All Library......

In [1]:
```
# import numpy as np
# import pandas as pd
# import matplotlib.pyplot as plt
# import seaborn as sns
# from scipy.stats import boxcox
# from sklearn.model_selection import train_test_split
# from sklearn.linear_model import LogisticRegression
# from sklearn.metrics import accuracy_score
# from sklearn.model_selection import cross_val_score
# from sklearn.model_selection import GridSearchCV
# from sklearn.neighbors import KNeighborsClassifier
# from sklearn.svm import SVC
# from sklearn.tree import DecisionTreeClassifier
# from sklearn.ensemble import RandomForestClassifier
# from sklearn.ensemble import AdaBoostClassifier
# import warnings
# warnings.filterwarnings('ignore')
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import boxcox
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
df  = pd.read_csv(r"D:\Excel file\LoanData.csv")
df.head()
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coa
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.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
```

In [5]:
```
# lets check the column names present in the dataset
df.columns
```

Out[5]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmoun
t',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Statu
s'],
      dtype='object')
```

Data Understandinng

- **Loan_ID** : Unique Loan ID
- **Gender** : Male / Female
- **Married** : Applicant married (Y/N)
- **Dependents** : Number of dependents
- **Education** : Applicant Education
- **Self_Employed** : Whether the Applicant is Self Employed (Y/N)
- **ApplicantIncome** : Applicant income
- **CoapplicantIncome** : Coapplicant Income
- **LoanAmount** : Loan Amount in Thousands
- **Loan_Amount_Term** : Term of Loan in Months
- **Credit_History** : Credit History meets Guidelines
- **Property_Area** : Urban / Semi Urban / Rural
- **Loan_Status** : Loan Approved **Target Variable** (Y/N)

In [6]:
```
df['Loan_ID'].nunique()
```

Out[6]:
```
614
```

In [7]:
```
df.drop(columns=['Loan_ID'],inplace=True)
```

In [8]:
```
df['Gender'].unique()
```

Out[8]:
```
array(['Male', 'Female', nan], dtype=object)
```

In [9]:
```
df['Gender'].value_counts()
```

Out[9]:
```
Gender
Male      489
Female    112
Name: count, dtype: int64
```

In [10]:
```
df['Married'].unique()
```

Out[10]:
```
array(['No', 'Yes', nan], dtype=object)
```

In [11]:
```
df['Married'].value_counts()
```

Out[11]:
```
Married
Yes    398
No     213
Name: count, dtype: int64
```

In [12]:
```
df['Dependents'].unique()
```

Out[12]:
```
array(['0', '1', '2', '3+', nan], dtype=object)
```

In [13]:
```
df['Dependents'].value_counts()
```

Out[13]:
```
Dependents
0     345
1     102
2     101
3+     51
Name: count, dtype: int64
```

In [14]:
```
df['Education'].unique()
```

Out[14]:
```
array(['Graduate', 'Not Graduate'], dtype=object)
```

In [15]:
```
df['Education'].value_counts()
```

Out[15]:
```
Education
Graduate        480
Not Graduate    134
Name: count, dtype: int64
```

In [16]:
```
df['Self_Employed'].unique()
```

Out[16]:
```
array(['No', 'Yes', nan], dtype=object)
```

In [17]:
```
df['Self_Employed'].value_counts()
```

Out[17]:
```
Self_Employed
No     500
Yes     82
Name: count, dtype: int64
```

In [18]:
```
df['ApplicantIncome'].unique()
```

Out[18]:
```
array([ 5849,  4583,  3000,  2583,  6000,  5417,  2333,  3036,  4006,
       12841,  3200,  2500,  3073,  1853,  1299,  4950,  3596,  3510,
        4887,  2600,  7660,  5955,  3365,  3717,  9560,  2799,  4226,
        1442,  3750,  4166,  3167,  4692,  3500, 12500,  2275,  1828,
        3667,  3748,  3600,  1800,  2400,  3941,  4695,  3410,  5649,
        5821,  2645,  4000,  1928,  3086,  4230,  4616, 11500,  2708,
        2132,  3366,  8080,  3357,  3029,  2609,  4945,  5726, 10750,
        7100,  4300,  3208,  1875,  4755,  5266,  1000,  3333,  3846,
        2395,  1378,  3988,  2366,  8566,  5695,  2958,  6250,  3273,
        4133,  3620,  6782,  2484,  1977,  4188,  1759,  4288,  4843,
       13650,  4652,  3816,  3052, 11417,  7333,  3800,  2071,  5316,
        2929,  3572,  7451,  5050, 14583,  2214,  5568, 10408,  5667,
        2137,  2957,  3692, 23803,  3865, 10513,  6080, 20166,  2014,
        2718,  3459,  4895,  3316, 14999,  4200,  5042,  6950,  2698,
       11757,  2330, 14866,  1538, 10000,  4860,  6277,  2577,  9166,
        2281,  3254, 39999,  9538,  2980,  1863,  7933,  3089,  4167,
        9323,  3707,  2439,  2237,  8000,  1820, 51763,  3522,  5708,
        4344,  3497,  2045,  5516,  6400,  1916,  4600, 33846,  3625,
       39147,  2178,  2383,   674,  9328,  4885, 12000,  6033,  3858,
        4191,  3125,  8333,  1907,  3416, 11000,  4923,  3992,  3917,
        4408,  3244,  3975,  2479,  3418,  3430,  7787,  5703,  3173,
        3850,   150,  3727,  5000,  4283,  2221,  4009,  2971,  7578,
        3250,  4735,  4758,  2491,  3716,  3189,  3155,  5500,  5746,
        3463,  3812,  3315,  5819,  2510,  2965,  3406,  6050,  9703,
        6608,  2882,  1809,  1668,  3427,  2661, 16250,  3083,  6045,
        5250, 14683,  4931,  6083,  2060,  3481,  7200,  5166,  4095,
        4708,  4333,  2876,  3237, 11146,  2833,  2620,  3900,  2750,
        3993,  3103,  4100,  4053,  3927,  2301,  1811, 20667,  3158,
        3704,  4124,  9508,  3075,  4400,  3153,  4416,  6875,  4666,
        2875,  1625,  2000,  3762, 20233,  7667,  2917,  2927,  2507,
        2473,  3399,  2058,  3541,  4342,  3601,  3166, 15000,  8666,
        4917,  5818,  4384,  2935, 63337,  9833,  5503,  1830,  4160,
        2647,  2378,  4554,  2499,  3523,  6333,  2625,  9083,  8750,
        2666,  2423,  3813,  3875,  5167,  4723,  4750,  3013,  6822,
        6216,  5124,  6325, 19730, 15759,  5185,  3062,  2764,  4817,
        4310,  3069,  5391,  5941,  7167,  4566,  2346,  3010,  5488,
        9167,  9504,  1993,  3100,  3276,  3180,  3033,  3902,  1500,
        2889,  2755,  1963,  7441,  4547,  2167,  2213,  8300, 81000,
        3867,  6256,  6096,  2253,  2149,  2995,  1600,  1025,  3246,
        5829,  2720,  7250, 14880,  4606,  5935,  2920,  2717,  8624,
        6500, 12876,  2425, 10047,  1926, 10416,  7142,  3660,  7901,
        4707, 37719,  3466,  3539,  3340,  2769,  2309,  1958,  3948,
        2483,  7085,  3859,  4301,  3708,  4354,  8334,  2083,  7740,
        3015,  5191,  2947, 16692,   210,  3450,  2653,  4691,  5532,
       16525,  6700,  2873, 16667,  4350,  3095, 10833,  3547, 18333,
        2435,  2699,  5333,  3691, 17263,  3597,  3326,  4625,  2895,
        6283,   645,  3159,  4865,  4050,  3814, 20833,  3583, 13262,
        3598,  6065,  3283,  2130,  5815,  2031,  3074,  4683,  3400,
        2192,  5677,  7948,  4680, 17500,  3775,  5285,  2679,  6783,
        4281,  3588, 11250, 18165,  2550,  6133,  3617,  6417,  4608,
        2138,  3652,  2239,  3017,  2768,  3358,  2526,  2785,  6633,
        2492,  2454,  3593,  5468,  2667, 10139,  3887,  4180,  3675,
       19484,  5923,  5800,  8799,  4467,  3417,  5116, 16666,  6125,
        6406,  3087,  3229,  1782,  3182,  6540,  1836,  1880,  2787,
        2297,  2165,  2726,  9357, 16120,  3833,  6383,  2987,  9963,
        5780,   416,  2894,  3676,  3987,  3232,  2900,  4106,  8072,
        7583], dtype=int64)
```

In [19]:
```
df['CoapplicantIncome'].unique()
```

Out[19]:
```
array([0.00000000e+00, 1.50800000e+03, 2.35800000e+03, 4.19600000e+03,
       1.51600000e+03, 2.50400000e+03, 1.52600000e+03, 1.09680000e+04,
       7.00000000e+02, 1.84000000e+03, 8.10600000e+03, 2.84000000e+03,
       1.08600000e+03, 3.50000000e+03, 5.62500000e+03, 1.91100000e+03,
       1.91700000e+03, 2.92500000e+03, 2.25300000e+03, 1.04000000e+03,
       2.08300000e+03, 3.36900000e+03, 1.66700000e+03, 3.00000000e+03,
       2.06700000e+03, 1.33000000e+03, 1.45900000e+03, 7.21000000e+03,
       1.66800000e+03, 1.21300000e+03, 2.33600000e+03, 3.44000000e+03,
       2.27500000e+03, 1.64400000e+03, 1.16700000e+03, 1.59100000e+03,
       2.20000000e+03, 2.25000000e+03, 2.85900000e+03, 3.79600000e+03,
       3.44900000e+03, 4.59500000e+03, 2.25400000e+03, 3.06600000e+03,
       1.87500000e+03, 1.77400000e+03, 4.75000000e+03, 3.02200000e+03,
       4.00000000e+03, 2.16600000e+03, 1.88100000e+03, 2.53100000e+03,
       2.00000000e+03, 2.11800000e+03, 4.16700000e+03, 2.90000000e+03,
       5.65400000e+03, 1.82000000e+03, 2.30200000e+03, 9.97000000e+02,
       3.54100000e+03, 3.26300000e+03, 3.80600000e+03, 3.58300000e+03,
       7.54000000e+02, 1.03000000e+03, 1.12600000e+03, 3.60000000e+03,
       2.33300000e+03, 4.11400000e+03, 2.28300000e+03, 1.39800000e+03,
       2.14200000e+03, 2.66700000e+03, 8.98000000e+03, 2.01400000e+03,
       1.64000000e+03, 3.85000000e+03, 2.56900000e+03, 1.92900000e+03,
       7.75000000e+03, 1.43000000e+03, 2.03400000e+03, 4.48600000e+03,
       1.42500000e+03, 1.66600000e+03, 8.30000000e+02, 3.75000000e+03,
       1.04100000e+03, 1.28000000e+03, 1.44700000e+03, 3.16600000e+03,
       3.33300000e+03, 1.76900000e+03, 7.36000000e+02, 1.96400000e+03,
       1.61900000e+03, 1.13000000e+04, 1.45100000e+03, 7.25000000e+03,
       5.06300000e+03, 2.13800000e+03, 5.29600000e+03, 2.58300000e+03,
       2.36500000e+03, 2.81600000e+03, 2.50000000e+03, 1.08300000e+03,
       1.25000000e+03, 3.02100000e+03, 9.83000000e+02, 1.80000000e+03,
       1.77500000e+03, 2.38300000e+03, 1.71700000e+03, 2.79100000e+03,
       1.01000000e+03, 1.69500000e+03, 2.05400000e+03, 2.59800000e+03,
       1.77900000e+03, 1.26000000e+03, 5.00000000e+03, 1.98300000e+03,
       5.70100000e+03, 1.30000000e+03, 4.41700000e+03, 4.33300000e+03,
       1.84300000e+03, 1.86800000e+03, 3.89000000e+03, 2.16700000e+03,
       7.10100000e+03, 2.10000000e+03, 4.25000000e+03, 2.20900000e+03,
       3.44700000e+03, 1.38700000e+03, 1.81100000e+03, 1.56000000e+03,
       1.85700000e+03, 2.22300000e+03, 1.84200000e+03, 3.27400000e+03,
       2.42600000e+03, 8.00000000e+02, 9.85799988e+02, 3.05300000e+03,
       2.41600000e+03, 3.33400000e+03, 2.54100000e+03, 2.93400000e+03,
       1.75000000e+03, 1.80300000e+03, 1.86300000e+03, 2.40500000e+03,
       2.13400000e+03, 1.89000000e+02, 1.59000000e+03, 2.98500000e+03,
       4.98300000e+03, 2.16000000e+03, 2.45100000e+03, 1.79300000e+03,
       1.83300000e+03, 4.49000000e+03, 6.88000000e+02, 4.60000000e+03,
       1.58700000e+03, 1.22900000e+03, 2.33000000e+03, 2.45800000e+03,
       3.23000000e+03, 2.16800000e+03, 4.58300000e+03, 6.25000000e+03,
       5.05000000e+02, 3.16700000e+03, 3.66700000e+03, 3.03300000e+03,
       5.26600000e+03, 7.87300000e+03, 1.98700000e+03, 9.23000000e+02,
       4.99600000e+03, 4.23200000e+03, 1.60000000e+03, 3.13600000e+03,
       2.41700000e+03, 2.11500000e+03, 1.62500000e+03, 1.40000000e+03,
       4.84000000e+02, 2.00000000e+04, 2.40000000e+03, 2.03300000e+03,
       3.23700000e+03, 2.77300000e+03, 1.41700000e+03, 1.71900000e+03,
       4.30000000e+03, 1.61200008e+01, 2.34000000e+03, 1.85100000e+03,
       1.12500000e+03, 5.06400000e+03, 1.99300000e+03, 8.33300000e+03,
       1.21000000e+03, 1.37600000e+03, 1.71000000e+03, 1.54200000e+03,
       1.25500000e+03, 1.45600000e+03, 1.73300000e+03, 2.46600000e+03,
       4.08300000e+03, 2.18800000e+03, 1.66400000e+03, 2.91700000e+03,
       2.07900000e+03, 1.50000000e+03, 4.64800000e+03, 1.01400000e+03,
       1.87200000e+03, 1.60300000e+03, 3.15000000e+03, 2.43600000e+03,
       2.78500000e+03, 1.13100000e+03, 2.15700000e+03, 9.13000000e+02,
       1.70000000e+03, 2.85700000e+03, 4.41600000e+03, 3.68300000e+03,
       5.62400000e+03, 5.30200000e+03, 1.48300000e+03, 6.66700000e+03,
       3.01300000e+03, 1.28700000e+03, 2.00400000e+03, 2.03500000e+03,
```

```
       6.66600000e+03, 3.66600000e+03, 3.42800000e+03, 1.63200000e+03,
       1.91500000e+03, 1.74200000e+03, 1.42400000e+03, 7.16600000e+03,
       2.08700000e+03, 1.30200000e+03, 5.50000000e+03, 2.04200000e+03,
       3.90600000e+03, 5.36000000e+02, 2.84500000e+03, 2.52400000e+03,
       6.63000000e+02, 1.95000000e+03, 1.78300000e+03, 2.01600000e+03,
       2.37500000e+03, 3.25000000e+03, 4.26600000e+03, 1.03200000e+03,
       2.66900000e+03, 2.30600000e+03, 2.42000000e+02, 2.06400000e+03,
       4.61000000e+02, 2.21000000e+03, 2.73900000e+03, 2.23200000e+03,
       3.38370000e+04, 1.52200000e+03, 3.41600000e+03, 3.30000000e+03,
       1.00000000e+03, 4.16670000e+04, 2.79200000e+03, 4.30100000e+03,
       3.80000000e+03, 1.41100000e+03, 2.40000000e+02])
```

In [20]:
```
df['LoanAmount'].unique()
```

Out[20]:
```
array([ nan, 128.,  66., 120., 141., 267.,  95., 158., 168., 349.,  70.,
       109., 200., 114.,  17., 125., 100.,  76., 133., 115., 104., 315.,
       116., 112., 151., 191., 122., 110.,  35., 201.,  74., 106., 320.,
       144., 184.,  80.,  47.,  75., 134.,  96.,  88.,  44., 286.,  97.,
       135., 180.,  99., 165., 258., 126., 312., 136., 172.,  81., 187.,
       113., 176., 130., 111., 167., 265.,  50., 210., 175., 131., 188.,
        25., 137., 160., 225., 216.,  94., 139., 152., 118., 185., 154.,
        85., 259., 194.,  93., 370., 182., 650., 102., 290.,  84., 242.,
       129.,  30., 244., 600., 255.,  98., 275., 121.,  63., 700.,  87.,
       101., 495.,  67.,  73., 260., 108.,  58.,  48., 164., 170.,  83.,
        90., 166., 124.,  55.,  59., 127., 214., 240.,  72.,  60., 138.,
        42., 280., 140., 155., 123., 279., 192., 304., 330., 150., 207.,
       436.,  78.,  54.,  89., 143., 105., 132., 480.,  56., 159., 300.,
       376., 117.,  71., 490., 173.,  46., 228., 308., 236., 570., 380.,
       296., 156., 103.,  45.,  65.,  53., 360.,  62., 218., 178., 239.,
       405., 148., 190., 149., 153., 162., 230.,  86., 234., 246., 500.,
       186., 119., 107., 209., 208., 243.,  40., 250., 311., 400., 161.,
       196., 324., 157., 145., 181.,  26., 211.,   9., 205.,  36.,  61.,
       146., 292., 142., 350., 496., 253.])
```

In [21]:
```
df['Loan_Amount_Term'].unique()
```

Out[21]:
```
array([360., 120., 240.,  nan, 180.,  60., 300., 480.,  36.,  84.,  12.])
```

In [22]:
```
df['Loan_Amount_Term'].value_counts()
```

Out[22]:
```
Loan_Amount_Term
360.0    512
180.0     44
480.0     15
300.0     13
240.0      4
84.0       4
120.0      3
60.0       2
36.0       2
12.0       1
Name: count, dtype: int64
```

In [23]:
```
df['Credit_History'].unique()
```

Out[23]:
```
array([ 1.,  0., nan])
```

In [24]:
```
df['Credit_History'] = df['Credit_History'].replace({1:'good',0:'bad'})
```

In [25]:
```
df['Credit_History'].unique()
```

Out[25]:
```
array(['good', 'bad', nan], dtype=object)
```

In [26]:
```
df['Credit_History'].value_counts()
```

Out[26]:
```
Credit_History
good    475
bad      89
Name: count, dtype: int64
```

In [27]:
```
df['Property_Area'].unique()
```

Out[27]:
```
array(['Urban', 'Rural', 'Semiurban'], dtype=object)
```

In [28]:
```
df['Property_Area'].value_counts()
```

Out[28]:
```
Property_Area
Semiurban    233
Urban        202
Rural        179
Name: count, dtype: int64
```

In [29]:
```
df['Loan_Status'].unique()
```

Out[29]:
```
array(['Y', 'N'], dtype=object)
```

In [30]:
```
df['Loan_Status'].value_counts()
```

Out[30]:
```
Loan_Status
Y    422
N    192
Name: count, dtype: int64
```

In [31]:
```
continous = ['ApplicantIncome','CoapplicantIncome','LoanAmount']

discrete_categorical = ['Gender','Married','Education','Self_Employed','Cre

discrete_count = ['Dependents','Loan_Amount_Term']
```

Exploratory Data Analysis (EDA)

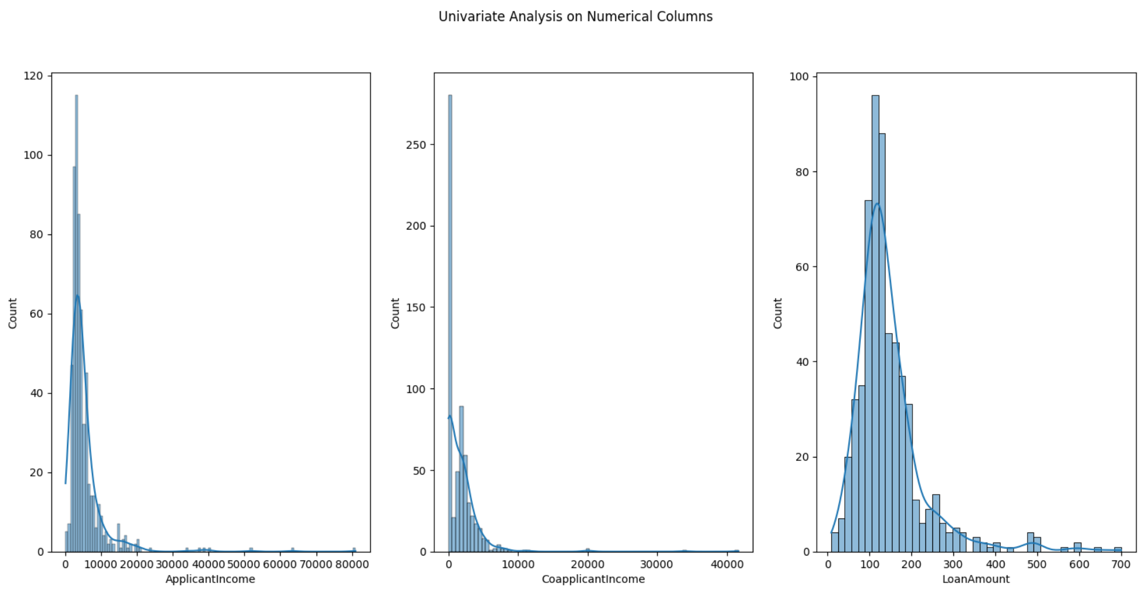
For Continous Variables

In [32]:
```
df[continous].describe()
```

Out[32]:

	ApplicantIncome	CoapplicantIncome	LoanAmount
count	614.000000	614.000000	592.000000
mean	5403.459283	1621.245798	146.412162
std	6109.041673	2926.248369	85.587325
min	150.000000	0.000000	9.000000
25%	2877.500000	0.000000	100.000000
50%	3812.500000	1188.500000	128.000000
75%	5795.000000	2297.250000	168.000000
max	81000.000000	41667.000000	700.000000

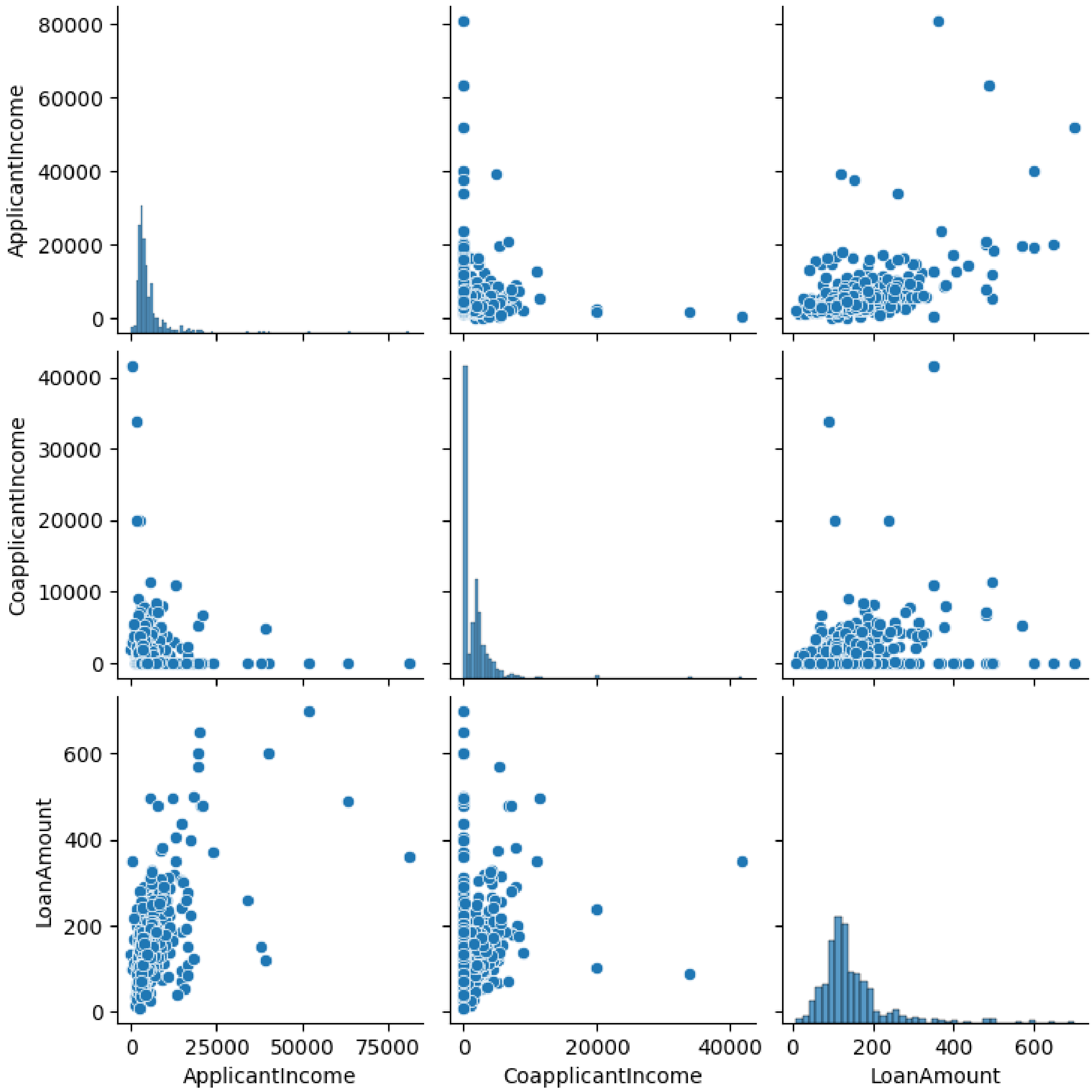
In [33]:
```
plt.rcParams['figure.figsize'] = (18,8)

plt.subplot(1,3,1)
sns.histplot(df['ApplicantIncome'],kde=True)

plt.subplot(1,3,2)
sns.histplot(df['CoapplicantIncome'],kde=True)

plt.subplot(1,3,3)
sns.histplot(df['LoanAmount'],kde=True)

plt.suptitle('Univariate Analysis on Numerical Columns')
plt.show()
```



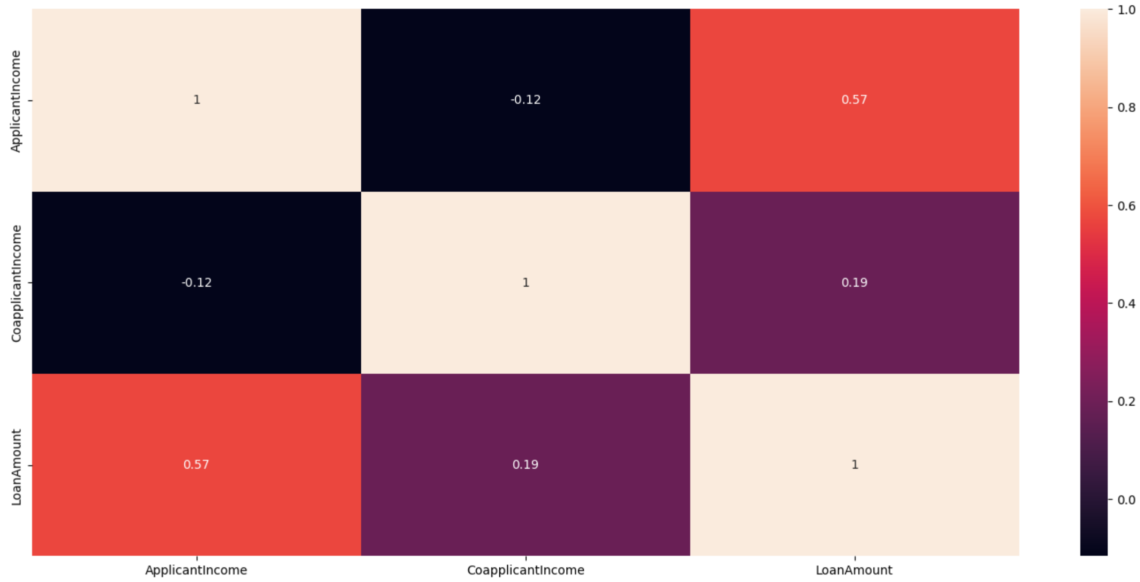
In [34]:
```
df[continous].skew()
```

Out[34]:
```
ApplicantIncome      6.539513
CoapplicantIncome    7.491531
LoanAmount           2.677552
dtype: float64
```

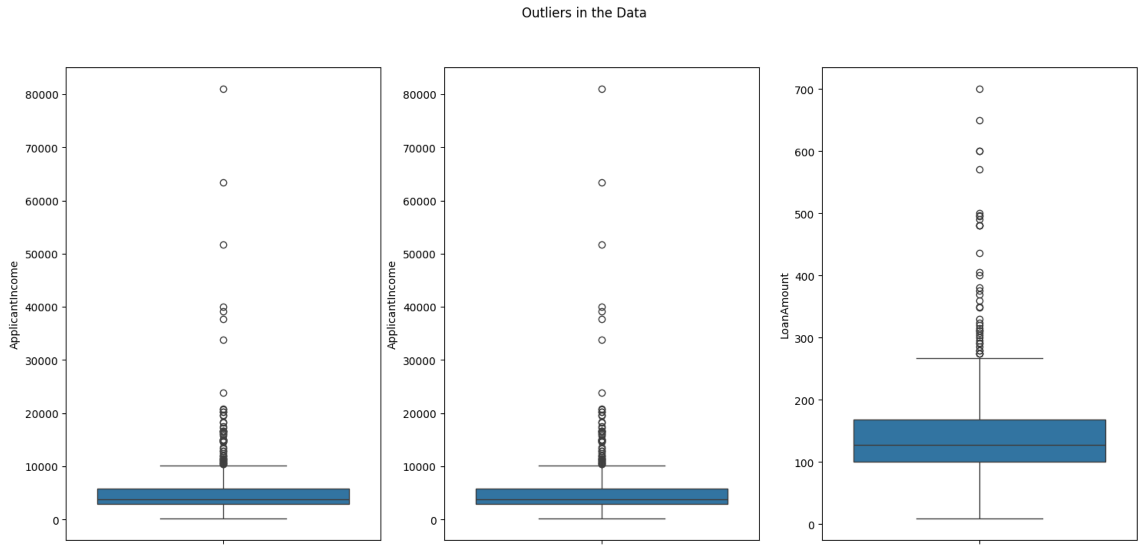
In [35]:
```
sns.pairplot(df[continous])
plt.show()
```



In [36]:
```
sns.heatmap(df[continous].corr(),annot=True)
plt.show()
```



In [37]:
```
# lets visualize the outliers using box plot

plt.subplot(1,3,1)
sns.boxplot(df['ApplicantIncome'])

plt.subplot(1,3,2)
sns.boxplot(df['ApplicantIncome'])

plt.subplot(1,3,3)
sns.boxplot(df['LoanAmount'])

plt.suptitle('Outliers in the Data')
plt.show()
```

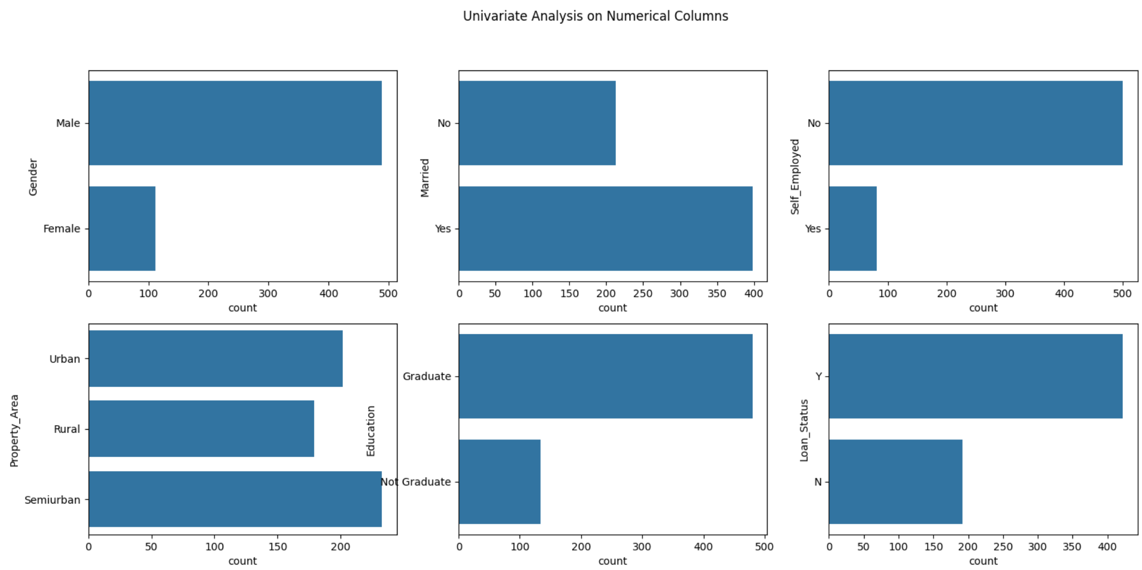


In [38]:
```
df[discrete_categorical].describe()
```

Out[38]:

	Gender	Married	Education	Self_Employed	Credit_History	Property_Area	Loan_Sta
count	601	611	614	582	564	614	(
unique	2	2	2	2	2	3	
top	Male	Yes	Graduate	No	good	Semiurban	
freq	489	398	480	500	475	233	

In [39]:
```
plt.rcParams['figure.figsize'] = (18,8)

plt.subplot(2,3,1)
sns.countplot(df['Gender'])

plt.subplot(2,3,2)
sns.countplot(df['Married'])

plt.subplot(2,3,3)
sns.countplot(df['Self_Employed'])

plt.subplot(2,3,4)
sns.countplot(df['Property_Area'])

plt.subplot(2,3,5)
sns.countplot(df['Education'])

plt.subplot(2,3,6)
sns.countplot(df['Loan_Status'])

plt.suptitle('Univariate Analysis on Numerical Columns')
plt.show()
```



Data Preparation

In [40]:
```
df['Income'] = df['ApplicantIncome'] + df['CoapplicantIncome']

df.drop(columns=['ApplicantIncome','CoapplicantIncome'],inplace=True)
```

Modifyinng the wrong data

In [41]:
```
df['Dependents'] = df['Dependents'].replace({'3+':3})
```

Missing Values Tretment

In [42]:
```
# checking no. of Missing values
df.isnull().sum()
```

Out[42]:
```
Gender              13
Married              3
Dependents          15
Education            0
Self_Employed       32
LoanAmount          22
Loan_Amount_Term    14
Credit_History      50
Property_Area        0
Loan_Status          0
Income               0
dtype: int64
```

In [43]:
```
# checking percentage of Missing values
df.isnull().sum()/len(df)*100
```

Out[43]:
```
Gender              2.117264
Married             0.488599
Dependents          2.442997
Education           0.000000
Self_Employed       5.211726
LoanAmount          3.583062
Loan_Amount_Term    2.280130
Credit_History      8.143322
Property_Area       0.000000
Loan_Status         0.000000
Income              0.000000
dtype: float64
```

In [44]:
```
df = df.dropna(subset=['Income','LoanAmount','Loan_Amount_Term','Credit_His
```

In [45]:
```
# count variable replace with 0
df['Dependents'] = df['Dependents'].fillna(0)
```

In [46]:
```
# categorical variables replace with mode
df['Gender'] = df['Gender'].fillna(df['Gender']).mode()[0]
df['Married'] = df['Married'].fillna(df['Married']).mode()[0]
df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed']).mode(
```

In [47]:
```
df.isnull().sum()
```

Out[47]:
```
Gender              0
Married             0
Dependents          0
Education           0
Self_Employed       0
LoanAmount          0
Loan_Amount_Term    0
Credit_History      0
Property_Area       0
Loan_Status         0
Income              0
dtype: int64
```

Outliers treatment

Encoding

In [48]:
```
df['Gender'] = df['Gender'].map({'Male':1,'Female':0}).astype('int')
df['Married'] = df['Married'].map({'Yes':1,'No':0}).astype('int')
df['Education'] = df['Education'].map({'Graduate':1,'Not Graduate':0}).asty
df['Self_Employed'] = df['Self_Employed'].map({'Yes':1,'No':0}).astype('int
df['Property_Area'] = df['Property_Area'].map({'Rural':1,'Semiurban':0,'Urb
df['Credit_History'] = df['Credit_History'].map({'good':1,'bad':0}).astype(
df['Loan_Status'] = df['Loan_Status'].map({'Y':1,'N':0}).astype('int')
```

data type conversion

In [49]:
```
df['Dependents'] = df['Dependents'].astype('int')
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].astype('int')
```

Transformation

In [50]:
```
df[['Income','LoanAmount']].skew()
```

Out[50]:
```
Income        5.777628
LoanAmount    2.607945
dtype: float64
```

In [51]:
```
# Lets apply boxcox transformations to remove skewness
from scipy.stats import boxcox
df['Income'],a = boxcox(df['Income'])
df['LoanAmount'],c = boxcox(df['LoanAmount'])
```

In [52]:
```
df[['Income','LoanAmount']].skew()
```

Out[52]:
```
Income       -0.027769
LoanAmount    0.038289
dtype: float64
```

In [53]:
```
df['Loan_Amount_Term'] = df['Loan_Amount_Term']/12
```

X&y

In [54]:
```
X = df.drop('Loan_Status',axis=1)
y = df['Loan_Status']
```

Identify the best random state number

In [55]:
```
train = []
test = []
cv=[]
for i in range(0,100):
    X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,rand
    lr_model = LogisticRegression()
    lr_model.fit(X_train,y_train)

    # Prediction
    train_pred = lr_model.predict(X_train)
    test_pred = lr_model.predict(X_test)

    # Evaluation

    train.append(lr_model.score(X_train,y_train))
    test.append(lr_model.score(X_test,y_test))
    cv.append(cross_val_score(lr_model,X,y,cv=5).mean())
em = pd.DataFrame({"Train":train,"test":test,"CV":cv})
gm = em[(abs(em['Train']-em['test'])<=0.05) & abs(em['test']-em['CV']<=0.05
gm[gm['test']==gm['test'].max()].index.tolist()[0]
```

Out[55]:
```
16
```

train-test split

In [56]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_s
```

Machine Learning Modelling & Evaluation

1. Logistic Regression

In [57]:
```
from sklearn.linear_model import LogisticRegression
log_model = LogisticRegression()
log_model.fit(X_train,y_train)

ypred_train = log_model.predict(X_train)
ypred_test = log_model.predict(X_test)

print('Train Accuracy:',accuracy_score(ypred_train,y_train))
print('Cross validation score:',cross_val_score(log_model,X_train,y_train,c
print('Test Accuracy:',accuracy_score(ypred_test,y_test))
```

```
Train Accuracy: 0.806146572104019
Cross validation score: [0.83529412 0.78823529 0.81176471 0.78571429 0.809
52381]
Test Accuracy: 0.8490566037735849
```

2. KNN

In [58]:
```
from sklearn.neighbors import KNeighborsClassifier

estimator = KNeighborsClassifier()
param_grid = {'n_neighbors': list(range(1,50))}

from sklearn.model_selection import GridSearchCV
knn_grid = GridSearchCV(estimator,param_grid,scoring='accuracy',cv=5)
knn_grid.fit(X_train,y_train)

knn_model = knn_grid.best_estimator_

ypred_train = knn_model.predict(X_train)
ypred_test = knn_model.predict(X_test)

print('Train Accuracy:',accuracy_score(ypred_train,y_train))
print('Cross validation score:',cross_val_score(knn_model,X_train,y_train,c
print('Test Accuracy:',accuracy_score(ypred_test,y_test))
```

```
Train Accuracy: 0.8226950354609929
Cross validation score: [0.77647059 0.76470588 0.70588235 0.75       0.785
71429]
Test Accuracy: 0.8490566037735849
```

3. Support Vector Machine (SVM)

In [59]:
```
from sklearn.svm import SVC

estimator = SVC()
param_grid = {'C':[0.01,0.1,1],'kernel':['linear','rbf','sigmoid','poly']}

from sklearn.model_selection import GridSearchCV
svm_model = GridSearchCV(estimator,param_grid,scoring='accuracy',cv=5)
svm_model.fit(X_train,y_train)

svm_model = svm_model.best_estimator_

ypred_train = svm_model.predict(X_train)
ypred_test = svm_model.predict(X_test)

print('Train Accuracy:',accuracy_score(ypred_train,y_train))
print('Cross validation score:',cross_val_score(svm_model,X_train,y_train,c
print('Test Accuracy:',accuracy_score(ypred_test,y_test))
```

```
Train Accuracy: 0.806146572104019
Cross validation score: [0.83529412 0.78823529 0.81176471 0.78571429 0.809
52381]
Test Accuracy: 0.8490566037735849
```

4. Decision Tree Classifier

In [60]:
```
from sklearn.tree import DecisionTreeClassifier
estimator = DecisionTreeClassifier(random_state=16)
param_grid = {'criterion':['gini','entropy'],
              'max_depth':list(range(1,16))}

from sklearn.model_selection import GridSearchCV
dt_grid = GridSearchCV(estimator,param_grid,scoring='accuracy',cv=5)
dt_grid.fit(X_train,y_train)

# identify the best model
dt = dt_grid.best_estimator_

# identify the importance of each feature
dt_fi = dt.feature_importances_

# identify the feature where the feature importance is greater than 0
index = [i for i,x in enumerate(dt_fi)if x>0]

# crete new dataset with importance features
X_train_dt = X_train.iloc[:,index]
X_test_dt = X_test.iloc[:,index]

# train with best model & with impotance features
dt.fit(X_train_dt,y_train)

ypred_train = dt.predict(X_train_dt)
ypred_test = dt.predict(X_test_dt)

# Evaluate the best model
print('Train Accuracy:',accuracy_score(ypred_train,y_train))
print('Cross validation score:',cross_val_score(dt,X_train,y_train,cv=5,sco
print('Test Accuracy:',accuracy_score(ypred_test,y_test))
```

```
Train Accuracy: 0.8368794326241135
Cross validation score: [0.83529412 0.78823529 0.88235294 0.79761905 0.809
52381]
Test Accuracy: 0.8301886792452831
```

In [61]:
```
dt_grid.best_estimator_
```

Out[61]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=4, random_state=16)
```

In [62]:
```
X_train_dt
```

Out[62]:

	Education	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Income
168	1	5.132078	40.0	0	0	1.852031
160	0	5.815384	30.0	1	0	1.856089
65	1	7.422117	30.0	1	0	1.869467
92	0	5.517040	30.0	1	2	1.863131
242	1	6.557014	5.0	1	2	1.868113
...	...	...	...	...	...	...
445	1	6.268459	30.0	1	1	1.862190
527	0	6.619989	30.0	0	0	1.865897
375	1	6.138816	15.0	1	2	1.864377
147	1	4.050366	30.0	1	2	1.856379
278	1	8.360169	30.0	1	0	1.871802

423 rows × 6 columns

5. Random Forest Classifier

In [63]:
```
from sklearn.ensemble import RandomForestClassifier
estimator = RandomForestClassifier(random_state=16)
param_grid = {'n_estimators':list(range(1,51))}

from sklearn.model_selection import GridSearchCV
rf_grid = GridSearchCV(estimator,param_grid,scoring="accuracy",cv=5)
rf_grid.fit(X_train,y_train)

rf = rf_grid.best_estimator_
rf_fi = rf.feature_importances_

index = [i for i, x in enumerate(rf_fi)if x>0]

X_train_rf = X_train.iloc[:,index]
X_test_rf = X_test.iloc[:,index]

rf.fit(X_train_rf,y_train)

ypred_train = rf.predict(X_train_rf)
ypred_test = rf.predict(X_test_rf)

print('Train Accuracy:',accuracy_score(ypred_train,y_train))
print('Cross validation score:',cross_val_score(rf,X_train_rf,y_train,cv=5,
print('Test Accuracy:',accuracy_score(ypred_test,y_test))
```

```
Train Accuracy: 1.0
Cross validation score: [0.78823529 0.77647059 0.8        0.77380952 0.726
19048]
Test Accuracy: 0.8018867924528302
```

6. AdaBoost Classifier

In [64]:
```
from sklearn.ensemble import AdaBoostClassifier
estimator = AdaBoostClassifier(random_state=16)
param_grid = {'n_estimators':list(range(1,51))}

from sklearn.model_selection import GridSearchCV
ab_grid = GridSearchCV(estimator,param_grid,scoring="accuracy",cv=5)
ab_grid.fit(X_train,y_train)

ab = ab_grid.best_estimator_
ab_fi = ab.feature_importances_

index = [i for i,x in enumerate(ab_fi) if x>0]

X_train_ab = X_train.iloc[:,index]
X_test_ab = X_test.iloc[:,index]

ab.fit(X_train_ab,y_train)

ypred_train = ab.predict(X_train_ab)
ypred_test = ab.predict(X_test_ab)

print('Train Accuracy:',accuracy_score(ypred_train,y_train))
print('Cross validation score:',cross_val_score(ab,X_train_ab,y_train,cv=5,
print('Test Accuracy:',accuracy_score(ypred_test,y_test))
```

```
Train Accuracy: 0.8321513002364066
Cross validation score: [0.82352941 0.76470588 0.84705882 0.80952381 0.821
42857]
Test Accuracy: 0.8113207547169812
```

7. Gradient Boost Classifier

In [65]:
```
from sklearn.ensemble import GradientBoostingClassifier
estimator = GradientBoostingClassifier(random_state=16)
param_grid = {'n_estimators': list(range(1, 10)), 'learning_rate': [0.1, 0.

from sklearn.model_selection import GridSearchCV
gb_grid = GridSearchCV(estimator, param_grid, scoring="accuracy", cv=5)
gb_grid.fit(X_train, y_train)

gb = gb_grid.best_estimator_
gb_fi = gb.feature_importances_

index = [i for i, x in enumerate(gb_fi) if x > 0]

X_train_gb = X_train.iloc[:, index]
X_test_gb = X_test.iloc[:, index]

gb.fit(X_train_gb, y_train)

ypred_train = gb.predict(X_train_gb)
ypred_test = gb.predict(X_test_gb)

print('Train Accuracy:', accuracy_score(ypred_train, y_train))
print('Cross-validation score:', cross_val_score(gb, X_train_gb, y_train, c
print('Test Accuracy:', accuracy_score(ypred_test, y_test))
```

```
Train Accuracy: 0.8723404255319149
Cross-validation score: [0.8        0.77647059 0.89411765 0.78571429 0.833
33333]
Test Accuracy: 0.8207547169811321
```

8. XGBoost Classifier

In [66]:
```
from xgboost import XGBClassifier
estimator = XGBClassifier(random_state=16)
param_grid = {'n_estimators': list(range(1, 10)), 'learning_rate': [0.1, 0.

from sklearn.model_selection import GridSearchCV
xgb_grid = GridSearchCV(estimator, param_grid, scoring="accuracy", cv=5)
xgb_grid.fit(X_train, y_train)

xgb = gb_grid.best_estimator_
xgb_fi = gb.feature_importances_

index = [i for i, x in enumerate(gb_fi) if x > 0]

X_train_xgb = X_train.iloc[:, index]
X_test_xgb = X_test.iloc[:, index]

xgb.fit(X_train_gb, y_train)

ypred_train = xgb.predict(X_train_xgb)
ypred_test = xgb.predict(X_test_xgb)

print('Train Accuracy:', accuracy_score(ypred_train, y_train))
print('Cross-validation score:', cross_val_score(xgb, X_train_xgb, y_train,
print('Test Accuracy:', accuracy_score(ypred_test, y_test))
```

```
Train Accuracy: 0.8723404255319149
Cross-validation score: [0.8        0.77647059 0.89411765 0.78571429 0.833
33333]
Test Accuracy: 0.8207547169811321
```

In [ ]: