

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)

■ #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

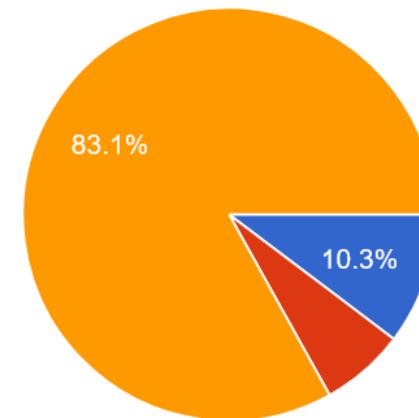
https://mboehm7.github.io/teaching/ss25_aml/index.htm



■ #2 Projects and Exercises

- **Project Selection May 01**

- Mentoring emails for projects **May 08**, **two corrections**
- Alternative exercise still possible



- SystemDS Project
- DAPHNE Project
- Alternative Exercise

**164 students
in 96 teams**

Agenda



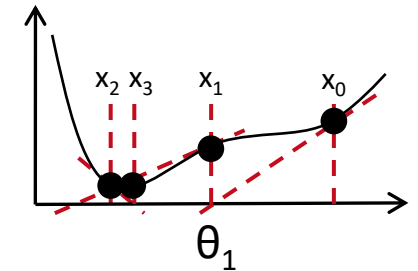
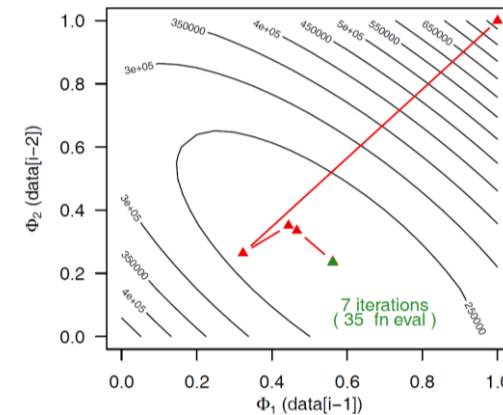
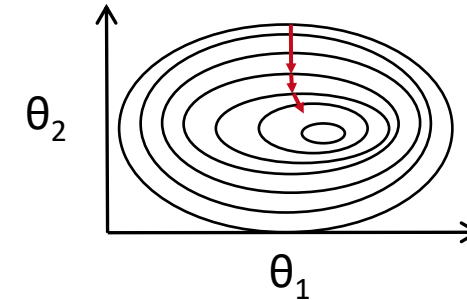
- **Motivation and Terminology**
- **Background MapReduce and Spark**
- **Data-Parallel Execution**
- **Task-Parallel Execution**

Motivation and Terminology

Terminology Optimization Methods



- **Problem:** Given a continuous, differentiable function $f(D, \theta)$, find optimal parameters $\theta^* = \operatorname{argmin} (f(D, \theta))$
- **#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

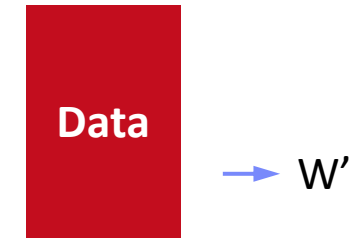


Terminology Batch/Mini-batch



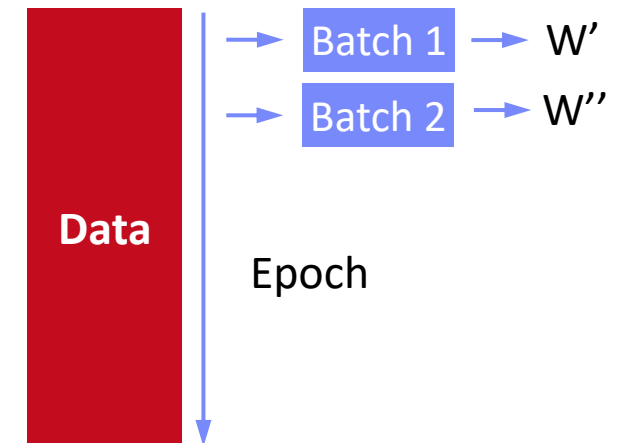
■ Batch ML Algorithms

- 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]

■ 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**

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

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

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

a								
b								
c								

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)

```
mboehm@alpha: ~/mv
mboehm@alpha:~/mv$ cpufetch
```



```
Name: Intel(R) Xeon(R) Gold 6238R CPU @ 2.20GHz
Microarchitecture: Cascade Lake
Technology: 14nm
Max Frequency: 4.000 GHz
Sockets: 2
Cores: 28 cores (56 threads)
Cores (Total): 56 cores (112 threads)
AVX: AVX,AVX2,AVX512
FMA: FMA3
L1i Size: 32KB (1.75MB Total)
L1d Size: 32KB (1.75MB Total)
L2 Size: 1MB (56MB Total)
L3 Size: 38.5MB (77MB Total)
Peak Performance: 14.34 TFLOP/s
```

Two red arrows point from the right towards the 'Sockets: 2' and 'Peak Performance: 14.34 TFLOP/s' lines in the terminal output.

```
mboehm@alpha:~/mv$
```

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

■ 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., Parameter Server)

Recap: Fault Tolerance & Resilience



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

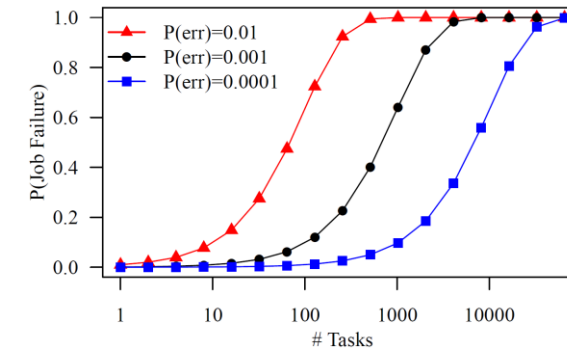
■ Resilience Problem

- 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



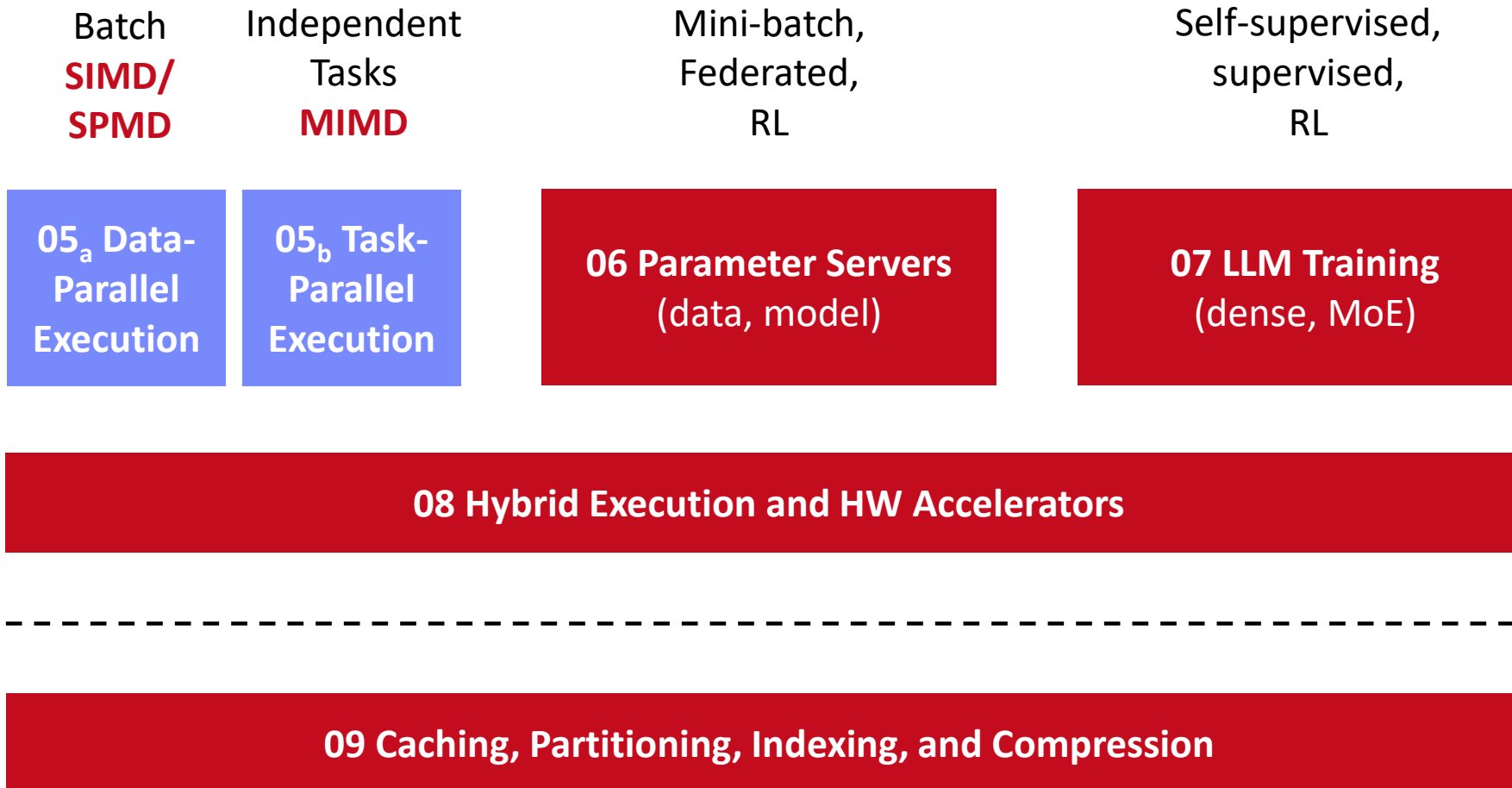
■ ML-specific Approaches (exploit app characteristics)

- Estimate contribution from lost partition to avoid stragglers
- 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



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)

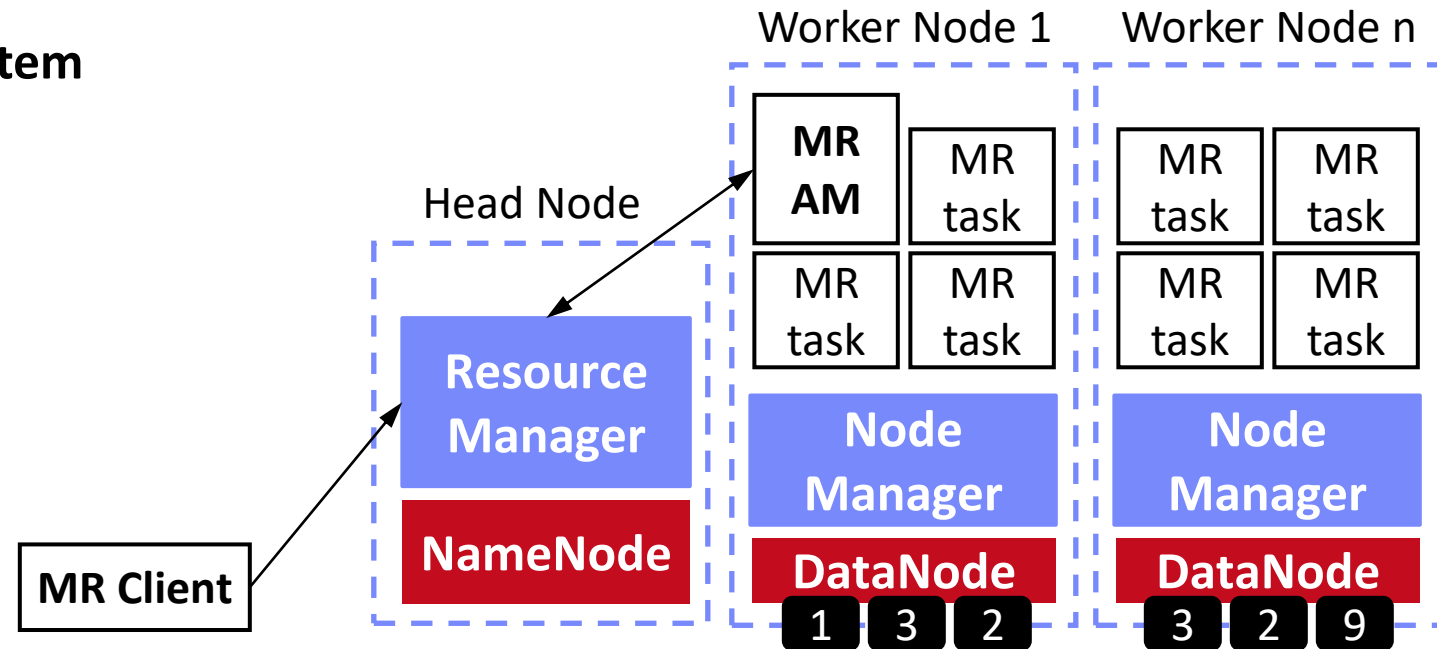


[Jeffrey Dean, Sanjay Ghemawat:
MapReduce: Simplified Data Processing
on Large Clusters. **OSDI 2004**]



■ 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

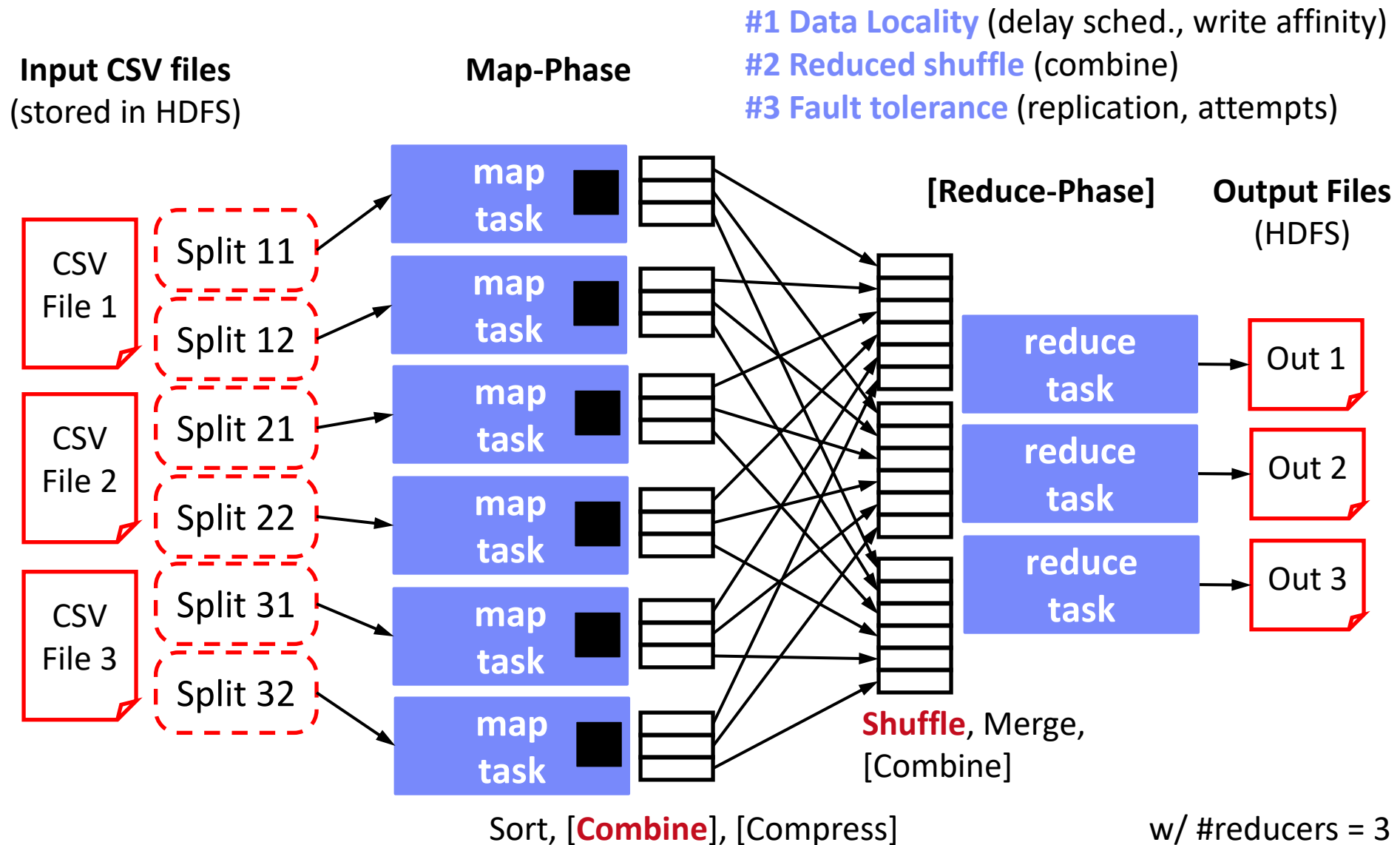
```
map(Long pos, String line) {  
  parts ← line.split(",")  
  emit(parts[1], 1)  
}
```

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



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

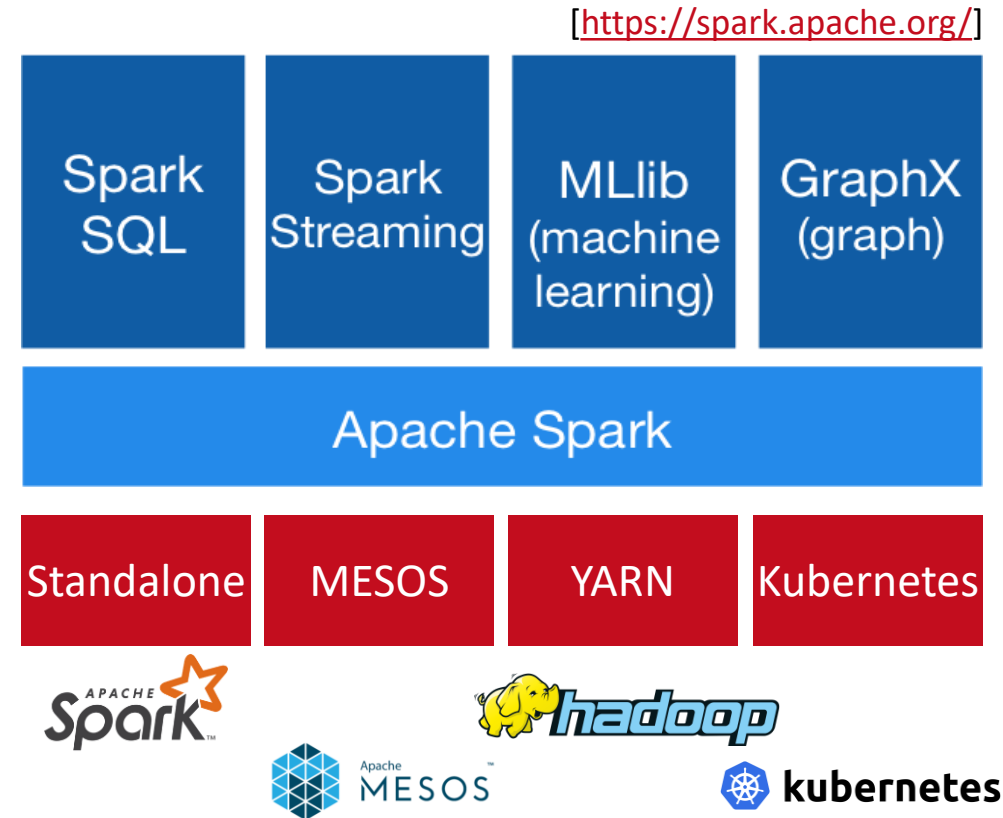
- **Implicit parallelism through dist. collections** (data access, fault tolerance)
- Resource negotiators (YARN, Mesos, Kubernetes)
- HDFS and object store connectors (e.g., Swift, S3)

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



- 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>`

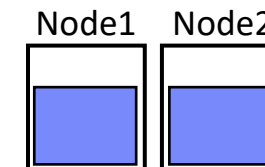
■ Operations

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

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

■ 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)

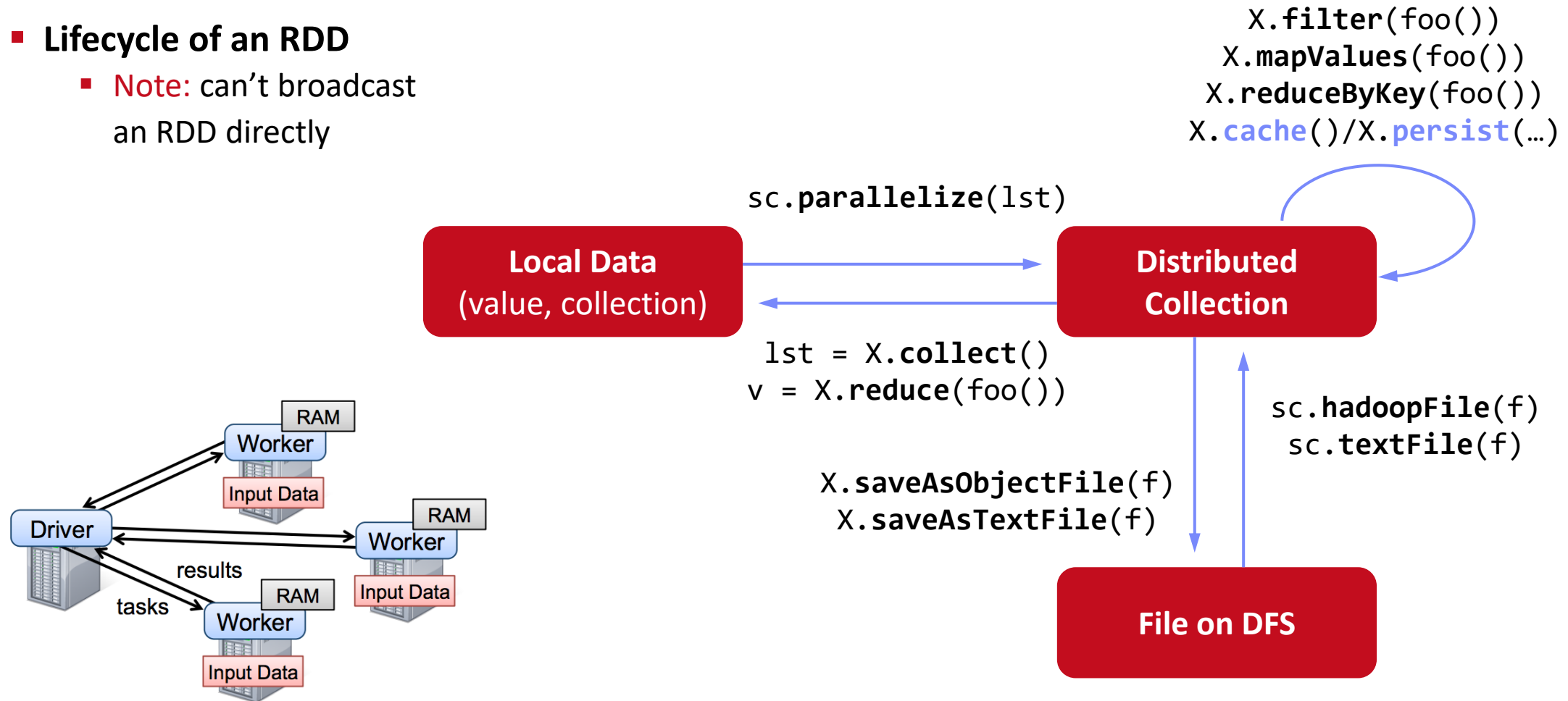


Spark Resilient Distributed Datasets (RDDs), cont.



■ 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:

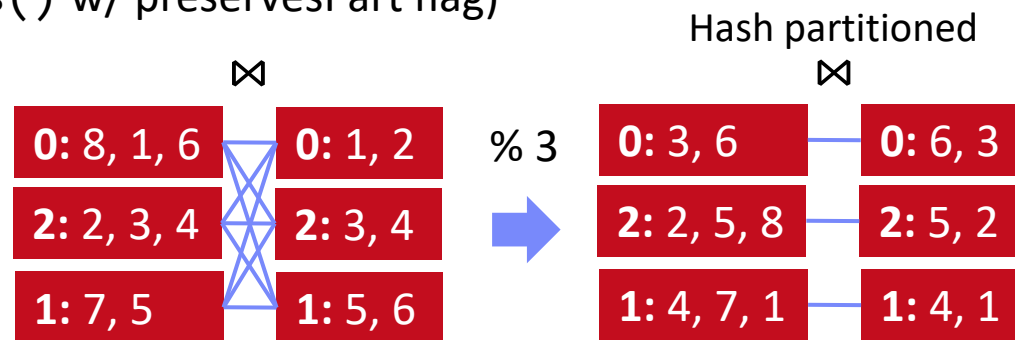
For all (k,v) of R:
 $pid = \text{hash}(k) \% n$

■ Partitioning-Preserving

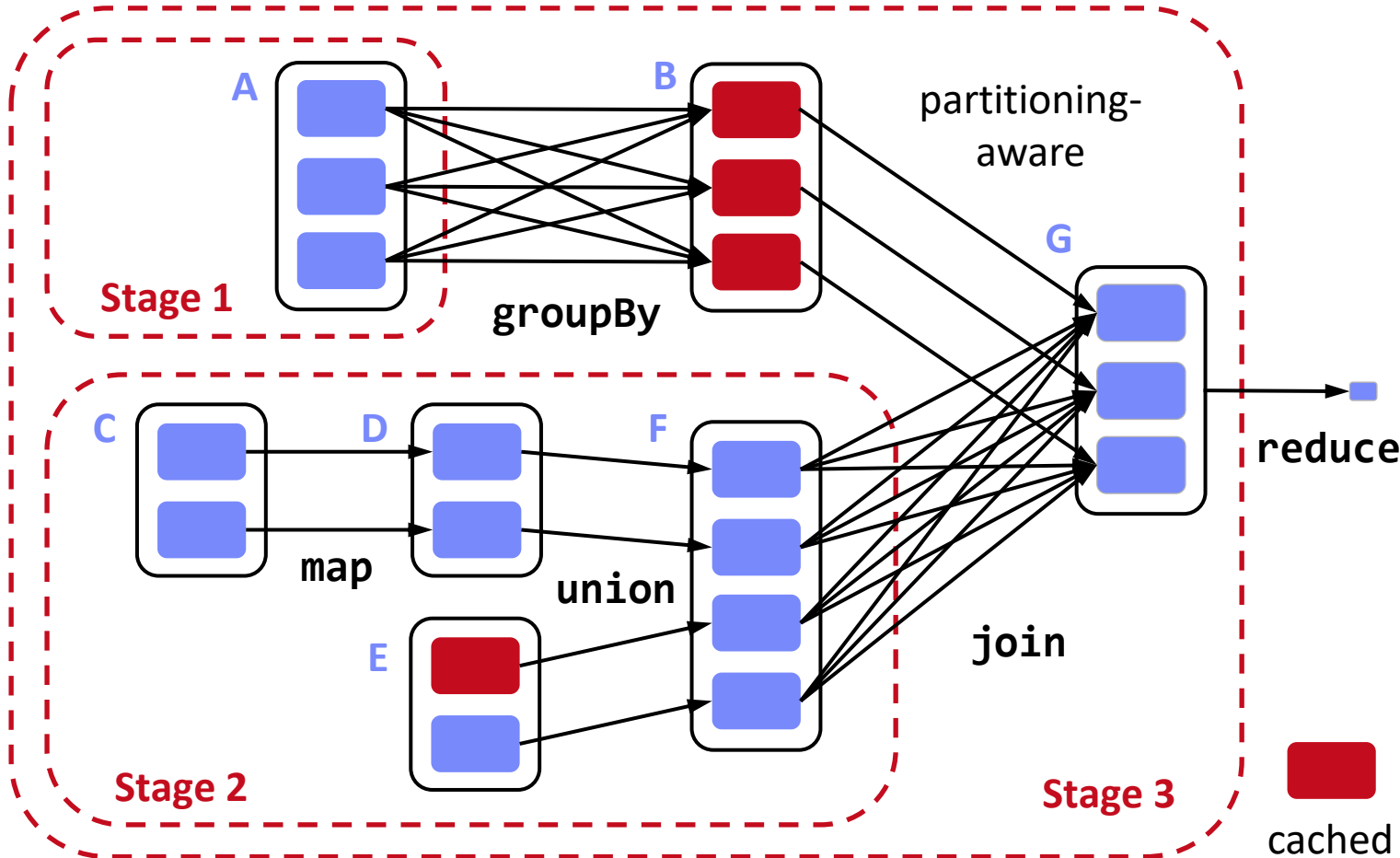
- All operations that are guaranteed to keep keys unchanged (e.g. `mapValues()`, `mapPartitions()` w/ `preservesPart` flag)

■ 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** ($m \times n$)

- 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)

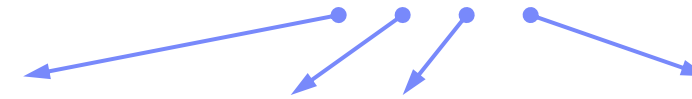
Dense (row-major)

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

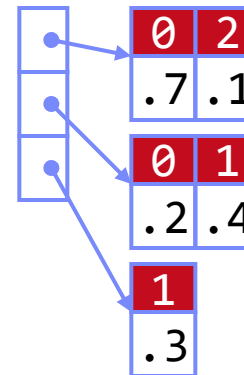
$O(mn)$

Example
3x3 Matrix

.7		.1
.2	.4	
	.3	

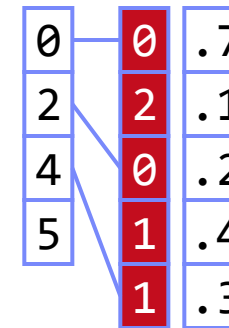


MCSR

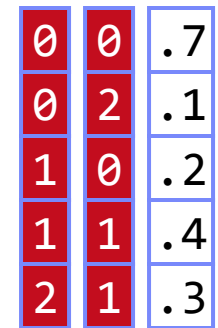


$O(m + \text{nnz}(X))$

CSR



COO



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

■ 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

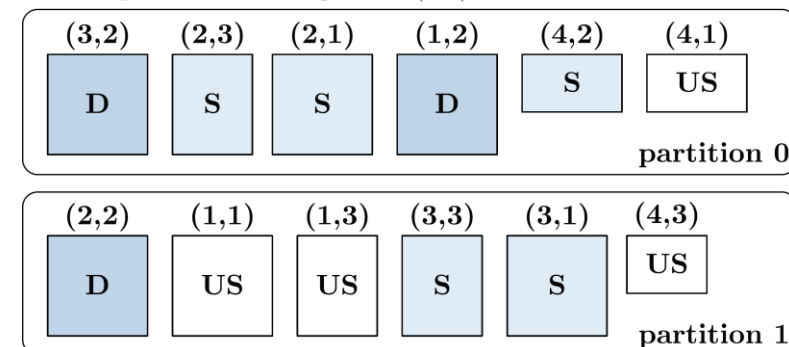
- Logical Partitioning
(e.g., row-/column-wise)
- Physical Partitioning
(e.g., hash / grid)
- Influences **partition-local aggregation**

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

(1,1)	(1,2)	(1,3)
(2,1)	(2,2)	(2,3)
(3,1)	(3,2)	(3,3)
(4,1)	(4,2)	(4,3)

**Physical Blocking
and Partitioning**

hash partitioned: e.g., $\text{hash}(3,2) \rightarrow 99,994 \% 2 = 0$

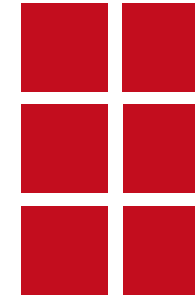


Distributed Matrix Representations, cont.



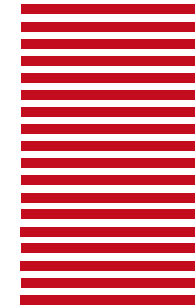
■ #1 Block-partitioned Matrices

- 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

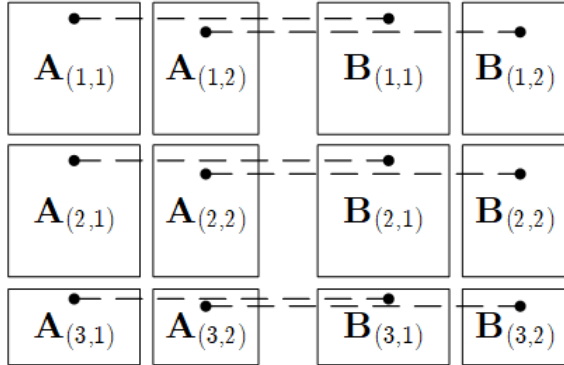


■ #3 Algorithm-specific Partitioning

- Operation and algorithm-centric data representations (e.g., matrix **inverse**, matrix **factorization**)

Elementwise Multiplication (Hadamard Product)

$$C = A * B$$

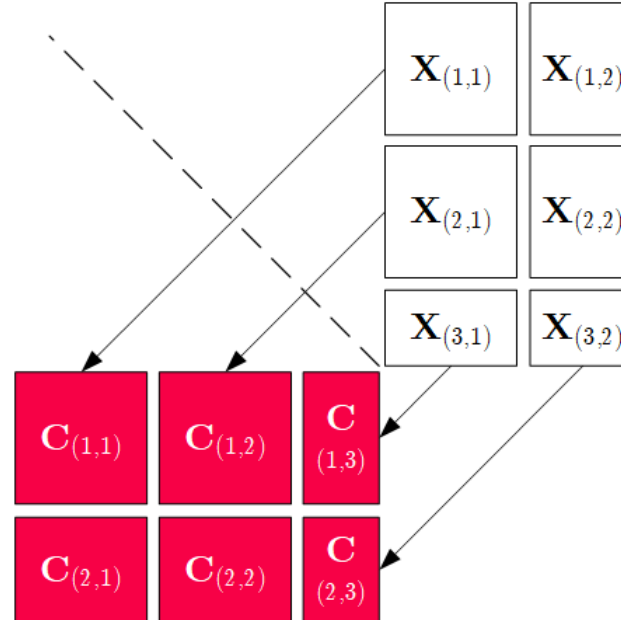


1:1 join

Note: also with
row/column vector rhs

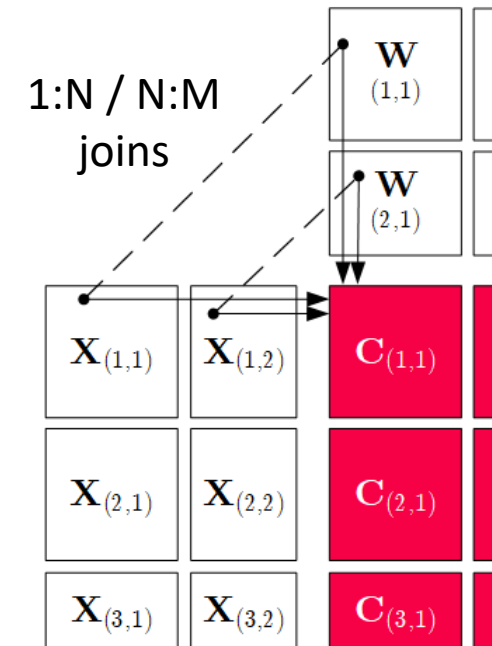
Transposition

$$C = t(X)$$



Matrix Multiplication

$$C = X \%* \% W$$



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`, `tmm`, `mmchain`; Samsara/Mllib local

■ #1 Special Operators (special patterns/sparsity)

- SystemML `tmm`, `mapmmchain`; Samsara AtA

■ #2 Broadcast-Based Operators (aka broadcast join)

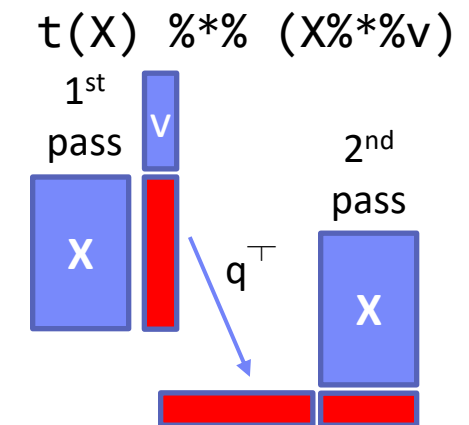
- SystemML `mapmm`, `mapmmchain`

■ #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

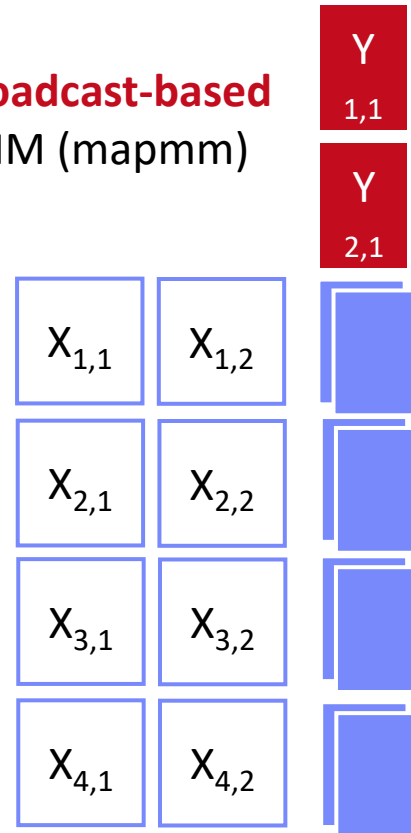


Physical Operator Selection – Example Matrix Multiplication, cont.

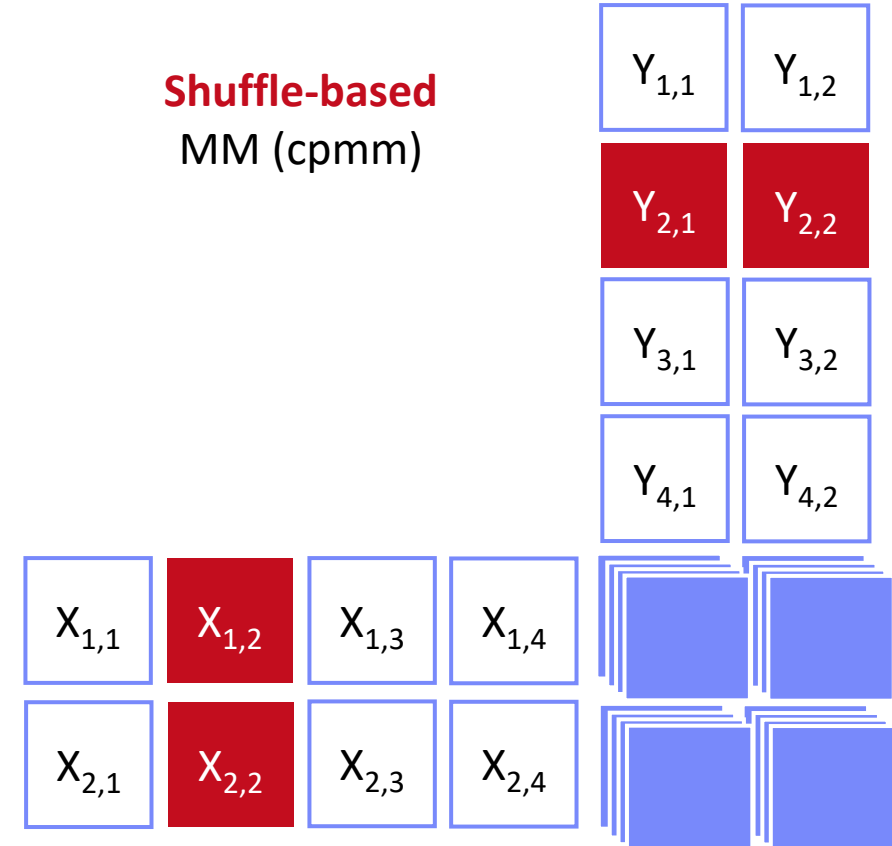


- Examples
Distributed
MM Operators

Broadcast-based
MM (mapmm)



Shuffle-based
MM (cpmm)



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
 - $\text{ncol}(X) \leq B_c$

```
parfor(iter_class in 1:num_classes) {  
    Y_local = 2 * (Y == iter_class) - 1  
    g_old = t(X) %*% Y_local  
    ...  
    while( continue ) {  
        Xd = X %*% s  
        ... 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) ...  
    }  
}
```

← **repart, chkpt X MEM_DISK**

← **chkpt y_local MEM_DISK**

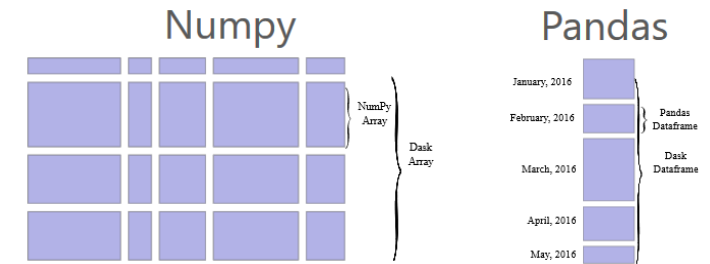
← **chkpt Xd, Xw MEM_DISK**

zipmm



■ 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()`

■ Discussion

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

```
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
```

Modin (UC Berkeley → Ponder → Snowflake)

[Devin Petersohn, et al.:
Towards Scalable Dataframe
Systems. **PVLDB 2020**]



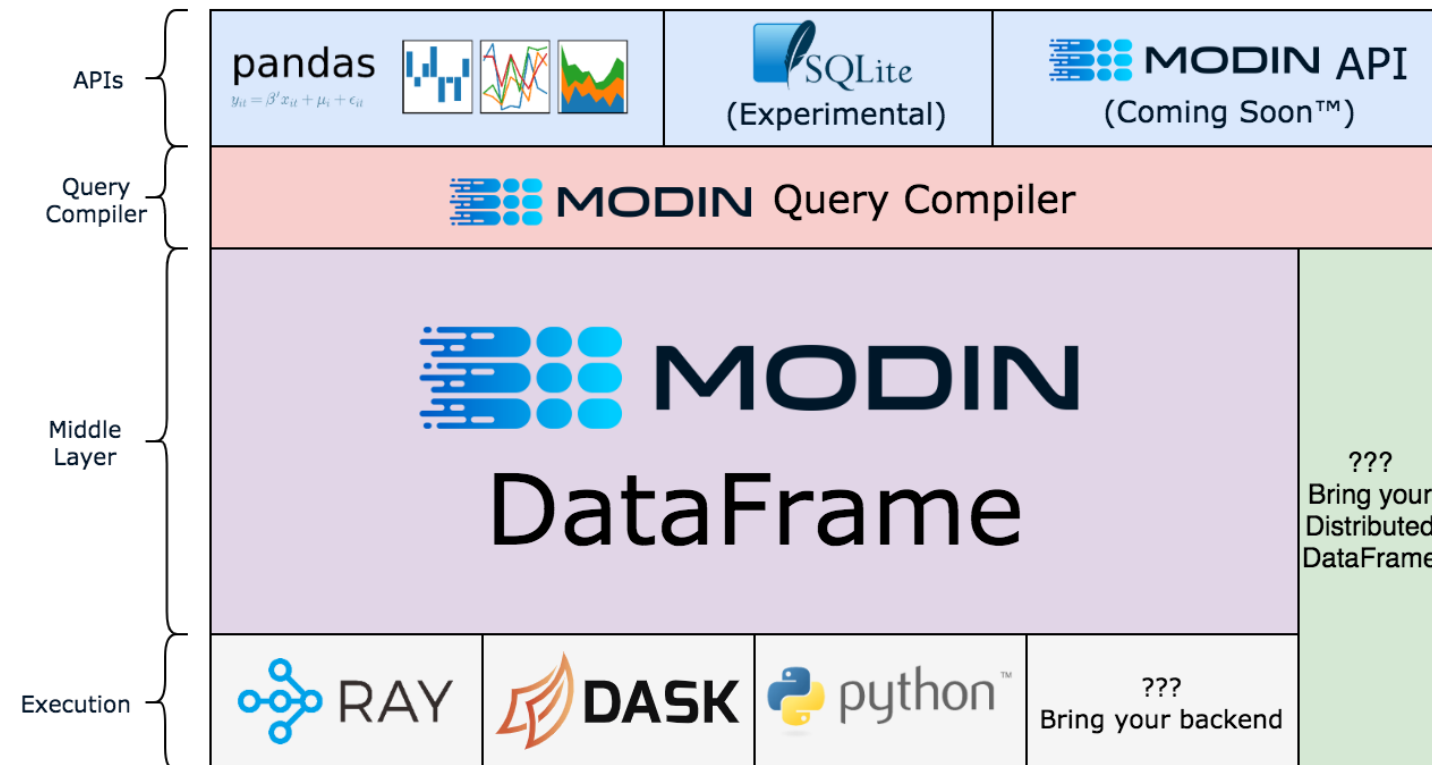
[Devin Petersohn, et al: Flexible Rule-Based
Decomposition and Metadata Independence in
Modin: A Parallel Dataframe System. **PVLDB 2021**]



■ Overview Modin

- **Goal:** Enhance **Pandas data frames**
- Convert Pandas API to **core algebra expressions**
- Different Backends:
Ray, Dask, MPI

[<https://github.com/modin-project/modin>]



Task-Parallel Execution

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



■ 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

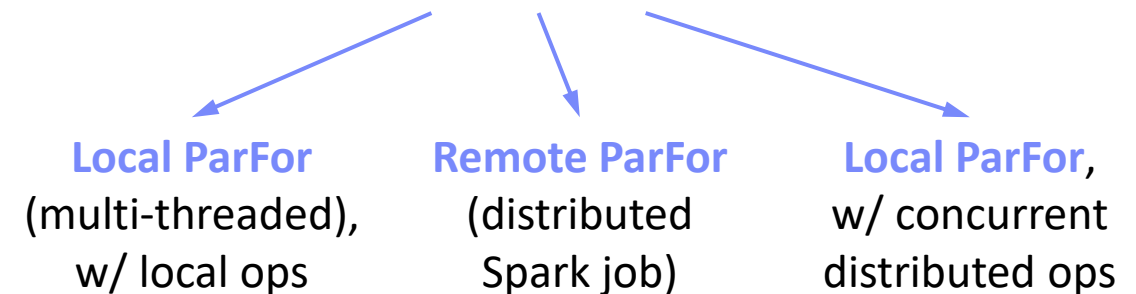
- Combination of **data- and task-parallel** ops
- Combination of **local and distributed** computation

■ 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);  
}
```



■ 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)

■ #1 Task Partitioning

- Fixed-size schemes: naive (1) , static (n/k), fixed (m)
- Self-scheduling: e.g., guided self scheduling, factoring

Factoring (n=101, k=4)

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

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

■ #2 Data Partitioning

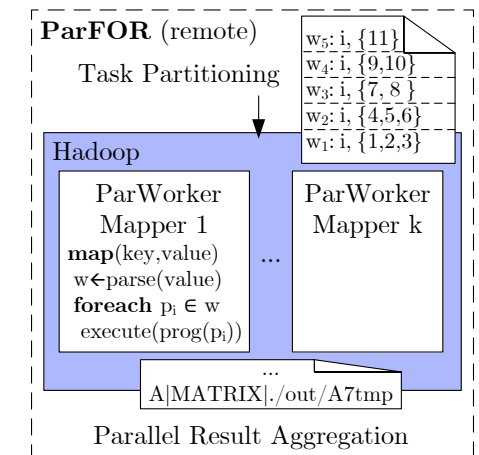
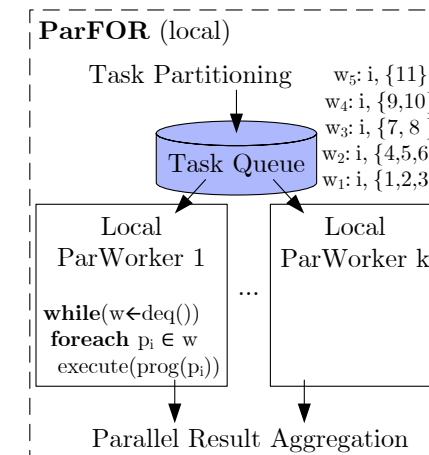
- Local or remote row/column partitioning (incl locality)

■ #3 Task Execution

- Local (multi-core) execution
- Remote (MR/Spark) execution

■ #4 Result Aggregation

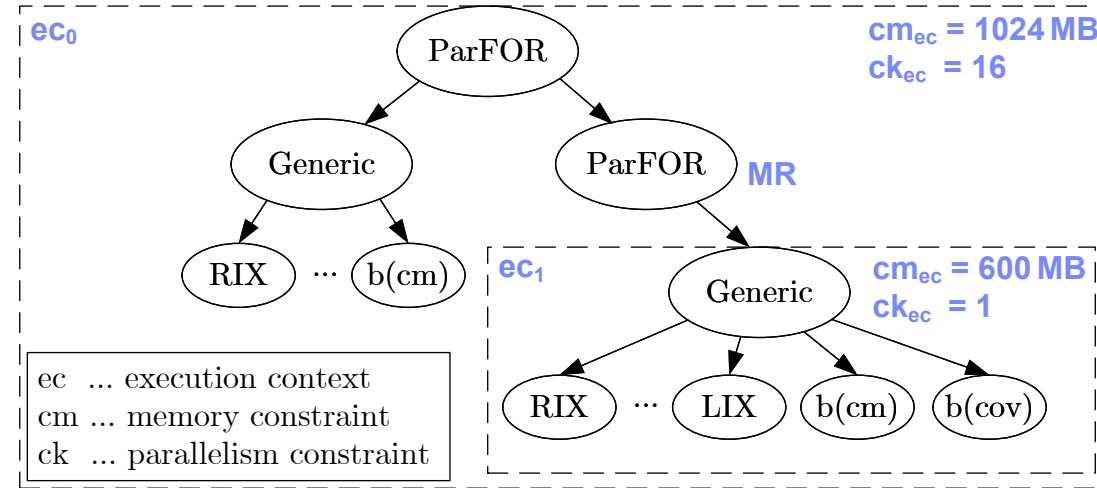
- With and without compare (non-empty output variable)
- Local in-memory / remote MR/Spark result aggregation



- **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

$$\phi_2 : \min \hat{T}(r(P))$$

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

- **Heuristic optimizer w/ transformation-based search strategy**

- Cost and memory estimates w/ plan tree aggregate statistics

■ 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);
}
```

[\[https://cran.r-project.org/web/packages/doMC/vignettes/gettingstartedMC.pdf\]](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);
```

[\[https://cran.r-project.org/web/packages/doSNOW/doSNOW.pdf\]](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/](https://docs.julialang.org/en/v1/manual/parallel-computing/)]

■ TensorFlow

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

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



[[https://www.tensorflow.org/
api_docs/python/tf/nn/parallel_loop_run](https://www.tensorflow.org/api_docs/python/tf/nn/parallel_loop_run)]

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



Part of
Next Lecture



[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**]



- **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** (mini-batch) [May 22]
 - **07 LLM Training and Inference** [Jun 05]
 - **08 Hybrid Execution and HW Accelerators** [Jun 12]
 - **09 Caching, Partitioning, Indexing and Compression** [Jun 19]