Day 5 Session 1 Loan Approval Prediction Machine Learning Model.

```
import pandas as pd
import numpy as np
#Coding for importing csv files in Google colab
from google.colab import files
import io
uploaded = files.upload()
df = pd.read_csv(io.BytesIO(uploaded['loan.csv']))
# Read csv loan.csv into a pandas dataframe
# Take a look at the first few rows
print(df)
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving loan.csv to loan.csv
       Loan_ID Gender Married  ... Loan_Amount_Term Credit_History Property_Area
0     LP001015   Male     Yes  ...            360.0            1.0         Urban
1     LP001022   Male     Yes  ...            360.0            1.0         Urban
2     LP001031   Male     Yes  ...            360.0            1.0         Urban
3     LP001035   Male     Yes  ...            360.0            NaN         Urban
4     LP001051   Male      No  ...            360.0            1.0         Urban
..         ...    ...     ...  ...              ...            ...           ...
362   LP002971   Male     Yes  ...            360.0            1.0         Urban
363   LP002975   Male     Yes  ...            360.0            1.0         Urban
364   LP002980   Male      No  ...            360.0            NaN     Semiurban
365   LP002986   Male     Yes  ...            360.0            1.0         Rural
366   LP002989   Male      No  ...            180.0            1.0         Rural

[367 rows x 12 columns]
```

To view the first 10 rows in the dataset

```
df.head(10)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cre
0	LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	360.0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	360.0	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	360.0	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	360.0	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	360.0	
5	LP001054	Male	Yes	0	Not Graduate	Yes	2165	3422	152.0	360.0	
6	LP001055	Female	No	1	Not Graduate	No	2226	0	59.0	360.0	
7	LP001056	Male	Yes	2	Not Graduate	No	3881	0	147.0	360.0	
8	LP001059	Male	Yes	2	Graduate	NaN	13633	0	280.0	240.0	
9	LP001067	Male	No	0	Not Graduate	No	2400	2400	123.0	360.0	

To view the columns of the dataset

To calculate the statistical calculations for all numerical fields

```
df.columns
```

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

```
df.describe()
```

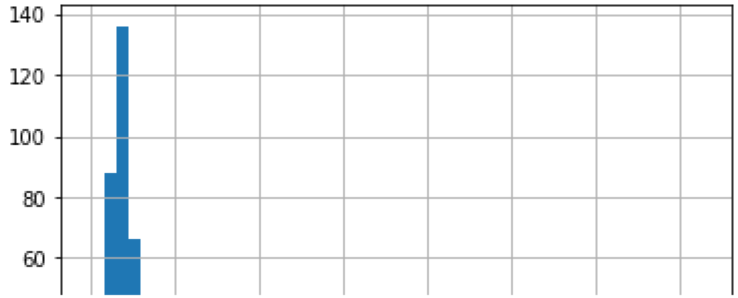
	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	367.000000	367.000000	362.000000	361.000000	338.000000
mean	4805.599455	1569.577657	136.132597	342.537396	0.825444
std	4910.685399	2334.232099	61.366652	65.156643	0.380150
min	0.000000	0.000000	28.000000	6.000000	0.000000
25%	2864.000000	0.000000	100.250000	360.000000	1.000000
50%	3786.000000	1025.000000	125.000000	360.000000	1.000000
75%	5060.000000	2430.500000	158.000000	360.000000	1.000000
max	72529.000000	24000.000000	550.000000	480.000000	1.000000

Distribution analysis using EDA

Analysis on Application income alone using histogram

```
df['ApplicantIncome'].hist(bins=50)
```

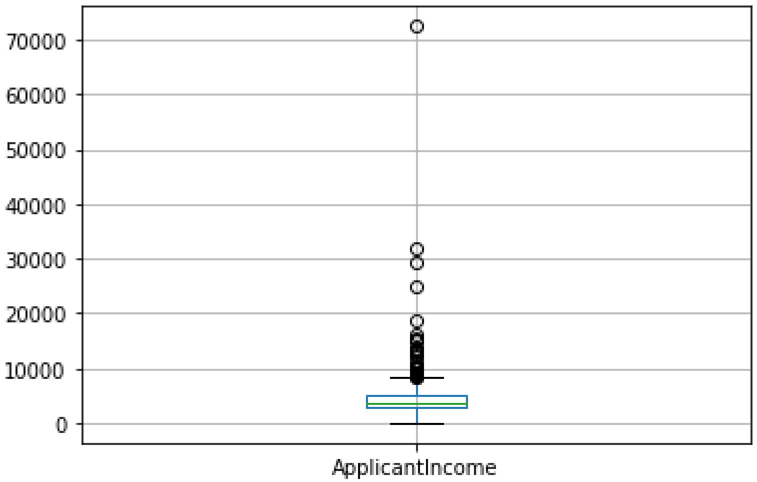
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e4aaaf28>
```



Analysis on Application income alone using boxplot


```
df.boxplot(column='ApplicantIncome')
```

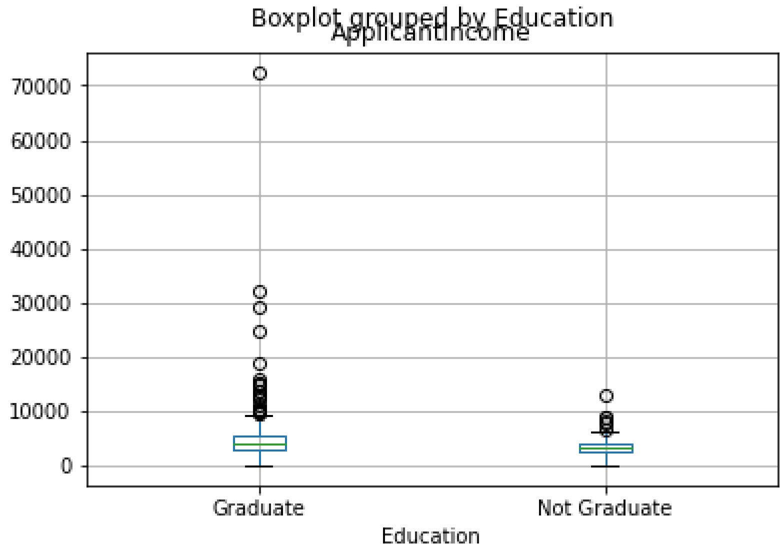
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e4f79e80>
```



Analysis on Application income and Education using boxplot

```
df.boxplot(column='ApplicantIncome', by = 'Education')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e44928d0>
```



Analysis on Application income and gender using boxplot

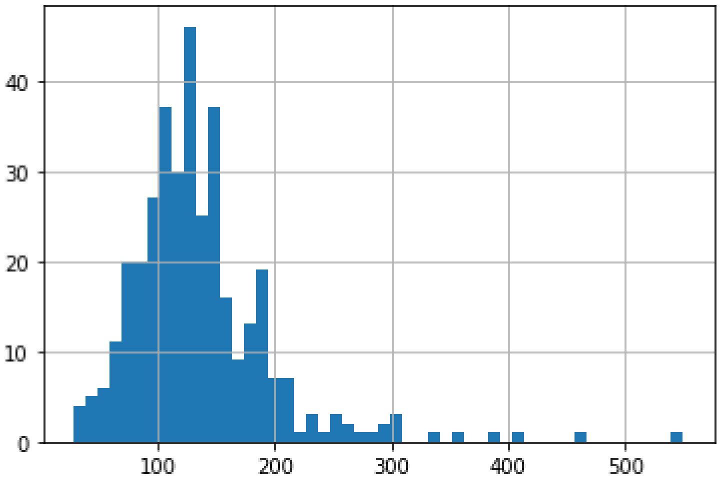
```
df.boxplot(column='ApplicantIncome', by = 'Gender')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e441bc50>
```

Analysis on Loan Amount alone using histogram

```
df['LoanAmount'].hist(bins=50)
```

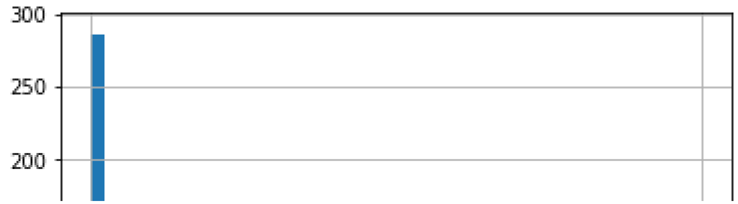
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e4a76208>
```



Analysis on Gender alone using histogram

```
df['Gender'].hist(bins=50)
```

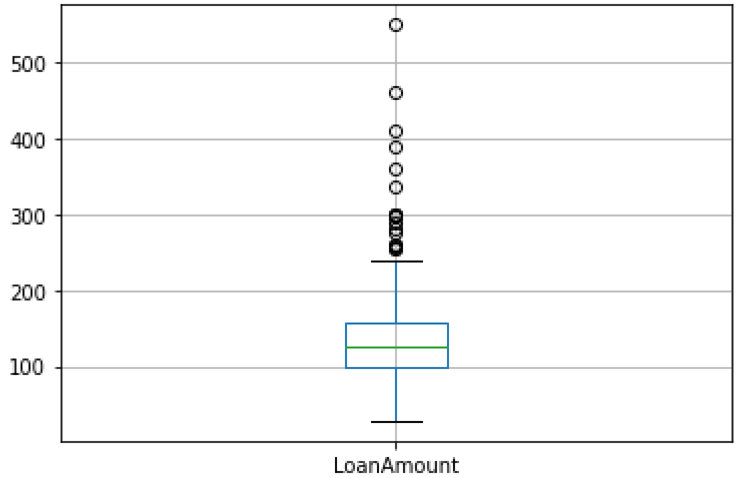
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e4a18208>



Analysis on Loan Amount alone using boxplot

```
df.boxplot(column='LoanAmount')
```

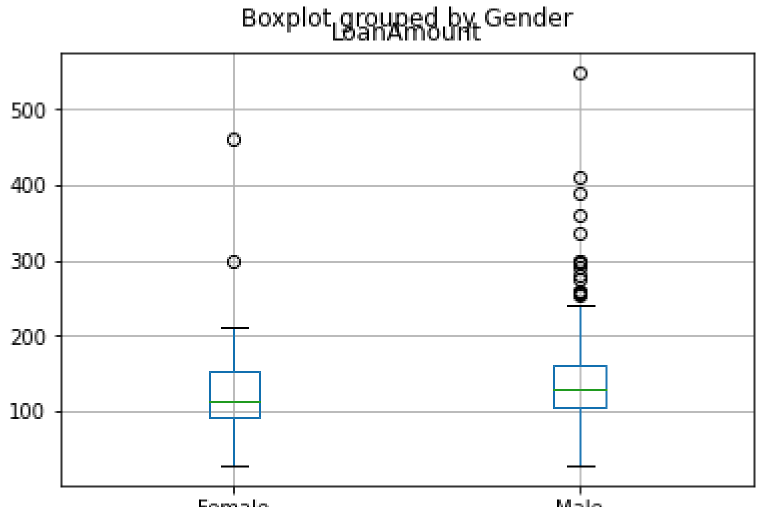
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e41e1d68>



Analysis on Loan Amount and gender using boxplot

```
df.boxplot(column='LoanAmount', by = 'Gender')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e41d60f0>
```



Categorical variable analysis

```
print ('Frequency Table for Credit History:')
temp1=df['Credit_History'].value_counts(ascending=True)
print(temp1)

print ('Frequency Table for Education:')
temp2=df['Education'].value_counts(ascending=True)
print(temp2)
```

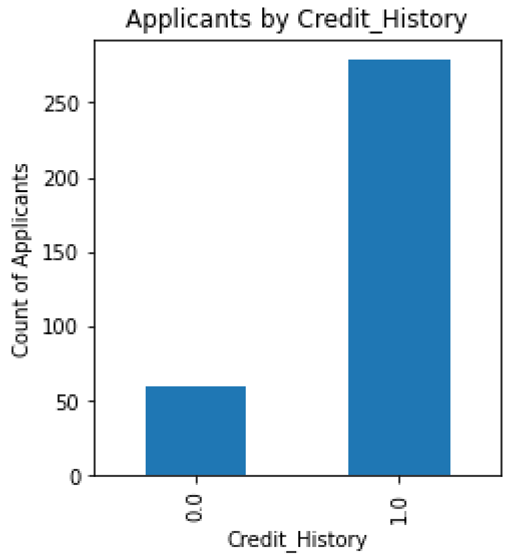
```
Frequency Table for Credit History:
0.0     59
1.0    279
Name: Credit_History, dtype: int64
Frequency Table for Education:
Not Graduate     84
Graduate        283
Name: Education, dtype: int64
```

Applicants by Credit_History Analysis

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(8,4))

#applicants by credit history
ax1 = fig.add_subplot(121)
ax1.set_xlabel('Credit_History')
ax1.set_ylabel('Count of Applicants')
ax1.set_title("Applicants by Credit_History")
temp1.plot(kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e4971438>
```



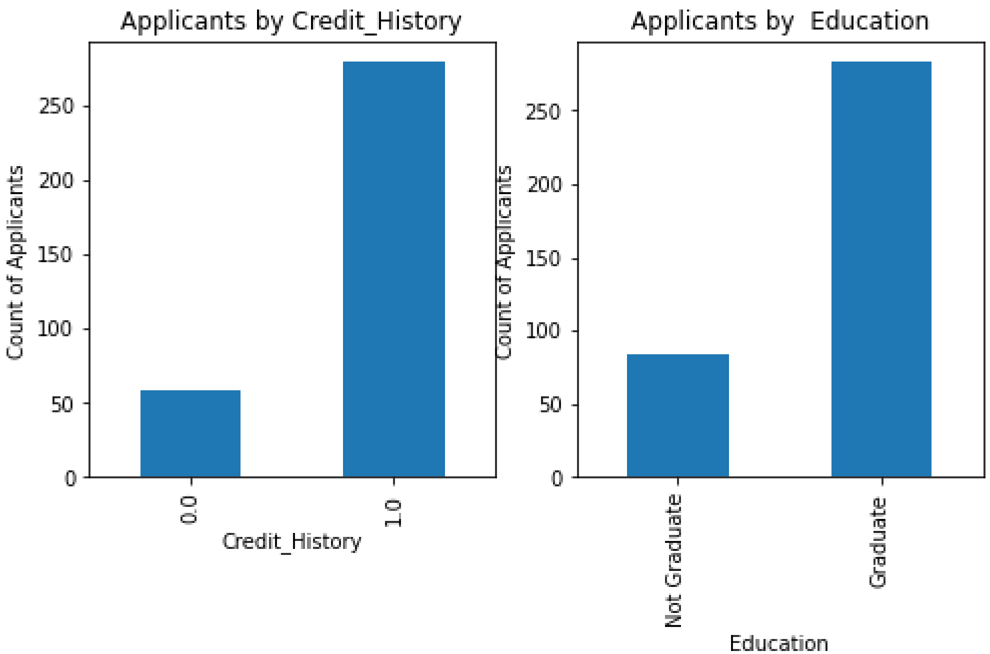
Applicants by Credit_History Analysis and Applicants by Education Analysis both hand in hand

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(8,4))

#applicants by credit history
ax1 = fig.add_subplot(121)
ax1.set_xlabel('Credit_History')
ax1.set_ylabel('Count of Applicants')
ax1.set_title("Applicants by Credit_History")
temp1.plot(kind='bar')
print('')

#applicants by education
ax2 = fig.add_subplot(122)
ax2.set_xlabel('Education')
ax2.set_ylabel('Count of Applicants')
ax2.set_title("Applicants by  Education")
temp2.plot(kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e41d64e0>
```



Check missing values in the dataset

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Loan_ID              0
Gender              11
Married              0
Dependents          10
Education            0
Self_Employed       23
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           5
Loan_Amount_Term     6
Credit_History      29
Property_Area        0
dtype: int64
```

replacing missing loan amount with mean of the loanamount

```
df['LoanAmount'].fillna(df['LoanAmount'].mean(), inplace=True)
```

viewing the data set

```
df
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	C
0	LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	360.0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	360.0	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	360.0	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	360.0	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	360.0	
...	...	...	...	...	...	...	...	...	...	...	
362	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	1777	113.0	360.0	
363	LP002975	Male	Yes	0	Graduate	No	4158	709	115.0	360.0	
364	LP002980	Male	No	0	Graduate	No	3250	1993	126.0	360.0	
365	LP002986	Male	Yes	0	Graduate	No	5000	2393	158.0	360.0	

once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

Loan_ID 0

checking Self_Employed

Education 0

```
df['Self_Employed'].value_counts()
```

```
No     307
Yes     37
Name: Self_Employed, dtype: int64
```

dtype: int64

As No is dominating, replacing the empty values with No

```
df['Self_Employed'].fillna('No',inplace=True)
```

checking Self_Employed once again

```
df['Self_Employed'].value_counts()
```

```
No     330
Yes     37
Name: Self_Employed, dtype: int64
```

checking Dependents

```
df['Dependents'].value_counts()
```

```
0     200
2      59
1      58
3+     40
Name: Dependents, dtype: int64
```

As 0 is dominating , replace empty values with 0

```
df['Dependents'].fillna('0',inplace=True)
```

once again checking Dependents

```
df['Dependents'].value_counts()
```

```
0     210
2      59
1      58
3+     40
Name: Dependents, dtype: int64
```

once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Loan_ID              0
Gender              11
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
```

checking Gender

```
dtype: int64
```

```
df['Gender'].value_counts()
```

```
Male      286
Female     70
Name: Gender, dtype: int64
```

male is dominated with 80% so replace empty values with Male

```
df['Gender'].fillna('Male',inplace=True)
```

once again checking Gender

```
df['Gender'].value_counts()
```

```
Male      297
Female     70
Name: Gender, dtype: int64
```

once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Loan_ID               0
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

checking Loan_Amount_Term

```
df['Loan_Amount_Term'].value_counts()
```

```
360.0    311
180.0     22
```

As Loan_Amount_Term=360 is dominating,replace empty values with 360

```
df['Loan_Amount_Term'].fillna(360.0,inplace=True)
```

checking Loan_Amount_Term

```
df['Loan_Amount_Term'].value_counts()
```

```
360.0    317
180.0     22
480.0      8
300.0      7
240.0      4
84.0       3
6.0        1
120.0      1
36.0       1
350.0      1
12.0       1
60.0       1
Name: Loan_Amount_Term, dtype: int64
```

once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
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       29
Property_Area         0
dtype: int64
```

checking Credit_History

```
df['Credit_History'].value_counts()
```

```
1.0    279
0.0     59
Name: Credit_History, dtype: int64
```

yes (1.0) is dominating

```
df['Credit_History'].fillna(1.0,inplace=True)
```

once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
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
```

Finally all missing values are clear

Then go to the next phase of normalization

how to treat for extreme values in distribution of LoanAmount and ApplicantIncome

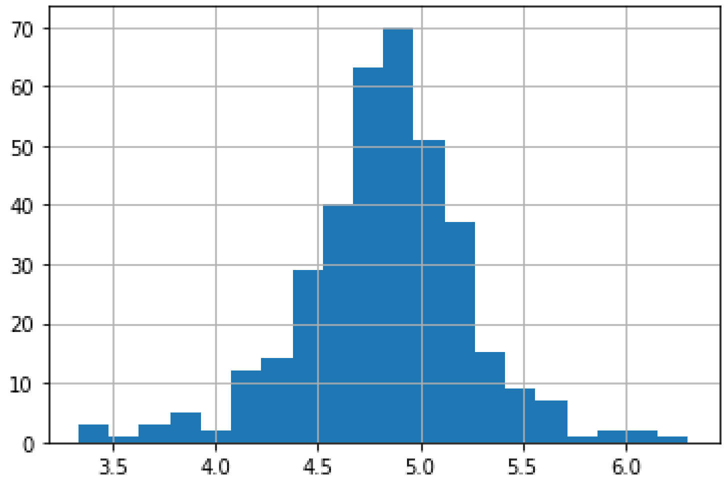
```
df['LoanAmount'].hist(bins=10)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e4436c50>
```

creating LoanAmount_log column to treate outliers and extreme values

```
df['LoanAmount_log'] = np.log(df['LoanAmount'])
df['LoanAmount_log'].hist(bins=20)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44e42c71d0>
```



The normalized data set with artificial field LoanAmount_log

```
df
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	C
0	LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	360.0	
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	360.0	
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	360.0	
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	360.0	
4	LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	360.0	
...	...	...	...	...	...	...	...	...	...	...	
362	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	1777	113.0	360.0	
363	LP002975	Male	Yes	0	Graduate	No	4158	709	115.0	360.0	
364	LP002980	Male	No	0	Graduate	No	3250	1993	126.0	360.0	

so far we have data munged an untreated data set from repository.But We have some treated data set with relevant key column which indicates the result of the model.

Loading already treated one such loan approval dataset from repository to predict the loan approval with Loan_status field

```
import pandas as pd
url = "https://raw.githubusercontent.com/callxpert/datasets/master/Loan-applicant-details.csv"
names = ['Loan_ID','Gender','Married','Dependents','Education','Self_Employed','ApplicantIncome','CoapplicantIncome'
df = pd.read_csv(url, names=names)
print(df)
```

```
      Loan_ID  Gender Married  ... Credit_History Property_Area Loan_Status
0    LP001003    Male     Yes  ...              1         Rural           N
1    LP001005    Male     Yes  ...              1         Urban           Y
2    LP001006    Male     Yes  ...              1         Urban           Y
3    LP001008    Male      No  ...              1         Urban           Y
4    LP001011    Male     Yes  ...              1         Urban           Y
..        ...     ...     ...  ...            ...           ...         ...
475  LP002978  Female      No  ...              1         Rural           Y
476  LP002979    Male     Yes  ...              1         Rural           Y
477  LP002983    Male     Yes  ...              1         Urban           Y
478  LP002984    Male     Yes  ...              1         Urban           Y
479  LP002990  Female      No  ...              0     Semiurban           N

[480 rows x 13 columns]
```

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
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
Loan_Status          0
dtype: int64
```

Lets take a peek at the data

```
print(df.head(20))
```

```
     Loan_ID  Gender Married  ... Credit_History Property_Area Loan_Status
0   LP001003    Male     Yes  ...              1         Rural           N
1   LP001005    Male     Yes  ...              1         Urban           Y
2   LP001006    Male     Yes  ...              1         Urban           Y
3   LP001008    Male      No  ...              1         Urban           Y
4   LP001011    Male     Yes  ...              1         Urban           Y
5   LP001013    Male     Yes  ...              1         Urban           Y
6   LP001014    Male     Yes  ...              0     Semiurban           N
7   LP001018    Male     Yes  ...              1         Urban           Y
8   LP001020    Male     Yes  ...              1     Semiurban           N
9   LP001024    Male     Yes  ...              1         Urban           Y
10  LP001028    Male     Yes  ...              1         Urban           Y
11  LP001029    Male      No  ...              1         Rural           N
12  LP001030    Male     Yes  ...              1         Urban           Y
13  LP001032    Male      No  ...              1         Urban           Y
14  LP001036  Female      No  ...              0         Urban           N
15  LP001038    Male     Yes  ...              1         Rural           N
16  LP001043    Male     Yes  ...              0         Urban           N
17  LP001046    Male     Yes  ...              1         Urban           Y
18  LP001047    Male     Yes  ...              0     Semiurban           N
19  LP001066    Male     Yes  ...              1     Semiurban           Y
```

Lets load the required libraries for our analysis

```
#Load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.model_selection import train_test_split
```

Steps involved in this machine learning project

Following are the steps involved in creating a well-defined ML project**

Understand and define the problem ,Analyse and prepare the data ,Apply the algorithms ,Reduce the errors ,Predict the result

```
from sklearn.preprocessing import LabelEncoder
var_mod = ['Gender','Married','Dependents','Education','Self_Employed','Property_Area','Loan_Status']
le = LabelEncoder()
for i in var_mod:
    df[i] = le.fit_transform(df[i])
```

sklearn requires all inputs to be numeric, we should convert all our categorical variables into numeric by encoding the categories. This can be done using the above code:

Splitting the Data set: As we have seen already, In Machine learning we have two kinds of datasets

Training dataset - used to train our model

Testing dataset - used to test if our model is making accurate predictions

Our dataset has 480 records. We are going to use 80% of it for training the model and 20% of the records to evaluate our model. copy paste the below commands to prepare our data sets

```
array = df.values
X = array[:,6:11]
Y = array[:,12]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_state=7)
df.columns
```

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

Evaluating the model and training the Model with 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount','Loan_Amount_Term', 'Credit_History'-ML model 1

Logistic Regression : Logistic Regression is a classification algorithm. It is used to predict a binary outcome (1 / 0, Yes / No, True / False) given a set of independent variables. To represent binary / categorical outcome, we use dummy variables

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7708333333333334
```

Decision tree : Decision tree is a type of supervised learning algorithm (having a pre-defined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.6354166666666666
```

Random forest : Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes

(classification) or mean prediction (regression) of the individual trees

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.75
```

Evaluating the model and training the Model with 'Married', 'Dependents', 'Education','Self_Employed', 'ApplicantIncome'-ML model 2

```
array = df.values
X = array[:,2:6]
Y = array[:,12]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_state=7)
df.columns
```

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

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.6354166666666666
```

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
print(accuracy_score(y_test, predictions))
```

```
0.6145833333333334
```

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.625
```

```
array = df.values
X = array[:,5:12]
Y = array[:,12]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_state=7)
df.columns
```

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

Evaluating the model and training the Model with 'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount','Loan_Amount_Term', 'Credit_History', 'Property_Area'-ML model 3

```
array = df.values
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```

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

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7708333333333334
```

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.65625
```

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.75
```