Exploratory Data Analysis on Covid Data

1.Importing data using pandas

```
import pandas as pd
data = pd.read_csv("/content/covid-data.csv")
```

- 2. High level data understanding
- a. Number of rows and columns

```
print(data.shape)

→ (20283, 49)
```

b.Datatypes,Information,Describe

print(data.dtypes)

\rightarrow	iso_code	object
	continent	object
	location	object
	date	object
	total_cases	float64
	new_cases	float64
	new_cases_smoothed	float64
	total_deaths	float64
	new deaths	float64
	new deaths smoothed	float64
	total_cases_per_million	float64
	new_cases_per_million	float64
	new_cases_smoothed_per_million	float64
	total_deaths_per_million	float64
	new_deaths_per_million	float64
	new_deaths_smoothed_per_million	float64
	reproduction_rate	float64
	icu_patients	float64
	icu_patients_per_million	float64
	hosp_patients	float64
	hosp_patients_per_million	float64
	weekly_icu_admissions	float64
	weekly_icu_admissions_per_million	float64
	weekly_hosp_admissions	float64
	weekly_hosp_admissions_per_million	float64
	total_tests	float64
	new tests	float64
	total_tests_per_thousand	float64
	new_tests_per_thousand	float64
	new_tests_smoothed	float64
	new_tests_smoothed_per_thousand	float64

float64 tests_per_case float64 positive_rate stringency index float64 population int64 population_density float64 median_age float64 aged_65_older float64 float64 aged_70_older gdp_per_capita float64 float64 extreme_poverty cardiovasc_death_rate float64 diabetes_prevalence float64 female_smokers float64 float64 male smokers handwashing_facilities float64 hospital_beds_per_thousand float64 life_expectancy float64 human_development_index float64 dtype: object

print(data.info)

\rightarrow	<bound< th=""><th>method DataFram</th><th>ne.info of</th><th>iso</th><th>o code conti</th><th>inent lo</th><th>ocation</th><th>dat</th><th></th></bound<>	method DataFram	ne.info of	iso	o code conti	inent lo	ocation	dat	
	0		ia Afghanist			NaN	0.0		
	1	AFG As	ia Afghanist	an 01	1-01-2020	NaN	0.0		
	2		ia Afghanist		2-01-2020	NaN	0.0		
	3		ia Afghanist		3-01-2020	NaN	0.0		
	4	AFG As	ia Afghanist	an 04	1-01-2020	NaN	0.0		
			• •						
	20278	GHA Afri	.ca Gha	na 11	1-10-2020	47005.0	18.0		
	20279	GHA Afri	.ca Gha	na 12	2-10-2020	47005.0	0.0		
	20280	GHA Afri	.ca Gha	na 13	3-10-2020	47030.0	25.0		
	20281	GHA Afri	.ca Gha	na 14	1-10-2020	47126.0	96.0		
	20282	GHA Afri	.ca Gha	na 15	5-10-2020	47126.0	0.0		
		new_cases_smoot	hed total de	aths	new deaths	new deaths	ssmoothed	\	
	0	ca3c3_5ooc	NaN	NaN	0.0	new_acaens	NaN		,
	1		NaN	NaN	0.0		NaN		
	2		NaN	NaN	0.0		NaN		
	3		NaN	NaN	0.0		NaN		
	4		NaN	NaN	0.0		NaN		
			• • •						
	20278	28.		06.0	0.0		0.429		
	20279	25.	143 3	06.0	0.0		0.429		
	20280	28.	714 3	08.0	2.0		0.714		
	20281	42.	429 3:	10.0	2.0		1.000		
	20282	42.	429 3	10.0	0.0		1.000		
		gdp_per_capita	extreme nove	rtv (cardiovasc c	death rate	\		
	0	1803.987		NaN		597.029	(
	1	1803.987		NaN		597.029			
	2	1803.987		NaN		597.029			
	3	1803.987		NaN		597.029			
	4	1803.987		NaN		597.029			
	20278	4227.630	1	2.0		298.245			
	20279	4227.630	1	2.0		298.245			
	20280	4227.630	1	2.0		298.245			
	20281	4227.630	1	2.0		298.245			

4227.630	12.0		NaN	
iabetes prevalence	female smokers	male smokers	\	
9.59	– NaN	– NaN		
9.59	NaN	NaN		
9.59	NaN	NaN		
9.59	NaN	NaN		
9.59	NaN	NaN		
• • •		• • •		
4.97	0.3	7.7		
4.97	0.3	7.7		
4.97	0.3	7.7		
4.97	0.3	7.7		
NaN	NaN	NaN		
andwashing facilitie	s hospital bed	s per thousand	life expectancy	\
				`
		0.5	64.83	
		0.5	64.83	
	Labetes_prevalence 9.59 9.59 9.59 9.59 9.59 4.97 4.97 4.97 4.97 NaN andwashing_facilitie 37.74 37.74	### dabetes_prevalence	### Association of the content of th	### Asabetes_prevalence female_smokers male_smokers \ 9.59

print(data.describe)

\rightarrow	20281	42.429	310.0	2.0	1.000	
	20282	42.429	310.0	0.0	1.000	

	gdp_per_capita	extreme_poverty	cardiovasc_death_rate	\
0	1803.987	NaN	597.029	
1	1803.987	NaN	597.029	
2	1803.987	NaN	597.029	
3	1803.987	NaN	597.029	
4	1803.987	NaN	597.029	
			• • •	
20278	4227.630	12.0	298.245	
20279	4227.630	12.0	298.245	
20280	4227.630	12.0	298.245	

8/3/24, 11:23 AM		Copy of AICTE intern - EDA Task - Cola	ıb
202/8	41.04/	0.9	64.0/
20279	41.047	0.9	64.07
20280	41.047	0.9	64.07
20281	41.047	0.9	64.07
20282	NaN	NaN	NaN
	human_development_index		
0	0.498		
1	0.498		
2	0.498		
3	0.498		
4	0.498		
	• • •		
20278	0.592		
20279	0.592		
20280	0.592		
20281	0.592		
20282	NaN		
[20283	rows x 49 columns]>		

3.Low level data understandng

a. Count unique values in each columns

```
print(data['new_deaths'].nunique)
```

```
<bound method IndexOpsMixin.nunique of 0</pre>
                                                   0.0
             0.0
    2
             0.0
    3
             0.0
            0.0
    20278
             0.0
    20279
            0.0
    20280
            2.0
    20281
            2.0
             0.0
    20282
    Name: new_deaths, Length: 20283, dtype: float64>
```

print(data.nunique)

\Rightarrow	<box< th=""><th>method Dat</th><th>aFrame.n</th><th>unique of</th><th>iso_code</th><th>continent</th><th>location</th></box<>	method Dat	aFrame.n	unique of	iso_code	continent	location
	0	AFG	Asia	Afghanistan	31-12-2019	NaN	0.0
	1	AFG	Asia	Afghanistan	01-01-2020	NaN	0.0
	2	AFG	Asia	Afghanistan	02-01-2020	NaN	0.0
	3	AFG	Asia	Afghanistan	03-01-2020	NaN	0.0
	4	AFG	Asia	Afghanistan	04-01-2020	NaN	0.0
	20278	GHA	Africa	Ghana	11-10-2020	47005.0	18.0
	20279	GHA	Africa	Ghana	12-10-2020	47005.0	0.0
	20280	GHA	Africa	Ghana	13-10-2020	47030.0	25.0
	20281	GHA	Africa	Ghana	14-10-2020	47126.0	96.0
	20282	GHA	Africa	Ghana	15-10-2020	47126.0	0.0

```
new_cases_smoothed
                             total_deaths
                                             new_deaths
                                                         new_deaths_smoothed
0
                                       NaN
                                                     0.0
                        NaN
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1
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2
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20278
                                     306.0
                                                                          0.429
                     28.857
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20279
                                                                          0.429
                     25.143
                                     306.0
                                                     0.0
20280
                     28.714
                                     308.0
                                                     2.0
                                                                          0.714
                                                                                  . . .
                    42.429
20281
                                     310.0
                                                     2.0
                                                                          1.000
20282
                    42.429
                                     310.0
                                                     0.0
                                                                          1.000
       gdp_per_capita extreme_poverty
                                            cardiovasc_death_rate
0
              1803.987
                                                            597.029
1
              1803.987
                                                            597.029
                                      NaN
2
              1803.987
                                      NaN
                                                            597.029
3
                                                            597.029
              1803.987
                                      NaN
4
              1803.987
                                                            597.029
                                      NaN
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20278
              4227.630
                                     12.0
                                                            298.245
20279
              4227.630
                                     12.0
                                                            298.245
20280
              4227.630
                                     12.0
                                                            298.245
                                                            298.245
20281
              4227.630
                                     12.0
20282
              4227.630
                                     12.0
                                                                NaN
       diabetes_prevalence female_smokers male_smokers
0
                        9.59
                                           NaN
                                                          NaN
1
                        9.59
                                           NaN
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                        9.59
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4
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20278
                        4.97
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                                                          7.7
20279
                        4.97
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                                                          7.7
                                                          7.7
20280
                        4.97
                                           0.3
20281
                        4.97
                                           0.3
                                                          7.7
20282
                         NaN
                                           NaN
                                                          NaN
       handwashing facilities
                                  hospital_beds_per_thousand
                                                                 life expectancy
0
                         37.746
                                                            0.5
                                                                            64.83
1
                         37.746
                                                            0.5
                                                                            64.83
                                                            0.5
2
                         37.746
                                                                            64 83
```

b. Find which continent have maximum frequency of values.

```
Maximum_Frequency=data['continent'].value_counts()
Maximum_Frequency_continent=Maximum_Frequency.idxmax()
print(Maximum_Frequency_continent,Maximum_Frequency.max())
```

→ Africa 5468

c.max & mean value in total_cases

NaN

```
2
            NaN
3
            NaN
            NaN
20278 47005.0
      47005.0
20279
20280 47030.0
20281
       47126.0
       47126.0
20282
Name: total_cases, Length: 20283, dtype: float64>
Mean <bound method Series.mean of 0
2
            NaN
3
            NaN
            NaN
20278 47005.0
20279 47005.0
20280 47030.0
20281
       47126.0
      47126.0
20282
Name: total_cases, Length: 20283, dtype: float64>
```

d.find interquartiles

```
print(data['total_deaths'].describe(percentiles=[.25,.50,.75]))
```

```
→ count
             15625.000000
              2936.541056
    std
              12890.630598
    min
                 1.000000
    25%
                 9.000000
    50%
                83.000000
    75%
                712.000000
             166014.000000
    max
    Name: total deaths, dtype: float64
```

e.Find which continent have highest human_value_development_index.

```
df=data.groupby('continent')['human_development_index'].max()
continent=df.idxmax()
df1=df.max()
print(continent,df1)

Oceania 0.939
```

f.Find Which continent have minimum gdp_per_captia

```
df2=data.groupby('continent')['gdp_per_capita'].min()
continent1=df2.idxmin()
mini=df2.min()
print(continent1,mini)
```

→ Africa 661.24

4. Filtering

tokeep=['continent','location','date','total_cases','total_deaths','gdp_per_capita','huma
df=data[tokeep]
print(df)

\Rightarrow		continent	location	n date	total_cases	total_deaths	١
	0	Asia	Afghanistar	31-12-2019	NaN	NaN	
	1	Asia	Afghanistar	01-01-2020	NaN	NaN	
	2	Asia	Afghanistar	02-01-2020	NaN	NaN	
	3	Asia	Afghanistar	03-01-2020	NaN	NaN	
	4	Asia	Afghanistar	04-01-2020	NaN	NaN	
				• • •	• • •		
	20278	Africa	Ghana	11-10-2020	47005.0	306.0	
	20279	Africa	Ghana	12-10-2020	47005.0	306.0	
	20280	Africa	Ghana	13-10-2020	47030.0	308.0	
	20281	Africa	Ghana	14-10-2020	47126.0	310.0	
	20282	Africa	Ghana	15-10-2020	47126.0	310.0	
		gdp_per_c	apita humar	_development	_index		
	0	180	3.987		0.498		
	1	180	3.987		0.498		
	2	180	3.987		0.498		
	3	180	3.987		0.498		
	4	180	3.987		0.498		

. 4227.630 0.592 20278 4227.630 0.592 20279 4227.630 0.592 20280 20281 4227.630 0.592 20282 4227.630 NaN

[20283 rows x 7 columns]

5. Data Cleaning.

```
df_cleaned=df.drop_duplicates()
df_3=df_cleaned.isna().sum()
df_cleaned = df_cleaned.dropna(subset=['continent'])
```

df_cleaned=df_cleaned.fillna(0)
print(df_cleaned)

\Rightarrow	continent	location	date	total_cases	total_deaths	١
0	Asia	Afghanistan	31-12-2019	0.0	0.0	
1	Asia	Afghanistan	01-01-2020	0.0	0.0	

```
0.0
3
          Asia Afghanistan 03-01-2020
                                                  0.0
                                                                 0.0
           Asia Afghanistan 04-01-2020
4
                                                  0.0
                                                                 0.0
                                     . . .
                                                   . . .
20278
         Africa
                       Ghana 11-10-2020
                                              47005.0
                                                               306.0
20279
        Africa
                       Ghana 12-10-2020
                                              47005.0
                                                               306.0
20280
         Africa
                       Ghana 13-10-2020
                                              47030.0
                                                               308.0
20281
         Africa
                       Ghana 14-10-2020
                                              47126.0
                                                               310.0
20282
        Africa
                       Ghana 15-10-2020
                                              47126.0
                                                               310.0
```

	gdp_per_capita	human_development_index
0	1803.987	0.498
1	1803.987	0.498
2	1803.987	0.498
3	1803.987	0.498
4	1803.987	0.498
		• • •
20278	4227.630	0.592
20279	4227.630	0.592
20280	4227.630	0.592
20281	4227.630	0.592
20282	4227.630	0.000

[20283 rows x 7 columns]

6.a.date time format

```
df_cleaned['date'] = pd.to_datetime(df_cleaned['date'], errors='coerce')
print(df_cleaned['date'])
```

```
0 2019-12-31
1 2020-01-01
2 2020-01-02
3 2020-01-03
4 2020-01-04
...
20278 2020-10-11
20279 2020-10-12
20280 2020-10-13
20281 2020-10-14
20282 2020-10-15
Name: date, Length: 20283, dtype: datetime64[ns]
```

<ipython-input-19-3aa3f2ac1bfa>:1: UserWarning: Parsing dates in %d-%m-%Y format when
 df_cleaned['date'] = pd.to_datetime(df_cleaned['date'], errors='coerce')



b.Extract month from date column

```
df_cleaned['month']=df_cleaned['date'].dt.month
print("New Extracted Month Column",df_cleaned['month'])
```

```
New Extracted Month Column 0 12
1 1
2 1
```

```
3 1
4 1
...
20278 10
20279 10
20280 10
20281 10
20282 10
Name: month, Length: 20283, dtype: int32
```

7.a Data Aggregation - Find maximum values in every columns grouped by continent

```
df_groupby=df_cleaned.groupby('continent').max()
print(df_groupby.reset_index())
```

₹	0 1 2 3 4 5		Georgia Germany	2020-11-17 2020-11-17 2020-11-17 2020-11-17 2020-11-17	111009.0 434472.0 1991233.0 302192.0 27750.0	total_deaths 6465.0 6215.0 45054.0 11027.0 907.0 166014.0	\
	0 1 2 3 4 5	gdp_per_capita 22604.873 71809.251 46682.515 50669.315 44648.710 22767.037	human_developmen	nt_index mo 0.754 0.853 0.936 0.926 0.939 0.843	nth 12 12 12 12 12 12		

8. Feature Engineering

df_groupby['totaldeaths_totalcases']=df_groupby['total_deaths']/df_groupby['total_cases']
print(df_groupby['totaldeaths_totalcases'])

```
continent
Africa 0.058239
Asia 0.014305
Europe 0.022626
North America 0.036490
Oceania 0.032685
South America 0.028251
```

Name: totaldeaths_totalcases, dtype: float64

9.Data Visualization

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

df = pd.DataFrame({
        'gdp_per_capita': [30000, 15000, 20000, 40000, 25000, 30000, 12000]
})

sns.histplot(df['gdp_per_capita'], kde=True) # `distplot` is deprecated; use `histplot`
plt.title('Histogram of GDP per Capita')
plt.xlabel('GDP per Capita')
plt.ylabel('Frequency')
plt.show()
```



0.00

15000

20000

1.75 - 1.50 - 1.00 - 0.75 - 0.50 - 0.25 - 0.25 -

```
import seaborn as sns
import matplotlib.pyplot as ply
sns.scatterplot(x=df_groupby['total_cases'], y=df_groupby['gdp_per_capita'], data=df_grou
plt.title('Scatter Plot of Total Cases vs. GDP per Capita')
plt.xlabel('Total Cases')
plt.ylabel('GDP per Capita')
plt.show()
```

25000

GDP per Capita

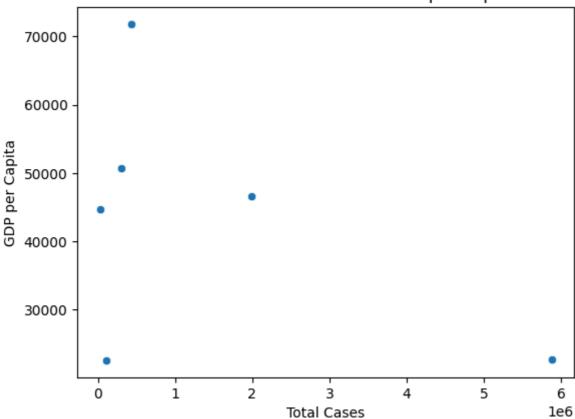
30000

35000

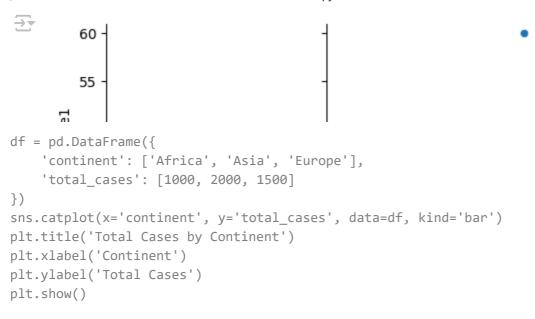
40000

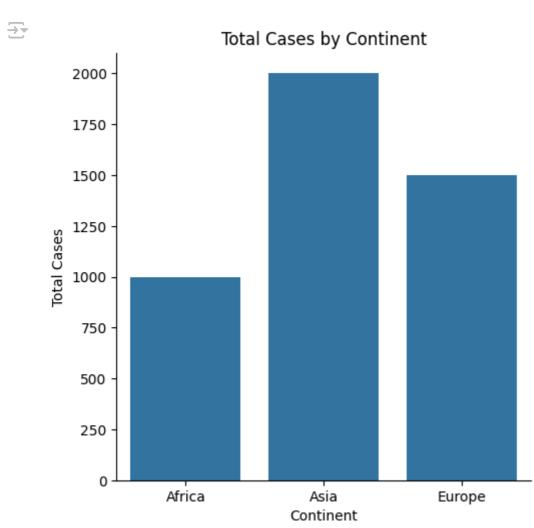


Scatter Plot of Total Cases vs. GDP per Capita



```
df_groupby = pd.DataFrame({
    'continent': ['Africa', 'Asia', 'Europe'],
    'value1': [60, 50, 40],
    'value2': [55, 45, 35]
})
sns.pairplot(df_groupby, hue='continent')
plt.show()
```





df_groupby.to_csv('df_groupby.csv', index=False)