Data Integration and Large-scale Analysis (DIA)

11 Distributed, Data-parallel Computation

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

Last update: Jan 13, 2024

Announcements / Administrative Items

- **#1 Video Recording**
  - Hybrid lectures: in-person H 0107, zoom live streaming, video recording
  - https://tu-berlin.zoom.us/j/9529634787?pwd=R1ZsN1M3SC9BOU1OcFdmem9zT202UT09

- **#2 Exam Registration**
  - **Time slots: Feb 08, 4pm** or **Feb 15, 4pm** (start 4.15pm, end 5.45pm, **48 seats per exam**)
  - Sign up for exam via ISIS (once you submitted the project/exercise), **opens Jan 18**
  - [If more capacity needed, additional slots Feb 08, 6pm and Feb 15, 6pm]

Course Outline Part B: Large-Scale Data Management and Analysis

12 Distributed Stream Processing

13 Distributed Machine Learning Systems

Compute/ Storage

11 Distributed Data-Parallel Computation

10 Distributed Data Storage

Infra

09 Cloud Resource Management and Scheduling

08 Cloud Computing Fundamentals

Agenda

- **Motivation and Terminology**
- **Data-Parallel Collection Processing**
- **Data-Parallel Data-Frame Operations**
- **Data-Parallel Computation in SystemDS**

Motivation and Terminology

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

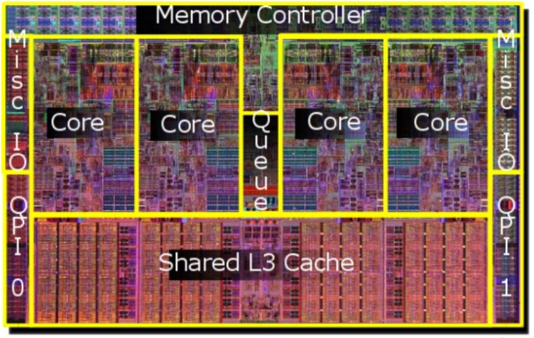
- **#2 Distributed Collections**
  - Logical multi-set (**bag**) of **key-value pairs** (**unsorted collection**)
  - Different physical representations
  - **Easy distribution** of pairs via horizontal partitioning (aka shards, partitions)
  - Can be created from single file, or directory of files (unsorted)

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

Excursus: Nehalem Architecture

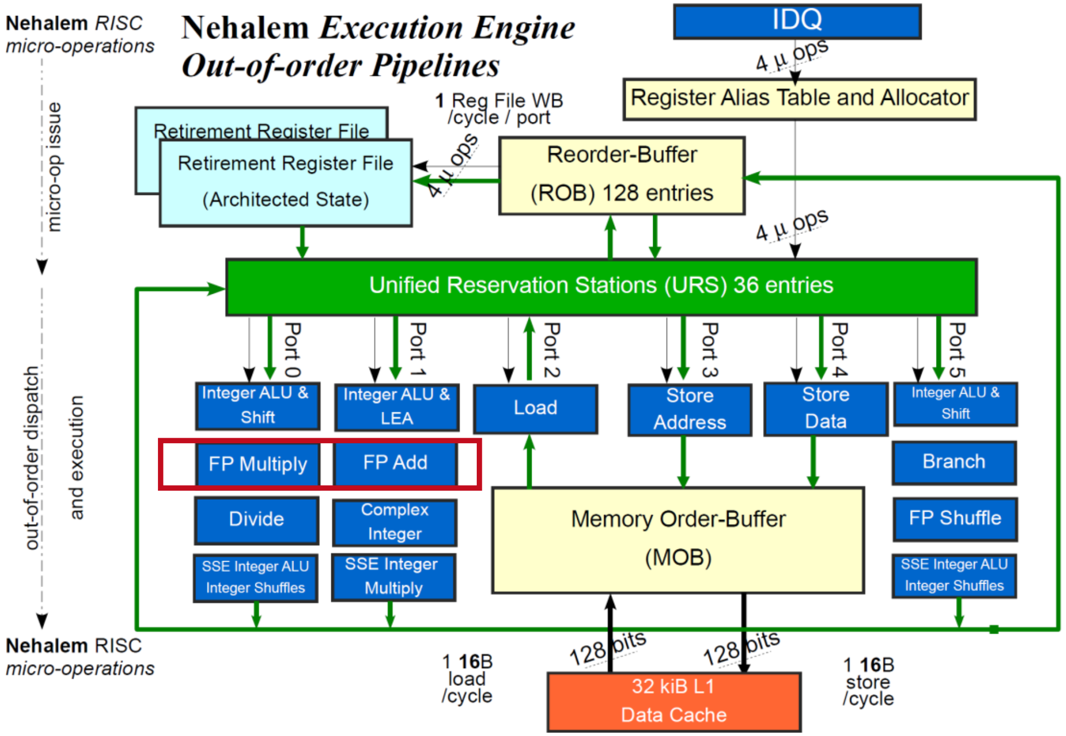
[Michael E. Thomadakis: The Architecture of the Nehalem Processor and Nehalem-EP SMP Platforms, Report, 2010]

- **Multi-core CPU**
  - 4 core w/ hyper-threading
  - **Per core:** L1i/L1d, L2 cache
  - **Per CPU:** L3 cache (8MB)
  - 3 memory channels (8B width, max 1.333Ghz)



QPI … Quick Path Interconnect

- **Instruction Pipeline**
  - **Frontend:** Instruction Fetch, Pre-Decode, and Decode
  - **Backend:** Rename/Allocate, Scheduler, Execute, Write-Back
- **Out-of-Order Execution Engine** (IPC=4)
  - 128b FP Multiply
  - 128b FP Add



Terminology Parallelism

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

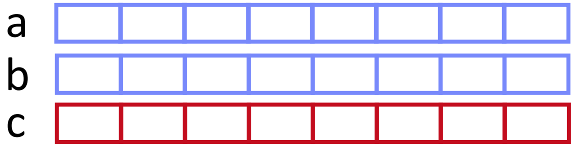
[Michael J. Flynn, Kevin W. Rudd: Parallel Architectures. **ACM Comput. Surv. 28(1) 1996**]

	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);
```



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., Parameter Server)

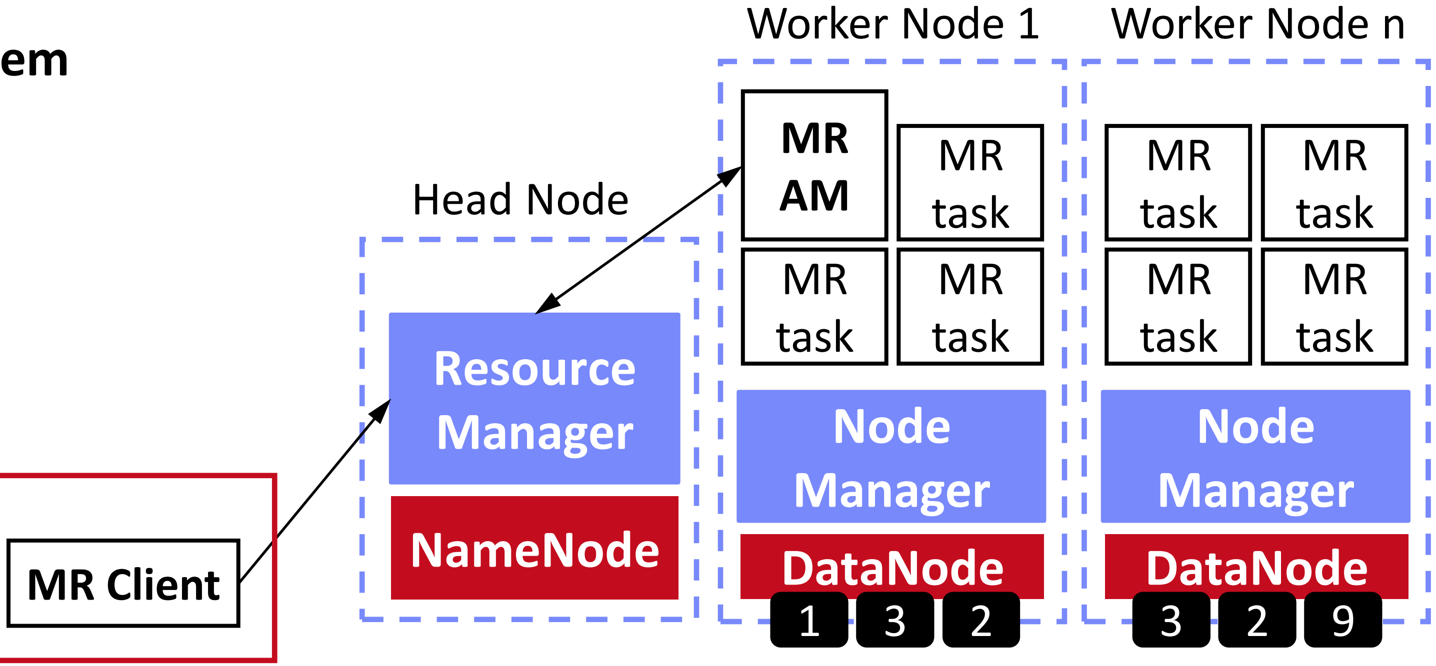
Data-Parallel Collection Processing

Hadoop History and Architecture

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

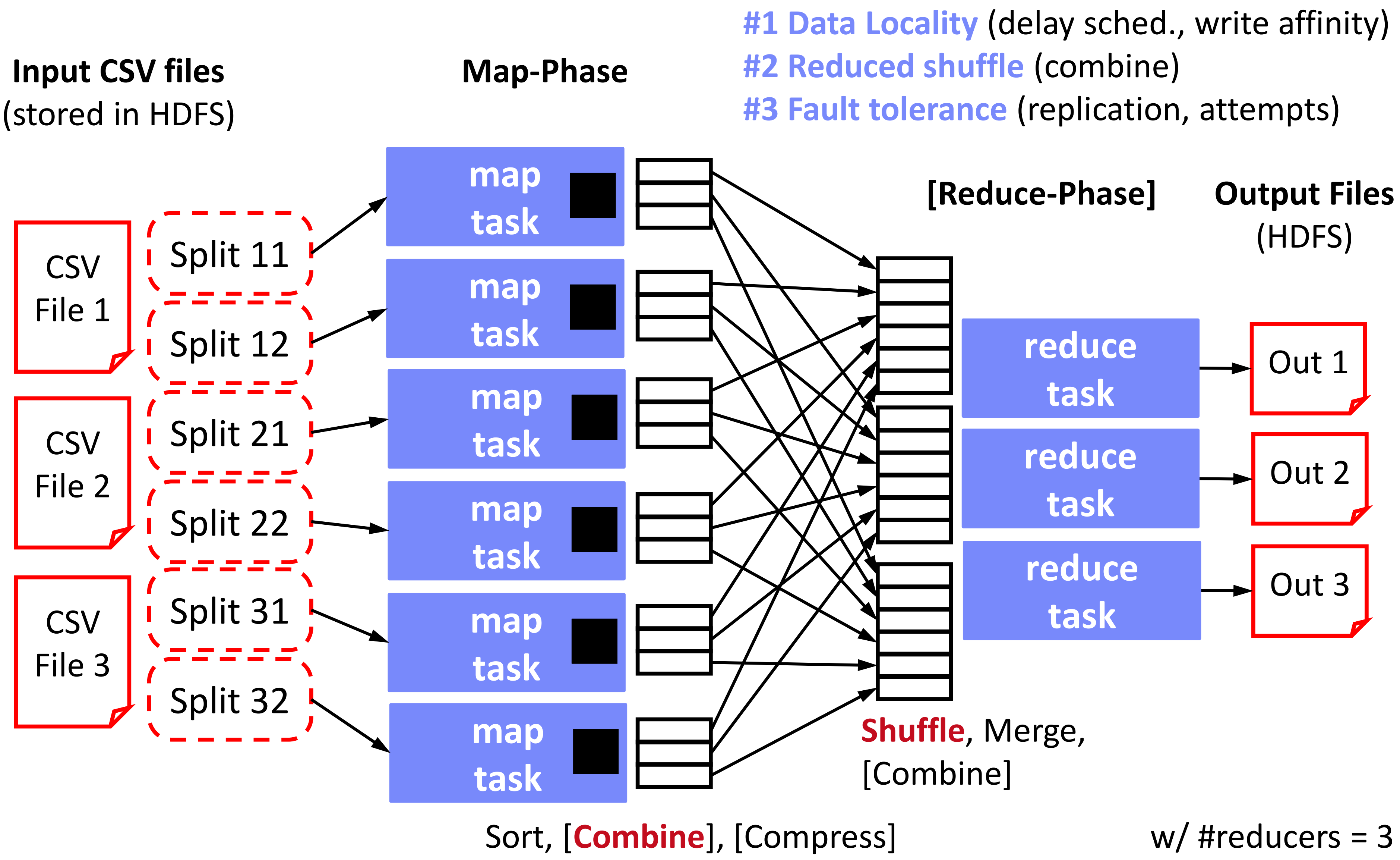
```
map(Long pos, String line) {
  parts ← line.split(“,”)
  emit(parts[1], 1)
}
```

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



MapReduce – Query Processing

- **Basic Unary Operations**
  - Selections (brute-force), projections
  - Ordering (e.g., **TeraSort**): Sample, pick k quantiles; shuffle-based partition sort
  - Additive and semi-additive aggregation with grouping, distinct

- **Binary Operations**
  - Set operations (union, intersect, difference) and joins
  - Different physical operators for R ⋈ S
    - **Broadcast join**: broadcast S, build HT S, map-side HJOIN
    - **Repartition join**: shuffle (repartition) R and S, reduce-side MJOIN
    - **Improved repartition join:** avoid buffering via key-tag sorting
    - **Directed join** (pre/co-partitioned): map-only, R input, S read side-ways

[Spyros Blanas et al.: A comparison of join algorithms for log processing in MapReduce. **SIGMOD 2010**]

- **Hybrid SQL-on-Hadoop Systems**
  - E.g.: Hadapt (HadoopDB), Impala, IBM BigSQL, Presto, Drill, Actian

[Daniel Abadi, Shivnath Babu, Fatma Ozcan, Ippokratis Pandis: Tutorial: SQL-on-Hadoop Systems. **PVLDB 2015**]

Spark History and Architecture

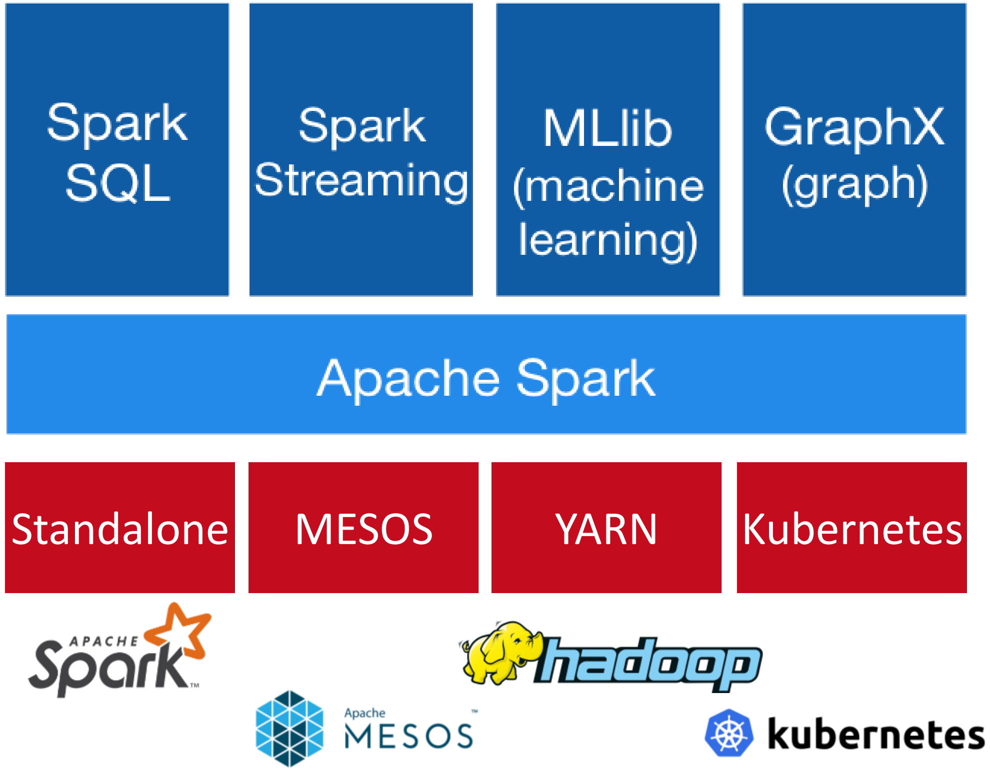
- **Summary MapReduce**
  - Large-scale & fault-tolerant processing w/ UDFs and files → **Flexibility**
  - Restricted functional APIs → **Implicit parallelism and fault tolerance**
  - **Criticism**: #1 **Performance**, #2 **Low-level APIs**, #3 **Many different systems**
- **Evolution to Spark** (and 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)

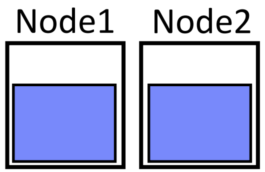
- **RDD Abstraction**
  - **Immutable**, partitioned **collections of key-value pairs**
  - **Coarse-grained** deterministic operations (transformations/actions)
  - Fault tolerance via lineage-based re-computation

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

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

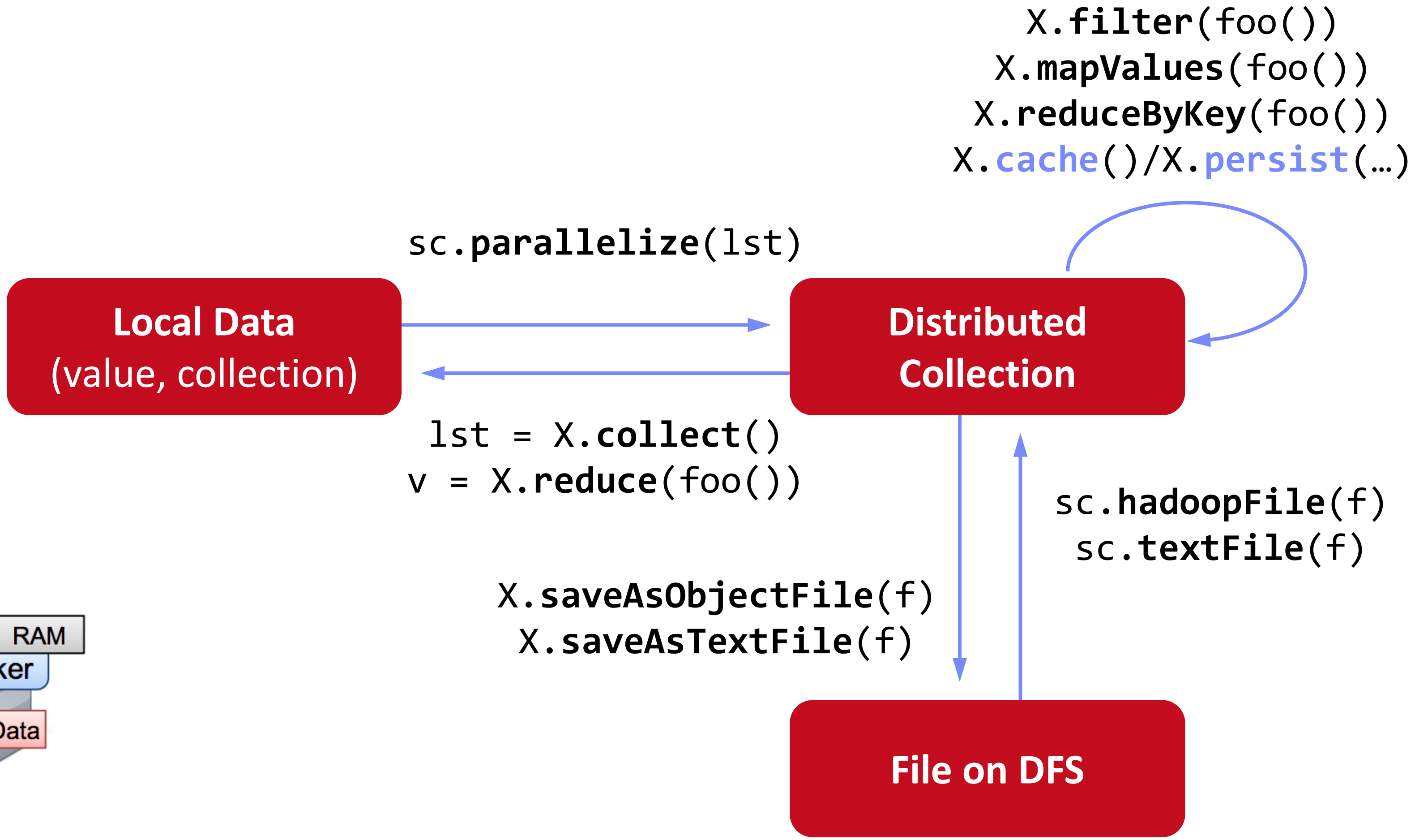
Type	Examples
Transformation (**lazy**)	`map`, `hadoopFile`, `textFile`, `flatMap`, `filter`, `sample`, `join`, `groupByKey`, `cogroup`, `reduceByKey`, `cross`, `sortByKey`, `mapValues`
Action	`reduce`, `save`, `collect`, `count`, `lookupKey`

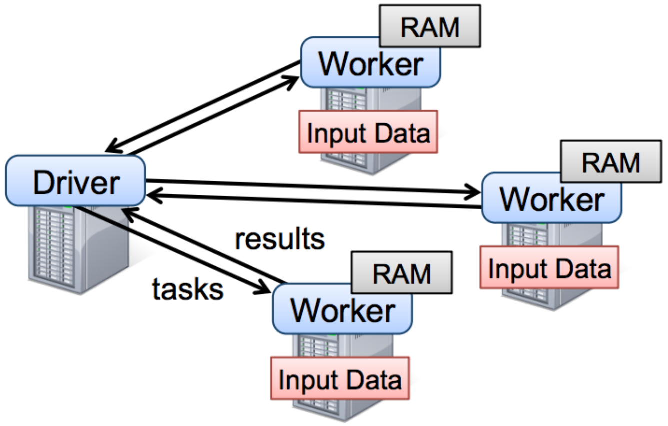
- **Distributed Caching**
  - Use fraction of worker **memory for caching**
  - Eviction at granularity of individual partitions
  - **Different storage levels** (e.g., mem/disk x serialization x compression)



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

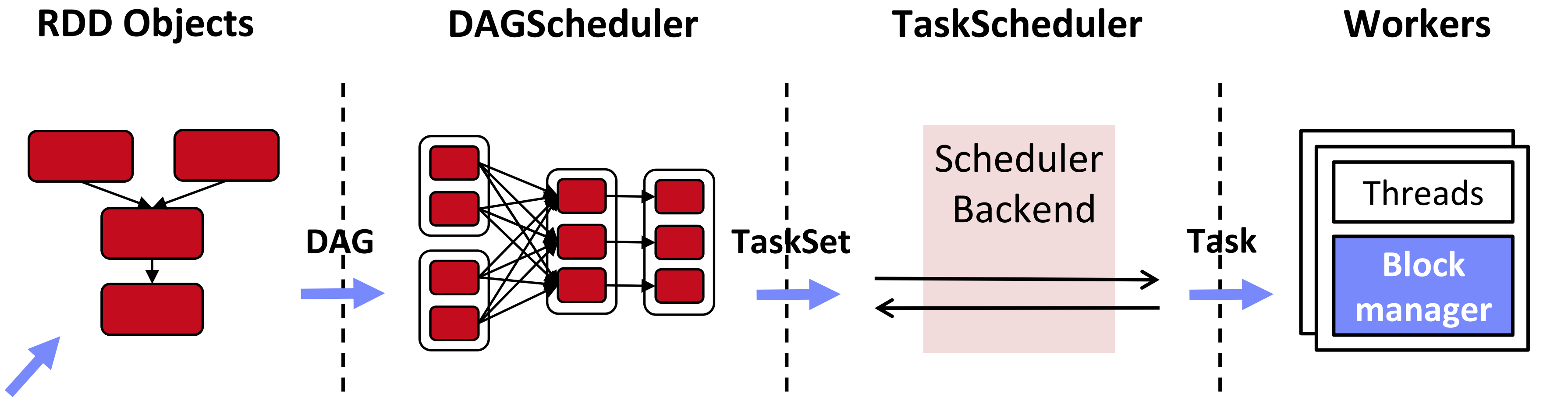
- **Partitioning via Partitioners**
  - Implicitly on every data shuffling
  - Explicitly via `R.repartition(n)`

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 Scheduling Process

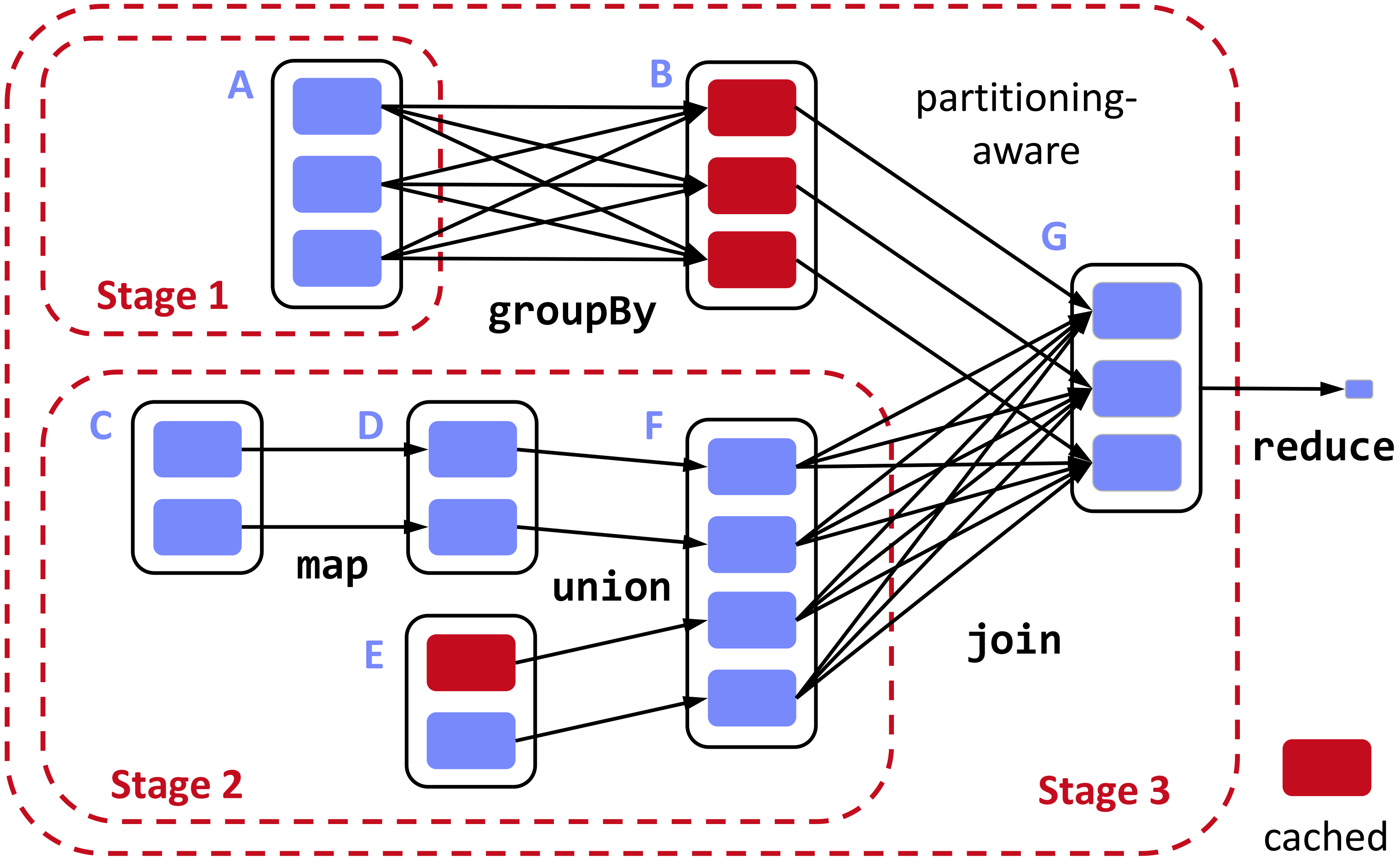
[Tilmann Rabl: Big Data Systems, HPI **WS2019/20**]




```
rdd1.join(rdd2)
    .reduceByKey(…)
    .filter(…)
```

RDD Objects	DAGScheduler	TaskScheduler	Workers
build operator DAG	split graph into stages of tasks	launch tasks at workers	execute tasks
	submit each stage as ready	retry failed or straggling tasks	store and serve blocks

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**]

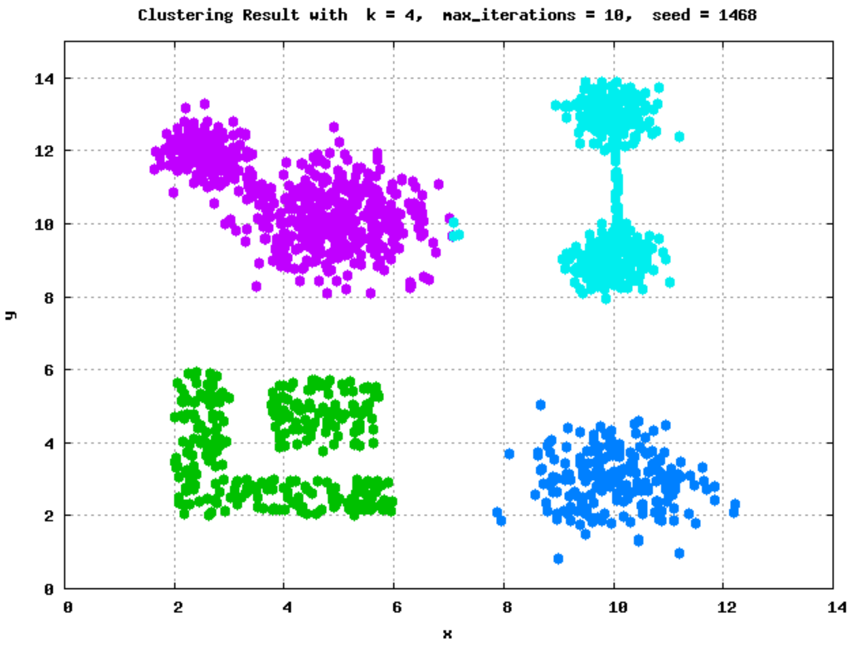
1. Reduce action triggers DAG compilation and evaluation
2. DAG compiled into job of multiple stages (3 here), demarcated by wide shuffle dependencies
3. Lost/evicted cached partitions are re-evaluated via partition lineage

Example: k-Means Clustering

- **k-Means Algorithm**
  - Given dataset D and number of clusters k, find cluster centroids ("mean" of assigned points) that minimize within-cluster variance
  - Euclidean distance: **sqrt**(**sum**((**a**-**b**)^2))

- **Pseudo Code**

```
function Kmeans(D, k, maxiter) {
  C‘ = randCentroids(D, k);
  C = {};
  i = 0; //until convergence
  while( C‘ != C & i<=maxiter ) {
    C = C‘;
    i = i + 1;
    A = getAssignments(D, C);
    C‘ = getCentroids(D, A, k);
  }
  return C‘
}
```



Example: k-Means Clustering in Spark

```
// create spark context (allocate configured executors)
JavaSparkContext sc = new JavaSparkContext();

// read and cache data, initialize centroids
JavaRDD<Row> D = sc.textFile("hdfs:/user/mboehm/data/D.csv")
  .map(new ParseRow()).cache(); // cache data in spark executors
Map<Integer,Mean> C = asCentroidMap(D.takeSample(false, k));

// until convergence
while( !equals(C, C2) & i<=maxiter ) {
  C2 = C; i++;
  // assign points to closest centroid, recompute centroid
  Broadcast<Map<Integer,Row>> bC = sc.broadcast(C)
  C = D.mapToPair(new NearestAssignment(bC))
       .foldByKey(new Mean(0), new IncComputeCentroids())
       .collectAsMap();
}

return C;
```

Note: Existing library algorithm
[https://github.com/apache/spark/blob/master/mllib/src/main/scala/org/apache/spark/mllib/clustering/KMeans.scala]

Data-Parallel Data-Frame Operations

Origins of DataFrames

- **Recap: Data Preparation Problem**
  - **80% Argument:** 80-90% time for finding, integrating, cleaning data
  - Data scientists prefer scripting languages and in-memory libraries

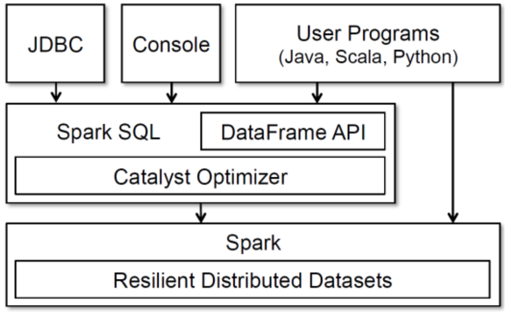
- **R and Python DataFrames**
  - R `data.frame/dplyr` and Python pandas DataFrame for seamless data manipulations (most popular packages/features)
  - DataFrame: **table with a schema**
  - Descriptive stats and basic math, reorganization, joins, grouping, windowing
  - **Limitation:** Only in-memory, single-node operations

- **Example Pandas**

```
import pandas as pd

df = pd.read_csv('data/tmp1.csv', index_col=2)
df.head() # df w/ indexes A-Z

df = pd.concat(df, df[['A','C']], axis=0)
```

Spark DataFrames and DataSets

- **Overview Spark DataFrame**
  - DataFrame is a **distributed collection of rows** with named/typed columns
  - Relational operations (e.g., projection, selection, joins, grouping, aggregation)
  - DataSources (e.g., json, jdbc, parquet, hdfs, s3, avro, hbase, csv, cassandra)



- **DataFrame and Dataset APIs**
  - DataFrame was introduced as basis for Spark SQL
  - DataSets allow **more customization** and compile-time analysis errors (Spark 2)

```
DataFrame = Dataset[Row]
```

- **Example DataFrame**

```
logs = spark.read.format("json").open("s3://logs")
logs.groupBy(logs.user_id).agg(sum(logs.time))
  .write.format("jdbc").save("jdbc:mysql//...")
```

[Michael Armbrust: Structuring Apache Spark – SQL, DataFrames, Datasets, and Streaming, **Spark Summit 2016**]

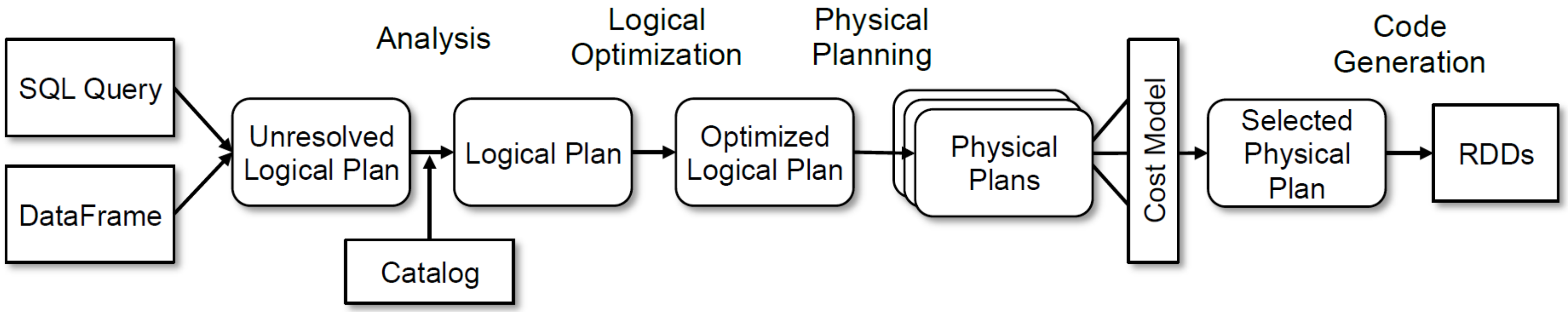
→ **PySpark**

SparkSQL and DataFrame/Dataset

[Michael Armbrust et al.: Spark SQL: Relational Data Processing in Spark. **SIGMOD 2015**]

- **Overview SparkSQL**
  - Shark (~2013): academic prototype for SQL on Spark
  - **SparkSQL** (~2015): reimplementation from scratch
  - Common IR and compilation of SQL and DataFrame operations

- **Catalyst: Query Planning**

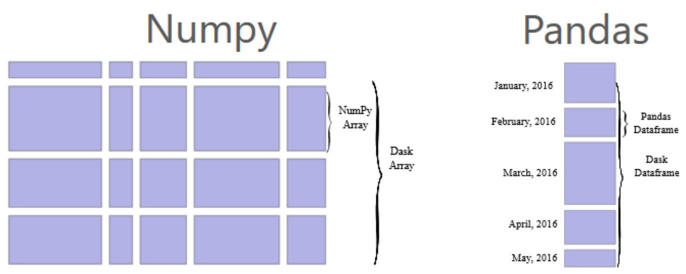


- **Performance features**
  - **#1 Whole-stage code generation** via Janino
  - **#2 Off-heap memory** (`sun.misc.Unsafe`) for caching and certain operations
  - **#3 Pushdown** of selection, projection, joins into data sources (+ join ordering)

Dask

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

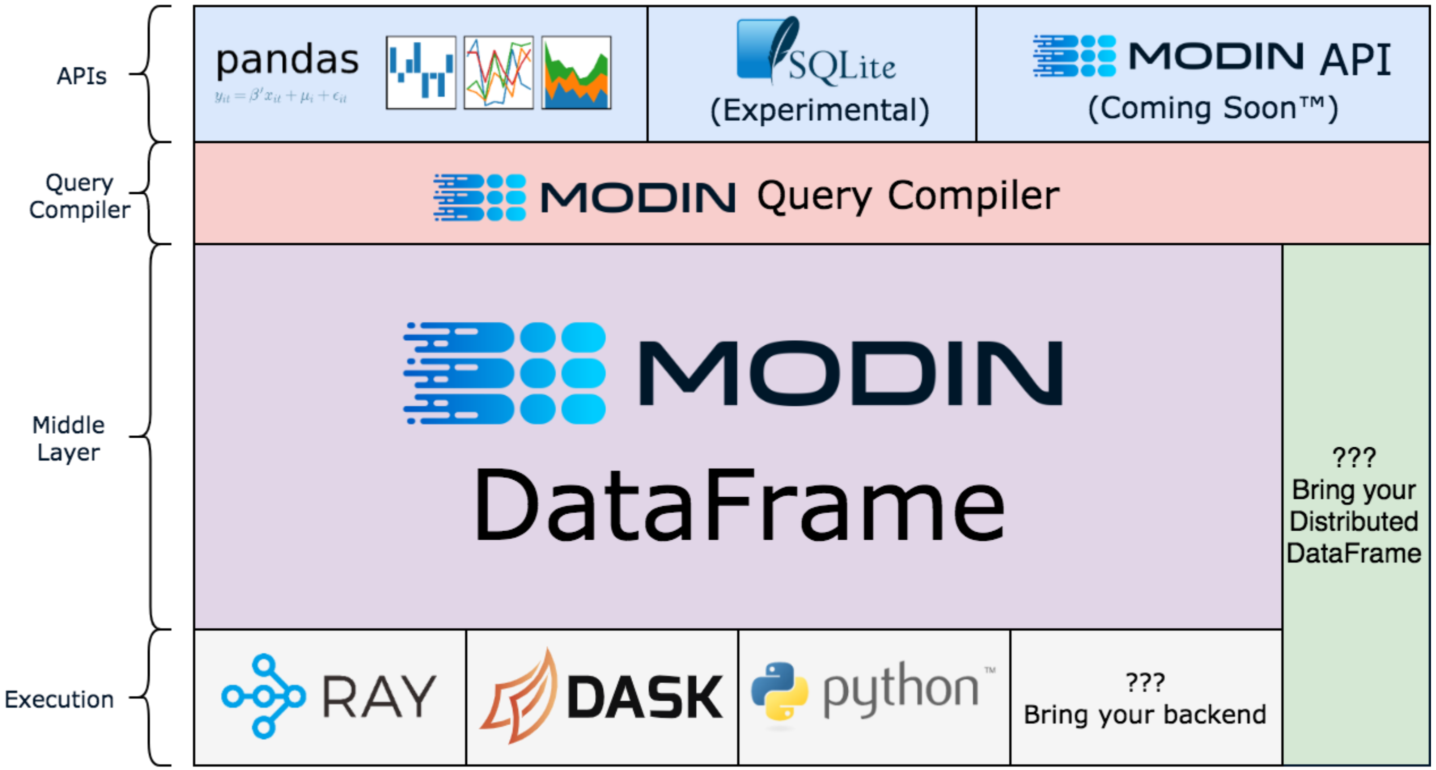
```
import dask.array as da

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]

Data-Parallel Computation in SystemDS

[Matthias Boehm et al.: SystemDS: A Declarative Machine Learning System for the End-to-End Data Science Lifecycle. **CIDR 2020**]

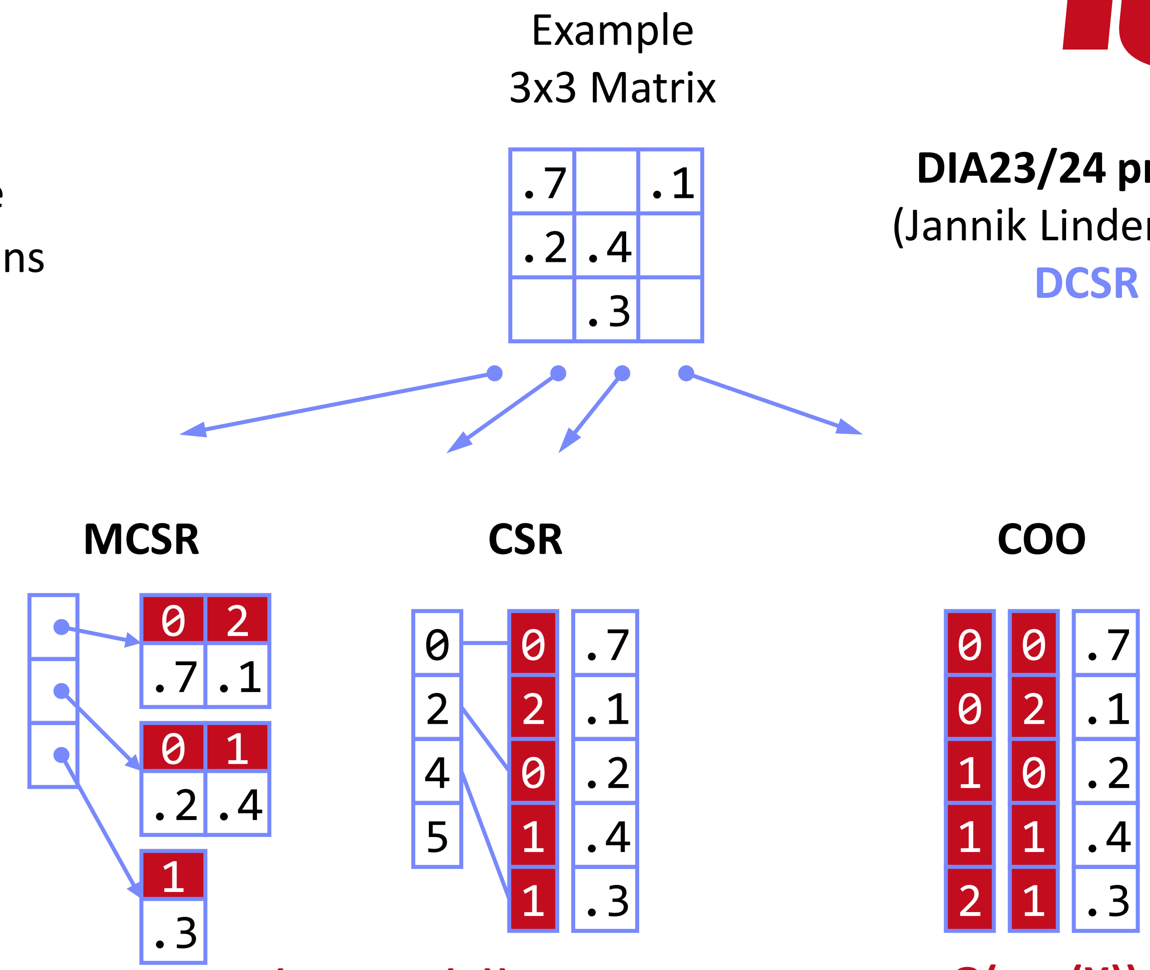
[Matthias Boehm et al.: SystemML: Declarative Machine Learning on Spark. **PVLDB 2016**]

[Amol Ghoting et al.: SystemML: Declarative Machine Learning on MapReduce. **ICDE 2011**]

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
  - DCSR (double compressed sparse rows)
  - COO (Coordinate matrix)

DIA23/24 project
(Jannik Lindemann):
DCSR



Dense (row-major)

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

O(mn)

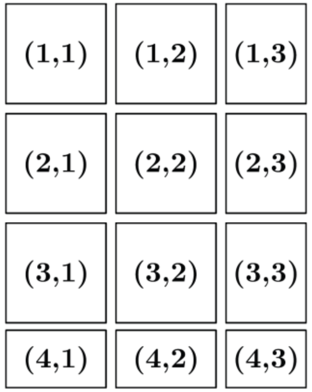
O(m + nnz(X))

O(nnz(X))

Distributed Matrix Representations

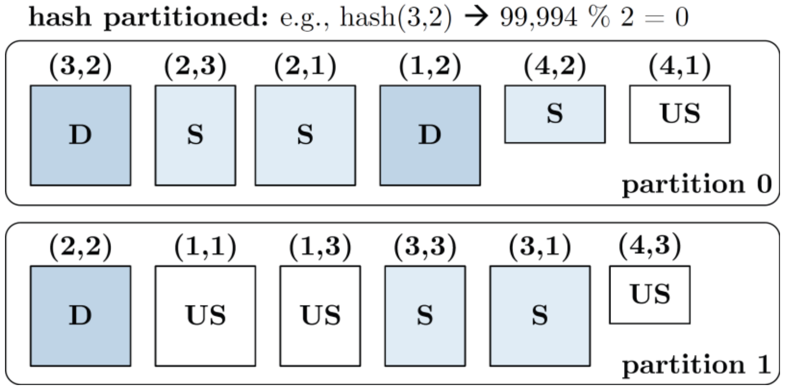
- **Collection of "Matrix Blocks" (and keys)**
  - **Bag semantics** (duplicates, unordered)
  - Logical (Fixed-Size) Blocking
    + join processing / independence
    - (sparsity skew)
  - E.g., SystemML on Spark: `JavaPairRDD<MatrixIndexes,MatrixBlock>`
  - Blocks encoded independently (dense/sparse)

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

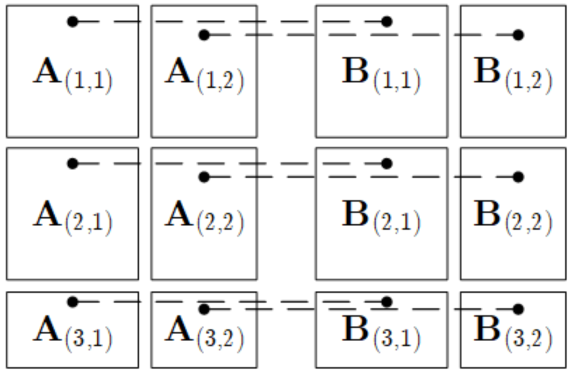


Distributed Matrix Operations

Q: How to implement these operations with Spark RDD Operations?

Elementwise Multiplication
(Hadamard Product)

`C = A * B`

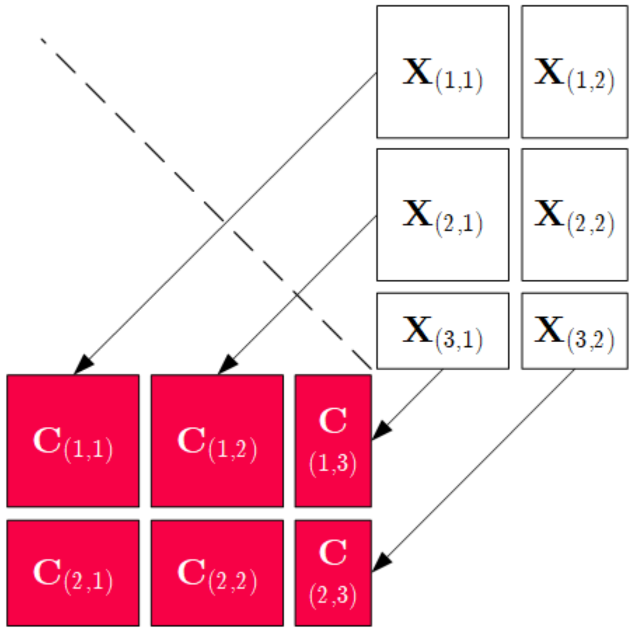


1:1 join

Note: also with row/column vector rhs

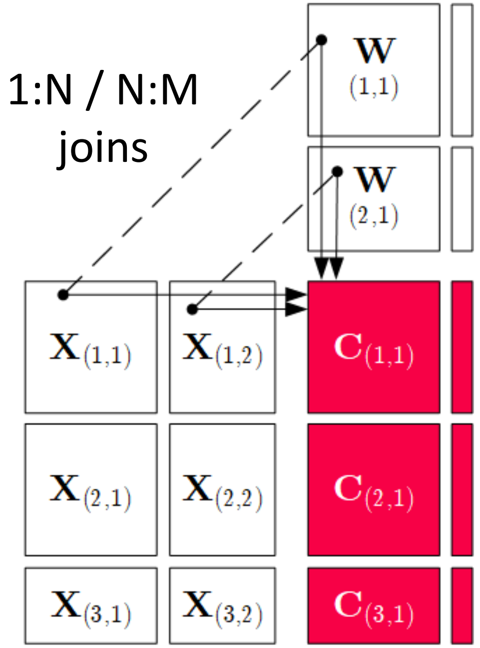
Transposition

`C = t(X)`



Matrix Multiplication

`C = X %*% W`



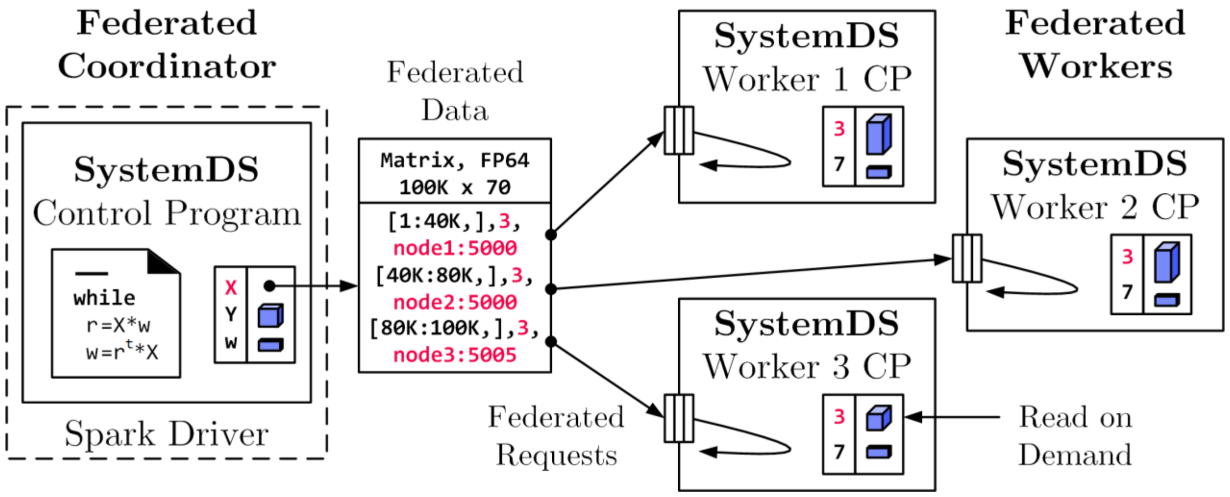
Partitioning-Preserving Operations

- **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) ≤ B_c

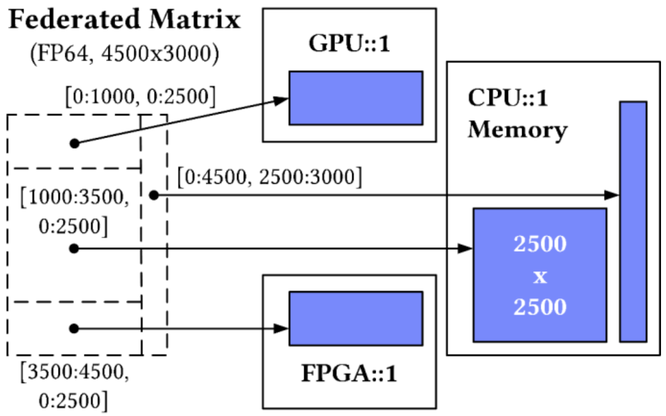
```
parfor(iter_class in 1:num_classes) {              repart, chkpt X MEM_DISK
   Y_local = 2 * (Y == iter_class) - 1
   g_old = t(X) %*% Y_local
   ...                                              chkpt y_local MEM_DISK
   while( continue ) {
      Xd = X %*% s                                  chkpt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

Federated Matrices / Frames

- **Federated Matrices**
  - Metadata on coordinator
  - Disjoint tiles at federated sites
  - Data-parallel operations on federated data



- **Generalization to Multi-device Settings**



Summary and Q&A

- **Motivation and Terminology**
- **Data-Parallel Collection Processing**
- **Data-Parallel Data-Frame Operations**
- **Data-Parallel Computation in SystemDS**

- **Next Lectures (Large-scale Data Management and Analysis)**
  - **12 Distributed Stream Processing** [Jan 25]
  - **13 Distributed Machine Learning Systems** [Feb 01]