Skill Vertex - Mini Project

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• Date: 5th July 2022

Project Topic: Loan Prediction

```
In [1]:
```

```
#Step 1, importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model selection import train test split
from sklearn import feature selection
from sklearn import model selection
from sklearn.metrics import accuracy score
#ML algos to create the Models
from sklearn.linear model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
```

Loading our data,

DataSet link:

- https://datahack.analyticsvidhya.com/contest/practice-problem-loan-prediction-iii/,
- https://www.kaggle.com/datasets/altruistdelhite04/loan-prediction-problem-dataset

```
In [12]:
```

```
data_trn=pd.read_csv("C:/Users/SSD/VITc_SSD1125_Progms/Training
SkillVertex_py/MinProj/LoanPred_train.csv")
```

```
In [13]:
```

```
data_trn
```

Out[13]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	LP001002	Male	No	0	Graduate	No	5849	0.0
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0

3	L-881006	Gender Male	Married Yes	Dependents		t Self_Employ	ed Appli	cantincome 2583	CoapplicantIncome 2358.
	I D004000	Mala	Na	^	Graduate		NI.	6000	0.4
4	LP001008	Male	No	0	Graduate	e	No	6000	0.0
		•••		•••				•••	••
609	LP002978	Female	No	0	Graduate	e I	No	2900	0.0
610	LP002979	Male	Yes	3+	Graduate	e I	No	4106	0.0
611	LP002983	Male	Yes	1	Graduate	e I	No	8072	240.0
612	LP002984	Male	Yes	2	Graduate	e I	No	7583	0.0
613	LP002990	Female	No	0	Graduate	e Y	'es	4583	0.0
044	40								
614 r	rows × 13	columns	•						
. 1 .									<u> </u>
In [[15]:								
data	a_trn.sha	ape							
Out.									
(014	1, 13)								
In [[16]:								
data	a_trn.inf	Ō							
Out	[16]:								
	ind metho	d Data	Eramo i	nfo of	Toor	n ID Gende	r Marri	ad Danana	lonta Educ
	nna metna on Self E			.1110 01	поат		I Malli	ed Depend	lents Educ
0	LP00100		ale	No	0	Gradua	te	No)
1	LP00100		ale	Yes	1	Gradua		No	
2	LP00100		ale	Yes	0	Gradua		Yes	
3	LP00100		ale	Yes		Not Gradua		No	
4	LP00100)8 M	ale	No	0	Gradua	te	No)
				· · ·	• • •		• •	• • •	
609	LP00297			No	0	Gradua		No	
610	LP00297		ale	Yes	3+	Gradua		No	
611	LP00298		ale	Yes	1	Gradua		No	
612	LP00298		ale	Yes	2	Gradua		No	
613	LP00299	00 Fem	ale	No	0	Gradua	te	Yes	
	Applica			ipplicantI:		LoanAmount	Loan_A	mount_Ter	
0		58	49		0.0	NaN		360.	0
1		45	83	15	508.0	128.0		360.	0
2		30	00		0.0	66.0		360.	0
3		25	83	23	358.0	120.0		360.	0
4		60			0.0	141.0		360.	0
609		29	0.0		0.0	71.0		360.	
610		41			0.0	40.0		180.	
611		80		2	240.0	253.0		360.	
612		75		•	0.0	187.0		360.	
613		45			0.0	133.0		360.	
	Credi+	Histor	v Propo	erty_Area 1	[.∩an C+≃	atus			
0	OTEUTL_	_nistor_ 1.		Urban	Louii_blo	Y			
1		1.		Rural		N			
2		1.		Urban		Y			
3		1.		Urban		Y			
-		-•							

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609
             1.0
                       Rural
                                      Y
              1.0
610
                        Rural
                                       Y
              1.0
                                      Y
611
                        Urban
                                      Y
612
              1.0
                        Urban
              0.0
613
                                      N
                     Semiurban
```

[614 rows x 13 columns] >

In [17]:

data trn.describe()

Out[17]:

	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

In [18]:

```
# Test data
data_tst=pd.read_csv('C:/Users/SSD/VITc_SSD1125_Progms/Training
SkillVertex_py/MinProj/LoanPred_test.csv')
```

In [19]:

```
print (data_trn.shape, data_tst.shape)
```

(614, 13) (367, 12)

Exploratory Data Analysis

In [20]:

```
data_trn.head()
```

Out[20]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	LP001002	Male	No	0	Graduate	No	5849	0.0
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0
4	LP001008	Male	No	0	Graduate	No	6000	0.0

```
In [21]:
data tst.head()
Out[21]:
     Loan_ID Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantIncome
   LP001015
                 Male
                           Yes
                                             Graduate
                                                                   No
                                                                                  5720
                                                                                                         0
   LP001022
                 Male
                                          1
                                             Graduate
                                                                   No
                                                                                  3076
                                                                                                      1500
                           Yes
   LP001031
                                          2
                                             Graduate
                                                                                  5000
                                                                                                      1800
                 Male
                           Yes
                                                                   No
    LP001035
                 Male
                                          2
                                             Graduate
                                                                   No
                                                                                  2340
                                                                                                      2546
                           Yes
                                                   Not
   LP001051
                 Male
                           No
                                          0
                                                                   No
                                                                                  3276
                                                                                                         0
                                             Graduate
                                                                                                          In [22]:
# Checking for any null NaN values
data trn.isnull()
Out[22]:
              Gender Married Dependents Education Self_Employed ApplicantIncome CoapplicantIncome
      Loan_ID
   0
         False
                 False
                          False
                                       False
                                                  False
                                                                 False
                                                                                   False
                                                                                                       False
   1
        False
                 False
                          False
                                       False
                                                  False
                                                                 False
                                                                                   False
                                                                                                       False
   2
         False
                 False
                          False
                                       False
                                                  False
                                                                 False
                                                                                   False
                                                                                                       False
   3
        False
                 False
                          False
                                       False
                                                  False
                                                                 False
                                                                                   False
                                                                                                       False
   4
        False
                 False
                                                                                   False
                                                                                                       False
                          False
                                       False
                                                  False
                                                                 False
           ...
                    ...
                                                                                                         ...
  ---
 609
         False
                 False
                          False
                                                  False
                                                                 False
                                                                                   False
                                                                                                       False
                                       False
 610
        False
                 False
                          False
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                                                                                   False
                                                                                                       False
 611
         False
                 False
                          False
                                       False
                                                  False
                                                                  False
                                                                                   False
                                                                                                       False
        False
                                                                                   False
                                                                                                       False
 612
                 False
                          False
                                       False
                                                  False
                                                                 False
 613
         False
                 False
                          False
                                       False
                                                  False
                                                                 False
                                                                                   False
                                                                                                       False
614 rows × 13 columns
In [23]:
data trn.isnull().sum()
Out[23]:
Loan ID
                             0
                            13
Gender
                             3
Married
                            15
Dependents
Education
                             0
```

Self Employed

ApplicantIncome

32

0

```
CoapplicantIncome
                       0
LoanAmount
                      22
Loan_Amount_Term
                      14
Credit_History
                      50
Property_Area
                       0
                       0
Loan Status
dtype: int64
In [24]:
data trn.isnull().sum().sum()
Out[24]:
149
```

Interference:

In [38]:

It can be observed that there are null values, so Removing them, later we'll instead add the Mode values

```
In [26]:
data trn1=data trn.dropna()
In [27]:
data trn1.isnull().sum().sum()
Out[27]:
0
In [25]:
data tst.isnull().sum().sum()
Out[25]:
84
In [33]:
data trn.dtypes
Out[33]:
Loan ID
                        object
Gender
                        object
Married
                        object
Dependents
                        object
Education
                        object
Self Employed
                        object
ApplicantIncome
                        int64
CoapplicantIncome
                       float64
LoanAmount
                       float64
Loan_Amount_Term
                       float64
Credit_History
                       float64
Property Area
                        object
Loan_Status
                      category
dtype: object
```

```
#Converting the 'object' datatypes, into 'category'
dat=data trn
dat['Loan Status']=dat['Loan Status'].astype("category")
dat.dtypes
Out[38]:
Loan ID
                      object
Gender
                       object
Married
                      object
Dependents
                      object
Education
                      object
Self Employed
                     object
ApplicantIncome
                       int64
                  float64
CoapplicantIncome
                     float64
LoanAmount
Loan Amount Term
                    float64
Credit History
                     float64
Property Area
                      object
Loan Status
                   category
dtype: object
In [50]:
### Visualization
import seaborn as sns
sns.set style("whitegrid")
#sns.pairplot(data trn[["ApplicantIncome", "CoapplicantIncome", "LoanAmount", "Loan
unt Term"]], hue="smoker", height=3, palette="Set1")
```

Data Visualization

Observing the frequency of each Features

```
In [41]:
data = [data trn,data tst]
for dataset in data:
    #Filter categorical variables
    categorical columns = [x for x in dataset.dtypes.index if dataset.dtypes[x] ==
'object']
    # Exclude ID cols and source:
    categorical columns = [x for x in categorical columns if x not in ['Loan ID'
]]
    #Print frequency of categories
for col in categorical columns:
    print ('\nFrequency of Categories for variable %s'%col)
    print (data trn[col].value counts())
Frequency of Categories for variable Gender
          489
          112
Female
Name: Gender, dtype: int64
Frequency of Categories for variable Married
Yes
       398
No
       213
Name: Married, dtype: int64
Frequency of Categories for variable Dependents
```

```
or oddogorrod ror .drrddro ropondonod
0
      345
1
      102
2
      101
       51
3+
Name: Dependents, dtype: int64
Frequency of Categories for variable Education
                480
Graduate
Not Graduate
                134
Name: Education, dtype: int64
Frequency of Categories for variable Self Employed
No
       500
        82
Yes
Name: Self Employed, dtype: int64
Frequency of Categories for variable Property Area
Semiurban
             233
             202
Urban
             179
Rural
Name: Property_Area, dtype: int64
```

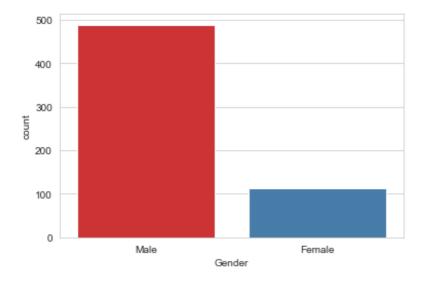
In [49]:

```
import seaborn as sns
sns.countplot(data_trn['Gender'],palette = "Set1")
plt.show

C:\Users\SSD\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
   warnings.warn(
```

Out[49]:

<function matplotlib.pyplot.show(close=None, block=None)>



In [52]:

```
pd.crosstab(data_trn.Gender, data_trn.Loan_Status, margins = True)
# Seeing the approval of loans b/w Males & Females
```

Out[52]:

Loan_Status N Y All

In [53]:

```
print("Original data shape: ",data_trn.shape)
print("Removad Na data shape: ",data_trn1.shape)
```

```
Original data shape: (614, 13)
Removad Na data shape: (480, 13)
```

It can be observed that 134 reading are being dropped, when we directly remove the NaN, which may decrease the Accuracy of our model. So, we'll add the Mode in those Null values.

In [137]:

```
data_trn=pd.read_csv("C:/Users/SSD/VITc_SSD1125_Progms/Training
SkillVertex_py/MinProj/LoanPred_train.csv")
```

In [138]:

```
data_tst=pd.read_csv("C:/Users/SSD/VITc_SSD1125_Progms/Training
SkillVertex_py/MinProj/LoanPred_test.csv")
```

In [139]:

```
data_t=data_trn
dtest=data_tst
data_t.Gender = data_t.Gender.fillna(data_t.Gender.mode())
dtest.Gender = dtest.Gender.fillna(dtest.Gender.mode())
```

In [141]:

```
#Converting 'M', 'F'(i.e., Categorical Var) to, (0,1)numerical variables
gendr=pd.get_dummies(data_t['Gender'] , drop_first = True )
data_t.drop(['Gender'], axis = 1 , inplace =True)
data_t = pd.concat([data_t , gend ] , axis = 1)
# For test
gendr1 = pd.get_dummies(dtest['Gender'] , drop_first = True )
dtest.drop(['Gender'], axis = 1 , inplace =True)
dtest = pd.concat([dtest , gendr1 ] , axis = 1)
```

In [143]:

```
data_t.head()
```

Out[143]:

	Loan_ID	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmo
0	LP001002	No	0	Graduate	No	5849	0.0	ı
1	LP001003	Yes	1	Graduate	No	4583	1508.0	12
2	LP001005	Yes	0	Graduate	Yes	3000	0.0	ť
3	LP001006	Yes	0	Not Graduate	No	2583	2358.0	12

```
4 LP001008 No Dependents Education Self_Employed ApplicantIncome CoapplicantIncome LoanAmo
```

In [144]:

data_t.isnull().sum()

Out[144]:

Loan ID 0 3 Married 15 Dependents Education 0 Self Employed 32 ApplicantIncome 0 CoapplicantIncome 0 LoanAmount 22 Loan Amount Term 14 Credit_History 50 Property Area 0 0 Loan Status Male dtype: int64

Now, filling the 'Married', 'Dependantas', 'Self_Employed', 'Credit_History', etc values with the Mode values.

In [145]:

```
# For, Married column,
sns.countplot(data_t.Married)

C:\Users\SSD\anaconda3\lib\site-packages\seaborn\_decorators.py:36:

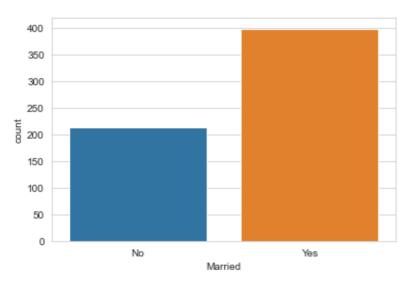
Enture Warning: Page the fallowing warishle as a keyword and the Frame warning of the column.
```

FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1 2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

Out[145]:

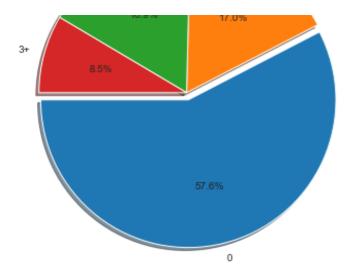
<AxesSubplot:xlabel='Married', ylabel='count'>



```
# Checking approval rate
pd.crosstab(data t.Married , data t.Loan Status, margins = True)
Out[146]:
Loan_Status
            N
                Y All
    Married
           79 134 213
       No
       Yes 113 285 398
        All 192 419 611
In [147]:
# Now, filling the NaN values with Mode
data t.Married = data t.Married.fillna(data t.Married.mode())
dtest.Married = dtest.Married.fillna(dtest.Married.mode())
married = pd.get dummies(data t['Married'] , prefix = 'married',drop first = True
)
data t.drop(['Married'], axis = 1 , inplace =True)
data t = pd.concat([data t , married ] , axis = 1)
married = pd.get dummies(dtest['Married'] , prefix = 'married', drop first = True
dtest.drop(['Married'], axis = 1 , inplace =True)
dtest = pd.concat([dtest , married ] , axis = 1)
In [150]:
# Visualizing No. of dependents
depnd=data trn['Dependents']
depnd.value counts()
Out[150]:
      345
\cap
      102
1
2
      101
3+
       51
Name: Dependents, dtype: int64
In [151]:
```

No. of Dependants





In [152]:

```
print("Approval of loans b/w diff. sizes of families")
pd.crosstab(data_t.Dependents , data_t.Loan_Status, margins = True)
```

Approval of loans b/w diff. sizes of families

Out[152]:

Loon Status

Loan_Statu	N	T	All	
Dependent	s			
	0	107	238	345
	1	36	66	102
:	2	25	76	101
3-	+	18	33	51
A	II	186	413	599

In [153]:

```
# Filling the NaN Values
data_t.Dependents = data_t.Dependents.fillna("0")
dtest.Dependents = dtest.Dependents.fillna("0")
# Converting categorial to Numerical variables
size = {'0':'0', '1':'1', '2':'2', '3+':'3'}
data_t.Dependents = data_t.Dependents.replace(size).astype(int)
dtest.Dependents = dtest.Dependents.replace(size).astype(int)
```

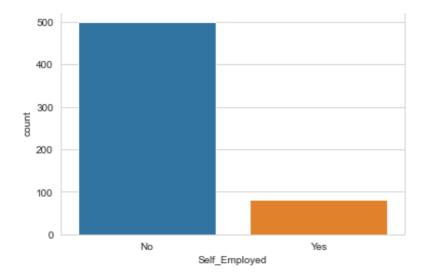
In [154]:

```
# For self employed
sns.countplot(data_t['Self_Employed'])

C:\Users\SSD\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
   warnings.warn(
```

Out[154]:

<AxesSubplot:xlabel='Self_Employed', ylabel='count'>



In [155]:

```
pd.crosstab(data_t.Self_Employed , data_t.Loan_Status,margins = True)
```

Out[155]:

Loan_Status N Y All

Self_Employed

No 157 343 500

Yes 26 56 82

All 183 399 582

In [157]:

```
data_t.Self_Employed = data_t.Self_Employed.fillna(data_t.Self_Employed.mode())
dtest.Self_Employed = dtest.Self_Employed.fillna(dtest.Self_Employed.mode())

self_Employed = pd.get_dummies(data_t['Self_Employed'] ,prefix = 'employed' ,drop_first = True )
data_t.drop(['Self_Employed'], axis = 1 , inplace =True)
data_t = pd.concat([data_t , self_Employed] , axis = 1)

self_Employed = pd.get_dummies(dtest['Self_Employed'] , prefix = 'employed' ,drop_first = True )
dtest.drop(['Self_Employed'], axis = 1 , inplace =True)
dtest = pd.concat([dtest , self_Employed] , axis = 1)
```

In [158]:

```
# For Loan amt term
data_t.drop(['Loan_Amount_Term'], axis = 1 , inplace =True)
dtest.drop(['Loan_Amount_Term'], axis = 1 , inplace =True)

data_t.LoanAmount = data_t.LoanAmount.fillna(data_t.LoanAmount.mean()).astype(int)
dtest.LoanAmount = dtest.LoanAmount.fillna(dtest.LoanAmount.mean()).astype(int)
```

In [159]:

```
sns.distplot(data_t['LoanAmount'])
# It can be onserver that there are no outliners

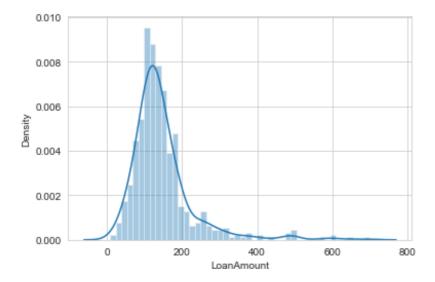
C:\Users\SSD\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
```

future version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for hist ograms).

warnings.warn(msg, FutureWarning)

Out[159]:

<AxesSubplot:xlabel='LoanAmount', ylabel='Density'>



In [160]:

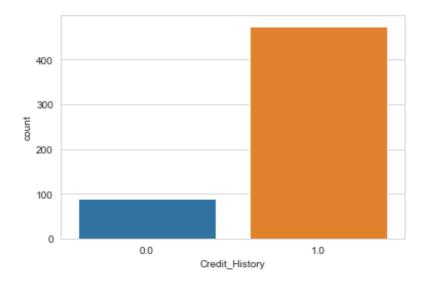
```
# For, Credit History
sns.countplot(data_t['Credit_History'])
```

C:\Users\SSD\anaconda3\lib\site-packages\seaborn_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.

warnings.warn(

Out[160]:

<AxesSubplot:xlabel='Credit History', ylabel='count'>



In [161]:

```
# CHecking the no. of people who have Credit history or not
pd.crosstab(data_t.Credit_History, data_t.Loan_Status, margins = True)
```

Out[161]:

```
        Loan_Status Loan_Status
        N Y All Y All
```

In [162]:

```
# Removing the NaN values, and adding the Mode insted
data_t.Credit_History = data_t.Credit_History.fillna(data_t.Credit_History.mode()
[0])
dtest.Credit_History = dtest.Credit_History.fillna(dtest.Credit_History.mode()[0])
```

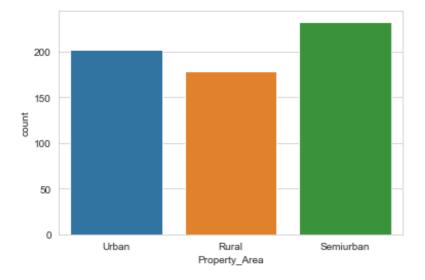
In [166]:

```
## Observing the Property Area
sns.countplot(data_t.Property_Area)

C:\Users\SSD\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
   warnings.warn(
```

Out[166]:

<AxesSubplot:xlabel='Property Area', ylabel='count'>



In [167]:

```
# Converting to Numerical variables, to better train our models
data_t['Property_Area'] = data_t['Property_Area'].map( {'Urban': 0, 'Semiurban':
1 ,'Rural': 2 } ).astype(int)

dtest.Property_Area = dtest.Property_Area.fillna(dtest.Property_Area.mode())
dtest['Property_Area'] = dtest['Property_Area'].map( {'Urban': 0, 'Semiurban': 1
,'Rural': 2 } ).astype(int)
```

In [170]:

```
sns.distplot(data_t['ApplicantIncome'])
plt.title("Applicants Income")

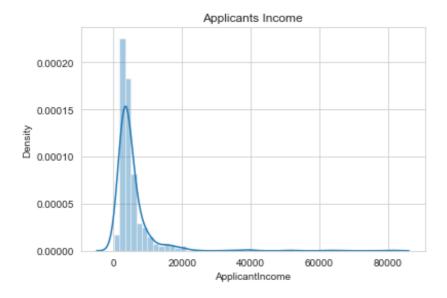
C.\Users\SSD\araconda3\lib\site=packages\seabern\distributions pw.2610.
```

FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level f unction with similar flexibility) or `histplot` (an axes-level function for hist ograms).

warnings.warn(msg, FutureWarning)

Out[170]:

Text(0.5, 1.0, 'Applicants Income')



In [171]:

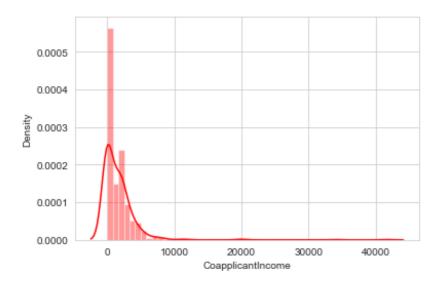
sns.distplot(data_t['CoapplicantIncome'], color="r")

C:\Users\SSD\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level f
unction with similar flexibility) or `histplot` (an axes-level function for hist
ograms).

warnings.warn(msg, FutureWarning)

Out[171]:

<AxesSubplot:xlabel='CoapplicantIncome', ylabel='Density'>



Observing the Education Column

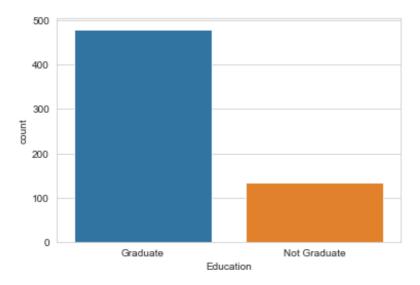
In [163]:

sns.countplot(data t.Education)

```
C:\Users\SSD\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

Out[163]:

<AxesSubplot:xlabel='Education', ylabel='count'>



In [164]:

```
# Converting to Numerical variables, to better train our models
data_t['Education'] = data_t['Education'].map( {'Graduate': 0, 'Not Graduate': 1}
).astype(int)
dtest['Education'] = dtest['Education'].map( {'Graduate': 0, 'Not Graduate': 1} )
.astype(int)
```

In [173]:

```
# Converting our Dependent/Target variable, from Categorial to Numerical
data_t['Loan_Status'] = data_t['Loan_Status'].map( {'N': 0, 'Y': 1 } ).astype(int)
```

In [175]:

data t.dtypes

Out[175]:

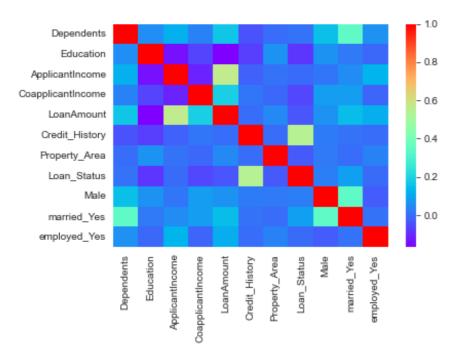
Loan_ID	object
Dependents	int32
Education	int32
ApplicantIncome	int64
CoapplicantIncome	float64
LoanAmount	int32
Credit_History	float64
Property_Area	int32
Loan_Status	int32
Male	uint8
married_Yes	uint8
employed_Yes	uint8
dtype: object	

In [184]:

```
sns.heatmap(data_t.corr(),cmap='rainbow')
```

Out[184]:

<AxesSubplot:>



Correlation between the explanatory variables and the response/target variable(y)

In [192]:

```
y=data_t['employed_Yes']
d=data_t[["Dependents", "Education", "ApplicantIncome", "CoapplicantIncome", "LoanAmc
unt", "Credit_History", "Property_Area", "Loan_Status", "Male", "employed_Yes"]]
d.corr()['employed_Yes']
```

Out[192]:

Dependents	0.056798
Education	-0.010383
ApplicantIncome	0.127180
CoapplicantIncome	-0.016100
LoanAmount	0.115259
Credit_History	-0.001550
Property_Area	0.030860
Loan_Status	-0.003700
Male	-0.027421
employed_Yes	1.000000
<pre>Name: employed_Yes,</pre>	dtype: float64

In [193]:

```
#In sorted order, for our convenience
d.corr()["employed_Yes"].abs().sort_values(ascending=False)
```

Out[193]:

employed_Yes	1.000000
ApplicantIncome	0.127180
LoanAmount	0.115259
Dependents	0.056798
Property_Area	0.030860
Male	0.027421

CoapplicantIncome 0.016100
Education 0.010383
Loan_Status 0.003700
Credit_History 0.001550
Name: employed Yes, dtype: float64

From above, It can be oberved that, althoug negligible, but still all are correlated to the Dependent variable.

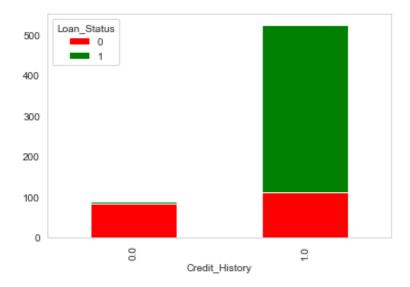
So, removing the insisgnificant varaible, 'Loan_ID', and checking the signigficance of Credit HIstory,

In [202]:

```
lc = pd.crosstab(data_t['Credit_History'], data_t['Loan_Status'])
lc.plot(kind='bar', stacked=True, color=['red','green'], grid=False)
# It can be observed that Credit history is related, so not removing it
```

Out[202]:

<AxesSubplot:xlabel='Credit_History'>



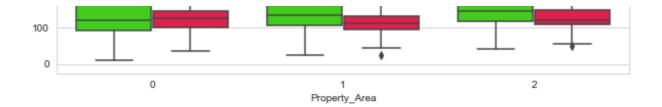
In [195]:

```
data_t.drop(['Loan_ID'], axis = 1 , inplace =True)
```

In [199]:

```
plt.figure(figsize=(10,5))
sns.boxplot(x="Property_Area", y="LoanAmount", hue="Education",data=data_t, palet
te="prism")
plt.title("Property Area Loan Amt Vs Education Qualified or Not")
plt.show()
```



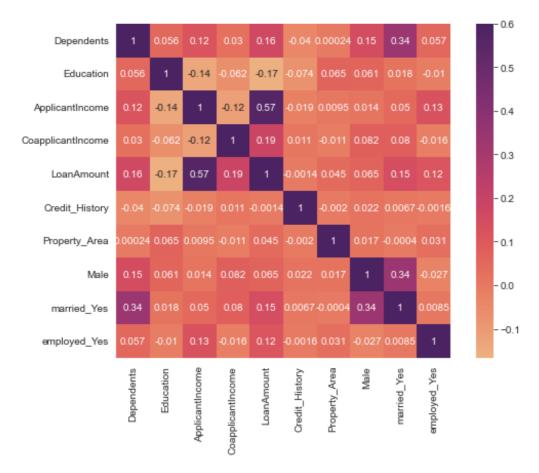


In [206]:

```
plt.figure(figsize=(9,6))
sns.heatmap(data_t.drop('Loan_Status',axis=1).corr(), vmax=0.6, square=True, anno
t=True, cmap='flare')
```

Out[206]:

<AxesSubplot:>



Building a Model

In [224]:

```
# Since it's classification problem(0,1)
#Firstly trying only one the train data
from sklearn.model_selection import train_test_split
X = data_t.drop('Loan_Status' , axis = 1 )
y = data_t['Loan_Status']
#20% train data
X_train ,X_test , y_train , y_test = train_test_split(X , y , test_size = 0.20 ,
random_state =10)
```

In [482]:

```
#Building the model, firstly we'll use Logistic Regression
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
```

```
logreg.fit(x train , y train)
Out[482]:
LogisticRegression()
Step 6: Model Evaluation
In [226]:
pred1 = logreg.predict(X test)
acc log = accuracy score(y test , pred1)*100
acc log
Out[226]:
79.67479674796748
In [227]:
logreg.score(X test,y test).round(3)
#It's not bad, but not that good
Out[227]:
0.797
In [232]:
# Trying different Train test split
X_train ,X_test , y_train , y_test = train_test_split(X , y , test_size = 0.25 ,
random state =10)
In [233]:
pred1 = logreg.predict(X test)
acc log = accuracy score(y test , pred1)*100
acc_log
Out[233]:
81.16883116883116
```

Still, not that better accuracy, so Normalizing it, to increase the accuracy

Trying with MinMax

```
In [251]:
```

```
# Normalization method used - sklern library and MinMaxScaler()
from sklearn import preprocessing
normalised = preprocessing.MinMaxScaler().fit_transform(data_t)
data1 = pd.DataFrame(normalised, columns = data_t.columns)
data1.head()
```

Out[251]:

	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount	Credit_History	Property_Area
0	0.000000	0.0	0.070489	0.000000	0.198263	1.0	0.0
1	0.333333	0.0	0.054830	0.036192	0.172214	1.0	1.0

```
Credit_History
                                                                                                   Property_Area
                 Education
                             Applicantingenge
                                               Coapplicant!neone
                                                                    Loan America
   Dependents
      0.000000
                                     0.030093
                                                          0.056592
                                                                        0.160637
                                                                                              1.0
3
                        1.0
                                                                                                              0.0
      0.000000
                        0.0
                                     0.072356
                                                          0.000000
                                                                        0.191027
                                                                                              1.0
                                                                                                              0.0
```

```
In [253]:
```

```
x=data1.drop('employed_Yes',axis=1)
y=data1['employed_Yes']
```

In [256]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20)
model2=LogisticRegression()
model2.fit(x_train,y_train)
y_predicted2=model2.predict(x_test)
accuracy_score(y_test,y_predicted2)
```

Out[256]:

0.8373983739837398

In [258]:

```
random_forest = RandomForestClassifier(n_estimators= 100)
random_forest.fit(x_train, y_train)
pred_rf = random_forest.predict(x_test)
acc_rf = accuracy_score(y_test , pred_rf)*100
acc_rf
```

Out[258]:

82.92682926829268

Still not that better even with Random Forest,

Now, Trying another pre-processing technique

```
In [321]:
```

```
df=data_t
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
df['Male']=le.fit_transform(df['Male'])
df['married_Yes']=le.fit_transform(df['married_Yes'])
df['Education']=le.fit_transform(df['Education'])
#df['Self_Employed']=le.fit_transform(df['Self_Employed'])
df['Property_Area']=le.fit_transform(df['Property_Area'])
df['employed_Yes']=le.fit_transform(df['employed_Yes'])
df
```

Out[321]:

	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount	Credit_History	Property_Area
0	0	0	5849	0.0	146	1.0	0
1	1	0	4583	1508.0	128	1.0	2
2	0	0	3000	0.0	66	1.0	0
•	^	4	0500	0250 0	400	4.0	0

3			2003	∠აეი.∪	120	1.0	U
	Dependents	Education		CoapplicantIncome		Credit_History	Property_Area
4	0	0	6000	0.0	141	1.0	0
				•••			
609	0	0	2900	0.0	71	1.0	2
610	3	0	4106	0.0	40	1.0	2
611	1	0	8072	240.0	253	1.0	0
612	2	0	7583	0.0	187	1.0	0
613	0	0	4583	0.0	133	0.0	1

614 rows × 11 columns

In [322]:

df.reset_index(inplace=True)

In [323]:

df.drop('index',axis=1,inplace=True)
df

Out[323]:

	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount	Credit_History	Property_Area
0	0	0	5849	0.0	146	1.0	0
1	1	0	4583	1508.0	128	1.0	2
2	0	0	3000	0.0	66	1.0	0
3	0	1	2583	2358.0	120	1.0	0
4	0	0	6000	0.0	141	1.0	0
609	0	0	2900	0.0	71	1.0	2
610	3	0	4106	0.0	40	1.0	2
611	1	0	8072	240.0	253	1.0	0
612	2	0	7583	0.0	187	1.0	0
613	0	0	4583	0.0	133	0.0	1

614 rows × 11 columns

4

In [324]:

x=df.drop('employed_Yes',axis=1)
y=df['employed_Yes']

In [366]:

```
x_train1,x_test1,y_train1,y_test1=train_test_split(x,y,test_size=0.20)
model11=LogisticRegression()
model11.fit(x_train1,y_train1)
y_predicted11=model11.predict(x_test1)
from sklearn.metrics import accuracy_score
```

```
acc log1=accuracy score(y test1,y predicted11)
acc log1
Out[366]:
0.8699186991869918
In [341]:
x train,x test,y train,y test=train test split(x,y,test size=0.20)
In [342]:
model1=LogisticRegression()
model1.fit(x train, y train)
Out[342]:
LogisticRegression()
In [343]:
y predicted1=model1.predict(x test)
In [312]:
from sklearn.metrics import accuracy score
acc log=accuracy score(y test,y predicted1)
acc_log
Out[312]:
0.8702702702702703
KNN
In [358]:
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n neighbors = 3)
knn.fit(x_train, y_train)
pred knn = knn.predict(x test)
acc_knn = accuracy_score(y_test , pred_knn)*100
```

```
acc knn
Out[358]:
```

86.99186991869918

Checking with other neighbours, to get the best KNN accuracy

Neighbours: 2 , Accuracy: 88.6178861788618 Neighbours: 3 , Accuracy: 87.8048780487805

```
In [367]:
for i in range (1,12):
    knn = KNeighborsClassifier(n neighbors = i)
    knn.fit(x train1, y train1)
    pred knn = knn.predict(x test1)
    acc knn = accuracy score(y test1 , pred knn)*100
    print("Neighbours: ",i,", Accuracy: ",acc_knn)
Neighbours: 1 , Accuracy: 82.11382113821138
```

```
Neighbours: 4 , Accuracy: 86.99186991869918
Neighbours: 5 , Accuracy: 86.99186991869918
Neighbours: 6 , Accuracy: 86.99186991869918
Neighbours: 7 , Accuracy: 86.99186991869918
Neighbours: 8 , Accuracy: 86.99186991869918
Neighbours: 9 , Accuracy: 87.8048780487805
Neighbours: 10 , Accuracy: 88.6178861788618
Neighbours: 11 , Accuracy: 88.6178861788618
```

Naive Bayes

```
In [369]:
```

```
from sklearn.naive_bayes import GaussianNB
gaussian = GaussianNB()
gaussian.fit(x_train1, y_train1)
pred_gb = gaussian.predict(x_test1)
acc_nb = accuracy_score(y_test1 , pred_gb)*100
acc_nb
```

Out[369]:

84.5528455284553

Random Forest

```
In [345]:
```

```
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier(n_estimators= 100)
rf_model.fit(x_train1, y_train1)
pred_rf = rf_model.predict(x_test1)
acc_rf = accuracy_score(y_test1 , pred_rf)*100
acc_rf
```

Out[345]:

92.6829268292683

```
In [375]:
```

```
gbk = GradientBoostingClassifier()
gbk.fit(x_train1, y_train1)
pred_gbc = gbk.predict(x_test1)
acc_gbc = accuracy_score(y_test1 , pred_gbc)*100
acc_gbc
```

Out[375]:

86.1788617886179

SVM

```
In [371]:
```

```
svc = SVC()
svc.fit(x_train1, y_train1)
pred_svm = svc.predict(x_test1)
acc_svm = accuracy_score(y_test1 , pred_svm)*100
```

Model Score 3 Random Forrest 91.869919 1 K- Nearest Neighbour 88.617886 5 SVM 87.804878 0 Logistic Regression 87.027027 **Gradient Boosting** 86.178862 4 Classifier 2 Naive Bayes 84.552846

In [389]:

acc_svm

Out[371]:

```
# Checking the importance of each Columns
importances = pd.DataFrame({'Features':x_train.columns,'Importance':np.round(ran
dom_forest.feature_importances_,3)})
importances =
importances.sort_values('Importance',ascending=False).set_index('Features')
importances.head(11)
```

Out[389]:

Importance

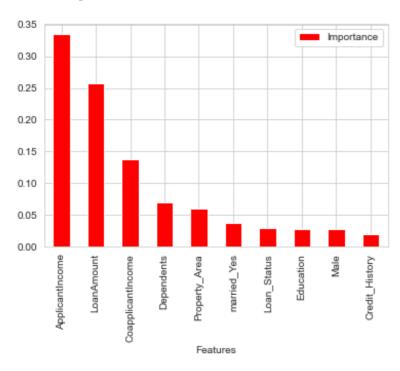
Features	
ApplicantIncome	0.335
LoanAmount	0.257
CoapplicantIncome	0.137
Dependents	0.069
Property_Area	0.060
married_Yes	0.037
Loan_Status	0.030
Education	0.028
Male	0.027
Credit_History	0.020

In [391]:

```
importances.plot.bar(color='red')
```

Out[391]:

<AxesSubplot:xlabel='Features'>

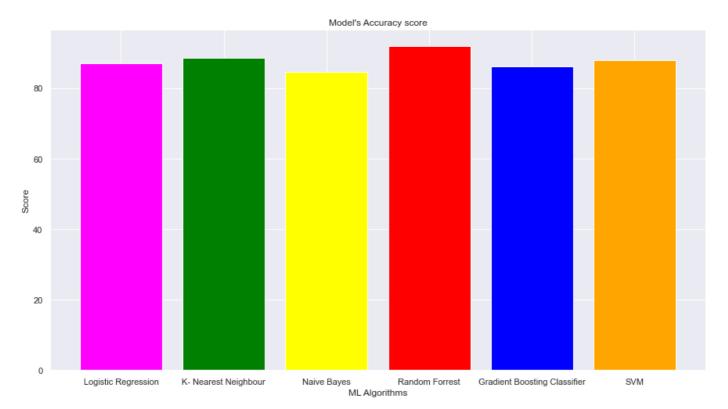


In [393]:

```
nam=['Logistic Regression', 'K- Nearest Neighbour', 'Naive Bayes', 'Random
Forrest','Gradient Boosting Classifier', 'SVM']
val=[acc_log , acc_knn , acc_nb, acc_rf, acc_gbc ,acc_svm]
sns.set(rc={'figure.figsize':(15,8)})
plt.bar(nam,val,color=["magenta","green","yellow","red","blue","orange"])
plt.xlabel("ML Algorithms")
plt.title("Model's Accuracy score")
plt.ylabel("Score")
```

Out[393]:

Text(0, 0.5, 'Score')



From the above bar plot, We can conclude that,

- Random Foest performed the best for our model.
- And, Naive Bayes was not that accurate as compared to the others

Conclusion:

- We were successfully able to create an accurate model with somewhat a great accuracy of 92%.
- We have even compared many ML models, and found that Random Forest worked best for this
 case.
- This model can be very useful for real life Loan allowance scenarios, and so, We have save it.
- The model has been used in the later part of this pdf/pynb file.

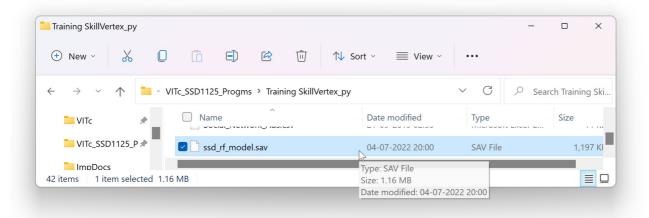
In [468]:

```
# Saving our best model
import pickle
filename = 'ssd_rf_model.sav'
pickle.dump(rf_model, open(filename, 'wb'))

# for loading the model from disk
"""
loaded_model = pickle.load(open(filename, 'rb'))
result = loaded_model.score(X_test, Y_test)
"""
```

Out[468]:

"\nloaded_model = pickle.load(open(filename, 'rb'))\nresult = loaded model.score(X test, Y test)\n"



Predicting the Loan approval Prediction for a Customer

```
In [408]:
```

```
Factors=[0]*x.shape[1]
np.array(Factors)
```

```
colm=np.array(x.columns)
Factors
Out[408]:
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
In [409]:
#print("Welcome to SSD's□Bank □")
#print("Kinkly enter the details to ")
for i in range(0, x.shape[1]):
    Factors[i]=int(input(print(f'Enter the value for',colm[i] ,": ")))
Factors=np.reshape (Factors, [1,10])
customer= pd.DataFrame(Factors, index=range(1), columns=x.columns)
loan Status=rf model.predict(customer)
if loan Status[0]==1:
    print('\n\n Congratulations: The Loan is approved for you')
    print('\n\n Sorry: The Loan is not approved for you')
Enter the value for Dependents :
None1
Enter the value for Education :
Enter the value for ApplicantIncome :
None456389
Enter the value for CoapplicantIncome :
None82726
Enter the value for LoanAmount:
None100
Enter the value for Credit History:
None10
Enter the value for Property Area:
None231
Enter the value for Loan Status:
None0
Enter the value for Male :
None0
Enter the value for married Yes:
None1
 Congratulations: The Loan is approved for you
```

For our comfort, making the columns more understandable

```
In [452]:
```

Out[452]:

	Dependets	1 Not Graduated: 0)	ApplicantIncome	CoapplicantIncome	LoanAmount	Credit_History
	Dependets Dependets	1. Not Graduated: 0) Education III (Graduated: 0) 1. Not Graduated: 0)	ApplicantIncome	CoapplicantIncome	LoanAmount	Credit_History
0	0	0	5849	0.0	146	1.0
1	1	0	4583	1508.0	128	1.0
2	0	0	3000	0.0	66	1.0
3	0	1	2583	2358.0	120	1.0
4	0	0	6000	0.0	141	1.0
•••						
609	0	0	2900	0.0	71	1.0
610	3	0	4106	0.0	40	1.0
611	1	0	8072	240.0	253	1.0
612	2	0	7583	0.0	187	1.0
613	0	0	4583	0.0	133	0.0

614 rows × 10 columns

```
In [459]:
```

```
Factors=[0]*ssd.shape[1]
np.array(Factors)
cols=np.array(x.columns)
org=df.drop('employed_Yes',axis=1)
Factors
```

Out[459]:

```
[0, 0, 0, 0, 0, 0, 0, 0, 0]
```

In [463]:

```
print("Welcome to SSD's□Bank □")
print ("Kindly enter the details to know if you are applicable for a loan or not.
")
n=input("Enter your name: ")
for i in range(0, ssd.shape[1]):
   print("Enter the value for, ",cols[i],": ",end=" ")
    inf=int(input(": "))
    #Factors[i]=int(input(print(f'Enter the value for',colm[i] ,": ")))
   Factors[i]=inf
Factors=np.reshape(Factors,[1,10])
customer= pd.DataFrame(Factors, index=range(1), columns=org.columns)
# Predicting the output
loan Status=rf model.predict(customer)
if loan Status[0]==1:
   print('\n Congratulations□',n,", The Loan is approved for you □")
else:
   print('\n Sorry ⊕',n,", The Loan is not approved for you⊕")
```

```
Welcome to SSD's Bank 
Kindly enter the details to know if you are applicable for a loan or not. 
Enter your name: SiddharthSD

Enter the value for, No. Of Dependets : : 2

Enter the value for, Education (Graduated: 1, Not Graduated: 0) : : 1

Enter the value for, ApplicantIncome : : 2500000

Enter the value for, CoapplicantIncome : : 100000

Enter the value for, LoanAmount : : 100000
```

```
Enter the value for, Credit History: : 5
Enter the value for, Property Area: : 320500
Enter the value for, Self Employed□(0: No, 1: Yes) : : 1
Enter the value for, Gender(Male\square: 1, Female\square: 0) : : 1
Enter the value for, Married\square (0 for No, 1 for Yes) : : 0
 Congratulations \square Siddharth SD , The Loan is approved for you \square
In [469]:
# Checking the model on another Real life situation
In [464]:
Factors=[0]*ssd.shape[1]
np.array(Factors)
cols=np.array(ssd.columns)
org=df.drop('employed Yes',axis=1)
In [466]:
print("Welcome to SSD's□Bank □")
print ("Kindly enter the details to know if you are applicable for a loan or not.
")
n=input("Enter your name: ")
for i in range(0, ssd.shape[1]):
    print("Enter the value for, ",cols[i],": ",end=" ")
    inf=int(input(": "))
    #Factors[i]=int(input(print(f'Enter the value for',colm[i],": ")))
    Factors[i]=inf
Factors=np.reshape(Factors,[1,10])
customer= pd.DataFrame(Factors, index=range(1), columns=org.columns)
# Predicting the output
loan Status=rf model.predict(customer)
if loan_Status[0]==1:
    print('\n Congratulations□',n,", The Loan is approved for you □")
else:
    print('\n Sorry \eftin ',n,", The Loan is not approved for you\eftin ")
Welcome to SSD's□Bank □
Kindly enter the details to know if you are applicable for a loan or not.
Enter your name: Amber
Enter the value for, No. Of Dependets \square : : 0
Enter the value for, Education \square (Graduated: 1, Not Graduated: 0): : 0
Enter the value for, ApplicantIncome: : 1000
Enter the value for, CoapplicantIncome : : 0
Enter the value for, LoanAmount: : 103500000
Enter the value for, Credit_History: : 2
Enter the value for, Property Area: : 100000
Enter the value for, Self Employed \square (0: No, 1: Yes) : : 0
Enter the value for, Gender(Male\square: 1, Female\square: 0) : : 0
Enter the value for, Married□(0 for No, 1 for Yes) : : 0
 Sorry 
Amber , The Loan is not approved for you
In [470]:
def Loan Predict SSD():
    Factors=[0]*ssd.shape[1]
    np.array(Factors)
    cols=np.array(ssd.columns)
    org=df.drop('employed_Yes',axis=1)
```

```
print("Welcome to SSD's Bank D")
    print ("Kindly enter the details to know if you are applicable for a loan or
not.")
    n=input("Enter your name: ")
    for i in range(0, ssd.shape[1]):
        print("Enter the value for, ",cols[i],": ",end=" ")
        inf=int(input(": "))
        #Factors[i]=int(input(print(f'Enter the value for',colm[i],": ")))
        Factors[i]=inf
    Factors=np.reshape(Factors, [1,10])
    customer= pd.DataFrame(Factors, index=range(1), columns=org.columns)
    # Predicting the output
    loan Status=rf model.predict(customer)
    if loan Status[0]==1:
        print('\n Congratulations□',n,", The Loan is approved for you □")
    else:
        print('\n Sorry \eftin ',n,", The Loan is not approved for you\eftin ")
```

Showing how the Model/Project asks for input:

```
In [*]: | Loan_Predict_SSD()
           Welcome to SSD's mank ❖
           Kindly enter the details to know if you are applicable for a loan or not.
           Enter your name: Johnny ■ D 👈
           Enter the value for, No. Of Dependets : : 1
           Enter the value for, Education ♠ ♠ (Graduated: 1, Not Graduated: 0) :
           : 301000000
```

In [476]:

```
Loan Predict SSD()
Welcome to SSD's□Bank □
Kindly enter the details to know if you are applicable for a loan or not.
Enter your name: Johnny□&D₺
Enter the value for, No. Of Dependets \square: : 2
Enter the value for, Education \square (Graduated: 1, Not Graduated: 0): : 1
Enter the value for, ApplicantIncome : : 301000000
Enter the value for, CoapplicantIncome: : 100000
Enter the value for, LoanAmount : : 100
Enter the value for, Credit History: : 5
Enter the value for, Property Area: : 7460378
Enter the value for, Self\_Employed\Box(0: No, 1: Yes) : : 1
Enter the value for, Gender(Male\square: 1, Female\square: 0) : : 1
Enter the value for, Married□(0 for No, 1 for Yes) :
In [480]:
```

```
Loan_Predict_SSD()
Welcome to SSD's□Bank □
Kindly enter the details to know if you are applicable for a loan or not.
Enter your name: Elon□ M□ ≶
Enter the value for, No. Of Dependets \square : : 0
Enter the value for, Education \square (Graduated: 1, Not Graduated: 0) : : 0
Enter the value for, ApplicantIncome : : 70000000000
Enter the value for, Credit History: : 0
```

```
Enter the value for, Property_Area: : 123 
Enter the value for, Self_Employed\Box (0: No, 1: Yes): : 0 
Enter the value for, Gender(Male\Box: 1, Female\Box: 0): : 1 
Enter the value for, Married\Box (0 for No, 1 for Yes): : 1 
Sorry \textcircled{2} Elon\Box M\Box$, The Loan is not approved for you\textcircled{3}
```

In [490]:

Loan Predict SSD()

```
Welcome to SSD's Bank 

Kindly enter the details to know if you are applicable for a loan or not. 
Enter your name: Siddharth Shankar Das 
Enter the value for, No. Of Dependets : : 2 
Enter the value for, Education (Graduated: 1, Not Graduated: 0) : : 1 
Enter the value for, Applicant Income : : 2500000 
Enter the value for, Coapplicant Income : : 100000 
Enter the value for, Loan Amount : : 6000 
Enter the value for, Credit History : : 5 
Enter the value for, Property Area : : 320500 
Enter the value for, Self Employed (0: No, 1: Yes) : : 1 
Enter the value for, Gender (Male : 1, Female : 0) : : 1 
Enter the value for, Married (0 for No, 1 for Yes) : : 0
```

Congratulations \square Siddharth Shankar Das , The Loan is approved for you \square

Mini Project Conclusion:

Thanks to SkillVertex, and our Mentor Soumya Ma'am, We were successfully able to make an accurate model which can predic Loan with given factors, and seeing the output, above program, It can be clearly stated that this can be used for real life scenarios as well

