

## ▼ Predicting loan eligibility

```
1 import numpy as np
2 import pandas as pd
3 import seaborn as sns
4 from sklearn.model_selection import train_test_split
5 from sklearn import svm
6 from sklearn.metrics import accuracy_score
```

## ▼ Data Processing

```
1 data = pd.read_csv('/content/loan_data.csv')
```

```
1 type(data)
```

```
pandas.core.frame.DataFrame
```

```
1 data.head(3)
2 # some datas are missing
```

	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

```
1 data.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

```

```

1 # number of datas missing in each column
2 # data.isnull(): it gives true and false in each data point in dataframe
3 data.isnull().sum()

```

```

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

```

```

1 # we can't replace missing values with mean or anyother statisticl thing(imputation) a
2 # so we are dropping them

```

```

1 data = data.dropna()
2 data.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
Loan_Status      0
dtype: int64

```

```

1 data.info()

```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 480 entries, 1 to 613
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   Loan_ID              480 non-null    object
 1   Gender               480 non-null    object
 2   Married              480 non-null    object
 3   Dependents           480 non-null    object
 4   Education             480 non-null    object

```

```

5   Self_Employed      480 non-null    object
6   ApplicantIncome    480 non-null    int64
7   CoapplicantIncome  480 non-null    float64
8   LoanAmount         480 non-null    float64
9   Loan_Amount_Term   480 non-null    float64
10  Credit_History     480 non-null    float64
11  Property_Area      480 non-null    object
12  Loan_Status        480 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 52.5+ KB

```

## ▼ Label encoding

(converting yes to 1 and no to 0)

```

1 data.replace({'Loan_Status':{'N':0, 'Y':1}}, inplace=True)
2 data['Loan_Status'].value_counts()

```

```

1    332
0    148
Name: Loan_Status, dtype: int64

```

```

1 data['Dependents'].value_counts()
2 # here the data contains 3+ as a value but it will be difficult for our model to inter
3 data.replace({'Dependents':{'3+' :4}}, inplace=True)
4 # data.replace(to_replace='3+', value='4')
5 data['Dependents'].value_counts()
6 # data['Property_Area'].value_counts()

```

```

0    274
2     85
1     80
4     41
Name: Dependents, dtype: int64

```

## Converting all categorical var to Numerical which are possible to convert

```

1 data.replace({'Married':{'No':0, 'Yes':1}, 'Self_Employed':{'No':0, 'Yes':1}, 'Gender':{'
2           'Property_Area':{'Rural':0, 'Semiurban':1, 'Urban':2}, 'Education':{'Gradu
3 data.head(8)

```

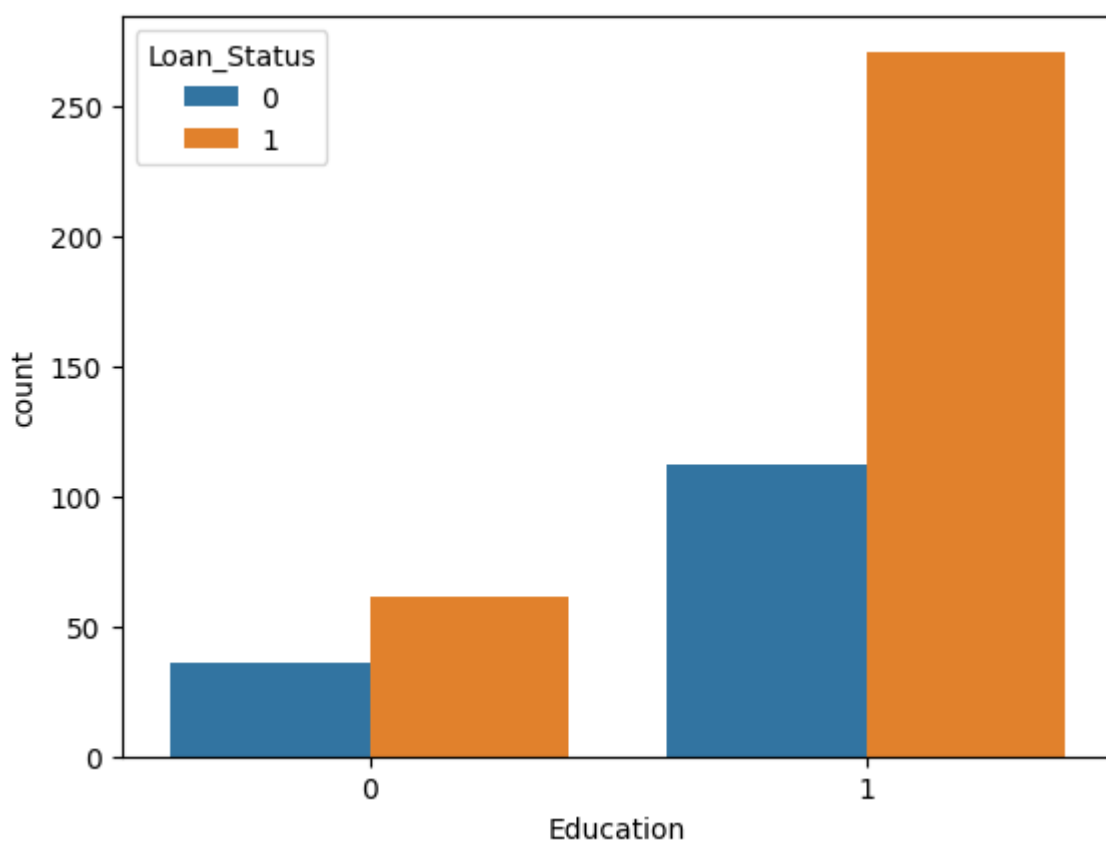
	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
1	LP001003	1	1	1	1	0	4583
2	LP001005	1	1	0	1	1	3000
3	LP001006	1	1	0	0	0	2583

## ▼ Data Visualisation

Double-click (or enter) to edit

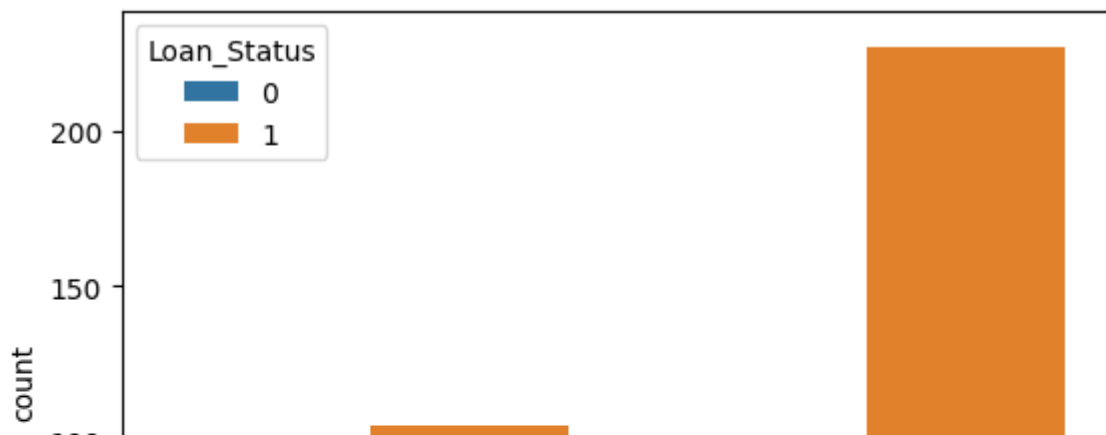
```
1 sns.countplot(x='Education', hue='Loan_Status', data=data)
```

<Axes: xlabel='Education', ylabel='count'>



```
1 sns.countplot(x='Married', hue='Loan_Status', data=data)
```

<Axes: xlabel='Married', ylabel='count'>



## Separating data and label and dropping unnecessary files

```
1 x = data.drop(columns=['Loan_ID', 'Loan_Status'], axis=1)
2 y = data['Loan_Status']
3 print(x.head(2))
4 print(y.head(2))
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	\
1	1	1	1	1	0	4583	
2	1	1	0	1	1	3000	

	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	\
1	1508.0	128.0	360.0	1.0	
2	0.0	66.0	360.0	1.0	

	Property_Area
1	0
2	2

1	0
2	1

Name: Loan\_Status, dtype: int64

## ▼ Splitting training and testing data

```
1 x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=
2 print(len(x_train))
3 print(len(x_test))
4 print(len(x_test)/(len(x_train) +len(x_test)))
```

384  
96  
0.2

## ▼ Training Model

(using svm)

```
1 classifier = svm.SVC(kernel='linear')
```

```
1 classifier.fit(x_train, y_train)
```

## ▼ Model Evaluation

```
1 # accuracy score on training data
2 x_train_prediction = classifier.predict(x_train)
3 training_data_accuracy = accuracy_score(x_train_prediction, y_train)
4 print('Accuracy score in training data is:', training_data_accuracy)
```

Accuracy score in training data is: 0.8046875

```
1 x_test_prediction = classifier.predict(x_test)
2 testing_data_accuracy = accuracy_score(x_test_prediction, y_test)
3 print('Accuracy score in testing data is:', testing_data_accuracy)
```

Accuracy score in testing data is: 0.8333333333333334