Final Project - Analyze the odds of approval based on various factors like income, credit history, etc. of a borrower applying for a loan

The purpose this project is to understand, based on given factors if it is possible to autoamte the process of a loan approval. I am using loan dataset obtained from kaggle.com. It has varous factors like education, gender, credit history that affects the odds of loan appproval.

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- Github: Tools 1 Final Project

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Data Processing

In [3]:

```
loan_data = 'loan_data.csv'

df = pd.read_csv(loan_data)

df.head()
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappli
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

In [4]:

```
df.shape
```

Out[4]:

```
(614, 13)
```

We have 614 rows and 13 columns in the dataset

In [5]:

```
df.dtypes
```

Out[5]:

```
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
```

Here , we are interested in `Loan_Status` where 'Y' means approved and 'N' means rejected.

Independent variables that can affect the `Loan_Status` :

- Gender
- Married
- Dependents
- Education
- Self_Employed
- Property_Area

In [6]:

```
df.isna().sum()
```

Out[6]:

```
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
```

There are null value columns which can cause problem to the loan approval prediction, we want to understand if any of these applicants are approved for a loan

In [7]:

```
missing_history = df[df['Credit_History'].isna()]
missing_history['Loan_Status'].value_counts()
```

Out[7]:

```
Y    37
N    13
Name: Loan_Status, dtype: int64
```

We do see some applicants approved without a credit history, this could be first time loan applicatnts or self-employed

In [8]:

```
employed = df['Self_Employed'].value_counts().index[0]
self_employed = df['Self_Employed'].value_counts().index[1]


df.loc[(df['Self_Employed'] == self_employed) & (df['Credit_History'].isna()), '
```

```
df.loc[(df['Self_Employed'] == employed) & (df['Credit_History'].isna()), 'Credi

df.loc[(df['Credit_History'].isnull()) & (df['Loan_Status'] == 'Y'), 'Credit_His

df['Credit_History'].fillna(0.0, inplace=True)
```

I have set the credit history to 0.0 for self-employed. For application who have a missing status for `self-employed`, I've used `loan_status` to determine if the person has a credit history, otherwise set 0.0 for all missing credit history

In [9]:

```
df.loc[(df['Self_Employed'].isnull()) & (df['Credit_History'] > 0.0), "Self_Empl
df.loc[(df['Self_Employed'].isnull()) & (df['Credit_History'] == 0.0), "Self_Emp
```

I've also set `Self-Employed` based on `Credit_History`. The borrowers who do not have a credit history are likely to be self-employed

In [10]:

```
df.loc[(df['Married'].isnull()) & (df['CoapplicantIncome'] > 0.0), "Married"] =
df.loc[(df['Married'].isnull()) & (df['CoapplicantIncome'] == 0.0), "Married"] =
```

Missing values for `Married` column, we are setting "yes" for entries with co-applicant income, otherwise "No"

In [11]:

```
married = df['Married'].value_counts().index[0]

male = df['Gender'].value_counts().index[0]
female = df['Gender'].value_counts().index[1]

df.loc[(df['Gender'].isnull()) & (df['Married'] == married) & (df['ApplicantInco
df.loc[(df['Gender'].isnull()) & (df['Married'] == married) & (df['ApplicantInco

df['Gender'].fillna(female, inplace=True)
```

For married couples, I am assuming gender is male for higher income applicant or coapplicant (we are applying bias based on norm)

I am setting `Female` for the rest of the missing values

In [12]:

```
df['Dependents'].fillna(df['Dependents'].value_counts().index[0], inplace=True)
```

I am assuming for missing values, there are no dependents for the applicant.

In [13]:

```
df.loc[(df['LoanAmount'].isna()) & (df['Loan_Status'] == 'N'), 'LoanAmount'] = 0
#rest
df['LoanAmount'].fillna( df['LoanAmount'].median(), inplace=True)
```

I have set the loan amount to zero for applicants whose loan is not approved, otherwise I've set the loan amount with median value.

In [14]:

```
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].median(), inplace=True)
```

I am also setting the missing loan amount term based on the median value.

In [15]:
```
df.isna().sum()
```

Out[15]:
```
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
```

Finally, I am verifying that data is clean and predictors do not have any null / missing values

In [16]:
```
dst_filename = "loan_data.pkl"
pd.to_pickle(df, dst_filename)
```

Saving the clean dataset to a pickle file for future processing

Data Analysis (EDA)

In [17]:
```
# Loading the data
dst_filename = "loan_data.pkl"
loan_clean_df = pd.read_pickle(dst_filename)
```

In [18]:
```
loan_clean_df['Loan_Status'].value_counts(normalize=True, dropna=False)
```

Out[18]:
```
Y    0.687296
N    0.312704
Name: Loan_Status, dtype: float64
```

Based on above data, around 68% of the applicants are approved for a loan

In [19]:
```
import math

categories = []

for col in loan_clean_df.columns:
    if loan_clean_df[col].dtype == 'object':
        categories.append(col)

# loan_id
categories.pop(0)
# loan_status
categories.pop(-1)
# include credit_history
categories.append('Credit_History')

cols = 3
rows = math.ceil(len(categories) / cols)
```

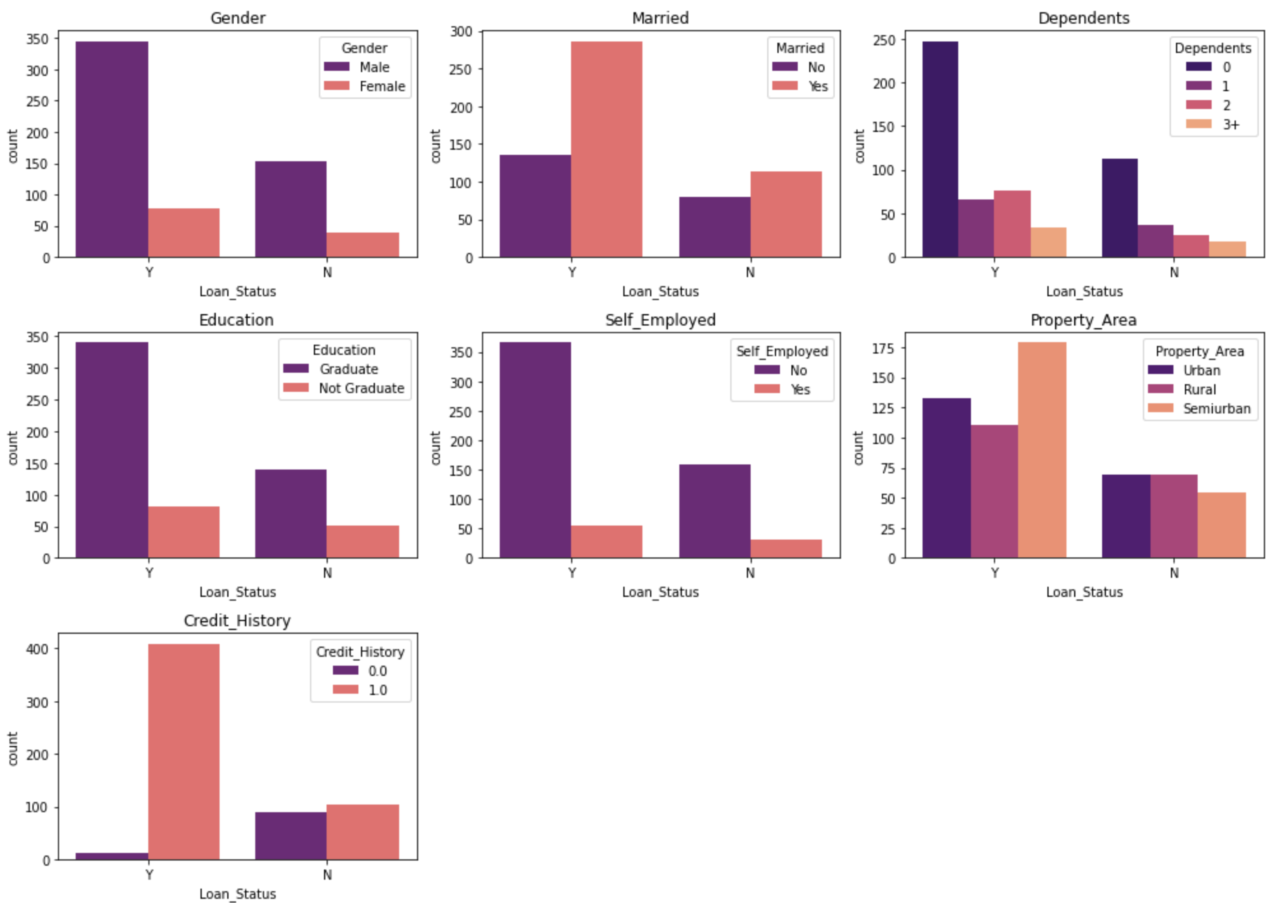
```
fig, axs = plt.subplots(rows, cols, figsize = (14, 10))

for i, ax in enumerate(axs.flat):
    if i < len(categories):
        sns.countplot(x='Loan_Status', hue=categories[i], data=loan_clean_df, ax
        ax.set_title(categories[i])
        ax.set(ylabel='count')


axs[2, 2].set_axis_off()
axs[2, 1].set_axis_off()

plt.tight_layout()

plt.show()
```

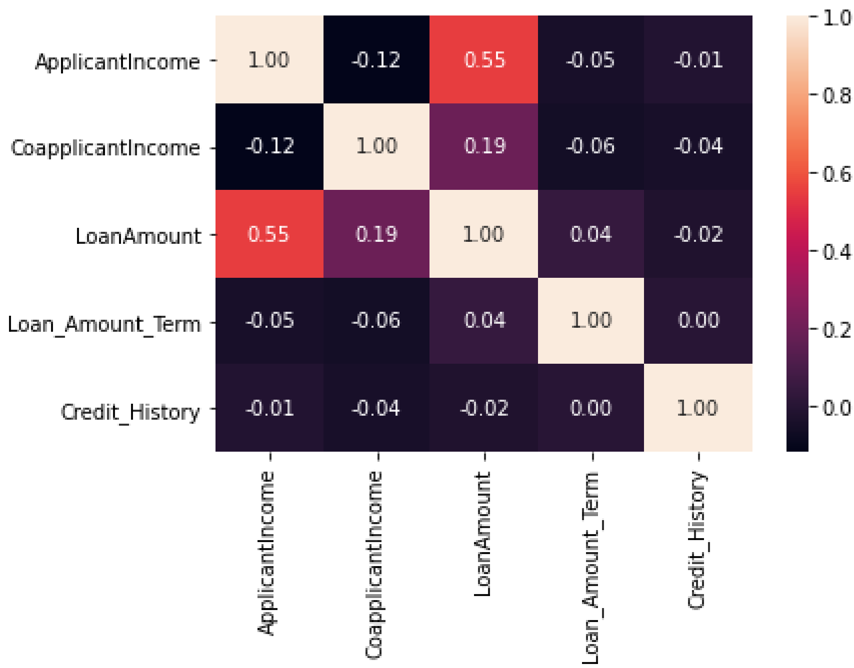


After observating the categorial variables against `Loan_Status` , we can see the following patterns:

- Married applicatants vs single have more influence on `Loan_Status`
- Married and male appplicants have almost similar approval odds
- Approval odds are higher in graduate borrowers
- Self-employed applicants have lower approval rate
- Applicants with no kids have much higher approval rate
- Applicatiant's location or where he / she lives (`Property_Area`) is not very imporant when applying for a loan

- Appearently people with no credit history have almost no chance of getting approved for a loan

In [20]:
```
sns.heatmap(loan_clean_df.corr(), annot=True, fmt='.2f')
plt.show()
```



Doing a correlation analysis of the numerical field, we see the following liner relationship:

- `Loan_Amount` , `ApplcantIncome`
- `Loan_Amount` , `CoapplicantIncome`

Based on the above correlation, we can conclude that loan amount is higher for higher income borrowers. Therefore, if we consider married couples and combined income, the chances should be much higher

Feature Engineering

In [21]:
```
loan_clean_df['TotalIncome']=  loan_clean_df['ApplicantIncome']+loan_clean_df['C
loan_clean_df.sample()
```

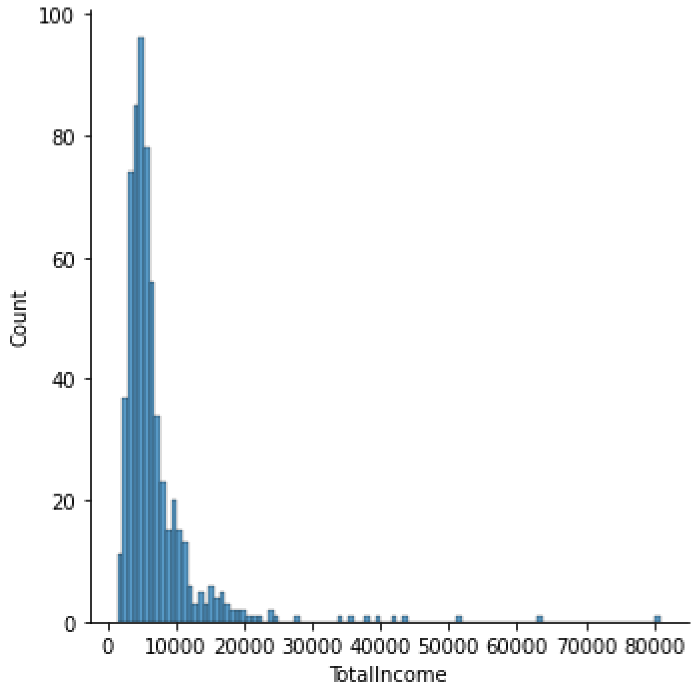
Out[21]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coap
257	LP001854	Male	Yes	3+	Graduate	No	5250	

Based on the observation there is a positive relationship between the loan approval rate and the income, therefore the rate will be even higher with combined income.

In [22]:
```
sns.displot(x='TotalIncome', data=loan_clean_df)
```

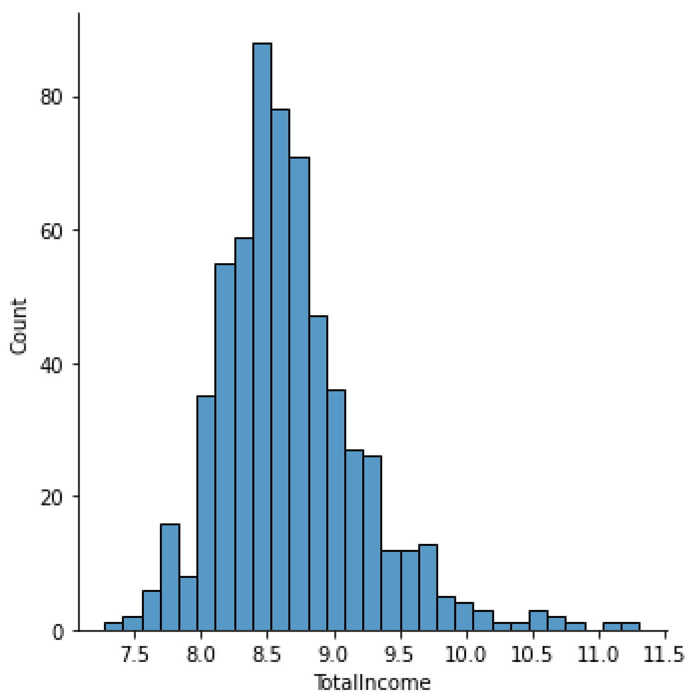
Out[22]: <seaborn.axisgrid.FacetGrid at 0x7fd5b3524190>



The data is shifted towards left, therefore it is right-skewed.

In [23]:
```
sns.displot(np.log(loan_clean_df['TotalIncome']))
```

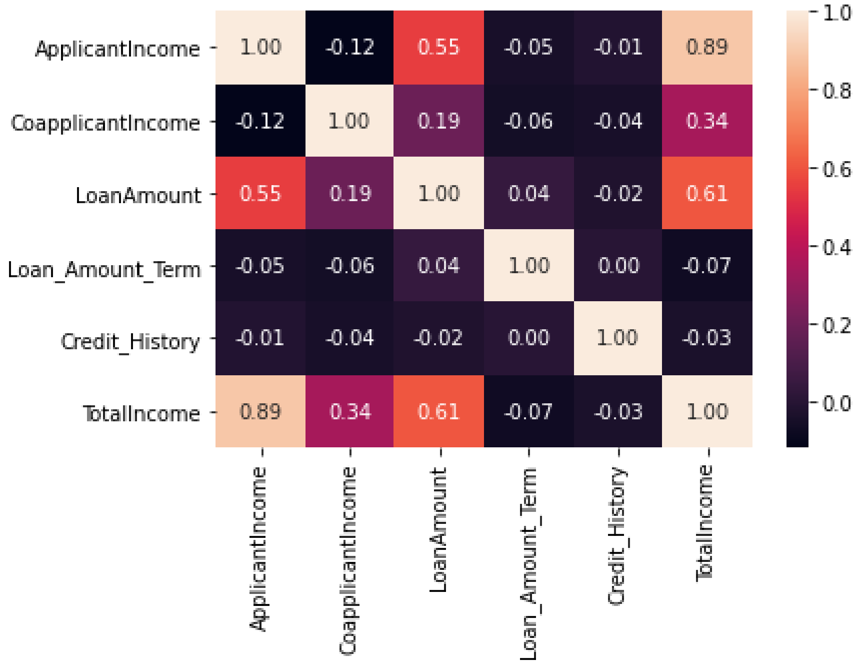
Out[23]: <seaborn.axisgrid.FacetGrid at 0x7fd5b375f640>



Taking `np.log`, we can see that data is normally distributed and there are no major outliers that can affect our analysis

In [24]:
```
sns.heatmap(loan_clean_df.corr(), annot=True, fmt='.2f')
```

Out[24]: <AxesSubplot:>



We can see from the heatmap that `TotalIncome` have most influence on `LoanAmount` .Now, based on `Loan_Amount_Term` and `LoanAmount` we can calculate the estimated monthy installment (EMI) of a borrower

In [25]:

```
loan_clean_df['EMI'] = (loan_clean_df['LoanAmount']) / (loan_clean_df['Loan_Amou
loan_clean_df[loan_clean_df.Loan_Status == 'Y'].sample()
```

Out[25]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coap
197	LP001669	Female	No	0	Not Graduate	No	1907	

Now, substracting EMI from total income, we get the balance avaialble. The borrower is likey to get approved as the amount is higher

In [26]:

```
# loan amount in the dataset is calcuated in thosands.
loan_clean_df['Balance'] = (loan_clean_df['TotalIncome']) - (loan_clean_df['EMI'

loan_clean_df.sample()
```

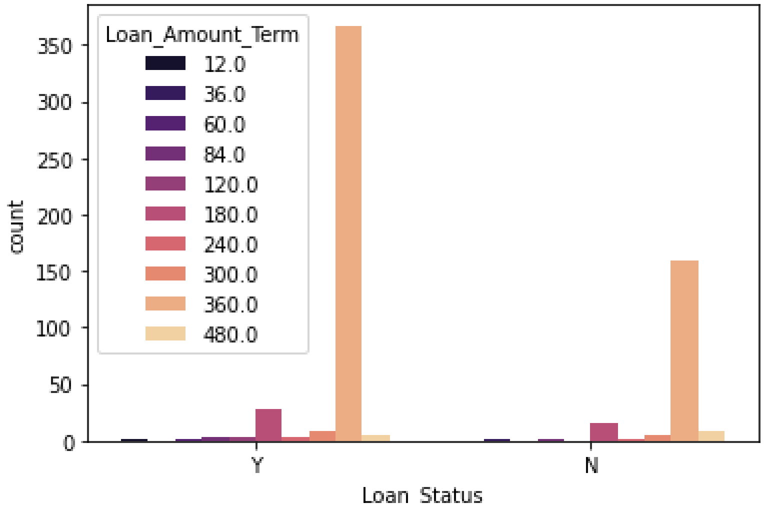
Out[26]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coap
155	LP001536	Male	Yes	3+	Graduate	No	39999	

In [27]:

```
sns.countplot(x="Loan_Status", hue="Loan_Amount_Term", data=loan_clean_df, palet
```

Out[27]: <AxesSubplot:xlabel='Loan_Status', ylabel='count'>



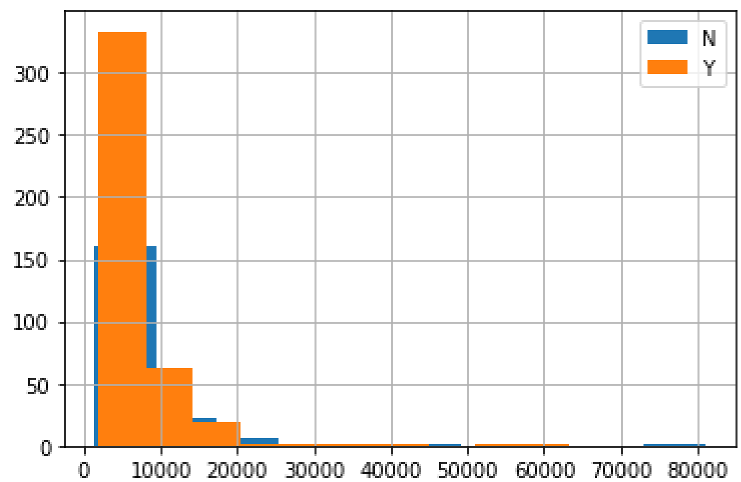
We can see that there is a greater chance of approval for a longer loan term (30 yrs) loan. Based on Income and loan term, we can assume that a person will be approved for a loan, if he has high income and paying it off in longer terms. Lenders will feel much confident since the borrower has a wider room to pay back the loan.

In [28]:

```
loan_clean_df.groupby('Loan_Status')['TotalIncome'].hist(legend=True)
```

Out[28]:

```
Loan_Status
N    AxesSubplot(0.125,0.125;0.775x0.755)
Y    AxesSubplot(0.125,0.125;0.775x0.755)
Name: TotalIncome, dtype: object
```



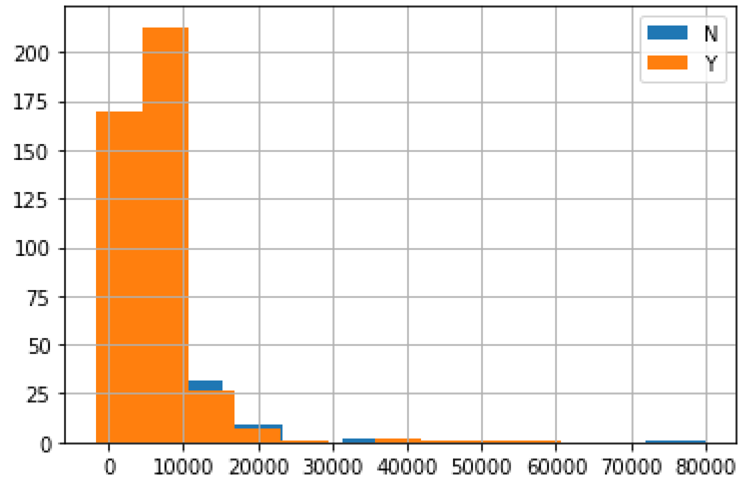
Here, we can also see that odds of approval is much higher with income.

In [29]:

```
loan_clean_df.groupby('Loan_Status')['Balance'].hist(legend=True)
```

Out[29]:

```
Loan_Status
N    AxesSubplot(0.125,0.125;0.775x0.755)
Y    AxesSubplot(0.125,0.125;0.775x0.755)
Name: Balance, dtype: object
```



Similary, more balance after `EMI` increases the chance of apprroval

Model Validation

In order to perform logistic regression, we first need to convert the categorical columns to numerical and remove the columns that do not have much effect on the target (based on our observation) or we have created new columns after performing featured engineering in the previous step

In [36]:

```
from sklearn.preprocessing import LabelEncoder

dat = loan_clean_df.drop(columns=['Loan_ID',
                                  'Dependents',
                                  'ApplicantIncome',
                                  'CoapplicantIncome',
                                  'Property_Area',
                                  'EMI',
                                  'Balance'])

encoder = LabelEncoder()

dat['Loan_Status'] = encoder.fit_transform(dat['Loan_Status'])
dat['Gender'] = encoder.fit_transform(dat['Gender'])
dat['Married'] = encoder.fit_transform(dat['Married'])
dat['Education'] = encoder.fit_transform(dat['Education'])
#dat['Dependents'] = encoder.fit_transform(dat['Dependents'])
dat['Self_Employed'] = encoder.fit_transform(dat['Self_Employed'])

dat.sample()
```

Out[36]:

	Gender	Married	Education	Self_Employed	LoanAmount	Loan_Amount_Term	Credit_History
17	0	0	0	0	76.0	360.0	0.0

Next, we split the data into train / test sets and perform logistic regression

In [37]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

Y = dat['Loan_Status']
```

```
X = dat.drop('Loan_Status', axis=1)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.30)

logistic_model = LogisticRegression()
logistic_model.fit(X_train, Y_train)

Y_pred = logistic_model.predict(X_test)
```

Finally, we calcuate the f1 score of the model

In [38]:

```
from sklearn.metrics import f1_score

f1_score(Y_test, Y_pred)
```

Out[38]: 0.8850174216027875

The model is almost 90% accurate

Conclusion

We can conclude that there is a relation between loan approval odds vs borrower's income, credit history, loan term, education, marital and employment status. Based on the factors, we can predict if a borrower will be approved for a loan.

In [ ]:

In [ ]: