```
In [1]:
          import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn as sns
          from sklearn.linear model import LogisticRegression
In [2]:
          df=pd.read_csv(r"C:\Users\user\Downloads\loan train.csv")
Out[2]:
               Loan_ID Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantIn
           0 LP001002
                           Male
                                     No
                                                   0
                                                       Graduate
                                                                           No
                                                                                           5849
              LP001003
                           Male
                                     Yes
                                                   1
                                                       Graduate
                                                                           No
                                                                                           4583
              LP001005
                                                       Graduate
                                                                                           3000
                           Male
                                     Yes
                                                                           Yes
                                                            Not
              LP001006
                                                   0
                                                                                           2583
                           Male
                                     Yes
                                                                           No
                                                       Graduate
                                                                                           6000
              LP001008
                                                   0
                                                       Graduate
                           Male
                                     No
                                                                           No
                                                                            ...
                                                                                             • • •
              LP002978
                                                       Graduate
         609
                         Female
                                     No
                                                   0
                                                                           No
                                                                                           2900
         610 LP002979
                                                  3+
                                                       Graduate
                                                                                           4106
                           Male
                                     Yes
                                                                           No
                                                   1
                                                       Graduate
         611 LP002983
                           Male
                                     Yes
                                                                           No
                                                                                           8072
                                                   2
                                                       Graduate
         612 LP002984
                           Male
                                     Yes
                                                                           No
                                                                                           7583
         613 LP002990
                        Female
                                     No
                                                       Graduate
                                                                           Yes
                                                                                           4583
        614 rows × 13 columns
In [3]:
          df.fillna(value=0)
Out[3]:
               Loan_ID Gender
                                Married Dependents
                                                      Education Self_Employed ApplicantIncome CoapplicantII
           0 LP001002
                           Male
                                     No
                                                       Graduate
                                                                           No
                                                                                           5849
              LP001003
                           Male
                                     Yes
                                                       Graduate
                                                                           No
                                                                                           4583
              LP001005
                           Male
                                     Yes
                                                       Graduate
                                                                           Yes
                                                                                           3000
                                                            Not
           3 LP001006
                                                                                           2583
                           Male
                                     Yes
                                                   0
                                                                           No
                                                       Graduate
              LP001008
                                                       Graduate
                                                                                           6000
                           Male
                                     No
                                                   0
                                                                           No
                                                   ...
         609
             LP002978
                         Female
                                     No
                                                   0
                                                       Graduate
                                                                           No
                                                                                           2900
         610 LP002979
                                                  3+
                                                       Graduate
                                                                                           4106
                           Male
                                     Yes
                                                                           No
         611 LP002983
                           Male
                                     Yes
                                                       Graduate
                                                                           No
                                                                                           8072
```

Loan_ID Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantII

613 LP002990 Female No 0 Graduate Yes 4583 614 rows x 13 columns In [4]: feature_matrix=df.iloc[:,6:7] target_vector=df.iloc[:,-1] In [5]: feature_matrix.shape Out[5]: (614, 1) In [6]: target_vector.shape Out[6]: (614,) In [7]: from sklearn.preprocessing import StandardScaler In [8]: fs=StandardScaler().fit_transform(feature_matrix) In [9]: logr=LogisticRegression() In [10]: logr.fit(fs, target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object) In [15]: logr.predict_proba(observation)[0][0]		612	LP002984	Male	Yes	2	Graduate	No	7583			
<pre>In [4]:</pre>		613	LP002990	Female	No	0	Graduate	Yes	4583			
In [5]: feature_matrix.shape Out[5]: (614, 1) In [6]: target_vector.shape Out[6]: (614,) In [7]: from sklearn.preprocessing import StandardScaler In [8]: fs=StandardScaler().fit_transform(feature_matrix) In [9]: logr=LogisticRegression() In [10]: logs.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)		614 rd	ows × 13 c	columns								
Out[5]: (614, 1) In [6]: target_vector.shape Out[6]: (614,) In [7]: from sklearn.preprocessing import StandardScaler In [8]: fs=StandardScaler().fit_transform(feature_matrix) In [9]: logr=LogisticRegression() In [10]: logr.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes Out[14]: array(['N', 'Y'], dtype=object)	In [4]:											
In [6]: target_vector.shape Out[6]: (614,) In [7]: from sklearn.preprocessing import StandardScaler In [8]: fs=StandardScaler().fit_transform(feature_matrix) In [9]: logr=LogisticRegression() In [10]: logr.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)	In [5]:	fea	feature_matrix.shape									
Out[6]: (614,) In [7]: from sklearn.preprocessing import StandardScaler In [8]: fs=StandardScaler().fit_transform(feature_matrix) In [9]: logr=LogisticRegression() In [10]: logr.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)	Out[5]:	(614	, 1)									
<pre>In [7]: from sklearn.preprocessing import StandardScaler In [8]: fs=StandardScaler().fit_transform(feature_matrix) In [9]: logr=LogisticRegression() In [10]: logr.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction)</pre>	In [6]:	tar										
In [8]: fs=StandardScaler().fit_transform(feature_matrix) In [9]: logr=LogisticRegression() In [10]: logr.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)	Out[6]:	(614	,)	learn.preprocessing import StandardScaler								
In [9]: logr=LogisticRegression() In [10]: logr.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)	In [7]:	<pre>from sklearn.preprocessing import StandardScaler</pre>										
<pre>In [10]: logr.fit(fs,target_vector) Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction)</pre>	In [8]:	<pre>fs=StandardScaler().fit_transform(feature_matrix)</pre>										
Out[10]: LogisticRegression() In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)	In [9]:	logr=LogisticRegression()										
<pre>In [11]: observation=[[1]] In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)</pre>	In [10]:	<pre>logr.fit(fs,target_vector)</pre>										
<pre>In [12]: prediction=logr.predict(observation) In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)</pre>	Out[10]:	LogisticRegression()										
<pre>In [13]: print(prediction) ['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)</pre>	In [11]:	observation=[[1]]										
['Y'] In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)	In [12]:	<pre>prediction=logr.predict(observation)</pre>										
<pre>In [14]: logr.classes_ Out[14]: array(['N', 'Y'], dtype=object)</pre>	In [13]:	print(prediction)										
Out[14]: array(['N', 'Y'], dtype=object)		['Y']									
To [45].	In [14]:	log	r.classes	_								
In [15]: logr.predict_proba(observation)[0][0]	Out[14]:	arra	y(['N', '	Y'], dtyp	e=object)							
	In [15]:	log	r.predict	_proba(ob	servation)	[0][0]						

```
Out[15]: 0.31484531849937436

In [16]: logr.predict_proba(observation)[0][1]

Out[16]: 0.6851546815006256
```

Logistic Regression 2

```
In [17]:
          import re
          from sklearn.datasets import load_digits
          from sklearn.model_selection import train_test_split
In [18]:
          digits=load digits()
          digits
Out[18]: {'data': array([[ 0., 0., 5., ..., 0., 0., 0.],
                  [ 0., 0., 0., ..., 10., 0., 0.],
                  [0., 0., 0., ..., 16., 9., 0.],
                  [0., 0., 1., ..., 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
```

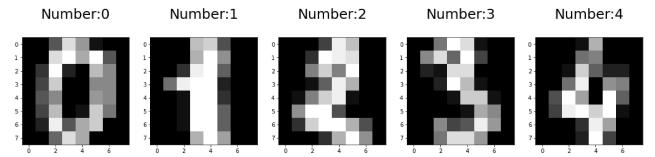
'pixel 4 0',

```
'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.], [ 0., 0., 13., ..., 15., 5., 0.],
              3., 15., ..., 11., 8., 0.],
       [ 0.,
              4., 11., ..., 12., 7.,
       [ 0.,
                                        0.],
               2., 14., ..., 12., 0.,
       [0., 0., 6., ..., 0., 0.,
                                        0.11,
       [[ 0., 0., 0., ..., 5., 0., 0.], [ 0., 0., 0., ..., 9., 0., 0.],
       [ 0.,
              0., 3., ..., 6.,
                                   0.,
                                        0.],
       [ 0.,
               0., 1., ..., 6., 0., 0.],
       Γ0.,
               0., 1., ..., 6., 0.,
                                         0.],
       Γ0.,
               0., 0., ..., 10., 0.,
                                        0.]],
       [[0., 0., 0., ..., 12., 0., 0.],
                                        0.],
       [ 0., 0., 3., ..., 14., 0.,
       [0., 0., 8., \ldots, 16., 0., 0.],
               9., 16., ..., 0., 0.,
       [ 0.,
               3., 13., ..., 11., 5.,
                                         0.],
              0., 0., ..., 16., 9.,
       [ 0.,
                                        0.]],
       . . . ,
       [[ 0., 0., 1., ..., 1., 0.,
       [ 0.,
              0., 13., ..., 2.,
                                   1.,
              0., 16., ..., 16.,
       [ 0.,
              0., 16., ..., 15., 0.,
       [0., 0., 15., ..., 16., 0., 0.],
       [0., 0., 2., \ldots, 6., 0., 0.]
```

```
[[ 0., 0., 2., ..., 0., 0., 0.], [ 0., 0., 14., ..., 15., 1., 0.], [ 0., 4., 16., ..., 16., 7., 0.], ..., [ 0., 0., 0., 0., ..., 16., 2., 0.], [ 0., 0., 4., ..., 16., 2., 0.], [ 0., 0., 5., ..., 12., 0., 0.]], [ 0., 2., 16., ..., 1., 0., 0.], [ 0., 2., 16., ..., 1., 0., 0.], [ 0., 0., 15., ..., 15., 0., 0.], ..., [ 0., 4., 16., ..., 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--------\n\n**Data Set Characteristics:**\n\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.figure(figsize=(20,4))
for index,(image,label)in enumerate(zip(digits.data[0:5],digits.target[0:5])):
    plt.subplot(1,5,index+1)
    plt.imshow(np.reshape(image,(8,8)),cmap=plt.cm.gray)
    plt.title("Number:%i\n"%label,fontsize=25)
```



```
In [20]: x_train,x_test,y_train,y_test=train_test_split(digits.data,digits.target,test_size=0.30
```

```
In [21]: logr=LogisticRegression(max_iter=10000)
```

```
In [22]:
           logr.fit(x_train,y_train)
Out[22]: LogisticRegression(max_iter=10000)
In [23]:
           print(logr.predict(x_test))
          [7 8 1 4 3 6 8 5 0 8 9 3 4 8 0 8 7 9 4 6 3 2 6 4 4 0 4 2 6 2 7 0 6 3 4 8 7
           4 6 9 3 5 9 8 6 3 3 1 9 0 8 6 9 2 0 6 1 2 1 7 9 2 9 4 8 3 4 3 6 0
                                                                                   8 0 9 2
           2 8 3 2 8 8 1 9 1 0 7 7 2 3 3 5 6 8 4 0 6 8 1 1 9 9 3 7 7 2 9 6 9 5 6 3 4
           5 1 2 5 4 5 4 3 2 7 8 6 9 7 9 4 1 6 8 3 2 8 4 3 8 4 3 8 9 2 8 9 2 8 0 7 0
           4 6 5 9 6 1 6 5 1 9 1 4 7 9 9 2 5 9 6 6 3 8 4 6 7 8 6 6 9 0 3 3 6 9 2 5 1
           3 3 8 8 3 6 7 3 3 3 5 8 0 4 9 7 0 8 5 7 7 4 5 6 9 2 2 5 5 6 2 2 9 3 9 2 8
           6\; 6\; 5\; 1\; 4\; 1\; 3\; 5\; 1\; 5\; 7\; 8\; 9\; 1\; 7\; 4\; 7\; 1\; 2\; 6\; 2\; 2\; 9\; 6\; 4\; 2\; 5\; 5\; 6\; 8\; 9\; 2\; 4\; 3\; 1\; 7\; 8
           6 0 1 0 8 5 5 2 2 2 0 2 2 7 6 2 3 0 4 8 2 4 3 8 4 8 5 7 6 7 5 3 9 8
           1 0 7 4 8 7 0 6 0 3 4 4 9 3 2 5 5 7 9 5 0 6 5 4 2 1 3 5 4 4 5 0 8 8 0 4
             0 4 8 6 9 5 1 8 9 7 3 4 3 2 9 4 4 2 4 4 6 6 7 3 2 6 8 4 4 3 8 1 4 2 3 1
           3 9 2 9 8 0 3 2 2 6 9 5 1 9 0 3 5 5 3 5 0 4 0 2 1 8 4 7 4 4 7 1 1 4 6 4 5
           5 8 7 7 8 1 4 8 5 7 7 8 1 4 8 6 9 5 8 9 4 3 5 5 6 0 0 1 8 3 2 9 7 9 2 7 9
           2817312569401025831989963664834385537
           6\; 5\; 8\; 4\; 5\; 0\; 5\; 9\; 2\; 8\; 3\; 1\; 8\; 8\; 5\; 0\; 8\; 0\; 4\; 3\; 8\; 1\; 7\; 7\; 0\; 1\; 5\; 9\; 0\; 7\; 8\; 6\; 7\; 2\; 3\; 5\; 4
           9 3 7 3 0 4 0 9 2 4 6 3 7 1 9 0 5 5 9 8 9 4]
In [24]:
           print(logr.score(x test,y test))
          0.966666666666667
 In [ ]:
```