Loan Default Classification - Logistic Regression

Tools & Pre-requesites:

1. Core - Python & Machine Learning (Logistics Classification Algorithm)
2. IDE - Jupyter Notebook, Google Colab, Etc..,
3. Loan Defaulter - Dataset (Taken from the Kaggle.com)
4. Python.org - Download Python (latest version 3.11.3)
5. pypi.org - Python Packages.

Classification Model

@ Install required Packages

```
!pip install pandas                  # Data Manipulation & Data Defintion
!pip install numpy                   # Mathmatical Operations
!pip install matplotlib              # Data Visualization
!pip install seaborn                 # Data Visualization
!pip install sklearn                 # Machine Learning Algorithm Package
```

@ Import Packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
get_ipython().run_line_magic('matplotlib', 'inline')
import seaborn as sns
from matplotlib.cm import get_cmap
from sklearn import preprocessing
from random import sample
from sklearn.preprocessing import OrdinalEncoder
import warnings #
warnings.filterwarnings("ignore")
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
from sklearn.metrics import roc_curve, roc_auc_score
```

@ Import the Dataset

```
df = pd.read_csv('/content/drive/MyDrive/Loan Default.csv') # Imported the Dataset as df.
```

@ Data Defintion

```
df.info()          # Data Info or Description.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32581 entries, 0 to 32580
Data columns (total 10 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   person_age            32581 non-null  int64  
 1   person_income         32581 non-null  int64  
 2   person_home_ownership  32581 non-null  object 
 3   person_emp_length     31686 non-null  float64
 4   loan_intent           32581 non-null  object 
 5   loan_grade            32581 non-null  object 
 6   loan_amnt             32581 non-null  int64  
 7   loan_int_rate         29465 non-null  float64
 8   loan_status           32581 non-null  int64  
 9   loan_percent_income   32581 non-null  float64
dtypes: float64(3), int64(4), object(3)
memory usage: 2.5+ MB
```

```
print('Total_Columns: ', len(df.columns),'\n')
print(df.columns,'\n')
print('Shape :',df.shape)          # Data Size or Length (Row, Column)
```

```
Total_Columns:  10

Index(['person_age', 'person_income', 'person_home_ownership',
       'person_emp_length', 'loan_intent', 'loan_grade', 'loan_amnt',
       'loan_int_rate', 'loan_status', 'loan_percent_income'],
      dtype='object')

Shape : (32581, 10)
```

```
df.head(5)        # Dataset First 5 Lines.
```

	person_age	person_income	person_home_ownership	person_emp_length	loan_intent	loa
0	22	59000	RENT	123.0	PERSONAL	
1	21	9600	OWN	5.0	EDUCATION	
2	25	9600	MORTGAGE	1.0	MEDICAL	
3	23	65500	RENT	4.0	MEDICAL	
4	24	54400	RENT	8.0	MEDICAL	

```
df.tail(5)        # Dataset Last 5 Lines.
```

	person_age	person_income	person_home_ownership	person_emp_length	loar
32576	57	53000	MORTGAGE	1.0	PE
32577	54	120000	MORTGAGE	4.0	PE
32578	65	76000	RENT	3.0	HOMEIMPRO
32579	56	150000	MORTGAGE	5.0	PE
32580	66	42000	RENT	2.0	I

```
df.describe()      # Data Summary
```

	person_age	person_income	person_emp_length	loan_amnt	loan_int_rate	loan
count	32581.000000	3.258100e+04	31686.000000	32581.000000	29465.000000	3258
mean	27.734600	6.607485e+04	4.789686	9589.371106	11.011695	(
std	6.348078	6.198312e+04	4.142630	6322.086646	3.240459	(
min	20.000000	4.000000e+03	0.000000	500.000000	5.420000	(
25%	23.000000	3.850000e+04	2.000000	5000.000000	7.900000	(
50%	26.000000	5.500000e+04	4.000000	8000.000000	10.990000	(
75%	30.000000	7.920000e+04	7.000000	12200.000000	13.470000	(
max	144.000000	6.000000e+06	123.000000	35000.000000	23.220000	

@ Data Visualization

Single Variate Analysis

```
df.isna().sum()    # Check for the Null's
```

```
person_age                 0
person_income              0
person_home_ownership      0
person_emp_length        895
loan_intent                0
loan_grade                 0
loan_amnt                  0
loan_int_rate           3116
loan_status                0
loan_percent_income        0
dtype: int64
```

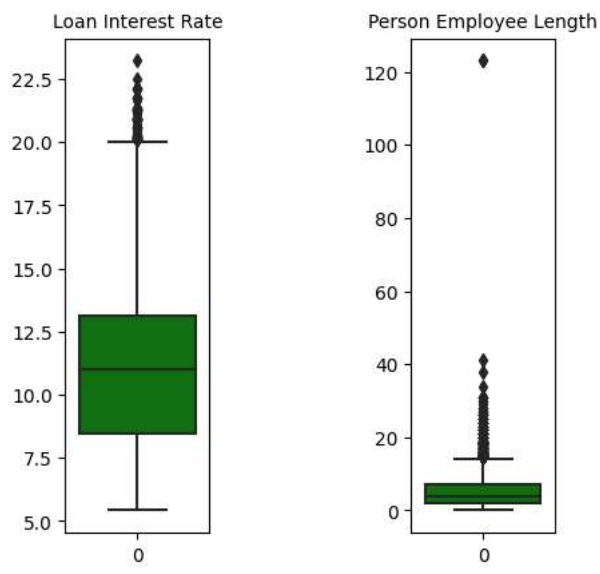
Null Treatment: --- Found a Null's in the "person_emp_length" and "loan_int_rate"

```
# Replace the Null values with it's Mean.

df.iloc[:,7] = df.iloc[:,7].fillna(df.iloc[:,7].mean())
df.iloc[:,3] = df.iloc[:,3].fillna(df.iloc[:,3].mean())
df.isna().sum()    # Check for the Null's
```

```
person_age                0
person_income             0
person_home_ownership     0
person_emp_length         0
loan_intent               0
loan_grade                0
loan_amnt                 0
loan_int_rate             0
loan_status               0
loan_percent_income       0
dtype: int64
```

```
# Check for Anamolies

# Loan Interest Rate
plt.subplot(1,4,1)
sns.boxplot(df.iloc[:,7], color = 'green')
plt.title("Loan Interest Rate", fontsize = 10)

# Person Employee Experiance
plt.subplot(1,4,3)
sns.boxplot(df.iloc[:,3], color = 'green')
plt.title("Person Employee Length", fontsize = 10)

# Skewness defines a measure of the asymmetry of a distribution
print('Skewness: ')
print(df.iloc[:,3].name,":", df.iloc[:,3].skew())
print(df.iloc[:,7].name,":", df.iloc[:,7].skew())
```

```
Skewness:
person_emp_length : 2.651118391390236
loan_int_rate : 0.21929952450406942
```



From the above Plots found that, "**Loan Interest Rate**" Attribute is in Linear. But for the "**Person Employee Length or Experiance**" is having a few **anamolies**, as we see in the above plot, a Few records have been at 120.

Anamoly Treatment - Person Employee Length

```
# Replacing the Anamolies with its 90% quantile value.

df.iloc[:,3] = np.where(df.iloc[:,3] > df.iloc[:,3].quantile(0.90), df.iloc[:,3].quantile(0.90), df.iloc[:,3])
df.iloc[:,3].describe()
```

```
count    32581.000000
mean         4.447708
std          3.181802
min          0.000000
25%          2.000000
50%          4.000000
75%          7.000000
max         10.000000
Name: person_emp_length, dtype: float64
```

```
# Converting the Categorical Text values into Numerical Values using Ordinal Encoder.

ord_enc = OrdinalEncoder()
df[['person_home_ownership', 'loan_intent', 'loan_grade']] = ord_enc.fit_transform(df[['person_home_ownership', 'loan_intent', 'loan_grade']]
df[['person_home_ownership', 'loan_intent', 'loan_grade']].head(11)
df.describe()
```

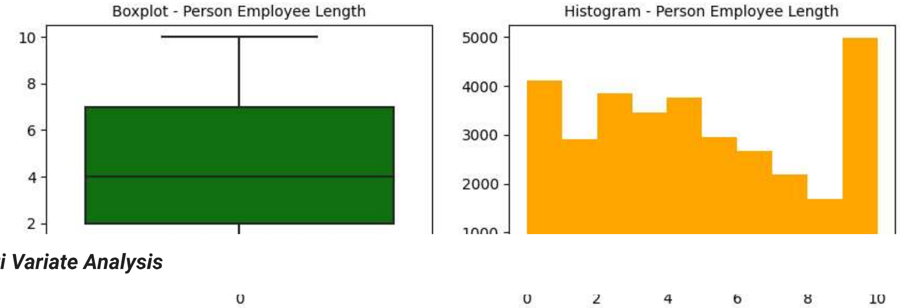
	person_age	person_income	person_home_ownership	person_emp_length	loan_inte
count	32581.000000	3.258100e+04	32581.000000	32581.000000	32581.0000
mean	27.734600	6.607485e+04	1.676222	4.447708	2.5338
std	6.348078	6.198312e+04	1.433116	3.181802	1.7311
min	20.000000	4.000000e+03	0.000000	0.000000	0.0000
25%	23.000000	3.850000e+04	0.000000	2.000000	1.0000
50%	26.000000	5.500000e+04	3.000000	4.000000	3.0000
75%	30.000000	7.920000e+04	3.000000	7.000000	4.0000
max	144.000000	6.000000e+06	3.000000	10.000000	5.0000

```
# Unique Values in the individual Fields.

def unique(x):
    return len(df[x].unique())

number_unique_vals = {x: unique(x) for x in df.columns}
number_unique_vals
```

```
{'person_age': 58,
 'person_income': 4295,
 'person_home_ownership': 4,
 'person_emp_length': 12,
 'loan_intent': 6,
 'loan_grade': 7,
 'loan_amnt': 753,
 'loan_int_rate': 349,
 'loan_status': 2,
 'loan_percent_income': 77}
```

```
# Person Employee Experiance
plt.subplot(2,4,1)
sns.boxplot(df.iloc[:,3], color = 'green')
plt.title("Boxplot - Person Employee Length", fontsize = 10)

plt.subplot(2,4,2)
plt.hist(df.iloc[:,3], color = 'orange')
plt.title("Histogram - Person Employee Length", fontsize = 10)
plt.subplots_adjust(left=1.4, bottom=0.1, right=4, top=1.2)

print('Skewness: ')
print(df.iloc[:,3].name,":", df.iloc[:,3].skew())
```

```
Skewness:
person_emp_length : 0.308977471910724
```



Multi Variate Analysis

CORRELATION PLOT

```
plt.figure(figsize = (10,8))
corr = df.corr()
corr.style.background_gradient(cmap='coolwarm').set_precision(2)
#sns.heatmap(df.corr(),annot = True)
#plt.show()
```

	person_age	person_income	person_home_ownership	person_emp_le
person_age	1.00	0.17	-0.03	
person_income	0.17	1.00	-0.20	
person_home_ownership	-0.03	-0.20	1.00	-
person_emp_length	0.08	0.13	-0.25	
loan_intent	0.04	0.00	0.01	
loan_grade	0.01	-0.00	0.12	-
loan_amnt	0.05	0.27	-0.13	
loan_int_rate	0.01	0.00	0.13	-
loan_status	-0.02	-0.14	0.21	-
loan_percent_income	-0.04	-0.25	0.14	-

@ Data Modelling

```
# Separation of Dependent Variable and Independent Variables.

X = df.loc[:,df.columns != 'loan_status']
Y = df.loc[:,df.columns == 'loan_status']


# Train and Test Data Split with the ratio of 80% : 20%

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, Y, train_size = 0.8, random_state = 42)

print('x_train shape :', x_train.shape)
print('x_test shape :', x_test.shape)
print('y_train shape :', y_train.shape)
print('y_test shape :', y_test.shape)
```

```
x_train shape : (26064, 9)
x_test shape : (6517, 9)
y_train shape : (26064, 1)
y_test shape : (6517, 1)
```

```
# Model Fitting in the Algorithm

model = LogisticRegression(C=0.01, penalty='l1', solver='liblinear')
model.fit(x_train, y_train)
```

```
LogisticRegression
LogisticRegression(C=0.01, penalty='l1', solver='liblinear')
```

```
# Train and Test Accuracy

print("Showing Performance Metrics for Logistic Regression\n")

print ("Training Accuracy: {}".format(model.score(x_train, y_train)))
predicted = model.predict(x_test)
print ("Testing Accuracy: {}".format(accuracy_score(y_test, predicted)))
```

```
Showing Performance Metrics for Logistic Regression

Training Accuracy: 0.8360190300798036
Testing Accuracy: 0.8287555623753261
```

```
# Confusion Matrix

labels = [0, 1]
cm = confusion_matrix(y_test, predicted, labels=labels)
print(cm)
```

```
[[4834  238]
 [ 878  567]]
```

1. Precision: Percentage of correct positive predictions relative to total positive predictions.
2. Recall: Percentage of correct positive predictions relative to total actual positives.
3. F1 Score: A weighted harmonic mean of precision and recall. The closer to 1, the better the model.

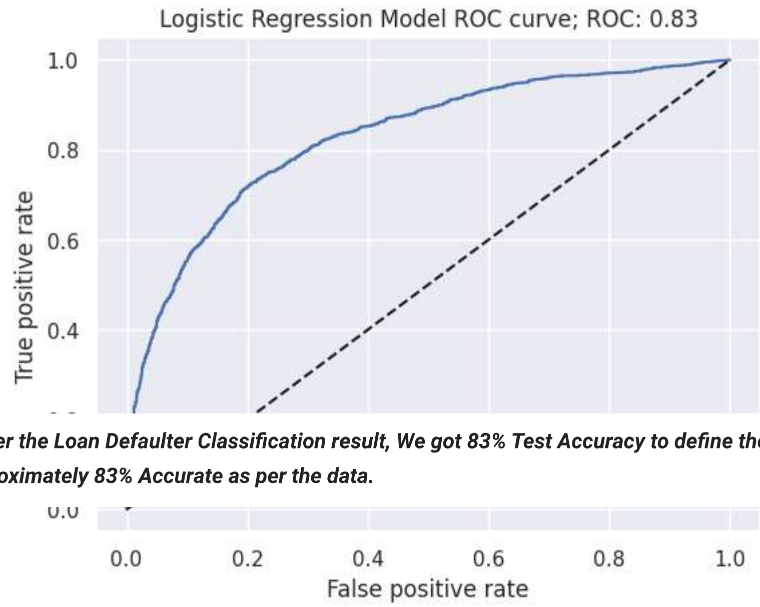
F1 Score: 2 * (Precision * Recall) / (Precision + Recall)

```
# Precision, Recall & F1 Scores.

print('Precision, Recall and f-1 Scores for Logistic Regression\n')
print(classification_report(y_test, predicted))
```

```
Precision, Recall and f-1 Scores for Logistic Regression

              precision    recall  f1-score   support

           0       0.85      0.95      0.90      5072
           1       0.70      0.39      0.50      1445

    accuracy                           0.83      6517
   macro avg       0.78      0.67      0.70      6517
weighted avg       0.81      0.83      0.81      6517
```

The AUROC is a way to measure how robust your model is across decision thresholds. It is the area under the plot of the true positive rate versus the false positive rate. The true positive rate (TPR) is (true positives)/(true positives + false negatives). The false positive rate is the (false positive)/(false positive + true negative)

```
# AUROC [Area Under Receiver-Operator Curve]

y_pred_proba = model.predict_proba(np.array(x_test))[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

sns.set()
plt.plot(fpr, tpr)
plt.plot(fpr, fpr, linestyle = '--', color = 'k')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
ROC = np.round(roc_auc_score(y_test, y_pred_proba), 2)
plt.title(f'Logistic Regression Model ROC curve; ROC: {ROC}');
plt.show()
```



As per the Loan Defaulter Classification result, We got 83% Test Accuracy to define the test results. So, our results for the predictions are Approximately 83% Accurate as per the data.

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