

```
In [2]: import pandas as pd
import numpy as np
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

```
In [7]: loan_ds = pd.read_csv('/content/loan_prediction_ML.csv')
```

```
In [8]: type(loan_ds)
```

Out[8]: **pandas.core.frame.DataFrame**

def __init__(data=None, index: Axes | None=None, columns: Axes | None=None, dtype: Dtype | None=None, copy: bool | None=None) -> None

Two-dimensional, size-mutable, potentially heterogeneous tabular data.

Data structure also contains labeled axes (rows and columns).

Arithmetic operations align on both row and column labels. Can be thought of as a dict-like container for Series objects. The primary

```
In [33]: loan_ds.head(10)
```

Out[33]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
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
5	LP001011	Male	Yes	2	Graduate	Yes	5417
6	LP001013	Male	Yes	0	Not Graduate	No	2333
7	LP001014	Male	Yes	4	Graduate	No	3036
8	LP001018	Male	Yes	2	Graduate	No	4006
9	LP001020	Male	Yes	1	Graduate	No	12841
10	LP001024	Male	Yes	2	Graduate	No	3200

```
In [11]: loan_ds.shape
```

Out[11]: (614, 13)

```
In [16]: # Statistical Measures in the datasets
loan_ds.describe()
```

Out[16]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_Hist
count	614.000000	614.000000	592.000000	600.00000	564.0000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842
std	6109.041673	2926.248369	85.587325	65.12041	0.364
min	150.000000	0.000000	9.000000	12.00000	0.000
25%	2877.500000	0.000000	100.000000	360.00000	1.000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000
max	81000.000000	41667.000000	700.000000	480.00000	1.000

```
In [17]: # no of missig values in each columns
loan_ds.isnull().sum()
```

Out[17]:

	0
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

```
In [22]: # dropping all the missing values
loan_ds = loan_ds.dropna()
```

```
In [23]: loan_ds.isnull().sum()
```

```
Out[23]:
```

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

```
In [25]: # Label Encoding
loan_ds.replace({"Loan_Status": {'Y':1 , 'N':0}}, inplace = True)
```

/tmp/ipython-input-25-2394663655.py:2: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`

```
loan_ds.replace({"Loan_Status": {'Y':1 , 'N':0}}, inplace = True)
```

/tmp/ipython-input-25-2394663655.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead


See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
loan_ds.replace({"Loan_Status": {'Y':1 , 'N':0}}, inplace = True)
```

```
In [27]: loan_ds.head(2)
```

Out[27]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Credit_History
1	LP001003	Male	Yes	1	Graduate	No	4583	1
2	LP001005	Male	Yes	0	Graduate	Yes	3000	1



In [28]: *# Dependent column all values*
loan_ds['Dependents'].value_counts()

Out[28]:

	count
Dependents	
0	274
2	85
1	80
3+	41

dtype: int64

In [29]: *# Replacing the '3+' value to '4'*
loan_ds = loan_ds.replace(to_replace = '3+', value = 4)

In [30]: loan_ds['Dependents'].value_counts()

Out[30]:

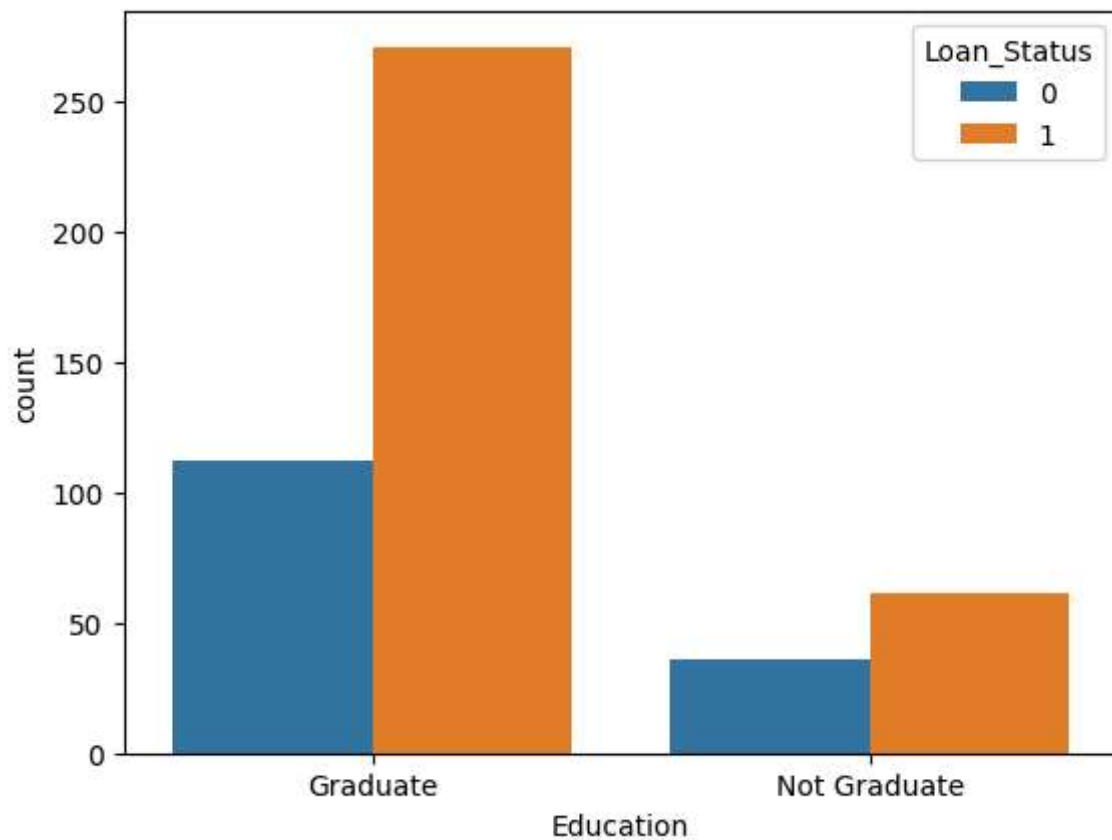
	count
Dependents	
0	274
2	85
1	80
4	41

dtype: int64

****Data Visualiztion ****

In [31]: *# Education & Loan_Status*
sns.countplot(x = 'Education', hue = 'Loan_Status', data = loan_ds)

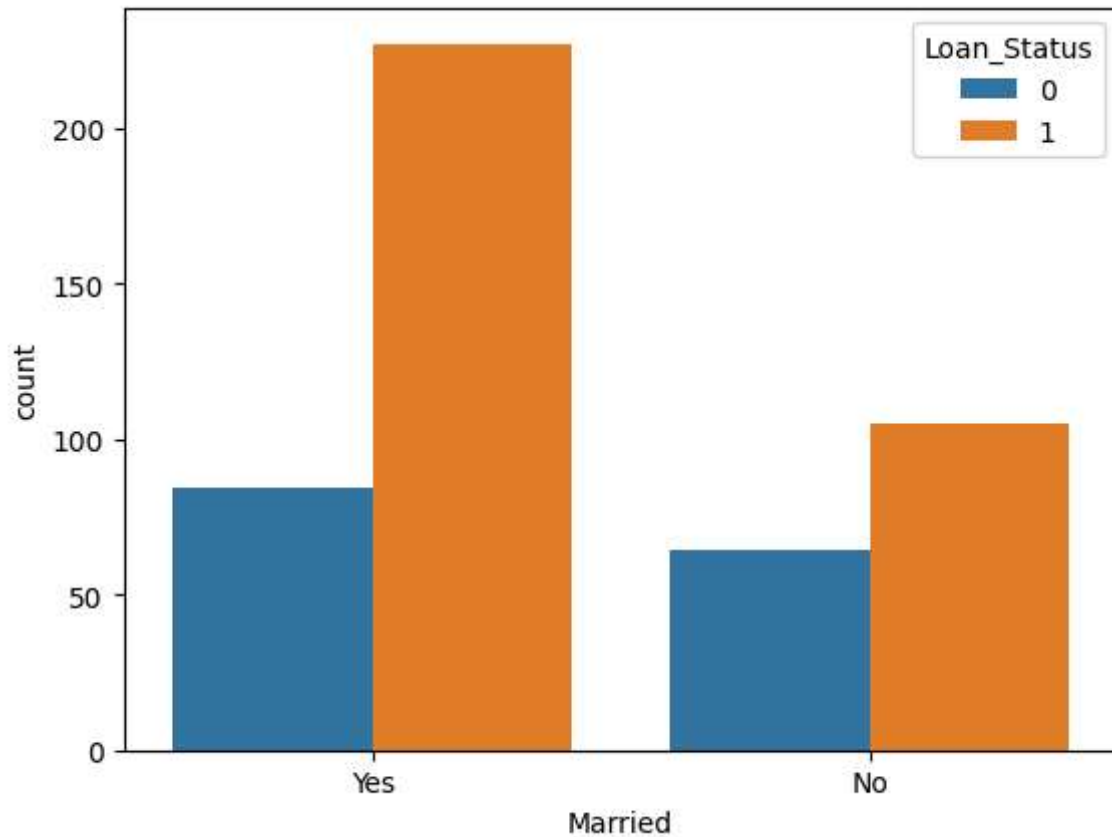
Out[31]: <Axes: xlabel='Education', ylabel='count'>



```
In [32]: # Marital status & Loan_Status
```

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

```
Out[32]: <Axes: xlabel='Married', ylabel='count'>
```



In [38]: *# Convert categorical(gendre, married etc...) columns to numerical values*

```
loan_ds.replace({"Married":{"Yes":1, 'No':0}, "Gender" :{'Male':1, 'Female':0}, "Self_employed":{"Self":1, 'NotSelf':0}, "Property_Area":{"Rural":0, 'Semiurban':1, 'Urban':2}, "Education":{"High":1, 'Low':0}})
```

In [39]: `loan_ds.head(7)`

Out[39]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Credit_History
1	LP001003	1	1	1	1	0	4583	1
2	LP001005	1	1	0	1	1	3000	1
3	LP001006	1	1	0	0	0	2583	1
4	LP001008	1	0	0	1	0	6000	1
5	LP001011	1	1	2	1	1	5417	1
6	LP001013	1	1	0	0	0	2333	1
7	LP001014	1	1	4	1	0	3036	1

In [40]: *# Separating the data and Label*

```
X = loan_ds.drop(columns = ['Loan_ID', 'Loan_Status'], axis = 1) # dataset without label
Y = loan_ds['Loan_Status']
```

```
In [41]: 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

```
In [42]: X_train , X_test , Y_train , Y_test = train_test_split(X,Y, test_size = 0.1, stratify
```

```
In [43]: print(X.shape, X_train.shape, X_test.shape)
```

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

Training the Model:

Support Vector Machine Model(SVM)

```
In [44]: classifier = svm.SVC(kernel = 'linear')
```

```
In [45]: # Training the SVM
```

```
classifier.fit(X_train, Y_train)
```

```
Out[45]: SVC
SVC(kernel='linear')
```

Model Evaluation

```
In [49]: # accuracy score on training data
```

```
X_train_prediction = classifier.predict(X_train)    # problems present in the textbo
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)
```

```
In [50]: print('Accuracy on the training data: ', training_data_accuracy)
```

```
Accuracy on the training data:  0.7986111111111112
```

```
In [52]: # accuracy score on training data (2)
```

```
X_test_prediction = classifier.predict(X_test)      # problems not present in bo
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

```
In [53]: print('Accuracy on the test data: ', test_data_accuracy)
```

```
Accuracy on the test data:  0.8333333333333334
```

```
In [ ]:
```