Big Data Wrangling With Google Books Ngrams

Author: Kartik

Contact: kkakar664@gmail.com

Date: Nov 14, 2023

Table of Contents

Part 1. Introduction

Part 2. Steps and Commands

- 2.1 Spin up a new EMR cluster on AWS for using Spark and EMR notebooks
- 2.2 Connect to the head node of the cluster using SSH
- 2.3 Copy the data folder from the S3 bucket directly into a directory on the Hadoop File System (HDFS)
- 2.4 Using PySpark, read the data into HDFS
 - a. Describe the dataset
 - b. Create a new DataFrame using Spark SQL
 - c. Write the filtered data back to a directory in HDFS
- 2.5 Collect the contents of the directory into a single file on the local drive
- 2.6 Read the CSV data from the S3 folder into a pandas DataFrame
- 2.7 Plot the number of occurrences of the token "data" over the years
- 2.8 Compare Hadoop and Spark as distributed file systems
 - a. list two advantages of Hadoop and Spark
 - b. Explain how HDFS stores the data

Part 3. Conclusion Screenshots (2.1)

Part 1. Introduction

This report outlines the steps taken to analyze the Google Books Ngrams dataset using cloud-based distributed computing tools such as Hadoop, Spark, Hive, and the S3 filesystem. The Google Ngrams dataset, created by Google's research team, represents approximately 4% of all books ever printed, spanning from the 1800s to the 2000s.

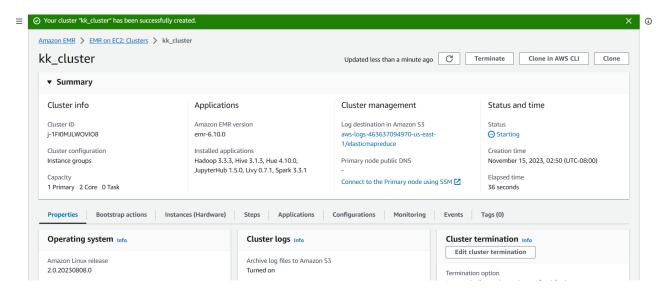
The dataset was accessed from a public S3 bucket, processed using Spark on an AWS EMR cluster, and visualized using matplotlib. The report also includes a comparison of Hadoop and Spark as distributed file systems.

Part 2. Steps and Commands

2.1 Spin up a new EMR cluster on AWS for using Spark and EMR notebooks.

Log in to your AWS account via this link: http://aws.amazon.com/console/

- 1) Create Cluster: We start by navigating to the EMR panel in AWS and clicking on 'Create Cluster'.
- **2)** Cluster Name and Application Bundle: We give our cluster a name and select 'emr-6.10.0' from the 'Release' dropdown. We then select the Custom application bundle and click the boxes for Hadoop, Hue, JupyterHub, Livy, Hive, and Spark. These are the software applications we want to run on our cluster. **3)** Instance Groups: We remove the task instance group and allocate 2 nodes to the core instance group. The core instance group contains the master node and core nodes that run Hadoop Distributed File System (HDFS) and other services.
- **4) Cluster Termination**: We set the cluster to terminate after 4 hours of idle time and turn off termination protection. This helps to manage costs by ensuring that we are not paying for resources that we are not using.
- **5) Security and Access Management**: We select our key pair for secure access to our cluster. In Identity and Access Management, we choose the 'EMR_DefaultRole' and 'EMR_EC2_DefaultRole'. These roles define the permissions for our cluster and the EC2 instances it uses.
- **6)** Create Cluster: Finally, we click the 'Create Cluster' button. The cluster creation process begins, which involves spinning up the EC2 instances and configuring the cluster software. Once the cluster is created, it enters a 'Waiting' state, indicating that it is ready for use.



Please see the screenshots at the end of the report.

2.2 Connect to the head node of the cluster using SSH.

- 1) SSH Command: We use the SSH command to establish a secure connection with the head node of the cluster. The command is structured as follows: ssh -i mykey.pem -L 9995:localhost:9443 hadoop@xxxxxxxxxxxxxxxxxcompute.amazonaws.com.
 - -i mykey.pem specifies the private key file (.pem) used for the connection. The file path and name should correspond to your actual .pem key. The command assumes that the current directory contains the .pem key file.
 - -L 9995:localhost:9443 sets up a secure tunnel by forwarding a port (9995) on your local machine to a port (9443) on the remote machine.
 - hadoop@xxxxxxxxxxxxxxx.compute.amazonaws.com is the username and the public DNS of the head node. The 'xxxxx......' should be replaced with your actual 'Primary node public DNS', which can be found on the overview page of your cluster.
- **2) Successful Connection**: If the connection is successful, you will see the EMR ASCII banner in your terminal. This indicates that you are now connected to the head node of the cluster.
- **3)** Bypassing the Security Warning: When you access JupyterHub in your web browser using the forwarded port (hbp://localhost:9995), you may encounter a security warning because the connec.on is not publicly verified. You can bypass this warning to proceed to JupyterHub. The exact steps to bypass the warning depend on your browser. Generally, you would click on "Advanced" and then "Proceed to localhost (unsafe)".

2.3 Copy the data folder from the S3 bucket directly into a directory on the Hadoop File System (HDFS) named /user/hadoop/eng 1M 1gram.

We are copying the data from an S3 bucket directly into a directory on the Hadoop File System (HDFS). Here's a summary of the steps:

1) Hadoop "distCp" Command: We use the Hadoop distCp (Distributed Copy) command to copy the data from the S3 bucket to the HDFS. The command is structured as follows: hadoop distcp s3://brainsta8on-ds0/eng_1M_1gram.csv/user/hadoop/eng_1M_1gram/eng_1M_1gram.csv. This command copies the eng_1M_1gram.csv file from the S3 bucket s3://brainsta8on-ds0/ to the directory /user/hadoop/eng_1M_1gram/ in the HDFS.

```
[hadoop@ip-172-31-5-51 ~]$ hadoop distcp s3://brainstation-dsft/eng_IM_Igram.csv /user/hadoop/eng_IM_Igram /eng_IM_Igram.csv /203-11-15 11:00:34,351 INFO tools.DistCp: Input Options: DistCpOptions{atomicCommit=false, syncFolder=false, edeteMissing=false, ignoreFailures=false, overwrite=false, append=false, useDiff=false, useRdiff=false, foromsnapshot=null, toSnapshot=null, skipCRC=false, blocking=true, numListStatusThreads=0, maxMaps=20, mapBandwidth=0.0, copyStrategy='uniformsize', preserveStatus=[], atomicWorkPath=null, logPath=null, sourceFileListing=null, sourcePaths=[s3://brainstation-dsft/eng_IM_Igram.csv], targetPath=/user/hadoop/eng_IM_Igram/eng_IM_Igram.csv, filtersFile='null', blocksPerchunk=0, copySufferFsize=8192, verboseLog=false, directWrite=false, useiterator=false}, sourcePaths=[s3://brainstation-dsft/eng_IM_Igram.csv], targetPathExists=false, preserveRawXattrs=false
2023-11-15 11:00:34,902 INFO client.DefaultNoHARMFailoverProxyProvider: Connecting to ResourceManager at ip=172-31-5-1.ecz. internal/172.31.5.51:8032
2023-11-15 11:00:35,247 INFO client.AHSProxy: Connecting to Application History server at ip=172-31-5-51.ecz. internal/172.31.5.51:10200
2023-11-15 11:00:40,603 INFO tools.SimpleCopyListing: Starting: Building listing using multi threaded approach for s3://brainstation-dsft/eng_IM_Igram.csv duration 0:00.002s
2023-11-15 11:00:40,605 INFO tools.SimpleCopyListing: Building listing using multi threaded approach for s3://brainstation-dsft/eng_IM_Igram.csv: duration 0:00.002s
2023-11-15 11:00:40,724 INFO tools.SimpleCopyListing: Build file listing completed.
2023-11-15 11:00:40,724 INFO tools.SimpleCopyListing: Build file listing completed.
2023-11-15 11:00:40,726 INFO Configuration.deprecation: io.sort.mb is deprecated. Instead, use mapreduce. ask.io.sort.mb
2023-11-15 11:00:41,41 INFO tools.DistCp: Number of paths in the copy list: 1
2023-11-15 11:00:41,912 INFO cilent.ABFroxy: Connecting to Application History server at ip=172-31-5-51.ecz. internal/172.31.5.51:8032
2023-11-15 11:00:42,92
```

2) Job Execution: After running the 'distcp' command, a MapReduce job is initiated to perform the copy operation. The job progress is displayed in the terminal, including the job ID, the job status, and the percentage of map and reduce tasks completed.

```
2023-11-15 11:00:43,200 INFO conf.Configuration: resource-types.xml not found
2023-11-15 11:00:43,200 INFO resource.Resourcetitis: unable to find 'resource-types.xml'.
2023-11-15 11:00:43,895 INFO impl.YarnClientImpl: Submitted application application_1700045950899_0001
2023-11-15 11:00:43,968 INFO mapreduce.lob: The url to track the job: http://ip-172-31-5-51.ec2.internal:2
2028-11-15 11:00:43,969 INFO tools.DistCp: DistCp job-id: job_1700045950899_0001
2023-11-15 11:00:43,969 INFO mapreduce.lob: Running job: job_1700045950899_0001
2023-11-15 11:00:52,118 INFO mapreduce.lob: Job job_1700045950899_0001
2023-11-15 11:00:52,118 INFO mapreduce.lob: map 100% reduce 0%
2023-11-15 11:00:52,118 INFO mapreduce.lob: map 100% reduce 0%
2023-11-15 11:00:52,118 INFO mapreduce.lob: map 100% reduce 0%
2023-11-15 11:00:52,118 INFO mapreduce.lob: Job job_1700045950899_0001 completed successfully
2023-11-15 11:00:52,118 INFO mapreduce.lob: Dist. counters: 42
File system Counters

FILE: Number of bytes read=0
FILE: Number of bytes written=294289
FILE: Number of bytes written=2522105197
HDFS: Number of bytes written=2522105197
HDFS: Number of bytes read-375
HDFS: Number of bytes read-375
HDFS: Number of bytes read-375
HDFS: Number of bytes read operations=0
S3: Number of bytes read erasure-coded=0
S3: Number of bytes read erasure-coded=0
S3: Number of bytes read erasure-coded=0
S3: Number of bytes read operations=0
S3: Number of bytes read operations=0
S3: Number of large read operations=0
S3: Number of bytes read erasure-coded=0
S3: Number of bytes read-source-coded=0
S3: Number of bytes read-source-coded=0
S3: Number of bytes read-source-coded=0
S3: Number of large read operations=0
S3: Number of bytes read-source-coded=0
S3: Number of bytes written=0
S3: Number of bytes read-source-coded=0
S3: Number
```

3) Job Completion: Once the job is completed successfully, the terminal displays a summary of the job, including the number of bytes read and written, the number of read and write operations and other job counters.

```
Map-Reduce Framework

Map input records=1

Map output records=0

Input split bytes=136

Spilled Records=0

Failed Shuffles=0

Merged Map outputs=0

GC time elapsed (ms)=351

CPU time spent (ms)=65730

Physical memory (bytes) snapshot=1054863360

Virtual memory (bytes) snapshot=4440735744

Total committed heap usage (bytes)=838860800

Peak Map Physical memory (bytes)=1059995648

Peak Map Virtual memory (bytes)=4440735744

File Input Format Counters

Bytes Read=239

File Output Format Counters

Bytes Written=0

DistCp Counters

Bandwidth in Bytes=91243193

Bytes Copied=5292105197

Bytes Expected=5292105197

Files Copied=1
```

4) Data Verification: After the copy operation, we verify the data transfer by listing the contents of the HDFS directory using the 'hadoop fs -ls' and 'hadoop fs -ls /user/hadoop/eng_1M_1gram' commands. These commands display the directories and files in the HDFS, confirming that the eng_1M_1gram.csv file has been successfully copied to the /user/hadoop/eng_1M_1gram/ directory.

```
[hadoop@ip-172-31-5-51 ~]$ hadoop fs -ls
Found 1 items

drwxrwxrwx - hadoop hdfsadmingroup 0 2023-11-15 11:01 eng_1M_1gram
[hadoop@ip-172-31-5-51 ~]$ hadoop fs -ls /user/hadoop/eng_1M_1gram.csv
ls: /user/hadoop@ip-172-31-5-51 ~]$ hadoop fs -ls /user/hadoop/eng_1M_1gram.csv
lhadoop@ip-172-31-5-51 ~]$ hadoop fs -ls /user/hadoop/eng_1M_1gram
Found 1 items
-rw-r--r-- 1 hadoop hdfsadmingroup 5292105197 2023-11-15 11:01 /user/hadoop/eng_1M_1gram/eng_1M_1gram.csv
```

2.4 Using pyspark, read the data you copied into HDFS in Step 3. You may either use Jupyterhub on EMR (the default user and password are jovyan and jupyter) or work from pyspark in the terminal if you prefer. Once you have created a pyspark DataFrame, complete the following steps below:

We are using PySpark to read the data that was previously copied into the Hadoop Distributed File System (HDFS). Here's a summary of the steps:

1) **Launch PySpark**: PySpark is launched either through Jupyterhub on EMR or directly from the terminal.



2) Read Data: We use the spark.read.csv function to read the eng_1M_1gram.csv file from the HDFS directory /user/hadoop/eng_1M_1gram/. The header=True argument is used to indicate that the first row of the CSV file contains the column names. The data is loaded into a Dataframe 'df'.

```
>>> df = spark.read.csv('/user/hadoop/eng_1M_1gram/eng_1M_1gram.csv', header=True)
>>> |
```

This step is crucial as it loads the data into a Spark DataFrame, which allows us to perform distributed data processing tasks using Spark's capabilities.

a. Describe the dataset (examples include size, shape, schema) in pyspark

We are exploring the dataset using PySpark's DataFrame API. Here's a summary of the steps:

1) Print Schema: The df.printSchema() function is used to print the schema of the DataFrame df. The schema includes the column names and their data types. The dataset contains five columns: 'token', 'year', 'frequency', 'pages', and 'books', all of which are of string data type.

```
>>> df.printSchema()
root
    |-- token: string (nullable = true)
    |-- year: string (nullable = true)
    |-- frequency: string (nullable = true)
    |-- pages: string (nullable = true)
    |-- books: string (nullable = true)
```

2) Descriptive Statistics: The df.describe().show() function is used to generate descriptive statistics of the DataFrame. It includes count, mean, standard deviation, min, and max for each column.

```
>> df.describe().show()
summary|
            token|
                                                frequency
                                                                                              books
                                  year
                                                                     261822832
 count | 261823225
                             261822832
                                                261822832
                                                                                          261822832
               NaN | 1910.5024307452102 | 396.6344411924442 | 210.
   mean
 stddev
               NaN
                   66.05224930213528|47883.07879567001|
                                  1520
   min
                                                frequency
                                                                                              books
   max
                                  vear
                                                                         pages
```

3) Count Rows and Columns: The **df.count()** function is used to count the number of rows in the DataFrame, and **len(df.columns)** is used to count the number of columns. The dataset contains 261,823,225 rows and 5 columns.

```
>>> print(df.count())
261823225
```

```
>>> print(len(df.columns))
5
```

4) View Column Names: The **df.columns** function is used to view the names of the columns in the DataFrame.

View Top Rows: The **df.head(5)** function is used to view the first 5 rows of the DataFrame.

```
>>> df.columns
['token', 'year', 'frequency', 'pages', 'books']
>>> df.head(5)
[Row(token='inGermany', year='1927', frequency='2', pages='2', books='2'), Row(token='inGermany', year='1929', frequency='1', pages='1', books='1'), Row(token='inGermany', year='1930', frequency='1', pages='1', books='1'), Row(token='inGermany', year='1933', frequency='1', pages='1', books='1'), Row(token='inGermany', year='1934', frequency='1', pages='1', books='1')]
```

5) Show Rows: The **df.show(10,vertical=True)** function is used to display the first 10 rows of the DataFrame in a vertical format for better readability.

sss df chowl	(10, vertical=True)
-RECORD 0	(10, vertical=irue)
	inGermany
year	1927
frequency	2
pages	2
books -RECORD 1	2
token 1	inGermany
year	1929
frequency	1
pages	1
books	1
-RECORD 2	
token	
year frequency	1930 1
pages	1
books	
-RECORD 3	
token	inGermany
year	1933
frequency	1
pages	1
books	1
-RECORD 4 token	inGermany
year	1934
frequency	1
pages	ī
books	1
-RECORD 5	
token	
year	1935
frequency	1
pages books	1
-RECORD 6	
token	inGermany
vear	1938
frequency	5
pages	
books	5
-RECORD 7	
token	
year frequency	1939 1
pages	1
books	i
-RECORD 8	
token	inGermany
year	1940
frequency	1
pages	1
books -RECORD 9	1
token	inGermany
year	1942
frequency	2
pages	2
books	2
only showing	top 10 rows

These steps provide a comprehensive overview of the dataset, including its size, structure, and some basic statistics.

b. Create a new DataFrame from a query using Spark SQL, filtering to include only the rows where the token is "data" and describe the new dataset.

We are creating a new DataFrame by filtering the original DataFrame to include only the rows where the token is "data". Here's a summary of the steps:

- 1) Create Temporary View: The df.createOrReplaceTempView("df_view") function is used to create a temporary view named "df_view". This view is a representation of the DataFrame df that can be used in SQL queries.
- 2) SQL Query: The spark.sql("SELECT * FROM df_view WHERE token = 'data'") function is used to execute a SQL query on the "df_view". The query selects all columns from the view where the token is "data". The result of this query is a new DataFrame, filtered_df.
- 3) Descriptive Statistics: The filtered_df.describe().show() function is used to generate descriptive statistics of the new DataFrame. It includes count, mean, standard deviation, min, and max for each column.

```
df.createOrReplaceTempView("df_view")
   filtered_df = spark.sql("SELECT * FROM df_view WHERE token = 'data'")
   filtered_df.describe().show()
Stage 9:>
summary|token|
                            year|
                                          frequency
                                                316|
         316
                             316
                                                                   316
        null|1847.5696202531647|38555.99367088608|21711.041139240508| 1493.110759493671
  meanl
              96.87438222401165| 69212.3664179185| 34901.79774004759|1560.0408024002788
 stddev|
        nu11|
                            1584
    min|
        data
        datal
                            2008
                                                                 99110
                                                                                       955 I
    maxl
```

The new DataFrame 'filtered_df' contains 316 rows where the token is "data". The descriptive statistics provide a summary of the 'year', 'frequency', 'pages', and 'books' columns for these rows.

c. Write the filtered data back to a directory in the HDFS from Spark using df.write.csv().

Be sure to pass the header=True parameter and examine the contents of what you've written.

We are writing the filtered DataFrame back to a directory in the Hadoop Distributed File System (HDFS) and examining the contents of the written file. Here's a summary of the steps:

- 1) Write to CSV: The filtered_df.write.csv('/user/hadoop/filtered_data.csv', header=True) function is used to write the DataFrame filtered_df to a CSV file in the HDFS. The path of the file is '/user/hadoop/filtered_data.csv'. The header=True parameter is passed to include the column names in the CSV file.
- 2) Exit Spark: The exit() command is used to exit the Spark shell.
- **3) Examine Contents**: The **hadoop fs -cat /user/hadoop/filtered_data.csv/*** command is used to concatenate and display the contents of the CSV file in the terminal. This command is executed in the Hadoop shell, not the Spark shell.

```
>> filtered_df.write.csv('/user/hadoop/filtered_data.csv', header=True)
 >> exit()
[hadoop@ip-172-31-5-51 ~] hadoop fs -cat /user/hadoop/filtered_data.csv/*
token, year, frequency, pages, books
token, year, frequency, pages, books
data, 1584, 16, 14, 1
data,1614,3,2,1
data,1627,1,1,1
data,1631,22,18,1
data,1637,1,1,1
data,1638,2,2,1
data,1640,1,1,1
data,1642,1,1,1
data,1644,4,4,1
data,1647,1,1,1
data,1651,1,1,1
data,1674,1,1,1
data,1690,1,1,1
data,1693,1,1,1
data,1697,1,1,1
data,1699,1,1,1
data,1700,1,1,1
data,1701,11,11,2
data,1702,1,1,1
data,1703,1,1,1
data,1705,3,3,1
data,1707,2,2,2
data,1708,1,1,1
data,1709,1,1,1
data,1711,4,4,4
data,1713,40,28,1
data,1714,3,3,3
data,1715,1,1,1
data,1717,1,1,1
data,1718,1,1,1
data,1720,7,7,3
data,1722,1,1,1
data,1723,1,1,1
data,1724,2,2,2
data,1725,1,1,1
data,1726,1,1,1
data,1727,11,11,4
data,1728,5,5,5
data,1729,4,4,3
data,1730,17,14,10
data,1731,15,15,4
data,1732,4,3,1
data,1734,1,1,1
data,1735,2,2,2
 data,1736,2,2,2
 data,1737,4,4,4
```

The output shows the contents of the CSV file. Each row corresponds to a record in the DataFrame, and the columns are 'token', 'year', 'frequency', 'pages', and 'books'. The 'token' for all rows is 'data', as per the filter applied in the SQL query.

2.5 Collect the contents of the directory into a single file on the local drive of the head node using "getmerge" and move this file into a S3 bucket in your account.

We are collecting the contents of the directory into a single file on the local drive of the head node and moving this file into an S3 bucket. Here's a summary of the steps:

- 1) Merge Files: The hadoop fs -getmerge /user/hadoop/filtered_data.csv/ filtered_data.csv command is used to merge all the part files in the '/user/hadoop/filtered_data.csv/' directory into a single file named 'filtered_data.csv' on the local file system of the head node. The 'getmerge' command is useful when the data is split into multiple part files, and we want to consolidate it into a single file.
- **2)** List S3 Buckets: The aws s3 ls command is used to list all the S3 buckets in the AWS account. In this case, there is a single bucket named 'kartik-bstn-bucket'.
- 3) Copy File to S3: The aws s3 cp filtered_data.csv s3://kartik-bstn-bucket/filtered_data.csv command is used to copy the 'filtered_data.csv' file from the local file system to the 'kartik-bstnbucket' S3 bucket. The 'cp' command is used to copy files between the local file system and S3, or between two S3 buckets.

```
[hadoop@ip-172-31-5-51 ~]$ hadoop fs -getmerge /user/hadoop/filtered_data.csv/ filtered_data.csv [hadoop@ip-172-31-5-51 ~]$ aws s3 ls 2023-11-14 23:48:50 aws-logs-463637094970-us-east-1 2023-11-15 05:58:03 kartik-bstn-bucket [hadoop@ip-172-31-5-51 ~]$ aws s3 cp filtered_data.csv s3://kartik-bstn-bucket/filtered_data.csv upload: ./filtered_data.csv to s3://kartik-bstn-bucket/filtered_data.csv
```

The output shows that the 'filtered_data.csv' file has been successfully uploaded to the 'kartik-bstn-bucket' S3 bucket.

2.6 On your local machine (or on AWS outside of Spark) in python, read the CSV data from the S3 folder into a pandas DataFrame (You will have to research how to read data into pandas from S3 buckets). Note You must have first authenticated on your machine using aws configure on the command line to complete this step).

We are preparing to read the CSV data from the S3 bucket into a pandas DataFrame on their local machine. Here's a summary of the steps:

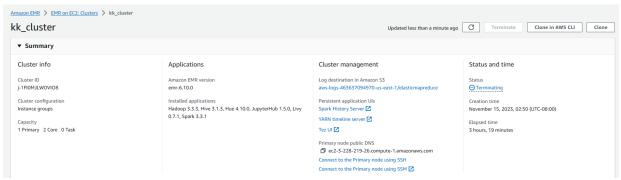
1) AWS Configuration: The aws configure command is used to set up AWS credentials and default region on the local machine. This step is necessary to interact with AWS services, including S3. We are prompted to enter their AWS Access Key ID, AWS Secret Access Key, Default region name, and Default output format.

```
[hadoop@ip-172-31-5-51 ~]$ aws configure
AWS Access Key ID [None]: Kartik
AWS Secret Access Key [None]: TwFwgi4hJnNDOqbJal/r2KNm9zr/t3G15PwBK+Mp
Default region name [None]:
Default output format [None]:
```

2) Exit SSH Session: The **exit** command is used to close the SSH session and return to the local terminal.

```
[hadoop@ip-172-31-5-51 ~]$ exit
logout
Connection to ec2-3-228-219-26.compute-1.amazonaws.com closed.
(base)
kkaka@Kartik MINGW64 ~/.aws
$
```

3) Terminate cluster on AWS.



4) Install s3fs: The **pip install s3fs** command is used to install the **s3fs** Python library if not already installed. This library is used to create a connection between Python and S3, allowing Python to read and write files in S3.

```
(cloud_lab) C:\Users\kkaka>conda activate cloud_lab

(cloud_lab) C:\Users\kkaka>pip install s3fs

Requirement already satisfied: s3fs in c:\users\kkaka\anaconda3\envs\cloud_lab\lib\site-packages (0.4.2)

Requirement already satisfied: botocore>=1.12.91 in c:\users\kkaka\anaconda3\envs\cloud_lab\lib\site-packages (from s3fs) (1.24.46)

Requirement already satisfied: fsspec>=0.6.0 in c:\users\kkaka\anaconda3\envs\cloud_lab\lib\site-packages (from s3fs) (2 023.9.2)

Requirement already satisfied: python-dateutil<3.0.0,>=2.1 in c:\users\kkaka\anaconda3\envs\cloud_lab\lib\site-packages (from botocore>=1.12.91->s3fs) (2.8.2)

Requirement already satisfied: urllib3<1.27,>=1.25.4 in c:\users\kkaka\anaconda3\envs\cloud_lab\lib\site-packages (from botocore>=1.12.91->s3fs) (1.26.18)

Requirement already satisfied: jmespath<2.0.0,>=0.7.1 in c:\users\kkaka\anaconda3\envs\cloud_lab\lib\site-packages (from botocore>=1.12.91->s3fs) (0.10.0)

Requirement already satisfied: six>=1.5 in c:\users\kkaka\anaconda3\envs\cloud_lab\lib\site-packages (from python-dateut il<3.0.0,>=2.1->botocore>=1.12.91->s3fs) (1.16.0)
```

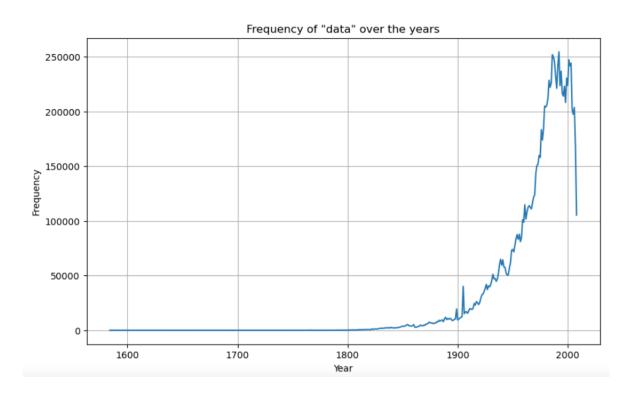
5) Launch Jupyter Notebook: The **jupyter notebook** command is used to start a Jupyter notebook server on the local machine.

6) We can then **create a new notebook** and write Python code to read the CSV data from the S3 bucket into a pandas DataFrame.



Please refer to the Jupyter notebook for further work.

2.7 Plot the number of occurrence of the token (the frequency column) of data over the years using matplotlib.



The plot shows how the frequency of the token 'data' has changed over the years, it was steadily increasing between 1900s and 2000s, and dropped rapidly after 2000s. The peak in frequency could be associated with significant events, technological advancements, or shifts in language usage during that timeframe. The rise and fall of the frequency could be linked to broader cultural or technological shifts. For example, the increase might be related to the proliferation of data-related technologies, while the decline could coincide with shifts in language usage or changes in the focus of content.

2.8 Compare Hadoop and Spark as distributed file systems.

a. What are the advantages/ differences between Hadoop and Spark? List two advantages for each.

Apache Hadoop and Apache Spark are both big data processing frameworks, but they have some key differences in terms of architecture, performance, and use cases. Here are two advantages for each framework:

1. Hadoop

 Batch Processing: Hadoop is well-suited for batch processing tasks. It excels in processing large volumes of data in a distributed and fault-tolerant manner. Hadoop's MapReduce paradigm allows for the efficient processing of massive datasets by dividing them into smaller chunks and processing them in parallel.

 Mature Ecosystem: Hadoop has a mature and well-established ecosystem with various components such as HDFS (Hadoop Distributed File System), MapReduce, Hive, Pig, and others. This ecosystem provides a comprehensive set of tools for data storage, data processing, and data analysis. Hadoop's ecosystem has been widely adopted and has a large community of users and contributors.

2. Spark

- In-Memory Processing: One of Spark's significant advantages is its ability to perform inmemory processing. Unlike Hadoop MapReduce, which relies heavily on disk-based storage
 between processing stages, Spark keeps intermediate data in memory. This results in
 significantly faster data processing as it reduces the need for data to be written to and read
 from disk, making Spark suitable for iterative algorithms and interactive data analysis.
- Unified Data Processing Engine: Spark provides a unified data processing engine that supports batch processing, interactive queries, streaming analytics, and machine learning within a single framework. This flexibility allows users to perform a wide range of data processing tasks using the same codebase, simplifying development and reducing the need for multiple specialized tools.

b. Explain how the HDFS stores the data.

Hadoop Distributed File System (HDFS) is the distributed file system used by Apache Hadoop for storing and managing large volumes of data across a cluster of commodity hardware. HDFS is designed to provide reliable, scalable, and fault-tolerant storage for big data applications. Here's an explanation of how HDFS stores data:

- **File Write:** When a new file is written to HDFS, the client application contacts the NameNode to request the creation of the file. The NameNode checks if the file already exists and allocates metadata space for the new file.
- **Block Division:** The file is divided into fixed-size blocks. The block size is configurable but is typically several megabytes or even gigabytes in size.
- **Block Replication:** Each block is replicated across multiple DataNodes in the cluster. The replication factor is configurable and determines how many copies of each block are stored. Replication helps in achieving fault tolerance and data availability.
- **DataNode Storage:** The actual data blocks are stored on the local file systems of the DataNodes. Each DataNode independently manages its block replicas.
- **Metadata Management:** The NameNode keeps track of the metadata, including the location and replication factor of each block. It maintains the file namespace, directory structure, and metadata about each file and directory.

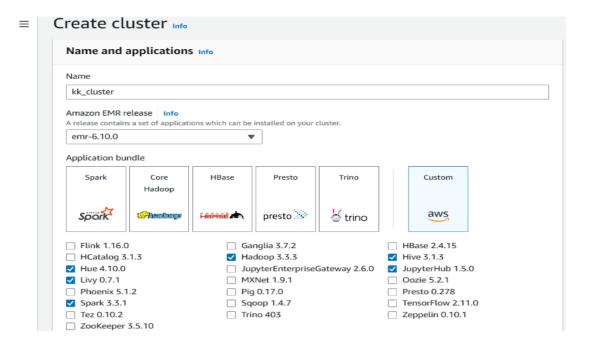
Part 3. Conclusion

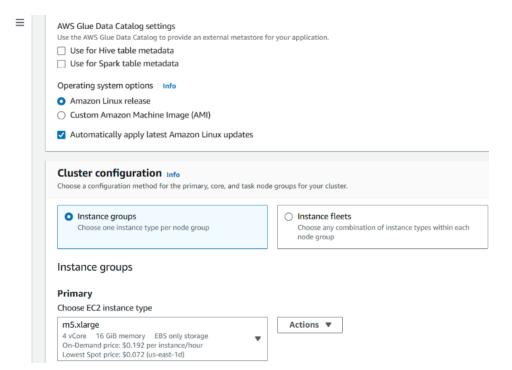
We have successfully completed a comprehensive data analysis workflow involving multiple technologies including Apache Hadoop, AWS S3, Python, pandas, and matplotlib. The workflow can be summarized as follows:

- **Data Filtering with Hadoop**: We utilized Apache Hadoop to filter a large dataset stored on an AWS EMR cluster. The Hadoop MapReduce job was written in Python and was used to filter out specific tokens from the dataset.
- Data Transfer to S3: After filtering the data, we collected the contents of the directory
 into a single file and moved this file into an S3 bucket in their AWS account using the
 aws s3 cp command.
- **Data Loading with pandas**: We then switched to their local machine and read the CSV data from the S3 bucket into a pandas DataFrame. This was done using the **s3fs** library to create a connection to S3 and then using pandas' **read_csv** function to load the data.
- **Data Visualization with matplotlib**: Finally, we visualized the frequency of the token 'data' over the years using matplotlib. The 'year' and 'frequency' columns were converted to integers and a line plot was created to show the trend over time.

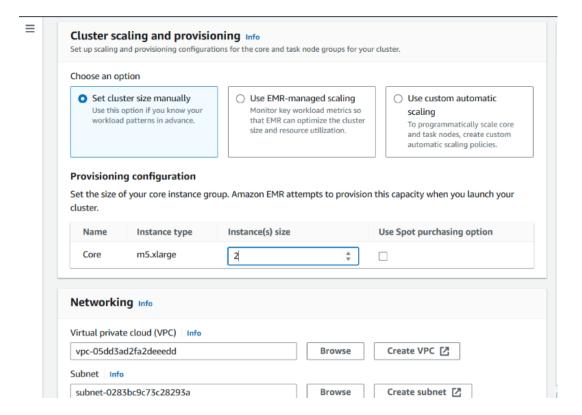
In conclusion, this workflow demonstrates a powerful combination of distributed computing, cloud storage, and data analysis tools to process, analyze, and visualize large datasets. We were able to filter a large dataset using Hadoop, store and retrieve the data using AWS S3, and then analyze and visualize the data using pandas and matplotlib. This workflow is a good example of how different technologies can be combined to handle big data tasks.

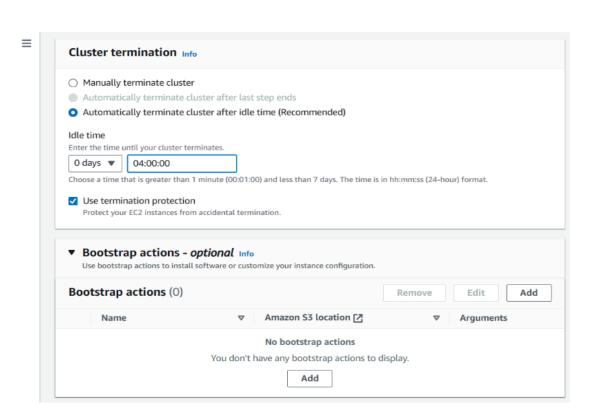
Part 2.1 Screenshots

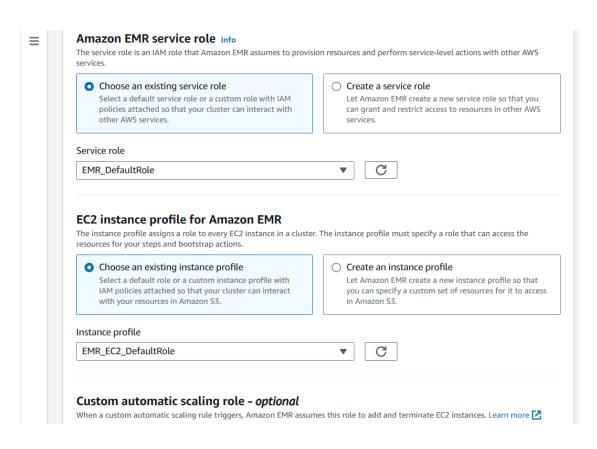




Instance groups Primary Choose EC2 instance type m5.xlarge Actions ▼ 4 vCore 16 GiB memory EBS only storage On-Demand price: \$0.192 per instance/hour Lowest Spot price: \$0.072 (us-east-1d) ☐ Use multiple primary nodes To improve cluster availability, use 3 primary nodes with the same configuration and bootstrap actions. You can not use multiple primary nodes with instance fleets. ▶ Node configuration - optional Core Remove instance group Choose EC2 instance type m5.xlarge Actions ▼ 4 vCore 16 GiB memory EBS only storage On-Demand price: \$0.192 per instance/hour Lowest Spot price: \$0.072 (us-east-1d) ▶ Node configuration - optional Add task instance group You can add up to 48 more task instance groups.







Sign in		
Username:		
Password:		