

Hadoop 101

November 2020 Brolinskyi Sergii



Plan of presentation

- How big is Big Data
- What do you need to do to be able to operate with the Big Data
- Hadoop origins
- What exactly is happening when you want to run a task on Hadoop
- Hadoop ecosystem/tech stack
- HDFS
- YARN
- Demo
- Summary



Big Data System Requirements



Store massive amounts of data

Process it in a timely manner

Scale easily as data grows

Google File System







What is Hadoop

Hadoop



A file system to manage the storage of data

A framework to process data across multiple servers

Hadoop



A framework to define a data processing task

A framework to run the data processing task

What happens when you run a job on Hadoop

- User must define map and reduce task using the MapReduce API (those two that we've seen in the lecture 2)
- The job is triggered on the cluster with the help of the YARN
- YARN then figures out where and how to run the job, and store the results files in HDFS

Hadoop Ecosystem



How to install Hadoop on Win 10

3 ways of installation:

- Standalone mode (no hdfs nor yarn, just checking the MapReduce logic)
- Pseudo-distributed mode (or a single-node mode) (advanced test and simulating an actual cluster)
- Fully distributed mode (the production mode)

How to install Hadoop on Win 10

Single-node mode: 2 JVM processes will run

- HDFS for storage
- YARN for managing tasks



Run Linux on Windows

Install and run Linux distributions side-by-side on the Windows Subsystem for Linux (WSL).



Enable the feature

\geq	Windows	PowerShell
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Windows PowerShell Copyright (C) Microsoft Corporation. All rights reserved.

Try the new cross-platform PowerShell https://aka.ms/pscore6

PS C:\Users\sebrolin> Enable-WindowsOptionalFeature -Online -FeatureName Microsoft-Windows-Subsystem-Linux

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Install Ubuntu



Run some code

1 # Install Java and ssh

- 2 sudo apt-get update
- 3 java -version # if not found than install is needed
- 4 sudo apt-get install openjdk-11-jre-headless
- 5 sudo apt-get install openjdk-11-jdk
- 6 sudo apt-get install ssh

Download and unzip Hadoop

- 1 wget https://miroir.univ-lorraine.fr/apache/hadoop/common/hadoop-3.3.0/hadoop-3.3.0.tar.gz
- 2 mkdir ~/hadoop
- 3 tar -xvzf hadoop-3.3.0.tar.gz -C ~/hadoop
- 4 cd ~/hadoop/hadoop-3.3.0/

Setup ssh in a passphrase less mode

- 6 ssh-keygen -t rsa -P '' -f ~/.ssh/id_rsa
- 7 cat ~/.ssh/id_rsa.pub >> ~/.ssh/authorized_keys
- 8 chmod 0600 ~/.ssh/authorized_keys

Format the namenode

10 bin/hdfs namenode -format

Configuration of a single node

Files that should be modified according to the setup doc:

- ~/.bashrc
- etc/hadoop/hadoop-env.sh
- etc/hadoop/core-site.xml
- etc/hadoop/hdfs-site.xml
- etc/hadoop/mapred-site.xml
- etc/hadoop/yarn-site.xml

Follow next guides to better help:

- <u>https://hadoop.apache.org/docs/stable/hadoop-project-dist/hadoop-common/SingleCluster.html</u>
- <u>https://kontext.tech/column/hadoop/445/install-hadoop-330-on-windows-10-using-wsl</u>

Configuration of a single node

Sebrolin@MININT-EA70061: ~/hadoop/hadoop-3.3.0

```
(?xml version="1.0" encoding="UTF-8"?>
?xml-stylesheet type="text/xsl" href="configuration.xsl"?>
<configuration>
        <property></property>
             <name>dfs.replication</name>
             <value>1</value>
       </property>
</configuration>
```

Run the hadoop

- 12 sbin/start-dfs.sh
- 13 **jps** # JPS stands for Java Virtual Machine Process Status Tool
- 14 sbin/start-yarn.sh

15 **jps**

sebrolin@MININT-EA70061:~/hadoop/hadoop-3.3.0\$ jps 4165 SecondaryNameNode 4598 NodeManager 3895 DataNode 4457 ResourceManager 8953 Jps 3756 NameNode

Hadoop cluster



Cluster	Cluster Metrics						
About	Apps Submitted	Apps	Pending	Apps	Running	App	s Completed
Nodes	11	0		0		11	
Node Labels	Cluster Nodes Metrics						
<u>Applications</u>	Active Nodes			Decommissioni	ng Nodes		
NEW SAVING	1	<u>0</u>			Ŭ		<u>0</u>
SUBMITTED	Scheduler Metrics						
ACCEPTED	Scheduler Type				Scheduling Reso	urce Type	
RUNNING	Capacity Scheduler		Imemo	orv-mb (unit=Mi) v	cores]	dice type	
FAILED			Incin	ing (and m), i	00100]		
KILLED	Show 20 v entries						
<u>Scheduler</u>	ID	User 🕴	Name 💧	Application	Application	Queue 💧	Application
Tools				iype	lags		Flority
	application_1604133744741_0014	sebrolin	grep- sort	MAPREDUCE		default	0
	application_1604133744741_0013	sebrolin	grep- search	MAPREDUCE		default	0
	application_1604133744741_0012	sebrolin	grep- sort	MAPREDUCE		default	0
	application_1604133744741_0011	sebrolin	grep- search	MAPREDUCE		default	0

Hadoop data node

Hadoop Overview Utilities

DataNode on MININT-EA70061.europe.corp.microsoft.com:9866

Cluster ID:	CID-3f7df37e-3028-42ca-a6de-594160fb1d0e
Version:	3.3.0, raa96f1871bfd858f9bac59cf2a81ec470da649af

Block Pools

Namenode Address	Block Pool ID	Actor State	Last Heartbeat	Last Block Report	Last Block Report Size (Max Size)
localhost:9000	BP-911422811-127.0.1.1-1604133558936	RUNNING	2s	4 hours	21.17 KB (128 MB)

Volume Information

Directory	Storage Type	Capacity Used	Capacity Left	Capacity Reserved	Reserved Space for Replicas	Blocks
/tmp/hadoop-sebrolin/dfs/data	DISK	65.06 MB	157.76 GB	0 B	0 B	2181

HDFS

- HDFS is Hadoop distributed file system
- - All files are immutable, you can't change them
- Data is stored in a semi-structured form
- It is still a file system





Built on commodity hardware

Highly fault tolerant, hardware failure is the norm

Suited to batch processing - data access has high throughput rather than low latency

Supports very large data sets



Manage file storage across multiple disks



HDFS

1 node is the master node





HDFS

Name node



Data nodes



Name node





The name node is the table of contents

Data nodes





The data nodes hold the actual text in each page

Name node



Manages the overall file system

Stores

- The directory structure
- Metadata of the files

Storing a File in HDFS

hext up previous contents index Next: Dynamic indexing Up: Index construction Previous: Single-pass in-memory indexing Contents Index

Distributed indexing

Collections are often so large that we cannot perform index construction efficiently on a single machine. This is particularly true of the World Wide Web for which we need large computer clusters [*]to construct any reasonably sized web index. Web search engines, therefore, use distributed indexing algorithms for index construction. The result of the construction process is a distributed index that is partitioned across several machines – either according to term or according to document. In this section, we describe distributed indexing for a

term-partitioned index . Most large search engines prefer a document-partitioned index (which can be easily generated from a termpartitioned index). We discuss this topic further in Section 20.3 (page [*]).

The distributed index construction method we describe in this section is an application of MapReduce , a general architecture for distributed computing. MapReduce is designed for large computer clusters. The point of a cluster is to solve large computing problems on cheap commodity machines or nodes that are built from standard parts (processor, memory, disk) as opposed to on a supercomputer with specialized hardware. Although hundreds or thousands of machines are available in such clusters, individual machines can fail at any time. One requirement for robust distributed indexing is, therefore, that we divide the work up into chunks that we can easily assign and - in case of failure - reassign. A master node directs the process of assigning and reassigning tasks to individual worker nodes.

The map and reduce phases of MapReduce split up the computing job into chunks that standard machines can process in a short time. The various steps of MapReduce are shown in Figure 4.5 and an example on a collection consisting of two documents is shown in Figure 4.6. First, the input data, in our case a collection of web pages, are split into \$n\$ splits where the size of the split is chosen to ensure that the work can be distributed evenly (chunks should not be too large) and efficiently (the total number of chunks we need to manage should not be too large); 16 or 64 MB are good sizes in distributed indexing. Splits are not preassigned to machines, but are instead assigned by the master node on an ongoing basis: As a machine finishes processing one split, it is assigned the next one. If a machine dies or becomes a laggard due to hardware problems, the split it is working on is simply reassigned to another machine.

Figure 4.5: An example of distributed indexing with MapReduce. Adapted from Dean and <u>Ghemawat</u> (2004). \includeoraphics[width=11.5cm]{art/mapreduce2.eps}

In general, MapReduce breaks a large computing problem into smaller parts by recasting it in terms of manipulation of key-value pairs. For indexing, a key-value pair has the form (termID,docID). In distributed indexing, the mapping from terms to termIDs is also distributed and therefore more complex than in single-machine indexing. A simple solution is to maintain a (perhaps precomputed) mapping for frequent terms that is copied to all nodes and to use terms directly (instead of termIDs) for infrequent terms. We do not address this problem here and assume that all nodes share a consistent term \$\rightarrow\$ termID mapping.

The map phase of MapReduce consists of mapping splits of the input data to key-value pairs. This is the same parsing task we also encountered in BSBI and SPIMI, and we therefore call the machines that execute the map phase parsers. Each parser writes its output to local intermediate files, the segment files (shown as \fbox{a-f\medstrut}\fbox{g-p\medstrut}\fbox{g-2\medstrut} in Figure 4.5).

For the reduce phase , we want all values for a given key to be stored close together, so that they can be read and processed quickly. This is achieved by partitioning the keys into \$j\$ term partitions and having the parsers write key-value pairs for each term partition into a separate segment file. In Figure 4.5, the term partitions are according to first letter: a-f, g-p, q-z, and \$j=3\$. (We chose these key ranges for ease of exposition. In general, key ranges need not correspond to contiguous terms or termIDs.) The term partitions are defined by the person who operates the indexing system (Exercise 4.6). The parsers then write corresponding segment files, one for each term partition. Each term partition thus corresponds to \$r\$ segments files, where \$r\$ is the number of parsers. For instance, Figure 4.5 shows three a-f segment files of the a-f partition, corresponding to the three parsers shown in the figure.

Collecting all values (here: docIDs) for a given key (here: termID) into one list is the task of the inverters in the reduce phase. The

A large text file

Storing a File in HDFS

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Break the data into blocks

Different length files are treated the same way

Storage is simplified

Unit for replication and fault tolerance

Storing a File in HDFS size 128 MB

Block size is a trade off

Reduces parallelism

Increases overhead

Storing a File in HDFS



Each node contains a partition or a split of data

Storing a File in HDFS



Reading a File in HDFS

- 1. Use metadata in the name node to look up block locations
- 2. Read the blocks from respective locations

Challenges of Distributed Storage



Failure management in the data nodes

Failure management for the name node

Managing Failures in Data Nodes



Define a replication factor

Replication

The replica locations are also stored in the name node

Name node

File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3
File 1	Block 1	DN 2

Choosing Replica Locations



Minimize write bandwidth



Store replicas "far away" i.e. on different nodes

Maximize redundancy





Data is forwarded from here to the next replica location





Forwarded further to the next replica location

Default Hadoop Replication Strategy

Third replica is on the same rack as the second but on different nodes

Default Hadoop Replication Strategy

Setting the Replication Factor

dfs.replication

This is the default in fully-distributed mode

Setting the Replication Factor

dfs.replication

The pseudo-distributed mode has just one node so the replication factor cannot be >1

Name Node Failures

Block locations are not persistent

i.e. they are stored in memory

block caching

Name Node Failures

If the name node fails

File-Block Location mapping is lost!

Name node

File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3

Managing Name Node Failures

Metadata Files Secondary Name Node

Metadata Files

fsimage edits

Two files that store the filesystem metadata

YARN

Yet Another Resource Negotiator

Co-ordinates tasks running on the cluster

Assigns new nodes in case of failure

YARN

YARN

Application Master Process

This is the logical unit for resources the process needs memory, CPU etc

YARN schedulers

- FIFO scheduler
- Capacity scheduler
- Fair scheduler

It is complicated to always think about the parallel data processing and manually define the rules of how it should be done, so frameworks add a level of abstraction so you would only need to think about what work should be done.

HDFS, MapReduce and YARN are the building blocks of any Hadoop application

