Architecture of ML Systems
08 Data Access Methods

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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

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

\[ X \]
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** \((m \times n)\)
  - 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)

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**Example 3x3 Matrix**

\[
\begin{bmatrix}
0.7 & 0.1 & 0.2 \\
0.4 & 0.0 & 0.3 \\
0.0 & 0.0 & 0.3 \\
\end{bmatrix}
\]

**Dense (row-major)**

- \(O(mn)\)

**MCSR**

- \(O(m + \text{nnz}(X))\)

**CSR**

- \(O(\text{nnz}(X))\)

**COO**

- \(O(\text{nnz}(X))\)
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)

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

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

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**Caching, Partitioning, and Indexing**

### parfor

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

---

\[ \sum \]

**Multi-Aggregate**

\[ a = \text{sum}(X^2) \]
\[ b = \text{sum}(X*Y) \]
\[ c = \text{sum}(Y^2) \]
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

- **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)

References:
- Ce Zhang, Christopher Ré: DimmWitted: A Study of Main-Memory Statistical Analytics. *PVLDB 2014*
Distributed Partitioning

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

- **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

**Example Hash Partitioning:**
For all \((k,v)\) of \(R\):
\[
\text{hash}(k) \mod \text{numPartitions} \rightarrow \text{pid}
\]

```
//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**
  - Bayer and McCreight 1972 (multiple papers), Block-based, Balanced, Boeing
  - Multiway tree (node size = page size); designed for DBMS

- **Definition B-Tree k**
  - Balanced tree: All paths from root to leaves have equal length \( h \)
  - All nodes (except root=leaf) have \([k, 2k]\) key entries
  - All nodes (except root, leaves) have \([k+1, 2k+1]\) successors
  - Data is a record or a reference to the record (RID)

![B-Tree Diagram]

Subtree w/ keys ≤ \(K_1\)
Subtree w/ \(K_2 < \) keys ≤ \(K_3\)
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)

![#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)

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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]
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

```python
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

- **Key Idea**
  - Use lightweight database compression techniques
  - Perform LA operations on compressed matrices

- **Goals of CLA**
  - Operations performance close to uncompressed
  - Good compression ratios

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

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)

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

* DDC1/2 in VLDBJ’17
CLA: Compressed Linear Algebra, cont. (3)

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

  - 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. (\( \sim \) 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**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Gzip</th>
<th>Snappy</th>
<th>CLA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Higgs</td>
<td>1.93</td>
<td>1.38</td>
<td>2.17</td>
</tr>
<tr>
<td>Census</td>
<td>17.11</td>
<td>6.04</td>
<td>35.69</td>
</tr>
<tr>
<td>Covtype</td>
<td>10.40</td>
<td>6.13</td>
<td>18.19</td>
</tr>
<tr>
<td>ImageNet</td>
<td>5.54</td>
<td>3.35</td>
<td>7.34</td>
</tr>
<tr>
<td>Mnist8m</td>
<td>4.12</td>
<td>2.60</td>
<td>7.32</td>
</tr>
<tr>
<td>Airline78</td>
<td>7.07</td>
<td>4.28</td>
<td>7.44</td>
</tr>
</tbody>
</table>

**End-to-End Performance [sec]**

- Uncompressed
- Snappy (RDD Compression)
- CLA

<table>
<thead>
<tr>
<th>Dataset</th>
<th>90GB</th>
<th>540GB</th>
<th>1.1TB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mnist40m</td>
<td>93</td>
<td>831</td>
<td>3148</td>
</tr>
<tr>
<td>Mnist240m</td>
<td>147</td>
<td>477</td>
<td>3148</td>
</tr>
<tr>
<td>Mnist480m</td>
<td>98</td>
<td>1085</td>
<td>3148</td>
</tr>
</tbody>
</table>

- **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
    \[ c = A \%\% b \]

```cpp
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)


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]
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: \( \text{value} = s \times m \times 2^e \) (simplified)

<table>
<thead>
<tr>
<th>Precision</th>
<th>Sign</th>
<th>Mantissa</th>
<th>Exponent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Double</strong></td>
<td>1</td>
<td>52</td>
<td>11</td>
</tr>
<tr>
<td><strong>Single</strong></td>
<td>1</td>
<td>23</td>
<td>8</td>
</tr>
<tr>
<td><strong>Half</strong></td>
<td>1</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td><strong>Quarter</strong></td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td><strong>Half-Quarter</strong></td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

[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

- **Example ResNet18** over ImageNet

  ![Graphs](image)

  - #1: Single precision baseline vs. Mult: 8 bit, Acc: 32 bit, Update: 32 bit. 2.0% degradation.
  - #2: Single precision baseline vs. Mult: 16 bit, Acc: 16 bit, Update: 32 bit. 1.0% degradation.


see 05 Execution Strategies, SIMD → speedup/reduced energy
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
  - #3 **Chunk-based Accumulation**
    - Divide long dot products into smaller chunks
    - Hierarchy of partial sums → **FP16 accumulators**
  - #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)

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Lossy and Lossless Compression

- **Numerical Stable Accumulation**
  - #1 **Sorting ASC + Summation** (accumulate small values first)
  - #2 **Kahan Summation**
    - 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**
  - #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)

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

[Credit: Intel @ NIPS 2017]
Low Fixed-Point Precision

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

- **#1 Quantization (reduce value domain)**
  - Split value domain into \texttt{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: \texttt{ZipML}, \texttt{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

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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]