hw2_regression_classification_webscraping_v2-1

March 1, 2018

1 Data-X Spring 2018: Homework 02

1.0.1 Regression, Classification, Webscraping

Authors: Sana Iqbal (Part 1, 2, 3), Alexander Fred-Ojala (Extra Credit)

In this homework, you will do some exercises with prediction-classification, regression and web-scraping.

1.1 Part 1

1.1.1 Data:

Data Source: Data file is uploaded to bCourses and is named: **Energy.csv**

The dataset was created by Angeliki Xifara (Civil/Structural Engineer) and was processed by Athanasios Tsanas, Oxford Centre for Industrial and Applied Mathematics, University of Oxford, UK).

Data Description:

The dataset contains eight attributes of a building (or features, denoted by X1...X8) and response being the heating load on the building, y1.

- X1 Relative Compactness
- X2 Surface Area
- X3 Wall Area
- X4 Roof Area
- X5 Overall Height
- X6 Orientation
- X7 Glazing Area
- X8 Glazing Area Distribution
- y1 Heating Load

Q1:Read the data file in python. Describe data features in terms of type, distribution range and mean values. Plot feature distributions.This step should give you clues about data sufficiency.

```
In [181]: # No warnings
          import warnings
          warnings.filterwarnings('ignore') # Filter out warnings

          # data analysis and wrangling
```

```
import pandas as pd
import numpy as np
import random as rnd
import math
# visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# machine learning
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB # Gaussian Naive Bays
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier #stochastic gradient descent
from sklearn.tree import DecisionTreeClassifier

# play styling
sns.set(style='white', context='notebook', palette='deep')
plt.rcParams[ 'figure.figsize' ] = 9 , 5
```

In [182]:
```
energy_df = pd.read_csv('Energy.csv')
```

In [183]:
```
energy_df.describe()
```

Out[183]:

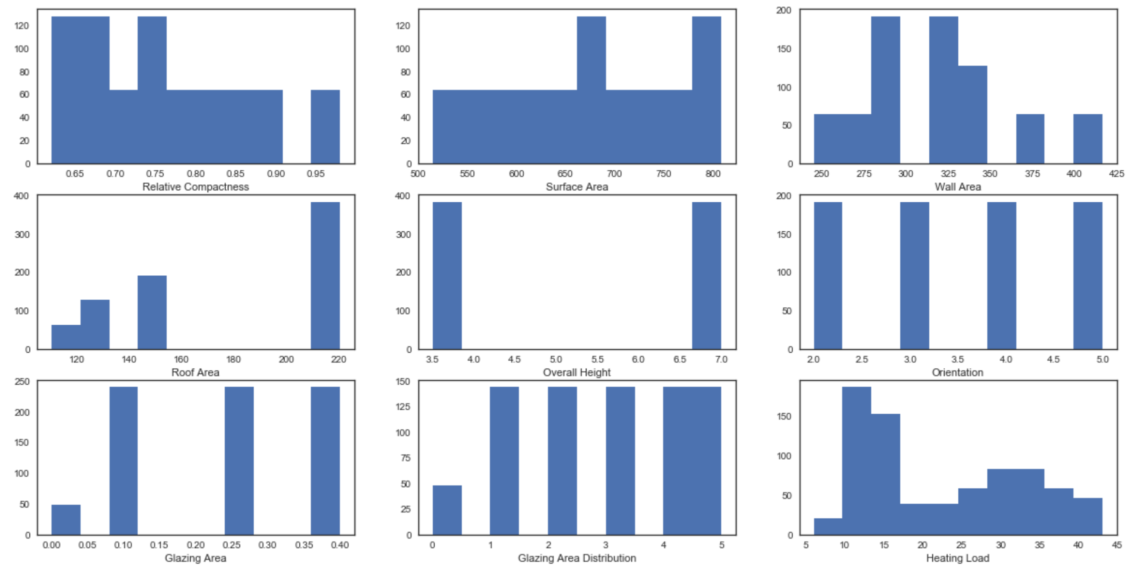
	X1	X2	X3	X4	X5	X6 \
count	768.000000	768.000000	768.000000	768.000000	768.00000	768.000000
mean	0.764167	671.708333	318.500000	176.604167	5.25000	3.500000
std	0.105777	88.086116	43.626481	45.165950	1.75114	1.118763
min	0.620000	514.500000	245.000000	110.250000	3.50000	2.000000
25%	0.682500	606.375000	294.000000	140.875000	3.50000	2.750000
50%	0.750000	673.750000	318.500000	183.750000	5.25000	3.500000
75%	0.830000	741.125000	343.000000	220.500000	7.00000	4.250000
max	0.980000	808.500000	416.500000	220.500000	7.00000	5.000000

	X7	X8	Y1
count	768.000000	768.00000	768.000000
mean	0.234375	2.81250	22.307201
std	0.133221	1.55096	10.090196
min	0.000000	0.00000	6.010000
25%	0.100000	1.75000	12.992500
50%	0.250000	3.00000	18.950000
75%	0.400000	4.00000	31.667500
max	0.400000	5.00000	43.100000

In [184]:
```
f, ax = plt.subplots(3,3,figsize = (20,10))
```

```
ax1 = plt.subplot(3,3,1)
ax1.hist(energy_df["X1"])
ax1.set_xlabel("Relative Compactness")

ax2 = plt.subplot(3,3,2)
ax2.hist(energy_df["X2"])
ax2.set_xlabel("Surface Area")

ax3 = plt.subplot(3,3,3)
ax3.hist(energy_df["X3"])
ax3.set_xlabel("Wall Area")

ax4 = plt.subplot(3,3,4)
ax4.hist(energy_df["X4"])
ax4.set_xlabel("Roof Area")

ax5 = plt.subplot(3,3,5)
ax5.hist(energy_df["X5"])
ax5.set_xlabel("Overall Height")

ax6 = plt.subplot(3,3,6)
ax6.hist(energy_df["X6"])
ax6.set_xlabel("Orientation")

ax7 = plt.subplot(3,3,7)
ax7.hist(energy_df["X7"])
ax7.set_xlabel("Glazing Area")

ax8 = plt.subplot(3,3,8)
ax8.hist(energy_df["X8"])
ax8.set_xlabel("Glazing Area Distribution")

ax9 = plt.subplot(3,3,9)
ax9.hist(energy_df["Y1"])
ax9.set_xlabel("Heating Load")
```

```
Out[184]: Text(0.5,0,'Heating Load')
```



REGRESSION: LABELS ARE CONTINUOUS VALUES. Here the model is trained to predict a continuous value for each instance. On inputting a feature vector into the model, the trained model is able to predict a continuous value for that instance.

Q2.1: Train a linear regression model on 85 percent of the given dataset, what is the intercept value and coefficient values.

In [185]:
```
# check the number of NaN value in the dataframe
energy_df.isnull().sum()
```

Out[185]:
```
X1    0
X2    0
X3    0
X4    0
X5    0
X6    0
X7    0
X8    0
Y1    0
dtype: int64
```

In [186]:
```
EX = energy_df.drop("Y1", axis = 1)
EY = energy_df["Y1"]
```

In [187]:
```
from sklearn.model_selection import train_test_split
ex_train, ex_test, ey_train, ey_test = train_test_split(EX, EY, test_size = 0.15, ra
print ('Number of samples in training data:',len(ex_train))
print ('Number of samples in validation data:',len(ex_test))
```

```
Number of samples in training data: 652
Number of samples in validation data: 116
```

```
In [262]: from sklearn import linear_model

          ene_lireg = linear_model.LinearRegression()

          print("Training a Linear Regression Model..")
          ene_lireg.fit(ex_train,ey_train)

          # print the intercept and the coefficients

          coeff_list = ["Relative Compactness", "Surface Area", "Wall Area", "Roof Area", "Ove
                        "Glazing Area", "Glazing Area Distribution"]
          print("Intercept:", ene_lireg.intercept_)
          print()
          print("Coeffiecients for X1 to X8:")
          for i,coeff in enumerate(ene_lireg.coef_):
              print(coeff_list[i], ": ", coeff)
```

```
Training a Linear Regression Model..
Intercept: 75.0961109706

Coeffiecients for X1 to X8:
Relative Compactness :  -60.5426731955
Surface Area :  248898603421.0
Wall Area :  -248898603421.0
Roof Area :  -497797206842.0
Overall Height :  4.33485674858
Orientation :  0.0185587629676
Glazing Area :  20.0668307384
Glazing Area Distribution :  0.235076511279
```

Q.2.2: Report model performance using 'ROOT MEAN SQUARE' error metric on: 1. Data that was used for training(Training error)
2. On the 15 percent of unseen data (test error)

```
In [263]: # training error
          Tr_pred = ene_lireg.predict(ex_train)
          print("Tranning error (Root Mean Square): ", np.sqrt(np.mean((Tr_pred-ey_train)**2)))

          Te_pred = ene_lireg.predict(ex_test)
          print("Test error (Root Mean Square): ", np.sqrt(np.mean((Te_pred-ey_test)**2)))
```

```
Tranning error (Root Mean Square):  2.92794825404
Test error (Root Mean Square):  2.87513191559
```

__ Q2.3: Lets us see the effect of amount of data on the performance of prediction model.Use varying amounts of Training data (100,200,300,400,500,all) to train regression models and report training error and validation error in each case. Validation data/Test data is the same as above for all these cases.__

Plot error rates vs number of training examples.Comment on the relationshipyou observe in the plot, between the amount of data used to train the model and the validation accuracy of the model.

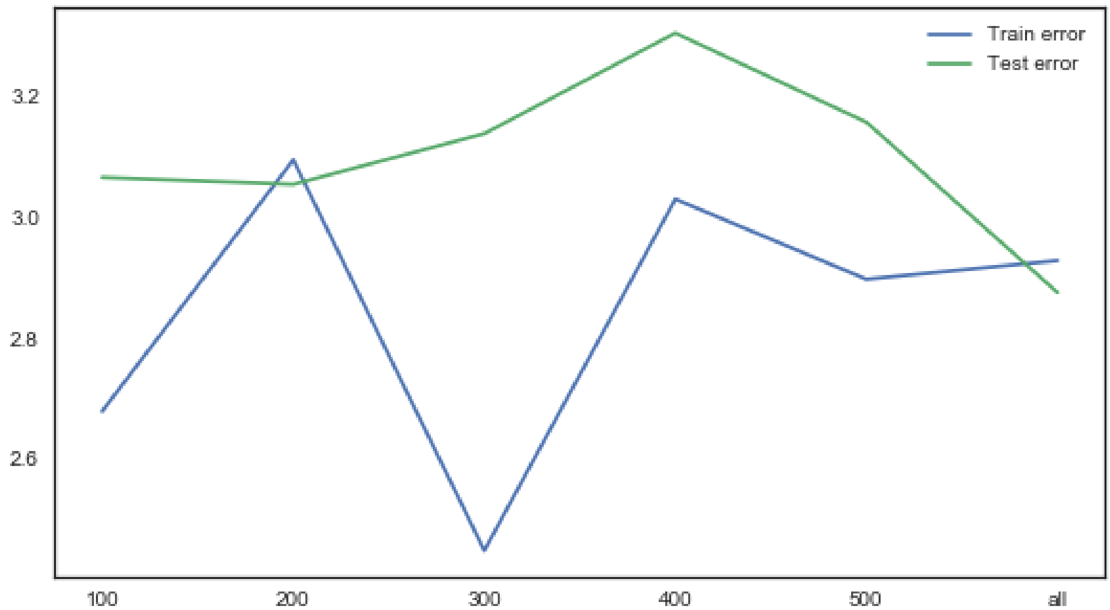
Hint: Use array indexing to choose varying data amounts

In [264]:
```
# There are some requirements when choosing the data? like the 200 data are
# based on the first 100 and add 100 more random data?
len_train = 652
Tr_err = []
Te_err = []
# used to  store the train data 100, 200 ...
X_train_store = []
Y_train_store = []
ex_train, ex_test, ey_train, ey_test = train_test_split(EX, EY, test_size = 0.15, ran

Ex_train = ex_train.copy()
Ey_train = ey_train.copy()
# print(type(Ex_train), type(Ey_train))
for i in np.arange(1,7,1):
    if i < 6:
        x_train, x_test, y_train, y_test = train_test_split(Ex_train, Ey_train, test_
#    concatenate the train data
        if len(X_train_store) > 0:
            X_train_store.append(x_train)
            Y_train_store.append(y_train)
            x_train = pd.concat(x_train)
            y_train = pd.concat(y_train)
    else:
        x_train, x_test, y_train, y_test = train_test_split(EX, EY,test_size = 0.15,

    ene_lireg.fit(x_train,y_train)
    tr_pred = ene_lireg.predict(x_train)
    te_pred = ene_lireg.predict(x_test)
#     append each Training error and testing error
    Tr_err.append(np.sqrt(np.mean((tr_pred-y_train)**2)))
    Te_err.append(np.sqrt(np.mean((te_pred-y_test)**2)))

#   store the train data
#     X_train_store.append(x_train)
#     Y_train_store.append(y_train)
#     update the train data,
#     print(list(Ex_train.index))
    if i < 6:
        Ex_train.drop(index = x_train.index, inplace = True)
#     print(type(Ex_train), type(Ey_train))
        Ey_train.drop(index = y_train.index, inplace = True)
```

```
# ex_train, ex_test, ey_train, ey_test = train_test_split(EX, EY, test_size = 0.15, 
```

In [265]:
```
f = plt.plot(figsize=(10,8))
plt.plot(np.arange(1,7,1),Tr_err, label = "Train error")
plt.plot(np.arange(1,7,1), Te_err, label = "Test error")

# labels = [item.get_text() for item in f.get_xticklabels()]
labels = [100,200,300,400,500,"all"]
plt.xticks(np.arange(1,7,1),labels)
plt.legend()
```

Out[265]: <matplotlib.legend.Legend at 0x2b3beeb1e48>



The relation between the size of training data and the train error is not clear, since the train error fluctuates with size.

But the test error increased first then dropped rapidly after the number of 400. It means the more training data was used to calibrate, the more accurate model could be obtained, as long as the number of test data is fixed.

CLASSIFICATION: LABELS ARE DISCRETE VALUES. Here the model is trained to classify each instance into a set of predefined discrete classes. On inputting a feature vector into the model, the trained model is able to predict a class of that instance. You can also output the probabilities of an instance belnging to a class.

__ Q 3.1: Bucket values of 'y1' i.e 'Heating Load' from the original dataset into 3 classes:__

0: 'Low' (< 15),
1: 'Medium' (15-30),
2: 'High' (>30)

This converts the given dataset into a classification problem, classes being, Heating load is: *low, medium or high*. Use this datset with transformed 'heating load' for creating a logistic regression classifiction model that predicts heating load type of a building. Use test-train split ratio of 0.15.

Report training and test accuracies and confusion matrices.

HINT: Use pandas.cut

```
In [266]: bins = [-math.inf, 15, 30, math.inf]
          labels = [0, 1, 2]
          energy_df["label"] = pd.cut(energy_df["Y1"], bins, labels = labels)
```

```
In [267]: X2 = energy_df.drop(["Y1","label"], axis = 1)
          Y2 = energy_df["label"]
```

```
In [268]: x_train, x_test, y_train, y_test = train_test_split(X2, Y2, test_size=0.15, random_s
          print ('Number of samples in training data:',len(x_train))
          print ('Number of samples in validation data:',len(x_test))
```

```
Number of samples in training data: 652
Number of samples in validation data: 116
```

```
In [272]: ene_logreg = linear_model.LogisticRegression(C=1e5)


          print("Training a logistic Regression Model...")
          ene_logreg.fit(x_train, y_train)
```

```
Training a logistic Regression Model...
```

```
Out[272]: LogisticRegression(C=100000.0, class_weight=None, dual=False,
                    fit_intercept=True, intercept_scaling=1, max_iter=100,
                    multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
                    solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

```
In [273]: # how to define the accuracy?
          training_accuracy = ene_logreg.score(x_train, y_train)
          print("Training Accuracy:", training_accuracy)

          validation_accuracy = ene_logreg.score(x_test,y_test)
          print("Validation Accuracy:", validation_accuracy)
```

```
Training Accuracy: 0.829754601227
Validation Accuracy: 0.827586206897
```

```
In [274]: # confusion matrix
          from sklearn.metrics import confusion_matrix
          y_true = y_test
```

```
y_pred = ene_logreg.predict(x_test)
cf = pd.DataFrame(confusion_matrix(y_true, y_pred), columns=['Pred 0',1,2],
                  index=['Act 0',1,2])
print ('Confusion matrix of test data is:')
display(cf)
```

```
Confusion matrix of test data is:
```

	Pred 0	1	2
Act 0	38	2	0
1	9	35	6
2	0	3	23

__ Q3.2: One of the preprocessing steps in Data science is Feature Scaling i.e getting all our data on the same scale by setting same Min-Max of feature values. This makes training less sensitive to the scale of features . Scaling is important in algorithms that use distance based classification, SVM or K means or involve gradient descent optimization.If we Scale features in the range [0,1] it is called unity based normalization.__

Perform unity based normalization on the above dataset and train the model again, compare model performance in training and validation with your previous model.

refer:http://scikit-learn.org/stable/modules/preprocessing.html#preprocessing-scaler
more at: https://en.wikipedia.org/wiki/Feature_scaling

```
In [275]: # when you scale the train data, you need to perform the same scaling to the
          # test data
          from sklearn import preprocessing

          X2 = energy_df.drop(["Y1","label"], axis = 1)
          Y2 = energy_df["label"]
          x_train, x_test, y_train, y_test = train_test_split(X2, Y2, test_size=0.15, random_s

          # seperate the train data and test data first?
          min_max_scaler = preprocessing.MinMaxScaler()
          print("Transforming the train data and the test data")
          X_train_minmax = min_max_scaler.fit_transform(x_train)
          X_test_minmax = min_max_scaler.transform(x_test)
```

```
Transforming the train data and the test data
```

```
In [276]: ene_logreg2 = linear_model.LogisticRegression(C=1e5)


          print("Training a logistic Regression Model...")
          ene_logreg2.fit(X_train_minmax, y_train)
```

```
Training a logistic Regression Model...
```

```
Out[276]: LogisticRegression(C=100000.0, class_weight=None, dual=False,
                    fit_intercept=True, intercept_scaling=1, max_iter=100,
                    multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
                    solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

```
In [277]: training_accuracy = ene_logreg2.score(X_train_minmax, y_train)
          print("Training Accuracy:", training_accuracy)

          validation_accuracy = ene_logreg2.score(X_test_minmax, y_test)
          print("Validation Accuracy:", validation_accuracy)
```

```
Training Accuracy: 0.820552147239
Validation Accuracy: 0.827586206897
```

```
In [278]: # confusion matrix

          y_true = y_test
          y_pred = ene_logreg2.predict(X_test_minmax)
          cf2 = pd.DataFrame(confusion_matrix(y_true, y_pred), columns=['Pred 0',1,2],
                             index=['Act 0',1,2])
          print ('Confusion matrix of test data is:')
          display(cf2)
```

```
Confusion matrix of test data is:
```

	Pred 0	1	2
Act 0	35	5	0
1	6	39	5
2	0	4	22

After the min max scale, the accuracy is nearly the same with before, slightly worse.

And from the confusion matrix we can see the model after scaling did better in predicting the 0(low heating load), but worse in predicting the other 2.

1.2 Part 2

__ 1. Read **diabetesdata.csv** file into a pandas dataframe. Analyze the data features, check for NaN values. About the data: __

1. **TimesPregnant**: Number of times pregnant
2. **glucoseLevel**: Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3. **BP**: Diastolic blood pressure (mm Hg)

4. **insulin**: 2-Hour serum insulin (mu U/ml)
5. **BMI**: Body mass index (weight in kg/(height in m)^2)
6. **pedigree**: Diabetes pedigree function

7. **Age**: Age (years)
8. **IsDiabetic**: 0 if not diabetic or 1 if diabetic)

__ 2. Preprocess data to replace NaN values in a feature(if any) using mean of the feature. Train logistic regression, SVM, perceptron, kNN, xgboost and random forest models using this preprocessed data with 20% test split.Report training and test accuracies.__

In [279]:
```
diabetes_df = pd.read_csv("diabetesdata.csv")
diabetes_df.head()
```

Out[279]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
0	6	148.0	72	0	33.6	0.627	50.0	1
1	1	NaN	66	0	26.6	0.351	31.0	0
2	8	183.0	64	0	23.3	0.672	NaN	1
3	1	NaN	66	94	28.1	0.167	21.0	0
4	0	137.0	40	168	43.1	2.288	33.0	1

In [280]:
```
diabetes_df.isnull().sum()
```

Out[280]:
```
TimesPregnant     0
glucoseLevel     34
BP                0
insulin           0
BMI               0
Pedigree          0
Age              33
IsDiabetic        0
dtype: int64
```

In [281]:
```
diabetes_df["glucoseLevel"].fillna(diabetes_df["glucoseLevel"].dropna().mean(),inplac
diabetes_df["Age"].fillna(diabetes_df["Age"].dropna().mean(),inplace = True)
diabetes_df.head()
```

Out[281]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	\
0	6	148.000000	72	0	33.6	0.627	50.000000	
1	1	121.016349	66	0	26.6	0.351	31.000000	
2	8	183.000000	64	0	23.3	0.672	33.353741	
3	1	121.016349	66	94	28.1	0.167	21.000000	
4	0	137.000000	40	168	43.1	2.288	33.000000	

	IsDiabetic
0	1
1	0
2	1
3	0
4	1

In [282]:
```
X3 = diabetes_df.drop("IsDiabetic", axis = 1)
Y3 = diabetes_df["IsDiabetic"]
x_train, x_test, y_train, y_test = train_test_split(X3, Y3, test_size=0.2, random_sta
```

In [206]:
```
# logistic regression
logreg = LogisticRegression()
logreg.fit(x_train, y_train)
y_pred = logreg.predict(x_test)
acc_tr_log = round(logreg.score(x_train, y_train)*100,2)
acc_te_log = round(logreg.score(x_test, y_test)*100, 2)
print("Train Accuracy:", acc_tr_log)
print("Test Accuracy:", acc_te_log)
```

```
Train Accuracy: 78.34
Test Accuracy: 73.38
```

In [207]:
```
# support vector machines
# how to score the support vector machines
svc = SVC()
svc.fit(x_train, y_train)
y_pred = svc.predict(x_test)
acc_tr_svc = round(svc.score(x_train, y_train)*100, 2)
acc_te_svc = round(svc.score(x_test, y_test)*100, 2)
print("Train Accuracy:", acc_tr_svc)
print("Test Accuracy:", acc_te_svc)
```

```
Train Accuracy: 100.0
Test Accuracy: 65.58
```

In [208]:
```
# Perceptron

perceptron = Perceptron()
perceptron.fit(x_train, y_train)
y_pred = perceptron.predict(x_test)

acc_tr_per = round(perceptron.score(x_train, y_train)*100, 2)
acc_te_per = round(perceptron.score(x_test, y_test)*100, 2)
print("Train Accuracy:", acc_tr_per)
print("Test Accuracy:", acc_te_per)
```

```
Train Accuracy: 64.17
Test Accuracy: 64.29
```

In [209]:
```
#  kNN
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(x_train, y_train)
y_pred = knn.predict(x_test)

acc_tr_knn = round(knn.score(x_train, y_train)*100, 2)
acc_te_knn = round(knn.score(x_test, y_test)*100, 2)
```

```
print("Train Accuracy:", acc_tr_knn)
print("Test Accuracy:", acc_te_knn)
```

```
Train Accuracy: 85.34
Test Accuracy: 67.53
```

```
In [283]: # XGBoost
          import xgboost as xgb
          gradboost = xgb.XGBClassifier(n_estimators=1000)
          gradboost.fit(x_train, y_train)
          y_pred = gradboost.predict(x_test)

          acc_tr_xgb = round(gradboost.score(x_train, y_train)*100, 2)
          acc_te_xgb = round(gradboost.score(x_test, y_test)*100, 2)
          print("Train Accuracy:", acc_tr_xgb)
          print("Test Accuracy:", acc_te_xgb)
```

```
---------------------------------------------------------------------------

ModuleNotFoundError                       Traceback (most recent call last)

<ipython-input-283-0f350e6c8bfe> in <module>()
  1 # XGBoost
----> 2 import xgboost as xgb
  3 gradboost = xgb.XGBClassifier(n_estimators=1000)
  4 gradboost.fit(x_train, y_train)
  5 y_pred = gradboost.predict(x_test)


ModuleNotFoundError: No module named 'xgboost'
```

```
In [284]: # Random Forest
          random_forest = RandomForestClassifier(n_estimators=1000)
          random_forest.fit(x_train, y_train)
          y_pred = random_forest.predict(x_test)

          acc_tr_rnd = round(random_forest.score(x_train, y_train) * 100, 2)
          acc_te_rnd = round(random_forest.score(x_test, y_test) * 100, 2)
          print("Train Accuracy:", acc_tr_rnd)
          print("Test Accuracy:", acc_te_rnd)
```

```
Train Accuracy: 100.0
Test Accuracy: 72.08
```

3. What is the ratio of diabetic persons in 3 equirange bands of 'BMI' and 'Pedigree' in the provided dataset.

Convert these features - 'BP','insulin','BMI' and 'Pedigree' into categorical values by mapping different bands of values of these features to integers 0,1,2.

HINT: USE pd.cut with bin=3 to create 3 bins

```
In [285]: diabetes_df["BPBand"] = pd.cut(diabetes_df["BP"], 3, labels = [0, 1, 2])
          diabetes_df["BMIBand"] = pd.cut(diabetes_df["BMI"], 3, labels = [0, 1, 2])
          diabetes_df["PedigreeBand"] = pd.cut(diabetes_df["Pedigree"], 3, labels = [0, 1, 2])
```

```
In [286]: display(diabetes_df[["BPBand","IsDiabetic"]].groupby(["BPBand"], as_index = False).me
          display(diabetes_df[["BMIBand", "IsDiabetic"]].groupby(["BMIBand"], as_index = False
          display(diabetes_df[["PedigreeBand", "IsDiabetic"]].groupby(["PedigreeBand"], as_inde
```

```
  BPBand  IsDiabetic
0      0    0.450000
1      1    0.307282
2      2    0.466667


  BMIBand  IsDiabetic
0       0    0.039216
1       1    0.358297
2       2    0.611111


  PedigreeBand  IsDiabetic
0            0    0.327007
1            1    0.540541
2            2    0.444444
```

People with normal blood pressure tends to have less risk of getting diabetes. People who are obese are more likely to get diabetes. It seems there is no direct relation between diabetes between pedigree.

4. Now consider the original dataset again, instead of generalizing the NAN values with the mean of the feature we will try assigning values to NANs based on some hypothesis. For example for age we assume that the relation between BMI and BP of people is a reflection of the age group.We can have 9 types of BMI and BP relations and our aim is to find the median age of each of that group:

Your Age guess matrix will look like this:

BP \ BMI	0	1	2
0	a00	a01	a02
1	a10	a11	a12
2	a20	a21	a22

Create a guess_matrix for NaN values of *'Age'* (using 'BMI' and 'BP') and *'glucoseLevel'* (using 'BP' and 'Pedigree') for the given dataset and assign values accordingly to the NaNs in

'Age' or *'glucoseLevel'* .
Refer to how we guessed age in the titanic notebook in the class.

In [214]:
```
diabetes_df2 = pd.read_csv("diabetesdata.csv")


diabetes_df2["BPBand"] = pd.cut(diabetes_df["BP"], 3, labels = [0, 1, 2])
diabetes_df2["BMIBand"] = pd.cut(diabetes_df["BMI"], 3, labels = [0, 1, 2])
diabetes_df2["PedigreeBand"] = pd.cut(diabetes_df["Pedigree"], 3, labels = [0, 1, 2]

X4 = diabetes_df2.drop("IsDiabetic", axis = 1)
Y4 = diabetes_df2["IsDiabetic"]

x_train, x_test, y_train, y_test = train_test_split(X4, Y4, test_size=0.2, random_sta
combine = [x_train, x_test]
x_train.shape, x_test.shape
```

Out[214]:
```
((614, 10), (154, 10))
```

In [215]:
```
guess_ages = np.zeros((3,3), dtype = int)
guess_glucoseLevel = np.zeros((3,3), dtype = float)
```

In [287]:
```
#  store the new dataframe after filling the NaN value
combine2 = []
for idx, dataset in enumerate(combine.copy()):
    if idx == 0:
        print("Working on Training Data set\n")
    else:
        print("-"*35)
        print("Working on Test Data set\n")

    print("Guess values of age and glucoseLevel based on BMI and BP...")
    for i in range(0,3):
        for j in range(0,3):
            guess_df1 = dataset[(dataset["BMIBand"] == i)&(dataset["BPBand"] == j)]['
            guess_df2 = dataset[(dataset["BPBand"] == i)&(dataset["PedigreeBand"] ==

#           get the median age and glucoseLevel of the group
#           in case no return in the guess dataframe
            if not len(guess_df1) == 0:
                age_guess  = guess_df1.median()
            else:
                age_guess = 0

            if not len(guess_df2) == 0:
                glu_guess = guess_df2.median()
            else:
                glu_guess = 0
```

```
                guess_ages[i,j] = int(age_guess)
                guess_glucoseLevel[i,j] = glu_guess

        print('Guess_Age table:\n',guess_ages)
        print('Guess_glucoseLevel table:\n',guess_glucoseLevel)
        print ('\nAssigning age values to NAN age values in the dataset...')

        for i in range(0,3):
            for j in range(0,3):
                Series1 = dataset.loc[(dataset.Age.isnull()) & (dataset.BMIBand == i) &
                          ]["Age"]
                if not len(Series1) == None:
#                   you need to put the "age" inside, or what you replace is not in th
                    dataset.loc[(dataset.Age.isnull()) & (dataset.BMIBand == i) & (datas
                          ,"Age"] = guess_ages[i,j]

                Series2 = dataset.loc[(dataset.glucoseLevel.isnull()) & (dataset.BPBand =
                          ]["glucoseLevel"]
                if not len(Series2) == None:
                    dataset.loc[(dataset.glucoseLevel.isnull()) & (dataset.BPBand == i) &
                          ,"glucoseLevel"] = guess_glucoseLevel[i,j]

#       dataset["Age"] = dataset["Age"].astype(int)
        print()
    print("Done")
```

```
Working on Training Data set

Guess values of age and glucoseLevel based on BMI and BP...
Guess_Age table:
 [[24 25 55]
 [29 29 37]
 [40 32 31]]
Guess_glucoseLevel table:
 [[ 114.5  127.5  137. ]
 [ 112.   118.   149. ]
 [ 136.   125.5  159.5]]

Assigning age values to NAN age values in the dataset...

-----------------------------------
Working on Test Data set

Guess values of age and glucoseLevel based on BMI and BP...
Guess_Age table:
 [[25 24  0]
 [37 26 37]
```

```
 [26 27 23]]
Guess_glucoseLevel table:
 [[ 115.     0.     0. ]
 [ 112.   111.     0. ]
 [ 126.   145.5    0. ]]

Assigning age values to NAN age values in the dataset...

Done
```

5. Now, convert 'glucoseLevel' and 'Age' features also to categorical variables of 5 categories each.

Use this dataset (with all features in categorical form) to train perceptron, logistic regression and random forest models using 20% test split. Report training and test accuracies.

In [288]:
```
# change the glucoseLevel and age to categorical variables
for dataset in combine:
    dataset["AgeBand"] = pd.cut(dataset["Age"], 5, labels = [0,1,2,3,4])
    dataset["GluBand"] = pd.cut(dataset["glucoseLevel"], 5, labels = [0,1,2,3,4])

x_train_re = combine[0].drop(["glucoseLevel", "BP", "BMI", "Pedigree", "Age"], axis =
x_test_re = combine[1].drop(["glucoseLevel", "BP", "BMI", "Pedigree", "Age"], axis =
```

In [240]:
```
# percetron
perceptron2 = Perceptron()
perceptron2.fit(x_train_re, y_train)
y_pred = perceptron2.predict(x_test_re)

acc_tr_per2 = round(perceptron.score(x_train_re, y_train)*100, 2)
acc_te_per2 = round(perceptron.score(x_test_re, y_test)*100, 2)
print("Train Accuracy:", acc_tr_per2)
print("Test Accuracy:", acc_te_per2)
```

```
Train Accuracy: 37.95
Test Accuracy: 42.21
```

In [241]:
```
# logistic regression
logreg2 = LogisticRegression()
logreg2.fit(x_train_re, y_train)
y_pred = logreg.predict(x_test_re)

acc_tr_log2 = round(logreg.score(x_train_re, y_train)*100,2)
acc_te_log2 = round(logreg.score(x_test_re, y_test)*100, 2)
print("Train Accuracy:", acc_tr_log2)
print("Test Accuracy:", acc_te_log2)
```

```
Train Accuracy: 68.08
Test Accuracy: 65.58
```