# Suicide Rate Prediction:

```
Suicide is a serious public health problem. The issue of  suicide rates
is becoming more and more pervasive in society.The World Health
Organization (WHO) estimates that nearly 800,000 people commit suicide
each year, based on historical data from 1985 to 2016. This is one person
every 40 seconds and there are suicide attempts.
The objective of this project is to predict the suicide rates using
Machine Learning algorithms and analyzing them.
```

# The steps followed in this project are:

1.Loading the data 2.Familiarizing with the data 3.Data Preprocessing 4.Visualizing the data 5.Splitting the data 6.Training the data 7.Conclusion

In [1]:

```
#import the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
```

# 1. Loading the data

The dataset is taken from Kaggle, https://www.kaggle.com/russellyates88/suicide-rates-overview-1985-to-2016. This dataset contains the suicide details of all the countries from year 1985 to 2016. The dataset contains 12 features with 27820 samples.

In [2]:

```
#Loading the data
df = pd.read_csv("master.csv")
df.head()
```

Out[2]:

| | country | year | sex | age | suicides_no | population | suicides/100k pop | country-year | HDI for year | gdp_for_year ($) |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Albania | 1987 | male | 15-24 years | 21 | 312900 | 6.71 | Albania1987 | NaN | 2,156,624,900 |
| **1** | Albania | 1987 | male | 35-54 years | 16 | 308000 | 5.19 | Albania1987 | NaN | 2,156,624,900 |
| **2** | Albania | 1987 | female | 15-24 years | 14 | 289700 | 4.83 | Albania1987 | NaN | 2,156,624,900 |

| | country | year | sex | age | suicides_no | population | suicides/100k pop | country-year | HDI for year | gdp_for_year ($ |
|---|---|---|---|---|---|---|---|---|---|---|
| **3** | Albania | 1987 | male | 75+ years | 1 | 21800 | 4.59 | Albania1987 | NaN | 2,156,624,900 |
| **4** | Albania | 1987 | male | 25-34 years | 9 | 274300 | 3.28 | Albania1987 | NaN | 2,156,624,900 |

# 2. Familiarizing with data:

```
Here we look the data and it's features.
```

In [3]:

```
#shape of the dataframe
df.shape
```

Out[3]:

```
(27820, 12)
```

In [4]:

```
#list all the features of the data
df.columns
```

Out[4]:

```
Index(['country', 'year', 'sex', 'age', 'suicides_no', 'population',
       'suicides/100k pop', 'country-year', 'HDI for year',
       ' gdp_for_year ($) ', 'gdp_per_capita ($)', 'generation'],
      dtype='object')
```

In [5]:

```
#dataset information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27820 entries, 0 to 27819
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   country             27820 non-null  object 
 1   year                27820 non-null  int64  
 2   sex                 27820 non-null  object 
 3   age                 27820 non-null  object 
 4   suicides_no         27820 non-null  int64  
 5   population          27820 non-null  int64  
 6   suicides/100k pop   27820 non-null  float64
 7   country-year        27820 non-null  object 
 8   HDI for year        8364 non-null   float64
 9    gdp_for_year ($)   27820 non-null  object 
 10  gdp_per_capita ($)  27820 non-null  int64  
 11  generation          27820 non-null  object 
dtypes: float64(2), int64(4), object(6)
memory usage: 2.5+ MB
```

In [6]:

```
#Here we find the age groups of the people and the count of age groups.
df.age.value_counts()
```

Out[6]:
```
15-24 years    4642
35-54 years    4642
75+ years      4642
25-34 years    4642
55-74 years    4642
5-14 years     4610
Name: age, dtype: int64
```

In [7]:
```
#Here we find the total number of countries in our dataset
country = df.country.unique()
print("Number of countries:", len(country))
```

```
Number of countries: 101
```

# Observations:

1. The total number of countries in the dataset are 101.
2. HDI for year feature has null values. So we will replace the null values with mean in the pre processing.
3. There are 6 different age groups of people.

# 3. Data Preprocessing:

In Data Preprocessing we clean the data and apply the preprocessing techniques to transform the data.

In [8]:
```
df.describe()
```

Out[8]:

| | year | suicides_no | population | suicides/100k pop | HDI for year | gdp_per_capita ($) |
|---|---|---|---|---|---|---|
| **count** | 27820.000000 | 27820.000000 | 2.782000e+04 | 27820.000000 | 8364.000000 | 27820.000000 |
| **mean** | 2001.258375 | 242.574407 | 1.844794e+06 | 12.816097 | 0.776601 | 16866.464414 |
| **std** | 8.469055 | 902.047917 | 3.911779e+06 | 18.961511 | 0.093367 | 18887.576472 |
| **min** | 1985.000000 | 0.000000 | 2.780000e+02 | 0.000000 | 0.483000 | 251.000000 |
| **25%** | 1995.000000 | 3.000000 | 9.749850e+04 | 0.920000 | 0.713000 | 3447.000000 |
| **50%** | 2002.000000 | 25.000000 | 4.301500e+05 | 5.990000 | 0.779000 | 9372.000000 |
| **75%** | 2008.000000 | 131.000000 | 1.486143e+06 | 16.620000 | 0.855000 | 24874.000000 |
| **max** | 2016.000000 | 22338.000000 | 4.380521e+07 | 224.970000 | 0.944000 | 126352.000000 |

In [9]:
```
#Here we check the missing values
df.isnull().sum()
```

Out[9]:
```
country                    0
year                       0
sex                        0
```

```
age                     0
suicides_no             0
population              0
suicides/100k pop       0
country-year            0
HDI for year        19456
 gdp_for_year ($)       0
gdp_per_capita ($)      0
generation              0
dtype: int64
```

In [10]:

```
#Here we found the HDI column has 19456 null values.
df.isna().head()
```

Out[10]:

| | country | year | sex | age | suicides_no | population | suicides/100k pop | country-year | HDI for year | gdp_for_year ($) | gd |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | False | False | False | False | False | False | False | False | True | False | |
| **1** | False | False | False | False | False | False | False | False | True | False | |
| **2** | False | False | False | False | False | False | False | False | True | False | |
| **3** | False | False | False | False | False | False | False | False | True | False | |
| **4** | False | False | False | False | False | False | False | False | True | False | |

In [11]:

```
#we use the mean of HDI column to replace the null values of the HDI column.
x = df['HDI for year'].mean()
```

In [12]:

```
x
```

Out[12]:

```
0.7766011477761785
```

In [13]:

```
#Replace the null values with mean of HDI.
df['HDI for year'].fillna(x, inplace = True)
```

In [14]:

```
#Data after replacing the null values.
df
```

Out[14]:

| | country | year | sex | age | suicides_no | population | suicides/100k pop | country-year | HDI for year |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Albania | 1987 | male | 15-24 years | 21 | 312900 | 6.71 | Albania1987 | 0.776601 |
| **1** | Albania | 1987 | male | 35-54 years | 16 | 308000 | 5.19 | Albania1987 | 0.776601 |

| | country | year | sex | age | suicides_no | population | suicides/100k pop | country-year | HDI for year |
|---|---|---|---|---|---|---|---|---|---|
| **2** | Albania | 1987 | female | 15-24 years | 14 | 289700 | 4.83 | Albania1987 | 0.776601 |
| **3** | Albania | 1987 | male | 75+ years | 1 | 21800 | 4.59 | Albania1987 | 0.776601 |
| **4** | Albania | 1987 | male | 25-34 years | 9 | 274300 | 3.28 | Albania1987 | 0.776601 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **27815** | Uzbekistan | 2014 | female | 35-54 years | 107 | 3620833 | 2.96 | Uzbekistan2014 | 0.675000 |
| **27816** | Uzbekistan | 2014 | female | 75+ years | 9 | 348465 | 2.58 | Uzbekistan2014 | 0.675000 |
| **27817** | Uzbekistan | 2014 | male | 5-14 years | 60 | 2762158 | 2.17 | Uzbekistan2014 | 0.675000 |
| **27818** | Uzbekistan | 2014 | female | 5-14 years | 44 | 2631600 | 1.67 | Uzbekistan2014 | 0.675000 |
| **27819** | Uzbekistan | 2014 | female | 55-74 years | 21 | 1438935 | 1.46 | Uzbekistan2014 | 0.675000 |

27820 rows × 12 columns

In [15]:

```
#Information of the new data after replacing the missing values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27820 entries, 0 to 27819
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   country             27820 non-null  object 
 1   year                27820 non-null  int64  
 2   sex                 27820 non-null  object 
 3   age                 27820 non-null  object 
 4   suicides_no         27820 non-null  int64  
 5   population          27820 non-null  int64  
 6   suicides/100k pop   27820 non-null  float64
 7   country-year        27820 non-null  object 
 8   HDI for year        27820 non-null  float64
 9    gdp_for_year ($)   27820 non-null  object 
 10  gdp_per_capita ($)  27820 non-null  int64  
 11  generation          27820 non-null  object 
dtypes: float64(2), int64(4), object(6)
memory usage: 2.5+ MB
```

In [16]:

```
df.columns
```

Out[16]:
```
Index(['country', 'year', 'sex', 'age', 'suicides_no', 'population',
       'suicides/100k pop', 'country-year', 'HDI for year',
       ' gdp_for_year ($) ', 'gdp_per_capita ($)', 'generation'],
      dtype='object')
```

In [17]:
```
#Here Country-year column is the combination of both the year and country so we drop th
df = df.drop(['country-year'], axis = 1)
df.shape
```

Out[17]:
```
(27820, 11)
```

In [18]:
```
df.columns
```

Out[18]:
```
Index(['country', 'year', 'sex', 'age', 'suicides_no', 'population',
       'suicides/100k pop', 'HDI for year', ' gdp_for_year ($) ',
       'gdp_per_capita ($)', 'generation'],
      dtype='object')
```

In [19]:
```
#Shape of the data after dropping the column and null rows.
df = df.dropna()
df.shape
```

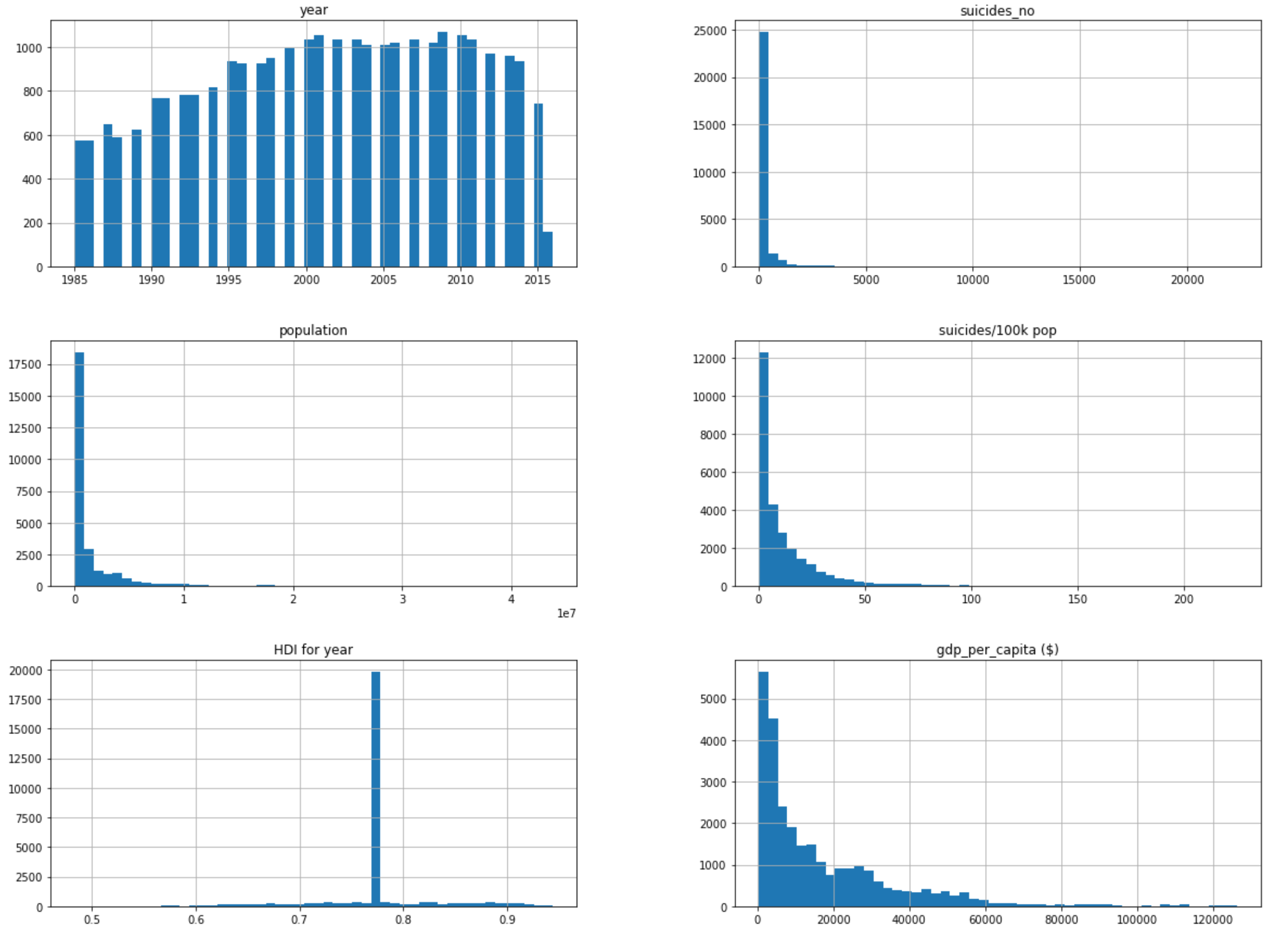
Out[19]:
```
(27820, 11)
```

# 4. Visualizing the data

Graphs are displayed to check how the data is distributed.

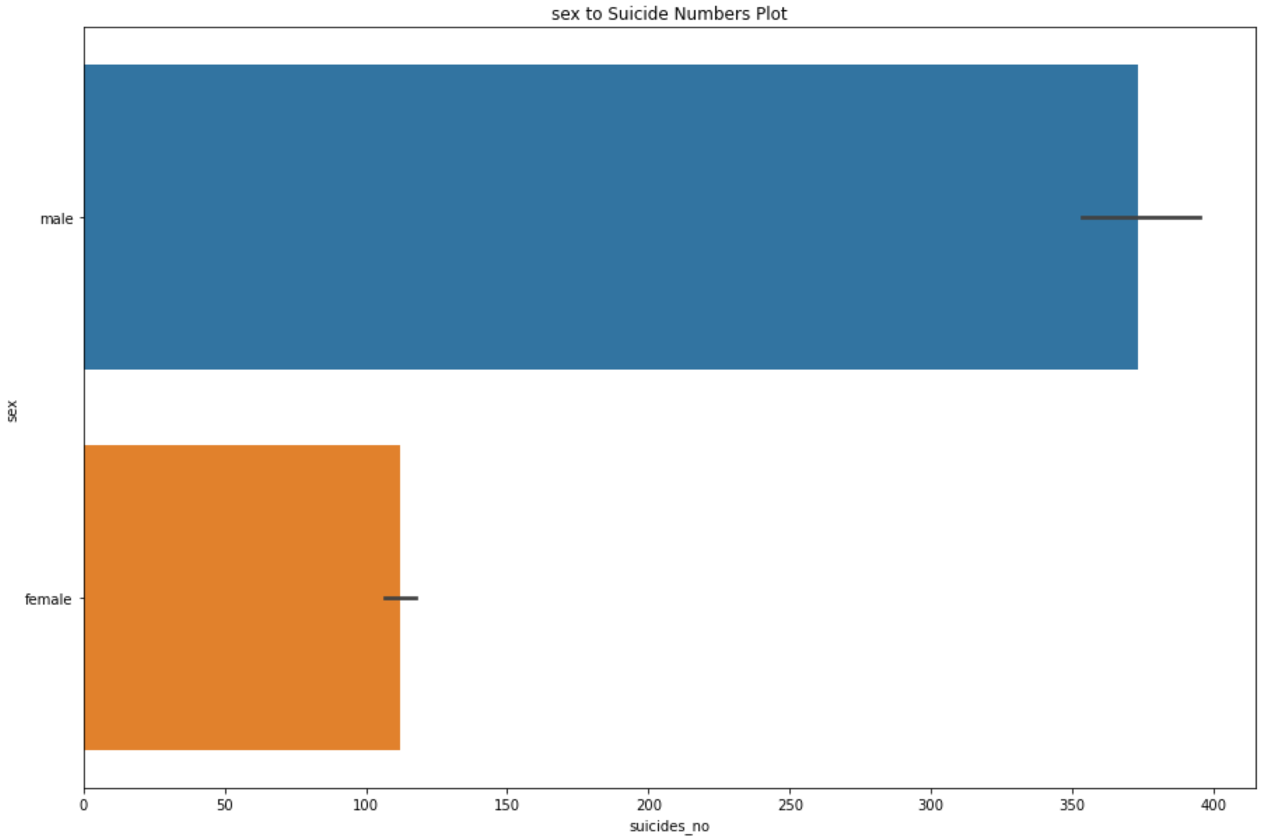
In [20]:
```
#Plotting the histogram for the data.
df.hist(bins = 50,figsize = (20,15))
```

Out[20]:
```
array([[<AxesSubplot:title={'center':'year'}>,
        <AxesSubplot:title={'center':'suicides_no'}>],
       [<AxesSubplot:title={'center':'population'}>,
        <AxesSubplot:title={'center':'suicides/100k pop'}>],
       [<AxesSubplot:title={'center':'HDI for year'}>,
        <AxesSubplot:title={'center':'gdp_per_capita ($)'}>]],
      dtype=object)
```



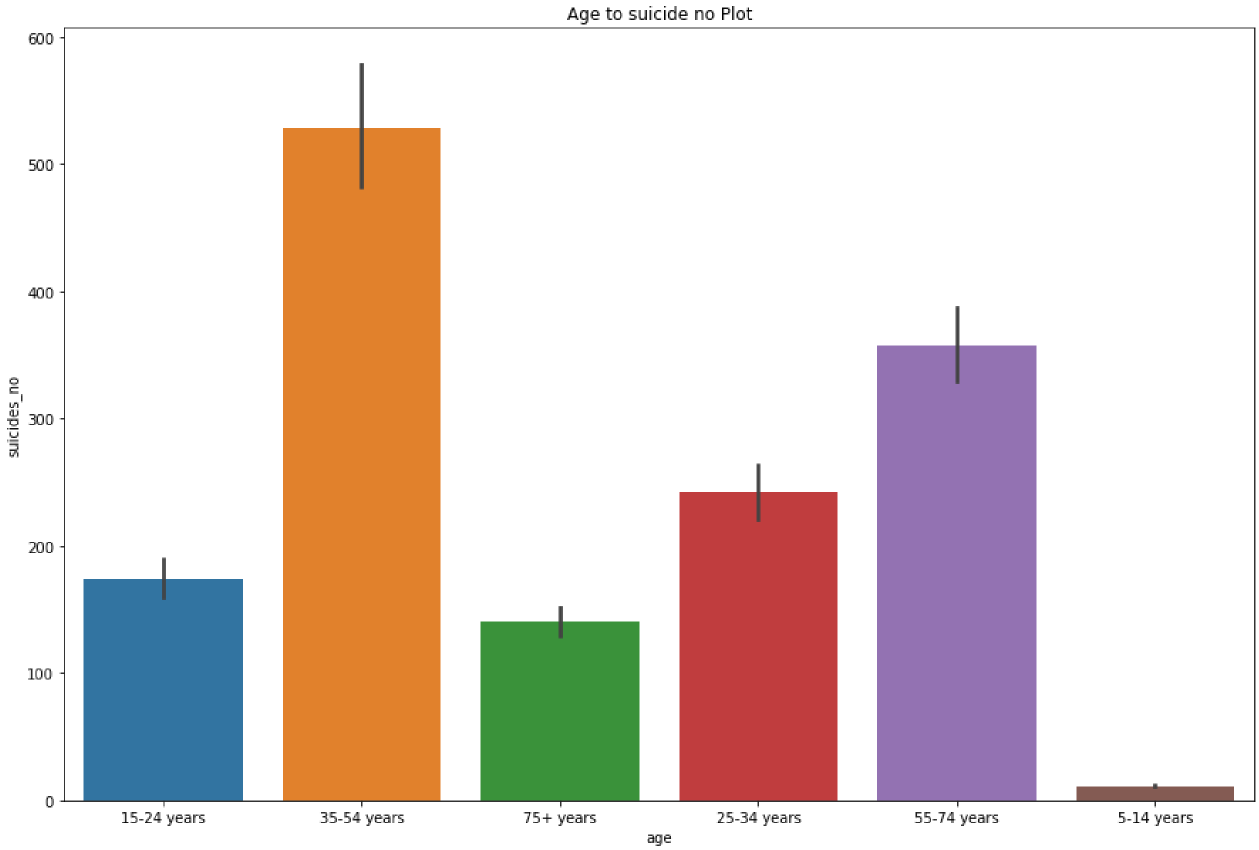

In [21]:

```
#Plotting the bar chart for the Number of suicides and Sex.
plt.figure(figsize=(15,10))
sns.barplot(x = "suicides_no", y = "sex", data = df)
plt.title('sex to Suicide Numbers Plot')
plt.show()
```



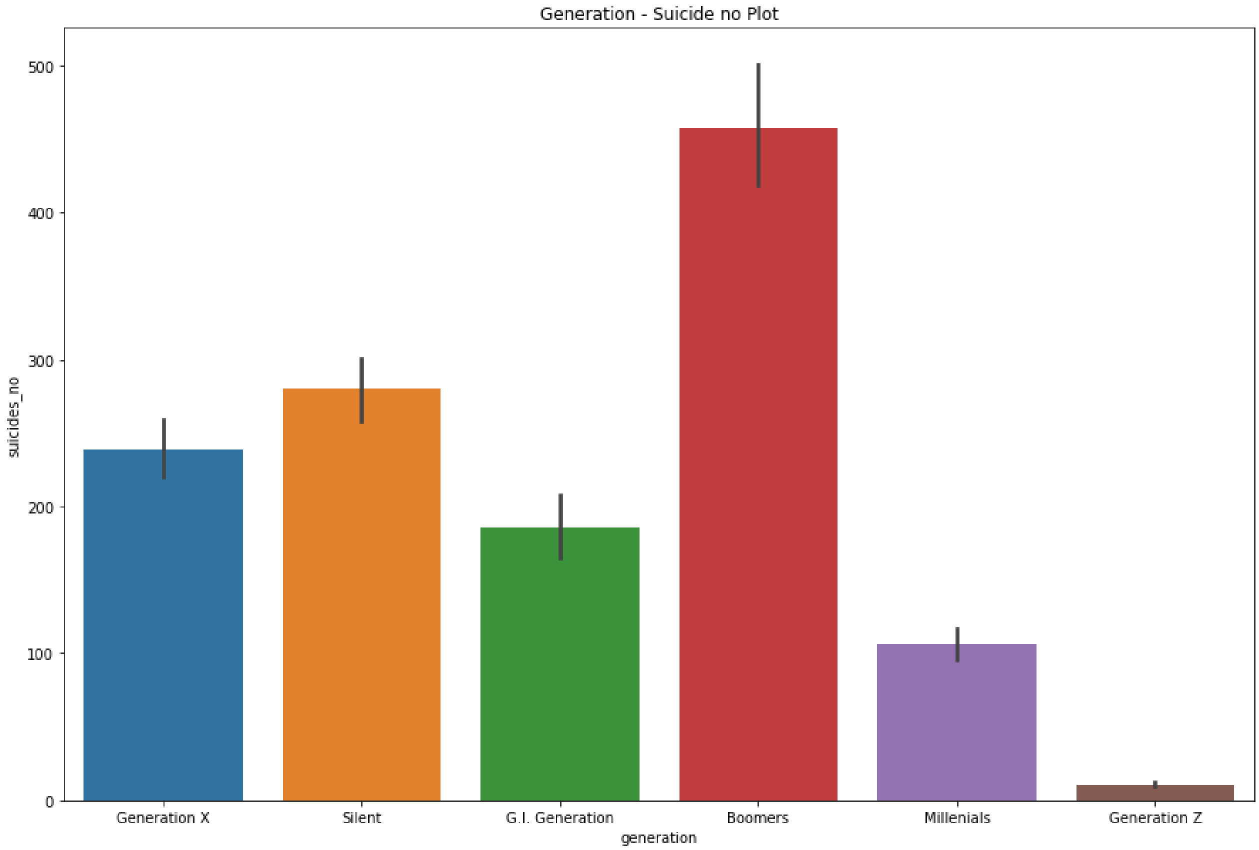

Here we can see that suicides in the male population is more compared to females.

In [22]:
```
#Here we plot the bar chart to the number of suicides to the age.
plt.figure(figsize=(15,10))
sns.barplot(x = "age", y = "suicides_no", data = df)
plt.title("Age to suicide no Plot")
plt.show()
```



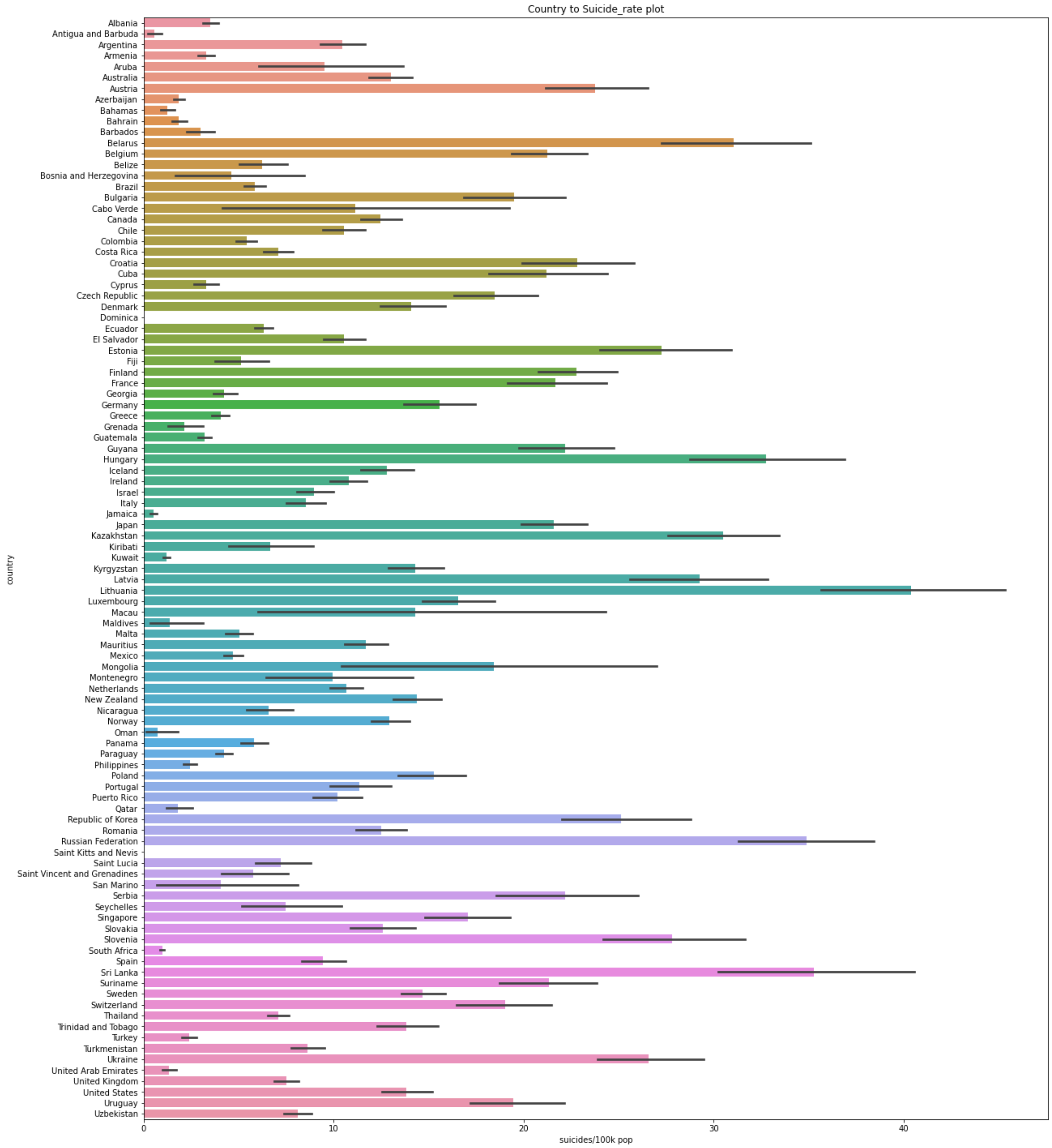

In [23]:

```
#Here we plot the bar chart for suicides numbers to the generations
plt.figure(figsize=(15,10))
sns.barplot(x = "generation", y = "suicides_no", data = df)
plt.title('Generation - Suicide no Plot')
plt.show()
```



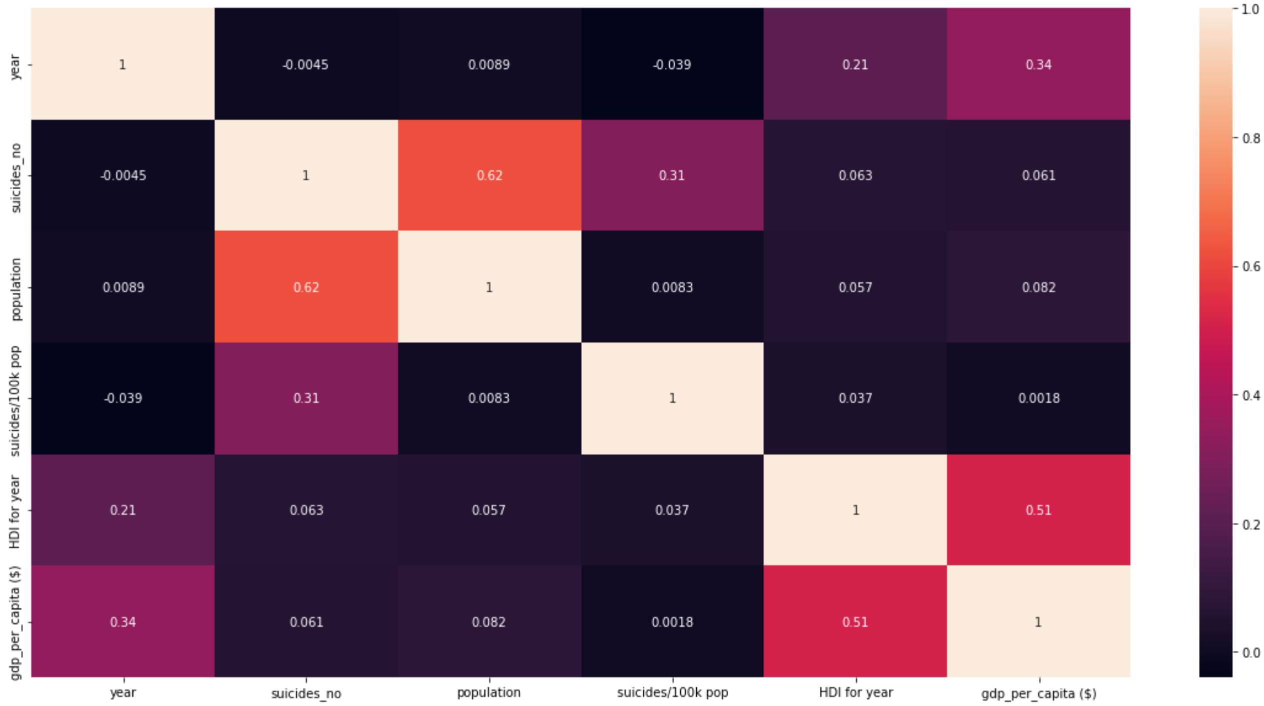

In [24]:

```
#Here we plot the bar chart to the number of suicide to countries.
plt.figure(figsize=(20,25))
sns.barplot(x = "suicides/100k pop", y = "country", data = df)
plt.title('Country to Suicide_rate plot')
plt.show()
```




In [25]:

```
#Correlation heatmap
plt.figure(figsize=(20,10))
sns.heatmap(df.corr(), annot=True)
plt.show()
```




# Observations:

```
1. The number of suicides in male population is higher than that of the
female population.
2. The age group of people between 35-54 years are commiting more
suicides.
3. In generations, boomers generation has more number of suicides.
4. From the bar chart we can see Lithuania country has more number of
suicides.
```

In [26]:

```python
#The non-numerical labeled columns, country, year, sex, age and generation are to be co
from sklearn.preprocessing import LabelEncoder
categorical = ['country', 'year','age', 'sex', 'generation']
label = sklearn.preprocessing.LabelEncoder()

for column in categorical:
    df[column] = label.fit_transform(df[column])
```

In [27]:

```python
data = df.copy()
data
```

Out[27]:

| | country | year | sex | age | suicides_no | population | suicides/100k pop | HDI for year | gdp_for_year ($) | gdp_p |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 2 | 1 | 0 | 21 | 312900 | 6.71 | 0.776601 | 2,156,624,900 | |
| **1** | 0 | 2 | 1 | 2 | 16 | 308000 | 5.19 | 0.776601 | 2,156,624,900 | |
| **2** | 0 | 2 | 0 | 0 | 14 | 289700 | 4.83 | 0.776601 | 2,156,624,900 | |
| **3** | 0 | 2 | 1 | 5 | 1 | 21800 | 4.59 | 0.776601 | 2,156,624,900 | |
| **4** | 0 | 2 | 1 | 1 | 9 | 274300 | 3.28 | 0.776601 | 2,156,624,900 | |

| | country | year | sex | age | suicides_no | population | suicides/100k pop | HDI for year | gdp_for_year ($) | gdp_p |
|---|---|---|---|---|---|---|---|---|---|---|
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **27815** | 100 | 29 | 0 | 2 | 107 | 3620833 | 2.96 | 0.675000 | 63,067,077,179 | |
| **27816** | 100 | 29 | 0 | 5 | 9 | 348465 | 2.58 | 0.675000 | 63,067,077,179 | |
| **27817** | 100 | 29 | 1 | 3 | 60 | 2762158 | 2.17 | 0.675000 | 63,067,077,179 | |
| **27818** | 100 | 29 | 0 | 3 | 44 | 2631600 | 1.67 | 0.675000 | 63,067,077,179 | |
| **27819** | 100 | 29 | 0 | 4 | 21 | 1438935 | 1.46 | 0.675000 | 63,067,077,179 | |

27820 rows × 11 columns

In [28]:

```
#Here we find the data types
df.dtypes
```

Out[28]:

```
country                  int32
year                     int64
sex                      int32
age                      int32
suicides_no              int64
population               int64
suicides/100k pop      float64
HDI for year           float64
 gdp_for_year ($)       object
gdp_per_capita ($)       int64
generation               int32
dtype: object
```

In [29]:

```
#We can observe one feature has object data type so we are converting it to the float v
df[' gdp_for_year ($) '] = df[' gdp_for_year ($) '].str.replace(',','').astype(float)
```

In [30]:

```
#we can observe the data types are changed from object to numericals.
df.dtypes
```

Out[30]:

```
country                  int32
year                     int64
sex                      int32
age                      int32
suicides_no              int64
population               int64
suicides/100k pop      float64
HDI for year           float64
 gdp_for_year ($)      float64
gdp_per_capita ($)       int64
generation               int32
dtype: object
```

In [31]:

```
#Scaling the numerical data columns with RobustScalar.
numerical = ['suicides_no', 'population', 'suicides/100k pop',
              ' gdp_for_year ($) ','gdp_per_capita ($)']
```

```
from sklearn.preprocessing import RobustScaler

robust = RobustScaler()
df[numerical] = robust.fit_transform(df[numerical])
```

In [32]:

```
df
```

Out[32]:

| | country | year | sex | age | suicides_no | population | suicides/100k pop | HDI for year | gdp_for_year ($) | gdp_p |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 2 | 1 | 0 | -0.031250 | -0.084435 | 0.045860 | 0.776601 | -0.182942 | - |
| **1** | 0 | 2 | 1 | 2 | -0.070312 | -0.087963 | -0.050955 | 0.776601 | -0.182942 | - |
| **2** | 0 | 2 | 0 | 0 | -0.085938 | -0.101142 | -0.073885 | 0.776601 | -0.182942 | - |
| **3** | 0 | 2 | 1 | 5 | -0.187500 | -0.294064 | -0.089172 | 0.776601 | -0.182942 | - |
| **4** | 0 | 2 | 1 | 1 | -0.125000 | -0.112232 | -0.172611 | 0.776601 | -0.182942 | - |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **27815** | 100 | 29 | 0 | 2 | 0.640625 | 2.297696 | -0.192994 | 0.675000 | 0.059520 | - |
| **27816** | 100 | 29 | 0 | 5 | -0.125000 | -0.058824 | -0.217197 | 0.675000 | 0.059520 | - |
| **27817** | 100 | 29 | 1 | 3 | 0.273438 | 1.679341 | -0.243312 | 0.675000 | 0.059520 | - |
| **27818** | 100 | 29 | 0 | 3 | 0.148438 | 1.585323 | -0.275159 | 0.675000 | 0.059520 | - |
| **27819** | 100 | 29 | 0 | 4 | -0.031250 | 0.726453 | -0.288535 | 0.675000 | 0.059520 | - |

27820 rows × 11 columns

# 5.Splitting the data

In [33]:

```
#Here we are separating the features and target columns and assigning to X and y.
y = df['suicides/100k pop']
X = df.drop('suicides/100k pop',axis=1)
X.shape, y.shape
```

Out[33]:

```
((27820, 10), (27820,))
```

In [34]:

```
#Splitting the datasets into training and test sets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
X_train.shape, X_test.shape
```

Out[34]:

```
((22256, 10), (5564, 10))
```

# 6. Model Building

# k-Nearest Neighbors Regression

The K-nearest neighbor method is a simple algorithm that stores all available cases and predicts a numerical. A simple implementation of KNN regression is to average k-nearest neighbor numerical targets.

In [35]:
```
#importing the libraries
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error
```

In [36]:
```
#Fit the model
clf = KNeighborsRegressor(n_neighbors=2)
clf.fit(X_train, y_train)
```

Out[36]:
```
KNeighborsRegressor(n_neighbors=2)
```

In [37]:
```
#predicting the target value for the samples.
clf.predict(X_test)
```

Out[37]:
```
array([-0.06942675,  0.11656051,  0.53025478, ...,  0.98980892,
        0.16847134,  1.22547771])
```

In [38]:
```
#Finding the accuracy for test data
print('Accuracy of test data: {:.2f}'.format(clf.score(X_test, y_test)))
```

```
Accuracy of test data: 0.80
```

In [39]:
```
#Finding the accuracy for train data
print('Accuracy of train data: {:.2f}'.format(clf.score(X_train, y_train)))
```

```
Accuracy of train data: 0.94
```

In [40]:
```
#predicting the target value from the model for the test and train data
y_pred_test = clf.predict(X_test)
y_pred_train = clf.predict(X_train)
```

In [41]:
```
#Finding the RMSE for train data
print('RMSE of train data: {:.2f}'.format(np.sqrt(mean_squared_error(y_train, y_pred_tr
```

```
RMSE of train data: 0.29
```

In [42]:
```
#Finding the RMSE for test data
print('RMSE of test data: {:.2f}'.format(np.sqrt(mean_squared_error(y_test, y_pred_test
```

```
RMSE of test data: 0.56
```

# KNN:

Accuracy of training Data: 0.94 Accuracy of test Data: 0.80 The RMSE of the train data is: 0.29 The RMSE of the test data is: 0.56

# Linear Regression

```
Linear regression is the simplest and most classic linear regression
method. Linear regression finds the parameters w and b that minimize the
mean square error between the predictions in the training dataset and the
true regression target y.
```

In [43]:

```
#import the libraries
from sklearn.linear_model import LinearRegression
```

In [44]:

```
#Fit the model
clf = LinearRegression()
clf.fit(X_train, y_train)
```

Out[44]:

```
LinearRegression()
```

In [45]:

```
clf.predict(X_test)
```

Out[45]:

```
array([-0.16837035,  0.06725699,  0.20856095, ...,  0.79618439,
        0.16467054,  0.95856969])
```

In [46]:

```
#Finding the accuracy for test data
print('Accuracy of test data: {:.2f}'.format(clf.score(X_test, y_test)))
```

```
Accuracy of test data: 0.30
```

In [47]:

```
#Finding the accuracy for train data
print('Accuracy of train data: {:.2f}'.format(clf.score(X_train, y_train)))
```

```
Accuracy of train data: 0.29
```

In [48]:

```
#predicting the target value from the model for the test and train data
y_pred_test = clf.predict(X_test)
y_pred_train = clf.predict(X_train)
```

In [49]:

```
#Finding the RMSE for train data
print('RMSE of train data: {:.2f}'.format(np.sqrt(mean_squared_error(y_train, y_pred_tr
```

```
RMSE of train data: 1.01
```

In [50]:

```
#Finding the RMSE for test data
print('RMSE of test data: {:.2f}'.format(np.sqrt(mean_squared_error(y_test, y_pred_test
```

```
RMSE of test data: 1.04
```

# Linear Regression:

Accuracy of training Data: 0.29 Accuracy of test Data: 0.30 The RMSE of the train data is: 1.01 The RMSE of the test data is: 1.04

# Decision Trees: Regression

```
Decision trees are a widely used model for classification and regression.
Basically, they learn a hierarchy of unknown questions that leads to
decisions. Learning a decision tree means learning a series of if / else
questions that lead us to the true answer the fastest.
```

In [53]:

```
#importing the libraries
from sklearn.tree import DecisionTreeRegressor
```

In [54]:

```
#Fit the model
clf = DecisionTreeRegressor(max_depth=10)
clf.fit(X_train, y_train)
```

Out[54]:

```
DecisionTreeRegressor(max_depth=10)
```

In [55]:

```
clf.predict(X_test)
```

Out[55]:

```
array([-0.14053203, -0.05619006, -0.1163482 , ...,  1.20294765,
       -0.38152866,  1.14099626])
```

In [56]:

```
#Finding the accuracy for test data
print('Accuracy of test data: {:.2f}'.format(clf.score(X_test, y_test)))
```

```
Accuracy of test data: 0.97
```

In [57]:

```
#Finding the accuracy for train data
print('Accuracy of train data: {:.2f}'.format(clf.score(X_train, y_train)))
```

```
Accuracy of train data: 0.98
```

In [58]:

```
#predicting the target value from the model for the test and train data
y_pred_test = clf.predict(X_test)
y_pred_train = clf.predict(X_train)
```

In [59]:

```
#Finding the RMSE for train data
print('RMSE of train data: {:.2f}'.format(np.sqrt(mean_squared_error(y_train, y_pred_tr
```

```
RMSE of train data: 0.15
```

In [60]:

```
#Finding the RMSE for test data
print('RMSE of test data: {:.2f}'.format(np.sqrt(mean_squared_error(y_test, y_pred_test
```

```
RMSE of test data: 0.22
```

# Decision Tree:

Accuracy of training Data: 0.98 Accuracy of test Data: 0.97 The RMSE of the train data is: 0.15 The RMSE of the test data is: 0.22

# Random Forest

```
Random forests for regression and classification are one of the most
widely used machine learning techniques. Random forests are basically a
collection of decision trees, with each tree being slightly different
from the others. Random Forest is that each tree can make good
predictions, but will miss some data.
```

In [61]:

```
#importing the libraries
from sklearn.ensemble import RandomForestRegressor
```

In [62]:

```
#Fit the model
clf = RandomForestRegressor(max_depth=10)
clf.fit(X_train, y_train)
```

Out[62]:

```
RandomForestRegressor(max_depth=10)
```

In [63]:

```
clf.predict(X_test)
```

Out[63]:

```
array([-0.1506874 , -0.03218204, -0.14876229, ...,  1.07463623,
       -0.38152866,  1.09030508])
```

In [64]:

```
#Finding the accuracy for test data
print('Accuracy of test data: {:.2f}'.format(clf.score(X_test, y_test)))
```

```
Accuracy of test data: 0.99
```

In [65]:

```
#Finding the accuracy for train data
print('Accuracy of train data: {:.2f}'.format(clf.score(X_train, y_train)))
```

```
Accuracy of train data: 0.99
```

In [66]:

```
#predicting the target value from the model for the test and train data
y_pred_test = clf.predict(X_test)
y_pred_train = clf.predict(X_train)
```

In [67]:

```
#Finding the RMSE for train data
print('RMSE of train data: {:.2f}'.format(np.sqrt(mean_squared_error(y_train, y_pred_tr
```

```
RMSE of train data: 0.10
```

In [68]:
```
#Finding the RMSE for test data
print('RMSE of test data: {:.2f}'.format(np.sqrt(mean_squared_error(y_test, y_pred_test
```

```
RMSE of test data: 0.14
```

# Random Forest:

Accuracy of training Data: 0.99 Accuracy of test Data: 0.99 The RMSE of the train data is: 0.10 The RMSE of the test data is: 0.14

# Gradient Boosted Regression Trees

Gradient Boosted Regression Tree is ensemble technique that combines multiple decision trees to create a more powerful model. These models can be used for regression and classification. Gradient boosting works by building trees in sequence, with each tree trying to fix errors in the previous tree.

In [69]:
```
#importing the libraries
from sklearn.ensemble import GradientBoostingRegressor
```

In [70]:
```
#Fit the model
clf = GradientBoostingRegressor(learning_rate=0.7)
clf.fit(X_train, y_train)
```

Out[70]:
```
GradientBoostingRegressor(learning_rate=0.7)
```

In [71]:
```
clf.predict(X_test)
```

Out[71]:
```
array([-0.25420824, -0.12388845, -0.23926434, ...,  1.23289683,
       -0.21098646,  1.11385618])
```

In [72]:
```
#Finding the accuracy for test data
print('Accuracy of test data: {:.2f}'.format(clf.score(X_test, y_test)))
```

```
Accuracy of test data: 0.98
```

In [73]:
```
#Finding the accuracy for train data
print('Accuracy of train data: {:.2f}'.format(clf.score(X_train, y_train)))
```

```
Accuracy of train data: 0.99
```

In [74]:
```
#predicting the target value from the model for the test and train data
y_pred_test = clf.predict(X_test)
y_pred_train = clf.predict(X_train)
```

In [75]:
```
#Finding the RMSE for train data
print('RMSE of train data: {:.2f}'.format(np.sqrt(mean_squared_error(y_train, y_pred_tr
```

```
RMSE of train data: 0.14
```

In [76]:
```
#Finding the RMSE for test data
print('RMSE of test data: {:.2f}'.format(np.sqrt(mean_squared_error(y_test, y_pred_test
```

```
RMSE of test data: 0.19
```

# Gradient Boosted Regression Trees:

Accuracy of training Data: 0.99 Accuracy of test Data: 0.98 The RMSE of the train data is: 0.14 The RMSE of the test data is: 0.19

# Bagging Regression

Bagging estimator is an ensemble estimator that fits a base estimator to each random subset of a train dataset, aggregates individual predictions, and uses a voting or mean method to form the final prediction.

In [77]:
```
#importing the libraries
from sklearn.ensemble import BaggingRegressor
```

In [78]:
```
#Fit the model
clf = BaggingRegressor(n_estimators=1)
clf.fit(X_train, y_train)
```

Out[78]:
```
BaggingRegressor(n_estimators=1)
```

In [79]:
```
clf.predict(X_test)
```

Out[79]:
```
array([-0.14394904, -0.03057325, -0.14904459, ...,  1.08917197,
       -0.38152866,  0.94840764])
```

In [80]:
```
#Finding the accuracy for test data
print('Accuracy of test data: {:.2f}'.format(clf.score(X_test, y_test)))
```

```
Accuracy of test data: 0.98
```

In [81]:
```
#Finding the accuracy for train data
print('Accuracy of train data: {:.2f}'.format(clf.score(X_train, y_train)))
```

```
Accuracy of train data: 0.99
```

In [82]:
```
#predicting the target value from the model for the test and train data
y_pred_test = clf.predict(X_test)
y_pred_train = clf.predict(X_train)
```

In [83]:
```
#Finding the RMSE for train data
print('RMSE of train data: {:.2f}'.format(np.sqrt(mean_squared_error(y_train, y_pred_tr
```

```
RMSE of train data: 0.11
```

In [84]:
```
#Finding the RMSE for test data
print('RMSE of test data: {:.2f}'.format(np.sqrt(mean_squared_error(y_test, y_pred_test
```

```
RMSE of test data: 0.18
```

# Bagging Regression:

```
Accuracy of training Data: 0.99 Accuracy of test Data: 0.98 The RMSE of
the train data is: 0.11 The RMSE of the test data is: 0.18
```

# 7. Conclusion

The main objective of the project is to work with various machine learning models on the dataset and understand their parameters. By working on this project, I've learned about the parameters of the model, how to adjust them, and how they affect the performance of the model. Also how the null values effect the performance of the models. The final conclusion of the dataset is the male population is more likely to commit suicide than the female population irrespective of the ages and countries. The suicides are more in elder male groups. The continents such as Central and Eastern Europe have a higher suicide rate compared to the developing countries.