Greetings to everyone!!

- Ill be creating a model on the basis of data of the Loan Defaulters

Importing the Libraries

- Numpy
- Pandas
- Matplotlib
- Seaborn
- From sklearn
  - Scipy
  - Label Encoder
  - Model Selection
  - Decision Tree
  - Random Forest
- From imblearn
  - Random OverSampling

In [1]:

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

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
#calling the data from csv file and checking the head of the data
df = pd.read_csv("credit_train.csv")
df.head()
```

Out[2]:

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Hor Ownersh
0	14dd8831-6af5-400b-83ec-68e61888a048	981165ec-3274-42f5-a3b4-d104041a9ca9	Fully Paid	445412.0	Short Term	709.0	1167493.0	8 years	Hor Mortga
1	4771cc26-131a-45db-b5aa-537ea4ba5342	2de017a3-2e01-49cb-a581-08169e83be29	Fully Paid	262328.0	Short Term	NaN	NaN	10+ years	Hor Mortga
2	4eed4e6a-aa2f-4c91-8651-ce984ee8fb26	5efb2b2b-bf11-4dfd-a572-3761a2694725	Fully Paid	99999999.0	Short Term	741.0	2231892.0	8 years	Own Hor
3	77598f7b-32e7-4e3b-a6e5-06ba0d98fe8a	e777faab-98ae-45af-9a86-7ce5b33b1011	Fully Paid	347666.0	Long Term	721.0	806949.0	3 years	Own Hor
4	d4062e70-befa-4995-8643-a0de73938182	81536ad9-5ccf-4eb8-befb-47a4d608658e	Fully Paid	176220.0	Short Term	NaN	NaN	5 years	Re

Exploratory Data Analysis

In [3]:

```
# Information about the data
df.info()
```

```
 1   Customer ID                   100000 non-null  object
 2   Loan Status                   100000 non-null  object
 3   Current Loan Amount           100000 non-null  float64
 4   Term                          100000 non-null  object
 5   Credit Score                  80846 non-null   float64
 6   Annual Income                 80846 non-null   float64
 7   Years in current job          95778 non-null   object
 8   Home Ownership                100000 non-null  object
 9   Purpose                       100000 non-null  object
 10  Monthly Debt                  100000 non-null  float64
 11  Years of Credit History       100000 non-null  float64
 12  Months since last delinquent  46859 non-null   float64
 13  Number of Open Accounts       100000 non-null  float64
 14  Number of Credit Problems     100000 non-null  float64
 15  Current Credit Balance        100000 non-null  float64
 16  Maximum Open Credit           99998 non-null   float64
 17  Bankruptcies                  99796 non-null   float64
 18  Tax Liens                     99990 non-null   float64
dtypes: float64(12), object(7)
memory usage: 14.6+ MB
```

In [4]:

```
# Descriptive analysis of the Data
df.describe()
```

Out[4]:

	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Months since last delinquent
count	1.000000e+05	80846.000000	8.084600e+04	100000.000000	100000.000000	46859.000000
mean	1.176045e+07	1076.456089	1.378277e+06	18472.412336	18.199141	34.901321
std	3.178394e+07	1475.403791	1.081360e+06	12174.992609	7.015324	21.997829
min	1.080200e+04	585.000000	7.662700e+04	0.000000	3.600000	0.000000
25%	1.796520e+05	705.000000	8.488440e+05	10214.162500	13.500000	16.000000
50%	3.122460e+05	724.000000	1.174162e+06	16220.300000	16.900000	32.000000
75%	5.249420e+05	741.000000	1.650663e+06	24012.057500	21.700000	51.000000
max	1.000000e+08	7510.000000	1.655574e+08	435843.280000	70.500000	176.000000

By looking at the above description we can say that

- The mean value of monthly Debt is 18742.4
- Maximum Credit problems arises are 15

In [5]:

```
#As the Loan ID and Customer ID column is not needed, so I dropped the columns

df.drop(["Loan ID","Customer ID"],axis=1, inplace = True)
```

In [6]:

```
df.isna().sum()

#To check the missing values in the Dataset
```

Out[6]:

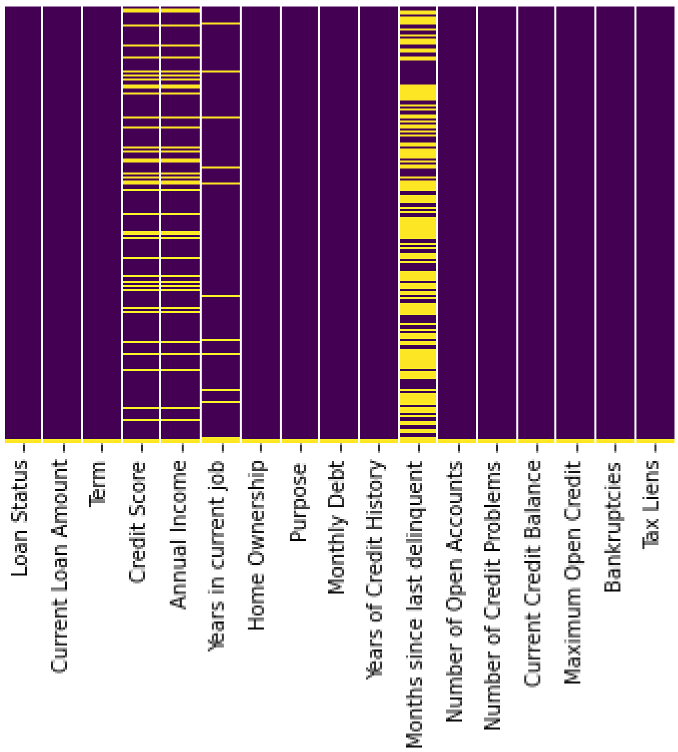
```
Loan Status                       514
Current Loan Amount               514
Term                              514
Credit Score                    19668
Annual Income                   19668
Years in current job             4736
Home Ownership                    514
Purpose                           514
Monthly Debt                      514
Years of Credit History           514
Months since last delinquent    53655
Number of Open Accounts           514
Number of Credit Problems         514
Current Credit Balance            514
Maximum Open Credit               516
Bankruptcies                      718
Tax Liens                         524
dtype: int64
```

In [7]:

```python
#To visualize the null values in the Data set
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap="viridis")
```

Out[7]:

```
<AxesSubplot:>
```



In [8]:

```python
#Looking at the dataset, columnns which have more than 50% missing values needs to be d

df.drop(["Months since last delinquent"],axis = 1, inplace = True)
df.drop(["Credit Score"],axis = 1, inplace = True)
df.drop(["Annual Income"],axis = 1, inplace = True)
```

In [9]:

```python
# Coulmns that has less than 50% missing values were simply handled by dropna feature
df.dropna(inplace = True)
```

In [10]:

```
df.head()
```

Out[10]:

	Loan Status	Current Loan Amount	Term	Years in current job	Home Ownership	Purpose	Monthly Debt	Years of Credit History	Number of Open Accounts	F
0	Fully Paid	445412.0	Short Term	8 years	Home Mortgage	Home Improvements	5214.74	17.2	6.0	
1	Fully Paid	262328.0	Short Term	10+ years	Home Mortgage	Debt Consolidation	33295.98	21.1	35.0	
2	Fully Paid	99999999.0	Short Term	8 years	Own Home	Debt Consolidation	29200.53	14.9	18.0	
3	Fully Paid	347666.0	Long Term	3 years	Own Home	Debt Consolidation	8741.90	12.0	9.0	
4	Fully Paid	176220.0	Short Term	5 years	Rent	Debt Consolidation	20639.70	6.1	15.0	

In [11]:

```
df.isna().sum()
```

Out[11]:

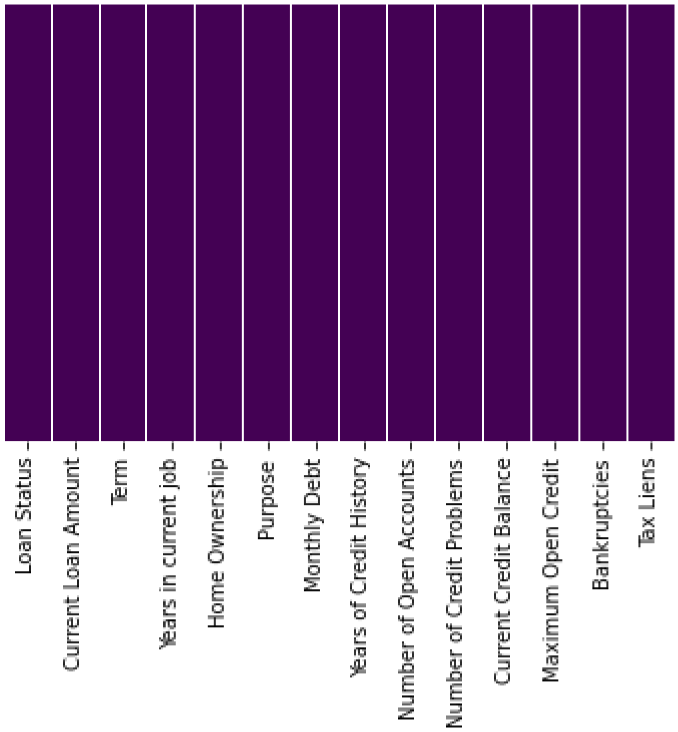
```
Loan Status                  0
Current Loan Amount          0
Term                         0
Years in current job         0
Home Ownership               0
Purpose                      0
Monthly Debt                 0
Years of Credit History      0
Number of Open Accounts      0
Number of Credit Problems    0
Current Credit Balance       0
Maximum Open Credit          0
Bankruptcies                 0
Tax Liens                    0
dtype: int64
```

In [12]:

```
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap="viridis")
```

Out[12]:

```
<AxesSubplot:>
```



Now there are no missing values!!

In [13]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 95572 entries, 0 to 99998
Data columns (total 14 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Loan Status                95572 non-null  object 
 1   Current Loan Amount        95572 non-null  float64
 2   Term                       95572 non-null  object 
 3   Years in current job       95572 non-null  object 
 4   Home Ownership             95572 non-null  object 
 5   Purpose                    95572 non-null  object 
 6   Monthly Debt               95572 non-null  float64
 7   Years of Credit History    95572 non-null  float64
 8   Number of Open Accounts    95572 non-null  float64
 9   Number of Credit Problems  95572 non-null  float64
 10  Current Credit Balance     95572 non-null  float64
 11  Maximum Open Credit        95572 non-null  float64
 12  Bankruptcies               95572 non-null  float64
 13  Tax Liens                  95572 non-null  float64
dtypes: float64(9), object(5)
memory usage: 10.9+ MB
```

In [14]:

```
# checking the correlation between the columns
df.corr().style.background_gradient()
```

Out[14]:

	Current Loan Amount	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems	Current Credit Balance	Maximum Open Credit	Bankru
Current Loan Amount	1.000000	-0.007967	0.018941	0.000731	-0.003692	0.003870	-0.001092	-0.
Monthly Debt	-0.007967	1.000000	0.218537	0.407513	-0.049283	0.482037	0.039326	-0.
Years of Credit History	0.018941	0.218537	1.000000	0.139674	0.057824	0.215992	0.030196	0.
Number of Open Accounts	0.000731	0.407513	0.139674	1.000000	-0.009716	0.225043	0.030088	-0.
Number of Credit Problems	-0.003692	-0.049283	0.057824	-0.009716	1.000000	-0.110298	-0.011487	0.
Current Credit Balance	0.003870	0.482037	0.215992	0.225043	-0.110298	1.000000	0.136555	-0.
Maximum Open Credit	-0.001092	0.039326	0.030196	0.030088	-0.011487	0.136555	1.000000	-0.
Bankruptcies	-0.001133	-0.072196	0.061097	-0.017804	0.751056	-0.119691	-0.013958	1.
Tax Liens	-0.003228	0.021759	0.017175	0.005862	0.581465	-0.015566	-0.001068	0.

- By this analysis we can say that,

- 1) Bankruptcies and Tax liens has high correlation with Number of credit problems
- 2) Current credit balance has some correlation with Monthly debt

In [15]:

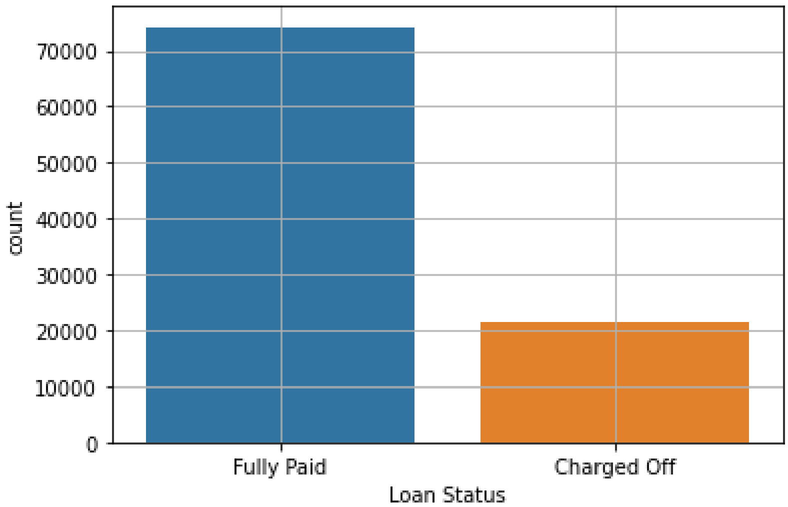
```
df["Loan Status"].value_counts()
```

Out[15]:

```
Fully Paid     74257
Charged Off    21315
Name: Loan Status, dtype: int64
```

In [16]:

```
# checking the count of people who have fully paid and failed to pay
sns.countplot(data = df, x= "Loan Status")
plt.grid(True)
```



In [17]:

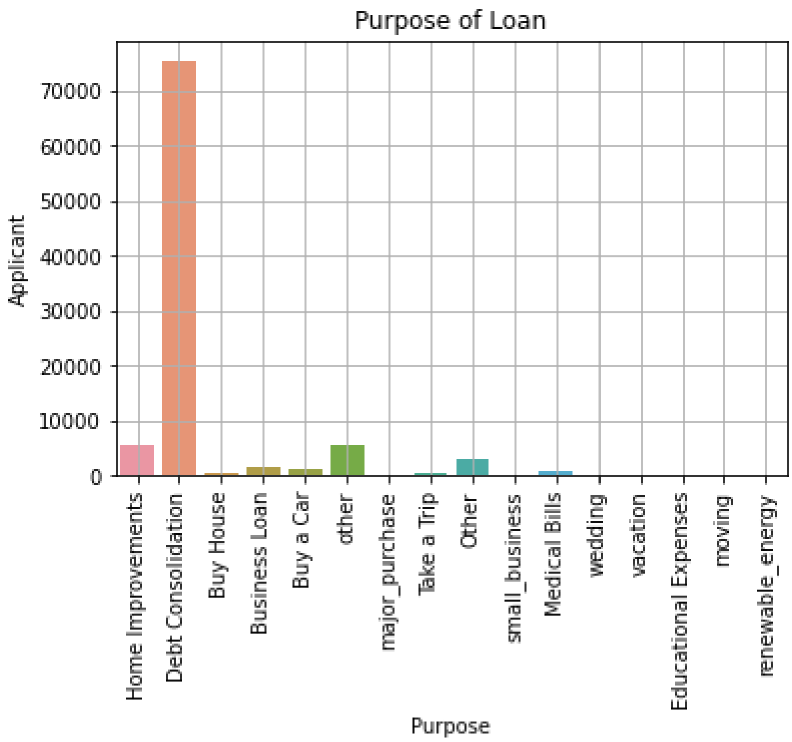
```
df["Purpose"].value_counts()
```

Out[17]:

```
Debt Consolidation      75277
other                    5665
Home Improvements        5511
Other                    3104
Business Loan            1519
Buy a Car                1208
Medical Bills            1041
Buy House                 652
Take a Trip               546
major_purchase            333
small_business            272
moving                    139
wedding                   111
vacation                   95
Educational Expenses       89
renewable_energy           10
Name: Purpose, dtype: int64
```

In [18]:

```
# Purpose of the Loan that was taken
sns.countplot(data = df, x= "Purpose")
plt.title("Purpose of Loan")
plt.xlabel("Purpose")
plt.ylabel("Applicant")
plt.xticks(rotation=90)
plt.grid(True)
```



By this visualization we can say that

- the highest reason for the loan was Debt consolidation

In [19]:

```
df["Years in current job"].value_counts()
```

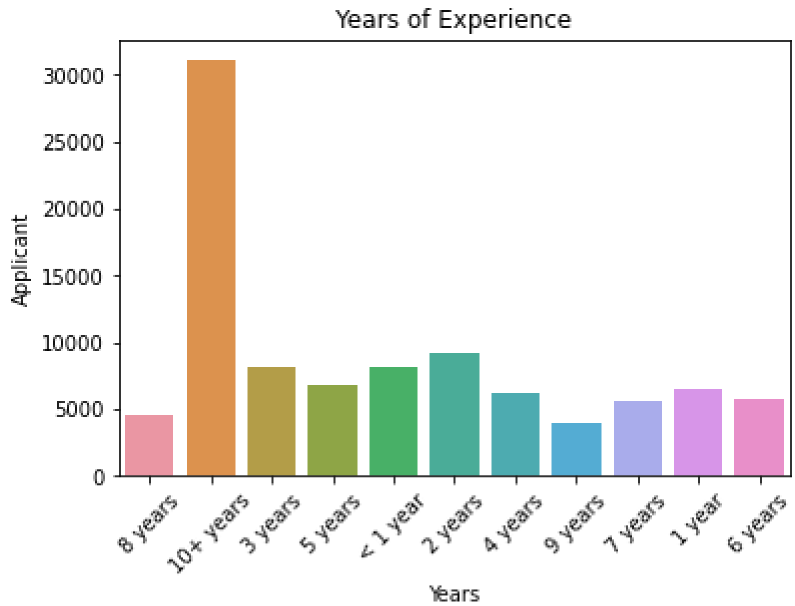
Out[19]:

```
10+ years    31090
2 years       9104
3 years       8151
< 1 year      8114
5 years       6778
1 year        6436
4 years       6132
6 years       5676
7 years       5573
8 years       4569
9 years       3949
Name: Years in current job, dtype: int64
```

In [20]:

```
sns.countplot(data = df, x= "Years in current job")
plt.title("Years of Experience")
plt.xlabel("Years")
plt.ylabel("Applicant")
plt.xticks(rotation=45)
plt.show()

```



In [21]:

```
# checking the pairplot for the Dataset
sns.pairplot(df, hue="Loan Status")
```

Out[21]:

<seaborn.axisgrid.PairGrid at 0x2bf0532c10>

In [22]:

```
df.head()
```

Out[22]:

	Loan Status	Current Loan Amount	Term	Years in current job	Home Ownership	Purpose	Monthly Debt	Years of Credit History	Number of Open Accounts	F
0	Fully Paid	445412.0	Short Term	8 years	Home Mortgage	Home Improvements	5214.74	17.2	6.0	
1	Fully Paid	262328.0	Short Term	10+ years	Home Mortgage	Debt Consolidation	33295.98	21.1	35.0	
2	Fully Paid	99999999.0	Short Term	8 years	Own Home	Debt Consolidation	29200.53	14.9	18.0	
3	Fully Paid	347666.0	Long Term	3 years	Own Home	Debt Consolidation	8741.90	12.0	9.0	
4	Fully Paid	176220.0	Short Term	5 years	Rent	Debt Consolidation	20639.70	6.1	15.0	

Data preprocessing

In [23]:

```
# splitting the data into X and Y
x = df.iloc[:,1:]
y = df.iloc[:,:1]
```

In [24]:

```
x
```

Out[24]:

	Current Loan Amount	Term	Years in current job	Home Ownership	Purpose	Monthly Debt	Years of Credit History	Number of Open Accounts	Nu of C Prob
0	445412.0	Short Term	8 years	Home Mortgage	Home Improvements	5214.74	17.2	6.0	
1	262328.0	Short Term	10+ years	Home Mortgage	Debt Consolidation	33295.98	21.1	35.0	
2	99999999.0	Short Term	8 years	Own Home	Debt Consolidation	29200.53	14.9	18.0	
3	347666.0	Long Term	3 years	Own Home	Debt Consolidation	8741.90	12.0	9.0	
4	176220.0	Short Term	5 years	Rent	Debt Consolidation	20639.70	6.1	15.0	
...	...	...	...	...	...	...	...	...	
99994	210584.0	Short Term	1 year	Home Mortgage	Other	3727.61	17.4	6.0	
99995	147070.0	Short Term	7 years	Own Home	other	2202.86	22.3	5.0	
99996	99999999.0	Short Term	1 year	Rent	Debt Consolidation	13109.05	9.4	22.0	
99997	103136.0	Short Term	6 years	Rent	Debt Consolidation	7315.57	18.8	12.0	
99998	530332.0	Short Term	9 years	Rent	Debt Consolidation	9890.07	15.0	8.0	

95572 rows × 13 columns

In [25]:

```
y
```

	Loan Status
0	Fully Paid
1	Fully Paid
2	Fully Paid
3	Fully Paid
4	Fully Paid
...	...
99994	Fully Paid
99995	Fully Paid
99996	Fully Paid
99997	Fully Paid
99998	Fully Paid

In [26]:

```
df_cat = df.select_dtypes(object)
df_num = df.select_dtypes(["int64", "float64"])
```

In [27]:

```
df_cat
```

Out[27]:

	Loan Status	Term	Years in current job	Home Ownership	Purpose
0	Fully Paid	Short Term	8 years	Home Mortgage	Home Improvements
1	Fully Paid	Short Term	10+ years	Home Mortgage	Debt Consolidation
2	Fully Paid	Short Term	8 years	Own Home	Debt Consolidation
3	Fully Paid	Long Term	3 years	Own Home	Debt Consolidation
4	Fully Paid	Short Term	5 years	Rent	Debt Consolidation
...	...	...	...	...	...
99994	Fully Paid	Short Term	1 year	Home Mortgage	Other
99995	Fully Paid	Short Term	7 years	Own Home	other
99996	Fully Paid	Short Term	1 year	Rent	Debt Consolidation
99997	Fully Paid	Short Term	6 years	Rent	Debt Consolidation
99998	Fully Paid	Short Term	9 years	Rent	Debt Consolidation

95572 rows × 5 columns

In [28]:

```
df_num
```

Out[28]:

	Current Loan Amount	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems	Current Credit Balance	Maximum Open Credit	Bankruptcies
0	445412.0	5214.74	17.2	6.0	1.0	228190.0	416746.0	1.0
1	262328.0	33295.98	21.1	35.0	0.0	229976.0	850784.0	0.0
2	99999999.0	29200.53	14.9	18.0	1.0	297996.0	750090.0	0.0
3	347666.0	8741.90	12.0	9.0	0.0	256329.0	386958.0	0.0
4	176220.0	20639.70	6.1	15.0	0.0	253460.0	427174.0	0.0
...	...	...	...	...	...	...	...	...
99994	210584.0	3727.61	17.4	6.0	0.0	456.0	259160.0	0.0
99995	147070.0	2202.86	22.3	5.0	0.0	47766.0	658548.0	0.0
99996	99999999.0	13109.05	9.4	22.0	0.0	153045.0	509234.0	0.0
99997	103136.0	7315.57	18.8	12.0	1.0	109554.0	537548.0	1.0
99998	530332.0	9890.07	15.0	8.0	0.0	404225.0	738254.0	0.0

95572 rows × 9 columns

In [29]:

```
df["Term"].value_counts()
```

Out[29]:

```
Short Term    68471
Long Term     27101
Name: Term, dtype: int64
```

In [30]:

```
df["Years in current job"].value_counts()
```

Out[30]:

```
10+ years    31090
2 years       9104
3 years       8151
< 1 year      8114
5 years       6778
1 year        6436
4 years       6132
6 years       5676
7 years       5573
8 years       4569
9 years       3949
Name: Years in current job, dtype: int64
```

In [31]:

```
df["Home Ownership"].value_counts()
```

Out[31]:

```
Home Mortgage    46414
Rent             40550
Own Home          8403
HaveMortgage       205
Name: Home Ownership, dtype: int64
```

In [32]:

```
df["Purpose"].value_counts()

```

Out[32]:

```
Debt Consolidation      75277
other                    5665
Home Improvements        5511
Other                    3104
Business Loan            1519
Buy a Car                1208
Medical Bills            1041
Buy House                 652
Take a Trip               546
major_purchase            333
small_business            272
moving                    139
wedding                   111
vacation                   95
Educational Expenses       89
renewable_energy           10
Name: Purpose, dtype: int64
```

In [33]:

```
# Label encoding the Data
from sklearn.preprocessing import LabelEncoder
```

In [34]:

```
for col in df_cat:
    le = LabelEncoder()
    df_cat[col]=le.fit_transform(df_cat[col])
```

In [35]:

```
df_cat["Loan Status"].value_counts()
```

Out[35]:

```
1    74257
0    21315
Name: Loan Status, dtype: int64
```

In [36]:

```
df_cat["Term"].value_counts()
```

Out[36]:

```
1    68471
0    27101
Name: Term, dtype: int64
```

In [37]:

```
df_cat["Years in current job"].value_counts()
```

Out[37]:

```
1     31090
2      9104
3      8151
10     8114
5      6778
0      6436
4      6132
6      5676
7      5573
8      4569
9      3949
Name: Years in current job, dtype: int64
```

In [38]:

```
df_cat["Home Ownership"].value_counts()
```

Out[38]:

```
1    46414
3    40550
2     8403
0      205
Name: Home Ownership, dtype: int64
```

In [39]:

```
df_cat["Purpose"].value_counts()
```

Out[39]:

```
3     75277
11     5665
5      5511
7      3104
0      1519
2      1208
6      1041
1       652
8       546
9       333
13      272
10      139
15      111
14       95
4        89
12       10
Name: Purpose, dtype: int64
```

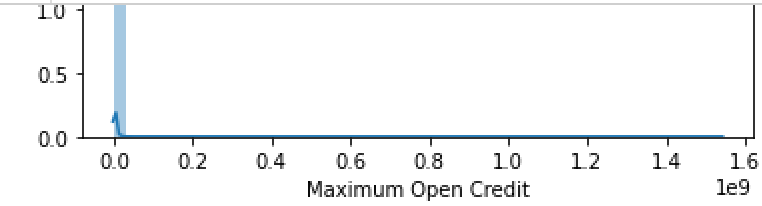
In [40]:

```
#to check the skewness in the data
from scipy.stats import skew
```

In [41]:

```
for col in df_num:
    print(col)
    print(skew( df_num[col] ))

    plt.figure()
    sns.distplot(df_num[col])
    plt.show()
```




```
Bankruptcies
3.5779160537124457
```

In [42]:

```
df =pd.concat([df_cat,df_num], axis = 1)
```

In [43]:

```
df.head()
```

Out[43]:

	Loan Status	Term	Years in current job	Home Ownership	Purpose	Current Loan Amount	Monthly Debt	Years of Credit History	Number of Open Accounts	Num of Cr Probl
0	1	1	8	1	5	445412.0	5214.74	17.2	6.0	
1	1	1	1	1	3	262328.0	33295.98	21.1	35.0	
2	1	1	8	2	3	99999999.0	29200.53	14.9	18.0	
3	1	0	3	2	3	347666.0	8741.90	12.0	9.0	
4	1	1	5	3	3	176220.0	20639.70	6.1	15.0	

In [44]:

```
x = df.iloc[:,1:]
y = df.iloc[:,:1]
```

In [45]:

```
x
```

Out[45]:

	Term	Years in current job	Home Ownership	Purpose	Current Loan Amount	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems
0	1	8	1	5	445412.0	5214.74	17.2	6.0	1.0
1	1	1	1	3	262328.0	33295.98	21.1	35.0	0.0
2	1	8	2	3	99999999.0	29200.53	14.9	18.0	1.0
3	0	3	2	3	347666.0	8741.90	12.0	9.0	0.0
4	1	5	3	3	176220.0	20639.70	6.1	15.0	0.0
...	...	...	...	...	...	...	...	...	...
99994	1	0	1	7	210584.0	3727.61	17.4	6.0	0.0
99995	1	7	2	11	147070.0	2202.86	22.3	5.0	0.0
99996	1	0	3	3	99999999.0	13109.05	9.4	22.0	0.0
99997	1	6	3	3	103136.0	7315.57	18.8	12.0	1.0
99998	1	9	3	3	530332.0	9890.07	15.0	8.0	0.0

95572 rows × 13 columns

In [46]:

```
y
```

Out[46]:

	Loan Status
0	1
1	1
2	1
3	1
4	1
...	...
99994	1
99995	1
99996	1
99997	1
99998	1

95572 rows × 1 columns

Model creation

In [47]:

```
from sklearn.model_selection import train_test_split, cross_val_score
xtrain, xtest, ytrain, ytest = train_test_split(x,y, test_size = 0.3, random_state =0 ,
```

In [48]:

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(xtrain,ytrain)
ypred = rfc.predict(xtest)
```

In [49]:

```
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
```

In [50]:

```
print(classification_report(ytest, ypred))
print()
print(accuracy_score(ytest, ypred))
print()
print(confusion_matrix(ytest, ypred))
```

```
              precision    recall  f1-score   support

           0       0.57      0.07      0.12      6395
           1       0.79      0.99      0.87     22277

    accuracy                           0.78     28672
   macro avg       0.68      0.53      0.50     28672
weighted avg       0.74      0.78      0.71     28672


0.7807268415178571

[[  440  5955]
 [  332 21945]]
```

In [51]:

```
ytrain.value_counts()
```

Out[51]:

```
Loan Status
1              51980
0              14920
dtype: int64
```

In [52]:

```
!pip install imblearn
```

```
Requirement already satisfied: imblearn in c:\users\arsalan\anaconda3\lib\si
te-packages (0.0)
Requirement already satisfied: imbalanced-learn in c:\users\arsalan\anaconda
3\lib\site-packages (from imblearn) (0.8.0)
Requirement already satisfied: scipy>=0.19.1 in c:\users\arsalan\anaconda3\l
ib\site-packages (from imbalanced-learn->imblearn) (1.6.2)
Requirement already satisfied: scikit-learn>=0.24 in c:\users\arsalan\anacon
da3\lib\site-packages (from imbalanced-learn->imblearn) (0.24.1)
Requirement already satisfied: joblib>=0.11 in c:\users\arsalan\anaconda3\li
b\site-packages (from imbalanced-learn->imblearn) (1.0.1)
Requirement already satisfied: numpy>=1.13.3 in c:\users\arsalan\anaconda3\l
ib\site-packages (from imbalanced-learn->imblearn) (1.20.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\arsalan\anac
onda3\lib\site-packages (from scikit-learn>=0.24->imbalanced-learn->imblear
n) (2.1.0)
```

As the data was highly imbalanced, we need to balance the data using imblearn

In [53]:

```
# Synthetic minority Oversampling technique(SMOTE)
from imblearn.combine import SMOTETomek
from imblearn.under_sampling import NearMiss
```

In [54]:

```
smk = SMOTETomek(random_state = 42)
x1, y1 = smk.fit_resample(x,y)
```

In [55]:

```
x1.shape, y1.shape
```

Out[55]:

```
((144380, 13), (144380, 1))
```

In [56]:

```
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler()
xtrain1, ytrain1 = ros.fit_resample(x,y)

```

In [57]:

```
xtrain1.shape,ytrain1.shape
```

Out[57]:

```
((148514, 13), (148514, 1))
```

In [58]:

```
xtrain1, xtest, ytrain1, ytest = train_test_split(x1,y1, test_size = 0.3, random_state
```

In [59]:

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(xtrain1,ytrain1)
ypred = dt.predict(xtest)
print(classification_report(ytest, ypred))
print()
print(accuracy_score(ytest, ypred))
print()
print(confusion_matrix(ytest, ypred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.78      0.80     21879
           1       0.79      0.82      0.80     21435

    accuracy                           0.80     43314
   macro avg       0.80      0.80      0.80     43314
weighted avg       0.80      0.80      0.80     43314


0.8023964538024657

[[17159  4720]
 [ 3839 17596]]
```

In [60]:

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(xtrain1,ytrain1)
ypred = rfc.predict(xtest)
```

In [61]:

```
print(classification_report(ytest, ypred))
print()
print(accuracy_score(ytest, ypred))
print()
print(confusion_matrix(ytest, ypred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.80      0.84     21879
           1       0.81      0.88      0.85     21435

    accuracy                           0.84     43314
   macro avg       0.84      0.84      0.84     43314
weighted avg       0.84      0.84      0.84     43314


0.8415523849101907

[[17557  4322]
 [ 2541 18894]]
```

HyperParameter Tuning to improve the accuracy

In [62]:

```
rfc1 = RandomForestClassifier(criterion = "entropy")
rfc1.fit(xtrain1,ytrain1)
ypred = rfc1.predict(xtest)
print(classification_report(ytest, ypred))
print()
print(accuracy_score(ytest, ypred))
print()
print(confusion_matrix(ytest, ypred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.80      0.84     21879
           1       0.81      0.88      0.85     21435

    accuracy                           0.84     43314
   macro avg       0.84      0.84      0.84     43314
weighted avg       0.84      0.84      0.84     43314


0.8412753382278247

[[17554  4325]
 [ 2550 18885]]
```

In [63]:

```
rfc2 = RandomForestClassifier(max_samples = 100)
rfc2.fit(xtrain1,ytrain1)
ypred = rfc2.predict(xtest)
print(classification_report(ytest, ypred))
print()
print(accuracy_score(ytest, ypred))
print()
print(confusion_matrix(ytest, ypred))
```

```
              precision    recall  f1-score   support

           0       0.67      0.71      0.69     21879
           1       0.69      0.65      0.67     21435

    accuracy                           0.68     43314
   macro avg       0.68      0.68      0.68     43314
weighted avg       0.68      0.68      0.68     43314


0.6788798079143002

[[15562  6317]
 [ 7592 13843]]
```

In [64]:

```
rfc3 = RandomForestClassifier(min_samples_leaf = 50)
rfc3.fit(xtrain1,ytrain1)
ypred = rfc3.predict(xtest)
print(classification_report(ytest, ypred))
print()
print(accuracy_score(ytest, ypred))
print()
print(confusion_matrix(ytest, ypred))
```

```
              precision    recall  f1-score   support

           0       0.77      0.71      0.74     21879
           1       0.73      0.79      0.76     21435

    accuracy                           0.75     43314
   macro avg       0.75      0.75      0.75     43314
weighted avg       0.75      0.75      0.75     43314


0.7490880546705453

[[15531  6348]
 [ 4520 16915]]
```

In [65]:

```
for i in range(1,100,10):
        rfc4 = RandomForestClassifier(min_samples_leaf = i)
        rfc4.fit(xtrain1,ytrain1)
        ypred = rfc4.predict(xtest)
        print(f" {i} -: {accuracy_score(ytest, ypred)}")
```

```
 1 -: 0.8421988271690447
 11 -: 0.7845962044604516
 21 -: 0.7694048113773837
 31 -: 0.7578611996121346
 41 -: 0.7579304612827261
 51 -: 0.746848593988087
 61 -: 0.7447245694232811
 71 -: 0.7412383986701759
 81 -: 0.7391143741053701
 91 -: 0.7372673962229302
```

In [66]:

```
for i in range (1,100,10):
    rfc5  = RandomForestClassifier(max_samples = i)
    rfc5.fit(xtrain1,ytrain1)
    ypred = rfc5.predict(xtest)
    print(f" {i}   -: {accuracy_score(ytest,ypred)}")
```

```
1   -: 0.5051253636237706
11   -: 0.6271413399824537
21   -: 0.649258900124671
31   -: 0.6483815856305121
41   -: 0.6692524357020825
51   -: 0.6713302858198273
61   -: 0.6721383386433948
71   -: 0.6758553816318049
81   -: 0.6835434270674609
91   -: 0.6780948423142633
```

In [67]:

```
for i in range(1,1000,50):
    rfc6  = RandomForestClassifier(n_estimators = i)
    rfc6.fit(xtrain1,ytrain1)
    ypred = rfc6.predict(xtest)
    print(f" {i}   -: {accuracy_score(ytest,ypred)}")
```

```
1   -: 0.7346585399639839
51   -: 0.8372812485570486
101   -: 0.8427067460867156
151   -: 0.8438149328161795
201   -: 0.843884194486771
251   -: 0.8459851318280464
301   -: 0.8433070138985086
351   -: 0.8449692939927045
401   -: 0.844484462298564
451   -: 0.844992381216235
501   -: 0.8461005679456989
551   -: 0.8451539917809484
601   -: 0.8457311723692109
651   -: 0.8451309045574179
701   -: 0.8450847301103569
751   -: 0.8447153345338689
801   -: 0.8454310384633144
851   -: 0.8453156023456619
901   -: 0.8461698296162904
951   -: 0.8456157362515584
```

In [68]:

```
from sklearn.ensemble import RandomForestClassifier
rfc7 = RandomForestClassifier(n_estimators = 950)
rfc7.fit(xtrain1,ytrain1)
ypred = rfc7 .predict(xtest)
```

In [69]:

```
print(classification_report(ytest, ypred))
print()
print(accuracy_score(ytest, ypred))
print()
print(confusion_matrix(ytest, ypred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.80      0.84     21879
           1       0.82      0.89      0.85     21435

    accuracy                           0.85     43314
   macro avg       0.85      0.85      0.85     43314
weighted avg       0.85      0.85      0.85     43314


0.8455003001339059

[[17574  4305]
 [ 2387 19048]]
```

Using cross validation getting the mean accuracy ¶

In [70]:

```
cvs = cross_val_score(rfc7, x1, y1, cv = 5, scoring = "accuracy")
print(f"Avg. Accuracy-: {cvs.mean()}\nStandard Deviation -: {cvs.std()}")
```

```
Avg. Accuracy-: 0.8503670868541351
Standard Deviation -: 0.10974338801027816
```

RESULTS

- being a dataset based on the defaulters the percentage of defaulters are really less
- approximately the ratio of people who have paid with who has not paid is 1:4
- balancing the Dataset for an improved accuracy and f1-score
- After splitting the data into train and test we came to know the categorical data needs to be label encoded
- Using two different models we came to know Random forest classifier can be used for this data for an improved accuracy
- did some hyperparameter tuning on the model to increase the accuracy

CONCLUSION

- The best fit model for this dataset is Random forest classifier with the value of n_estimator parameter at 950
- The average accuracy of the model is 85%

In [ ]:

```

```