

BIT2203

ADVANCED DATABASE MANAGEMENT SYSTEM

GROUP 10

james mwangi nyoro sct221-0086/2021

1. How data was compiled:

We got our data source from this link;

<https://coronavirus.jhu.edu/>

The data came in three excel sheets that included;

time_series_covid19_recovered_global.csv

time_series_covid19_deaths_global.csv

time_series_covid19_confirmed_global.csv

The data sources included data from all the countries in the world.

1	Province/Country	Lat	Long	2/1/2020	2/2/2020	2/3/2020	2/4/2020	2/5/2020	2/6/2020	2/7/2020
2	Afghanistan	33.93911	67.70995	0	0	0	0	0	0	0
3	Albania	41.1533	20.1683	0	0	0	0	0	0	0
4	Algeria	28.0339	1.6596	0	0	0	0	0	0	0
5	Andorra	42.5063	1.5218	0	0	0	0	0	0	0
6	Angola	-11.2027	17.8739	0	0	0	0	0	0	0
7	Antarctica	-71.9499	23.347	0	0	0	0	0	0	0
8	Antigua and Barbuda	17.0608	-61.7964	0	0	0	0	0	0	0
9	Argentina	-38.4161	-63.6167	0	0	0	0	0	0	0
10	Armenia	40.0691	45.0382	0	0	0	0	0	0	0
11	Australia	-35.4735	149.0124	0	0	0	0	0	0	0
12	New South Wales	-33.8688	151.2093	0	0	0	0	0	0	0
13	Northern Territory	-12.4634	130.8456	0	0	0	0	0	0	0

We created a separate excel sheets and copied Kenya covid 19 data to it from the three csv files.

1	Province/	Country/R	Lat	Long	1/22/2020	1/23/2020	1/24/2020	1/25/2020	1/26/2020	1/27/2020	1/28/2020	1/29/2020	1/30/2020	1/31/2020	2/1/2020	2/2/2020	2/3/2020	2/4/2020
2		Kenya	-0.0236	37.9062	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3		Kenya	-0.0236	37.9062	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4		Kenya	-0.0236	37.9062	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5																		

We then transposed the data cells and added new column heads the transformed the excel sheet to a csv file.

1		Infected	Recovered	Deaths						
2	Province/State									
3	Country/R	Kenya	Kenya	Kenya						
4	Lat	-0.0236	-0.0236	-0.0236						
5	Long	37.9062	37.9062	37.9062						
6	1/22/2020	0	0	0						
7	1/23/2020	0	0	0						
8	1/24/2020	0	0	0						
9	1/25/2020	0	0	0						
10	1/26/2020	0	0	0						
11	1/27/2020	0	0	0						
12	1/28/2020	0	0	0						
13	1/29/2020	0	0	0						

2. How data was ingested into Hadoop data lake:

We created a directory using the command **hdfs dfs -mkdir /kenyac19data** and inserted the prepared csv file into it using the command **hdfs dfs -put D:\filepath /kenyac19data**

```

C:\hadoop\hadoop-2.9.0\bin>hdfs dfs -mkdir /kenyac19data

C:\hadoop\hadoop-2.9.0\bin>hdfs dfs -ls /
Found 1 items
drwxr-xr-x  - hp supergroup          0 2023-12-01 21:56 /kenyac19data

C:\hadoop\hadoop-2.9.0\bin>hdfs dfs -put D:\class_units\3.1\AdvDB\TakeAwayCat\kenyac19data.csv /kenyac19data

C:\hadoop\hadoop-2.9.0\bin>hdfs dfs -ls /
Found 1 items
drwxr-xr-x  - hp supergroup          0 2023-12-01 21:58 /kenyac19data

C:\hadoop\hadoop-2.9.0\bin>hdfs dfs -ls /kenyac19data/kenyac19data.csv
-rw-r--r--  1 hp supergroup    28681 2023-12-01 21:58 /kenyac19data/kenyac19data.csv

```

<input type="checkbox"/>	Permission	Owner	Group	Size	Last Modified	Replication	Block Size	Name	
<input type="checkbox"/>	drwxr-xr-x	hp	supergroup	0 B	Dec 01 21:58	0	0 B	kenyac19data	

Show entries
 Search:

<input type="checkbox"/>	Permission	Owner	Group	Size	Last Modified	Replication	Block Size	Name	
<input type="checkbox"/>	-rw-r--r--	hp	supergroup	28.01 KB	Dec 01 21:58	1	128 MB	kenyac19data.csv	

3. How data was extracted using pyspark:

We imported the SparkSession library, created a session then loaded our file from our Hadoop data lake into pyspark by specifying the files path. We then displayed the csv file.

```
>>> from pyspark.sql import SparkSession
>>> spark = SparkSession.builder.appName("DataLakeExtract").getOrCreate()
>>> csv_files_path = "hdfs://localhost:9000/kenyac19data/kenyac19data.csv"
>>> data = spark.read.format("csv").option("header", "true").load(csv_files_path)
>>> data.show()
```

Dates	Infected	Recovered	Deaths
Province/State	null	null	null
Country/Region	Kenya	Kenya	Kenya
Lat	-0.0236	-0.0236	-0.0236
Long	37.9062	37.9062	37.9062
2/1/2020	0	0	0
2/2/2020	0	0	0
2/3/2020	0	0	0
2/4/2020	0	0	0
2/5/2020	0	0	0
2/6/2020	0	0	0
2/7/2020	0	0	0
2/8/2020	0	0	0
2/9/2020	0	0	0
3/1/2020	0	0	0
3/2/2020	0	0	0
3/3/2020	0	0	0
3/4/2020	0	0	0
3/5/2020	0	0	0
3/6/2020	0	0	0
3/7/2020	0	0	0

only showing top 20 rows

4. Pre-processing tasks/techniques used to prepare data.

We removed all the rows with null values, string values and floating point values. We remained with only integer values in the Infected, Recovered and Deaths columns which would be easier to work with.

```
>>> from pyspark.sql.functions import col
>>> data_filtered = data.filter((col("Infected") % 1 == 0) | (col("Recovered") % 1 == 0) | (col("Deaths") % 1 == 0))
>>> data_filtered.show()
```

Dates	Infected	Recovered	Deaths
2/1/2020	0	0	0
2/2/2020	0	0	0
2/3/2020	0	0	0
2/4/2020	0	0	0
2/5/2020	0	0	0
2/6/2020	0	0	0
2/7/2020	0	0	0
2/8/2020	0	0	0
2/9/2020	0	0	0
3/1/2020	0	0	0
3/2/2020	0	0	0
3/3/2020	0	0	0
3/4/2020	0	0	0
3/5/2020	0	0	0
3/6/2020	0	0	0
3/7/2020	0	0	0
3/8/2020	0	0	0
3/9/2020	0	0	0
3/10/2020	0	0	0
3/11/2020	0	0	0

only showing top 20 rows

Next we removed all the rows that had zero (0) values in all the columns. The zero values in all columns makes the rows irrelevant as we need real numbers to work with.

```
>>> df = data_filtered.filter((col("Infected") != 0) | (col("Recovered") != 0) | (col("Deaths") != 0))
>>> df.show()
```

Dates	Infected	Recovered	Deaths
3/13/2020	1	0	0
3/14/2020	1	0	0
3/15/2020	3	0	0
3/16/2020	3	0	0
3/17/2020	3	0	0
3/18/2020	3	0	0
3/19/2020	7	0	0
3/20/2020	7	0	0
3/21/2020	7	0	0
3/22/2020	15	0	0
3/23/2020	16	0	0
3/24/2020	25	0	0
3/25/2020	28	1	0
3/26/2020	31	1	1
3/27/2020	31	1	1
3/28/2020	38	1	1
3/29/2020	42	1	1
3/30/2020	50	1	1
3/31/2020	59	1	1
4/1/2020	81	3	1

only showing top 20 rows

5. Test Results and Interpretation:

We used the Mean Squared Error predictive analytics method to predict the number of deaths. The MSE we found was as 88540, that for all the infections recorded and the rate of recovery, this is the number of people that are expected to perish from the virus.

```

>>> print(df)
   Dates      Infected  Recovered  Deaths
0  3/13/2020          1          0         0
1  3/14/2020          1          0         0
2  3/15/2020          3          0         0
3  3/16/2020          3          0         0
4  3/17/2020          3          0         0
...
1087  3/5/2023      342919          0      5688
1088  3/6/2023      342919          0      5688
1089  3/7/2023      342932          0      5688
1090  3/8/2023      342937          0      5688
1091  3/9/2023      342937          0      5688

[1092 rows x 4 columns]
>>>
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.linear_model import LinearRegression
>>> from sklearn.metrics import mean_squared_error
>>> df = pd.DataFrame(df)
>>> x = df[['Infected', 'Recovered']]
>>> y = df['Deaths']
>>> x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random
_state=40)
>>> model = LinearRegression()
>>> model.fit(x_train, y_train)
>>> LinearRegression()
>>> predictions = model.predict(x_test)
>>> mse = mean_squared_error(y_test, predictions)
>>> print(f"Mean Squared Error: {mse}")
Mean Squared Error: 88540.72813249362
>>>

```

6. Validations results and interpretations:

We validated the value we got from the Mean Squared Error technique using the Root Mean Squared Error technique. The value we got was the exact root of the value we found in the MSE.

$$\sqrt{88540.73} = 297.56$$

```

>>>
>>> from sklearn.metrics import mean_squared_error
>>> rmse = mean_squared_error(y_test, predictions, squared=False)
>>> print("Root Mean Squared Error (RMSE):", rmse)
Root Mean Squared Error (RMSE): 297.5579407989201
>>>
>>>

```

7. Potential applications of the interpreted results:

- a. **Public Awareness:** Communicating anticipated death rates based on infection numbers can raise public awareness about the seriousness of the situation. This information can encourage adherence to preventive measures and vaccination, potentially reducing the spread of the virus.

- b. **Mitigation Strategies:** Knowing the potential death toll can prompt the implementation of targeted interventions in high-risk areas or among vulnerable populations, such as the elderly or those with preexisting health conditions.
- c. **Policy Making:** Predictions can inform policymakers about the potential impact of the virus, guiding decisions on lockdowns, social distancing measures, travel restrictions, and vaccination drives. It helps in creating a more targeted and effective response.

Data Visualization:

We imported the python matplotlib library to visualize the model.

```
>>> import matplotlib.pyplot as plt
>>> residuals = y_test - predictions
>>> plt.scatter(predictions, residuals)
<matplotlib.collections.PathCollection object at 0x000001E14192D250>
>>> plt.xlabel('Predicted')
Text(0.5, 0, 'Predicted')
>>> plt.ylabel('Residuals')
Text(0, 0.5, 'Residuals')
>>> plt.axhline(y=0, color='r', linestyle='--')
<matplotlib.lines.Line2D object at 0x000001E1414766D0>
>>> plt.title('Visualize Deaths Residual Plot')
Text(0.5, 1.0, 'Visualize Deaths Residual Plot')
>>> plt.show()
```

The result was;

Figure 1

