covid-19-analysis

April 16, 2024

Importing of Libraries

[1]:
```
import pandas as pd
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
import plotly.offline as py
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Data Collection

[2]:
```
#Loading the datasets

data1 = pd.read_csv("Datasets/transformed_data.csv")
data2 = pd.read_csv("Datasets/raw_data.csv")
vdata = pd.read_csv("Datasets/country_vaccinations.csv")
```

[3]:
```
#Raw Data for Covid-19 Impact Analysis

data2
```

[3]:
```
      iso_code     location        date  total_cases  total_deaths  \
0          AFG  Afghanistan  2019-12-31          0.0           0.0
1          AFG  Afghanistan  2020-01-01          0.0           0.0
2          AFG  Afghanistan  2020-01-02          0.0           0.0
3          AFG  Afghanistan  2020-01-03          0.0           0.0
4          AFG  Afghanistan  2020-01-04          0.0           0.0
…        …           …          …            …             …
50413      ZWE     Zimbabwe  2020-10-15       8055.0         231.0
50414      ZWE     Zimbabwe  2020-10-16       8075.0         231.0
50415      ZWE     Zimbabwe  2020-10-17       8099.0         231.0
50416      ZWE     Zimbabwe  2020-10-18       8110.0         231.0
50417      ZWE     Zimbabwe  2020-10-19       8147.0         231.0

       stringency_index  population  gdp_per_capita  human_development_index  \
```

```
0                0.00    38928341       1803.987                   0.498
1                0.00    38928341       1803.987                   0.498
2                0.00    38928341       1803.987                   0.498
3                0.00    38928341       1803.987                   0.498
4                0.00    38928341       1803.987                   0.498
…               …        …             …                      …
50413           76.85    14862927       1899.775                   0.535
50414           76.85    14862927       1899.775                   0.535
50415           76.85    14862927       1899.775                   0.535
50416           76.85    14862927       1899.775                   0.535
50417           76.85    14862927       1899.775                   0.535

        Unnamed: 9  Unnamed: 10 Unnamed: 11  Unnamed: 12  Unnamed: 13
0            #NUM!        #NUM!       #NUM!    17.477233  7.497754494
1            #NUM!        #NUM!       #NUM!    17.477233  7.497754494
2            #NUM!        #NUM!       #NUM!    17.477233  7.497754494
3            #NUM!        #NUM!       #NUM!    17.477233  7.497754494
4            #NUM!        #NUM!       #NUM!    17.477233  7.497754494
…              …          …          …          …        …
50413  8.994048296  5.442417711  4.34185547    16.514381  7.549490737
50414  8.996528148  5.442417711  4.34185547    16.514381  7.549490737
50415  8.999495876  5.442417711  4.34185547    16.514381  7.549490737
50416  9.000853147  5.442417711  4.34185547    16.514381  7.549490737
50417   9.00540504  5.442417711  4.34185547    16.514381  7.549490737

[50418 rows x 14 columns]
```

[4]:
```
#Data for Covid-19 Vaccine Analysis

vdata
```

[4]:
```
           country iso_code        date  total_vaccinations  \
0      Afghanistan      AFG  2021-02-22                 0.0
1      Afghanistan      AFG  2021-02-23                 NaN
2      Afghanistan      AFG  2021-02-24                 NaN
3      Afghanistan      AFG  2021-02-25                 NaN
4      Afghanistan      AFG  2021-02-26                 NaN
…             …      …          …                 …
86507     Zimbabwe      ZWE  2022-03-25           8691642.0
86508     Zimbabwe      ZWE  2022-03-26           8791728.0
86509     Zimbabwe      ZWE  2022-03-27           8845039.0
86510     Zimbabwe      ZWE  2022-03-28           8934360.0
86511     Zimbabwe      ZWE  2022-03-29           9039729.0

       people_vaccinated  people_fully_vaccinated  daily_vaccinations_raw  \
0                    0.0                      NaN                     NaN
1                    NaN                      NaN                     NaN
```

```
2                   NaN                     NaN                    NaN
3                   NaN                     NaN                    NaN
4                   NaN                     NaN                    NaN
…                    …                       …                      …
86507         4814582.0               3473523.0               139213.0
86508         4886242.0               3487962.0               100086.0
86509         4918147.0               3493763.0                53311.0
86510         4975433.0               3501493.0                89321.0
86511         5053114.0               3510256.0               105369.0

       daily_vaccinations  total_vaccinations_per_hundred  \
0                     NaN                            0.00
1                  1367.0                             NaN
2                  1367.0                             NaN
3                  1367.0                             NaN
4                  1367.0                             NaN
…                    …                             …
86507             69579.0                           57.59
86508             83429.0                           58.25
86509             90629.0                           58.61
86510            100614.0                           59.20
86511            103751.0                           59.90

       people_vaccinated_per_hundred  people_fully_vaccinated_per_hundred  \
0                               0.00                                  NaN
1                                NaN                                  NaN
2                                NaN                                  NaN
3                                NaN                                  NaN
4                                NaN                                  NaN
…                              …                                  …
86507                          31.90                                23.02
86508                          32.38                                23.11
86509                          32.59                                23.15
86510                          32.97                                23.20
86511                          33.48                                23.26

       daily_vaccinations_per_million  \
0                                 NaN
1                                34.0
2                                34.0
3                                34.0
4                                34.0
…                                …
86507                          4610.0
86508                          5528.0
86509                          6005.0
86510                          6667.0
```

```
86511                         6874.0

                                                  vaccines  \
0      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
1      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
2      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
3      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
4      Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
…                                                  …
86507  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac…
86508  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac…
86509  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac…
86510  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac…
86511  Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac…

                     source_name  \
0      World Health Organization
1      World Health Organization
2      World Health Organization
3      World Health Organization
4      World Health Organization
…                            …
86507         Ministry of Health
86508         Ministry of Health
86509         Ministry of Health
86510         Ministry of Health
86511         Ministry of Health

                                          source_website
0                              https://covid19.who.int/
1                              https://covid19.who.int/
2                              https://covid19.who.int/
3                              https://covid19.who.int/
4                              https://covid19.who.int/
…                                                  …
86507  https://www.arcgis.com/home/webmap/viewer.html…
86508  https://www.arcgis.com/home/webmap/viewer.html…
86509  https://www.arcgis.com/home/webmap/viewer.html…
86510  https://www.arcgis.com/home/webmap/viewer.html…
86511  https://www.arcgis.com/home/webmap/viewer.html…

[86512 rows x 15 columns]
```

To know the information about the datatypes in the datasets

[5]:
```
#Metadata about Raw Data of Covid-19 Impact
```

```
data2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50418 entries, 0 to 50417
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   iso_code                 50418 non-null  object
 1   location                 50418 non-null  object
 2   date                     50418 non-null  object
 3   total_cases              47324 non-null  float64
 4   total_deaths             39228 non-null  float64
 5   stringency_index         43292 non-null  float64
 6   population               50418 non-null  int64
 7   gdp_per_capita           44706 non-null  float64
 8   human_development_index  44216 non-null  float64
 9   Unnamed: 9               50418 non-null  object
 10  Unnamed: 10              50418 non-null  object
 11  Unnamed: 11              50418 non-null  object
 12  Unnamed: 12              50418 non-null  float64
 13  Unnamed: 13              50418 non-null  object
dtypes: float64(6), int64(1), object(7)
memory usage: 5.4+ MB
```

[6]:
```
#Metadata about Dataset of Covid-19 Vaccines

vdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 86512 entries, 0 to 86511
Data columns (total 15 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   country                              86512 non-null  object
 1   iso_code                             86512 non-null  object
 2   date                                 86512 non-null  object
 3   total_vaccinations                   43607 non-null  float64
 4   people_vaccinated                    41294 non-null  float64
 5   people_fully_vaccinated              38802 non-null  float64
 6   daily_vaccinations_raw               35362 non-null  float64
 7   daily_vaccinations                   86213 non-null  float64
 8   total_vaccinations_per_hundred       43607 non-null  float64
 9   people_vaccinated_per_hundred        41294 non-null  float64
 10  people_fully_vaccinated_per_hundred  38802 non-null  float64
 11  daily_vaccinations_per_million       86213 non-null  float64
 12  vaccines                             86512 non-null  object
 13  source_name                          86512 non-null  object
 14  source_website                       86512 non-null  object
```

```
dtypes: float64(9), object(6)
memory usage: 9.9+ MB
```

Data Cleaning

[7]:
```
#First 10 rows of Raw Data of Covid-19 Impact

data2.head(10)
```

[7]:
```
  iso_code     location        date  total_cases  total_deaths  \
0      AFG  Afghanistan  2019-12-31          0.0           0.0
1      AFG  Afghanistan  2020-01-01          0.0           0.0
2      AFG  Afghanistan  2020-01-02          0.0           0.0
3      AFG  Afghanistan  2020-01-03          0.0           0.0
4      AFG  Afghanistan  2020-01-04          0.0           0.0
5      AFG  Afghanistan  2020-01-05          0.0           0.0
6      AFG  Afghanistan  2020-01-06          0.0           0.0
7      AFG  Afghanistan  2020-01-07          0.0           0.0
8      AFG  Afghanistan  2020-01-08          0.0           0.0
9      AFG  Afghanistan  2020-01-09          0.0           0.0

   stringency_index  population  gdp_per_capita  human_development_index  \
0               0.0    38928341        1803.987                    0.498
1               0.0    38928341        1803.987                    0.498
2               0.0    38928341        1803.987                    0.498
3               0.0    38928341        1803.987                    0.498
4               0.0    38928341        1803.987                    0.498
5               0.0    38928341        1803.987                    0.498
6               0.0    38928341        1803.987                    0.498
7               0.0    38928341        1803.987                    0.498
8               0.0    38928341        1803.987                    0.498
9               0.0    38928341        1803.987                    0.498

  Unnamed: 9 Unnamed: 10 Unnamed: 11  Unnamed: 12  Unnamed: 13
0      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
1      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
2      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
3      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
4      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
5      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
6      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
7      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
8      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
9      #NUM!       #NUM!       #NUM!    17.477233  7.497754494
```

[8]:
```
#Shape of Raw Data of Covid-19 Impact

data2.shape
```

[8]: (50418, 14)

[9]:
```
#Checking of duplicacy of data in the Raw Data of Covid-19 Impact

data2.duplicated().sum()
```

[9]: 0

[10]:
```
#Checking of NULL values or empty values in the Raw Data of Covid-19 Impact

data2.isnull().sum()
```

[10]:
```
iso_code                     0
location                     0
date                         0
total_cases               3094
total_deaths             11190
stringency_index          7126
population                   0
gdp_per_capita            5712
human_development_index   6202
Unnamed: 9                   0
Unnamed: 10                  0
Unnamed: 11                  0
Unnamed: 12                  0
Unnamed: 13                  0
dtype: int64
```

[11]:
```
#First 10 rows of Dataset of Covid-19 Vaccines

vdata.head(10)
```

[11]:
```
       country iso_code        date  total_vaccinations  people_vaccinated  \
0  Afghanistan      AFG  2021-02-22                 0.0                0.0
1  Afghanistan      AFG  2021-02-23                 NaN                NaN
2  Afghanistan      AFG  2021-02-24                 NaN                NaN
3  Afghanistan      AFG  2021-02-25                 NaN                NaN
4  Afghanistan      AFG  2021-02-26                 NaN                NaN
5  Afghanistan      AFG  2021-02-27                 NaN                NaN
6  Afghanistan      AFG  2021-02-28              8200.0             8200.0
7  Afghanistan      AFG  2021-03-01                 NaN                NaN
8  Afghanistan      AFG  2021-03-02                 NaN                NaN
9  Afghanistan      AFG  2021-03-03                 NaN                NaN

   people_fully_vaccinated  daily_vaccinations_raw  daily_vaccinations  \
0                      NaN                     NaN                 NaN
1                      NaN                     NaN              1367.0
```

```
2                    NaN                    NaN             1367.0
3                    NaN                    NaN             1367.0
4                    NaN                    NaN             1367.0
5                    NaN                    NaN             1367.0
6                    NaN                    NaN             1367.0
7                    NaN                    NaN             1580.0
8                    NaN                    NaN             1794.0
9                    NaN                    NaN             2008.0

   total_vaccinations_per_hundred  people_vaccinated_per_hundred  \
0                            0.00                           0.00
1                             NaN                            NaN
2                             NaN                            NaN
3                             NaN                            NaN
4                             NaN                            NaN
5                             NaN                            NaN
6                            0.02                           0.02
7                             NaN                            NaN
8                             NaN                            NaN
9                             NaN                            NaN

   people_fully_vaccinated_per_hundred  daily_vaccinations_per_million  \
0                                  NaN                             NaN
1                                  NaN                            34.0
2                                  NaN                            34.0
3                                  NaN                            34.0
4                                  NaN                            34.0
5                                  NaN                            34.0
6                                  NaN                            34.0
7                                  NaN                            40.0
8                                  NaN                            45.0
9                                  NaN                            50.0

                                          vaccines  \
0  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
1  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
2  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
3  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
4  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
5  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
6  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
7  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
8  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…
9  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…

                source_name            source_website
0  World Health Organization  https://covid19.who.int/
```

```
1  World Health Organization  https://covid19.who.int/
2  World Health Organization  https://covid19.who.int/
3  World Health Organization  https://covid19.who.int/
4  World Health Organization  https://covid19.who.int/
5  World Health Organization  https://covid19.who.int/
6  World Health Organization  https://covid19.who.int/
7  World Health Organization  https://covid19.who.int/
8  World Health Organization  https://covid19.who.int/
9  World Health Organization  https://covid19.who.int/
```

[12]:
```
#Shape of Dataset of Covid-19 Vaccines

vdata.shape
```

[12]:
```
(86512, 15)
```

[13]:
```
#Checking of duplicacy of data in the Dataset of Covid-19 Vaccines

vdata.duplicated().sum()
```

[13]:
```
0
```

[14]:
```
#Checking of availability of NULL values or empty values in the Dataset of␣
↪Covid-19 Vaccines

vdata.isnull().sum()
```

[14]:
```
country                                    0
iso_code                                   0
date                                       0
total_vaccinations                     42905
people_vaccinated                      45218
people_fully_vaccinated                47710
daily_vaccinations_raw                 51150
daily_vaccinations                       299
total_vaccinations_per_hundred         42905
people_vaccinated_per_hundred          45218
people_fully_vaccinated_per_hundred    47710
daily_vaccinations_per_million           299
vaccines                                   0
source_name                                0
source_website                             0
dtype: int64
```

[15]:
```
#Conversion of datetime objects into pandas datetime objects for smooth␣
↪operations
```

```python
pd.to_datetime(vdata.date)
```

[15]:
```
0       2021-02-22
1       2021-02-23
2       2021-02-24
3       2021-02-25
4       2021-02-26
           …
86507   2022-03-25
86508   2022-03-26
86509   2022-03-27
86510   2022-03-28
86511   2022-03-29
Name: date, Length: 86512, dtype: datetime64[ns]
```

[16]:
```python
#Transformed Dataset of Covid-19 Impact after Data Cleaning

data1
```

[16]:
```
      CODE      COUNTRY        DATE    HDI        TC        TD       STI  \
0      AFG  Afghanistan  2019-12-31  0.498  0.000000  0.000000  0.000000
1      AFG  Afghanistan  2020-01-01  0.498  0.000000  0.000000  0.000000
2      AFG  Afghanistan  2020-01-02  0.498  0.000000  0.000000  0.000000
3      AFG  Afghanistan  2020-01-03  0.498  0.000000  0.000000  0.000000
4      AFG  Afghanistan  2020-01-04  0.498  0.000000  0.000000  0.000000
…     …          …          …     …       …         …         …
50413  ZWE     Zimbabwe  2020-10-15  0.535  8.994048  5.442418  4.341855
50414  ZWE     Zimbabwe  2020-10-16  0.535  8.996528  5.442418  4.341855
50415  ZWE     Zimbabwe  2020-10-17  0.535  8.999496  5.442418  4.341855
50416  ZWE     Zimbabwe  2020-10-18  0.535  9.000853  5.442418  4.341855
50417  ZWE     Zimbabwe  2020-10-19  0.535  9.005405  5.442418  4.341855

             POP    GDPCAP
0      17.477233  7.497754
1      17.477233  7.497754
2      17.477233  7.497754
3      17.477233  7.497754
4      17.477233  7.497754
…            …         …
50413  16.514381  7.549491
50414  16.514381  7.549491
50415  16.514381  7.549491
50416  16.514381  7.549491
50417  16.514381  7.549491

[50418 rows x 9 columns]
```

[17]:
```
#Shape of the Transformed Dataset of Covid-19 Impact

data1.shape
```

[17]: (50418, 9)

[18]:
```
#First 10 rows of Transformed Dataset of Covid-19 Impact

data1.head(10)
```

[18]:

	CODE	COUNTRY	DATE	HDI	TC	TD	STI	POP	GDPCAP
0	AFG	Afghanistan	2019-12-31	0.498	0.0	0.0	0.0	17.477233	7.497754
1	AFG	Afghanistan	2020-01-01	0.498	0.0	0.0	0.0	17.477233	7.497754
2	AFG	Afghanistan	2020-01-02	0.498	0.0	0.0	0.0	17.477233	7.497754
3	AFG	Afghanistan	2020-01-03	0.498	0.0	0.0	0.0	17.477233	7.497754
4	AFG	Afghanistan	2020-01-04	0.498	0.0	0.0	0.0	17.477233	7.497754
5	AFG	Afghanistan	2020-01-05	0.498	0.0	0.0	0.0	17.477233	7.497754
6	AFG	Afghanistan	2020-01-06	0.498	0.0	0.0	0.0	17.477233	7.497754
7	AFG	Afghanistan	2020-01-07	0.498	0.0	0.0	0.0	17.477233	7.497754
8	AFG	Afghanistan	2020-01-08	0.498	0.0	0.0	0.0	17.477233	7.497754
9	AFG	Afghanistan	2020-01-09	0.498	0.0	0.0	0.0	17.477233	7.497754

[19]:
```
#Metadata about Transformed Dataset of Covid-19 Impact

data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50418 entries, 0 to 50417
Data columns (total 9 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CODE     50418 non-null  object
 1   COUNTRY  50418 non-null  object
 2   DATE     50418 non-null  object
 3   HDI      44216 non-null  float64
 4   TC       50418 non-null  float64
 5   TD       50418 non-null  float64
 6   STI      50418 non-null  float64
 7   POP      50418 non-null  float64
 8   GDPCAP   50418 non-null  float64
dtypes: float64(6), object(3)
memory usage: 3.5+ MB
```

Summary Statistics

[20]:
```
#Statistical inference about the Raw Data of Covid-19 Impact

data2.describe()
```

[20]:

	total_cases	total_deaths	stringency_index	population
count	4.732400e+04	39228.000000	43292.000000	5.041800e+04
mean	6.621927e+04	2978.767819	56.162022	4.251601e+07
std	4.045582e+05	13836.644013	27.532685	1.564607e+08
min	0.000000e+00	0.000000	0.000000	8.090000e+02
25%	1.260000e+02	10.000000	37.960000	1.399491e+06
50%	1.594000e+03	64.000000	61.110000	8.278737e+06
75%	1.584775e+04	564.000000	78.700000	2.913681e+07
max	8.154595e+06	219674.000000	100.000000	1.439324e+09

	gdp_per_capita	human_development_index	Unnamed: 12
count	44706.000000	44216.000000	50418.000000
mean	20818.706240	0.720139	15.442097
std	20441.365392	0.160902	2.495039
min	661.240000	0.000000	6.695799
25%	5338.454000	0.601000	14.151619
50%	13913.839000	0.752000	15.929201
75%	31400.840000	0.847000	17.187513
max	116935.600000	0.953000	21.087439

[21]:

```
#Statistical inference about the Transformed Dataset of Covid-19 Impact

data1.describe()
```

[21]:

	HDI	TC	TD	STI	POP
count	44216.000000	50418.000000	50418.000000	50418.000000	50418.000000
mean	0.720139	6.762125	3.413681	3.178897	15.442097
std	0.160902	3.637347	3.082761	1.673451	2.495039
min	0.000000	0.000000	0.000000	0.000000	6.695799
25%	0.601000	4.158883	0.000000	2.867331	14.151619
50%	0.752000	7.092574	3.178054	4.000583	15.929201
75%	0.847000	9.504669	5.620401	4.335852	17.187513
max	0.953000	15.914092	12.299900	4.605170	21.087439

	GDPCAP
count	50418.000000
mean	8.318580
std	3.177130
min	0.000000
25%	7.955479
50%	9.368531
75%	10.237704
max	11.669379

[22]:

```
#Statistical inference about the Dataset of Covid-19 Vaccines

vdata.describe()
```

[22]:
```
       total_vaccinations  people_vaccinated  people_fully_vaccinated  \
count        4.360700e+04       4.129400e+04             3.880200e+04
mean         4.592964e+07       1.770508e+07             1.413830e+07
std          2.246004e+08       7.078731e+07             5.713920e+07
min          0.000000e+00       0.000000e+00             1.000000e+00
25%          5.264100e+05       3.494642e+05             2.439622e+05
50%          3.590096e+06       2.187310e+06             1.722140e+06
75%          1.701230e+07       9.152520e+06             7.559870e+06
max          3.263129e+09       1.275541e+09             1.240777e+09

       daily_vaccinations_raw  daily_vaccinations  \
count            3.536200e+04        8.621300e+04
mean             2.705996e+05        1.313055e+05
std              1.212427e+06        7.682388e+05
min              0.000000e+00        0.000000e+00
25%              4.668000e+03        9.000000e+02
50%              2.530900e+04        7.343000e+03
75%              1.234925e+05        4.409800e+04
max              2.474100e+07        2.242429e+07

       total_vaccinations_per_hundred  people_vaccinated_per_hundred  \
count                    43607.000000                   41294.000000
mean                        80.188543                      40.927317
std                         67.913577                      29.290759
min                          0.000000                       0.000000
25%                         16.050000                      11.370000
50%                         67.520000                      41.435000
75%                        132.735000                      67.910000
max                        345.370000                     124.760000

       people_fully_vaccinated_per_hundred  daily_vaccinations_per_million
count                         38802.000000                    86213.000000
mean                             35.523243                     3257.049157
std                              28.376252                     3934.312440
min                               0.000000                        0.000000
25%                               7.020000                      636.000000
50%                              31.750000                     2050.000000
75%                              62.080000                     4682.000000
max                             122.370000                   117497.000000
```

Data Aggregation

[23]:
```
data1["COUNTRY"].value_counts()
```

[23]:
```
COUNTRY
Afghanistan         294
Indonesia           294
```

```
Macedonia           294
Luxembourg          294
Lithuania           294
                   …
Tajikistan          172
Comoros             171
Lesotho             158
Hong Kong            51
Solomon Islands       4
Name: count, Length: 210, dtype: int64
```

[24]:
```python
vdata.country.value_counts()
```

[24]:
```
country
Norway                              482
Latvia                              480
Denmark                             476
United States                       471
Russia                              470
                                   …
Bonaire Sint Eustatius and Saba     146
Tokelau                             114
Saint Helena                         92
Pitcairn                             85
Falkland Islands                     67
Name: count, Length: 223, dtype: int64
```

[25]:
```python
data1["COUNTRY"].value_counts().mode()
```

[25]:
```
0    294
Name: count, dtype: int64
```

[26]:
```python
# Aggregating the data of Covid-19 Impact

code = data1["CODE"].unique().tolist()
country = data1["COUNTRY"].unique().tolist()
hdi = []
tc = []
td = []
sti = []
population = data1["POP"].unique().tolist()
gdp = []

for i in country:
    hdi.append((data1.loc[data1["COUNTRY"] == i, "HDI"]).sum()/294)
    tc.append((data2.loc[data2["location"] == i, "total_cases"]).sum())
    td.append((data2.loc[data2["location"] == i, "total_deaths"]).sum())
```

```
    sti.append((data1.loc[data1["COUNTRY"] == i, "STI"]).sum()/294)
    population.append((data2.loc[data2["location"] == i, "population"]).sum()/
 ↪294)

aggregated_data = pd.DataFrame(list(zip(code, country, hdi, tc, td, sti,␣
 ↪population)),
                               columns = ["Country Code", "Country", "HDI",
                                          "Total Cases", "Total Deaths",
                                          "Stringency Index", "Population"])
aggregated_data.head()
```

[26]:

```
  Country Code      Country       HDI  Total Cases  Total Deaths  \
0          AFG  Afghanistan  0.498000    5126433.0      165875.0
1          ALB      Albania  0.600765    1071951.0       31056.0
2          DZA      Algeria  0.754000    4893999.0      206429.0
3          AND      Andorra  0.659551     223576.0        9850.0
4          AGO       Angola  0.418952     304005.0       11820.0

   Stringency Index  Population
0          3.049673   17.477233
1          3.005624   14.872537
2          3.195168   17.596309
3          2.677654   11.254996
4          2.965560   17.307957
```

[27]:

```
# Sorting Data of Aggregated Data of Covid-19 Impact according to Total Cases

data3 = aggregated_data.sort_values(by=["Total Cases"], ascending=False)
data3.head()
```

[27]:

```
    Country Code        Country      HDI  Total Cases  Total Deaths  \
200          USA  United States  0.92400  746014098.0    26477574.0
27           BRA         Brazil  0.75900  425704517.0    14340567.0
90           IND          India  0.64000  407771615.0     7247327.0
157          RUS         Russia  0.81600  132888951.0     2131571.0
150          PER           Peru  0.59949   74882695.0     3020038.0

     Stringency Index  Population
200          3.350949   19.617637
27           3.136028   19.174732
90           3.610552   21.045353
157          3.380088   18.798668
150          3.430126   17.311165
```

[28]:

```
# Top 10 Countries with Highest Covid Cases

data = data3.head(10)
```

```
data
```

[28]:
```
     Country Code         Country       HDI  Total Cases  Total Deaths  \
200          USA   United States  0.924000  746014098.0    26477574.0
27           BRA          Brazil  0.759000  425704517.0    14340567.0
90           IND           India  0.640000  407771615.0     7247327.0
157          RUS          Russia  0.816000  132888951.0     2131571.0
150          PER            Peru  0.599490   74882695.0     3020038.0
125          MEX          Mexico  0.774000   74347548.0     7295850.0
178          ESP           Spain  0.887969   73717676.0     5510624.0
175          ZAF    South Africa  0.608653   63027659.0     1357682.0
42           COL        Colombia  0.581847   60543682.0     1936134.0
199          GBR  United Kingdom  0.922000   59475032.0     7249573.0

     Stringency Index  Population
200          3.350949   19.617637
27           3.136028   19.174732
90           3.610552   21.045353
157          3.380088   18.798668
150          3.430126   17.311165
125          3.019289   18.674802
178          3.393922   17.660427
175          3.364333   17.898266
42           3.357923   17.745037
199          3.353883   18.033340
```

[29]:
```
#Collected this data manually from Internet

data["GDP Before Covid"] = [65279.53, 8897.49, 2100.75,
                            11497.65, 7027.61, 9946.03,
                            29564.74, 6001.40, 6424.98, 42354.41]
data["GDP During Covid"] = [63543.58, 6796.84, 1900.71,
                            10126.72, 6126.87, 8346.70,
                            27057.16, 5090.72, 5332.77, 40284.64]
print(data)
```

```
    Country Code         Country       HDI  Total Cases  Total Deaths  \
200          USA   United States  0.924000  746014098.0    26477574.0
27           BRA          Brazil  0.759000  425704517.0    14340567.0
90           IND           India  0.640000  407771615.0     7247327.0
157          RUS          Russia  0.816000  132888951.0     2131571.0
150          PER            Peru  0.599490   74882695.0     3020038.0
125          MEX          Mexico  0.774000   74347548.0     7295850.0
178          ESP           Spain  0.887969   73717676.0     5510624.0
175          ZAF    South Africa  0.608653   63027659.0     1357682.0
42           COL        Colombia  0.581847   60543682.0     1936134.0
199          GBR  United Kingdom  0.922000   59475032.0     7249573.0
```

```
     Stringency Index  Population  GDP Before Covid  GDP During Covid
200          3.350949   19.617637          65279.53          63543.58
27           3.136028   19.174732           8897.49           6796.84
90           3.610552   21.045353           2100.75           1900.71
157          3.380088   18.798668          11497.65          10126.72
150          3.430126   17.311165           7027.61           6126.87
125          3.019289   18.674802           9946.03           8346.70
178          3.393922   17.660427          29564.74          27057.16
175          3.364333   17.898266           6001.40           5090.72
42           3.357923   17.745037           6424.98           5332.77
199          3.353883   18.033340          42354.41          40284.64
```

[30]:
```
#Statistical Inference about the TOP 10 Countires with highest impact of␣
 ↪Covid-19

data.describe()
```

[30]:
```
             HDI   Total Cases  Total Deaths  Stringency Index  Population  \
count  10.000000  1.000000e+01  1.000000e+01         10.000000   10.000000
mean    0.751296  2.118373e+08  7.656694e+06          3.339709   18.595943
std     0.136178  2.358654e+08  7.662294e+06          0.160389    1.129353
min     0.581847  5.947503e+07  1.357682e+06          3.019289   17.311165
25%     0.616490  6.570016e+07  2.353688e+06          3.351682   17.783344
50%     0.766500  7.461512e+07  6.378976e+06          3.361128   18.354071
75%     0.869977  3.390509e+08  7.284281e+06          3.390464   19.080716
max     0.924000  7.460141e+08  2.647757e+07          3.610552   21.045353

       GDP Before Covid  GDP During Covid
count         10.000000         10.000000
mean       18909.459000      17460.671000
std        20534.775267      20160.187284
min         2100.750000       1900.710000
25%         6575.637500       5531.295000
50%         9421.760000       7571.770000
75%        25047.967500      22824.550000
max        65279.530000      63543.580000
```

[31]:
```
vdata.vaccines.value_counts()
```

[31]:
```
vaccines
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech
7608
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech
6263
Oxford/AstraZeneca
6022
```

```
Oxford/AstraZeneca, Pfizer/BioNTech
4629
Johnson&Johnson, Moderna, Novavax, Oxford/AstraZeneca, Pfizer/BioNTech
3564
  …
Johnson&Johnson, Oxford/AstraZeneca, Sinovac
312
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac, Sputnik V
311
Johnson&Johnson, Moderna
251
Johnson&Johnson, Pfizer/BioNTech, Sinopharm/Beijing
228
EpiVacCorona, Oxford/AstraZeneca, QazVac, Sinopharm/Beijing, Sputnik V, ZF2001
190
Name: count, Length: 84, dtype: int64
```

[32]:
```
#Creating a new dataframe containing the only Vaccines and Contries

vdf = vdata[["vaccines", "country"]]
vdf.head()
```

[32]:
```
                                            vaccines      country
0  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…  Afghanistan
1  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…  Afghanistan
2  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…  Afghanistan
3  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…  Afghanistan
4  Johnson&Johnson, Oxford/AstraZeneca, Pfizer/Bi…  Afghanistan
```

[33]:
```
#Listed data of Covid-19 Vaccines with respect to countries

dict_ = {}
for i in vdf.vaccines.unique(): dict_[i] = [vdf["country"][j] for j in␣
 ↪vdf[vdf["vaccines"]==i].index]
vaccines = {}
for key, value in dict_.items(): vaccines[key] = set(value)
for i, j in vaccines.items(): print(f"{i} :>> {j}")
```

```
Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing :>>
{'Belize', 'Cameroon', 'Namibia', 'Afghanistan', 'Trinidad and Tobago'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac, Sputnik V :>> {'Albania', 'Oman',
'Bosnia and Herzegovina', 'Azerbaijan'}
Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac, Sputnik V :>> {'Zimbabwe',
'Algeria'}
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech :>> {'Fiji', 'Sint Maarten (Dutch
part)', 'Jersey', 'United Kingdom', 'Australia', 'England', 'Northern Ireland',
'Wales', 'Finland', 'Guernsey', 'Isle of Man', 'Andorra', 'Scotland', 'Japan',
```

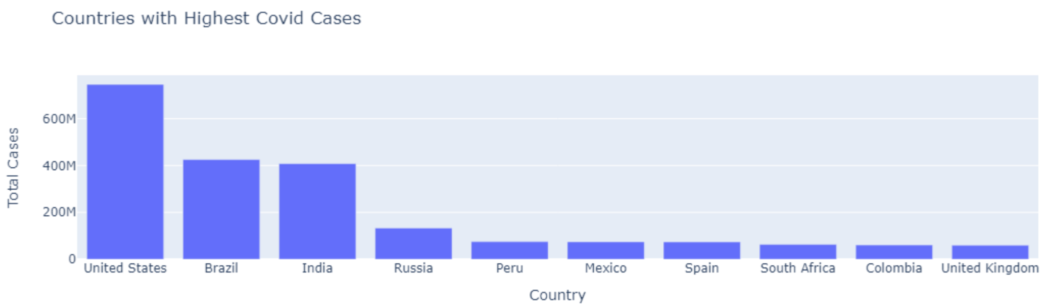
```
'Sweden'}
Oxford/AstraZeneca :>> {'Nauru', 'Mali', 'Tuvalu', 'Saint Vincent and the
Grenadines', 'Montserrat', 'Samoa', 'Kiribati', 'Falkland Islands', 'Tonga',
'Solomon Islands', 'Democratic Republic of Congo', 'Liberia', 'Vanuatu',
'Nigeria', 'Angola', 'Saint Helena', 'Papua New Guinea', 'Pitcairn', 'Togo',
'Sao Tome and Principe'}
Oxford/AstraZeneca, Pfizer/BioNTech :>> {'Saudi Arabia', 'Bermuda', 'Cayman
Islands', 'Anguilla', 'Saint Lucia', 'New Zealand', 'Kosovo', 'Gibraltar',
'Panama', 'Costa Rica', 'Saint Kitts and Nevis'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sputnik V :>> {'Antigua and Barbuda'}
CanSino, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing,
Sputnik V :>> {'Argentina'}
Moderna, Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac, Sputnik V :>>
{'Armenia'}
Pfizer/BioNTech :>> {'New Caledonia', 'Cook Islands', 'Tokelau', 'Aruba',
'Niue', 'Monaco', 'Turks and Caicos Islands'}
Johnson&Johnson, Moderna, Novavax, Oxford/AstraZeneca, Pfizer/BioNTech :>>
{'Germany', 'Austria', 'Italy', 'Lithuania', 'Czechia', 'Slovenia', 'South
Korea', 'Netherlands'}
Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech :>> {'Bahamas', 'Grenada',
'Eswatini'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech,
Sinopharm/Beijing, Sputnik Light, Sputnik V :>> {'Bahrain'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech,
Sinopharm/Beijing, Sinovac :>> {'Bangladesh'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing :>> {'Barbados',
'Dominica', 'Maldives', 'Suriname', 'Peru'}
Sinopharm/Beijing, Sputnik V :>> {'Kyrgyzstan', 'Belarus'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech :>> {'Estonia',
'Belgium', 'Jamaica', 'Romania', 'Canada', 'Greece', 'Luxembourg', 'Croatia',
'Spain', 'Iceland', 'Bulgaria', 'Poland', 'Ireland', 'Portugal', 'Malta',
'Cyprus', 'France'}
Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac :>> {'Brazil',
'Benin'}
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing :>> {'Cape
Verde', 'Bhutan'}
Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sputnik
V :>> {'Bolivia', 'Moldova', 'Morocco', "Cote d'Ivoire"}
Moderna, Pfizer/BioNTech :>> {'Norway', 'Israel', 'Bonaire Sint Eustatius and
Saba', 'Faeroe Islands', 'Curacao', 'Qatar'}
Covaxin, Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac
:>> {'Botswana'}
Johnson&Johnson, Oxford/AstraZeneca :>> {'South Sudan', 'British Virgin
Islands', 'Malawi'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing
:>> {'Kuwait', 'Kenya', 'Brunei', 'Nepal'}
Johnson&Johnson, Oxford/AstraZeneca, Sinopharm/Beijing :>> {'Zambia', 'Burkina
Faso', 'Mozambique', 'Lesotho', 'Senegal', 'Gambia', 'Madagascar'}
```

```
Sinopharm/Beijing :>> {'Chad', 'Burundi', 'Equatorial Guinea'}
Johnson&Johnson, Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac :>> {'Cambodia',
'Somalia'}
Covaxin, Oxford/AstraZeneca :>> {'Central African Republic'}
CanSino, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac :>> {'Ecuador', 'Chile'}
CanSino, Sinopharm/Beijing, Sinopharm/Wuhan, Sinovac, ZF2001 :>> {'China'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac :>>
{'Colombia', 'Uganda', 'Ukraine'}
Covaxin, Oxford/AstraZeneca, Sinopharm/Beijing :>> {'Comoros', 'Mauritius'}
Moderna, Oxford/AstraZeneca, Sinopharm/Beijing, Sputnik V :>> {'Congo'}
Abdala, Soberana Plus, Soberana02 :>> {'Cuba'}
Johnson&Johnson, Moderna, Pfizer/BioNTech :>> {'Liechtenstein', 'Switzerland',
'United States', 'Denmark'}
Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing,
Sinovac, Sputnik V :>> {'Egypt', 'Djibouti', 'Guinea'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sinovac :>> {'Georgia',
'Dominican Republic', 'El Salvador'}
Covaxin, Johnson&Johnson, Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac :>>
{'Ethiopia'}
Johnson&Johnson, Pfizer/BioNTech :>> {'French Polynesia', 'South Africa'}
Pfizer/BioNTech, Sinopharm/Beijing, Sputnik V :>> {'Gabon'}
Oxford/AstraZeneca, Sputnik V :>> {'Ghana'}
Moderna :>> {'Wallis and Futuna', 'Greenland'}
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sputnik V :>> {'Guatemala'}
Oxford/AstraZeneca, Sinopharm/Beijing :>> {'Niger', 'Myanmar', 'Guinea-Bissau',
'Mauritania', 'Sierra Leone'}
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sputnik V :>>
{'Guyana', 'Sri Lanka'}
Johnson&Johnson, Moderna :>> {'Haiti'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sputnik V :>>
{'Honduras'}
Pfizer/BioNTech, Sinovac :>> {'Hong Kong'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech,
Sinopharm/Beijing, Sputnik V :>> {'Jordan', 'Hungary'}
Covaxin, Oxford/AstraZeneca, Sputnik V :>> {'India'}
Johnson&Johnson, Moderna, Novavax, Oxford/AstraZeneca, Pfizer/BioNTech,
Sinopharm/Beijing, Sinovac :>> {'Indonesia'}
COVIran Barekat, Covaxin, FAKHRAVAC, Oxford/AstraZeneca, Razi Cov Pars,
Sinopharm/Beijing, Soberana02, SpikoGen, Sputnik V :>> {'Iran'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sputnik V :>>
{'Montenegro', 'Mongolia', 'Iraq', 'Lebanon', 'Serbia'}
QazVac, Sinopharm/Beijing, Sputnik V :>> {'Kazakhstan'}
Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing,
Sinovac, Sputnik Light, Sputnik V :>> {'Laos'}
Johnson&Johnson, Moderna, Novavax, Pfizer/BioNTech :>> {'Latvia'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sinovac, Sputnik V :>>
{'Libya', 'North Macedonia'}
Pfizer/BioNTech, Sinopharm/Beijing :>> {'Macao'}
```

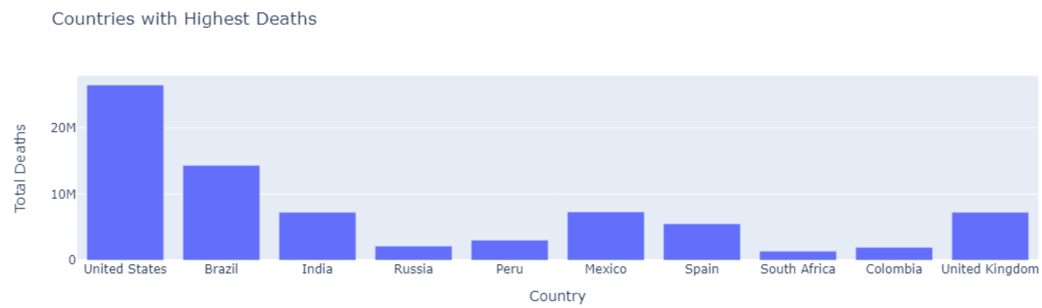
```
CanSino, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sinovac :>>
{'Malaysia'}
CanSino, Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac,
Sputnik V :>> {'Mexico'}
Abdala, Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Soberana02,
Sputnik Light, Sputnik V :>> {'Nicaragua'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac :>> {'Uruguay', 'Northern Cyprus',
'Timor'}
CanSino, Covaxin, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech,
Sinopharm/Beijing, Sinovac, Sputnik V :>> {'Pakistan'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech,
Sinopharm/Beijing, Sinovac, Sputnik Light, Sputnik V :>> {'Philippines',
'Palestine'}
Covaxin, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing,
Sinovac, Sputnik V :>> {'Paraguay'}
EpiVacCorona, Sputnik V :>> {'Russia'}
Johnson&Johnson, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech,
Sinopharm/Beijing, Sinovac, Sputnik V :>> {'Rwanda', 'Tunisia'}
Pfizer/BioNTech, Sputnik V :>> {'San Marino'}
Oxford/AstraZeneca, Sinopharm/Beijing, Sputnik V :>> {'Seychelles'}
Moderna, Pfizer/BioNTech, Sinopharm/Beijing, Sinovac :>> {'Singapore'}
Johnson&Johnson, Moderna, Novavax, Oxford/AstraZeneca, Pfizer/BioNTech, Sputnik
V :>> {'Slovakia'}
Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sinovac
:>> {'Sudan'}
Johnson&Johnson, Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac, Sputnik Light,
Sputnik V :>> {'Syria'}
Medigen, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech :>> {'Taiwan'}
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac, Sputnik V :>>
{'Tajikistan'}
Johnson&Johnson, Pfizer/BioNTech, Sinopharm/Beijing :>> {'Tanzania'}
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sinovac :>>
{'Thailand'}
Pfizer/BioNTech, Sinovac, Turkovac :>> {'Turkey'}
EpiVacCorona, Oxford/AstraZeneca, QazVac, Sinopharm/Beijing, Sputnik V, ZF2001
:>> {'Turkmenistan'}
Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sinopharm/Wuhan, Sputnik
V :>> {'United Arab Emirates'}
Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinovac, Sputnik Light, Sputnik V,
ZF2001 :>> {'Uzbekistan'}
Abdala, Sinopharm/Beijing, Sinovac, Soberana02, Sputnik Light, Sputnik V :>>
{'Venezuela'}
Abdala, Moderna, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing, Sputnik
V :>> {'Vietnam'}
Johnson&Johnson, Oxford/AstraZeneca, Sinovac :>> {'Yemen'}
```

Data Visualization

```
[34]: figure = px.bar(data, y='Total Cases', x='Country',
                  title="Countries with Highest Covid Cases")
      figure.show()
```

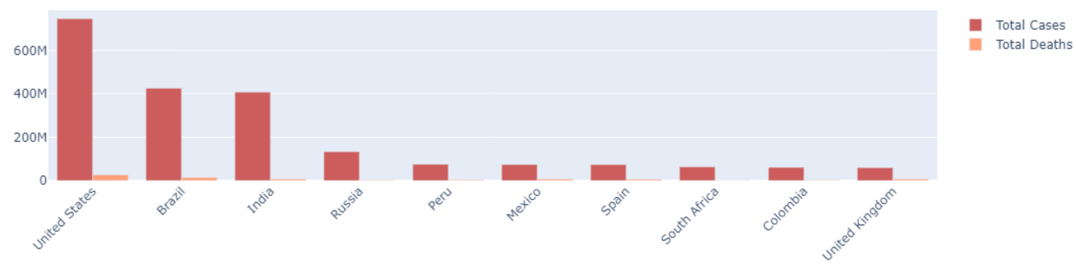



```
[35]: figure = px.bar(data, y='Total Deaths', x='Country',
                  title="Countries with Highest Deaths")
      figure.show()
```

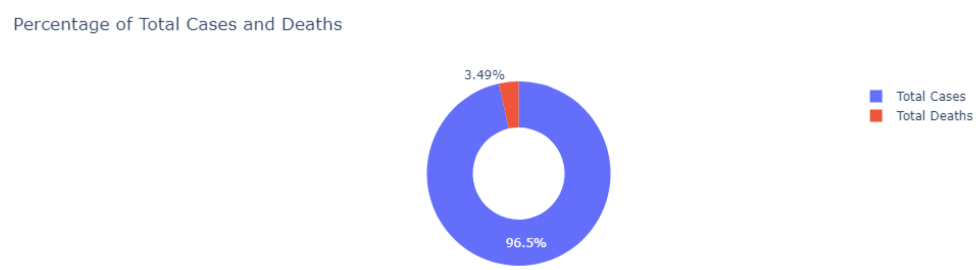



```
[36]: fig = go.Figure()
      fig.add_trace(go.Bar(
          x=data["Country"],
          y=data["Total Cases"],
          name='Total Cases',
          marker_color='indianred'
      ))
      fig.add_trace(go.Bar(
          x=data["Country"],
          y=data["Total Deaths"],
          name='Total Deaths',
          marker_color='lightsalmon'
```

```
))
fig.update_layout(barmode='group', xaxis_tickangle=-45)
fig.show()
```



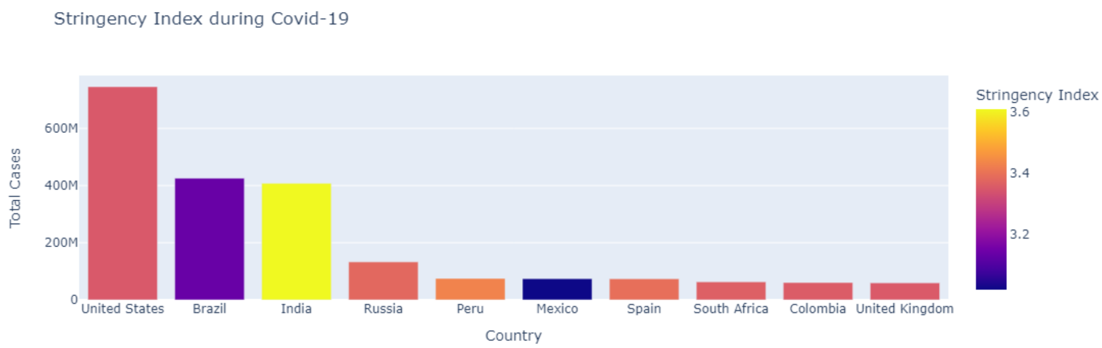
[37]:
```
# Percentage of Total Cases and Deaths
cases = data["Total Cases"].sum()
deceased = data["Total Deaths"].sum()

labels = ["Total Cases", "Total Deaths"]
values = [cases, deceased]

fig = px.pie(data, values=values, names=labels,
             title='Percentage of Total Cases and Deaths', hole=0.5)
fig.show()
```



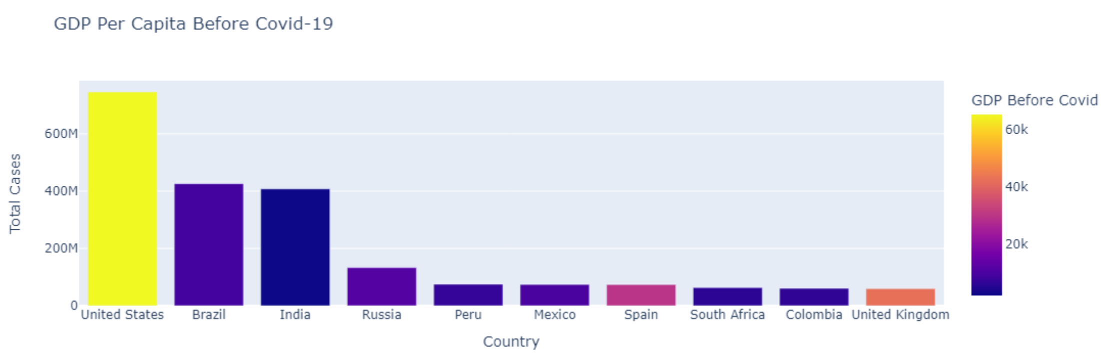
[38]:
```
#Calculating the Death Rate

death_rate = (data["Total Deaths"].sum() / data["Total Cases"].sum()) * 100
print("Death Rate = ", death_rate)
```

```
Death Rate =  3.6144212045653767
```

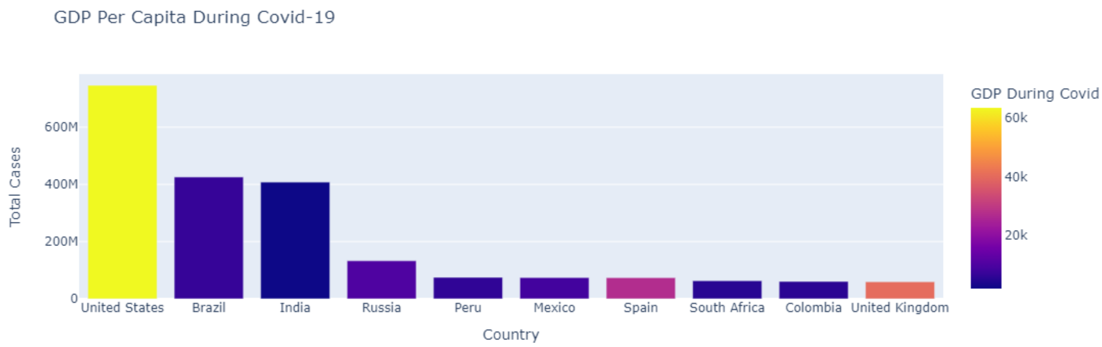
[39]:
```
fig = px.bar(data, x='Country', y='Total Cases',
             hover_data=['Population', 'Total Deaths'],
             color='Stringency Index', height=400,
             title= "Stringency Index during Covid-19")
fig.show()
```



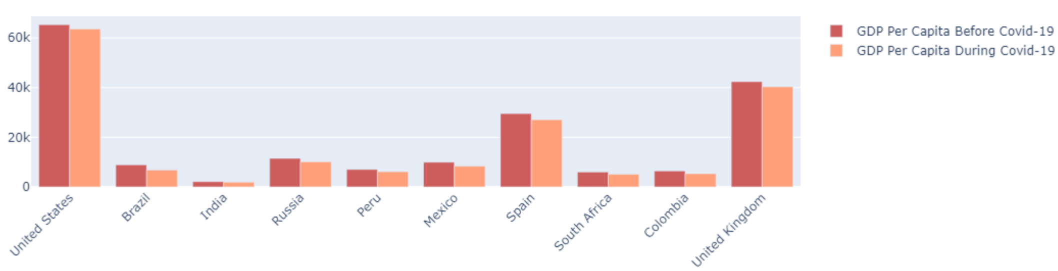
[40]:
```
fig = px.bar(data, x='Country', y='Total Cases',
             hover_data=['Population', 'Total Deaths'],
             color='GDP Before Covid', height=400,
             title="GDP Per Capita Before Covid-19")
fig.show()
```



[41]:
```
fig = px.bar(data, x='Country', y='Total Cases',
             hover_data=['Population', 'Total Deaths'],
             color='GDP During Covid', height=400,
             title="GDP Per Capita During Covid-19")
fig.show()
```

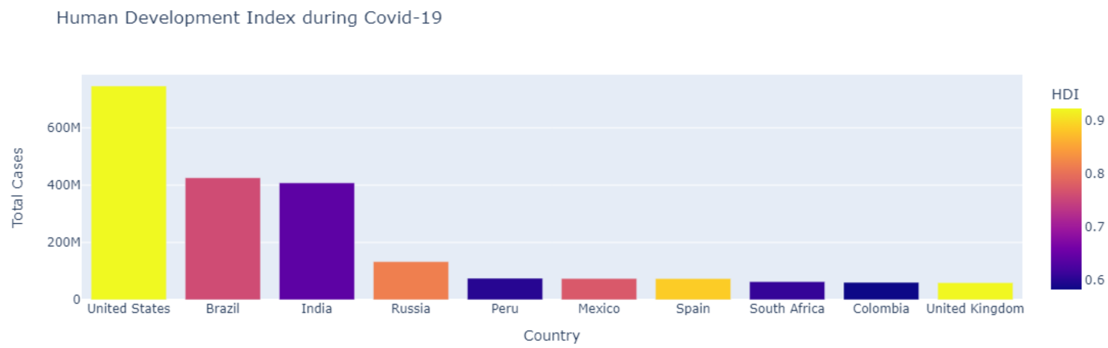


[42]:
```
fig = go.Figure()
fig.add_trace(go.Bar(
    x=data["Country"],
    y=data["GDP Before Covid"],
    name='GDP Per Capita Before Covid-19',
    marker_color='indianred'
))
fig.add_trace(go.Bar(
    x=data["Country"],
    y=data["GDP During Covid"],
    name='GDP Per Capita During Covid-19',
    marker_color='lightsalmon'
))
fig.update_layout(barmode='group', xaxis_tickangle=-45)
fig.show()
```



[43]:
```
fig = px.bar(data, x='Country', y='Total Cases',
             hover_data=['Population', 'Total Deaths'],
             color='HDI', height=400,
```

```
              title="Human Development Index during Covid-19")
fig.show()
```



[44]:

```
vaccine_map = px.choropleth(vdata, locations = 'iso_code', color = 'vaccines', title = 'Vaccines Over the Globe')
vaccine_map.update_layout(height=300, margin={"r":0,"t":0,"l":0,"b":0})
vaccine_map.show()
```