```
In [1]:
           import numpy as np
           import pandas as pd
           import seaborn as sns
           from sklearn.linear_model import LogisticRegression
 In [2]:
           df=pd.read csv("C4 framingham - C4 framingham.csv")
                male age education currentSmoker cigsPerDay BPMeds prevalentStroke prevalentHyp diabe
 Out[2]:
             0
                       39
                                                 0
                                                                                    0
                                                                                                 0
                   1
                                 4.0
                                                           0.0
                                                                   0.0
             1
                   0
                       46
                                 2.0
                                                 0
                                                           0.0
                                                                   0.0
                                                                                    0
                                                                                                 0
             2
                                                 1
                                                          20.0
                                                                                    0
                                                                                                  0
                   1
                       48
                                 1.0
                                                                   0.0
             3
                                                 1
                                                          30.0
                                                                                    0
                                                                                                  1
                   0
                       61
                                 3.0
                                                                   0.0
             4
                   0
                       46
                                 3.0
                                                 1
                                                          23.0
                                                                   0.0
                                                                                    0
                                                                                                 0
                        ...
                                  ...
                                                 ...
                                                                    ...
             •••
                                                                                                 ...
          4233
                       50
                                                 1
                                                           1.0
                                                                   0.0
                                                                                    0
                                                                                                  1
                   1
                                 1.0
          4234
                                                 1
                                                          43.0
                                                                                    0
                                                                                                 0
                   1
                       51
                                 3.0
                                                                   0.0
          4235
                                 2.0
                                                 1
                                                          20.0
                                                                                    0
                                                                                                 0
                   0
                       48
                                                                  NaN
          4236
                   0
                       44
                                 1.0
                                                 1
                                                          15.0
                                                                   0.0
                                                                                    0
                                                                                                 0
                                                 0
                                                           0.0
                                                                   0.0
                                                                                    0
                                                                                                  0
          4237
                   0
                       52
                                 2.0
         4238 rows × 16 columns
In [10]:
           df.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 4238 entries, 0 to 4237
          Data columns (total 16 columns):
           #
               Column
                                 Non-Null Count Dtype
          - - -
                                                   int64
           0
               male
                                  4238 non-null
           1
               age
                                  4238 non-null
                                                   int64
           2
               education
                                 4133 non-null
                                                   float64
           3
               currentSmoker
                                 4238 non-null
                                                   int64
           4
                                  4209 non-null
                                                   float64
               cigsPerDay
           5
                                  4185 non-null
                                                   float64
               BPMeds
           6
               prevalentStroke
                                 4238 non-null
                                                   int64
           7
               prevalentHyp
                                  4238 non-null
                                                   int64
           8
               diabetes
                                  4238 non-null
                                                   int64
           9
               totChol
                                  4188 non-null
                                                   float64
           10 sysBP
                                  4238 non-null
                                                   float64
           11 diaBP
                                  4238 non-null
                                                   float64
                                                   float64
           12
               BMI
                                  4219 non-null
                                                   float64
           13
               heartRate
                                 4237 non-null
                                 3850 non-null
                                                   float64
           14
               glucose
           15 TenYearCHD
                                 4238 non-null
                                                   int64
```

dtypes: float64(9), int64(7)
memory usage: 529.9 KB

```
In [11]:
    df1=df.fillna(value=0)
    df1
```

Out[11]:	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabe
0	1	39	4.0	0	0.0	0.0	0	0	
1	0	46	2.0	0	0.0	0.0	0	0	
2	1	48	1.0	1	20.0	0.0	0	0	
3	0	61	3.0	1	30.0	0.0	0	1	
4	0	46	3.0	1	23.0	0.0	0	0	
•••									
4233	1	50	1.0	1	1.0	0.0	0	1	
4234	1	51	3.0	1	43.0	0.0	0	0	
4235	0	48	2.0	1	20.0	0.0	0	0	
4236	0	44	1.0	1	15.0	0.0	0	0	
4237	0	52	2.0	0	0.0	0.0	0	0	

4238 rows × 16 columns

```
In [27]:
          feature_matrix=df1.iloc[:,0:15]
          target_vector=df1.iloc[:,-1]
In [28]:
          feature_matrix.shape
Out[28]: (4238, 15)
In [29]:
          target_vector.shape
         (4238,)
Out[29]:
In [30]:
          from sklearn.preprocessing import StandardScaler
In [31]:
          fs=StandardScaler().fit_transform(feature_matrix)
In [32]:
          logr =LogisticRegression()
          logr.fit(fs,target_vector)
Out[32]: LogisticRegression()
```

```
In [35]:
          observation=[[1.4,2.3,5.0,11,12,13,14,15,3,4,5,7,6,7,13]]
In [36]:
          prediction=logr.predict(observation)
          print(prediction)
         [1]
In [37]:
          logr.classes
Out[37]: array([0, 1], dtype=int64)
In [38]:
          logr.predict_proba(observation)[0][0]
Out[38]: 0.00016936367260200758
In [39]:
          logr.predict proba(observation)[0][1]
Out[39]:
         0.999830636327398
In [40]:
          import re
          from sklearn.datasets import load digits
          import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn as sns
          from sklearn.linear model import LogisticRegression
          from sklearn.model selection import train test split
In [41]:
          digits = load_digits()
          digits
Out[41]: {'data': array([[ 0., 0., 5., ..., 0., 0., 0.],
                 [0., 0., 0., \dots, 10., 0., 0.],
                 [0., 0., 0., ..., 16., 9., 0.],
                  [0., 0., 1., \ldots, 6., 0., 0.],
                  [ 0., 0., 2., ..., 12., 0., 0.],
                  [ 0., 0., 10., ..., 12., 1., 0.]]),
          'target': array([0, 1, 2, ..., 8, 9, 8]),
          'frame': None,
          'feature_names': ['pixel_0_0',
           'pixel_0_1',
           'pixel_0_2',
           'pixel_0_3',
           'pixel_0_4',
           'pixel 0 5',
           'pixel 0 6',
           'pixel_0_7'
           'pixel_1_0',
            'pixel_1_1',
            'pixel_1_2'
            'pixel_1_3',
```

```
'pixel_1_4',
 'pixel_1_5',
 'pixel_1_6',
 'pixel_1_7',
 'pixel_2_0',
 'pixel_2_1',
 'pixel_2_2',
 'pixel_2_3',
'pixel_2_4',
 'pixel_2_5',
 'pixel_2_6',
 'pixel_2_7',
 'pixel_3_0',
 'pixel_3_1',
 'pixel_3_2',
 'pixel_3_3'
 'pixel 3 4'
 'pixel_3_5',
 'pixel_3_6',
 'pixel_3_7',
 'pixel_4_0',
 'pixel_4_1',
 'pixel_4_2',
 'pixel_4_3'
 'pixel 4 4'
 'pixel_4_5',
 'pixel_4_6',
 'pixel_4_7',
 'pixel_5_0',
 'pixel_5_1',
 'pixel_5_2'
 'pixel_5_3'
 'pixel_5_4',
 'pixel_5_5',
 'pixel_5_6',
 'pixel_5_7',
 'pixel_6_0',
 'pixel_6_1'
'pixel_6_2',
 'pixel_6_3',
 'pixel_6_4',
 'pixel_6_5',
 'pixel_6_6',
 'pixel_6_7',
 'pixel_7_0',
 'pixel_7_1'
 'pixel_7_2',
'pixel_7_3',
'pixel_7_4',
 'pixel_7_5',
 'pixel_7_6',
 'pixel_7_7'],
'target_names': array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
'images': array([[[ 0., 0., 5., ..., 1., [ 0., 0., 13., ..., 15., 5., 0.], [ 0., 3., 15., ..., 11., 8., 0.],
                                                  0., 0.],
        [ 0.,
              4., 11., ..., 12., 7., 0.],
        [ 0., 2., 14., ..., 12., 0.,
        [ 0., 0., 6., ..., 0., 0.,
                                             0.]],
        [[ 0., 0., 0., ..., 5., 0., 0.],
        [ 0., 0., 0., ..., 9., 0., 0.],
        [0., 0., 3., \ldots, 6., 0., 0.],
         . . . ,
```

```
[ 0., 0., 1., ..., 6., 0.,
       0., 1., ..., 6., 0.,
                              0.],
[ 0.,
       0., 0., ..., 10.,
                         0.,
[[ 0., 0., 0., ..., 12., 0.,
                              0.],
[ 0., 0., 3., ..., 14., 0.,
[ 0., 0., 8., ..., 16., 0.,
ſ 0.,
       9., 16., ..., 0., 0.,
                              0.],
      3., 13., ..., 11., 5., 0.],
[ 0., 0., 0., ..., 16., 9.,
[[ 0., 0., 1., ..., 1., 0.,
[ 0., 0., 13., ..., 2., 1.,
                              0.],
      0., 16., ..., 16., 5.,
[ 0.,
Γ0.,
      0., 16., ..., 15., 0.,
[0., 0., 15., \ldots, 16., 0., 0.],
[ 0.,
      0., 2., \ldots, 6., 0., 0.
[[ 0.,
      0., 2., ..., 0., 0.,
[ 0.,
       0., 14., ..., 15., 1.,
                              0.],
      4., 16., ..., 16., 7.,
[ 0.,
                              0.1,
. . . ,
[ 0.,
      0., 0., ..., 16., 2., 0.],
[ 0., 0., 4., ..., 16., 2.,
                              0.],
       0., 5., ..., 12., 0.,
[[ 0., 0., 10., ..., 1., 0.,
[ 0., 2., 16., ..., 1., 0.,
                              0.],
      0., 15., ..., 15., 0.,
[0., 4., 16., \ldots, 16., 6., 0.],
[0., 8., 16., ..., 16., 8., 0.],
[0., 1., 8., ..., 12., 1., 0.]]),
```

'DESCR': ".. _digits_dataset:\n\nOptical recognition of handwritten digits dataset\n---:Number of Instances: 1797\n :Number of Attributes: 64\n :Attribute Information: 8 x8 image of integer pixels in the range 0..16.\n :Missing Attribute Values: None\n :Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)\n :Date: July; 1998\n\nThis is a cop y of the test set of the UCI ML hand-written digits datasets\nhttps://archive.ics.uci.ed u/ml/datasets/Optical+Recognition+of+Handwritten+Digits\n\nThe data set contains images of hand-written digits: 10 classes where\neach class refers to a digit.\n\nPreprocessing programs made available by NIST were used to extract\nnormalized bitmaps of handwritten digits from a preprinted form. From a\ntotal of 43 people, 30 contributed to the trainin g set and different 13\nto the test set. 32x32 bitmaps are divided into nonoverlapping b locks of\n4x4 and the number of on pixels are counted in each block. This generates\nan input matrix of 8x8 where each element is an integer in the range\n0..16. This reduces d imensionality and gives invariance to small\ndistortions.\n\nFor info on NIST preprocess ing routines, see M. D. Garris, J. L. Blue, G.\nT. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C.\nL. Wilson, NIST Form-Based Handprint Recognition Syste m, NISTIR 5469,\n1994.\n\n.. topic:: References\n\n - C. Kaynak (1995) Methods of Combi ning Multiple Classifiers and Their\n Applications to Handwritten Digit Recognition, MSc Thesis, Institute of\n Graduate Studies in Science and Engineering, Bogazici Univ ersity.\n - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.\n - Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin.\n Linear dimensionalityr eduction using relevance weighted LDA. School of\n Electrical and Electronic Engineer ing Nanyang Technological University.\n 2005.\n - Claudio Gentile. A New Approximate Maximal Margin Classification\n Algorithm. NIPS. 2000.\n"}

```
plt.subplot(1,5,index+1)
               plt.imshow(np.reshape(image,(8,8)))
               plt.title('Number:%i\n' %label, fontsize=15)
               Number:0
                                  Number:1
                                                     Number:2
                                                                        Number:3
                                                                                          Number:4
                            2 -
3 -
In [45]:
          x_train,x_test,y_train,y_test=train_test_split(digits.data,digits.target,test_size=0.30
In [46]:
           print(x train.shape)
          print(x_test.shape)
          print(y train.shape)
          print(y test.shape)
          (1257, 64)
          (540, 64)
          (1257,)
          (540,)
In [47]:
          logre=LogisticRegression(max iter=10000) # if error comes declare max iter=10000
          logre.fit(x train,y train)
Out[47]: LogisticRegression(max_iter=10000)
In [49]:
          print(logre.predict(x test))
          [3 6 2 5 4 3 7 6 7 0 5 3 3 2 5 1 1 0 4 5 2 5 5 4 2 2 4 6 8 6 6 8 9 8 6 5 5
           5 2 8 5 6 6 8 7 6 2 2 2 3 4 5 9 5 0 9 1 4 2 6 4 0 3 9 7 2 6 1 9 7 5 7 7 5
           3 2 4 8 7 5 7 6 1 1 5 3 5 2 7 1 8 3 1 1 3 5 7 7 9 2 7 6 2 4 1 5 0 3 7 8 3
           9 4 2 3 4 9 2 6 0 9 6 4 6 5 0 5 4 4 6 5 6 1 3 9 2 6 2 5 8 6 9 5 3 3 5 7 1
           9 1 7 7 7 4 3 1 9 0 0 1 6 1 1 8 4 0 5 9 3 1 3 0 6 7 8 2 2 0 2 3 5 6 4 2 6
           6 2 8 4 7 7 4 8 5 2 6 8 4 0 8 3 9 1 0 2 9 4 2 8 0 9 9 5 1 9 4 4 9 4 7 1 3
           4 6 9 6 3 2 0 9 8 0 7 7 8 1 1 0 6 0 4 5 6 0 0 8 9 8 6 9 3 2 5 8 7 5 6
           6\ 6\ 2\ 5\ 7\ 5\ 1\ 9\ 7\ 8\ 4\ 4\ 5\ 7\ 3\ 2\ 8\ 6\ 1\ 2\ 5\ 3\ 8\ 3\ 7\ 0\ 5\ 5\ 3\ 5\ 4\ 3\ 6
           9 5 7 4 2 6 3 9 6 1 8 9 6 2 7 9 4 4 2 2 3 1 5 5 0 2 3 5 8 3 8 3 6
                                                                               1 9 2 3
           9 7 6 4 8 4 7 2 3 2 2 2 8 5 0 8 7 3 5 7 2 0 9 0 4 6 4 8 3 9 5 8 5 0 7 5 8
           4 6 7 0 0 7 8 8 5 1 2 9 2 9 9 0 3 5 5 5 1 9 3 4 8 9 5 0 0 2 5 6 9 9 7 3 5
           1 9 0 8 3 1 4 0 8 2 0 1 4 0 5 2 8 2 9 8 7 0 2 9 3 8 0 0 2 0 4 2 7 1 1 5 9
           4 2 8 6 4 5 3 6 6 4 3 9 4 2 8 0 8 1 0 4 6 5 7 7 7 3 9 4 8 0 7 5 9 2 7 9 9
           0 0 2 1 7 5 4 9 5 8 0 2 9 1 4 5 8 0 4 2 9 8 5 9 8 9 7 4 6 3 6 9 2 2 2 3 5
          8 8 1 9 3 0 3 7 3 7 2 8 0 0 1 5 1 1 3 3 1 0
In [48]:
          print(logre.score(x_test,y_test))
          0.9685185185185186
 In [ ]:
```