

```
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 = pd.read_csv('/content/train_u6lujuX_CVtuZ9i (1).csv')

data.head()
```

	lents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_A
	0	Graduate	No	5849	0.0	NaN	
	1	Graduate	No	4583	1508.0	128.0	
	0	Graduate	Yes	3000	0.0	66.0	
	0	Not Graduate	No	2583	2358.0	120.0	
	0	Graduate	No	6000	0.0	141.0	

Next steps:

Generate code with data

 View recommended plots

```
data.tail()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coa
	LP002978	Female	No	0	Graduate	No	2900	
	LP002979	Male	Yes	3+	Graduate	No	4106	
	LP002983	Male	Yes	1	Graduate	No	8072	
	LP002984	Male	Yes	2	Graduate	No	7583	
	LP002990	Female	No	0	Graduate	Yes	4583	

```
data.describe()
```

	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

```
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
```

```
data.shape
```

```
(614, 13)
```

```
#no.of missing values in each column
```

```
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
```

```
data = data.dropna()
```

```
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
```

```
#label_encoding
```

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

```
data.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0
5	LP001011	Male	Yes	2	Graduate	Yes	5417	4196.0	267.0	360.0

Next steps:

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[View recommended plots](#)

```
# dependent columns
```

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

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

```
data = data.replace(to_replace = '3+' , value=4)
```

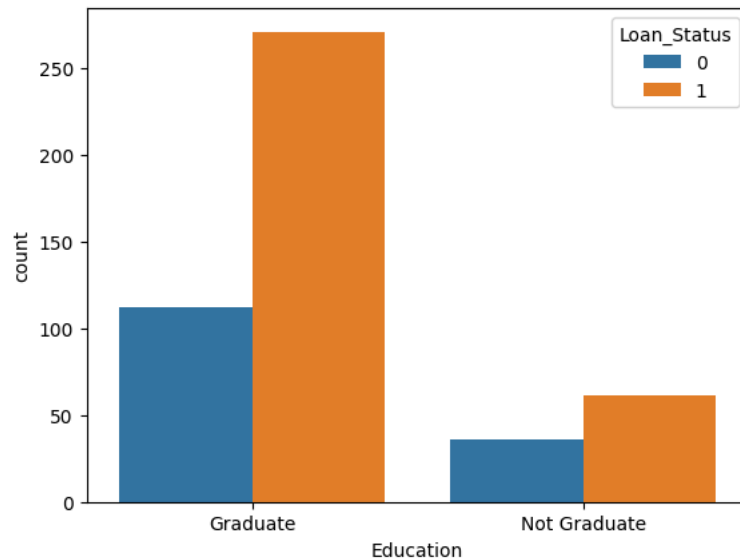
```
data['Dependents'].value_counts()
```

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

```
#DATA VISUALISATION
```

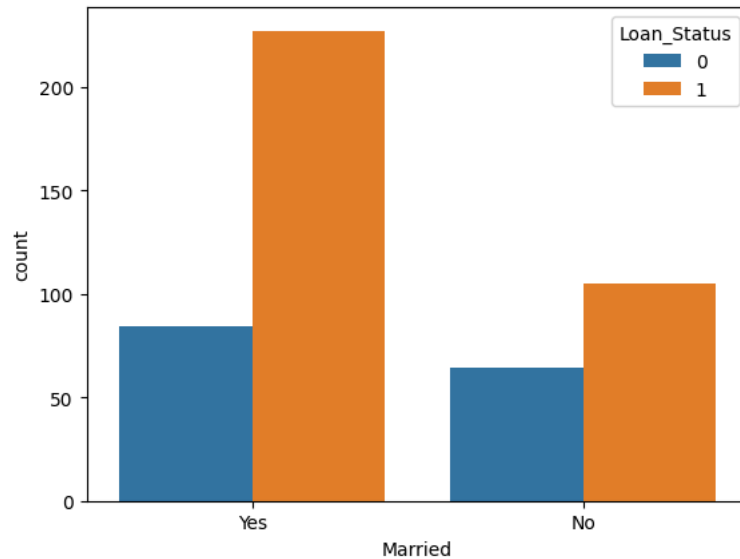
```
sns.countplot(x='Education', hue = 'Loan_Status', data = data)
```

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



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

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



```
#converting all categorical to numerical
```

```
data.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)
```

```
data.head()
```

l_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
003	1	1	1	1	0	4583	
005	1	1	0	1	1	3000	
006	1	1	0	0	0	2583	
008	1	0	0	1	0	6000	
l011	1	1	2	1	1	5417	

Next steps:

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#separating the data and label

```
X = data.drop(columns = ['Loan_ID', 'Loan_Status'], axis = 1)
Y = data['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

#Splitting into training and testing

```
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)

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

```
#training the model
```

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

```
▼ SVC  
SVC(kernel='linear')
```

```
#model_evaluation
```

```
X_train_prediction = classifier.predict(X_train)
```

```
training_accuracy = accuracy_score(X_train_prediction, Y_train)
```

Start coding or [generate](#) with AI.

```
print("Accuracy on Training :", training_accuracy)
```

```
Accuracy on Training : 0.7986111111111112
```

```
X_test_prediction = classifier.predict(X_test)
```

```
test_accuracy = accuracy_score(X_test_prediction, Y_test)
```

```
print("Accuracy on Testing :", test_accuracy)
```

```
Accuracy on Testing : 0.8333333333333334
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
rf_clf = RandomForestClassifier()
```

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

```
▼ RandomForestClassifier  
RandomForestClassifier()
```

```
X_test_prediction_2 = rf_clf.predict(X_test)
```

```
Accuracy_RF = accuracy_score(X_test_prediction_2, Y_test)
```

```
print("Accuracy: ", Accuracy_RF)
```

```
Accuracy: 0.8125
```

```
from sklearn.naive_bayes import GaussianNB
```

```
nb_clf = GaussianNB()
```

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

```
▼ GaussianNB  
GaussianNB()
```

```
X_test_prediction_3 = nb_clf.predict(X_test)
```

```
Accuracy_NB = accuracy_score(X_test_prediction_3, Y_test)
```

```
print("Accuracy for GuassianNB: ", Accuracy_NB)
```

```
Accuracy for GuassianNB: 0.8333333333333334
```

```
from sklearn.tree import DecisionTreeClassifier
```

```
dt_clf = DecisionTreeClassifier()
```

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

```
▼ DecisionTreeClassifier  
DecisionTreeClassifier()
```

```
X_test_prediction_4 = dt_clf.predict(X_test)
Accuracy_DT = accuracy_score(X_test_prediction_4, Y_test)
```

```
print("Accuracy for DT: ", Accuracy_DT)
```

```
Accuracy for DT: 0.75
```

```
from sklearn.neighbors import KNeighborsClassifier
```

```
kn_clf = KNeighborsClassifier()
kn_clf.fit(X_train, Y_train)
```

```
▼ KNeighborsClassifier
KNeighborsClassifier()
```

```
X_test_prediction_5 = kn_clf.predict(X_test)
Accuracy_KN = accuracy_score(X_test_prediction_5, Y_test)
```

```
print("Accuracy for KN: ", Accuracy_KN)
```

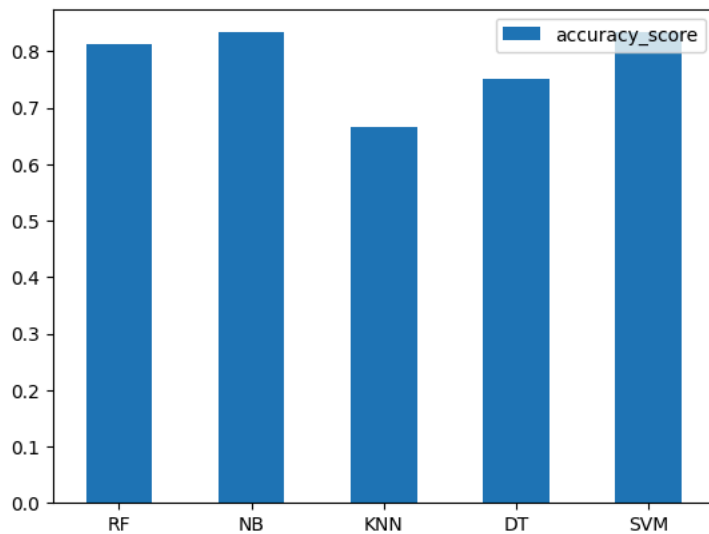
```
Accuracy for KN: 0.6666666666666666
```

```
import matplotlib.pyplot as plt
```

```
Y_set = [Accuracy_RF, Accuracy_NB, Accuracy_KN, Accuracy_DT, test_accuracy]
X_set = ['RF', 'NB', 'KNN', 'DT', 'SVM']
```

```
index = ['RF', 'NB', 'KNN', 'DT', 'SVM']
```

```
df = pd.DataFrame({'accuracy_score': Y_set, 'Models': X_set}, index = index)
ax = df.plot.bar(rot=0)
```



```
#INFERENCE
```

```
#puttin input data any values for prediction based on information given
```

```
#we can see from graph gaussianNB and SVM both have equal accuracy ( we can chose any 1 but since SVM takes bit time to train its recomm
input_data = (1,1,2,1,1,5417,4196,267,360,1,2)
```

```
input_data_as_array = np.asarray(input_data)
```

```
input_data_resaped = input_data_as_array.reshape(1,-1)
```

```
prediction = nb_clf.predict(input_data_resaped)
#print(prediction)
```

```
if(prediction[0]==1):
    print("Yes")
else:
    print("No")
```

```
Yes
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but GaussianNB was f
warnings.warn(
```

