assignment1-1-mariam-v2

November 16, 2023

[ ]:
```
#Team
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```

[83]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.utils import shuffle
from sklearn.linear_model import LinearRegression
```

[84]:
```
data = pd.read_csv("loan_old.csv")
data_new = pd.read_csv("loan_new.csv")

print ("\ndata\n",data.head(20))
print ("\ndata_new\n",data_new.head(20))
# data.shape[0]
```

```
data
      Loan_ID  Gender Married Dependents     Education  Income  \
0    LP001002    Male      No          0      Graduate    5849
1    LP001003    Male     Yes          1      Graduate    4583
2    LP001005    Male     Yes          0      Graduate    3000
3    LP001006    Male     Yes          0  Not Graduate    2583
4    LP001008    Male      No          0      Graduate    6000
5    LP001011    Male     Yes          2      Graduate    5417
6    LP001013    Male     Yes          0  Not Graduate    2333
7    LP001014    Male     Yes         3+      Graduate    3036
8    LP001018    Male     Yes          2      Graduate    4006
9    LP001020    Male     Yes          1      Graduate   12841
10   LP001024    Male     Yes          2      Graduate    3200
11   LP001027    Male     Yes          2      Graduate    2500
```

```
12  LP001028    Male     Yes          2      Graduate    3073
13  LP001029    Male      No          0      Graduate    1853
14  LP001030    Male     Yes          2      Graduate    1299
15  LP001032    Male      No          0      Graduate    4950
16  LP001034    Male      No          1  Not Graduate    3596
17  LP001036  Female      No          0      Graduate    3510
18  LP001038    Male     Yes          0  Not Graduate    4887
19  LP001041    Male     Yes          0      Graduate    2600

    Coapplicant_Income  Loan_Tenor  Credit_History Property_Area  \
0                  0.0       144.0             1.0         Urban
1               1508.0       144.0             1.0         Rural
2                  0.0       144.0             1.0         Urban
3               2358.0       144.0             1.0         Urban
4                  0.0       144.0             1.0         Urban
5               4196.0       144.0             1.0         Urban
6               1516.0       144.0             1.0         Urban
7               2504.0       144.0             0.0     Semiurban
8               1526.0       144.0             1.0         Urban
9              10968.0       144.0             1.0     Semiurban
10               700.0       144.0             1.0         Urban
11              1840.0       144.0             1.0         Urban
12              8106.0       144.0             1.0         Urban
13              2840.0       144.0             1.0         Rural
14              1086.0       120.0             1.0         Urban
15                 0.0       144.0             1.0         Urban
16                 0.0        96.0             NaN         Urban
17                 0.0       144.0             0.0         Urban
18                 0.0       144.0             1.0         Rural
19              3500.0         NaN             1.0         Urban

    Max_Loan_Amount Loan_Status
0               NaN           Y
1            236.99           N
2             81.20           Y
3            179.03           Y
4            232.40           Y
5            414.50           Y
6            123.99           Y
7            209.22           N
8            208.81           Y
9            449.00           N
10           126.56           Y
11           148.74           Y
12           363.42           Y
13           166.53           N
14            30.17           Y
15           179.48           Y
```

```
16           50.83           Y
17          106.90           N
18          176.30           N
19             NaN           Y

data_new
      Loan_ID  Gender Married Dependents     Education  Income  \
0   LP001015    Male     Yes          0      Graduate    5720
1   LP001022    Male     Yes          1      Graduate    3076
2   LP001031    Male     Yes          2      Graduate    5000
3   LP001035    Male     Yes          2      Graduate    2340
4   LP001051    Male      No          0  Not Graduate    3276
5   LP001054    Male     Yes          0  Not Graduate    2165
6   LP001055  Female      No          1  Not Graduate    2226
7   LP001056    Male     Yes          2  Not Graduate    3881
8   LP001059    Male     Yes          2      Graduate   13633
9   LP001067    Male      No          0  Not Graduate    2400
10  LP001078    Male      No          0  Not Graduate    3091
11  LP001082    Male     Yes          1      Graduate    2185
12  LP001083    Male      No         3+      Graduate    4166
13  LP001094    Male     Yes          2      Graduate   12173
14  LP001096  Female      No          0      Graduate    4666
15  LP001099    Male      No          1      Graduate    5667
16  LP001105    Male     Yes          2      Graduate    4583
17  LP001107    Male     Yes         3+      Graduate    3786
18  LP001108    Male     Yes          0      Graduate    9226
19  LP001115    Male      No          0      Graduate    1300

    Coapplicant_Income  Loan_Tenor  Credit_History Property_Area
0                    0       144.0             1.0         Urban
1                 1500       144.0             1.0         Urban
2                 1800       144.0             1.0         Urban
3                 2546       144.0             NaN         Urban
4                    0       144.0             1.0         Urban
5                 3422       144.0             1.0         Urban
6                    0       144.0             1.0     Semiurban
7                    0       144.0             0.0         Rural
8                    0        96.0             1.0         Urban
9                 2400       144.0             1.0     Semiurban
10                   0       144.0             1.0         Urban
11                1516       144.0             1.0     Semiurban
12                   0        72.0             NaN         Urban
13                   0       144.0             0.0     Semiurban
14                   0       144.0             1.0     Semiurban
15                   0       144.0             1.0         Urban
16                2916       144.0             1.0         Urban
17                 333       144.0             1.0     Semiurban
18                7916       144.0             1.0         Urban
```

```
19                 3470        72.0              1.0     Semiurban
```

[85]:
```
#drop loan_id ->loan_old
data = data.drop('Loan_ID', axis=1)
print("\ndata\n",data)

#drop loan_id ->loan_new
data_new = data_new.drop('Loan_ID', axis=1)
print("\ndata_new\n",data_new)
```

```
data
      Gender Married Dependents     Education  Income  Coapplicant_Income  \
0       Male      No          0      Graduate    5849                 0.0
1       Male     Yes          1      Graduate    4583              1508.0
2       Male     Yes          0      Graduate    3000                 0.0
3       Male     Yes          0  Not Graduate    2583              2358.0
4       Male      No          0      Graduate    6000                 0.0
..       …       …          …           …       …                  …
609   Female      No          0      Graduate    2900                 0.0
610     Male     Yes         3+      Graduate    4106                 0.0
611     Male     Yes          1      Graduate    8072               240.0
612     Male     Yes          2      Graduate    7583                 0.0
613   Female      No          0      Graduate    4583                 0.0

     Loan_Tenor  Credit_History Property_Area  Max_Loan_Amount Loan_Status
0         144.0             1.0         Urban              NaN           Y
1         144.0             1.0         Rural           236.99           N
2         144.0             1.0         Urban            81.20           Y
3         144.0             1.0         Urban           179.03           Y
4         144.0             1.0         Urban           232.40           Y
..          …             …           …              …          …
609       144.0             1.0         Rural            76.16           Y
610        72.0             1.0         Rural            33.47           Y
611       144.0             1.0         Urban           348.92           Y
612       144.0             1.0         Urban           312.18           Y
613       144.0             0.0     Semiurban           160.98           N

[614 rows x 11 columns]

data_new
     Gender Married Dependents     Education  Income  Coapplicant_Income  \
0      Male     Yes          0      Graduate    5720                   0
1      Male     Yes          1      Graduate    3076                1500
2      Male     Yes          2      Graduate    5000                1800
3      Male     Yes          2      Graduate    2340                2546
4      Male      No          0  Not Graduate    3276                   0
..      …       …          …           …       …                  …
```

```
362   Male      Yes          3+  Not Graduate    4009                 1777
363   Male      Yes           0      Graduate    4158                  709
364   Male       No           0      Graduate    3250                 1993
365   Male      Yes           0      Graduate    5000                 2393
366   Male       No           0      Graduate    9200                    0

     Loan_Tenor  Credit_History Property_Area
0         144.0             1.0         Urban
1         144.0             1.0         Urban
2         144.0             1.0         Urban
3         144.0             NaN         Urban
4         144.0             1.0         Urban
..          …              …           …
362       144.0             1.0         Urban
363       144.0             1.0         Urban
364       144.0             NaN     Semiurban
365       144.0             1.0         Rural
366        72.0             1.0         Rural

[367 rows x 9 columns]
```

[86]:
```python
#analysis
datanull= data.isnull().any(axis = 1)
data[datanull]
```

[86]:
```
     Gender Married Dependents     Education  Income  Coapplicant_Income  \
0      Male      No          0      Graduate    5849                 0.0
16     Male      No          1  Not Graduate    3596                 0.0
19     Male     Yes          0      Graduate    2600              3500.0
23      NaN     Yes          2  Not Graduate    3365              1917.0
24     Male     Yes          1      Graduate    3717              2925.0
..      …       …         …            …     …                 …
583    Male     Yes          1      Graduate    1880                 0.0
588     NaN      No          0      Graduate    4750                 0.0
592     NaN      No         3+      Graduate    9357                 0.0
597    Male      No        NaN      Graduate    2987                 0.0
600  Female      No         3+      Graduate     416             41667.0

     Loan_Tenor  Credit_History Property_Area  Max_Loan_Amount Loan_Status
0         144.0             1.0         Urban              NaN           Y
16         96.0             NaN         Urban            50.83           Y
19          NaN             1.0         Urban              NaN           Y
23        144.0             0.0         Rural           196.21           N
24        144.0             NaN     Semiurban           264.76           N
..          …              …           …               …          …
583       144.0             NaN         Rural            24.75           N
588       144.0             1.0     Semiurban           169.40           Y
```

```
592        144.0               1.0     Semiurban            401.59            Y
597        144.0               0.0     Semiurban             80.54            N
600         72.0               NaN         Urban            990.49            N

[101 rows x 11 columns]
```

[87]:

```
# check the type of each feature (categorical or numerical
feature_types = data.dtypes
print(feature_types)
values = data['Gender'].unique()
#print(values)
```

```
Gender                  object
Married                 object
Dependents              object
Education               object
Income                   int64
Coapplicant_Income     float64
Loan_Tenor             float64
Credit_History         float64
Property_Area           object
Max_Loan_Amount        float64
Loan_Status             object
dtype: object
```

[88]:

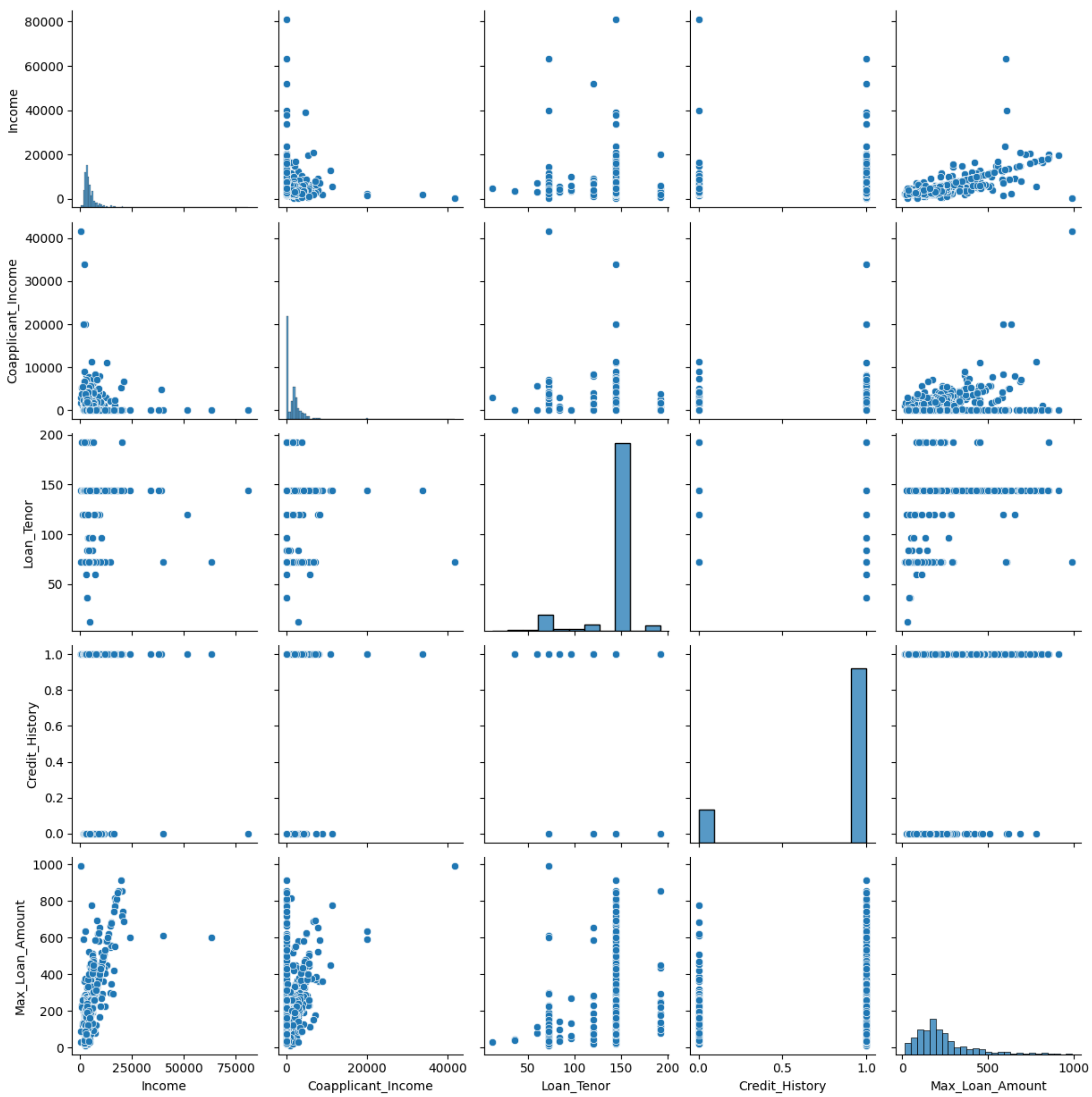
```
# Isolating numerical columns
numerical_data = data.select_dtypes(include=[np.number])

# Calculating mean and standard deviation
means = np.mean(numerical_data, axis=0)
std_devs = np.std(numerical_data, axis=0)

print ("\n Data is not scaled\n")
print("Means of numerical features:\n", means)
print("Standard Deviations of numerical features:\n", std_devs)
```

```

 Data is not scaled

Means of numerical features:
 Income                5403.459283
Coapplicant_Income    1621.245798
Loan_Tenor             137.689482
Credit_History           0.842199
Max_Loan_Amount        230.499474
dtype: float64
Standard Deviations of numerical features:
 Income                6104.064857
```

```
Coapplicant_Income    2923.864460
Loan_Tenor              23.346781
Credit_History           0.364555
Max_Loan_Amount        161.839407
dtype: float64
```

[89]:
```
# sns.pairplot(data, hue="Max_Loan_Amount")
sns.pairplot(data)
```

[89]: <seaborn.axisgrid.PairGrid at 0x1f1ab12f2f0>



[ ]:

```
[90]: def RemoveMissingValue(data):
          datanull= data.isnull().any(axis = 1)  #remove row with missing value
          return data[~datanull]
```

```
[91]: #preprocssing remove rows with missing in loan_old , loan_new
      data = RemoveMissingValue(data)
      data_new=RemoveMissingValue(data_new)
      print ("\ndata\n",data.head(20))
      print ("\ndata_new\n",data_new.head(20))
      values = data['Married'].unique()
      # print(values)
```

```
data
    Gender Married Dependents     Education  Income  Coapplicant_Income  \
1     Male     Yes          1      Graduate    4583              1508.0
2     Male     Yes          0      Graduate    3000                 0.0
3     Male     Yes          0  Not Graduate    2583              2358.0
4     Male      No          0      Graduate    6000                 0.0
5     Male     Yes          2      Graduate    5417              4196.0
6     Male     Yes          0  Not Graduate    2333              1516.0
7     Male     Yes         3+      Graduate    3036              2504.0
8     Male     Yes          2      Graduate    4006              1526.0
9     Male     Yes          1      Graduate   12841             10968.0
10    Male     Yes          2      Graduate    3200               700.0
11    Male     Yes          2      Graduate    2500              1840.0
12    Male     Yes          2      Graduate    3073              8106.0
13    Male      No          0      Graduate    1853              2840.0
14    Male     Yes          2      Graduate    1299              1086.0
15    Male      No          0      Graduate    4950                 0.0
17  Female      No          0      Graduate    3510                 0.0
18    Male     Yes          0  Not Graduate    4887                 0.0
20    Male     Yes          0  Not Graduate    7660                 0.0
21    Male     Yes          1      Graduate    5955              5625.0
22    Male     Yes          0  Not Graduate    2600              1911.0

    Loan_Tenor  Credit_History Property_Area  Max_Loan_Amount Loan_Status
1        144.0             1.0         Rural           236.99           N
2        144.0             1.0         Urban            81.20           Y
3        144.0             1.0         Urban           179.03           Y
4        144.0             1.0         Urban           232.40           Y
5        144.0             1.0         Urban           414.50           Y
6        144.0             1.0         Urban           123.99           Y
7        144.0             0.0     Semiurban           209.22           N
8        144.0             1.0         Urban           208.81           Y
9        144.0             1.0     Semiurban           449.00           N
10       144.0             1.0         Urban           126.56           Y
```

```
11       144.0               1.0        Urban          148.74            Y
12       144.0               1.0        Urban          363.42            Y
13       144.0               1.0        Rural          166.53            N
14       120.0               1.0        Urban           30.17            Y
15       144.0               1.0        Urban          179.48            Y
17       144.0               0.0        Urban          106.90            N
18       144.0               1.0        Rural          176.30            N
20       144.0               0.0        Urban          316.06            N
21       144.0               1.0        Urban          513.63            Y
22       144.0               0.0    Semiurban          157.35            N

data_new
     Gender Married Dependents     Education  Income  Coapplicant_Income  \
0      Male     Yes          0      Graduate    5720                   0
1      Male     Yes          1      Graduate    3076                1500
2      Male     Yes          2      Graduate    5000                1800
4      Male      No          0  Not Graduate    3276                   0
5      Male     Yes          0  Not Graduate    2165                3422
6    Female      No          1  Not Graduate    2226                   0
7      Male     Yes          2  Not Graduate    3881                   0
8      Male     Yes          2      Graduate   13633                   0
9      Male      No          0  Not Graduate    2400                2400
10     Male      No          0  Not Graduate    3091                   0
11     Male     Yes          1      Graduate    2185                1516
13     Male     Yes          2      Graduate   12173                   0
14   Female      No          0      Graduate    4666                   0
15     Male      No          1      Graduate    5667                   0
16     Male     Yes          2      Graduate    4583                2916
17     Male     Yes         3+      Graduate    3786                 333
18     Male     Yes          0      Graduate    9226                7916
19     Male      No          0      Graduate    1300                3470
20     Male     Yes          1  Not Graduate    1888                1620
21   Female      No         3+  Not Graduate    2083                   0

    Loan_Tenor  Credit_History Property_Area
0        144.0             1.0         Urban
1        144.0             1.0         Urban
2        144.0             1.0         Urban
4        144.0             1.0         Urban
5        144.0             1.0         Urban
6        144.0             1.0     Semiurban
7        144.0             0.0         Rural
8         96.0             1.0         Urban
9        144.0             1.0     Semiurban
10       144.0             1.0         Urban
11       144.0             1.0     Semiurban
13       144.0             0.0     Semiurban
14       144.0             1.0     Semiurban
```

```
15        144.0              1.0         Urban
16        144.0              1.0         Urban
17        144.0              1.0     Semiurban
18        144.0              1.0         Urban
19         72.0              1.0     Semiurban
20        144.0              1.0         Urban
21         72.0              1.0         Urban
```

[92]:
```python
#shuffling data ->loan_old
shuffled_data = shuffle(data, random_state=42)
print('\nshuffled_data\n',shuffled_data)
```

```
shuffled_data
      Gender Married Dependents     Education  Income  Coapplicant_Income  \
366    Male      No          0      Graduate    2500                 0.0
595    Male      No          0  Not Graduate    3833                 0.0
527    Male     Yes          1  Not Graduate    5285              1430.0
184  Female     Yes          0      Graduate    3625                 0.0
598    Male     Yes          0      Graduate    9963                 0.0
..      …       …          …           …       …                 …
132    Male      No          0      Graduate    2718                 0.0
325    Male     Yes          1      Graduate    8666              4983.0
417    Male     Yes          2      Graduate    1600             20000.0
523    Male     Yes          2      Graduate    7948              7166.0
124    Male     Yes          0  Not Graduate    4300              2014.0

     Loan_Tenor  Credit_History Property_Area  Max_Loan_Amount Loan_Status
366       192.0             1.0     Semiurban            98.00           N
595       144.0             1.0         Rural           123.18           Y
527       144.0             0.0     Semiurban           268.44           Y
184       144.0             1.0     Semiurban           112.70           Y
598       144.0             1.0         Rural           432.14           Y
..          …              …           …               …         …
132       144.0             1.0     Semiurban            66.99           Y
325       144.0             0.0         Rural           617.91           N
417       144.0             1.0         Urban           588.64           N
523       144.0             1.0         Rural           691.75           Y
124       144.0             1.0         Rural           248.23           Y

[513 rows x 11 columns]
```

[93]:
```python
#separate features and target and split
x = shuffled_data.drop(columns=['Max_Loan_Amount','Loan_Status'])
y = shuffled_data[['Max_Loan_Amount','Loan_Status']]
x_predict = data_new
```

```python
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=100)
print("x_train ",x_train) , print("x_test",x_test),print("y_train ",y_train),print("y test ",y_test)
print(x_test.shape)
```

```
x_train      Gender Married Dependents     Education  Income  Coapplicant_Income
\
92     Male     Yes          2  Not Graduate    3273               1820.0
108    Male     Yes          2      Graduate    3800               3600.0
278    Male     Yes          0      Graduate   14583                  0.0
239    Male     Yes          1      Graduate    3315                  0.0
351    Male      No          0      Graduate    8750               4167.0
..      …      …        …           …      …                 …
249    Male     Yes          0      Graduate    1809               1868.0
458    Male      No          2      Graduate    4354                  0.0
569    Male     Yes          0      Graduate    3166               2064.0
594    Male     Yes          0      Graduate   16120                  0.0
21     Male     Yes          1      Graduate    5955               5625.0

     Loan_Tenor  Credit_History Property_Area
92        144.0             1.0         Urban
108       144.0             0.0         Urban
278       144.0             1.0     Semiurban
239       144.0             1.0     Semiurban
351       144.0             1.0         Rural
..          …             …          …
249       144.0             1.0         Urban
458       144.0             1.0         Rural
569       144.0             0.0         Urban
594       144.0             1.0         Urban
21        144.0             1.0         Urban

[384 rows x 9 columns]
x_test      Gender Married Dependents     Education  Income  Coapplicant_Income
\
428    Male     Yes          0      Graduate    2920           16.120001
312  Female      No          0      Graduate    2507            0.000000
320    Male     Yes          0      Graduate    2400         2167.000000
398    Male      No          0  Not Graduate    3902         1666.000000
212    Male     Yes          1      Graduate    7787            0.000000
..      …      …        …           …      …                 …
353  Female     Yes          0      Graduate    5500            0.000000
396  Female      No          0      Graduate    3180            0.000000
560    Male     Yes          2  Not Graduate    3675          242.000000
505    Male     Yes          2      Graduate    3510         4416.000000
148  Female      No          0      Graduate   10000         1666.000000
```

```
     Loan_Tenor  Credit_History Property_Area
428       144.0             1.0         Rural
312       144.0             1.0         Rural
320       144.0             1.0     Semiurban
398       144.0             1.0         Rural
212       144.0             1.0         Urban
..          …               …           …
353       144.0             0.0         Rural
396       144.0             0.0         Urban
560       144.0             1.0     Semiurban
505       144.0             1.0         Rural
148       144.0             1.0         Rural

[129 rows x 9 columns]
y_train       Max_Loan_Amount Loan_Status
92             186.69           Y
108            302.96           N
278            664.98           Y
239             97.08           Y
351            581.02           N
..                …          …
249            115.32           Y
458            149.44           Y
569            193.59           N
594            742.45           Y
21             513.63           Y

[384 rows x 2 columns]
y test       Max_Loan_Amount Loan_Status
428             77.98           Y
312             56.35           Y
320            160.18           Y
398            210.63           Y
212            322.46           Y
..                …          …
353            207.20           N
396             90.27           N
560            127.42           Y
505            329.47           Y
148            517.97           N

[129 rows x 2 columns]
(129, 9)
```

[94]:

```
#categorical features are encoded->loan_old
x_train = x_train.replace({
```

```
    'Gender' :{'Male':0 , 'Female':1},
    'Married' : {'No':0,'Yes':1},
    'Education':{'Not Graduate':0, 'Graduate':1  },
    'Dependents':{'0':0,'1':1,'2':2,'3+':3  },
    'Property_Area':{'Rural':0 ,'Urban':1 ,'Semiurban':2}
})
x_predict = x_predict.replace({
    'Gender' :{'Male':0 , 'Female':1},
    'Married' : {'No':0,'Yes':1},
    'Education':{'Not Graduate':0, 'Graduate':1  },
    'Dependents':{'0':0,'1':1,'2':2,'3+':3  },
    'Property_Area':{'Rural':0 ,'Urban':1 ,'Semiurban':2}
})

x_test = x_test.replace({
    'Gender' :{'Male':0 , 'Female':1},
    'Married' : {'No':0,'Yes':1},
    'Education':{'Not Graduate':0, 'Graduate':1  },
    'Dependents':{'0':0,'1':1,'2':2,'3+':3  },
    'Property_Area':{'Rural':0 ,'Urban':1 ,'Semiurban':2}
})
print("\nx_train\n",x_train.head(20))
print("\nx_test\n",x_test.head(20))
print("\nx_predict\n",x_predict.head(20))
```

```
x_train
     Gender  Married  Dependents  Education  Income  Coapplicant_Income  \
92        0        1           2          0    3273              1820.0
108       0        1           2          1    3800              3600.0
278       0        1           0          1   14583                 0.0
239       0        1           1          1    3315                 0.0
351       0        0           0          1    8750              4167.0
410       1        0           1          0    3867                 0.0
404       1        0           0          1    7441                 0.0
589       0        1           2          1    2726                 0.0
472       0        1           3          1    4691                 0.0
502       0        1           2          1    4865              5624.0
306       1        0           0          1    3762              1666.0
82        1        1           2          1    1378              1881.0
10        0        1           2          1    3200               700.0
478       0        1           1          1   16667              2250.0
336       0        1           1          1    5250               688.0
215       0        1           3          0    3850               983.0
227       0        1           2          1    6250              1695.0
253       0        1           1          0    2661              7101.0
500       1        0           0          1     645              3683.0
```

```
344       0        1           2          1    2583              2330.0

     Loan_Tenor  Credit_History  Property_Area
92        144.0             1.0              1
108       144.0             0.0              1
278       144.0             1.0              2
239       144.0             1.0              2
351       144.0             1.0              0
410       144.0             1.0              2
404       144.0             1.0              0
589       144.0             0.0              2
472       144.0             1.0              2
502       144.0             1.0              2
306       144.0             1.0              0
82        144.0             1.0              1
10        144.0             1.0              1
478       144.0             1.0              2
336       144.0             1.0              0
215       144.0             1.0              2
227       144.0             1.0              2
253        72.0             1.0              2
500       192.0             1.0              0
344       144.0             1.0              0

x_test
      Gender  Married  Dependents  Education  Income  Coapplicant_Income  \
428        0        1           0          1    2920           16.120001
312        1        0           0          1    2507            0.000000
320        0        1           0          1    2400         2167.000000
398        0        0           0          0    3902         1666.000000
212        0        1           1          1    7787            0.000000
52         1        0           0          1    4230            0.000000
5          0        1           2          1    5417         4196.000000
211        0        1           3          1    3430         1250.000000
520        0        1           2          0    2192         1742.000000
140        0        1           2          1    5042         2083.000000
337        0        1           2          1    2500         4600.000000
190        0        0           0          0    4885            0.000000
388        0        1           0          1    2333         2417.000000
546        0        0           0          0    3358            0.000000
29         1        0           2          1    3750         2083.000000
534        1        0           0          0   18165            0.000000
9          0        1           1          1   12841        10968.000000
509        1        0           1          1   13262            0.000000
494        0        1           0          1    3597         2157.000000
63         0        1           1          1    4945            0.000000

     Loan_Tenor  Credit_History  Property_Area
```

```
428        144.0              1.0              0
312        144.0              1.0              0
320        144.0              1.0              2
398        144.0              1.0              0
212        144.0              1.0              1
52         144.0              1.0              2
5          144.0              1.0              1
211        144.0              0.0              2
520        144.0              1.0              2
140        144.0              1.0              0
337        144.0              1.0              0
190        144.0              1.0              0
388        144.0              1.0              1
546         36.0              1.0              2
29         144.0              1.0              2
534        144.0              1.0              1
9          144.0              1.0              2
509        144.0              1.0              1
494        144.0              0.0              0
63         144.0              0.0              0

x_predict
     Gender  Married  Dependents  Education  Income  Coapplicant_Income  \
0         0        1           0          1    5720                   0
1         0        1           1          1    3076                1500
2         0        1           2          1    5000                1800
4         0        0           0          0    3276                   0
5         0        1           0          0    2165                3422
6         1        0           1          0    2226                   0
7         0        1           2          0    3881                   0
8         0        1           2          1   13633                   0
9         0        0           0          0    2400                2400
10        0        0           0          0    3091                   0
11        0        1           1          1    2185                1516
13        0        1           2          1   12173                   0
14        1        0           0          1    4666                   0
15        0        0           1          1    5667                   0
16        0        1           2          1    4583                2916
17        0        1           3          1    3786                 333
18        0        1           0          1    9226                7916
19        0        0           0          1    1300                3470
20        0        1           1          0    1888                1620
21        1        0           3          0    2083                   0

    Loan_Tenor  Credit_History  Property_Area
0        144.0             1.0              1
1        144.0             1.0              1
2        144.0             1.0              1
```

```
4        144.0          1.0           1
5        144.0          1.0           1
6        144.0          1.0           2
7        144.0          0.0           0
8         96.0          1.0           1
9        144.0          1.0           2
10       144.0          1.0           1
11       144.0          1.0           2
13       144.0          0.0           2
14       144.0          1.0           2
15       144.0          1.0           1
16       144.0          1.0           1
17       144.0          1.0           2
18       144.0          1.0           1
19        72.0          1.0           2
20       144.0          1.0           1
21        72.0          1.0           1
```

[95]:

```
#categorical target are encoded->loan_old
y_train = y_train.replace({
    # 'Property_Area':{'Rural':0 ,'Urban':1 ,'Semiurban':2},
    'Loan_Status':{'N':0,'Y':1}
})

y_test = y_test.replace({
    # 'Property_Area':{'Rural':0 ,'Urban':1 ,'Semiurban':2},
    'Loan_Status':{'N':0,'Y':1}
})
print("\ny_train\n",y_train.head(20))
print("\ny_test\n",y_test.head(20))
```

```
y_train
      Max_Loan_Amount  Loan_Status
92             186.69            1
108            302.96            0
278            664.98            1
239             97.08            1
351            581.02            0
410            124.90            0
404            305.03            0
589             67.39            0
472            166.43            1
502            458.65            1
306            203.57            1
82              94.25            0
10             126.56            1
478            553.42            1
```

```
336           229.28            1
215           173.58            1
227           330.43            1
253           176.00            1
500           220.84            1
344           177.62            1

y_test
      Max_Loan_Amount  Loan_Status
428             77.98            1
312             56.35            1
320            160.18            1
398            210.63            1
212            322.46            1
52             143.19            0
5              414.50            1
211            165.87            0
520            128.27            1
140            289.10            0
337            287.84            1
190            176.20            1
388            169.40            1
546             42.31            0
29             223.98            1
534            845.52            1
9              449.00            0
509            598.40            1
494            220.00            0
63             179.23            0
```

[96]:

```
#categorical features are encoded->loan_new
data_new = data_new.replace({
    'Gender' :{'Male':0 , 'Female':1},
    'Married' : {'No':0,'Yes':1},
    'Education':{'Not Graduate':0, 'Graduate':1  },
    'Dependents':{'0':0,'1':1,'2':2,'3+':3  },
    'Property_Area':{'Rural':0 ,'Urban':1 ,'Semiurban':2}
})
print(data_new.head(20))
```

```
    Gender  Married  Dependents  Education  Income  Coapplicant_Income  \
0        0        1           0          1    5720                   0
1        0        1           1          1    3076                1500
2        0        1           2          1    5000                1800
4        0        0           0          0    3276                   0
5        0        1           0          0    2165                3422
6        1        0           1          0    2226                   0
7        0        1           2          0    3881                   0
```

```
8          0        1           2          1   13633                   0
9          0        0           0          0    2400                2400
10         0        0           0          0    3091                   0
11         0        1           1          1    2185                1516
13         0        1           2          1   12173                   0
14         1        0           0          1    4666                   0
15         0        0           1          1    5667                   0
16         0        1           2          1    4583                2916
17         0        1           3          1    3786                 333
18         0        1           0          1    9226                7916
19         0        0           0          1    1300                3470
20         0        1           1          0    1888                1620
21         1        0           3          0    2083                   0

    Loan_Tenor  Credit_History  Property_Area
0        144.0             1.0              1
1        144.0             1.0              1
2        144.0             1.0              1
4        144.0             1.0              1
5        144.0             1.0              1
6        144.0             1.0              2
7        144.0             0.0              0
8         96.0             1.0              1
9        144.0             1.0              2
10       144.0             1.0              1
11       144.0             1.0              2
13       144.0             0.0              2
14       144.0             1.0              2
15       144.0             1.0              1
16       144.0             1.0              1
17       144.0             1.0              2
18       144.0             1.0              1
19        72.0             1.0              2
20       144.0             1.0              1
21        72.0             1.0              1
```

[97]:

```
#numerical features are standardized ->loan_old
cols_to_standardize_data = ['Income','Coapplicant_Income','Loan_Tenor']
scaler = StandardScaler()
scaler.fit(x_train[cols_to_standardize_data])
x_train[cols_to_standardize_data] = scaler.
 ↪transform(x_train[cols_to_standardize_data])  #transform fn turn dp to numpy␣
 ↪so i change y to numpy also
x_test[cols_to_standardize_data] = scaler.
 ↪transform(x_test[cols_to_standardize_data])
```

```
x_train = x_train.to_numpy().reshape(-1,9)
x_test = x_test.to_numpy().reshape(-1,9)
print(y_test.shape)
y_train = y_train.to_numpy().reshape(-1,2)
y_test = y_test.to_numpy()
y_test_logistic = y_test[:,1]
x_test , x_train
x_predict = x_predict.to_numpy()
print("\n x_train\n",x_train)
print("\n x_test\n",x_test)
#loan_new ->numerical features are standardized
cols_to_standardize_data = ['Income','Coapplicant_Income','Loan_Tenor']
scaler.fit(data_new[cols_to_standardize_data])
data_new[cols_to_standardize_data] = scaler.
 ↪transform(data_new[cols_to_standardize_data])  #transform fn turn dp to␣
 ↪numpy so i change y to numpy also
data_new = data_new.to_numpy().reshape(-1,9)
print("\ndata_new\n",data_new)
```

```
(129, 2)

 x_train
 [[0.         1.         2.         … 0.28947624 1.         1.        ]
 [0.         1.         2.         … 0.28947624 0.         1.        ]
 [0.         1.         0.         … 0.28947624 1.         2.        ]
 …
 [0.         1.         0.         … 0.28947624 0.         1.        ]
 [0.         1.         0.         … 0.28947624 1.         1.        ]
 [0.         1.         1.         … 0.28947624 1.         1.        ]]

 x_test
 [[0.         1.         0.         … 0.28947624 1.         0.        ]
 [1.         0.         0.         … 0.28947624 1.         0.        ]
 [0.         1.         0.         … 0.28947624 1.         2.        ]
 …
 [0.         1.         2.         … 0.28947624 1.         2.        ]
 [0.         1.         2.         … 0.28947624 1.         0.        ]
 [1.         0.         0.         … 0.28947624 1.         0.        ]]

data_new
 [[ 0.          1.          0.         …  0.25159989  1.
   1.        ]
 [ 0.          1.          1.         …  0.25159989  1.
   1.        ]
 [ 0.          1.          2.         …  0.25159989  1.
   1.        ]
 …
```

```
 [ 0.          1.          0.         …  0.25159989  1.
   1.        ]
 [ 0.          1.          0.         …  0.25159989  1.
   0.        ]
 [ 0.          0.          0.         … -2.88065253  1.
   0.        ]]
```

[98]:
```python
y_train_linear = y_train[:,0]
```

[99]:
```python
# linear regression model using sickit learn
linear_regression_model = LinearRegression()
linear_regression_model.fit(x_train, y_train_linear)
```

[99]:
```
LinearRegression()
```

[100]:
```python
linear_regression_model.intercept_
```

[100]:
```
212.75062524201152
```

[101]:
```python
linear_regression_model.coef_
```

[101]:
```
array([-13.86739371,   5.30506888,   2.14816224,  23.02807925,
       121.17792062,  72.403961  ,  55.21041384,   4.82355384,
        -5.02054247])
```

[102]:
```python
# return the predicted y-values for each feature row in the x_test df
linear_model_predictions = linear_regression_model.predict(x_test)
linear_model_predictions
```

[102]:
```
array([ 155.30563892,  125.23058118,  202.14019375,  205.30069032,
        274.21336596,  158.48727963,  353.25170798,  199.82506066,
        164.36128403,  280.13767912,  298.10746037,  175.82737032,
        213.60663821, -119.16717413,  218.45707638,  490.65653418,
        752.85658276,  392.62381924,  237.11231399,  202.99288483,
        236.02221241,  181.1826978 ,  127.37196774,  138.89657413,
        251.52846737,  152.0554506 ,  211.92287571,   99.21450258,
        257.79166279,  163.00657384,  470.19097681,  202.5151763 ,
        143.70615285,  194.78953251,  141.20546177,  148.58912218,
        240.24623636,  134.35917218,  189.17302893,  356.47452141,
        315.45632607,  255.5907149 ,  223.98187492,  200.04465466,
        236.65639908,  154.01220987,  289.17959884,  261.92359462,
        214.96335471,  230.71240225,  132.47313696,    0.9882364 ,
        254.73539758,  204.96033279,  539.22696061,  205.30379645,
        194.77362635,  185.33696257,  183.55274298,  124.64296656,
         29.86052054,  199.0108861 ,  178.99303183,  226.1131583 ,
        133.37381203,  280.79038818,  205.95454791,  244.09882398,
        165.31315195,  247.75716867,  187.93519279,  348.8275082 ,
```

```
        197.55548963,  156.72822865,  133.6956395 ,  238.78558509,
         32.54921673,  187.87792533,  232.56664947,  206.96423079,
        246.13661045,  188.94162322,  188.44679241,  170.98974597,
        286.41912509,  148.12337321,  227.8454886 ,  285.03207537,
        246.0107145 ,  207.81737542,  241.02214956,  153.46413547,
        149.39134704,  151.94968197,  226.03239356,  191.45472975,
        184.41641171,  211.10136101,  147.62531892,   -8.83142897,
        165.7355185 ,  137.05477362,  275.73408147,  315.02820209,
        129.0021195 ,  276.81341316,  194.94230652,  221.85407627,
        332.59326087,  499.48458025,  168.57752998,  121.98890152,
        301.41343913,   69.15559245,   84.71574641,  150.66277022,
        231.47534941,  182.35939855,  160.17247953,  148.51580128,
        155.42277676,  193.06466169,  188.77959461,  470.29286035,
        200.92409022,  132.29850356,  152.85064509,  317.50469318,
        367.69984544])
```

[103]:
```python
# evaluating the model using R^2
y_test_linear = y_test[:,0]
linear_regression_model.score(x_test, y_test_linear)
```

[103]:
```
0.7294339056659824
```

[104]:
```python
# predicting in the new loan data
linear_model_predictions_new = linear_regression_model.predict(data_new)
linear_model_predictions_new
```

[104]:
```
array([ 232.5286667 ,  213.59600339,  274.27735205,  141.67129517,
        224.77269452,   98.0696413 ,  166.94723655,  323.97259991,
        188.73618425,  136.93848776,  186.27787651,  392.06633414,
        181.37145074,  228.01587469,  298.24994842,  194.81189449,
        567.93412008,   43.90305564,  163.9004214 ,  -69.20477651,
        140.31386269,  360.29723249,  826.04644004,  394.46581488,
         57.15898066,  102.36833024,  275.83661556,  211.71442987,
        241.44837434,  204.1246781 ,  151.63185252,  230.65192542,
        230.85503605,  230.11444776,  235.01969089,  255.59132787,
        160.24643007,  165.74144375,  322.86150183,  160.80925041,
        172.15264136,  277.01317635,  203.21341397,  268.37256751,
         53.89728345,  198.57675627,  146.41929787,  161.63061233,
        114.81909063,  251.60508367,   35.43691561,  173.34885854,
        274.74757093,  193.39376355,  167.52919296,  184.47830053,
        267.01588814,  173.56209348,  164.48383052,  277.29214171,
        307.7337659 ,  190.04554766,   46.13870425,  255.98630245,
        290.88097643,  279.17555372,  241.2503401 ,  248.51476471,
        296.44187401,  275.71078943,  220.00971354, 1948.13061697,
        288.759471  ,  307.36451426,   17.41503094,  289.4750193 ,
        237.05496393,  154.30645597,  202.44371273,  201.44097085,
        443.48792423,  272.5659979 ,  235.46221402,  268.82654201,
```

```
233.89989836,  303.9786718 ,  271.59431909,  341.27854187,
199.80522242,  235.64068712,  188.14181979,  -31.70795705,
194.67210787,  213.11532534,  196.29717802,  220.78199608,
183.31573919,  154.43914745,  251.76825931,  345.38319973,
 93.6046307 ,  190.02869901,  218.16087137,  160.83638026,
268.94544342,  226.76439725,  344.13448544,  381.98364644,
195.26442719,  242.35458336,  282.36227336,  -13.42687491,
210.88341426,  172.66193232,  225.97481757,  161.78060648,
 39.11048642,  195.12669673,  210.63458744,  235.67962208,
202.01692285,  154.4857174 ,  254.98648723,   57.06456758,
340.44487234,  136.6507527 ,  280.70582896,  226.8920184 ,
231.82849152,  293.20611818,  202.58633908,  213.82456548,
196.75651822,  219.71646113,  112.89704711,  330.91171658,
263.57111679,  305.48630973,  270.1635955 ,  324.18532202,
146.87346236,  223.71876206,  141.32152528,  106.03979412,
149.13251787,  262.32164832,  204.80046962,  170.67358423,
173.29995378,  187.17160156,  224.88575148,   68.62563599,
182.04866998,  364.3930726 ,  234.87668102,  226.70054992,
268.42484185,  283.46313748,  201.98129549,  303.41120012,
214.85397854,  319.98816314,  402.88686513,  420.08629988,
 46.23591965,  185.34464786,  254.87966919,  199.72322199,
422.64792952,  230.11444776,  201.19427828,  169.01726954,
172.37629023,  184.58276016,  429.22791419,  159.47417669,
221.81220139,  147.31418448,  223.04613599,  290.91730904,
195.58063033,  174.80301072,  127.4493538 ,  292.01597922,
225.35680938,  231.93714738,  146.18621753,  -54.68064601,
359.28903847,  280.79656911,  250.59656097,  225.02208344,
256.8398813 ,  146.04714655,  194.09608215,  132.13099573,
206.38677708,  299.49761075,  233.13152867,  197.30683922,
907.63080601,   -2.23077184,  258.57938035,  183.00941651,
219.24671523,  277.10322991,  664.25917803,  161.18687365,
307.02896859,  156.20229308,  222.87902863,  196.67135306,
204.2390496 ,   92.87713267,  285.63797897,  159.01951103,
-12.19257838,  299.60866235,  167.19782307,  224.89446437,
218.81671026,  154.20277656,  175.4071798 ,  304.56202642,
283.76709485,  217.31192721,  205.57451906,  575.34295691,
206.89731951,  303.47891697,  260.72730377,  263.19280295,
175.65511322,  173.43384881,  278.86323959,  712.39320194,
239.28259378,  146.71841879,  205.02709444,  252.48320608,
 36.65626349,  180.98174387,  195.13119395,  219.12963436,
293.12745741,  694.56395978,  312.19253962,  271.29074495,
208.36911638,  425.68439294,  237.0666818 ,  259.42288485,
146.56392393,  186.91528549,  190.77724433,  250.79966905,
160.30185681,  143.97373485,  200.91314518,  280.21411112,
244.69126592,  169.41794169,  287.38281583,  171.20797006,
267.9663022 ,  321.92347777,  216.83700425,  297.83585174,
223.42595884,  105.74878992,  122.71339341,  186.91941406,
```

```
        191.85030393,  244.74932723,  209.45688255,  146.12709937,
        121.97687262,  642.54163488,  227.64868771,  145.99274761,
        241.18228381,  319.46252106,  232.15125044,  340.76688702,
        228.41876176,  187.77657756,  180.51724379,  146.58521622,
        193.19128872,  142.58980069,  250.48616511,  125.29948461,
        320.22135312,   -8.19820457,  208.58243129,  261.35730159,
        305.8464431 ,  234.1680171 ,  131.23353611,  197.7405887 ,
        106.71628927,  317.23787668,  263.25656023,  339.16360607,
         28.63707054,  324.79693477,  245.42108891,  144.84716601,
        260.98432244,  208.63384364,  227.33101775,  214.57575712,
        293.40826884,  148.33913268])
```

[105]:
```
#define sigmoid function to calculate 1 / 1 + e^ (-z)
def sigmoid(z):
    g = 1 / (1 + np.exp(-z))
    return g
```

[106]:
```
# compute cost function for the logistic regression j(w,b) = 1/m*summation␣
 ↪[loss(f w,b(x^(i))),y^(i)]
# loss function is cost per data point  = -y^(i)*log(fw,b(x^(i))) - (1-y^(i)) *␣
 ↪log(1-fw,b(x^(i)))
def compute_cost_function(X,y,w,b):
    m = X.shape[0]
    cost = 0.0
    for i in range(m):
        z = np.dot(X[i],w)+b
        f_wb_i = sigmoid(z)
        loss = -y[i] * np.log(f_wb_i) - (1-y[i]) * np.log(1-f_wb_i)
        cost+=loss
    cost = cost /m
    return cost
```

[107]:
```
w_tmp = np.array([1,1,1,1,1,1,1,1,1]) # **********delete one 1
print(w_tmp)
b_tmp = -3
print(compute_cost_function(x_train, y_train[:,1], w_tmp, b_tmp))
```

```
[1 1 1 1 1 1 1 1 1]
0.7426850132681208
```

[108]:
```
def compute_gradient(X,y,w,b,lambda_):
    m,n = X.shape
    dj_dw = np.zeros((n,))
    dj_db = 0.0
    for i in range(m):
        z = np.dot(X[i],w)+b
        f_wb_i = sigmoid(z)
```

```
        error = f_wb_i - y[i]
        for j in range(n):
            dj_dw[j] = dj_dw[j] + error * X[i,j]
        dj_db += error
    dj_dw = dj_dw/m
    dj_db = dj_db /m
    for i in range(n):
        dj_dw[i] = dj_dw[i]+(lambda_/m)*w[i]
    return dj_db , dj_dw
```

[109]:

```
# compute gradient descent for logistic regression
def gradient_descent(X, y, w_initial, b_initial, alpha, num_iters):
    #store the cost at each iteration
    old_j = []
    w = copy.deepcopy(w_initial)  #avoid modifying global w within function
    b = b_initial

    for i in range(num_iters):
        #get dj_dw , dj_dw
        dj_db, dj_dw = compute_gradient(X, y, w, b,0.7)

        # Update w, b
        w = w - alpha * dj_dw
        b = b - alpha * dj_db

        # Save cost J at each iteration
        if i<100000:      #get only the first 100000 value of the cost j
            old_j.append( compute_cost_function(X, y, w, b) )

        #print cost at every 20 interval to see the progress
        if i% math.ceil(num_iters / 20) == 0:
            print(f"Iteration {i:4d}: Cost {old_j[-1]}   ")

    return w, b, old_j
```

[110]:

```
import copy
import math
# w_tmp = np.array([2.,3.])
# X_tmp = np.array([[0.5, 1.5], [1,1], [1.5, 0.5], [3, 0.5], [2, 2], [1, 2.5]])
# y_tmp = np.array([0, 0, 0, 1, 1, 1])
w_tmp = np.zeros(9)# *******make it 9 instead of 10
new_array = y_train[:, 1]  # Remove the reshape operation
print(w_tmp)
b_tmp = 1.
dj_db_tmp, dj_dw_tmp = compute_gradient(x_train, new_array, w_tmp, b_tmp, 0.7)
print(f"dj_db: {dj_db_tmp}" )
print(f"dj_dw: {dj_dw_tmp.tolist()}" )
```

```
w,b,j = gradient_descent(x_train,new_array,w_tmp,b_tmp,0.1,1000)
print(w)
print(b)
```

```
[0. 0. 0. 0. 0. 0. 0. 0. 0.]
dj_db: 0.020121078630005004
dj_dw: [0.011767728153516455, -0.015932149198147717, 0.013058621997608206,
-0.005476300008667928, -0.013198721496750861, 0.0016810155722760609,
-0.006784599403490289, -0.06064727055947475, -0.041550512956765255]
Iteration    0: Cost 0.6016699912457534
Iteration   50: Cost 0.5799873919258072
Iteration  100: Cost 0.5641257581917023
Iteration  150: Cost 0.5510580712255222
Iteration  200: Cost 0.5400687990897405
Iteration  250: Cost 0.5307552821889933
Iteration  300: Cost 0.5228142604128393
Iteration  350: Cost 0.5160030416228987
Iteration  400: Cost 0.5101258186988665
Iteration  450: Cost 0.5050245367996083
Iteration  500: Cost 0.5005714907312828
Iteration  550: Cost 0.4966632376067535
Iteration  600: Cost 0.49321566558541957
Iteration  650: Cost 0.4901600539173026
Iteration  700: Cost 0.48743995268204515
Iteration  750: Cost 0.48500872297022396
Iteration  800: Cost 0.48282760062375346
Iteration  850: Cost 0.4808641711407589
Iteration  900: Cost 0.47909116592608103
Iteration  950: Cost 0.4774855092409634
[-0.45851224  0.27640032 -0.07061178  0.03839925  0.08954305 -0.04205998
  0.04243122  2.06577239  0.4073778 ]
-1.247873494340398
```

[111]:

```
#predict function to predict if an entered user would get a loan or not
def predict_logistic(X, w, b):
    # number of training examples
    m, n = X.shape
    p = np.zeros(m)
    for i in range(m):
        z_wb = np.dot(X[i],w)
        z_wb += b
        f_wb = sigmoid(z_wb)
        p[i] = 1 if f_wb>0.5 else 0
    return p
```

[112]:

```
tmp_p = predict_logistic(x_predict,w, b)
print(f'Output of predict: shape {tmp_p.shape}, value {tmp_p}')
```

```
Output of predict: shape (314,), value [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
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 1. 1.]

C:\Users\heba\AppData\Local\Temp\ipykernel_18980\1802866382.py:3:
RuntimeWarning: overflow encountered in exp
  g = 1 / (1 + np.exp(-z))
```

[113]:
```python
print(x_test.shape)
prediction = predict_logistic(x_test,w,b)
print(prediction.shape)
print(y_test.shape)
print('Train Accuracy: %f'%(np.mean(prediction == y_test_logistic) * 100))
```

```
(129, 9)
(129,)
(129, 2)
Train Accuracy: 80.620155
```

[ ]:

[ ]: