

In [1]: `#SWETHA JENIFER_S_15-02-23`

STEP 1:

In [2]: `import pandas as pd`

In [3]: `df=pd.read_csv("train_loan.csv")`
df

					Graduate		
7	LP001014	Male	Yes	3+	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
11	LP001027	Male	Yes	2	Graduate	NaN	2500
12	LP001028	Male	Yes	2	Graduate	No	3073
13	LP001029	Male	No	0	Graduate	No	1853
14	LP001030	Male	Yes	2	Graduate	No	1299
15	LP001032	Male	No	0	Graduate	No	4950
16	LP001034	Male	No	1	Not Graduate	No	3596
17	LP001036	Female	No	0	Graduate	No	3510

In [4]: `df.head()`

Out[4]:

	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 [5]: `df.shape`

Out[5]: (614, 13)

In [26]: df.columns

Out[26]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education', 'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'Credit_History', 'Property_Area'], dtype='object')

In [27]: df.dtypes

Out[27]: Loan_ID object
Gender object
Married object
Dependents int64
Education object
Self_Employed object
ApplicantIncome int64
CoapplicantIncome float64
LoanAmount float64
Loan_Amount_Term float64
Credit_History float64
Property_Area object
dtype: object

In [28]: df.info

Out[28]: <bound method DataFrame.info of
Education Self_Employed \

	Loan_ID	Gender	Married	Dependents
0	LP001002	Male	No	No
1	LP001003	Male	Yes	No
2	LP001005	Male	Yes	Yes
3	LP001006	Male	Yes	No
4	LP001008	Male	No	No
5	LP001011	Male	Yes	Yes
6	LP001013	Male	Yes	No
7	LP001014	Male	Yes	No
8	LP001018	Male	Yes	No
9	LP001020	Male	Yes	No
10	LP001024	Male	Yes	No
11	LP001027	Male	Yes	No
12	LP001028	Male	Yes	No
13	LP001029	Male	No	No
14	LP001030	Male	Yes	No
15	LP001032	Male	No	No
16	LP001034	Male	No	No
17	LP001036	Male	No	No

In [29]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
Loan_ID          614 non-null object
Gender           614 non-null object
Married          614 non-null object
Dependents       614 non-null int64
Education        614 non-null object
Self_Employed    614 non-null object
ApplicantIncome  614 non-null int64
CoapplicantIncome 614 non-null float64
LoanAmount       614 non-null float64
Loan_Amount_Term 614 non-null float64
Credit_History   614 non-null float64
Property_Area    614 non-null object
dtypes: float64(4), int64(2), object(6)
memory usage: 57.6+ KB
```

```
In [30]: df.Gender.value_counts
```

```
Out[30]: <bound method IndexOpsMixin.value_counts of 0      Male
1      Male
2      Male
3      Male
4      Male
5      Male
6      Male
7      Male
8      Male
9      Male
10     Male
11     Male
12     Male
13     Male
14     Male
15     Male
16     Male
17     Female
18     Male
19     Male
20     Male
21     Male
22     Male
23     Male
24     Male
25     Male
26     Male
27     Male
28     Male
29     Female
...
584    Male
585    Male
586    Male
587    Female
588    Male
589    Male
590    Male
591    Male
592    Male
593    Male
594    Male
595    Male
596    Male
597    Male
598    Male
599    Male
600    Female
601    Male
602    Male
603    Male
604    Female
605    Male
606    Male
607    Male
```

```
608      Male
609    Female
610      Male
611      Male
612      Male
613    Female
Name: Gender, Length: 614, dtype: object>
```

STEP 2:

```
In [6]: df["Dependents"].fillna("NO_dep",inplace=True)
```

```
In [7]: df["Dependents"]
```

```
Out[7]: 0          0
1          1
2          0
3          0
4          0
5          2
6          0
7          3+
8          2
9          1
10         2
11         2
12         2
13         0
14         2
15         0
16         1
17         0
18         0
19         0
20         0
21         1
22         0
23         2
24         1
25         0
26         0
27         2
28         0
29         2

...
584        1
585        1
586        0
587        0
588        0
589        2
590        0
591        2
592        3+
593        0
594        0
595        0
596        2
597    NO_dep
598        0
599        2
600        3+
601        0
602        3+
603        0
604        1
605        0
606        1
607        2
```

```
608      0
609      0
610     3+
611      1
612      2
613      0
```

Name: Dependents, Length: 614, dtype: object

```
In [24]: dept={"0":0,"1":1,"2":2,"3+":3,"NO_dep":0}
df.Dependents=[dept[item]for item in df.Dependents]
```

```
In [25]: df['Dependents'].astype(int)
```

```
Out[25]: 0      0
1      1
2      0
3      0
4      0
5      2
6      0
7      3
8      2
9      1
10     2
11     2
12     2
13     0
14     2
15     0
16     1
17     0
18     0
19     0
20     0
21     1
22     0
23     2
24     1
25     0
26     0
27     2
28     0
29     2
...
584    1
585    1
586    0
587    0
588    0
589    2
590    0
591    2
592    3
593    0
594    0
595    0
596    2
597    0
598    0
599    2
600    3
601    0
602    3
603    0
604    1
605    0
606    1
607    2
```



```
608    0
609    0
610    3
611    1
612    2
613    0
```

Name: Dependents, Length: 614, dtype: int32

```
In [8]: df['Gender'].fillna(df["Gender"].mode()[0],inplace=True)
df['Married'].fillna(df['Married'].mode()[0],inplace=True)
df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)
df['Education'].fillna(df['Education'].mode()[0],inplace=True)
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0],inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)
```

```
In [9]: df['LoanAmount'].fillna(df['LoanAmount'].mean(),inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mean(),inplace=True)
```

```
In [10]: df.drop(["Loan_ID"],axis=1)
```

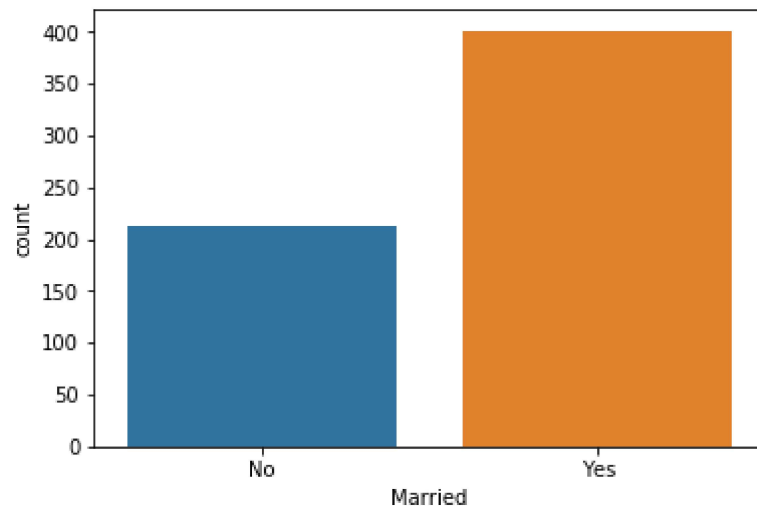
Out[10]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Male	No	0	Graduate	No	5849	0
1	Male	Yes	1	Graduate	No	4583	1508
2	Male	Yes	0	Graduate	Yes	3000	0
3	Male	Yes	0	Not Graduate	No	2583	2358
4	Male	No	0	Graduate	No	6000	0
5	Male	Yes	2	Graduate	Yes	5417	4196
6	Male	Yes	0	Not Graduate	No	2333	1516
7	Male	Yes	3+	Graduate	No	3036	2504
8	Male	Yes	2	Graduate	No	4006	1526
9	Male	Yes	1	Graduate	No	12841	10060

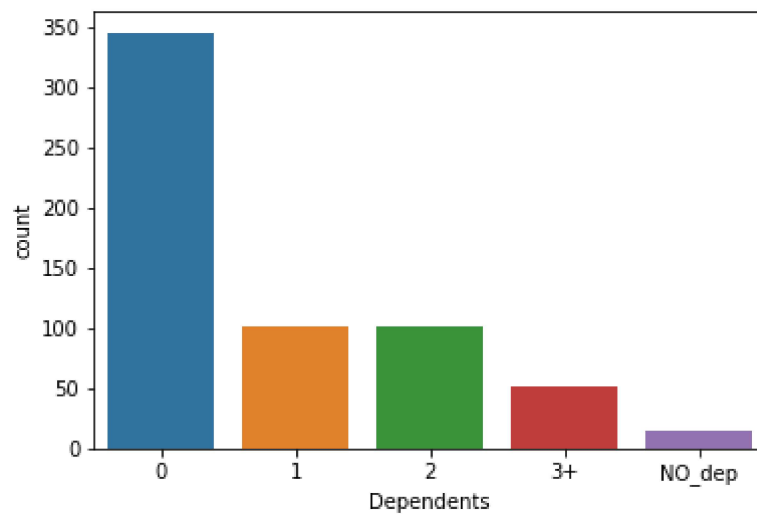
STEP 3:

```
In [11]: import seaborn as sns
import matplotlib.pyplot as plt
```

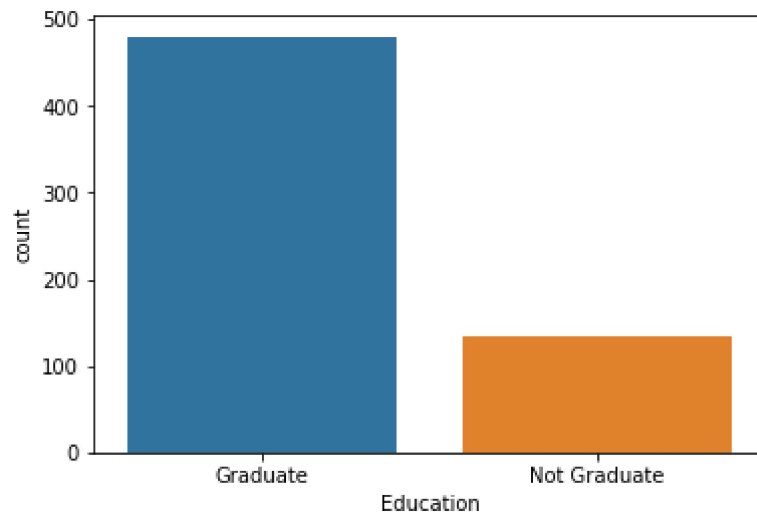
```
In [23]: sns.countplot(x='Married',data=df)  
plt.show()
```



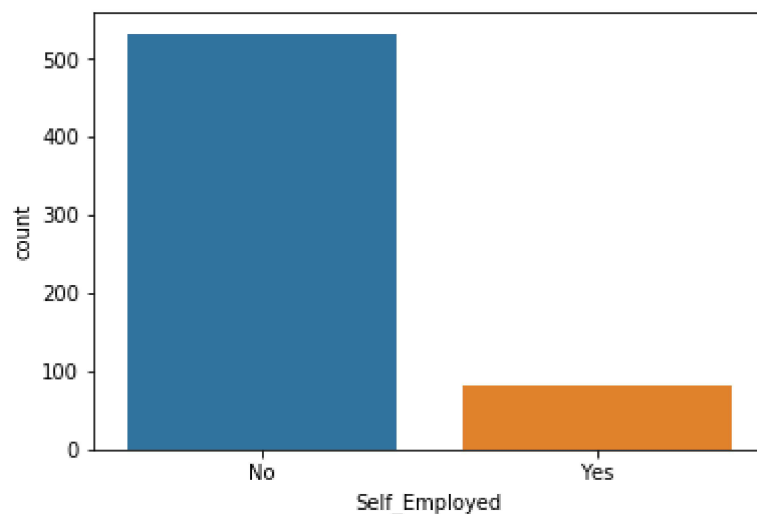
```
In [14]: sns.countplot(x='Dependents',data=df)  
plt.show()
```



```
In [22]: sns.countplot(x='Education',data=df)  
plt.show()
```



```
In [21]: sns.countplot(x='Self_Employed',data=df)  
plt.show()
```



STEP 4:

```
In [16]: x=df.drop(['Loan_Status'],axis=1)
```

```
In [17]: y=df.pop('Loan_Status')
```

STEP 5:

```
In [19]: x=pd.get_dummies(x)
```

STEP 6:

```
In [20]: from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.30,random_state=42)
```

```
In [34]: from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
```

```
In [35]: x_train_ss=ss.fit_transform(x_train)
x_train_ss
```

```
Out[35]: array([[ -0.50133384,  0.27865737,  0.40368493, ..., -0.62317695,
                -0.79056942,  1.40682858],
                [ -0.42803179,  0.45103751,  0.09632945, ...,  1.60468065,
                -0.79056942, -0.71081865],
                [ -0.5669725 ,  0.23208844, -0.15191921, ..., -0.62317695,
                 1.26491106, -0.71081865],
                ...,
                [ -0.37088951, -0.59751445, -1.38134113, ..., -0.62317695,
                -0.79056942,  1.40682858],
                [  0.76362634, -0.59751445, -0.00519051, ..., -0.62317695,
                 1.26491106, -0.71081865],
                [  1.36387019, -0.59751445, -0.00519051, ..., -0.62317695,
                -0.79056942,  1.40682858]])
```

```
In [36]: x_test_ss=ss.fit_transform(x_test)
x_test_ss
```

```
Out[36]: array([[ 0.60310661, -0.4897835 ,  1.00133607, ..., -0.68429085,
                 1.31171195, -0.67579058],
                [-0.1508012 , -0.4897835 , -0.18660311, ..., -0.68429085,
                 1.31171195, -0.67579058],
                [-0.17338842, -0.07075971,  0.15280809, ...,  1.4613669 ,
                -0.7623625 , -0.67579058],
                ...,
                [ 1.02547189, -0.4897835 ,  0.50434111, ..., -0.68429085,
                -0.7623625 ,  1.47974835],
                [-0.34587267,  0.20984434, -0.07750665, ...,  1.4613669 ,
                -0.7623625 , -0.67579058],
                [ 0.03716241, -0.4897835 , -0.48964881, ...,  1.4613669 ,
                -0.7623625 , -0.67579058]])
```

```
In [37]: from sklearn.svm import LinearSVC
lvc=LinearSVC()
lvc.fit(x_train_ss,y_train)
l_pred=lvc.predict(x_test_ss)
l_pred
```

```
In [63]: from sklearn.metrics import accuracy_score as acs
lvc_acc=acs(y_test,l_pred)
lvc_acc
```

```
Out[63]: 0.745945945945946
```

```
In [50]: from sklearn.metrics import confusion_matrix as cm
mat=cm(y_test,l_pred)
mat
```

```
Out[50]: array([[ 20,  45],
               [  2, 118]], dtype=int64)
```

```
In [52]: from sklearn.metrics import classification_report as cr
cre=cr(y_test,l_pred)
print(cre)
```

	precision	recall	f1-score	support
N	0.91	0.31	0.46	65
Y	0.72	0.98	0.83	120
avg / total	0.79	0.75	0.70	185

STEP 7:

```
In [62]: from sklearn.linear_model import LogisticRegression
lor=LogisticRegression()
lor.fit(x_train_ss,y_train)
lr_pred=lor.predict(x_test_ss)

from sklearn.svm import LinearSVC
lvc=LinearSVC()
lvc.fit(x_train_ss,y_train)
l_pred=lvc.predict(x_test_ss)

from sklearn.metrics import accuracy_score as acs
lvc_acc=acs(y_test,l_pred)
print("linear accuracy score:",lvc_acc)

lvc_acc=acs(y_test,lr_pred)
print("logistic regression accuracy score:",lvc_acc)
```

```
linear accuracy score: 0.745945945945946
logistic regression accuracy score: 0.7567567567567568
```