ANALYSIS OF HEALTHY LIFESTYLE ACROSS CITIES

Health as an indicator of the quality of life of the population Indicators of health and morbidity refer to mental groups of healthy and sick people. This obliges us to approach the characterization of a person's lifestyle not only from biological, but also from medical and social positions. An important quality of health as an element of quality is the level of self-determination of behavior, that is, a responsible attitude to the preservation and occurrence of people in their health. In this sense, health as a real human resource, amateurs can dispose of differently with different results.

The main aim of this is to find relationships between various factors that lead to healthy or unhealthy lifestyle in cities and visualize them. Based on given data set we need to cluster healthy life style city in 2021 into certain group. This data contain different feature and overall 44 healthy lifestyle cities in world. And to perform exploratory data analysis for top 5 healthiest cities as well as unhealthiest cities. And perform k-means clustering to improve statistical analysis

Import packages and load the csv file into DataFrame format

In [1]:
```
import pandas as pd
file=pd.read_csv("C:/Users/deepika sakthivel/Downloads/Healthy lifestyle across cities.csv")
df=pd.DataFrame(file)
df
```

Out[1]:

	City	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)
0	Amsterdam	1	1858.0	£1.92	20.40%	81.2	30.93	1434.0	7.44	422	1048
1	Sydney	2	2636.0	£1.48	29.00%	82.1	26.86	1712.0	7.22	406	1103
2	Vienna	3	1884.0	£1.94	20.10%	81.0	17.33	1501.0	7.29	132	1008
3	Stockholm	4	1821.0	£1.72	20.60%	81.8	19.63	1452.0	7.35	129	598
4	Copenhagen	5	1630.0	£2.19	19.70%	79.8	21.24	1380.0	7.64	154	523
5	Helsinki	6	1662.0	£1.60	22.20%	80.4	13.08	1540.0	7.80	113	309
6	Fukuoka	7	2769.0	£0.78	4.30%	83.2	NaN	1644.0	5.87	35	539
7	Berlin	8	1626.0	£1.55	22.30%	80.6	39.41	1386.0	7.07	254	1729

	City	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)
8	Barcelona	9	2591.0	£1.19	23.80%	82.2	65.19	1686.0	6.40	585	2344
9	Vancouver	10	1938.0	£1.08	29.40%	81.7	24.26	1670.0	7.23	218	788
10	Melbourne	11	2363.0	£1.57	29.00%	82.1	25.90	1712.0	7.22	243	813
11	Beijing	12	2671.0	£0.26	6.20%	75.4	85.43	NaN	5.12	223	261
12	Bangkok	13	2624.0	£0.22	10.00%	74.1	76.64	NaN	5.99	377	1796
13	Buenos Aires	14	2525.0	£0.57	28.30%	75.9	52.64	NaN	5.97	246	1435
14	Toronto	15	2066.0	£1.09	29.40%	81.7	37.83	1670.0	7.23	174	1656
15	Madrid	16	2769.0	£1.30	23.80%	82.2	52.68	1686.0	6.40	216	2491
16	Jakarta	17	2983.0	£0.21	6.90%	68.5	84.39	NaN	5.28	114	833
17	Seoul	18	2066.0	£0.59	4.70%	81.3	57.82	1967.0	5.87	144	389
18	Frankfurt	19	1662.0	£1.95	22.30%	80.6	37.78	1386.0	7.07	23	551
19	Geneva	20	NaN	£2.62	19.50%	82.6	27.25	1557.0	7.56	44	444
20	Tel Aviv	21	3311.0	£1.63	26.10%	81.9	47.28	1898.0	7.12	139	420
21	Istanbul	22	2218.0	£0.15	32.10%	74.7	69.49	1832.0	5.13	419	934
22	Cairo	23	3542.0	£0.16	32.00%	70.7	91.74	NaN	4.15	323	250
23	Taipei	24	1405.0	£0.57	6.20%	75.4	49.32	NaN	5.12	134	717
24	Los Angeles	25	3254.0	£1.52	36.20%	78.8	66.07	1779.0	6.94	223	1439
25	Mumbai	26	2584.0	£0.15	3.90%	67.3	82.84	NaN	3.57	187	1183
26	Boston	27	2634.0	£1.39	36.20%	78.8	27.03	1779.0	6.94	88	588
27	Dublin	28	1453.0	£1.40	25.30%	80.5	40.07	1772.0	7.09	159	659
28	Tokyo	29	1877.0	£0.76	4.30%	83.2	42.84	1644.0	5.87	387	5802
29	Chicago	30	2508.0	£1.20	36.20%	78.8	43.33	1779.0	6.94	171	1320
30	Hong Kong	31	1836.0	£0.75	6.20%	75.4	67.46	NaN	5.51	277	1257
31	Shanghai	32	1776.0	£0.29	6.20%	75.4	77.40	NaN	5.12	108	346
32	Brussels	33	1546.0	£2.11	22.10%	80.4	62.67	1583.0	6.86	55	988
33	San Francisco	34	3062.0	£1.60	36.20%	78.8	47.36	1779.0	6.94	242	1031
34	Paris	35	1662.0	£1.95	21.60%	81.8	65.10	1505.0	6.66	331	4363
35	Sao Paulo	36	2003.0	£0.44	22.10%	73.9	79.78	NaN	6.37	158	3355
36	Zurich	37	1566.0	£3.20	19.50%	82.6	17.31	1557.0	7.56	69	538
37	London	38	1633.0	£1.16	27.80%	80.4	58.91	1538.0	7.16	433	6417
38	Johannesburg	39	3124.0	£0.59	28.30%	56.3	61.83	NaN	4.81	194	492
39	Milan	40	1915.0	£1.15	19.90%	82.7	67.19	1718.0	6.38	110	2396
40	Washington, D.C.	41	2528.0	£1.45	36.20%	78.8	39.18	1779.0	6.94	83	744
41	New York	42	2535.0	£1.32	36.20%	78.8	57.36	1779.0	6.94	359	3081
42	Moscow	43	1901.0	£0.41	23.10%	69.5	57.63	1965.0	5.54	322	3206
43	Mexico City	44	2555.0	£0.45	28.90%	76.4	82.78	2137.0	6.46	192	1313

In [2]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 44 entries, 0 to 43
Data columns (total 12 columns):
 #   Column                                Non-Null Count  Dtype  
---  ------                                --------------  -----  
 0   City                                  44 non-null     object 
 1   Rank                                  44 non-null     int64  
 2   Sunshine hours(City)                  43 non-null     float64
 3   Cost of a bottle of water(City)       44 non-null     object 
 4   Obesity levels(Country)               44 non-null     object 
 5   Life expectancy(years) (Country)      44 non-null     float64
 6   Pollution(Index score) (City)         43 non-null     float64
```

```
 7   Annual avg. hours worked               33 non-null     float64
 8   Happiness levels(Country)              44 non-null     float64
 9   Outdoor activities(City)               44 non-null     int64
 10  Number of take out places(City)        44 non-null     int64
 11  Cost of a monthly gym membership(City)  44 non-null     object
dtypes: float64(5), int64(3), object(4)
memory usage: 4.2+ KB
```

In [3]:
```
df.shape
```

Out[3]:
```
(44, 12)
```

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

Out[4]:

	City	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)	Co me
0	Amsterdam	1	1858.0	£1.92	20.40%	81.2	30.93	1434.0	7.44	422	1048	
1	Sydney	2	2636.0	£1.48	29.00%	82.1	26.86	1712.0	7.22	406	1103	
2	Vienna	3	1884.0	£1.94	20.10%	81.0	17.33	1501.0	7.29	132	1008	
3	Stockholm	4	1821.0	£1.72	20.60%	81.8	19.63	1452.0	7.35	129	598	
4	Copenhagen	5	1630.0	£2.19	19.70%	79.8	21.24	1380.0	7.64	154	523	

we need to replace "£" and "%"

In [5]:
```
df['Cost of a bottle of water(City)'] = df['Cost of a bottle of water(City)'].replace(to_replace ='£', value = '', regex = True)
df['Obesity levels(Country)'] = df['Obesity levels(Country)'].replace(to_replace ='%', value = '', regex = True)
df['Cost of a monthly gym membership(City)'] = df['Cost of a monthly gym membership(City)'].replace(to_replace ='£', value = '', reg
df['Cost of a monthly gym membership(City)']
```

Out[5]:
```
0     34.90
1     41.66
2     25.74
3     37.31
4     32.53
5     35.23
6     55.87
7     26.11
8     37.80
9     31.04
10    36.89
11    38.62
12    50.03
13    22.45
14    32.64
15    34.54
16    29.94
17    43.03
18    39.01
19    70.00
20    58.31
21    16.97
22    23.25
23    34.76
24    32.00
25    19.54
26    46.27
27    37.35
28    70.82
29    41.14
30    57.95
31    44.68
32    25.34
33    65.13
34    35.93
35    16.07
36    73.11
37    42.71
38    24.28
39    53.49
40    65.99
41    64.66
42    31.40
```

```
43    41.99
Name: Cost of a monthly gym membership(City), dtype: object
```

Data preprocessing

In [6]:
```
df['Sunshine hours(City)']=df['Sunshine hours(City)'].map(float)
df['Cost of a bottle of water(City)']=df['Cost of a bottle of water(City)'].map(float)
df['Obesity levels(Country)']=df['Obesity levels(Country)'].map(float)
df['Pollution(Index score) (City)']=df['Pollution(Index score) (City)'].map(float)
df['Annual avg. hours worked']=df['Annual avg. hours worked'].map(float)
df['Cost of a monthly gym membership(City)']=df['Cost of a monthly gym membership(City)'].map(float)
```

In [7]:
```
df['Annual avg. hours worked'].unique()
```

Out[7]:
```
array([1434., 1712., 1501., 1452., 1380., 1540., 1644., 1386., 1686.,
       1670.,   nan, 1967., 1557., 1898., 1832., 1779., 1772., 1583.,
       1505., 1538., 1718., 1965., 2137.])
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 44 entries, 0 to 43
Data columns (total 12 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   City                                  44 non-null     object
 1   Rank                                  44 non-null     int64
 2   Sunshine hours(City)                  43 non-null     float64
 3   Cost of a bottle of water(City)       44 non-null     float64
 4   Obesity levels(Country)               44 non-null     float64
 5   Life expectancy(years) (Country)      44 non-null     float64
 6   Pollution(Index score) (City)         43 non-null     float64
 7   Annual avg. hours worked              33 non-null     float64
 8   Happiness levels(Country)             44 non-null     float64
 9   Outdoor activities(City)              44 non-null     int64
 10  Number of take out places(City)       44 non-null     int64
 11  Cost of a monthly gym membership(City)  44 non-null     float64
dtypes: float64(8), int64(3), object(1)
memory usage: 4.2+ KB
```

Let us look out missing values

In [9]:
```
df.isna().sum()
```

Out[9]:
```
City                                  0
Rank                                  0
Sunshine hours(City)                  1
Cost of a bottle of water(City)       0
Obesity levels(Country)               0
Life expectancy(years) (Country)      0
Pollution(Index score) (City)         1
Annual avg. hours worked             11
Happiness levels(Country)             0
Outdoor activities(City)              0
Number of take out places(City)       0
Cost of a monthly gym membership(City)    0
dtype: int64
```

Fill the missing values

In [10]:
```
x=df["Sunshine hours(City)"].mean()
df["Sunshine hours(City)"].fillna(x,inplace=True)
```

In [11]:
```
x=df["Pollution(Index score) (City)"].mean()
df["Pollution(Index score) (City)"].fillna(x,inplace=True)
```

In [12]:
```
x=df["Annual avg. hours worked"].mean()
df["Annual avg. hours worked"].fillna(x,inplace=True)
```

In [13]:
```
df.isna().sum()
```

Out[13]:
```
City                                  0
Rank                                  0
```

```
Sunshine hours(City)                    0
Cost of a bottle of water(City)         0
Obesity levels(Country)                 0
Life expectancy(years) (Country)        0
Pollution(Index score) (City)           0
Annual avg. hours worked                0
Happiness levels(Country)               0
Outdoor activities(City)                0
Number of take out places(City)         0
Cost of a monthly gym membership(City)  0
dtype: int64
```

Let us check for duplicates

In [14]:
```
df.duplicated().sum()
# THERE IS NO DUPLICATED VALUES IN THE DATASET
```

Out[14]:
```
0
```

Let us look at the descriptive statistics of the dataset

In [15]:
```
df.describe()
```

Out[15]:

	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)	Co m
count	44.000000	44.000000	44.000000	44.00000	44.00000	44.000000	44.000000	44.000000	44.000000	44.000000	
mean	22.500000	2245.860465	1.173409	21.92500	78.17500	51.122326	1672.909091	6.435000	213.977273	1443.113636	
std	12.845233	560.767190	0.718642	10.19567	5.30437	21.600553	154.957363	0.991202	127.190297	1388.803270	
min	1.000000	1405.000000	0.150000	3.90000	56.30000	13.080000	1380.000000	3.570000	23.000000	250.000000	
25%	11.750000	1809.750000	0.570000	19.50000	75.40000	36.067500	1576.500000	5.870000	125.250000	548.000000	
50%	22.500000	2142.000000	1.195000	22.30000	80.40000	51.881163	1672.909091	6.900000	189.500000	998.000000	
75%	33.250000	2626.500000	1.600000	29.00000	81.80000	66.350000	1773.750000	7.175000	288.250000	1674.250000	
max	44.000000	3542.000000	3.200000	36.20000	83.20000	91.740000	2137.000000	7.800000	585.000000	6417.000000	

General exploratory data analysis

In [16]:
```
import matplotlib.pyplot as plt
df.corr()
```

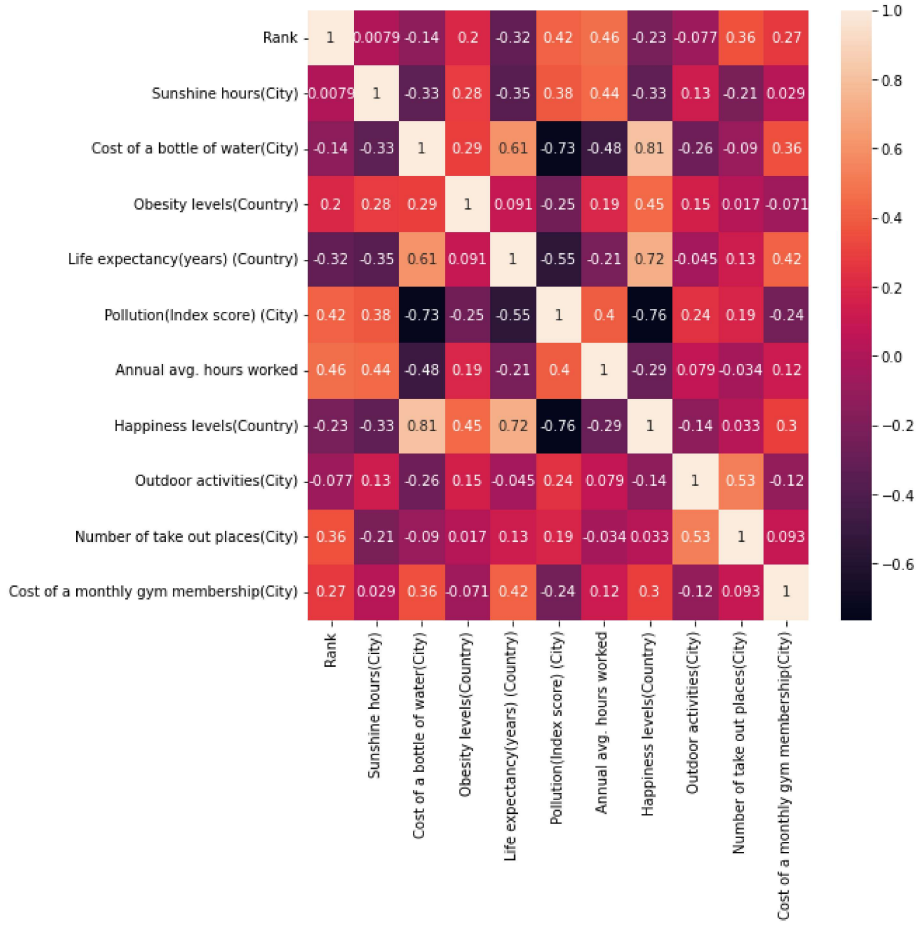
Out[16]:

	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Numbe take places(C
Rank	1.000000	0.007937	-0.141420	0.197486	-0.320034	0.419829	0.463708	-0.231970	-0.076972	0.363
Sunshine hours(City)	0.007937	1.000000	-0.331239	0.281115	-0.353388	0.383466	0.443596	-0.328979	0.126767	-0.210
Cost of a bottle of water(City)	-0.141420	-0.331239	1.000000	0.293047	0.612382	-0.732659	-0.479196	0.813159	-0.260297	-0.089
Obesity levels(Country)	0.197486	0.281115	0.293047	1.000000	0.091071	-0.246972	0.193710	0.446399	0.150171	0.016
Life expectancy(years) (Country)	-0.320034	-0.353388	0.612382	0.091071	1.000000	-0.552715	-0.212952	0.724587	-0.044864	0.128
Pollution(Index score) (City)	0.419829	0.383466	-0.732659	-0.246972	-0.552715	1.000000	0.395422	-0.762935	0.236837	0.186
Annual avg. hours worked	0.463708	0.443596	-0.479196	0.193710	-0.212952	0.395422	1.000000	-0.290647	0.078753	-0.033
Happiness levels(Country)	-0.231970	-0.328979	0.813159	0.446399	0.724587	-0.762935	-0.290647	1.000000	-0.137612	0.033
Outdoor activities(City)	-0.076972	0.126767	-0.260297	0.150171	-0.044864	0.236837	0.078753	-0.137612	1.000000	0.528

	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Numbe take places(C
Number of take out places(City)	0.363058	-0.210539	-0.089963	0.016833	0.128163	0.186281	-0.033546	0.033116	0.528200	1.000
Cost of a monthly gym membership(City)	0.272521	0.029244	0.356461	-0.070904	0.417986	-0.241757	0.123009	0.297425	-0.115400	0.092

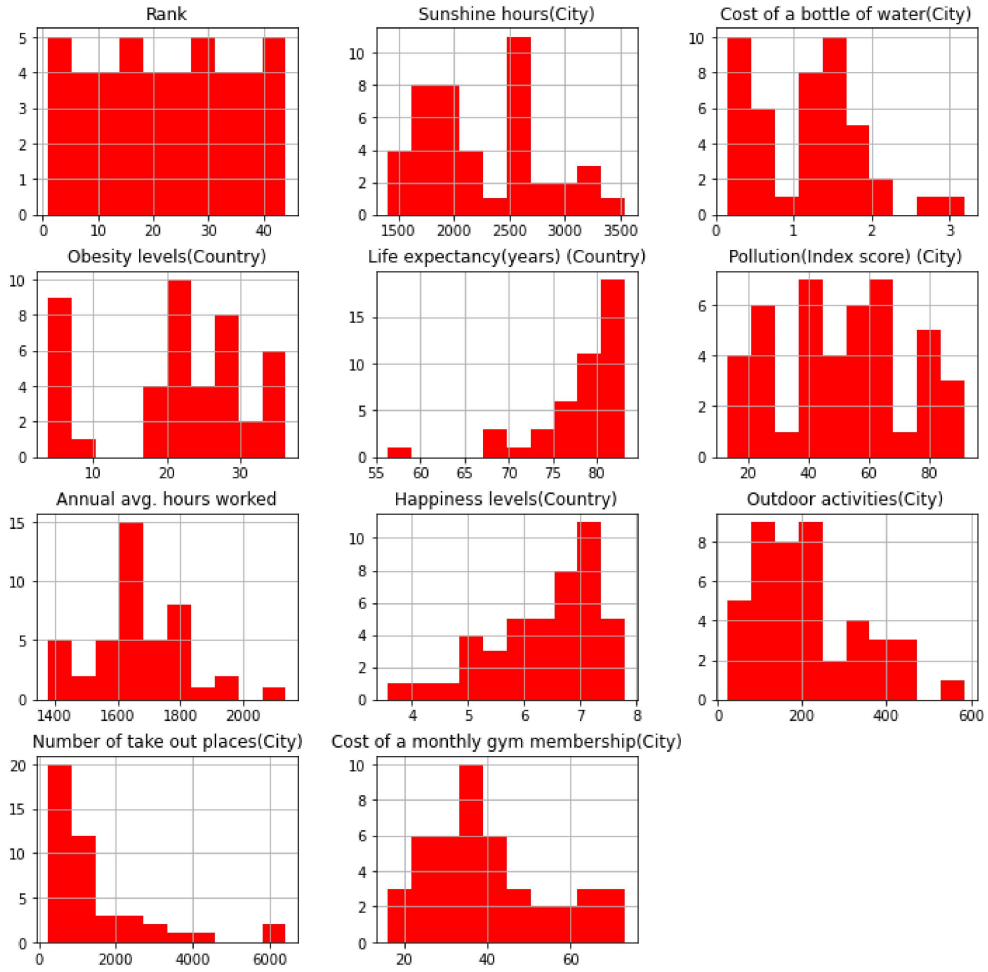
In [17]:

```
import seaborn as sns
plt.figure(figsize=(8, 8))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



In [18]:

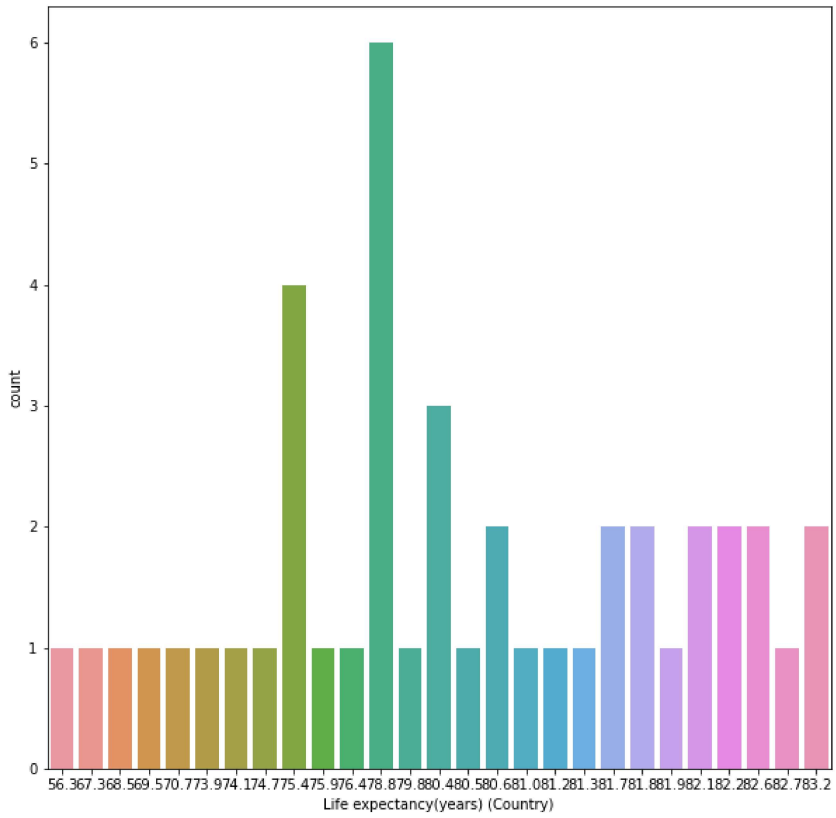
```
plotting=df.hist(figsize=(12,12),color="red")
```



In [19]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [20]:
```
plt.figure(figsize=(10, 10))
sns.countplot(df["Life expectancy(years) (Country)"])
```

Out[20]:
```
<AxesSubplot:xlabel='Life expectancy(years) (Country)', ylabel='count'>
```



Relationship between happiness level and life expectancy

In [21]:
```
plt.scatter(df["Happiness levels(Country)"],df['Life expectancy(years) (Country)'],c="g",s=70)
plt.xlabel("Happiness levels");
plt.ylabel("Life expectancy");
plt.title("Relation between Happiness levels and Life expectancy")
```

Out[21]:
```
Text(0.5, 1.0, 'Relation between Happiness levels and Life expectancy')
```

This clearly shows that happiness levels leads to the higher levels of expectancy. And clearly shows that all lead healthy life because of happiness level

Exploratory analysis of data for the 5 healthiest cities.

In [22]:
```
df.columns
```

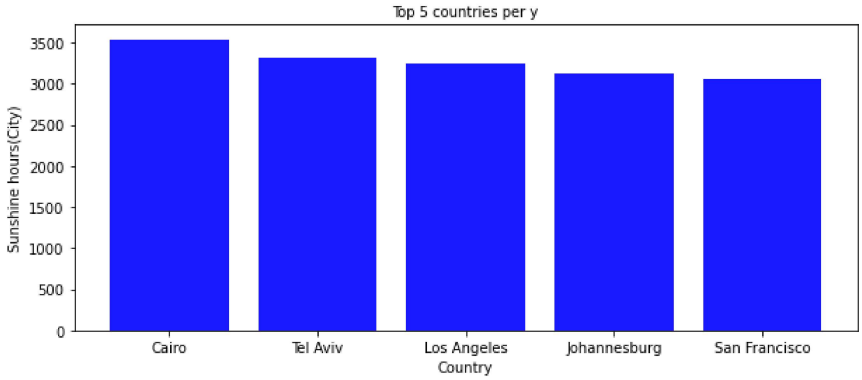
Out[22]:
```
Index(['City', 'Rank', 'Sunshine hours(City)',
       'Cost of a bottle of water(City)', 'Obesity levels(Country)',
       'Life expectancy(years) (Country)', 'Pollution(Index score) (City)',
       'Annual avg. hours worked', 'Happiness levels(Country)',
       'Outdoor activities(City)', 'Number of take out places(City)',
       'Cost of a monthly gym membership(City)'],
      dtype='object')
```

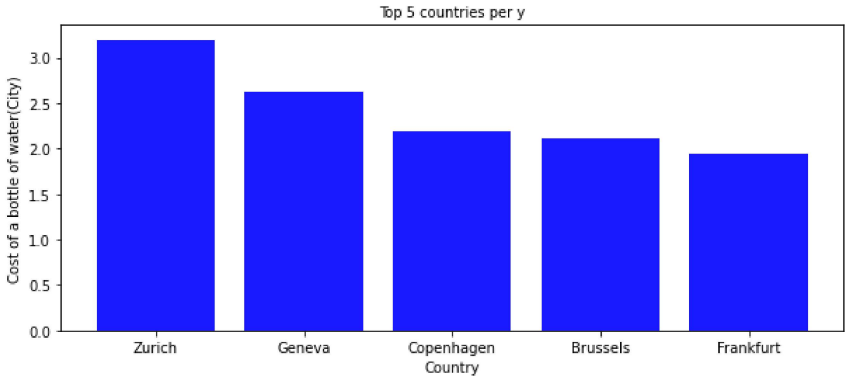
In [23]:
```
columns=['Sunshine hours(City)', 'Cost of a bottle of water(City)',
       'Obesity levels(Country)', 'Life expectancy(years) (Country)',
```

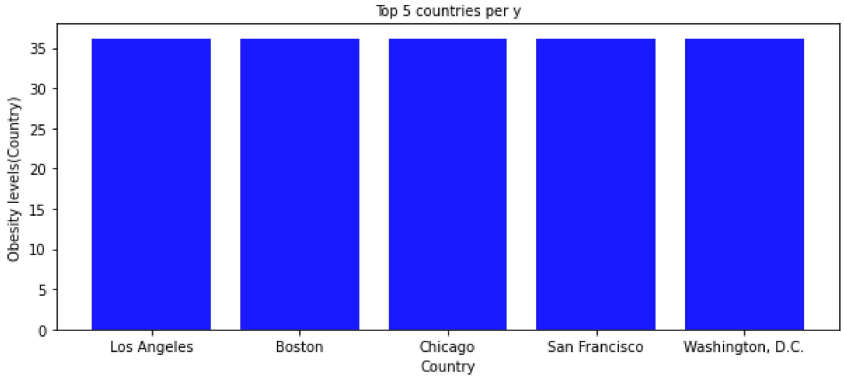
```
        'Pollution(Index score) (City)', 'Annual avg. hours worked',
        'Happiness levels(Country)', 'Outdoor activities(City)',
        'Number of take out places(City)',
        'Cost of a monthly gym membership(City)']
```

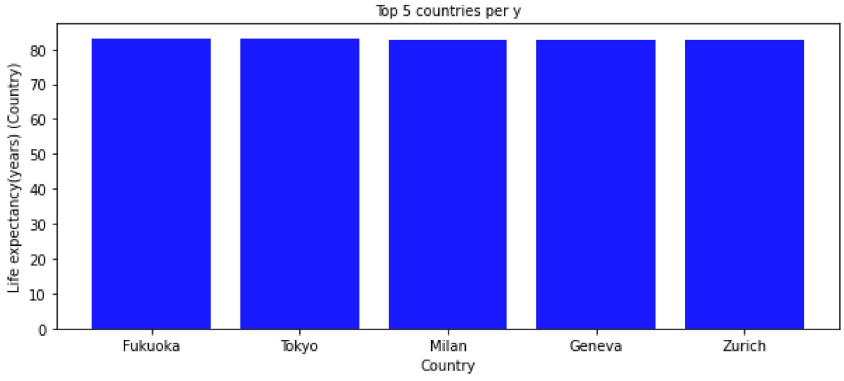
In [24]:

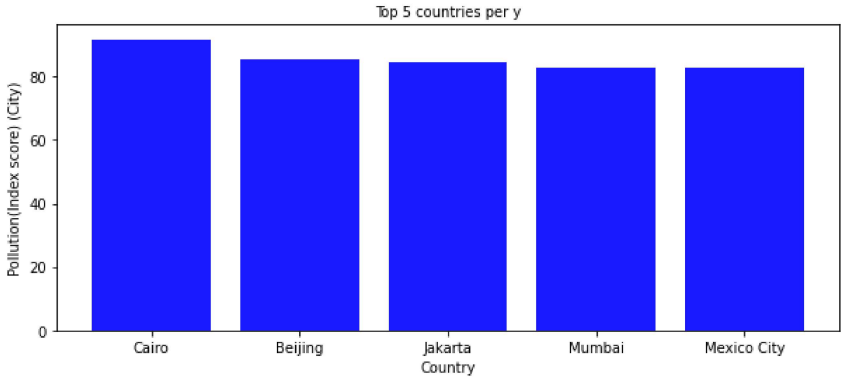
```
import matplotlib.pyplot as plt
for column in columns:
  top10 = df.nlargest(5,column)
  plt.figure(figsize=(10,4))
  plt.bar(top10['City'], top10[column],color='blue',alpha=0.9)
  plt.ylabel(column, fontsize = 10)
  plt.xlabel("Country", fontsize = 10)
  plt.title("Top 5 countries per y", fontsize = 10)
```

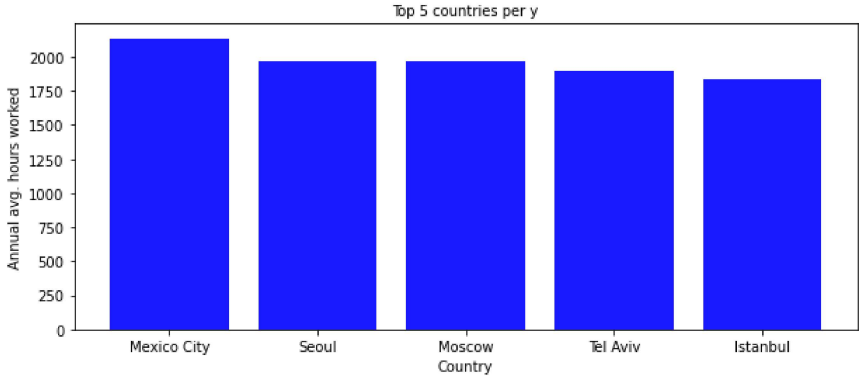


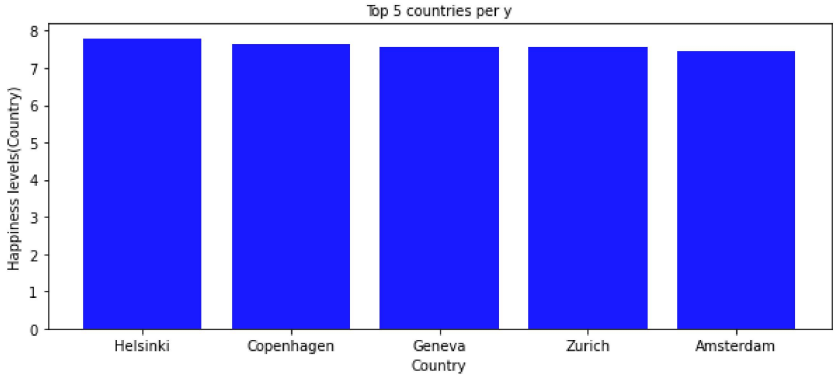


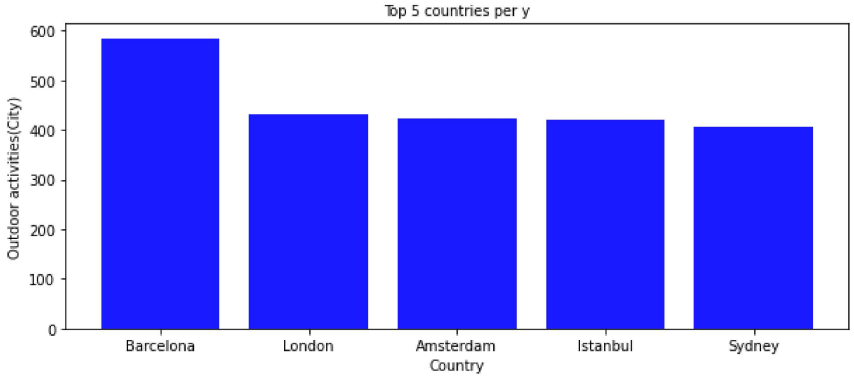


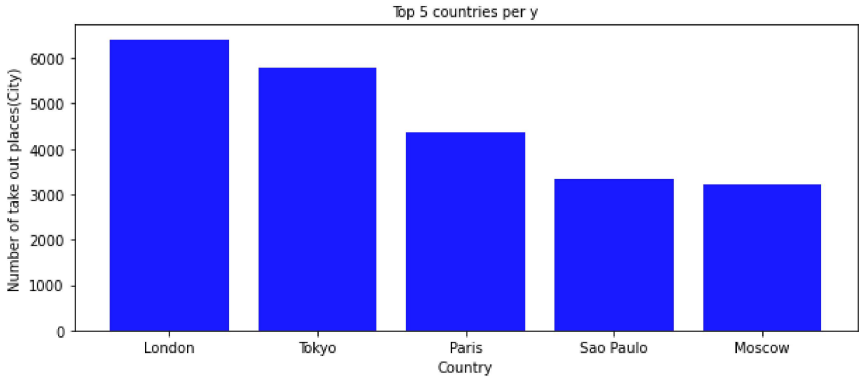


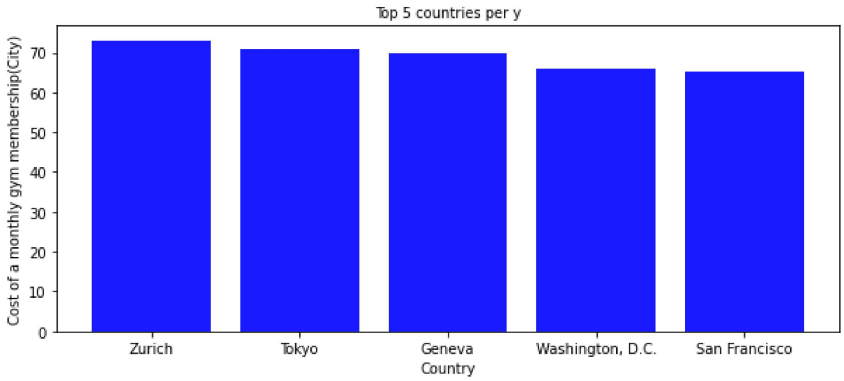

Top 5 countries per y
Pollution(Index score) (City)
0
20
40
60
80
Cairo
Beijing
Jakarta
Mumbai
Mexico City
Country


Top 5 countries per y
Annual avg. hours worked
0
250
500
750
1000
1250
1500
1750
2000
Mexico City
Seoul
Moscow
Tel Aviv
Istanbul
Country


Top 5 countries per y
Happiness levels(Countny)
0
1
2
3
4
5
6
7
8
Helsinki
Copenhagen
Geneva
Zurich
Amsterdam
Country


Top 5 countries per y
Outdoor activities(City)
0
100
200
300
400
500
600
Barcelona
London
Amsterdam
Istanbul
Sydney
Country

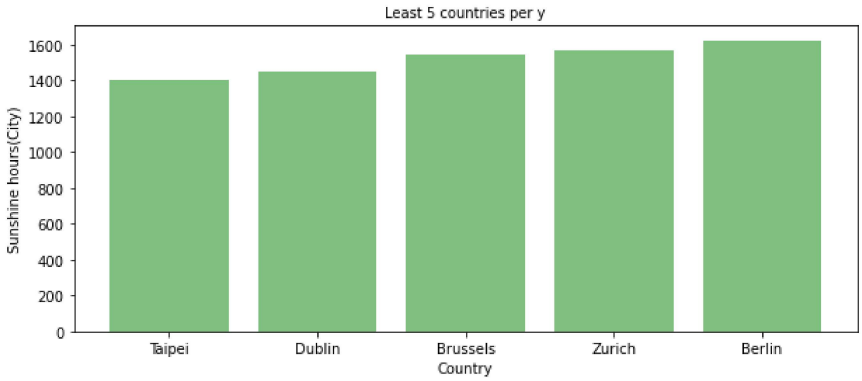


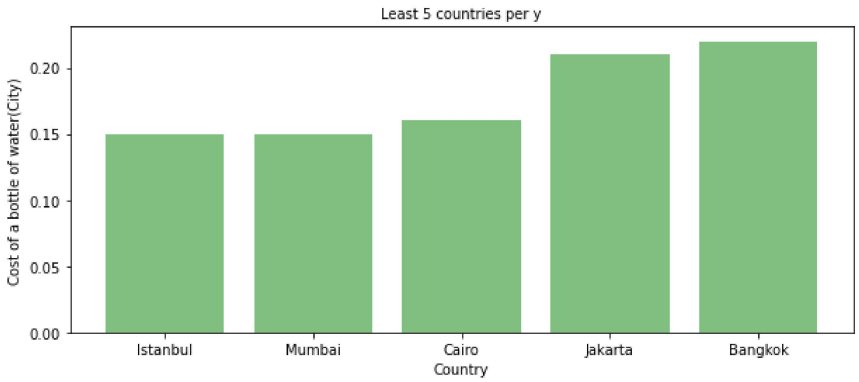


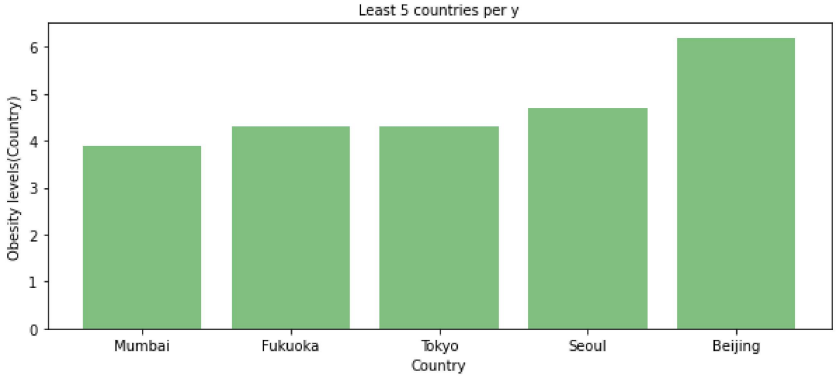
Now we have analyzed the top 5 healthiest cities based on various categories like - Sunshine hours,Cost of Bottle of water,Obesity levels,Life expectancy,pollution,Annual average hours,Happiness level,Outdoor activities,Number of take out places and Cost of monthly gym membership

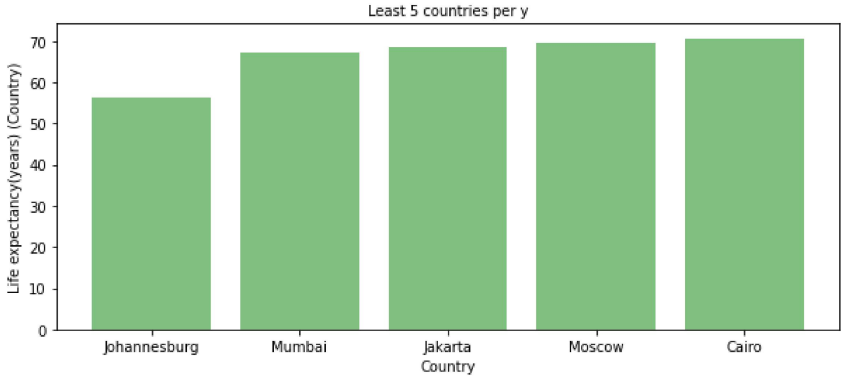
Exploratory analysis of data for least 5 healthiest cities

In [25]:
```
for column in columns:
  top10 = df.nsmallest(5,column)
  plt.figure(figsize=(10,4))
  plt.bar(top10['City'], top10[column],color='green',alpha=0.5)
  plt.ylabel(column, fontsize = 10)
  plt.xlabel("Country", fontsize = 10)
  plt.title("Least 5 countries per y", fontsize = 10)
```

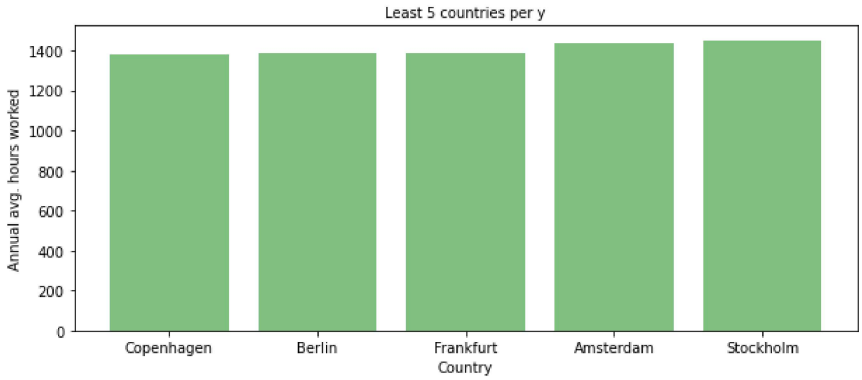


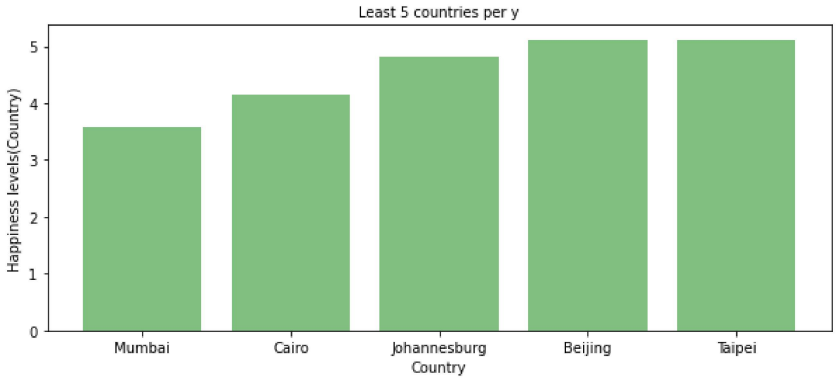


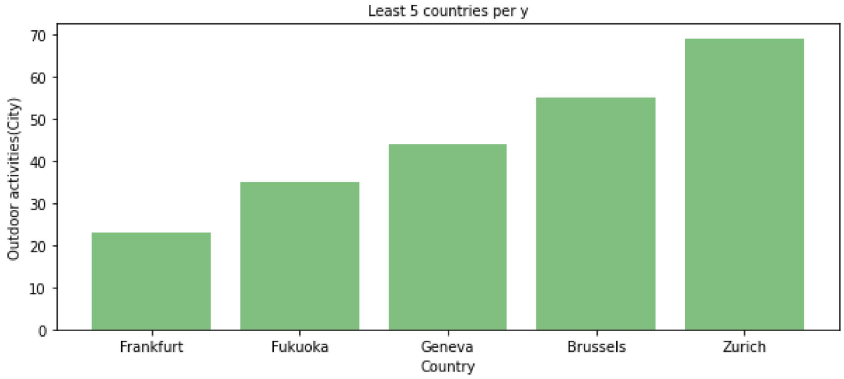

Least 5 countries per y
Obesity levels(Country)
0
1
2
3
4
5
6
Mumbai
Fukuoka
Tokyo
Seoul
Beijing
Country

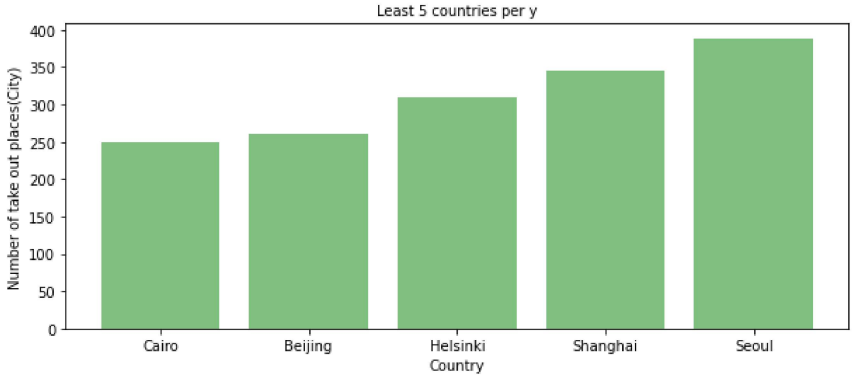

Least 5 countries per y
Life expectancy(years) (Country)
0
10
20
30
40
50
60
70
Johannesburg
Mumbai
Jakarta
Moscow
Cairo
Country

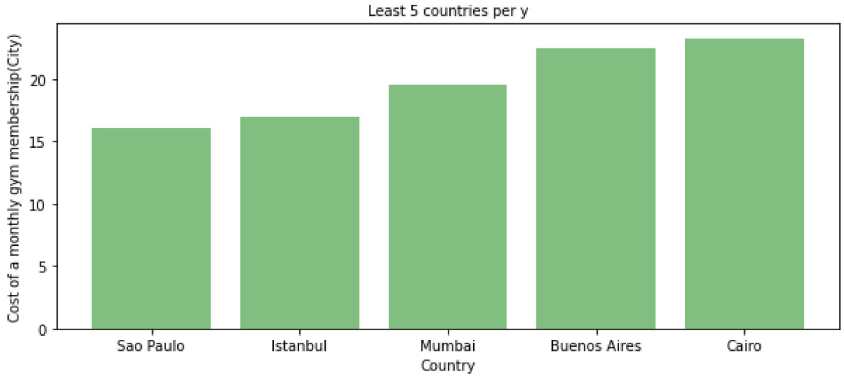

Least 5 countries per y
Pollution(Index score) (City)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Helsinki
Zurich
Vienna
Stockholm
Copenhagen
Country


Least 5 countries per y
Annual avg. hours worked
0
200
400
600
800
1000
1200
1400
Copenhagen
Berlin
Frankfurt
Amsterdam
Stockholm
Country





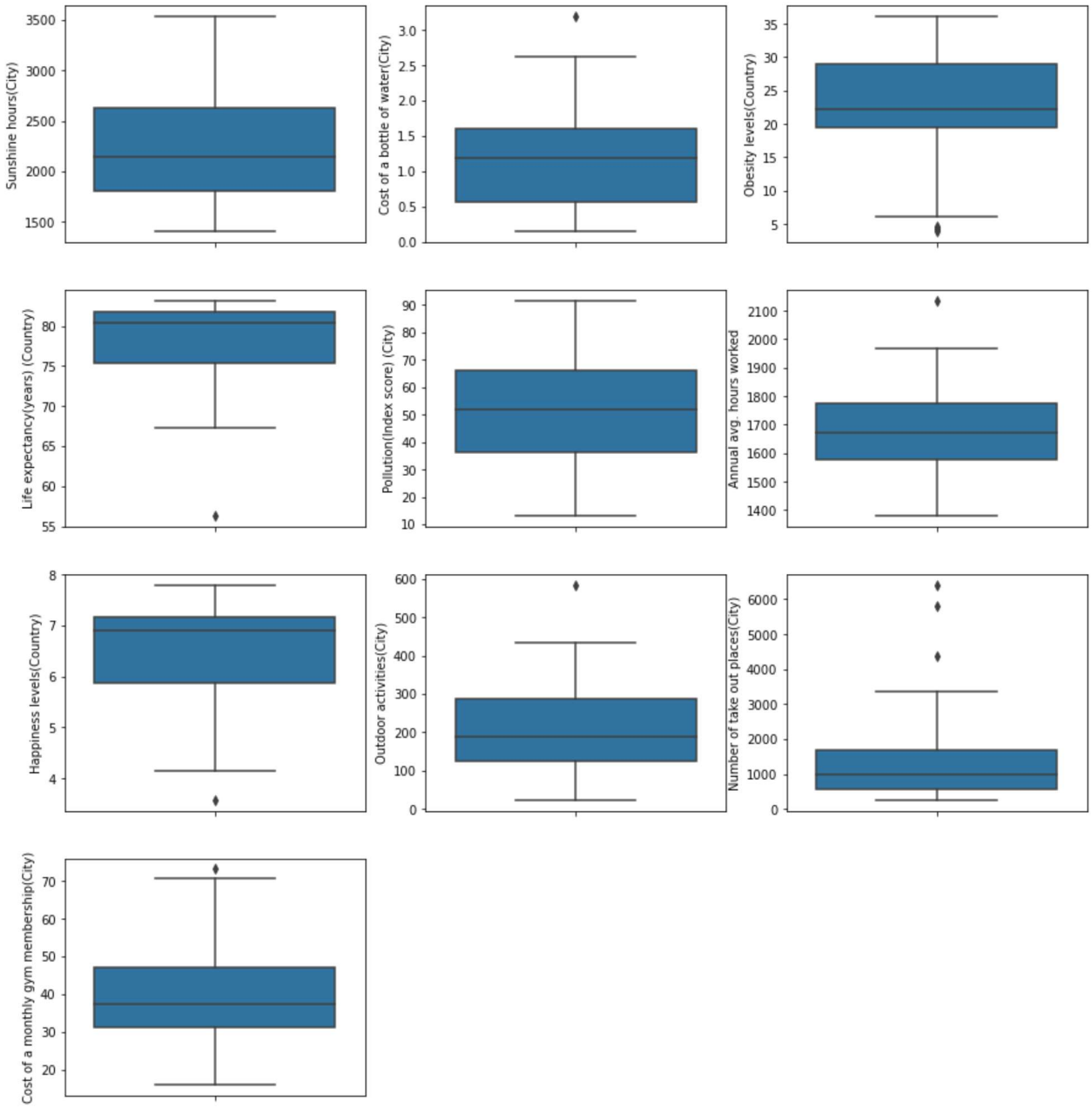




Lets look outliers in data

In [26]:

```
import seaborn as sns
i=1
plt.figure(figsize=(15,25))
for feature in columns:
    plt.subplot(6,3,i)
    sns.boxplot(y=df[feature])
    i+=1
```



Let us analyze cities in asia

Asia - is Earth's largest and most populous continent, located primarily in the Eastern and Northern Hemispheres. It shares the continental landmass of Eurasia with the continent of Europe, and the continental landmass of Afro-Eurasia with Africa and Europe. Asia covers an area of 44,579,000 square kilometres (17,212,000 sq mi), about 30% of Earth's total land area and 8.7% of the Earth's total surface area. The continent, which has long been home to the majority of the human population, was the site of many of the first civilizations. Its 4.7 billion people constitutes roughly 60% of the world's population.

In [27]:

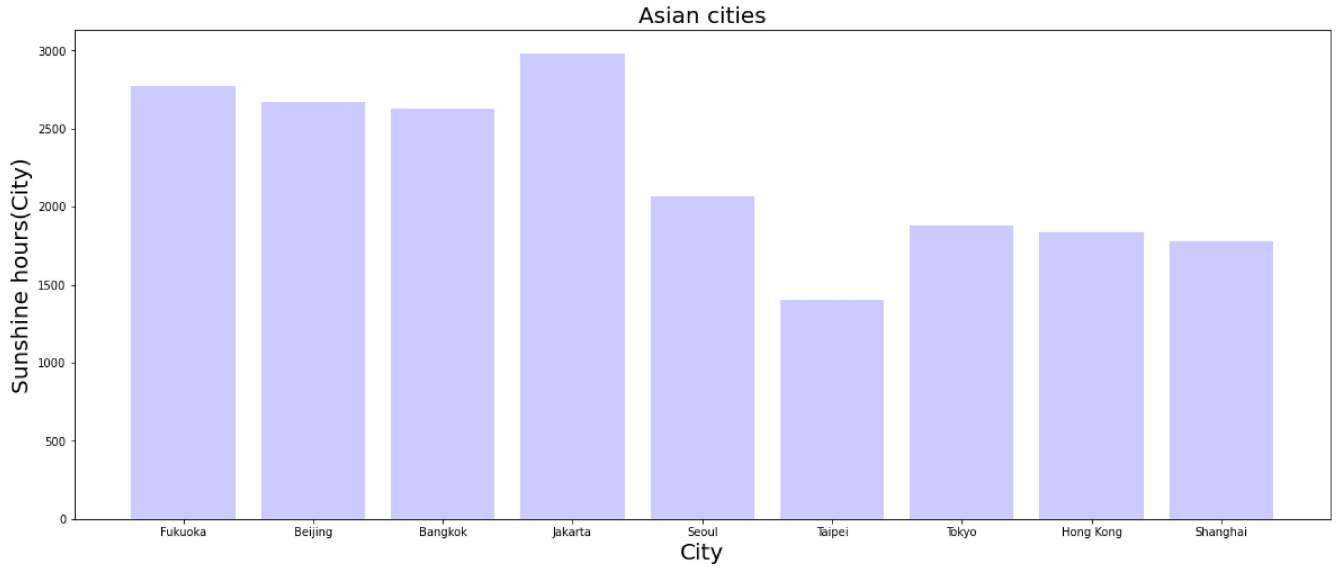
```
Asia=df.loc[[6,11,12,16,17,23,28,30,31]]
Asia
```

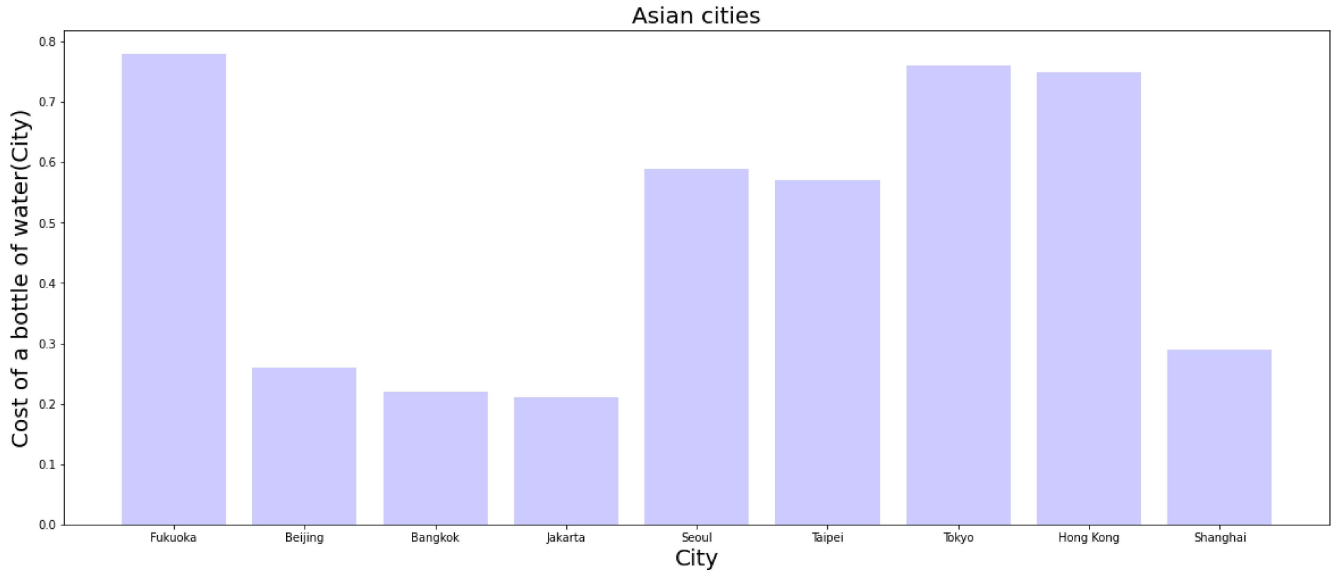
Out[27]:

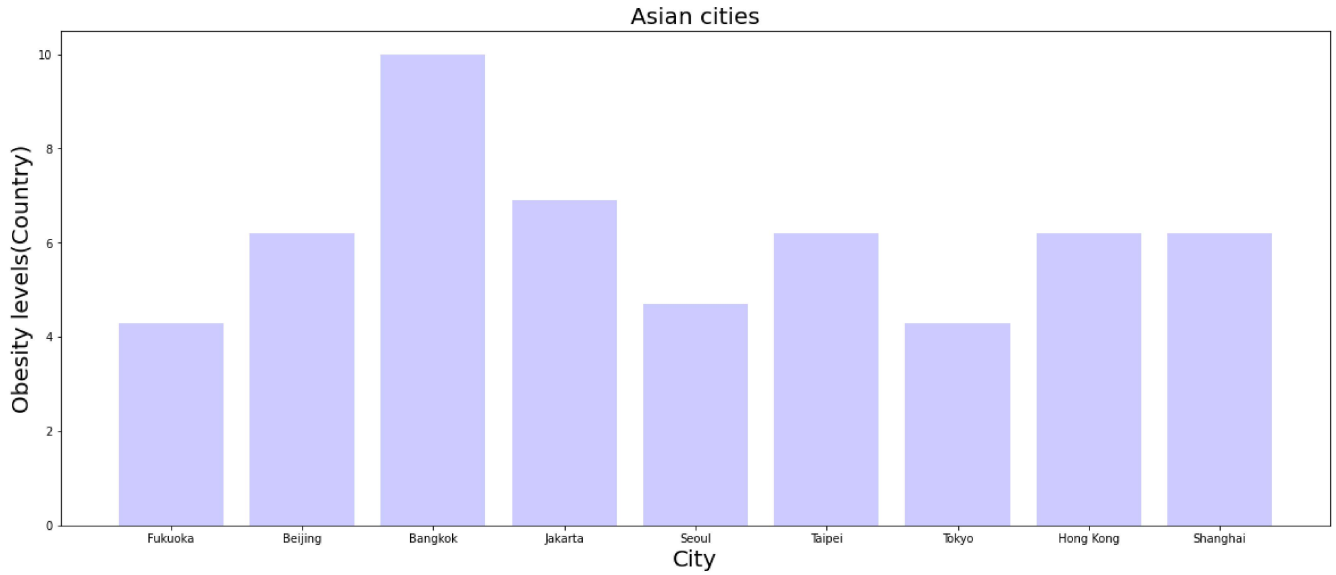
	City	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)
6	Fukuoka	7	2769.0	0.78	4.3	83.2	51.122326	1644.000000	5.87	35	539
11	Beijing	12	2671.0	0.26	6.2	75.4	85.430000	1672.909091	5.12	223	261
12	Bangkok	13	2624.0	0.22	10.0	74.1	76.640000	1672.909091	5.99	377	1796
16	Jakarta	17	2983.0	0.21	6.9	68.5	84.390000	1672.909091	5.28	114	833
17	Seoul	18	2066.0	0.59	4.7	81.3	57.820000	1967.000000	5.87	144	389
23	Taipei	24	1405.0	0.57	6.2	75.4	49.320000	1672.909091	5.12	134	717
28	Tokyo	29	1877.0	0.76	4.3	83.2	42.840000	1644.000000	5.87	387	5802
30	Hong Kong	31	1836.0	0.75	6.2	75.4	67.460000	1672.909091	5.51	277	1257
31	Shanghai	32	1776.0	0.29	6.2	75.4	77.400000	1672.909091	5.12	108	346

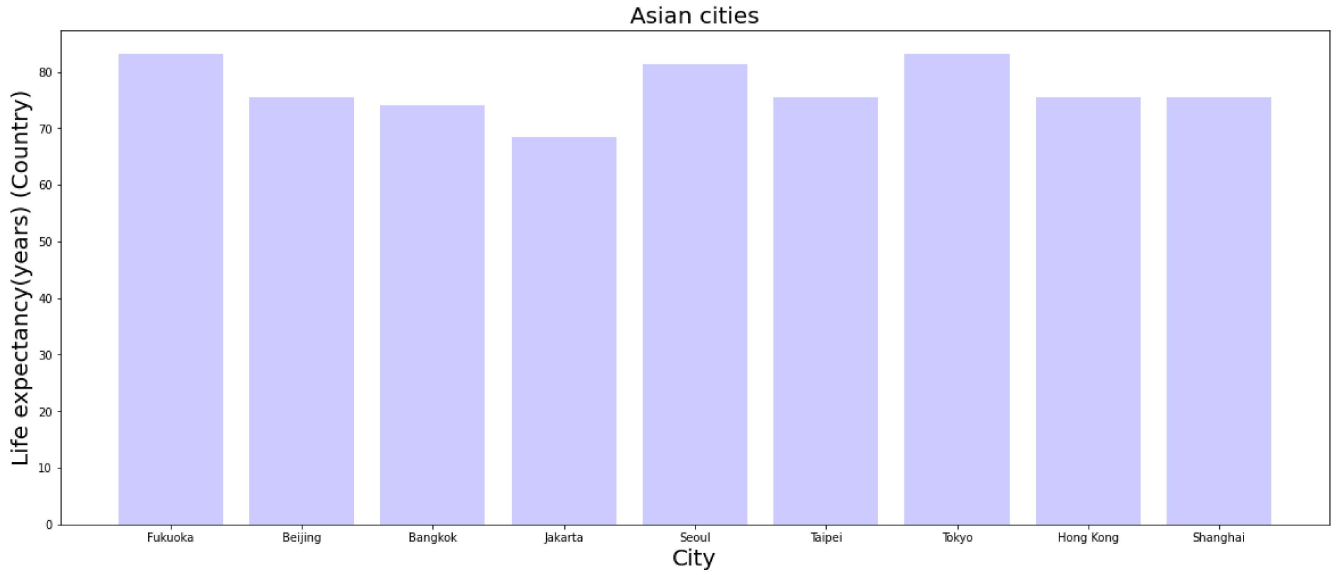
In [28]:

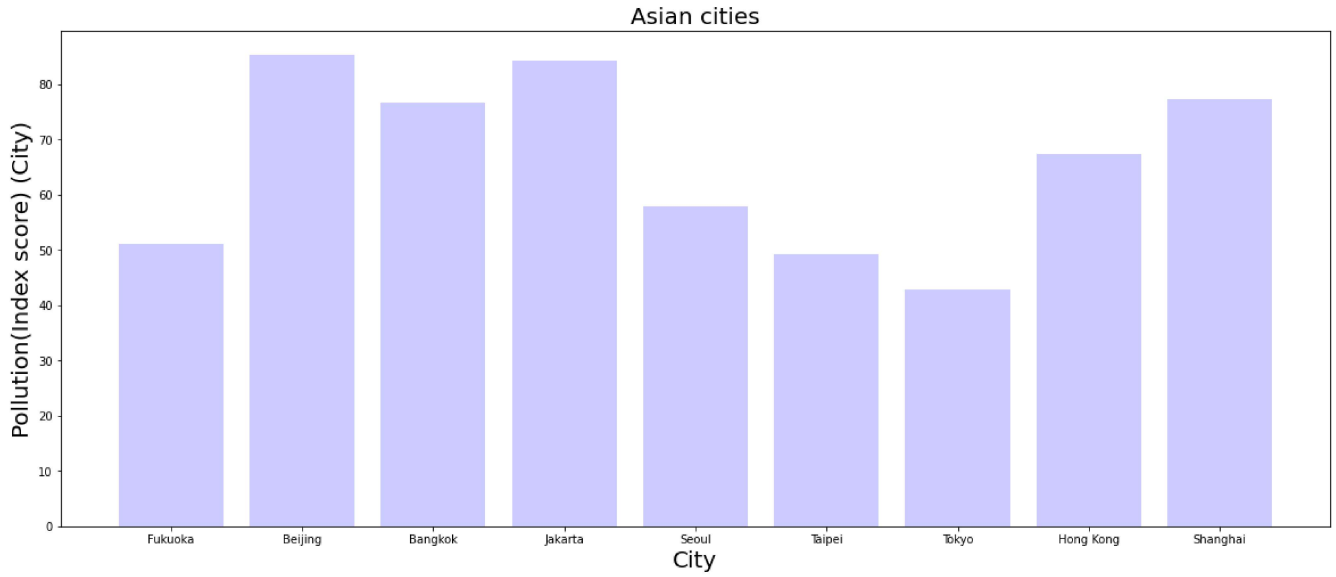
```
for column in columns:
  plt.figure(figsize=(20,8))
  plt.bar(Asia['City'], Asia[column],color='blue',alpha=0.2)
  plt.ylabel(column, fontsize = 20)
  plt.xlabel("City", fontsize = 20)
  plt.title("Asian cities", fontsize = 20)
```

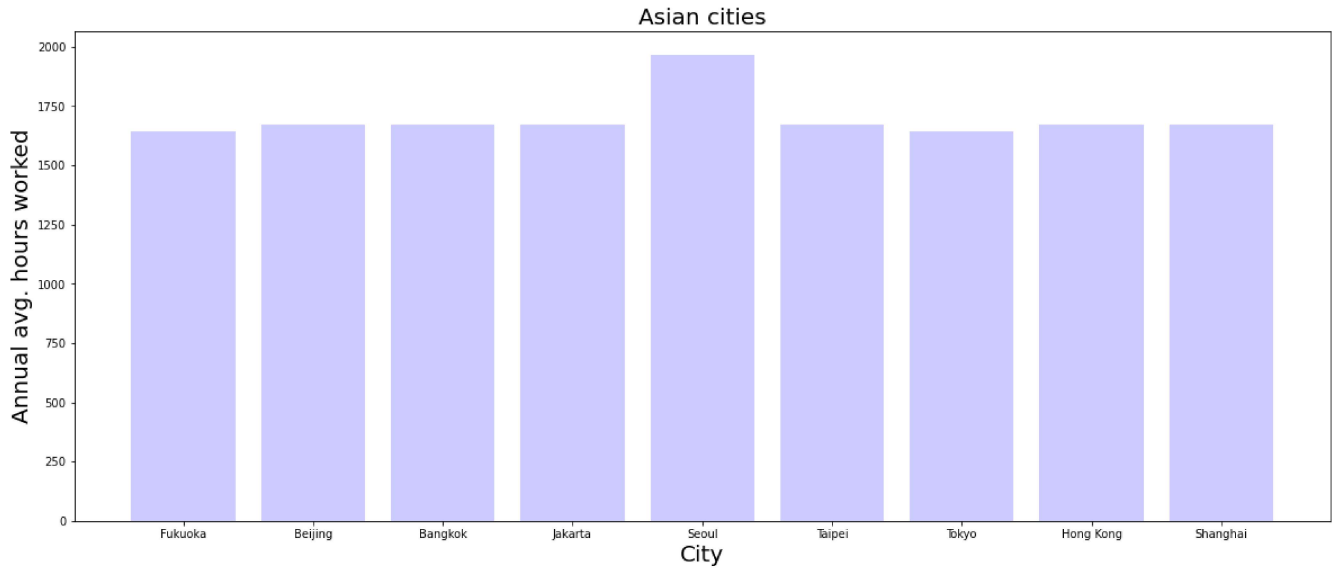

Asian cities
Sunshine hours(City)
3000
2500
2000
1500
1000
500
0
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City

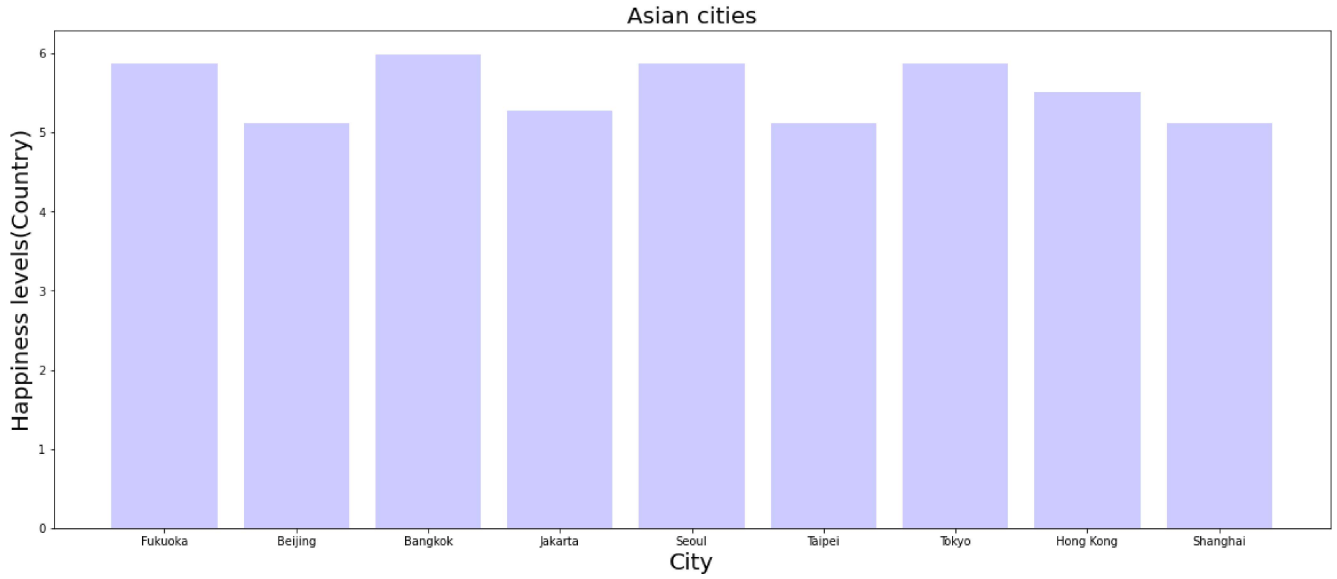

Asian cities
Cost of a bottle of water(City)
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City

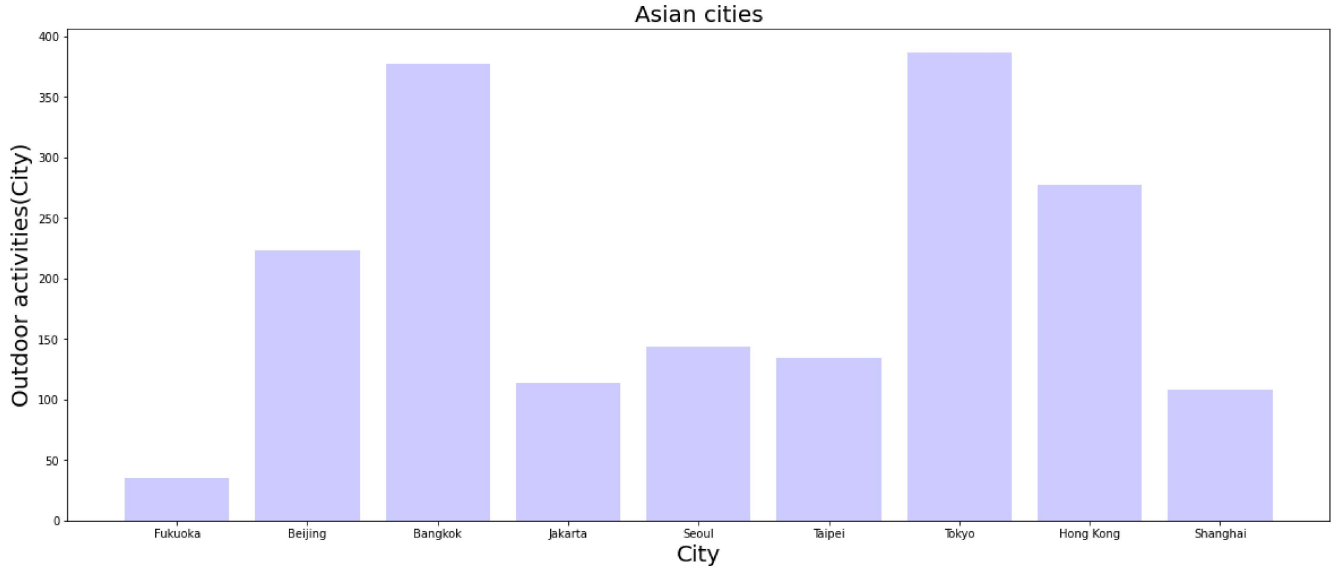

Asian cities
Obesity levels(Country)
10
8
6
4
2
0
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City

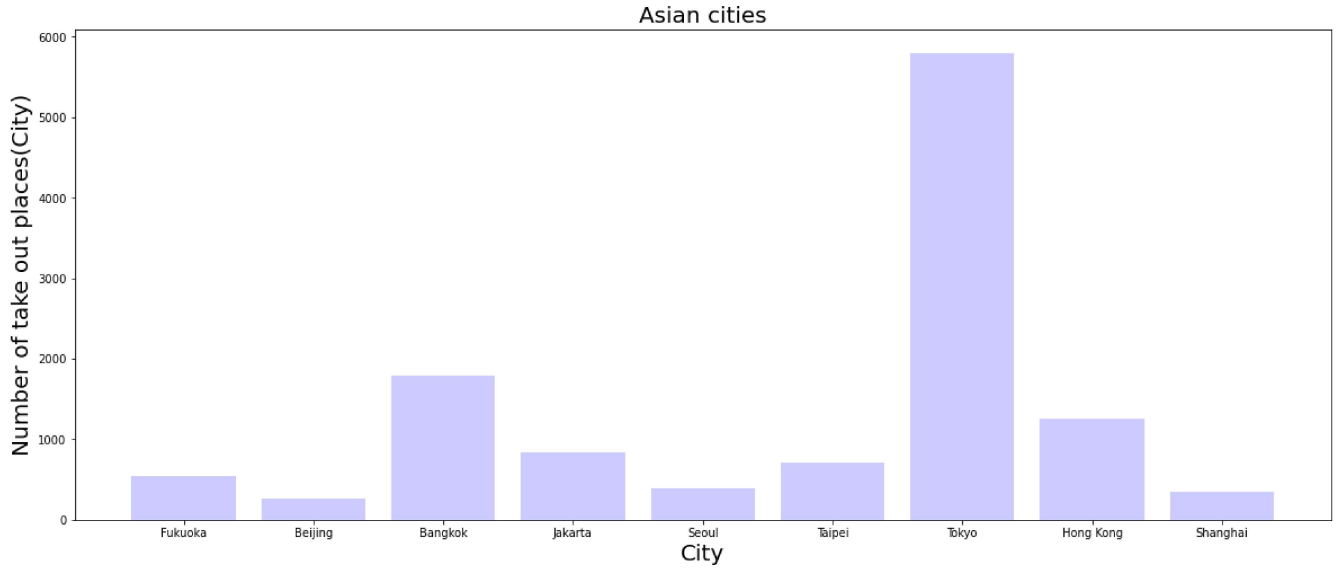

Asian cities
Life expectancy(years) (Country)
0
10
20
30
40
50
60
70
80
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City

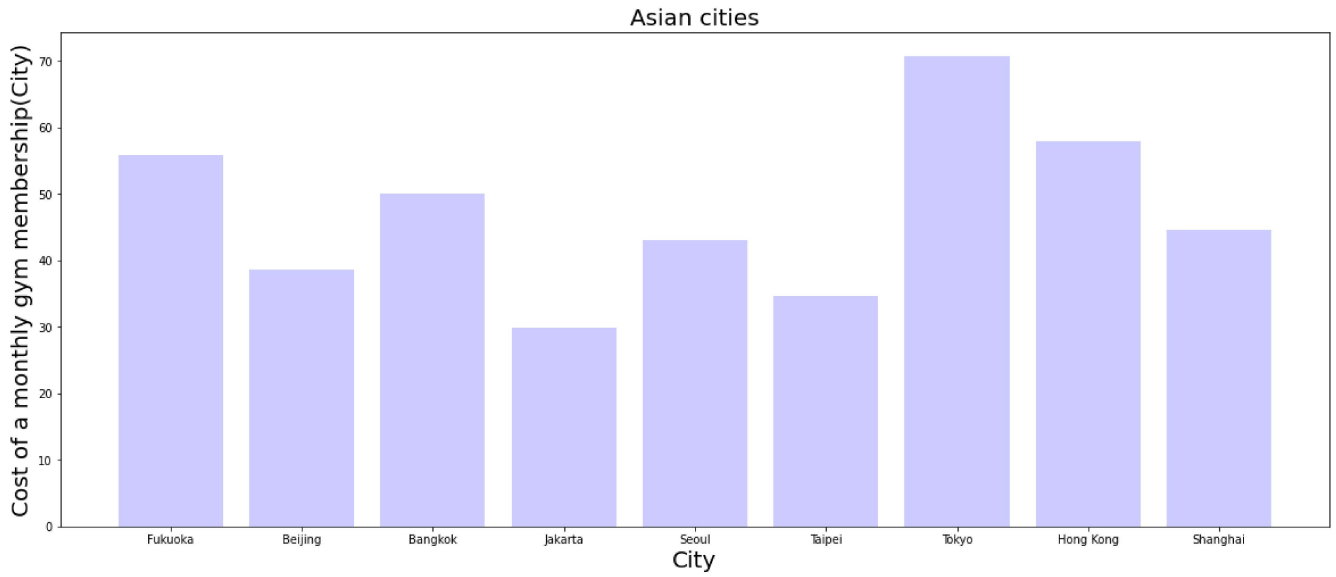

Asian cities
Pollution(Index score) (City)
0
10
20
30
40
50
60
70
80
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City


Asian cities
Annual avg. hours worked
0
250
500
750
1000
1250
1500
1750
2000
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City


Asian cities
Happiness levels(Country)
0
1
2
3
4
5
6
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City


Asian cities
Outdoor activities(City)
0
50
100
150
200
250
300
350
400
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City


Asian cities
Number of take out places(City)
0
1000
2000
3000
4000
5000
6000
Fukuoka
Beijing
Bangkok
Jakarta
Seoul
Taipei
Tokyo
Hong Kong
Shanghai
City



Clustering cities

In [29]:
```
Healthy = df.groupby('City').mean()
Healthy.head()
```

Out[29]:

City	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)	Co
Amsterdam	1.0	1858.0	1.92	20.4	81.2	30.93	1434.000000	7.44	422.0	1048.0	
Bangkok	13.0	2624.0	0.22	10.0	74.1	76.64	1672.909091	5.99	377.0	1796.0	
Barcelona	9.0	2591.0	1.19	23.8	82.2	65.19	1686.000000	6.40	585.0	2344.0	
Beijing	12.0	2671.0	0.26	6.2	75.4	85.43	1672.909091	5.12	223.0	261.0	
Berlin	8.0	1626.0	1.55	22.3	80.6	39.41	1386.000000	7.07	254.0	1729.0	

In [30]:
```
Healthy.head()
```

Out[30]:

City	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)	Co
Amsterdam	1.0	1858.0	1.92	20.4	81.2	30.93	1434.000000	7.44	422.0	1048.0	
Bangkok	13.0	2624.0	0.22	10.0	74.1	76.64	1672.909091	5.99	377.0	1796.0	
Barcelona	9.0	2591.0	1.19	23.8	82.2	65.19	1686.000000	6.40	585.0	2344.0	
Beijing	12.0	2671.0	0.26	6.2	75.4	85.43	1672.909091	5.12	223.0	261.0	
Berlin	8.0	1626.0	1.55	22.3	80.6	39.41	1386.000000	7.07	254.0	1729.0	

Drop the column rank

In [31]:
```
x=df.drop(['Rank'],axis=1)
x
```

Out[31]:

	City	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)	Co
0	Amsterdam	1858.000000	1.92	20.4	81.2	30.930000	1434.000000	7.44	422	1048	
1	Sydney	2636.000000	1.48	29.0	82.1	26.860000	1712.000000	7.22	406	1103	

	City	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)	Co m
2	Vienna	1884.000000	1.94	20.1	81.0	17.330000	1501.000000	7.29	132	1008	
3	Stockholm	1821.000000	1.72	20.6	81.8	19.630000	1452.000000	7.35	129	598	
4	Copenhagen	1630.000000	2.19	19.7	79.8	21.240000	1380.000000	7.64	154	523	
5	Helsinki	1662.000000	1.60	22.2	80.4	13.080000	1540.000000	7.80	113	309	
6	Fukuoka	2769.000000	0.78	4.3	83.2	51.122326	1644.000000	5.87	35	539	
7	Berlin	1626.000000	1.55	22.3	80.6	39.410000	1386.000000	7.07	254	1729	
8	Barcelona	2591.000000	1.19	23.8	82.2	65.190000	1686.000000	6.40	585	2344	
9	Vancouver	1938.000000	1.08	29.4	81.7	24.260000	1670.000000	7.23	218	788	
10	Melbourne	2363.000000	1.57	29.0	82.1	25.900000	1712.000000	7.22	243	813	
11	Beijing	2671.000000	0.26	6.2	75.4	85.430000	1672.909091	5.12	223	261	
12	Bangkok	2624.000000	0.22	10.0	74.1	76.640000	1672.909091	5.99	377	1796	
13	Buenos Aires	2525.000000	0.57	28.3	75.9	52.640000	1672.909091	5.97	246	1435	
14	Toronto	2066.000000	1.09	29.4	81.7	37.830000	1670.000000	7.23	174	1656	
15	Madrid	2769.000000	1.30	23.8	82.2	52.680000	1686.000000	6.40	216	2491	
16	Jakarta	2983.000000	0.21	6.9	68.5	84.390000	1672.909091	5.28	114	833	
17	Seoul	2066.000000	0.59	4.7	81.3	57.820000	1967.000000	5.87	144	389	
18	Frankfurt	1662.000000	1.95	22.3	80.6	37.780000	1386.000000	7.07	23	551	
19	Geneva	2245.860465	2.62	19.5	82.6	27.250000	1557.000000	7.56	44	444	
20	Tel Aviv	3311.000000	1.63	26.1	81.9	47.280000	1898.000000	7.12	139	420	
21	Istanbul	2218.000000	0.15	32.1	74.7	69.490000	1832.000000	5.13	419	934	
22	Cairo	3542.000000	0.16	32.0	70.7	91.740000	1672.909091	4.15	323	250	
23	Taipei	1405.000000	0.57	6.2	75.4	49.320000	1672.909091	5.12	134	717	
24	Los Angeles	3254.000000	1.52	36.2	78.8	66.070000	1779.000000	6.94	223	1439	
25	Mumbai	2584.000000	0.15	3.9	67.3	82.840000	1672.909091	3.57	187	1183	
26	Boston	2634.000000	1.39	36.2	78.8	27.030000	1779.000000	6.94	88	588	
27	Dublin	1453.000000	1.40	25.3	80.5	40.070000	1772.000000	7.09	159	659	
28	Tokyo	1877.000000	0.76	4.3	83.2	42.840000	1644.000000	5.87	387	5802	
29	Chicago	2508.000000	1.20	36.2	78.8	43.330000	1779.000000	6.94	171	1320	
30	Hong Kong	1836.000000	0.75	6.2	75.4	67.460000	1672.909091	5.51	277	1257	
31	Shanghai	1776.000000	0.29	6.2	75.4	77.400000	1672.909091	5.12	108	346	
32	Brussels	1546.000000	2.11	22.1	80.4	62.670000	1583.000000	6.86	55	988	
33	San Francisco	3062.000000	1.60	36.2	78.8	47.360000	1779.000000	6.94	242	1031	
34	Paris	1662.000000	1.95	21.6	81.8	65.100000	1505.000000	6.66	331	4363	
35	Sao Paulo	2003.000000	0.44	22.1	73.9	79.780000	1672.909091	6.37	158	3355	
36	Zurich	1566.000000	3.20	19.5	82.6	17.310000	1557.000000	7.56	69	538	
37	London	1633.000000	1.16	27.8	80.4	58.910000	1538.000000	7.16	433	6417	
38	Johannesburg	3124.000000	0.59	28.3	56.3	61.830000	1672.909091	4.81	194	492	
39	Milan	1915.000000	1.15	19.9	82.7	67.190000	1718.000000	6.38	110	2396	
40	Washington, D.C.	2528.000000	1.45	36.2	78.8	39.180000	1779.000000	6.94	83	744	
41	New York	2535.000000	1.32	36.2	78.8	57.360000	1779.000000	6.94	359	3081	
42	Moscow	1901.000000	0.41	23.1	69.5	57.630000	1965.000000	5.54	322	3206	
43	Mexico City	2555.000000	0.45	28.9	76.4	82.780000	2137.000000	6.46	192	1313	

Perform K-Means Clustering algorithm to find different clusters

In [32]:
```
import sklearn
```

```
from sklearn import datasets
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score,silhouette_samples
```

In [33]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
col = Healthy.columns
Healthy_Clust = scaler.fit_transform(Healthy)
```

SilhouetteVisualizer

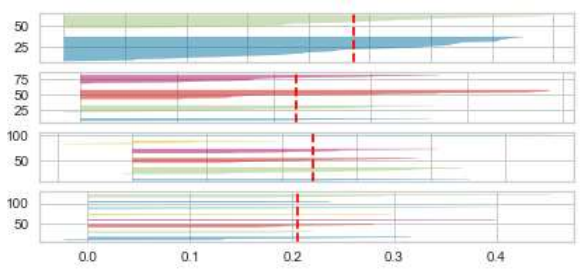
In [34]:

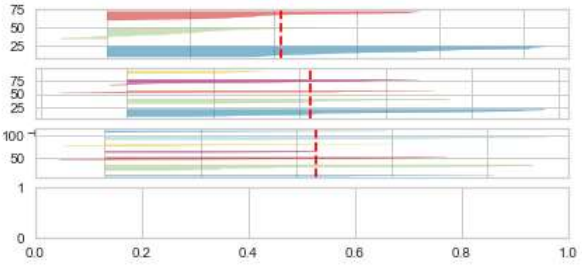
```
import yellowbrick
import matplotlib.pyplot as plt
from yellowbrick.cluster import SilhouetteVisualizer

fig,ax=plt.subplots(4,2,figsize=(15,3))
for i in[2,3,4,5,6,7,8]:
    '''
     Create KMeans instance for different number of clusters
     '''
    km=KMeans(n_clusters=i,init='k-means++',n_init=10,max_iter=100,random_state=42)
    q,mod=divmod(i,2)

    #create silhouettevisualization instance with kmeans instance
    #Fit the visualizer

    visualizer=SilhouetteVisualizer(km,colors='yellowbrick',ax=ax[q-1][mod])
    visualizer.fit(Healthy_Clust)
```





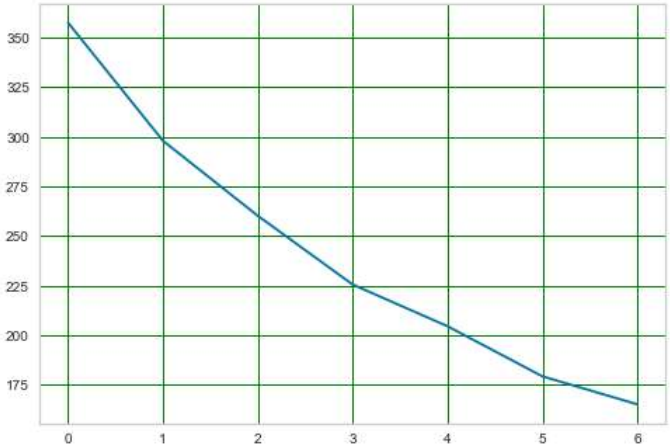
Elbow graph

In [35]:

```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
ssd = []
range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
for num_clusters in range_n_clusters:
    kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
    kmeans.fit(Healthy_Clust)

    ssd.append(kmeans.inertia_)

plt.plot(ssd)
plt.grid(linestyle='-',linewidth='1',color='green')
plt.show()
```



Silhouette Score

In [36]:
```
range_n_clusters = [2, 3, 4, 5, 6, 7, 8]

for num_clusters in range_n_clusters:

    kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
    kmeans.fit(Healthy_Clust)

    cluster_labels = kmeans.labels_

    silhouette_avg = silhouette_score(Healthy_Clust, cluster_labels)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, silhouette_avg))
```

```
For n_clusters=2, the silhouette score is 0.23656060232304474
For n_clusters=3, the silhouette score is 0.2132276901540575
For n_clusters=4, the silhouette score is 0.22664721065505794
For n_clusters=5, the silhouette score is 0.20583280427627795
For n_clusters=6, the silhouette score is 0.21098734711124506
For n_clusters=7, the silhouette score is 0.24579948176404862
For n_clusters=8, the silhouette score is 0.21455601779284217
```

In [37]:
```
kmeans = KMeans(n_clusters=5,max_iter=100)
kmeans.fit(Healthy_Clust)
```

Out[37]:
```
KMeans(max_iter=100, n_clusters=5)
```

In [38]:
```
Healthy['Cluster_ID'] = kmeans.labels_
Healthy.head()
```

Out[38]:

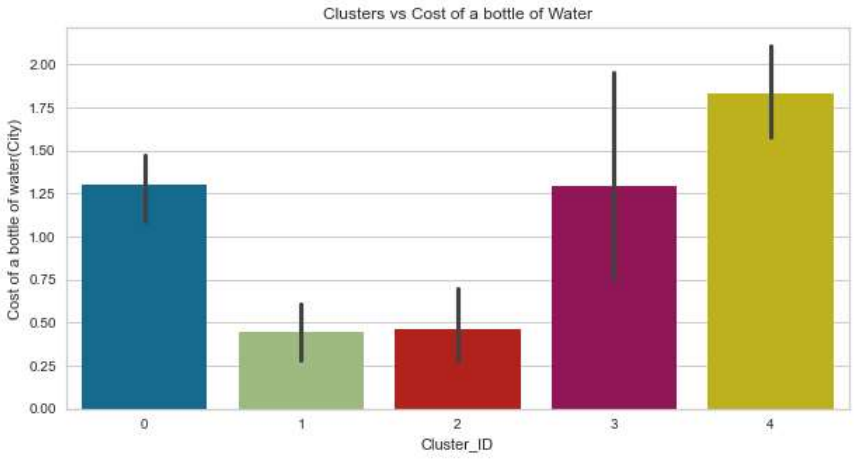
City	Rank	Sunshine hours(City)	Cost of a bottle of water(City)	Obesity levels(Country)	Life expectancy(years) (Country)	Pollution(Index score) (City)	Annual avg. hours worked	Happiness levels(Country)	Outdoor activities(City)	Number of take out places(City)	Co...
Amsterdam	1.0	1858.0	1.92	20.4	81.2	30.93	1434.000000	7.44	422.0	1048.0	
Bangkok	13.0	2624.0	0.22	10.0	74.1	76.64	1672.909091	5.99	377.0	1796.0	
Barcelona	9.0	2591.0	1.19	23.8	82.2	65.19	1686.000000	6.40	585.0	2344.0	
Beijing	12.0	2671.0	0.26	6.2	75.4	85.43	1672.909091	5.12	223.0	261.0	
Berlin	8.0	1626.0	1.55	22.3	80.6	39.41	1386.000000	7.07	254.0	1729.0	

Plotting the clusters

In [39]:
```
plt.figure(figsize=(10,5))
sns.barplot(y='Happiness levels(Country)',x='Cluster_ID',data=Healthy)
plt.title('Clusters vs Happiness Levels')
plt.show()
```

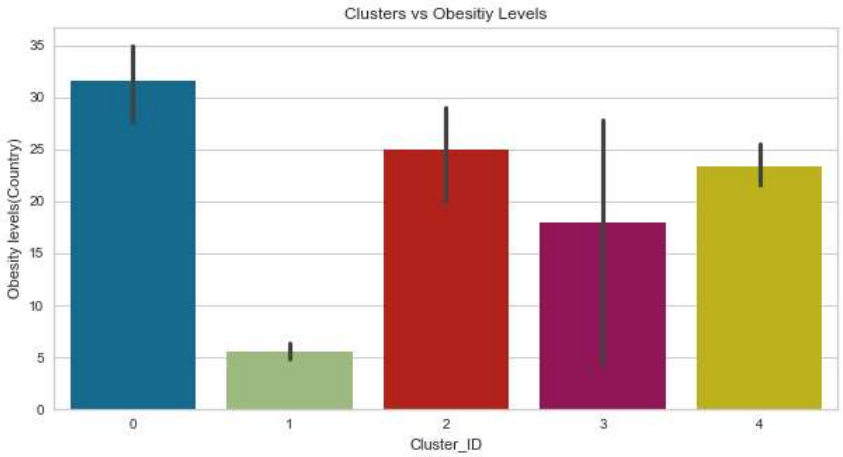
In [40]:

```
plt.figure(figsize=(10,5))
sns.barplot(y='Cost of a bottle of water(City)',x='Cluster_ID',data=Healthy)
plt.title('Clusters vs Cost of a bottle of Water')
plt.show()
```



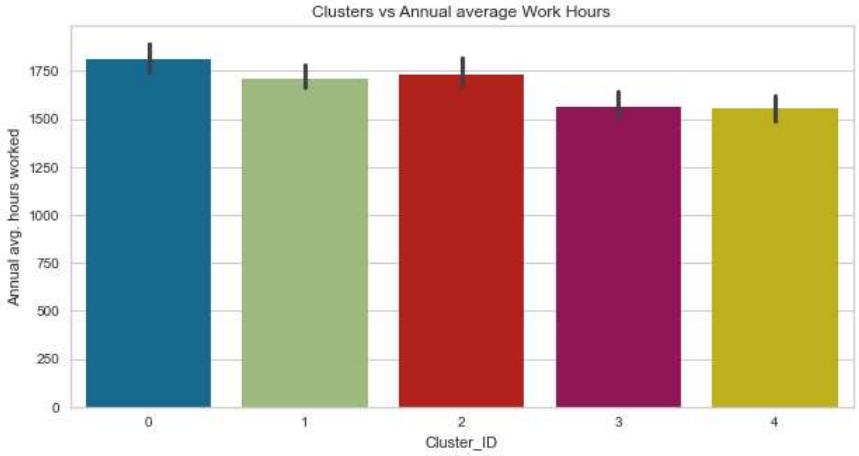
In [41]:

```
plt.figure(figsize=(10,5))
sns.barplot(y='Obesity levels(Country)',x='Cluster_ID',data=Healthy)
plt.title('Clusters vs Obesitiy Levels')
plt.show()
```



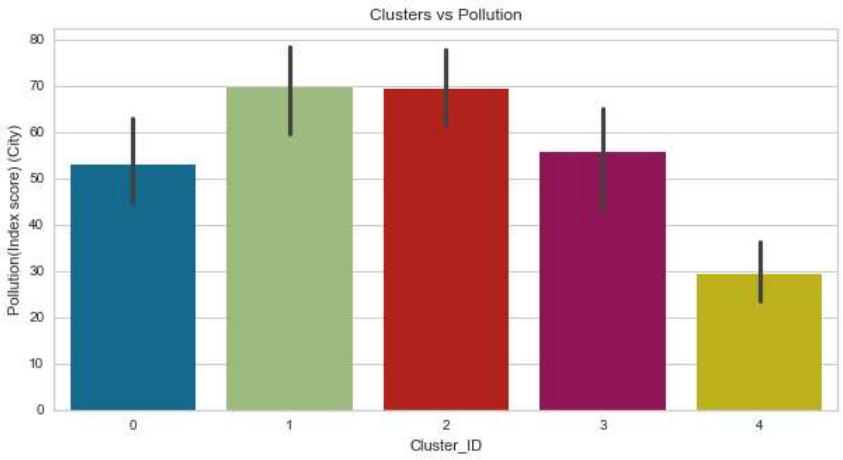
In [42]:

```
plt.figure(figsize=(10,5))
sns.barplot(y='Annual avg. hours worked',x='Cluster_ID',data=Healthy)
plt.title('Clusters vs Annual average Work Hours')
plt.show()
```

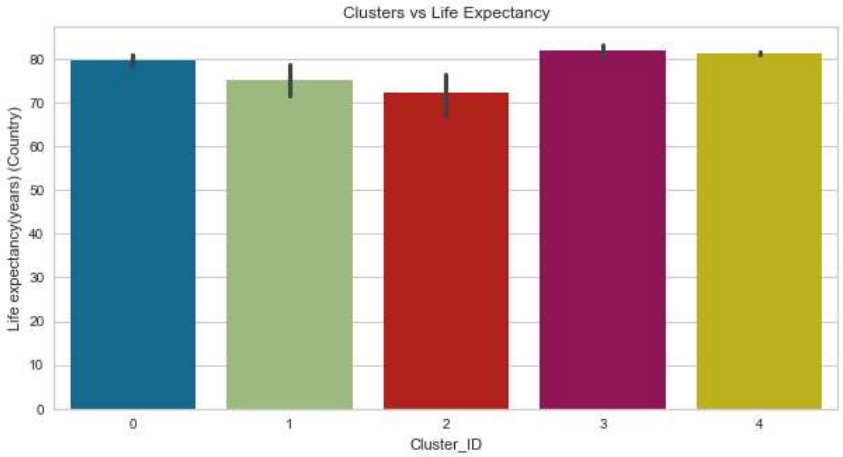


In [43]:

```
plt.figure(figsize=(10,5))
sns.barplot(y='Pollution(Index score) (City)',x='Cluster_ID',data=Healthy)
plt.title('Clusters vs Pollution')
plt.show()
```



In [44]:
```
plt.figure(figsize=(10,5))
sns.barplot(y='Life expectancy(years) (Country)',x='Cluster_ID',data=Healthy)
plt.title('Clusters vs Life Expectancy')
plt.show()
```



Printing the clusters

In [45]:
```
print('Cluster 1:',list(Healthy[Healthy.Cluster_ID==0].index))
```

```
Cluster 1: ['Boston', 'Chicago', 'Los Angeles', 'Madrid', 'Mexico City', 'Milan', 'New York', 'San Francisco', 'Tel Aviv', 'Washingt
on, D.C.']
```

In [46]:
```
print('Cluster 2 :',list(Healthy[Healthy.Cluster_ID==1].index))
```

```
Cluster 2 : ['Beijing', 'Fukuoka', 'Hong Kong', 'Jakarta', 'Mumbai', 'Seoul', 'Shanghai', 'Taipei']
```

In [47]:
```
print('Cluster 3 :',list(Healthy[Healthy.Cluster_ID==2].index))
```

```
Cluster 3 : ['Bangkok', 'Barcelona', 'Buenos Aires', 'Cairo', 'Istanbul', 'Johannesburg', 'Moscow', 'Sao Paulo']
```

In [51]:
```
print('Cluster 4 :',list(Healthy[Healthy.Cluster_ID==3].index))
```

```
Cluster 4 : ['London', 'Paris', 'Tokyo']
```

In [49]:
```
print('Cluster 5 :',list(Healthy[Healthy.Cluster_ID==4].index))
```

```
Cluster 5 : ['Amsterdam', 'Berlin', 'Brussels', 'Copenhagen', 'Dublin', 'Frankfurt', 'Geneva', 'Helsinki', 'Melbourne', 'Stockholm',
'Sydney', 'Toronto', 'Vancouver', 'Vienna', 'Zurich']
```

From this project we have successfully clustered cities based on healthy lifestyle using k-means clustering algorithm.Because it consists of different features and continuous data so we use clustering to improve statistical analysis. The number of clusters we have found is five. A healthier lifestyle is consistently associated with a longer life expectancy across various individual risks and irrespective of the presence of multiple long-term medical conditions. The major factor be behind longer life expectancy is happiness. Higher levels of happiness leads to higher life expectancy rates.The main aim

is to find relationships between various factors that lead to healthy or unhealthy lifestyle in cities and visualize them.

In [ ]: