Outliers and Pearsons

November 14, 2021

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from pingouin import corr
import dataframe_image as dfi
```

0.0.1 Pulling all three DataSets

Renamed all data sets and saved their csv's:

dataset1: World CSV

dataset2: Euro10 CSV

dataset3: EuroAll CSV

[2]:
```
ds1 = pd.read_csv('ADmergeVOM.csv')
```

[3]:
```
ds1.head()
```

[3]:

	Unnamed: 0	Entity	Year	Vegetable Oil	Deaths
0	0	Afghanistan	2007	3.48	707.188774
1	1	Albania	2007	7.00	339.928986
2	2	Algeria	2007	13.60	328.078554
3	3	Angola	2007	9.05	344.017796
4	4	Argentina	2007	14.60	220.586059

[4]:
```
ds1.to_csv('dataset1.csv')
```

[5]:
```
ds2 = pd.read_csv('mergeEuro.csv')
```

[6]:
```
ds2.head()
```

[6]:

	Unnamed: 0	Entity	Year	Vegetable Oil	Deaths
0	0	France	2007	507.945205	112.366845
1	1	Germany	2007	451.232877	176.248974
2	2	Italy	2007	673.150685	141.709672
3	3	Netherlands	2007	389.589041	138.289634
4	4	Poland	2007	276.164384	302.017225

[7]:
```
ds2.to_csv('dataset2.csv')
```

[8]:
```python
ds3 =  pd.read_csv('EuroWVOMR.csv')
```

[9]:
```python
ds3
```

[9]:
```
     Unnamed: 0           Entity  Year  Vegetable Oil      Deaths
0             0          Albania  2007     172.602740  339.928986
1             1          Armenia  2007     182.465753  410.791211
2             2          Austria  2007     542.465753  182.027111
3             3       Azerbaijan  2007      71.506849  632.724097
4             4          Belarus  2007     387.123288  533.504417
..          …               …   …            …         …
200         200           Sweden  2011     416.712329  153.603971
201         201      Switzerland  2011     495.616438  114.813790
202         202           Turkey  2011     613.972603  184.849933
203         203          Ukraine  2011     315.616438  546.286540
204         204   United Kingdom  2011     431.506849  129.259572

[205 rows x 5 columns]
```

[10]:
```python
ds3.to_csv('dataset3.csv')
```

0.0.2 Filtering outliers

Dataset1

[11]:
```python
#VO
len(ds1[['Vegetable Oil','Deaths']])
```

[11]: 740

[12]:
```python
ds1['Vegetable Oil'] *= 1000
```

[13]:
```python
ds1['Vegetable Oil'] /= 365
```

[14]:
```python
ds1['Vegetable Oil'] *= 9
```

[15]:
```python
max_threshold = ds1['Vegetable Oil'].quantile(0.95)
max_threshold
```

[15]: 559.9726027397259

[16]:
```python
min_threshold = ds1['Vegetable Oil'].quantile(0.05)
min_threshold
```

[16]: 71.97534246575343

[17]:
```python
ds1 = ds1[(ds1['Vegetable Oil']<max_threshold) & (ds1['Vegetable␣
↪Oil']>min_threshold)]
```

[18]:
```
#MR
max_threshold = ds1['Deaths'].quantile(0.95)
max_threshold
```

[18]: 544.595158512821

[19]:
```
min_threshold = ds1['Deaths'].quantile(0.05)
min_threshold
```

[19]: 125.31255406465945

[20]:
```
ds1 = ds1[(ds1['Deaths']<max_threshold) & (ds1['Deaths']>min_threshold)]
```

[21]:
```
len(ds1)
```

[21]: 598

[22]:
```
ds1Trim = ds1.drop(columns=['Unnamed: 0'], inplace=True)
```

[23]:
```
ds1Trim = ds1
```

Dataset2

[24]:
```
len(ds2[['Vegetable Oil','Deaths']])
```

[24]: 50

[25]:
```
max_threshold = ds2['Vegetable Oil'].quantile(0.95)
max_threshold
```

[25]: 717.5342465753422

[26]:
```
min_threshold = ds2['Vegetable Oil'].quantile(0.05)
min_threshold
```

[26]: 295.64383561643837

[27]:
```
ds2 = ds2[(ds2['Vegetable Oil']<max_threshold) & (ds2['Vegetable␣
↪Oil']>min_threshold)]
```

[28]:
```
max_threshold = ds2['Deaths'].quantile(0.95)
max_threshold
```

[28]: 565.144680208295

[29]:
```
min_threshold = ds2['Deaths'].quantile(0.05)
min_threshold
```

[29]: 108.21761349857361

[30]:
```
ds2 = ds2[(ds2['Deaths']<max_threshold) & (ds2['Deaths']>min_threshold)]
```

[31]:
```
len(ds2)
```

[31]: 38

[32]:
```
ds2Trim = ds2.drop(columns=['Unnamed: 0'], inplace=True)
```

[33]:
```
ds2Trim = ds2
```

Dataset3

[34]:
```
len(ds3[['Vegetable Oil','Deaths']])
```

[34]: 205

[35]:
```
max_threshold = ds3['Vegetable Oil'].quantile(0.95)
max_threshold
```

[35]: 657.8630136986301

[36]:
```
min_threshold = ds3['Vegetable Oil'].quantile(0.05)
min_threshold
```

[36]: 152.87671232876713

[37]:
```
ds3 = ds3[(ds3['Vegetable Oil']<max_threshold) & (ds3['Vegetable␣
↪Oil']>min_threshold)]
```

[38]:
```
#MR
max_threshold = ds3['Deaths'].quantile(0.95)
max_threshold
```

[38]: 536.4335539107747

[39]:
```
min_threshold = ds3['Deaths'].quantile(0.05)
min_threshold
```

[39]: 129.20907594078224

[40]:
```
ds3 = ds3[(ds3['Deaths']<max_threshold) & (ds3['Deaths']>min_threshold)]
```

[41]:
```
len(ds3)
```

[41]: 162

[42]:
```
ds3Trim = ds3.drop(columns=['Unnamed: 0'], inplace=True)
```

[43]:
```
ds3Trim = ds3
```

0.0.3 Saving all tables to CSV

[44]:
```
ds1Trim.to_csv('ds1Trim.csv')
```

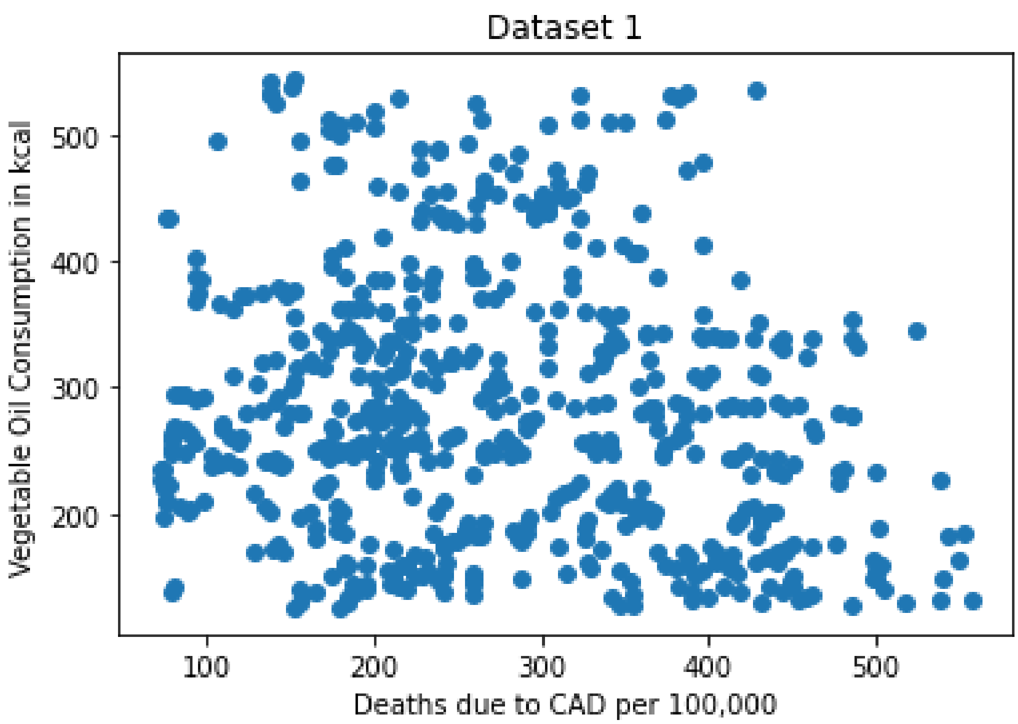
[45]:
```
ds2Trim.to_csv('ds2Trim.csv')
```

[46]:
```
ds3Trim.to_csv('ds3Trim.csv')
```

0.0.4 Plotting just in case

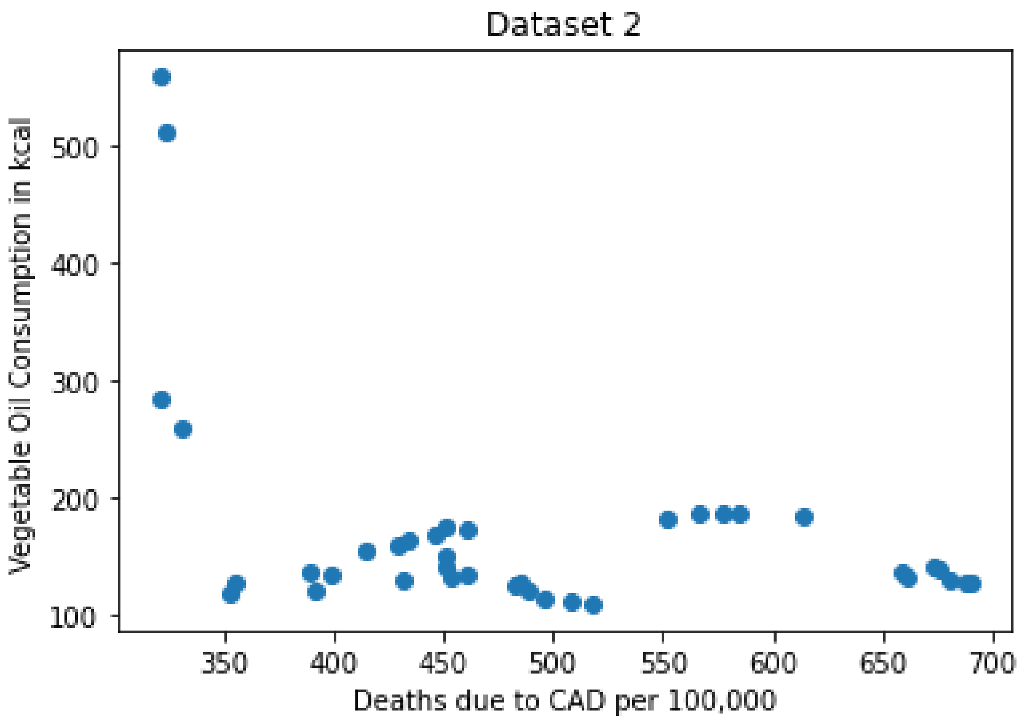
[47]:
```
plt.title('Dataset 1')
plt.xlabel('Deaths due to CAD per 100,000')
plt.ylabel('Vegetable Oil Consumption in kcal')
plt.scatter(ds1Trim['Vegetable Oil'], ds1Trim['Deaths'])
```

[47]:
```
<matplotlib.collections.PathCollection at 0x1cf158a7d30>
```



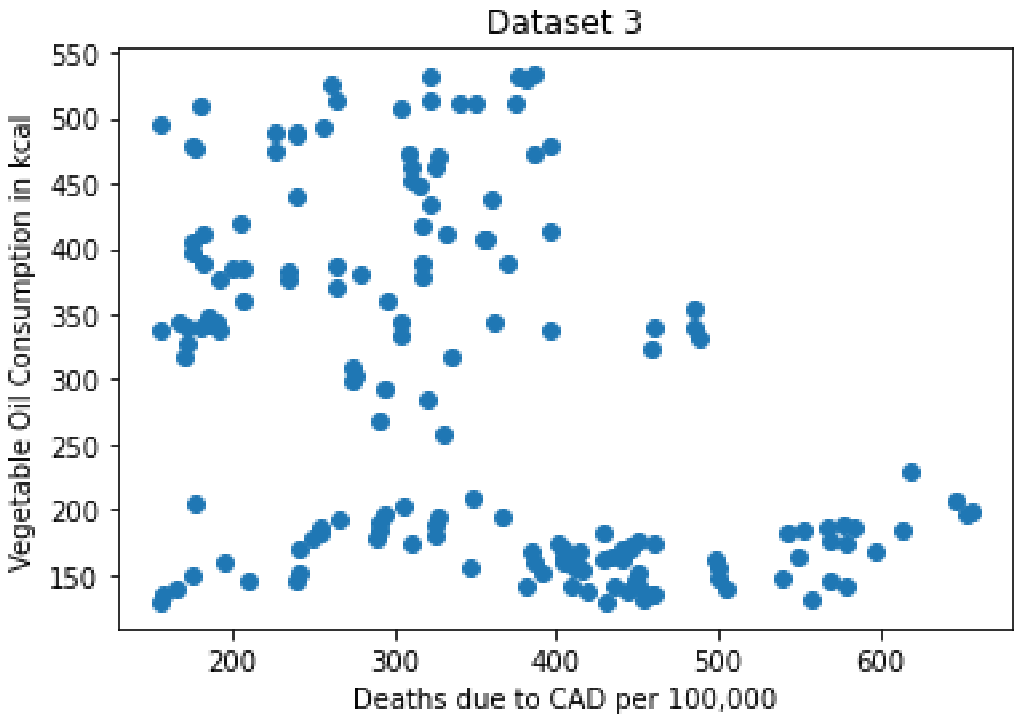
[48]:
```
plt.title('Dataset 2')
plt.xlabel('Deaths due to CAD per 100,000')
plt.ylabel('Vegetable Oil Consumption in kcal')
plt.scatter(ds2Trim['Vegetable Oil'], ds2Trim['Deaths'])
```

[48]:
```
<matplotlib.collections.PathCollection at 0x1cf0ab72b80>
```



[49]:
```
plt.title('Dataset 3')
plt.xlabel('Deaths due to CAD per 100,000')
plt.ylabel('Vegetable Oil Consumption in kcal')
plt.scatter(ds3Trim['Vegetable Oil'], ds3Trim['Deaths'])
```

[49]: <matplotlib.collections.PathCollection at 0x1cf0abbe550>



0.0.5 Pearsons Tables

Pearson Correlation varies between -1 and +1. If it is -1 there is a perfect negative lineair relationship, if it is 0 there is no lineair relationship and at +1 there is a perfect positive lineair relationship.

A positive relation means that if one variable goes up, the other also goes up (for example number of ice cream sold versus temperature), a negative relation indicates if one goes down, the other goes up (for example number of winter jackets sold versus temperature).

We can test if Pearson Correlation might be significantly different from 0 in the population. In the example the significance of this test is .000. This is the chance of finding a correlation coefficient of .880 or even higher in a sample, if in the population it would be 0 (no association). This is such a low chance, that we can say that in the population the correlation coefficient will be indeed different from zero, and conclude that there is a significant linear association between the two variables.

To determine the strength we only look at the absolute value (which means to ignore any minus sign, so the absolute value of for example -0.4 is simply 0.4).

Unfortunately there is no formal way to determine if 0.880 is high or low (although almost everyone would agree this is pretty high), and the rules of thumb floating around on the internet vary quite a lot, often depending on the field (e.g. biology, medicine, business, etc.). For example the same rule of thumb sizes from Rea and Parker (1992):

|r|

Strenght

0.00 < 0.10

Negligible

0.10 < 0.20

Weak

0.20 < 0.40

Moderate

0.40 < 0.60

Relatively strong

0.60 < 0.80

Strong

```
   <tr>
  <td><p>0.80 < 1.00</p></td>
<td>Very strong</td>
```

[50]:
```
ds1Trim[['Vegetable Oil', 'Deaths']].corr()
```

[50]:
```
               Vegetable Oil    Deaths
Vegetable Oil       1.000000 -0.163823
Deaths             -0.163823  1.000000
```

[58]:
```
dfi.export(corr(ds1Trim['Vegetable Oil'], ds1Trim['Deaths'] ), 'ds1Pearsons.
 ↪png')
```

[52]:
```
ds2Trim[['Vegetable Oil', 'Deaths']].corr()
```

[52]:
```
               Vegetable Oil    Deaths
Vegetable Oil       1.000000 -0.417375
Deaths             -0.417375  1.000000
```

[57]:
```
dfi.export(corr(ds2Trim['Vegetable Oil'], ds2Trim['Deaths'] ), 'ds2Pearsons.
 ↪png')
```

[54]:
```
ds3Trim[['Vegetable Oil', 'Deaths']].corr()
```

[54]:
```
               Vegetable Oil    Deaths
Vegetable Oil       1.000000 -0.438487
Deaths             -0.438487  1.000000
```

[56]:
```
dfi.export(corr(ds3Trim['Vegetable Oil'], ds3Trim['Deaths'] ), 'ds3Pearsons.
 ↪png')
```