Machine Learning Engineer Nanodegree

Capstone Project

Bank Loan Prediction

Project Overview

Our objective in this project is helping the Bank to make decisions on loans requests, accepting or rejecting the loan request based on these data which contains more than one hundred thousand rows of the above loan data.

- we will classify these data into two classes :
- **1. loan can be accepted**
- **2. loan must be rejected**

Data Exploration & Visualization

In [1]:
```
# Import libraries
from IPython.display import display
from time import time
from sklearn import preprocessing
import numpy as np
import pandas as pd
pd.set_option('display.max_columns', 999)
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```python
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.dummy import DummyClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import recall_score,precision_score,fbeta_score,ac
curacy_score
from imblearn.under_sampling import NearMiss
from sklearn.model_selection import GridSearchCV

# Warnings
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

# Import dataset
data = pd.read_csv('credit.csv')

# Display first records
data.head()
```

```
Using TensorFlow backend.
```

Out[1]:

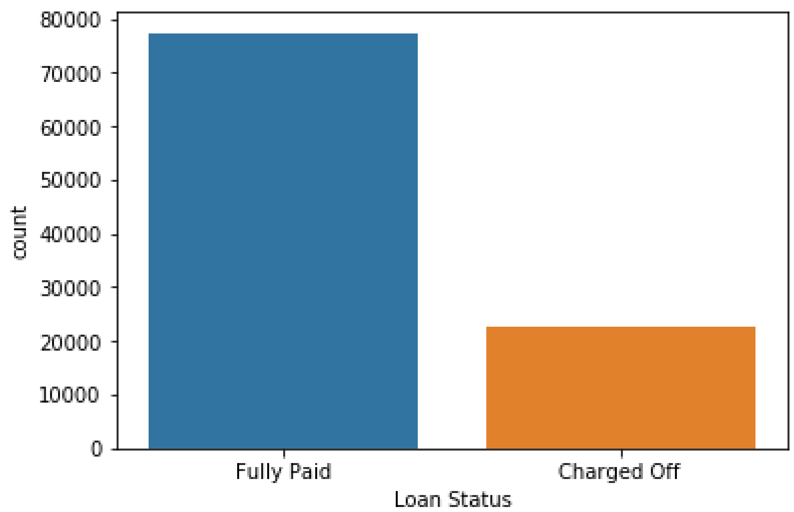
	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership
0	14dd8831-6af5-400b-83ec-68e61888a048	981165ec-3274-42f5-a3b4-d104041a9ca9	Fully Paid	445412.0	Short Term	709.0	1167493.0	8 years	Home Mortgage
1	4771cc26-131a-45db-b5aa-537ea4ba5342	2de017a3-2e01-49cb-a581-08169e83be29	Fully Paid	262328.0	Short Term	NaN	NaN	10+ years	Home Mortgage
2	4eed4e6a-aa2f-4c91-8651-	5efb2b2b-bf11-4dfd-a572-	Fully Paid	99999999.0	Short Term	741.0	2231892.0	8 years	Own Home

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership
	ce984ee8fb26	3761a2694725							
3	77598f7b-32e7-4e3b-a6e5-06ba0d98fe8a	e777faab-98ae-45af-9a86-7ce5b33b1011	Fully Paid	347666.0	Long Term	721.0	806949.0	3 years	Own Home
4	d4062e70-befa-4995-8643-a0de73938182	81536ad9-5ccf-4eb8-befb-47a4d608658e	Fully Paid	176220.0	Short Term	NaN	NaN	5 years	Rent

In [2]:

```python
# Number of records
n_records = data.shape[0]

fully_paid = data[data['Loan Status'] == 'Fully Paid'].shape[0]

charged_off = data[data['Loan Status'] == 'Charged Off'].shape[0]

charged_of_percentage = charged_off * 100 / n_records
# Display statistics about target variable (Loan Status)
print("Total number of records: {}".format(n_records))
print("Individuals charged off: {}".format(charged_off))
print("Individuals fully paid: {}".format(fully_paid))
print("Percentage of Individuals charged off : {}%".format(charged_of_p
ercentage))

# Visualize Target Variable (Loan Status)
ax = sns.countplot(data['Loan Status'])
plt.show()
```

```
Total number of records: 100514
Individuals charged off: 22639
Individuals fully paid: 77361
Percentage of Individuals charged off : 22.52323059474302%
```




```
In [3]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100514 entries, 0 to 100513
Data columns (total 19 columns):
Loan ID                         100000 non-null object
Customer ID                     100000 non-null object
Loan Status                     100000 non-null object
Current Loan Amount             100000 non-null float64
Term                            100000 non-null object
Credit Score                    80846 non-null float64
Annual Income                   80846 non-null float64
Years in current job            95778 non-null object
Home Ownership                  100000 non-null object
Purpose                         100000 non-null object
Monthly Debt                    100000 non-null float64
Years of Credit History         100000 non-null float64
Months since last delinquent    46859 non-null float64
Number of Open Accounts         100000 non-null float64
Number of Credit Problems       100000 non-null float64
Current Credit Balance          100000 non-null float64
Maximum Open Credit             99998 non-null float64
```

```
Bankruptcies                        99796 non-null float64
Tax Liens                           99990 non-null float64
dtypes: float64(12), object(7)
memory usage: 14.6+ MB
```

Data Preprocessing

We have some missing values in our dataset.

In [4]:
```
# calculate missing values by column
def missingValues_table(df):
        # Total missing values
        missingValues = df.isnull().sum()

        # Percentage of missing values
        missingValues_percent = 100 * df.isnull().sum() / len(df)

        # Create table with results
        missingValues_table = pd.concat([missingValues, missingValues_p
ercent], axis=1)

        # Rename the columns
        missingValues_table_renamed = missingValues_table.rename(column
s = {0 : 'Missing Values', 1 : '% of Total Values'})

        # Sort the table by percentage of missing descending
        missingValues_table_renamed = missingValues_table_renamed[
        missingValues_table_renamed.iloc[:,1] != 0].sort_values(
        '% of Total Values', ascending=False).round(1)

        # Print some summary information
        print ("Selected dataframe has " + str(df.shape[1]) + " column
s.\n"
            "There are " + str(missingValues_table_renamed.shape[0]) +
              " Columns that have missing values.")
```

```python
    # Return the dataframe with missing information
    return missingValues_table_renamed
```

In [5]:
```python
missingValues_table(data)
```

```
Selected dataframe has 19 columns.
There are 19 Columns that have missing values.
```

Out[5]:

	Missing Values	% of Total Values
Months since last delinquent	53655	53.4
Credit Score	19668	19.6
Annual Income	19668	19.6
Years in current job	4736	4.7
Bankruptcies	718	0.7
Tax Liens	524	0.5
Maximum Open Credit	516	0.5
Years of Credit History	514	0.5
Current Credit Balance	514	0.5
Number of Credit Problems	514	0.5
Number of Open Accounts	514	0.5
Loan ID	514	0.5
Monthly Debt	514	0.5
Customer ID	514	0.5
Home Ownership	514	0.5
Term	514	0.5
Current Loan Amount	514	0.5
Loan Status	514	0.5
Purpose	514	0.5

As we see there is 514 missing values in all variables, this means there is 514 of all null rows

In [6]:
```
data[data['Loan Status'].isnull() == True]
```

Out[6]:

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership	Purpose
100000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100002	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100003	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100004	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100005	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100006	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100007	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100008	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100009	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100010	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100011	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100012	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100013	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100014	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100015	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100016	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100017	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership	Purpose
100018	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100019	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100020	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100022	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100023	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100024	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100025	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100026	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100027	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100028	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100029	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...
100484	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100485	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100486	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100487	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100488	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100489	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100490	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100491	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100492	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100493	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership	Purpose
100494	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100495	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100496	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100497	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100498	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100499	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100500	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100501	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100502	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100503	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100504	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100505	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100506	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100507	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100508	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100509	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100510	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100511	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100512	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
100513	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

514 rows × 19 columns

In [7]:
```
# Drop these Null rows
```

```
data.drop(data.tail(514).index, inplace=True)
missingValues_table(data)
```

```
Selected dataframe has 19 columns.
There are 7 Columns that have missing values.
```

Out[7]:

	Missing Values	% of Total Values
Months since last delinquent	53141	53.1
Credit Score	19154	19.2
Annual Income	19154	19.2
Years in current job	4222	4.2
Bankruptcies	204	0.2
Tax Liens	10	0.0
Maximum Open Credit	2	0.0

'Months since last delinquent' Feature has more than 50% of missing values so we should drop it

In [8]:
```
data = data.drop(['Months since last delinquent'], axis=1)
```

'Bankruptcies' & 'Tax Liens' & 'Maximum Open Credit' has very small percentage of missing values no problem with drop them

In [9]:
```
for i in data['Tax Liens'][data['Tax Liens'].isnull() == True].index:
    data.drop(labels=i, inplace=True)
```

In [10]:
```
for i in data['Bankruptcies'][data['Bankruptcies'].isnull() == True].in
dex:
    data.drop(labels=i, inplace=True)
```

In [11]:
```
for i in data['Maximum Open Credit'][data['Maximum Open Credit'].isnull
```

```
() == True].index:
    data.drop(labels=i, inplace=True)
missingValues_table(data)
```

```
Selected dataframe has 18 columns.
There are 3 Columns that have missing values.
```

Out[11]:

	Missing Values	% of Total Values
Credit Score	19111	19.2
Annual Income	19111	19.2
Years in current job	4222	4.2

Credit Score & Annual Income Are continues variables, we should describe some statistics to handle thier missing values

In [12]:

```
pd.set_option('float_format', '{:.2f}'.format)
data.describe()
```

Out[12]:

	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems	Curre Cre Balan
count	99794.00	80683.00	80683.00	99794.00	99794.00	99794.00	99794.00	99794.
mean	11757279.22	1076.28	1378339.05	18486.12	18.19	11.13	0.17	294660.
std	31779846.84	1475.03	1080909.86	12172.47	7.02	5.01	0.48	376066.
min	15422.00	585.00	76627.00	0.00	3.60	0.00	0.00	0.
25%	179696.00	705.00	849110.00	10228.32	13.50	8.00	0.00	112769.
50%	312477.00	724.00	1174371.00	16237.21	16.90	10.00	0.00	209912.
75%	525096.00	741.00	1650701.00	24025.22	21.70	14.00	0.00	368068.
max	99999999.00	7510.00	165557393.00	435843.28	70.50	76.00	15.00	32878968.

As we see, some of the **credit score** are just scaled up by 10. , we should rescale them.

In [13]:
```
data['Credit Score'] = data['Credit Score'].apply(lambda val: (val /10)
 if val>850 else val)
data.describe()
```

Out[13]:

	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Number of Open Accounts	Number of Credit Problems	Curre Cre Balan
count	99794.00	80683.00	80683.00	99794.00	99794.00	99794.00	99794.00	99794.
mean	11757279.22	716.28	1378339.05	18486.12	18.19	11.13	0.17	294660.
std	31779846.84	28.30	1080909.86	12172.47	7.02	5.01	0.48	376066.
min	15422.00	585.00	76627.00	0.00	3.60	0.00	0.00	0.
25%	179696.00	703.00	849110.00	10228.32	13.50	8.00	0.00	112769.
50%	312477.00	722.00	1174371.00	16237.21	16.90	10.00	0.00	209912.
75%	525096.00	738.00	1650701.00	24025.22	21.70	14.00	0.00	368068.
max	99999999.00	751.00	165557393.00	435843.28	70.50	76.00	15.00	32878968.

We will use mean to handle mising values of **Credit Score** but Short/Long term is effect on Credit Score, so we will calculate Short/Long term means to assign each's mean to those have same term value

In [14]:
```
credit_short = data[data['Term']=='Short Term']
shortTermAvg = credit_short['Credit Score'].mean()

credit_long = data[data['Term']=='Long Term']
longTermAvg = credit_long['Credit Score'].mean()
print(shortTermAvg,longTermAvg)
```

```
724.6238081178249 695.483727170432
```

In [15]:
```
data.loc[(data.Term =='Short Term') & (data['Credit Score'].isnull()),
'Credit Score'] = shortTermAvg
data.loc[(data.Term =='Long Term') & (data['Credit Score'].isnull()),'C
redit Score'] = longTermAvg
missingValues_table(data)
```

```
Selected dataframe has 18 columns.
There are 2 Columns that have missing values.
```

Out[15]:

	Missing Values	% of Total Values
Annual Income	19111	19.20
Years in current job	4222	4.20

Filling **Annual Income** missing values using the Median value because there is outliers in incomes

In [16]:
```
data['Annual Income'].fillna(data['Annual Income'].median(), inplace=Tr
ue)
missingValues_table(data)
```

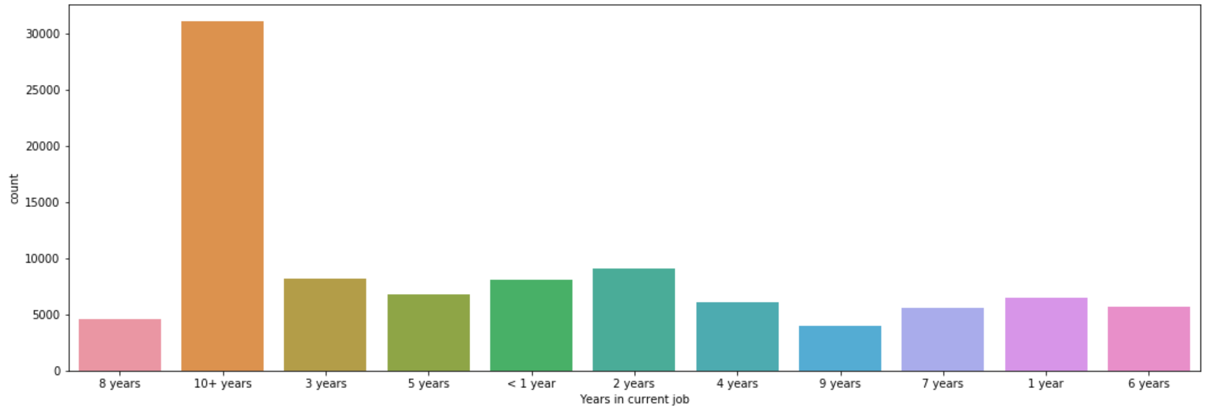
```
Selected dataframe has 18 columns.
There are 1 Columns that have missing values.
```

Out[16]:

	Missing Values	% of Total Values
Years in current job	4222	4.20

i will use mode value to handle **Years in current job** because its categorical variable

In [17]:
```
plt.figure(figsize=(18,6))
ax = sns.countplot(data['Years in current job'])
plt.show()
```



In [18]:
```
data.fillna('10+ years', inplace=True)
missingValues_table(data)
```

```
Selected dataframe has 18 columns.
There are 0 Columns that have missing values.
```

Out[18]:

Missing Values	% of Total Values

In [19]:
```
data.head()
```

Out[19]:

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Ho Owners
0	14dd8831-6af5-400b-83ec-68e61888a048	981165ec-3274-42f5-a3b4-d104041a9ca9	Fully Paid	445412.00	Short Term	709.00	1167493.00	8 years	Ho Mortga
1	4771cc26-131a-45db-b5aa-537ea4ba5342	2de017a3-2e01-49cb-a581-08169e83be29	Fully Paid	262328.00	Short Term	724.62	1174371.00	10+ years	Ho Mortga

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Ho Owners
2	4eed4e6a-aa2f-4c91-8651-ce984ee8fb26	5efb2b2b-bf11-4dfd-a572-3761a2694725	Fully Paid	99999999.00	Short Term	741.00	2231892.00	8 years	Own Ho
3	77598f7b-32e7-4e3b-a6e5-06ba0d98fe8a	e777faab-98ae-45af-9a86-7ce5b33b1011	Fully Paid	347666.00	Long Term	721.00	806949.00	3 years	Own Ho
4	d4062e70-befa-4995-8643-a0de73938182	81536ad9-5ccf-4eb8-befb-47a4d608658e	Fully Paid	176220.00	Short Term	724.62	1174371.00	5 years	R

Some features should dropped from our dataset

- **Loan ID & Customer ID** : these is only references with no benefits
- **Purpose & Number of Open Accounts & Current Credit Balance** : Not important in this problem we will not need any of them
- **Monthly Debt' & 'Maximum Open Credit** if we study this domain and our problem deeply, we covered these 2 features by other features in our data , **Monthly Debt** related to (Current Loan Amount, Annual Income) & **Maximum Open Credit** related to (Annual Income, Credit Score)

In [20]:

```
data = data.drop(['Loan ID','Customer ID','Purpose','Monthly Debt','Number of Open Accounts','Current Credit Balance',
                  'Maximum Open Credit'], axis=1)
data.head()
```

Out[20]:

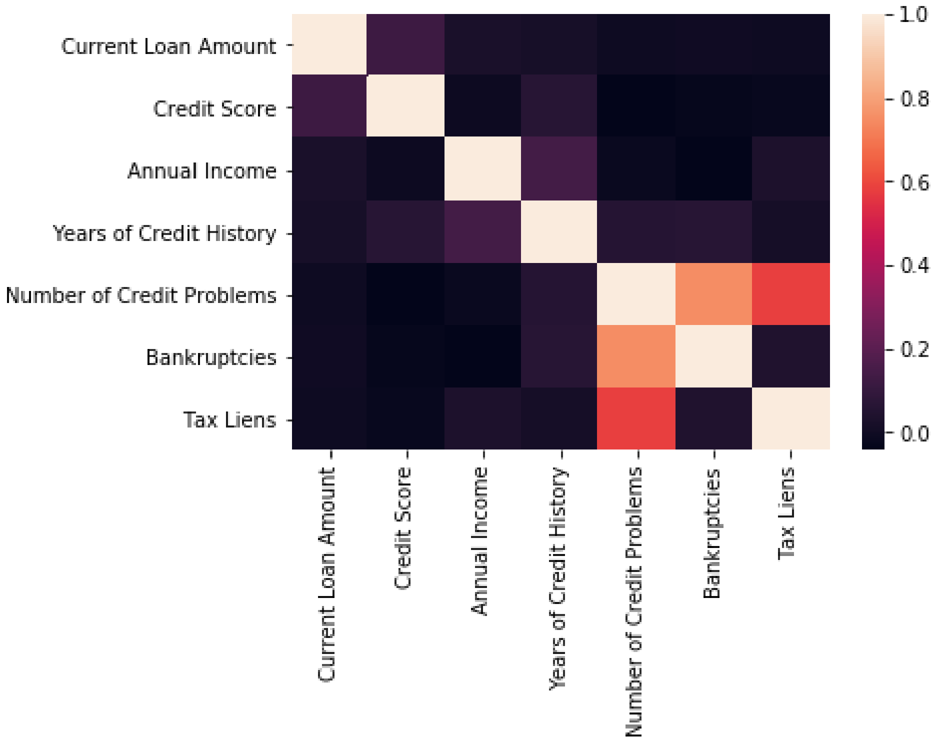
	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Home Ownership	Years of Credit History	Number of Credit Problems	Bankr
0	Fully Paid	445412.00	Short Term	709.00	1167493.00	8 years	Home Mortgage	17.20	1.00	
1	Fully Paid	262328.00	Short Term	724.62	1174371.00	10+ years	Home Mortgage	21.10	0.00	
2	Fully Paid	99999999.00	Short Term	741.00	2231892.00	8 years	Own Home	14.90	1.00	
3	Fully Paid	347666.00	Long Term	721.00	806949.00	3 years	Own Home	12.00	0.00	
4	Fully Paid	176220.00	Short Term	724.62	1174371.00	5 years	Rent	6.10	0.00	

In [21]:

```
corr = data.corr()
sns.heatmap(corr)
```

Out[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x15d83a574e0>
```



One-Hot Encoding

I will convert all continuous variables to Ordinal variables then apply One-Hot Encoding On all of them, in my openion this technique will be better for our problem we dont have strong corelation between any two variables to keep it as a numirical also this will help us to avoid overfitting.. Moreover, this technique will certainly reduce processing time and cost

Current Loan Amount with respect to outliers

In [22]:
```
meanWithoutOutliers = data[data['Current Loan Amount'] < 99999999.00 ][
'Current Loan Amount'].mean()
stdWithoutOutliers = data[data['Current Loan Amount'] < 99999999.00 ][
```

```
'Current Loan Amount'].std()
lowrange = meanWithoutOutliers - stdWithoutOutliers
highrange = meanWithoutOutliers + stdWithoutOutliers
```

In [23]:
```
data['Current Loan Amount'] =  data['Current Loan Amount'].apply(lambda
 x: 'Small Loan' if x<=lowrange else ('Medium Loan' if x>lowrange and x
< highrange else 'Big Loan'))
```

Credit Score Based on Experian's Credit Score Range

In [24]:
```
data['Credit Score'] = data['Credit Score'].apply(lambda val: "Bad" if
np.isreal(val) and val < 630 else val)
data['Credit Score'] = data['Credit Score'].apply(lambda val: "Fair" if
 np.isreal(val) and (val >= 630 and val < 690) else val)
data['Credit Score'] = data['Credit Score'].apply(lambda val: "Good" if
 np.isreal(val) and (val >= 690 and val < 720) else val)
data['Credit Score'] = data['Credit Score'].apply(lambda val: "Excellen
t" if np.isreal(val) and (val >= 720 and val < 850) else val)
```

Annual Income with respect to outliers

In [25]:
```
meanWithoutOutliers = data[data['Annual Income'] < 99999999.00 ]['Annua
l Income'].mean()
stdWithoutOutliers = data[data['Annual Income'] < 99999999.00 ]['Annual
 Income'].std()
poorLine = meanWithoutOutliers -  stdWithoutOutliers
richLine = meanWithoutOutliers + stdWithoutOutliers
```

In [26]:
```
data['Annual Income'] = data['Annual Income'].apply(lambda x: "Low Inco
me" if x<=poorLine else ("Average Income" if x>poorLine and x<richLine
else "High Income"))
```

Years in current job to be **Employment History**

In [27]:
```
data['Years in current job']=data['Years in current job'].str.extract(r
```

```
"(\d+)")
data['Years in current job'] = data['Years in current job'].astype(floa
t)
```

In [28]:
```
data['Employment History'] = data['Years in current job'].apply(lambda
x: "Junior" if x<4 else ("Semi-Senior" if x>4 and x<8 else "Senior"))
```

In [29]:
```
data=data.drop(['Years in current job'],axis=1)
```

Years of Credit History to be **Credit Age**

In [30]:
```
data['Credit Age'] = data['Years of Credit History'].apply(lambda x: "S
hort Credit Age" if x<5 else ("Good Credit Age" if x>=5 and x<17 else
"Exceptional Credit Age"))
```

In [31]:
```
data = data.drop(['Years of Credit History'],axis= 1)
```

- **Tax Liens**
- **Bankruptcies**
- **Number of Credit Problems** to be **Credit Problems**

In [32]:
```
data['Tax Liens'] = data['Tax Liens'].apply(lambda x: "No Tax Lien" if
x==0 else "Some Tax Liens")
```

In [33]:
```
data['Bankruptcies'] = data['Bankruptcies'].apply(lambda x: "No Bankrup
tcies" if x==0 else "Some Bankruptcies")
```

In [34]:
```
data['Credit Problems'] = data['Number of Credit Problems'].apply(lambd
a x: "No Credit Problem" if x==0 else "Some Credit promblem")
```

In [35]:
```
data = data.drop(['Number of Credit Problems'],axis = 1)
```

Loan Status Because we searching for 'Charged Off', thats will be our Positive class with value

1, when 'Fully Paid' will be negative class with value 0 .

In [36]:
```
data['Loan Status'] =  data['Loan Status'].apply(lambda x: 1 if x=='Cha
rged Off' else 0)
```

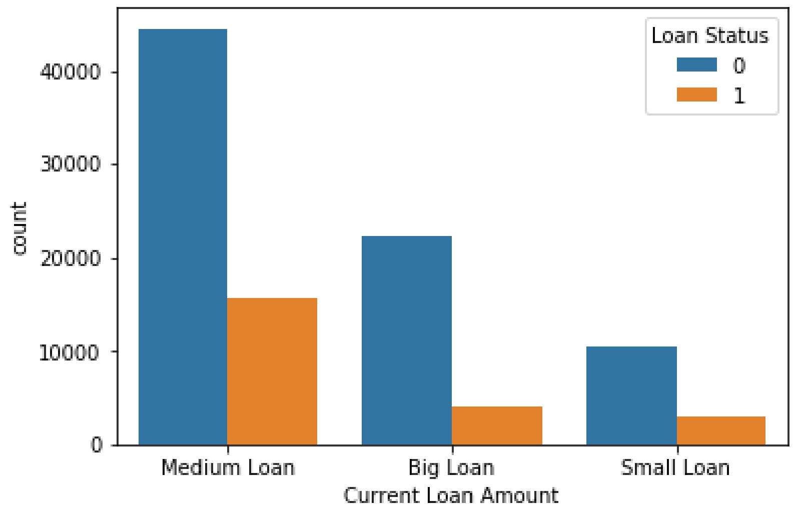
In [37]:
```
data.head()
```

Out[37]:

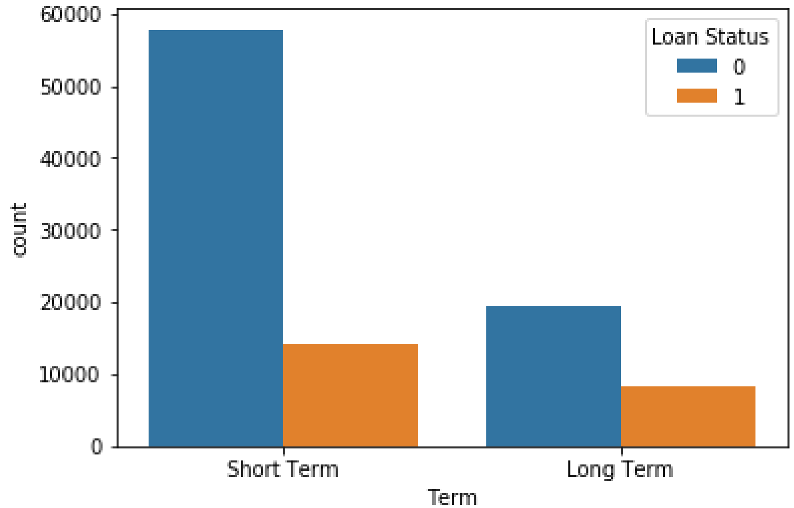
	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Home Ownership	Bankruptcies	Tax Liens	Employment History	Cre(
0	0	Medium Loan	Short Term	Good	Average Income	Home Mortgage	Some Bankruptcies	No Tax Lien	Senior	Exce Cre
1	0	Medium Loan	Short Term	Excellent	Average Income	Home Mortgage	No Bankruptcies	No Tax Lien	Senior	Exce Cre
2	0	Big Loan	Short Term	Excellent	High Income	Own Home	No Bankruptcies	No Tax Lien	Senior	Cre
3	0	Medium Loan	Long Term	Excellent	Average Income	Own Home	No Bankruptcies	No Tax Lien	Junior	Cre
4	0	Medium Loan	Short Term	Excellent	Average Income	Rent	No Bankruptcies	No Tax Lien	Semi-Senior	Cre

Visualize all of our variables in The final form and its correlation with Target variable

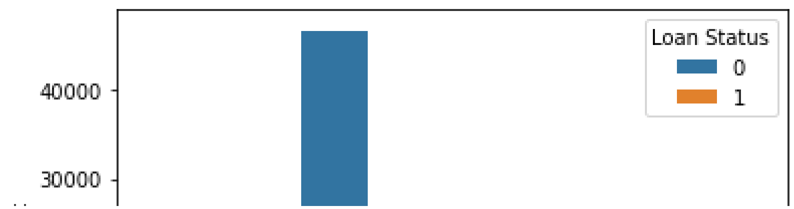
In [38]:
```
features_list = ['Current Loan Amount','Term','Credit Score','Annual In
come','Home Ownership','Bankruptcies','Tax Liens',
                 'Employment History','Credit Age','Credit Problems']
for i in range(len(features_list)):
    ax = sns.countplot(data[features_list[i]], hue=data['Loan Status'])

    plt.show()
```



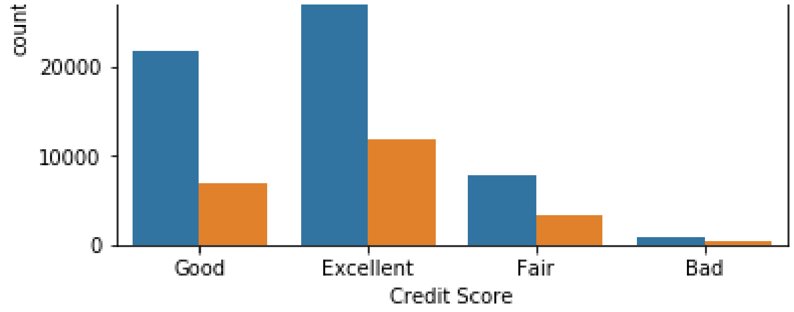
Loan Status
0
1
40000
30000
20000
10000
0
count
Medium Loan
Big Loan
Small Loan
Current Loan Amount

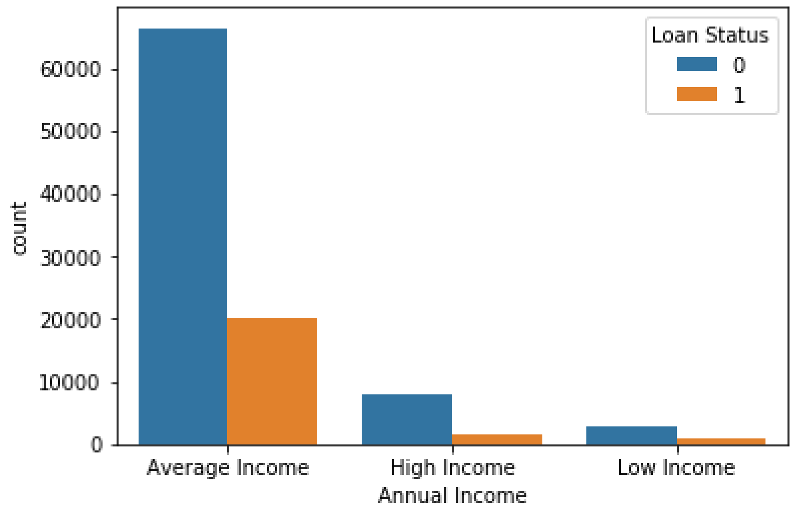


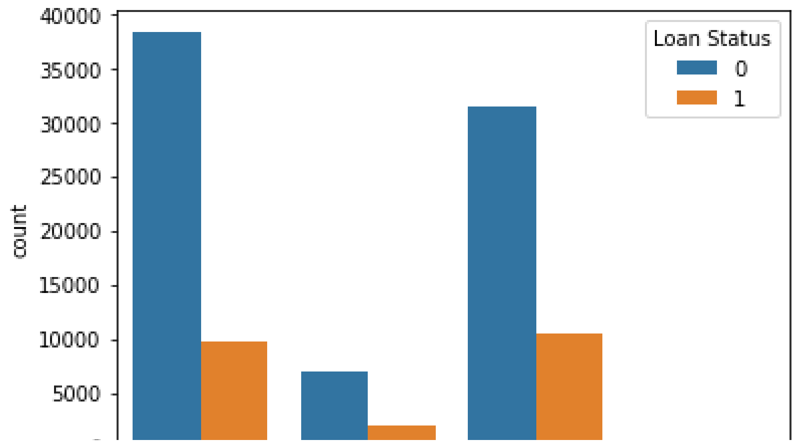
Loan Status
0
1
60000
50000
40000
30000
20000
10000
0
count
Short Term
Long Term
Term



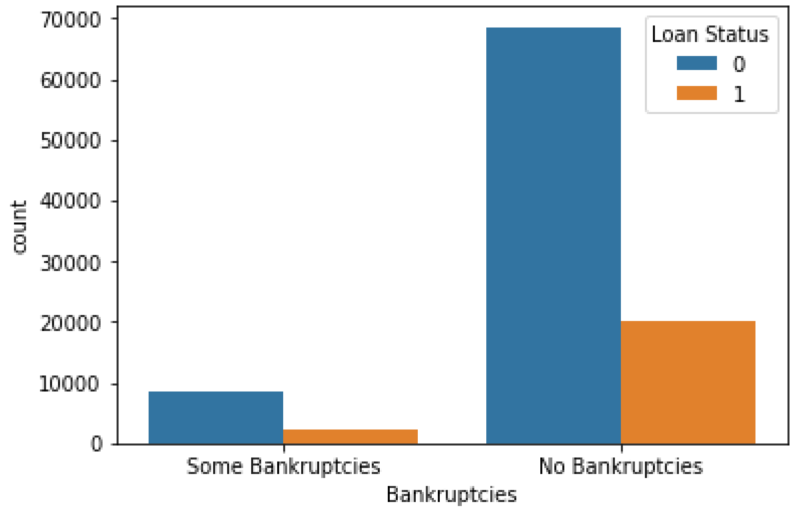
Loan Status
0
1
40000
30000

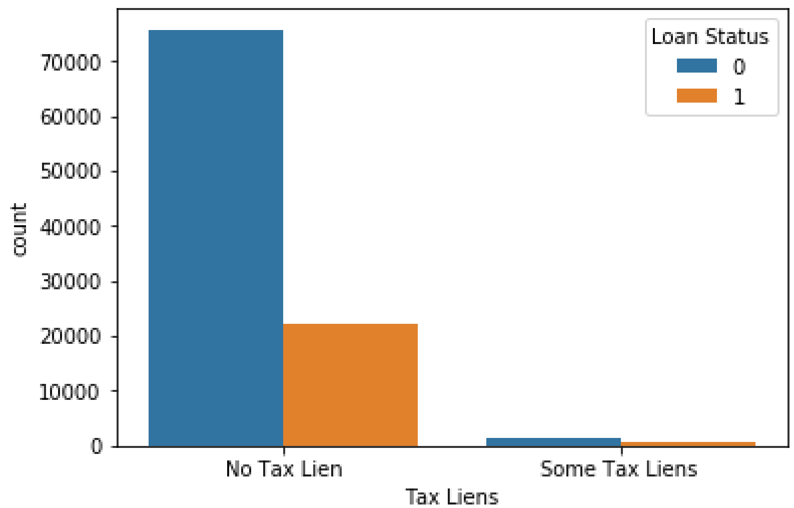

count
20000
10000
0
Good
Excellent
Fair
Bad
Credit Score

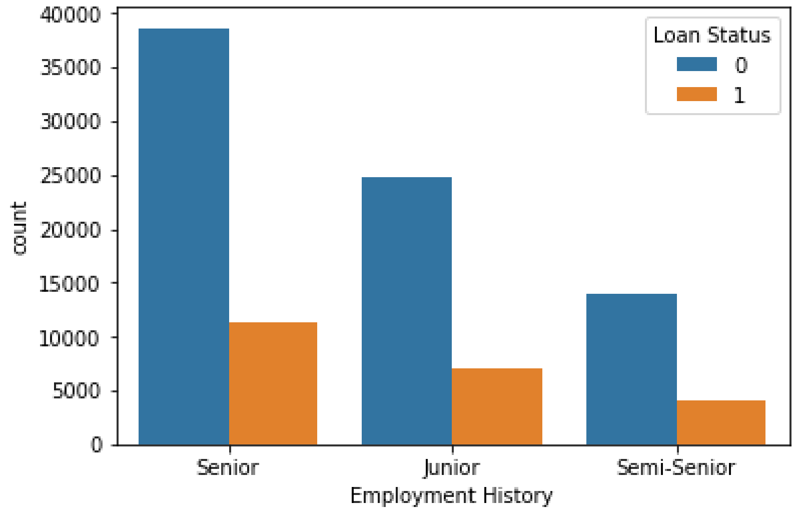

Loan Status
0
1
count
60000
50000
40000
30000
20000
10000
0
Average Income
High Income
Low Income
Annual Income

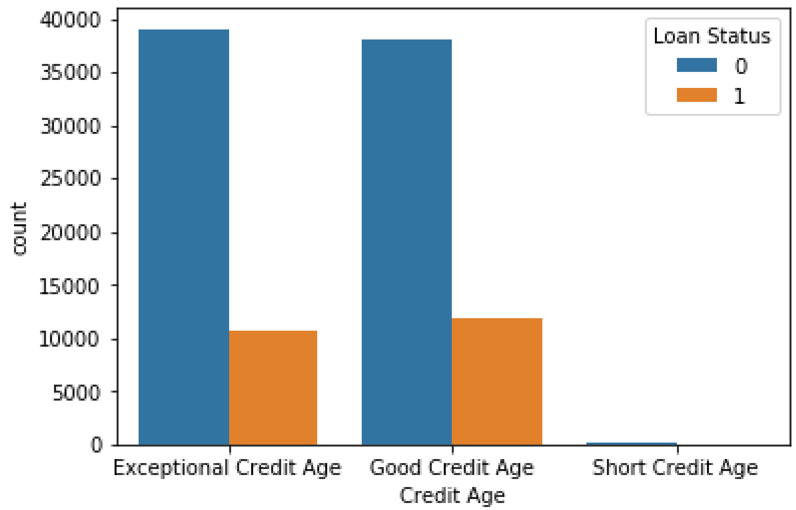

Loan Status
0
1
count
40000
35000
30000
25000
20000
15000
10000
5000

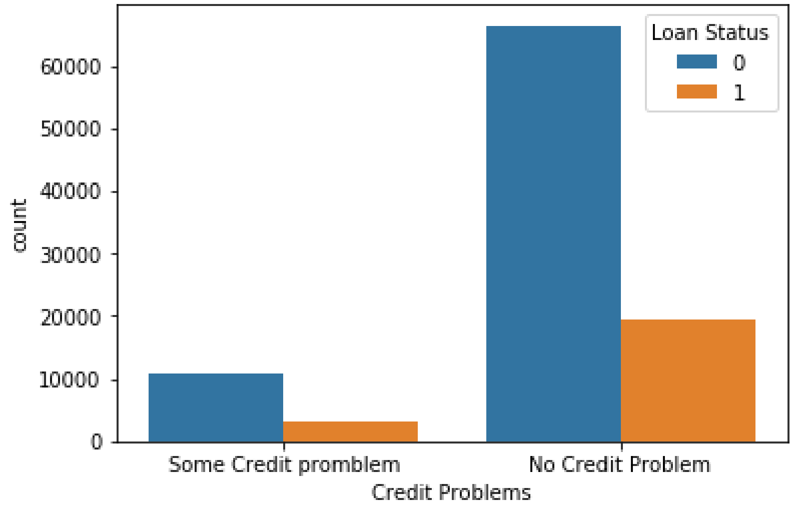

0
Home Mortgage
Own Home
Rent
HaveMortgage
Home Ownership


70000
60000
50000
40000
30000
20000
10000
0
count
Loan Status
0
1
Some Bankruptcies
No Bankruptcies
Bankruptcies


70000
60000
50000
40000
30000
20000
10000
0
count
Loan Status
0
1
No Tax Lien
Some Tax Liens
Tax Liens


Loan Status
0
1
count
40000
35000
30000
25000
20000
15000
10000
5000
0
Senior
Junior
Semi-Senior
Employment History


Loan Status
0
1
count
40000
35000
30000
25000
20000
15000
10000
5000
0
Exceptional Credit Age
Good Credit Age
Short Credit Age
Credit Age



In [39]:
```
y = data['Loan Status']
x = data.drop(['Loan Status'],axis=1)
```

```
x.head()
```

Out[39]:

	Current Loan Amount	Term	Credit Score	Annual Income	Home Ownership	Bankruptcies	Tax Liens	Employment History	Credit Age
0	Medium Loan	Short Term	Good	Average Income	Home Mortgage	Some Bankruptcies	No Tax Lien	Senior	Exceptional Credit Age
1	Medium Loan	Short Term	Excellent	Average Income	Home Mortgage	No Bankruptcies	No Tax Lien	Senior	Exceptional Credit Age
2	Big Loan	Short Term	Excellent	High Income	Own Home	No Bankruptcies	No Tax Lien	Senior	Good Credit Age
3	Medium Loan	Long Term	Excellent	Average Income	Own Home	No Bankruptcies	No Tax Lien	Junior	Good Credit Age
4	Medium Loan	Short Term	Excellent	Average Income	Rent	No Bankruptcies	No Tax Lien	Semi-Senior	Good Credit Age

Apply One-Hot Encoding

In [40]:

```
x = pd.get_dummies(x)
encoded = list(x.columns)
print("{} total features after one-hot encoding.".format(len(encoded)))
display(x.head())
```

```
28 total features after one-hot encoding.
```

	Current Loan Amount_Big Loan	Current Loan Amount_Medium Loan	Current Loan Amount_Small Loan	Term_Long Term	Term_Short Term	Credit Score_Bad	Score_Exc
0	0	1	0	0	1	0	

	Current Loan Amount_Big Loan	Current Loan Amount_Medium Loan	Current Loan Amount_Small Loan	Term_Long Term	Term_Short Term	Credit Score_Bad	Score_Exc
1	0	1	0	0	1	0	
2	1	0	0	0	1	0	
3	0	1	0	1	0	0	
4	0	1	0	0	1	0	

Rename features Labels

In [41]:

```
x.columns = ['Big Loan', 'Medium Loan', 'Small Loan', 'Long Term', 'Sho
rt Term', 'Bad Credit Score', 'Excellent Credit Score',
             'Fair Credit Score', 'Good Credit Score', 'Average Income'
, 'High Income', 'Low Income', 'HaveMortgage',
             'Home Mortgage', 'Own Home', 'Rent', 'No Bankruptcies', 'S
ome Bankruptcies', 'No Tax Lien', 'Some Tax Liens',
             'Junior', 'Semi-Senior', 'Senior', 'Exceptional Credit Ag
e', 'Good Credit Age', 'Short Credit Age',
             'No Credit Problem', 'Some Credit promblems']
x.head()
```

Out[41]:

	Big Loan	Medium Loan	Small Loan	Long Term	Short Term	Bad Credit Score	Excellent Credit Score	Fair Credit Score	Good Credit Score	Average Income	High Income	Lo Incom
0	0	1	0	0	1	0	0	0	1	1	0	
1	0	1	0	0	1	0	1	0	0	1	0	
2	1	0	0	0	1	0	1	0	0	0	1	
3	0	1	0	1	0	0	1	0	0	1	0	
4	0	1	0	0	1	0	1	0	0	1	0	

under_sampling

one of the common technique to handle imbalanced data, our data is imbalanced

- 75% of our data set is negative while only 25% is positive. **What Under_sampling do ?**
- removes some of the majority class to be close or equal miniority class to avoid bias to The majority class
- **I used under_sampling because our dataset is big enough so no big problem with reduce it if this will handle imbalance problem.**

In [42]:
```
nm = NearMiss(random_state=42)
x_res,y_res = nm.fit_sample(x,y)
x_res.shape,y_res.shape
```

Out[42]:
```
((45174, 28), (45174,))
```

Splitting data

In [43]:
```
x_train, x_test, y_train, y_test = train_test_split(x_res, y_res, test_size=0.25, random_state=42)
print("Training set has {} samples.".format(x_train.shape[0]))
print("Testing set has {} samples.".format(x_test.shape[0]))
```

```
Training set has 33880 samples.
Testing set has 11294 samples.
```

Benchmark models

- DummyClassifier * DummyClassifier with most_frequent strategy is working same of ZeroR algorithm , I used it because its already implemented in skLearn.

In [44]:
```
dClassifier = DummyClassifier(strategy='most_frequent')
dClassifier.fit(x_train, y_train)
dPrediction = dClassifier.predict(x_test)
```

```
#print("Score: ",dClassifier.score(x_test, y_test)* 100)
print('Accuracy =',accuracy_score(y_test,dPrediction)*100,'F-Beta =',fb
eta_score(y_test,dPrediction,beta=.5)*100)
```

```
Accuracy = 49.59270409066761 F-Beta = 55.15292356775705
```

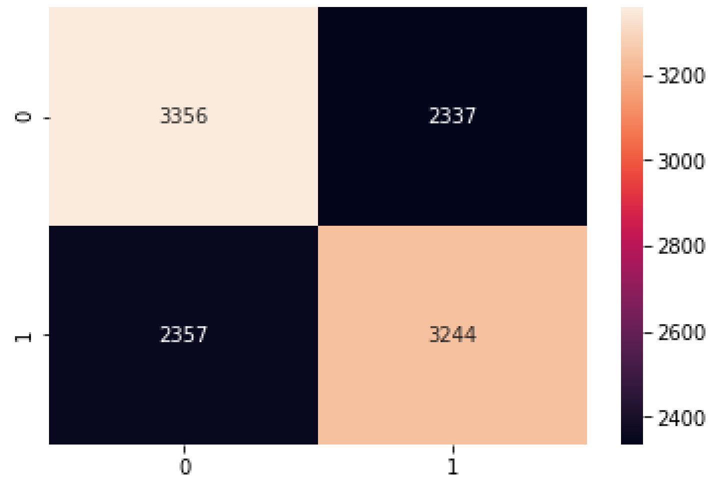
- RandomForest500

In [45]:
```
rfClassifier = RandomForestClassifier(n_estimators=500,random_state=12)
rfClassifier.fit(x_train, y_train)
rfPrediction = rfClassifier.predict(x_test)
print('Accuracy =',accuracy_score(y_test,rfPrediction)*100,'F-Beta =',f
beta_score(y_test,rfPrediction,beta=.5)*100)
```

```
Accuracy = 58.43810873029928 F-Beta = 58.0841539838854
```

In [46]:
```
rfc_con = confusion_matrix(y_test, rfPrediction)
sns.heatmap(rfc_con, annot=True, fmt="d")
plt.show
# note that confusion_matrix sort values as follows
# | TN | FP |
# | FN | TP |

# as written in confusion_matrix documentation :
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.con
fusion_matrix.html
```

Out[46]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```



Model Selection

- RandomForest
- KNN
- LogisticRegression

In [47]:
```
randomForest = RandomForestClassifier(random_state=42)
randomForest.fit(x_train, y_train)
randomForestPrediction = randomForest.predict(x_test)
print('Accuracy =',accuracy_score(y_test,randomForestPrediction)*100,'F-Beta =',fbeta_score(y_test,randomForestPrediction,beta=.5)*100)
```

```
Accuracy = 58.30529484682132 F-Beta = 57.8397212543554
```

In [48]:
```
knn = KNeighborsClassifier()
knn.fit(x_train,y_train)
knnPrediction = knn.predict(x_test)
print('Accuracy =',accuracy_score(y_test,knnPrediction)*100,'F-Beta =',fbeta_score(y_test,knnPrediction,beta=.5)*100)
```

Accuracy = 55.68443421285638 F-Beta = 54.67076827226354

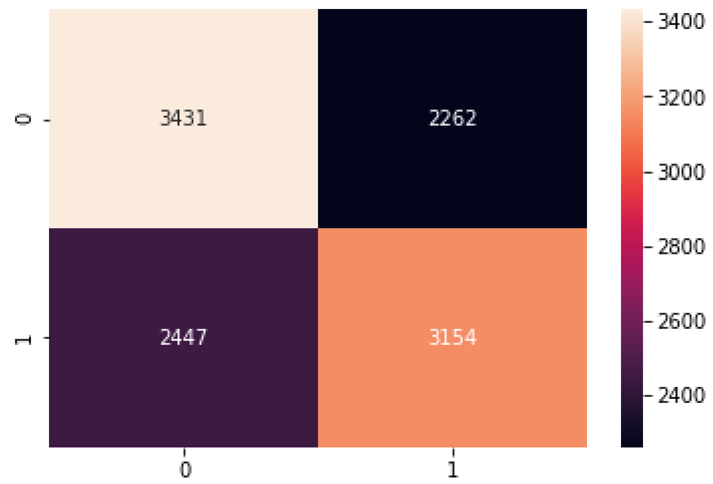
In [49]:
```
logisticReg = LogisticRegression(random_state=42)
logisticReg.fit(x_train,y_train)
logisticRegPrediction = logisticReg.predict(x_test)
print('Accuracy =',accuracy_score(y_test,logisticRegPrediction)*100,'F-Beta =',fbeta_score(y_test,logisticRegPrediction,beta=.5)*100)
```

Accuracy = 57.331326367983 F-Beta = 56.25176860573231

As we see **RandomForest** is the best, So i will go with it to next stage.

In [50]:
```
rfc_con = confusion_matrix(y_test, randomForestPrediction)
sns.heatmap(rfc_con, annot=True, fmt="d")
plt.show
```

Out[50]: <function matplotlib.pyplot.show(*args, **kw)>



Model Tuning

In [51]:
```
clf = RandomForestClassifier(random_state=42)
```

```python
param_grid = {'n_estimators': [200, 600, 1000],\
              'max_depth': [10, 50, 100],\
              'min_samples_split': [2,6]}

grid_obj = GridSearchCV(clf, param_grid=param_grid, cv=3)


grid_fit = grid_obj.fit(x_train, y_train)

print("Best parameter: ", grid_obj.best_params_)

# Get the estimator/ clf
best_clf = grid_fit.best_estimator_

grid_y_pred = best_clf.predict(x_test)

print("Optimal accuracy score on the testing data: {:.2f}".format(accur
acy_score(y_test, grid_y_pred)*100))
```

```
Best parameter:  {'max_depth': 10, 'min_samples_split': 2, 'n_estimator
s': 600}
Optimal accuracy score on the testing data: 59.12
```

In [52]:
```python
fbeta_score(y_test, grid_y_pred,beta=2)*100
```

Out[52]:
```
59.75557766093505
```

Our model should be high Recall Model because we want to catch any Loan request will not paid back .. so beta value should be > .5

In [53]:
```python
beta_values = [.5,1,2,3,4,5,6,7,8,9]
for i in range(len(beta_values)):
    print(fbeta_score(y_test, grid_y_pred,beta=beta_values[i])*100)
```

```
58.85852258809533
59.303657999118556
59.75557766093505
```

```
59.9077520346197
59.97063758389262
60.001783643984666
60.019288263091916
60.03005071504285
60.0371216447744
60.04200903303041
```

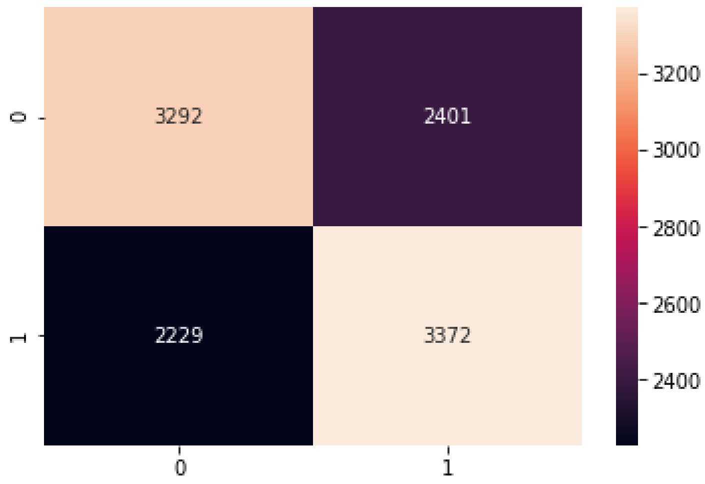
Final Model

In [54]:
```
final_randomForest = RandomForestClassifier(max_depth=10,n_estimators=6
00,min_samples_split=2,random_state=13)
final_randomForest.fit(x_train, y_train)
randomForestPrediction = final_randomForest.predict(x_test)
print('Accuracy =',accuracy_score(y_test,randomForestPrediction)*100,
      'F-Beta =',fbeta_score(y_test,randomForestPrediction,beta=2)*100)
```

```
Accuracy = 59.00478129980521 F-Beta = 59.83603648365688
```

In [56]:
```
final_randomForest = confusion_matrix(y_test, randomForestPrediction)
sns.heatmap(final_randomForest, annot=True, fmt="d")
plt.show
```

Out[56]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [ ]: