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Due 20220327

Week 3

MSDS 650

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Week 3 Lab - Exploratory Data Analysis (EDA)

This week's assignment will focus on EDA techniques and practices for a given dataset.

Dataset for Week3:

Dataset Name::
Use any dataset that is of interest to you for this assignment.

- https://archive.ics.uci.edu/ml/datasets.php
- https://www.data.gov/
- https://www.kaggle.com/datasets

Assignment Requirements

Complete an Exploratory data analysis for the CHR 2021 dataset. Your analysis should include the following. For each of the following sections, please provide a narritive of your approach, reasoning for your treatment of the data and insights or conclusions that you have reached.

Define a few questions that you wish to discover about your dataset to guide your EDA effort.

1. Describe the data within the dataset.
   - Data types: Categorical vs Continuous variables
   - Statistical summary, etc.
2. Data Cleaning
   - Identify and handle missing values
   - Identify and handle outliers
3. Feature Selection

- Graphical visualization of features
- Examine the relationships within the dataset - using 2 different methods
- Reduction of the dimensionality of the dataset

4. Insights and Findings
   - Describe an insights and/or findings from within the datset.
5. Bonus: Feature Engineering
   - Create a new feature based for findings.

Important: Make sure your provide complete and thorough explanations for all of your analysis steps. You need to defend your thought processes and reasoning.

Deliverables:

Upload your Jupyter Notebook to the corresponding location in WorldClass. Also, you will need to provide a copy of your dataset.

Note:: Make sure you have clearly indicated each assignment requirement within your notebook.

I. Introduction

In this week's assignment I explored the step of the data science process which precedes model creation. This step is Exploratory Data Analysis, or EDA. Throughout the course of this week's assignment, I will perform various steps to view metadata as well as clean the data and prepare it for the next step of the data science process.

II. Methods, III. Code, and IV. Analysis of Results

In [1]:

```
import pandas as pd
import numpy as np
from scipy import stats
import matplotlib.pylab as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import LocalOutlierFactor
from sklearn.metrics import mean_absolute_error
%matplotlib inline
```

The assignment this week focused on 5 different prompts. The first prompt dealt with just describing the data. I chose to use the "Healthy Lifestyle Cities Report 2021" dataset as it seemed interesting and maybe could help me discern what contributes most towards a healthy lifestyle. I thought the hours of sunshine would be a major contributor to happiness but we will soon see that is not the case, at least according to this particular dataset.

Prompt 1: Describe the data within the dataset

- Data types: Categorical vs. Continuous variables
- Statistical summary, etc.

The first thing I did was run basic commands on the data to show me the general shape and type and how much cleaning may be involved. I used the info(), shape, describe(), and isnull() functions to achieve this.

In [2]:

```
data_df = pd.read_csv('healthy_lifestyle_city_2021_clean04.csv')
data_df.head(20)
```

Out[2]:

	City	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	pollution_index	avg_hours_worked	outdoor_activities	num_takeout_p
0	Amsterdam	1	1858.0	1.92	20.40%	81.2	30.93	1434.0	422	
1	Sydney	2	2636.0	1.48	29.00%	82.1	26.86	1712.0	406	
2	Vienna	3	1884.0	1.94	20.10%	81.0	17.33	1501.0	132	
3	Stockholm	4	1821.0	1.72	20.60%	81.8	19.63	1452.0	129	
4	Copenhagen	5	1630.0	2.19	19.70%	79.8	21.24	1380.0	154	
5	Helsinki	6	1662.0	1.60	22.20%	80.4	13.08	1540.0	113	
6	Fukuoka	7	2769.0	0.78	4.30%	83.2	NaN	1644.0	35	
7	Berlin	8	1626.0	1.55	22.30%	80.6	39.41	1386.0	254	
8	Barcelona	9	2591.0	1.19	23.80%	82.2	65.19	1686.0	585	
9	Vancouver	10	1938.0	1.08	29.40%	81.7	24.26	1670.0	218	
10	Melbourne	11	2363.0	1.57	29.00%	82.1	25.90	1712.0	243	
11	Beijing	12	2671.0	0.26	6.20%	75.4	85.43	NaN	223	
12	Bangkok	13	2624.0	0.22	10.00%	74.1	76.64	NaN	377	
13	Buenos Aires	14	2525.0	0.57	28.30%	75.9	52.64	NaN	246	
14	Toronto	15	2066.0	1.09	29.40%	81.7	37.83	1670.0	174	
15	Madrid	16	2769.0	1.30	23.80%	82.2	52.68	1686.0	216	
16	Jakarta	17	2983.0	0.21	6.90%	68.5	84.39	NaN	114	
17	Seoul	18	2066.0	0.59	4.70%	81.3	57.82	1967.0	144	
18	Frankfurt	19	1662.0	1.95	22.30%	80.6	37.78	1386.0	23	
19	Geneva	20	NaN	2.62	19.50%	82.6	27.25	1557.0	44	

In [3]:

```
data_df.describe()
```

Out[3]:

	Rank	sunshine_hrs	bottle_water_cost	life_expect_yrs	pollution_index	avg_hours_worked	outdoor_activities	num_takeout_places	gym_cost	hap
count	44.000000	43.000000	44.000000	44.00000	43.000000	33.000000	44.000000	44.000000	44.000000	
mean	22.500000	2245.860465	1.173409	78.17500	51.122326	1672.909091	213.977273	1443.113636	40.420000	
std	12.845233	567.403719	0.718642	5.30437	21.856190	179.626933	127.190297	1388.803270	15.006457	
min	1.000000	1405.000000	0.150000	56.30000	13.080000	1380.000000	23.000000	250.000000	16.070000	
25%	11.750000	1798.500000	0.570000	75.40000	34.355000	1540.000000	125.250000	548.000000	31.310000	
50%	22.500000	2066.000000	1.195000	80.40000	52.640000	1686.000000	189.500000	998.000000	37.330000	
75%	33.250000	2629.000000	1.600000	81.80000	66.630000	1779.000000	288.250000	1674.250000	47.210000	
max	44.000000	3542.000000	3.200000	83.20000	91.740000	2137.000000	585.000000	6417.000000	73.110000	

In [4]:

```
data_df.isnull().sum()
```

Out[4]:

```
City                   0
Rank                   0
sunshine_hrs           1
bottle_water_cost      0
obesity_levels         0
life_expect_yrs        0
pollution_index        1
avg_hours_worked      11
outdoor_activities     0
num_takeout_places     0
gym_cost               0
happiness_levels       0
dtype: int64
```

So, you can see we have some null values to deal with. I'm not too concerned with the pollution index or the average hours worked, but I still want to go through the exercise of cleaning the data.

In [5]:

```
type(data_df)
```

```
pandas.core.frame.DataFrame
```

Out[5]:

In [6]:

```
data_df.shape
```

Out[6]:

```
(44, 12)
```

In [7]:

```
data_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_hrs         43 non-null     float64
 3   bottle_water_cost    44 non-null     float64
 4   obesity_levels       44 non-null     object 
 5   life_expect_yrs      44 non-null     float64
 6   pollution_index      43 non-null     float64
 7   avg_hours_worked     33 non-null     float64
 8   outdoor_activities   44 non-null     int64  
 9   num_takeout_places   44 non-null     int64  
 10  gym_cost             44 non-null     float64
 11  happiness_levels     44 non-null     float64
dtypes: float64(7), int64(3), object(2)
memory usage: 4.2+ KB
```

In [8]:

```
data_df[data_df.isnull().values.any(axis=1)]
```

Out[8]:

	City	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	pollution_index	avg_hours_worked	outdoor_activities	num_takeout_
6	Fukuoka	7	2769.0	0.78	4.30%	83.2	NaN	1644.0	35	
11	Beijing	12	2671.0	0.26	6.20%	75.4	85.43	NaN	223	
12	Bangkok	13	2624.0	0.22	10.00%	74.1	76.64	NaN	377	
13	Buenos Aires	14	2525.0	0.57	28.30%	75.9	52.64	NaN	246	
16	Jakarta	17	2983.0	0.21	6.90%	68.5	84.39	NaN	114	
19	Geneva	20	NaN	2.62	19.50%	82.6	27.25	1557.0	44	
22	Cairo	23	3542.0	0.16	32.00%	70.7	91.74	NaN	323	
23	Taipei	24	1405.0	0.57	6.20%	75.4	49.32	NaN	134	

	City	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	pollution_index	avg_hours_worked	outdoor_activities	num_takeout_
25	Mumbai	26	2584.0	0.15	3.90%	67.3	82.84	NaN	187	
30	Hong Kong	31	1836.0	0.75	6.20%	75.4	67.46	NaN	277	
31	Shanghai	32	1776.0	0.29	6.20%	75.4	77.40	NaN	108	
35	Sao Paulo	36	2003.0	0.44	22.10%	73.9	79.78	NaN	158	
38	Johannesburg	39	3124.0	0.59	28.30%	56.3	61.83	NaN	194	

Prompt 2: Data Cleaning

- Identify and handle missing values
- Identify and handle outliers

In [9]:

```
#there is no categorical data here, only continuous.
#the 'city' feature may be considered categorical but i consider it a label
#let's check variance of columns
data_df.nunique()
```

Out[9]:

```
City                  44
Rank                  44
sunshine_hrs          39
bottle_water_cost     39
obesity_levels        28
life_expect_yrs       27
pollution_index       43
avg_hours_worked      22
outdoor_activities    43
num_takeout_places    44
gym_cost              44
happiness_levels      30
dtype: int64
```

So there is a healthy variance within each of the columns

Next I wanted to remove the "%" character from the obesity levels column, and turn the column into a numerical column in Panda's mind.

In [10]:

```
#(float)(data_df.obesity_levels[1][:-1]) * 2
data_df.obesity_levels
```

Out[10]:

```
0      20.40%
1      29.00%
```

```
2      20.10%
3      20.60%
4      19.70%
5      22.20%
6       4.30%
7      22.30%
8      23.80%
9      29.40%
10     29.00%
11      6.20%
12     10.00%
13     28.30%
14     29.40%
15     23.80%
16      6.90%
17      4.70%
18     22.30%
19     19.50%
20     26.10%
21     32.10%
22     32.00%
23      6.20%
24     36.20%
25      3.90%
26     36.20%
27     25.30%
28      4.30%
29     36.20%
30      6.20%
31      6.20%
32     22.10%
33     36.20%
34     21.60%
35     22.10%
36     19.50%
37     27.80%
38     28.30%
39     19.90%
40     36.20%
41     36.20%
42     23.10%
43     28.90%
Name: obesity_levels, dtype: object
```

In [11]:

```
data_df['obesity_levels'] = data_df.obesity_levels.apply(lambda x: (float)(x[:-1]))
```

In [12]:

```
data_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_hrs         43 non-null     float64
 3   bottle_water_cost    44 non-null     float64
 4   obesity_levels       44 non-null     float64
 5   life_expect_yrs      44 non-null     float64
 6   pollution_index      43 non-null     float64
 7   avg_hours_worked     33 non-null     float64
 8   outdoor_activities   44 non-null     int64  
 9   num_takeout_places   44 non-null     int64  
 10  gym_cost             44 non-null     float64
 11  happiness_levels     44 non-null     float64
dtypes: float64(8), int64(3), object(1)
memory usage: 4.2+ KB
```

The following steps below I performed 2 times, in order to use a model to predict what values the null values would take. I had to run this process 2 times since there were multiple columns with null values.

In [13]:

```
#time to clean data, sunshine hrs column
cols = [c for c in data_df.columns if c != 'sunshine_hrs' and c != 'City' and c != 'avg_hours_worked' and c != 'pollution_index']
X1 = data_df[data_df.sunshine_hrs.notnull()].loc[:,cols]
X1
```

Out[13]:

	Rank	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
0	1	1.92	20.4	81.2	422	1048	34.90	7.44
1	2	1.48	29.0	82.1	406	1103	41.66	7.22
2	3	1.94	20.1	81.0	132	1008	25.74	7.29
3	4	1.72	20.6	81.8	129	598	37.31	7.35
4	5	2.19	19.7	79.8	154	523	32.53	7.64
5	6	1.60	22.2	80.4	113	309	35.23	7.80
6	7	0.78	4.3	83.2	35	539	55.87	5.87
7	8	1.55	22.3	80.6	254	1729	26.11	7.07
8	9	1.19	23.8	82.2	585	2344	37.80	6.40
9	10	1.08	29.4	81.7	218	788	31.04	7.23
10	11	1.57	29.0	82.1	243	813	36.89	7.22

	Rank	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
11	12	0.26	6.2	75.4	223	261	38.62	5.12
12	13	0.22	10.0	74.1	377	1796	50.03	5.99
13	14	0.57	28.3	75.9	246	1435	22.45	5.97
14	15	1.09	29.4	81.7	174	1656	32.64	7.23
15	16	1.30	23.8	82.2	216	2491	34.54	6.40
16	17	0.21	6.9	68.5	114	833	29.94	5.28
17	18	0.59	4.7	81.3	144	389	43.03	5.87
18	19	1.95	22.3	80.6	23	551	39.01	7.07
20	21	1.63	26.1	81.9	139	420	58.31	7.12
21	22	0.15	32.1	74.7	419	934	16.97	5.13
22	23	0.16	32.0	70.7	323	250	23.25	4.15
23	24	0.57	6.2	75.4	134	717	34.76	5.12
24	25	1.52	36.2	78.8	223	1439	32.00	6.94
25	26	0.15	3.9	67.3	187	1183	19.54	3.57
26	27	1.39	36.2	78.8	88	588	46.27	6.94
27	28	1.40	25.3	80.5	159	659	37.35	7.09
28	29	0.76	4.3	83.2	387	5802	70.82	5.87
29	30	1.20	36.2	78.8	171	1320	41.14	6.94
30	31	0.75	6.2	75.4	277	1257	57.95	5.51
31	32	0.29	6.2	75.4	108	346	44.68	5.12
32	33	2.11	22.1	80.4	55	988	25.34	6.86
33	34	1.60	36.2	78.8	242	1031	65.13	6.94
34	35	1.95	21.6	81.8	331	4363	35.93	6.66
35	36	0.44	22.1	73.9	158	3355	16.07	6.37
36	37	3.20	19.5	82.6	69	538	73.11	7.56
37	38	1.16	27.8	80.4	433	6417	42.71	7.16
38	39	0.59	28.3	56.3	194	492	24.28	4.81
39	40	1.15	19.9	82.7	110	2396	53.49	6.38

	Rank	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
40	41	1.45	36.2	78.8	83	744	65.99	6.94
41	42	1.32	36.2	78.8	359	3081	64.66	6.94
42	43	0.41	23.1	69.5	322	3206	31.40	5.54
43	44	0.45	28.9	76.4	192	1313	41.99	6.46

In [14]:

```
y1 = data_df[data_df.sunshine_hrs.notnull()]['sunshine_hrs']
y1
```

Out[14]:

```
0     1858.0
1     2636.0
2     1884.0
3     1821.0
4     1630.0
5     1662.0
6     2769.0
7     1626.0
8     2591.0
9     1938.0
10    2363.0
11    2671.0
12    2624.0
13    2525.0
14    2066.0
15    2769.0
16    2983.0
17    2066.0
18    1662.0
20    3311.0
21    2218.0
22    3542.0
23    1405.0
24    3254.0
25    2584.0
26    2634.0
27    1453.0
28    1877.0
29    2508.0
30    1836.0
31    1776.0
32    1546.0
33    3062.0
34    1662.0
35    2003.0
36    1566.0
```

```
37    1633.0
38    3124.0
39    1915.0
40    2528.0
41    2535.0
42    1901.0
43    2555.0
Name: sunshine_hrs, dtype: float64
```

In [15]:
```
from sklearn.model_selection import train_test_split
```

In [16]:
```
x_train1, x_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.70)
```

In [17]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [18]:
```
clf1 = RandomForestClassifier(n_estimators=100)
clf1.fit(x_train1, y_train1)
```

Out[18]:
```
RandomForestClassifier()
```

In [19]:
```
y_pred1 = clf1.predict(x_test1)
```

In [20]:
```
from sklearn import metrics
```

In [21]:
```
print(f'Model accuracy = {metrics.accuracy_score(y_test1,y_pred1)}')
```

```
Model accuracy = 0.0
```

UGH! THe model is not too accurate! This is not good at all. However, the sunshine_hrs only has 1 missing value, so honestly I'm not too concerned with the value that is filled in.

In [22]:
```
x_missing1 = data_df[data_df.sunshine_hrs.isnull()].loc[:, cols]
x_missing1
```

Out[22]:

	Rank	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
19	20	2.62	19.5	82.6	44	444	70.0	7.56

In [23]:

```
y_missing1 = clf1.predict(x_missing1)
y_missing1
```

Out[23]:
```
array([1566.])
```

In [24]:
```
data_dfclean1 = data_df.copy()
```

In [25]:
```
x_missing1['sunshine_hrs'] = y_missing1.astype('float64')
x_missing1
```

Out[25]:

	Rank	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels	sunshine_hrs
19	20	2.62	19.5	82.6	44	444	70.0	7.56	1566.0

In [26]:
```
j = 0
for i in x_missing1.Rank.to_list():
    #print(i)
    data_df['sunshine_hrs'].iloc[i-1] = x_missing1['sunshine_hrs'].iloc[j]
    j += 1
```

```
C:\Users\jerem\AppData\Local\Temp\ipykernel_2448\4011901866.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data_df['sunshine_hrs'].iloc[i-1] = x_missing1['sunshine_hrs'].iloc[j]
```

In [27]:
```
data_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_hrs        44 non-null     float64
 3   bottle_water_cost   44 non-null     float64
 4   obesity_levels      44 non-null     float64
 5   life_expect_yrs     44 non-null     float64
 6   pollution_index     43 non-null     float64
 7   avg_hours_worked    33 non-null     float64
 8   outdoor_activities  44 non-null     int64
 9   num_takeout_places  44 non-null     int64
```

```
 10  gym_cost            44 non-null     float64
 11  happiness_levels    44 non-null     float64
dtypes: float64(8), int64(3), object(1)
memory usage: 4.2+ KB
```

In [28]:

```
#time to clean data, sunshine hrs column
cols = [c for c in data_df.columns if c != 'City' and c != 'avg_hours_worked' and c != 'pollution_index']
X2 = data_df[data_df.avg_hours_worked.notnull()].loc[:,cols]
X2
```

Out[28]:

	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
0	1	1858.0	1.92	20.4	81.2	422	1048	34.90	7.44
1	2	2636.0	1.48	29.0	82.1	406	1103	41.66	7.22
2	3	1884.0	1.94	20.1	81.0	132	1008	25.74	7.29
3	4	1821.0	1.72	20.6	81.8	129	598	37.31	7.35
4	5	1630.0	2.19	19.7	79.8	154	523	32.53	7.64
5	6	1662.0	1.60	22.2	80.4	113	309	35.23	7.80
6	7	2769.0	0.78	4.3	83.2	35	539	55.87	5.87
7	8	1626.0	1.55	22.3	80.6	254	1729	26.11	7.07
8	9	2591.0	1.19	23.8	82.2	585	2344	37.80	6.40
9	10	1938.0	1.08	29.4	81.7	218	788	31.04	7.23
10	11	2363.0	1.57	29.0	82.1	243	813	36.89	7.22
14	15	2066.0	1.09	29.4	81.7	174	1656	32.64	7.23
15	16	2769.0	1.30	23.8	82.2	216	2491	34.54	6.40
17	18	2066.0	0.59	4.7	81.3	144	389	43.03	5.87
18	19	1662.0	1.95	22.3	80.6	23	551	39.01	7.07
19	20	1566.0	2.62	19.5	82.6	44	444	70.00	7.56
20	21	3311.0	1.63	26.1	81.9	139	420	58.31	7.12
21	22	2218.0	0.15	32.1	74.7	419	934	16.97	5.13
24	25	3254.0	1.52	36.2	78.8	223	1439	32.00	6.94
26	27	2634.0	1.39	36.2	78.8	88	588	46.27	6.94
27	28	1453.0	1.40	25.3	80.5	159	659	37.35	7.09

	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
28	29	1877.0	0.76	4.3	83.2	387	5802	70.82	5.87
29	30	2508.0	1.20	36.2	78.8	171	1320	41.14	6.94
32	33	1546.0	2.11	22.1	80.4	55	988	25.34	6.86
33	34	3062.0	1.60	36.2	78.8	242	1031	65.13	6.94
34	35	1662.0	1.95	21.6	81.8	331	4363	35.93	6.66
36	37	1566.0	3.20	19.5	82.6	69	538	73.11	7.56
37	38	1633.0	1.16	27.8	80.4	433	6417	42.71	7.16
39	40	1915.0	1.15	19.9	82.7	110	2396	53.49	6.38
40	41	2528.0	1.45	36.2	78.8	83	744	65.99	6.94
41	42	2535.0	1.32	36.2	78.8	359	3081	64.66	6.94
42	43	1901.0	0.41	23.1	69.5	322	3206	31.40	5.54
43	44	2555.0	0.45	28.9	76.4	192	1313	41.99	6.46

In [29]:

```
y2 = data_df[data_df.avg_hours_worked.notnull()]['avg_hours_worked']
y2
```

Out[29]:

```
0     1434.0
1     1712.0
2     1501.0
3     1452.0
4     1380.0
5     1540.0
6     1644.0
7     1386.0
8     1686.0
9     1670.0
10    1712.0
14    1670.0
15    1686.0
17    1967.0
18    1386.0
19    1557.0
20    1898.0
21    1832.0
24    1779.0
26    1779.0
27    1772.0
28    1644.0
```

```
29    1779.0
32    1583.0
33    1779.0
34    1505.0
36    1557.0
37    1538.0
39    1718.0
40    1779.0
41    1779.0
42    1965.0
43    2137.0
Name: avg_hours_worked, dtype: float64
```

In [30]:

```
x_train2, x_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.70)
```

In [31]:

```
clf2 = RandomForestClassifier(n_estimators=100)
clf2.fit(x_train2, y_train2)
```

Out[31]:

```
RandomForestClassifier()
```

In [32]:

```
y_pred2 = clf2.predict(x_test2)
```

In [33]:

```
print(f'Model accuracy = {metrics.accuracy_score(y_test2,y_pred2)}')
```

```
Model accuracy = 0.25
```

This model is NOT very accurate either! That's a bummer. It's definitely more accurate than the previous model but it's still not so accurate. But I'm not concerned with the average hours worked, I mainly want to concentrate on sunshine hours and life expectancy.

In [34]:

```
x_missing2 = data_df[data_df.avg_hours_worked.isnull()].loc[:, cols]
x_missing2
```

Out[34]:

	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
11	12	2671.0	0.26	6.2	75.4	223	261	38.62	5.12
12	13	2624.0	0.22	10.0	74.1	377	1796	50.03	5.99
13	14	2525.0	0.57	28.3	75.9	246	1435	22.45	5.97
16	17	2983.0	0.21	6.9	68.5	114	833	29.94	5.28
22	23	3542.0	0.16	32.0	70.7	323	250	23.25	4.15
23	24	1405.0	0.57	6.2	75.4	134	717	34.76	5.12

	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels
25	26	2584.0	0.15	3.9	67.3	187	1183	19.54	3.57
30	31	1836.0	0.75	6.2	75.4	277	1257	57.95	5.51
31	32	1776.0	0.29	6.2	75.4	108	346	44.68	5.12
35	36	2003.0	0.44	22.1	73.9	158	3355	16.07	6.37
38	39	3124.0	0.59	28.3	56.3	194	492	24.28	4.81

In [35]:
```
y_missing2 = clf2.predict(x_missing2)
y_missing2
```

Out[35]:
```
array([1832., 2137., 2137., 1832., 1832., 1832., 1832., 1718., 1832.,
       1832., 2137.])
```

In [36]:
```
data_dfclean2 = data_df.copy()
```

In [37]:
```
x_missing2['avg_hours_worked'] = y_missing2.astype('float64')
x_missing2
```

Out[37]:

	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	outdoor_activities	num_takeout_places	gym_cost	happiness_levels	avg_hours_worl
11	12	2671.0	0.26	6.2	75.4	223	261	38.62	5.12	183
12	13	2624.0	0.22	10.0	74.1	377	1796	50.03	5.99	213
13	14	2525.0	0.57	28.3	75.9	246	1435	22.45	5.97	213
16	17	2983.0	0.21	6.9	68.5	114	833	29.94	5.28	183
22	23	3542.0	0.16	32.0	70.7	323	250	23.25	4.15	183
23	24	1405.0	0.57	6.2	75.4	134	717	34.76	5.12	183
25	26	2584.0	0.15	3.9	67.3	187	1183	19.54	3.57	183
30	31	1836.0	0.75	6.2	75.4	277	1257	57.95	5.51	171
31	32	1776.0	0.29	6.2	75.4	108	346	44.68	5.12	183
35	36	2003.0	0.44	22.1	73.9	158	3355	16.07	6.37	183
38	39	3124.0	0.59	28.3	56.3	194	492	24.28	4.81	213

In [38]:

```
j = 0
for i in x_missing2.Rank.to_list():
    #print(i)
    data_df['avg_hours_worked'].iloc[i-1] = x_missing2['avg_hours_worked'].iloc[j]
    j += 1
```

```
C:\Users\jerem\AppData\Local\Temp\ipykernel_2448\2198421830.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-
a-copy
  data_df['avg_hours_worked'].iloc[i-1] = x_missing2['avg_hours_worked'].iloc[j]
```

In [39]:

```
data_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_hrs        44 non-null     float64
 3   bottle_water_cost   44 non-null     float64
 4   obesity_levels      44 non-null     float64
 5   life_expect_yrs     44 non-null     float64
 6   pollution_index     43 non-null     float64
 7   avg_hours_worked    44 non-null     float64
 8   outdoor_activities  44 non-null     int64  
 9   num_takeout_places  44 non-null     int64  
 10  gym_cost            44 non-null     float64
 11  happiness_levels    44 non-null     float64
dtypes: float64(8), int64(3), object(1)
memory usage: 4.2+ KB
```

Finally, I wanted to just drop the one pollution_index row that contained a null value, to practice dropping columns entirely. I think in hindsight, I should have just dropped the entire pollution_index column from the beginning, but I wanted to keep it just in case there was a surprise positive correlation.

In [40]:

```
data_df = data_df[data_df.pollution_index.notnull()]
```

In [41]:

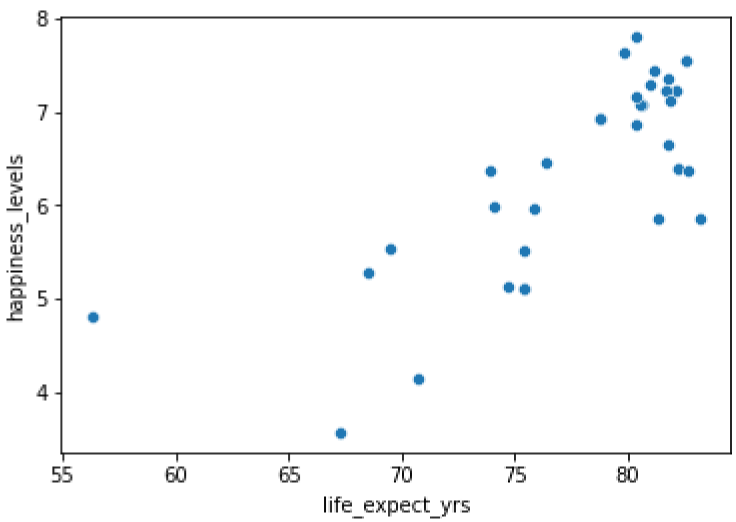
```
data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 43 entries, 0 to 43
```

```
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   City                 43 non-null     object 
 1   Rank                 43 non-null     int64  
 2   sunshine_hrs         43 non-null     float64
 3   bottle_water_cost    43 non-null     float64
 4   obesity_levels       43 non-null     float64
 5   life_expect_yrs      43 non-null     float64
 6   pollution_index      43 non-null     float64
 7   avg_hours_worked     43 non-null     float64
 8   outdoor_activities   43 non-null     int64  
 9   num_takeout_places   43 non-null     int64  
 10  gym_cost             43 non-null     float64
 11  happiness_levels     43 non-null     float64
dtypes: float64(8), int64(3), object(1)
memory usage: 4.4+ KB
```

In [42]:
```python
sns.scatterplot(data=data_df, x='life_expect_yrs', y='happiness_levels')
```

Out[42]:
```
<AxesSubplot:xlabel='life_expect_yrs', ylabel='happiness_levels'>
```



You can see a clear correlation between life expectancy and happiness!

Since the happiness_levels column is the last column, I will see if there are any outliers in this column. I will use the mean absolute error method to reduce the outlier effect on the dataset.

In [43]:
```python
data = data_df.values
data[:, 1:]
#data[:, -1]
```

```
Out[43]: array([[1, 1858.0, 1.92, 20.4, 81.2, 30.93, 1434.0, 422, 1048, 34.9,
         7.44],
        [2, 2636.0, 1.48, 29.0, 82.1, 26.86, 1712.0, 406, 1103, 41.66,
         7.22],
        [3, 1884.0, 1.94, 20.1, 81.0, 17.33, 1501.0, 132, 1008, 25.74,
         7.29],
        [4, 1821.0, 1.72, 20.6, 81.8, 19.63, 1452.0, 129, 598, 37.31,
         7.35],
        [5, 1630.0, 2.19, 19.7, 79.8, 21.24, 1380.0, 154, 523, 32.53,
         7.64],
        [6, 1662.0, 1.6, 22.2, 80.4, 13.08, 1540.0, 113, 309, 35.23, 7.8],
        [8, 1626.0, 1.55, 22.3, 80.6, 39.41, 1386.0, 254, 1729, 26.11,
         7.07],
        [9, 2591.0, 1.19, 23.8, 82.2, 65.19, 1686.0, 585, 2344, 37.8, 6.4],
        [10, 1938.0, 1.08, 29.4, 81.7, 24.26, 1670.0, 218, 788, 31.04,
         7.23],
        [11, 2363.0, 1.57, 29.0, 82.1, 25.9, 1712.0, 243, 813, 36.89,
         7.22],
        [12, 2671.0, 0.26, 6.2, 75.4, 85.43, 1832.0, 223, 261, 38.62,
         5.12],
        [13, 2624.0, 0.22, 10.0, 74.1, 76.64, 2137.0, 377, 1796, 50.03,
         5.99],
        [14, 2525.0, 0.57, 28.3, 75.9, 52.64, 2137.0, 246, 1435, 22.45,
         5.97],
        [15, 2066.0, 1.09, 29.4, 81.7, 37.83, 1670.0, 174, 1656, 32.64,
         7.23],
        [16, 2769.0, 1.3, 23.8, 82.2, 52.68, 1686.0, 216, 2491, 34.54,
         6.4],
        [17, 2983.0, 0.21, 6.9, 68.5, 84.39, 1832.0, 114, 833, 29.94,
         5.28],
        [18, 2066.0, 0.59, 4.7, 81.3, 57.82, 1967.0, 144, 389, 43.03,
         5.87],
        [19, 1662.0, 1.95, 22.3, 80.6, 37.78, 1386.0, 23, 551, 39.01,
         7.07],
        [20, 1566.0, 2.62, 19.5, 82.6, 27.25, 1557.0, 44, 444, 70.0, 7.56],
        [21, 3311.0, 1.63, 26.1, 81.9, 47.28, 1898.0, 139, 420, 58.31,
         7.12],
        [22, 2218.0, 0.15, 32.1, 74.7, 69.49, 1832.0, 419, 934, 16.97,
         5.13],
        [23, 3542.0, 0.16, 32.0, 70.7, 91.74, 1832.0, 323, 250, 23.25,
         4.15],
        [24, 1405.0, 0.57, 6.2, 75.4, 49.32, 1832.0, 134, 717, 34.76,
         5.12],
        [25, 3254.0, 1.52, 36.2, 78.8, 66.07, 1779.0, 223, 1439, 32.0,
         6.94],
        [26, 2584.0, 0.15, 3.9, 67.3, 82.84, 1832.0, 187, 1183, 19.54,
         3.57],
        [27, 2634.0, 1.39, 36.2, 78.8, 27.03, 1779.0, 88, 588, 46.27,
         6.94],
        [28, 1453.0, 1.4, 25.3, 80.5, 40.07, 1772.0, 159, 659, 37.35,
```

```
        7.09],
       [29, 1877.0, 0.76, 4.3, 83.2, 42.84, 1644.0, 387, 5802, 70.82,
        5.87],
       [30, 2508.0, 1.2, 36.2, 78.8, 43.33, 1779.0, 171, 1320, 41.14,
        6.94],
       [31, 1836.0, 0.75, 6.2, 75.4, 67.46, 1718.0, 277, 1257, 57.95,
        5.51],
       [32, 1776.0, 0.29, 6.2, 75.4, 77.4, 1832.0, 108, 346, 44.68, 5.12],
       [33, 1546.0, 2.11, 22.1, 80.4, 62.67, 1583.0, 55, 988, 25.34,
        6.86],
       [34, 3062.0, 1.6, 36.2, 78.8, 47.36, 1779.0, 242, 1031, 65.13,
        6.94],
       [35, 1662.0, 1.95, 21.6, 81.8, 65.1, 1505.0, 331, 4363, 35.93,
        6.66],
       [36, 2003.0, 0.44, 22.1, 73.9, 79.78, 1832.0, 158, 3355, 16.07,
        6.37],
       [37, 1566.0, 3.2, 19.5, 82.6, 17.31, 1557.0, 69, 538, 73.11, 7.56],
       [38, 1633.0, 1.16, 27.8, 80.4, 58.91, 1538.0, 433, 6417, 42.71,
        7.16],
       [39, 3124.0, 0.59, 28.3, 56.3, 61.83, 2137.0, 194, 492, 24.28,
        4.81],
       [40, 1915.0, 1.15, 19.9, 82.7, 67.19, 1718.0, 110, 2396, 53.49,
        6.38],
       [41, 2528.0, 1.45, 36.2, 78.8, 39.18, 1779.0, 83, 744, 65.99,
        6.94],
       [42, 2535.0, 1.32, 36.2, 78.8, 57.36, 1779.0, 359, 3081, 64.66,
        6.94],
       [43, 1901.0, 0.41, 23.1, 69.5, 57.63, 1965.0, 322, 3206, 31.4,
        5.54],
       [44, 2555.0, 0.45, 28.9, 76.4, 82.78, 2137.0, 192, 1313, 41.99,
        6.46]], dtype=object)
```

In [44]:

```
data = data_df.values
# split into input and output elements
X, y = data[:, 1:-1], data[:, -1]
# split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
# fit the model
model = LinearRegression()
model.fit(X_train, y_train)
# evaluate the model
yhat = model.predict(X_test)
# evaluate predictions
mae = mean_absolute_error(y_test, yhat)
print('MAE: %.3f' % mae)
```

```
MAE: 0.425
```

In [45]:

```
data = data_df.values
```

```python
X, y = data[:, 1:-1], data[:, -1]
# split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
# summarize the shape of the training dataset
print(X_train.shape, y_train.shape)
# identify outliers in the training dataset
lof = LocalOutlierFactor()
yhat = lof.fit_predict(X_train)
# select all rows that are not outliers
mask = yhat != -1
X_train, y_train = X_train[mask, :], y_train[mask]
# summarize the shape of the updated training dataset
print(X_train.shape, y_train.shape)
# fit the model
model = LinearRegression()
model.fit(X_train, y_train)
# evaluate the model
yhat = model.predict(X_test)
# evaluate predictions
mae = mean_absolute_error(y_test, yhat)
print('MAE: %.3f' % mae)
```

```
(28, 10) (28,)
(26, 10) (26,)
MAE: 0.397
```

So, since the mean absolute error increased, it seems the effect of the outliers was not reduced. Hmm...that means there has been a decrease in accuracy. This may be due to the terrible model we used earlier...

In [ ]:

```python

```

Prompt 3: Feature Selection

- Graphical visualization of features
- Examine the relationships within the dataset - using 2 different methods
- Reduction of the dimensionality of the dataset

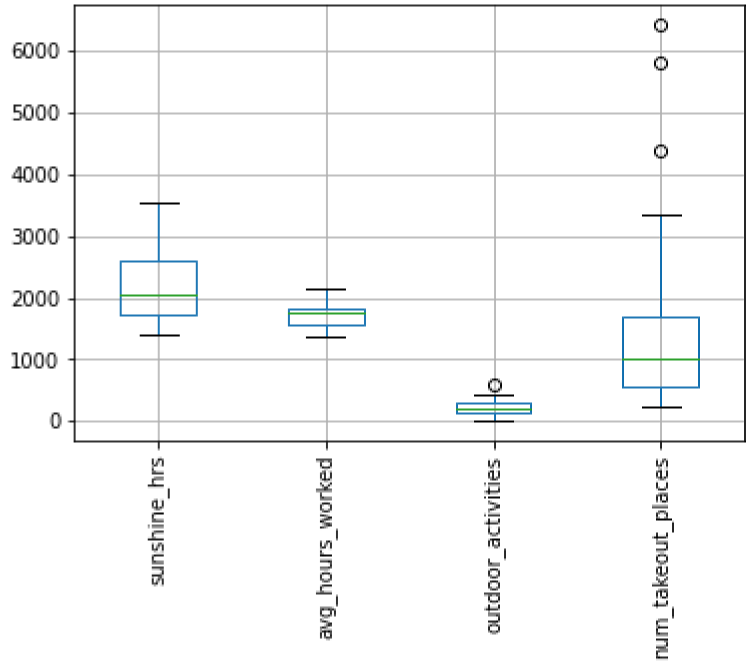
Since the features all had different ranges, I grouped them in 3 plots to group similar-range features together. You can see how the box and whisker plots differ from each other below.

In [46]:

```python
data_df.boxplot(['sunshine_hrs', 'avg_hours_worked', 'outdoor_activities', 'num_takeout_places'], rot=90)
```

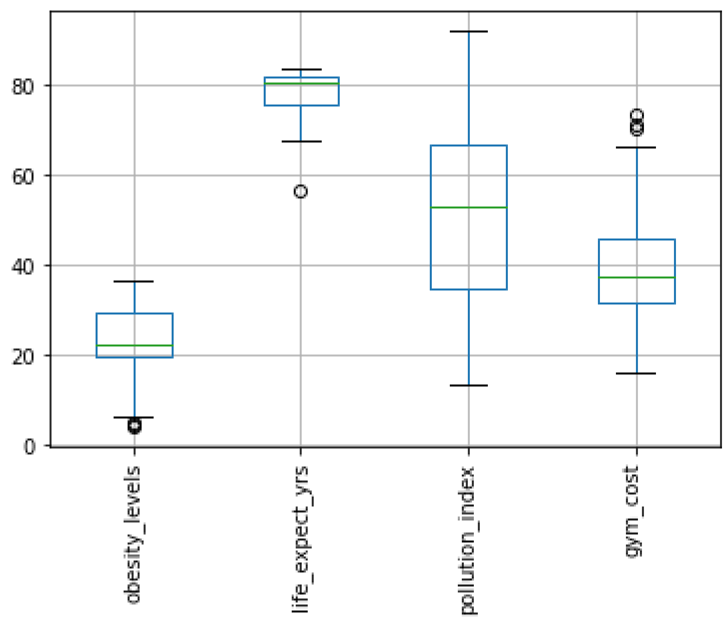
Out[46]:

```
<AxesSubplot:>
```



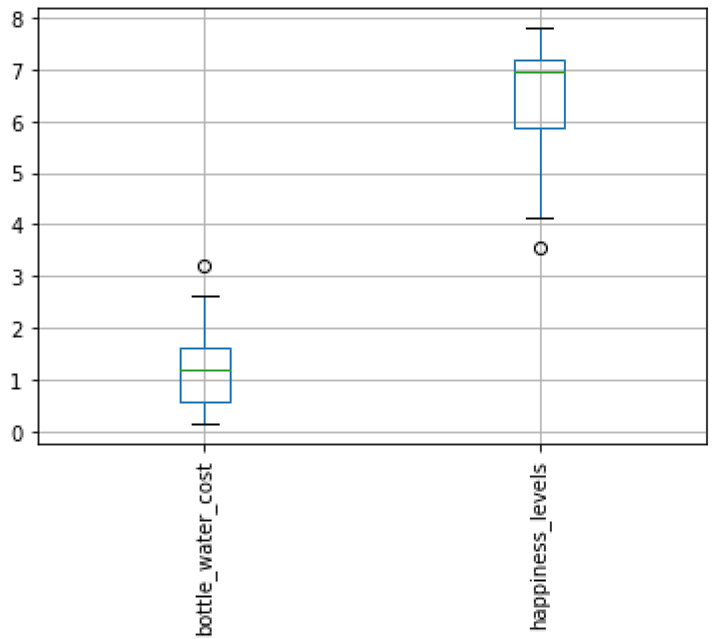
In [47]:
```
data_df.boxplot(['obesity_levels', 'life_expect_yrs', 'pollution_index', 'gym_cost'], rot=90)
```

Out[47]: <AxesSubplot:>



In [48]:
```
data_df.boxplot(['bottle_water_cost', 'happiness_levels'], rot=90)
```

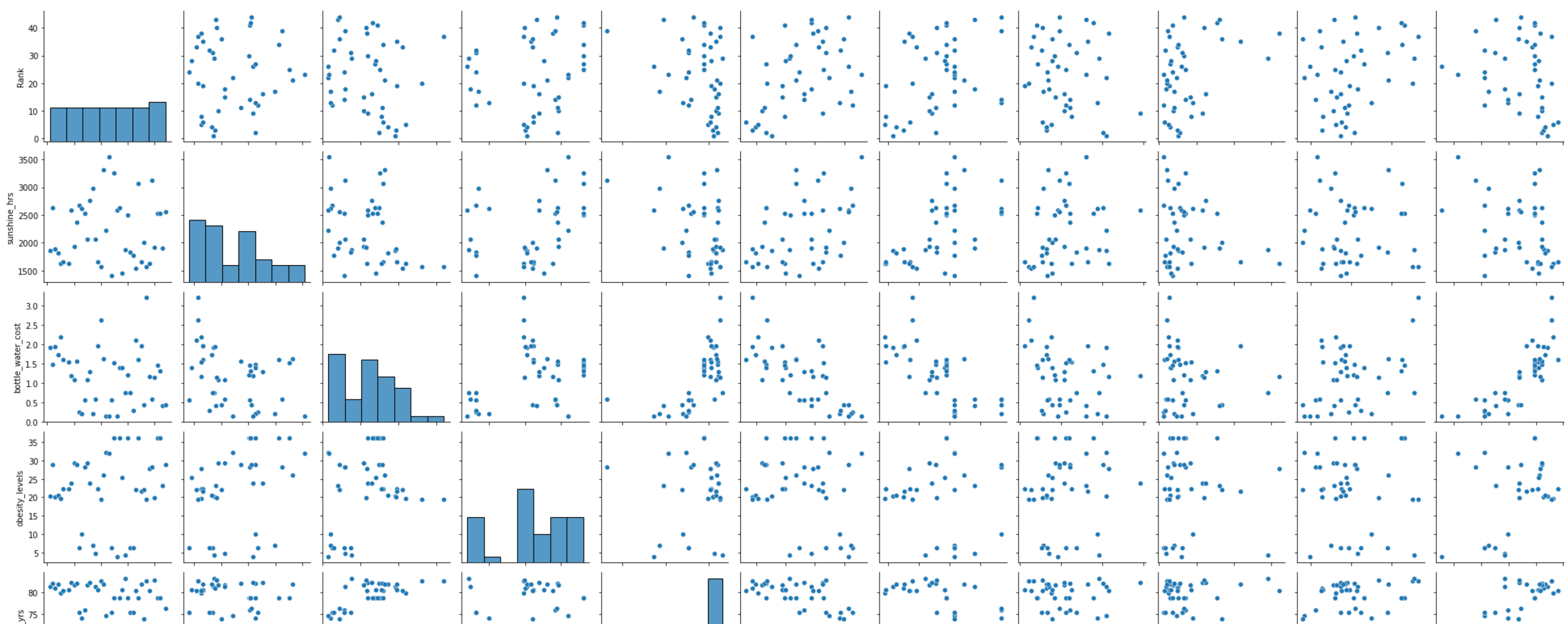
Out[48]: <AxesSubplot:>

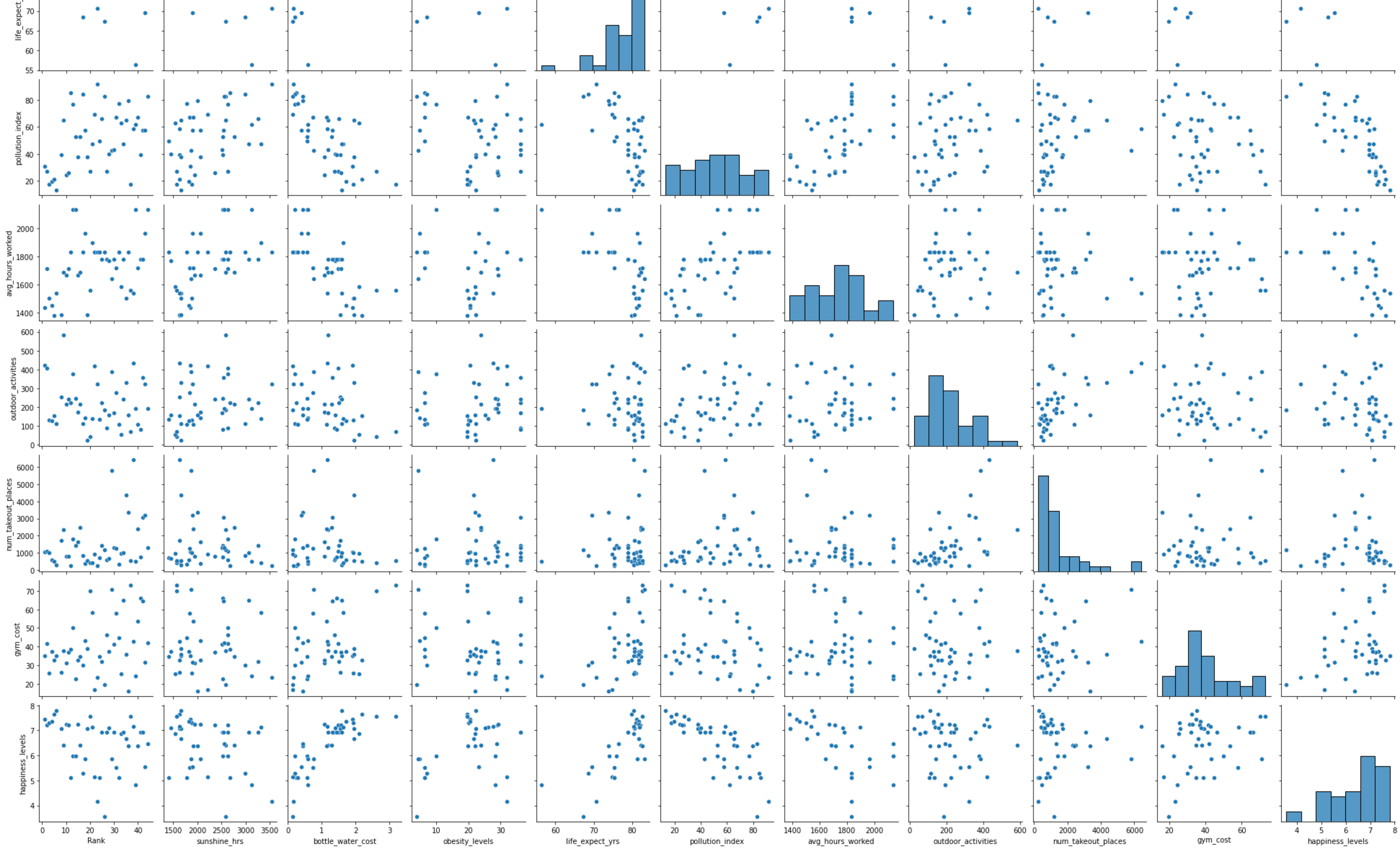


In [49]:

```
sns.pairplot(data_df)
```

Out[49]: <seaborn.axisgrid.PairGrid at 0x270b6d301c0>





Next I wanted to create a heatmap of the correlations between the variables. I also take it a step further and sort the correlations by which ones are most positive between happiness_levels and other features.

In [50]:

```
cormat = data_df.corr()
cormat
```

Out[50]:

	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	pollution_index	avg_hours_worked	outdoor_activities	num_ta
Rank	1.000000	0.041496	-0.160508	0.156132	-0.301275	0.427297	0.370327	-0.122384	
sunshine_hrs	0.041496	1.000000	-0.374688	0.337700	-0.400598	0.412271	0.562782	0.200267	

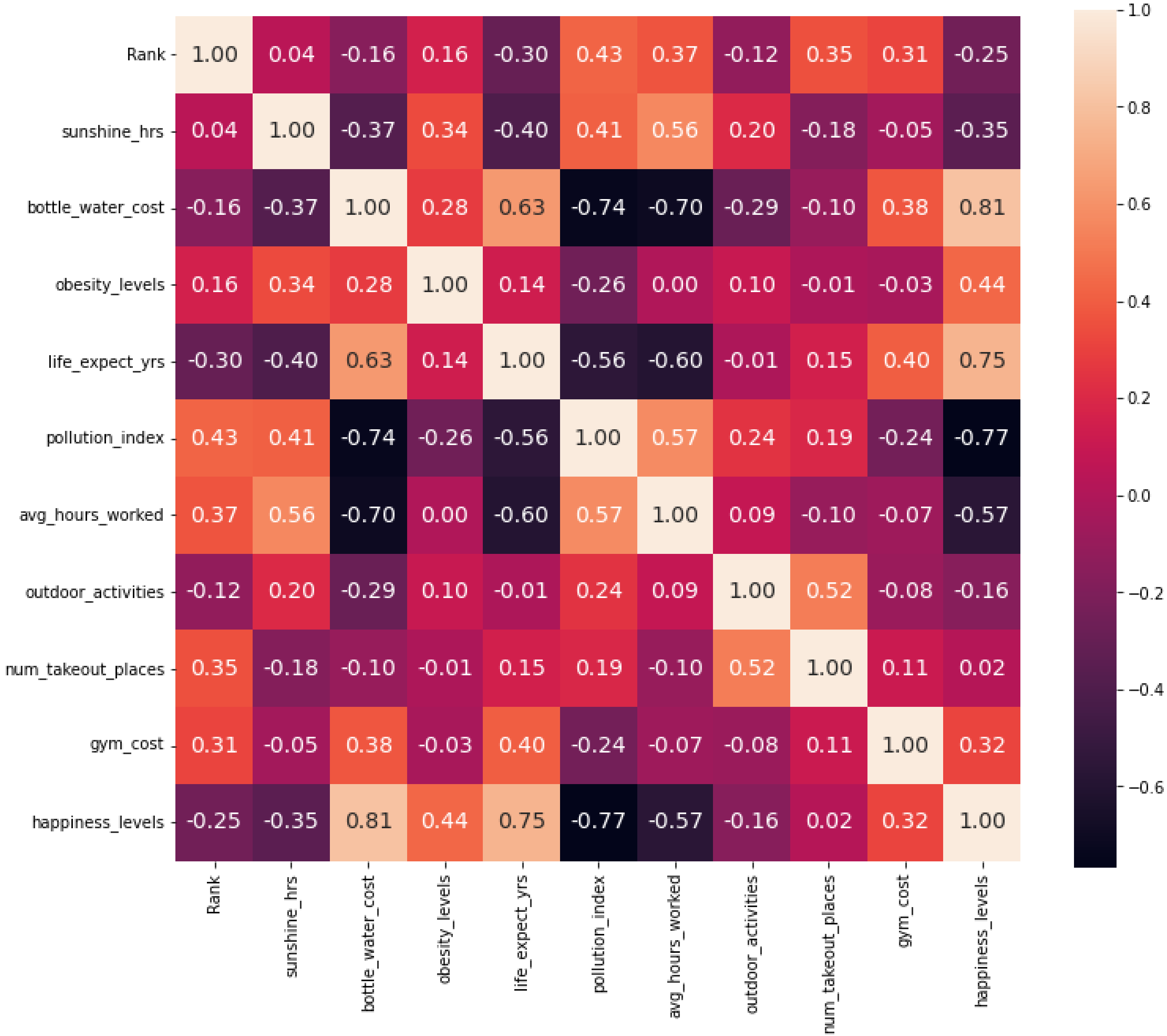
	Rank	sunshine_hrs	bottle_water_cost	obesity_levels	life_expect_yrs	pollution_index	avg_hours_worked	outdoor_activities	num_ta
bottle_water_cost	-0.160508	-0.374688	1.000000	0.281698	0.633767	-0.735286	-0.704788	-0.286457	
obesity_levels	0.156132	0.337700	0.281698	1.000000	0.136392	-0.256251	0.001597	0.098091	
life_expect_yrs	-0.301275	-0.400598	0.633767	0.136392	1.000000	-0.558713	-0.596225	-0.013609	
pollution_index	0.427297	0.412271	-0.735286	-0.256251	-0.558713	1.000000	0.572918	0.242622	
avg_hours_worked	0.370327	0.562782	-0.704788	0.001597	-0.596225	0.572918	1.000000	0.089447	
outdoor_activities	-0.122384	0.200267	-0.286457	0.098091	-0.013609	0.242622	0.089447	1.000000	
num_takeout_places	0.352271	-0.175267	-0.099299	-0.010373	0.145122	0.187227	-0.100054	0.521406	
gym_cost	0.311411	-0.050218	0.375971	-0.030005	0.404191	-0.244865	-0.071081	-0.083967	
happiness_levels	-0.253738	-0.347322	0.811766	0.440548	0.748339	-0.765902	-0.571663	-0.161151	

In [51]:

```
f, ax = plt.subplots(figsize=(12,10)) #setting some parameters of the plot to help readability
hm = sns.heatmap(corrmat, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size':14})
plt.show
```

Out[51]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [52]:

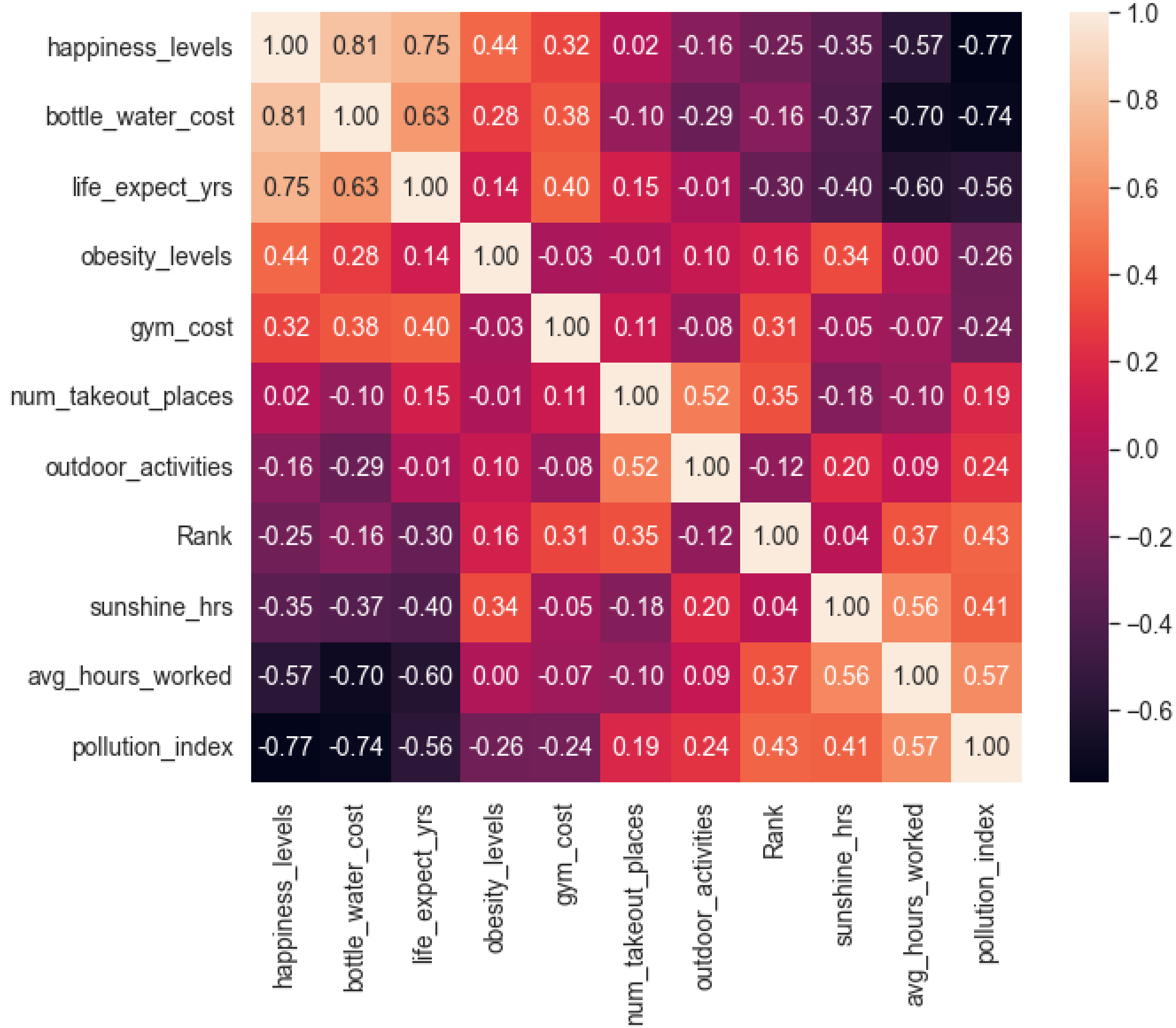
```
k = 15
cols = corrmat.nlargest(k, 'happiness_levels')['happiness_levels'].index

#Numpy corrcoef gives a pearson correlation coefficient
cm = np.corrcoef(data_df[cols].values.T)
sns.set(font_scale = 1.25)
f, ax = plt.subplots(figsize=(10,8))
```

```
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size':14},yticklabels=cols.values, xticklabels=cols
plt.show
```

Out[52]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Since polution index, average hours worked, outdoor activities, and Rank are the most negatively correlated with happiness_levels, I dropped these columns to reduce the dataset. I then created the same heatmaps with the new reduced dataset.

In [53]:

```
data_df = data_df.drop('pollution_index', 1)
data_df = data_df.drop('avg_hours_worked', 1)
data_df = data_df.drop('outdoor_activities', 1)
```

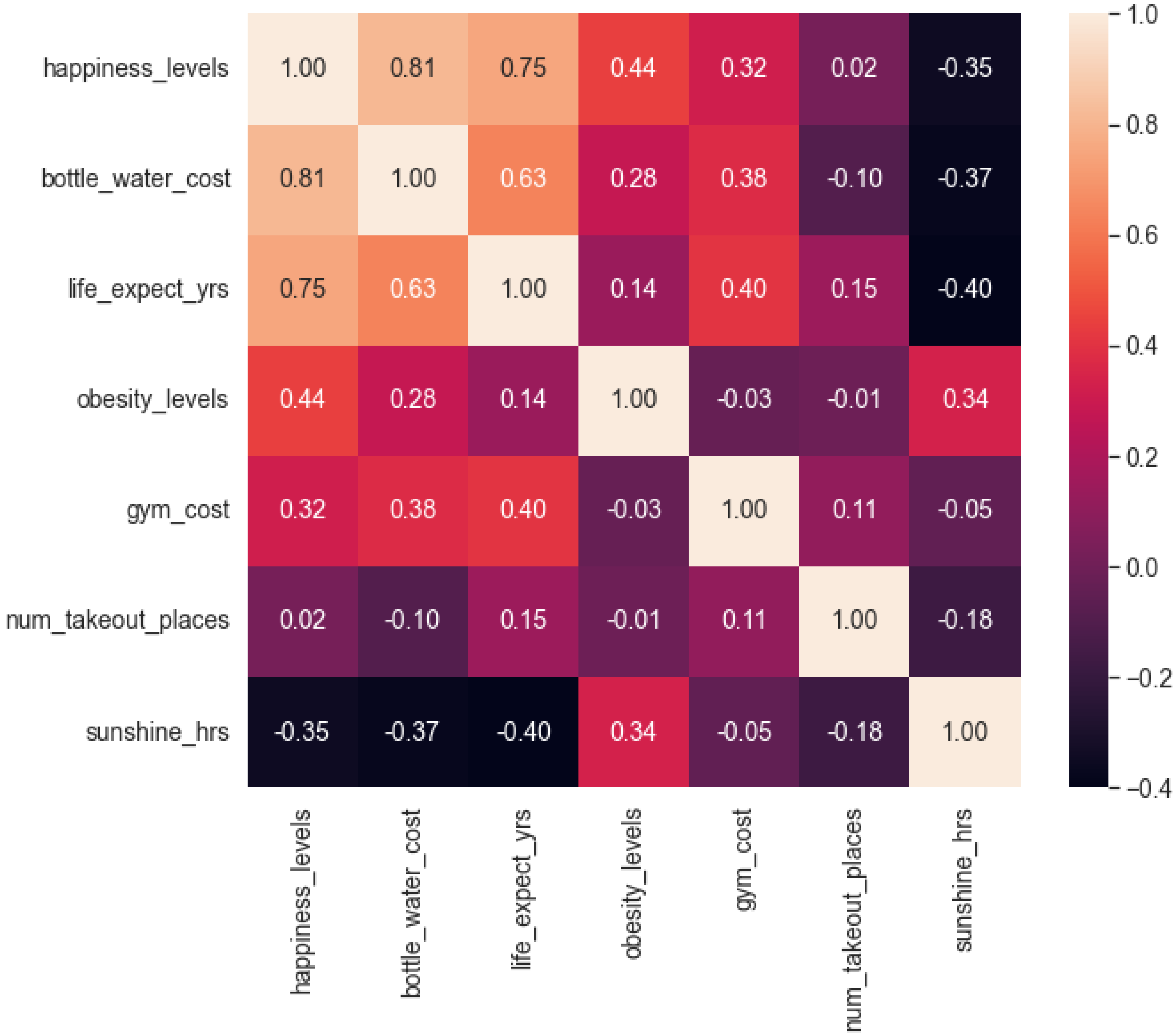
```python
data_df = data_df.drop('Rank', 1)
corrmat = data_df.corr()
k = 10
cols = corrmat.nlargest(k, 'happiness_levels')['happiness_levels'].index

#Numpy corrcoef gives a pearson correlation coefficient
cm = np.corrcoef(data_df[cols].values.T)
sns.set(font_scale = 1.25)
f, ax = plt.subplots(figsize=(10,8))
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size':14},yticklabels=cols.values, xticklabels=cols
plt.show
```

```
C:\Users\jerem\AppData\Local\Temp\ipykernel_2448\3315944743.py:1: FutureWarning: In a future version of pandas all arguments of Data
Frame.drop except for the argument 'labels' will be keyword-only.
  data_df = data_df.drop('pollution_index', 1)
C:\Users\jerem\AppData\Local\Temp\ipykernel_2448\3315944743.py:2: FutureWarning: In a future version of pandas all arguments of Data
Frame.drop except for the argument 'labels' will be keyword-only.
  data_df = data_df.drop('avg_hours_worked', 1)
C:\Users\jerem\AppData\Local\Temp\ipykernel_2448\3315944743.py:3: FutureWarning: In a future version of pandas all arguments of Data
Frame.drop except for the argument 'labels' will be keyword-only.
  data_df = data_df.drop('outdoor_activities', 1)
C:\Users\jerem\AppData\Local\Temp\ipykernel_2448\3315944743.py:4: FutureWarning: In a future version of pandas all arguments of Data
Frame.drop except for the argument 'labels' will be keyword-only.
  data_df = data_df.drop('Rank', 1)
```

Out[53]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [ ]:

Prompt 4: Insights and Findings

- Describe an insight and/or findings from within the dataset.

It's really interesting! According the this dataset, a few odd findings could be stated. First, the amount of hours of sunshine is actually negatively correlated with happiness levels. This is extremely counterintuitive, as sunshine has been associated with a higher happiness level typically. Interesting. Additionally, the cost of bottled water was positively associated with happiness levels. I believe this is a misleading correlation and doesn't tell a complete picture. If this is true, this means that the more expensive water is, the happier people are. This is definitely not true as typically people are happiest when their expenses are lowest, by logic.

However, it's straightforward that happiness levels is correlated postively with life expectancy. When people are happier, they live longer. This makes sense.

In [ ]:

```

```

Prompt 5: Bonus: Feature Engineering

- Create a new feature based for findings

I chose to create the feature "life per sunshine" which takes the person's average life expectancy and divides it by the amount of hours of sunshine this person gets in this location. This may tell us something interesting about how big of a percentage the person's life is filled with sunshine compared to other locations, and how this may correlate to a higher happiness level.

In [54]:

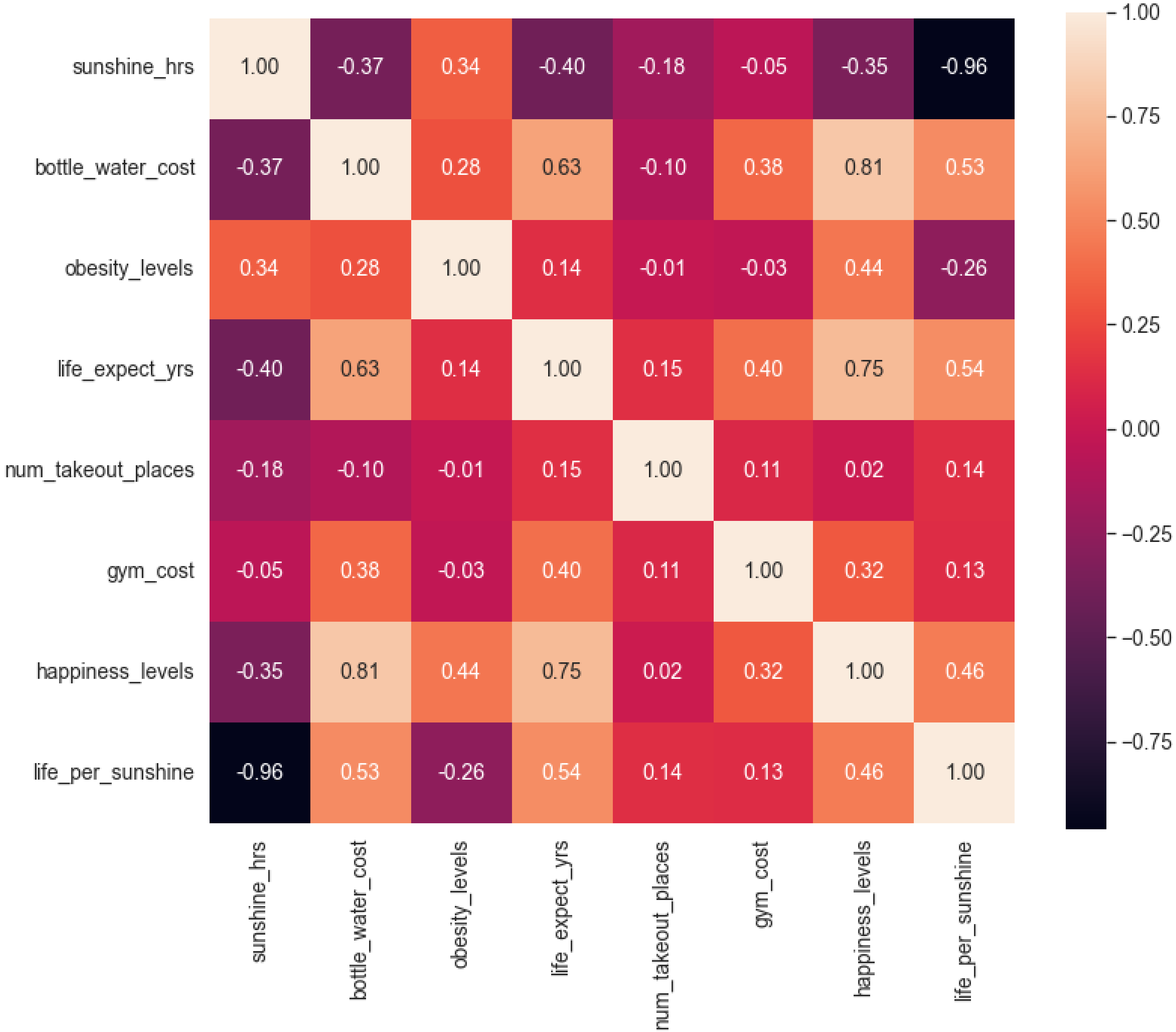
```
data_df['life_per_sunshine'] = data_df.life_expect_yrs / data_df.sunshine_hrs
```

In [55]:

```
cormat = data_df.corr()
f, ax = plt.subplots(figsize=(12,10)) #setting some parameters of the plot to help readability
hm = sns.heatmap(corrmat, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size':14})
plt.show
```

Out[55]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



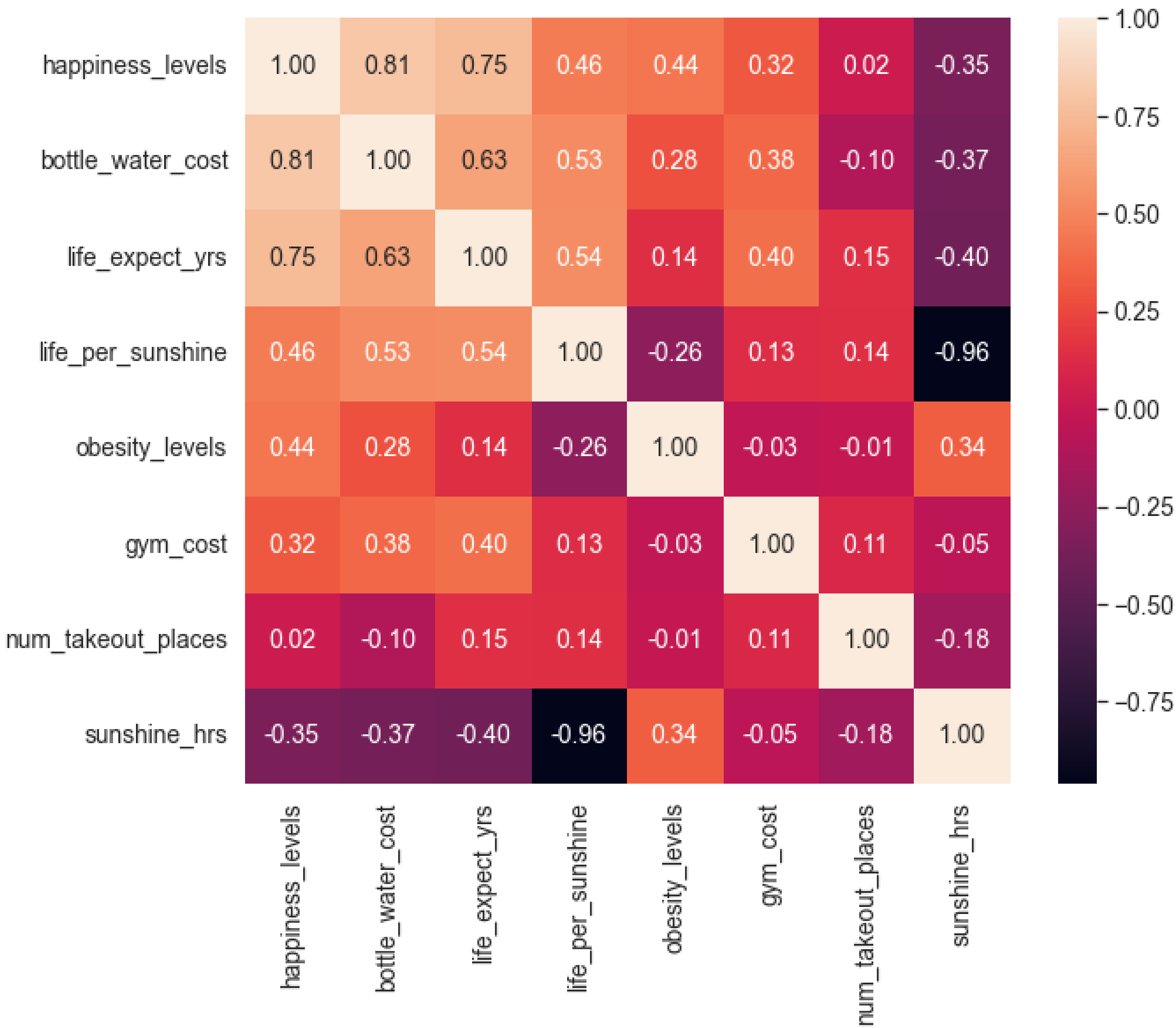
In [56]:

```
k = 14
cols = corrmat.nlargest(k, 'happiness_levels')['happiness_levels'].index

#Numpy corrcoef gives a pearson correlation coefficient
cm = np.corrcoef(data_df[cols].values.T)
```

```
sns.set(font_scale = 1.25)
f, ax = plt.subplots(figsize=(10,8))
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size':14},yticklabels=cols.values, xticklabels=cols
plt.show
```

Out[56]: <function matplotlib.pyplot.show(close=None, block=None)>



V. Conclusion

In this week's assignment, I cleaned and summarized the "Healthy Lifestyle Cities Report 2021" dataset and sought to explore how different factors may contribute towards a person's happiness. I found that while life expectancy was positively correlated with happiness, hours of sunshine was negatively correlated. I also found that the most expensive water was, the happier people were. This was puzzling. However, I still found the assignment interesting and challenging as cleaning the dataset is something I don't have much experience with. I was glad to have some examples to follow from Professor Hayes.

VI. References

https://www.kaggle.com/datasets/prasertk/healthy-lifestyle-cities-report-2021

MSDS 650 - Week 2 Content:

1.) "Healthy Lifestyle Cities Report 2021" dataset downloaded for this assignment: healthy_lifestyle_city_2021_clean04.csv
https://www.kaggle.com/datasets/prasertk/healthy-lifestyle-cities-report-2021

2.) From the Experts PDF: Week 3