Introduction

> ### Steps are:

1. Gathering Data
2. Exploratory Data Analysis
3. Data Visualizations
4. Machine Learning Model Decision.
5. Traing the ML Model
6. Predict Model

Import Packages

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

You can load this data with the `read_csv()` method from `pandas` package. It converts the data set to a python dataframe.

Dataset Key Information.

> - `Loan_ID` --------------> Unique Loan ID.
> - `Gender` --------------> Male/ Female
> - `Married` --------------> Applicant married (Y/N)
> - `Dependents` ------------> Number of dependents
> - `Education` -------------> Applicant Education (Graduate/ Under Graduate)
> - `Self_Employed` ---------> Self-employed (Y/N)
> - `ApplicantIncome` -------> Applicant income
> - `CoapplicantIncome` -----> Coapplicant income
> - `LoanAmount` -----------> Loan amount in thousands
> - `Loan_Amount_Term` ------> Term of a loan in months
> - `Credit_History` --------> Credit history meets guidelines
> - `Property_Area` ---------> Urban/ Semi-Urban/ Rural
> - `Loan_Status` -----------> Loan approved (Y/N)

1. Gathering Data

```
from google.colab import drive
drive.mount('/gdrive/')
%cd /gdrive
```

```
Mounted at /gdrive/
/gdrive
```

```
ls
```

```
MyDrive/  Shareddrives/
```

```
cd/gdrive/My Drive/Loan Prediction/
```

```
/gdrive/My Drive/Loan Prediction
```

```
ls
```

```
'Loan payments data.csv'   loan-test.csv   loan-train.csv
```

```
#  Create New Variable and stores the dataset values as Data Frame
loan_train = pd.read_csv('/gdrive/My Drive/Loan Prediction/loan-train.csv')
loan_test = pd.read_csv('/gdrive/My Drive/Loan Prediction/loan-test.csv')
```

- Lets display the some few information from our large datasets

Here, We shows the first five rows from datasets

```
loan_train.head()
```

- As we can see in the above output, there are too many columns, (columns known as features as well.)

We can also use `loan_train` to show few rows from the first five and last five record from the dataset

```
loan_train
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001002	Male	No	0	Graduate	No	5849
1	LP001003	Male	Yes	1	Graduate	No	4583
2	LP001005	Male	Yes	0	Graduate	Yes	3000
3	LP001006	Male	Yes	0	Not Graduate	No	2583
4	LP001008	Male	No	0	Graduate	No	6000
...	...	...	...	...	...	...	...
609	LP002978	Female	No	0	Graduate	No	2900
610	LP002979	Male	Yes	3+	Graduate	No	4106
611	LP002983	Male	Yes	1	Graduate	No	8072
612	LP002984	Male	Yes	2	Graduate	No	7583
613	LP002990	Female	No	0	Graduate	Yes	4583

614 rows × 13 columns

> Here, we can see there are many rows and many columns, To know how many records and columns are available in our dataset, we can use the `shape` attribute or we can use `len()` to know how many records and how many features available in the dataset.

```
print("Rows: ", len(loan_train))
```

```
Rows:  614
```

Pandas has inbuild attribute to get all column from the dataset, With the help of this feature we can get the how many column available we have.

```
print("Columns: ", len(loan_train.columns))
```

```
Columns:  13
```

Also we can get the shape of the dataset using `shape` attribute

```
print("Shape : ", loan_train.shape)
```

```
Shape :  (614, 13)
```

> *After we collecting the data, Next step we need to understand what kind of data we have.*

Also we can get the column as an list(array) from dataset

> **Note: DataFrame.columns returns the total columns of the dataset, Store the number of columns in variable** `loan_train_columns`

```
loan_train_columns = loan_train.columns # assign to a variable
loan_train_columns # print the list of columns
```

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

Now, Understanding the Data

- First of all we use the `loan_train.describe()` method to shows the important information from the dataset
- It provides the `count`, `mean`, `standard deviation (std)`, `min`, `quartiles` and `max` in its output.

```
loan_train.describe()
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000

As I said the above cell, this the information of all the methamatical details from dataset. Like `count`, `mean`, `standard deviation (std)`, `min`, `quartiles(25%, 50%, 75%)` and `max`.

> ## Another method is `info()`, This method show us the information about the dataset, Like

1. What's the type of culumn have?

- How many rows available in the dataset?
- What are the features are there?
- How many null values available in the dataset?
- Ans so on...

```
loan_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            614 non-null    object 
 1   Gender             601 non-null    object 
 2   Married            611 non-null    object 
 3   Dependents         599 non-null    object 
 4   Education          614 non-null    object 
 5   Self_Employed      582 non-null    object 
 6   ApplicantIncome    614 non-null    int64  
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object 
 12  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

As we can see in the output.

1. There are `614` entries

- There are total 13 features (0 to 12)
- There are three types of datatype `dtypes: float64(4), int64(1), object(8)`
- It's Memory usage that is, `memory usage: 62.5+ KB`
- Also, We can check how many missing values available in the `Non-Null Count` column

2. Exploratory Data Analysis

In this section, We learn about extra information about data and it's characteristics.

- First of all, We explore object type of data So let's make a function to know how many types of values available in the column

```
def explore_object_type(df ,feature_name):
    """
    To know, How many values available in object('categorical') type of features
    And Return Categorical values with Count.
    """
    if df[feature_name].dtype ==  'object':
        print(df[feature_name].value_counts())
```

- After defined a function, Let's call it. and check what's the output of our created function.

```
# Now, Test and Call a function for gender only
explore_object_type(loan_train, 'Gender')
```

```
Male      489
Female    112
Name: Gender, dtype: int64
```

- Here's one little issue occurred, Suppose in your datasets there are lots of feature to defined like this above code.

```
# Solution is, Do you remember we have variable with name of `loan_train_columns`,
# 'Loan_ID', 'Gender', 'Married', 'Dependents', 'Education', 'Self_Employed', 'Pro
```

```
for featureName in loan_train_columns:
    if loan_train[featureName].dtype == 'object':
        print('\n"' + str(featureName) + '\'s" Values with count are :')
        explore_object_type(loan_train, str(featureName))
```

```
"Loan_ID's" Values with count are :
LP001047    1
LP001157    1
LP002398    1
LP001430    1
LP002142    1
           ..
LP002446    1
LP001326    1
LP002368    1
LP002888    1
LP002842    1
Name: Loan_ID, Length: 614, dtype: int64

"Gender's" Values with count are :
Male      489
Female    112
Name: Gender, dtype: int64

"Married's" Values with count are :
Yes    398
No     213
Name: Married, dtype: int64

"Dependents's" Values with count are :
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64

"Education's" Values with count are :
Graduate        480
Not Graduate    134
Name: Education, dtype: int64

"Self_Employed's" Values with count are :
No     500
Yes     82
Name: Self_Employed, dtype: int64

"Property_Area's" Values with count are :
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64

"Loan_Status's" Values with count are :
Y    422
```

```
N    192
Name: Loan_Status, dtype: int64
```

> *Note: Your output maybe shorter or longer, It's totally depend upon your dataset's columns*

Double-click (or enter) to edit

- We need to fill null values with `mean` and `median` using `missingno` package

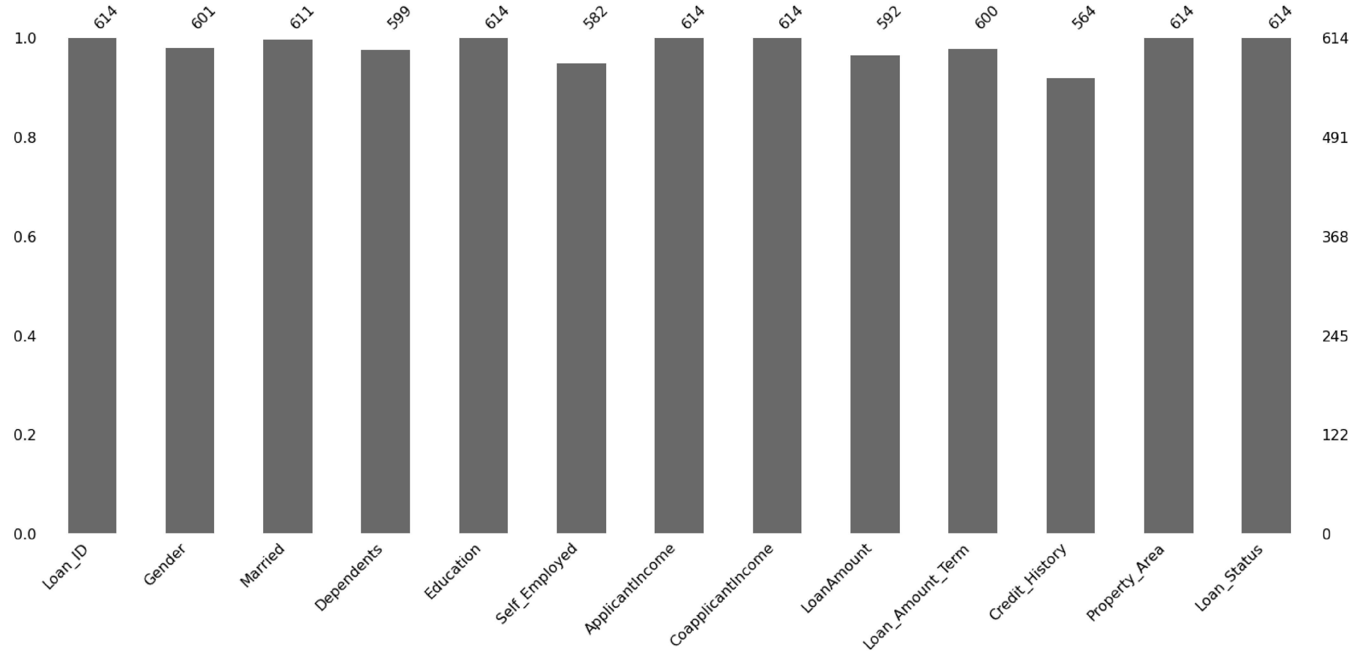
```
import missingno as msno
```

```
# list of how many percentage values are missing
loan_train

loan_train.isna().sum()
# round((loan_train.isna().sum() / len(loan_train)) * 100, 2)
```

```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

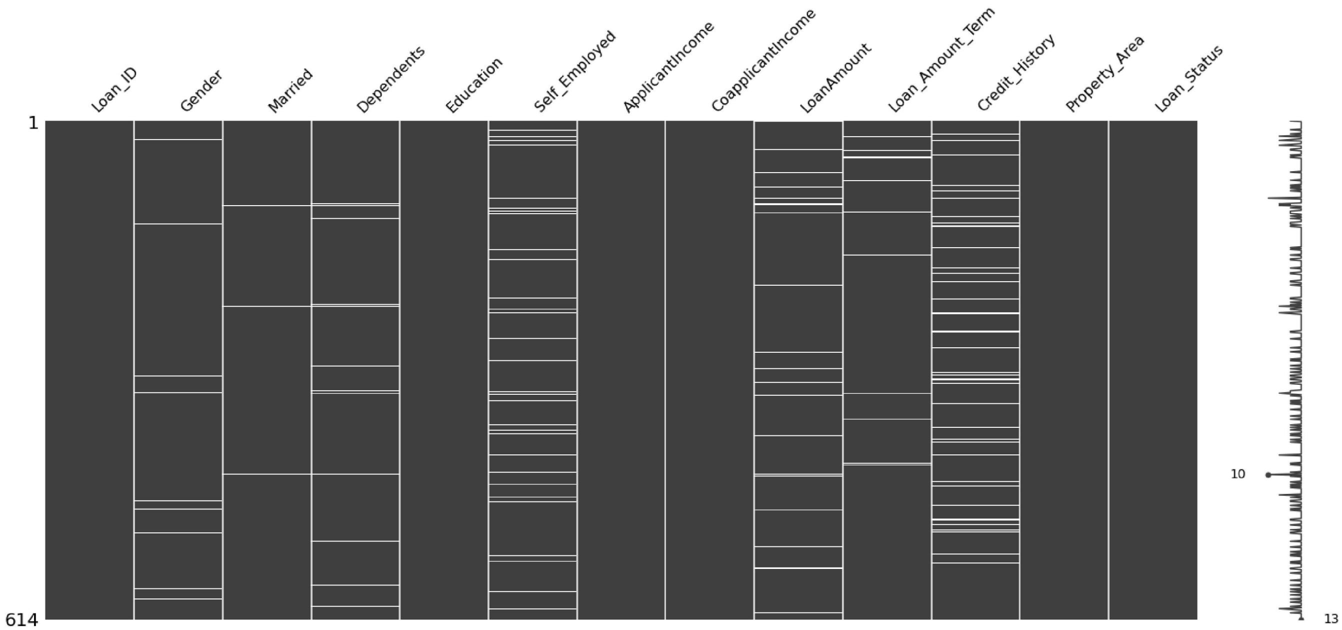
```
msno.bar(loan_train)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4d561c8a90>
```




```
msno.matrix(loan_train )
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4d4c3519d0>
```



- As we can see here, there are too many columns missing with small amount of null values so we use `mean` amd `mode` to replace with `NaN` values.

```
loan_train['Credit_History'].fillna(loan_train['Credit_History'].mode(), inplace=T
loan_test['Credit_History'].fillna(loan_test['Credit_History'].mode(), inplace=Tru


loan_train['LoanAmount'].fillna(loan_train['LoanAmount'].mean(), inplace=True) # M
loan_test['LoanAmount'].fillna(loan_test['LoanAmount'].mean(), inplace=True) # Mea
```

convert Categorical variable with Numerical values.

`Loan_Status` feature boolean values, So we replace `Y` values with `1` and `N` values with `0` and same for other `Boolean` types of columns

```
loan_train.Loan_Status = loan_train.Loan_Status.replace({"Y": 1, "N" : 0})
# loan_test.Loan_Status = loan_test.Loan_Status.replace({"Y": 1, "N" : 0})

loan_train.Gender = loan_train.Gender.replace({"Male": 1, "Female" : 0})
loan_test.Gender = loan_test.Gender.replace({"Male": 1, "Female" : 0})

loan_train.Married = loan_train.Married.replace({"Yes": 1, "No" : 0})
loan_test.Married = loan_test.Married.replace({"Yes": 1, "No" : 0})

loan_train.Self_Employed = loan_train.Self_Employed.replace({"Yes": 1, "No" : 0})
```

```
loan_test.Self_Employed = loan_test.Self_Employed.replace({"Yes": 1, "No" : 0})
```

```
loan_train['Gender'].fillna(loan_train['Gender'].mode()[0], inplace=True)
loan_test['Gender'].fillna(loan_test['Gender'].mode()[0], inplace=True)

loan_train['Dependents'].fillna(loan_train['Dependents'].mode()[0], inplace=True)
loan_test['Dependents'].fillna(loan_test['Dependents'].mode()[0], inplace=True)

loan_train['Married'].fillna(loan_train['Married'].mode()[0], inplace=True)
loan_test['Married'].fillna(loan_test['Married'].mode()[0], inplace=True)

loan_train['Credit_History'].fillna(loan_train['Credit_History'].mean(), inplace=
loan_test['Credit_History'].fillna(loan_test['Credit_History'].mean(), inplace=Tru
```

- Here, `Property_Area`, `Dependents` and `Education` has multiple values so now we can use `LabelEncoder` from `sklearn` package

```
from sklearn.preprocessing import LabelEncoder
feature_col = ['Property_Area','Education', 'Dependents']
le = LabelEncoder()
for col in feature_col:
    loan_train[col] = le.fit_transform(loan_train[col])
    loan_test[col] = le.fit_transform(loan_test[col])
```

> Finally, We have all the features with numerical values,

3. Data Visualizations

In this section, We are showing the visual information from the dataset, For that we need some pakages that are `matplotlib` and `seaborn`

```
import matplotlib.pyplot as plt
%matplotlib inline
```

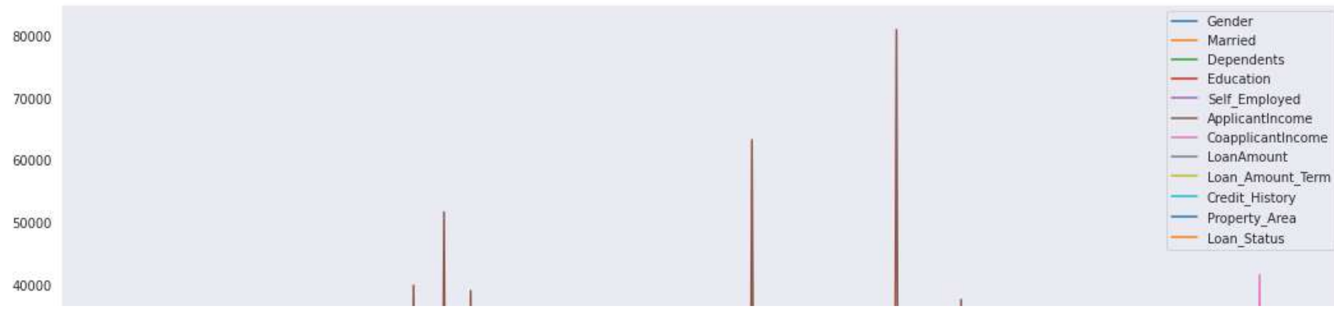
```
import seaborn as sns
sns.set_style('dark')
```

```
loan_train
```

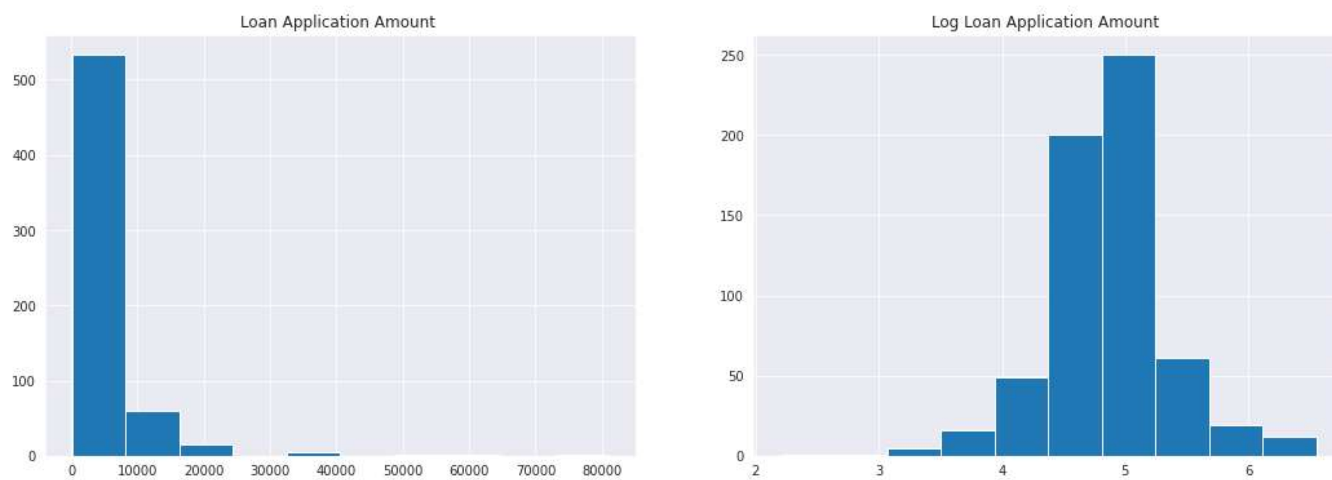
	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001002	1.0	0.0	0	0	0.0	5849
1	LP001003	1.0	1.0	1	0	0.0	4583
2	LP001005	1.0	1.0	0	0	1.0	3000
3	LP001006	1.0	1.0	0	1	0.0	2583
4	LP001008	1.0	0.0	0	0	0.0	6000
...	...	...	...	...	...	...	...
609	LP002978	0.0	0.0	0	0	0.0	2900
610	LP002979	1.0	1.0	3	0	0.0	4106
611	LP002983	1.0	1.0	1	0	0.0	8072
612	LP002984	1.0	1.0	2	0	0.0	7583
613	LP002990	0.0	0.0	0	0	1.0	4583

614 rows × 13 columns

```
loan_train.plot(figsize=(18, 8))

plt.show()
```

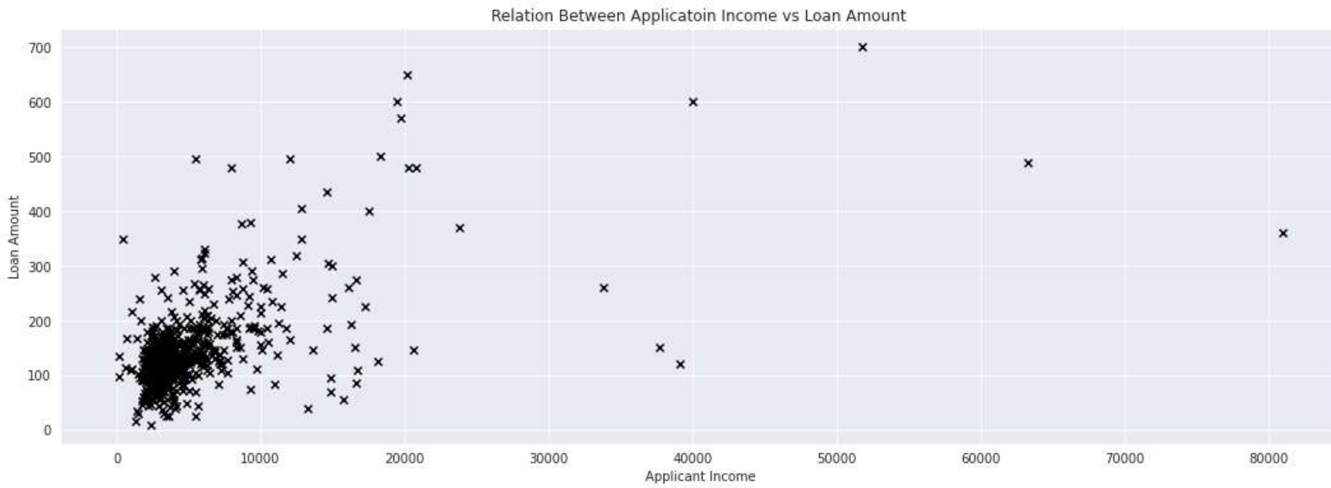



```
plt.figure(figsize=(18, 6))
plt.subplot(1, 2, 1)


loan_train['ApplicantIncome'].hist(bins=10)
plt.title("Loan Application Amount ")

plt.subplot(1, 2, 2)
plt.grid()
plt.hist(np.log(loan_train['LoanAmount']))
plt.title("Log Loan Application Amount ")

plt.show()
```




```
plt.figure(figsize=(18, 6))
plt.title("Relation Between Applicatoin Income vs Loan Amount ")

plt.grid()
plt.scatter(loan_train['ApplicantIncome'] , loan_train['LoanAmount'], c='k', marke
```

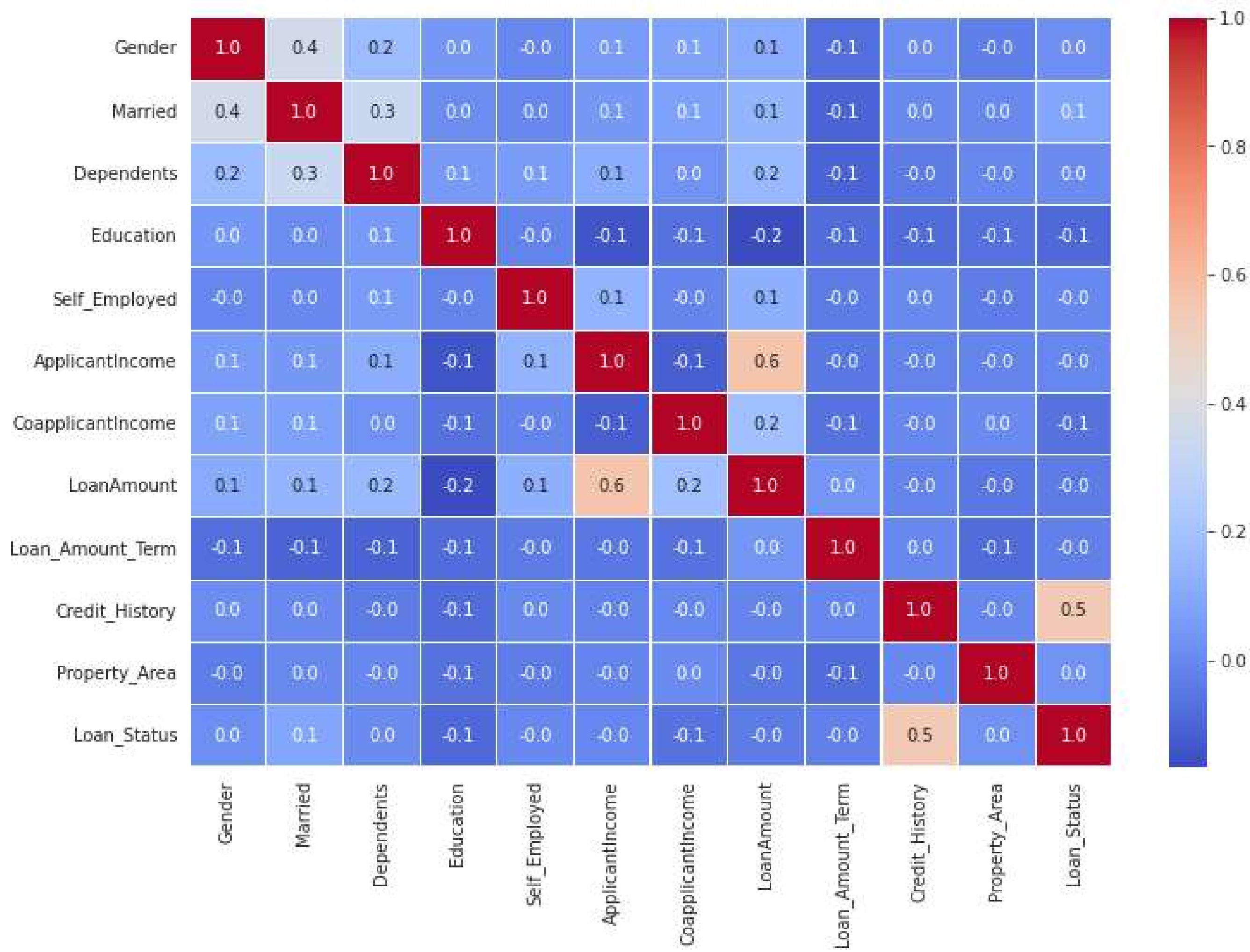
```
plt.xlabel("Applicant Income")
plt.ylabel("Loan Amount")
plt.show()
```




```
plt.figure(figsize=(12, 6))
plt.plot(loan_train['Loan_Status'], loan_train['LoanAmount'])
plt.title("Loan Application Amount ")
plt.show()
```

Loan Application Amount

```
plt.figure(figsize=(12,8))
sns.heatmap(loan_train.corr(), cmap='coolwarm', annot=True, fmt='.1f', linewidths=
plt.show()
```



In this heatmap, we can clearly seen the relation between two variables

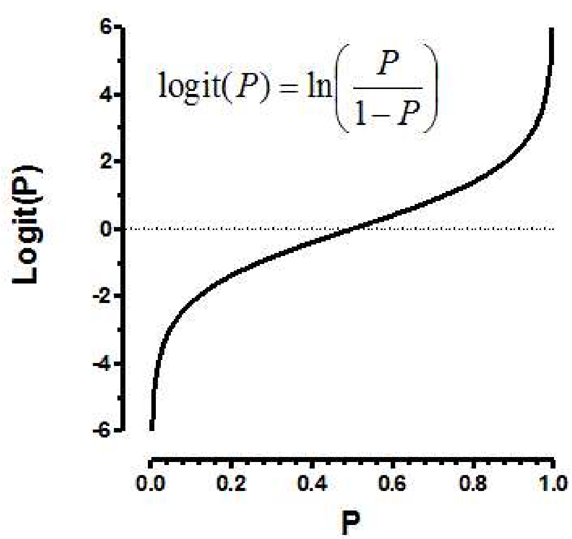
4. Choose ML Model.

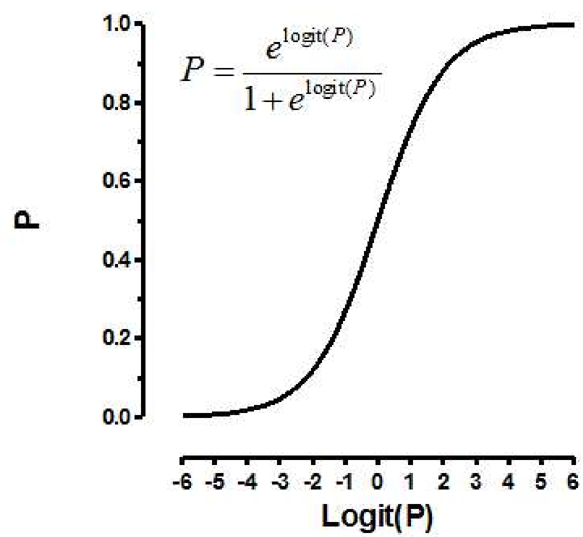
- In this step, We have a lots of Machine Learning Model from sklearn package, and we need to decide which model is give us the better performance. then we use that model in final stage and send to the production level.

```
# import ml model from sklearn pacakge

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score
```

First of all, we are use `LogisticRegression` from `sklearn.linear_model` package. Here is the little information about `LogisticRegression`.

`Logistic Regression` is a **classification algorithm**. It is used to predict a binary outcome (`1 / 0`, `Yes / No`, and `True / False`) given a set of independent variables. To represent binary / categorical outcome, we use dummy variables. You can also think of logistic regression as a special case of linear regression when the outcome variable is categorical, where we are using log of odds as the dependent variable.





- Let's build the model

```
logistic_model = LogisticRegression()
```

5. Traing the ML Model

> ### Before fitting the model, We need to decide how many feature are available for testing and training, then after complete this step. fitt the model

Currently, we are using `Credit_History', 'Education', 'Gender` features for training so let's

```
train_features = ['Credit_History', 'Education', 'Gender']

x_train = loan_train[train_features].values
y_train = loan_train['Loan_Status'].values

x_test = loan_test[train_features].values
```

```
logistic_model.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=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

6. Predict Model

```
# Predict the model for testin data

predicted = logistic_model.predict(x_test)
```

```
# check the coefficeints of the trained model
print('Coefficient of model :', logistic_model.coef_)
```

```
Coefficient of model : [[ 3.316164   -0.3059193   0.09398266]]
```

```
# check the intercept of the model
print('Intercept of model',logistic_model.intercept_)
```

```
Intercept of model [-1.98307795]
```

```
# Accuray Score on train dataset
# accuracy_train = accuracy_score(x_test, predicted)
score = logistic_model.score(x_train, y_train)
print('accuracy_score overall :', score)
print('accuracy_score percent :', round(score*100,2))
```

```
accuracy_score overall : 0.8094462540716613
accuracy_score percent : 80.94
```

```
# predict the target on the test dataset
predict_test = logistic_model.predict(x_test)
print('Target on test data',predict_test)
```

```
Target on test data [1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 0 1 1 0 0 1 0 1 1 1 1
 1 1 1 1 1 1 0 1 0 1 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1
 1 1 1 1 1 1 0 0 0 1 1 1 0 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 0 1 1 1 1 0
 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 0 0 1 0 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 0 0 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1
 1 1 0 1 1 1 1 0 1 1 1 1 1 0 0 1 1 1 1 0 1 0 1 0 1 1 1 1 0 1 1 1 1 0 1 1 1
 1 1 1 1 1 1 1 0 1 0 1 1 1 1 0 0 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1
 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1
 1 1 1 1 1 1 0 1 1 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1]
```

0s completed at 20:16