COVID-19 Data Analysis Project

This project aims to analyze the spread and impact of the COVID-19 pandemic using publicly available datasets. We will use data from the Johns Hopkins University COVID-19 dataset to explore the number of confirmed cases, recoveries, and deaths across various countries and regions. Additionally, we'll incorporate data from the World Happiness Report to investigate potential correlations between a country's socio-economic factors (such as GDP, social support, and life expectancy) and the maximum infection rates.

Import the module

[40]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Load the dataset

[41]:

```
df = pd.read_csv("C:/Users/hp/Downloads/covid19_Confirmed_dataset.csv")
df
```

[41]:

	Province/State	Country/Region	Lat	Long	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/20	...	4/21/20	4/22/20	4/23/20	4/24/20	4/25/20
0	NaN	Afghanistan	33.000000	65.000000	0	0	0	0	0	0	...	1092	1176	1279	1351	1463
1	NaN	Albania	41.153300	20.168300	0	0	0	0	0	0	...	609	634	663	678	712
2	NaN	Algeria	28.033900	1.659600	0	0	0	0	0	0	...	2811	2910	3007	3127	3256
3	NaN	Andorra	42.506300	1.521800	0	0	0	0	0	0	...	717	723	723	731	738
4	NaN	Angola	-11.202700	17.873900	0	0	0	0	0	0	...	24	25	25	25	25
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
261	NaN	Western Sahara	24.215500	-12.885800	0	0	0	0	0	0	...	6	6	6	6	6
262	NaN	Sao Tome and Principe	0.186360	6.613081	0	0	0	0	0	0	...	4	4	4	4	4
263	NaN	Yemen	15.552727	48.516388	0	0	0	0	0	0	...	1	1	1	1	1
264	NaN	Comoros	-11.645500	43.333300	0	0	0	0	0	0	...	0	0	0	0	0
265	NaN	Tajikistan	38.861034	71.276093	0	0	0	0	0	0	...	0	0	0	0	0

266 rows × 104 columns

Check the shape of dataset

[42]:

```
df.shape
```

[42]:

```
(266, 104)
```

```
[43]: df.columns
```

```
[43]: Index(['Province/State', 'Country/Region', 'Lat', 'Long', '1/22/20', '1/23/20',
       '1/24/20', '1/25/20', '1/26/20', '1/27/20',
       ...
       '4/21/20', '4/22/20', '4/23/20', '4/24/20', '4/25/20', '4/26/20',
       '4/27/20', '4/28/20', '4/29/20', '4/30/20'],
      dtype='object', length=104)
```

Deleting the Columns

Latitude and Longitude are not important features for us here, so I remove them.

```
[44]:
df.drop(["Lat","Long"],
        axis=1, # default value, operations will be applied across columns, (axis = 0 for rows)
        inplace = True # inplace=True modifies the original dataset directly instead of returning
        )
```

```
[47]: df
```

[47]:

	Country/Region	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/20	1/28/20	1/29/20	1/30/20	...	4/21/20	4/22/20	4/23/20	4/24/20	4/25/20	4/26/20
0	Afghanistan	0	0	0	0	0	0	0	0	0	...	1092	1176	1279	1351	1463	1531
1	Albania	0	0	0	0	0	0	0	0	0	...	609	634	663	678	712	726
2	Algeria	0	0	0	0	0	0	0	0	0	...	2811	2910	3007	3127	3256	3382
3	Andorra	0	0	0	0	0	0	0	0	0	...	717	723	723	731	738	738
4	Angola	0	0	0	0	0	0	0	0	0	...	24	25	25	25	25	26
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
261	Western Sahara	0	0	0	0	0	0	0	0	0	...	6	6	6	6	6	6
262	Sao Tome and Principe	0	0	0	0	0	0	0	0	0	...	4	4	4	4	4	4
263	Yemen	0	0	0	0	0	0	0	0	0	...	1	1	1	1	1	1
264	Comoros	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
265	Tajikistan	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0

266 rows × 101 columns

The line of code df_agregated = df.groupby("Country/Region").sum() groups the data by the "Country/Region" column and calculates the sum of all numerical columns for each group.

```
[51]:
df_agregated.shape
```

```
[51]:
(187, 100)
```

Visualizing the data related to Country:

[52]:

```
df_agregated.loc["China"]
```

[52]:

```
1/22/20      548
1/23/20      643
1/24/20      920
1/25/20     1406
1/26/20     2075
           ...
4/26/20    83912
4/27/20    83918
4/28/20    83940
4/29/20    83944
4/30/20    83956
Name: China, Length: 100, dtype: int64
```

[53]:

```
df_agregated.loc["Pakistan"]
```

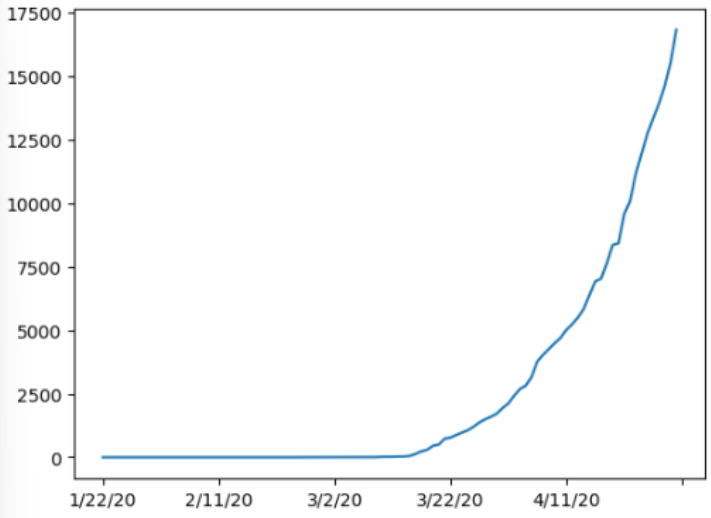
[53]:

```
1/22/20        0
1/23/20        0
1/24/20        0
1/25/20        0
1/26/20        0
             ...
4/26/20    13328
4/27/20    13915
4/28/20    14612
4/29/20    15525
4/30/20    16817
Name: Pakistan, Length: 100, dtype: int64
```

```
df_agregated.loc['Pakistan'].plot()
```

[55]:

```
<Axes: >
```

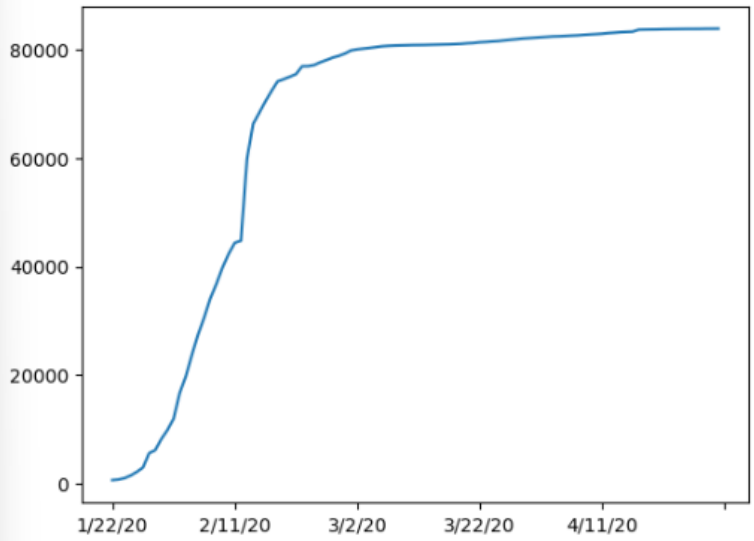


[56]:

```
df_agregated.loc['China'].plot()
```

[56]:

```
<Axes: >
```

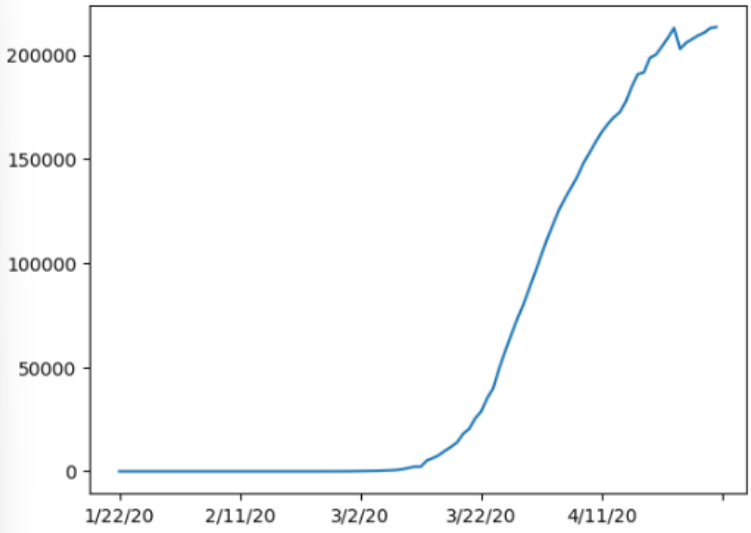


[58]:

```
df_agregated.loc['Spain'].plot()
```

[58]:

```
<Axes: >
```

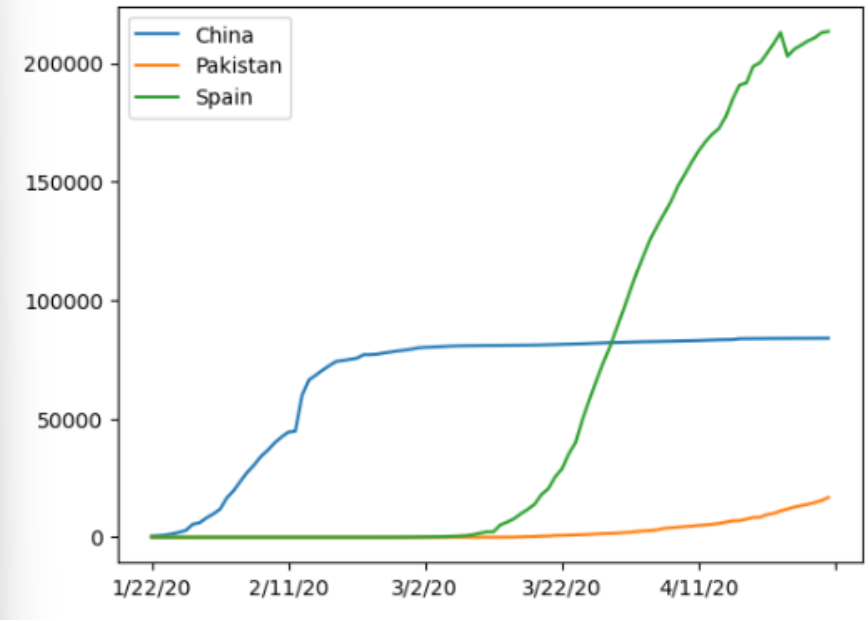


[59]:

```
df_agregated.loc['China'].plot()
df_agregated.loc['Pakistan'].plot()
df_agregated.loc['Spain'].plot()
plt.legend()
```

[59]:

```
<matplotlib.legend.Legend at 0x1c039d06b40>
```



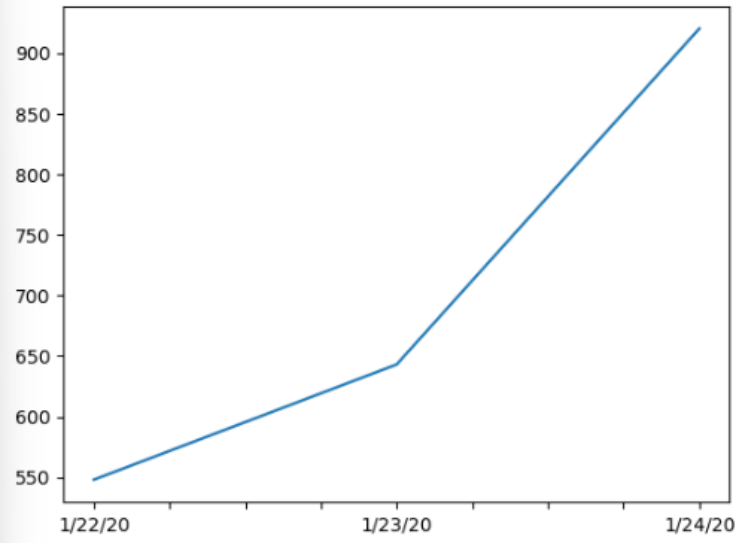
Spread of the virus in China for the first 5 dates only

[65]:

```
df_agregated.loc['China'][:3].plot()
```

[65]:

```
<Axes: >
```

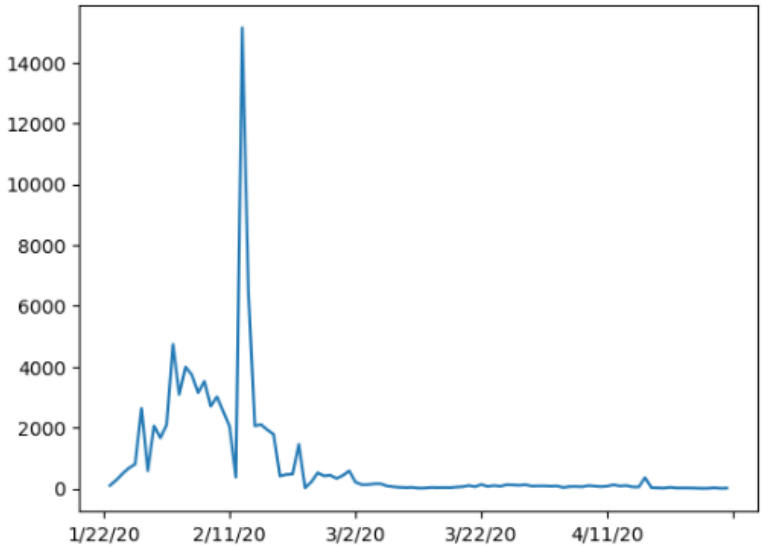


In the first 24 hours, there was an increase of 100 new cases, and in the second 24 hours, an increase of 250 new cases. The average number of new cases per 24 hours is 175, while the maximum increase in a single 24-hour period is 250.

Caculating the first derivative of the curve¶

```
[21]: df_agregated.loc["China"].diff().plot()
```

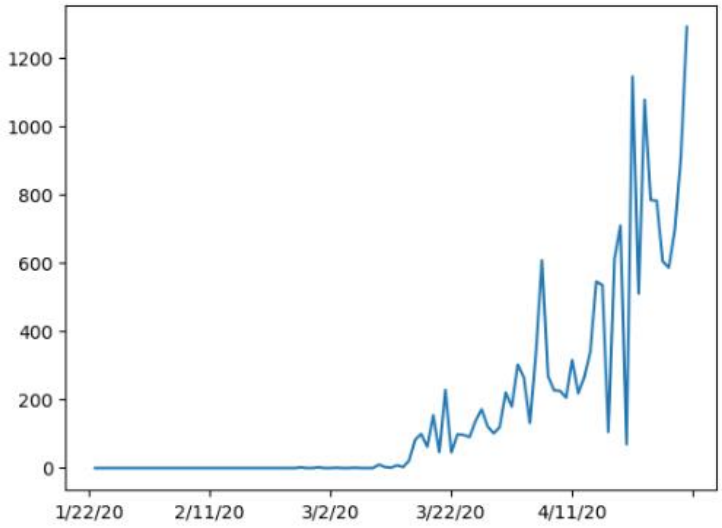
```
[21]: <Axes: >
```



The code df_agregated.loc["China"].diff().plot() selects the data for China from the DataFrame, calculates the difference between consecutive values (e.g., daily new cases), and then plots these differences. This visualizes the trend of new cases over time.

```
: df_agregated.loc["Pakistan"].diff().plot()
```

```
: <Axes: >
```



Find maxmimum infection rate for Different Countries:

[67]:

```
df_agregated.loc["China"].diff().max()
#In only 24 hrs, the difference was 15136
```

[67]:

```
15136.0
```

[71]:

```
df_agregated.loc["Italy"].diff().max() # in Italy
```

[71]:

```
6557.0
```

[72]:

```
df_agregated.loc["Pakistan"].diff().max() # in Pakistan
```

[72]:

```
1292.0
```

Find maximum infection rate for all of the countries.

[73]:

```
countries = list(df_agregated.index)
max_infection_rates = []
for c in countries :
    max_infection_rates.append(df_agregated.loc[c].diff().max())
max_infection_rates
```

[73]:

```
[232.0,
 34.0,
 199.0,
 43.0,
 5.0,
 6.0,
 291.0,
 134.0,
 497.0,
 1321.0,
 105.0,
 7.0,
 301.0,
 641.0,
```

[74]:

```
df_agregated["max_infection_rates"] = max_infection_rates
```

[76]:

Country/Region	1/22/20	1/23/20	1/24/20	1/25/20	1/26/20	1/27/20	1/28/20	1/29/20	1/30/20	1/31/20	...	4/22/20	4/23/20	4/24/20	4/25/20	4/26/20	4/27
Afghanistan	0	0	0	0	0	0	0	0	0	0	...	1176	1279	1351	1463	1531	1
Albania	0	0	0	0	0	0	0	0	0	0	...	634	663	678	712	726	
Algeria	0	0	0	0	0	0	0	0	0	0	...	2910	3007	3127	3256	3382	3
Andorra	0	0	0	0	0	0	0	0	0	0	...	723	723	731	738	738	
Angola	0	0	0	0	0	0	0	0	0	0	...	25	25	25	25	26	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
West Bank and Gaza	0	0	0	0	0	0	0	0	0	0	...	474	480	484	342	342	
Western Sahara	0	0	0	0	0	0	0	0	0	0	...	6	6	6	6	6	
Yemen	0	0	0	0	0	0	0	0	0	0	...	1	1	1	1	1	
Zambia	0	0	0	0	0	0	0	0	0	0	...	74	76	84	84	88	
Zimbabwe	0	0	0	0	0	0	0	0	0	0	...	28	28	29	31	31	

187 rows × 101 columns

[76]:

```
df_agregated
```

[76]:

0	1/26/20	1/27/20	1/28/20	1/29/20	1/30/20	1/31/20	...	4/22/20	4/23/20	4/24/20	4/25/20	4/26/20	4/27/20	4/28/20	4/29/20	4/30/20	max_infection_rates
0	0	0	0	0	0	0	...	1176	1279	1351	1463	1531	1703	1828	1939	2171	232.0
0	0	0	0	0	0	0	...	634	663	678	712	726	736	750	766	773	34.0
0	0	0	0	0	0	0	...	2910	3007	3127	3256	3382	3517	3649	3848	4006	199.0
0	0	0	0	0	0	0	...	723	723	731	738	738	743	743	743	745	43.0
0	0	0	0	0	0	0	...	25	25	25	25	26	27	27	27	27	5.0
..	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
0	0	0	0	0	0	0	...	474	480	484	342	342	342	343	344	344	66.0
0	0	0	0	0	0	0	...	6	6	6	6	6	6	6	6	6	4.0
0	0	0	0	0	0	0	...	1	1	1	1	1	1	1	6	6	5.0
0	0	0	0	0	0	0	...	74	76	84	84	88	88	95	97	106	9.0
0	0	0	0	0	0	0	...	28	28	29	31	31	32	32	32	40	8.0

Create a new dataframe with only needed column

[83]:

```
corona_data = pd.DataFrame(df_agregated["max_infection_rates"])
corona_data.head()
```

[83]:

Country/Region	max_infection_rates
Afghanistan	232.0
Albania	34.0
Algeria	199.0
Andorra	43.0
Angola	5.0

Happiness Correlation Analysis

In this analysis, we will import the WorldHappinessReport.csv dataset and select relevant columns such as country names, happiness scores, and key indicators like GDP per capita and social support. We will then join this dataset with additional relevant datasets to provide a comprehensive view of happiness determinants. Finally, we will calculate the correlations between happiness scores and the selected indicators to identify significant relationships that inform policies aimed at enhancing well-being.

[85]:

```
happiness_report = pd.read_csv("C:\\Users\\hp\\Downloads\\worldwide_happiness_report.csv")
```

[86]:

```
happiness_report.head()
```

[86]:

	Overall rank	Country or region	Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption
0	1	Finland	7.769	1.340	1.587	0.986	0.596	0.153	0.393
1	2	Denmark	7.600	1.383	1.573	0.996	0.592	0.252	0.410
2	3	Norway	7.554	1.488	1.582	1.028	0.603	0.271	0.341
3	4	Iceland	7.494	1.380	1.624	1.026	0.591	0.354	0.118
4	5	Netherlands	7.488	1.396	1.522	0.999	0.557	0.322	0.298

Delete the useless Columns¶

[87]:

```
happiness_report.drop(["Overall rank", "Score", "Generosity", "Perceptions of corruption"], axis=1
```

[89]:

```
happiness_report.head()
```

[89]:

	Country or region	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices
0	Finland	1.340	1.587	0.986	0.596
1	Denmark	1.383	1.573	0.996	0.592
2	Norway	1.488	1.582	1.028	0.603
3	Iceland	1.380	1.624	1.026	0.591
4	Netherlands	1.396	1.522	0.999	0.557

Changing the index of the dataframe

[90]:

```
happiness_report.set_index("Country or region", inplace=True)
```

[91]:

```
happiness_report.head()
```

[91]:

Country or region	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices
Finland	1.340	1.587	0.986	0.596
Denmark	1.383	1.573	0.996	0.592
Norway	1.488	1.582	1.028	0.603
Iceland	1.380	1.624	1.026	0.591
Netherlands	1.396	1.522	0.999	0.557

Now join two dataset we have prepared

Corona Dataset

[93]:

```
corona_data.head()
```

[93]:

Country/Region	max_infection_rates
Afghanistan	232.0
Albania	34.0
Algeria	199.0
Andorra	43.0
Angola	5.0

[94]:

```
corona_data.shape
```

[94]:

```
(187, 1)
```

Wolrd Happiness Report Dataset :¶

[96]:

```
happiness_report.head()
```

[96]:

Country or region	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices
Finland	1.340	1.587	0.986	0.596
Denmark	1.383	1.573	0.996	0.592
Norway	1.488	1.582	1.028	0.603
Iceland	1.380	1.624	1.026	0.591
Netherlands	1.396	1.522	0.999	0.557

[98]:

```
happiness_report.shape
```

[98]:

```
(156, 4)
```

[99]:

```
#Inner join
data = corona_data.join(happiness_report,
                how = "inner"    #method/type of join
                )
data.head()
```

[99]:

	max_infection_rates	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices
Afghanistan	232.0	0.350	0.517	0.361	0.000
Albania	34.0	0.947	0.848	0.874	0.383
Algeria	199.0	1.002	1.160	0.785	0.086
Argentina	291.0	1.092	1.432	0.881	0.471
Armenia	134.0	0.850	1.055	0.815	0.283

This code merges the two datasets based on their indices, resulting in a new dataset that includes only the rows with matching indices from both corona_data and happiness_report_csv, allowing for a combined analysis of COVID-19 data and happiness metrics.

Correlation Matrix¶

```
[100]:
data.corr()
```

[100]:

	max_infection_rates	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices
max_infection_rates	1.000000	0.250118	0.191958	0.289263	0.078196
GDP per capita	0.250118	1.000000	0.759468	0.863062	0.394603
Social support	0.191958	0.759468	1.000000	0.765286	0.456246
Healthy life expectancy	0.289263	0.863062	0.765286	1.000000	0.427892
Freedom to make life choices	0.078196	0.394603	0.456246	0.427892	1.000000

data.corr() is a powerful function for quantifying and analyzing the relationships between variables in the dataset, helping to uncover insights about how different factors may influence each other. The function calculates the correlation coefficients, which measure the strength and direction of the linear relationship between two variables. The values range from -1 to 1:

1 indicates a perfect positive correlation (as one variable increases, the other also increases).

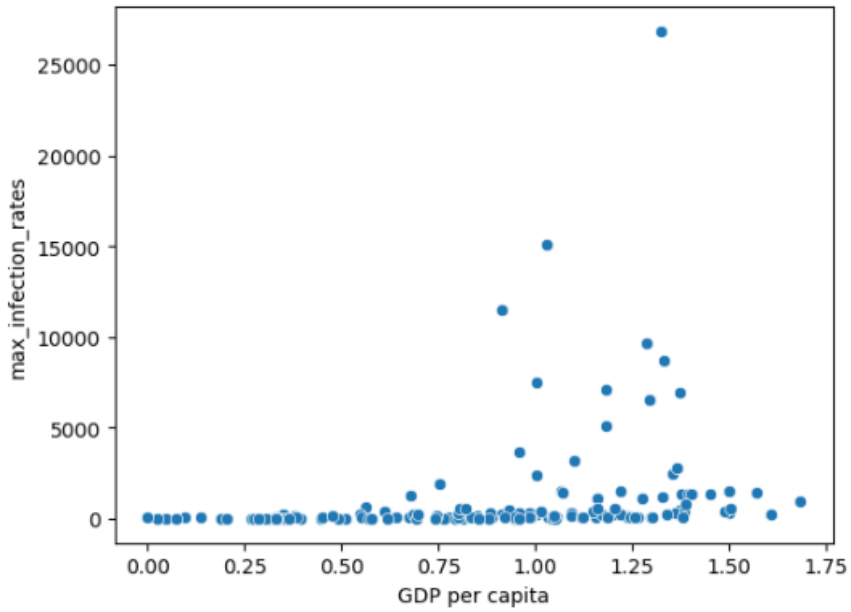
-1 indicates a perfect negative correlation (as one variable increases, the other decreases).

0 indicates no correlation (there is no linear relationship between the variables).

Visualization of the results:

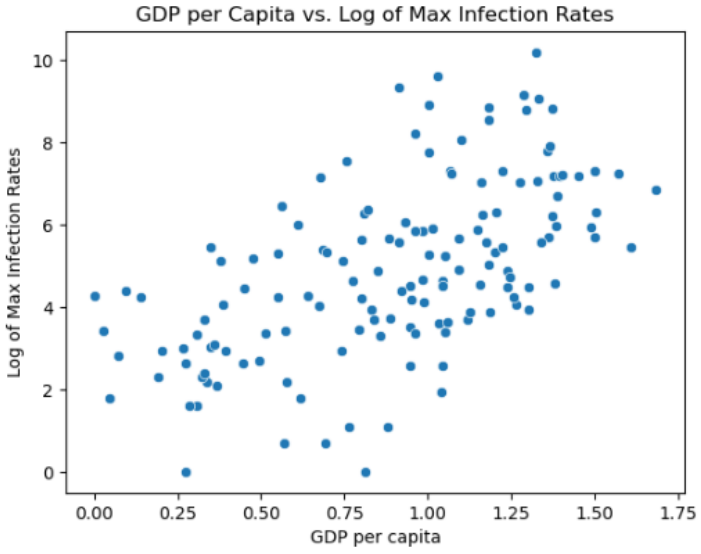
- **Plotting GDP vs maximum Infection rate**

```
sns.scatterplot(data=data, x="GDP per capita", y="max_infection_rates")
plt.show()
```



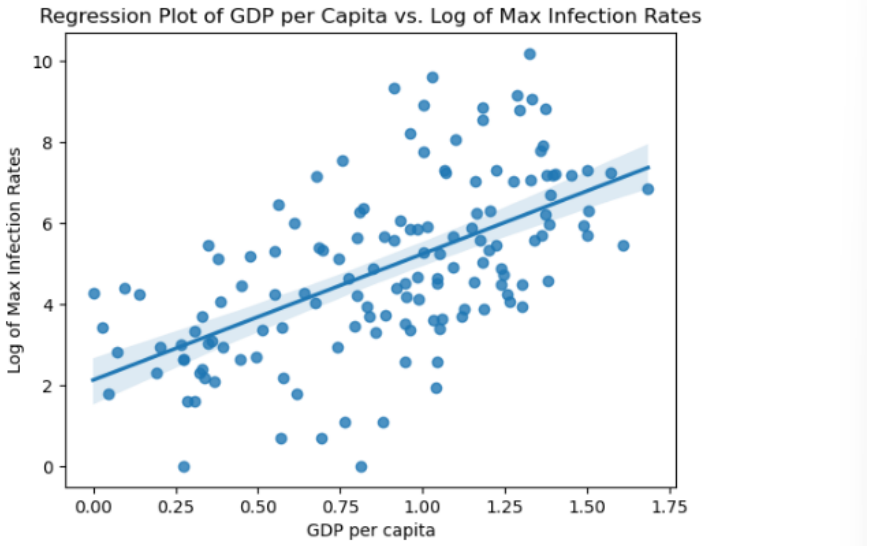
- **Scatter Plot¶**

```
sns.scatterplot(data=data, x="GDP per capita", y=np.log(data["max_infection_rates"]))
plt.xlabel("GDP per capita")
plt.ylabel("Log of Max Infection Rates")
plt.title("GDP per Capita vs. Log of Max Infection Rates")
plt.show()
```



- **Regression Plot**

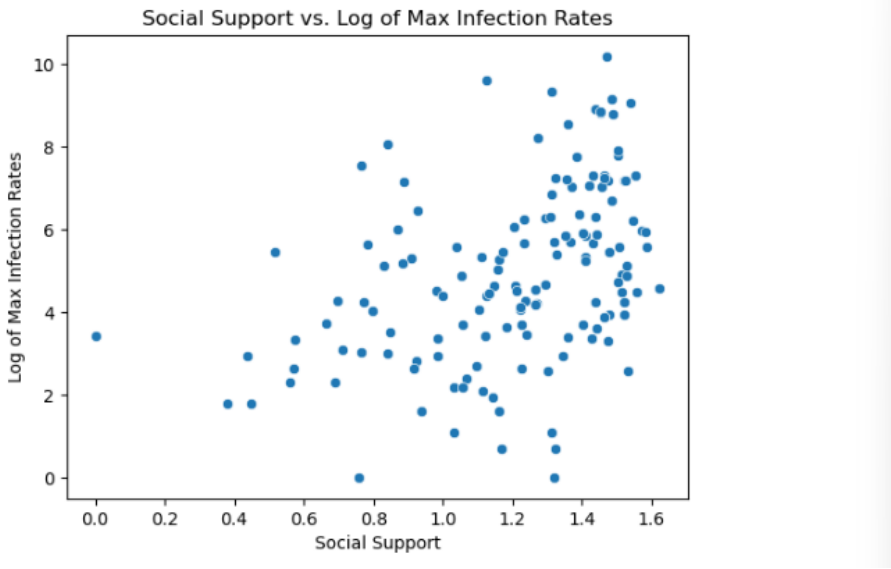
```
sns.regplot(data=data, x="GDP per capita", y=np.log(data["max_infection_rates"]))
plt.xlabel("GDP per capita")
plt.ylabel("Log of Max Infection Rates")
plt.title("GDP per Capita vs. Log of Max Infection Rates")
plt.show()
```



Plotting Social support vs maximum Infection:

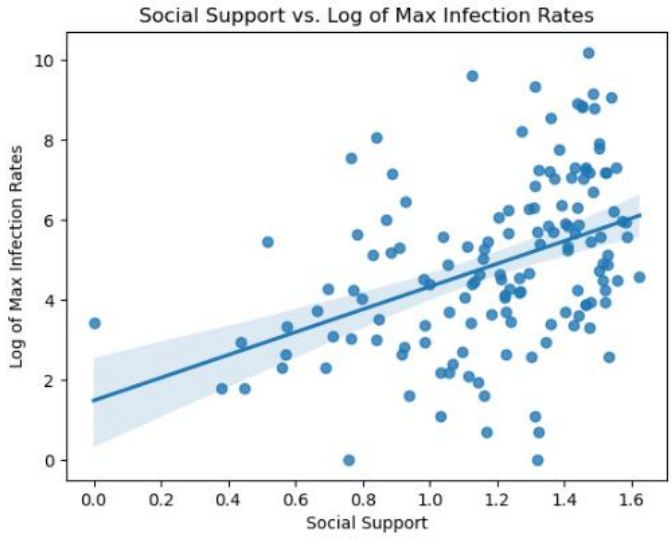
- **Scatter Plot Social Support vs. Log of Max Infection Rates**

```
sns.scatterplot(data=data, x="Social support", y=np.log(data["max_infection_rates"]))
plt.xlabel("Social Support")
plt.ylabel("Log of Max Infection Rates")
plt.title("Social Support vs. Log of Max Infection Rates")
plt.show()
```



- **Regression Plot of Social Support vs. Log of Max Infection Rates**

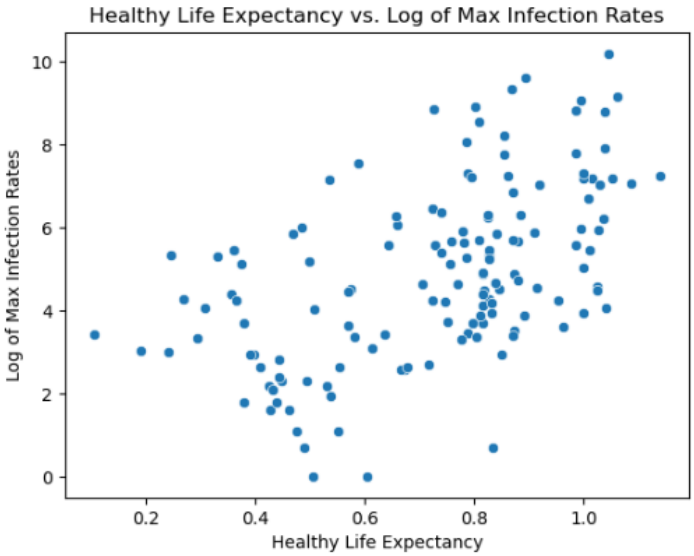
```
[120]:
sns.regplot(data=data, x="Social support", y=np.log(data["max_infection_rates"]))
plt.xlabel("Social Support")
plt.ylabel("Log of Max Infection Rates")
plt.title("Social Support vs. Log of Max Infection Rates")
plt.show()
```



Plotting Healthy life expectancy vs maximum Infection rate

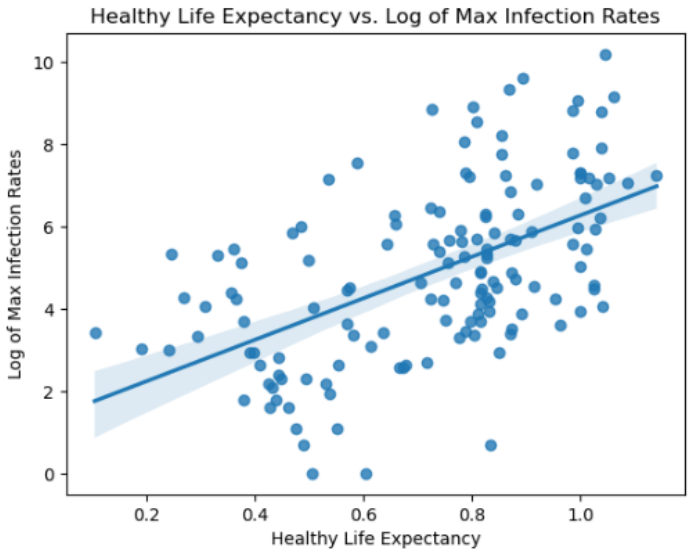
- **Scatter Plot of Healthy Life Expectancy vs. Log of Max Infection Rates**

```
sns.scatterplot(data=data, x="Healthy life expectancy", y=np.log(data["max_infection_rates"]))
plt.xlabel("Healthy Life Expectancy")
plt.ylabel("Log of Max Infection Rates")
plt.title("Healthy Life Expectancy vs. Log of Max Infection Rates")
plt.show()
```



- **Regression Plot of Healthy Life Expectancy vs. Log of Max Infection Rates**

```
sns.regplot(data=data, x="Healthy life expectancy", y=np.log(data["max_infection_rates"]))
plt.xlabel("Healthy Life Expectancy")
plt.ylabel("Log of Max Infection Rates")
plt.title("Healthy Life Expectancy vs. Log of Max Infection Rates")
plt.show()
```

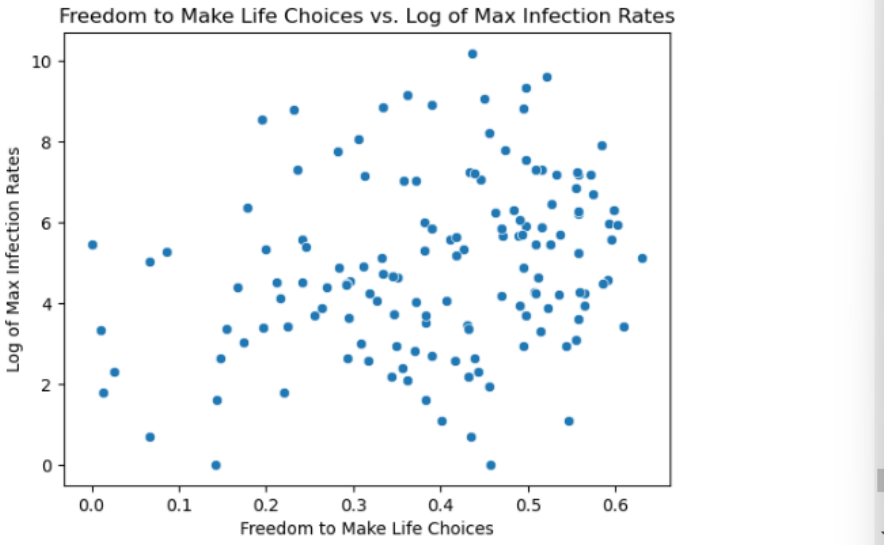


-

Plotting Freedom to make life choices vs maximum Infection rate:

- **Scatter Plot of Freedom to Make Life Choices vs. Log of Max Infection Rates**

```
sns.scatterplot(data=data, x="Freedom to make life choices", y=np.log(data["max_infection_rates"]))
plt.xlabel("Freedom to Make Life Choices")
plt.ylabel("Log of Max Infection Rates")
plt.title("Freedom to Make Life Choices vs. Log of Max Infection Rates")
plt.show()
```



Regression Plot of Freedom to Make Life Choices vs. Log of Max Infection Rates

[130]:

```
sns.regplot(data=data, x="Freedom to make life choices", y=np.log(data["max_infection_rates"]))
plt.xlabel("Freedom to Make Life Choices")
plt.ylabel("Log of Max Infection Rates")
plt.title("Freedom to Make Life Choices vs. Log of Max Infection Rates")
plt.show()
```