Analysis of COVID-19 Cases and Deaths Worldwide

Coronavirus disease or most popularly known as COVID-19 is an infectious disease caused by the SARS-CoV-2 virus. It has infected millions of people around the globe and has also resulted in a large number of deaths worldwide. A large number of vaccinations have helped bring down the total number of cases but there is still an alarming number of cases in some parts pf the world.

image.png

The dataset that I have chosen will give us an insight into the number of cases each country including total and active cases as well as the number of deaths and number of people that recovered from the disease. This dataset has been taken from the open datasets on Kaggle. In this exploratory data analysis project, I will explore this entire dataset and help analyse it using visualizations tools like Matplotlib and Seaborn.

Downloading the dataset

```
!pip install jovian opendatasets --upgrade --quiet
```

Let's begin by downloading the data, and listing the files within the dataset.

```
dataset_url = 'https://www.kaggle.com/datasets/themrityunjaypathak/covid-cases-and-deat
```

```
import opendatasets as od
od.download(dataset_url)
```

```
Please provide your Kaggle credentials to download this dataset. Learn more:
http://bit.ly/kaggle-creds
Your Kaggle username: samriddhibajpai
Your Kaggle Key: ········
Downloading covid-cases-and-deaths-worldwide.zip to ./covid-cases-and-deaths-worldwide

100%|██████████| 7.73k/7.73k [00:00<00:00, 6.11MB/s]
```

The dataset has been downloaded and extracted.

```
data_dir = './covid-cases-and-deaths-worldwide'
```

```
import os
os.listdir(data_dir)
```

```
['covid_worldwide.csv']
```

Let us save and upload our work to Jovian before continuing.

```
project_name = "Data-Analysis-Project"
```

```
!pip install jovian --upgrade -q
```

```
import jovian
```

```
jovian.commit(project=project_name)
```

```
[jovian] Updating notebook "bajpaisamriddhi6/data-analysis-project" on
https://jovian.com
[jovian] Committed successfully! https://jovian.com/bajpaisamriddhi6/data-analysis-
project
```

```
'https://jovian.com/bajpaisamriddhi6/data-analysis-project'
```

Data Preparation and Cleaning

After downloading our dataset, we will now analyse it thoroughly. We will do this by first loading the dataset using Pandas, which is a popular python library used for working in tabular data. After loading the dataset, we will explore the entire dataset i.e. number of rows and columns, missing values (if any), incorrect data and perform additional steps (if required) like creating additional columns etc. All these steps would help in making the dataset easier to read and make visualizations easier.

Loading the dataset

We begin the data cleaning process by loading the dataset. This is done using the read_csv command from Pandas. Data from the file is read and stored in a Data Frame object with _df suffix. We begin by importing Pandas as pd.

```
!pip install pandas --upgrade --quiet
```

```
import pandas as pd
```

```
covid_df = pd.read_csv('covid-cases-and-deaths-worldwide/covid_worldwide.csv')
```

```
covid_df
```

	Serial Number	Country	Total Cases	Total Deaths	Total Recovered	Active Cases	Total Test	Population
0	1	USA	104,196,861	1,132,935	101,322,779	1,741,147	1,159,832,679	334,805,269
1	2	India	44,682,784	530,740	44,150,289	1,755	915,265,788	1,406,631,776
2	3	France	39,524,311	164,233	39,264,546	95,532	271,490,188	65,584,518
3	4	Germany	37,779,833	165,711	37,398,100	216,022	122,332,384	83,883,596
4	5	Brazil	36,824,580	697,074	35,919,372	208,134	63,776,166	215,353,593

	Serial Number	Country	Total Cases	Total Deaths	Total Recovered	Active Cases	Total Test	Population
...	...	...	...	...	...	...	...	...
226	227	Diamond Princess	712	13	699	0	NaN	NaN
227	228	Vatican City	29	NaN	29	0	NaN	799
228	229	Western Sahara	10	1	9	0	NaN	626,161
229	230	MS Zaandam	9	2	7	0	NaN	NaN
230	231	Tokelau	5	NaN	NaN	5	NaN	1,378

231 rows × 8 columns

Data Cleaning

By reading this CSV file, we get this data frame with 231 rows and 8 columns. It shows the population, number of active cases, total deaths, etc. of a particular country. However, the data frame also contains some NaN values with which we will deal later.

```
covid_df = covid_df.rename(columns = {"Serial Number":"Serial_Number","Total Cases":"To
```

```
covid_df
```

	Serial_Number	Country	Total_Cases	Total_Deaths	Total_Recovered	Active_Cases	Total_Tests	Populatio
0	1	USA	104,196,861	1,132,935	101,322,779	1,741,147	1,159,832,679	334,805,26
1	2	India	44,682,784	530,740	44,150,289	1,755	915,265,788	1,406,631,77
2	3	France	39,524,311	164,233	39,264,546	95,532	271,490,188	65,584,51
3	4	Germany	37,779,833	165,711	37,398,100	216,022	122,332,384	83,883,59
4	5	Brazil	36,824,580	697,074	35,919,372	208,134	63,776,166	215,353,59
...	...	...	...	...	...	...	...	..
226	227	Diamond Princess	712	13	699	0	NaN	Na
227	228	Vatican City	29	NaN	29	0	NaN	79
228	229	Western Sahara	10	1	9	0	NaN	626,16
229	230	MS Zaandam	9	2	7	0	NaN	Na
230	231	Tokelau	5	NaN	NaN	5	NaN	1,37

231 rows × 8 columns

As seen above, I have changed the column names for some of the columns to make my analysis easier.

```
covid_df['Country'] = covid_df['Country'].str.replace('USA', 'United States of America'
```

Here, I have replaced USA with United States of America which will be helpful later on when we use Geopandas to plot our data.

After changing column names, I have removed all the commas from the values inside each column converting the values from string to integer values. This is done using the replace() command in Pandas and also the regex command. The regex command filters data according to a specified regular expression. In our case, putting regex= True implies filtering all data with commas into values without commas.

```
covid_df['Total_Cases'] = covid_df['Total_Cases'].str.replace(',','',regex=True)
```

```
covid_df['Total_Deaths'] = covid_df['Total_Deaths'].str.replace(',','',regex=True)
```

```
covid_df['Total_Recovered'] = covid_df['Total_Recovered'].str.replace(',','',regex=True
```

```
covid_df['Active_Cases'] = covid_df['Active_Cases'].str.replace(',','',regex=True)
```

```
covid_df['Total_Tests'] = covid_df['Total_Tests'].str.replace(',','',regex=True)
```

```
covid_df['Population'] = covid_df['Population'].str.replace(',','',regex=True)
```

```
covid_df
```

	Serial_Number	Country	Total_Cases	Total_Deaths	Total_Recovered	Active_Cases	Total_Tests	Population
0	1	United States of America	104196861	1132935	101322779	1741147	1159832679	334805269
1	2	India	44682784	530740	44150289	1755	915265788	1406631776
2	3	France	39524311	164233	39264546	95532	271490188	65584518
3	4	Germany	37779833	165711	37398100	216022	122332384	83883596
4	5	Brazil	36824580	697074	35919372	208134	63776166	215353593
...	...	...	...	...	...	...	...	...
226	227	Diamond Princess	712	13	699	0	NaN	NaN
227	228	Vatican City	29	NaN	29	0	NaN	799
228	229	Western Sahara	10	1	9	0	NaN	626161
229	230	MS Zaandam	9	2	7	0	NaN	NaN
230	231	Tokelau	5	NaN	NaN	5	NaN	1378

231 rows × 8 columns

To get some information about the data frame and the data type, we use the df.info command. This gives us a brief of our dataset.

```
covid_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 231 entries, 0 to 230
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Serial_Number   231 non-null    int64
 1   Country         231 non-null    object
 2   Total_Cases     231 non-null    object
 3   Total_Deaths    225 non-null    object
 4   Total_Recovered 210 non-null    object
 5   Active_Cases    212 non-null    object
 6   Total_Tests     213 non-null    object
 7   Population      228 non-null    object
dtypes: int64(1), object(7)
memory usage: 14.6+ KB
```

The above information shows us that there are 231 entries in our dataset and the data type of only one column, that is the serial number column, is in numeric form even though there are other columns that contain numeric values like Population, Total_Cases,etc. Most of the columns have the data type object, either because they contain values of different types or they contain empty values, represented as NaN.

Null Values

To make our analysis easier, we will try to eliminate these NaN values. Since we do not have accurate information about the NaN values, we will replace them by 0. Let's first begin by gathering information about the number of NaN values in total and in each column. We do this by using the isnull() and sum() commands.

```
covid_df.isnull().sum().sum()
```

```
67
```

```
covid_df.isnull().sum()
```

```
Serial_Number       0
Country             0
Total_Cases         0
Total_Deaths        6
Total_Recovered    21
Active_Cases       19
Total_Tests        18
Population          3
dtype: int64
```

The above information shows us that there are a total of 67 NaN values with Total_Recovered, Active_Cases and Total_Tests containing the maximum number of null values. Let's now eliminate these null values by substituting 0 in place of the NaN values.However an important distinction needs to be made between 0 and NaN. Both the values are different. We have substituted 0 here in place of NaN and also changed the data tye to integer to make our analysis easier and help us in reading the data properly. Null values replaced with 0 mean that the data for that particular column was not available or was missing or was faulty.

```
covid_df['Total_Deaths'] = covid_df['Total_Deaths'].fillna(0).astype(int)
covid_df['Total_Recovered'] = covid_df['Total_Recovered'].fillna(0).astype(int)
covid_df['Active_Cases'] = covid_df['Active_Cases'].fillna(0).astype(int)
covid_df['Total_Tests'] = covid_df['Total_Tests'].fillna(0).astype(int)
covid_df['Population'] = covid_df['Population'].fillna(0).astype(int)
```

```
covid_df['Total_Cases'] = covid_df['Total_Cases'].astype(int)
```

```
covid_df
```

	Serial_Number	Country	Total_Cases	Total_Deaths	Total_Recovered	Active_Cases	Total_Tests	Population
0	1	United States of America	104196861	1132935	101322779	1741147	1159832679	334805269
1	2	India	44682784	530740	44150289	1755	915265788	1406631776
2	3	France	39524311	164233	39264546	95532	271490188	65584518
3	4	Germany	37779833	165711	37398100	216022	122332384	83883596
4	5	Brazil	36824580	697074	35919372	208134	63776166	215353593
...	...	...	...	...	...	...	...	...
226	227	Diamond Princess	712	13	699	0	0	0
227	228	Vatican City	29	0	29	0	0	799
228	229	Western Sahara	10	1	9	0	0	626161
229	230	MS Zaandam	9	2	7	0	0	0
230	231	Tokelau	5	0	0	5	0	1378

231 rows × 8 columns

```
covid_df.isnull().values.any()
```

```
False
```

We have now converted all the NaN values to 0 by using the fillna command. This command helps us to fill the NaN values with a value of our choice. In our case, we have substituted the NaN values with 0. Post converting, we have also checked whether our data frame still consists of any null values using df.isnull().values.any() command which gives us a boolean answer i.e. False meaning that there are no null values in our dataset.

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "bajpaisamriddhi6/data-analysis-project" on
```

```
https://jovian.com
[jovian] Committed successfully! https://jovian.com/bajpaisamriddhi6/data-analysis-project
```

```
'https://jovian.com/bajpaisamriddhi6/data-analysis-project'
```

We have now completed with cleaning our data by handling null values and changing the data type of the values. Further, we can sort the data according to our requirements when we plot graphs using Matplotlib and Seaborn.

Exploratory Analysis and Visualization

After cleaning our dataset, we now turn to analysing and visualising our dataset using Pandas, Matplotlib and Seaborn. We can also describe our dataset by computing various statistics such as the average values, sum etc and also thriugh bar plots, countplots, pie charts and other visualization tools. Let's start by looking at our dataset again and start exploring.

Let's begin by importing `matplotlib.pyplot and seaborn` .

```
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
```

```
covid_df
```

	Serial_Number	Country	Total_Cases	Total_Deaths	Total_Recovered	Active_Cases	Total_Tests	Population
0	1	United States of America	104196861	1132935	101322779	1741147	1159832679	334805269
1	2	India	44682784	530740	44150289	1755	915265788	1406631776
2	3	France	39524311	164233	39264546	95532	271490188	65584518
3	4	Germany	37779833	165711	37398100	216022	122332384	83883596
4	5	Brazil	36824580	697074	35919372	208134	63776166	215353593
...	...	...	...	...	...	...	...	...
226	227	Diamond Princess	712	13	699	0	0	0
227	228	Vatican City	29	0	29	0	0	799
228	229	Western Sahara	10	1	9	0	0	626161
229	230	MS Zaandam	9	2	7	0	0	0
230	231	Tokelau	5	0	0	5	0	1378

231 rows × 8 columns

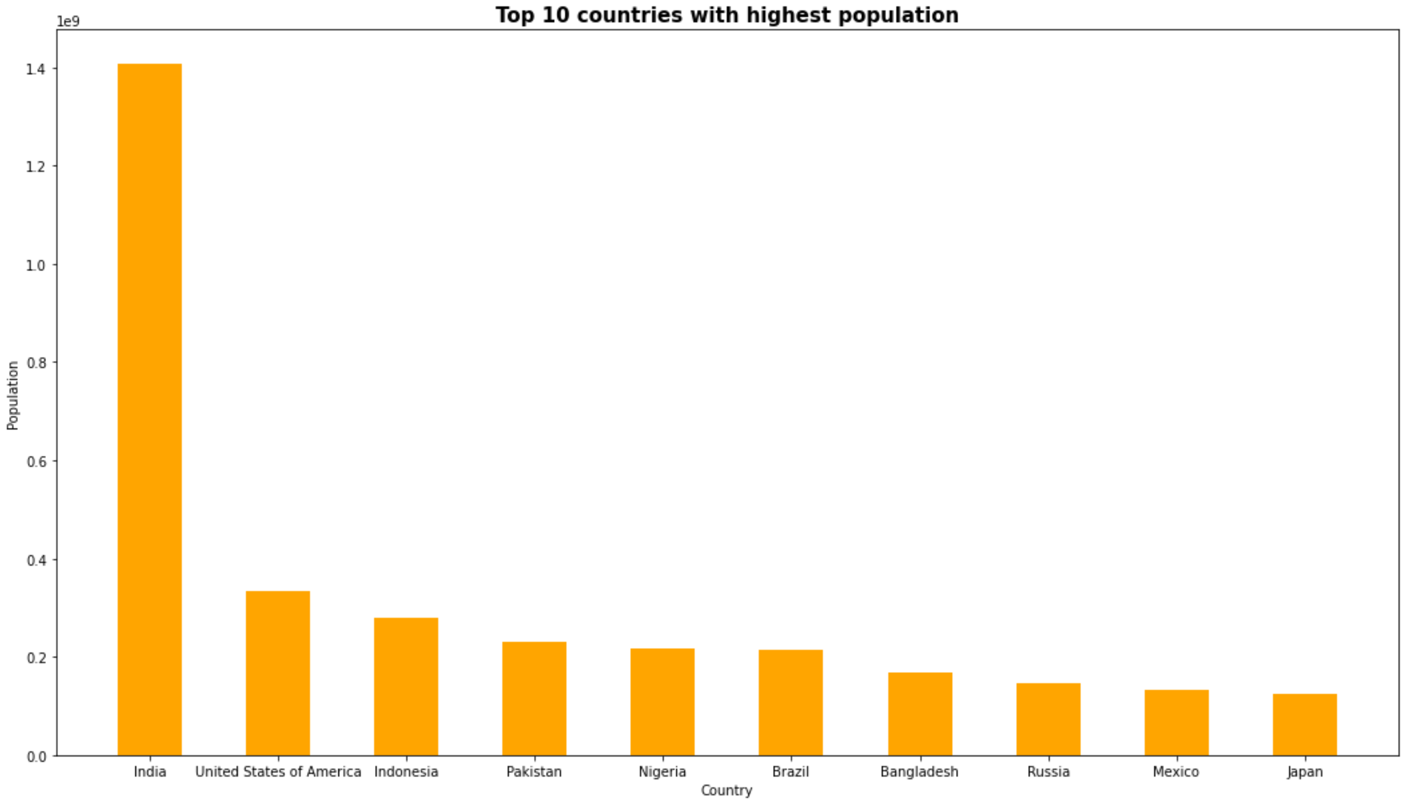
Let's begin by seeing the top 10 countries with the highest population. We will do this by plotting a bar graph. First, we will sort the values in a descending order to show the highest values and by using the head command and substituting the value of 10 in it, we get the top 10 countries with the highest values, in our case, Population

```
highest_population = covid_df[['Country','Population']].sort_values(by = 'Population',a
```

```
highest_population.head(10)
```

	Country	Population
1	India	1406631776
0	United States of America	334805269
19	Indonesia	279134505
52	Pakistan	229488994
107	Nigeria	216746934
4	Brazil	215353593
47	Bangladesh	167885689
9	Russia	145805947
18	Mexico	131562772
5	Japan	125584838

```
plt.figure(figsize = (18,10))
plt.bar(highest_population['Country'],highest_population['Population'], width = 0.5, co
plt.xlabel('Country', fontsize = 10)
plt.ylabel('Population', fontsize = 10)
plt.title('Top 10 countries with highest population', fontsize = 15, fontweight = 'bold
```



- The above bar graph shows us the top 10 countries with the highest population.
- We have created the bar plot using the plt.bar function.
- On the X axis we have the names of countries and on the Y axis we have the population values.

- Labelling of the axes has been done using the plt.xlabel and plt.ylabel functions. The size of the bar plot has been adjusted using the plt.figure command.
- Finally a title has also been added using the plt.title function.

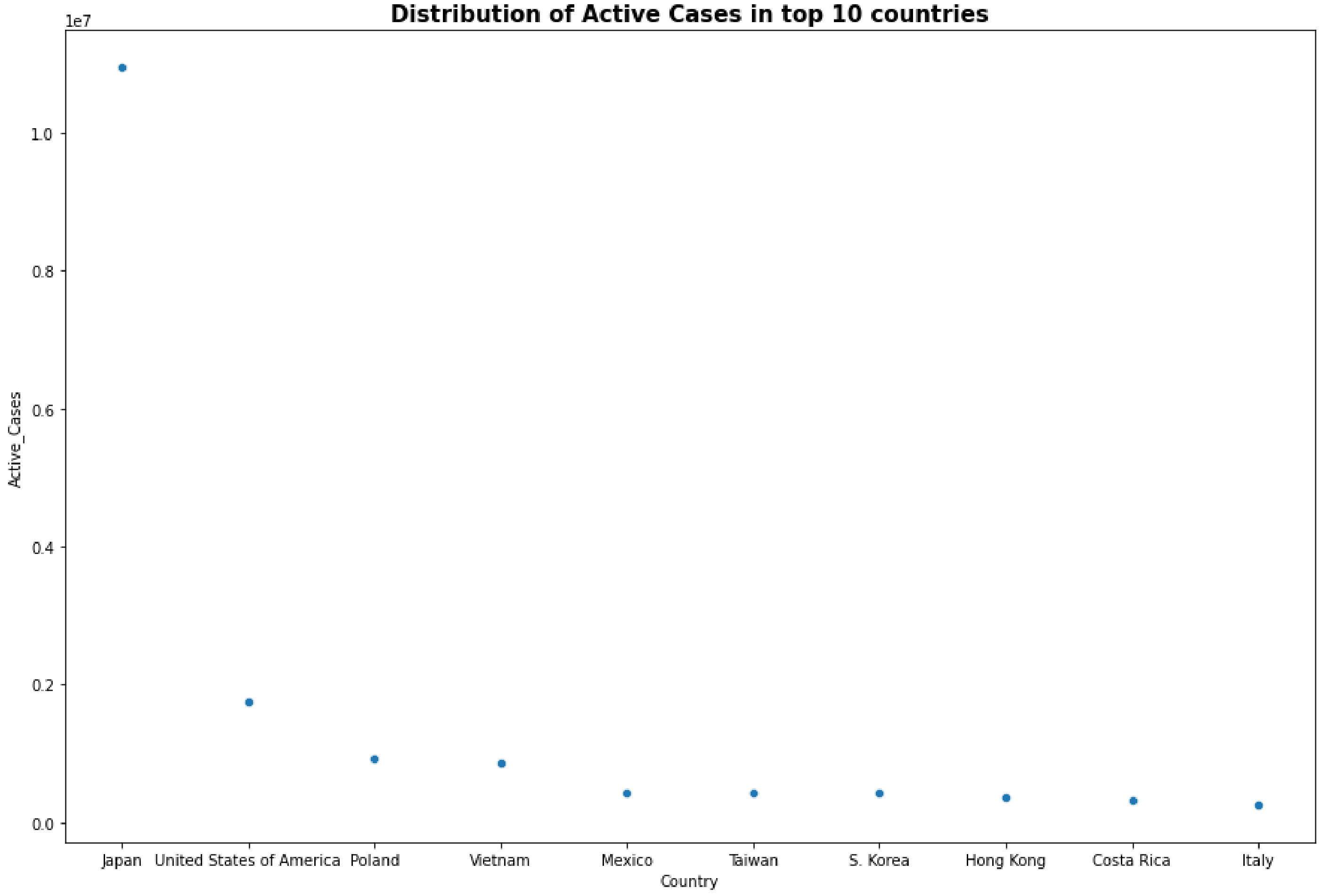
Let's try to show the distribution of active cases in the top 10 countries. We can do this by plotting a scatterplot. In a scatterplot, the values of two variables are plotted as points on a two-dimensional grid. Lets's use it for our dataset.

```
cases_active = covid_df[['Country','Active_Cases']].sort_values(by = 'Active_Cases',asc
```

```
cases_active
```

	Country	Active_Cases
5	Japan	10952618
0	United States of America	1741147
20	Poland	925549
12	Vietnam	870843
18	Mexico	429421
15	Taiwan	423489
6	S. Korea	422703
40	Hong Kong	354439
64	Costa Rica	316307
7	Italy	251970

```
plt.figure(figsize = (15,10))
sns.scatterplot(x = cases_active['Country'], y = cases_active['Active_Cases'])
plt.title('Distribution of Active Cases in top 10 countries', fontsize = 15, fontweight
```

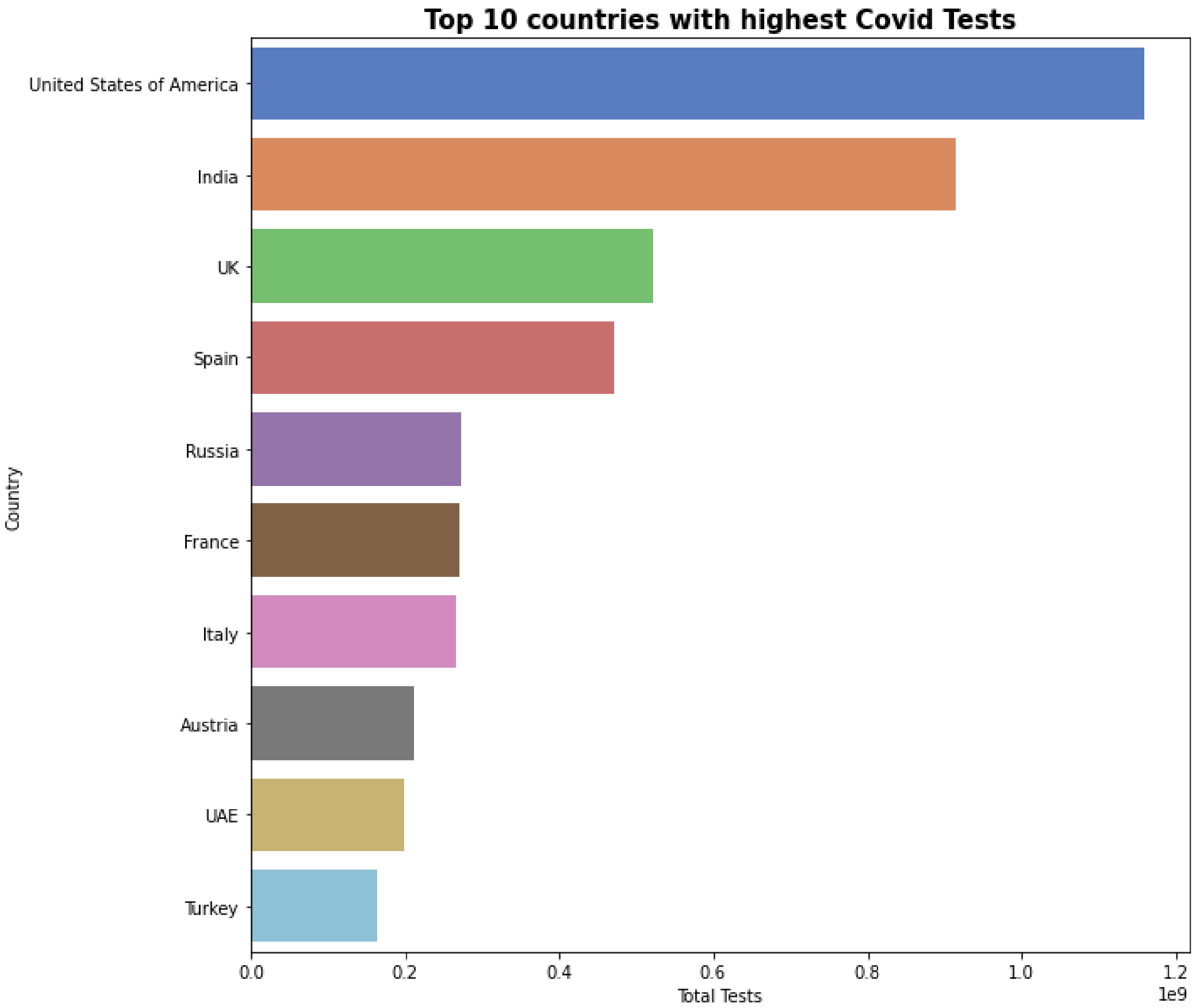


- Most of the cases in top 10 countries are closely concentrated except for Japan which has the highest number of active cases.
- We have created the scatterplot using sns.scatterplot from the Seaborn library.
- On the x axes we have the country names and on the y axis we have the number of active cases.

Let's now analyse the top 10 countries with the highest number of tests conducted. A country's performance in recovery can be easily guessed with the number of tests that are being taken. We can show the number of tests by plotting a horizontal barplot.

```
no_of_tests = covid_df[['Country','Total_Tests']].sort_values(by = 'Total_Tests', ascen
```

```
plt.figure(figsize = (10,10))
sns.barplot(x =no_of_tests['Total_Tests'],y = no_of_tests['Country'],data = no_of_tests
plt.title('Top 10 countries with highest Covid Tests', fontsize = 15, fontweight = 'bol
plt.xlabel('Total Tests')
plt.ylabel('Country');
```

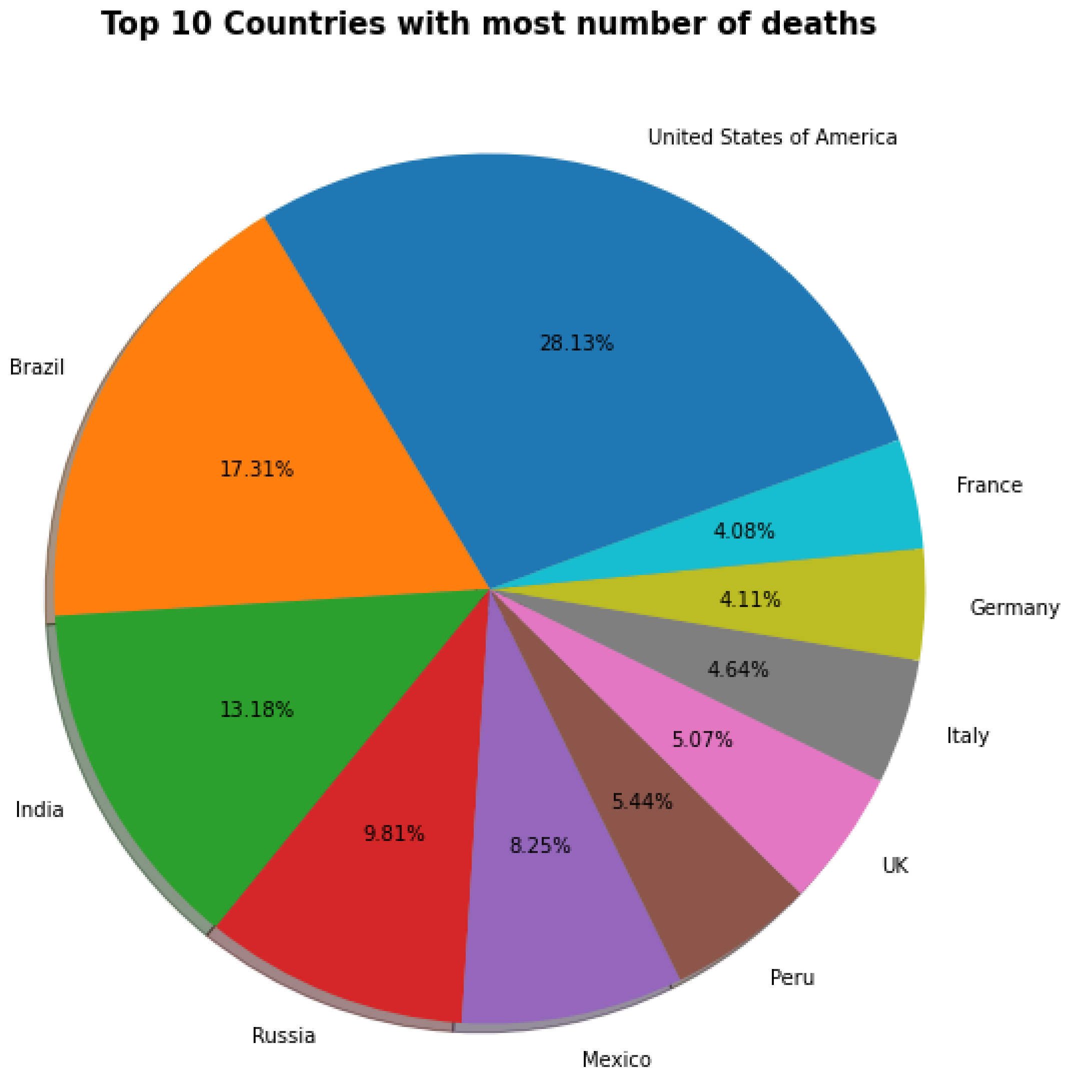


- USA and India were the top two countries with the highest number of tests done.
- We have used the sns.barplot function from the Seaborn library to plot the graph.
- Styled the plot using color palette from the seaborn library.

Let's now analyse the top 10 countries with the most number of deaths reported. We can show the number of deaths by plotting a piechart. We will sort the values of the top 10 countries and calculate the percentage of the countries with the most number of deaths.

```
most_deaths = covid_df[['Country','Total_Deaths']].sort_values(by = 'Total_Deaths', asc
```

```
plt.figure(figsize = (10,10))
plt.pie(most_deaths['Total_Deaths'], labels = most_deaths['Country'],autopct = '%0.2f%%
plt.title('Top 10 Countries with most number of deaths', fontsize = 15, fontweight = 'b
```



- USA, Brazil and India had the highest number of deaths.
- We have used the plt.pie function here to plot the piechart
- To convert the values to percentage, we have used the autopct command inside the plt.pie function.
- The autopct command enables us to display the percent value using Python string formatting.

Let's now analyse the top 10 countries with the highest number of recoveries and highest number of cases. We can do so by plotting grouped bar plots.This would help us give an insight into the recovery rate which we will calculate later on.

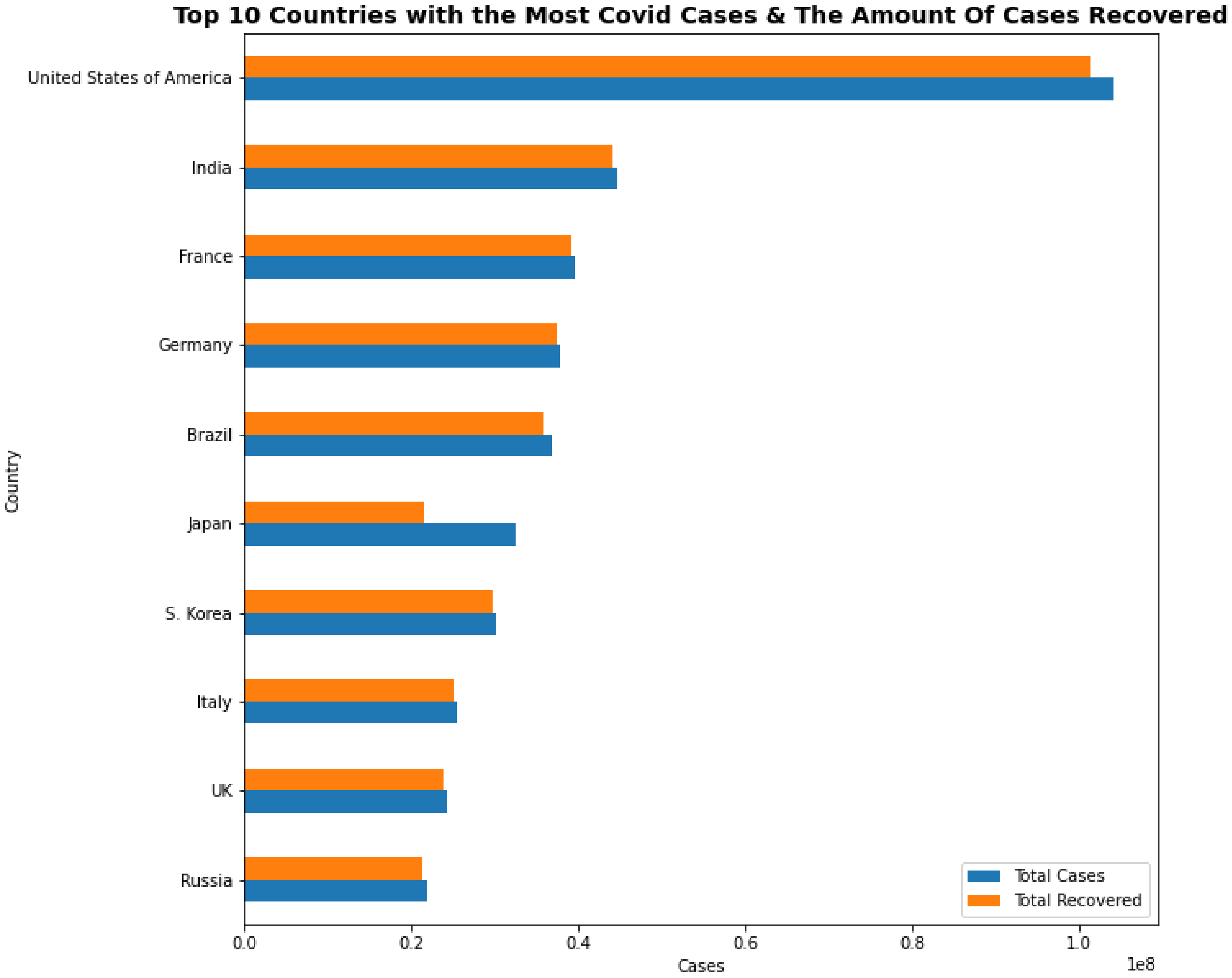
```
covid1_df = covid_df[['Country','Total_Cases','Total_Recovered']]
```

```
covid1_df[:10].sort_values('Total_Cases',ascending = False)
```

	Country	Total_Cases	Total_Recovered
0	United States of America	104196861	101322779
1	India	44682784	44150289
2	France	39524311	39264546
3	Germany	37779833	37398100

	Country	Total_Cases	Total_Recovered
4	Brazil	36824580	35919372
5	Japan	32588442	21567425
6	S. Korea	30197066	29740877
7	Italy	25453789	25014986
8	UK	24274361	24020088
9	Russia	21958696	21356008

```
dataplot = covid1_df[:10].sort_values('Total_Cases').plot(x = 'Country',kind = 'barh',f
plt.title("Top 10 Countries with the Most Covid Cases & The Amount Of Cases Recovered",
plt.xlabel("Cases")
plt.ylabel("Country")
plt.legend(['Total Cases', 'Total Recovered']);
```



- USA has the highest number of cases but at the same is recovering fast too.
- Similar is the case with India.
- We have used the plot function from the Matplotlib library to plot our barplot and then styled it according to our requirements.

Let us save and upload our work to Jovian before continuing

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "bajpaisamriddhi6/data-analysis-project" on
https://jovian.com
[jovian] Committed successfully! https://jovian.com/bajpaisamriddhi6/data-analysis-
project
```

```
'https://jovian.com/bajpaisamriddhi6/data-analysis-project'
```

Asking and Answering Questions

After analysing some of the columns of our dataset and getting an insight of it, we now move to answering certain questions related to our dataset which are of relevance. This would help us in further analysis and exploration and give us some helpful insights, things which we might not even think about.So let's begin!

Q1: What is the recovery rate of the top 10 countries with the highest number of total cases? (in percentage)

While exploring our dataset, we had created a variable named covid1_df which included the country, total cases and total recovered columns of our dataset. To get the recovery rate, we will first get the top 10 values of these columns and then divide the number of total recovered by the number of total cases. On multiplying this with 100, we get the recovery rate or the recovery percentage of the top 10 countries.

```
covid2_df = covid1_df.head(10)
covid2_df
```

	Country	Total_Cases	Total_Recovered
0	United States of America	104196861	101322779
1	India	44682784	44150289
2	France	39524311	39264546
3	Germany	37779833	37398100
4	Brazil	36824580	35919372
5	Japan	32588442	21567425
6	S. Korea	30197066	29740877
7	Italy	25453789	25014986
8	UK	24274361	24020088
9	Russia	21958696	21356008

```
covid2_df['recovery_rate'] = (covid_df['Total_Recovered']/covid_df['Total_Cases'])*100
covid2_df['recovery_rate']
```

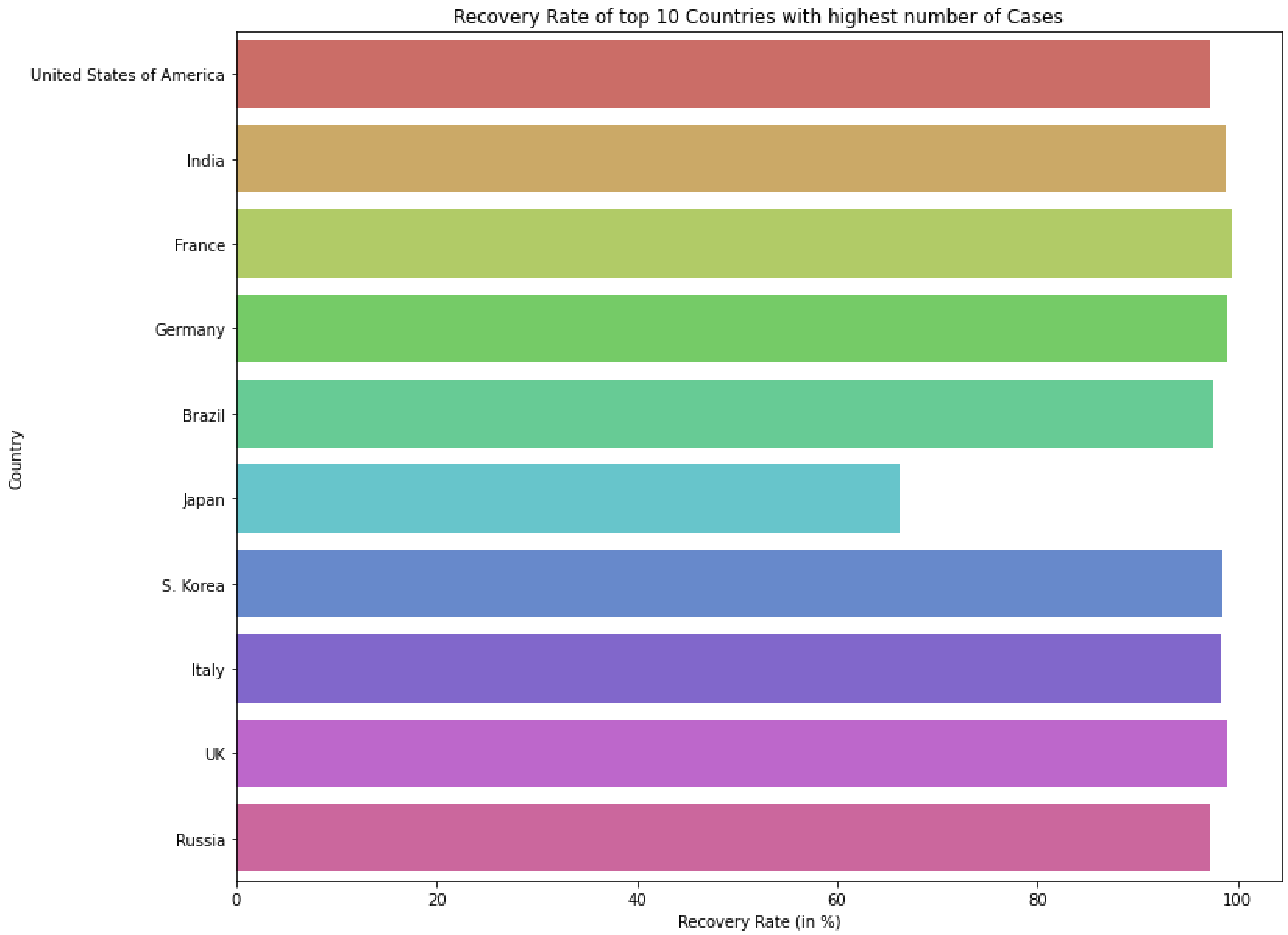
```
/tmp/ipykernel_37/1160059470.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  covid2_df['recovery_rate'] = (covid_df['Total_Recovered']/covid_df['Total_Cases'])*100
```

```
0    97.241681
1    98.808277
2    99.342772
3    98.989585
4    97.541838
5    66.181209
6    98.489294
7    98.276080
8    98.952504
9    97.255356
Name: recovery_rate, dtype: float64
```

- Analysing the data shows us that France is recovering the fastest.
- The other countries are following closely and are recovering at a similar pace.

```
plt.figure(figsize = (12,10))
sns.barplot(x = 'recovery_rate', y ='Country',data = covid2_df, color = 'yellow', palet
plt.title('Recovery Rate of top 10 Countries with highest number of Cases')
plt.xlabel('Recovery Rate (in %)')
plt.ylabel('Country');
```



- The above barplot shows us the recovery rate of the top 10 countries with the highest number of cases.
- We can infer from it that France is recovering faster as compared to other countries with an almost full recovery rate.
- We have created the barplot using sns.barplot function from the Seaborn library and styled it as required.

Q2: In which continent are the maximum number of total cases concentrated?

To understand the distribution of total cases in each country, we can use the plot function and to further understand how the cases are distributed in each continent, we can use a world map. To do this, we will first import the Geopandas library of Python which is a great tool for data visualization. GeoPandas is an open source project to make working with geospatial data in python easier. GeoPandas extends the datatypes used by pandas to allow spatial operations on geometric types.

```
!pip install geopandas
```

```
Collecting geopandas
  Downloading geopandas-0.12.2-py3-none-any.whl (1.1 MB)
     |████████████████████████████████| 1.1 MB 7.3 MB/s
Requirement already satisfied: packaging in /opt/conda/lib/python3.9/site-packages
(from geopandas) (21.2)
Collecting shapely>=1.7
  Downloading shapely-2.0.1-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(2.3 MB)
```

```
     |████████████████████████████████| 2.3 MB 68.7 MB/s
Collecting pyproj>=2.6.1.post1
  Downloading pyproj-3.5.0-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(7.8 MB)
     |████████████████████████████████| 7.8 MB 67.9 MB/s
Requirement already satisfied: pandas>=1.0.0 in /opt/conda/lib/python3.9/site-packages
(from geopandas) (2.0.0)
Collecting fiona>=1.8
  Downloading Fiona-1.9.2-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(16.1 MB)
     |████████████████████████████████| 16.1 MB 68.6 MB/s
Requirement already satisfied: click~=8.0 in /opt/conda/lib/python3.9/site-packages
(from fiona>=1.8->geopandas) (8.0.3)
Collecting click-plugins>=1.0
  Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
Requirement already satisfied: attrs>=19.2.0 in /opt/conda/lib/python3.9/site-packages
(from fiona>=1.8->geopandas) (21.2.0)
Collecting cligj>=0.5
  Downloading cligj-0.7.2-py3-none-any.whl (7.1 kB)
Requirement already satisfied: certifi in /opt/conda/lib/python3.9/site-packages (from
fiona>=1.8->geopandas) (2021.10.8)
Collecting munch>=2.3.2
  Downloading munch-2.5.0-py2.py3-none-any.whl (10 kB)
Requirement already satisfied: importlib-metadata in /opt/conda/lib/python3.9/site-
packages (from fiona>=1.8->geopandas) (4.8.2)
Requirement already satisfied: numpy>=1.20.3 in /opt/conda/lib/python3.9/site-packages
(from pandas>=1.0.0->geopandas) (1.20.3)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.9/site-packages
(from pandas>=1.0.0->geopandas) (2021.3)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.9/site-packages
(from pandas>=1.0.0->geopandas) (2023.3)
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/conda/lib/python3.9/site-
packages (from pandas>=1.0.0->geopandas) (2.8.2)
Requirement already satisfied: pyparsing<3,>=2.0.2 in /opt/conda/lib/python3.9/site-
packages (from packaging->geopandas) (2.4.7)
Requirement already satisfied: six in /opt/conda/lib/python3.9/site-packages (from
munch>=2.3.2->fiona>=1.8->geopandas) (1.16.0)
Requirement already satisfied: zipp>=0.5 in /opt/conda/lib/python3.9/site-packages
(from importlib-metadata->fiona>=1.8->geopandas) (3.6.0)
Installing collected packages: munch, cligj, click-plugins, shapely, pyproj, fiona,
geopandas
Successfully installed click-plugins-1.1.1 cligj-0.7.2 fiona-1.9.2 geopandas-0.12.2
munch-2.5.0 pyproj-3.5.0 shapely-2.0.1
```

```python
import geopandas as gpd
```

```python
world_map = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
world_map
```

	pop_est	continent	name	iso_a3	gdp_md_est	geometry
0	889953.0	Oceania	Fiji	FJI	5496	MULTIPOLYGON (((180.00000 -16.06713, 180.00000...
1	58005463.0	Africa	Tanzania	TZA	63177	POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...
2	603253.0	Africa	W. Sahara	ESH	907	POLYGON ((-8.66559 27.65643, -8.66512 27.58948...
3	37589262.0	North America	Canada	CAN	1736425	MULTIPOLYGON (((-122.84000 49.00000, -122.9742...
4	328239523.0	North America	United States of America	USA	21433226	MULTIPOLYGON (((-122.84000 49.00000, -120.0000...
...	...	...	...	...	...	...
172	6944975.0	Europe	Serbia	SRB	51475	POLYGON ((18.82982 45.90887, 18.82984 45.90888...
173	622137.0	Europe	Montenegro	MNE	5542	POLYGON ((20.07070 42.58863, 19.80161 42.50009...
174	1794248.0	Europe	Kosovo	-99	7926	POLYGON ((20.59025 41.85541, 20.52295 42.21787...
175	1394973.0	North America	Trinidad and Tobago	TTO	24269	POLYGON ((-61.68000 10.76000, -61.10500 10.890...
176	11062113.0	Africa	S. Sudan	SSD	11998	POLYGON ((30.83385 3.50917, 29.95350 4.17370, ...

177 rows × 6 columns

```
!pip install pycountry
```

```
Collecting pycountry
  Downloading pycountry-22.3.5.tar.gz (10.1 MB)
     |████████████████████████████████| 10.1 MB 6.1 MB/s
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
Requirement already satisfied: setuptools in /opt/conda/lib/python3.9/site-packages (fr
pycountry) (58.5.3)
Building wheels for collected packages: pycountry
  Building wheel for pycountry (pyproject.toml) ... done
  Created wheel for pycountry: filename=pycountry-22.3.5-py2.py3-none-any.whl
size=10681832 sha256=82b3d0c72e46fb4186a347c367b9f088296ba8d6fe225f45cce5f7f477cea5be
  Stored in directory:
/home/jovyan/.cache/pip/wheels/47/15/92/e6dc85fcb0686c82e1edbcfdf80cfe4808c058813fed0baa
Successfully built pycountry
```

```
Installing collected packages: pycountry
Successfully installed pycountry-22.3.5
```

```
import pycountry
```

```
def alpha3code (column):
    CODE=[]
    for Country in column:
        try :
            code = pycountry.countries.get(name = Country).alpha_3
            CODE.append(code)
        except :
            CODE.append('None')
    return CODE
```

```
covid_df['CODE'] = alpha3code(covid_df.Country)
covid_df
```

	Serial_Number	Country	Total_Cases	Total_Deaths	Total_Recovered	Active_Cases	Total_Tests	Population
0	1	United States of America	104196861	1132935	101322779	1741147	1159832679	334805269
1	2	India	44682784	530740	44150289	1755	915265788	1406631776
2	3	France	39524311	164233	39264546	95532	271490188	65584518
3	4	Germany	37779833	165711	37398100	216022	122332384	83883596
4	5	Brazil	36824580	697074	35919372	208134	63776166	215353593
...	...	...	...	...	...	...	...	...
226	227	Diamond Princess	712	13	699	0	0	0
227	228	Vatican City	29	0	29	0	0	799
228	229	Western Sahara	10	1	9	0	0	626161
229	230	MS Zaandam	9	2	7	0	0	0
230	231	Tokelau	5	0	0	5	0	1378

231 rows × 9 columns

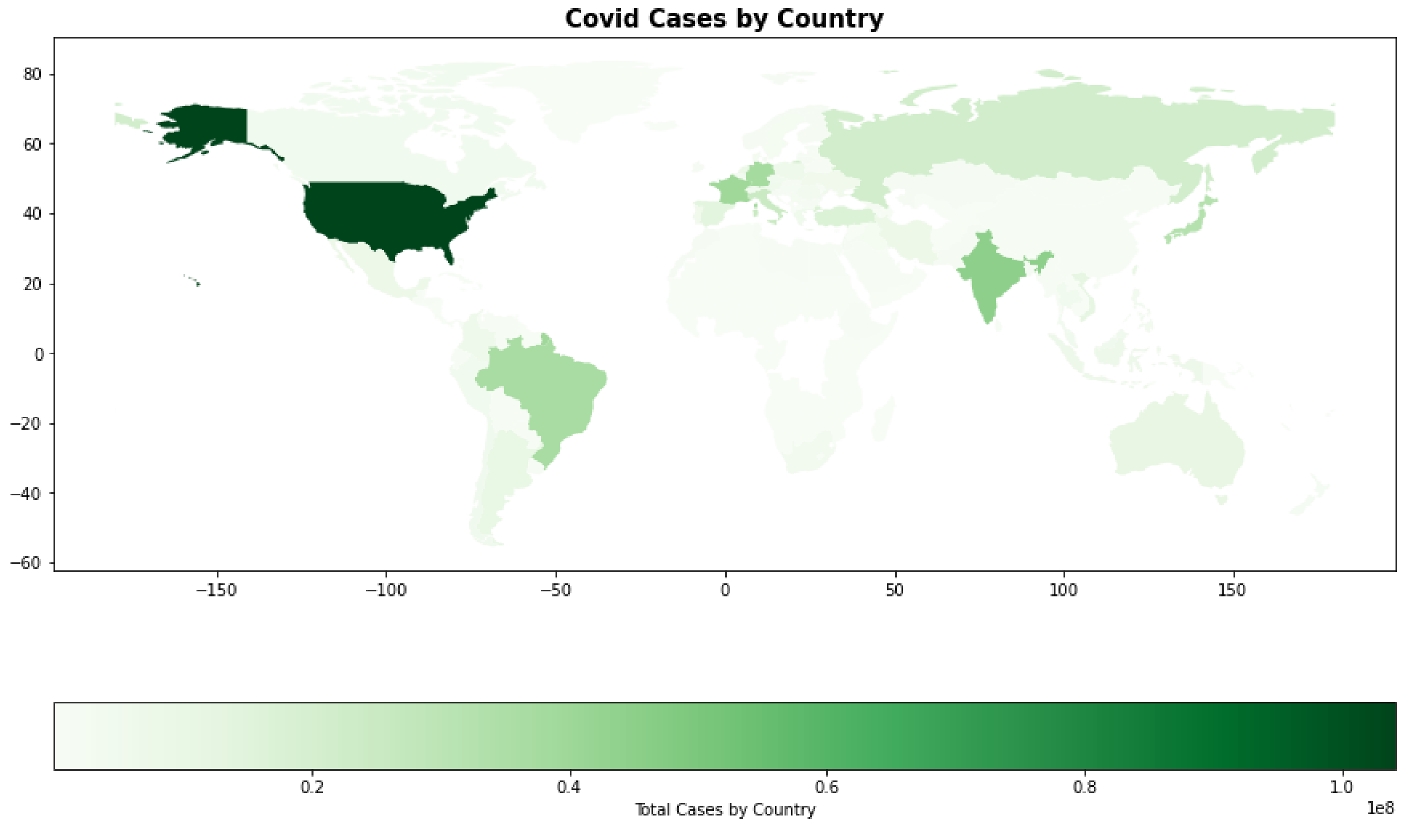
```
from geopandas import GeoDataFrame
```

```
covid_data_merge = covid_df.merge(world_map, left_on = 'Country', right_on = 'name')
covid_data_merged = GeoDataFrame(covid_data_merge)
```

- To show the distribution, we first started off by installing and importing geopandas. Geopandas makes reading geospatial data easier.

- From the geopandas dataset we have taken 'naturalearth_lowres' which is a base map provided with geopandas.
- This gives us the names of countries, continents to which they belong, estimated populations, country codes, etc. After this, we have installed and imported pycountry, which provides the ISO databases for the standards: languages, countries, deleted countries, subdivision of countries, currencies and scripts.
- We have then created a new column, called CODE by defining a new function alpha3code and appending the country name in CODE.
- We have then imported the GeoDataFrame and merged the world data with our covid dataset.

```
fig, ax = plt.subplots(figsize = (15,10))
ax.set_title('Covid Cases by Country', fontsize = 15, fontweight = 'bold')
covid_data_merged.plot(column = 'Total_Cases', legend = True, cmap = 'Greens', ax=ax, l
plt.show()
```



- We have plotted the merged dataset using the plot function.
- The plot function styles the map through setting the column name, legend and color of the map.
- The result shows us that most of the cases are concentrated in North America followed by Asia and South America.

Q3: What is the case fatality rate (CFR) in countries with very large number of tests?

Let's find out the CFR of the top 10 countries where the number of tests were higher even than the population of the country. This would give us an insight into how the country is dealing with the pandemic. Let's first find out the countries with the number of tests greater than the population.

```
covid3_df = covid_df[covid_df['Total_Tests']> covid_df['Population']]
covid3_df
```

	Serial_Number	Country	Total_Cases	Total_Deaths	Total_Recovered	Active_Cases	Total_Tests	Population
0	1	United States of America	104196861	1132935	101322779	1741147	1159832679	334805269
2	3	France	39524311	164233	39264546	95532	271490188	65584518
3	4	Germany	37779833	165711	37398100	216022	122332384	83883596
7	8	Italy	25453789	186833	25014986	251970	265478247	60262770
8	9	UK	24274361	204171	24020088	50102	522526476	68497907
...	...	...	...	...	...	...	...	...
217	218	Anguilla	3904	12	3879	13	51382	15230
219	220	Saint Pierre Miquelon	3452	2	2449	1001	25400	5759
220	221	Wallis and Futuna	3427	7	438	2982	20508	10982
223	224	Falkland Islands	1930	0	1930	0	8632	3539
224	225	Montserrat	1403	8	1376	19	17762	4965

104 rows × 9 columns

```
covid3_df.head(10)
```

	Serial_Number	Country	Total_Cases	Total_Deaths	Total_Recovered	Active_Cases	Total_Tests	Population	CO
0	1	United States of America	104196861	1132935	101322779	1741147	1159832679	334805269	Nc
2	3	France	39524311	164233	39264546	95532	271490188	65584518	F
3	4	Germany	37779833	165711	37398100	216022	122332384	83883596	D
7	8	Italy	25453789	186833	25014986	251970	265478247	60262770	I
8	9	UK	24274361	204171	24020088	50102	522526476	68497907	Nc
9	10	Russia	21958696	395108	21356008	207580	273400000	145805947	Nc
10	11	Turkey	17042722	101492	0	0	162743369	85561976	T
11	12	Spain	13731478	118434	13557699	55345	471036328	46719142	E
13	14	Australia	11295446	18615	11235771	41060	78835048	26068792	A
15	16	Taiwan	9569611	16356	9129766	423489	30207485	23888595	Nc

Out of the countries with total tests greater than the total population, USA tops the list followed by France and Germany.

```
covid4_df = covid3_df[['Country','Total_Cases','Total_Deaths']].sort_values(by = 'Total
covid4_df
```

	Country	Total_Cases	Total_Deaths
0	United States of America	104196861	1132935
2	France	39524311	164233

	Country	Total_Cases	Total_Deaths
3	Germany	37779833	165711
7	Italy	25453789	186833
8	UK	24274361	204171
9	Russia	21958696	395108
10	Turkey	17042722	101492
11	Spain	13731478	118434
13	Australia	11295446	18615
15	Taiwan	9569611	16356

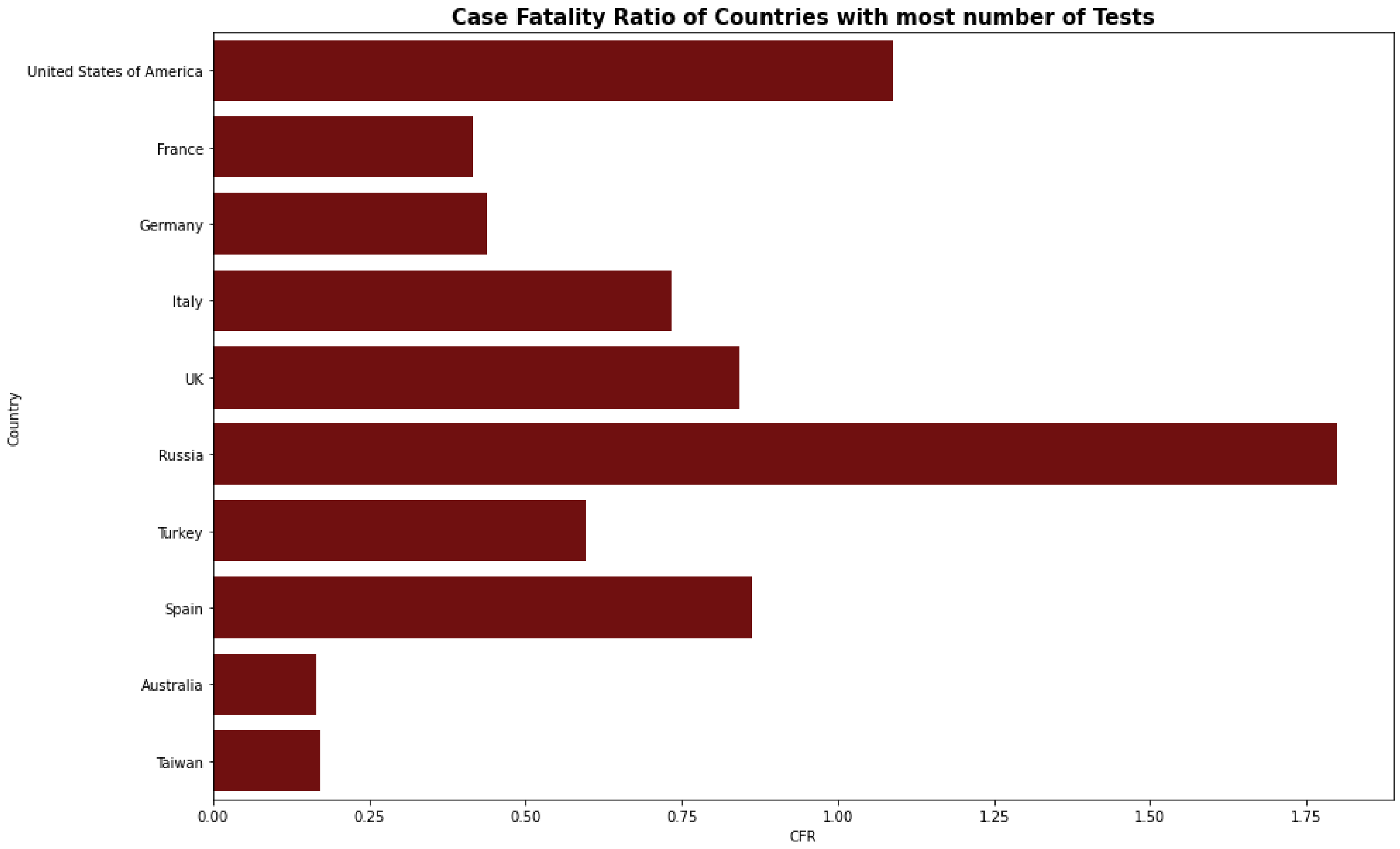
- Case Fatality Rate is measured by dividing the total number of deaths by the total number of cases and then multiplying the result by 100.
- The CFR tells us how severe a disease is and the lower the fatality rate, the better it is for the country.

```
covid4_df['cfr_rate'] = (covid3_df['Total_Deaths']/covid3_df['Total_Cases'])*100
covid4_df['cfr_rate']
```

```
0     1.087302
2     0.415524
3     0.438623
7     0.734009
8     0.841097
9     1.799324
10    0.595515
11    0.862500
13    0.164801
15    0.170916
Name: cfr_rate, dtype: float64
```

- Sorting out the values and calculating the Case Fatality Ratio, we find out that Russia has the highest CFR ratio of 1.79%.
- Closely following it are USA and Spain with a CFR of 1.08% and 0.86% respectively.

```
plt.figure(figsize = (15,10))
sns.barplot(x = 'cfr_rate', y ='Country', data = covid4_df, color = 'maroon')
plt.title('Case Fatality Ratio of Countries with most number of Tests', fontsize = 15,
plt.xlabel('CFR')
plt.ylabel('Country');
```



- We have calculated the CFR based on the countries having tests greater than the population.
- Plotted the CFR using the sns.barplot function.
- Despite conducting a large number of tests, Russia had a very high CFR, followed by USA.
- An important point needs to be noted here that CFR is different from mortality rate.
- CFR is measured as a proportion of total cases, whereas mortality rate is measured as a proportion of the population.

Q4: What is the proportion of active cases as a proportion of total number of cases?

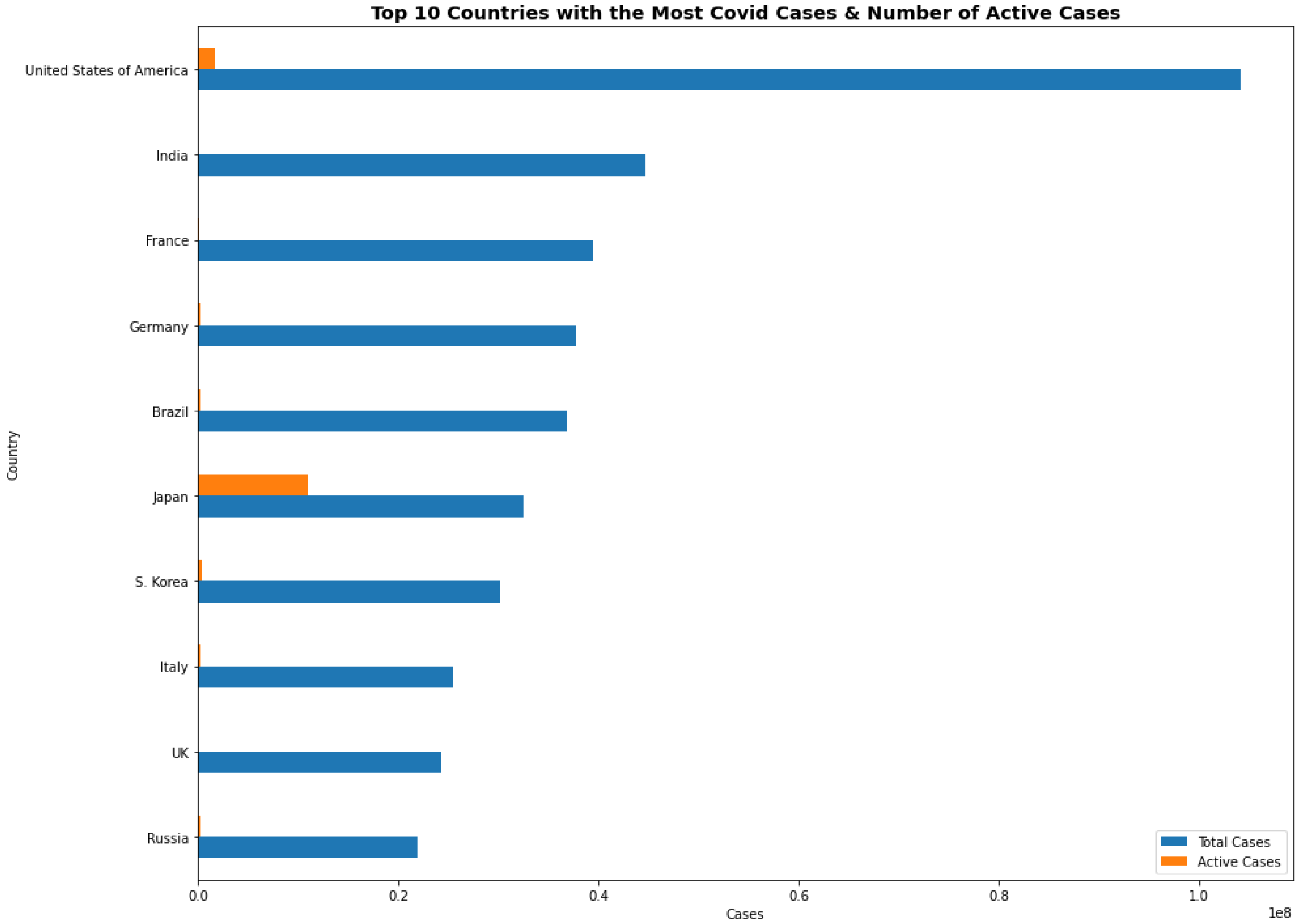
Calculating the proportion of active cases to the total number of cases would also give us an insight into the situation of the country. If the number of active cases are less in a country, the country is doing a great job in controlling the spread of the disease. We will calculate the proportion of active cases to the total number of cases and then see which country is doing better or worse.

```
proportion = covid_df[['Country','Total_Cases','Active_Cases']].sort_values('Total_Case
proportion
```

	Country	Total_Cases	Active_Cases
0	United States of America	104196861	1741147
1	India	44682784	1755
2	France	39524311	95532
3	Germany	37779833	216022
4	Brazil	36824580	208134
5	Japan	32588442	10952618
6	S. Korea	30197066	422703

	Country	Total_Cases	Active_Cases
7	Italy	25453789	251970
8	UK	24274361	50102
9	Russia	21958696	207580

```
dataplot = proportion[:10].sort_values('Total_Cases').plot(x = 'Country',kind = 'barh',
plt.title("Top 10 Countries with the Most Covid Cases & Number of Active Cases", fontsi
plt.xlabel("Cases")
plt.ylabel("Country")
plt.legend(['Total Cases', 'Active Cases']);
```



We have simply plotted the top 10 countries with highest number of active cases and total cases to give us an insight into our main question.

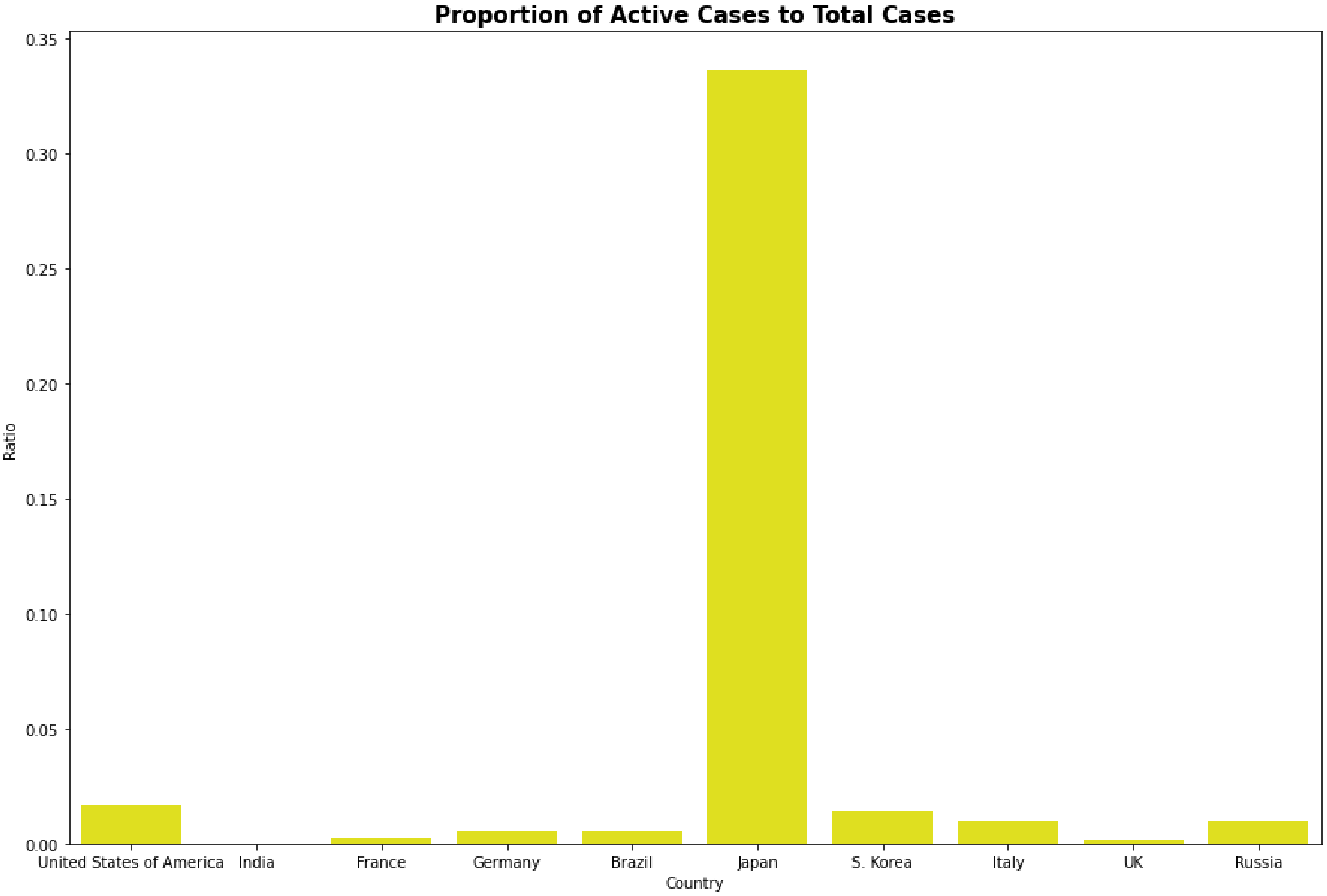
```
proportion['ratio'] = (proportion['Active_Cases']/proportion['Total_Cases'])
proportion['ratio']
```

```
0    0.016710
1    0.000039
2    0.002417
3    0.005718
4    0.005652
5    0.336089
6    0.013998
```

```
7    0.009899
8    0.002064
9    0.009453
Name: ratio, dtype: float64
```

- The proportion of active cases to total cases shows that cases in Japan have been rising rapidly.
- USA and Russia also have rising cases but their proportion is far lesser than Japan.

```
plt.figure(figsize = (15,10))
sns.barplot(x = 'Country', y = 'ratio', data = proportion, color = 'yellow')
plt.title('Proportion of Active Cases to Total Cases', fontsize = 15, fontweight = 'bol
plt.xlabel('Country')
plt.ylabel('Ratio');
```

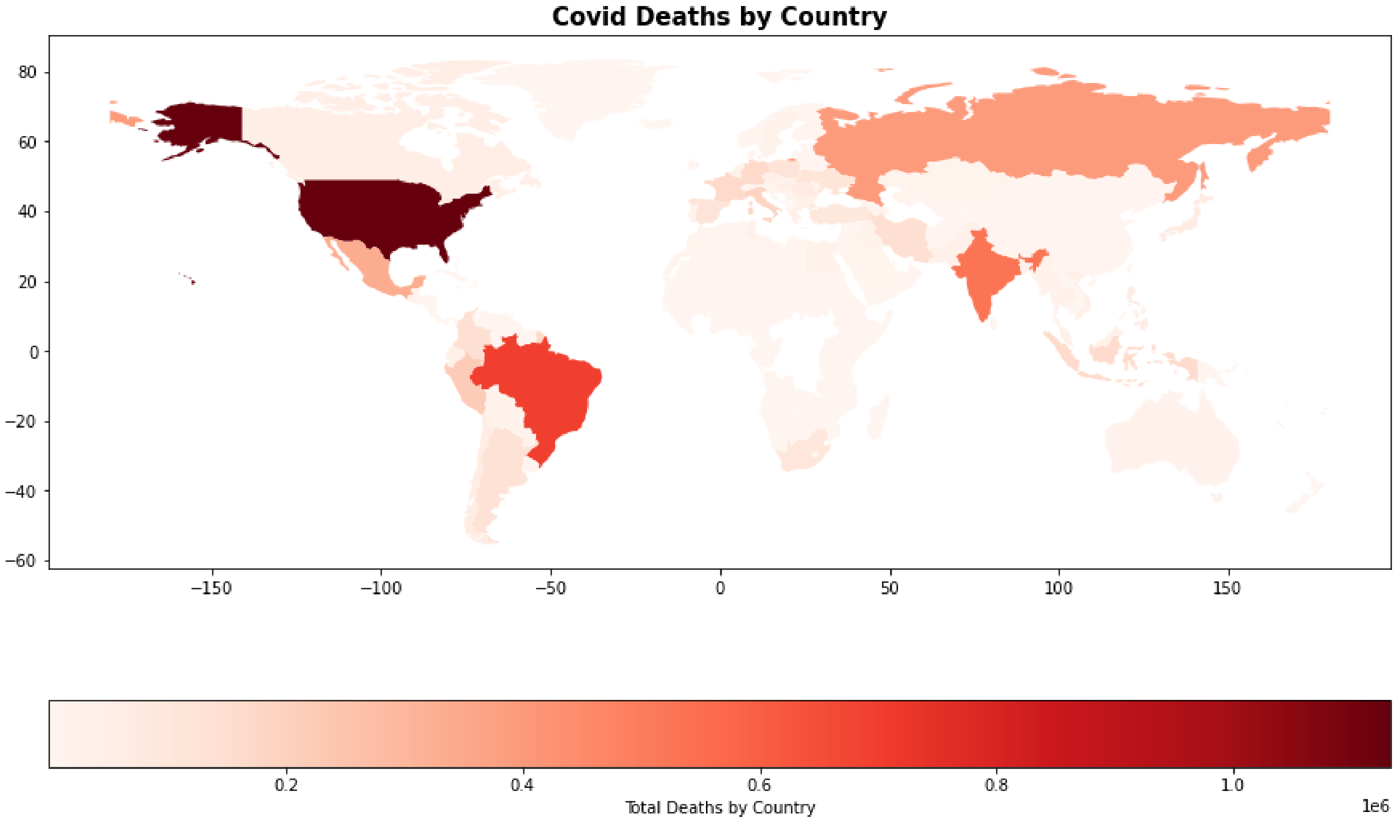


- It is quite clear from the above barplot that Japan is not doing well as the number of cases are rising at a greater pace.
- We have used the sns.barplot function from the Seaborn library to plot the graph.

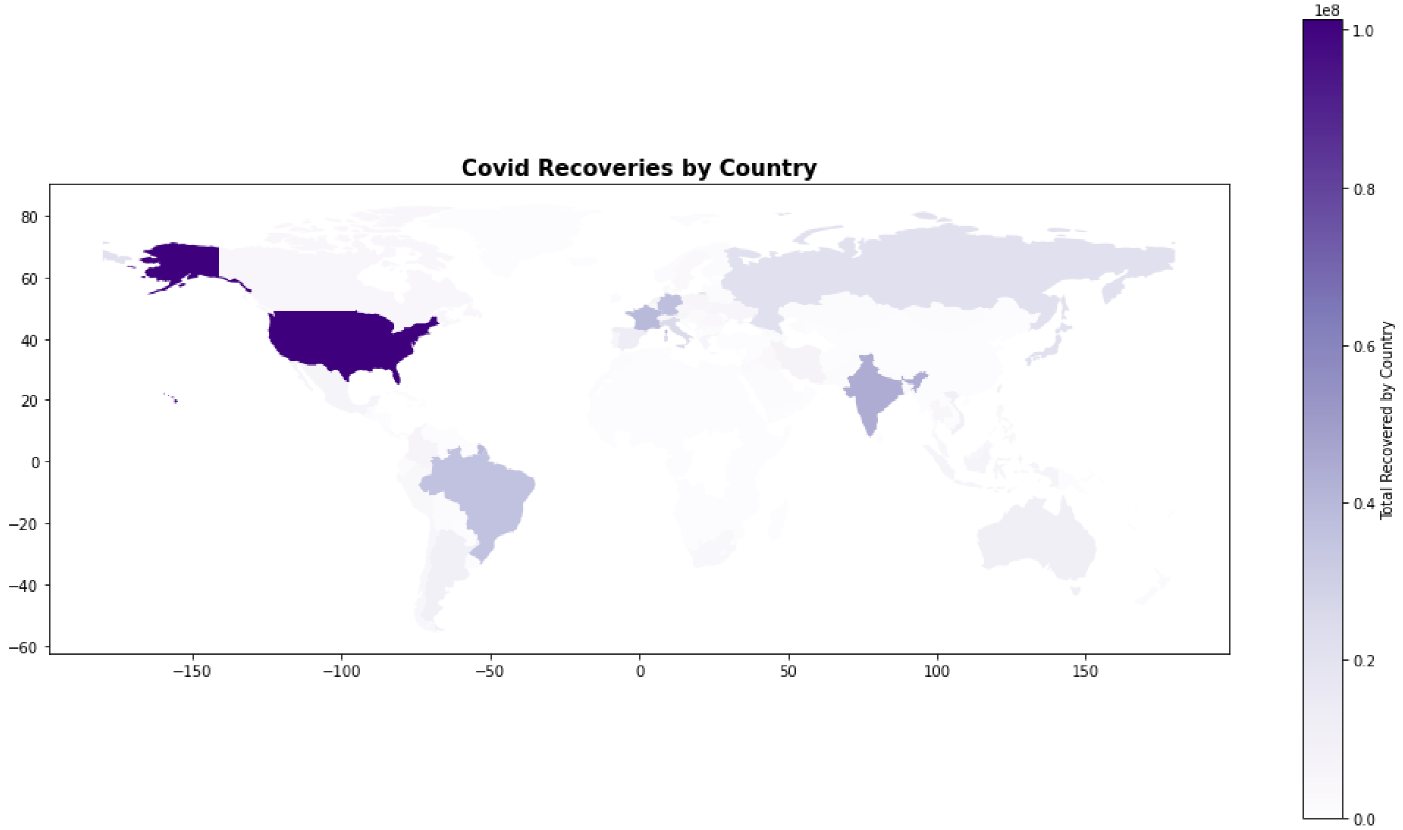
Q5: Where are the maximum (minimum) number of deaths and the maximum (minimum) number of recoveries concentrated?

We have the total number of recoveries and the total number of deaths in our dataset. We can merge this data with the world data to arrive at which continent and country has the maximum and minimum number of deaths and recoveries.

```
fig, ax = plt.subplots(figsize = (15,10))
ax.set_title('Covid Deaths by Country', fontsize = 15, fontweight = 'bold')
covid_data_merged.plot(column = 'Total_Deaths', legend = True, cmap = 'Reds', ax=ax, le
plt.show()
```



```
fig, ax = plt.subplots(figsize = (18,10))
ax.set_title('Covid Recoveries by Country', fontsize = 15, fontweight = 'bold')
covid_data_merged.plot(column = 'Total_Recovered', legend = True, cmap = 'Purples', ax=
plt.show()
```



- It is quite clear from the above world maps that the maximum number of deaths are concentrated around North America followed by South America and Asia.
- Parts of North America, South America, Europe and Africa have minimum number of deaths.
- Almost similar is the case with recoveries, where North America leads the amount of recoveries followed by Asia and South America.
- The other continents, on the other hand, are recovering at a slower pace.

Let us save and upload our work to Jovian before continuing.

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "bajpaisamriddhi6/data-analysis-project" on
https://jovian.com
[jovian] Committed successfully! https://jovian.com/bajpaisamriddhi6/data-analysis-
project
```

```
'https://jovian.com/bajpaisamriddhi6/data-analysis-project'
```

Inferences and Conclusion

We have completed our entire analysis of the dataset and now are ready to draw some inferences and conclusions. Let's look at some of these:

1. Japan has the highest number of active cases and the proportion of active cases to the total number of cases is also the highest in Japan as the the number of active cases are rapidly rising. This may be due to lack of

health infrastructure, carelessness on the part of citizens and the authorities and other problems that lead to a rise in cases.

2. The highest number of tests were in the United States of America, followed by India and these two countries are where the population is also large. A large number of tests give us an idea about the recovery pattern of the country.
3. In terms of deaths, USA, Brazil and India occupied a larger share of the total number of deaths with 28.13% in USA, 17.31% in Brazil and 13.18% in India respectively. The Case Fatality Ratio (CFR), which we calculated based on the countries where total tests were greater than the population, showed that CFR was highest in Russia, followed by the USA.The maximum number of deaths are concentrated around North America followed by South America and Asia.
4. The country with the most number of total COVID cases included USA followed by India and France. Plotting our dataset on the world map, we find out that maximum number of cases are concentrated in North America, followed by Asia and South America.
5. In terms of recoveries, even with a very high number of cases, USA and India were the quickest to recover. However, the recovery rate of France was the highest with almost full recovery rate of about 99%. When plotted on the world map, we find out that most of the recoveries were concentrated in North America, followed by Asia and South America.

In conclusion, we find out that most of the COVID cases, deaths, and recoveries were concentrated majorly in North America, Asia and South America.

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "bajpaisamriddhi6/data-analysis-project" on
https://jovian.com
[jovian] Committed successfully! https://jovian.com/bajpaisamriddhi6/data-analysis-
project
```

```
'https://jovian.com/bajpaisamriddhi6/data-analysis-project'
```

References and Future Work

- The analysis of the COVID dataset covers all the major aspects that are required for studying this dataset, that is, total cases, population, total deaths, total recoveries and number of active cases.
- However, the dataset would provide us with even more accurate information if date, month and year of the aspects would be provided.
- This would help us in analysing the trends over the years or over the months.
- We would also be able to get the positivity rate of countries which is measured by using a 7 day time period.
- We can also include vaccinations as part of this dataset to analyze how a country is doing in terms of vaccinations which would also require time periods.

I have taken help from the following resources to calculate certain metrics as well as make colourful plots and graphs.

1. https://www.nebraskamed.com/COVID/how-to-calculate-covid-19-stats-for-your-area

2. https://betterprogramming.pub/how-to-use-colormaps-with-matplotlib-to-create-colorful-plots-in-python-969b5a892f0c
3. https://melaniesoek0120.medium.com/data-visualization-how-to-plot-a-map-with-geopandas-in-python-73b10dcd4b4b

```
import jovian
```

```
jovian.commit()
```

```
[jovian] Updating notebook "bajpaisamriddhi6/data-analysis-project" on
https://jovian.com
[jovian] Committed successfully! https://jovian.com/bajpaisamriddhi6/data-analysis-
project
```

```
'https://jovian.com/bajpaisamriddhi6/data-analysis-project'
```