CSE 4/587
Data Intensive Computing

Dr. Eric Mikida
epmikida@buffalo.edu
208 Capen Hall

Dr. Shamshad Parvin
shamsadp@buffalo.edu
313 Davis Hall

Introduction to Spark

Announcements

- Midterm grading is wrapping up
- HW #2 is coming soon…
  - All about Spark, if you want to get a headstart, install pyspark https://spark.apache.org/docs/latest/api/python/getting_started/install.html

References

- **Advanced Analytics with Spark** by S. Ryza, U. Laserson, S. Owen and J. Wills
- **Apache Spark documentation**
  - http://spark.apache.org/
  - http://spark.apache.org/docs/latest/programming-guide.html
- **Pyspark**
  - https://spark.apache.org/docs/latest/api/python/getting_started/install.html
- **Resilient Distributed Dataset: A Fault-tolerant Abstraction for in-Memory Cluster Computing.** M. Zaharia et al.
  - https://www.usenix.org/system/files/conference/nsdi12/nsdi12-final138.pdf

Challenges

Data cleaning: Majority of the work that goes into analyses lies in pre-processing data

- Munging, fusing, mushing and cleansing
- We need computational methods to clean data and data pipeline certainly should include an important step of “data cleaning” and “feature engineering”.
- Choosing from many features, the relevant features.
- Designing a math model from a 2D array (Ex: page rank)

Challenges

Data cleaning: Majority of the work that goes into analyses lies in pre-processing data

- Munging, fusing, mushing and cleansing
- We need computational methods to clean data and data pipeline certainly should include an important step of “data cleaning” and “feature engineering”.
- Choosing from many features, the relevant features.
- Designing a math model from a 2D array (Ex: page rank)

Need to avoid delays in repeated reading of data

Challenges

Iteration: Iteration is a fundamental part of data science.

- Modeling and analysis require typically multiple passes over the same data
- Machine learning algorithms and statistical procedures like stochastic gradient and expected maximization involve repeated scans to reach convergence
- Choosing the right features, picking the right algorithms, running the right significance tests, finding the right hyperparameters: **all require experimentation**

Challenges

Iteration: Iteration is a fundamental part of data science.

- Modeling and analysis require typically multiple passes over the same data
- Machine learning algorithms and statistical procedures like stochastic gradient and expected maximization involve repeated scans to reach convergence
- Choosing the right features, picking the right algorithms, running the right significance tests, finding the right hyperparameters: **all require experimentation**

Need to avoid delays in repeated reading of data

Challenges

Information updates: The results of data analysis presented and **the application becomes part of the production system**…

- This system must frequently or in real time update itself driven by the availability of new data; ie fraud detection system.

Challenges

Information updates: The results of data analysis presented and **the application becomes part of the production system**…

- This system must frequently or in real time update itself driven by the availability of new data; ie fraud detection system.

How about the existing approaches?

- C++, Java are not good for EDA
- R is slow for large data sets and does not integrate well with production stacks
- Read-Evaluate-Print-Loop (REPL) are good for interaction but not work production

Challenges

Information updates: The results of data analysis presented and **the application becomes part of the production system**…

- This system must frequently or in real time update itself driven by the availability of new data; ie fraud detection system.

How about the existing approaches?

- C++, Java are not good for EDA
- R is slow for large data sets and does not integrate well with production stacks
- Read-Evaluate-Print-Loop (REPL) are good for interaction but not work production

Want a framework that makes modeling easy, but also fits well in production systems

Apache Spark

Apache Spark is an open-source, distributed processing system commonly used for big data workloads.

- Utilizes in-memory caching
- Optimized execution for fast performance
- Supports general batch processing, streaming analytics, machine learning, graph databases, and ad hoc queries

Spark vs MapReduce

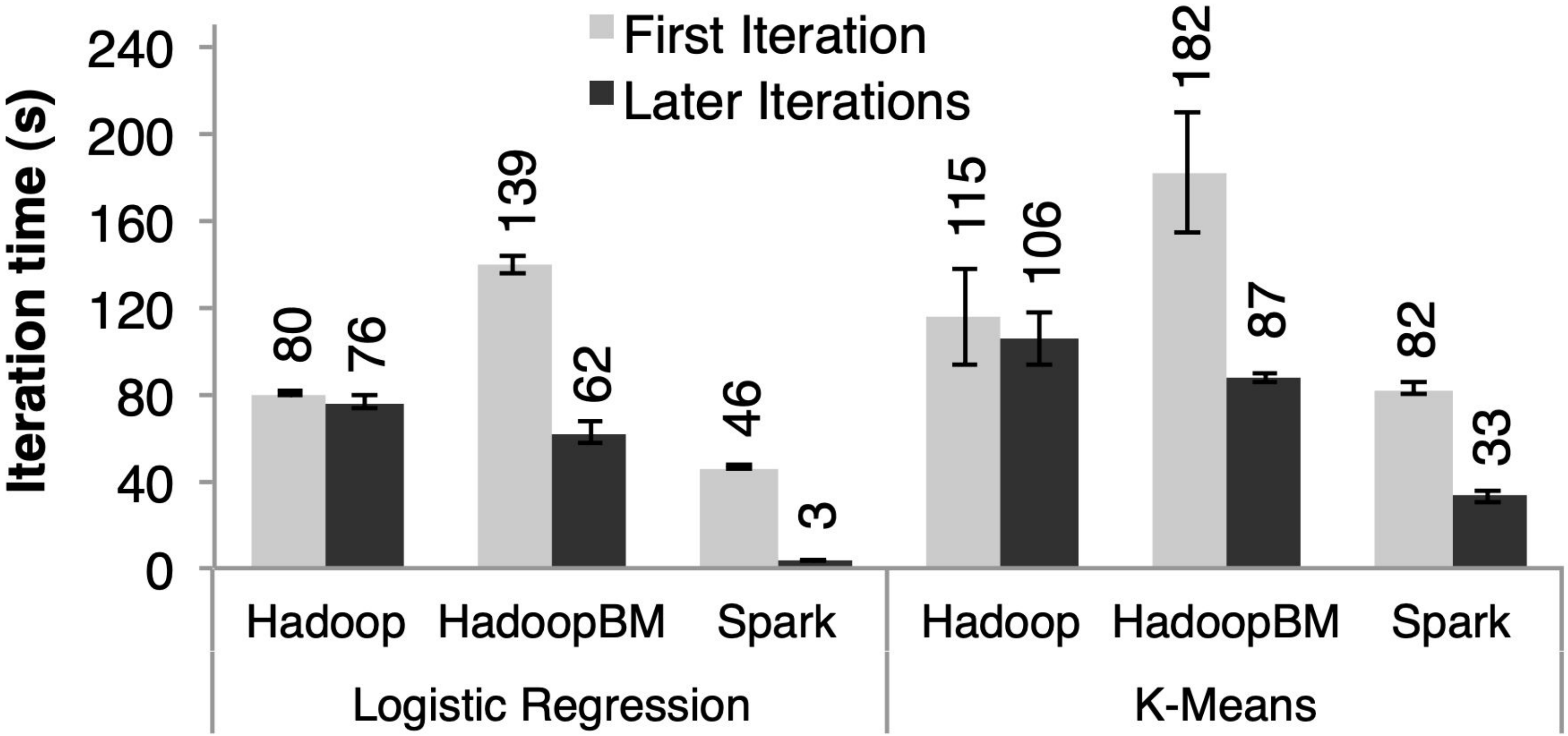
MapReduce offers linear scalability and fault tolerance for processing very large data sets

Spark maintains this revolutionary approach brought about by MapReduce

It also improves it in four different ways:

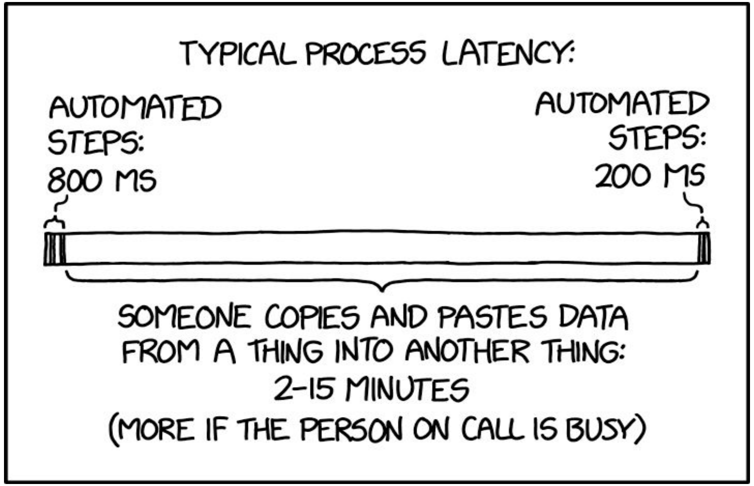
- Executes a series of operations specified in a DAG
  - Allows one stage of "MR" to send the results to the next *(Similar to Microsoft Dryad)*
- Provides a rich set of operations to express computation more naturally *(Similar to Pig)*
- Improves on in-memory computations through its **Resilient Distributed Dataset (RDD)**
  - Future steps dealing with the same data do not have reload it from the disk
- Well-suited for highly iterative computing

Sample of Performance Results



Programming Productivity

Biggest bottleneck in data applications is not CPU, disk, or network but analyst productivity



https://xkcd.com/2565/

Programming Productivity

Biggest bottleneck in data applications is not CPU, disk, or network but analyst productivity

If only we could collapse the entire pipeline from pre-processing of data to model evaluation into a single programming environment…

Spark transitions seamlessly between exploratory analytics and operational analytics

Word Count in Spark (Python API)

```
text_file = spark.textFile("hdfs://...")

text_file.flatMap(lambda line: line.split())
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a+b)
```

Spark APIs

Spark runs on Hadoop, Mesos, standalone, or in the cloud. It can access diverse data sources including HDFS, Cassandra, HBase, and S3

It also provides APIs in many common languages:

- Scala API
- Java API
- Python API
- Dataframes API
- R API

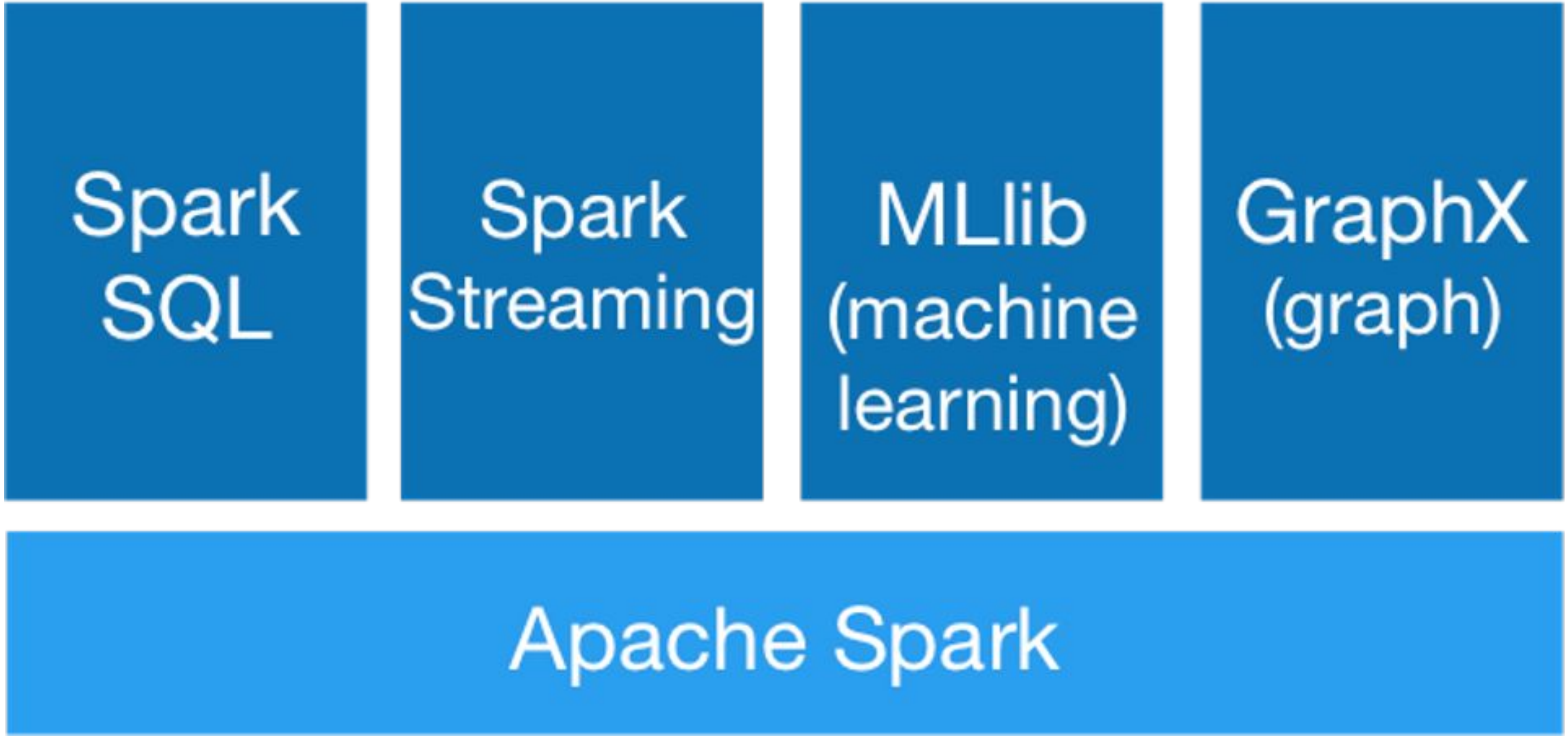
Python Lambda Functions

Spark's Python API allows the use of lambda functions to transform data

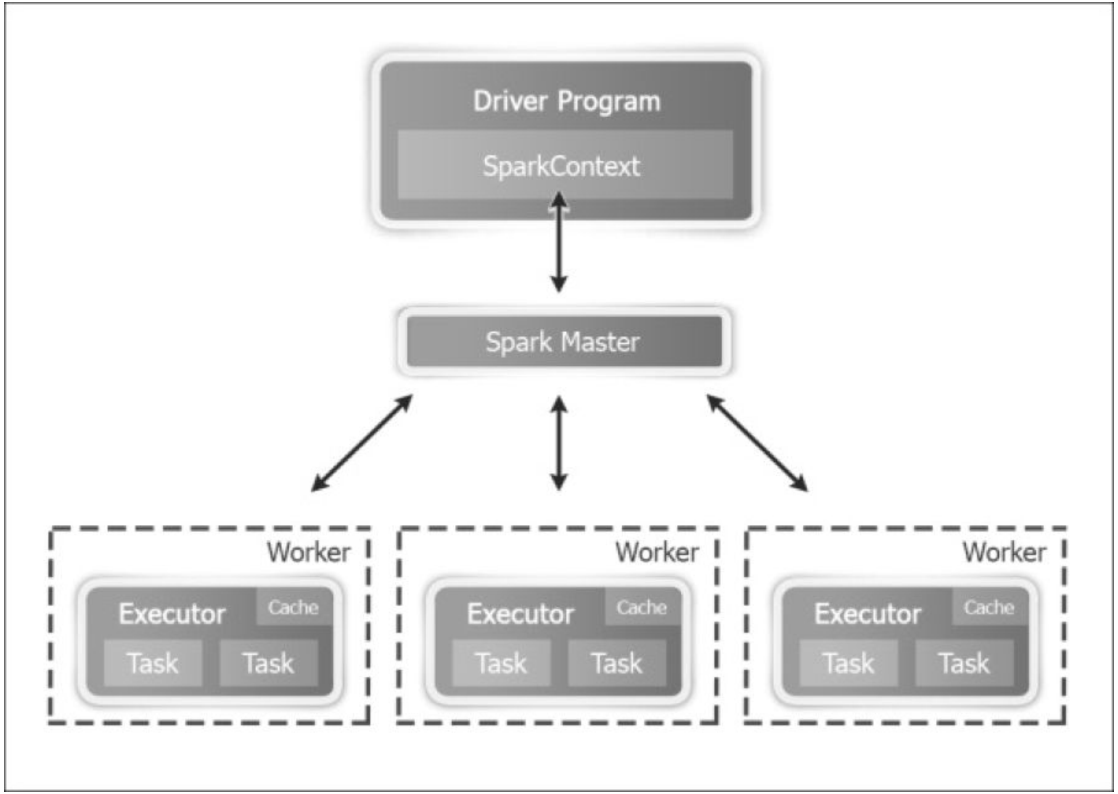
```
x = lambda a : a + 10
print(x(5))
```

```
x = lambda a, b : a * b
print(x(5, 6))
```

Spark Ecosystem



Spark Architecture



Programming Model

- **Spark Context:** sc
- **RDD:** Resilient Distributed Datasets
  - Transformations and actions on RDDs
- **Diverse set of data sources:** HDFS, relational databases
- **Diverse APIs:** JavaAPI, Python API, Scala API, Dataframe API, R API

Spark Context

Spark Context (sc) is an object

- Main entry point for Spark applications
- Just like any object it has methods associated with it
- Some of the methods:
    - getConf
    - runJob
    - addFile
    - cancelAllJobs
    - makeRDD

Resilient Distributed Datasets (RDDs)

A core Spark concept is **Resilient Distributed Datasets (RDD)** which is a fault tolerant collection of elements that can be operated on in parallel

An RDD is a convenient way to describe the computations that we want to perform in small independent steps and in parallel

There are two ways to create RDDs:

- Parallelizing an existing collection in the driver program; performing a transformation on one or more existing RDDs, like filtering records, aggregating records by a common key or by joining multiple RDDs together.
- Using SparkContext to create an RDD from an external dataset in an external storage system such as a shared filesystem, HDFS, HBase or any data source offering a Hadoop input format

Examples

A few transformations to build a dataset and store into a file:

```
text-file = sc.textFile(“hdfs://…”)
counts = text_file.flatMap(lambda line: line.split(“ “))
    .map(lambda word: (word,1))
    .reduceByKey(lambda a,b: a+b)
counts.saveAsTextFile(“hdfs://..”)
```

Resilient Distributed Datasets (RDDs)

The building block of the Spark API
(http://spark.apache.org/docs/latest/programming-guide.html#resilient-distributed-datasets-rdds)

In RDD API there are two types of operations:

1. *Transformations* that define a new data set based on previous ones
2. *Actions* which kick off a job to execute on a cluster

RDD Transformations and Actions

Transformations	Actions
map (func)	reduce(func)
flatMap(func)	collect()
filter(func)	count()
groupByKey()	first()
reduceByKey(func)	take(n)
mapValues(func)	saveAsTextFile(path)
sample(...)	countByKey()
union(other)	foreach(func)
distinct()	...
sortByKey()	
...	

RDD Transformations and Actions

Transformations	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	:	RDD[T] $\Rightarrow$ RDD[U]
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	:	RDD[T] $\Rightarrow$ RDD[T]
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	RDD[T] $\Rightarrow$ RDD[U]
	$sample(fraction : \mathrm{Float})$	:	RDD[T] $\Rightarrow$ RDD[T] (Deterministic sampling)
	$groupByKey()$	:	RDD[(K, V)] $\Rightarrow$ RDD[(K, Seq[V])]
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
	$union()$	:	(RDD[T], RDD[T]) $\Rightarrow$ RDD[T]
	$join()$	:	(RDD[(K, V)], RDD[(K, W)]) $\Rightarrow$ RDD[(K, (V, W))]
	$cogroup()$	:	(RDD[(K, V)], RDD[(K, W)]) $\Rightarrow$ RDD[(K, (Seq[V], Seq[W]))]
	$crossProduct()$	:	(RDD[T], RDD[U]) $\Rightarrow$ RDD[(T, U)]
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	RDD[(K, V)] $\Rightarrow$ RDD[(K, W)] (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	:	RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
	$partitionBy(p : \mathrm{Partitioner[K]})$	:	RDD[(K, V)] $\Rightarrow$ RDD[(K, V)]
Actions	$count()$	:	RDD[T] $\Rightarrow$ Long
	$collect()$	:	RDD[T] $\Rightarrow$ Seq[T]
	$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	:	RDD[T] $\Rightarrow$ T
	$lookup(k : \mathrm{K})$	:	RDD[(K, V)] $\Rightarrow$ Seq[V] (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	:	Outputs RDD to a storage system, *e.g.*, HDFS

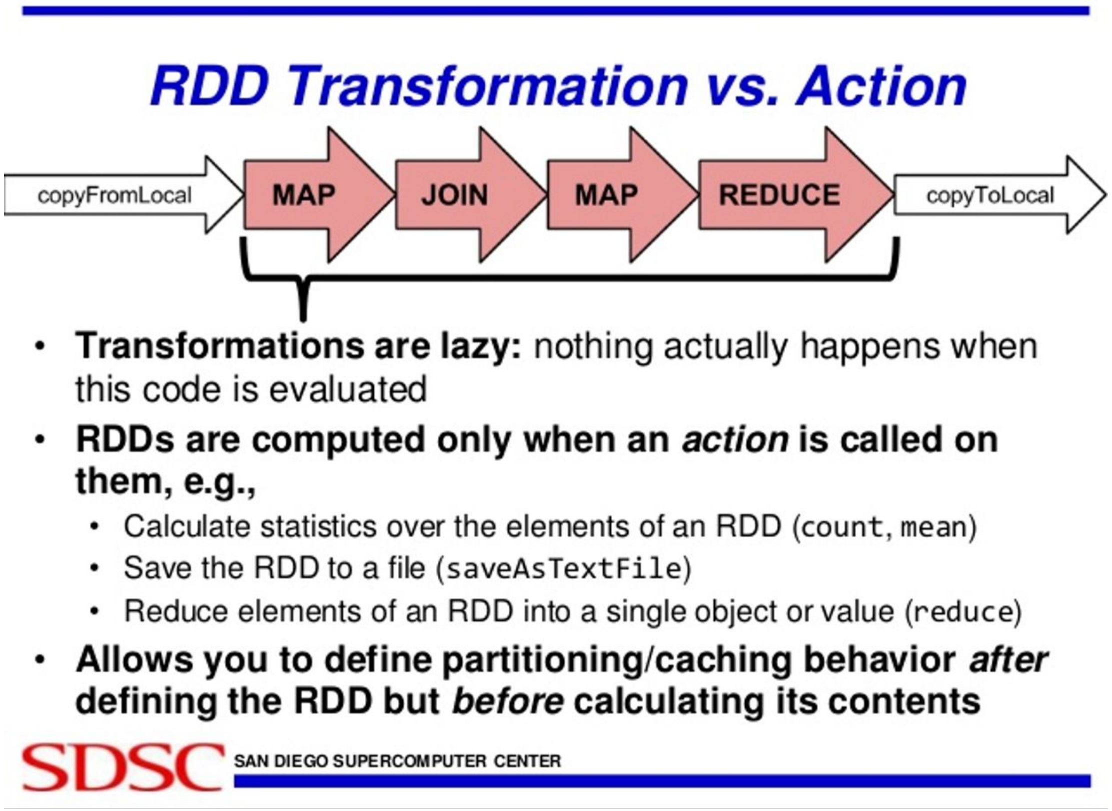
Table 2: Transformations and actions available on RDDs in Spark. Seq[T] denotes a sequence of elements of type T.

Resilient Distributed Datasets (RDDs)

A **distributed memory abstraction** that enables **in-memory computations** on large clusters in a **fault-tolerant** manner

- Motivation: iterative algorithms, interactive data mining tools
    - In both cases above keeping data in memory will help enormously for performance improvement
- RDDs are parallel data structures allowing coarse grained transformations
- It ***provides fault tolerance by storing the lineage as opposed to the actual data*** as done in Hadoop

Transformations vs Actions



RDD Lineage

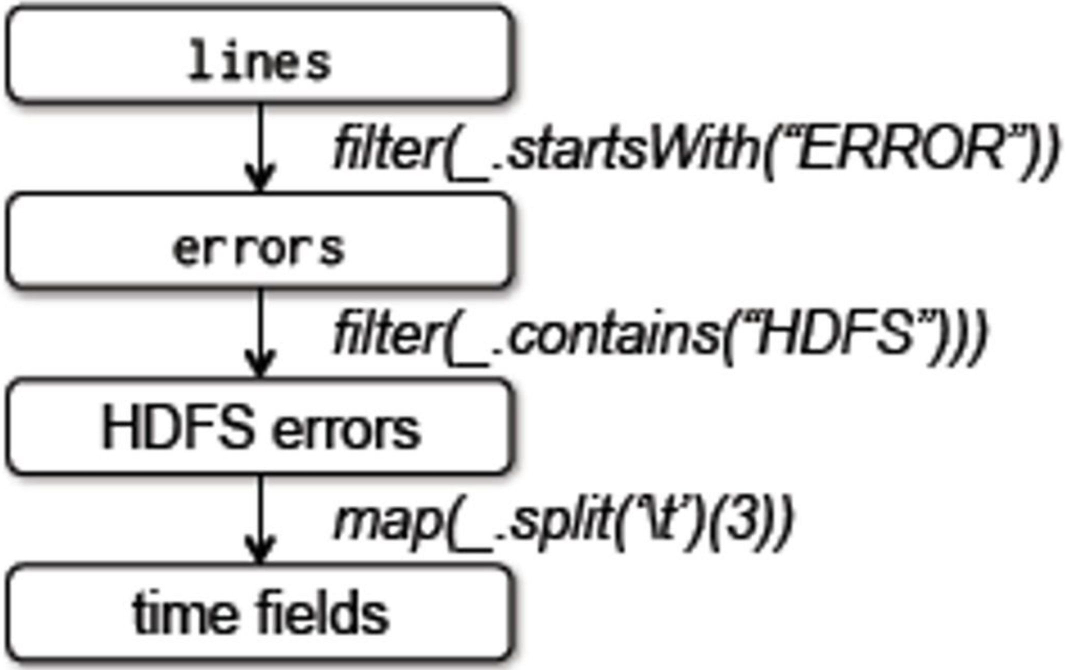
An RDD can depend on zero or more other RDDs

- ie when `x = y.map(...)`, x will depend on y
- These dependency relationships can be thought of as a graph.

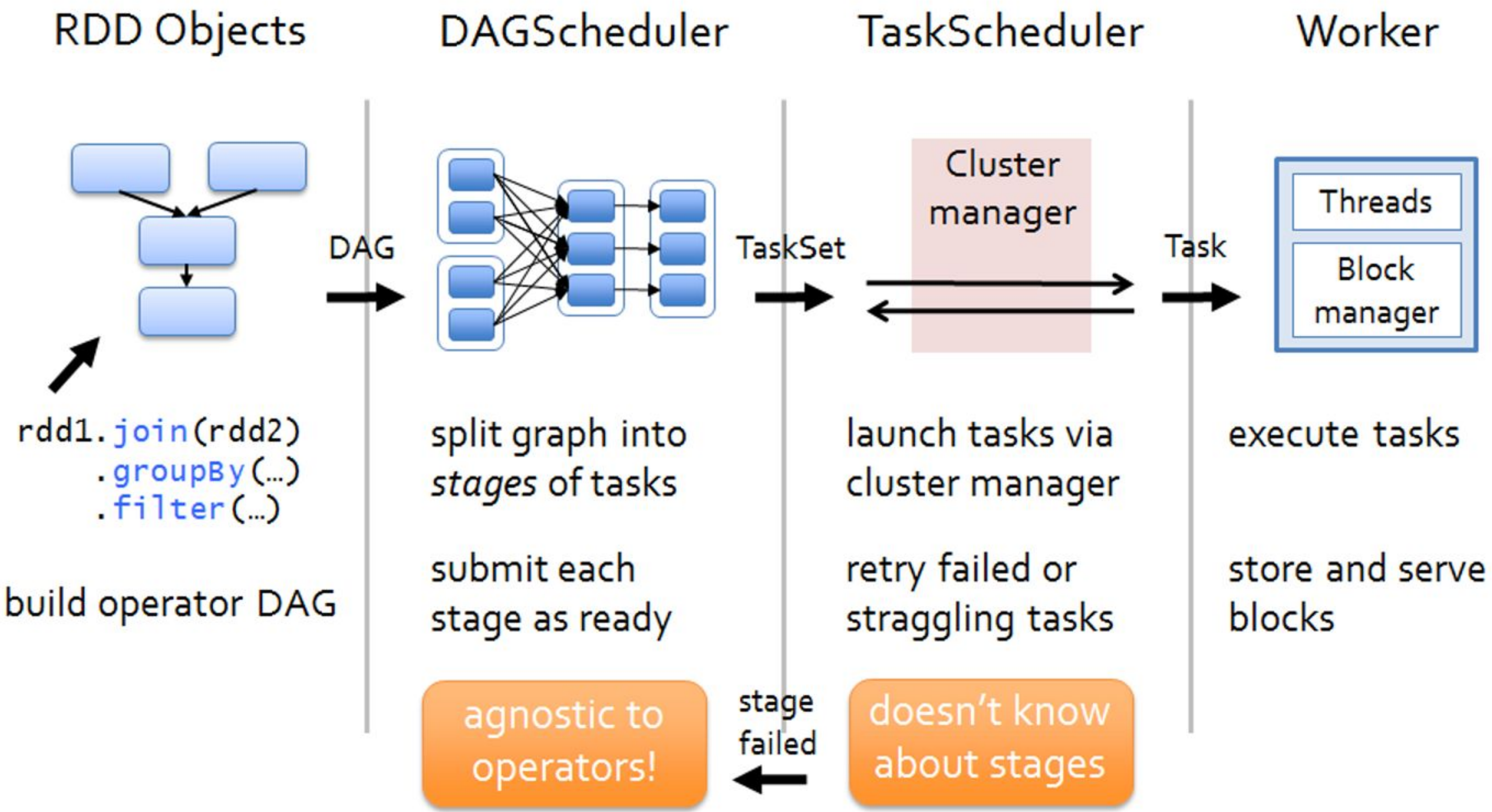
You can call this graph a lineage graph, as it represents the derivation of each RDD

- It is also necessarily a ***DAG***, since a loop is impossible to be present in it.
- Narrow dependencies, where a shuffle is not required (think map and filter) can be collapsed into a single **stage**.
  - A stage is a unit of execution, created by the scheduler from RDD dependency graph
  - Stages also depend on each other and the scheduler builds and uses this dependency graph (which is also necessarily a DAG) to schedule the stages

RDD Lineage



lines
filter(_.startsWith("ERROR"))
errors
filter(_.contains("HDFS")))
HDFS errors
map(_.split('\t')(3))
time fields


RDD Objects
DAGScheduler
TaskScheduler
Worker
DAG
TaskSet
Cluster manager
Task
Threads
Block manager
rdd1.join(rdd2)
.groupBy(…)
.filter(…)
build operator DAG
split graph into stages of tasks
submit each stage as ready
launch tasks via cluster manager
retry failed or straggling tasks
execute tasks
store and serve blocks
agnostic to operators!
stage failed
doesn't know about stages

Representing RDDs

Each RDD is represented through a common interface that exposes 5 pieces of information:

1. A set of partitions, atomic pieces of datasets
2. Set of dependencies on the parent RDDs
3. Function for computing the RDD from the parents
4. Metadata about partitioning scheme
5. Data placement

See table 3 in the RDD paper.

Dependencies

Narrow dependencies: each parent RDD partition used by at most one child; ie map()

- allow pipelined execution: example map() and filter() in iterative fashion
- recovery after node failure is more efficient

Wide dependencies: multiple child partitions may depend on a parent RDD; ie join()

- Single failed node in a wide dependency lineage graph may cause loss of partition in many ancestral dependencies