

Group Members

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Flow

Getting Data

We scoured the internet to find a good dataset that fit the following criteria:

1. Had Kenyan data
2. Had death cases
3. Had confirmed cases
4. Had recovery cases – ideally

The data we found was <https://covid19.who.int/WHO-COVID-19-global-data.csv> from World Health Organization

```
[ ] import pandas as pd

[ ] data = pd.read_csv('covid.csv')

[ ] data.head
```

	Date_reported	Country_code	Country	WHO_region	New_cases	\
0	2020-01-03	AF	Afghanistan	EMRO	0	
1	2020-01-04	AF	Afghanistan	EMRO	0	
2	2020-01-05	AF	Afghanistan	EMRO	0	
3	2020-01-06	AF	Afghanistan	EMRO	0	
4	2020-01-07	AF	Afghanistan	EMRO	0	
...	
336535	2023-11-18	ZW	Zimbabwe	AFRO	0	
336536	2023-11-19	ZW	Zimbabwe	AFRO	0	
336537	2023-11-20	ZW	Zimbabwe	AFRO	0	
336538	2023-11-21	ZW	Zimbabwe	AFRO	0	
336539	2023-11-22	ZW	Zimbabwe	AFRO	0	

	Cumulative_cases	New_deaths	Cumulative_deaths
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...
336535	265890	0	5725
336536	265890	0	5725
336537	265890	0	5725
336538	265890	0	5725
336539	265890	0	5725

```
[336540 rows x 8 columns]>
```

Pre-Processing the Data

The library used here was Pandas

The first step was to read the data

We explored the dataset

We filtered the data to include only Kenyan data

We chose the columns we would use

We added the recoveries column by subtracting deaths from cases

We filtered to remove 0s from the cases column

Lastly, we renamed the columns for easier use

```
[ ] data = data.loc[data['Country_code'] == "KE"]

[ ] features = ["Cumulative_cases", "Cumulative_deaths"]
data = data[features]
data

[ ] # Create column cumulative recoveries
data['Cumulative_recoveries'] = data['Cumulative_cases'] - data['Cumulative_deaths']
data

[ ] # Remove all rows where cumulative cases is 0
data = data.loc[data['Cumulative_cases'] != 0]
data
```

	Cumulative_cases	Cumulative_deaths	Cumulative_recoveries
154851	1	0	1
154852	1	0	1
154853	3	0	3
154854	3	0	3
154855	4	0	4
...
156195	344077	5689	338388
156196	344077	5689	338388
156197	344077	5689	338388
156198	344077	5689	338388

Model training and visualization

The library involved was scikit-learn

To be more specific LinearRegression and train_test_split

We divided the data into train_data and test_data using train_test_split

We fit the model, using the train_data

We used the model to predict the test_data

Visualizing the model's prediction alongside the test data

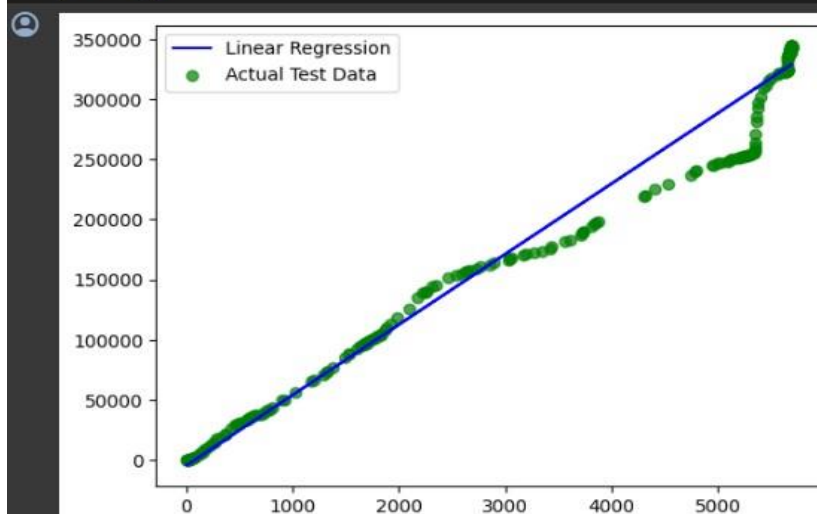
```
[ ] from sklearn.linear_model import LinearRegression
    from sklearn.model_selection import train_test_split
    from matplotlib import pyplot as plt

[ ] X_train,X_test,y_train,y_test = train_test_split(data.deaths,data.cases)

#Create linear model
model = LinearRegression()
model.fit(X_train.values.reshape(-1,1),y_train.values)

#Use model to predict test data
prediction = model.predict(X_test.values.reshape(-1,1))

plt.plot(X_test,prediction,label="Linear Regression",color='b')
plt.scatter(X_test,y_test,label="Actual Test Data",color='g',alpha=.7)
plt.legend()
plt.show()
```



Data interpretation

The model was pretty on spot roughly 80%.

We can deduce that when cases hit above 150,00 deaths sky rocketed above the prediction. This is a speculation of as cases rise the pool of infection rate also rises hence leading to more deaths

This may be due to constraints such as limited resources to combat high number of viral cases thus leading to more deaths

Data Applications

Outbreaks – For example the Ebola outbreak in West Africa

This is because the model is used to predict high population of disease cases and deaths. Thus health bodies can adequately plan on how to accommodate them

Example: Gather adequate resources, like provision of masks during Covid-19 outbreak