

Importing the Dependencies

```
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.metrics import accuracy_score
```

Data Collection and Processing

```
#loading the dataset to pandas Dataframe
loan_dataset = pd.read_csv('/content/train_u6lujuX_CVtuZ9i.csv')
```

```
type(loan_dataset)

pandas.core.frame.DataFrame
```

```
#printing the first 5 rows of the dataframe
loan_dataset.head()
```

1 to 5 of 5 entries Filter ?

x	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
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	

Show 25 per page
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```
# number of rows and columns
loan_dataset.shape
```

(614, 13)

```
#statistical measures
loan_dataset.describe()
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.000000	564.000000
mean	5403.459283	1621.245798	146.412162	342.000000	0.842182
std	6109.041673	2926.248369	85.587325	65.120411	0.364111
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.000000	360.000000	1.000000
50%	3812.500000	1188.500000	128.000000	360.000000	1.000000
75%	5795.000000	2297.250000	168.000000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

```
# number of missing values in each column
loan_dataset.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
```

```
# dropping the missing values
loan_dataset = loan_dataset.dropna()

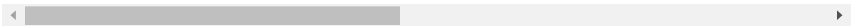
# number of missing values in each column
loan_dataset.isnull().sum()

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

#label encoding
loan_dataset.replace({"Loan_Status":{"N":0,'Y':1}},inplace=True)

#printing the first 5 rows of the dataframe
loan_dataset.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
1	LP001003	Male	Yes	1	Graduate	No	458
2	LP001005	Male	Yes	0	Graduate	Yes	300
3	LP001006	Male	Yes	0	Not Graduate	No	258
4	LP001008	Male	No	0	Graduate	No	600
5	LP001011	Male	Yes	2	Graduate	Yes	541



```
#Dependent column values
loan_dataset['Dependents'].value_counts()

0      274
2       85
1       80
3+       41
Name: Dependents, dtype: int64
```

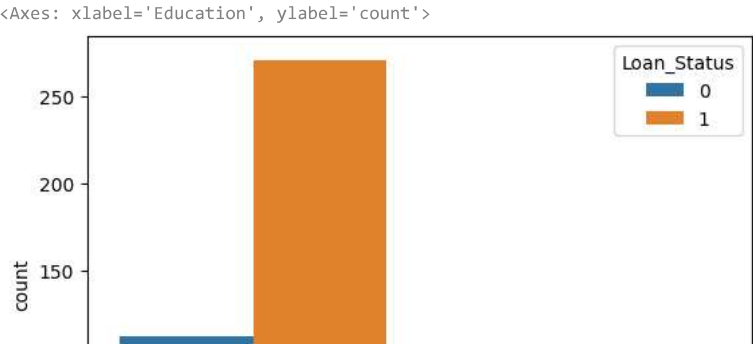
```
#replacing the value of 3+ to 4
loan_dataset = loan_dataset.replace(to_replace='3+', value=4)
```

```
#Dependent values
loan_dataset['Dependents'].value_counts()

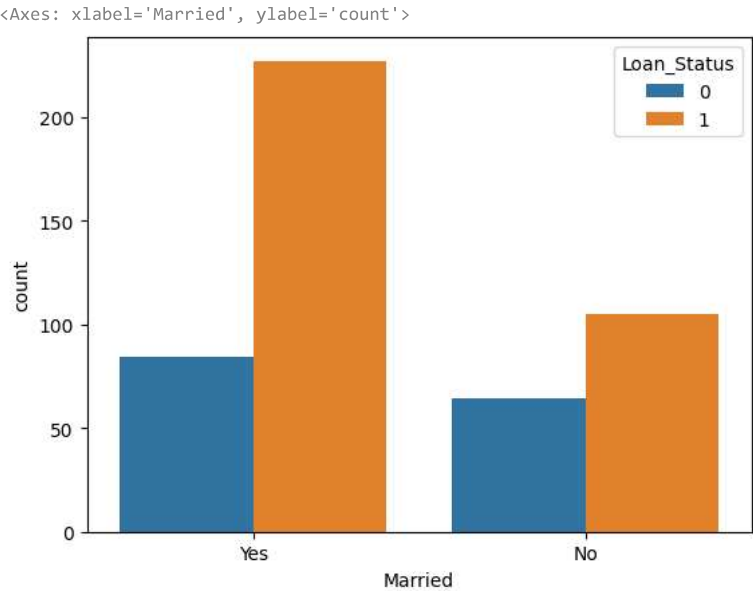
0      274
2       85
1       80
4       41
Name: Dependents, dtype: int64
```

Data Visualization

```
# education & loan status
sns.countplot(x='Education' ,hue='Loan_Status',data=loan_dataset)
```



```
# marital status & loan status
sns.countplot(x='Married', hue='Loan_Status', data=loan_dataset)
```



```
# converting categorical columns to numerical values
loan_dataset.replace({'Married':{'No':0,'Yes':1}, 'Gender':{'Male':1,'Female':0}, 'Self_Employed':{'No':0,'Yes':1},
                    'Property_Area':{'Rural':0,'Semiurban':1,'Urban':2}, 'Education':{'Graduate':1,'Not Graduate':0}}, inplace=True)
```

```
loan_dataset.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
1	LP001003	1	1	1	1	0	458
2	LP001005	1	1	0	1	1	300
3	LP001006	1	1	0	0	0	258
4	LP001008	1	0	0	1	0	600
5	LP001011	1	1	2	1	1	541



```
# separating the data and label
X = loan_dataset.drop(columns=['Loan_ID', 'Loan_Status'], axis=1)
Y = loan_dataset['Loan_Status']
```

```
print(X)
print(Y)
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	\
1	1	1	1	1	0	4583	
2	1	1	0	1	1	3000	
3	1	1	0	0	0	2583	
4	1	0	0	1	0	6000	
5	1	1	2	1	1	5417	
...	
609	0	0	0	1	0	2900	
610	1	1	4	1	0	4106	
611	1	1	1	1	0	8072	
612	1	1	2	1	0	7583	

```
613      0      0      0      1      1      4583

      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
3      2358.0      120.0      360.0      1.0
4      0.0      141.0      360.0      1.0
5      4196.0      267.0      360.0      1.0
..      ...      ...      ...      ...
609      0.0      71.0      360.0      1.0
610      0.0      40.0      180.0      1.0
611      240.0      253.0      360.0      1.0
612      0.0      187.0      360.0      1.0
613      0.0      133.0      360.0      0.0

      Property_Area
1      0
2      2
3      2
4      2
5      2
..      ...
609      0
610      0
611      2
612      2
613      1

[480 rows x 11 columns]
1      0
2      1
3      1
4      1
5      1
..
609      1
610      1
611      1
612      1
613      0
Name: Loan_Status, Length: 480, dtype: int64
```

Train Test Split

```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.1,stratify=Y,random_state=2)

print(X.shape,X_train.shape,X_test.shape)

(480, 11) (432, 11) (48, 11)
```

Training the model: Support Vector Machine

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

#training the support vector machine model
classifier.fit(X_train,Y_train)
```

▼

SVC

SVC(kernel='linear')

Model Evaluation

```
# accuracy score on training data
X_train_prediction = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction,Y_train)

print('Accuracy on training data : ',training_data_accuracy)

Accuracy on training data :  0.7986111111111112

# accuracy score on training data
X_test_prediction = classifier.predict(X_test)
training_data_accuracy = accuracy_score(X_test_prediction,Y_test)

print('Accuracy on training data : ',training_data_accuracy)

Accuracy on training data :  0.8333333333333334
```

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