#### Importing the Requires Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
```

### **Uploading and Reading the Train\_Data**

```
In [2]: dt = pd.read_csv("train.csv")
         dt.head()
                                      Dependents Education Self_Employed ApplicantIncome Coapplicant
Out[2]:
             Loan_ID Gender Married
         0 LP001002
                        Male
                                                    Graduate
                                                                                      5849
                                  No
                                                                       No
         1 LP001003
                                                                                      4583
                        Male
                                  Yes
                                                    Graduate
                                                                       No
         2 LP001005
                        Male
                                                0
                                                    Graduate
                                                                       Yes
                                                                                      3000
                                  Yes
                                                        Not
         3 LP001006
                        Male
                                  Yes
                                                                       No
                                                                                      2583
                                                    Graduate
         4 LP001008
                                                   Graduate
                                                                                      6000
                        Male
                                  No
                                                                       No
         #checking the shape of the dataset
In [3]:
         dt.shape
         (614, 13)
Out[3]:
In [4]:
         #summary statistics of the dataset
         dt.describe()
```

ut[4]:		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
	50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
	75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
	max	81000.000000	41667.000000	700.000000	480.00000	1.000000
n [5]:	dt.des	cribe()				
ut[5]:		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
	50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
	<b>75%</b> 5795.000000 <b>max</b> 81000.000000		2297.250000	168.000000	360.00000	1.000000
			41667.000000	700.000000	480.00000	1.000000
n [6]:	<pre>#checking the missing dt.isnull().sum()</pre>		the values			
ut[6]:	Applica Coappla LoanAm Loan_Am Credit	d ents ion mployed antIncome icantIncome ount mount_Term _History ty_Area	0 13 3 15 0 32 0 0 0 22 14 50 0			

# Droping the column with missing data for numerical and categorical variable

dtype: int64

```
In [7]: # fill the missing values for numerical terms
        dt['LoanAmount'] = dt['LoanAmount'].fillna(dt['LoanAmount'].mean())
        dt['Loan_Amount_Term'] = dt['Loan_Amount_Term'].fillna(dt['Loan_Amount_Term'].mean())
        dt['Credit_History'] = dt['Credit_History'].fillna(dt['Credit_History'].mean())
        dt['CoapplicantIncome'] = dt['CoapplicantIncome'].fillna(dt['CoapplicantIncome'].mean(
In [8]:
        # fill the missing values for categorical terms
        dt['Gender'] = dt["Gender"].fillna(dt['Gender'].mode()[0])
        dt['Married'] = dt["Married"].fillna(dt['Married'].mode()[0])
        dt['Dependents'] = dt["Dependents"].fillna(dt['Dependents'].mode()[0])
        dt['Self Employed'] = dt["Self Employed"].fillna(dt['Self Employed'].mode()[0])
In [9]:
        #checking the missing values
        dt.isnull().sum()
        Loan ID
Out[9]:
        Gender
                              0
        Married
                              0
        Dependents
                              0
        Education
        Self Employed
                             0
        ApplicantIncome
                             0
        CoapplicantIncome
        LoanAmount
        Loan Amount Term
        Credit_History
                             0
        Property_Area
                             0
        Loan Status
                             0
        dtype: int64
```

### Visualization of the categorical attributes columns

```
In [10]: # categorical attributes visualization
sns.countplot(dt['Gender'])

Out[10]: 

AxesSubplot:xlabel='Gender', ylabel='count'>

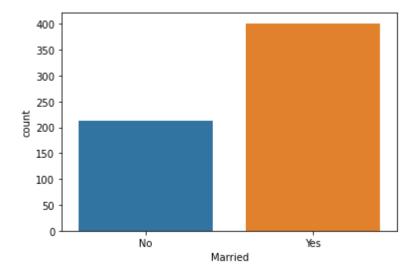
500
400
400
100
Male Female
Gender
```

#visualization for the married column on categorical attributes

sns.countplot(dt['Married'])

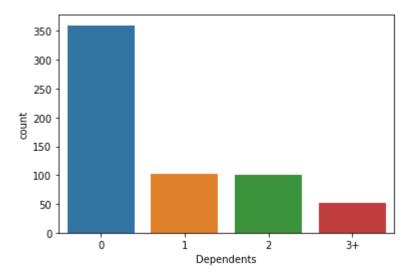
In [11]:

Out[11]: <AxesSubplot:xlabel='Married', ylabel='count'>



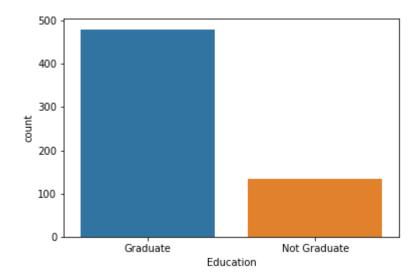
```
In [12]: #visualization for the Dependent column
sns.countplot(dt['Dependents'])
```

Out[12]: <AxesSubplot:xlabel='Dependents', ylabel='count'>



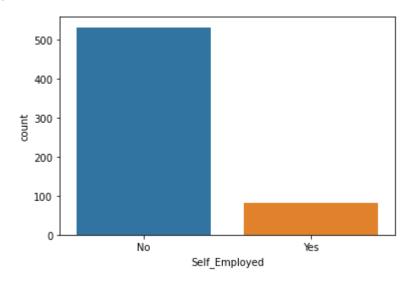
```
In [13]: #visualization for the Education column
sns.countplot(dt['Education'])
```

Out[13]: <AxesSubplot:xlabel='Education', ylabel='count'>



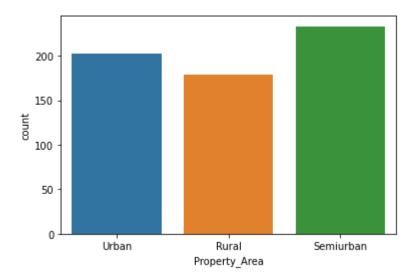
In [14]: #visualization for the Self\_Employed column
sns.countplot(dt['Self\_Employed'])

Out[14]: <AxesSubplot:xlabel='Self\_Employed', ylabel='count'>



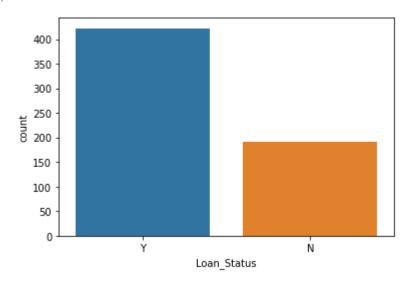
```
In [15]: #visualization for the Property_Area column
sns.countplot(dt['Property_Area'])
```

Out[15]: <AxesSubplot:xlabel='Property\_Area', ylabel='count'>



In [16]: #visualization for the Loan\_Status column
sns.countplot(dt['Loan\_Status'])

Out[16]: <AxesSubplot:xlabel='Loan\_Status', ylabel='count'>



In [17]: #checking the some head of he data
dt.head()

Out[17]:		Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplicant
	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	

```
In [18]: #dropping the columns
    cols = ['CoapplicantIncome', 'Loan_Amount_Term', 'Loan_ID', 'CoapplicantIncome']
    dt = dt.drop(columns=cols, axis=1)
```

In [19]:	dt.head()										
Out[19]:	Gender	Married	Dependents	Education	n Self	_Employe	ed App	licantInc	ome L	oanAmount	Credit_H
	<b>0</b> Male	No	(	Graduate	е	١	No		849	146.412162	
	1 Male	Yes	1	Graduate	e	١	Мо	2	1583	128.000000	
	2 Male	Yes	C	Graduate	Э	Υ	es	3	3000	66.000000	
	3 Male	Yes	C	No Graduate		N	Ю	ã	2583	120.000000	
	4 Male	No	(	Graduate	е	١	No.	6	5000	141.000000	
4											•
In [20]:	<pre>#applying the labelencoder from sklearn.preprocessing import LabelEncoder cols = ['Gender', "Married", "Education", 'Self_Employed', "Property_Area", "Loan_Status",' le = LabelEncoder() for col in cols:     dt[col] = le.fit_transform(dt[col])</pre>										
In [21]:	<pre>#correlation of the data corr = dt.corr() plt.figure(figsize=(15,10)) sns.heatmap(corr, annot = True, cmap="BuPu")</pre>										
Out[21]:	<axessubp< th=""><th>lot:&gt;</th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th></axessubp<>	lot:>									
	Gender -	1	0.36 0.17	0.045	-0.00052	0.059	0.11	0.013	-0.026	0.018	-1.0
	Married -	0.36	1 0.33	0.012	0.0045	0.052	0.15	0.0059	0.0043	0.091	- 0.8
	Dependents -	0.17	0.33	0.056	0.057	0.12	0.16	-0.037	-0.00024	0.01	
	Education -	0.045	0.012 0.056	1	-0.01	-0.14	-0.17	-0.078	-0.065	-0.086	- 0.6
	Self_Employed -	-0.00052	0.0045 0.057	-0.01	1	0.13	0.12	-0.0023	-0.031	-0.0037	
	ApplicantIncome -	0.059	0.052 0.12	-0.14	0.13	1	0.57	-0.014	-0.0095	-0.0047	- 0.4
	LoanAmount -	0.11	0.15 0.16	-0.17	0.12	0.57	1	-0.0077	-0.045	-0.036	- 0.2
	Credit_History -	0.013	0.0059 -0.037	-0.078	-0.0023	-0.014	-0.0077	1	-0.0019	0.54	
	Property_Area -	-0.026	0.0043 -0.0002	4 -0.065	-0.031	-0.0095	-0.045	-0.0019	1	0.032	- 0.0
	Loan_Status -	0.018	0.091 0.01	-0.086	-0.0037	-0.0047	-0.036	0.54	0.032	1	
		Gender -	Married -	Education -	Self_Employed -	ApplicantIncome –	LoanAmount -	Gredit_History -	Property_Area -	Loan_Status -	

```
In [22]: #dropping the loan_status columns for looking the target columns
           X = dt.drop(columns=['Loan_Status'], axis=1)
          y = dt['Loan_Status']
In [23]: X
Out[23]:
                Gender Married
                                 Dependents Education Self_Employed ApplicantIncome
                                                                                         LoanAmount Credit
             0
                     1
                              0
                                           0
                                                      0
                                                                     0
                                                                                   5849
                                                                                           146.412162
             1
                                                      0
                                                                     0
                                                                                   4583
                                                                                           128.000000
                                           0
                                                      0
             2
                     1
                              1
                                                                     1
                                                                                   3000
                                                                                            66.000000
             3
                                           0
                                                                     0
                                                                                   2583
                                                                                           120.000000
                                                      1
                     1
                              0
                                           0
                                                      0
                                                                     0
             4
                                                                                   6000
                                                                                           141.000000
           609
                     0
                              0
                                           0
                                                      0
                                                                     0
                                                                                   2900
                                                                                            71.000000
                                                                                   4106
           610
                                           3
                                                      0
                                                                     0
                                                                                            40.000000
           611
                     1
                              1
                                           1
                                                      0
                                                                     0
                                                                                   8072
                                                                                           253.000000
           612
                                           2
                                                      0
                                                                     0
                                                                                   7583
                                                                                           187.000000
                                           0
           613
                     0
                              0
                                                      0
                                                                     1
                                                                                   4583
                                                                                           133.000000
          614 rows × 9 columns
```

```
In [24]:
                 1
Out[24]:
                 0
          2
                 1
          3
                 1
          4
                 1
          609
                 1
          610
                 1
          611
                 1
                 1
          612
          613
          Name: Loan_Status, Length: 614, dtype: int32
```

## Splitting the dataset in to the training set and test set

```
In [25]: #splitting the dataset in to 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=0.2, random_state=0)
In [26]: #applying the logistic regression algorithm
    from sklearn.linear_model import LogisticRegression
    model = LogisticRegression()
```

```
model.fit(x_train, y_train)
In [27]:
         LogisticRegression()
Out[27]:
In [28]:
         #printing the model accuracy
         print("Accuracy is", model.score(x_test, y_test)*100)
         Accuracy is 84.5528455284553
         Model prediction
         #predicting the test set results
In [29]:
         y_pred = model.predict(x_test)
         #importing confusion_matrix
In [30]:
         from sklearn.metrics import confusion_matrix
         cm = confusion_matrix(y_test, y_pred)
         array([[16, 17],
Out[30]:
                [ 2, 88]], dtype=int64)
         import seaborn as sns
In [31]:
         sns.heatmap(cm, annot=True)
         <AxesSubplot:>
Out[31]:
                                                      - 80
                     16
                                       17
                                                      - 60
                                                      - 30
                                                      - 20
                                                      - 10
                                        1
         #importing and applying the classification_report
In [32]:
         from sklearn.metrics import classification_report
         # Predicting the values of test data
         #y_pred = classifier.predict(x_test)
         print('Classification report - \n', classification_report(y_test, y_pred))
```

```
precision recall f1-score
                                                      support
                    0
                           0.89
                                     0.48
                                               0.63
                                                          33
                    1
                           0.84
                                     0.98
                                               0.90
                                                          90
             accuracy
                                               0.85
                                                         123
                                     0.73
                                               0.77
                           0.86
                                                         123
            macro avg
                           0.85
                                     0.85
                                                         123
         weighted avg
                                              0.83
In [33]:
        #importing DecisionTreeClassifier
         from sklearn.tree import DecisionTreeClassifier
         DTModel = DecisionTreeClassifier()
         DTModel.fit(x_train, y_train)
         print("Accuracy is", DTModel.score(x_test, y_test)*100)
         In [34]: #predicting the test set results
         y_predDT = DTModel.predict(x_test)
In [35]: from sklearn.metrics import confusion_matrix
         cm = confusion matrix(y test, y predDT)
         array([[17, 16],
Out[35]:
                [25, 65]], dtype=int64)
In [36]: from sklearn.metrics import classification_report
         # Predicting the values of test data
         #y_pred = classifier.predict(x_test)
         print('Classification report - \n', classification_report(y_test, y_predDT))
         Classification report -
                       precision
                                    recall f1-score
                                                      support
                    0
                           0.40
                                     0.52
                                              0.45
                                                          33
                    1
                           0.80
                                     0.72
                                               0.76
                                                          90
                                               0.67
                                                         123
             accuracy
                                              0.61
            macro avg
                           0.60
                                     0.62
                                                         123
                           0.70
                                     0.67
                                               0.68
                                                         123
         weighted avg
         from sklearn.ensemble import RandomForestClassifier,ExtraTreesClassifier
In [37]:
         RFModel = RandomForestClassifier()
         RFModel.fit(x_train, y_train)
         print("Accuracy is", RFModel.score(x_test, y_test)*100)
         Accuracy is 78.04878048780488
In [38]:
         #predicting the test set results
         y predRF = RFModel.predict(x test)
         from sklearn.metrics import confusion matrix
In [39]:
         cm = confusion_matrix(y_test, y_predRF)
         \mathsf{cm}
```

Classification report -

```
Out[39]: array([[14, 19],
                [ 8, 82]], dtype=int64)
In [40]: from sklearn.metrics import classification_report
         # Predicting the values of test data
         #y_pred = classifier.predict(x_test)
         print('Classification report - \n', classification_report(y_test, y_predRF))
         Classification report -
                        precision
                                     recall f1-score
                                                        support
                                      0.42
                    0
                            0.64
                                                0.51
                                                            33
                                      0.91
                                                0.86
                                                            90
                    1
                            0.81
                                                0.78
                                                           123
             accuracy
                            0.72
                                      0.67
                                                0.68
                                                           123
            macro avg
                                      0.78
         weighted avg
                            0.76
                                                0.76
                                                           123
```

#### Importing the test dataset

```
In [41]: #Importing the test dataset
    dt1 = pd.read_csv("test.csv")
    dt1
```

Out[41]:		Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplica
	0	LP001015	Male	Yes	0	Graduate	No	5720	
	1	LP001022	Male	Yes	1	Graduate	No	3076	
	2	LP001031	Male	Yes	2	Graduate	No	5000	
	3	LP001035	Male	Yes	2	Graduate	No	2340	
	4	LP001051	Male	No	0	Not Graduate	No	3276	
	•••		•••	•••					
	362	LP002971	Male	Yes	3+	Not Graduate	Yes	4009	
	363	LP002975	Male	Yes	0	Graduate	No	4158	
	364	LP002980	Male	No	0	Graduate	No	3250	
	365	LP002986	Male	Yes	0	Graduate	No	5000	
	366	LP002989	Male	No	0	Graduate	Yes	9200	

367 rows × 12 columns

```
In [42]: # fill the missing values for numerical terms
    dt1['LoanAmount'] = dt1['LoanAmount'].fillna(dt1['LoanAmount'].mean())
    dt1['Loan_Amount_Term'] = dt1['Loan_Amount_Term'].fillna(dt1['Loan_Amount_Term'].mean())
    dt1['Credit_History'] = dt1['Credit_History'].fillna(dt1['Credit_History'].mean())
    dt1['CoapplicantIncome'] = dt1['CoapplicantIncome'].fillna(dt1['CoapplicantIncome'].mean())
```

```
In [43]:
        # fill the missing values for categorical terms
         dt1['Gender'] = dt1["Gender"].fillna(dt1['Gender'].mode()[0])
         dt1['Married'] = dt1["Married"].fillna(dt1['Married'].mode()[0])
         dt1['Dependents'] = dt1["Dependents"].fillna(dt1['Dependents'].mode()[0])
         dt1['Self Employed'] = dt1["Self Employed"].fillna(dt1['Self Employed'].mode()[0])
In [44]: dt1.isnull().sum()
        Loan ID
                            0
Out[44]:
        Gender
                            0
        Married
                            0
        Dependents
                            0
        Education
                            0
        Self Employed
                            0
        ApplicantIncome
                            0
        CoapplicantIncome
                            0
         LoanAmount
                            0
         Loan Amount Term
                            0
                            0
        Credit_History
        Property_Area
                            0
         dtype: int64
        cols = ['CoapplicantIncome', 'Loan_Amount_Term', 'Loan_ID', 'CoapplicantIncome']
In [45]:
         dt1 = dt1.drop(columns=cols, axis=1)
        from sklearn.preprocessing import LabelEncoder
In [46]:
         cols = ['Gender', "Married", "Education", 'Self_Employed', "Property_Area", "Dependents"]
         le = LabelEncoder()
         for col in cols:
            dt1[col] = le.fit_transform(dt1[col])
In [47]: new_pred=model.predict(dt1)
In [48]: new_pred
        Out[48]:
               1, 1, 1, 0, 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, 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, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0,
               1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 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, 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, 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, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
               1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)
        prediction=pd.DataFrame(new pred, columns=['Predictions']).to csv("predictionLoad.csv'
In [49]:
```

By comparison the LogisticRegression perform more than the 2 alrogrithm for this model.