Project Details:

Title: CYO Project

Due Date: 13 May 2024

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GitHub Link: https://github.com/Zoe21354/MLG382_GroupF_CYOProject.git

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Creditworthiness Assessment and Risk Analysis for Loan Default Prediction

This project is a comprehensive study aimed at building a predictive model to assess the creditworthiness of individuals or businesses. The purpose of this project is to predict the risk of default on loans or credit lines, which is a critical aspect of financial risk assessment.

The project utilizes a dataset titled “Credit Risk Assessment” authored by Urvish Vekariya and sourced from Kaggle. The dataset will undergo a series of data analysis and preprocessing steps, including dataset analysis, univariate and bi-variate analysis, handling missing values, removing duplicates, and outlier value handling. Two models will be built and their predictions will be evaluated. The feature importance from each model will be analyzed and the models will be saved as pickle files for future use. The second model will undergo additional cross-validation to ensure its robustness.

Finally, the validated model will be deployed as a server in a web application using DASH, providing a practical interface for credit risk assessment. This project is a significant step towards leveraging machine learning for effective and efficient credit risk management. It aims to provide a reliable tool for financial institutions to make informed decisions regarding loan approvals and credit line extensions.

This notebook will take the following structure:

```
1. Prepare Data (Data Analysis)
    A. Dataset Analysis
    B. Univariate Analysis
    C. Bi-variate Analysis
2. Hypotheses
3. Preprocess Data (Data Cleaning)
    A. Handling missing values
    B. Removing duplicates
    C. Outlier value Handling
5. Model 1
    A. Split the Data
    B. Build the Model
6. Feature Engineering
7. Model 2
    A. Split the Data
    B. Build the Model
8. Validate Model 2
9. Web Application
```

===

Before any coding can take place, certain libraries in python need to be imported to perform different functions and make various features available for use.

In [1]:

```
# Import Libraries
```

```
import csv                                                                # Handles CSV file operations
import pandas as pd                                                       # Data manipulation and analys
is
import numpy as np                                                        # Performs mathematical operat
ions
import matplotlib.pyplot as plt                                           # Creates static, animated, and
interactive visualizations
import seaborn as sns                                                     # Creates attractive and inform
ative statistical graphics
from sklearn.model_selection import train_test_split, GridSearchCV        # Splits data into random train a
nd test subsets
import pickle                                                             # Serializes and de-serializes
Python object structures
from sklearn.model_selection import cross_val_predict                     # Provides train/test indices to
split data in train/test sets
from sklearn.linear_model import LogisticRegression                       # Implements logistic regression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, precision_score               # Computes subset accuracy classi
fication score
from sklearn import tree                                                  # Contains classes for differen
t decision tree algorithms
from sklearn.ensemble import RandomForestClassifier
import dash
from dash import html, dcc
import plotly.graph_objs as go
from dash.dependencies import Input, Output, State
import warnings                                                           # Handles warnings during runt
ime
warnings.filterwarnings('ignore')                                         # Ignores displaying warnings
```

1. Prepare Data

The CSV files named credit_risk_raw_data and validation_data are read so that the unclean data contained in these files can be analyses.

In [2]:

```
# Read Unclean CSV Files
raw_data = pd.read_csv('credit_risk_raw_data.csv')
raw_data_copy = raw_data.copy()

validation_data = pd.read_csv('validation_data.csv')
validation_data_copy = validation_data.copy()
```

A. Dataset Analysis

Dataset Attributes:

- **Feature Variable (Independent variables) are variables that stand alone and are not changed by other variables that are being measured. They are denoted as X in ML algorithms.**
- **Target Variables (Dependent variables) are the variables that are to be predicted. It is often denoted as Y in ML algorithms.**

In [3]:

```
print(f"Raw Data Columns:\n{raw_data_copy.columns}\n")
print(f"Validation Data Columns:\n{validation_data_copy.columns}\n")
```

```
Raw Data Columns:
Index(['person_age', 'person_income', 'person_home_ownership',
       'person_emp_length', 'loan_intent', 'loan_amnt', 'loan_int_rate',
       'loan_percent_income', 'cb_person_cred_hist_length', 'loan_status'],
      dtype='object')

Validation Data Columns:
Index(['person_age', 'person_income', 'person_home_ownership',
       'person_emp_length', 'loan_intent', 'loan_amnt', 'loan_int_rate',
       'loan_percent_income', 'cb_person_cred_hist_length'],
      dtype='object')
```

Insight Gained:

- **The attribute names are inconsistent and will need standardizing in the data processing section.**
- **Feature Variable (Independent variable): This variable stands alone and is not changed by other variables that are being measured. It is denoted as X in ML algorithms.**
- **Target Variable (Dependent variable): This is the variable that is to be predicted. It is often denoted as Y in ML algorithms.**

- Target variable (Dependent variable). This is the variable that is to be predicted. It is often denoted as Y in ML algorithms.
- In both datasets there are 10 feature variables but only the raw_data dataset has 1 target variable.
- The target variable in the raw_data dataset is the loan_status attribute.
- This variable will be predicted using models for the validation_data dataset.

Dataset Datatypes:

Attributes can have different datatypes, such as numerical, categorical, or ordinal. Knowing the data type of each attribute is important because it determines what kind of statistical analysis or data processing is appropriate.

In [4]:

```
print(f"Raw Dataset Datatypes:\n{raw_data_copy.dtypes}\n")
print(f"Validation Dataset Datatypes:\n{validation_data_copy.dtypes}\n")
```

```
Raw Dataset Datatypes:
person_age                      int64
person_income                   int64
person_home_ownership          object
person_emp_length             float64
loan_intent                    object
loan_amnt                       int64
loan_int_rate                 float64
loan_percent_income           float64
cb_person_cred_hist_length      int64
loan_status                     int64
dtype: object

Validation Dataset Datatypes:
person_age                      int64
person_income                   int64
person_home_ownership          object
person_emp_length               int64
loan_intent                    object
loan_amnt                       int64
loan_int_rate                 float64
loan_percent_income           float64
cb_person_cred_hist_length      int64
dtype: object
```

Insight Gained:

- There is a discrepancy between the two datasets: the "person_emp_length" attribute is of datatype float64 in the raw_data.csv file but of datatype int64 in the validation_data.csv file.
- This could lead to potentially issues when modeling, as the model might be expecting the same data type for a given attribute.
- This discrepancy will need to be fixed in the data processing section.

Dataset Shape:

Knowing the number of rows in your datasets provides you with an idea of the volume of the data available to you.

In [5]:

```
print(f"Raw Data Shape:\n{raw_data_copy.shape}")
print(f"Validation Data Shape:\n{validation_data_copy.shape}")
```

```
Raw Data Shape:
(1526, 10)
Validation Data Shape:
(470, 9)
```

Insight Gained:

- Raw Data Shape: 1498 rows and 10 columns
- Validation Data Shape: 470 rows and 9 columns

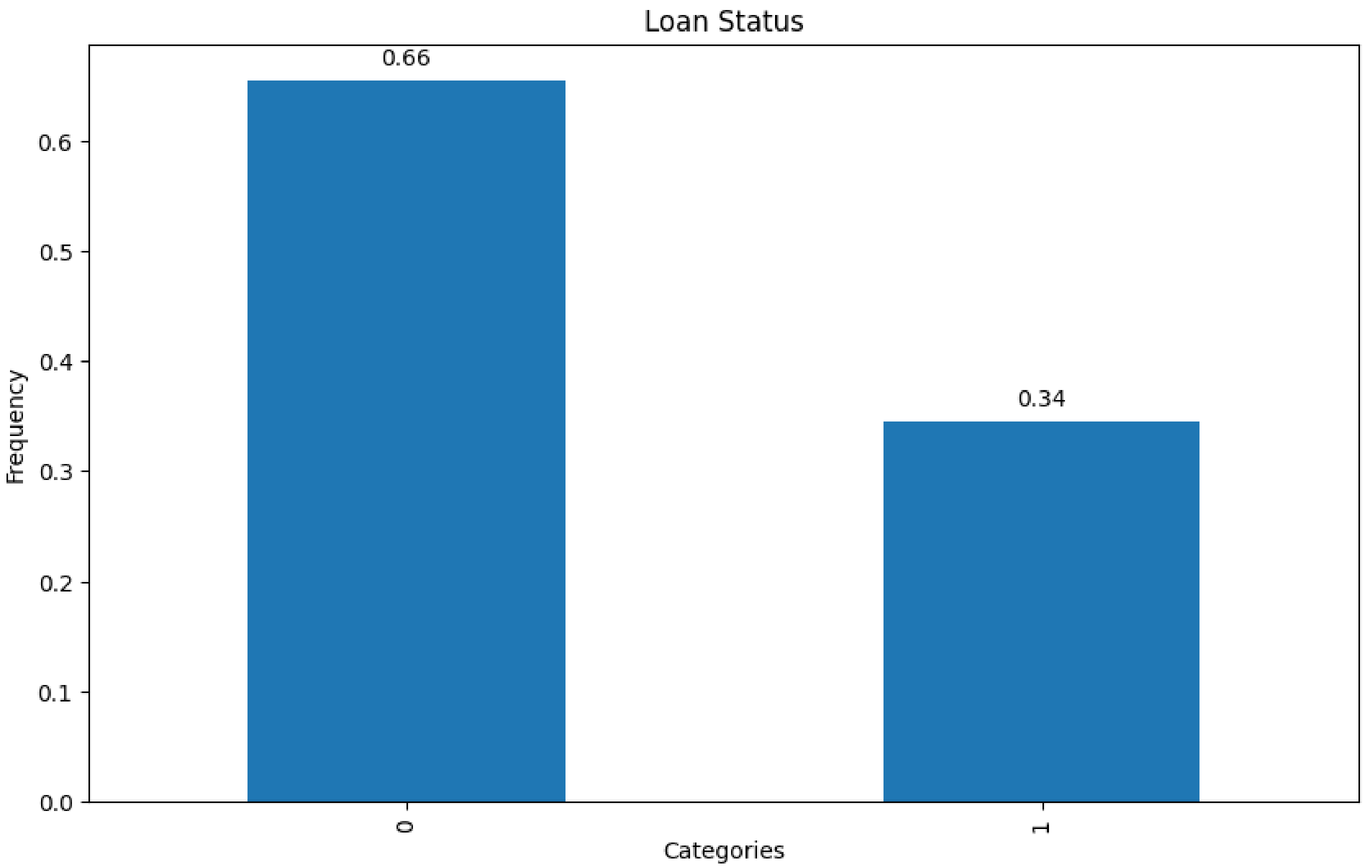
B. Univariate Analysis

Univariate analysis is the process of analysising individual (one variable) at a time. This is the most basic type of data analysis to finds patterns in the data.

Dependent (Target) Attribute:

In [6]:

```
#Dependent Variable
plt.figure(figsize=(10, 6))
count = raw_data_copy['loan_status'].value_counts(normalize = True)
chart = count.plot.bar(title = 'Loan Status', xlabel = 'Categories', ylabel = 'Frequency')
for i, v in enumerate(count):
    chart.text(i, v + 0.01, str(round(v, 2)), ha='center', va='bottom')
plt.show()
```



Insight Gained:

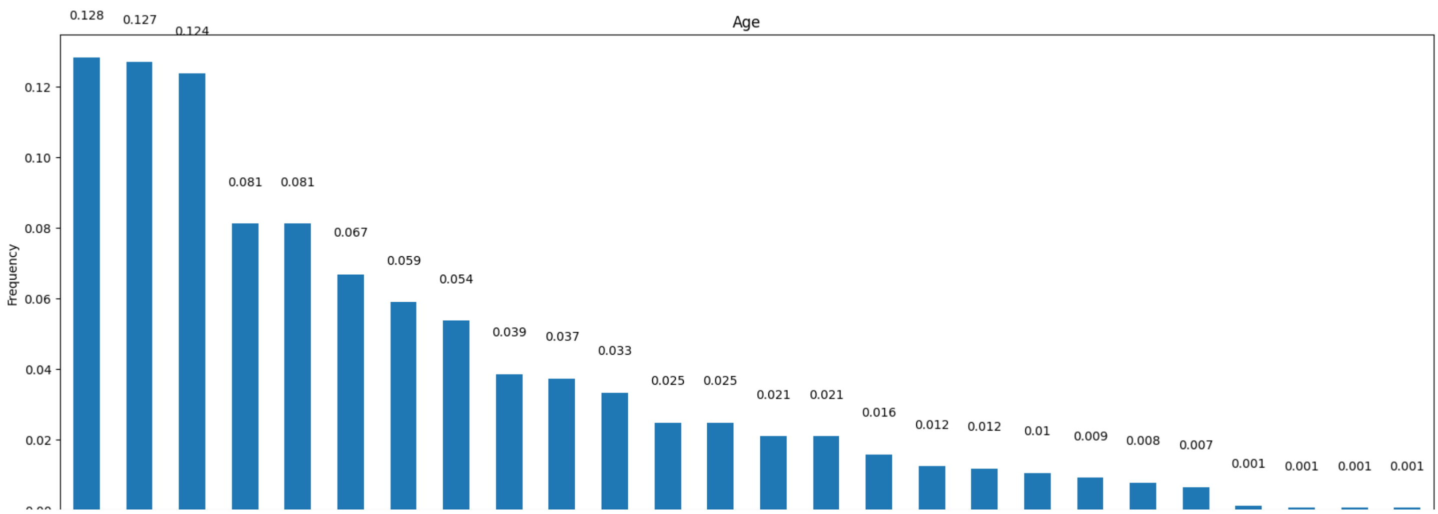
- **0.66 or 66% of the people were approved for a loan (i.e Loan_Status = Yes)**
- **0.34 or 34% of the people were not approved for a loan (i.e Loan_Status = No)**

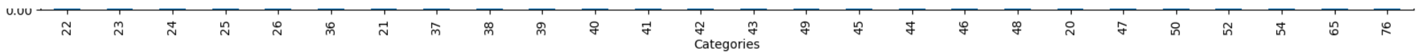
Independent Attributes (Ordinal):

Ordinal data have a clear ordering or hierarchy in the categories. For example, customer satisfaction ratings can include: unsatisfied, neutral, or satisfied.

In [7]:

```
#person_age
plt.figure(figsize=(20, 7))
count = raw_data_copy['person_age'].value_counts('normalize = True')
chart = count.plot.bar(title='Age', xlabel = 'Categories', ylabel = 'Frequency')
for i, v in enumerate(count):
    chart.text(i, v + 0.01, str(round(v, 3)), ha='center', va='bottom')
plt.show()
```



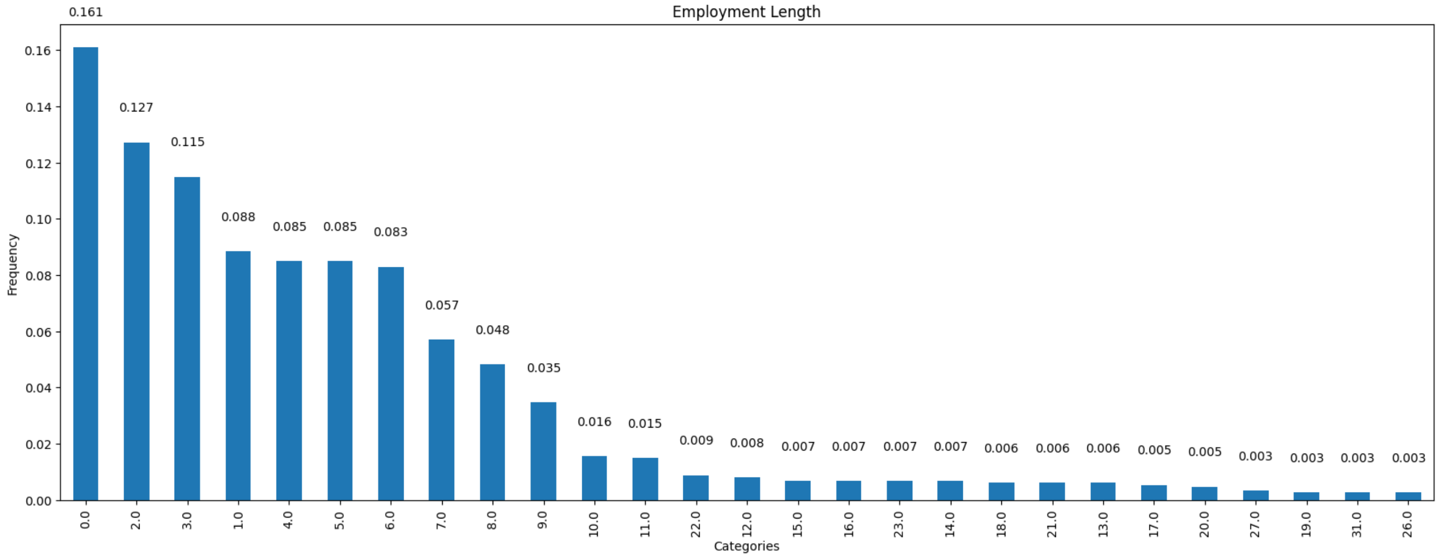


Insight Gained:

- **The age group ranges from early 20s to 50s**
- **With the largest number of people being of age 22 to 24**
- **There are outlier ages that need to be addressed in the processing stage.**

In [8]:

```python
#person_emp_length
plt.figure(figsize=(20, 7))
count =raw_data_copy['person_emp_length'].value_counts('normalize = True')
chart = count.plot.bar(title='Employment Length', xlabel = 'Categories', ylabel = 'Frequency')
for i, v in enumerate(count):
    chart.text(i, v + 0.01, str(round(v, 3)), ha='center', va='bottom')
plt.show()
```

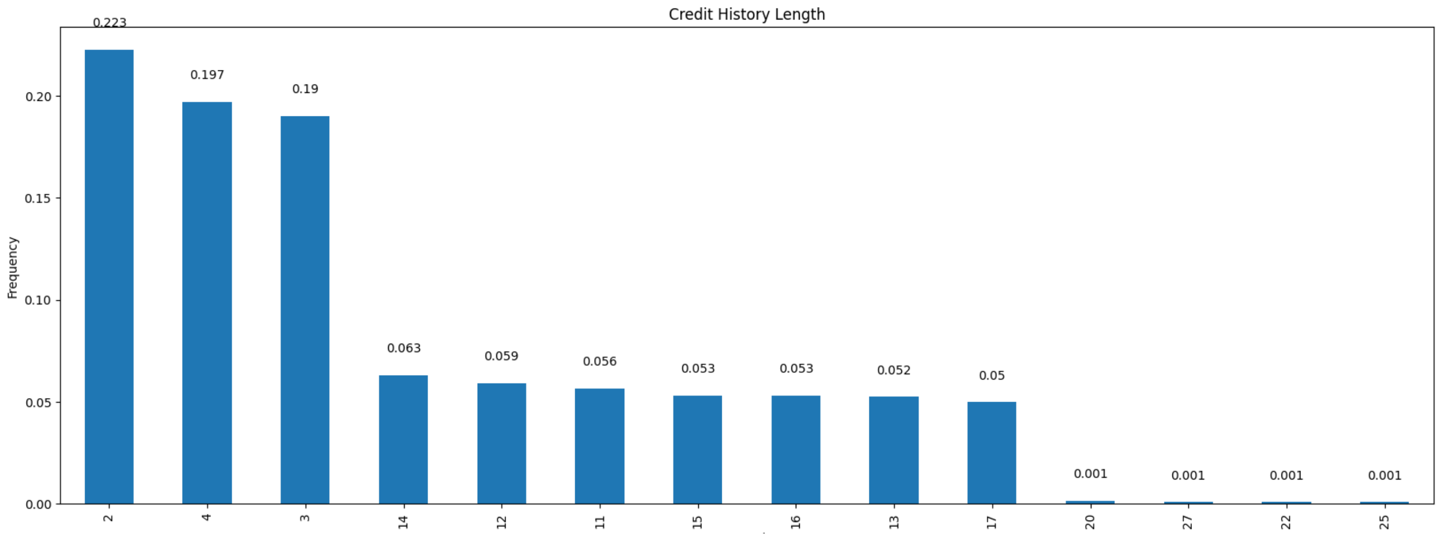


Insight Gained:

- **The most common employment length is less than a year, suggesting a high turnover rate or many short-term positions.**
- **There is a noticeable trend of decreasing frequency as employment length increases, showing that longer tenures are less common.**
- **Overall, the graph sheds light on the dynamics of the workforce, particularly in terms of employment longevity and the distribution of tenure lengths.**

In [9]:

```python
#cb_person_cred_hist_length
plt.figure(figsize=(20, 7))
count =raw_data_copy['cb_person_cred_hist_length'].value_counts('normalize = True')
chart = count.plot.bar(title='Credit History Length', xlabel = 'Categories', ylabel = 'Frequency')
for i, v in enumerate(count):
    chart.text(i, v + 0.01, str(round(v, 3)), ha='center', va='bottom')
plt.show()
```

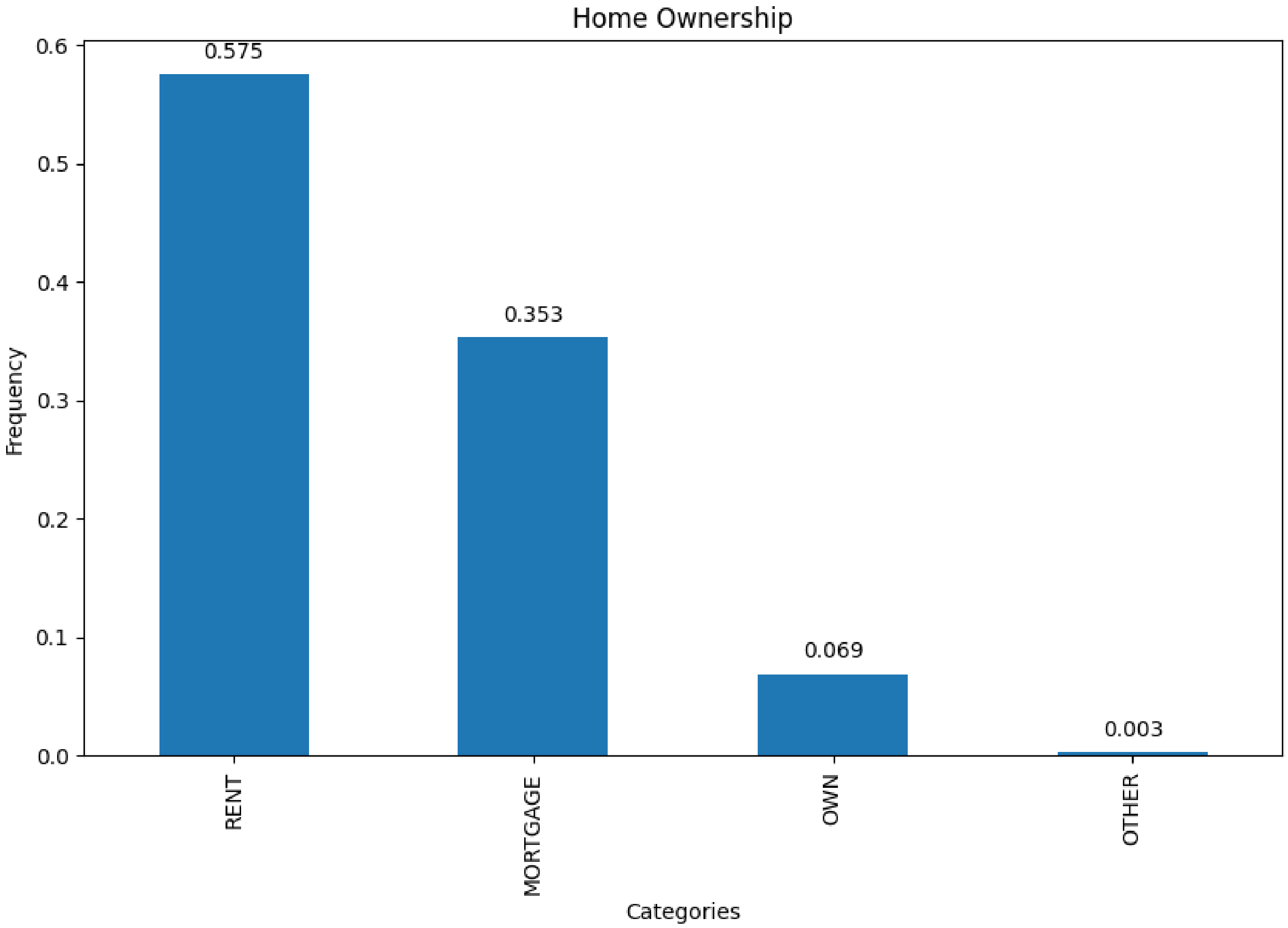


Insight Gained:

- **The distribution appears to be right-skewed, meaning there are more individuals with shorter credit histories than those with longer ones.**

In [10]:

```
#person_home_ownership
plt.figure(figsize=(10, 6))
count =raw_data_copy['person_home_ownership'].value_counts('normalize = True')
chart = count.plot.bar(title='Home Ownership', xlabel = 'Categories', ylabel = 'Frequency')
for i, v in enumerate(count):
    chart.text(i, v + 0.01, str(round(v, 3)), ha='center', va='bottom')
plt.show()
```

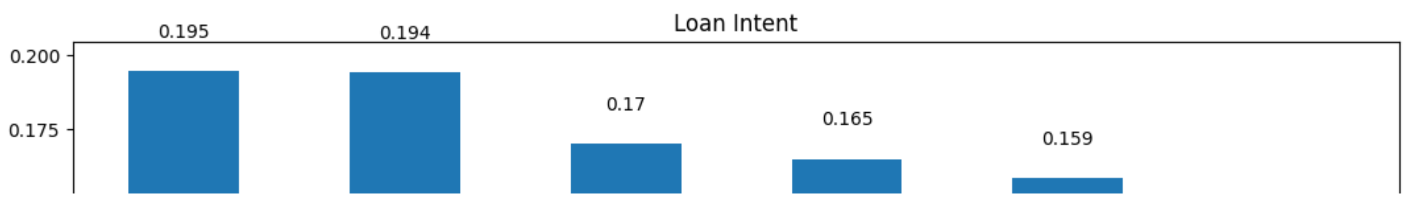


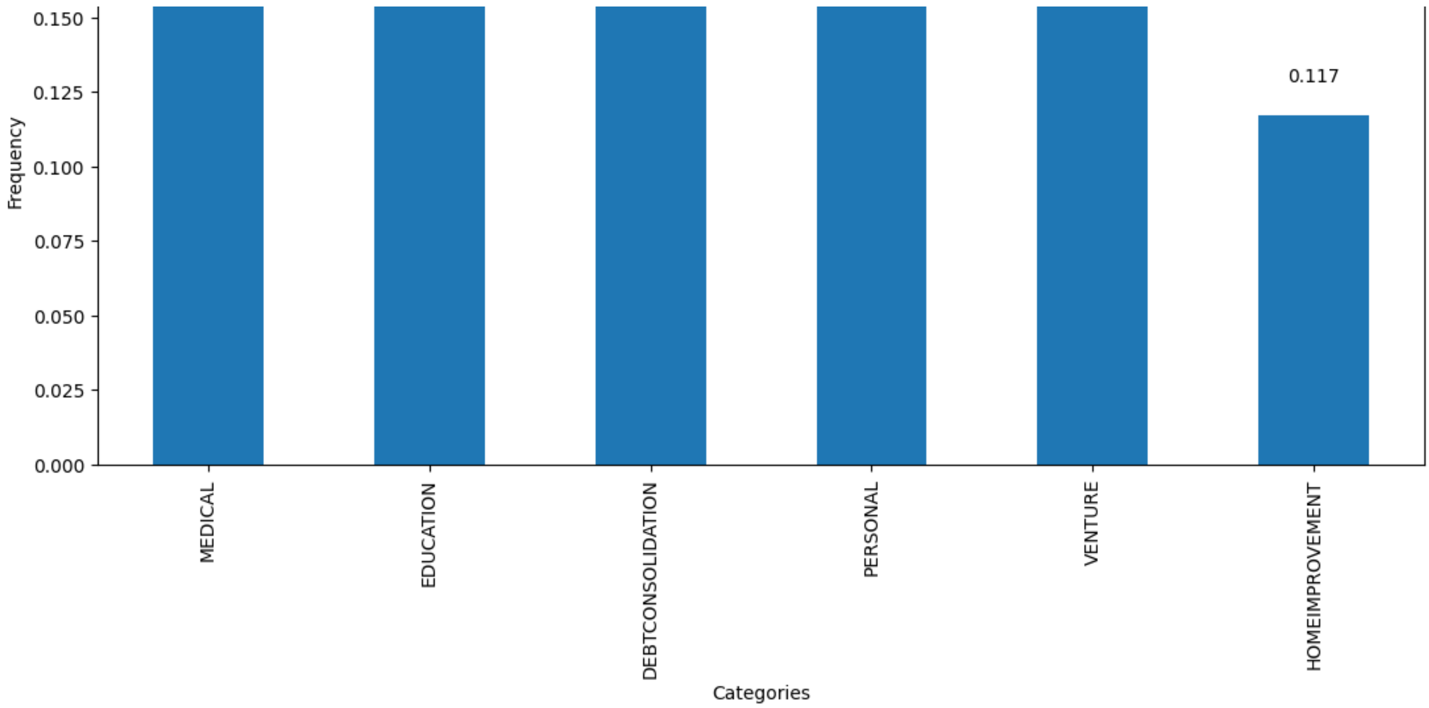
Insight Gained:

- **57.5% of the people who apply for a loan pay rent**
- **35.3% of the people who apply for a loan pay a mortgage**
- **6.9% of the people who apply for a loan own a house**
- **0.3% of the people who apply for a loan have other living arrangements**

In [11]:

```
#loan_intent
plt.figure(figsize=(13, 6))
count =raw_data_copy['loan_intent'].value_counts('normalize = True')
chart = count.plot.bar(title='Loan Intent', xlabel = 'Categories', ylabel = 'Frequency')
for i, v in enumerate(count):
    chart.text(i, v + 0.01, str(round(v, 3)), ha='center', va='bottom')
plt.show()
```





Insight Gained:

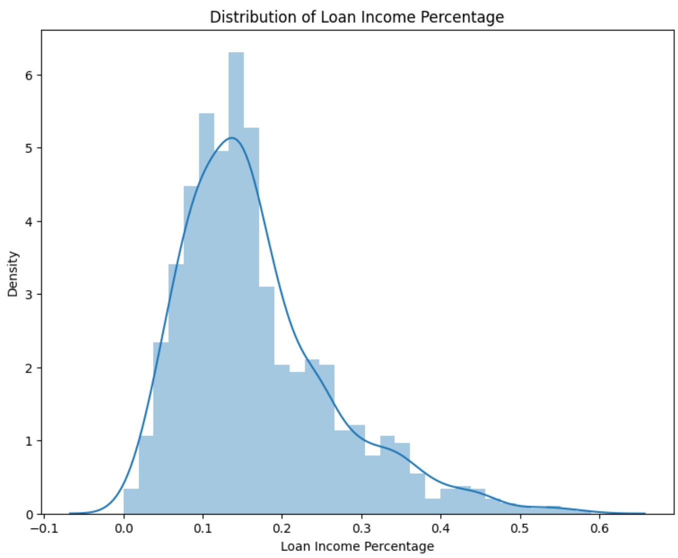
- **19.6% of the people apply for a loan for their Education**
- **19.4% of the people apply for a loan for their Medical bills**
- **17.0% of the people apply for a loan for their Debt Consolidations**
- **16.5% of the people apply for a loan for Personal reason**
- **15.9% of the people apply for a loan for Venture funding**
- **11.7% of the people apply for a loan for Home Improvements**

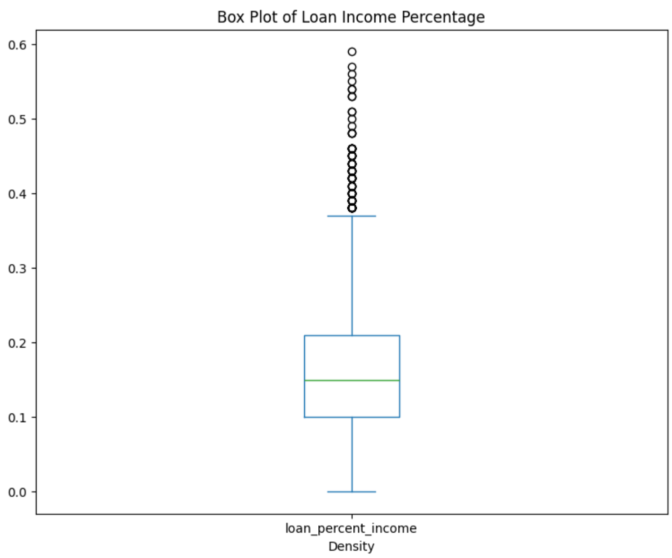
Independent Attributes (Nominal)

Nominal data does not have any kind of order or hierarchy but rather each category are different from each other. For example, the different breeds of dogs (Labrador, Beagle, Poodle) constitute nominal data because there is no inherent order among them.

In [12]:

```
#loan_percent_income
plt.figure(1, figsize=(20, 7))
plt.subplot(121)
raw_data_copy.dropna()
sns.distplot(raw_data_copy['loan_percent_income'])
plt.title('Distribution of Loan Income Percentage')
plt.xlabel('Loan Income Percentage')
plt.ylabel('Density')
plt.subplot(122)
boxplot =raw_data_copy['loan_percent_income'].plot.box()
boxplot.set_title('Box Plot of Loan Income Percentage')
boxplot.set_xlabel('Density')
plt.show()
```



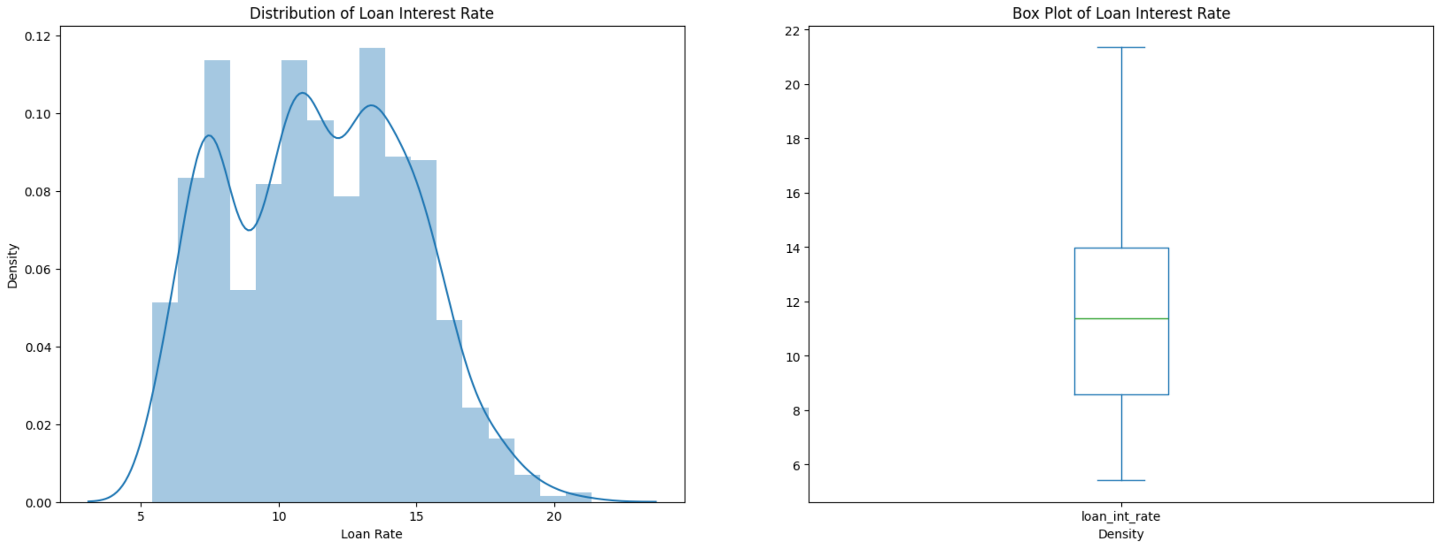


Insight Gained:

- **The distribution graph shows a right-skewed distribution, indicating most loan income percentages are low, with fewer high values.**
- **The box plot reveals the quartiles of the data and potential outliers above the upper whisker.**

In [13]:

```
#loan_int_rate
plt.figure(1, figsize=(20, 7))
plt.subplot(121)
raw_data_copy.dropna()
sns.distplot(raw_data_copy['loan_int_rate'])
plt.title('Distribution of Loan Interest Rate')
plt.xlabel('Loan Rate')
plt.ylabel('Density')
plt.subplot(122)
boxplot =raw_data_copy['loan_int_rate'].plot.box()
boxplot.set_title('Box Plot of Loan Interest Rate')
boxplot.set_xlabel('Density')
plt.show()
```

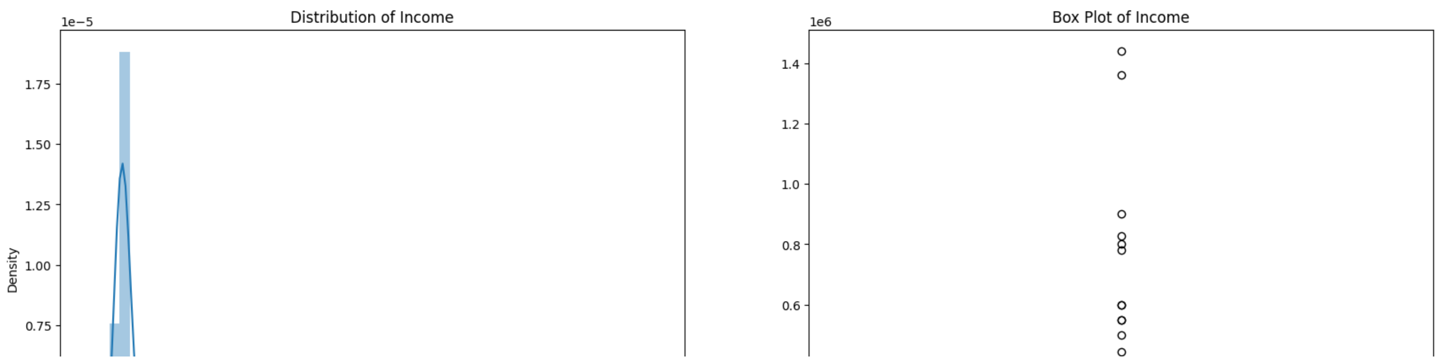


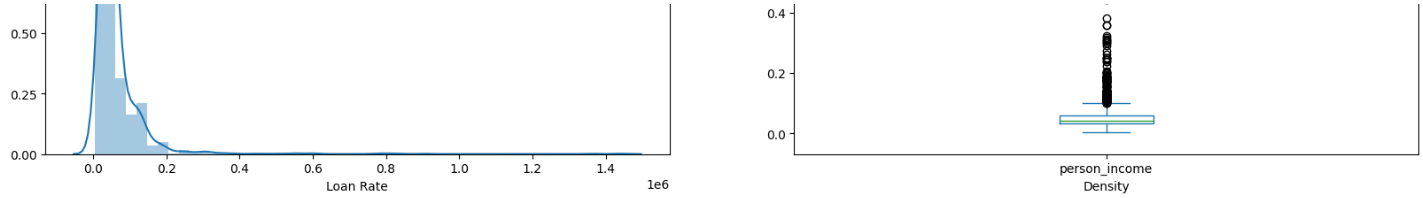
Insight Gained:

- **The distribution graph shows a right-skewed distribution of loan rates, with the majority of values clustered between 5% and 10%.**
- **The box plot indicates the median rate at around 10%, with half of the rates falling between approximately 7.5% and 12.5%.**
- **The box plot indicates that outliers are present above the upper whisker.**

In [14]:

```
#person_income
plt.figure(1, figsize=(20, 7))
plt.subplot(121)
raw_data_copy.dropna()
sns.distplot(raw_data_copy['person_income'])
plt.title('Distribution of Income')
plt.xlabel('Loan Rate')
plt.ylabel('Density')
plt.subplot(122)
boxplot =raw_data_copy['person_income'].plot.box()
boxplot.set_title('Box Plot of Income')
boxplot.set_xlabel('Density')
plt.show()
```



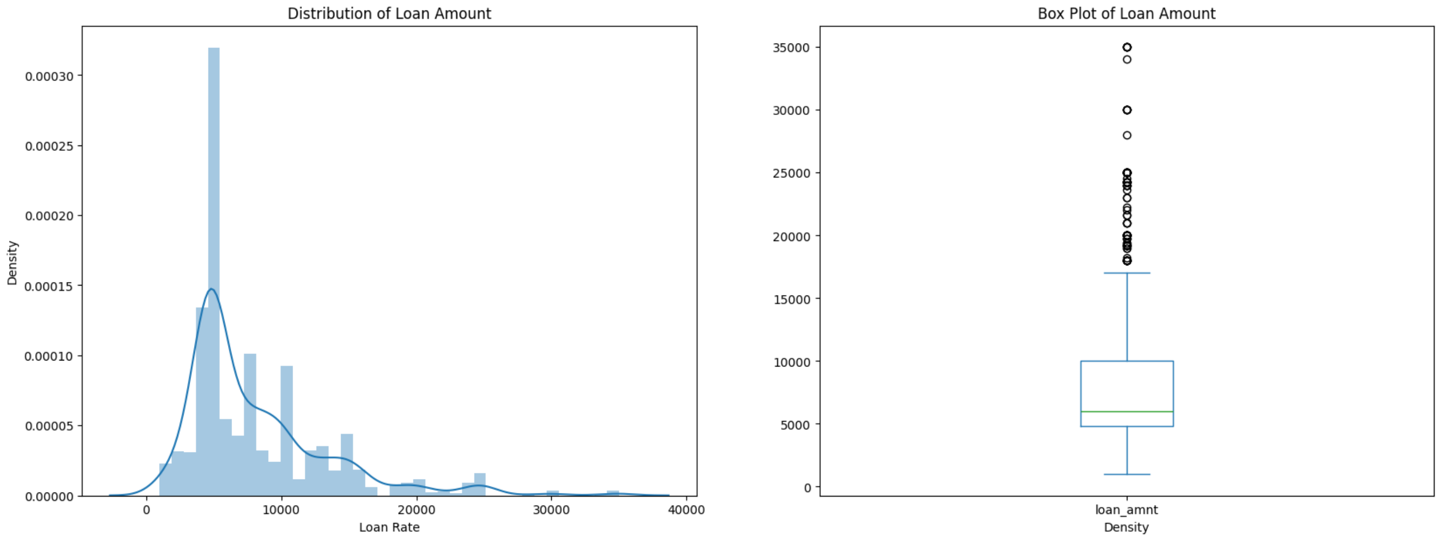


Insight Gained:

- **The distribution graph indicates a peak near zero with a long tail, suggesting a large number of individuals with low income and fewer with high income, reflecting economic inequality.**
- **The box plot shows there are outliers indicating individuals with significantly higher incomes.**

In [15]:

```
#loan_amnt
plt.figure(1, figsize=(20, 7))
plt.subplot(121)
raw_data_copy.dropna()
sns.distplot(raw_data_copy['loan_amnt'])
plt.title('Distribution of Loan Amount')
plt.xlabel('Loan Rate')
plt.ylabel('Density')
plt.subplot(122)
boxplot =raw_data_copy['loan_amnt'].plot.box()
boxplot.set_title('Box Plot of Loan Amount')
boxplot.set_xlabel('Density')
plt.show()
```



Insight Gained:

- **The distribution graph shows a right-skewed distribution with a majority of the loans being of lower amounts, indicating that smaller loans are more common.**
- **The box plot shows that their are outliers of loans significantly larger than the majority.**

C. Bi-variate Analysis

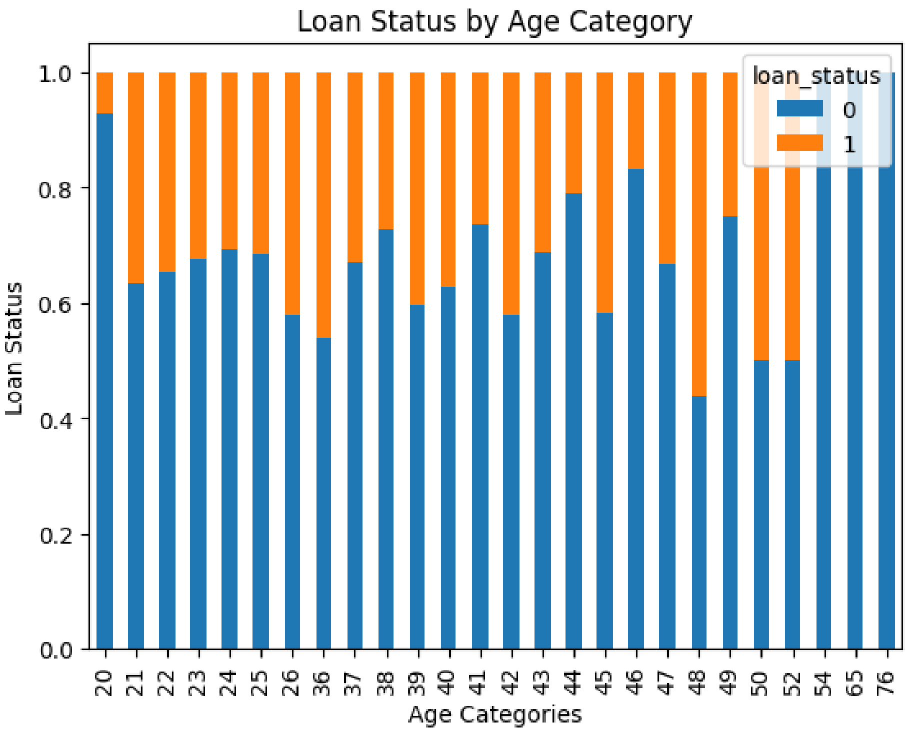
When there are two variables in the data it is called bi-variate analysis. The data is analyzed to find the relationship between the dependent and independent variables. Stacked bar graphs can be utilised to view the correlation between the coefficients.

The graphs created below will display how the Dependent Attribute 'loan_status' is distributed within each Independent Attribute, regardless of how many observations there are.

Ordinal Independent Variables and Dependent Variable:

In [16]:

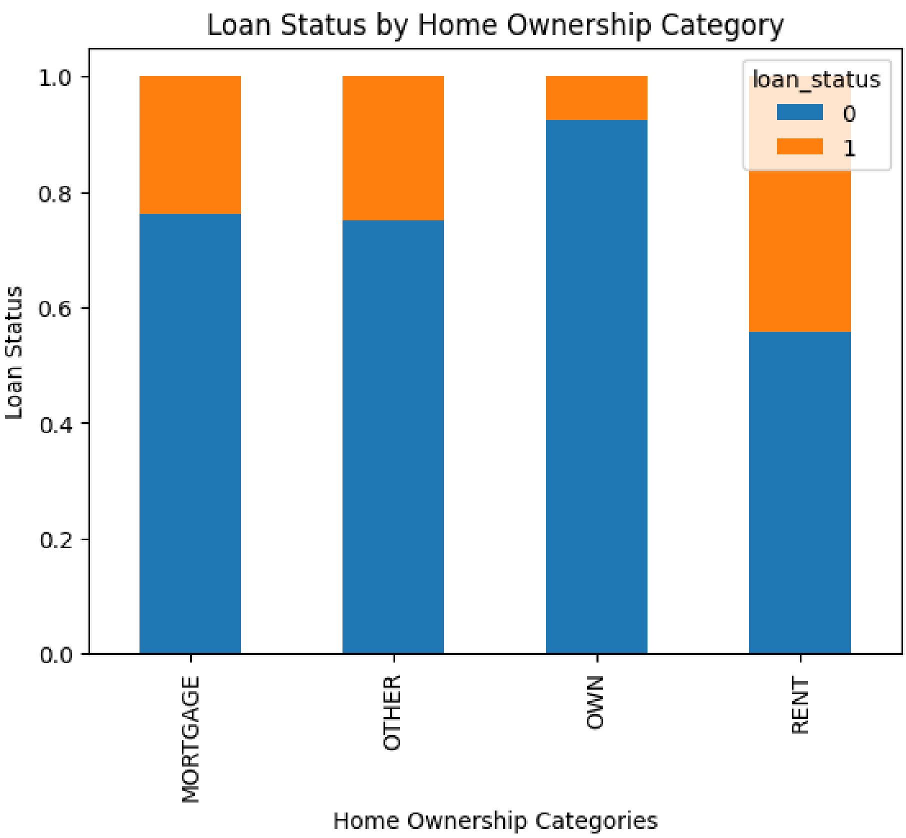
```
# Loan_Status vs person_age
person_age = pd.crosstab(raw_data_copy['person_age'], raw_data_copy['loan_status'])
person_age.div(person_age.sum(1).astype(float),axis=0).plot(kind='bar', stacked=True)
plt.title('Loan Status by Age Category')
plt.xlabel('Age Categories')
plt.ylabel('Loan Status')
plt.show()
```



Insight Gained:

In [17]:

```
# Loan_Status vs person_home_ownership
person_home_ownership = pd.crosstab(raw_data_copy['person_home_ownership'], raw_data_copy['loan_status'])
person_home_ownership.div(person_home_ownership.sum(1).astype(float),axis=0).plot(kind='bar', stacked=Tru
e)
plt.title('Loan Status by Home Ownership Category')
plt.xlabel('Home Ownership Categories')
plt.ylabel('Loan Status')
plt.show()
```

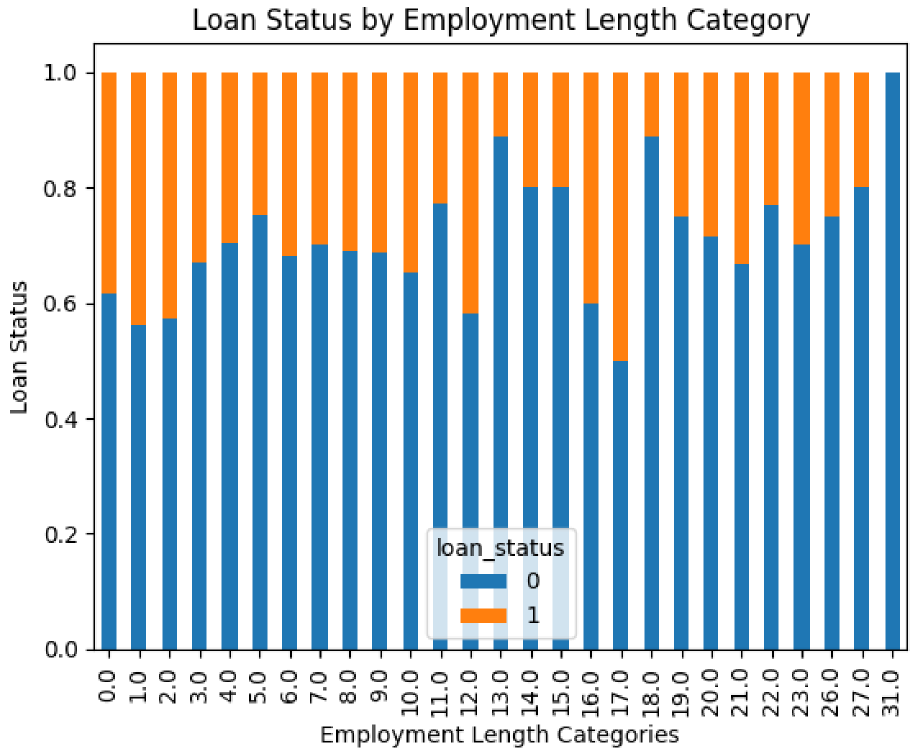


Insight Gained:

In [18]:

```
# Loan_Status vs person_emp_length
person_emp_length = pd.crosstab(raw_data_copy['person_emp_length'], raw_data_copy['loan_status'])
```

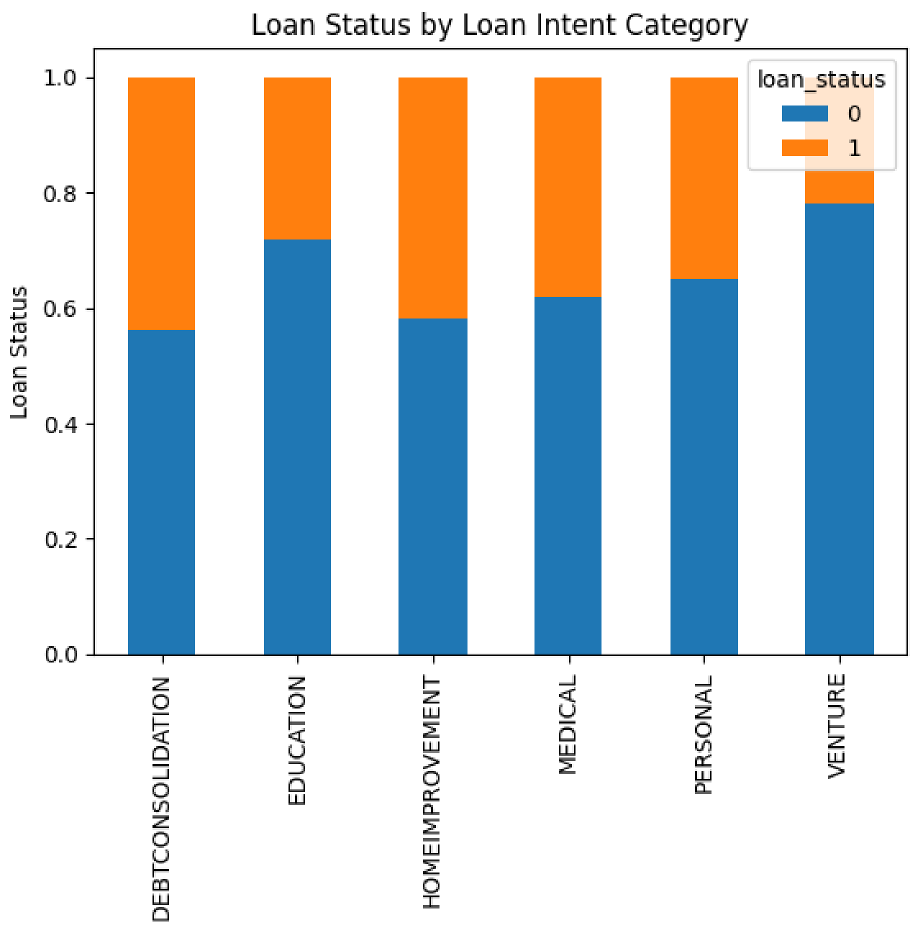
```
person_emp_length.div(person_emp_length.sum(1).astype(float),axis=0).plot(kind='bar', stacked=True)
plt.title('Loan Status by Employment Length Category')
plt.xlabel('Employment Length Categories')
plt.ylabel('Loan Status')
plt.show()
```



Insight Gained:

In [19]:

```
# Loan_Status vs loan_intent
loan_intent = pd.crosstab(raw_data_copy['loan_intent'], raw_data_copy['loan_status'])
loan_intent.div(loan_intent.sum(1).astype(float),axis=0).plot(kind='bar', stacked=True)
plt.title('Loan Status by Loan Intent Category')
plt.xlabel('Loan Intent Categories')
plt.ylabel('Loan Status')
plt.show()
```

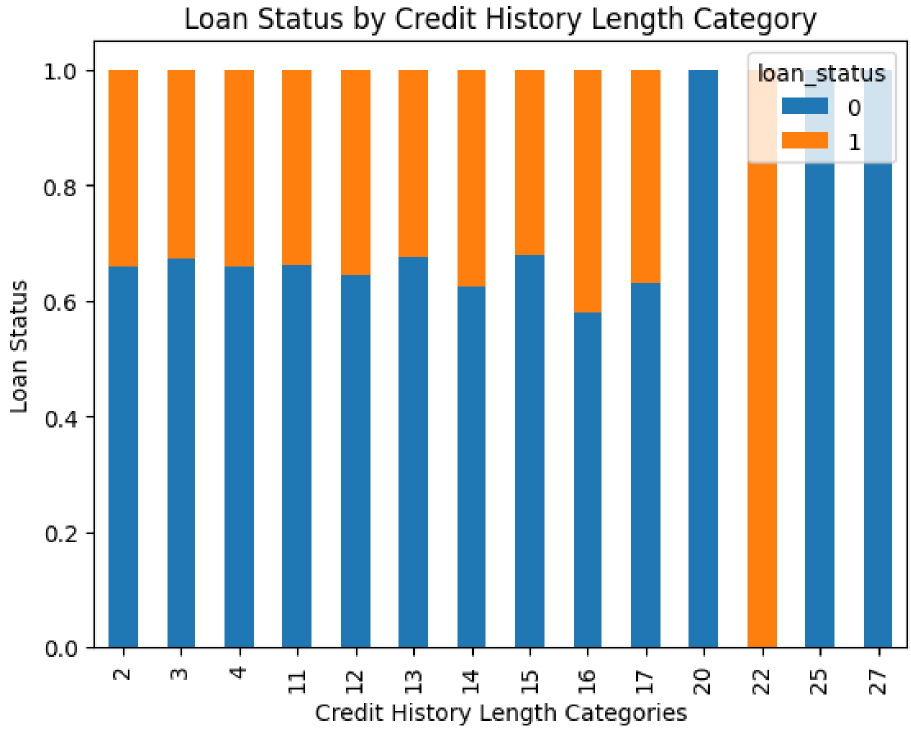


Loan Intent Categories

Insight Gained:

In [20]:

```
# Loan_Status vs cb_person_cred_hist_length
cb_person_cred_hist_length = pd.crosstab(raw_data_copy['cb_person_cred_hist_length'], raw_data_copy['loan
_status'])
cb_person_cred_hist_length.div(cb_person_cred_hist_length.sum(1).astype(float),axis=0).plot(kind='bar', s
tacked=True)
plt.title('Loan Status by Credit History Length Category')
plt.xlabel('Credit History Length Categories')
plt.ylabel('Loan Status')
plt.show()
```



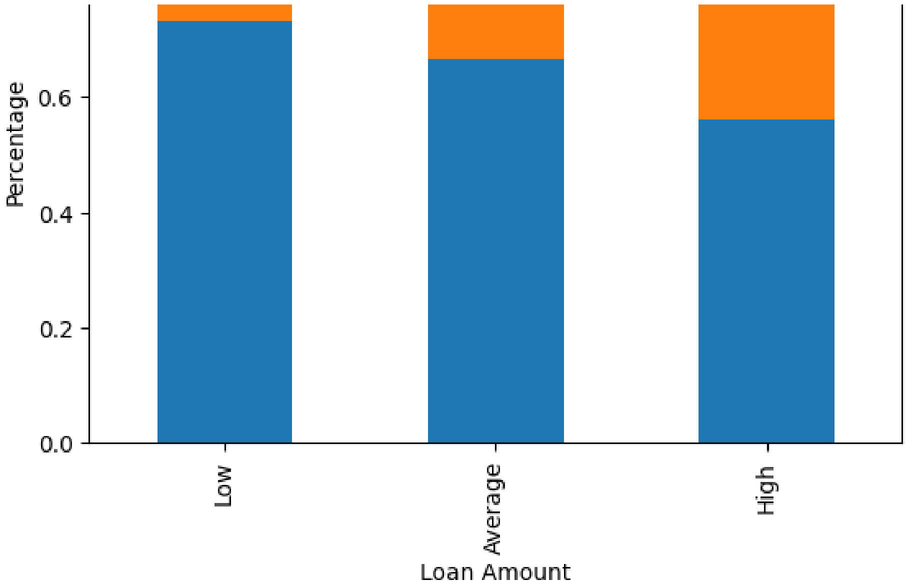
Insight Gained:

*Numerical Independent Variables and Dependent Variable

Binning will transform the continuous numerical variables into discrete categorical 'bins'. Brackets such as "Low", "Average", "Above Average", and "High" are used to provide a qualitative understanding of the ranges in the data.

In [21]:

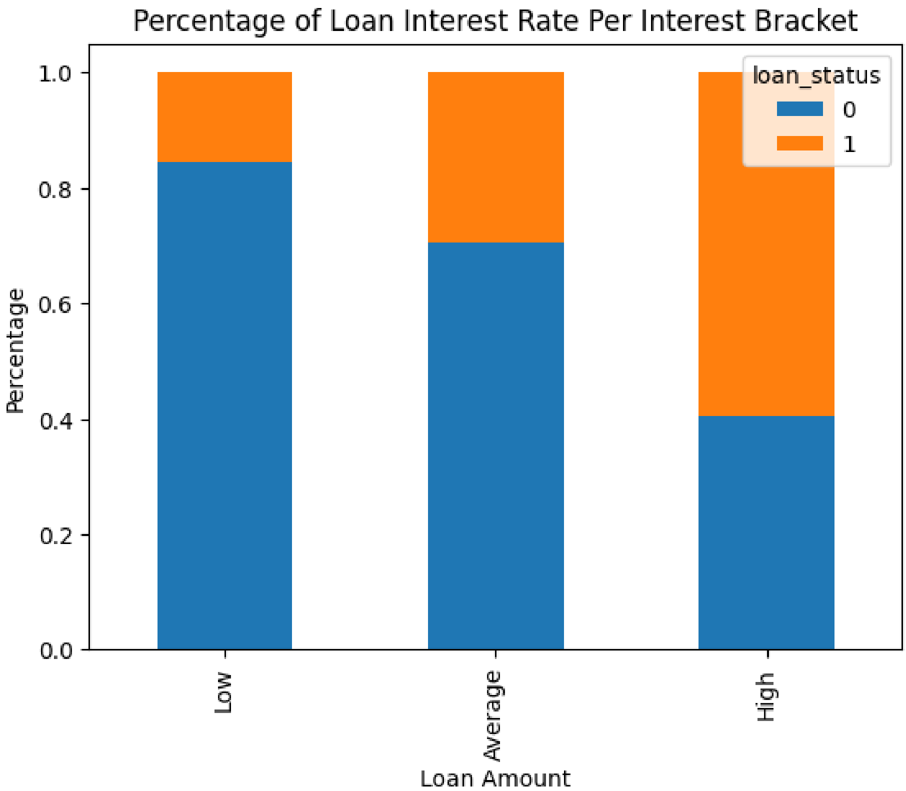
```
# Loan_Status vs loan_percent_income
low = raw_data_copy['loan_percent_income'].quantile(0.333) # 33.3th percentile
average = raw_data_copy['loan_percent_income'].quantile(0.666) # 66.6th percentile
high = 0.6

bins = [0, low, average, high]
group=['Low','Average','High']

raw_data_copy['loan_percent_income_bin']=pd.cut(raw_data_copy['loan_percent_income'],bins,labels=group)
loan_percent_income_bin=pd.crosstab(raw_data_copy['loan_percent_income_bin'],raw_data_copy['loan_status'])
loan_percent_income_bin.div(loan_percent_income_bin.sum(1).astype(float),axis=0).plot(kind='bar',stacked=
True)
plt.title('Percentage of Loan Income Percentage Per Income Bracket')
plt.xlabel('Loan Amount')
plt.ylabel('Percentage')
plt.show()
```



Insight Gained:

In [22]:

```
# Loan_Status vs loan_int_rate
low = raw_data_copy['loan_int_rate'].quantile(0.333) # 33.3th percentile
average = raw_data_copy['loan_int_rate'].quantile(0.666) # 66.6th percentile
high = 22

bins = [0, low, average, high]
group=['Low','Average','High']

raw_data_copy['loan_int_rate_bin']=pd.cut(raw_data_copy['loan_int_rate'],bins,labels=group)
loan_int_rate_bin=pd.crosstab(raw_data_copy['loan_int_rate_bin'],raw_data_copy['loan_status'])
loan_int_rate_bin.div(loan_int_rate_bin.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True)
plt.title('Percentage of Loan Interest Rate Per Interest Bracket')
plt.xlabel('Loan Amount')
plt.ylabel('Percentage')
plt.show()
```

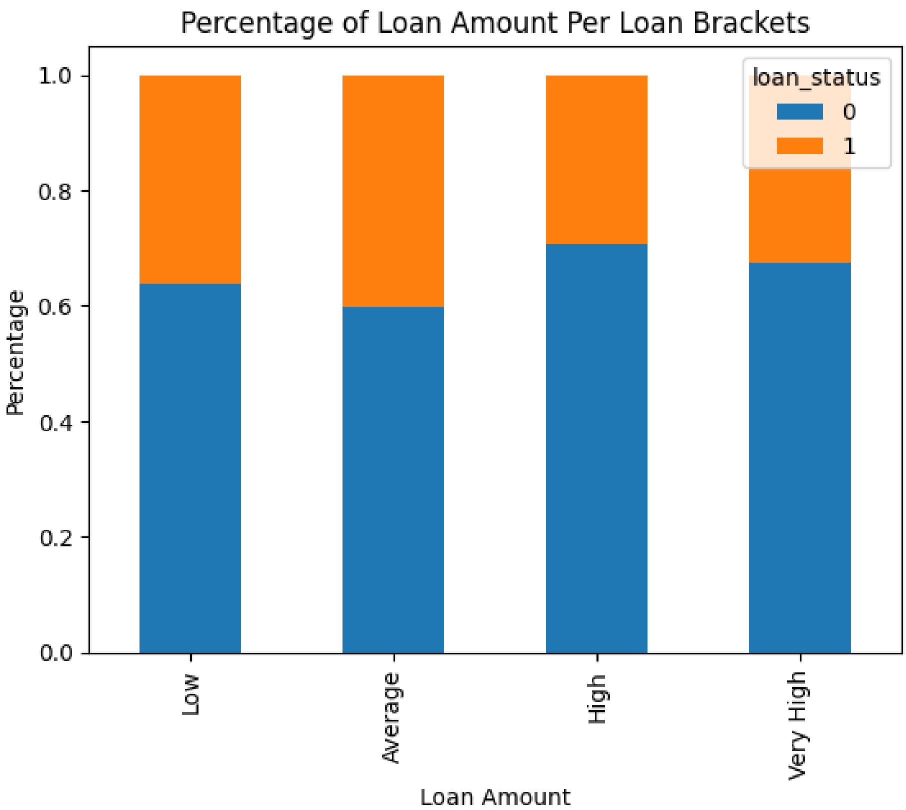


Insight Gained:

In [23]:

```
# Loan_Status vs loan_amnt
low = raw_data_copy['loan_amnt'].quantile(0.25) # 25th percentile
```

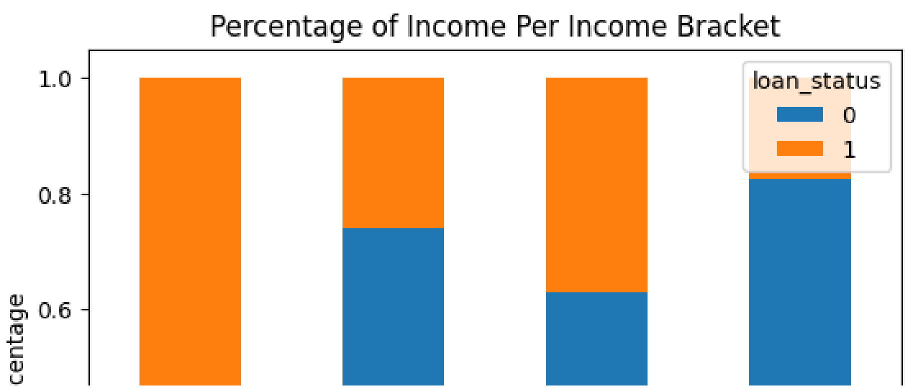
```
average = raw_data_copy['loan_amnt'].quantile(0.50) # 50th percentile
above_average = raw_data_copy['loan_amnt'].quantile(0.75) # 75th percentile
veryHigh = raw_data_copy['loan_amnt'].max() + 1 # maximum loan amount plus 1

bins = [0, low, average, above_average, veryHigh]
group=['Low','Average','High', 'Very High']

raw_data_copy['loan_amnt_bin'] = pd.cut(raw_data_copy['loan_amnt'], bins, labels=group)
loan_amnt_bin = pd.crosstab(raw_data_copy['loan_amnt_bin'], raw_data_copy['loan_status'])
loan_amnt_bin.div(loan_amnt_bin.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Percentage of Loan Amount Per Loan Brackets')
plt.xlabel('Loan Amount')
plt.ylabel('Percentage')
plt.show()
```

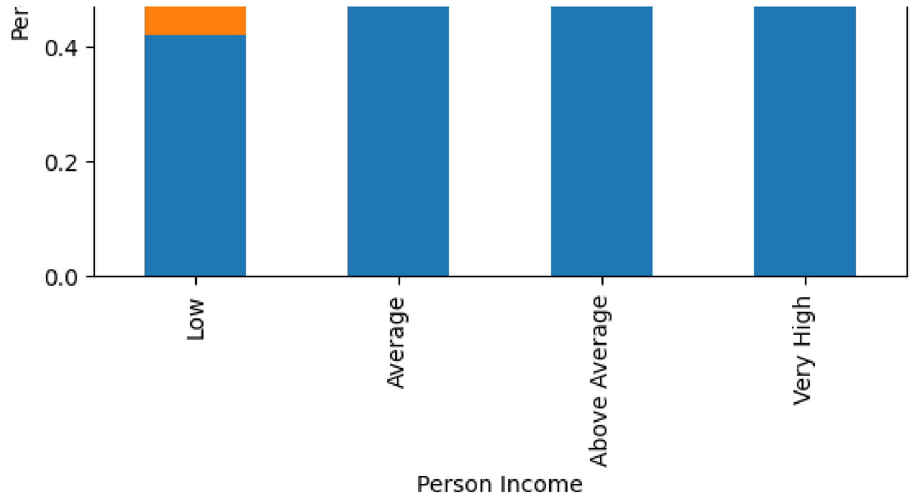


Insight Gained:

In [24]:

```
# Loan_Status vs person_income
low = raw_data_copy['person_income'].quantile(0.25) # 25th percentile
average = raw_data_copy['person_income'].quantile(0.50) # 50th percentile
above_average = raw_data_copy['person_income'].quantile(0.75) # 75th percentile
veryHigh = raw_data_copy['person_income'].max()+ 1

bins = [0, low, average, above_average, veryHigh]
group=['Low','Average','Above Average', 'Very High']

raw_data_copy['person_income_bin'] = pd.cut(raw_data_copy['person_income'], bins, labels=group)
person_income_bin = pd.crosstab(raw_data_copy['person_income_bin'], raw_data_copy['loan_status'])
person_income_bin.div(person_income_bin.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Percentage of Income Per Income Bracket')
plt.xlabel('Person Income')
plt.ylabel('Percentage')
plt.show()
```





Insight Gained:

We must now remove all bins created to avoid redundancy and reduce data complexity.

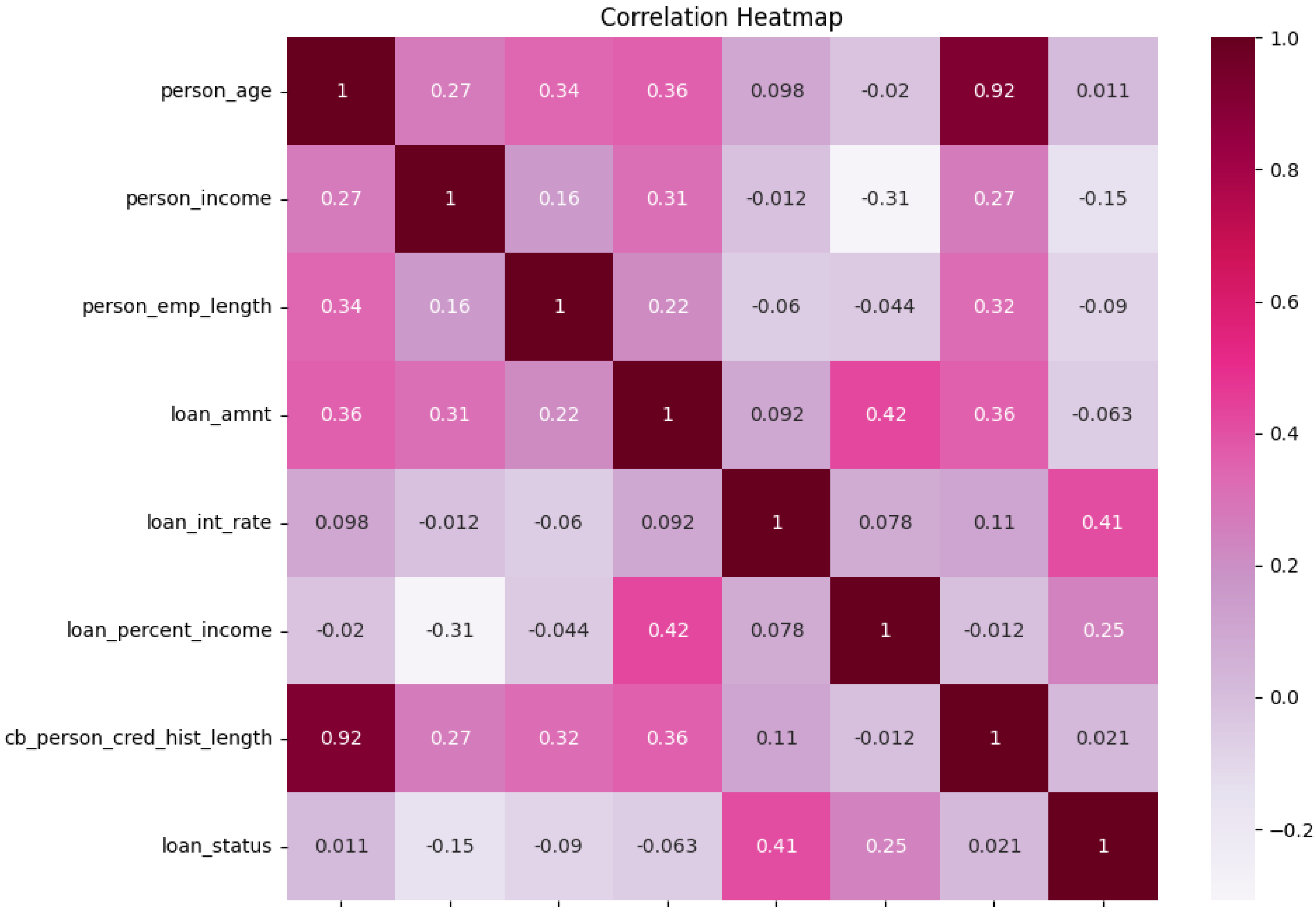
In [25]:

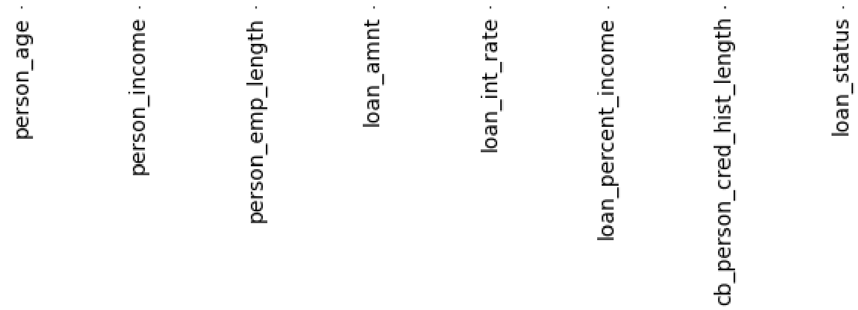
```
# Drop all bins created:
raw_data_copy=raw_data_copy.drop(['loan_percent_income_bin', 'loan_int_rate_bin', 'loan_amnt_bin', 'person
_income_bin'],axis=1)
```

Heatmaps are a powerful visualization tool that display data through variations in coloring. When used with datasets, the colors correspond to the values in each cell of a matrix. Darker colors typically represent higher correlation values (either positive or negative), while lighter colors represent lower correlation values or no correlation. This allows for an intuitive, visual interpretation of how different numerical attributes relate to each other in the dataset.

In [26]:

```
numeric_cols = raw_data_copy.select_dtypes(include=[np.number])
plt.figure(figsize=(10,8))
sns.heatmap(numeric_cols.corr(), annot=True, cmap='PuRd')
plt.title('Correlation Heatmap')
plt.show()
```





Insight Gained:

Having now seen how the different attributes impact the outcome in our datasets, several hypotheses can be drawn from the results.

==

2. Hypotheses

- **Hypothesis 1:**
  - **Justification:**
- **Hypothesis 2:**
  - **Justification:**
- **Hypothesis 3:**
  - **Justification:**
- **Hypothesis 4:**
  - **Justification:**
- **Hypothesis 5:**
  - **Justification:**

==

3. Data Cleaning

Through the analysis process, it can be seen that the data required cleaning. The most important step is to import the necessary libraries and read in the relevant CSV files.

In [27]:

```
# Read both CSV Files
credit_risk_raw_data = pd.read_csv('credit_risk_raw_data.csv')
credit_risk_raw_data_copy = credit_risk_raw_data.copy()

credit_risk_validation_data = pd.read_csv('validation_data.csv')
credit_risk_validation_data_copy = credit_risk_validation_data.copy()
```

1. Attribute Name Standardization Process for both dataset

Based on the insight gained from analysing the datasets, it was seen that the attribute names were inconsistant therefore the attribute require a renaming. Using a dictionary, the attribute cb_person_cred_hist_length is renamed to person_cred_hist_length.

In [28]:

```
raw_data_column_name_mapping = {
    'cb_person_cred_hist_length': 'person_cred_hist_length'
}

validation_data_column_name_mapping = {
    'cb_person_cred_hist_length': 'person_cred_hist_length'
}

#Replace the original column names with the formatted names:
credit_risk_raw_data_copy.rename(columns=raw_data_column_name_mapping, inplace=True)
credit_risk_validation_data_copy.rename(columns=validation_data_column_name_mapping, inplace=True)
```

2. Checking for missing values in both datasets

Ensuring that the datasets have no missing values is essencial because missing values can significantly impact the quality and performance of the machine learning models. Missing data can lead to biased or incorrect results, reduce the statistical power of the

model, and make the data harder to interpret. Therefore, it's crucial to handle missing values appropriately, either by filling them in using a suitable method (like mean, median, or mode imputation), or by removing the instances or features with missing values, depending on the nature and amount of the missing data.

In [29]:

```
print(f"Number of Missing Values in credit_risk_raw_data_copy:\n{credit_risk_raw_data_copy.isnull().sum()}
\n")
print(f"Number of Missing Values in credit_risk_validation_data_copy:\n{credit_risk_validation_data_copy.i
snull().sum()}\n")
```

```
Number of Missing Values in credit_risk_raw_data_copy:
person_age                      0
person_income                   0
person_home_ownership           0
person_emp_length              56
loan_intent                     0
loan_amnt                       0
loan_int_rate                 156
loan_percent_income             0
person_cred_hist_length         0
loan_status                     0
dtype: int64

Number of Missing Values in credit_risk_validation_data_copy:
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
person_cred_hist_length       0
dtype: int64
```

Fill in missing values

- **Based on the missing value check above, it was noted that there are missing values in the following attributes for the credit_risk_raw_data_copy dataset:**
  - **person_emp_length**
  - **loan_int_rate**

Ordinal Attributes

The *mode* of all the values in the attribute to fill in the missing data values, person_emp_length (0 - 23, 27 or 31)

In [30]:

```
credit_risk_raw_data_copy['person_emp_length'].fillna(credit_risk_raw_data_copy['person_emp_length'].mode(
)[0],inplace=True)
```

Numerical Attributes

The *median* is used instead of mean due to the outliers in the attribute data which could negatively impact the outcome.

In [31]:

```
credit_risk_raw_data_copy['loan_int_rate'].fillna(credit_risk_raw_data_copy['loan_int_rate'].median(),inp
lace=True)

#Check the file to see whether the missing values have been added
print(f"Number of Missing Values in credit_risk_raw_data_copy:\n{credit_risk_raw_data_copy.isnull().sum()}
\n")
```

```
Number of Missing Values in credit_risk_raw_data_copy:
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
person_cred_hist_length       0
loan_status                   0
dtype: int64
```

3. Handling Duplicates

Having resolved the missing values in the datasets, we run the risk of producing duplicate records. To resolve this we need to identify and remove these duplicates. This can be done using various techniques such as the 'drop_duplicates' function in pandas, which removes duplicate rows based on all or selected columns.

Removing duplicates is crucial as they can skew the results of the data analysis and lead to incorrect conclusions.

In [32]:

```
print(f"Number of duplicate rows in raw_data_copy: {credit_risk_raw_data_copy.duplicated().sum()}")
print(f"Number of duplicate rows in validation_data_copy: {credit_risk_validation_data_copy.duplicated().s
um()}\n")
```

```
Number of duplicate rows in raw_data_copy: 1
Number of duplicate rows in validation_data_copy: 0
```

In [33]:

```
# There is a duplicate record in the credit_risk_raw_data_copy dataset, as a result it will need to be dro
pped
credit_risk_raw_data_copy = credit_risk_raw_data_copy.drop_duplicates()

#Check that the duplicate record was removed
print(f"Number of duplicate rows in raw_data_copy: {credit_risk_raw_data_copy.duplicated().sum()}\n")
```

```
Number of duplicate rows in raw_data_copy: 0
```

4. Datatype Conversion

The attribute 'person_emp_length' in credit_risk_validation_data is converted to the datatype float64 in order to match the datatype of the credit_risk_raw_data dataset

In [34]:

```
credit_risk_validation_data_copy['person_emp_length'] = credit_risk_validation_data_copy['person_emp_lengt
h'].astype('float64')
print(f"person_emp_length datatype: {credit_risk_validation_data_copy['person_emp_length'].dtypes}\n")
```

```
person_emp_length datatype: float64
```

5. Outlier Data Handling

The next step to clean our data is to perform outlier handling.

***Person Income**

In [35]:

```
# For the 'credit_risk_validation_data_copy' dataset
credit_risk_validation_data_copy = credit_risk_validation_data_copy[credit_risk_validation_data_copy['pers
on_income'] < 1000000]
credit_risk_raw_data_copy = credit_risk_raw_data_copy[credit_risk_raw_data_copy['person_income'] < 100000
0]

print(f"credit_risk_raw_data_copy person_emp_length datatype:\n{credit_risk_raw_data_copy['person_income']
.describe()}\n")
print(f"credit_risk_validation_data_copy person_emp_length datatype:\n{credit_risk_validation_data_copy['p
erson_income'].describe()}\n")
```

```
credit_risk_raw_data_copy person_emp_length datatype:
count      1523.000000
mean      60931.252791
std       66339.170965
min        4000.000000
25%       34000.000000
50%       42000.000000
75%       60758.000000
max      900000.000000
Name: person_income, dtype: float64

credit_risk_validation_data_copy person_emp_length datatype:
```

```
credit_risk_validation_data_copy person_emp_length datatype:
count       469.000000
mean      68590.279318
std       69577.787894
min        9600.000000
25%       34000.000000
50%       55000.000000
75%       77052.000000
max      762000.000000
Name: person_income, dtype: float64
```

7. Write the new datasets to CSV files

The clean datasets are now written to csv files to be split and used during the model building phases.

In [36]:

```
credit_risk_raw_data_copy.to_csv('cleaned_credit_risk_raw_data.csv', index=False)
credit_risk_validation_data_copy.to_csv('cleaned_credit_risk_validation_data.csv', index=False)
```

===

Now that we have our training and test data, we can move onto building the initial model.

5. MODEL 1

A. Split Dataset

The use of dummy data is a common practice to transform categorical data into a binary format. This transformation assists with easier quantification and comparisons in future models.

When it comes to splitting the data into training and testing sets, a typical weightage of 80% (0.8) is assigned to the *training* dataset, while the remaining 20% (0.2) is allocated to the *testing* dataset. Additionally, to ensure the consistency of the train/test split across multiple executions of the code, 'random_state=42' is used. This guarantees that the same train/test split is reproduced every time the code is run, thereby ensuring reproducibility.

In [37]:

```
# Read Cleaned CSV Files
cleaned_raw_data = pd.read_csv('cleaned_credit_risk_raw_data.csv')
cleaned_raw_data_copy = cleaned_raw_data.copy()

# Define the independent variables (features) and the target variable
X = cleaned_raw_data_copy.drop('loan_status', axis=1)
y = cleaned_raw_data_copy['loan_status']

# Convert categorical variable in the X dataset(all columns except 'loan_status') into dummy variables
X = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create new DataFrames for training and testing sets
train_data = pd.concat([X_train, y_train], axis=1)
test_data = pd.concat([X_test, y_test], axis=1)

# Save the training and testing sets to CSV files
train_data.to_csv('train_data_ML1.csv', index=False)
test_data.to_csv('test_data_ML1.csv', index=False)
```

B. Build the Model

A Logistics Regression model is chosen for the first model to be built. It will be trained to make predictions, the accuracy of the predictions will be determined and stored in a csv file.

In [38]:

```
# 1. Train a Logistic Regression model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)

# 2. Make predictions with the model
y_pred = logreg.predict(X_test)
```

```
# 3. Check the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy}")

# 4. Save the predictions to a csv file
predictions = pd.DataFrame(y_pred, columns=['predictions'])
predictions.to_csv('logreg_predictions.csv', index=False)
```

```
Model Accuracy: 0.7344262295081967
```

Cross Validation

A cross validation model will be built using a different data split to validate the accuracy of the predictions made. A new split will result in a more accurate Logistics Regression model. Predictions are made on the new model and the accuracy is calculated and compared to determine which model has the best accuracy.

In [39]:

```
# For this, we'll use a new split of the data
X_train_cv, X_test_cv, y_train_cv, y_test_cv = train_test_split(X, y, test_size=0.2, random_state=0)
logreg_cv = LogisticRegression()
logreg_cv.fit(X_train_cv, y_train_cv)

# 6. Make predictions on the cross validate model
y_pred_cv = logreg_cv.predict(X_test_cv)

# 7. Check the accuracy score of the cross validate model
accuracy_cv = accuracy_score(y_test_cv, y_pred_cv)
print(f"Cross-Validated Model Accuracy: {accuracy_cv}")

# 8. Save the cross validate predictions to csv file
predictions_cv = pd.DataFrame(y_pred_cv, columns=['predictions_cv'])
predictions_cv.to_csv('logreg_predictions_cv.csv', index=False)

# 9. Determine which model is the most accurate
if accuracy > accuracy_cv:
    most_accurate_model = logreg
    print("The original model is the most accurate.")
else:
    most_accurate_model = logreg_cv
    print("The cross-validated model is the most accurate.")
```

```
Cross-Validated Model Accuracy: 0.7377049180327869
The cross-validated model is the most accurate.
```

As the split for the cross validate model is not set the results might vary, however, in this instance the best model see is the cross-validated model with an accuracy of 73.77%. This model is then taken an hyperparameter tuning is conducted to try an build a more accurate model.

Hyperparameter Tuning

The tuning is conducted using a technique called Grid Search. In this method, a grid of hyperparameters is defined in the param_grid dictionary. For the hyperparameter *'C'*, which controls the inverse of regularization strength, a logarithmic space of values ranging from *10^-3 to 10^3* is explored. The *'penalty'* hyperparameter is set to 'l2', indicating the use of L2 or Ridge regularization. Lastly, the *'solver'* hyperparameter is set to explore three different types of optimization algorithms: *'newton-cg'*, *'lbfgs'*, and *'liblinear'*.

The Grid Search method will then train the model on the different combinations of these hyperparameters and identify the combination that produces the best model performance.

In [40]:

```
# Define the parameter grid
param_grid = {
    'C': np.logspace(-3, 3, 10),
    'penalty': ['l2'],
    'solver': ['newton-cg', 'lbfgs', 'liblinear']
}

# Create a GridSearchCV object
grid_search = GridSearchCV(most_accurate_model, param_grid, cv=5, scoring='accuracy')

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
```

```python
print(f"Best parameters: {best_params}")

# Get the best score
best_score = grid_search.best_score_
print(f"Best score: {best_score}")
```

```
Best parameters: {'C': 1000.0, 'penalty': 'l2', 'solver': 'newton-cg'}
Best score: 0.7717870876340822
```

The best parameters *'C': 1000.0, 'penalty': 'l2', 'solver': 'newton-cg'* resulted in an accuracy score of 77.18%. Compared to the untuned model with an accuracy of 73.77%, it can be seen that the tuning was a success.

Retrain and Rebuild the model

The cross validated model is then updated with the best parameters and retrained to get new predictions and the accuracy of those predictions.

In [41]:

```python
# Update the most accurate model with the best parameters and retrain
most_accurate_model = LogisticRegression(C=best_params['C'], penalty=best_params['penalty'])
most_accurate_model.fit(X_train, y_train)

# Make predictions with the retrained model
y_pred_updated = most_accurate_model.predict(X_test)

# Check the accuracy of the retrained model
accuracy_updated = accuracy_score(y_test, y_pred_updated)
print(f"Updated Model Accuracy: {accuracy_updated}")

# Save the updated predictions to a csv file
predictions_updated = pd.DataFrame(y_pred_updated, columns=['predictions_updated'])
predictions_updated.to_csv('logreg_predictions_updated.csv', index=False)

# Determine which model is the most accurate
if accuracy_updated > accuracy and accuracy_updated > accuracy_cv:
    print("The updated model is the most accurate.")
elif accuracy > accuracy_cv:
    print("The original model is the most accurate.")
else:
    print("The cross-validated model is the most accurate.")
```

```
Updated Model Accuracy: 0.7278688524590164
The cross-validated model is the most accurate.
```

The original model, the cross validate model and the newly trained model with the updated parameters are compared to determine which model has the most accurate predictions. This model is still the cross validate model.

Feature Importance

Using the cross validate model, feature importance is calculated to gain insight into the feature that has the highest weight in the determining of the 'loan_status' outcome.

In [42]:

```python
# 12. Create feature importance values for the most accurate model
feature_importance_updated = pd.DataFrame({'feature': X.columns, 'importance': most_accurate_model.coef_[
0]})
feature_importance_updated = feature_importance_updated.sort_values('importance', ascending=False)

# 13. Save the updated feature importance values to a csv file
feature_importance_updated.to_csv('most_accurate_model_feature_importance_updated.csv', index=False)
```

Pickle File

Lastly the best model is stored in a pickle file for later retrieval.

In [43]:

```python
# 14. Save the model that is the most accurate to a pickle file named 'Model_1.pkl'
with open('Model_1.pkl', 'wb') as file:
    pickle.dump(most_accurate_model, file)
```

===

6. Feature Engineering

6. Feature Engineering

Feature engineering involves creating new input features from the existing ones in the dataset. This process enhances the predictive power of the learning algorithm by creating features that help to uncover complex patterns in the data. It can involve a range of activities such as extracting more information from existing data, combining features to create new ones, or transforming features to a form more suitable for the model.

Feature engineering can significantly improve model accuracy because it allows the model to visualise the data from different perspectives and thus capture more patterns or reduce noise. In the case of our dataset new features were created by combining existing features in various ways.

Feature 1: Income to Age Ratio

The creation of this feature could provide additional insight into the financial maturity of the borrowers. A higher ratio might indicate that the borrower has a high income relative to their age, which could potentially lead to a lower risk of default.

In [44]:

```
# Feature 1: Income to Age Ratio
cleaned_raw_data_copy['income_to_age_ratio'] = cleaned_raw_data_copy['person_income'] / cleaned_raw_data_c
opy['person_age']
```

Feature 2: Loan Amount to Income Ratio

Creating this feature could provide insight into the borrower's ability to repay the loan. A lower ratio might indicate that the borrower has sufficient income to repay the loan, which could potentially lead to a lower risk of default.

In [45]:

```
# Feature 2: Loan Amount to Income Ratio
cleaned_raw_data_copy['loan_amt_to_income_ratio'] = cleaned_raw_data_copy['loan_amnt'] / cleaned_raw_data_
copy['person_income']
```

Feature 3: Employment Length to Age Ratio

This feature could provide insight into the stability of the borrower's income. A higher ratio might indicate that the borrower has had a stable source of income for a significant portion of their life, which could potentially lead to a lower risk of default.

In [46]:

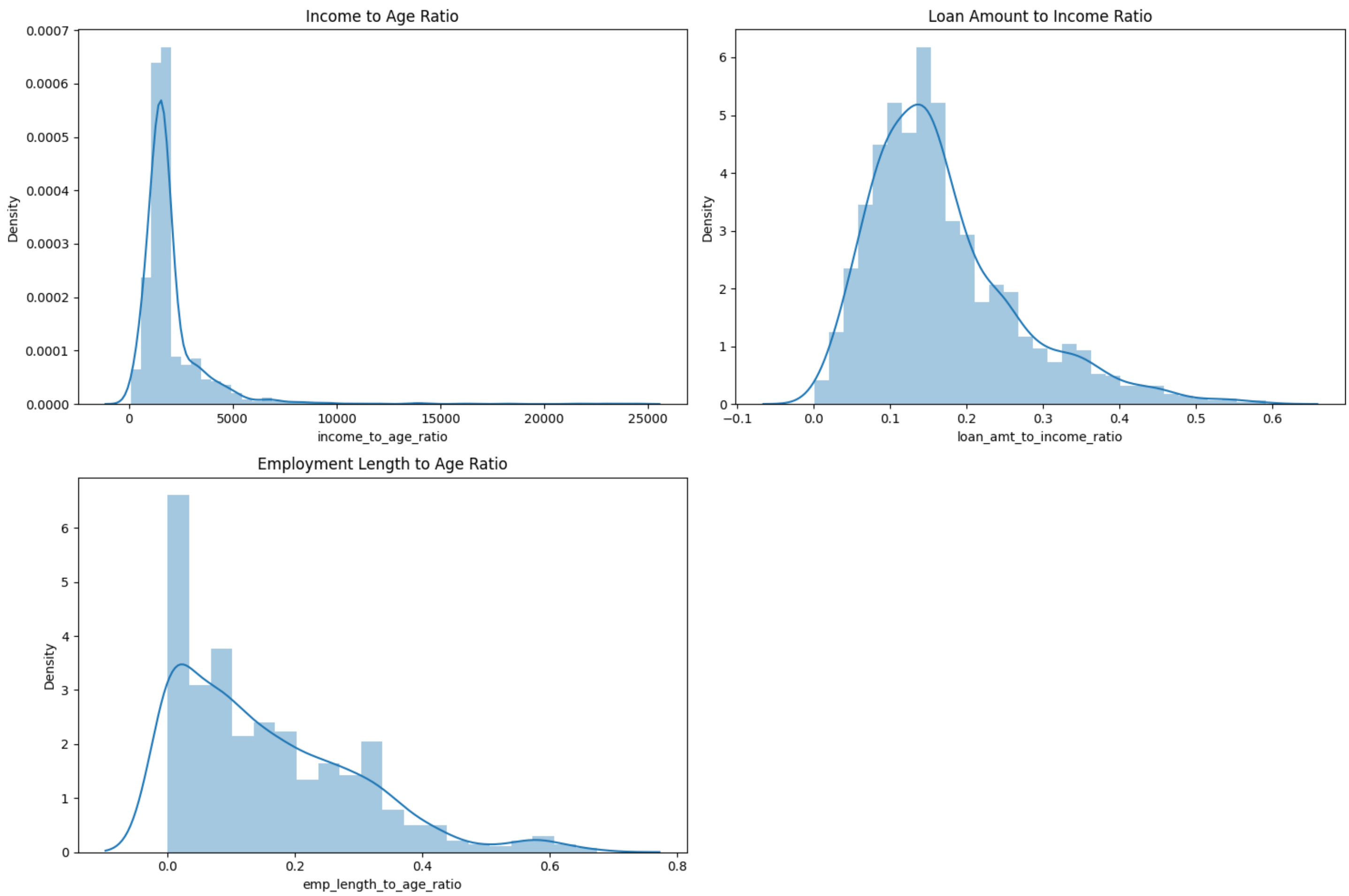
```
# Feature 3: Employment Length to Age Ratio
cleaned_raw_data_copy['emp_length_to_age_ratio'] = cleaned_raw_data_copy['person_emp_length'] / cleaned_ra
w_data_copy['person_age']
```

The new features are visualised on distribution graphs to see their distribution across the various data categories. Following this the features used to create the new features are dropped to reduce the high correlation between them as well as to reduce the noise in the dataset for a more accurate result. Lastly the new data is stored in a csv file to be retrieved by the 2nd model.

In [47]:

```
# Plotting the distribution of the new features
plt.figure(figsize=(15,10))

plt.subplot(2, 2, 1)
sns.distplot(cleaned_raw_data_copy['income_to_age_ratio'])
plt.title('Income to Age Ratio')

plt.subplot(2, 2, 2)
sns.distplot(cleaned_raw_data_copy['loan_amt_to_income_ratio'])
plt.title('Loan Amount to Income Ratio')

plt.subplot(2, 2, 3)
sns.distplot(cleaned_raw_data_copy['emp_length_to_age_ratio'])
plt.title('Employment Length to Age Ratio')

plt.tight_layout()
plt.show()


## Remove all features that created the new features
    # The correlation between those old feature and the new features are very high.
    # Logistic regression assume that the variables are not highly correlated.
    # Due to this the excess noise in the datasets are removed.

cleaned_raw_data_copy = cleaned_raw_data_copy.drop(['person_income', 'person_age', 'loan_amnt', 'person_em
```

```
p_length'], axis=1)

# Store new Features in CSV files
cleaned_raw_data_copy.to_csv('new_features_engineered.csv', index=False)
```



===

7. Model 2

In this new model that is going to be build, the dataset that will be used will be the datset that contains the newly formed features.

A. Split Dataset

The use of dummy data is a common practice to transform categorical data into a binary format. This transformation assists with easier quantification and comparisons in future models.

When it comes to splitting the data into training and testing sets, a typical weightage of 80% (0.8) is assigned to the *training* dataset, while the remaining 20% (0.2) is allocated to the *testing* dataset. Additionally, to ensure the consistency of the train/test split across multiple executions of the code, 'random_state=42' is used. This guarantees that the same train/test split is reproduced every time the code is run, thereby ensuring reproducibility.

In [48]:

```
# Read Cleaned CSV Files
cleaned_raw_data = pd.read_csv('new_features_engineered.csv')
cleaned_raw_data_copy = cleaned_raw_data.copy()

# Define the independent variables (features) and the target variable
X = cleaned_raw_data_copy.drop('loan_status', axis=1)
y = cleaned_raw_data_copy['loan_status']

# Convert categorical variable in the X dataset(all columns except 'loan_status') into dummy variables
X = pd.get_dummies(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create new DataFrames for training and testing sets
train_data = pd.concat([X_train, y_train], axis=1)
test_data = pd.concat([X_test, y_test], axis=1)
```

```
# Save the training and testing sets to CSV files
train_data.to_csv('train_data_ML2.csv', index=False)
test_data.to_csv('test_data.ML2.csv', index=False)
```

B. Build the Model

Instead of a Logistics Regression Model, this model will us a Random Forest Classification build. A Random Forest Classification model is a supervised learning technique that can be used for both Classification and Regression problems in Machine Learning.

A Random Forest Classification model operates by constructing several decision trees during the training and outputs the class that is the mode of all the classes. In other words, each decision tree in the forest gives a classification result and the class with the most votes becomes the model's prediction.

The advantage of utilising a Random Forest Classification model is that it can limit overfitting without substantially increasing errors due to bias. It does this by creating random subsets of the features and building smaller trees using these subsets. Afterwards, it combines the subtrees. The build of multiple decision trees and the merging of them together results in a more accurate and stable prediction.

In [49]:

```
# 1. Train a Random Forest model
rf = RandomForestClassifier()
rf.fit(X_train, y_train)

# 2. Make predictions with the model
y_pred_rf = rf.predict(X_test)

# 3. Check the accuracy of the model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print(f"Model Accuracy: {accuracy_rf}")

# 4. Save the predictions to a csv file
predictions_rf = pd.DataFrame(y_pred_rf, columns=['predictions'])
predictions_rf.to_csv('rf_predictions.csv', index=False)
```

```
Model Accuracy: 0.8459016393442623
```

Cross Validation

As with the first model, the second model also undergoes cross validation using a new split of the dataset.

In [50]:

```
# 5. Cross Validate the model by building another model
# For this, we'll use a new split of the data
X_train_cv, X_test_cv, y_train_cv, y_test_cv = train_test_split(X, y, test_size=0.2, random_state=0)
rf_cv = RandomForestClassifier()
rf_cv.fit(X_train_cv, y_train_cv)

# 6. Make predictions on the cross validate model
y_pred_cv_rf = rf_cv.predict(X_test_cv)

# 7. Check the accuracy score of the cross validate model
accuracy_cv_rf = accuracy_score(y_test_cv, y_pred_cv_rf)
print(f"Cross-Validated Model Accuracy: {accuracy_cv_rf}")

# 8. Save the cross validate predictions to csv file
predictions_cv_rf = pd.DataFrame(y_pred_cv_rf, columns=['predictions_cv'])
predictions_cv_rf.to_csv('rf_predictions_cv.csv', index=False)

# 9. Determine which model is the most accurate
if accuracy_rf > accuracy_cv_rf:
    most_accurate_model_rf = rf
    print("The original model is the most accurate")
else:
    most_accurate_model_rf = rf_cv
    print("The cross-validated model is the most accurate")
```

```
Cross-Validated Model Accuracy: 0.8491803278688524
The cross-validated model is the most accurate
```

The model that has the highest accuracy score undergoes hyperparameter tuning.

Hyperparameter Tuning

Once again the tuning is conducted using the Grid Search method. The *'n_estimators'* hyperparameter, which specifies the number of

trees in the forest, is set to explore two values: *100 and 200*.

The *'max_depth'* hyperparameter, which determines the maximum depth of the tree, is set to explore three values: *None, 10, and 20*. The 'min_samples_split'and 'min_samples_leaf' hyperparameters, which control the minimum number of samples required to split an internal node and the minimum number of samples required to be at a leaf node respectively, are set to explore two values each: *5 and 10* for *'min_samples_split'*, and *2 and 4* for *'min_samples_leaf'*. The *'bootstrap'* hyperparameter, which determines whether bootstrap samples are used when building trees, is set to *False*. Lastly, the *'criterion'* hyperparameter, which measures the quality of a split, is set to explore two values: *'gini'* for Gini impurity and *'entropy'* for information gain.

In [51]:

```
# 10. Hyperparameter tuning
# Define the parameter grid
param_grid_rf = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [5, 10],
    'min_samples_leaf': [2, 4],
    'bootstrap': [False],
    'criterion': ['gini', 'entropy']
}

# Create a GridSearchCV object
grid_search_rf = GridSearchCV(most_accurate_model_rf, param_grid_rf, cv=5, scoring='accuracy')

# Fit the GridSearchCV object to the data
grid_search_rf.fit(X_train, y_train)

# Get the best parameters
best_params_rf = grid_search_rf.best_params_
print(f"Best parameters: {best_params_rf}")

# Get the best score
best_score_rf = grid_search_rf.best_score_
print(f"Best score: {best_score_rf}")
```

```
Best parameters: {'bootstrap': False, 'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 2, 'min
_samples_split': 5, 'n_estimators': 200}
Best score: 0.8349996626863658
```

Retrain and Rebuild the model

The Grid Search method will then train the model on the different combinations of these hyperparameters and identify the combination that produces the best model performance.

In [52]:

```
# 11. Retrain the most accurate model
# Update the most accurate model with the best parameters and retrain
most_accurate_model_rf = RandomForestClassifier(n_estimators=best_params_rf['n_estimators'],
                                                max_depth=best_params_rf['max_depth'],
                                                min_samples_split=best_params_rf['min_samples_split'],
                                                min_samples_leaf=best_params_rf['min_samples_leaf'],
                                                bootstrap=best_params_rf['bootstrap'])
most_accurate_model_rf.fit(X_train, y_train)

# Make predictions with the retrained model
y_pred_updated_rf = most_accurate_model_rf.predict(X_test)

# Check the accuracy of the retrained model
accuracy_updated_rf = accuracy_score(y_test, y_pred_updated_rf)
print(f"Updated Model Accuracy: {accuracy_updated_rf}")

# Save the updated predictions to a csv file
predictions_updated_rf = pd.DataFrame(y_pred_updated_rf, columns=['predictions_updated'])
predictions_updated_rf.to_csv('rf_predictions_updated.csv', index=False)

# Determine which model is the most accurate
if accuracy_updated_rf > accuracy_rf and accuracy_updated_rf > accuracy_cv_rf:
    print("The updated model is the most accurate")
elif accuracy_rf > accuracy_cv_rf:
    print("The original model is the most accurate")
else:
    print("The cross-validated model is the most accurate")
```

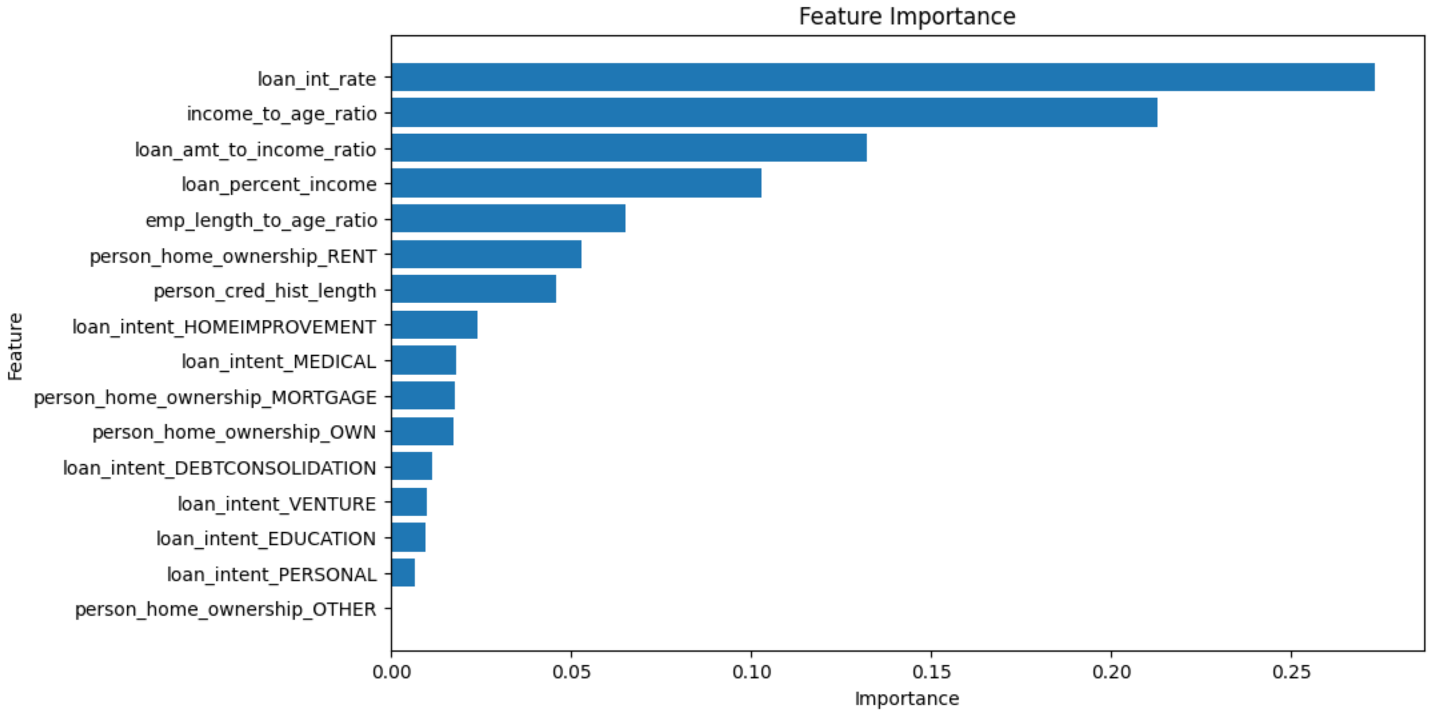
```
Updated Model Accuracy: 0.8524590163934426
The updated model is the most accurate
```

Feature Importance

The updated model is the most accurate and as such feature importance is performed on it to determine which features have the greatest weight in the determining of the 'loan_status' outcome.

In [53]:

```
# 12. Create feature importance values for the most accurate model
feature_importance_updated_rf = pd.DataFrame({'feature': X.columns, 'importance': most_accurate_model_rf.
feature_importances_})
feature_importance_updated_rf = feature_importance_updated_rf.sort_values('importance', ascending=False)

# Feature Importance graph
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_updated_rf['feature'], feature_importance_updated_rf['importance'])
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Feature Importance')
plt.gca().invert_yaxis()
plt.show()

# 13. Save the updated feature importance values to a csv file
feature_importance_updated_rf.to_csv('most_accurate_model_rf_feature_importance_updated.csv', index=False)
```



Pickle File

Lastly the best model is stored in a pickle file for later retrieval during the validation testing of the model.

In [54]:

```
# 14. Save the model that is the most accurate to a pickle file
with open('Model_2.pkl', 'wb') as file:
    pickle.dump(most_accurate_model_rf, file)
```

==

8. Validate Model 2

The model and the cleaned validation dataset is loaded

In [55]:

```
# Load the model
with open('Model_2.pkl', 'rb') as file:
    model = pickle.load(file)

# Load the data
data = pd.read_csv('cleaned_credit_risk_validation_data.csv')
validation_data = data.copy()
```

As the model take new features created in the previous section to train it, it is vitally important to ensure the validation dataset has

those same features.

Therfore the new features and the dropping of the old features is performed on the validation dataset as well. Additionally the code then converts categorical variables into dummy/indicator variables, a process known as one-hot encoding. This is done to allow the machine learning model to process these categorical variables.

In [56]:

```
# Create new features
validation_data['income_to_age_ratio'] = validation_data['person_income'] / validation_data['person_age']
validation_data['loan_amt_to_income_ratio'] = validation_data['loan_amnt'] / validation_data['person_income']
validation_data['emp_length_to_age_ratio'] = validation_data['person_emp_length'] / validation_data['person_age']

# Drop the original features
validation_data.drop(['person_income', 'person_age', 'loan_amnt', 'person_emp_length'], axis=1, inplace=True)

# Convert categorical variables into dummy/indicator variables (i.e. one-hot encoding)
validation_data = pd.get_dummies(validation_data)
```

The feature names are retrieves from the model using an if statement. If the model does not have an attribute feature_names *in*, a predefined list of feature names is used.

A template DataFrame is created with all the necessary features. The values from validation_data are then filled into this template. If a feature in the template does not exist in validation_data, it is filled with 0.

In [57]:

```
# Get the feature names from the model
try:
    feature_names = model.feature_names_in_
except AttributeError:
    feature_names = ['loan_int_rate', 'income_to_age_ratio', 'loan_amt_to_income_ratio', 'loan_percent_income',
                     'emp_length_to_age_ratio', 'person_home_ownership_RENT', 'person_cred_hist_length',
                     'loan_intent_HOMEIMPROVEMENT', 'person_home_ownership_MORTGAGE', 'loan_intent_MEDICAL',
                     'person_home_ownership_OWN', 'loan_intent_DEBTCONSOLIDATION', 'loan_intent_EDUCATION',
                     'loan_intent_VENTURE', 'loan_intent_PERSONAL', 'person_home_ownership_OTHER']

# Create a template DataFrame with all the necessary features
template = pd.DataFrame(columns=feature_names)

# Fill in the values from the validation data
for feature in feature_names:
    if feature in validation_data.columns:
        template[feature] = validation_data[feature]
    else:
        template[feature] = 0
```

The model then makes predictions on the template DataFrame. The predictions, which are in the form of 0 and 1, are converted to 'N' and 'Y' for readability and are appended to the validation_data dataset under the column 'loan_status'.

In [58]:

```
# Perform predictions
predictions = model.predict(template)

# Convert predictions from 0 and 1 to 'N' and 'Y'
predictions = ['Y' if prediction == 1 else 'N' for prediction in predictions]

# Append predictions to the validation_data
validation_data['loan_status'] = predictions
```

==

Now that our model we want to use is built and we are satisfied with the performance, a web application can be designed and created to integrate with the model.

9. Web Application

A web application for automating the application process for a credit loan is created. This application form is built using Dash, a Python framework for building analytical web applications.

Python framework for building analytical web applications.

The code begins by loading a pre-trained machine learning model from a pickle file. It then defines the feature names used by the model. If the model does not have an attribute feature_names*in*, a predefined list of feature names is used.

In [59]:

```
#Import the models pickle file
with open('Model_2.pkl', 'rb') as file:
    model = pickle.load(file)
```

The application's layout is defined using Dash's HTML and core components. The layout includes input fields for the user to enter their details, such as age, income, home ownership, employment length, loan intent, loan amount, interest rate, loan percent income, and credit history length. There's also a button for the user to submit their details.

In [60]:

```
# Define feature_names as a global variable
try:
    feature_names = model.feature_names_in_
except AttributeError:
    feature_names = ['loan_int_rate', 'income_to_age_ratio', 'loan_amt_to_income_ratio', 'loan_percent_in
come',
                        'emp_length_to_age_ratio', 'person_home_ownership_RENT', 'person_cred_hist_lengt
h',
                        'loan_intent_HOMEIMPROVEMENT', 'person_home_ownership_MORTGAGE', 'loan_intent_ME
DICAL',
                        'person_home_ownership_OWN', 'loan_intent_DEBTCONSOLIDATION', 'loan_intent_EDUCA
TION',
                        'loan_intent_VENTURE', 'loan_intent_PERSONAL', 'person_home_ownership_OTHER']

# Initialize Dash app
app = dash.Dash(__name__)

# Define app layout
app.layout = html.Div([
    html.H1("Credit Risk Assessment Application"),
    html.Div(id='container', children=[
        html.Label("Age:"),
        dcc.Input(id='person_age', type='number', placeholder = 'Age'),
        html.Label("Income"),
        dcc.Input(id = "person_income", type = 'number', placeholder = "Income"),
        html.Label("Home Ownership:"),
        dcc.Dropdown(id="person_home_ownership", options = [
            {'label': 'Own', 'value':'OWN'},
            {'label':'Rent','value':'RENT'},
            {'label':'Mortgage','value': 'MORTGAGE'},
            {'label':'Other', 'value':'OTHER'}
        ], placeholder="Select Your Home Ownership"),
        html.Label("Employment Length in years"),
        dcc.Input(id="person_emp_length",type='number',placeholder='Enter years in employment'),
        html.Label("Loan Intent"),
        dcc.Dropdown(id='loan_intent', options = [
            {'label':'Personal','value':'Personal'},
            {'label':'Education','value':'EDUCATIONAL'},
            {'label':'Medical', 'value':'MEDICAL'},
            {'label':'Venture','value':'VENTURE'},
            {'label':'Home Improvements','value':'HOMEIMPROVEMENTS'},
            {'label':'Debt Consolidation','value':'DEBTCONSOLIDATION'}],
        placeholder = 'Select Loan Intent'),
        html.Label("Loan Amount:"),
        dcc.Input(id = 'loan_amnt', type='number', placeholder='Loan Amount'),
        html.Label("Interest Rate:"),
        dcc.Slider(
            id='loan_int_rate',
            min=0,
            max=20,  # Assuming the interest rate ranges from 0% to 20%
            step=0.1,
            value=5,  # Default value set at 5%
            tooltip={'always_visible': True, 'placement': 'bottom'},  # Tooltip to show the value always
            marks={i: f'{i}%' for i in range(0, 21, 5)}  # Marks at every 5%
        ),
        html.Label("Loan Percent of Income:"),
        dcc.Slider(
            id='loan_percent_income',
            min=0,
            max=1,
            step=0.01,
            value=0.1,
            tooltip={'always_visible': True, 'placement': 'bottom'},     marks={i/10: f'{int(i*10)}%' fo
r i in range(0, 11, 2)}  # Marks at every 20%
```

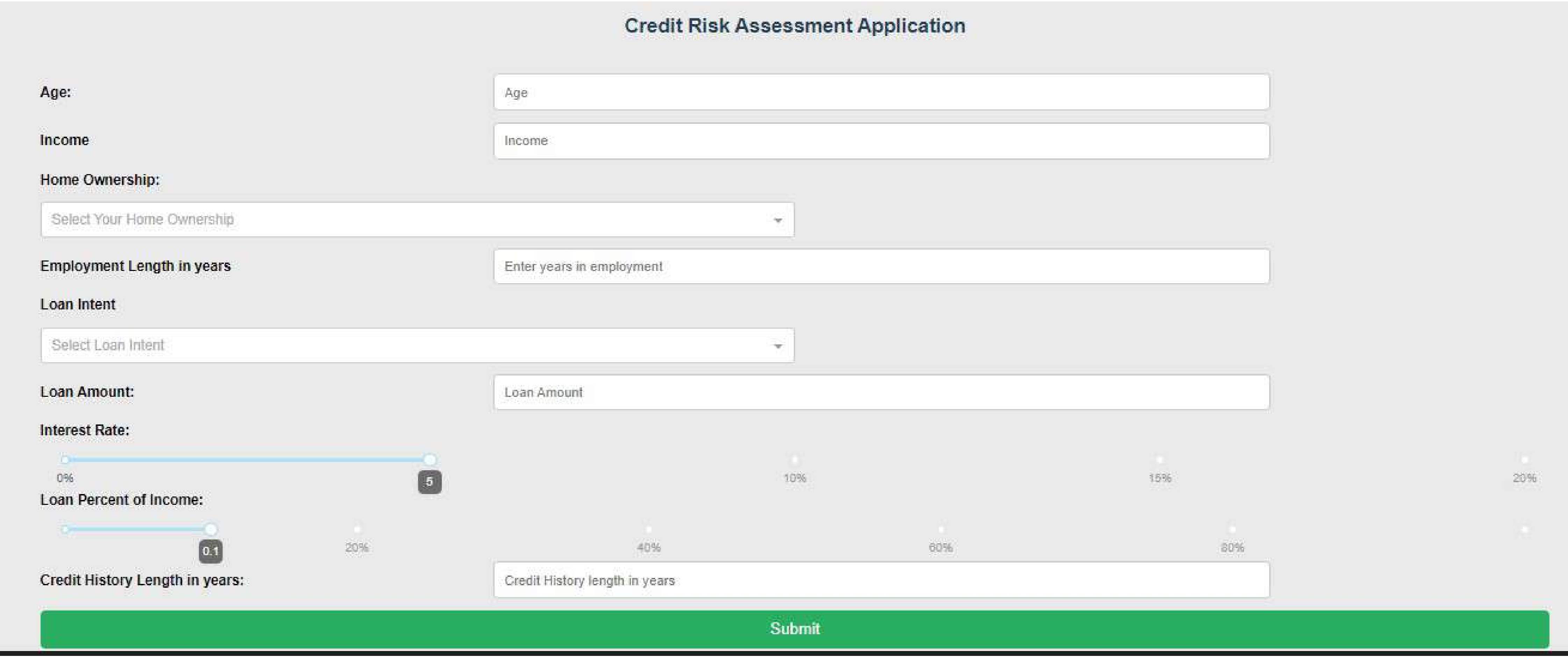
```
        ),
        html.Label("Credit History Length in years:"),
        dcc.Input(id='person_cred_hist_length',type='number',placeholder='Credit History length in years'
),
        html.Button("Submit", id = 'submit',n_clicks=0),
        ]),
        html.Div(id='prediction-output', children='Fill in the form and press Enter')
])
```

When the user clicks the submit button, the update_output function is triggered. This function calculates ratios based on the user's input, creates a template DataFrame with all the necessary features, updates the values based on the user's input, makes a prediction using the model, and returns the prediction result. If the prediction is 1, it returns 'Yes' in green text, indicating that the loan application is to be approved. If the prediction is 0, it returns 'No' in red text, indicating that the loan application is being rejected.

In [61]:

```
@app.callback(
    Output('prediction-output', 'children'),
    [Input('submit', 'n_clicks')],
    [State('person_age', 'value'),
        State('person_income', 'value'),
        State('person_home_ownership', 'value'),
        State('person_emp_length', 'value'),
        State('loan_intent', 'value'),
        State('loan_amnt', 'value'),
        State('loan_int_rate', 'value'),
        State('loan_percent_income', 'value'),
        State('person_cred_hist_length', 'value')])

def update_output(n_clicks, person_age, person_income, person_home_ownership, person_emp_length,
                    loan_intent, loan_amnt, loan_int_rate, loan_percent_income,person_cred_hist_length):
    if n_clicks > 0:
        income_to_age_ratio = person_income / person_age if person_age != 0 else 0
        loan_amt_to_income_ratio = loan_amnt / person_income if person_income != 0 else 0
        emp_length_to_age_ratio = person_emp_length / person_age if person_age != 0 else 0

        # Create a template DataFrame with all the necessary features
        template = pd.DataFrame(columns=feature_names, data=np.zeros((1, len(feature_names))))

        # Update the values based on the user's input
        template.at[0, 'loan_int_rate'] = loan_int_rate
        template.at[0, 'income_to_age_ratio'] = income_to_age_ratio
        template.at[0, 'loan_amt_to_income_ratio'] = loan_amt_to_income_ratio
        template.at[0, 'loan_percent_income'] = loan_percent_income
        template.at[0, 'emp_length_to_age_ratio'] = emp_length_to_age_ratio
        template.at[0, 'person_home_ownership_' + person_home_ownership] = 1
        template.at[0, 'person_cred_hist_length'] = person_cred_hist_length
        template.at[0, 'loan_intent_' + loan_intent] = 1
        # Make prediction
        prediction = model.predict(template)

        # Return the prediction result
        if prediction[0] == 1:
            return html.Div('Approved', style={'color': 'green'})
        else:
            return html.Div('Rejected', style={'color': 'red'})
    else:
        return 'Fill in the form and press Enter'

if __name__ == "__main__":
    app.run_server(debug=True)
```

The reason it was done this way is to provide an interactive, user-friendly interface for users to input their details and receive a prediction on their loan status. The use of a pre-trained model allows for quick and accurate predictions, while the use of Dash allows for the creation of a visually appealing and easy-to-use application.


Credit Risk Assessment Application
Age:
Age
Income
Income
Home Ownership:
Select Your Home Ownership
Employment Length in years
Enter years in employment
Loan Intent
Select Loan Intent
Loan Amount:
Loan Amount
Interest Rate:
0%
.5
10%
15%
20%
Loan Percent of Income:
0.1
20%
40%
60%
80%
Credit History Length in years:
Credit History length in years
Submit