In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv ('loan_prediction.csv')
df.head(10)
```

Out[2]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplicar
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	
5	LP001011	Male	Yes	2	Graduate	Yes	5417	
6	LP001013	Male	Yes	0	Not Graduate	No	2333	
7	LP001014	Male	Yes	3+	Graduate	No	3036	
8	LP001018	Male	Yes	2	Graduate	No	4006	
9	LP001020	Male	Yes	1	Graduate	No	12841	

In [3]:
```
df.shape
```

Out[3]:
```
(614, 13)
```

In [4]:
```
df.dtypes
# here we found the following datatypes in our dataset :
# there are three different types of datatypes are present in our dataset :-
# 1) 'object' = 8 columns
# 2) 'int64' = 1 column
# 3) 'float64' = 4 columns
#  total columns= 13 columns
```

Out[4]:
```
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 [5]:
```
df.columns
```

Out[5]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [6]:
```
column = ['loan_id','gender','marital_status','dependents','education','self_empl
       'loan_amount','loan_amount_term','credit_history','property_area','loan
```

```
Loan_Status          object
dtype: object
```

In [5]:
```
df.columns
```

Out[5]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [6]:
```
column = ['loan_id','gender','marital_status','dependents','education','self_empl
          'loan_amount','loan_amount_term','credit_history','property_area','loan

# for further easier use, we are assigning column names into single formate (Lowe
```

In [7]:
```
df.columns=column
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['loan_id', 'gender', 'marital_status', 'dependents', 'education',
       'self_employed', 'applicant_income', 'coapplicant_income',
       'loan_amount', 'loan_amount_term', 'credit_history', 'property_area',
       'loan_status'],
      dtype='object')
```

In [9]:
```
df.head(2)
```

Out[9]:

	loan_id	gender	marital_status	dependents	education	self_employed	applicant_income	coap
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	

In [10]:
```
df.columns.unique()
# Name of unique columns present in the dataset
```

Out[10]:
```
Index(['loan_id', 'gender', 'marital_status', 'dependents', 'education',
       'self_employed', 'applicant_income', 'coapplicant_income',
       'loan_amount', 'loan_amount_term', 'credit_history', 'property_area',
       'loan_status'],
      dtype='object')
```

In [11]:
```
df.columns.nunique()
# no. of unique columns present in the dataset
```

Out[11]:
```
13
```

In [12]:
```
df.shape
```

Out[12]:
```
(614, 13)
```

In [13]:
```
df.info()

# total number of columns present are 614
# here in the below table we can found that , there are some columns which are ho
# ...that means that there may be presence of NULL VALUES in the dataset.
# No. of Columns with : float64(4), int64(1) & object(8)
# Total Number of columns (13)
# Total number of rows (614)
```

In [13]:
```
df.info()

# total number of columns present are 614
# here in the below table we can found that , there are some columns which are ha
# ...that means that there may be presence of NULL VALUES in the dataset.
# No. of Columns with : float64(4), int64(1) & object(8)
# Total Number of columns (13)
# Total number of rows (614)
```

```
<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   marital_status      611 non-null    object 
 3   dependents          599 non-null    object 
 4   education           614 non-null    object 
 5   self_employed       582 non-null    object 
 6   applicant_income    614 non-null    int64  
 7   coapplicant_income  614 non-null    float64
 8   loan_amount         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 [ ]:

================== DROPPING IRRELEVANT COLUMNS ================================

In [14]:
```
# here in the above list of colunms we can found that , out of all columns 'loan_
# so we can drop this column.
```

In [15]:
```
df.drop(['loan_id'], axis=1, inplace=True)
```

In [16]:
```
df.head(2)
```

Out[16]:

_status	dependents	education	self_employed	applicant_income	coapplicant_income	loan_amount	l
No	0	Graduate	No	5849	0.0	NaN	
Yes	1	Graduate	No	4583	1508.0	128.0	

In [17]:
```
df.columns.nunique()
# succesfully dropped 1 ('loan_id') column
```

Out[17]: 12

In [ ]:

============= CHECKING FOR NAN-NULL VALUES ===========================

In [18]:
```
df.isnull().sum()
# here in the below table we can find the null/nan values present in the dataset.
```

Out[18]:
```
gender               13
marital_status        3
dependents           15
education             0
self_employed        32
applicant_income      0
```

In [ ]:

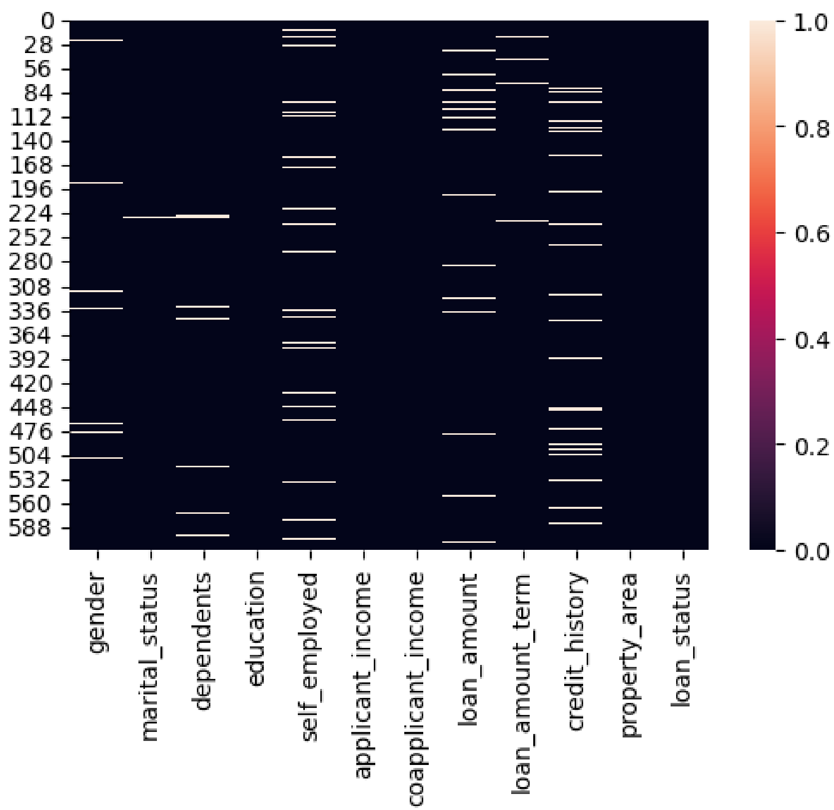
In [18]:
```
df.isnull().sum()
# here in the below table we can find the null/nan values present in the dataset.
```

============== CHECKING FOR NAN-NULL VALUES ============================

Out[18]:
```
gender                13
marital_status         3
dependents            15
education              0
self_employed         32
applicant_income       0
coapplicant_income     0
loan_amount           22
loan_amount_term      14
credit_history        50
property_area          0
loan_status            0
dtype: int64
```

In [19]:
```
plt.figure(figsize=(6,4))
sns.heatmap(df.isnull())

# with the help of heatmap also we can clearly seen the presence of NULL VALUES ,
```

Out[19]: <AxesSubplot:>



In [ ]:

========= removing nan/null values =========

In [22]:
```
#  here above as we found the NULL VALUES in : gender,  marital_status,  dependen
#                                               self_employed,  loan_amount,  loan
# out of these columns we can REPLACE NAN with = 'MOST FREQUENT VALUES'
# but in only 'LOAN_AMOUNT' column, we have to replace NAN with = 'MEAN'
```

In [20]:
```
# To remove the null values present in our dataset, we can use SIMPLE IMPUTER TEC
```

In [21]:
```
from sklearn.impute import SimpleImputer
```

In [ ]:

In [23]:
```
imp1 = SimpleImputer(strategy="most_frequent")
```

In [22]:
```
#  here above as we found the NULL VALUES in : gender,  marital_status,  depender
#                                            self_employed,  loan_amount,  loar
```

In [20]:
```
# To remove the null values present in our dataset, we can use SIMPLE IMPUTER TEC
# out of these columns we can REPLACE NAN with = 'MOST FREQUENT VALUES'
# but in only 'LOAN AMOUNT' column , we have to replace NAN with = 'MEAN'
```

In [21]:
```
from sklearn.impute import SimpleImputer
```

In [ ]:

In [23]:
```
imp1 = SimpleImputer(strategy="most_frequent")
#  we can replace the null values with the 'most-frequent' values present in the
#  so the null values can be replaced by the most - frequent values ARRIVED in th
```

In [24]:
```
df.columns
```

Out[24]:
```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

In [25]:
```
df['gender']= imp1.fit_transform(df['gender'].values.reshape(-1,1))
df['marital_status']= imp1.fit_transform(df['marital_status'].values.reshape(-1,1
df['dependents']= imp1.fit_transform(df['dependents'].values.reshape(-1,1))
df['self_employed']= imp1.fit_transform(df['self_employed'].values.reshape(-1,1))
df['loan_amount_term']= imp1.fit_transform(df['loan_amount_term'].values.reshape(
df['credit_history']= imp1.fit_transform(df['credit_history'].values.reshape(-1,1
```

In [ ]:

In [26]:
```
imp2 = SimpleImputer(strategy="mean")
#  we can replace the null values with the 'mean' values present in the columns.
#  so the null values can be replaced by the MEAN OF VALUES  in the column.
```

In [27]:
```
df['loan_amount']= imp2.fit_transform(df['loan_amount'].values.reshape(-1,1))
```

In [ ]:

In [28]:
```
df.isnull().sum()
# here in the below table we can see that the all NULL/NAN VALUES are successfull
```

Out[28]:
```
gender                0
marital_status        0
dependents            0
education             0
self_employed         0
applicant_income      0
coapplicant_income    0
loan_amount           0
loan_amount_term      0
credit_history        0
property_area         0
loan_status           0
dtype: int64
```

In [ ]:

In [29]:
```
df.columns
```

Out[29]:
```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

In [ ]:

======= CHECKING FOR UNIQUE/CATEGORICAL IN EACH COLUMNS
=======================================

In [ ]:

====================== UNIVARIATE ANALYSIS =====================

In [ ]:

===================== CHECKING FOR UNIQUE/CATEGORICAL IN EACH COLUMNS =====================

In [29]:

```
df.columns
```

Out[29]:

```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

In [ ]:

===================== UNIVARIATE ANALYSIS =====================

In [30]:

```
#  1) Analysing GENDER COLUMN ====>>>>
```

In [31]:

```
df['gender'].unique()
# male & femoale two different unique values are present in our dataset.
```

Out[31]:

```
array(['Male', 'Female'], dtype=object)
```

In [32]:

```
df['gender'].nunique()
```

Out[32]:

```
2
```

In [33]:

```
df['gender'].value_counts()
# we can see that the MALE APPLICANT'S are very much HIGHER then the FEMALE APPLI
```

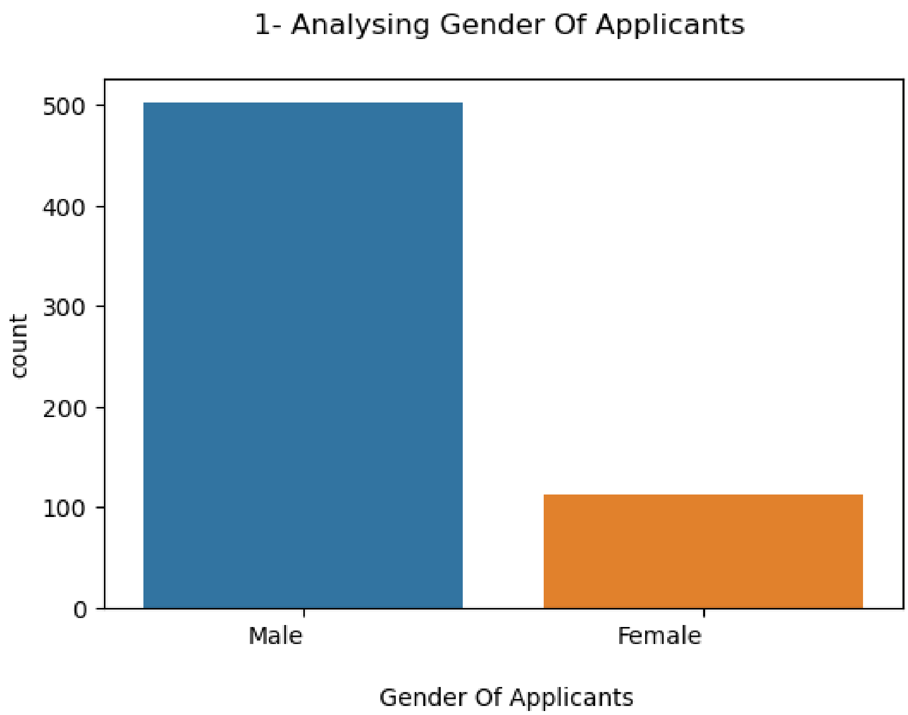
Out[33]:

```
Male      502
Female    112
Name: gender, dtype: int64
```

In [34]:

```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n1- Analysing Gender Of Applicants \n')
sns.countplot(x='gender', data=df)
plt.xlabel('\n Gender Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='right')
# plt.ylabel('no. of counts', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```

In [34]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n1- Analysing Gender Of Applicants \n')
sns.countplot(x='gender', data=df)
plt.xlabel('\n Gender Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='right')
# plt.ylabel('no. of counts', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()

# here in the following bargraph we can clearly see that the MALE LOAN APPLICNATS
```



In [ ]:

In [35]:
```
# 2) Analysing MARITAL STATUS of Applicants ======>>>>>
```

In [36]:
```
df['marital_status'].unique()
# offcourse they are YES-MARRIED OR NO-MARRIED
```

Out[36]:
```
array(['No', 'Yes'], dtype=object)
```

In [37]:
```
df['marital_status'].nunique()
```

Out[37]:
```
2
```

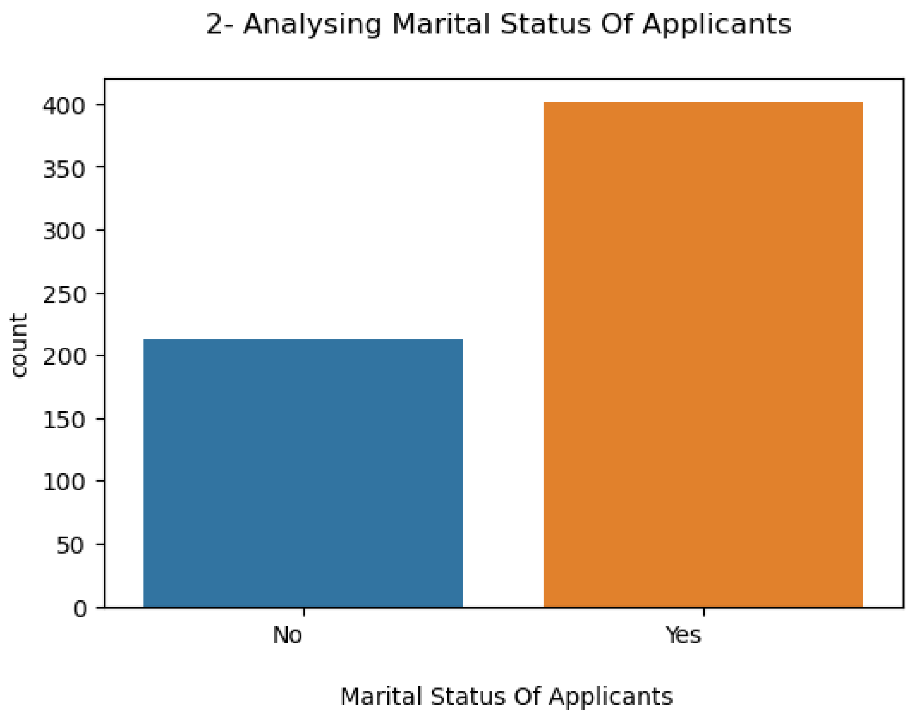
In [38]:
```
df['marital_status'].value_counts()
```

Out[38]:
```
Yes    401
No     213
Name: marital_status, dtype: int64
```

In [39]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n2- Analysing Marital Status Of Applicants \n')
sns.countplot(x='marital_status', data=df)
plt.xlabel('\n Marital Status Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='right')
# plt.ylabel('no. of counts', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```

```
Name: marital_status, dtype: int64
```

In [39]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n2- Analysing Marital Status Of Applicants \n')
sns.countplot(x='marital_status', data=df)
plt.xlabel('\n Marital Status Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='right')
# plt.ylabel('no. of counts', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()

# here in the following bargraph we can clearly see that the the Number Of Marrie
```



In [ ]:

In [40]:
```
# 3) Analysing Dependents in the DataSet =====>>>>
```

In [41]:
```
df['dependents'].unique()
# here we can see that no. of unique values of dependents are following.
```

Out[41]:
```
array(['0', '1', '2', '3+'], dtype=object)
```

In [42]:
```
df['dependents'].nunique()
# there are 4 no. of unique values are present in the dataset.
```

Out[42]:
```
4
```

In [43]:
```
df['dependents'].value_counts()
# here we can see the distribution of dependents with the applicant.
```

Out[43]:
```
0     360
1     102
2     101
3+     51
Name: dependents, dtype: int64
```

In [ ]:

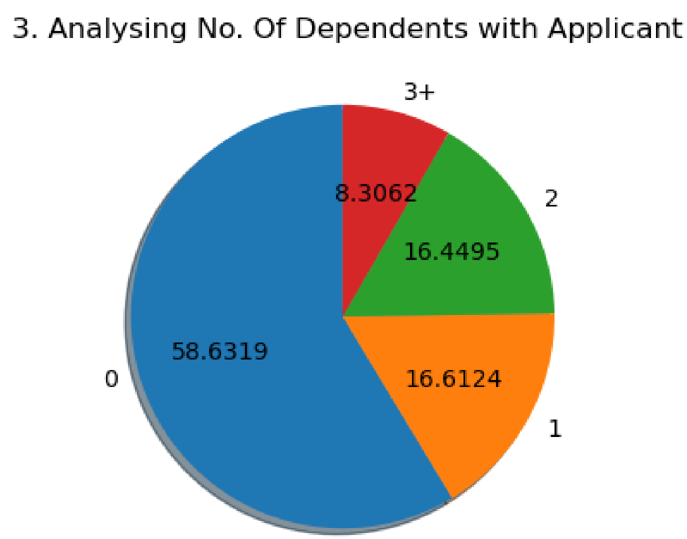
In [44]:
```
plt.figure(figsize=(4,4))
plt.title('\n 3. Analysing No. Of Dependents with Applicant')
plt.pie(df['dependents'].value_counts(),startangle=90,autopct='%.4f',labels=['0',
plt.show()

# here in the following PIE CHART we can found that,
```

In [ ]:

```
1      102
2      101
3+      51
Name: dependents, dtype: int64
```

In [44]:

```
plt.figure(figsize=(4,4))
plt.title('\n 3. Analysing No. Of Dependents with Applicant')
plt.pie(df['dependents'].value_counts(),startangle=90,autopct='%.4f',labels=['0',
plt.show()

# here in the following PIE CHART we can found that,
# 1) Applicant with '0 dependents' = 58.63 %
# 2) Applicant with '1 dependents' = 16.61 %
# 3) Applicant with '2 dependents' = 16.44 % (1 & 2 dependent applicants are almo
# 4) Applicant with '3+ dependents' = 8.30 %

#  from the bleow PIE CHART it is cleared that , Highest No. Of Applicants are Ha
# & LOWEST NO. APPLICANTS are having '3+ dependents'= may they MARRIED , HAVING C
```



In [ ]:

In [45]:

```
# 4) Analysing Education Of Applicants =====>>>>
```

In [46]:

```
df['education'].unique()
# there are only two categories 'graduate' & 'Non-Graduate'
```

Out[46]:

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

In [47]:

```
df['education'].value_counts()
# Maximum Number of applicants are GRADUATE
```

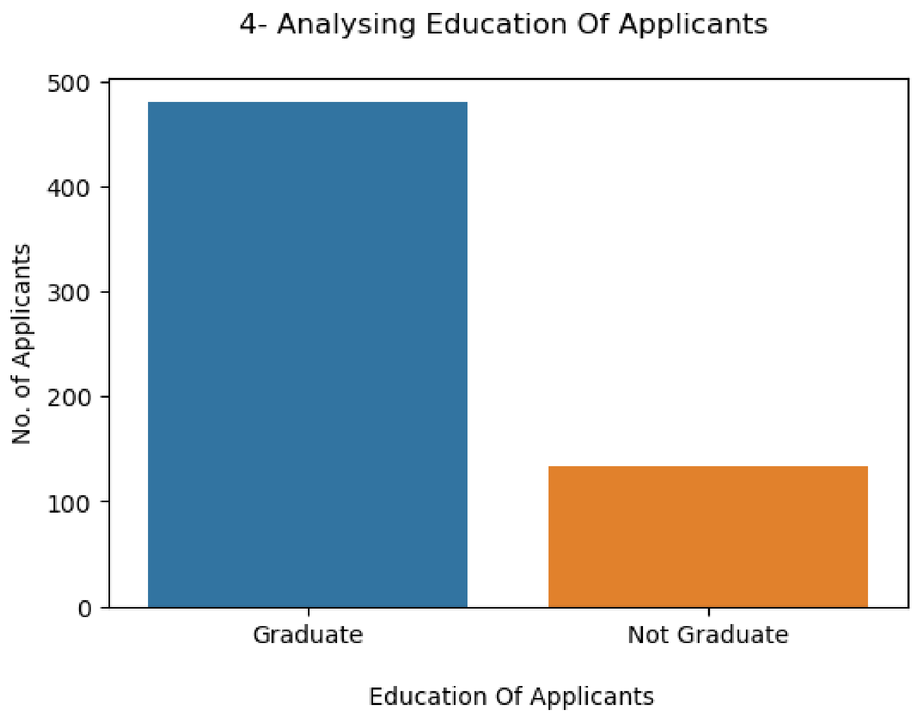
Out[47]:

```
Graduate        480
Not Graduate    134
Name: education, dtype: int64
```

In [48]:

```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n4- Analysing Education Of Applicants \n')
sns.countplot(x='education', data=df)
plt.xlabel('\n Education Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```

In [48]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n4- Analysing Education Of Applicants \n')
sns.countplot(x='education', data=df)
plt.xlabel('\n Education Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()

# GRADUATE Applicants are almost more then double compared to NON-GRADUATE APPLIC
```



In [ ]:

In [49]:
```
# 5) Analysing Employeemnet Of Applicant =======>>>
```

In [50]:
```
df['self_employed'].unique()
# Applicant's 'self_employement' status
```

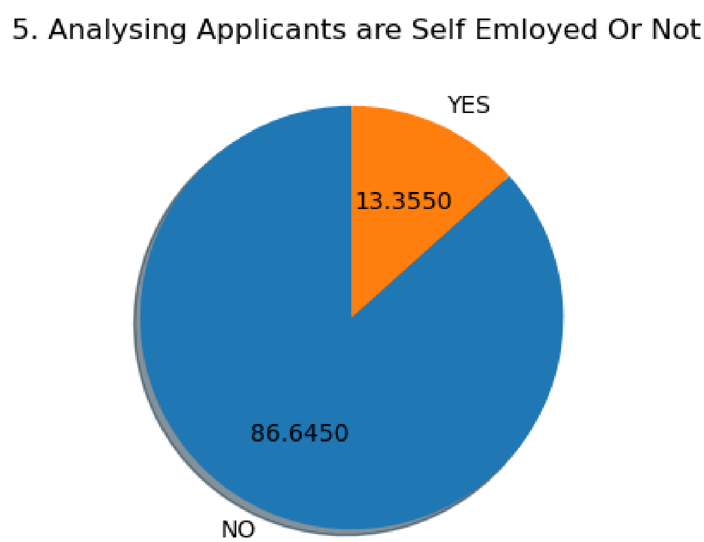
Out[50]:
```
array(['No', 'Yes'], dtype=object)
```

In [51]:
```
df['self_employed'].value_counts()

# here Maximum Applicants are not self_employed , that mean they may SALARIED.
```

Out[51]:
```
No     532
Yes     82
Name: self_employed, dtype: int64
```

In [52]:
```
plt.figure(figsize=(4,4))
plt.title('\n 5. Analysing Applicants are Self Emloyed Or Not')
plt.pie(df['self_employed'].value_counts(),startangle=90,autopct='%.4f',labels=[
plt.show()

# here in the following PIE CHART we can found that,
# 1) Applicant with 'YES - SELF-EMPLOYED' = 13.35 %
# 2) Applicant with 'NO - SELF-EMPLOYED' = 86.64 %
```

In [52]:
```
plt.figure(figsize=(4,4))
plt.title('\n 5. Analysing Applicants are Self Emloyed Or Not')
plt.pie(df['self_employed'].value_counts(),startangle=90,autopct='%.4f',labels=[
plt.show()

# here in the following PIE CHART we can found that,
# 1) Applicant with 'YES - SELF-EMPLOYED' = 13.35 %
# 2) Applicant with 'NO - SELF-EMPLOYED' = 86.64 %

# in the below pie chart we find that MAXIMUM NO. OF APPLICANT'S are NOT-SELF_EMP
# that means the Maximum No. Of Applicants are may SALARIED.
# and the YES - SELF_EMPLOYED APPLICANTS are only 13.35 %
```



In [ ]:

In [53]:
```
#  6) Analysing Applicants Income =======>>>>>>
```

In [54]:
```
df['applicant_income'].nunique()

# out of 614 columns , there are 505 unique values are present in this column.
# that means it is not a categorical column.
```

Out[54]: 505

In [55]:
```
df['applicant_income'].min()
# here in the column the minimum vlaue of income present in the column is - $ 15(
```

Out[55]: 150

In [56]:
```
df['applicant_income'].max()
# the highest INCOME OF ANY APPLICANT is $ 81000
```

Out[56]: 81000

In [57]:
```
df['applicant_income'].mean()

# the Mean Of Income Of ALL Applicant's is $ 5403
```

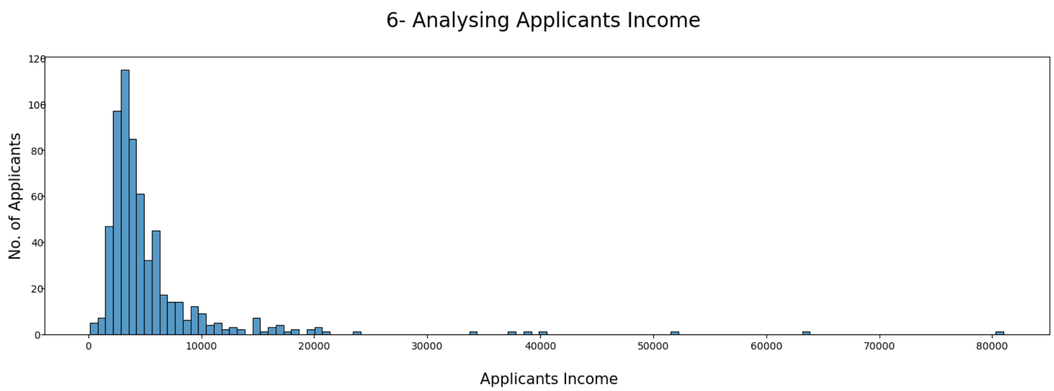
Out[57]: 5403.459283387622

In [58]:
```
plt.figure(figsize = (18,5), facecolor='white')
plt.title('\n6. Analysing Applicants Income \n', fontsize=20)
sns.histplot(x='applicant_income', data=df)
plt.xlabel('\n Applicants Income', fontsize = 15)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants', fontsize = 15)
```

In [57]:
```
df['applicant_income'].mean()

# the Mean Of Income Of ALL Applicant's is $ 5403
```

Out[57]: 5403.459283387622

In [58]:
```
plt.figure(figsize = (18,5), facecolor='white')
plt.title('\n6- Analysing Applicants Income \n', fontsize=20)
sns.histplot(x='applicant_income', data=df)
plt.xlabel('\n Applicants Income', fontsize = 15)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants', fontsize = 15)
plt.yticks(rotation=0, ha = 'center')
plt.show()

# here as we can see in following HISTOGRAM PLOT that :
# 1) the Highest No. Of Applicants Are getting Salary in between = $ 5000 - $ 550
# 2) Maximum No. Of Applicants are getting salary in between - $ 0 -$ 10,000
# 3) there may be presence of some of outliers on $ 50,000, $ 60,000 , $ 70 & 80,
# 4) there are also few of the applicants near $ 20,000
```



In [ ]:

In [59]:
```
# 7) Analysing Co-Applicant's Income =====>>>>>
```

In [60]:
```
df['coapplicant_income'].nunique()

# Out Of 614 values , there are only 287 unique values are present inside the col
```

Out[60]: 287

In [61]:
```
df['coapplicant_income'].min()
```

Out[61]: 0.0

In [62]:
```
df['coapplicant_income'].max()
#  $ 41,667 is the Highest income of Coapplicant
```

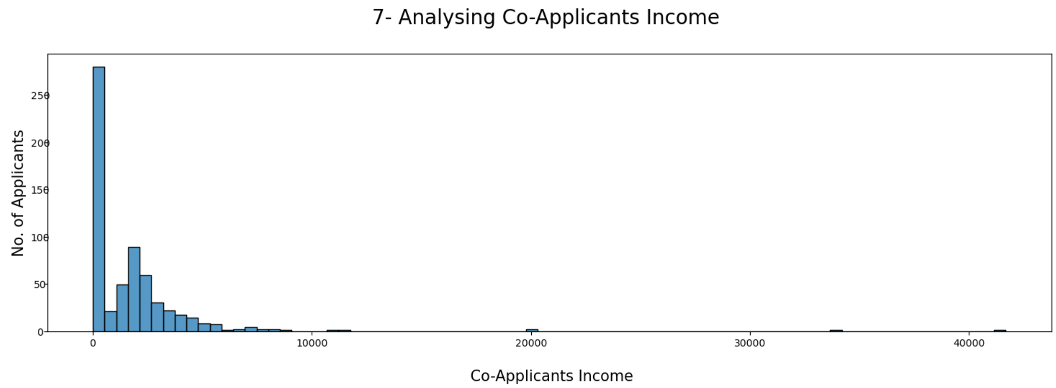
Out[62]: 41667.0

In [63]:
```
df['coapplicant_income'].mean()
# $ 1621 is the mean of coapplicants income.
```

Out[63]: 1621.245798027101

In [64]:
```
plt.figure(figsize = (18,5), facecolor='white')
plt.title('\n7- Analysing Co-Applicants Income \n', fontsize=20)
sns.histplot(x='coapplicant_income', data=df)
plt.xlabel('\n Co-Applicants Income', fontsize = 15)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants', fontsize = 15)
plt.yticks(rotation=0, ha = 'center')
plt.show()
```

In [64]:
```
plt.figure(figsize = (18,5), facecolor='white')
plt.title('\n7- Analysing Co-Applicants Income \n', fontsize=20)
sns.histplot(x='coapplicant_income', data=df)
plt.xlabel('\n Co-Applicants Income', fontsize = 15)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants', fontsize = 15)
plt.yticks(rotation=0, ha = 'center')
plt.show()

# here as we can see in following HISTOGRAM PLOT that :
# 1) the Highest No. Of Co-Applicants Are getting Salary in between = $ 0 - $ 100
# 2) Maximum No. Of Co-Applicants are getting salary in between - $ 0 -$ 8,000
# 3) there may be presence of some of outliers on $ 20,000, $ 30,000 , $ 40,000 a
# 4) there are also few of the Co-applicants are above $ 40,000
```



In [ ]:

In [65]:
```
# 8) Analysing Required Loan_Amount by Applicants ==========>>>>>
```

In [66]:
```
df['loan_amount'].nunique()
# 204 no. of unique values are present , outof 614
```

Out[66]: 204

In [67]:
```
df['loan_amount'].min()

# the Minimum Required Loan Amount by any applicant is only $ 9.0 (it may be in t
```

Out[67]: 9.0

In [68]:
```
df['loan_amount'].max()

# the Highest Required Loan Amount by an Any Applicant is $ 700.0
```

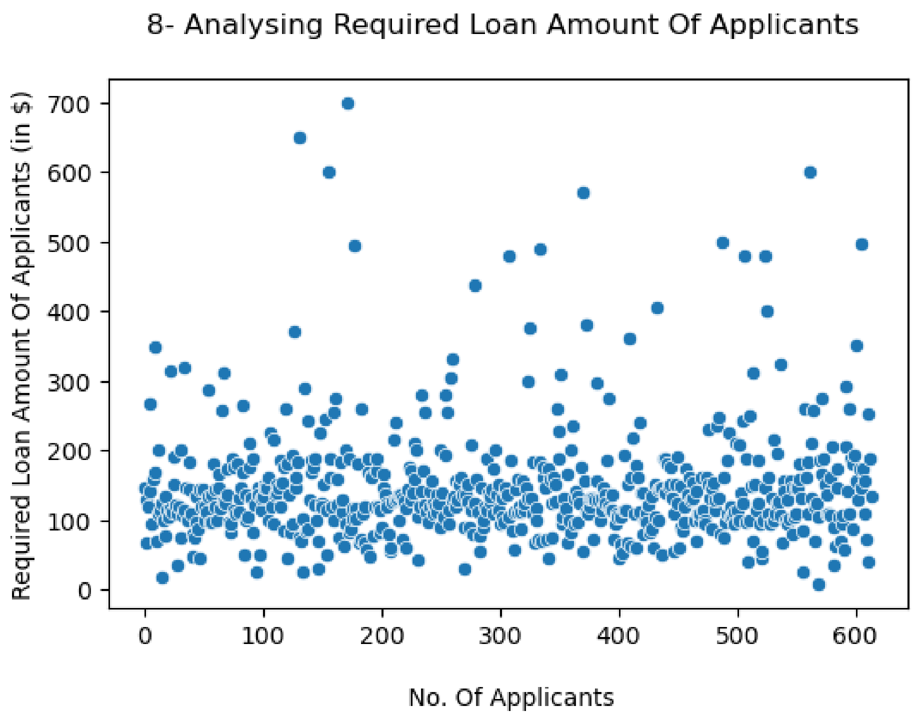
Out[68]: 700.0

In [69]:
```
df['loan_amount'].mean()

# the mean of all reqired loan amount quoted by applicants is $ 146
```

Out[69]: 146.41216216216213

In [70]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n8- Analysing Required Loan Amount Of Applicants \n')
sns.scatterplot(x=df.index,y='loan_amount', data=df)
plt.xlabel('\n No. Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('Required Loan Amount Of Applicants (in $)', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```

In [70]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n8- Analysing Required Loan Amount Of Applicants \n')
sns.scatterplot(x=df.index,y='loan_amount', data=df)
plt.xlabel('\n No. Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('Required Loan Amount Of Applicants (in $)', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()

# here in the below scatter plot , we find that the Most of Applicant are applie
# there are few of the applicants who applied for $ 500, 600 & 700 also.
# but the density is highest in between $ 0 - $ 200 only.
```



In [ ]:

In [71]:
```
# 9) Analysing Term For Loan Amount =======>>>>>>
```

In [72]:
```
df['loan_amount_term'].unique()
# following are the unique TERM which are assigned as a LOAN DURATION
```

Out[72]:
```
array([360., 120., 240., 180.,  60., 300., 480.,  36.,  84.,  12.])
```

In [73]:
```
df['loan_amount_term'].nunique()
# there are 10 numbers of unique values are present in the column.
```

Out[73]:
```
10
```

In [74]:
```
df['loan_amount_term'].min()
# the MINIMUM REQUIRED TERM FOR LOAN is 12 Months
```

Out[74]:
```
12.0
```

In [75]:
```
df['loan_amount_term'].max()
# the MAXIMUM REQUIED TERM FOR LOAN IS 480 months (40 years)
```

Out[75]:
```
480.0
```

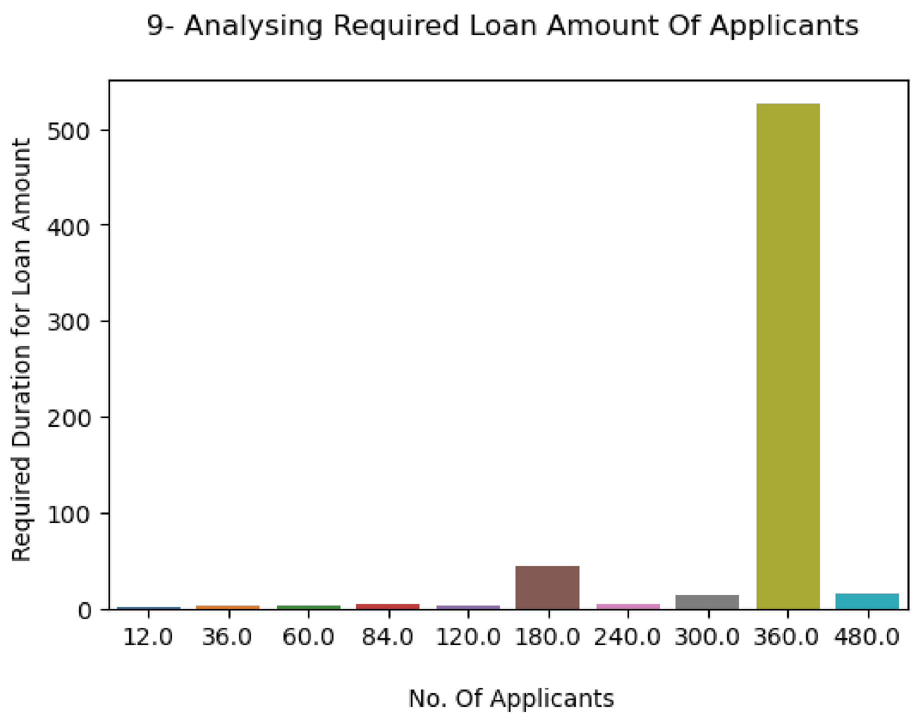
In [76]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n9- Analysing Required Loan Amount Of Applicants \n')
sns.countplot(x='loan_amount_term', data=df)
plt.xlabel('\n No. Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('Required Duration for Loan Amount ', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```

Out[74]:
```
12.0
```

In [75]:
```python
df['loan_amount_term'].max()
# the MAXIMUM REQUIED TERM FOR LOAN IS 480 months (40 years)
```

Out[75]:
```
480.0
```

In [76]:
```python
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n9- Analysing Required Loan Amount Of Applicants \n')
sns.countplot(x='loan_amount_term', data=df)
plt.xlabel('\n No. Of Applicants', fontsize = 10)
plt.xticks(rotation=0,ha = 'center')
plt.ylabel('Required Duration for Loan Amount ', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()

# here in the below bar plot , we find that the Highest No. of Applicant are appl
# the 2nd Highest No. of Applicants who applied for the duration of = 180 months
# there are few of the applicants who applied for $ 480 Months & 300 Months [40 Y
# very few of the applicants are applied for the duration of 12, 36,60,84, & 120
# the LOWEST NO. OF APPLICANTS are applied for 12 Months (1  year)
```



In [ ]:

In [77]:
```python
#  10) Analysing Credit Histroy Of Applicants =======>>>>>
```

In [78]:
```python
df['credit_history'].unique()
# there is only 1 & 0 unique value present inside the column.
```

Out[78]:
```
array([1., 0.])
```

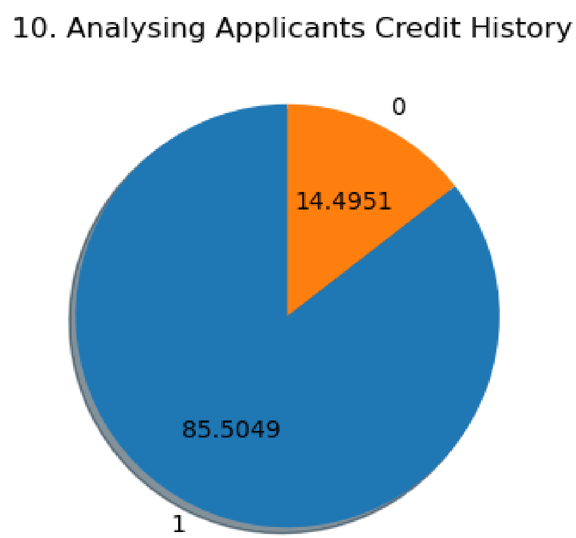
In [79]:
```python
df['credit_history'].value_counts()

# Highest Numbers of applicants with credit history-1
```

Out[79]:
```
1.0    525
0.0     89
Name: credit_history, dtype: int64
```

In [80]:
```python
plt.figure(figsize=(4,4))
plt.title('\n 10. Analysing Applicants Credit History')
plt.pie(df['credit_history'].value_counts(),startangle=90,autopct='%.4f',labels=[
plt.show()

# here in the below PIE CHART we found that :
# Applicant with 1 credit History = 85.50 %
# Applicant with 0 credit History = 14.49 %
```

```
0.0      89
Name: credit_history, dtype: int64
```

In [80]:
```
plt.figure(figsize=(4,4))
plt.title('\n 10. Analysing Applicants Credit History')
plt.pie(df['credit_history'].value_counts(),startangle=90,autopct='%.4f',labels=|
plt.show()

# here in the below PIE CHART we found that :
# Applicant with 1 credit History = 85.50 %
# Applicant with 0 credit History = 14.49 %
```



In [ ]:
```
```

In [81]:
```
# 11) Analysing Mordgaged Propert Area ======>>>
```

In [82]:
```
df['property_area'].unique()
# there is 'urban' 'rural' & 'semiurban' unique areas are present in the column
```

Out[82]:
```
array(['Urban', 'Rural', 'Semiurban'], dtype=object)
```

In [83]:
```
df['property_area'].nunique()
# there are 3 unique values are present in the column
```

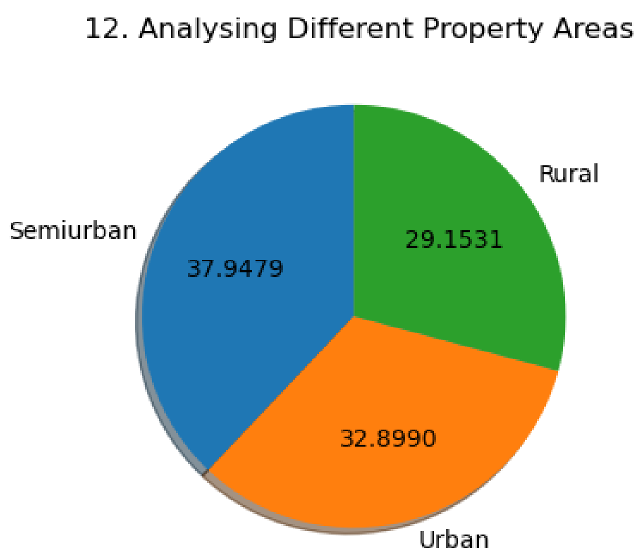
Out[83]:
```
3
```

In [84]:
```
df['property_area'].value_counts()
# below is the distribution of different areas of property
```

Out[84]:
```
Semiurban    233
Urban        202
Rural        179
Name: property_area, dtype: int64
```

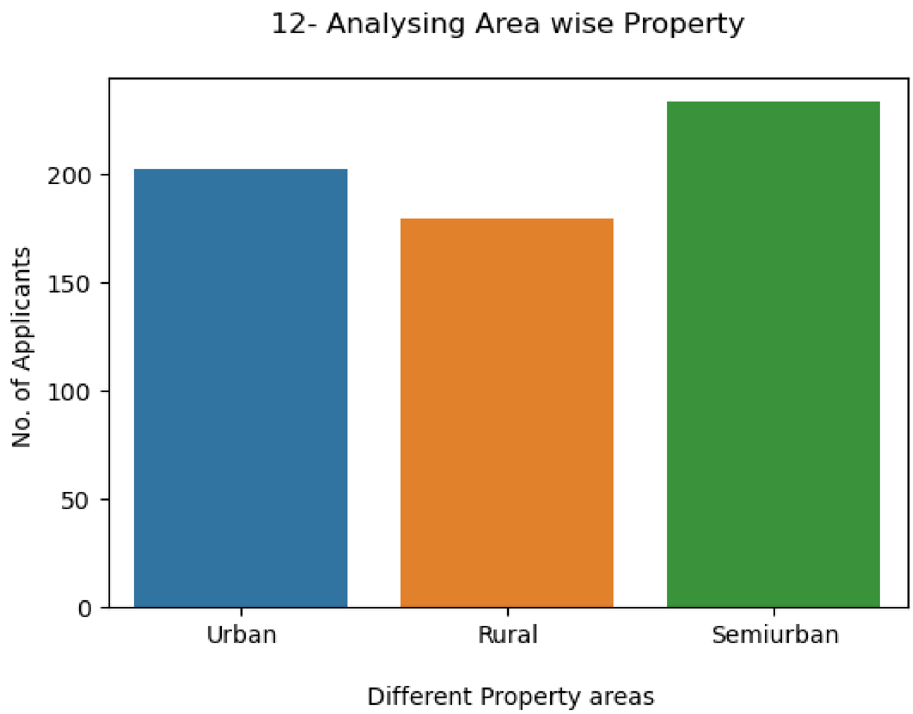
In [85]:
```
plt.figure(figsize=(4,4))
plt.title('\n 12. Analysing Different Property Areas')
plt.pie(df['property_area'].value_counts(),startangle=90,autopct='%.4f',labels=[
plt.show()

# here in the below PIE CHART we found that :
# all the three area are almost similar but with minor differences i.e :
# 1) Semi-Urban area properties with = 37.94 %
# 2) Urban Area Properties with = 32.89 %
```

In [85]:
```
plt.figure(figsize=(4,4))
plt.title('\n 12. Analysing Different Property Areas')
plt.pie(df['property_area'].value_counts(),startangle=90,autopct='%.4f',labels=[
plt.show()

# here in the below PIE CHART we found that :
# all the three area are almost similar but with minor differences i.e :
# 1) Semi-Urban area properties with = 37.94 %
# 2) Urban Area Properties with = 32.89 %
# 3) Rural Area Properties with = 29.15 %
```



In [86]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n 12- Analysing Area wise Property \n')
sns.countplot(x='property_area', data=df)
plt.xlabel('\n Different Property areas', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants ', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```

In [86]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n 12- Analysing Area wise Property \n')
sns.countplot(x='property_area', data=df)
plt.xlabel('\n Different Property areas', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants ', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```



In [ ]:

In [87]:
```
# 13) Analysing Loan Status ====>>>>>>
```

In [88]:
```
df['loan_status'].unique()
```

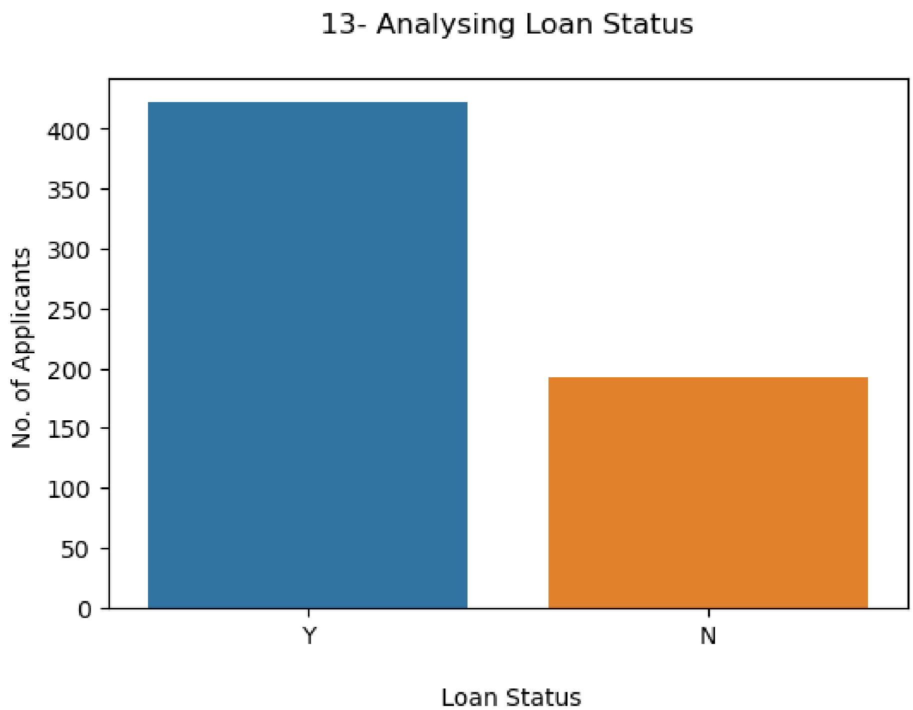
Out[88]:
```
array(['Y', 'N'], dtype=object)
```

In [89]:
```
df['loan_status'].value_counts()
```

Out[89]:
```
Y    422
N    192
Name: loan_status, dtype: int64
```

In [90]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n 13- Analysing Loan Status \n')
sns.countplot(x='loan_status', data=df)
plt.xlabel('\n Loan Status', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants ', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()
```

In [90]:
```
plt.figure(figsize = (6,4), facecolor='white')
plt.title('\n 13- Analysing Loan Status \n')
sns.countplot(x='loan_status', data=df)
plt.xlabel('\n Loan Status', fontsize = 10)
plt.xticks(rotation=0,ha ='center')
plt.ylabel('No. of Applicants ', fontsize = 10)
# plt.yticks(rotation=0, ha = 'center')
plt.show()

# out of 614 Applicants = 422 got their loans & 192 rejected
```



In [ ]:

In [ ]:

=== UNIVARIATE ANALYSIS COMPLETED ==

In [ ]:

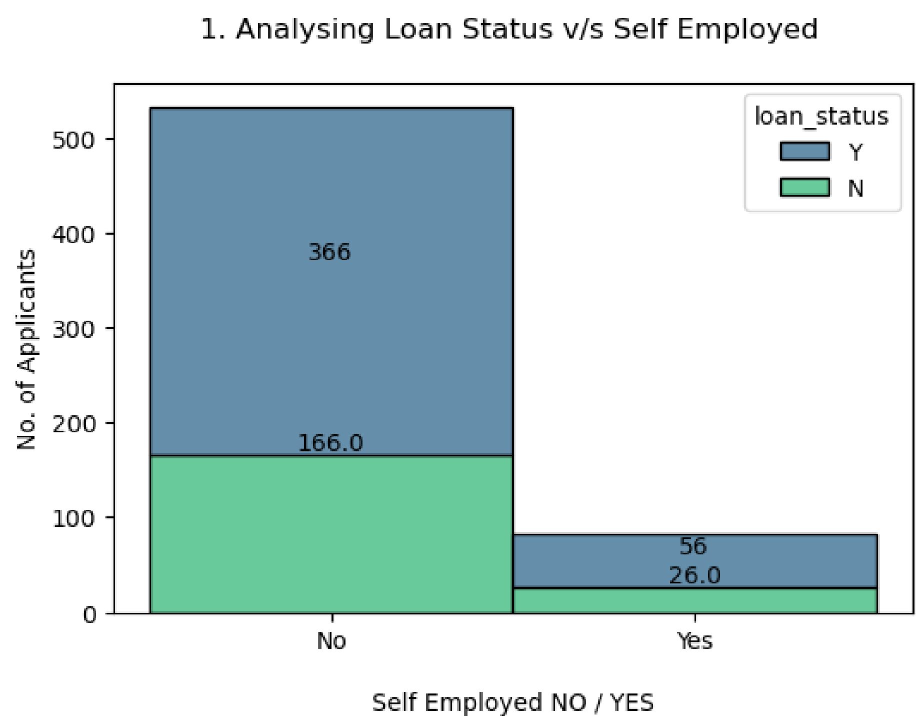
================ APPLYINNG BIVARIATE & MULTI-VARIATE ANALYSIS ================================

In [91]:
```
# HERE BELOW WE ARE GOING TO ANALYSE SOME RELEVANT COLUMNS WITH LOAN STATUS BY BI
```

In [92]:
```
# 1) Analysing Loan Status with Self Employement ========>
```

In [93]:
```
plt.figure (figsize = (6,4), facecolor = "white")
plt.title('\n1. Analysing Loan Status v/s Self Employed \n')
ax = sns.histplot (x= 'self_employed', hue = 'loan_status', data= df,palette = "\
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{height}',
                (p.get_x() + p.get_width() / 2., height),
                ha='center', va='bottom', fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
```

In [93]:
```
plt.figure (figsize = (6,4), facecolor = "white")
plt.title('\n1. Analysing Loan Status v/s Self Employed \n')
ax = sns.histplot (x= 'self_employed', hue = 'loan_status', data= df,palette = "v
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{height}',
                (p.get_x() + p.get_width() / 2., height),
                ha='center', va='bottom', fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('\n Self Employed NO / YES ')
plt.xticks (rotation = 0, ha= 'center')
plt.ylabel('No. of Applicants')
# plt.yticks (rotation = 0, ha='center')
# plt.legend(loc= 'center', fontsize=6)
plt.show()

#  here below we are comparing LOAN STATUS with SELF EMPLOYEMENT of applicant.
#  so we found here that, we saw earlier that......
#                   TOTAL NO. OF NON-SELF EMPLOYED APPLICANTS ARE = 532 (APPROV
# Similarly for ......TOTAL SELF EMPLOYED APPLICANTS ARE = 82 (APPROVED= 56,  REJ
```



In [ ]:

In [94]:
```
# 2) Analysing Loan Status with Dependents =========>>>>>>
```

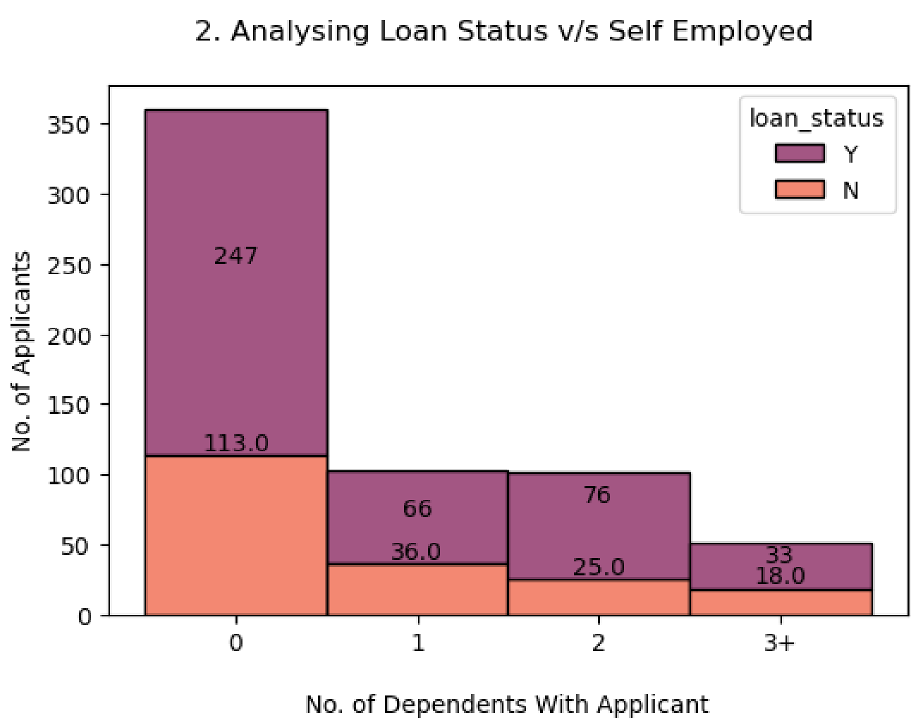
In [95]:
```
df['dependents'].value_counts()
```

Out[95]:
```
0     360
1     102
2     101
3+     51
Name: dependents, dtype: int64
```

In [96]:
```
plt.figure (figsize = (6,4), facecolor = "white")
plt.title('\n2. Analysing Loan Status v/s Self Employed \n')
ax = sns.histplot (x= 'dependents', hue = 'loan_status', data= df,palette = "rock
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{height}',
                (p.get_x() + p.get_width() / 2., height),
                ha='center', va='bottom', fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
```

```
1      102
2      101
3+      51
Name: dependents, dtype: int64
```

In [96]:
```
plt.figure (figsize = (6,4), facecolor = "white")
plt.title('\n2. Analysing Loan Status v/s Self Employed \n')
ax = sns.histplot (x='dependents', hue = 'loan_status', data= df,palette = "rock
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{height}',
                (p.get_x() + p.get_width() / 2., height),
                ha='center', va='bottom', fontsize=10)
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('\n No. of Dependents With Applicant ')
plt.xticks (rotation = 0, ha= 'center')
plt.ylabel('No. of Applicants')
# plt.yticks (rotation = 0, ha='center')
# plt.legend(loc= 'center', fontsize=6)
plt.show()

#  here below we are comparing LOAN STATUS with DEPENDENTS of applicant.
#  so we found here that, we saw earlier that......
#  TOTAL NO. OF APPLICANTS WITH '0' DEPENDENTS ARE = 360 (out of which- APPROVED
#  TOTAL NO. OF APPLICANTS WITH '1' DEPENDENTS ARE = 102 (out of which- APPROVED
#  TOTAL NO. OF APPLICANTS WITH '2' DEPENDENTS ARE = 101 (out of which- APPROVED
#  TOTAL NO. OF APPLICANTS WITH '3+' DEPENDENTS ARE = 51 (out of which- APPROVED

# here from the above analysis we found that , Highest No. Of Applicants are havi
# .....
# the HIGHEST APPROVAL (% wise) is with '2' DEPENDENTS = 75.24%
```



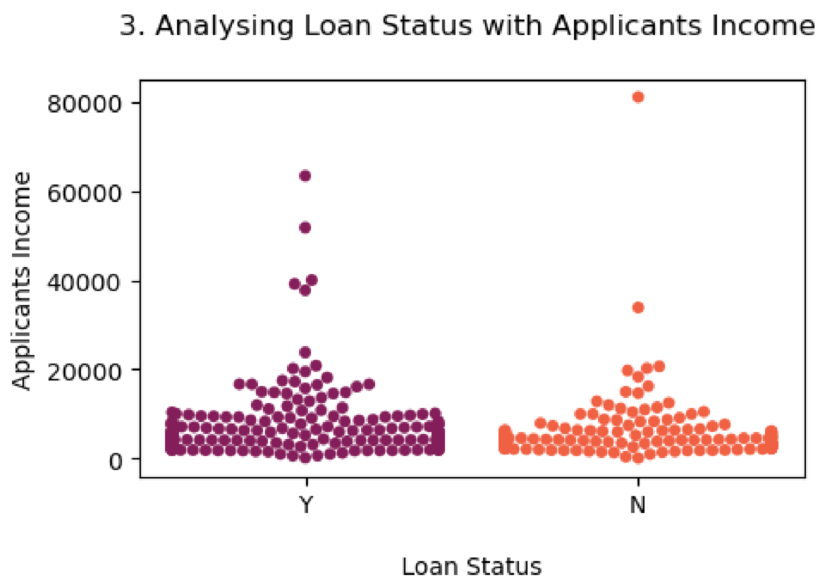
In [ ]:

In [97]:
```
# 3) Analysing Loan Status v/s Applicants Income =========>>>>>
```

In [98]:
```
plt.figure (figsize = (5,3), facecolor = "white")
plt.title('\n3. Analysing Loan Status with Applicants Income \n')
sns.swarmplot (x= 'loan_status', y = 'applicant_income', data= df, palette = "roc
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('\n Loan Status ')
plt.xticks (rotation = 0, ha= 'center')
plt.ylabel('Applicants Income')
# plt.yticks (rotation = 0, ha='center')
# plt.legend(loc= 'center', fontsize=6)
```

In [97]: # 3) Analysing Loan Status v/s Applicants Income ========>>>>>

In [98]:
```
plt.figure (figsize = (5,3), facecolor = "white")
plt.title('\n3. Analysing Loan Status with Applicants Income \n')
sns.swarmplot (x= 'loan_status', y = 'applicant_income', data= df, palette = "roc
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('\n Loan Status ')
plt.xticks (rotation = 0, ha= 'center')
plt.ylabel('Applicants Income')
# plt.yticks (rotation = 0, ha='center')
# plt.legend(loc= 'center', fontsize=6)
plt.show()

# we can find here in the below swarmplot , that with higher income ,approaval ra
# here we can see an exception also in REJECTED AREA , with the income of 80,000
#  ....there may be some other reasons behind it. we can analyse them further.
```

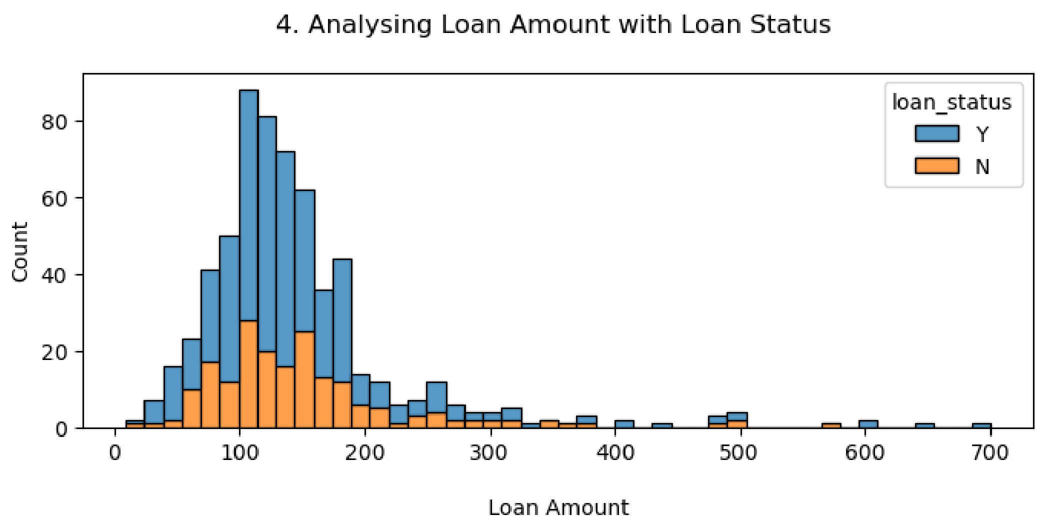


In [ ]:

In [99]: # 4) Analysing Loan Status with Loan Amount ====>>>>

In [100]:
```
plt.figure (figsize = (8,3), facecolor = "white")
plt.title('\n4. Analysing Loan Amount with Loan Status \n')
sns.histplot(data=df, x="loan_amount", hue="loan_status", multiple="stack")
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('\n Loan Amount ')
# plt.xticks (rotation = 0, ha= 'center')
# plt.ylabel('No. of employees')
# plt.yticks (rotation = 0, ha='center')
# plt.legend(loc= 'center', fontsize=6)
```

In [100]:
```
plt.figure (figsize = (8,3), facecolor = "white")
plt.title('\n4. Analysing Loan Amount with Loan Status \n')
sns.histplot(data=df, x="loan_amount", hue="loan_status", multiple="stack")
# plt.xticks(rotation=30, ha = 'right')
plt.xlabel('\n Loan Amount ')
# plt.xticks (rotation = 0, ha= 'center')
# plt.ylabel('No. of employees')
# plt.yticks (rotation = 0, ha='center')
# plt.legend(loc= 'center', fontsize=6)
plt.show()

# here in the below histogram we find that maximum no. of applicants are applied
# ... and the highest loan amount sanctioned is in between $ 100 -120
# there is also a few approvals near about $ 500
```

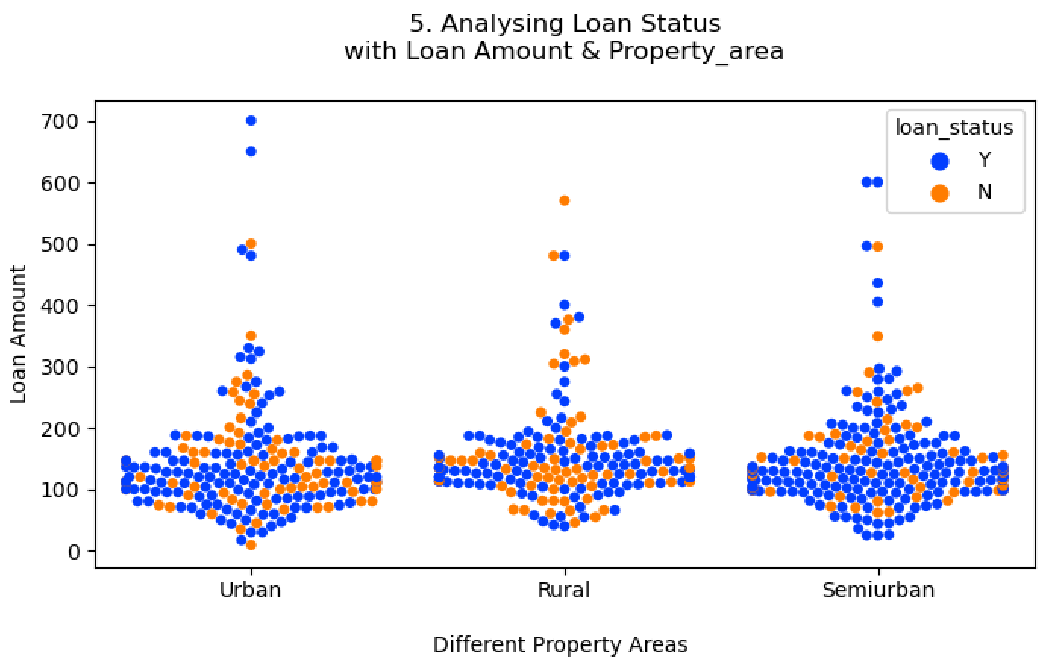


In [ ]:

In [101]:
```
# 5) Analysing Loan Status with Loan Amount & Property_area ==========>>>>
```

In [102]:
```
plt.figure(figsize=(8,4),facecolor="white")
plt.title('\n 5. Analysing Loan Status \n with Loan Amount & Property_area \n')
sns.swarmplot (x= 'property_area', y= 'loan_amount',hue = 'loan_status', data= df
plt.xlabel ('\nDifferent Property Areas ')
plt.xticks(rotation=0, ha='center',fontsize=10)
plt.ylabel('Loan Amount')
plt.show()

# here in below SWARM PLOT we can clealry identifies that :
```

In [102]:
```
plt.figure(figsize=(8,4),facecolor="white")
plt.title('\n 5. Analysing Loan Status \n with Loan Amount & Property_area \n')
sns.swarmplot (x= 'property_area', y= 'loan_amount',hue = 'loan_status', data= df
plt.xlabel ('\nDifferent Property Areas ')
plt.xticks(rotation=0, ha='center',fontsize=10)
plt.ylabel('Loan Amount')
plt.show()

# here in below SWARM PLOT we can clealry identifies that :
# 1) Maximum Number Of Applicants Are in SEMI-URBAN AREA > URBAN-AREA > RURAL-ARE
# 2) Maximum No. of Loan Sanctions are from SEMI-URBAN AREA
# 3) Maximum No. of Loan Rejections are from RURAL AREA
# 4) HIGHEST AMOUNT of SANCTIONED LOAN is from URBAN-AREA , then SEMI-URBAN
```

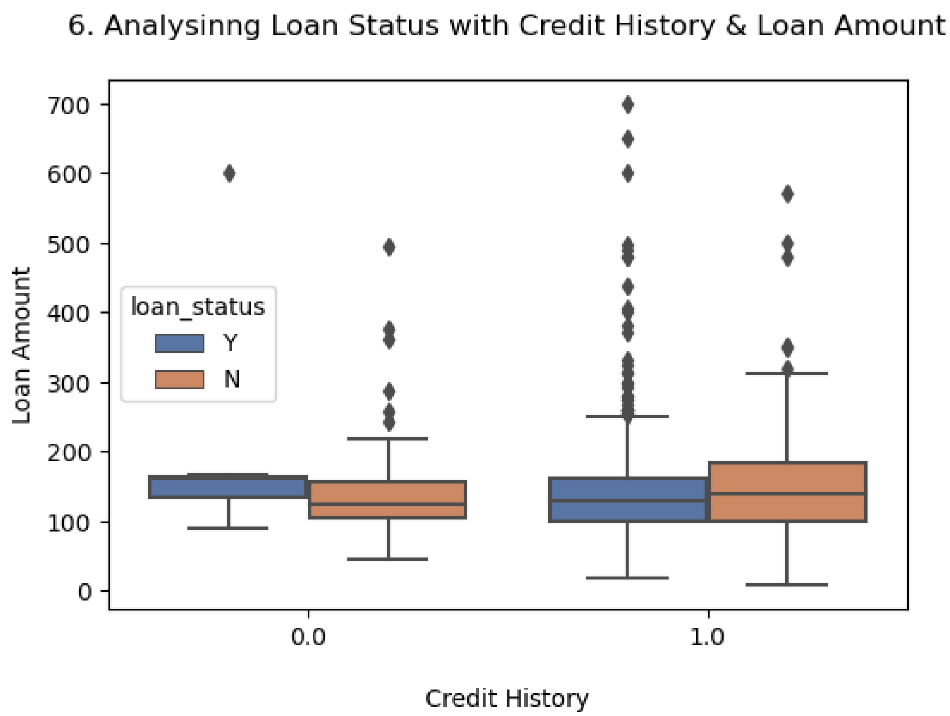


In [ ]:

In [103]:
```
# 6) Analysinng Loan Status with Credit History & Loan Amount =======>>>>>>
```

In [104]:
```
plt.figure(figsize=(6,4),facecolor="white")
plt.title('\n 6. Analysinng Loan Status with Credit History & Loan Amount \n')
sns.boxplot (x= 'credit_history', y= 'loan_amount',hue = 'loan_status', data= df,
plt.xlabel ('\n Credit History ')
plt.xticks(rotation=0, ha='center',fontsize=10)
plt.ylabel('Loan Amount')
# plt.legend(loc='center')
plt.show()
```

In [104]:
```
plt.figure(figsize=(6,4),facecolor="white")
plt.title('\n 6. Analysinng Loan Status with Credit History & Loan Amount \n')
sns.boxplot (x= 'credit_history', y= 'loan_amount',hue = 'loan_status', data= df,
plt.xlabel ('\n Credit History ')
plt.xticks(rotation=0, ha='center',fontsize=10)
plt.ylabel('Loan Amount')
# plt.legend(loc='center')
plt.show()

# credit history = 0 & 1 (0- it could may be 'Not Available') & ('1' could may 'A
# so in the below boxplot we can see clearly , those applicnats with 'available'
# ...CHANCES of APPROVAL OF LOAN
# and we can see that with "credit history-1" HIGHESHT NUMBER OF LOAN APPROVALS c
```



In [ ]:

============= UPTO HERE UNIVARIATE, BIVARIATE & MULTIVARIATE ANALYSIS PART OF EDA IS COMPLETED =========================

In [105]:
```
df.shape
```

Out[105]: (614, 12)

In [106]:
```
df.head()
```

Out[106]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant_inc
0	Male	No	0	Graduate	No	5849	
1	Male	Yes	1	Graduate	No	4583	15
2	Male	Yes	0	Graduate	Yes	3000	
3	Male	Yes	0	Not Graduate	No	2583	23
4	Male	No	0	Graduate	No	6000	

In [107]:
```
# here above we can fidn that there are 'object' datatype is also present in our
# so before moving ahead , we have to ENCODE them.
# by using ENCODING TECHNIQUES
```

In [108]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
```

1	Male	Yes	1	Graduate	No	4583	15
2	Male	Yes	0	Graduate	Yes	3000	
3	Male	Yes	0	Not Graduate	No	2583	23
4	Male	No	0	Graduate	No	6000	

In [107]:
```
# here above we can fidn that there are 'object' datatype is also present in our
# so before moving ahead , we have to ENCODE them.
# by using ENCODING TECHNIQUES
```

In [108]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   gender              614 non-null    object 
 1   marital_status      614 non-null    object 
 2   dependents          614 non-null    object 
 3   education           614 non-null    object 
 4   self_employed       614 non-null    object 
 5   applicant_income    614 non-null    int64  
 6   coapplicant_income  614 non-null    float64
 7   loan_amount         614 non-null    float64
 8   loan_amount_term    614 non-null    float64
 9   credit_history      614 non-null    float64
 10  property_area       614 non-null    object 
 11  loan_status         614 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 57.7+ KB
```

In [109]:
```
# out of 12 columns we are having 7- object datatype columns:
# gender, marital_status, dependents, education, self_employed, property area, lo
# these all above columns are also CATEGORICAL COLUMNS
#  so we need to ENCODE them first, with the help of LABEL INCODER.
# for this we need to import LABEL INCODER FIRST
```

In [110]:
```
from sklearn.preprocessing import LabelEncoder
```

In [111]:
```
le = LabelEncoder()
```

In [112]:
```
df["gender"] = le.fit_transform(df["gender"])
df["marital_status"] = le.fit_transform(df["marital_status"])
df["dependents"] = le.fit_transform(df["dependents"])
df["education"] = le.fit_transform(df["education"])
df["self_employed"] = le.fit_transform(df["self_employed"])
df["property_area"] = le.fit_transform(df["property_area"])
df["loan_status"] = le.fit_transform(df["loan_status"])
```

In [ ]:

In [113]:
```
df.dtypes
# here we can see that the all 'object' datatypes are successfully converted into
```

Out[113]:
```
gender                  int32
marital_status          int32
dependents              int32
education               int32
self_employed           int32
applicant_income        int64
coapplicant_income    float64
loan_amount           float64
loan_amount_term      float64
credit_history        float64
property_area           int32
loan_status             int32
dtype: object
```

In [114]:
```
df.head()
# here also we can see the change
```

Out[114]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant_inc
0	1	0	0	0	0	5849	
1	1	1	1	0	0	4583	15
2	1	1	0	0	1	3000	

```
applicant_income        int64
coapplicant_income    float64
loan_amount           float64
loan_amount_term      float64
credit_history        float64
property_area           int32
loan_status             int32
dtype: object
```

In [114]:

```python
df.head()
# here also we can see the change
```

Out[114]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant_inc
0	1	0	0	0	0	5849	
1	1	1	1	0	0	4583	15
2	1	1	0	0	1	3000	
3	1	1	0	1	0	2583	23
4	1	0	0	0	0	6000	

In [ ]:

============ FINDING CORRELATION IN DATASET ========================

In [115]:

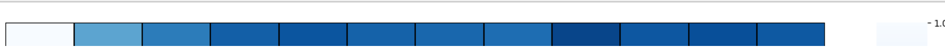
```python
cor = df.corr()
cor

# here finding non graphically correlation, here we can see that it is difficult
# ....so further we find the correlation graphically by HEAT MAP.
```

Out[115]:

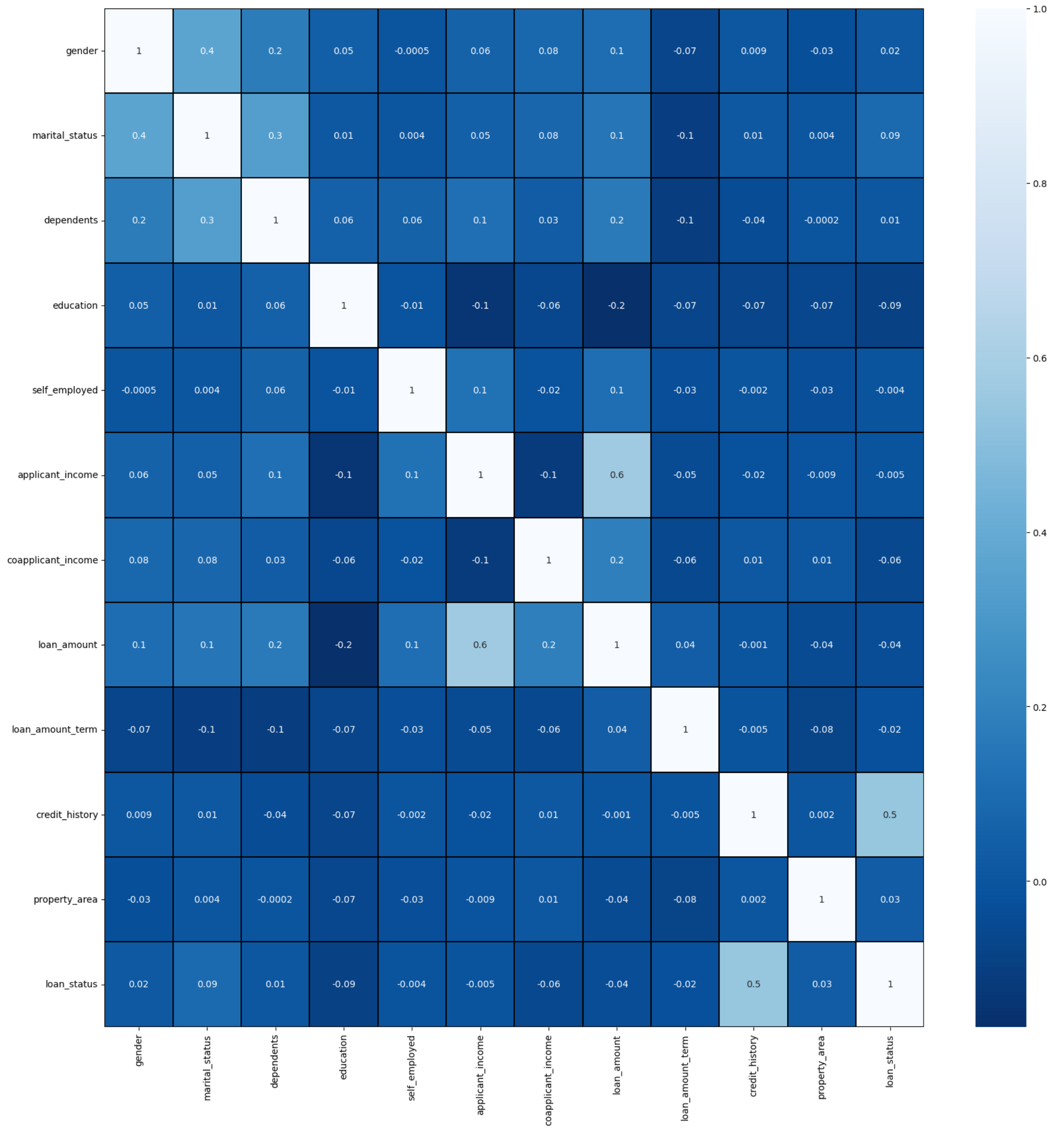
	gender	marital_status	dependents	education	self_employed	applicant_inco
gender	1.000000	0.364569	0.172914	0.045364	-0.000525	0.0588
marital_status	0.364569	1.000000	0.334216	0.012304	0.004489	0.0517
dependents	0.172914	0.334216	1.000000	0.055752	0.056798	0.1182
education	0.045364	0.012304	0.055752	1.000000	-0.010383	-0.1407
self_employed	-0.000525	0.004489	0.056798	-0.010383	1.000000	0.1271
applicant_income	0.058809	0.051708	0.118202	-0.140760	0.127180	1.0000
coapplicant_income	0.082912	0.075948	0.030430	-0.062290	-0.016100	-0.1160
loan_amount	0.107930	0.147141	0.163106	-0.166998	0.115260	0.5650
loan_amount_term	-0.074030	-0.100912	-0.103864	-0.073928	-0.033739	-0.0465
credit_history	0.009170	0.010938	-0.040160	-0.073658	-0.001550	-0.0180
property_area	-0.025752	0.004257	-0.000244	-0.065243	-0.030860	-0.0095
loan_status	0.017987	0.091478	0.010118	-0.085884	-0.003700	-0.0047

In [116]:

```python
plt.figure (figsize = (20,20), facecolor = "white")
sns.heatmap(df.corr(),linewidth=0.1,fmt="0.1g",linecolor="black",annot=True,cmap=
plt.yticks(rotation=0);
plt.show()


# here we can see below that NO COLUMNS are having Highly Correlation with each c
```



In [116]:
```
plt.figure (figsize = (20,20), facecolor = "white")
sns.heatmap(df.corr(),linewidth=0.1,fmt="0.1g",linecolor="black",annot=True,cmap=
plt.yticks(rotation=0);
plt.show()


# here we can see below that NO COLUMNS are having Highly Correlation with each c
```



In [117]:
```
cor['loan_status'].sort_values(ascending=False)
# here in the below table we can see that the HIGHLY CORRELATED COLUMN IS- CREDIT
# which considered as not much value.
# that means there is no CORRELATION of columns with each other.
```

Out[117]:
```
loan_status           1.000000
credit_history        0.540556
marital_status        0.091478
property_area         0.032112
gender                0.017987
dependents            0.010118
self_employed        -0.003700
applicant_income     -0.004710
loan_amount_term     -0.022549
loan_amount          -0.036416
coapplicant_income   -0.059187
education            -0.085884
Name: loan_status, dtype: float64
```

In [ ]:

CHECKING FOR OUTLIERS

===

In [118]:
```
df.describe()
# here in the describe methode we are getting see many STATISTICAL INFORMATION al
```

```
gender                 0.017987
dependents             0.010118
self_employed         -0.003700
applicant_income      -0.004710
loan_amount_term      -0.022549
loan_amount           -0.036416
coapplicant_income    -0.059187
education             -0.085884
Name: loan_status, dtype: float64
```

In [ ]:

CHECKING FOR OUTLIERS

==

In [118]:

```
df.describe()
# here in the describe methode we are getting soo many STATISTICAL INFORMATION ab
# 1. first of all above we are getting 'count' for each of the column.
#                  as we know the total number of row counts for each column is 1,
#                  ... column is smame. not a single blank/'nan' is present in any

# 2. MEAN : In this, we can get MEAN VALUE for the every column.
# 3. STD : which is Standard Deviation , which shows that how the data of the col
# 4. MIN : It shows the Minimum value present in the column.
# 5. 25% : It gives us the 25th Percentile Value in the column.
# 6. 50% : It gives us the 50th Percentile Value in the column.
# 7. 75% : It gives us the 75th Percentile Value in the column.
# 8. Max : It gives us the MAXIMUM VALUE present the column.

# As If in any column the Difference between the value at 75th Percentile & MAX i
# so we have to check the 75th% & MAX for each of the column.


#  here we find that in the following columns there is huge difference betweeen 7
#  1)- Applicant Income, 2)- Co-Applicant Income, 3)-Loan Amount,
# so in the above mentioned columns there may be presence of outliers, but we hav
```

Out[118]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coappl
count	614.000000	614.000000	614.000000	614.000000	614.000000	614.000000	
mean	0.817590	0.653094	0.744300	0.218241	0.133550	5403.459283	
std	0.386497	0.476373	1.009623	0.413389	0.340446	6109.041673	
min	0.000000	0.000000	0.000000	0.000000	0.000000	150.000000	
25%	1.000000	0.000000	0.000000	0.000000	0.000000	2877.500000	
50%	1.000000	1.000000	0.000000	0.000000	0.000000	3812.500000	
75%	1.000000	1.000000	1.000000	0.000000	0.000000	5795.000000	
max	1.000000	1.000000	3.000000	1.000000	1.000000	81000.000000	

In [ ]:

In [119]:

```
df.columns
```

Out[119]:

```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

In [120]:

```
df.columns.nunique()
```

Out[120]:

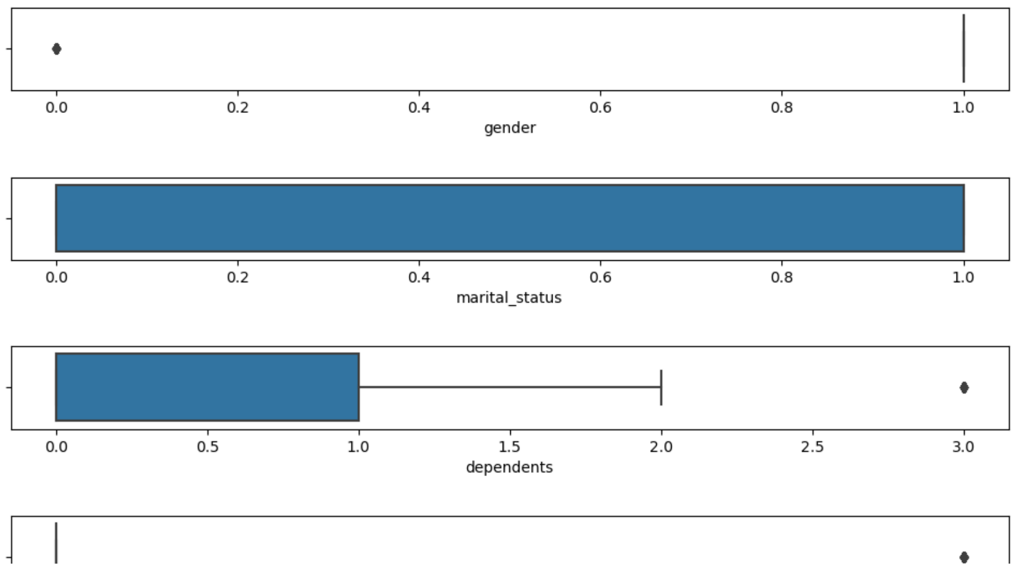
```
12
```

In [121]:

```
for i in df.columns[0:12]:
    plt.figure (figsize = (12,1), facecolor = "white")
    sns.boxplot(x=i,data=df)
    plt.show()

#  here below we can find the outliers for all the cloumns by using boxplot.
#  and we are found outliers in :
#  (1)dependents, (2) Applicant Income,(3) Co-Applicant Income,(4) Loan Amount,(5
# .....are having outliers.
```

Out[120]: 12

In [121]:
```
for i in df.columns[0:12]:
    plt.figure (figsize = (12,1), facecolor = "white")
    sns.boxplot(x=i,data=df)
    plt.show()

#  here below we can find the outliers for all the cloumns by using boxplot.
#  and we are found outliers in :
#  (1)dependents, (2) Applicant Income,(3) Co-Applicant Income,(4) Loan Amount,(5
# .....are having outliers.
# so out of 12 columns we found OUTLIERS IN 5 COLUMNS , now we have to remove the
```



In [ ]:

========== REMOVING OF OUTLIERS BY USING Z-SCORE METHOD ====================

In [122]:
```
#  we can not remove outliers from out TARGET COLUMN, so first we have to seprate
# For this first we need to identify the ZSCORE VALUES, for which we have to impo
```

In [123]:
```
from scipy.stats import zscore
```

In [124]:
```
z = np.abs(zscore(df))
z.head(5)

# by applying 'abs' (absolute method), we are getting all the entries whose z-sco
#  Ideally we can call the OUTLIERS whos ZSCORE VALUE is LESS THEN 3 AND MORE THE
# so we have to remove all the data whose ZSCORE >3 & <3
#  below here we apllying "abs" i.e absolute method it returns us the all zscore
#  so we just need to remove lesserr then 3 zscore values.
```

Out[124]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant_in
0	0.472343	1.372089	0.737806	0.528362	0.392601	0.072991	0.5
1	0.472343	0.728816	0.253470	0.528362	0.392601	0.134412	0.0
2	0.472343	0.728816	0.737806	0.528362	2.547117	0.393747	0.5
3	0.472343	0.728816	0.737806	1.892641	0.392601	0.462062	0.2
4	0.472343	1.372089	0.737806	0.528362	0.392601	0.097728	0.5

In [125]:
```
threshold = 3
print(np.where(z>3))

# here below we found only 38 values, whose z-score is more then > 3
# i.e means we are having 38 values which might be outliers,are still present in
# ...and we have to remove those outliers
```

```
(array([  9,  14,  68,  94, 126, 130, 133, 155, 155, 171, 171, 177, 177,
       183, 185, 242, 262, 278, 308, 313, 333, 333, 369, 402, 409, 417,
```

2	0.472343	0.728816	0.737806	0.528362	2.547117	0.393747	0.5
3	0.472343	0.728816	0.737806	1.892641	0.392601	0.462062	0.2
4	0.472343	1.372089	0.737806	0.528362	0.392601	0.097728	0.5

In [125]:
```python
threshold = 3
print(np.where(z>3))

# here below we found only 38 values, whose z-score is more then > 3
# i.e means we are having 38 values which might be outliers,are still present in
# ...and we have to remove those outliers
```

```
(array([  9,  14,  68,  94, 126, 130, 133, 155, 155, 171, 171, 177, 177,
       183, 185, 242, 262, 278, 308, 313, 333, 333, 369, 402, 409, 417,
       432, 443, 487, 495, 497, 506, 523, 525, 546, 561, 575, 581, 585,
       600, 604], dtype=int64), array([6, 8, 8, 8, 5, 7, 8, 5, 7, 5, 7, 6, 7,
5, 5, 8, 8, 7, 7, 8, 5, 7,
       7, 6, 5, 6, 7, 5, 7, 8, 8, 7, 7, 7, 8, 7, 8, 6, 8, 6, 7],
      dtype=int64))
```

In [126]:
```python
df_new = df[(z<3).all(axis=1)]
df_new

# here we can see the difference clearly that, earlier there was 614 total rows a
# ...there are only 577 rows are present in our dataset.
# so there are  37 OUTLIERS are removed during this process.
```

Out[126]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant_i
0	1	0	0	0	0	5849	
1	1	1	1	0	0	4583	
2	1	1	0	0	1	3000	
3	1	1	0	1	0	2583	
4	1	0	0	0	0	6000	
...	...	...	...	...	...	...	
609	0	0	0	0	0	2900	
610	1	1	3	0	0	4106	
611	1	1	1	0	0	8072	
612	1	1	2	0	0	7583	
613	0	0	0	0	1	4583	

577 rows × 12 columns

In [127]:
```python
df.shape
```

Out[127]: (614, 12)

In [128]:
```python
df_new.shape
```

Out[128]: (577, 12)

In [ ]:

===============CHECKING REMOVAL OF OUTLIERS BY BOXPLOT (COMPARING 'df' & 'df_new')========================

In [130]:
```python
df.columns
```

Out[130]:
```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

In [129]:
```python
#  (1)dependents, (2) Applicant Income,(3) Co-Applicant Income,(4) Loan Amount,(5
```

In [131]:
```python
# 1) Analysing 'Dependents column', Before & After Removing Outliers =======>>>>
```

```
CHECKING REMOVAL OF OUTLIERS BY BOXPLOT (COMPARING df &
'df_new')========================
```

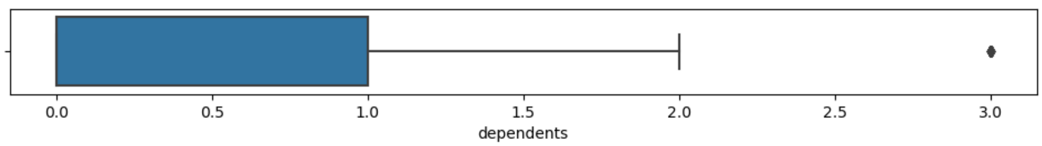
In [129]:
```
#  (1)dependents, (2) Applicant Income,(3) Co-Applicant Income,(4) Loan Amount,(5
```

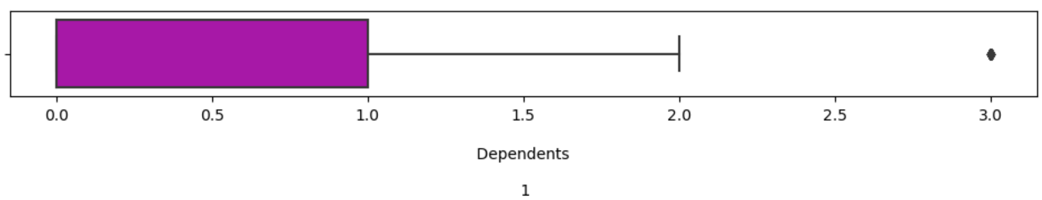
In [130]:
```
df.columns
```

Out[130]:
```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

In [131]:
```
# 1) Analysing 'Dependents column', Before & After Removing Outliers =======>>>>
```

In [132]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='dependents',data=df)
plt.show()

# it is the EARLIER (df dataset) WITH PRESENCE OF OUTLIERS

plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='dependents',data=df_new, color='m')
plt.xlabel('\n Dependents \n\n 1')
plt.show()

# NO- Outliers are removed.
# or we can say algorith is not considered this as a OUTLIER/
```



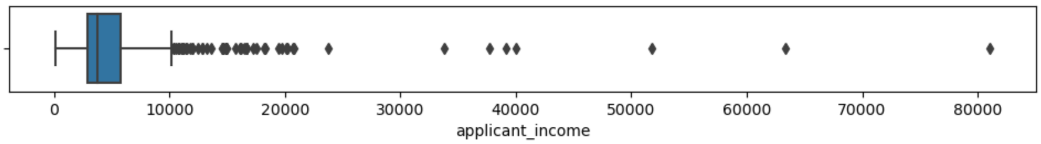


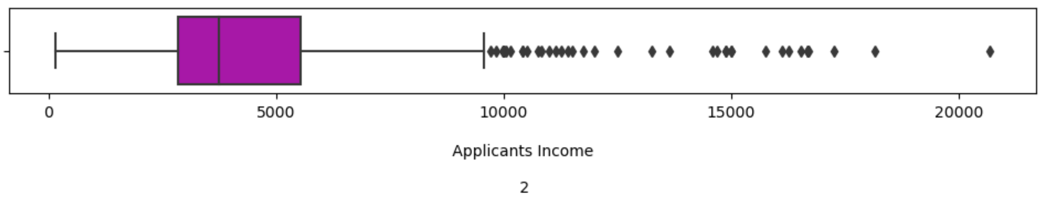
In [ ]:

In [133]:
```
# 2) Analysing 'Applicant Income column' before & after removing Outlier ======>>
```

In [134]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='applicant_income',data=df)
plt.show()

# it is the EARLIER (df dataset) WITH PRESENCE OF OUTLIERS

plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='applicant_income',data=df_new, color='m')
plt.xlabel('\n Applicants Income \n\n 2')
```

In [134]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='applicant_income',data=df)
plt.show()

# it is the EARLIER (df dataset) WITH PRESENCE OF OUTLIERS

plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='applicant_income',data=df_new, color='m')
plt.xlabel('\n Applicants Income \n\n 2')
plt.show()

# outliers are succesfully removed.
# it is the Newer (df_new dataset)  OUTLIERS ARE REMOVED.
# So as we can see , outlier which is removed above by Z-SCORE METHOD is from 'AP
```

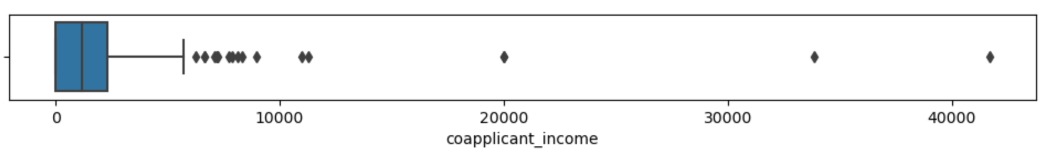


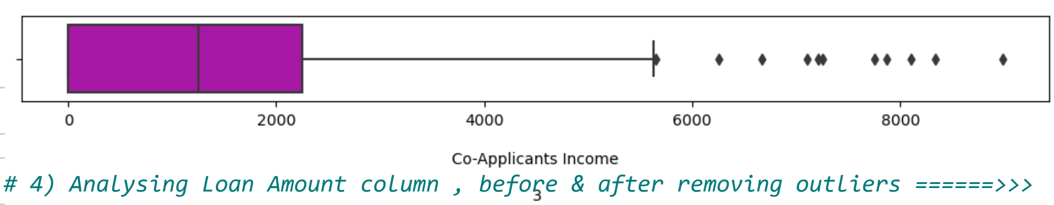


In [ ]:

In [135]:
```
# 3) Analysing Co-Applicant Income after Removing Outliers =====>>>>>
```

In [136]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='coapplicant_income',data=df)
plt.show()

# it is the EARLIER (df dataset) WITH PRESENCE OF OUTLIERS

plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='coapplicant_income',data=df_new, color='m')
plt.xlabel('\n Co-Applicants Income \n\n 3')
plt.show()

# outliers are succesfully removed.
# it is the Newer (df_new dataset)  OUTLIERS ARE REMOVED.
# So as we can see , outlier which is removed above by Z-SCORE METHOD is from 'Co
```

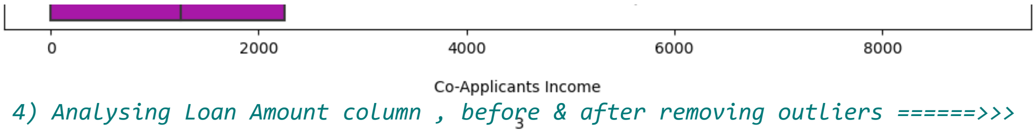




In [ ]:

In [137]:
```
# 4) Analysing Loan Amount column , before & after removing outliers ======>>>
```

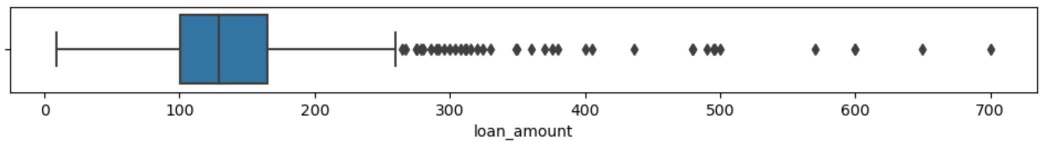
In [138]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='loan_amount',data=df)
plt.show()
```

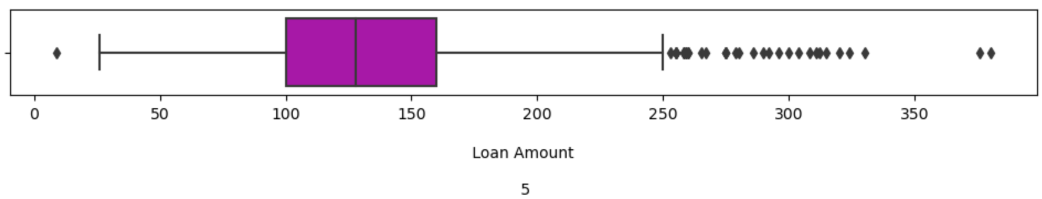


In [ ]:

In [137]:
```
# 4) Analysing Loan Amount column , before & after removing outliers ======>>>
```

In [138]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='loan_amount',data=df)
plt.show()

# it is the EARLIER (df dataset) WITH PRESENCE OF OUTLIERS

plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='loan_amount',data=df_new, color='m')
plt.xlabel('\n Loan Amount \n\n 5')
plt.show()

# outliers are succesfully removed.
# it is the Newer (df_new dataset)  OUTLIERS ARE REMOVED.
# So as we can see , outlier which is removed above by Z-SCORE METHOD is from 'LO
```



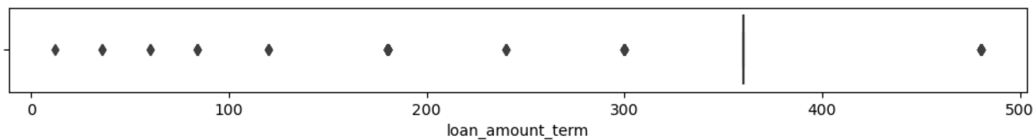


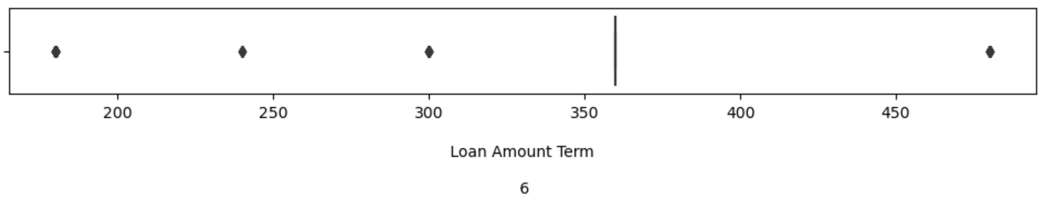
In [ ]:

In [139]:
```
# 6) Analysing Loan AMount Term column, before & after removing Outliers ========
```

In [140]:
```
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='loan_amount_term',data=df)
plt.show()

# it is the EARLIER (df dataset) WITH PRESENCE OF OUTLIERS

plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='loan_amount_term',data=df_new, color='m')
plt.xlabel('\n Loan Amount Term \n\n 6')
```

In [140]:
```python
plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='loan_amount_term',data=df)
plt.show()

# it is the EARLIER (df dataset) WITH PRESENCE OF OUTLIERS

plt.figure (figsize = (12,1), facecolor = "white")
sns.boxplot(x='loan_amount_term',data=df_new, color='m')
plt.xlabel('\n Loan Amount Term \n\n 6')
plt.show()

# outliers are succesfully removed.
# it is the Newer (df_new dataset)  OUTLIERS ARE REMOVED.
# So as we can see , outlier which is removed above by Z-SCORE METHOD is from 'Lo
```





In [ ]:

============== CHECKING & REMOVING OF OUTLIERS ARE COMPLETED HERE ==

In [ ]:

CHECKING SKEWNESS ==

In [141]:
```python
# the skewness shows the distribution of data, if the data is widely skewed that
#  ideal range of skewness is ( -0.5 to +0.5)
# We can't remove skewness from our Target Column
```

In [142]:
```python
df_new.skew()
# here in the below table we can see the skewness in the following columns:
# 'gender', dependents, education, self_employed, applicant_income, co-applicant
# credit_hitory
#  so we have to remove the skewness from the mentioned columns for better result
```

Out[142]:
```
gender               -1.622920
marital_status       -0.630211
dependents            1.052106
education             1.306588
self_employed         2.252848
applicant_income      2.148522
coapplicant_income    1.350517
loan_amount           1.113132
loan_amount_term     -2.098806
credit_history       -1.976043
property_area        -0.055332
loan_status          -0.822635
dtype: float64
```

In [143]:
```python
# so here we are removing the skewness by using 'cuberoot method'
```

In [144]:
```python
# here we cant remove skewness from the CATEGORICAL COLUMN.
# so we can remove skewness only from the non categorical columns
```

In [145]:
```python
df_new['applicant_income'] = np.cbrt(df_new['applicant_income'])
df_new['coapplicant_income'] = np.cbrt(df_new['coapplicant_income'])
df_new['loan_amount'] = np.cbrt(df_new['loan_amount'])
```

```
coapplicant_income    1.350517
loan_amount           1.113132
loan_amount_term     -2.098806
credit_history       -1.976043
property_area        -0.055332
loan_status          -0.822635
dtype: float64
```

In [143]:
```python
# so here we are removing the skewness by using 'cuberoot method'
```

In [144]:
```python
# here we cant remove skewness from the CATEGORICAL COLUMN.
# so we can remove skewness only from the non categorical columns
```

In [145]:
```python
df_new['applicant_income'] = np.cbrt(df_new['applicant_income'])
df_new['coapplicant_income'] = np.cbrt(df_new['coapplicant_income'])
df_new['loan_amount'] = np.cbrt(df_new['loan_amount'])
df_new['loan_amount_term'] = np.cbrt(df_new['loan_amount_term'])
```

In [146]:
```python
df_new.skew()
```

Out[146]:
```
gender               -1.622920
marital_status       -0.630211
dependents            1.052106
education             1.306588
self_employed         2.252848
applicant_income      0.845845
coapplicant_income   -0.038951
loan_amount           0.017152
loan_amount_term     -2.572549
credit_history       -1.976043
property_area        -0.055332
loan_status          -0.822635
dtype: float64
```

=============== REMOVED SKEWNESS, HOWEVER IT IS POSSIBLE ==================

In [ ]:

DIVIDING DATA INTO INDEPENDENT & TARGET VARIABLE ===

In [147]:
```python
df_new.columns
```

Out[147]:
```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

In [148]:
```python
x = df_new[['gender', 'marital_status', 'dependents', 'education', 'self_employe
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area']]
```

In [149]:
```python
y = df_new [['loan_status']]
```

In [150]:
```python
x.shape
```

Out[150]:
```
(577, 11)
```

In [151]:
```python
y.shape
```

Out[151]:
```
(577, 1)
```

In [152]:
```python
# here we need to apply scaling techniques on our dataset,by scaling techniques w
#  we can't apply SCALING TECHNIQUES on TARGET VARIABLE
#  to aplly scaling techinuque we need to import some libraries first.
```

In [ ]:

APPLYING SCALING TECHNIQUES

In [153]:
```python
from sklearn.preprocessing import StandardScaler
```

In [154]:
```python
st = StandardScaler()
```

In [151]:
```
y.shape
```

Out[151]:
```
(577, 1)
```

In [152]:
```
# here we need to apply scaling techniques on our dataset,by scaling techniques w
#  we can't apply SCALING TECHNIQUES on TARGET VARIABLE
#  to aplly scaling techinuque we need to import some libraries first.
```

In [ ]:

APPLYING SCALING TECHNIQUES

In [153]:
```
from sklearn.preprocessing import StandardScaler
```

In [154]:
```
st = StandardScaler()
```

In [155]:
```
x = st.fit_transform(x)
x
```

Out[155]:
```
array([[ 0.47713685, -1.36251079, -0.72331271, ...,  0.25126491,
         0.41851254,  1.22747207],
       [ 0.47713685,  0.73393914,  0.2823534 , ...,  0.25126491,
         0.41851254, -1.30652215],
       [ 0.47713685,  0.73393914, -0.72331271, ...,  0.25126491,
         0.41851254,  1.22747207],
       ...,
       [ 0.47713685,  0.73393914,  0.2823534 , ...,  0.25126491,
         0.41851254,  1.22747207],
       [ 0.47713685,  0.73393914,  1.28801951, ...,  0.25126491,
         0.41851254,  1.22747207],
       [-2.09583477, -1.36251079, -0.72331271, ...,  0.25126491,
        -2.38941464, -0.03952504]])
```

In [156]:
```
xf = pd.DataFrame(data=x)
print(xf)

# here we get our dataset (xf1) after applying SCALING TECHING (STANDARD SCALER)
```

```
            0         1         2         3         4         5         6  \
0    0.477137 -1.362511 -0.723313 -0.541961 -0.380580  0.622825 -1.093504
1    0.477137  0.733939  0.282353 -0.541961 -0.380580  0.157351  0.596681
2    0.477137  0.733939 -0.723313 -0.541961  2.627567 -0.566533 -1.093504
3    0.477137  0.733939 -0.723313  1.845150 -0.380580 -0.798730  0.868268
4    0.477137 -1.362511 -0.723313 -0.541961 -0.380580  0.673686 -1.093504
..        ...       ...       ...       ...       ...       ...       ...
572 -2.095835 -1.362511 -0.723313 -0.541961 -0.380580 -0.620151 -1.093504
573  0.477137  0.733939  2.293686 -0.541961 -0.380580 -0.040329 -1.093504
574  0.477137  0.733939  0.282353 -0.541961 -0.380580  1.298514 -0.177556
575  0.477137  0.733939  1.288020 -0.541961 -0.380580  1.161699 -1.093504
576 -2.095835 -1.362511 -0.723313 -0.541961  2.627567  0.157351 -1.093504

            7         8         9        10
0    0.318405  0.251265  0.418513  1.227472
1   -0.012836  0.251265  0.418513 -1.306522
2   -1.445145  0.251265  0.418513  1.227472
3   -0.166705  0.251265  0.418513  1.227472
4    0.224069  0.251265  0.418513  1.227472
..        ...       ...       ...       ...
572 -1.302297  0.251265  0.418513 -1.306522
573 -2.336409 -3.368603  0.418513 -1.306522
574  1.830577  0.251265  0.418513  1.227472
575  0.960923  0.251265  0.418513  1.227472
576  0.080100  0.251265 -2.389415 -0.039525

[577 rows x 11 columns]
```

In [157]:
```
xf.columns
```

Out[157]:
```
RangeIndex(start=0, stop=11, step=1)
```

In [158]:
```
column1 = ['gender', 'marital_status', 'dependents', 'education', 'self_employed'
        'applicant_income', 'coapplicant_income', 'loan_amount',
        'loan_amount_term', 'credit_history', 'property_area']
```

In [159]:
```
xf.columns = column1
```

In [160]:
```
xf.columns
```

[577 rows x 11 columns]

In [158]:
```
column1 = ['gender', 'marital_status', 'dependents', 'education', 'self_employed',
          'applicant_income', 'coapplicant_income', 'loan_amount',
          'loan_amount_term', 'credit_history', 'property_area']
```

In [157]:
```
xf.columns
```

Out[157]:
```
RangeIndex(start=0, stop=11, step=1)
```

In [159]:
```
xf.columns = column1
```

In [160]:
```
xf.columns
```

Out[160]:
```
Index(['gender', 'marital_status', 'dependents', 'education', 'self_employed',
       'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area'],
      dtype='object')
```

In [161]:
```
xf.head(5)
```

Out[161]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant_in
0	0.477137	-1.362511	-0.723313	-0.541961	-0.380580	0.622825	-1.0
1	0.477137	0.733939	0.282353	-0.541961	-0.380580	0.157351	0.5
2	0.477137	0.733939	-0.723313	-0.541961	2.627567	-0.566533	-1.0
3	0.477137	0.733939	-0.723313	1.845150	-0.380580	-0.798730	0.8
4	0.477137	-1.362511	-0.723313	-0.541961	-0.380580	0.673686	-1.0

In [162]:
```
yf=y
```

In [163]:
```
yf.head(2)
```

Out[163]:

	loan_status
0	1
1	0

In [164]:
```
xf.shape
```

Out[164]:
```
(577, 11)
```

In [165]:
```
yf.shape
```

Out[165]:
```
(577, 1)
```

In [166]:
```
yf.value_counts()
# here we can see that the data isnot balanced.
```

Out[166]:
```
loan_status
1              398
0              179
dtype: int64
```

In [ ]:

In [167]:
```
# We have to find the multicollinearity between the features and to remove it we
# we can not apply VIF on the TARGET COLUMN
# for apllyin VIF we have to import some libraries as follows
```

FINDING MULTICOLINEARITY

==

In [168]:
```
import statsmodels.api as sm
from scipy import stats
from statsmodels .stats.outliers_influence import variance_inflation_factor
```

FINDING MULTICOLINEARITY

==

In [167]:
```
# We have to find the multicollinearity between the features and to remove it we
# we can not apply VIF on the TARGET COLUMN
# for apllyin VIF we have to import some libraries as follows
```

In [168]:
```
import statsmodels.api as sm
from scipy import stats
from statsmodels .stats.outliers_influence import variance_inflation_factor
```

In [169]:
```
# here we are making "def function" for calculating VIF
def calc_vif(xf):
    vif = pd.DataFrame()
    vif["FETURES"] = xf.columns
    vif["VIF FACTOR"] = [variance_inflation_factor(xf.values,i) for i in range (x
    return (vif)
```

In [170]:
```
calc_vif(xf)
# here we can't find any Multicolinearity in our dataset
```

Out[170]:

	FETURES	VIF FACTOR
0	gender	1.219442
1	marital_status	1.401732
2	dependents	1.171122
3	education	1.071820
4	self_employed	1.060607
5	applicant_income	1.800793
6	coapplicant_income	1.599874
7	loan_amount	1.617452
8	loan_amount_term	1.058103
9	credit_history	1.010478
10	property_area	1.026979

In [ ]:

RESAMPLING TECHNIQUE (APPLYING SMOTE)

==

In [171]:
```
# Here we know that our Target Column is a Categorical column. which is having va
# so we have to chek the distribution of values are equal or not, offcourse i wou
#  'equally balanced distributed' for better results.

# SOLVING CLASS IMMBALANCE PROBLEM BY SMOTE TECHNIQUE.
```

In [172]:
```
yf.value_counts()
# here we can clearly see the imbalance in TARGET COULUMN
# for better result and performance of model, we have to first make it balanced.
```

Out[172]:
```
loan_status
1    398
0    179
dtype: int64
```

In [173]:
```
# To solve this prolem we need import SMOTE LIBRARY from the IMBLEARN.
```

In [174]:
```
from imblearn.over_sampling import SMOTE
```

In [175]:
```
smt = SMOTE()
```

In [176]:
```
trainx, trainy = smt.fit_resample(xf,yf)
```

In [177]:
```
trainy.value_counts()
# here as you can see below the immbalanceness is cleared now
```

Out[172]:
```
loan_status
1              398
0              179
dtype: int64
```

In [173]:
```
# To solve this prolem,we need import SMOTE LIBRARY from the IMBLEARN.
```

In [174]:
```
from imblearn.over_sampling import SMOTE
```

In [175]:
```
smt = SMOTE()
```

In [176]:
```
trainx, trainy = smt.fit_resample(xf,yf)
```

In [177]:
```
trainy.value_counts()
# here as you can see below the immbalancenes is cleared now.
# and now our Target Column Categories are BALANCED NOW.
```

Out[177]:
```
loan_status
0              398
1              398
dtype: int64
```

In [178]:
```
trainx.shape
```

Out[178]:
```
(796, 11)
```

In [179]:
```
trainy.shape
```

Out[179]:
```
(796, 1)
```

================ UPTO HERE EDA AND OTHER TECHINIQUES ARE COMPLETED ==================================

============================== NOW WE NEED TO APPLY ML MODELS ==

In [180]:
```
trainy.nunique()
```

Out[180]:
```
loan_status    2
dtype: int64
```

In [181]:
```
# here above as we know that our target column is CATEGORICAL and having 2 values
# therefore it as an CLASSIFICATION PROBLEM. and we need to apply classification
```

In [182]:
```
#  Applying TRAIN_TEST_SPLIT ====>>>
#  IMPORTING SOME IMPORTANT REQUIRED LIBRARIES
```

In [183]:
```
from sklearn.model_selection import train_test_split
```

In [184]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_repo
```

In [185]:
```
import sklearn
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,classification_repor
```

In [186]:
```
lg = LogisticRegression()
gnb = GaussianNB()
svc = SVC()
dtc = DecisionTreeClassifier()
knn = KNeighborsClassifier()
```

In [187]:
```
model = [lg,gnb,svc,dtc,knn]
```

===== FINDING BEST RANDOM STATE FOR LOGISTIC REGRESSION =======

In [188]:
```
#  FINDING BEST RANDOM STATE FOR LOGISTIC REGRESSION MODEL =====>>>>
```

In [194]:
```
maxaccu = 0
```

In [186]:
```
lg = LogisticRegression()
gnb = GaussianNB()
svc = SVC()
dtc = DecisionTreeClassifier()
knn = KNeighborsClassifier()
```

In [187]:
```
model = [lg,gnb,svc,dtc,knn]
```

====== FINDING BEST RANDOM STATE FOR LOGISTIC REGRESSION =======

In [188]:
```
#  FINDING BEST RANDOM STATE FOR LOGISTIC REGRESSION MODEL =====>>>>
```

In [194]:
```
maxaccu = 0
maxrs = 0

for i in range(1,200):
    x_train,x_test,y_train,y_test = train_test_split(trainx,trainy,test_size=0.20
    for m in model:
        m.fit(x_train,y_train)
        pred = m.predict(x_test)
        acc = accuracy_score(y_test,pred)

    if acc > maxaccu :
        maxaccu = acc
        maxrs = i

print ("Best accuracy is",maxaccu, "at random state", maxrs)
print ("with Best Fitted Model is :",m)
```

```
Best accuracy is 0.8125 at random state 26
with Best Fitted Model is : KNeighborsClassifier()
```

In [193]:
```
# here above we got our...
# ...Best fitted model = KNEIGHBORS CLASSIFIER
# ...with Accuracy of = 81 %
# ...& with BEST RANDOM STATE of = 26.
# we can also chek it INDIVIDUALLY.
```

In [ ]:

====== CHECKING MODEL INDIVIDUALLY =======

In [ ]:

In [195]:
```
x_train,x_test,y_train,y_test = train_test_split(trainx,trainy,test_size=0.20,rar
knn.fit(x_train,y_train)
knn.score(x_train,y_train)
knn_pred = knn.predict(x_train)

print('Accuracy Score of ', knn,'is:')
print (accuracy_score(y_train,knn_pred))

print(confusion_matrix(y_train,knn_pred))
```

In [195]:
```
x_train,x_test,y_train,y_test = train_test_split(trainx,trainy,test_size=0.20,rar
knn.fit(x_train,y_train)
knn.score(x_train,y_train)
knn_pred = knn.predict(x_train)

print('Accuracy Score of ', knn,'is:')
print (accuracy_score(y_train,knn_pred))

print(confusion_matrix(y_train,knn_pred))
print(classification_report(y_train,knn_pred))
print('\n')
```

```
Accuracy Score of  KNeighborsClassifier() is:
0.8333333333333334
[[267  51]
 [ 55 263]]
              precision    recall  f1-score   support

           0       0.83      0.84      0.83       318
           1       0.84      0.83      0.83       318

    accuracy                           0.83       636
   macro avg       0.83      0.83      0.83       636
weighted avg       0.83      0.83      0.83       636
```

In [197]:
```
#  Here above we are getting best results with =  KNeighbors Classifier
# ...with Best Accuracy Score of = 83 %
# ... with Random State of = 26

# Now we can use KNN MODEL as a FINAL MODEL
```

In [ ]:

========= APPLYING KNEIGHBORS CLASSIFIERS AS A FINAL MODEL ================

In [198]:
```
final_model = KNeighborsClassifier()
```

In [200]:
```
x_train,x_test,y_train,y_test = train_test_split(trainx,trainy,test_size=0.20,rar
final_model.fit(x_train,y_train)
final_model.score(x_train,y_train)
final_model_pred = final_model.predict(x_test)
print(accuracy_score(y_test,final_model_pred))
print(confusion_matrix(y_test,final_model_pred))
print(classification_report(y_test,final_model_pred))

# here KNEIGHBORS CLASSIFIER as FINAL MODEL with ACCURACY OF = 81 %
```

In [200]:
```
x_train,x_test,y_train,y_test = train_test_split(trainx,trainy,test_size=0.20,rar
final_model.fit(x_train,y_train)
final_model.score(x_train,y_train)
final_model_pred = final_model.predict(x_test)
print(accuracy_score(y_test,final_model_pred))
print(confusion_matrix(y_test,final_model_pred))
print(classification_report(y_test,final_model_pred))

# here KNEIGHBORS CLASSIFIER as FINAL MODEL with ACCURACY OF = 81 %
```

```
0.8125
[[66 14]
 [16 64]]
              precision    recall  f1-score   support

           0       0.80      0.82      0.81        80
           1       0.82      0.80      0.81        80

    accuracy                           0.81       160
   macro avg       0.81      0.81      0.81       160
weighted avg       0.81      0.81      0.81       160
```

In [ ]:

In [202]:
```
# Making 'def' function to CHECK / VERIFY samples :
```

In [203]:
```
xf.shape
```

Out[203]: (577, 11)

In [204]:
```
def pred_func(lp):
    lp= lp.reshape(1,11)
    loan_prediction = final_model.predict(lp)
    print(loan_prediction)

    if loan_prediction == 0:
        print("Loan Rejected")
    elif (loan_prediction == 1):
        print ("Loan Approved")
    else:
        print('Not Processed')
# making 'def' function to predict Loan Status .
```

In [205]:
```
pd.set_option('display.max_columns', None)
xf

# here by making 'display.amx_columns' we can see all the 11 columns of dataset.
```

Out[205]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant
0	0.477137	-1.362511	-0.723313	-0.541961	-0.380580	0.622825	-

In [205]:
```
pd.set_option('display.max_columns', None)
xf

# here by making 'display.amx_columns' we can see all the 11 columns of dataset.
```

Out[205]:

	gender	marital_status	dependents	education	self_employed	applicant_income	coapplicant
0	0.477137	-1.362511	-0.723313	-0.541961	-0.380580	0.622825	-
1	0.477137	0.733939	0.282353	-0.541961	-0.380580	0.157351	
2	0.477137	0.733939	-0.723313	-0.541961	2.627567	-0.566533	-
3	0.477137	0.733939	-0.723313	1.845150	-0.380580	-0.798730	
4	0.477137	-1.362511	-0.723313	-0.541961	-0.380580	0.673686	-
...	...	...	...	...	...	...	
572	-2.095835	-1.362511	-0.723313	-0.541961	-0.380580	-0.620151	-
573	0.477137	0.733939	2.293686	-0.541961	-0.380580	-0.040329	-
574	0.477137	0.733939	0.282353	-0.541961	-0.380580	1.298514	-
575	0.477137	0.733939	1.288020	-0.541961	-0.380580	1.161699	-
576	-2.095835	-1.362511	-0.723313	-0.541961	2.627567	0.157351	-

577 rows × 11 columns

In [206]:
```
yf
```

Out[206]:

	loan_status
0	1
1	0
2	1
3	1
4	1
...	...
609	1
610	1
611	1
612	1
613	0

577 rows × 1 columns

In [210]:
```
yf.shape
```

Out[210]: (577, 1)

In [207]:
```
# Test Sample 1 (taking data from row no. '0')
```

In [ ]:

In [208]:
```
lp= np.array([0.477137,-1.362511,-0.723313,-0.541961,-0.380580,0.622825,-1.093504
pred_func(lp)
```

In [209]:
```
# Test Sample 2 (taking data from row no '613')
```

```
# here below we can see that our model is predictiong [1] Yes Attrition, which as
```

In [211]:
```
lp= np.array([-2.095835,-1.362511,-0.723313,-0.541961,2.627567,0.157351,-1.093504
pred_func(lp)
```

```
[1]
Loan Approved
```

```
# here below we can see that our model is predictiong [1] Yes Attrition, which as
```

In [207]:
```
# Test Sample 1 (taking data from row no. '0')
```

In [ ]:

In [208]:
```
lp= np.array([0.477137,-1.362511,-0.723313,-0.541961,-0.380580,0.622825,-1.093504
pred_func(lp)
```

In [209]:
```
# Test Sample 2 (taking data from row no '613')
```

In [211]:
```
lp= np.array([-2.095835,-1.362511,-0.723313,-0.541961,2.627567,0.157351,-1.093504
pred_func(lp)
# here below we can see that our model is predictiong [1] Yes Attrition, which as
```

```
[1]
Loan Approved
```

```
# here below we can see that our model is predictiong [1] Yes Attrition, which as
```

```
[0]
Loan Rejected
```

In [ ]:

SAVING MODEL
===

In [213]:
```
import pickle
```

In [214]:
```
file_name = 'loan_prediction.pkl'
pickle.dump(final_model,open(file_name,'wb'))
```

In [ ]:

== FINISHED
==