TU Graz

SCIENCE
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TECHNOLOGY

Architecture of ML Systems
08 Data Access Methods

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ISDS

Announcements/Org

- **#1 Programming/Analysis Projects**
  - **#1 Auto Differentiation**
  - **#5 LLVM Code Generator**
  - **#12 Information Extraction from Unstructured PDF/HTML**
  - ➔ Keep code PRs / status updates in mind

- **#2 Open Positions (2x PhD/Student Assistant)**
  - **ExDRa: Exploratory Data Science over Raw Data** (Siemens, DFKI, TU Berlin, TU Graz), **starting June 1**
  - **Federated ML + ML over raw data** (integration/cleaning/preprocessing)

- **#3 Open Master Thesis w/ AVL**
  - Topic: **Anomaly Detection on Test beds** (durability runs on engine test bed with periodically repeating cycles)
  - Contact: Dr. Christa Simon

Agenda

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

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

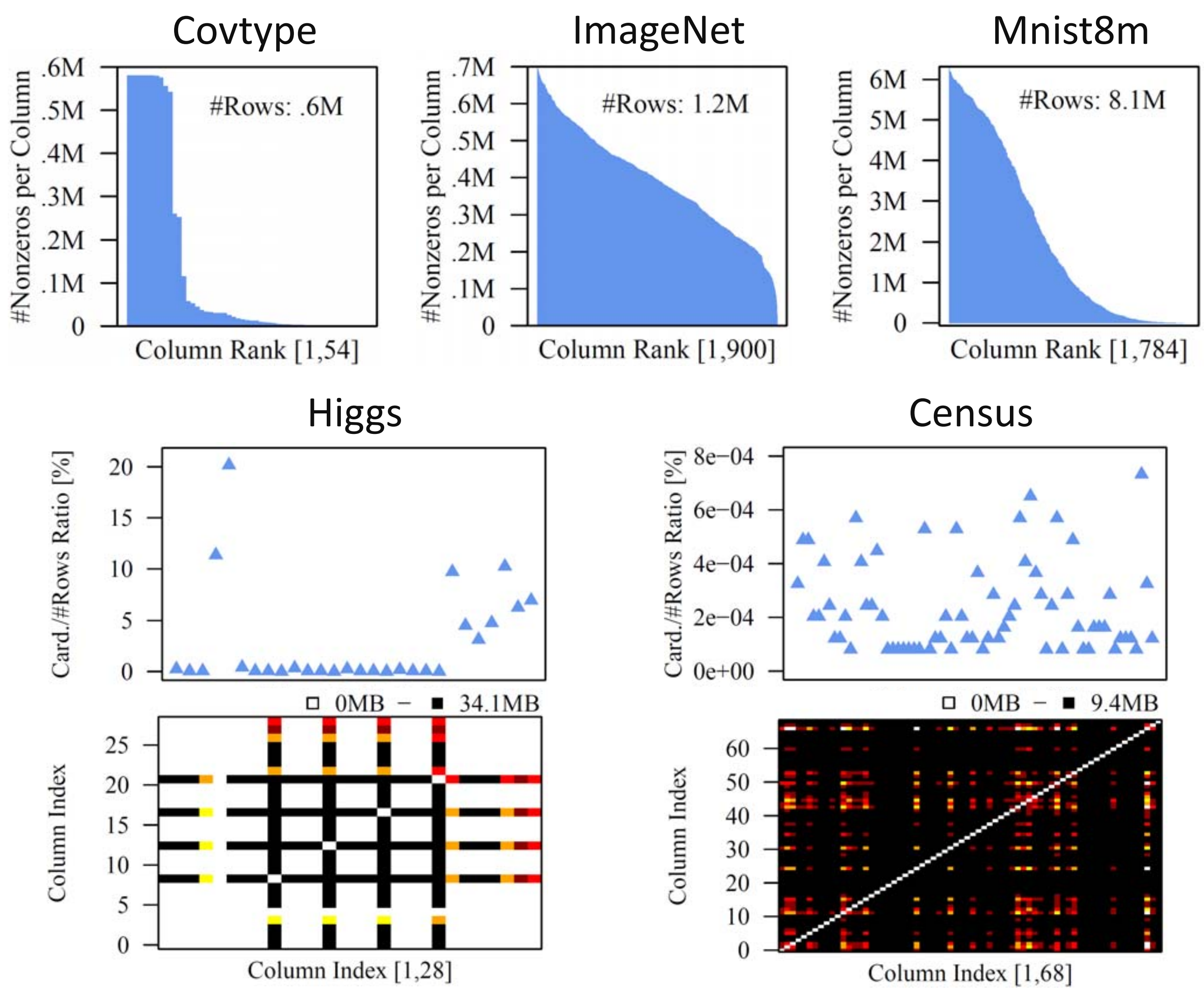
X

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

Motivation, Background, and Overview

Motivation: Data Characteristics

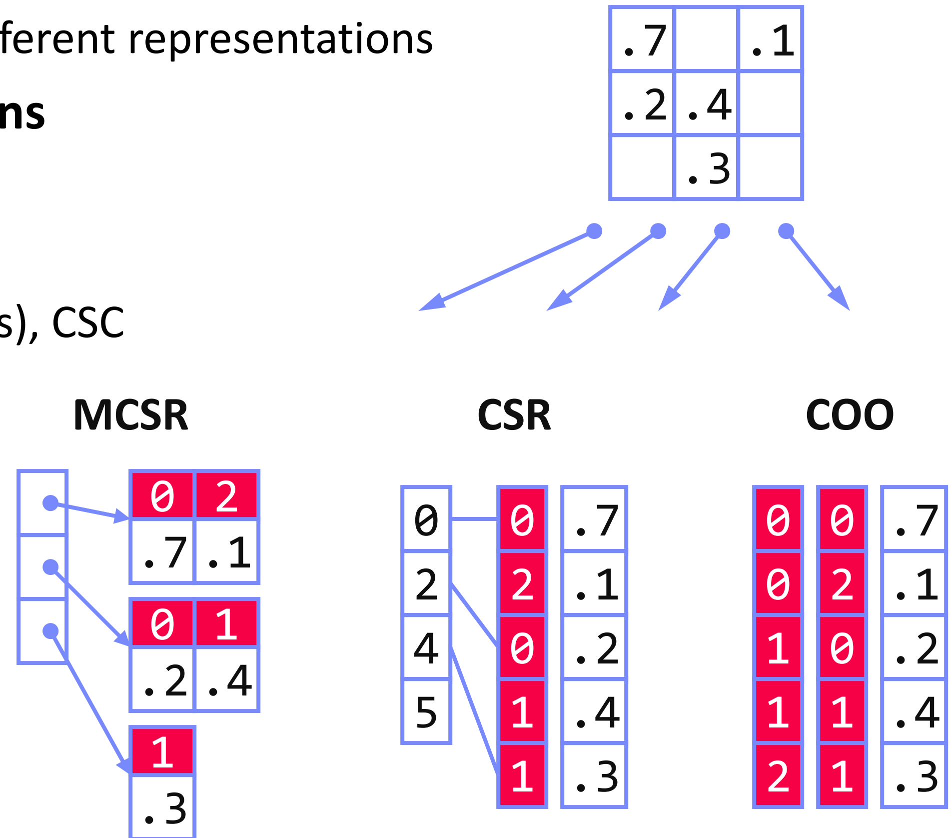
- **Tall and Skinny**
  (#rows >> #cols)
- **Non-Uniform Sparsity**
- **Low Column Cardinalities**
  (e.g., categorical, dummy-coded)
- **Column Correlations**
  (on census: **12.8x → 35.7x**)



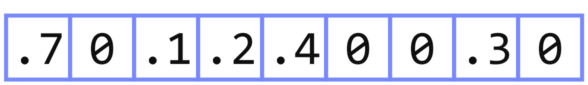
Recap: Matrix Formats

- **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)

Example
3x3 Matrix



Dense (row-major)



O(mn)

O(m + nnz(X))

O(nnz(X))

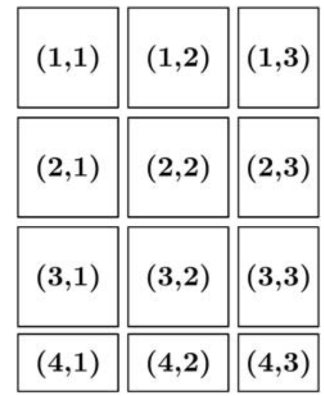
Recap: Distributed Matrices

- **Collection of "Matrix Blocks" (and keys)**
  - Bag semantics (duplicates, unordered)
  - Logical (Fixed-Size) Blocking

    + join processing / independence

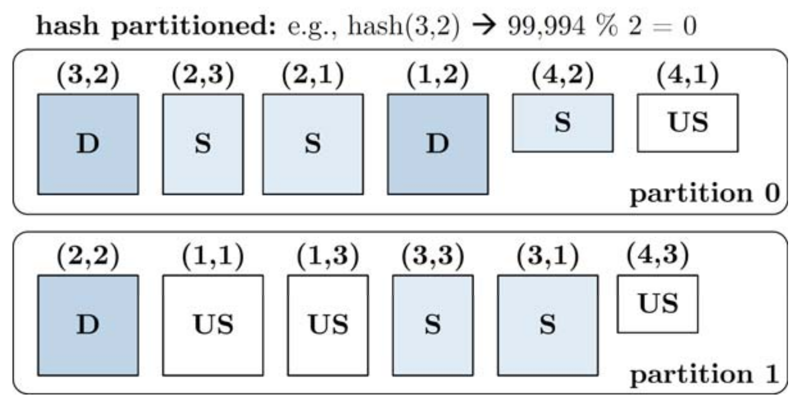
    - (sparsity skew)
  - E.g., SystemML on Spark:
    JavaPairRDD<MatrixIndexes,MatrixBlock>
  - Blocks encoded independently (dense/sparse)

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



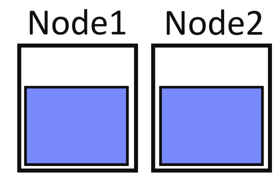
- **Partitioning**
  - Logical Partitioning
    (e.g., row-/column-wise)
  - Physical Partitioning
    (e.g., hash / grid)

Physical Blocking and Partitioning

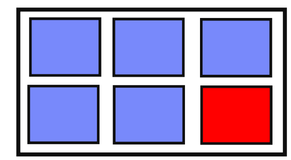


Overview Data Access Methods

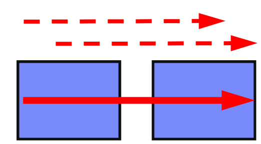
- **#1 (Distributed) Caching**
  - Keep read only feature matrix in (distributed) memory



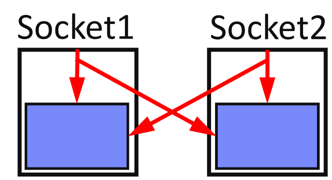
- **#2 Buffer Pool Management**
  - Graceful eviction of intermediates, out-of-core ops



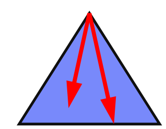
- **#3 Scan Sharing (and operator fusion)**
  - Reduce the number of scans as well as read/writes



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



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

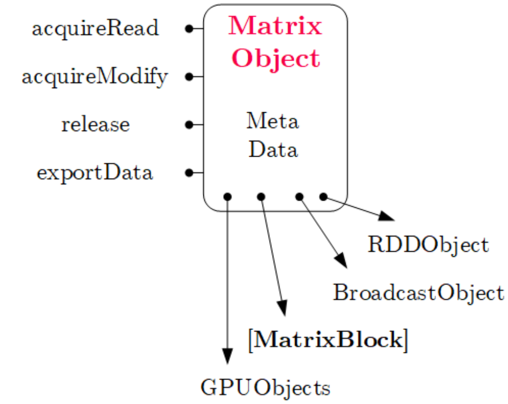


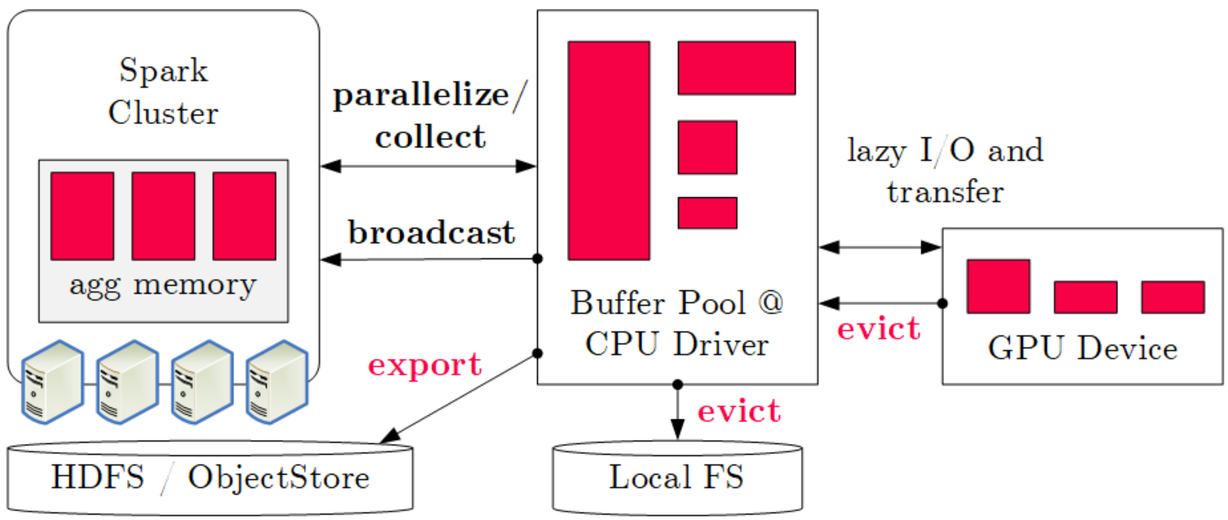
- **#6 Compression**
  - Fit larger datasets into available memory

Caching, Partitioning, and Indexing

Buffer Pool Management

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

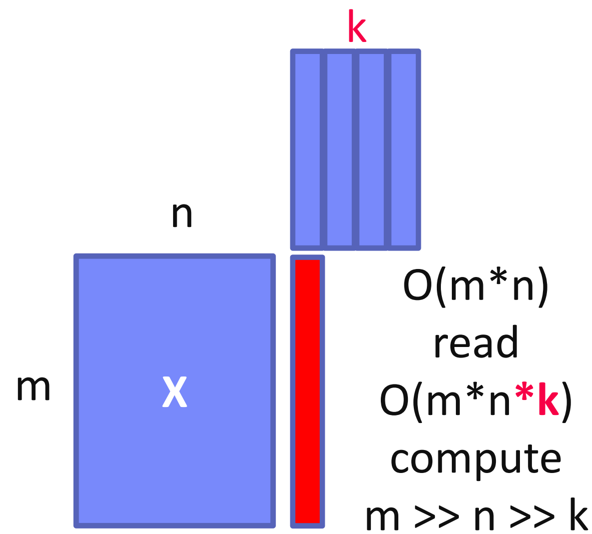




- **#2 Algorithm-Specific Buffer Management**
  - Operations/algorithms over out-of-core matrices and factor graphs
  - Examples: **RIOT** (op-aware I/O), **Elementary** (out-of-core factor graphs)

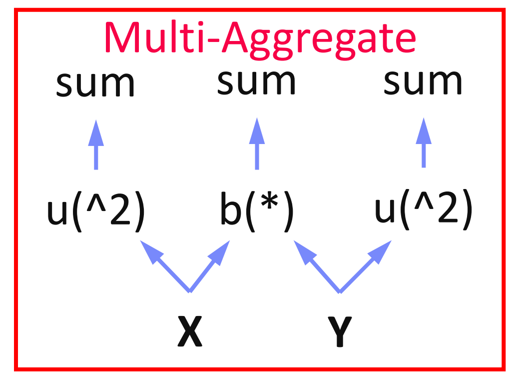
Scan Sharing

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



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

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



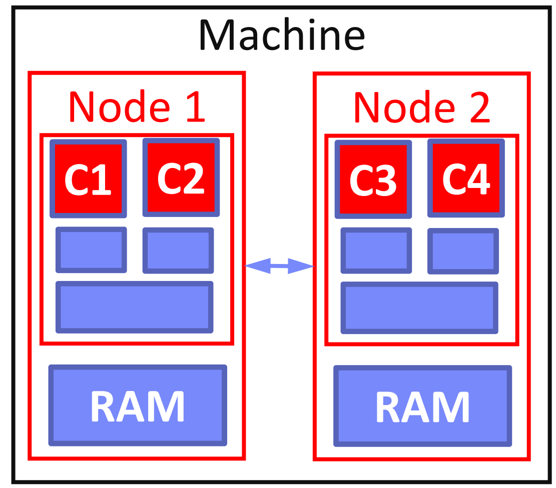
- **#3 Runtime Piggybacking**
  - Merge concurrent data-parallel jobs
  - "Wait-Merge-Submit-Return"-loop
  - E.g.: **SystemML parfor** [PVLDB'14]

```
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)

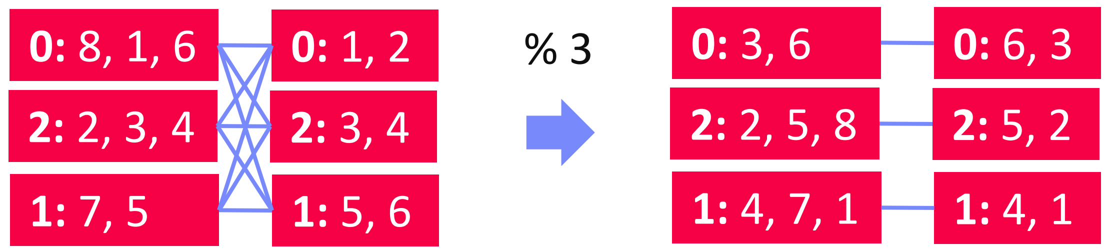
[David Kernert, Wolfgang Lehner, Frank Köhler: Topology-aware optimization of big sparse matrices and matrix multiplications on main-memory systems. **ICDE 2016**]

Distributed Partitioning

- **Spark RDD Partitioning**
  - Implicitly on every data shuffling
  - Explicitly via `R.repartition(n)`

Example Hash Partitioning:
For all (k,v) of R:
hash(k) % numPartitions → pid

- **Distributed Joins**



- **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

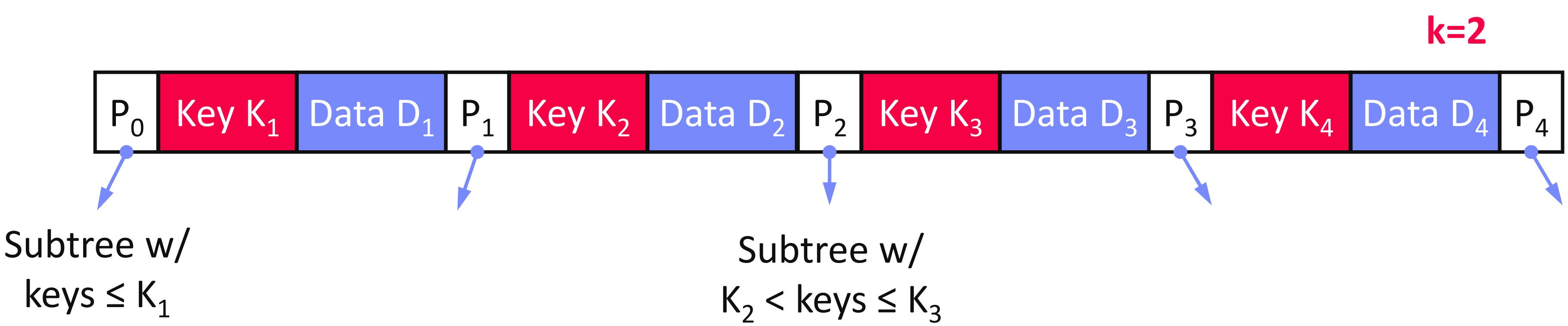
- **Multi-Key Lookups**
  - Without partitioning: scan all keys
  - With partitioning: lookup relevant partitions

```
//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));
```

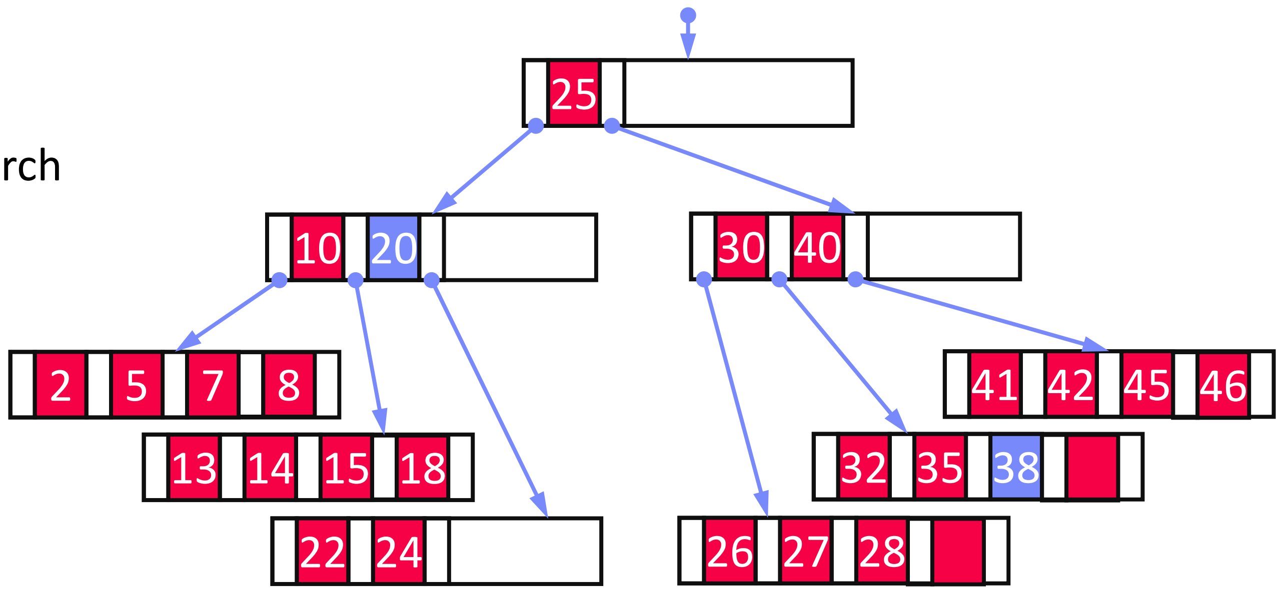
Recap: B-Trees

- **History B-Tree**
  - **B**ayer and McCreight 1972 (multiple papers), **B**lock-based, **B**alanced, **B**oeing
  - Multiway tree (node size = page size); designed for DBMS
- **Definition B-Tree k**
  - **Balanced tree:** All paths from root to leafs have equal length h
  - All nodes (except root=leaf) 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)



Recap: B-Trees, cont.

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



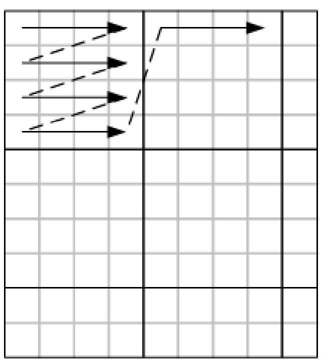
- **B-Tree Insertion**
  - Insert into leaf nodes
  - Split the 2k+1 entries into two leaf nodes
- **B-Tree Deletion**
  - Lookup key and delete if existing
  - Move entry from fullest successor; if underflow merge with sibling

Linearized Array B-Tree (LAB-Tree)

- **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)

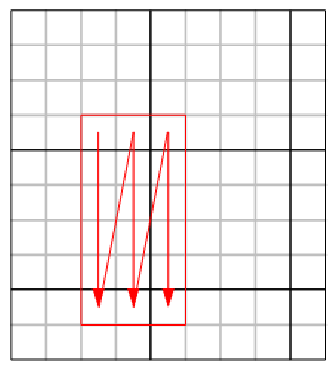
[Yi Zhang, Kamesh Munagala, Jun Yang: Storing Matrices on Disk: Theory and Practice Revisited. **PVLDB 2011**]

#1 Example linearized storage order



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

#2 Example linearized iterator order



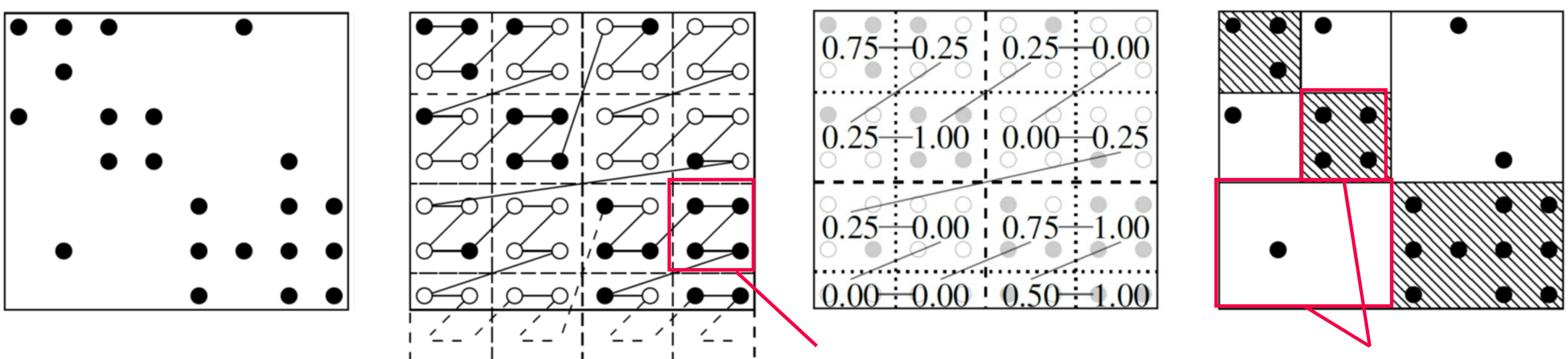
range query A[4:9,3:5]
with column-major
iterator order

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.)



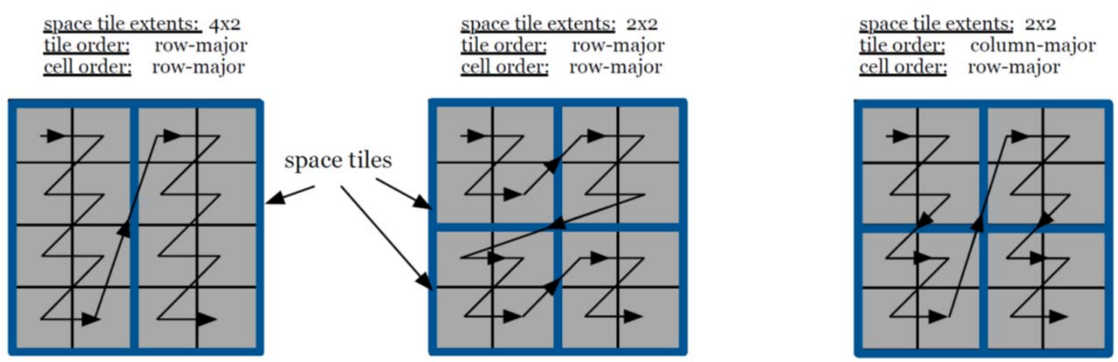
block

tiles

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**]



Fragment #1 (dense)

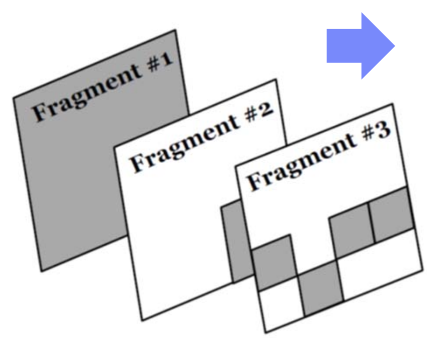
	1	2	3	4
1	0 a	1 bb	4 e	5 ff
2	2 ccc	3 dddd	6 ggg	7 hhhh
3	8 i	9 jj	12 m	13 nn
4	10 kkk	11 llll	14 ooo	15 pppp

Fragment #2 (dense)

	1	2	3	4
1				
2				
3			112 M	113 NN
4			114 OOO	115 PPPP

Fragment #3 (sparse)

	1	2	3	4
1				
2				
3	208 u		212 x	213 yy
4		211 wwww		



Collective logical array view

	1	2	3	4
1	0 a	1 bb	4 e	5 ff
2	2 ccc	3 dddd	6 ggg	7 hhhh
3	208 u	9 jj	212 x	213 yy
4	10 kkk	211 wwww	114 OOO	115 PPPP

Pipelining for Mini-batch Algorithms

- **Motivation**
  - Overlap data access and computation in mini-batch algorithms (e.g., DNN)
  - Specify approach and configuration at level of linear algebra program

  ➔ **Simple pipelining of I/O and compute via queueing / prefetching**

- **Example TensorFlow**
  - #1: Queueing and threading
  - #2: **Dataset API prefetching**

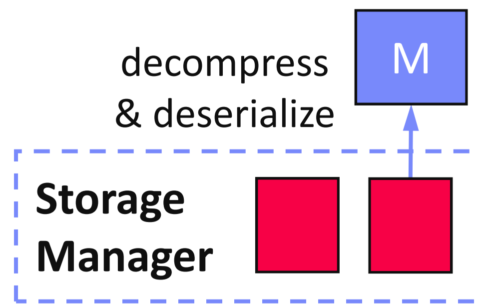

```
dataset = dataset.batch(batch_size=32)
dataset = dataset.prefetch(buffer_size=1)
```

[**Credit:** https://www.tensorflow.org/guide/performance/datasets]

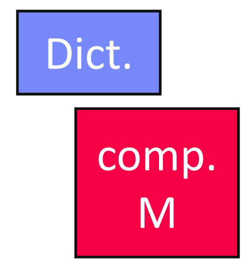
Lossy and Lossless Compression

Overview Lossless Compression Techniques

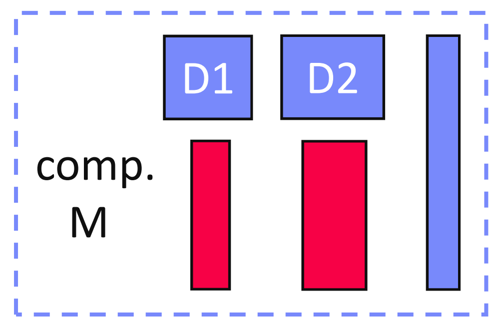
- **#1 Block-Level General-Purpose Compression**
  - Heavyweight or lightweight compression schemes
  - Decompress matrices block-wise for each operation
  - E.g.: Spark RDD compression (Snappy/LZ4), **SciDB** SM [SSDBM'11], **TileDB** SM [PVLDB'16], scientific formats **NetCDF**, **HDF5** at chunk granularity



- **#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) [CoRR'17]



- **#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]



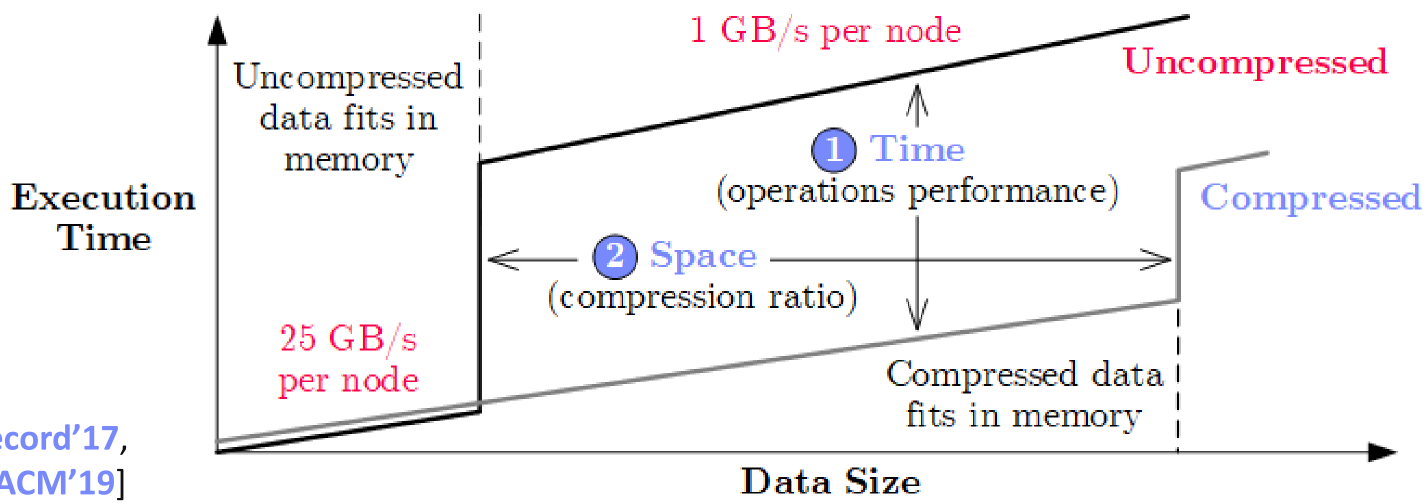
CLA: Compressed Linear Algebra

[Ahmed Elgohary 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 …
}
```

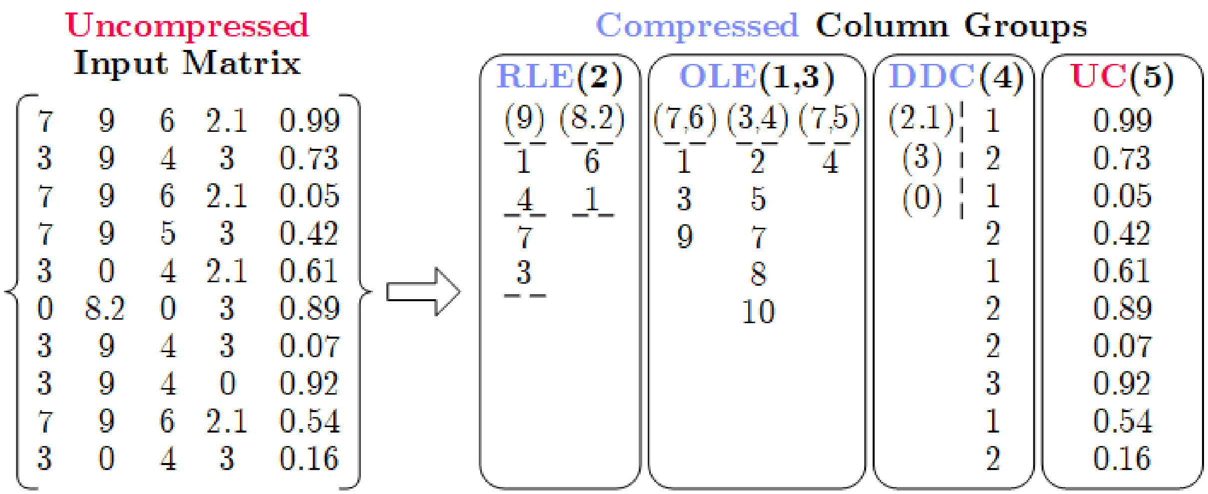


[**SIGMOD Record'17**, **VLDBJ'18**, **CACM'19**]

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)



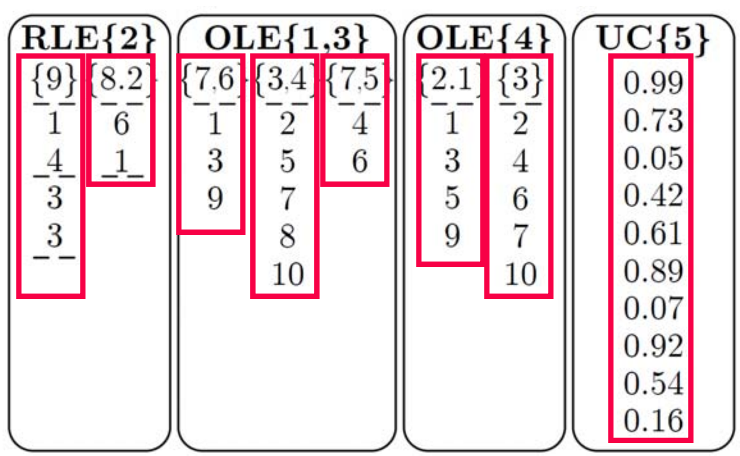
* DDC1/2 in VLDBJ'17

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

CLA: Compressed Linear Algebra, cont. (3)

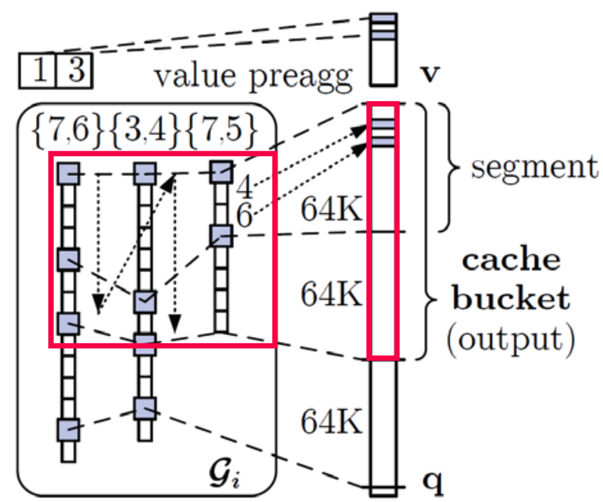
- **Matrix-Vector Multiplication**
  - Naïve: for each tuple, pre-aggregate values, add values at offsets to q
    Example: q = X v, with v = (7, 11, 1, 3, 2)

9*11=99 90.2 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)

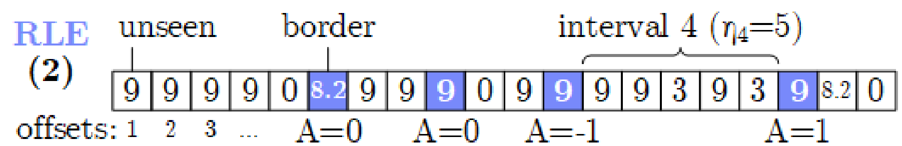


  - Cache-conscious: Horizontal, segment-aligned scans, maintain positions

- **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 OLE segments b_{ij}: **Expected value under maximum-entropy model**
  - \# 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

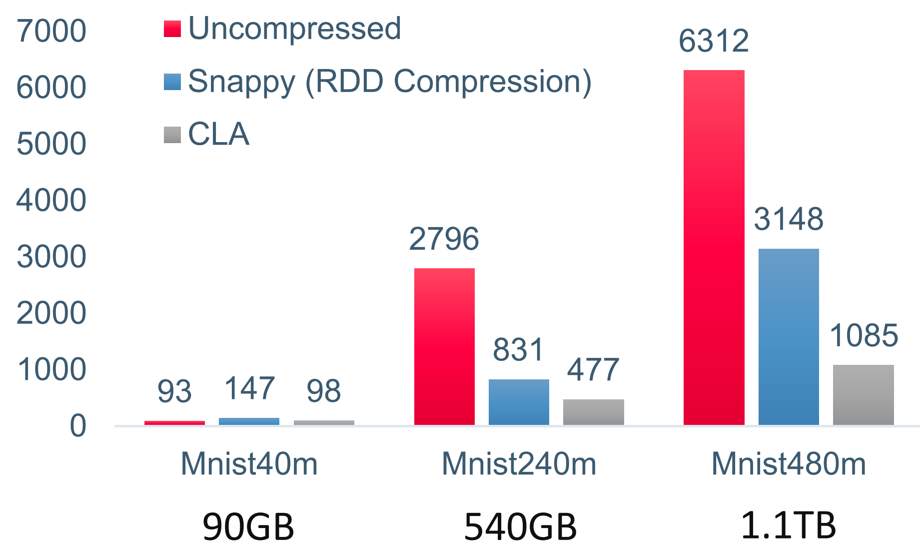
CLA: Compressed Linear Algebra, cont. (5)

- **Experimental Setup**
  - **LinregCG**, **10 iterations** (incl. compression), InfiMNIST data generator
  - 1+6 node cluster (216GB aggregate 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?

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

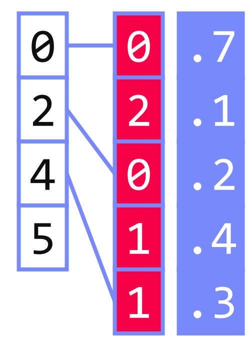
[Kornilios Kourtis, Georgios I. Goumas, Nectarios Koziris: Optimizing sparse matrix-vector multiplication using index and value compression. **CF 2008**]

[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)

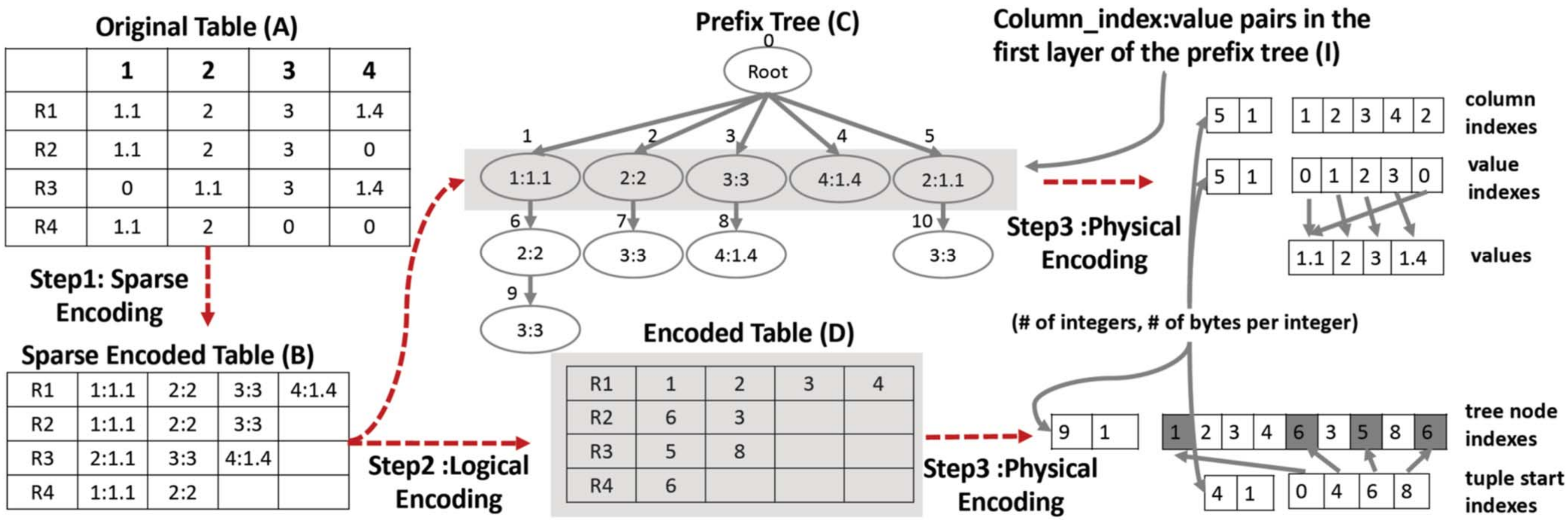
CSR



Tuple-oriented Compression (TOC)

[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**]

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



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)

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]

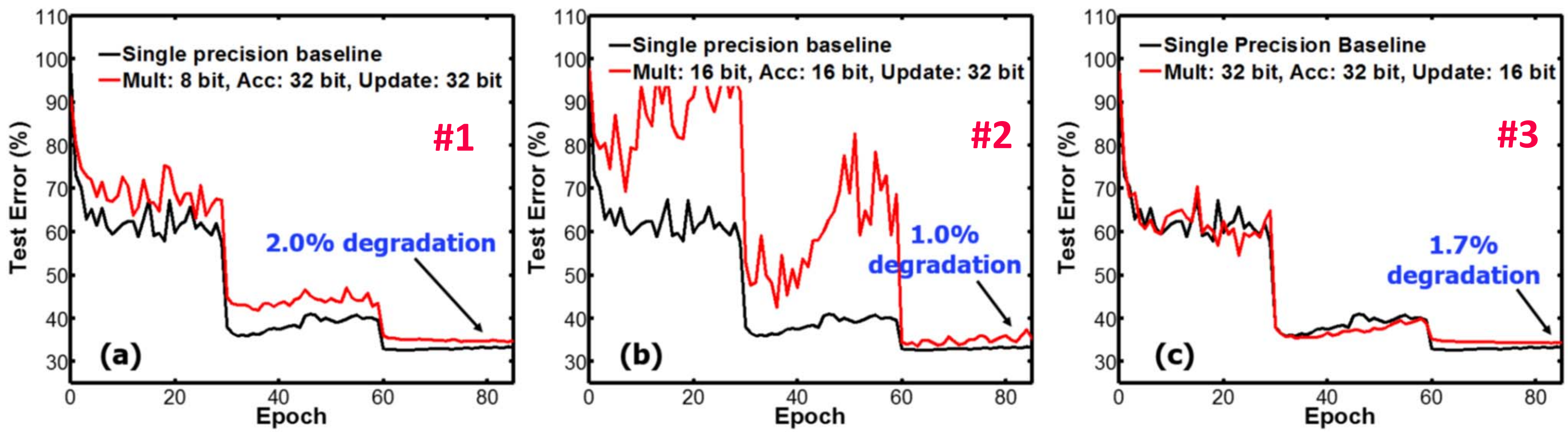
Low and Ultra-low FP Precision

- **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 s+L)
  - **#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 over ImageNet**



Low and Ultra-low FP Precision, cont.

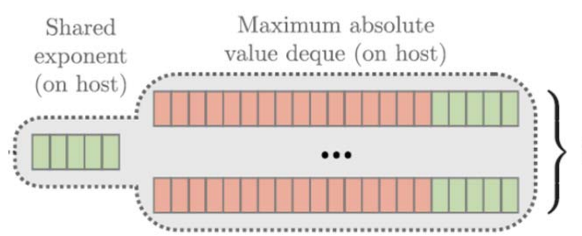
- **Numerical Stable Accumulation**
  - **#1 Sorting ASC + Summation** (accumulate small values first)
  - **#2 Kahan Summation** w/ error independent of number of values n

```
sumOld = sum;
sum = sum + (input + corr);
corr = (input + corr) - (sum - sumOld);
```

- **#3 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**]

- **#4 Stochastic Rounding**
  - Replace nearest with probabilistic rounding
  - Probability accounts for number of bits
- **#5 Intel FlexPoint**
  - Blocks of values w/ shared exponent (16bit w/ 5bit shared exponent)

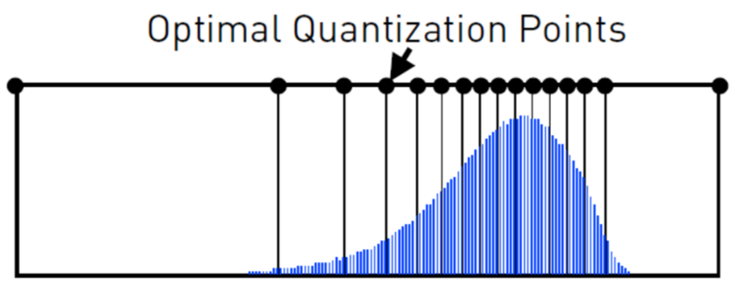


[Credit: Intel @ **NIPS 2017**]

Low Fixed-Point Precision

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

- **#1 Quantization (reduce value domain)**
  - **Split value domain into N buckets** such that $k = \log_2 N$ can encode the data
  - Static quantization very simple but inefficient on skewed data
  - 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 Compression Techniques

- **#2 Mantissa Truncation**
  - Mantissa truncation of FP32 from 23bit to 16bit for remote transfers
  - E.g., **TensorFlow**, **PStore**
- **#3 Sparsification (reduce #non-zeros)**
  - **Value clipping:** zero-out very small values below a threshold
- **#4 No FK-PK joins in Factorized Learning**
  - View the **foreign key** as lossy compressed representation of the joined attributes
- **#5 Sampling**
  - User specifies **approximation contract** for error (regression/classification) and scale
  - Estimate minimum necessary sample size for **maximum likelihood estimators**

[Yongjoo Park, Jingyi Qing, Xiaoyang Shen, Barzan Mozafari: BlinkML: Efficient Maximum Likelihood Estimation with Probabilistic Guarantees. **SIGMOD 2019**]

Summary and Conclusions

- **Data Access Methods → High Performance Impact**
  - Caching, Partitioning, and Indexing
  - Lossy and Lossless Compression

- **Next Lectures**
  - **09 Data Acquisition, Cleaning, and Preparation** [Jun 07]
  - **10 Model Selection and Management** [Jun 14]
  - **11 Model Deployment and Serving** [Jun 21]
  - **12 Project Presentations, Conclusions, Q&A** [Jun 28]