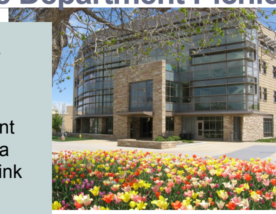
9/8/2016 CS535 Big Data - Fall 2016 W3.B.0

Computer Science Department Picnic

Welcome to the 2016-2017 Academic year !

Meet your faculty, department staff, and fellow students in a social setting. Food and drink will be provided.



When: Saturday, September 10th
Time: 11am – 2pm
Where: City Park Shelter #7

CS535 BIG DATA

PART 1. BATCH COMPUTING MODELS FOR BIG DATA ANALYTICS

1. DISTRIBUTED MODEL FOR SCALABLE BATCH COMPUTING - MAPREDUCE

Sangmi Lee Pallickara
Computer Science, Colorado State University
http://www.cs.colostate.edu/~cs535

9/8/2016 CS535 Big Data - Fall 2016 W3.B.2

FAQs

- Questions about PA1
  - Send an email to cs535@cs.colostate.edu
- Use the posted configuration file with 2GB memory for the worker node

---

9/8/2016 CS535 Big Data - Fall 2016 W3.B.3

Objectives

- In-Memory Cluster Computing
- Introduction to Apache Spark
- RDD
- Spark cluster
- Scheduling

9/8/2016 CS535 Big Data - Fall 2016 W3.B.4

In-Memory Cluster Computing: Apache Spark

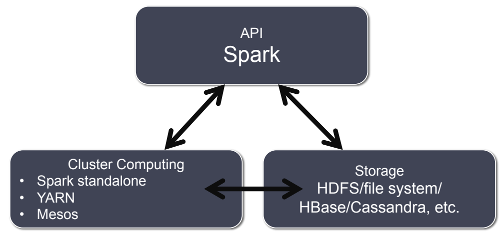
9/8/2016 CS535 Big Data - Fall 2016 W3.B.5

In-Memory Cluster Computing: Apache Spark
Introduction

This material is built based on

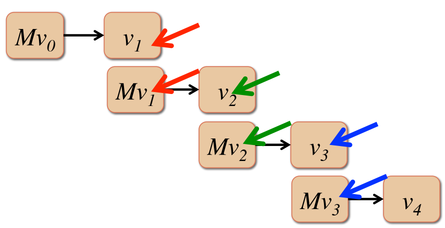
- Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael J. Franklin, Scott Shenker, and Ion Stoica, "*Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing,*" The 9th USENIX Symposium on Networked Systems Design and Implementation (NSDI 12)
- Holden Karau, Andy Komwinski, Patrick Wendell and Matei Zaharia, "Learning Spark", O'Reilly, 2015
- Spark Overview, https://spark.apache.org/docs/2.0.0-preview/
  - Spark programming guide
    - https://spark.apache.org/docs/2.0.0-preview/programming-guide.html
  - Job Scheduling
    - https://spark.apache.org/docs/2.0.0-preview/job-scheduling.html

Distributed processing with the Spark framework



Inefficiencies for emerging applications: (1) Data reuse

- Data reuse is common in many iterative machine learning and graph algorithms
  - PageRank, K-means clustering, and logistic regression



Inefficiencies for emerging applications: (2) Interactive data analytics

- User runs multiple ad-hoc queries on the **same subset** of the data

Existing approaches

- Hadoop
  - Writing output to an external stable storage system
    - e.g. HDFS
    - Substantial overheads due to data replication, disk I/O, and serialization
- Pregel
  - Iterative graph computations
- HaLoop
  - Iterative MapReduce interface
- Pregel/HaLoop support specific computation patterns
  - e.g. looping a series of MapReduce steps

In-Memory Cluster Computing: Apache Spark

RDD (Resilient Distributed Dataset)

RDD (Resilient Distributed Dataset)

- **Read-only, partitioned collection of records**
  - A fault-tolerant collection of elements that can be operated on in parallel
- RDDs are the core unit of data in Spark
  - Most Spark programming involves performing operations on RDDs

Overview of RDD

- ***Lineage***
  - How it was derived from other dataset to compute its partitions from data in stable storage?
    - RDDs do not need to be materialized at all times
  - Program **CANNOT** reference an RDD if it cannot reconstruct after a failure
- ***Persistence***
  - Users can indicate which RDDs they will reuse and the storage strategy
- ***Partitioning***
  - Users can specify the partitioning method across machines based on a key in each record

Spark Programming Interface to RDD [1/3]

- ***transformations***
  - Operations that create RDDs
    - Return pointers to new RDDs
    - e.g. `map`, `filter`, and `join`
  - RDDs can only be created through deterministic operations on either
    - Data in stable storage
    - Other RDDs

Spark Programming Interface to RDD [2/3]

- ***actions***
  - Operations that return a value to the application or export data to a storage system
    - e.g. `count`: returns the number of elements in the dataset
    - e.g. `collect`: returns the elements themselves
    - e.g. `save`: outputs the dataset to a storage system

Spark Programming Interface to RDD [3/3]

- ***persist***
  - Indicates which RDDs they want to **reuse in future operations**
  - Spark keeps persistent RDDs **in memory** by default
  - If there is not enough RAM
    - It can spill them to disk
  - Users are allowed to,
    - store the RDD only on disk
    - replicate the RDD across machines
    - specify a persistence priority on each RDD

Example: Console Log Mining [1/3]

- Suppose that a web service is experiencing errors and an operator wants to search terabytes of logs in the Hadoop file system (HDFS) to find the cause
- The user can load just **the error messages** from the logs into the RAM across a set of nodes and query them interactively

```
lines = spark.textFile("hdfs://…")
errors=lines.filter(_.startsWith("ERROR"))
errors.persist()
```

No work has been performed
User can use the RDD in actions

Example: Console Log Mining [2/3]

- Users can perform further transformations and actions on the RDD

```
//To count number of error messages
errors.count()

//Count errors mentioning MySQL:
errors.filter(_.contains("MySQL")).count()

//Return the time fields of errors mentioning
//HDFS as an array (assuming time is field
//number 3 in a tab-separated format
errors.filter(_.contains("HDFS"))
       .map(_.split('/t')(3))
       .collect()
```

After the first **action** involving `errors` runs, Spark will store the partitions of errors in memory.

Example: Console Log Mining [3/3]

Spark code

```
lines = spark.textFile("hdfs://…")
errors=lines.filter(_.startsWith("
ERROR"))
errors.persist()
errors.filter(_.contains("HDFS"))
       .map(_.split('/t')(3))
       .collect()
```

Lineage graph

```
lines
  | filter(_.startsWith("ERROR"))
errors
  | filter(_.contains("HDFS"))
HDFS errors
  | map(_.split('/t')(3))
Time fields
```

If a partition of `errors` is lost Spark rebuilds it by applying a filter on only the corresponding partition of `lines`

Lazy Evaluation

- Transformations on RDDs are **lazily evaluated**
  - Spark will **NOT** begin to execute until it sees an action
  - Spark internally records metadata to indicate that this operation has been requested
- Loading data into an RDD is lazily evaluated
- Reduces the number of passes it has to take over our data by grouping operations together

Benefits of RDDs as a distributed memory abstraction [1/3]

- RDDs can only be created ("written") through **coarse-grained transformations**
  - Distributed shared memory (DSM) allows reads and writes to each memory location
  - Reads on RDDs can still be fine-grained
    - A large read-only lookup table
  - Applications perform bulk writes
  - More efficient fault tolerance
    - Lineage based bulk recovery

Benefits of RDDs as a distributed memory abstraction [2/3]

- RDDs' immutable data
  - System can mitigate slow nodes (Stragglers)
    - Creates backup copies of slow tasks
      - without accessing the same memory
    - Spark distributes the data over different working nodes that run computations in parallel
      - Orchestrates communicating between nodes to Integrate intermediate results and combine them for the final result

Benefits of RDDs as a distributed memory abstraction [3/3]

- Runtime can schedule tasks based on data locality
  - To improve performance
- RDDs degrade gracefully when there is insufficient memory
  - Partitions that do not fit in the RAM are stored on disk

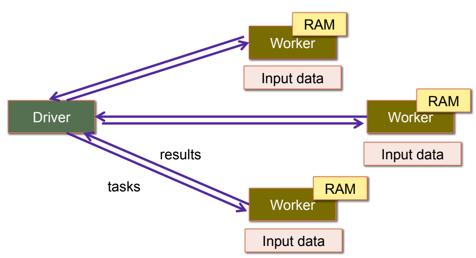
Applications not suitable for RDDs

- RDDs are best suited for batch applications that apply the same operations to all elements of a dataset
  - Steps are managed by lineage graph efficiently
  - Recovery is managed effectively
- RDDs would not be suitable for applications
  - Making asynchronous fine-grained updates to shared state
  - e.g. a storage system for a web application or an incremental web crawler

In-Memory Cluster Computing: Apache Spark

RDDs in Spark

RDDs in Spark: The Runtime



User's driver program launches multiple workers, which read data blocks from a distributed file system and can persist computed RDD partitions in memory

Representing RDDs

- A set of partitions
  - Atomic pieces of the dataset
- A set of dependencies on parent RDDs
- A function for computing the dataset based on its parents
- Metadata about its partitioning scheme
- Data placement

In-Memory Cluster Computing: Apache Spark

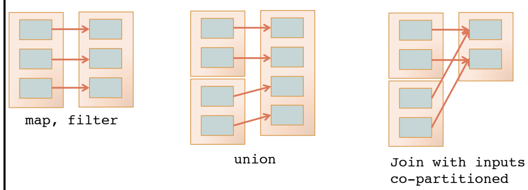
RDD Dependency in Spark

Dependency between RDDs [1/2]

- ***Narrow*** dependency
- ***Wide*** dependency

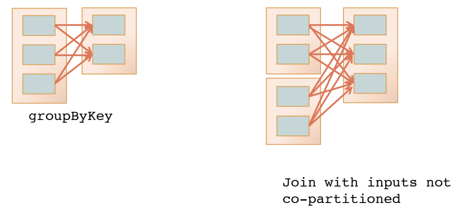
Dependency between RDDs [1/2]

- ***Narrow*** dependency
  - Each partition of the parent RDD is used by **at most one partition** of the child RDD



Dependency between RDDs [1/2]

- ***Wide*** dependency
  - **Multiple child partitions** may depend on a single partition of parent RDD



Dependency between RDDs [2/2]

- Narrow dependency
  - Pipelined execution on one cluster node
  - e.g. a map followed by a filter
  - Failure recovery is more straightforward
- Wide dependency
  - Requires data from all parent partitions to be available and to be shuffled across the nodes
  - Failure recovery could involve a large number of RDDs
    - Complete re-execution may be required

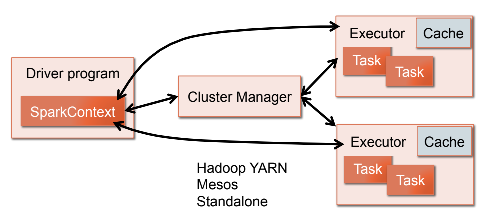
Interface used to represent RDDs in Spark

- `partitions()`
  - Returns a list of partition objects
- `preferredLocations(p)`
  - List nodes where partition p can be accessed faster due to data locality
- `dependencies()`
  - Return a list of dependencies
- `iterator (p, parentIters)`
  - Compute the elements of partition p given iterators for its parent partitions
- `partitioner()`
  - Return metadata specifying whether the RDD is hash/range partitioned

In-Memory Cluster Computing: Apache Spark

Spark Cluster

Spark cluster and resources



Spark cluster [1/3]

- Each application gets its own executor processes
  - Must be up and running for the duration of the entire application
  - Run tasks in multiple threads
  - Isolate applications from each other
    - Scheduling side (each driver schedules its own tasks)
    - Executor side (tasks from different applications run in different JVMs)
  - Data cannot be shared across different Spark applications (instances of SparkContext) without writing it to an external storage system

Spark cluster [2/3]

- Spark is agnostic to the underlying cluster manager
  - As long as it can acquire executor processes, and these communicate with each other, it is relatively easy to run it even on a cluster manager that also supports other applications (e.g. Mesos/YARN)

Spark cluster [3/3]

- Driver program must listen for and accept incoming connections from its executors throughout its lifetime
  - Driver program must be network addressable from the worker nodes
- Driver program should run close to the worker nodes
  - On the same local area network

Cluster Manager Types

- Standalone
  - Simple cluster manager included with Spark
- Mesos
  - Fine-grained sharing option
    - Frequently shared objects for Interactive applications
  - Mesos master determines the machines that handle the tasks
- Hadoop YARN
  - Resource manager in Hadoop 2

Dynamic Resource Allocation

- Dynamically adjust the resources that the applications occupy
  - Based on the workload
  - Your application may give resources back to the cluster if they are no longer used
- Only available on coarse-grained cluster managers
  - Standalone mode, YARN mode, Mesos coarse grained mode

In-Memory Cluster Computing: Apache Spark

Scheduling

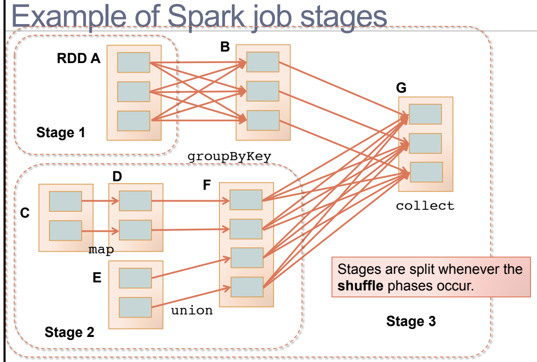
Jobs in Spark application

- "Job"
  - A Spark action (e.g. save, collect) and any tasks that need to run to evaluate that action
- Within a given Spark application, multiple parallel tasks can run simultaneously
  - If they were submitted from separate threads

Job scheduling

- User runs an action (e.g. count or save) on an RDD
- Scheduler examines that RDD's lineage graph to build a DAG of stages to execute
- Each stage contains as many pipelined transformations as possible
  - With narrow dependencies
- The boundaries of the stages are the shuffle operations
  - For wide dependencies
  - For any already computed partitions that can short circuit the computation of a parent RDD

Example of Spark job stages



Default FIFO scheduler

- By default, Spark's scheduler runs jobs in **FIFO** fashion
- First job gets the first priority on all available resources
  - Then the second job gets the priority, etc.
  - As long as the resource is available, jobs in the queue will start right away

Fair Scheduler

- Assigns tasks between jobs in a "**round robin**" fashion
  - All jobs get a roughly equal share of cluster resources
- Short jobs that were submitted when a long job is running can start receiving resources right away
  - Good response times, without waiting for the long job to finish
- Best for multi-user settings

Fair Scheduler Pools

- Supports grouping jobs into pools
  - With different options (e.g. weights)
  - "high-priority" pool for more important jobs
- This approach is modeled after the **Hadoop Fair Scheduler**
- **Default behavior of pools**
  - Each pool gets **an equal share of the cluster**
  - Inside each pool, jobs run in **FIFO** order
  - If the Spark cluster creates one pool per user
    - Each user will get an equal share of the cluster
    - Each user's queries will run in order

Questions?