Lucy Lee, Robin Wixom | IMT 575 | Winter 2023

Happiness Around the World Project

Import Libraries

In [ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import cv2
from google.colab import files
from IPython.display import Image
from sklearn import model_selection, metrics
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
warnings.filterwarnings('ignore')
%matplotlib inline
```

Data Understanding

In [ ]:
```
# Working in Google Colab
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:
```
# Change Directory within Google Drive
import os
os.chdir("/content/drive/My Drive/Colab Notebooks/IMT-575")
```

In [ ]:
```
# Read Data
df = pd.read_csv('2019.csv')
df.head()
```

Out[ ]:

	Overall rank	Country or region	Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption
0	1	Finland	7.769	1.340	1.587	0.986	0.596	0.153	0.393
1	2	Denmark	7.600	1.383	1.573	0.996	0.592	0.252	0.410
2	3	Norway	7.554	1.488	1.582	1.028	0.603	0.271	0.341
3	4	Iceland	7.494	1.380	1.624	1.026	0.591	0.354	0.118
4	5	Netherlands	7.488	1.396	1.522	0.999	0.557	0.322	0.298

In [ ]:
```
# Data Information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 156 entries, 0 to 155
Data columns (total 9 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Overall rank                  156 non-null    int64  
 1   Country or region             156 non-null    object 
 2   Score                         156 non-null    float64
 3   GDP per capita                156 non-null    float64
 4   Social support                156 non-null    float64
 5   Healthy life expectancy       156 non-null    float64
 6   Freedom to make life choices  156 non-null    float64
 7   Generosity                    156 non-null    float64
 8   Perceptions of corruption     156 non-null    float64
dtypes: float64(7), int64(1), object(1)
memory usage: 11.1+ KB
```

In [ ]:
```
# Structure Check
df.shape
```

Out[ ]:
```
(156, 9)
```

In [ ]:
```
# Statistics
df.describe()
```

Out[ ]:

	Overall rank	Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption
count	156.000000	156.000000	156.000000	156.000000	156.000000	156.000000	156.000000	156.000000
mean	78.500000	5.407096	0.905147	1.208814	0.725244	0.392571	0.184846	0.110603
std	45.177428	1.113120	0.398389	0.299191	0.242124	0.143289	0.095254	0.094538
min	1.000000	2.853000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	39.750000	4.544500	0.602750	1.055750	0.547750	0.308000	0.108750	0.047000
50%	78.500000	5.379500	0.960000	1.271500	0.789000	0.417000	0.177500	0.085500
75%	117.250000	6.184500	1.232500	1.452500	0.881750	0.507250	0.248250	0.141250
max	156.000000	7.769000	1.684000	1.624000	1.141000	0.631000	0.566000	0.453000

In [ ]:
```
# Remove Unnecessary Columns
df.drop('Overall rank', axis = 1, inplace = True)
```

In [ ]:
```
# Rename Columns
df.rename(columns = {'Country or region': 'Country',
                     'Score': 'Happiness Score',
                     'Perceptions of corruption': 'Absence of corruption'},
                     inplace = True)
df.head()
```

Out[ ]:

	Country	Happiness Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Absence of corruption
0	Finland	7.769	1.340	1.587	0.986	0.596	0.153	0.393
1	Denmark	7.600	1.383	1.573	0.996	0.592	0.252	0.410
2	Norway	7.554	1.488	1.582	1.028	0.603	0.271	0.341
3	Iceland	7.494	1.380	1.624	1.026	0.591	0.354	0.118
4	Netherlands	7.488	1.396	1.522	0.999	0.557	0.322	0.298

In [73]:
```
# Check Column Names
column_names = df.columns
```

```
print(column_names)
```

```
Index(['Country', 'Happiness Score', 'GDP per capita', 'Social support',
       'Healthy life expectancy', 'Freedom to make life choices', 'Generosity',
       'Absence of corruption'],
      dtype='object')
```

Correlation Matrix

In [64]:

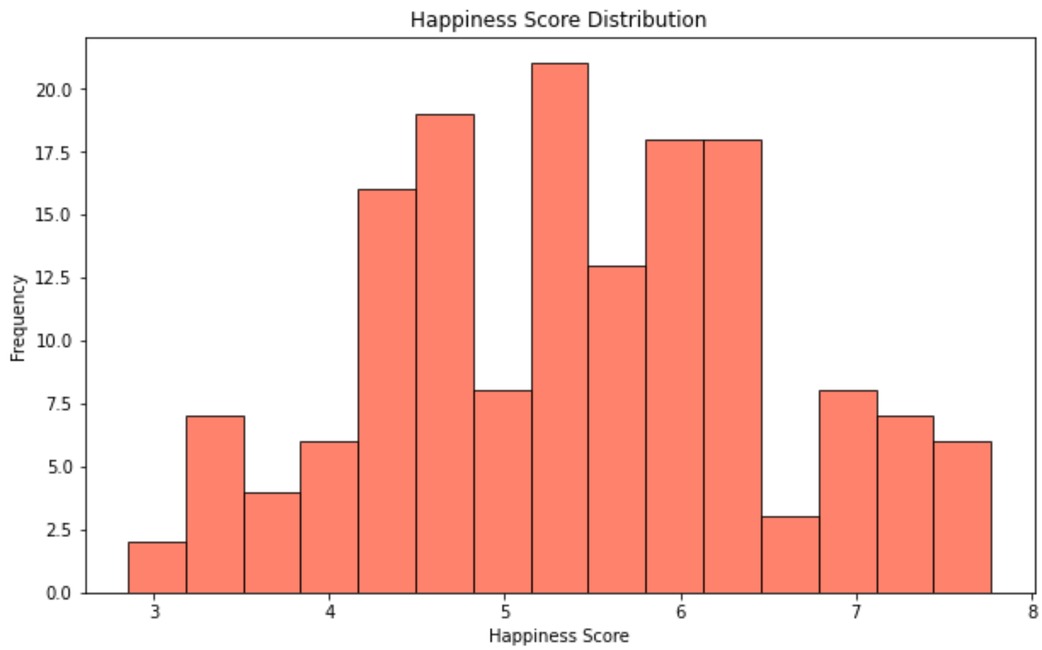
```
# Set Figure Size
plt.figure(figsize = (10, 10))

# Plot the Correlation Matrix
cmap = sns.diverging_palette(1, 200, as_cmap = True)
sns.heatmap(df.corr(), cmap = cmap,
            annot = True, linewidths = 0.1)
plt.show()
```

Before conducting the analysis, we developed a heatmap to examine the correlation among the attributes. The heatmap revealed strong correlations between several features, where green represents positive correlations, and darker pink represents negative correlations.

In [82]:

```
# Set Figure Size
plt.figure(figsize = (10, 6))
```

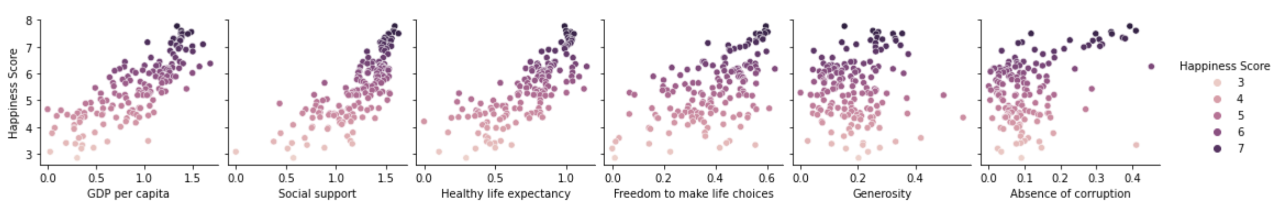
```python
# Overall Happiness Scores
plt.hist(df["Happiness Score"], bins = 15, edgecolor = 'k',
         color = 'tomato', alpha = 0.8)
plt.xlabel("Happiness Score")
plt.ylabel("Frequency")
plt.title("Happiness Score Distribution")
plt.show()
```



Pairwise Relationship

In [ ]:
```python
sns.pairplot(df,
             y_vars = ["Happiness Score"],
             x_vars = ["GDP per capita", "Social support",
                     "Healthy life expectancy",
                     "Freedom to make life choices",
                     "Generosity", "Absence of corruption"],
             hue = "Happiness Score")
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x7f0745dd7220>
```

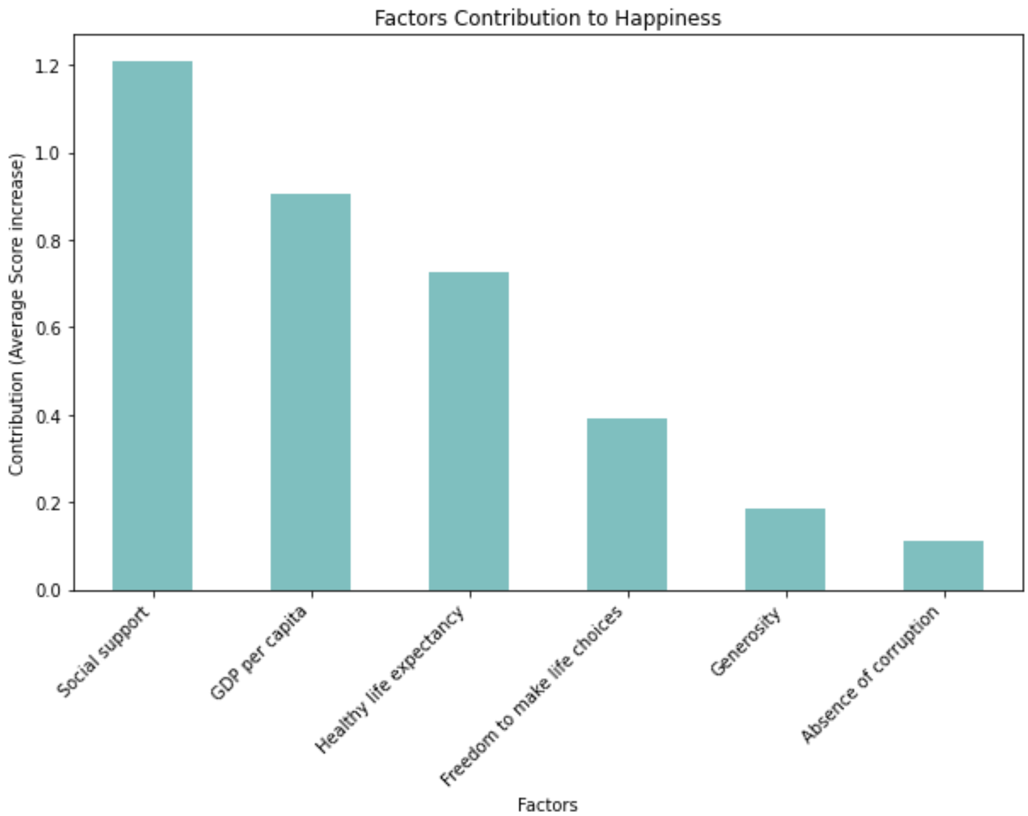


Gross Domestic Product (GDP), social support, and healthy life expectancy are the three factors that exhibit the strongest correlation with high happiness scores. In contrast, life choices, generosity, and perceptions of corruption are less strongly correlated with increased happiness scores.

Countries with higher scores tend to exhibit a correspondingly high GDP per capita. The presence of social support is a crucial contributor to happiness, while countries with lower healthy life expectancies are generally less happy. Additionally, while generosity is relatively common throughout, countries with lower happiness scores often display heightened levels of generosity. Finally, while perceived corruption is generally low, the countries with the highest levels of perceived corruption often exhibit higher levels of happiness.

Factors Contributing to High Happiness Score

In [61]:
```
# Set Figure Size
plt.figure(figsize = (10, 6))

# Plot the Chart
f_mean = df.mean().sort_values(ascending = False)
f_mean.iloc[1:].plot(kind = "bar", stacked = "True",
                     color = "Teal", alpha = 0.50,
                     linewidth = 2.5, fontsize = 10)
f_mean.index.name = "Factors"
plt.xticks(rotation = 45, ha = 'right')
plt.xlabel("Factors")
plt.ylabel("Contribution (Average Score increase)")
plt.title("Factors Contribution to Happiness")
plt.show()
```

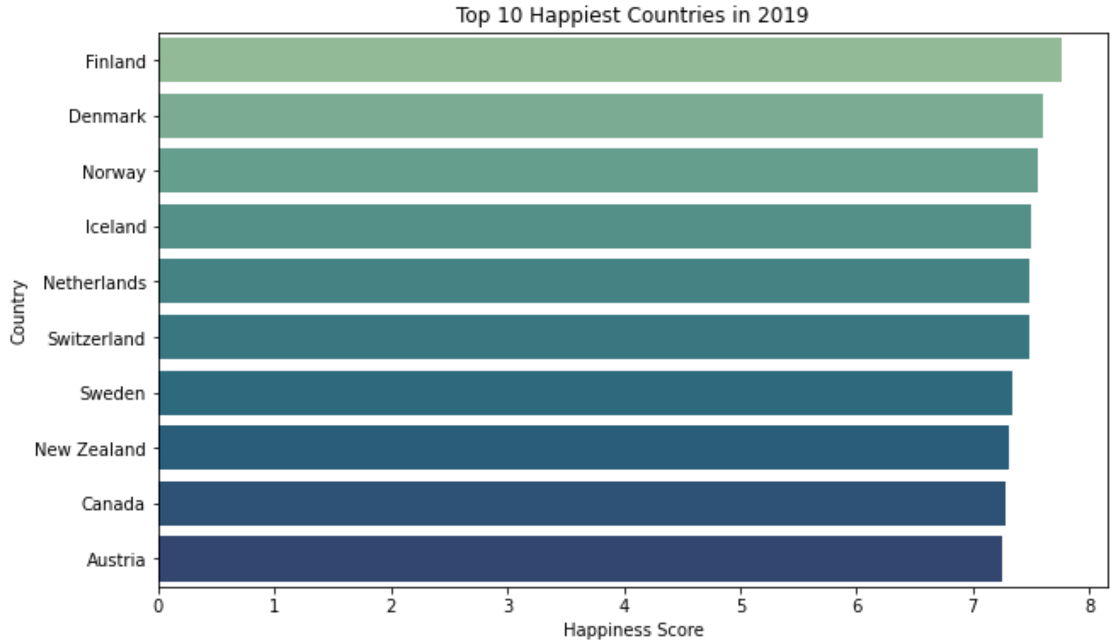


The most important factors to happiness, ranked in order of significance, are social support, GDP per capita, and life expectancy. Following closely are freedom to make life choices, generosity, and the absence of corruption.

Happiness Score Based On Countries

In [62]:
```
# Sort Data for Highest Happiness Countries
top_ten_score = df.nlargest(10, "Happiness Score")

# Set Figure Size
plt.figure(figsize = (10, 6))

# Plot Five Highest Scoring Countries in Happiness
sns.barplot(x = top_ten_score["Happiness Score"],
            y = top_ten_score["Country"], palette = "crest"
            ).set(title = "Top 10 Happiest Countries in 2019")
```

Out[62]:
```
[Text(0.5, 1.0, 'Top 10 Happiest Countries in 2019')]
```



In [ ]:

```
# Top Ten Happiness Scores
top_ten_score["Country"]
```

Out[ ]:

```
0        Finland
1        Denmark
2         Norway
3        Iceland
4    Netherlands
5    Switzerland
6         Sweden
7    New Zealand
8         Canada
9        Austria
Name: Country, dtype: object
```

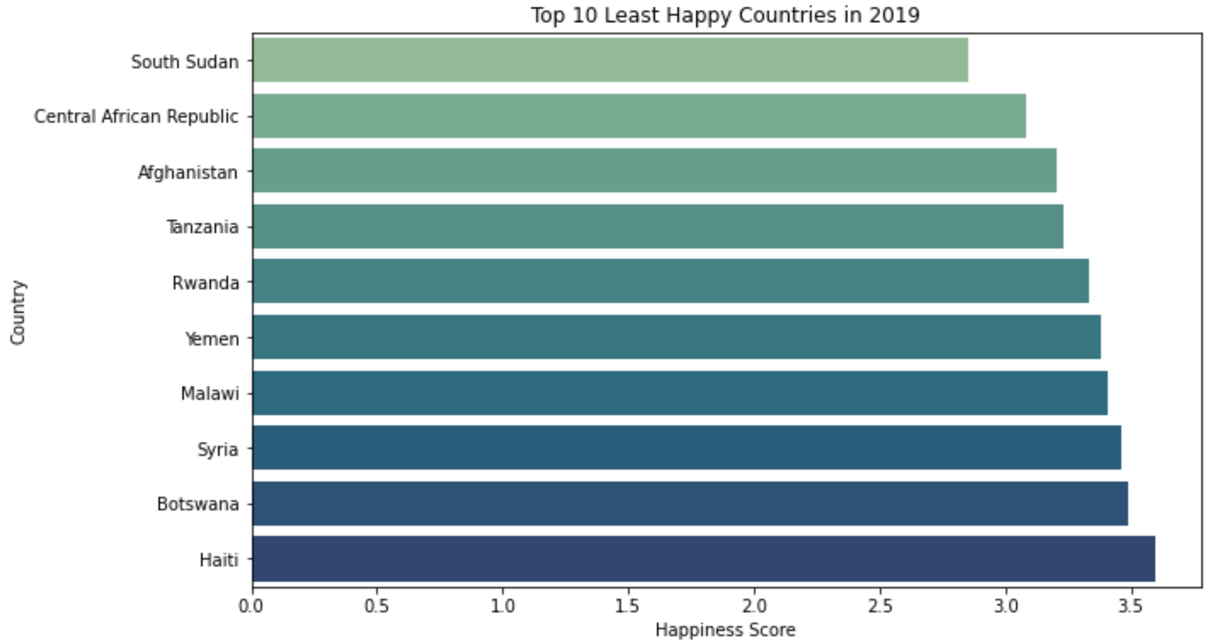
According to the 2019 World Happiness Report, the top 10 countries with the highest happiness scores are Finland, Denmark, Norway, Iceland, Netherlands, Switzerland, Sweden, New Zealand, Canada, and Austria.

In [63]:

```
# Sort Data for Lowest Happiness Countries
bottom_ten_score = df.nsmallest(10, "Happiness Score").sort_values(["Happiness Score"], ascending = True

# Set Figure Size
plt.figure(figsize = (10, 6))

# Plot Five Lowest Scoring Countries in Happiness
sns.barplot(x = bottom_ten_score["Happiness Score"],
            y = bottom_ten_score["Country"], palette = "crest"
           ).set(title = "Top 10 Least Happy Countries in 2019")
```

Out[63]:

```
[Text(0.5, 1.0, 'Top 10 Least Happy Countries in 2019')]
```



In [ ]:

```
# Low Ten Happiness Scores
bottom_ten_score["Country"]
```

Out[ ]:

```
155                South Sudan
154    Central African Republic
153                Afghanistan
152                   Tanzania
151                     Rwanda
150                      Yemen
149                     Malawi
148                      Syria
147                   Botswana
146                      Haiti
Name: Country, dtype: object
```

According to the 2019 World Happiness Report, South Sudan, the Central African Republic, Afghanistan, Tanzania, Rwanda, Yemen, Malawi, Syria, Botswana, and Haiti are the bottom ten countries with the lowest happiness scores.

Happiness Score Based On Geographic Location

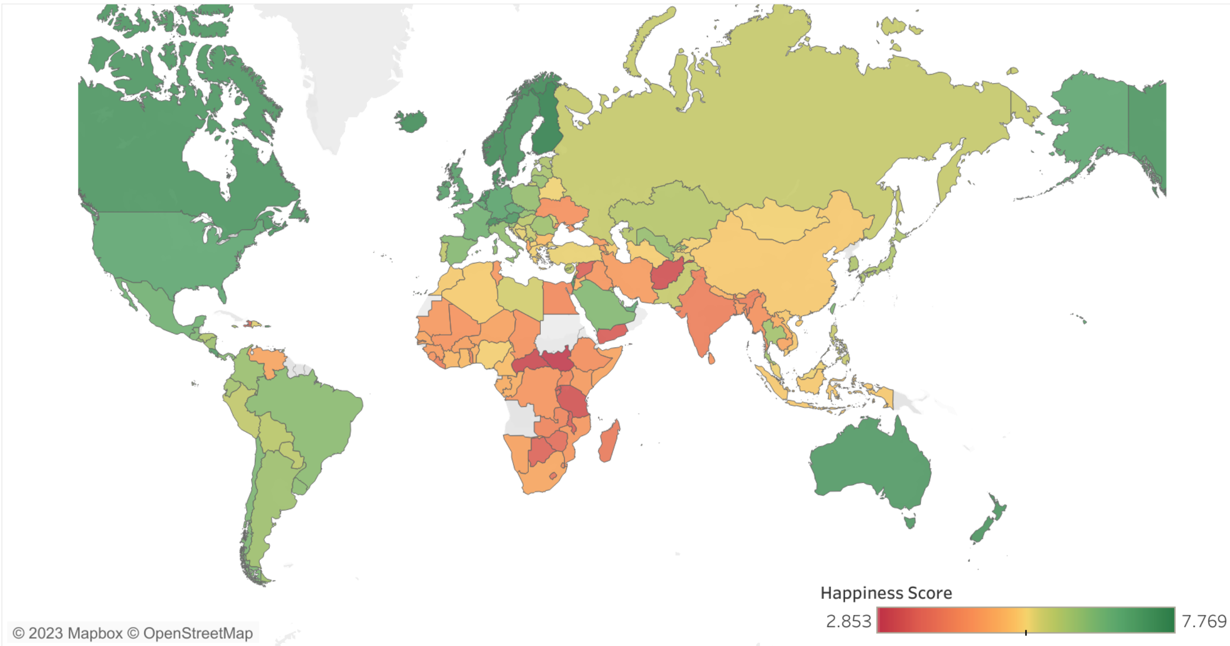
Next, we examined the happiness scores based on geographic location.

In [ ]:

```
Image('Dashboard 1.png', width = 800)
```

Out[ ]:

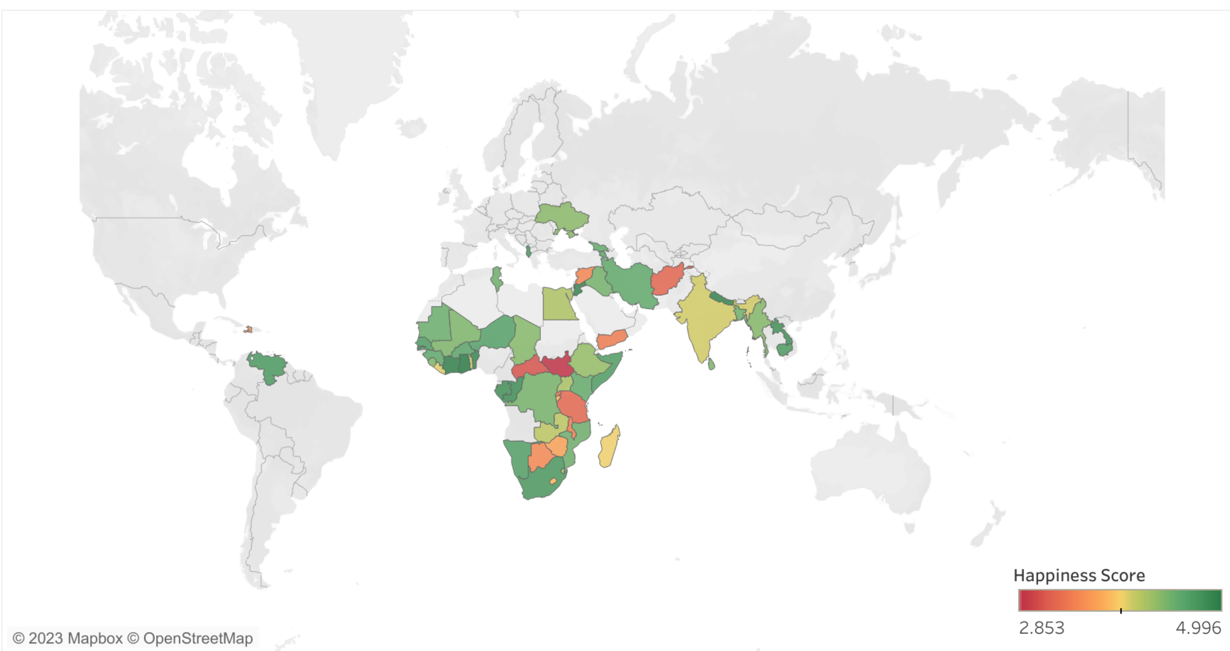
Happiness Score by Countries



In [ ]:
```
Image('Dashboard 2.png', width = 800)
```

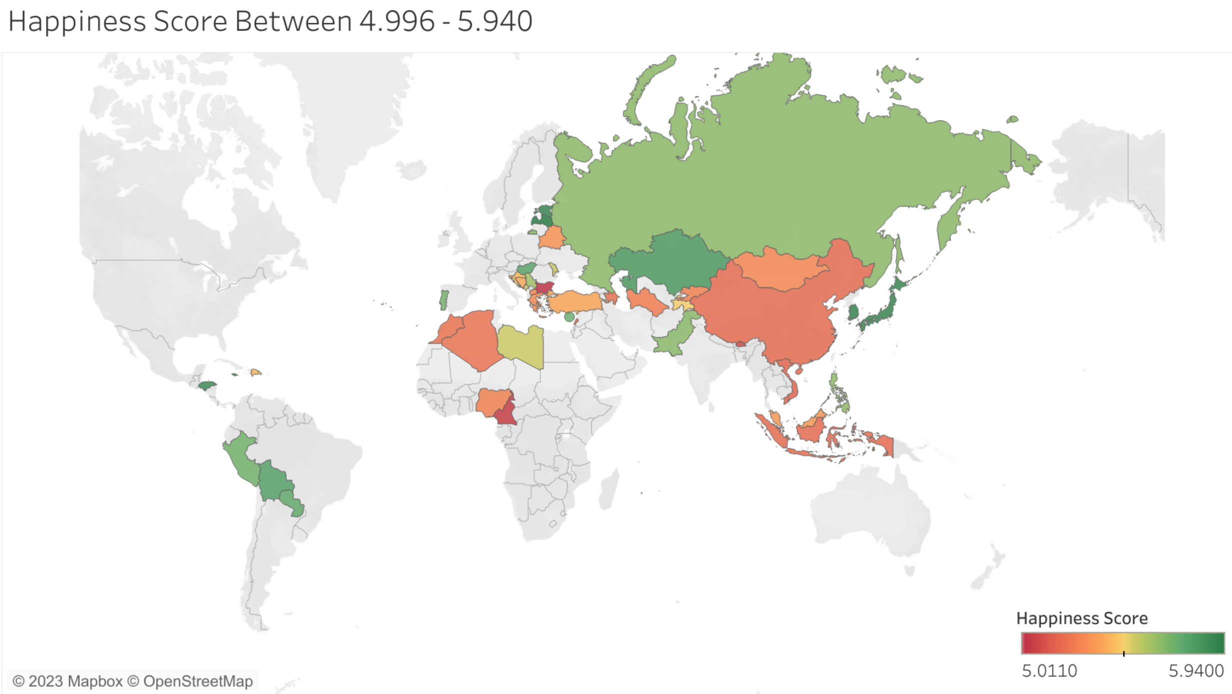
Out[ ]:

Lowest Happiness Score (< 4.996)



In [ ]:
```
Image('Dashboard 3.png', width = 800)
```

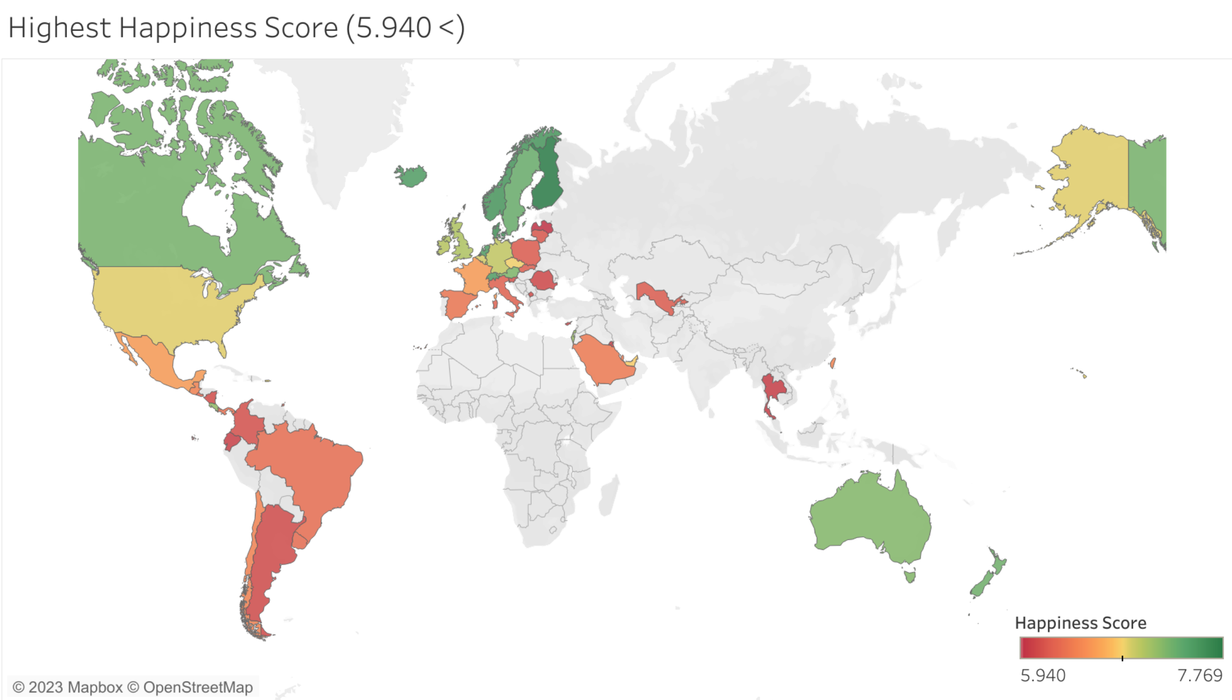
Out[ ]:



In [ ]:

```
Image('Dashboard 4.png', width = 800)
```

Out[ ]:



According to the map, a majority of the countries with lower happiness scores are in Africa, followed by Asia. In general, regions like North America, South America, Antarctica, Europe, and Australia scored higher than Africa and Asia in the happiness ranking.

Happiness Score Based On Economy

Looking at the table, there is a strong relationship between a country's GDP per capita (a measure of its economic output per person) and its happiness score.

In [ ]:
```
# Top Five Economy Score
df.sort_values(by = "GDP per capita", ascending = False).head()
```

Out[ ]:

	Country	Happiness Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Absence of corruption
28	Qatar	6.374	1.684	1.313	0.871	0.555	0.220	0.167
13	Luxembourg	7.090	1.609	1.479	1.012	0.526	0.194	0.316
33	Singapore	6.262	1.572	1.463	1.141	0.556	0.271	0.453
20	United Arab Emirates	6.825	1.503	1.310	0.825	0.598	0.262	0.182
50	Kuwait	6.021	1.500	1.319	0.808	0.493	0.142	0.097

In [ ]:
```
# Lowest Five Economy Score
df.sort_values(by = "GDP per capita").head()
```

Out[ ]:

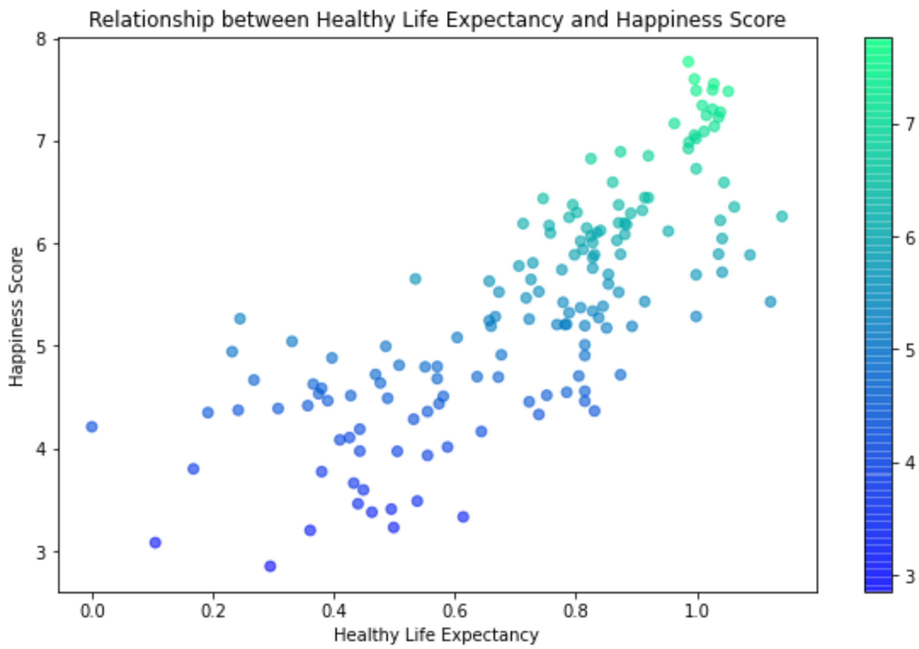
	Country	Happiness Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Absence of corruption
111	Somalia	4.668	0.000	0.698	0.268	0.559	0.243	0.270
154	Central African Republic	3.083	0.026	0.000	0.105	0.225	0.235	0.035
144	Burundi	3.775	0.046	0.447	0.380	0.220	0.176	0.180
140	Liberia	3.975	0.073	0.922	0.443	0.370	0.233	0.033
126	Congo (Kinshasa)	4.418	0.094	1.125	0.357	0.269	0.212	0.053

For instance, the four countries with the lowest GDP per capita in the table (Somalia, Central African Republic, Burundi, and Liberia) also have some of the lowest happiness scores. In contrast, countries with higher GDP per capita, such as Qatar, Luxembourg, Singapore, United Arab Emirates, and Kuwait, tend to have higher happiness scores.

This suggests a correlation between a country's economic prosperity and the happiness of its citizens. However, it's worth noting that GDP per capita is just one factor that can affect a country's overall happiness, and the relationship is not always straightforward.

Happiness Score Based on Healthy Life Expectancy

In [106…
```
# Set Figure Size
plt.figure(figsize = (10, 6))

# Define Colors
cmap = plt.cm.get_cmap('winter')

# Plot the Chart
plt.scatter(df["Healthy life expectancy"], df["Happiness Score"],
            alpha = 0.6, c = df["Happiness Score"], cmap = cmap)
plt.xlabel("Healthy Life Expectancy")
plt.ylabel("Happiness Score")
plt.title("Relationship between Healthy Life Expectancy and Happiness Score")

# Add Legend
cbar = plt.colorbar()
plt.show()
```

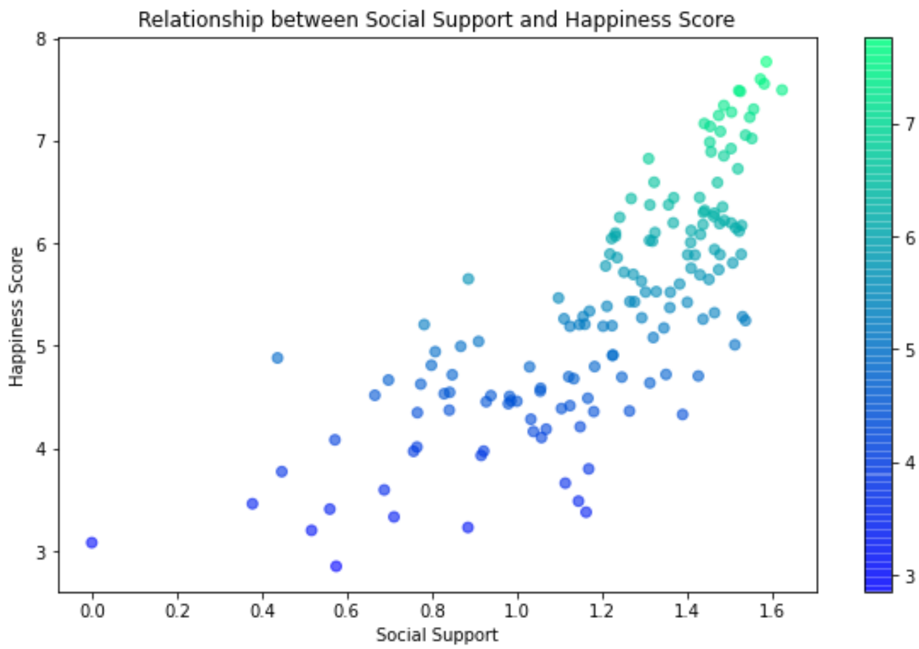


There is a positive correlation between healthy life expectancy and happiness scores, indicating that countries with higher healthy life expectancy tend to have higher happiness scores. This suggests that healthcare infrastructure and policies that promote healthy living may significantly impact individuals' happiness scores.

Happiness Score Based on Social Support

In [108…

```
# Set Figure Size
plt.figure(figsize = (10, 6))

# Define Colors
cmap = plt.cm.get_cmap('winter')

# Plot the Chart
plt.scatter(df["Social support"], df["Happiness Score"],
            alpha = 0.6, c = df["Happiness Score"], cmap = cmap)
plt.xlabel("Social Support")
plt.ylabel("Happiness Score")
plt.title("Relationship between Social Support and Happiness Score")

# Add Legend
cbar = plt.colorbar()
plt.show()
```



There is also a positive correlation between social support and happiness scores, suggesting that government policies and welfare programs can significantly impact a country's happiness. This highlights the importance of social support as a critical factor in overall well-being.

Predictive Model

The analysis shows the performance of three machine learning algorithms: linear regression, random forest, and decision tree. The evaluation metrics used to compare the models are the mean absolute error (MAE) and the accuracy score.

In [ ]:
```
# New Table for the Predictive Model
df_model = df.groupby(by = 'Country')['Happiness Score',
                                      'GDP per capita',
                                      'Social support',
                                      'Healthy life expectancy',
                                      'Freedom to make life choices',
                                      'Generosity',
                                      'Absence of corruption'].mean().reset_index()
```

In [ ]:
```
# Define X and Y Variables
X = df_model[['Happiness Score', 'GDP per capita', 'Social support',
              'Healthy life expectancy', 'Freedom to make life choices',
              'Generosity', 'Absence of corruption']]
y = df_model['Happiness Score']
```

In [ ]:
```
# Split Data for the Train and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,
                                                    random_state = 50)
```

In [ ]:
```
# Linear Regression
lm = LinearRegression()
lm.fit(X_train, y_train)

lm_pred = lm.predict(X_test)
lm_mae = metrics.mean_absolute_error(y_test, lm_pred)

print('Mean Absolute Error (MAE): ', round(lm_mae, 3))
print('Accuracy Score: ', round(lm.score(X_test, y_test), 3))
```

```
Mean Absolute Error (MAE):  0.0
Accuracy Score:  1.0
```

The linear regression model has an MAE of 0.0, meaning it has perfect predictions. However, this is most likely a result of overfitting, where the model has memorized the training data and cannot generalize to new data.

In [ ]:
```
# Random Forest
rf = RandomForestRegressor()
rf.fit(X_train, y_train)

rf_pred = rf.predict(X_test)
rf_mae = metrics.mean_absolute_error(y_test, rf_pred)

print('Mean Absolute Error (MAE): ', round(rf_mae, 3))
print('Accuracy Score: ', round(rf.score(X_test, y_test), 3))
```

```
Mean Absolute Error (MAE):  0.036
Accuracy Score:  0.998
```

In [ ]:
```
# Decision Tree
dt = DecisionTreeRegressor()
dt.fit(X_train, y_train)

dt_pred = dt.predict(X_test)
dt_mae = metrics.mean_absolute_error(y_test, dt_pred)

print('Mean Absolute Error (MAE): ', round(dt_mae, 3))
print('Accuracy Score: ', round(dt.score(X_test, y_test), 3))
```

```
Mean Absolute Error (MAE):  0.034
Accuracy Score:  0.998
```

The random forest and decision tree models have similar MAE values of 0.036 and 0.034, respectively, indicating that they make predictions that are, on average, about 0.034 to 0.036 units away from the actual values. In addition, the accuracy scores for both models are very high, indicating that they can classify the data correctly with a high degree of confidence.

Overall, the random forest and decision tree models are performing well in prediction accuracy and error, while the linear regression model may not be a reliable predictor. However, further evaluation and testing may be necessary to ensure that the models are generalizable to new data and not just memorizing the training data.

Happiness Around the World

Lucy Lee, Robin Wixom

IMT 575 Winter 2023

7.11 Project Milestone: Final Project Write-Up

DATA

This project is based on the "World Happiness Report" dataset published by the Sustainable Development Solutions Network, which is a landmark global happiness survey released at the United Nations to celebrate the International Day of Happiness ("Sustainable Development Solutions Network," 2019). In addition, the dataset comprises 155 countries with 11 associated attributes, including but not limited to Economy, Family, Health (life expectancy), Freedom, and Trust (the perceived absence of government corruption).

QUESTION

This project aims to use the "World Happiness Report" dataset to answer the question: *"Is there a significant factor that makes one country happier than others?"* By answering this question, we attempt to understand better whether nationally represented values impact the happiness score.

APPROACH

We collaborated on the code using Google Colab and utilized Python and Tableau to develop predictive models and visualizations. Our analysis focused on the data from 2019, comparing the happiness score to various factors such as "GDP per capita," "Social support," "Healthy life expectancy," "Freedom to make life choices," "Generosity," and "Absence of corruption."

FINAL RESULTS

The correlation matrix (Figure 1) and the pair plot (Figure 2) revealed strong correlations between several features. In the correlation matrix, green represents positive correlations, and darker pink represents negative correlations. For example, gross Domestic Product (GDP), social support, and healthy life expectancy are the three factors that exhibit the strongest correlation with high happiness scores. In contrast, life choices, generosity, and perceptions of corruption are less strongly correlated with increased happiness scores. The pair plot provides a detailed visualization of each attribute and its correlation with the happiness score, again showing that GPD, social support, and healthy life expectancy strongly correlate with the happiness score. Freedom to make life choices is positively correlated, yet less strongly. Interestingly, a lower happiness score is related to higher levels of generosity, and finally, when the perceived absence of corruption is low, the happiness score appears to be higher.

Next, the correlation between countries and regions was compared to the happiness score. According to the 2019 World Happiness Report, the top 10 countries with the highest happiness scores are Finland, Denmark, Norway, Iceland, Netherlands, Switzerland, Sweden, New Zealand, Canada, and Austria (Figure 3). On the other hand, South Sudan, the Central African Republic, Afghanistan, Tanzania, Rwanda, Yemen, Malawi, Syria, Botswana, and Haiti are the bottom ten countries with the lowest happiness scores (Figure 4). Furthermore, according to the choropleth map in Figure 5, most countries with lower happiness scores are in Africa, followed by Asia. In general, regions like North America, South America, Antarctica, Europe, and Australia scored higher than Africa and Asia in the happiness ranking.

Figures 6 and 7 show tables that display the strong relationship between a country's GDP per capita (a measure of its economic output per person) and its happiness score. Countries with higher scores tend to exhibit a correspondingly high GDP per capita. For instance, the four countries with the lowest GDP per capita in the table (Somalia, Central African Republic, Burundi, and Liberia) also have some of the lowest happiness scores. In contrast, countries with higher GDP per capita, such as Qatar, Luxembourg, Singapore, United Arab Emirates, and Kuwait, tend to have higher happiness scores. This suggests a correlation between a country's economic prosperity and the happiness of its citizens. However, it's worth noting that GDP per capita is just one factor that can affect a country's overall happiness, and the relationship can be complicated.

Additionally, there is a positive correlation between healthy life expectancy and happiness scores, indicated in Figure 8, that countries with higher healthy life expectancy tend to have higher happiness scores. This suggests that healthcare infrastructure and policies that promote healthy living may significantly impact individuals' happiness scores. There is also a positive correlation between social support and happiness scores, indicated in Figure 9, suggesting that government policies and welfare programs can significantly impact a country's happiness. This highlights the importance of social support as a critical factor in overall well-being.

Lastly, the data was analyzed to show the performance of three machine learning algorithms: linear regression, random forest, and decision tree. The evaluation metrics used to compare the models are the mean absolute error (MAE) and the accuracy score. The linear regression model has an MAE of 0.0, meaning it has perfect predictions. However, this is most likely a result of overfitting, where the model has memorized the training data and cannot generalize to new data. On the other hand, the random forest and decision tree models have similar MAE values of 0.036 and 0.034, respectively, indicating that they make predictions that are, on average, about 0.034 to 0.036 units away from the actual values. In addition, the accuracy scores for both models are very high, indicating that they can classify the data correctly with a high degree of confidence.

The random forest and decision tree models perform well in prediction accuracy and error, while the linear regression model may not be a reliable predictor. Further evaluation and testing may be necessary to ensure that the models are generalizable to new data rather than just memorizing the training data.

LIMITATIONS

Several limitations in this project should be considered when reviewing the analysis. First, the subjective nature of the dataset is essential to consider. Happiness is a social construct, which by nature can vary between societies and other defined social groups; what one group perceives as happiness or success could be different from another group, which also applies to individual attributes. An example is how the Freedom to Make Life Choices feature is associated with the overall rank of the country or region. Uzbekistan and Cambodia ranked highest for their score on Freedom to Make Life Choices (.631 and .609, respectively). Yet their overall rank for happiness is significantly lower than Norway, which ranks third for its Freedom to Make Life Choices score. Figure 11 shows that the correlation between the two is not strong enough to conclude that one indicates the other. Similarly, high generosity is not necessarily representative of a high happiness score. As shown in Figure 12, the countries with the highest generosity rankings are widely spread amongst overall happiness rankings.

This is illustrated in other ways as well. Holidays are often a celebration, joyous and happy. The three countries that report the highest number of public holidays and celebrations are Cambodia (28 holidays), Sri Lanka (25 holidays), and India (21 holidays) (Worldatlas.com, 2018). Yet, none of these countries even make the top 100 in their overall happiness ranking. They rank 109th, 130th, and 140th, respectively. Finland, which ranks number one for overall happiness, only reports having 14 holidays, which is about half as many holidays as the "less happy" countries (Infofinland.fi, 2022).

In 2022, The Washington Post explained that in the eyes of Finnish people, happiness was more about being satisfied with very little. Their version of happiness is derived from simplicity and moderation (Washington Post, 2022). This is indicative that happiness is not always something that can be measured and equally compared from society to society. For example, a society that defines happiness with wealth accumulation may feel very happy when that goal is achieved, while simplicity is the goal elsewhere. Furthermore, it is essential to consider that happiness and success are defined differently in different cultures, and one country's version may be significantly different than another country's. Therefore, there is a possibility that we cannot correctly compare features as the subjective definitions can vary.

Another limitation of this analysis is that it focuses on data from 2019. Further research could benefit from additional data over multiple years. With that in mind, the impacts of significant economic fluctuations, COVID, natural disasters, and international conflicts could have extreme consequences on individual happiness ratings. The values someone once had may have changed significantly in the past three years. It may need to be adequately accounted for with weighted data, as the impacts that have been felt are incomparable with any previous experiences in recent history.

Lastly, the limitations of the possibility of overfitting data must be considered. In the machine learning models, there is an indication of overfitting data. A model that is overfitting can give predictions on new data that are inaccurate. The model may fit too closely with the training set and may have a variance that is too high. This could be resolved by increasing the amount of data mentioned above or removing features that are considered non-important. With a larger dataset, tools such as LASSO or RIDGE could be applied to remove any attributes that are not useful in the overall analysis.

CONCLUSION

This report is a valuable analysis that can be used to understand happiness and the driving causes that improve happiness. By studying countries that rank happiest or least happy, we can find ways to improve other countries' happiness. For example, recognizing the connections between happiness, GDP, and Healthy Life Expectancy can assist governments in making decisions that can increase happiness, along with economic growth and healthcare. In 2011, the United Nations recognized through a resolution that happiness is a fundamental human goal which suggests that it is indeed essential for countries to approach public policies in ways that "promote and improve the happiness and well-being of all peoples" (Dayofhappiness.net, 2023). In response to the resolution, countries worldwide have appointed "ministers of happiness" with this exact goal in mind. In addition, countries such as Venezuela, Ecuador, Bhutan, and the UAE all have recognized that the success of their country is not only economically measurable, it is also measurable through levels of happiness felt by its citizens.

An analysis like the one in this report can provide valuable and actionable insight for people in these appointed roles. The human experience is unique and often subjective. However, improving it for its citizens should be a primary goal for all countries. A collaborative effort of public policies and the creation of mutual or symbiotic goal-setting can create strong societies that are ultimately resistant to failure.

APPENDIX

Figure 1. Correlation Matrix

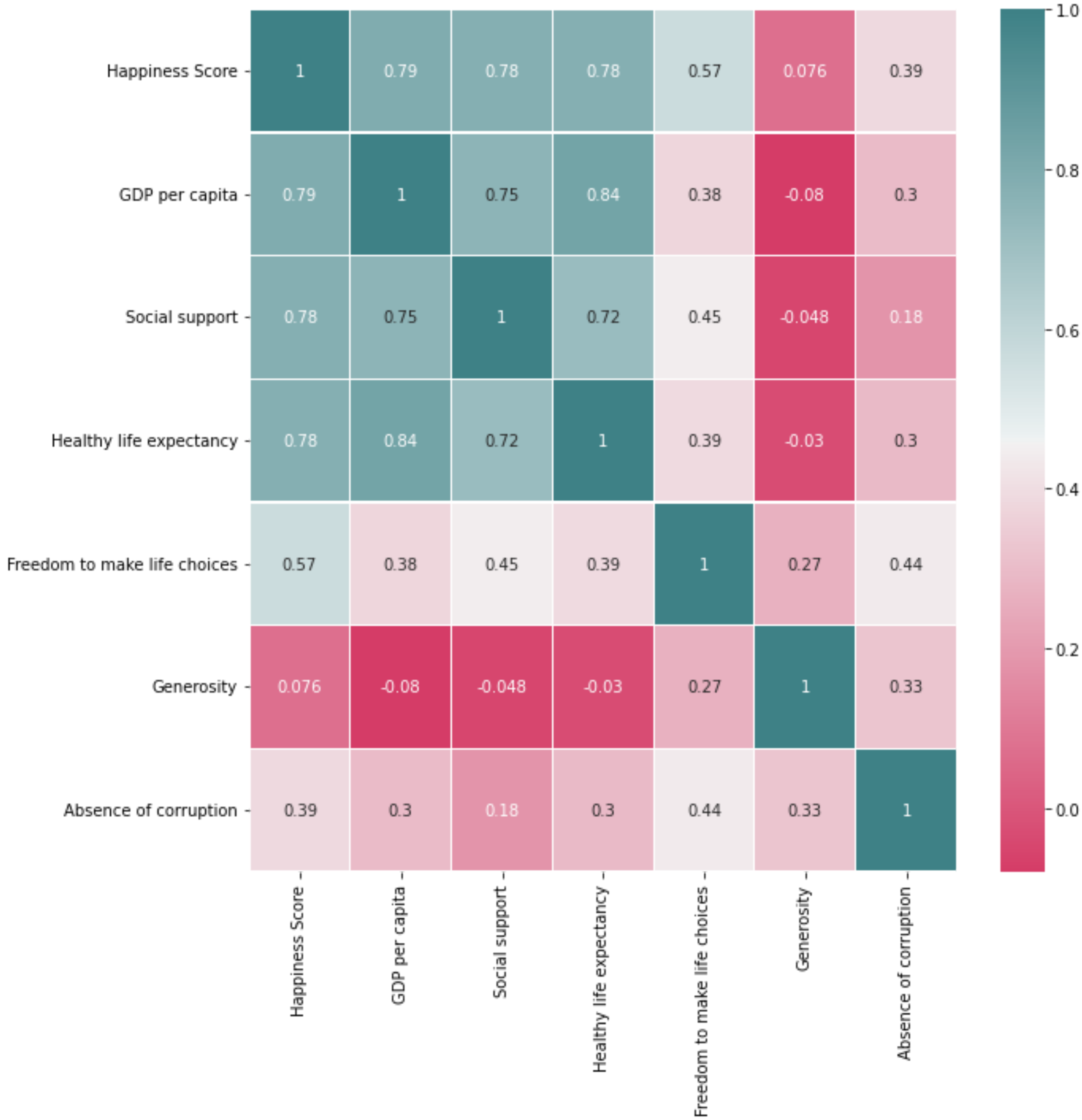


Figure 2. Pair Plot

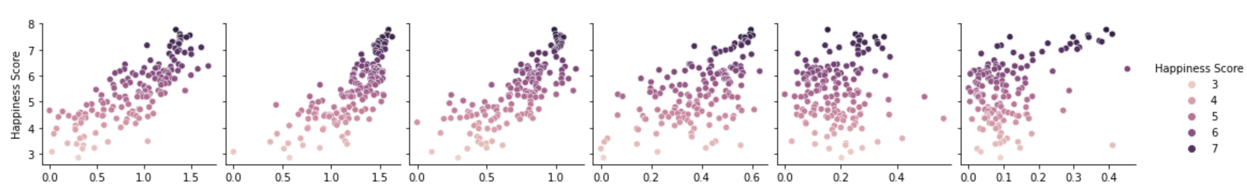


Figure 3. Top 10 Happiest Countries

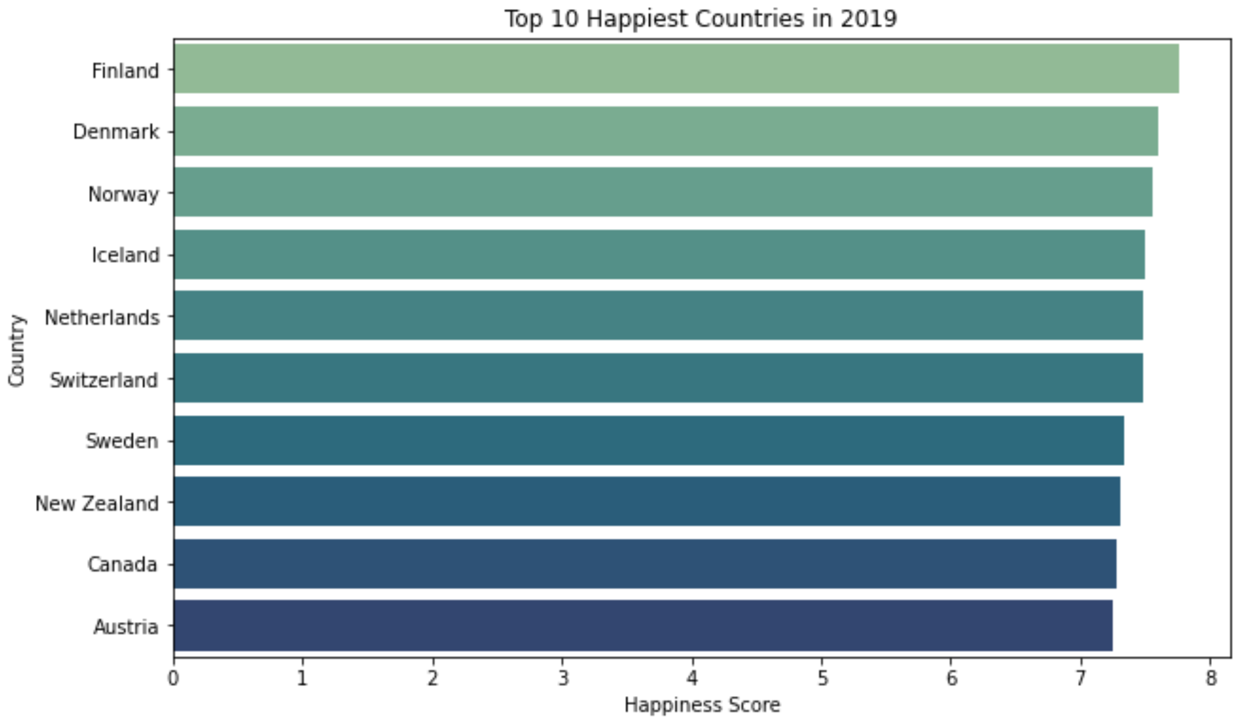


Figure 4. Top 10 Least Happiest Countries

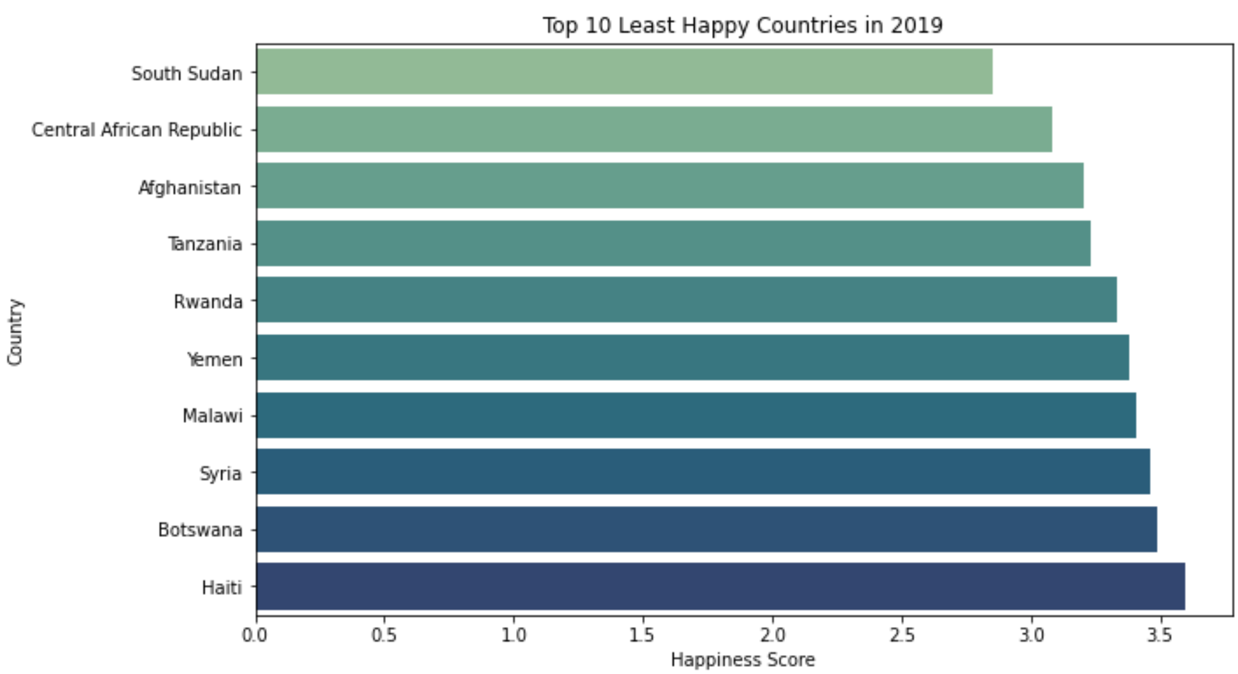


Figure 5. Choropleth Map Based on Happiness Score

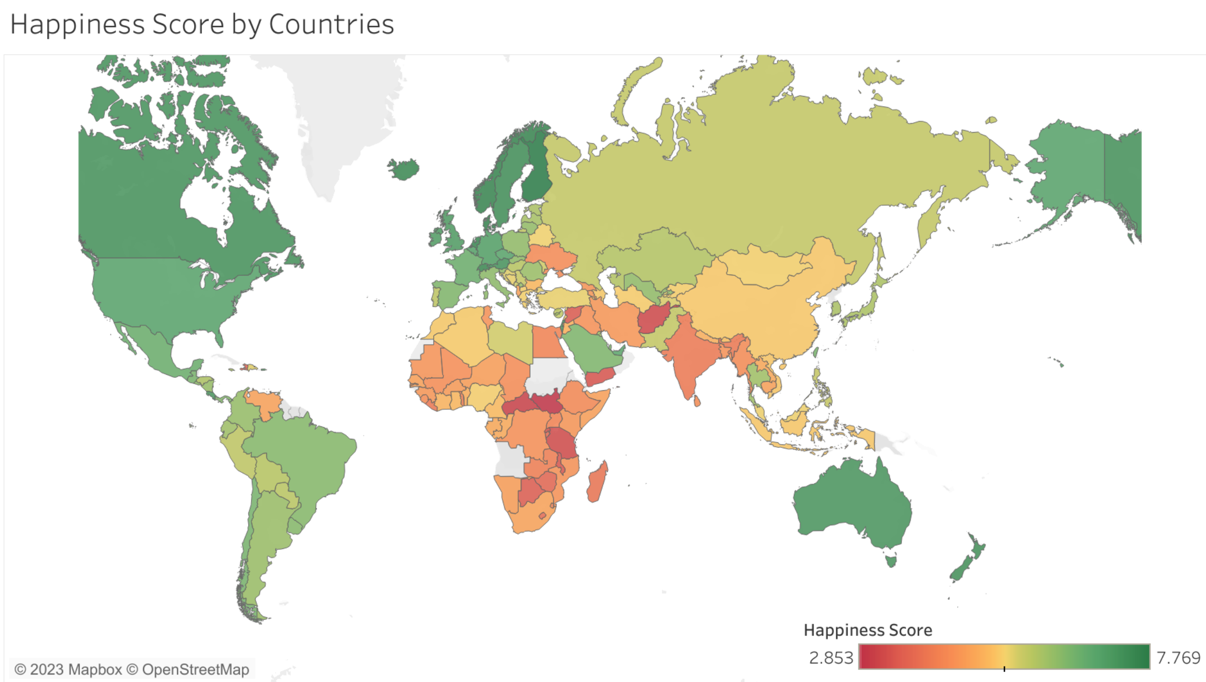


Figure 6. Countries with Highest GDP per Capita

	Country	Happiness Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Absence of corruption
28	Qatar	6.374	1.684	1.313	0.871	0.555	0.220	0.167
13	Luxembourg	7.090	1.609	1.479	1.012	0.526	0.194	0.316
33	Singapore	6.262	1.572	1.463	1.141	0.556	0.271	0.453
20	United Arab Emirates	6.825	1.503	1.310	0.825	0.598	0.262	0.182
50	Kuwait	6.021	1.500	1.319	0.808	0.493	0.142	0.097

Figure 7. Countries with Lowest GDP per Capita

	Country	Happiness Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Absence of corruption
111	Somalia	4.668	0.000	0.698	0.268	0.559	0.243	0.270
154	Central African Republic	3.083	0.026	0.000	0.105	0.225	0.235	0.035
144	Burundi	3.775	0.046	0.447	0.380	0.220	0.176	0.180
140	Liberia	3.975	0.073	0.922	0.443	0.370	0.233	0.033
126	Congo (Kinshasa)	4.418	0.094	1.125	0.357	0.269	0.212	0.053

Figure 8. Health Life Expectancy vs. Happiness Score

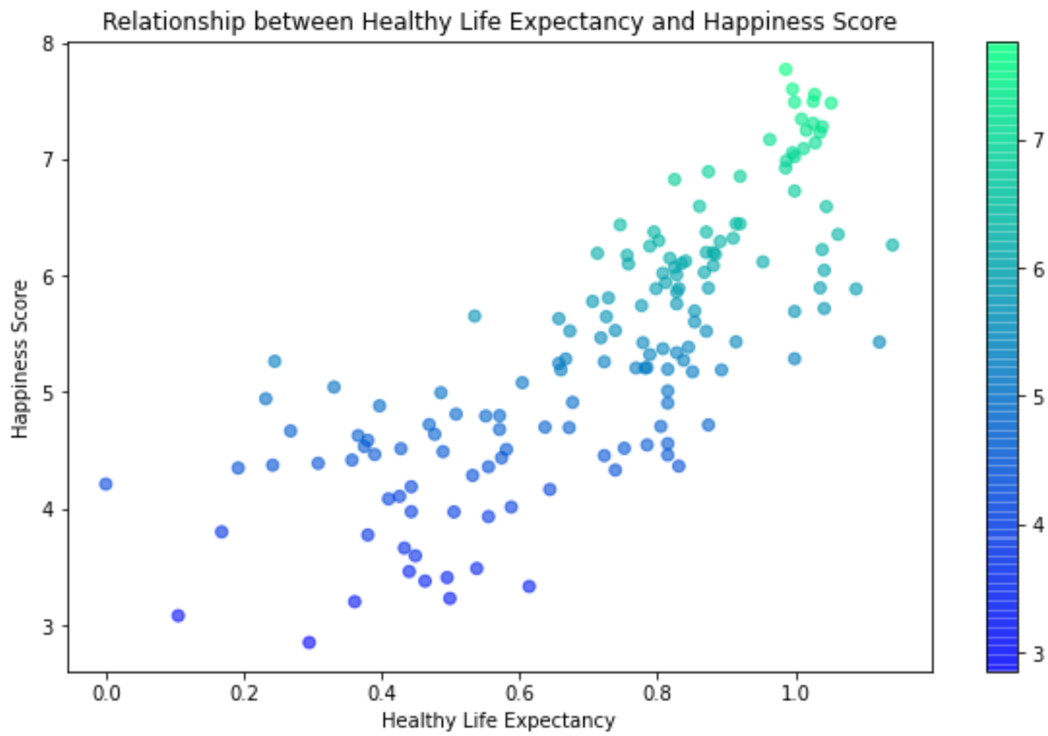


Figure 9. Social Support vs. Happiness Score

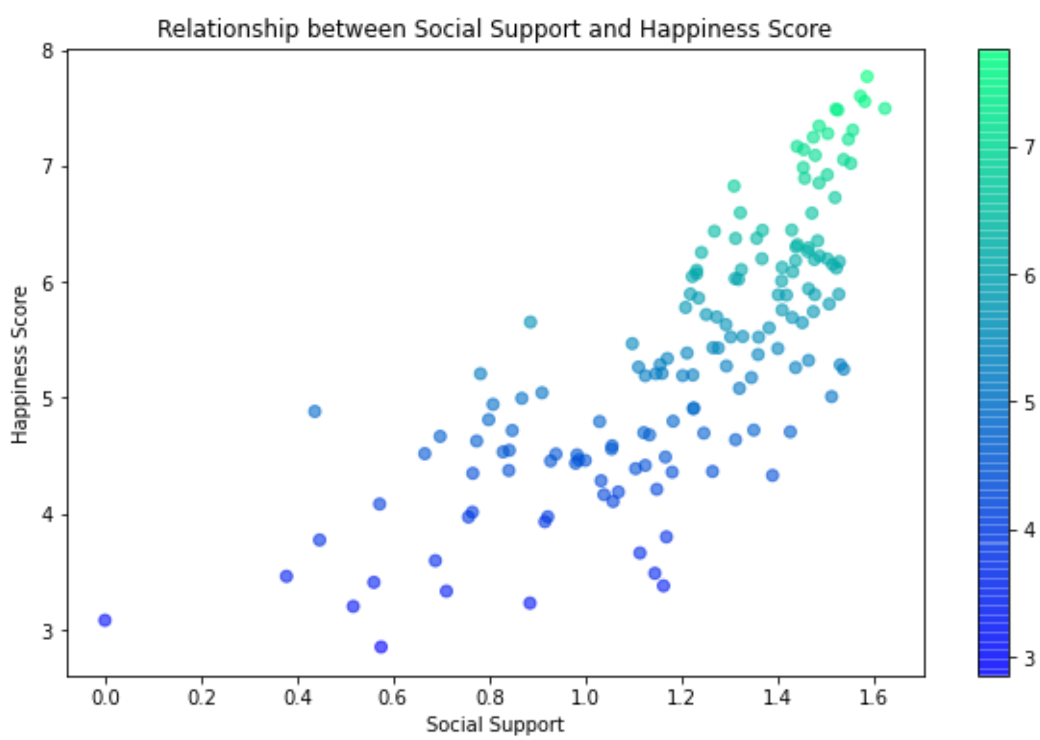


Figure 10. Factors Contributing to Happiness

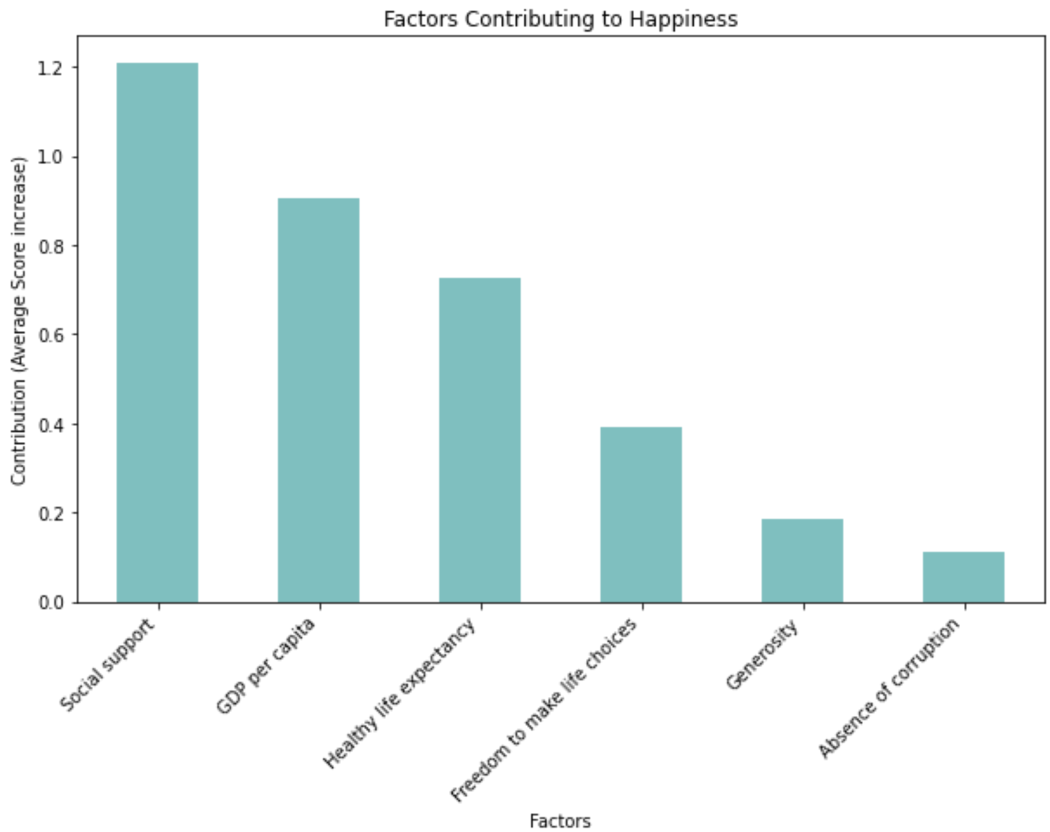
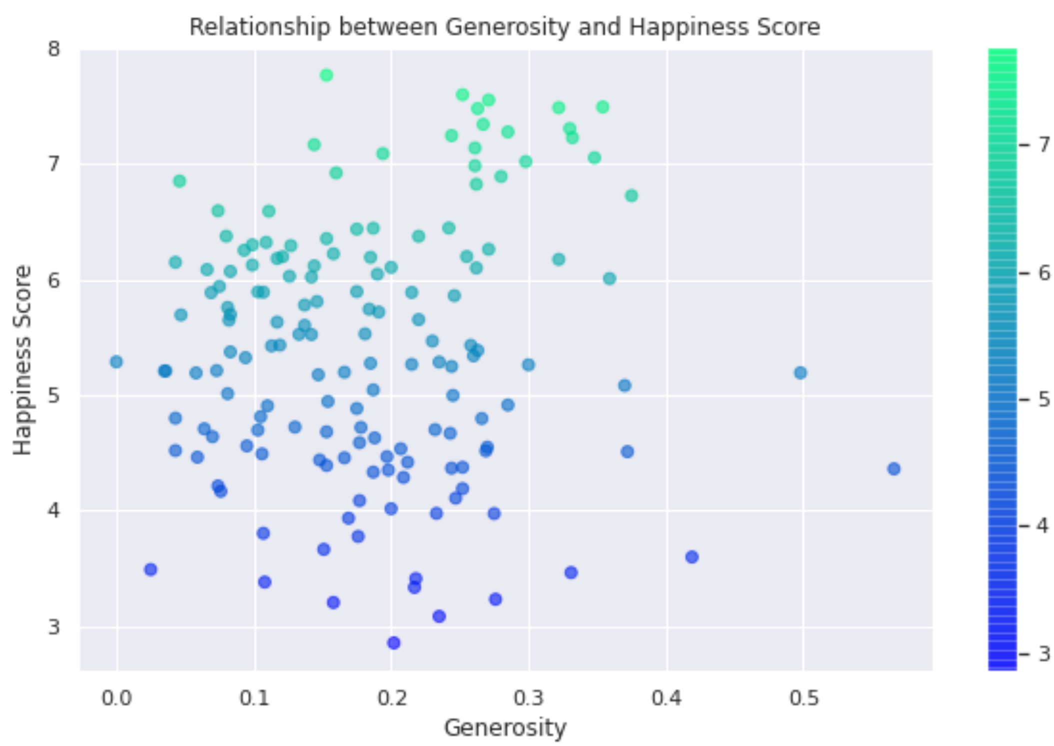


Figure 11. Happiness Score Based on Freedom to Make Life Choices

Figure 12. Happiness Score Based on Generosity



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