## Loan Eligibility Prediction

#### September 7, 2024

```
[1]: # import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

### 1 preform EDA

```
[3]: df = pd.read_csv('loan-test.csv')
     df.head()
[3]:
         Loan_ID Gender Married Dependents
                                                  Education Self_Employed
     0 LP001015
                    Male
                              Yes
                                                   Graduate
                                                                         No
     1 LP001022
                    Male
                              Yes
                                            1
                                                   Graduate
                                                                         No
                                            2
     2 LP001031
                    Male
                              Yes
                                                   Graduate
                                                                         No
     3 LP001035
                    Male
                              Yes
                                                   Graduate
                                                                         No
     4 LP001051
                    Male
                               No
                                               Not Graduate
                                                                         No
        ApplicantIncome
                          CoapplicantIncome
                                               LoanAmount
                                                           Loan_Amount_Term
     0
                    5720
                                                                        360.0
                                            0
                                                    110.0
                    3076
                                                    126.0
     1
                                         1500
                                                                        360.0
     2
                    5000
                                         1800
                                                    208.0
                                                                        360.0
     3
                    2340
                                         2546
                                                    100.0
                                                                        360.0
                    3276
                                            0
                                                     78.0
                                                                        360.0
        Credit_History Property_Area
     0
                    1.0
                                 Urban
     1
                    1.0
                                 Urban
     2
                    1.0
                                 Urban
     3
                                 Urban
                    NaN
                    1.0
                                 Urban
[4]: df.tail()
```

```
[4]: Loan_ID Gender Married Dependents Education Self_Employed \
362 LP002971 Male Yes 3+ Not Graduate Yes
```

					_			
	363	LP002975	Male	Yes	0	Graduat		
	364	LP002980	Male	No	0	Graduat		
	365	LP002986	Male	Yes	0	Graduat		
	366	LP002989	Male	No	0	Graduat	e Yes	
		ApplicantIn	ncome C	oapplican	tIncome 1	${ t LoanAmount}$	Loan_Amount_Term \	
	362		4009		1777	113.0	360.0	
	363		4158		709	115.0	360.0	
	364		3250		1993	126.0	360.0	
	365		5000		2393	158.0	360.0	
	366		9200		0	98.0	180.0	
		Credit_Hist	tory Pro	perty_Are	a			
	362		1.0	Urba				
	363		1.0	Urba	n			
	364		NaN	Semiurba				
	365		1.0	Rura				
	366		1.0	Rura				
					. <u> </u>			
[5]:	df.de	escribe(inc	lude='al	1')				
[0]				_ /				
[5]:		Loan II	) Gender	Married	Dependents	s Education	Self_Employed \	
[0]	count				35		344	
	uniqu					4 2	2	
	top	LP002989				O Graduate	No	
	freq		1 286		200		307	
	mean	Nal			Nal		NaN	
	std	Nai			Nal		NaN	
	min	Nal			Nal		NaN NaN	
	25%	Nal			Nal		NaN	
	50%	Nal			Nal		NaN	
	75%	Nal			Nal		NaN	
	max	Nal	NaN	NaN	Nal	N NaN	NaN	
			_		_			,
			ntIncome		cantIncom			
	count		7.000000		367.000000			
	uniqu	ıe	NaN		Nal		aN NaN	
	top		NaN		Nal		aN NaN	
	freq		NaN		Nal	N N	aN NaN	Í
	${\tt mean}$	480	5.599455	1	569.57765	7 136.1325	97 342.537396	;
	$\operatorname{\mathtt{std}}$	4910	0.685399	2	334.232099	9 61.3666	52 65.156643	•
	min	(	0.000000		0.00000	28.0000	00 6.000000	1
	25%	2864	1.000000		0.00000	0 100.2500	360.000000	1
	50%	3786	3.000000	1	025.00000	0 125.0000	360.00000	1
	75%		0.00000		430.50000			
	max		9.000000		.000.00000			
		<b>3 _</b> (						

	Credit_History	Property_Area
count	338.000000	367
unique	NaN	3
top	NaN	Urban
freq	NaN	140
mean	0.825444	NaN
std	0.380150	NaN
min	0.000000	NaN
25%	1.000000	NaN
50%	1.000000	NaN
75%	1.000000	NaN
max	1.000000	NaN

#### [6]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	Loan_ID	367 non-null	object
1	Gender	356 non-null	object
2	Married	367 non-null	object
3	Dependents	357 non-null	object
4	Education	367 non-null	object
5	Self_Employed	344 non-null	object
6	ApplicantIncome	367 non-null	int64
7	${\tt CoapplicantIncome}$	367 non-null	int64
8	LoanAmount	362 non-null	float64
9	Loan_Amount_Term	361 non-null	float64
10	Credit_History	338 non-null	float64
11	Property_Area	367 non-null	object
	67 .04(0)	(4(0) 1: (7)	

dtypes: float64(3), int64(2), object(7)

memory usage: 34.5+ KB

### [7]: df.isnull().sum()

[7]: Loan\_ID 0 Gender 11 Married 0 Dependents 10 Education 0 Self\_Employed 23 ApplicantIncome 0  ${\tt CoapplicantIncome}$ 0 LoanAmount 5 Loan\_Amount\_Term 6

```
Property_Area
                            0
      dtype: int64
 [8]: df['Credit_History'] = df['Credit_History'].fillna( df['Credit_History'].

¬dropna().mode().values[0] )

      df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna( df['Loan_Amount_Term'].

dropna().mode().values[0] )

 [9]: # fill na with mode fro categorical data and mean for the numerical data
      df['Gender'] = df['Gender'].fillna(df['Gender'].mode()[0])
      df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode()[0])
      df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])
      df['Credit_History'] = df['Credit_History'].fillna(df['Credit_History'].mean())
      df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].mean())
      df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].
       →mean())
      df['Property_Area'] = df['Property_Area'].map({'Rural':0, 'Semiurban':2, 'Urban':
       →1}).astype('int')
      df['Dependents'].replace('3+','3',inplace=True)
[18]: df['Dependents'] = df['Dependents'].astype('int')
[20]: df.drop(columns='Loan_ID',inplace=True)
[26]: # creat new column with total income
      df['total_income'] = df['ApplicantIncome'] + df['CoapplicantIncome']
[28]: # check for NAN
      df.isnull().sum()
[28]: Gender
                           0
      Married
                           0
      Dependents
                           0
      Education
                           0
                           0
      Self Employed
      ApplicantIncome
                           0
      CoapplicantIncome
                           0
      LoanAmount
                           0
     Loan_Amount_Term
                           0
      Credit_History
                           0
                           0
      Property_Area
      total_income
                           0
      dtype: int64
[24]: df.info()
```

Credit\_History

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<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 11 columns):

#	Column	Non-Null Count	Dtype
0	Gender	367 non-null	int64
1	Married	367 non-null	int64
2	Dependents	367 non-null	int64
3	Education	367 non-null	int64
4	Self_Employed	367 non-null	int64
5	ApplicantIncome	367 non-null	int64
6	${\tt CoapplicantIncome}$	367 non-null	int64
7	LoanAmount	367 non-null	float64
8	Loan_Amount_Term	367 non-null	float64
9	Credit_History	367 non-null	float64
10	Property_Area	367 non-null	int64
	07 .04(0)	04(0)	

dtypes: float64(3), int64(8)

memory usage: 31.7 KB

## [30]: df.head()

[30]:		Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
	0	1	1	0	1	0	5720
	1	1	1	1	1	0	3076
	2	1	1	2	1	0	5000
	3	1	1	2	1	0	2340
	4	1	0	0	0	0	3276

	${ t CoapplicantIncome}$	${\tt LoanAmount}$	Loan_Amount_Term	Credit_History	\
0	0	110.0	360.0	1.0	
1	1500	126.0	360.0	1.0	
2	1800	208.0	360.0	1.0	
3	2546	100.0	360.0	1.0	
4	0	78.0	360.0	1.0	

	Property_Area	total_income
0	1	5720
1	1	4576
2	1	6800
3	1	4886
4	1	3276

# 2 Modeling

#### []: df.columns

```
[32]: # split our data in to target and feature
      X = df.drop('Married',axis=1)
      y= df['Married']
[34]: # scale our data
      from sklearn.preprocessing import StandardScaler
      scale = StandardScaler()
[36]: X=scale.fit_transform(X)
[38]: X
[38]: array([[ 0.48547939, -0.75822199, 0.5448117 , ..., 0.4376739 ,
             -0.01732564, -0.12618159],
             [ 0.48547939, 0.18187082, 0.5448117, ..., 0.4376739,
             -0.01732564, -0.34650636],
             [ 0.48547939, 1.12196363, 0.5448117, ..., 0.4376739,
             -0.01732564, 0.08181731],
             [0.48547939, -0.75822199, 0.5448117, ..., 0.4376739,
               1.25437613, -0.21804778],
             [0.48547939, -0.75822199, 0.5448117, ..., 0.4376739,
             -1.28902741, 0.19602411],
             [0.48547939, -0.75822199, 0.5448117, ..., 0.4376739,
             -1.28902741, 0.54403709]])
[40]: from sklearn.model_selection import train_test_split
      from sklearn.model_selection import cross_val_score
      from sklearn.metrics import accuracy_score
[42]: model_df = {}
      def model_val(model,X,y):
          # spliting dataset for training and testing
          X_train, X_test, y_train, y_test = train_test_split(X,y,
                                                         test_size=0.20,
                                                         random_state=42)
          # training the model
          model.fit(X_train, y_train)
          # asking model for prediction
          y_pred = model.predict(X_test)
          # checking model's prediction accuracy
          print(f"{model} accuracy is {accuracy_score(y_test,y_pred)}")
```

```
# to find the best model we use cross-validation, thru this we can compare
       \hookrightarrow different algorithms
          # In this we use whole dataset to for testing not just 20%, but one at a_{\sf L}
       \rightarrow time and summarize
          # the result at the end.
          # 5-fold cross-validation (but 10-fold cross-validation is common in _{\!\!\!\perp}
       ⇔practise)
          score = cross_val_score(model, X, y, cv=3) # it will divides the dataset into_
       ⇔5 parts and during each iteration
                                                    # uses (4,1) combination for
       ⇔training and testing
          print(f"{model} Avg cross val score is {np.mean(score)}")
          model_df[model] = round(np.mean(score)*100,2)
[44]: from sklearn.linear_model import LogisticRegression
      model = LogisticRegression()
      # passing this model object of LogisticRegression Class in the function we've_
       \hookrightarrow created
      model_val(model,X,y)
     LogisticRegression() accuracy is 0.6891891891891
     LogisticRegression() Avg cross val score is 0.6811053356435203
[46]: from sklearn import svm
      model = svm.SVC()
      model_val(model,X,y)
     SVC() accuracy is 0.6756756756757
     SVC() Avg cross val score is 0.6728864009951575
[48]: from sklearn.tree import DecisionTreeClassifier
      model = DecisionTreeClassifier()
      model_val(model,X,y)
     DecisionTreeClassifier() accuracy is 0.6081081081081081
     DecisionTreeClassifier() Avg cross val score is 0.6293704740326092
[50]: from sklearn.ensemble import RandomForestClassifier
      model =RandomForestClassifier()
      model_val(model,X,y)
```

RandomForestClassifier() accuracy is 0.6486486486486487 RandomForestClassifier() Avg cross val score is 0.6893464836287707

```
[52]: from sklearn.ensemble import GradientBoostingClassifier

model = GradientBoostingClassifier()
model_val(model,X,y)
```

GradientBoostingClassifier() accuracy is 0.6891891891891891 GradientBoostingClassifier() Avg cross val score is 0.7056732862410592