Architecture of DB Systems
05 Compression Techniques

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SCIENCE
PASSION
TECHNOLOGY

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Announcements/Org

- **#1 Video Recording**
  - Link in **TeachCenter** & **TUbe** (lectures will be public)
  - Optional attendance (independent of COVID)

- **#2 COVID-19 Restrictions** (HS i5)
  - Corona Traffic Light: **Orange + Lockdown**
  - Max 25% room capacity (TC registrations)
  - Temporarily webex lectures and recording

max 18/74

Agenda

- **Motivation and Terminology**
- **Compression Techniques**
- **Compressed Query Processing**
- **Time Series Compression**

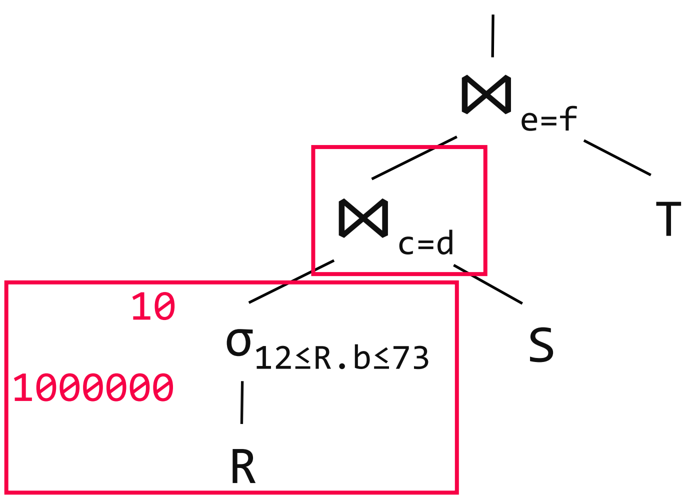
Motivation and Terminology

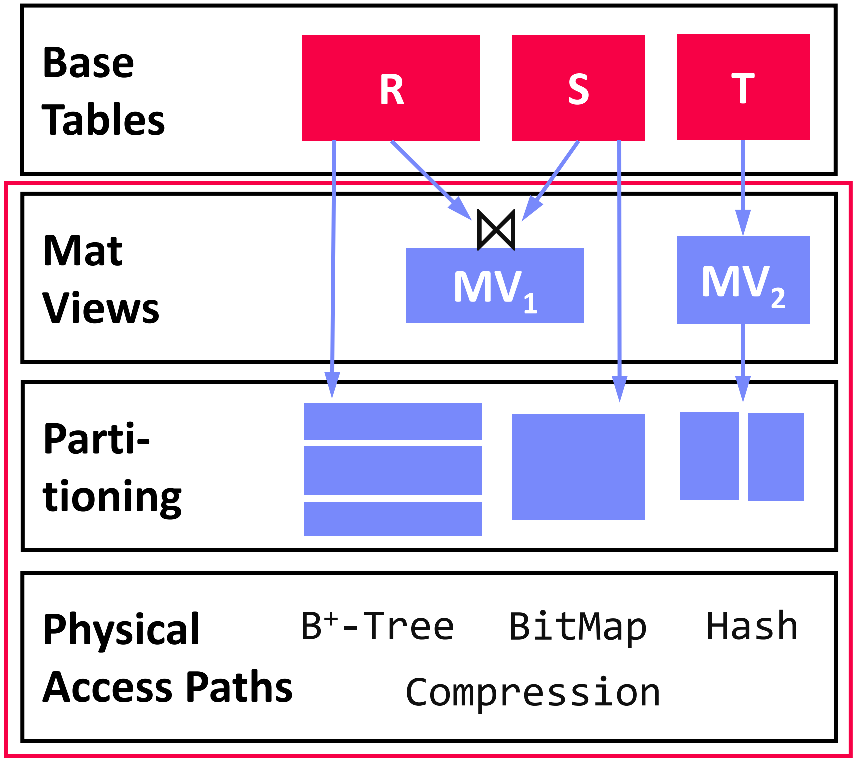
Recap: Access Methods and Physical Design

- **Performance Tuning via Physical Design**
  - Select physical data structures for relational schema and query workload
  - **#1:** User-level, manual physical design by DBA (database administrator)
  - **#2:** User/system-level automatic physical design via advisor tools

- **Example**

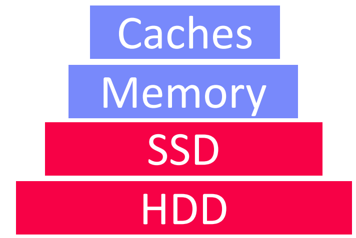
```
SELECT * FROM R, S, T
  WHERE R.c = S.d AND S.e = T.f
    AND R.b BETWEEN 12 AND 73
```



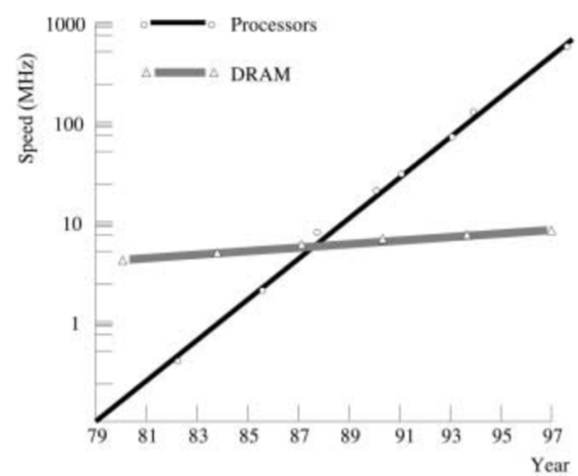


Motivation Storage Hierarchy

- **#1 Capacity**
  - Limited capacity of fast storage
  - Keep larger datasets higher in storage hierarchy
  - Avoid unnecessary I/O



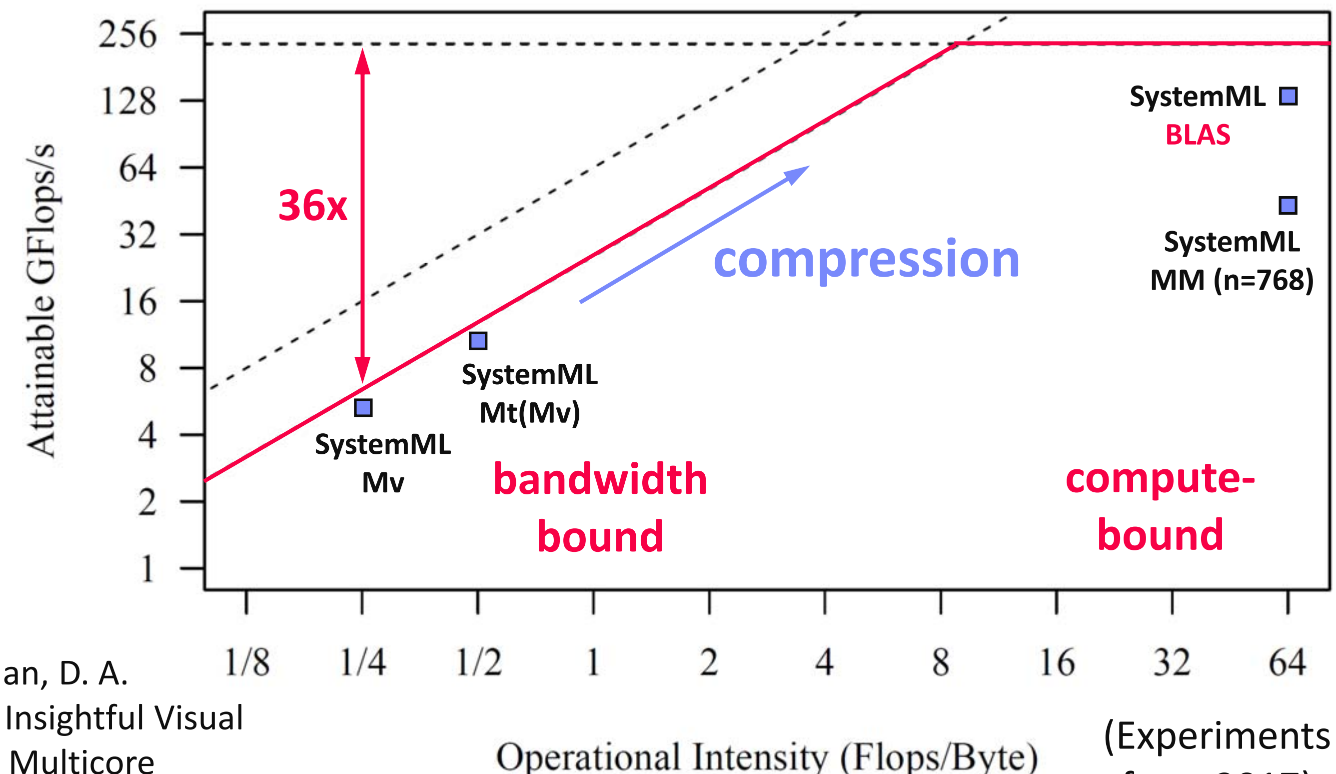
- **#2 Bandwidth**
  - **Memory Wall:** increasing gap
    CPU vs Memory latency/bandwidth
  - Reduce bandwidth requirements



[Stefan Manegold, Peter A. Boncz, Martin L. Kersten: Optimizing database architecture for the new bottleneck: memory access. **VLDB J. 9(3) 2000**]

Excursus: Roofline Analysis

- **Setup:** 2x6 E5-2440 @2.4GHz–2.9GHz, DDR3 RAM @1.3GHz (ECC)
  - Max mem bandwidth (local): 2 sock x 3 chan x 8B x 1.3G trans/s → **2 x 32GB/s**
  - Max mem bandwidth (QPI, full duplex) → **2 x 12.8GB/s**
  - Max floating point ops: 12 cores x 2*4dFP-units x 2.4GHz → **2 x 115.2GFlops/s**
- **Roofline Analysis**
  - Off-chip memory traffic
  - Peak compute



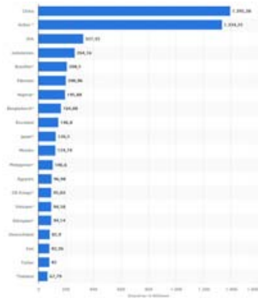
(Experiments from 2017)

[S. Williams, A. Waterman, D. A. Patterson: Roofline: An Insightful Visual Performance Model for Multicore Architectures. **Commun. ACM 2009**]

Motivation Data Characteristics

- **Skew**
  - Highly skewed **value distributions** (frequencies of distinct values)
  - Small number of distinct items

China **1.4**
India **1.3**
USA **0.33**
Germany **0.08**
Austria **0.009**



- **Correlation**
  - Correlation between tuple attributes
  - Co-occurrences of attribute values

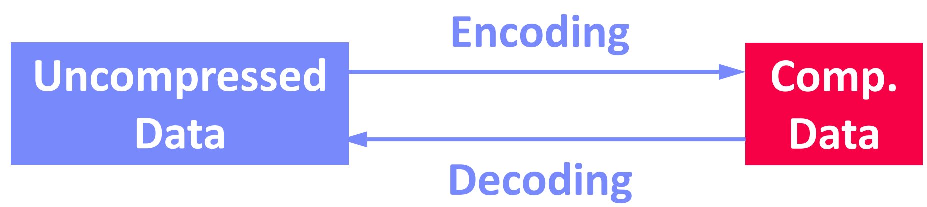
`OrderDate < ReceiptDate`
(usually 2-3 days)

- **Lack of Tuple Order**
  - Relations are multi-sets of tuples (no ordering requirements)
  - Flexibility for internal reorganization

[Vijayshankar Raman, Garret Swart: How to Wring a Table Dry: Entropy Compression of Relations and Querying of Compressed Relations. **VLDB 2006**]

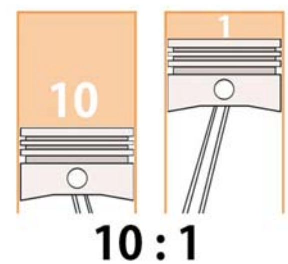
Compression Overview

- **Compression Codec**
  - Encoder
  - Decoder



- **Lossless vs Lossy**
  - **Lossless:** guaranteed recovery of uncompressed data
  - **Lossy:** moderate degradation / approximation
    → Images, video, audio; ML training/scoring

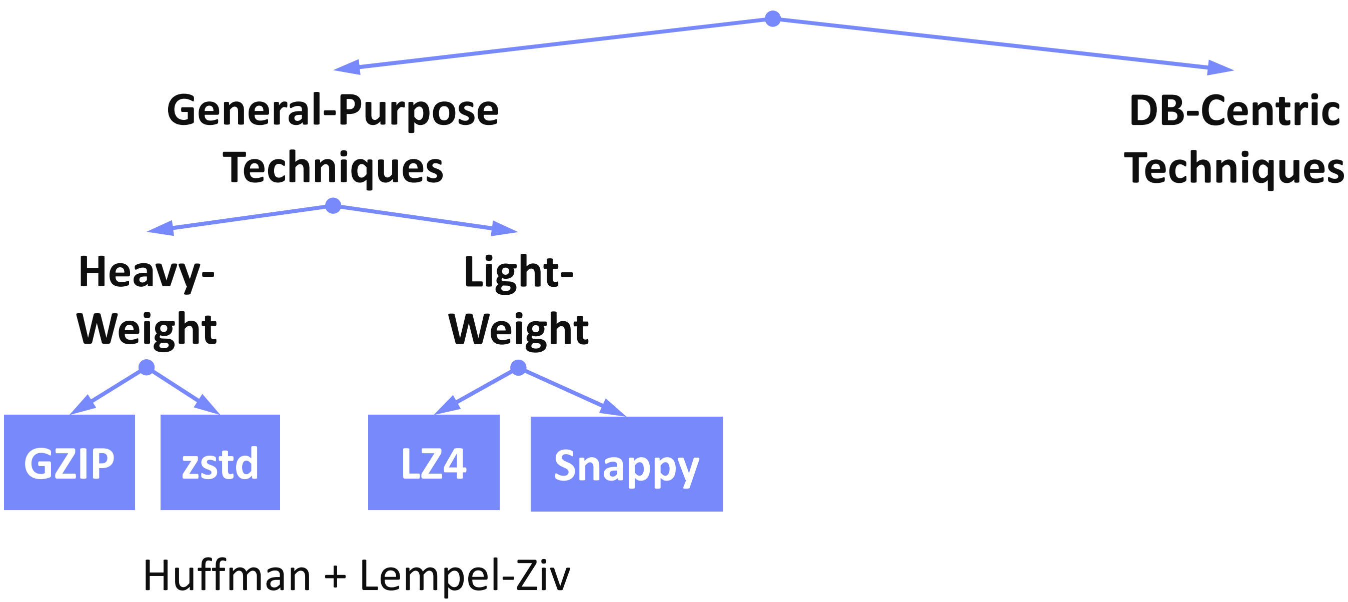
- **Compression Ratio**
  - CR = Size-Uncompressed / Size-compressed
  - Ineffective compression: CR < 1



- **Metrics**
  - Compression ratio vs encode/decode time vs encode/decode space
  - Block-wise vs random access, operation performance, etc

Classification of Compression Techniques

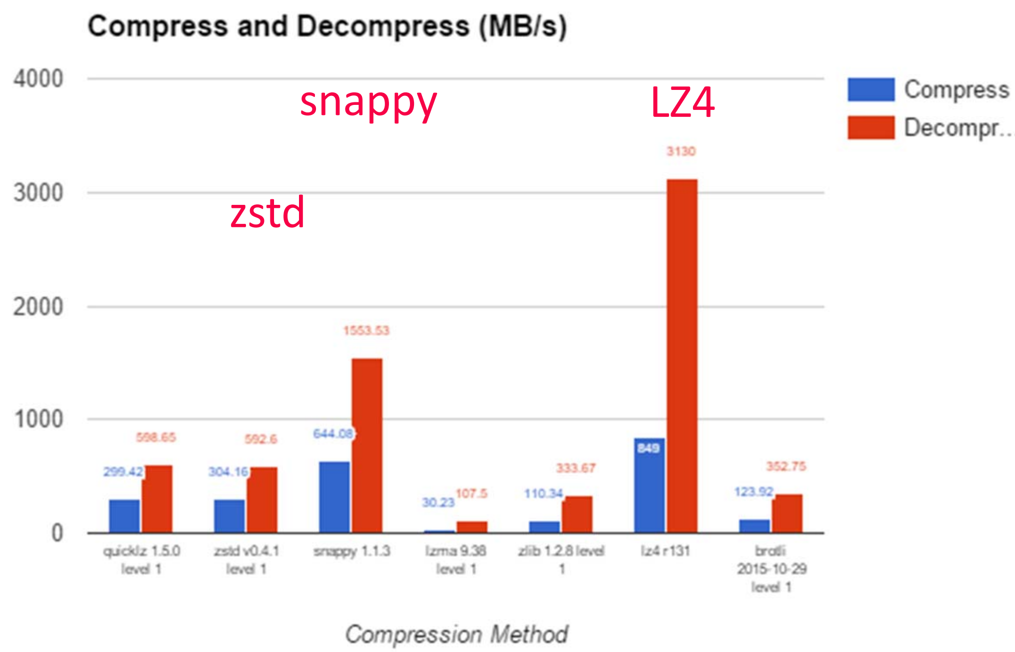
- **Lossless Compression Schemes**



Excursus: General-purpose Compression

- **Compression/ Decompression**
  - CR zstd: 5.24
  - CR snappy: 3.65
  - CR LZ4: 3.89

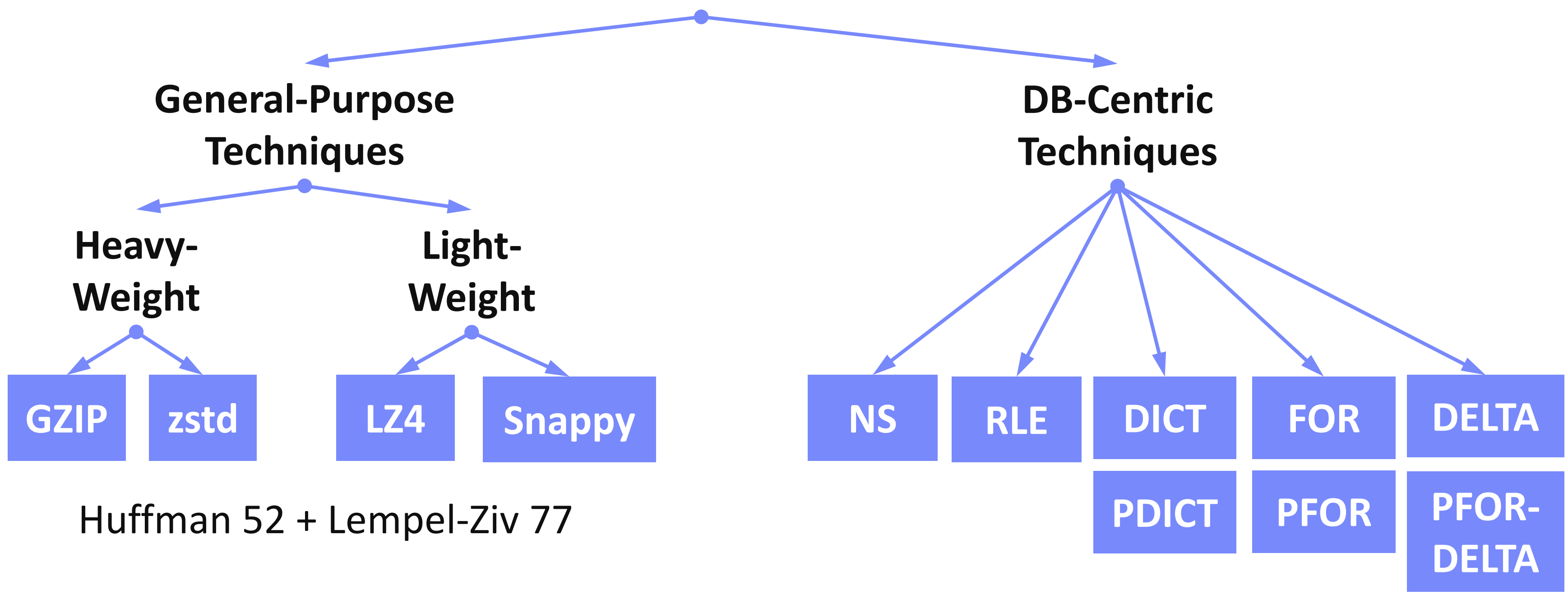
[https://web.archive.org/web/20200229161007/https://www.percona.com/blog/2016/04/13/evaluating-database-compression-methods-update/]



- **Example Apache Spark RDD Compression**
  - `org.apache.spark.io.LZ4CompressionCodec` (**default in 2.x, 3.x**)
  - `org.apache.spark.io.SnappyCompressionCodec` (**default in 1.x**)
  - `org.apache.spark.io.LZFCompressionCodec` (**default in 0.x**)
  - `org.apache.spark.io.ZStdCompressionCodec`

Classification of Compression Techniques, cont.

- **Lossless Compression Schemes**



(all heavy-weight from a DB perspective)

Compression Techniques

Null Suppression (NS)

[Benjamin Schlegel, Rainer Gemulla, Wolfgang Lehner: Fast integer compression using SIMD instructions. **DaMoN 2010**]

- **Overview**
  - Compress **integers** by omitting **leading zeros** via variable-length codes
  - Universal compression scheme w/o need for upper bound

42
`00000000 | 00000000 | 00000000 | 00101010`

- **Byte-Aligned**
  - Store mask of two bits to indicate leading zero bytes
  - 2 bits + [1,4] bytes → max CR (INT32) = 3.2

42 `11 | 00101010`
7 `11 | 00000111`

- **Bit-Aligned** (Elias Gamma Encoding)
  - Store $\mathrm{N} = \lfloor \log_2 x \rfloor$ zero bits followed by effective bits
  - 2 * [1,32] -1 bits → max CR (INT32) = 32

42 `00000 | 101010`
7 `00 | 111`

- **Word-Aligned** (Simple-8b)
  - Pack a variable number of integers (max 2^{60}) into 64bit
  - 60 data bits, 4 selector bits (16 classes: 60x1b, 30x2b, 20x3b, 15x4b, 12x5b, …)

Null Suppression (NS), cont.

[Jeff Dean: Challenges in Building Large-Scale Information Retrieval Systems, Keynote **WSDM 2009**]

- **Varint (Variable-Length Integers)**
  - Base 128 Varint (continuation bits)

    `0|0000001` → 1
    `1|1111111` `0|0000011` → 511
    `1|1111111` `1|1111111` `0|0000111` → 131071

  - Prefix Varint (2 bit #bytes)

    `00|000001` → 1
    `01|111111` `00000111` → 511
    `10|111111` `11111111` `00000111` → 131071

  - Group Varint

    `00|01|10|00` `00000001` `11111111` `00000001`
    `11111111` `11111111` `00000001` `00000011`
    131071

  - **Examples:**
    - Google Protobuf messages, SQLite custom varint

- **Zig-Zag Encoding**
  - Map signed integers to unsigned integers to have small varint byte length

Run-Length Encoding (RLE)

- **Overview**
  - Compress sequences of equal values via runs of `(value[,start],run-length)`
  - Redundant 'start' allows parallelization / unordered storage
  - Applicable to arbitrary data types (defined `equals()`)

- **Example**
  - Uncompressed

C	C	C	C	C	A	A	A	A	F	F	F	F	F	B	B	B

  - **Compressed**

C	**5**	A	**4**	F	**5**	B	**3**

    - Different physical encodings for values and lengths:
    - E.g., split runs w/ length ≥ 2^{16} to fit into fixed 2 byte

Dictionary Encoding (DICT)

- **Overview**
  - Build dictionary of distinct items and encode values as dictionary positions
  - Applicable to arbitrary data types → integer codes

- **Example**
  - Uncompressed

A	C	B	B	A	C	D	A	A	D	C	B	A	B	B	C	D

  - **Compressed**

Dict	
0	A
1	C
2	B
3	D

0	1	2	2	0	1	3	0	0	3	1	2	0	2	2	1	3

- Explicit or implicit (position) codes
- Fixed bit width: $\log_2 |\text{Dict}|$
- Different ordering of dictionary (alphanumeric, frequency)

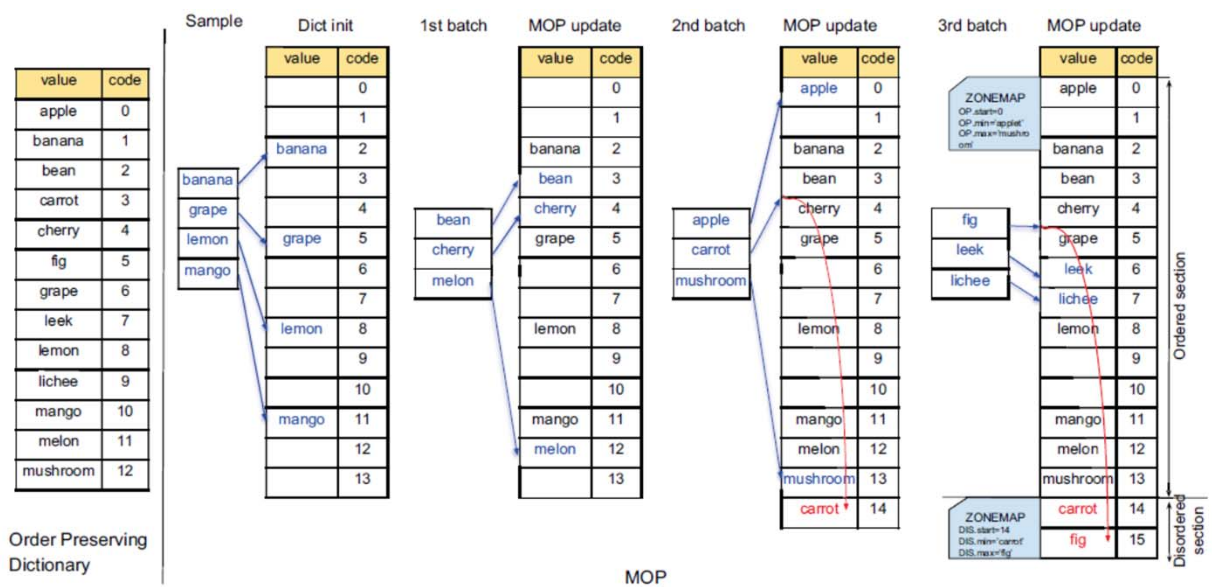
Dictionary Encoding (DICT), cont.

- **Order-preserving Dictionaries**
  - Create sorted dictionary where `order(codes) = order(values)`
  - Support for updates via sparse code assignment (e.g., 10, 20, 30)
  - CS-Array-Trie / CS-Prefix-Tree as encode/decode index w/ shared leafs

[Carsten Binnig, Stefan Hildenbrand, Franz Färber: Dictionary-based order-preserving string compression for main memory column stores. **SIGMOD 2009**]

- **Mostly Order-preserving Dictionaries**
  - Ordered and disordered dictionary sections

[Chunwei Liu et al: Mostly Order Preserving Dictionaries. **ICDE 2019**]



Ordered Section

Disordered Section

Frame of Reference Encoding (FOR)

- **Overview**
  - Compress values by storing **delta (difference) to reference value**
  - Mostly integer types → smaller integer domain

- **Example**
  - Uncompressed

701	698	702	700	699	698	700	701	701	700	703	702

  - **Compressed**

700

1	-2	2	0	-1	-2	0	1	1	0	3	2

Cannot handle trends very well

Delta Encoding (DELTA)

- **Overview**
  - Compress values by storing **delta (difference) to previous value**
  - Mostly integer types (good when sorted) → smaller integer domain
  - Dedicated techniques for differences of file contents (diff/git)

- **Example**
  - Uncompressed

5	5	6	6	7	7	7	9	9	12	13	14	15	16	17	17	18

  - **Compressed**

5	0	1	0	1	0	0	2	0	3	1	1	1	1	1	0	1

    - Delta
    - Double Delta (differences of differences)

Can create RLE opportunities for linear trend

Patched Compression Methods (PFOR)

- **Patched Frame of Reference (PFOR)**
  - Store positive offsets to reference value
  - Exceptions in uncompressed form
    (accessible via entry points and offsets to next exception)
  - Branchless two-pass decoding

[Marcin Zukowski, Sándor Héman, Niels Nes, Peter A. Boncz: Super-Scalar RAM-CPU Cache Compression. **ICDE 2006**]

- **Example**
  - Uncompressed

Outliers would destroy fixed-width codes

22	**982**	21	20	23	20	24	**850**	21	22	**867**	21

  - **Compressed**

20	Base

2	5	1	0	3	0	4	2	1	2		1

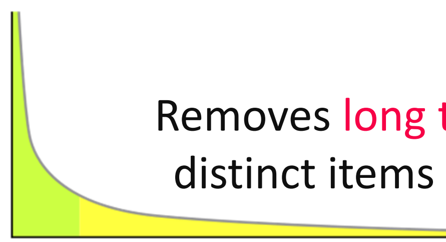
982	850	867	Exceptions

Patched Compression Methods (Others)

- **PFOR-DELTA**
  - Apply cascade of DELTA – PFOR (PFOR on differences)
  - Handling of exceptions to handle large differences of subsequent values

[Marcin Zukowski, Sándor Héman, Niels Nes, Peter A. Boncz: Super-Scalar RAM-CPU Cache Compression. **ICDE 2006**]

- **Patched Dictionary Compression (PDICT)**
  - Dictionary encoding, where only frequent values are encoded
  - Exceptions for infrequent values, previous/new dictionary per block
  - Reduces dictionary size



Removes long tail of infrequent distinct items from dictionary

Excursus: SIMD Implementation and Evaluation

- **Experimental Survey**
  - Different data characteristics
  - Compression methods:

    DELTA, RLE, FOR, RLE, DICT,
    SIMD-BP128, SIMD-FastPFOR,
    4-Wise NS, 4-Gamme, Masked VByte,
    Simple-8b, SIMD-GroupSimple
  - Cascades of compression methods

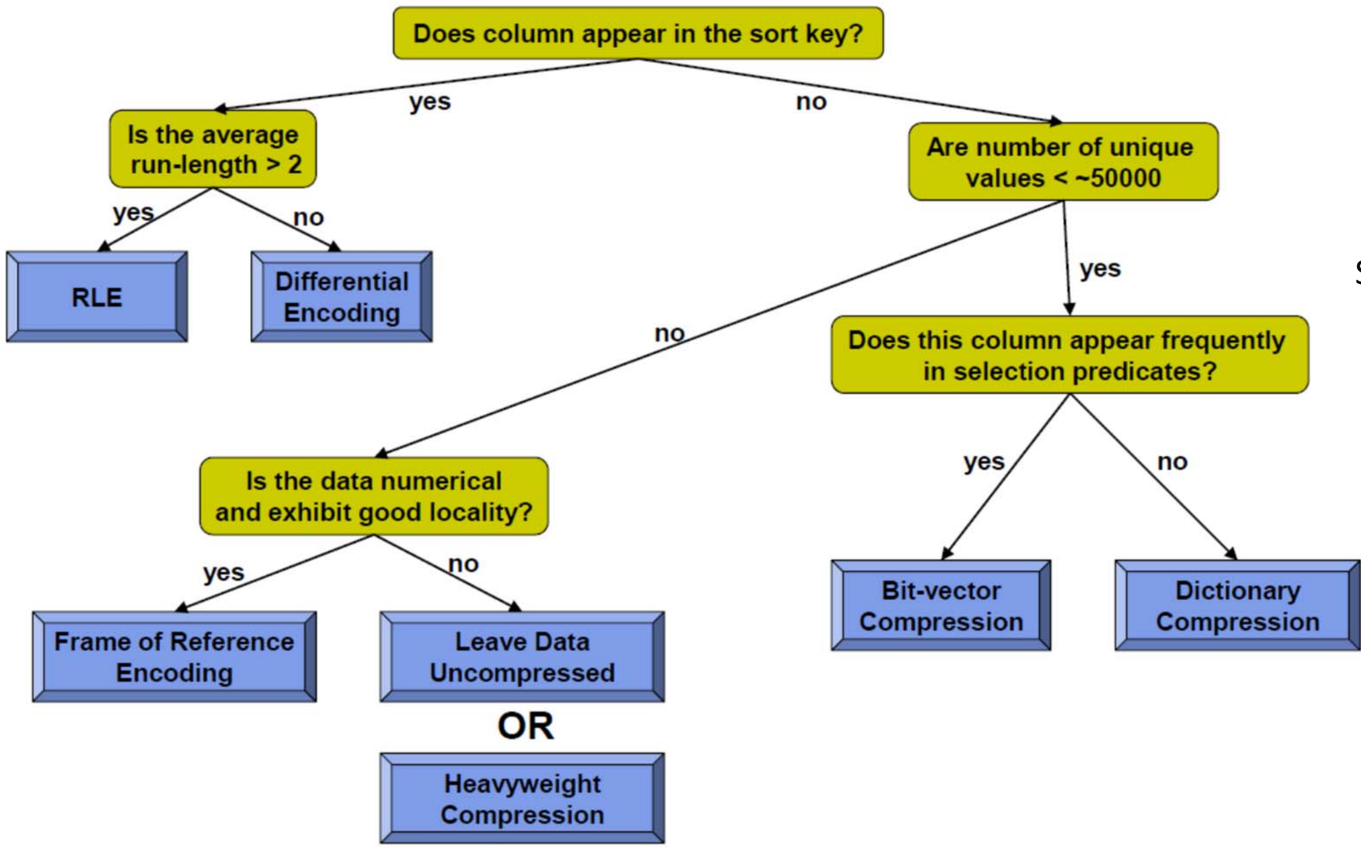
[Patrick Damme, Dirk Habich, Juliana Hildebrandt, Wolfgang Lehner: Lightweight Data Compression Algorithms: An Experimental Survey (Experiments and Analyses). **EDBT 2017**]

"[…] there is **no single-best lightweight integer compression algorithm**. The compression rates and performances of all algorithms differ significantly, depending on the data characteristics and the employed SIMD extension."

- **Towards a Cost-based Selection**
  - Logical and physical level
  - Cost estimation functions

[Patrick Damme, Annett Ungethüm, Juliana Hildebrandt, Dirk Habich, Wolfgang Lehner: From a Comprehensive Experimental Survey to a Cost-based Selection Strategy for Lightweight Integer Compression Algorithms. **ACM Trans. Database Syst. 44(3) 2019**]

Selecting Compression Methods



[Peter Boncz: Column-Oriented Database Systems, adapted from **VLDB'09 tutorial**]

- **Inspired by**
  C-Store Compression Paper

[Daniel J. Abadi, Samuel Madden, Miguel Ferreira: Integrating compression and execution in column-oriented database systems. **SIGMOD 2006**]

Compressed Query Processing

Selection Predicates

- **Equivalence Predicates $\sigma_{attr='D'}(R)$**
  - DICT: code lookup

Dict	
0	A
1	C
2	B
3	D

D → 3

0	1	2	2	0	1	3	0	0	3	1	2	0	2	2	1	3

position vector

6	9	16

  - RLE: return RLE runs

C	5	A	4	D	5	F	3

- **Range Predicates $\sigma_{3<a<7}$ (R)**
  - **#1** sort the dictionary by value (insert tradeoff)
  - **#2** expand small integer domains + dictionary lookup (e.g., $\sigma_{a=4 \vee a=5 \vee a=6}$ (R))
  - **#3** decompress otherwise

Selection Predictions, cont.

- **Order Preserving Dictionaries**
  - Direct support for **range predicates** on encoded data
  - Support for **LIKE predicates** (suffix)

[Carsten Binnig, Stefan Hildenbrand, Franz Färber: Dictionary-based order-preserving string compression for main memory column stores. **SIGMOD 2009**]

String-dictionary (order preserving)

value	code
…	…
Whole Milk - Gallon	32000
Whole Milk - Quart	32100
…	…

Product column (encoded)

rid	p_name
1	32000
…	…
499	32100

Query (original):

```
Select SUM(o_total), p_name
From Sales, Products
Where p_name='Whole Milk*'
Group by p_name
```

value	code
…	…
Whole Milk – Gallon	32000
Whole Milk - Half Gallon	32050
Whole Milk – Quart	32100
…	…

rid	p_name
…	…
499	32100
500	32000
…	
999	32050

Query (rewritten):

```
Select SUM(o_total), p_name
From Sales, Products
Where p_name ≥ 32000
And p_name ≤ 32100
Group by p_name
```

Grouping and Aggregations

- **Basic Hash Aggregates**
  - Grouping directly with compressed codes
  - DICT, FOR, RLE, etc

Dict	
0	A
1	C
2	B
3	D

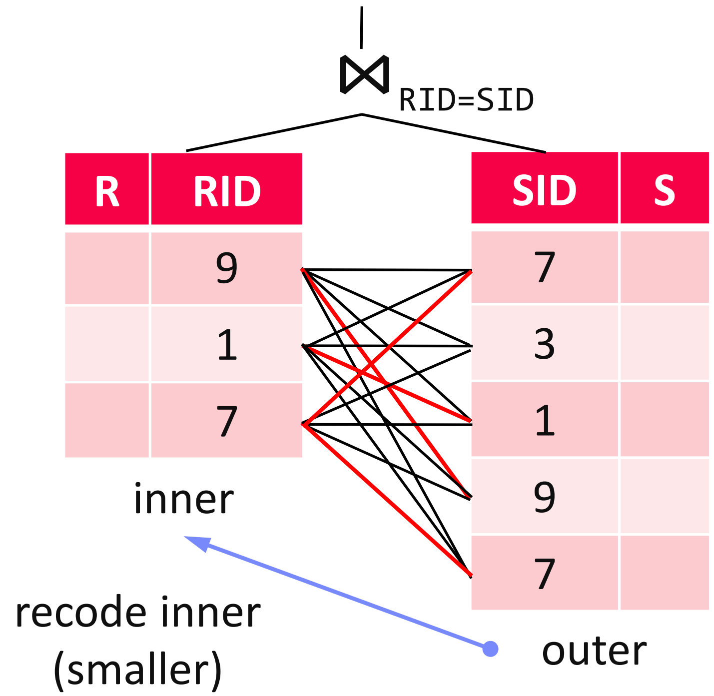
0	1	2	2	0	1	3	0	0	3	1	2	0	2	2	1	3

Hash Table	
0	Agg A
3	Agg D
1	Agg C
2	Agg B

- **Encoding-Specific Aggregation**
  - RLE sum → agg += run-length*run-value
  - RLE min → agg = min(agg, run-value)
  - FOR sum → for all codes: agg += code; agg += |codes| * base-value

Joins

- **Overview Compressed Joins**
  - (Equi-)Joins directly over compressed data
  - **Beware:** binary operation
    → encodings need to match (**global code**)
  - Recoding of one of the inputs if necessary
    (e.g., DB2 BLU recode inner)



- **Encoding-Specific Aggregation**
  - One input RLE: decompress other
    and output RLE encoded data
  - One input bitvector: decompress other
    and output RLE encoded data (obtained from bitvector)

Abstractions for Simpler Code

- **Motivation**
  - **Code complexity** for combinations of encoding schemes
  - Affects all operators → maintenance operators/compression schemes

- **Compressed Block Properties**

[Daniel J. Abadi, Samuel Madden, Miguel Ferreira: Integrating compression and execution in column-oriented database systems. **SIGMOD 2006**]

  - `isOneValue()`: block contains just one value and many positions for that value
  - `isValueSorted()`: all values of the block are sorted
  - `isPosContig()`: block contains consecutive subset of column

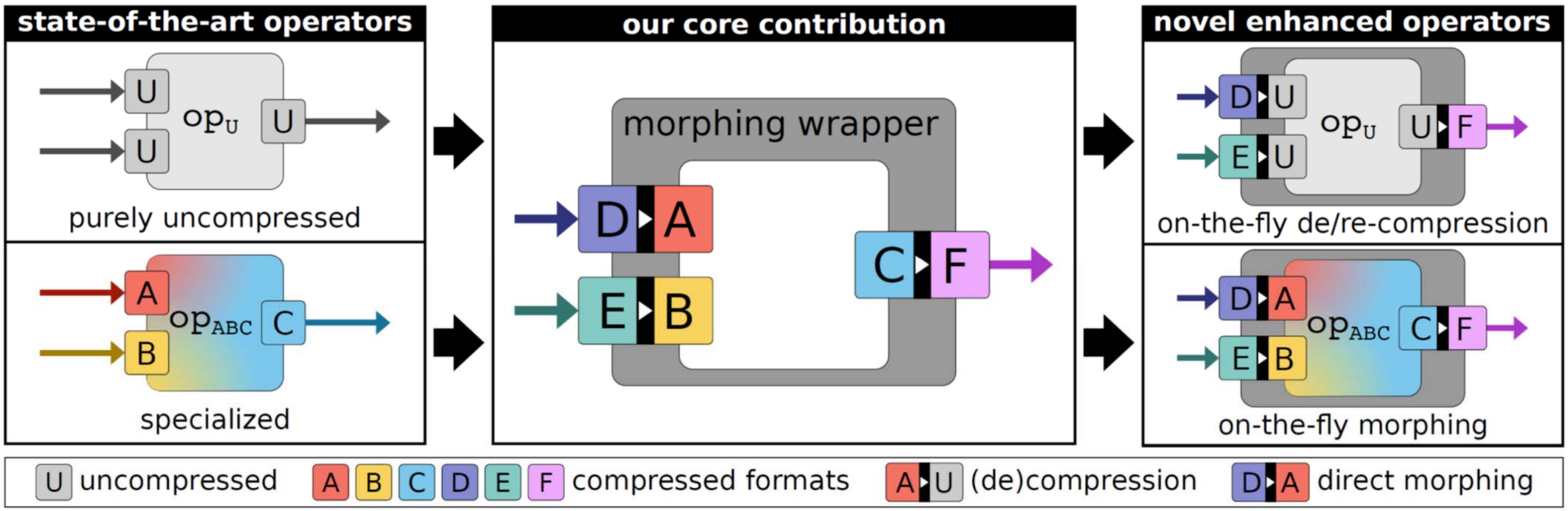
- **Iterator Access:** `getNext()`, `asArray()`
- **Block Information:** `getSize()`, `getStartValue()`, `getEndPosition()`

Encoding Type	Sorted?	1 value?	Pos. contig.?
RLE	yes	yes	yes
Bit-string	yes	yes	no
Null Supp.	no/yes	no	yes
Lempel-Ziv	no/yes	no	yes
Dictionary	no/yes	no	yes
Uncompressed	no/yes	no	no/yes

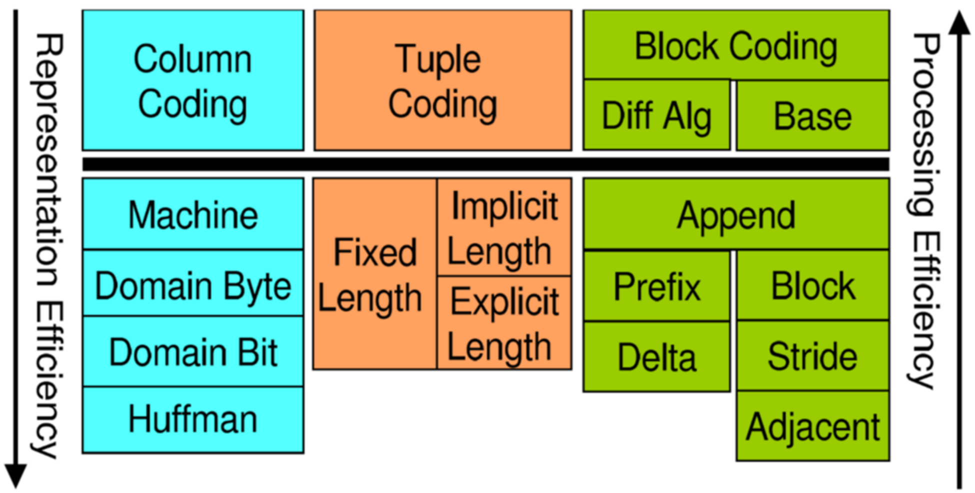
Abstractions for Simpler Code, cont.

- **Motivation**
  - Improve query performance by (re)compressing intermediates
  - Change from one compressed format to another

[Patrick Damme, Annett Ungethüm, Johannes Pietrzyk, Alexander Krause, Dirk Habich, Wolfgang Lehner: **MorphStore:** Analytical Query Engine with a Holistic Compression-Enabled Processing Model. **PVLDB 13(11) 2020**]



Data Layout – Compression Granularity



[Allison L. Holloway, Vijayshankar Raman, Garret Swart, David J. DeWitt: How to barter bits for chronons: compression and bandwidth trade offs for database scans. **SIGMOD 2007**]

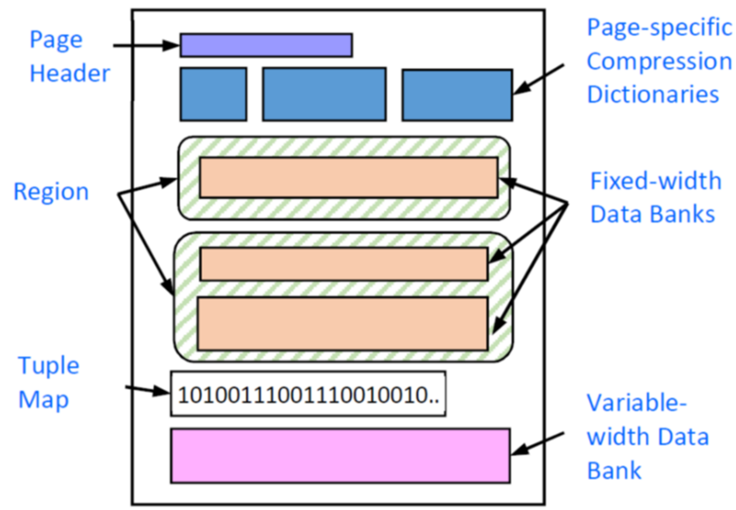
"All the results have shown that the Huffman coded and delta coded formats compress better but normally take more CPU time. […] When I/O and memory subsystem times are also included in the decision, the format to choose becomes less clear-cut. If a physical format optimizer or system administrator had this information and a fast scan generator, they could make a more informed choice as to the best way to store the data."

- **Column Coding**
  - Select encoding for individual attributes (column values) – tradeoffs
- **Tuple Coding**
  - Combine column codes into tuple codes (fixed, variable)
- **Block Coding**
  - Compress a sequence of tuples into a compressed block (concat, diff)

03 Buffer Pool Management

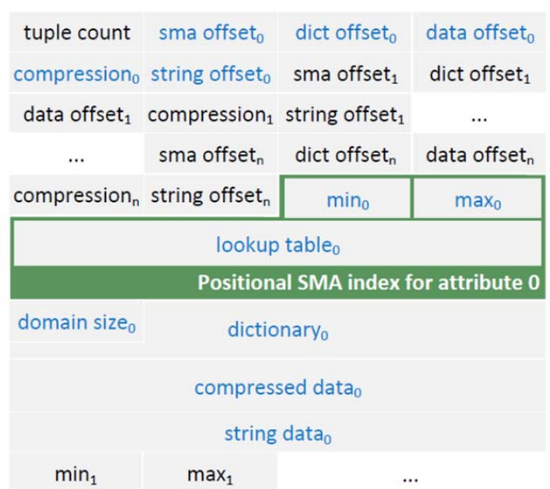
Data Layout – Example Block Layouts

- **DB2 BLU**



[Vijayshankar Raman et al: DB2 with BLU Acceleration: So Much More than Just a Column Store. **PVLDB 6(11) 2013**]

- **Data Blocks**



[Harald Lang: Data Blocks: Hybrid OLTP and OLAP on Compressed Storage using both Vectorization and Compilation. **SIGMOD 2016**]

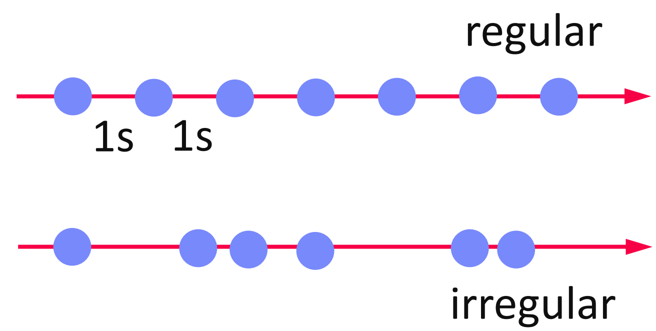
03 Buffer Pool Management
04 Index Structures and Partitioning
07 Query Compilation and Parallelization

Time Series Compression

Motivation and Terminology

- **Ubiquitous Time Series**
  - **Domains:** Internet-of-Things (IoT), sensor networks, smart production/planet, telemetry, stock trading, server/application metrics, event/log streams
  - **Applications:** monitoring, anomaly detection, time series forecasting
  - Dedicated storage and analysis techniques → Specialized systems

- **Terminology**
  - Time series X is a sequence of data points x_i for a specific measurement identity (e.g., sensor) and time granularity
  - **Regular** (equidistant) time series (x_i) vs **irregular** time series (t_i, x_i)

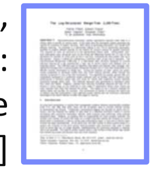






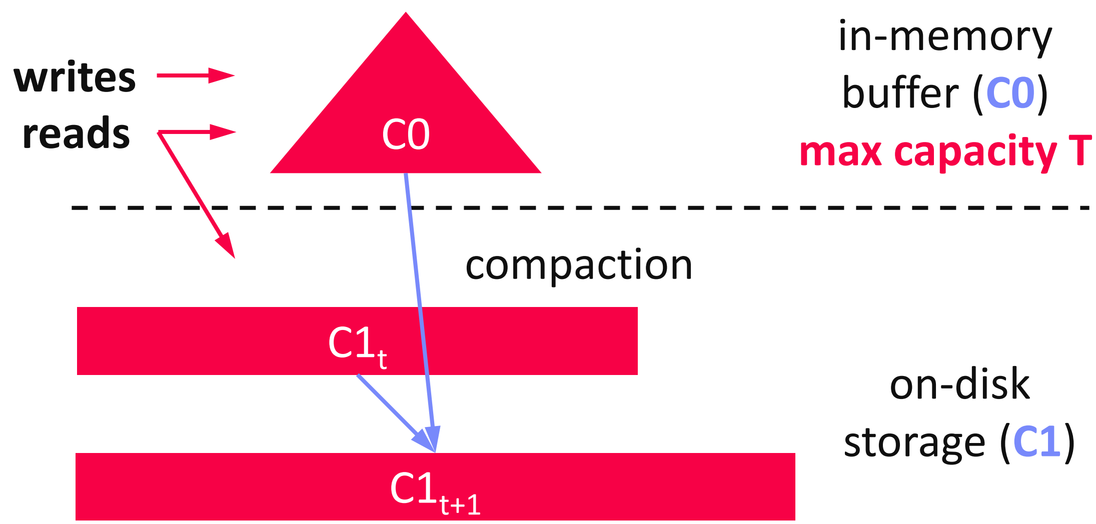

Log-structured Merge Trees

[Patrick E. O'Neil, Edward Cheng, Dieter Gawlick, Elizabeth J. O'Neil: The Log-Structured Merge-Tree (LSM-Tree). **Acta Inf. 1996**]



- **LSM Overview**
  - Many KV-stores rely on LSM-trees as their storage engine (e.g., **BigTable**, **DynamoDB**, **LevelDB**, **Riak**, **RocksDB**, **Cassandra**, **HBase**)
  - **Approach:** Buffers writes in memory, flushes data as sorted runs to storage, merges runs into larger runs of next level (compaction)

- **System Architecture**
  - Writes in C0
  - Reads against C0 and C1 (w/ buffer for C1)
  - Compaction (rolling merge): sort, merge, including **deduplication**



Example InfluxDB

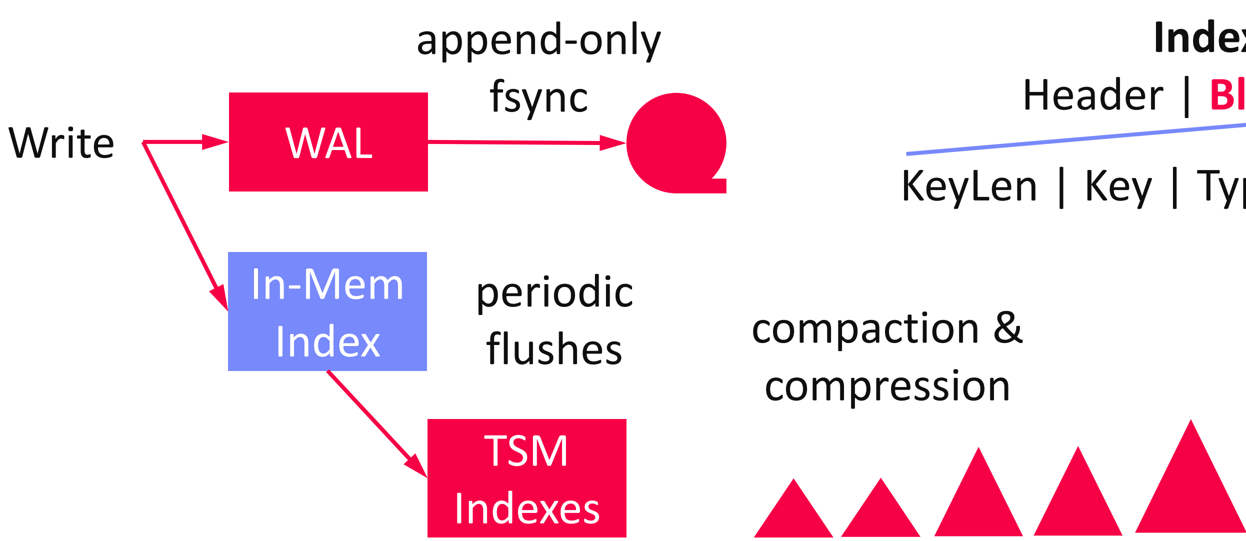
- **Input Data**

```
cpu,region=west,host=A
 user=85,sys=2,idle=10 1443782126
```

cpu = Measurement; region=west,host=A = Tags; user=85,sys=2,idle=10 = Fields (values); 1443782126 = Time

[Paul Dix: InfluxDB Storage Engine Internals, CMU Seminar, 09/2017]

- **System Architecture**
  - Written in Go, originally **key-value store**, now **dedicated storage engine**
  - **Time Structured Merge Tree (TSM)**, similar to LSM
  - Organized in shards, TSM indexes and inverted index for reads



Index per TSM file:

Header | **Blocks** | Index | Footer

KeyLen | Key | Type | Min T | Max T| Off | …

periodic drop of shards (files) according to retention policy

Example InfluxDB, cont.

- **Compression (of blocks)**
  - Compress up to 1000 values per block (Type | Len | Timestamps | Values)
  - **Timestamps:** Delta + Run-length encoding for regular time series; Simple8B or uncompressed for irregular
  - **Values:** double delta for FP64, bits for Bool, double delta + zig zag for INT64, Snappy for strings

- **Query Processing**
  - SQL-like and functional APIs for filtering (e.g., range) and aggregation
  - Inverted indexes

```
SELECT percentile(90, user)
  FROM cpu WHERE time>now()-12h
  AND "region"='west'
  GROUP BY time(10m), host
```

Measurement to fields:
cpu → [user,sys,idle]
host → [A, B]
Region → [west, east]

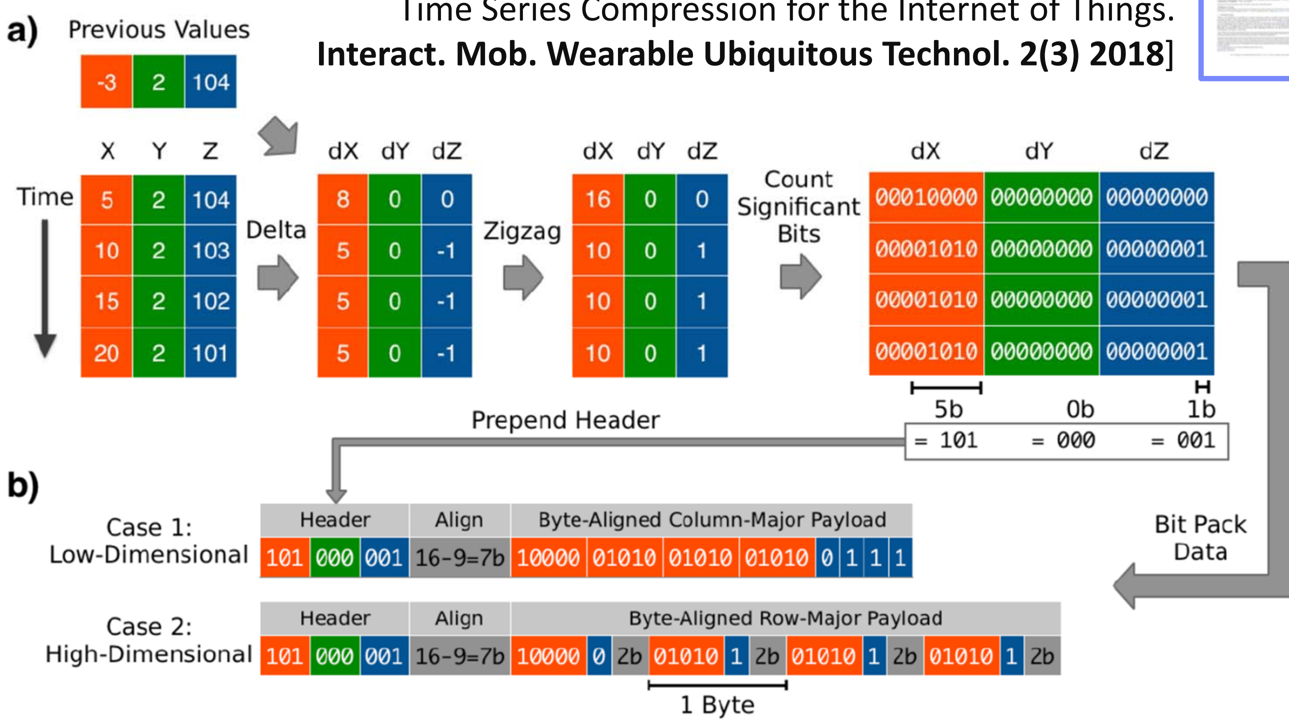
Posting lists:
cpu → [1,2,3,4,5,6]
host=A → [1,2,3]
host=B → [4,5,6]
region=west → [1,2,3]

Lossless, Predictive Time Series Compression

- **Motivation**
  - Sampled sensor data with lots of compression potential
  - Small blocksize (end devices), fast decompression, lossless

- **Sprintz**
  - Forecasting
  - Bit packing
  - RLE zeros
  - Entropy coding

[Davis W. Blalock, Samuel Madden, John V. Guttag: Sprintz: Time Series Compression for the Internet of Things. **Interact. Mob. Wearable Ubiquitous Technol. 2(3) 2018**]



Summary and Q&A

- **Motivation and Terminology**
- **Compression Techniques**
- **Compressed Query Processing**
- **Time Series Compression**

- **Next Lectures** (Part B)
  - **Nov 11:** no lecture, work on your programming projects
  - **06 Query Processing** (operators, execution models) [Nov 18]
  - **07 Query Compilation and Parallelization** [Nov 25]
  - **08 Query Optimization I** (normalization, rewrites, unnesting) [Dec 02]
  - **09 Query Optimization II** (cost models, join ordering) [Dec 09]
  - **10 Adaptive Query Processing** [Dec 16]