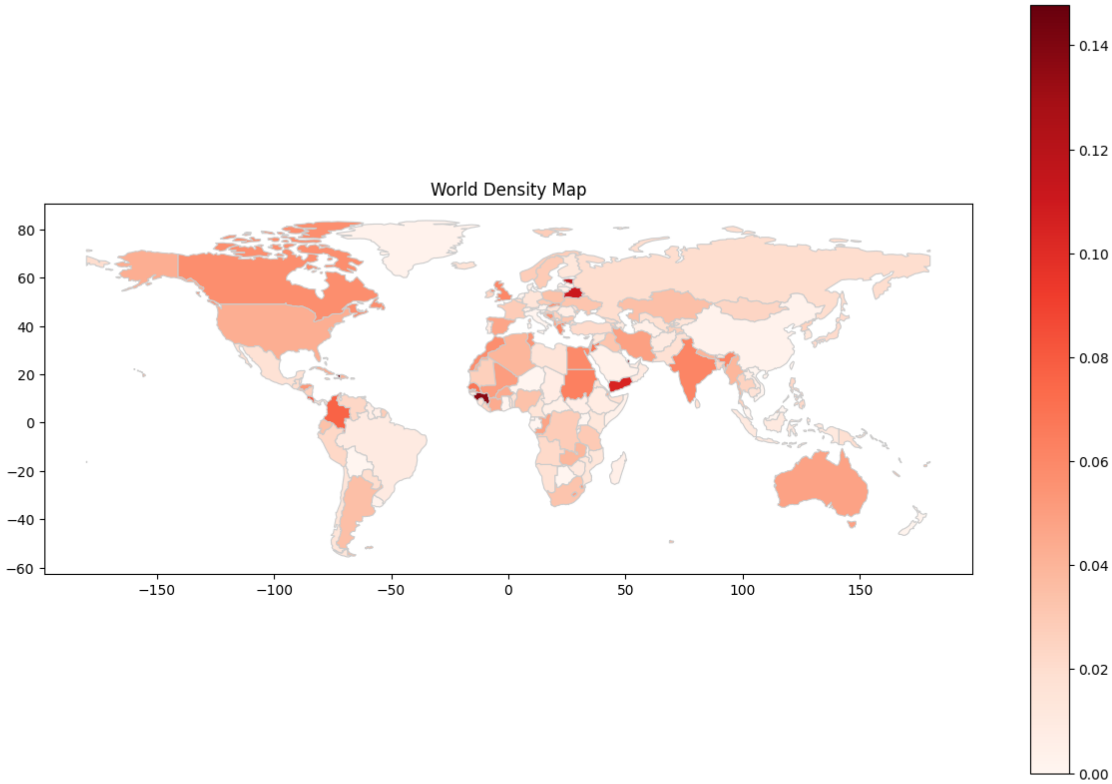
covid-19-project

January 11, 2025

[4]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import geopandas as gpd
import matplotlib.ticker as ticker
```

[5]:
```python
country = pd.read_csv("/kaggle/input/covid-dataset/country_wise_latest.csv")

toll = country[['Country/Region','Confirmed', 'Deaths', 'Recovered']]
toll['Result'] = toll['Deaths'] / toll['Confirmed']
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
world = world[world['name'] != 'Antarctica']
world = world.merge(toll[['Result']], left_index=True, right_index=True)



fig, ax = plt.subplots(figsize=(15, 10))
ax.set_title('World Density Map')
world.plot(column='Result', cmap='Reds', linewidth=0.8, ax=ax, edgecolor='0.8',␣
↪legend=True)
plt.show()
```

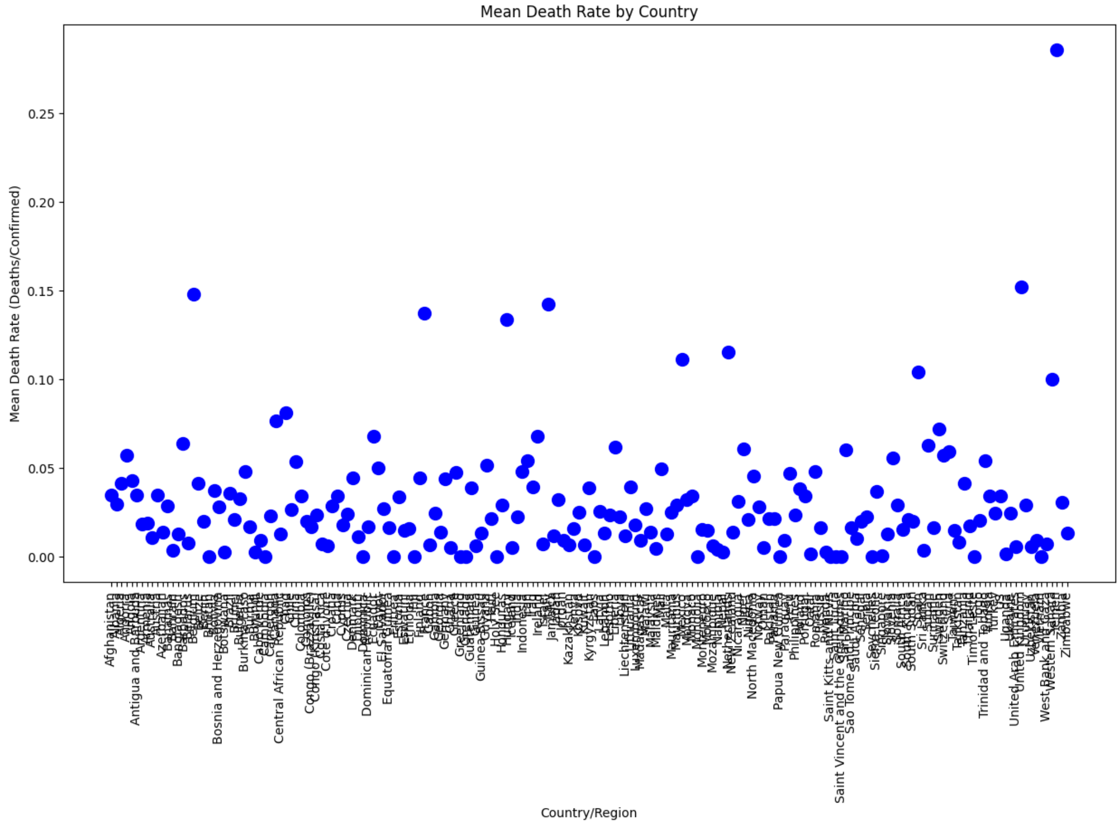
```
/tmp/ipykernel_47/1974193342.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  toll['Result'] = toll['Deaths'] / toll['Confirmed']
/tmp/ipykernel_47/1974193342.py:5: FutureWarning: The geopandas.dataset module
is deprecated and will be removed in GeoPandas 1.0. You can get the original
'naturalearth_lowres' data from
https://www.naturalearthdata.com/downloads/110m-cultural-vectors/.
  world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
```



I created a map that would just show the density of deaths per confirmed as you can see that they is not really a pattern, which we can conclude that every country followed their own protocols based on their capabilities. It was an event that we we learned from.

How would this look in the scatterplot? Would it be easier to see?

[50]:
```python
mean_death_rate = toll.groupby('Country/Region')['Result'].mean().reset_index()



plt.figure(figsize=(15, 8))
plt.scatter(mean_death_rate['Country/Region'], mean_death_rate['Result'],␣
 ↪s=100, color='blue')
plt.title('Mean Death Rate by Country')
plt.xlabel('Country/Region')
plt.ylabel('Mean Death Rate (Deaths/Confirmed)')
plt.xticks(rotation=90)
plt.show()
```

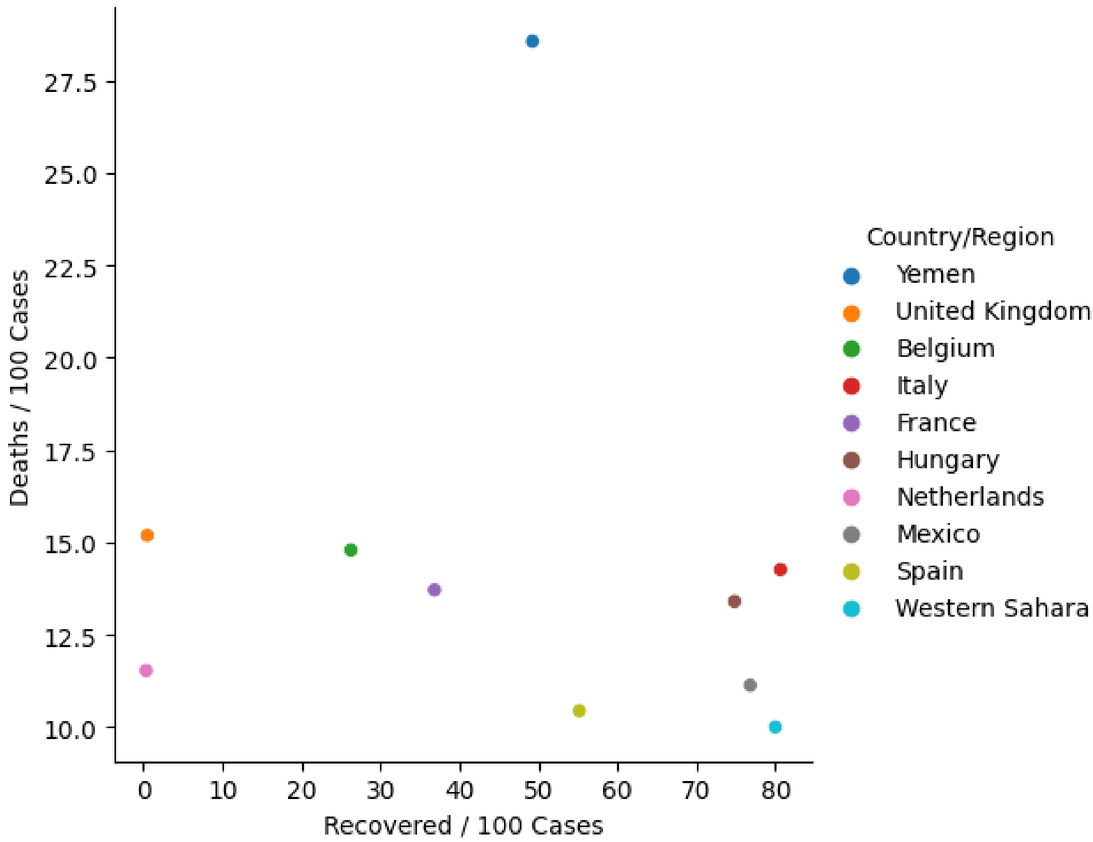


As we can it pretty similar death rates for most countries, we would see some few outliers implying that that COVID-19 did heavily affect them.

What are those countries?

Let's graph them! By just comparing the top 10 highest rates of deaths.

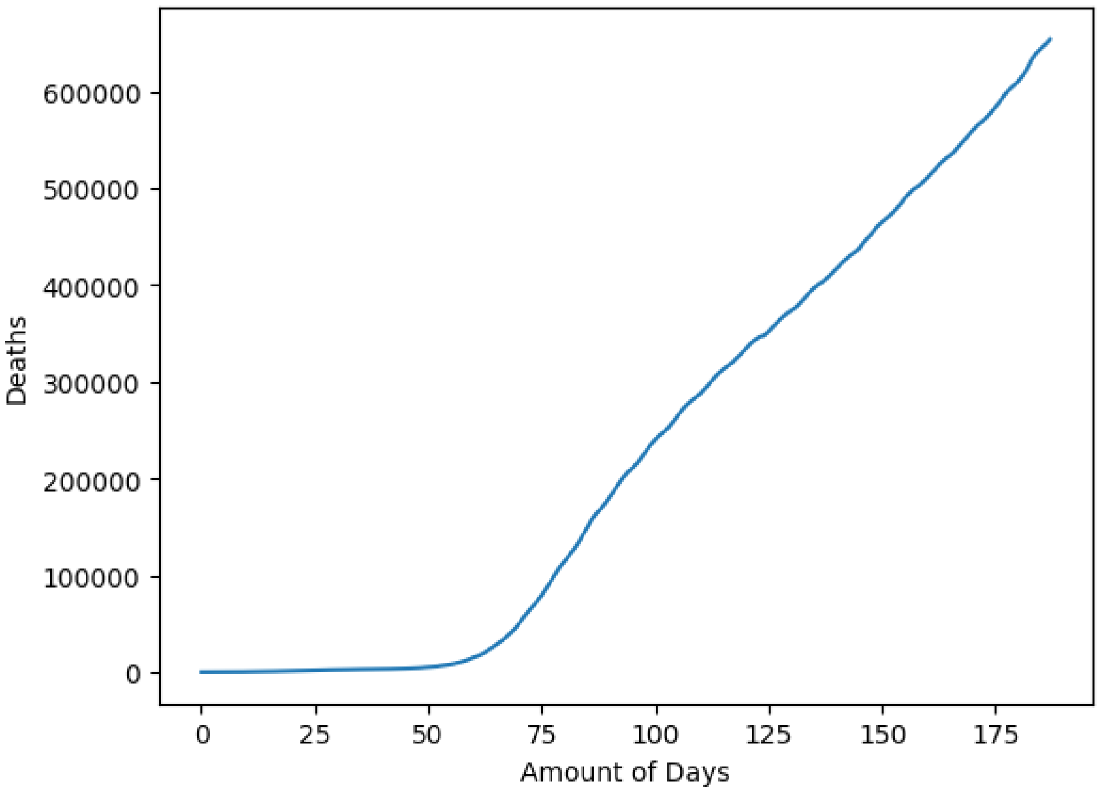
[20]:
```
country['Deaths / Confirmed'] = country['Deaths'] / country['Confirmed']
sortedcountries = country.sort_values(by='Deaths / Confirmed', ascending=False)
top10 = sortedcountries.head(10)

sns.relplot(data=top10, x='Recovered / 100 Cases', y='Deaths / 100 Cases',␣
 ↪hue='Country/Region', kind='scatter')
plt.show()
```



These top 10 Countries, suprise me I would suggest a country to be in Asian. We can see that COVID was spreading before we even had a clue.

Lets analyze a daily trend maybe we can see a pattern that could suggest that COVID was spreading as a specific pattern.

[22]:
```
daily = pd.read_csv('/kaggle/input/covid-dataset/day_wise.csv')
daily['date'] = pd.to_datetime(daily['Date'])
x = range(len(daily['date']))
plt.plot(x, daily['Deaths'])
plt.xlabel('Amount of Days')
plt.ylabel('Deaths')
plt.show()
```



The dataset had 175 days and as we can see after the day 75 the amounts of death increased pretty heavily, it was increasing by an estimate of 100,000 people per 25 days. Which could suggest that after 2 months of COVID spread had the most impact in our communities.

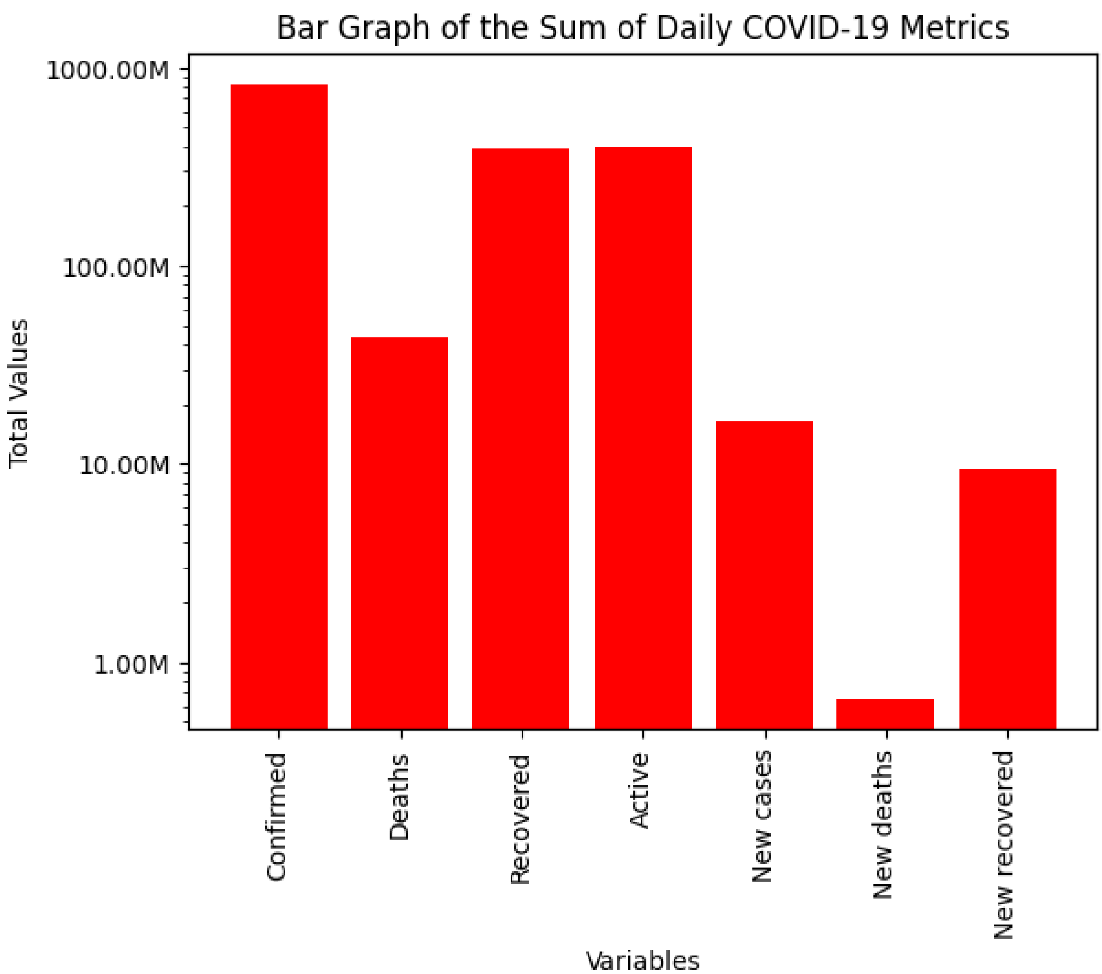
Maybe we can sum all our variables of our data and maybe we can see more patterns.

We want to compare the sum , of Confirmed, Deaths, Recovered, Active, New cases, New deaths, New recovered.

[ ]:
```
a = daily['Confirmed'].sum()
b = daily['Deaths'].sum()
c = daily['Recovered'].sum()
d = daily['Active'].sum()
e = daily['New cases'].sum()
f = daily['New deaths'].sum()
g = daily['New recovered'].sum()
variables = ['Confirmed', 'Deaths', 'Recovered', 'Active', 'New cases', 'New␣
↪deaths', 'New recovered']
values = [a, b , c , d , e , f ,g]
```

[24]:
```
plt.bar(variables, values, color='red')
plt.yscale('log')
plt.xticks(rotation='vertical')
```

```
plt.gca().yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: f'{x/
 ↪1e6:.2f}M'))
plt.xlabel('Variables')
plt.ylabel('Total Values')
plt.title('Bar Graph of the Sum of Daily COVID-19 Metrics')
plt.show()
```



As we can see in our bargraph that that Death and Recorvered compare to each other it the difference or ratio could be compared with the new deaths and new recovered.

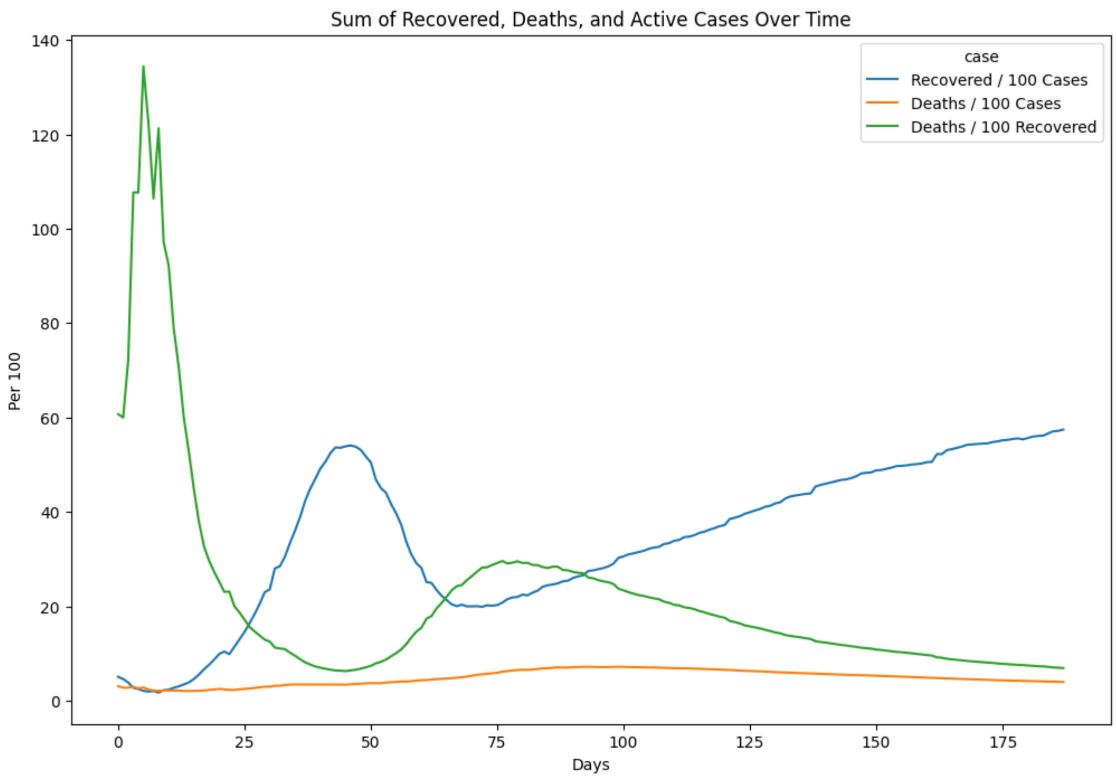
What does this suggest?

It can suggest that throughtout time we got better at handling COVID cases and saving lifes!

Let's graph it!

```
[40]: daily['date'] = pd.to_datetime(daily['Date'])
x = range(len(daily['date']))
```

```
daily['index'] = x

graph = daily.groupby('index')[['Deaths / 100 Cases', 'Recovered / 100 Cases',␣
↪'Deaths / 100 Recovered']].sum().reset_index()
graph = graph.melt(id_vars="index", value_vars=['Recovered / 100 Cases',␣
↪'Deaths / 100 Cases', 'Deaths / 100 Recovered'],
                   var_name='case', value_name='count')

plt.figure(figsize=(12, 8))
sns.lineplot(x='index', y='count', hue='case', data=graph)
plt.title('Sum of Recovered, Deaths, and Active Cases Over Time')
plt.xlabel('Days')
plt.ylabel('Per 100')
plt.show()
```



We can see patterns in graph, deaths and recovered go aganist each other when deaths decrease recovered increase. Which is a reasonable pattern to see!

Let's talk about the United States!

[25]:
```
usa = pd.read_csv('/kaggle/input/covid-dataset/usa_county_wise.csv')
```

Let's group everything by State.

[26]:
```
usa['Total_Confirmed'] = usa.groupby('Province_State')['Confirmed'].
    ↪transform('sum')
usa['Total_Deaths'] = usa.groupby('Province_State')['Deaths'].transform('sum')
```

There is territories that are not states, lets remove them! SORRY!

Made it into a dataframe!

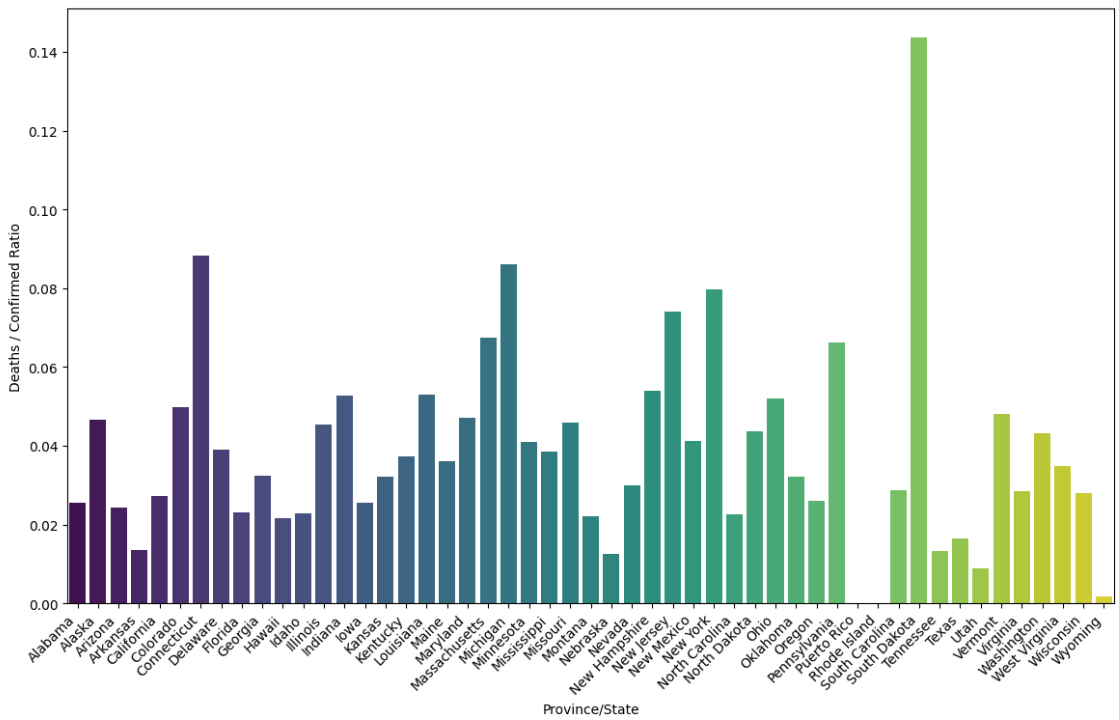
[47]:
```
usa['Confirmed'] = usa['Confirmed'].astype(int)
usa['Deaths'] = usa['Deaths'].astype(int)

usa_grouped = usa.groupby('Province_State', as_index=False).agg({'Confirmed':␣
    ↪'sum', 'Deaths': 'sum'})
states_to_remove = ['American Samoa', 'Diamond Princess', 'District of␣
    ↪Columbia', 'Grand Princess','Guam','Northern Mariana Islands','Virgin␣
    ↪Islands']
usa_grouped = usa_grouped[~usa_grouped['Province_State'].isin(states_to_remove)]
print(usa_grouped)
```

```
    Province_State  Confirmed  Deaths
0          Alabama    2880805   73446
1           Alaska      85686    3999
3          Arizona    5272303  128478
4         Arkansas    1415802   19171
5       California   17618695  481757
6         Colorado    2860699  142506
7      Connecticut    4239220  374346
8         Delaware     962637   37494
11         Florida   12657802  292541
12         Georgia    6859759  222262
15          Hawaii      92930    2003
16           Idaho     565768   12980
17        Illinois   11900637  541672
18         Indiana    3792618  200183
19            Iowa    2231209   57245
20          Kansas    1188588   38359
21        Kentucky    1253913   46743
22       Louisiana    5383429  285084
23           Maine     257125    9256
24        Maryland    5393907  254828
25   Massachusetts    9874030  666157
26        Michigan    6690544  576093
27       Minnesota    2637428  107860
28     Mississippi    2124940   81848
29        Missouri    1842504   84491
30         Montana     102564    2265
31        Nebraska    1445593   18039
32          Nevada    1508128   45082
33   New Hampshire     471598   25438
```

```
34       New Jersey  16506714  1221339
35       New Mexico    949764    39170
36         New York  39808447  3176945
37   North Carolina   4573238   103531
38     North Dakota    290875    12743
40             Ohio   4275663   222951
41         Oklahoma   1106729    35470
42           Oregon    695008    18165
43     Pennsylvania   8096993   537261
44      Puerto Rico    574636        2
45     Rhode Island   1457931       60
46   South Carolina   2656164    76249
47     South Dakota    539323    77572
48        Tennessee   3550017    47601
49            Texas  12698726   210547
50             Utah   1596769    14229
51          Vermont    120956     5812
53         Virginia   4778268   136648
54       Washington   2892060   124895
55    West Virginia    260095     9042
56        Wisconsin   2250614    62924
57          Wyoming    120404      212
```

Let's see our data! Let's see if we can see a pattern!

[48]:
```
usa_grouped['Deaths / Confirmed'] = usa_grouped['Deaths'] /␣
↪usa_grouped['Confirmed']

plt.figure(figsize=(14, 8))
sns.barplot(data=usa_grouped, x='Province_State', y='Deaths / Confirmed',␣
↪palette='viridis')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Province/State')
plt.ylabel('Deaths / Confirmed Ratio')
plt.show()
```



As we can see in our bar graph some states were relatively low and some were relatively high, which is surprising.

Now, lets talk globably.

[32]:
```
worldwide = pd.read_csv('/kaggle/input/covid-dataset/worldometer_data.csv')
```

Let's group them by continent. Maybe we can compare each continent.

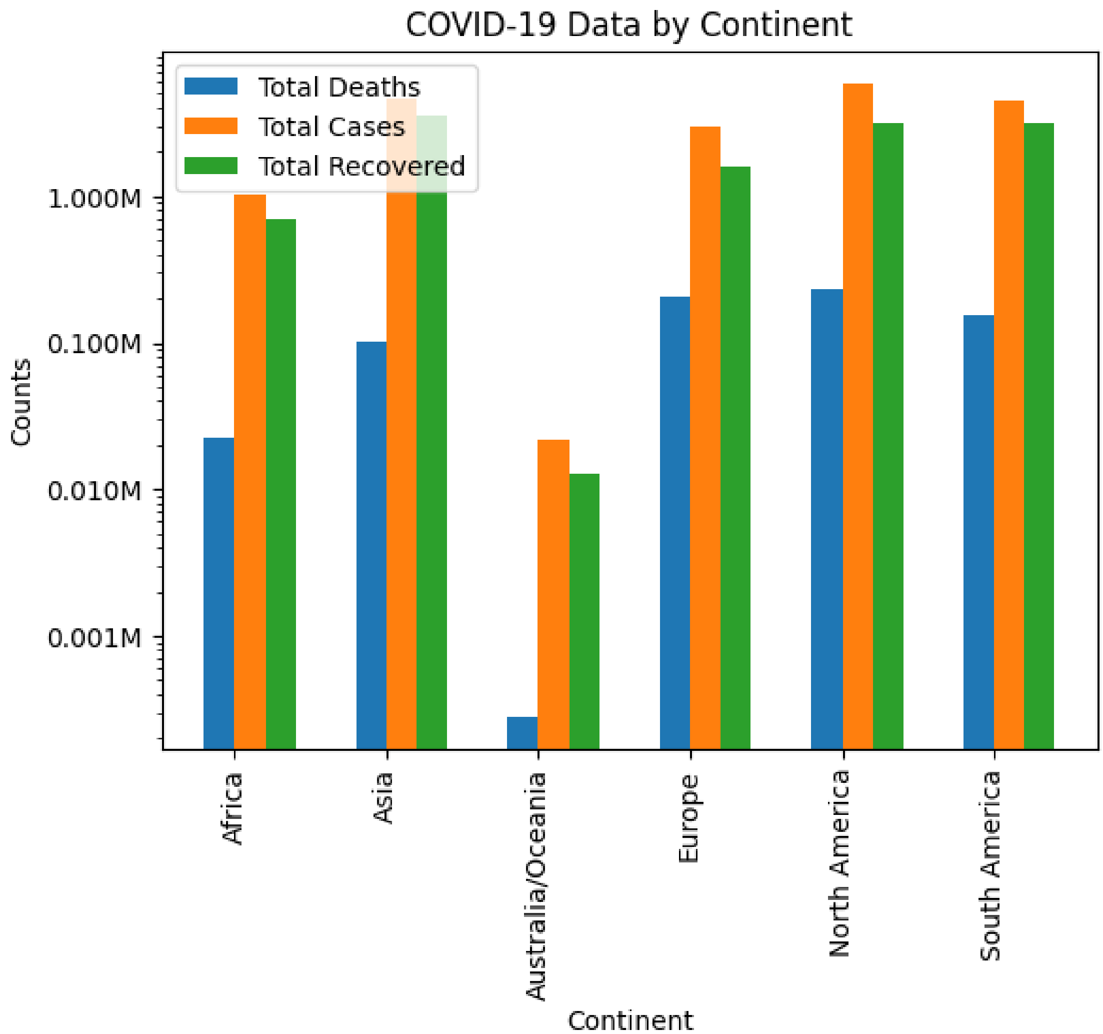
[33]:
```
grouped_data = worldwide.groupby('Continent')[['TotalDeaths',␣
↪'TotalCases','TotalRecovered']].sum().reset_index()
editworldwide = pd.DataFrame(grouped_data)
print(editworldwide)
```

```
           Continent  TotalDeaths  TotalCases  TotalRecovered
0             Africa      22114.0     1011867        693620.0
1               Asia     100627.0     4689794       3508170.0
2  Australia/Oceania        281.0       21735         12620.0
3             Europe     205232.0     2982576       1587302.0
4      North America     229855.0     5919209       3151678.0
5      South America     154885.0     4543273       3116150.0
```

Let's graph them and see their total death, total cases, and total recovered.

[36]:
```
X_axis = np.arange(len(grouped_data['Continent']))
bar_width = 0.2
```

```
plt.bar(X_axis - 0.2, height=grouped_data['TotalDeaths'], label='Total Deaths',␣
↪width=bar_width, align='edge')
plt.bar(X_axis, height=grouped_data['TotalCases'], label='Total Cases',␣
↪width=bar_width, align='edge')
plt.bar(X_axis + 0.2, height=grouped_data['TotalRecovered'], label='Total␣
↪Recovered', width=bar_width, align='edge')

plt.yscale('log')
plt.xticks(rotation='vertical')
## plt.gca().yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: f'{x/
↪1e4:.0f}10K'))
plt.gca().yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: f'{x/
↪1e6:.3f}M'))



plt.legend()
plt.title('COVID-19 Data by Continent')
plt.xlabel('Continent')
plt.ylabel('Counts')

# Set x-axis ticks to be the actual continent names
plt.xticks(X_axis, grouped_data['Continent'])

plt.show()
```

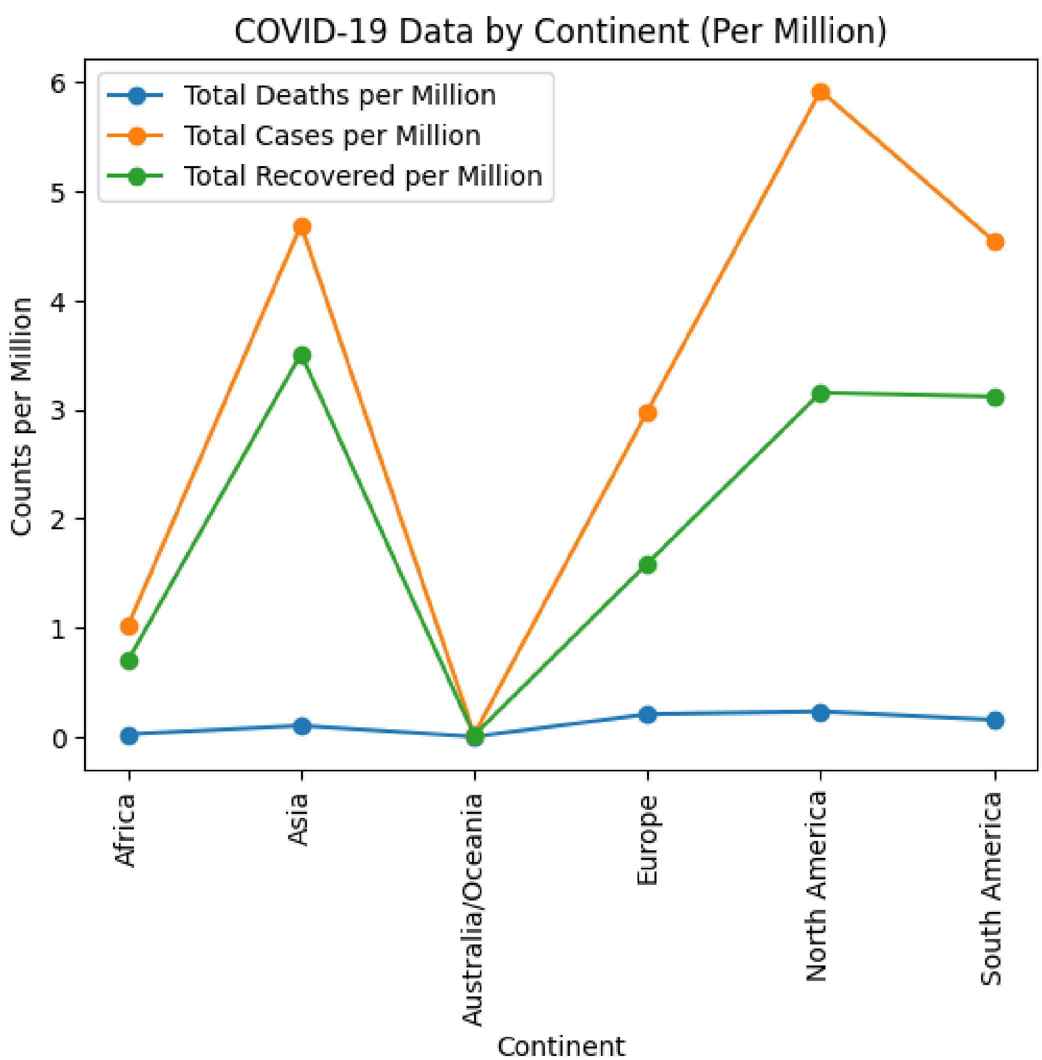


I will say that my data might not be normally distributed but, its hard to see, let's keep in mind that the scale of y-axis might be hard to understand.

Maybe we can see it better in a graph.

[38]:
```
grouped_dataa = worldwide.groupby('Continent')[['TotalDeaths', 'TotalCases',␣
↪'TotalRecovered']].sum().reset_index()

X_axis = np.arange(len(grouped_dataa['Continent']))

total_deaths_per_million = grouped_dataa['TotalDeaths'] / 1e6
total_cases_per_million = grouped_dataa['TotalCases'] / 1e6
total_recovered_per_million = grouped_dataa['TotalRecovered'] / 1e6
```

```
plt.plot(X_axis, total_deaths_per_million, label='Total Deaths per Million',␣
    ↪marker='o')
plt.plot(X_axis, total_cases_per_million, label='Total Cases per Million',␣
    ↪marker='o')
plt.plot(X_axis, total_recovered_per_million, label='Total Recovered per␣
    ↪Million', marker='o')

plt.xticks(X_axis, grouped_dataa['Continent'], rotation='vertical')

# Custom formatter for y-axis ticks in millions (M)
plt.legend()
plt.title('COVID-19 Data by Continent (Per Million)')
plt.xlabel('Continent')
plt.ylabel('Counts per Million')

plt.show()
```



We scaled the y-axis by million, which can be easier to see.

We can see the deaths on every continent was relatively low. We can that North America and Asia was really high their cases. In Asia, we can recovered and cases ratio was pretty high.