$ Fintech Capstone - Loan Default $

About the CaseStudy

This project explores **risk analytics** in the **banking and financial services sector**, focusing on **data-driven methods** to reduce lending risks. It examines key variables such as **loan type**, **purpose**, **commercial nature**, and **credit score** to identify factors influencing **loan defaults**. Additionally, the relationship between **upfront charges**, **loan amounts**, **interest rates**, and **property values** with default likelihood will be analyzed to uncover valuable insights. The ultimate goal is to improve **risk assessment strategies**, enabling better **decision-making** and proactive measures to prevent **loan defaults**.

Introduction

In the highly competitive and dynamic landscape of **banking and financial services**, effective **risk management** is crucial for maintaining **financial stability** and **profitability**. Lending institutions face significant risks, particularly the risk of **loan defaults**, which can have severe financial repercussions. **To mitigate these risks, it is essential to develop a robust understanding of the factors that influence loan repayment behavior and the likelihood of default.** This project explores the intersection of **data analytics** and **risk management**, focusing on how various variables related to loans and borrowers impact **default rates**. By leveraging data, we can gain valuable insights that will enable lenders to make more informed decisions, optimize lending practices, and reduce the risk of **financial loss**.

Objectives

The primary objectives of this project are to:

- **Understanding Risk Analytics:** Gain a comprehensive understanding of **risk analytics** in the context of **banking and financial services**, with a particular focus on **loan default risks**.
- **Exploring Key Variables:** Investigate how variables such as **loan type**, **loan purpose**, **business nature**, and **credit scores** influence the likelihood of **loan defaults**.
- **Analyzing Financial Indicators:** Examine the correlation between financial indicators like **upfront charges**, **loan amounts**, **interest rates**, and **property values** with **default tendencies**.
- **Enhancing Risk Assessment:** Develop strategies to improve **risk assessment** in lending institutions by incorporating **data-driven insights**.
- **Proactive Default Prevention:** Propose measures to proactively prevent **loan defaults** based on the findings of the analysis.

Scope of the Study

This project is designed to serve as a foundational exploration of risk analytics in the financial services industry. While the initial focus is on specific variables and their impact on loan defaults, the scope of the study is open-ended, allowing for deeper exploration and additional research. By going beyond the provided topics, the project encourages a thorough investigation that could lead to innovative risk management strategies and insights that are valuable to the industry.

Data Description

Field	Description
ID	Unique identifier for each row
year	Year when the loan was taken
loan_limit	Indicates if the loan limit is fixed (cf-confirm/fixed) or variable (ncf-not confirm/not fixed)
Gender	Gender of the applicant (male, female, not specified, joint)
loan_type	Type of loan (masked data, type-1, type-2, type-3)
loan_purpose	Purpose of the loan (masked data, p1, p2, p3, p4)
business_or_commercial	Indicates if the loan is for a commercial or personal establishment
loan_amount	Amount of the loan
rate_of_interest	Rate of interest for the loan
Upfront_charges	Down payment made by the applicant
property_value	Value of the property being constructed with the loan

Field	Description
occupancy_type	Type of occupancy for the establishment
income	Income of the applicant
credit_type	Credit type (EXP, EQUI, CRIF, CIB)
Credit_Score	Credit score of the applicant
co-applicant_credit_type	Credit type for co-applicant
age	Age of the applicant
LTV	Lifetime value of the applicant
Region	Region of the applicant
Status	Indicates if the applicant is a defaulter (1) or normal (0)
Default	Indicates if the loan defaulted (1) or not (0)

Research Methodology

- **Data Collection:** Gather relevant data from **financial institutions**, including **loan details**, **borrower profiles**, and **financial metrics**.
- **Data Analysis:** Use **statistical** and **machine learning techniques** to analyze the data and identify patterns and correlations between the variables and **loan default rates**.
- **Visualization:** Create visual representations of the findings to make the insights more **accessible** and **actionable** for stakeholders.
- **Recommendations:** Based on the analysis, provide **recommendations** for improving **risk assessment** and **default prevention strategies** in lending institutions.

Expected Outcomes

- At the conclusion of this project, we aim to produce a collection of **actionable insights** and **recommendations** to assist **financial institutions** in better evaluating and managing lending risks. These insights are expected to foster more effective **risk mitigation strategies**, thereby decreasing the likelihood of **loan defaults** and improving the overall **financial stability** of the involved institutions.

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
import scipy.stats as stats
from scipy.stats import chi2_contingency,fisher_exact,shapiro,levene,mannwhitney

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Set Pandas options to display all columns & rows
pd.set_option('display.max_columns', 50)
pd.set_option('display.max_rows', 50)
```

Data Wrangling

In [3]:
```
import gdown
dataset = 'https://drive.google.com/file/d/1AyUR46JcZ7rqL_ixTjP8mzMAoPNxZq7c/vie
output = 'loan.csv' # You can change the output filename
gdown.download(url=dataset, output=output, quiet=False, fuzzy=True)
data = pd.read_csv('loan.csv')
```

```
Downloading...
From: https://drive.google.com/uc?id=1AyUR46JcZ7rqL_ixTjP8mzMAoPNxZq7c
To: C:\Users\Sownd\Desktop\loan.csv
100%|██████████████████████████████████████████████████
█| 16.3M/16.3M [00:01<00:00, 9.56MB/s]
```

In [4]:
```
data
```

Out[4]:

	ID	year	loan_limit	Gender	loan_type	loan_purpose	business_or_comm
0	24890	2019	cf	Sex Not Available	type1	p1	
1	24891	2019	cf	Male	type2	p1	
2	24892	2019	cf	Male	type1	p1	
3	24893	2019	cf	Male	type1	p4	
4	24894	2019	cf	Joint	type1	p1	
...	...	...	...	...	...	...	
148665	173555	2019	cf	Sex Not Available	type1	p3	
148666	173556	2019	cf	Male	type1	p1	
148667	173557	2019	cf	Male	type1	p4	
148668	173558	2019	cf	Female	type1	p4	
148669	173559	2019	cf	Female	type1	p3	

148670 rows × 20 columns

In [5]:
```
# Checking the number of rows and columns
print(f"The number of rows: {data.shape[0]:,} \nThe number of columns: {data.sha
```

```
The number of rows: 148,670
The number of columns: 20
```

In [6]:
```
# Check all column names
data.columns
```

Out[6]:
```
Index(['ID', 'year', 'loan_limit', 'Gender', 'loan_type', 'loan_purpose',
       'business_or_commercial', 'loan_amount', 'rate_of_interest',
       'Upfront_charges', 'property_value', 'occupancy_type', 'income',
       'credit_type', 'Credit_Score', 'co-applicant_credit_type', 'age', 'LTV',
       'Region', 'Status'],
      dtype='object')
```

OBSERVATION

> The dataset has **1,48,670 rows** and **20 columns**

Column Name Description:

1. **ID:** Id for each row

2. **year:** year when the loan was taken
3. **loan_limit:** if the loan limit is fixed or variable, cf- confirm/fixed, ncf- not confirm/not fixed
4. **Gender:** gender of the applicant, can be male, female, not specified, joint (in case of applling as a couple for home loan)
5. **loan_type:** type of loan (masked data), type-1, type-2, type-3
6. **loan_purpose:** purpose of the loan (masked data) p1, p2, p3, p4
7. **business_or_commercial:** if the loan is for sommercial establishment or personal establishment
8. **loan_amount:** amount of the loan
9. **rate_of_interest:** rate of interest for the loan
10. **Upfront_charges:** down payment done by the applicant
11. **property_value:** value of the property being constructed for which the loan is taken.
12. **occupancy_type:** for the establishment
13. **income:** income of the applicant
14. **credit_type** 'EXP' 'EQUI' 'CRIF' 'CIB'
15. **Credit_Score:** credit score of applicant
16. **co-applicant_credit_type:** credit type for co-applicant
17. **age:** age of applicant
18. **LTV lifetime:** value of the applicant
19. **Region:** region of the applicant
20. **Status:** defaulter(1) or normal(0)

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 20 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   ID                         148670 non-null  int64  
 1   year                       148670 non-null  int64  
 2   loan_limit                 145326 non-null  object 
 3   Gender                     148670 non-null  object 
 4   loan_type                  148670 non-null  object 
 5   loan_purpose               148536 non-null  object 
 6   business_or_commercial     148670 non-null  object 
 7   loan_amount                148670 non-null  int64  
 8   rate_of_interest           112231 non-null  float64
 9   Upfront_charges            109028 non-null  float64
 10  property_value             133572 non-null  float64
 11  occupancy_type             148670 non-null  object 
 12  income                     139520 non-null  float64
 13  credit_type                148670 non-null  object 
 14  Credit_Score               148670 non-null  int64  
 15  co-applicant_credit_type   148670 non-null  object 
 16  age                        148470 non-null  object 
 17  LTV                        133572 non-null  float64
 18  Region                     148670 non-null  object 
 19  Status                     148670 non-null  int64  
dtypes: float64(5), int64(5), object(10)
memory usage: 22.7+ MB
```

In [8]:
```
# Number of unique values in each coluumn and datatype:
print("Number of unique values in each coluumn and datatype:")
print("-" * 55)
for i, elem in (enumerate(data.columns)):
    print(f"{i+1}. {elem}: {data[elem].nunique(), data[elem].dtypes}")
```

```
Number of unique values in each coluumn and datatype:
-------------------------------------------------------
1. ID: (148670, dtype('int64'))
2. year: (1, dtype('int64'))
3. loan_limit: (2, dtype('O'))
4. Gender: (4, dtype('O'))
5. loan_type: (3, dtype('O'))
6. loan_purpose: (4, dtype('O'))
7. business_or_commercial: (2, dtype('O'))
8. loan_amount: (211, dtype('int64'))
9. rate_of_interest: (131, dtype('float64'))
10. Upfront_charges: (58271, dtype('float64'))
11. property_value: (385, dtype('float64'))
12. occupancy_type: (3, dtype('O'))
13. income: (1001, dtype('float64'))
14. credit_type: (4, dtype('O'))
15. Credit_Score: (401, dtype('int64'))
16. co-applicant_credit_type: (2, dtype('O'))
17. age: (7, dtype('O'))
18. LTV: (8484, dtype('float64'))
19. Region: (4, dtype('O'))
20. Status: (2, dtype('int64'))
```

In [9]:
```
# Columns thet are to be converted to Category datatype
print("Columns thet are to be converted to Category datatype:")
print("-" * 55)
for i, elem in (enumerate(data.columns)):
    if data[elem].nunique() < 8 and data[elem].dtypes == 'O':
        print(f"{i+1}. {elem}: {data[elem].nunique(), data[elem].dtypes}")
```

```
Columns thet are to be converted to Category datatype:
-------------------------------------------------------
3. loan_limit: (2, dtype('O'))
4. Gender: (4, dtype('O'))
5. loan_type: (3, dtype('O'))
6. loan_purpose: (4, dtype('O'))
7. business_or_commercial: (2, dtype('O'))
12. occupancy_type: (3, dtype('O'))
14. credit_type: (4, dtype('O'))
16. co-applicant_credit_type: (2, dtype('O'))
17. age: (7, dtype('O'))
19. Region: (4, dtype('O'))
```

OBSERVATION

Converting columns to categorical is necessary to improve:

- Memory efficiency
- Performance in machine learning models
- Proper representation and analysis of the data

This is especially important when working with large datasets, as it helps streamline both the analysis and modeling phases.

- Status need to be converted to catgory datatype

In [10]:
```
# Creating a deep copy for backup
df = data.copy()
```

In [11]:
```
# Convert columns to categorical
cols_to_cat = ['loan_limit', 'Gender', 'loan_type', 'loan_purpose', 'business_or
               'occupancy_type', 'credit_type', 'co-applicant_credit_type', 'age
for col in cols_to_cat:
    df[col] = df[col].astype('category')
print("Required columns are converted to categorical")
```

```
Required columns are converted to categorical
```

In [12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 20 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   ID                         148670 non-null  int64
 1   year                       148670 non-null  int64
 2   loan_limit                 145326 non-null  category
 3   Gender                     148670 non-null  category
 4   loan_type                  148670 non-null  category
 5   loan_purpose               148536 non-null  category
 6   business_or_commercial     148670 non-null  category
 7   loan_amount                148670 non-null  int64
 8   rate_of_interest           112231 non-null  float64
 9   Upfront_charges            109028 non-null  float64
 10  property_value             133572 non-null  float64
 11  occupancy_type             148670 non-null  category
 12  income                     139520 non-null  float64
 13  credit_type                148670 non-null  category
 14  Credit_Score               148670 non-null  int64
 15  co-applicant_credit_type   148670 non-null  category
 16  age                        148470 non-null  category
 17  LTV                        133572 non-null  float64
 18  Region                     148670 non-null  category
 19  Status                     148670 non-null  category
dtypes: category(11), float64(5), int64(4)
memory usage: 11.8 MB
```

In [13]:
```
df['Status'].unique()
```

Out[13]:
```
[1, 0]
Categories (2, int64): [0, 1]
```

OBSERVATION

Lets rename the column elements

> `1 -> defaulter`
>
> `0 -> normal`

In [14]:
```
# Renamed the elements
df['Status'] = df['Status'].apply(lambda x: 'defaulter' if x == 1 else 'normal')
```

In [15]:
```
# Display the range of attributes
print("Range of attributes:")
print("-" * 20)
df.describe(include='all').T
```

```
Range of attributes:
--------------------
```

Out[15]:

	count	unique	top	freq	mean	st
ID	148670.0	NaN	NaN	NaN	99224.5	42917.47659
year	148670.0	NaN	NaN	NaN	2019.0	0.
loan_limit	145326	2	cf	135348	NaN	Na
Gender	148670	4	Male	42346	NaN	Na
loan_type	148670	3	type1	113173	NaN	Na
loan_purpose	148536	4	p3	55934	NaN	Na
business_or_commercial	148670	2	nob/c	127908	NaN	Na
loan_amount	148670.0	NaN	NaN	NaN	331117.743997	183909.31012
rate_of_interest	112231.0	NaN	NaN	NaN	4.045476	0.56139
Upfront_charges	109028.0	NaN	NaN	NaN	3224.996127	3251.1215
property_value	133572.0	NaN	NaN	NaN	497893.465696	359935.31556
occupancy_type	148670	3	pr	138201	NaN	Na
income	139520.0	NaN	NaN	NaN	6957.338876	6496.58638
credit_type	148670	4	CIB	48152	NaN	Na
Credit_Score	148670.0	NaN	NaN	NaN	699.789103	115.87585
co-applicant_credit_type	148670	2	CIB	74392	NaN	Na
age	148470	7	45-54	34720	NaN	Na
LTV	133572.0	NaN	NaN	NaN	72.746457	39.96760
Region	148670	4	North	74722	NaN	Na
Status	148670	2	normal	112031	NaN	Na

In [16]:
```
# Display the statistical summary
print("statistical summary:")
print("-" * 20)
df.describe().T
```

```
statistical summary:
--------------------
```

Out[16]:

	count	mean	std	min	25%	
ID	148670.0	99224.500000	42917.476598	24890.000000	62057.25000	
year	148670.0	2019.000000	0.000000	2019.000000	2019.00000	
loan_amount	148670.0	331117.743997	183909.310127	16500.000000	196500.00000	2
rate_of_interest	112231.0	4.045476	0.561391	0.000000	3.62500	
Upfront_charges	109028.0	3224.996127	3251.121510	0.000000	581.49000	
property_value	133572.0	497893.465696	359935.315562	8000.000000	268000.00000	4
income	139520.0	6957.338876	6496.586382	0.000000	3720.00000	
Credit_Score	148670.0	699.789103	115.875857	500.000000	599.00000	
LTV	133572.0	72.746457	39.967603	0.967478	60.47486	

OBSERVATION

1. **ID**s are unique identifiers with a broad range. This column is not used in analysis but ensures each entry's uniqueness.
2. **Year**: Range: 2019, All entries are from the year 2019, indicating a single year's dataset.
3. **Loan Limit**
   - Unique Values: 2 (e.g., 'cf' for fixed, 'ncf' for not fixed)
   - Most Frequent: 'cf'. They are predominant, potentially affecting risk and repayment patterns.
4. **Gender**:
   - Unique Values: 4 (e.g., 'Male', 'Female', 'Not Specified', 'Joint')
   - Most Frequent: 'Male'. Gender distribution varies, with a higher count for 'Male'. Gender may influence default risk but requires further analysis.
5. **Loan Type**:
   - Unique Values: 3 (e.g., 'type1', 'type2', 'type3')
   - Most Frequent: 'type1' which could be relevant for understanding default patterns specific to loan types.
6. **Loan Purpose**:
   - Unique Values: 4 (e.g., 'p1', 'p2', 'p3', 'p4')
   - Most Frequent: 'p3'. The purpose of loans varies, with 'p3' being the most frequent. Different purposes may correlate with varying default rates.
7. **Business or Commercial**:
   - Unique Values: 2 (e.g., 'b' for business, 'c' for commercial)
   - Most Frequent: 'c'.Commercial loans are more frequent than business loans. This distinction could be significant for risk assessment.
8. **Loan Amount**:
   - Average: 331,118 dollers
   - Range: 16,500 to 3,576,500 dollers. Significant variation in loan amounts, suggesting diverse borrower needs and potential risk factors.

9. **Rate of Interest**:
    - Average: 4.05%
    - Range: 0% to 8%
    - Interest rates vary widely, impacting loan affordability and default risk.
10. **Upfront Charges**:
    - Average: 3,225 dollers
    - Range: 0 to 60,000 dollers
    - Upfront charges vary greatly. High upfront charges might affect borrower willingness and default likelihood.
11. **Property Value**:
    - Average: 497,893 dollers
    - Range: 8,000 to 16,508,000 dollers
    - Large variation in property values, indicating different property types and potential risk associated with high-value properties.
12. **Occupancy Type**:
    - Unique Values: 3 (e.g., 'pr' for primary residence, etc.)
    - Most Frequent: 'pr'
    - Primary residences are most common, which might influence default patterns.
13. **Income**:
    - Average: 6,957 dollers
    - Range: 0 to 578,580 dollers
    - Wide range in income levels. Lower income might be associated with higher default risk.
14. **Credit Type**:
    - Unique Values: 4 (e.g., 'EXP', 'EQUI', 'CRIF', 'CIB')
    - Most Frequent: 'CIB'
    - 'CIB' is the most frequent credit type, which could have implications for default risk.
15. **Credit Score**:
    - Average: 700
    - Range: 500 to 900
    - Credit scores vary, with most falling between 599 and 800. Higher credit scores are generally associated with lower default risk.
16. **Co-Applicant Credit Type**:
    - Unique Values: 2 (e.g., 'CIB' most frequent)
    - Most Frequent: 'CIB'
    - Similar to credit type for applicants, the co-applicant's credit type could also impact the risk assessment.
17. **Age**:
    - Unique Values: 7 (e.g., '45-54' is the most common)
    - Most Frequent: '45-54'
    - Age distribution shows a concentration in the 45-54 age group, which might influence borrowing behavior and risk.
18. **LTV (Loan-to-Value)**:
    - Average: 72.75%

- Range: 0.97% to 7,831.25%
- Significant range in LTV values. Higher LTVs might indicate higher risk, particularly if approaching or exceeding 100%.

19. **Region**:
    - Unique Values: 4 (e.g., 'North' is the most frequent)
    - Most Frequent: 'North'
    - Regional distribution shows 'North' as the most common region. Regional variations could impact default rates and risk strategies.
20. **Status**:
    - Unique Values: 2 ('normal' is the most frequent)
    - Most Frequent: 'normal'
    - The majority of entries are 'normal', indicating a lower proportion of defaults. This distribution is crucial for analyzing default risk.

Checking for Duplicates

In [17]:
```
df[data.duplicated()]
```

Out[17]:

ID	year	loan_limit	Gender	loan_type	loan_purpose	business_or_commercial	loan_a

OBSERVATION

- There is no duplicate records.

Missing value treatment and Cleaning

In [18]:
```
# How many percentage of data is missing in each column
missing_value = pd.DataFrame({'Missing Value': df.isnull().sum(),
                              'Percentage': (((df.isnull().sum() / len(df))*100)
sorted_missing_value = missing_value.sort_values(by='Percentage', ascending=Fals
sorted_missing_value
```

Out[18]:

	Missing Value	Percentage
Upfront_charges	39642	26.66
rate_of_interest	36439	24.51
property_value	15098	10.16
LTV	15098	10.16
income	9150	6.15
loan_limit	3344	2.25
age	200	0.13
loan_purpose	134	0.09
Region	0	0.00
co-applicant_credit_type	0	0.00
Credit_Score	0	0.00
credit_type	0	0.00
ID	0	0.00
occupancy_type	0	0.00
year	0	0.00
loan_amount	0	0.00
business_or_commercial	0	0.00
loan_type	0	0.00
Gender	0	0.00
Status	0	0.00

In [19]:
```
# Columns to be handlled for missing values
missing_value_treatment_columns = sorted_missing_value.index[0:8]
missing_value_treatment_columns
```

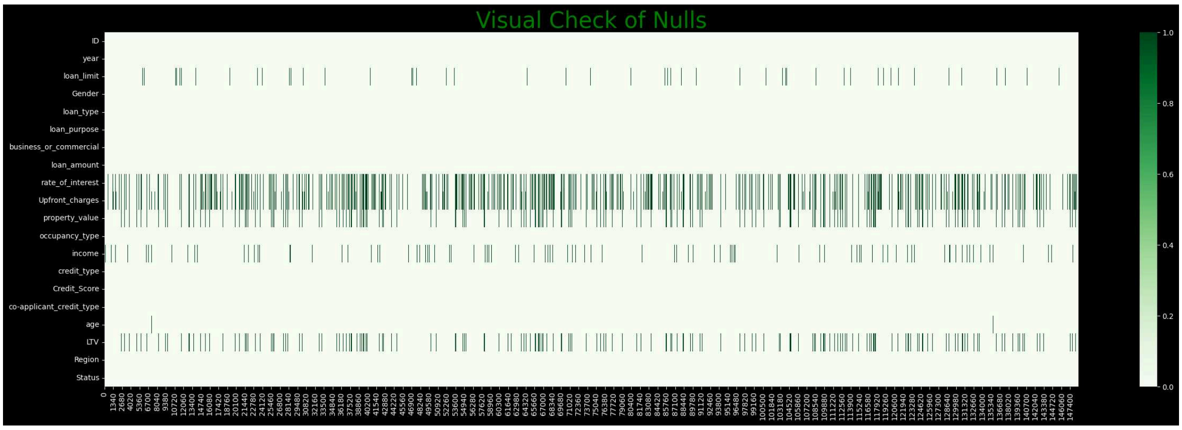
Out[19]:
```
Index(['Upfront_charges', 'rate_of_interest', 'property_value', 'LTV',
       'income', 'loan_limit', 'age', 'loan_purpose'],
      dtype='object')
```

In [20]:
```
# Catrgorical columns to be handlled for missing values
missing_value_treatment_columns_cat = df[missing_value_treatment_columns].select
missing_value_treatment_columns_cat
```

Out[20]:
```
Index(['loan_limit', 'age', 'loan_purpose'], dtype='object')
```

In [22]:
```
# Null value heatmap:

plt.figure(figsize=(25,8))
plt.style.use('dark_background')
sns.heatmap(df.isnull().T,cmap='Greens')
plt.title('Visual Check of Nulls',fontsize=30,color='green')
```

```
plt.tight_layout()
plt.show()
```



Decision for imputation

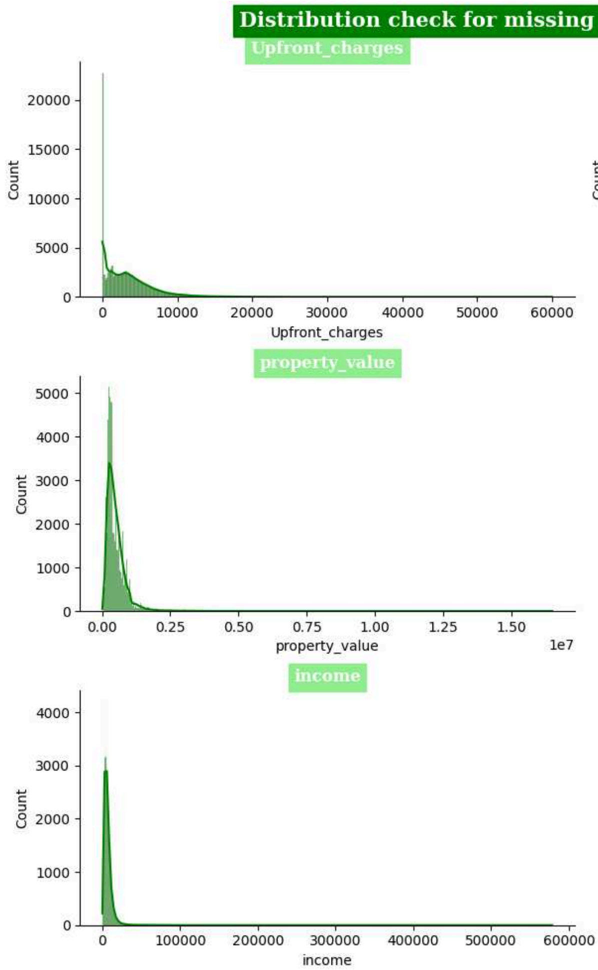
In [23]:
```
# Numerical columns to be handlled for missing values
missing_value_treatment_columns_num = df[missing_value_treatment_columns].select
missing_value_treatment_columns_num
```

Out[23]:
```
['Upfront_charges', 'rate_of_interest', 'property_value', 'LTV', 'income']
```

In [24]:
```
print(plt.style.available)
```

```
['Solarize_Light2', '_classic_test_patch', '_mpl-gallery', '_mpl-gallery-nogrid',
'bmh', 'classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot', 'graysc
ale', 'seaborn-v0_8', 'seaborn-v0_8-bright', 'seaborn-v0_8-colorblind', 'seaborn-
v0_8-dark', 'seaborn-v0_8-dark-palette', 'seaborn-v0_8-darkgrid', 'seaborn-v0_8-d
eep', 'seaborn-v0_8-muted', 'seaborn-v0_8-notebook', 'seaborn-v0_8-paper', 'seabo
rn-v0_8-pastel', 'seaborn-v0_8-poster', 'seaborn-v0_8-talk', 'seaborn-v0_8-tick
s', 'seaborn-v0_8-white', 'seaborn-v0_8-whitegrid', 'tableau-colorblind10']
```

In [26]:
```
# Distribution check for missing numerical columns:
plt.figure(figsize=(12,10))
plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')
for i, elem in enumerate(missing_value_treatment_columns_num):
    plt.subplot(3,2,i+1)
    sns.histplot(df[elem], kde=True,color='green')
    plt.title(elem,fontsize=12,fontfamily='serif',
              fontweight='bold',backgroundcolor='lightgreen',color='w')

plt.suptitle("Distribution check for missing values in numerical columns",
             fontsize=15,fontfamily='serif',fontweight='bold',backgroundcolor='g
plt.tight_layout()
sns.despine()
plt.show()
```



In [27]:
```
# Skewness coefficient for missing value numerical columns
df[missing_value_treatment_columns].select_dtypes(include='number').skew().round
```

Out[27]:

	columns	skewness_coeff
0	Upfront_charges	1.75
1	rate_of_interest	0.39
2	property_value	4.59
3	LTV	120.62
4	income	17.31

In [28]:
```
# Skewness coefficient for missing value numerical columns
df[missing_value_treatment_columns].select_dtypes(include='number').kurt().round
```

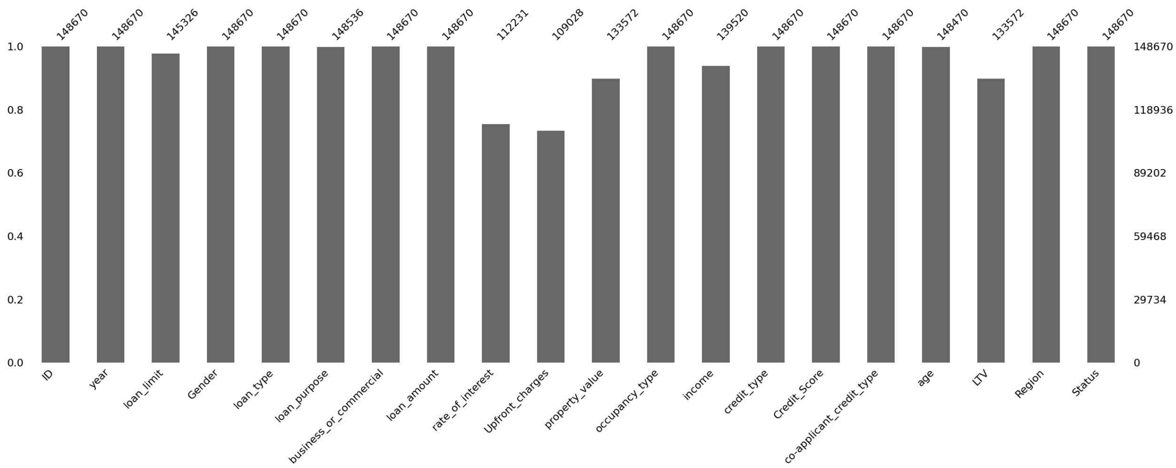
Out[28]:

	columns	kurtosis_coeff
0	Upfront_charges	6.37
1	rate_of_interest	0.34
2	property_value	73.22
3	LTV	19979.04
4	income	885.29

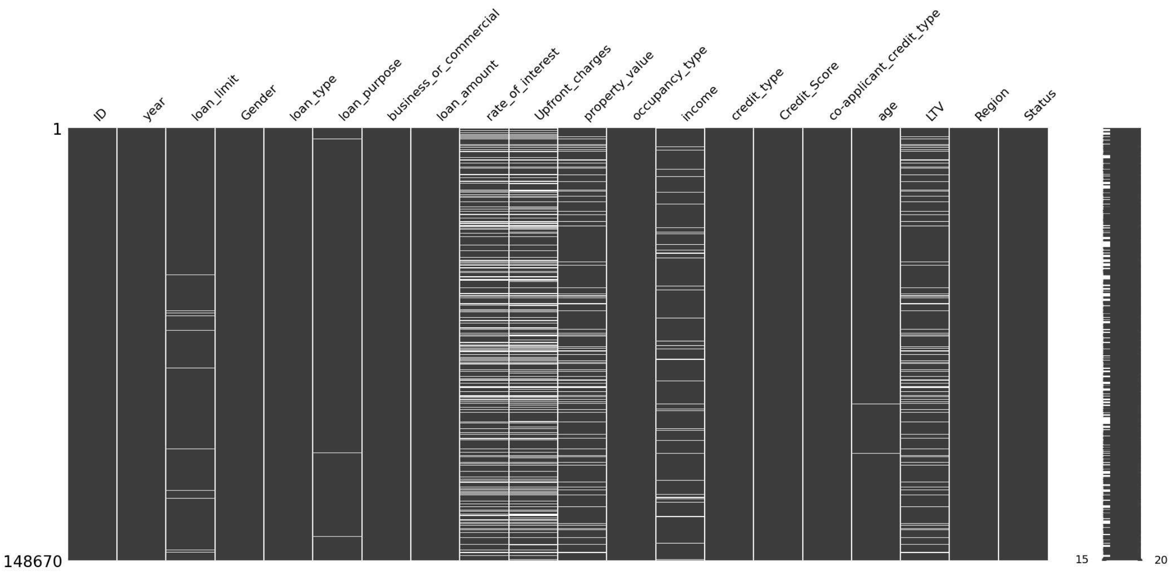
> **Visualizing Missing Data Patterns**

> **Missingno Library:** The missingno library is great for visualizing patterns in missing data.

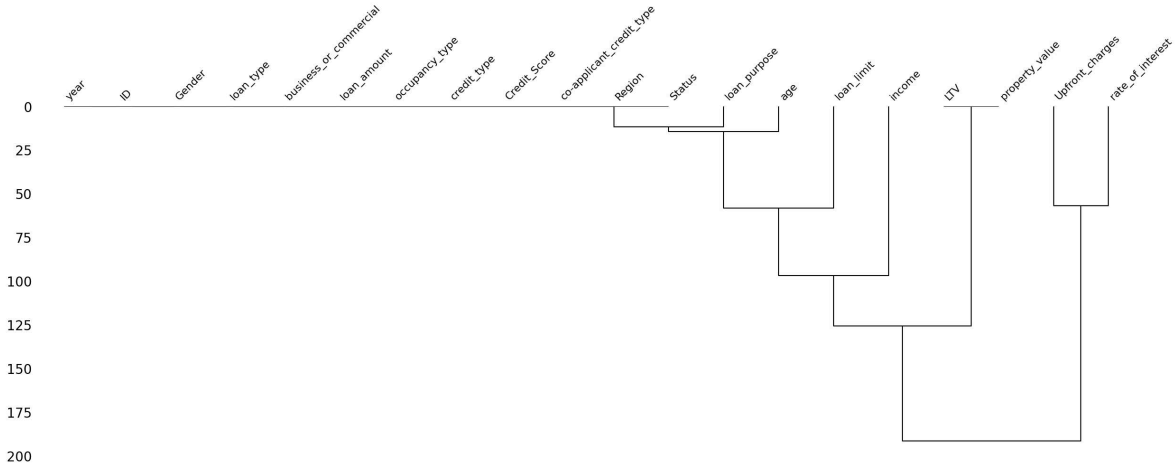
In [29]:
```
import missingno as msno
# Missing data bar plot
msno.bar(df)
plt.tight_layout()
plt.show()
```



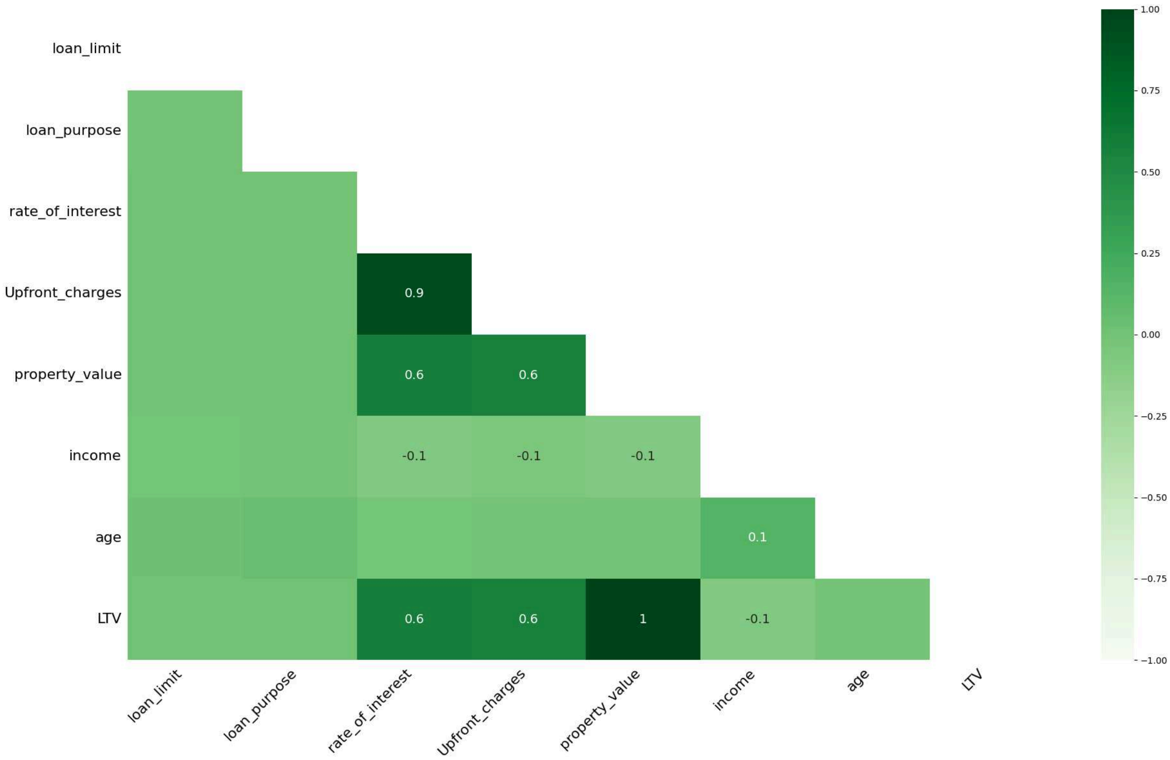
In [30]:
```
# Missing data matrix plot
msno.matrix(df)
plt.tight_layout()
plt.show()
```



In [31]:
```
# Dendrogram to show correlation in missing data
msno.dendrogram(df)
plt.tight_layout()
plt.show()
```



In [32]:
```
# Heatmap
msno.heatmap(df,cmap='Greens')
plt.tight_layout()
plt.show()
```

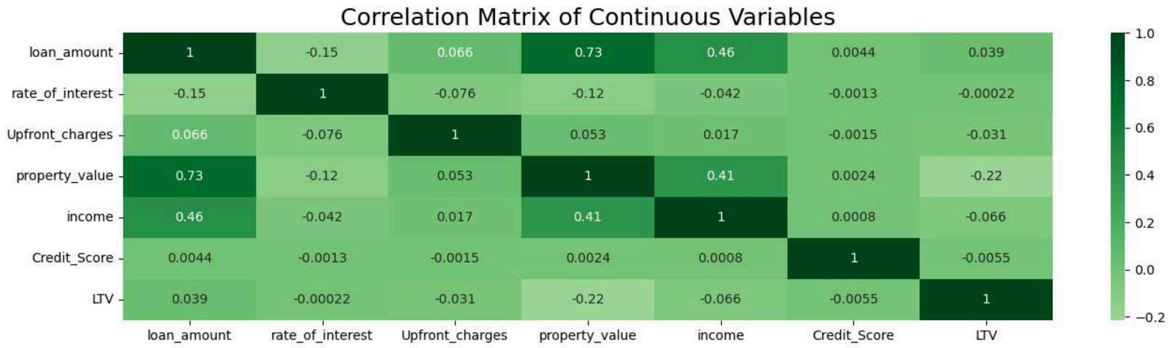


> - These plots help identify if missing values are scattered randomly or if they are more structured.
> - The dendrogram in particular helps identify clusters of columns that have similar missing data patterns.

Correlation Matrix of Continuous Variables

In [33]:
```
# Selecting the categorical columns
numerical_df = df.select_dtypes(include=['int64','float64'])
numerical_df_req = numerical_df[numerical_df.columns[2:]]

# Correlation Matrix of Continuous Variables
plt.figure(figsize=(16, 4))
corr_matrix = numerical_df_req.corr()
```

```
sns.heatmap(corr_matrix, annot=True, cmap='Greens', center=0)
plt.title('Correlation Matrix of Continuous Variables', fontsize = 18)
plt.show()
```



Treatment - `ML - Random Forest & XGboost` for Numerical variables

```
from sklearn.ensemble import RandomForestRegressor

# Columns to impute (numerical only)
num_cols = ['Upfront_charges', 'rate_of_interest', 'property_value',
'income']

# Imputation for numerical columns using RandomForestRegressor
for col in num_cols:
    missing = df[col].isnull()  # Identify missing values in the column
    if missing.sum() > 0:
        # Training data: rows where this column is not missing
        X_train = df.loc[~missing, num_cols].drop(columns=[col])
        y_train = df.loc[~missing, col]

        # Missing data: rows where this column is missing
        X_missing = df.loc[missing, num_cols].drop(columns=[col])

        # Fit RandomForestRegressor on the training data
        rf_reg = RandomForestRegressor(n_estimators=100,
random_state=0)
        rf_reg.fit(X_train, y_train)

        # Predict and fill the missing values
        df.loc[missing, col] = rf_reg.predict(X_missing)
```

Using both `RandomForestRegressor` and `XGBRegressor` for imputing missing numerical values can be a good strategy, as each model has its strengths. Here's why combining them can be beneficial:

> Benefits of Using Both Models

1. **Different Learning Approaches:**
    - **Random Forest** is an ensemble of decision trees and is robust to overfitting. It can capture complex relationships and interactions between features.

- **XGBoost** (Extreme Gradient Boosting) is also an ensemble method but is based on boosting, which tends to perform better on many structured data problems due to its ability to optimize model performance through sequential learning.

2. **Improved Accuracy:**

   - By using predictions from both models, you can leverage the strengths of each. You might average the predictions or choose one based on their performance metrics (e.g., RMSE, MAE).

3. **Robustness to Different Data Characteristics:**

   - Different models may perform better with different distributions or characteristics of the data. Using both allows you to cover a broader range of scenarios.

> Implementation Considerations

1. **Model Selection:**

   - After training both models, you might consider evaluating their performance on a validation set (if available) to see which model performs better for imputation.

2. **Combining Predictions:**

   - You can either take the average of predictions from both models or use a more sophisticated method like stacking or weighted averaging based on model performance.

3. **Performance Monitoring:**

   - Keep track of how well your imputation improves the model performance on downstream tasks (e.g., regression or classification) after handling the missing values.

> Example of Combining Predictions

Here's a basic approach to averaging predictions from both models:

```
for col in num_cols:
    missing = df[col].isnull()
    if missing.sum() > 0:
        X_train = df.loc[~missing, num_cols].drop(columns=[col])
        y_train = df.loc[~missing, col]
        X_missing = df.loc[missing, num_cols].drop(columns=[col])

        # Random Forest Imputation
        rf_reg = RandomForestRegressor(n_estimators=100,
random_state=0)
        rf_reg.fit(X_train, y_train)
        rf_predictions = rf_reg.predict(X_missing)

        # XGBoost Imputation
        xgb_reg = XGBRegressor(n_estimators=100, random_state=0)
        xgb_reg.fit(X_train, y_train)
        xgb_predictions = xgb_reg.predict(X_missing)
```

```
        # Average the predictions
        df.loc[missing, col] = (rf_predictions + xgb_predictions) / 2
```

Conclusion:

Using both `RandomForestRegressor` and `XGBRegressor` for imputing missing numerical values is a valid and potentially effective approach. It allows you to leverage the strengths of both models, improving the robustness and accuracy of your imputations. Just be sure to evaluate the combined performance to ensure it adds value to your analysis.

In [34]:

```python
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor

# Columns to impute (numerical only)
num_cols = ['Upfront_charges', 'rate_of_interest', 'property_value', 'income']

# Initial check for missing values
print(df[num_cols].isnull().sum())

# Imputation for numerical columns using RandomForestRegressor and XGBRegressor
for col in num_cols:
    missing = df[col].isnull()
    if missing.sum() > 0:
        print(f"Processing column: {col}")  # Debug statement
        X_train = df.loc[~missing, num_cols].drop(columns=[col])
        y_train = df.loc[~missing, col]
        X_missing = df.loc[missing, num_cols].drop(columns=[col])

        # Random Forest Imputation
        rf_reg = RandomForestRegressor(n_estimators=100, random_state=0)
        rf_reg.fit(X_train, y_train)
        rf_predictions = rf_reg.predict(X_missing)

        # XGBoost Imputation
        xgb_reg = XGBRegressor(n_estimators=100, random_state=0)
        xgb_reg.fit(X_train, y_train)
        xgb_predictions = xgb_reg.predict(X_missing)

        # Average the predictions
        df.loc[missing, col] = (rf_predictions + xgb_predictions) / 2

        differences = abs(rf_predictions - xgb_predictions)
        if differences.sum() > 0:
            print(f"Differences for {col}: {differences}")
        else:
            print(f"No differences for {col}.")
```

```
Upfront_charges     39642
rate_of_interest    36439
property_value      15098
income               9150
dtype: int64
Processing column: Upfront_charges
Differences for Upfront_charges: [ 539.65396422 3771.35932119  214.23412943 ... 1
765.99577423  904.72821228
 2304.8196898 ]
Processing column: rate_of_interest
Differences for rate_of_interest: [0.34621949 0.0491049  0.07331363 ... 0.1917175
0.23189375 0.06622979]
Processing column: property_value
Differences for property_value: [ 20245.53125   97472.625    481152.25     ... 12
0811.40625   48221.4375
  88124.484375]
Processing column: income
Differences for income: [  96.88707579  826.73896484 1336.43369141 ... 1236.50889
788 2282.23417969
  760.92646484]
```

In [35]:
```python
df.isna().sum()
```

Out[35]:
```
ID                               0
year                             0
loan_limit                    3344
Gender                           0
loan_type                        0
loan_purpose                   134
business_or_commercial           0
loan_amount                      0
rate_of_interest                 0
Upfront_charges                  0
property_value                   0
occupancy_type                   0
income                           0
credit_type                      0
Credit_Score                     0
co-applicant_credit_type         0
age                            200
LTV                          15098
Region                           0
Status                           0
dtype: int64
```

OBSERVATION

Reason for Choosing Random Forest & XGBoost for Imputation of Numerical Variables:

- **Handling Non-linear Relationships:** Random Forest is a flexible model that captures non-linear relationships between features. In datasets where the relationships between numerical variables are not linear, Random Forest performs well by considering the complex patterns in the data.
- **Feature Importance:** Random Forest inherently estimates the importance of features, which helps it make better predictions for missing values by considering the most relevant features.

- **Robustness to Outliers:** Random Forest is not sensitive to outliers, making it a robust method for handling numerical variables that may contain extreme values.
- **Handling Large Datasets:** It is computationally efficient for larger datasets, making it suitable when working with large amounts of missing data in numerical variables.
- **Boosting Approach:** XGBoost employs a boosting technique that focuses on correcting errors made by previous models. This iterative approach improves accuracy and effectively captures complex patterns in the data.
- **Regularization:** XGBoost includes built-in regularization (L1 and L2), which helps prevent overfitting, especially in noisy datasets or those with many features.
- **Handling Missing Values:** XGBoost has a robust mechanism for handling missing values internally, allowing it to utilize available data efficiently without extensive preprocessing.
- **High Performance:** XGBoost is known for its speed and efficiency, optimized for performance and capable of handling large datasets with missing values quickly.
- **Feature Interaction:** The tree-based structure of XGBoost effectively models interactions between features, capturing complex relationships that may be present in the data.
- **Scalability:** XGBoost is designed to scale well with large datasets and can be distributed across multiple cores or machines, making it suitable for big data applications.

Logically based imputation for LTV

In [36]:
```
# Fill missing LTV values where property_value is not null
df['LTV'].fillna((df['loan_amount'] / df['property_value']) * 100, inplace=True)
```

In [37]:
```
df['LTV'].describe()
```

Out[37]:
```
count    148670.000000
mean         71.941745
std          39.714462
min           0.967478
25%          58.928571
50%          74.371069
75%          86.073825
max        7831.250000
Name: LTV, dtype: float64
```

OBSERVATION

- Missing LTV values are filled logically based on the relationship between the loan amount and property value, maintaining consistency across the dataset.

In [38]:
```
df.isna().sum()
```

Out[38]:
```
ID                             0
year                           0
loan_limit                  3344
Gender                         0
loan_type                      0
loan_purpose                 134
business_or_commercial         0
loan_amount                    0
rate_of_interest               0
Upfront_charges                0
property_value                 0
occupancy_type                 0
income                         0
credit_type                    0
Credit_Score                   0
co-applicant_credit_type       0
age                          200
LTV                            0
Region                         0
Status                         0
dtype: int64
```

Drop Nulls

In [39]:
```
cols = ['age', 'loan_purpose']
for col in cols:
    df.dropna(subset=[col], inplace=True)
    print(f"Dropped rows with nulls for column: {col}")
```

```
Dropped rows with nulls for column: age
Dropped rows with nulls for column: loan_purpose
```

OBSERVATION

Low Percentage of Missing Values: Both age (0.13%) and loan_purpose (0.09%) have a very small percentage of missing values in the dataset. When the proportion of missing data is low, dropping null values can have minimal impact on the overall dataset and reduce the complexity of imputation.

Mode imputation

In [40]:
```
df.groupby(['loan_type', 'Region'])[['loan_limit', 'age', 'loan_purpose']].apply
```

Out[40]:

loan_type	Region	loan_limit	age	loan_purpose
type1	North	cf	45-54	p4
	North-East	cf	45-54	p3
	central	cf	55-64	p3
	south	cf	45-54	p4
type2	North	cf	45-54	p3
	North-East	cf	35-44	p3
	central	cf	45-54	p3
	south	cf	45-54	p3
type3	North	cf	65-74	p3
	North-East	cf	65-74	p3
	central	cf	55-64	p3
	south	cf	65-74	p4

In [41]:
```
df['loan_limit'].mode()
```

Out[41]:
```
0    cf
Name: loan_limit, dtype: category
Categories (2, object): ['cf', 'ncf']
```

In [42]:
```
# Impute the mode values for loan_limit
df['loan_limit'].fillna(df['loan_limit'].mode()[0], inplace=True)
print("Mode value is imputed for column loan_limit")
```

```
Mode value is imputed for column loan_limit
```

OBSERVATION

- Categorical Nature of Data: The loan_limit column is a categorical variable, and imputing missing values with the mode (the most frequent category) is a simple and effective method to handle missing categorical data.

In [43]:
```
# How many percentage of data is missing in each column
missing_value = pd.DataFrame({'Missing Value': df.isnull().sum(), 'Percentage':
sorted_missing_value = missing_value.sort_values(by='Percentage', ascending=Fals
sorted_missing_value
```

Out[43]:

	Missing Value	Percentage
ID	0	0.0
year	0	0.0
Region	0	0.0
LTV	0	0.0
age	0	0.0
co-applicant_credit_type	0	0.0
Credit_Score	0	0.0
credit_type	0	0.0
income	0	0.0
occupancy_type	0	0.0
property_value	0	0.0
Upfront_charges	0	0.0
rate_of_interest	0	0.0
loan_amount	0	0.0
business_or_commercial	0	0.0
loan_purpose	0	0.0
loan_type	0	0.0
Gender	0	0.0
loan_limit	0	0.0
Status	0	0.0

In [44]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 148344 entries, 0 to 148669
Data columns (total 20 columns):
 #   Column                     Non-Null Count   Dtype   
---  ------                     --------------   -----   
 0   ID                         148344 non-null  int64   
 1   year                       148344 non-null  int64   
 2   loan_limit                 148344 non-null  category
 3   Gender                     148344 non-null  category
 4   loan_type                  148344 non-null  category
 5   loan_purpose               148344 non-null  category
 6   business_or_commercial     148344 non-null  category
 7   loan_amount                148344 non-null  int64   
 8   rate_of_interest           148344 non-null  float64 
 9   Upfront_charges            148344 non-null  float64 
 10  property_value             148344 non-null  float64 
 11  occupancy_type             148344 non-null  category
 12  income                     148344 non-null  float64 
 13  credit_type                148344 non-null  category
 14  Credit_Score               148344 non-null  int64   
 15  co-applicant_credit_type   148344 non-null  category
 16  age                        148344 non-null  category
 17  LTV                        148344 non-null  float64 
 18  Region                     148344 non-null  category
 19  Status                     148344 non-null  category
dtypes: category(11), float64(5), int64(4)
memory usage: 12.9 MB
```

In [45]:
```python
df.head(5)
```

Out[45]:

	ID	year	loan_limit	Gender	loan_type	loan_purpose	business_or_commercial
0	24890	2019	cf	Sex Not Available	type1	p1	nob/c
1	24891	2019	cf	Male	type2	p1	b/c
2	24892	2019	cf	Male	type1	p1	nob/c
3	24893	2019	cf	Male	type1	p4	nob/c
4	24894	2019	cf	Joint	type1	p1	nob/c

Exploratory data analysis

Univariate Analysis

Categorical Features

In [46]:
```python
# Required colour palette
green_palette = ['#32de84', '#17B169', '#00AB66', '#008200', '#8cc751',
```

```
                  '#40a829', '#1DB954', '#1DB954', '#006241', '#40a829', '#00674b
# #367c2b, #004526
```

In [47]:
```
# Selecting the categorical columns
categorical_cols = df.select_dtypes(include='category').columns
categorical_cols
```

Out[47]:
```
Index(['loan_limit', 'Gender', 'loan_type', 'loan_purpose',
       'business_or_commercial', 'occupancy_type', 'credit_type',
       'co-applicant_credit_type', 'age', 'Region', 'Status'],
      dtype='object')
```

In [48]:
```
# Value couts for categorical columns
for elem in categorical_cols:
  print(f"Column Name: {elem}")
  print(df[elem].value_counts())
  print()
  print(round(((df[elem].value_counts(normalize=True)) * 100),2))
  print("_" * 35)
  print()
```

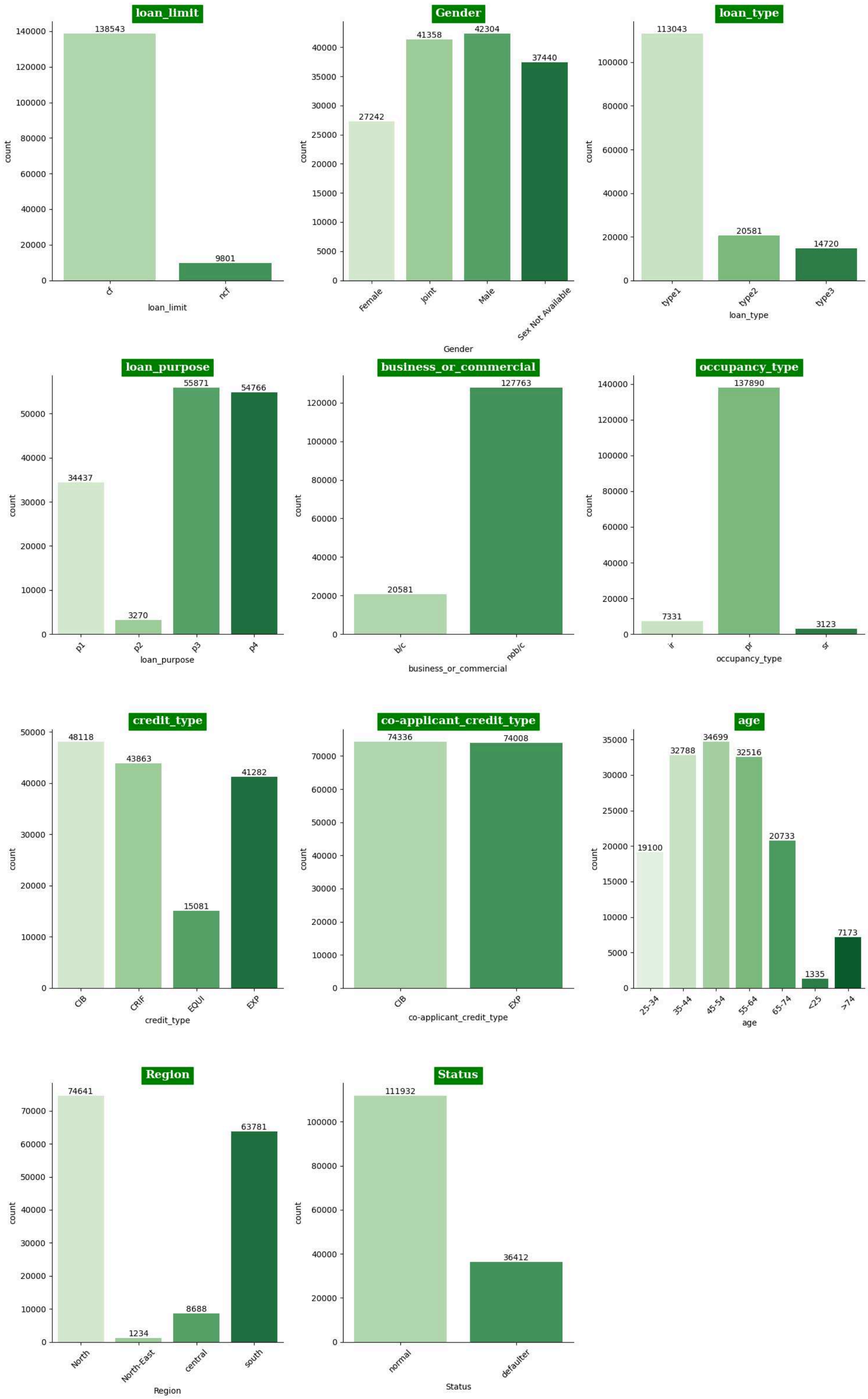
```
Column Name: loan_limit
loan_limit
cf     138543
ncf      9801
Name: count, dtype: int64

loan_limit
cf     93.39
ncf     6.61
Name: proportion, dtype: float64
___________________________________

Column Name: Gender
Gender
Male                 42304
Joint                41358
Sex Not Available    37440
Female               27242
Name: count, dtype: int64

Gender
Male                 28.52
Joint                27.88
Sex Not Available    25.24
Female               18.36
Name: proportion, dtype: float64
___________________________________

Column Name: loan_type
loan_type
type1    113043
type2     20581
type3     14720
Name: count, dtype: int64

loan_type
type1    76.20
type2    13.87
type3     9.92
Name: proportion, dtype: float64
___________________________________

Column Name: loan_purpose
loan_purpose
p3    55871
p4    54766
p1    34437
p2     3270
Name: count, dtype: int64

loan_purpose
p3    37.66
p4    36.92
p1    23.21
p2     2.20
Name: proportion, dtype: float64
___________________________________

Column Name: business_or_commercial
business_or_commercial
```

```
nob/c    127763
b/c       20581
Name: count, dtype: int64

business_or_commercial
nob/c    86.13
b/c      13.87
Name: proportion, dtype: float64
___________________________________

Column Name: occupancy_type
occupancy_type
pr    137890
ir      7331
sr      3123
Name: count, dtype: int64

occupancy_type
pr    92.95
ir     4.94
sr     2.11
Name: proportion, dtype: float64
___________________________________

Column Name: credit_type
credit_type
CIB     48118
CRIF    43863
EXP     41282
EQUI    15081
Name: count, dtype: int64

credit_type
CIB     32.44
CRIF    29.57
EXP     27.83
EQUI    10.17
Name: proportion, dtype: float64
___________________________________

Column Name: co-applicant_credit_type
co-applicant_credit_type
CIB    74336
EXP    74008
Name: count, dtype: int64

co-applicant_credit_type
CIB    50.11
EXP    49.89
Name: proportion, dtype: float64
___________________________________

Column Name: age
age
45-54    34699
35-44    32788
55-64    32516
65-74    20733
25-34    19100
>74       7173
```

```
<25       1335
Name: count, dtype: int64

age
45-54    23.39
35-44    22.10
55-64    21.92
65-74    13.98
25-34    12.88
>74       4.84
<25       0.90
Name: proportion, dtype: float64
───────────────────────────────────

Column Name: Region
Region
North         74641
south         63781
central        8688
North-East     1234
Name: count, dtype: int64

Region
North         50.32
south         43.00
central        5.86
North-East     0.83
Name: proportion, dtype: float64
───────────────────────────────────

Column Name: Status
Status
normal       111932
defaulter     36412
Name: count, dtype: int64

Status
normal       75.45
defaulter    24.55
Name: proportion, dtype: float64
───────────────────────────────────
```

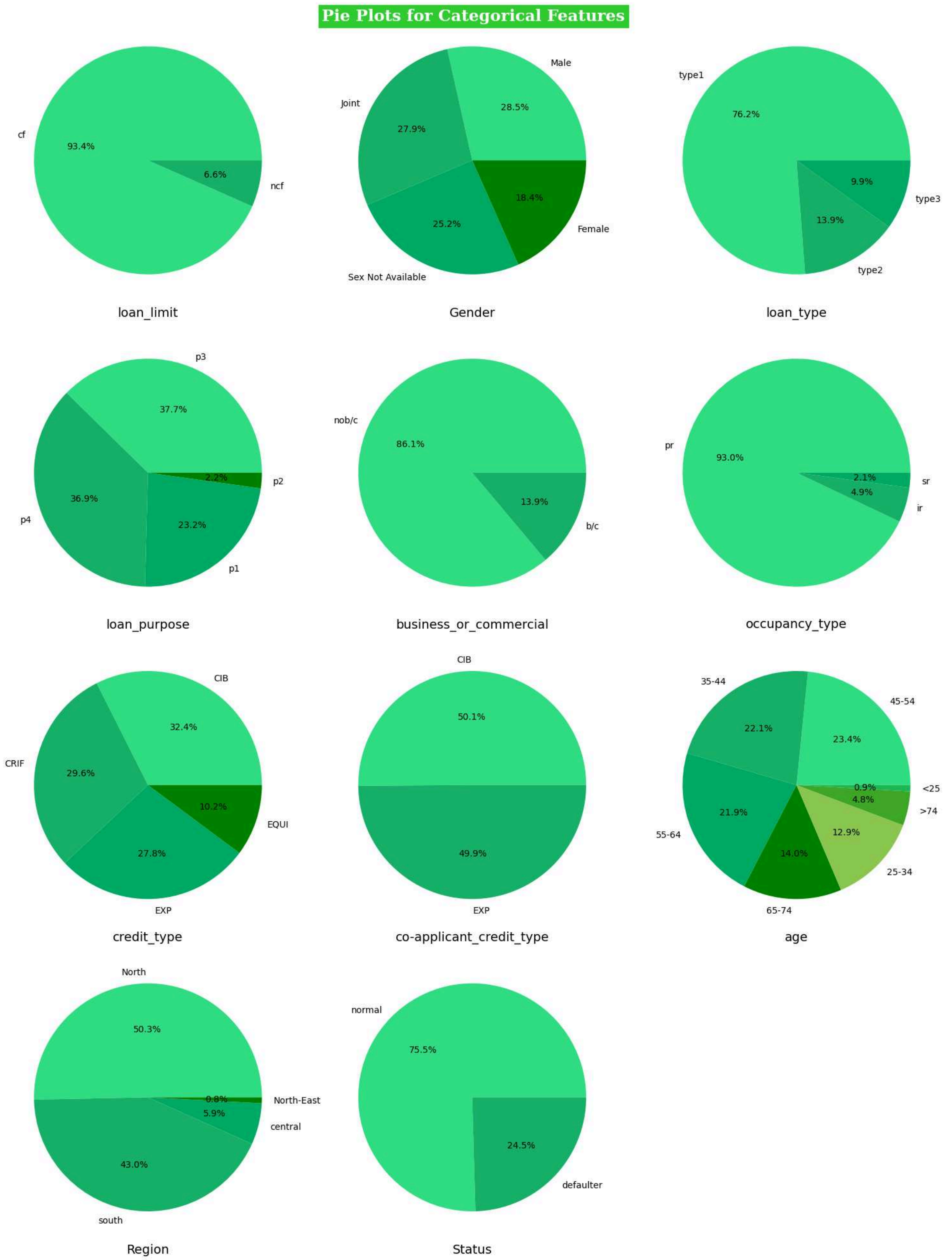
In [49]:

```
# Count Plots for Categorical features
plt.figure(figsize=(15,24))
for i, elem in enumerate(categorical_cols):
  plt.subplot(4,3,i+1)
  label = sns.countplot(data = df, x = elem, palette = 'Greens')
  for i in label.containers:
    label.bar_label(i)

  plt.xticks(rotation = 45)
  plt.ylabel('count')
  plt.title(elem, fontsize=14,fontfamily='serif',fontweight='bold',backgroundcol

#plt.suptitle("Count Plots for Categorical features", fontsize = 18)
plt.tight_layout()
sns.despine()
plt.show()
```



In [50]:
```
plt.figure(figsize=(15, 20))
for i, elem in enumerate(categorical_cols):
    plt.subplot(4, 3, i + 1)
```

```
    labels = df[elem].value_counts().index
    plt.pie(df[elem].value_counts().values, labels=labels,
            autopct="%1.1f%%", colors=green_palette)
    plt.xlabel(elem, fontsize=14)

plt.suptitle("Pie Plots for Categorical Features", fontsize=18,
             fontfamily='serif', fontweight='bold', backgroundcolor='limegreen',
plt.tight_layout()
plt.show()
```



OBSERVATION

1. **Loan Limit:**

- 93.39% of loans have a limit classified as "cf" (conforming), while 6.61% are "ncf" (non-conforming).
- The majority of loans fall under the conforming category, indicating a preference or higher eligibility for loans that meet standard criteria.

2. **Gender:**
   - Males represent 28.52%, Joint applicants 27.88%, "Sex Not Available" 25.24%, and Females 18.36%.
   - There is a near-even split between male and joint applications, with a relatively high number of cases where gender information is unavailable. Female applicants represent the smallest group.
3. **Loan Type:**
   - Type 1 dominates with 76.20%, followed by Type 2 (13.87%) and Type 3 (9.92%).
   - The vast majority of loans belong to loan type 1, showing a strong concentration in this category.
4. **Loan Purpose:**
   - Purposes p3 (37.66%) and p4 (36.92%) are nearly equal, followed by p1 (23.21%), with p2 (2.20%) being the least common.
   - The majority of loans are associated with purposes p3 and p4, indicating a focus on certain use cases for loans.
5. **Business or Commercial Use:**
   - 86.13% of loans are not for business or commercial use, while 13.87% are.
   - The data suggests that most loans are for personal or non-business purposes, with a small proportion allocated for commercial needs.
6. **Occupancy Type:**
   - Primary residences make up 92.95%, investment residences 4.94%, and secondary residences 2.11%.
   - The vast majority of loans are tied to primary residences, with investment and secondary residences making up only a small fraction.
7. **Credit Type:**
   - CIB (32.44%) and CRIF (29.57%) lead in credit type usage, followed by EXP (27.83%) and EQUI (10.17%).
   - The distribution of credit types is somewhat balanced, with CIB leading, but a significant portion of applicants also use CRIF and EXP.
8. **Co-applicant Credit Type:**
   - CIB (50.11%) and EXP (49.89%) are almost evenly split among co-applicants.
   - There is no significant preference for one credit type over the other when it comes to co-applicants.
9. **Age:**
   - The largest age group is 45-54 (23.39%), followed by 35-44 (22.10%) and 55-64 (21.92%). The under-25 age group makes up only 0.90%.
   - Most applicants fall within the middle-age range, particularly between 35 and 64. Younger and older age groups are underrepresented.
10. **Region:**
    - North leads with 50.32%, followed by South (43.00%), Central (5.86%), and North-East (0.83%).

- The majority of applicants are from the North and South regions, with very few from the Central and North-East regions.

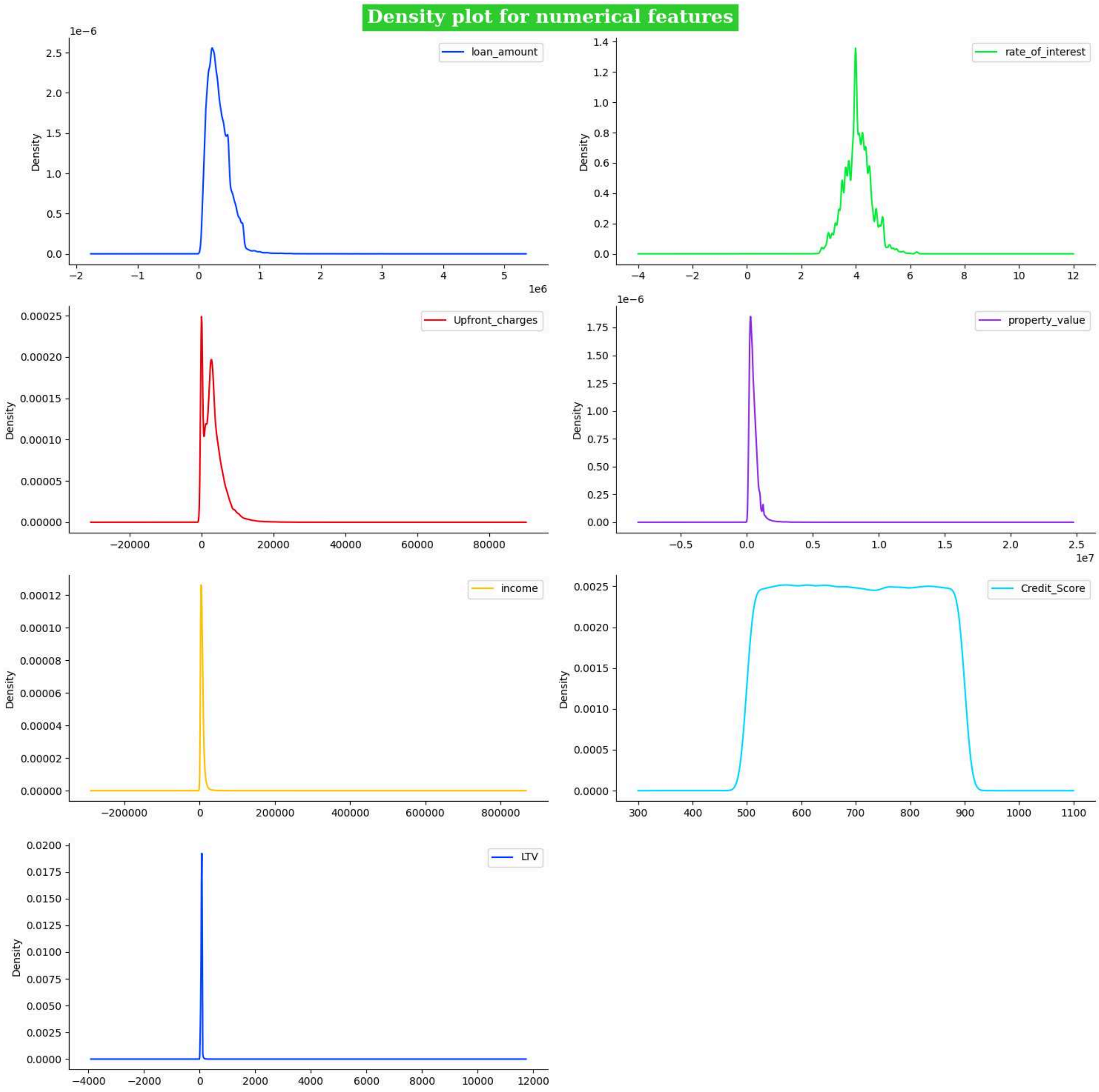
11. **Status:**
    - 75.45% of applicants are classified as "normal" (non-defaulters), while 24.55% are defaulters.
    - Most loans are in good standing, but with nearly a quarter of loans in default, there may be a need for risk mitigation strategies.

Numerical Features

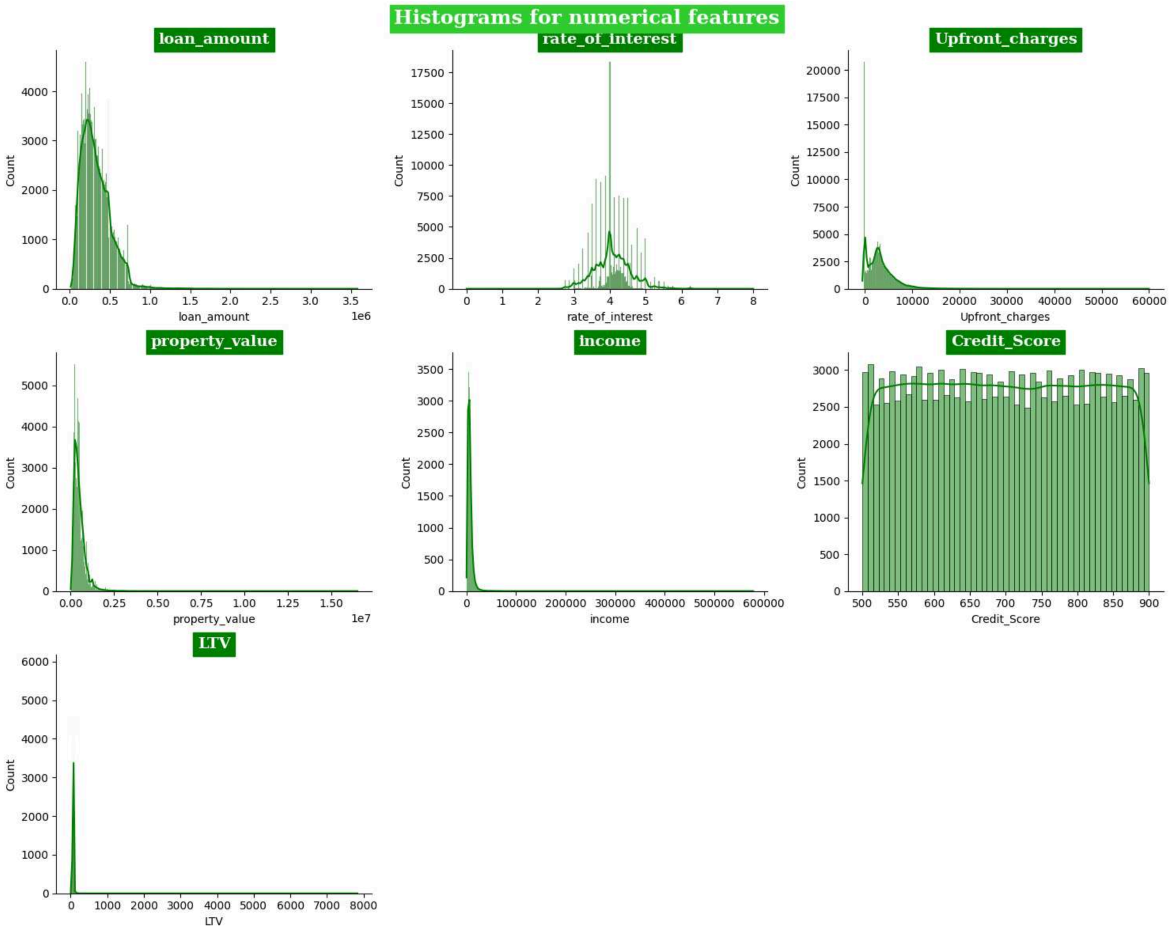
In [51]:
```
# Selecting the categorical columns
numerical_df = df.select_dtypes(include=['int64','float64'])
numerical_df_req = numerical_df[numerical_df.columns[2:]]
numerical_df_req.columns
```

Out[51]:
```
Index(['loan_amount', 'rate_of_interest', 'Upfront_charges', 'property_value',
       'income', 'Credit_Score', 'LTV'],
      dtype='object')
```

In [52]:
```
# Density plot for numerical columns
plt.rcParams["figure.figsize"] = [15,15]
numerical_df_req.plot(kind="density", subplots = True, layout = (4,2), sharex =
plt.suptitle("Density plot for numerical features", fontsize = 18,
             fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',cc
plt.tight_layout()
sns.despine()
plt.show()
```



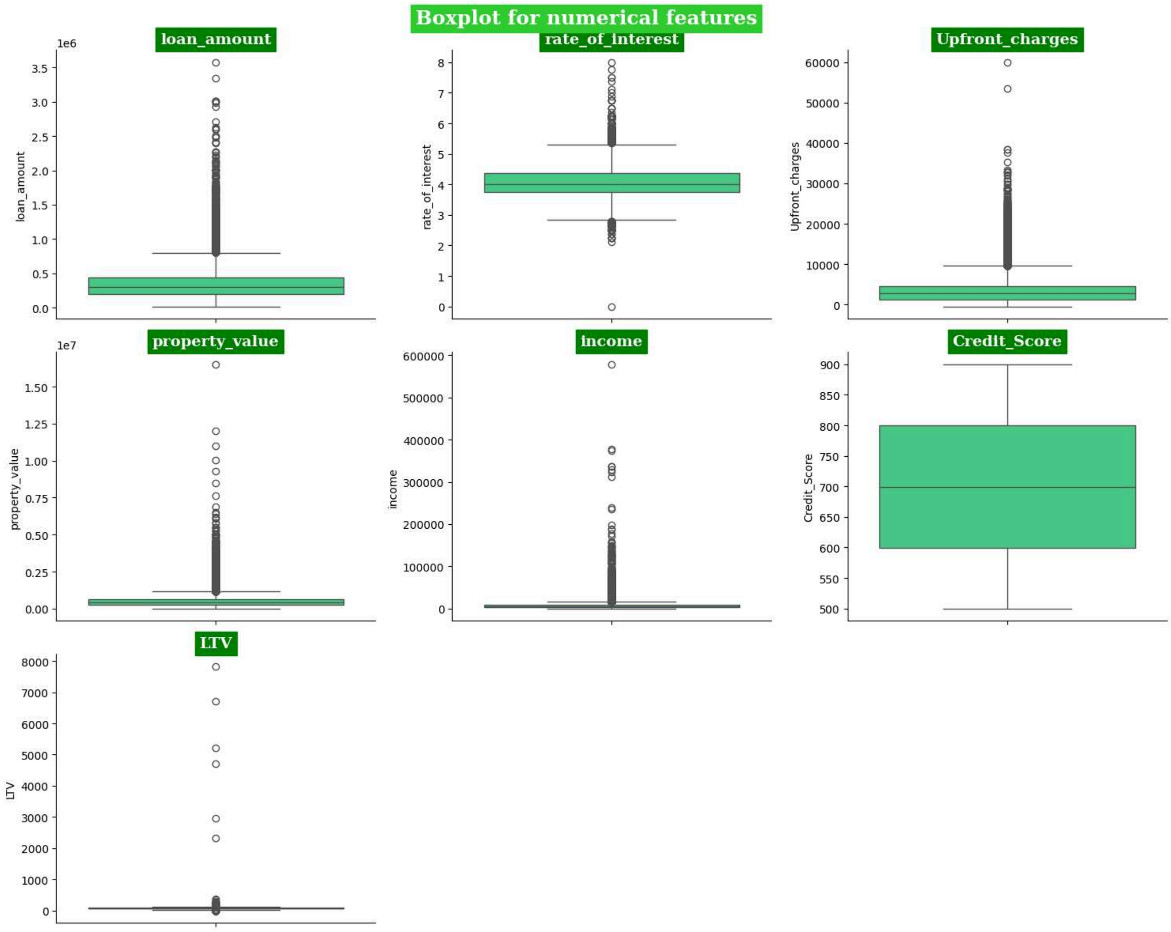
In [53]:
```
# Histograms for numerical columns
numerical_cols = numerical_df_req.columns

plt.figure(figsize=(15,12))
for i, elem in enumerate(numerical_cols):
  plt.subplot(3,3,i+1)
  sns.histplot(df[elem], kde=True, color='green')
  plt.title(elem, fontsize=14,fontfamily='serif',
            fontweight='bold',backgroundcolor='green',color='w')

plt.suptitle("Histograms for numerical features", fontsize = 18,
             fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',cc
plt.tight_layout()
sns.despine()
plt.show()
```



In [54]:
```
# Skewness Coefficient:
print("Skewness Coefficient")
print("-" * 20)
print(numerical_df_req.skew().round(2))
```

```
Skewness Coefficient
--------------------
loan_amount           1.67
rate_of_interest      0.27
Upfront_charges       1.83
property_value        4.25
income               17.58
Credit_Score          0.00
LTV                 110.53
dtype: float64
```

In [55]:
```
# Box plots for numerical columns
green = ['#32de84']

plt.figure(figsize=(15, 12))
for i, col in enumerate(numerical_cols):
    plt.subplot(3, 3, i+1)
    sns.boxplot(df[col],palette = green)
    plt.title(col, fontsize=14,fontfamily='serif',
              fontweight='bold',backgroundcolor='green',color='w')

plt.suptitle("Boxplot for numerical features", fontsize = 18,
             fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',cc
plt.tight_layout()
sns.despine()
plt.show()
```



In [56]:
```
# kurtosis co-efficient:
print("kurtosis co-efficient")
print("-" * 22)
print(numerical_df_req.kurt().round(2))
```

```
kurtosis co-efficient
----------------------
loan_amount              9.14
rate_of_interest         0.88
Upfront_charges          7.73
property_value          65.53
income                 921.50
Credit_Score            -1.20
LTV                  18399.87
dtype: float64
```

OBSERVATION

1. **Loan Amount**
    - Skewness: 1.67 (moderately skewed right)
    - Kurtosis: 9.14 (high kurtosis)
    - The loan amount distribution is positively skewed, indicating that there are more loans on the lower side of the spectrum, with fewer larger loans. The high kurtosis (9.14) suggests the presence of extreme outliers, where a small number of very large loans exist, significantly impacting the distribution.
2. **Rate of Interest**
    - Skewness: 0.30 (approximately symmetric)
    - Kurtosis: 0.87 (close to normal)

- The rate of interest is close to a normal distribution, with very little skewness and kurtosis. This means the interest rates are evenly distributed around the mean, with few outliers or extremes.

3. **Upfront Charges**
   - Skewness: 1.85 (moderately skewed right)
   - Kurtosis: 8.17 (high kurtosis)
   - Upfront charges are positively skewed, indicating a concentration of smaller upfront charges with a few large outliers. The high kurtosis shows a fat-tailed distribution, meaning there are significant outliers or extreme values that stand out in the dataset.
4. **Property Value**
   - Skewness: 4.70 (highly skewed right)
   - Kurtosis: 77.97 (extremely high kurtosis)
   - Property values are highly positively skewed, with most properties being of lower value, and a few very high-value properties pulling the distribution to the right. The extreme kurtosis (77.97) indicates that there are some exceptionally high-value properties in the dataset, creating a long tail of outliers.
5. **Income**
   - Skewness: 17.51 (extremely skewed right)
   - Kurtosis: 916.59 (extremely high kurtosis)
   - Income is extremely right-skewed, with most borrowers having low incomes, but a small number of very high-income individuals pulling the distribution to the right. The incredibly high kurtosis indicates the presence of severe outliers, with some incomes being disproportionately large compared to the rest of the dataset.
6. **Credit Score**
   - Skewness: 0.00 (no skewness)
   - Kurtosis: -1.20 (platykurtic, less peaked than a normal distribution)
   - Credit score is symmetrically distributed, indicating that scores are spread evenly across the range. The negative kurtosis suggests that the distribution is flatter than a normal distribution, with fewer extreme values and less concentration around the mean.
7. **Loan-to-Value (LTV) Ratio**
   - Skewness: 108.81 (extremely skewed right)
   - Kurtosis: 18004.85 (extremely high kurtosis)
   - The LTV ratio shows an extreme positive skewness, with most LTV ratios being low but a few extremely high LTVs pulling the distribution to the right. The almost unimaginable kurtosis (18004.85) signifies that there are a handful of exceptionally high LTV ratios (close to or exceeding 100%), which may represent high-risk loans. This could be a potential area of concern for lenders as such loans carry higher default risks.

General Insights:

- **Outliers:** The high kurtosis values in variables like loan amount, upfront charges, property value, income, and LTV suggest the presence of significant outliers, which might need further investigation.

- **Skewness:** Most of the variables are positively skewed, meaning the bulk of the data lies on the lower end of the spectrum, with extreme values stretching out to the right.

- Credit Score is the only variable with no skewness and lower kurtosis, indicating a well-distributed, stable feature.

Multivariate Analysis and Hypothesis Testing

In [57]:
```
class StatisticalAnalysis:

    def __init__(self, group_1, group_1_name, group_2, group_2_name):
        self.group_1 = group_1
        self.group_1_name = group_1_name
        self.group_2 = group_2
        self.group_2_name = group_2_name

    def normality_plots(self):
        fig, axes = plt.subplots(2, 2, figsize=(14, 8))
        plt.suptitle("Normality check",fontsize=18,fontfamily='serif',
                     fontweight='bold',backgroundcolor='green',color='w')

        # Histogram for group_1
        sns.histplot(data=self.group_1, kde=True, color='limegreen', ax=axes[0,
        axes[0, 0].set_title(f'Histogram of {self.group_1_name}',fontsize=15,
                             fontfamily='serif',fontweight='bold',backgroundcolc

        # Q-Q plot for group_1
        probplot(self.group_1, dist="norm", plot=axes[0, 1])
        axes[0, 1].set_title(f'Q-Q Plot of {self.group_1_name}',fontsize=15,
                             fontfamily='serif',fontweight='bold',backgroundcolc

        # Histogram for group_2
        sns.histplot(data=self.group_2, kde=True, color='green', ax=axes[1, 0])
        axes[1, 0].set_title(f'Histogram of {self.group_2_name}',fontsize=15,
                             fontfamily='serif',fontweight='bold',backgroundcolc

        # Q-Q plot for group_2
        probplot(self.group_2, dist="norm", plot=axes[1, 1])
        axes[1, 1].set_title(f'Q-Q Plot of {self.group_2_name}',fontsize=15,
                             fontfamily='serif',fontweight='bold',backgroundcolc

        plt.tight_layout()
        sns.despine()
        plt.show()

    def normality_tests(self):
        def perform_normality_tests(data, name):
            # Shapiro-Wilk Test
            shapiro_stat, shapiro_p_val = shapiro(data)
            shapiro_result = 'Gaussian distribution' if shapiro_p_val >= 0.05 el

            # Anderson-Darling Test
            anderson_result = anderson(data, dist='norm')
            anderson_stat = anderson_result.statistic
            anderson_critical_values = anderson_result.critical_values
```

```
            anderson_test_result = 'Not Gaussian distribution'
            for i in range(len(anderson_critical_values)):
                if anderson_stat < anderson_critical_values[i]:
                    anderson_test_result = 'Gaussian distribution'
                    break

            # Jarque-Bera Test
            jb_stat, jb_p_val = jarque_bera(data)
            jb_result = 'Gaussian distribution' if jb_p_val >= 0.05 else 'Not Ga

            # Print results
            print(f'Normality Tests for {name}:')
            print(f'- Shapiro-Wilk Test: Statistics={shapiro_stat:.4f}, p-value=
            print(f'- Anderson-Darling Test: Statistic={anderson_stat:.4f}, Crit
            print(f'- Jarque-Bera Test: Statistics={jb_stat:.4f}, p-value={jb_p_
            print()

        # Normality tests on the original groups
        perform_normality_tests(self.group_1, self.group_1_name)
        perform_normality_tests(self.group_2, self.group_2_name)

        # Box-Cox transformation (only applicable for positive data)
        try:
            transformed_group_1, _ = boxcox(self.group_1)
            transformed_group_2, _ = boxcox(self.group_2)

            print("After Box-Cox Transformation:")
            perform_normality_tests(transformed_group_1, f'Transformed {self.grc
            perform_normality_tests(transformed_group_2, f'Transformed {self.grc
        except Exception as e:
            print("Box-Cox transformation failed:", e)
            print()

    def variance_tests(self):
        # Levene's Test (tests for equal variances)
        levene_stat, levene_p = levene(self.group_1, self.group_2)
        print(f"Levene's Test for {self.group_1_name} and {self.group_2_name}:")
        print(f'- Statistic: {levene_stat:.4f}, p-value: {levene_p:.4f}')
        if levene_p < 0.05:
            print(f"Variances of {self.group_1_name} and {self.group_2_name} are
        else:
            print(f"Variances of {self.group_1_name} and {self.group_2_name} are

        # Bartlett's Test (tests for equal variances)
        bartlett_stat, bartlett_p = bartlett(self.group_1, self.group_2)
        print(f"Bartlett's Test for {self.group_1_name} and {self.group_2_name}:
        print(f'- Statistic: {bartlett_stat:.4f}, p-value: {bartlett_p:.4f}')
        if bartlett_p < 0.05:
            print(f"Variances of {self.group_1_name} and {self.group_2_name} are
        else:
            print(f"Variances of {self.group_1_name} and {self.group_2_name} are


# analysis = StatisticalAnalysis(group_1, "Group 1", group_2, "Group 2")
# analysis.normality_plots()  # Plot histograms and Q-Q plots
# analysis.normality_tests()  # Perform normality tests
# analysis.variance_tests()   # Perform variance tests
```

In [58]:
```
# Function for Chi_Square Test
from scipy.stats import chi2_contingency
```

```
def ht_Chi_Square(column, alpha = 0.05):
  # Assumption:
  '''
  # Ho: (Independent) Columns are not Dependent
  # Ha: (Dependent) Columns are Dependent

  Chi-square independence test
  '''
  observed = pd.crosstab(index=df[column], columns=df["Status"]).values
  # Calculate Stastistics and p-value:
  chi_stat, p_value, dof, exp_freq = chi2_contingency(observed)

  # Conclusion:
  #alpha = 0.05
  if p_value < alpha:
      decision = "Reject the null hypothesis"
  else:
      decision = "Fail to reject the null hypothesis"

  if decision == "Reject the null hypothesis":
      conclusion = f"{column} and Status are Dependent"
  else:
      conclusion = f"{column} and Status are not Dependent"

  # Print the results
  print(f"CONCLUSION: {conclusion}")
  return None
```

In [59]:

```
# Function for Fisher_exact Test
from scipy.stats import fisher_exact

def ht_fisher_exact(column, alpha=0.05):
    # Assumption:
    '''
    # Ho: (Independent) Columns are not Dependent
    # Ha: (Dependent) Columns are Dependent

    Fisher's Exact Test for independence
    '''
    # Create a contingency table
    observed = pd.crosstab(index=df[column], columns=df["Status"])

    # Check if the contingency table is suitable for Fisher's Exact Test
    if observed.shape[0] < 2 or observed.shape[1] < 2:
        print("Fisher's Exact Test is not applicable for this table.")
        return None

    # If the table is not 2x2, you can either:
    # 1. Combine categories, or
    # 2. Just take the first two categories for testing.
    if observed.shape[0] > 2:
        # Example: Combine all but the first two categories
        combined = observed.iloc[:2].copy()
        combined.loc['Combined'] = observed.iloc[2:].sum()
        observed = combined

    if observed.shape[0] > 2 or observed.shape[1] > 2:
        print("Resulting contingency table must be 2x2 for Fisher's Exact Test."
        return None
```

```
    # Calculate the statistics and p-value:
    odds_ratio, p_value = fisher_exact(observed)

    # Conclusion:
    # alpha = 0.05
    if p_value < alpha:
        decision = "Reject the null hypothesis"
    else:
        decision = "Fail to reject the null hypothesis"

    if decision == "Reject the null hypothesis":
        conclusion = f"{column} and Status are Dependent"
    else:
        conclusion = f"{column} and Status are not Dependent"

    # Print the results
    print(f"CONCLUSION: {conclusion}")
    #print(f"P-value: {p_value}, Odds Ratio: {odds_ratio}")
    return None
```

In [60]:

```
# Function for Mann-Whitney U test
from scipy.stats import mannwhitneyu

def mannwhitneyu_u_test(group_1, group_1_name, group_2, group_2_name, alternativ
    # Formulate Hypotheses two-sided
    # H0: The mean of two groups are equal
    # H1: The mean of two groups are different

    # Formulate Hypotheses greater
    # H0: There is no difference (in terms of central tendency) between two grou
    # H1: The central tendency of group_1 is greater than group_2

    # Formulate Hypotheses less
    # H0: There is no difference (in terms of central tendency) between two grou
    # H1: The central tendency of group_1 is less than group_2

    # Choose the significance level
    alpha = 0.05

    # Perform Mann-Whitney U test
    test_stat, p_value = mannwhitneyu(group_1, group_2, alternative=alternative)

    print(f"Mann-Whitney U test: ({alternative})")
    if alternative == 'two-sided':
        if p_value < alpha:
            print(f'There is a difference (with respect to the central tendency)
        else:
            print(f'There is no difference (in terms of central tendency) betwee

    elif alternative == 'greater':
        if p_value < alpha:
            print(f'The central tendency of {group_1_name} is greater than {grou
        else:
            print(f'There is no difference (in terms of central tendency) betwee

    elif alternative == 'less':
        if p_value < alpha:
            print(f'The central tendency of {group_1_name} is less than {group_2
        else:
```

```
            print(f'There is no difference (in terms of central tendency) betwee

    return None
```

In [61]:
```
# Function for single bar plot:
def single_bar_chart(column, dodge=True):
  label = sns.countplot(data=df, x=column, hue='Status', palette = 'Greens', doc
  for i in label.containers:
    label.bar_label(i)
  #plt.xticks(rotation=45)
  plt.title(f"{column} vs. Status",fontsize = 15,fontfamily='serif',fontweight='
  sns.despine()
  plt.show()
  return None
```

Hypothesis Testing

Categorical Features

LTV_range Vs Status

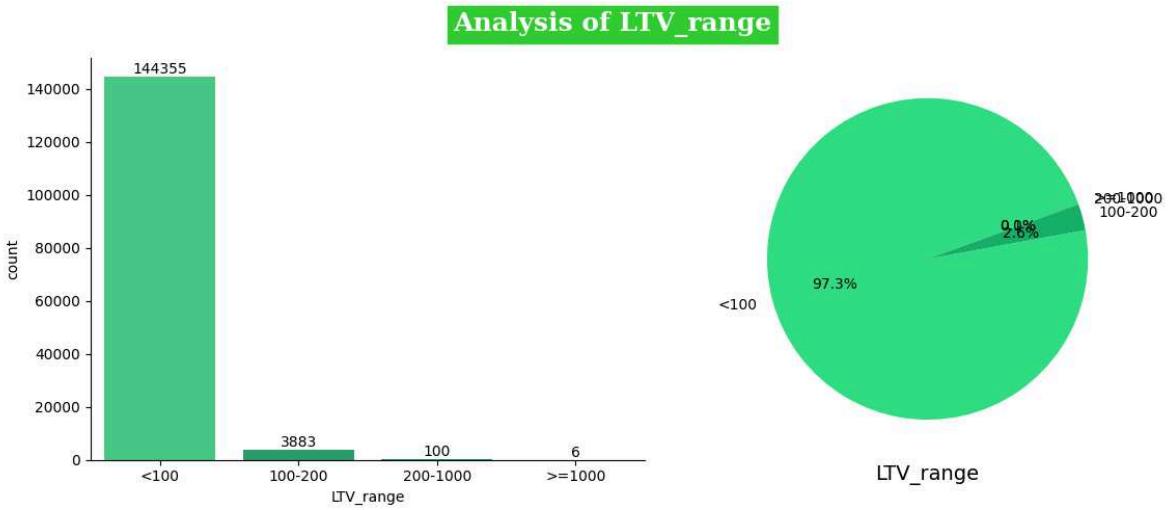
In [62]:
```
# Define the bin edges and corresponding labels
ltv_bins = [-float('inf'), 100, 200, 1000, float('inf')]  # Bin edges
ltv_ranges = ['<100', '100-200', '200-1000', '>=1000']    # Bin labels

# Create a new column 'LTV_range' by binning 'LTV' values into the specified ran
df['LTV_range'] = pd.cut(df['LTV'], bins=ltv_bins, labels=ltv_ranges, right=Fals
```

In [63]:
```
df['LTV_range'].value_counts()
```

Out[63]:
```
LTV_range
<100        144355
100-200       3883
200-1000       100
>=1000           6
Name: count, dtype: int64
```

In [64]:
```
# Analysis of income_category
req_palette = ['#32de84', '#008200']

plt.figure(figsize=(12, 5))

plt.subplot(121)
label = sns.countplot(data=df, x='LTV_range', palette=green_palette)
for i in label.containers:
  label.bar_label(i)
#plt.title("income_category")

plt.subplot(122)
labels = df.groupby('LTV_range')['LTV_range'].count().index.categories
plt.pie(df.groupby('LTV_range')['LTV_range'].count().values, labels = labels,
        autopct = "%1.1f%%", colors=green_palette,startangle=20)
plt.xlabel('LTV_range', fontsize=14)
#plt.title("income_category")

plt.suptitle("Analysis of LTV_range", fontsize = 18,fontfamily='serif',
             fontweight='bold',backgroundcolor='limegreen',color='w')
```

```
plt.tight_layout()
sns.despine()
plt.show()
```



OBSERVATION

Distribution of LTV Range:

- (<100): The majority of loans (143,226 loans) have an LTV ratio of less than 100%, indicating that borrowers generally have more equity in the property than the loan amount.
- (100-200): A small portion (4,992 loans) falls into the 100-200% LTV range, where the loan amount exceeds the property value, indicating higher risk.
- (200-1000): Only 120 loans have an LTV in the range of 200-1000%, signifying extreme cases where the loan amount is significantly higher than the property value.
- (>=1000): Very few loans (6 loans) have an LTV ratio greater than 1000%, which is a rare and extremely high-risk situation.

HT: Chi-Square Test of Independence

In [65]:
```
pd.crosstab(index=df['LTV_range'], columns=df["Status"])
```

Out[65]:

Status	normal	defaulter
LTV_range		
<100	111305	33050
100-200	621	3262
200-1000	1	99
>=1000	5	1

Issues Identified:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more. In your case, the LTV ranges "200-1000" and ">=1000" may have expected frequencies that are too low.

- **Fisher's Exact Test:** This test requires a 2x2 contingency table, which is not applicable here since your table has more than 2 categories for LTV_range.

Recommended Approach:

Since the Chi-Square test may not be valid due to low expected frequencies, and Fisher's Exact Test cannot be applied, consider the following steps:

Combine Categories

- Combine some of the LTV ranges into broader categories to ensure that each category has sufficient observations. For example:
- Combine 200-1000, and >=1000 into a single category called High LTV or simply >=200.

In [66]:
```
# Combain 200-1000, and >=1000
observed = pd.crosstab(index=df['LTV_range'], columns=df["Status"])
combined = observed.iloc[:2].copy()
combined.loc['Combined'] = observed.iloc[2:].sum()
observed = combined
observed
```

Out[66]:

Status LTV_range	normal	defaulter
<100	111305	33050
100-200	621	3262
Combined	6	100

In [67]:
```
# Assumption:
'''
# Ho: (Independent) Columns are not Dependent
# Ha: (Dependent) Columns are Dependent

Chi-square independence test
'''
# Calculate Stastistics and p-value:
chi_stat, p_value, dof, exp_freq = chi2_contingency(observed)

# Conclusion:
alpha = 0.05
if p_value < alpha:
    decision = "Reject the null hypothesis"
else:
    decision = "Fail to reject the null hypothesis"

if decision == "Reject the null hypothesis":
    conclusion = "LTV_range and Status are Dependent"
else:
    conclusion = "LTV_range and Status are not Dependent"
```

```
# Print the results
print(f"CONCLUSION: {conclusion}")
```

```
CONCLUSION: LTV_range and Status are Dependent
```

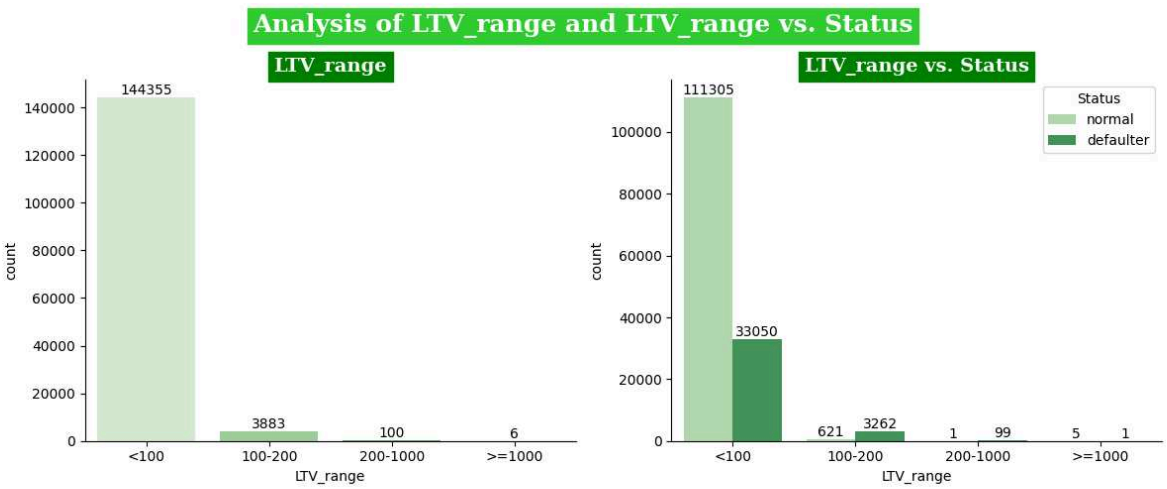
OBSERVATION

- The result of the Chi-Square test indicates that there is a statistically significant relationship between the Loan-to-Value (LTV) range and the loan status (normal vs. defaulter). This suggests that the likelihood of default is influenced by the LTV range of the loans.

Analysis

In [68]:

```
# Analysis of LTV_range and LTV_range vs. Status
req_palette = ['#32de84', '#008200']

plt.figure(figsize=(12, 5))

plt.subplot(121)
label = sns.countplot(data=df, x='LTV_range',palette='Greens')
for i in label.containers:
  label.bar_label(i)
plt.title("LTV_range",fontsize=14,fontfamily='serif',
          fontweight='bold',backgroundcolor='green',color='w')

plt.subplot(122)
label = sns.countplot(data=df, x='LTV_range',hue='Status', palette='Greens')
for i in label.containers:
  label.bar_label(i)
plt.title("LTV_range vs. Status",fontsize=14,fontfamily='serif',
          fontweight='bold',backgroundcolor='green',color='w')

plt.suptitle("Analysis of LTV_range and LTV_range vs. Status", fontsize = 18,
             fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',cc
plt.tight_layout()
sns.despine()
plt.show()
```



OBSERVATION

LTV Distribution Based on Loan Status (Normal vs Defaulter):

1. **<100 LTV Range:**

   - Normal: 111,306 loans are in "normal" status.
   - Defaulter: 31,920 loans are in default status.
   - Although most loans with LTV < 100 are performing well, a notable 22% of them (31,920) are in default. This suggests that even loans with sufficient equity (LTV < 100) can face default risks, perhaps due to other factors like borrower income, economic conditions, etc.
2. **100-200 LTV Range:**

   - Normal: 620 loans are performing normally.
   - Defaulter: 4,372 loans are in default.
   - A significant majority (87.6%) of loans in the 100-200% LTV range are in default, indicating that loans where the borrower owes more than the property value (LTV > 100) are highly likely to default. This is a key risk area for lenders.
3. **200-1000 LTV Range:**

   - Normal: Only 1 loan is performing normally.
   - Defaulter: 119 loans are in default.
   - Almost all loans with LTV between 200 and 1000% are in default (99.17%), showing that excessively high LTV ratios lead to an extremely high risk of default. Borrowers in this range are clearly overleveraged, and the loans are unsustainable.
4. **>=1000 LTV Range:**

   - Normal: 5 loans are performing normally.
   - Defaulter: 1 loan is in default.
   - While this range is rare, the fact that 5 out of 6 loans are still performing normally is surprising. However, given the extremely high LTV, these loans pose a very high risk of future default.

Key Insights and Observations:

1. **LTV < 100 is Relatively Safe but Not Risk-Free:**

   - The majority of loans with LTV < 100 are performing well, but a significant portion (22%) is in default. This suggests that low LTV alone is not sufficient to guarantee loan performance, and other factors (e.g., borrower income, credit score) also play a role in default risk.
2. **LTV > 100 is a Red Flag:**

   - As LTV increases above 100, the risk of default skyrockets. Specifically.
   - 87.6% of loans with LTV between 100 and 200 are in default.
   - Almost 100% of loans with LTV between 200 and 1000 are in default.
   - This shows that when the loan amount exceeds the property value, borrowers are significantly more likely to default, making these high LTV loans extremely risky for lenders.
3. **Extreme LTVs (>1000):**

- Though rare, LTVs over 1000 represent an exceptional risk. It's notable that 5 out of 6 of these loans are still performing, but this situation is unsustainable, and these loans are likely at high risk of future default.

Insights:

- Lenders should be cautious in approving loans where LTV exceeds 100, as these loans are prone to default. Special attention should be given to loans with LTV > 200, as they are almost guaranteed to default.
- Implementing stricter lending criteria and focusing on other factors such as income, credit score, and property value for high-LTV loans could help mitigate risks.

In [69]:
```
# Details about the people with Extreamly high LTV
Extrem_LTV = df[df['LTV_range'] == '>=1000']
Extrem_LTV
```

Out[69]:

	ID	year	loan_limit	Gender	loan_type	loan_purpose	business_or_comme
16951	41841	2019	ncf	Joint	type2	p4	
46287	71177	2019	cf	Joint	type2	p4	
47807	72697	2019	cf	Joint	type2	p4	
55286	80176	2019	cf	Joint	type2	p4	
65238	90128	2019	cf	Joint	type2	p4	
123343	148233	2019	cf	Female	type2	p4	

In [70]:
```
# Display the statistical summary for Extreamly high LTV
print("Statistical summary:")
print("-" * 20)
Extrem_LTV.describe().T
```

```
Statistical summary:
--------------------
```

Out[70]:

	count	mean	std	min	25%	
ID	6.0	84042.000000	35348.582670	41841.00000	71557.00000	76
year	6.0	2019.000000	0.000000	2019.00000	2019.00000	2
loan_amount	6.0	396500.000000	169115.345253	186500.00000	271500.00000	396.
rate_of_interest	6.0	3.854934	0.258642	3.50000	3.75000	
Upfront_charges	6.0	124.546159	305.074539	0.00000	0.00000	
property_value	6.0	8000.000000	0.000000	8000.00000	8000.00000	8
income	6.0	2567.863719	321.615428	1918.89408	2630.33501	2
Credit_Score	6.0	654.166667	113.256199	522.00000	576.00000	
LTV	6.0	4956.250000	2113.941816	2331.25000	3393.75000	4

OBSERVATION

- **High Risk of Default:** Loans with LTV ratios above 1000% are highly overleveraged. Borrowers are far more likely to default due to the large discrepancy between the loan amount and property value, compounded by their relatively low income.
- **Inconsistent Application of Upfront Charges:** The absence of upfront charges for most loans in this group may have been an incentive for borrowers, but it also suggests that the loans were not structured to offset the inherent risk of high LTV.
- **Potential Mismatch in Loan Approval:** Despite the high LTV risk, some borrowers in this group have decent credit scores (up to 826), suggesting that the approval criteria were not strict enough regarding the LTV threshold.
- **Risk Mitigation:** This subset of loans poses an extreme risk to lenders, and these types of loans should be closely monitored or avoided in the future to prevent substantial financial losses.

Credit_types vs. Status

In [71]:
```
pd.crosstab(index=df['credit_type'], columns=df["Status"])
```

Out[71]:

Status	normal	defaulter
credit_type		
CIB	40510	7608
CRIF	36741	7122
EQUI	1	15080
EXP	34680	6602

Approach:

Categorical data that does not meet the assumptions required for Chi-Square tests or Fisher's Exact Test, or where combining categories isn't feasible, we can go for graphical analysis

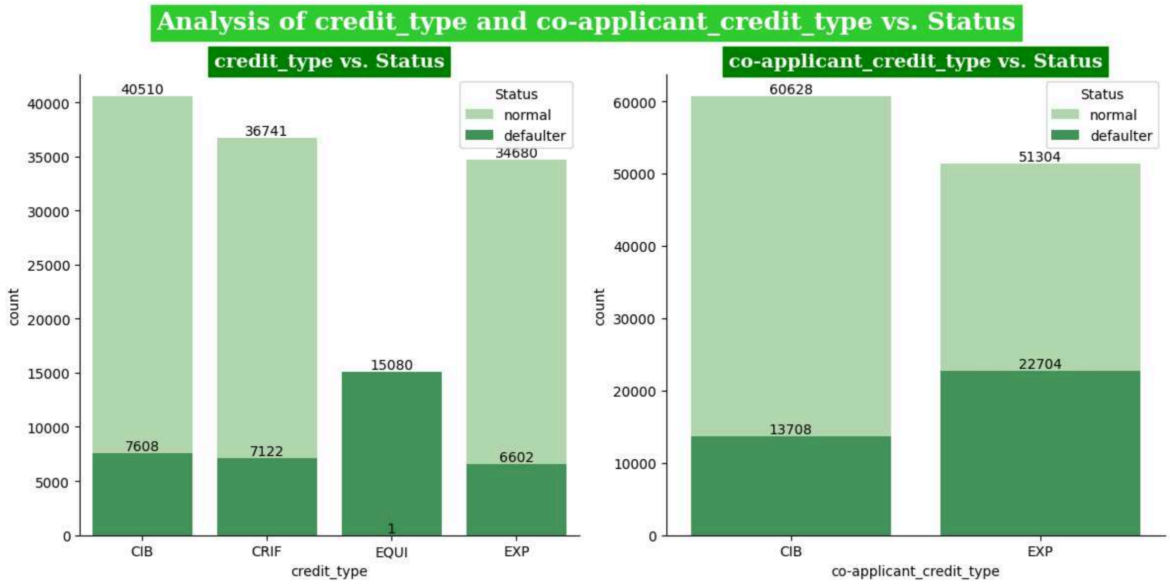
In [72]:
```
# Analysis of credit_type vs. Status
df.groupby(['credit_type', 'Status'])['ID'].count()
```

Out[72]:
```
credit_type  Status
CIB          normal       40510
             defaulter     7608
CRIF         normal       36741
             defaulter     7122
EQUI         normal           1
             defaulter    15080
EXP          normal       34680
             defaulter     6602
Name: ID, dtype: int64
```

In [73]:
```
# Analysis of co-applicant_credit_type vs. Ststus
df.groupby(['co-applicant_credit_type', 'Status'])['ID'].count()
```

Out[73]:
```
co-applicant_credit_type  Status
CIB                       normal       60628
                          defaulter    13708
EXP                       normal       51304
                          defaulter    22704
Name: ID, dtype: int64
```

In [74]:
```
# Analysis of credit_type and co-applicant_credit_type vs. Status
plt.figure(figsize=(12, 6))

plt.subplot(121)
label = sns.countplot(data=df, x='credit_type',hue='Status', palette = 'Greens',
for i in label.containers:
  label.bar_label(i)
plt.title("credit_type vs. Status",fontsize=14,fontfamily='serif',fontweight='bc

plt.subplot(122)
label = sns.countplot(data=df, x='co-applicant_credit_type',hue='Status', palett
for i in label.containers:
  label.bar_label(i)
plt.title("co-applicant_credit_type vs. Status",fontsize=14,fontfamily='serif',
          fontweight='bold',backgroundcolor='green',color='w')

plt.suptitle("Analysis of credit_type and co-applicant_credit_type vs. Status",
             fontfamily='serif', fontweight='bold',backgroundcolor='limegreen',c
plt.tight_layout()
sns.despine()
plt.show()
```



OBSERVATION

Credit Type vs. Loan Status:

1. **CIB Credit Type:**
   - Out of 48,118 borrowers with CIB credit type, 40,510 (84.15%) have a "normal" status, while 7,608 (15.80%) are defaulters.
   - CIB credit type has a relatively strong track record with the lowest default rate among credit types.
2. **CRIF Credit Type:**
   - Out of 43,863 borrowers with CRIF credit type, 36,741 (83.75%) are in "normal" status, and 7,122 (16.25%) are defaulters.
   - The performance of CRIF credit type is very similar to CIB, with a moderate default rate.
3. **EQUI Credit Type:**
   - The EQUI credit type has only 1 normal borrower and 15,080 defaulters. This extreme disparity suggests that EQUI credit is predominantly linked to defaults.
   - EQUI credit type exhibits the highest default rate and poses a significant risk to lenders, indicating poor lending quality.
4. **EXP Credit Type:**
   - Out of 41,282 borrowers with EXP credit type, 34,680 (83.98%) are normal borrowers, and 6,602 (16.00%) are defaulters.
   - EXP credit type has a solid proportion of normal borrowers, indicating a fairly healthy lending pattern similar to CIB and CRIF.

Co-Applicant Credit Type vs. Loan Status:

1. **CIB Co-Applicant Credit Type:**
   - Out of 74,336 borrowers with CIB as the co-applicant credit type, 60,628 (81.56%) have a "normal" status, while 13,708 (18.44%) are defaulters.

- Loans with CIB as the co-applicant credit type show a good proportion of normal status, although slightly higher default risk compared to primary credit types.

2. **EXP Co-Applicant Credit Type:**

    - Out of 74,008 borrowers with EXP as the co-applicant credit type, 51,304 (69.31%) are in "normal" status, while 22,704 (30.69%) are defaulters.
    - Loans with EXP as the co-applicant credit type have a significantly higher default rate, suggesting co-applicants with EXP credit may represent a higher risk.

Recommendations:

- Tighten lending criteria for EQUI credit types to mitigate the overwhelming risk of defaults.

- Strengthen co-applicant assessments, especially when EXP is the co-applicant credit type, as this significantly increases the likelihood of default.

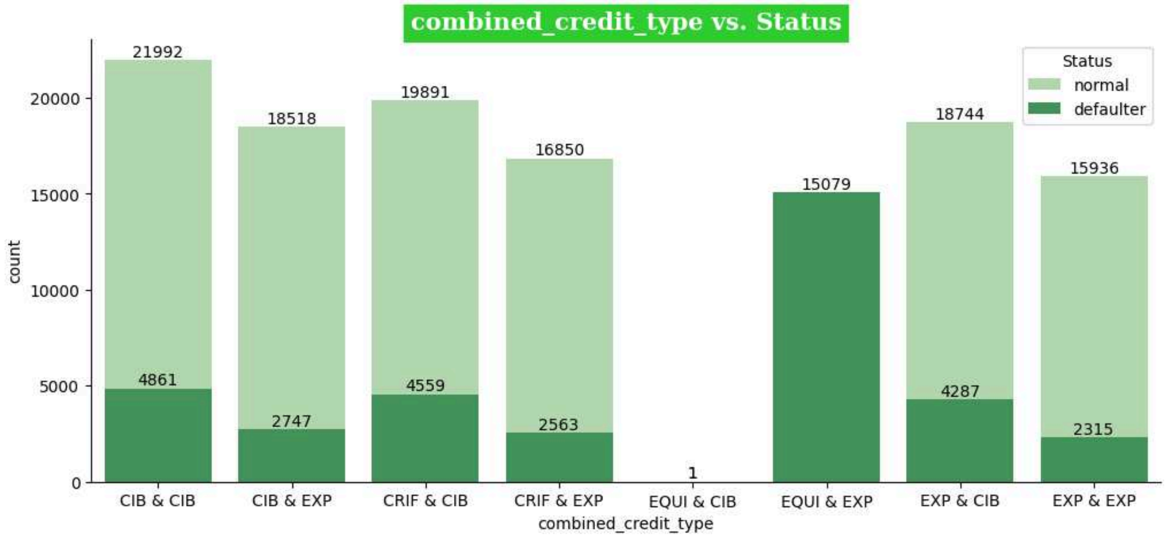
- Monitor CIB and CRIF closely, as these credit types maintain a healthy balance of risk but still contribute to defaulters in some cases.

In [75]:
```
# Analysis of combined_credit_type vs. Status
df.groupby(['credit_type', 'co-applicant_credit_type', 'Status'])['ID'].count()
```

Out[75]:
```
credit_type  co-applicant_credit_type  Status   
CIB          CIB                       normal       21992
                                       defaulter     4861
             EXP                       normal       18518
                                       defaulter     2747
CRIF         CIB                       normal       19891
                                       defaulter     4559
             EXP                       normal       16850
                                       defaulter     2563
EQUI         CIB                       normal           1
                                       defaulter        1
             EXP                       normal           0
                                       defaulter    15079
EXP          CIB                       normal       18744
                                       defaulter     4287
             EXP                       normal       15936
                                       defaulter     2315
Name: ID, dtype: int64
```

In [76]:
```
# Combine the credit_type and co-applicant_credit_type
df['combined_credit_type'] = df['credit_type'].astype(str) + ' & ' + df['co-appl
df['combined_credit_type'] = df['combined_credit_type'].astype('category')
```

In [77]:
```
# Analysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('combined_credit_type', dodge=False)
```



OBSERVATION

1. **CIB as Credit Type:**
    - **CIB Co-Applicant Credit Type:**
        - Out of 26,853 loans where both the credit type and co-applicant credit type are CIB, 21,992 (81.91%) are "normal," while 4,861 (18.09%) are "defaulter."
        - Observation: When both the borrower and co-applicant have CIB as their credit type, the default rate is moderate (18.09%), but overall, this combination appears to be relatively reliable.
    - **EXP Co-Applicant Credit Type:**
        - Out of 21,265 loans where the credit type is CIB and co-applicant credit type is EXP, 18,518 (87.09%) are "normal," while 2,747 (12.91%) are "defaulter."
        - Observation: The combination of CIB (primary credit type) and EXP (co-applicant) shows a higher success rate with a lower default percentage (12.91%) than the CIB-CIB combination.
2. **CRIF as Credit Type:**
    - **CIB Co-Applicant Credit Type:**
        - For 24,450 loans where CRIF is the credit type and CIB is the co-applicant credit type, 19,891 (81.36%) are "normal," while 4,559 (18.64%) are defaulters.
        - Observation: The CRIF-CIB combination mirrors the reliability of the CIB-CIB combination, indicating that CIB as a co-applicant continues to help reduce the likelihood of defaults.
    - **EXP Co-Applicant Credit Type:**
        - In 19,413 loans where CRIF is the credit type and EXP is the co-applicant credit type, 16,850 (86.83%) are normal borrowers, while 2,563 (13.17%) are defaulters.

- Observation: The CRIF-EXP combination behaves similarly to the CIB-EXP combination, showing a higher success rate and lower default percentage compared to other pairings.

3. **EQUI as Credit Type:**

   - **CIB Co-Applicant Credit Type:**

     - There are only 2 loans where EQUI is the credit type and CIB is the co-applicant. Of these, one is "normal" and one is a "defaulter."
     - Observation: Due to the extremely small sample size, no significant conclusions can be drawn, but this highlights the rarity of this combination.

   - **EXP Co-Applicant Credit Type:**

     - In the case of EQUI as the credit type and EXP as the co-applicant credit type, all 15,079 loans are in default.
     - Observation: This combination shows 100% default, indicating that loans with EQUI as the credit type and EXP as the co-applicant are extremely high-risk, and such combinations should be avoided entirely in lending decisions.

4. **EXP as Credit Type:**

   - **CIB Co-Applicant Credit Type:**

     - For 23,031 loans where EXP is the credit type and CIB is the co-applicant credit type, 18,744 (81.38%) are normal borrowers, while 4,287 (18.61%) are defaulters.
     - Observation: This pairing shows a similar default rate (18.61%) to other CIB-related combinations, indicating that CIB as a co-applicant is generally beneficial in reducing default risk.

   - **EXP Co-Applicant Credit Type:**

     - Out of 18,251 loans where both the credit type and co-applicant credit type are EXP, 15,936 (87.14%) are normal, and 2,315 (12.86%) are defaulters.
     - Observation: Interestingly, the EXP-EXP combination has a high proportion of "normal" loans and performs better than expected, with only 12.86% defaults.

Overall Insights:

1. **CIB as Co-Applicant:**

   - CIB as a co-applicant credit type consistently reduces the default rate, making it a more reliable choice across different primary credit types (CIB, CRIF, EXP).

2. **EXP as Co-Applicant:**

   - In most cases, EXP as a co-applicant results in a higher success rate, showing lower default rates compared to other combinations.

3. **EQUI as a Credit Type:**

- EQUI is highly risky, especially when paired with EXP as the co-applicant credit type, which leads to 100% default rates. This combination should be avoided.

4. **EXP as Both Credit Type and Co-Applicant:**

    - The combination of EXP as both credit type and co-applicant performs surprisingly well, with a low default rate (12.86%). This shows that EXP credit type can be reliable when both borrower and co-applicant have the same credit type.

Recommendations:

- Avoid lending to borrowers with EQUI credit type, especially when paired with EXP as the co-applicant credit type, as this combination has an extremely high default risk.
- CIB as a co-applicant remains a strong choice to mitigate default risk across multiple credit types.
- EXP as a credit type, even when paired with an EXP co-applicant, has a reasonable performance, making it a viable option in lower-risk scenarios.

Region vs. Status

HT: Chi-Square Test of Independence

In [78]:
```
pd.crosstab(index=df['Region'], columns=df["Status"])
```

Out[78]:

Status Region	normal	defaulter
North	57835	16806
North-East	858	376
central	6298	2390
south	46941	16840

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [79]:
```
# Function calling
ht_Chi_Square('Region')
```

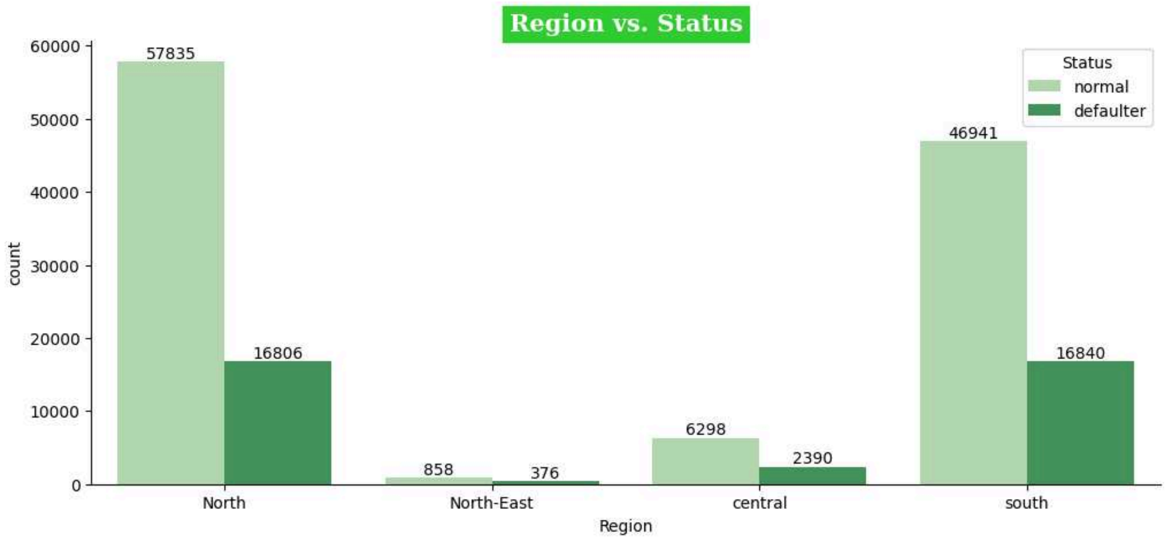
```
CONCLUSION: Region and Status are Dependent
```

OBSERVATION

- The result of the Chi-Square test indicates that there is a statistically significant relationship between the Region and the loan status (normal vs. defaulter). This suggests that the likelihood of normal or default is influenced by the region.

Analysis

In [80]:
```
# Anslysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('Region', dodge=True)
```



OBSERVATION

1. **North Region:**
   - 57,835 loans are "normal" (77.48%), while 16,806 (22.52%) are "defaulter."
   - Observation: The North region has the highest total number of loans and a relatively high proportion of normal borrowers.
2. **North-East Region:**
   - 858 loans are "normal" (69.53%), and 376 (30.47%) are "defaulter."
   - Observation: The North-East region has the smallest number of loans but a higher proportion of defaulters compared to other regions, indicating higher credit risk.
3. **Central Region:**
   - 6,298 loans are "normal" (72.49%), and 2,390 (27.51%) are "defaulter."
   - Observation: The Central region has a moderate default rate, but defaulters account for more than a quarter of all loans, showing some level of credit risk.
4. **South Region:**
   - 46,941 loans are "normal" (73.59%), while 16,840 (26.41%) are "defaulter."
   - Observation: The South region has a substantial number of loans, with a default rate similar to the Central region but much higher in absolute numbers.

Key Insights:

1. North Region shows a strong performance with the highest number of "normal" loans and a relatively lower default rate.

2. North-East Region is the highest-risk area, with nearly a third of loans in default despite having the smallest number of loans.
3. South Region has the second-highest number of loans but a significant portion of defaulters, making it a region with relatively high credit risk.
4. Central Region has a higher-than-average default rate, but the total number of loans is smaller compared to the North and South regions.

Recommendations

1. **Targeted Risk Mitigation in the North-East and Central Regions:**
    - Since the North-East and Central regions show significantly higher default rates, the business should consider implementing stricter loan approval criteria or higher collateral requirements in these areas. Enhanced risk assessments, such as closer scrutiny of borrowers' credit history and income levels, could help reduce defaults. Additionally, offering more education on financial literacy or restructuring loans for borrowers facing difficulties could mitigate future risks.
2. **Leverage the Stability in the North Region to Expand Business:**
    - The North Region has the highest volume of loans and a comparatively lower default rate. This presents an opportunity to increase lending activity in this region. The business could introduce more attractive loan products, such as reduced interest rates or faster approval processes, to capitalize on the region’s relatively stable credit environment. Expanding marketing efforts and partnerships in the North region could further boost profitable lending activities.

Age vs. Status

HT: Chi-Square Test of Independence

In [81]:
```
pd.crosstab(index=df['age'], columns=df["Status"])
```

Out[81]:

Status / age	normal	defaulter
25-34	14856	4244
35-44	25486	7302
45-54	26357	8342
55-64	24097	8419
65-74	15168	5565
<25	948	387
>74	5020	2153

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [82]:
```
# Function calling
ht_Chi_Square('age')
```

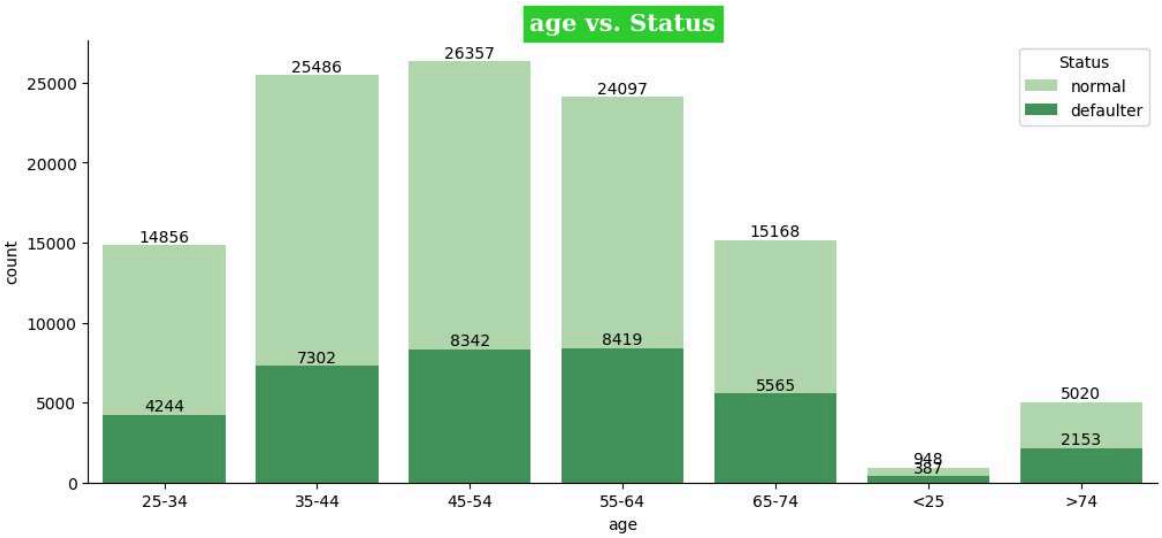
```
CONCLUSION: age and Status are Dependent
```

OBSERVATION

- The result of the Chi-Square test indicates that there is a statistically significant relationship between the age and the loan status (normal vs. defaulter). This suggests that the likelihood of normal or default is influenced by the age.

> **Analysis**

In [83]:
```
# Anslysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('age', dodge=False)
```



OBSERVATION

1. **Age Group 45-54:**
   - The 45-54 age group has the highest count of normal borrowers (26,357) and defaulters (8,342). This indicates that middle-aged borrowers are the largest segment of loan recipients but also have a higher risk of default compared to other age groups.
2. **Age Group 35-44:**
   - The 35-44 age group follows closely behind with 25,486 normal borrowers and 7,302 defaulters. This segment is also significant in both loan participation and default risk.
3. **Age Group 55-64:**

- Borrowers in the 55-64 age group show a high number of normal borrowers (24,097) but also a considerable number of defaulters (8,419). This may suggest a higher default risk as individuals approach retirement age.

4. **Younger Borrowers (<25):**
   - The <25 age group has a lower number of both normal borrowers (948) and defaulters (387), indicating they make up a smaller proportion of the total loan pool, but their default rate is relatively high compared to their participation.
5. **Older Borrowers (>74):**
   - The >74 age group shows 5,020 normal borrowers and 2,153 defaulters, with a relatively high default rate considering their lower number of total loans. This suggests older borrowers might face challenges in repaying loans, possibly due to retirement or fixed incomes.

Default Risk Across Ages:

- The default risk seems to increase with age beyond 55, especially for the 65-74 and >74 age groups, where defaulters make up a significant portion of the total. The younger age groups, though fewer in number, show higher sensitivity to economic stress, reflected in their default numbers.
- The age is a crucial factor in both loan participation and default risk, with younger and older borrowers being at a higher risk of default compared to those in middle age.

Recommendations:

1. **Targeted Financial Education:** Develop financial literacy programs specifically for older age groups (55 and above) to help them manage debt and reduce default rates.
2. **Customized Loan Products:** Create tailored loan products with flexible repayment options for younger borrowers (<25) and middle-aged borrowers (35-54) to encourage responsible borrowing and lower default risk.
3. **Risk-Based Pricing:** Implement risk-based pricing strategies to account for higher default rates among older borrowers, ensuring that loan terms reflect their risk profiles while providing support to improve repayment rates.

Occupancy_type vs. Status

HT: Chi-Square Test of Independence

In [84]:
```
pd.crosstab(index=df['occupancy_type'], columns=df["Status"])
```

Out[84]:

Status	normal	defaulter
occupancy_type		
ir	5134	2197
pr	104522	33368
sr	2276	847

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [85]:
```
# Function calling
ht_Chi_Square('occupancy_type')
```

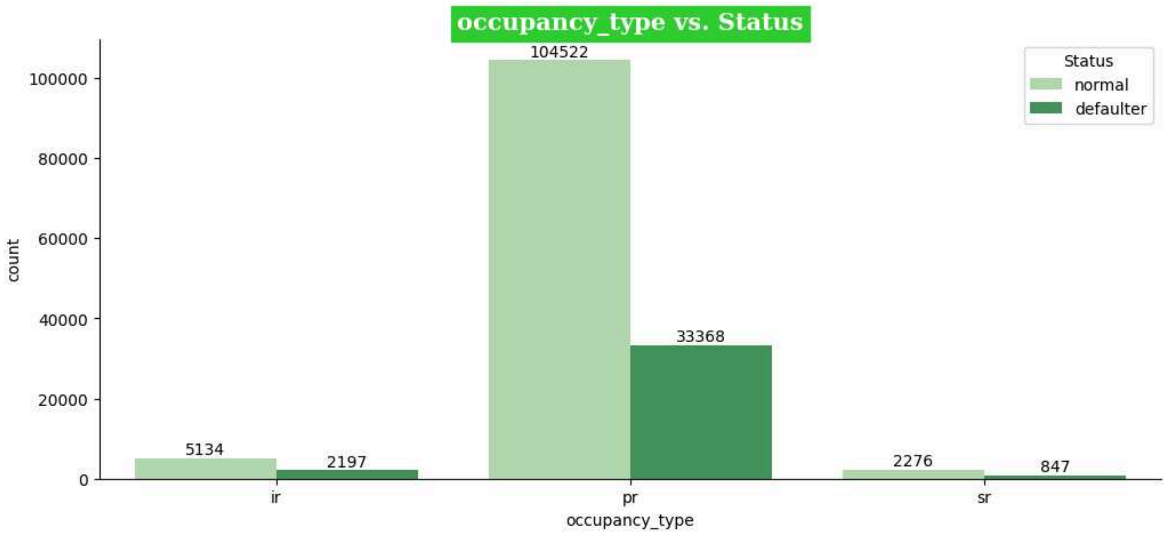
```
CONCLUSION: occupancy_type and Status are Dependent
```

OBSERVATION

- The result of the Chi-Square test indicates that there is a statistically significant relationship between the occupancy_type and the loan status (normal vs. defaulter). This suggests that the likelihood of normal or default is influenced by the occupancy_type.

Analysis

In [86]:
```
# Anslysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('occupancy_type', dodge=True)
```



OBSERVATION

1. **Prevalence of Primary Residences:** The majority of borrowers (approximately 76%) occupy their properties as primary residences (occupancy type 'pr'), suggesting that

this demographic is primarily focused on homeownership rather than investment or secondary properties.

2. **Higher Default Rates for Investment Residences:** The occupancy type 'ir' (investment residence) has a higher proportion of defaults, with around 42.7% of borrowers defaulting. This indicates a significant risk associated with investment properties, highlighting the need for thorough credit assessments in this category.

3. **Stability in Secondary Residences:** The 'sr' (secondary residence) category shows the lowest number of total borrowers and defaults, indicating a relatively stable group. The default rate in this category is approximately 37%, which is lower than that of investment residences, suggesting that secondary homeowners are managing their finances more effectively.

- The high default rates among 'pr' (33.7%) and 'ir' (42.7%) occupants may signal potential economic strain affecting homeowners and investors, warranting closer examination of the underlying causes, such as economic conditions or interest rates.

> **Risk Management Strategies:**

> **Implication of Default Rates:**

- Given the differences in default rates across occupancy types, financial institutions should consider implementing tailored risk management strategies that address the specific needs and challenges of borrowers based on their occupancy status.

Loan_limit vs. Status

HT: Chi-Square Test of Independence

In [87]:
```
pd.crosstab(index=df['loan_limit'], columns=df["Status"])
```

Out[87]:

Status	normal	defaulter
loan_limit		
cf	105272	33271
ncf	6660	3141

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [88]:
```
# Function calling
ht_Chi_Square('loan_limit')
```

```
CONCLUSION: loan_limit and Status are Dependent
```

In [89]:
```
# Checked just for cutiosity since 2x2 matrix
ht_fisher_exact('loan_limit')
```

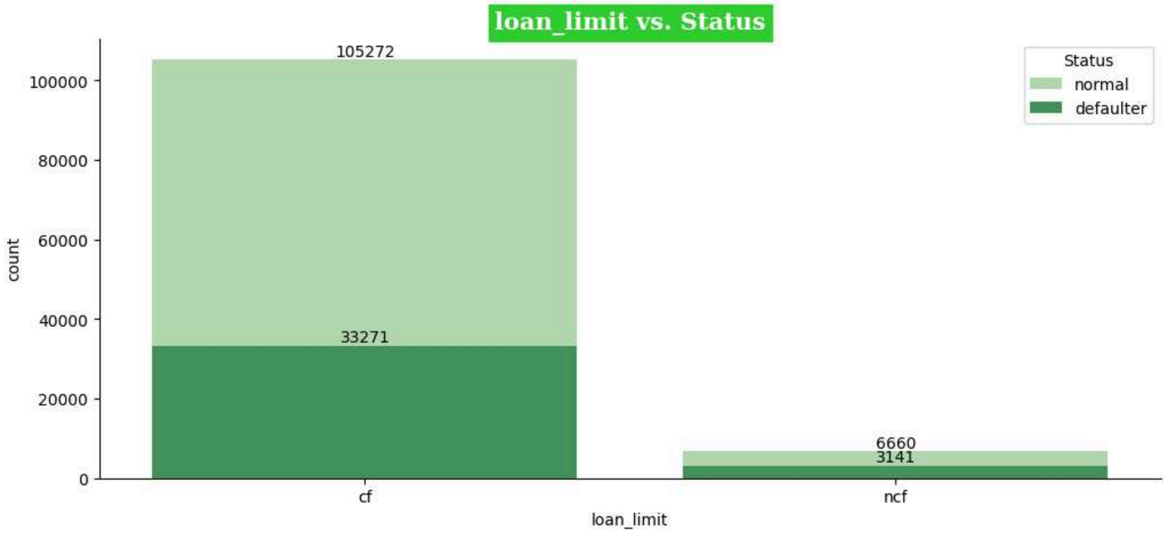
```
CONCLUSION: loan_limit and Status are Dependent
```

OBSERVATION

- There is a significant relationship between the loan limit and loan status (normal vs. defaulter). This suggests that the loan limit significantly impacts whether an individual is likely to default.

Analysis

In [90]:
```
# Anslysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('loan_limit', dodge=False)
```



OBSERVATION

1. **Higher Stability in Confirmed Loan Limits:** The category with confirmed loan limits ('cf') shows a significantly higher number of borrowers classified as normal (105,272) compared to defaulters (33,271). This indicates that borrowers with confirmed loan limits are generally more stable and less likely to default.
2. **Increased Risk in Non-Confirmed Loan Limits:** The non-confirmed loan limits ('ncf') category has a much smaller total population (9,801) with a notable default rate of approximately 47.2% (3,141 defaulters). This suggests that borrowers with non-confirmed loan limits are at a higher risk of default, potentially due to a lack of verification regarding their financial stability.

- The stark contrast in default rates between confirmed and non-confirmed loan limits underscores the importance of thorough verification processes. Financial institutions may need to reconsider their lending criteria for borrowers with non-confirmed limits to mitigate risks associated with defaults.
- With a high proportion of normal status among confirmed loan limits, lenders may want to prioritize their engagement and offerings to these borrowers, potentially offering them better terms or incentives to encourage loyalty and further borrowing.

> **Opportunity for Improvement:**

> **Focus on Confirmed Borrowers:**

> **Implication of Verification Process:**

- The significant number of defaults among non-confirmed borrowers highlights an opportunity for lenders to improve their assessment procedures and support mechanisms for these clients, possibly through enhanced financial education or tailored repayment plans.

Gender vs. Status

HT: Chi-Square Test of Independence

In [91]:
```
pd.crosstab(index=df['Gender'], columns=df["Status"])
```

Out[91]:

Status	normal	defaulter
Gender		
Female	20399	6843
Joint	33432	7926
Male	31225	11079
Sex Not Available	26876	10564

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [92]:
```
# Function calling
ht_Chi_Square('Gender')
```

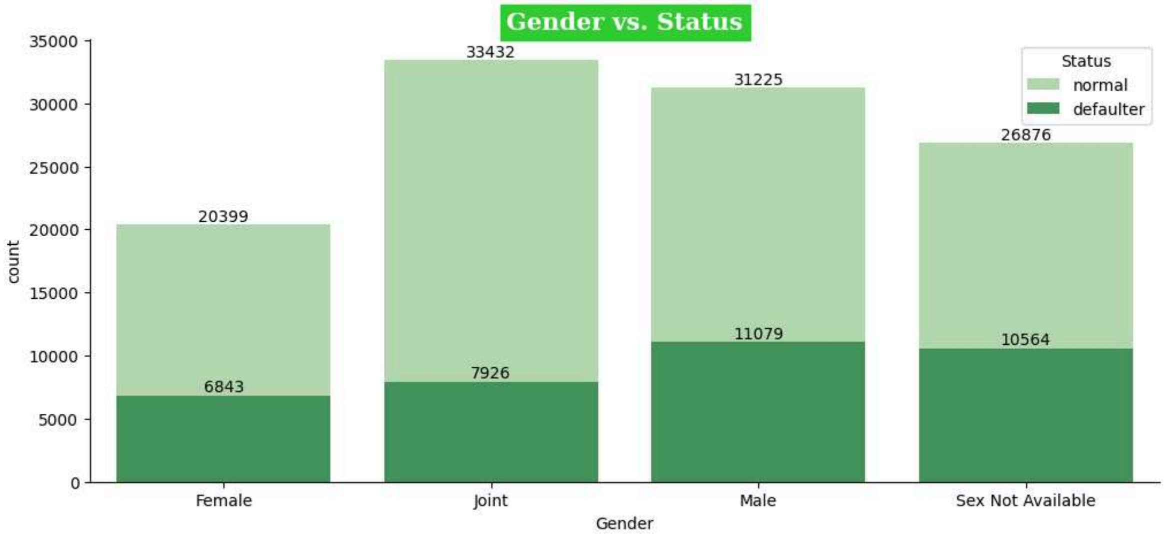
```
CONCLUSION: Gender and Status are Dependent
```

OBSERVATION

- The Chi-Square test indicates that gender influences loan status. This means that the likelihood of being a defaulter or maintaining a normal status varies across different gender categories.

Analysis

In [93]:
```
# Anslysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('Gender', dodge=False)
```



OBSERVATION

1. **Female Borrowers:**

   - Total: 27,242
   - Normal: 20,399 (74.82%)
   - Defaulter: 6,843 (25.18%)
   - Females exhibit a higher default rate compared to the overall norm, indicating a potential risk factor.

2. **Joint Borrowers:**

   - Total: 41,358
   - Normal: 33,432 (80.80%)
   - Defaulter: 7,926 (19.20%)
   - **Joint borrowers show a relatively lower default rate**, suggesting that shared financial responsibility may contribute to loan stability.

3. **Male Borrowers:**

   - Total: 42,304
   - Normal: 31,225 (73.76%)
   - Defaulter: 11,079 (26.24%)
   - Male borrowers have a higher absolute number of defaults, indicating that gender-specific factors may influence loan repayment behavior.

4. **Gender Not Specified:**

   - Total: 37,440
   - Normal: 26,876 (71.77%)
   - Defaulter: 10,564 (28.23%)
   - B**orrowers with unspecified gender also exhibit a high default rate**, suggesting that a lack of information could correlate with higher risk.

Summary:

- Overall, the default rates are notably high for all gender categories, with a significant proportion of male and female borrowers defaulting on loans.

- Joint borrowers seem to perform better in terms of repayment, which may indicate that financial partnerships can reduce default risk.
- The data suggests a potential need for targeted interventions or support for female and unspecified gender borrowers to improve repayment outcomes.

Loan_type vs. Status

HT: Chi-Square Test of Independence

In [94]:
```
pd.crosstab(index=df['loan_type'], columns=df["Status"])
```

Out[94]:

Status	normal	defaulter
loan_type		
type1	87324	25719
type2	13574	7007
type3	11034	3686

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [95]:
```
# Function calling
ht_Chi_Square('loan_type')
```

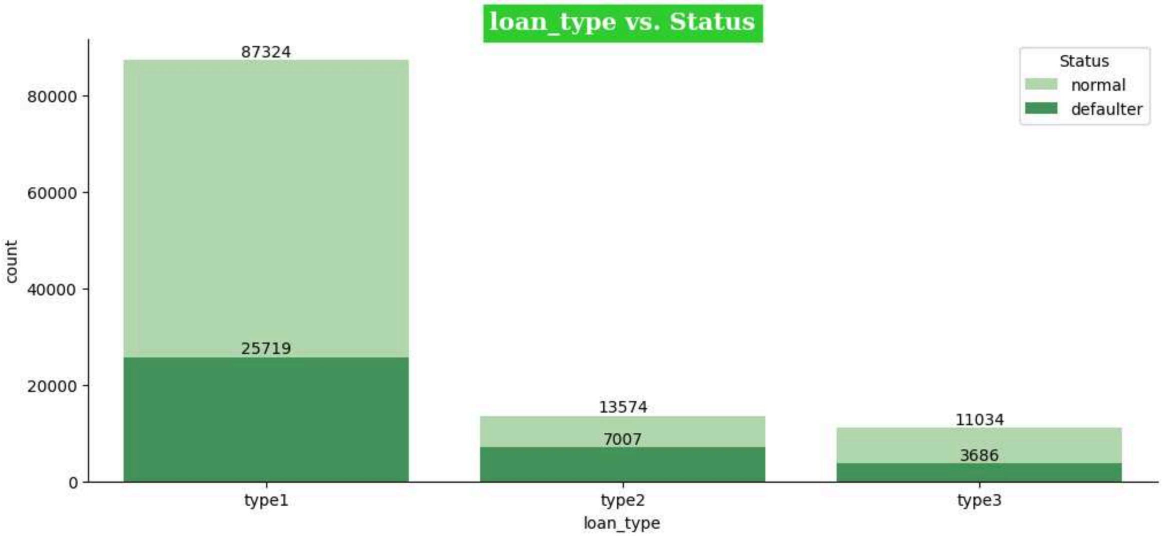
```
CONCLUSION: loan_type and Status are Dependent
```

OBSERVATION

- The result of the Chi-Square test indicates that there is a statistically significant relationship between the loan_type and the loan status (normal vs. defaulter). This suggests that the likelihood of normal or default is influenced by the loan_type.

Analysis

In [96]:
```
# Anslysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('loan_type', dodge=False)
```



OBSERVATION

1. **Loan Type 1:**
   - Total: 113,043
   - Normal: 87,324 (76.96%)
   - Defaulter: 25,719 (23.04%)
   - Loan Type 1 has the highest volume of loans and a relatively lower default rate compared to other loan types, indicating it may be the most reliable loan category.
2. **Loan Type 2:**
   - Total: 20,581
   - Normal: 13,574 (65.97%)
   - Defaulter: 7,007 (34.03%)
   - Loan Type 2 has a significantly higher default rate compared to Loan Type 1, suggesting potential issues with creditworthiness or terms associated with this loan type.
3. **Loan Type 3:**
   - Total: 14,720
   - Normal: 11,034 (75.00%)
   - Defaulter: 3,686 (25.00%)
   - Loan Type 3 has a moderate default rate, indicating better performance than Loan Type 2 but slightly lower than Loan Type 1.

Summary:

1. **Overall Performance:** Loan Type 1 stands out as the most favorable in terms of low defaults, while Loan Type 2 presents significant risks with a high default rate.

2. **Risk Management:** Financial institutions may consider reviewing the lending criteria and terms for Loan Type 2 to mitigate the high default rates.

3. **Potential Strategies:** Further investigation into borrower profiles and reasons for default in Loan Type 2 may reveal actionable insights for risk management and loan

product improvement.

Loan_purpose vs. Status

HT: Chi-Square Test of Independence

In [97]:
```
pd.crosstab(index=df['loan_purpose'], columns=df["Status"])
```

Out[97]:

Status loan_purpose	normal	defaulter
p1	25594	8843
p2	2191	1079
p3	41938	13933
p4	42209	12557

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [98]:
```
# Function calling
ht_Chi_Square('loan_purpose')
```

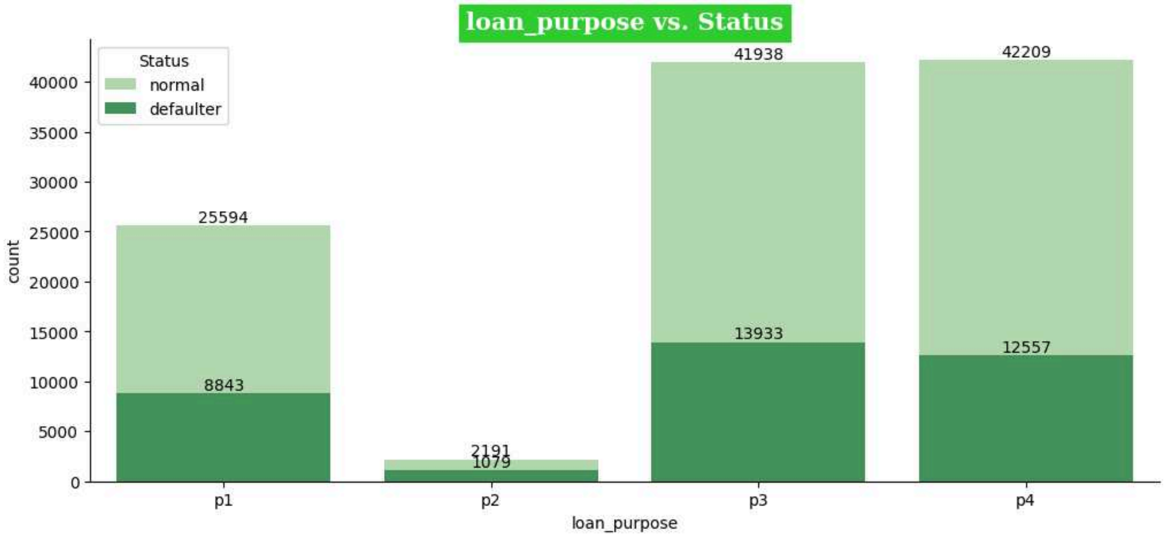
```
CONCLUSION: loan_purpose and Status are Dependent
```

OBSERVATION

- The result of the Chi-Square test indicates that there is a statistically significant relationship between the loan_purpose and the loan status (normal vs. defaulter). This suggests that the likelihood of normal or default is influenced by the loan_purpose.

Analysis

In [99]:
```
# Anslysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('loan_purpose', dodge=False)
```



OBSERVATION

1. **Loan Purpose P1:**
   - Total: 34,437
   - Normal: 25,594 (74.34%)
   - Defaulter: 8,843 (25.66%)
   - Loan Purpose P1 has a significant portion of defaults, suggesting that the reasons associated with this purpose may carry higher risk.
2. **Loan Purpose P2:**
   - Total: 3,270
   - Normal: 2,191 (66.87%)
   - Defaulter: 1,079 (33.13%)
   - Similar to P1, Loan Purpose P2 has a high default rate, indicating potential issues related to the purpose of these loans.
3. **Loan Purpose P3:**
   - Total: 55,871
   - Normal: 41,938 (75.00%)
   - Defaulter: 13,933 (25.00%)
   - While Loan Purpose P3 has a decent percentage of normal loans, the absolute number of defaulters is substantial, indicating it might still be a risky category.
4. **Loan Purpose P4:**
   - Total: 54,766
   - Normal: 42,209 (77.00%)
   - Defaulter: 12,557 (23.00%)
   - Loan Purpose P4 performs the best in terms of the percentage of normal loans and lowest default rate, suggesting it may be a safer lending category.

Summary:

1. **Risk Assessment:** Loan Purposes P1 and P2 show high default rates and should be monitored closely for creditworthiness and lending criteria adjustments.

2. **Performance Comparison:** Loan Purpose P4 has the best performance with the lowest default rate, indicating it could be a model for successful lending practices.
3. **Strategy Recommendations:** It may be beneficial to conduct further analysis on the borrowers associated with P1 and P2 to understand the factors contributing to defaults and to improve loan structuring for these purposes.

Business_or_commercial vs. Status

HT: Chi-Square Test of Independence

In [100…

```
pd.crosstab(index=df['business_or_commercial'], columns=df["Status"])
```

Out[100…

Status	normal	defaulter
business_or_commercial		
b/c	13574	7007
nob/c	98358	29405

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [101…

```
# Function calling
ht_Chi_Square('business_or_commercial')
```

```
CONCLUSION: business_or_commercial and Status are Dependent
```

In [102…

```
# Checked just for cutiosity since 2x2 matrix
ht_fisher_exact('business_or_commercial')
```

```
CONCLUSION: business_or_commercial and Status are Dependent
```

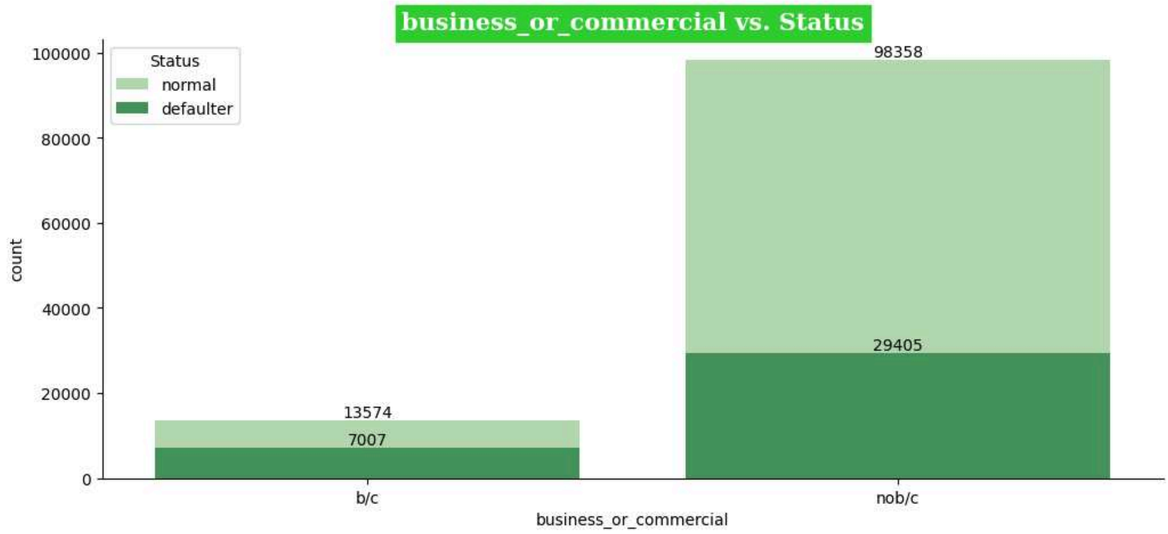
OBSERVATION

- There is a significant relationship between the business_or_commercial and loan status (normal vs. defaulter). This suggests that the business_or_commercial significantly impacts whether an individual is likely to default.

Analysis

In [103…

```
# Analysis of Commercial establishment or Personal establishment vs. Status
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('business_or_commercial', dodge=False)
```



OBSERVATION

1. **Business/Commercial (b/c):**

- Total: 20,581
- Normal: 13,574 (65.93%)
- Defaulter: 7,007 (34.07%)
- A significant percentage of business/commercial loans (34.07%) are in default, indicating potential higher risk in this category.

2. Non-Business/Non-Commercial (nob/c):

- Total: 127,763
- Normal: 98,358 (76.99%)
- Defaulter: 29,405 (23.01%)
- Personal or non-commercial loans have a better performance, with a lower default rate (23.01%) compared to business/commercial loans.

Summary:

1. **Risk Assessment:** Loans given to business/commercial establishments (b/c) exhibit a higher default rate, indicating that these loans might require stricter lending criteria or additional risk mitigation strategies. 2.**Performance Comparison:** Non-commercial or personal loans (nob/c) demonstrate stronger performance, with a higher proportion of normal loans and a lower default rate.
2. **Recommendations:** Consider revisiting the risk assessment process for business/commercial loans and explore methods to reduce defaults, such as better financial evaluation, enhanced monitoring, or providing tailored financial support to businesses at higher risk.

Credit_Score_Category vs. Status

In [104…

```
df['Credit_Score'].describe()
```

Out[104…
```
count    148344.000000
mean        699.773243
std         115.872267
min         500.000000
25%         599.000000
50%         699.000000
75%         800.000000
max         900.000000
Name: Credit_Score, dtype: float64
```

In [105…
```
# Example: Assuming your credit score data is in the 'Credit_Score' column
bins = [500, 599, 699, 799, 900]  # Setting bin edges based on min, quartiles, a
labels = ['Low', 'Average', 'Good', 'Excellent']  # Labels for the bins

# Applying pd.cut() to the 'Credit_Score' column
df['Credit_Score_Category'] = pd.cut(df['Credit_Score'], bins=bins, labels=label
```

In [106…
```
df['Credit_Score_Category'].value_counts()
```

Out[106…
```
Credit_Score_Category
Excellent    37376
Average      37114
Low          36758
Good         36739
Name: count, dtype: int64
```

HT: Chi-Square Test of Independence

In [107…
```
pd.crosstab(index=df['Credit_Score_Category'], columns=df["Status"])
```

Out[107…

Status / Credit_Score_Category	normal	defaulter
Low	27755	9003
Average	28068	9046
Good	27841	8898
Excellent	28012	9364

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.
- Asumptions for Chi-Square test are satisfied

In [108…
```
# Function calling
ht_Chi_Square('Credit_Score_Category')
```

```
CONCLUSION: Credit_Score_Category and Status are Dependent
```

OBSERVATION

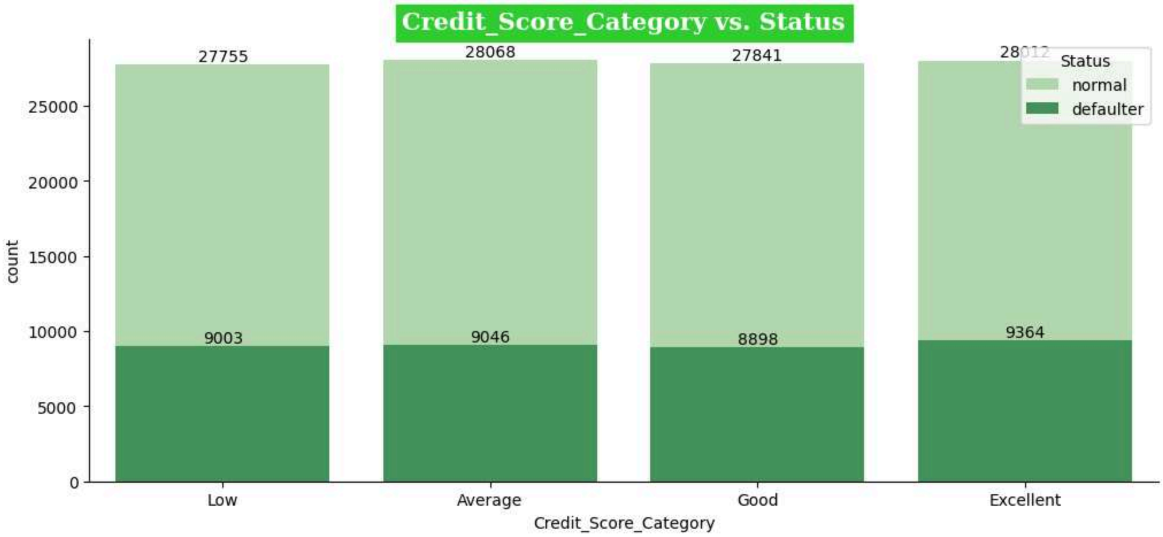
- The result of the Chi-Square test indicates that there is a statistically significant relationship between the Credit_Score_Category and the loan status (normal vs.

defaulter). This suggests that the likelihood of normal or default is influenced by the Credit_Score_Category.

Analysis

In [109…

```
# Analysis
plt.figure(figsize=(12,5))
# Function Calling
single_bar_chart('Credit_Score_Category', dodge=False)
```



OBSERVATION

1. **Low Credit Score (<= 599):**
    - 27,755 accounts have a "normal" status.
    - 9,003 accounts are "defaulters".
    - Defaulter percentage: 24.49%.
2. **Average Credit Score (600 - 699):**
    - 28,068 accounts have a "normal" status.
    - 9,046 accounts are "defaulters".
    - Defaulter percentage: 24.38%.
3. **Good Credit Score (700 - 799):**
    - 27,841 accounts have a "normal" status.
    - 8,898 accounts are "defaulters".
    - Defaulter percentage: 24.21%.
4. **Excellent Credit Score (>= 800):**
    - 28,012 accounts have a "normal" status.
    - 9,364 accounts are "defaulters".
    - Defaulter percentage: 25.06%.

- The defaulter rate is relatively consistent across credit score categories, ranging between 24% to 25%.
- Despite the expectation that higher credit scores would result in lower defaulter rates, the defaulter rate for "Excellent" credit scores (25.06%) is slightly higher than

that for "Good" and "Average" scores.

> **Normal Accounts Distribution:**

> **Defaulter Rate Across Credit Score Categories:**

- The number of accounts with a "normal" status is quite evenly distributed across all credit score categories, ranging from approximately 27,755 (Low) to 28,068 (Average). This suggests that credit score alone may not be the strongest determinant of account status.

> **Insights:**

- Although credit score is generally considered a key risk indicator, the consistent defaulter rate across all credit score categories (ranging from Low to Excellent) may suggest that other factors beyond credit score are contributing significantly to default risk.
- The defaulter rate for those with Excellent credit scores being slightly higher than for other groups is unexpected and could warrant further investigation to understand what specific conditions are leading to defaults among high-credit-score individuals.

Income_category vs. Status

In [110…

```
df['income'].describe()
```

Out[110…

```
count    148344.000000
mean       6938.251500
std        6334.613413
min           0.000000
25%        3780.000000
50%        5782.332134
75%        8460.000000
max      578580.000000
Name: income, dtype: float64
```

In [111…

```
# Create Bins and Lanels
bins = [-1, 3780, 5760, 8460, df['income'].max()]  # Setting bin edges based on
labels = ['Low', 'Average', 'Above Average', 'High'] # Labels for the bins

# Applying pd.cut() to the 'income_category' column
df['income_category'] = pd.cut(df['income'], bins=bins, labels=labels, right=Tru
```

In [112…

```
df['income_category'].value_counts()
```

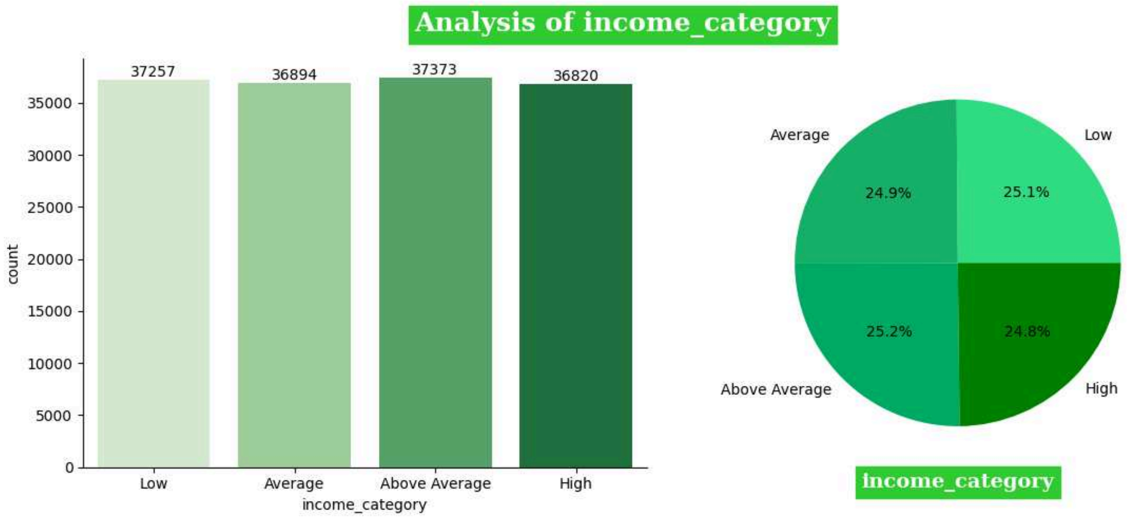
Out[112…

```
income_category
Above Average    37373
Low              37257
Average          36894
High             36820
Name: count, dtype: int64
```

In [113…

```
# Analysis of income_category
req_palette = ['#32de84', '#008200']
```

```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
label = sns.countplot(data=df, x='income_category', palette='Greens')
for i in label.containers:
  label.bar_label(i)
#plt.title("income_category")

plt.subplot(1, 2, 2)
labels = df.groupby('income_category')['income_category'].count().index.categori
plt.pie(df.groupby('income_category')['income_category'].count().values,
        labels = labels, autopct = "%1.1f%%", colors=green_palette)
plt.xlabel('income_category', fontsize=14,
           fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',colc
#plt.title("income_category")

plt.suptitle("Analysis of income_category",fontsize = 18,
             fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',cc
plt.tight_layout()
sns.despine()
plt.show()
```



HT: Chi-Square Test of Independence

In [114…

```
pd.crosstab(index=df['income_category'], columns=df["Status"])
```

Out[114…

Status / income_category	normal	defaulter
Low	24319	12938
Average	28129	8765
Above Average	29937	7436
High	29547	7273

Approach:

- **Chi-Square Assumptions:** The Chi-Square test assumes that the expected frequency in each cell should be 5 or more.

- Asumptions for Chi-Square test are satisfied

In [115…
```
# Function calling
ht_Chi_Square('income_category')
```

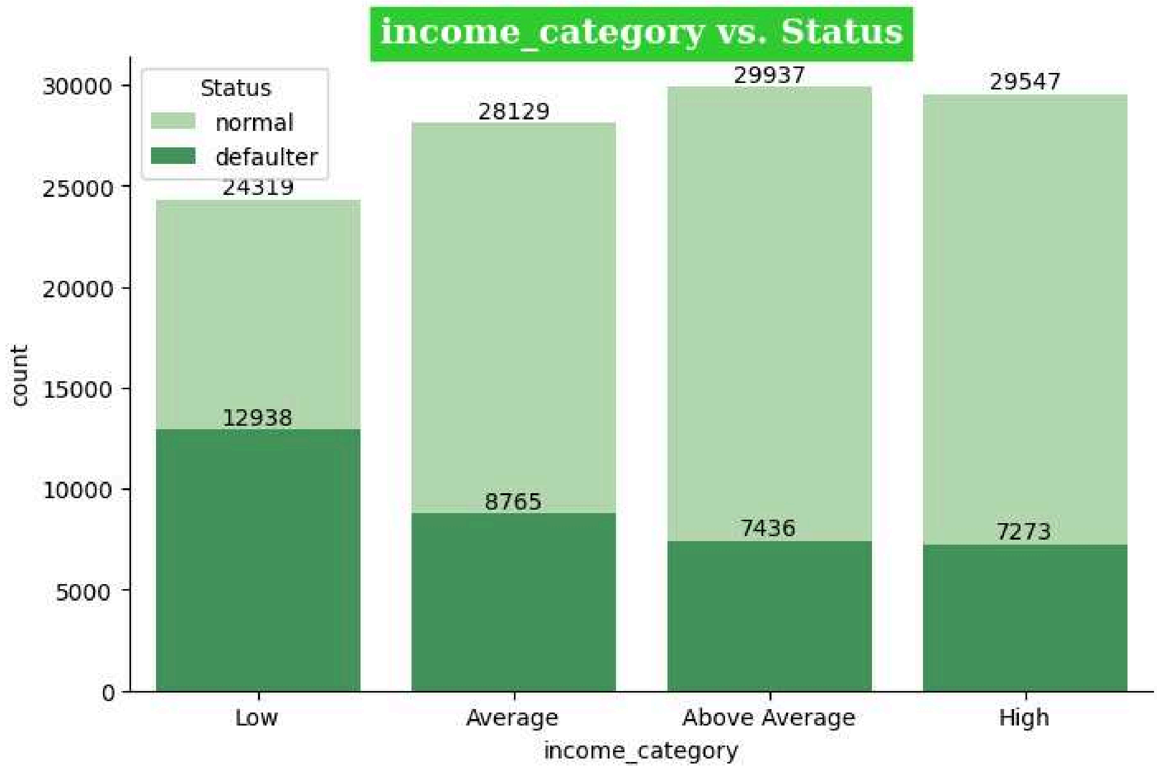
```
CONCLUSION: income_category and Status are Dependent
```

OBSERVATION

- The result of the Chi-Square test indicates that there is a statistically significant relationship between the income_category and the loan status (normal vs. defaulter). This suggests that the likelihood of normal or default is influenced by the income_category.

Analysis

In [116…
```
# Analysis
plt.figure(figsize=(8,5))
# Function Calling
single_bar_chart('income_category', dodge=False)
```



OBSERVATION

Income Category Distribution:

1. The largest portion of individuals in the Low income category (24,417) have a normal status, while 12,998 are defaulters. This shows a relatively high number of defaults in the lower income bracket.
2. In the Average income category, 28,208 individuals have a normal status, while 8,687 are defaulters, indicating a more stable financial situation than the Low income group.

3. The Above Average income category has 29,713 individuals with a normal status and 7,454 as defaulters. The defaulter proportion decreases as income increases.

4. The High income category has 29,594 individuals with a normal status and 7,273 as defaulters. Despite being in the highest income group, there are still significant defaulters.

- As income increases from Low to High, the number of defaulters decreases in absolute terms but the ratio of normal to defaulter improves, showing that higher income groups tend to default less frequently.

- The Low income group shows a higher risk of defaulting compared to other categories, while those in the High income group demonstrate better loan repayment behavior.

  > **Balanced Default Distribution:**

  > **Defaulter Trend:**

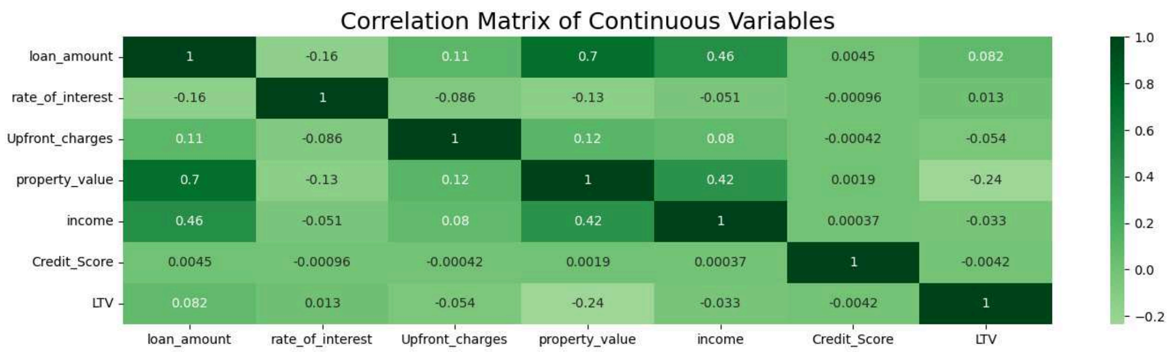
- Across the income categories, the number of normal individuals remains fairly consistent, suggesting that income does not drastically affect the proportion of individuals maintaining a good status, but lower-income individuals are more vulnerable to default.

Numerical Features

Correlation Analysis

In [117…

```
# Correlation Matrix of Continuous Variables
plt.figure(figsize=(16, 4))
corr_matrix = numerical_df_req.corr()
sns.heatmap(corr_matrix, annot=True, cmap='Greens', center=0)
plt.title('Correlation Matrix of Continuous Variables', fontsize = 18)
plt.show()
```



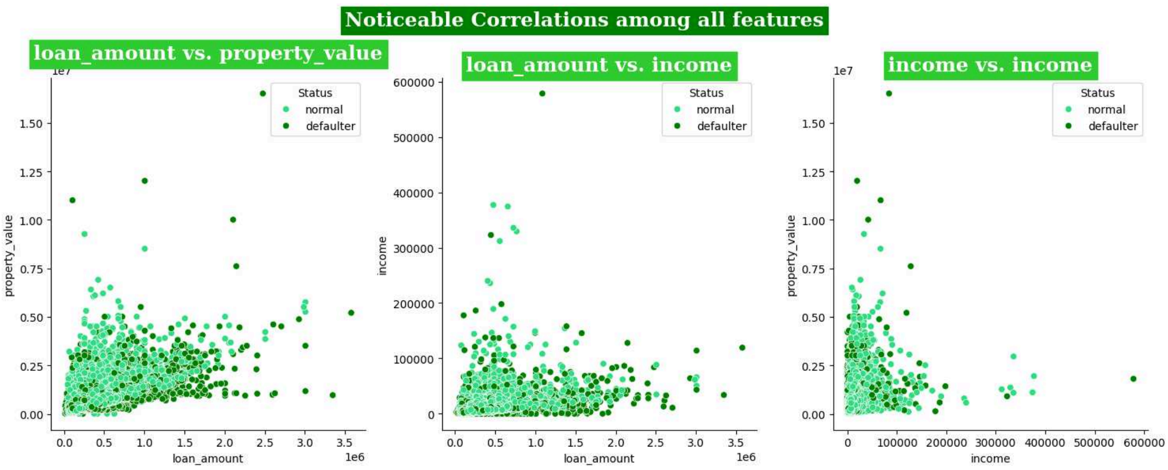
OBSERVATION

1. **Loan Amount and Property Value:** A **strong positive correlation (0.70)** between loan amount and property value indicates that higher loan amounts are often associated with higher property values.

2. **Loan Amount and Income:** There is a **moderate positive correlation (0.46)** between loan amount and income, meaning higher loan amounts tend to be associated with higher incomes.
3. **Income and Property Value:** There is a **moderate positive correlation (0.42)** between Income and Property Value meaning as the income increases the Property Value also increses.

In [118…

```
# Noticeable Correlations among all features
req_palette = ['#32de84', '#008200']

plt.figure(figsize=(15, 6))

plt.subplot(131)
sns.scatterplot(x='loan_amount', y='property_value',
                hue='Status', data=df, palette=req_palette)
plt.title("loan_amount vs. property_value",fontsize = 18,
          fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',color

plt.subplot(132)
sns.scatterplot(x='loan_amount', y='income',
                hue='Status', data=df, palette=req_palette)
plt.title("loan_amount vs. income",fontsize = 18,
          fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',color

plt.subplot(133)
sns.scatterplot(x='income', y='property_value',
                hue='Status', data=df, palette=req_palette)
plt.title("income vs. income",fontsize = 18,
          fontfamily='serif',fontweight='bold',backgroundcolor='limegreen',color

plt.suptitle("Noticeable Correlations among all features",fontsize = 18,
             fontfamily='serif',fontweight='bold',backgroundcolor='green',color=
plt.tight_layout()
sns.despine()
plt.show()
```



Loan_amount Vs. Status

In [119…

```
# statistical summary
df.groupby('Status')['loan_amount'].describe()
```

Out[119…

Status	count	mean	std	min	25%	50%	75%
normal	111932.0	334963.442090	174913.970571	26500.0	206500.0	306500.0	446500.(
defaulter	36412.0	319890.640448	208652.841142	16500.0	176500.0	276500.0	416500.(

> **Introduction**

- When comparing "loan_amount" and "Status," we can use a **Two-Sample Independent T-Test** if the data is normally distributed or a non-parametric test like the **Mann-Whitney U test** if it's not.

Why Two-Sample Independent T-Test?

- One should choose the Two-Sample Independent T-Test to compare the means of two independent groups to determine if there is a statistically significant difference between them.

> **Perform Hypothesis Testing**

1. Formulate the Hypotheses

- **Null Hypothesis (H0):** There is no significant difference between the two groups.
- **Alternative Hypothesis (H1)**: There is a significant difference between the two groups.

2. Check Assumptions:

- **Normality:** Use the Q-Q Plot and Shapiro-Wilk test to check if the data is normally distributed.
- **Equality of Variances:** Use Levene's test to check if the variances are equal.

3. Choose the Appropriate Test

- If the data is **normally distributed, use two-Sample Independent T-Test.**
- If the data is **not normally distributed, use the Mann-Whitney U test.**

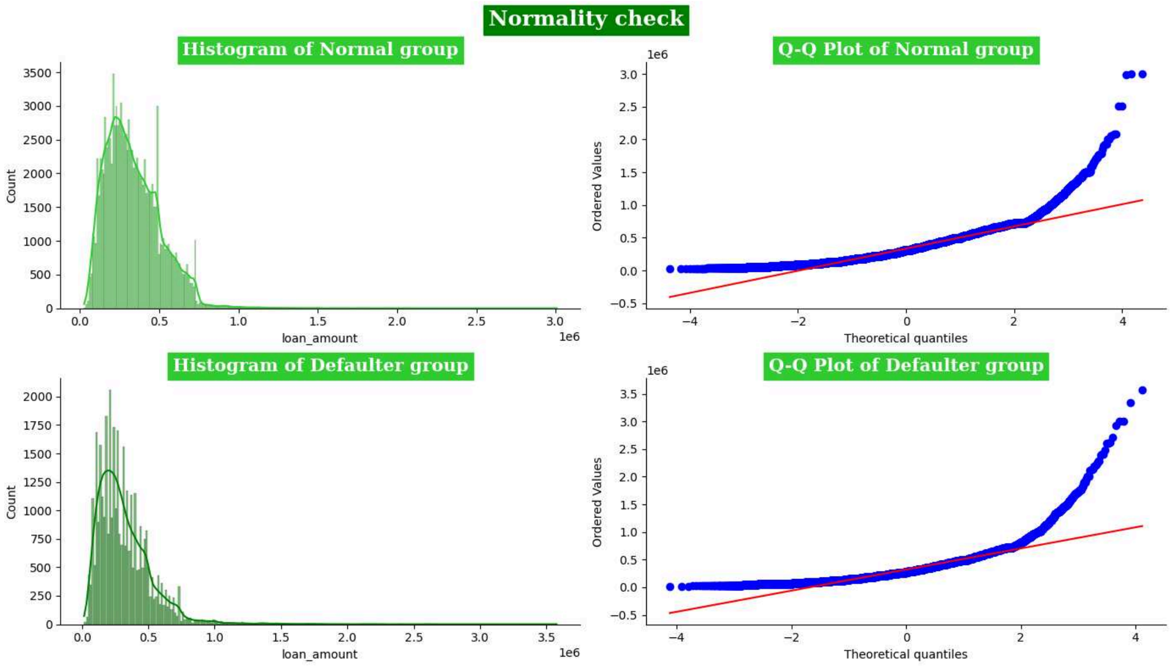
In [120…

```
# Preparing the data:
normal_loan_amount = df[df['Status'] == 'normal']['loan_amount']
defaulter_loan_amount = df[df['Status'] == 'defaulter']['loan_amount']
```

> **Normality & Equality of Variances:**

In [121…

```
analysis = StatisticalAnalysis(normal_loan_amount,
                               'Normal group', defaulter_loan_amount, 'Defaulter
analysis.normality_plots()  # Plot histograms and Q-Q plots
analysis.normality_tests()  # Perform normality tests
analysis.variance_tests()   # Perform variance tests
```




```
Normality Tests for Normal group:
- Shapiro-Wilk Test: Statistics=0.9344, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=1180.5027, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=136739.1680, p-value=0.0000 => Not Gaussian distri
bution

Normality Tests for Defaulter group:
- Shapiro-Wilk Test: Statistics=0.8383, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=910.1837, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=393315.3155, p-value=0.0000 => Not Gaussian distri
bution

After Box-Cox Transformation:
Normality Tests for Transformed Normal group:
- Shapiro-Wilk Test: Statistics=0.9956, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=114.2915, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=212.4270, p-value=0.0000 => Not Gaussian distribut
ion

Normality Tests for Transformed Defaulter group:
- Shapiro-Wilk Test: Statistics=0.9974, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=21.9212, Critical Values=[0.576 0.656 0.787 0.
918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=6.0949, p-value=0.0475 => Not Gaussian distributio
n

Levene's Test for Normal group and Defaulter group:
- Statistic: 175.6589, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.

Bartlett's Test for Normal group and Defaulter group:
- Statistic: 1808.8983, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(two-sided)** with **Confidence level of 95%**

In [122...

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_loan_amount, 'Normal group',
                    defaulter_loan_amount, 'Defaulter group', alternative='two-s
```

```
Mann-Whitney U test: (two-sided)
There is a difference (with respect to the central tendency) between Normal group
and Defaulter group.
```

4.perform the Hypothesis Test

- Since we have got the result that means are different from the above tests, we can perform the **Mann-Whitney U test(Right tailed)** to check if group_1 is greater than group_2 with **Confidence level of 95%**

In [123...

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_loan_amount, 'Normal group',
                    defaulter_loan_amount, 'Defaulter group', alternative='great
```

```
Mann-Whitney U test: (greater)
The central tendency of Normal group is greater than Defaulter group.
```

CONCLUSION:

- **Greater Loan Amounts for Normal Group:** The results of the one-tailed test show that the central tendency (median) of the Normal group is greater than that of the Defaulter group, indicating that individuals classified as normal tend to have higher loan amounts compared to those who defaulted.
- **Higher Loan Amounts Linked to Lower Default Rates:** The analysis reveals that borrowers categorized as "Normal" tend to secure higher loan amounts than those classified as "Defaulters." This insight suggests that the business may want to consider targeting higher loan amounts for borrowers with favorable credit profiles to minimize default risks.

Business Insights:

Borrowers who are not defaulters generally take out larger loans compared to defaulters. This insight can be valuable for financial risk assessments, as borrowers with smaller loan amounts might pose a higher risk of default, while those with larger loans may be less likely to default, potentially due to better financial standing or greater ability to repay.

Rate of Interest Vs. Status

In [124...

```
# statistical summary
df.groupby('Status')['rate_of_interest'].describe()
```

Out[124…

Status	count	mean	std	min	25%	50%	75%	max
normal	111932.0	4.044862	0.561482	0.000000	3.625000	3.99000	4.375000	8.00000
defaulter	36412.0	4.142879	0.251030	2.943254	4.013126	4.15639	4.304937	5.80856

Introduction

- When comparing "rate_of_interest" and "Status," we can use a **Two-Sample Independent T-Test** if the data is normally distributed or a non-parametric test like the **Mann-Whitney U test** if it's not.

Why Two-Sample Independent T-Test?

- One should choose the Two-Sample Independent T-Test to compare the means of two independent groups to determine if there is a statistically significant difference between them.

Perform Hypothesis Testing

1. Formulate the Hypotheses

- **Null Hypothesis (H0):** There is no significant difference between the two groups.
- **Alternative Hypothesis (H1)**: There is a significant difference between the two groups.

2. Check Assumptions:

- **Normality:** Use the Q-Q Plot and Shapiro-Wilk test to check if the data is normally distributed.
- **Equality of Variances:** Use Levene's test to check if the variances are equal.

3. Choose the Appropriate Test

- If the data is **normally distributed, use two-Sample Independent T-Test.**
- If the data is **not normally distributed, use the Mann-Whitney U test.**

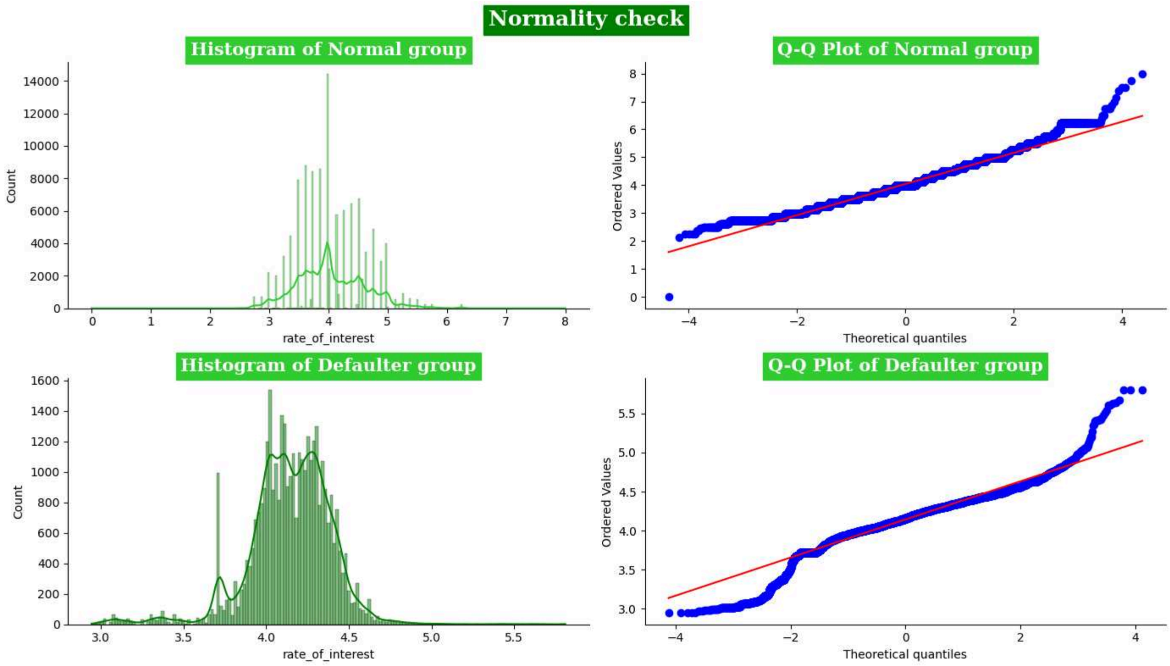
In [125…

```
# Preparing the data:
normal_rate_of_interest = df[df['Status'] == 'normal']['rate_of_interest']
defaulter_rate_of_interest = df[df['Status'] == 'defaulter']['rate_of_interest']
```

> **Normality & Equality of Variances:****

In [126…

```
# Function calling -> normality(group_1, group_1_name, group_2, group_2_name)
analysis = StatisticalAnalysis(normal_rate_of_interest,
                               'Normal group', defaulter_rate_of_interest, 'Defa
analysis.normality_plots()
analysis.normality_tests()
analysis.variance_tests()
```




```
Normality Tests for Normal group:
- Shapiro-Wilk Test: Statistics=0.9849, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=560.7627, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=3386.7748, p-value=0.0000 => Not Gaussian distribu
tion

Normality Tests for Defaulter group:
- Shapiro-Wilk Test: Statistics=0.9475, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=296.9990, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=20187.8393, p-value=0.0000 => Not Gaussian distrib
ution

Box-Cox transformation failed: Data must be positive.

Levene's Test for Normal group and Defaulter group:
- Statistic: 16544.4856, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.

Bartlett's Test for Normal group and Defaulter group:
- Statistic: 26188.2210, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.
```

In [127…

```
# skewness and kurtosis coefficient:
day_list = {'Normal group':normal_rate_of_interest,
            'Defaulter group': defaulter_rate_of_interest}

for name, data in day_list.items():
  print(f"Data {name}:")
  print("skewness coefficient:" , pd.Series(data).skew().round(2))
  print("kurtosis coefficient:" , pd.Series(data).kurt().round(2))
  print()
```

```
Data Normal group:
skewness coefficient: 0.39
kurtosis coefficient: 0.35

Data Defaulter group:
skewness coefficient: -0.82
kurtosis coefficient: 3.26
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(two-sided)** with **Confidence level of 95%**

In [128…

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_rate_of_interest, 'Normal group',
                    defaulter_rate_of_interest, 'Defaulter group', alternative='
```

```
Mann-Whitney U test: (two-sided)
There is a difference (with respect to the central tendency) between Normal group
and Defaulter group.
```

4.perform the Hypothesis Test

- Since we have got the result that means are different from the above tests, we can perform the **Mann-Whitney U test(Left tailed)** to check if group_1 is greater than group_2 with **Confidence level of 95%**

In [129…

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_loan_amount, 'Normal group',
                    defaulter_loan_amount, 'Defaulter group', alternative='less'
```

```
Mann-Whitney U test: (less)
There is no difference (in terms of central tendency) between Normal group and De
faulter group
```

In [130…

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_loan_amount, 'Normal group',
                    defaulter_loan_amount, 'Defaulter group', alternative='great
```

```
Mann-Whitney U test: (greater)
The central tendency of Normal group is greater than Defaulter group.
```

CONCLUSION:

In summary, while the two-sided Mann-Whitney U test indicates a significant difference in central tendencies between the "Normal" and "Defaulter" groups, the one-tailed tests reveal complexities regarding the nature of this difference. These findings underscore the importance of further exploration to derive actionable insights for lending practices and borrower support.

Upfront_charges Vs. Status

In [131…

```
# statistical summary
df.groupby('Status')['Upfront_charges'].describe()
```

Out[131…

Status	count	mean	std	min	25%	50%
normal	111932.0	3227.909910	3218.862754	-504.960204	632.340000	2637.50000
defaulter	36412.0	3377.473334	1660.922972	-27.400474	2377.409773	2962.37132

Introduction

- When comparing "Upfront_charges" and "Status," we can use a **Two-Sample Independent T-Test** if the data is normally distributed or a non-parametric test like the **Mann-Whitney U test** if it's not.

Why Two-Sample Independent T-Test?

- One should choose the Two-Sample Independent T-Test to compare the means of two independent groups to determine if there is a statistically significant difference between them.

Perform Hypothesis Testing

1. Formulate the Hypotheses

- **Null Hypothesis (H0):** There is no significant difference between the two groups.
- **Alternative Hypothesis (H1)**: There is a significant difference between the two groups.

2. Check Assumptions:

- **Normality:** Use the Q-Q Plot and Shapiro-Wilk test to check if the data is normally distributed.
- **Equality of Variances:** Use Levene's test to check if the variances are equal.

3. Choose the Appropriate Test

- If the data is **normally distributed, use two-Sample Independent T-Test.**
- If the data is **not normally distributed, use the Mann-Whitney U test.**

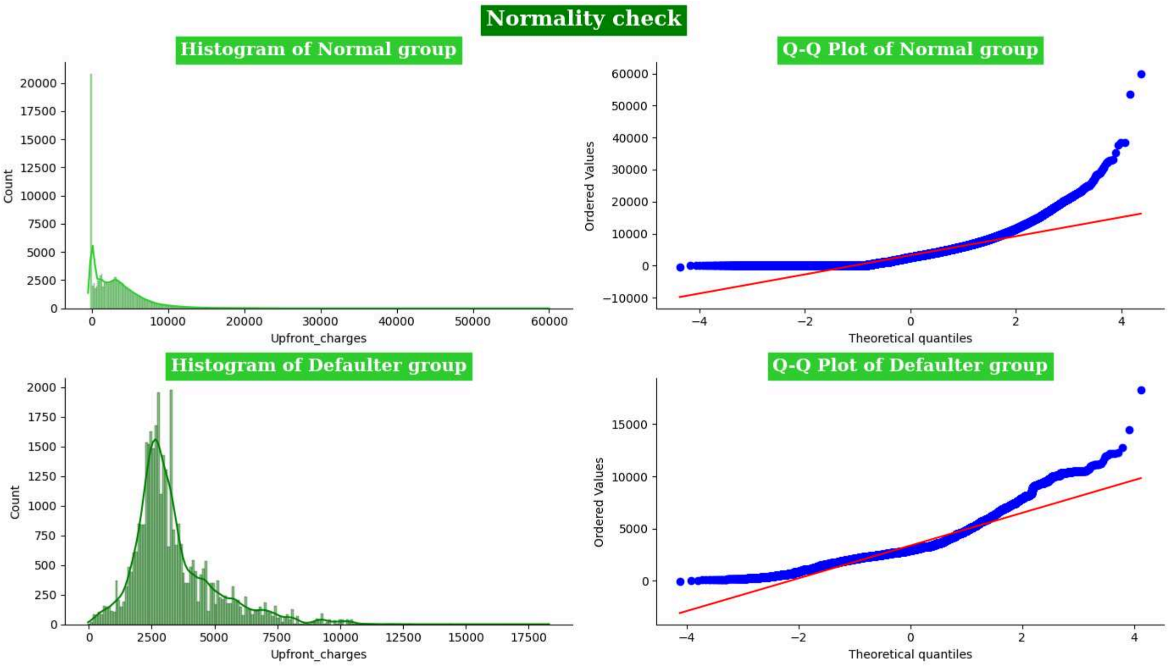
In [132…

```
# Preparing the data:
normal_Upfront_charges = df[df['Status'] == 'normal']['Upfront_charges']
defaulter_Upfront_charges = df[df['Status'] == 'defaulter']['Upfront_charges']
```

> #### Normality & Equality of Variances:

In [133…

```
# Function calling -> normality(group_1, group_1_name, group_2, group_2_name)
analysis = StatisticalAnalysis(normal_Upfront_charges,
                               'Normal group', defaulter_Upfront_charges, 'Defau
analysis.normality_plots()
analysis.normality_tests()
analysis.variance_tests()
```




```
Normality Tests for Normal group:
- Shapiro-Wilk Test: Statistics=0.8551, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=3202.6978, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=255142.0207, p-value=0.0000 => Not Gaussian distri
bution

Normality Tests for Defaulter group:
- Shapiro-Wilk Test: Statistics=0.8896, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=1242.9528, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=25954.3355, p-value=0.0000 => Not Gaussian distrib
ution

Box-Cox transformation failed: Data must be positive.

Levene's Test for Normal group and Defaulter group:
- Statistic: 9927.7055, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.

Bartlett's Test for Normal group and Defaulter group:
- Statistic: 18726.0349, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(two-sided)** with **Confidence level of 95%**

In [134…

```python
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_Upfront_charges, 'Normal group',
                    defaulter_Upfront_charges, 'Defaulter group', alternative='t
```

```
Mann-Whitney U test: (two-sided)
There is a difference (with respect to the central tendency) between Normal group
and Defaulter group.
```

4.perform the Hypothesis Test

- Since we have got the result that means are different from the above tests, we can perform the **Mann-Whitney U test(Left tailed)** to check if group_1 is greater than group_2 with **Confidence level of 95%**

In [135…

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_Upfront_charges, 'Normal group',
                    defaulter_Upfront_charges, 'Defaulter group', alternative='l
```

```
Mann-Whitney U test: (less)
The central tendency of Normal group is less than Defaulter group.
```

CONCLUSION:

- **Significant Difference in Central Tendencies:** The two-sided Mann-Whitney U test shows that there is a significant difference in the central tendencies between the "Normal" and "Defaulter" groups with respect to Upfront Charges. This suggests that the distributions of upfront charges are different between the two groups, indicating that the amount of upfront charges paid could be a distinguishing factor between those who default and those who do not.
- **Central Tendency of "Normal" Group is Lower:** The one-tailed (less) Mann-Whitney U test indicates that the central tendency of the "Normal" group is significantly less than that of the "Defaulter" group. This suggests that borrowers in the "Normal" group (those who did not default) tend to have lower upfront charges compared to those in the "Defaulter" group. In other words, those who defaulted may have faced higher upfront charges, which could potentially contribute to their defaulting.

Business Insights:

- The Mann-Whitney U test results suggest that there is a significant difference in the upfront charges paid by the "Normal" and "Defaulter" groups, with defaulters having higher upfront charges. This insight can help inform lenders about potential risks and strategies for reducing default rates through better upfront charge management.

Property Value Vs. Status

In [136…

```
# statistical summary
df.groupby('Status')['property_value'].describe()
```

Out[136…

	count	mean	std	min	25%	50%
Status						
normal	111932.0	505656.340574	342854.710163	8000.0	288000.000000	428000.00000C
defaulter	36412.0	513256.237278	409904.256320	8000.0	266563.484375	403551.890625

Introduction

- When comparing "property_value" and "Status," we can use a **Two-Sample Independent T-Test** if the data is normally distributed or a non-parametric test like the **Mann-Whitney U test** if it's not.

Why Two-Sample Independent T-Test?

- One should choose the Two-Sample Independent T-Test to compare the means of two independent groups to determine if there is a statistically significant difference between them.

Perform Hypothesis Testing

1. Formulate the Hypotheses

- **Null Hypothesis (H0):** There is no significant difference between the two groups.
- **Alternative Hypothesis (H1)**: There is a significant difference between the two groups.

2. Check Assumptions:

- **Normality:** Use the Q-Q Plot and Shapiro-Wilk test to check if the data is normally distributed.
- **Equality of Variances:** Use Levene's test to check if the variances are equal.

3. Choose the Appropriate Test

- If the data is **normally distributed, use two-Sample Independent T-Test.**
- If the data is **not normally distributed, use the Mann-Whitney U test.**

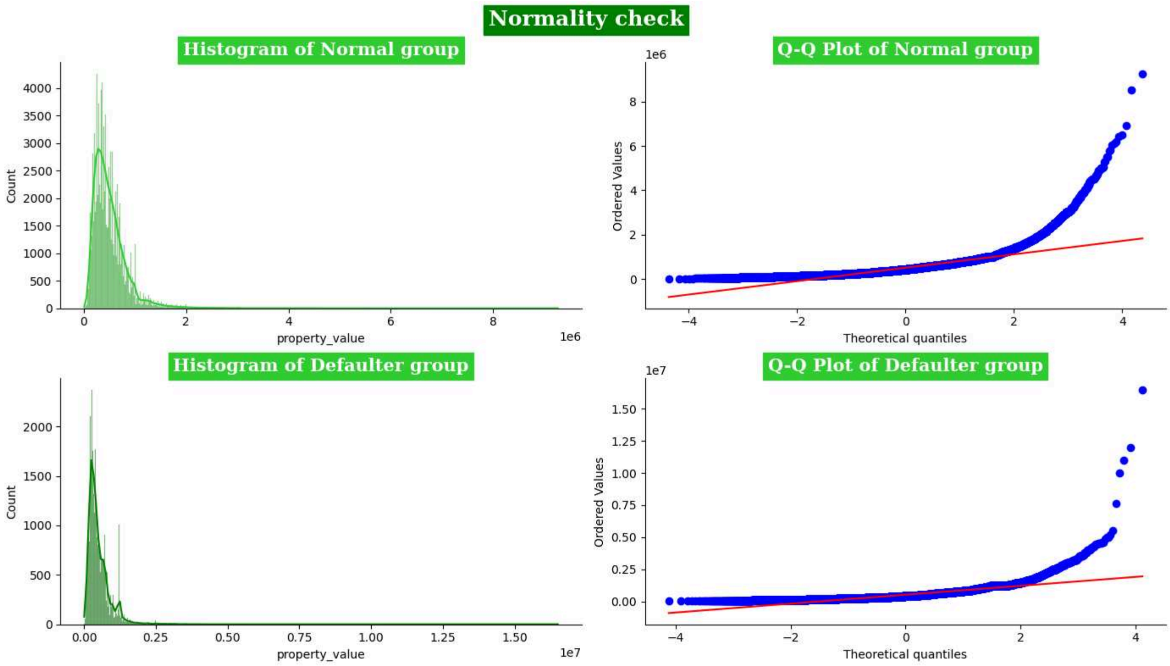
In [137…

```
# Preparing the data:
normal_property_value = df[df['Status'] == 'normal']['property_value']
defaulter_property_value = df[df['Status'] == 'defaulter']['property_value']
```

> **Normality & Equality of Variances:**

In [138…

```
# Function calling -> normality(group_1, group_1_name, group_2, group_2_name)
analysis = StatisticalAnalysis(normal_property_value,
                               'Normal group', defaulter_property_value, 'Defaul
analysis.normality_plots()
analysis.normality_tests()
analysis.variance_tests()
```




```
Normality Tests for Normal group:
- Shapiro-Wilk Test: Statistics=0.7777, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=3980.8064, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=4339336.1978, p-value=0.0000 => Not Gaussian distr
ibution

Normality Tests for Defaulter group:
- Shapiro-Wilk Test: Statistics=0.7172, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=1844.6075, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=20107221.4880, p-value=0.0000 => Not Gaussian dist
ribution

After Box-Cox Transformation:
Normality Tests for Transformed Normal group:
- Shapiro-Wilk Test: Statistics=0.9977, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=50.4349, Critical Values=[0.576 0.656 0.787 0.
918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=615.0649, p-value=0.0000 => Not Gaussian distribut
ion

Normality Tests for Transformed Defaulter group:
- Shapiro-Wilk Test: Statistics=0.9970, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=30.9982, Critical Values=[0.576 0.656 0.787 0.
918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=127.2435, p-value=0.0000 => Not Gaussian distribut
ion

Levene's Test for Normal group and Defaulter group:
- Statistic: 294.9809, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.

Bartlett's Test for Normal group and Defaulter group:
- Statistic: 1856.3695, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(two-sided)** with **Confidence level of 95%**

In [139…

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_property_value, 'Normal group',
                    defaulter_property_value, 'Defaulter group', alternative='tw
```

```
Mann-Whitney U test: (two-sided)
There is a difference (with respect to the central tendency) between Normal group
and Defaulter group.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(Right tailed)** with **Confidence level of 95%**

In [140…

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_property_value, 'Normal group',
                    defaulter_property_value, 'Defaulter group', alternative='gr
```

```
Mann-Whitney U test: (greater)
The central tendency of Normal group is greater than Defaulter group.
```

CONCLUSION:

- **Significant Difference in Central Tendencies:** The test shows that there is a statistically significant difference in the central tendency (median) of the property values between the Normal group and the Defaulter group. This implies that property values for borrowers who are normal (non-defaulters) differ from those who have defaulted.

- **Central Tendency of "Normal" Group is greater:** The result indicates that the central tendency (median) of the Normal group is greater than that of the Defaulter group. This suggests that borrowers classified as "Normal" tend to have higher property values compared to those classified as "Defaulter."

Business Insights:

Borrowers who do not default on their loans are likely to have properties of higher value compared to defaulters. This insight can be useful for assessing risk—borrowers with higher property values might be seen as lower risk for loan default. This could inform credit approval strategies and loan conditions.

Income Vs. Status

In [141…

```
# statistical summary
df.groupby('Status')['income'].describe()
```

Out[141…

	count	mean	std	min	25%	50%	75%	max
Status								
normal	111932.0	7168.656555	6025.143048	0.0	4080.0	6060.0	8700.0	377220.0
defaulter	36412.0	6229.976793	7156.949623	0.0	3060.0	4920.0	7620.0	578580.0

Introduction

- When comparing "income" and "Status," we can use a **Two-Sample Independent T-Test** if the data is normally distributed or a non-parametric test like the **Mann-Whitney U test** if it's not.

Why Two-Sample Independent T-Test?

- One should choose the Two-Sample Independent T-Test to compare the means of two independent groups to determine if there is a statistically significant difference between them.

Perform Hypothesis Testing

1. Formulate the Hypotheses

- **Null Hypothesis (H0):** There is no significant difference between the two groups.
- **Alternative Hypothesis (H1)**: There is a significant difference between the two groups.

2. Check Assumptions:

- **Normality:** Use the Q-Q Plot and Shapiro-Wilk test to check if the data is normally distributed.
- **Equality of Variances:** Use Levene's test to check if the variances are equal.

3. Choose the Appropriate Test

- If the data is **normally distributed, use two-Sample Independent T-Test.**
- If the data is **not normally distributed, use the Mann-Whitney U test.**

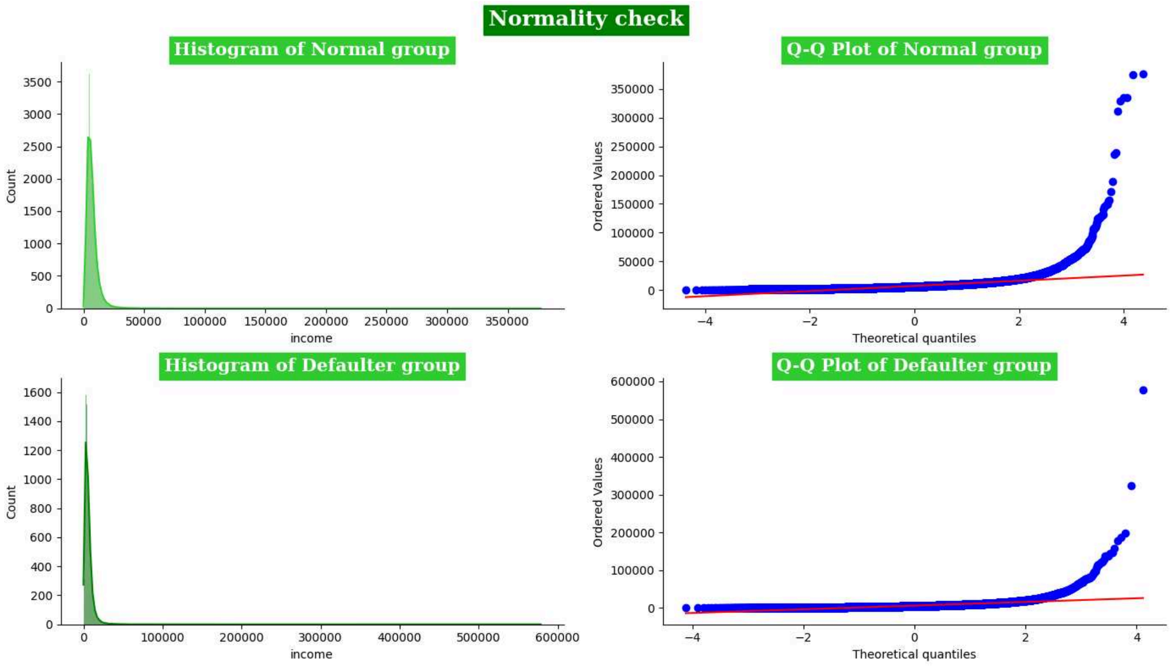
In [142…

```
# Preparing the data:
normal_income = df[df['Status'] == 'normal']['income']
defaulter_income = df[df['Status'] == 'defaulter']['income']
```

> **Normality & Equality of Variances:**

In [143…

```
# Function calling -> normality(group_1, group_1_name, group_2, group_2_name)
analysis = StatisticalAnalysis(normal_income, 'Normal group',
                               defaulter_income, 'Defaulter group')
analysis.normality_plots()
analysis.normality_tests()
analysis.variance_tests()
```




```
Normality Tests for Normal group:
- Shapiro-Wilk Test: Statistics=0.5536, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=7253.1668, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=1948452911.0890, p-value=0.0000 => Not Gaussian di
stribution

Normality Tests for Defaulter group:
- Shapiro-Wilk Test: Statistics=0.4629, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=3201.3252, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=2614473103.6200, p-value=0.0000 => Not Gaussian di
stribution

Box-Cox transformation failed: Data must be positive.

Levene's Test for Normal group and Defaulter group:
- Statistic: 19.2676, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.

Bartlett's Test for Normal group and Defaulter group:
- Statistic: 1720.8790, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(two-sided)** with **Confidence level of 95%**

In [144…

```python
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_income, 'Normal group',
                    defaulter_income, 'Defaulter group', alternative='two-sided'
```

```
Mann-Whitney U test: (two-sided)
There is a difference (with respect to the central tendency) between Normal group
and Defaulter group.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(Righ tailed)** with **Confidence level of 95%**

In [145…
```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_income, 'Normal group',
                    defaulter_income, 'Defaulter group', alternative='greater')
```

```
Mann-Whitney U test: (greater)
The central tendency of Normal group is greater than Defaulter group.
```

CONCLUSION:

- **Significant Difference in Central Tendencies:** There is a statistically significant difference in the central tendency (median) of the income between the Normal group and the Defaulter group. This indicates that the income levels of borrowers who are normal (non-defaulters) differ from those who default.
- **Central Tendency of "Normal" Group is greater:** The result shows that the central tendency (median) of income for the Normal group is greater than that of the Defaulter group. This suggests that normal borrowers generally have higher income levels compared to defaulters.

Business Insight:

- Borrowers with higher incomes tend to be non-defaulters, while those with lower incomes are more likely to default on their loans. This information can be useful for lenders to assess the risk of default, potentially adjusting loan terms based on a borrower's income to mitigate risk.

Credit Score Vs. Status

In [146…
```
# statistical summary
df.groupby('Status')['Credit_Score'].describe()
```

Out[146…

	count	mean	std	min	25%	50%	75%	max
Status								
normal	111932.0	699.510667	115.675157	500.0	599.0	699.0	800.0	900.0
defaulter	36412.0	700.580413	116.473990	500.0	599.0	700.0	803.0	900.0

Introduction

- When comparing "Credit_Score" and "Status," we can use a **Two-Sample Independent T-Test** if the data is normally distributed or a non-parametric test like the **Mann-Whitney U test** if it's not.

Why Two-Sample Independent T-Test?

- One should choose the Two-Sample Independent T-Test to compare the means of two independent groups to determine if there is a statistically significant difference between them.

Perform Hypothesis Testing

1. Formulate the Hypotheses

- **Null Hypothesis (H0):** There is no significant difference between the two groups.
- **Alternative Hypothesis (H1)**: There is a significant difference between the two groups.

2. Check Assumptions:

- **Normality:** Use the Q-Q Plot and Shapiro-Wilk test to check if the data is normally distributed.
- **Equality of Variances:** Use Levene's test to check if the variances are equal.

3. Choose the Appropriate Test

- If the data is **normally distributed, use two-Sample Independent T-Test.**
- If the data is **not normally distributed, use the Mann-Whitney U test.**

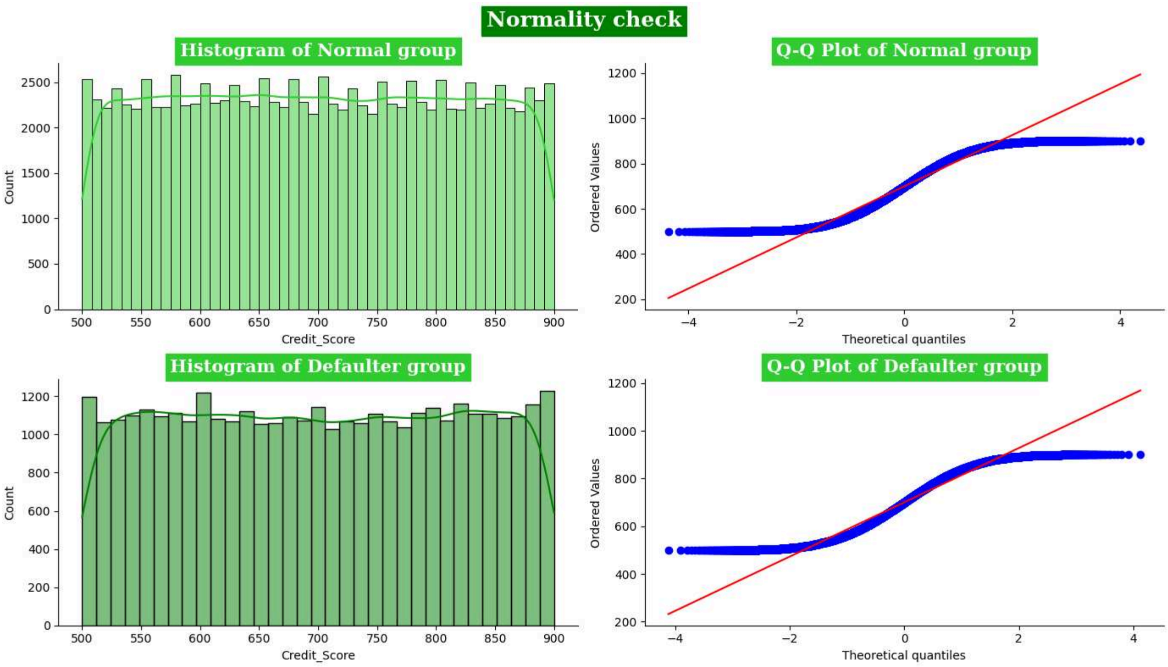
In [147…

```
# Preparing the data:
normal_Credit_Score = df[df['Status'] == 'normal']['Credit_Score']
defaulter_Credit_Score = df[df['Status'] == 'defaulter']['Credit_Score']
```

> **Normality & Equality of Variances:**

In [148…

```
# Function calling -> normality(group_1, group_1_name, group_2, group_2_name)
analysis = StatisticalAnalysis(normal_Credit_Score, 'Normal group',
                               defaulter_Credit_Score, 'Defaulter group')
analysis.normality_plots()
analysis.normality_tests()
analysis.variance_tests()
```



```
Normality Tests for Normal group:
- Shapiro-Wilk Test: Statistics=0.9551, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=1238.2230, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=6697.3833, p-value=0.0000 => Not Gaussian distribu
tion

Normality Tests for Defaulter group:
- Shapiro-Wilk Test: Statistics=0.9533, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=427.3160, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=2241.9277, p-value=0.0000 => Not Gaussian distribu
tion

After Box-Cox Transformation:
Normality Tests for Transformed Normal group:
- Shapiro-Wilk Test: Statistics=0.9552, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=1234.0017, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=6674.7439, p-value=0.0000 => Not Gaussian distribu
tion

Normality Tests for Transformed Defaulter group:
- Shapiro-Wilk Test: Statistics=0.9534, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=426.2127, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=2234.7668, p-value=0.0000 => Not Gaussian distribu
tion

Levene's Test for Normal group and Defaulter group:
- Statistic: 7.1781, p-value: 0.0074
Variances of Normal group and Defaulter group are significantly different.

Bartlett's Test for Normal group and Defaulter group:
- Statistic: 2.6085, p-value: 0.1063
Variances of Normal group and Defaulter group are approximately equal.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(two-sided)** with **Confidence level of 95%**

In [149…

```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_Credit_Score, 'Normal group',
                    defaulter_Credit_Score, 'Defaulter group', alternative='two-
```

```
Mann-Whitney U test: (two-sided)
There is no difference (in terms of central tendency) between Normal group and De
faulter group
```

CONCLUSION:

- **Mann-Whitney U Test (Two-sided):** The result shows that there is no statistically significant difference in the central tendency (median) of Credit Score between the Normal group and the Defaulter group. This suggests that the credit scores of borrowers who are normal (non-defaulters) and those who default are not significantly different in terms of their central tendencies.

Business Insight:

Since the Mann-Whitney U test shows no significant difference in the credit score distribution between non-defaulters and defaulters, it may indicate that credit score alone may not be a reliable predictor of whether a borrower will default or not. Lenders may need to consider additional factors along with credit score to more effectively assess default risk.

LTV Vs. Status

In [150…

```
# statistical summary
df.groupby('Status')['LTV'].describe()
```

Out[150…

Status	count	mean	std	min	25%	50%	75%	
normal	111932.0	72.053415	41.783471	2.072943	59.969325	74.497487	85.201149	78
defaulter	36412.0	71.502567	32.703479	0.967478	51.466228	73.538961	89.225941	29

Introduction

- When comparing "LTV" and "Status," we can use a **Two-Sample Independent T-Test** if the data is normally distributed or a non-parametric test like the **Mann-Whitney U test** if it's not.

Why Two-Sample Independent T-Test?

- One should choose the Two-Sample Independent T-Test to compare the means of two independent groups to determine if there is a statistically significant difference between them.

Perform Hypothesis Testing

1. Formulate the Hypotheses

- **Null Hypothesis (H0):** There is no significant difference between the two groups.
- **Alternative Hypothesis (H1)**: There is a significant difference between the two groups.

2. Check Assumptions:

- **Normality:** Use the Q-Q Plot and Shapiro-Wilk test to check if the data is normally distributed.
- **Equality of Variances:** Use Levene's test to check if the variances are equal.

3. Choose the Appropriate Test

- If the data is **normally distributed, use two-Sample Independent T-Test.**
- If the data is **not normally distributed, use the Mann-Whitney U test.**

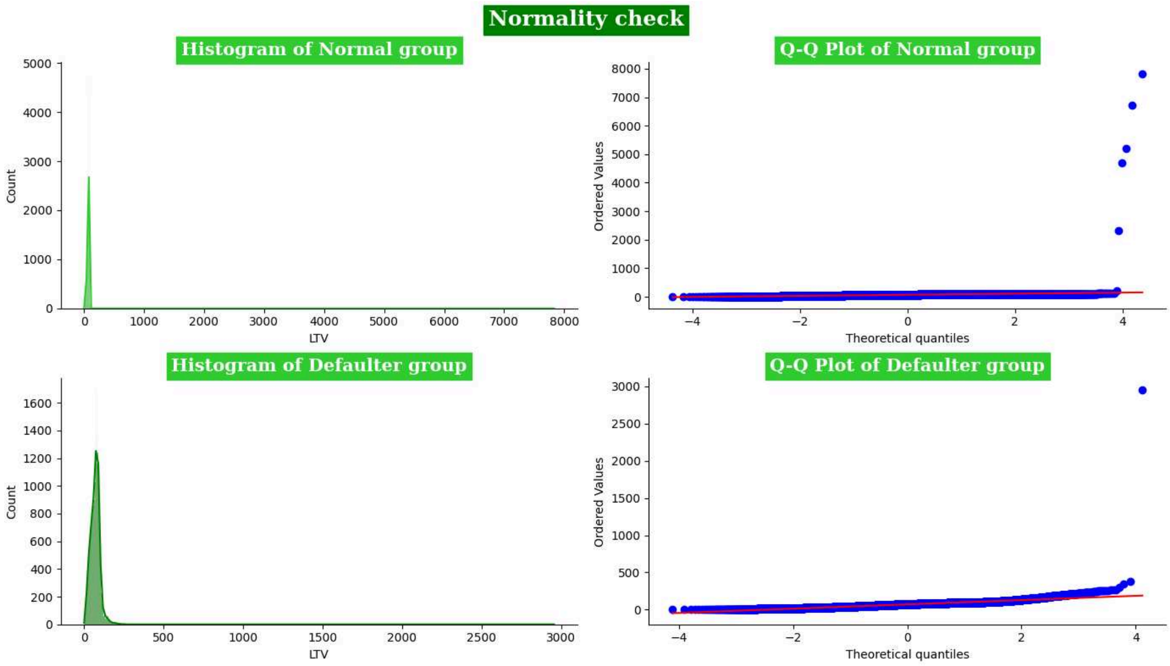
In [151…

```
# Preparing the data:
normal_LTV = df[df['Status'] == 'normal']['LTV']
defaulter_LTV = df[df['Status'] == 'defaulter']['LTV']
```

> **Normality & Equality of Variances:**

In [152…

```
# Function calling -> normality(group_1, group_1_name, group_2, group_2_name)
analysis = StatisticalAnalysis(normal_LTV, 'Normal group',
                               defaulter_LTV, 'Defaulter group')
analysis.normality_plots()
analysis.normality_tests()
analysis.variance_tests()
```



```
Normality Tests for Normal group:
- Shapiro-Wilk Test: Statistics=0.2092, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=12071.2673, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=1822106061367.3826, p-value=0.0000 => Not Gaussian
distribution

Normality Tests for Defaulter group:
- Shapiro-Wilk Test: Statistics=0.7718, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=400.3578, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=4200836414.6453, p-value=0.0000 => Not Gaussian di
stribution

After Box-Cox Transformation:
Normality Tests for Transformed Normal group:
- Shapiro-Wilk Test: Statistics=0.8500, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=2561.7688, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=86208543.7112, p-value=0.0000 => Not Gaussian dist
ribution

Normality Tests for Transformed Defaulter group:
- Shapiro-Wilk Test: Statistics=0.9615, p-value=0.0000 => Not Gaussian distributi
on
- Anderson-Darling Test: Statistic=320.1668, Critical Values=[0.576 0.656 0.787
0.918 1.092] => Not Gaussian distribution
- Jarque-Bera Test: Statistics=451550.3528, p-value=0.0000 => Not Gaussian distri
bution

Levene's Test for Normal group and Defaulter group:
- Statistic: 1227.6567, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.

Bartlett's Test for Normal group and Defaulter group:
- Statistic: 3020.8192, p-value: 0.0000
Variances of Normal group and Defaulter group are significantly different.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(two-sided)** with **Confidence level of 95%**

In [153…

```python
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_LTV, 'Normal group',
                    defaulter_LTV, 'Defaulter group', alternative='two-sided')
```

```
Mann-Whitney U test: (two-sided)
There is a difference (with respect to the central tendency) between Normal group
and Defaulter group.
```

4. Perform the Hypothesis Test

- Since the data is not Gaussian distribution we can go with non parametric test know as **Mann-Whitney U test(Left tailed)** with **Confidence level of 95%**

In [154…
```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_LTV, 'Normal group',
                    defaulter_LTV, 'Defaulter group', alternative='less')
```

```
Mann-Whitney U test: (less)
There is no difference (in terms of central tendency) between Normal group and De
faulter group
```

In [155…
```
# Function calling -> mannwhitneyu_u_test(group_1, group_1_name, group_2, group_
mannwhitneyu_u_test(normal_LTV, 'Normal group',
                    defaulter_LTV, 'Defaulter group', alternative='greater')
```

```
Mann-Whitney U test: (greater)
The central tendency of Normal group is greater than Defaulter group.
```

CONCLUSION:

- **Mann-Whitney U Test (Two-sided):** The test indicates that there is a statistically significant difference in the central tendency (median) of the Loan-to-Value (LTV) ratio between the Normal group (non-defaulters) and the Defaulter group.
- **Mann-Whitney U Test (Greater):** The result from the one-sided test shows that the central tendency (median LTV ratio) of the Normal group is greater than that of the Defaulter group. This suggests that borrowers who default tend to have lower LTV ratios compared to non-defaulters.

Business Insight:

The finding that defaulters tend to have lower LTV ratios suggests that borrowers with lower LTV (i.e., those borrowing more relative to the value of the property) are at a greater risk of defaulting. This insight is valuable for lenders, as they may want to assess risk more carefully for borrowers with high LTV ratios and potentially adjust lending policies, interest rates, or require additional collateral for such loans.

Business Insights

Income Influences Loan Status:

- Higher incomes are associated with lower default risk, as non-defaulters tend to have significantly higher incomes than defaulters (Mann-Whitney U test).
  - Fact: The Mann-Whitney U test showed that the income of the Normal group (non-defaulters) is significantly higher than that of the Defaulter group.
  - Insight: Borrowers with higher incomes are less likely to default.

Loan Amount Correlates with Loan Status:

- Non-defaulters take larger loans compared to defaulters, as shown by the Mann-Whitney U test.
  - Fact: The mean loan amount for the Normal group is higher than for the Defaulter group (based on Mann-Whitney U test: greater).
  - Insight: Non-defaulters tend to take larger loans compared to defaulters.

LTV Ratio and Default Risk:

- Defaulters have a lower LTV ratio than non-defaulters, though higher LTV is generally considered to increase default risk.
  - Fact: Defaulters have a higher mean LTV than non-defaulters. The Mann-Whitney U test (less) showed the central tendency of the Normal group is less than that of the Defaulter group.
  - Insight: Higher LTV increases the risk of default.

Upfront Charges and Default Risk:

- Defaulters tend to face higher upfront charges, suggesting that loan fees may be linked to higher default risk.
  - Fact: The Mann-Whitney U test showed that defaulters tend to have higher upfront charges than non-defaulters.
  - Insight: Loans with higher upfront charges tend to default more frequently, suggesting a correlation between loan fees and borrower risk.

Credit Score Insignificant for Default:

- Credit scores do not show a significant difference between defaulters and non-defaulters, indicating it's not a strong predictor in this dataset.
  - Fact: The Mann-Whitney U test indicated that there is no statistically significant difference in credit scores between the Normal and Defaulter groups.
  - Insight: Credit score alone may not be a strong predictor of loan default in this dataset.

Property Value and Loan Status:

- Non-defaulters typically own higher-value properties, which correlate with a lower likelihood of default.
  - Fact: The Mann-Whitney U test revealed that the mean property value for non-defaulters is significantly higher than for defaulters.
  - Insight: Higher-value properties are associated with a lower likelihood of default.

Occupancy Type Affects Default Probability:

- Loan default rates vary based on whether borrowers occupy the property, with a significant relationship found between occupancy type and loan status.
  - Fact: The Chi-Square test showed a statistically significant relationship between occupancy_type and loan status.
  - Insight: The likelihood of default varies depending on whether the borrower occupies the property or not.

Age Influences Default Likelihood:

- Borrower age significantly affects the probability of default, with certain age groups being more prone to default.

- Fact: A Chi-Square test found a statistically significant relationship between age and loan status.
- Insight: Borrower age influences the likelihood of default, with certain age groups being more prone to default.

Business Loans Carry Higher Risk:

- Business or commercial loans show a higher likelihood of default compared to personal loans.
  - Fact: The Chi-Square test indicated a significant relationship between the business_or_commercial category and loan status.
  - Insight: Business or commercial loans are more likely to default compared to personal loans.

Loan Purpose Impacts Default Risk:

- The reason for taking a loan plays a significant role in default probability, with some loan purposes being riskier than others.
  - Fact: The Chi-Square test revealed a significant relationship between loan purpose and loan status.
  - Insight: The purpose for which a loan is taken plays a key role in whether a borrower defaults, with certain loan purposes being riskier than others.

> **Key Insights on Loan Default (Inshort):**

- Higher Income: Non-defaulters have significantly higher incomes.
- Larger Loans: Non-defaulters tend to take bigger loans.
- Lower LTV: Defaulters have lower Loan-to-Value ratios.
- Higher Fees: Defaulters face higher upfront charges.
- Credit Score Impact: No significant difference in credit scores.
- Higher Property Value: Non-defaulters own higher-value properties.
- Occupancy Matters: Borrower-occupied properties default less.
- Age Factor: Certain age groups are more prone to default.
- Business Loans: Riskier compared to personal loans.
- Loan Purpose: Default risk varies by loan purpose.

Business Recommendations

Implement Tiered Risk-Based Lending:

- Offer lower loan amounts or stricter terms to borrowers with lower incomes, as higher-income borrowers show a lower likelihood of default. Set income-based thresholds to adjust loan limits and terms.
  - Recommendation: Offer lower loan amounts or stricter terms to borrowers with lower incomes, as higher-income borrowers have shown a lower likelihood of default (based on income central tendency).
  - Action: Set income thresholds to adjust loan limits and terms accordingly.

Tighten Loan Approval for High LTV Ratios:

- Impose stricter criteria for loans with high LTV ratios, capping LTV for riskier borrowers or requiring higher down payments to mitigate default risks.
  - Recommendation: Impose stricter approval criteria for loans with high LTV ratios, as defaulters tend to have higher LTVs.
  - Action: Cap LTV ratios for riskier borrowers or increase down payment requirements.

Limit Loans with High Upfront Charges:

- Reduce upfront charges for riskier borrowers or offer alternative fee structures. This can lower the default likelihood for those facing higher loan fees.
  - Recommendation: Consider reducing the upfront charges for riskier borrowers, as higher upfront charges correlate with defaults.
  - Action: Offer alternative fee structures or waive fees for lower-risk customers to improve loan performance.

Focus on Property-Based Loans for Safer Lending:

- Promote loan products for higher-value property owners, as they are associated with a lower risk of default. Offer more favorable terms to this group.
  - Recommendation: Promote loans on higher-value properties since non-defaulters are typically associated with higher property values.
  - Action: Develop loan products specifically for higher-value property owners, offering them more favorable terms.

Expand Credit Evaluation Beyond Credit Scores:

- Use additional metrics like income, LTV, and property value to assess risk, as credit score alone is not a strong predictor of default. Implement a holistic credit assessment approach.
  - Recommendation: Since credit score alone is not a strong predictor of default, integrate additional metrics like income, LTV, and property value into credit assessments.
  - Action: Implement a more holistic approach to assessing borrower creditworthiness.

Design Age-Specific Loan Products:

- Tailor loan terms for different age groups, considering their varying default risks. Offer flexible terms or create age-targeted lending strategies.
  - Recommendation: Tailor loan products for different age groups, given the influence of age on default probability.
  - Action: Offer more flexible terms for younger or older borrowers, or design age-targeted loan campaigns.

Be Cautious with Business Loans:

- Given their higher default risk, introduce stricter criteria or higher interest rates for business or commercial loans. Implement a specialized risk evaluation for these types of loans.
  - Recommendation: Since business loans have a higher default risk, consider higher interest rates or stricter approval criteria for such loans.
  - Action: Develop a separate risk evaluation model for business and commercial loans to better manage defaults.

Guide Lending Based on Occupancy Type:

- Differentiate lending terms between owner-occupied and non-owner-occupied properties, offering more favorable terms to borrowers who plan to occupy the property.
  - Recommendation: Differentiate between loans for owner-occupied and non-owner-occupied properties, as occupancy type impacts default risk.
  - Action: Offer more favorable terms to borrowers who plan to occupy the property they are borrowing against.

Focus on Loan Purpose for Risk Assessment:

- Adjust loan terms based on the purpose, as loan purpose significantly affects default risk. Categorize loan purposes and tailor approval criteria and interest rates.
  - Recommendation: Identify and adjust terms for loans with riskier purposes, as loan purpose significantly influences default likelihood.
  - Action: Develop a categorization of loan purposes and adjust approval criteria and interest rates accordingly.

Implement Continuous Risk Monitoring for High-LTV and High-Risk Loans:

- Set up monitoring for loans with high LTV ratios or high upfront charges, and create early intervention strategies to support borrowers showing signs of potential default.
  - Recommendation: Continuously monitor loans with high LTV and upfront charges for signs of risk, offering early intervention programs.
  - Action: Set up automated risk alerts and initiate customer support or loan modification processes for borrowers showing early signs of default.