LOAN PREDICTION

This project use some basic imformation of a person like sallary, no of dependants , age, gender and on the bases of it it will try to predict the whether the loan application of the person would accept or not ?

1. Importing libraries

In [1]:

```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statistics import median
from statistics import mode
from statistics import mean
from statistics import stdev
```

2. Importing Data

In [2]:

```
#import data
data = pd.read_csv("train.csv")
data1 = pd.read_csv("test.csv")
```

3.Unserstanding The data

In [3]:

```
print(data.head())

sz=data.shape


Z=data1.shape
print(sz)
print (Z)
```

```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term
\
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
(614, 13)
(367, 12)
```

In [4]:

```
data.describe()
```

Out[4]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

From all the above outputs we can understand that the data have 13 features and 614 samples from which some of features are catagorials ie. gender , married or not , self employed or not etc... while some of them are non catagorial ie income ,loan amount etc

4. Preprocessing of the Data

4.1 Replacing Missing Values in data

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

from the above output we can see that the data have many missing values so wee need to clean all the missing values

In [6]:

```
#checking count of each catagories in gender column
data['Gender'].value_counts()
```

Out[6]:

```
Male      489
Female    112
Name: Gender, dtype: int64
```

as from the above information we can see most of the values in our data are of male catagories so we can replace missing values with male

In [7]:

```
#relacing null values in gender column with male
data['Gender']=data['Gender'].fillna('Male')
```

In [8]:

```
#checking count of each catagories in Maried column
data['Married'].value_counts()
```

Out[8]:

```
Yes    398
No     213
Name: Married, dtype: int64
```

as from the above information we can see most of the values in our data are of married catagories so we can replace missing values with Yes

In [9]:

```
#repalcing null values in Married column with yes
data['Married']=data['Married'].fillna('Yes')
```

In [10]:

```
#checking count of each catagories in Maried column
data['Dependents'].value_counts()
```

Out[10]:

```
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
```

as from the above information we can see most of the values in our data are of 0 dependent catagories so we can replace missing values with 0

In [11]:

```
#repalcing null values in Married column with yes
data['Dependents']=data['Dependents'].fillna('0')
```

In [12]:

```
#checking count of each catagories in Maried column
data['Self_Employed'].value_counts()
```

Out[12]:

```
No     500
Yes     82
Name: Self_Employed, dtype: int64
```

As from the above observation we can see all most of the values are of not self employed catagories so we can replace all the missing values with not self employed

In [13]:

```
#repalcing null values in Married column with yes
data['Self_Employed']=data['Self_Employed'].fillna('No')
```

In [14]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             614 non-null    object 
 2   Married            614 non-null    object 
 3   Dependents         614 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      614 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

As we can see we have replaced all the missing values with Dtype = object .

Now we need to replace all the float type values.as they are of float type they can have a wide range of values so we cannot replace them with the help of frequency wise

we will relalce all the values with mean/median of the variable

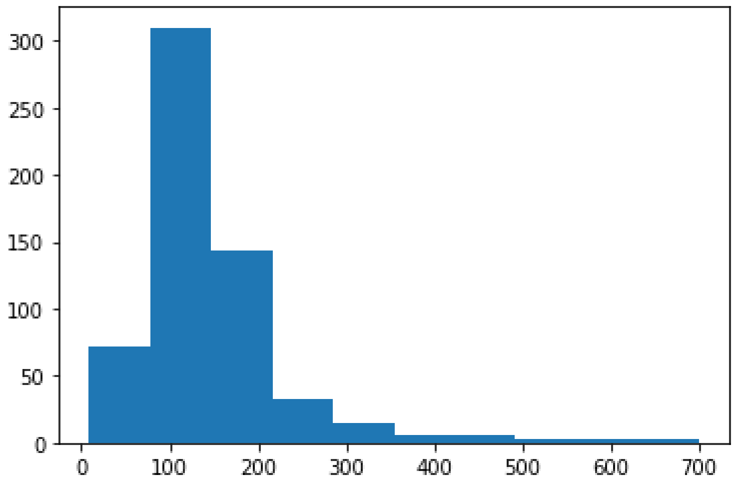
In [15]:

```
#visulising distribution of the loan ammount
plt.hist(data['LoanAmount'])
```

```
/home/kapil/anaconda3/lib/python3.7/site-packages/numpy/lib/histogra
ms.py:839: RuntimeWarning: invalid value encountered in greater_equa
l
  keep = (tmp_a >= first_edge)
/home/kapil/anaconda3/lib/python3.7/site-packages/numpy/lib/histogra
ms.py:840: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

Out[15]:

```
(array([ 72., 310., 143.,  33.,  15.,   6.,   5.,   3.,   3.,
2.]),
 array([  9. ,  78.1, 147.2, 216.3, 285.4, 354.5, 423.6, 492.7, 561.
8,
        630.9, 700. ]),
 <a list of 10 Patch objects>)
```



as we can see most of the data (loan ammount) is left skewed . so any data with high value can affect the value very much so we will replace the missing value with the median of the data

In [16]:

```
#calculating median of non null values
median_data = data['LoanAmount'].isnull()
d1=data['LoanAmount'][median_data==False ]
print(d1.shape)
medd = median(d1)
print(medd)
data['LoanAmount']=data['LoanAmount'].fillna(medd)
```

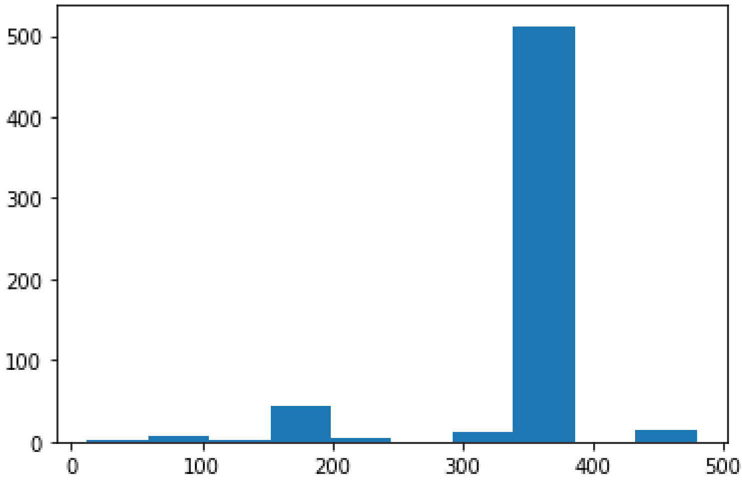
```
(592,)
128.0
```

In [17]:

```
#Loan_Amount_Term
#visulising distribution of the Loan_Amount_Term

plt.hist(data['Loan_Amount_Term'])
```

Out[17]:

```
(array([  3.,   6.,   3.,  44.,   4.,   0.,  13., 512.,   0.,  1
5.]),
 array([ 12. ,  58.8, 105.6, 152.4, 199.2, 246. , 292.8, 339.6, 386.
4,
        433.2, 480. ]),
 <a list of 10 Patch objects>)
```



as we can see most of the data points have a same term period so we can repalce the missing values with mode of the data

In [18]:

```
mdd = mode(data['Loan_Amount_Term'])
print(mdd)
data['Loan_Amount_Term'] = data['Loan_Amount_Term'].fillna(mdd)
```

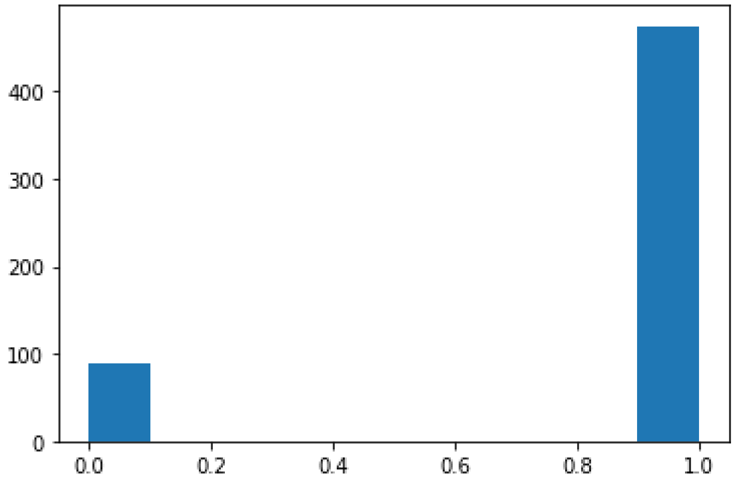
```
360.0
```

In [19]:

```
plt.hist(data['Credit_History'])
```

Out[19]:

```
(array([ 89.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0., 47
5.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <a list of 10 Patch objects>)
```



As from the above plot we can see it is a catagorial variable so we will check value count

In [20]:

```
data['Credit_History'].value_counts()
```

Out[20]:

```
1.0    475
0.0     89
Name: Credit_History, dtype: int64
```

from the above value count we can see most of the credit history data have value equals to 1

so we will replace missing value with 1

In [21]:

```
data['Credit_History'] = data['Credit_History'].fillna(1.0)
```

In [22]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             614 non-null    object 
 2   Married            614 non-null    object 
 3   Dependents         614 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      614 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         614 non-null    float64
 9   Loan_Amount_Term   614 non-null    float64
 10  Credit_History     614 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

As from the above information we conclude that we have replaced all the null values with appropiate data using diffrent statistical technics

Now we will convert all the catagorial variable into numerical values

4.2 Handling Catagorial Variables

As we have many catagororial data like gender, married or not etc... these data cannot be used directly to over model because as a machine learning prediction model we have to dealt with numerical values so we need convert all catagorial variables into numerical values.

In [23]:

```
data['Male']=pd.get_dummies(data['Gender'],drop_first='True')
#print(data['Male'])
data['IsMarried']=pd.get_dummies(data['Married'],drop_first='True')
#print(data['IsMarried'])
#print(data['Married'])
data['IsEducation']=pd.get_dummies(data['Education'],drop_first='True')
data['IsSelf_Employed']=pd.get_dummies(data['Self_Employed'],drop_first='True')
df = pd.get_dummies(data['Property_Area'],drop_first='True')
#print(df)
data['Loan_Status']=pd.get_dummies(data['Loan_Status'],drop_first='True')
data['IsSemiurban']=df['Semiurban']
data['IsUrban']=df['Urban']
```

As the Dependents is a quantative variable we can convert 0 to 0 , 1 to 1 2 to 2 and 3+ with 3

In [24]:

```
def get_value(X):
    y = []
    for i in range (0,614):
        if(X[i]=='0'):
            y.append(0)
        if(X[i]=='1'):
            y.append(1)
        if(X[i]=='2'):
            y.append(2)
        if(X[i]=='3+'):
            y.append(3)
    return y

dt = get_value(data['Dependents'])
print(dt)
data['no_of_Dependent']=dt
```

```
[0, 1, 0, 0, 0, 2, 0, 3, 2, 1, 2, 2, 2, 0, 2, 0, 1, 0, 0, 0, 0, 1,
0, 2, 1, 0, 0, 2, 0, 2, 1, 0, 1, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 1, 0, 0, 0, 0, 0, 0, 2, 1, 2, 0, 0, 1, 2, 0, 3, 0, 1, 0, 0, 0, 1,
3, 0, 0, 2, 0, 3, 3, 0, 0, 1, 3, 3, 0, 1, 2, 0, 1, 0, 2, 0, 0, 0, 0,
2, 2, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 1, 2, 0, 2, 3, 0, 0, 0, 1,
0, 1, 0, 1, 0, 0, 0, 0, 0, 2, 0, 0, 3, 0, 1, 0, 0, 0, 0, 0, 0, 3, 0,
2, 0, 2, 2, 0, 0, 0, 2, 0, 2, 1, 0, 0, 0, 0, 0, 2, 0, 3, 1, 1, 0, 0,
0, 0, 1, 2, 0, 0, 0, 0, 0, 2, 0, 3, 3, 0, 0, 0, 2, 3, 1, 0, 1, 0, 0,
1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 2, 3, 1, 2, 0,
0, 0, 0, 0, 0, 3, 1, 3, 0, 3, 0, 0, 2, 2, 0, 2, 0, 0, 0, 0, 0, 2, 0,
0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 2, 1, 0, 2, 0, 0, 2, 1, 1, 0, 0, 2,
0, 1, 0, 3, 0, 3, 0, 3, 1, 0, 1, 0, 0, 0, 2, 3, 0, 1, 0, 0, 0, 0, 2,
1, 0, 0, 0, 0, 1, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 0, 0, 3, 1, 1,
0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 2, 0, 0, 0, 2, 0, 1, 2, 0, 1, 1, 0,
3, 2, 0, 3, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 2, 3, 0, 3, 0, 1, 3,
2, 0, 0, 2, 0, 0, 0, 0, 3, 0, 0, 0, 2, 1, 0, 3, 1, 2, 0, 0, 0, 0, 0,
0, 1, 0, 0, 2, 2, 1, 0, 0, 3, 0, 0, 2, 0, 0, 0, 0, 2, 1, 0, 0, 0, 0,
3, 3, 0, 2, 2, 2, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 1, 3, 1, 0, 0,
0, 0, 0, 1, 2, 0, 0, 0, 0, 0, 1, 0, 0, 1, 2, 0, 0, 1, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 3, 1, 0, 1, 2, 0, 2, 1, 2, 2, 0, 0, 0, 2, 0, 0, 2,
0, 0, 3, 0, 1, 0, 0, 3, 0, 2, 0, 1, 1, 3, 0, 2, 2, 2, 2, 1, 2, 0, 3,
0, 0, 2, 1, 2, 1, 2, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 2, 1, 0,
2, 0, 0, 0, 1, 0, 1, 2, 0, 0, 3, 2, 0, 0, 0, 2, 0, 3, 2, 0, 2, 0, 1,
1, 0, 0, 3, 2, 1, 0, 0, 0, 2, 0, 3, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 2,
1, 1, 0, 0, 1, 0, 3, 0, 0, 2, 1, 0, 0, 2, 0, 0, 3, 0, 0, 1, 0, 2, 2,
3, 2, 0, 0, 1, 0, 2, 0, 0, 1, 1, 1, 0, 0, 0, 2, 0, 2, 3, 0, 0, 0, 2,
0, 0, 2, 3, 0, 3, 0, 1, 0, 1, 2, 0, 0, 3, 1, 2, 0]
```

In [25]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 20 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             614 non-null    object 
 2   Married            614 non-null    object 
 3   Dependents         614 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      614 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         614 non-null    float64
 9   Loan_Amount_Term   614 non-null    float64
 10  Credit_History     614 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    uint8  
 13  Male               614 non-null    uint8  
 14  IsMarried          614 non-null    uint8  
 15  IsEducation        614 non-null    uint8  
 16  IsSelf_Employed    614 non-null    uint8  
 17  IsSemiurban        614 non-null    uint8  
 18  IsUrban            614 non-null    uint8  
 19  no_of_Dependent    614 non-null    int64  
dtypes: float64(4), int64(2), object(7), uint8(7)
memory usage: 66.7+ KB
```

In [26]:

```
data.head()
```

Out[26]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Co
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

In [27]:

```
data.shape
```

Out[27]:

```
(614, 20)
```

As we done with all the column and replacing all the missing values , converting catagorial variable into appropiate format we can do further analysis easily

4.3 Removing the unnecessary variables

As we have already convert Gender , Married , dependents,Education,Self_employed,property_area we can drop the following data

In [28]:

```
X=data.drop(['Loan_ID','Gender','Married','Dependents','Education','Self_Employe
d','Property_Area','Loan_Status'],axis=1)
y=data['Loan_Status']
```

In [29]:

```
X.head()
```

Out[29]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Ma
0	5849	0.0	128.0	360.0	1.0	
1	4583	1508.0	128.0	360.0	1.0	
2	3000	0.0	66.0	360.0	1.0	
3	2583	2358.0	120.0	360.0	1.0	
4	6000	0.0	141.0	360.0	1.0	

In [30]:

```
X.shape
```

Out[30]:

```
(614, 12)
```

4.4 Standard Scaler

As in the given data all the the data have various range so need to convert the data into its standard scaling such that we can make uniform model and any variable can not take advantage on other variables

In [31]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   ApplicantIncome    614 non-null    int64  
 1   CoapplicantIncome  614 non-null    float64
 2   LoanAmount         614 non-null    float64
 3   Loan_Amount_Term   614 non-null    float64
 4   Credit_History     614 non-null    float64
 5   Male               614 non-null    uint8  
 6   IsMarried          614 non-null    uint8  
 7   IsEducation        614 non-null    uint8  
 8   IsSelf_Employed    614 non-null    uint8  
 9   IsSemiurban        614 non-null    uint8  
 10  IsUrban            614 non-null    uint8  
 11  no_of_Dependent    614 non-null    int64  
dtypes: float64(4), int64(2), uint8(6)
memory usage: 32.5 KB
```

In [32]:

```
X.describe()
```

Out[32]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	145.752443	342.410423	0.855049
std	6109.041673	2926.248369	84.107233	64.428629	0.352339
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.250000	360.000000	1.000000
50%	3812.500000	1188.500000	128.000000	360.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

from the above discription we can see that we need to scale only the Applicantincome, CoApplicantincome, Loanammount , Loan_amount_trm

In [33]:

```
# scandard scaling  fnction by x = (x-xmin)/(xmax-xmin)
def standardised_1(A):
    mi = min(A)
    ma = max(A)
    P = (A-mi)/(ma-mi)
    return P
    #print(P,A)
    #print(mi,ma)
standardised_1(data['ApplicantIncome'])
```

Out[33]:

```
0      0.070489
1      0.054830
2      0.035250
3      0.030093
4      0.072356
         ...
609    0.034014
610    0.048930
611    0.097984
612    0.091936
613    0.054830
Name: ApplicantIncome, Length: 614, dtype: float64
```

In [34]:

```
# scandard scaling  fnction by x = (x-xmean)/sigma
def standardised_2(A):
    me = mean(A)
    sigma = stdev(A)
    P= (A-me)/sigma
    return P
```

In [35]:

```
X['ApplicantIncome']=standardised_1(data['ApplicantIncome'])
X['CoapplicantIncome']=standardised_1(data['CoapplicantIncome'])
X['LoanAmount']=standardised_1(data['LoanAmount'])
X['Loan_Amount_Term']=standardised_1(data['Loan_Amount_Term'])
X['no_of_Dependent']=standardised_1(X['no_of_Dependent'])
```

In [36]:

```
X.describe()
```

Out[36]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	0.064978	0.038910	0.197905	0.706005	0.855049
std	0.075560	0.070229	0.121718	0.137668	0.352339
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.033735	0.000000	0.132055	0.743590	1.000000
50%	0.045300	0.028524	0.172214	0.743590	1.000000
75%	0.069821	0.055134	0.225398	0.743590	1.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

As we convert all the variable in range of 0 to 1

5.Visulising Data

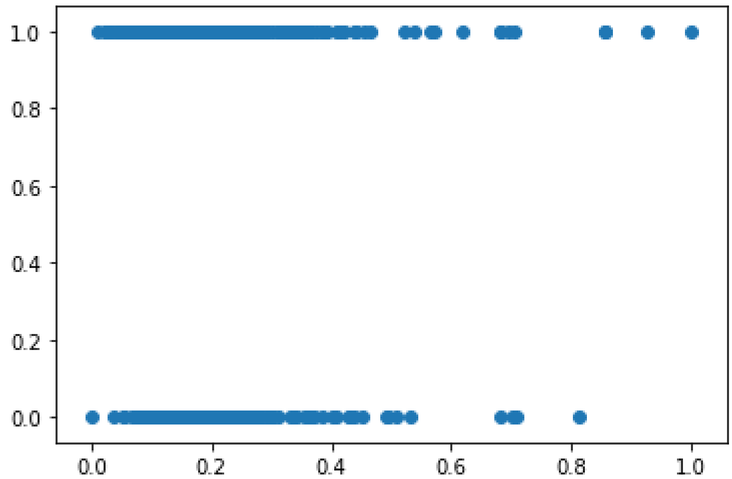
Now we are going to visulising the data such that we can get the relation between diffrent features of datasets and the output variable

In [37]:

```
#visulising Loan amount
plt.scatter(X['LoanAmount'],y)
```

Out[37]:

```
<matplotlib.collections.PathCollection at 0x7fb19ab31110>
```



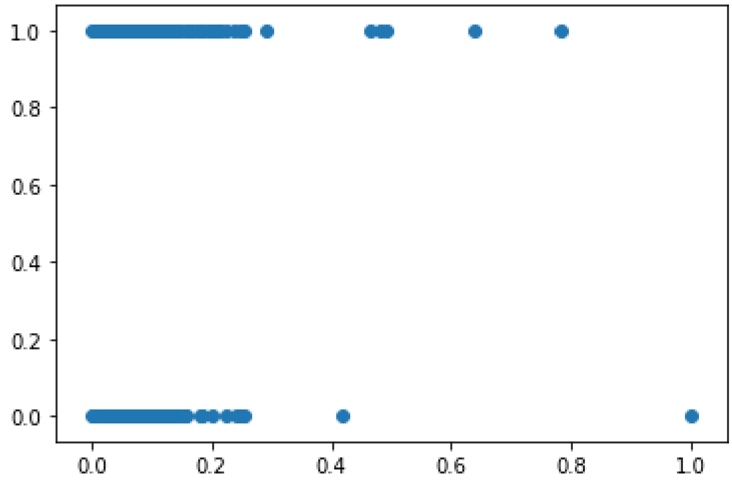
from the above plot we can see that the data have very mix behaviour both the small and big ammount data get accepted and rejected we didnt get any pattern from the above plot

In [38]:

```
#visulisng Applicant Income
plt.scatter(X['ApplicantIncome'],y)
```

Out[38]:

```
<matplotlib.collections.PathCollection at 0x7fb19ab49c10>
```



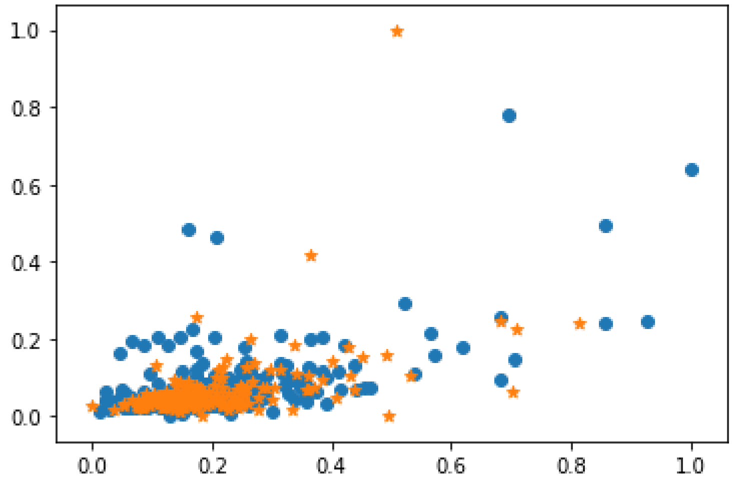
from the above plot we can see that the data have very mix behaviour both the small and big ammount data get accepted and rejected we didnt get any pattern from the above plot

In [39]:

```
plt.scatter(X['LoanAmount'][y==1],X['ApplicantIncome'][y==1] )
plt.scatter(X['LoanAmount'][y==0],X['ApplicantIncome'][y==0] ,marker = '*')
```

Out[39]:

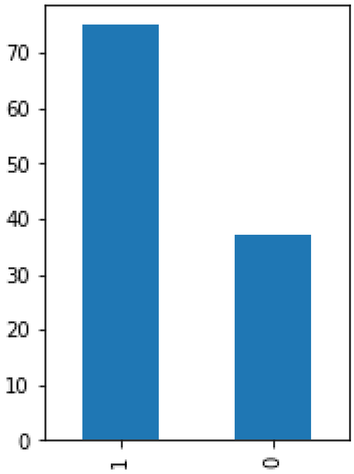
```
<matplotlib.collections.PathCollection at 0x7fb19aa78810>
```

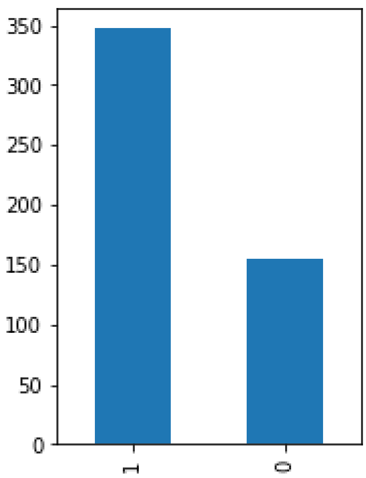


from the above plot we can see that most of the loan ammount is directly praposnal to their income

In [40]:

```
# visulisng the male female feature
plt.subplot(121)
y[data['Male']==0].value_counts().plot(kind='bar')
#y.value_counts()[data['Male']==0].plot(kind='bar')
plt.show()

plt.subplot(121)
y[data['Male']==1].value_counts().plot(kind='bar')
#y.value_counts()[data['Male']==0].plot(kind='bar')
plt.show()
```

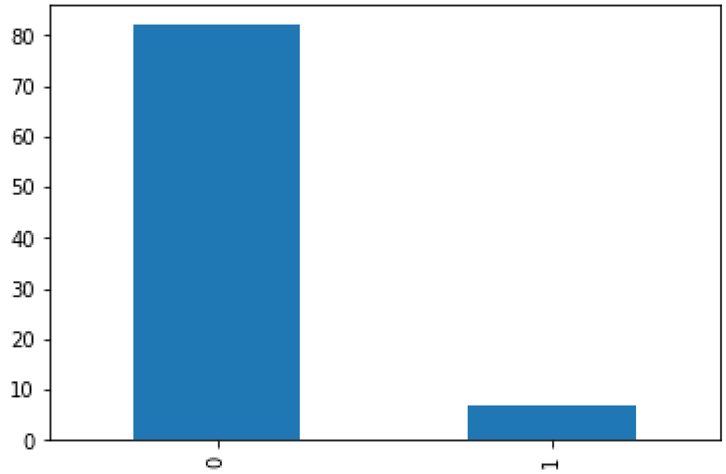




both the male and female get the loan with almost equal probabiliy

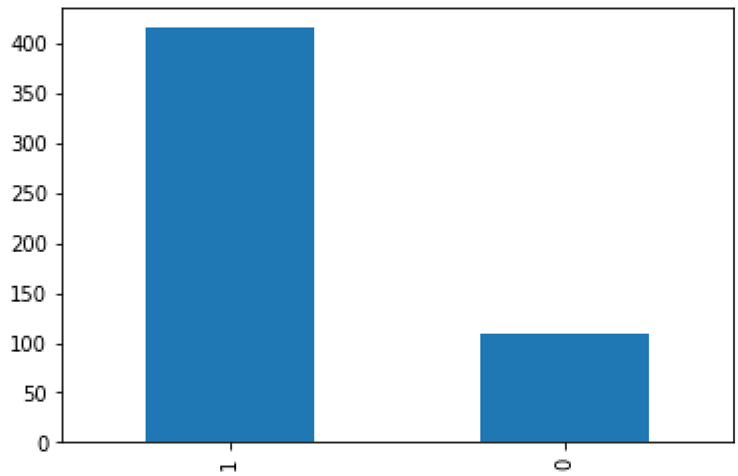
In [41]:

```
# visulising Credit History
y[data['Credit_History']==0].value_counts().plot(kind='bar')
plt.show()
y[data['Credit_History']==1].value_counts().plot(kind='bar')
```



Out[41]:

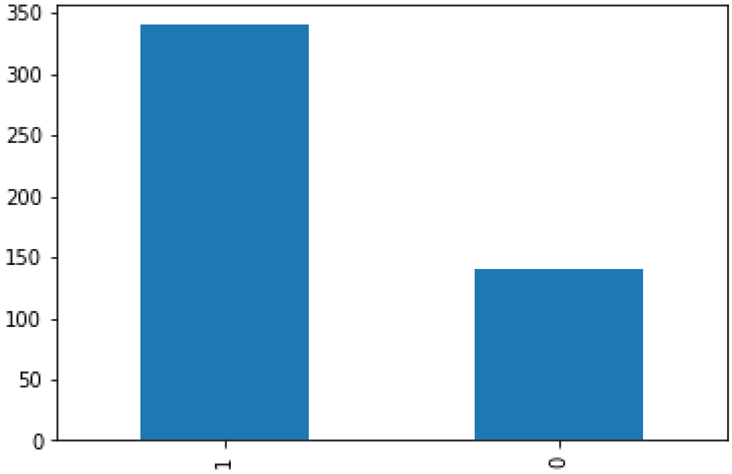
<matplotlib.axes._subplots.AxesSubplot at 0x7fb19a8ab790>



from the above two plot we can see that loan status is proposnal to the credit history most of time when the credit history is 1 then loan status is also 1 an vice versa

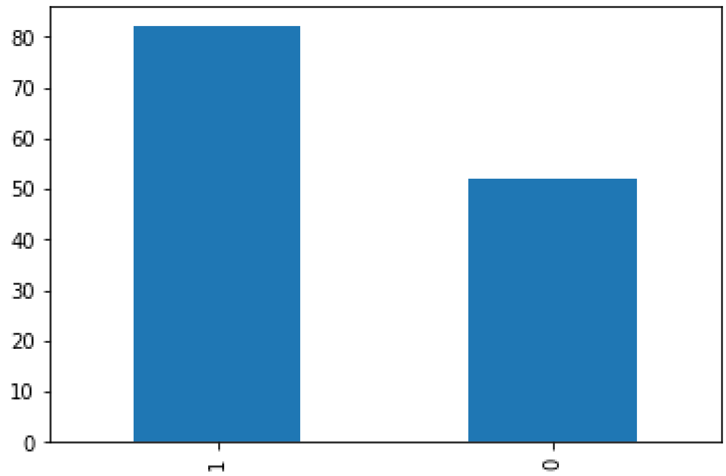
In [42]:

```
# visulising the Education
y[data['IsEducation']==0].value_counts().plot(kind='bar')
plt.show()
y[data['IsEducation']==1].value_counts().plot(kind='bar')
```



Out[42]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb19a810690>
```



can not get any significant result

From the above data we are enable to find any specific pattern in our data so we will reduce the dimension of the dataset and try to visulise the data

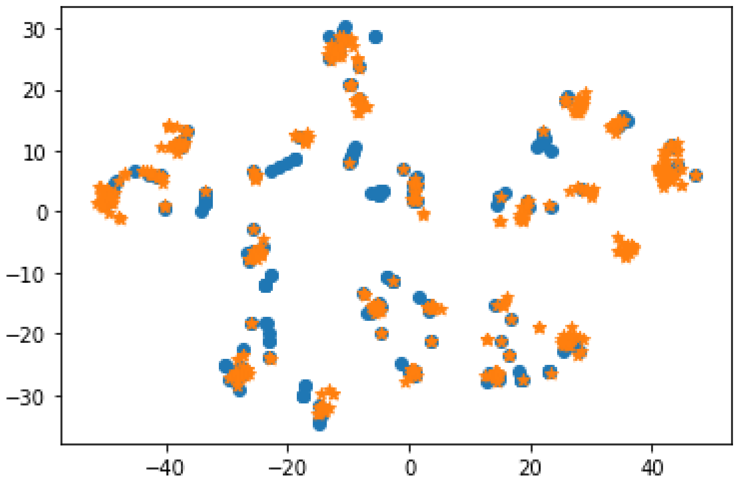
In [43]:

```
from sklearn.manifold import TSNE

da = X
la=y
model = TSNE(n_components=2,random_state = 0,n_iter=4000,perplexity=20.0)
tsne_data = model.fit_transform(da)
#?? model
tsne_data = np.vstack((tsne_data.T,y)).T
tsne_df = pd.DataFrame(data=tsne_data,columns = ('dim1','dim2','lab'))
print(tsne_data.shape)
print(y.shape)

plt.scatter(tsne_df['dim1'][y==0],tsne_df['dim2'][y==0],marker='o')
plt.scatter(tsne_df['dim1'][y==1],tsne_df['dim2'][y==1],marker='*')
```

```
(614, 3)
(614,)
```

Out[43]:

```
<matplotlib.collections.PathCollection at 0x7fb194e2ac50>
```



6. Spliting the data into train and test

As we analysis the complete data and we can built our model for building our model we need to split our data into train and test data.

In [44]:

```
def spliting(X,y):
    indices=np.random.permutation(len(data))
    #print(indices)
    num_of_rows =  int(614* 0.8)
    #print(num_of_rows)
    train_data = indices[:num_of_rows] #indexes rows for training data
    test_data =  indices[num_of_rows:] #indexes rows for test data


    #print(y.shape)
    X_train = X.loc[train_data,:]
    X_test = X.loc[test_data,:]
    y_train = y.loc[train_data]
    y_test = y.loc[test_data]
    return X_train,X_test,y_train,y_test
X_train,X_test,y_train,y_test = spliting(X,y)
```

In [45]:

```
X_test
```

Out[45]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
565	0.053395	0.000000	0.160637	0.74359	1.0
260	0.073383	0.101999	0.464544	0.74359	1.0
317	0.023599	0.051216	0.114327	0.74359	1.0
200	0.030303	0.060000	0.117221	0.74359	1.0
558	0.046221	0.064055	0.221418	0.74359	1.0
...	...	...	...	...	...
538	0.034224	0.012864	0.082489	0.74359	1.0
221	0.047730	0.041208	0.154848	0.74359	1.0
191	0.146568	0.000000	0.224313	0.74359	1.0
148	0.121831	0.039984	0.312590	0.74359	1.0
116	0.037316	0.054792	0.209841	0.74359	1.0

123 rows × 12 columns

In [46]:

```
X_test
```

Out[46]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
565	0.053395	0.000000	0.160637	0.74359	1.0
260	0.073383	0.101999	0.464544	0.74359	1.0
317	0.023599	0.051216	0.114327	0.74359	1.0
200	0.030303	0.060000	0.117221	0.74359	1.0
558	0.046221	0.064055	0.221418	0.74359	1.0
...	...	...	...	...	...
538	0.034224	0.012864	0.082489	0.74359	1.0
221	0.047730	0.041208	0.154848	0.74359	1.0
191	0.146568	0.000000	0.224313	0.74359	1.0
148	0.121831	0.039984	0.312590	0.74359	1.0
116	0.037316	0.054792	0.209841	0.74359	1.0

123 rows × 12 columns

In [47]:

```
y_train
```

Out[47]:

```
541    0
3      1
470    1
323    1
313    1
      ..
563    1
30     0
430    1
15     1
259    0
Name: Loan_Status, Length: 491, dtype: uint8
```

In [48]:

```
y_test
```

Out[48]:

```
565    1
260    1
317    1
200    1
558    1
      ..
538    0
221    1
191    0
148    0
116    1
Name: Loan_Status, Length: 123, dtype: uint8
```

7. Designing the model

As we have split the data into train and test datasets now we built diffrent models and test their accuracy

diffrent Classification Algorithms

```
Linear Classifiers :
    Logistic regression.
    Naive Bayes classifier.
    Fisher's linear discriminant.
Support vector machines :
    Least squares support vector machines.
Quadratic classifiers
Kernel estimation.
k-nearest neighbor.
Decision trees.
Random forests.
Neural networks.
Learning vector quantization.
```

we are using logistic regression to predict the output

In [49]:

```
from sklearn.linear_model import LogisticRegression
reg = LogisticRegression()
reg.fit(X_train,y_train)
y_pred = reg.predict(X_test)
```

8.EVAluation of the models

In [50]:

```
reg.score(X_test,y_test)
```

Out[50]:

```
0.8130081300813008
```

from the above output we find the accuracy of the algorithm prediction on the given data is 0.81

9.predicting the final output

In [ ]:

```
# enter a data
s = input()
t = s.split(,)
```

10. Conclusion

WE can conclude that from the given data if we have some information of the user we can predict whether the person get the loan or not . Or this model can be used by the bank to predict whether the loan should provide or not to the person