loan_prediction_problem

September 2, 2020

In this dataset, we need to predict whether or not to approve a loan based on the past information of the person. This is a classification problem and we will use machine learning, Decision Tree Classifier model, to make the prediction.

1 Import Libraries

First, we import necessary libraries, such as:

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()

import warnings
warnings.filterwarnings('ignore')
```

2 Import The Data

[2]:
```
train = pd.read_csv('/kaggle/input/loan-prediction-problem-dataset/
↪train_u6lujuX_CVtuZ9i.csv')
```

3 Read The Data

First, let's see the first 5 rows to familiarize ourself with the data.

[3]:
```
train.head()
```

[3]:
```
    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
```

To get more details, we are going to print `info()` and `describe()` to make a quick observation and gain some insight from it.

[4]:
```
train.info()
```

```
<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
```

[5]:
```
train.describe(include='all')
```

[5]:
```
         Loan_ID Gender Married Dependents Education Self_Employed  \
count        614    601     611        599       614           582
```

```
unique      614    2     2     4        2          2
top     LP002239 Male   Yes     0  Graduate        No
freq          1  489   398   345      480        500
mean        NaN  NaN   NaN   NaN      NaN        NaN
std         NaN  NaN   NaN   NaN      NaN        NaN
min         NaN  NaN   NaN   NaN      NaN        NaN
25%         NaN  NaN   NaN   NaN      NaN        NaN
50%         NaN  NaN   NaN   NaN      NaN        NaN
75%         NaN  NaN   NaN   NaN      NaN        NaN
max         NaN  NaN   NaN   NaN      NaN        NaN

        ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count        614.000000         614.000000  592.000000         600.00000
unique              NaN                NaN         NaN               NaN
top                 NaN                NaN         NaN               NaN
freq                NaN                NaN         NaN               NaN
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 Property_Area Loan_Status
count       564.000000           614         614
unique             NaN             3           2
top                NaN     Semiurban           Y
freq               NaN           233         422
mean          0.842199           NaN         NaN
std           0.364878           NaN         NaN
min           0.000000           NaN         NaN
25%           1.000000           NaN         NaN
50%           1.000000           NaN         NaN
75%           1.000000           NaN         NaN
max           1.000000           NaN         NaN
```

[6]:
```python
train.isnull().sum().sort_values(ascending=False)
```

[6]:
```
Credit_History       50
Self_Employed        32
LoanAmount           22
Dependents           15
Loan_Amount_Term     14
Gender               13
Married               3
Loan_Status           0
```

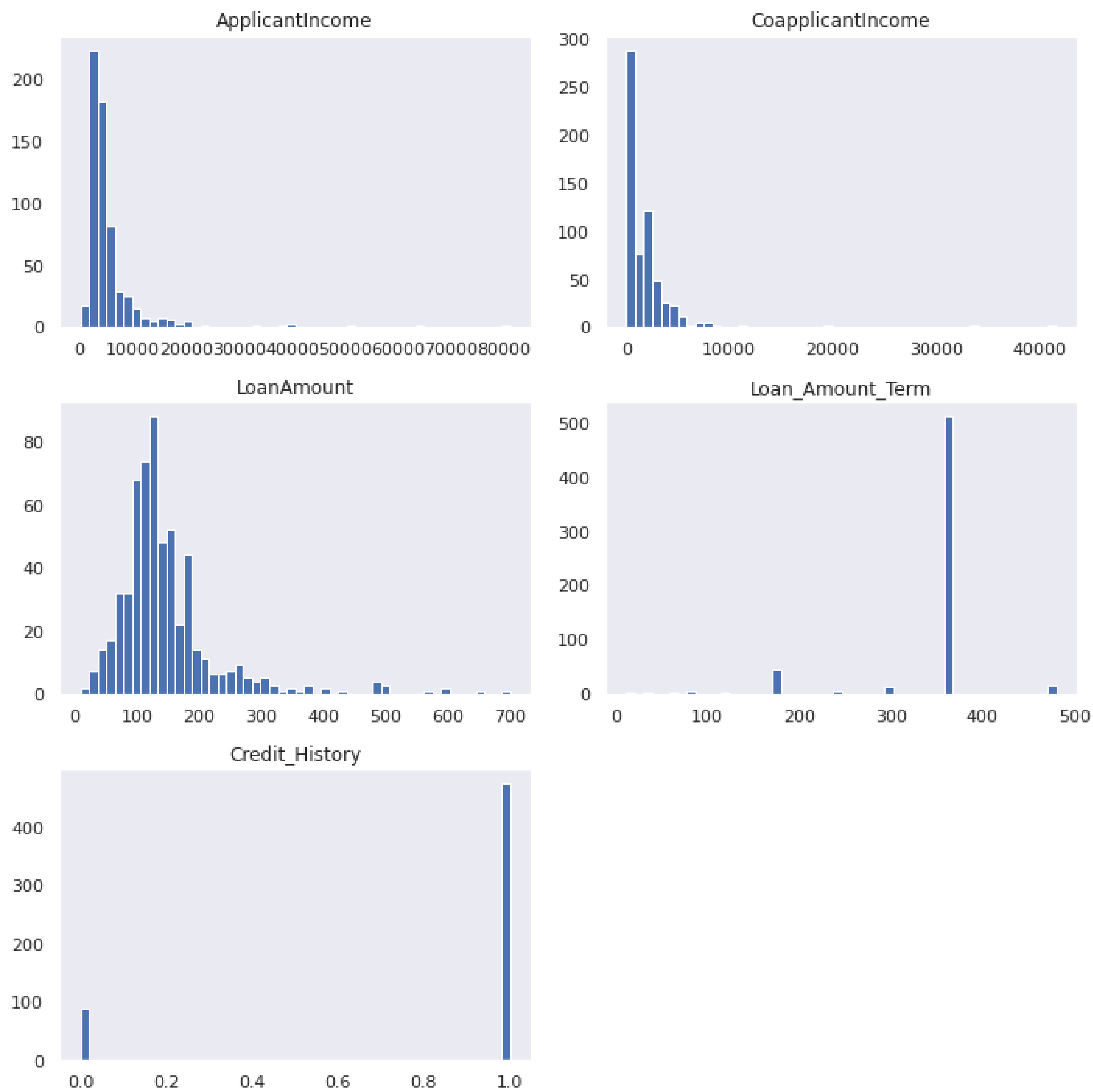
```
Property_Area        0
CoapplicantIncome    0
ApplicantIncome      0
Education            0
Loan_ID              0
dtype: int64
```

3.0.1 Quick observation on the combined data

- Total loaner: 614
- Feature that can be dropped from training immediately:
  - **Loan_ID**
- The **Loan_Status** feature, as target array, can be used as a reference to fill missing values, so we will not drop it immediately.
- The **Dependents** feature is given in categorical but contain numerical variables. Therefore, we have to converted it to numerical variables.
- The **Credit_History** feature is given in numerical, with 1 means 'Yes' and 0 means 'No'. We will converted it to categorical feature.
- Features that have missing values:
  - **Credit_History:** 50
  - **Self_Employed:** 32
  - **LoanAmount:** 22
  - **Dependents:** 15
  - **Gender:** 14
  - **Loan_Amount_Term:** 13
  - **Married:** 3

3.0.2 Plot The Distribution of Numerical Features

[7]:
```
#plot the distribution of numerical features
train.hist(bins=50,figsize=(10,10),grid=False)
plt.tight_layout()
plt.show()
```



We can see we got right-skewed and left-skewed. We will fix this in the next step by taking the log of the values to make it normally distributed. By making it normally distributed, we can improve our model.

4 Exploratory Data Analysis

4.0.1 Drop Features

[8]:
```
#drop feature
train.drop(['Loan_ID'], axis=1, inplace=True)
```

4.0.2 Change to Numerical

[9]:
```
#check unique values
train['Dependents'].unique()
```

[9]:
```
array(['0', '1', '2', '3+', nan], dtype=object)
```

[10]:
```
#replace '3+' with '3'
train['Dependents'].replace('3+', '3', inplace=True)

#change to numerical
train['Dependents'] = train['Dependents'].astype('float')
```

4.0.3 Changet to Categorical

[11]:
```
#check unique values
train['Credit_History'].unique()
```

[11]:
```
array([ 1.,  0., nan])
```

[12]:
```
#replace 1.0 with 'Y' and 0.0 with 'N'
train['Credit_History'].replace({1.: 'Y', 0.: 'N'}, inplace=True)

#change to categorical
train['Credit_History'] = train['Credit_History'].astype('object')
```

4.0.4 Fill Missing Value:

- Fill with mode()

[13]:
```
#fill missing values with mode
features_fill_with_mode = ['Self_Employed',
                           'Dependents',
                           'Gender',
                           'Loan_Amount_Term']

for feature in features_fill_with_mode:
    train[feature].fillna(train[feature].mode()[0], inplace=True)
```

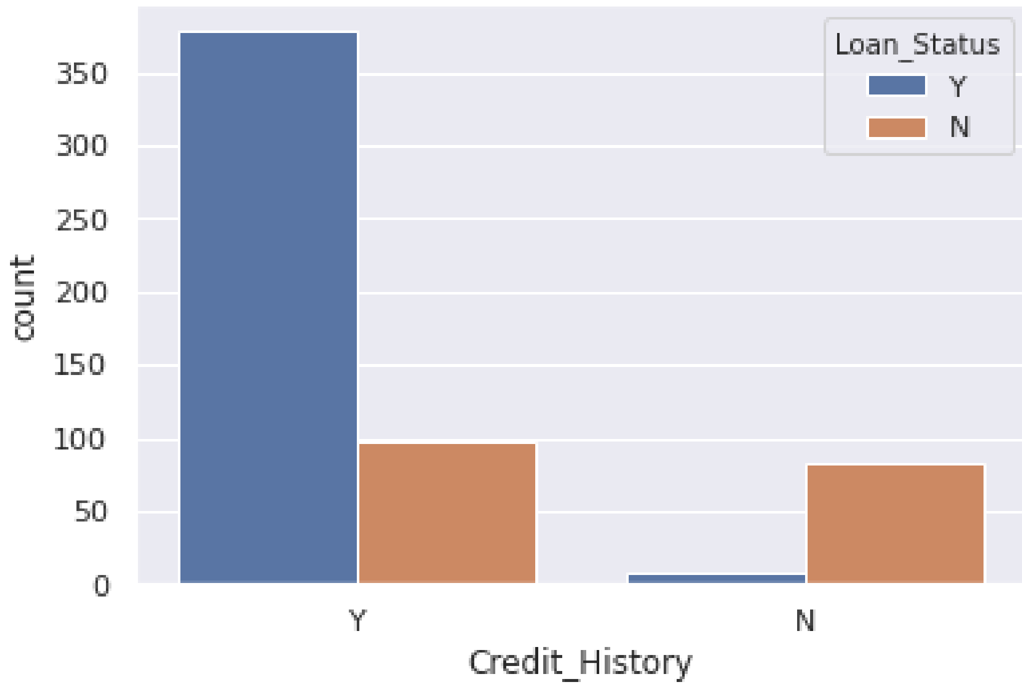
- Fill with mean()

[14]:
```
#fill missing values with mean
train['LoanAmount'].fillna(train['LoanAmount'].mean(), inplace=True)
```

- Credit_History Feature

Before we fill missing values in Credit_History feature, we will take a deeper look by plotting it.

[15]:
```
sns.countplot(x='Credit_History', hue='Loan_Status', data=train);
```



From the plot above, we can see that Credit_History is important feature. Most people with 0 credit history didn't get a loan. But, most people who got credit history have so much better chance to get a loan.

Since Credit_History = 'Y' is the value that appears most often in both Loan_Status, so we will fill missing values with 'Y'

[16]:
```
train['Credit_History'].fillna('Y', inplace=True)
```

- Married Feature

For start, we will check if the missing values in the Married feature have Dependets or CoapplicantIncome more than 0, and fill it with 'Yes' if true and 'No' if otherwise.

[17]:
```
#check Dependents and CoapplicantIncome
mask = ((train['Dependents'] > 0) | (train['CoapplicantIncome'] > 0)) \
        & \
        train['Married'].isnull()

train[mask][['Married','Dependents','CoapplicantIncome']]
```

[17]:

```
     Married  Dependents  CoapplicantIncome
104      NaN         0.0              754.0
```

[18]:

```python
#Fill missing values
train.loc[mask,'Married'] = 'Yes'
train['Married'].fillna('No', inplace=True)
```

4.0.5 Target Array

let's look at the target distribution

[19]:

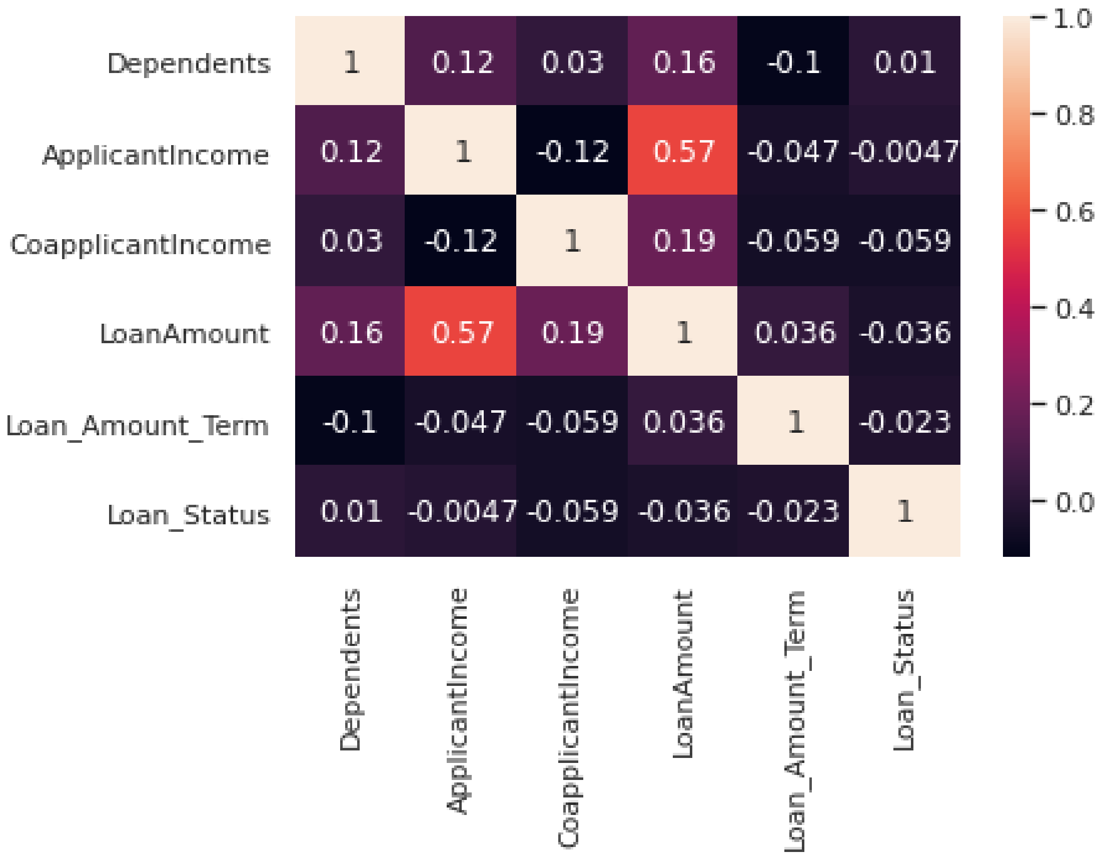
```python
sns.countplot(train['Loan_Status']);
```

From the distribution above, we can consider that the data is not imbalanced. So, we can straight to the next step: change it to numerical feature.

[20]:

```python
#transform to numerical
train['Loan_Status'] = train['Loan_Status'].apply(lambda x: 1 if x=='Y' else 0)

#correlation
sns.heatmap(train.corr(),annot=True);
```



[21]:
```
#copy
target_array = train['Loan_Status'].copy()

#drop
train.drop(['Loan_Status'], axis=1, inplace=True)
```

4.0.6 Creating new features

[22]:
```
#create total income feature
train['Total_Income'] = train['ApplicantIncome'] + train['CoapplicantIncome']

#create average loan amount feature (per day)
train['Loan_Amount_Avg'] = train['LoanAmount'] / train['Loan_Amount_Term']

#drop
train.drop(['ApplicantIncome','CoapplicantIncome'], axis=1, inplace=True)
```

4.0.7 Epilogue

- Chech for any missing values

[23]:
```
#missing values
print(train.isnull().any().sum())
```

```
0
```

- Normality Test

[24]:
```
#define a normality test function
def normalityTest(data, alpha=0.05):
    """data (array)   : The array containing the sample to be tested.
           alpha (float)  : Significance level.
           return True if data is normal distributed"""

    from scipy import stats

    statistic, p_value = stats.normaltest(data)

    #null hypothesis: array comes from a normal distribution
    if p_value < alpha:
        #The null hypothesis can be rejected
        is_normal_dist = False
    else:
        #The null hypothesis cannot be rejected
        is_normal_dist = True

    return is_normal_dist
```

[25]:
```
#check normality of all numericaal features and transform it if not normal␣
 ↪distributed
for feature in train.columns:
    if (train[feature].dtype != 'object'):
        if normalityTest(train[feature]) == False:
            train[feature] = np.log1p(train[feature])
```

- Creating Dummies

[26]:
```
#create dummies
train = pd.get_dummies(train, drop_first=True)

print(train.shape)
display(train.head())
```

```
(614, 12)

   Dependents  LoanAmount  Loan_Amount_Term  Total_Income  Loan_Amount_Avg  \
```

```
0    0.000000    4.993232          5.888878      8.674197          0.341247
1    0.693147    4.859812          5.888878      8.714732          0.304211
2    0.000000    4.204693          5.888878      8.006701          0.168335
3    0.000000    4.795791          5.888878      8.505525          0.287682
4    0.000000    4.955827          5.888878      8.699681          0.330502

   Gender_Male  Married_Yes  Education_Not Graduate  Self_Employed_Yes  \
0            1            0                       0                  0
1            1            1                       0                  0
2            1            1                       0                  1
3            1            1                       1                  0
4            1            0                       0                  0

   Credit_History_Y  Property_Area_Semiurban  Property_Area_Urban
0                 1                        0                    1
1                 1                        0                    0
2                 1                        0                    1
3                 1                        0                    1
4                 1                        0                    1
```

- Creating features matrix (X) and target array (y)

[27]:
```python
X = train
y = target_array
```

5 Creating a Model

We begin by splitting data into two subsets: for training data and for testing data.

[28]:
```python
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
 ↪random_state = 0)
```

Model training : Decision Tree Classifier

[29]:
```python
from sklearn.tree import DecisionTreeClassifier

#create a model
model = DecisionTreeClassifier()
```

[30]:
```python
#search grid for optimal parameters
from sklearn.model_selection import GridSearchCV

param_grid = {'random_state' : [0,42],
              'max_depth': [1,10,100]}
```

```
grid = GridSearchCV(model, param_grid, cv=5)

grid.fit(X_train, y_train)

print(grid.best_params_)
print(grid.best_score_)
```

```
{'max_depth': 1, 'random_state': 0}
0.8028504260946224
```

[31]:
```
from sklearn.metrics import classification_report

#use the best model
model = grid.best_estimator_

#make a prediction
y_predict = model.predict(X_test)

#calculate classification report
print(classification_report(y_test,y_predict))
```

```
              precision    recall  f1-score   support

           0       0.92      0.41      0.57        58
           1       0.81      0.99      0.89       145

    accuracy                           0.82       203
   macro avg       0.87      0.70      0.73       203
weighted avg       0.84      0.82      0.80       203
```

[ ]:
```

```