

# Spark for Scientific Computing

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# What is Spark?

- A distributed computing framework

# Problem 1: Storage

- Big data
- Commodity hardware (Cloud)

Solution: Distributed File System

- redundant
- fault tolerant

# Problem 2: Computation

- Slow to move data across network
- Computations fail

Solution: Hadoop Mapreduce / Spark

- Execute computation where data are located
- Rerun failed jobs

# Problem 3: Communication

- Most of the times, need to summarize data to get a result
- Reduction phase in MapReduce
- Need data transfer across network

Solution: highly optimized Shuffle (All-to-All)

# Spark and Hadoop

- Works within the Hadoop ecosystem
- Extends MapReduce
- Initially developed at UC Berkeley
- Now within the Apache Foundation
- ~400 and more developers

# Key features of Spark

- **Resiliency:** tolerant to node failures
- **Speed:** supports in-memory caching
- **Ease of use:**
  - Python/Scala interfaces
  - interactive shells
  - many distributed primitives

	<b>Hadoop MR Record</b>	<b>Spark Record</b>	<b>Spark 1 PB</b>
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400 physical	6592 virtualized	6080 virtualized
Cluster disk throughput	3150 GB/s (est.)	618 GB/s	570 GB/s
Sort Benchmark Daytona Rules	Yes	Yes	No
Network	dedicated data center, 10Gbps	virtualized (EC2) 10Gbps network	virtualized (EC2) 10Gbps network
<b>Sort rate</b>	<b>1.42 TB/min</b>	<b>4.27 TB/min</b>	<b>4.27 TB/min</b>
<b>Sort rate/node</b>	<b>0.67 GB/min</b>	<b>20.7 GB/min</b>	<b>22.5 GB/min</b>

## Spark 100TB benchmark



# HPC: Distributed TBs of data

- Fault-tolerant batch processing
- Data exploration with an interactive console
- SQL operations with Spark-SQL
- Iterative Machine Learning algorithms with Spark-MLlib

# Comparison with MPI

- MPI: describe computation and communication explicitly
- Spark: use a graph of high-level operators, the framework decides how and where to run tasks

# Million Songs Dataset

- Metadata about 1 million songs
- Fields like title, artist, year, loudness, hotness
- Created by Columbia University
- Dedicated to Machine Learning studies
- 280 GB compressed

# Example Input

input file: “songs.tsv”

0	.4
1	.9
2	.2
3	.12
4	.55
5	.98

# Example (Serial)

```
lines = open("songs.tsv").readlines()
```

```
def extract_hotness(line):  
    return float(line.split()[1])
```

```
songs_hotness = map(extract_hotness, lines)  
max_hotness = max(songs_hotness)
```

# Example (Lambda)

```
def extract_hotness(line):
```

```
    return float(line.split()[1])
```

```
songs_hotness = map(extract_hotness, lines)
```

```
songs_hotness = map(lambda x: float(x.split()  
[1]), lines)
```

# Interactive spark on Comet

Add to .bashrc:

```
module load python scipy
```

Navigate to the comet-interactive/ folder,  
submit a spark job with:

```
> qsub spark.cmd
```

# Connect to Spark

```
source slurm-env.sh
```

```
ssh $SLURMD_NODENAME
```

```
source slurm-env.sh
```

```
pyspark
```



# First example

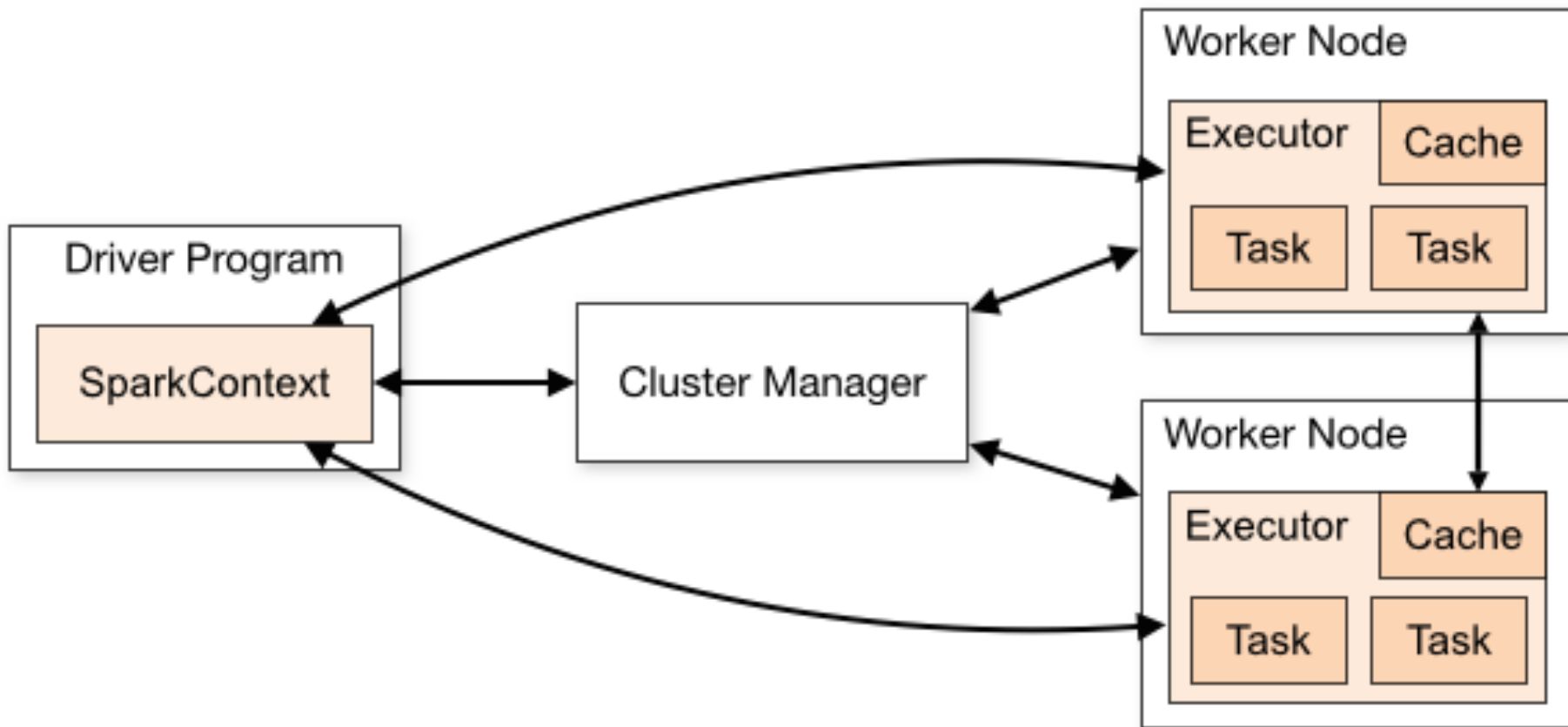
```
local_data = range(100)
data = sc.parallelize(local_data)
def myfilter(d):
    return d < 10
data.glom().collect()
data.filter(myfilter).collect()
```

# Example (PySpark)

```
data = sc.textFile('songs.tsv')
```

```
def extract_hotness(line):  
    return float(line.split()[1])
```

```
songs_hotness = data.map(extract_hotness)  
max_hotness = songs_hotness.max()
```



## Spark architecture

# Resilient Distributed Dataset

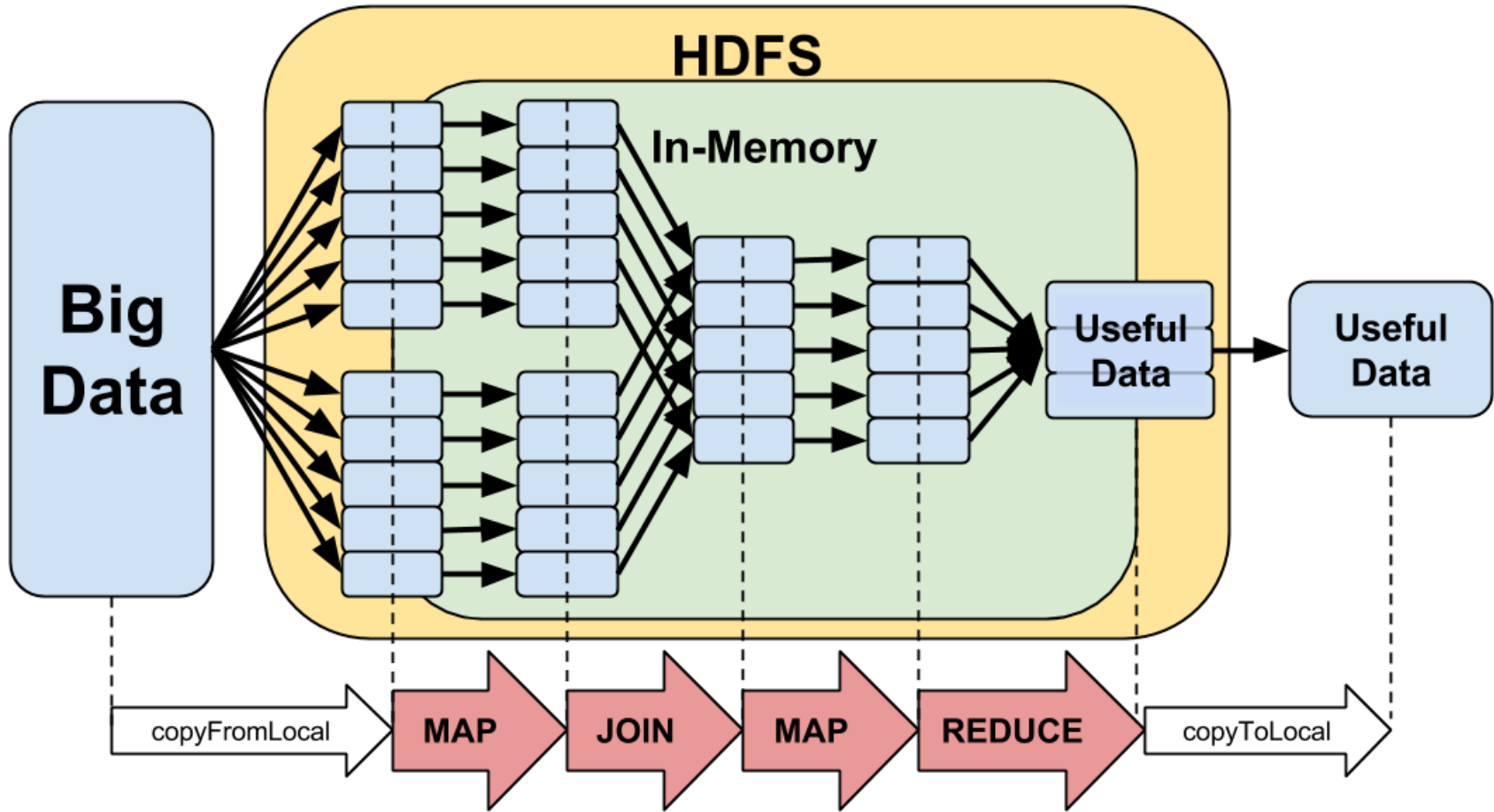
- Resilient: fault tolerant, lineage is saved, lost partitions can be recovered
- Distributed: partitions are automatically distributed across nodes
- Created from: HDFS, S3, HBase, Local file, Local hierarchy of folders

# Read from HDFS

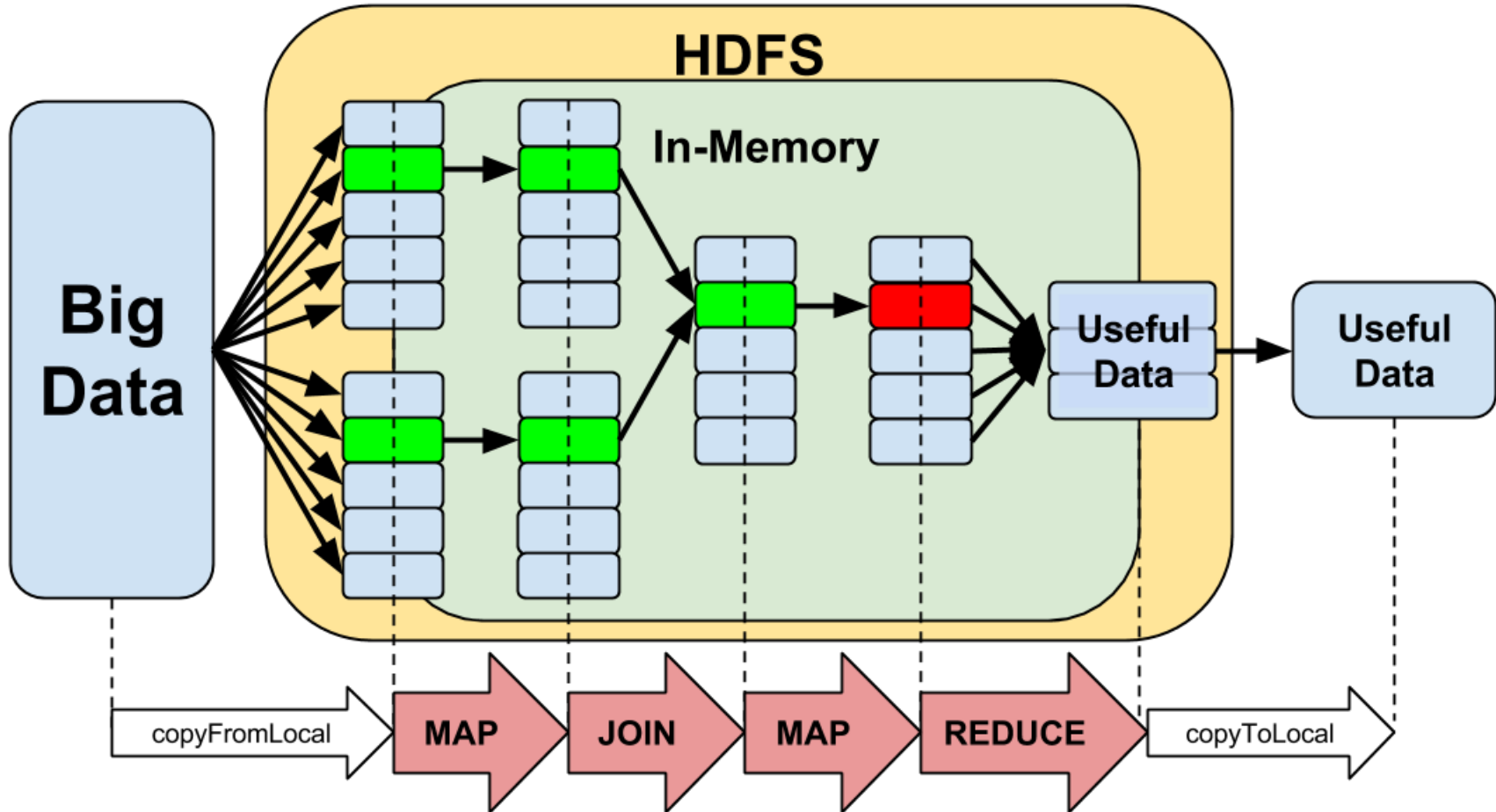
```
$ hdfs dfs -mkdir -p /user/$USER
```

```
$ hdfs dfs -put songs.tsv /user/$USER/
```

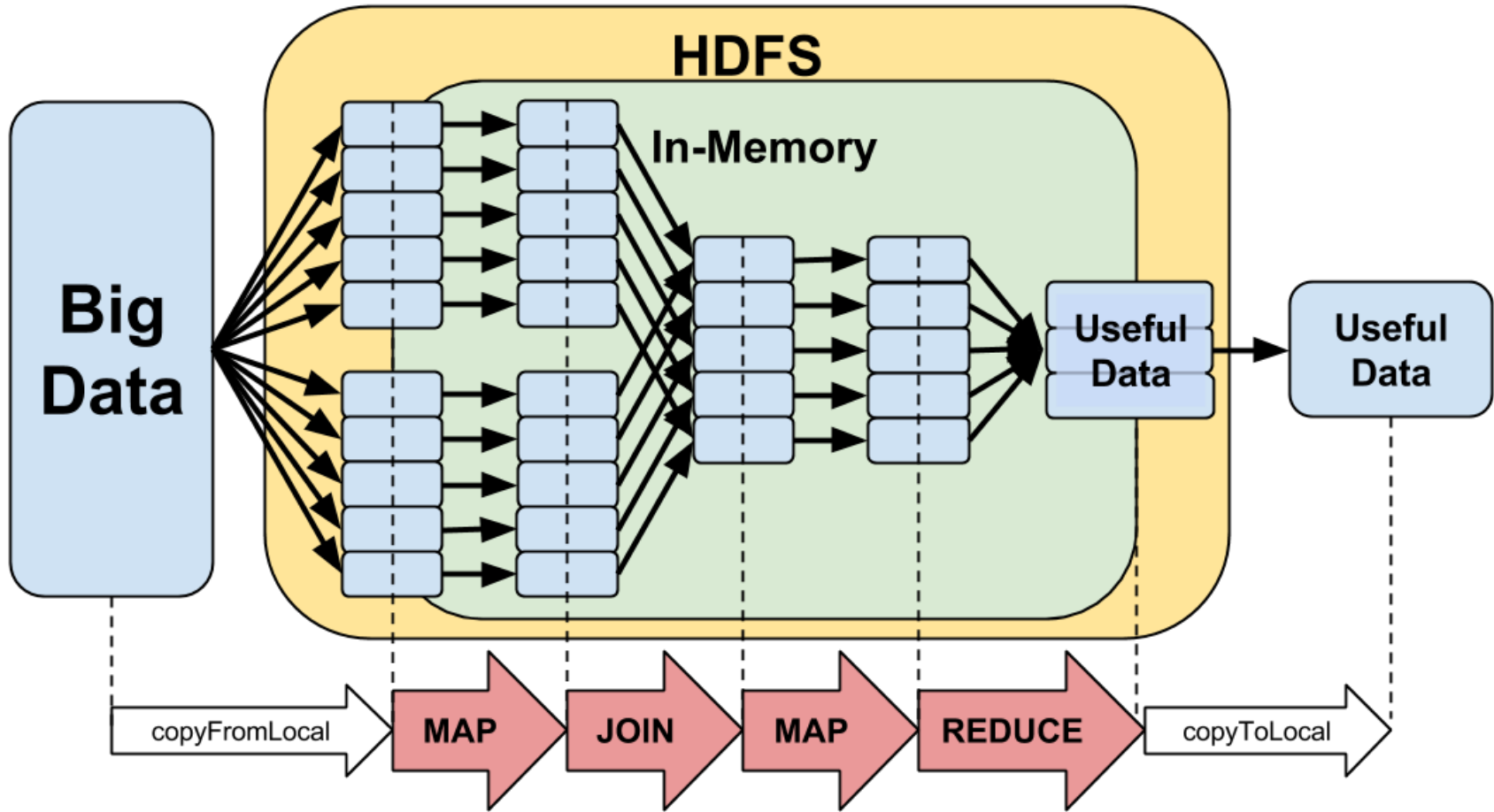
```
sc.textFile('hdfs:///user/%s/songs.tsv' % os.  
environ["USER"])
```



**Spark flow**



**Resiliency**



**Transformations and actions**

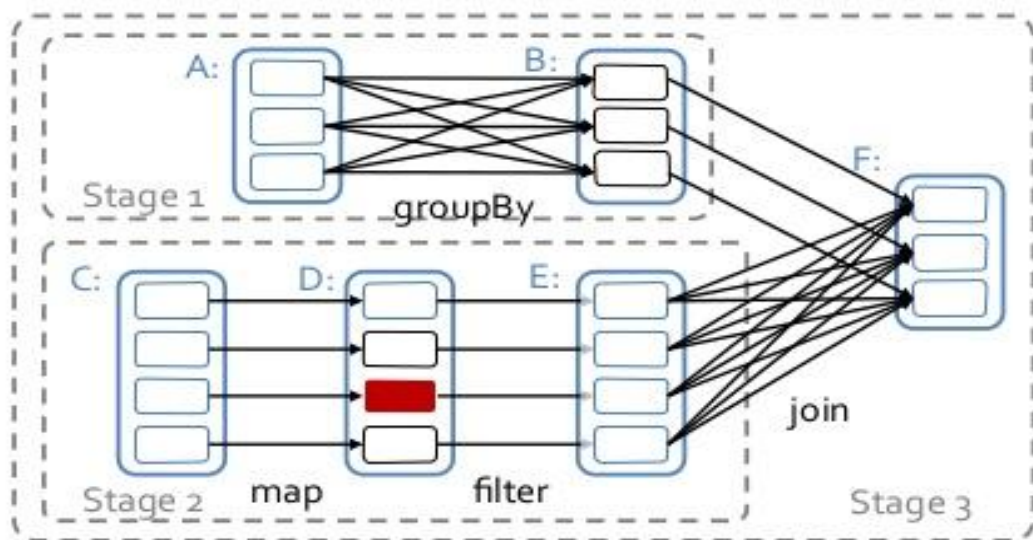


# Example Stages

 = RDD

 = cached partition

 = lost partition



# Transformations

- `map(func)` - apply func to all elements
- `flatMap(func)` - map then flatten output
- `filter(func)` - keep only elements where func is true
- `sample(withReplacement, fraction, seed)` - get a random data fraction

# Hands-on

Print all the values of hotness larger than .5

# Example (PySpark)

```
songs_hotness.filter(lambda x:x>.5).collect()  
[0.9, 0.55, 0.98]
```

# Transformations (2)

- `union(otherDataset)` - merge datasets
- `coalesce(numPartitions)` - decrease number of partitions

# Extract data from RDD

- `collect()` - copy all elements to the driver
- `take(n)` - copy first n elements
- `saveAsTextFile(filename)` - save to file
- `reduce(func)` - aggregate elements with func (takes 2 elements, returns 1)

# Cache data in memory

```
max_hotness = songs_hotness.max()  
min_hotness = songs_hotness.min()
```

Each operation reads the data back again,  
Spark does not keep intermediate results in  
memory. Can trigger cache with:

```
songs_hotness.cache()
```

# Cached RDD

- Generally recommended after data cleaning
- Reusing cached data: 10x speedup
- Great for iterative algorithms
- If RDD too large, will only be partially cached in memory



```
data = sc.textFile('songs.tsv')
```

```
def extract_hotness(line):  
    return float(line.split()[1])
```

```
songs_hotness = data.map(extract_hotness)  
songs_hotness.cache()  
max_hotness = songs_hotness.max()
```

**Spark is lazy**

# Broadcast variables

- Large variable used in all nodes, possibly in many functions
- Transfer just once per Executor
- For example large configuration dictionary or lookup table

```
config = sc.broadcast({"order":3, "filter":True})  
config.value
```

# Accumulators

- Common pattern of accumulating to a variable across the cluster

```
accum = sc.accumulator(0)
```

```
sc.parallelize([1, 2, 3, 4]).foreach(lambda x:  
accum.add(x))
```

```
accum.value
```

```
10
```

# SparkUI

from your local machine:

```
$ ssh username@comet.sdsc.edu -L 4040:IP:  
4040
```

Open browser at localhost:4040

# Spark SQL

**Tabular data processing in Spark**

# What is Spark SQL?

- High-level interface for structured data (i.e. tables)
- Provides Dataframes (data organized in columns), ~pandas, R
- Runs distributed SQL queries

# Advantages of Spark SQL

- Same interface in Java/Scala/Python/R
- Native speed even in Python/R
- More expressive code -> easier to maintain

# Spark SQL demo

Open pyspark



# Hands-on

1. find maximum hotness for each decade
2. find how many songs for each decade

# Spark MLlib

Machine Learning with Spark

# Spark MLlib introduction

- Machine learning library
- Built on top of Spark
- Distributed linear algebra primitives:
  - Labeled points  $[y, X]$
  - Dense vectors and matrices
  - Sparse vectors, matrices, block matrices

# Spark MLlib features

- linear SVM and logistic regression
- classification and regression tree
- random forest and gradient-boosted trees
- recommendation via alternating least squares
- clustering via k-means, Gaussian mixtures, and power iteration clustering
- singular value decomposition

# Spark MLlib demo

- open pyspark

# Hands-on

- print the KMeans cluster centers (k=4)  
adding also the year as a features column

# Thanks

**Questions?**

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# View partitioning

- glom gathers all data in a partition as a list:

```
songs_hotness.repartition(2).glom().collect()  
[[0.4, 0.12, 0.55], [0.98, 0.9, 0.2]]
```

```
songs_hotness.repartition(3).glom().collect()  
[[0.12], [0.55, 0.4], [0.9, 0.2, 0.98]]
```