Problem Statement

The purpose is to predict whether the Pima Indian women shows signs of diabetes or not. We are using a da "National Institute of Diabetes and Digestive and Kidney Diseases" which consists of a number of attributes us to perform this prediction.

Constraints on data collection

All patients whose data has been collected are females at least 21 years old of Pima Indian heritage

```
#Import all the necessary modules
import numpy as np
import sklearn
from sklearn.tree import DecisionTreeClassifier
import pandas as pd
#import pylab as plb
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, ca
```

Q1. Load the PIMA Indian Diabetes file into Python Da

The file can be accessed directly from the URL (https://archive.ics.uci.edu/ml/machine-learning-databases/ diabetes/pima-indians-diabetes.data or you may first download it to a local folder and then load it into Pytho us assume the data frame is named pima_df

```
file = '/content/drive/My Drive/PGML/supervisedlearning/Residency-III-lab/pima-indians
df = pd.read_csv(file)
df.head()
```

	Preg	Plas	Pres	skin	test	mass	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

It is always a good practice to eye-ball raw data to get a feel of the data in terms of number of structure of th attributes, types of attributes and a general idea of likely challenges in the dataset. You would notice that it i

separated file. There are no column names!. Check the associated folders and find out about each attribute
information is available about the data.

Q2. Print 10 samples from the dataset

```
df.head(10)
```

	Preg	Plas	Pres	skin	test	mass	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
5	5	116	74	0	0	25.6	0.201	30	0
6	3	78	50	32	88	31.0	0.248	26	1
7	10	115	0	0	0	35.3	0.134	29	0
8	2	197	70	45	543	30.5	0.158	53	1
9	8	125	96	0	0	0.0	0.232	54	1

Q3 Print the datatypes of each column and the shape dataset

```
df.dtypes
```

```
Preg        int64
Plas        int64
Pres        int64
skin        int64
test        int64
mass      float64
pedi      float64
age         int64
class       int64
dtype: object
```

```
df.shape
```

```
(768, 9)
```

There are '0's in the data. Are they really valid '0's or they are missing values? Plasma, BP, skin thickness etc. cannot be 0. look at column by column logically to understand this.

Q4 Replace all the 0s in the column with the median c same column value accordingly.

```
# column not required for replace wirth 0 are class,preg,plas,pres,skin
collist = ['test','mass','pedi','age']
for i in collist:
    df[i] = df[i].replace(0,df[i].median(skipna=True))
df.head()
```

	Preg	Plas	Pres	skin	test	mass	pedi	age	class
0	6	148	72	35	30.5	33.6	0.627	50	1
1	1	85	66	29	30.5	26.6	0.351	31	0
2	8	183	64	0	30.5	23.3	0.672	32	1
3	1	89	66	23	94.0	28.1	0.167	21	0
4	0	137	40	35	168.0	43.1	2.288	33	1

Q5 Print the descriptive statistics of each & every col using describe() function

```
df.describe()
```

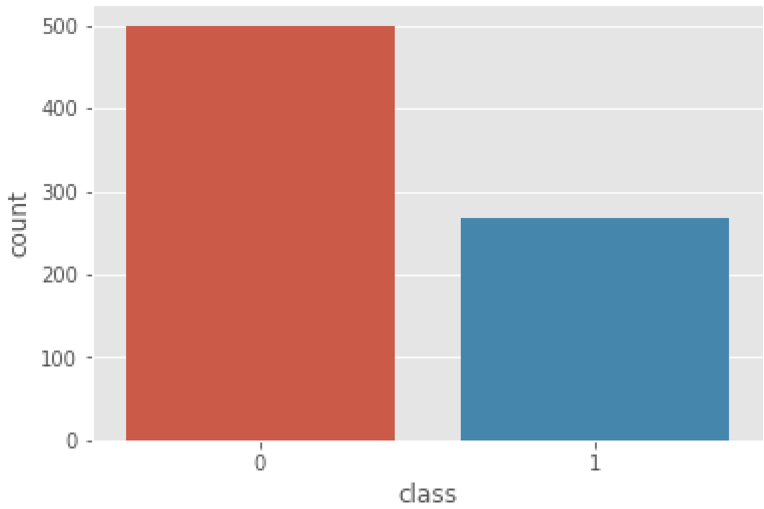
	Preg	Plas	Pres	skin	test	mass	
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.00
mean	3.845052	120.894531	69.105469	20.536458	94.652344	32.450911	0.47
std	3.369578	31.972618	19.355807	15.952218	105.547598	6.875366	0.33
min	0.000000	0.000000	0.000000	0.000000	14.000000	18.200000	0.07
25%	1.000000	99.000000	62.000000	0.000000	30.500000	27.500000	0.24
50%	3.000000	117.000000	72.000000	23.000000	31.250000	32.000000	0.37
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.62
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.42

Q6 See the distribution of 'Class' variable and plot it u appropriate graph.

```
import seaborn as sns
```

```
sns.countplot(x='class',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa26551d2b0>
```



Just for your understanding - Using univariate analys the individual attributes for their basic statistic such a values, spread, tails etc. What are your observations (attributes). Its an optional step and will not be graded

```
df.corr()
```

	Preg	Plas	Pres	skin	test	mass	pedi	a
Preg	1.000000	0.129459	0.141282	-0.081672	-0.055697	0.021546	-0.033523	0.544
Plas	0.129459	1.000000	0.152590	0.057328	0.355252	0.218806	0.137337	0.263
Pres	0.141282	0.152590	1.000000	0.207371	0.085221	0.184220	0.041265	0.239
skin	-0.081672	0.057328	0.207371	1.000000	0.397161	0.381740	0.183928	-0.113
test	-0.055697	0.355252	0.085221	0.397161	1.000000	0.189022	0.178029	-0.015
mass	0.021546	0.218806	0.184220	0.381740	0.189022	1.000000	0.153506	0.025
pedi	-0.033523	0.137337	0.041265	0.183928	0.178029	0.153506	1.000000	0.033
age	0.544341	0.263514	0.239528	-0.113970	-0.015413	0.025744	0.033561	1.000
class	0.221898	0.466581	0.065068	0.074752	0.148457	0.312249	0.173844	0.238

Please find my findings.

- Plas is highly correlated to class(target feature) as given data.
- age is less correlated and pres and skin is poorly correlated again to class(target feature)
- Plas is normally distributed.

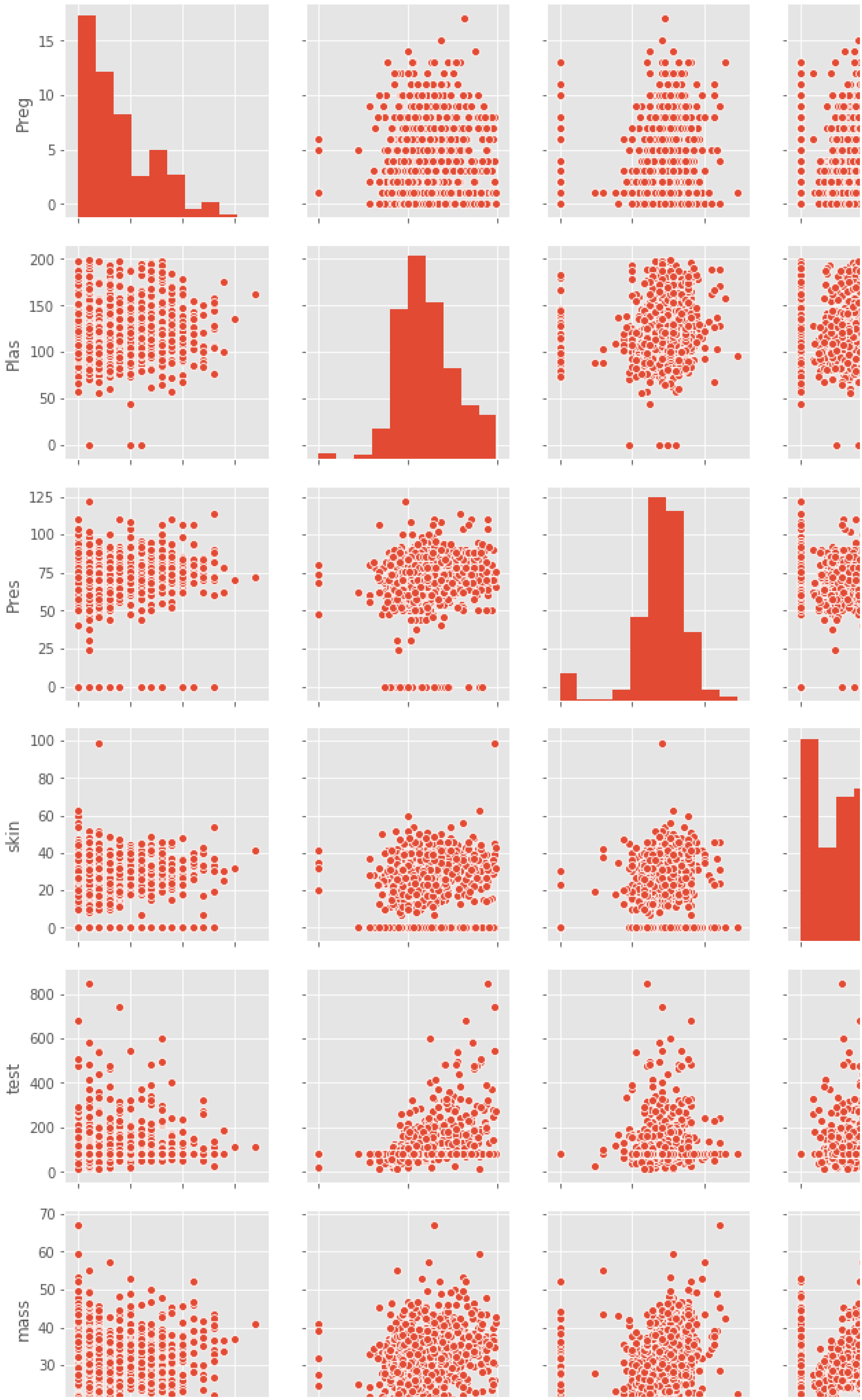
Q7. Use pairplots and correlation method to observe t relationship between different variables and state you insights.

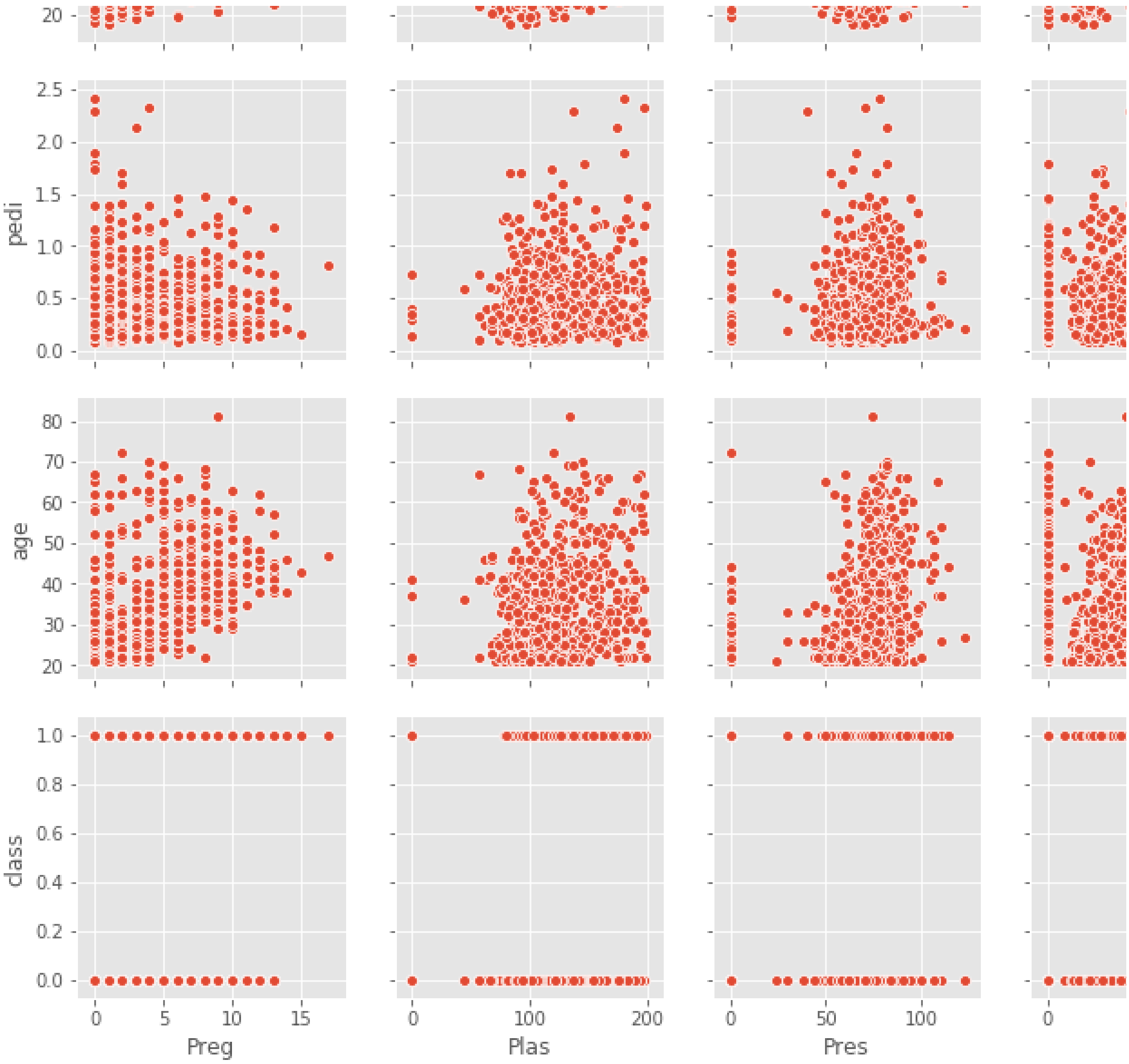
Hint: Use seaborn plot and check the relationship between different variables

Using the plot - infer the relationship between different variables

```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7fa268dcef98>
```





Q8 Split the pima_df into training and test set in the ra 70:30 (Training:Test).

```
# Store the inputs as a Pandas Dataframe and set the column names
x = df.drop(['class'], axis=1)

y = df[['class']]

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=
```

Q9 Create the decision tree model using “entropy” me reducing the entropy and fit it to training data.

```
clf_entropy = DecisionTreeClassifier(
            criterion = "entropy", random_state = 100,
```

```
              max_depth = 3, min_samples_leaf = 5)

# Performing training
clf entropy.fit(X_train, y_train)
y pred entropy=clf_entropy.predict(X_test)
y_pred_entropy
```

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

Q10 Print the accuracy of the model & print the confu matrix

```
y_pred_entropy
```

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

```
accuracy = accuracy_score(y_test, y_pred_entropy)

print(accuracy)

confusion matrix = confusion_matrix(y_test, y_pred_entropy)
print(confusion_matrix)
```

```
0.7662337662337663
[[123  23]
 [ 31  54]]
```

Print the feature importance of the decision model - Optional