

```
In [135]: import pandas as pd
import pandas as pd
import numpy as np
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score, recall_score, precision_score, confusion_matrix, classification_report
from sklearn import tree
from sklearn.metrics import roc_auc_score
```

```
In [136]: loan_data=pd.read_csv("loan_data.csv")
```

```
In [137]: loan_data.head()
```

Out[137]:

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | Loan_Status |
|---|----------|--------|---------|------------|--------------|---------------|-----------------|-------------------|-------------|
| 0 | LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | |
| 4 | LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | |

```
In [138]: loan_data.isnull().sum()
```

```
Out[138]: 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 [139]: loan_data.dtypes
```

```
Out[139]: Loan_ID          object
Gender          object
Married         object
Dependents      object
Education       object
Self_Employed   object
ApplicantIncome int64
CoapplicantIncome float64
LoanAmount      float64
Loan_Amount_Term float64
Credit_History  float64
Property_Area   object
Loan_Status     object
dtype: object
```

```
In [140]: loan_data.nunique()
```

```
Out[140]: Loan_ID          614
Gender          2
Married         2
Dependents      4
Education       2
Self_Employed   2
ApplicantIncome 505
CoapplicantIncome 287
LoanAmount      203
Loan_Amount_Term 10
Credit_History  2
Property_Area   3
Loan_Status     2
dtype: int64
```

```
In [141]: loan_data.isnull().sum()
```

```
Out[141]: 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 [142]: loan_data['Loan_Status'].value_counts()
```

```
Out[142]: Y    422
N    192
Name: Loan_Status, dtype: int64
```

```
In [143]: loan_data['Credit_History'].value_counts()
```

```
Out[143]: 1.0    475  
         0.0     89  
         Name: Credit_History, dtype: int64
```

```
In [144]: loan_data['Dependents'].value_counts()
```

```
Out[144]: 0      345  
         1     102  
         2     101  
         3+     51  
         Name: Dependents, dtype: int64
```

```
In [145]: loan_data['Gender'].value_counts()
```

```
Out[145]: Male      489  
         Female    112  
         Name: Gender, dtype: int64
```

```
In [146]: loan_data['Loan_Amount_Term'].value_counts()
```

```
Out[146]: 360.0    512  
         180.0     44  
         480.0     15  
         300.0     13  
         240.0      4  
         84.0      4  
         120.0      3  
         60.0       2  
         36.0       2  
         12.0       1  
         Name: Loan_Amount_Term, dtype: int64
```

```
In [147]: loan_data['Self_Employed'].value_counts()
```

```
Out[147]: No      500  
         Yes      82  
         Name: Self_Employed, dtype: int64
```

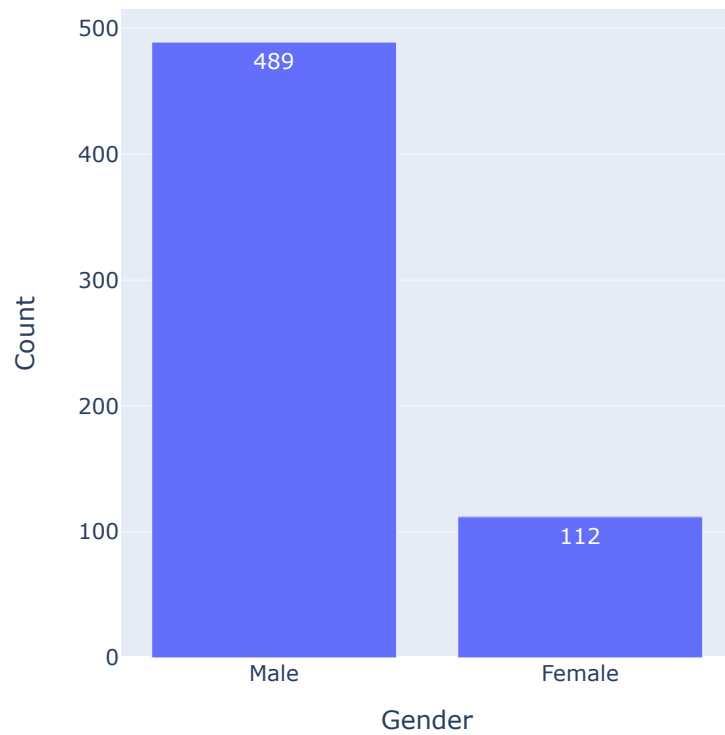
```
In [148]: loan_data['Gender'].value_counts()
```

```
Out[148]: Male      489  
         Female    112  
         Name: Gender, dtype: int64
```

```
In [ ]:
```

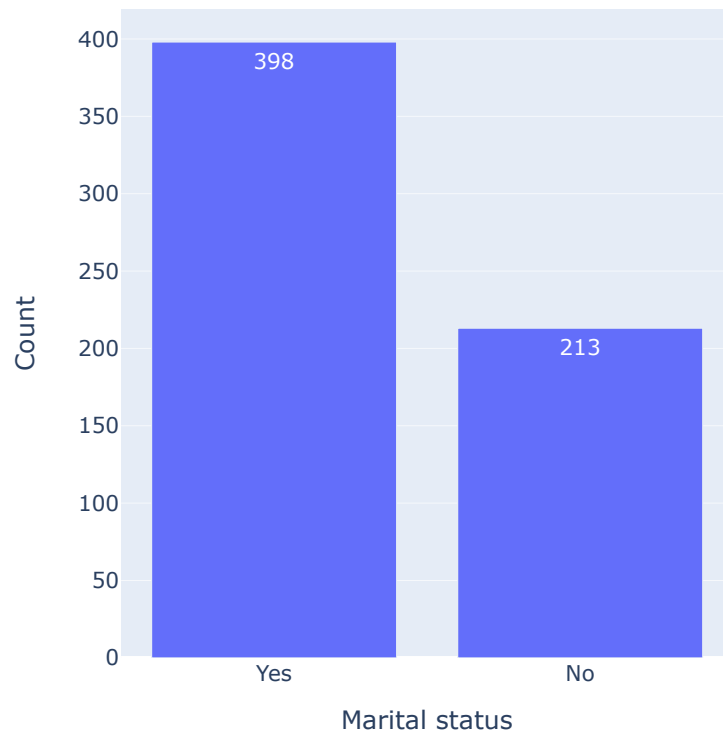
```
In [149]: fig = px.bar(data_frame=loan_data, x=loan_data['Gender'].value_counts().index, y=loan_data[  
fig.update_layout(title='Number of Males and Females',xaxis_title='Gender',yaxis_title='Cou  
fig.show()
```

Number of Males and Females



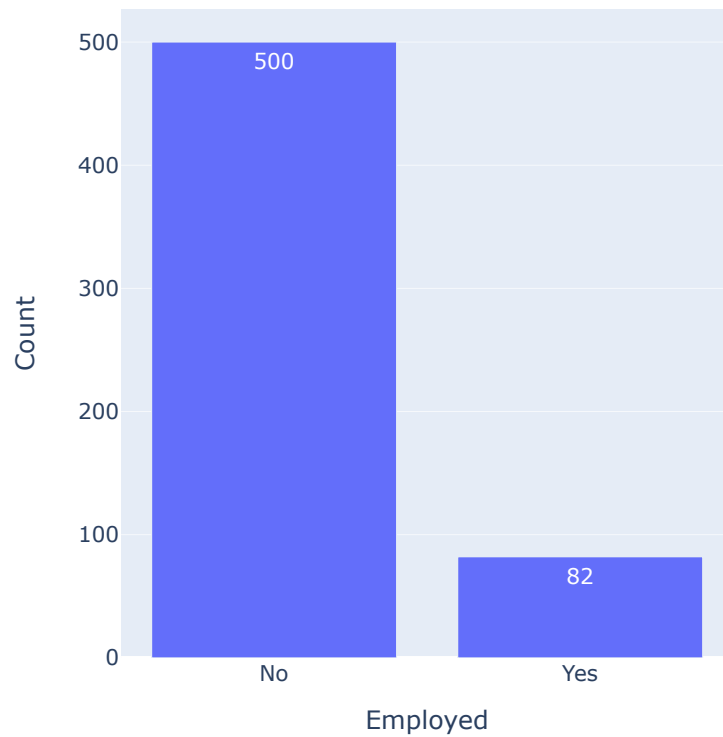
```
In [150]: fig = px.bar(data_frame=loan_data, x=loan_data['Married'].value_counts().index, y=loan_data  
fig.update_layout(title='Number of Married and Unmarried',xaxis_title='Marital status',yaxis  
fig.show()
```

Number of Married and Unmarried

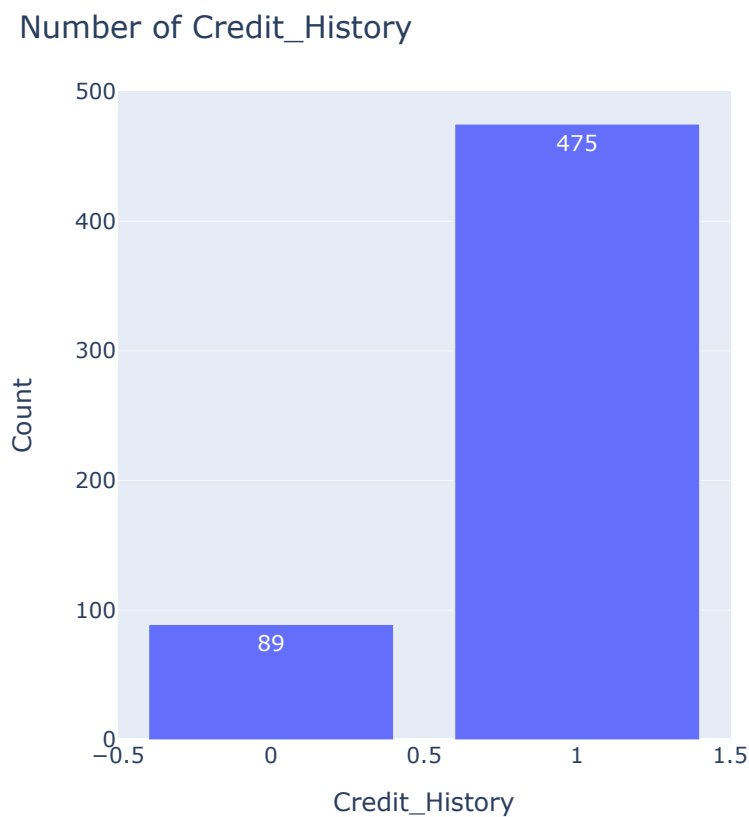


```
In [151]: fig = px.bar(data_frame=loan_data, x=loan_data['Self_Employed'].value_counts().index, y=loan_data['Self_Employed'].value_counts().values)
fig.update_layout(title='Number of Self_Employed or Not',xaxis_title='Employed',yaxis_title='Count')
fig.show()
```

Number of Self_Employed or Not



```
In [152]: fig = px.bar(data_frame=loan_data, x=loan_data['Credit_History'].value_counts().index, y=loan_data['Credit_History'].value_counts().values)
fig.update_layout(title='Number of Credit_History',xaxis_title='Credit_History',yaxis_title='Count')
fig.show()
```

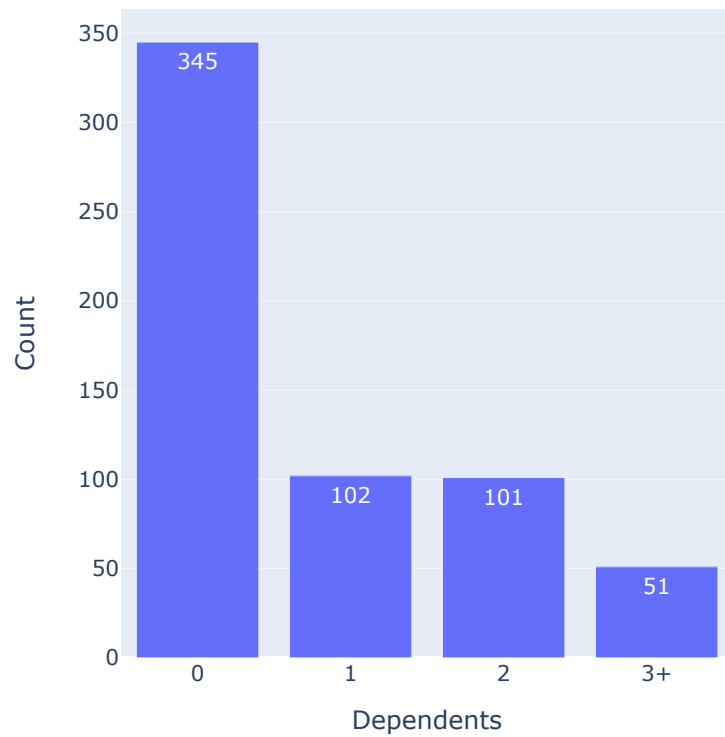


```
In [153]: loan_data.dtypes
```

```
Out[153]: Loan_ID          object
Gender          object
Married         object
Dependents      object
Education       object
Self_Employed  object
ApplicantIncome int64
CoapplicantIncome float64
LoanAmount      float64
Loan_Amount_Term float64
Credit_History  float64
Property_Area   object
Loan_Status     object
dtype: object
```

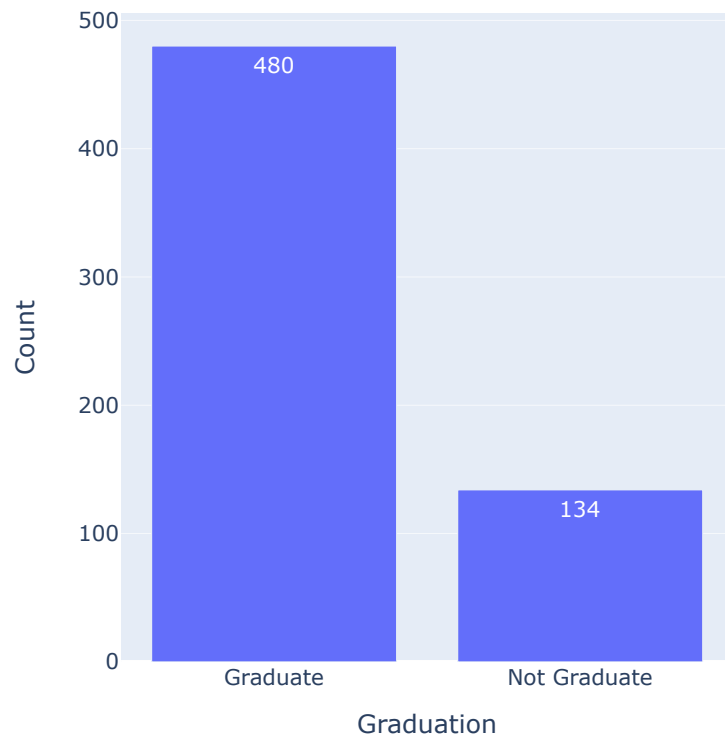
```
In [154]: fig = px.bar(data_frame=loan_data, x=loan_data['Dependents'].value_counts().index, y=loan_data['Dependents'].value_counts().values)
fig.update_layout(title='Number of Dependents',xaxis_title='Dependents',yaxis_title='Count')
fig.show()
```

Number of Dependents



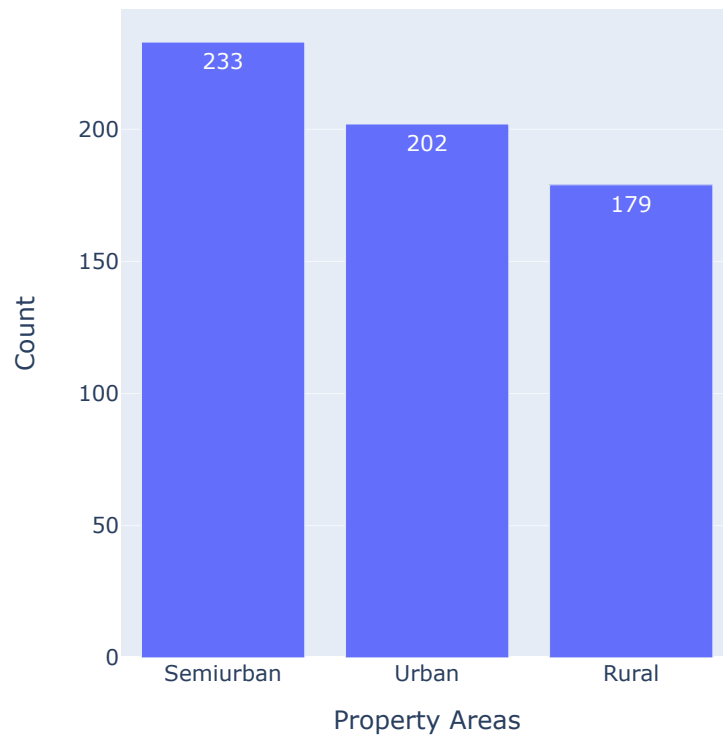

```
In [155]: fig = px.bar(data_frame=loan_data, x=loan_data['Education'].value_counts().index, y=loan_data['Education'].value_counts().values)
fig.update_layout(title='Number of Graduate and Not Graduate',xaxis_title='Graduation',yaxis_title='Count')
fig.show()
```

Number of Graduate and Not Graduate

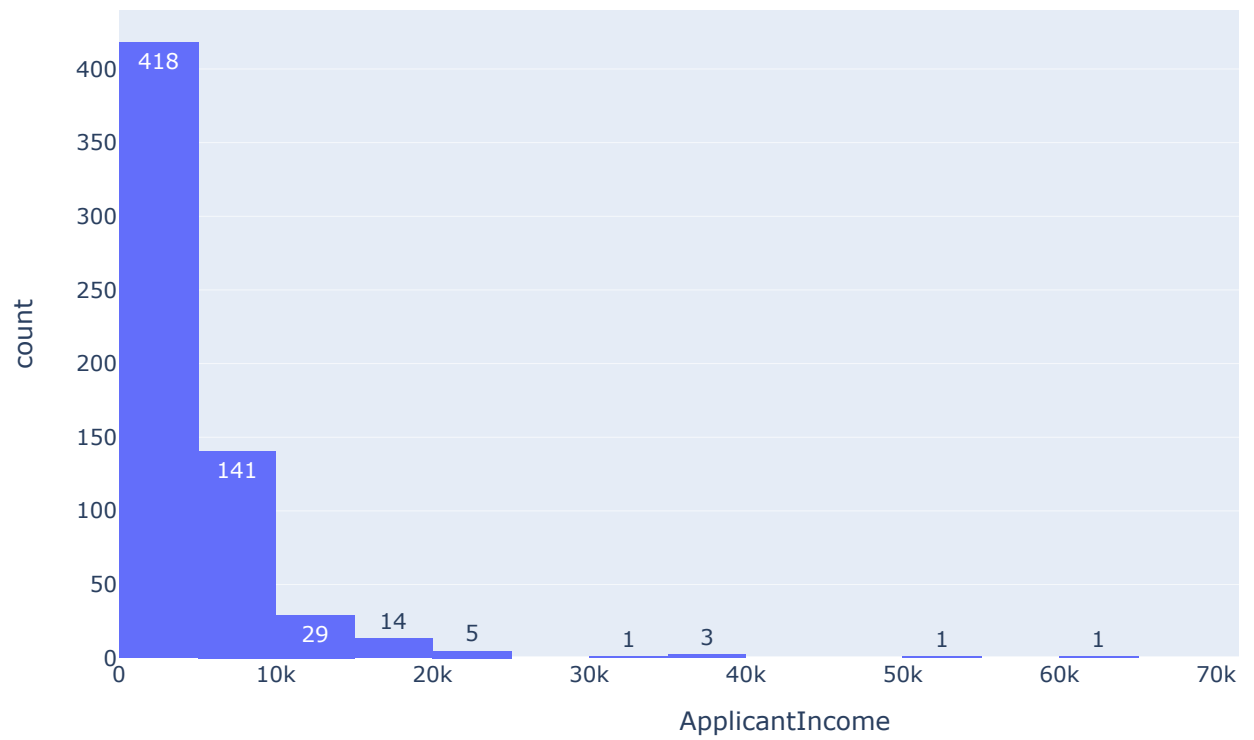


```
In [156]: fig = px.bar(data_frame=loan_data, x=loan_data['Property_Area'].value_counts().index, y=loan_data['Property_Area'].value_counts().values)
fig.update_layout(title='Number of Property Areas',xaxis_title='Property Areas',yaxis_title='Count')
fig.show()
```

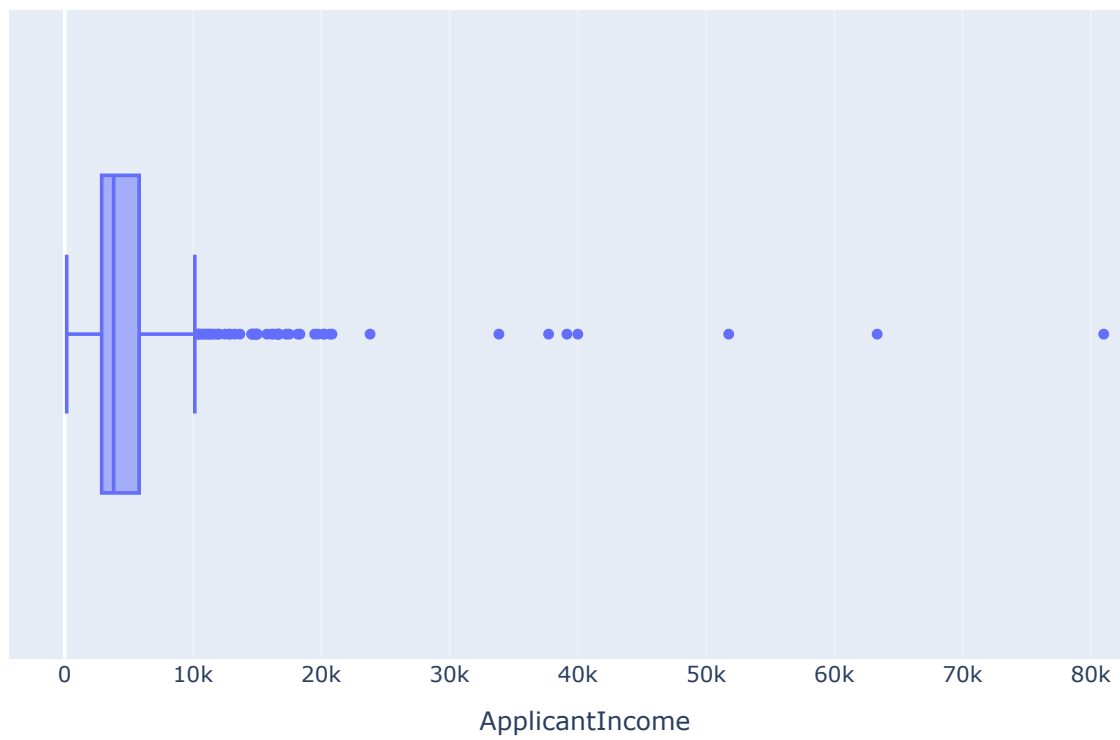
Number of Property Areas



```
In [157]: fig=px.histogram(data_frame=loan_data,x='ApplicantIncome',text_auto=True,nbins=20)  
fig.update_layout(width=900,height=500)  
fig.show()
```



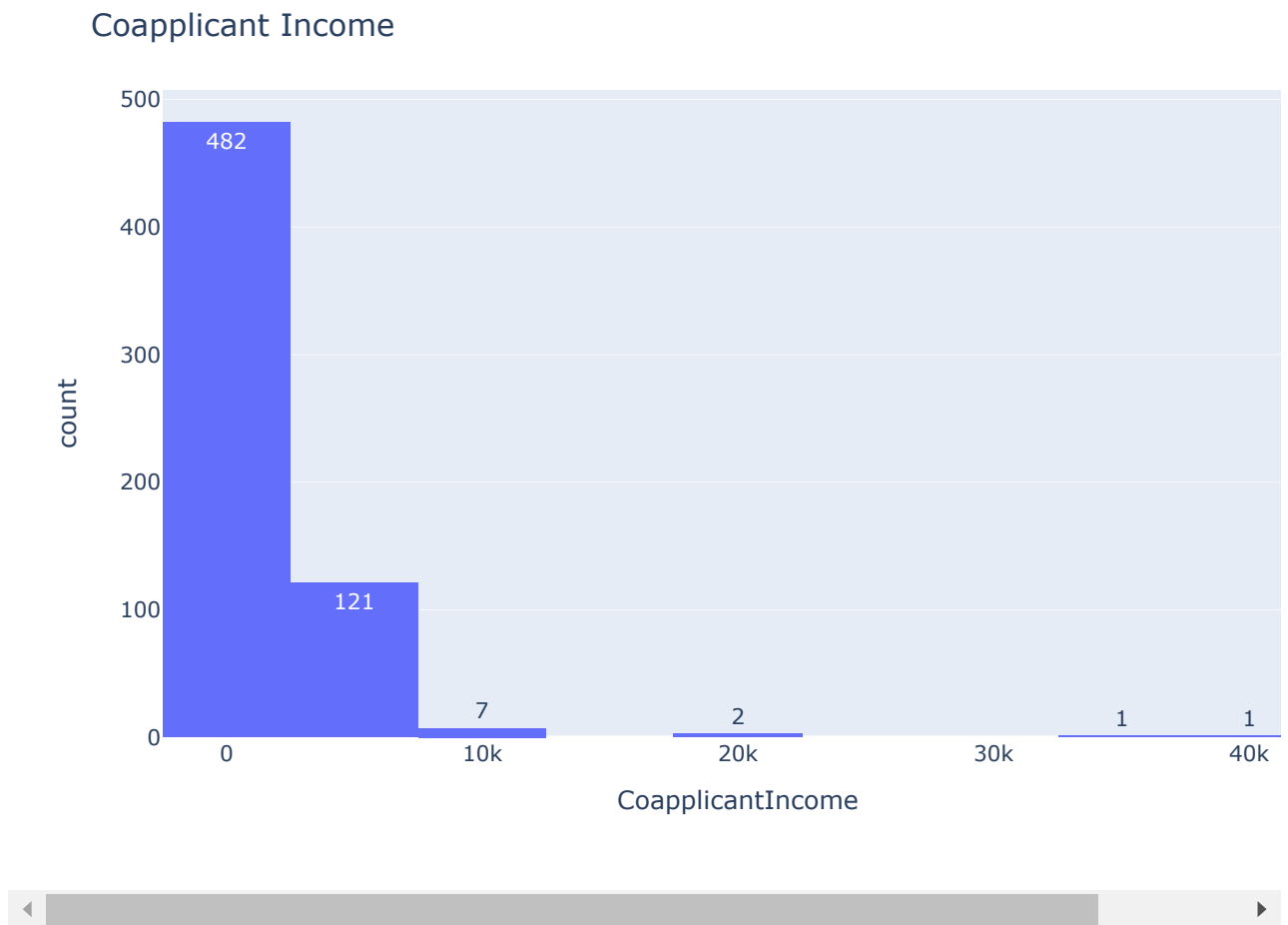
```
In [158]: fig=px.box(data_frame=loan_data,x='ApplicantIncome')  
fig.update_layout(width=800,height=500)  
fig.show()
```



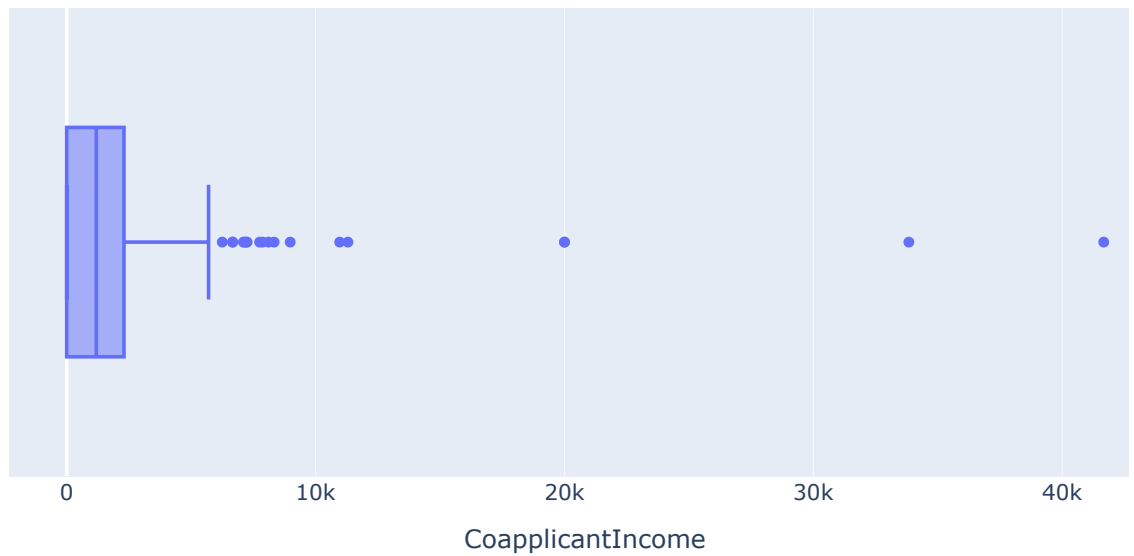
```
In [159]: fig=px.box(data_frame=loan_data,x='ApplicantIncome',y='Education',orientation='h', color='Education')
fig.update_layout(title='Applicant Income',width=800,height=500)
fig.show()
```



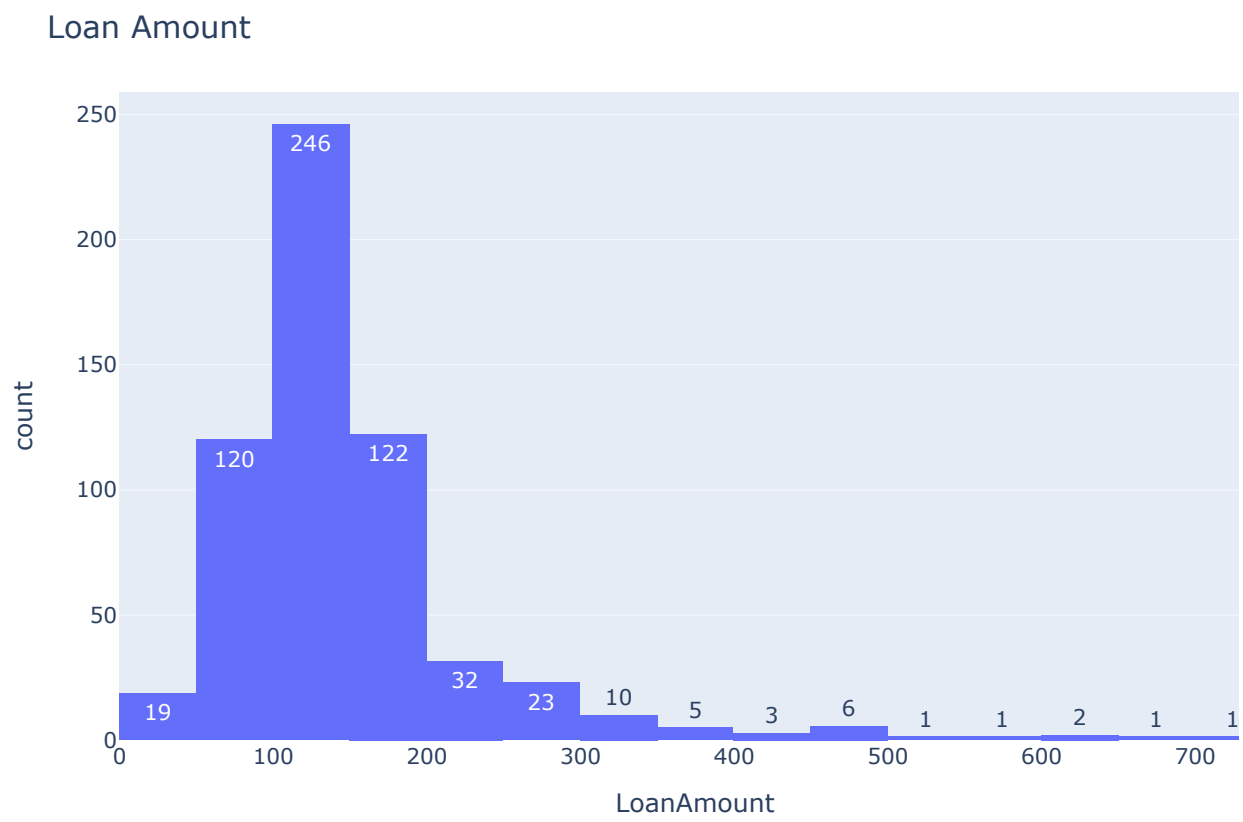
```
In [160]: fig=px.histogram(data_frame=loan_data,x='CoapplicantIncome',text_auto=True,nbins=20)
fig.update_layout(title='Coapplicant Income',width=800,height=500)
fig.show()
```



```
In [161]: fig=px.box(data_frame=loan_data,x='CoapplicantIncome')  
fig.update_layout(width=800,height=400)  
fig.show()
```

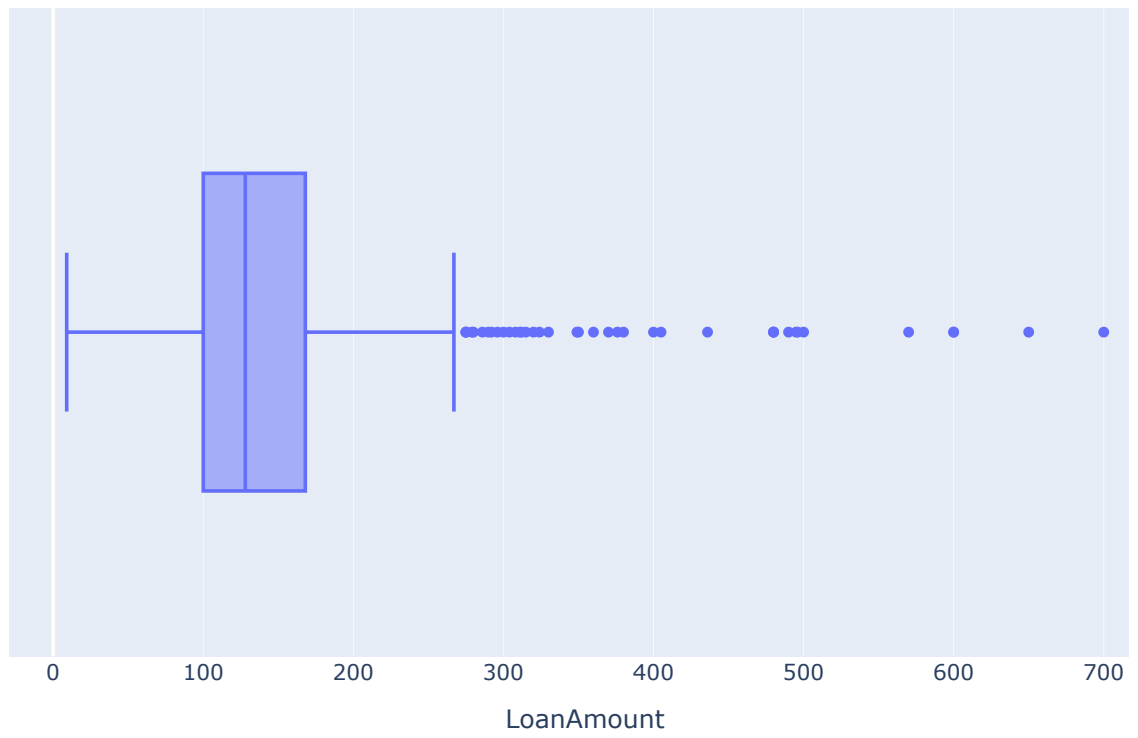


```
In [162]: fig=px.histogram(data_frame=loan_data,x='LoanAmount',text_auto=True,nbins=20)  
fig.update_layout(title='Loan Amount',width=800,height=500)  
fig.show()
```

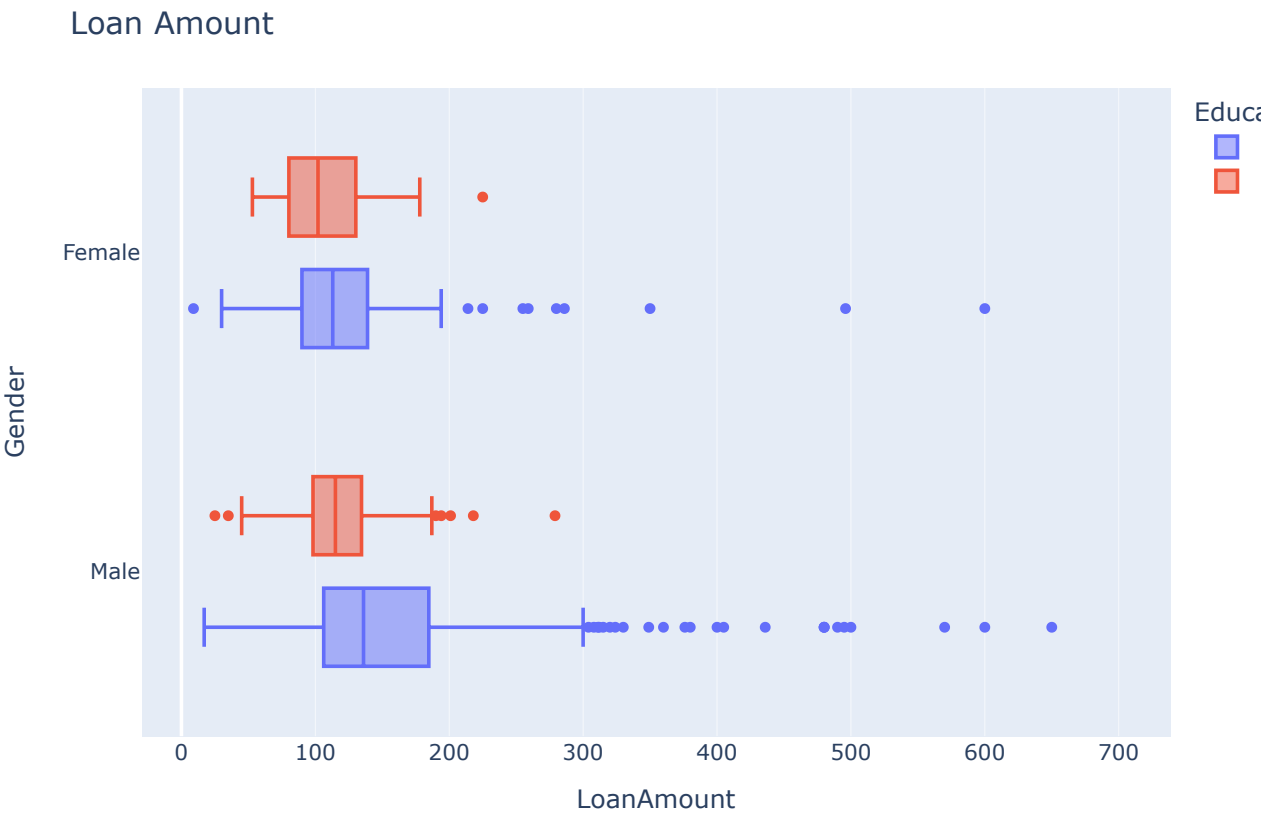



```
In [163]: fig=px.box(data_frame=loan_data,x='LoanAmount',orientation='h', )  
fig.update_layout(title='Loan Amount',width=800,height=500)  
fig.show()
```

Loan Amount



```
In [164]: fig=px.box(data_frame=loan_data,x='LoanAmount',y='Gender',orientation='h', color='Education')
fig.update_layout(title='Loan Amount',width=800,height=500)
fig.show()
```



```
In [165]: Gender_vise_Loan_Status= loan_data.groupby(['Gender', 'Loan_Status']).size().reset_index(name='Gender_vise_Loan_Status')
```

Out[165]:

| | Gender | Loan_Status | Count |
|---|--------|-------------|-------|
| 0 | Female | N | 37 |
| 1 | Female | Y | 75 |
| 2 | Male | N | 150 |
| 3 | Male | Y | 339 |

```
In [166]: Married_vise_Loan_Status= loan_data.groupby(['Married', 'Loan_Status']).size().reset_index(name='Married_vise_Loan_Status')
```

Out[166]:

| | Married | Loan_Status | Count |
|---|---------|-------------|-------|
| 0 | No | N | 79 |
| 1 | No | Y | 134 |
| 2 | Yes | N | 113 |
| 3 | Yes | Y | 285 |

In [167]: `loan_data.dtypes`

```
Out[167]: Loan_ID      object
Gender      object
Married     object
Dependents  object
Education   object
Self_Employed  object
ApplicantIncome  int64
CoapplicantIncome float64
LoanAmount      float64
Loan_Amount_Term float64
Credit_History  float64
Property_Area   object
Loan_Status     object
dtype: object
```

In [168]: `Dependents_vise_Loan_Status= loan_data.groupby(['Dependents', 'Loan_Status']).size().reset_index()`
`Dependents_vise_Loan_Status`

Out[168]:

| | Dependents | Loan_Status | Count |
|---|------------|-------------|-------|
| 0 | 0 | N | 107 |
| 1 | 0 | Y | 238 |
| 2 | 1 | N | 36 |
| 3 | 1 | Y | 66 |
| 4 | 2 | N | 25 |
| 5 | 2 | Y | 76 |
| 6 | 3+ | N | 18 |
| 7 | 3+ | Y | 33 |

In [169]: `Education_vise_Loan_Status= loan_data.groupby(['Education', 'Loan_Status']).size().reset_index()`
`Education_vise_Loan_Status`

Out[169]:

| | Education | Loan_Status | Count |
|---|--------------|-------------|-------|
| 0 | Graduate | N | 140 |
| 1 | Graduate | Y | 340 |
| 2 | Not Graduate | N | 52 |
| 3 | Not Graduate | Y | 82 |

In [170]: `Self_Employed_vise_Loan_Status= loan_data.groupby(['Self_Employed', 'Loan_Status']).size().reset_index()`
`Self_Employed_vise_Loan_Status`

Out[170]:

| | Self_Employed | Loan_Status | Count |
|---|---------------|-------------|-------|
| 0 | No | N | 157 |
| 1 | No | Y | 343 |
| 2 | Yes | N | 26 |
| 3 | Yes | Y | 56 |

```
In [171]: Credit_History_vise_Loan_Status= loan_data.groupby(['Credit_History', 'Loan_Status']).size()
Credit_History_vise_Loan_Status
```

Out[171]:

| | Credit_History | Loan_Status | Count |
|---|----------------|-------------|-------|
| 0 | 0.0 | N | 82 |
| 1 | 0.0 | Y | 7 |
| 2 | 1.0 | N | 97 |
| 3 | 1.0 | Y | 378 |

```
In [172]: Property_Area_vise_Loan_Status= loan_data.groupby(['Property_Area', 'Loan_Status']).size()
Property_Area_vise_Loan_Status
```

Out[172]:

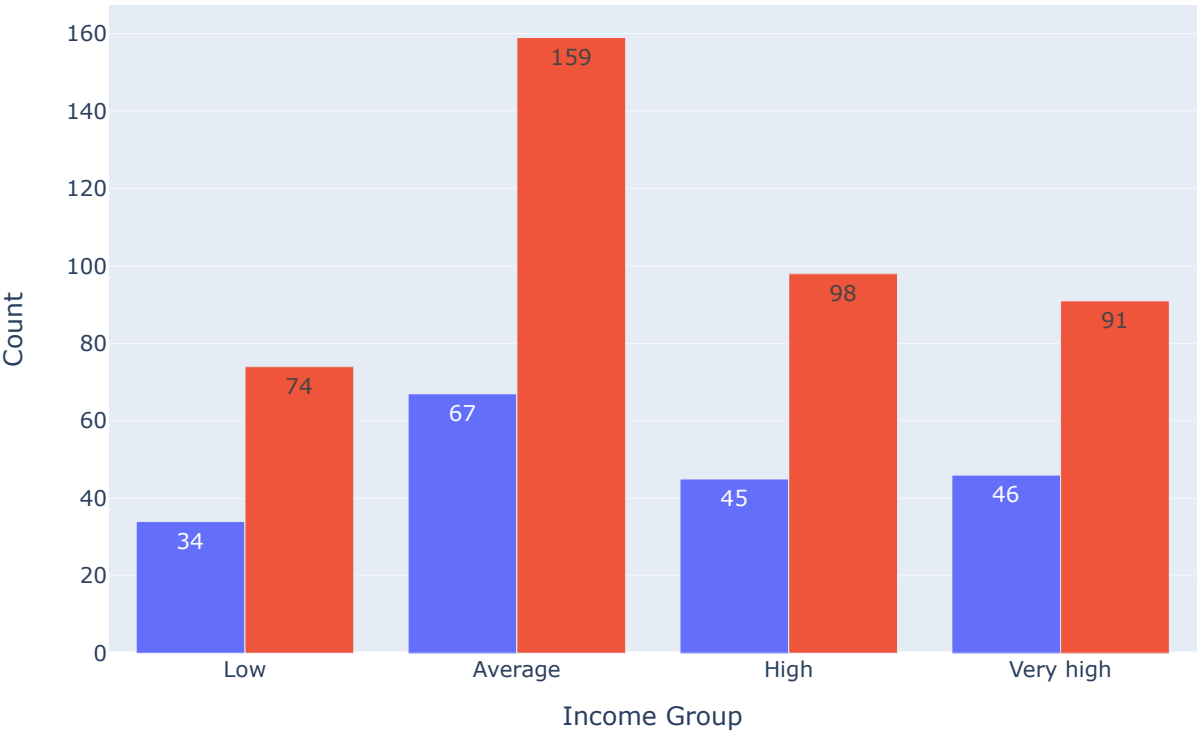
| | Property_Area | Loan_Status | Count |
|---|---------------|-------------|-------|
| 0 | Rural | N | 69 |
| 1 | Rural | Y | 110 |
| 2 | Semiurban | N | 54 |
| 3 | Semiurban | Y | 179 |
| 4 | Urban | N | 69 |
| 5 | Urban | Y | 133 |

```
In [173]: bins=[0,2500,4000,6000,81000]
group=['Low','Average','High','Very high']
loan_data['Income_Group']=pd.cut(loan_data['ApplicantIncome'],bins=bins,labels=group,include
Income_Group_vise_Loan_Status= loan_data.groupby(['Income_Group', 'Loan_Status']).size().re
Income_Group_vise_Loan_Status
```

Out[173]:

| | Income_Group | Loan_Status | Count |
|---|--------------|-------------|-------|
| 0 | Low | N | 34 |
| 1 | Low | Y | 74 |
| 2 | Average | N | 67 |
| 3 | Average | Y | 159 |
| 4 | High | N | 45 |
| 5 | High | Y | 98 |
| 6 | Very high | N | 46 |
| 7 | Very high | Y | 91 |

```
In [174]: fig = px.bar(Income_Group_vise_Loan_Status,x='Income_Group',y='Count',color='Loan_Status',b
fig.update_layout(xaxis_title='Income_Group',yaxis_title='Count',width=800,height=500)
fig.show()
```

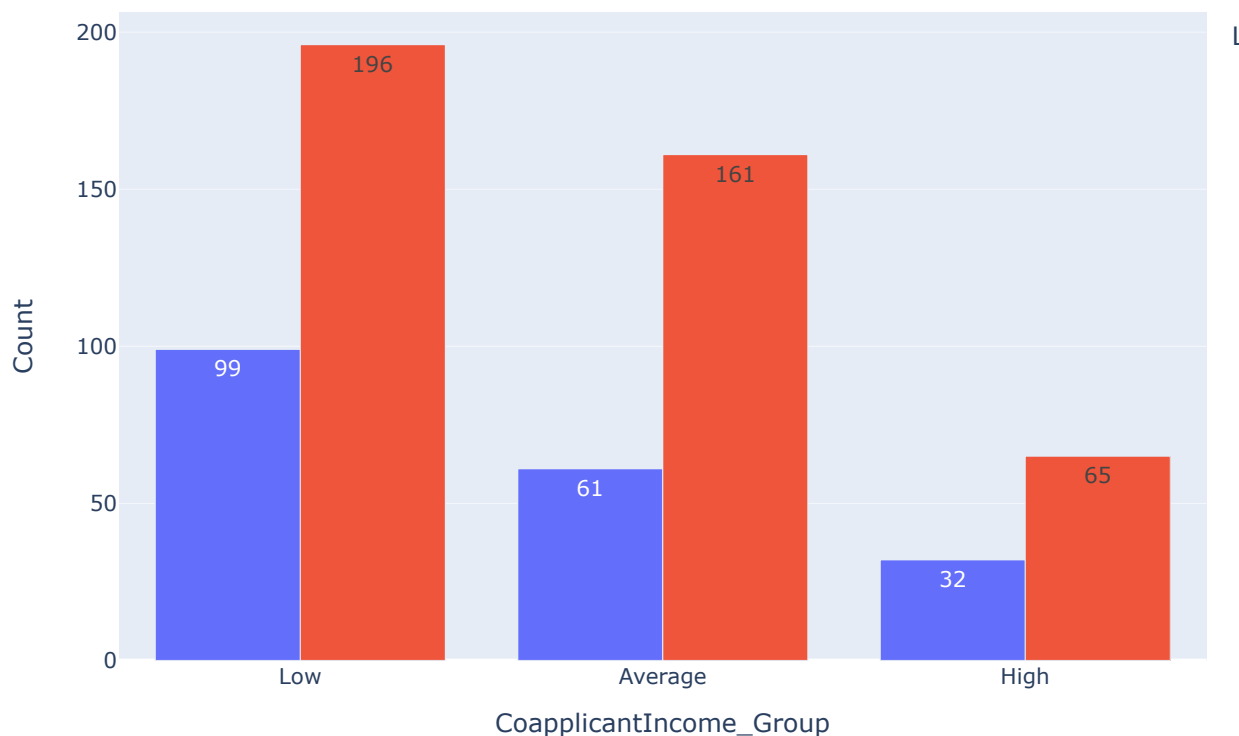


```
In [175]: bins=[0,1000,3000,42000]
group=['Low', 'Average', 'High']
loan_data['CoapplicantIncome_Group']=pd.cut(loan_data['CoapplicantIncome'],bins=bins,labels=
CoapplicantIncome_Group_vise_Loan_Status= loan_data.groupby(['CoapplicantIncome_Group', 'Lo
CoapplicantIncome_Group_vise_Loan_Status
```

Out[175]:

| | CoapplicantIncome_Group | Loan_Status | Count |
|---|-------------------------|-------------|-------|
| 0 | Low | N | 99 |
| 1 | Low | Y | 196 |
| 2 | Average | N | 61 |
| 3 | Average | Y | 161 |
| 4 | High | N | 32 |
| 5 | High | Y | 65 |

```
In [176]: fig = px.bar(CoapplicantIncome_Group_vise_Loan_Status,x='CoapplicantIncome_Group',y='Count')
fig.update_layout(xaxis_title='CoapplicantIncome_Group',yaxis_title='Count',width=800,height=800)
fig.show()
```

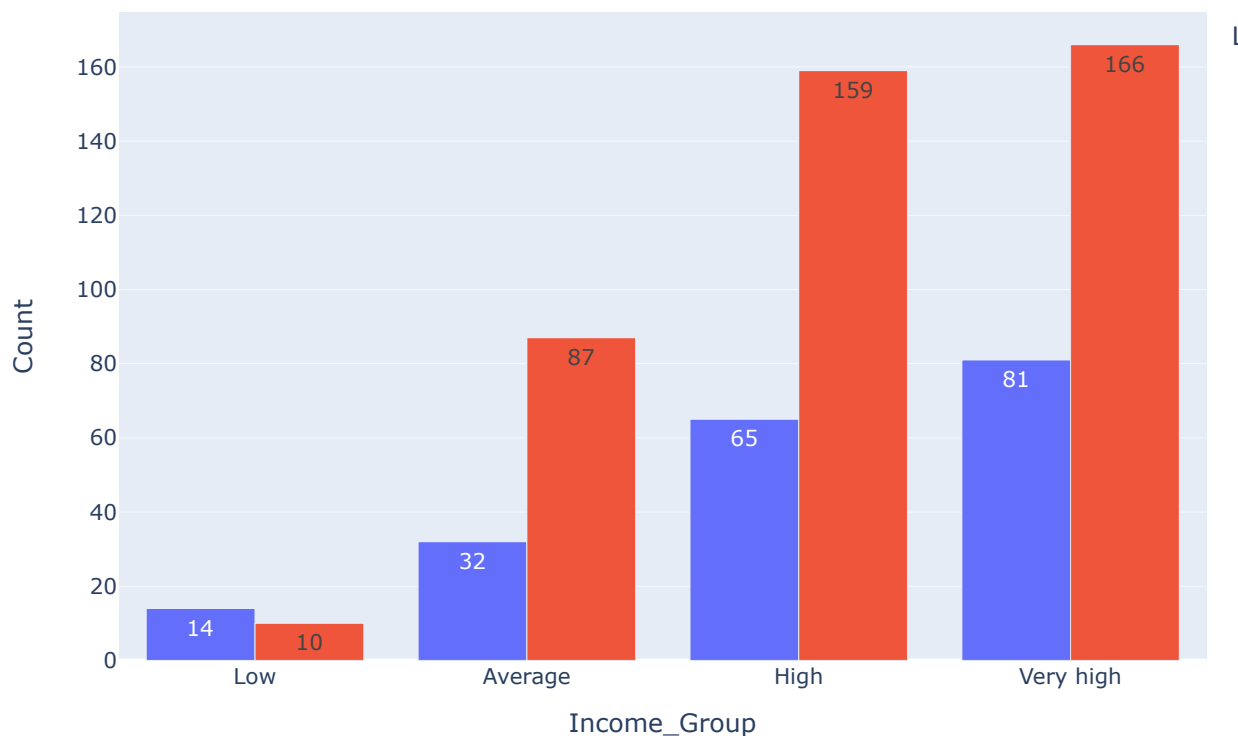


```
In [177]: loan_data['Total_Income']=loan_data['ApplicantIncome']+loan_data['CoapplicantIncome']
bins=[0,2500,4000,6000,81000]
group=['Low','Average','High','Very high']
loan_data['Total_Income_Group']=pd.cut(loan_data['Total_Income'],bins=bins,labels=group,include_lowest=True)
Total_Income_Group_vise_Loan_Status= loan_data.groupby(['Total_Income_Group', 'Loan_Status']).size().reset_index(name='Count')
```

Out[177]:

| | Total_Income_Group | Loan_Status | Count |
|---|--------------------|-------------|-------|
| 0 | Low | N | 14 |
| 1 | Low | Y | 10 |
| 2 | Average | N | 32 |
| 3 | Average | Y | 87 |
| 4 | High | N | 65 |
| 5 | High | Y | 159 |
| 6 | Very high | N | 81 |
| 7 | Very high | Y | 166 |

```
In [178]: fig = px.bar(Total_Income_Group_vise_Loan_Status,x='Total_Income_Group',y='Count',color='Loan_Status')
fig.update_layout(xaxis_title='Income_Group',yaxis_title='Count',width=800,height=500)
fig.show()
```

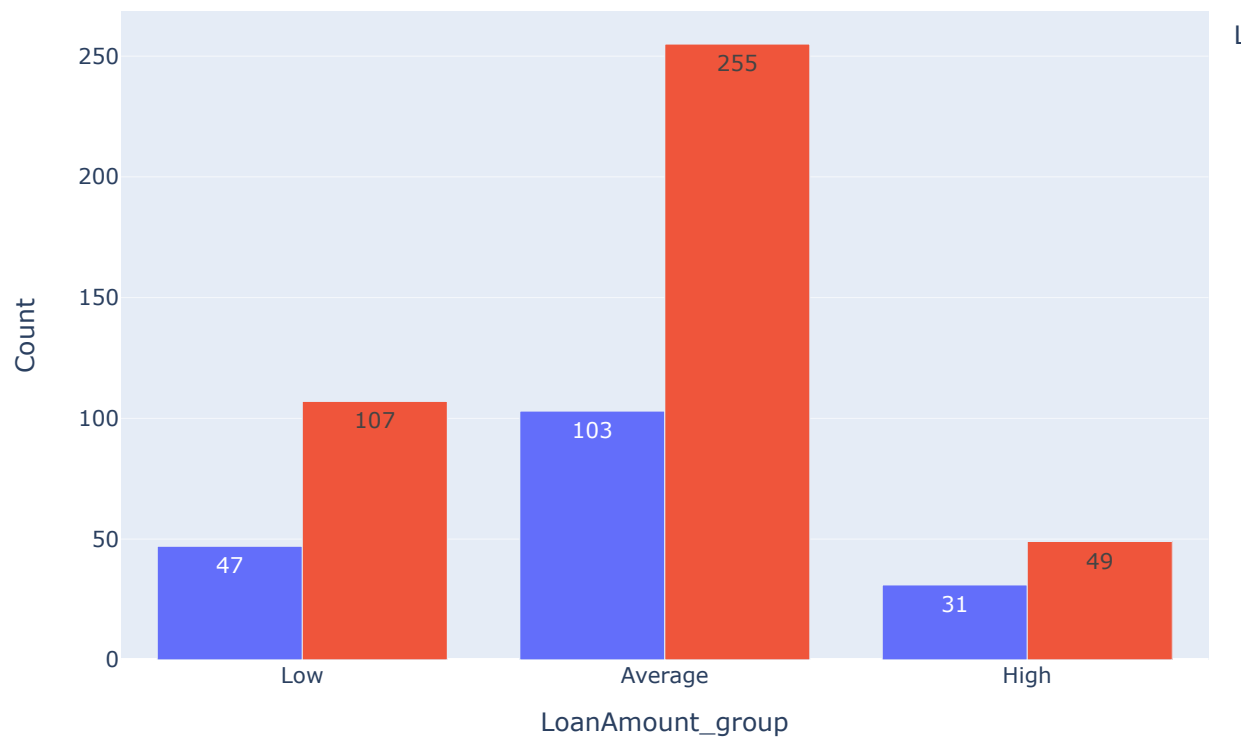


```
In [179]: bins=[0,100,200,700]
group=['Low','Average','High']
loan_data['LoanAmount_group']=pd.cut(loan_data['LoanAmount'],bins,labels=group)
LoanAmount_group_vise_Loan_Status= loan_data.groupby(['LoanAmount_group', 'Loan_Status']).size()
LoanAmount_group_vise_Loan_Status
```

Out[179]:

| | LoanAmount_group | Loan_Status | Count |
|---|------------------|-------------|-------|
| 0 | Low | N | 47 |
| 1 | Low | Y | 107 |
| 2 | Average | N | 103 |
| 3 | Average | Y | 255 |
| 4 | High | N | 31 |
| 5 | High | Y | 49 |

```
In [180]: fig = px.bar(LoanAmount_group_vise_Loan_Status,x='LoanAmount_group',y='Count',color='Loan_Status')
fig.update_layout(xaxis_title='LoanAmount_group',yaxis_title='Count',width=800,height=500)
fig.show()
```



```
In [181]: loan_data=loan_data.drop(['Income_Group', 'CoapplicantIncome_Group', 'Total_Income_Group'],
```

```
In [182]: loan_data['Dependents'].replace('3+', 3,inplace=True)
loan_data['Loan_Status'].replace('N', 0,inplace=True)
loan_data['Loan_Status'].replace('Y', 1,inplace=True)
```

```
In [183]: loan_data.head()
```

Out[183]:

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | Loan_Status |
|---|----------|--------|---------|------------|--------------|---------------|-----------------|-------------------|-------------|
| 0 | LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | 0 |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 1 |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 1 |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 1 |
| 4 | LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | 0 |


```
In [184]: Correlation=loan_data.corr(method='pearson')
print(Correlation)
```

| | ApplicantIncome | CoapplicantIncome | LoanAmount | \ |
|-------------------|-----------------|-------------------|------------|---|
| ApplicantIncome | 1.000000 | -0.116605 | 0.570909 | |
| CoapplicantIncome | -0.116605 | 1.000000 | 0.188619 | |
| LoanAmount | 0.570909 | 0.188619 | 1.000000 | |
| Loan_Amount_Term | -0.045306 | -0.059878 | 0.039447 | |
| Credit_History | -0.014715 | -0.002056 | -0.008433 | |
| Loan_Status | -0.004710 | -0.059187 | -0.037318 | |

| | Loan_Amount_Term | Credit_History | Loan_Status |
|-------------------|------------------|----------------|-------------|
| ApplicantIncome | -0.045306 | -0.014715 | -0.004710 |
| CoapplicantIncome | -0.059878 | -0.002056 | -0.059187 |
| LoanAmount | 0.039447 | -0.008433 | -0.037318 |
| Loan_Amount_Term | 1.000000 | 0.001470 | -0.021268 |
| Credit_History | 0.001470 | 1.000000 | 0.561678 |
| Loan_Status | -0.021268 | 0.561678 | 1.000000 |

C:\Users\Suyash\AppData\Local\Temp\ipykernel_25672\4188836588.py:1: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
In [185]: fig=go.Figure(go.Heatmap(x=Correlation.columns,y=Correlation.columns,z=Correlation.values.to
fig.update_layout(title='Correlation Heatmap',xaxis_title='Variables',yaxis_title='Variable
fig.show())
```



Correlation Heatmap



```
In [186]: loan_data.isnull().sum()
```

```
Out[186]: 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 [187]: loan_data['Gender'].fillna(method='ffill', inplace=True)
```

```
In [188]: loan_data['Dependents'].fillna( loan_data['Dependents'].mode()[0], inplace=True)
```

```
In [189]: loan_data['Married'].fillna(loan_data['Married'].mode()[0], inplace=True)
```

```
In [190]: loan_data['Self_Employed'].fillna(method='ffill', inplace=True)
```

```
In [191]: loan_data['Credit_History'].fillna(method='bfill', inplace=True)
```

```
In [192]: loan_data['LoanAmount'].fillna(loan_data['LoanAmount'].median(), inplace=True)
```

```
In [193]: loan_data['Loan_Amount_Term'].fillna( loan_data['Loan_Amount_Term'].mode()[0], inplace=True)
```

```
In [194]: loan_data.isnull().sum()
```

```
Out[194]: 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 [195]: `loan_data.describe()`

Out[195]:

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Loan_Status |
|--------------|-----------------|-------------------|------------|------------------|----------------|-------------|
| count | 614.000000 | 614.000000 | 614.000000 | 614.000000 | 614.000000 | 614.000000 |
| mean | 5403.459283 | 1621.245798 | 145.752443 | 342.410423 | 0.84202 | 0.687296 |
| std | 6109.041673 | 2926.248369 | 84.107233 | 64.428629 | 0.36502 | 0.463973 |
| min | 150.000000 | 0.000000 | 9.000000 | 12.000000 | 0.00000 | 0.000000 |
| 25% | 2877.500000 | 0.000000 | 100.250000 | 360.000000 | 1.00000 | 0.000000 |
| 50% | 3812.500000 | 1188.500000 | 128.000000 | 360.000000 | 1.00000 | 1.000000 |
| 75% | 5795.000000 | 2297.250000 | 164.750000 | 360.000000 | 1.00000 | 1.000000 |
| max | 81000.000000 | 41667.000000 | 700.000000 | 480.000000 | 1.00000 | 1.000000 |

In [196]: `loan_data`

Out[196]:

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | L |
|------------|----------|--------|---------|------------|--------------|---------------|-----------------|-------------------|---|
| 0 | LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | |
| 4 | LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 609 | LP002978 | Female | No | 0 | Graduate | No | 2900 | 0.0 | |
| 610 | LP002979 | Male | Yes | 3 | Graduate | No | 4106 | 0.0 | |
| 611 | LP002983 | Male | Yes | 1 | Graduate | No | 8072 | 240.0 | |
| 612 | LP002984 | Male | Yes | 2 | Graduate | No | 7583 | 0.0 | |
| 613 | LP002990 | Female | No | 0 | Graduate | Yes | 4583 | 0.0 | |

614 rows × 13 columns



In [197]: `loan_data['NormLoanAmount'] = np.log(loan_data['LoanAmount'])`

In [198]: loan_data

Out[198]:

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount |
|-----|----------|--------|---------|------------|--------------|---------------|-----------------|-------------------|------------|
| 0 | LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | |
| 4 | LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 609 | LP002978 | Female | No | 0 | Graduate | No | 2900 | 0.0 | |
| 610 | LP002979 | Male | Yes | 3 | Graduate | No | 4106 | 0.0 | |
| 611 | LP002983 | Male | Yes | 1 | Graduate | No | 8072 | 240.0 | |
| 612 | LP002984 | Male | Yes | 2 | Graduate | No | 7583 | 0.0 | |
| 613 | LP002990 | Female | No | 0 | Graduate | Yes | 4583 | 0.0 | |

614 rows × 14 columns



In [199]: loan_data=loan_data.drop('Loan_ID',axis=1)

In [200]: X = loan_data.drop(labels='Loan_Status',axis=1)
Y = loan_data['Loan_Status']

In [201]: X

Out[201]:

| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount |
|-----|--------|---------|------------|--------------|---------------|-----------------|-------------------|------------|
| 0 | Male | No | 0 | Graduate | No | 5849 | 0.0 | 128.0 |
| 1 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 128.0 |
| 2 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 66.0 |
| 3 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 120.0 |
| 4 | Male | No | 0 | Graduate | No | 6000 | 0.0 | 141.0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 609 | Female | No | 0 | Graduate | No | 2900 | 0.0 | 71.0 |
| 610 | Male | Yes | 3 | Graduate | No | 4106 | 0.0 | 40.0 |
| 611 | Male | Yes | 1 | Graduate | No | 8072 | 240.0 | 253.0 |
| 612 | Male | Yes | 2 | Graduate | No | 7583 | 0.0 | 187.0 |
| 613 | Female | No | 0 | Graduate | Yes | 4583 | 0.0 | 133.0 |

614 rows × 12 columns



In [202]:

Y

```
Out[202]: 0      1
          1      0
          2      1
          3      1
          4      1
          ..
        609      1
        610      1
        611      1
        612      1
        613      0
Name: Loan_Status, Length: 614, dtype: int64
```

In [203]: columns = X.columns

```
cat_col= [col for col in X.columns if X[col].dtypes=='O']
cat_col
```

```
Out[203]: ['Gender',
           'Married',
           'Dependents',
           'Education',
           'Self_Employed',
           'Property_Area']
```

```
In [204]: dummy = pd.get_dummies(X[cat_col])
dummy.shape
```

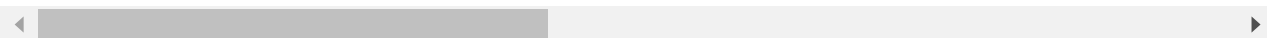
```
Out[204]: (614, 15)
```

In [205]: dummy

Out[205]:

| | Gender_Female | Gender_Male | Married_No | Married_Yes | Dependents_3 | Dependents_0 | Dependents_1 | Depei |
|-----|---------------|-------------|------------|-------------|--------------|--------------|--------------|-------|
| 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | |
| 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | |
| 2 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | |
| 3 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | |
| 4 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | |
| ... | ... | ... | ... | ... | ... | ... | ... | |
| 609 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 610 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 611 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | |
| 612 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | |
| 613 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |

614 rows × 15 columns



```
In [206]: final = pd.concat([X,dummy],axis=1)
          final.shape
```

Out[206]: (614, 27)

```
In [207]: final.drop(cat_col,inplace=True,axis=1)
```

```
In [208]: final.shape
```

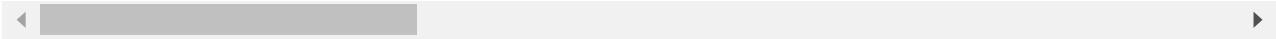
Out[208]: (614, 21)

```
In [209]: final
```

Out[209]:

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | NormLoanAmount | G |
|-----|-----------------|-------------------|------------|------------------|----------------|----------------|-----|
| 0 | 5849 | 0.0 | 128.0 | 360.0 | 1.0 | 4.852030 | |
| 1 | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 | 4.852030 | |
| 2 | 3000 | 0.0 | 66.0 | 360.0 | 1.0 | 4.189655 | |
| 3 | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 | 4.787492 | |
| 4 | 6000 | 0.0 | 141.0 | 360.0 | 1.0 | 4.948760 | |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 609 | 2900 | 0.0 | 71.0 | 360.0 | 1.0 | 4.262680 | |
| 610 | 4106 | 0.0 | 40.0 | 180.0 | 1.0 | 3.688879 | |
| 611 | 8072 | 240.0 | 253.0 | 360.0 | 1.0 | 5.533389 | |
| 612 | 7583 | 0.0 | 187.0 | 360.0 | 1.0 | 5.231109 | |
| 613 | 4583 | 0.0 | 133.0 | 360.0 | 0.0 | 4.890349 | |

614 rows × 21 columns

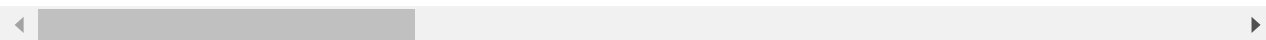


In [210]: `X=final`
`X`

Out[210]:

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | NormLoanAmount | G |
|-----|-----------------|-------------------|------------|------------------|----------------|----------------|-----|
| 0 | 5849 | 0.0 | 128.0 | 360.0 | 1.0 | 4.852030 | |
| 1 | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 | 4.852030 | |
| 2 | 3000 | 0.0 | 66.0 | 360.0 | 1.0 | 4.189655 | |
| 3 | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 | 4.787492 | |
| 4 | 6000 | 0.0 | 141.0 | 360.0 | 1.0 | 4.948760 | |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 609 | 2900 | 0.0 | 71.0 | 360.0 | 1.0 | 4.262680 | |
| 610 | 4106 | 0.0 | 40.0 | 180.0 | 1.0 | 3.688879 | |
| 611 | 8072 | 240.0 | 253.0 | 360.0 | 1.0 | 5.533389 | |
| 612 | 7583 | 0.0 | 187.0 | 360.0 | 1.0 | 5.231109 | |
| 613 | 4583 | 0.0 | 133.0 | 360.0 | 0.0 | 4.890349 | |

614 rows × 21 columns



In [211]: `Y`

Out[211]:

```

0      1
1      0
2      1
3      1
4      1
..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status, Length: 614, dtype: int64

```

In [212]: `x_train,x_test,y_train,y_test = train_test_split(X,Y, test_size = 0.2)`

LogisticRegression

In [213]: `clf = LogisticRegression()`

In [214]: `x_train.shape,x_test.shape`

Out[214]: `((491, 21), (123, 21))`

```
In [215]: clf.fit(x_train,y_train)
```

D:\New folder\Lib\site-packages\sklearn\linear_model_logistic.py:460: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html> (<https://scikit-learn.org/stable/modules/preprocessing.html>)

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression ([http://scikit-learn.org/stable/modules/linear_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression))

```
Out[215]: LogisticRegression
LogisticRegression()
```

```
In [216]: pred = clf.predict(x_test)
```

```
In [217]: pred
```

```
Out[217]: array([1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1,
                0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1,
                1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1,
                1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0], dtype=int64)
```

```
In [218]: accuracy_score(y_test,pred)
```

```
Out[218]: 0.7560975609756098
```

```
In [219]: f1_score(y_test,pred)
```

```
Out[219]: 0.8295454545454545
```

```
In [220]: precision_score(y_test,pred)
```

```
Out[220]: 0.73
```

```
In [221]: recall_score(y_test,pred)
```

```
Out[221]: 0.9605263157894737
```

```
In [222]: confusion_matrix(y_test,pred)
```

```
Out[222]: array([[20, 27],
                [ 3, 73]], dtype=int64)
```

```
In [223]: from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
```

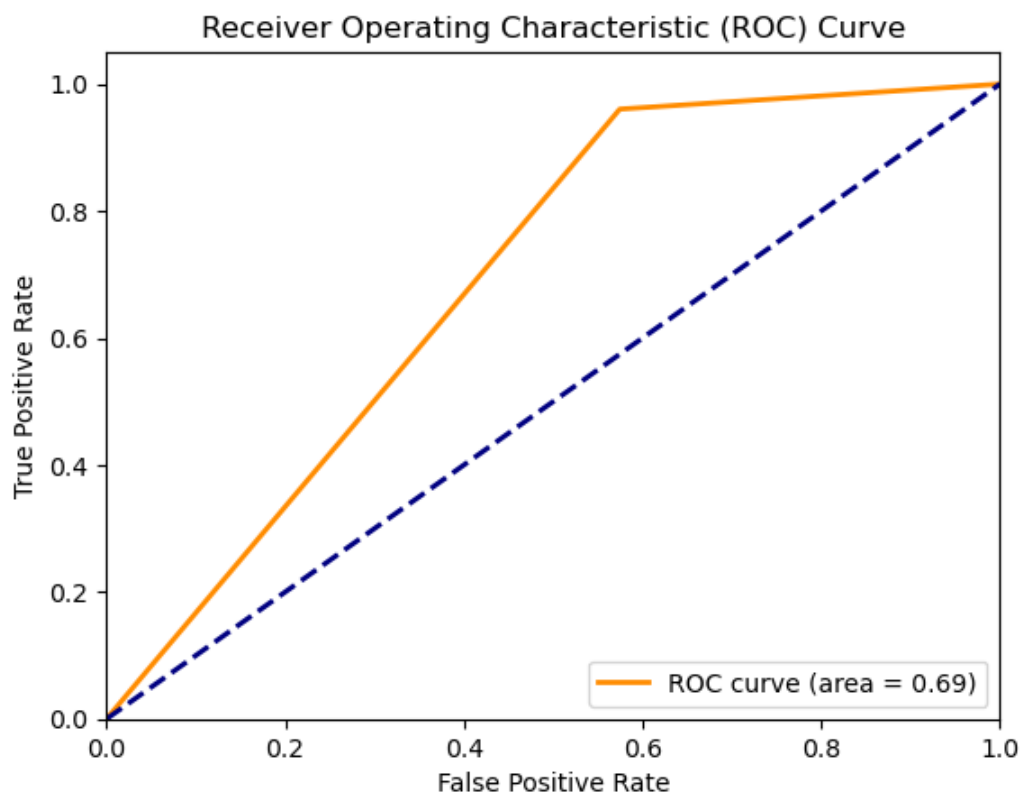


```
In [224]: fpr, tpr, thresholds = roc_curve(y_test, pred)
```

```
In [225]: roc_auc = auc(fpr, tpr)
print("ROC AUC:", roc_auc)
```

ROC AUC: 0.6930291153415453

```
In [226]: plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



Dicision_Tree

```
In [227]: dct = tree.DecisionTreeClassifier()
```

```
In [228]: dct.fit(x_train, y_train)
```

```
Out[228]: ▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

```
In [229]: pred = dct.predict(x_test)
```

```
In [230]: pred
```

```
Out[230]: array([1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1,
                1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1,
                1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1,
                1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1,
                1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1,
                1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
```

```
In [231]: accuracy_score(y_test, pred)
```

```
Out[231]: 0.6422764227642277
```

```
In [232]: f1_score(y_test, pred)
```

```
Out[232]: 0.725
```

```
In [233]: precision_score(y_test, pred)
```

```
Out[233]: 0.6904761904761905
```

```
In [234]: recall_score(y_test, pred)
```

```
Out[234]: 0.7631578947368421
```

```
In [235]: confusion_matrix(y_test, pred)
```

```
Out[235]: array([[21, 26],
                [18, 58]], dtype=int64)
```

```
In [236]: roc_auc_score(y_test, pred)
```

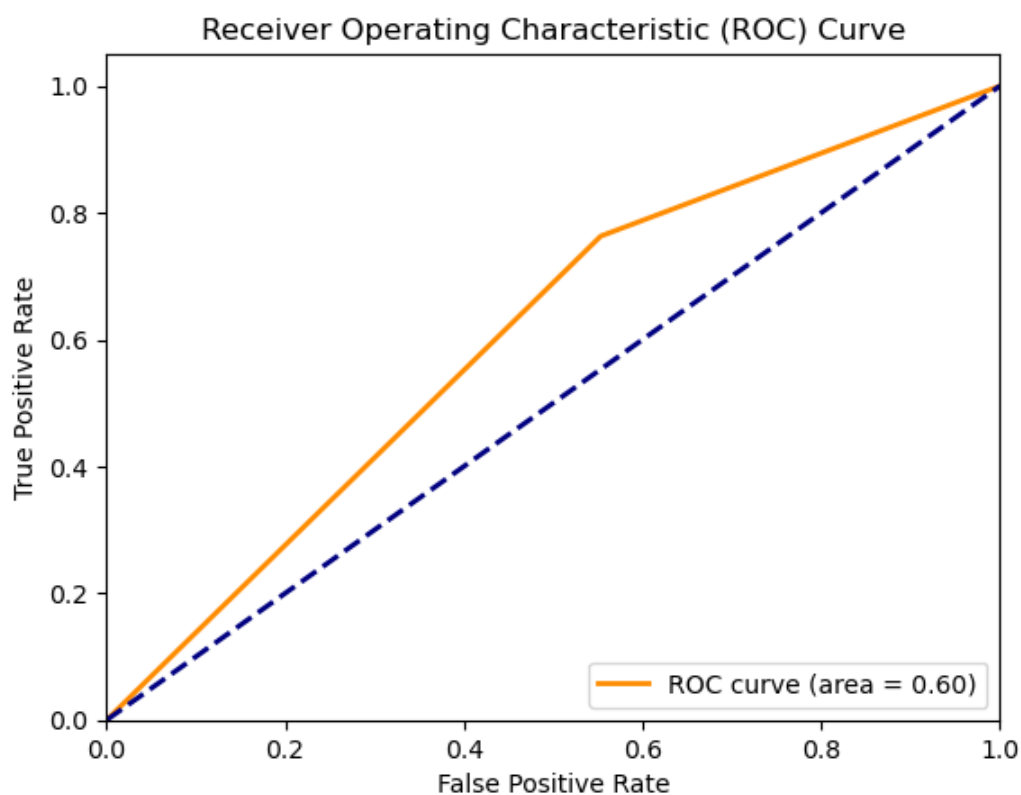
```
Out[236]: 0.6049832026875699
```

```
In [237]: import matplotlib.pyplot as plt

          from sklearn.metrics import RocCurveDisplay
```

```
In [238]: fpr, tpr, thresholds = roc_curve(y_test, pred)
roc_auc = auc(fpr, tpr)
print("ROC AUC:", roc_auc)
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

ROC AUC: 0.6049832026875699



In []:

In []:

Random Forest

```
In [239]: rfc=RandomForestClassifier()
```

```
In [240]: rfc.fit(x_train,y_train)
```

```
Out[240]: ▾ RandomForestClassifier  
RandomForestClassifier()
```

```
In [241]: pred=rfc.predict(x_test)
```

```
In [242]: accuracy_score(y_test,pred)
```

```
Out[242]: 0.7398373983739838
```

```
In [243]: precision_score(y_test,pred)
```

```
Out[243]: 0.72
```

```
In [244]: recall_score(y_test,pred)
```

```
Out[244]: 0.9473684210526315
```

```
In [245]: f1_score(y_test,pred)
```

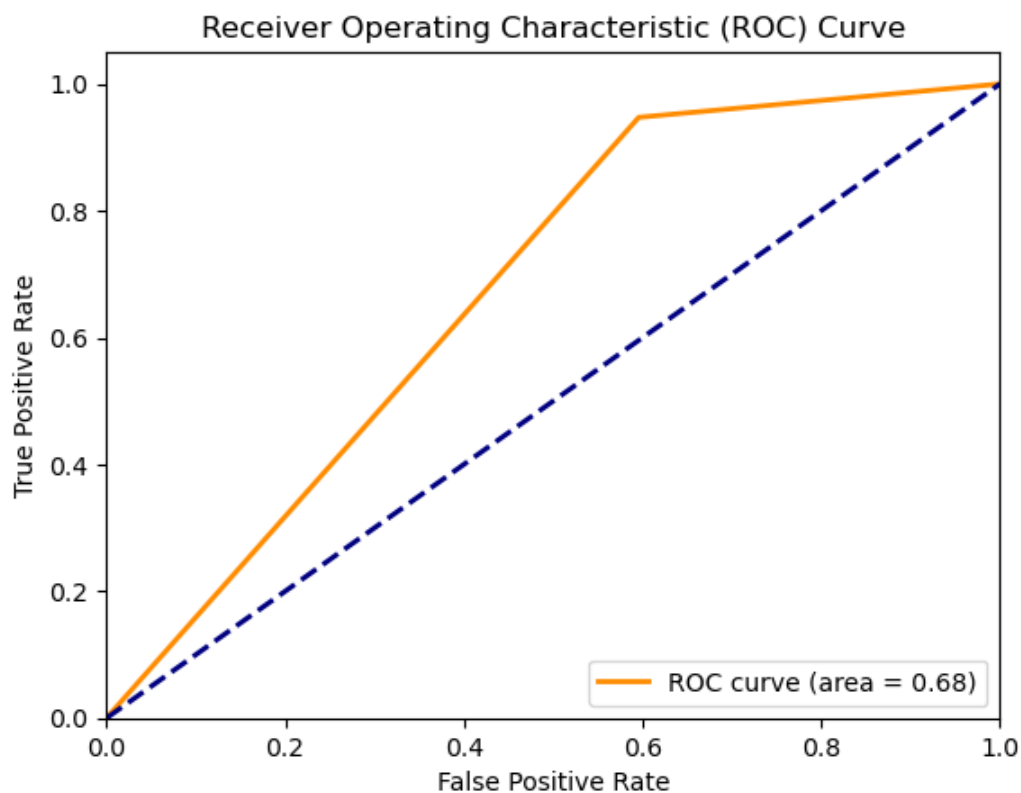
```
Out[245]: 0.8181818181818181
```

```
In [246]: confusion_matrix(y_test,pred)
```

```
Out[246]: array([[19, 28],  
                [ 4, 72]], dtype=int64)
```

```
In [247]: fpr, tpr, thresholds = roc_curve(y_test, pred)
roc_auc = auc(fpr, tpr)
print("ROC AUC:", roc_auc)
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

ROC AUC: 0.6758118701007838



In []:

In []:

In []:

In []: