videos: https://www.youtube.com/user/saphanaacademy
- SAP Help Portal SAP HANA Platform:
 https://help.sap.com/viewer/product/SAP_HANA_PLATFORM/

Appendix

SAP HANA, express edition



Thank you.

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Positions at SAP Labs Czech Republic in Brno can be found here.