## In [3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

## In [57]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\C8_loan-test.csv")
a
```

## Out[57]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	C
0	LP001015	Male	Yes	0	Graduate	No	5720	
1	LP001022	Male	Yes	1	Graduate	No	3076	
2	LP001031	Male	Yes	2	Graduate	No	5000	
3	LP001035	Male	Yes	2	Graduate	No	2340	
4	LP001051	Male	No	0	Not Graduate	No	3276	
362	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	
363	LP002975	Male	Yes	0	Graduate	No	4158	
364	LP002980	Male	No	0	Graduate	No	3250	
365	LP002986	Male	Yes	0	Graduate	No	5000	
366	LP002989	Male	No	0	Graduate	Yes	9200	
207								

#### 367 rows × 12 columns

## In [58]:

from sklearn.linear\_model import LogisticRegression

## In [61]:

```
a=a.head(10)
a
```

## Out[61]:

Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Ter
Graduate	No	5720	0	110.0	360
Graduate	No	3076	1500	126.0	360
Graduate	No	5000	1800	208.0	360
Graduate	No	2340	2546	100.0	360
Not Graduate	No	3276	0	78.0	360
Not Graduate	Yes	2165	3422	152.0	360
Not Graduate	No	2226	0	59.0	360
Not Graduate	No	3881	0	147.0	360
Graduate	NaN	13633	0	280.0	240
Not Graduate	No	2400	2400	123.0	360
4					<b>&gt;</b>

## In [62]:

```
a.columns
```

## Out[62]:

```
In [64]:
b=a[['Dependents', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
        'Loan_Amount_Term']]
b
Out[64]:
   Dependents ApplicantIncome CoapplicantIncome LoanAmount Loan_Amount_Term
 0
            0
                         5720
                                               0
                                                        110.0
                                                                           360.0
 1
             1
                         3076
                                            1500
                                                        126.0
                                                                           360.0
                         5000
                                                                           360.0
 2
            2
                                            1800
                                                        208.0
 3
            2
                                                                           360.0
                         2340
                                            2546
                                                        100.0
```

0

0

0

0

2400

3422

78.0

152.0

59.0

147.0

280.0

123.0

360.0

360.0

360.0

360.0

240.0

360.0

## In [65]:

4

5

6

7

8

9

0

0

1

2

2

0

3276

2165

2226

3881

13633

2400

```
c=b.iloc[:,0:11]
d=a.iloc[:,-1]
```

#### In [66]:

```
c.shape
```

#### Out[66]:

(10, 5)

### In [67]:

d.shape

#### Out[67]:

(10,)

#### In [68]:

```
from sklearn.preprocessing import StandardScaler
```

## In [69]:

```
fs=StandardScaler().fit_transform(c)
```

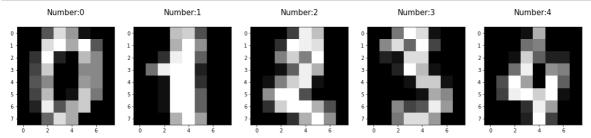
```
In [70]:
logr=LogisticRegression()
logr.fit(fs,d)
Out[70]:
LogisticRegression()
In [71]:
e=[[2,5,77,5,7]]
In [72]:
prediction=logr.predict(e)
prediction
Out[72]:
array(['Urban'], dtype=object)
In [73]:
logr.classes_
Out[73]:
array(['Rural', 'Semiurban', 'Urban'], dtype=object)
In [74]:
logr.predict_proba(e)[0][0]
Out[74]:
3.893396859975968e-31
In [75]:
logr.predict_proba(e)[0][1]
Out[75]:
6.319103730318476e-12
In [76]:
import re
from sklearn.datasets import load_digits
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

## In [77]:

```
digits=load_digits()
digits
  '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.],
         [0., 3., 15., ..., 11., 8., 0.],
         . . . ,
         [0., 4., 11., ..., 12., 7., 0.],
         [0., 2., 14., ..., 12., 0., 0.],
```

#### In [78]:

```
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)
```



#### In [79]:

x\_train,x\_test,y\_train,y\_test=train\_test\_split(digits.data,digits.target,test\_size=0.30)

#### In [80]:

```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)

(1257, 64)
```

```
(540, 64)
(1257,)
(540,)
```

```
In [81]:
```

```
logre=LogisticRegression(max_iter=10000)
logre.fit(x_train,y_train)
```

#### Out[81]:

LogisticRegression(max\_iter=10000)

### In [82]:

```
logre.predict(x_test)
```

#### Out[82]:

```
array([1, 1, 9, 9, 0, 2, 3, 3, 9, 0, 3, 9, 3, 5, 4, 0, 9, 8, 7, 3, 4, 8,
       5, 5, 7, 7, 3, 7, 5, 3, 9, 9, 7, 7, 5, 5, 5, 9, 5, 2, 6, 0, 7, 4,
      4, 0, 5, 6, 3, 6, 8, 6, 2, 3, 1, 7, 2, 0, 3, 1, 8, 4, 6, 3, 8, 2,
       1, 4, 7, 9, 8, 5, 4, 8, 5, 1, 1, 4, 5, 2, 2, 7, 9, 9, 8, 5, 6, 1,
      0, 7, 9, 5, 1, 8, 3, 7, 0, 4, 3, 6, 1, 3, 6, 0, 3, 9, 1, 8, 5, 8,
       5, 0, 0, 7, 6, 7, 4, 0, 4, 5, 7, 9, 6, 8, 6, 8, 2, 2, 1, 0, 1, 6,
      4, 3, 3, 6, 4, 4, 2, 1, 8, 2, 5, 8, 5, 3, 7, 7, 0, 3, 0, 2, 4, 2,
       3, 1, 8, 1, 6, 4, 9, 5, 4, 2, 8, 0, 4, 5, 6, 0, 4, 1, 3, 9, 8, 3,
      9, 0, 4, 0, 9, 1, 4, 0, 6, 6, 1, 1, 7, 8, 0, 0, 8, 7, 7, 8, 1, 2,
       2, 1, 3, 1, 6, 0, 3, 7, 1, 4, 4, 7, 9, 8, 0, 8, 0, 5, 2, 6, 6, 4,
      6, 1, 8, 9, 7, 7, 7, 5, 7, 5, 4, 8, 5, 6, 6, 0, 3, 7, 3, 7, 2, 6,
      9, 6, 8, 9, 1, 9, 7, 8, 3, 5, 3, 3, 0, 6, 4, 7, 4, 2, 2, 5, 0, 6,
      7, 8, 3, 6, 7, 5, 6, 2, 7, 9, 0, 1, 7, 7, 3, 7, 6, 8, 7, 0, 6, 0,
      7, 8, 6, 0, 5, 5, 8, 9, 2, 4, 0, 1, 5, 5, 4, 8, 9, 1, 0, 4, 8, 7,
       2, 0, 7, 4, 1, 9, 3, 2, 1, 8, 7, 8, 3, 3, 0, 5, 9, 4, 5, 5, 6, 2,
      0, 4, 1, 8, 9, 5, 4, 1, 7, 6, 3, 1, 8, 4, 3, 8, 9, 9, 1, 7, 0, 5,
       2, 1, 5, 5, 6, 6, 3, 7, 5, 7, 9, 9, 7, 0, 1, 4, 0, 4, 1, 9, 2, 9,
      4, 6, 8, 8, 6, 3, 4, 7, 4, 2, 7, 9, 7, 4, 8, 9, 0, 1, 4, 9, 4, 7,
      5, 1, 6, 1, 7, 4, 4, 3, 3, 1, 4, 8, 9, 0, 6, 9, 0, 2, 4, 9, 2, 3,
      4, 7, 0, 8, 1, 3, 1, 3, 3, 4, 9, 7, 6, 6, 1, 3, 0, 8, 2, 2, 1, 9,
      2, 3, 9, 4, 2, 2, 2, 8, 5, 8, 5, 1, 7, 0, 8, 0, 0, 5, 4, 5, 2, 8,
      1, 4, 8, 2, 1, 3, 7, 9, 0, 9, 5, 9, 6, 9, 4, 1, 2, 3, 9, 6, 0, 2,
      4, 3, 2, 1, 5, 3, 1, 3, 6, 2, 3, 9, 7, 7, 5, 1, 8, 5, 1, 0, 5, 6,
      7, 5, 3, 3, 4, 1, 2, 3, 2, 6, 4, 2, 5, 6, 8, 4, 6, 0, 4, 2, 1, 6,
      1, 9, 2, 3, 6, 4, 8, 6, 0, 7, 3, 5])
```

#### In [83]:

```
logre.score(x_test,y_test)
```

#### Out[83]:

0.9537037037037037

#### In [84]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

# In [90]:

```
b=a.head(10)
b
```

## Out[90]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coal
0	LP001015	Male	Yes	0	Graduate	No	5720	
1	LP001022	Male	Yes	1	Graduate	No	3076	
2	LP001031	Male	Yes	2	Graduate	No	5000	
3	LP001035	Male	Yes	2	Graduate	No	2340	
4	LP001051	Male	No	0	Not Graduate	No	3276	
5	LP001054	Male	Yes	0	Not Graduate	Yes	2165	
6	LP001055	Female	No	1	Not Graduate	No	2226	
7	LP001056	Male	Yes	2	Not Graduate	No	3881	
8	LP001059	Male	Yes	2	Graduate	NaN	13633	
9	LP001067	Male	No	0	Not Graduate	No	2400	
4.6								

# In [91]:

# Out[91]:

	Dependents	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Prope
0	0	5720	0	110.0	360.0	
1	1	3076	1500	126.0	360.0	
2	2	5000	1800	208.0	360.0	
3	2	2340	2546	100.0	360.0	
4	0	3276	0	78.0	360.0	
5	0	2165	3422	152.0	360.0	
6	1	2226	0	59.0	360.0	S
7	2	3881	0	147.0	360.0	
8	2	13633	0	280.0	240.0	
9	0	2400	2400	123.0	360.0	S
4 6						

```
In [92]:
b['Property_Area'].value_counts()
Out[92]:
Urban
              7
              2
Semiurban
Rural
              1
Name: Property_Area, dtype: int64
In [93]:
x=b.drop('Property_Area',axis=1)
y=b['Property_Area']
In [116]:
g1={"Property_Area":{'Urban':1,'Semiurban ':2,'Rural':3}}
b=b.replace(g1)
print(b)
               ApplicantIncome CoapplicantIncome
  Dependents
                                                      LoanAmount
0
           0
                           5720
                                                           110.0
1
            1
                           3076
                                               1500
                                                           126.0
            2
2
                           5000
                                               1800
                                                           208.0
3
            2
                           2340
                                               2546
                                                           100.0
4
            0
                           3276
                                                  0
                                                            78.0
5
            0
                                               3422
                           2165
                                                           152.0
6
            1
                           2226
                                                  0
                                                            59.0
7
            2
                                                           147.0
                           3881
                                                  0
8
            2
                          13633
                                                  0
                                                           280.0
9
            0
                           2400
                                               2400
                                                           123.0
   Loan_Amount_Term Property_Area
0
               360.0
                                  1
1
               360.0
                                  1
2
               360.0
                                  1
3
               360.0
                                  1
4
                                  1
               360.0
5
               360.0
                                  1
6
               360.0
                          Semiurban
7
               360.0
                                  3
8
               240.0
                                  1
9
               360.0
                          Semiurban
In [117]:
from sklearn.model_selection import train_test_split
```

#### In [118]:

from sklearn.ensemble import RandomForestClassifier

x\_train,x\_test,y\_train,y\_test=train\_test\_split(x,y,train\_size=0.70)

```
In [119]:
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
Out[119]:
RandomForestClassifier()
In [120]:
parameters={'max_depth':[1,2,3,4,5],
           'min samples leaf':[5,10,15,20,25],
           'n_estimators':[10,20,30,40,50]}
In [121]:
from sklearn.model_selection import GridSearchCV
In [122]:
grid_search=GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:666: UserWarning: The least populated class in y has only 1 members, wh
ich is less than n_splits=2.
  warnings.warn(("The least populated class in y has only %d"
Out[122]:
GridSearchCV(cv=2, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 2, 3, 4, 5],
                          'min_samples_leaf': [5, 10, 15, 20, 25],
                          'n_estimators': [10, 20, 30, 40, 50]},
             scoring='accuracy')
In [123]:
grid_search.best_score_
Out[123]:
0.75
In [124]:
rfc_best=grid_search.best_estimator_
In [125]:
from sklearn.tree import plot_tree
```

```
In [127]:
```

```
plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes','No','5'],fi
```

#### Out[127]:

```
[Text(2232.0, 1087.2, 'gini = 0.449\nsamples = 6\nvalue = [1, 1, 5]\nclass = 5')]
```

```
In [ ]:
```