```
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
        from sklearn.preprocessing import StandardScaler
In [ ]:
In [2]: df_train=pd.read_csv(r"E:\154\C8_loan-train - C8_loan-train.csv")
        df test=pd.read csv(r"E:\154\C8 loan-test - C8 loan-test.csv")
In [3]: df train.dropna(inplace=True)
        df_test.dropna(inplace=True)
In [4]: df_train.info()
        <class 'pandas.core.frame.DataFrame'>
        Int64Index: 480 entries, 1 to 613
        Data columns (total 13 columns):
            Column
                                Non-Null Count Dtype
         #
        ---
             ____
                                -----
         0
             Loan ID
                                480 non-null
                                                object
         1
             Gender
                                480 non-null
                                                object
             Married
                                480 non-null
         2
                                                object
             Dependents
                                480 non-null
                                                object
                                480 non-null
             Education
                                                object
             Self_Employed
                                480 non-null
                                                object
             ApplicantIncome
                                480 non-null
                                                int64
             CoapplicantIncome 480 non-null
                                                float64
                                480 non-null
                                                float64
             LoanAmount
             Loan_Amount_Term
                                480 non-null
                                                float64
         10 Credit_History
                                480 non-null
                                                float64
         11 Property_Area
                                480 non-null
                                                object
         12 Loan_Status
                                480 non-null
                                                object
        dtypes: float64(4), int64(1), object(8)
        memory usage: 52.5+ KB
In [5]: feature_matrix = df_train[['ApplicantIncome','CoapplicantIncome','LoanAmount', 'Loan_Amount_Term','Credit_History
        target_vector = df_train[['Gender']]
In [6]: fs = StandardScaler().fit_transform(feature_matrix)
        logr = LogisticRegression()
        logr.fit(fs,target_vector)
        C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vecto
        r y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ra
        vel().
          return f(*args, **kwargs)
Out[6]: LogisticRegression()
```

```
In [7]: observation = df_test[['ApplicantIncome','CoapplicantIncome','LoanAmount', 'Loan_Amount_Term','Credit_History']]
       prediction = logr.predict(observation)
       print(prediction)
        ['Male' 'Male' 'Male' 'Male' 'Male' 'Male' 'Male' 'Male' 'Male'
         'Male' 'Male' 'Male' 'Male' 'Male' 'Male'
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         'Male' 'Male' 'Male' 'Male' 'Male'
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         'Male' 'Male' 'Male' 'Male' 'Male'
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                                                             'Male'
         'Male' 'Male' 'Male' 'Male'
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         'Male' 'Male' 'Male' 'Male' 'Male' 'Male' 'Male' 'Male' 'Male'
         'Male' 'Male' 'Male' 'Male' 'Male'
                                               'Male'
In [8]: logr.classes_
Out[8]: array(['Female', 'Male'], dtype=object)
In [9]: logr.predict_proba(observation)[0][0]
```

## **Logistic Regression 2**

Out[9]: 0.0

```
In [10]: 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 [11]: digits =load_digits()
         digits
                         T., 10., ..., 10.,
                  [ 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 A
         ttributes: 64\n :Attribute Information: 8x8 image of integer pixels in the range 0..16.\n :Missing Attri
         bute Values: None\n :Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)\n
                                                                                   :Date: July; 1998\n\nThis is a co
         py of the test set of the UCI ML hand-written digits datasets\nhttps://archive.ics.uci.edu/ml/datasets/Optical
         +Recognition+of+Handwritten+Digits\n\nThe data set contains images of hand-written digits: 10 classes where\ne
         ach 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 traini
         ng set and different 13\nto the test set. 32x32 bitmaps are divided into nonoverlapping blocks 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 dimensionality and gives invariance to small\ndistortions.\n\nFor in
         fo on NIST preprocessing 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 System, NISTIR 5469,\n199
         4.\n\n.. topic:: References\n\n - C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their\n
         pplications to Handwritten Digit Recognition, MSc Thesis, Institute of\n
                                                                                  Graduate Studies in Science and En
         gineering, Bogazici University.\n - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.\n - Ke
         n Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin.\n Linear dimensionalityreduction using relev
In [12]: 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=15)
                 Number:0
                                       Number:1
                                                              Number:2
                                                                                    Number:3
                                                                                                          Number:4
In [13]: |x_train,x_test,y_train,y_test=train_test_split(digits.data,digits.target,test_size=0.30)
In [14]: print(x_train.shape)
         print(x_test.shape)
         print(y_train.shape)
         print(y_test.shape)
         (1257, 64)
         (540, 64)
         (1257,)
         (540,)
In [15]: logre=LogisticRegression(max iter=10000)
         logre.fit(x_train,y_train)
Out[15]: LogisticRegression(max_iter=10000)
```

```
In [16]: print(logre.predict(x_test))
           [3 3 9 4 6 6 4 0 5 7 6 3 3 5 3 6 1 9 8 7 8 0 0 8 0 1 2 8 8 5 7 0 2 2 1 3 9
            6 1 4 0 3 1 2 6 7 8 9 3 5 2 9 0 4 1 1 0 3 4 0 7 1 4 9 5 7 5 8 2 7 9 2 8 7
            6\; 9\; 4\; 6\; 6\; 1\; 1\; 9\; 4\; 5\; 1\; 4\; 0\; 2\; 6\; 3\; 0\; 9\; 7\; 3\; 5\; 4\; 7\; 8\; 6\; 7\; 0\; 5\; 2\; 6\; 6\; 4\; 2\; 2\; 8\; 3\; 2
            0 1 6 6 1 0 3 9 3 3 3 0 0 5 7 6 1 0 0 6 0 4 0 4 0 3 1 4 6 8 2 3 0 5 2 3 7
            2 6 3 0 6 9 2 9 3 4 4 4 1 9 5 0 9 0 1 7 2 0 9 1 0 7 5 5 4 9 3 2 0 9 1 6 5
            1 4 9 8 1 9 1 1 8 3 5 7 3 5 2 7 2 9 5 6 7 1 0 5 7 9 5 5 2 6 3 5 4 4 4 1 5
            2 0 2 4 9 0 4 0 5 3 4 6 3 4 5 0 4 5 5 0 8 9 1 3 1 9 0 7 7 8 6 6 9 7 1 6 4
            7 8 3 4 5 3 2 2 8 1 9 6 3 7 1 6 2 3 0 0 1 4 9 3 3 2 0 6 1 1 0 9 8 9 0 7 7
            1 8 8 4 6 2 4 3 2 4 1 3 1 0 4 5 0 7 0 2 4 2 0 2 5 5 1 2 5 7 2 2 0 5 2 5 2
            5 1 6 5 6 8 9 2 3 9 4 5 4 7 7 2 5 4 9 8 4 4 2 3 3 8 0 5 2 1 6 1 2 7 5 3 6
            3 5 6 6 8 4 1 1 5 9 5 1 5 0 7 3 6 3 0 0 0 6 0 2 2 4 0 6 7 6 4 2 9 6 0 0 8
            1 1 3 1 4 8 5 3 4 0 0 0 4 6 2 5 9 7 7 3 4 7 7 3 0 4 7 8 7 2 2 0 9 9 1 7 2
            0\; 8\; 0\; 7\; 6\; 2\; 7\; 8\; 7\; 5\; 0\; 6\; 0\; 9\; 9\; 2\; 3\; 2\; 6\; 6\; 7\; 4\; 3\; 8\; 5\; 8\; 6\; 6\; 3\; 8\; 0\; 9\; 1\; 8\; 8\; 3\; 0
            6\ 5\ 4\ 7\ 8\ 7\ 0\ 4\ 8\ 4\ 2\ 9\ 2\ 7\ 2\ 8\ 5\ 5\ 7\ 9\ 2\ 4\ 9\ 8\ 8\ 9\ 8\ 3\ 7\ 6\ 5\ 8\ 4\ 8\ 8\ 0\ 8
            9 9 6 9 6 3 6 5 5 0 2 7 3 2 4 0 9 5 9 4 6 3]
In [17]: print(logre.score(x_test,y_test))
```

0.9611111111111111