In [55]:
```
# import necessary library
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
import matplotlib.lines as mlines
import matplotlib.transforms as mtransforms
%matplotlib inline
```

In [56]:
```
#Read the data
df_2019 = pd.read_csv("./world_happiness/2019.csv")
df_2018 = pd.read_csv("./world_happiness/2018.csv")
df_2017 = pd.read_csv("./world_happiness/2017.csv")
df_2016 = pd.read_csv("./world_happiness/2016.csv")
df_2015 = pd.read_csv("./world_happiness/2015.csv")
```

In [57]:
```
# Check how 2019 data looks like
df_2019.info()
```

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

In [58]:
```
# Add year attribute to data
df_2019['year'] = 2019
df_2019.head(10)
```

Out[58]:

	Overall rank	Country or region	Score	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption	y
0	1	Finland	7.769	1.340	1.587	0.986	0.596	0.153	0.393	2
1	2	Denmark	7.600	1.383	1.573	0.996	0.592	0.252	0.410	2
2	3	Norway	7.554	1.488	1.582	1.028	0.603	0.271	0.341	2
3	4	Iceland	7.494	1.380	1.624	1.026	0.591	0.354	0.118	2
4	5	Netherlands	7.488	1.396	1.522	0.999	0.557	0.322	0.298	2
5	6	Switzerland	7.480	1.452	1.526	1.052	0.572	0.263	0.343	2
6	7	Sweden	7.343	1.387	1.487	1.009	0.574	0.267	0.373	2
7	8	New Zealand	7.307	1.303	1.557	1.026	0.585	0.330	0.380	2
8	9	Canada	7.278	1.365	1.505	1.039	0.584	0.285	0.308	2
9	10	Austria	7.246	1.376	1.475	1.016	0.532	0.244	0.226	2

In [59]:
```
# Check how 2018 data looks like
df_2018.info()
```

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

In [60]:
```
# Add year attribute to data
df_2018['year'] = 2018
```

In [61]:
```
df_2018.head(10)
```

Out[61]:

	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	7.632	1.305	1.592	0.874	0.681	0.202	0.393	2
1	2	Norway	7.594	1.456	1.582	0.861	0.686	0.286	0.340	2
2	3	Denmark	7.555	1.351	1.590	0.868	0.683	0.284	0.408	2
3	4	Iceland	7.495	1.343	1.644	0.914	0.677	0.353	0.138	2
4	5	Switzerland	7.487	1.420	1.549	0.927	0.660	0.256	0.357	2
5	6	Netherlands	7.441	1.361	1.488	0.878	0.638	0.333	0.295	2
6	7	Canada	7.328	1.330	1.532	0.896	0.653	0.321	0.291	2
7	8	New Zealand	7.324	1.268	1.601	0.876	0.669	0.365	0.389	2
8	9	Sweden	7.314	1.355	1.501	0.913	0.659	0.285	0.383	2
9	10	Australia	7.272	1.340	1.573	0.910	0.647	0.361	0.302	2

In [62]:
```
# Check how 2017 data looks like
df_2017.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 155 entries, 0 to 154
Data columns (total 12 columns):
Country                           155 non-null object
Happiness.Rank                    155 non-null int64
Happiness.Score                   155 non-null float64
Whisker.high                      155 non-null float64
Whisker.low                       155 non-null float64
Economy..GDP.per.Capita.          155 non-null float64
Family                            155 non-null float64
Health..Life.Expectancy.          155 non-null float64
Freedom                           155 non-null float64
Generosity                        155 non-null float64
Trust..Government.Corruption.     155 non-null float64
Dystopia.Residual                 155 non-null float64
dtypes: float64(10), int64(1), object(1)
memory usage: 14.7+ KB
```

In [63]:
```
# Now we have found that we had to rename certain countries by checking
 World Happiness Report Website
# Since we will use 2019 as test set, we will use the columns that exist
in 2019
# Add a year column
df_2017['year'] = 2017
df_2017.rename(columns={"Country": "Country or region",
 "Happiness.Rank": "Overall rank",
  'Happiness.Score': 'Score',
 'Health..Life.Expectancy.' : 'Healthy life expectancy',
  'Freedom':'Freedom to make life choices',
 'Trust..Government.Corruption.' :'Perceptions of corruption',
   'Economy..GDP.per.Capita.' : 'GDP per capita',
     'Family':'Social support'
 },inplace = True)
df_2017.columns
```

Out[63]:
```
Index(['Country or region', 'Overall rank', 'Score', 'Whisker.high',
       'Whisker.low', 'GDP per capita', 'Social support',
       'Healthy life expectancy', 'Freedom to make life choices', 'Gene
rosity',
       'Perceptions of corruption', 'Dystopia.Residual', 'year'],
      dtype='object')
```

In [64]:
```
df_2017.head(10)
```

Out[64]:

	Country or region	Overall rank	Score	Whisker.high	Whisker.low	GDP per capita	Social support	Healthy life expectancy	Freed to ma l choic
0	Norway	1	7.537	7.594445	7.479556	1.616463	1.533524	0.796667	0.6354
1	Denmark	2	7.522	7.581728	7.462272	1.482383	1.551122	0.792566	0.6260
2	Iceland	3	7.504	7.622030	7.385970	1.480633	1.610574	0.833552	0.6271
3	Switzerland	4	7.494	7.561772	7.426227	1.564980	1.516912	0.858131	0.6200
4	Finland	5	7.469	7.527542	7.410458	1.443572	1.540247	0.809158	0.6179
5	Netherlands	6	7.377	7.427426	7.326574	1.503945	1.428939	0.810696	0.5853
6	Canada	7	7.316	7.384403	7.247597	1.479204	1.481349	0.834558	0.6111
7	New Zealand	8	7.314	7.379510	7.248490	1.405706	1.548195	0.816760	0.6140
8	Sweden	9	7.284	7.344095	7.223905	1.494387	1.478162	0.830875	0.6129
9	Australia	10	7.284	7.356651	7.211349	1.484415	1.510042	0.843887	0.6016

In [65]:
```
# Check how 2016 data looks like
df_2016.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 157 entries, 0 to 156
Data columns (total 13 columns):
Country                          157 non-null object
Region                           157 non-null object
Happiness Rank                   157 non-null int64
Happiness Score                  157 non-null float64
Lower Confidence Interval        157 non-null float64
Upper Confidence Interval        157 non-null float64
Economy (GDP per Capita)         157 non-null float64
Family                           157 non-null float64
Health (Life Expectancy)         157 non-null float64
Freedom                          157 non-null float64
Trust (Government Corruption)    157 non-null float64
Generosity                       157 non-null float64
Dystopia Residual                157 non-null float64
dtypes: float64(10), int64(1), object(2)
memory usage: 16.1+ KB
```

In [66]:
```
# Add a year column
df_2016['year'] = 2016
df_2016.rename(columns={
    "Country": "Country or region",
 "Happiness Rank": "Overall rank",
  'Happiness Score': 'Score',
 'Health (Life Expectancy)' : 'Healthy life expectancy',
  'Freedom':'Freedom to make life choices',
 'Trust (Government Corruption)' :'Perceptions of corruption',
  'Economy (GDP per Capita)' : 'GDP per capita',
    'Family':'Social support'
 },inplace = True)
df_2016.columns
```

Out[66]:
```
Index(['Country or region', 'Region', 'Overall rank', 'Score',
       'Lower Confidence Interval', 'Upper Confidence Interval',
       'GDP per capita', 'Social support', 'Healthy life expectancy',
       'Freedom to make life choices', 'Perceptions of corruption',
       'Generosity', 'Dystopia Residual', 'year'],
      dtype='object')
```

In [67]:
```
df_2016.head(5)
```

Out[67]:

	Country or region	Region	Overall rank	Score	Lower Confidence Interval	Upper Confidence Interval	GDP per capita	Social support	Healthy life expectancy	F
0	Denmark	Western Europe	1	7.526	7.460	7.592	1.44178	1.16374	0.79504	
1	Switzerland	Western Europe	2	7.509	7.428	7.590	1.52733	1.14524	0.86303	
2	Iceland	Western Europe	3	7.501	7.333	7.669	1.42666	1.18326	0.86733	
3	Norway	Western Europe	4	7.498	7.421	7.575	1.57744	1.12690	0.79579	
4	Finland	Western Europe	5	7.413	7.351	7.475	1.40598	1.13464	0.81091	

In [68]:
```
df_2015.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 158 entries, 0 to 157
Data columns (total 12 columns):
Country                          158 non-null object
Region                           158 non-null object
Happiness Rank                   158 non-null int64
Happiness Score                  158 non-null float64
Standard Error                   158 non-null float64
Economy (GDP per Capita)         158 non-null float64
Family                           158 non-null float64
Health (Life Expectancy)         158 non-null float64
Freedom                          158 non-null float64
Trust (Government Corruption)    158 non-null float64
Generosity                       158 non-null float64
Dystopia Residual                158 non-null float64
dtypes: float64(9), int64(1), object(2)
memory usage: 14.9+ KB
```

In [69]:
```
# Add a year column
df_2015['year'] = 2015
# Rename columns
df_2015.rename(columns={
    "Country": "Country or region",
 "Happiness Rank": "Overall rank",
  'Happiness Score': 'Score',
 'Health (Life Expectancy)' : 'Healthy life expectancy',
  'Freedom':'Freedom to make life choices',
 'Trust (Government Corruption)' :'Perceptions of corruption',
  'Economy (GDP per Capita)' : 'GDP per capita',
 'Trust (Government Corruption)' :'Perceptions of corruption',
    'Family':'Social support'
 },inplace = True)
df_2015.columns
```

Out[69]:
```
Index(['Country or region', 'Region', 'Overall rank', 'Score',
       'Standard Error', 'GDP per capita', 'Social support',
       'Healthy life expectancy', 'Freedom to make life choices',
       'Perceptions of corruption', 'Generosity', 'Dystopia Residual',
'year'],
      dtype='object')
```

In [70]:
```
df_2015.head(5)
```

Out[70]:

	Country or region	Region	Overall rank	Score	Standard Error	GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Perce corr
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0.66557	0
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.62877	0
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.64938	0
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.66973	0
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.63297	0

In [71]:
```
dfs = [df_2015, df_2016, df_2017, df_2018]
df = pd.concat(dfs)
```

```
/Applications/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.
py:2: FutureWarning: Sorting because non-concatenation axis is not alig
ned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=Tru
e'.
```

Q1

Merge

In [72]:
```
# Select attributes and target variable from our merged data of 2015 to
 2018
train = pd.DataFrame(df,columns = ['Overall rank', 'Country or region',
'Score', 'GDP per capita',
        'Healthy life expectancy', 'Social support',
       'Freedom to make life choices', 'Generosity',
       'Perceptions of corruption','year'])
# Selected data:
train.sample(8)
```

Out[72]:

	Overall rank	Country or region	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptio corrupt
17	18	Belgium	6.929	1.425390	0.819590	1.052490	0.513540	0.242400	0.262
154	155	Benin	3.340	0.286650	0.319100	0.353860	0.484500	0.182600	0.080
96	97	Bhutan	5.011	0.885416	0.495879	1.340127	0.501538	0.474055	0.173
142	143	South Sudan	3.832	0.393940	0.157810	0.185190	0.196620	0.258990	0.130
66	67	Libya	5.615	1.066880	0.523040	0.950760	0.406720	0.170870	0.103
117	118	Gabon	4.465	1.198210	0.356579	1.155620	0.312329	0.043785	0.076
43	44	Venezuela	6.084	1.133670	0.619040	1.033020	0.198470	0.042500	0.083
140	141	Afghanistan	3.794	0.401477	0.180747	0.581543	0.106180	0.311871	0.061

In [73]:
```
# Select attributes and target variable from our merged data in 2019
test =  pd.DataFrame(df_2019,columns = ['Overall rank', 'Country or regi
on', 'Score', 'GDP per capita',
        'Healthy life expectancy', 'Social support',
       'Freedom to make life choices', 'Generosity',
       'Perceptions of corruption','year'])
```

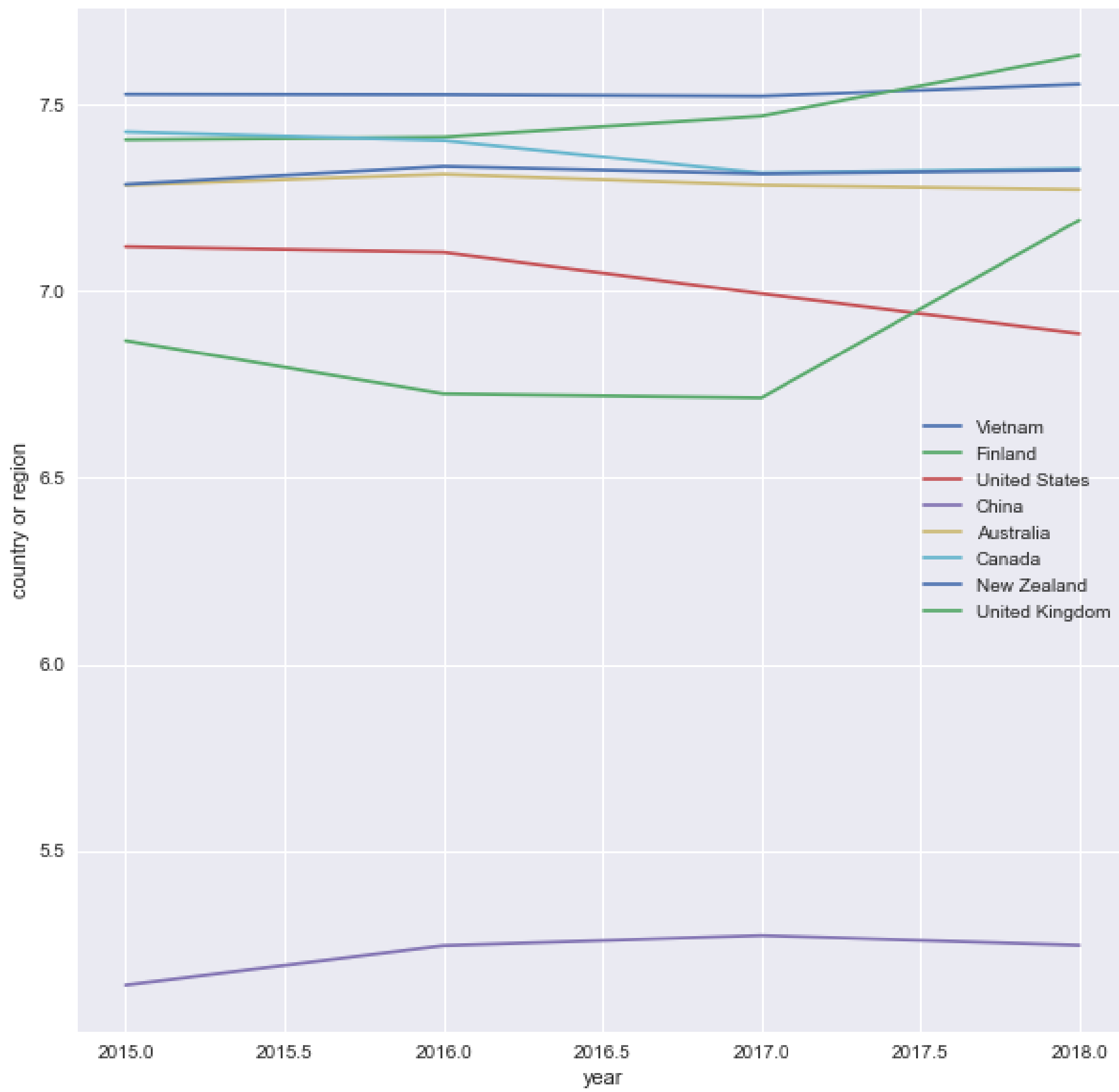
Q2

We will take different countries to see the trend

In [74]:
```
# Select some example countries or regions prepared for later analysis
d1 = train[train['Country or region']=='Denmark']
d2 = train[train['Country or region']=='Finland']
d3 = train[train['Country or region']=='United States']
d4 = train[train['Country or region']=='China']
d5 = train[train['Country or region']=='Australia']
d6 = train[train['Country or region']=='Canada']
d7 = train[train['Country or region']=='New Zealand']
d8 = train[train['Country or region']=='United Kingdom']
d9 = train[train['Country or region']=='Norway']
```

In [75]:
```python
# Plot the trend of our selected examples's Scores
plt.figure(figsize=(10, 10))
plt.style.use('seaborn')
plt.plot(d1['year'],d1['Score'], label="Vietnam")
plt.plot(d2['year'],d2['Score'], label="Finland")
plt.plot(d3['year'],d3['Score'], label="United States")
plt.plot(d4['year'],d4['Score'], label="China")
plt.plot(d5['year'],d5['Score'], label="Australia")
plt.plot(d6['year'],d6['Score'], label="Canada")
plt.plot(d7['year'],d7['Score'], label="New Zealand")
plt.plot(d8['year'],d8['Score'], label="United Kingdom")
plt.legend(loc=0)
plt.xlabel('year')
plt.ylabel('country or region')
```

Out[75]:
```
Text(0, 0.5, 'country or region')
```

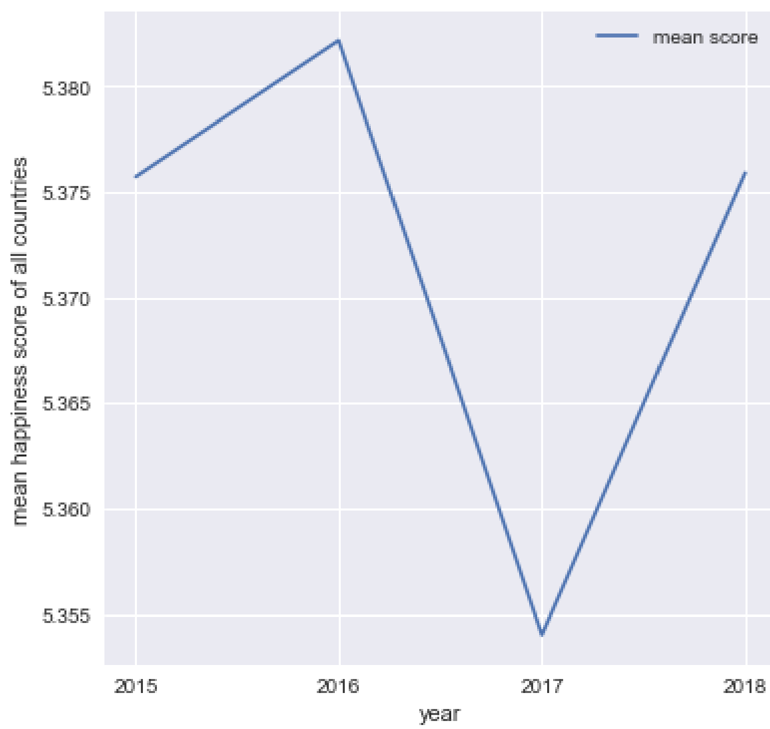


In [76]:
```
# Calculate the mean(of all countries or regions) in each year
mean_score = train.groupby("year").mean()["Score"]
mean_score
```

Out[76]:
```
year
2015    5.375734
2016    5.382185
2017    5.354019
2018    5.375917
Name: Score, dtype: float64
```

In [77]:
```
# Plot the mean of Score of all countries or regions from 2015 to 2018
plt.figure(figsize=(6, 6))
plt.xlabel("year")
plt.ylabel("mean happiness score of all countries")
plt.style.use('seaborn')
plt.plot(mean_score, label="mean score")
plt.legend(loc = 0)
plt.xticks([2015, 2016, 2017, 2018])
```

Out[77]:
```
([<matplotlib.axis.XTick at 0x1a1b07f350>,
  <matplotlib.axis.XTick at 0x1a1b02b610>,
  <matplotlib.axis.XTick at 0x1a1b02b410>,
  <matplotlib.axis.XTick at 0x1a185be750>],
 <a list of 4 Text xticklabel objects>)
```



In [78]:
```
d3
# The happiness score seems to decrease for United States
```

Out[78]:

	Overall rank	Country or region	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptions of corruption
14	15	United States	7.119	1.394510	0.861790	1.247110	0.546040	0.401050	0.158900
12	13	United States	7.104	1.507960	0.779000	1.047820	0.481630	0.410770	0.148680
13	14	United States	6.993	1.546259	0.774287	1.419921	0.505741	0.392579	0.135639
17	18	United States	6.886	1.398000	0.819000	1.471000	0.547000	0.291000	0.133000

In [79]:
```
d6
# The happiness score decreased from 2015 to 2017 and then increased in
 2018 for Canada
```

Out[79]:

	Overall rank	Country or region	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptions of corruption
4	5	Canada	7.427	1.326290	0.905630	1.322610	0.632970	0.45811	0.329570
5	6	Canada	7.404	1.440150	0.827600	1.096100	0.573700	0.44834	0.313290
6	7	Canada	7.316	1.479204	0.834558	1.481349	0.611101	0.43554	0.287372
6	7	Canada	7.328	1.330000	0.896000	1.532000	0.653000	0.32100	0.291000

In [80]:
```
d8
# The happiness score decreased from 2015 to 2018 and then incresed in 2
018 for United Kingdom
```

Out[80]:

	Overall rank	Country or region	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptions of corruption
20	21	United Kingdom	6.867	1.266370	0.909430	1.28548	0.59625	0.519120	0.320670
22	23	United Kingdom	6.725	1.402830	0.809910	1.08672	0.50036	0.501560	0.273990
18	19	United Kingdom	6.714	1.441634	0.805336	1.49646	0.50819	0.492774	0.265428
10	11	United Kingdom	7.190	1.244000	0.888000	1.43300	0.46400	0.262000	0.082000

Q3

Stable rankings (They had the least standard deviation in Overall Rankings)

In [81]:
```
train.groupby('Country or region').std().nsmallest(10, 'Overall rank')
# These countries have rather stable rannkings
```

Out[81]:

Country or region	Overall rank	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptio corrupti
Suriname	0.000000	0.000000	0.071785	0.069912	0.136712	0.052489	0.002305	0.0066
Australia	0.500000	0.017443	0.075521	0.043293	0.211970	0.039472	0.054186	0.0258
New Zealand	0.500000	0.020680	0.074325	0.042004	0.200009	0.037209	0.063242	0.0225
Austria	0.577350	0.081023	0.076340	0.046484	0.190345	0.038927	0.042145	0.0169
Netherlands	0.577350	0.042264	0.082897	0.043109	0.204586	0.037329	0.070330	0.0147
Iceland	0.816497	0.030729	0.080501	0.050398	0.213269	0.045371	0.058064	0.0071
Sweden	0.816497	0.036179	0.077483	0.046712	0.192601	0.037851	0.047031	0.0260
Costa Rica	0.957427	0.073589	0.067377	0.048461	0.199314	0.040157	0.047514	0.0029
Canada	0.957427	0.055011	0.077611	0.040553	0.196074	0.033955	0.063837	0.0198
Denmark	0.957427	0.015155	0.074132	0.044848	0.195993	0.043515	0.035427	0.0380

In [82]:
```python
train.groupby('Country or region').mean().nsmallest(10, 'Overall rank')
# These countries are ranked very high on average from 2015 tto 2018
```

Out[82]:

Country or region	Overall rank	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptions of corruption
Denmark	2.25	7.53250	1.400161	0.832561	1.416360	0.634449	0.335595	0.434218
Norway	2.75	7.53775	1.527226	0.834667	1.393343	0.646811	0.343488	0.344688
Iceland	3.00	7.51525	1.388153	0.890681	1.460016	0.624793	0.435405	0.145682
Switzerland	3.00	7.51925	1.477205	0.897398	1.390165	0.632803	0.281040	0.388954
Finland	4.25	7.48000	1.361200	0.845794	1.396287	0.627920	0.233978	0.399843
Canada	6.25	7.36875	1.393911	0.865947	1.358015	0.617693	0.415747	0.305308
Netherlands	6.50	7.38375	1.414766	0.848462	1.306557	0.597814	0.438437	0.298768
New Zealand	8.25	7.31450	1.321137	0.858022	1.410411	0.625978	0.458506	0.405019
Sweden	9.00	7.31325	1.408227	0.871489	1.338968	0.628476	0.353890	0.403627
Australia	9.75	7.28825	1.400606	0.884162	1.374258	0.617054	0.437097	0.320716

Improved countries

In [83]:
```python
d2
# Finland increased its rank from 6th in 2015 to 1st in 2018
```

Out[83]:

	Overall rank	Country or region	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptions of corruption
5	6	Finland	7.406	1.290250	0.889110	1.318260	0.641690	0.233510	0.413720
4	5	Finland	7.413	1.405980	0.810910	1.134640	0.571040	0.254920	0.410040
4	5	Finland	7.469	1.443572	0.809158	1.540247	0.617951	0.245483	0.382612
0	1	Finland	7.632	1.305000	0.874000	1.592000	0.681000	0.202000	0.393000

In [84]:
```
d9
# Norway increased its rank from 4th in 2015 to 2nd in 2018
```

Out[84]:

	Overall rank	Country or region	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptions of corruption
3	4	Norway	7.522	1.459000	0.885210	1.330950	0.669730	0.346990	0.365030
3	4	Norway	7.498	1.577440	0.795790	1.126900	0.596090	0.378950	0.357760
0	1	Norway	7.537	1.616463	0.796667	1.533524	0.635423	0.362012	0.315964
1	2	Norway	7.594	1.456000	0.861000	1.582000	0.686000	0.286000	0.340000

In [85]:
```
d8
# UK increased its rank from 21st in 2015 to 11st in 2018
```

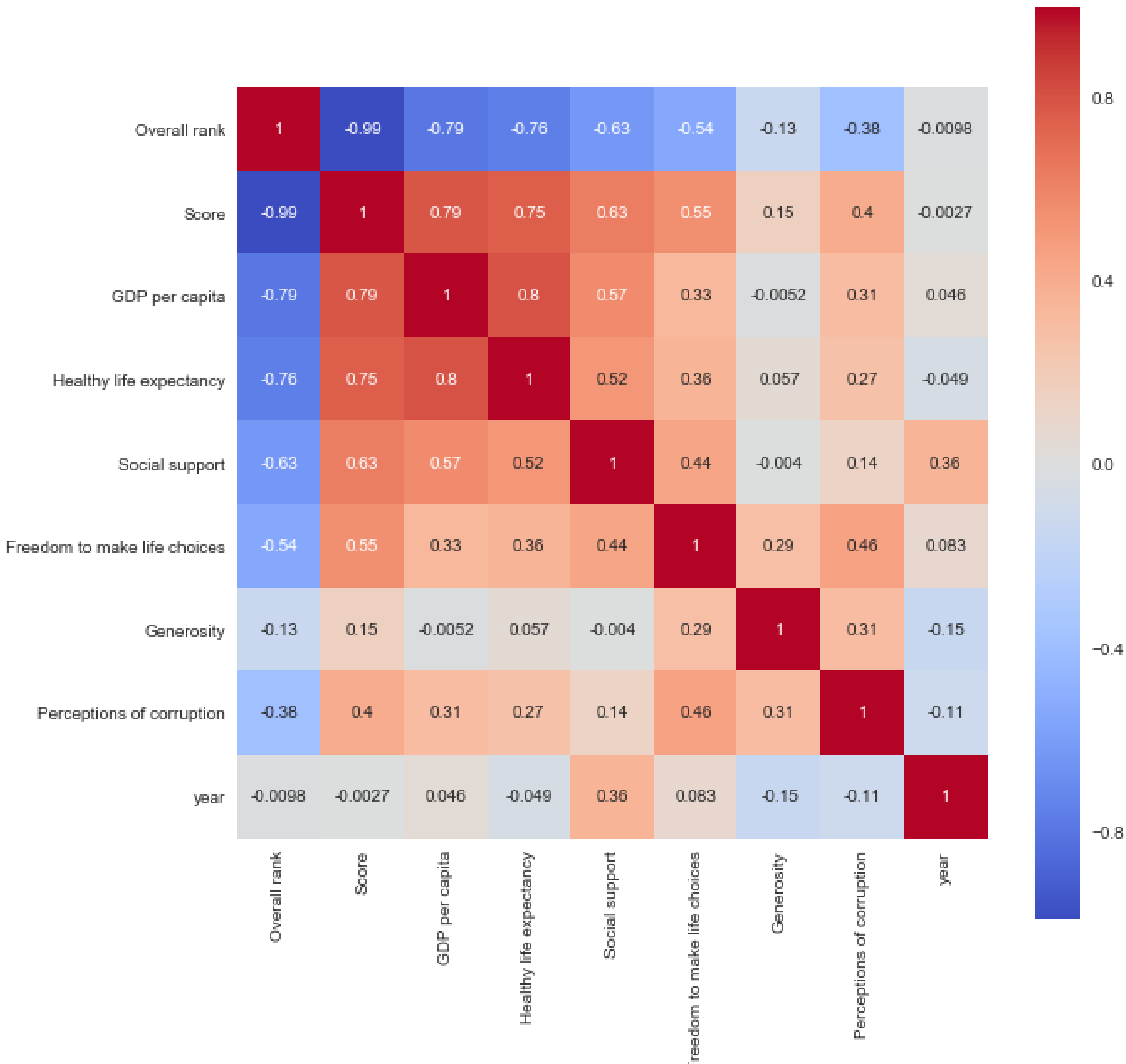
Out[85]:

	Overall rank	Country or region	Score	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices	Generosity	Perceptions of corruption
20	21	United Kingdom	6.867	1.266370	0.909430	1.28548	0.59625	0.519120	0.320670
22	23	United Kingdom	6.725	1.402830	0.809910	1.08672	0.50036	0.501560	0.273990
18	19	United Kingdom	6.714	1.441634	0.805336	1.49646	0.50819	0.492774	0.265428
10	11	United Kingdom	7.190	1.244000	0.888000	1.43300	0.46400	0.262000	0.082000

Q4

In [86]:
```
# make a heatmap tp show the correlation between happiness score and oth
er numerical variables such as GDP per capita, life expectancy
plt.figure(figsize=(10, 10))
sns.heatmap(train.corr(),cmap = 'coolwarm',annot = True, square = True)
# plot the heatmap
bot, top = plt.ylim()
bot+=0.5
top-=0.5
plt.ylim(bot, top)
```

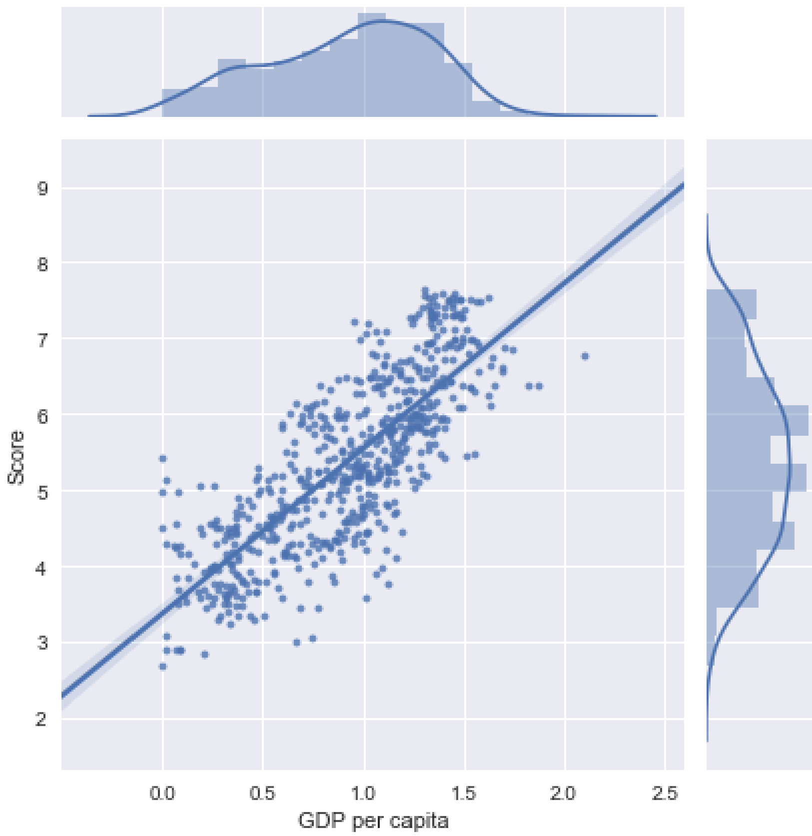
Out[86]:
```
(9.0, 0.0)
```



From the heatmap above we can see that the happniess score has a strong correlation with GDP per capita, life expectancy, social support, and freedom

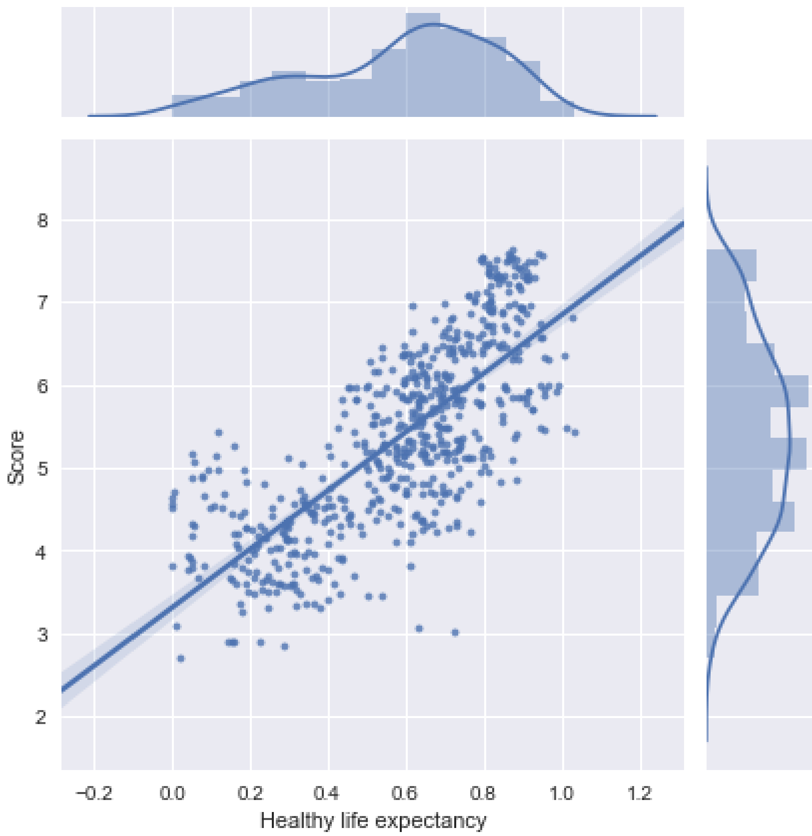
In [87]:
```
# visulize the relation between GDP per capita and happiness score, we c
an see there is a strong correlattion
sns.jointplot(x="GDP per capita", y="Score", data=train, kind="reg", sca
tter_kws={'s':15})
```

Out[87]: <seaborn.axisgrid.JointGrid at 0x1a1b3c7310>



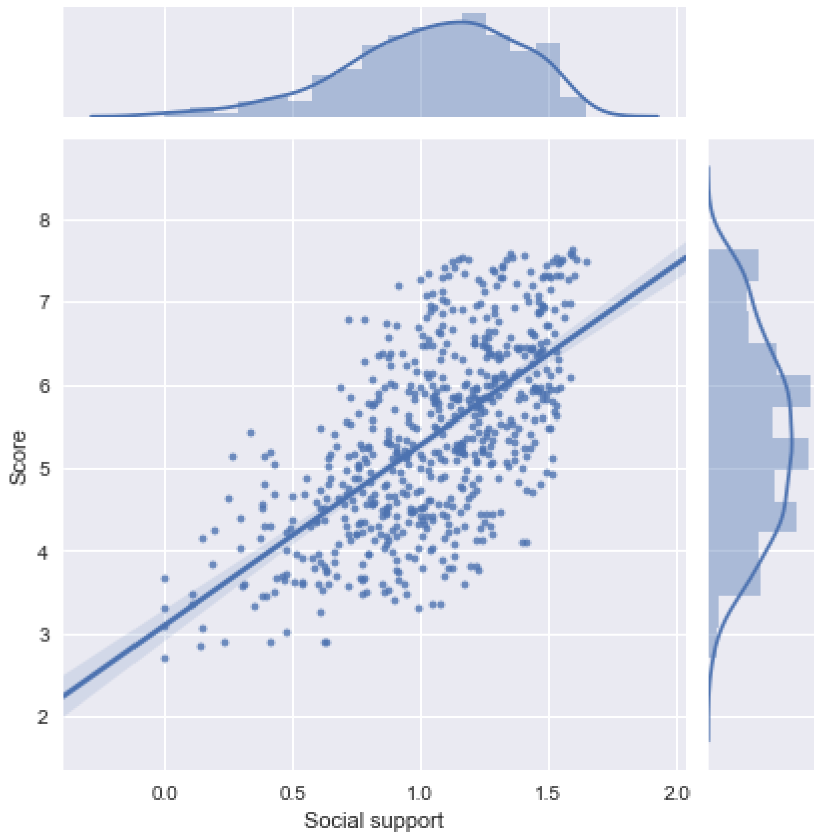
In [88]:
```
# visulize the relation between life expectancy and happiness score, we
 can see there is a strong correlattion
sns.jointplot(x="Healthy life expectancy", y="Score", data=train, kind=
"reg", scatter_kws={'s':15})
```

Out[88]: <seaborn.axisgrid.JointGrid at 0x1a1b65ced0>



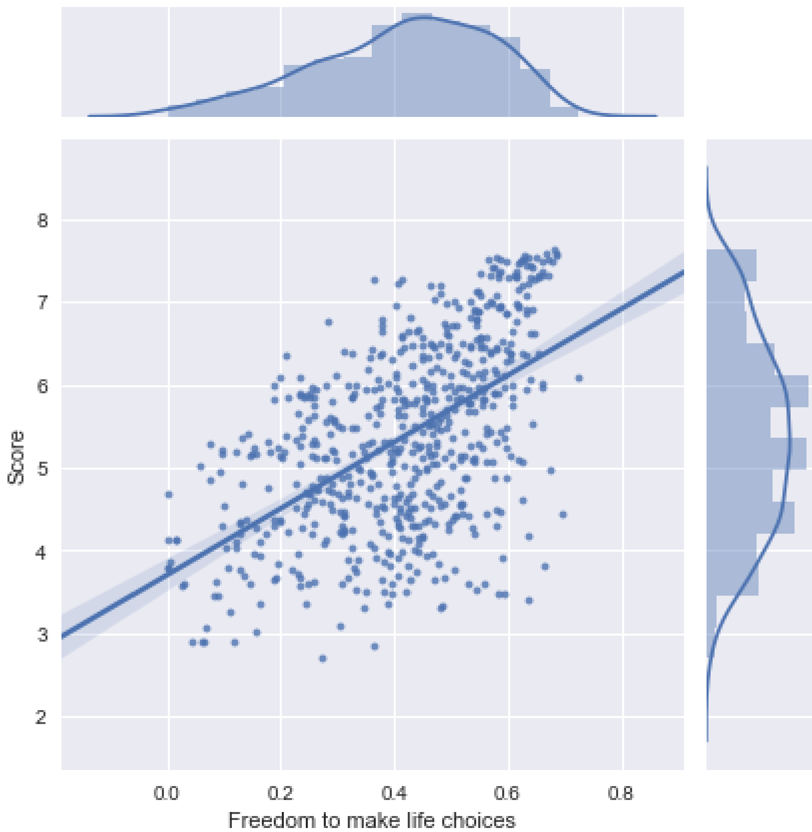
In [89]:
```
# visulize the relation between social support and happiness score, we c
an see there is a strong correlattion
sns.jointplot(x="Social support", y="Score", data=train, kind="reg", sca
tter_kws={'s':15})
```

Out[89]: <seaborn.axisgrid.JointGrid at 0x1a1ba843d0>



In [90]:
```
# visulize the relation between freedom and happiness score, we can see
 there is a strong correlattion
sns.jointplot(x="Freedom to make life choices", y="Score", data=train, k
ind="reg", scatter_kws={'s':15})
```

Out[90]: <seaborn.axisgrid.JointGrid at 0x1a1b3161d0>



Q5

From the visualization we can see that GDP per capita, life expectancy, social support, and freedom play an importanct role in countries' happiness scores. As a result, If I were a president, I would develop the economy (GDP per capita), build a strong health care system & encourage people to do exercise frequently (Life expectancy), encourage people to support the needed people (social support), and create a free environment where people can make life dicision freely in order to make my citizens happier.

Modeling and Analysis

In [91]:
```
X_train = train[["GDP per capita", "Healthy life expectancy", 'Social su
pport', 'Freedom to make life choices']]
X_train
```

Out[91]:

	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices
0	1.39651	0.94143	1.34951	0.66557
1	1.30232	0.94784	1.40223	0.62877
2	1.32548	0.87464	1.36058	0.64938
3	1.45900	0.88521	1.33095	0.66973
4	1.32629	0.90563	1.32261	0.63297
...	...	...	...	...
151	0.44200	0.34300	1.07300	0.24400
152	0.45500	0.38100	0.99100	0.48100
153	0.33700	0.17700	0.60800	0.11200
154	0.02400	0.01000	0.00000	0.30500
155	0.09100	0.14500	0.62700	0.06500

626 rows × 4 columns

In [92]:
```
y_train = train["Score"]
y_train
```

Out[92]:
```
0      7.587
1      7.561
2      7.527
3      7.522
4      7.427
       ...
151    3.355
152    3.303
153    3.254
154    3.083
155    2.905
Name: Score, Length: 626, dtype: float64
```

In [93]:
```
X_test = df_2019[["GDP per capita", "Healthy life expectancy", 'Social s
upport', 'Freedom to make life choices']]
X_test
```

Out[93]:

	GDP per capita	Healthy life expectancy	Social support	Freedom to make life choices
0	1.340	0.986	1.587	0.596
1	1.383	0.996	1.573	0.592
2	1.488	1.028	1.582	0.603
3	1.380	1.026	1.624	0.591
4	1.396	0.999	1.522	0.557
...	...	...	...	...
151	0.359	0.614	0.711	0.555
152	0.476	0.499	0.885	0.417
153	0.350	0.361	0.517	0.000
154	0.026	0.105	0.000	0.225
155	0.306	0.295	0.575	0.010

156 rows × 4 columns

In [94]:
```
y_test = df_2019["Score"]
y_test
```

Out[94]:
```
0      7.769
1      7.600
2      7.554
3      7.494
4      7.488
       ...
151    3.334
152    3.231
153    3.203
154    3.083
155    2.853
Name: Score, Length: 156, dtype: float64
```

In [95]:
```
score_original = df_2019["Score"] #Original Score
rank_original = df_2019["Overall rank"] #Original Rank
```

Model 1: Multiple Linear Regression

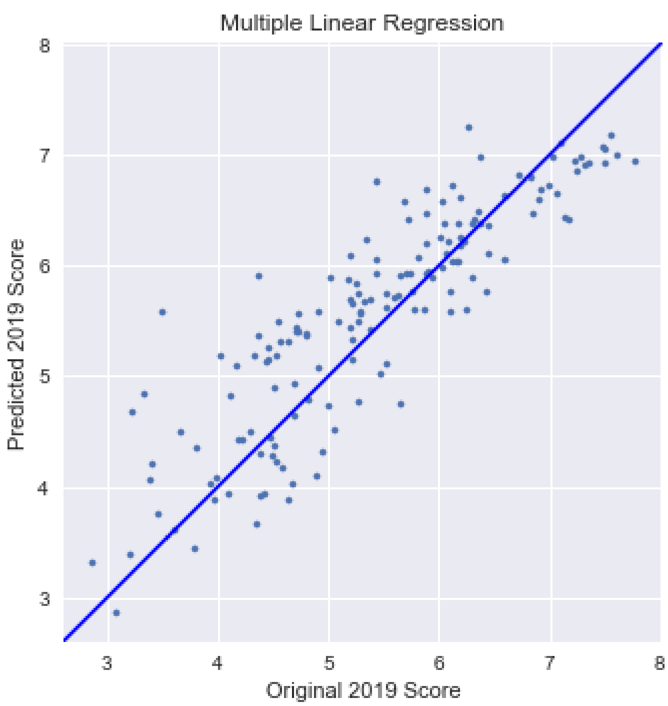
Multiple linear regression is used to estimate the relationship between two or more independent variables and one dependent variable. It uses Least Squares Estimation to estimate the coefficient of each variable. The least squares provides a way of choosing the coefficients effectively by minimizing the sum of the squared errors.

In [96]:
```
# Build the model
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
regression = lm.fit(X_train, y_train)
score_predict1 = lm.predict(X_test) # predictted score for 2019
regression.score(X_test, y_test)
```

Out[96]: 0.7426353989015174

In [97]:
```
fig, ax = plt.subplots()
plt.scatter(y_test, score_predict1.flatten(),s = 10)
plt.xlabel('Original 2019 Score')
plt.ylabel('Predicted 2019 Score')
plt.title('Multiple Linear Regression')
# Adding a blue line which indicates: Original 2019 Score = Predicted 20
19 Score
lims = [
    np.min([ax.get_xlim(), ax.get_ylim()]),  # min of both axes
    np.max([ax.get_xlim(), ax.get_ylim()]),  # max of both axes
]
ax.plot(lims, lims, 'b-')
ax.set_aspect('equal')
ax.set_xlim(lims)
ax.set_ylim(lims)
```

Out[97]: (2.603303824567446, 8.018696175432556)



In [98]:
```
from sklearn.metrics import mean_squared_error
# Here we compute the root mean squared error to evaluate the multiple l
inear regression model.
RMSE = np.sqrt(mean_squared_error(score_original, score_predict1))
mean = np.mean(score_original)
print(RMSE)
print(mean)
# Evaluating the performance by score
# The RMSE of our predicted score is quite small, so we can say that the
multiple linear regression model did well.
```

```
0.5628852790041101
5.407096153846153
```

In [99]:
```
rank_predict1 = pd.Series(score_predict1).rank(ascending = 0) # predicte
d rank for 2019
RMSE = np.sqrt(mean_squared_error(df_2019["Overall rank"], rank_predict1
))
print(RMSE)
# Evaluating the performance by rank
# The RMSE of our predicted rank is small, so we can say that the multip
le linear regression model did well.
```

```
20.692808115195668
```

Model 2: Epsilon-Support Vector Regression.

The second model is called support-vector machines. This algorithm deals with both classfication and regression problems. Here we used the regression version of SVM:SVR. SVR allows us to decide how much error is acceptable in our model and finds hyperplanes to fit the data. The algorithm sets up contraints to minimize error: making it less than or equal to a margin or maximum error ϵ (epsilon). In this way, it sets up the hyperplane that maximizes the margin.

In [100]:
```
# Build the model
from sklearn.svm import SVR
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
X = train[['GDP per capita', 'Social support',
       'Healthy life expectancy', 'Freedom to make life choices',]]
y = train['Score']
svr = make_pipeline(StandardScaler(), SVR(C=1, epsilon=0.1, kernel = 'rb
f'))
svr.fit(X_train, y_train)
```

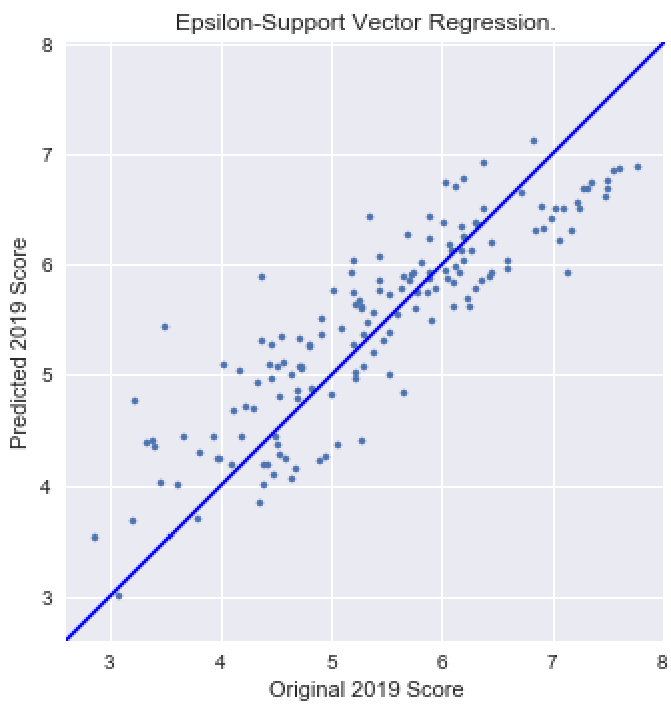
Out[100]:
```
Pipeline(memory=None,
         steps=[('standardscaler',
                 StandardScaler(copy=True, with_mean=True, with_std=Tru
e)),
                ('svr',
                 SVR(C=1, cache_size=200, coef0=0.0, degree=3, epsilon=
0.1,
                     gamma='auto_deprecated', kernel='rbf', max_iter=-
1,
                     shrinking=True, tol=0.001, verbose=False))],
         verbose=False)
```

In [101]:
```
score_predict2 = svr.predict(X_test) # predicted score for year 2019
svr.score(X_test, y_test)# The best possible value is 1, might be negati
ve
```

Out[101]:
```
0.7460792506453284
```

In [102]:
```
fig, ax = plt.subplots()
plt.scatter(y_test, score_predict2.flatten(),s = 10)
plt.xlabel('Original 2019 Score')
plt.ylabel('Predicted 2019 Score')
plt.title('Epsilon-Support Vector Regression.')
# Adding a blue line which indicates: Original 2019 Score = Predicted 20
19 Score
lims = [
    np.min([ax.get_xlim(), ax.get_ylim()]),  # min of both axes
    np.max([ax.get_xlim(), ax.get_ylim()]),  # max of both axes
]
ax.plot(lims, lims, 'b-')
ax.set_aspect('equal')
ax.set_xlim(lims)
ax.set_ylim(lims)
```

Out[102]:
```
(2.603303824567446, 8.018696175432556)
```



In [103]:
```
RMSE = np.sqrt(mean_squared_error(score_original, score_predict2))
mean = np.mean(score_original)
print(RMSE)
print(mean)
# Evaluating the performance by score
# The RMSE of our predicted score is quite small, so we can say that the
multiple linear regression model did well.
```

```
0.5591065502163332
5.407096153846153
```

In [104]:
```
rank_predict2 = pd.Series(score_predict2).rank(ascending = 0) # predicte
d rank for 2019
RMSE = np.sqrt(mean_squared_error(df_2019["Overall rank"], rank_predict2
))
print(RMSE)
# Evaluating the performance by rank
# The RMSE of our predicted rank is small, so we can say that the multip
le linear regression model did well.
```

```
21.908024522113774
```

Model 3: Neural Network

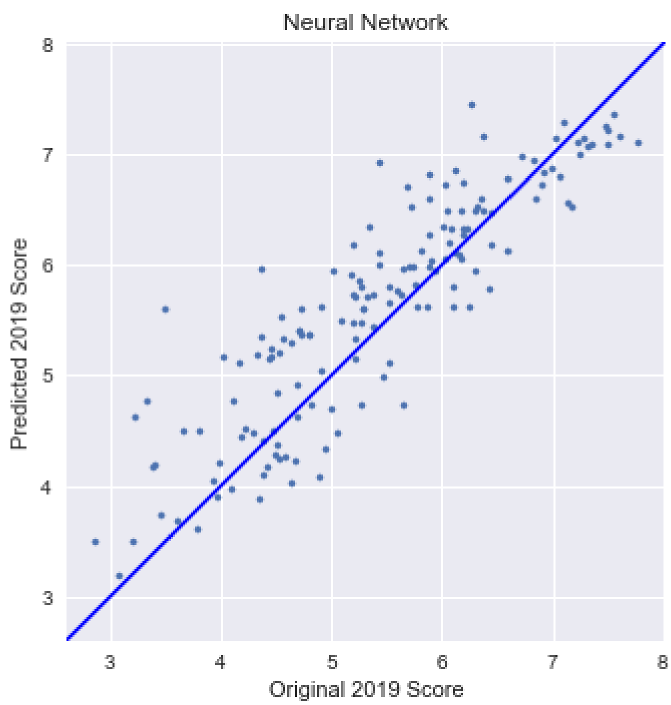
The third model we used is Neural Network. Multi-Layer Perceptron is one example of feedforward neural networks. It has three layers: Input layer, Hidden layer, Output layer. Each layer has many neurons. Neurons are the most fundamental units of a neural network. A neuron takes in data, processes the information, and produces output. The idea behinds the algorithm is: feed the input, then use some math to minimize the loss in the neural network, finally we get the output at the end.

In [105]:
```
# Build the model
from sklearn.neural_network import MLPRegressor
neural_net = MLPRegressor(hidden_layer_sizes=500, max_iter=1000)
net = neural_net.fit(X_train, y_train)
score_predict3 = neural_net.predict(X_test) # predicted score for 2019
net.score(X_test, y_test)# The best possible value is 1, might be negati
ve
```

Out[105]:
```
0.7353499634363319
```

In [106]:
```
fig, ax = plt.subplots()
plt.scatter(y_test, score_predict3.flatten(),s = 10)
plt.xlabel('Original 2019 Score')
plt.ylabel('Predicted 2019 Score')
plt.title('Neural Network')
# Adding a blue line which indicates: Original 2019 Score = Predicted 20
19 Score
lims = [
    np.min([ax.get_xlim(), ax.get_ylim()]),  # min of both axes
    np.max([ax.get_xlim(), ax.get_ylim()]),  # max of both axes
]
ax.plot(lims, lims, 'b-')
ax.set_aspect('equal')
ax.set_xlim(lims)
ax.set_ylim(lims)
```

Out[106]:
```
(2.603303824567446, 8.018696175432556)
```



In [107]:
```
RMSE = np.sqrt(mean_squared_error(score_original, score_predict3))
mean = np.mean(score_original)
print(RMSE)
print(mean)
# Evaluating the performance by score
# The RMSE of our predicted score is quite small, so we can say that the
multiple linear regression model did well.
```

```
0.5707967135011314
5.407096153846153
```

In [108]:
```
rank_predict3 = pd.Series(score_predict3).rank(ascending = 0) # predicte
d rank for 2019
RMSE = np.sqrt(mean_squared_error(df_2019["Overall rank"], rank_predict3
))
print(RMSE)
# Evaluating the performance by rank
# The RMSE of our predicted rank is small, so we can say that the multip
le linear regression model did well.
```

```
20.73644135332772
```

Fomula:

In [109]:
```
regression.intercept_
# Multiple linear regression intercept
```

Out[109]:
```
2.29937623994713
```

In [110]:
```
regression.coef_
# Multiple linear regression coeffcients
```

Out[110]:
```
array([1.14588287, 1.16559883, 0.5446503 , 1.85021572])
```

Score = 2.29937623994713 + GDP per capita *1.14588287 +Social support* 1.16559883 + Healthy life expectancy *0.5446503 +Freedom to make life choices* 1.85021572