Project: **Big Data Wrangling With Google Books Ngrams**
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Due Date: 26/01/2024

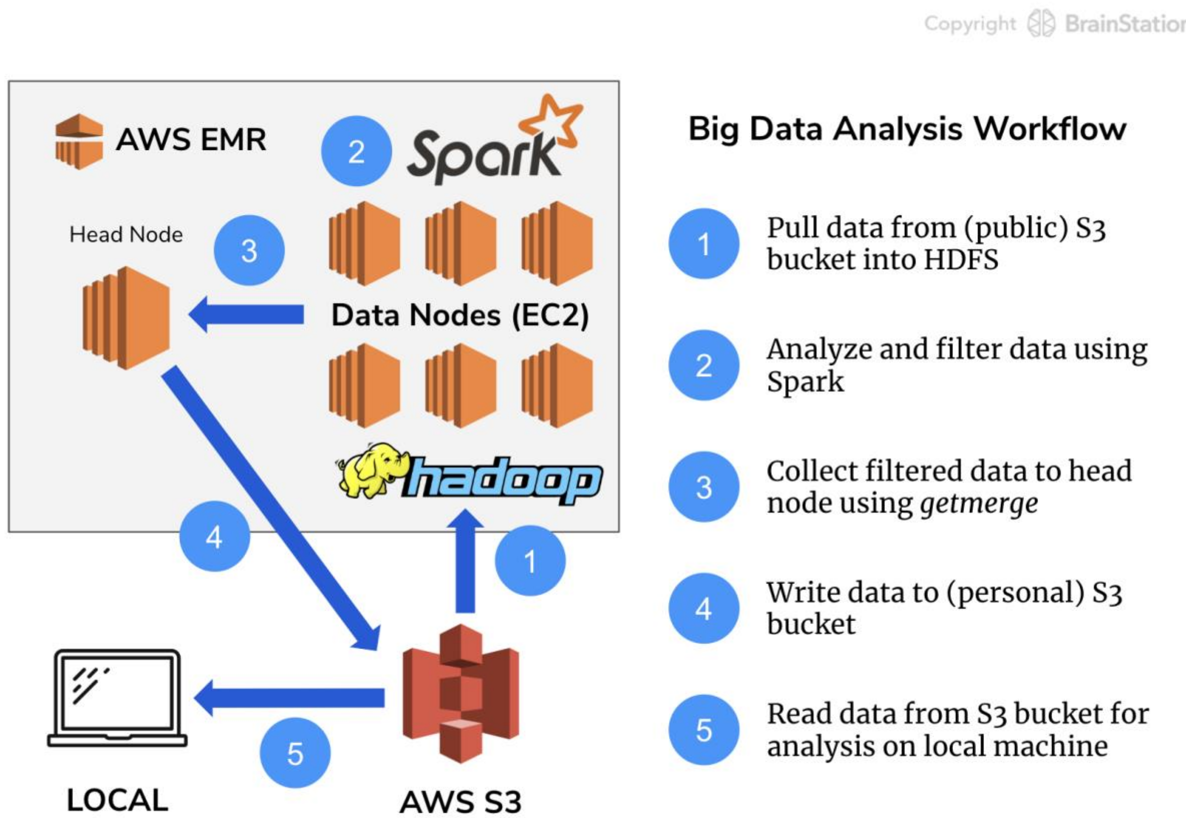
Assignment overview

In this assignment, you will apply the skills you've learned in the Big Data Fundamentals unit to load, filter, and visualize a large real-world dataset in a cloud-based distributed computing environment using Hadoop, Spark, Hive, and the S3 filesystem. Prepare a professional report to summarize the findings and be sure to include an appendix with screenshots of the steps completed for Questions 1 and 2.

The Google Ngrams dataset was created by Google's research team by analyzing all of the content in Google Books - these digitized texts represent approximately 4% of all books ever printed, and span a time period from the 1800s into the 2000s.

The dataset is hosted in a public S3 bucket as part of the Amazon S3 Open Data Registry. For this assignment, we have converted the data to CSV and hosted it on a public S3 bucket which may be accessed here: s3://brainstation-dsft/eng_1M_1gram.csv

For this deliverable, you will produce a report, as well as a jupyter notebook, which will follow a Big Data analysis workflow. As part of this workflow you will filter and reduce data down to a manageable size, and then do some analysis locally on our machine after extracting data from the Cloud and processing it using Big Data tools. The workflow and steps in the process are illustrated



below:

The scope of data processing and analysis is outlined in the questions below. Please document all your steps and commands/ code; there are several format options to submit both the code and a written report.

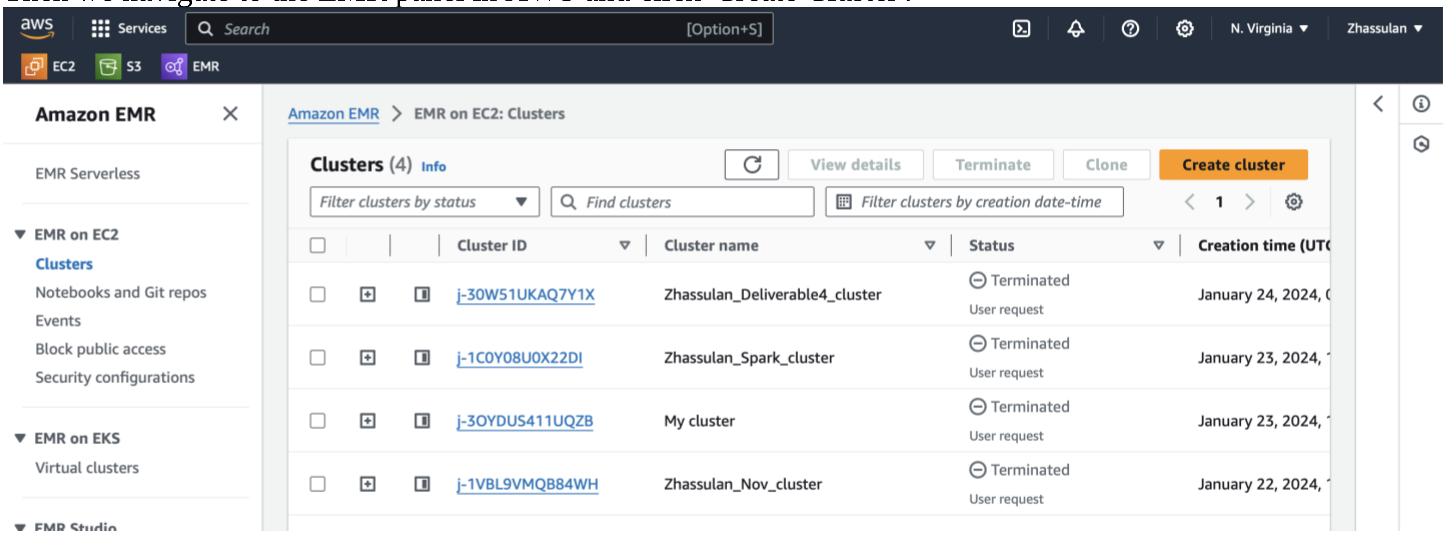
Assignment questions:

1. Spin up a new EMR cluster on AWS for using Spark and EMR notebooks - **follow the same instructions as for the Spark Lab**.
2. Connect to the head node of the cluster using SSH.
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.
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:
    a. Describe the dataset (examples include size, shape, schema) in pyspark
    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
    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.
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.
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).
7. Plot the number of occurrences of the token (the *frequency* column) of data over the years using matplotlib.
8. Compare Hadoop and Spark as distributed file systems.
    a. What are the advantages/ differences between Hadoop and Spark? List two advantages for each.
    b. Explain how the HDFS stores the data.

Question 1. Spin up a new EMR cluster on AWS for using Spark and EMR notebooks - **follow the same instructions as for the Spark Lab**.

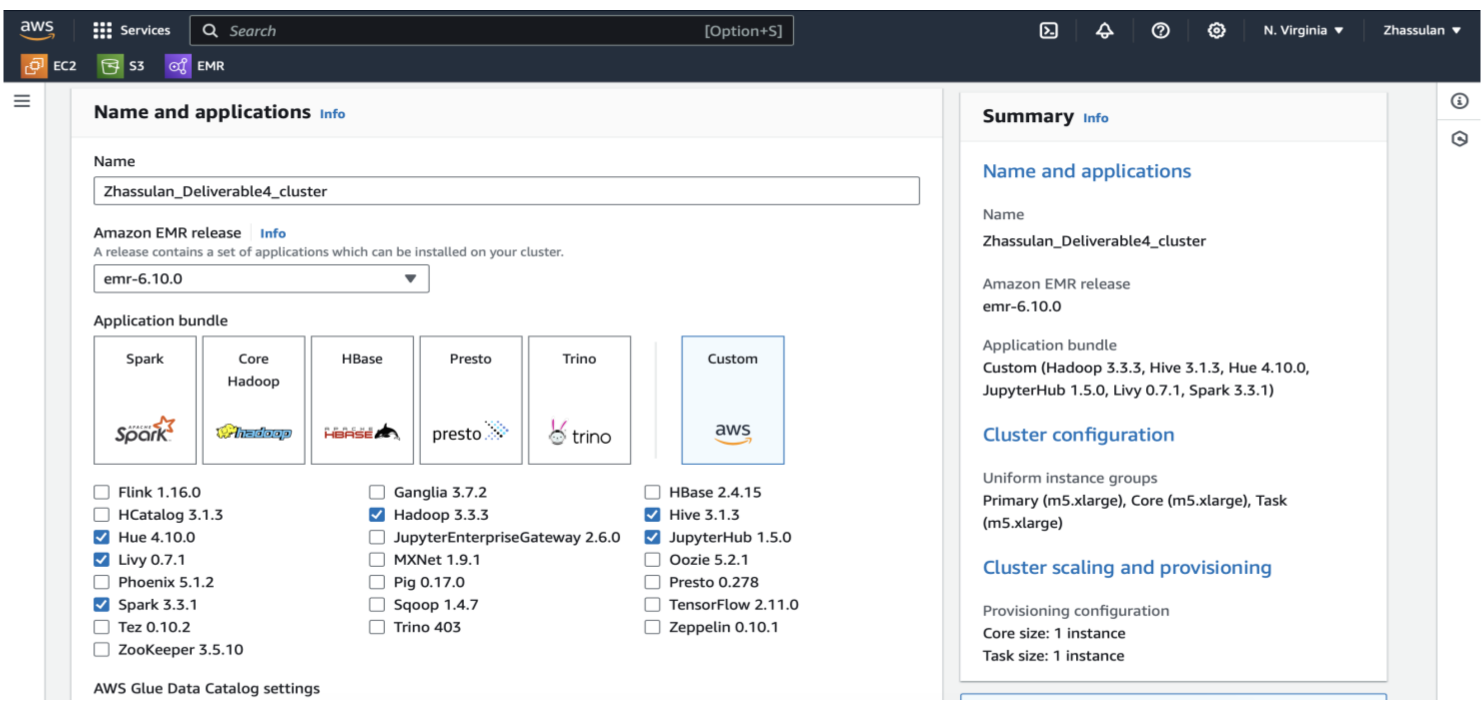
Create Cluster

First, we need to sign in to the AWS Management Console.
Then we navigate to the EMR panel in AWS and click 'Create Cluster'.



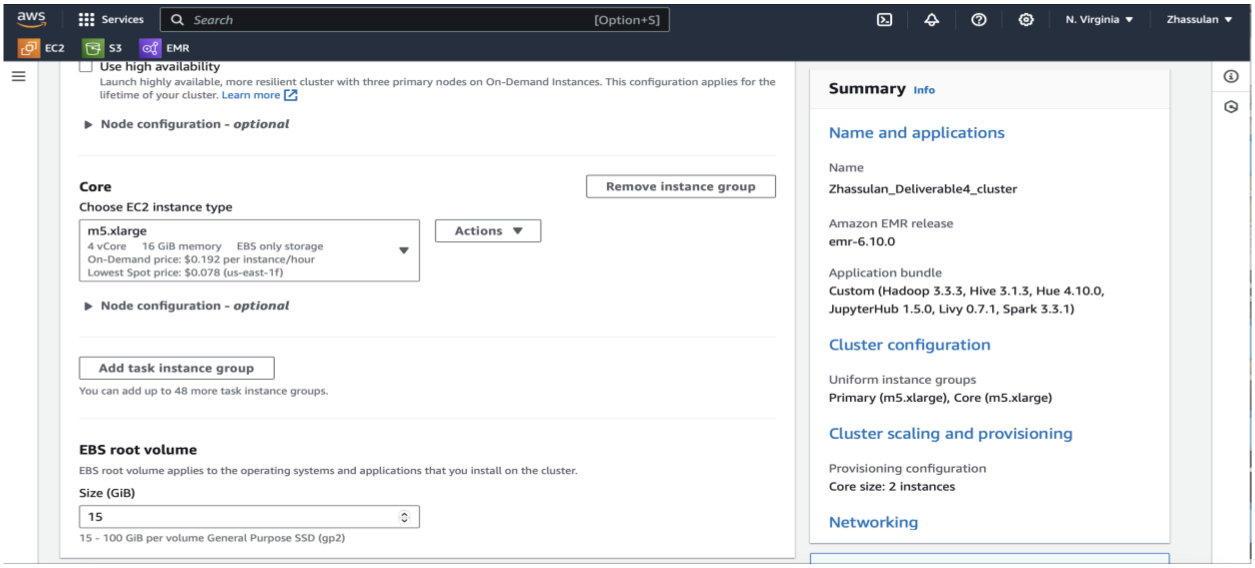
Cluster name and software

In name and application section I named cluster as "Zhassulan_Deliverable4_cluster"
Here we set Amazon EMR release as emr-6.10.0.
Next we choose application bundle. I choose "Custom" and included necessary applications in my bundle.

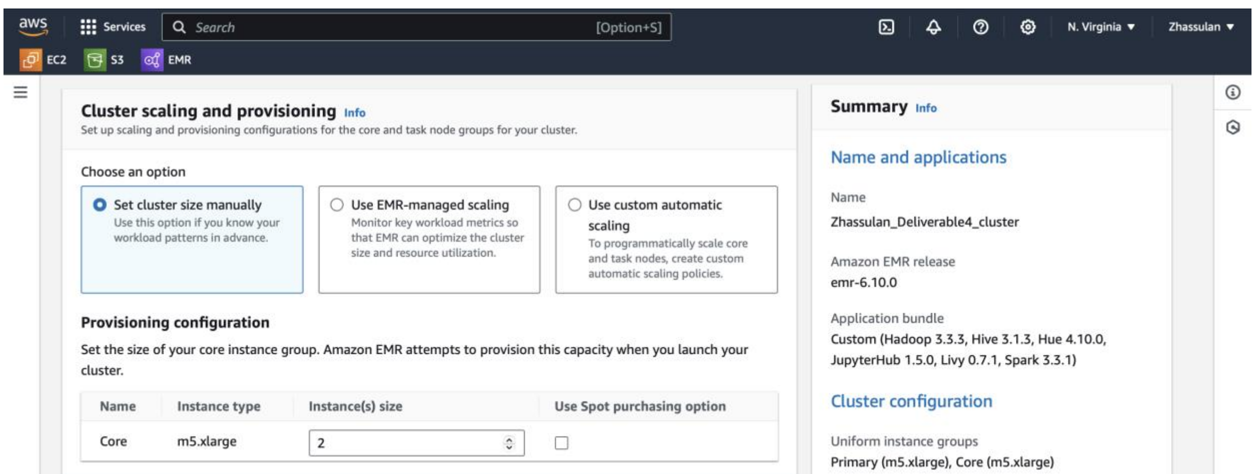


Instance Groups

WE removing the task instance group, as we no need it and it helps in cost optimization by stopping the billing for those instances. Also we no need additional computation capacity.

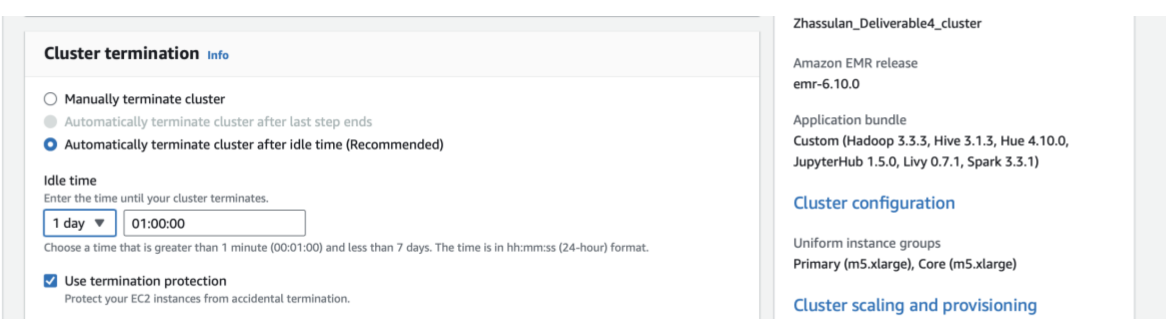


By allocating 2 nodes to the core instance group we are dedicating two virtual machines (instances) to handle the core task within the cluster.

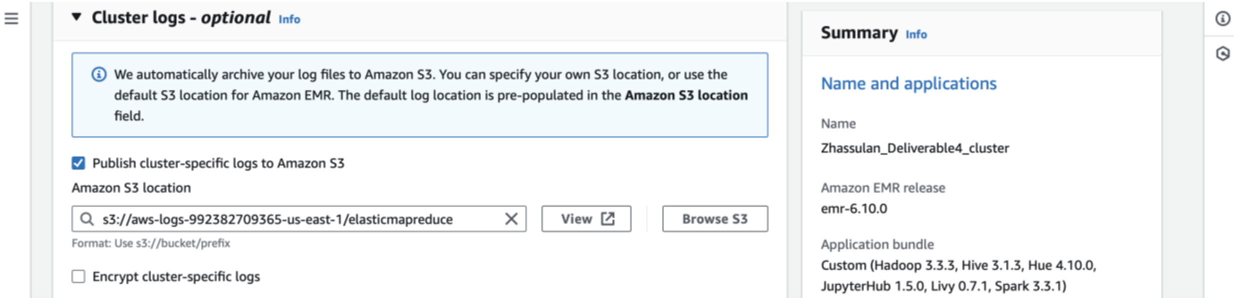


Cluster Termination

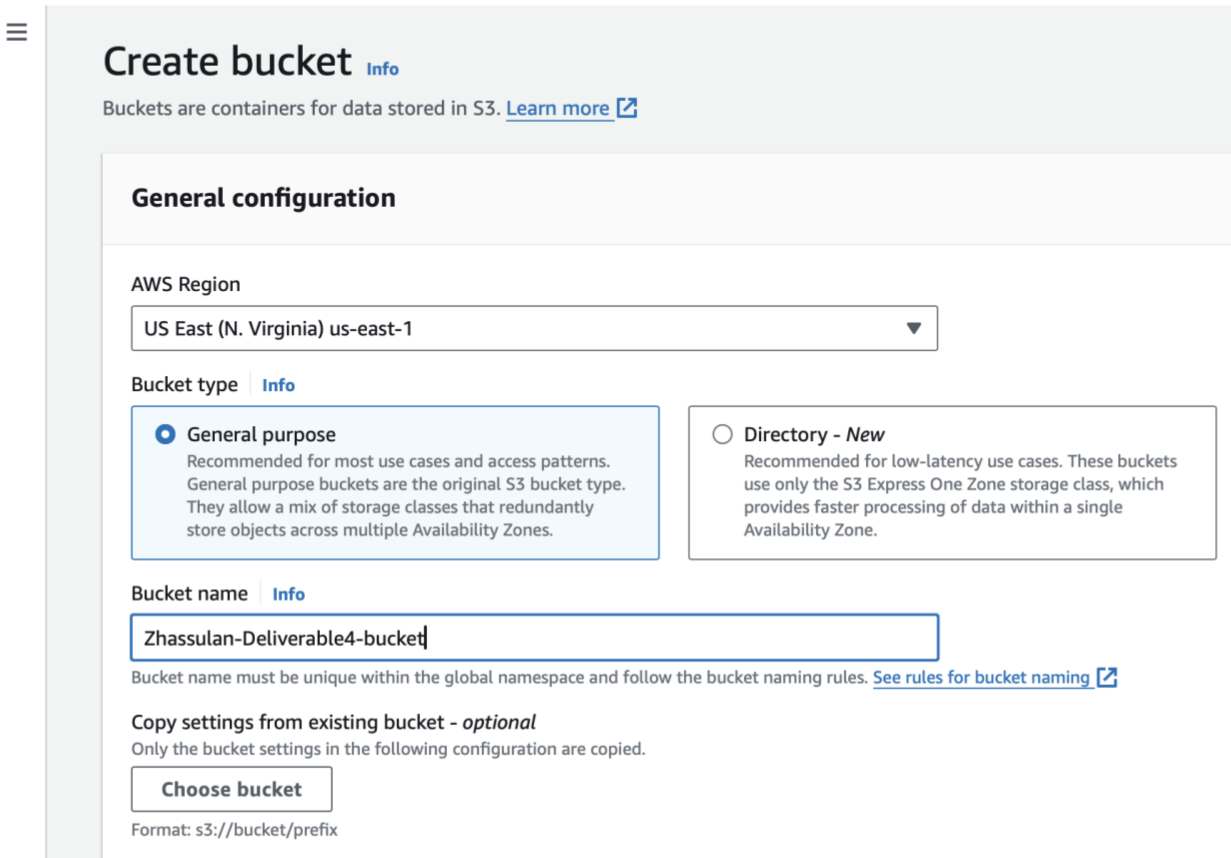
I set Idle time to 1 day, to make sure I have enough time to finish Assignment.
And I decided to keep “Use termination protection”, not to terminate cluster accidently before I done Deliverable4.



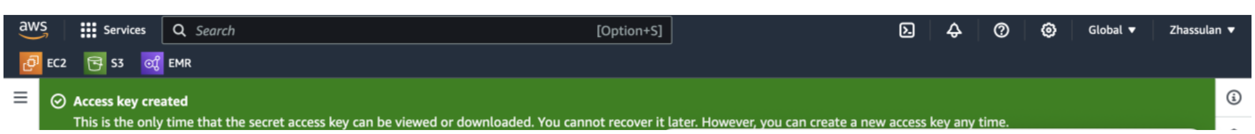
Cluster logs

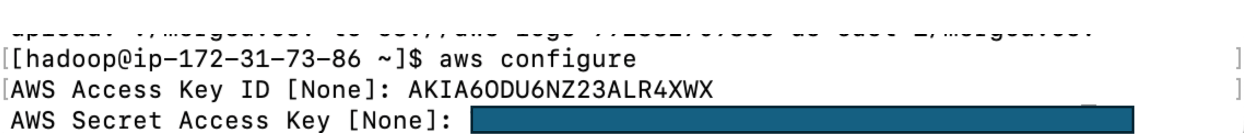


Bucket was created automatically here, and I used it for my Deliverable.
I could create it myself, how we did during the class.



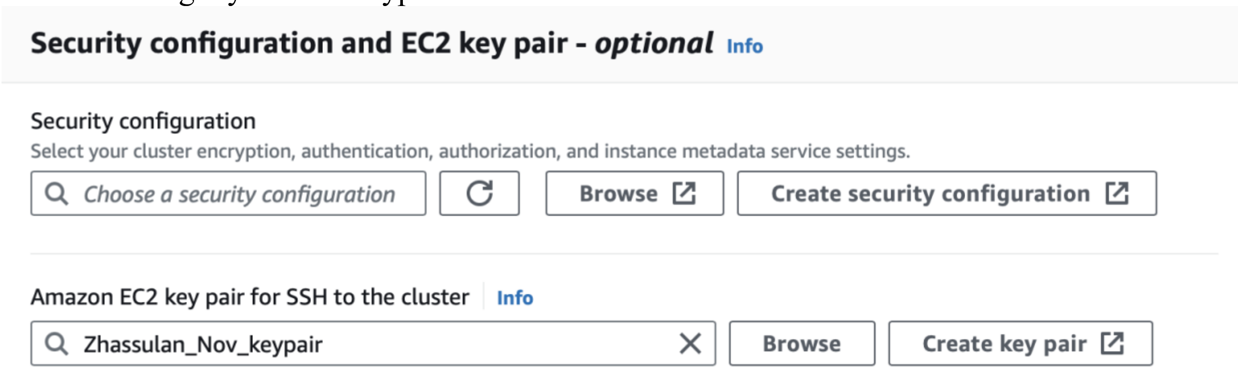
To create a new bucket we need to access S3 in AWS Management Console and click “Create bucket”. Define name for the bucket and choose “AWS region” In bucket we need to create Access key pair. This consists of an Access Key ID and a Secret Access Key. These keys are used to authenticate your requests when making API calls or using AWS SDKs. In Terminal on Mac we need to run aws configure and here we will enter our keys.



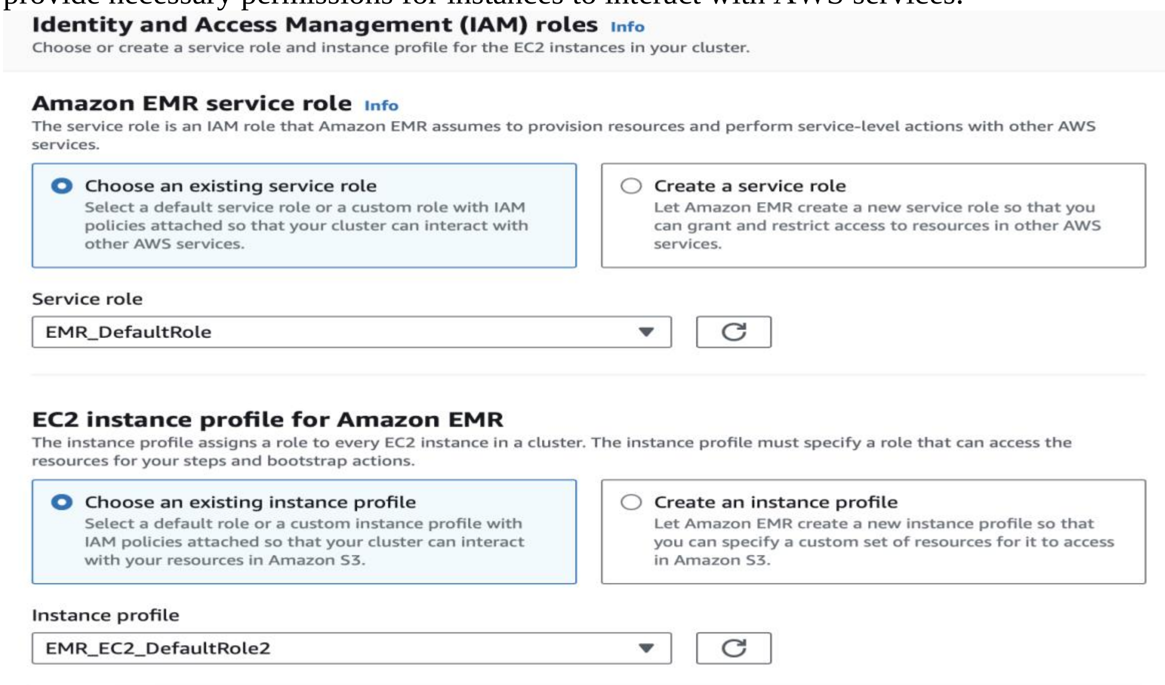


Security and Access Management

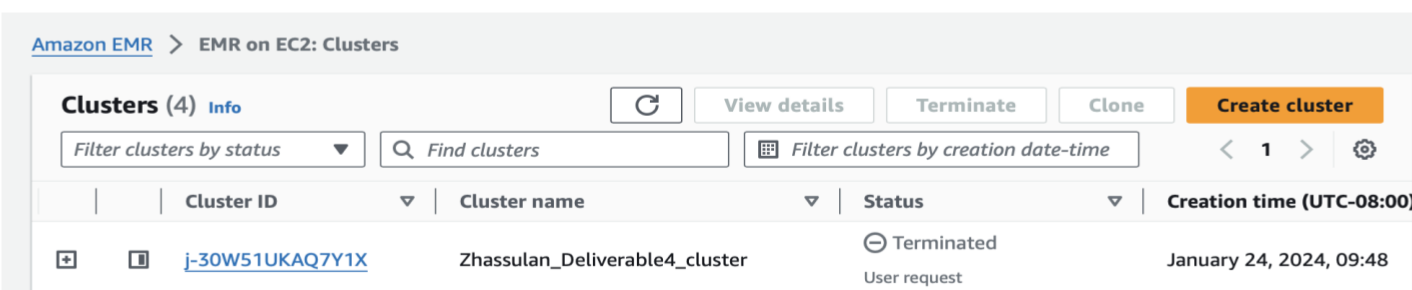
Here I'm using my created keypair for SSH access to the master node of the EMR cluster



By choosing EMR_DefaultRole we grant permission to access AWS services, in our case is Amazon S3. By choosing EMR_EC2_DefaultRole2 it assigned to the EC2 instances that make up our cluster. This role provide necessary permissions for instances to interact with AWS services.



And we Finish with clicking the "Create cluster" button.

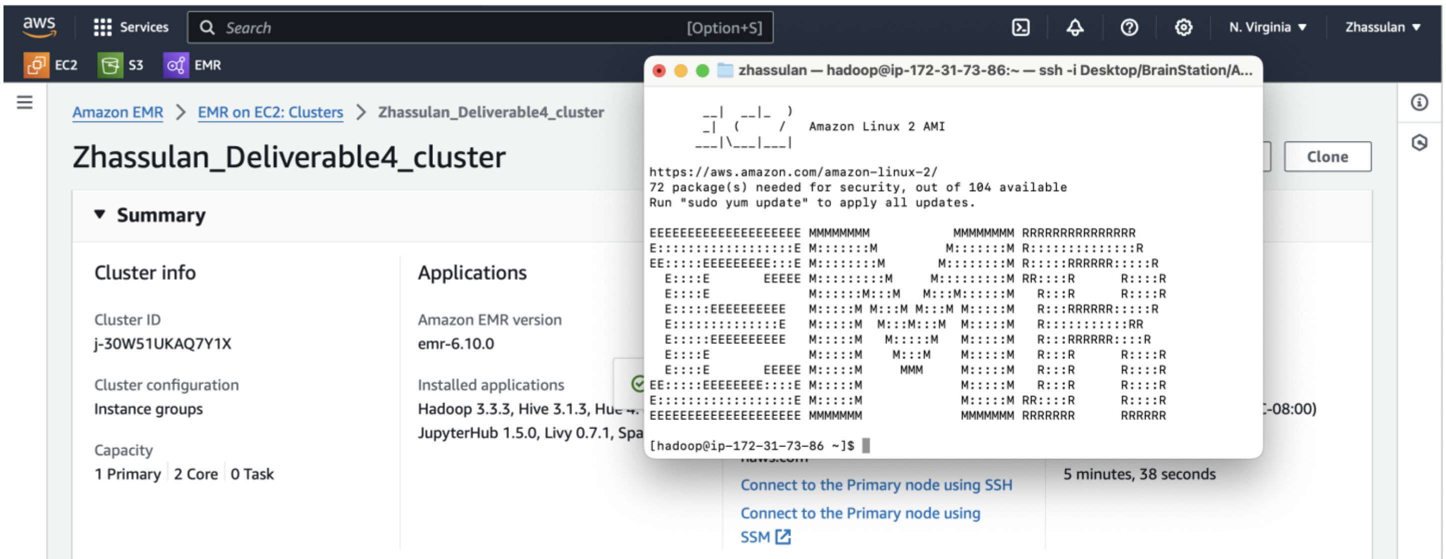


P.S. I print screen it after termination

Question 2. Connect to the head node of the cluster using SSH.

I've done through Terminal on Mac.
First, I activated cloud_lab environment, by using **conda activate cloud_lab** command
And connected to head note by using:
ssh -i /path/to/your/keypair.pem hadoop@xxxxxxx.compute.amazonaws.com

```
(base) zhassulan@MacBook-Air-Zasulan ~ % conda activate cloud_lab
(cloud_lab) zhassulan@MacBook-Air-Zasulan ~ % ssh -i Desktop/BrainStation/AWS\ k
eypair/Zhassulan_Nov_keypair.pem hadoop@ec2-3-235-65-30.compute-1.amazonaws.com
```



Question 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.

To do this, we are using command: **hadoop distcp s3://brainstation-dsft/eng_1M_1gram.csv /user/Hadoop/eng_1M_1gram.csv**

```
[hadoop@ip-172-31-73-86 ~]$ hadoop distcp s3://brainstation-dsft/eng_1M_1gram.cs
v /user/hadoop/eng_1M_1gram.csv
2024-01-24 18:42:32,992 INFO tools.DistCp: Input Options: DistCpOptions{atomicCo
mmit=false, syncFolder=false, deleteMissing=false, ignoreFailures=false, overwri
te=false, append=false, useDiff=false, useRdiff=false, fromSnapshot=null, toSnap
shot=null, skipCRC=false, blocking=true, numListstatusThreads=0, maxMaps=20, map
Bandwidth=0.0, copyStrategy='uniformsize', preserveStatus=[], atomicWorkPath=nul
l, logPath=null, sourceFileListing=null, sourcePaths=[s3://brainstation-dsft/eng
_1M_1gram.csv], targetPath=/user/hadoop/eng_1M_1gram.csv, filtersFile='null', bl
ocksPerChunk=0, copyBufferSize=8192, verboseLog=false, directWrite=false, useite
rator=false}, sourcePaths=[s3://brainstation-dsft/eng_1M_1gram.csv], targetPathE
xists=false, preserveRawXattrs=false
2024-01-24 18:42:33,259 INFO client.DefaultNoHARMFailoverProxyProvider: Connecti
ng to ResourceManager at ip-172-31-73-86.ec2.internal/172.31.73.86:8032
2024-01-24 18:42:33,414 INFO client.AHSProxy: Connecting to Application History
server at ip-172-31-73-86.ec2.internal/172.31.73.86:10200
2024-01-24 18:42:36,412 INFO tools.SimpleCopyListing: Starting: Building listing
 using multi threaded approach for s3://brainstation-dsft/eng_1M_1gram.csv
2024-01-24 18:42:36,414 INFO tools.SimpleCopyListing: Building listing using mul
ti threaded approach for s3://brainstation-dsft/eng_1M_1gram.csv: duration 0:00.
002s
2024-01-24 18:42:36,537 INFO tools.SimpleCopyListing: Paths (files+dirs) cnt = 1
; dirCnt = 0
```

Sanity check by using command: **hadoop fs -ls /user/hadoop**

```
[hadoop@ip-172-31-73-86 ~]$ hadoop fs -ls /user/hadoop
Found 1 items
-rw-r--r--   1 hadoop hdfsadmingroup 5292105197 2024-01-24 18:43 /user/hadoop/en
g_1M_1gram.csv
```

We see that have our csv file successfully copied.

Question 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).

I choose to work with Jupyterhub on EMR.
And here how I accessed it, by using command below:

```
(cloud_lab) zhassulan@MacBook-Air-Zasulan ~ % ssh -i Desktop/BrainStation/AWS\ k
eypair/Zhassulan_Nov_keypair.pem -L 9995:localhost:9443 hadoop@ec2-3-235-65-30.c
ompute-1.amazonaws.com
```

Here is a view on Jupyterhub on EMR

Next answers for question 4 will be on Jupyterhub and fail will be attached for submission.

Question 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.

First we check if we done everything right with passing filtered data to HDFS

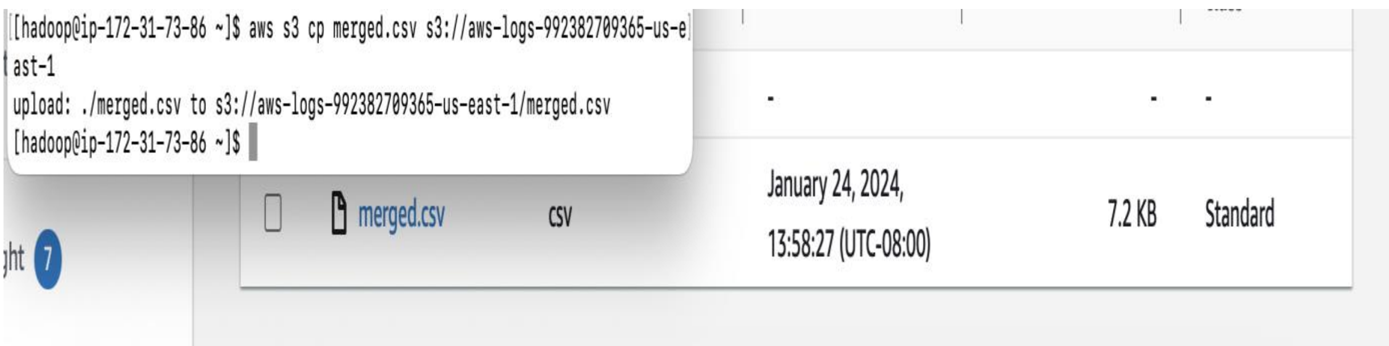
```
[hadoop@ip-172-31-73-86 ~]$ hadoop fs -ls /user/hadoop
Found 2 items
-rw-r--r--   1 hadoop hdfsadmingroup 5292105197 2024-01-24 18:43 /user/hadoop/en
g_1M_1gram.csv
drwxr-xr-x   - livy   hdfsadmingroup          0 2024-01-24 19:36 /user/hadoop/fi
ltered_data_csv
[hadoop@ip-172-31-73-86 ~]$
```

After sanity check, we can use **getmerge** and move file into S3 bucket.

```
[hadoop@ip-172-31-73-86 ~]$ hadoop fs -ls /user/hadoop
Found 2 items
-rw-r--r--   1 hadoop hdfsadmingroup 5292105197 2024-01-24 18:43 /user/hadoop/en
g_1M_1gram.csv
drwxr-xr-x   - livy   hdfsadmingroup          0 2024-01-24 20:13 /user/hadoop/fi
ltered_data.csv
[hadoop@ip-172-31-73-86 ~]$ hadoop fs -getmerge /user/hadoop/filtered_data.csv m
erged.csv
[hadoop@ip-172-31-73-86 ~]$
```

Here we **getmerge** our filtered data and saved as **merged.csv.**
We need to run **getmerge** command as our filtered data is batched. AS Data is often processed in parallel by dividing it into smaller chunks or "batches." This is primarily done to enable parallel processing and efficient storage across multiple nodes in a HDFS.
It's important to understand that Hadoop and Spark, by default, output results into multiple files, one per partition or task. This is again for parallelism and distributed processing.
So why we using **getmerge** command to view of the results, especially for visualization or analysis in Jupyter Notebook, it's convenient to merge the results into a single file.

Now we need to file to the S3 bucket.
And we use next command: **aws s3 cp our_file_name.csv s3://bucket-name**



As we can see, merged.csv successfully moved to bucket.

Question 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).

Question 7. Plot the number of occurrences of the token (the *frequency* column) of data over the years using matplotlib.

Answers for question 6 and 7 will be on Jupyter notebook and will be attached as well for submition.

Question 8.

Compare Hadoop and Spark as distributed file systems.

a. What are the advantages/ differences between Hadoop and Spark? List two advantages for each.
b. Explain how the HDFS stores the data.

Q8 a.

Apache Hadoop and Apache Spark are tools for handling big data in analytics. Businesses need to process data quickly and at scale for real-time insights. Hadoop allows you to cluster multiple computers to analyze large datasets in parallel more quickly. Spark, a more advanced tool, speeds up analytic queries with in-memory caching and optimized execution. It even incorporates AI and machine learning. Despite their differences, many companies use both Spark and Hadoop together to achieve their data analytics objectives.

Advantages of Hadoop:

Mature Ecosystem:
Hadoop boasts a mature ecosystem with a range of tools such as MapReduce, Hive, and HBase. This established toolkit provides a comprehensive solution for distributed storage and processing, making it suitable for various big data tasks.
Scalability:
Hadoop's HDFS scales horizontally, meaning it can efficiently handle massive amounts of data by distributing it across multiple nodes. This inherent scalability is crucial for accommodating the ever-growing demands of data storage and processing.

Advantages of Spark:

In-Memory Processing:
Spark leverages in-memory processing, allowing data to be stored and processed in the system's memory rather than on disk. This results in significantly faster data access and computation compared to Hadoop's traditional disk-based processing.
Versatility:
Spark stands out for its versatility, supporting diverse workloads. Whether it's batch processing, machine learning, or real-time stream processing, Spark provides a flexible framework that caters to a wide range of data processing needs.

Q8 b.

How HDFS Stores Data:
HDFS stores data by breaking it into blocks (typically 64 MB or 128 MB in size) and distributing these blocks across multiple nodes in a Hadoop cluster. Each block is replicated across different nodes for fault tolerance. This distributed storage approach allows parallel processing of data, as multiple nodes can work on different blocks simultaneously. The master node, called the NameNode, keeps track of the metadata and the locations of these blocks, facilitating efficient data retrieval and fault recovery in case of node failures.

File System Structure:

- The HDFS file system comprises master services, including the NameNode, secondary NameNode, and DataNodes.

Master Services:

- NameNode and Secondary NameNode: These manage HDFS metadata, tracking file and directory information. The secondary NameNode aids the NameNode by periodically merging and compacting log files to reduce the risk of data loss.
- DataNodes: Host the actual data stored in HDFS, responsible for storage, retrieval, and reading/writing of data.

Data Division:

- HDFS breaks data into blocks, typically sized at 64 MB or 128 MB. Each block is considered a unit for storage and processing.

Replication for Fault Tolerance:

- Each data block is replicated across multiple DataNodes to ensure fault tolerance. The default replication factor is usually three, providing redundancy and reliability.

Parallel Processing:

- The distributed storage approach enables parallel processing, allowing multiple nodes to work simultaneously on different blocks. This enhances the overall efficiency of data processing tasks.

Metadata Management:

- The NameNode keeps track of which DataNodes contain the contents of specific files in HDFS. It manages metadata, including file names, permissions, and block locations.

Replica Distribution:

- The NameNode distributes replicas of data blocks across the Hadoop cluster. This ensures that data is stored redundantly across different nodes.

Access Instructions:

- The NameNode instructs users or applications on where to locate the desired information. It directs them to the specific DataNodes hosting the relevant data blocks.

Efficient Retrieval and Fault Recovery:

- The NameNode's management of metadata and block locations facilitates efficient data retrieval. In case of node failures, the replicated nature of data blocks allows for fault recovery without data loss.