Exploratory Data Analysis (EDA)

Problem statement : Perform an EDA and also Write your observations as you explore

Theory

Exploratory Data Analysis is a process of examining or understanding the data and extracting insights or main characteristics of the data.

EDA is generally classified into two methods, i.e. graphical analysis and non-graphical analysis.

EDA is very essential because it is a good practice to first understand the problem statement and the various relationships between the data features before getting your hands dirty.

Technically, The primary motive of EDA is to

1. Examine the data distribution
2. Handling missing values of the dataset(a most common issue with every dataset)
3. Handling the outliers
4. Removing duplicate data
5. Encoding the categorical variables
6. Normalizing and Scaling

First, we will import all the python libraries that are required for this, which include NumPy for numerical calculations and scientific computing, Pandas for handling data, and Matplotlib and Seaborn for visualization.

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

df = pd.read_csv("2015.csv")
```

We can observe the dataset by checking a few of the rows using the head() method, which returns the first five records from the dataset.

```
df.head()

       Country          Region  Happiness Rank  Happiness Score  \
0  Switzerland  Western Europe               1            7.587
1      Iceland  Western Europe               2            7.561
2      Denmark  Western Europe               3            7.527
3       Norway  Western Europe               4            7.522
4       Canada   North America               5            7.427

   Standard Error  Economy (GDP per Capita)   Family  \
0         0.03411                   1.39651  1.34951
1         0.04884                   1.30232  1.40223
2         0.03328                   1.32548  1.36058
```

```
3        0.03880                  1.45900  1.33095
4        0.03553                  1.32629  1.32261

   Health (Life Expectancy)  Freedom  Trust (Government Corruption)  \
0                   0.94143  0.66557                        0.41978
1                   0.94784  0.62877                        0.14145
2                   0.87464  0.64938                        0.48357
3                   0.88521  0.66973                        0.36503
4                   0.90563  0.63297                        0.32957

   Generosity  Dystopia Residual
0     0.29678            2.51738
1     0.43630            2.70201
2     0.34139            2.49204
3     0.34699            2.46531
4     0.45811            2.45176
```

```
df.isnull().sum()
```

```
Country                          0
Region                           0
Happiness Rank                   0
Happiness Score                  0
Standard Error                   0
Economy (GDP per Capita)         0
Family                           0
Health (Life Expectancy)         0
Freedom                          0
Trust (Government Corruption)    0
Generosity                       0
Dystopia Residual                0
dtype: int64
```

Our dataset doesn't have any null values now.

We can remove duplicate values using drop_duplicates()

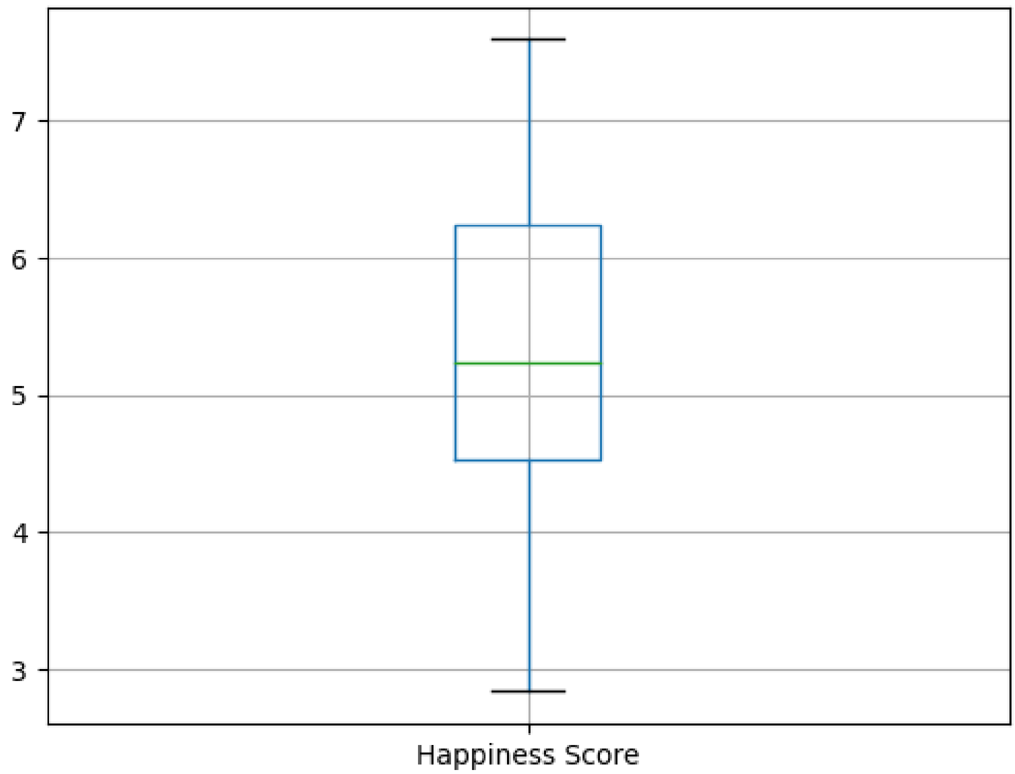
```
dup = df.duplicated()
print(dup.sum())
df[dup]

0

Empty DataFrame
Columns: [Country, Region, Happiness Rank, Happiness Score, Standard
Error, Economy (GDP per Capita), Family, Health (Life Expectancy),
Freedom, Trust (Government Corruption), Generosity, Dystopia Residual]
Index: []

dup.sum()
```

```
0
```

Handling the outliers in the data, i.e. the extreme values in the data. We can find the outliers in our data using a Boxplot.

```
df.boxplot(column=['Happiness Score'])
```

```
<Axes: >
```




```
from sklearn.preprocessing import StandardScaler
stdScale = StandardScaler()
stdScale
```

```
StandardScaler()
```

```
df.shape
```

```
(158, 12)
```

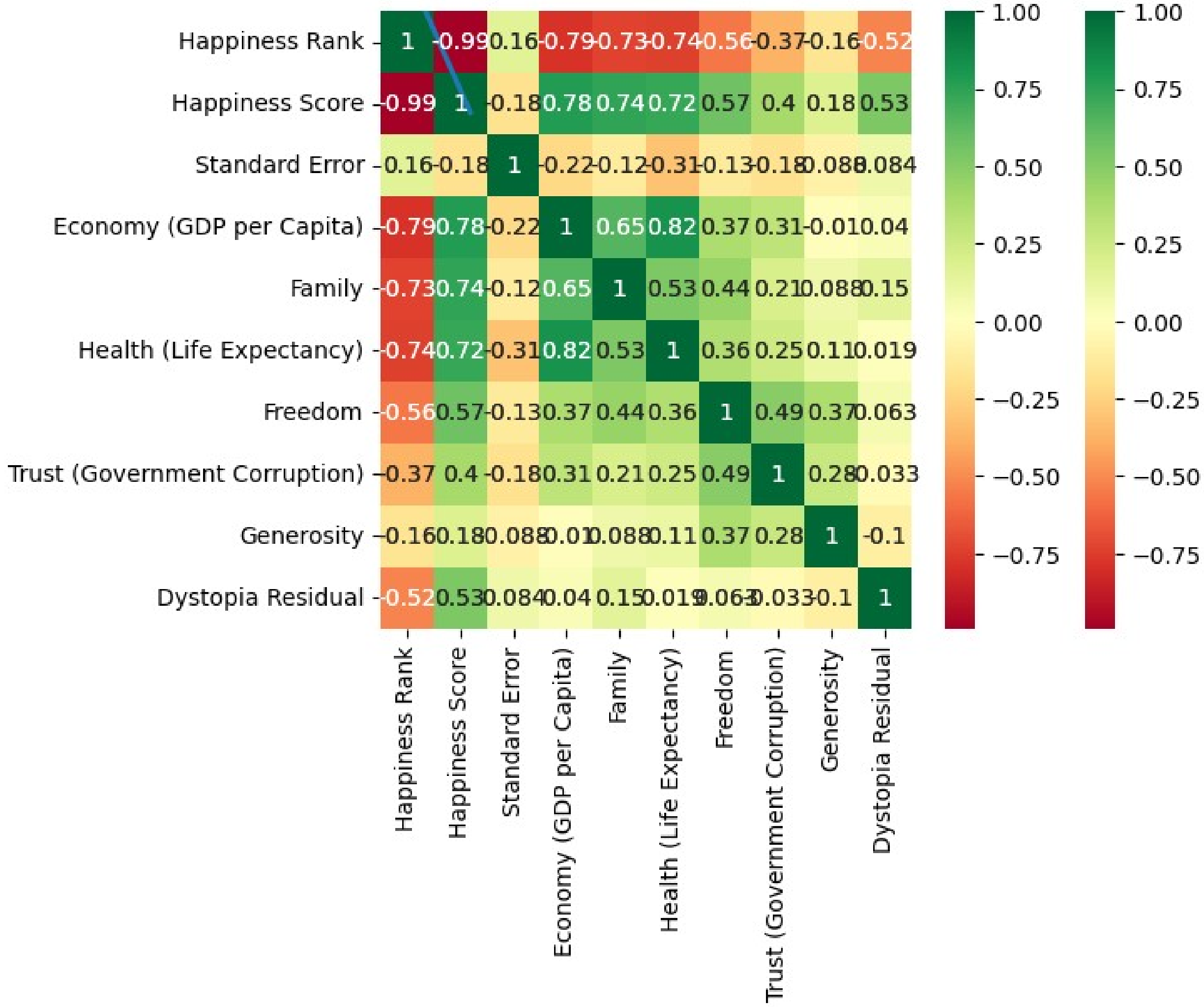
```
import seaborn as sns
```

```
df['Happiness Score'] = stdScale.fit_transform(df[['Happiness Score']])
```

```
df.head()
```

```
       Country          Region  Happiness Rank  Happiness Score  \
0  Switzerland  Western Europe               1         1.937360   
1      Iceland  Western Europe               2         1.914581   
2      Denmark  Western Europe               3         1.884792   
3       Norway  Western Europe               4         1.880411   
4       Canada   North America               5         1.797179   

   Standard Error  Economy (GDP per Capita)   Family  \
0         0.03411                   1.39651  1.34951   
1         0.04884                   1.30232  1.40223   
2         0.03328                   1.32548  1.36058   
3         0.03880                   1.45900  1.33095   
4         0.03553                   1.32629  1.32261   

   Health (Life Expectancy)  Freedom  Trust (Government Corruption)  \
0                   0.94143  0.66557                        0.41978   
1                   0.94784  0.62877                        0.14145   
2                   0.87464  0.64938                        0.48357   
3                   0.88521  0.66973                        0.36503   
4                   0.90563  0.63297                        0.32957   

   Generosity  Dystopia Residual  
0     0.29678            2.51738  
1     0.43630            2.70201  
2     0.34139            2.49204  
3     0.34699            2.46531  
4     0.45811            2.45176  
```

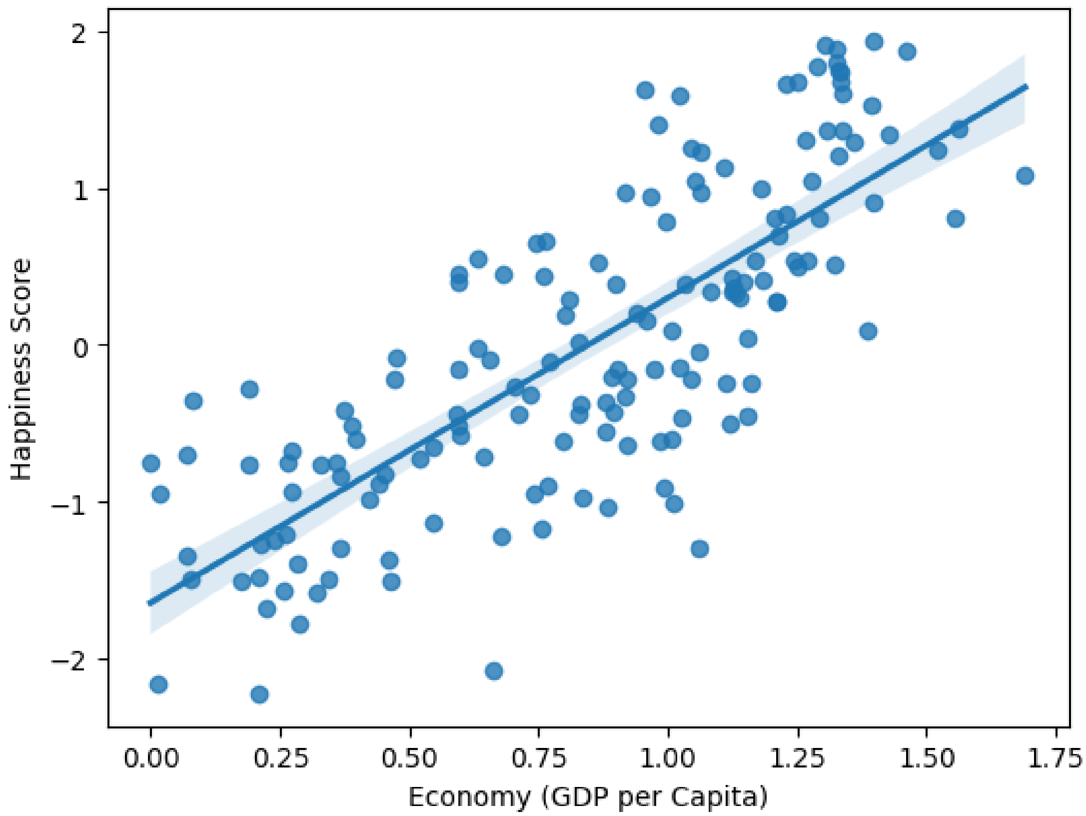
```python
sns.heatmap(df.corr(),annot=True,cmap='RdYlGn')
plt.show()
```



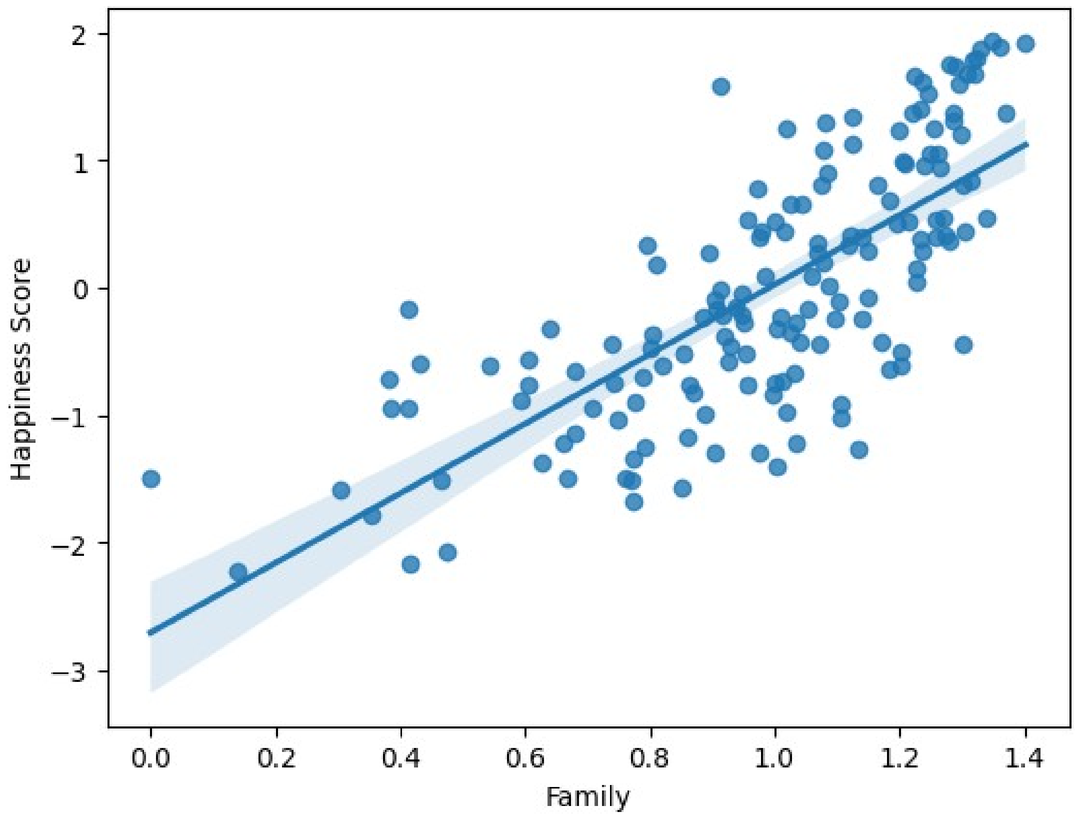
As we can observe from the above heatmap of correlations, there is a high correlation between –

- Happiness Score – Economy (GDP per Capita) = 0.78
- Happiness Score – Family = 0.74
- Happiness Score – Health (Life Expectancy) = 0.72
- Economy (GDP per Capita) – Health (Life Expectancy) = 0.82

```
sns.regplot(x='Economy (GDP per Capita)', y='Happiness Score',
data=df)
plt.show()
```




```
sns.regplot(x='Family', y='Happiness Score', data=df)
plt.show()
```



Conclusion

Both economic strength and family support appear to be positively correlated with happiness scores in the respective analyses. This suggests that these factors contribute to people's overall happiness.

The distribution of values indicates varying degrees of economic strength and family support perceptions.

Outliers may provide insights into exceptional cases where countries perform significantly better or worse in terms of economy and family support than the majority.

EDA on these datasets provides valuable insights to guide further analysis. Consideration of additional factors and more advanced analyses can help in building predictive models and understanding complex relationships that contribute to happiness scores.

In summary, EDA serves as the foundation for a comprehensive and meaningful data analysis process by providing insights into the data's characteristics and informing subsequent analytical decisions.