Project : Lending Club Loan Data Analysis

by SHAKTI NATH SAINI

1. Exploratory Data Analysis

In [252]:

```
########################################################################
''' Step 0: Import all libraries'''
########################################################################

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import tensorflow as tf
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

import warnings

warnings.filterwarnings('ignore')
```

In [253]:

```
########################################################################
'''Step 1: Load the data'''
########################################################################

data = pd.read_csv(r'C:\Users\Shakti\Documents\Python Scripts\Projects\Lending Club Loan Da
```

In [254]:

```
data.shape
```

Out[254]:

```
(9578, 14)
```

In [255]:

```
data.head()
```

Out[255]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.li
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000

In [256]:

```
# Handling missing values

data.isnull().sum()
```

Out[256]:

```
credit.policy        0
purpose              0
int.rate             0
installment          0
log.annual.inc       0
dti                  0
fico                 0
days.with.cr.line    0
revol.bal            0
revol.util           0
inq.last.6mths       0
delinq.2yrs          0
pub.rec              0
not.fully.paid       0
dtype: int64
```

In [257]:

```
#NO missing values
```

2: Exploratory data analysis of different factors of the dataset.

In [258]:

```
##########################################################################
'''Step 2: Handling Non-Numerical Values'''
##########################################################################

dummy = pd.get_dummies(data['purpose'])
dummy.head()
```

Out[258]:

	all_other	credit_card	debt_consolidation	educational	home_improvement	major_purchase
0	0	0	1	0	0	0
1	0	1	0	0	0	0
2	0	0	1	0	0	0
3	0	0	1	0	0	0
4	0	1	0	0	0	0

In [259]:

```
##########################################################################
'''Step 3: Handling (droping) Categorical Columns'''
##########################################################################

data.drop(['purpose'], axis=1, inplace=True)
```

In [260]:

```
df = pd.concat([data, dummy], axis=1)
```

In [261]:

```
df.head()
```

Out[261]:

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revo
0	1	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	
1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	
2	1	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	
3	1	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	
4	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	

In [262]:

```
df.shape
```

Out[262]:

```
(9578, 20)
```

In [263]:

```
y = df['credit.policy']
X = df.drop(['credit.policy'], axis=1)
```

In [264]:

```
# Standardize features by removing the mean and scaling to unit variance

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [265]:

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_stat
```

3. Additional Feature Engineering

You will check the correlation between features and will drop those features which have a strong correlation

This will help reduce the number of features and will leave you with the most relevant features

In [266]:

```
# Check if the data is balanced

data['credit.policy'].value_counts(normalize=True)
```

Out[266]:

```
1    0.80497
0    0.19503
Name: credit.policy, dtype: float64
```

In [267]:

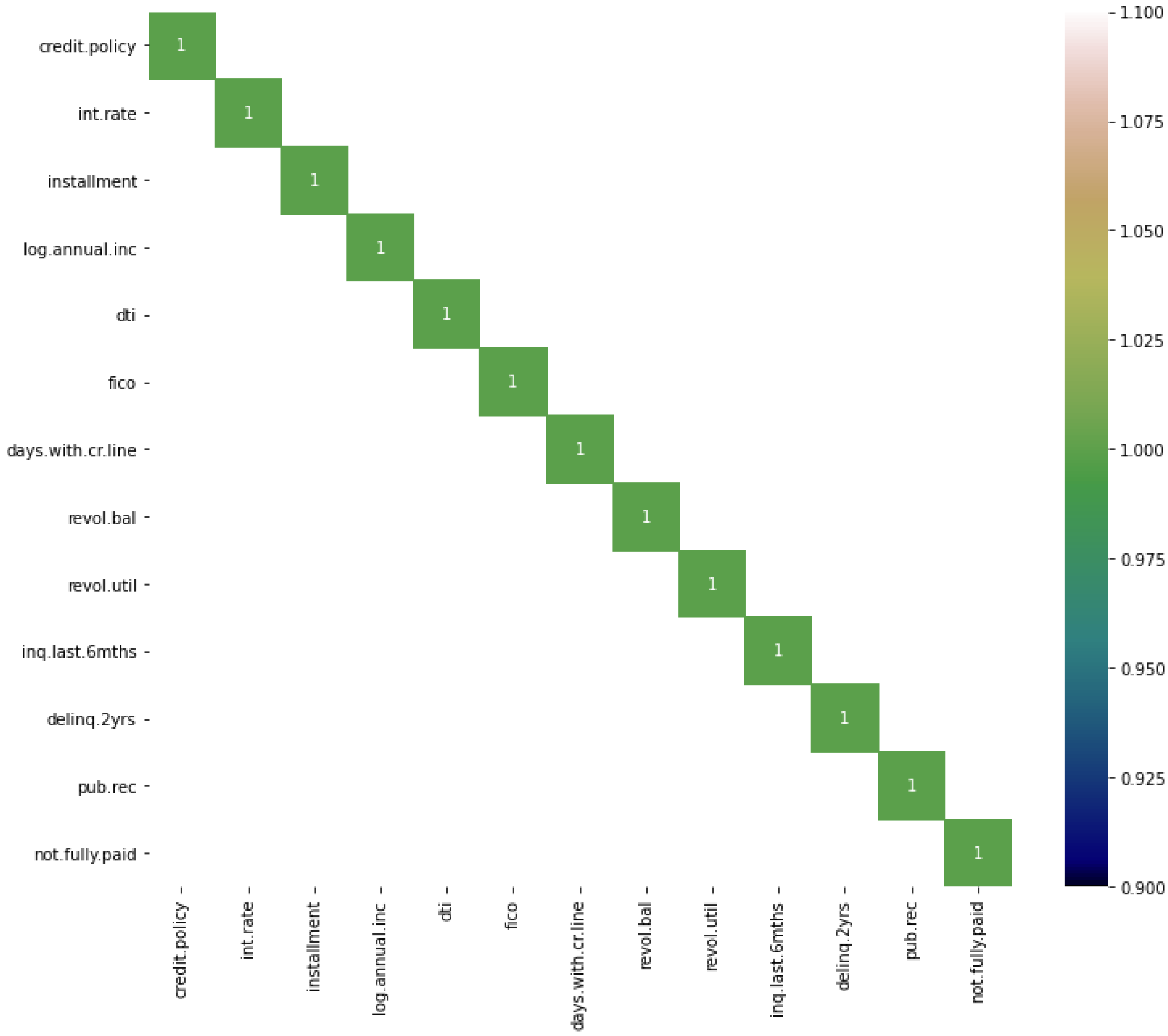
```
#####################################################################
'''Step 4: Check for Correlation'''
#####################################################################

# Check for correlation between features

corr_matrix = data.corr()

high_corr = corr_matrix[corr_matrix>=0.5]
```

In [268]:

```
plt.figure(figsize = (12,10))
sns.heatmap(high_corr, cmap='gist_earth', annot=True, annot_kws={"size": 10})
```

Out[268]:

<AxesSubplot:>



Some of the features are correlated:

- revol.util & int.rate
- log.annual.inc & installment

But since the correlation is less than 0.5, there is no need to drop any of them.

4: Modelling

After applying EDA and feature engineering, you are now ready to build the predictive models

In this part, you will create a deep learning model using Keras with Tensorflow backend

In [269]:

```
####################################################################
'''Step 5: Building the Network'''
####################################################################

initializer = tf.keras.initializers.GlorotNormal()

model = tf.keras.models.Sequential()

model.add(tf.keras.layers.Dropout(0.1))
model.add(tf.keras.layers.Dense(units = 57 , activation= "relu", input_shape=(19,)))

model.add(tf.keras.layers.Dropout(0.01))
model.add(tf.keras.layers.Dense(units = 19 , activation= "relu"))

model.add(tf.keras.layers.Dropout(0.01))
model.add(tf.keras.layers.Dense(units = 19 , activation= "relu"))

model.add(tf.keras.layers.Dropout(0.01))
model.add(tf.keras.layers.Dense(units = 19 , activation= "relu"))

model.add(tf.keras.layers.Dropout(0.01))
model.add(tf.keras.layers.Dense(units = 1 , activation= "sigmoid"))
```

In [270]:

```
####################################################################
'''Step 6: Compiling the Model'''
####################################################################

model.compile(optimizer=tf.keras.optimizers.RMSprop(learning_rate=0.005),
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

In [271]:

```
####################################################################
'''Step 7: Early Stopping Condition'''
####################################################################

class MyThresholdCallback(tf.keras.callbacks.Callback):
    def __init__(self,cl):
        super(MyThresholdCallback,self).__init__()
        self.cl=cl

    def on_epoch_end(self, epoch, logs=None):
        testScore = logs['val_accuracy']
        trainScore = logs['accuracy']

        if testScore > trainScore and testScore >= self.cl:
            self.model.stop_training = True
```

In [272]:

```
#####################################################################
'''Step 8: Fitting the Model'''
#####################################################################

model.fit(X_train, y_train, epochs=1000, validation_data=(X_test,y_test), callbacks=[MyThre
```

```
Epoch 1/1000
240/240 [==============================] - 2s 3ms/step - loss: 0.3051 - ac
curacy: 0.8807 - val_loss: 0.2626 - val_accuracy: 0.8909
Epoch 2/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.2717 - ac
curacy: 0.8923 - val_loss: 0.2396 - val_accuracy: 0.8987
Epoch 3/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.2486 - ac
curacy: 0.9042 - val_loss: 0.2119 - val_accuracy: 0.9175
Epoch 4/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.2381 - ac
curacy: 0.9133 - val_loss: 0.2071 - val_accuracy: 0.9238
Epoch 5/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.2331 - ac
curacy: 0.9126 - val_loss: 0.2004 - val_accuracy: 0.9264
Epoch 6/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.2231 - ac
curacy: 0.9190 - val_loss: 0.1880 - val_accuracy: 0.9295
Epoch 7/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1969 - ac
curacy: 0.9304 - val_loss: 0.1808 - val_accuracy: 0.9332
Epoch 8/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1976 - ac
curacy: 0.9304 - val_loss: 0.1667 - val_accuracy: 0.9410
Epoch 9/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1949 - ac
curacy: 0.9323 - val_loss: 0.1756 - val_accuracy: 0.9379
Epoch 10/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1938 - ac
curacy: 0.9358 - val_loss: 0.1978 - val_accuracy: 0.9374
Epoch 11/1000
240/240 [==============================] - 1s 3ms/step - loss: 0.1871 - ac
curacy: 0.9392 - val_loss: 0.1581 - val_accuracy: 0.9426
Epoch 12/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1854 - ac
curacy: 0.9383 - val_loss: 0.1470 - val_accuracy: 0.9473
Epoch 13/1000
240/240 [==============================] - 1s 3ms/step - loss: 0.1773 - ac
curacy: 0.9415 - val_loss: 0.1659 - val_accuracy: 0.9436
Epoch 14/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1829 - ac
curacy: 0.9390 - val_loss: 0.1563 - val_accuracy: 0.9473
Epoch 15/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1791 - ac
curacy: 0.9422 - val_loss: 0.2048 - val_accuracy: 0.9337
Epoch 16/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1748 - ac
curacy: 0.9421 - val_loss: 0.1591 - val_accuracy: 0.9452
Epoch 17/1000
240/240 [==============================] - 1s 2ms/step - loss: 0.1628 - ac
curacy: 0.9478 - val_loss: 0.1601 - val_accuracy: 0.9478
Epoch 18/1000
```

```
240/240 [==============================] - 1s 2ms/step - loss: 0.1656 - ac
curacy: 0.9477 - val_loss: 0.1315 - val_accuracy: 0.9603
```

Out[272]:

```
<tensorflow.python.keras.callbacks.History at 0x2b0f77651f0>
```

In [273]:

```
####################################################################
'''Step 9: Check for Generalization'''
####################################################################

print("\n\nTraining Score  {} \nTesting Score   {}".format(model.evaluate(X_train,y_train)[
                                                            model.evaluate(X_test,y_test)[1
```

```
240/240 [==============================] - 0s 1ms/step - loss: 0.0990 - accu
racy: 0.9692
60/60 [==============================] - 0s 1ms/step - loss: 0.1315 - accura
cy: 0.9603


Training Score  0.9691986441612244
Testing Score   0.9603340029716492
```

In [274]:

```
####################################################################
'''Step 10: Prediction'''
####################################################################

y_pred = model.predict_classes(X_test)
```

In [275]:

```
# Confusion Matrix
print(confusion_matrix(y_test, y_pred))
```

```
[[ 306   66]
 [  10 1534]]
```

In [276]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.82      0.89       372
           1       0.96      0.99      0.98      1544

    accuracy                           0.96      1916
   macro avg       0.96      0.91      0.93      1916
weighted avg       0.96      0.96      0.96      1916
```

In [277]:

```
#####################################################################
'''                            End                            '''
#####################################################################
```

Out[277]:

```
'                            End                            '
```