## In [1]:

import pandas as pd

# In [2]:

db = pd.read\_csv('credit\_train\_loan.csv')

# In [3]:

db

# Out[3]:

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Annual Income	Years in current job	Ow
0	14dd8831- 6af5-400b- 83ec- 68e61888a048	981165ec- 3274-42f5- a3b4- d104041a9ca9	Fully Paid	445412.0	Short Term	709.0	1167493.0	8 years	N
1	4771cc26- 131a-45db- b5aa- 537ea4ba5342	2de017a3- 2e01-49cb- a581- 08169e83be29	Fully Paid	262328.0	Short Term	NaN	NaN	10+ years	N
2	4eed4e6a- aa2f-4c91- 8651- ce984ee8fb26	5efb2b2b-bf11- 4dfd-a572- 3761a2694725	Fully Paid	99999999.0	Short Term	741.0	2231892.0	8 years	Ov
3	77598f7b- 32e7-4e3b- a6e5- 06ba0d98fe8a	e777faab- 98ae-45af- 9a86- 7ce5b33b1011	Fully Paid	347666.0	Long Term	721.0	806949.0	3 years	Ov
4	d4062e70- befa-4995- 8643- a0de73938182	81536ad9- 5ccf-4eb8- befb- 47a4d608658e	Fully Paid	176220.0	Short Term	NaN	NaN	5 years	
100509	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
100510	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
100511	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
100512	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
100513	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

100514 rows × 19 columns

### In [4]:

Term = db['Term']

#### In [5]:

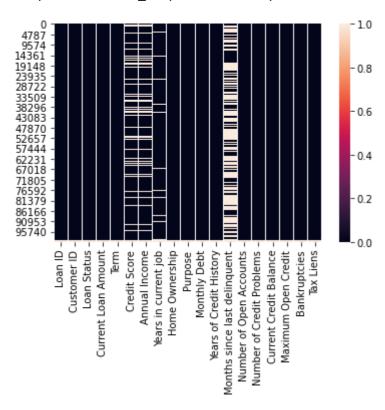
```
import seaborn as sns
```

### In [6]:

```
sns.heatmap(db.isnull())
```

#### Out[6]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x1d6c875ec40>



### In [7]:

```
y = db.iloc[0:99999,2]
```

#### In [8]:

```
y.shape
```

#### Out[8]:

(99999,)

#### In [22]:

```
X = db.iloc[0:99999,4:19]
```

### In [23]:

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### Out[23]:

	Term	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Number of Credit Problems	Maximum Open Credit	Bankruptcies
0	Short Term	709.0	1167493.0	5214.74	17.2	1.0	416746.0	1.0
1	Short Term	NaN	NaN	33295.98	21.1	0.0	850784.0	0.0
2	Short Term	741.0	2231892.0	29200.53	14.9	1.0	750090.0	0.0
3	Long Term	721.0	806949.0	8741.90	12.0	0.0	386958.0	0.0
4	Short Term	NaN	NaN	20639.70	6.1	0.0	427174.0	0.0
99994	Short Term	719.0	783389.0	3727.61	17.4	0.0	259160.0	0.0
99995	Short Term	725.0	475437.0	2202.86	22.3	0.0	658548.0	0.0
99996	Short Term	732.0	1289416.0	13109.05	9.4	0.0	509234.0	0.0
99997	Short Term	742.0	1150545.0	7315.57	18.8	1.0	537548.0	1.0
99998	Short Term	746.0	1717524.0	9890.07	15.0	0.0	738254.0	0.0

99999 rows × 8 columns

### In [11]:

```
X = db.drop('Purpose' , axis=1 , inplace=True)
```

### In [12]:

```
X = db.drop('Tax Liens' , axis=1 , inplace=True)
```

### In [13]:

```
X = db.drop('Home Ownership' , axis=1 , inplace=True)
```

```
In [14]:
X = db.drop('Number of Open Accounts' , axis=1 , inplace=True)
In [15]:
X = db.drop('Current Credit Balance' , axis=1 , inplace=True)
In [16]:
X = db.drop('Years in current job', axis=1, inplace=True)
In [17]:
X = db.drop('Months since last delinquent' , axis=1 , inplace=True)
In [18]:
#X = db.drop('Term' , axis=1 , inplace=True)
In [19]:
import numpy as np
In [20]:
from sklearn.impute import SimpleImputer
In [24]:
miss = SimpleImputer(missing_values=np.nan , strategy='mean')
In [25]:
miss = miss.fit(X.iloc[:,1:])
In [26]:
X.iloc[:,1:] = miss.transform(X.iloc[:,1:])
In [27]:
#miss = miss.fit(X.iloc[:,1:3])
In [28]:
#X.iloc[:,1:3] = miss.transform(X.iloc[:,1:3])
```

```
In [ ]:
```

In [29]:

X = pd.get\_dummies(X)

In [30]:

Х

Out[30]:

Credit Score	Annual Income	Monthly Debt	Years of Credit History	Number of Credit Problems	Maximum Open Credit	Bankruptcies	Term_
709.000000	1.167493e+06	5214.74	17.2	1.0	416746.0	1.0	
1076.460214	1.378282e+06	33295.98	21.1	0.0	850784.0	0.0	
741.000000	2.231892e+06	29200.53	14.9	1.0	750090.0	0.0	
721.000000	8.069490e+05	8741.90	12.0	0.0	386958.0	0.0	
1076.460214	1.378282e+06	20639.70	6.1	0.0	427174.0	0.0	
719.000000	7.833890e+05	3727.61	17.4	0.0	259160.0	0.0	
725.000000	4.754370e+05	2202.86	22.3	0.0	658548.0	0.0	
732.000000	1.289416e+06	13109.05	9.4	0.0	509234.0	0.0	
742.000000	1.150545e+06	7315.57	18.8	1.0	537548.0	1.0	
746.000000	1.717524e+06	9890.07	15.0	0.0	738254.0	0.0	
	\$core  709.000000  1076.460214  741.000000  721.000000  1076.460214   719.000000  725.000000  732.000000  742.000000	Score         Income           709.000000         1.167493e+06           1076.460214         1.378282e+06           741.000000         2.231892e+06           721.000000         8.069490e+05           1076.460214         1.378282e+06               719.000000         7.833890e+05           725.000000         4.754370e+05           732.000000         1.289416e+06           742.000000         1.150545e+06	Score         Income         Debt           709.000000         1.167493e+06         5214.74           1076.460214         1.378282e+06         33295.98           741.000000         2.231892e+06         29200.53           721.000000         8.069490e+05         8741.90           1076.460214         1.378282e+06         20639.70                719.000000         7.833890e+05         3727.61           725.000000         4.754370e+05         2202.86           732.000000         1.289416e+06         13109.05           742.000000         1.150545e+06         7315.57	Credit Score         Annual Income         Monthly Debt         of Credit History           709.000000         1.167493e+06         5214.74         17.2           1076.460214         1.378282e+06         33295.98         21.1           741.000000         2.231892e+06         29200.53         14.9           721.000000         8.069490e+05         8741.90         12.0           1076.460214         1.378282e+06         20639.70         6.1           719.000000         7.833890e+05         3727.61         17.4           725.000000         4.754370e+05         2202.86         22.3           732.000000         1.289416e+06         13109.05         9.4           742.000000         1.150545e+06         7315.57         18.8	Credit Score         Annual Income         Monthly Debt         of Credit History         Number of Credit Problems           709.000000         1.167493e+06         5214.74         17.2         1.0           1076.460214         1.378282e+06         33295.98         21.1         0.0           741.000000         2.231892e+06         29200.53         14.9         1.0           721.000000         8.069490e+05         8741.90         12.0         0.0           1076.460214         1.378282e+06         20639.70         6.1         0.0           719.000000         7.833890e+05         3727.61         17.4         0.0           725.000000         4.754370e+05         2202.86         22.3         0.0           732.000000         1.289416e+06         13109.05         9.4         0.0           742.000000         1.150545e+06         7315.57         18.8         1.0	Credit Score         Annual Income         Monthly Debt         of Credit History         Number of Credit Problems         Maximum Open Credit Problems           709.000000         1.167493e+06         5214.74         17.2         1.0         416746.0           1076.460214         1.378282e+06         33295.98         21.1         0.0         850784.0           741.000000         2.231892e+06         29200.53         14.9         1.0         750090.0           721.000000         8.069490e+05         8741.90         12.0         0.0         386958.0           1076.460214         1.378282e+06         20639.70         6.1         0.0         427174.0                   719.000000         7.833890e+05         3727.61         17.4         0.0         259160.0           725.000000         4.754370e+05         2202.86         22.3         0.0         658548.0           732.000000         1.289416e+06         13109.05         9.4         0.0         509234.0           742.000000         1.150545e+06         7315.57         18.8         1.0         537548.0	Credit Score         Annual Income         Monthly Debt Poble         of Credit History         Number of Credit Problems         Waximum Open Credit Problems         Bankruptcies           709.000000         1.167493e+06         5214.74         17.2         1.0         416746.0         1.0           1076.460214         1.378282e+06         33295.98         21.1         0.0         850784.0         0.0           741.000000         2.231892e+06         29200.53         14.9         1.0         750090.0         0.0           721.000000         8.069490e+05         8741.90         12.0         0.0         386958.0         0.0           1076.460214         1.378282e+06         20639.70         6.1         0.0         427174.0         0.0           719.000000         7.833890e+05         3727.61         17.4         0.0         259160.0         0.0           725.000000         4.754370e+05         2202.86         22.3         0.0         658548.0         0.0           732.000000         1.289416e+06         13109.05         9.4         0.0         509234.0         0.0           742.000000         1.150545e+06         7315.57         18.8         1.0         537548.0         1.0

99999 rows × 9 columns

### In [31]:

from sklearn.linear\_model import LogisticRegression

### In [32]:

model = LogisticRegression()

### In [33]:

from sklearn.model\_selection import train\_test\_split

```
In [34]:
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.20, random_state=42)
In [35]:
model.fit(X_train , y_train)
Out[35]:
LogisticRegression()
In [36]:
y_pred = model.predict(X_test)
In [39]:
from sklearn.metrics import confusion_matrix,accuracy_score
In [40]:
confusion_matrix(y_test , y_pred)
Out[40]:
array([[
          938, 3571],
           99, 15392]], dtype=int64)
In [41]:
# computer method for calculating accuracy
accuracy_score(y_test , y_pred)
Out[41]:
0.8165
In [42]:
# human method of calculating accuracy
(938+15392)/(938+3571+99+15392) * 100
```

#### Out[42]:

81.65

```
In [43]:
```

```
y_test
Out[43]:
          Fully Paid
26002
80420
         Fully Paid
         Charged Off
19864
81525
          Fully Paid
57878
          Fully Paid
         Charged Off
99336
         Fully Paid
29311
          Fully Paid
97599
61294
          Fully Paid
          Fully Paid
84226
Name: Loan Status, Length: 20000, dtype: object
In [44]:
y_pred
Out[44]:
array(['Fully Paid', 'Fully Paid', 'Fully Paid', ..., 'Fully Paid',
       'Fully Paid', 'Fully Paid'], dtype=object)
In [ ]:
```