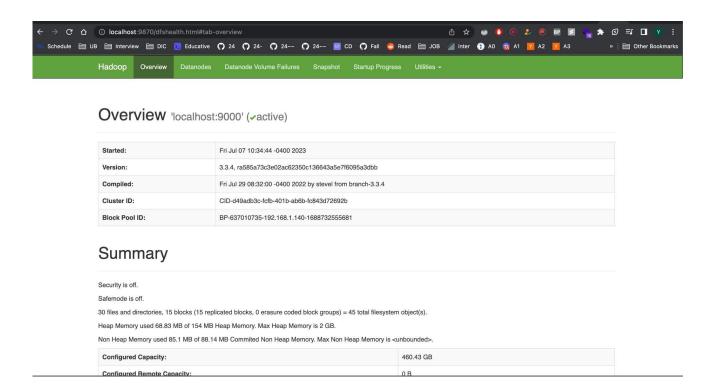
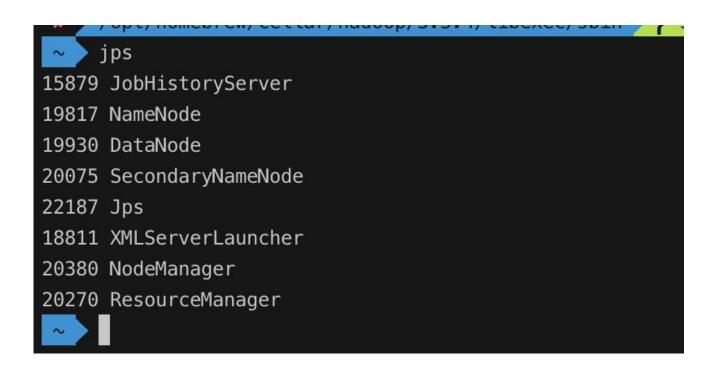
Team members : Dhiraj Gunasheela Nikitha Sadhanandha, Rakshith Venkatesh Murthy Gowda, Yashwanth Rama Krishna Reddy, Dhiraj

1.

Created local instance of Hadoop



To check Hadoop health in command prompt



The 'jps' command lists out all Java processes running on a machine, useful in Hadoop since its services are Java processes. It aids in debugging by allowing you to verify if all Hadoop services (like NameNode, DataNode, ResourceManager, etc.) are operational.

```
:
    1
       import pandas as pd
       import time
    2
    3
    4 filename = 'test.ft.txt'
    5
    6 try:
    7
           start_time = time.time()
    8
           df = pd.read_csv(filename, sep="\t", header=None)
    9
           end time = time.time()
   10
           total time = end time - start time
   11
           print(f"Time taken to load the DataFrame: {total time} seconds")
   12 except FileNotFoundError:
   13
           print(f"File {filename} not found.")
           df = None
   14
   15
   16
   17
```

Time taken to load the DataFrame: 2.4636619091033936 seconds

```
hdfs dfs -mkdir /phase-3

2023-07-07 17:35:11,714 WARN util.NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable hdfs dfs -put /Users/yashwanth/DIC/archive/test.ft.txt /phase-3

2023-07-07 17:35:17,924 WARN util.NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
```

Created dir phase-3

Loaded amazon review dataset to phase-3 using Hadoop File system put command, which does write operation

We have used textual dataset

```
time hdfs dfs -put /Users/yashwanth/DIC/archive/test.ft.txt /phase-3

2023-07-07 17:46:40,189 WARN util.NativeCodeLoader: Unable to load native-hadoop library for your platform... using hdfs dfs -put /Users/yashwanth/DIC/archive/test.ft.txt /phase-3

2.63s user 0.34s system 213% cpu 1.390 total
```

In simple terms, hdfs dfs -put command took 1.39 seconds to complete in real time which is 2x faster than loading in pandas dataframe

2.

hadoop jar

/opt/homebrew/Cellar/hadoop/3.3.4/libexec/share/hadoop/mapreduce/hadoop-mapreduce-ex amples-3.3.4.jar wordcount /phase-3/test.ft.txt /output

Performing mapreduce job on test.ft.txt dataset

```
haddony jear /opt/homethrew/Cellar/haddony/3.3.4/Libesec/share/haddony/hagreduce/haddony-magneduce-camples-3.3.4.jear variount /phase-3/test.ft.tet /output

2022-07-07 19:14:03.211 Will citate-theadulthol@Miss land in a control the control theadulthol@Miss land in control the control theadulthol@Miss land in control the control theadulthol@Miss land in control the control theadulthol theadulth
```



MapReduce Job job_1688740494980_0008

Logged in as: dr.who

Total time elapsed is 22 seconds which includes various factors mapping time, shuffling, interprocess communication, reduce tim.

Average Map Time (13 sec): This is the average time taken by the 'Map' function to process the input data chunks and output key-value pairs. This includes breaking down the text into individual words and emitting a key-value pair for each word, with the word as the key and '1' as the value.

Average Shuffle Time (8 sec): This is the average time taken to perform the 'Shuffle & Sort' phase. This phase collects the outputs from all the 'Map' tasks, sorts these key-value pairs based on the keys (the words), and groups the values (counts) for each unique key together.

ApplicationMaster						
Attempt Number	Start 7	Start Time			le	Logs
Fri Jul 07 19:14:05 EDT 2023			yashwanth.lan:8042			<u>logs</u>
Task Type		Total		Complete		
<u>Map</u>	2		2			
Reduce	1		1			
Attempt Type	Failed		Killed		Successful	
Maps	<u>0</u>	<u>1</u>		2		
Reduces	<u>0</u>	<u>0</u>		<u>1</u>		

Performing word count operation without mapreduce.

Couldn't run the code, my system couldn't handle the load and I had to restart the kernel everytime

```
[8]:
      1 from collections import Counter
      2 import re
      3
         def count words(filename):
      5
                 with open(filename, 'r') as file:
      6
      7
                     text = file.read()
                     words = re.findall(r'\b\w+\b', text)
      8
      9
                     counter = Counter(words)
     10
                     return counter
     11
             except FileNotFoundError:
                 print(f"Sorry, the file {filename} does not exist.")
     12
     13
                 return None
     14
     15
         counter = count words('test.ft.txt')
     16
     17
     18
```

MapReduce is essentially a programming paradigm that uses the power of parallel processing to handle and analyze vast datasets efficiently. It operates on the principle of breaking down a large task into smaller subtasks, which can be processed independently and parallelly

The MapReduce consists of three main stages: Map, Shuffle & Sort, and Reduce.

- Map: In this stage, the input data is divided into chunks and processed in parallel by multiple
 worker nodes. Each worker applies a given function, called the "map function," to the input
 data it receives. The map function transforms the input data into a set of intermediate
 key-value pairs.
- **Shuffle & Sort**: Once the map stage is complete, the intermediate key-value pairs generated by the workers are collected and sorted based on the keys. This sorting step is crucial to ensure that all the values associated with a particular key are grouped together.
- Reduce: In the reduce stage, another set of worker nodes takes the sorted intermediate data
 and applies a given function, called the "reduce function," to produce the final output. The
 reduce function aggregates the values associated with each key and generates a set of final
 output key-value pairs.

Throughout the MapReduce process, there are two key actors involved:

- 1. Master: The master node coordinates the overall execution of the MapReduce job. It assigns map and reduce tasks to the available worker nodes, monitors their progress, and manages the data exchange between the workers.
- 2. Workers: The worker nodes are responsible for performing the actual computation. They execute the assigned map and reduce tasks on their allocated portions of the data. Each worker processes its data independently of other workers.

In the context of word count

Map phase

- Input: The input data for the word count task is a collection of text documents.
- **Map function**: Each mapper processes a portion of the input data. The map function takes a document as input and emits key-value pairs. The map function tokenizes the document into

individual words and emits a key-value pair for each word, where the word is the key and the value is set to 1.

Shuffle and Sort Phase

- **Shuffle**: The MapReduce framework collects all the intermediate key-value pairs generated by the map function and redistributes them based on the keys.
- **Sort**: Within each group, the intermediate key-value pairs are sorted based on the keys in ascending order.

Reduce phase

• Reduce function: Each reducer takes a group of key-value pairs with the same key as input. The reduce function receives a key (a word) and a list of values (a list of 1s).

The final output of the MapReduce job is a collection of key-value pairs where the key represents a unique word, and the value represents the total count of occurrences of that word across all the input documents.

Extra Credit

```
In [7]: import pandas as pd
        from gensim.models import Word2Vec, FastText
        from sklearn.model selection import train test split
        from sklearn.linear_model import LogisticRegression
        import numpy as np
        # Read the CSV file into a DataFrame
        df = pd.read_csv('twitter_training.csv')
        # Keep the first 2000 rows and drop any rows with missing text values
        df = df[:2000].dropna(subset=['text'])
        # Tokenize the text
        df['tokenized_text'] = df['text'].apply(lambda x: x.split())
        # Train Word2Vec model
        word2vec = Word2Vec(df['tokenized_text'], min_count=2)
        # Train FastText model
        fasttext = FastText(df['tokenized_text'], min_count=2)
        # Convert each tweet's tokenized text to a vector representation
        def text_to_vector(text):
            vectors = [word2vec.wv.get_vector(w) for w in text if w in word2vec.wv.key_to_index]
           return np.mean(vectors, axis=0) if vectors else np.zeros(word2vec.vector_size)
```

```
df['text_vec'] = df['tokenized_text'].apply(text_to_vector)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(df['text_vec'].tolist(), df['sentiment'], test_size=0.2, random_state=42)

# Train a logistic regression classifier
clf = LogisticRegression().fit(X_train, y_train)

# Evaluate the classifier's accuracy on the test set
score = clf.score(X_test, y_test)
print("Accuracy:", score)
```

0.45112781954887216