CS 455: INTRODUCTION TO DISTRIBUTED SYSTEMS
[SPARK]

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Topics covered in this lecture

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

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

Frequently asked questions from the previous class survey

- Do datanodes know about each other?
- When you form a topology, how do they know about each other?
- If you do not receive an acknowledgement from one of the nodes, is it resent to the entire topology?
- Should you check to see if the compressed file is bigger than the original?
- Is it ever more efficient to send to multiple nodes (e.g. 2 or 4) than to only one node?
- HDFS aims for availability and partition-tolerance at the expense of consistency?

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

<table>
<thead>
<tr>
<th>Item</th>
<th>Time</th>
<th>Scaled time in human terms (2 billion times slower)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processor cycle</td>
<td>0.2 ns (2 GHz)</td>
<td>1 second</td>
</tr>
<tr>
<td>Cache access</td>
<td>1 ns (1 GHz)</td>
<td>2 seconds</td>
</tr>
<tr>
<td>Memory access</td>
<td>70 ns</td>
<td>1.67 minutes</td>
</tr>
<tr>
<td>Context switch</td>
<td>5,600 ns (5 ms)</td>
<td>167 minutes</td>
</tr>
<tr>
<td>Disk access</td>
<td>7,000,000 ns (7 ms)</td>
<td>162 days</td>
</tr>
<tr>
<td>Quorum</td>
<td>100,000,000,000 ns (100 ms)</td>
<td>6.3 years</td>
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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

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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

- Spark SQL
  - structured data
  - Streaming
  - ML & ML machine learning
  - GraphX
  - Graph processing

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 (RDDs)
  - Spark’s main programming abstraction
  - Represents collection of data items dispersed across many compute nodes
  - Can be manipulated concurrently (parallel)

Benefits of tight integration

- 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

- 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 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**
- 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 web servers
  - 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

**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

**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
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.

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

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 RDDs 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 even 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

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```
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

```python
>>> 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:
    ```python
    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?
    ```python
    # 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