```
!pip install pandas
!pip install numpy
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2023.4)
Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.10/dist-packages (from pandas) (1.23.5)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas) (1.16.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (1.23.5)
```

```
!pip install matplotlib
```

```
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.47.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.23.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
```

+ Code + Text

```
import pandas as pd
import numpy as np
```

```
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/2 DSPL/loan_data_set.csv')
```

```
df.dtypes # each column's datatype
```

```
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
```

```
# 1. Identify the most frequent values for all categorical features

# Select only categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns
print(categorical_columns)

# Iterate over each categorical column and find the most frequent value
for column in categorical_columns:
    most_frequent_value = df[column].mode()[0] # Get the most frequent value
    count = df[column].value_counts()[most_frequent_value]  # Count its occurrences
    print(f"Categorical Feature: {column}, Most frequent value: {most_frequent_value}, Count: {count}")
```

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'Property_Area', 'Loan_Status'],
      dtype='object')
Categorical Feature: Loan_ID, Most frequent value: LP001002, Count: 1
Categorical Feature: Gender, Most frequent value: Male, Count: 489
Categorical Feature: Married, Most frequent value: Yes, Count: 398
Categorical Feature: Dependents, Most frequent value: 0, Count: 345
Categorical Feature: Education, Most frequent value: Graduate, Count: 480
Categorical Feature: Self_Employed, Most frequent value: No, Count: 500
Categorical Feature: Property_Area, Most frequent value: Semiurban, Count: 233
Categorical Feature: Loan_Status, Most frequent value: Y, Count: 422
```

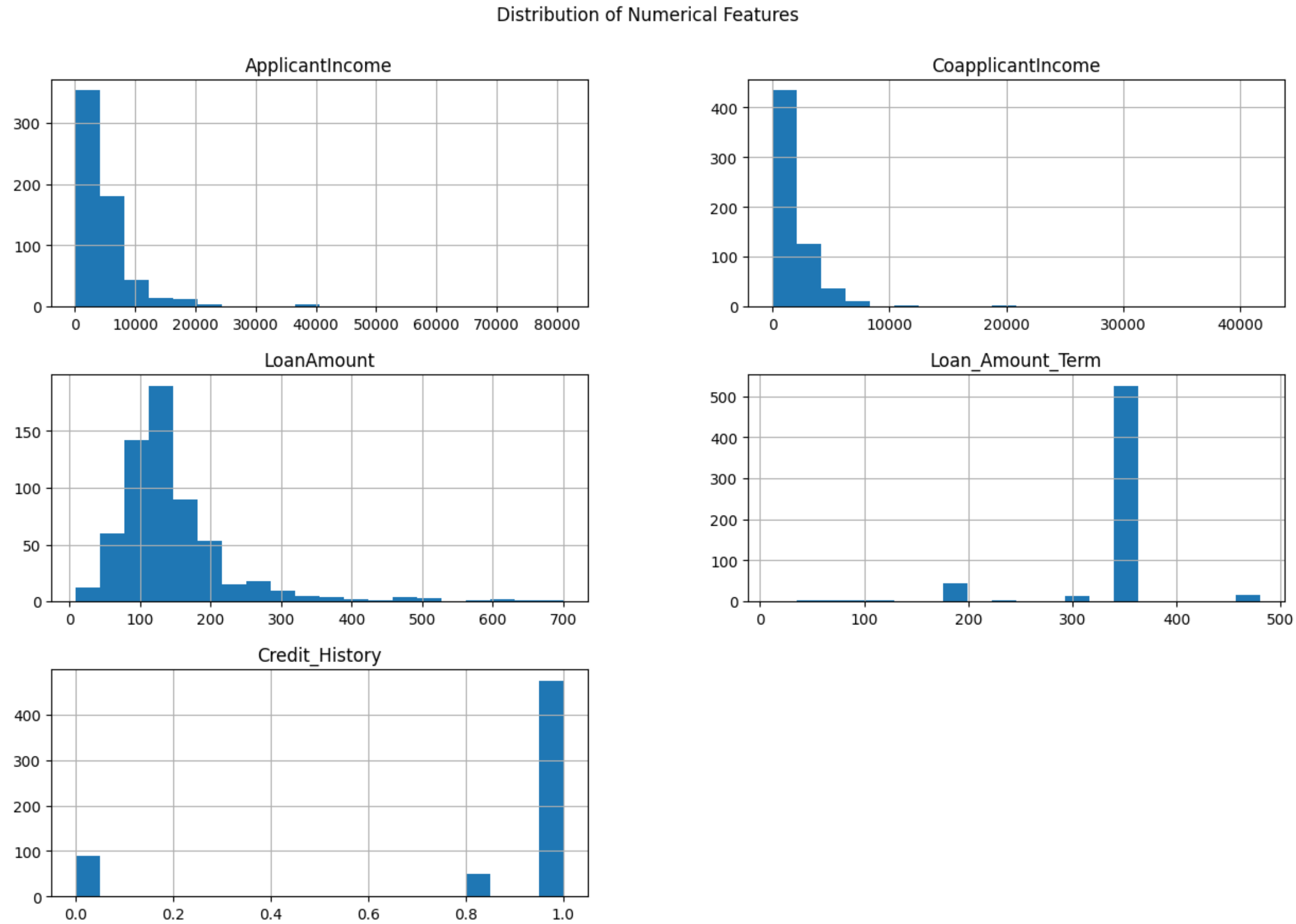
```
# Q2.  Give descriptive statistics of numerical features in the dataset. Comment about the distribution of data from it.
numerical_cols = df.select_dtypes(include=['number']).columns

numerical_stats=df[numerical_cols].describe()
numerical_stats
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

```
categorical_cols = df.select_dtypes(include=['object', 'category']).columns
categorical_stats=df[categorical_cols].describe(include='O')
categorical_stats
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
count	614	614	614	614	614	614	614	614
unique	614	2	2	4	2	2	3	2
top	LP001002	Male	Yes	0	Graduate	No	Semiurban	Y
freq	1	502	401	360	480	532	233	422

```
import matplotlib.pyplot as plt
import seaborn as sns

df.hist(bins=20, figsize=(15, 10))
plt.suptitle("Distribution of Numerical Features", y=0.95)
plt.show()
```



Inference from above data :

- Numerical Features:

ApplicantIncome and CoapplicantIncome: Both have a positive skew, indicating more applicants with lower incomes.

LoanAmount: The mean and median are close, implying a relatively symmetrical distribution.

Loan_Amount_Term: The mean and median are also close, suggesting a relatively even spread.

Credit_History: The mean is slightly lower than the median, but most values are concentrated around 1 (positive credit history).

- Categorical Features:

Gender: Most applicants are male (most frequent value).

Married: Most applicants are married.

Dependents: A significant portion of applicants have no dependents.

Education: Graduates are the most common education level among applicants.

Self_Employed: A majority of applicants are not self-employed.

Property_Area: Semiurban areas are the most common property location.

Loan_Status: Most loan applications have been approved (most frequent value is "Y").

```
# Q3. Replace the missing values in categorial features using appropriate techniques.

# Identify categorical columns objects
categorical_columns_with_missing = df.select_dtypes(include=['object']).columns

print("Number of missing values before mode imputation:")
print(df[categorical_columns_with_missing].isnull().sum())

# Replace missing values with the most frequent category (mode)
for column in categorical_columns_with_missing:
    most_frequent_category = df[column].mode().iloc[0]
    df[column].fillna(most_frequent_category, inplace=True)

# Verify that missing values have been replaced
print("Number of missing values after mode imputation:")
print(df[categorical_columns_with_missing].isnull().sum())
```

```
Number of missing values before mode imputation:
Loan_ID           0
Gender           13
Married           3
Dependents       15
Education         0
Self_Employed    32
Property_Area     0
Loan_Status       0
dtype: int64
Number of missing values after mode imputation:
Loan_ID          0
Gender           0
Married          0
Dependents       0
Education        0
Self_Employed    0
Property_Area    0
Loan_Status      0
dtype: int64
```

```
print(df.isnull().sum()) #numerical nulls are still present
```

```
Loan_ID               0
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

```
!pip install scikit-learn category_encoders
from sklearn.preprocessing import LabelEncoder
from category_encoders import OrdinalEncoder, TargetEncoder
```

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.2.2)
Requirement already satisfied: category_encoders in /usr/local/lib/python3.10/dist-packages (2.6.3)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.11.4)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.2.0)
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.14.1)
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.5.3)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.5.6)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_enco
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_encoders) (2023
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.1->category_encoders) (1.16.0)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.9.0->category_encoder
```

```
# Q4. Demonstrate various encoding techniques for categorical features.
categorical_columns = df.select_dtypes(include=['object']).columns

# a. Label Encoding
label_encoded_df = df.copy()
label_encoder = LabelEncoder()
for column in categorical_columns:
    label_encoded_df[column] = label_encoder.fit_transform(df[column])

print("Label Encoding:")
print(label_encoded_df)
```

```
Label Encoding:
     Loan_ID  Gender  Married  Dependents  Education  Self_Employed  \
0          0       1        0           0          0              0
1          1       1        1           1          0              0
2          2       1        1           0          0              1
3          3       1        1           0          1              0
4          4       1        0           0          0              0
..       ...     ...      ...         ...        ...            ...
609      609       0        0           0          0              0
610      610       1        1           3          0              0
611      611       1        1           1          0              0
612      612       1        1           2          0              0
613      613       0        0           0          0              1

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0         NaN             360.0
1               4583             1508.0       128.0             360.0
2               3000                0.0        66.0             360.0
3               2583             2358.0       120.0             360.0
4               6000                0.0       141.0             360.0
..               ...                ...         ...               ...
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History  Property_Area  Loan_Status
0               1.0              2            1
1               1.0              0            0
2               1.0              2            1
3               1.0              2            1
4               1.0              2            1
..              ...            ...          ...
609             1.0              0            1
610             1.0              0            1
611             1.0              2            1
612             1.0              2            1
613             0.0              1            0

[614 rows x 13 columns]
```

```
# b. One-Hot Encoding
one_hot_encoded_df = pd.get_dummies(df, columns=categorical_columns)

print("One-Hot Encoding:")
print(one_hot_encoded_df)
```

```
610             1.0                  0                  0                  0
611             1.0                  0                  0                  0
612             1.0                  0                  0                  0
```

```
609                 1                      0                1
610                 1                      0                1
611                 1                      0                1
612                 1                      0                1
613                 1                      0                0

     Self_Employed_Yes  Property_Area_Rural  Property_Area_Semiurban  \
0                    0                    0                        0
1                    0                    1                        0
2                    1                    0                        0
3                    0                    0                        0
4                    0                    0                        0
..                 ...                  ...                      ...
609                  0                    1                        0
610                  0                    1                        0
611                  0                    0                        0
612                  0                    0                        0
613                  1                    0                        1

     Property_Area_Urban  Loan_Status_N  Loan_Status_Y
0                      1              0              1
1                      0              1              0
2                      1              0              1
3                      1              0              1
4                      1              0              1
..                   ...            ...            ...
609                    0              0              1
610                    0              0              1
611                    1              0              1
612                    1              0              1
613                    0              1              0

[614 rows x 636 columns]
```

```
# c. Ordinal Encoding
ordinal_encoder = OrdinalEncoder()
ordinal_encoded_df = df.copy()
ordinal_encoded_df[categorical_columns] = ordinal_encoder.fit_transform(df[categorical_columns])

print("Ordinal Encoding:")
print(ordinal_encoded_df)
```

```
Ordinal Encoding:
     Loan_ID  Gender  Married  Dependents  Education  Self_Employed  \
0          1       1        1           1          1              1
1          2       1        2           2          1              1
2          3       1        2           1          1              2
3          4       1        2           1          2              1
4          5       1        1           1          1              1
..       ...     ...      ...         ...        ...            ...
609      610       2        1           1          1              1
610      611       1        2           4          1              1
611      612       1        2           2          1              1
612      613       1        2           3          1              1
613      614       2        1           1          1              2

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0         NaN             360.0
1               4583             1508.0       128.0             360.0
2               3000                0.0        66.0             360.0
3               2583             2358.0       120.0             360.0
4               6000                0.0       141.0             360.0
..               ...                ...         ...               ...
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History  Property_Area  Loan_Status
0               1.0              1            1
1               1.0              2            2
2               1.0              1            1
3               1.0              1            1
4               1.0              1            1
..              ...            ...          ...
609             1.0              2            1
610             1.0              2            1
611             1.0              1            1
612             1.0              1            1
613             0.0              3            2

[614 rows x 13 columns]
```

```
# Q5. for numerical features, replace missing values using
# a. using simple imputer (mean, median)
from sklearn.impute import SimpleImputer

# Select numerical columns
numerical_columns = df.select_dtypes(include=np.number).columns

# Replace missing values with mean
imputer_mean = SimpleImputer(strategy='mean')
df_mean_imputed = pd.DataFrame(imputer_mean.fit_transform(df[numerical_columns]), columns=numerical_columns)


# Replace missing values with median
imputer_median = SimpleImputer(strategy='median')
df_median_imputed = pd.DataFrame(imputer_median.fit_transform(df[numerical_columns]), columns=numerical_columns)

# Print the resulting DataFrames
print("Simple Imputer with Mean:")
print(df_mean_imputed.head())
print(df_mean_imputed.isnull().sum())

print("\nSimple Imputer with Median:")
print(df_median_imputed.head())
print(df_median_imputed.isnull().sum())
```

```
Simple Imputer with Mean:
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0           5849.0                0.0  146.412162             360.0
1           4583.0             1508.0  128.000000             360.0
2           3000.0                0.0   66.000000             360.0
3           2583.0             2358.0  120.000000             360.0
4           6000.0                0.0  141.000000             360.0

   Credit_History
0             1.0
1             1.0
2             1.0
3             1.0
4             1.0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
dtype: int64

Simple Imputer with Median:
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0           5849.0                0.0  146.412162             360.0
1           4583.0             1508.0  128.000000             360.0
2           3000.0                0.0   66.000000             360.0
3           2583.0             2358.0  120.000000             360.0
4           6000.0                0.0  141.000000             360.0

   Credit_History
0             1.0
1             1.0
2             1.0
3             1.0
4             1.0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
dtype: int64
```

```
# b. using random sample imputation
# Define function for random sample imputation
def random_sample_imputation(data, column):
    random_sample = data[column].dropna().sample(data[column].isnull().sum(), random_state=0)
    random_sample.index = data[data[column].isnull()].index
    data.loc[data[column].isnull(), column] = random_sample

# Perform random sample imputation for each numerical column
df_random_sample_imputed = df[numerical_columns].copy()
for column in numerical_columns:
    random_sample_imputation(df_random_sample_imputed, column)

print("Random Sample Imputation:")
print(df_random_sample_imputed.head())
```

```
Random Sample Imputation:
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0           5849.0                0.0  146.412162             360.0
1           4583.0             1508.0  128.000000             360.0
2           3000.0                0.0   66.000000             360.0
3           2583.0             2358.0  120.000000             360.0
4           6000.0                0.0  141.000000             360.0

   Credit_History
0             1.0
1             1.0
2             1.0
3             1.0
4             1.0
```

```
df[numerical_columns] = df_mean_imputed  # Change to df_median_imputed or df_random_sample_imputed if needed

print(df.isnull().sum()) #numerical nulls are still present
```

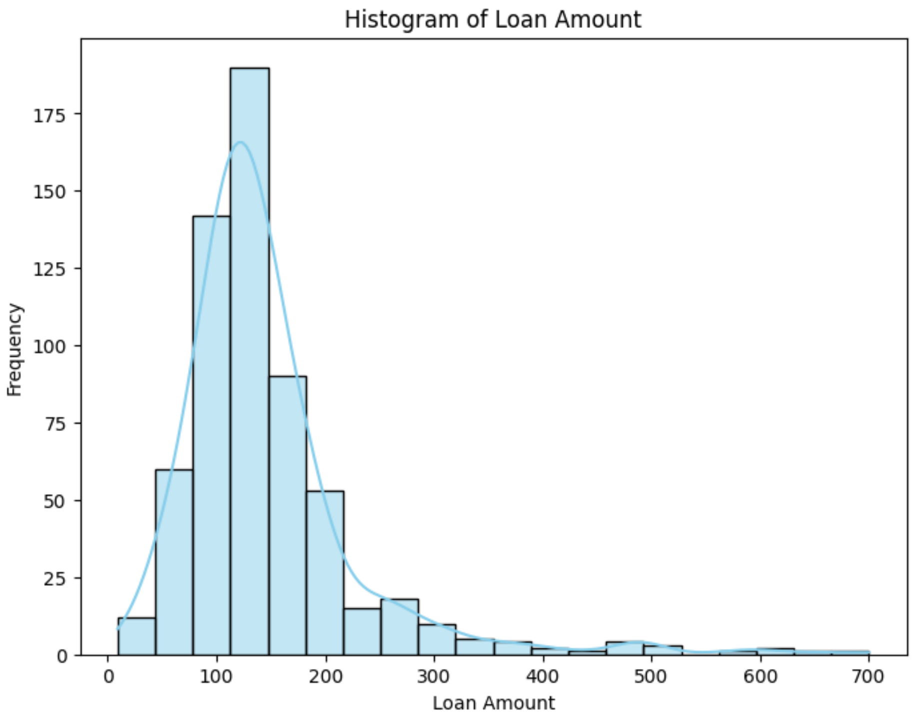
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

```
# Q6. Give descriptive statistics of numerical features in the dataset after handling missing values. Comment about the distribution of

numerical_cols = df.select_dtypes(include=['number']).columns
numerical_stats=df[numerical_cols].describe()
numerical_stats
```

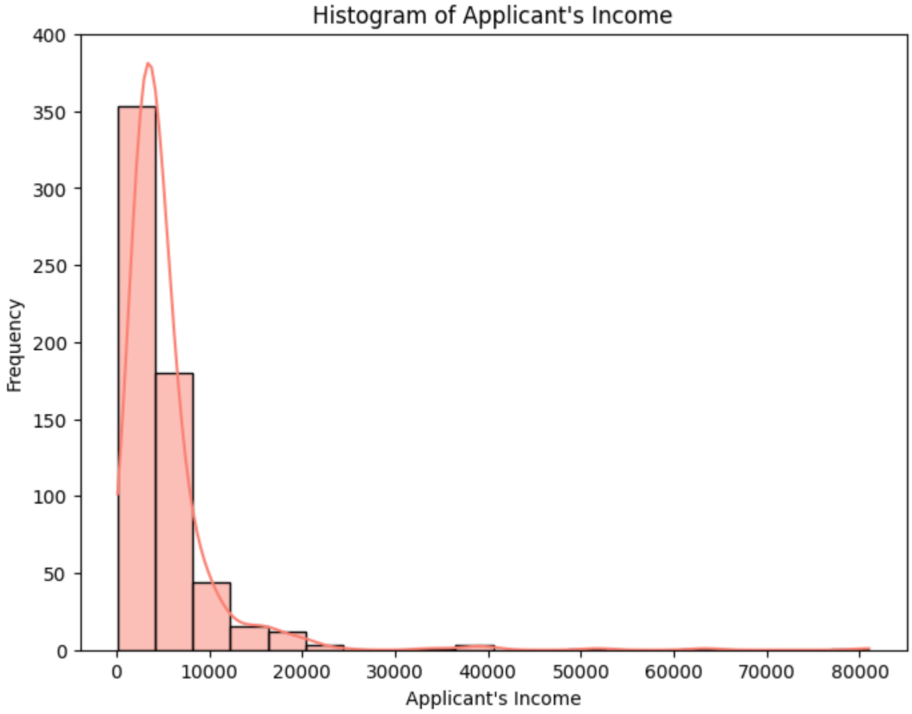
	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	146.412162	342.000000	0.842199
std	6109.041673	2926.248369	84.037468	64.372489	0.349681
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.250000	360.000000	1.000000
50%	3812.500000	1188.500000	129.000000	360.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

```
'''
7. Plot following graphs. Label X and Y axis, give appropriate title to the graph.
 a. Plot histogram for Loan Amount and mention ur observations
 b. Plot histogram for Loan Amount and mention ur observations
 c. plot bar graph showing income for graduate and non-graduate applicant and mention ur
observations
 d. Plot the boxplot for Loan amount. Give the five value summary from it.
 e. Comment on the correlation between Applicant's income and Loan amount using
appropriate graph.
 f. Give descriptive statistics of numerical features in the dataset. Comment about the
distribution of data from it.
'''
```

```
#  a. Plot histogram for Loan Amount and mention ur observations

plt.figure(figsize=(8, 6))
sns.histplot(df['LoanAmount'], bins=20, kde=True, color='skyblue')
plt.title('Histogram of Loan Amount')
plt.xlabel('Loan Amount')
plt.ylabel('Frequency')
plt.show()

# Observations:
# - The histogram shows the distribution of loan amounts in the dataset.
# - The distribution appears to be slightly right-skewed, with a peak around the lower loan amounts.
# - There are some outliers on the higher end of the loan amount, which contribute to the right-skewness.
```

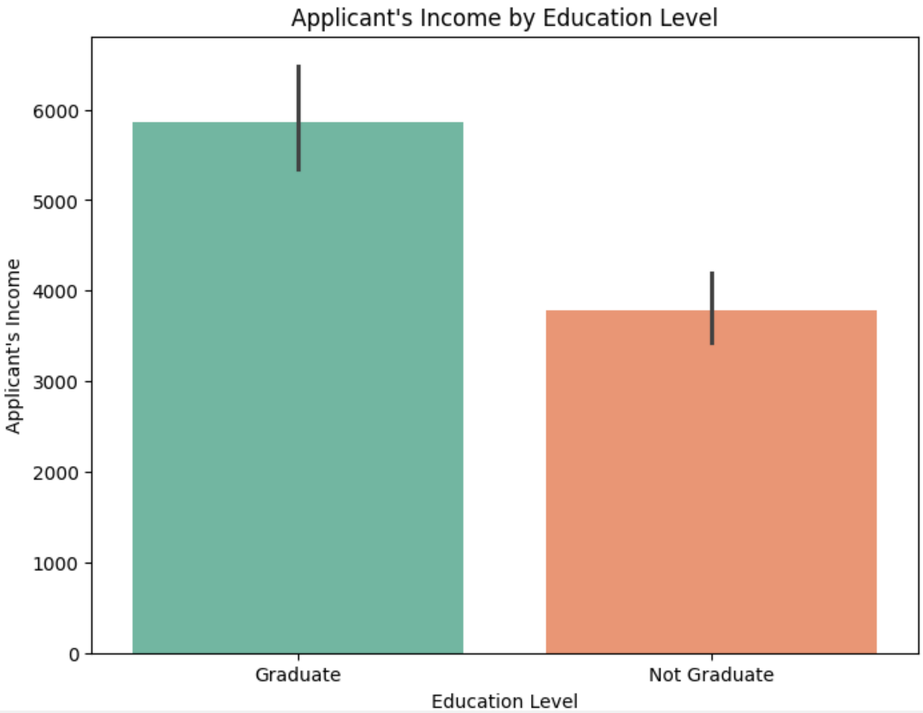



```
#  b. Plot histogram for Loan Amount and mention ur observations

plt.figure(figsize=(8, 6))
sns.histplot(df['ApplicantIncome'], bins=20, kde=True, color='salmon')
plt.title("Histogram of Applicant's Income")
plt.xlabel("Applicant's Income")
plt.ylabel('Frequency')
plt.show()

# Observations:
# - The histogram displays the distribution of applicant incomes in the dataset.
# - The distribution is heavily right-skewed, with a large number of applicants having relatively low incomes.
# - There are some outliers on the higher end of the income scale.
```

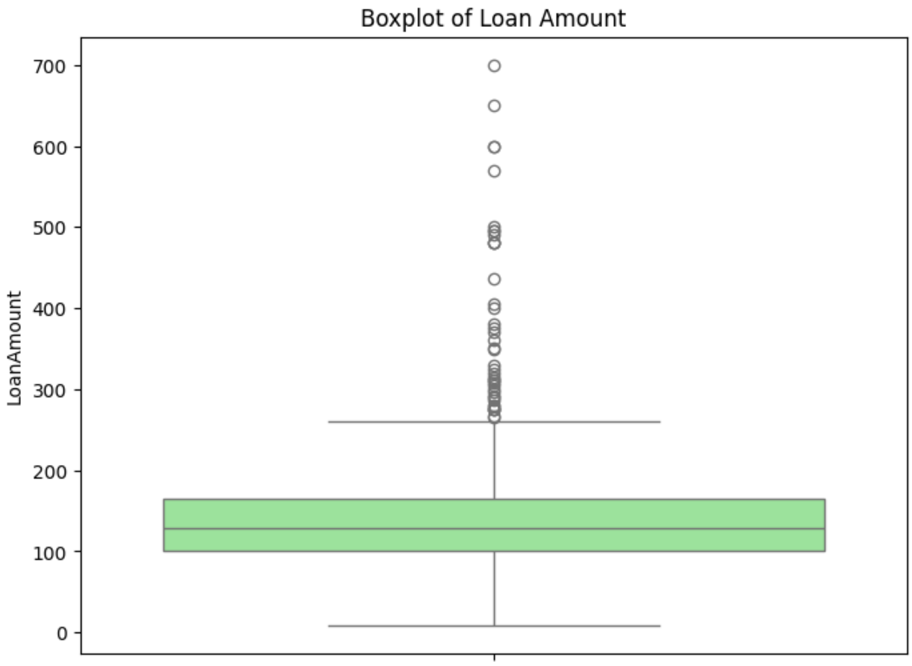



```
#  c. plot bar graph showing income for graduate and non-graduate applicant and mention ur observations

plt.figure(figsize=(8, 6))
sns.barplot(x='Education', y='ApplicantIncome', data=df, palette='Set2')
plt.title("Applicant's Income by Education Level")
plt.xlabel('Education Level')
plt.ylabel("Applicant's Income")
plt.show()

# Observations:
# - The bar graph compares the incomes of graduate and non-graduate applicants.
# - On average, graduate applicants tend to have higher incomes compared to non-graduate applicants.
```

```
<ipython-input-66-0e8e05d87e27>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.barplot(x='Education', y='ApplicantIncome', data=df, palette='Set2')
```



```
#  d. Plot the boxplot for Loan amount. Give the five value summary from it.

plt.figure(figsize=(8, 6))
sns.boxplot(df['LoanAmount'], color='lightgreen')
plt.title('Boxplot of Loan Amount')
plt.xlabel('Loan Amount')
plt.show()

# Observations:
# - The boxplot provides a visual summary of the distribution of loan amounts.
# - The five-number summary (minimum, Q1, median, Q3, maximum) can be observed from the boxplot.
```




```
#  e. Comment on the correlation between Applicant's income and Loan amount using appropriate graph.

plt.figure(figsize=(8, 6))
```