EDA on Loan Data

Import Libraries and load data

In [1]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import zscore
import warnings
warnings.filterwarnings('ignore')
```

Loading Data in Pandas DataFrame

In [2]:
```
data = pd.read_csv('LoanData.csv')
```

Printing rows of the Data

In [3]:
```
# Print the first 5 rows
display(data.head())
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coa
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

In [4]:
```
# Print the last 5 rows
display(data.tail())
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	C
609	LP002978	Female	No	0	Graduate	No	2900	
610	LP002979	Male	Yes	3+	Graduate	No	4106	
611	LP002983	Male	Yes	1	Graduate	No	8072	
612	LP002984	Male	Yes	2	Graduate	No	7583	
613	LP002990	Female	No	0	Graduate	Yes	4583	

In [5]:
```
# Print a specific row by index
display(data.iloc[22])
```

```
Loan_ID                LP001047
Gender                     Male
Married                     Yes
Dependents                    0
Education          Not Graduate
Self_Employed                No
ApplicantIncome            2600
CoapplicantIncome        1911.0
LoanAmount                116.0
Loan_Amount_Term          360.0
Credit_History              0.0
Property_Area          Semiurban
Loan_Status                    N
Name: 22, dtype: object
```

In [6]:
```
display(data)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	C
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	
...	...	...	...	...	...	...	...	
609	LP002978	Female	No	0	Graduate	No	2900	
610	LP002979	Male	Yes	3+	Graduate	No	4106	
611	LP002983	Male	Yes	1	Graduate	No	8072	
612	LP002984	Male	Yes	2	Graduate	No	7583	
613	LP002990	Female	No	0	Graduate	Yes	4583	

614 rows × 13 columns

Printing the column names of the DataFrame

In [7]:
```
print(list(data.columns))
print("\n")
list_val = list(data.columns)
for li in list_val:
    print(li)
```

```
['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education', 'Self_Employe
d', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Ter
m', 'Credit_History', 'Property_Area', 'Loan_Status']


Loan_ID
Gender
Married
Dependents
Education
Self_Employed
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Property_Area
Loan_Status
```

Summary of Data Frame

In [8]:
```
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
None
```

Descriptive Statistical Measures of a DataFrame

In [9]:
```
data.describe()
```

Out[9]:

	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

Missing Data Handing

In [10]:
```
tot_records = data.shape
print("Data Shape: ",tot_records)
print("\n")
tot_null=data.isnull().sum()
print("---Total Null Value---")
print(tot_null)
print("\n")
tot_not_null=data.notnull().sum()
print("---Total no Null Value---")
print(tot_not_null)
```

```
Data Shape:  (614, 13)


---Total Null Value---
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64


---Total no Null Value---
Loan_ID              614
Gender               601
Married              611
Dependents           599
Education            614
Self_Employed        582
ApplicantIncome      614
CoapplicantIncome    614
LoanAmount           592
Loan_Amount_Term     600
Credit_History       564
Property_Area        614
Loan_Status          614
dtype: int64
```

Drop null

In [11]:
```
data_n = data.copy()
data_n = data_n.dropna()
tot_null=data_n.isnull().sum()
print("---Total Null Value---")
print(tot_null)
d=data.shape
dn = data_n.shape
print("Shape before: ",d)
print("Shape after: ",dn)
```

```
---Total Null Value---
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
Shape before:  (614, 13)
Shape after:  (480, 13)
```

Handling with Mean, Meadian & Mode

In [12]:
```
data_copy = data.copy()
# Handling missing values in categorical columns using mode
categorical_columns = ['Gender', 'Married', 'Dependents', 'Self_Employed']
for col in categorical_columns:
    data_copy[col].fillna(data_copy[col].mode()[0], inplace=True)

# Handling numerical columns with mean
mean_columns = ['Loan_Amount_Term']  # Example: Loan_Amount_Term has no ext
for col in mean_columns:
    data_copy[col].fillna(data_copy[col].mean(), inplace=True)

# Handling numerical columns with median
median_columns = ['LoanAmount', 'Credit_History']  # Example: Columns with
for col in median_columns:
    data_copy[col].fillna(data_copy[col].median(), inplace=True)

# Check if all missing values are handled
print("Missing values after imputation:")
print(data_copy.isnull().sum())
d=data.shape
dn = data_copy.shape
print("Shape before: ",d)
print("Shape after: ",dn)
data_handled = data_copy.copy()
```

```
Missing values after imputation:
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
Shape before:  (614, 13)
Shape after:  (614, 13)
```

Visualizing Dataframe

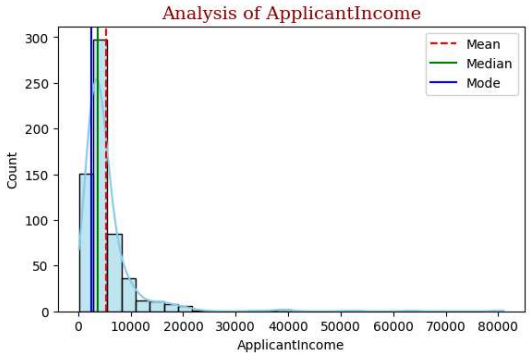
Mean, Median, Mode plotting

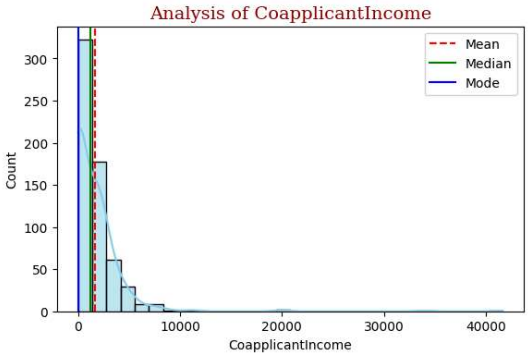
In [13]:
```
import matplotlib.pyplot as plt
import seaborn as sns

def generate_distribution_plot(raw_data, continuous_features):
    # Create a copy of the dataset containing only continuous features
    data = raw_data[continuous_features].copy()

    # Create subplots
    num_features = len(data.columns)
    rows = (num_features + 1) // 2  # Calculate rows needed for subplots
    fig, axes = plt.subplots(nrows=rows, ncols=2, figsize=(15, rows * 5))
    fig.subplots_adjust(hspace=0.5, wspace=0.3)
    axes = axes.flatten()  # Flatten axes for easy iteration

    # Font settings
    font = {
        'family': 'serif',
        'color': 'darkred',
        'weight': 'normal',
        'size': 14,
    }

    # Generate distribution plots
    for i, feature in enumerate(data.columns):
        ax = axes[i]
        feature_mean = data[feature].mean()
        feature_median = data[feature].median()
        feature_mode = data[feature].mode().values[0]

        sns.histplot(data[feature], kde=True, ax=ax, color='skyblue', bins=
        ax.set_title(f'Analysis of {feature}', fontdict=font)
        ax.axvline(feature_mean, color='r', linestyle='--', label="Mean")
        ax.axvline(feature_median, color='g', linestyle='-', label="Median"
        ax.axvline(feature_mode, color='b', linestyle='-', label="Mode")
        ax.legend()

    # Remove any unused subplots
    for j in range(len(data.columns), len(axes)):
        fig.delaxes(axes[j])

    plt.show()
```

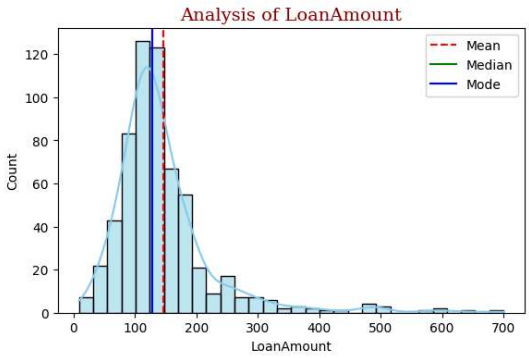
In [14]:
```
# Separate numerical and categorical features
numerical_features = [feature for feature in data.columns if data[feature].
categorical_features = [feature for feature in data.columns if feature not

# Discrete numerical features: Numeric but with fewer unique values (<25 is
discrete_features = [feature for feature in numerical_features if len(data[

# Continuous numerical features: Remaining numerical features
continuous_features = [feature for feature in numerical_features if feature

# Binary categorical features: Categorical features with 2 or 3 unique valu
binary_categorical_features = [feature for feature in categorical_features

# Print the categorized features
print("Numerical Features:", numerical_features)
print("Discrete Features:", discrete_features)
print("Continuous Features:", continuous_features)
print("Categorical Features:", categorical_features)
print("Binary Categorical Features:", binary_categorical_features)
```

```
Numerical Features: ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
'Loan_Amount_Term', 'Credit_History']
Discrete Features: ['Loan_Amount_Term', 'Credit_History']
Continuous Features: ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmoun
t']
Categorical Features: ['Loan_ID', 'Gender', 'Married', 'Dependents', 'Educ
ation', 'Self_Employed', 'Property_Area', 'Loan_Status']
Binary Categorical Features: ['Gender', 'Married', 'Education', 'Self_Empl
oyed', 'Property_Area', 'Loan_Status']
```

In [15]:
```
generate_distribution_plot(data_handled, continuous_features)
```







Encoding categorical data to numeric data

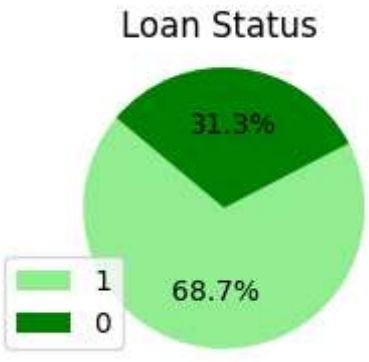
In [16]:
```
# Convert categorical features to continuous features with Label Encoding
encod_data = data_handled.copy()
from sklearn.preprocessing import LabelEncoder
lencoders = {}
for col in encod_data.select_dtypes(include=['object']).columns:
    lencoders[col] = LabelEncoder()
    encod_data[col] = lencoders[col].fit_transform(encod_data[col])
encod_data.dtypes
```

Out[16]:
```
Loan_ID               int32
Gender                int32
Married               int32
Dependents            int32
Education             int32
Self_Employed         int32
ApplicantIncome       int64
CoapplicantIncome   float64
LoanAmount          float64
Loan_Amount_Term    float64
Credit_History      float64
Property_Area         int32
Loan_Status           int32
dtype: object
```

Loan Status distribution

In [17]:
```
pic_data = encod_data.copy()
pic_data['Loan_Status'].replace({'N': 0, 'Y': 1},inplace = True)
```

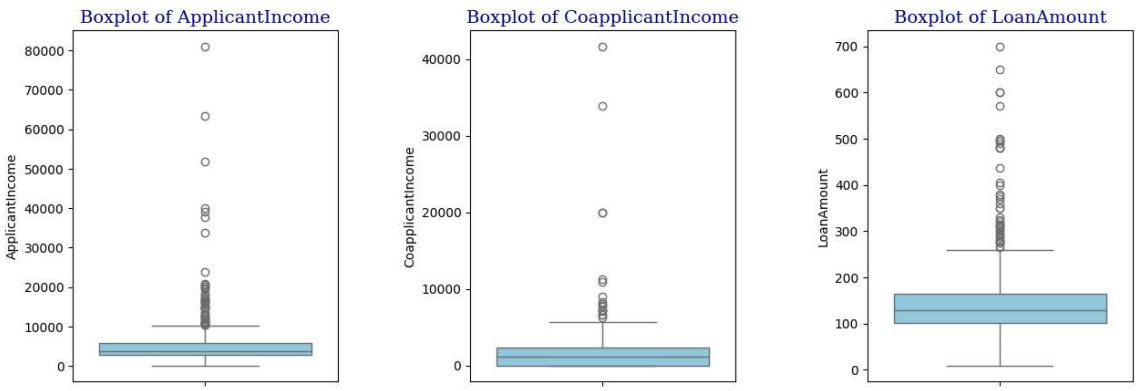
In [18]:
```
value_counts = pic_data.Loan_Status.value_counts(normalize=True)
plt.figure(figsize=(3, 2))
plt.pie(value_counts,  autopct='%1.1f%%', colors=['lightgreen', 'green'], s
plt.title('Loan Status ')
plt.legend( value_counts.index, loc="best")
plt.axis('equal')
plt.show()
```



Box plot and outlier removal

In [19]:
```
import matplotlib.pyplot as plt
import seaborn as sns

def plot_boxplot(df, continuous_features):
    # Create a copy of the dataset containing only continuous features
    data = df[continuous_features].copy()

    # Number of features and subplots configuration
    num_features = len(data.columns)
    cols = 3  # Number of columns for subplots
    rows = (num_features + cols - 1) // cols  # Calculate rows dynamically

    # Create subplots
    fig, axes = plt.subplots(nrows=rows, ncols=cols, figsize=(cols * 5, row
    fig.subplots_adjust(hspace=0.5, wspace=0.5)
    axes = axes.flatten()  # Flatten the axes array for easier iteration

    # Font settings for titles
    font = {
        'family': 'serif',
        'color': 'darkblue',
        'weight': 'normal',
        'size': 14,
    }

    # Generate boxplots
    for i, feature in enumerate(data.columns):
        sns.boxplot(data=data, y=feature, ax=axes[i], color='skyblue')
        axes[i].set_title(f'Boxplot of {feature}', fontdict=font)
        axes[i].set_xlabel('')

    # Remove unused subplot axes
    for j in range(num_features, len(axes)):
        fig.delaxes(axes[j])

    plt.show()
```

In [20]:
```
#Box plot before outlier removal
plot_boxplot(encod_data, continuous_features)
```



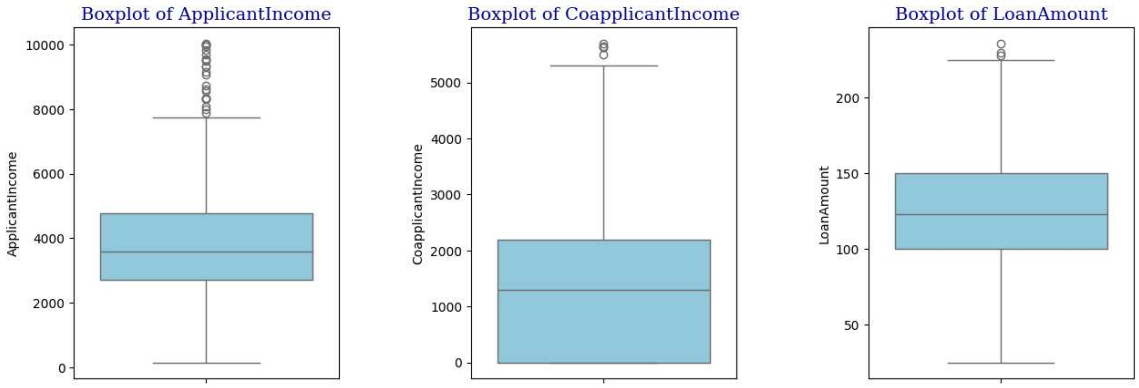
In [21]:
```
def remove_outliers(df,outliers_features):
    # create copy of dataframe
    data = df.copy()
    for feature in data[outliers_features].columns:
        Q3 = data[feature].quantile(0.75)
        Q1 = data[feature].quantile(0.25)
        IQR = Q3 - Q1
        lower_limit = round(Q1 - 1.5 * IQR)
        upper_limit = round(Q3 + 1.5 * IQR)
        data = data[(data[feature] <= upper_limit) & (data[feature] >= lowe
    return data
```

In [22]:
```
#outlier removal using IQR technique
data_iqr = remove_outliers(encod_data,continuous_features)
data_afteroutlier = data_iqr.copy()
print(data.shape)
data_afteroutlier.shape
```

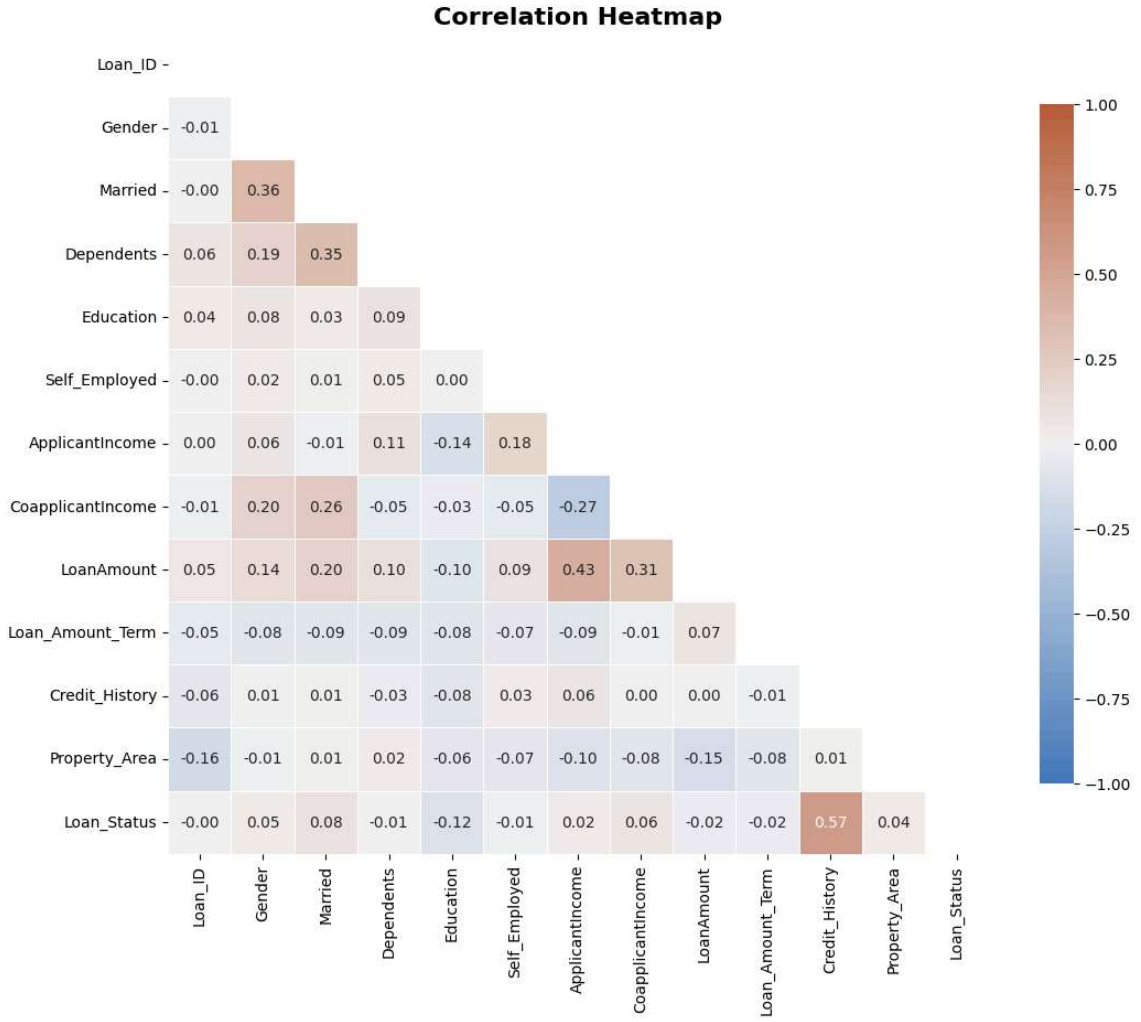
```
(614, 13)
```

Out[22]:
```
(520, 13)
```

In [23]:
```
#Box plot after outlier removal
plot_boxplot(data_afteroutlier, continuous_features)
```

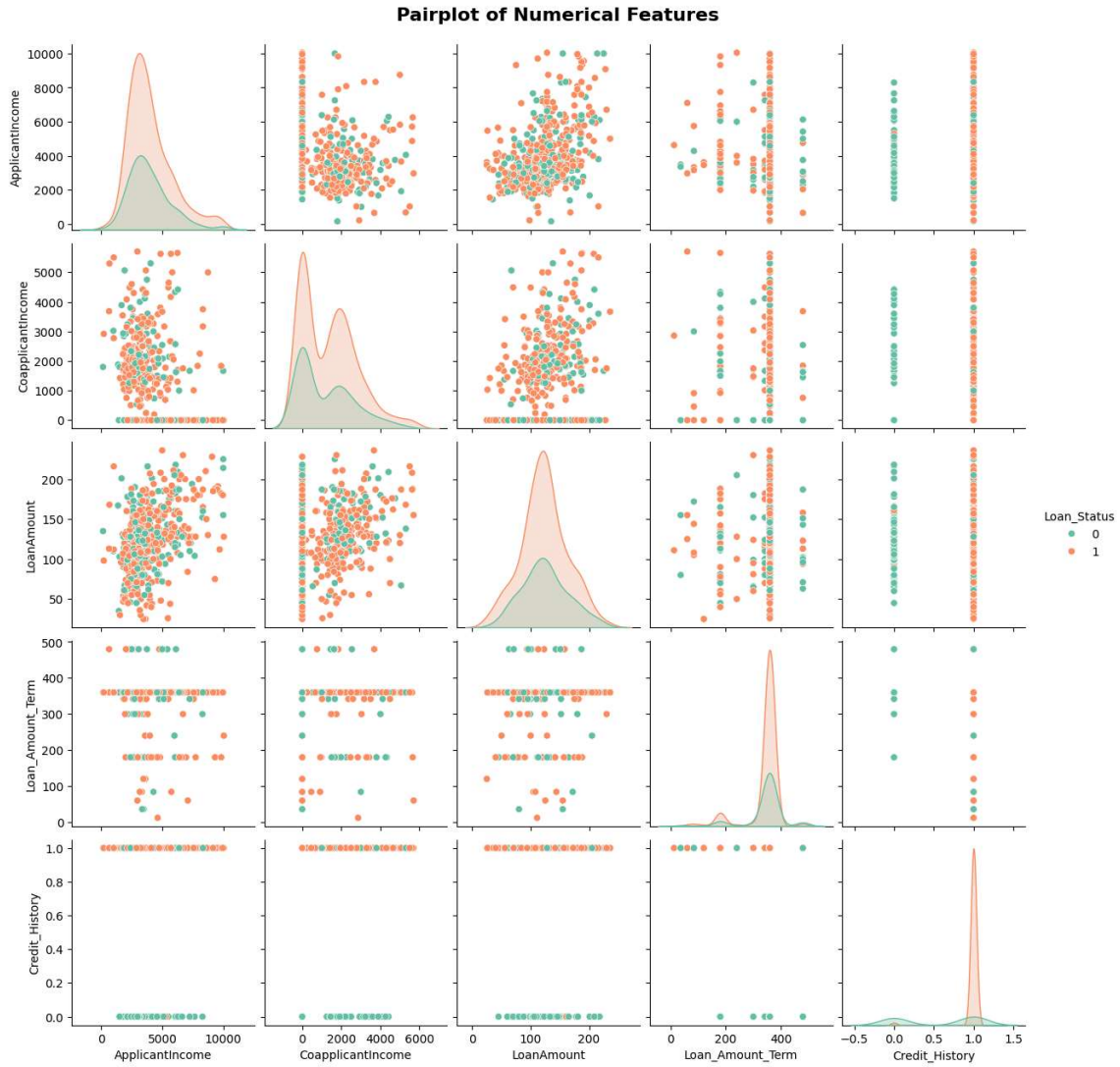


In [24]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

def plot_correlation_heatmap(df):

    corr = df.corr()
    mask = np.triu(np.ones_like(corr, dtype=bool))
    f, ax = plt.subplots(figsize=(12, 10))  # Adjust figure size for readab
    cmap = sns.diverging_palette(250, 25, as_cmap=True)

    sns.heatmap(
        corr, mask=mask, cmap=cmap, vmax=1, vmin=-1, center=0, square=True,
        annot=True, fmt=".2f", linewidths=0.5, cbar_kws={"shrink": 0.8}
    )

    ax.set_title("Correlation Heatmap", fontsize=16, weight='bold')
    plt.show()

plot_correlation_heatmap(data_afteroutlier)
```



Pair plot to visualize data correlation

In [25]:
```
import seaborn as sns
import matplotlib.pyplot as plt

def plot_pairplot(df, hue=None):
    numerical_columns = [col for col in df.columns if df[col].dtypes in ['i

    sns.pairplot(data=df, vars=numerical_columns, hue=hue, diag_kind="kde",
    plt.suptitle("Pairplot of Numerical Features", y=1.02, fontsize=16, wei
    plt.show()

plot_pairplot(data_afteroutlier, hue='Loan_Status')
```



Sorting DataFrame values

In [26]:
```
# with single parameter - Value
data_new = data_afteroutlier.copy()
sorted_data_single = data_new.sort_values(by='ApplicantIncome')
display(sorted_data_single)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Co
216	216	1	1	0	0	0	150	
468	468	0	1	2	1	0	210	
500	500	0	0	0	0	0	645	
188	188	1	1	0	0	1	674	
77	77	1	1	1	0	1	1000	
...	...	...	...	...	...	...	...	...
598	598	1	1	0	0	1	9963	
210	210	0	0	0	0	0	10000	
319	319	1	1	1	0	1	10000	
148	148	0	0	0	0	0	10000	
435	435	0	1	0	0	0	10047	

520 rows × 13 columns

In [27]:
```
# sorting with multi parameter with order ascending or descending
sort_multi = data_new.sort_values(by=['LoanAmount', 'ApplicantIncome', 'Coa
display(sort_multi)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Co
133	133	1	1	0	0	1	3459	
94	94	1	0	0	1	0	3620	
555	555	1	1	1	0	0	5468	
147	147	1	1	1	0	0	1538	
270	270	0	0	0	0	0	3237	
...	...	...	...	...	...	...	...	...
412	412	1	1	0	1	0	6096	
148	148	0	0	0	0	0	10000	
350	350	1	1	0	0	0	9083	
476	476	1	1	2	0	0	6700	
361	361	1	1	2	0	0	5000	

520 rows × 13 columns

Merge Data Frames

In [28]:
```
df1 = encod_data.copy()
df2 = data_new.copy()
df_merged  = pd.merge(df1,df2)
```

Apply Function

In [29]:
```
# if year greater than 2019 it is termed as COVID
def fun(value):
    if value>100:
        return "HIGH"
    else:
        return "LOW"

data_c=data_afteroutlier.copy()
data_c['AmountLevel'] = data_c['LoanAmount'].apply(fun)
display(data_c)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Co
0	0	1	0	0	0	0	5849	
1	1	1	1	1	0	0	4583	
2	2	1	1	0	0	1	3000	
3	3	1	1	0	1	0	2583	
4	4	1	0	0	0	0	6000	
...	...	...	...	...	...	...	...	...
608	608	1	1	0	0	0	3232	
609	609	0	0	0	0	0	2900	
610	610	1	1	3	0	0	4106	
612	612	1	1	2	0	0	7583	
613	613	0	0	0	0	1	4583	

520 rows × 14 columns

By using the lambda operator

In [30]:
```
# adding 10 years to the existing year
data_cpy = data_afteroutlier.copy()
data_cpy['Inc'] = data_copy['ApplicantIncome'].apply(lambda x: x / 10)
display(data_cpy)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Co
0	0	1	0	0	0	0	5849	
1	1	1	1	1	0	0	4583	
2	2	1	1	0	0	1	3000	
3	3	1	1	0	1	0	2583	
4	4	1	0	0	0	0	6000	
...	...	...	...	...	...	...	...	
608	608	1	1	0	0	0	3232	
609	609	0	0	0	0	0	2900	
610	610	1	1	3	0	0	4106	
612	612	1	1	2	0	0	7583	
613	613	0	0	0	0	1	4583	

520 rows × 14 columns

Thank You

Sivaprakash V