Architecture of ML Systems (AMLS)
08 Data Access Methods

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Last update: Jun 13, 2024

Announcements / Org

- **#1 Hybrid & Video Recording**
  - Hybrid lectures (in-person, zoom) with optional attendance https://tu-berlin.zoom.us/j/9529634787?pwd=R1ZsN1M3SC9BOU1OcFdmem9zT202UT09
  - Zoom **video recordings**, links from website https://mboehm7.github.io/**teaching**/ss24_amls/index.htm

- **#2 Course Evaluation**
  - **Jun 17 - Jun 28**, Link available Jun 13, shared via ISIS announcement
  - **Lecture:** https://befragung.tu-berlin.de/evasys/online.php?pswd=KTRLR
  - **Project/Exercises:** not yet available

- **#3 Exam Registration**
  - Thu, **Jul 18, 4.15pm** in H0107 (**24**/144 seats) → **15** registration(s)
  - Sa, **Aug 10, 2.15pm** in A053 and EB 301 (**106**/639 seats) → **5** registration(s)

Categories of Execution Strategies

Batch **SIMD/SPMD**	Batch/Mini-batch, Independent Tasks **MIMD**	Mini-batch
05_a Data-Parallel Execution	**05_b Task-Parallel Execution**	**06 Parameter Servers** (data, model)

07 Hybrid Execution and HW Accelerators

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08 Caching, Partitioning, Indexing, and Compression

Agenda

- **Motivation, Background, and Overview**
- **Caching, Partitioning, and Indexing**
- **Lossy and Lossless Compression**

Iterative, I/O-bound ML algorithms
➔ **Data access crucial for performance**

X

```
while(!converged) {
  … q = X %*% v …
}
```

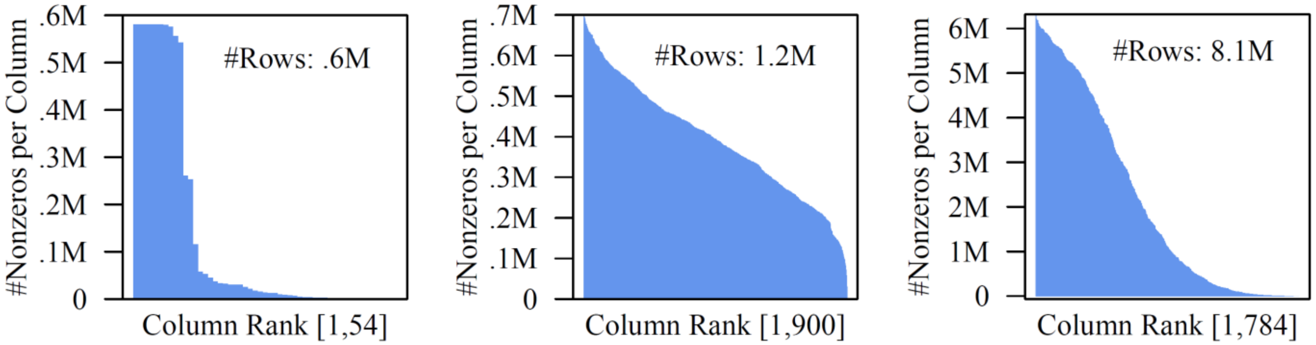
Data **Weights**

Training	**read-only**	updated
Inference/Scoring	new data	**read-only**

Motivation, Background, and Overview

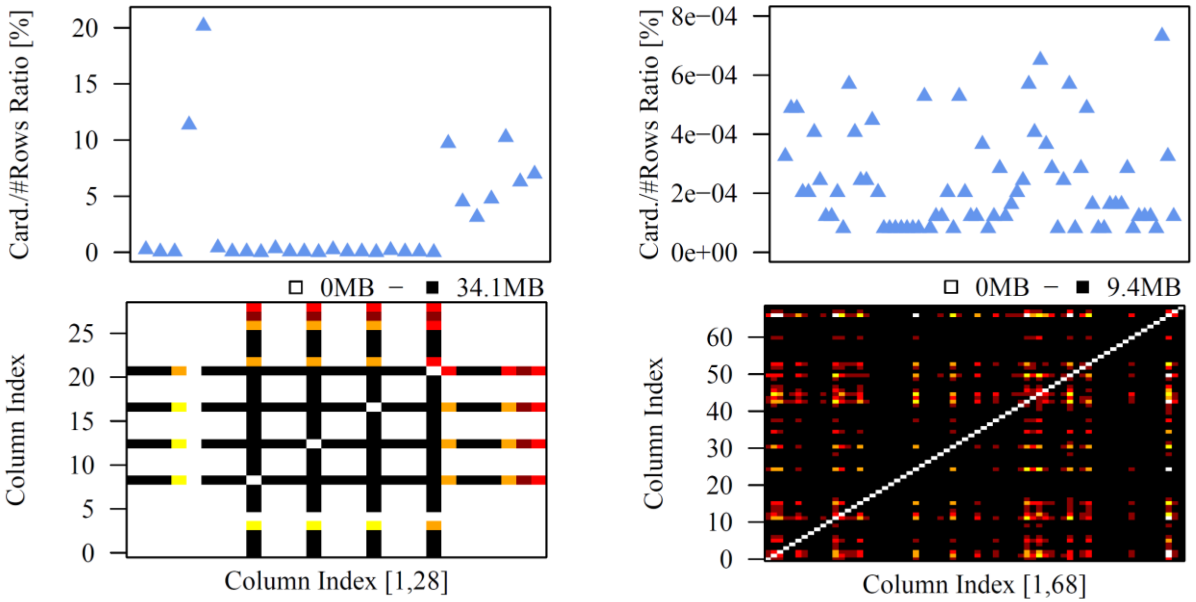
Motivation: Data Characteristics

- **Tall and Skinny**
  (#rows >> #cols)
- **Non-Uniform Sparsity**



- **Small Column Cardinalities**
- **Small Val Range**
- **Column Correlations**
  (on census:
  12.8x → 35.7x)

Higgs



Census

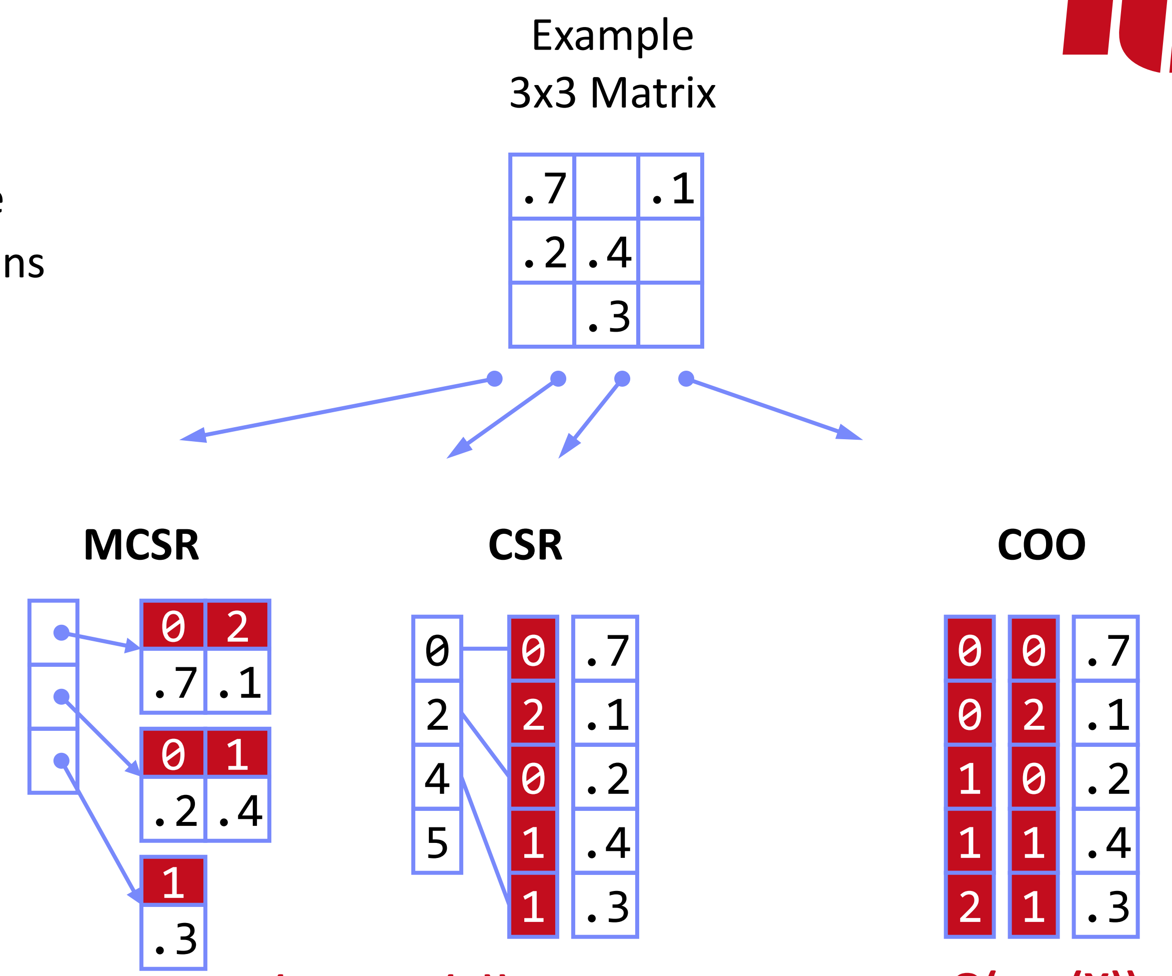
Recap: Background Matrix Formats

- **Matrix Block** (m x n)
  - A.k.a. tiles/chunks, most operations defined here
  - Local matrix: single block, different representations
- **Common Block Representations**
  - Dense (linearized arrays)
  - MCSR (modified CSR)
  - CSR (compressed sparse rows), CSC
  - COO (Coordinate matrix)

Dense (row-major)

.7	0	.1	.2	.4	0	0	.3	0

O(mn)



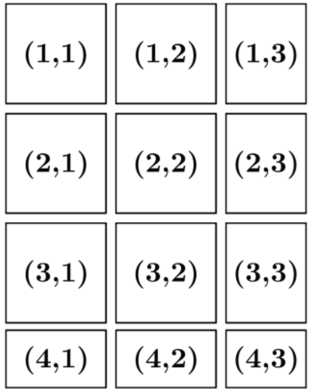
O(m + nnz(X))

O(nnz(X))

Recap: Distributed Matrix Representations

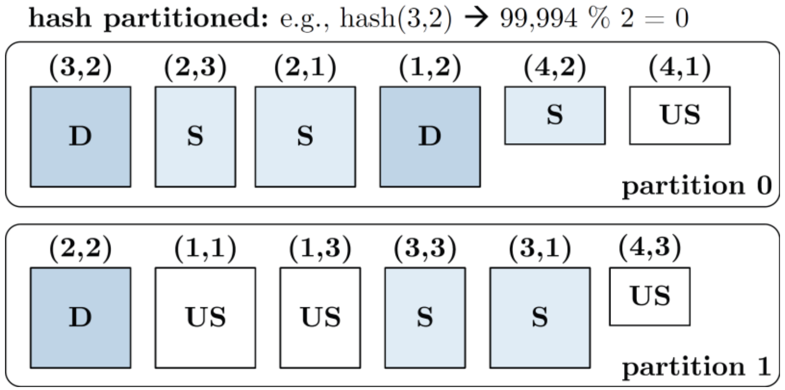
- **Collection of "Matrix Blocks" (and keys)**
  - Bag semantics (duplicates, unordered)
  - Logical (Fixed-Size) Blocking
    + join processing / independence
    - (sparsity skew)
  - E.g., SystemML on Spark:
    `JavaPairRDD<MatrixIndexes,MatrixBlock>`
  - Blocks encoded independently (dense/sparse)

Logical Blocking
3,400x2,700 Matrix
(w/ B_c=1,000)



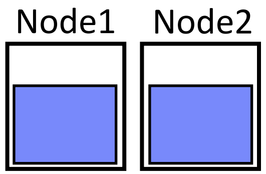
- **Partitioning**
  - Logical Partitioning
    (e.g., row-/column-wise)
  - Physical Partitioning
    (e.g., hash / grid)
  - Influences partition-local aggregation

Physical Blocking
and Partitioning

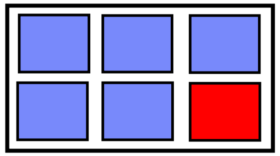


Overview Data Access Methods

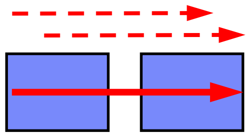
- **#1 (Distributed) Caching**
  - Keep read only feature matrix in (distributed) memory



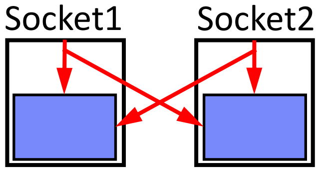
- **#2 Buffer Pool Management**
  - Graceful eviction of intermediates, out-of-core ops



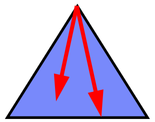
- **#3 Scan Sharing (and operator fusion)**
  - Reduce the number of scans as well as read/writes



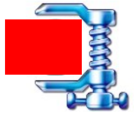
- **#4 NUMA-Aware Partitioning and Replication**
  - Matrix partitioning / replication → data locality



- **#5 Index Structures**
  - Out-of-core data, I/O-aware ops, updates



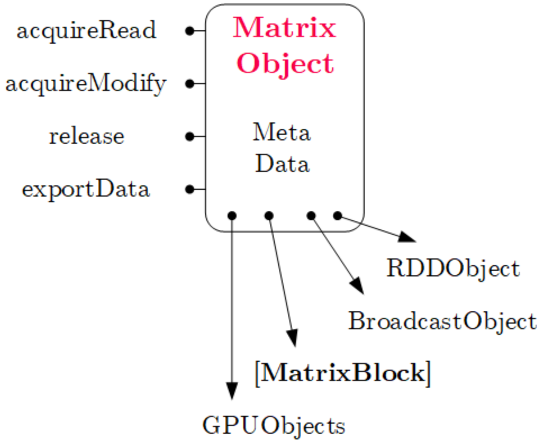
- **#6 Compression**
  - Fit larger datasets into available memory

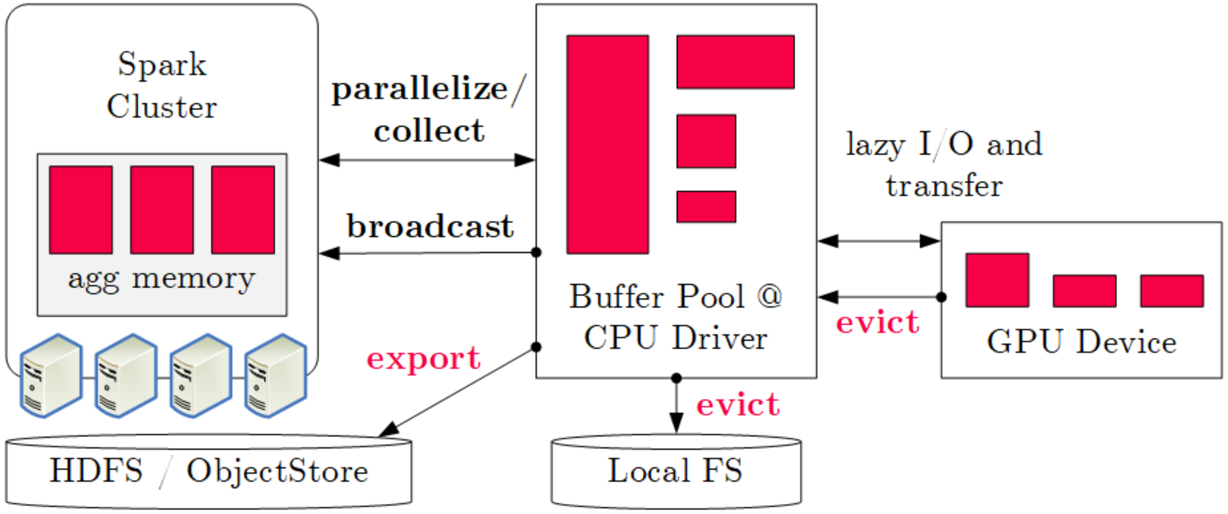


Caching, Partitioning, and Indexing

#2 Buffer Pool Management
#3 Scan Sharing (and operator fusion)
#4 NUMA-Aware Partitioning and Replication
#5 Index Structures

- **#1 Classic Buffer Management** (SystemDS)
  - Hybrid plans of in-memory and distributed ops
  - Graceful eviction of intermediate variables

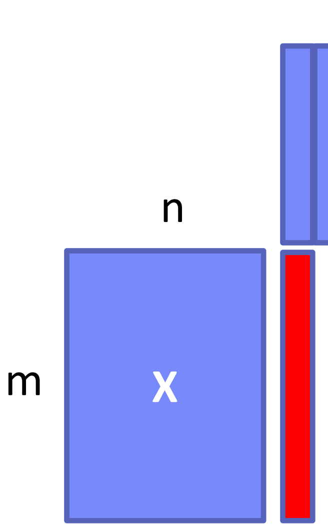




- **#2 Algorithm-Specific Buffer Management**
  - Operations/algorithms over out-of-core matrices and factor graphs
  - Examples: RIOT [CIDR'2009] (ops), Elementary [SIGMOD'13] (factor graphs)

Scan Sharing

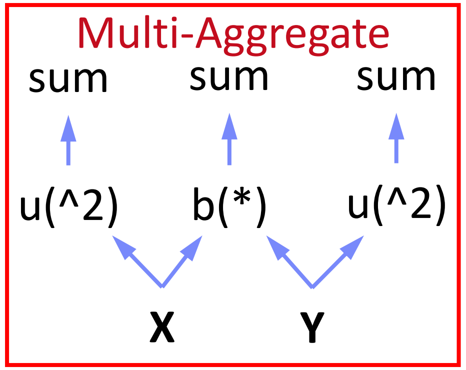
- **#1 Batching**
  - One-pass evaluation of multiple configurations
  - Use cases: EL, CV, feature selection, hyper parameter tuning, multi-user scoring
  - E.g.: **TUPAQ** [SoCC'16], **Columbus** [SIGMOD'14]



O(m*n) read
O(m*n***k**) compute
m >> n >> k

- **#2 Fused Operator DAGs**
  - Avoid unnecessary scans, (e.g., mmchain)
  - Avoid unnecessary writes / reads
  - Multi-aggregates, redundancy
  - E.g.: **SystemML codegen** [PVLDB'18]

```
a = sum(X^2)
b = sum(X*Y)
c = sum(Y^2)
```



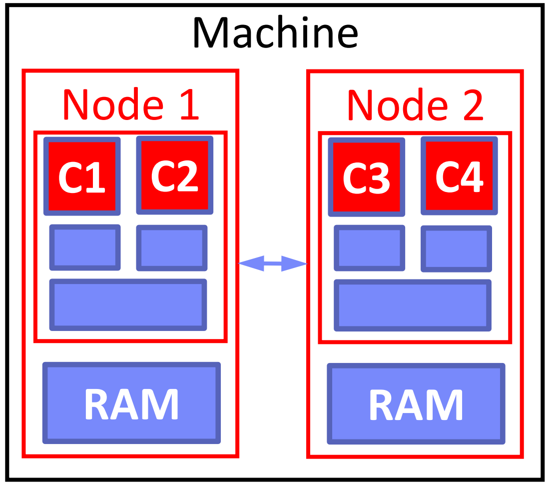
- **#3 Runtime Piggybacking**
  - Merge concurrent data-parallel jobs
  - "Wait-Merge-Submit-Return"-loop
  - E.g.: **SystemML parfor** [PVLDB'14]

```
parfor( i in 1:numModels )
   while( !converged )
      q = X %*% v; ...
```

In-Memory Partitioning (NUMA-aware)

- **NUMA-Aware Model and Data Replication**
  - Model Replication (06 Parameter Servers)
    - PerCore (BSP epoch), PerMachine (Hogwild!), PerNode (hybrid)
  - Data Replication
    - Partitioning (sharding)
    - Full replication

[Ce Zhang, Christopher Ré: DimmWitted: A Study of Main-Memory Statistical Analytics. **PVLDB 2014**]



- **AT MATRIX (Adaptive Tile Matrix)**
  - Recursive NUMA-aware partitioning into dense/sparse tiles
  - Inter-tile (worker teams) and intra-tile (threads in team) parallelization
  - Job scheduling framework from SAP HANA (horizontal range partitioning, socket-local queues with task-stealing)

[David Kernert, Wolfgang Lehner, Frank Köhler: Topology-aware optimization of big sparse matrices and matrix multiplications on main-memory systems. **ICDE 2016**]

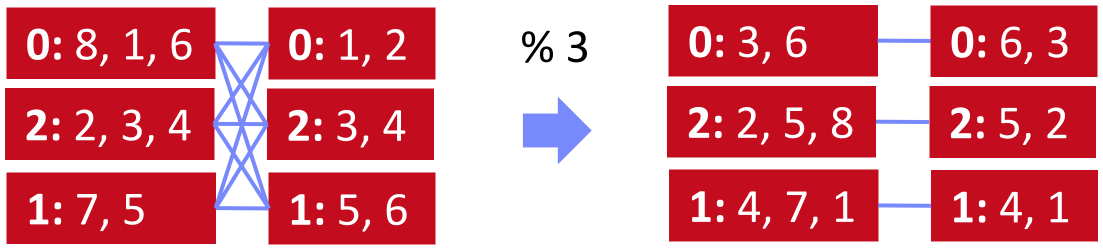
Distributed Partitioning

- **Spark RDD Partitioning**
  - Implicitly on every data shuffling
  - Explicitly via `R.repartition(n)`
- **Distributed Joins**
  - R3 = R1.join(R2)
- **Single-Key Lookups** `v = C.lookup(k)`
  - **Without partitioning:** scan all keys (reads/deserializes out-of-core data)
  - **With partitioning:** lookup partition, scan keys of partition
- **Multi-Key Lookups**
  - Without partitioning: scan all keys
  - With partitioning: lookup relevant partitions

Example Hash Partitioning:

For all (k,v) of R:

hash(k) % numPartitions → pid




```java
//build hashset of required partition ids
HashSet<Integer> flags = new HashSet<>();
for( MatrixIndexes key : filter )
   flags.add(partitioner.getPartition(key));

//create partition pruning rdd
ppRDD = PartitionPruningRDD.create(in.rdd(),
     new PartitionPruningFunction(flags));
```

Recap: B-Tree Overview

[Rudolf Bayer, Edward M. McCreight: Organization and Maintenance of Large Ordered Indices. **Acta Inf. (1) 1972**]

- **History B-Tree**
  - **B**ayer and McCreight 1972, **B**lock-based, **B**alanced, **B**oeing Labs
  - **Multiway tree** (node size = page size); designed for DBMS
  - Extensions: **B+-Tree/B*-Tree** (data only in leafs, double-linked leaf nodes)
- **Definition B-Tree (k, h)**
  - All paths from root to leafs have equal length h
  - All nodes (except root) have **[k, 2k]** key entries
  - All nodes (except root, leafs) have **[k+1, 2k+1]** successors
  - Data is a record or a reference to the record (RID)

$$\lceil \log_{2k+1}(n+1) \rceil \le h \le \left\lfloor \log_{k+1}\left(\frac{n+1}{2}\right) \right\rfloor + 1$$

All nodes adhere to max constraints

k=2

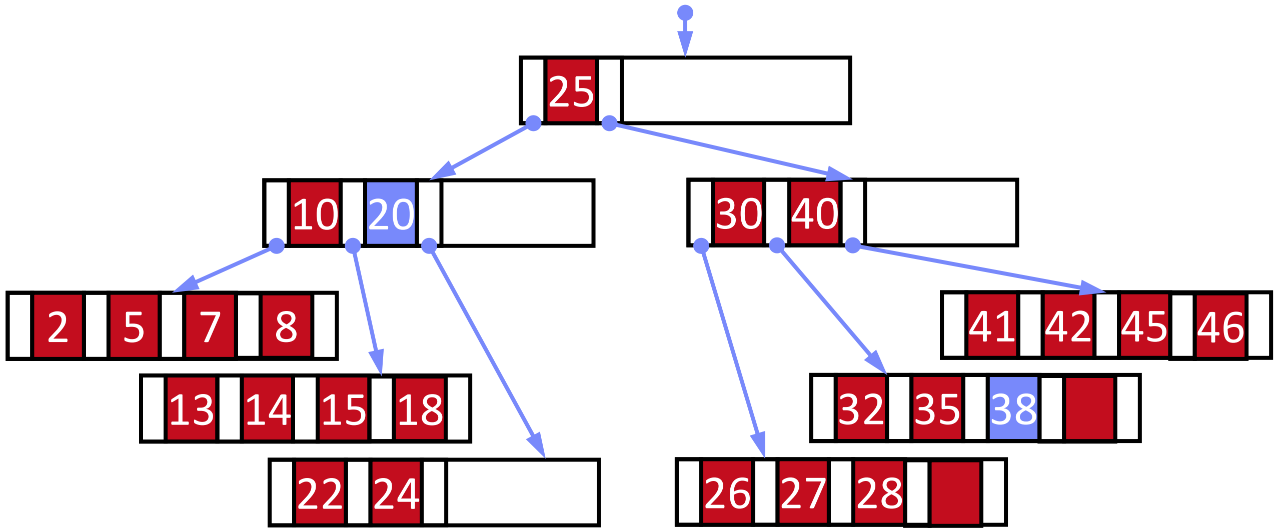
P_0	Key K_1	Data D_1	P_1	Key K_2	Data D_2	P_2	Key K_3	Data D_3	P_3	Key K_4	Data D_4	P_4

Subtree w/ keys $\le K_1$

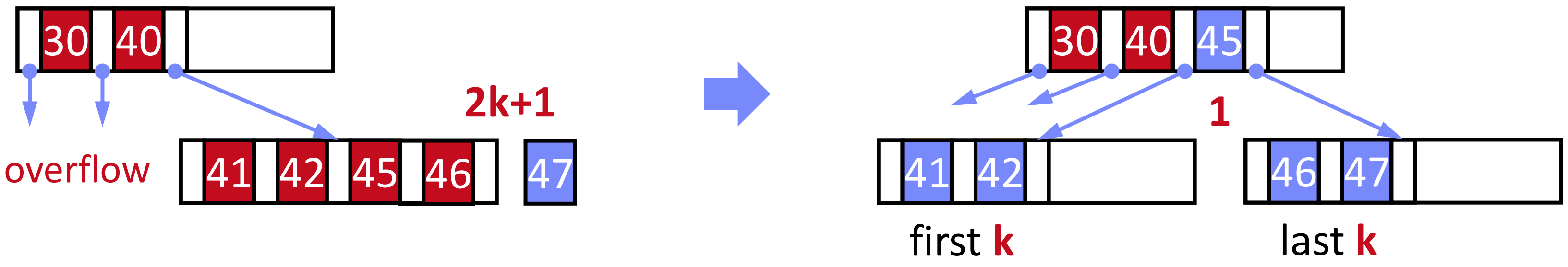
Subtree w/ $K_2 <$ keys $\le K_3$

Recap: B-Tree Overview, cont.

- **B-Tree Search**
  - Scan/binary search within nodes
  - Descend along matching key ranges



- **B-Tree Insertion**
  - Insert into leaf nodes
  - Split the 2k+1 entries into two leaf nodes



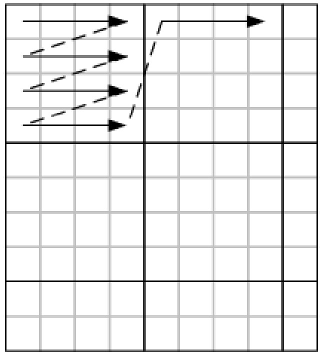
- **B-Tree Deletion**
  - Lookup key and delete if existing
  - Move entry from fullest successor; if underflow merge with sibling

Linearized Array B-Tree (LAB-Tree)

[Yi Zhang, Kamesh Munagala, Jun Yang: Storing Matrices on Disk: Theory and Practice Revisited. **PVLDB 2011**]

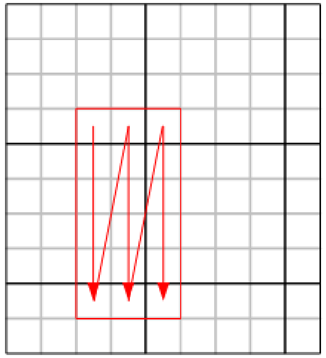
- **Basic Ideas**
  - **B-tree over linearized array representation** (e.g., row-/col-major, Z-order, UDF)
  - New **leaf splitting strategies**; dynamic **leaf storage format** (sparse and dense)
  - Various **flushing policies** for update batching (all, LRU, smallest page, largest page, largest page probabilistically, largest group)

#1 Example linearized storage order



matrix A:
4 x 4 blocking
row-major block order
row-major cell order

#2 Example linearized iterator order



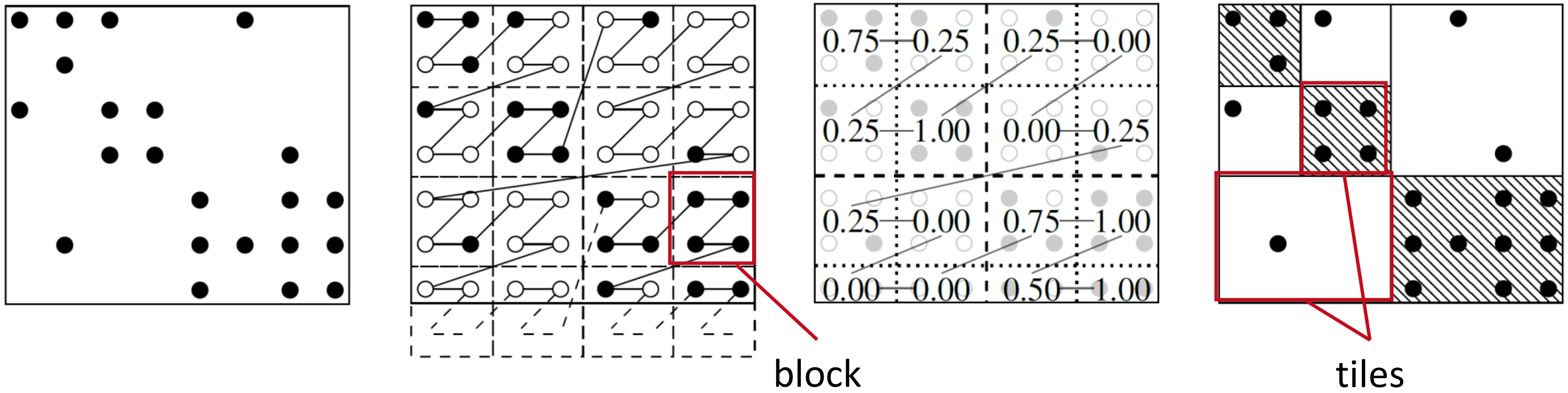
range query A[4:9,3:5]
with column-major
iterator order

Adaptive Tile (AT) Matrix

- **Basic Ideas**
  - Two-level blocking and NUMA-aware range partitioning (tiles, blocks)
  - Z-order linearization, and **recursive quad-tree partitioning** to find var-sized tiles (tile contains N blocks)

[David Kernert, Wolfgang Lehner, Frank Köhler: Topology-aware optimization of big sparse matrices and matrix multiplications on main-memory systems. **ICDE 2016**]

Input Matrix **Z-ordering** **Density Map** (see sparsity est.)

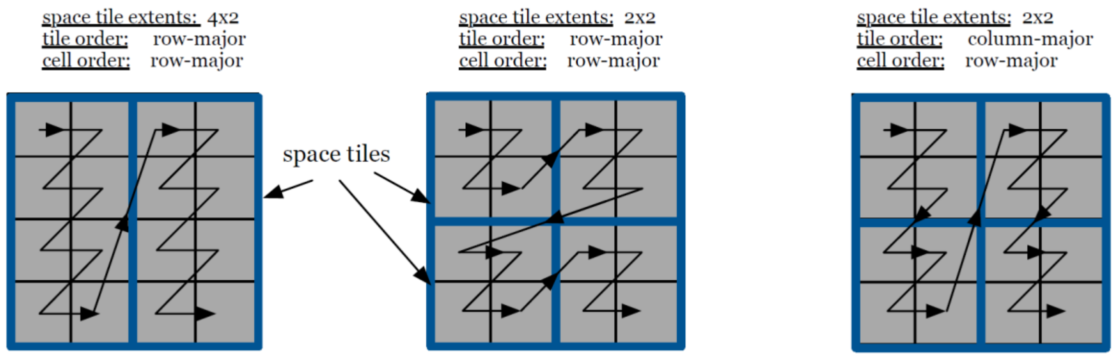


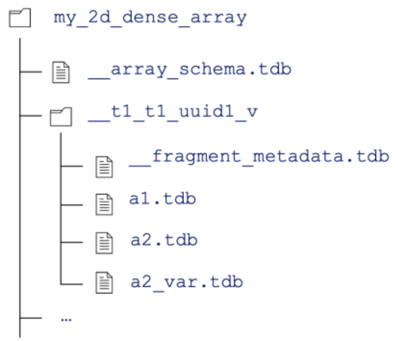
TileDB Storage Manager

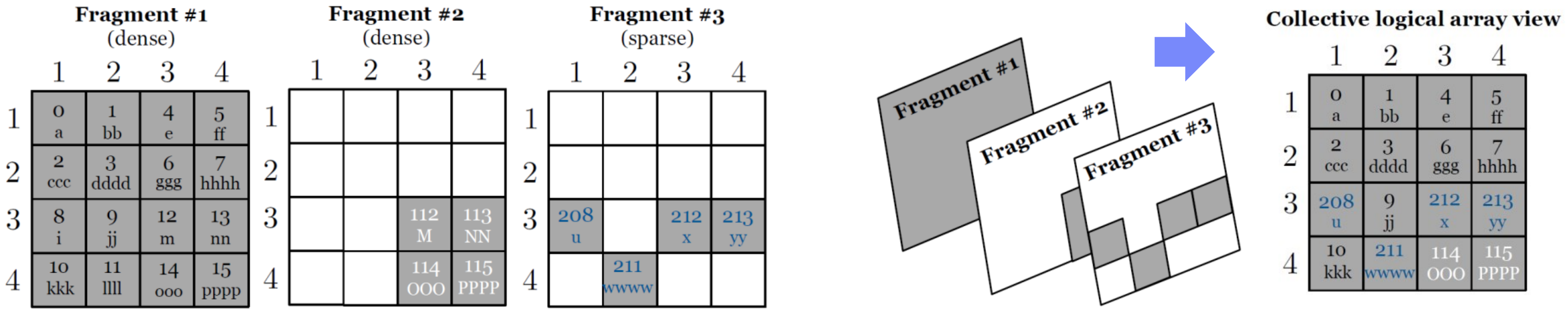
- **Basic Ideas**
  - Storage manager for 2D arrays of different data types (incl. vector, 3D)
  - **Two-level blocking** (space/data tiles), update batching via **fragments**

[Stavros Papadopoulos, Kushal Datta, Samuel Madden, Timothy G. Mattson: The TileDB Array Data Storage Manager. **PVLDB 2016**]

https://docs.tiledb.com



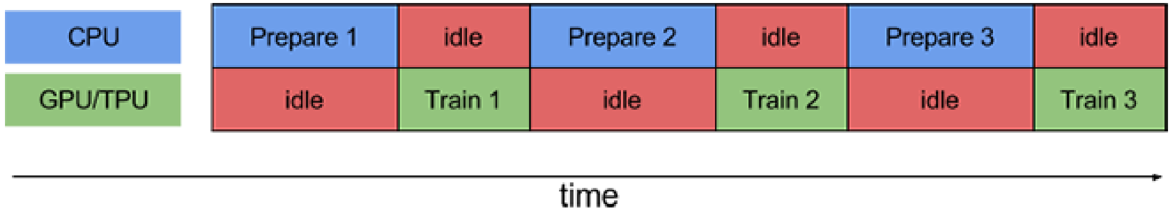




Pipelining for Mini-batch Algorithms

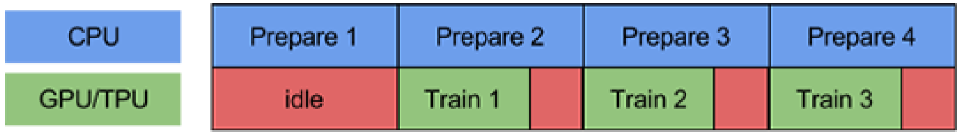
- **Motivation**
  - Overlap data access and computation in mini-batch algorithms (e.g., DNN)
  - ➔ **Simple pipelining of I/O and compute via queueing / prefetching**

- **Example TensorFlow**
  - **#1** Queueing and Threading



  - **#2 Dataset API Prefetching**

```
dataset = dataset.batch(batch_size=32)
dataset = dataset.prefetch(buffer_size=1)
```



  - **#3** Reuse via **Data Echoing**

[https://ai.googleblog.com/2020/05/speeding-up-neural-network-training.html]

Lossy and Lossless Compression

#6 Compression

Recap: Database Compression Schemes

- **Null Suppression**
  - Compress integers by **omitting leading zero** bytes/bits (e.g., NS, gamma)

```
                                   106
00000000 00000000 00000000 01101010
                       11 01101010
```

- **Run-Length Encoding**
  - Compress sequences of equal values by **runs** of (value, start, run length)

```
1 1 1 1 7 7 7 7 7 3 3 3 3 3 3 ...
1,1,4   7,5,5   3,10,6
```

- **Dictionary Encoding**
  - Compress column w/ few distinct values as **pos in dictionary** (→ code size)

```
1 7 7 3 1 7 1 3 3 7 1 3 3 7 3 ...
1,3,7  dictionary (code size 2 bit)
1 3 3 2 1 3 1 2 2 3 1 2 2 3 2 ...
```

- **Delta Encoding**
  - Compress sequence w/ small changes by storing **deltas to previous value**

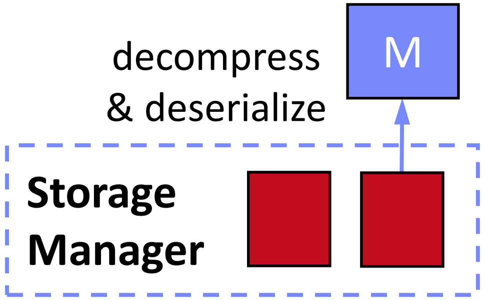
```
20 21 22 20 19 18 19 20 21 20 ...
 0  1  1 -2 -1 -1  1  1  1 -1...
```

- **Frame-of-Reference Encoding**
  - Compress values by storing **delta to reference value** (outlier handling)

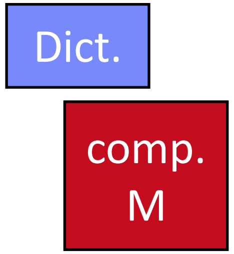
```
20 21 22 20 71 70 71 69 70 21 ...
21          70             22
-1  0  1 -1  1  0  1 -1  0 -1 ...
```

Overview Lossless Compression Techniques

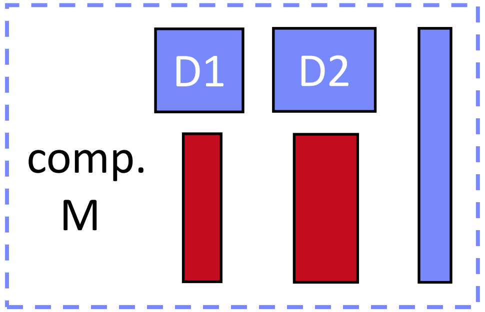
- **#1 Block-Level General-Purpose Compression**
  - Heavyweight or lightweight compression schemes
  - Decompress matrices block-wise for each operation
  - E.g.: Spark RDD compression (Snappy/LZ4), **SciDB** SM [SSDBM'11], **TileDB** SM [PVLDB'16], **NetCDF**, **HDF5** at chunk granularity



- **#2 Block-Level Matrix Compression**
  - Compress matrix block with homogeneous encoding scheme
  - Perform LA ops over compressed representation
  - E.g.: **CSR-VI** (dict) [CF'08], **cPLS** (grammar) [KDD'16], **TOC** (LZW w/ trie) [SIGMOD'19]



- **#3 Column-Group-Level Matrix Compression**
  - Compress column groups w/ heterogeneous schemes
  - Perform LA ops over compressed representation
  - E.g.: **SystemML CLA** (RLE, OLE, DDC, UC) [PVLDB'16]



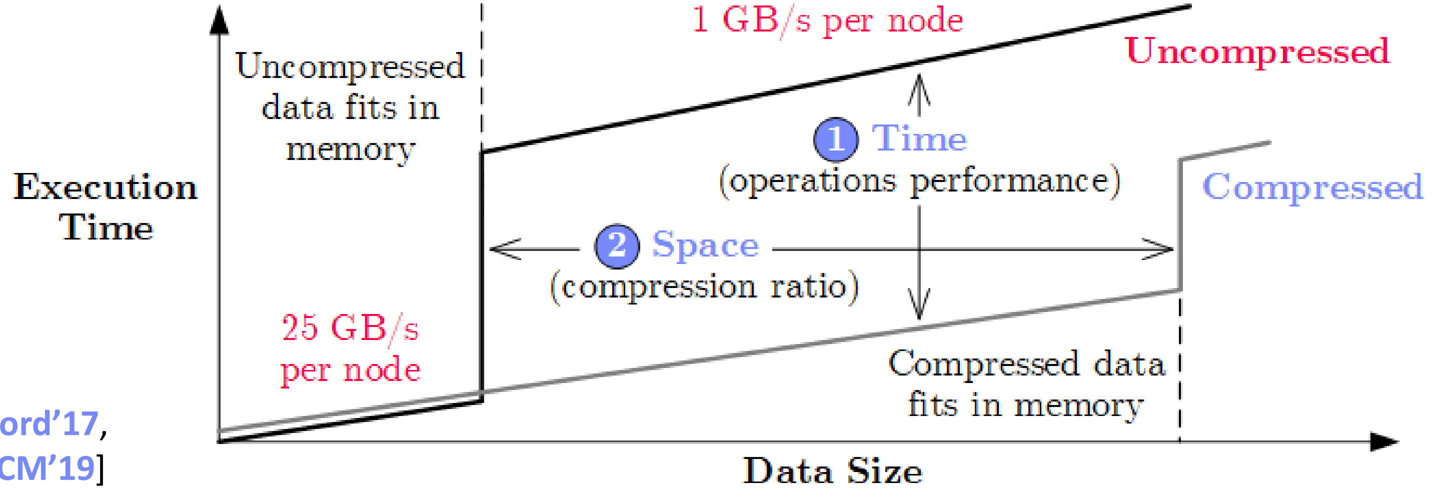
CLA: Compressed Linear Algebra

[Ahmed Elgohary, Matthias Boehm et al: Compressed Linear Algebra for Large-Scale Machine Learning. **PVLDB 2016**]

- **Key Idea**
  - Use lightweight database compression techniques
  - Perform LA operations **on compressed matrices**
- **Goals of CLA**
  - Operations performance close to uncompressed
  - Good compression ratios

X

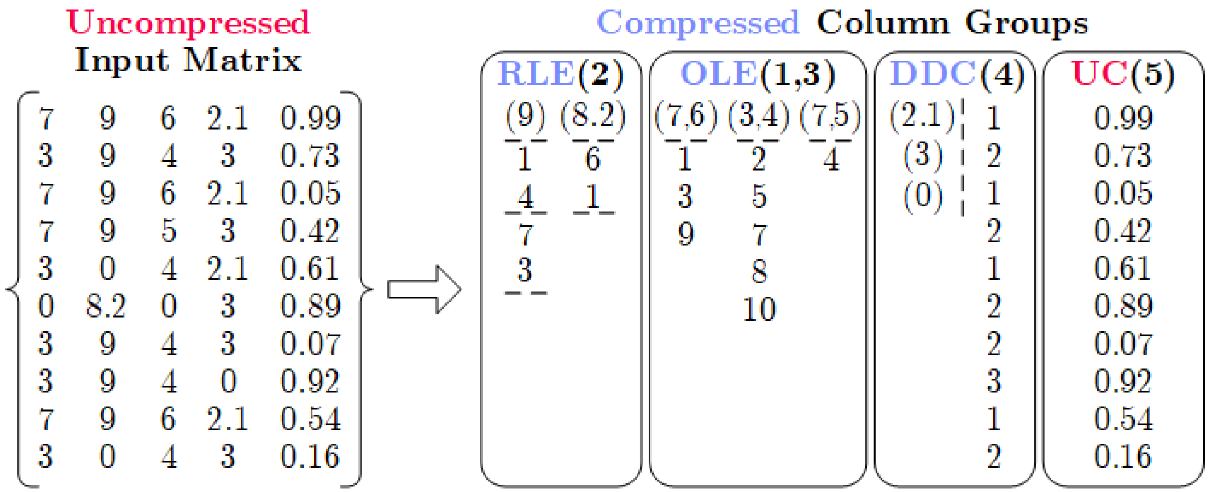
```
while(!converged) {
  … q = X %*% v …
}
```



[SIGMOD Record'17, VLDBJ'18, CACM'19]

CLA: Compressed Linear Algebra, cont. (2)

- **Overview Compression Framework**
  - Column-wise matrix compression (values + compressed offsets / references)
  - **Column co-coding** (column groups, encoded as single unit)
  - **Heterogeneous column encoding formats** (w/ dedicated **physical encodings**)
- **Column Encoding Formats**
  - Offset-List (OLE)
  - Run-Length (RLE)
  - Dense Dictionary Coding (DDC)*
  - Uncompressed Columns (UC)



* DDC1/2
in VLDBJ'18

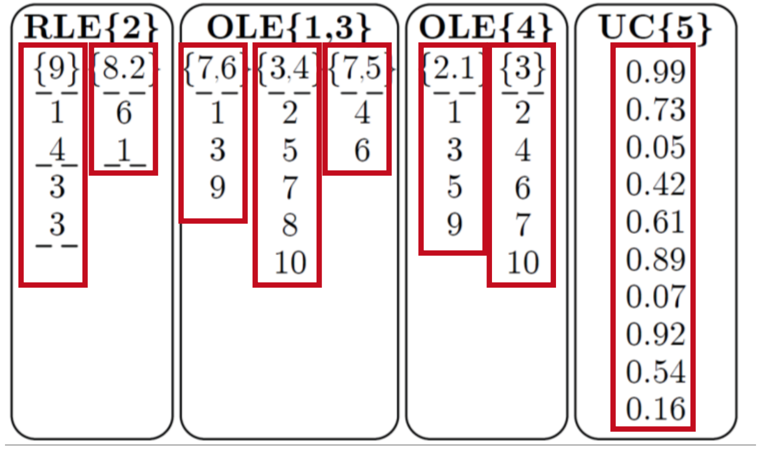
- **Automatic Compression Planning** (**sampling-based**)
  - Select column groups and formats per group (data dependent)

CLA: Compressed Linear Algebra, cont. (3)

- **Matrix-Vector Multiplication**
  - Naïve: for each tuple, pre-aggregate values, add values at offsets to q
  - **Example:** q = X v, with

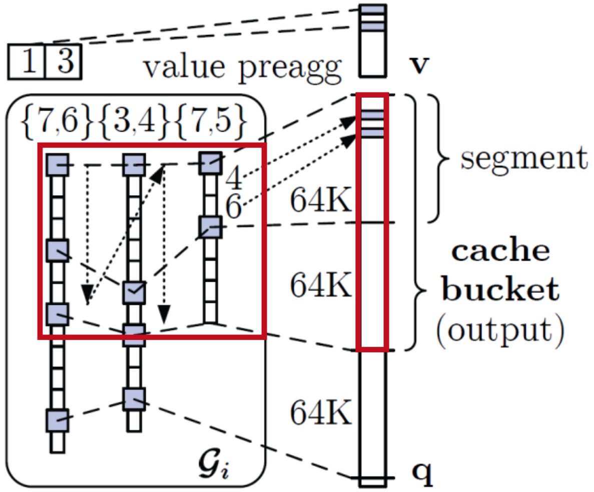
v = (7, 11, 1, 3, 2)

9*11=99 99.2 55 25 54 6.3 9



162.3
134.5
160.4
162.8
32.5
155
133.1
125.8
161.4
34.3

➔ cache unfriendly on output (q)

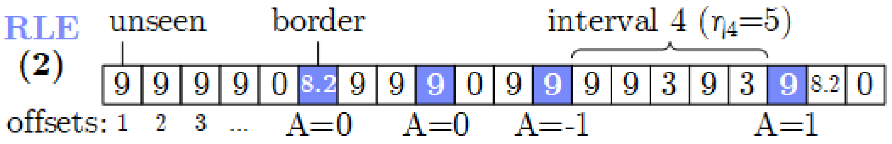


  - Cache-conscious: Horizontal, segment-aligned scans, maintain positions

- **Vector-Matrix Multiplication**
  - Naïve: **cache-unfriendly on input (v)**
  - Cache-conscious: again use horizontal, segment-aligned scans

CLA: Compressed Linear Algebra, cont. (4)

- **Estimating Compressed Size:** $S^C = \min(S^{OLE}, S^{RLE}, S^{DDC})$
  - # of distinct tuples d_i: **"Hybrid generalized jackknife" estimator** [JASA'98]
  - # of non-zero tuples z_i: **Scale from sample with "coverage" adjustment**
  - # of runs r_{ij}: **maxEnt model + independent-interval approx.** (~ Ising-Stevens)



- **Compression Planning**
  - **#1 Classify compressible columns**
    - Draw random sample of rows (from transposed X)
    - Classify C^C and C^{UC} based on estimate compression ratio
  - **#2 Group compressible columns** (exhaustive $O(m^m)$, greedy $O(m^3)$)
    - Bin-packing-based column partitioning
    - Greedy grouping per bin **w/ pruning and memoization $O(m^2)$**
  - **#3 Compression**
    - Extract uncompressed offset lists and exact compression ratio
    - Graceful corrections and UC group creation

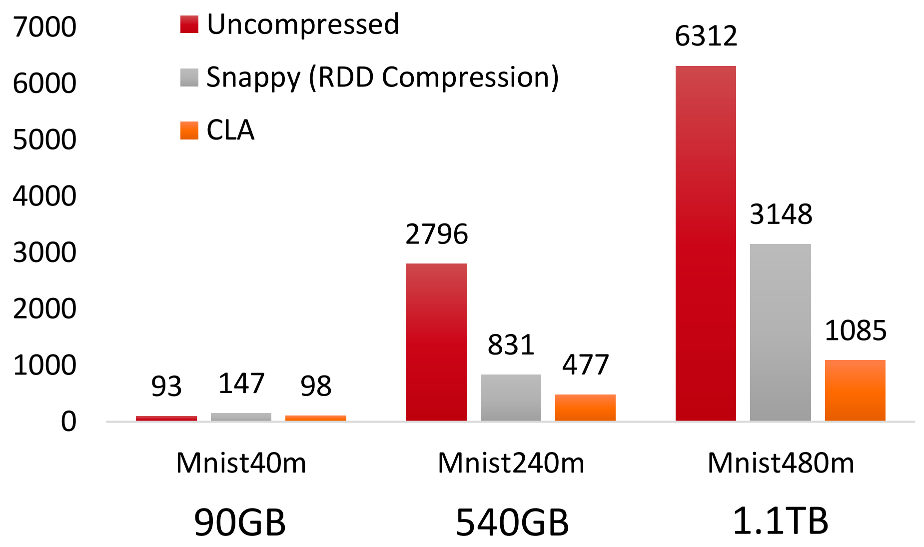
CLA: Compressed Linear Algebra, cont. (5)

- **Experimental Setup**
  - **LinregCG**, 10 iterations (incl. compression), InfiMNIST data generator
  - 1+6 node cluster (**216GB** memory), Spark 2.3, SystemML 1.1

Compression Ratios

Dataset	Gzip	Snappy	CLA
Higgs	1.93	1.38	**2.17**
Census	17.11	6.04	**35.69**
Covtype	10.40	6.13	**18.19**
ImageNet	5.54	3.35	**7.34**
Mnist8m	4.12	2.60	**7.32**
Airline78	7.07	4.28	**7.44**

End-to-End Performance [sec]

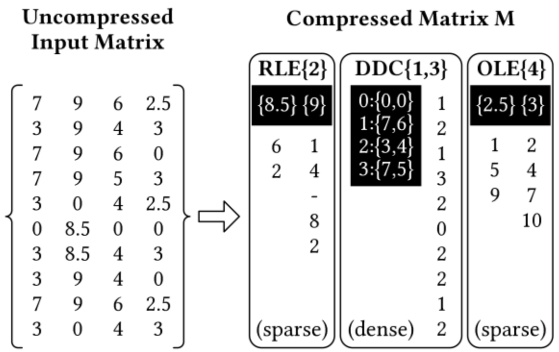


- **Open Challenges**
  - **Ultra-sparse datasets**, tensors, automatic operator fusion
  - Operations beyond matrix-vector/unary, applicability to deep learning?

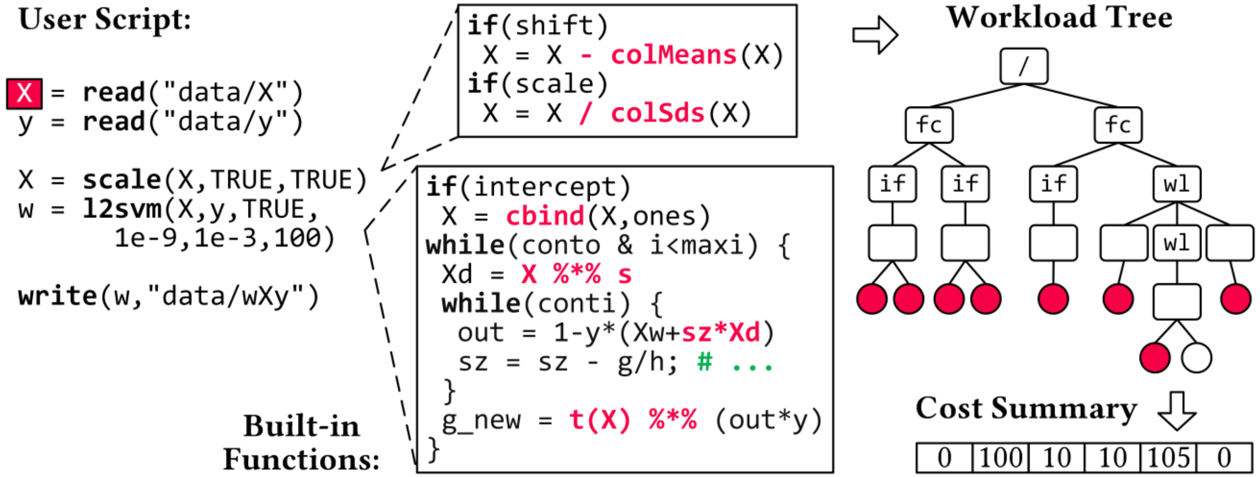
Compressed Linear Algebra Extended

[Sebastian Baunsgaard, Matthias Boehm: AWARE: Workload-aware, Redundancy-exploiting Linear Algebra, **SIGMOD 2023**]

- **Lossless Matrix Compression**
  - **Improved general applicability** (adaptive compression time, new compression schemes, new kernels, intermediates, workload-aware)
  - Sparsity → **Redundancy exploitation** (data redundancy, structural redundancy)



- **Workload-aware Compression**
  - Workload summary → compression
  - Compressed Representation → execution planning



- **Next Steps**
  - Frame compression, compressed I/O
  - Compressed feature transformations
  - Morphing of compressed data

Block-level Compression w/ D-VI, CSR-VI, CSX

- **CSR-VI (CSR-Value Indexed) / D-VI**
  - **Create dictionary** for distinct values
  - **Encode 8 byte values as 1, 2, or 4-byte codes** (positions in the dictionary)
  - Extensions w/ delta coding of indexes
  - Example CSR-VI matrix-vector multiply
    c = A %*% b

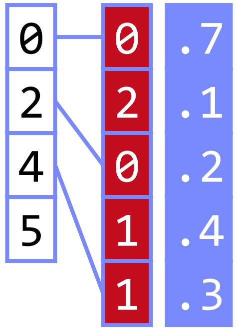
[Kornilios Kourtis, Georgios I. Goumas, Nectarios Koziris: Optimizing sparse matrix-vector multiplication using index and value compression. **CF 2008**]

[Vasileios Karakasis et al.: An Extended Compression Format for the Optimization of Sparse Matrix-Vector Multiplication. **IEEE Trans. Parallel Distrib. Syst. 2013**]

```
for(int i=0; i<a.nrow; i++) {
   int pos = A.rptr[i];
   int end = A.rptr[i+1];
   for(int k=pos; k<end; k++)
      b[i] += dict[A.val[k]] * b[A.ix[k]];
}
```

value decoding
(MV over compressed representation)

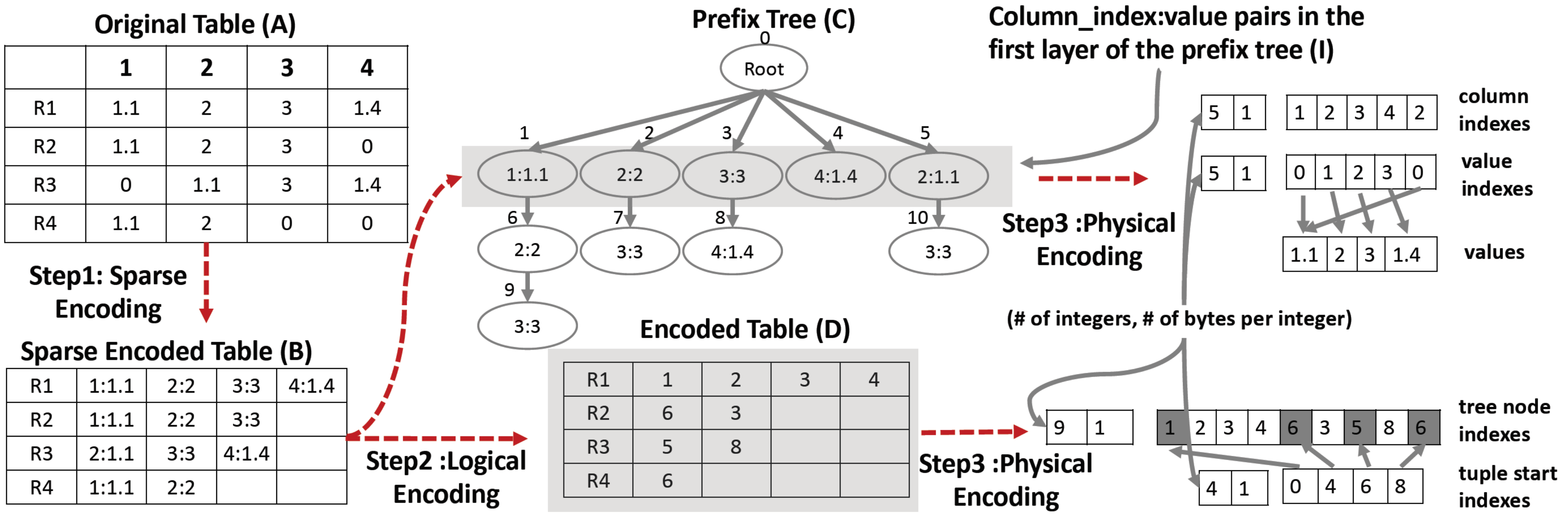
CSR



Tuple-oriented Compression (TOC)

- **Motivation**
  - DNN and ML often trained with **mini-batch SGD**
  - Effective compression for small batches (#rows)

[Fengan Li, Lingjiao Chen, Yijing Zeng, Arun Kumar, Xi Wu, Jeffrey F. Naughton, Jignesh M. Patel: Tuple-oriented Compression for Large-scale Mini-batch Stochastic Gradient Descent, **SIGMOD 2019**]



Original Table (A)

	1	2	3	4
R1	1.1	2	3	1.4
R2	1.1	2	3	0
R3	0	1.1	3	1.4
R4	1.1	2	0	0

Sparse Encoded Table (B)

R1	1:1.1	2:2	3:3	4:1.4
R2	1:1.1	2:2	3:3	
R3	2:1.1	3:3	4:1.4	
R4	1:1.1	2:2		

Encoded Table (D)

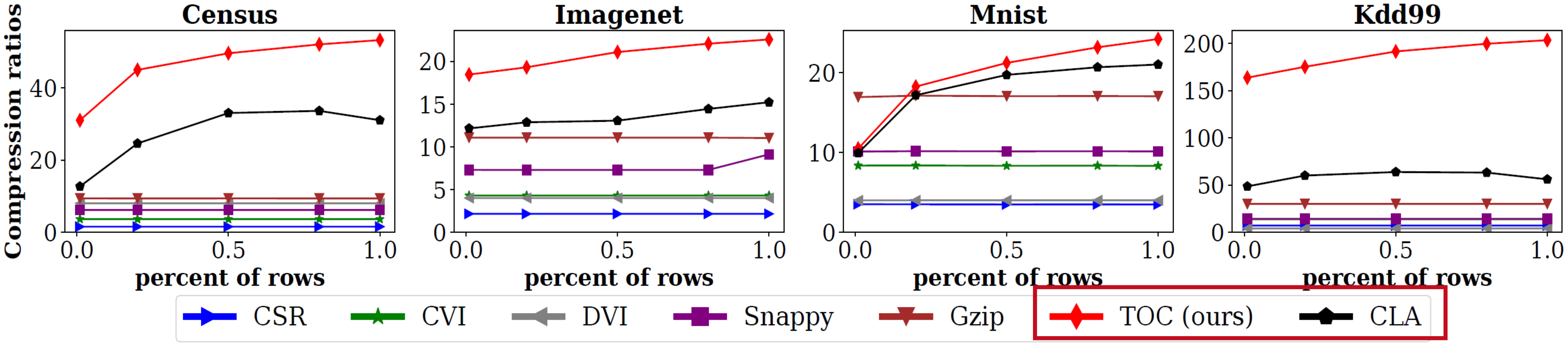
R1	1	2	3	4
R2	6	3		
R3	5	8		
R4	6			

Tuple-oriented Compression (TOC), cont.

- **Example Compression Ratios**

[Fengan Li, Lingjiao Chen, Yijing Zeng, Arun Kumar, Xi Wu, Jeffrey F. Naughton, Jignesh M. Patel: Tuple-oriented Compression for Large-scale Mini-batch Stochastic Gradient Descent, **SIGMOD 2019**]

dense baseline?



Take-away: specialized lossless matrix compression

➔ **reduce memory bandwidth requirements and #FLOPs**

Lossy Compression

- **Overview**
  - Extensively used in DNN (runtime vs accuracy) ➔ **data format + compute**
  - **Careful manual application** regarding data and model
  - **Note:** ML algorithms approximate by nature + noise generalization effect

- **Background Floating Point Numbers (IEEE 754)**
  - Sign s, Mantissa m, Exponent e: `value = s * m * 2`^{e} (simplified)

[IEEE 754-228 Revision: https://ieeexplore.ieee.org/document/4610935]

Precision	Sign	Mantissa	Exponent
Double (FP64)	1	52	11
Single (FP32)	1	23	8
Half (FP16)	1	10	5
Quarter (FP8)	1	3	4
Half-Quarter (FP4)	1	1	2

[bits]

Unums/Posits (2015), with regime bits:

$$x = s\, u^k\, 2^e f = (-1)^b\, f\, 2^{e+k2^{es}}$$

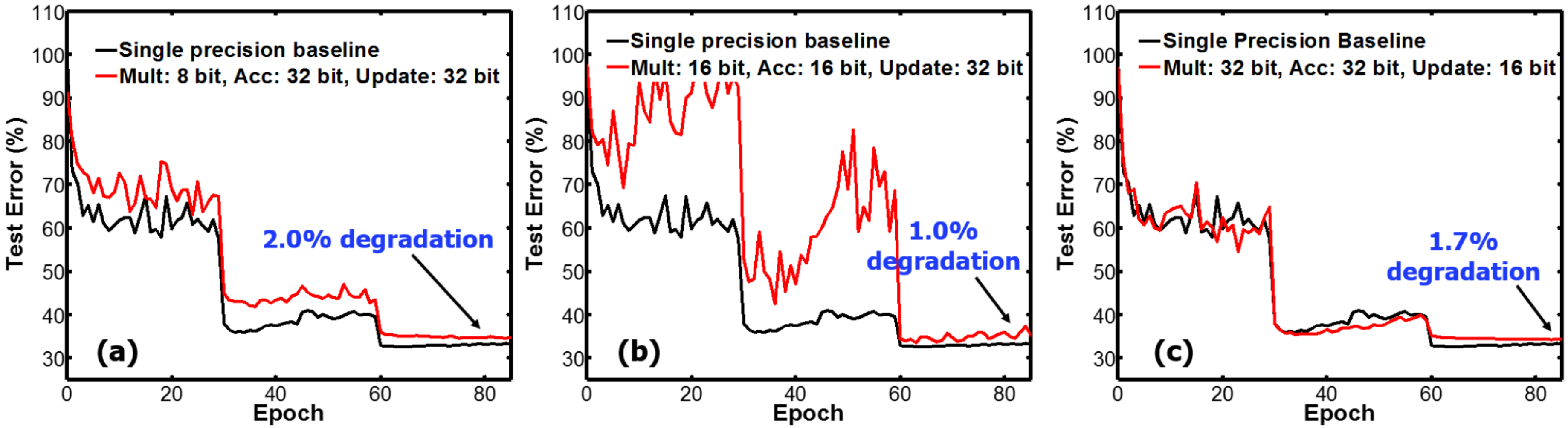
Low and Ultra-low FP Precision

- **Model Training w/ low FP Precision**
  - Trend: from **FP32/FP16** to **FP8**
  - **#1: Precision of intermediates** (weights, act, errors, grad) → loss in accuracy
  - **#2: Precision of accumulation** → impact on convergence (swamping small+Large)
  - **#3: Precision of weight updates** → loss in accuracy

see **05 Execution Strategies**, SIMD
→ speedup/reduced energy

[Naigang Wang et al.: Training Deep Neural Networks with **8-bit** Floating Point Numbers. **NeurIPS 2018**]

- **Example ResNet18 on ImageNet**

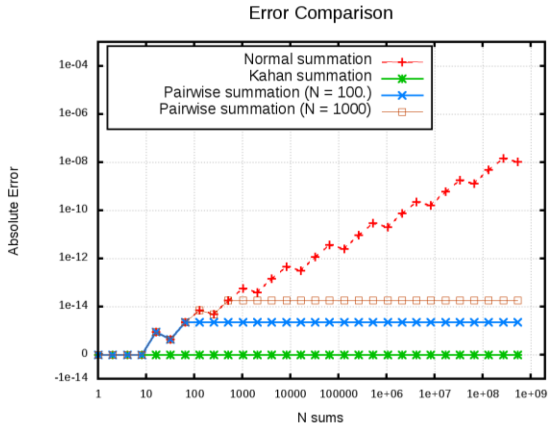


Low and Ultra-low FP Precision, cont.

- **Numerical Stable Accumulation**
  - **#1 Sorting ASC + Summation**
  - **#2 Kahan Summation** w/ error independent of number of values n

```
sumOld = sum;
sum = sum + (input + corr);
corr = (input + corr) – (sum – sumOld);
uak+:  5.000000005E17 //sum(seq(1,1e9))
ua+:   5.000000109721722E17
ua+:   5.000000262154688E17 //rev
```

[Yuanyuan Tian, Shirish Tatikonda, Berthold Reinwald: Scalable and Numerically Stable Descriptive Statistics in SystemML. **ICDE 2012**]



  - **#3 Pairwise Summation** (divide & conquer)

julia

[https://github.com/NaveenKaliannan/FloatingPointSummation]

- **#4 Chunk-based Accumulation**
  - Divide long dot products into smaller chunks
  - Hierarchy of partial sums → **FP16 accumulators**

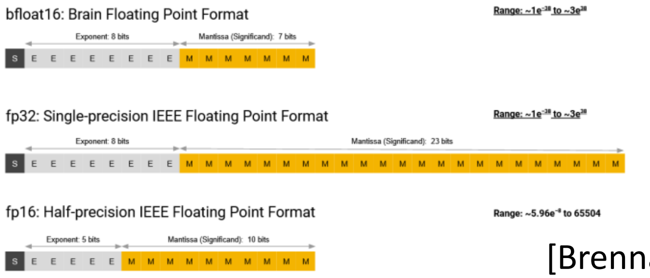
[N. Wang et al.: Training Deep Neural Networks with **8-bit** Floating Point Numbers. **NeurIPS 2018**]

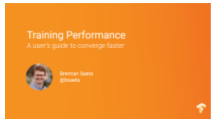
- **#5 Stochastic Rounding**
  - Replace nearest w/ prob. rounding

$$Round(x) = \begin{cases} s \cdot 2^e \cdot (1 + \lfloor m \rfloor + \epsilon) & \text{with probability } \frac{m - \lfloor m \rfloor}{\epsilon}, \\ s \cdot 2^e \cdot (1 + \lfloor m \rfloor) & \text{with probability } 1 - \frac{m - \lfloor m \rfloor}{\epsilon}, \end{cases}$$

Low and Ultra-low FP Precision – New Datatypes

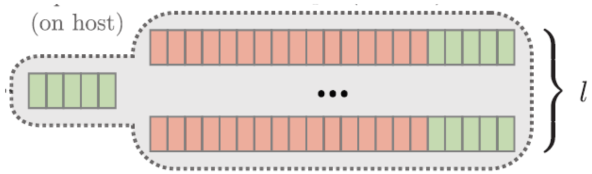
- **Google** `bfloat16`
  - "Brain" Float16 w/ range of FP32
  - Drop in replacement for FP32, no need for loss scaling





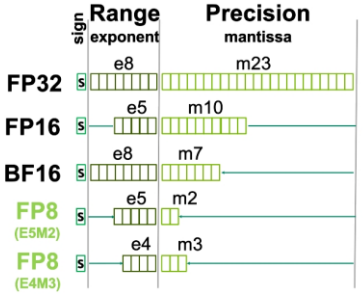
[Brennan Saeta: Training Performance A user's guide to converge faster, **TF Dev Summit 2018**]

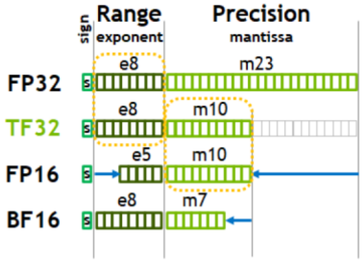
- **Intel** `FlexPoint`
  - Blocks of values w/ shared exponent (N=16bit w/ M=5bit exponent)
  - Example: flex16+5



[Urs Köster et al.: Flexpoint: An Adaptive Numerical Format for Efficient Training of Deep Neural Networks. **NeurIPS 2017**]

- **NVIDIA** `TF32`
  - Range of FP32 w/ precision of FP16
  - FP8 variants





[NVIDIA A100 Tensor Core GPU Architecture - UNPRECEDENTED ACCELERATION AT EVERY SCALE, Whitepaper, **Aug 2020**]

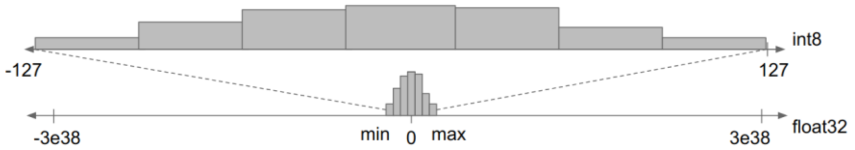
[NVIDIA H100 Tensor Core GPU Architecture, Whitepaper, **May 2023**]

Fixed-Point Arithmetic

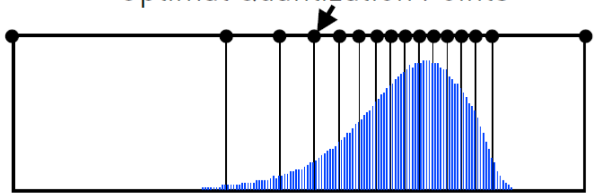
Recommended "Reading"
[Inside TensorFlow: Model Optimization Toolkit (Quantization and Pruning), **2020**, https://www.youtube.com/watch?v=4iq-d2AmfRU]

- **Motivation**
  - Forward-pass for model scoring (inference) can be done in **UINT8** and below
  - **Static, dynamic, and learned quantization** schemes (**weights** and **inputs**)

[https://blog.tensorflow.org/2020/04/quantization-aware-training-with-tensorflow-model-optimization-toolkit.html]



- **Quantization** (reduce value domain)
  - **Split value domain into N buckets** such that $k = \log_2 N$ can encode the data
  - **a) Static Quantization** (e.g., min/max) per tensor or per tensor channel
  - **b) Learned Quantization** Schemes
    - Dynamic programming
    - Various heuristics
    - Example systems: **ZipML**, **SketchML**



[Hantian Zhang, Jerry Li, Kaan Kara, Dan Alistarh, Ji Liu, Ce Zhang: ZipML: Training Linear Models with End-to-End Low Precision, and a Little Bit of Deep Learning. **ICML 2017**]

Other Lossy Techniques

- **#1 Sparsification/Pruning** (reduce #non-zeros)
  - **Value clipping:** zero-out very small values below a threshold to reduce size of weights
  - **Training w/ target sparsity:** remove connections
  - Training w/ penalty terms of number-of-nonzeros (or differentiable approximations)

Sparse Accuracy	NNZ
78.1% @ sp=1.0	27.1M
78.0% @ sp=0.5	13.6M
76.1% @ sp=0.25	6.8M
74.6% @ sp=0.125	3.3M

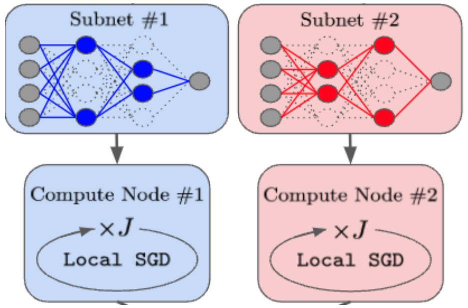
[https://blog.tensorflow.org/2019/05/tf-model-optimization-toolkit-pruning-API.html]

$$W' = arg \min_{W} \; E_D(W) + \lambda \cdot R(W) + \cdots + \lambda_S \cdot \Sigma_{i=1}^{n}(W_i \neq 0)$$

- Hoyer-Square regularizer: $\Rightarrow$ $\ldots + \lambda_S \cdot \frac{(\Sigma_i W_i)^2}{\Sigma_i W_i^2}$

[Huanrui Yang, Wei Wen, Hai Li: DeepHoyer: Learning Sparser Neural Network with Differentiable Scale-Invariant Sparsity Measures. **ICLR 2020**]

- **#2 Connection Sampling**
  - Sample mask for weights
  - Independent subnet training without synchronization (see 06 Parameter Servers)



[Binhang Yuan et al.: Distributed Learning of Fully Connected Neural Networks using Independent Subnet Training, **PVLDB 2022**]

Other Lossy Techniques, cont.

- **#3 Mantissa Truncation**
  - Truncate m of FP32 from 23bit to 16bit
  - E.g., TensorFlow (transfers), PStore

[Souvik Bhattacherjee et al: PStore: an efficient storage framework for managing scientific data. **SSDBM 2014**]

- **#4 Aggregated Data Representations**
  - a) Dim reduction (e.g., auto encoders)
  - b) No FK-PK joins in Factorized Learning (**foreign key** as lossy compressed rep)

[Amir Ilkhechi et al: DeepSqueeze: Deep Semantic Compression for Tabular Data, **SIGMOD 2020**]

[Arun Kumar et al: To Join or Not to Join?: Thinking Twice about Joins before Feature Selection. **SIGMOD 2016**]

- **#5 Sampling**
  - User specifies approximation contract for error (regression/classification) and scale
  - Min sample size for **max likelihood estimators**

[Yongjoo Park et al: BlinkML: Efficient Maximum Likelihood Estimation with Probabilistic Guarantees. **SIGMOD 2019**]

Summary & QA

- **Motivation, Background, and Overview**
- **Caching, Partitioning, and Indexing**
- **Lossy and Lossless Compression**

High Impact on Performance/Energy

- **Next Lectures** (Part B)
  - **09 Data Acquisition, Cleaning, and Preparation** [Jun 20]
  - **10 Model Selection and Management** [Jun 27, **virtual only**]
  - **11 Model Debugging, Fairness, Explainability** [Jul 04]
  - **12 Model Serving Systems and Techniques** [Jul 11]

  Q&A and Exam Preparation [Jul 11]

(**Part B:** ML Lifecycle Systems)