CONTENTS

INTRODUCTION

1. Loan-Prediction – It is the process by which a machine learning algorithm can predict whether a person will get loan or not.

2. Understanding the problem statement is the first and foremost step. This would help you give an intuition of what you will face ahead of time. Let us see the problem statement.

3. Dream Housing Finance company deals in all home loans. They have presence across all urban, semi urban and rural areas. Customer first apply for home loan after that company validates the customer eligibility for loan. Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History and others. To automate this process, they have given a problem to identify the customer segments, those are eligible for loan amount so that they can specifically target these customers.

4. It is a classification problem where we have to predict whether a loan would be approved or not. In a classification problem, we have to predict discrete values based on a given set of independent variable(s). Classification can be of two types:

5. Binary Classification : In this classification we have to predict either of the two given classes. For example: classifying the gender as male or female, predicting the result as win or loss, etc. Multiclass Classification : Here we have to classify the data into three or more classes. For example: classifying a movie's genre as comedy, action or romantic, classify fruits as oranges, apples, or pears, etc.

6. Loan prediction is a very common real-life problem that each retail bank faces atleast once in its lifetime. If done correctly, it can save a lot of man hours at the end of a retail bank.

Steps involved in machine learning

1. Data Collection

- The quantity & quality of your data dictate how accurate our model is
- The outcome of this step is generally a representation of data which we will use for training
- Using pre-collected data, by way of datasets from Kaggle, UCI, etc., still fits into this step.

2. Data Preparation

- Wrangle data and prepare it for training
- Clean that which may require it (remove duplicates, correct errors, deal with missing values, normalization, data type conversions, etc.)
- Randomize data, which erases the effects of the particular order in which we collected and/or otherwise prepared our data.

3. Choose a Model

- Different algorithms are for different tasks; choose the right one

4. Train the Model

- The goal of training is to answer a question or make a prediction correctly as often as possible
- Linear regression example: algorithm would need to learn values for *m* (or *W*) and *b* (*x* is input, *y* is output)
- Each iteration of process is a training step.

5. Evaluate the Model

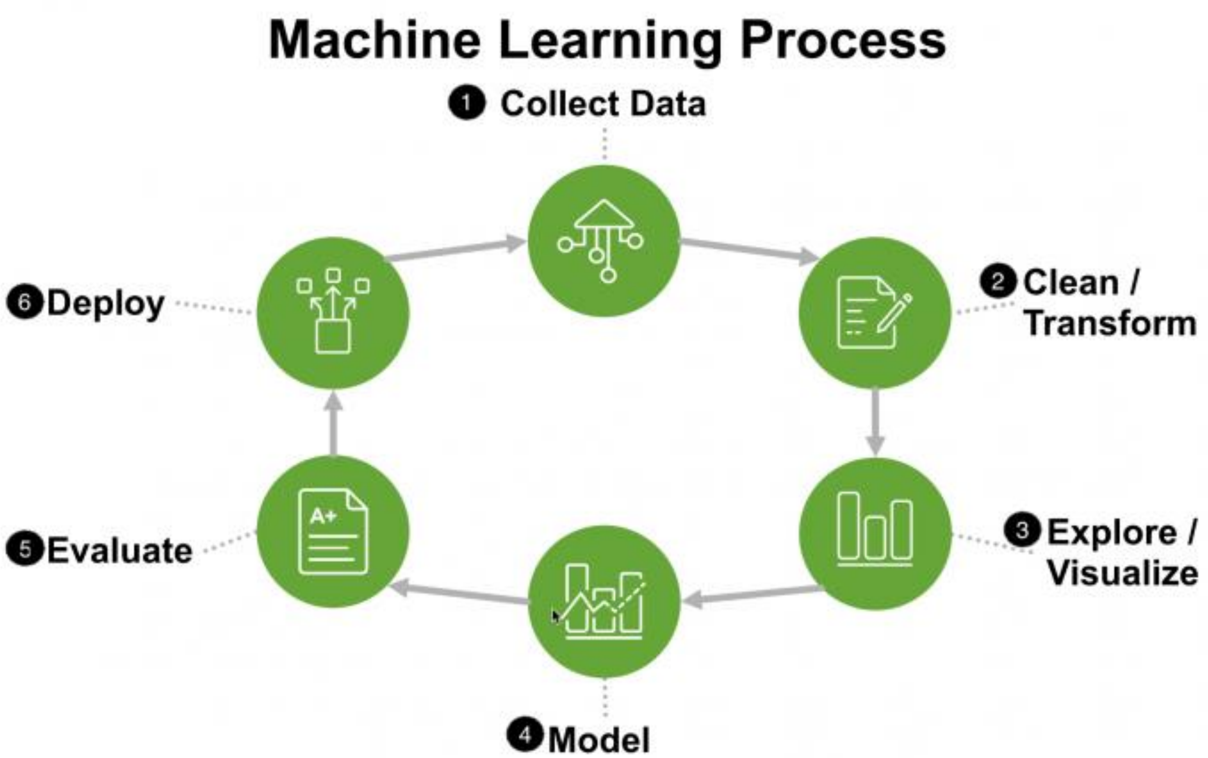
- Uses some metric or combination of metrics to "measure" objective performance of model
- Test the model against previously unseen data
- This unseen data is meant to be somewhat representative of model performance in the real world, but still helps tune the model (as opposed to test data, which does not)
- Good train/evaluate split 80/20, 70/30, or similar, depending on domain, data availability, dataset particulars, etc.

6. Parameter Tuning

- This step refers to *hyper-parameter* tuning, which is an "art form" as opposed to a science
- Tune model parameters for improved performance
- Simple model hyper-parameters may include: number of training steps, learning rate, initialization values and distribution, etc.

7. **Make Predictions**

- Using further (test set) data which have, until this point, been withheld from the model (and for which class labels are known), are used to test the model; a better approximation of how the model will perform in the real world.



DATASETS

- Here we have two datasets. First is train_dataset.csv, test_dataset.csv.
- These are datasets of loan approval applications which are featured with annualincome, married or not, dependents are there or not, educated or not, credit history present or not, loan amount etc.
- The outcome of the dataset is represented by loan_status in the train dataset.
- This column is absent in test_dataset.csv as we need to assign loan status with the help of training dataset.
- These two datasets are already uploaded on google colab.

FEATURES PRESENT IN LOAN PREDICTION

- Loan_ID – The ID number generated by the bank which is giving loan.
- Gender – Whether the person taking loan is male or female.
- Married – Whether the person is married or unmarried.
- Dependents – Family members who stay with the person.
- Education – Educational qualification of the person taking loan.
- Self_Employed – Whether the person is self-employed or not.
- ApplicantIncome – The basic salary or income of the applicant per month.
- CoapplicantIncome – The basic income or family members.
- LoanAmount – The amount of loan for which loan is applied.
- Loan_Amount_Term – How much time does the loan applicant take to pay the loan.
- Credit_History – Whether the loan applicant has taken loan previously from same bank.
- Property_Area – This is about the area where the person stays (Rural/Urban).

LABELS

- LOAN_STATUS – Based on the mentioned features, the machine learning algorithm decides whether the person should be give loan or not.

Visualizing data using google Colab

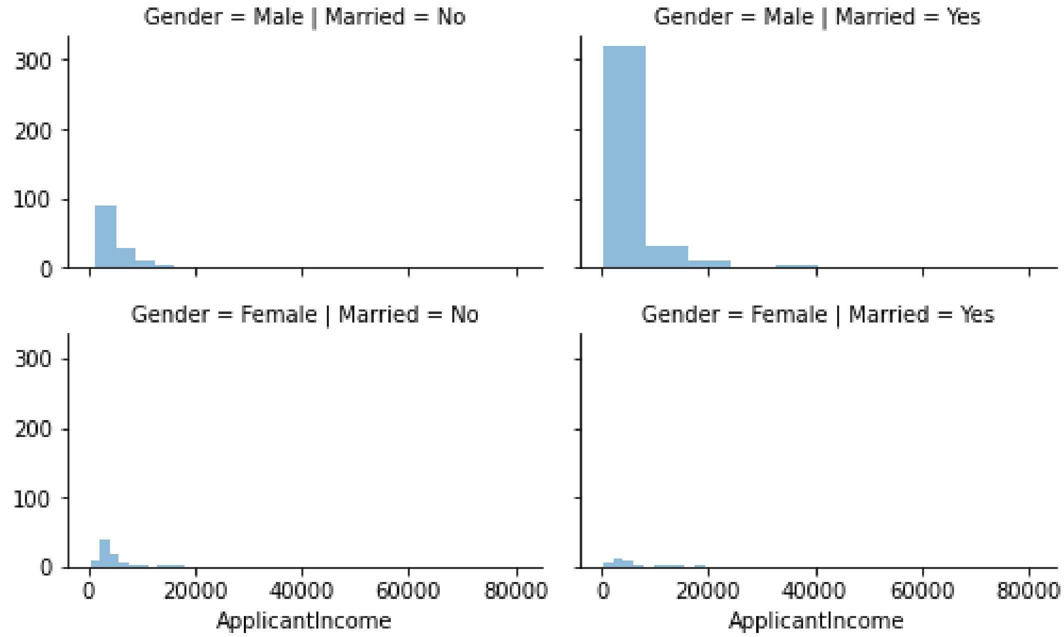
Code and output

```
#Importing required libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import norm
from sklearn.preprocessing import StandardScaler
```

```
from scipy import stats
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline

df_train = pd.read_csv('train_dataset.csv')

# take a look at the top 5 rows of the train set, notice the column "Loan_Status"
df_train.head()
```

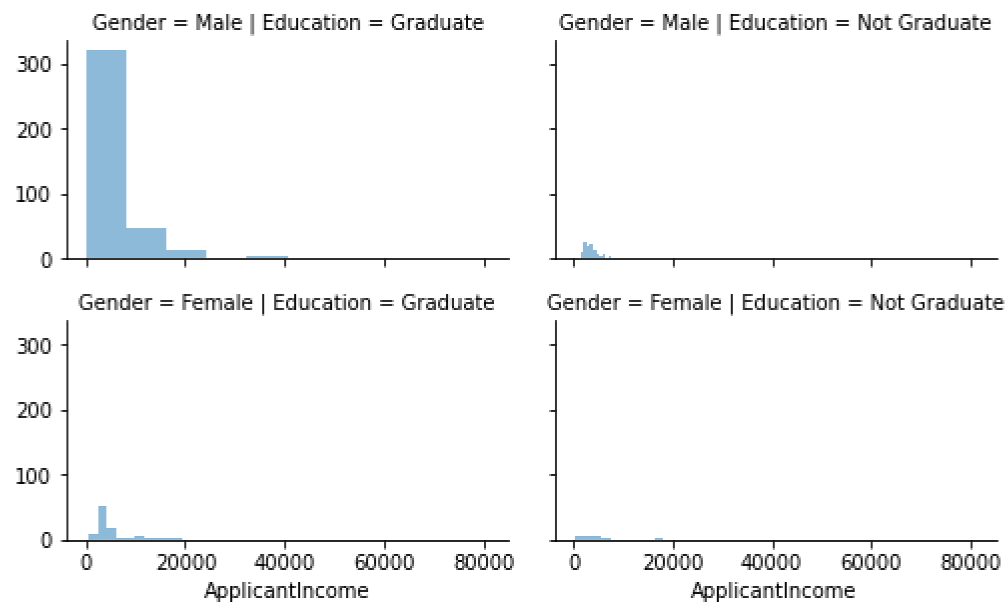
Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y

```
# This code visualizes the people applying for loan who are categorized based on gender and marriage

grid = sns.FacetGrid(df_train, row='Gender', col='Married', size=2.2, aspect=1.6)
grid.map(plt.hist, 'ApplicantIncome', alpha=.5, bins=10)
grid.add_legend()
```

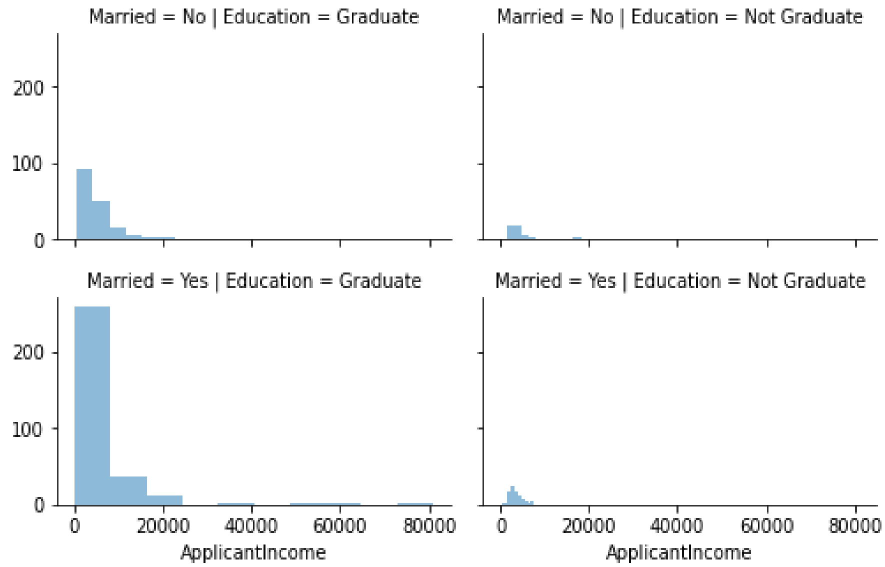



```
# Graphs plotted based on categories gender and education
grid = sns.FacetGrid(df_train, row='Gender', col='Education', size=2.2, as
pect=1.6)
grid.map(plt.hist, 'ApplicantIncome', alpha=.5, bins=10)
grid.add_legend()
```

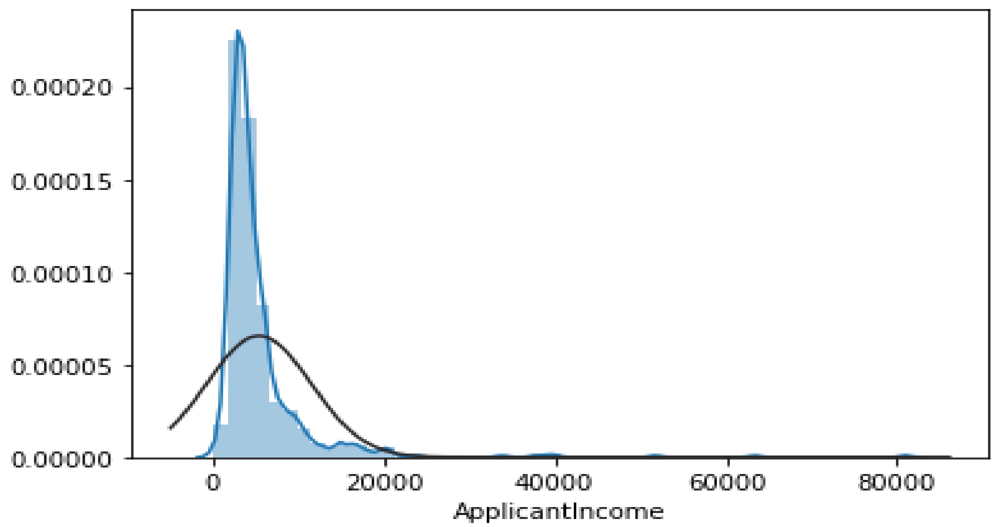
```
<seaborn.axisgrid.FacetGrid at 0x7fa17e8d9e80>
```

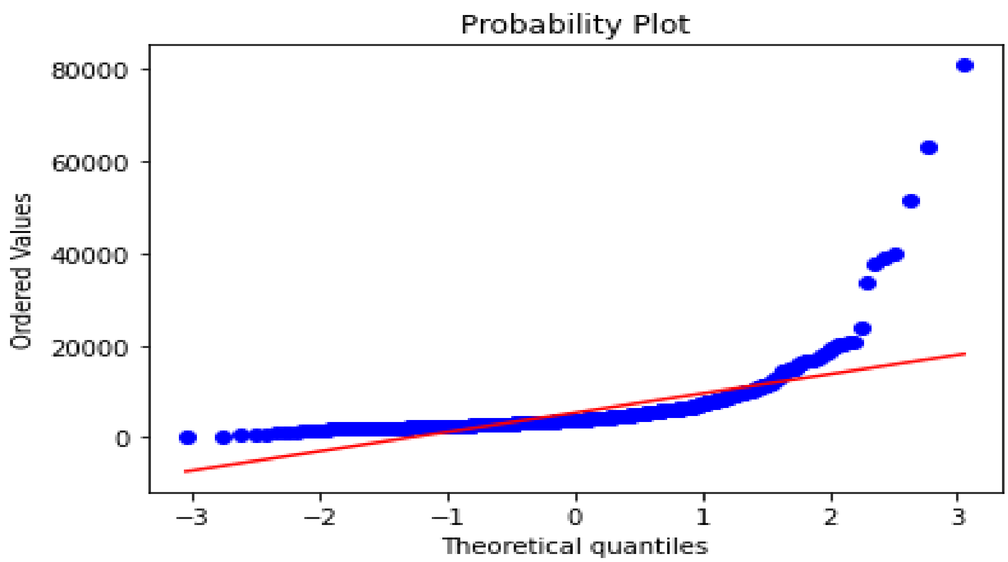



```
# Graphs plotted based on categories marriage and education
grid = sns.FacetGrid(df_train, row='Married', col='Education', size=2.2, a
spect=1.6)
grid.map(plt.hist, 'ApplicantIncome', alpha=.5, bins=10)
grid.add_legend()
```

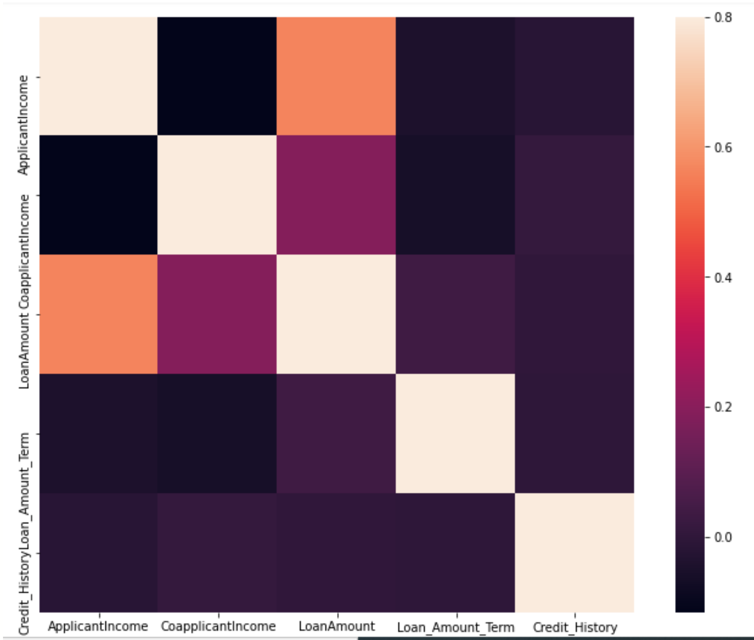



```
#histogram and normal probability plot
sns.distplot(df_train['ApplicantIncome'], fit=norm);
fig = plt.figure()
res = stats.probplot(df_train['ApplicantIncome'], plot=plt)
```

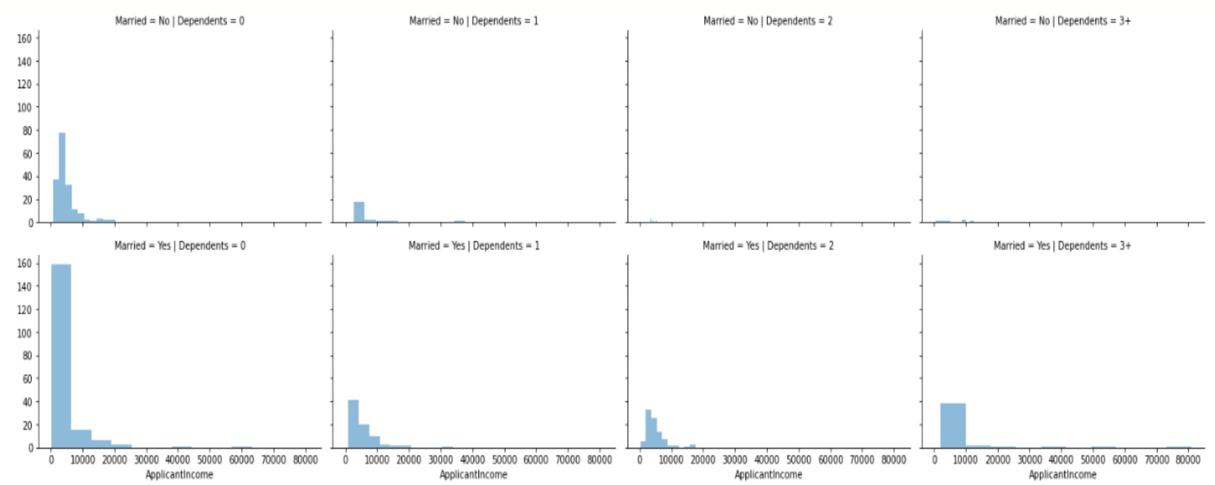





```
#correlation matrix
corrmat = df_train.corr()
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, vmax=.8, square=True);
```

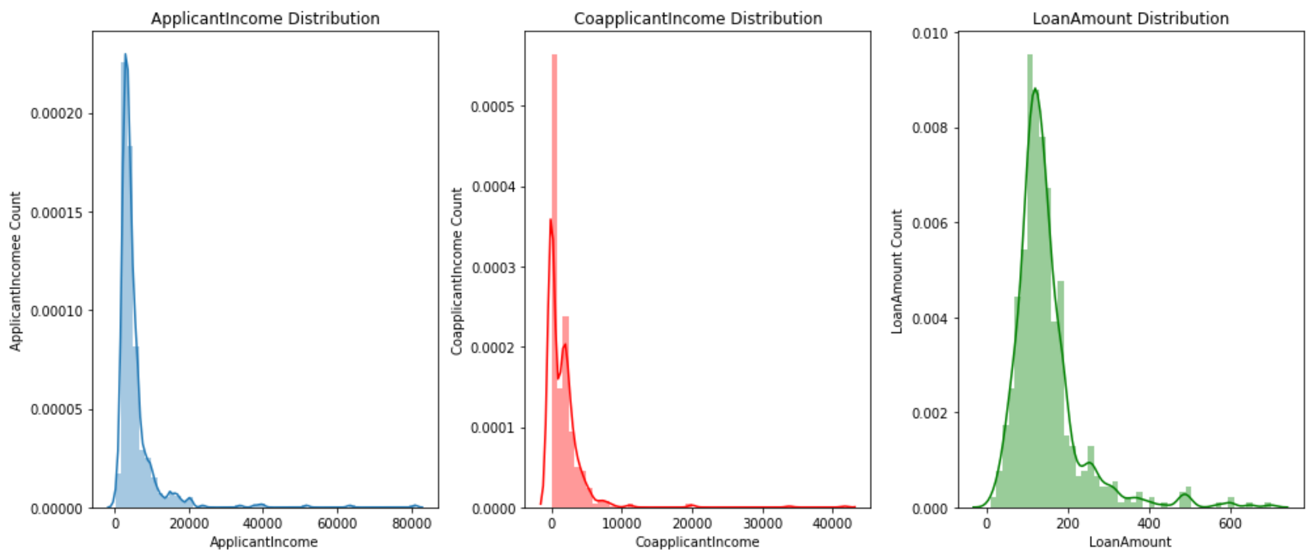



```
# This graph depicts the combination of applicant income, married people and dependent people in a family
grid = sns.FacetGrid(df_train, row='Married', col='Dependents', size=3.2, aspect=1.6)
grid.map(plt.hist, 'ApplicantIncome', alpha=.5, bins=10)
grid.add_legend()
```



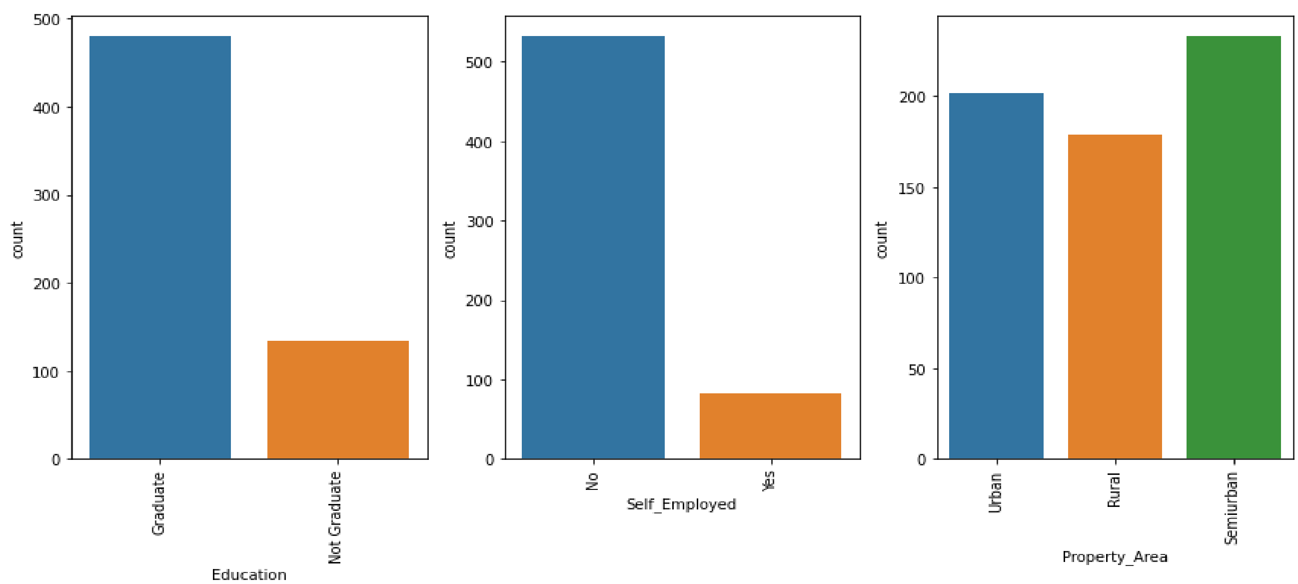

```
# The graph which differentiates the applicant income distribution, Coapplicant income distribution, loan amount distribution
flg, axes = plt.subplots(nrows = 1, ncols = 3, figsize = (14,6))
```

```
sns.distplot(df_train['ApplicantIncome'], ax = axes[0]).set_title('ApplicantIncome Distrib
ution')
axes[0].set_ylabel('ApplicantIncomee Count')

sns.distplot(df_train['CoapplicantIncome'], color = "r", ax = axes[1]).set_title('Coapplican
tIncome Distribution')
axes[1].set_ylabel('CoapplicantIncome Count')

sns.distplot(df_train['LoanAmount'],color = "g", ax = axes[2]).set_title('LoanAmount Dist
ribution')
axes[2].set_ylabel('LoanAmount Count')

plt.tight_layout()
plt.show()
plt.gcf().clear()
```



This figure shows the count of people differentiated based on education, self_employed, and property_area

```
fig, axes = plt.subplots(ncols=3,figsize=(12,6))

g = sns.countplot(df_train["Education"], ax=axes[0])
plt.setp(g.get_xticklabels(), rotation=90)
g = sns.countplot(df_train["Self_Employed"], ax=axes[1])
plt.setp(g.get_xticklabels(), rotation=90)
g = sns.countplot(df_train["Property_Area"], ax=axes[2])
plt.setp(g.get_xticklabels(), rotation=90)

plt.tight_layout()
plt.show()
plt.gcf().clear()
```



Explanation of the Main Code using Google Colab

1. Logistic Regression model

```
# Importing required Libraries
import pandas as pd
import numpy as np              # For mathematical calculations
import seaborn as sns           # For data visualization
import matplotlib.pyplot as plt    # For plotting graphs

# Importing dataset
```

```
train = pd.read_csv('train_dataset.csv')
test = pd.read_csv('test_dataset.csv')

# Converting the values to number
train['Dependents'].replace('3+', 3,inplace=True)
test['Dependents'].replace('3+', 3,inplace=True)

# take a look at the top 5 rows of the train set, notice the column "Loan_Status"
train.head()
```

Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y

```
# take a look at the top 5 rows of the test set, notice the absense of "Loan_Status" that we will predict
test.head()
```

Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	360.0	1.0	Urban
LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	360.0	1.0	Urban
LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	360.0	1.0	Urban
LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	360.0	NaN	Urban
LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	360.0	1.0	Urban

```python
# Handling Missing Values

# Check How many Null Values in each columns
train.isnull().sum()

# Train Categorical Variables Missisng values
train['Gender'].fillna(train['Gender'].mode()[0], inplace=True)
train ['Married'].fillna(train['Married'].mode()[0],inplace=True)
train['Dependents'].fillna(train['Dependents'].mode()[0], inplace=True)
train['Self_Employed'].fillna(train['Self_Employed'].mode()[0], inplace=True)
train['Credit_History'].fillna(train['Credit_History'].mode()[0], inplace=True)

# Train Numerical Variables Missing Values
train['Loan_Amount_Term'].fillna(train['Loan_Amount_Term'].mode()[0], inplace=True)
train['LoanAmount'].fillna(train['LoanAmount'].median(), inplace=True)

# Train Check if any Null Values Exits
train.isnull().sum()

# Test Check How many Null Values in each columns
test.isnull().sum()

# test Categorical Variables Missisng values
test['Gender'].fillna(test['Gender'].mode()[0], inplace=True)
test ['Married'].fillna(test['Married'].mode()[0],inplace=True)
test['Dependents'].fillna(test['Dependents'].mode()[0], inplace=True)
test['Self_Employed'].fillna(test['Self_Employed'].mode()[0], inplace=True)
test['Credit_History'].fillna(test['Credit_History'].mode()[0], inplace=True)

# test Numerical Variables Missing Values
test['Loan_Amount_Term'].fillna(test['Loan_Amount_Term'].mode()[0], inplace=True)
test['LoanAmount'].fillna(test['LoanAmount'].median(), inplace=True)

# test Check if any Null Values Exits
test.isnull().sum()
```

```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
dtype: int64
```

```
# Outlier treatment
train['LoanAmount'] = np.log(train['LoanAmount'])
test['LoanAmount'] = np.log(test['LoanAmount'])

# Separting the Variable into Independent and Dependent
X = train.iloc[:, 1:-1].values
y = train.iloc[:, -1].values

# Converting Categorical variables into dummy
from sklearn.preprocessing import LabelEncoder,OneHotEncoder
labelencoder_X = LabelEncoder()

# Gender
X[:,0] = labelencoder_X.fit_transform(X[:,0])

# Marraige
X[:,1] = labelencoder_X.fit_transform(X[:,1])

# Education
X[:,3] = labelencoder_X.fit_transform(X[:,3])

# Self Employed
X[:,4] = labelencoder_X.fit_transform(X[:,4])

# Property Area
X[:,-1] = labelencoder_X.fit_transform(X[:,-1])
```

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Fitting Logistic Regression to our training set
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state=0)
classifier.fit(X_train, y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
# Predecting the results
y_pred = classifier.predict(X_test)

# Printing values of whether loan is accepted or rejected
y_pred[:100]
```

```
array(['Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y'], dtype=object)
```

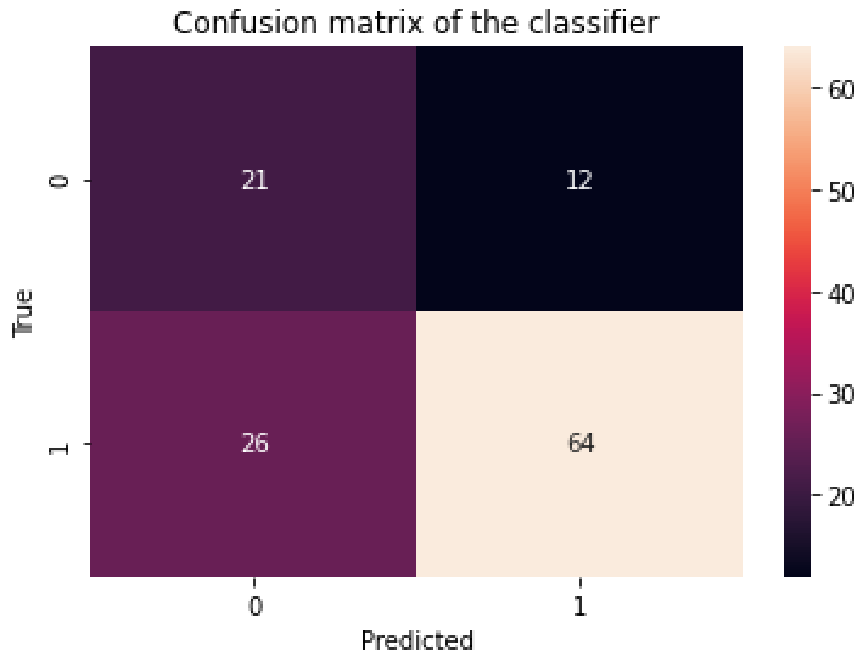
```
# import classification_report
```

```python
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           N       0.88      0.45      0.60        33
           Y       0.83      0.98      0.90        90

    accuracy                           0.84       123
   macro avg       0.86      0.72      0.75       123
weighted avg       0.84      0.84      0.82       123
```

```python
# implementing the confusion matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)

# f, ax = plt.subplots(figsize=(9, 6))
sns.heatmap(cm, annot=True, fmt="d")
plt.title('Confusion matrix of the classifier')
plt.xlabel('Predicted')
plt.ylabel('True')
```

```
[[21 12]
 [26 64]]
Text(33.0, 0.5, 'True')
```




```
# Check Accuracy
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)
```

```
0.8373983739837398
```

```
# Applying k-Fold Cross Validation
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv = 10)

accuracies.mean()
# accuracies.std()
```

```
0.8024081632653062
```

2. Using Random Forest Classification

The code till feature scaling is same, there onwards code is slightly different

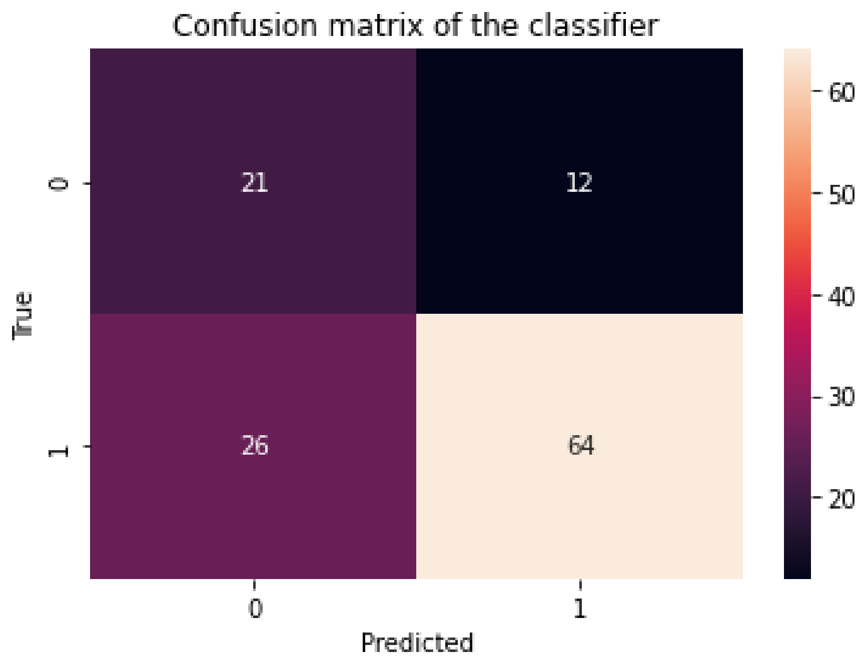
```
# Fitting Random Forest Classification to the Training set
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion="entropy", random_state=0)
classifier.fit(X_train,y_train)
```

```
# Printing values of whether loan is accepted or rejected
y_pred[:100]
```

```
array(['N', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'N', 'N', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y',
       'N', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'N', 'N', 'N', 'Y', 'Y', 'Y',
       'Y', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N',
       'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N',
       'Y', 'Y', 'N', 'N', 'N', 'Y', 'Y', 'Y', 'N'], dtype=object)
```

```
#confusion matrix
```

```
[[21 12]
 [26 64]]
Text(33.0, 0.5, 'True')
```




```
# Check Accuracy
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)
```

```
0.6910569105691057
```

```
# Applying k-Fold Cross Validation
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv = 10)

accuracies.mean()
# accuracies.std()
```

```
0.7148163265306122
```

3. Using Decision Tree Classifiaction Model

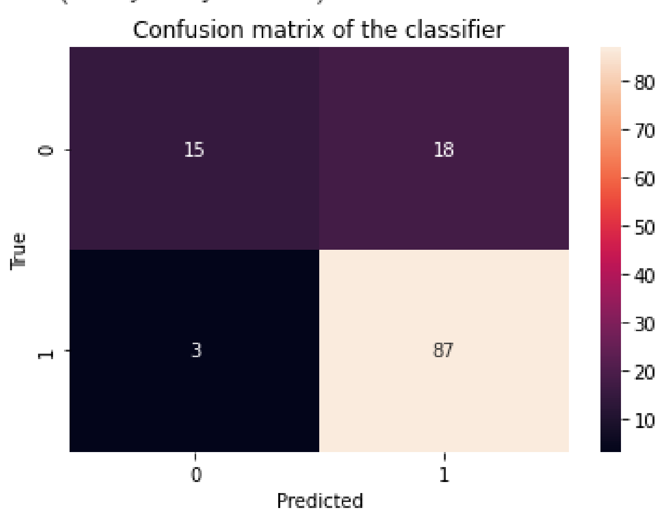
```
# Fitting Decision Tree Classification to the Training set
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train,y_train)
```

```
# Predecting the results
y_pred = classifier.predict(X_test)

# Printing values of whether loan is accepted or rejected
y_pred[:100]
```

```
array(['Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y'], dtype='<U1')
```

#confusion matrix

```
[[15 18]
 [ 3 87]]
Text(33.0, 0.5, 'True')
```




```
# Check Accuracy
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)
```

```
0.8292682926829268
```

```
# Applying k-Fold Cross Validation
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_tr
ain, cv = 10)

accuracies.mean()
# accuracies.std()
```

```
0.7922448979591836
```

Loan prediction models comparison

Loan Prediction	**Accuracy**	**Accuracy using K-fold Cross Validation**
Using Logistic Regression	**0.8373983739837398**	**0.8024081632653062**
Using Random Forest Classification	**0.6910569105691057**	**0.7148163265306122**
Using Decision Tree Classification	**0.8292682926829268**	**0.7922448979591836**

SUMMARY

The task of this machine learning project is to train the model for accepting loan or rejecting loan. Now there are 3 models wherein we can train the model and test it to predict whether other applicants could get loan or not. First model is about using logistic regression model for which the accuracy is 0.8373 and accuracy using k-fold cross validation comes to 0.8024. Second model gives 0.6910 accuracy and 0.7148 accuracy using k-fold cross validation. Third model gives 0.8292 and 0.7922 as accuracies. Among all the models, Logistic regression gives better accuracy. This Logistic regression model has been trained with a datasets and tested with another dataset.