Loan Approval Prediction

Loan approval prediction involves the analysis of various factors, such as the applicant’s financial history, income, credit rating, employment status, and other relevant attributes. By leveraging historical loan data and applying machine learning algorithms, businesses can build models to determine loan approvals for new applicants.

In [1]:
```
#Let’s start this task by importing the necessary Python libraries and the datas
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier

df = pd.read_csv('loan_prediction.csv')
print(df.head())
```

```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
```

In [2]:
```
#I’ll drop the loan id column and move further:
df = df.drop('Loan_ID', axis=1)
```

In [3]:
```
#Now let’s have a look if the data has missing values or not:
df.isnull().sum()
```

Out[3]:
```
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 [4]:
```
#Let’s have a look at the descriptive statistics of the dataset before filling i
print(df.describe())
```

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

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

Now let’s fill in the missing values. In categorical columns, we can fill in missing values with the mode of each column.

In [5]:
```
# Fill missing values in categorical columns with mode
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['Self_Employed'].fillna(df['Self_Employed'].mode()[0], inplace=True)
```

We can fill in the missing values of the loan amount column with the median value. The median is an appropriate measure to fill in missing values when dealing with skewed distributions or when outliers are present in the data;

We can fill in the missing values of the loan amount term column with the mode value of the column. Since the term of the loan amount is a discrete value, the mode is an appropriate metric to use;

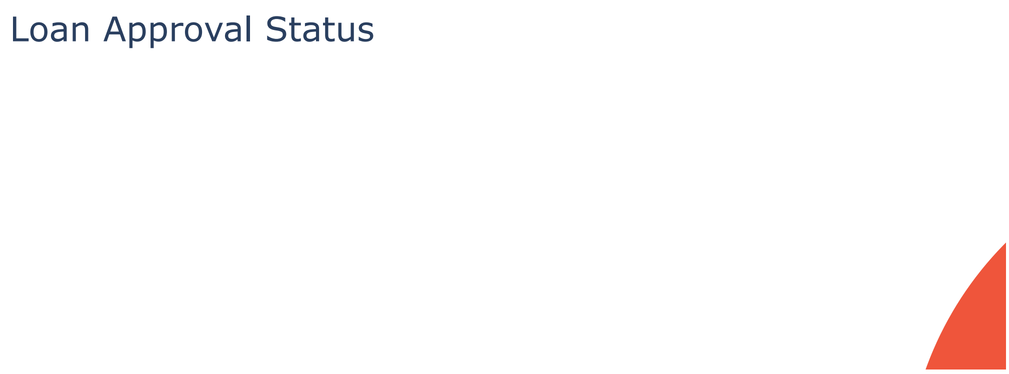
We can fill in the missing values of the credit history column with the mode value. Since credit history is a binary variable (0 or 1), the mode represents the most common value and is an appropriate choice for filling in missing values.

In [6]:
```
# Fill missing values in LoanAmount with the median
df['LoanAmount'].fillna(df['LoanAmount'].median(), inplace=True)

# Fill missing values in Loan_Amount_Term with the mode
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0], inplace=True)
```

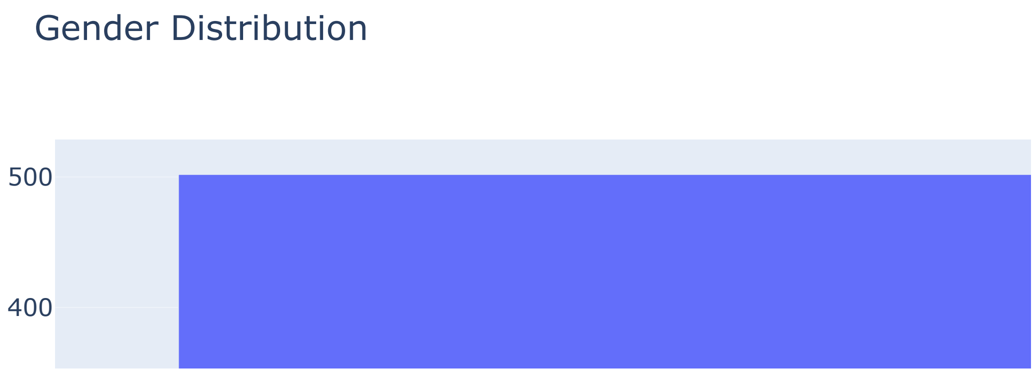
```
# Fill missing values in Credit_History with the mode
df['Credit_History'].fillna(df['Credit_History'].mode()[0], inplace=True)
```

Exploratory Data Analysis

In [7]:
```
#Now let’s have a look at the distribution of the loan status column:

import plotly.express as px
loan_status_count = df['Loan_Status'].value_counts()
fig_loan_status = px.pie(loan_status_count,
                         names=loan_status_count.index,
                         title='Loan Approval Status')
fig_loan_status.show()
```



In [8]:
```
#Now let’s have a look at the distribution of the gender column:
gender_count = df['Gender'].value_counts()
fig_gender = px.bar(gender_count,
                    x=gender_count.index,
                    y=gender_count.values,
                    title='Gender Distribution')
fig_gender.show()
```



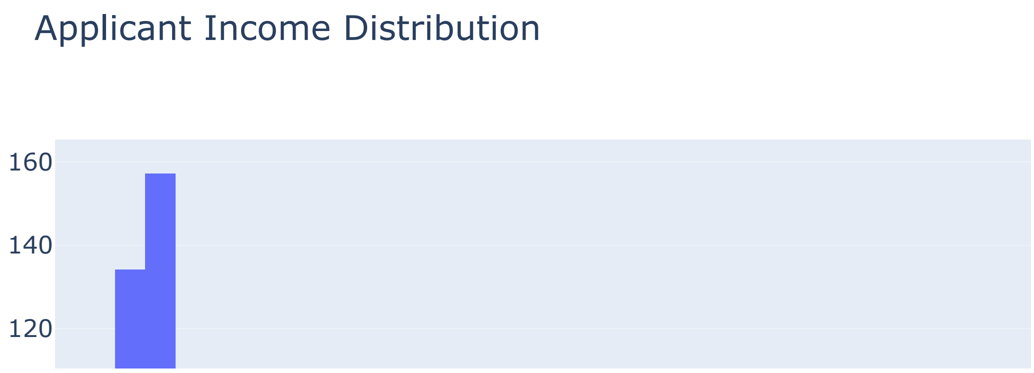
In [9]:
```
#Now let’s have a look at the distribution of the martial status column:
married_count = df['Married'].value_counts()
fig_married = px.bar(married_count,
                     x=married_count.index,
                     y=married_count.values,
                     title='Marital Status Distribution')
fig_married.show()
```

In [10]:
```
#Now let’s have a look at the distribution of the education column:
education_count = df['Education'].value_counts()
fig_education = px.bar(education_count,
                       x=education_count.index,
                       y=education_count.values,
                       title='Education Distribution')
fig_education.show()
```

In [11]:

```
#Now let’s have a look at the distribution of the self-employment column:
self_employed_count = df['Self_Employed'].value_counts()
fig_self_employed = px.bar(self_employed_count,
                           x=self_employed_count.index,
                           y=self_employed_count.values,
                           title='Self-Employment Distribution')
fig_self_employed.show()
```

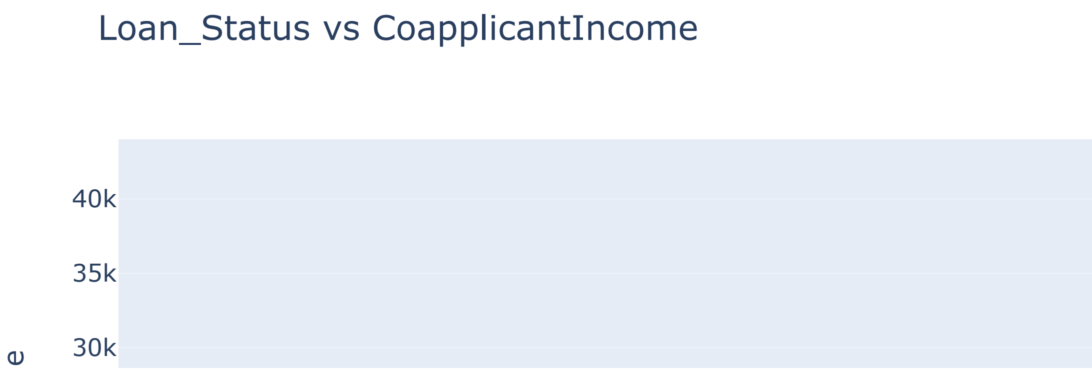
In [12]:
```
#Now let’s have a look at the distribution of the Applicant Income column:
fig_applicant_income = px.histogram(df, x='ApplicantIncome',
                                    title='Applicant Income Distribution')
fig_applicant_income.show()
```



In [13]:
```
#Now let’s have a look at the relationship between the income of the loan applic
fig_income = px.box(df, x='Loan_Status',
                    y='ApplicantIncome',
                    color="Loan_Status",
                    title='Loan_Status vs ApplicantIncome')
fig_income.show()
```

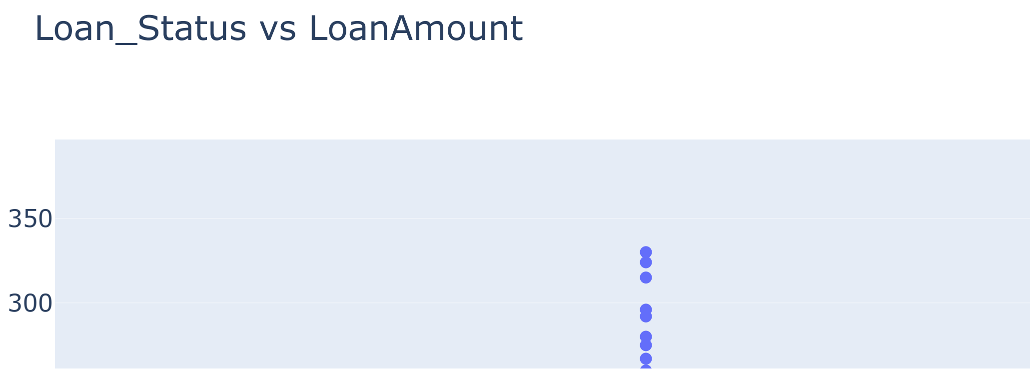
In [14]:
```
#The “ApplicantIncome” column contains outliers which need to be removed before
# Calculate the IQR
Q1 = df['ApplicantIncome'].quantile(0.25)
Q3 = df['ApplicantIncome'].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove outliers
df = df[(df['ApplicantIncome'] >= lower_bound) & (df['ApplicantIncome'] <= upper
```

In [15]:
```
#the relationship between the income of the loan co-applicant and the loan statu
fig_coapplicant_income = px.box(df,
                                x='Loan_Status',
                                y='CoapplicantIncome',
                                color="Loan_Status",
                                title='Loan_Status vs CoapplicantIncome')
fig_coapplicant_income.show()
```

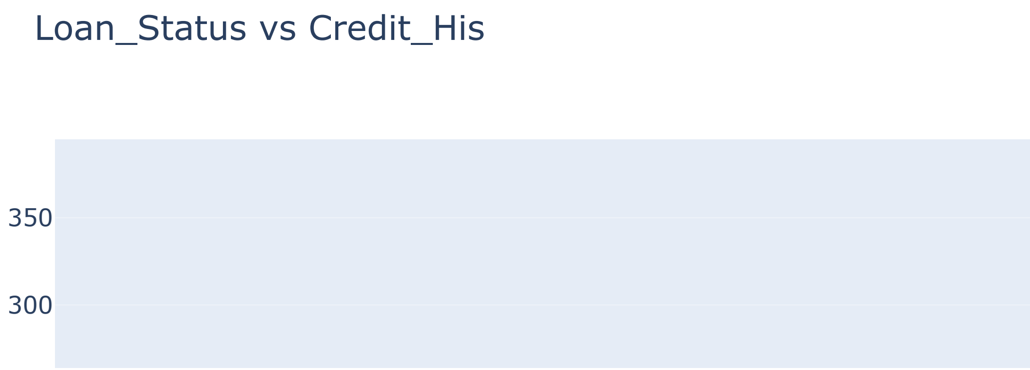


In [16]:
```
#The income of the loan co-applicant also contains outliers. Let’s remove the ou
# Calculate the IQR
Q1 = df['CoapplicantIncome'].quantile(0.25)
Q3 = df['CoapplicantIncome'].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove outliers
df = df[(df['CoapplicantIncome'] >= lower_bound) & (df['CoapplicantIncome'] <= u
```

In [17]:
```
#Now let’s have a look at the relationship between the loan amount and the loan
fig_loan_amount = px.box(df, x='Loan_Status',
                         y='LoanAmount',
                         color="Loan_Status",
                         title='Loan_Status vs LoanAmount')
fig_loan_amount.show()
```



In [18]:
```
#Now let’s have a look at the relationship between credit history and loan statu
fig_credit_history = px.histogram(df, x='Credit_History', color='Loan_Status',
                                  barmode='group',
                                  title='Loan_Status vs Credit_His')
fig_credit_history.show()
```



In [19]:

```
#Now let’s have a look at the relationship between the property area and the loa
fig_property_area = px.histogram(df, x='Property_Area', color='Loan_Status',
                                  barmode='group',
                                 title='Loan_Status vs Property_Area')
fig_property_area.show()
```

Data Preparation and Training Loan Approval Prediction Model

The step, we will:

convert categorical columns into numerical ones;

split the data into training and test sets;

scale the numerical features;

train the loan approval prediction model.

In [20]:
```
# Convert categorical columns to numerical using one-hot encoding
cat_cols = ['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed', 'Pr
df = pd.get_dummies(df, columns=cat_cols)

# Split the dataset into features (X) and target (y)
X = df.drop('Loan_Status', axis=1)
y = df['Loan_Status']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Scale the numerical columns using StandardScaler
```

```
scaler = StandardScaler()
numerical_cols = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Am
X_train[numerical_cols] = scaler.fit_transform(X_train[numerical_cols])
X_test[numerical_cols] = scaler.transform(X_test[numerical_cols])

from sklearn.svm import SVC
model = SVC(random_state=42)
model.fit(X_train, y_train)
```

Out[20]:

```
▾ SVC
SVC(random_state=42)
```

In [21]:

```
#Now let’s make predictions on the test set:
y_pred = model.predict(X_test)
print(y_pred)
```

```
['Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y'
 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y'
 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y'
 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y'
 'Y' 'Y' 'Y' 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y'
 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y'
 'Y' 'Y']
```

Now let’s add the predicted loan approval values to the testing set as a new column in a DataFrame called X_test_df and show the predicted loan approval values alongside the original features

In [22]:

```
# Convert X_test to a DataFrame
X_test_df = pd.DataFrame(X_test, columns=X_test.columns)

# Add the predicted values to X_test_df
X_test_df['Loan_Status_Predicted'] = y_pred
print(X_test_df.head())
```

```
     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
277        -0.544528          -0.037922   -0.983772          0.305159   
84         -0.067325          -0.931554   -1.571353         -1.430680   
275        -0.734870           0.334654   -0.298262          0.305159   
392        -0.824919           0.522317   -0.200332          0.305159   
537        -0.267373          -0.931554   -0.454950          0.305159   

     Credit_History  Gender_Female  Gender_Male  Married_No  Married_Yes  \
277        0.402248          False         True       False         True   
84         0.402248          False         True       False         True   
275        0.402248          False         True       False         True   
392        0.402248          False         True       False         True   
537        0.402248          False         True        True        False   

     Dependents_0  ...  Dependents_2  Dependents_3+  Education_Graduate  \
277          True  ...         False          False                True   
84          False  ...         False          False                True   
275         False  ...         False          False                True   
392          True  ...         False          False                True   
537         False  ...          True          False                True   

     Education_Not Graduate  Self_Employed_No  Self_Employed_Yes  \
277                   False              True              False   
84                    False              True              False   
275                   False              True              False   
392                   False              True              False   
537                   False              True              False   

     Property_Area_Rural  Property_Area_Semiurban  Property_Area_Urban  \
277                False                    False                 True   
84                 False                    False                 True   
275                False                     True                False   
392                False                    False                 True   
537                False                     True                False   

     Loan_Status_Predicted  
277                      Y  
84                       Y  
275                      Y  
392                      Y  
537                      Y  

[5 rows x 21 columns]
```

In [ ]: