Word Count with Spark in AWS EMR

1. Introduction

1.1 What is EMR?

Amazon EMR (Elastic MapReduce) is a cloud-native big data platform provided by AWS. It allows users to process vast amounts of data using open-source frameworks such as Apache Hadoop, Apache Spark, Hive, Presto, and others. EMR enables fast, cost effective processing of large datasets by distributing the work across multiple EC2 instances.

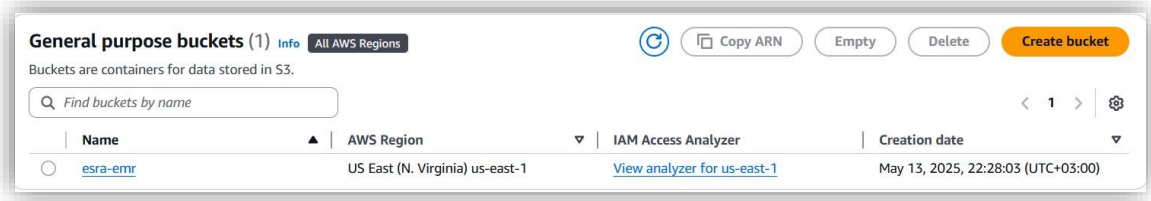
1.2 Project Objective

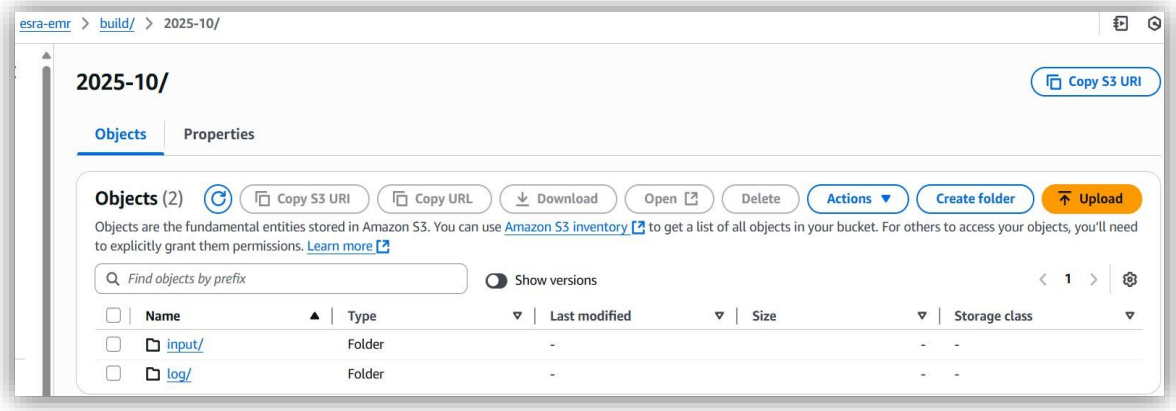
The objective of this project is to perform a Word Count operation using Apache Spark on an EMR cluster. The input text is stored in Amazon S3, processed by the Spark job, and the result (word frequencies) is written back to S3.

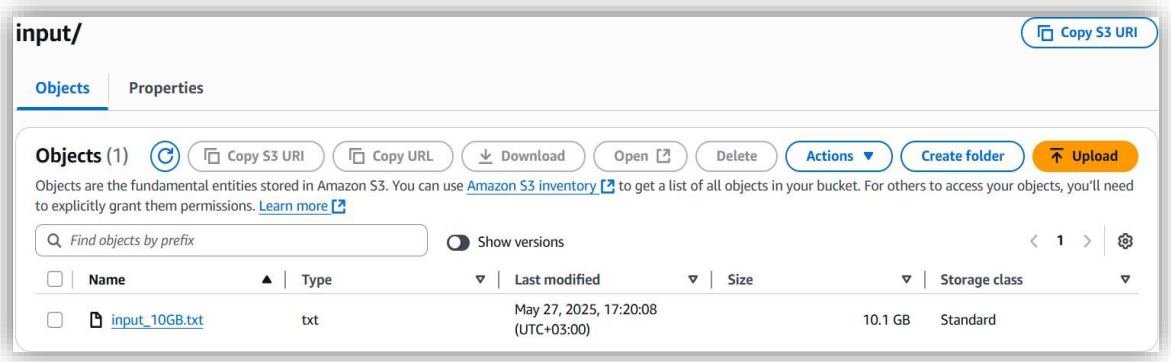
2. AWS Resources

2.1 Creating an S3 Bucket

- An S3 bucket was created to store both the input files.The following files were uploaded:
- **input/:** This folder contains the input.txt file, which is a 10 GB text file used as the input for the word count operation.
- **log/:** This folder was created to store the application and system logs generated by the Spark job during execution.



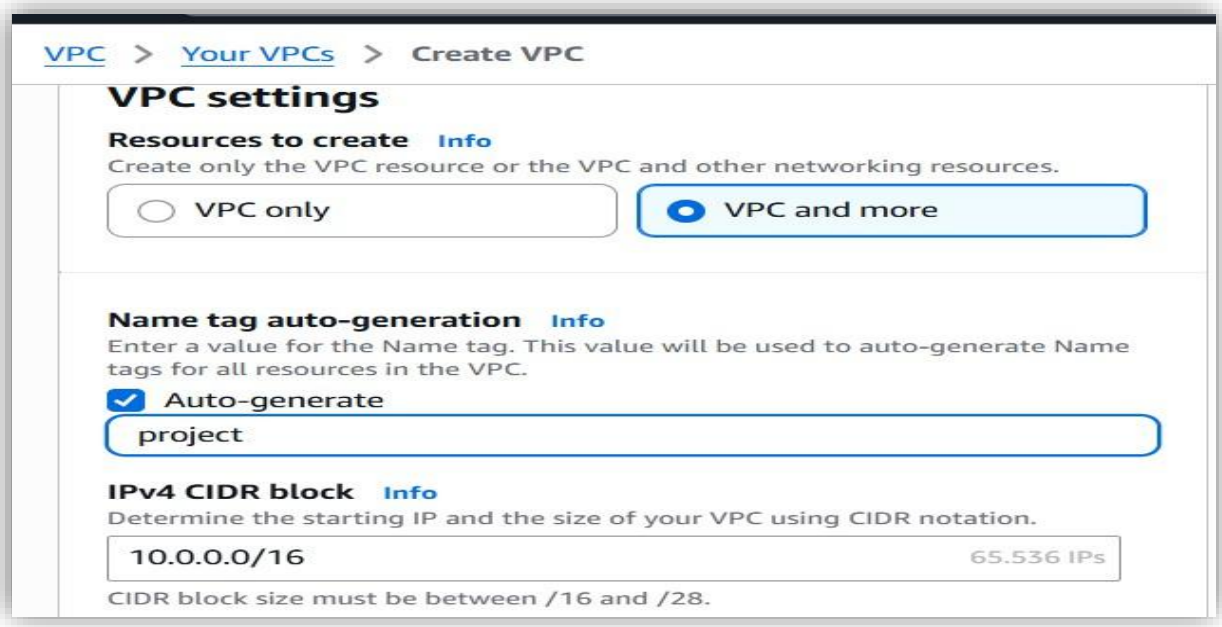




2.2 Creating a VPC

A dedicated Virtual Private Cloud (VPC) named project-vpc was created to provide a secure and isolated network environment for the EMR cluster. The following network components were configured:

- **Public and Private Subnets**: Subnets were created across multiple Availability Zones to ensure high availability and proper distribution of EMR nodes.
- **Internet Gateway**: An internet gateway was attached to the VPC and properly routed to allow the cluster to access the internet when necessary (e.g., downloading dependencies or writing to S3).
- **Route Tables**: Custom route tables were configured to manage traffic between the subnets and the internet gateway.
- **Security Groups**: Security groups were defined to control inbound and outbound access to EMR nodes, ensuring that only necessary ports (such as SSH and application ports) were open.



Number of public subnets Info

The number of public subnets to add to your VPC. Use public subnets for web applications that need to be publicly accessible over the internet.

0 | 2

Number of private subnets Info

The number of private subnets to add to your VPC. Use private subnets to secure backend resources that don't need public access.

0 | 2 | 4

▶ Customize subnets CIDR blocks

NAT gateways ($) Info

Choose the number of Availability Zones (AZs) in which to create NAT gateways. Note that there is a charge for each NAT gateway

None | In 1 AZ | 1 per AZ

VPC endpoints Info

Endpoints can help reduce NAT gateway charges and improve security by accessing S3 directly from the VPC. By default, full access policy is used. You can customize this policy at any time.

None | S3 Gateway

review

VPC Show details

Your AWS virtual network

project-vpc

Subnets (2)

Subnets within this VPC

us-east-1a

project-subnet-public1-us-east-1a

us-east-1b

project-subnet-public2-us-east-1b

Route tables (1)

Route network traffic to resources

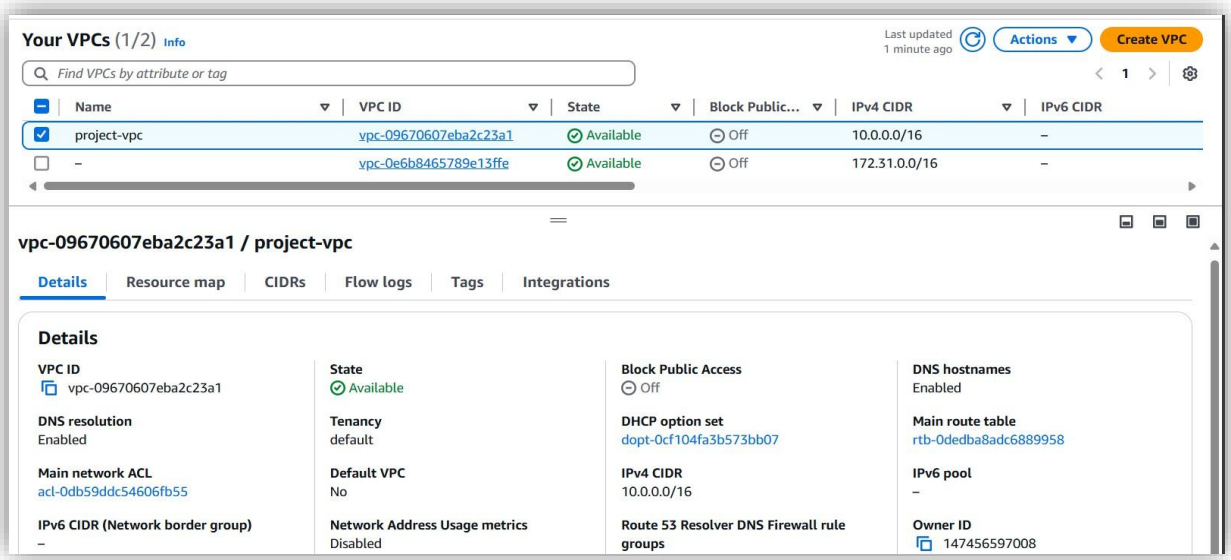
project-rtb-public

Network connections (2)

Connections to other networks

project-igw

project-vpce-s3



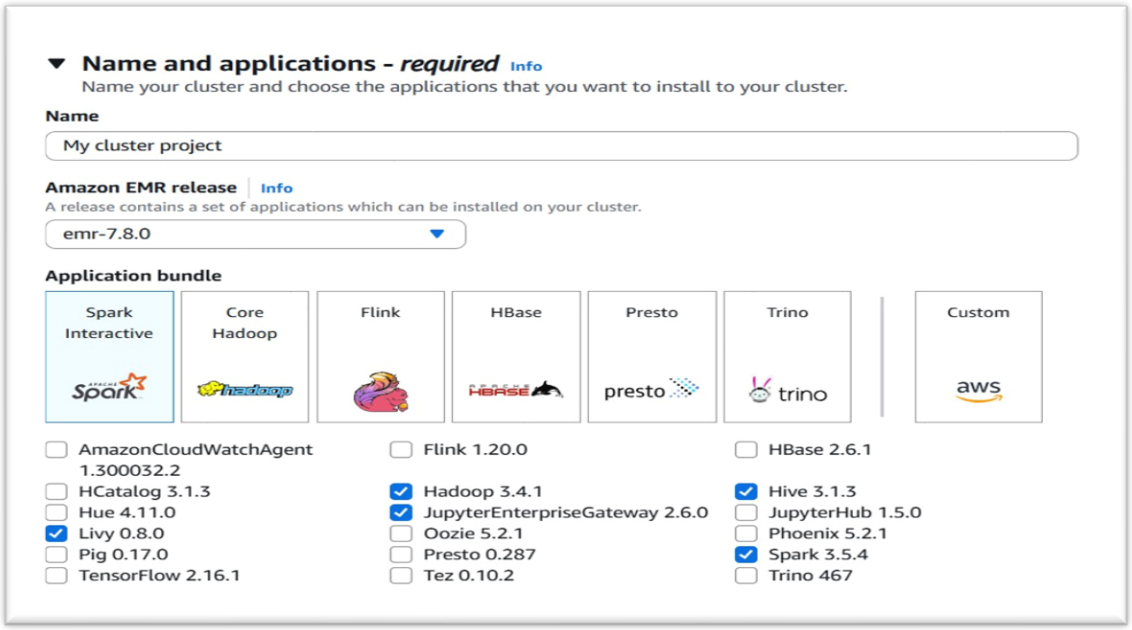
2.3 Configuring the EMR Cluster

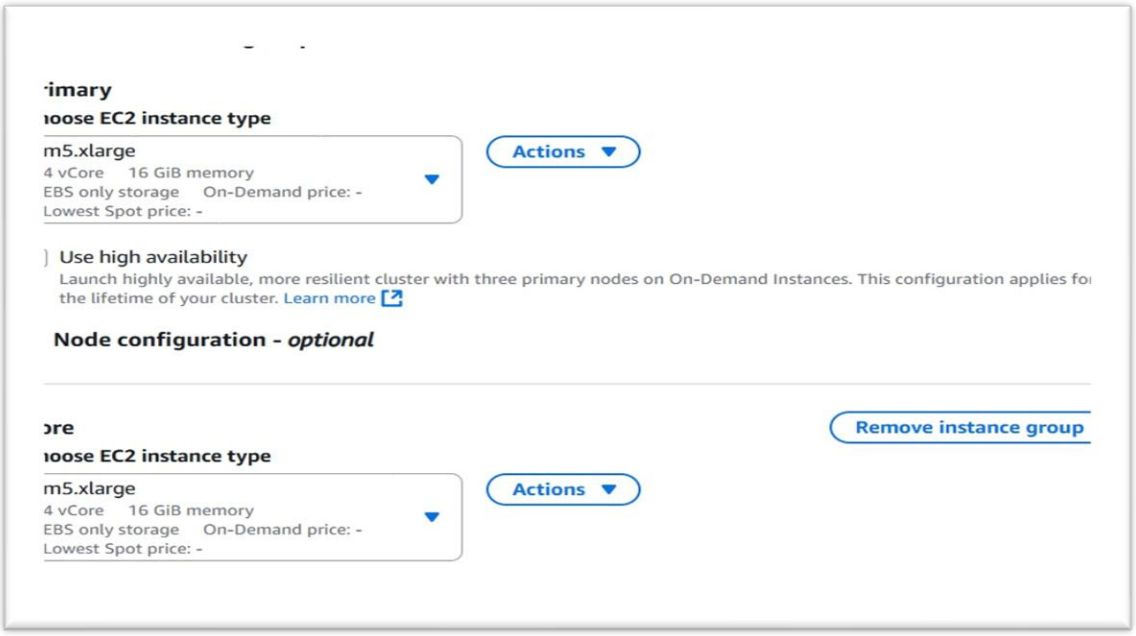
To process the 10GB word count job efficiently, an Amazon EMR cluster was configured with the following specifications:

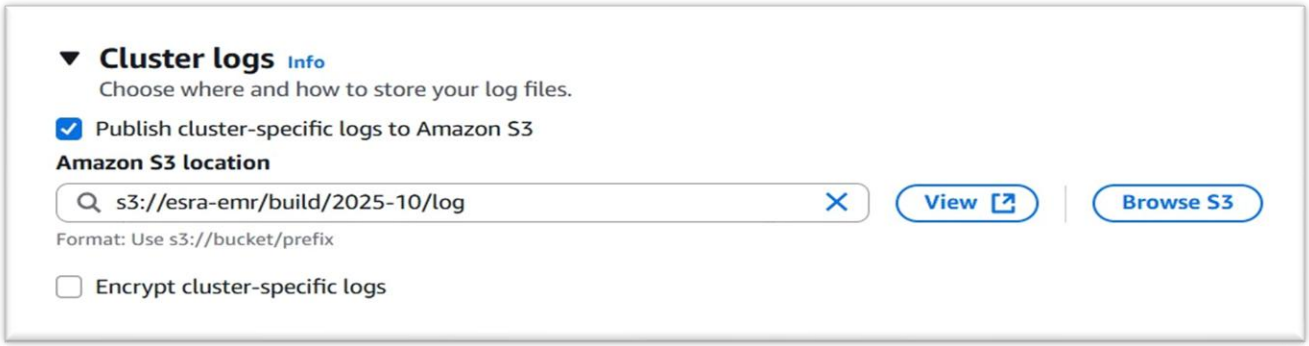
- **Cluster Type**: Temporary, configured to auto-terminate once the Spark job is completed, ensuring cost-efficiency.
- **Number of Instances:**
  - **1 Master node:** Responsible for managing the cluster and coordinating the job execution.
  - **3 Core nodes:** Handled the distributed storage (HDFS) and performed the actual computation in parallel.
  - **Total Nodes:** 4
- **Instance Type:** Each node was provisioned with m5.xlarge instances (or specify if different), providing a balance of compute, memory, and networking capacity.
- **Applications Installed:**
  - Apache Spark: Used for distributed processing of the word count job.
  - Hadoop: Provided the underlying distributed file system and YARN resource management.
- **Logging:**
  - Enabled to monitor job progress, diagnose issues, and audit execution.
  - All logs (stdout, stderr, application logs, system metrics) were stored in the S3 bucket's log/ folder for persistence and easy access after cluster termination.
- **Cluster Configuration:**

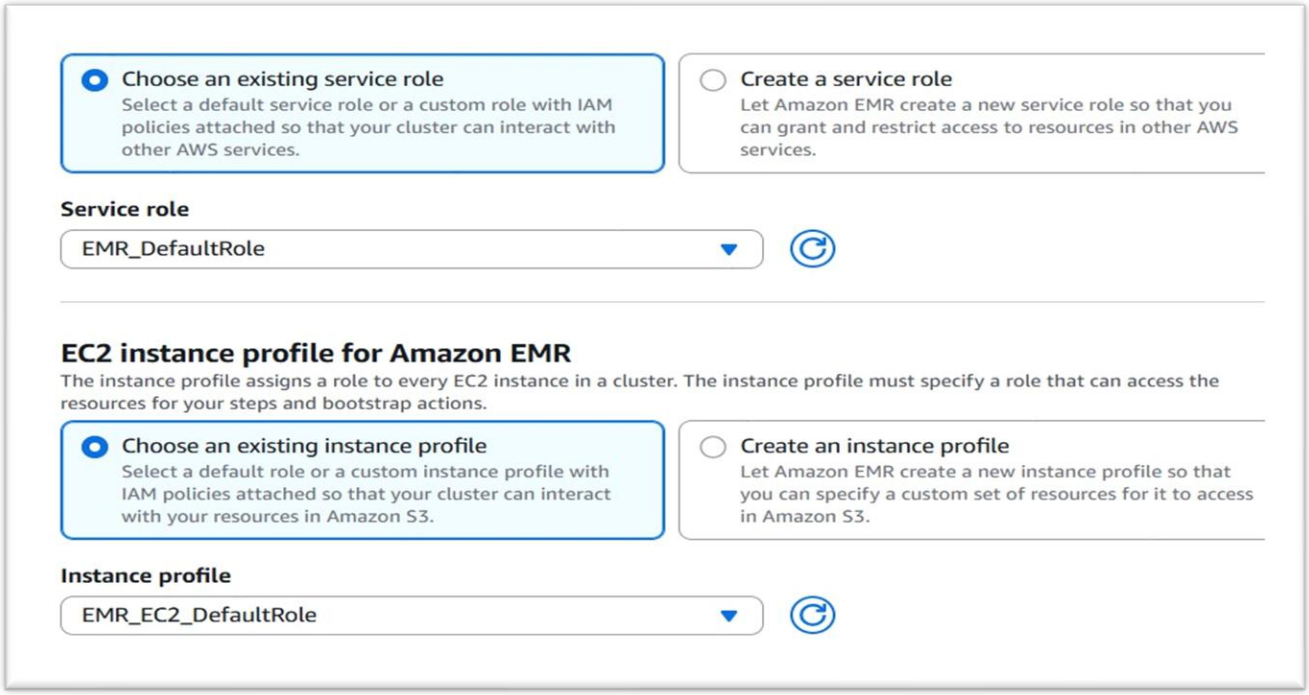
• Spark and Hadoop default settings were used with minor tuning for performance (e.g., executor memory, number of partitions, if applicable).

• The cluster was launched in the previously created project-vpc, ensuring secure networking.

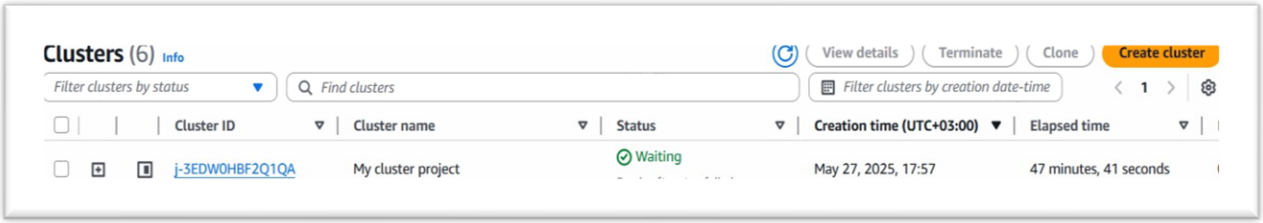


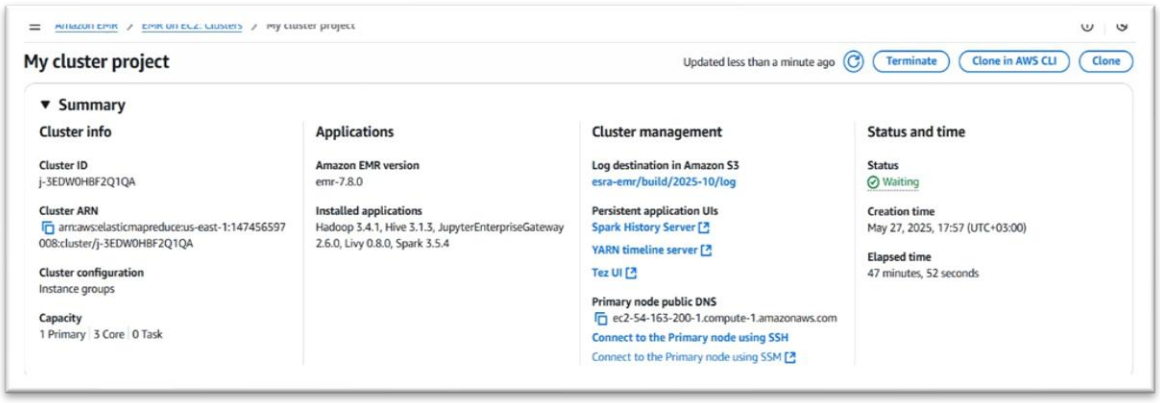


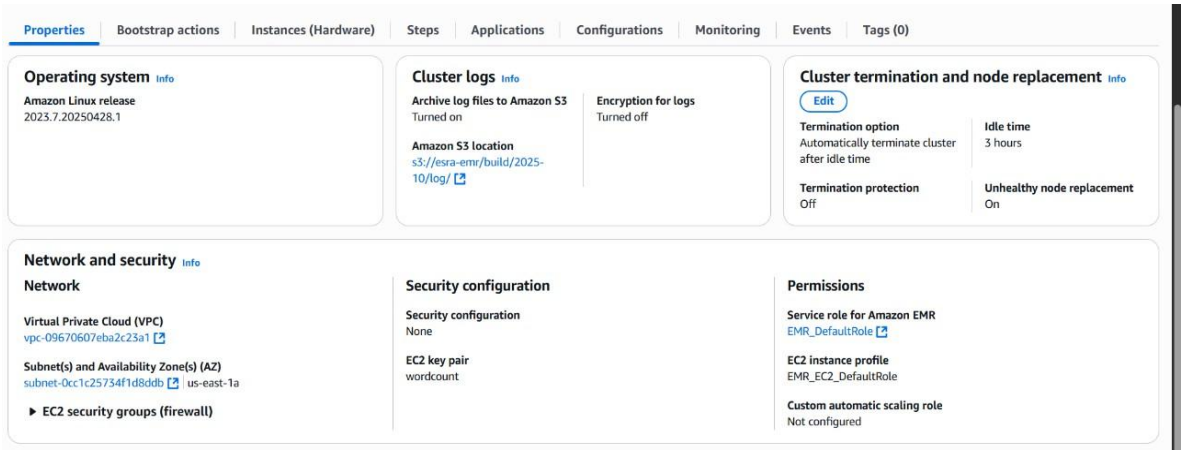




To demonstrate the EMR cluster setup process, screenshots were taken during key stages of configuration and launch. These images serve as visual documentation of the cluster setup.







2.4 Instance Groups Overview

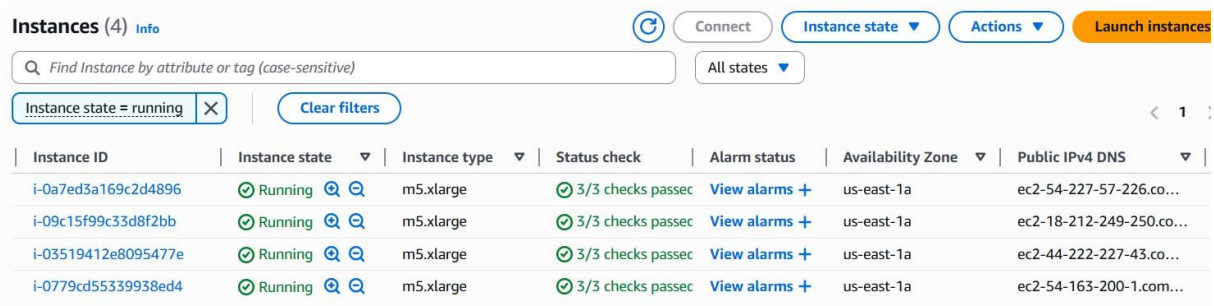
The screenshot below shows the instance groups configured for the EMR cluster:

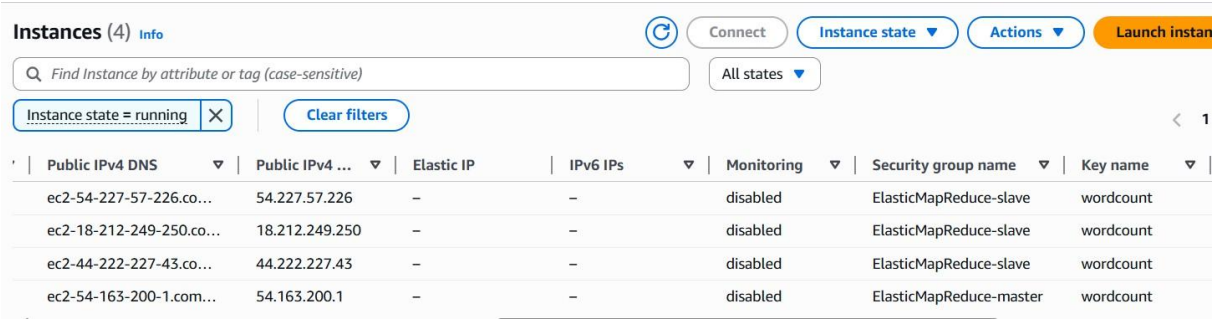
- **Master Node:**

Handles cluster management, job coordination, and resource tracking.

- **Core Nodes (3 instances):**

Responsible for processing data and storing it using HDFS. These nodes ran the actual Spark tasks during the word count job.





2.5 Security Group Configuration

A custom security group was configured for the EMR cluster to define the allowed inbound traffic.

- **SSH (Port 22)** access was enabled with the following rule:
- **Type:** SSH
- **Protocol**: TCP
- **Port Range**: 22
- **Source**: 0.0.0.0/0 (temporarily enabled for open access during development)

3.Connecting to Master Node using PuTTY with Authentication

1. Open PuTTY.
2. In the “Host Name (or IP address)” field, enter the **Master DNS** address.
3. On the left panel, navigate to **Connection > SSH > Auth**.
4. Click on **Browse** next to the “Private key file for authentication” field.
5. Select your **.ppk** private key file.
6. Click **Open** to start the SSH session.

3.1 Python Code Explanation

The core script used for the word count is shown below:

```
from pyspark import SparkContext
import re
import argparse
def normalize(line):
```

```
        line = line.lower()
        line = re.sub(r'[^a-z\s]', '', line)
        return line.strip()
def wordcount(data_source: str, output_url: str) -> None:
        sc = SparkContext(appName="WordCountMapReduce")
        try:
                lines = sc.textFile(data_source)
                normalized = lines.map(normalize).filter(lambda x: x != "")
                words = normalized.flatMap(lambda line: line.split())
                word_pairs = words.map(lambda word: (word, 1))
                word_counts = word_pairs.reduceByKey(lambda a, b: a + b)
                sorted_word_counts = word_counts.sortBy(lambda x: x[1], ascending=False)
                top10 = sorted_word_counts.take(10)
                sorted_word_counts.map(lambda x: f"{x[0]},{x[1]}").saveAsTextFile(output_url)
        for word, count in top10:
                print(f"{word}: {count}")
    finally: sc.stop()
if __name__ == "__main__":
parser = argparse.ArgumentParser()
parser.add_argument('--data_source', required=True)
parser.add_argument('--output_url', required=True)
args = parser.parse_args()
wordcount(args.data_source, args.output_url)
```

Explanation:

✓ The script normalizes each line: it converts all characters to lowercase and removes non-alphabetic characters (via the normalize function).

✓ Lines are split into words using flatMap, and each word is mapped to a (word, 1) pair.

✓ Using reduceByKey, the script aggregates word counts by summing up the occurrences of each word. ✓ The word counts are sorted in descending order by frequency using sortBy.

✓ The top 10 most frequent words are retrieved using take(10) and printed to the terminal.

✓ The complete word count result is saved to the specified output path (output_url) in the format "word,count".

✓ Functions like flatMap, reduceByKey, and sortBy utilize Spark's distributed computing capabilities, making the script efficient for large-scale text data.

✓ Finally, results are sorted in descending order and saved to the output S3 path.

✓ parser.add_argument('--data_source', required=True)

✓ parser.add_argument('--output_url', required=True)

These lines define the input text source (--data_source) and the output directory (--output_url).

3.2 Submitting the Spark Job

To execute the word count application on the EMR cluster, the Spark job was submitted using the spark-submit command. The job was configured to read the 10GB input file from S3, perform the word count transformation, and write the results back to another S3 location.

➢ spark- submit projectemr.py –data_source s3://esra-emr/build/2025 10/input/input_10GB.txt --output_url s3://esra-emr/build/2025-10/output/

4.Result

```
25/05/27 15:24:54 INFO DAGScheduler: Job 3 is finished. Cancelling potential speculative or zomb
ie tasks for this job
25/05/27 15:24:54 INFO YarnScheduler: Killing all running tasks in stage 9: Stage finished
25/05/27 15:24:54 INFO DAGScheduler: Job 3 finished: runJob at SparkHadoopWriter.scala:83, took
1.665813 s
25/05/27 15:24:54 INFO SparkHadoopWriter: Start to commit write Job job_20250527152452134599806
964600471_0015.
25/05/27 15:24:54 INFO FileOutputCommitter: File Output Committer Algorithm version is 2
25/05/27 15:24:54 INFO FileOutputCommitter: FileOutputCommitter skip cleanup _temporary folders
under output directory:false, ignore cleanup failures: true
25/05/27 15:24:54 INFO DirectFileOutputCommitter: Direct Write: ENABLED
25/05/27 15:24:54 INFO DirectFileOutputCommitter: Nothing to clean up since no temporary files w
ere written.
25/05/27 15:24:54 INFO MultipartUploadOutputStream: close closed:false s3://esra-emr/build/2025-
10/output/_SUCCESS
25/05/27 15:24:54 INFO SparkHadoopWriter: Write Job job_20250527152452134599806896460047l_0015 c
ommitted. Elapsed time: 133 ms.
the: 113487575
of: 49348051
to: 46901844
a: 42054224
in: 39221935
and: 37142850
said: 17880910
for: 17786780
that: 16731362
is: 14556402
25/05/27 15:24:54 INFO SparkContext: SparkContext is stopping with exitCode 0.
25/05/27 15:24:54 INFO SparkUI: Stopped Spark web UI at http://ip-10-0-12-203.ec2.internal:4040
25/05/27 15:24:54 INFO YarnClientSchedulerBackend: Interrupting monitor thread
25/05/27 15:24:54 INFO YarnClientSchedulerBackend: Shutting down all executors
25/05/27 15:24:54 INFO YarnSchedulerBackend$YarnDriverEndpoint: Asking each executor to shut dow
```

4.1 Output and Logs Folders in S3

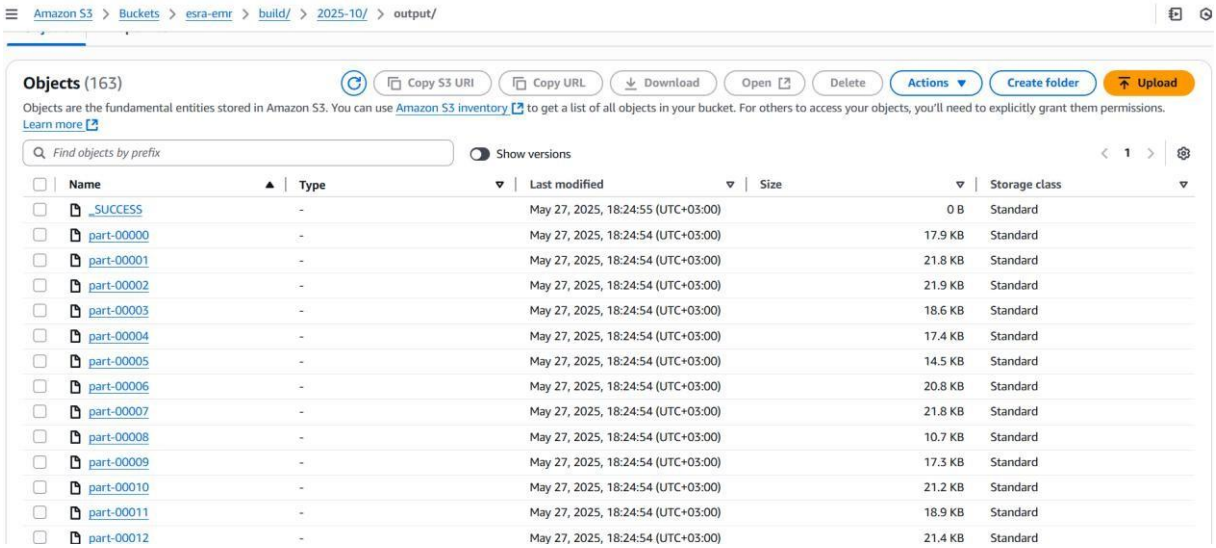
After the successful execution of the Spark word count job, the output results and execution logs were automatically saved to their respective folders in the S3 bucket.

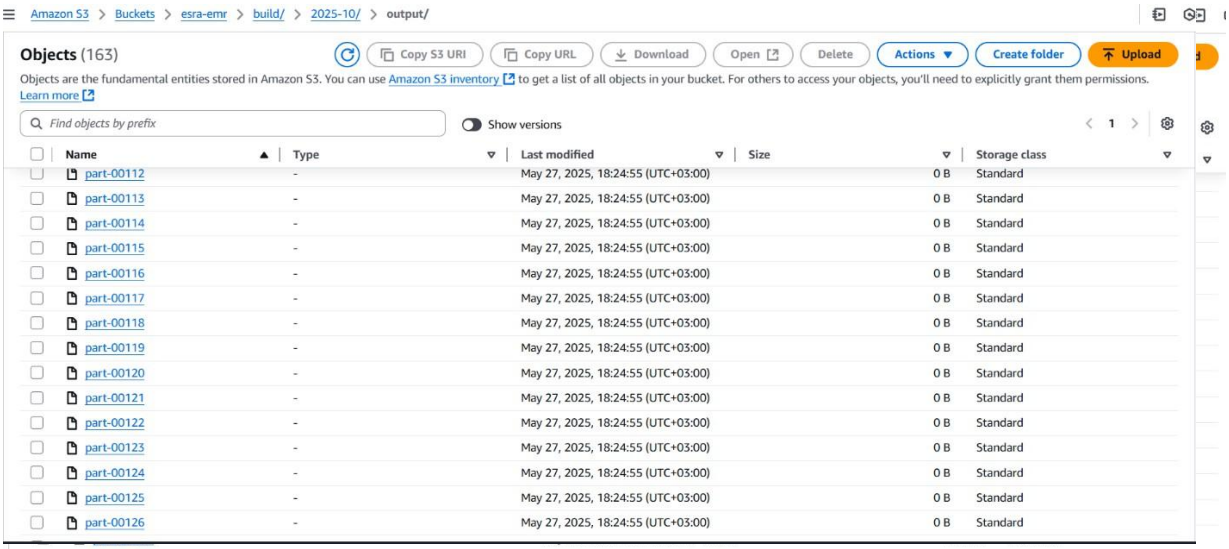
Output Folder:

• Path: s3://esra-emr/build/2025-10/output/

• This folder contains the result files generated by the Spark job.

• The output is split across one or more part files (e.g., part-00000, part-00001, etc.), each containing key-value pairs in the form (word, count).





4.2 Verifying the Output from S3 bucket

✓ After the Spark job completed, the output was stored in the specified S3 output folder. To quickly verify the results, the following command was used to preview the first 10 lines of the output:

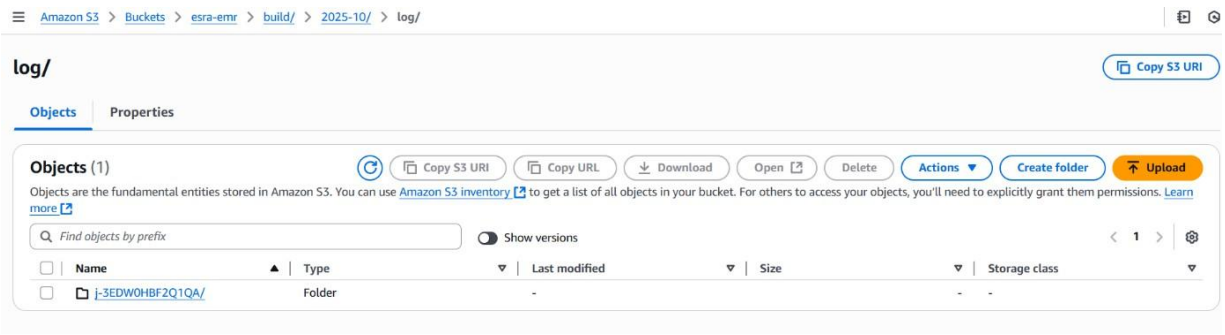
✓ aws s3 cp s3:///output/wordcount_result/part-00000 - | head 10

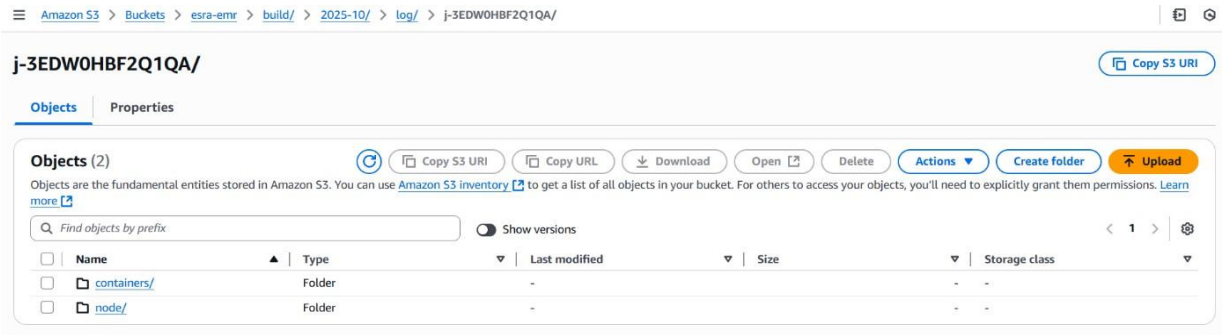
✓ This command downloads the output file from S3 and displays the first 10 lines, allowing a quick check of the word count results without downloading the entire dataset

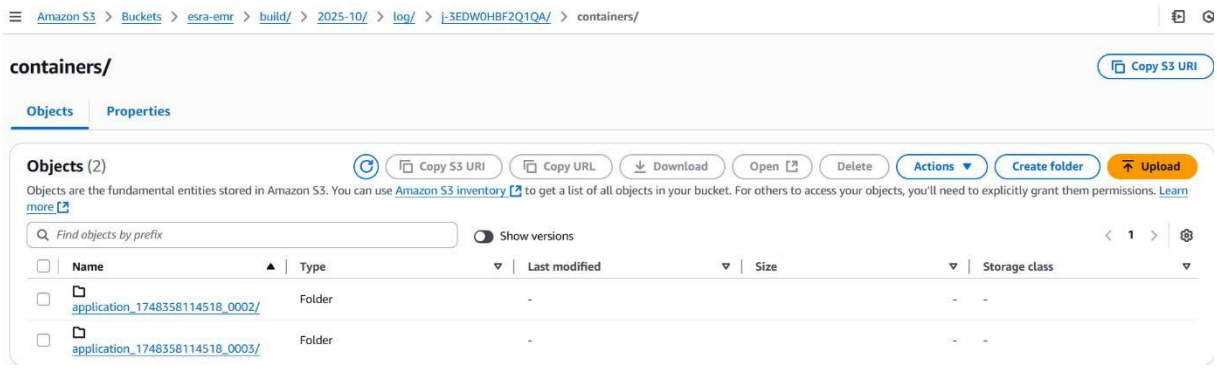
```
[hadoop@ip-10-0-12-203 ~]$ aws s3 cp s3://esra-emr/build/2025-10/output/part-00000 - | head -n 10
the,113487575
of,49348051
to,46901844
a,42054224
in,39221935
and,37142850
said,17880910
for,17786780
that,16731362
is,14556402
```

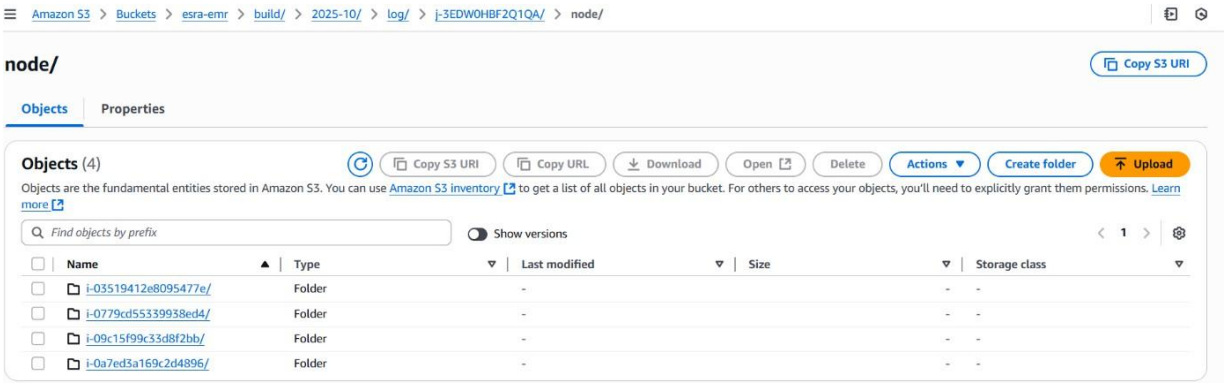
Log Folder:

- **Path:** s3://esra-emr/build/2025-10/log/
- This folder contains detailed logs for the EMR cluster and Spark application, including:
    - **stdout/stderr logs**
    - **YARN application logs**
    - **Cluster step execution logs**
    - Useful for debugging, performance analysis, and auditing






Amazon S3 > Buckets > esra-emr > build/ > 2025-10/ > log/ > j-3EDW0HBF2Q1QA/ > containers/
containers/
Copy S3 URI
Objects
Properties
Objects (2)
Copy S3 URI
Copy URL
Download
Open
Delete
Actions
Create folder
Upload
Objects are the fundamental entities stored in Amazon S3. You can use Amazon S3 inventory to get a list of all objects in your bucket. For others to access your objects, you'll need to explicitly grant them permissions. Learn more
Find objects by prefix
Show versions
Name
Type
Last modified
Size
Storage class
application_1748358114518_0002/
Folder
application_1748358114518_0003/
Folder


Amazon S3 > Buckets > esra-emr > build/ > 2025-10/ > log/ > j-3EDW0HBF2Q1QA/ > node/
node/
Copy S3 URI
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Copy S3 URI
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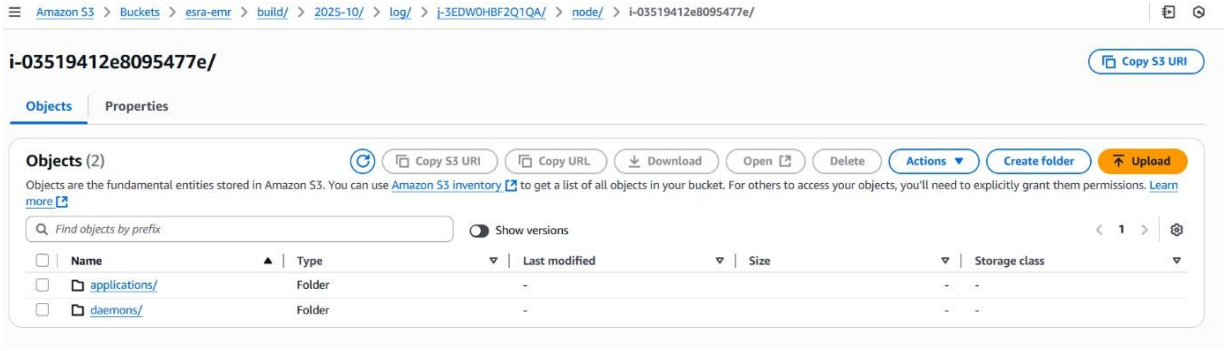
Objects are the fundamental entities stored in Amazon S3. You can use Amazon S3 inventory to get a list of all objects in your bucket. For others to access your objects, you'll need to explicitly grant them permissions. Learn more
Find objects by prefix
Show versions
Name
Type
Last modified
Size
Storage class
i-03519412e8095477e/
Folder
i-0779cd55339938ed4/
Folder
i-09c15f99c33d8f2bb/
Folder
i-0a7ed3a169c2d4896/
Folder


Amazon S3 > Buckets > esra-emr > build/ > 2025-10/ > log/ > j-3EDW0HBF2Q1QA/ > node/ > i-03519412e8095477e/
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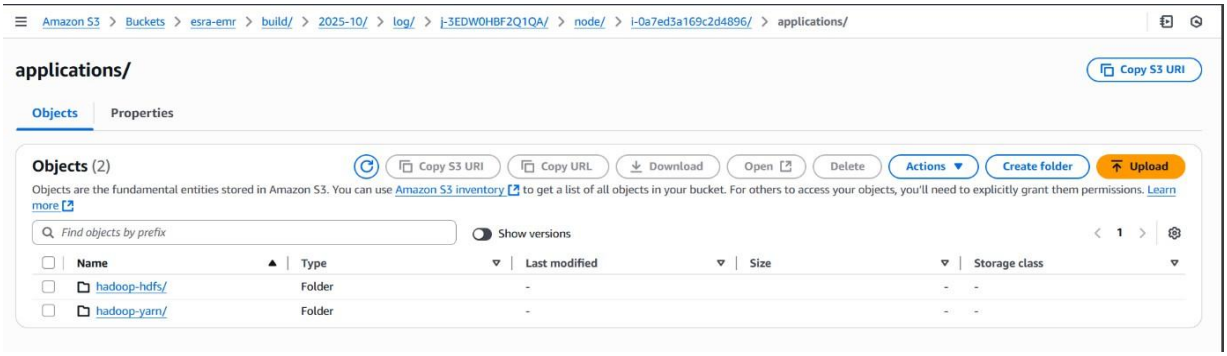
Find objects by prefix
Show versions
Name
Type
Last modified
Size
Storage class
applications/
Folder
daemons/
Folder


Amazon S3 > Buckets > esra-emr > build/ > 2025-10/ > log/ > j-3EDW0HBF2Q1QA/ > node/ > i-0a7ed3a169c2d4896/ > applications/
applications/
Copy S3 URI
Objects
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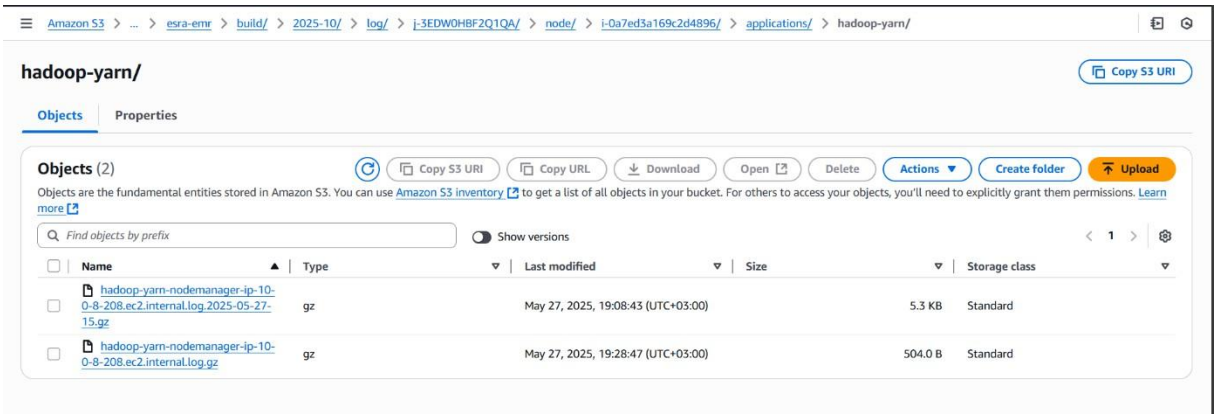
Find objects by prefix
Show versions
Name
Type
Last modified
Size
Storage class
hadoop-hdfs/
Folder
hadoop-yarn/
Folder



Verifying Node Activity

The screenshot below shows that all nodes in the EMR cluster were actively participating in the job.

```
25/05/27 15:24:54 INFO TaskSetManager: Finished task 152.0 in stage 9.0 (TID 802) in 84 ms on ip
-10-0-14-121.ec2.internal (executor 1) (154/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 153.0 in stage 9.0 (TID 803) in 74 ms on ip
-10-0-7-233.ec2.internal (executor 2) (155/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 154.0 in stage 9.0 (TID 804) in 81 ms on ip
-10-0-14-121.ec2.internal (executor 1) (156/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 155.0 in stage 9.0 (TID 805) in 77 ms on ip
-10-0-14-121.ec2.internal (executor 1) (157/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 156.0 in stage 9.0 (TID 806) in 79 ms on ip
-10-0-8-208.ec2.internal (executor 3) (158/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 157.0 in stage 9.0 (TID 807) in 77 ms on ip
-10-0-7-233.ec2.internal (executor 2) (159/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 159.0 in stage 9.0 (TID 809) in 78 ms on ip
-10-0-8-208.ec2.internal (executor 3) (160/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 158.0 in stage 9.0 (TID 808) in 79 ms on ip
-10-0-8-208.ec2.internal (executor 3) (161/162)
25/05/27 15:24:54 INFO TaskSetManager: Finished task 160.0 in stage 9.0 (TID 810) in 98 ms on ip
-10-0-7-233.ec2.internal (executor 2) (162/162)
```

5. Conclusion

In this project, a 10GB word count operation was successfully performed using Apache Spark on an AWS EMR (Elastic MapReduce) cluster. The entire process was built on a scalable and secure cloud infrastructure, making use of key AWS services such as S3, VPC, and EMR.

Key achievements include:

- Efficient processing of a large dataset using a distributed computing framework.
- Secure and isolated networking setup via a custom **VPC** and security groups.
- Centralized storage and logging using **Amazon S3**, allowing easy access to both input/output data and execution logs.
- Automated cluster lifecycle management by configuring EMR to **auto-terminate** after job completion, optimizing resource usage and cost.

This project demonstrates the power and flexibility of AWS for handling big data workloads, and the effectiveness of EMR and Spark in performing distributed data processing tasks at scale.