CSx55: DISTRIBUTED SYSTEMS [SPARK]

Spark: What fuels it?

Memory residency, of course
With frugal I/O that it must reinforce

How? By …
Procrastinating (through lazy evaluations)
Avoiding repeated sweeps
And doing it only as a last resort

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Frequently asked questions from the previous class survey

- Does HDFS proactively account for performance by migrating data away from overloaded nodes?
- What happens if I wipe all data from a data node on HDFS?
- What happens if I manually copy a "block" to another node?
- Who determines the data traffic topology? Client, namenode, or datanode?
- Who accounts for threading in this setting?

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Topics covered in this lecture

- Spark
  - Software stack
  - Interactive shells in Spark
  - Core Spark concepts

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

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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

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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 in 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

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Running Spark

- You can use Spark from Python, Java, Scala, R, or SQL
- Spark itself is written in **Scala**, and runs on the Java Virtual Machine (JVM)
  - You can run Spark either on your laptop or a cluster, all you need is an installation of Java
- If you want to use the Python API, you will also need a Python interpreter (version 2.7 or later)
- If you want to use R, you will need a version of R on your machine

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Spark 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

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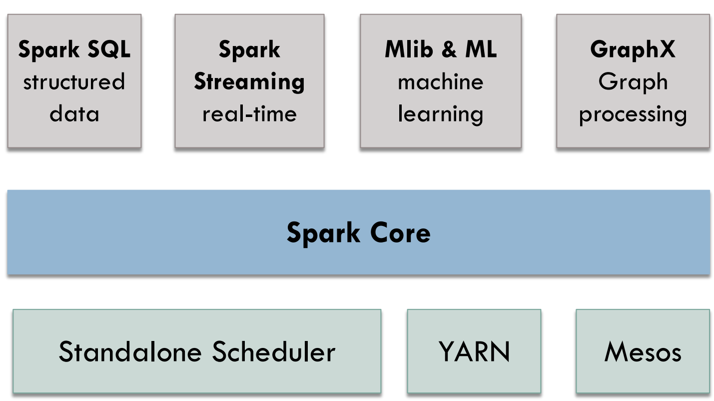
The Spark stack



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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 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?

- Has 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**
- The plan originally was 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, since version 8, Java now incorporates 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

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SPARK APIs

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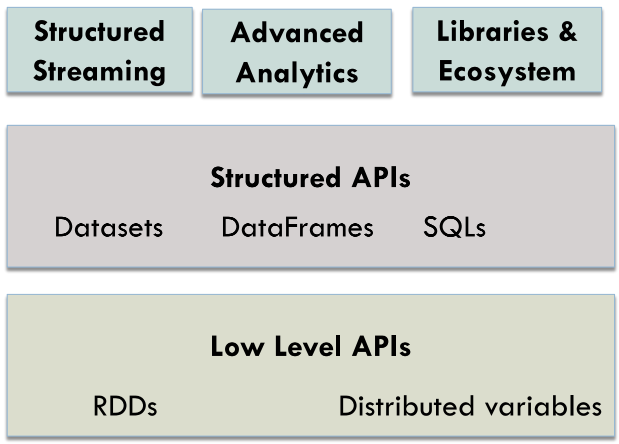
Spark APIs

- Spark has two fundamental sets of APIs:
  - The low-level "unstructured" APIs, and
  - The higher-level structured APIs

Structured APIs

- Structured APIs are a tool for manipulating all sorts of data
  - From unstructured log files to semi-structured CSV files and highly structured Parquet files
- Refers to three core types of distributed collection APIs:
  - Datasets
  - DataFrames
  - SQL tables and views
- Majority of the Structured APIs apply to both batch and streaming computation

Spark's Toolset



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Spark has two notions of structured collections: DataFrames and Datasets

- DataFrames and Datasets are (distributed) table-like collections with well-defined rows and columns
- Each column:
  - Must have the same number of rows as all the other columns (although you can use null to specify the absence of a value)
  - Has type information that must be consistent for every row in the collection.

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DataFrames versus Datasets

- DataFrames are considered "untyped"
- Datasets are considered "typed"

How does Spark view DataFrames and Datasets?

- To Spark, DataFrames and Datasets represent **immutable, lazily evaluated** plans that specify what operations to apply to data residing at a location to generate some output
- When we perform an action on a DataFrame, we instruct Spark to perform the actual transformations and return the result
- These represent **plans** of how to manipulate rows and columns to compute the user's desired result

The DataFrame is the most common Structured API

- Simply represents a **table** of data with rows and columns
- The list that defines the columns and the types within those columns is called the **schema**

The DataFrame concept is not unique to Spark

- R and Python both have similar concepts
  - However, Python/R DataFrames (with some exceptions) exist on one machine rather than multiple machines
  - This limits what you can do with a given DataFrame to the resources that exist on that specific machine
- A Spark DataFrame can span thousands of computers

CORE SPARK CONCEPTS

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Core Spark Concepts

- Drivers
- SparkContext
- Executors

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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

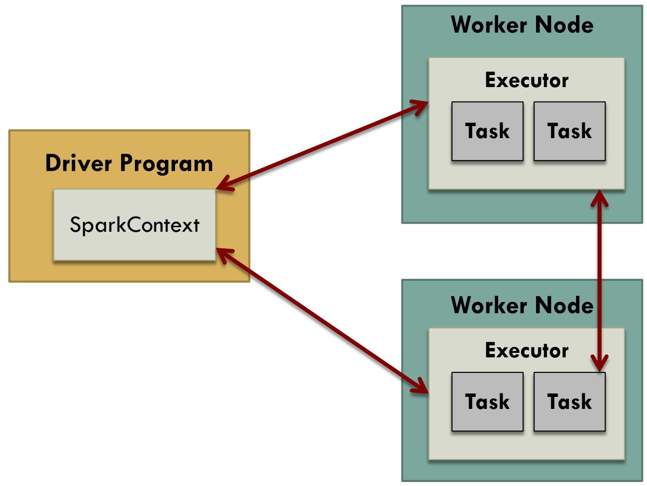
SparkContext

- 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 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



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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

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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") );
```


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]
- Chambers, Bill,Zaharia, Matei. Spark: The Definitive Guide: Big Data Processing Made Simple. O'Reilly Media. ISBN-13: 978-1491912218. 2018. [Chapters 1, 2, and 3].