Project Flow

- Load Dataset
- EDA
- Create Baseline Models
- Feature Engineering, Transformations & Feature Selections
- Cross Validation of Models
- Finalise Dataset
- Model Selection via CV
- HyperParameter Tuning of Selected Model
- Train Tuned Model using Entire new Data
- Save & Deploy Data
- Predict

In [1]:

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

import warnings
warnings.filterwarnings("ignore")

pd.set_option('display.max_columns', None)
```

In [2]:

```
train = pd.read_csv('train.csv')
train.shape
```

Out[2]:

```
(614, 13)
```

In [3]:

```
test = pd.read_csv('test.csv')
test.shape

test_backup = test.copy()
```

In [4]:

```
train.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappl
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 [ ]:

```

```

Data Validation

since we have categorical features, we would encode that, but need to check if all categories present in testing set are present in training data as well, otherwise we need to handle that separately

In [5]:

```
categorical_features = ['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed

for col in categorical_features:
    print('=> ',col)
    print('Train -> ', train[col].unique())
    print('Test  -> ', test[col].unique())
    print('*'*33)
```

```
=>  Gender
Train ->  ['Male' 'Female' nan]
Test  ->  ['Male' 'Female' nan]
*********************************
=>  Married
Train ->  ['No' 'Yes' nan]
Test  ->  ['Yes' 'No']
*********************************
=>  Dependents
Train ->  ['0' '1' '2' '3+' nan]
Test  ->  ['0' '1' '2' '3+' nan]
*********************************
=>  Education
Train ->  ['Graduate' 'Not Graduate']
Test  ->  ['Graduate' 'Not Graduate']
*********************************
=>  Self_Employed
Train ->  ['No' 'Yes' nan]
Test  ->  ['No' 'Yes' nan]
*********************************
=>  Property_Area
Train ->  ['Urban' 'Rural' 'Semiurban']
Test  ->  ['Urban' 'Semiurban' 'Rural']
*********************************
```

> There are no unique categories present in Test set, which are not in Trianing data => Validiated

EDA has not been performed yet. Covered in another notebook

Outliers Detection

IQR

In [6]:

```
def IQR(df, col):

    # calculate quantiles
    q25, q75 = np.quantile(df[col], 0.25), np.quantile(df[col], 0.75)

    # calculate IQR
    iqr = q75 - q25

    # defining boundaries
    lower, upper = q25 - (1.5 * iqr), q75 + (1.5 * iqr)

    print('IQR is ',iqr)
    print('lower bound is ', lower)
    print('upper bound is ', upper)

    # calculate records count beyond range
    df_upper = df[df[col] > upper]
    df_lower = df[df[col] < lower]

    print('Total number of outliers are', df_upper.shape[0] + df_lower.shape[0])

    # Visualising
    plt.figure(figsize = (10,6))
    sns.distplot(df[col], kde=False)
    plt.axvspan(xmin = lower,xmax= df[col].min(),alpha=0.2, color='red')
    plt.axvspan(xmin = upper,xmax= df[col].max(),alpha=0.2, color='red')
```

In [7]:

```
numerical_features = [ 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amou
```

In [8]:

```
for col in numerical_features:
    print('=> ', col)
    IQR(train, col)
    print('*'*33)
```

```
=>  ApplicantIncome
IQR is  2917.5
lower bound is  -1498.75
upper bound is  10171.25
Total number of outliers are 50
*********************************
=>  CoapplicantIncome
IQR is  2297.25
lower bound is  -3445.875
upper bound is  5743.125
Total number of outliers are 18
*********************************
=>  LoanAmount
IQR is  nan
lower bound is  nan
upper bound is  nan
Total number of outliers are 0
*********************************
=>  Loan_Amount_Term
```

Z Score

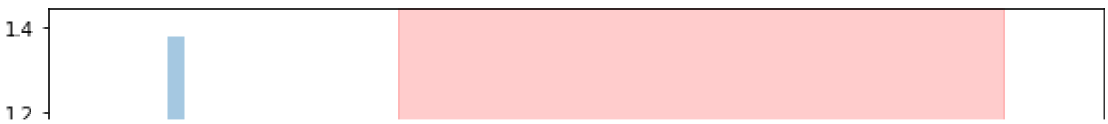
In [9]:

```
def zscore(col):

    outliers = []
    z_scores = []
    threshold = 3

    # calculate the mean and standard deviation of the data frame
    data_mean, data_std = col.mean(), col.std()

    for i in col:
        z_score = (i - data_mean)/ data_std
        z_scores.append(z_score)

        if np.abs(z_score) > threshold:
            outliers.append(i)

    print('Total Outliers are ', len(outliers))

    # Visualising
    plt.figure(figsize = (10,6))
    sns.distplot(z_scores)
    plt.axvspan(xmin = 3 ,xmax= max(z_scores),alpha=0.2, color='red')
```

In [10]:

```
for col in numerical_features:
    print('=> ', col)
    zscore(train[col])
    print('*'*33)
```

```
=>  ApplicantIncome
Total Outliers are  8
*********************************
=>  CoapplicantIncome
Total Outliers are  6
*********************************
=>  LoanAmount
Total Outliers are  14
*********************************
=>  Loan_Amount_Term
Total Outliers are  12
*********************************
=>  Credit_History
Total Outliers are  0
*********************************
```



Standard Deviation

In [11]:

```
def std(df, col):

    # calculate the mean and standard deviation of the data frame
    data_mean, data_std = df[col].mean(), df[col].std()

    # initialise the cutoff value
    cut_off = data_std * 3

    # calculate the lower and upper bound value
    lower, upper = data_mean - cut_off, data_mean + cut_off

    print('The lower bound value is', lower)
    print('The upper bound value is', upper)

    # calculate records count beyond range
    df_upper = df[df[col] > upper]
    df_lower = df[df[col] < lower]

    print('Total number of outliers are', df_upper.shape[0] + df_lower.shape[0])

    # Visualising
    plt.figure(figsize = (10,6))
    sns.distplot(df[col], kde=False)
    plt.axvspan(xmin = lower,xmax= df[col].min(),alpha=0.2, color='red')
```

In [12]:

```
for col in numerical_features:
    print('=> ', col)
    std(train, col)
    print('*'*33)
```

```
=>  ApplicantIncome
The lower bound value is -12923.665736773899
The upper bound value is 23730.584303549145
Total number of outliers are 8
*********************************
=>  CoapplicantIncome
The lower bound value is -7157.499309645475
The upper bound value is 10399.990905699677
Total number of outliers are 6
*********************************
=>  LoanAmount
The lower bound value is -110.34981354495417
The upper bound value is 403.1741378692785
Total number of outliers are 14
*********************************
=>  Loan_Amount_Term
The lower bound value is 146.6387704361623
The upper bound value is 537.3612295638377
Total number of outliers are 12
*********************************
```

In [13]:

```
train.dtypes
```

Out[13]:

```
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
```

In [14]:

```
# Removing outliers from ApplicantIncome considering Standard Deviation
train = train[(train['ApplicantIncome'] < 23730) & (train['ApplicantIncome'] > -12923)
```

In [15]:

```
# Removing outliers from CoApplicantIncome considering Standard Deviation
train = train[(train['CoapplicantIncome'] < 10399) & (train['CoapplicantIncome'] > -71
```

In [16]:

```
train.shape
```

Out[16]:

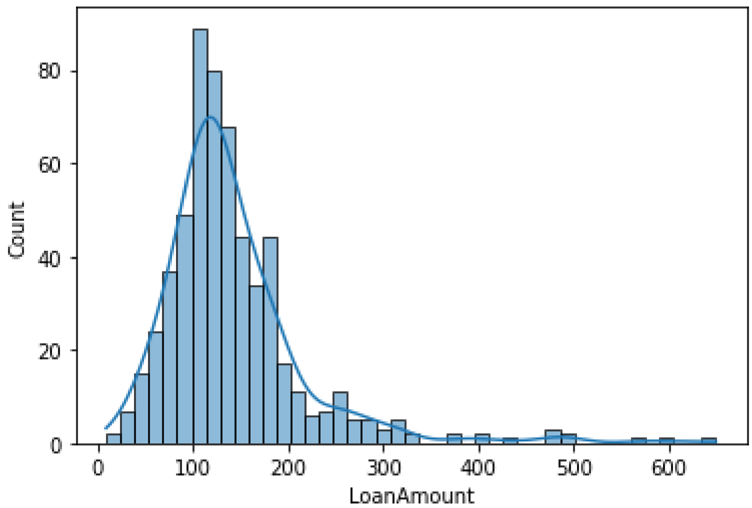
```
(600, 13)
```

In [17]:

```
sns.histplot(data= train['LoanAmount'], kde= True)
```

Out[17]:

```
<AxesSubplot: xlabel='LoanAmount', ylabel='Count'>
```



In [18]:

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 600 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Loan_ID            600 non-null    object 
 1   Gender             589 non-null    object 
 2   Married            597 non-null    object 
 3   Dependents         585 non-null    object 
 4   Education          600 non-null    object 
 5   Self_Employed      570 non-null    object 
 6   ApplicantIncome    600 non-null    int64  
 7   CoapplicantIncome  600 non-null    float64
 8   LoanAmount         578 non-null    float64
 9   Loan_Amount_Term   586 non-null    float64
 10  Credit_History     551 non-null    float64
 11  Property_Area      600 non-null    object 
 12  Loan_Status        600 non-null    object 
dtypes: float64(4), int64(1), object(8)
memory usage: 65.6+ KB
```

In [19]:

```
test.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   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 
dtypes: float64(3), int64(2), object(7)
memory usage: 34.5+ KB
```

In [20]:

```
train[train.duplicated(keep= 'first')].shape
```

Out[20]:

```
(0, 13)
```

In [21]:

```
train.isnull().sum()
```

Out[21]:

```
Loan_ID               0
Gender               11
Married               3
Dependents           15
Education             0
Self_Employed        30
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       49
Property_Area         0
Loan_Status           0
dtype: int64
```

In [22]:

```
test.isnull().sum()
```

Out[22]:

```
Loan_ID               0
Gender               11
Married               0
Dependents           10
Education             0
Self_Employed        23
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

Splitting Train data into Train & Val

In [23]:

```
from sklearn.model_selection import train_test_split

X = train.drop(['Loan_Status'], axis= 1)
y = train['Loan_Status']

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=9,

X_train.shape, X_val.shape, y_train.shape, y_val.shape
```

Out[23]:

```
((480, 12), (120, 12), (480,), (120,))
```

In [24]:

```
X_train['Gender'].value_counts(normalize= True)
```

Out[24]:

```
Male      0.817021
Female    0.182979
Name: Gender, dtype: float64
```

Why this is important : Suppse `if one of the values were dominant (covering > 80% suppose), then we could have used that value to impute in these missing values`

if suppose both were too close, and if we assign there missing values to a particular class (using MODE) , then the `distribution will significantly change` , in that case we need to think other way around

check column transformer to do all tasks together

In [25]:

```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OrdinalEncoder
```

In [26]:

```
Imputer = ColumnTransformer(transformers = [
    ('mode', SimpleImputer(strategy= 'most_frequent'), ['Gender', 'Married', 'Dependent
    ('mean', SimpleImputer(strategy= 'mean'), ['LoanAmount'])
], remainder= 'drop')
```

In [27]:

```
Imputed_data_train = Imputer.fit_transform(X_train)
Imputed_data_train
```

Out[27]:

```
array([['Male', 'Yes', '2', ..., 360.0, 1.0, 155.0],
       ['Male', 'No', '0', ..., 360.0, 1.0, 311.0],
       ['Male', 'Yes', '0', ..., 180.0, 0.0, 90.0],
       ...,
       ['Male', 'No', '0', ..., 360.0, 1.0, 144.1459694989107],
       ['Female', 'No', '1', ..., 360.0, 1.0, 144.1459694989107],
       ['Male', 'Yes', '0', ..., 360.0, 1.0, 144.1459694989107]],
      dtype=object)
```

In [28]:

```
Imputer.named_transformers_['mode'].get_feature_names_out()
```

Out[28]:

```
array(['Gender', 'Married', 'Dependents', 'Self_Employed',
       'Loan_Amount_Term', 'Credit_History'], dtype=object)
```

In [29]:

```
Imputer.named_transformers_['mean'].get_feature_names_out()
```

Out[29]:

```
array(['LoanAmount'], dtype=object)
```

In [30]:

```
new_cols = Imputer.get_feature_names_out()
new_cols
```

Out[30]:

```
array(['mode__Gender', 'mode__Married', 'mode__Dependents',
       'mode__Self_Employed', 'mode__Loan_Amount_Term',
       'mode__Credit_History', 'mean__LoanAmount'], dtype=object)
```

In [31]:

```
Imputed_df_train = pd.DataFrame(Imputed_data_train, columns=new_cols)
Imputed_df_train.tail()
```

Out[31]:

	mode__Gender	mode__Married	mode__Dependents	mode__Self_Employed	mode__Loan_A
475	Male	Yes	0	No	
476	Male	Yes	2	No	
477	Male	No	0	No	
478	Female	No	1	Yes	
479	Male	Yes	0	No	

In [32]:

```
Imputed_df_train.isnull().sum()
```

Out[32]:

```
mode__Gender            0
mode__Married           0
mode__Dependents        0
mode__Self_Employed     0
mode__Loan_Amount_Term  0
mode__Credit_History    0
mean__LoanAmount        0
dtype: int64
```

In [33]:

```
Imputed_df_train.shape
```

Out[33]:

```
(480, 7)
```

In [34]:

```
X_train = X_train.reset_index(drop= True)
Imputed_df_train = Imputed_df_train.reset_index(drop=True)

X_train = pd.concat([X_train, Imputed_df_train], axis=1)
X_train.tail()
```

Out[34]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coap
475	LP001578	Male	Yes	0	Graduate	No	2439	
476	LP002832	Male	Yes	2	Graduate	No	8799	
477	LP002697	Male	No	0	Graduate	No	4680	
478	LP001392	Female	No	1	Graduate	Yes	7451	
479	LP001356	Male	Yes	0	Graduate	No	4652	

In [35]:

```
X_train.isnull().sum()
```

Out[35]:

```
Loan_ID                  0
Gender                  10
Married                  3
Dependents              14
Education                0
Self_Employed           22
ApplicantIncome          0
CoapplicantIncome        0
LoanAmount              21
Loan_Amount_Term        11
Credit_History          40
Property_Area            0
mode__Gender             0
mode__Married            0
mode__Dependents         0
mode__Self_Employed      0
mode__Loan_Amount_Term   0
mode__Credit_History     0
mean__LoanAmount         0
dtype: int64
```

One Hot Encoding

In [36]:

```
encoder = ColumnTransformer(transformers = [
    ('encOH', OneHotEncoder(sparse= False, drop= 'first'), ['mode__Gender', 'mode__Marı
    ('encOR', OrdinalEncoder(categories =[[ 'Not Graduate', 'Graduate']]), ['Education
], remainder= 'drop')
```

In [37]:

```
encoded_data_train = encoder.fit_transform(X_train)
encoded_data_train
```

Out[37]:

```
array([[1., 1., 0., ..., 1., 0., 1.],
       [1., 0., 0., ..., 0., 0., 1.],
       [1., 1., 0., ..., 0., 0., 1.],
       ...,
       [1., 0., 0., ..., 1., 0., 1.],
       [0., 0., 1., ..., 1., 0., 1.],
       [1., 1., 0., ..., 1., 0., 1.]])
```

In [38]:

```
encoder.named_transformers_['encOH'].get_feature_names_out()
```

Out[38]:

```
array(['mode__Gender_Male', 'mode__Married_Yes', 'mode__Dependents_1',
       'mode__Dependents_2', 'mode__Dependents_3+',
       'mode__Self_Employed_Yes', 'Property_Area_Semiurban',
       'Property_Area_Urban'], dtype=object)
```

In [39]:

```
new_cols = encoder.get_feature_names_out()
new_cols
```

Out[39]:

```
array(['encOH__mode__Gender_Male', 'encOH__mode__Married_Yes',
       'encOH__mode__Dependents_1', 'encOH__mode__Dependents_2',
       'encOH__mode__Dependents_3+', 'encOH__mode__Self_Employed_Yes',
       'encOH__Property_Area_Semiurban', 'encOH__Property_Area_Urban',
       'encOR__Education'], dtype=object)
```

In [40]:

```
encoded_df_train = pd.DataFrame(encoded_data_train, columns=new_cols, dtype= int)
encoded_df_train.head()
```

Out[40]:

	encOH__mode__Gender_Male	encOH__mode__Married_Yes	encOH__mode__Dependents_1	enc
0	1	1	0	
1	1	0	0	
2	1	1	0	
3	1	0	0	
4	1	1	0	

In [41]:

```
X_train = X_train.reset_index(drop= True)
encoded_df_train = encoded_df_train.reset_index(drop=True)

X_train = pd.concat([X_train, encoded_df_train], axis=1)
X_train.head()
```

Out[41]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappl
0	LP002197	Male	Yes	2	Graduate	No	5185	
1	LP002652	Male	No	0	Graduate	No	5815	
2	LP002449	Male	Yes	0	Graduate	No	2483	
3	LP001761	Male	No	0	Graduate	Yes	6400	
4	LP001926	Male	Yes	0	Graduate	No	3704	

In [42]:

```
X_train.isnull().sum()
```

Out[42]:

```
Loan_ID                     0
Gender                     10
Married                     3
Dependents                 14
Education                   0
Self_Employed              22
ApplicantIncome             0
CoapplicantIncome           0
LoanAmount                 21
Loan_Amount_Term           11
Credit_History             40
Property_Area               0
mode__Gender                0
mode__Married               0
mode__Dependents            0
mode__Self_Employed         0
mode__Loan_Amount_Term      0
mode__Credit_History        0
```

Imputing & Encoding Validation & Test Dataset

Imputing Val

In [43]:

```
Imputed_data_val = Imputer.transform(X_val)
new_cols = Imputer.get_feature_names_out()
Imputed_df_val = pd.DataFrame(Imputed_data_val, columns=new_cols)

X_val = X_val.reset_index(drop= True)
Imputed_df_val = Imputed_df_val.reset_index(drop=True)

X_val = pd.concat([X_val, Imputed_df_val], axis=1)
```

Encoding Val

In [44]:

```
encoded_data_val = encoder.transform(X_val)
new_cols = encoder.get_feature_names_out()
encoded_df_val = pd.DataFrame(encoded_data_val, columns=new_cols, dtype= int)

X_val = X_val.reset_index(drop= True)
encoded_df_val = encoded_df_val.reset_index(drop=True)

X_val = pd.concat([X_val, encoded_df_val], axis=1)
```

Imputing Test

In [45]:

```
Imputed_data_test = Imputer.transform(test)
new_cols = Imputer.get_feature_names_out()
Imputed_df_test = pd.DataFrame(Imputed_data_test, columns=new_cols)

test = test.reset_index(drop= True)
Imputed_df_test = Imputed_df_test.reset_index(drop=True)

test = pd.concat([test, Imputed_df_test], axis=1)
```

Encoding Test

In [46]:

```
encoded_data_test = encoder.transform(test)
new_cols = encoder.get_feature_names_out()
encoded_df_test = pd.DataFrame(encoded_data_test, columns=new_cols, dtype= int)

test = test.reset_index(drop= True)
encoded_df_test = encoded_df_test.reset_index(drop=True)

test = pd.concat([test, encoded_df_test], axis=1)
```

Dropping Index Identifier : loan_id

In [47]:

```
X_train.drop(['Loan_ID'], axis= 1, inplace= True)
X_val.drop(['Loan_ID'], axis= 1, inplace= True)
test.drop(['Loan_ID'], axis= 1, inplace= True)
```

Validating Data Types of Features

In [48]:

```
# Train
X_train['mode__Loan_Amount_Term'] = X_train['mode__Loan_Amount_Term'].astype('int')
X_train['mode__Credit_History'] = X_train['mode__Credit_History'].astype('int')
X_train['mean__LoanAmount'] = X_train['mean__LoanAmount'].astype('float')

# Test
X_val['mode__Loan_Amount_Term'] = X_val['mode__Loan_Amount_Term'].astype('int')
X_val['mode__Credit_History'] = X_val['mode__Credit_History'].astype('int')
X_val['mean__LoanAmount'] = X_val['mean__LoanAmount'].astype('float')

# Val
test['mode__Loan_Amount_Term'] = test['mode__Loan_Amount_Term'].astype('int')
test['mode__Credit_History'] = test['mode__Credit_History'].astype('int')
test['mean__LoanAmount'] = test['mean__LoanAmount'].astype('float')
```

In [ ]:

```
1
```

Separating Numerical Features for Further Analysis

In [49]:

```
numerical_features = [ 'ApplicantIncome', 'CoapplicantIncome', 'mean__LoanAmount', 'moc
```

Detecting `Multi-Collinearity`

In [50]:

```
X_train[numerical_features].corr().round(2)
```

Out[50]:

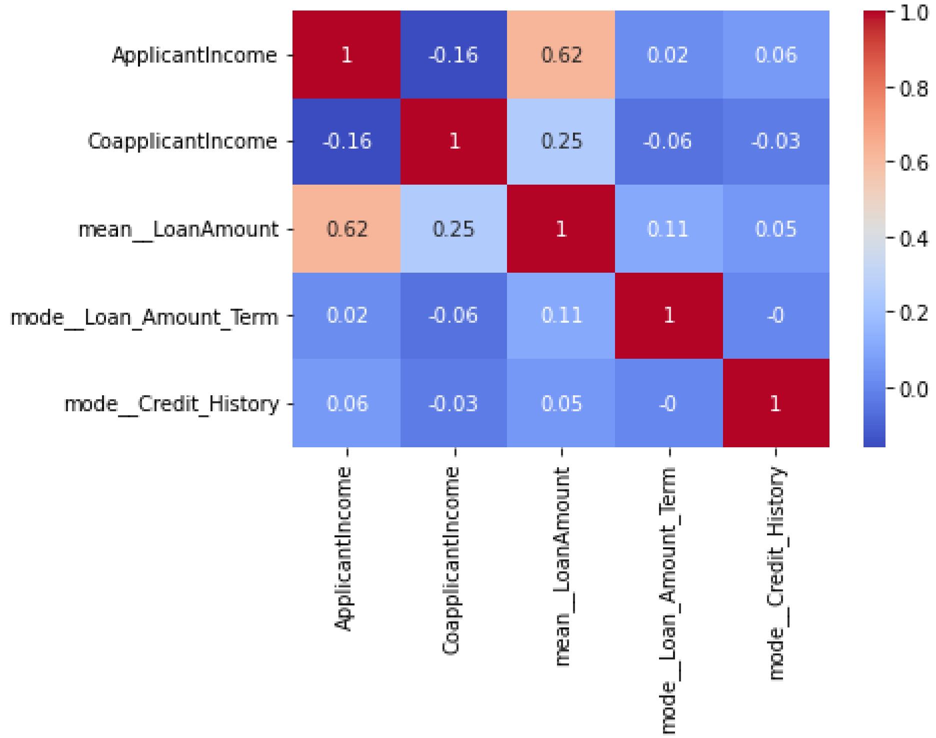
	ApplicantIncome	CoapplicantIncome	mean__LoanAmount	mode__Lc
ApplicantIncome	1.00	-0.16	0.62	
CoapplicantIncome	-0.16	1.00	0.25	
mean__LoanAmount	0.62	0.25	1.00	
mode__Loan_Amount_Term	0.02	-0.06	0.11	
mode__Credit_History	0.06	-0.03	0.05	

In [51]:

```
sns.heatmap(X_train[numerical_features].corr().round(2), annot= True, cmap='coolwarm')
```

Out[51]:

<AxesSubplot: >



Quick Statistical Summary of Data

In [52]:

```
X_train[numerical_features].describe().round(2)
```

Out[52]:

	ApplicantIncome	CoapplicantIncome	mean__LoanAmount	mode__Loan_Amount_Term	m
count	480.00	480.00	480.00	480.00	
mean	5008.53	1441.32	144.15	342.00	
std	3555.31	1723.58	77.87	66.39	
min	150.00	0.00	9.00	12.00	
25%	2912.75	0.00	100.75	360.00	
50%	3807.00	1128.50	129.50	360.00	
75%	5818.25	2259.25	165.00	360.00	
max	20833.00	8980.00	650.00	480.00	

- verify the minimum values of feature, if they are negative.
- verify if max values of features make sense and are logical
- verify if it contains outliers, an idea could be generated by looking min, max & Mean

Building Base Model

In [53]:

```
final_processed_features = [ 'encOH__mode__Gender_Male', 'encOH__mode__Married_Yes',
       'encOH__mode__Dependents_1', 'encOH__mode__Dependents_2',
       'encOH__mode__Dependents_3+', 'encOH__mode__Self_Employed_Yes',
       'encOH__Property_Area_Semiurban', 'encOH__Property_Area_Urban',
       'encOR__Education' , 'mode__Loan_Amount_Term', 'mode__Credit_History', 'mean__Lo
```

In [54]:

```
### Let's try out a few more models

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier

```

In [55]:

```
models = []

models.append(('LR', LogisticRegression(class_weight='balanced', random_state=9)))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier(random_state=9)))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC( random_state=9)))
models.append(('RF', RandomForestClassifier(random_state=9)))
models.append(('GB', GradientBoostingClassifier(random_state=9)))
models.append(('AdaB', AdaBoostClassifier(random_state=9)))

models
```

Out[55]:

```
[('LR', LogisticRegression(class_weight='balanced', random_state=9)),
 ('LDA', LinearDiscriminantAnalysis()),
 ('KNN', KNeighborsClassifier()),
 ('CART', DecisionTreeClassifier(random_state=9)),
 ('NB', GaussianNB()),
 ('SVM', SVC(random_state=9)),
 ('RF', RandomForestClassifier(random_state=9)),
 ('GB', GradientBoostingClassifier(random_state=9)),
 ('AdaB', AdaBoostClassifier(random_state=9))]
```

In [56]:

```
train_base_scores = []
val_base_scores = []
model_names = []

for name, model in models:
    model.fit(X_train[final_processed_features], y_train)
    model_names.append(name)
    train_base_scores.append(model.score(X_train[final_processed_features], y_train ))
    val_base_scores.append(model.score(X_val[final_processed_features], y_val ))
```

In [57]:

```
for model, train_score, val_score in zip(model_names, train_base_scores, val_base_score
    print('Model -> ', model)
    print('Train Score -> ', round(train_score,2))
    print('Val Score -> ', round(val_score,2))
    print('*'*30)
```

```
Model ->  NB
Train Score ->  0.82
Val Score ->  0.79
******************************
Model ->  SVM
Train Score ->  0.69
Val Score ->  0.69
******************************
Model ->  RF
Train Score ->  0.99
Val Score ->  0.73
******************************
Model ->  GB
Train Score ->  0.88
Val Score ->  0.79
******************************
Model ->  AdaB
Train Score ->  0.84
Val Score ->  0.78
******************************
```

```
Findings
--------
Logistic - fine
LDA - fine
KNN - fine
CART - Overfitting, could be used if tuned
NB - fine
SVM - fine
RF - OVerfitting, could be used if tuned
GB - Overfitting, coule be used if tuned
AdaB - Overfitting, coule be used if tuned

```

```
NOTE
====

we simply can't proceed with the model performing best with test data, as it's not guaranteed that with new test data, the model performance would be consistent given the pattern is same.

answer is CROSSVALIDATION
as it is repeated training and testing, we can see the variation in the models performance.

So we need to check how close are models predicted values among themselves on similar dataset.
Even if is consistently predictiong wrong, it is highly precise.
a model which is sometimes good and sometimes bad, thats not good.

```

```
THIS IS THE REAL USE CASE OF CROSS VALIDATION
```

In [58]:

```
y_train.value_counts(normalize=True)
```

Out[58]:

```
Y    0.691667
N    0.308333
Name: Loan_Status, dtype: float64
```

In [59]:

```
from sklearn.model_selection import StratifiedKFold, cross_val_score

results = []
model_names = []
n_splits= 5

for name, model in models:
    kfold = StratifiedKFold(n_splits= 5, shuffle= True, random_state= 9)
    cv_results = cross_val_score(model, X_train[final_processed_features], y_train, cv=
    results.append(cv_results)
    model_names.append(name)

    msg = "%s: %5.2f (%5.2f)" % (name, cv_results.mean()*100, cv_results.std()*100)
    print(msg)

results_df = pd.DataFrame(results, index = model_names, columns = 'CV1 CV2 CV3 CV4 CV5
results_df['CV Mean'] = results_df.iloc[:, 0:n_splits].mean(axis=1)
results_df['CV Std Dev'] = results_df.iloc[:, 0:n_splits].std(axis=1)
results_df.sort_values(by= 'CV Mean', ascending= False)*100
```

```
LR: 75.83 ( 2.02)
LDA: 81.88 ( 1.06)
KNN: 60.42 ( 1.98)
CART: 69.79 ( 5.02)
NB: 81.04 ( 0.78)
SVM: 69.17 ( 0.51)
RF: 79.38 ( 2.83)
GB: 77.08 ( 2.95)
AdaB: 78.96 ( 1.21)
```

Out[59]:

	CV1	CV2	CV3	CV4	CV5	CV Mean	CV Std Dev
LDA	83.333333	80.208333	82.291667	81.250000	82.291667	81.875000	1.187683
NB	82.291667	80.208333	81.250000	80.208333	81.250000	81.041667	0.871521
RF	84.375000	78.125000	80.208333	78.125000	76.041667	79.375000	3.159531
AdaB	78.125000	78.125000	81.250000	79.166667	78.125000	78.958333	1.358167
GB	78.125000	71.875000	80.208333	79.166667	76.041667	77.083333	3.294039
LR	72.916667	77.083333	78.125000	77.083333	73.958333	75.833333	2.258280
CART	62.500000	72.916667	69.791667	77.083333	66.666667	69.791667	5.609547
SVM	69.791667	69.791667	68.750000	68.750000	68.750000	69.166667	0.570544
KNN	60.416667	63.541667	60.416667	60.416667	57.291667	60.416667	2.209709

```
 Note
=====

We should use whole Training Data for Cross Validation (not X_Train or any splitted
part.
```

```
Reason being, the data is already pslitted in Cross Validation in n folds, and here also if we are passing Splitted data then the overall % of data used to train individual models becomes insufficient to get descent scores and understand real predictive power of our model.
```

Scaling Features

In [60]:

```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
```

In [61]:

```python
cols_to_scale = ['mode__Loan_Amount_Term', 'mean__LoanAmount']
```

In [62]:

```python
scaler.fit(X_train[cols_to_scale])
```

Out[62]:

```
▾ StandardScaler
StandardScaler()
```

In [63]:

```python
X_train[cols_to_scale] = scaler.transform(X_train[cols_to_scale])
X_val[cols_to_scale] = scaler.transform(X_val[cols_to_scale])
test[cols_to_scale] = scaler.transform(test[cols_to_scale])
```

Re Training & Evaluating Models

In [64]:

```
from sklearn.model_selection import StratifiedKFold, cross_val_score

results = []
model_names = []
n_splits= 5

for name, model in models:
    kfold = StratifiedKFold(n_splits= 5, shuffle= True, random_state= 9)
    cv_results = cross_val_score(model, X_train[final_processed_features], y_train, cv=
    results.append(cv_results)
    model_names.append(name)

    msg = "%s: %5.2f (%5.2f)" % (name, cv_results.mean()*100, cv_results.std()*100)
    print(msg)

results_df = pd.DataFrame(results, index = model_names, columns = 'CV1 CV2 CV3 CV4 CV5
results_df['CV Mean'] = results_df.iloc[:, 0:n_splits].mean(axis=1)
results_df['CV Std Dev'] = results_df.iloc[:, 0:n_splits].std(axis=1)
results_df.sort_values(by= 'CV Mean', ascending= False)*100
```

```
LR: 76.04 ( 2.47)
LDA: 81.88 ( 1.06)
KNN: 74.17 ( 2.83)
CART: 69.79 ( 5.02)
NB: 81.04 ( 0.78)
SVM: 81.04 ( 2.02)
RF: 79.38 ( 2.83)
GB: 77.29 ( 2.59)
AdaB: 79.17 ( 1.14)
```

Out[64]:

	CV1	CV2	CV3	CV4	CV5	CV Mean	CV Std Dev
LDA	83.333333	80.208333	82.291667	81.250000	82.291667	81.875000	1.187683
NB	82.291667	80.208333	81.250000	80.208333	81.250000	81.041667	0.871521
SVM	83.333333	80.208333	83.333333	80.208333	78.125000	81.041667	2.258280
RF	84.375000	78.125000	80.208333	78.125000	76.041667	79.375000	3.159531
AdaB	78.125000	79.166667	81.250000	79.166667	78.125000	79.166667	1.275776
GB	78.125000	72.916667	80.208333	79.166667	76.041667	77.291667	2.890508
LR	71.875000	79.166667	77.083333	77.083333	75.000000	76.041667	2.755991
KNN	71.875000	77.083333	76.041667	76.041667	69.791667	74.166667	3.159531
CART	62.500000	72.916667	69.791667	77.083333	66.666667	69.791667	5.609547

```
Naive Bayes is performing better with appropriate Standard Deviation
```

```
Let's perform Hyperparameter Tuning for it.
```

In [65]:

```
from sklearn.model_selection import GridSearchCV

clf = GaussianNB()

# define parameter grid for grid search
param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5]}
```

In [66]:

```
# perform grid search using 5-fold cross-validation
grid_search = GridSearchCV(clf, param_grid=param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train[final_processed_features], y_train)

# print the best parameters and corresponding accuracy score
print("Best parameters: ", grid_search.best_params_)
print("Best accuracy score: ", grid_search.best_score_)
```

```
Best parameters:  {'var_smoothing': 1e-09}
Best accuracy score:  0.7979166666666667
```

In [67]:

```
clf = GaussianNB(var_smoothing= 1e-09)
```

Training Final Model

In [68]:

```
clf.fit(X_train[final_processed_features], y_train)
```

Out[68]:

```
▾ GaussianNB
GaussianNB()
```

In [69]:

```
# Trianing Score
clf.score(X_train[final_processed_features], y_train)
```

Out[69]:

```
0.8166666666666667
```

In [70]:

```
# Validation Score
clf.score(X_val[final_processed_features], y_val)
```

Out[70]:

```
0.7916666666666666
```

In [71]:

```
#checking predictions son Validation set
pred_test = clf.predict(test[final_processed_features])
pred_test
```

Out[71]:

```
array(['Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', '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', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'N',
       'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y',
       'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y',
       'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y',
       'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y'], dtype='<U1')
```

In [72]:

```
pred_test_df = pd.DataFrame({'Loan_ID' : test_backup['Loan_ID'], 'Loan_Status' : pred_t
pred_test_df.head()
```

Out[72]:

	Loan_ID	Loan_Status
0	LP001015	Y
1	LP001022	Y
2	LP001031	Y
3	LP001035	Y
4	LP001051	Y

In [73]:

```
# saving File
pred_test_df.to_csv("predicted_Loan_Defaulter.csv", index=False)
```

In [ ]:

```

```

Trying Lazy Predictor

```
!pip install lazypredict
```

In [77]:

```
import lazypredict
from lazypredict.Supervised import LazyClassifier
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
```

In [79]:

```
clf = LazyClassifier(verbose=0,ignore_warnings=True, custom_metric=None)
models,predictions = clf.fit(X_train[final_processed_features], X_val[final_processed_f
models
```

```
100%|██████████████████████████████████████████████| 29/29 [00:01<00:00, 25.33it/s]
```

Out[79]:

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken
AdaBoostClassifier	0.78	0.71	None	0.77	0.13
LGBMClassifier	0.78	0.70	None	0.77	0.14
BernoulliNB	0.80	0.69	None	0.77	0.02
LinearDiscriminantAnalysis	0.80	0.69	None	0.77	0.01
RidgeClassifierCV	0.80	0.69	None	0.77	0.02
RidgeClassifier	0.80	0.69	None	0.77	0.02
NuSVC	0.80	0.69	None	0.77	0.02
CalibratedClassifierCV	0.80	0.69	None	0.77	0.11
LogisticRegression	0.80	0.69	None	0.77	0.02
LinearSVC	0.80	0.69	None	0.77	0.03
GaussianNB	0.79	0.68	None	0.77	0.02
SVC	0.79	0.68	None	0.77	0.03
Perceptron	0.76	0.68	None	0.75	0.01
NearestCentroid	0.78	0.68	None	0.76	0.01
SGDClassifier	0.78	0.68	None	0.76	0.01
LabelSpreading	0.75	0.68	None	0.74	0.03
QuadraticDiscriminantAnalysis	0.78	0.67	None	0.75	0.01
LabelPropagation	0.74	0.67	None	0.73	0.02
DecisionTreeClassifier	0.71	0.66	None	0.71	0.02
KNeighborsClassifier	0.77	0.66	None	0.74	0.02
RandomForestClassifier	0.73	0.66	None	0.72	0.19
ExtraTreesClassifier	0.72	0.65	None	0.71	0.16
BaggingClassifier	0.70	0.64	None	0.70	0.05
ExtraTreeClassifier	0.68	0.64	None	0.69	0.01
PassiveAggressiveClassifier	0.63	0.59	None	0.64	0.01
DummyClassifier	0.69	0.50	None	0.57	0.01

In [ ]:

```

```