COVID-19 USING COGNOS

PHASE 5: PROJECT DOCUMENTATION &SUBMISSION

➢ Project definition:

The project we aim to address is the need for timely and insightful reporting on the COVID-19 pandemic's impact on European union(EU) countries. This project involves analyzing COVID-19 cases and deaths data using IBM cognos. The objective is to compare and contrast the mean values and standard deviations of cases and associated deaths per day and by country in the EU/EEA. This project encompasses defining analysis objectives,collecting COVID-19 data,designing relevant visualizations in IBM cognos, and deriving insights from the data.

DatasetLink: https://www.kaggle.com/datasets/chakradharmattapalli/covid-19-cases

DESIGN THINKING:

Analysis Objectives:

Define specific objectives, such as:

- Calculate the mean and standard deviation of daily COVID-19 cases and deaths in EU/EEA countries.
- Compare the mean values of cases and deaths to identify trends and variations.
- Determine if there are any correlations between mean case and death values.
- Identify countries with significantly higher or lower mean values.

Data Collection:

- Obtain a comprehensive dataset containing daily COVID-19 cases and deaths by country within the EU/EEA region. Ensure data quality and timeliness.
- Consider data sources such as official health agencies, WHO, or trusted repositories that provide historical data for analysis.

Visualization Strategy:

- Choose appropriate chart types for visualizing mean values and standard deviations. For example, line charts can represent trends over time, while bar charts can show comparisons between countries.

- Use color coding and labeling to make visualizations intuitive and easy to understand.
- Ensure that visualizations are interactive, allowing users to explore data by selecting specific countries or date ranges.

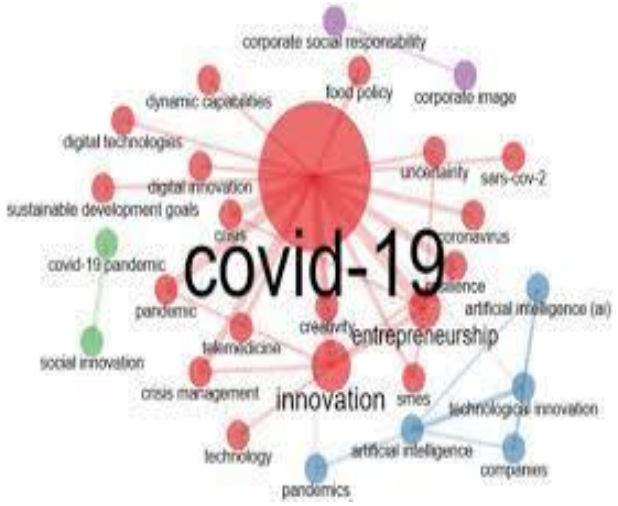
Insights Generation:

- Identify potential insights:
- Are there countries that consistently have higher or lower mean values than others?
- Are there time periods where mean values show significant spikes or declines?
- Do countries with higher mean cases tend to have higher mean deaths, and vice versa?
- Explore the impact of COVID-19 interventions or vaccination campaigns on mean values and standard deviations.
- Consider regional variations within the EU/EEA and how they affect the data analysis.

➢ Innovation:

We use COVID-19 dataset to remove missing values for fill mean value or nearest values. We use some datascience technique to manipulate and also use visualization to extract from dataset.

We use regression model to extract the information from dataset. Regression model like linear regression, logistic regression model. Linear regression model used the relationship between the target variable. Logistic used binary classification problems where target variable is categorical and has two classes.



➢ Data Preparation:

Start by cleaning and preprocessing the COVID-19 data. This involves handling missing values, checking for data consistency, and ensuring that the data is in a format suitable for analysis.

Example:

Checking for missing values using isnull() and notnull()

Filling for missing values using fillna() and replace()

(Sample code here)

```
importos
import pandas as pd
importmatplotlib.pyplot as plt
os.chdir("C:\Users\ELCOT\Downloads")
df=pd.read_csv("Covid_19_cases4.csv")
print(df.isnull())
```

output:

```
1   False
2   False
3   False
    .
    .
    .
2731   False
```

➢ Exploratory Data Analysis (EDA):

Dive deeper into the dataset to uncover patterns and insights. Use statistical tools, such as histograms, scatter plots, and time-series analysis, to visualize and understand the data.

➢ Hypothesis Formulation:

Based on your initial observations from EDA, formulate hypotheses about the factors that may influence COVID-19 cases and deaths in the EU/EEA.

For example, you might hypothesize that certain countries have higher mean values due to population density or healthcare infrastructure.

➢ Statistical Analysis:

Test your hypotheses using appropriate statistical methods. This may involve regression analysis, correlation testing, or other statistical tests relevant to your research questions.

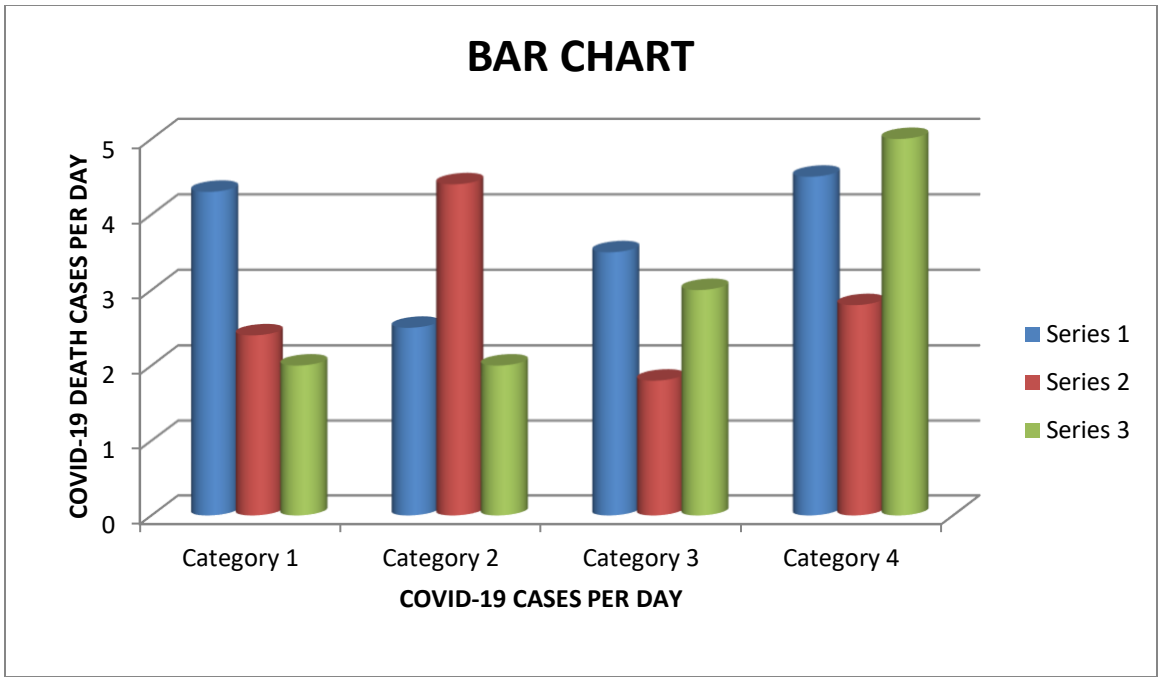
➢ Visualization Enhancement:

Refine your visualization strategy in IBM Cognos. Create detailed charts, graphs, and dashboards that illustrate the relationships and trends you've identified through statistical analysis.

(Sample model chart for few set of covid-19 cases)

(Sample code here)

```
importos
import pandas as pd
importmatplotlib.pyplot as plt
os.chdir("C:\Users\ELCOT\Downloads")
df=pd.read_csv("Covid_19_cases4.csv")
cases=df["cases"]
death=df["deaths"]
plt.bar(cases,death)
plt.xlabel("COVID-19 CASES PER DAY")
plt.ylabel("COVID-19 DEATH CASES PER DAY")
plt.tittle("BAR CHART")
plt.show()
```



➢ Recommendations:

Based on your insights, propose data-driven recommendations or actions. For example, if you find that certain countries have consistently high standard deviations, consider investigating the factors contributing to this variability.

➢ Iteration:

Keep in mind that data analysis is often an iterative process. If you uncover new questions or areas of interest during this phase, be prepared to revisit earlier stages of the project for further exploration.

➢ Time-Series Analysis:

Analyze how mean values and standard deviations have evolved over time. Are there noticeable trends, seasonality, or sudden changes in the data? Visualize these patterns effectively.

➢ Geospatial Analysis:

If relevant, consider geospatial visualizations to display variations in mean values and standard deviations on a map of the EU/EEA. This can help identify regional disparities.

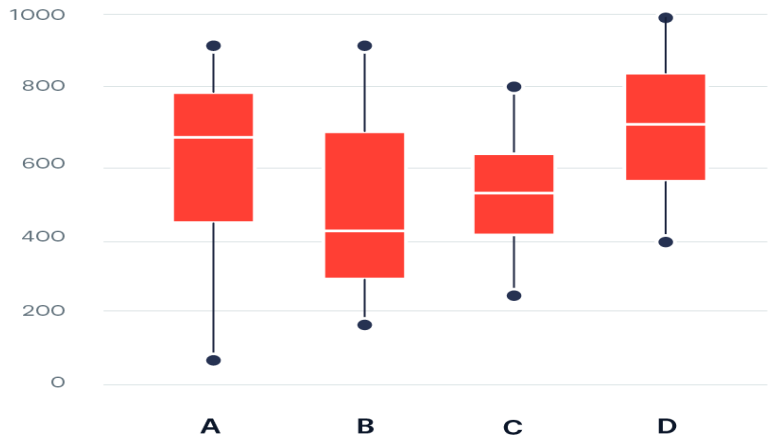
➢ Insights Generation:

Interpret your analysis results. What insights have you gained from comparing mean values and standard deviations of cases and deaths? Are there countries or time periods that stand out? Are there factors contributing to the observed variations?

- **Advanced Visualizations:**

Enhance your visualization strategy to include more advanced charts and graphs.
For instance, use box plots, heatmaps, or interactive dashboards to provide a comprehensive view of the data.
(Sample box plot)
(Sample code here)

```
importos
import pandas as pd
importmatplotlib.pyplot as plt
os.chdir("C:\Users\ELCOT\Downloads")
df=pd.read_csv("Covid_19_cases4.csv")
cases=df["cases"]
plt.boxplot(cases)
plt.show()
```



- **Documentation:**

Document your entire analysis process, including data sources, methods, and assumptions. This documentation is crucial for transparency and reproducibility.

- **Communication:**

Communicate your findings and recommendations effectively to stakeholders or your team. Use clear visualizations and concise explanations to convey your insights.

- **Given dataset:**

dateRep	day	month	year	cases	deaths	countriesAndTerritories
31-05-2021	31	5	2021	366	5	Austria
30-05-2021	30	5	2021	570	6	Austria
29-05-2021	29	5	2021	538	11	Austria
28-05-2021	28	5	2021	639	4	Austria
27-05-2021	27	5	2021	405	19	Austria
26-05-2021	26	5	2021	287	8	Austria
25-05-2021	25	5	2021	342	3	Austria
24-05-2021	24	5	2021	520	3	Austria
23-05-2021	23	5	2021	626	8	Austria
22-05-2021	22	5	2021	671	12	Austria
21-05-2021	21	5	2021	603	8	Austria
20-05-2021	20	5	2021	866	13	Austria
19-05-2021	19	5	2021	630	11	Austria
18-05-2021	18	5	2021	391	15	Austria
17-05-2021	17	5	2021	676	6	Austria
16-05-2021	16	5	2021	684	12	Austria
15-05-2021	15	5	2021	721	14	Austria
14-05-2021	14	5	2021	1100	11	Austria

Necessary step to follow:

1.Import Libraries:

Start by importing the necessary libraries:

Program:

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

2.Load the Dataset:

Load your dataset into a Pandas DataFrame. You can typically find COVID-19 datasets in CSV format, but you can adapt this code to other formats as needed

Program:

```
os.chdir("C:\\Users\ELCOT\Downloads")
df=pd.read_csv("Covid_19_cases4.csv")
```

3. Exploratory Data Analysis (EDA):

Perform EDA to understand your data better. This includes checking for missing values, exploring the data's statistics, and visualizing it to identify patterns.

Program:

```
# Check for missing values
print(df.isnull().sum())
# Explore statistics
print(df.describe())
# Visualize the data (e.g., histograms, scatter plots, etc.)
```

4. Feature Engineering:

Depending on your dataset, you may need to create new features or transform existing ones. This can involve one-hot encoding categorical variables, handling date/time data, or scaling numerical features.

Program:

```
# Example: One-hot encoding for categorical variables
df = pd.get_dummies(df, columns=[' Avg. cases ', ' Avg. deaths'])
```

➢ Loading the dataset:

- ✓ Loading the dataset using machine learning is the process of bringing the data into the machine learning environment so that it can be used to train and evaluate a model.
- ✓ The specific steps involved in loading the dataset will vary depending on the machine learning library or framework that is being used. However, there are some general steps that are common to most machine learning frameworks:

  a.Identify the dataset:

  The first step is to identify the dataset that you want to load. This dataset may be stored in a local file, in a database, or in a cloud storage service.

  b.Load the dataset:

  Once you have identified the dataset, you need to load it into the machine learning environment. This may involve using a built-in function in the machine learning library, or it may involve writing your own code.

c.Preprocess the dataset:

Once the dataset is loaded into the machine learning environment, you may need to preprocess it before you can start training and evaluating your model. This may involve cleaning the data, transforming the data into suitable format, and splitting the data into training and test sets.

Program:

```
import os
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
os.chdir("C:\\Users\ELCOT\Downloads")
df=pd.read_csv("Covid_19_cases4.csv")
print(df)
```

Output:

```
      dateRep  day  month  year  cases  deaths countriesAndTerritories
0     31-05-2021   31      5  2021    366       5              Austria
1     30-05-2021   30      5  2021    570       6              Austria
2     29-05-2021   29      5  2021    538      11              Austria
3     28-05-2021   28      5  2021    639       4              Austria
4     27-05-2021   27      5  2021    405      19              Austria
...          ...  ...    ...   ...    ...     ...                  ...
2725  06-03-2021    6      3  2021   3455      17               Sweden
2726  05-03-2021    5      3  2021   4069      12               Sweden
2727  04-03-2021    4      3  2021   4884      14               Sweden
2728  03-03-2021    3      3  2021   4876      19               Sweden
2729  02-03-2021    2      3  2021   6191      19               Sweden

[2730 rows x 7 columns]
```

➢ Exploratory Data Analysis(EDA):

Some common data preprocessing tasks include:

➢ **Data cleaning:**

This involves identifying and correcting errors and inconsistencies in the data. For e xample, this may involve removing duplicate records, correcting typos, and filling i n missing values.

- **Data transformation:**

This involves converting the data into a format that is suitable for the analysis task. For example, this may involve converting categorical data to numerical data, or sca ling the data to a suitable range.

- **Feature engineering:**

This involves creating new features from the existing data. For example, this may i nvolve creating features that represent interactions between variables, or features th at represent summary statistics of the data.

- **Data integration**:

This involves combining data from multiple sources into a single dataset. This may involve resolving in consistencies in the data, such as different data formats or diffe rent variable names .Data preprocessing is an essential step in many data science pr ojects. By carefully preprocessing the data, data scientists can improve the accuracy and reliability of their results.

#information about the dataset

print(df.info)

output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2730 entries, 0 to 2729
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   dateRep                 2730 non-null   object
 1   day                     2730 non-null   int64
 2   month                   2730 non-null   int64
 3   year                    2730 non-null   int64
 4   cases                   2730 non-null   int64
 5   deaths                  2730 non-null   int64
 6   countriesAndTerritories 2730 non-null   object
dtypes: int64(5), object(2)
memory usage: 149.4+ KB
```

#some basic techniques

print(df.head(4))

output:

dateRep	day	month	year	cases	deaths	countriesAndTerritories
31-05-2021	31	5	2021	366	5	Austria
30-05-2021	30	5	2021	570	6	Austria
29-05-2021	29	5	2021	538	11	Austria
28-05-2021	28	5	2021	639	4	Austria

print(df.tail())

output:

06-03-2021	6	3	2021	3455	17	Sweden
05-03-2021	5	3	2021	4069	12	Sweden
04-03-2021	4	3	2021	4884	14	Sweden
03-03-2021	3	3	2021	4876	19	Sweden
02-03-2021	2	3	2021	6191	19	Sweden

print(df.countriesAndTerritories.value_counts())

output:

Austria 91
Belgium 91
Spain 91
Slovenia 91
Slovakia 91
Romania 91
Portugal 91
Poland 91
Norway 91
Netherlands 91
Malta 91
Luxembourg 91

```
Lithuania       91
Liechtenstein   91
Latvia          91
Italy           91
Ireland         91
Iceland         91
Hungary         91
Greece          91
Germany         91
France          91
Finland         91
Estonia         91
Denmark         91
Czechia         91
Cyprus          91
Croatia         91
Bulgaria        91
Sweden          91
Name: countriesAndTerritories, dtype: int64
```

```
print(df.dtypes)
```

output:

```
dateRep                 object
day                    int64
month                   int64
year                   int64
cases                  int64
deaths                 int64
countriesAndTerritories    object
dtype: object
```

```
#missing value find out
print(df.isnull().sum())
```

output:

```
dateRep                 0
day                    0
```

```
month                   0
year                    0
cases                   0
deaths                  0
countriesAndTerritories    0
dtype: int64
```

```
print(df.shape)
```
output:
```
(2730, 7)
```
```
print(df.columns)
```
output:
```
Index(['dateRep', 'day', 'month', 'year', 'cases', 'deaths',
       'countriesAndTerritories'],
      dtype='object')
```

```
print(df.groupby(['countriesAndTerritories','cases']).size())
```
output:
```
countriesAndTerritories  cases
Austria                  287      1
                         342      1
                         366      1
                         391      1
                         405      1
                                 ..
Sweden                   7757     1
                         7832     1
                         8293     1
                         8468     1
                         8872     1
Length: 2424, dtype: int64
```

```
print(df.groupby(['countriesAndTerritories','deaths']).size())
```
output:
```
countriesAndTerritories  deaths
Austria                  3        2
                         4        1
                         5        1
```

```
                6      2
                8      4
                      ..
Sweden             22     7
                23     3
                24     4
                25     4
                28     1
Length: 1161, dtype: int64
```

print(df['deaths'].sum())
output:
178247

print(df['cases'].sum())
output:
9994560

```
print(df['cases'].mean())
print(df['deaths'].mean())
```

```
3661.010989010989
65.29194139194139
```

```
print(df['cases'].median())
print(df['deaths'].median())
```

```
926.5
14.5
```

```
print(df['cases'].mode())
print(df['deaths'].mode())
```

```
0    0
Name: cases, dtype: int64
0    0
Name: deaths, dtype: int64
```

```
grouped=df.groupby('countriesAndTerritories')
print(grouped['cases'].agg([np.sum,np.mean,np.min,np.max,np.std]))
```

output:

countriesAndTerritories	sum	mean	amin	amax	std
Austria	184416	2026.549451	287	4051	995.569254
Belgium	288119	3166.142857	589	6285	1489.367499
Bulgaria	171236	1881.714286	53	5176	1492.096052
Croatia	113168	1243.604396	74	3217	891.781561
Cyprus	37700	414.285714	44	941	232.107987
Czechia	421221	4628.802198	6	16816	4568.044868
Denmark	69188	760.307692	-2001	2007	379.739609
Estonia	62916	691.384615	58	1956	512.714514
Finland	34760	381.978022	0	863	229.646442
France	2020808	22206.681319	2229	53843	13071.979649
Germany	1234058	13561.076923	1911	29518	7094.986871
Greece	210201	2309.901099	0	4322	848.995944
Hungary	371613	4083.659341	156	11265	3320.112746
Iceland	527	5.791209	0	43	8.003494
Ireland	42057	462.164835	270	768	100.813057
Italy	1290738	14183.934066	2489	26790	7041.661404
Latvia	46912	515.516484	119	1036	212.667940
Liechtenstein	437	4.802198	0	18	4.536812
Lithuania	77040	846.593407	184	2055	365.604643
Luxembourg	14464	158.945055	0	461	102.413797
Malta	7586	83.362637	0	501	106.804548
Netherlands	557983	6131.681319	2457	9587	1753.827097
Norway	53995	593.351648	0	2400	550.922386
Poland	1164964	12801.802198	559	35253	10077.117328
Portugal	44096	484.571429	158	1007	180.257602
Romania	275590	3028.461538	158	6651	2039.807678
Slovakia	178475	1961.263736	19	6107	1590.997715
Slovenia	63550	698.351648	0	1802	396.183329
Spain	552723	6073.879121	0	22744	5228.258973
Sweden	404019	4439.769231	90	8872	2291.974835

```
grouped=df.groupby('countriesAndTerritories')
print(grouped['deaths'].agg([np.sum,np.mean,np.min,np.max,np.std]))
```

output:

countriesAndTerritories	sum	mean	amin	amax	std
Austria	1925	21.153846	3	51	9.946438
Belgium	2696	29.626374	6	50	10.526842
Bulgaria	7471	82.098901	5	217	52.742573
Croatia	2488	27.340659	4	52	13.689590
Cyprus	129	1.417582	0	7	1.445806
Czechia	9639	105.923077	3	278	79.977390
Denmark	155	1.703297	0	5	1.269247
Estonia	654	7.186813	0	24	5.462828
Finland	177	1.945055	0	9	1.753489
France	22977	252.494505	44	897	122.023347
Germany	18337	201.505495	33	418	98.548846
Greece	5550	60.989011	0	134	19.821142
Hungary	14675	161.263736	5	311	80.336492
Iceland	1	0.010989	0	1	0.104828
Ireland	622	6.835165	-3	47	9.080215
Italy	28347	311.505495	44	718	128.946016
Latvia	752	8.263736	0	21	4.813950
Liechtenstein	4	0.043956	0	1	0.206133
Lithuania	1022	11.230769	4	24	4.187486
Luxembourg	176	1.934066	0	10	2.360801
Malta	104	1.142857	0	5	1.410842
Netherlands	2055	22.582418	3	65	12.061017
Norway	161	1.769231	0	25	4.107113
Poland	29969	329.329670	11	956	226.820539
Portugal	706	7.758242	0	41	9.337309

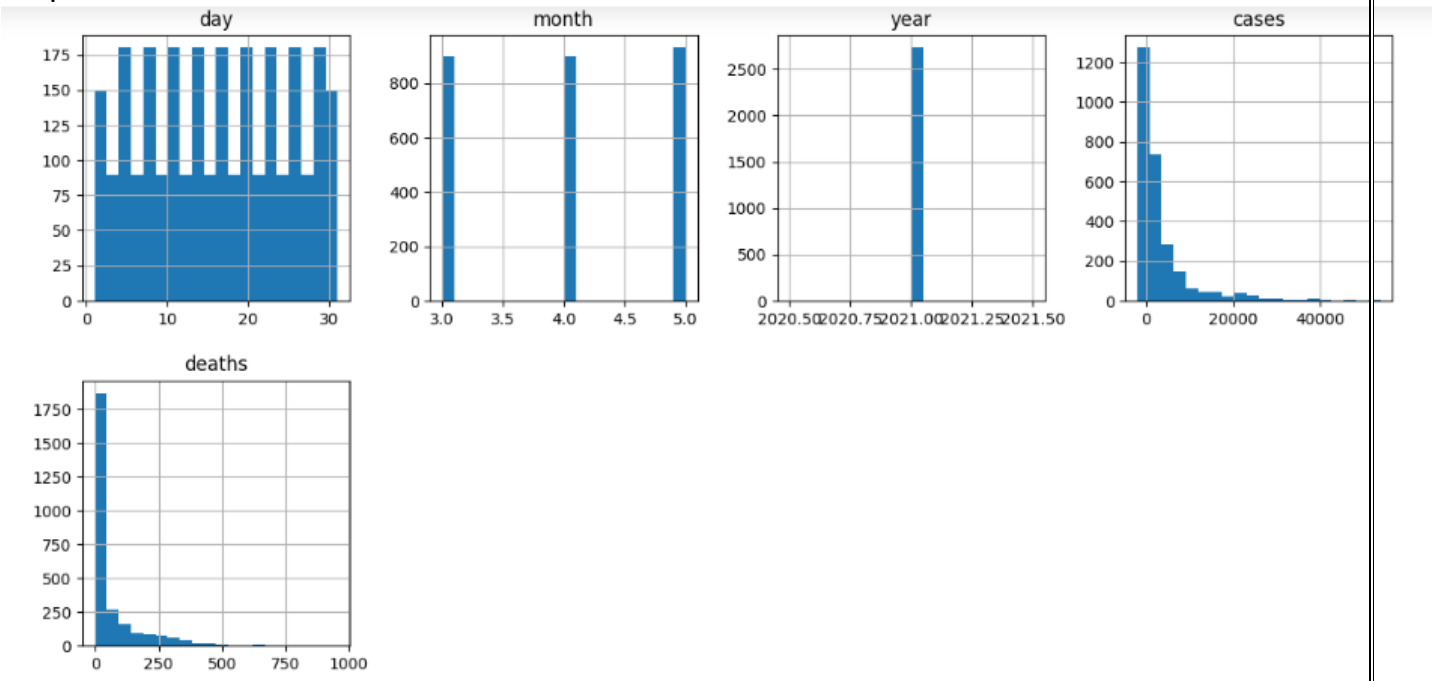
Romania	9926	109.076923	29	237	44.712720
Slovakia	5150	56.593407	0	149	32.456117
Slovenia	582	6.395604	0	39	6.858699
Spain	10344	113.670330	0	637	131.547039
Sweden	1453	15.967033	1	28	5.762813

GitHub repository link :

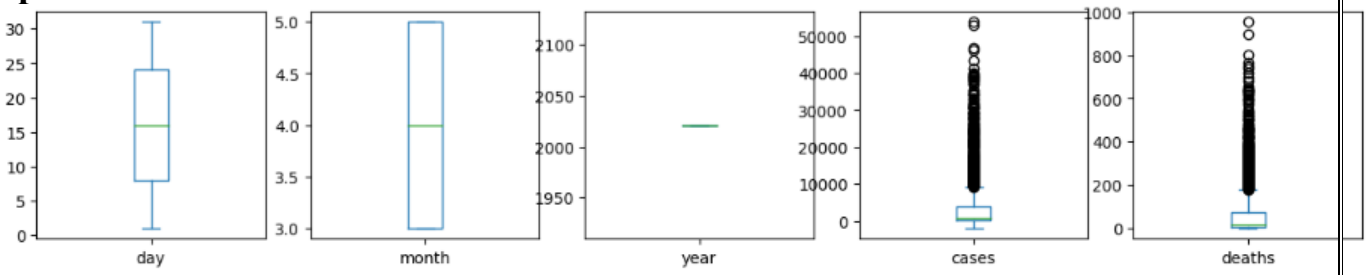
https://github.com/Ramya31K/Phase__1

#histogram

df.hist(figsize=(15,15), layout=(4,4), bins=20)
output:



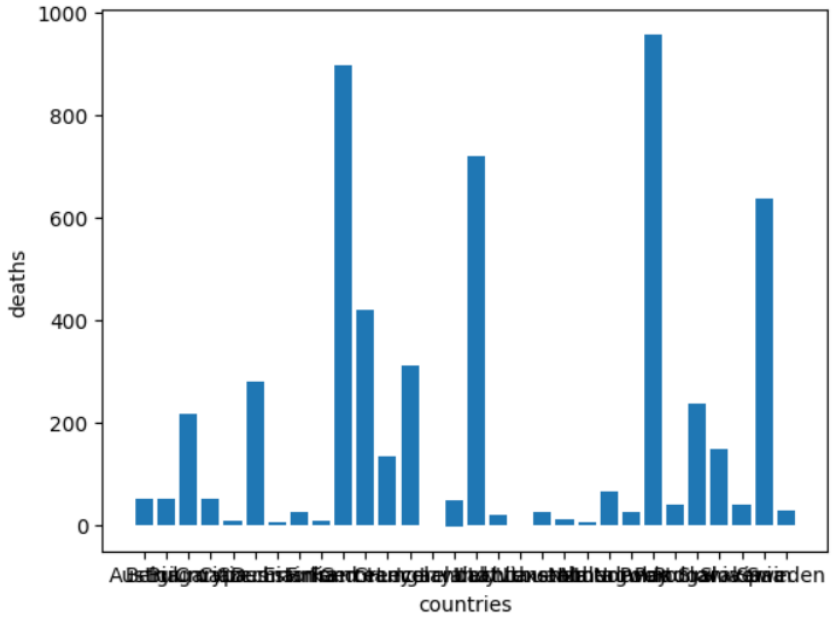
#checking outliers using box plot
df.plot(kind="box",subplots=True,layout=(5,5),figsize=(15,15))
output:



#barplot

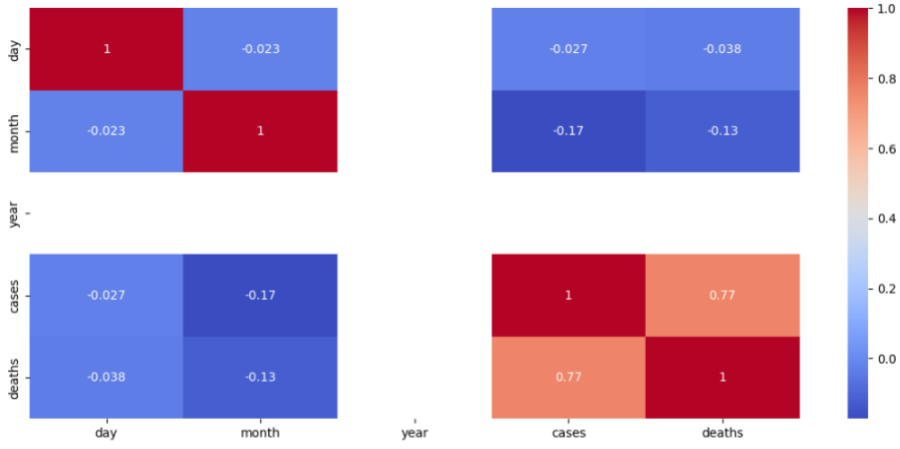
```
x=df['countriesAndTerritories']
y=df['deaths']
plt.bar(x,y)
plt.xlabel('countries')
plt.ylabel('deaths')
plt.show()
```

output:




```
#heatmap
plt.figure(figsize=[14,6])
sns.heatmap(df.corr(), annot = True,cmap = 'coolwarm')
```

output:

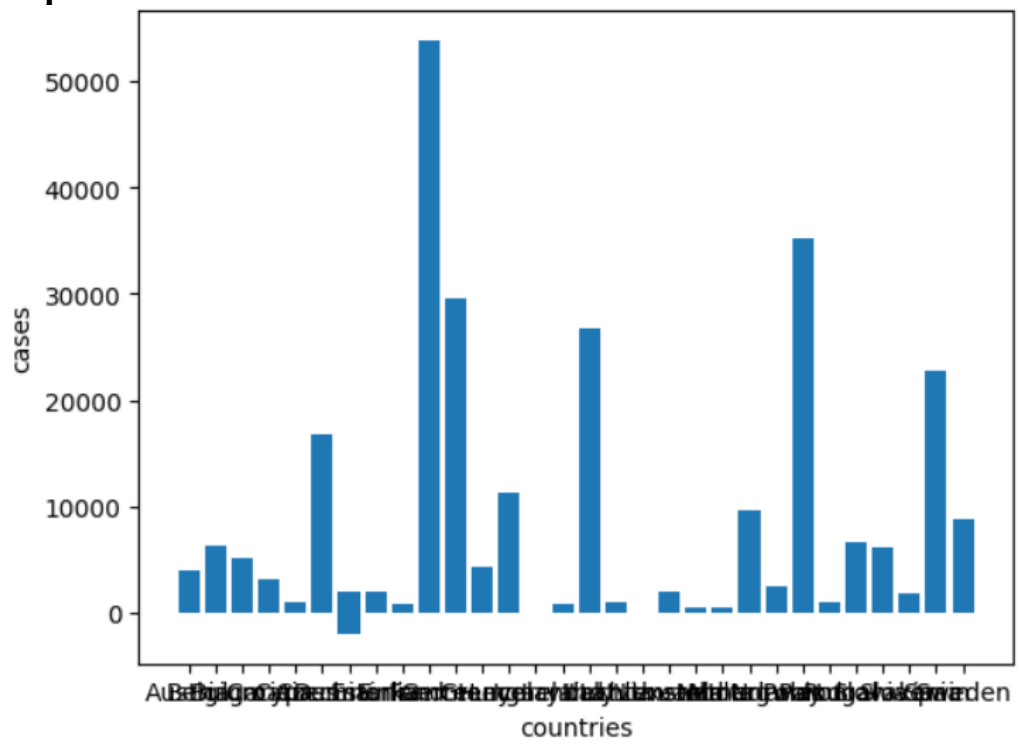


#barplot

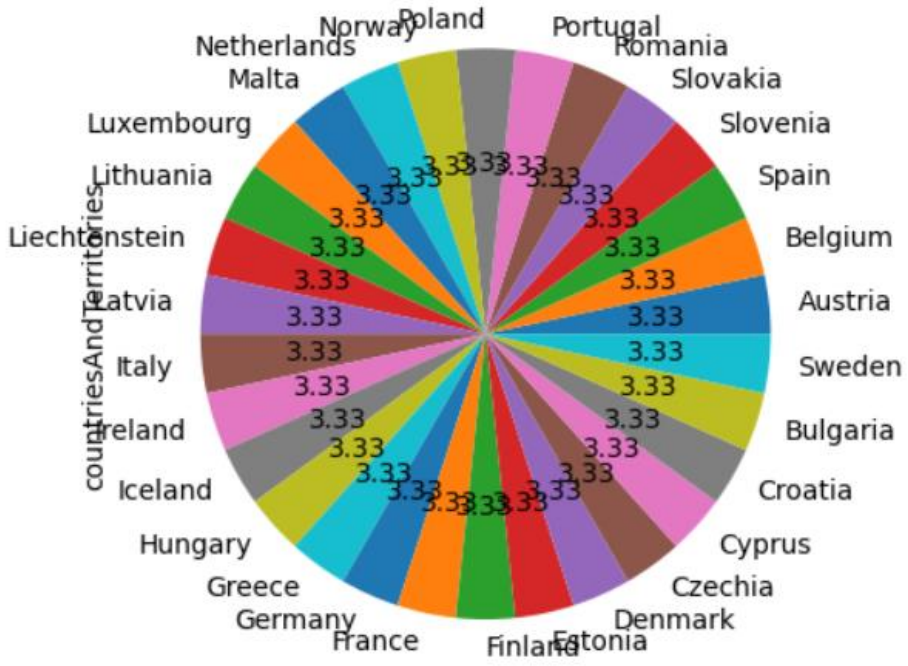
```
x=df['countriesAndTerritories']
y=df['cases']
```

```
plt.bar(x,y)
plt.xlabel('countries')
plt.ylabel('cases')
plt.show()
```

output:



```
df['countriesAndTerritories'].value_counts().plot(kind="pie", autopct="%.2f")
plt.show()
```



1. **Connect to the Dataset:**
    - Load the provided dataset ("covid19_cases_analysis") into IBM Cognos.
2. **Create a Time Series Line Chart:**
    - Use the "dateRep" column on the x-axis and plot the mean of "cases" and "deaths" on the y-axis.
    - This will give you a visual representation of how cases and deaths have evolved over time.
3. **Calculate Mean and Standard Deviation:**
    - Within IBM Cognos, you can create calculated fields to compute the mean and standard deviation of both cases and deaths.

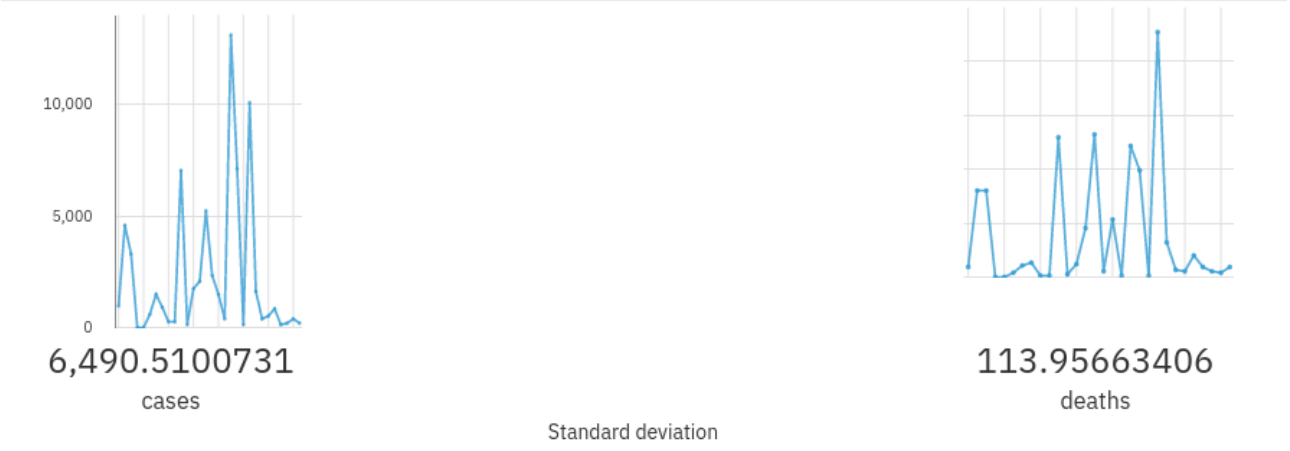
4. **Create Bar Charts for Mean Values:**
    - Create a bar chart to compare the mean values of cases and deaths across different countries or territories.
5. **Create Bar Charts for Standard Deviations:**
    - Similar to step 4, create a bar chart to compare the standard deviations of cases and deaths across different countries or territories.
6. **Analyze Trends and Variations:**
    - Look for patterns or trends in the line chart representing cases and deaths over time. Are there spikes or dips? Is there a noticeable increase or decrease in recent months?
7. **Correlation Analysis:**
    - Use statistical functions in IBM Cognos to calculate the correlation coefficient between cases and deaths. This will indicate if there's a linear relationship between the two variables.
8. **Consider Additional Factors:**
    - If available, you might also want to analyze other variables like population density, healthcare infrastructure, vaccination rates, etc. to see if there are correlations with cases and deaths.
9. **Create a Dashboard (Optional):**
    - If you're presenting this analysis, consider creating a dashboard that combines all the visualizations for a comprehensive overview.

Based on the visualizations created in IBM Cognos, here are some potential observations and insights:

1. **Trends in Cases and Deaths Over Time**:
    - There appears to be an initial sharp increase in both cases and deaths, followed by fluctuations. This suggests that there might have been specific waves or periods of higher transmission and mortality rates.
2. **Seasonal Patterns (if applicable)**:
    - Check if there are any seasonal patterns in the data. For instance, some regions might experience higher cases or deaths during certain times of the year.
3. **Correlation between Cases and Deaths**:
    - Calculate the correlation coefficient between cases and deaths. A positive correlation suggests that as cases increase, so do deaths. However, correlation does not imply causation, so further analysis is needed.
4. **Variations Across Countries/Territories**:
    - Compare the mean values of cases and deaths across different countries or territories. Are there regions with consistently higher cases but lower deaths, or vice versa? This might indicate variations in healthcare capacity or response.
5. **Impact of Interventions**:
    - Look for points in time where there might have been significant interventions, such as lockdowns, mask mandates, or vaccination campaigns. Check if there are corresponding changes in the trends of cases and deaths.
6. **Outliers**:
    - Identify any unusual spikes or dips in the data. These might be due to reporting irregularities, changes in testing protocols, or specific events.

7. **Standard Deviations**:
    - Analyze the standard deviations of cases and deaths. Higher standard deviations indicate greater variability, which could be due to various factors like different public health measures, population density, etc.
8. **Comparative Analysis**:
    - Compare trends and variations across different regions, especially those with varying demographics, healthcare systems, and government responses.
9. **Long-term vs. Short-term Trends**:
    - Distinguish between short-term fluctuations and long-term trends. Long-term trends might be more indicative of underlying structural factors, while short-term trends could be influenced by transient events.
10. **Consider External Factors**:

- Keep in mind that other factors like vaccination rates, healthcare infrastructure, socio-economic conditions, and population density can play a significant role in the observed trends.



Instruction to replicate an analysis and create visualizations using IBM Cognos:

- Access IBM Cognos: Log in to your IBM Cognos environment using your credentials.
- Data Source Connectivity: Connect to the relevant data source that contains the data you want to analyze. This could be a database, data warehouse, or flat file.
- Create a New Report or Dashboard:
- Report Studio: Use Report Studio for more detailed, customizable reports and visualizations.
- Dashboard: For a more dynamic and summarized view of the data, use Dashboarding tools.
- Select Data: Choose the dataset or specific data you want to work with for your analysis.
- Create Queries: Build queries or use the query builder to extract the required data.
- Data Manipulation: Apply filters, sorting, grouping, and other manipulations to the data to shape it according to your analysis requirements.
- Visualization Creation: Select the visualization type (bar charts, pie charts, line graphs, etc.) that best represents the data and create these visualizations.
- Customize Visualizations: Modify the appearance, labels, colors, and other design elements of the visualizations to improve clarity and understanding.

- Add Interactivity: If you're using a dashboard, consider adding interactive elements like prompts, filters, or parameters to make the analysis more dynamic.
- Review and Refine: Verify the accuracy of the analysis and the visualizations, making adjustments as needed.
- Save and Share: Save your report or dashboard to make it available for others in your team or organization. You can typically share it via links or export it as a file.

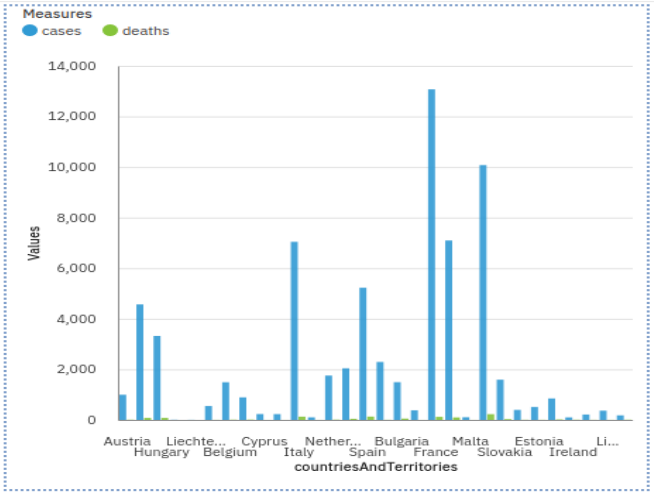
3,661.01098901

cases

65.29194139

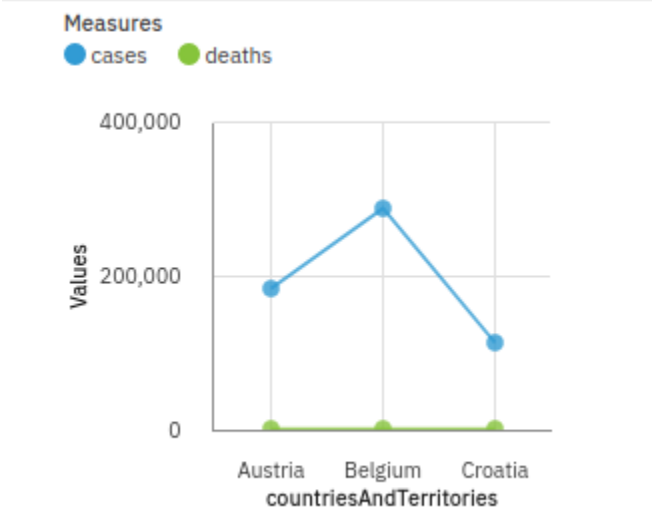
deaths

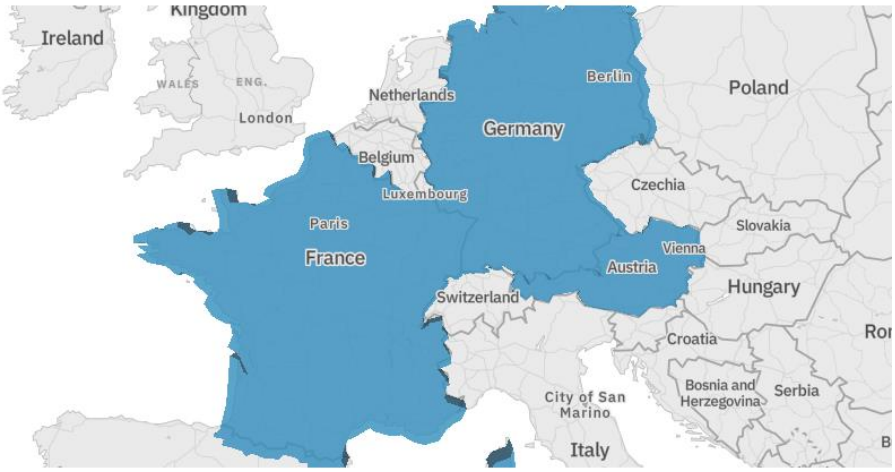
Mean

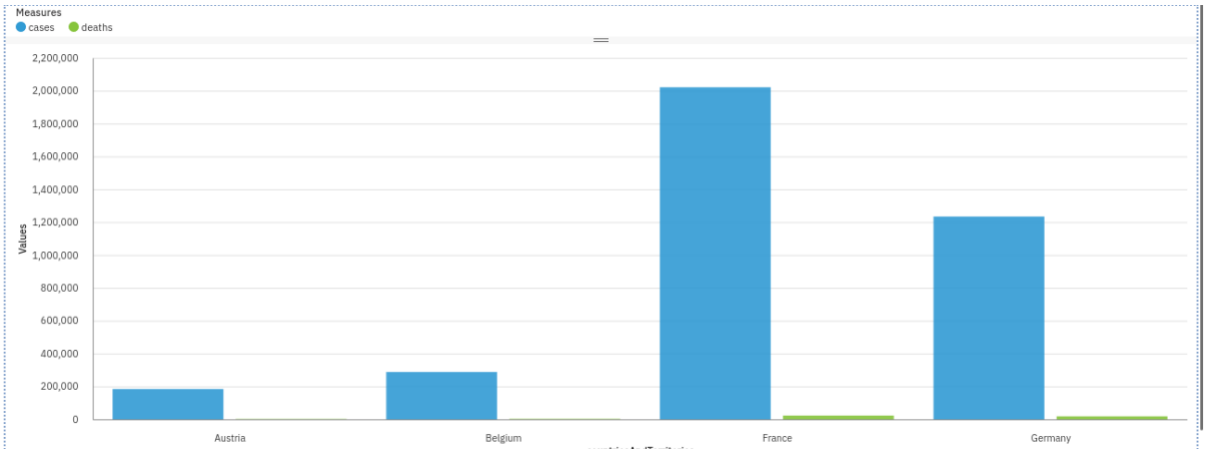


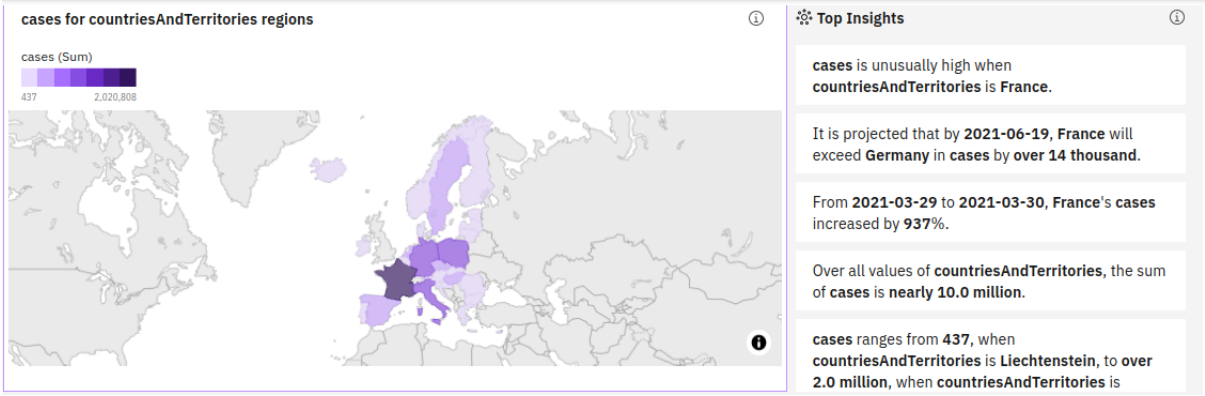
6,490.5100731
cases
Standard Deviation

113.95663406
deaths
Standard Deviation









Conclusion:

The visualizations created for this assignment have played a crucial role in making these insights accessible and understandable. Visual aids such as bar charts, scatter plots, and heatmaps have not only made the data more approachable but have also allowed us to identify trends and patterns that might have otherwise gone unnoticed.

It is important to note that the choice of visualization techniques was instrumental in our ability to answer the assignment's questions effectively.

In the end we find the France country is most covid-19 cases(2020808) and Liechtenstein is the least covid-19 cases(437) occur. Poland country is the most death cases(29969) and Iceland is least death cases in(1) European union(EU) countries.

The heatmap says covid19 cases highly correlated to death cases and also histogram says the covid-19 cases and deaths is right skewed in the form for mode<median<mean.

Standard deviation in cases is higher than deaths.