# Mental Fitness Tracker

- *This Notebook Grapples with Mental Fitness through the implementation of different ML Algorithms.*

# About Project

*The Mental Health Fitness Tracker project is dedicated to examining and predicting the mental fitness levels of individuals across different countries, considering a range of mental disorders. The project employs "**Supervised learning**" where "**Regression techniques**" to gain valuable insights into mental health and utilizes the available data to make predictions about individuals' well-being.*

# Importing the Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import plotly.express as px
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,r2_score
```

# Mount the google drive to Google colab

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True
```

# Exploratory Data Analysis

# Reading the data from the csv files

```
# Reading mental-and-substance-use-as-share-of-disease csv file
df1 = pd.read_csv('/content/drive/MyDrive/Share mental-and-substance-use-as-share-of-disease.csv')

# Reading prevalence-by-mental-and-substance-use-disorder csv file
df2 = pd.read_csv('/content/drive/MyDrive/Share prevalence-by-mental-and-substance-use-disorder.csv')
```

```
numeric_columns = df1.select_dtypes(include=[np.number]).columns
df1[numeric_columns] = df1[numeric_columns].fillna(df1[numeric_columns].mean())

numeric_columns = df2.select_dtypes(include=[np.number]).columns
df2[numeric_columns] = df2[numeric_columns].fillna(df2[numeric_columns].mean())
```

# Preview of the dataset

```
#mental-and-substance-use-as-share-of-disease
df1.head(5)
```

| | Entity | Code | Year | DALYs (Disability-Adjusted Life Years) - Mental disorders - Sex: Both - Age: All Ages (Percent) |
|---|---|---|---|---|
| 0 | Afghanistan | AFG | 1990 | 1.70 |
| 1 | Afghanistan | AFG | 1991 | 1.73 |
| 2 | Afghanistan | AFG | 1992 | 1.79 |
| 3 | Afghanistan | AFG | 1993 | 1.78 |
| 4 | Afghanistan | AFG | 1994 | 1.71 |

```
df1.tail(5)
```

| | Entity | Code | Year | DALYs (Disability-Adjusted Life Years) - Mental disorders - Sex: Both - Age: All Ages (Percent) |
|---|---|---|---|---|
| **6835** | Zimbabwe | ZWE | 2015 | 2.19 |
| **6836** | Zimbabwe | ZWE | 2016 | 2.28 |
| **6837** | Zimbabwe | ZWE | 2017 | 2.36 |
| **6838** | Zimbabwe | ZWE | 2018 | 2.47 |
| **6839** | Zimbabwe | ZWE | 2019 | 2.53 |

```
#prevalence-by-mental-and-substance-use-disorder
df2.head(5)
```

| | Entity | Code | Year | Schizophrenia disorders (share of population) - Sex: Both - Age: Age-standardized | Bipolar disorders (share of population) - Sex: Both - Age: Age-standardized | Eating disorders (share of population) - Sex: Both - Age: Age-standardized | Anxiety disorders (share of population) - Sex: Both - Age: Age-standardized | Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent) | [ pc - - sta |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Afghanistan | AFG | 1990 | 0.223206 | 0.703023 | 0.127700 | 4.713314 | 0.45 | |
| **1** | Afghanistan | AFG | 1991 | 0.222454 | 0.702069 | 0.123256 | 4.702100 | 0.45 | |
| **2** | Afghanistan | AFG | 1992 | 0.221751 | 0.700792 | 0.118844 | 4.683743 | 0.44 | |
| **3** | Afghanistan | AFG | 1993 | 0.220987 | 0.700087 | 0.115089 | 4.673549 | 0.44 | |
| **4** | Afghanistan | AFG | 1994 | 0.220183 | 0.699898 | 0.111815 | 4.670810 | 0.43 | |

```
df2.tail(4)
```

| | Entity | Code | Year | Schizophrenia disorders (share of population) - Sex: Both - Age: Age-standardized | Bipolar disorders (share of population) - Sex: Both - Age: Age-standardized | Eating disorders (share of population) - Sex: Both - Age: Age-standardized | Anxiety disorders (share of population) - Sex: Both - Age: Age-standardized | Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent) | s |
|---|---|---|---|---|---|---|---|---|---|
| **7106** | Zimbabwe | ZWE | 2016 | 0.201319 | 0.538593 | 0.096662 | 3.187148 | 0.60 | |
| **7107** | Zimbabwe | ZWE | 2017 | 0.201639 | 0.538589 | 0.097330 | 3.188418 | 0.61 | |
| **7108** | Zimbabwe | ZWE | 2018 | 0.201976 | 0.538585 | 0.097909 | 3.172111 | 0.61 | |
| **7109** | Zimbabwe | ZWE | 2019 | 0.202482 | 0.538580 | 0.098295 | 3.137017 | 0.61 | |

## View Dimensions of the dataset

```
#mental-and-substance-use-as-share-of-disease
print('mental-and-substance-use-as-share-of-disease : ',df1.shape)

print()

#prevalence-by-mental-and-substance-use-disorder
print('prevalence-by-mental-and-substance-use-disorder : ',df2.shape)
```

```
mental-and-substance-use-as-share-of-disease :  (6840, 4)

prevalence-by-mental-and-substance-use-disorder :  (7110, 10)
```

## Check Null Values if present

```
#Gives null value count of each column in mental-and-substance-use-as-share-of-disease
df1.isnull().sum()
```

```
Entity                                                                                 0
Code                                                                                 690
Year                                                                                   0
DALYs (Disability-Adjusted Life Years) - Mental disorders - Sex: Both - Age: All Ages (Percent)      0
dtype: int64
```

```
#Gives null value count of each column in prevalence-by-mental-and-substance-use-disorder
df2.isnull().sum()
```

```
Entity                                                                              0
Code                                                                              960
Year                                                                                0
Schizophrenia disorders (share of population) - Sex: Both - Age: Age-standardized   0
Bipolar disorders (share of population) - Sex: Both - Age: Age-standardized         0
Eating disorders (share of population) - Sex: Both - Age: Age-standardized          0
Anxiety disorders (share of population) - Sex: Both - Age: Age-standardized         0
Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent)       0
Depressive disorders (share of population) - Sex: Both - Age: Age-standardized      0
Prevalence - Alcohol use disorders - Sex: Both - Age: Age-standardized (Percent)    0
dtype: int64
```

## Merging the datasets

```
#merging two datasets mental-and-substance-use-as-share-of-disease and prevalence-by-mental-and-substance-use-disorder

data = pd.merge(df2,df1)
data.head(5)
```

| | Entity | Code | Year | Schizophrenia disorders (share of population) - Sex: Both - Age: Age-standardized | Bipolar disorders (share of population) - Sex: Both - Age: Age-standardized | Eating disorders (share of population) - Sex: Both - Age: Age-standardized | Anxiety disorders (share of population) - Sex: Both - Age: Age-standardized | Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent) | [ po - - sta |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Afghanistan | AFG | 1990 | 0.223206 | 0.703023 | 0.127700 | 4.713314 | 0.45 | |
| 1 | Afghanistan | AFG | 1991 | 0.222454 | 0.702069 | 0.123256 | 4.702100 | 0.45 | |
| 2 | Afghanistan | AFG | 1992 | 0.221751 | 0.700792 | 0.118844 | 4.683743 | 0.44 | |
| 3 | Afghanistan | AFG | 1993 | 0.220987 | 0.700087 | 0.115089 | 4.673549 | 0.44 | |
| 4 | Afghanistan | AFG | 1994 | 0.220183 | 0.699898 | 0.111815 | 4.670810 | 0.43 | |

## Data Cleaning

```
#missing values in the dataset

data.isnull().sum()
```

```
Entity                                                                                     0
Code                                                                                     690
Year                                                                                       0
Schizophrenia disorders (share of population) - Sex: Both - Age: Age-standardized          0
Bipolar disorders (share of population) - Sex: Both - Age: Age-standardized                0
Eating disorders (share of population) - Sex: Both - Age: Age-standardized                 0
Anxiety disorders (share of population) - Sex: Both - Age: Age-standardized                0
Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent)              0
Depressive disorders (share of population) - Sex: Both - Age: Age-standardized             0
Prevalence - Alcohol use disorders - Sex: Both - Age: Age-standardized (Percent)           0
DALYs (Disability-Adjusted Life Years) - Mental disorders - Sex: Both - Age: All Ages (Percent)  0
dtype: int64
```

## Drop the Column

```
data.drop('Code', axis=1, inplace=True)
```

## View the data after dropping Code column

```
data.head(5)
```

| | Entity | Year | Schizophrenia disorders (share of population) - Sex: Both - Age: Age-standardized | Bipolar disorders (share of population) - Sex: Both - Age: Age-standardized | Eating disorders (share of population) - Sex: Both - Age: Age-standardized | Anxiety disorders (share of population) - Sex: Both - Age: Age-standardized | Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent) | Depres: disor( (shar( populat: - Sex: I - Age: / standard: |
|---|---|---|---|---|---|---|---|---|
| 0 | Afghanistan | 1990 | 0.223206 | 0.703023 | 0.127700 | 4.713314 | 0.45 | 4.99( |

## Dimesions of the merged dataframe

```
print('data size : ',data.size)
print('data shape ',data.shape)
```

```
data size :  68400
data shape  (6840, 10)
```

## Renaming the Columns

```
data.set_axis(['Country','Year','Schizophrenia','Bipolar_disorder','Eating_disorder','Anxiety','drug_usage','depression','alcohol',
```

```
<ipython-input-230-950118c2d406>:1: FutureWarning:

DataFrame.set_axis 'inplace' keyword is deprecated and will be removed in a future version. Use `obj = obj.set_axis(..., copy=
```

```
#dataframe after renaming the columns
data.head(5)
```

| | Country | Year | Schizophrenia | Bipolar_disorder | Eating_disorder | Anxiety | drug_usage | depressi |
|---|---|---|---|---|---|---|---|---|
| 0 | Afghanistan | 1990 | 0.223206 | 0.703023 | 0.127700 | 4.713314 | 0.45 | 4.9961 |
| 1 | Afghanistan | 1991 | 0.222454 | 0.702069 | 0.123256 | 4.702100 | 0.45 | 4.9892 |
| 2 | Afghanistan | 1992 | 0.221751 | 0.700792 | 0.118844 | 4.683743 | 0.44 | 4.9813 |
| 3 | Afghanistan | 1993 | 0.220987 | 0.700087 | 0.115089 | 4.673549 | 0.44 | 4.9769 |
| 4 | Afghanistan | 1994 | 0.220183 | 0.699898 | 0.111815 | 4.670810 | 0.43 | 4.9777 |

## Information about the dataframe

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6840 entries, 0 to 6839
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Country           6840 non-null   object
 1   Year              6840 non-null   int64
 2   Schizophrenia     6840 non-null   float64
 3   Bipolar_disorder  6840 non-null   float64
 4   Eating_disorder   6840 non-null   float64
 5   Anxiety           6840 non-null   float64
 6   drug_usage        6840 non-null   float64
 7   depression        6840 non-null   float64
 8   alcohol           6840 non-null   float64
 9   mental_fitness    6840 non-null   float64
dtypes: float64(8), int64(1), object(1)
memory usage: 587.8+ KB
```

## Data Visualization

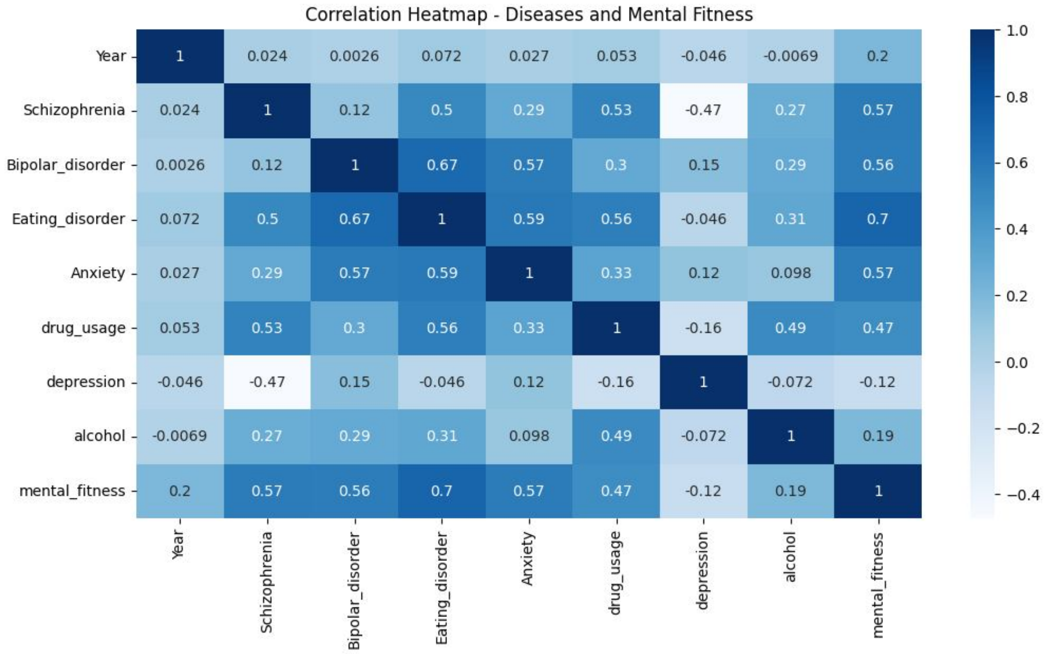
```
#VISUALISING THE CORRELATION HEATMAP OF DISEASES AND MENTAL FITNESS

plt.figure(figsize=(12,6))
sns.heatmap(data.corr(),annot=True,cmap='Blues')
```

```
plt.title('Correlation Heatmap - Diseases and Mental Fitness')
plt.show()
```

```
<ipython-input-233-80fd782051a3>:4: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will def
```

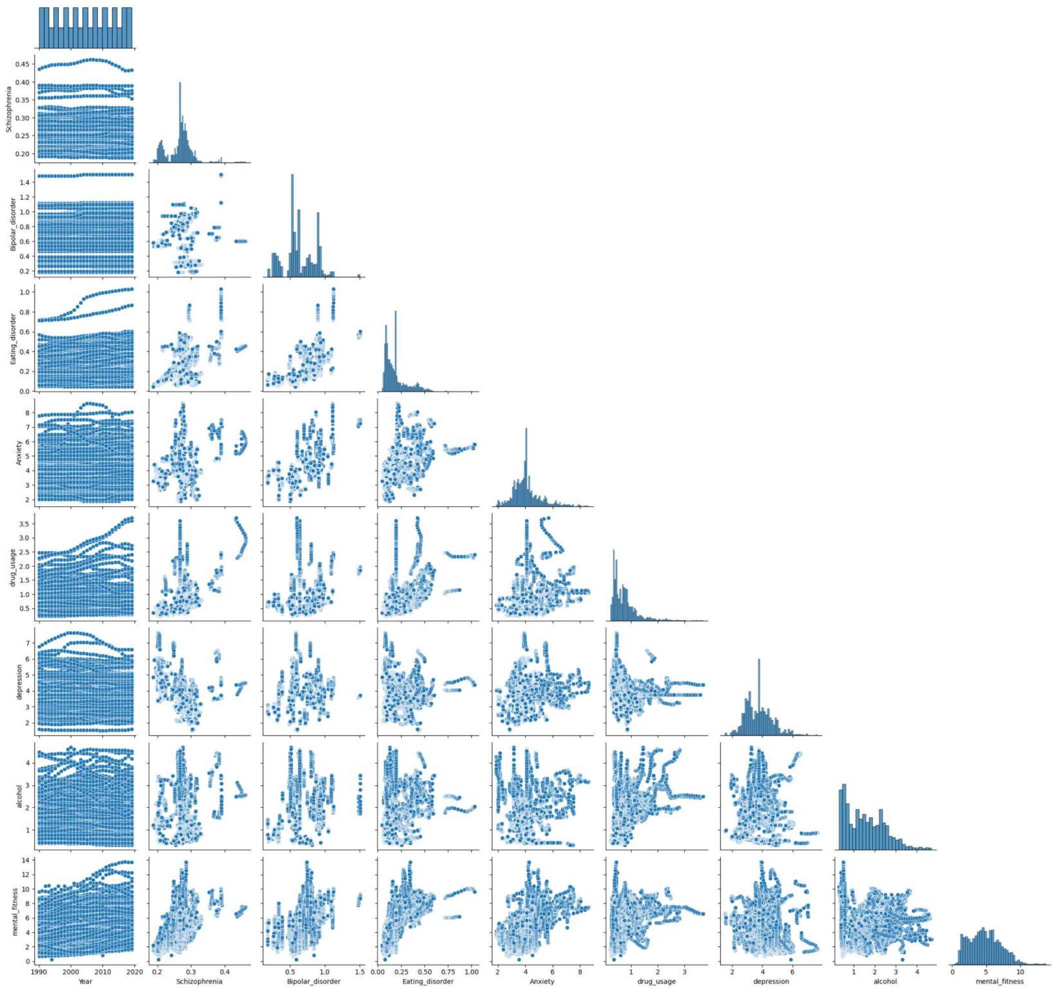



## Note:

- Eating disorder is positively correlated(0.7) observe in the above plot

## Pairwise relations in the dataset using pairplot()

```
sns.pairplot(data,corner=True)
plt.show()
```

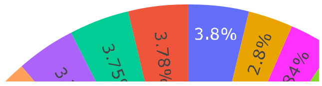



```
mean  = data['mental_fitness'].mean()
mean
```

    4.8180701754385975

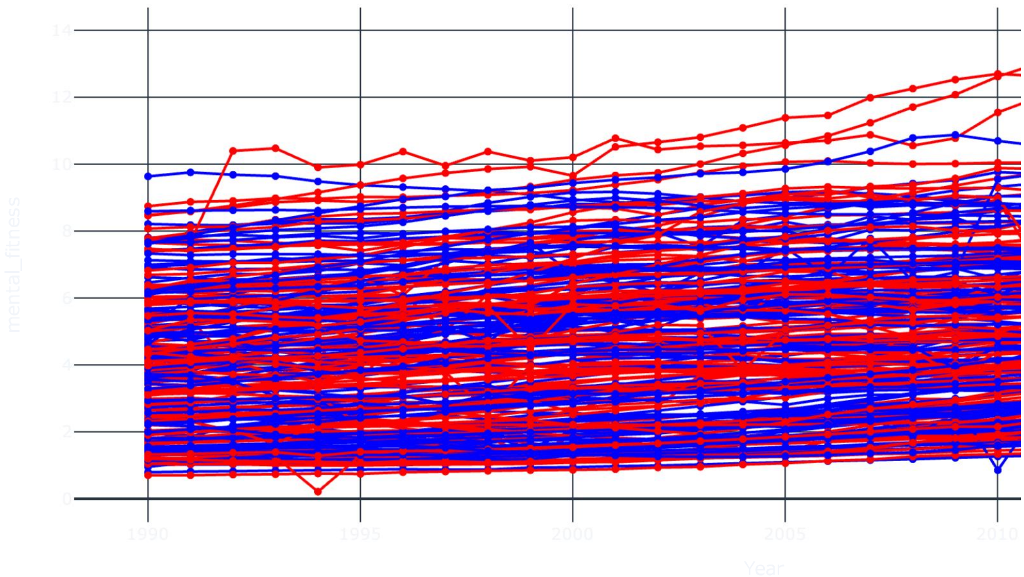
## Piechart representation of the data

```
fig = px.pie(data,values='mental_fitness',names='Year')
fig.show()
```




### *yearwise variations in mental_fitness of different countries*

```
fig = px.line(data,x="Year",y="mental_fitness",color='Country',markers=True,color_discrete_sequence=['red','blue'],template = 'plotl
fig.show()
```




## Transforming the non-numerical labels(objects) to numerical labels using encoders

```
from sklearn.preprocessing import LabelEncoder
l = LabelEncoder()
for i in data.columns:
  if data[i].dtype == 'object':
    data[i]=l.fit_transform(data[i])
```

```
df = data
df.shape
```

```
(6840, 10)
```

## Splitting the data into training and testing datsets

```
X = df.drop('mental_fitness',axis=1)
y = df['mental_fitness']
```

```
x_train,x_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=2)
```

```
print('shapes of training and testing datasets\n')
print('x_train : ',x_train.shape)
print('y_train : ',y_train.shape)
print('x_test : ',x_test.shape)
print('y_train : ',y_test.shape)
```

```
shapes of training and testing datasets

x_train :  (4788, 9)
y_train :  (4788,)
```

```
x_test :  (2052, 9)
y_train :  (2052,)
```

### NOTE:

- We usally take data 80% for training and 20% for testing

# Model Trainig

## FIT THE LINEAR REGRESSION MODEL

```
lr = LinearRegression()
lr.fit(x_train,y_train)

y_predict = lr.predict(x_train) #Predicting the y based on training
mse = mean_squared_error(y_train,y_predict) #difference blw observed value and predicted value
rmse = np.sqrt(mse) #differenct blw predicted and actual values
r2 = r2_score(y_train,y_predict)
print("Linear Regression Model Performance : \n")
print("MSE : {}".format(mse))
print("RMSE : {}".format(rmse))
print("r2 : {}".format(r2))
```

```
Linear Regression Model Performance :

MSE : 1.8740231363002033
RMSE : 1.368949647101822
r2 : 0.6534965515777855
```

## FIT THE LASSO REGRESSION MODEL

```
from sklearn.linear_model import  Lasso
ls = Lasso(alpha=0.5)
ls.fit(x_train, y_train)
y_predict2 = ls.predict(x_train) #Predicting the y based on training
mse = mean_squared_error(y_train,y_predict2) #difference blw observed value and predicted value
rmse = np.sqrt(mse) #differenct blw predicted and actual values
r2 = r2_score(y_train,y_predict2)
print("  Lasso Regression Model Performance : \n")
print("MSE : {}".format(mse))
print("RMSE : {}".format(rmse))
print("r2 : {}".format(r2))
```

```
  Lasso Regression Model Performance :

MSE : 3.735273992919651
RMSE : 1.932685694291664
r2 : 0.30935467429515284
```

## FIT THE RANDOM FOREST REGRESSION MODEL

```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf.fit(x_train,y_train)

y_predict3 = rf.predict(x_train)#Predicting the y based on training
mse = mean_squared_error(y_train,y_predict3) #difference blw observed value and predicted value
rmse = np.sqrt(mse) #differenct blw predicted and actual values
r2 = r2_score(y_train,y_predict3)
print(" Random Forest Regression Model Performance : \n")
print("MSE : {}".format(mse))
print("RMSE : {}".format(rmse))
print("r2 : {}".format(r2))
```

```
 Random Forest Regression Model Performance :

MSE : 0.005477180482456138
RMSE : 0.07400797580299125
r2 : 0.9989872793520849
```

## Note

- The most precise model is: Random Forest Regression
- The least precise model is: Lasso Regression