Github Repository URL

[Link to our repo]()

1. Problem Statement

BC Finance plans to improve its loan application process by using a real-time automated system. They asked us to help complete their plan. This system intends to evaluate client information given via online application forms in a timely and accurate manner. Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, and Credit History are some of the important data factors reviewed during the eligibility examination. The organization has realized they need to identify certain consumer categories that are more likely to qualify for loans, allowing for more targeted and effective marketing campaigns. BC Finance has given us a partial dataset for this project, which can be found in the "data-for-project-1" folder, to help design a system that can anticipate loan eligibility in real time and properly categorize consumers.

2. Hypothesis Generation

Based on the variables impacting the loan application process at BC Finance, we developed various hypotheses to better understand the influence of socioeconomic characteristics on loan approval outcomes. First, we assume that candidates with no credit history are less likely to be accepted than those with a favourable credit record, emphasizing the relevance of credit history in risk assessment. Second, we believe that the ratio of an applicant's income to their requested loan amount has a major impact on acceptance decisions, with bigger loan requests resulting in more disapprovals due to heightened risk perceptions. Furthermore, we argue that including a co-applicant with a consistent income may increase the chance of loan acceptance by mitigating the risks associated with insufficient main income or low credit. However, dependents might lower the probability of approval due to fact that they consume a portion of the monthly income. This increases directly proportionally to the number of dependents. Finally, we believe that work stability is important, with candidates in stable employment positions more likely to receive loan approval due to a perceived lower chance of default. These hypotheses seek to systematically investigate how these selected socioeconomic characteristics influence the chance of loan refusal or acceptance.

3. Prepare Data

In [1]:

```
# Importing the libraries
import numpy as np
import pandas as pd
```

In [2]:

```
# Importing the dataset
df = pd.read_csv('../../data/raw_data.csv')
print(df.info())
df.head()
```

```
<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
None
```

Out[2]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Lo
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	

Understanding each feature

- **Loan_ID:** Identification (Primary Key) of each applicant
- **Gender:** Applicant's gender
- **Married:** Applicant's marital status (Is the applicant married or not?)
- **Dependents:** The amount of people that are dependant of the applicant (eg. Children)
- **Education:** Applicant's education level
- **Self_Employed:** Applicant's type of employment (Do they work for themselves)
- **ApplicantIncome:** Applicant's income
- **CoapplicantIncome:** The co-applicant's income
- **LoanAmount:** The amount that the applicant wants to loan
- **Loan_Amount_Term:** The term for which the loan will be payed back
- **Credit_History:** Applicant's credit history
- **Property_Area:** The type of area in which the applicant wants to buy a home
- **Loan_Status:** This indicated whether the applicant is approved for the home loan or not

In [3]:

```
# Remove irrelevant columns
df.drop(columns='Loan_ID', inplace=True)
```

4. Exploratory Data Analysis (EDA)

i) Univariate Analysis

Displaying the data

In [4]:

```
df.sample(5)
```

Out[4]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amou
				Not					

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amou
471	Male	Yes	1	Not Graduate	No	2653	1500.0	113.0	
179	Male	No	0	Not Graduate	No	2333	1451.0	102.0	
387	Male	Yes	0	Not Graduate	No	3010	3136.0	NaN	
21	Male	Yes	1	Graduate	No	5955	5625.0	315.0	
351	Male	No	0	Graduate	No	8750	4167.0	308.0	

Check dimensions of the dataframe

In [5]:

```
df.describe()
```

Out[5]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

Visualizing categorical and numerical columns separately

Import necessary libraries

In [6]:

```
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
```

Categorical Visualization

In [7]:

```
fig = px.box(
    data_frame= df,
    x='ApplicantIncome',
    orientation='h',
    title='Boxplot of the Target (Applicant_Income) - With Outliers'
)

fig.update_layout(xaxis_title='Target')
fig.show()
```

In [8]:

```
fig = px.box(
    data_frame= df,
    x='CoapplicantIncome',
    orientation='h',
```

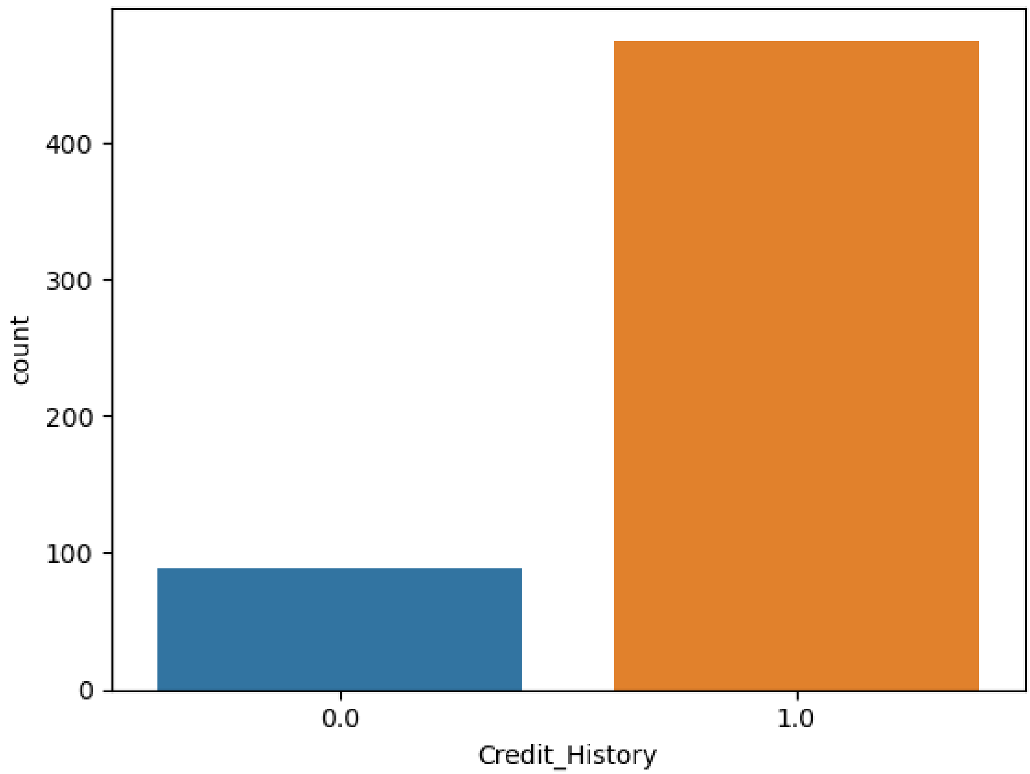
```
    title='Boxplot of the Target (Coapplicant_Income) - With Outliers'
)

fig.update_layout(xaxis_title='Target')
fig.show()
```

In [9]:

```
sns.countplot(x='Credit_History', data=df)
```

Out[9]:

<Axes: xlabel='Credit_History', ylabel='count'>



Comparing Yes and No Loan Statuses for Categorical Imbalances

In [10]:

```
labels = (
    df['Loan_Status']
    .astype('str')
    .str.replace('0','No', regex=True)
    .str.replace('1','Yes', regex=True)
    .value_counts()
)

fig = px.bar(
    data_frame=labels,
    x=labels.index,
    y=labels.values,
    title=f'Class Imbalance',
    color=labels.index
)

fig.update_layout(xaxis_title='Loan Status', yaxis_title='Number of Loan Applicants')
fig.show()
```

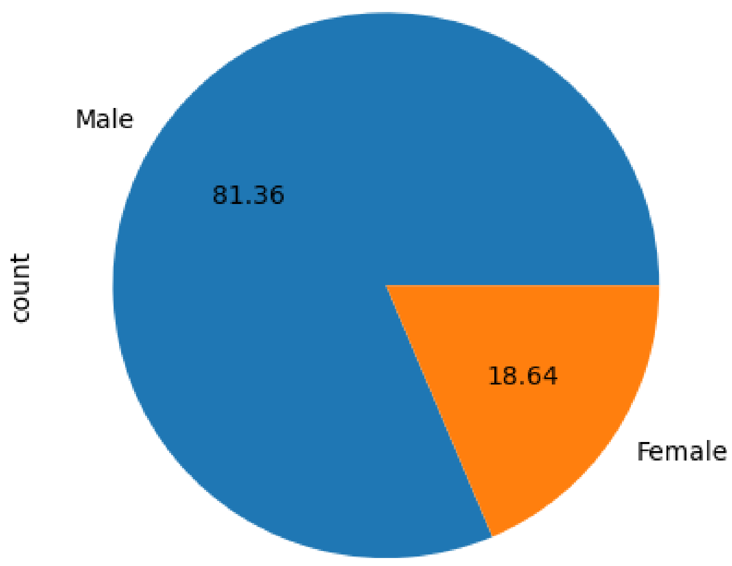
What is the percentage of Gender between male and female

In [11]:

```
df['Gender'].value_counts().plot(kind='pie',autopct='%.2f')
```

Out[11]:

<Axes: ylabel='count'>



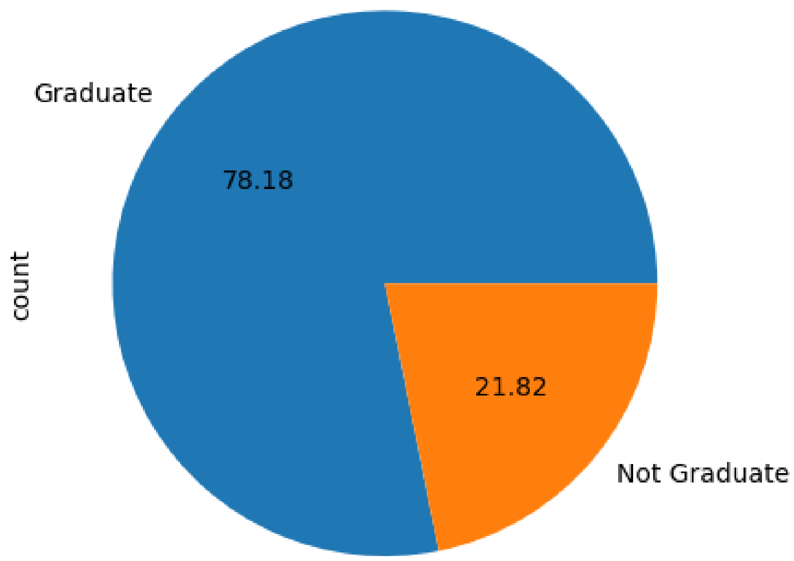
What is the percentage of people who are gradutes and not graduates

In [12]:

```
df['Education'].value_counts().plot(kind='pie',autopct='%.2f')
```

Out[12]:

<Axes: ylabel='count'>



ii) Bivariate Analysis

1. applicant income and loan status numerical and categorical

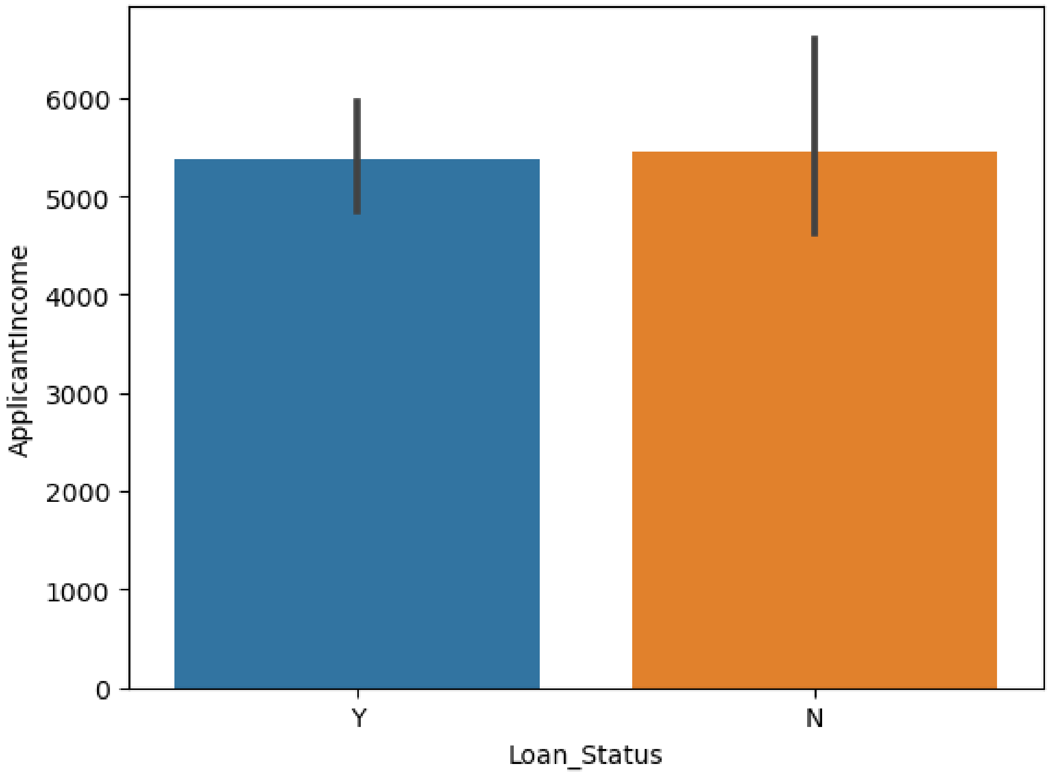
In [13]:

```
sns.barplot(x = 'Loan_Status' , y='ApplicantIncome' , data=df )
```

```
sns.barplot(x = 'Loan_Status' , y= 'ApplicantIncome' , data=df)
```

Out[13]:

```
<Axes: xlabel='Loan_Status', ylabel='ApplicantIncome'>
```



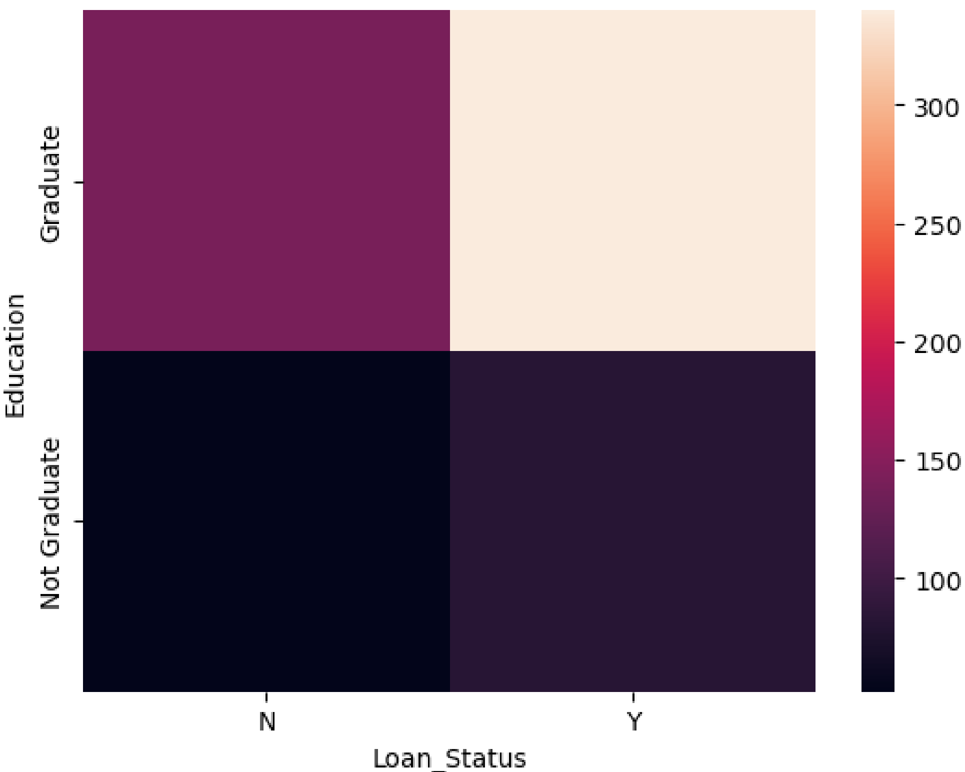
2 .Education and loan status

In [14]:

```
sns.heatmap(pd.crosstab(df['Education'] , df['Loan_Status']))
```

Out[14]:

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



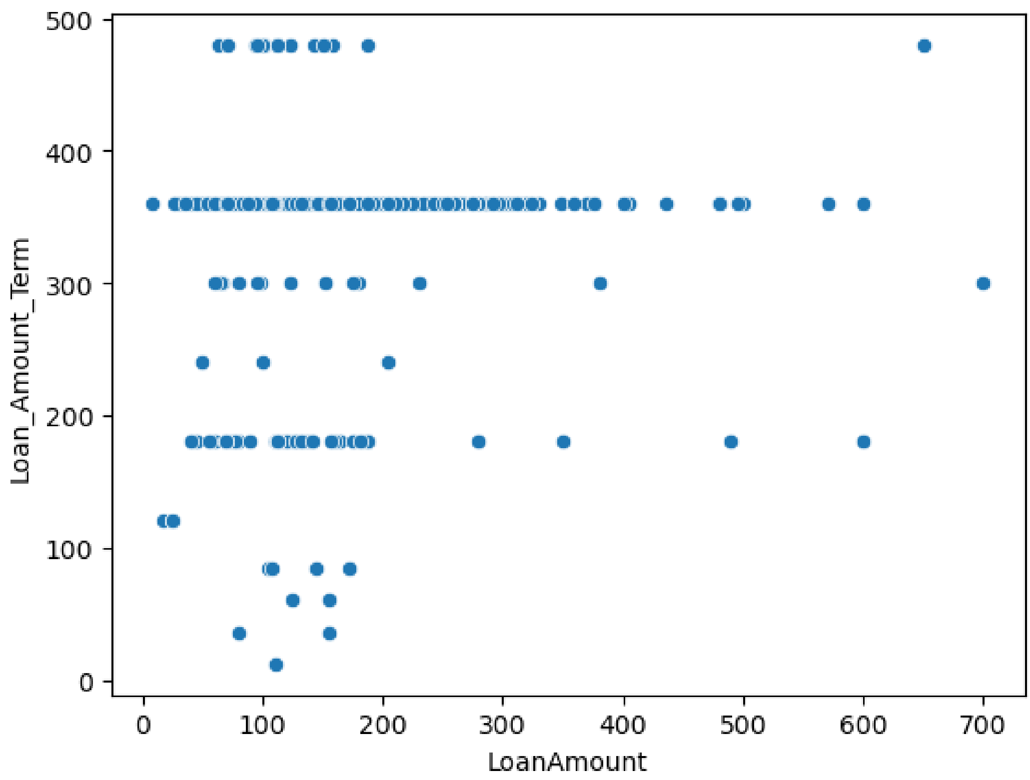
3. loan_amount and loan_amount_term

In [15]:

```
sns.scatterplot( x = 'LoanAmount' , y = 'Loan_Amount_Term' , data=df )
```

Out[15]:

```
&lt;Axes: xlabel='LoanAmount', ylabel='Loan_Amount_Term'&gt;
```



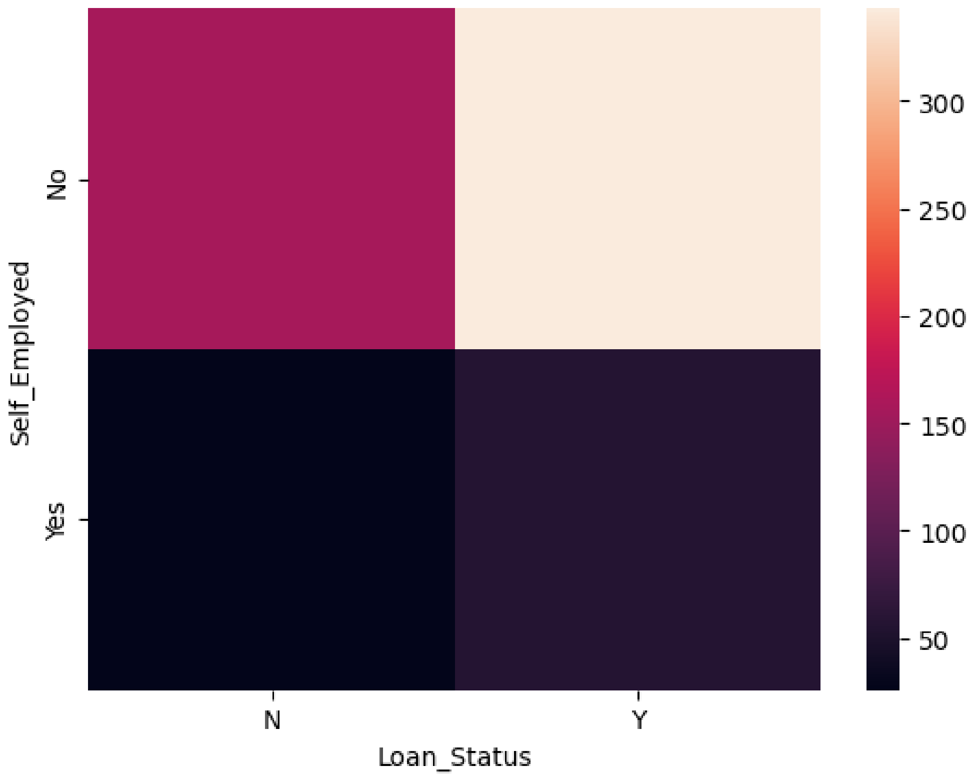
4. Self-employmed and loan status

In [16]:

```
sns.heatmap(pd.crosstab(df['Self_Employed'] , df['Loan_Status']))
```

Out[16]:

```
&lt;Axes: xlabel='Loan_Status', ylabel='Self_Employed'&gt;
```



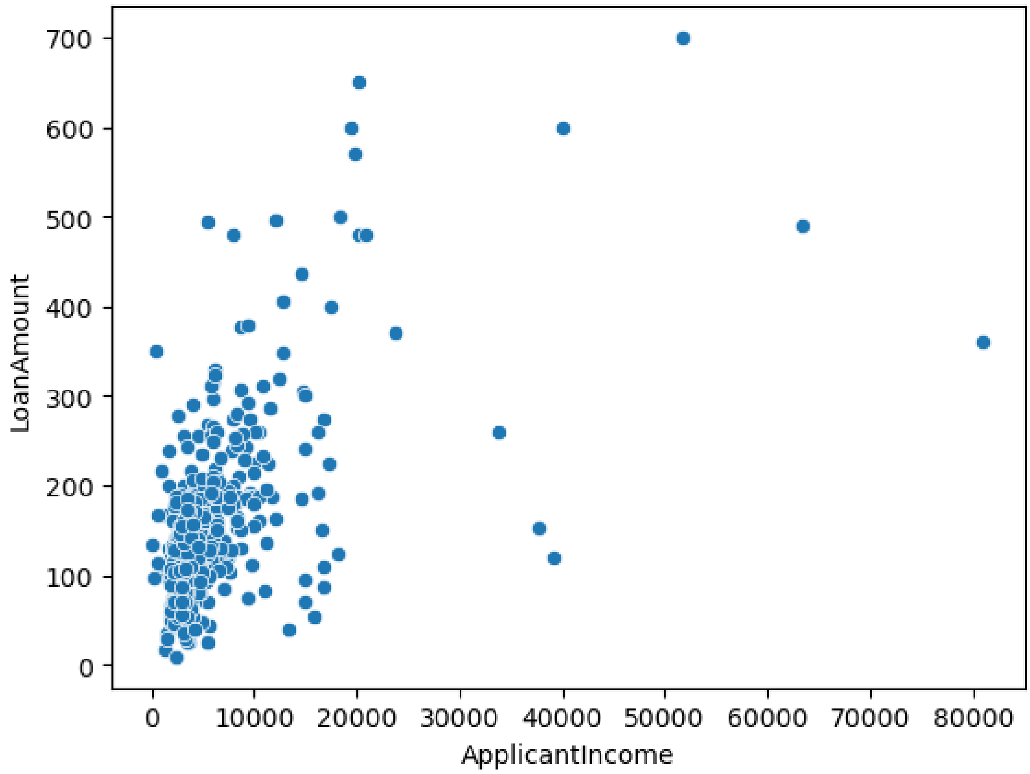
5. Applicant income and loan amount

In [17]:

```
sns.scatterplot( x = 'ApplicantIncome' , y = 'LoanAmount' , data=df )
```

Out[17]:

```
<Axes: xlabel='ApplicantIncome', ylabel='LoanAmount'>
```



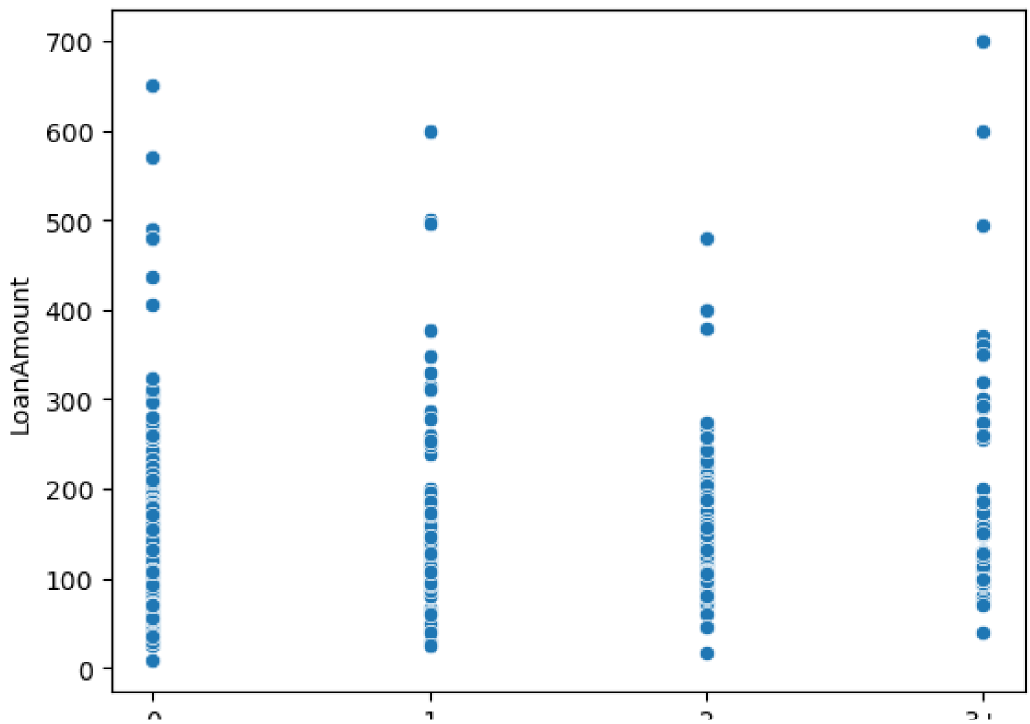
6. Dependents and loan amount

In [18]:

```
sns.scatterplot( x = 'Dependents' , y = 'LoanAmount' , data = df)
```

Out[18]:

```
<Axes: xlabel='Dependents', ylabel='LoanAmount'>
```



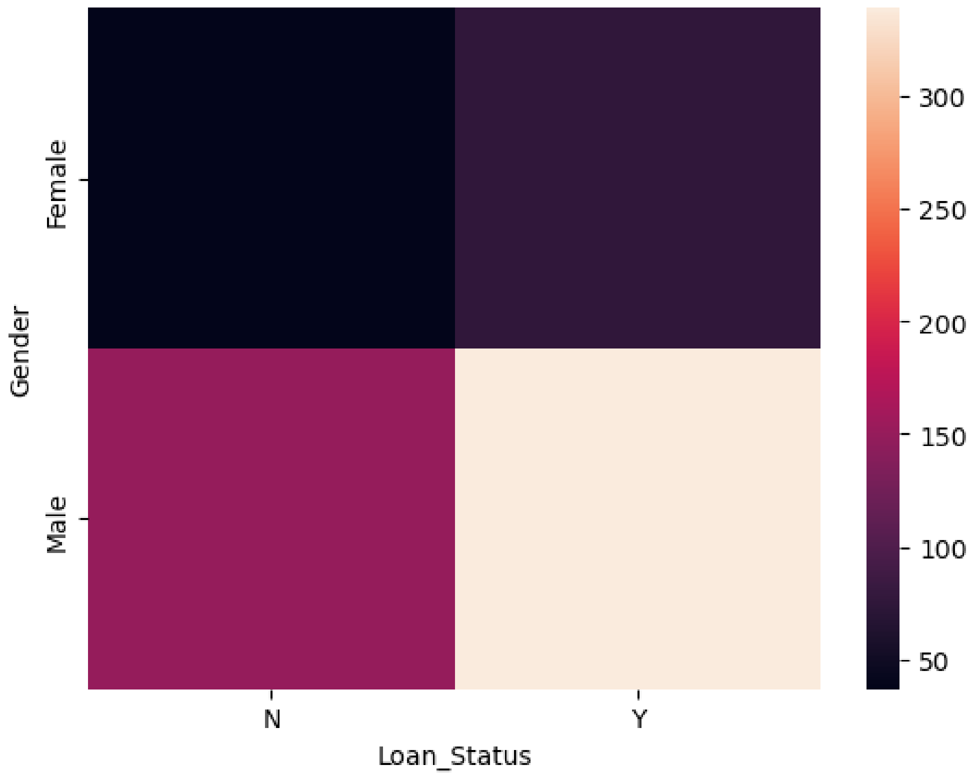
7. Gender and loan status

In [19]:

```
sns.heatmap(pd.crosstab(df['Gender'] , df['Loan_Status']))
```

Out[19]:

```
<Axes: xlabel='Loan_Status', ylabel='Gender'>
```



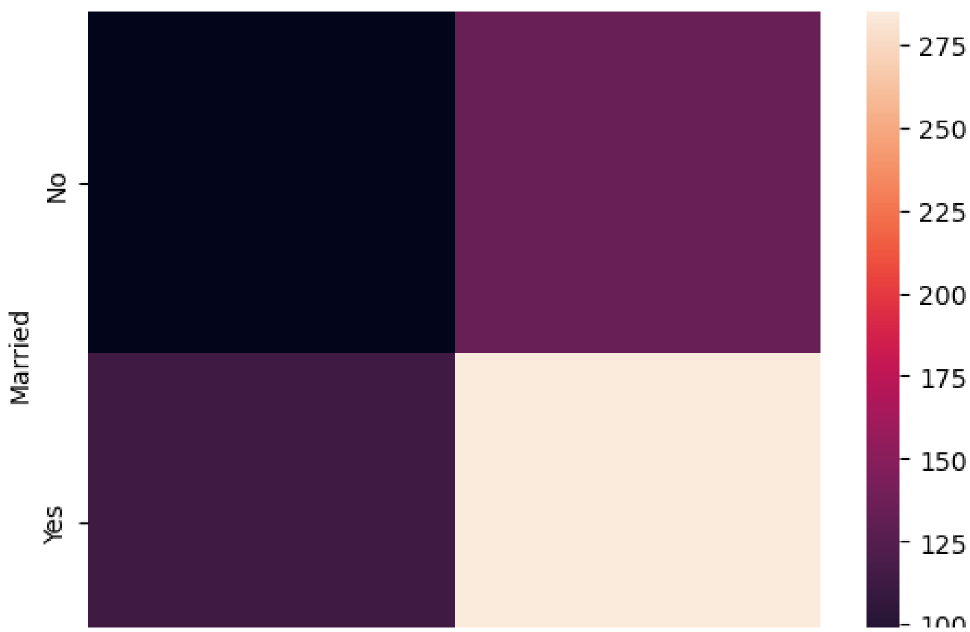
8. Married and loan status

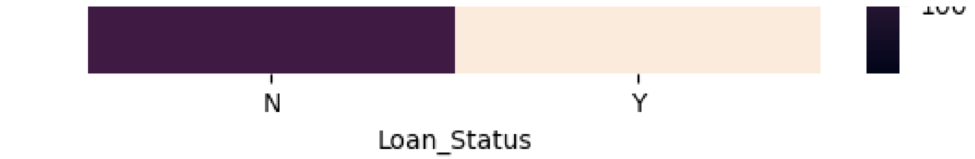
In [20]:

```
sns.heatmap(pd.crosstab(df['Married'] , df['Loan_Status']))
```

Out[20]:

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





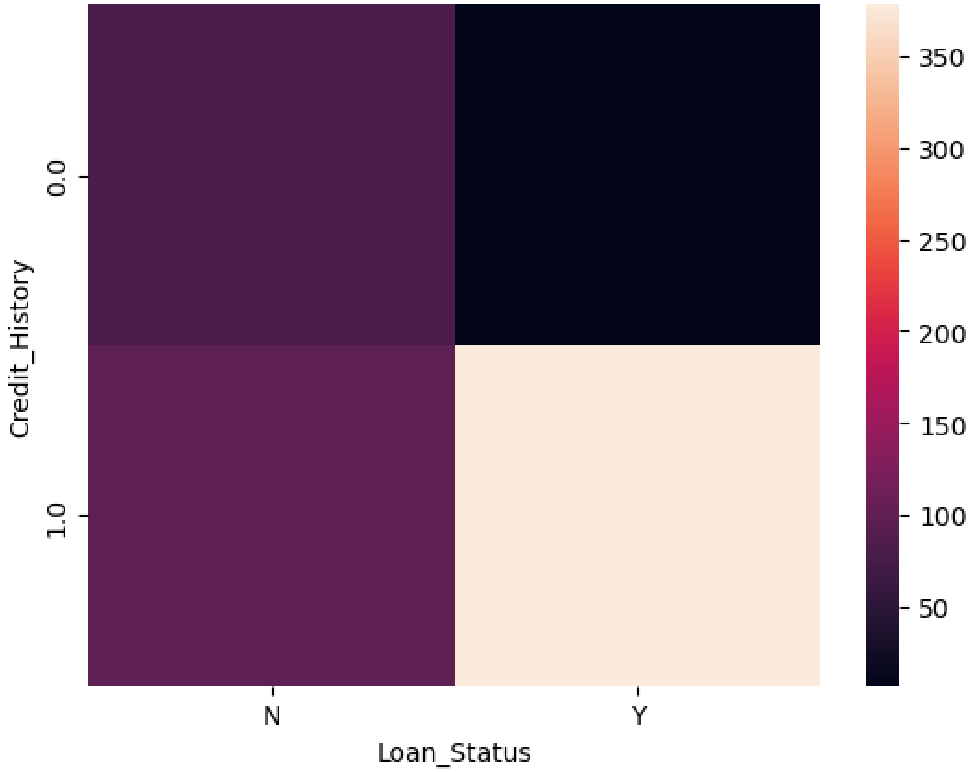
9. Credit history and loan status

In [21]:

```
sns.heatmap(pd.crosstab(df['Credit_History'] , df['Loan_Status']))
```

Out[21]:

```
<Axes: xlabel='Loan_Status', ylabel='Credit_History'>
```



5. Preprocess Data

Analyze the data

In [22]:

```
import skimpy as sk
sk.skim(df)
```

```
╭──────────────────────────────────────────────── skimpy summary ─────────────────────────────────────────╮
│          Data Summary                        Data Types
│ ┏━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━┓ ┏━━━━━━━━━━━━━┳━━━━━━━┓
│ ┃ dataframe           ┃ Values ┃ ┃ Column Type ┃ Count ┃
│ ┡━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━┩ ┡━━━━━━━━━━━━━╇━━━━━━━┩
│ │ Number of rows      │ 614    │ │ string      │ 7     │
│ │ Number of columns   │ 12     │ │ float64     │ 4     │
```

int32	1

number

column_name	NA	NA %	mean	sd	p0	p25	p50	p75	p100	hist
ApplicantIncome	0	0	5400	6100	150	2900	3800	5800	81000	█
CoapplicantIncome	0	0	1600	2900	0	0	1200	2300	42000	█
LoanAmount	22	3.58	150	86	9	100	130	170	700	█▁
Loan_Amount_Term	14	2.28	340	65	12	360	360	360	480	▁ █
Credit_History	50	8.14	0.84	0.36	0	1	1	1	1	▁ █

string

column_name	NA	NA %	words per row	total words
Gender	13	2.12	0.98	601
Married	3	0.49	1	611
Dependents	15	2.44	0.98	599
Education	0	0	1.2	748
Self_Employed	32	5.21	0.95	582
Property_Area	0	0	1	614
Loan_Status	0	0	1	614

End

Handling incomplete applications

In [23]:

```
# Remove rows with missing values
df.dropna(subset=['Gender', 'Dependents', 'LoanAmount', 'Loan_Amount_Term'], inplace=Tru
e)

print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 553 entries, 1 to 613
```

```
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             553 non-null    object 
 1   Married            553 non-null    object 
 2   Dependents         553 non-null    object 
 3   Education          553 non-null    object 
 4   Self_Employed      523 non-null    object 
 5   ApplicantIncome    553 non-null    int64  
 6   CoapplicantIncome  553 non-null    float64
 7   LoanAmount         553 non-null    float64
 8   Loan_Amount_Term   553 non-null    float64
 9   Credit_History     505 non-null    float64
 10  Property_Area      553 non-null    object 
 11  Loan_Status        553 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 56.2+ KB
None
```

Out[23]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount
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	
5	Male	Yes	2	Graduate	Yes	5417	4196.0	267.0	

Handling duplicate values

In [24]:

```
print(df.duplicated().value_counts())
df.drop_duplicates()
```

```
False    553
Name: count, dtype: int64
```

Out[24]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amou
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	
5	Male	Yes	2	Graduate	Yes	5417	4196.0	267.0	
...	...	...	...	...	...	...	...	...	
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	

553 rows × 12 columns

Handling high and low cardinality features

In [25]:

```
# checking the cardinality of features
df.select_dtypes("object").nunique()
```

Out[25]:

```
Gender           2
Married          2
Dependents       4
Education        2
Self_Employed    2
Property_Area    3
Loan_Status      2
dtype: int64
```

Handling empty cells

In [26]:

```
(df.isnull().sum()/len(df)*100).round(4)
```

Out[26]:

```
Gender               0.0000
Married              0.0000
Dependents           0.0000
Education            0.0000
Self_Employed        5.4250
ApplicantIncome      0.0000
CoapplicantIncome    0.0000
LoanAmount           0.0000
Loan_Amount_Term     0.0000
Credit_History       8.6799
Property_Area        0.0000
Loan_Status          0.0000
dtype: float64
```

Fill categorical value(s)

In [27]:

```
# Fill categorical value(s)
df['Self_Employed']=df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])

(df.isnull().sum()/len(df)*100).round(4)
```

Out[27]:

```
Gender               0.0000
Married              0.0000
Dependents           0.0000
Education            0.0000
Self_Employed        0.0000
ApplicantIncome      0.0000
CoapplicantIncome    0.0000
LoanAmount           0.0000
Loan_Amount_Term     0.0000
Credit_History       8.6799
Property_Area        0.0000
Loan_Status          0.0000
dtype: float64
```

Fill numerical value(s)

In [28]:

```
# Fill numerical value(s)
df['Credit_History'].fillna(df['Credit_History'].mean(), inplace=True)

(df.isnull().sum()/len(df)*100).round(4)
```

Out[28]:

```
Gender               0.0
Married              0.0
Dependents           0.0
Education            0.0
Self_Employed        0.0
ApplicantIncome      0.0
CoapplicantIncome    0.0
LoanAmount           0.0
Loan_Amount_Term     0.0
Credit_History       0.0
Property_Area        0.0
Loan_Status          0.0
dtype: float64
```

Outlier Treatment

Visualize the outliers of the numerical features

In [29]:

```
# Plot / Visualize the outliers of the numerical features
import matplotlib.pyplot as plt
import plotly.express as px

for col in df[['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term']
]:
    fig = px.box(
        data_frame=df,
        x=col,
        orientation='h',
        title=f'Boxplot of the Target ({col}) - With Outliers'
    )
    fig.show()
```

Handling outliers

In [30]:

```
# Create a mask to filter out the outliers for 'ApplicantIncome'
mask_ApplicantIncome = df['ApplicantIncome'] <= 7441

print(df[mask_ApplicantIncome].head())
print(df[mask_ApplicantIncome].info())

fig = px.box(
    data_frame=df[mask_ApplicantIncome],
    x='ApplicantIncome',
    orientation='h',
    title='Boxplot of the Target (ApplicantIncome) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
1   Male     Yes          1      Graduate            No             4583
2   Male     Yes          0      Graduate           Yes             3000
3   Male     Yes          0  Not Graduate            No             2583
4   Male      No          0      Graduate            No             6000
5   Male     Yes          2      Graduate           Yes             5417
```

```
   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

  Property_Area Loan_Status
1         Rural           N
2         Urban           Y
3         Urban           Y
4         Urban           Y
5         Urban           Y
<class 'pandas.core.frame.DataFrame'>
Index: 469 entries, 1 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Gender             469 non-null    object
 1   Married            469 non-null    object
 2   Dependents         469 non-null    object
 3   Education          469 non-null    object
 4   Self_Employed      469 non-null    object
 5   ApplicantIncome    469 non-null    int64
 6   CoapplicantIncome  469 non-null    float64
 7   LoanAmount         469 non-null    float64
 8   Loan_Amount_Term   469 non-null    float64
 9   Credit_History     469 non-null    float64
 10  Property_Area      469 non-null    object
 11  Loan_Status        469 non-null    object
dtypes: float64(4), int64(1), object(7)
memory usage: 47.6+ KB
None
```

In [31]:

```
# Create a mask to filter out the outliers for 'CoapplicantIncome'
mask_CoapplicantIncome = df['CoapplicantIncome'] <= 5302

print(df[mask_CoapplicantIncome].head())
print(df[mask_CoapplicantIncome].info())

fig = px.box(
    data_frame=df[mask_CoapplicantIncome],
    x='CoapplicantIncome',
    orientation='h',
    title='Boxplot of the Target (CoapplicantIncome) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
1   Male     Yes          1      Graduate            No             4583
2   Male     Yes          0      Graduate           Yes             3000
3   Male     Yes          0  Not Graduate            No             2583
4   Male      No          0      Graduate            No             6000
5   Male     Yes          2      Graduate           Yes             5417

   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

  Property_Area Loan_Status
1         Rural           N
2         Urban           Y
3         Urban           Y
4         Urban           Y
5         Urban           Y
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 528 entries, 1 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             528 non-null    object 
 1   Married            528 non-null    object 
 2   Dependents         528 non-null    object 
 3   Education          528 non-null    object 
 4   Self_Employed      528 non-null    object 
 5   ApplicantIncome    528 non-null    int64  
 6   CoapplicantIncome  528 non-null    float64
 7   LoanAmount         528 non-null    float64
 8   Loan_Amount_Term   528 non-null    float64
 9   Credit_History     528 non-null    float64
 10  Property_Area      528 non-null    object 
 11  Loan_Status        528 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 53.6+ KB
None
```

In [32]:

```
# Create a mask to filter out the outliers for 'LoanAmount'
mask_LoanAmount1 = df['LoanAmount'] >= 25
mask_LoanAmount2 = df['LoanAmount'] <= 230

print(df[mask_LoanAmount1].head())
print(df[mask_LoanAmount2].info())

fig = px.box(
    data_frame=df[mask_LoanAmount1 & mask_LoanAmount2],
    x='LoanAmount',
    orientation='h',
    title='Boxplot of the Target (LoanAmount) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
1   Male     Yes          1      Graduate            No             4583   
2   Male     Yes          0      Graduate           Yes             3000   
3   Male     Yes          0  Not Graduate            No             2583   
4   Male      No          0      Graduate            No             6000   
5   Male     Yes          2      Graduate           Yes             5417   

   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   

  Property_Area Loan_Status  
1         Rural           N  
2         Urban           Y  
3         Urban           Y  
4         Urban           Y  
5         Urban           Y  
<class 'pandas.core.frame.DataFrame'>
Index: 495 entries, 1 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             495 non-null    object 
 1   Married            495 non-null    object 
 2   Dependents         495 non-null    object 
 3   Education          495 non-null    object 
 4   Self_Employed      495 non-null    object 
 5   ApplicantIncome    495 non-null    int64  
 6   CoapplicantIncome  495 non-null    float64
 7   LoanAmount         495 non-null    float64
```

```
 8   Loan_Amount_Term   495 non-null    float64
 9   Credit_History     495 non-null    float64
 10  Property_Area      495 non-null    object 
 11  Loan_Status        495 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 50.3+ KB
None
```

In [33]:

```
# Create a mask to filter out the outliers for 'LoanAmount'
mask_Loan_Amount_Term = df['Loan_Amount_Term'] == 360

print(df[mask_Loan_Amount_Term].head())
print(df[mask_Loan_Amount_Term].info())

fig = px.box(
    data_frame=df[mask_Loan_Amount_Term],
    x='Loan_Amount_Term',
    orientation='h',
    title='Boxplot of the Target (Loan_Amount_Term) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
1   Male     Yes          1      Graduate            No             4583   
2   Male     Yes          0      Graduate           Yes             3000   
3   Male     Yes          0  Not Graduate            No             2583   
4   Male      No          0      Graduate            No             6000   
5   Male     Yes          2      Graduate           Yes             5417   

   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   

  Property_Area Loan_Status  
1         Rural           N  
2         Urban           Y  
3         Urban           Y  
4         Urban           Y  
5         Urban           Y  
<class 'pandas.core.frame.DataFrame'>
Index: 473 entries, 1 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             473 non-null    object 
 1   Married            473 non-null    object 
 2   Dependents         473 non-null    object 
 3   Education          473 non-null    object 
 4   Self_Employed      473 non-null    object 
 5   ApplicantIncome    473 non-null    int64  
 6   CoapplicantIncome  473 non-null    float64
 7   LoanAmount         473 non-null    float64
 8   Loan_Amount_Term   473 non-null    float64
 9   Credit_History     473 non-null    float64
 10  Property_Area      473 non-null    object 
 11  Loan_Status        473 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 48.0+ KB
None
```

Filtering out the outliers

In [34]:

```
df = df[mask_ApplicantIncome & mask_CoapplicantIncome & mask_LoanAmount1 & mask_LoanAmou
```

```
nt2 & mask_Loan_Amount_Term]

print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 371 entries, 1 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             371 non-null    object 
 1   Married            371 non-null    object 
 2   Dependents         371 non-null    object 
 3   Education          371 non-null    object 
 4   Self_Employed      371 non-null    object 
 5   ApplicantIncome    371 non-null    int64  
 6   CoapplicantIncome  371 non-null    float64
 7   LoanAmount         371 non-null    float64
 8   Loan_Amount_Term   371 non-null    float64
 9   Credit_History     371 non-null    float64
 10  Property_Area      371 non-null    object 
 11  Loan_Status        371 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 37.7+ KB
None
```

Out[34]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount
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	
6	Male	Yes	0	Not Graduate	No	2333	1516.0	95.0	

Scaling

In [35]:

```
df['Loan_Status'] = df['Loan_Status'].map({'Y' : 1, 'N' : 0}).astype('int')
```

7. Modeling

Split Data

In [36]:

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split

X = df.drop(columns=['Loan_Status'], inplace=False)
y = df['Loan_Status']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

Model and Predict

In [37]:

```python
from sklearn.pipeline import make_pipeline
from category_encoders import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression

model_dt = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    DecisionTreeClassifier()) # build model

model_rf = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    RandomForestClassifier()) # build model

model_lr = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    LogisticRegression()) # build model

# fit the model
model_dt.fit(X_train, y_train)
model_rf.fit(X_train, y_train)
model_lr.fit(X_train, y_train)
```

Out[37]:

```
▸ Pipeline
▸ OneHotEncoder
▸ StandardScaler
▸ LogisticRegression
```

Accuracy of Model

In [38]:

```python
from sklearn.metrics import accuracy_score

y_pred = model_dt.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Decision Tree Accuracy:", (accuracy*100).__round__(4))

y_pred = model_rf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Random Forest Classifier:", (accuracy*100).__round__(4))

y_pred = model_lr.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Logistic Regression:", (accuracy*100).__round__(4))
```

```
Decision Tree Accuracy: 74.6667
Random Forest Classifier: 84.0
Logistic Regression: 86.6667
```

Evaluate

In [39]:

```python
from sklearn.metrics import mean_absolute_error

# Decision Tree
```

```
# Predict the train data
y_pred_training = model_dt.predict(X_train)
y_pred_test = model_dt.predict(X_test)

# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))

# Random Forest Regressor
# Predict the train data
y_pred_training = model_rf.predict(X_train)
y_pred_test = model_rf.predict(X_test)

# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))

# Logistic Regression
# Predict the train data
y_pred_training = model_lr.predict(X_train)
y_pred_test = model_lr.predict(X_test)

# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))
```

```
Training MAE: 0.0
Test data MAE: 0.25
Training MAE: 0.0
Test data MAE: 0.16
Training MAE: 0.18
Test data MAE: 0.13
```

In [40]:

```
def make_prediction(row):

    data = {
        "Gender": row[1],
        "Married": row[2],
        "Dependents": row[3],
        "Education": row[4],
        "Self_Employed": row[5],
        "ApplicantIncome": row[6],
        "CoapplicantIncome": row[7],
        "LoanAmount": row[8],
        "Loan_Amount_Term": row[9],
        "Credit_History": row[10],
        "Property_Area": row[11]
    }

    df_predict = pd.DataFrame(data, index=[0])
    prediction_dt = model_dt.predict(df_predict)[0]
    prediction_rf = model_rf.predict(df_predict)[0]
    prediction_lr = model_lr.predict(df_predict)[0]
    return f"Decision Tree: {prediction_dt}; Random Forest: {prediction_rf} Logistic Regr
ession: {prediction_lr}"
```

In [41]:

```
print(make_prediction(pd.Series(['dfgd', 'Male', 'Yes', '1', 'Graduate', 'No', 4583, 150
8.0, 128.0, 360.0, 1.0, 'Rural']))) # Should output 1
print(make_prediction(pd.Series(['dfgd', 'Male', 'No', '0', 'Graduate', 'No', 6000, 0.0,
141.0, 360.0, 1.0, 'Urban']))) # Should output 1
print(make_prediction(pd.Series(['dfgd', 'Female', 'No', '4', 'Not Graduate', 'Yes', 200
, 0.0, 1000.0, 360.0, 0.0, 'Rural']))) # Should output 0
```

```
Decision Tree: 0; Random Forest: 0 Logistic Regression: 1
Decision Tree: 1; Random Forest: 1 Logistic Regression: 1
Decision Tree: 0; Random Forest: 0 Logistic Regression: 0
```

In [42]:

In [42]:

```
df_val = pd.read_csv("../../data/validation.csv")

for i in range(0, 2):#df_val.shape[0]):
    row = df_val.iloc[i]
    print(make_prediction(row))
```

```
Decision Tree: 1; Random Forest: 1 Logistic Regression: 1
Decision Tree: 1; Random Forest: 1 Logistic Regression: 1
```

```
C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:4: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:5: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:6: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:7: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:8: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:9: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:10: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:11: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:12: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:13: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:14: FutureWarning:
```

```
Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:4: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:5: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:6: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:7: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:8: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:9: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:10: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:11: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:12: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:13: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`

C:\Users\hroux\AppData\Local\Temp\ipykernel_234920\2255154042.py:14: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future version, integer
keys will always be treated as labels (consistent with DataFrame behavior). To access a v
alue by position, use `ser.iloc[pos]`
```

8. Feature Engineering

In [43]:

```
# Feature Engineering
df['Income'] = df['ApplicantIncome'] + df['CoapplicantIncome']
df.drop(columns=['ApplicantIncome', 'CoapplicantIncome'], inplace=True)
print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 371 entries, 1 to 613
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             371 non-null    object 
 1   Married            371 non-null    object 
 2   Dependents         371 non-null    object 
 3   Education          371 non-null    object 
 4   Self_Employed      371 non-null    object 
 5   LoanAmount         371 non-null    float64
 6   Loan_Amount_Term   371 non-null    float64
 7   Credit_History     371 non-null    float64
 8   Property_Area      371 non-null    object 
 9   Loan_Status        371 non-null    int32  
 10  Income             371 non-null    float64
dtypes: float64(4), int32(1), object(6)
memory usage: 33.3+ KB
None
```

Out[43]:

	Gender	Married	Dependents	Education	Self_Employed	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
1	Male	Yes	1	Graduate	No	128.0	360.0	1.0	Rural
2	Male	Yes	0	Graduate	Yes	66.0	360.0	1.0	Urban
3	Male	Yes	0	Not Graduate	No	120.0	360.0	1.0	Urban
4	Male	No	0	Graduate	No	141.0	360.0	1.0	Urban
6	Male	Yes	0	Not Graduate	No	95.0	360.0	1.0	Urban

9. Modeling (With Feature Engineering)

Split Data

In [44]:

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split

X = df.drop(columns=['Loan_Status'], inplace=False)
y = df['Loan_Status']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

Model and Predict

In [45]:

```
from sklearn.pipeline import make_pipeline
from category_encoders import OneHotEncoder
```

```python
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression

model_dt = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    DecisionTreeClassifier()) # build model

model_rf = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    RandomForestClassifier()) # build model

model_lr = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    LogisticRegression()) # build model

# fit the model
model_dt.fit(X_train, y_train)
model_rf.fit(X_train, y_train)
model_lr.fit(X_train, y_train)
```

Out[45]:

```
▸ Pipeline
▸ OneHotEncoder
▸ StandardScaler
▸ LogisticRegression
```

Accuracy of Model (With Feature Engineering)

In [46]:

```python
from sklearn.metrics import accuracy_score

y_pred = model_dt.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Decision Tree Accuracy:", (accuracy*100).__round__(4))

y_pred = model_rf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Random Forest Classifier:", (accuracy*100).__round__(4))

y_pred = model_lr.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Logistic Regression:", (accuracy*100).__round__(4))
```

```
Decision Tree Accuracy: 74.6667
Random Forest Classifier: 80.0
Logistic Regression: 86.6667
```

Evaluate

In [47]:

```python
from sklearn.metrics import mean_absolute_error

# Decision Tree
# Predict the train data
y_pred_training = model_dt.predict(X_train)
y_pred_test = model_dt.predict(X_test)
```

```
# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))

# Random Forest Regressor
# Predict the train data
y_pred_training = model_rf.predict(X_train)
y_pred_test = model_rf.predict(X_test)

# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))

# Logistic Regression
# Predict the train data
y_pred_training = model_lr.predict(X_train)
y_pred_test = model_lr.predict(X_test)

# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))
```

```
Training MAE: 0.0
Test data MAE: 0.25
Training MAE: 0.0
Test data MAE: 0.2
Training MAE: 0.18
Test data MAE: 0.13
```

In [48]:

```
def make_prediction_FE(row):

    data = {
        "Gender": row[0],
        "Married": row[1],
        "Dependents": row[2],
        "Education": row[3],
        "Self_Employed": row[4],
        "LoanAmount": row[5],
        "Loan_Amount_Term": row[6],
        "Credit_History": row[7],
        "Property_Area": row[8],
        "Income": row[9]
    }

    df_predict = pd.DataFrame(data, index=[0])
    prediction_dt = model_dt.predict(df_predict)[0]
    prediction_rf = model_rf.predict(df_predict)[0]
    prediction_lr = model_lr.predict(df_predict)[0]
    return f"Decision Tree: {prediction_dt}; Random Forest: {prediction_rf} Logistic Regr
ession: {prediction_lr}"
```

In [49]:

```
print(make_prediction_FE(pd.Series(['Male', 'Yes', '1', 'Graduate', 'No', 128.0, 360.0,
1.0, 'Rural', (4583 + 1508)]))) # Should output 1
print(make_prediction_FE(pd.Series(['Male', 'No', '0', 'Graduate', 'No', 141.0, 360.0, 1
.0, 'Urban', (6000 + 0)]))) # Should output 1
print(make_prediction_FE(pd.Series(['Female', 'No', '4', 'Not Graduate', 'Yes', 1000.0,
360.0, 0.0, 'Rural', (200 + 0)]))) # Should output 0
```

```
Decision Tree: 0; Random Forest: 0 Logistic Regression: 1
Decision Tree: 1; Random Forest: 1 Logistic Regression: 1
Decision Tree: 0; Random Forest: 0 Logistic Regression: 0
```

10. Dash App

In [50]:

```
import dash
from dash import dcc, html
from dash.dependencies import Input, Output
import joblib
import pandas as pd

# Load the trained model
model = joblib.load("../../artifacts/model_1.pkl")

# Initialize the Dash app
app = dash.Dash(__name__)

# Define the layout of the app
app.layout = html.Div([
    html.H1("Loan Prediction System"),
    html.Label("Gender"),
    dcc.Dropdown(
        id="gender-dropdown",
        options=[
            {'label': 'Male', 'value': 'Male'},
            {'label': 'Female', 'value': 'Female'}
        ],
        value='Male'
    ),
    html.Label("Married"),
    dcc.Dropdown(
        id="married-dropdown",
        options=[
            {'label': 'Yes', 'value': 'Yes'},
            {'label': 'No', 'value': 'No'}
        ],
        value='No'
    ),
    html.Label("Dependents"),
    dcc.Input(id="dependents-number",
        type="number",
        value=0
    ),
    html.Label("Education"),
    dcc.Dropdown(
        id="education-dropdown",
        options=[
            {'label': 'Graduate', 'value': 'Graduate'},
            {'label': 'Not Graduate', 'value': 'Not Graduate'}
        ],
        value='Not Graduate'
    ),
    html.Label("Self Employed"),
    dcc.Dropdown(
        id="self-employed-dropdown",
        options=[
            {'label': 'Yes', 'value': 'Yes'},
            {'label': 'No', 'value': 'No'}
        ],
        value='No'
    ),
    html.Label("Applicant's Income"),
    dcc.Input(id="applicantIncome", type="number", value=5000),
    html.Label("Co-Applicant's Income"),
    dcc.Input(id="coapplicantIncome", type="number", value=0),
    html.Label("Loan Amount"),
    dcc.Input(id="loan_amount", type="number", value=120),
    html.Label("Loan Term (months)"),
    dcc.Input(id="loan_term", type="number", value=360),
    html.Label("Credit History"),
    dcc.Dropdown(
        id="credit_history-dropdown",
        options=[
            {'label': 'Yes', 'value': 1},
            {'label': 'No', 'value': 0}
        ],
```

```
        value=0
    ),
    html.Label("Property Area"),
    dcc.Dropdown(
        id="property_area-dropdown",
        options=[
            {'label': 'Urban', 'value': 'Urban'},
            {'label': 'Semiurban', 'value': 'Semiurban'},
            {'label': 'Rural', 'value': 'Rural'}
        ],
        value='Urban'
    ),
    html.Button("Predict", id="predict_button", n_clicks=0),
    html.Div(id="prediction_output")
])

# Define callback to update prediction result
@app.callback(
    Output("prediction_output", "children"),
    [Input("predict_button", "n_clicks")],
    [Input("gender-dropdown", "value"),
     Input("married-dropdown", "value"),
     Input("dependents-number", "value"),
     Input("education-dropdown", "value"),
     Input("self-employed-dropdown", "value"),
     Input("applicantIncome", "value"),
     Input("coapplicantIncome", "value"),
     Input("loan_amount", "value"),
     Input("loan_term", "value"),
     Input("credit_history-dropdown", "value"),
     Input("property_area-dropdown", "value")]
)
def update_prediction(n_clicks, gender, married, dependents, education, self_employed, i
ncome, co_income, loan_amount, loan_term, credit_history, property_area):
    if n_clicks > 0:
        # Preprocess input data
        data = pd.DataFrame({
            "Gender": [gender],
            "Married": [married],
            "Dependents": [dependents],
            "Education": [education],
            "Self_Employed": [self_employed],
            "ApplicantIncome": [income],
            "CoapplicantIncome": [co_income],
            "LoanAmount": [loan_amount],
            "Loan_Amount_Term": [loan_term],
            "Credit_History": [credit_history],
            "Property_Area": [property_area]
        })
        # Make prediction
        prediction = model.predict(data)[0]
        return html.Div(f"Loan Status: {'Approved' if prediction == 1 else 'Rejected'}")
    else:
        return ""

# Run the app
if __name__ == "__main__":
    app.run_server(debug=True)
```