CS 455: INTRODUCTION TO DISTRIBUTED SYSTEMS [SPARK]

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Frequently asked questions from the previous class survey

- Is `distcp` across different clusters possible?
- For what application would `sync` be slow?
- Write pipeline: D1, D2, and D3 … what if D2 fails?
- Uncompress and then MapReduce?
- How slow is slow?

Topics covered in this lecture

- Spark
  - Software stack
  - Interactive shells in Spark
  - Core Spark concepts
  - Resilient Distributed Datasets

HDFS WRAP-UP

HDFS does not split `gzip` files

- Single map will process 16 HDFS blocks
- Most of these blocks will not be local to the map
  - Loss of locality
  - Job is not granular … takes much longer to run

The same story plays out if you were dealing with LZO files, but …

- It is possible to *preprocess* LZO files using an indexer tool
- Build an **index** of split points

Bzip2

- This does provide a **synchronization marker** between blocks
  - 48-bit approximation of pi
- The marker is used to support splitting

Dealing with large, unbounded files [Log files]

1. Store the files uncompressed
2. Use compression format that supports
   - Splitting: Bzip2
   - Indexing to support splitting: LZO
3. Split the file into chunks in the application and compress each chunk separately
   - Choose chunk sizes such that the *compressed chunks* are approximately the size of an HDFS block

Using compression in MapReduce

- To compress the output of MapReduce job
  - In the job config set `mapred.output.compress` property to true
  - Use `mapred.output.compression.codec` to specify the codec
- Alternatively, we can do this using the `FileOutputFormat`

Using the FileOutputFormat

```
public class MaxTemperatureWithCompression {

   public static void main(String[] args) throws Exception {
    Job job = Job.getInstance();
    job.setJarByClass(MaxTemperature.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);

    FileOutputFormat.setCompressOutput(job, true);
    FileOutputFormat.setOutputCompressorClass(job, GzipCodec.class);

    job.setMapperClass(MaxTemperatureMapper.class);
    job.setCombinerClass(MaxTemperatureReducer.class);
    job.setReducerClass(MaxTemperatureReducer.class);
    System.exit(job.waitForCompletion(true) ? 0 : 1);
   }

}
```


Main reason why Hadoop does not use Java Serialization

- Deserialization creates new instance of each object being deserialized
- Writable objects can be (and are often) reused
- Large MapReduce jobs often serialize/deserialize billions of records
  - Savings from not having to allocate new objects is significant

Apache Spark

As distributed data analytics have grown common …

- Practitioners have sought easier tools for the task
- Apache Spark has emerged as one of the most popular
  - Extending and generalizing MapReduce

Spark: What is it?

- **Cluster computing platform**
  - Designed to be fast and general purpose
- Speed
  - Extends MapReduce to support more types of computations
    - Interactive queries, iterative tasks, and stream processing
- Why is speed important?
  - Difference between waiting for hours versus exploring data interactively

Spark: Influences and Innovations

- Spark has inherited parts of its API, design, and supported formats from other existing computational frameworks
  - Particularly DryadLINQ
- Spark's internals, especially how it handles failures, differ from many traditional systems
- Spark's ability to leverage **lazy evaluation** within memory computations makes it particularly unique

Where does Spark fit in the Analytics Ecosystem?

- Spark provides methods to process data in parallel that are **generalizable**
- On its own, Spark is ***not*** a data storage solution
  - Performs computations on Spark JVMs that last only for the duration of a Spark application
- Spark is used in tandem with:
  - A distributed storage system (e.g., HDFS, Cassandra, or S3)
    - To house the data processed with Spark
  - A cluster manager — to orchestrate the distribution of Spark applications across the cluster

Key enabling idea in Spark

- **Memory resident data**
- Spark loads data into the memory of worker nodes
  - Processing is performed on memory-resident data

A look at the memory hierarchy

Item	time	Scaled time in human terms (2 billion times slower)
Processor cycle	0.5 ns (2 GHz)	1 second
Cache access	1 ns (1 GHz)	2 seconds
Memory access	70 ns	140 seconds
Context switch	5,000 ns (5 µs)	167 minutes
Disk access	7,000,000 ns (7 ms)	162 days
Quantum	100,000,000 ns (100 ms)	6.3 years

Source: Kay Robbins & Steve Robbins. *Unix Systems Programming*, 2nd edition, Prentice Hall.

Spark covers a wide range of workloads

- Batch applications
- Iterative algorithms
- Queries
- Stream processing

- This has previously required multiple, independent tools

APIs

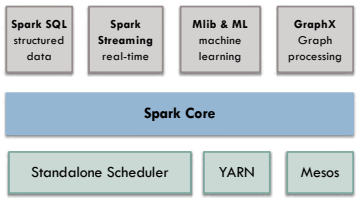
- Java, Python, Scala, and SQL
- Integrates well with other tools
  - Can run in Hadoop clusters
  - Access Hadoop data sources, including Cassandra

At its core, Spark is a **computational engine**

- Spark is responsible for several aspects of applications that comprise
  - Many tasks across many machines (compute clusters)
- Responsibilities include:
  1. Scheduling
  2. Distributions
  3. Monitoring

The Spark Software Stack

The Spark stack



Benefits of tight integration [1/2]

- All libraries and higher-level components benefit from improvements at the lower layers
- E.g.: Spark's core engine adds optimization? SQL and ML libraries automatically speed-up as well

Benefits of tight integration [2/2]

- Biggest advantage is ability to build applications that **seamlessly combine different processing models**
- An application may use ML to classify data in real time as it is being ingested
  - Analysts can query this resulting data, also in real time, via SQL (e.g.: join data with unstructured log-files)

Spark Core

- **Basic functionality** of Spark
- Task scheduling, memory management, fault recovery, and interacting with storage systems
- Also, the API that defines Resilient Distributed Datasets (**RDD**s)
  - Spark's *main programming abstraction*
  - Represents collection of data items dispersed across many compute nodes
    - Can be manipulated concurrently (parallel)

Spark SQL

- Package for working with **structured data**
- Allows querying data using SQL and HQL (Hive Query Language)
  - Data sources: Hive tables, Parquet, and JSON
- Allows intermixing queries with programmatic data manipulations support by RDDs
  - Using Scala, Java, and Python

Semi-structured data and Spark SQL

- Spark SQL defines an interface for a semi-structured data type, called **DataFrames**
  - And as of Spark 1.6, a semi-structured, typed version of RDDs called **Datasets**
- Spark SQL is a very important component for Spark performance
- Much of what can be accomplished with Spark Core can be done by leveraging Spark SQL.

Spark Streaming

- Enables processing of **live streams** of data from sources such as:
  - Logfiles generated by production webservers
  - Messages containing web service status updates
- Uses the scheduling of the Spark Core for streaming analytics on **minibatches** of data
- Has a number of unique considerations, such as the *window sizes* used for batches

MLib

- Library that contains common machine learning functionality
- Algorithms include:
  - Classification, regression, clustering, and collaborative filtering
- Low-level primitives
  - Generic gradient descent optimization algorithm
- Alternatives?
  - Mahout, sci–kit learn, VW, WEKA, and R among others

What about Spark ML?

- Still in the early stages, and has only existed since Spark 1.2
- Spark ML provides a higher-level API than MLlib
  - Goal is to allow users to more easily create practical machine learning **pipelines**
  - Spark MLlib is primarily built on top of RDDs and uses functions from Spark Core, while ML is **built on top of Spark SQL DataFrames**
- Eventually the Spark community plans to move over to ML and deprecate MLlib

Graph X

- Library for manipulating graphs
- Graph-parallel computations
- Extends Spark RDD API
  - Create a **directed graph**, with arbitrary properties attached to each vertex and edge

Cluster Managers

- Spark runs over a variety of cluster managers
- These include:
  - Hadoop YARN
  - Apache Mesos
  - Standalone Scheduler
    - Included within Spark

Storage Layers for Spark

- Spark can create distributed datasets from any file stored in HDFS
- Plus, other storage systems supported by the Hadoop API
  - Amazon S3, Cassandra, Hive, HBase, etc.

Interactive Shells in Spark

Spark Shells

- Interactive [Python and Scala]
  - Similar to shells like Bash or Windows command prompt
- *Ad hoc* data analysis
- Traditional shells manipulate data using disk and memory on a single machine
  - Spark shells allow interaction with **data that is distributed** across many machines
  - Spark manages complexity of distributing processing

Several software were designed to run on the Java Virtual Machine

- Languages that compile to run on the JVM and can interact with Java software packages but are *not actually* Java
- There are a number of non-Java JVM languages
  - The two most popular ones used in real-time application development: **Scala** and **Clojure**

Scala

- Has spent most of its life as an academic language
  - Still largely developed at universities
  - Has a rich standard library that has made it appealing to developers of high-performance server applications
- Like Java, Scala is a strongly typed object-oriented language
  - Includes many features from functional programming languages that are not in standard Java
  - Interestingly, Java 8 incorporate several of the more useful features of Scala and other functional languages.

What is functional programming?

- When a method is compiled by Java, it is converted to instructions called byte code and …
  - Then largely disappears from the Java environment
    - Except when it is called by other methods
- In a functional language, **functions are treated the same way as data**
  - Can be stored in objects similar to integers or strings, returned from functions, and passed to other functions

What about Clojure?

- Based on Lisp
- Javascript?
  - Name was a marketing gimmick
  - Closer to Clojure and Scala than it is to Java

Core Spark Concepts

Core Spark Concepts

- Drivers
- SparkContext
- Executors

Spark in a nutshell

- Spark allows users to write a program for the **driver** (or master node) on a cluster computing system that can perform *operations* on data in parallel
- Spark represents large datasets as **RDD**s which are stored in the executors (or worker nodes)
- The objects that comprise RDDs are called **partitions** and may be (but do not need to be) computed on different nodes of a distributed system
- The Spark cluster manager handles starting and distributing the Spark executors across a distributed system

Drivers

- Every Spark application consists of a **driver** program
- Driver **launches various parallel operations** on the cluster
- Constituent elements
  - Application's main function
  - Defines distributed datasets on the clusters
  - Applies operations to these datasets

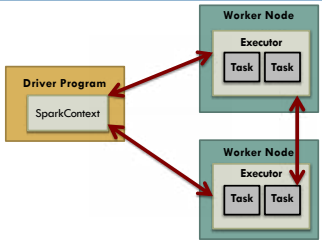
SparkContext

- Driver programs access Spark through a `SparkContext` object
  - Represents a **connection** to a computing cluster
- Within the shell?
  - Created as the variable `sc`
    - You can event print out `sc` to see the the type
- Once you have a `SparkContext`, you can use it to build RDDs
  - And then run operations on the data …

Executors

- Driver programs manage a number of nodes, called **executors**
- Executors are responsible for running operations
- For example:
  - If we were running a `count()` operation on cluster
    - Different machines might count lines in different ranges of the file

Components for distributed execution in Spark



Lot of Spark's API revolves around passing functions to its operators

```
def hasPython(line)
   return "Python" in line

pythonLines =
    lines.filter(hasPython)
```

```
pythonLines =
 lines.filter(line => line.contains("Python")
```

Also known as the **lambda or =>** syntax

Lot of Spark's API revolves around passing functions to its operators

```
JavaRDD<String> pythonLines = lines.filter(
   new Function<String, Boolean> () {
     Boolean call(String line) {
        return line.contains("Python");
     }
   }
);
```

```
JavaRDD<String> pythonLines =
    lines.filter(line -> line.contains("Python") );
```


Resilient Distributed Dataset [RDD]

Resilient Distributed Dataset (RDD)

- RDD is an **immutable distributed collection** of objects
- Each RDD is split into *multiple partitions*
  - Maybe computed on different nodes in the cluster
- Can contain any type of Java, Scala, or Python objects
  - Including user-defined classes

Creation of RDDs

① Loading an external dataset

② Distributing a collection of objects via the driver program

```
>>> lines = sc.textFile("README.md")
```


Once created, RDDs offer two types of operations

- **Transformations**
  - Construct a new RDD from a previous one
  - E.g.: Filtering data that matches a predicate
- **Actions**
  - Compute a result based on an RDD
  - Return result to the driver program or save it in external storage system (HDFS)

Some more about RDDs

- Although you can define new RDDs anytime
  - Spark computes them in a **lazy fashion**
  - When?
    - The first time they are used in an *action*
- Loading lazily allows transformations to be performed *before* the action

Lazy loading allows Spark to see the whole chain of transformations

- Allows it to **compute just the data needed** for the result
- Example:

```
lines = sc.textFile("README.md")
pythonLines= lines.filter(lambda line: "Python" in line)
```

- If Spark were to load and store all lines in the file, as soon as we wrote `lines=sc.textFile()`?
  - Would waste a lot of storage space, since we immediately filter out a lot of lines

RDD and actions

- RDDs are **recomputed** (by default) every time you run an action on them
- If you wanted to reuse an RDD?
  - Ask Spark to **persist** it using `RDD.persist()`
  - After computing it the first time, Spark will store RDD contents in memory (*partitioned* across cluster machines)
  - Persisted RDD is used in future actions

Every Spark program and shell works as follows

1. **Create** some input RDD from external data
2. **Transform** them to define new RDDs using transformations like `filter()`
3. Ask Spark to **`persist()`** any intermediate RDDs that needs to be reused
4. **Launch actions** such as `count()`, etc. to kickoff a parallel computation
   - Computing is optimized and executed by Spark

The contents of this slide-set are based on the following references

- *Learning Spark: Lightning-Fast Big Data Analysis. 1st Edition. Holden Karau, Andy Konwinski, Patrick Wendell, and Matei Zaharia. O'Reilly. 2015. ISBN-13: 978-1449358624.* [Chapters 1-4]
- Karau, Holden; Warren, Rachel. High Performance Spark: Best Practices for Scaling and Optimizing Apache Spark. O'Reilly Media. 2017. ISBN-13: 978-1491943205. [Chapter 2]
- *Real-Time Analytics: Techniques to Analyze and Visualize Streaming Data.* Byron Ellis. Wiley. [Chapter 2]