MN5813: Global COVID-19 Analysis

The COVID-19 pandemic had significantly affected the global health, economies and daily life. Tracking and analyzing the spread, recovery, and mortality rates of the virus is essential for understanding its dynamics and implementing effective solutions.

Project AIM: This project aims to find trends, patterns, and insights into how the epidemic has spread over the world. The goal is to produce insightful visualizations and useful information by examining data on confirmed cases, recoveries, and deaths across nations and different time periods.

Objectives:

1. To identify patterns in confirmed cases, recoveries, and deaths across different countries and regions.
2. To analyse the number of confirmed, recovered cases and deaths over different waves (First, Second and Post-Second).
3. To use the data to predict potential future scenarios, enabling better preparedness and response strategies.

Context:
The COVID-19 pandemic has seen a rise in requirements for data analysis and visualization in understanding and mitigating the effects of this pandemic. The role of analysis in pandemic has been reflected in studies of Dong et al. (2020), where the Johns Hopkins COVID-19 Dashboard provided real-time tracking of the virus. This work shows the importance of accessible and interactive platforms for public awareness and decision-making. This project aims to contribute to this growing literature by exploring COVID-19 data through various analysis of confirmed cases, deaths, and recoveries globally. This project provides a comprehensive analysis of the COVID-19 pandemic, offering insights into global and country-specific trends. The findings aim to inform better preparedness for future public health crises and underscore the importance of data-driven decision-making.

Data Source:
Covid-19:
https://www.kaggle.com/datasets/sudalairajkumar/novel-corona-virus-2019-dataset
This dataset contains information on the number of impacted patients, deaths, and recovery from the 2019 new coronavirus along with its date, province and country. It also contains different files specific to confirmed, recovered and death cases along with latitude and longitude.
The data is available starting from 22nd January 2020 to 29th May 2021.
The COVID-19 dataset was chosen because it provides a global view of one of the most significant public health crises in recent history. This dataset allows for meaningful analysis of trends, patterns, and disparities across countries. It also offers valuable insights into the spread, recovery, and impact of the virus.

World Population:
https://www.kaggle.com/code/hasibalmuzdadid/world-population-analysis/input?select=world_population.csv
This dataset contains the world population recorded for selected years from 1970 to 2022. It included the rank of country along with its area, density, growth rate and world population percentage. This dataset is chosen for specific analysis purposes that would only require the country and 2020 population.

Tools:

1. *pandas*: used it for data manipulation and analysis
2. *matplotlib*: creating basic visualisations
3. *seaborn*: used to provide advance statistical visualisation with minimal code
4. *plotly*: used for interactive visualisation

DATA LOADING:

In [1]:
```
# Read the covid_19_data.csv file
import pandas as pd

df1 = pd.read_csv('covid_19_data.csv')
```

```
#df1.head(10)
df1
```

Out[1]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered
0	1	01/22/2020	Anhui	Mainland China	1/22/2020 17:00	1.0	0.0	0.0
1	2	01/22/2020	Beijing	Mainland China	1/22/2020 17:00	14.0	0.0	0.0
2	3	01/22/2020	Chongqing	Mainland China	1/22/2020 17:00	6.0	0.0	0.0
3	4	01/22/2020	Fujian	Mainland China	1/22/2020 17:00	1.0	0.0	0.0
4	5	01/22/2020	Gansu	Mainland China	1/22/2020 17:00	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...
306424	306425	05/29/2021	Zaporizhia Oblast	Ukraine	2021-05-30 04:20:55	102641.0	2335.0	95289.0
306425	306426	05/29/2021	Zeeland	Netherlands	2021-05-30 04:20:55	29147.0	245.0	0.0
306426	306427	05/29/2021	Zhejiang	Mainland China	2021-05-30 04:20:55	1364.0	1.0	1324.0
306427	306428	05/29/2021	Zhytomyr Oblast	Ukraine	2021-05-30 04:20:55	87550.0	1738.0	83790.0
306428	306429	05/29/2021	Zuid-Holland	Netherlands	2021-05-30 04:20:55	391559.0	4252.0	0.0

306429 rows × 8 columns

In [2]:

```
# Convert the .csv file to .json file
df1.to_json("covid_data.json", orient="records")
covid_data = pd.read_json("covid_data.json")

# Print first 10 records
covid_data.head(10)
```

Out[2]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered
0	1	01/22/2020	Anhui	Mainland China	1/22/2020 17:00	1	0	0
1	2	01/22/2020	Beijing	Mainland China	1/22/2020 17:00	14	0	0
2	3	01/22/2020	Chongqing	Mainland China	1/22/2020 17:00	6	0	0
3	4	01/22/2020	Fujian	Mainland China	1/22/2020 17:00	1	0	0
4	5	01/22/2020	Gansu	Mainland China	1/22/2020 17:00	0	0	0
5	6	01/22/2020	Guangdong	Mainland China	1/22/2020 17:00	26	0	0
6	7	01/22/2020	Guangxi	Mainland China	1/22/2020 17:00	2	0	0
7	8	01/22/2020	Guizhou	Mainland China	1/22/2020 17:00	1	0	0
8	9	01/22/2020	Hainan	Mainland China	1/22/2020 17:00	4	0	0
9	10	01/22/2020	Hebei	Mainland China	1/22/2020 17:00	1	0	0

The following csv files contain individual records of Confirmed, Recovered and Death cases. This data contains date wise information. This not only contains country and province but also Latitude and Longitude (which is later used for visualisation).

In [3]:
```
# Read the time_series_covid_19_confirmed.csv file
df2 = pd.read_csv('time_series_covid_19_confirmed.csv')
df2.head(10)
```

Out[3]:

	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/2
0	NaN	Afghanistan	33.93911	67.709953	0	0	0	0	0	
1	NaN	Albania	41.15330	20.168300	0	0	0	0	0	
2	NaN	Algeria	28.03390	1.659600	0	0	0	0	0	
3	NaN	Andorra	42.50630	1.521800	0	0	0	0	0	
4	NaN	Angola	-11.20270	17.873900	0	0	0	0	0	
5	NaN	Antigua and Barbuda	17.06080	-61.796400	0	0	0	0	0	
6	NaN	Argentina	-38.41610	-63.616700	0	0	0	0	0	
7	NaN	Armenia	40.06910	45.038200	0	0	0	0	0	
8	Australian Capital Territory	Australia	-35.47350	149.012400	0	0	0	0	0	
9	New South Wales	Australia	-33.86880	151.209300	0	0	0	0	3	

10 rows × 498 columns

In [4]:
```
# Read the time_series_covid_19_deaths.csv file
df3 = pd.read_csv('time_series_covid_19_deaths.csv')
df3.head(10)
```

Out[4]:

	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/2
0	NaN	Afghanistan	33.93911	67.709953	0	0	0	0	0	
1	NaN	Albania	41.15330	20.168300	0	0	0	0	0	
2	NaN	Algeria	28.03390	1.659600	0	0	0	0	0	
3	NaN	Andorra	42.50630	1.521800	0	0	0	0	0	
4	NaN	Angola	-11.20270	17.873900	0	0	0	0	0	
5	NaN	Antigua and Barbuda	17.06080	-61.796400	0	0	0	0	0	
6	NaN	Argentina	-38.41610	-63.616700	0	0	0	0	0	
7	NaN	Armenia	40.06910	45.038200	0	0	0	0	0	
8	Australian Capital Territory	Australia	-35.47350	149.012400	0	0	0	0	0	
9	New South Wales	Australia	-33.86880	151.209300	0	0	0	0	0	

10 rows × 498 columns

In [5]:
```
# Read the time_series_covid_19_recovered.csv file
df4 = pd.read_csv('time_series_covid_19_recovered.csv')
df4.head(10)
```

Out[5]:

	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/2
0	NaN	Afghanistan	33.93911	67.709953	0	0	0	0	0	
1	NaN	Albania	41.15330	20.168300	0	0	0	0	0	
2	NaN	Algeria	28.03390	1.659600	0	0	0	0	0	
3	NaN	Andorra	42.50630	1.521800	0	0	0	0	0	
4	NaN	Angola	-11.20270	17.873900	0	0	0	0	0	
5	NaN	Antigua and Barbuda	17.06080	-61.796400	0	0	0	0	0	
6	NaN	Argentina	-38.41610	-63.616700	0	0	0	0	0	
7	NaN	Armenia	40.06910	45.038200	0	0	0	0	0	
8	Australian Capital Territory	Australia	-35.47350	149.012400	0	0	0	0	0	
9	New South Wales	Australia	-33.86880	151.209300	0	0	0	0	0	

10 rows × 498 columns

DATA CLEANING:

1. Check datatypes
2. Tidy up the data (using melt())
3. Check for duplicates
4. Check and handle null values
5. Check and handle negative values

In [6]:

```
# Printing info to check the datatypes
print(df1.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306429 entries, 0 to 306428
Data columns (total 8 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   SNo              306429 non-null  int64
 1   ObservationDate  306429 non-null  object
 2   Province/State   228326 non-null  object
 3   Country/Region   306429 non-null  object
 4   Last Update      306429 non-null  object
 5   Confirmed        306429 non-null  float64
 6   Deaths           306429 non-null  float64
 7   Recovered        306429 non-null  float64
dtypes: float64(3), int64(1), object(4)
memory usage: 18.7+ MB
None
```

In [7]:

```
print(df2.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 276 entries, 0 to 275
Columns: 498 entries, Province/State to 5/29/21
dtypes: float64(2), int64(494), object(2)
memory usage: 1.0+ MB
None
```

In [8]:

```
print(df3.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 276 entries, 0 to 275
Columns: 498 entries, Province/State to 5/29/21
dtypes: float64(2), int64(494), object(2)
memory usage: 1.0+ MB
None
```

In [9]:
```
print(df4.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 261 entries, 0 to 260
Columns: 498 entries, Province/State to 5/29/21
dtypes: float64(2), int64(494), object(2)
memory usage: 1015.6+ KB
None
```

The following cleaning is performed to reduce the number of columns present and then further the dates are grouped by months, having fewer rows, for easier analysis.

In [10]:
```
# Converting date columns to long format
# Specify start and end column names
start_col = '1/22/20'
end_col = '5/29/21'

# Get the list of columns for melting
columns_to_melt = df2.loc[:, start_col:end_col].columns

# melt() used to convert "wide" dataframe into "long"
df2_melted = pd.melt(
    df2,
    id_vars = ["Country/Region","Province/State","Lat","Long"],
    value_vars = columns_to_melt,
    var_name = "Date",
    value_name = "Confirmed"
)

print("Melted Dataframe:")
df2_melted
```

Melted Dataframe:

Out[10]:

	Country/Region	Province/State	Lat	Long	Date	Confirmed
0	Afghanistan	NaN	33.939110	67.709953	1/22/20	0
1	Albania	NaN	41.153300	20.168300	1/22/20	0
2	Algeria	NaN	28.033900	1.659600	1/22/20	0
3	Andorra	NaN	42.506300	1.521800	1/22/20	0
4	Angola	NaN	-11.202700	17.873900	1/22/20	0
...	...	...	...	...	...	...
136339	Vietnam	NaN	14.058324	108.277199	5/29/21	6908
136340	West Bank and Gaza	NaN	31.952200	35.233200	5/29/21	307838
136341	Yemen	NaN	15.552727	48.516388	5/29/21	6731
136342	Zambia	NaN	-13.133897	27.849332	5/29/21	94751
136343	Zimbabwe	NaN	-19.015438	29.154857	5/29/21	38933

136344 rows × 6 columns

In [11]:
```
# Convert date column to datetime datatype
df2_melted["Date"] = pd.to_datetime(df2_melted["Date"])

# Create a new column for Month
df2_melted["Month"] = df2_melted["Date"].dt.to_period("M")  # 'M' indicates Month

# Group by Country, Province, Latitude, Longitude and Month, summing up the confirmed cases
monthly_confirmed = df2_melted.groupby(["Country/Region","Province/State","Lat","Long", "Month"])["Conf
monthly_confirmed
```

```
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\2923253125.py:2: UserWarning: Could not inf
er format, so each element will be parsed individually, falling back to `dateutil`. To ensure parsing is
consistent and as-expected, please specify a format.
  df2_melted["Date"] = pd.to_datetime(df2_melted["Date"])
```

Out[11]:

	Country/Region	Province/State	Lat	Long	Month	Confirmed
0	Australia	Australian Capital Territory	-35.4735	149.0124	2020-01	0
1	Australia	Australian Capital Territory	-35.4735	149.0124	2020-02	0
2	Australia	Australian Capital Territory	-35.4735	149.0124	2020-03	579
3	Australia	Australian Capital Territory	-35.4735	149.0124	2020-04	3028
4	Australia	Australian Capital Territory	-35.4735	149.0124	2020-05	3314
...	...	...	...	...	...	...
1423	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-01	34597
1424	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-02	51735
1425	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-03	69457
1426	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-04	70874
1427	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-05	69709

1428 rows × 6 columns

In [12]:

```
# Converting date columns to long format
# Specify start and end column names
start_col = '1/22/20'
end_col = '5/29/21'

# Get the list of columns for melting
columns_to_melt = df2.loc[:, start_col:end_col].columns

# melt() used to convert "wide" dataframe into "long"
df3_melted = pd.melt(
    df3,
    id_vars = ["Country/Region"],
    value_vars = columns_to_melt,
    var_name = "Date",
    value_name = "Deaths"
)

print("Melted Dataframe:")
df3_melted
```

```
Melted Dataframe:
```

Out[12]:

	Country/Region	Date	Deaths
0	Afghanistan	1/22/20	0
1	Albania	1/22/20	0
2	Algeria	1/22/20	0
3	Andorra	1/22/20	0
4	Angola	1/22/20	0
...	...	...	...
136339	Vietnam	5/29/21	47
136340	West Bank and Gaza	5/29/21	3492
136341	Yemen	5/29/21	1319
136342	Zambia	5/29/21	1276
136343	Zimbabwe	5/29/21	1594

136344 rows × 3 columns

In [13]:
```
# Convert date column to datetime datatype
df3_melted["Date"] = pd.to_datetime(df3_melted["Date"])

# Create a new column for Month
df3_melted["Month"] = df3_melted["Date"].dt.to_period("M")  # 'M' indicates Month

# Group by Country and Month, summing up the death cases
monthly_deaths = df3_melted.groupby(["Country/Region", "Month"])["Deaths"].sum().reset_index()
monthly_deaths
```

```
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\2009798306.py:2: UserWarning: Could not infer format, so each element will be parsed individually, falling back to `dateutil`. To ensure parsing is consistent and as-expected, please specify a format.
  df3_melted["Date"] = pd.to_datetime(df3_melted["Date"])
```

Out[13]:

	Country/Region	Month	Deaths
0	Afghanistan	2020-01	0
1	Afghanistan	2020-02	0
2	Afghanistan	2020-03	27
3	Afghanistan	2020-04	890
4	Afghanistan	2020-05	5007
...	...	...	...
3276	Zimbabwe	2021-01	23012
3277	Zimbabwe	2021-02	38753
3278	Zimbabwe	2021-03	46556
3279	Zimbabwe	2021-04	46375
3280	Zimbabwe	2021-05	45855

3281 rows × 3 columns

In [14]:
```
# Converting date columns to long format
# Specify start and end column names
start_col = '1/22/20'
end_col = '5/29/21'

# Get the list of columns for melting
columns_to_melt = df2.loc[:, start_col:end_col].columns

# melt() used to convert "wide" dataframe into "long"
df4_melted = pd.melt(
    df4,
    id_vars = ["Country/Region"],
    value_vars = columns_to_melt,
    var_name = "Date",
    value_name = "Recovered"
)

print("Melted Dataframe:")
df4_melted
```

```
Melted Dataframe:
```

Out[14]:

	Country/Region	Date	Recovered
0	Afghanistan	1/22/20	0
1	Albania	1/22/20	0
2	Algeria	1/22/20	0
3	Andorra	1/22/20	0
4	Angola	1/22/20	0
...	...	...	...
128929	Vietnam	5/29/21	2896
128930	West Bank and Gaza	5/29/21	300524
128931	Yemen	5/29/21	3399
128932	Zambia	5/29/21	91594
128933	Zimbabwe	5/29/21	36578

128934 rows × 3 columns

In [15]:

```
# Convert date column to datetime datatype
df4_melted["Date"] = pd.to_datetime(df4_melted["Date"])

# Create a new column for Month
df4_melted["Month"] = df4_melted["Date"].dt.to_period("M")  # 'M' indicates Month

# Group by Country and Month, summing up the recovered cases
monthly_recovered = df4_melted.groupby(["Country/Region", "Month"])["Recovered"].sum().reset_index()
monthly_recovered
```

```
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\1221428022.py:2: UserWarning: Could not inf
er format, so each element will be parsed individually, falling back to `dateutil`. To ensure parsing is
consistent and as-expected, please specify a format.
  df4_melted["Date"] = pd.to_datetime(df4_melted["Date"])
```

Out[15]:

	Country/Region	Month	Recovered
0	Afghanistan	2020-01	0
1	Afghanistan	2020-02	0
2	Afghanistan	2020-03	26
3	Afghanistan	2020-04	2927
4	Afghanistan	2020-05	24129
...	...	...	...
3276	Zimbabwe	2021-01	531530
3277	Zimbabwe	2021-02	849842
3278	Zimbabwe	2021-03	1056857
3279	Zimbabwe	2021-04	1050250
3280	Zimbabwe	2021-05	1050714

3281 rows × 3 columns

In [16]:

```
# Check if duplicate values are present
print(covid_data.duplicated().sum())
print(monthly_confirmed.duplicated().sum())
print(monthly_deaths.duplicated().sum())
print(monthly_recovered.duplicated().sum())
```

```
0
0
0
0
```

In [17]:
```
# Check if null values are present inorder to deal with them
print(covid_data.isnull().sum())
print("-----------------------------")
print("\n",monthly_confirmed.isnull().sum())
print("-----------------------------")
print("\n",monthly_deaths.isnull().sum())
print("-----------------------------")
print("\n",monthly_recovered.isnull().sum())
```

```
SNo                    0
ObservationDate        0
Province/State     78103
Country/Region         0
Last Update            0
Confirmed              0
Deaths                 0
Recovered              0
dtype: int64
-----------------------------

 Country/Region    0
Province/State    0
Lat               0
Long              0
Month             0
Confirmed         0
dtype: int64
-----------------------------

 Country/Region    0
Month             0
Deaths            0
dtype: int64
-----------------------------

 Country/Region    0
Month             0
Recovered         0
dtype: int64
```

Handle null values:

In the dataset, there are null values for Province/State. In order to handle it, I have printed the records that are null and then checked for what it can be replaced with. Therefore, the null values are replaced with 'Unknown' as one cannot be sure and guess the province in a country to replace it with.

In [18]:
```
# Print null records
null_records = covid_data[covid_data["Province/State"].isnull()]
null_records
```

Out[18]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered
35	36	01/22/2020	None	Japan	1/22/2020 17:00	2	0	0
36	37	01/22/2020	None	Thailand	1/22/2020 17:00	4	0	2
37	38	01/22/2020	None	South Korea	1/22/2020 17:00	1	0	0
39	40	01/22/2020	None	Kiribati	1/22/2020 17:00	0	0	0
75	76	01/23/2020	None	Japan	1/23/20 17:00	1	0	0
...	...	...	...	...	...	...	...	...
305831	305832	05/29/2021	None	Vietnam	2021-05-30 04:20:55	6908	47	2896
305832	305833	05/29/2021	None	West Bank and Gaza	2021-05-30 04:20:55	307838	3492	300524
305833	305834	05/29/2021	None	Yemen	2021-05-30 04:20:55	6731	1319	3399
305834	305835	05/29/2021	None	Zambia	2021-05-30 04:20:55	94751	1276	91594
305835	305836	05/29/2021	None	Zimbabwe	2021-05-30 04:20:55	38933	1594	36578

78103 rows × 8 columns

In [19]:

```
# Check for 'Unknown' value records to replace null
unknown_records = covid_data[covid_data.isin(['Unknown']).any(axis=1)]
unknown_records
```

Out[19]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered
38	39	01/22/2020	Unknown	China	1/22/2020 17:00	0	0	0
86	87	01/23/2020	Unknown	China	1/23/20 17:00	0	0	0
129	130	01/24/2020	Unknown	China	1/24/20 17:00	0	0	0
175	176	01/25/2020	Unknown	China	1/25/20 17:00	0	0	0
224	225	01/26/2020	Unknown	China	1/26/20 16:00	0	0	0
...	...	...	...	...	...	...	...	...
306369	306370	05/29/2021	Unknown	Mexico	2021-05-30 04:20:55	0	0	1924865
306370	306371	05/29/2021	Unknown	Netherlands	2021-05-30 04:20:55	3882	14	0
306371	306372	05/29/2021	Unknown	Peru	2021-05-30 04:20:55	0	0	1897522
306372	306373	05/29/2021	Unknown	Spain	2021-05-30 04:20:55	0	0	0
306373	306374	05/29/2021	Unknown	UK	2021-05-30 04:20:55	0	0	0

4123 rows × 8 columns

In [20]:

```
# Change the value to 'Unknown' because we do have Province/State that is not known
covid_data['Province/State'] = covid_data['Province/State'].fillna('Unknown')
```

In [21]:

```
# Check whether null values are replaced
null_records = covid_data[covid_data["Province/State"].isnull()]
null_records
```

Out[21]:

SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered

The following operations are performed to deal with negative values that are present in the Confirmed, Recovered and Deaths columns. As the value cannot be negative, it is replaced with 0.

In [22]:

```
# Identify records with negative values

negative_records = covid_data[covid_data['Confirmed'] < 0]
negative_records
```

Out[22]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered
147524	147525	11/02/2020	Unknown	Colombia	2021-04-02 15:13:53	-302844	0	0

In [23]:

```
negative_records1 = covid_data[covid_data['Deaths'] < 0]
negative_records1
```

Out[23]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered
118363	118364	09/24/2020	Unknown	Colombia	2021-04-02 15:13:53	0	-178	-12684
141534	141535	10/25/2020	Unknown	Colombia	2021-04-02 15:13:53	0	-154	-8072

In [24]:
```
negative_records2 = covid_data[covid_data['Recovered'] < 0]
negative_records2
```

Out[24]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered
118363	118364	09/24/2020	Unknown	Colombia	2021-04-02 15:13:53	0	-178	-12684
141534	141535	10/25/2020	Unknown	Colombia	2021-04-02 15:13:53	0	-154	-8072
145277	145278	10/30/2020	Unknown	Colombia	2021-04-02 15:13:53	0	505	-854405

In [25]:
```
# Replace negative values with 0
covid_data.loc[covid_data['Confirmed'] < 0, 'Confirmed'] = 0
covid_data.loc[covid_data['Deaths'] < 0, 'Deaths'] = 0
covid_data.loc[covid_data['Recovered'] < 0, 'Recovered'] = 0
```

In [26]:
```
# Check values have been replaced
negative_records = covid_data[covid_data['Confirmed'] < 0]
negative_records
```

Out[26]:

SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered

In [27]:
```
negative_records1 = covid_data[covid_data['Deaths'] < 0]
negative_records1
```

Out[27]:

SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered

In [28]:
```
negative_records2 = covid_data[covid_data['Recovered'] < 0]
negative_records2
```

Out[28]:

SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered

Data Cleaning Insights:

1. Ensures each column has the appropriate data type for its intended operations.
2. Tidy data allows for a more easier data manipulation, filtering, and visualization.
3. It was necessary to drop duplicates because even a small number of duplicates in columns can lead to inaccurate analysis.
4. Handling missing values helps identify data completeness.
5. Negative values in the dataset made no sense and thus handling them was necessary.

DATA WRANGLING:

The purpose to add a new column "Wave" is to better analyse the impact of Covid-19 in specific waves, whether the situation has improved or worsened and where the impact is low/high inorder for actions to be taken accordingly.

In [29]:
```
# Create new column "Wave" based on specific time period
covid_data["Wave"] = pd.cut(covid_data["ObservationDate"], bins=["01/21/2020","01/22/2021","04/01/2021"
```

```
# Printing few records to show the results
range_1 = covid_data.iloc[0:4]
range_2 = covid_data.iloc[10000:10005]
range_3 = covid_data.iloc[306423:306429]
result = pd.concat([range_1, range_2, range_3])
result
```

Out[29]:

	SNo	ObservationDate	Province/State	Country/Region	Last Update	Confirmed	Deaths	Recovered	
0	1	01/22/2020	Anhui	Mainland China	1/22/2020 17:00	1	0	0	
1	2	01/22/2020	Beijing	Mainland China	1/22/2020 17:00	14	0	0	
2	3	01/22/2020	Chongqing	Mainland China	1/22/2020 17:00	6	0	0	
3	4	01/22/2020	Fujian	Mainland China	1/22/2020 17:00	1	0	0	
10000	10001	03/29/2020	Unknown	Namibia	3/8/20 5:31	11	0	2	S
10001	10002	03/29/2020	Unknown	Nepal	3/8/20 5:31	5	0	1	S
10002	10003	03/29/2020	Unknown	Netherlands	3/8/20 5:31	10866	771	250	S
10003	10004	03/29/2020	Unknown	New Zealand	3/8/20 5:31	514	1	56	S
10004	10005	03/29/2020	Unknown	Nicaragua	3/8/20 5:31	4	1	0	S
306423	306424	05/29/2021	Zakarpattia Oblast	Ukraine	2021-05-30 04:20:55	61611	1586	58882	S
306424	306425	05/29/2021	Zaporizhia Oblast	Ukraine	2021-05-30 04:20:55	102641	2335	95289	S
306425	306426	05/29/2021	Zeeland	Netherlands	2021-05-30 04:20:55	29147	245	0	S
306426	306427	05/29/2021	Zhejiang	Mainland China	2021-05-30 04:20:55	1364	1	1324	S
306427	306428	05/29/2021	Zhytomyr Oblast	Ukraine	2021-05-30 04:20:55	87550	1738	83790	S
306428	306429	05/29/2021	Zuid-Holland	Netherlands	2021-05-30 04:20:55	391559	4252	0	S

Merging the time_series_covid_19_confirmed.csv, time_series_covid_19_deaths.csv and time_series_covid_19_recovered.csv for further visualisation process. It will be used to showcase the confirmed/recovered/deaths based on latitude and longitude over the time period.

In [30]:
```
# Using left join to merge data as monthly_confirmed has the required columns.
merge1 = pd.merge(monthly_confirmed, monthly_deaths, how="left", on="Country/Region")          # (Stack
```

In [31]:
```
merged_data = pd.merge(merge1, monthly_recovered, how="left", on="Country/Region")
```

In [32]:
```
# All 3 csv files merged and displayed
merged_data
```

Out[32]:

	Country/Region	Province/State	Lat	Long	Month_x	Confirmed	Month_y	Deaths	Month	R
0	Australia	Australian Capital Territory	-35.4735	149.0124	2020-01	0	2020-01	0	2020-01	
1	Australia	Australian Capital Territory	-35.4735	149.0124	2020-01	0	2020-01	0	2020-02	
2	Australia	Australian Capital Territory	-35.4735	149.0124	2020-01	0	2020-01	0	2020-03	
3	Australia	Australian Capital Territory	-35.4735	149.0124	2020-01	0	2020-01	0	2020-04	
4	Australia	Australian Capital Territory	-35.4735	149.0124	2020-01	0	2020-01	0	2020-05	
...	...	...	...	...	...	...	...	...	...	
412687	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-05	69709	2021-05	3709653	2021-01	
412688	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-05	69709	2021-05	3709653	2021-02	
412689	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-05	69709	2021-05	3709653	2021-03	
412690	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-05	69709	2021-05	3709653	2021-04	
412691	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	2021-05	69709	2021-05	3709653	2021-05	

412692 rows × 10 columns

In [33]:

```
# Drop the duplicate columns of Month
merged_data.drop(["Month_x","Month_y"],axis=1)
```

Out[33]:

	Country/Region	Province/State	Lat	Long	Confirmed	Deaths	Month	Recovered
0	Australia	Australian Capital Territory	-35.4735	149.0124	0	0	2020-01	4
1	Australia	Australian Capital Territory	-35.4735	149.0124	0	0	2020-02	195
2	Australia	Australian Capital Territory	-35.4735	149.0124	0	0	2020-03	2307
3	Australia	Australian Capital Territory	-35.4735	149.0124	0	0	2020-04	91483
4	Australia	Australian Capital Territory	-35.4735	149.0124	0	0	2020-05	195488
...	...	...	...	...	...	...	...	...
412687	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	69709	3709653	2021-01	242466
412688	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	69709	3709653	2021-02	303091
412689	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	69709	3709653	2021-03	376948
412690	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	69709	3709653	2021-04	415975
412691	United Kingdom	Turks and Caicos Islands	21.6940	-71.7979	69709	3709653	2021-05	440507

412692 rows × 8 columns

DATA ANALYSIS:

1. Top 10 countries with highest Confirmed, Recovered and Death cases.
2. Calculated the mortality and recovery rates based on Confirmed, Recovered and Deaths columns.
3. Total number of Confirmed, Recovered and Death cases worldwide.
4. Total number of Confirmed, Recovered and Death cases in First, Second and Post-Second waves.
5. Per Capita Analysis for confirmed, recovered, and deaths per million people country-wise.

In [34]:

```
# Top 10 countries with highest recovery rates based on time range
# Feel free to change the time period
# First wave time period
start_date = "01/21/2020"
end_date = "01/22/2021"

# Filter the data for the given time period
covid_data_filtered = covid_data[(covid_data['ObservationDate'] >= start_date) & (covid_data['Observati

# Group by 'Country' and calculate total recoveries
recovery_by_country = covid_data_filtered.groupby("Country/Region")["Recovered"].sum().reset_index()

# Find the country with the highest recovery
highest_recovery = recovery_by_country.sort_values("Recovered", ascending=False).head(10)

print("Countries with highest recovery:")
highest_recovery
```

```
Countries with highest recovery:
```

Out[34]:

	Country/Region	Recovered
79	India	20584540
23	Brazil	15420002
145	Russia	6070698
181	Turkey	4586082
85	Italy	3682578
37	Colombia	3612686
65	Germany	3611542
6	Argentina	3262581
117	Mexico	2556720
141	Poland	2431464

In [35]:

```
# Top 10 countries with highest death cases based on time range
# Feel free to change the time period
# Second wave time period
start_date = "01/22/2021"
end_date = "04/01/2021"

# Filter the data for the given time period
covid_data_filtered = covid_data[(covid_data['ObservationDate'] >= start_date) & (covid_data['Observati

# Group by 'Country' and calculate total deaths
deaths_by_country = covid_data_filtered.groupby("Country/Region")["Deaths"].sum().reset_index()

# Find the country with the highest deaths
highest_deaths = deaths_by_country.sort_values("Deaths", ascending=False).head(10)

print("Countries with highest deaths:")
highest_deaths
```

```
Countries with highest deaths:
```

Out[35]:

	Country/Region	Deaths
214	US	35217322
27	Brazil	18064447
137	Mexico	12654002
96	India	11005119
213	UK	8320460
102	Italy	6929110
71	France	5995174
172	Russia	5832983
194	Spain	4780198
77	Germany	4739093

In [36]:

```
# Top 10 countries with highest confirmed cases in 2020
# Feel free to change the time period
# First wave time period
start_date = "01/01/2020"
end_date = "12/31/2020"

# Filter the data for the given time period
covid_data_filtered = covid_data[(covid_data['ObservationDate'] >= start_date) & (covid_data['Observati

# Group by 'Country' and calculate total confirmed cases
confirmed_by_country = covid_data_filtered.groupby("Country/Region")["Confirmed"].sum().reset_index()

# Find the country with the highest confirmed cases
```

```
highest_confirmed = confirmed_by_country.sort_values("Confirmed", ascending=False).head(10)

print("Countries with highest confirmed cases:")
highest_confirmed
```

```
Countries with highest confirmed cases:
```

Out[36]:

	Country/Region	Confirmed
214	US	6049145667
96	India	3226768088
27	Brazil	2653587540
172	Russia	930548849
71	France	855188962
213	UK	783794384
194	Spain	649111763
102	Italy	636694305
212	Turkey	618940956
77	Germany	524166833

Observation:
By the above analysis, it is clear that US was the most affected country, with highest number of confirmed cases as well as deaths. Surprisingly, China did not make any list where it all begun. India being the second country where most number of confirmed cases were found, but also India has a high number of recovered cases.
Let's check the mortality rate and recovery rate of each country.
Mortality Rate: helps in understanding how severe the disease is and
Recovery Rate: helps to understand how effective treatment is in patient recovery.
This can also help in predicting future outcomes such as whether the disease is becoming less severe over time and treatments given are working and which regions require more attention.

In [37]:
```
# Group the confirmed, recovered and death cases by country
total = covid_data.groupby('Country/Region')[['Confirmed', 'Deaths', 'Recovered']].sum().reset_index()

# Calculate mortality and recovery rates
total['Mortality Rate (%)'] = ((total['Deaths'] / total['Confirmed']) * 100).round(2)
total['Recovery Rate (%)'] = ((total['Recovered'] / total['Confirmed']) * 100).round(2)

# Handle cases where 0
total['Mortality Rate (%)'] = total['Mortality Rate (%)'].fillna(0)
total['Recovery Rate (%)'] = total['Recovery Rate (%)'].fillna(0)

total
```

Out[37]:

	Country/Region	Confirmed	Deaths	Recovered	Mortality Rate (%)	Recovery Rate (%)
0	Azerbaijan	1	0	0	0.00	0.00
1	('St. Martin',)	2	0	0	0.00	0.00
2	Afghanistan	17026442	669075	13464399	3.93	79.08
3	Albania	19768869	375955	13945256	1.90	70.54
4	Algeria	27684358	834464	18959299	3.01	68.48
...	...	...	...	...	...	...
224	West Bank and Gaza	41819444	440378	37003116	1.05	88.48
225	Yemen	962066	237613	506523	24.70	52.65
226	Zambia	13493953	205990	12625626	1.53	93.57
227	Zimbabwe	6484581	237234	5594887	3.66	86.28
228	occupied Palestinian territory	25	0	0	0.00	0.00

229 rows × 6 columns

In [38]:

```
# Total number of Confirmed cases worldwide within the entire time period
global_statistics = {
    "Total Confirmed Cases": covid_data['Confirmed'].sum(),
    "Total Recovered Cases": covid_data['Recovered'].sum(),
    "Total Deaths": covid_data['Deaths'].sum()
}

print("Global Statistics:")
for key, value in global_statistics.items():
    print(f"{key}: {value:,}") # Comma used as seperator
```

```
Global Statistics:
Total Confirmed Cases: 26,252,354,602
Total Recovered Cases: 15,451,113,073
Total Deaths: 624,013,349
```

In [39]:

```
# Total number of confirmed, recovered and death cases in first, second and post-second wave
# Group data by 'wave'
wave_cases = covid_data.groupby('Wave')[['Confirmed', 'Deaths', 'Recovered']].sum().reset_index()
print("COVID-19 Cases by Wave:")
wave_cases
```

```
COVID-19 Cases by Wave:
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\1713386618.py:3: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed
=False to retain current behavior or observed=True to adopt the future default and silence this warning.
  wave_cases = covid_data.groupby('Wave')[['Confirmed', 'Deaths', 'Recovered']].sum().reset_index()
```

Out[39]:

	Wave	Confirmed	Deaths	Recovered
0	First Wave	195861462	4214952	107912611
1	Second Wave	7857470784	173169280	4416264042
2	Post-Second Wave	8971520516	198749808	5251065257

In [40]:

```
# Read the world_population.csv file for performing per capita analysis
population = pd.read_csv('world_population.csv')
population.head()
```

Out[40]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	2010 Population	20 Populati
0	36	AFG	Afghanistan	Kabul	Asia	41128771	38972230	33753499	28189672	195429
1	138	ALB	Albania	Tirana	Europe	2842321	2866849	2882481	2913399	31820
2	34	DZA	Algeria	Algiers	Africa	44903225	43451666	39543154	35856344	307746
3	213	ASM	American Samoa	Pago Pago	Oceania	44273	46189	51368	54849	582
4	203	AND	Andorra	Andorra la Vella	Europe	79824	77700	71746	71519	660

In [41]:

```
# Filter column in new dataset because only country and one population column is needed
# 2020 Population is considered because it is closest to the covid data
selected_columns = ["Country/Territory", "2020 Population"]
world_population = population[selected_columns]
world_population.head()
```

Out[41]:

	Country/Territory	2020 Population
0	Afghanistan	38972230
1	Albania	2866849
2	Algeria	43451666
3	American Samoa	46189
4	Andorra	77700

In [42]:

```
# Filter column in new dataset because only country, confirmed, recovered and deaths column is needed
selected_columns1 = ["Country/Region", "Confirmed","Recovered","Deaths"]
covid_data1 = covid_data[selected_columns1]
covid_data1.head()
```

Out[42]:

	Country/Region	Confirmed	Recovered	Deaths
0	Mainland China	1	0	0
1	Mainland China	14	0	0
2	Mainland China	6	0	0
3	Mainland China	1	0	0
4	Mainland China	0	0	0

In [43]:

```
# Change the column name in order to merge the datasets
world_population.rename(columns={"Country/Territory": "Country/Region"}, inplace=True)
world_population.rename(columns={"2020 Population": "Population"}, inplace=True)
world_population.head()
```

```
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\3532130815.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.h
tml#returning-a-view-versus-a-copy
  world_population.rename(columns={"Country/Territory": "Country/Region"}, inplace=True)
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\3532130815.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.h
tml#returning-a-view-versus-a-copy
  world_population.rename(columns={"2020 Population": "Population"}, inplace=True)
```

Out[43]:

	Country/Region	Population
0	Afghanistan	38972230
1	Albania	2866849
2	Algeria	43451666
3	American Samoa	46189
4	Andorra	77700

In [44]:
```
# Merge covid and population dataset
merge_datasets = pd.merge(covid_data1, world_population, how="left", on="Country/Region")
merge_datasets
```

Out[44]:

	Country/Region	Confirmed	Recovered	Deaths	Population
0	Mainland China	1	0	0	NaN
1	Mainland China	14	0	0	NaN
2	Mainland China	6	0	0	NaN
3	Mainland China	1	0	0	NaN
4	Mainland China	0	0	0	NaN
...	...	...	...	...	...
306424	Ukraine	102641	95289	2335	43909666.0
306425	Netherlands	29147	0	245	17434557.0
306426	Mainland China	1364	1324	1	NaN
306427	Ukraine	87550	83790	1738	43909666.0
306428	Netherlands	391559	0	4252	17434557.0

306429 rows × 5 columns

In [45]:
```
# Drop rows with missing population data
merge_datasets = merge_datasets.dropna(subset=['Population'])

# Calculate per capita metrics (per million people)
merge_datasets['Cases per Million'] = (merge_datasets['Confirmed'] / merge_datasets['Population']) * 1_
merge_datasets['Deaths per Million'] = (merge_datasets['Deaths'] / merge_datasets['Population']) * 1_00
merge_datasets['Recoveries per Million'] = (merge_datasets['Recovered'] / merge_datasets['Population'])

# Group by country and calculate average per capita metrics
per_capita_stats = merge_datasets.groupby('Country/Region')[['Cases per Million', 'Deaths per Million',

print("Per Capita Analysis (per million people) Country-wise:")
per_capita_stats
```

```
Per Capita Analysis (per million people) Country-wise:
```

```
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\2254658848.py:5: 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.h
tml#returning-a-view-versus-a-copy
  merge_datasets['Cases per Million'] = (merge_datasets['Confirmed'] / merge_datasets['Population']) * 1
_000_000
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\2254658848.py:6: 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.h
tml#returning-a-view-versus-a-copy
  merge_datasets['Deaths per Million'] = (merge_datasets['Deaths'] / merge_datasets['Population']) * 1_0
00_000
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\2254658848.py:7: 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.h
tml#returning-a-view-versus-a-copy
  merge_datasets['Recoveries per Million'] = (merge_datasets['Recovered'] / merge_datasets['Populatio
n']) * 1_000_000
```

Out[45]:

	Country/Region	Cases per Million	Deaths per Million	Recoveries per Million
0	Afghanistan	947.69	37.24	749.43
1	Albania	15426.57	293.38	10882.14
2	Algeria	1385.07	41.75	948.55
3	Andorra	67462.74	909.97	61301.88
4	Angola	326.92	7.99	252.70
...	...	...	...	...
199	Venezuela	2855.45	27.54	2601.15
200	Vietnam	12.93	0.21	10.21
201	Yemen	71.81	17.74	37.81
202	Zambia	1627.67	24.85	1522.93
203	Zimbabwe	949.15	34.72	818.93

204 rows × 4 columns

Data Analysis Insights:

1. Identifying top 10 countries with highest recovery shows how well a country is treating the patients; with highest confirmed cases it shows that the country is struggling in handling the situation; with highest deaths it shows no proper treatment is given or working and requires external help.
2. Global analysis of total number of confirmed, recovered and death cases provide a view of the pandemic's impact. It highlights how the pandemic has evolved globally.
3. Total number of cases in different waves helps identify the impact in stages and reveals actions like lockdowns, vaccinations, and public awareness campaigns to be taken.
4. Per capita analysis makes it easier to compare countries for example countries with high deaths per capita but low recoveries per capita indicate challenges in healthcare systems or pandemic response strategies.

DATA VISUALISATION:

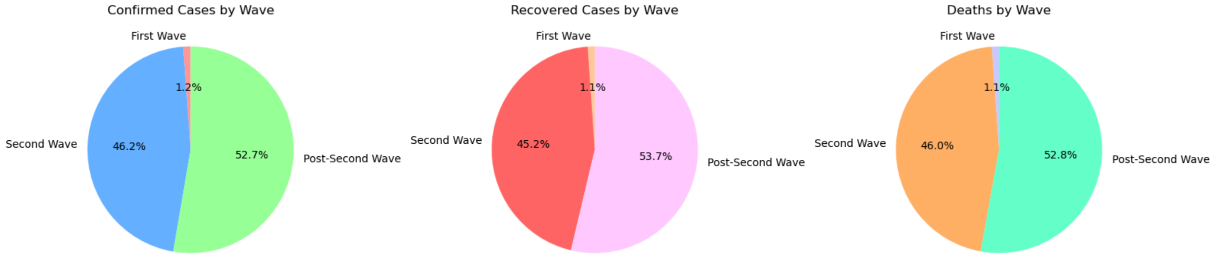
1) Pie Chart showing COVID-19 Case Distribution Across Waves: Confirmed, Recovered, and Deaths

In [46]:

```python
import matplotlib.pyplot as plt

# Aggregate data by 'Wave'
wave_data = covid_data.groupby('Wave')[['Confirmed', 'Recovered', 'Deaths']].sum()
```

```
# Define color schemes for each chart
colors_confirmed = ['#FF9999', '#66B2FF', '#99FF99']  # Colors for Confirmed
colors_recovered = ['#FFCC99', '#FF6666', '#FFCCFF']  # Colors for Recovered
colors_deaths = ['#CCCCFF', '#FFB266', '#66FFCC']     # Colors for Deaths

# Create pie chart for Confirmed cases
plt.figure(figsize=(16, 8))

plt.subplot(1, 3, 1)
plt.pie(                                                  #(Mckinney, 2023, CH 9.2, Table 9.3)
    wave_data['Confirmed'],
    labels=wave_data.index,
    autopct='%1.1f%%',
    colors=colors_confirmed,
    startangle=90
)
plt.title('Confirmed Cases by Wave')

# Create pie chart for Recovered cases
plt.subplot(1, 3, 2)
plt.pie(
    wave_data['Recovered'],
    labels=wave_data.index,
    autopct='%1.1f%%',
    colors=colors_recovered,
    startangle=90
)
plt.title('Recovered Cases by Wave')

# Create pie chart for Deaths
plt.subplot(1, 3, 3)
plt.pie(
    wave_data['Deaths'],
    labels=wave_data.index,
    autopct='%1.1f%%',
    colors=colors_deaths,
    startangle=90
)
plt.title('Deaths by Wave')

# Display the charts
plt.tight_layout()
plt.show()
```

```
C:\Users\Riddhi Shelwante\AppData\Local\Temp\ipykernel_21756\1468707277.py:4: FutureWarning: The default
of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed
=False to retain current behavior or observed=True to adopt the future default and silence this warning.
  wave_data = covid_data.groupby('Wave')[['Confirmed', 'Recovered', 'Deaths']].sum()
```



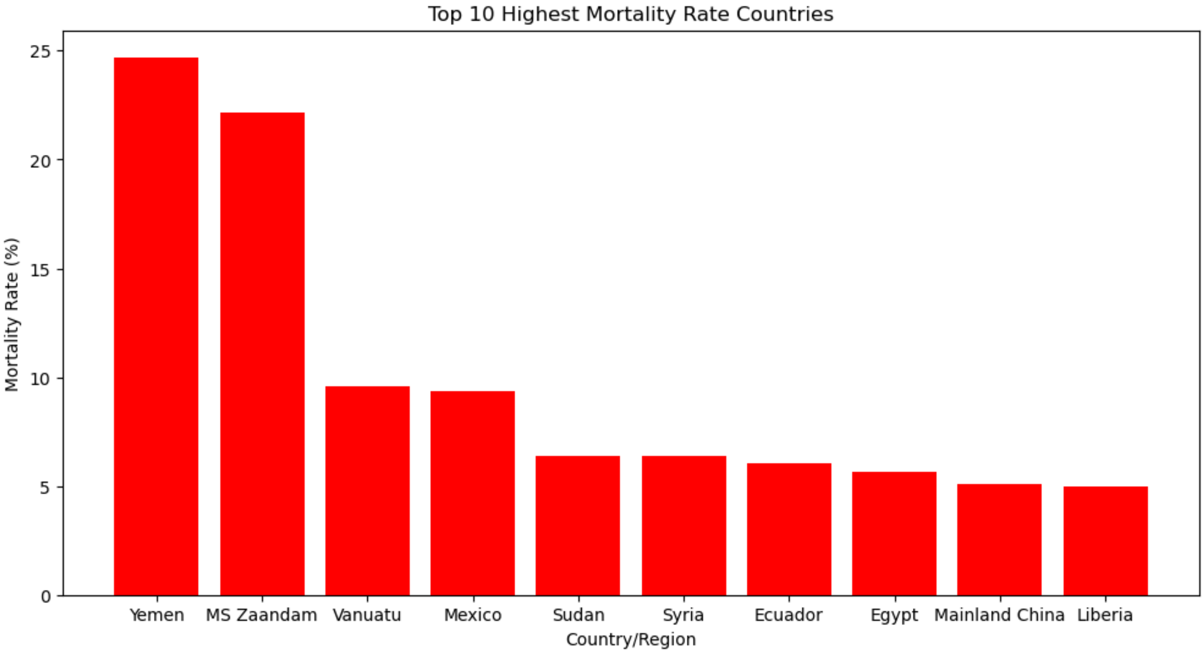
This pie charts allow us to compare the number of confirmed, recovered, and death cases across the different waves. This helps in identifying which wave had the highest impact in terms of infections, recoveries, and fatalities. It is observed that confirmed cases have increased in the post-second wave where the situation should've been stable if proper strategies were undertaken. On the other hand, recovery rates have also increased in that period which shows that the treatment given were working fine.

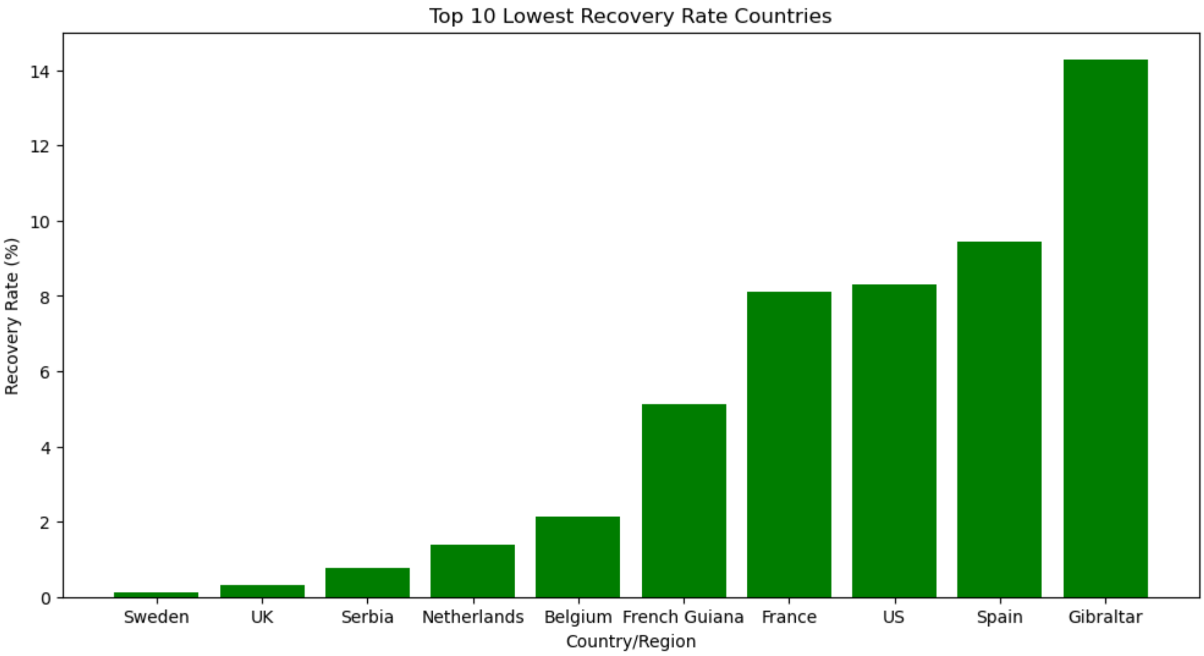
2) Top 10 Countries with High Mortality Rates and Low Recovery Rates

In [47]:

```
# Top 10 Highest Mortality Rate Countries
high_mortality = total.groupby('Country/Region')[['Mortality Rate (%)']].sum().reset_index()
top_high_mortality = high_mortality.sort_values(by='Mortality Rate (%)', ascending=False).head(10)

# Top 10 Lowest Recovery Rate Countries
```

```
low_recovery = total.groupby('Country/Region')[['Recovery Rate (%)']].sum().reset_index()
# Excluding the countries with 0.00 recover rate, comment below line if you want to include those
low_recovery = low_recovery[low_recovery['Recovery Rate (%)'] > 0]
top_low_recovery = low_recovery.sort_values(by='Recovery Rate (%)', ascending=True).head(10)

# Plotting Top 10 Highest Mortality Rate
plt.figure(figsize=(12, 6))
plt.bar(top_high_mortality['Country/Region'], top_high_mortality['Mortality Rate (%)'], color='red')
plt.title('Top 10 Highest Mortality Rate Countries')
plt.xlabel('Country/Region')
plt.ylabel('Mortality Rate (%)')
plt.show()

# Plotting Top 10 Lowest Recovery Rate
plt.figure(figsize=(12, 6))
plt.bar(top_low_recovery['Country/Region'], top_low_recovery['Recovery Rate (%)'], color='green')
plt.title('Top 10 Lowest Recovery Rate Countries')
plt.xlabel('Country/Region')
plt.ylabel('Recovery Rate (%)')
plt.show()
```



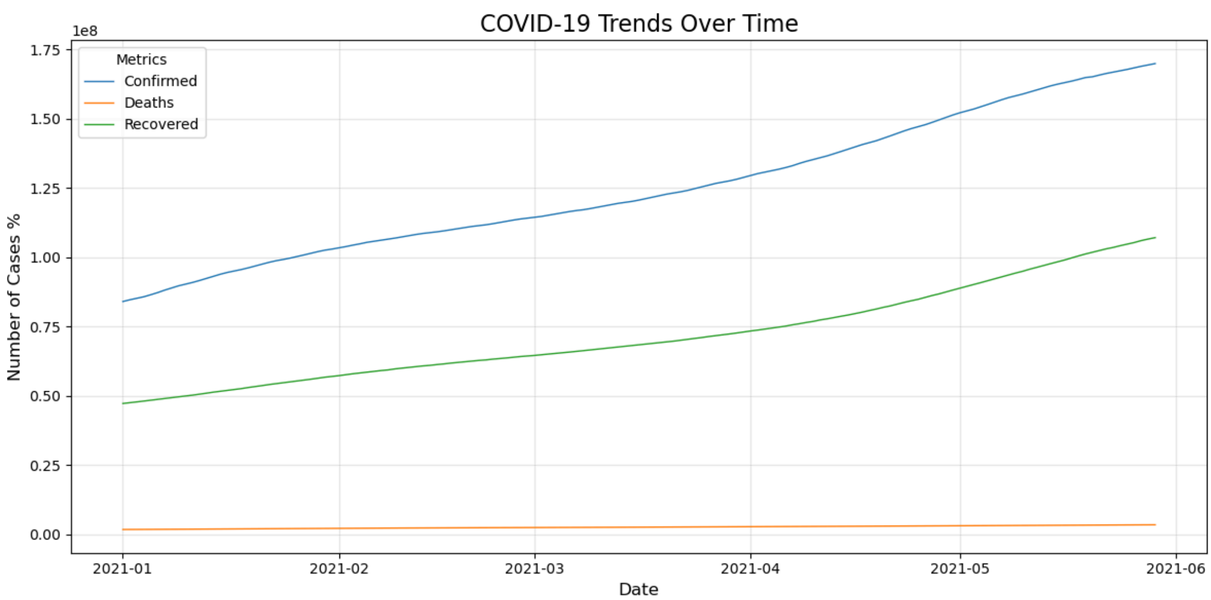


The above bar chart identifies countries with the highest fatality rates and reveals places where the pandemic's impact was most severe. Therefore, the countries with high mortality rates can be prioritized for assistance during future pandemics, with a focus on increasing emergency medical response and healthcare access.

Countries with low recovery rates may face unique challenges, such as delays in seeking treatment, poor healthcare infrastructure, or limited access to medication and vaccines. Hence, these countries can be targeted to provide faster and immediate medical services.

3) Number of Confirmed, Recovered and Death Cases w.r.t Total Number of Cases over given Time Period

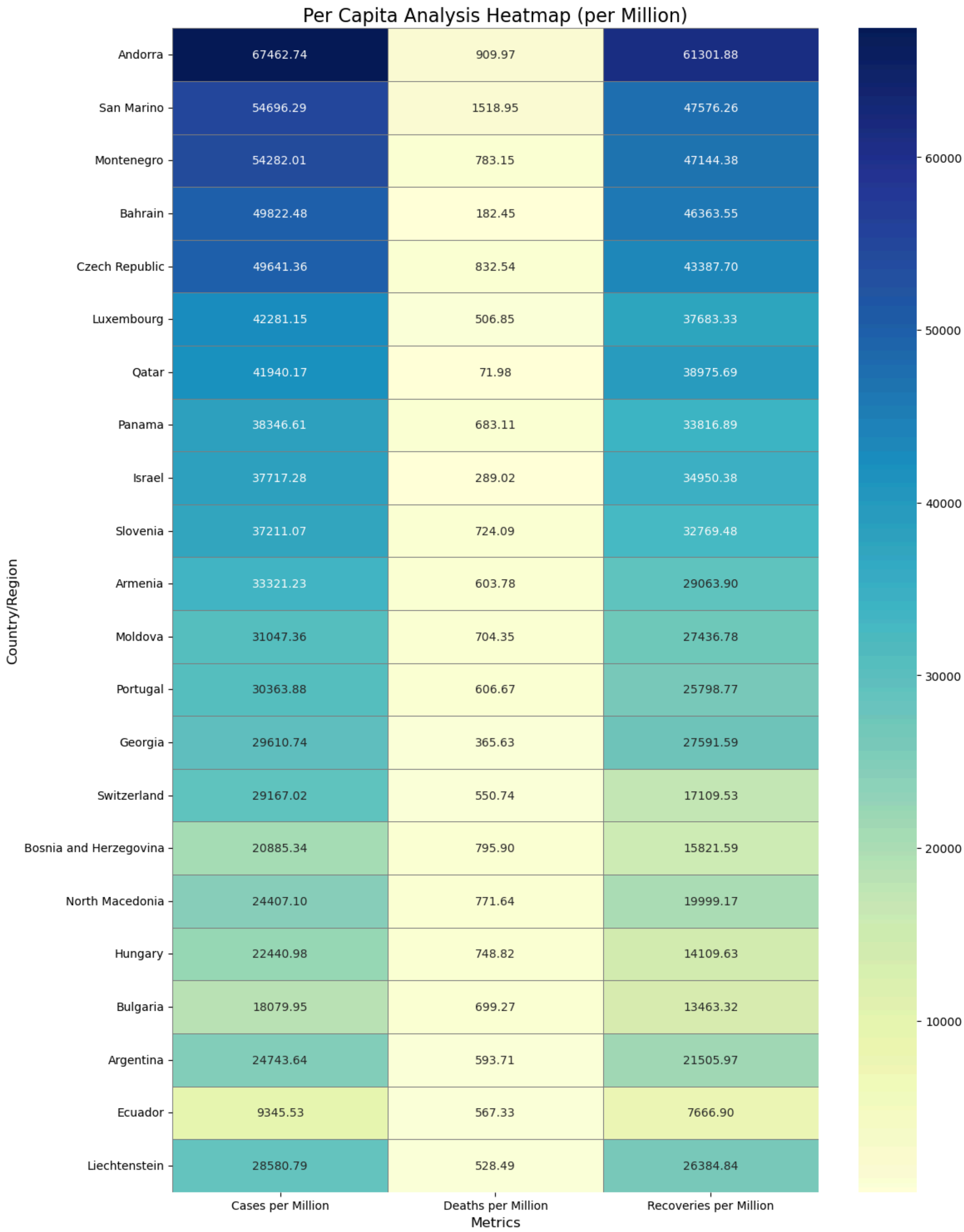
In [48]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Specify the date range
start_date = "01/01/2021"
end_date = "05/29/2021"

covid_data['ObservationDate'] = pd.to_datetime(covid_data['ObservationDate'])

# Filter the dataset by the date range
cvd_filter = covid_data[(covid_data['ObservationDate'] >= start_date) & (covid_data['ObservationDate']
trends = cvd_filter.groupby('ObservationDate')[['Confirmed', 'Deaths', 'Recovered']].sum().reset_index(


trends_melted = trends.melt(id_vars="ObservationDate",
                            value_vars=["Confirmed", "Deaths", "Recovered"],
                            var_name="Metric",
                            value_name="Count")

# Plot trends
plt.figure(figsize=(12, 6))
sns.lineplot(data=trends_melted, y="Count", x="ObservationDate", hue="Metric", linewidth=1)

# Add labels, title, legend, and grid
plt.title("COVID-19 Trends Over Time", fontsize=16)
plt.xlabel("Date", fontsize=12)
plt.ylabel("Number of Cases %", fontsize=12)
plt.legend(title="Metrics", fontsize=10)
plt.grid(alpha=0.3)

# Show the plot
plt.tight_layout()
plt.show()
```



This linechart shows the number of cases against time period. It gives the percent of those cases w.r.t the total number of cases. In this it is observed that even though the number of confirmed cases is very high, the deaths are at the bottom. This indicates the strategies taken by each country w.r.t medications has been working better. It also indicates that recovery rates are climbing and not falling down. This can be used to track if there's a downfall in recovery cases and actions to be taken rigorously.

4) Per Capita Analysis of Top 15 Countries

In [49]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt


# Sort data to get the top 15 countries by each metric
top_cases = per_capita_stats.nlargest(15, "Cases per Million")
top_deaths = per_capita_stats.nlargest(15, "Deaths per Million")
top_recoveries = per_capita_stats.nlargest(15, "Recoveries per Million")

# Combine the top 15 data into one DataFrame
top_combined = pd.concat([top_cases, top_deaths, top_recoveries]).drop_duplicates()

# Pivot DataFrame for heatmap compatibility
heatmap_data = top_combined.set_index("Country/Region")

# Create a heatmap
plt.figure(figsize=(12, 15))
sns.heatmap(                                                                # (Seaborn, n.d)
    heatmap_data,
    annot=True,  # Display data values on the heatmap
    fmt=".2f",  # Format the values to two decimal places
    cmap="YlGnBu",  # Color palette
    linewidths=0.5,  # Line width between cells
    linecolor="gray",  # Line color between cells
)

# Add titles and labels
plt.title("Per Capita Analysis Heatmap (per Million)", fontsize=16)
plt.xlabel("Metrics", fontsize=12)
plt.ylabel("Country/Region", fontsize=12)

plt.tight_layout()
plt.show()
```



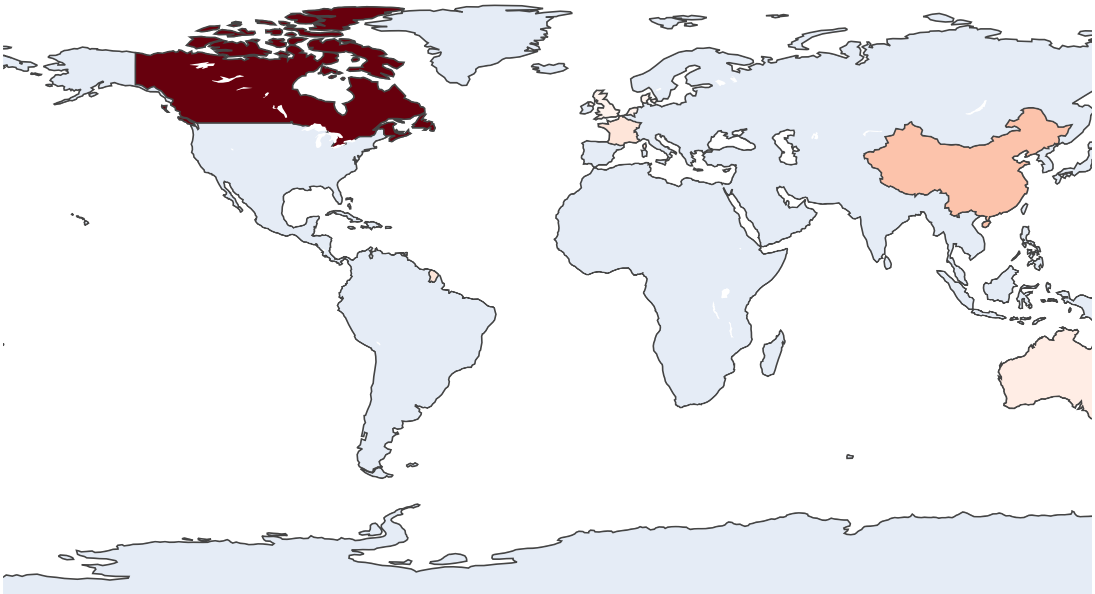
The heatmap represents how different countries perform across the three metrics: Cases per Million, Deaths per Million, and Recoveries per Million. This allows for a quick comparison of how the pandemic impacted countries per capita. It showcases how countries with high cases and recoveries but low deaths might indicate better healthcare responses or management of the pandemic and countries with high cases but lower recovery rates may need more medical resources or international support.

5) Global distribution of COVID-19 confirmed cases. Countries focused: Australia, Canada, China, Denmark, France, Netherlands, United Kingdom

In [50]:
```
import plotly.express as px

# Sample Data Preparation: Aggregate data by country
choropleth_data = merged_data.groupby('Country/Region')[['Confirmed', 'Deaths', 'Recovered', 'Lat', 'Lo
```

```
metric= 'Confirmed'

# Create a Choropleth Map for total confirmed cases
fig = px.choropleth(                                                                         # (Plotly, n.d)
    choropleth_data,
    locations="Country/Region",  # Column with country names
    locationmode="country names",  # Match country names
    color=metric,  # Column to base color intensity
    hover_name="Country/Region",
    hover_data={metric: True, 'Lat': True, 'Long': True},
    color_continuous_scale="Reds",  # Color scale
    title="Global COVID-19 Confirmed Cases",
    labels={'Confirmed': 'Total Confirmed Cases'}
)

# Update layout for better visuals
fig.update_layout(
    autosize=True,
    width=1000,
    height=800,
    geo=dict(showframe=False, showcoastlines=True, projection_type="equirectangular"),
    coloraxis_colorbar=dict(title="Confirmed Cases")
)

# Show the plot

fig.show()
```

Global COVID-19 Confirmed Cases



This choropleth map provides a worldwide perspective on the pandemic, giving a birds-eye view of its impact on many countries. It allows to identify regions where resources such as vaccines, PPE, or medical staff are most needed. It would also help in raising public awareness as this map shows confirmed cases and proper lockdown strategies are to be followed. Here, one can easily point out that Canada needs to improvise in various terms as it has most number of confirmed cases as compared to others.

CONCLUSION:

This project has provided me with insights into COVID-19 data analysis by examining the trends and patterns, calculating additional factors like mortality and recovery rates and visualising global as well as country-specific statistics. Performing analysis on this has highlighted how effectively a country has managed the pandemic in terms of implementing precautions and providing treatment. These findings reveal patterns in confirmed cases, recoveries, and deaths, allowing for a deeper understanding of how different countries and regions have been affected over time.

Findings:
I have learnt about how countries have done during the COVID-19 pandemic. The number of cases have given insights on which countries need a helping hand and which countries are dealing it well.
I have calculated the mortality and recovery rates across different countries to show variation in how different

regions coped with the pandemic.
Furthermore, I have analysed 3 waves: The first, second, and post-second waves with the purpose to portray a trend in COVID-19 progress, and how the pandemic evolved.
Later I calculated the Per Capita Analysis that presented insights into how COVID-19 spread is affecting various countries on a much minute scale and reflects the impact of population size on healthcare accessibility.
Finally, the visualisations have provided a quick-look analysis to drive decision-making.
Analysis of this dataset gave me an insider look into how these numbers and data could help in current situation as well as if any further pandemic occurs, we would know which countries are to be taken into urgent considerations.
This also means, the countries with high recovery or low confirmed cases are well equipped and have strict strategies in place.

Limitations:
I could have enhanced this project by using this historical data inorder to forecast future. Furthermore, I could have included gender and age data which would reveal deeper analysis and provided views on which age group or gender was affected the most. These would be the furture improvements in this project.

REFERENCES:

1. Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases*, 20(5), 533-534.
2. Reppel, A. and colleagues (2024) *MN5813: Module Handbook. MSc Business Analytics.* Version 1.5. 26 December.
3. McKinney, W., n.d. Python for Data Analysis. [online] Available at: https://wesmckinney.com/book/ [Accessed 20 December 2024].
4. Plotly (n.d.) *Choropleth Maps in Python*. Available at: https://plotly.com/python/choropleth-maps/ (Accessed: 10 January 2025).
5. Stack Overflow (2022) *Merging 2 datasets in Python*. Available at: https://stackoverflow.com/questions/74834625/merging-2-datasets-in-python (Accessed: 02 January 2025).
6. pandas (n.d.) *pandas.Series.dt.to_period*. Available at: https://pandas.pydata.org/docs/reference/api/pandas.Series.dt.to_period.html (Accessed: 27 December 2024).
7. Seaborn (n.d.) *seaborn.heatmap*. Available at: https://seaborn.pydata.org/generated/seaborn.heatmap.html (Accessed: 11 January 2025).

Link to GitHub:
https://github.com/riyashelwante/2502398_MN5813_Individual

In [51]:
```
!pip install pandoc
```

```
Collecting pandoc
  Downloading pandoc-2.4.tar.gz (34 kB)
  Preparing metadata (setup.py): started
  Preparing metadata (setup.py): finished with status 'done'
Collecting plumbum (from pandoc)
  Downloading plumbum-1.9.0-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: ply in c:\users\riddhi shelwante\anaconda3\lib\site-packages (from pando
c) (3.11)
Requirement already satisfied: pywin32 in c:\users\riddhi shelwante\anaconda3\lib\site-packages (from pl
umbum->pandoc) (305.1)
Downloading plumbum-1.9.0-py3-none-any.whl (127 kB)
   ---------------------------------------- 0.0/128.0 kB ? eta -:--:--
   -------------------------------------- - 122.9/128.0 kB 3.6 MB/s eta 0:00:01
   ---------------------------------------- 128.0/128.0 kB 3.8 MB/s eta 0:00:00
Building wheels for collected packages: pandoc
  Building wheel for pandoc (setup.py): started
  Building wheel for pandoc (setup.py): finished with status 'done'
  Created wheel for pandoc: filename=pandoc-2.4-py3-none-any.whl size=34823 sha256=c0c4f40c16196b3479302
000d2b6fae57645c366b83d9c04634112c551952543
  Stored in directory: c:\users\riddhi shelwante\appdata\local\pip\cache\wheels\9c\2f\9f\b1aac8c3e74b4ee
327dc8c6eac5128996f9eadf586e2c0ba67
Successfully built pandoc
Installing collected packages: plumbum, pandoc
Successfully installed pandoc-2.4 plumbum-1.9.0
```

In [ ]:

```
In [ ]:
```