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BÁCH KHOA

25 YEARS ANNIVERSARY

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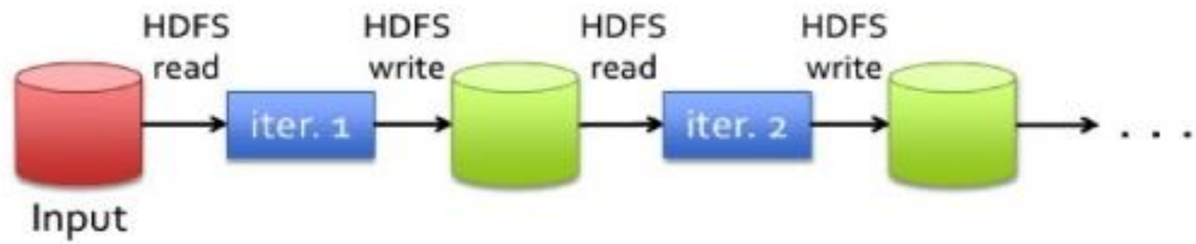
Chapter 6
Batch processing - part 2
Apache Spark

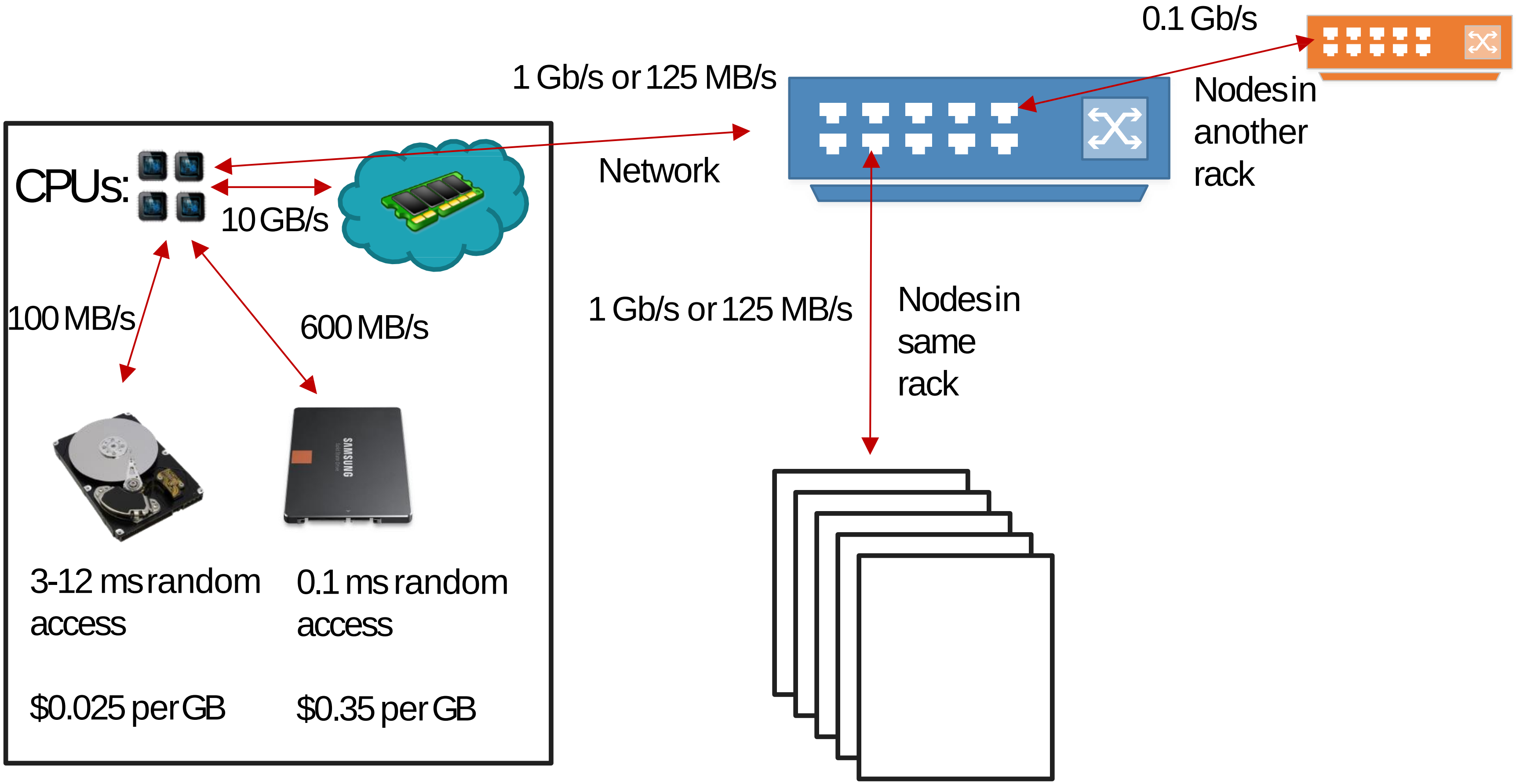
An unified analytics engine for large-scale data processing

Map Reduce: Iterative jobs

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



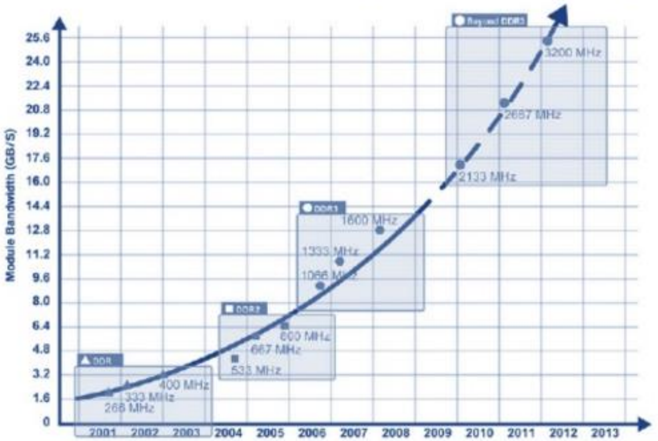
- ➔ Disk I/O is very slow!



0.1 Gb/s
1 Gb/s or 125 MB/s
Nodes in another rack
CPUs:
10 GB/s
Network
100 MB/s
600 MB/s
1 Gb/s or 125 MB/s
Nodes in same rack
3-12 ms random access
0.1 ms random access
$0.025 per GB
$0.35 per GB

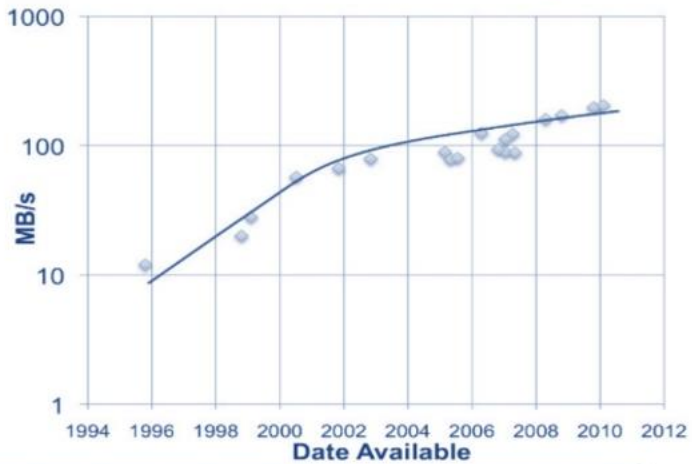
RAM is the new disk

- RAM throughput increasing **exponentially**



Bandwidths shown for 64-bit memory module. Date indicates approximate industry product introduction.

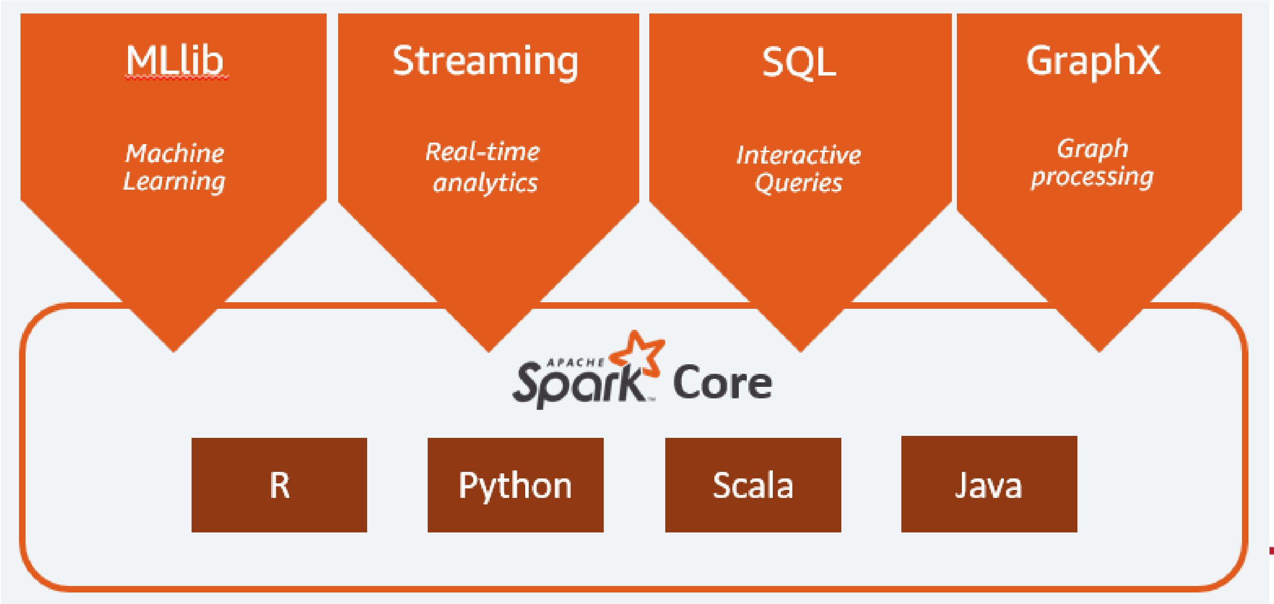
- Disk throughput increasing **slowly**



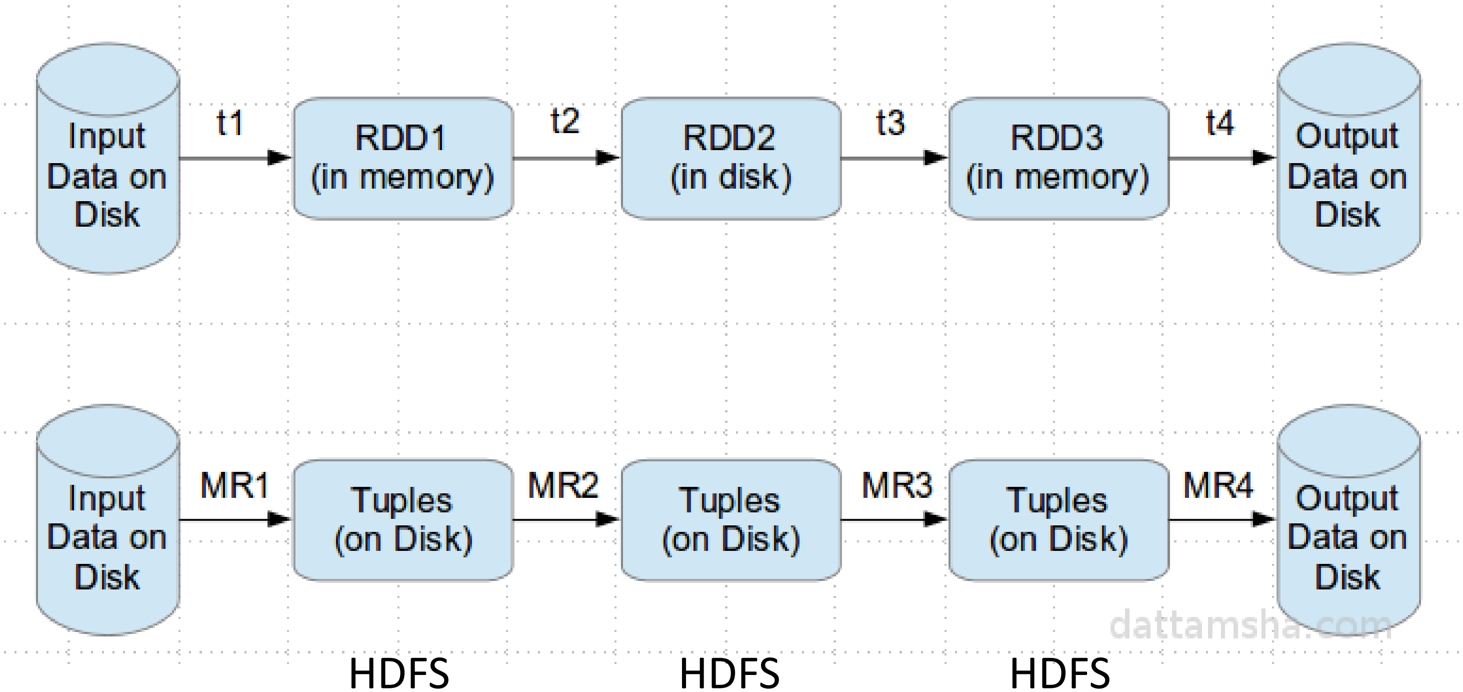
Memory-locality key to interactive response times

A unified analytics engine for large-scale data processing

- Better support for
  - Iterative algorithms
  - Interactive data mining
- Fault tolerance, data locality, scalability
- Hide complexites: 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

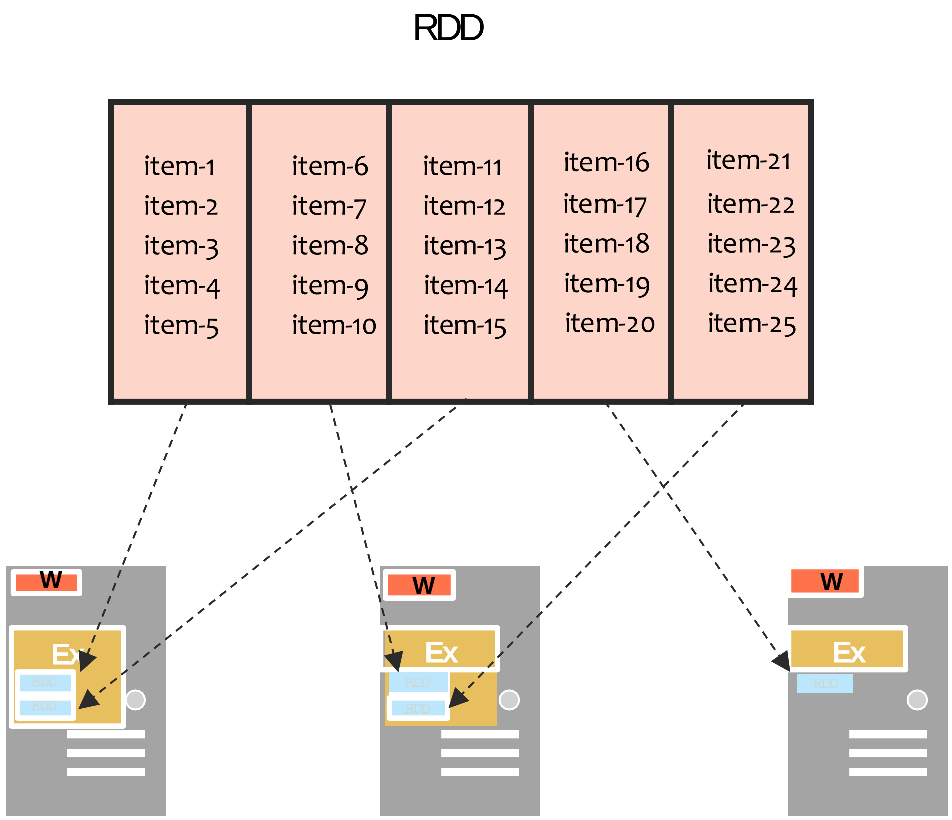
	Hadoop World Record	Spark 100 TB *	Spark 1 PB
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400	6592	6080
# Reducers	10,000	29,000	250,000
Rate	1.42 TB/min	4.27 TB/min	4.27 TB/min
Rate/node	0.67 GB/min	20.7 GB/min	22.5 GB/min
Sort Benchmark Daytona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

https://databricks.com/blog/2014/10/10/spark-petabyte-sort.html

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
  - e.g., map, filter and join) that apply the same operation to many data items at once.

more partitions=more parallelism



RDD with 4 partitions

Error, ts, msg1 Warn, 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 Warn, ts, msg9 Error, ts, msg1	logLinesRDD

A base RDD can be created 2 ways:

- 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"))
```

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

```
// Parallelize in Java
JavaRDD<String> wordsRDD = sc.parallelize(Arrays.asList("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

Read from Text File

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

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

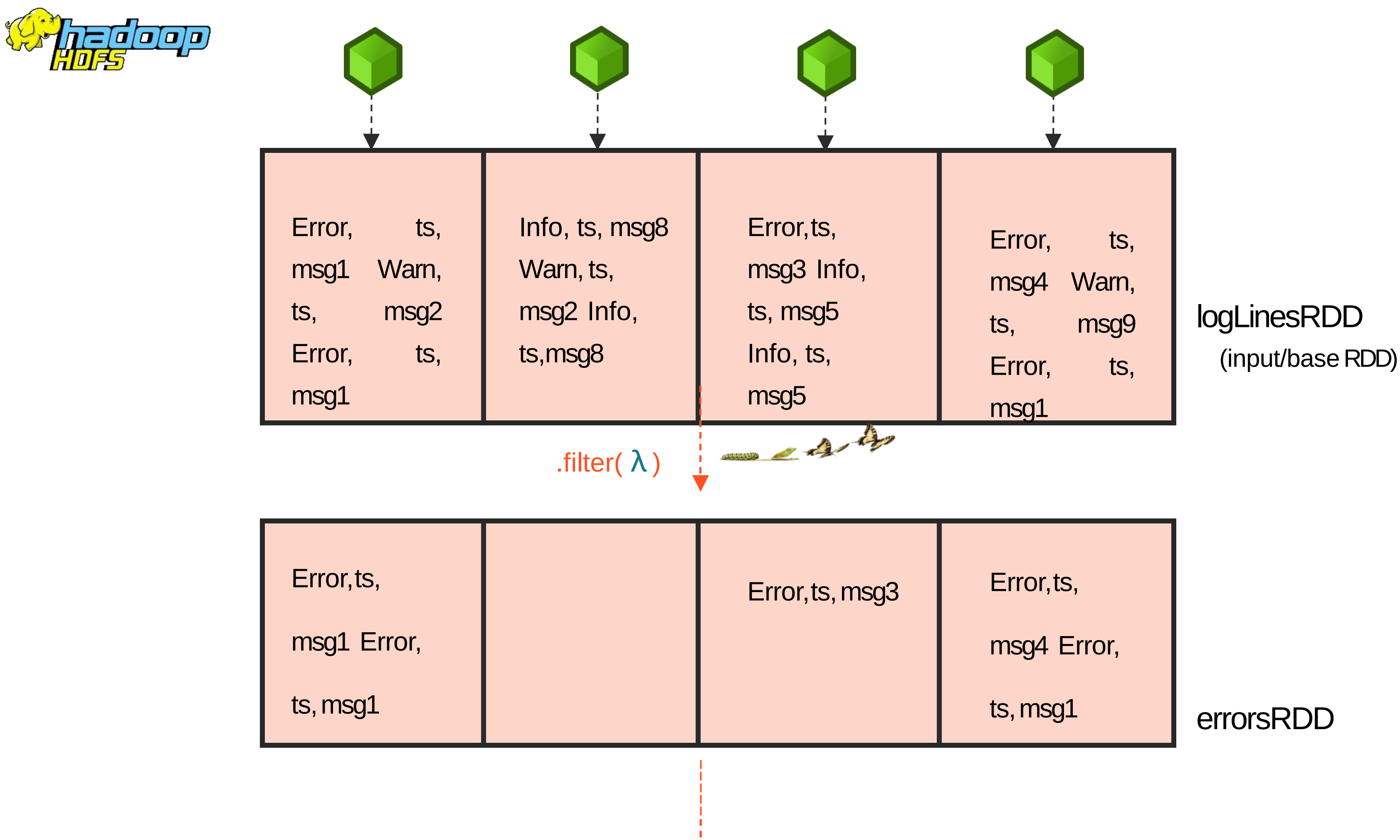
```java
// Read a local txt file in Java
JavaRDD<String> lines = sc.textFile("/path/to/README.md");
```

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

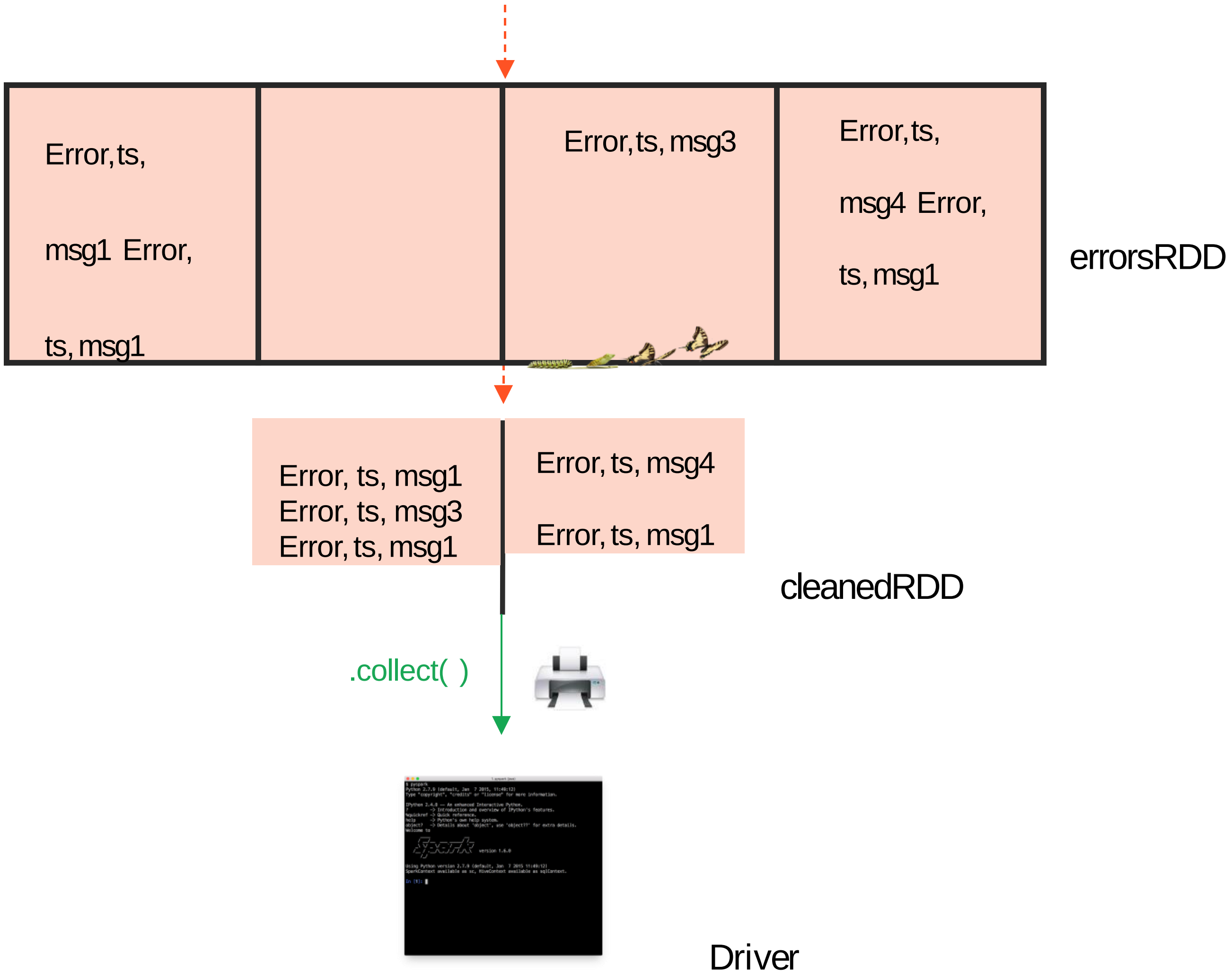
Operations on Distributed Data

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

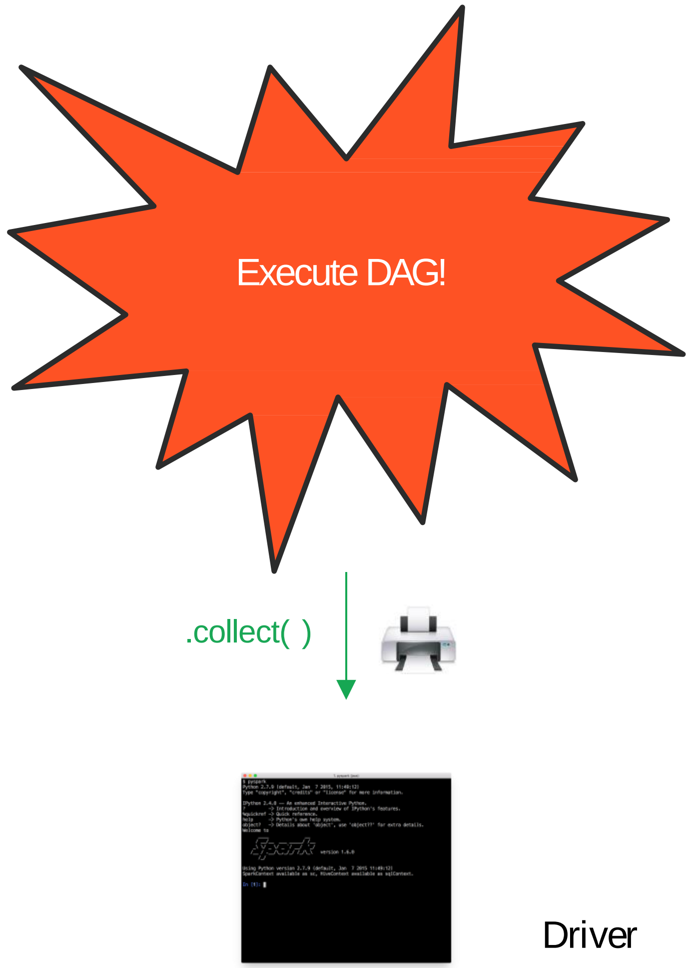
Transformation: Filter



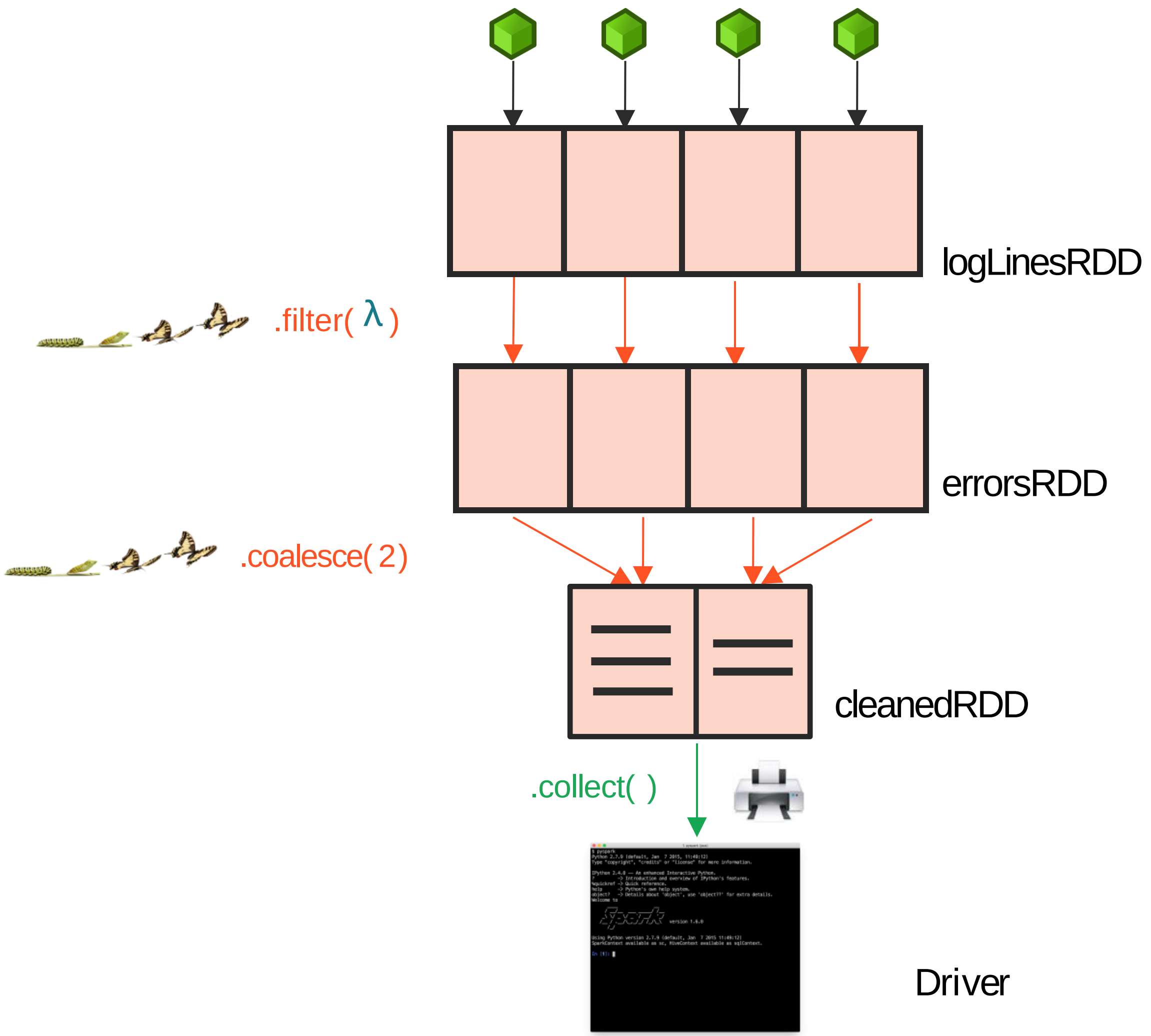
Action: Collect



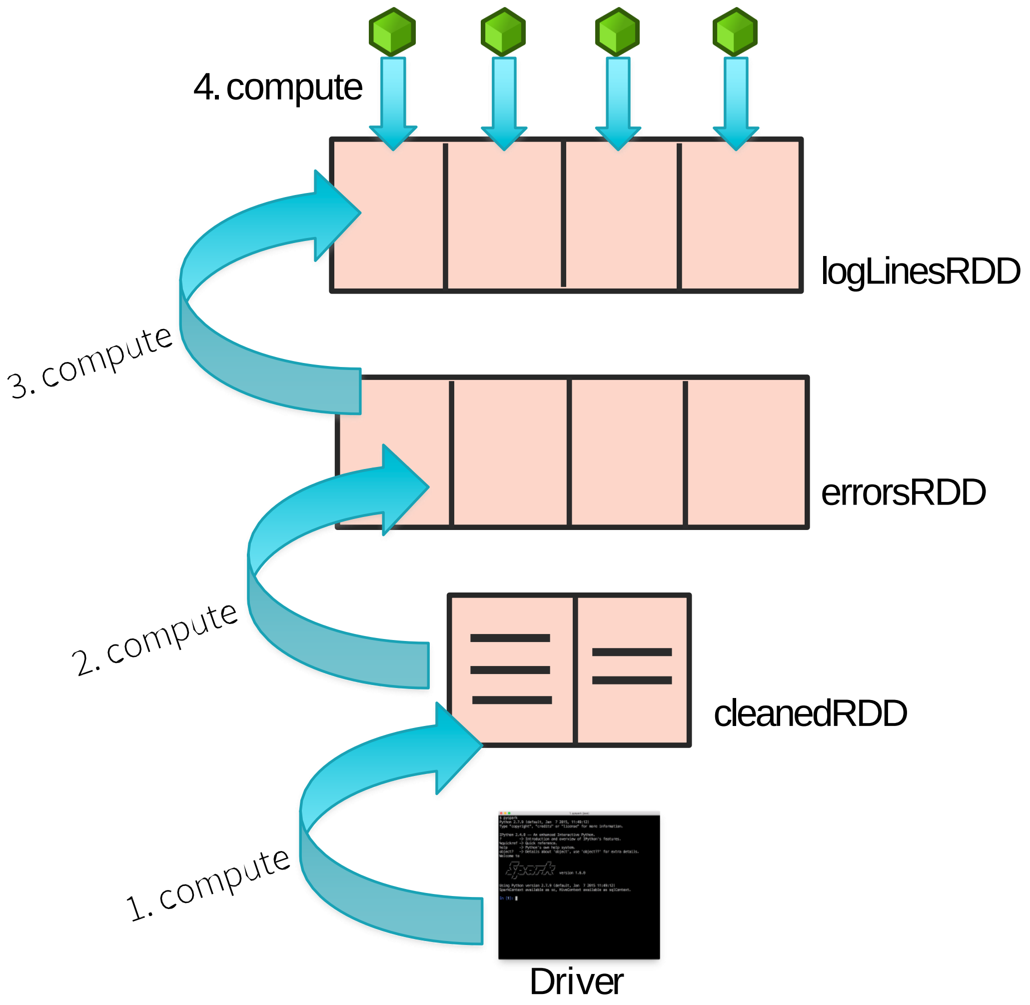
DAG execution



Logical


logLinesRDD
.filter(λ)
errorsRDD
.coalesce(2)
cleanedRDD
.collect( )
Driver

Physical



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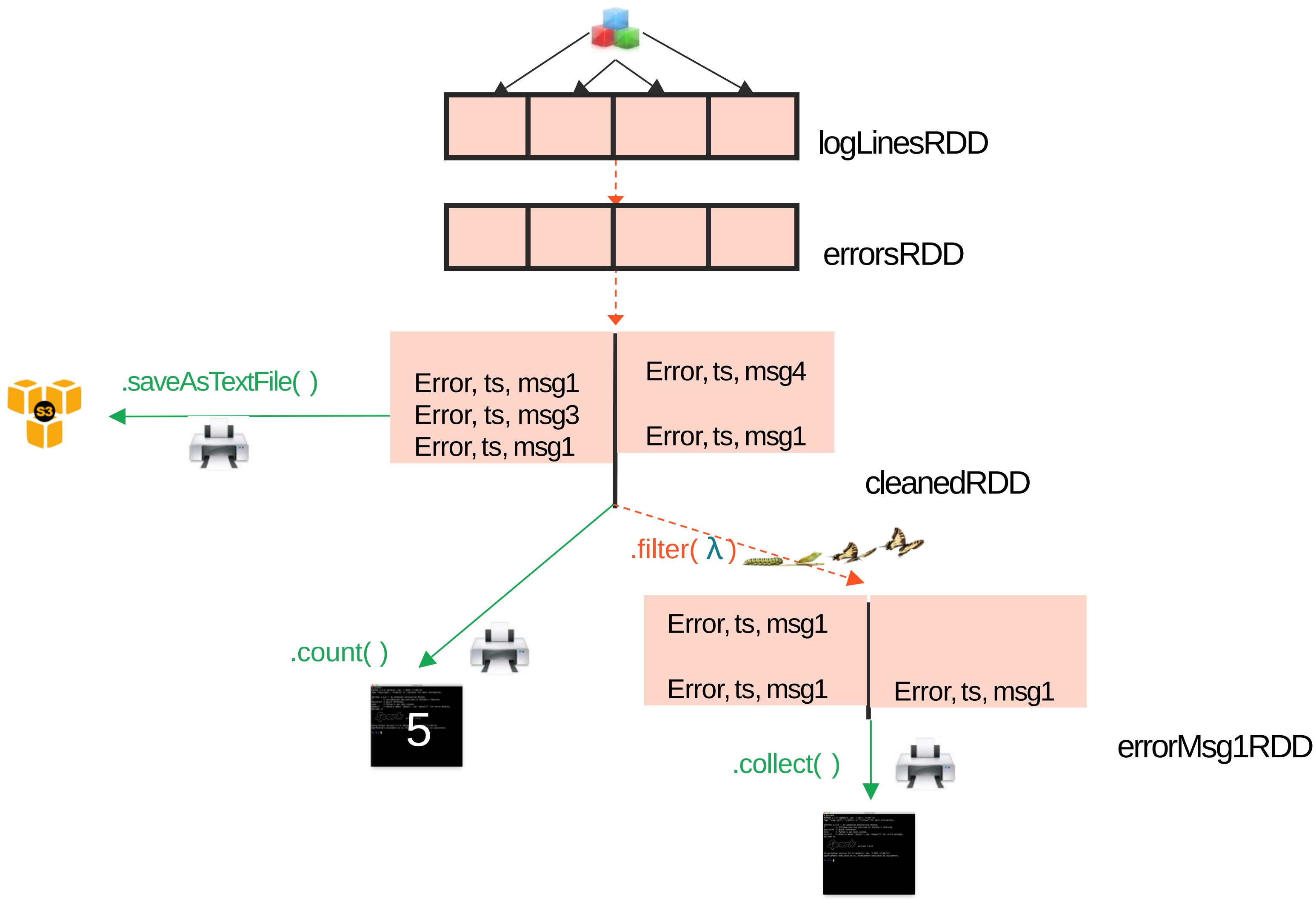
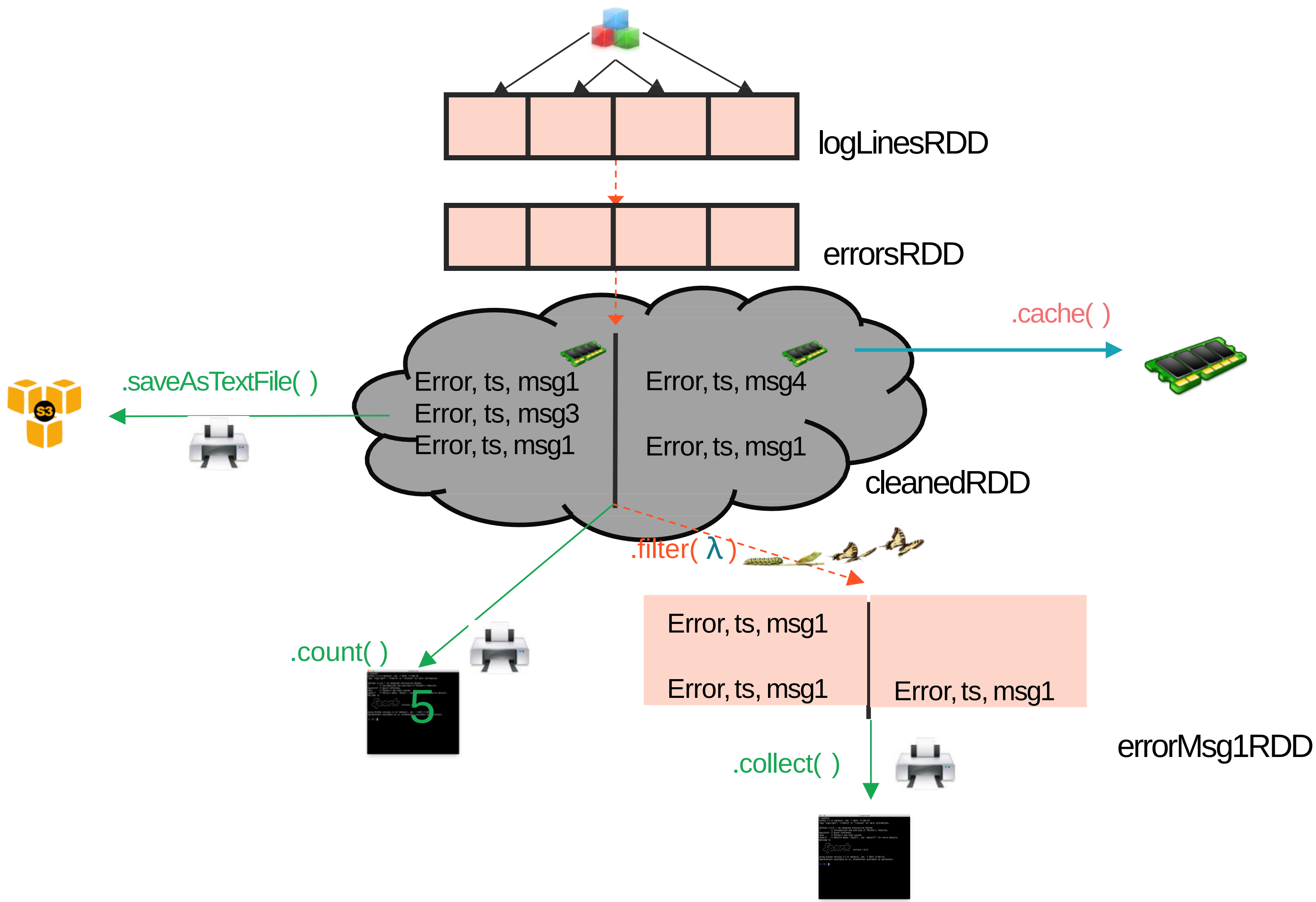
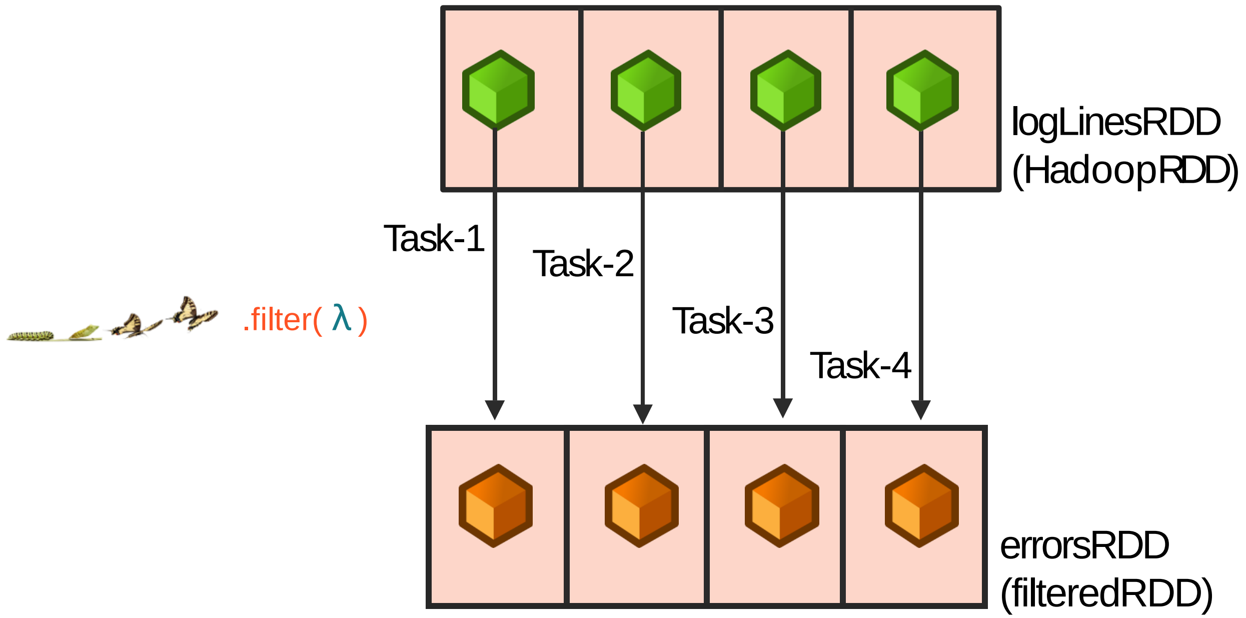
DAG


logLinesRDD
errorsRDD
.saveAsTextFile( )
Error, ts, msg1
Error, ts, msg3
Error, ts, msg1
Error, ts, msg4
Error, ts, msg1
cleanedRDD
.filter(λ)
.count( )
5
Error, ts, msg1
Error, ts, msg1
Error, ts, msg1
errorMsg1RDD
.collect( )

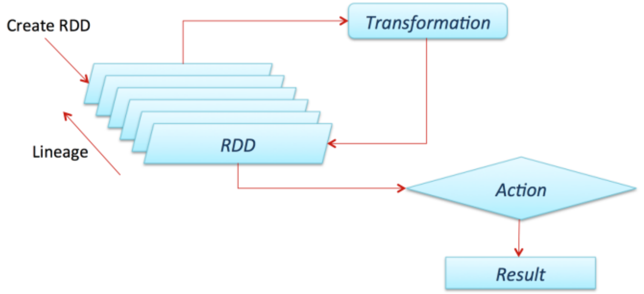
Cache

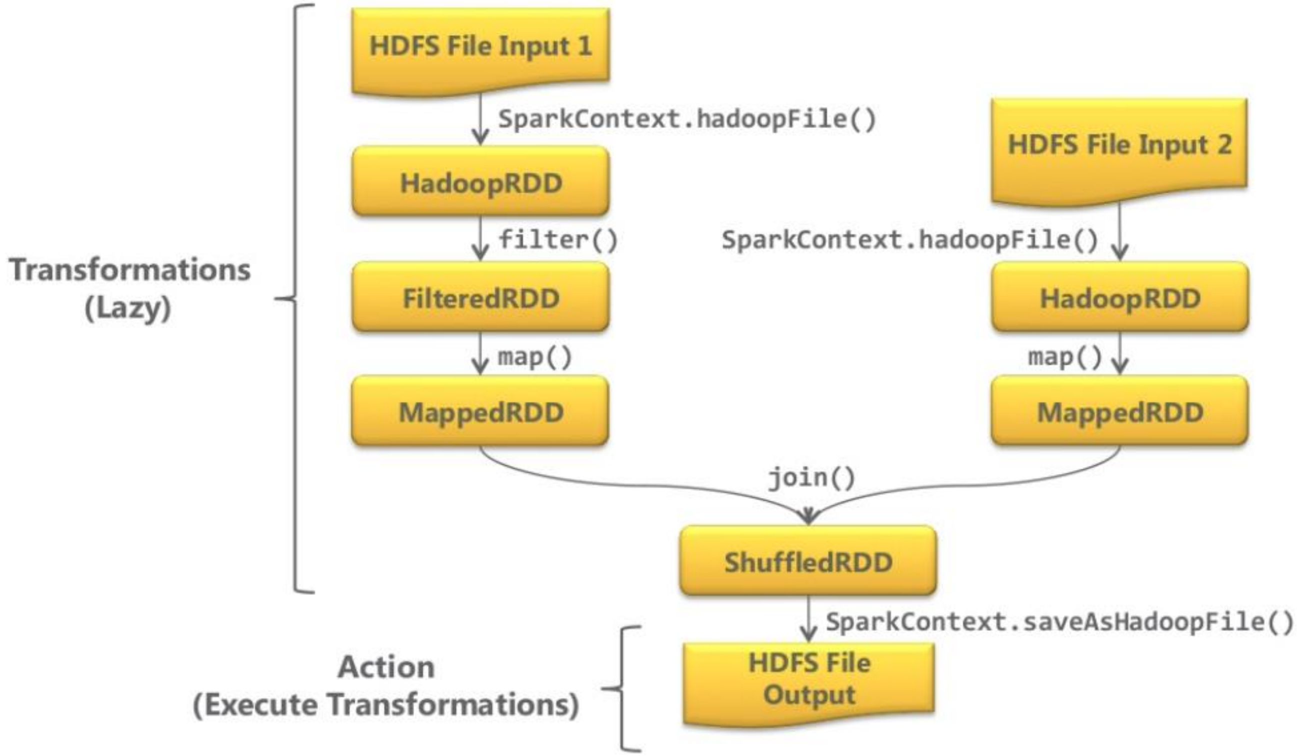

logLinesRDD
errorsRDD
.cache( )
.saveAsTextFile( )
Error, ts, msg1
Error, ts, msg3
Error, ts, msg1
Error, ts, msg4
Error, ts, msg1
cleanedRDD
.filter(λ)
.count( )
5
Error, ts, msg1
Error, ts, msg1
Error, ts, msg1
errorMsg1RDD
.collect( )

Partition >>> Task >>> Partition



RDD Lineage


Create RDD
Transformation
Lineage
RDD
Action
Result


HDFS File Input 1
SparkContext.hadoopFile()
HadoopRDD
filter()
FilteredRDD
map()
MappedRDD
HDFS File Input 2
SparkContext.hadoopFile()
HadoopRDD
map()
MappedRDD
Transformations
(Lazy)
join()
ShuffledRDD
SparkContext.saveAsHadoopFile()
HDFS File
Output
Action
(Execute Transformations)

Resilient Distributed Dataset (RDD)

- Initial RDD on **disks** (HDFS, etc)
- Intermediate RDD on **RAM**
- Fault recovery based on **lineage**
- RDD operations is 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 *func* 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 *kw*

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”, asceding=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(*n, truncate*)	Prints the first n rows of this DataFrame
take(*n*)	Returns the first n 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'Alice', age=1), Row=(name=u'Bob', age=2)]
>>> 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")

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

Builder methods specify:

- format
- 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").
  load("/Users/spark/data/stuff.json")

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

`load(…)`, `save(…)`, or `saveAsTable(…)` finish the I/O specification

Data Sources supported by DataFrames

built-in

- Parquet
- JDBC
- { JSON }
- MySQL
- PostgreSQL
- HIVE
- HDFS
- amazon web services S3

external

- AVRO
- CSV
- dBase
- APACHE HBASE
- elasticsearch.
- cassandra
- amazon web services Amazon Redshift
- 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 (e.g., with Pandas)

Write Less Code: Compute an Average

```java
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);
}
```

```scala
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()
```

```python
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 an 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()
```

Using DataFrames

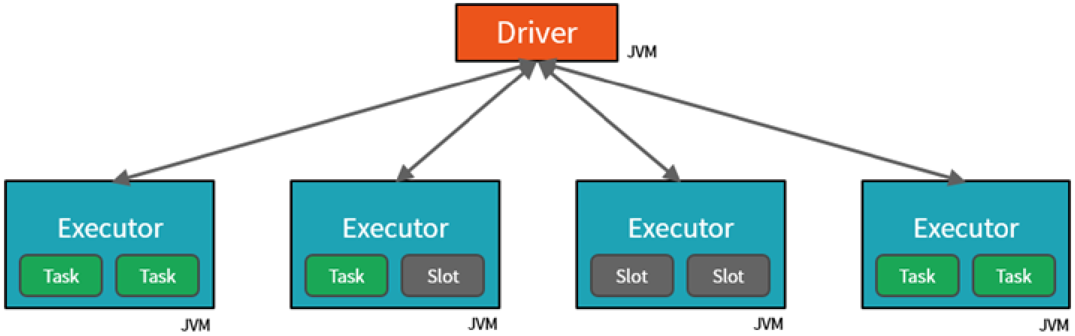
```
import org.apache.spark.sql.functions._

val df = rdd.map(a => (a(0), a(1))).toDF("key", "value")
df.groupBy("key")
  .agg(avg("value"))
  .collect()
```

Full API Docs

- [Scala]
- [Java]
- [Python]
- [R]

Architecture

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



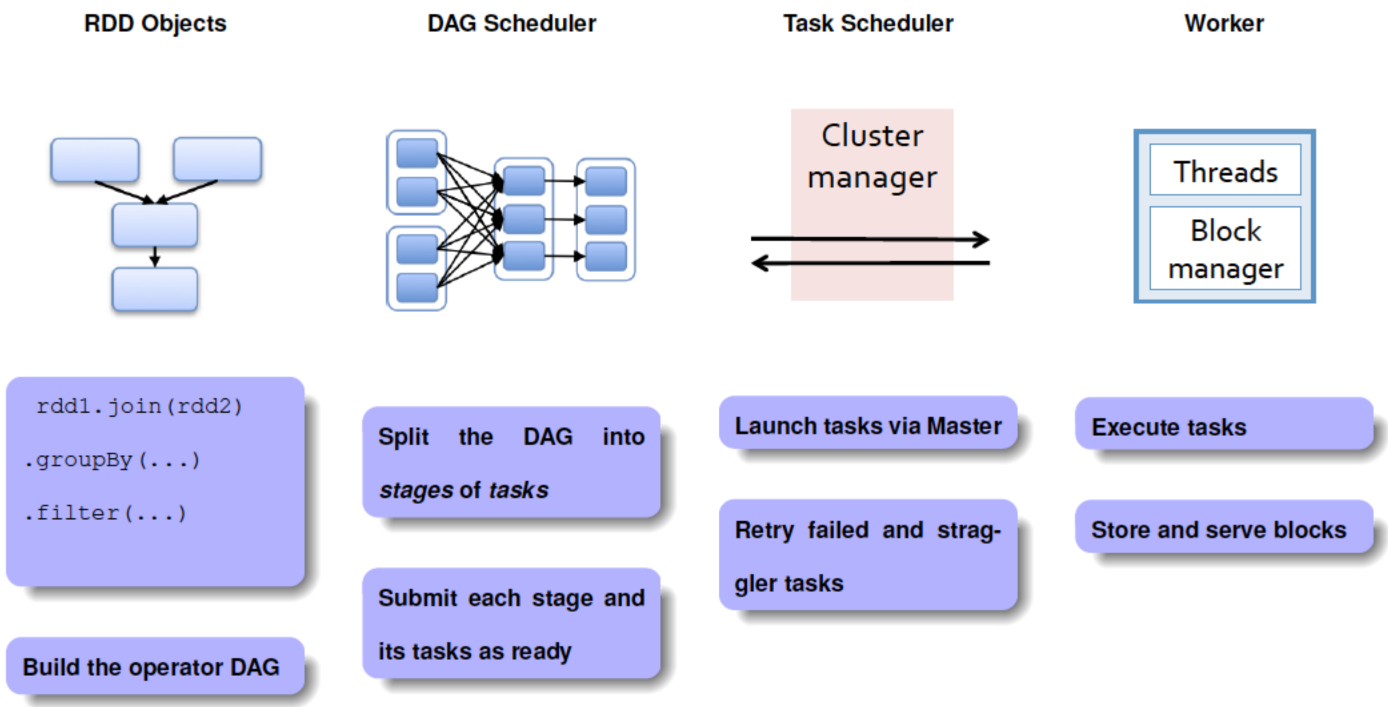
- The master send works to the workers and either instructs them to pull data from memory or from hard disk (or from another source like S3 or HDSF)

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

Lifetime of a Job in Spark



Demo

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.

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