Homework

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 [83]:
```
# 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

# 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

import xgboost as xgb

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

In [84]:
```
# Special distribution plot (will be used later)
def plot_distribution( df , var , target , **kwargs ):
    row = kwargs.get( 'row' , None )
    col = kwargs.get( 'col' , None )
    facet = sns.FacetGrid( df , hue=target , aspect=4 , row = row , col = col )
    facet.map( sns.kdeplot , var , shade= True )
    facet.set( xlim=( 0 , df[ var ].max() ) )
    facet.add_legend()
    plt.tight_layout()
```

In [85]:
```
data = pd.read_csv('diabetesdata.csv')

print(data.describe())
```

```
       TimesPregnant  glucoseLevel          BP     insulin         BMI  \
count     768.000000    734.000000  768.000000  768.000000  768.000000
mean        3.845052    121.016349   69.105469   79.799479   31.992578
std         3.369578     31.660240   19.355807  115.244002    7.884160
min         0.000000      0.000000    0.000000    0.000000    0.000000
25%         1.000000     99.000000   62.000000    0.000000   27.300000
50%         3.000000    117.000000   72.000000   30.500000   32.000000
75%         6.000000    141.000000   80.000000  127.250000   36.600000
max        17.000000    199.000000  122.000000  846.000000   67.100000

         Pedigree         Age  IsDiabetic
count  768.000000  735.000000  768.000000
mean     0.471876   33.353741    0.348958
std      0.331329   11.772944    0.476951
min      0.078000   21.000000    0.000000
25%      0.243750   24.000000    0.000000
50%      0.372500   29.000000    0.000000
75%      0.626250   41.000000    1.000000
max      2.420000   81.000000    1.000000
```

In [86]:
```
print(data.isnull().sum())

data.fillna(data.mean(),inplace=True)

print(data.isnull().sum())

print(data.info())
```

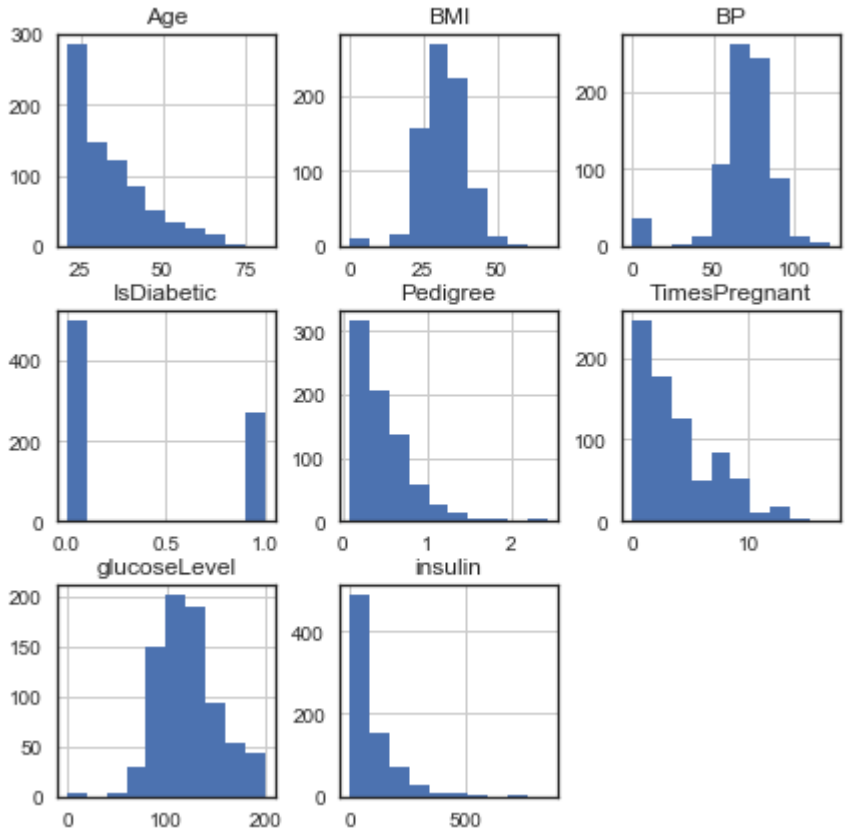
```
TimesPregnant     0
glucoseLevel     34
BP                0
insulin           0
BMI               0
Pedigree          0
Age              33
IsDiabetic        0
dtype: int64
TimesPregnant    0
glucoseLevel     0
BP               0
insulin          0
BMI              0
Pedigree         0
Age              0
IsDiabetic       0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 8 columns):
TimesPregnant    768 non-null int64
glucoseLevel     768 non-null float64
BP               768 non-null int64
insulin          768 non-null int64
BMI              768 non-null float64
Pedigree         768 non-null float64
Age              768 non-null float64
IsDiabetic       768 non-null int64
dtypes: float64(4), int64(4)
memory usage: 48.1 KB
None
```

In [87]:
```
from sklearn.utils import shuffle
data = shuffle(data).reset_index(drop=True)
```

In [88]:
```
from sklearn.model_selection import train_test_split

X_data = data.iloc[:,:-1]
Y_data = data['IsDiabetic']

print("Feature vector shape=", X_data.shape)
print("Class shape=", Y_data.shape)
```

```
Feature vector shape= (768, 7)
Class shape= (768,)
```

In [89]:
```
data.hist(figsize=(7,7))
plt.show()
```



In [90]:
```
x_train, x_test, y_train, y_test = train_test_split(X_data, Y_data, test_size = 0
```

In [91]:
```
# Logistic Regression

logreg = LogisticRegression()
logreg.fit(x_train, y_train)
y_pred_log = logreg.predict(x_test)

acc_log_train = round(logreg.score(x_train, y_train) * 100, 2)
print("Train accuracy: ",acc_log_train)

acc_log_test = round(logreg.score(x_test,y_test) * 100, 2)
print("Test accuracy: ",acc_log_test)
```

```
Train accuracy:  78.01
Test accuracy:  75.97
```

In [92]:
```
# Support Vector Machines

svc = SVC()
svc.fit(x_train, y_train)
y_pred_svm = svc.predict(x_test)

acc_svc_train = round(svc.score(x_train, y_train) * 100, 2)
print("Train accuracy: ",acc_svc_train)

acc_svc_test = round(svc.score(x_test,y_test) * 100, 2)
print("Test accuracy: ",acc_svc_test)
```

```
Train accuracy:  100.0
Test accuracy:  62.99
```

In [93]:
```
#K Nearest Neighbors

knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(x_train, y_train)
y_pred_knn = knn.predict(x_test)

acc_knn_train = round(knn.score(x_train, y_train) * 100, 2)
print("Train accuracy: ",acc_knn_train)

acc_knn_test = round(knn.score(x_test,y_test) * 100, 2)
print("Test accuracy: ",acc_knn_test)
```

```
Train accuracy:  84.04
Test accuracy:  70.78
```

In [94]:
```
# Perceptron

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

acc_perceptron_train = round(perceptron.score(x_train, y_train) * 100, 2)
print("Train accuracy: ",acc_perceptron_train)

acc_perceptron_test = round(perceptron.score(x_test,y_test) * 100, 2)
print("Test accuracy: ",acc_perceptron_test)
```

```
Train accuracy:  54.56
Test accuracy:  50.0
```

```
C:\Anaconda\envs\Data-X\lib\site-packages\sklearn\linear_model\stochastic_gradi
ent.py:84: FutureWarning: max_iter and tol parameters have been added in <class
'sklearn.linear_model.perceptron.Perceptron'> in 0.19. If both are left unset,
 they default to max_iter=5 and tol=None. If tol is not None, max_iter defaults
to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol wil
l be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

In [95]:
```
# XGBoost

gradboost = xgb.XGBClassifier(n_estimators=1000)
gradboost.fit(x_train, y_train)
y_pred_xgb = gradboost.predict(x_test)

acc_gradboost_train = round(gradboost.score(x_train, y_train) * 100, 2)
print("Train accuracy: ",acc_gradboost_train)

acc_gradboost_test = round(gradboost.score(x_test,y_test) * 100, 2)
print("Test accuracy: ",acc_gradboost_test)
```

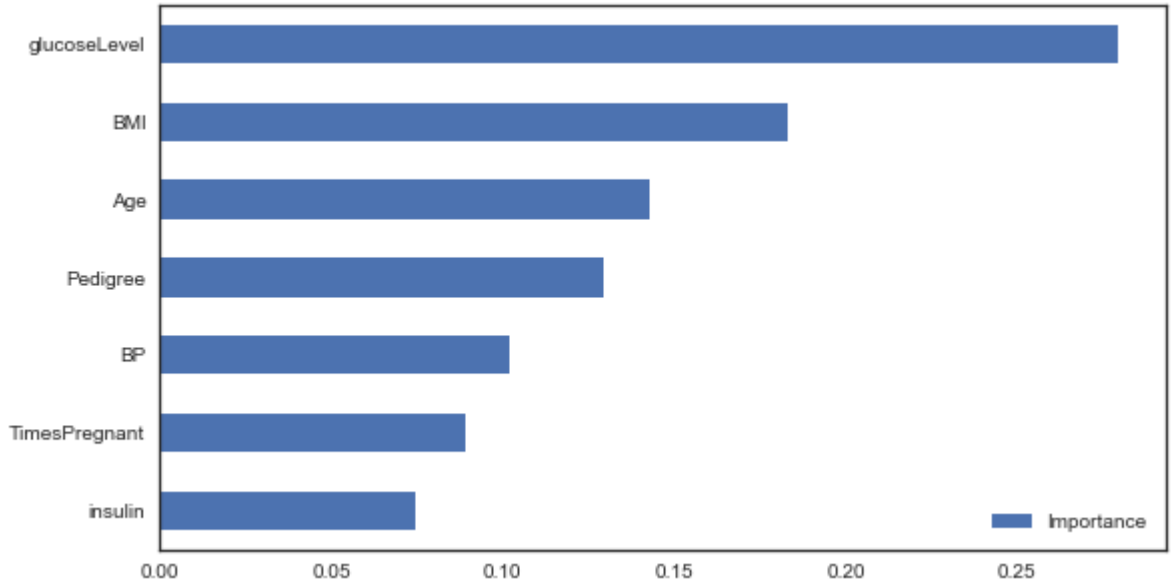
```
Train accuracy:  100.0
Test accuracy:  70.13
```

In [96]:
```
# Random Forest

random_forest = RandomForestClassifier(n_estimators=1000)
random_forest.fit(x_train, y_train)
y_pred_rnf = random_forest.predict(x_test)
random_forest.score(x_train, y_train)

acc_random_forest_train = round(random_forest.score(x_train, y_train) * 100, 2)
print("Train accuracy: ",acc_random_forest_train)

acc_random_forest_test = round(random_forest.score(x_test,y_test) * 100, 2)
print("Test accuracy: ",acc_random_forest_test)
```

```
Exception ignored in: <bound method DMatrix.__del__ of <xgboost.core.DMatrix ob
ject at 0x00000265F57D5A20>>
Traceback (most recent call last):
  File "C:\Anaconda\envs\Data-X\lib\site-packages\xgboost\core.py", line 324, i
n __del__
    _check_call(_LIB.XGDMatrixFree(self.handle))
AttributeError: 'DMatrix' object has no attribute 'handle'

Train accuracy:  100.0
Test accuracy:  75.97
```

In [97]:
```
# Look at importnace of features for random forest

def plot_model_var_imp( model , X , y ):
    imp = pd.DataFrame(
        model.feature_importances_  ,
        columns = [ 'Importance' ] ,
        index = X.columns
    )
    imp = imp.sort_values( [ 'Importance' ] , ascending = True )
    imp[ : 10 ].plot( kind = 'barh' )
    print (model.score( X , y ))

plot_model_var_imp(random_forest, x_train, y_train)
```

```
1.0
```



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 [98]:
```
data['BMI_Groups'] = pd.cut(data['BMI'], 3)
data['Pedigree_Groups'] = pd.cut(data['Pedigree'], 3)

data.head()
```

Out[98]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic	BMI_Groups	Pedigr
0	4	173.0	70	168	29.7	0.361	33.0	1	(22.367, 44.733]	(0.0
1	11	120.0	80	150	42.3	0.785	48.0	1	(22.367, 44.733]	(0.0
2	1	143.0	86	330	30.1	0.892	23.0	0	(22.367, 44.733]	(0.
3	5	132.0	80	0	26.8	0.186	69.0	0	(22.367, 44.733]	(0.0
4	8	99.0	84	0	35.4	0.388	50.0	0	(22.367, 44.733]	(0.0

In [99]:
```
data_cat = data.copy()

data_cat['BP']=pd.cut(data['BP'],[-np.inf,(data_cat['BP'].max())*1/3,(data_cat['B
           labels=[0,1,2])

data_cat['insulin']=pd.cut(data['insulin'],[-np.inf,(data_cat['insulin'].max())*1
           labels=[0,1,2])

data_cat['BMI']=pd.cut(data['BMI'],[-np.inf,(data_cat['BMI'].max())*1/3,(data_cat
           labels=[0,1,2])

data_cat['Pedigree']=pd.cut(data['Pedigree'],[-np.inf,(data_cat['Pedigree'].max()
           labels=[0,1,2])
```

In [100]:
```
# BMI ratio by equirange band

low_band = (data_cat["BMI"] == 0).sum()
mid_band = (data_cat["BMI"] == 1).sum()
high_band = (data_cat["BMI"] == 2).sum()

print("Ratio of diabetic persons in 3 equirange bands for BMI:", str(low_band)+":
```

```
Ratio of diabetic persons in 3 equirange bands for BMI: 51:681:36
```

In [101]:
```
# Pedigree ratio by equirange band
low_band_p = (data_cat["Pedigree"] == 0).sum()
mid_band_p = (data_cat["Pedigree"] == 1).sum()
high_band_p = (data_cat["Pedigree"] == 2).sum()

print("Ratio of diabetic persons in 3 equirange bands for Pedigree:", str(low_ban
```

```
Ratio of diabetic persons in 3 equirange bands for Pedigree: 667:92:9
```

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:

BMI	0	1	2
BP			
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 [103]:
```
data = pd.read_csv('diabetesdata.csv')

guess_ages = np.zeros((3,3),dtype=int) #initialize
guess_ages
```

Out[103]:
```
array([[0, 0, 0],
       [0, 0, 0],
       [0, 0, 0]])
```

In [104]:
```
bins = 3
labels = [0, 1, 2]

data['BP'] = pd.cut(data['BP'], bins, labels = labels)
data['BMI'] = pd.cut(data['BMI'], bins, labels = labels)
data['Pedigree'] = pd.cut(data['Pedigree'], bins, labels = labels)
```

In [105]:
```
# Fill the NA's for the Age columns
# with "qualified guesses"
combine = [data]

for idx,dataset in enumerate(combine):
    if idx == 0:
        print("Working on data...\n")

    print('Guess values of age based on BP and BMI...')
    for i in range(0, 3):
        for j in range(0,3):

            guess_df = dataset[(dataset.BMI == i) & (dataset.BP == j)]['Age'].dro

            age_guess = guess_df.median()

            guess_ages[i,j] = int(age_guess)


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

    for i in range(0, 3):
        for j in range(0, 3):
            #dataset.loc[ (dataset.Age.isnull()) & (dataset.BMI == i) & (dataset.
             #       'Age'] = guess_ages[i,j]

            dataset.loc[ (dataset.Age.isnull()) & (dataset.BMI == i) & (dataset.B
    dataset['Age'] = dataset['Age'].astype(int)


    dataset['Age'] = dataset['Age'].astype(int)
    print()
print('Done!')
data.head()
```

```
Working on data...

Guess values of age based on BP and BMI...
Guess_Age table:
 [[24 25 55]
 [29 29 37]
 [33 32 31]]

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

Done!
```

Out[105]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
0	6	148.0	1	0	1	0	50	1
1	1	NaN	1	0	1	0	31	0
2	8	183.0	1	0	1	0	29	1
3	1	NaN	1	94	1	0	21	0

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
4	0	137.0	0	168	1	2	33	1

In [106]:
```
# Guessing glucoseLevel using Pedigree and BP

guess_glucose = np.zeros((3,3), dtype = int)
guess_glucose
```

Out[106]:
```
array([[0, 0, 0],
       [0, 0, 0],
       [0, 0, 0]])
```

In [107]:
```
# Fill the NA's for the glucoseLevel columns with "qualified guesses"

combine = [data]

for idx, dataset in enumerate(combine):
    if idx == 0:
        print("Working on data...\n")

    print('Guess values of glucoseLevel based on BP and Pedigree...')
    for i in range (0,3):
        for j in range (0,3):

            guess_df = dataset[(dataset.Pedigree == i) & (dataset.BP == j)]["gluc
            glucose_guess = guess_df.median()
            guess_glucose[i,j] = int(glucose_guess)

    print('Guess_Age table:\n', guess_glucose)
    print ('\nAssigning glucoseLevel values to NAN glucoseLevel values in the dat

    for i in range (0,3):
        for j in range (0,3):
            dataset.loc[ (dataset.glucoseLevel.isnull()) & (dataset.Pedigree == i
    dataset['glucoseLevel'] = dataset['glucoseLevel'].astype(int)

print("Done!")
data.head()
```

```
Working on data...

Guess values of glucoseLevel based on BP and Pedigree...
Guess_Age table:
 [[115 112 133]
 [127 115 129]
 [137 149 159]]

Assigning glucoseLevel values to NAN glucoseLevel values in the dataset...
Done!
```

Out[107]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
0	6	148	1	0	1	0	50	1
1	1	112	1	0	1	0	31	0
2	8	183	1	0	1	0	29	1
3	1	112	1	94	1	0	21	0
4	0	137	0	168	1	2	33	1

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 [108]:
```
data_cats = data.copy()
data_cats.head()
```

Out[108]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
0	6	148	1	0	1	0	50	1
1	1	112	1	0	1	0	31	0
2	8	183	1	0	1	0	29	1
3	1	112	1	94	1	0	21	0
4	0	137	0	168	1	2	33	1

In [109]:
```
bins = 5
labels = [0, 1, 2, 3, 4]

data_cats['glucoseLevel'] = pd.cut(data_cats['glucoseLevel'], bins, labels = labe
data_cats['Age'] = pd.cut(data_cats['Age'], bins, labels = labels)
```

In [110]:
```
bins = 3
labels = [0, 1, 2]

data_cats['insulin'] = pd.cut(data_cats['insulin'], bins, labels = labels)
```

In [111]:
```
data_cats.head()
```

Out[111]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
0	6	3	1	0	1	0	2	1
1	1	2	1	0	1	0	0	0
2	8	4	1	0	1	0	0	1
3	1	2	1	0	1	0	0	0
4	0	3	0	0	1	2	0	1

In [112]:
```
data_cats = shuffle(data_cats).reset_index(drop = True)
data_cats.head()
```

Out[112]:

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
0	0	3	1	0	1	0	0	0
1	0	3	2	0	1	0	1	0
2	2	3	0	0	1	0	0	1
3	0	2	1	0	1	0	0	0
4	2	3	2	0	1	0	0	0
5	5	3	2	0	0	0	2	0
6	10	2	1	0	1	0	2	0
7	13	3	2	0	1	0	1	1
8	8	2	1	0	1	0	0	0
9	10	4	1	0	1	0	2	1
10	6	2	1	0	1	0	0	0
11	0	2	1	0	1	0	0	1
12	8	2	1	0	1	0	3	0
13	0	4	1	0	2	1	3	0
14	3	3	1	0	0	0	2	0
15	8	2	1	0	1	0	0	1
16	11	3	1	0	1	1	2	1
17	4	3	0	0	1	0	0	1
18	4	3	1	0	1	0	1	0
19	8	3	1	0	1	0	1	1
20	14	2	1	0	1	0	2	1
21	4	3	1	0	1	0	0	0
22	0	2	0	0	0	0	0	0
23	3	3	1	1	1	0	0	0
24	8	2	1	0	1	0	2	0
25	0	3	2	0	1	0	0	0
26	1	2	1	2	1	0	3	1
27	6	2	1	0	1	0	0	0
28	13	2	1	0	1	0	1	1
29	3	2	1	0	1	0	0	0
...	...	...	...	...	...	...	...	...
738	9	3	2	0	1	0	2	1
739	7	3	2	0	1	0	2	0

	TimesPregnant	glucoseLevel	BP	insulin	BMI	Pedigree	Age	IsDiabetic
740	0	2	2	0	1	0	2	0
741	1	2	1	0	1	0	0	0
742	2	1	1	0	1	0	0	0
743	9	4	1	0	1	0	1	1
744	6	2	1	0	1	0	0	0
745	1	2	1	0	1	0	0	0
746	5	3	2	1	1	0	1	0
747	3	2	2	0	1	0	0	0
748	2	2	1	0	1	0	0	0
749	9	4	2	0	1	1	2	1
750	1	2	1	0	1	1	0	0
751	4	3	2	0	1	0	0	0
752	1	3	1	0	1	0	1	1
753	1	2	1	0	1	0	0	0
754	0	2	1	0	1	0	0	0
755	2	3	1	0	1	0	0	0
756	6	2	1	0	1	0	1	0
757	11	3	2	0	1	0	2	0
758	3	2	1	0	0	0	0	0
759	0	2	2	0	1	0	0	1
760	1	3	1	0	1	0	0	0
761	3	4	1	0	1	0	0	1
762	1	3	1	0	1	0	0	0
763	1	2	1	0	1	0	1	0
764	5	0	1	0	1	0	1	1
765	4	2	1	0	1	0	0	0
766	4	2	1	0	0	0	1	0
767	2	2	1	0	1	0	0	0

768 rows × 8 columns

In [113]:
```
X = data_cats.iloc[:,:-1]
X.head()

Y = data_cats["IsDiabetic"]
Y.head()
```

Out[113]:
```
0    0
1    0
2    1
3    0
4    0
Name: IsDiabetic, dtype: int64
```

In [114]:
```
print("Feature vector shape=", X.shape)
print("Class shape=", Y.shape)# Train-test split

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_s
print ('Number of samples in training data:', len(x_train))
print ('Number of samples in validation data:', len(x_test))
```

```
Feature vector shape= (768, 7)
Class shape= (768,)
Number of samples in training data: 614
Number of samples in validation data: 154
```

In [115]:
```
# Logistic Regression

logreg = LogisticRegression()
logreg.fit(x_train, y_train)
#y_pred = logreg.predict(x_test)

acc_log_train = round(logreg.score(x_train, y_train) * 100, 2)
print("Train accuracy:", acc_log_train)
acc_log_test = round(logreg.score(x_test, y_test) * 100, 2)
print("Test accuracy:", acc_log_test)
```

```
Train accuracy: 76.38
Test accuracy: 68.83
```

In [116]:
```
# Perceptron

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

acc_perceptron_train = round(perceptron.score(x_train, y_train) * 100, 2)
print("Train accuracy:", acc_perceptron_train)
acc_perceptron_test = round(perceptron.score(x_test, y_test) * 100, 2)
print("Test accuracy:", acc_perceptron_test)
```

```
Train accuracy: 53.09
Test accuracy: 53.9

C:\Anaconda\envs\Data-X\lib\site-packages\sklearn\linear_model\stochastic_gradi
ent.py:84: FutureWarning: max_iter and tol parameters have been added in <class
'sklearn.linear_model.perceptron.Perceptron'> in 0.19. If both are left unset,
 they default to max_iter=5 and tol=None. If tol is not None, max_iter defaults
to max_iter=1000. From 0.21, default max_iter will be 1000, and default tol wil
l be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

In [117]:
```
# Random Forest

random_forest = RandomForestClassifier(n_estimators = 5000)
random_forest.fit(x_train, y_train)
y_pred = random_forest.predict(x_test)

acc_random_forest_train = round(random_forest.score(x_train, y_train) * 100, 2)
print("Train accuracy:", acc_random_forest_train)
acc_random_forest_test = round(random_forest.score(x_test, y_test) * 100, 2)
print("Test accuracy:", acc_random_forest_test)
```

```
Train accuracy: 88.76
Test accuracy: 73.38
```

In [ ]:
```

```