Assignment 5

Details

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Problem Statement

Perform the following operations using Python on the Air quality and Heart Diseases data sets

1. Data cleaning
2. Data integration
3. Data transformation
4. Error correcting
5. Data model building

Implementation details

1. Dataset URL : https://archive.ics.uci.edu/ml/datasets/Heart+Disease (https://archive.ics.uci.edu/ml/datasets/Heart+Disease)
2. Python version : 3.7.4
3. Imports :
   A. pandas
   B. numpy
   C. matplotlib.pyolot
   D. seaborn
   E. sklearn.linear_model.LogisticRegression

Dataset details

1. This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to this date.
2. The "goal" field refers to the presence of heart disease in the patient.
3. It is integer valued from 0 (no presence) to 4. Experiments with the Cleveland database have concentrated on simply attempting to distinguish presence (values 1,2,3,4) from absence (value 0).
4. The names and social security numbers of the patients were recently removed from the database, replaced with dummy values.

Importing required libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Loading the dataset

In [2]:

```
dataset = pd.read_csv("./preprocessed_data.csv", index_col=0)
```

Displaying metadata for dataset (Statistical)

In [3]:

```
dataset.shape
```

Out[3]:

```
(682, 14)
```

In [4]:

```
dataset.isnull().sum()
```

Out[4]:

```
age           0
sex           0
chest_pain    0
trestbps      0
cholestrol    0
fbs           0
restecg       0
thalach       0
exang         0
oldpeak       0
slope         0
ca            0
thal          0
num           0
dtype: int64
```

In [5]:

```
dataset.head(15)
```

Out[5]:

	age	sex	chest_pain	trestbps	cholestrol	fbs	restecg	thalach	exang	oldpeak
0	0.714286	1	1	0.541667	0.386401	1.0	2.0	0.633803	0.0	0.890909
1	0.795918	1	4	0.666667	0.474295	0.0	2.0	0.338028	1.0	0.745455
2	0.795918	1	4	0.333333	0.379768	0.0	2.0	0.485915	1.0	0.945455
4	0.265306	0	2	0.416667	0.338308	0.0	2.0	0.788732	0.0	0.727273
5	0.571429	1	2	0.333333	0.391376	0.0	0.0	0.830986	0.0	0.618182
7	0.591837	0	4	0.333333	0.587065	0.0	0.0	0.725352	1.0	0.581818
8	0.714286	1	4	0.416667	0.421227	0.0	2.0	0.612676	0.0	0.727273
10	0.591837	1	4	0.500000	0.318408	0.0	0.0	0.619718	0.0	0.545455
11	0.571429	0	2	0.500000	0.487562	0.0	2.0	0.654930	0.0	0.709091
12	0.571429	1	3	0.416667	0.424544	1.0	2.0	0.577465	1.0	0.581818
13	0.326531	1	2	0.333333	0.436153	0.0	0.0	0.795775	0.0	0.472727
14	0.489796	1	3	0.766667	0.330017	1.0	0.0	0.718310	0.0	0.563636
15	0.591837	1	3	0.583333	0.278607	0.0	0.0	0.802817	0.0	0.763636
16	0.408163	1	2	0.250000	0.379768	0.0	0.0	0.760563	0.0	0.654545
17	0.530612	1	4	0.500000	0.396352	0.0	0.0	0.704225	0.0	0.690909

Observations :

1. There are 682 data points with 14 columns (including target column)
2. Null values are removed / replaced and dataset is scaled for numerical variables

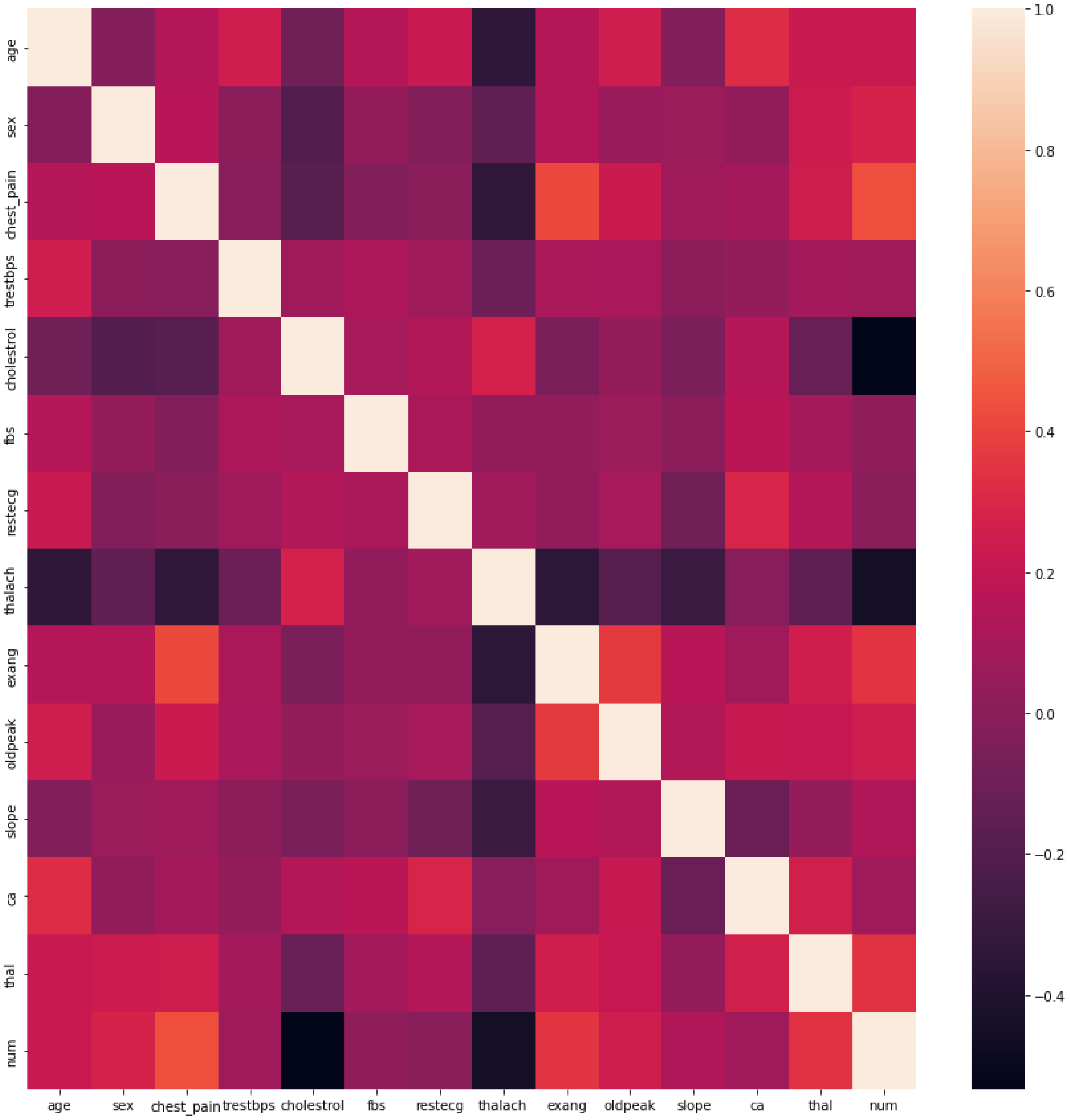
A) Feature selection

In [6]:

```
# Displaying heatmap for correlation matrix
fig = plt.figure(figsize=(15, 15))

# Adds subplot on position 1
ax = fig.add_subplot(111)

sns.heatmap(dataset.corr())
plt.show()
```



In [7]:

```
dataset.corr()
```

Out[7]:

	age	sex	chest_pain	trestbps	cholestrol	fbs	restecg	thal
age	1.000000	-0.023624	0.145740	0.247017	-0.089696	0.154740	0.223164	-0.340
sex	-0.023624	1.000000	0.163370	0.003323	-0.199176	0.037774	-0.036257	-0.148
chest_pain	0.145740	0.163370	1.000000	-0.009134	-0.182046	-0.026207	-0.002091	-0.334
trestbps	0.247017	0.003323	-0.009134	1.000000	0.066543	0.120023	0.074495	-0.111
cholestrol	-0.089696	-0.199176	-0.182046	0.066543	1.000000	0.097576	0.143226	0.272
fbs	0.154740	0.037774	-0.026207	0.120023	0.097576	1.000000	0.113193	0.027
restecg	0.223164	-0.036257	-0.002091	0.074495	0.143226	0.113193	1.000000	0.082
thalach	-0.340013	-0.148256	-0.334507	-0.111419	0.272218	0.027782	0.082551	1.000
exang	0.146912	0.147096	0.415408	0.118941	-0.054860	0.036641	0.024909	-0.351
oldpeak	0.246984	0.056113	0.229230	0.106618	0.039519	0.062684	0.098591	-0.186
slope	-0.024984	0.063177	0.074927	0.000372	-0.058404	0.001531	-0.104784	-0.295
ca	0.321673	0.025315	0.093902	0.037259	0.148186	0.173009	0.289584	-0.006
thal	0.222136	0.233270	0.239361	0.084489	-0.125926	0.084525	0.147006	-0.152
num	0.225453	0.279127	0.434501	0.067330	-0.533687	0.019112	-0.000813	-0.450

Note :

1. The above heatmap and the correlation table suggests that all of the data features are significantly correlated with the target variables
2. The following features are negatively correlated with the target variable :
   A. cholestrol
   B. thalach

Further action :

1. No feature drop is necessary due to significant correlation with target variable
2. The target variable is considered to be "num" (last column of the dataset)

B) Building the data model

1) Understanding the target variable

In [8]:

```
# checking the unique values (categories in the dataset)
dataset.num.unique()
```

Out[8]:

```
array([0, 1, 3, 2, 4])
```

Note :

1. The values beyond 0 are indicative of the fact that there is presence of heart disease

Further action :

1. Binarize the target variable for the classes as presence or absence of heart disease

2) Binarizing the target variable

In [9]:

```
dataset["num"] = dataset["num"].replace([2, 3, 4], 1)
```

In [10]:

```
dataset.num.unique()
```

Out[10]:

```
array([0, 1])
```

3) Checking distribution of target variable

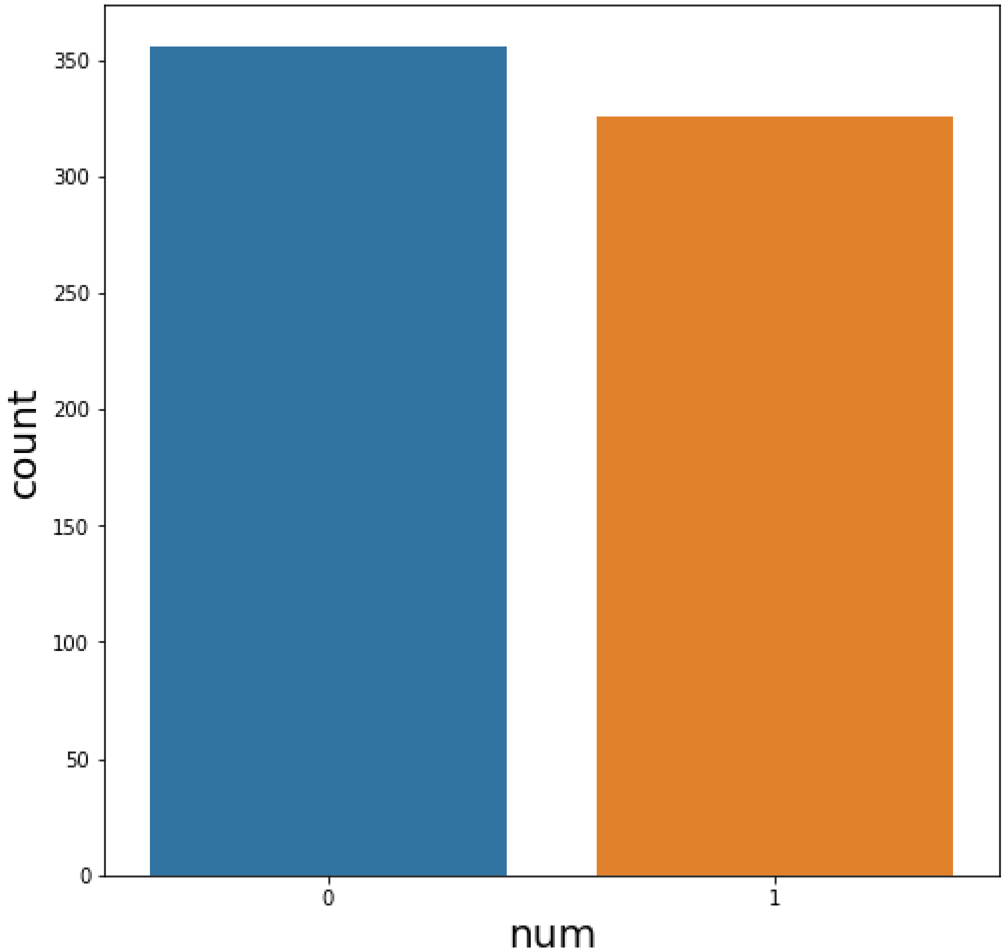
In [11]:

```
# Plotting the count plot for target variable
fig = plt.figure(figsize=(8, 8))

# Adds subplot on position 1
ax = fig.add_subplot(111)

plt.xlabel("num", fontsize=20)
plt.ylabel("count", fontsize=20)

sns.countplot(x=dataset.num)
plt.show()
```



In [12]:

```
# creating subsets for target variables for fair distribution in training and testi
dataset_target_0 = dataset[dataset.num == 0]
dataset_target_1 = dataset[dataset.num == 1]
print("Shape of target 1 data : ", dataset_target_1.shape)
print("Shape of target 0 data : ", dataset_target_0.shape)
```

```
Shape of target 1 data :  (326, 14)
Shape of target 0 data :  (356, 14)
```

In [13]:

```
# Shuffling the data subsets
dataset_target_1 = dataset_target_1.sample(frac=1)
dataset_target_0 = dataset_target_0.sample(frac=1)

# Confirming shapes for no value loss
print("Shape of target 1 data : ", dataset_target_1.shape)
print("Shape of target 0 data : ", dataset_target_0.shape)
```

```
Shape of target 1 data :  (326, 14)
Shape of target 0 data :  (356, 14)
```

4) Creating training and testing data with 80:20 ratio

In [14]:

```
# Calculating 80 percent mark
target_0_mark = int(dataset_target_0.shape[0]*0.8)
target_1_mark = int(dataset_target_1.shape[0]*0.8)

# Generating train data
train_data = pd.concat(
    objs=[
        dataset_target_0.iloc[:target_0_mark, :],
        dataset_target_1.iloc[:target_1_mark, :]
    ],
    axis=0
)

# Generating test data
test_data = pd.concat(
    objs=[
        dataset_target_0.iloc[target_0_mark:, :],
        dataset_target_1.iloc[target_1_mark:, :]
    ],
    axis=0
)

# Shuffling the training and testing data
train_data = train_data.sample(frac=1)
test_data = test_data.sample(frac=1)

# Checking data shapes
print("Training data shape : ", train_data.shape)
print("Testing data shape  : ", test_data.shape)
```

```
Training data shape :  (544, 14)
Testing data shape  :  (138, 14)
```

5) Splitting training and testing inputs and targets

In [15]:

```
# Splitting training data
train_inputs = train_data.iloc[:, :-1]
train_targets = train_data.iloc[:, -1]

# Splitting testing data
test_inputs = test_data.iloc[:, :-1]
test_targets = test_data.iloc[:, -1]

# Checking shape of data
print("Train inputs shape : ", train_inputs.shape)
print("Train targets shape : ", train_targets.shape)
print("Test inputs shape : ", test_inputs.shape)
print("Test targets shape : ", test_targets.shape)
```

```
Train inputs shape :  (544, 13)
Train targets shape :  (544,)
Test inputs shape :  (138, 13)
Test targets shape :  (138,)
```

6) Building the data model

In [16]:

```
# Importing model
from sklearn.linear_model import LogisticRegression
```

In [17]:

```
logReg_model = LogisticRegression()
```

In [18]:

```
# Training the model
logReg_model.fit(train_inputs, train_targets)
print("Model trained")
```

```
Model trained
```

7) Checking accuracy of model on testing data

In [19]:

```
logReg_model.score(test_inputs, test_targets)
```

Out[19]:

```
0.8985507246376812
```

In [20]:

```
logReg_model.score(train_inputs, train_targets)
```

Out[20]:

```
0.8253676470588235
```

Conclusion

1. The logistic regression model was fit on the given dataset
2. The model gave 89.85% accuracy on testing data and 82.53% accuracy on testing data

End of Notebook