CA01

February 14, 2020

1 Compulsory Assignment 01

1.1 Starting by importing the nessescary packages

[73]:
```
import pandas as pd
from pandas.plotting import scatter_matrix
import seaborn as sns; sns.set(context = 'paper', style = 'whitegrid')
import matplotlib.pyplot as plt
import numpy as np
from itertools import chain
from pprint import pprint
```

2 Part 1

[74]:
```
A = pd.read_excel("A.xlsx")
B = pd.read_excel("B.xlsx")
C = pd.read_excel("C.xlsx")
D = pd.read_excel("D.xlsx")
```

[75]:
```
dataset = {"A" : A, "B" : B, "C" : C, "D" : D}
```

3 Part 2

3.0.1 I'm creating a dictionary with the datasets. It will make it easier to get the names of the datasets for the printout, as well as the data

[76]:
```
for x in dataset:
    sets = dataset[x]
    if sets.isna().values.any(): #using pandas method chaining
        print(f'Missing values in dataframe {x}: True')
    else:
        print(f'Missing values in dataframe {x}: False')
```

```
Missing values in dataframe A: True
Missing values in dataframe B: False
Missing values in dataframe C: True
Missing values in dataframe D: True
```

Accessing each dataset in the dictionary

is.na() stores each value as a True/False statement. If True, there is a NaN in the value. So the output will be a dataset containing only True/False statements

Values.any() tells us if there is any NaN in the whole dataset.

[77]:
```
for x in dataset:
    sets = dataset[x]
    columns = list(sets.loc[:, sets.columns!= "id"].isna().sum()) #storing a␣
 ↪variale to make the code easier to read
    print(f'Number of missing values in each column in {x}: {columns}')
```

```
Number of missing values in each column in A: [1, 2, 1, 2]
Number of missing values in each column in B: [0, 0, 0, 0, 0, 0, 0]
Number of missing values in each column in C: [4, 3, 4, 3, 0]
Number of missing values in each column in D: [1, 0, 1, 0, 1, 2, 3, 3, 3, 3]
```

The first thing I do is to exclude every column that contains "ID", as that's not the data we're interested in. Using "loc" to locate those columns

Again using is.na() but including the sum() function to get the amount of NaN in each column

In the end I store the values in a list

[78]:
```
for x in dataset:
    sets = dataset[x]
    sum_of_NaN = sum(list(sets.loc[:, sets.columns!= "id"].isna().sum()))
    print(f'total number of missing values in {x}: {sum_of_NaN}')
```

```
total number of missing values in A: 6
total number of missing values in B: 0
total number of missing values in C: 14
total number of missing values in D: 17
```

Excluding every column that is "ID" again.

The procedure is pretty much the same. The difference is that I use the sum function to get the summation of the values in the list

[79]:
```
for x in dataset:
    sets = dataset[x]
    indexing = pd.isna(sets).any(1).to_numpy().nonzero()[0]
    objects = list(sets['id'][indexing])
    print(f'ID of rows with missing values in {x}: {objects}')
```

```
ID of rows with missing values in A: ['obj 5', 'obj 36', 'obj 120', 'obj 166']
ID of rows with missing values in B: []
ID of rows with missing values in C: ['obj 5', 'obj 138', 'obj 141', 'obj 143']
ID of rows with missing values in D: ['obj 55', 'obj 80', 'obj 120', 'obj 162',
'obj 184', 'obj 185']
```

I try to get the index values of every column that is NaN so I can easily extract the object that belongs to the NaN value.

I then use the indexing variable, which contains the index of every NaN value, to get a list of all the objects which has NaN value.

4 Part 3

[80]:
```
index_verdi = []
for x in dataset:
    sets = dataset[x]
    index_verdi.append(pd.isna(sets).any(1).to_numpy().nonzero()[0])
index_verdi = list(chain(*index_verdi))

print(index_verdi)

for y in dataset:
    dataset[y] = dataset[y].drop(index_verdi)
```

```
[4, 35, 119, 165, 4, 137, 140, 142, 54, 79, 119, 161, 183, 184]
```

Creating an empty list which later will contain each index value for us to remove

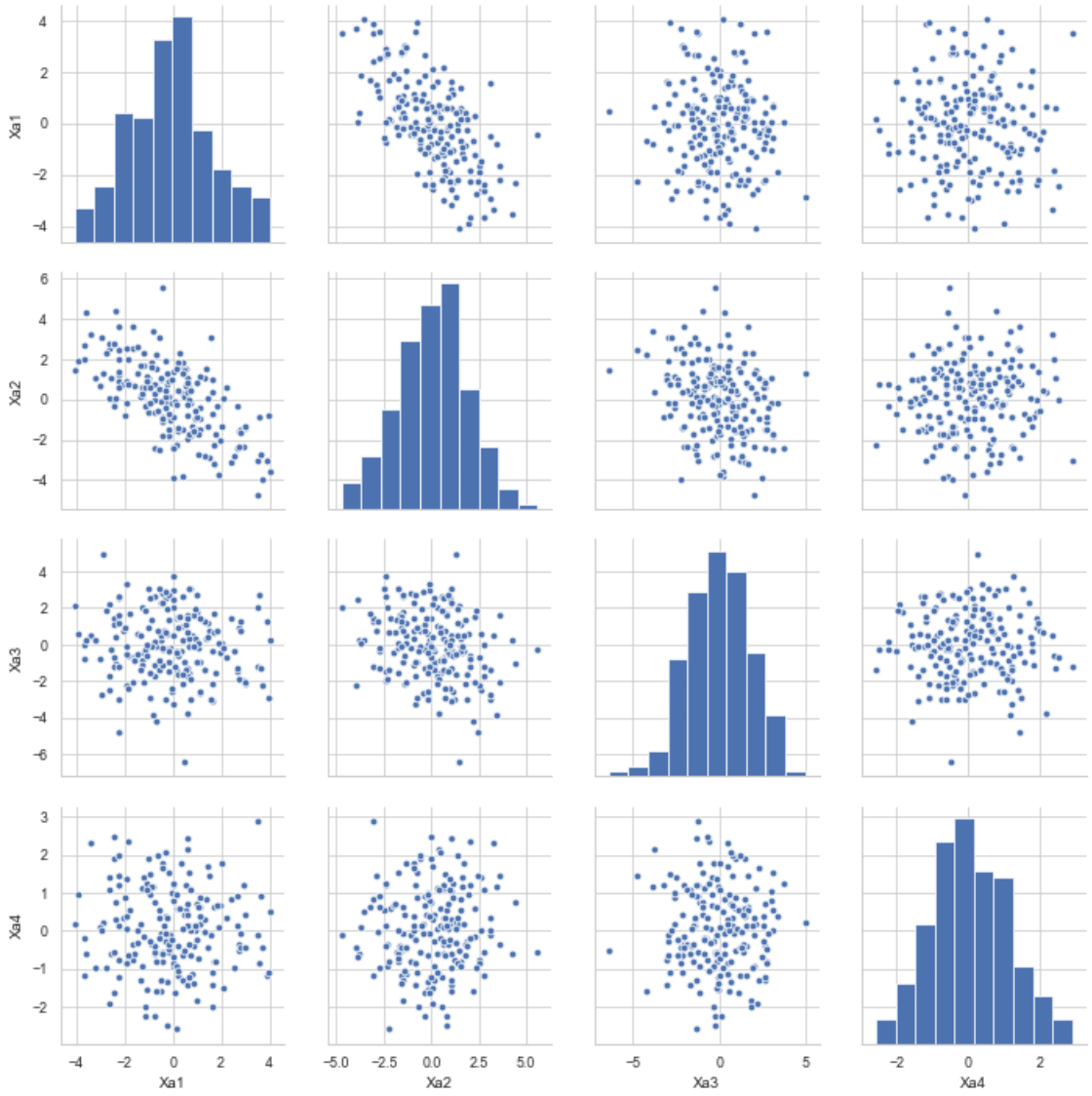
Using chain to "unlist" multiple lists within a list

Then iterating through each dataset and dropping the same index values (12 in total)

5 Part 4

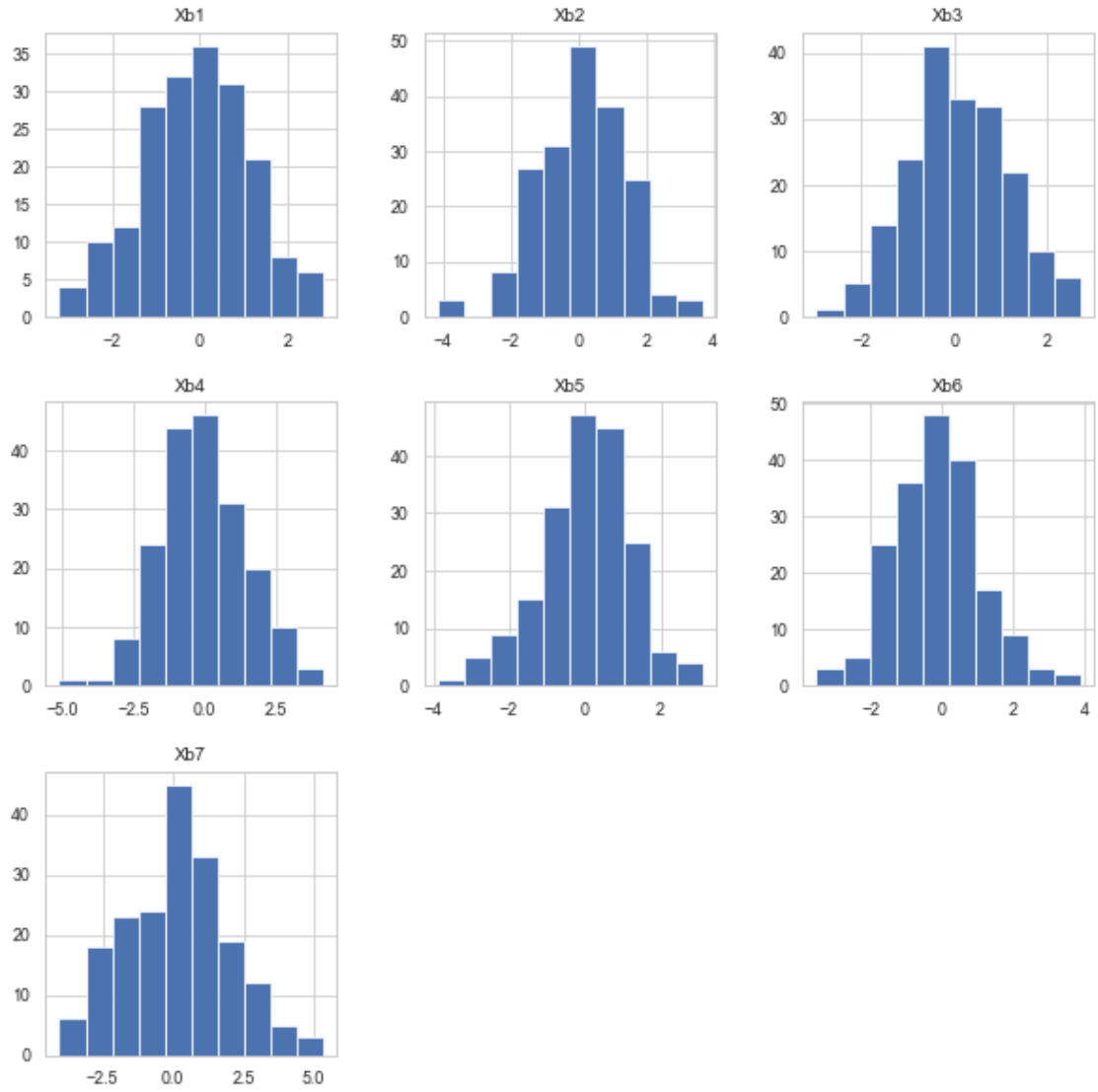
[81]:
```
sns.pairplot(dataset['A'])
rows_columns = dataset['A'].shape
print(f'amount of rows and columns in the dataset is: {rows_columns}')
```

```
amount of rows and columns in the dataset is: (188, 5)
```



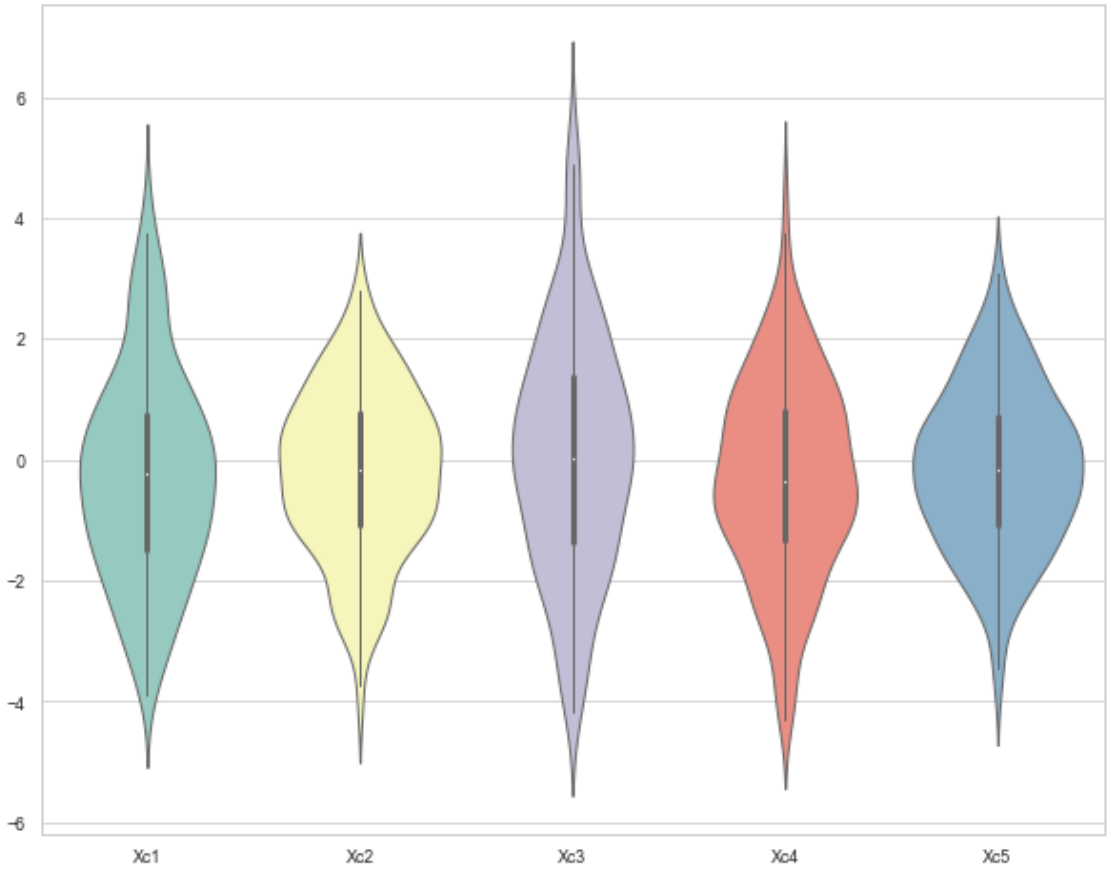
[82]:
```
dataset['B'].hist(figsize= (10,10))
rows_columns = dataset['B'].shape
print(f'Amount of rows and columns in the dataset is: {rows_columns}')
```

```
Amount of rows and columns in the dataset is: (188, 8)
```



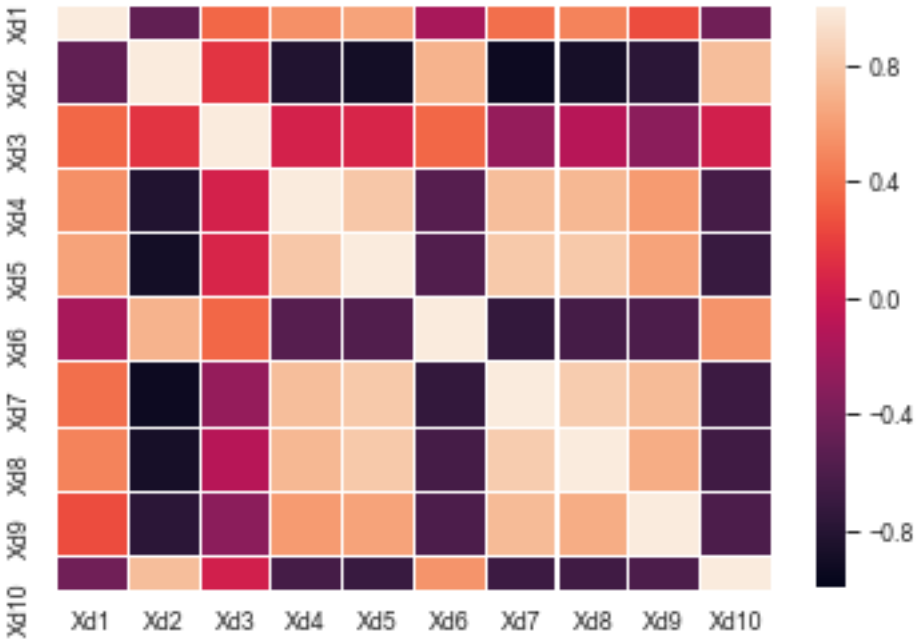
[83]:
```
fig, ax = plt.subplots(figsize = (10,8))
sns.violinplot(data = dataset['C'], palette = "Set3", ax = ax, linewidth = 1)
rows_columns = dataset['C'].shape
print(f'Amount of rows and columns in the dataset is: {rows_columns}')
```

```
Amount of rows and columns in the dataset is: (188, 6)
```



[84]:
```
sns.heatmap(dataset['D'].corr(), linewidth = .1, vmax = 1, vmin = -1)
rows_columns = dataset['D'].shape
print(f'Amount of rows and columns in the dataset is: {rows_columns}')
```

```
Amount of rows and columns in the dataset is: (188, 11)
```


Xd1
Xd2
Xd3
Xd4
Xd5
Xd6
Xd7
Xd8
Xd9
Xd10
0.8
0.4
0.0
−0.4
−0.8