World Happiness Data Preprocessing Project

1. Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2. Importing Source Datasets

In [2]:
```
wh15 = pd.read_csv('wh_2015.csv')
wh16 = pd.read_csv('wh_2016.csv')
wh17 = pd.read_csv('wh_2017.csv')
```

3. Combining Datasets

In [3]:
```
df = pd.concat([wh15 , wh16 , wh17] , ignore_index = True)
```

In [4]:
```
df.head()
```

Out[4]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Generosity	Dystopia Residual	Yea
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0.66557	0.41978	0.29678	2.51738	201
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.62877	0.14145	0.43630	2.70201	201
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.64938	0.48357	0.34139	2.49204	201
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.66973	0.36503	0.34699	2.46531	201
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.63297	0.32957	0.45811	2.45176	201

4. Dimensions of the Dataset

In [5]:
```
print('Number of rows:' ,df.shape[0])
print('Number of columns:', df.shape[1])
```

```
Number of rows: 468
Number of columns: 17
```

5. Data types, Memory Usage , Null\Non-null Values

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 468 entries, 0 to 467
Data columns (total 17 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Country                        463 non-null    object 
 1   Region                         316 non-null    object 
 2   Happiness Rank                 468 non-null    int64  
 3   Happiness Score                468 non-null    float64
 4   Standard Error                 158 non-null    float64
 5   Economy (GDP per Capita)       468 non-null    float64
 6   Family                         419 non-null    float64
 7   Health (Life Expectancy)       468 non-null    float64
 8   Freedom                        468 non-null    float64
 9   Trust (Government Corruption)  468 non-null    float64
 10  Generosity                     468 non-null    float64
 11  Dystopia Residual              468 non-null    float64
 12  Year                           468 non-null    int64  
 13  Lower Confidence Interval      158 non-null    float64
 14  Upper Confidence Interval      158 non-null    float64
 15  Whisker high                   152 non-null    float64
 16  Whisker low                    152 non-null    float64
dtypes: float64(13), int64(2), object(2)
memory usage: 62.3+ KB
```

We can see that this method prints information of all columns. Several columns contain missing values. Either we have to drop them or replaced with a suitable test statistic.Lets investigate!

6. Handling Duplicates

In [7]:
```
print('Is there any duplicate value?' , df.duplicated(subset = ['Country' , ('Year')]).any())
```

```
Is there any duplicate value? False
```

Country name can be written like (nORWAY , NORWAY) to rectify this type of problem, we need to capitalize 'country' column

In [8]:
```
df['Country'] = df['Country'].str.upper()
df['Country']
```

Out[8]:
```
0      SWITZERLAND
1          ICELAND
2          DENMARK
3           NORWAY
4           CANADA
          ...
463        LIBERIA
464         GUINEA
465           TOGO
466         RWANDA
467          SYRIA
Name: Country, Length: 468, dtype: object
```

In [9]:
```
print('Is there any duplicate value?' , df.duplicated(subset = ['Country' , ('Year')]).any())
```

```
Is there any duplicate value? True
```

In [10]:
```
df[df.duplicated(subset = ['Country' , ('Year')])]
```

Out[10]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Generosity	Dystop Residu
255	SOMALILAND REGION	SUB-SAHARAN AFRICA	97	5.057	NaN	0.25558	0.75862	0.33108	0.3913	0.36794	0.51479	2.438(

In [11]:
```
df.drop_duplicates(subset = ['Year' , 'Country'] , inplace = True)
```

In [12]:
```
print('Is there any duplicate value?' , df.duplicated(subset = ['Country' , ('Year')]).any())
```

```
Is there any duplicate value? False
```

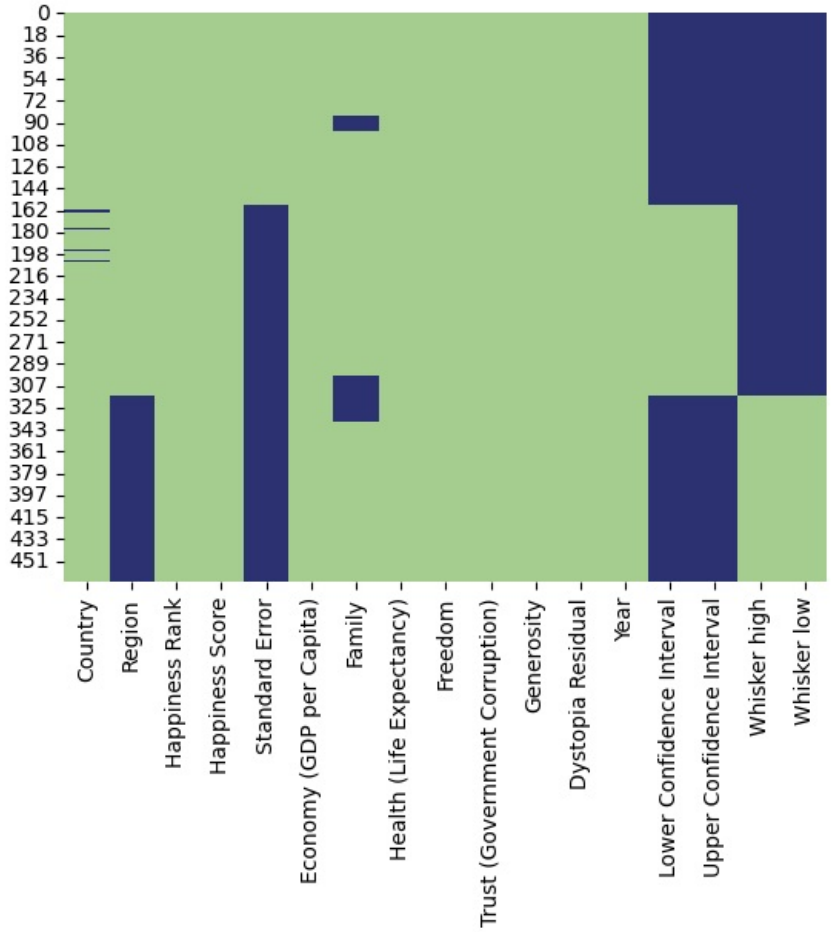
We can see that there is no duplicate value left in the dataset

Handling Null / Missing Values

In [13]:
```
print('Is there any Null value?' , df.isnull().sum().any())
```

```
Is there any Null value? True
```

In [14]:
```
sns.heatmap(df.isnull() , cmap = 'crest' , cbar = False)
plt.show()
```



We can see that there are many null values in 'Country', 'Region', 'Standard Error', 'Family', 'Lower Conf Interval', 'Upper Conf Interval' columns

Finding Null values percentage

In [15]:
```
null_perc = (df.isnull().mean() * 100).sort_values(ascending = False)
null_perc
```

Out[15]:
```
Whisker low                     67.451820
Whisker high                    67.451820
Upper Confidence Interval       66.381156
Lower Confidence Interval       66.381156
Standard Error                  66.167024
Region                          32.548180
Family                          10.492505
Country                          1.070664
Health (Life Expectancy)         0.000000
Trust (Government Corruption)    0.000000
Generosity                       0.000000
Dystopia Residual                0.000000
Year                             0.000000
Economy (GDP per Capita)         0.000000
Happiness Score                  0.000000
Happiness Rank                   0.000000
Freedom                          0.000000
dtype: float64
```

Dropping columns having high perc of null values

In [16]:
```
null_perc.index[:5]
```

Out[16]:
```
Index(['Whisker low', 'Whisker high', 'Upper Confidence Interval',
       'Lower Confidence Interval', 'Standard Error'],
      dtype='object')
```

In [17]:
```
df.drop(null_perc.index[:5], axis = 1 , inplace  = True)
```

Checking columns with lower percentage of missingness

In [18]:
```
df.isnull().sum().sort_values(ascending = False)
```

Out[18]:
```
Region                             152
Family                              49
Country                              5
Happiness Rank                       0
Happiness Score                      0
Economy (GDP per Capita)             0
Health (Life Expectancy)             0
Freedom                              0
Trust (Government Corruption)        0
Generosity                           0
Dystopia Residual                    0
Year                                 0
dtype: int64
```

Dealing with Categorical Values

Target column: 'Country'

In [19]:
```
df[df['Country'].isnull()]
```

Out[19]:

	Country	Region	Happiness Rank	Happiness Score	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Generosity	Dystopia Residual	Year
162	NaN	Western Europe	5	7.413	1.40598	1.13464	0.81091	0.57104	0.41004	0.25492	2.82596	0
163	NaN	Western Europe	6	7.404	1.44015	1.09610	0.82760	0.57370	0.31329	0.44834	2.70485	1
177	NaN	Latin America and Caribbean	20	6.871	1.69752	1.03999	0.84542	0.54870	0.35329	0.27571	2.11055	2
195	NaN	Middle East and Northern Africa	38	6.355	1.05266	0.83309	0.61804	0.21006	0.16157	0.07044	3.40904	3
203	NaN	Central and Eastern Europe	46	6.068	0.87370	0.80975	0.59600	0.37269	0.10613	0.08877	3.22134	4

We can see that above shown rows have missing data in 'Country' column

Dropping those rows

In [20]:
```
df.dropna(subset = ['Country'] , how = 'any' , inplace = True)
```

Dropping row disturbs indexing so we are reseting index number

In [21]:
```
df.reset_index(drop = True , inplace = True)
```

Target column: 'Region'

In [22]:
```
df[df['Region'].isnull()]
```

Out[22]:

	Country	Region	Happiness Rank	Happiness Score	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Generosity	Dystopia Residual	Year
310	NORWAY	NaN	1	7.537	1.616463	NaN	0.796667	0.635423	0.362012	0.315964	2.277027	2017
311	DENMARK	NaN	2	7.522	1.482383	NaN	0.792566	0.626007	0.355280	0.400770	2.313707	2017
312	ICELAND	NaN	3	7.504	1.480633	NaN	0.833552	0.627163	0.475540	0.153527	2.322715	2017
313	SWITZERLAND	NaN	4	7.494	1.564980	NaN	0.858131	0.620071	0.290549	0.367007	2.276716	2017
314	FINLAND	NaN	5	7.469	1.443572	NaN	0.809158	0.617951	0.245483	0.382612	2.430182	2017
...	...	...	...	...	...	...	...	...	...	...	...	...
457	LIBERIA	NaN	148	3.533	0.119042	0.872118	0.229918	0.332881	0.266550	0.038948	1.673286	2017
458	GUINEA	NaN	149	3.507	0.244550	0.791245	0.194129	0.348588	0.264815	0.110938	1.552312	2017
459	TOGO	NaN	150	3.495	0.305445	0.431883	0.247106	0.380426	0.196896	0.095665	1.837229	2017
460	RWANDA	NaN	151	3.471	0.368746	0.945707	0.326425	0.581844	0.252756	0.455220	0.540061	2017
461	SYRIA	NaN	152	3.462	0.777153	0.396103	0.500533	0.081539	0.493664	0.151347	1.061574	2017

152 rows × 12 columns

There are 152 rows having 'NaN' values in the dataset.

Lets impute them with appropriate regions.

In [23]:
```
df2 = pd.read_csv('region.csv')
```

In [24]:
```
df2.head()
```

Out[24]:

	Country	Region
0	SWITZERLAND	Western Europe
1	ICELAND	Western Europe
2	DENMARK	Western Europe
3	NORWAY	Western Europe
4	CANADA	North America

In [25]:
```
left_table = df['Country']
right_table = df2
```

In [26]:
```
pd.merge(left = left_table , right = right_table, on = 'Country' , how = 'inner')
```

Out[26]:

	Country	Region
0	SWITZERLAND	Western Europe
1	SWITZERLAND	Western Europe
2	SWITZERLAND	Western Europe
3	ICELAND	Western Europe
4	ICELAND	Western Europe
...	...	...
459	SOMALIA	Sub-Saharan Africa
460	NAMIBIA	Sub-Saharan Africa
461	NAMIBIA	Sub-Saharan Africa
462	SOUTH SUDAN	Sub-Saharan Africa
463	SOUTH SUDAN	Sub-Saharan Africa

464 rows × 2 columns

In [27]:
```
region = pd.merge(left = left_table , right = right_table, \
                  on = 'Country' , how = 'inner')['Region']

region
```

Out[27]:
```
0          Western Europe
1          Western Europe
2          Western Europe
3          Western Europe
4          Western Europe
              ...
459    Sub-Saharan Africa
460    Sub-Saharan Africa
461    Sub-Saharan Africa
462    Sub-Saharan Africa
463    Sub-Saharan Africa
Name: Region, Length: 464, dtype: object
```

In [28]:
```
df['Region'] = region
df['Region']
```

Out[28]:
```
0                  Western Europe
1                  Western Europe
2                  Western Europe
3                  Western Europe
4                  Western Europe
                   ...
457    Latin America and Caribbean
458             Sub-Saharan Africa
459             Sub-Saharan Africa
460             Sub-Saharan Africa
461             Sub-Saharan Africa
Name: Region, Length: 462, dtype: object
```

In [29]:
```
df.isnull().sum().sort_values(ascending = False)
```

Out[29]:
```
Family                           49
Country                           0
Region                            0
Happiness Rank                    0
Happiness Score                   0
Economy (GDP per Capita)          0
Health (Life Expectancy)          0
Freedom                           0
Trust (Government Corruption)     0
Generosity                        0
Dystopia Residual                 0
Year                              0
dtype: int64
```

There is no null value left in 'Country' , 'Region' Column.

Now, Dealing with Numerical Values

Target Column: 'Family'

Finding skewness Co efficient

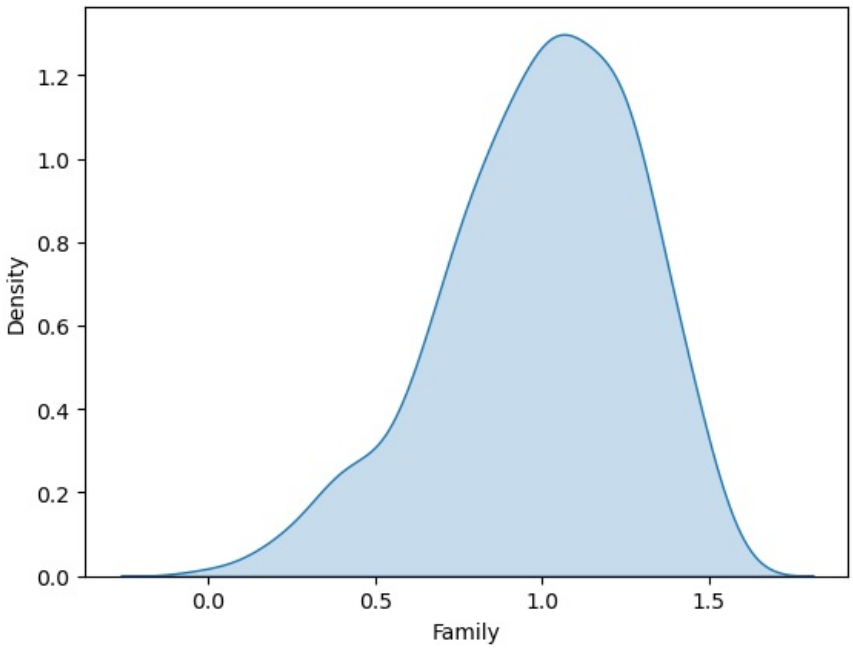
In [30]:
```
df['Family'].skew()
```

Out[30]:
```
-0.575432431765158
```

Checking skewness by Graph

In [31]:
```
sns.kdeplot(df['Family'] , \
            fill = True)

plt.show()
```



we can see that the distribution of values is approximately normal,

so we are imputing missing values with a mean value.

In [32]:
```
fam_mean = df['Family'].mean()
fam_mean
```

Out[32]:
```
0.9910465390024213
```

In [33]:
```
df['Family'] = df['Family'].fillna(df['Family'].skew())
df['Family']
```

Out[33]:
```
0      1.349510
1      1.402230
2      1.360580
3      1.330950
4      1.322610
         ...
457    0.872118
458    0.791245
459    0.431883
460    0.945707
461    0.396103
Name: Family, Length: 462, dtype: float64
```

In [34]:
```
df.isnull().sum().sort_values(ascending = False)
```

Out[34]:
```
Country                          0
Region                           0
Happiness Rank                   0
Happiness Score                  0
Economy (GDP per Capita)         0
Family                           0
Health (Life Expectancy)         0
Freedom                          0
Trust (Government Corruption)    0
Generosity                       0
Dystopia Residual                0
Year                             0
dtype: int64
```

Now, when we look at our data, we can see that there are no missing or null values.

This concludes the data preprocessing for World Happiness Datasets

In [ ]: