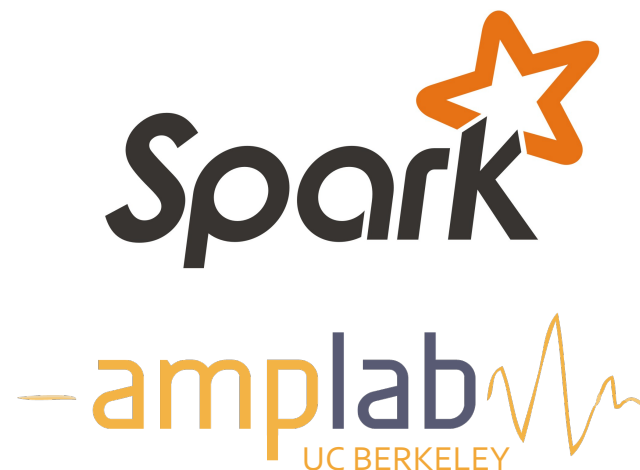


# Introduction to Spark Internals

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[www.spark-project.org](http://www.spark-project.org)



# Outline

Project goals

Components

Life of a job

Extending Spark

How to contribute

# Project Goals

Generality: diverse workloads, operators, job sizes

Low latency: sub-second

Fault tolerance: faults shouldn't be special case

Simplicity: often comes from generality

# Codebase Size

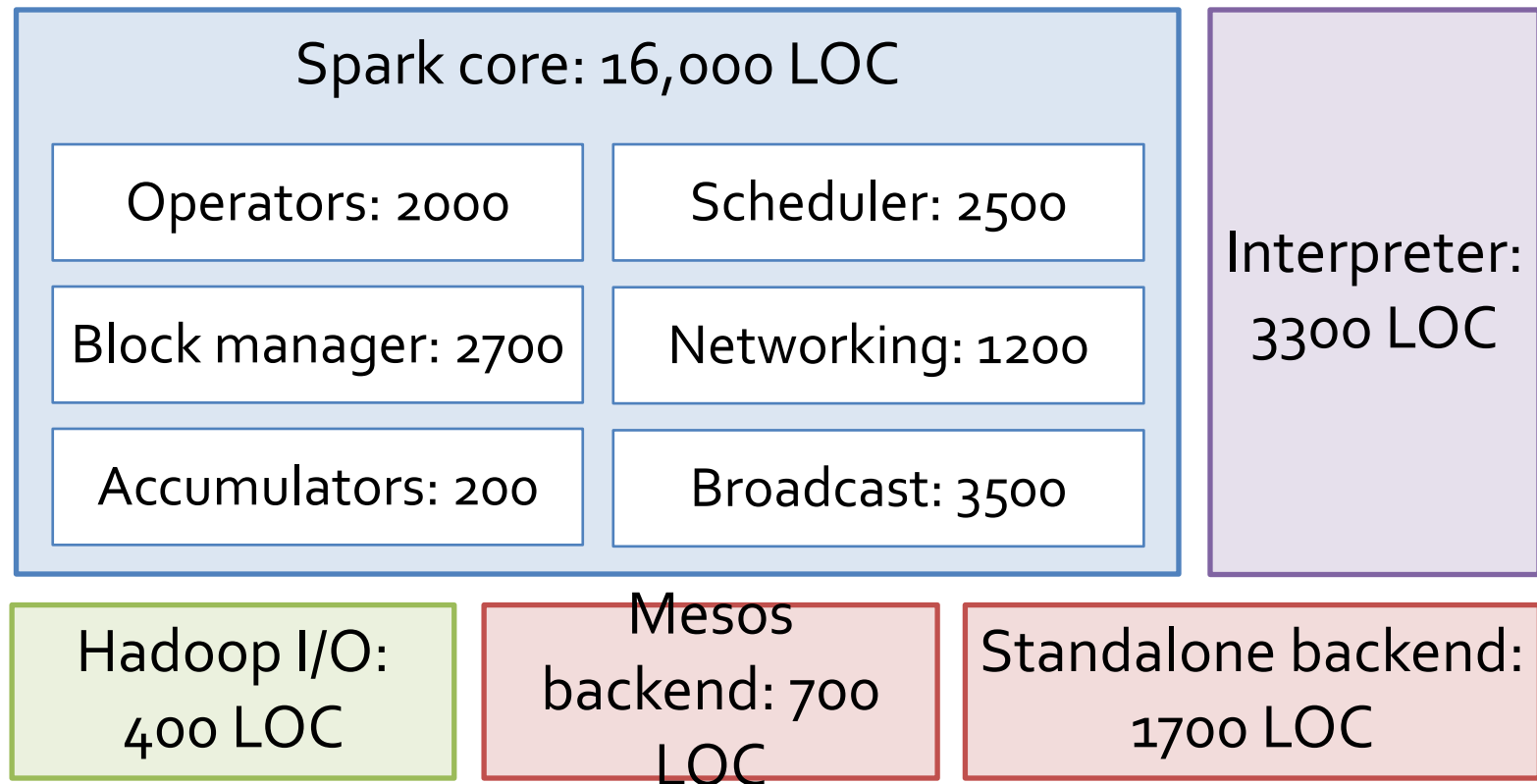
Spark: 20,000 LOC

Hadoop 1.0: 90,000 LOC

Hadoop 2.0: 220,000 LOC

(non-test, non-example sources)

# Codebase Details



# Outline

Project goals

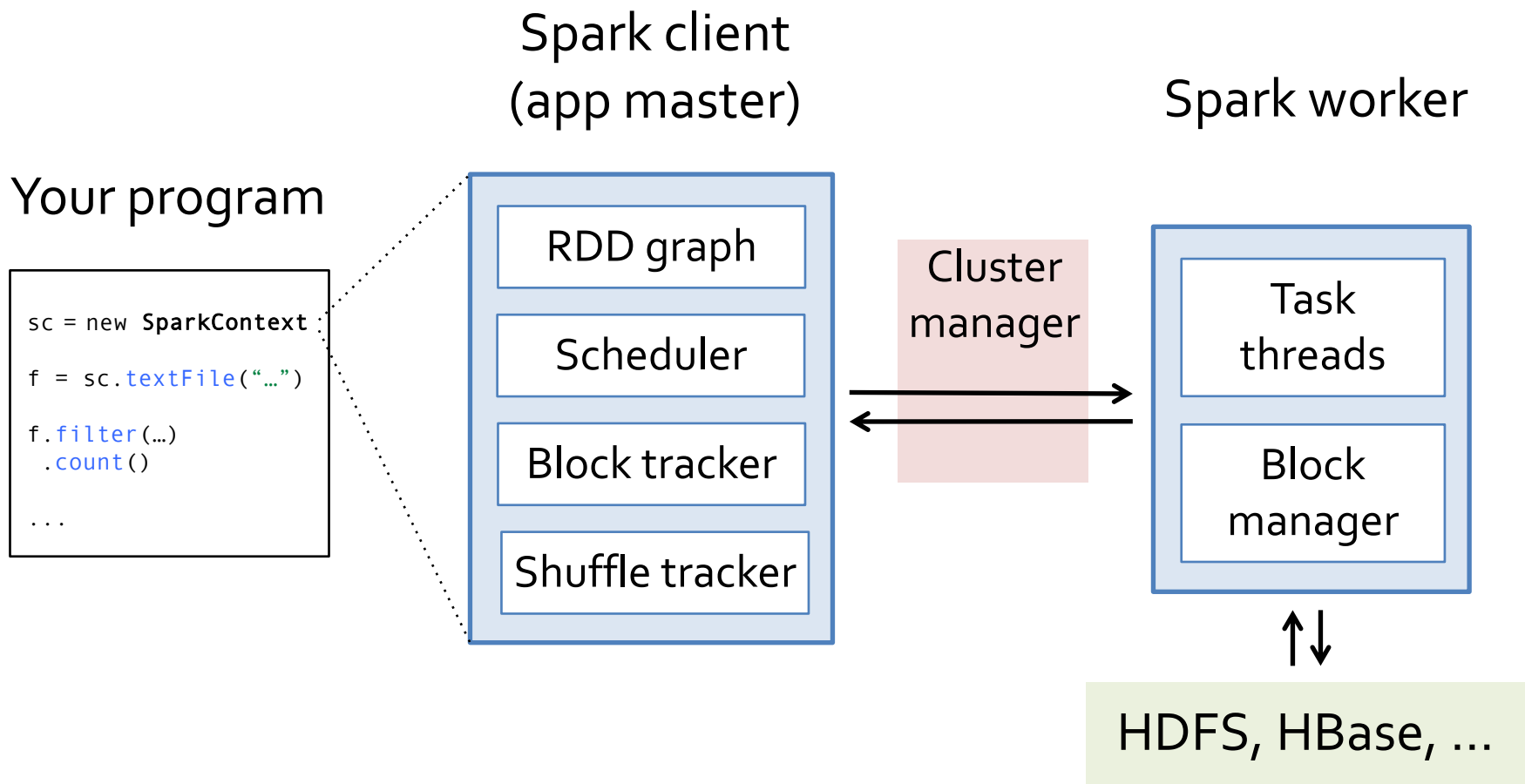
Components

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# Components



# Example Job

```
val sc = new SparkContext(  
  "spark://...", "MyJob", home, jars)
```

```
val file = sc.textFile("hdfs://...")
```

```
val errors = file.filter(_.contains("ERROR"))
```

```
errors.cache()
```

```
errors.count()
```

Resilient distributed  
datasets (RDDs)

Two orange arrows originate from the 'Resilient distributed datasets (RDDs)' box. One arrow points to the 'textFile' method in the second line of code, and the other points to the 'filter' method in the third line of code.

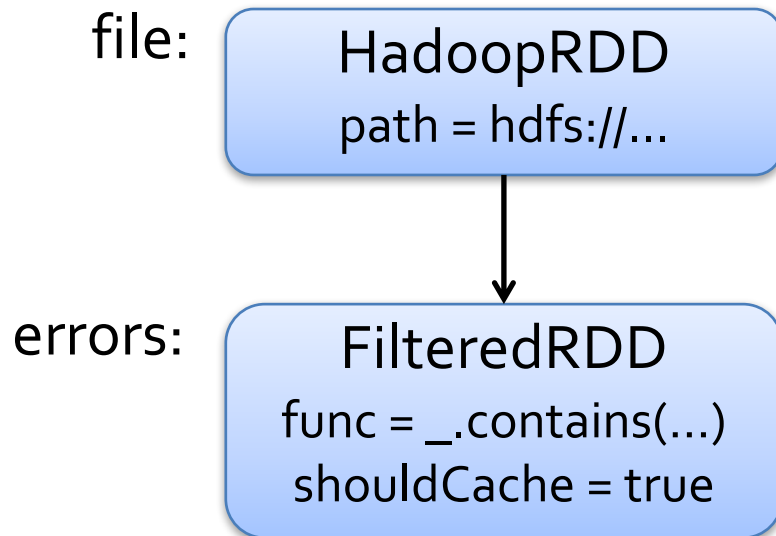
Action

An orange arrow points from the 'Action' box to the 'count' method in the final line of code.

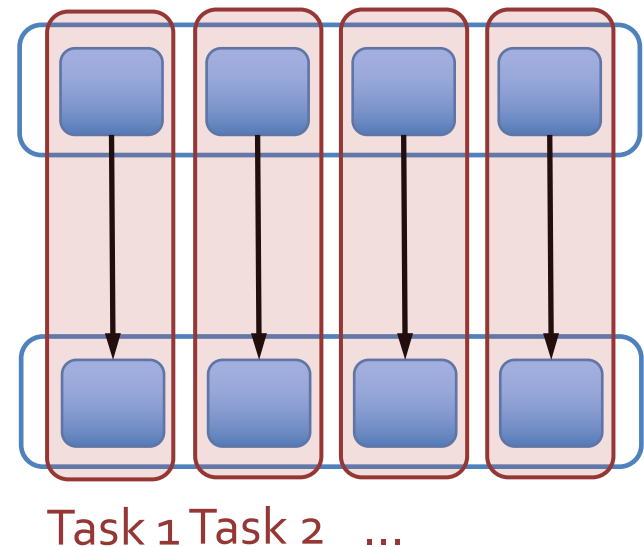


# RDD Graph

Dataset-level view:



Partition-level view:



# Data Locality

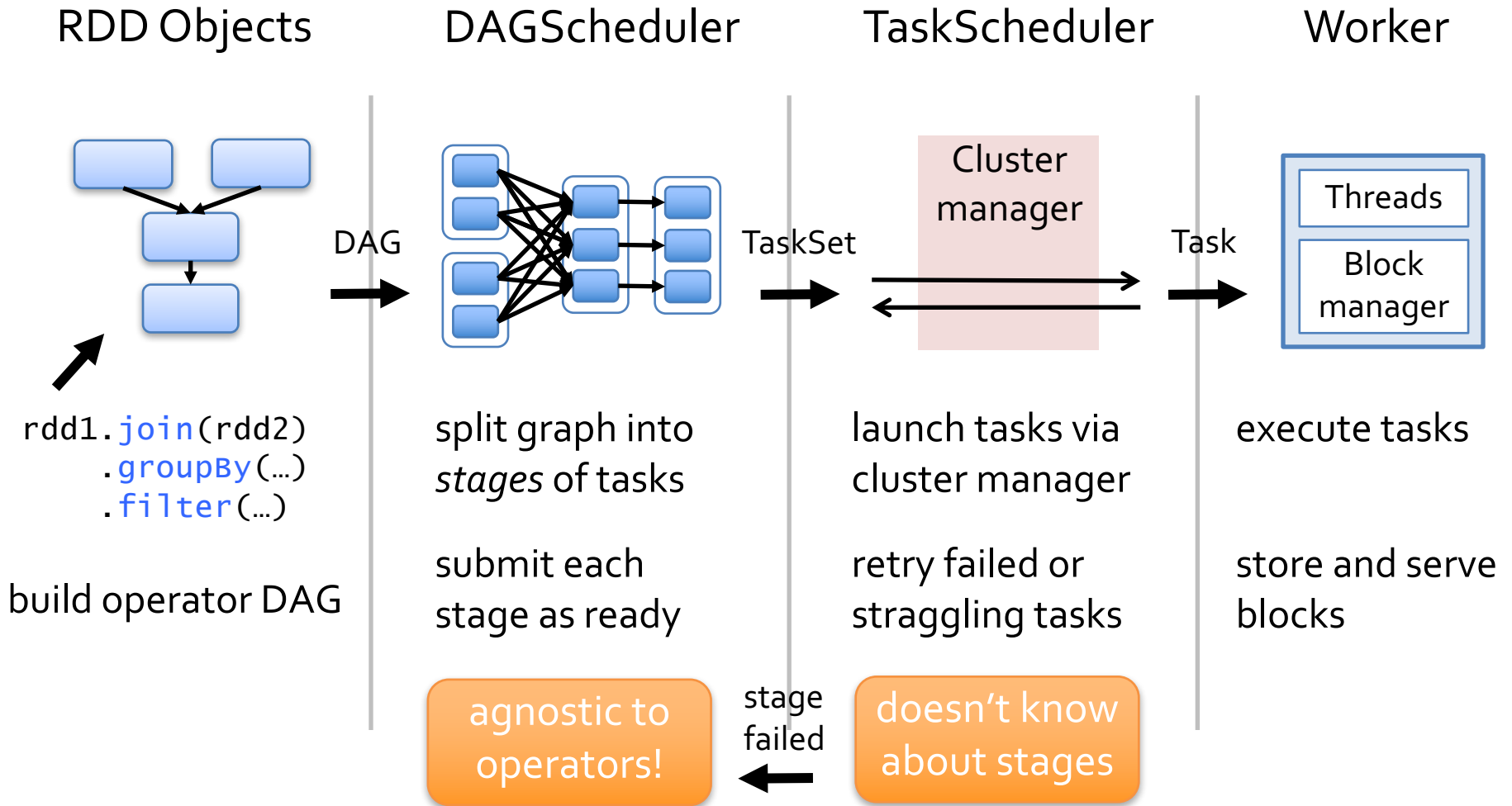
First run: data not in cache, so use HadoopRDD's locality prefs (from HDFS)

Second run: FilteredRDD is in cache, so use its locations

If something falls out of cache, go back to HDFS

# **In More Detail: Life of a Job**

# Scheduling Process



# RDD Abstraction

Goal: wanted to support wide array of operators and let users compose them arbitrarily

Don't want to modify scheduler for each one

*How to capture dependencies generically?*

# RDD Interface

Set of *partitions* (“splits”)

List of *dependencies* on parent RDDs

Function to *compute* a partition given parents

Optional *preferred locations*

Optional *partitioning info* (Partitioner)

Captures all current Spark operations!

# Example: HadoopRDD

`partitions` = one per HDFS block

`dependencies` = none

`compute(partition)` = read corresponding block

`preferredLocations(part)` = HDFS block location

`partitioner` = none

# Example: FilteredRDD

`partitions` = same as parent RDD

`dependencies` = “one-to-one” on parent

`compute(partition)` = compute parent and filter it

`preferredLocations(part)` = none (ask parent)

`partitioner` = none



# Example: JoinedRDD

`partitions` = one per reduce task

`dependencies` = “shuffle” on each parent

`compute(partition)` = read and join shuffled data

`preferredLocations(part)` = none

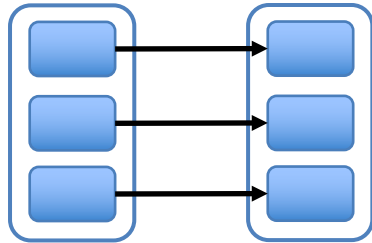
`partitioner` = HashPartitioner(numTasks)



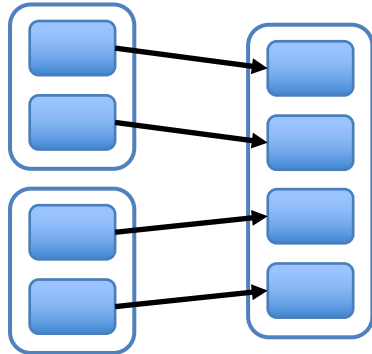
Spark will now know  
this data is hashed!

# Dependency Types

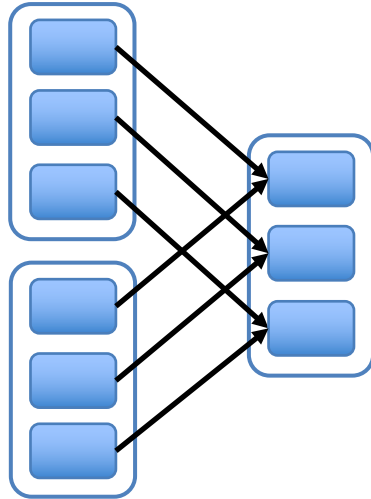
“Narrow” deps:



map, filter

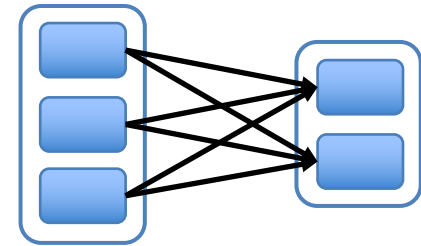


union

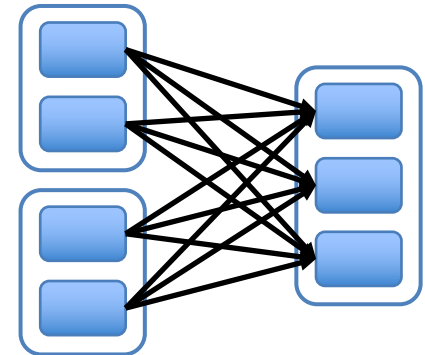


join with  
inputs co-  
partitioned

“Wide” (shuffle) deps:



groupByKey



join with inputs not  
co-partitioned

# DAG Scheduler

Interface: receives a “target” RDD, a function to run on each partition, and a listener for results

Roles:

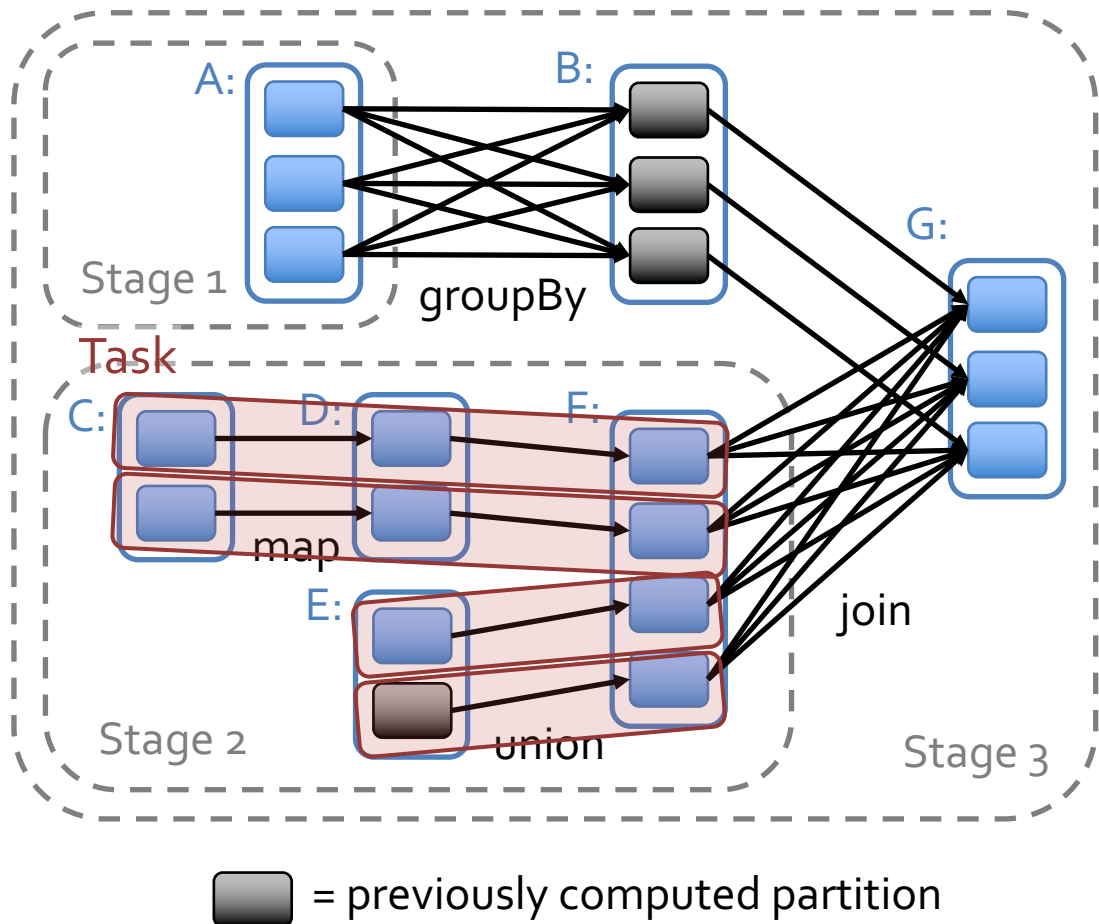
- » Build stages of Task objects (code + preferred loc.)
- » Submit them to TaskScheduler as ready
- » Resubmit failed stages if outputs are lost

# Scheduler Optimizations

Pipelines narrow ops.  
within a stage

Picks join algorithms  
based on partitioning  
(minimize shuffles)

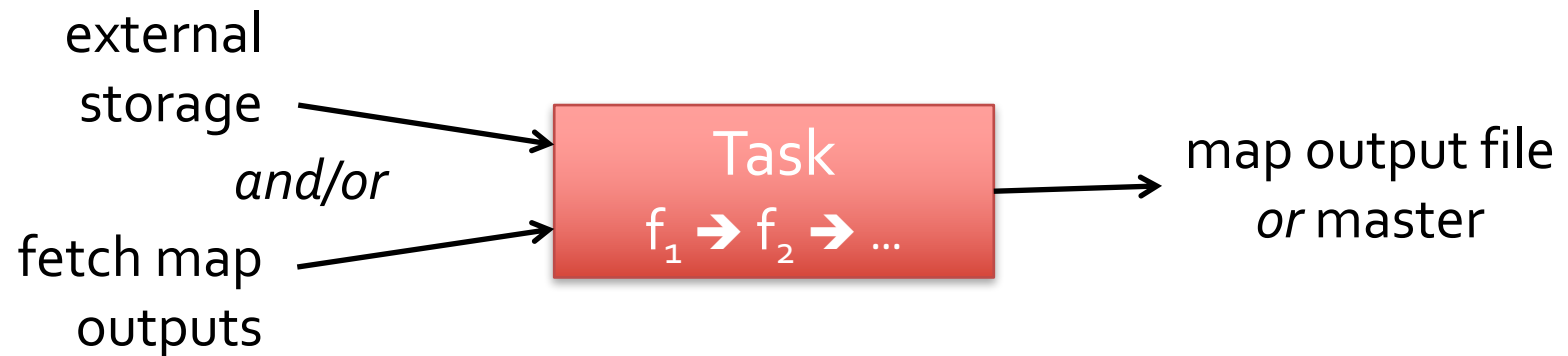
Reuses previously  
cached data



# Task Details

Stage boundaries are only at input RDDs or “shuffle” operations

So, each task looks like this:



(Note: we write shuffle outputs to RAM/disk to allow retries)

# Task Details

Each Task object is self-contained

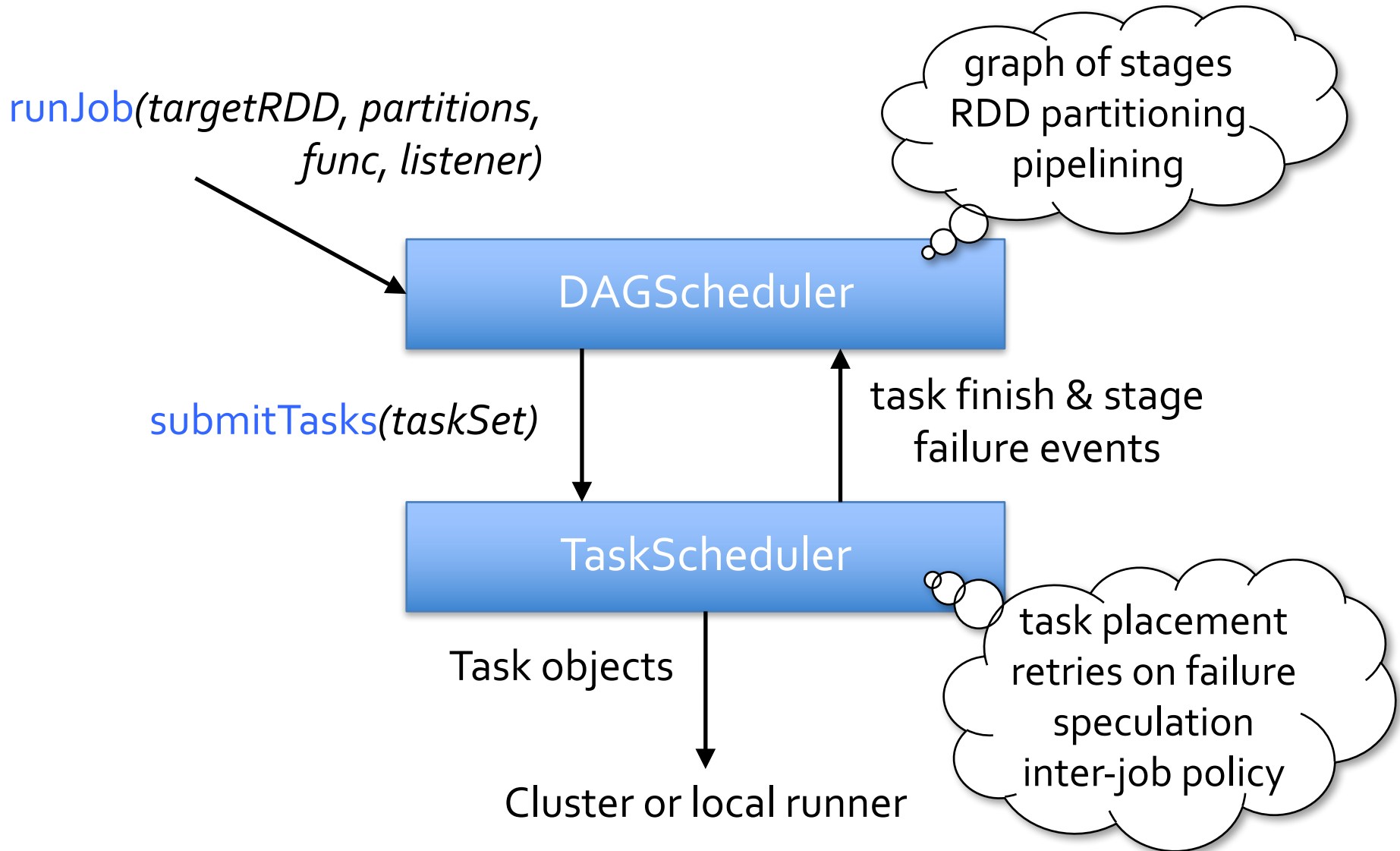
» Contains all transformation code up to input boundary  
(e.g. HadoopRDD => filter => map)

Allows Tasks on cached data to even if they fall out of cache

Design goal: any Task can run on any node

Only way a Task can fail is lost map output files

# Event Flow



# TaskScheduler

## Interface:

- » Given a TaskSet (set of Tasks), run it and report results
- » Report “fetch failed” errors when shuffle output lost

## Two main implementations:

- » LocalScheduler (runs locally)
- » ClusterScheduler (connects to a cluster manager using a pluggable “SchedulerBackend” API)



# TaskScheduler Details

Can run multiple concurrent TaskSets, but currently does so in FIFO order

- » Would be really easy to plug in other policies!
- » If someone wants to suggest a plugin API, please do

Maintains one TaskSetManager per TaskSet that tracks its locality and failure info

Polls these for tasks in order (FIFO)

# Worker

Implemented by the Executor class

Receives self-contained Task objects and calls run() on them in a thread pool

Reports results or exceptions to master

» Special case: FetchFailedException for shuffle

Pluggable ExecutorBackend for cluster

# Other Components

## BlockManager

- » “Write-once” key-value store on each worker
- » Serves shuffle data as well as cached RDDs
- » Tracks a StorageLevel for each block (e.g. disk, RAM)
- » Can drop data to disk if running low on RAM
- » Can replicate data across nodes

# Other Components

## CommunicationManager

- » Asynchronous IO based networking library
- » Allows fetching blocks from BlockManagers
- » Allows prioritization / chunking across connections  
(would be nice to make this pluggable!)
- » Fetch logic tries to optimize for block sizes

# Other Components

## MapOutputTracker

- » Tracks where each “map” task in a shuffle ran
- » Tells reduce tasks the map locations
- » Each worker caches the locations to avoid refetching
- » A “generation ID” passed with each Task allows invalidating the cache when map outputs are lost

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# Extension Points

Spark provides several places to customize functionality:

**Extending RDD:** add new input sources or transformations

**SchedulerBackend:** add new cluster managers

**spark.serializer:** customize object storage

# What People Have Done

New RDD transformations (`sample`, `glom`,  
`mapPartitions`, `leftOuterJoin`, `rightOuterJoin`)

New input sources (`DynamoDB`)

Custom serialization for memory and  
bandwidth efficiency

New language bindings (`Java`, `Python`)



# Possible Future Extensions

Pluggable inter-job scheduler

Pluggable cache eviction policy (ideally with priority flags on StorageLevel)

Pluggable instrumentation / event listeners

*Let us know if you want to contribute these!*

# As an Exercise

Try writing your own input RDD from the local filesystem (say one partition per file)

Try writing your own transformation RDD (pick a Scala collection method not in Spark)

Try writing your own action (e.g. `product()`)

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# Development Process

Issue tracking: [spark-project.atlassian.net](https://spark-project.atlassian.net)

Development discussion: spark-developers

Main work: “master” branch on GitHub

- » Submit patches through GitHub pull requests

Be sure to follow code style and add tests!

# Build Tools

SBT and Maven currently both work (but switching to only Maven)

IDEA is the most common IDE; Eclipse may be made to work

# Thanks!

Stay tuned for future developer meetups.