SPARK

@CrazyJvm

What is Spark

- a fast and general-purpose cluster computing system.
- high efficiency
- high level api (Scala, Java, Python)

How to run

- Local
- Standalone
- Mesos
- YARN

and an interactive shell (Scala supported)

About Scala

- JVM based
- Statically typed
- Interoperate with Java (vice-versa)

try in interactive shell!

The most important concept: RDD

RDDs: resilient distributed datasets

internally, each RDD is characterized by five main properties:

- * A list of partitions
- * A function for computing each split
- * A list of dependencies on other RDDs
- * Optionally, a Partitioner for key-value RDDs (e.g. to say that the RDD is hash-partitioned)
- * Optionally, a list of preferred locations to compute each split on (e.g. block locations for an HDFS file)

The most important concept: RDD

- immutable collections of objects spread across a cluster
- build through parallel transformations
- automatically rebuild on failure
- different storage level (memory management)

Over view

- RDDs
- Transformations (Lazy evaluation!!!)
- Action (def runJob[T, U: ClassManifest]

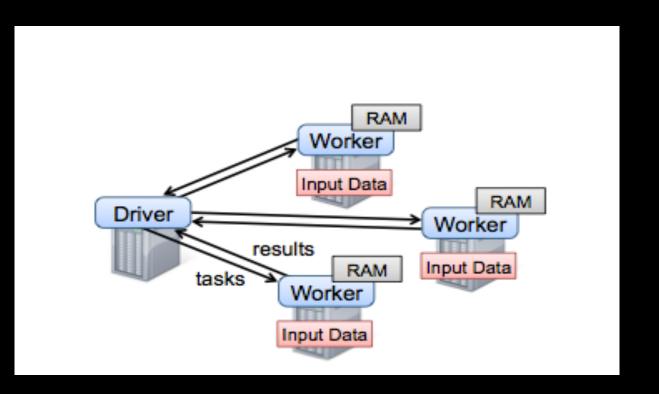
```
(rdd: RDD[T],
```

func: Iterator[T] => U): Array[U])

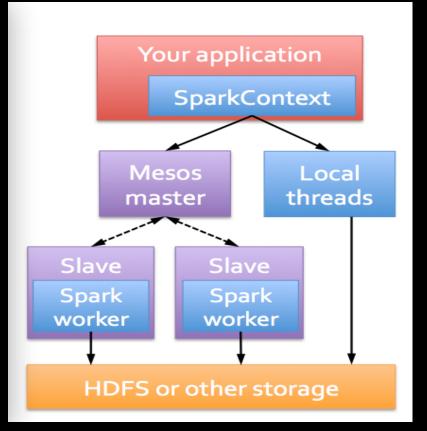
RDD:transformations & actions

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

Spark runtime



Components



Just do it

- interactive shell
- local mode (get local data)
- standalone mode (get data from hdfs)
- programming in IDE(eclipse,idea)

Word Count

```
val text = sc.textFile("README.md")
val wc = text.flatMap(_.split(" ")).map((_,1)).reduceByKey(_+_)
wc.collect
```

notice: reduceByKey is called by implicit conversion implicit def rddToPairRDDFunctions[K: ClassManifest, V: ClassManifest] (rdd: RDD[(K, V)]) = new PairRDDFunctions(rdd)

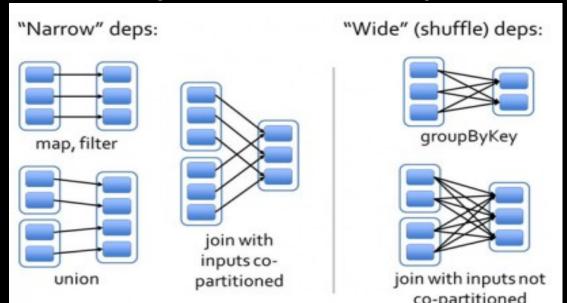
if we let wc.cache, what will happen?

RDD Lineage

- Narrow dependency:each partition of the parent RDD is used by at most one partition of the child RDD.
- Wide dependency: multiple child partitions may depend on a partition of parent RDD.

RDD Lineage

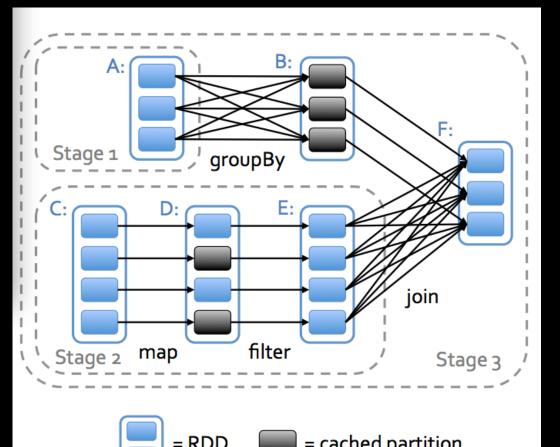
- optimization? -> pipeline
- the importance of co-partitioned



Task scheduler

- run general task graphs
- pipeline functions where possible
- Cache-aware data reuse and locality
- Partitioning-aware to avoid shuffles

Task scheduler



Schedule process

- RDD objects
- DAGScheduler
- TaskScheduler
- Worker

RDD fault tolerance

- recovery by lineage
- checkpoint

Q & A

thanks!