Project title: Covid-19 Vaccines Analysis

Phase 3: Development

Part 1

In this part you will begin building your project by loading and preprocessing the dataset.

Begin conducting the Covid-19 vaccines analysis by collecting and preprocessing the data.

Collect and preprocess the Covid-19 vaccine data for analysis.

Data Preprocessing:

- Data preprocessing is a crucial step within the statistics analysis and gadget gaining knowledge of pipeline.
- It includes a sequence of strategies and operations finished on uncooked statistics to clean, organize, and transform it right into a layout that is suitable for analysis or device mastering version schooling.
- Data preprocessing goals to enhance the first-class of the records, making it greater reliable and conducive to generating accurate consequences.

Here are some common tasks and techniques involved in data preprocessing:

Data Cleaning:

- Handling missing values: Deciding how to deal with missing data, whether by imputing values or removing incomplete records.
- Outlier detection and treatment: Identifying and handling data points that significantly deviate from the norm.

Noise reduction:

- Smoothing noisy data through techniques like filtering.

Data Transformation:

- **Data normalization:** Scaling numerical features to a standard range (e.g., between 0 and 1) to ensure that they have similar influence in the analysis.
- **Encoding categorical variables:** Converting categorical data into numerical format, such as one-hot encoding or label encoding.
- **Feature engineering:** Creating new features or modifying existing ones to capture more meaningful information from the data.
- **Dimensionality reduction:** Reducing the number of features while retaining essential information, using methods like Principal Component Analysis (PCA).

Data Integration:

- **Merging or joining datasets:** Combining data from multiple sources into a single dataset for analysis.

Aggregation: Summarizing data at a higher level of granularity, such as aggregating daily sales into monthly totals.

Data Reduction:

- **Sampling:** Reducing the size of a large dataset by randomly selecting a representative subset.
- **Binning:** Grouping continuous data into discrete bins to simplify analysis.
- **Filtering:** Selecting a subset of data based on specific criteria.

Data Standardization:

- Ensuring that data follows a consistent format and structure.
- Date and time format conversion: Converting date and time data into a uniform format.
- Currency conversion: Converting monetary values into a common currency.

Data Scaling:

- Scaling numerical data to a common range to prevent some features from dominating the analysis.

Data preprocessing is an iterative process that may involve several of these steps in various orders, depending on the specific dataset and the analysis goals. Proper data preprocessing is essential for improving the accuracy and effectiveness of machine learning models, as well as for making data more accessible for traditional statistical analysis.

Here is the data preprocessing codes along with the output of the given dataset:

Importing the libraries:

Import three basic libraries which are very common in machine learning and will be used every time you train a model

- **NumPy:** it is a library that allows us to work with arrays and as most machine learning models work on arrays NumPy makes it easier
- **matplotlib:** this library helps in plotting graphs and charts, which are very useful while showing the result of your model

Pandas: pandas allows us to import our dataset and also creates a matrix of features containing the dependent and indep**Code:**

- endent variable.

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

Output:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```
✓ 0.0s

Load the dataset: (DATASET 1)

- Data sets are available in .csv format. A CSV file stores tabular data in plain text.
- Each line of the file is a data record. We use the read_csv method of the pandas library to read a local CSV file as a dataframe.
- Load our customer data from the CSV file

Code:

```
import pandas as pd
# Try reading the file with different encodings
encodings = ['utf-8', 'latin1', 'ISO-8859-1']
for encoding in encodings:
try:
dataset =
pd.read_csv(r'C:\\Users\\KISHORE\\OneDrive\\Documents\\country_vaccinations.cs
v', encoding=encoding)
print(f"Successfully read with encoding: {encoding}")
break  # If successful, no need to try other encodings
except UnicodeDecodeError:
print(f"Failed to read with encoding: {encoding}")
# Now 'dataset' should contain your data
```

Output:

```python
import pandas as pd

# Try reading the file with different encodings
encodings = ['utf-8', 'latin1', 'ISO-8859-1']

for encoding in encodings:
    try:
        dataset = pd.read_csv(r'C:\\Users\\KISHORE\\OneDrive\\Documents\\country_vaccinations.csv', encoding=encoding)
        print(f"Successfully read with encoding: {encoding}")
        break  # If successful, no need to try other encodings
    except UnicodeDecodeError:
        print(f"Failed to read with encoding: {encoding}")

# Now 'dataset' should contain your data
```
✓ 0.1s

```
Successfully read with encoding: utf-8
```

Head() Function:

- The head() function is used to get the first n rows.
- This function returns the first n rows for the object based on position.
- It is useful for quickly testing if your object has the right type of data in it.
- If the value of the n is not assigned it returns a default value of first 5 rows

Code:

```
dataset.head()
```

Output:

```
dataset.head
✓ 0.0s

<bound method NDFrame.head of          country iso_code        date  total_vaccinations  \
0      Afghanistan      AFG  22-02-2021                 0.0
1      Afghanistan      AFG  23-02-2021                 NaN
2      Afghanistan      AFG  24-02-2021                 NaN
3      Afghanistan      AFG  25-02-2021                 NaN
4      Afghanistan      AFG  26-02-2021                 NaN
...            ...      ...         ...                 ...
86507     Zimbabwe      ZWE  25-03-2022           8691642.0
86508     Zimbabwe      ZWE  26-03-2022           8791728.0
86509     Zimbabwe      ZWE  27-03-2022           8845039.0
86510     Zimbabwe      ZWE  28-03-2022           8934360.0
86511     Zimbabwe      ZWE  29-03-2022           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
...
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]>
```

Info() Function:

- The info() method prints information about the DataFrame.
- The information contains the number of columns, column labels, column data types, memory usage, range index, and the number of cells in each column (non-nullvalues).

Code:

```
dataset.info()
```

Output:

```
dataset.info()
✓ 0.0s

<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
```

Df.isnull().sum() Function:

- This code is used to count the number of missing (null) values in each column of a DataFrame, denoted as df.
- It returns a summary of the missing data for each column, showing how many missing values are there in each column.
- This information is essential in data preprocessing and analysis to identify and handle missing data appropriately.Top of Form

Code:

```
dataset.isnull().sum()
```

Output:

```
dataset.isnull().sum()

✓ 0.0s

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
```

Describe Function:

- The describe() function in pandas, a popular Python data analysis library, is used to generate summary statistics of a DataFrame or Series.

It provides a quick overview of the key statistics for numerical data in the dataset, including:

- **Count:** The number of non-null values.
- **Mean:** The average of the values.
- **Standard Deviation (std):** A measure of the spread or dispersion of the data.
- **Minimum:** The minimum value in the dataset.
- **25th Percentile (25%):** The value below which 25% of the data falls (the first quartile).
- **Median (50% or the 2nd quartile):** The middle value when the data is sorted.
- **75th Percentile (75%):** The value below which 75% of the data falls (the third quartile).
- **Maximum:** The maximum value in the dataset.

Code:

```
dataset.describe()
```

Output:

```
dataset.describe()
✓ 0.0s
```

	total_vaccinations	people_vaccinated	people_fully_vaccinated	daily_vaccinations_raw	daily_vaccinations	total_vaccinations_per_hundred	people_vaccinated_per_hundred	people_fully_vaccinatec
count	4.360700e+04	4.129400e+04	3.880200e+04	3.536200e+04	8.621300e+04	43607.000000	41294.000000	
mean	4.592964e+07	1.770508e+07	1.413830e+07	2.705996e+05	1.313055e+05	80.188543	40.927317	
std	2.246004e+08	7.078731e+07	5.713920e+07	1.212427e+06	7.682388e+05	67.913577	29.290759	
min	0.000000e+00	0.000000e+00	1.000000e+00	0.000000e+00	0.000000e+00	0.000000	0.000000	
25%	5.264100e+05	3.494642e+05	2.439622e+05	4.668000e+03	9.000000e+02	16.050000	11.370000	
50%	3.590096e+06	2.187310e+06	1.722140e+06	2.530900e+04	7.343000e+03	67.520000	41.435000	
75%	1.701230e+07	9.152520e+06	7.559870e+06	1.234925e+05	4.409800e+04	132.735000	67.910000	
max	3.263129e+09	1.275541e+09	1.240777e+09	2.474100e+07	2.242429e+07	345.370000	124.760000	

Outliers:

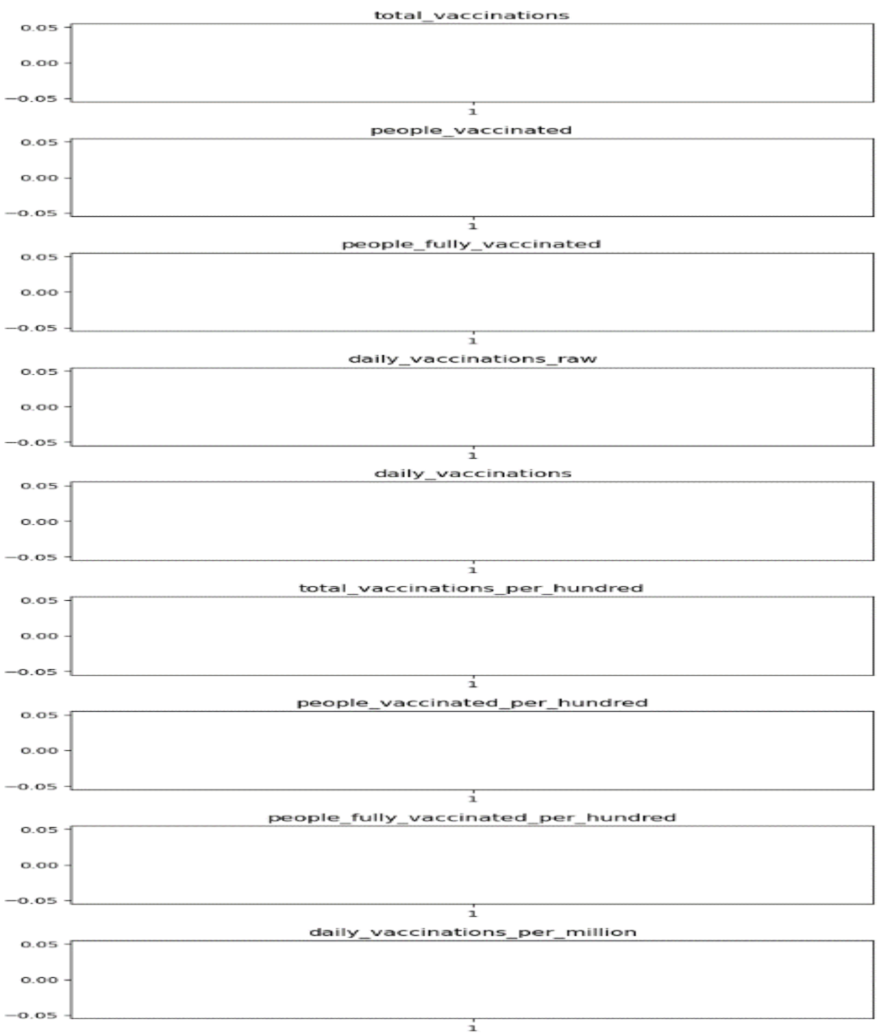
- Outliers are data points that significantly deviate from the rest of the data in a dataset.
- They can be exceptionally high or low values compared to the majority of the data.

Code:

```
import matplotlib.pyplot as plt
# Ensure your dataset contains only numerical data for box plotting
numerical_data = dataset.select_dtypes(include='number')
# Transpose the data to prepare for box plotting
data_to_plot = numerical_data.values.T
# Create subplots
fig, axs = plt.subplots(9, 1, dpi=95, figsize=(7, 17))
# Iterate through columns and create boxplots
for i, col in enumerate(numerical_data.columns):
    axs[i].boxplot(data_to_plot[i], vert=False)
    axs[i].set_ylabel(col)
plt.show()
```

Output:

```
import matplotlib.pyplot as plt

# Ensure your dataset contains only numerical data for box plotting
numerical_data = dataset.select_dtypes(include='number')

# Transpose the data to prepare for box plotting
data_to_plot = numerical_data.values.T

# Create subplots
fig, axs = plt.subplots(9, 1, dpi=95, figsize=(7, 17))

# Iterate through columns and create boxplots
for i, col in enumerate(numerical_data.columns):
    axs[i].boxplot(data_to_plot[i], vert=False)
    axs[i].set_ylabel(col)

plt.show()
```



Corelation:

- Correlation is a statistical measure that indicates the extent to which two or more variables fluctuate in relation to each other.
- Correlation describes the relationship between variables. It can be described as either strong or weak, and as either positive or negative.

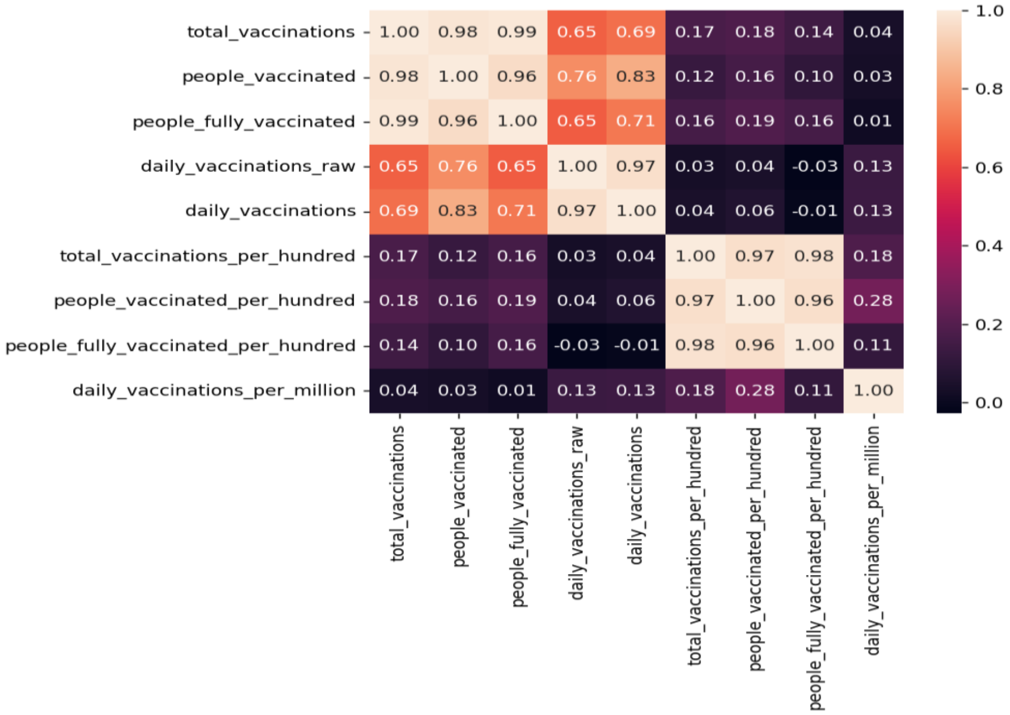
Code:

```
numeric_dataset = dataset.select_dtypes(include=['number'])
corr = numeric_dataset.corr()
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(dpi=130)
sns.heatmap(corr, annot=True, fmt='.2f')
plt.show()
```

Output:

```
numeric_dataset = dataset.select_dtypes(include=['number'])
corr = numeric_dataset.corr()
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(dpi=130)
sns.heatmap(corr, annot=True, fmt='.2f')
plt.show()
```

✓ 0.4s



Normalization

- MinMaxScaler scales the data so that each feature is in the range [0, 1].
- It works well when the features have different scales and the algorithm being used is sensitive to the scale of the features, such as k-nearest neighbors or neural networks.
- Rescale your data using scikit-learn using the MinMaxScalar.

Code:

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
numeric_cols = dataset.select_dtypes(include=['number']).columns
categorical_cols = dataset.select_dtypes(exclude=['number']).columns
numeric_transformer = Pipeline(steps=[
('scaler', MinMaxScaler(feature_range=(0, 1)))])
categorical_transformer = Pipeline(steps=[
('encoder', OneHotEncoder())])
preprocessor = ColumnTransformer(
transformers=[
('num', numeric_transformer, numeric_cols),
('cat', categorical_transformer, categorical_cols)])
X_transformed = preprocessor.fit_transform(dataset)
X_transformed[:5]
```

Output:

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
numeric_cols = dataset.select_dtypes(include=['number']).columns
categorical_cols = dataset.select_dtypes(exclude=['number']).columns
numeric_transformer = Pipeline(steps=[
    ('scaler', MinMaxScaler(feature_range=(0, 1)))
])
categorical_transformer = Pipeline(steps=[
    ('encoder', OneHotEncoder())
])
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])
X_transformed = preprocessor.fit_transform(dataset)
X_transformed[:5]
```
✓ 0.0s

```
✓ 0.1s

<10x1222 sparse matrix of type '<class 'numpy.float64'>'
	with 146 stored elements in Compressed Sparse Row format>
```

Standardization

- Standardization is a useful technique to transform attributes with a Gaussian distribution and differing means and standard deviations to a standard Gaussian distribution with a mean of 0 and a standard deviation of 1.
- We can standardize data using scikit-learn with the StandardScalar class.
- It works well when the features have a normal distribution or when the algorithm being used is not sensitive to the scale of the features

Code:

```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
numeric_cols = dataset.select_dtypes(include=['number']).columns
categorical_cols = dataset.select_dtypes(exclude=['number']).columns
numeric_transformer = Pipeline(steps=[('scaler', StandardScaler())])
categorical_transformer = Pipeline(steps=[('encoder', OneHotEncoder())])
preprocessor = ColumnTransformer(
transformers=[
('num', numeric_transformer, numeric_cols),
('cat', categorical_transformer, categorical_cols)])
X_transformed = preprocessor.fit_transform(dataset)
X_transformed[:5]
```

Output:

```python
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
numeric_cols = dataset.select_dtypes(include=['number']).columns
categorical_cols = dataset.select_dtypes(exclude=['number']).columns
numeric_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('encoder', OneHotEncoder())
])
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])
X_transformed = preprocessor.fit_transform(dataset)
X_transformed[:5]
```

✓ 0.0s

✓ 0.1s

```
<10x1222 sparse matrix of type '<class 'numpy.float64'>'
	with 150 stored elements in Compressed Sparse Row format>
```

K-means Clustering Function:

K-means clustering is a machine learning and data analysis technique used for grouping data points into clusters based on their similarity. It's primarily used for:

- **Unsupervised Learning:** K-means helps identify patterns or structure in data without labelled categories.
- **Segmentation:** It can segment data into distinct groups, making it useful for customer segmentation, image compression, and more.
- **Pattern Recognition:** It's used in pattern recognition tasks, such as image analysis and natural language processing.
- **Anomaly Detection:** It can identify outliers by placing data points that don't fit well into any cluster.

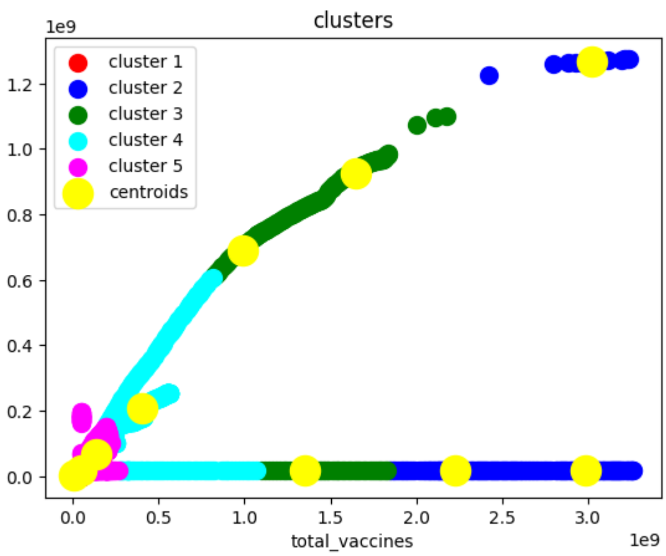
- **Data Compression:** K-means can reduce the dimensionality of data while preserving important information.
- **Recommendation Systems:** It can be applied to recommend items or services based on user preferences.

Code:

```
plt.scatter(x[y_kmeans==0,0],x[y_kmeans==0,1],s=100,c="red",label = "cluster 1")
plt.scatter(x[y_kmeans==1,0],x[y_kmeans==1,1],s=100,c="blue",label = "cluster 2")
plt.scatter(x[y_kmeans==2,0],x[y_kmeans==2,1],s=100,c="green",label = "cluster 3")
plt.scatter(x[y_kmeans==3,0],x[y_kmeans==3,1],s=100,c="cyan",label = "cluster 4")
plt.scatter(x[y_kmeans==4,0],x[y_kmeans==4,1],s=100,c="magenta",label = "cluster 5")
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],s=300,c="yellow",label="centroids")
plt.title("clusters of customers")
plt.xlabel("Annual Income")
plt.ylabel=("Spending Score")
plt.legend()
plt.show()
```

Output:

```
plt.scatter(x[y_kmeans==0,0],x[y_kmeans==0,1],s=100,c="red",label = "cluster 1")
plt.scatter(x[y_kmeans==1,0],x[y_kmeans==1,1],s=100,c="blue",label = "cluster 2")
plt.scatter(x[y_kmeans==2,0],x[y_kmeans==2,1],s=100,c="green",label = "cluster 3")
plt.scatter(x[y_kmeans==3,0],x[y_kmeans==3,1],s=100,c="cyan",label = "cluster 4")
plt.scatter(x[y_kmeans==4,0],x[y_kmeans==4,1],s=100,c="magenta",label = "cluster 5")
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],s=300,c="yellow",label="centroids")
plt.title("clusters of customers")
plt.xlabel("Annual Income")
plt.ylabel=("Spending Score")
plt.legend()
plt.show()
✓ 0.1s
```



WCSS Function:

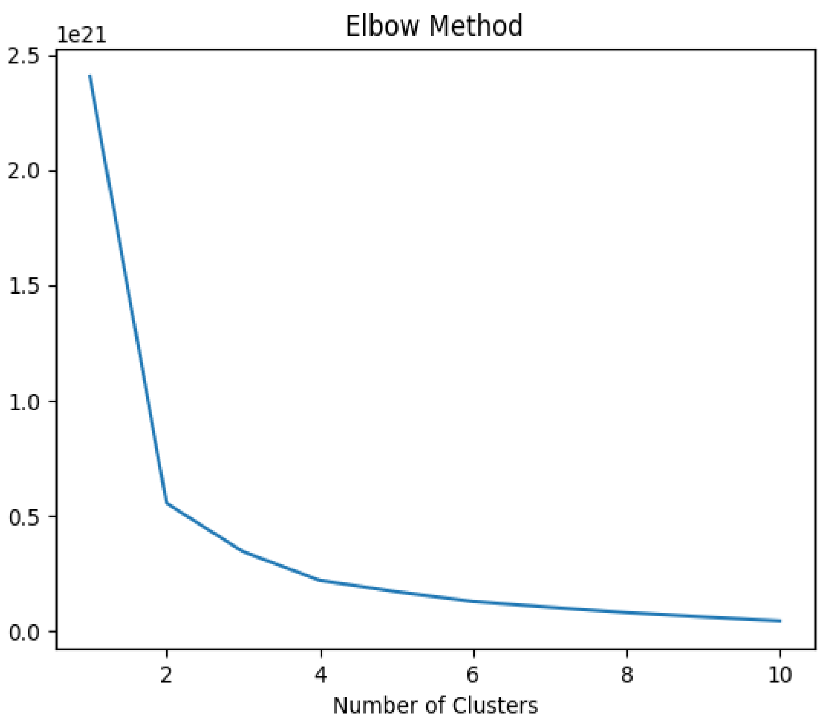
- WCSS is the sum of the squared distance between each point and the centroid in a cluster.
- When we plot the WCSS with the K value, the plot looks like an Elbow.
- As the number of clusters increases, the WCSS value will start to decrease.

Code:

```
plt.plot(range(1,11),wcss)
plt.title("elbow method")
plt.xlabel("no of cluster")
plt.ylabel("wcss")
plt.show()
```

Output:

```
plt.plot(range(1,11),wcss)
plt.title("elbow method")
plt.xlabel("no of cluster")
plt.ylabel("wcss")
plt.show()
✓ 0.0s
```



Dataset.columns :

- We can use the loc and iloc functions to access columns in a Pandas DataFrame.
- for example the Grades column, we could simply use the loc function and specify the name of the column in order to retrieve it.

Code:

```
dataset.columns
```

Output:

```
dataset.columns
✓ 0.0s

Index(['country', 'iso_code', 'date', 'total_vaccinations',
       'people_vaccinated', 'people_fully_vaccinated',
       'daily_vaccinations_raw', 'daily_vaccinations',
       'total_vaccinations_per_hundred', 'people_vaccinated_per_hundred',
       'people_fully_vaccinated_per_hundred', 'daily_vaccinations_per_million',
       'vaccines', 'source_name', 'source_website'],
      dtype='object')
```

Memory Function:

- Pandas **dataframe.memory_usage()** function return the memory usage of each column in bytes.
- The memory usage can optionally include the contribution of the index and elements of object dtype. This value is displayed in DataFrame.info by default.

Code:

```
memory = dataset.memory_usage()
print(memory)
print("Total Memory Usage = ",sum(memory))
```

Output:

```
memory = dataset.memory_usage()
print(memory)
print("Total Memory Usage = ",sum(memory))
✓ 0.0s

Index                                     132
country                                692096
iso_code                               692096
date                                   692096
total_vaccinations                     692096
people_vaccinated                      692096
people_fully_vaccinated                692096
daily_vaccinations_raw                 692096
daily_vaccinations                     692096
total_vaccinations_per_hundred         692096
people_vaccinated_per_hundred          692096
people_fully_vaccinated_per_hundred    692096
daily_vaccinations_per_million         692096
vaccines                               692096
source_name                            692096
source_website                         692096
dtype: int64
Total Memory Usage =  10381572
```

Dropna() Function:

- dropna() is a function used in data preprocessing, often in the context of data analysis and cleaning, to remove or drop rows or columns with missing (NaN or null) values from a dataset.
- It's a method to eliminate incomplete or unreliable data from your dataset, which can be important to ensure the quality of your analysis or machine learning models

Code:

```
print("Size before dropping NaN rows",dataset.shape,"\n")
nan_dropped = dataset.dropna()
print(nan_dropped.isnull().sum())
print("\nSize after dropping NaN rows",nan_dropped.shape)
```

Output:

```
print("Size before dropping NaN rows",dataset.shape,"\n")

nan_dropped = dataset.dropna()

print(nan_dropped.isnull().sum())
print("\nSize after dropping NaN rows",nan_dropped.shape)
```

✓ 0.0s

```
Size before dropping NaN rows (86512, 15)

country                                0
iso_code                               0
date                                   0
total_vaccinations                     0
people_vaccinated                      0
people_fully_vaccinated                0
daily_vaccinations_raw                 0
daily_vaccinations                     0
total_vaccinations_per_hundred         0
people_vaccinated_per_hundred          0
people_fully_vaccinated_per_hundred    0
daily_vaccinations_per_million         0
vaccines                               0
source_name                            0
source_website                         0
dtype: int64

Size after dropping NaN rows (30847, 15)
```

Iloc() Function:

The iloc() function is a method in pandas, a popular Python library for data manipulation and analysis. It is primarily used to select and access data in a DataFrame by integer-based indexing.

- Select specific rows and columns from a DataFrame using integer-based indexing.
- Provide a way to slice and filter data by row and column positions.

Code:

```
X = dataset.iloc[:,:-1].values
Y = dataset.iloc[:,3].values
print ('X: %s'%(str(X)))
print ('-----------------------------------')
print ('Y: %s'%(str(Y)))
```

Output:

```
X = dataset.iloc[:,:-1].values
Y = dataset.iloc[:,3].values
print ('X: %s'%(str(X)))
print ('----------------------------------')
print ('Y: %s'%(str(Y)))
```

✓ 0.0s

```
X: [['Afghanistan' 'AFG' '22-02-2021' ... nan
  'Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing'
  'World Health Organization']
 ['Afghanistan' 'AFG' '23-02-2021' ... 34.0
  'Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing'
  'World Health Organization']
 ['Afghanistan' 'AFG' '24-02-2021' ... 34.0
  'Johnson&Johnson, Oxford/AstraZeneca, Pfizer/BioNTech, Sinopharm/Beijing'
  'World Health Organization']
 ...
 ['Zimbabwe' 'ZWE' '27-03-2022' ... 6005.0
  'Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac, Sputnik V'
  'Ministry of Health']
 ['Zimbabwe' 'ZWE' '28-03-2022' ... 6667.0
  'Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac, Sputnik V'
  'Ministry of Health']
 ['Zimbabwe' 'ZWE' '29-03-2022' ... 6874.0
  'Oxford/AstraZeneca, Sinopharm/Beijing, Sinovac, Sputnik V'
  'Ministry of Health']]
----------------------------------
Y: [      0.      nan      nan ... 8845039. 8934360. 9039729.]
```

Subplots Function:

- Subplots are a feature in data visualization that allow you to create multiple smaller plots within a larger figure.
- They are useful for displaying multiple related visualizations side by side, making it easier to compare and analyze data.
- subplots help you arrange and present multiple charts, graphs, or plots in a single figure, improving the overall clarity and readability of your data visualizations.

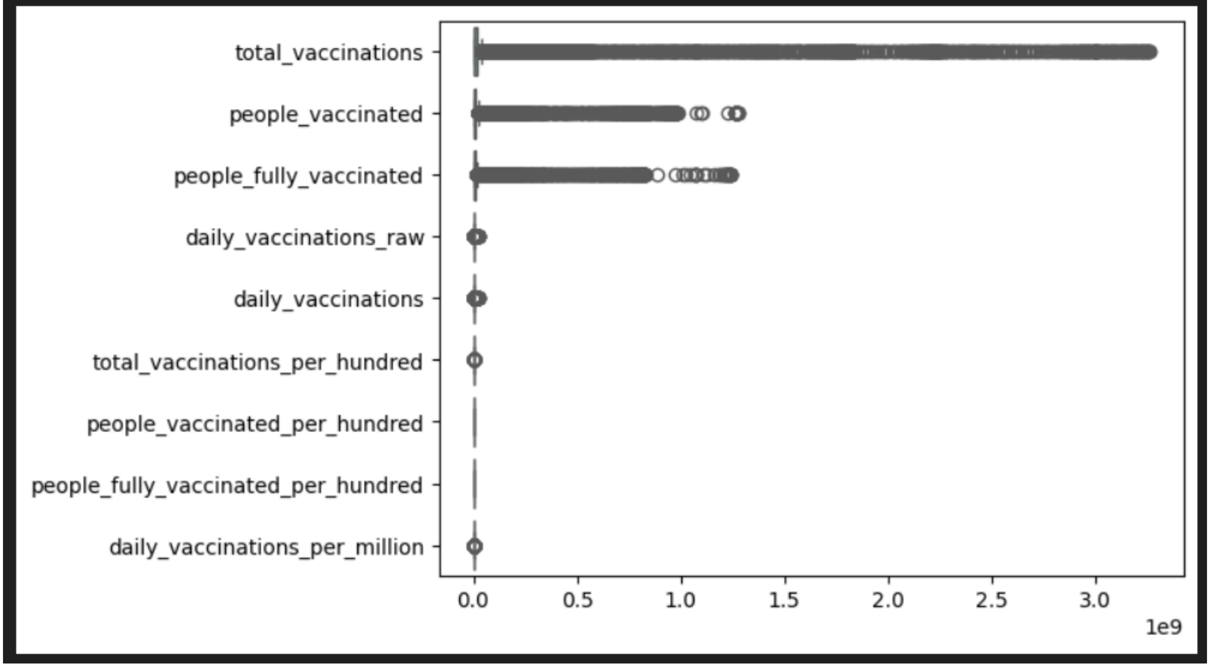
Code:

```
fig, axs = plt.subplots()
sns.boxplot(data=dataset,orient='h',palette="Set2")
plt.show()
```

Output:

```
fig, axs = plt.subplots()
sns.boxplot(data=dataset,orient='h',palette="Set2")
plt.show()
```

✓ 1.7s



Missingno Function:

- "missingno" is a Python library used for visualizing and analyzing missing data in a dataset.
- It provides various visualization tools to quickly understand and identify missing values in your data, allowing you to make informed decisions on how to handle or impute missing data.

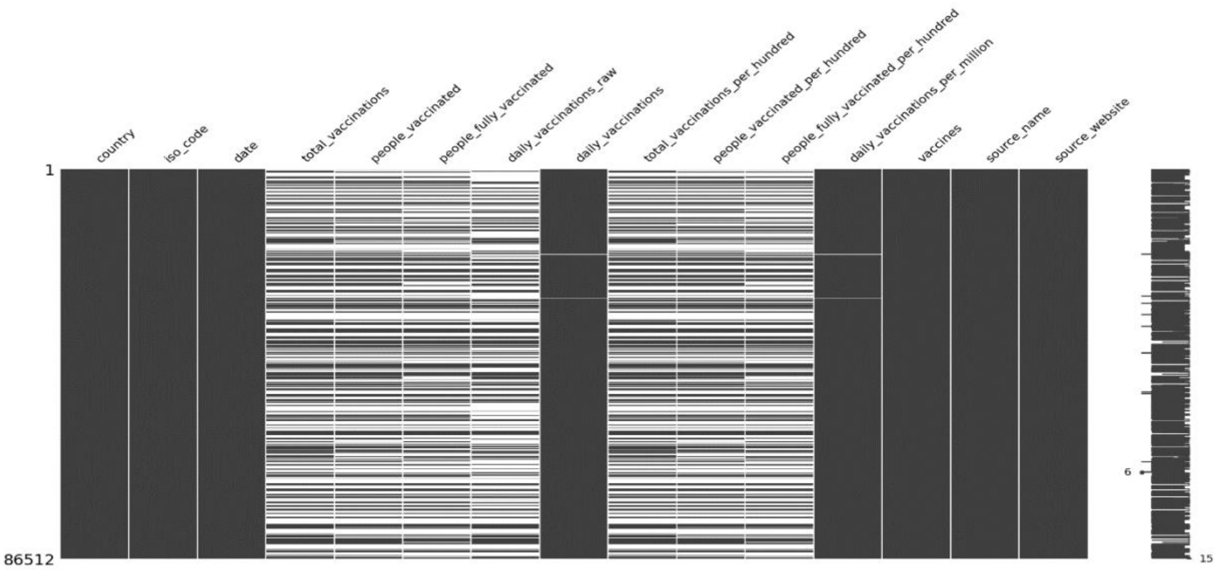
Code:

```
import missingno as msno
msno.matrix(dataset)
plt.figure(figsize = (15,9))
plt.show()
```

Output:

```
import missingno as msno
msno.matrix(dataset)
plt.figure(figsize = (15,9))
plt.show()
```

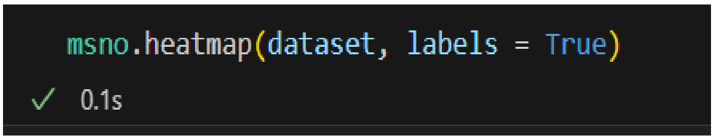
✓ 0.2s

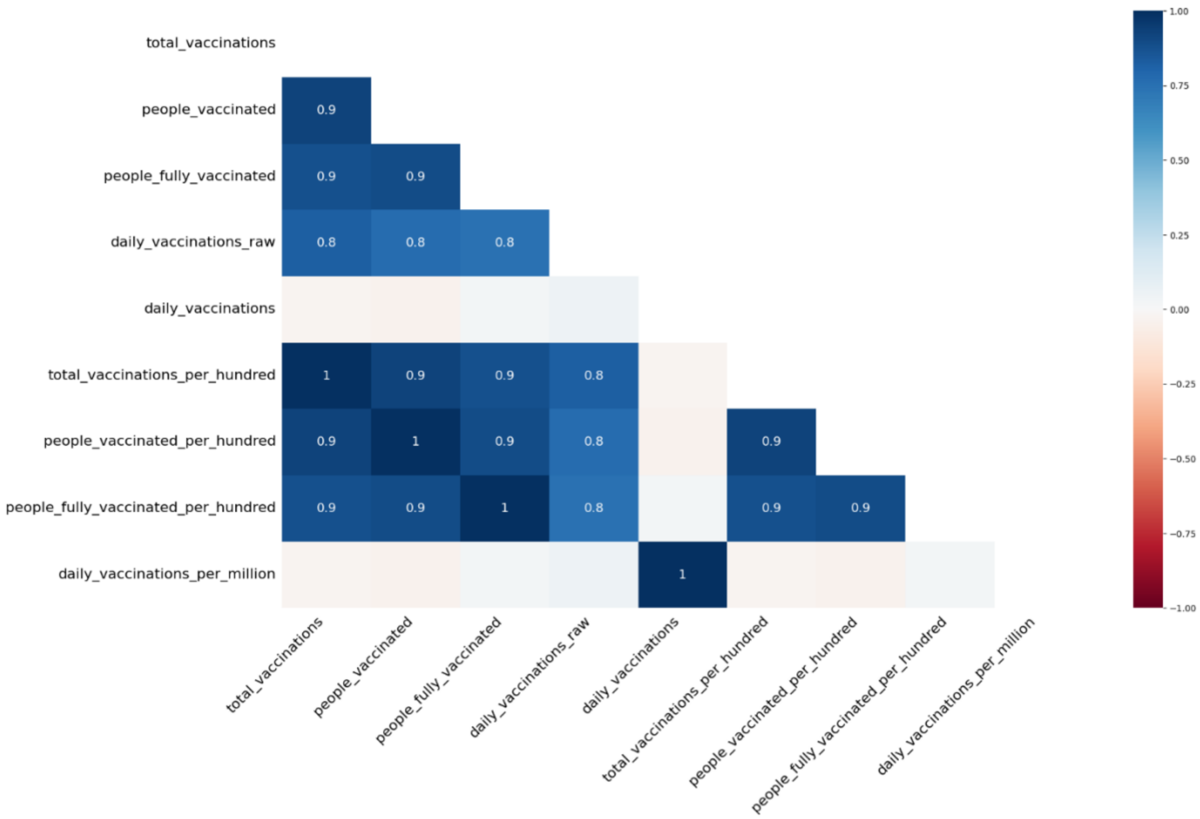


Code:

```
msno.heatmap(dataset, labels = True)
```

Output:





Load the dataset: (DATASET 2):

Head() Function:

Output:

```
dataset.head
✓ 0.0s

<bound method NDFrame.head of           location        date          vaccine  total_vaccinations
0            Argentina  29-12-2020            Moderna                   2
1            Argentina  29-12-2020  Oxford/AstraZeneca                   3
2            Argentina  29-12-2020   Sinopharm/Beijing                   1
3            Argentina  29-12-2020          Sputnik V               20481
4            Argentina  30-12-2020            Moderna                   2
...                ...         ...                ...                 ...
35618   European Union  29-03-2022  Oxford/AstraZeneca            67403106
35619   European Union  29-03-2022     Pfizer/BioNTech           600519998
35620   European Union  29-03-2022   Sinopharm/Beijing             2301516
35621   European Union  29-03-2022            Sinovac                1809
35622   European Union  29-03-2022          Sputnik V             1845103

[35623 rows x 4 columns]>
```

Info() Function:

Output:

```
dataset.info()
✓ 0.0s

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35623 entries, 0 to 35622
Data columns (total 4 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   location            35623 non-null  object
 1   date                35623 non-null  object
 2   vaccine             35623 non-null  object
 3   total_vaccinations  35623 non-null  int64
dtypes: int64(1), object(3)
memory usage: 1.1+ MB
```

Df. isnull() .sum() Function:

Output:

```
dataset.isnull().sum()

✓ 0.0s

location            0
date                0
vaccine             0
total_vaccinations  0
dtype: int64
```

Describe Function:

Output:

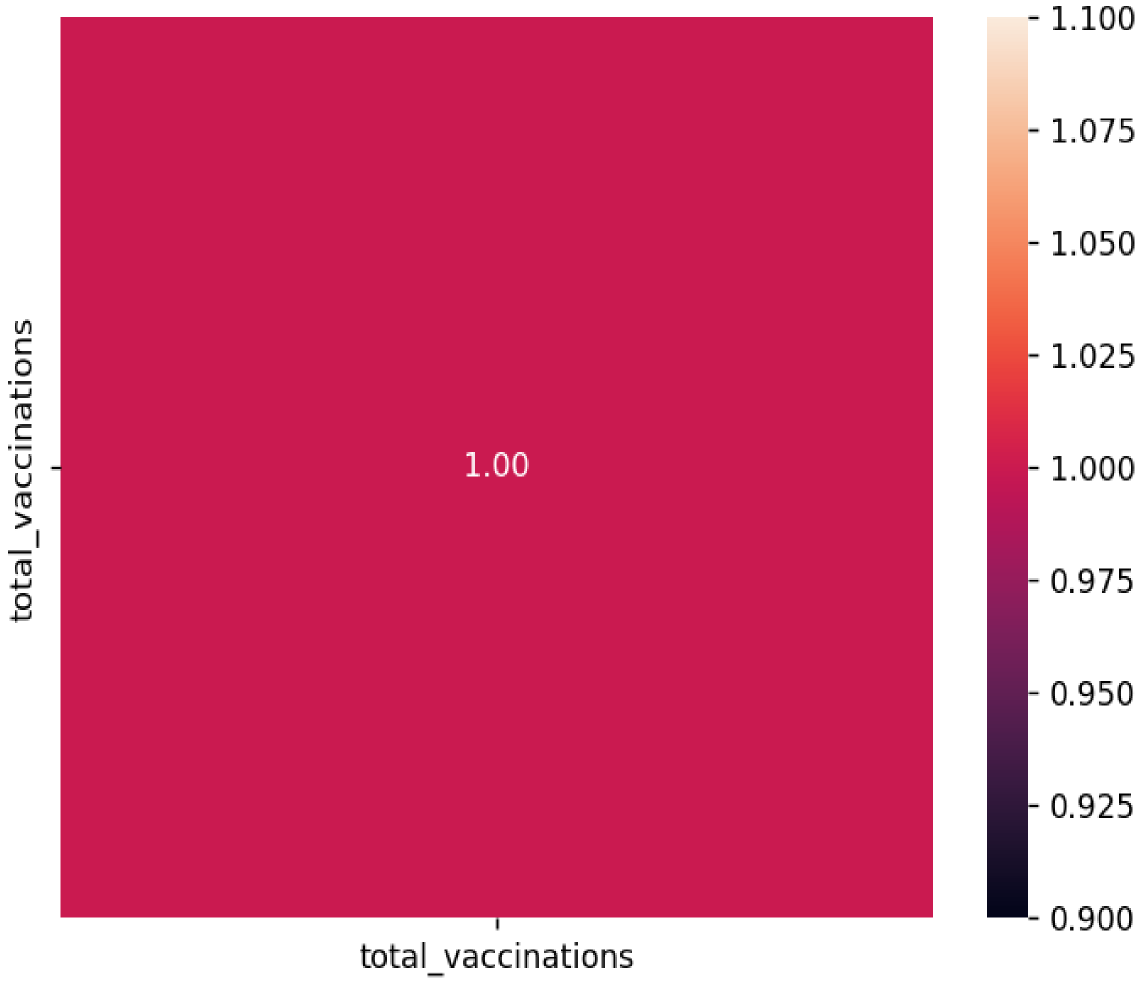
```
dataset.describe()
✓ 0.0s
```

	total_vaccinations
count	3.562300e+04
mean	1.508357e+07
std	5.181768e+07
min	0.000000e+00
25%	9.777600e+04
50%	1.305506e+06
75%	7.932423e+06
max	6.005200e+08

Corelation:

Output:

```
numeric_dataset = dataset.select_dtypes(include=['number'])
corr = numeric_dataset.corr()
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(dpi=130)
sns.heatmap(corr, annot=True, fmt='.2f')
plt.show()

✓ 0.0s
```



Normalization:

Output:

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
numeric_cols = dataset.select_dtypes(include=['number']).columns
categorical_cols = dataset.select_dtypes(exclude=['number']).columns
numeric_transformer = Pipeline(steps=[
('scaler', MinMaxScaler(feature_range=(0, 1)))])
categorical_transformer = Pipeline(steps=[
('encoder', OneHotEncoder())])
preprocessor = ColumnTransformer(
transformers=[
('num', numeric_transformer, numeric_cols),
('cat', categorical_transformer, categorical_cols)])
X_transformed = preprocessor.fit_transform(dataset)
X_transformed[:5]
```

✓ 0.0s

```
<5x527 sparse matrix of type '<class 'numpy.float64'>'
	with 20 stored elements in Compressed Sparse Row format>
```

Standardization:

Output:

```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

numeric_cols = dataset.select_dtypes(include=['number']).columns
categorical_cols = dataset.select_dtypes(exclude=['number']).columns

numeric_transformer = Pipeline(steps=[('scaler', StandardScaler())])
categorical_transformer = Pipeline(steps=[('encoder', OneHotEncoder())])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_cols),
        ('cat', categorical_transformer, categorical_cols)
    ]
)

X_transformed = preprocessor.fit_transform(dataset)
X_transformed[:10]
```

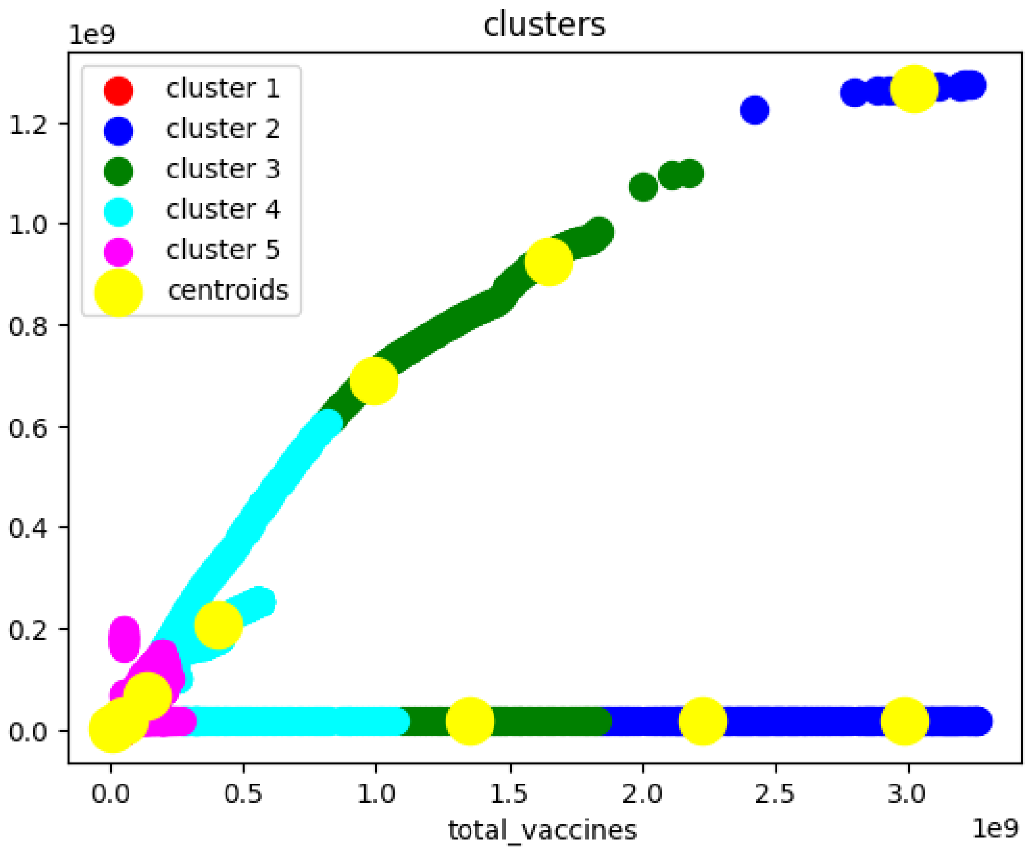
✓ 0.0s

```
<10x527 sparse matrix of type '<class 'numpy.float64'>'
	with 40 stored elements in Compressed Sparse Row format>
```

K-means Clustering Function:

Output:

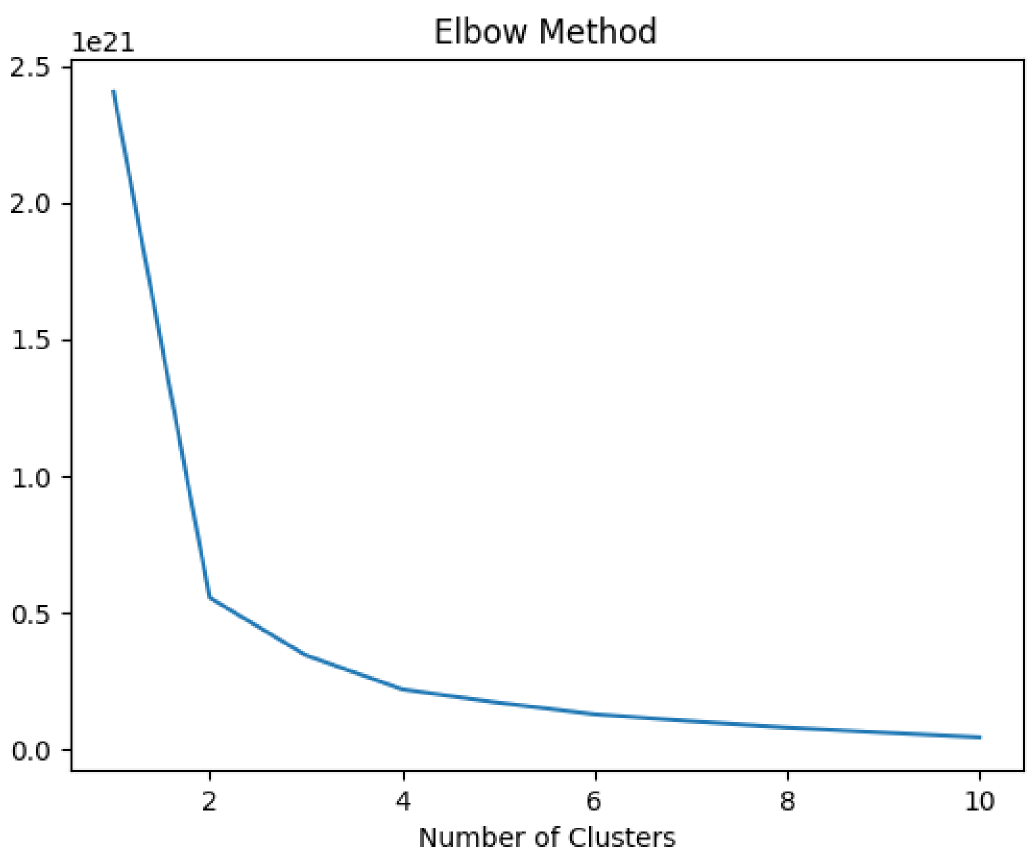
```
plt.scatter(x[y_kmeans==0,0],x[y_kmeans==0,1],s=100,c="red",label = "cluster 1")
plt.scatter(x[y_kmeans==1,0],x[y_kmeans==1,1],s=100,c="blue",label = "cluster 2")
plt.scatter(x[y_kmeans==2,0],x[y_kmeans==2,1],s=100,c="green",label = "cluster 3")
plt.scatter(x[y_kmeans==3,0],x[y_kmeans==3,1],s=100,c="cyan",label = "cluster 4")
plt.scatter(x[y_kmeans==4,0],x[y_kmeans==4,1],s=100,c="magenta",label = "cluster 5")
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],s=300,c="yellow",label="centroids")
plt.title("clusters")
plt.xlabel("total_vaccines")
plt.ylabel=("People_vaccinated")
plt.legend()
plt.show()
✓ 0.7s
```



WCSS Function:

Output:

```
import matplotlib.pyplot as plt

# Your K-Means clustering code

# Create the elbow plot
plt.plot(range(1, 11), wcss)
plt.title("Elbow Method")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS")  # Use plt.ylabel to set the y-axis label
plt.show()
```



Dataset.columns:

Output:

```
dataset.columns
✓ 0.0s

Index(['location', 'date', 'vaccine', 'total_vaccinations'], dtype='object')
```

Memory Function:

Output:

```
memory = dataset.memory_usage()
print(memory)
print("Total Memory Usage = ",sum(memory))
✓ 0.0s

Index                    132
location              284984
date                  284984
vaccine               284984
total_vaccinations    284984
dtype: int64
Total Memory Usage =  1140068
```

Dropna() Function:

Output:

```
memory = dataset.memory_usage()
print(memory)
print("Total Memory Usage = ",sum(memory))
✓ 0.0s

Index                    132
location              284984
date                  284984
vaccine               284984
total_vaccinations    284984
dtype: int64
Total Memory Usage =  1140068
```

Iloc() Function:

Output:

```
X = dataset.iloc[:,:-1].values
Y = dataset.iloc[:,3].values
print ('X: %s'%(str(X)))
print ('---------------------------------')
print ('Y: %s'%(str(Y)))
```

✓ 0.0s

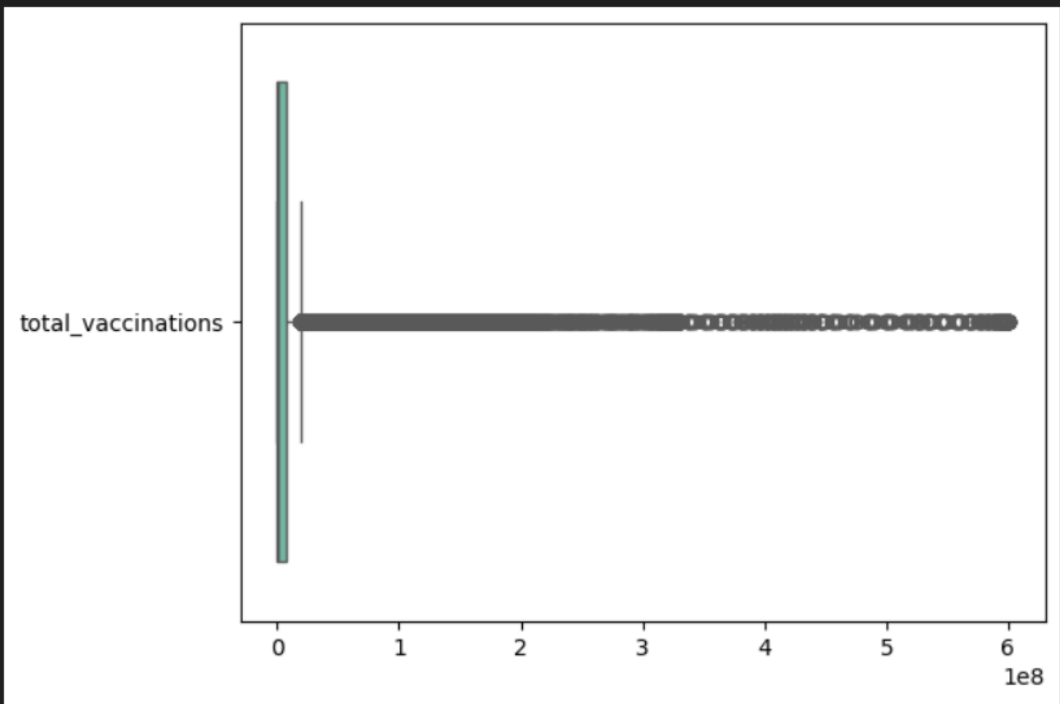
```
X: [['Argentina' '29-12-2020' 'Moderna']
 ['Argentina' '29-12-2020' 'Oxford/AstraZeneca']
 ['Argentina' '29-12-2020' 'Sinopharm/Beijing']
 ...
 ['European Union' '29-03-2022' 'Sinopharm/Beijing']
 ['European Union' '29-03-2022' 'Sinovac']
 ['European Union' '29-03-2022' 'Sputnik V']]
---------------------------------
Y: [      2       3       1 ... 2301516    1809 1845103]
```

Subplots Function:

Output:

```
fig, axs = plt.subplots()
sns.boxplot(data=dataset,orient='h',palette="Set2")
plt.show()
```

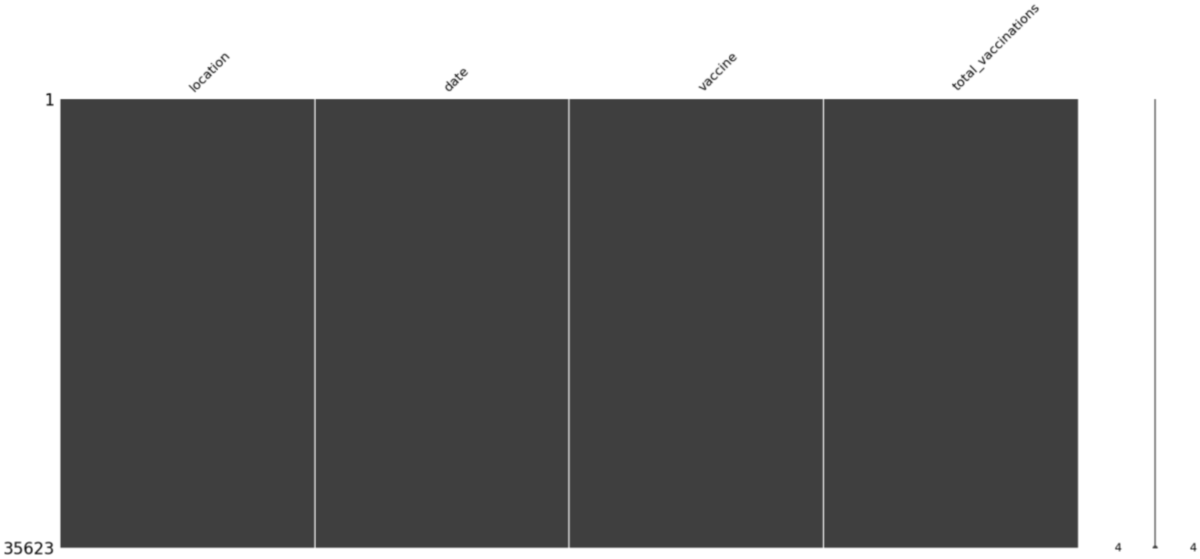
✓ 0.2s



Missingno Function:

Output:

```
msno.heatmap(dataset, labels = True)
✓ 0.1s
```




```
import missingno as msno
msno.matrix(dataset)
plt.figure(figsize = (15,9))
plt.show()
✓ 0.2s
```