### Spark Performance

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### About me

Work on performance benchmarking and testing in Spark

Co-author of spark-perf

Wrote instrumentation/UI components in Spark



### This talk

Geared towards existing users

Current as of Spark 0.8.1



### Outline

Part 1: Spark deep dive

Part 2: Overview of UI and

instrumentation

Part 3: Common performance mistakes



# Why gain a deeper understanding?

```
(patrick, $24), (matei, $30), (patrick, $1), (aaron, $23), (aaron, $2), (reynold, $10), (aaron, $10).....
```

**RDD** 

```
spendPerUser = rdd
.groupByKey()
.map(lambda pair: sum
```

.collect()

Copies all data over the network

```
spendPerUser = rdd
.reduceByKey(lambda x
.collect()
```

Reduces locally before shuffling



#### Let's look under the hood



## How Spark works

RDD: a parallel collection w/ partitions

User application creates RDDs, transforms them, and runs actions

These result in a DAG of operators

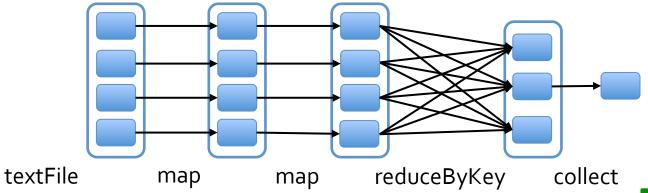
DAG is compiled into stages

Each stage is executed as a series of tasks



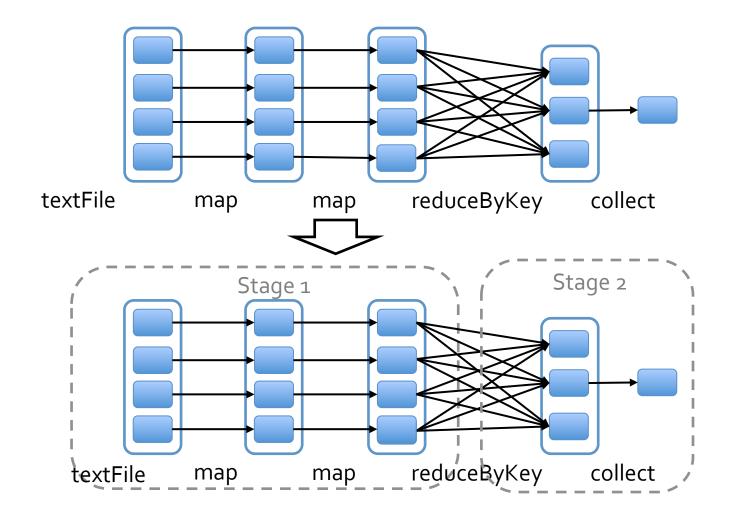
# Example

```
sc.textFile("/some-hdfs-data")
    .map(line => line.split("\t"))
    .map(parts =>
        (parts[0], int(parts[1])))
    .reduceByKey(_ + _, 3)
    .collect()
RDD[String]
RDD[List[String]]
RDD[(String, Int)]
RDD[(String, Int)]
Array[(String, Int)]
```



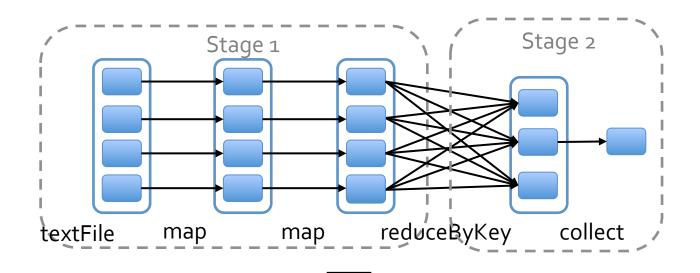
**-**databricks<sup>™</sup>

## **Execution Graph**

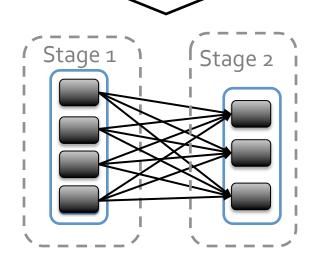




## **Execution Graph**



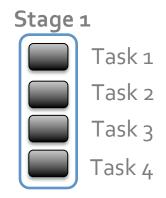
read HDFS split apply both maps partial reduce write shuffle data



read shuffle data final reduce send result to driver



## Stage execution



Create a task for each partition in the new RDD

Serialize task

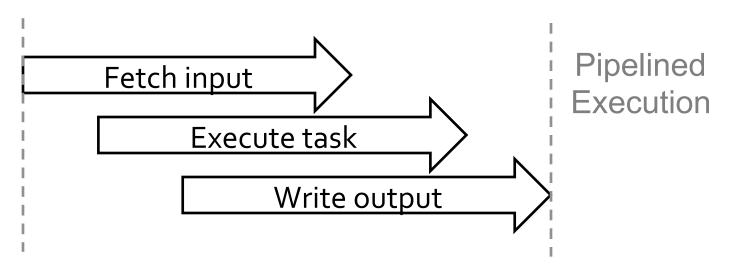
Schedule and ship task to slaves



### Task execution

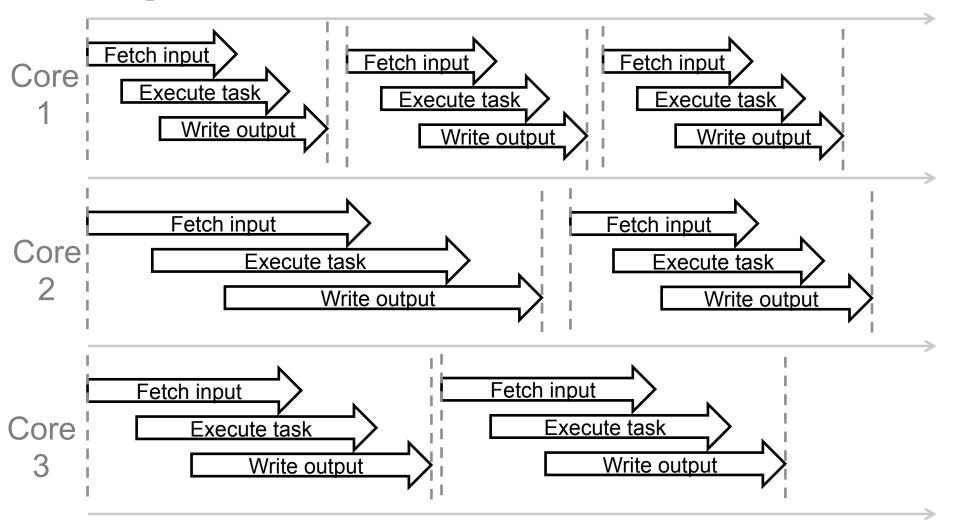
# Fundamental unit of execution in Spark

- A. Fetch input from InputFormat or a shuffle
- B. Execute the task
- C. Materialize task output as shuffle or driver result





# Spark Executor





# Summary of Components

Tasks: Fundamental unit of work

Stage: Set of tasks that run in parallel

**DAG**: Logical graph of RDD operations

RDD: Parallel dataset with partitions



## Demo of perf UI



# Where can you have problems?

- Scheduling and launching tasks
- 2. Execution of tasks
- 3. Writing data between stages
- 4. Collecting results



# 1. Scheduling and launching tasks

# Serialized task is large due to a closure

```
hash_map = some_massive_hash_map()
rdd.map(lambda x: hash_map(x))
    .count_by_value()
```

**Detecting:** Spark will warn you! (starting in 0.9...)

#### **Fixing**

Use broadcast variables for large object Make your large object into an RDD



# Large number of "empty" tasks due to selective filter

```
rdd = sc.textFile("s3n://bucket/2013-data")
.map(lambda x: x.split("\t"))
.filter(lambda parts: parts[0] == "2013-10-17")
.filter(lambda parts: parts[1] == "19:00")

rdd.map(lambda parts: (parts[2], parts[3]).reduceBy...
```

**Detecting** Many short-lived (< 20ms) tasks **Fixing** 

Use `coalesce` or `repartition` operator to shrink RDD number of partitions after filtering: rdd.coalesce(30).map(lambda parts: (parts[2]...\_

### 2. Execution of Tasks

### Tasks with high perrecord overhead

```
conn.write(str(x))
 conn.close())
Detecting: Task run time is high
Fixing
Use mapPartitions or mapWith (scala)
rdd.mapPartitions(lambda records:
 conn = new mong db cursor()
 [conn.write(str(x)) for x in records]
 conn.close())
```

conn = new mongo db cursor()

rdd.map(lambda x:



### Skew between tasks

#### **Detecting**

Stage response time dominated by a few slow tasks

#### **Fixing**

Data skew: poor choice of partition key

- → Consider different way of parallelizing the problem
- → Can also use intermediate partial aggregations

Worker skew: some executors slow/flakey nodes

- → Set spark.speculation to true
- → Remove flakey/slow nodes over time



# 3. Writing data between stages

# Not having enough buffer cache

spark writes out shuffle data to OS-buffer cache

#### **Detecting**

tasks spend a lot of time writing shuffle data

#### **Fixing**

if running large shuffles on large heaps, allow several GB for buffer cash

rule of thumb, leave 20% of memory free for OS and caches \_\_\_\_databricks \_\_\_\_\_

# Not setting spark.local.dir

spark.local.dir is where shuffle files are written

ideally a dedicated disk or set of disks

spark.local.dir=/mnt1/spark,/mnt2/spark,/mnt3/spark

mount drives with noattime, nodiratime



# Not setting the number of reducers

Default behavior: inherits # of reducers from parent RDD

Too many reducers:

→ Task launching overhead becomes an issue (will see many small tasks)

Too few reducers:

→ Limits parallelism in cluster



# 4. Collecting results

# Collecting massive result sets

sc.textFile("/big/hdfs/file/").collect()

#### **Fixing**

If processing, push computation into Spark

If storing, write directly to parallel storage



## Advanced Profiling

#### JVM Utilities:

```
jstack <pid>jvm stack trace
jmap –histo:live <pid> heap summary
```

#### System Utilities:

dstat io and cpu stats

iostat disk stats

Isof -p <pid> tracks open files



### Conclusion

Spark 0.8 provides good tools for monitoring performance

Understanding Spark concepts provides a major advantage in perf debugging



### Questions?

