SCIENCE
PASSION
TECHNOLOGY

Data Management
11 Distributed Storage & Analysis

Matthias Boehm

Graz University of Technology, Austria
Computer Science and Biomedical Engineering
Institute of Interactive Systems and Data Science
BMK endowed chair for Data Management

Last update: May 28, 2022

Announcements/Org

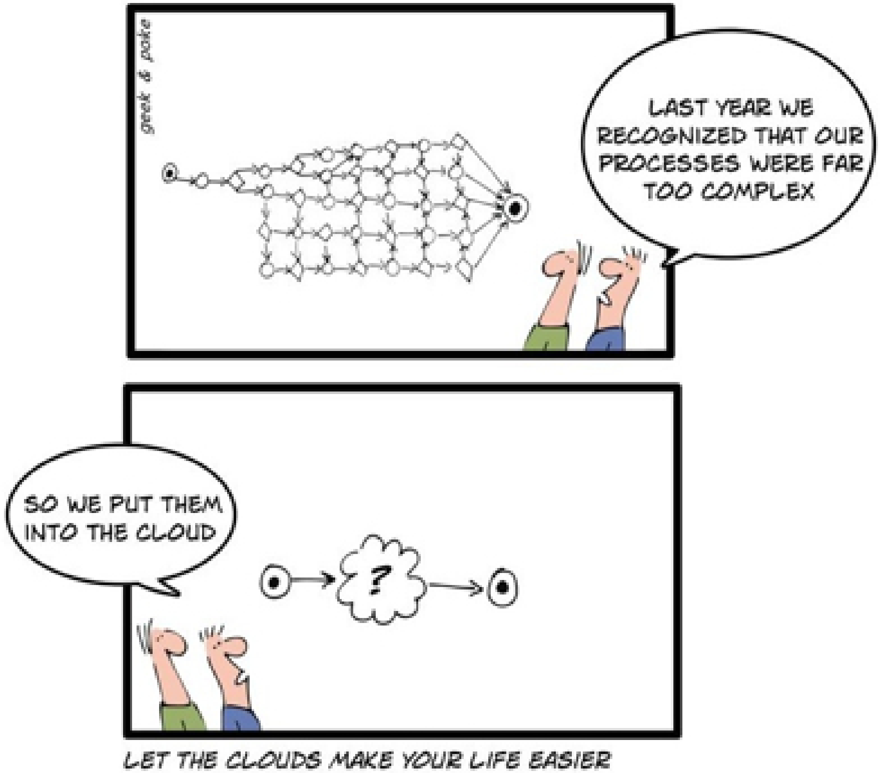
- **#1 Video Recording**
  - Link in **TeachCenter** & **TUbe** (lectures will be public)
  - Hybrid: HSi13 / https://tugraz.webex.com/meet/m.boehm
- **#2 Exercise Submissions**
  - **Exercise 2:** in progress of being graded (target Jun 04)
  - **Exercise 3: due May 31** + 7 late days
  - **Exercise 4:** extra credit, **due Jun 21** + 7 late days

Q&A

- **#3 Course Evaluation and Exam**
  - Evaluation period: **Jun 15 – Jul 31**
  - **Exams: Jun 27, 4pm** (i13), **Jul 07, 2.30pm** (i12+i13), **Jul 07, 5.30pm** (i12+13), **Jul 28, 5.30pm** (i13)

Agenda

- **Cloud Computing Overview**
- **Distributed Data Storage**
- **Distributed Data Analysis**
- **Exercise 4: Large-scale Data Analysis**



Data Integration and Large-Scale Analysis (DIA)
(bachelor/master)

Cloud Computing Overview

Motivation Cloud Computing

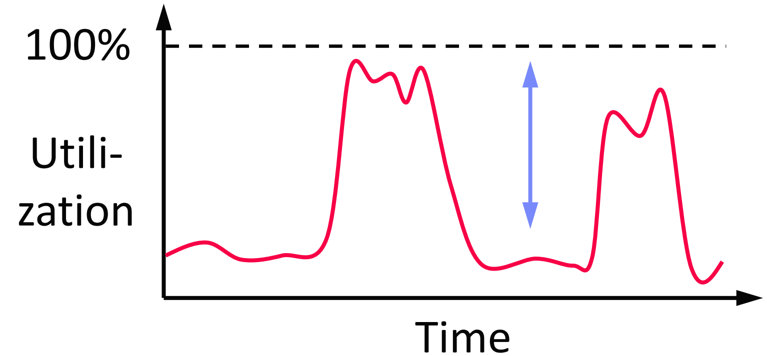
- **Definition Cloud Computing**
  - **On-demand, remote storage and compute resources, or services**
  - **User:** computing as a utility (similar to energy, water, internet services)
  - **Cloud provider:** computation in data centers / multi-tenancy

- **Service Models**
  - **IaaS: Infrastructure as a service** (e.g., storage/compute nodes)
  - **PaaS: Platform as a service** (e.g., distributed systems/frameworks)
  - **SaaS: Software as a Service** (e.g., email, databases, office, github)

→ **Transforming IT Industry/Landscape**
  - Since ~2010 increasing move from on-prem to cloud resources
  - System software licenses become increasingly irrelevant
  - Few cloud providers dominate IaaS/PaaS/SaaS markets (w/ 2018 revenue): **Microsoft Azure Cloud** ($ 32.2B), **Amazon AWS** ($ 25.7B), **Google Cloud** (N/A), **IBM Cloud** ($ 19.2B), **Oracle Cloud** ($ 5.3B), **Alibaba Cloud** ($ 2.1B)

Motivation Cloud Computing, cont.

- **Argument #1: Pay as you go**
  - No upfront cost for infrastructure
  - Variable utilization ➔ over-provisioning
  - **Pay per use or acquired resources**



- **Argument #2: Economies of Scale**
  - Purchasing and managing IT infrastructure at scale ➔ **lower cost** (applies to both HW resources and IT infrastructure/system experts)
  - Focus on **scale-out on commodity HW** over scale-up ➔ **lower cost**

- **Argument #3: Elasticity**
  - Assuming perfect scalability, work done in **constant time * resources**
  - Given virtually unlimited resources allows to reduce time as necessary

100 days @ 1 node

≈

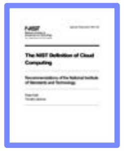
1 day @ 100 nodes

(but beware Amdahl's law: max speedup **sp = 1/s**)

Characteristics and Deployment Models

- **Extended Definition**
  - ANSI recommended definitions for service types, characteristics, deployment models

[Peter Mell and Timothy Grance: The NIST Definition of Cloud Computing, **NIST 2011**]



- **Characteristics**
  - **On-demand self service:** unilateral resource provision
  - **Broad network access:** network accessibility
  - **Resource pooling:** resource virtualization / multi-tenancy
  - **Rapid elasticity:** scale out/in on demand
  - **Measured service:** utilization monitoring/reporting
- **Deployment Models**
  - **Public cloud:** general public, on premise of cloud provider
  - **Hybrid cloud:** combination of two or more of the above
  - **Community cloud:** single community (one or more orgs)
  - **Private cloud:** single org, on/off premises

MS Azure Private Cloud

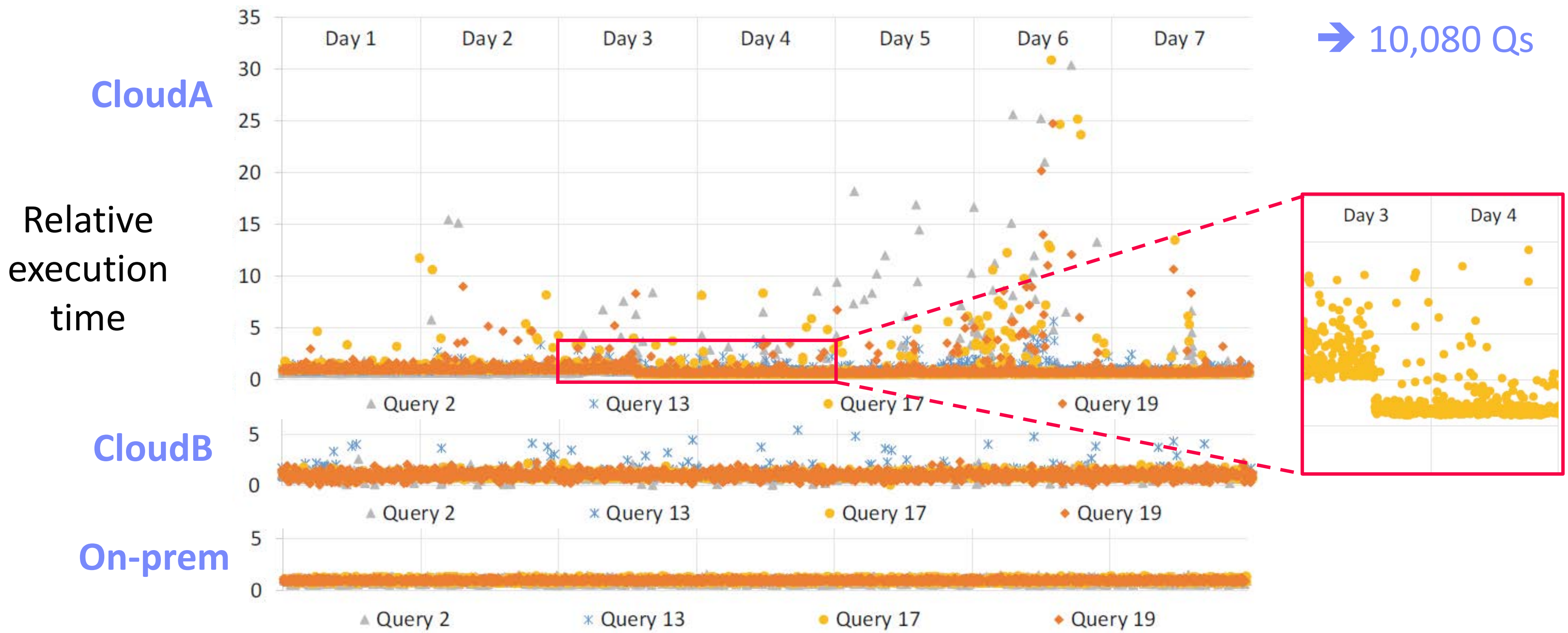
IBM Cloud Private

Excursus: 1 Query/Minute for 1 Week

- **Experimental Setup**
  - 1GB TPC-H database, 4 queries on 2 cloud DBs / 1 on-prem DB

[Tim Kiefer, Hendrik Schön, Dirk Habich, Wolfgang Lehner: **A Query, a Minute**: Evaluating Performance Isolation in Cloud Databases. TPCTC 2014]

→ 10,080 Qs



Anatomy of a Data Center

Commodity CPU:
Xeon E5-2440: 6/12 cores
Xeon Gold 6148: 20/40 cores

Server:
Multiple sockets,
RAM, disks

Rack:
16-64 servers +
top-of-rack switch

Cluster:
Multiple racks + cluster switch

Data Center:
>100,000 servers

[Google
Data Center,
Eemshaven,
Netherlands]

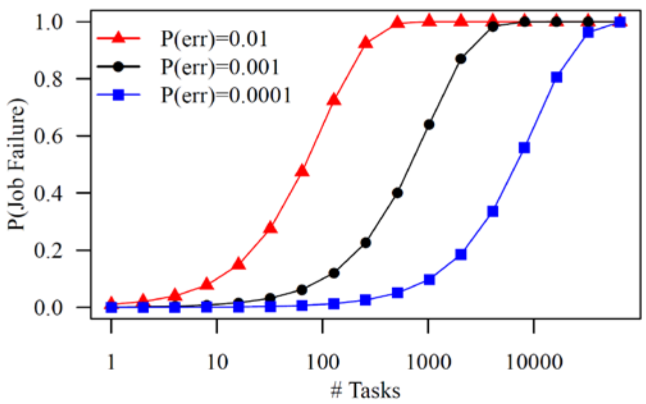
Fault Tolerance

[Christos Kozyrakis and Matei Zaharia: CS349D: Cloud Computing Technology, lecture, **Stanford 2018**]

- **Yearly Data Center Failures**
  - ~0.5 overheating (power down most machines in <5 mins, ~1-2 days)
  - ~1 PDU failure (~500-1000 machines suddenly disappear, ~6 hrs)
  - ~1 rack-move (plenty of warning, ~500-1000 machines powered down, ~6 hrs)
  - ~1 network rewiring (rolling ~5% of machines down over 2-day span)
  - ~20 rack failures (40-80 machines instantly disappear, 1-6 hrs)
  - ~5 racks go wonky (40-80 machines see 50% packet loss)
  - ~8 network maintenances (~30-minute random connectivity losses)
  - ~12 router reloads (takes out DNS and external vIPs for a couple minutes)
  - ~3 router failures (immediately pull traffic for an hour)
  - ~dozens of minor 30-second blips for dns
  - ~1000 individual machine failures (2-4% failure rate, at least twice)
  - ~thousands of hard drive failures (1-5% of all disks will die)

Fault Tolerance, cont.

- **Other Common Issues**
  - **Configuration issues**, partial SW updates, SW bugs
  - **Transient errors:** no space left on device, memory corruption, stragglers
- **Recap: Error Rates at Scale**
  - Cost-effective commodity hardware
  - Error rate increases with increasing scale
  - Fault Tolerance for distributed/cloud storage and data analysis



➔ **Cost-effective Fault Tolerance**
  - **BASE** (basically **available**, soft state, **eventual consistency**)
  - Effective techniques
    - ECC (error correction codes), CRC (cyclic redundancy check) for detection
    - **Resilient storage:** replication/erasure coding, checkpointing, and lineage
    - **Resilient compute:** task re-execution / speculative execution

Containerization

- **Docker Containers**
  - **Shipping container analogy**
    - Arbitrary, self-contained goods, standardized units
    - Containers reduced loading times ➔ efficient international trade
  - **#1 Self-contained package** of necessary SW and data (read-only image)
  - **#2 Lightweight virtualization** w/ shared OS and resource isolation via **cgroups**

- **Cluster Schedulers**
  - Container orchestration: scheduling, deployment, and management
  - Resource negotiation with clients
  - Typical resource bundles (CPU, memory, device)
  - Examples: **Kubernetes**, **Mesos**, (**YARN**), **Amazon ECS**, **Microsoft ACS**, **Docker Swarm**

[Brendan Burns, Brian Grant, David Oppenheimer, Eric Brewer, John Wilkes: Borg, Omega, and Kubernetes. **CACM 2016**]

➔ **from machine- to application-oriented scheduling**

Example Amazon Services – Pricing (current gen)

- **Amazon EC2 (Elastic Compute Cloud)**
  - IaaS offering of different node types and generations
  - **On-demand**, **reserved**, and **spot** instances

	vCores		Mem		
m4.large	2	6.5	8 GiB	EBS Only	$0.12 per Hour
m4.xlarge	4	13	16 GiB	EBS Only	$0.24 per Hour
m4.2xlarge	8	26	32 GiB	EBS Only	$0.48 per Hour
m4.4xlarge	16	53.5	64 GiB	EBS Only	$0.96 per Hour
m4.10xlarge	40	124.5	160 GiB	EBS Only	$2.40 per Hour
m4.16xlarge	64	188	256 GiB	EBS Only	$3.84 per Hour

- **Amazon ECS (Elastic Container Service)**
  - PaaS offering for Docker containers
  - Automatic setup of Docker environment

Pricing according to EC2
(in EC2 launch mode)

- **Amazon EMR (Elastic Map Reduce)**
  - PaaS offering for Hadoop workloads
  - Automatic setup of YARN, HDFS, and specialized frameworks like Spark
  - **Prices in addition to EC2 prices**

m4.large	$0.117 per Hour	$0.03 per Hour
m4.xlarge	$0.234 per Hour	$0.06 per Hour
m4.2xlarge	$0.468 per Hour	$0.12 per Hour
m4.4xlarge	$0.936 per Hour	$0.24 per Hour
m4.10xlarge	$2.34 per Hour	$0.27 per Hour
m4.16xlarge	$3.744 per Hour	$0.27 per Hour

Distributed Data Storage

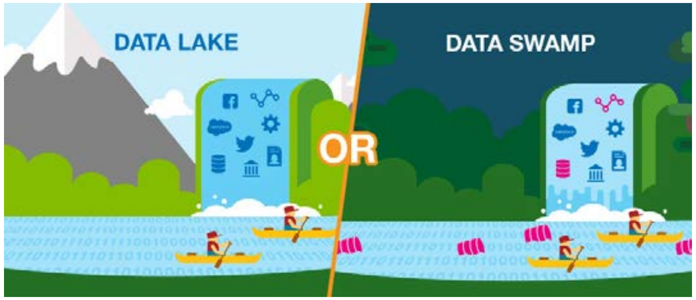
Cloud Object Storage

Distributed File Systems

Data Lakes

- **Concept "Data Lake"**
  - **Store massive amounts of un/semi-structured, and structured data** (append only, no update in place)
  - **No need for architected schema** or upfront costs (unknown analysis)
  - Typically: file storage in open, raw formats (inputs and intermediates)
  - ➔ **Distributed storage and analytics** for scalability and agility

- **Criticism: Data Swamp**
  - Low data quality (lack of schema, integrity constraints, validation)
  - Missing meta data (context) and data catalog for search
  - ➔ **Requires proper data curation / tools** According to priorities (data governance)

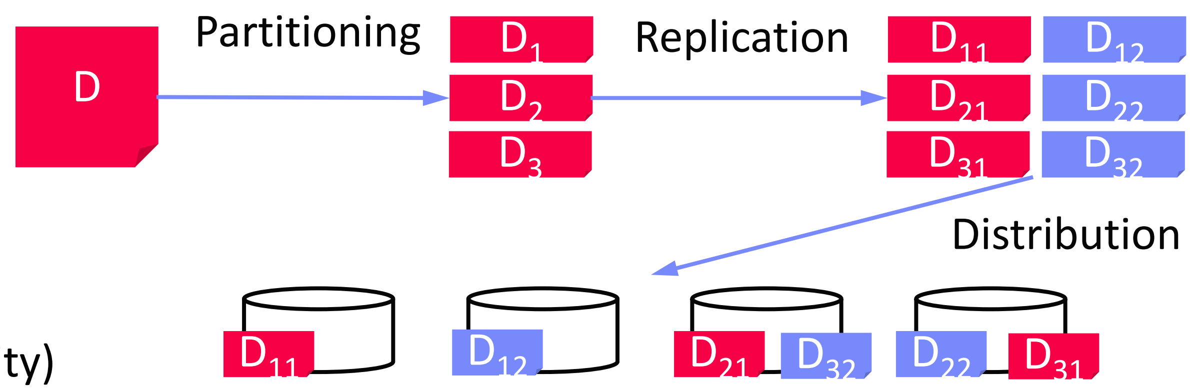


[**Credit:** www.collibra.com]

- **Excursus: Research Data Management**
  - FAIR data principles: findable, accessible, interoperable, re-usable

Object Storage

- **Recap: Key-Value Stores**
  - **Key**-value mapping, where values can be of a variety of data types
  - APIs for CRUD operations; scalability via sharding (**objects** or object segments)
- **Object Store**
  - Similar to key-value stores, but: **optimized for large objects in GBs and TBs**
  - Object identifier (**key**), **meta data**, and object as binary large object (**BLOB**)
  - APIs: often REST APIs, SDKs, sometimes implementation of DFS APIs
- **Key Techniques**
  - Partitioning
  - Replication & Distribution
  - Erasure Coding (partitioning + parity)



Object Storage, cont.

- **Example Object Stores / Protocols**
  - Amazon Simple Storage Service (S3)
  - OpenStack Object Storage (Swift)
  - IBM Object Storage
  - Microsoft Azure Blob Storage

- **Amazon S3**
  - Reliable object store for photos, videos, documents or any binary data
  - **Bucket:** Uniquely named, static data container
    `http://s3.aws-eu-central-1.amazonaws.com/mboehm-b1`
  - **Object:** key, version ID, value, metadata, access control
  - Single (5GB)/multi-part (5TB) upload and direct/BitTorrent download
  - **Storage classes:** STANDARD, STANDARD_IA, GLACIER, DEEP_ARCHIVE
  - **Operations:** GET/PUT/LIST/DEL, and SQL over CSV/JSON objects

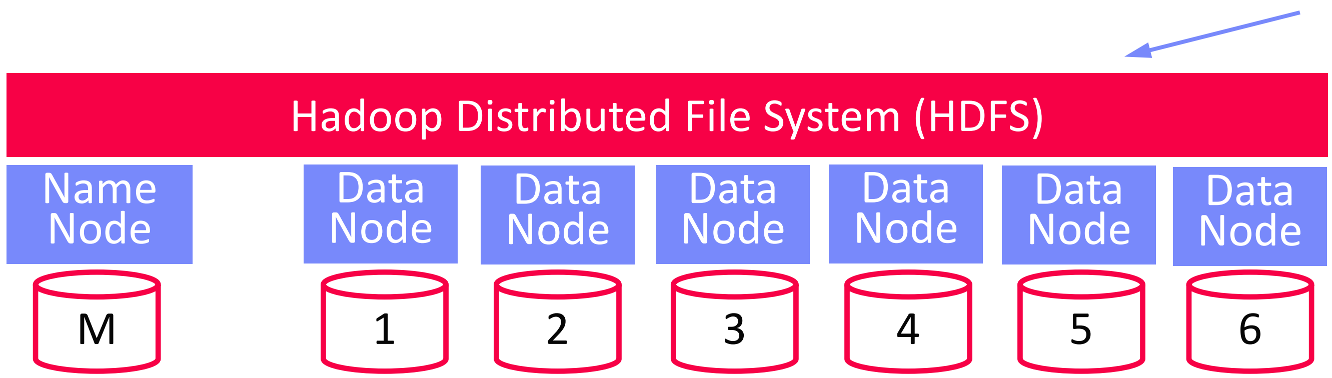
Hadoop Distributed File System (HDFS)

- **Brief Hadoop History**
  - Google's GFS + MapReduce [ODSI'04] → Apache Hadoop (2006)
  - Apache Hive (SQL), Pig (ETL), Mahout/SystemML (ML), Giraph (Graph)

[Sanjay Ghemawat, Howard Gobioff, Shun-Tak Leung: The Google file system. **SOSP 2003**]

- **HDFS Overview**
  - Hadoop's distributed file system, for large clusters and datasets
  - Implemented in Java, w/ native libraries for compression, I/O, CRC32
  - Files split into 128MB blocks, replicated (3x), and distributed

Client



Head Node **Worker Nodes** (shared-nothing cluster)

Hadoop Distributed File System, cont.

- **HDFS NameNode**
  - Master daemon that manages file system namespace and access by clients
  - Metadata for all files (e.g., replication, permissions, sizes, block ids, etc)
  - **FSImage:** checkpoint of FS namespace
  - **EditLog:** **write-ahead-log (WAL)** of file write operations (merged on startup)

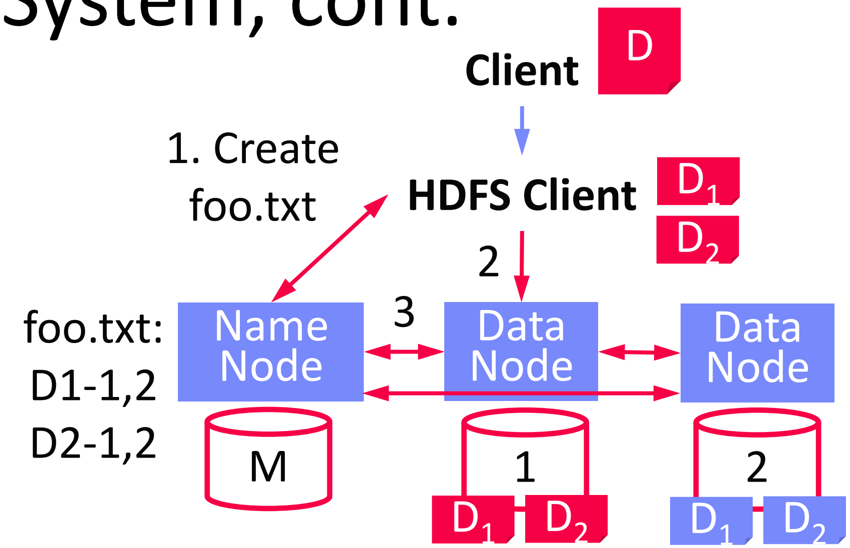
```
hadoop fs -ls ./data/mnist1m.bin
```

```
-rw-r--r--   3 mboehm hdfs  104510159 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00000
-rw-r--r--   3 mboehm hdfs  137887319 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00001
-rw-r--r--   3 mboehm hdfs  139012247 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00002
-rw-r--r--   3 mboehm hdfs  139123247 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00003
-rw-r--r--   3 mboehm hdfs  139053743 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00004
-rw-r--r--   3 mboehm hdfs  138928955 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00005
-rw-r--r--   3 mboehm hdfs  139016375 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00006
-rw-r--r--   3 mboehm hdfs  139047923 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00007
-rw-r--r--   3 mboehm hdfs  139042307 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00008
-rw-r--r--   3 mboehm hdfs  139068143 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00009
-rw-r--r--   3 mboehm hdfs  139029875 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00010
-rw-r--r--   3 mboehm hdfs  138901043 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00011
-rw-r--r--   3 mboehm hdfs  139042763 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00012
-rw-r--r--   3 mboehm hdfs  139030751 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00013
-rw-r--r--   3 mboehm hdfs  139172051 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00014
-rw-r--r--   3 mboehm hdfs  138962735 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00015
-rw-r--r--   3 mboehm hdfs  139079495 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00016
-rw-r--r--   3 mboehm hdfs   63417008 2018-10-20 22:59 /user/mboehm/data/mnist1m.bin/0-m-00017
```

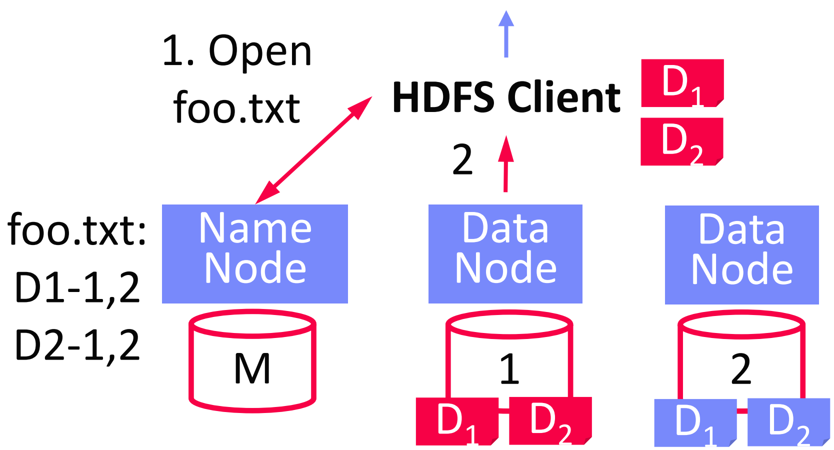
- **HDFS DataNode**
  - Worker daemon per cluster node that manages block storage (list of disks)
  - Block creation, deletion, replication as individual files in local FS
  - On startup: scan local blocks and send **block report** to name node
  - Serving block read and write requests
  - Send heartbeats to NameNode (capacity, current transfers) and receives replies (replication, removal of block replicas)

Hadoop Distributed File System, cont.

- **HDFS Write**
  - #1 Client RPC to NameNode to create file → lease/replica DNs
  - #2 Write blocks to DNs, pipelined replication to other DNs
  - #3 DNs report to NN via heartbeat



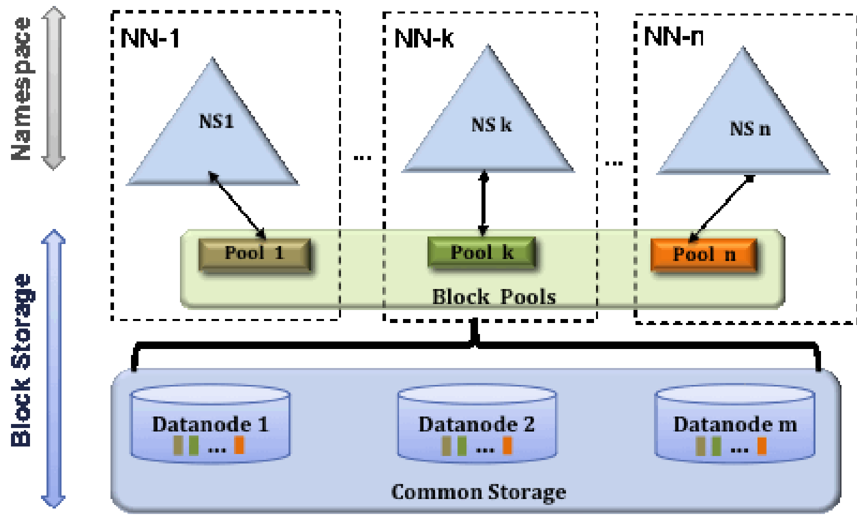
- **HDFS Read**
  - #1 Client RPC to NameNode to open file → DNs for blocks
  - #2 Read blocks sequentially from closest DN w/ block
  - InputFormats and RecordReaders as abstraction for multi-part files (incl. compression/encryption)



Hadoop Distributed File System, cont.

- **Data Locality**
  - HDFS is generally rack-aware (node-local, rack-local, other)
  - Schedule reads from closest data node
  - Replica placement (rep 3): local DN, other-rack DN, same-rack DN
  - MapReduce/Spark: locality-aware execution (**function vs data shipping**)

- **HDFS Federation**
  - Eliminate NameNode as namespace scalability bottleneck
  - Independent NameNodes, responsible for name spaces
  - DataNodes store blocks of all NameNodes
  - Client-side mount tables



[**Credit:** https://hadoop.apache.org/docs/current/hadoop-project-dist/hadoop-hdfs/Federation.html]

Excursus: Amazon Redshift

[Anurag Gupta et al.: Amazon Redshift and the Case for Simpler Data Warehouses. **SIGMOD 2015**]

[Mengchu Cai et al.: Integrated Querying of SQL database data and S3 data in Amazon Redshift. **IEEE Data Eng. Bull. 41(2) 2018**]

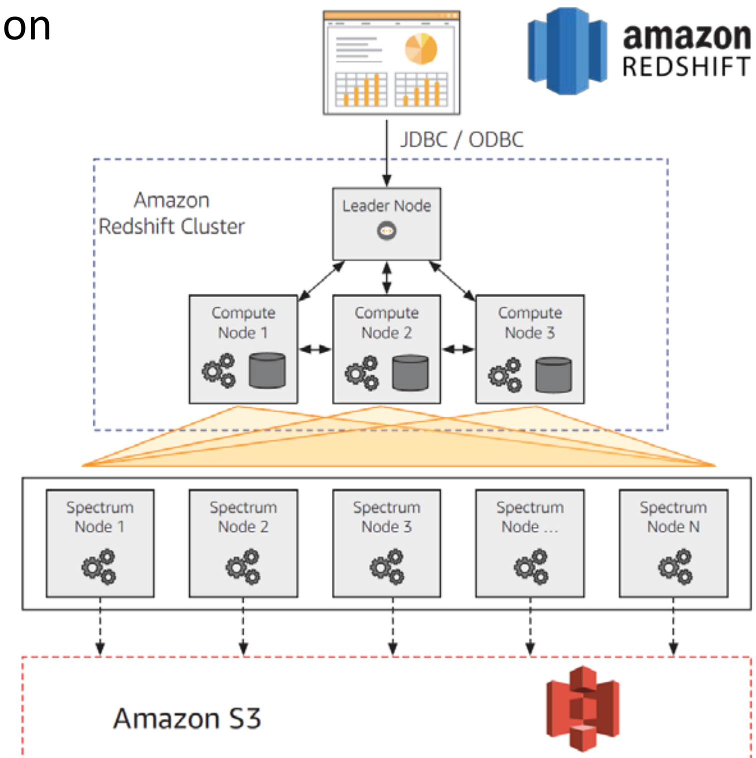
[Nikos Armenatzoglou et al.: Amazon Redshift Re-invented. **SIGMOD 2022**]

- **Motivation** (release 02/2013)
  - **Simplicity and cost-effectiveness** (fully-managed DWH at petabyte scale)
- **System Architecture**
  - **Data plane:** data storage and **SQL** execution
  - **Control plane:** workflows for monitoring, and managing databases, AWS services
- **Data Plane**
  - Leader node + sliced compute nodes in **EC2** with **local storage**
  - Replication across nodes + **S3 backup**
  - **Query compilation** in C++ code
  - Support for **flat and nested files**
- **Similar Systems**

Google BigQuery

snowflake

Microsoft



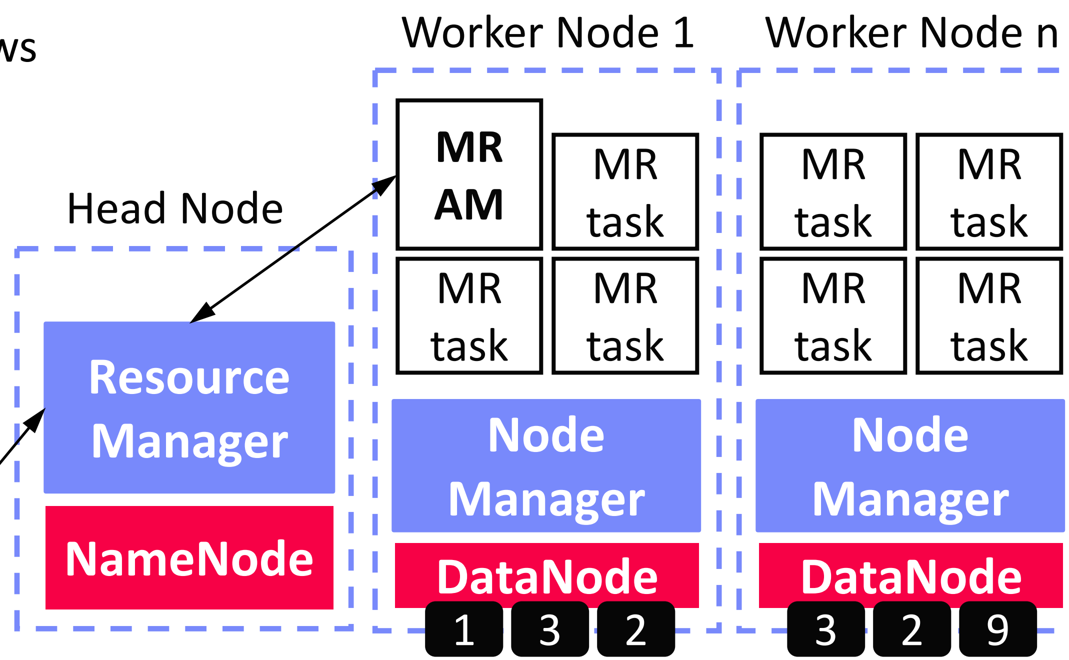
Distributed Data Analysis

Data-Parallel Computation (MapReduce, Spark)

Hadoop History and Architecture

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

- **Recap: Brief History**
  - Google's GFS [SOSP'03] + MapReduce
    → Apache Hadoop (2006)
  - Apache Hive (SQL), Pig (ETL), Mahout (ML), Giraph (Graph)
- **Hadoop Architecture / Eco System**
  - Management (Ambari)
  - Coordination / workflows (Zookeeper, Oozie)
  - Storage (**HDFS**)
  - Resources (**YARN**) [SoCC'13]
  - Processing (**MapReduce**)



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
  - Facilitates 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

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)
}
```

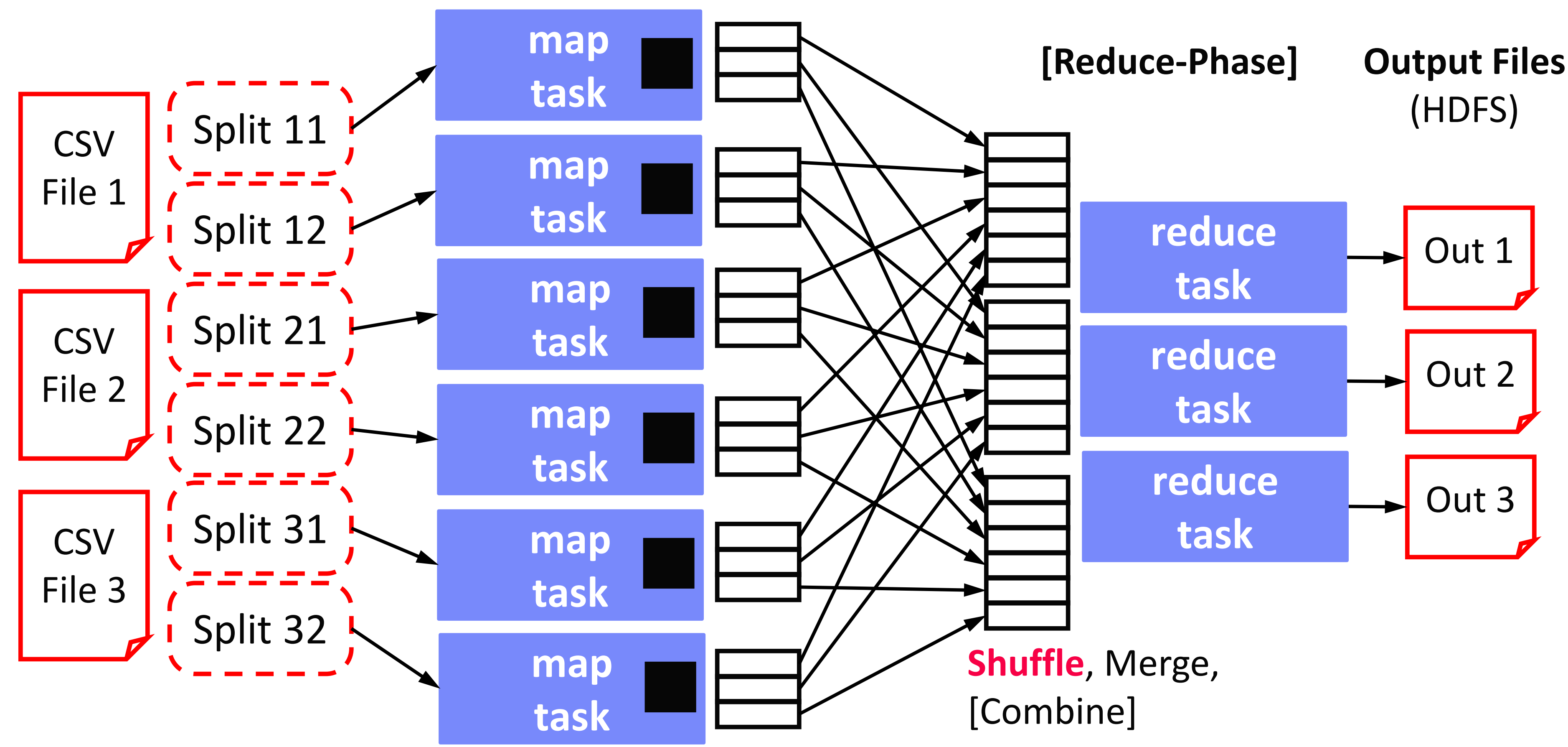
CS	3
EE	1

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



Sort, [Combine], [Compress]

w/ #reducers = 3

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, and 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

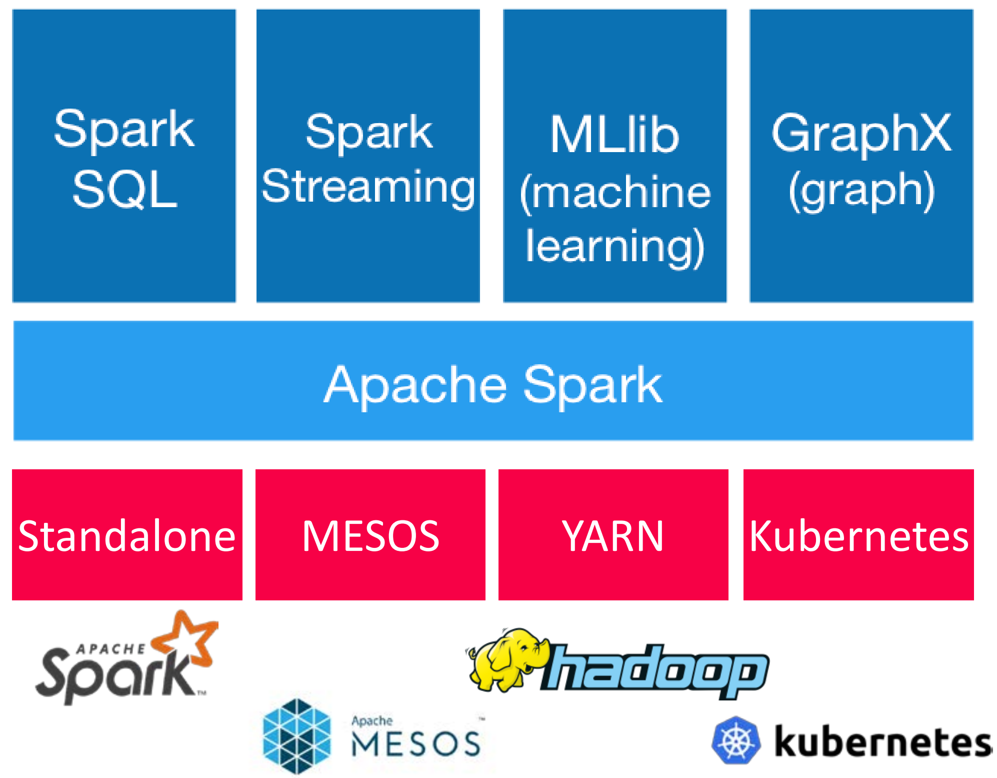
→ **But many shared concepts/infrastructure**

- **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**

Resilient Distributed Datasets (RDDs)

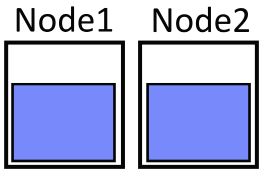
- **RDD Abstraction**
  - **Immutable**, partitioned **collections of key-value pairs**
  - **Coarse-grained** deterministic operations (transformations/actions)
  - Fault tolerance via lineage-based re-computation

```
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)



Resilient Distributed Datasets (RDDs), cont.

- **RDD Abstraction & Lifecycle**
  - **Immutable**, partitioned **collections of KV pairs**
  - **Coarse-grained** transformations and actions

`X.filter(foo())`
`X.mapValues(foo())`
`X.reduceByKey(foo())`
`X.cache()/X.persist(…)`

`sc.parallelize(lst)`

Local Data
(value, collection)

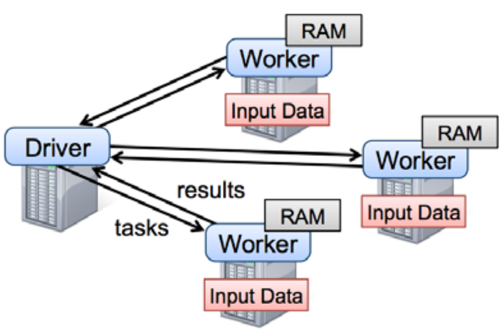
Distributed Collection

`lst = X.collect()`
`v = X.reduce(foo())`

`sc.hadoopFile(f)`
`sc.textFile(f)`

`X.saveAsObjectFile(f)`
`X.saveAsTextFile(f)`

File on DFS



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**

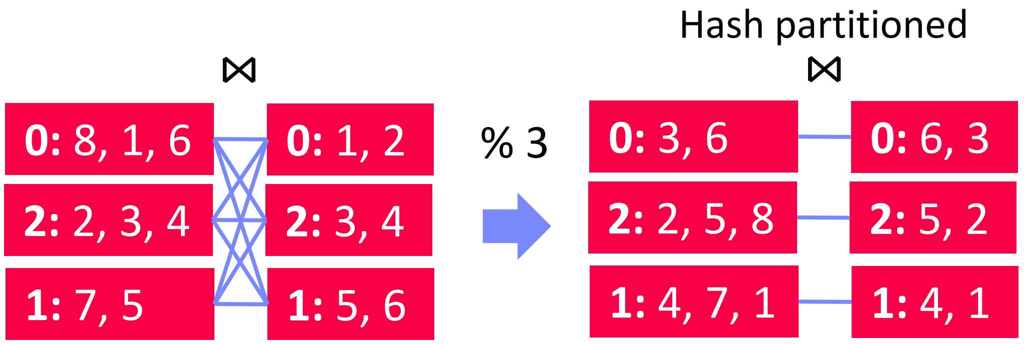
~128MB

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

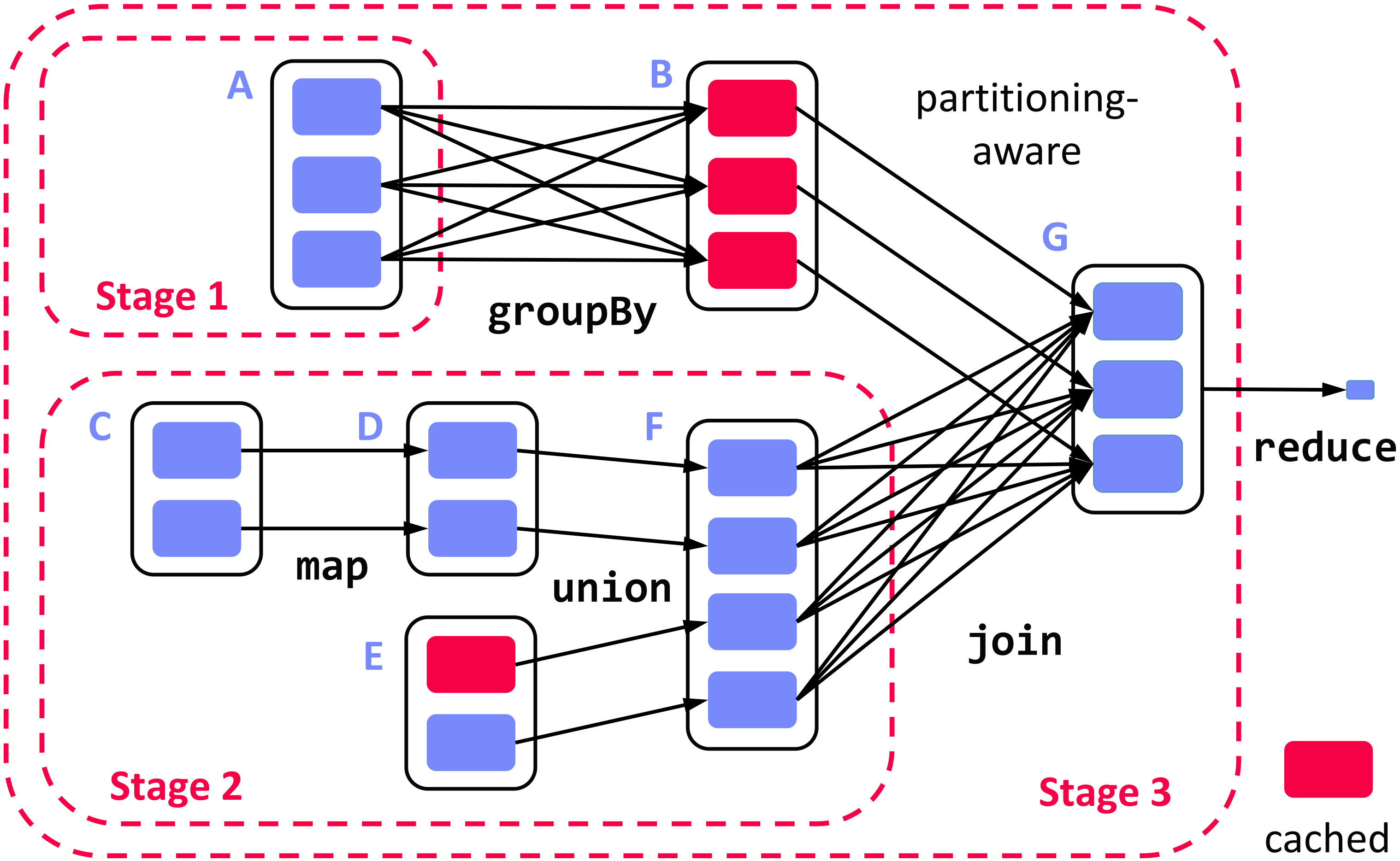
Example Hash Partitioning:
For all (k,v) of R:
pid = hash(k) % n

- **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



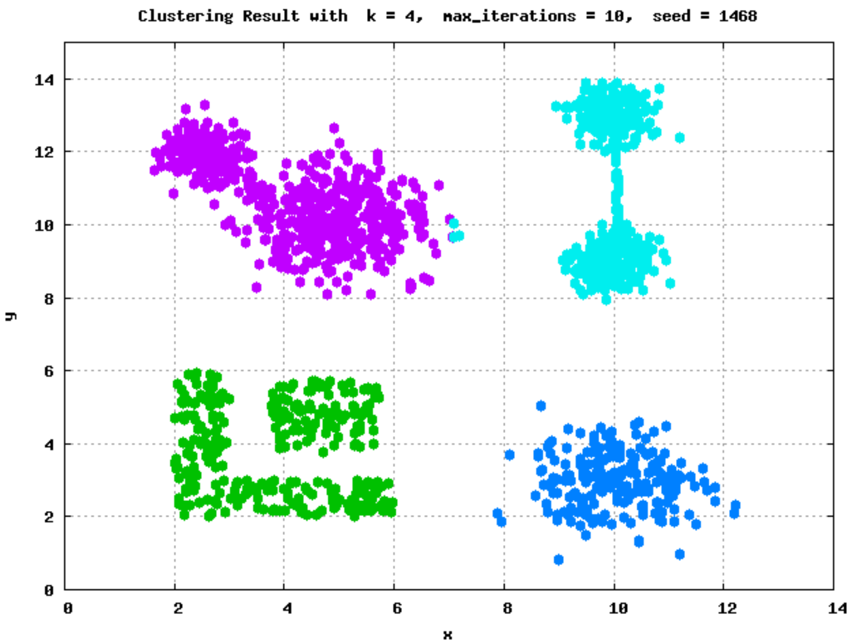
[Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauly, Michael J. Franklin, Scott Shenker, Ion Stoica: Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. **NSDI 2012**]

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‘
}
```



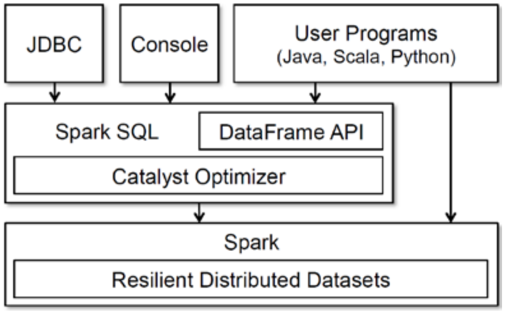
Example: K-Means Clustering in Spark

```
// 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]

Spark DataFrames and DataSets

- **Overview Spark DataFrame**
  - DataFrame is **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 = Dataset[Row]
```

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

- **Example DataFrame**

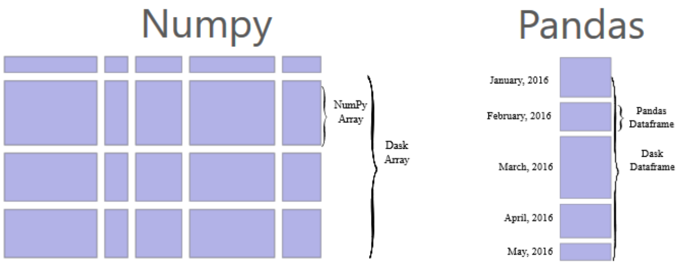
```
logs = spark.read.format("json").open("s3://logs")
logs.groupBy(logs.user_id).agg(sum(logs.time))
   .write.format("jdbc").save("jdbc:mysql//...")
```

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

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

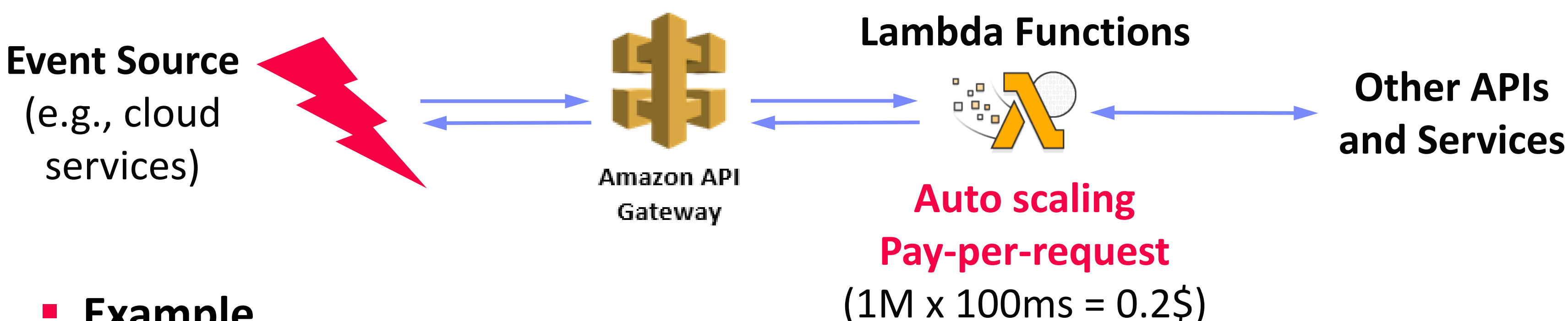
- **Execution**
  - Lazy evaluation
  - Limitation: requires **static size inference**
  - Triggered via `compute()`

```
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
```

Serverless Computing

[Joseph M. Hellerstein et al: Serverless Computing: One Step Forward, Two Steps Back. **CIDR 2019**]

- **Definition Serverless**
  - **FaaS:** functions-as-a-service (event-driven, stateless input-output mapping)
  - Infrastructure for deployment and auto-scaling of APIs/functions
  - Examples: **Amazon Lambda**, **Microsoft Azure Functions**, etc



- **Example**

```java
import com.amazonaws.services.lambda.runtime.Context;
import com.amazonaws.services.lambda.runtime.RequestHandler;

public class MyHandler implements RequestHandler<Tuple, MyResponse> {
    @Override
    public MyResponse handleRequest(Tuple input, Context context) {
        return expensiveStatelessComputation(input);
    }
}
```

Exercise 4:
Large-Scale Data Analysis

Published: May 28

Deadline: Jun 21

Entire Exercise is Extra Credit

Task 4.1 Apache Spark Setup

3/25 points

- **#1 Pick your Spark Language Binding**
  - Java, Scala, Python
- **#2 Install Dependencies**
  - Java: Maven
    spark-core, spark-sql
  - Python:
    pip install pyspark

```
<dependency>
  <groupId>org.apache.spark</groupId>
  <artifactId>spark-core_2.12</artifactId>
  <version>3.2.0</version>
 </dependency>
<dependency>
  <groupId>org.apache.spark</groupId>
  <artifactId>spark-sql_2.12</artifactId>
  <version>3.2.0</version>
</dependency>
```

- **(#3 Win Environment)**
  - Download https://github.com/cdarlint/winutils/blob/master/hadoop-3.2.2/bin/winutils.exe
  - Create environment variable HADOOP_HOME="<some-path>/hadoop"

Task 4.2 Query Processing via Spark RDDs

11/25 points

- **#1 Spark Context Creation**
  - Create a spark context sc w/ local master (`local[*]`)
- **#2 Implement Q02/05 via RDD Operations**
  - Implement Q02/05 in self-contained `executeQ02RDD()` and `executeQ05RDD()`
  - All reads should use `sc.textFile(fname)`
  - RDD operations only → stdout

https://spark.apache.org/docs/latest/rdd-programming-guide.html

Task 4.3 Query Processing via Spark SQL

5/25 points

- **#1 Spark Session Creation**
  - Create a spark session via a spark session builder and w/ local master (`local[*]`)

→ **SQL processing of high importance in modern data management**

- **#2 Implement Q02/05 via Dataset Operations**
  - Implement Q02/05 in self-contained `executeQ02Dataset()` and `executeQ05Dataset()`
  - All reads should use `sc.read().format("csv")`
  - SQL or Dataset operations only → `out07.json`

- **WebUI**

```
INFO Utils: Successfully started service 'SparkUI' on port 4040.
INFO SparkUI: Bound SparkUI to […] http://192.168.108.220:4040
```

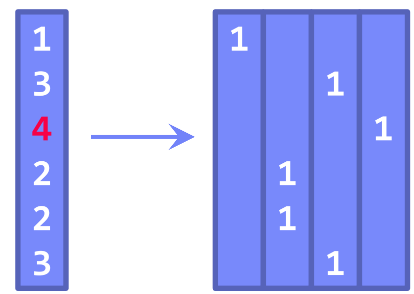
Task 4.4 Distributed PopCount Prediction

6/25 points

- **Input: Population Data**
  - PopByCitizenship (see exported data)

	dkey integer	ckey integer	popdate date	popcount integer
1	17	1	2006-01-01	23
2	9	1	2006-01-01	13
3	5	1	2006-01-01	210
4	8	1	2006-01-01	6

- **Population Count Prediction**
  - Regression model for predicting popcount for any (district, country, date)
  - Leverage **Spark Mllib** (RDD) or **spark.ml** (Dataset)
  - One-hot encoding Dkey, Ckey; time popdate
  - Compute average residuals, sum of squared residuals, and R2 (determination)



- **Ex: Apache SystemDS**
  - Local and distributed Spark operations
  - Runtime: 4.39 sec
  - AVG_RES: 199.26
  - R2: 0.81 (0.83 icpt=1)

```
# read input frame
F = read($1, data_type="frame", format="csv");
F[,3] = map(F[,3], "v -> UtilFunctions.toMillis(v, \"yyyy-mm-dd\")");

# one-hot encoding / pass-through, std scaling
jspec = "{ids: true, dummycode: [1,2]}";
[X0, M] = transformencode(target=F, spec=jspec);
X = scale(X0[,1:(ncol(X0)-1)], TRUE, TRUE);
y = X0[,ncol(X0)]

# model training and scoring
B = lm(X=X, y=y, reg=1e-9, verbose=TRUE);
yhat = X %*% B;
R2 = 1 - sum((y-yhat)^2) / sum((y-sum(y)/nrow(y))^2);
```

Conclusions and Q&A

- **Cloud Computing Overview**
- **Distributed Data Storage**
- **Distributed Data Analysis**
- **Exercise 4: Large-scale Data Analysis**

- **Next Lectures** (Part B: Modern Data Management)
  - **12 Data Stream Processing Systems** and **Q&A** [Jun 13, Patrick]
  - News group and office hour until end of June

Thanks & Goodbye