

25 YEARS ANNIVERSARY  
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY  
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY



HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY  
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

# Chapter 6

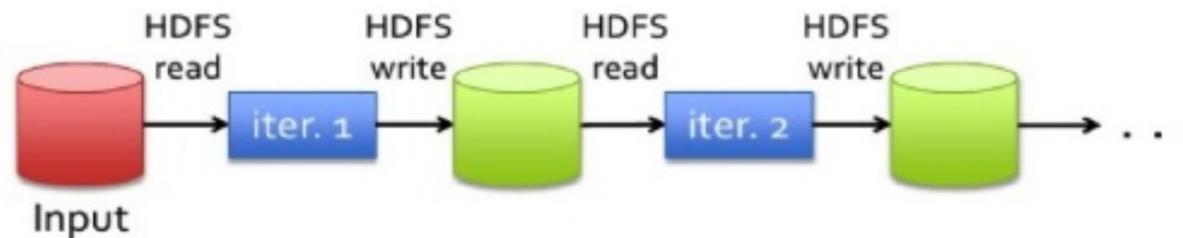
# Batch processing - part 2

## Apache Spark

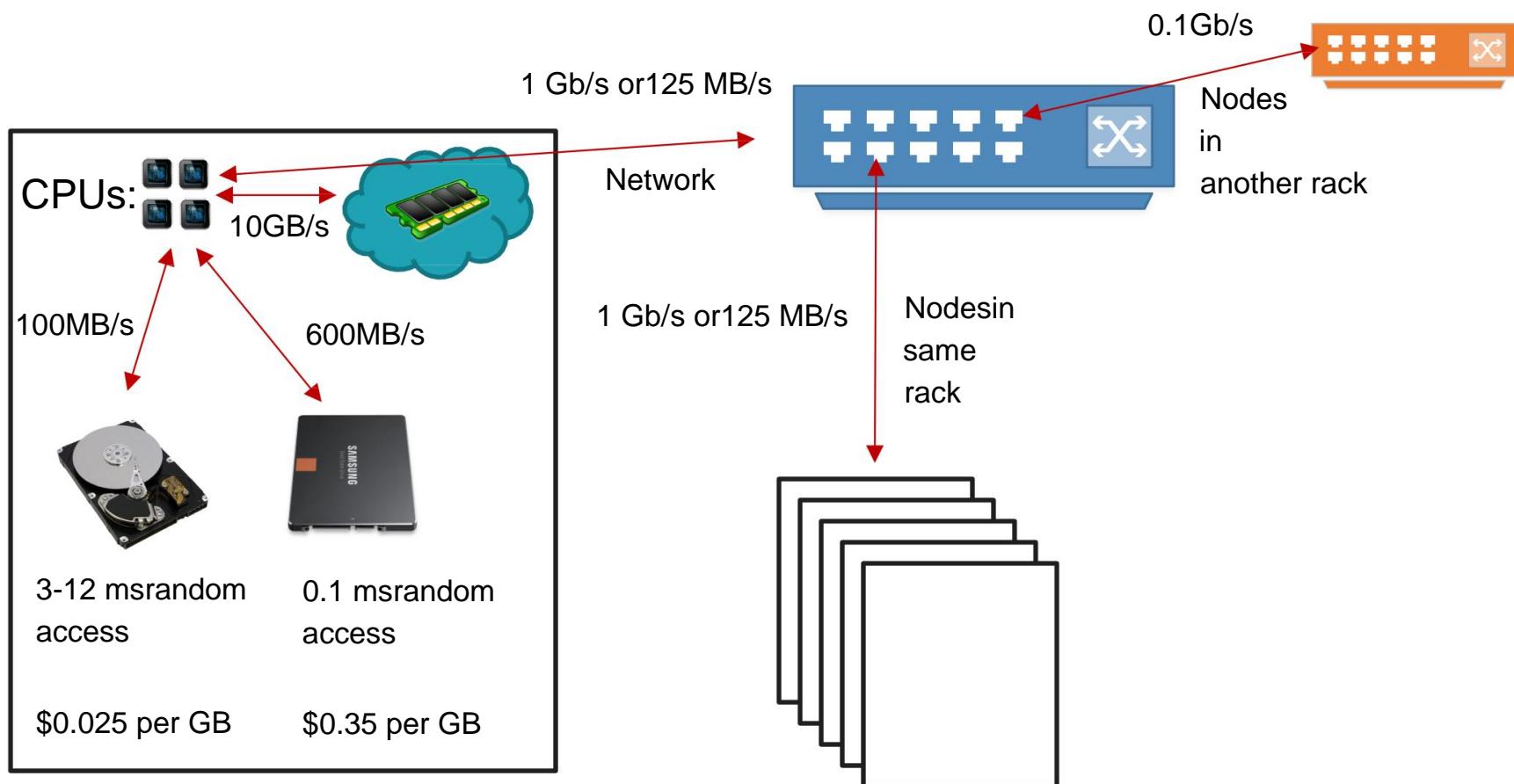
An unified analytics engine for large-scale data  
processing

# Map Reduce: Iterative jobs

- Iterative jobs involve a lot of disk I/O for each repetition

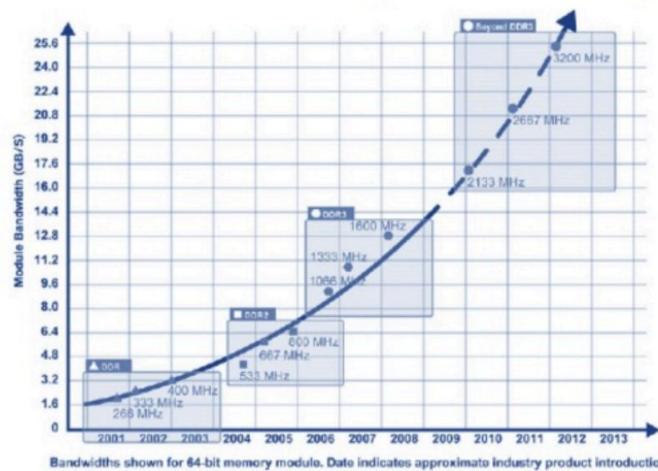


- è Disk I/O is very slow!

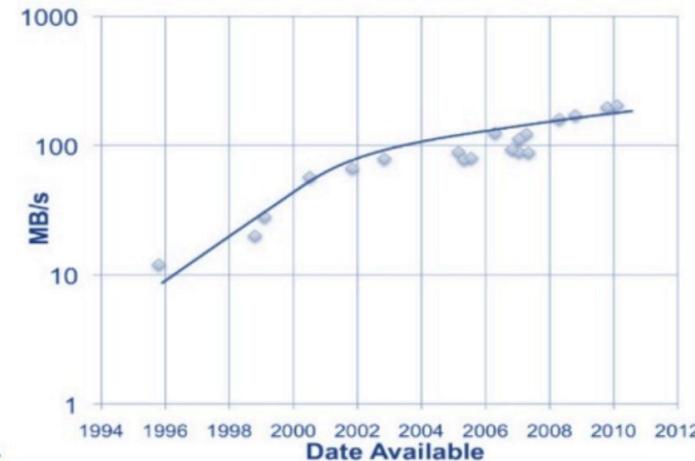


# RAM is the new disk

- RAM throughput increasing **exponentially**



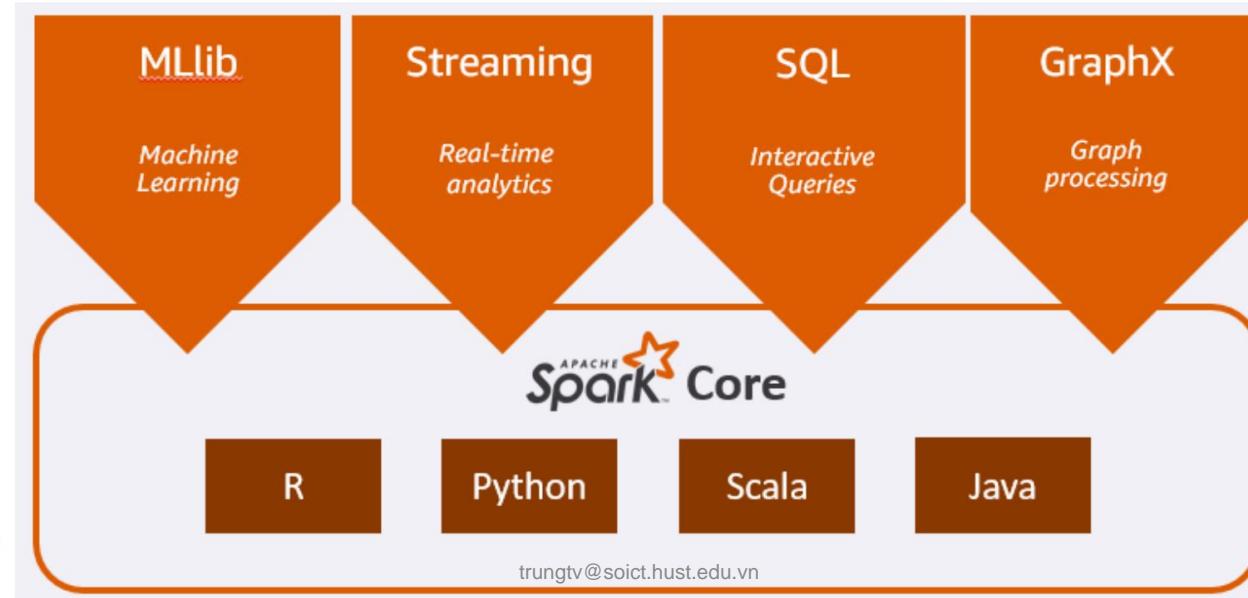
- Disk throughput increasing **slowly**



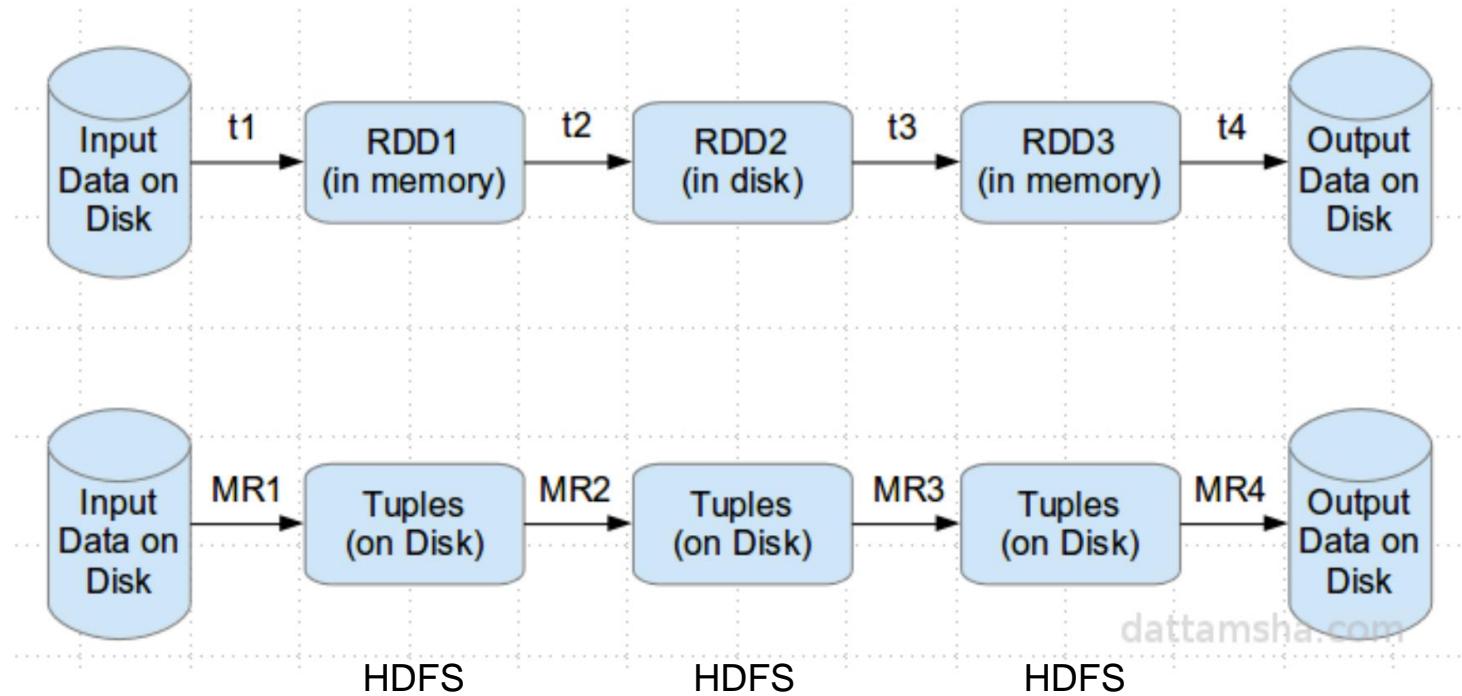
**Memory-locality** key to interactive response times

# A unified analytics engine for large-scale data processing

- Better support for
  - Iterative algorithms
  - Interactive data mining
- Fault tolerance, data locality, scalability • Hide complexities: help users avoid the coding for structure the distributed mechanism.



# Memory instead of disk



# Spark and Map Reduce differences

	Apache Hadoop MR	Apache Spark
Storage	Disk only	In-memory or on disk
Operations	Map and Reduce	Many transformations and actions, including Map and Reduce
Execution model	Batch	Batch, iterative, streaming
Languages	Java	Scala, Java, Python and R

# Apache Spark vs Apache Hadoop

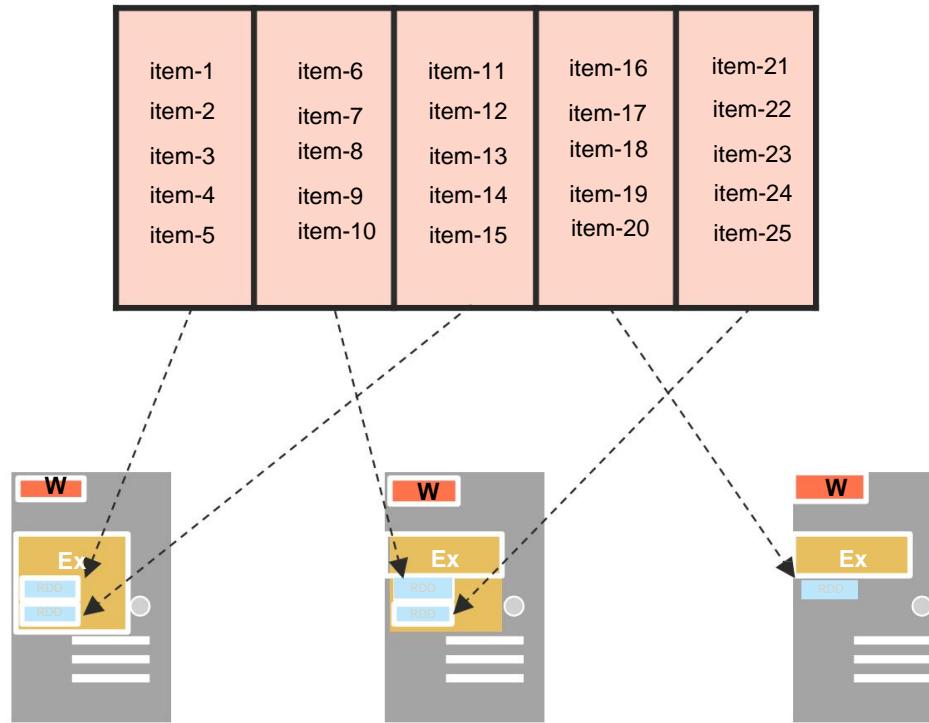
	Hadoop World Record	Spark 100 TB *	Spark 1 PB
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400	6592	6080
# Reducers	10,000	29,000	250,000
Rate	1.42 TB/min	4.27 TB/min	4.27 TB/min
Rate/node	0.67 GB/min	20.7 GB/min	22.5 GB/min
Sort Benchmark	Yes	Yes	No
Daytona Rules			
Environment	dedicated data center	EC2 (i2.8xlarge)	EC2 (i2.8xlarge)

# Resilient Distributed Dataset (RDD)

- RDDs are ***fault-tolerant, parallel data structures*** that let users explicitly persist ***intermediate results in memory***, control their partitioning to optimize data placement, and manipulate them using ***a rich set of operators***.
- coarse-grained transformations vs. fine-grained updates
  - eg, map, filter and join) that applies the same operation to many data items at once.

*more partitions= more parallelism*

RDD



# RDD with 4 partitions

logLinesRDD			
Error, ts, msg1 Warning, ts, msg2 Error, ts, msg1	Info, ts, msg8 Warn, ts, msg2 Info, ts, msg8	Error, ts, msg3 Info, ts, msg5 Info, ts, msg5	Error, ts, msg4 Warning, ts, msg9 Error, ts, msg1

A base RDD can be created 2ways:

- Parallelize a collection
- Read data from an external source (S3, C\*, HDFS, etc)

# Parallelize



```
// Parallelize in Scala  
val wordsRDD = sc.parallelize(List("fish", "cats", "dogs"))
```

---

- Take an existing in-memory collection and pass it to `SparkContext's parallelize` method

- Not generally used outside of prototyping and testing since it requires entire dataset in memory on one machine



```
# Parallelize in Python  
wordsRDD = sc.parallelize(["fish", "cats", "dogs"])
```

---



```
// Parallelize in Java  
JavaRDD<String> wordsRDD = sc.parallelize(Arrays.asList("fish", "cats", "dogs"));
```

# Read from Text File



```
// Read a local txt file in Scala  
val linesRDD = sc.textFile("/path/to/README.md")
```

---

There are other methods to read data from HDFS, C\*, S3, HBase, etc.



```
# Read a local txt file in Python  
linesRDD = sc.textFile("/path/to/README.md")
```

---

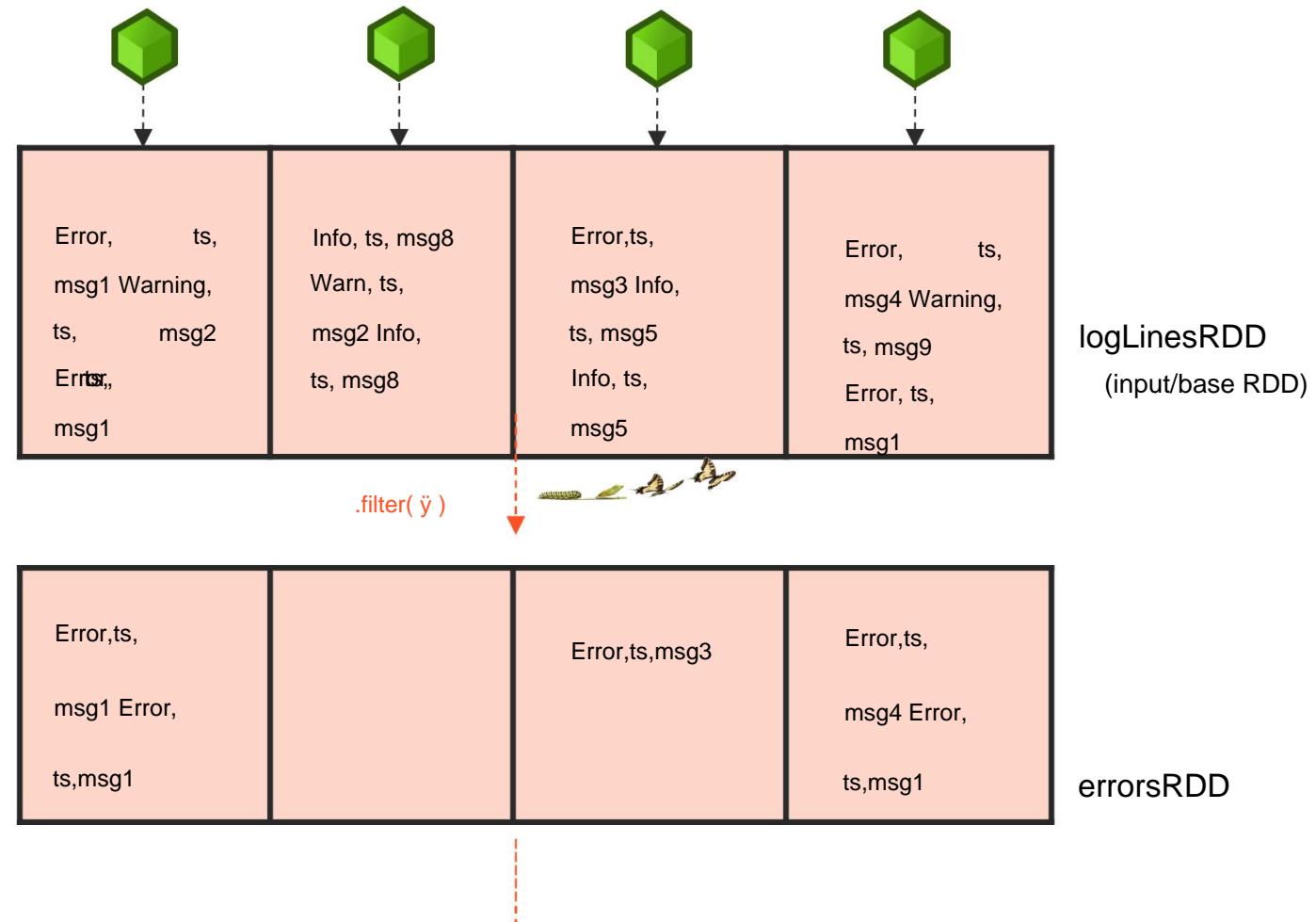


```
// Read a local txt file in Java  
JavaRDD<String> lines = sc.textFile("/path/to/README.md");
```

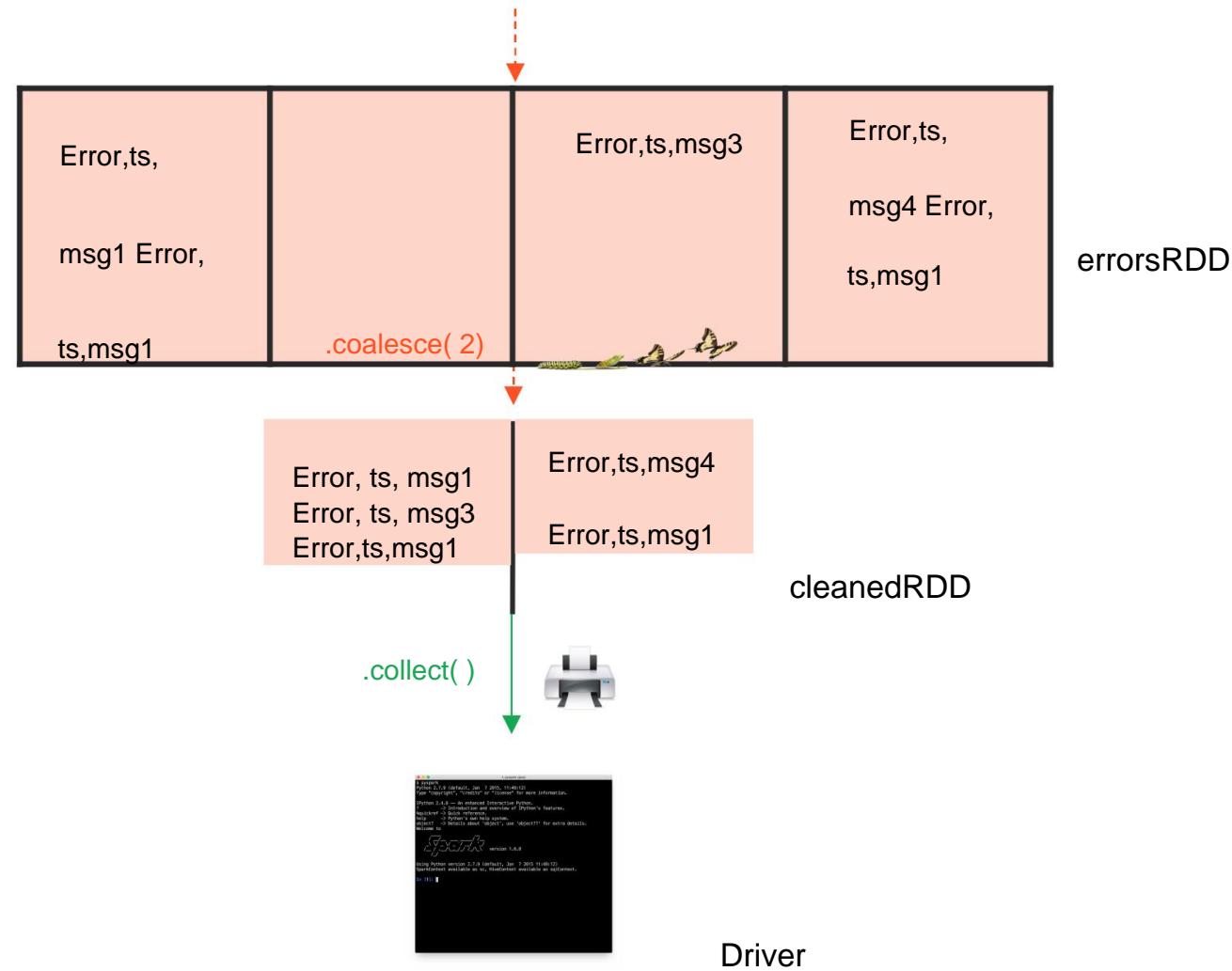
# Operations on Distributed Data

- Two types of operations: transformations and actions •  
Transformations are lazy (not computed immediately) • Transformations  
are executed when an action is run
- Persist (cache) distributes data in memory or disk

# Transformation: Filter



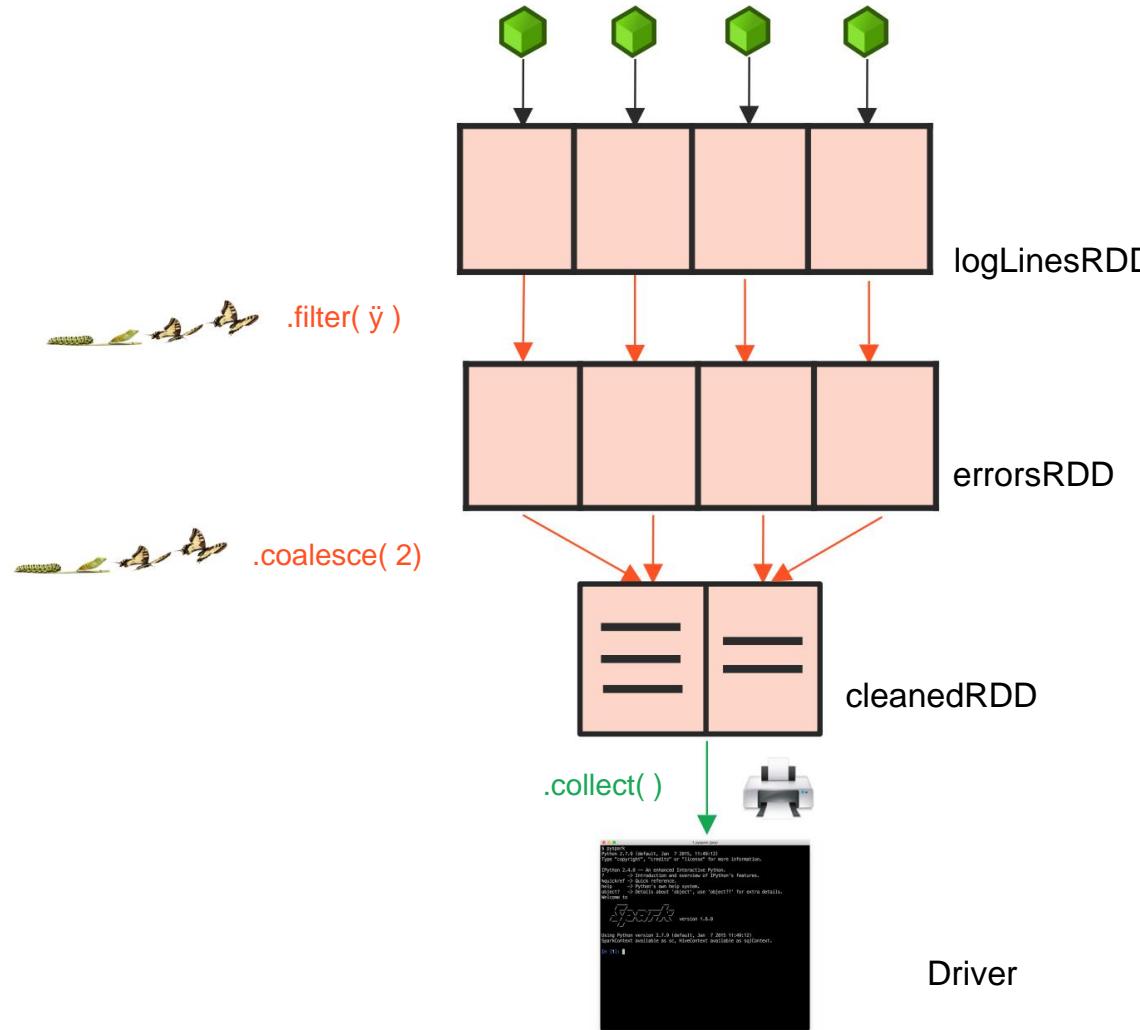
# Action: Collect



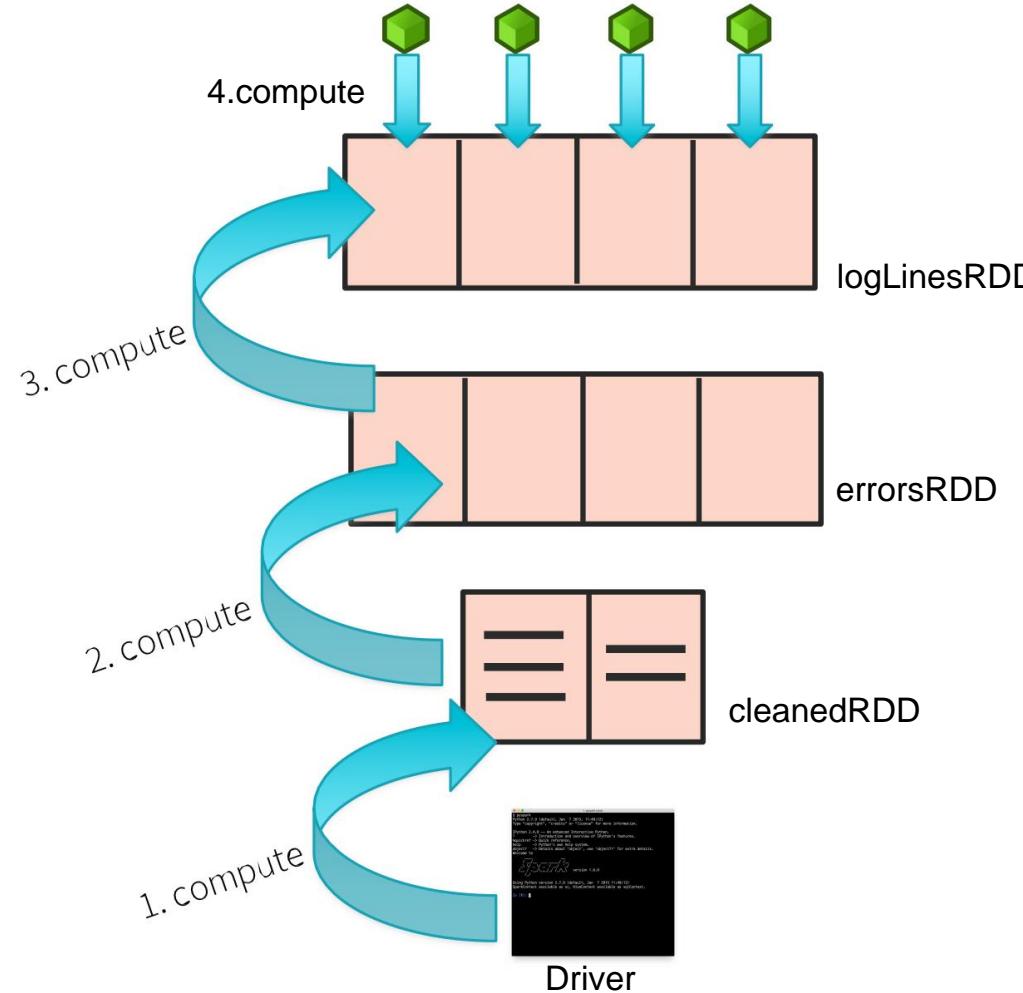
# DAG execution



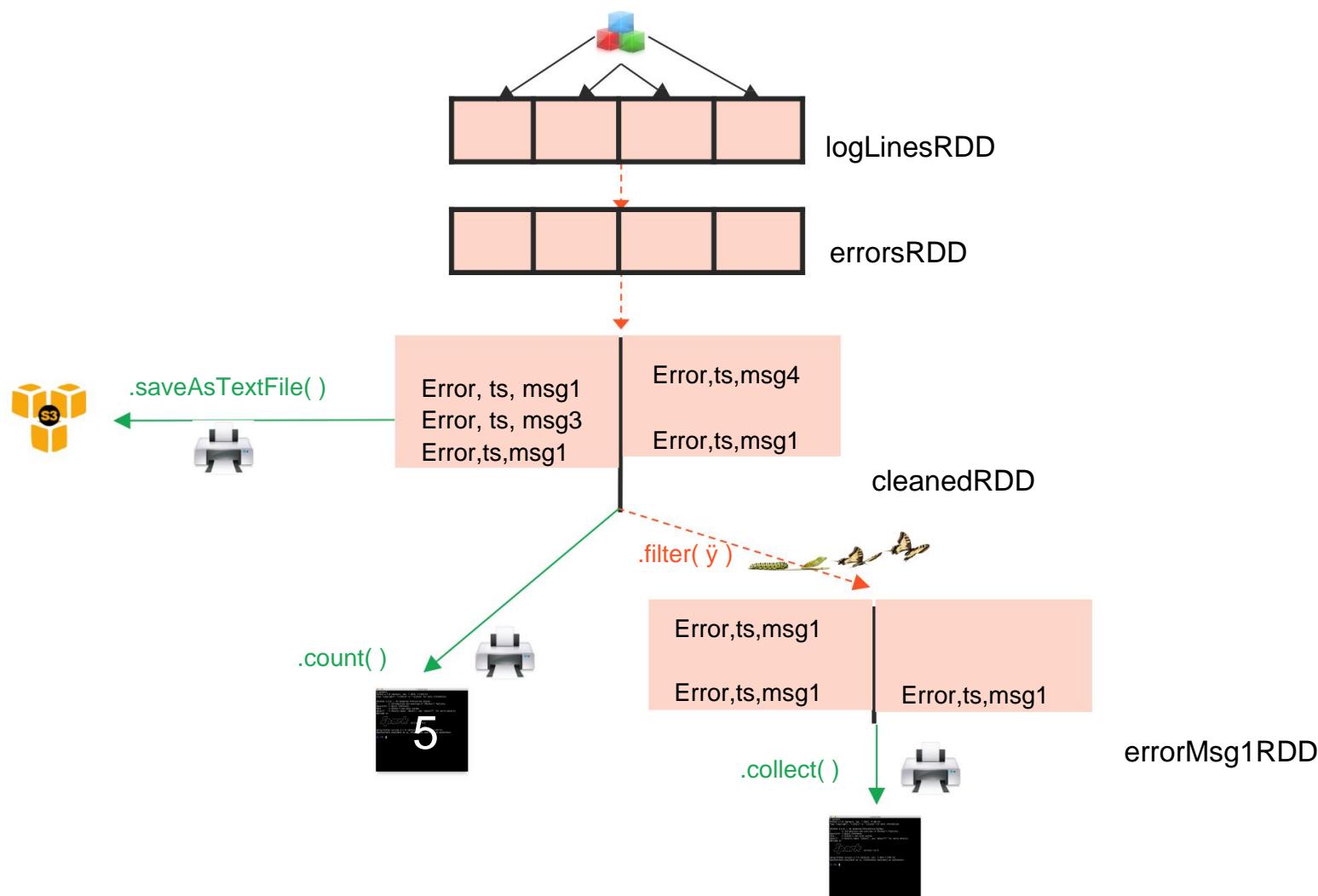
# Logical



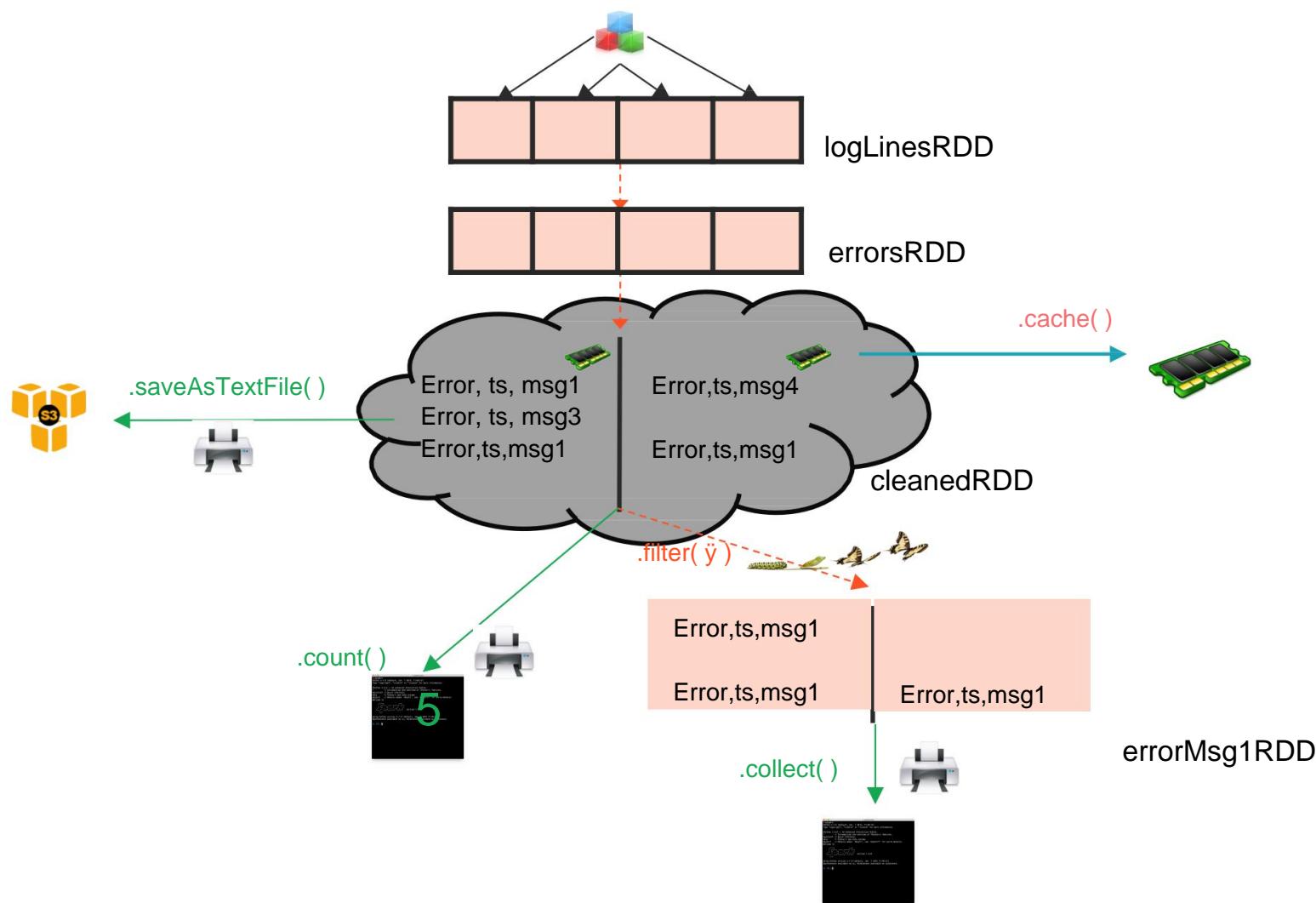
# Physical



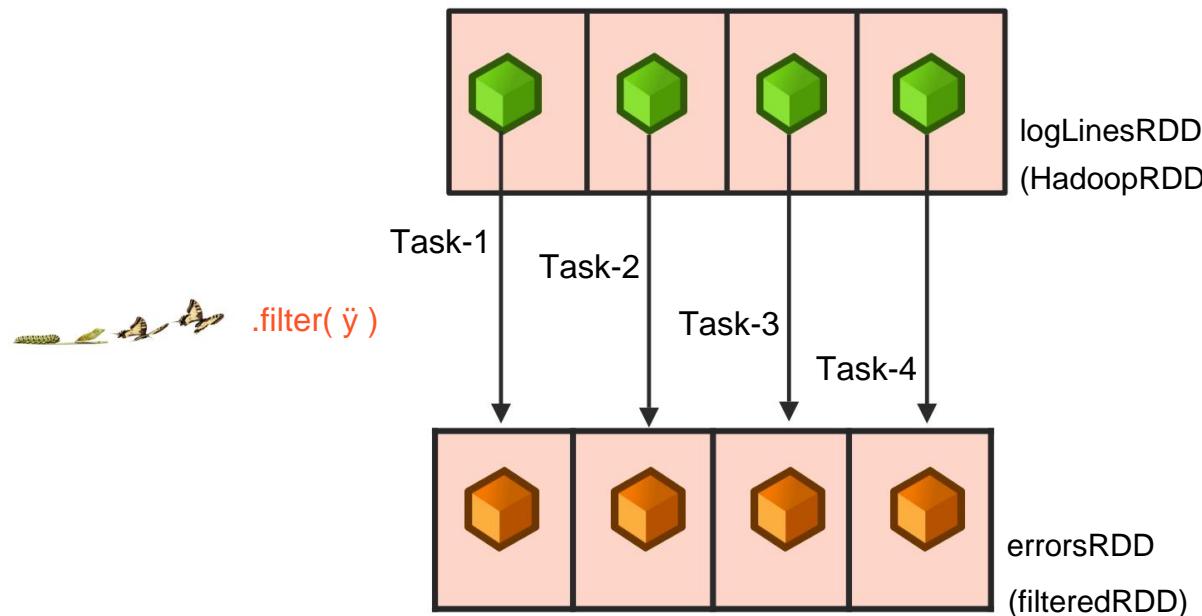
# DAG



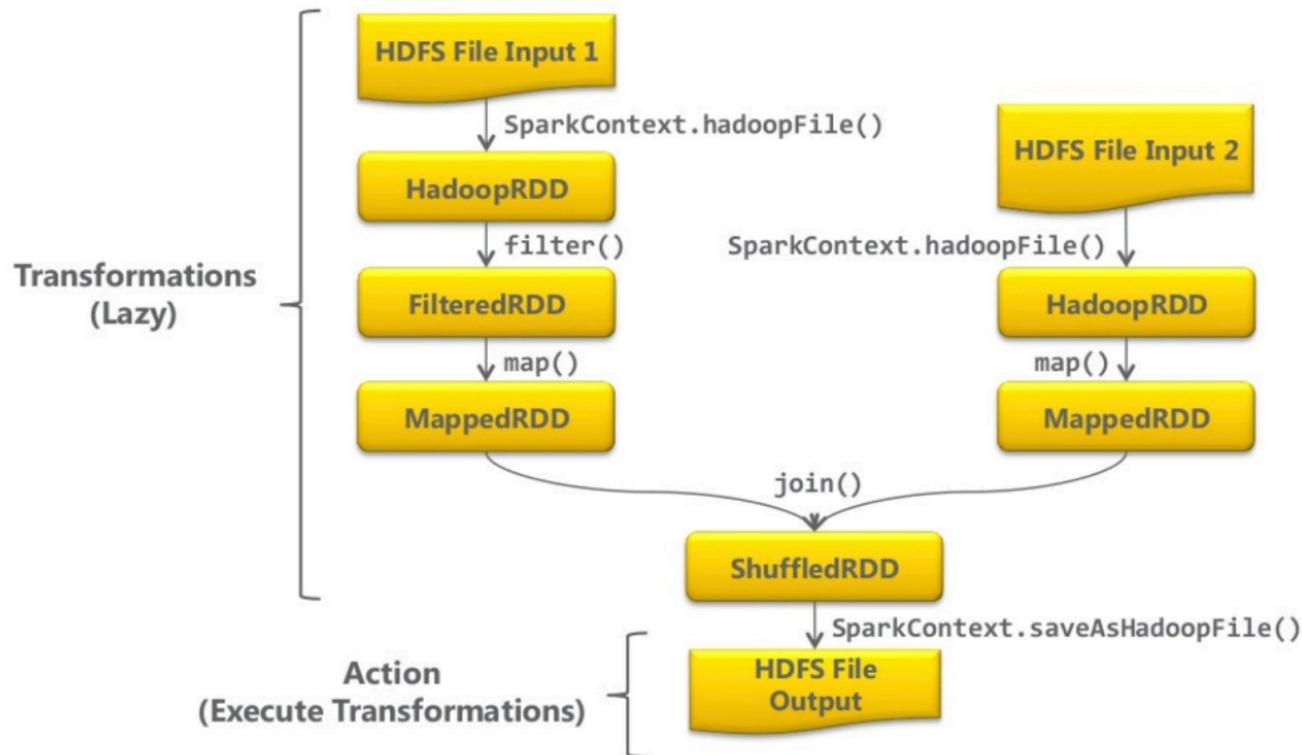
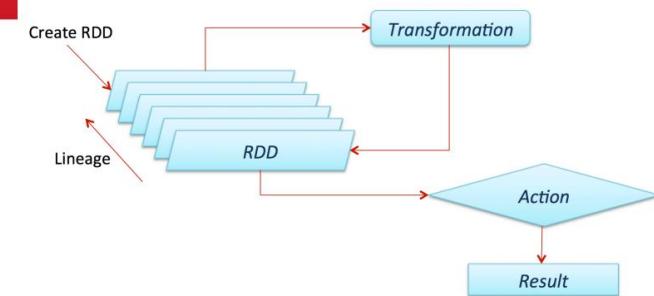
# Cache



# Partition >>> Task >>> Partition



# RDD Lineage



# Resilient Distributed Dataset (RDD)

- Initial RDD on **disks** (HDFS, etc) •  
Intermediate RDD on **RAM**
- Fault recovery is based on **lineage** • RDD  
operations are distributed

# DataFrame

- A primary abstraction in Spark 2.0
  - Immutable once constructed • Track lineage information to efficiently re-compute lost data
  - Enable operations on collection of elements in parallel
- To construct DataFrame
  - By parallelizing existing Python collections (lists)
  - By transforming an existing Spark or pandas DataFrame
  - From files in HDFS or other storage system

# Using DataFrame

```
>>> data = [('Alice', 1), ('Bob', 2), ('Bob', 2)]  
>>> df1 = sqlContext.createDataFrame(data, ['name',  
'age'])  
[Row(name=u'Alice', age=1),  
 Row=(name=u'Bob', age=2),  
 Row=(name=u'Bob', age=2)]
```

# Transformations

- Create new DataFrame from an existing one
- Use lazy evaluation
  - Nothing executes
  - Spark saves recipe for transformation source

Transformation	Description
select(*cols)	Selects columns from this DataFrame
drop(col)	Returns a new Dataframe that drops the specific column
filter(func)	Returns a new DataFrame formed by selecting those rows of the source on which <i>func</i> returns true
where(func)	Where is an alias for filter
distinct()	Returns a new DataFrame that contains the distinct rows of the source DataFrame
sort(*cols, **kw)	Returns a new DataFrame sorted by the specified columns and in the sort order specified by <i>kw</i>

# Using Transformations

```
>>> data = [('Alice', 1), ('Bob', 2), ('Bob', 2)]  
>>> df1 = sqlContext.createDataFrame(data, ['name',  
'age'])  
>>> df2 = df1.distinct()  
[Row(name=u'Alice', age=1), Row=(name=u'Bob',  
age=2)]  
>>> df3 = df2.sort("age", ascending=False)  
[Row=(name=u'Bob', age=2), Row(name=u'Alice',  
age=1)]
```

# Actions

- Cause Spark to execute recipe to transform source
- Mechanisms for getting results out of Spark

Action	Description
show( <i>n</i> , <i>truncate</i> )	Prints the first <i>n</i> rows of this DataFrame
take( <i>n</i> )	Returns the first <i>n</i> rows as a list of Row
collect()	Returns all the records as a list of Row (*)
count()	Returns the number of rows in this DataFrame
describe(*cols)	Exploratory Data Analysis function that computes statistics (count, mean, stddev, min, max) for numeric columns

# Using Actions

```
>>> data = [('Alice', 1), ('Bob', 2)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.collect()
[Row(name=u'Bob', age=2), Row(name=u'Alice', age=1)]
>>> df.count()
2
>>> df.show()
+---+---+
|name| age |
+---+---+
|Alice|    1|
|Bob |    2|
+---+---+
```

# Caching

```
>>> linesDF = sqlContext.read.text('...')

>>> linesDF.cache()

>>> commentsDF = linesDF.filter(isComment)

>>> print linesDF.count(), commentsDF.count()

> >> commentsDF.cache()
```

# Spark Programming Routine

- Create DataFrames from external data or `createDataFrame` from a collection in driver program
- Lazily transform them into new DataFrames
- `cache()` some DataFrames for reuse
- Perform actions to execute parallel computation and produce results

# DataFrames versus RDDs

- For new users familiar with data frames in other programming languages, this API should make them feel at home
- For existing Spark users, the API will make Spark easier to program than using RDDs
- For both sets of users, DataFrames will improve performance through intelligent optimizations and code-generation

# Write Less Code: Input & Output

Unified interface to reading/writing data in a variety of formats.

```
val df = sqlContext.  
    read.  
    format("json").  
    option("samplingRatio", "0.1").  
    load("/Users/spark/data/stuff.json")  
  
df.write.  
    format("parquet").  
    mode("append").  
    partitionBy("year").  
    saveAsTable("faster-stuff")
```



# Write Less Code: Input & Output

Unified interface to reading/writing data in a variety of formats.

```
val df = sqlContext.read.  
    format("json").  
    option("samplingRatio", "0.1").  
    load("/Users/spark/data/stuff.json")  
  
df.write.  
    format("parquet").  
    mode("append").  
    partitionBy("year").  
    saveAsTable("faster-stuff")
```

read and write  
functions create  
new builders for  
doing I/O

# Write Less Code: Input & Output

Unified interface to reading/writing data in a variety of formats.

```
val df = sqlContext.read.  
  format("json").  
  
  }option("samplingRatio", "0.1").  
  load("/Users/spark/data/stuff.json") • format  
  
df.write.  
  mode("append").  
  
  }format("parquet").  
  
partitionBy("year").  
  saveAsTable("faster-  
  stuff")
```

Builder  
" methods )  
**specify:**  
  
• partitioning •  
  
handling of  
  
existing data

# Write Less Code: Input & Output

Unified interface to reading/writing data in a variety of formats.

```
val df = sqlContext.read.
```

```
format("json").  
option("samplingRatio", "0.1").  
Users/spark/data/stuff.json")
```

```
df.write.
```

```
format("parquet").  
mode("append").  
partitionBy("year").  
saveAsTable("faster-stuff")
```



load(...), save(...), load("/  
or saveAsTable(...) finish  
the I/O  
specification

# Data Sources supported by DataFrames

built-in



external



and more...

# Write Less Code: High-Level Operations

- Solve common problems concisely with DataFrame functions:
  - selecting columns and filtering
  - joining different data sources
  - aggregation (count, sum, average, etc.)
  - plotting results (eg, with Pandas)

# Write Less Code: Compute an Average



```
private IntWritable one = new IntWritable(1); private IntWritable
output =new IntWritable(); protected void map(LongWritable
key,
        Text value,
        Context context) {
    String[] fields = value.split("t");
    output.set(Integer.parseInt(fields[1])); context.write(one,
    output);
}
```

```
IntWritable one = new IntWritable(1)
DoubleWritable average = new DoubleWritable();

protected void reduce(IntWritable key,
        Iterable<IntWritable> values,
        Context context) {
    int sum = 0; int
    count = 0; for
    (IntWritable value: values) { sum +=
        value.get(); count++;

    } average.set(sum / (double) count);
    context.write(key, average);
}
```



```
rdd = sc.textFile(...).map(_.split(" ")) rdd.map { x => (x(0),
(x(1).toFloat, 1)) }. reduceByKey { case ((num1, count1),
(num2, count2)) =>
    (num1 + num2, count1 + count2)
}.
map { case (key, (num, count)) => (key, num / count) }. collect()
```



```
rdd = sc.textFile(...).map(lambda s: s.split()) rdd.map(lambda x:
(x[0], (float(x[1]), 1))).\ reduceByKey(lambda t1, t2: (t1[0] + t2[0],
t1[1] + t2[1])).\ map(lambda t: (t[0], t[1][0] / t[1][1])).\ collect()
```

# Write Less Code: Compute safely

## Average

### Using RDDs

```
rdd = sc.textFile(...).map(_.split(" ")).rdd.map { x =>  
  (x(0), (x(1).toFloat, 1)) }.reduceByKey { case ((num1,  
  count1), (num2, count2)) =>  
  (num1 + num2, count1 + count2) }.  
  
  map { case (key, (num, count)) => (key, num / count) }.collect()
```



[Full API Docs](#) •

[Scala](#) •

[Java](#) •

[Python](#) • [R](#)

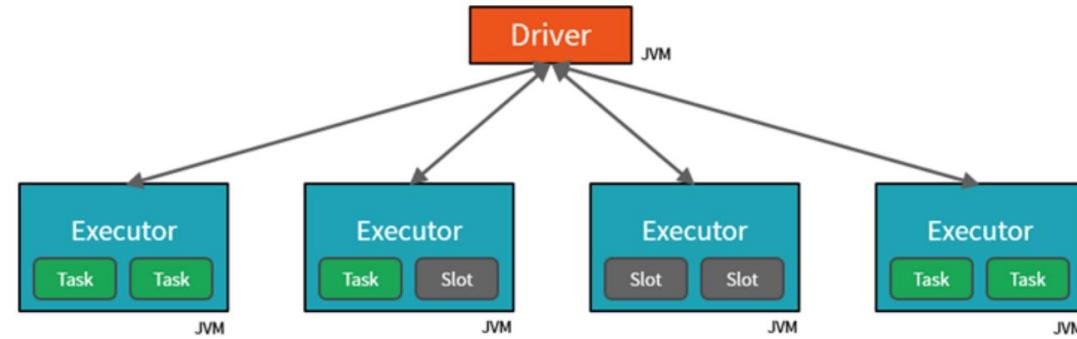
### Using DataFrames

```
import org.apache.spark.sql.functions._  
  
val df = rdd.map(a => (a(0), a(1))).toDF("key", "value") df.groupBy("key")  
  
.agg(avg("value")).collect()
```



# Architecture

- A master-worker type architecture
  - A driver or master node
  - Worker nodes



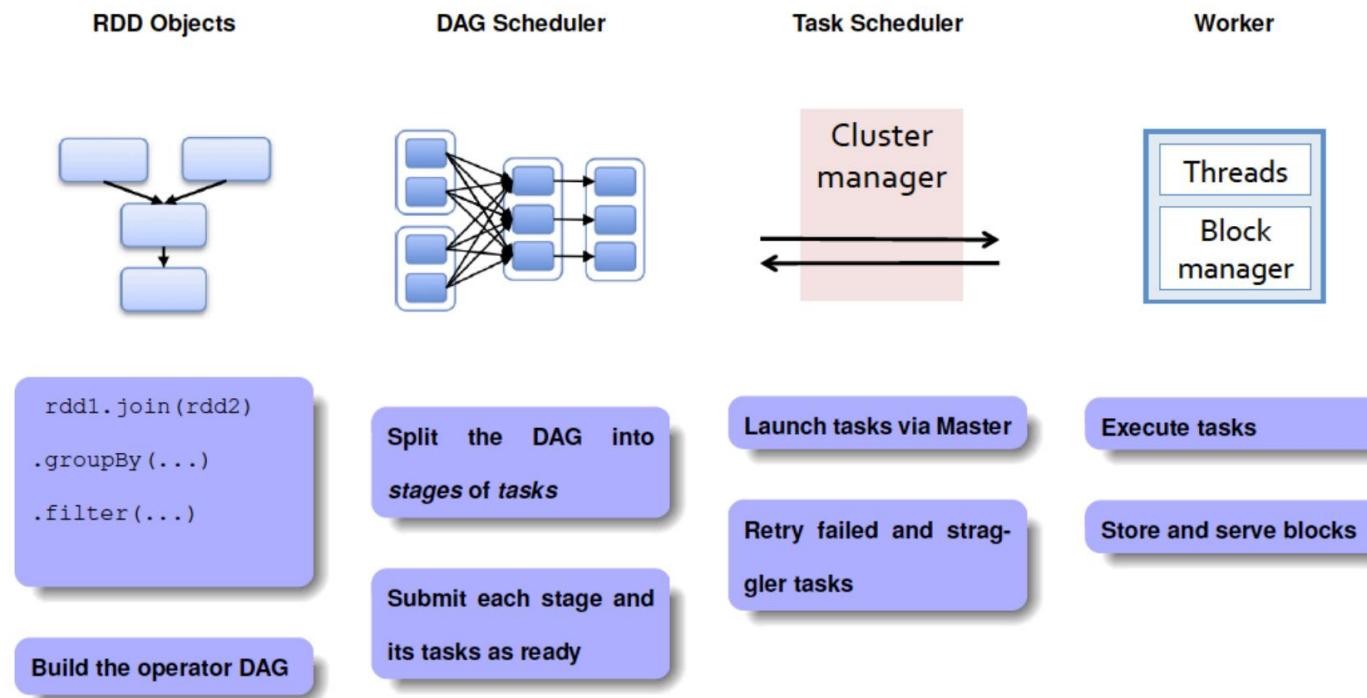
- The master sends works to the workers and either instructs them to pull data from memory or from hard disk (or from another source like S3 or HDFS)

# Architecture(2)

- A Spark program first creates a `SparkContext` object
  - `SparkContext` tells Spark how and where to access a cluster
  - The master parameter for a `SparkContext` determines which type and size of cluster to use

Master parameter	Description
<code>local</code>	Run Spark locally with one worker thread (no parallelism)
<code>local[K]</code>	Run Spark locally with K worker threads (ideal set to number of cores)
<code>spark://HOST:PORT</code>	Connect to a Spark standalone cluster
<code>mesos://HOST:PORT</code>	Connect to a Mesos cluster
<code>yarn</code>	Connect to a YARN cluster

# Lifetime of a Job in Spark



# Demo



SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

# References

- Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.
- Armbrust, Michael, et al. "Spark sql: Relational data processing in spark." *Proceedings of the 2015 ACM SIGMOD international conference on management of data*. 2015.
- Zaharia, Matei, et al. "Discretized streams: Fault-tolerant streaming computation at scale." *Proceedings of the twenty-fourth ACM symposium on operating systems principles*. 2013.
- Chambers, Bill, and Matei Zaharia. *Spark: The definitive guide: Big data processing made simple*. "O'Reilly Media, Inc.", 2018.



**25**  
YEARS ANNIVERSARY  
**SOICT**

**VIỆN CÔNG NGHỆ THÔNG TIN VÀ TRUYỀN THÔNG**  
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Thank you  
for your  
attention!!!

