Architecture of ML Systems (AMLS)
05 Data- and Task-Parallel Execution

Prof. Dr. Matthias Boehm
Technische Universität Berlin
Berlin Institute for the Foundations of Learning and Data
Big Data Engineering (DAMS Lab)

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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/ss23_amls/index.htm

- **#2 Reminder Project / Exercise Selection**
  - **Assignment of projects and mentors**, exercise registration still possible
  - Submission due: **July 04** (TUB: ISIS, TUG: TeachCenter, Other: via email)

- **#3 Next Lecture**
  - Conflict due to EECS faculty retreat **June 01/02** (Lakeside Burghotel zu Strausberg)
  - **May 31 6pm-8pm virtual zoom lecture** + recording

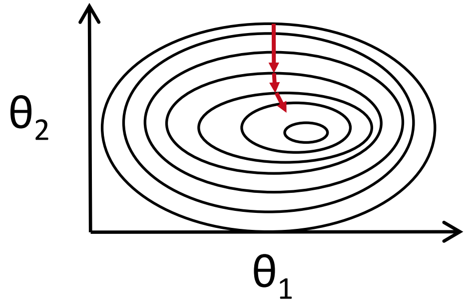
Agenda

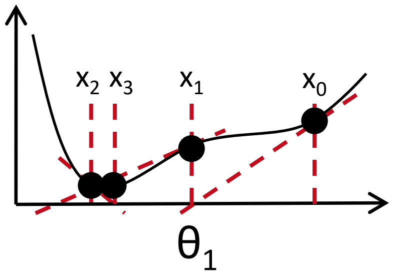
- Motivation and Terminology
- Background MapReduce and Spark
- Data-Parallel Execution
- Task-Parallel Execution

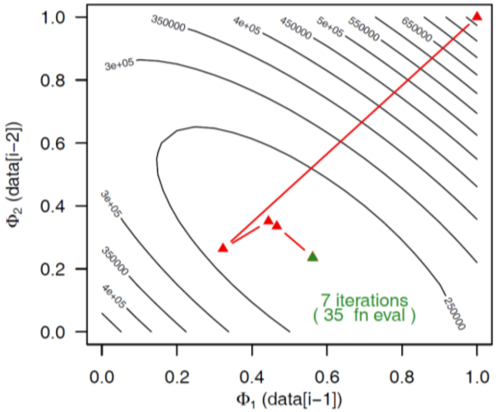
Motivation and Terminology

Terminology Optimization Methods

- **Problem: Given a continuous, differentiable function $f(D, \theta)$, find optimal parameters $\theta^* = \text{argmin}\,(f(D, \theta))$**
- **#1 Gradient Methods (1st order)**
  - Pick a starting point, compute gradient, descent in opposite direction of gradient $-\gamma\nabla f(D, \theta)$
- **#2 Newton's Method (2nd order)**
  - Pick a starting point, compute gradient, descend to where derivative = 0 (via 2nd derivate)
  - Jacobian/Hessian matrices for multi-dimensional
- **#3 Quasi-Newton Methods**
  - Incremental approximation of Hessian
  - Algorithms: BFGS, L-BFGS, Conjugate Gradient (CG)
  - **Example:** L-BFGS-B, AR(2), MSE, N=100 EnBW energy-demand time series



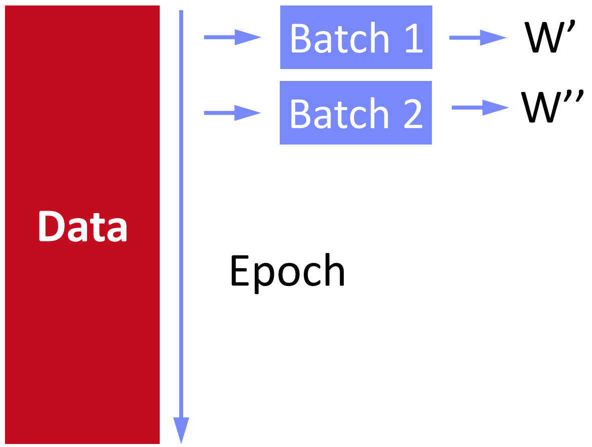




Terminology Batch/Mini-batch

- **Batch ML Algorithms**
  - Iterative ML algorithms, where each iteration uses the **entire dataset** to compute gradients ΔW
  - For (pseudo-)**second-order methods**, many features
  - **Dedicated optimizers** for traditional ML algorithms

- **Mini-batch ML Algorithms**
  - Iterative ML algorithms, where each iteration only uses a **batch of rows** to make the next model update (in **epochs** or w/ **sampling**)
  - For large and **highly redundant training sets**
  - **Applies to almost all iterative**, model-based ML algorithms (LDA, reg., class., factor., DNN)
  - **Stochastic Gradient Descent** (SGD)



Recap: Central Data Abstractions

- **#1 Files and Objects**
  - **File:** Arbitrarily large sequential data in specific file format (CSV, binary, etc)
  - **Object:** binary large object, with certain meta data

- **#2 Distributed Collections**
  - Logical multi-set (**bag**) of **key-value pairs** (**unsorted collection**)
  - Different physical representations
  - **Easy distribution** of pairs via horizontal partitioning (aka shards, partitions)
  - Can be created from single file, or directory of files (unsorted)

Key	Value
4	Delta
2	Bravo
1	Alfa
3	Charlie
5	Echo
6	Foxtrot
7	Golf
1	Alfa

Terminology Parallelism

- **Flynn's Classification**
  - SISD, SIMD
  - (MISD), MIMD

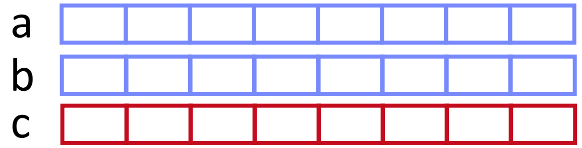
[Michael J. Flynn, Kevin W. Rudd: Parallel Architectures. **ACM Comput. Surv. 28(1) 1996**]

	Single Data	Multiple Data
Single Instruction	**SISD** (uni-core)	**SIMD** (vector)
Multiple Instruction	**MISD** (pipelining)	**MIMD** (multi-core)

- **Example: SIMD Processing**
  - Streaming SIMD Extensions (SSE)
  - Process the same operation on multiple elements at a time (**packed** vs scalar SSE instructions)
  - **Data parallelism** (aka: instruction-level parallelism)
  - Example: **VFMADD132PD**

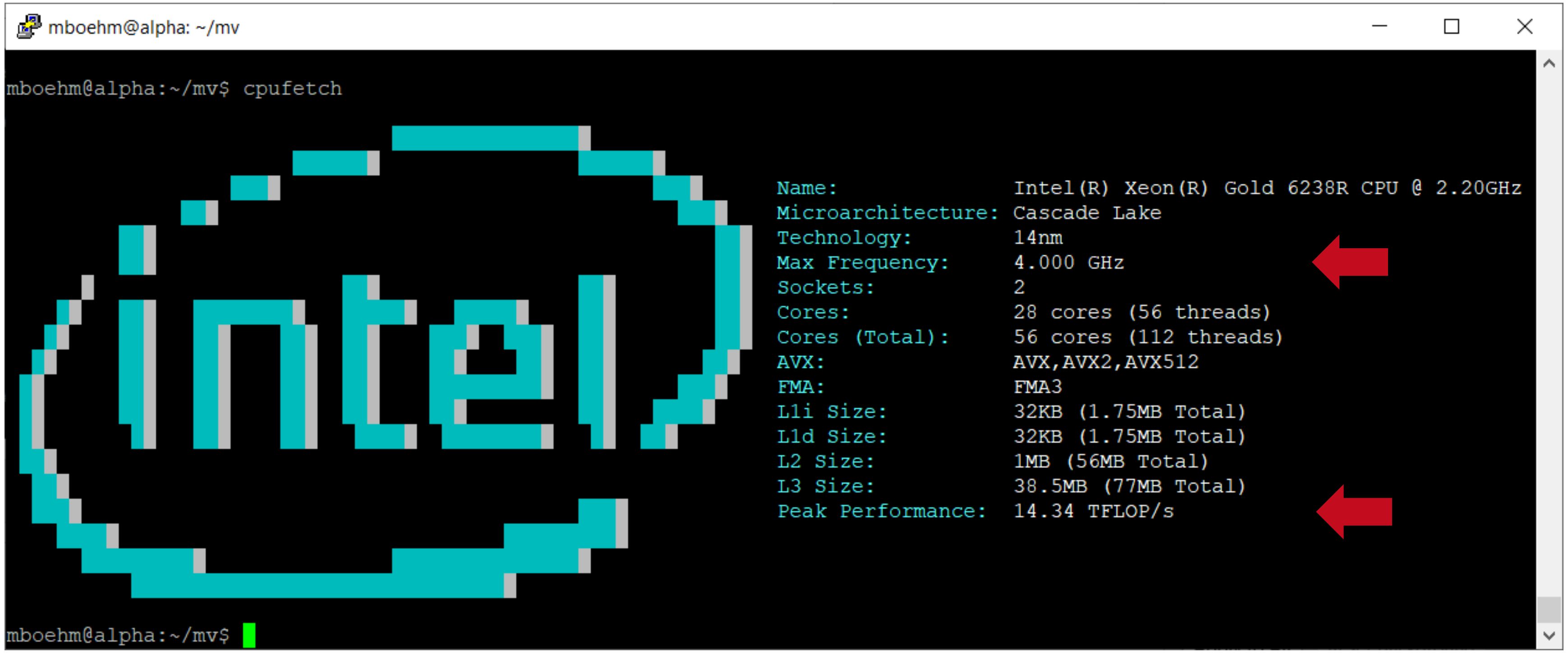
2009 Nehalem: **128b** (2xFP64)
2012 Sandy Bridge: **256b** (4xFP64)
2017 Skylake: **512b** (8xFP64)

```
c = _mm512_fmadd_pd(a, b);
```



Excursus: Peak Performance

- **Example Scale-up Node (DM cluster)**
  - Peak := 2 Sockets * 28 Cores * 2.2 GHz * 2 FMA units * 16 FP32 slots (AVX512) * 2 (FMA)
    = **7.7 TFLOP/s** (FP32) = **3.85 TFLOP/s** (FP64)



SystemDS **matmult**
w/ BLAS (Intel MKL):
2.23 TFLOP/s (FP64)

Terminology Parallelism, cont.

- **Distributed, Data-Parallel Computation**
  - Parallel computation of function foo() ➔ **single instruction**
  - Collection X of data items (key-value pairs) ➔ **multiple data**
  - Data parallelism similar to **SIMD** but more coarse-grained notion of “instruction” and “data” ➔ **SPMD** (single program, multiple data)

```
Y = X.map(x -> foo(x))
```

[Frederica Darema: The SPMD Model : Past, Present and Future. **PVM/MPI 2001**]

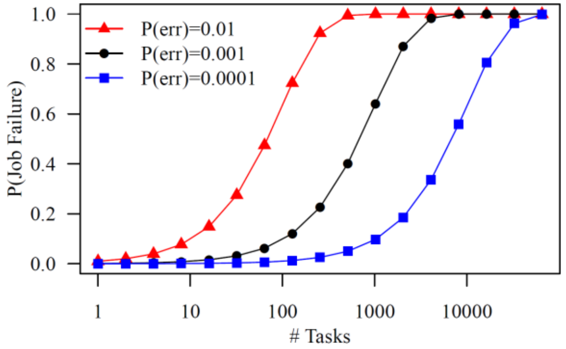
- **Additional Terminology**
  - **BSP:** Bulk Synchronous Parallel (global barriers)
  - **ASP:** Asynchronous Parallel (no barriers, often with accuracy impact)
  - **SSP:** Stale-synchronous parallel (staleness constraint on fastest-slowest)
  - Other: Fork&Join, Hogwild!, event-based, decentralized

- **Beware: data parallelism** used in very different contexts (e.g., Param Server)

Recap: Fault Tolerance & Resilience

[Google Data Center: https://www.youtube.com/watch?v=XZmGGAbHqa0]

- **Resilience Problem**
  - Increasing error rates **at scale** (soft/hard mem/disk/net errors)
  - Robustness for preemption
  - **Need for cost-effective resilience**



- **Fault Tolerance in Large-Scale Computation**
  - Block replication in distributed file systems
  - ECC; checksums for blocks, broadcast, shuffle
  - Checkpointing (all task outputs / on request)
  - Lineage-based recomputation for recovery in Spark

- **ML-specific Approaches** (exploit app characteristics)
  - Estimate contribution from lost partition to avoid strugglers
  - Example: user-defined "compensation" functions
  - Model replication and checkpointing (e.g., for LLMs)

[Sebastian Schelter, Stephan Ewen, Kostas Tzoumas, Volker Markl: "All roads lead to Rome": optimistic recovery for distributed iterative data processing. **CIKM 2013**]

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

Background MapReduce and Spark (Data-Parallel Collection Processing)

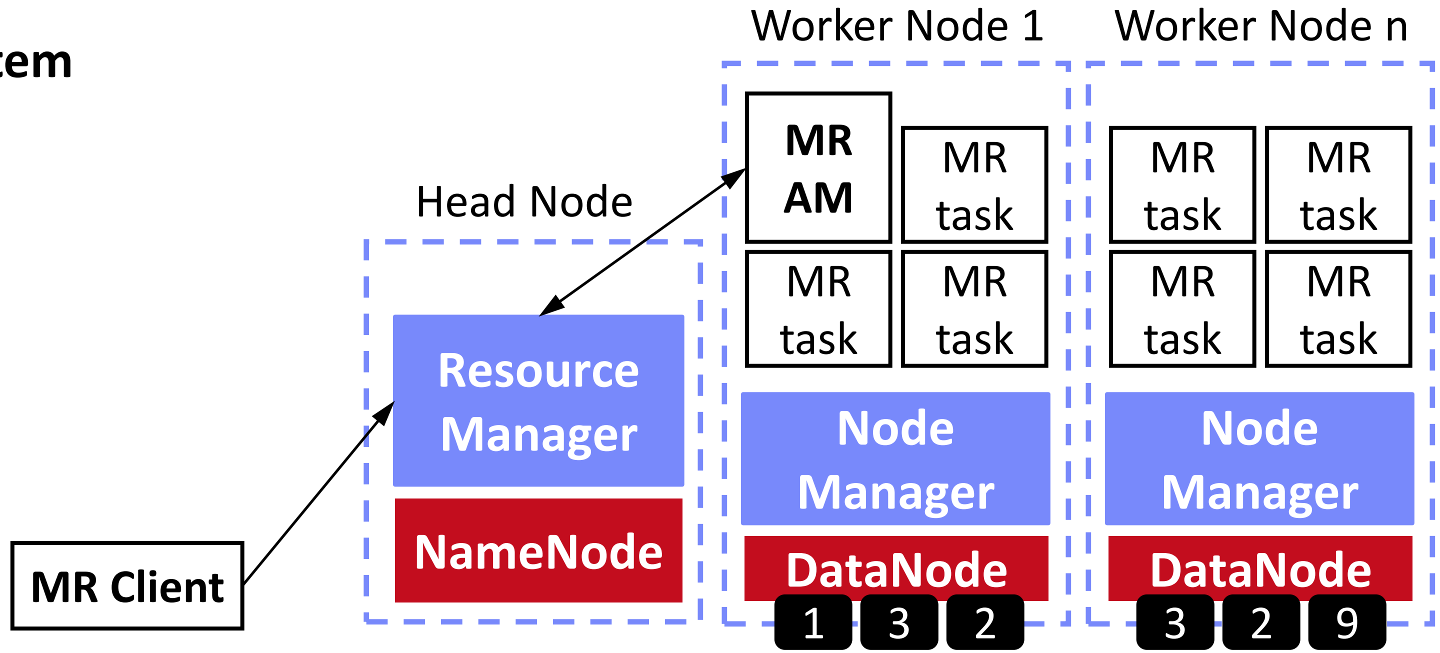
Abstractions for Fault-tolerant, Distributed Storage and Computation

Hadoop History and Architecture

- **Recap: Brief History**
  - Google's GFS [SOSP'03] + MapReduce
    → Apache Hadoop (2006)
  - Apache Hive (SQL), Pig (ETL), Mahout (ML), Giraph (Graph)

[Jeffrey Dean, Sanjay Ghemawat: MapReduce: Simplified Data Processing on Large Clusters. **OSDI 2004**]

- **Hadoop Architecture / Eco System**
  - Management (Ambari)
  - Coordination / workflows (Zookeeper, Oozie)
  - Storage (**HDFS**)
  - Resources (**YARN**) [SoCC'13]
  - Processing (**MapReduce**)



MapReduce – Programming Model

- **Overview Programming Model**
  - Inspired by functional programming languages
  - **Implicit parallelism** (abstracts distributed storage and processing)
  - Map function: key/value pair → set of intermediate key/value pairs
  - Reduce function: merge all intermediate values by key

- **Example**

```
SELECT Dep, count(*) FROM csv_files GROUP BY Dep
```

Name	Dep
X	CS
Y	CS
A	EE
Z	CS

Collection of key/value pairs

```
map(Long pos, String line) {
  parts ← line.split(“,”)
  emit(parts[1], 1)
}
```

CS	1
CS	1
EE	1
CS	1

```
reduce(String dep,
       Iterator<Long> iter) {
  total ← iter.sum();
  emit(dep, total)
}
```

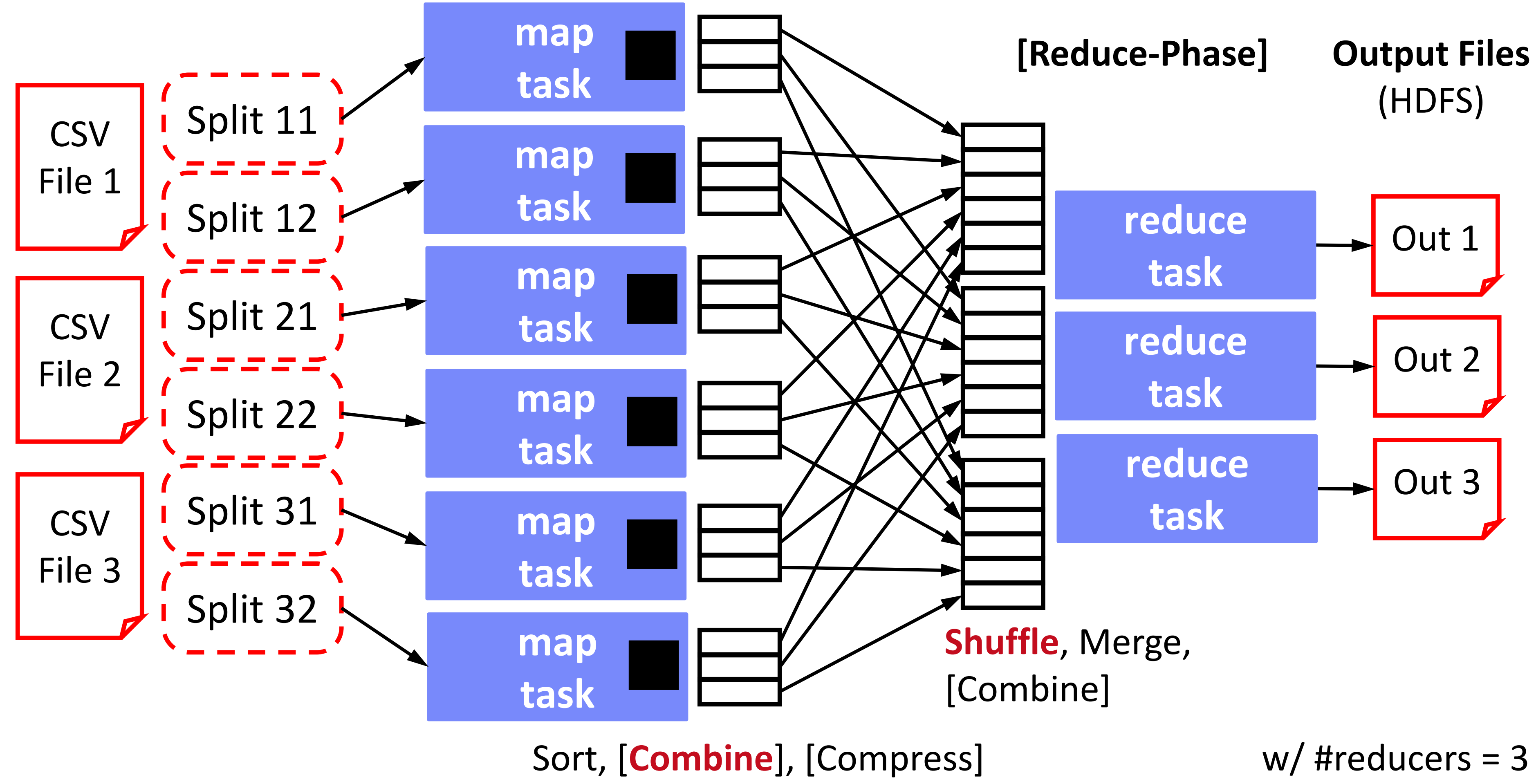
CS	3
EE	1

MapReduce – Execution Model

#1 Data Locality (delay sched., write affinity)
#2 Reduced shuffle (combine)
#3 Fault tolerance (replication, attempts)

Input CSV files (stored in HDFS)

Map-Phase



Spark History and Architecture

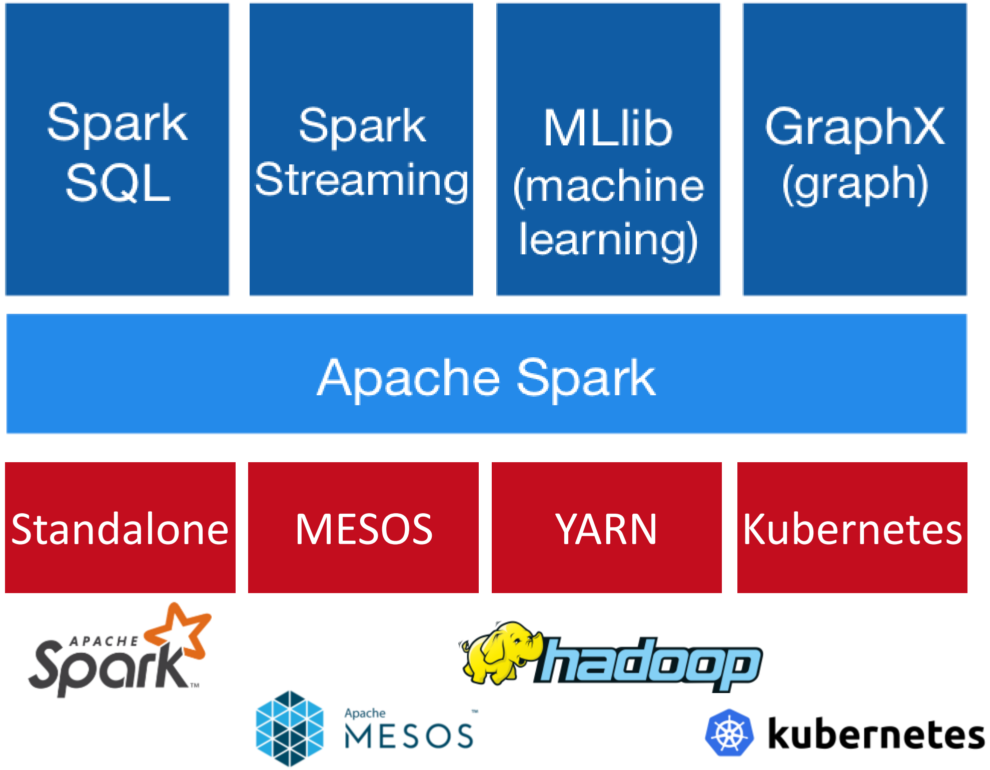
- **Summary MapReduce**
  - Large-scale & fault-tolerant processing w/ UDFs and files ➔ **Flexibility**
  - Restricted functional APIs ➔ **Implicit parallelism and fault tolerance**
  - **Criticism**: #1 **Performance**, #2 **Low-level APIs**, #3 **Many different systems**
- **Evolution to Spark** (and Flink)
  - Spark [HotCloud'10] + RDDs [NSDI'12] → **Apache Spark** (2014)
  - **Design: standing executors with in-memory storage**, lazy evaluation, fault-tolerance via RDD lineage
  - **Performance:** In-memory storage and fast job scheduling (100ms vs 10s)
  - **APIs:** Richer functional APIs and general computation DAGs, high-level APIs (e.g., DataFrame/Dataset), unified platform

➔ **But many shared concepts/infrastructure**
  - **Implicit parallelism through dist. collections** (data access, fault tolerance)
  - Resource negotiators (YARN, Mesos, Kubernetes)
  - HDFS and object store connectors (e.g., Swift, S3)

Spark History and Architecture, cont.

- **High-Level Architecture**
  - **Different language bindings**:
    Scala, Java, Python, R
  - **Different libraries**:
    SQL, ML, Stream, Graph
  - Spark core (incl RDDs)
  - **Different cluster managers**:
    Standalone, Mesos, **Yarn**, **Kubernetes**
  - Different file systems/
    formats, and data sources:
    HDFS, **S3**, SWIFT, **DBs**, **NoSQL**

[https://spark.apache.org/]



- **Focus on a unified platform for data-parallel computation** (**Apache Flink** w/ similar goals)

Spark Resilient Distributed Datasets (RDDs)

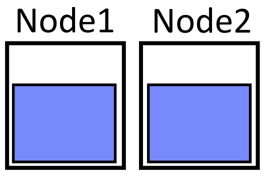
- **RDD Abstraction**
  - **Immutable**, partitioned **collections of key-value pairs**
  - **Coarse-grained** deterministic operations (transformations/actions)
  - Fault tolerance via lineage-based re-computation

```
JavaPairRDD<MatrixIndexes,MatrixBlock>
```

- **Operations**
  - **Transformations:** define new RDDs
  - **Actions:** return result to driver

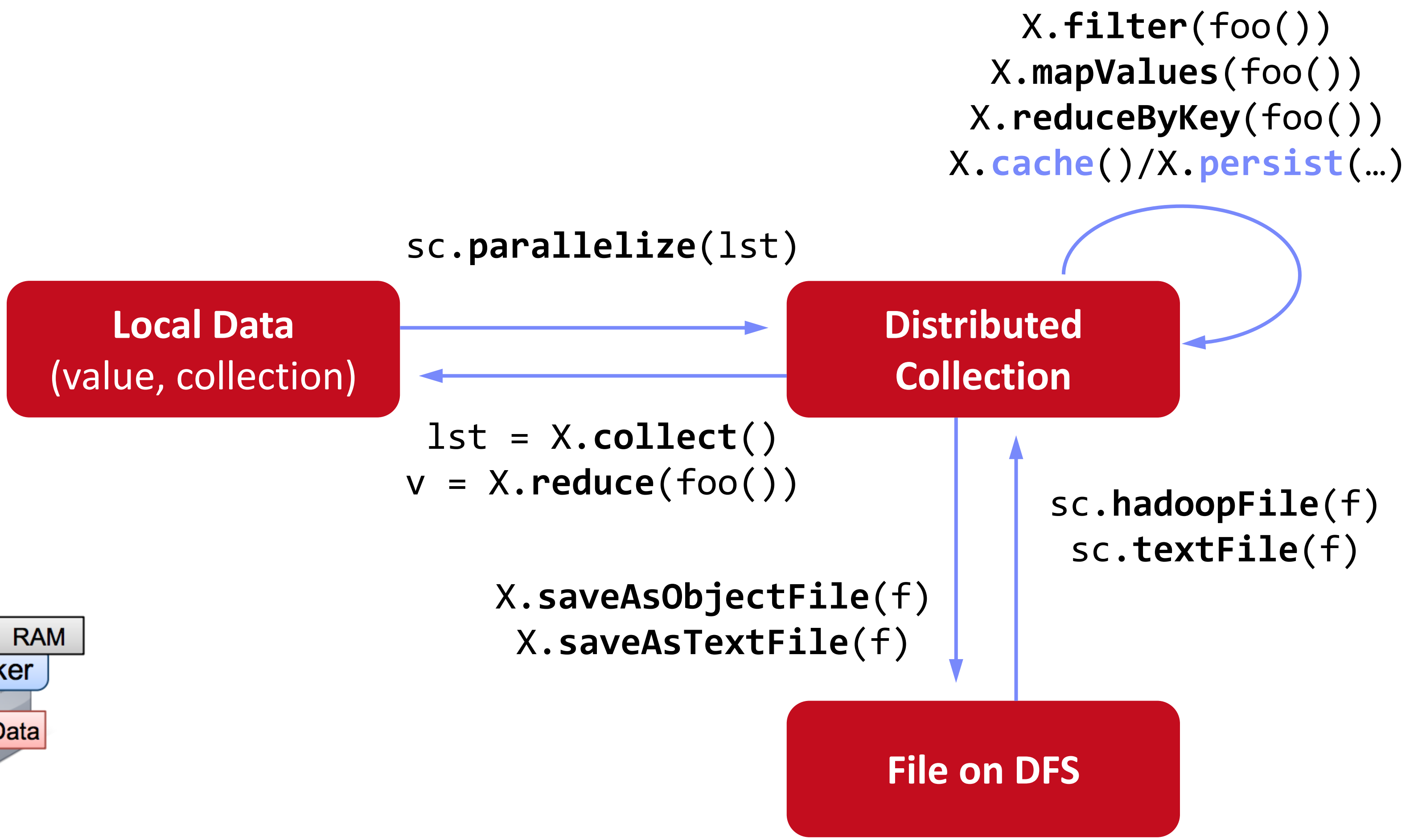
Type	Examples
Transformation (**lazy**)	`map`, `hadoopFile`, `textFile`, `flatMap`, `filter`, `sample`, `join`, `groupByKey`, `cogroup`, `reduceByKey`, `cross`, `sortByKey`, `mapValues`
Action	`reduce`, `save`, `collect`, `count`, `lookupKey`

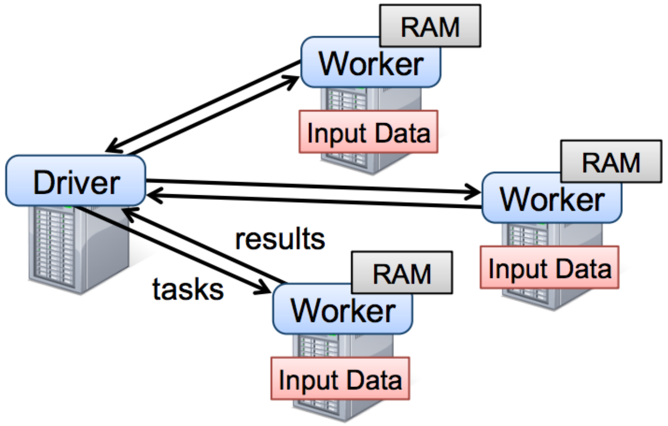
- **Distributed Caching**
  - Use fraction of worker **memory for caching**
  - Eviction at granularity of individual partitions
  - **Different storage levels** (e.g., mem/disk x serialization x compression)



Spark Resilient Distributed Datasets (RDDs), cont.

- **Lifecycle of an RDD**
  - Note: can't broadcast an RDD directly





Spark Partitions and Implicit/Explicit Partitioning

- **Spark Partitions**
  - Logical key-value collections are split into **physical partitions**
  - Partitions are granularity of **tasks, I/O, shuffling, evictions**

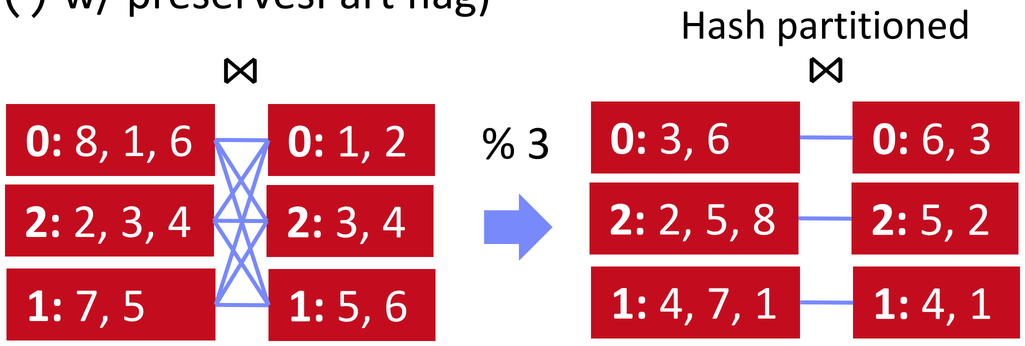
~128MB

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

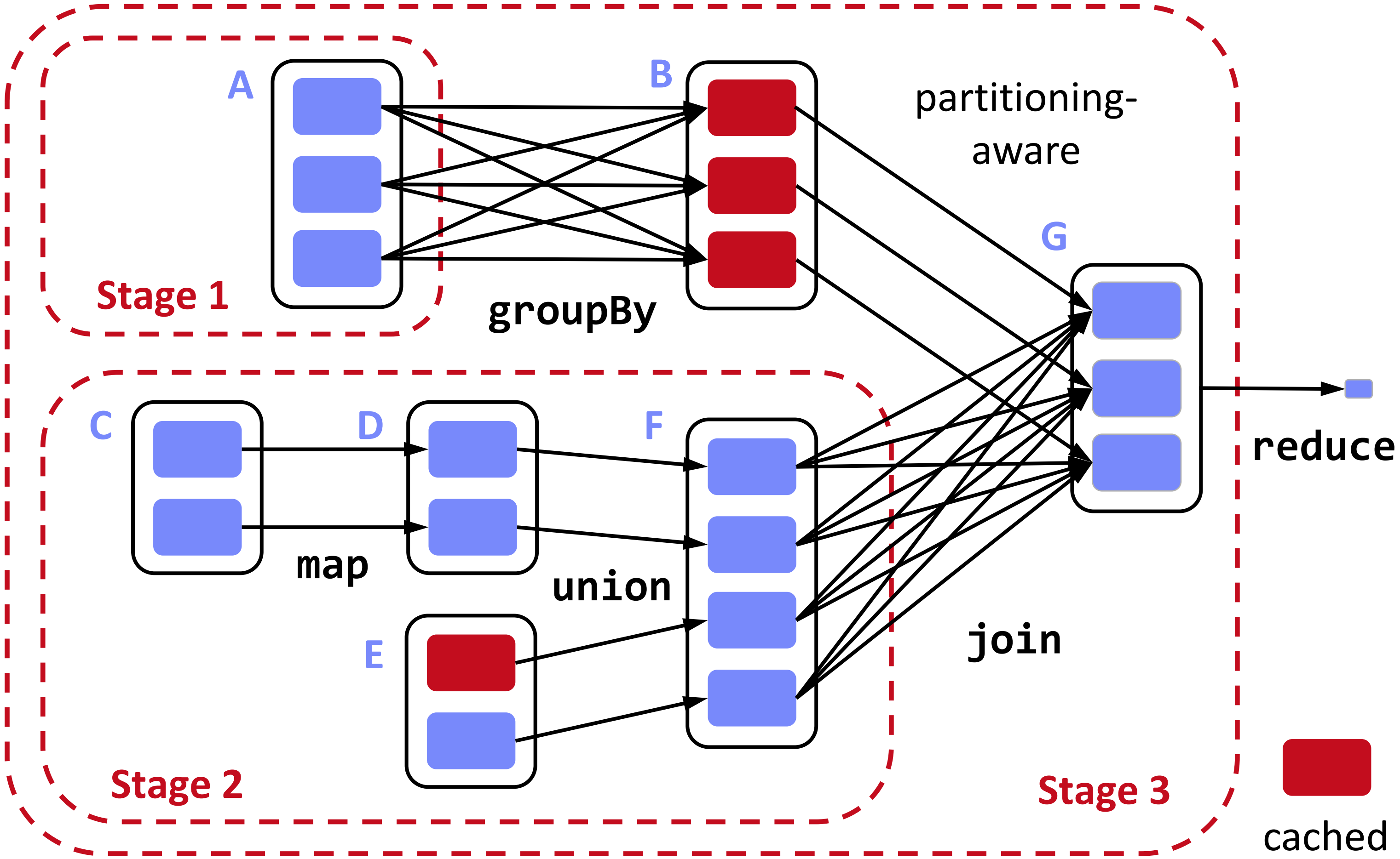
Example Hash Partitioning:
For all (k,v) of R:
pid = hash(k) % n

- **Partitioning-Preserving**
  - All operations that are guaranteed to keep keys unchanged (e.g. `mapValues()`, `mapPartitions()` w/ preservesPart flag)

- **Partitioning-Exploiting**
  - Join: `R3 = R1.join(R2)`
  - Lookups: `v = C.lookup(k)`



Spark Lazy Evaluation, Caching, and Lineage



[Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauly, Michael J. Franklin, Scott Shenker, Ion Stoica: Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. **NSDI 2012**]

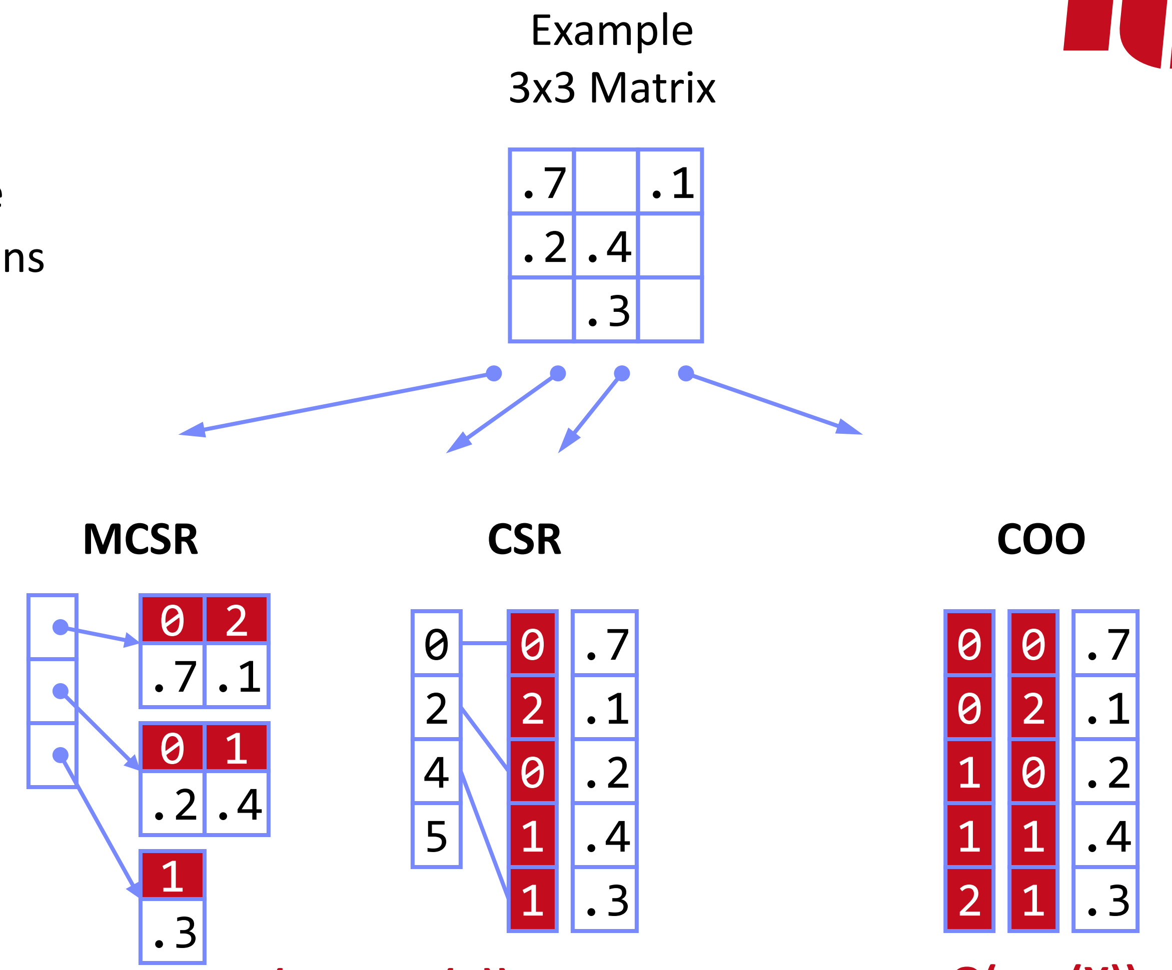
1. Reduce action triggers DAG compilation and evaluation
2. DAG compiled into job of multiple stages (3 here), demarcated by wide shuffle dependencies
3. Lost/evicted cached partitions are re-evaluated via partition lineage

Data-Parallel Execution

Batch ML Algorithms

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)

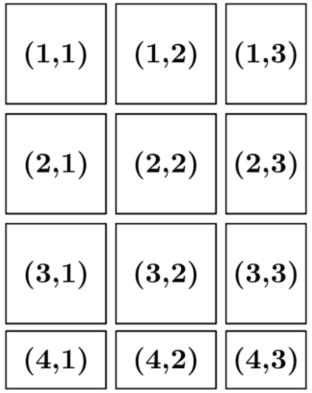
O(m + nnz(X))

O(nnz(X))

Distributed Matrix Representations

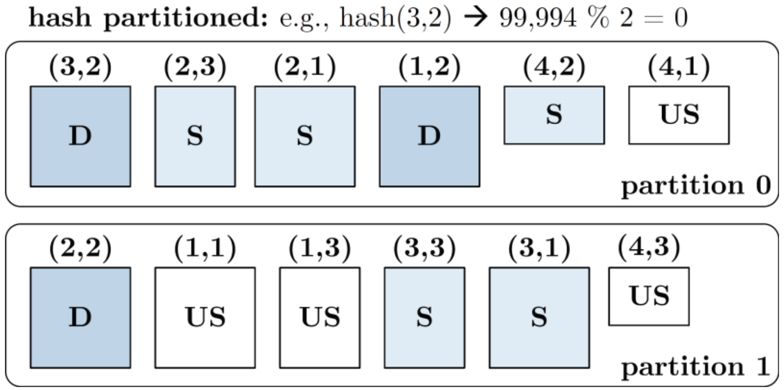
- **Collection of "Matrix Blocks" (and keys)**
  - Bag semantics (duplicates, unordered)
  - Logical (Fixed-Size) Blocking
    + join processing / independence
    - (sparsity skew)
  - E.g., SystemML on Spark:
    JavaPairRDD<MatrixIndexes,MatrixBlock>
  - Blocks encoded independently (dense/sparse)

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



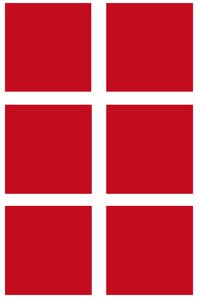
- **Partitioning**
  - Logical Partitioning
    (e.g., row-/column-wise)
  - Physical Partitioning
    (e.g., hash / grid)
  - Influences partition-local aggregation

Physical Blocking
and Partitioning

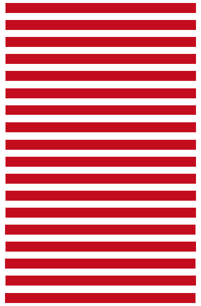


Distributed Matrix Representations, cont.

- #1 **Block-partitioned Matrices**
  - Fixed-size, square or rectangular blocks
  - **Pros:** Input/output alignment, block-local transpose, amortize block overheads, bounded mem, cache-conscious
  - **Cons:** Converting row-wise inputs (e.g., text) requires shuffle
  - **Examples: RIOT, PEGASUS, SystemML, SciDB, Cumulon, Distributed R, DMac, Spark Mllib, Gilbert, MatFast,** and **SimSQL**



- #2 **Row/Column-partitioned Matrices**
  - Collection of row indexes and rows (or columns respectively)
  - **Pros:** Seamless data conversion and access to entire rows
  - **Cons:** Storage overhead in Java, and cache unfriendly operations
  - Examples: **Spark MLlib**, **Mahout Samsara**, **Emma**, **SimSQL**

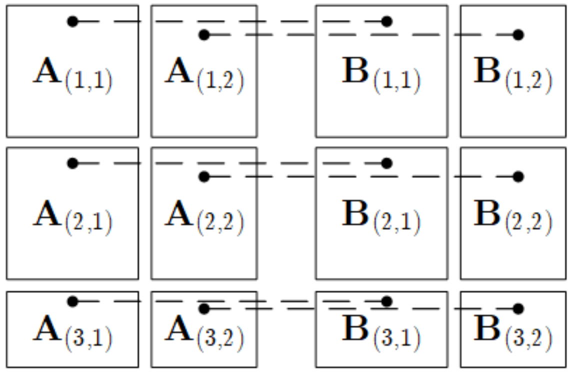


- **#3 Algorithm-specific Partitioning**
  - Operation and algorithm-centric data representations (e.g., matrix inverse, matrix factorization)

Distributed Matrix Operations

Elementwise Multiplication
(Hadamard Product)

`C = A * B`

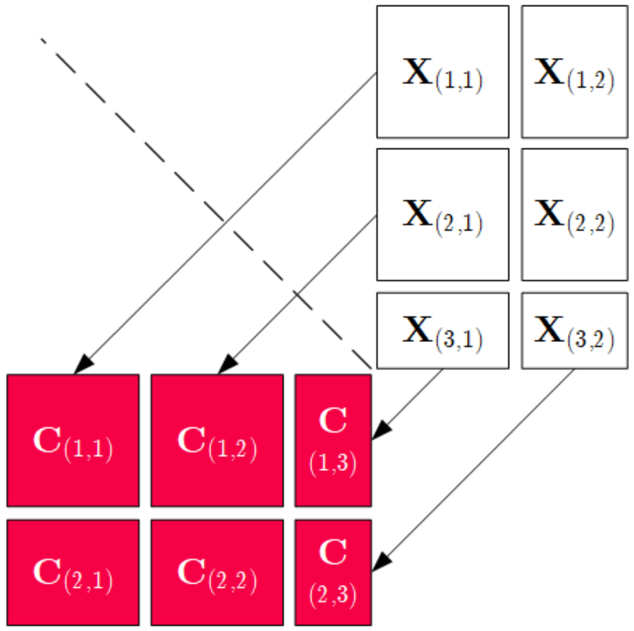


1:1 join

Note: also with
row/column vector rhs

Transposition

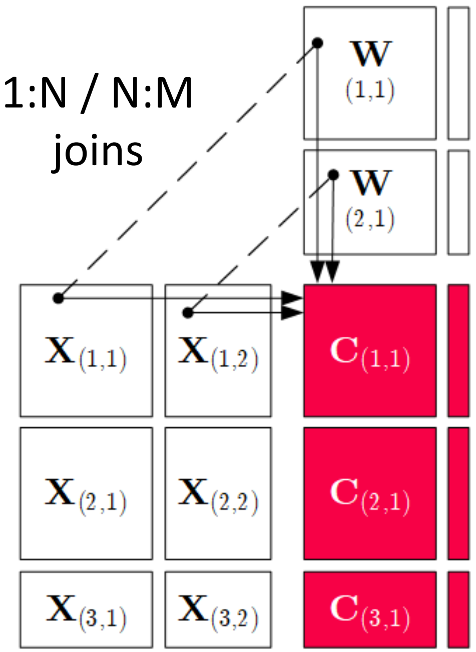
`C = t(X)`



Matrix Multiplication

`C = X %*% W`

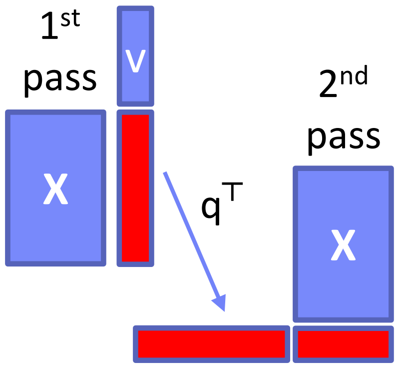
1:N / N:M
joins



Physical Operator Selection – Example Matrix Multiplication

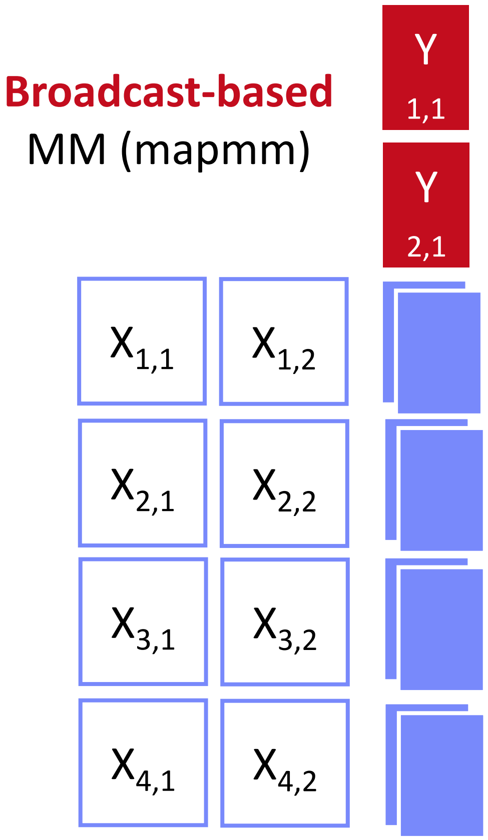
- **Common Selection Criteria**
  - **Data and cluster characteristics** (e.g., data size/shape, diagonal/symmetric, memory, parallelism)
  - **Operation and data-flow properties** (e.g., sparse-safe ops, co-partitioning, co-location, data locality)
- **#0 Local Operators**
  - SystemML mm, tsmm, mmchain; Samsara/Mllib local
- **#1 Special Operators** (special patterns/sparsity)
  - SystemML **tsmm**, **mapmmchain**; Samsara AtA
- **#2 Broadcast-Based Operators** (aka broadcast join)
  - SystemML **mapmm**, **mapmmchain**
- **#3 Co-Partitioning-Based Operators** (aka improved repartition join)
  - SystemML **zipmm**; Emma, Samsara OpAtB
- **#4 Shuffle-Based Operators** (aka repartition join)
  - SystemML **cpmm**, **rmm**; Samsara OpAB

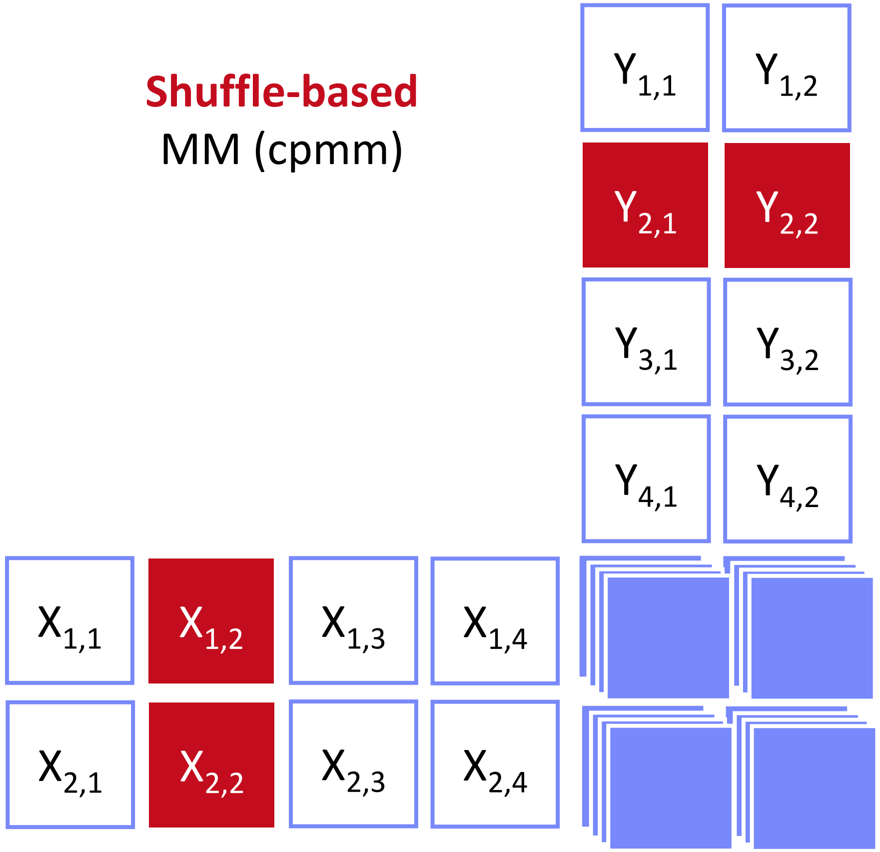
`t(X) %*% (X%*%v)`



Physical Operator Selection – Example Matrix Multiplication, cont.

- **Examples Distributed MM Operators**





Partitioning-Preserving Operations

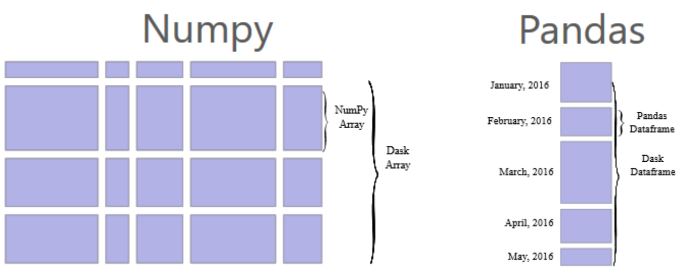
- **Shuffle is major bottleneck for ML on Spark**
- **Preserve Partitioning**
  - Op is partitioning-preserving if keys unchanged (guaranteed)
  - Implicit: Use restrictive APIs (`mapValues()` vs `mapToPair()`)
  - Explicit: Partition computation w/ declaration of partitioning-preserving
- **Exploit Partitioning**
  - Implicit: Operations based on `join`, `cogroup`, etc
  - Explicit: Custom operators (e.g., zipmm)
- **Example: Multiclass SVM**
  - Vectors fit neither into driver nor broadcast
  - $ncol(X) \leq B_c$

```
parfor(iter_class in 1:num_classes) {        repart, chkpt X MEM_DISK
   Y_local = 2 * (Y == iter_class) - 1
   g_old = t(X) %*% Y_local
   ...                                        chkpt y_local MEM_DISK
   while( continue ) {
      Xd = X %*% s                            chkpt Xd, Xw MEM_DISK
      ... inner while loop (compute step_sz)
      Xw = Xw + step_sz * Xd;
      out = 1 - Y_local * Xw;
      out = (out > 0) * out;
      g_new = t(X) %*% (out * Y_local) ...    zipmm
```

Dash

[Matthew Rocklin: Dask: Parallel Computation with Blocked algorithms and Task Scheduling, **Python in Science 2015**]
[Dask Development Team: Dask: Library for dynamic task scheduling, 2016, https://dask.org]

- **Overview Dask**
  - Multi-threaded and distributed operations for arrays, bags, and dataframes
  - `dask.array:` list of numpy n-dim arrays
  - `dask.dataframe:` list of pandas data frames
  - `dask.bag:` unordered list of tuples (second order functions)
  - **Local and distributed schedulers:**
    threads, processes, YARN, Kubernetes, containers, HPC, and cloud, GPUs



- **Execution**
  - **Lazy evaluation**
  - Limitation: requires **static size inference**
  - Triggered via `compute()`

```
import dask.array as da

x = da.random.random(
  (10000,10000), chunks=(1000,1000))
y = x + x.T
y.persist() # cache in memory
z = y[::2, 5000:].mean(axis=1) # colMeans
ret = z.compute() # returns NumPy array
```

- **Discussion**
  - PySpark Competition (but not out-of-core), scalable ML algorithms via https://ml.dask.org/ (partnering w/ scikit-learn)

Task-Parallel Execution

Parallel Computation of Independent Tasks,
Emulation of Data-Parallel Operations/Programs

Overview Task-Parallelism

- **Historic Perspective**
  - Since 1980s: various parallel Fortran extensions, especially in HPC
  - **DOALL parallel loops** (independent iterations)
  - OpenMP (since 1997,Open Multi-Processing)

```
#pragma omp parallel for reduction(+: nnz)
for (int i = 0; i < N; i++) {
  int threadID = omp_get_thread_num();
  R[i] = foo(A[i]);
  nnz += (R[i]!=0) ? 1 : 0;
}
```

- **Motivation: Independent Tasks in ML Workloads**
  - **Use cases:** Ensemble learning, cross validation, hyper-parameter tuning, complex models with disjoint/overlapping/all data per task
  - **Challenge #1:** Adaptation to data and cluster characteristics
  - **Challenge #2:** Combination with data-parallelism

Parallel For Loops (ParFor)

[M. Boehm et al.: Hybrid Parallelization Strategies for Large-Scale Machine Learning in SystemML. **PVLDB 2014**]

- **Hybrid Parallelization Strategies**
  - Combination of **data- and task-parallel** ops
  - Combination of **local and distributed** computation
- **Key Aspects**
  - Dependency Analysis
  - Task partitioning
  - Data partitioning, scan sharing, rewrites
  - Execution strategies
  - Result agg strategies
  - **ParFor optimizer**

```
reg = 10^(seq(-1,-10))
B_all = matrix(0, nrow(reg), n)

parfor( i in 1:nrow(reg) ) {
   B = lm(X, y, reg[i,1]);
   B_all[i,] = t(B);
}
```

Local ParFor (multi-threaded), w/ local ops

Remote ParFor (distributed Spark job)

Local ParFor, w/ concurrent distributed ops

Additional ParFor Examples

- **Pairwise Pearson Correlation**
  - In practice: uni/bivariate stats
  - Pearson's R, Anova F, Chi-squared, Degree of freedom, P-value, Cramers V, Spearman, etc)

```
D = read("./input/D");
R = matrix(0, ncol(D), ncol(D));
parfor(i in 1:(ncol(D)-1)) {
   X = D[ ,i];
   sX = sd(X);
   parfor(j in (i+1):ncol(D)) {
      Y = D[ ,j];
      sY = sd(Y);
      R[i,j] = cov(X,Y)/(sX*sY);
}  }
write(R, "./output/R");
```

- **Batch-wise CNN Scoring**
  - Emulate data-parallelism for complex functions

```
prob = matrix(0, Ni, Nc)
parfor( i in 1:ceil(Ni/B) ) {
   Xb = X[((i-1)*B+1):min(i*B,Ni),];
   prob[((i-1)*B+1):min(i*B,Ni),] =
      ... # CNN scoring
}
```

➔ **Conceptual Design: Coordinator/worker** (task: group of parfor iterations)

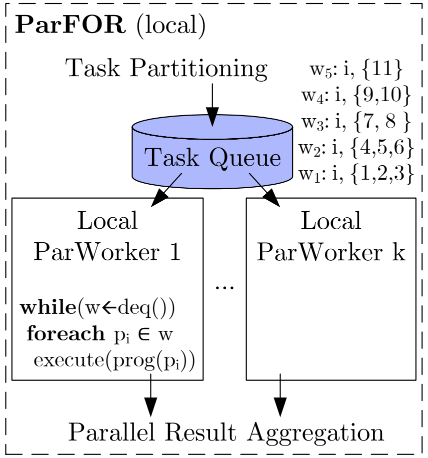
ParFor Execution Strategies

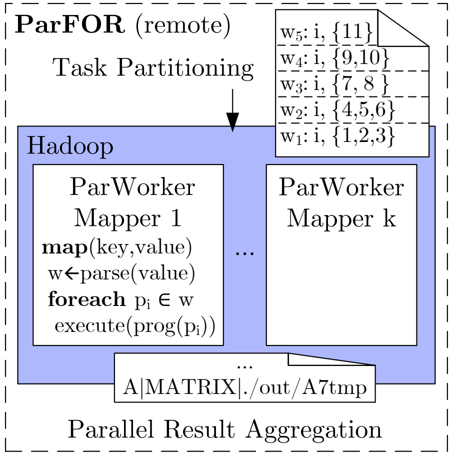
- **#1 Task Partitioning**
  - Fixed-size schemes: naive (1) , static (n/k), fixed (m)
  - Self-scheduling: e.g., guided self scheduling, factoring
- **#2 Data Partitioning**
  - Local or remote row/column partitioning (incl locality)
- **#3 Task Execution**
  - Local (multi-core) execution
  - Remote (MR/Spark) execution
- **#4 Result Aggregation**
  - With and without compare (non-empty output variable)
  - Local in-memory / remote MR/Spark result aggregation

Factoring (n=101, k=4)

$$R_0 = N, \quad R_{i+1} = R_i - k \cdot l_i, \qquad l_i = \left\lceil \frac{R_i}{x_i \cdot k} \right\rceil = \left\lceil \left(\frac{1}{x_i}\right)^{i+1} \frac{N}{k} \right\rceil$$

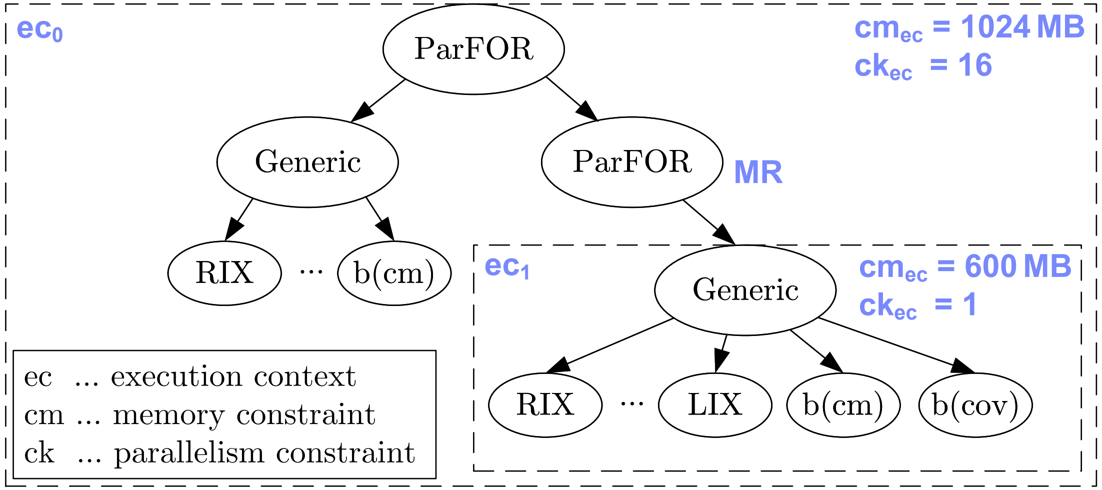
(13,13,13,13, 7,7,7,7, 3,3,3,3, 2,2,2,2, 1)





ParFor Optimizer Framework

- **Design: Runtime optimization for each top-level parfor**
- **Plan Tree P**
  - Nodes N_P
    - Exec type et
    - Parallelism k
    - Attributes A
  - Height h
  - Exec contexts EC_P



- **Plan Tree Optimization Objective**

$$\phi_2 : \min \quad \hat{T}(r(P))$$
$$s.t. \quad \forall ec \in \mathcal{EC}_P : \hat{M}(r(ec)) \leq cm_{ec} \ \wedge \ K(r(ec)) \leq ck_{ec}.$$

- **Heuristic optimizer w/ transformation-based search strategy**
  - Cost and memory estimates w/ plan tree aggregate statistics

Task-Parallelism in R

- **Multi-Threading**
  - doMC as multi-threaded foreach backend
  - Foreach w/ parallel (%dopar%) or sequential (%do%) execution

```
library(doMC)
registerDoMC(32)
R <- foreach(i=1:(ncol(D)-1),
             .combine=rbind) %dopar% {
   X = D[,i]; sX = sd(X);
   Ri = matrix(0, 1, ncol(D))
   for(j in (i+1):ncol(D)) {
      Y = D[,j]; sY = sd(Y)
      Ri[1,j] = cov(X,Y)/(sX*sY);
   }
   return(Ri);
}
```

[https://cran.r-project.org/web/packages/doMC/vignettes/gettingstartedMC.pdf]

- **Distribution**
  - doSNOW as distributed foreach backend
  - MPI/SOCK as comm methods

```
library(doSNOW)
clust = makeCluster(
   c("192.168.0.1", "192.168.0.2",
   "192.168.0.3"), type="SOCK");
registerDoSNOW(clust);
... %dopar% ...
stopCluster(clust);
```

[https://cran.r-project.org/web/packages/doSNOW/doSNOW.pdf]

Task-Parallelism in Other Systems

- **MATLAB**
  - Parfor loops for multi-process & distributed loops
  - Use-defined par

```
matlabpool 32
c = pi; z = 0;
r = rand(1,10)
parfor i = 1 : 10
  z = z+1;  # reduction
  b(i) = r(i); # sliced
end
```

[Gaurav Sharma, Jos Martin: MATLAB®: A Language for Parallel Computing. Int. **Journal on Parallel Prog. 2009**]

- **Julia**
  - Dedicated macros: `@threads` `@distributed`

```
a = zeros(1000)
@threads for i in 1:1000
  a[i] = rand(r[threadid()])
end
```

[https://docs.julialang.org/en/v1/manual/parallel-computing/]

- **TensorFlow**
  - User-defined parallel iterations
  - Responsible for correct results or acceptable approximate results

```
tf.while_loop(cond, body, loop_vars,
  parallel_iterations=10,
  swap_memory=False,
  maximum_iterations=None, ...)
```

[https://www.tensorflow.org/api_docs/python/tf/while_loop]

Task-Parallelism in Other Systems, cont.

- **sk-dist** [https://pypi.org/project/sk-dist/]
  - Distributed training of local scikit-learn models (via **PySpark**)
  - **Grid Search** / **Cross Validation** (hyper-parameter optimization)
  - **Multi-class Training** (one-against the rest)
  - **Tree Ensembles** (many decision trees)

- **Model Hopper Parallelism (MOP)**
  - Given a dataset D, p workers, and several NN configurations S
  - Partition D into worker-local partitions D_p
  - **Schedule tasks for sub-epochs** of $S' \subseteq S$ on p without moving the partitioned data
  - Checkpointing of models between tasks

[Supun Nakandala, Yuhao Zhang, Arun Kumar: Cerebro: Efficient and Reproducible Model Selection on Deep Learning Systems. **DEEM@SIGMOD 2019**]

[Supun Nakandala, Yuhao Zhang, Arun Kumar: Cerebro: A Data System for Optimized Deep Learning Model Selection. **PVLDB 2020**]

- **Reinforcement Learning Frameworks**
- **Future-based Task Graphs (Ray, Pathways,** UPLIFT**)**

$\Big\}$ Part of **Next Lecture**

Summary & QA

- **Categories of Execution Strategies**
  - Data-parallel execution for batch ML algorithms
  - Task-parallel execution for custom parallelization of independent tasks
  - Parameter servers (data-parallel vs model-parallel) for mini-batch ML algorithms

- **#1 Different strategies (and systems) for different ML workloads → Specialization & abstraction**
- **#2 Awareness of underlying execution frameworks**
- **#3 Awareness of effective compilation and runtime techniques**

- **Next Lectures**
  - 06 Parameter Servers [**May 31, virtual**]
  - 07 Hybrid Execution and HW Accelerators [Jun 08]
  - 08 Caching, Partitioning, Indexing, and Compression [Jun 15]