



# Database Systems 12 Distributed Analytics

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## Hadoop History and Architecture

## Recap: Brief History



- Google's GFS [SOSP'03] + MapReduce [ODSI'04] → Apache Hadoop (2006)
- Apache Hive (SQL), Pig (ETL), Mahout (ML), Giraph (Graph)

## Hadoop Architecture / Eco System

Management (Ambari) Worker Node 1 Worker Node n Coordination / workflows (Zookeeper, Oozie) MR MR MR MR Storage (HDFS) **Head Node AM** task task task Resources (YARN) MR MR MR MR [SoCC'13] task task task task **Processing** Resource (MapReduce) Node Node Manager Manager Manager NameNode **DataNode DataNode MR Client** 



# 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
Χ	CS
Υ	CS
Α	EE
Z	CS

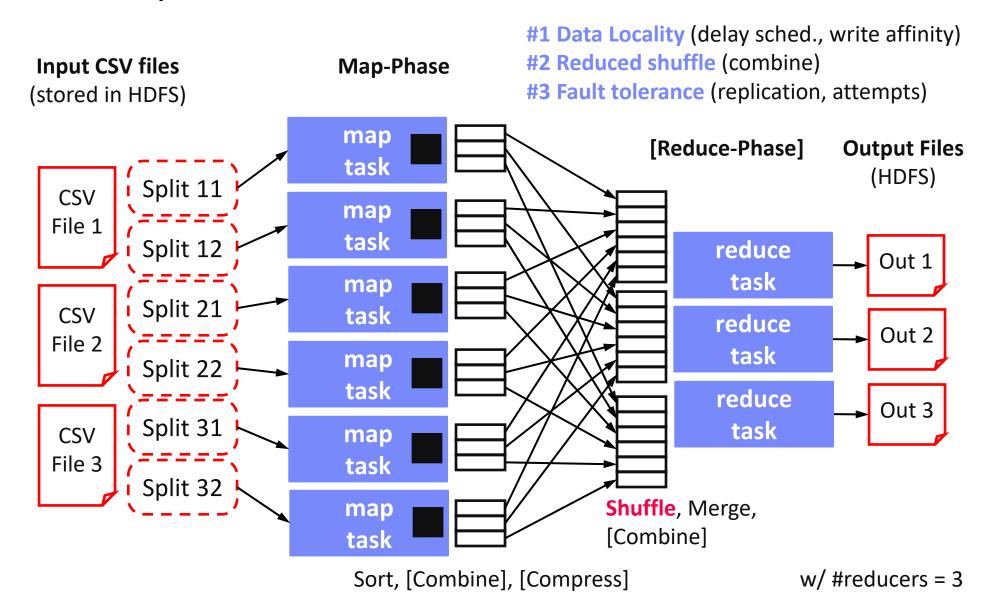
Collection of key/value pairs

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

CS	1
CS	1
EE	1
CS	1



## 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, 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/] Spark GraphX Spark MLlib (machine (graph) SQL Streaming learning) Apache Spark **MESOS** Standalone **YARN** Kubernetes Apache MESOS 🚳 kubernetes

Focus on a unified platform for data-parallel computation





# Resilient Distributed Datasets (RDDs)

#### RDD Abstraction

Immutable, partitioned collections of key-value pairs

JavaPairRDD
 <MatrixIndexes,MatrixBlock>

- Coarse-grained deterministic operations (transformations/actions)
- Fault tolerance via lineage-based re-computation

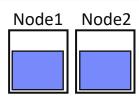
## Operations

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

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

## 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)







# Partitions and Implicit/Explicit Partitioning

## Spark Partitions

- Logical key-value collections are split into physical partitions
- Partitions are granularity of tasks, I/O (HDFS blocks/files), shuffling, evictions

### Partitioning via Partitioners

- Implicitly on every data shuffling
- Explicitly via R.repartition(n)

#### **Example Hash Partitioning:**

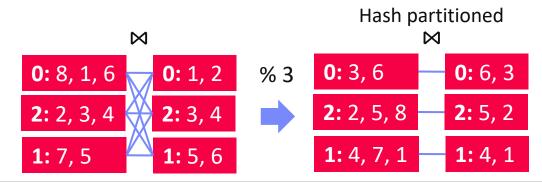
For all (k,v) of R: pid = hash(k) % n

## Partitioning-Preserving

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

## Partitioning-Exploiting

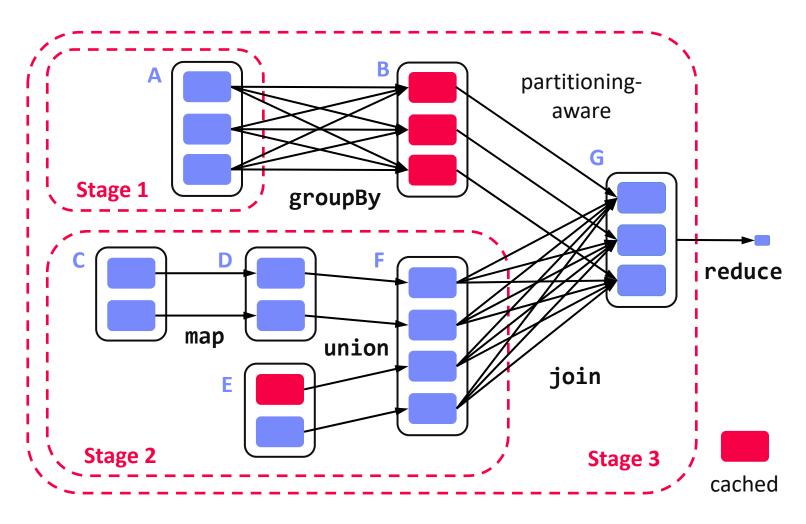
- Join: R3 = R1.join(R2)
- Lookups: v = C.lookup(k)







## 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**]



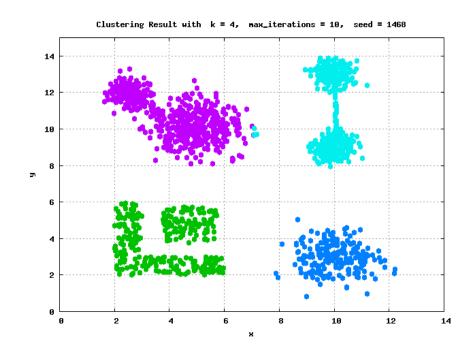
# Example: k-Means Clustering

## 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'
}</pre>
```







## 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 ) {</pre>
    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();
                                             Note: Existing library algorithm
                                      [https://github.com/apache/spark/blob/master/mllib/src/
return C;
                                     main/scala/org/apache/spark/mllib/clustering/KMeans.scalal
```





## Serverless Computing

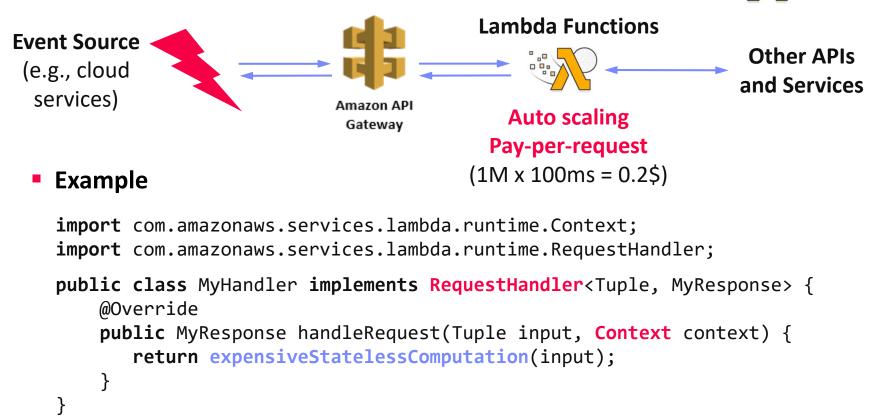
[Joseph M. Hellerstein et al: Serverless Computing: One Step Forward, Two Steps Back. CIDR 2019]



#### 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







# Exercise 4: Large-Scale Data Analysis

Published: Dec 31

Deadline: Jan 21





# Task 4.1 Apache Spark Setup

## #1 Pick your Spark Language Binding

■ Java, Scala, Python

4/25 points

## #2 Install Dependencies

- Java: Maven spark-core, spark-sql
- Python: pip install pyspark

```
<dependency>
    <groupId>org.apache.spark</groupId>
    <artifactId>spark-core_2.11</artifactId>
    <version>2.4.3</version>
    </dependency>
    <groupId>org.apache.spark</groupId>
        <artifactId>spark-sql_2.11</artifactId>
        <version>2.4.3</version>
    </dependency>
</dependency>
</dependency>
</dependency>
</dependency>
</dependency>
```

## (#3 Win Environment)

- Download <a href="https://github.com/steveloughran/winutils/tree/master/hadoop-2.7.1/bin/winutils.exe">https://github.com/steveloughran/winutils/tree/master/hadoop-2.7.1/bin/winutils.exe</a>
- Create environment variable HADOOP\_HOME="<some-path>/hadoop"





# Task 4.2 SQL Query Processing

### Q09: Top 5 Cities by Route Departures

- Consider all their airports
- Total number of route departures
- Return (City Name, Number of departures)
- Sorted in descending order of the number of routes

## Q10: Frequently used Plane Types

- Plane types used on more than 2048 routes
- Return (Plane type name, Number of routes it is used on)

5/25 points





# Task 4.2 SQL Query Processing, cont.

Expected Results with provided Schema and Data

Q09: Top 5 Cities by Route
Departures

name	count
London Atlanta Paris Shanghai Beijing (5 rows)	1090 760 681 603 600

Q10: Frequently used Plane
Types

name	count
	<b></b>
Airbus A320	15406
Airbus A319	7847
Boeing 737	2751
Boeing 737-800	10329
Airbus A321	3611
(5 rows)	





# Task 4.3 Query Processing via Spark RDDs

### #1 Spark Context Creation

Create a spark context sc w/ local master (local[\*])

**10/25 points** 

## #2 Implement Q09 via RDD Operations

- Implement Q09 self-contained in executeQ09RDD()
- All reads should use sc.textFile(fname)
- RDD operations only → stdout

See Spark online documentation for details

## #3 Implement Q10 via RDD Operations

- Implement Q10 self-contained in executeQ10RDD()
- All reads should use sc.textFile(fname)
- RDD operations only → stdout





# Task 4.4 Query Processing via Spark SQL

#### #1 Spark Session Creation

Create a spark session via a spark session builder and w. local master (local[\*]) 6/25 points

## #2 Implement Q09 via Dataset Operations

- Implement Q09 self-contained in executeQ09Dataset()
- All reads should use sc.read().format("csv")
- SQL or Dataset operations only → JSON

See Spark online documentation for details

## #3 Implement Q10 via Dataset Operations

- Implement Q10 self-contained in executeQ10Dataset()
- All reads should use sc.read().format("csv")
- SQL or Dataset operations only → JSON

→ SQL processing of high importance in modern data management





## Task 4.4 Query Processing via Spark SQL, cont.

- Optional: Explore Spark Web UI
  - Web UI started even in local mode
  - Explore distributed jobs and stages
  - Explore effects of caching on repeated query processing
  - Explore statistics

INFO Utils: Successfully started
 service 'SparkUI' on port 4040.

INFO SparkUI: Bound SparkUI to 0.0.0.0, and

started at http://192.168.108.220:4040





## Task 4.5 Extra Credit: SQL Query Processing

## Q11: Longest route computed via Haversine distance

5 points

- Longest route in km
- Computed via Haversine distance (using longitude & latitude)
- Return (Departure City Name, Arrival City Name, Distance in km)

$$\operatorname{haversine}\left(\frac{d}{r}\right) = \operatorname{haversine}(\phi_2 - \phi_1) + \cos(\phi_1)\cos(\phi_2)\operatorname{haversine}(\lambda_2 - \lambda_1)$$
 
$$(\phi_1, \lambda_1)$$
 
$$(\phi_2, \lambda_2)$$

$$d = 2r\arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

Where,  $\emptyset$  = latitude and  $\lambda$  = longitude





## Conclusions and Q&A

- Summary 11/12 Distributed Storage/Data Analysis
  - Cloud Computing Overview
  - Distributed Storage
  - Distributed Data Analytics
- Next Lectures (Part B: Modern Data Management)
  - 13 Data stream processing systems [Jan 20]
  - Jan 27: Q&A and exam preparation

