# ISA 414 – Managing Big Data

**Lecture 21 – Introduction to Hadoop** 

(Part I)

Dr. Arthur Carvalho arthur.carvalho@miamioh.edu



Copyright © 2021 Arthur Carvalho

#### **Lecture Objectives**

Quick review of Homework 9

Introduction to the Hadoop ecosystem



#### **Lecture Instructions**

- There are several new concepts today
  - Suggestion: actively take notes
  - Important keywords are highlighted in the slides

Recall that several of such concepts will be in the final exam



#### **Agenda**

- First part of the course: CRISP-DM
  - Managing big data projects
- Second part of the course: technologies/big-data enablers
  - Cloud computing and storage (previous 2 lectures)
    - laaS and PaaS help with the required infrastructure
    - SaaS might help with the analysis
  - Hadoop framework (rest of the course)
- Before learning about Hadoop, we must first learn about two relevant concepts
  - Distributed storage
  - Distributed computations



Data are stored inside files

For our purposes, a file provides a way of storing and retrieving

data/information

Different technologies

E.g., paper records, computer files

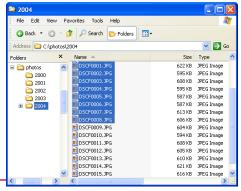
Different formats

CSV, JSON, XML, XLSX, ...

data about a patient

of the Char Emply Course Cla Sitalle helpstutte Treatment Inside of the Academy 110 (19 in human termi Please don't hesitate to call for additional infor Additional Information "Weakness to cold may fall into coma Emergency Contact / Additional info 9-220-0123-556 human phone has not relapsed for 25 years now Gaundiane 3-445-2235-556 human phone Rienna N. Shar & Aevai He. Shar, Inner Class (Iron, silver) Treat iron/silver burns like other severe burns you are sick or injured? e purging if iron/silver digested, call emergency n If it's an emergency, he'll come.

computer files



- How can we organize files?
  - Example: file cabinets organize paper-based files
    - File/folder organization/sorting is subjective





- How to organize computer files?
  - (Computer) file system
    - Managed by the operating system
      - Linux, Windows, Android,...

 Often use file directories (like a file cabinet) and hierarchies (hierarchical trees)

- Folders might contain subfolders
- Files have exact addresses in the file system
  - Paths = branch of the hierarchical tree
  - E.g., C:\carvalag\ISA414\Lecture19.pdf



HP Universal Print Driver

LogTwitter

PerfLogs

Common Files

oraclexe

be.txt

on.txt

br.txt

o.txt

cs.txt

cy.txt
da.txt
de.txt
el.txt
en.ttt

- What about computer (digital) files? How can we store and organize them?
  - Series of bytes
  - Stored inside **storage devices** (*e.g.*, hard-drive disks, flash-based solid-state drives, ...)
    - Non-volatile memory
    - More on this in future lectures









Different computers have different storage capacities



- What happens when one runs out of storage space?
  - Remember that big data is often defined in terms of volume
- Should one just replace an old storage device with a new one?
  - Big hassle: transfer all the data to the new device
    - Think about an organization: potentially, hundreds of terabytes or even petabytes of data

- One way of tackling the previous problem is by storing data across multiple machines/storage devices
  - One can simply add a new machine or a storage device to a collection of machines when running out of storage
    - Distributed storage
    - No need to transfer data or replace old computers
  - How does one know where a certain file is?
    - Each machine has its own file system
    - The collection of machines has a Distributed File System (DFS)
      - Helps to store and index files across multiple machines



- Distributed storage tackles one issue related to big data
  - Namely the increasing need for storage space due to the volume aspect of big data
  - Summary of the main idea (we will elaborate on this later):
    - One can use the storage devices (e.g., SSD devices) of many commodity computers to store data in a distributed fashion
      - "Many computers" = a cluster of computers
    - A distributed file system helps to organize and determine where each file is stored in a cluster (computer + file path)



- (Over) simplified example of a file system
  - Every file in the system is associated with a path

File	Path	
Picture1.jpeg	C:/users/carvalag/pictures/Picture1.jpeg	
data1.csv	C:/users/carvalag/data/data1.csv	

- (Over) simplified example of a distributed file system
  - Every file in the system is associated with a path and storage device

File	Device ID	(Local) Path
noshow.csv	173.16.157.4	/user/carvalag/noshow.csv
data.csv	173.16.157.2	/user/smith2/data.csv



- Distributed storage does not tackle another problem associated with data volume
  - The increasing need for computational power

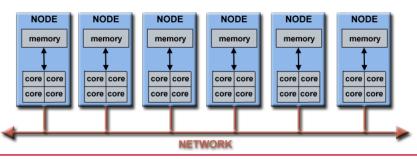
Complex data-analytics tasks can often benefit from parallel computation



- Different ways of performing parallel computations
  - 1. Single **nodes** (computers)
    - Multi-core processors: single computing component (CPU) with two or more independent units ("cores")
    - Relatively cheap and easy to program (threads)
      - For example, see the Python module threading



- Different ways of performing parallel computations
  - 2. Parallel computers (or "super computers")
    - Multiple CPUs:
      - Very large number of single computing nodes
      - Connected via some network (part of the machine)
      - Very expensive
        - From a few to hundreds of millions of dollars



Sunway TaihuLight RAM: 1,310,000 GB

Storage: 20,000 TB

CPUs: 40,960

Cores: 10,649,600 Cost: \$273 million





- Different ways of performing parallel computations
  - 3. Commodity cluster
    - Distributed computations across many relatively cheap (commodity) individual computers, each one having potentially many cores
    - Example: ISA 414 cluster (first request)
      - 5 Computer Nodes
        - 2 Nodes with 48 cores, 256 GB RAM each
        - 3 Nodes with 72 cores, 768 GB RAM each
        - 500 TB of shared storage capacity
      - Price tag: \$116,351.64
        - Including service, racks, and other hardware





- Different ways of performing parallel computations
  - 3. Commodity cluster
    - Distributed computations across many relatively cheap (commodity) individual computers, each one having potentially many cores
    - Yahoo! Cluster (2010)
      - 3500 nodes. A typical cluster node has:
        - 2 quad core Xeon processors @ 2.5ghz
        - 4 hard disks (one terabyte each)
        - 16GB RAM

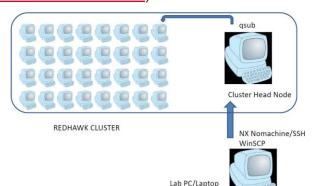
Source: paper "The Hadoop Distributed File System"



Different ways of performing parallel computations

#### 3. Commodity cluster

RedHawks Cluster
 (https://www.miamioh.edu/research/research/computing-support/services/hpc-cluster/index.html)



Miami's current HPC cluster consists of:

- 2 login nodes 24 cores, 384 GB of memory each. Machine names:
  - o mualhplp01
  - o mualhplp02
- 26 compute nodes 24 cores, Intel Xeon Gold 6126 2.6 GHz processors, 96 GB of memory each. Machine names:
  - mualhpcp10.mpi-mualhpcp26.mpi
  - mualhpcp28.mpi-mualhpcp35.mpi
  - mualhpcp37.mpi
- 5 compute nodes 24 cores, Intel Xeon Gold 6226 2.7 GHz processors, 96 GB memory each. Machine names:
  - mualhpcp42.mpi-mualhpcp45.mpi
  - mualhpcp47.mpi
- 2 large memory nodes 24 cores, Intel Xeon Gold 6126 2.6 GHz processors, 1.5 TB of memory each.
   Machine names:
  - mualhpcp27.mpi
  - mualhpcp36.mpi
- 4 GPU nodes 96 GB of RAM, 24 cores, Intel Xeon Gold 6126 2.6 GHz processors and each with 2 Nvidia Tesla V100-PCIE-16GB GPUs. Machine names:
  - mualhpcp38.mpi-mualhpcp41.mpi
- Shared storage system with approximately 30 TB of storage, expandable.



- Example of a top-of-the-line "commodity" computer
  - Cisco UCS C240 M4 Rack Server
    - 128 GB RAM



- 2 disks, each on having 1TB HDD
- NvidiaTesla K80 GPU
- Price tag: \$6,500
- Individual computers are stacked one on top of another in racks



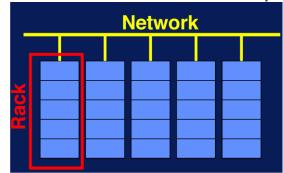
- Commodity cluster
  - Much cheaper than supercomputers
  - Less powerful
  - One can also have a cluster of old, very cheap

computers





- Computer clusters
  - Many jobs and/or applications can run in parallel
    - Different machines
  - This tackle the problem with growing computational demand due to big data
    - Main idea: one can break down a demanding computation into pieces, which will be executed in parallel in different nodes





- Let's put things together now
  - A cluster of computers allows for:
    - Distributed storage
      - Requires a distributed file system
    - Distributed computing
      - Different computers can work on different (sub)tasks in parallel
  - Hence, a cluster of computers can solve some storage and computational challenges brought by big data
    - Big-data enabler
  - Commodity cluster means that the above can be done cheaply

- Let's put things together now
  - New computation paradigm: move computation to data
    - Different computers store different pieces of data
    - A task/job that needs access to a piece of data will be executed in the computer where the data are stored
  - Benefit: moving task/jobs require less bandwidth than moving data
    - *I.e.*, it does not mess up the network
  - We did the opposite in class
    - Move data (from a database server) to computation (Python code)
    - Assignment 3: we downloaded data from a MongoDB database

- How to manage a commodity cluster?
  - How to distribute data and computations across nodes?
  - Ideal <u>storage</u> operations:
    - Split volumes of data across nodes
    - Quickly retrieve distributed data
    - Enable the addition of more racks (nodes) without losing performance
    - Fault-tolerant
      - Replicate data partitions across nodes



- How to manage a commodity cluster?
  - How to distribute data and computations across nodes?
  - Ideal <u>computational</u> operations:
    - Scheduling many tasks at the same time running in different nodes
    - Automatic job restart when a node fail:
      - A rack (or individual computer) stop working
      - Network connection is lost



#### Hadoop

- Framework used for distributed storage and computing
  - I.e., a tool that manages commodity clusters
  - Accomplishes all the ideal operations listed before
- Distributed storage
  - Hadoop Distributed File System (HDFS)
- Distributed computation
  - MapReduce
  - Spark

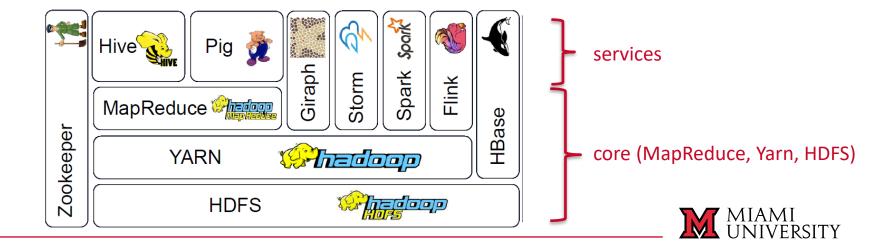
. . .



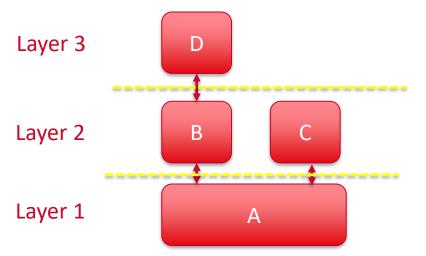
- Hadoop: timeline
  - 2004: MapReduce paper released by Google
    - Title: "The Google File System"
    - Google File System as distributed file system
    - MapReduce as distributed computing model
  - 2005: Yahoo! releases an open-source implementation of Google's framework called *Hadoop*
  - 2006: Apache continues to develop Hadoop
  - 2006 present: many services built on top of core Hadoop
    - The zoo: Hive, Pig, Giraph ... over 100+ services and counting

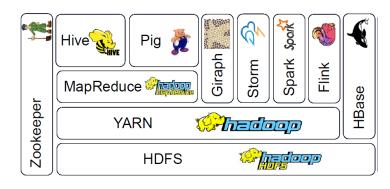


- Hadoop version 2
  - Simplified version
    - Many more services: Flume (log collector) Sqoop (data exchange), ...



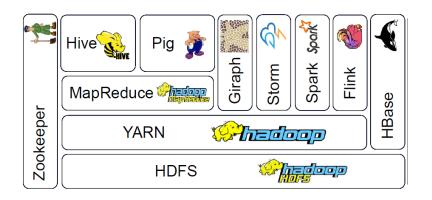
- Hadoop version 2
  - Layer diagram (or stack)
    - A component uses the functionalities/capabilities of the layer below it







- Hadoop version 2
  - Layer diagram (or stack)
    - A component uses the functionalities/capabilities of the layer below it



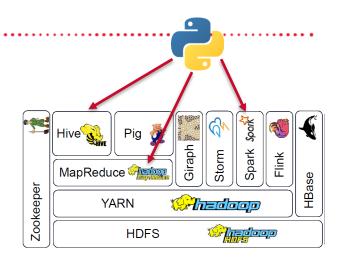
higher levels: interactivity



lower levels: storage and task scheduling

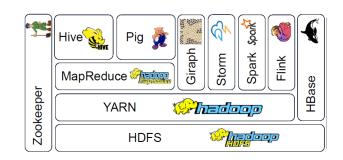


- Overview and agenda
  - HDFS (Lecture 22)
    - Hadoop Distributed File System
    - Scalable and reliable storage
  - Yarn (Lecture 22 brief discussion)
    - Schedule jobs/task over HDFS storage
  - Spark (Lecture 23 and 24)
    - Built for real-time, in memory processing of data





- Other services
  - Pig (created by Yahoo!)
    - Dataflow scripting
  - Giraph (created by Facebook)
    - Processing large graphs (social networks)
  - Storm/Flink (created by Twitter/Data Artisans)
    - Built for real-time, in memory processing of data
  - HBase (created by Facebook)
    - NoSQL database
    - Used by Facebook's messaging platform
  - Zookeeper (created by Yahoo!)
    - Manage services named after animals





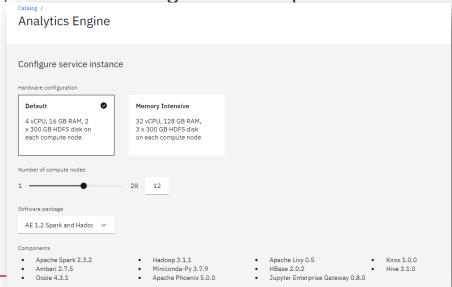
- How to install Hadoop
  - All the previous tools are free and open-source (why?)
    - Large community for support
  - One can download and install each service/tool separately
    - Obviously, one must install lower-level services first (e.g., HDFS, YARN) before installing higher-level services
    - Requires technical expertise (e.g., advanced Linux/Unix skills)
  - Alternative #1: install a pre-built system (i.e., stacks of these tools)
    - Cloudera, MAPR, Hortonworks
    - Offer commercial support for production environments



- Alternative #2: cloud service (PaaS)
  - E.g., you can have your own cluster of computers on IBM Cloud
    - Service name: Analytics Engine

Few clicks to add extra nodes (i.e., increase storage and computational

power) and Hadoop services



# **Demonstration**

Creating a Hadoop Cluster on IBM Cloud



#### **Hadoop on IBM Cloud**

- After creating an account on IBM Cloud
  - Go to <a href="https://www.ibm.com/cloud">https://www.ibm.com/cloud</a>
  - Log in
  - Select Catalog -> Analytics
  - Search for "Analytics Engine"



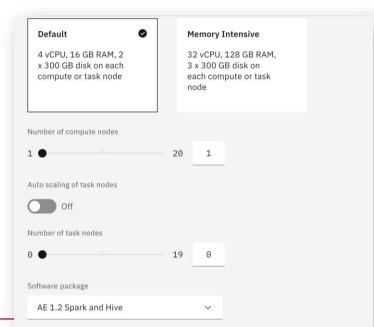
### **Hadoop on IBM Cloud**

Select the cloud's region

> Select the pricing plan, configure the cluster, and

click on Create

 It might take a few minutes for the cluster to be created



### **Hadoop on IBM Cloud**

- Creating a cluster is incredibly easy
  - Difficult part: integrate a cluster with current business processes and in-house infrastructure

- We learn a few more details about Hadoop, HDFS, and Hadoop (PaaS) in our next class
  - Real-time demo with a cluster



## **Summary**

- We learned how distributed storage and computing can tackle volume-related problems associated with big data
  - Hadoop = framework that manages distributed storage and computing
- Next lecture: we study the core of Hadoop
  - HDFS
  - Yarn (brief discussion)

