loan-approval-prediction-3

October 31, 2024

[3]:
```python
# Importing necessary libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, roc_auc_score, accuracy_score
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
import xgboost as xgb
from imblearn.under_sampling import RandomUnderSampler
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.subplots as sp
import plotly.graph_objects as go
from plotly.subplots import make_subplots


# Suppress warnings for clarity
import warnings
warnings.filterwarnings("ignore")
# Set Seaborn color palette for the notebook
sns.set_palette("deep")
sns.set_theme(style="whitegrid", palette="deep")
```

[4]:
```python
# Load Train Data
df_train = pd.read_csv('loan_train.csv')
df_train
```

[4]:
```
          id  person_age  person_income person_home_ownership  \
0          0          37          35000                  RENT
1          1          22          56000                   OWN
2          2          29          28800                   OWN
```

```
3          3         30         70000                   RENT
4          4         22         60000                   RENT
…          …         …           …                     …
58640  58640         34        120000               MORTGAGE
58641  58641         28         28800                   RENT
58642  58642         23         44000                   RENT
58643  58643         22         30000                   RENT
58644  58644         31         75000               MORTGAGE

       person_emp_length loan_intent loan_grade  loan_amnt  loan_int_rate  \
0                    0.0   EDUCATION          B       6000          11.49
1                    6.0     MEDICAL          C       4000          13.35
2                    8.0    PERSONAL          A       6000           8.90
3                   14.0     VENTURE          B      12000          11.11
4                    2.0     MEDICAL          A       6000           6.92
…                    …          …          …         …            …
58640                5.0   EDUCATION          D      25000          15.95
58641                0.0     MEDICAL          C      10000          12.73
58642                7.0   EDUCATION          D       6800          16.00
58643                2.0   EDUCATION          A       5000           8.90
58644                2.0     VENTURE          B      15000          11.11

       loan_percent_income cb_person_default_on_file  \
0                     0.17                         N
1                     0.07                         N
2                     0.21                         N
3                     0.17                         N
4                     0.10                         N
…                     …                        …
58640                 0.21                         Y
58641                 0.35                         N
58642                 0.15                         N
58643                 0.17                         N
58644                 0.20                         N

       cb_person_cred_hist_length  loan_status
0                              14            0
1                               2            0
2                              10            0
3                               5            0
4                               3            0
…                            …          …
58640                          10            0
58641                           8            1
58642                           2            1
58643                           3            0
58644                           5            0
```

```
[58645 rows x 13 columns]
```

[5]:
```python
# Load Test Data
df_test = pd.read_csv('loan_test.csv')
df_test
```

[5]:
```
          id  person_age  person_income person_home_ownership  \
0      58645          23          69000                  RENT
1      58646          26          96000              MORTGAGE
2      58647          26          30000                  RENT
3      58648          33          50000                  RENT
4      58649          26         102000              MORTGAGE
…      …             …              …                     …
39093  97738          22          31200              MORTGAGE
39094  97739          22          48000              MORTGAGE
39095  97740          51          60000              MORTGAGE
39096  97741          22          36000              MORTGAGE
39097  97742          31          45000                  RENT

       person_emp_length        loan_intent loan_grade  loan_amnt  \
0                    3.0    HOMEIMPROVEMENT          F      25000
1                    6.0           PERSONAL          C      10000
2                    5.0            VENTURE          E       4000
3                    4.0  DEBTCONSOLIDATION          A       7000
4                    8.0    HOMEIMPROVEMENT          D      15000
…                    …                  …        …        …
39093                2.0  DEBTCONSOLIDATION          B       3000
39094                6.0          EDUCATION          A       7000
39095                0.0           PERSONAL          A      15000
39096                4.0           PERSONAL          D      14000
39097                6.0  DEBTCONSOLIDATION          B      19450

       loan_int_rate  loan_percent_income cb_person_default_on_file  \
0              15.76                 0.36                         N
1              12.68                 0.10                         Y
2              17.19                 0.13                         Y
3               8.90                 0.14                         N
4              16.32                 0.15                         Y
…                …                    …                        …
39093          10.37                 0.10                         N
39094           6.03                 0.15                         N
39095           7.51                 0.25                         N
39096          15.62                 0.39                         Y
39097           9.91                 0.44                         N

       cb_person_cred_hist_length
```

```
0                               2
1                               4
2                               2
3                               7
4                               4
…                           …
39093                           4
39094                           3
39095                          25
39096                           4
39097                           9

[39098 rows x 12 columns]
```

[6]:
```python
# Data Overview
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58645 entries, 0 to 58644
Data columns (total 13 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          58645 non-null  int64
 1   person_age                  58645 non-null  int64
 2   person_income               58645 non-null  int64
 3   person_home_ownership       58645 non-null  object
 4   person_emp_length           58645 non-null  float64
 5   loan_intent                 58645 non-null  object
 6   loan_grade                  58645 non-null  object
 7   loan_amnt                   58645 non-null  int64
 8   loan_int_rate               58645 non-null  float64
 9   loan_percent_income         58645 non-null  float64
 10  cb_person_default_on_file   58645 non-null  object
 11  cb_person_cred_hist_length  58645 non-null  int64
 12  loan_status                 58645 non-null  int64
dtypes: float64(3), int64(6), object(4)
memory usage: 5.8+ MB
```

[7]:
```python
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39098 entries, 0 to 39097
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          39098 non-null  int64
 1   person_age                  39098 non-null  int64
 2   person_income               39098 non-null  int64
```

```
 3   person_home_ownership       39098 non-null  object
 4   person_emp_length           39098 non-null  float64
 5   loan_intent                 39098 non-null  object
 6   loan_grade                  39098 non-null  object
 7   loan_amnt                   39098 non-null  int64
 8   loan_int_rate               39098 non-null  float64
 9   loan_percent_income         39098 non-null  float64
 10  cb_person_default_on_file   39098 non-null  object
 11  cb_person_cred_hist_length  39098 non-null  int64
dtypes: float64(3), int64(5), object(4)
memory usage: 3.6+ MB
```

[8]:
```
df_train.describe()
```

[8]:
```
                 id    person_age  person_income  person_emp_length  \
count  58645.000000  58645.000000   5.864500e+04       58645.000000
mean   29322.000000     27.550857   6.404617e+04           4.701015
std    16929.497605      6.033216   3.793111e+04           3.959784
min        0.000000     20.000000   4.200000e+03           0.000000
25%    14661.000000     23.000000   4.200000e+04           2.000000
50%    29322.000000     26.000000   5.800000e+04           4.000000
75%    43983.000000     30.000000   7.560000e+04           7.000000
max    58644.000000    123.000000   1.900000e+06         123.000000

          loan_amnt  loan_int_rate  loan_percent_income  \
count  58645.000000   58645.000000         58645.000000
mean    9217.556518      10.677874             0.159238
std     5563.807384       3.034697             0.091692
min      500.000000       5.420000             0.000000
25%     5000.000000       7.880000             0.090000
50%     8000.000000      10.750000             0.140000
75%    12000.000000      12.990000             0.210000
max    35000.000000      23.220000             0.830000

       cb_person_cred_hist_length   loan_status
count                58645.000000  58645.000000
mean                     5.813556      0.142382
std                      4.029196      0.349445
min                      2.000000      0.000000
25%                      3.000000      0.000000
50%                      4.000000      0.000000
75%                      8.000000      0.000000
max                     30.000000      1.000000
```

[9]:
```
df_test.describe()
```

[9]:

```
                 id    person_age  person_income  person_emp_length  \
count  39098.000000  39098.000000   3.909800e+04       39098.000000
mean   78193.500000     27.566781   6.406046e+04           4.687068
std    11286.764749      6.032761   3.795583e+04           3.868395
min    58645.000000     20.000000   4.000000e+03           0.000000
25%    68419.250000     23.000000   4.200000e+04           2.000000
50%    78193.500000     26.000000   5.800000e+04           4.000000
75%    87967.750000     30.000000   7.588500e+04           7.000000
max    97742.000000     94.000000   1.900000e+06          42.000000

          loan_amnt  loan_int_rate  loan_percent_income  \
count  39098.000000   39098.000000         39098.000000
mean    9251.466188      10.661216             0.159573
std     5576.254680       3.020220             0.091633
min      700.000000       5.420000             0.000000
25%     5000.000000       7.880000             0.090000
50%     8000.000000      10.750000             0.140000
75%    12000.000000      12.990000             0.210000
max    35000.000000      22.110000             0.730000

       cb_person_cred_hist_length
count                39098.000000
mean                     5.830707
std                      4.072157
min                      2.000000
25%                      3.000000
50%                      4.000000
75%                      8.000000
max                     30.000000
```

[10]:

```python
# Train and Test Data Missing Values
print(df_train.isnull().sum())
print(df_test.isnull().sum())
```

```
id                            0
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_grade                    0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
cb_person_default_on_file     0
cb_person_cred_hist_length    0
loan_status                   0
```

```
dtype: int64
id                            0
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_grade                    0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
cb_person_default_on_file     0
cb_person_cred_hist_length    0
dtype: int64
```

[11]:
```
# Duplicate Check
duplicates = df_train.duplicated()
print(df_train[duplicates])
```

```
Empty DataFrame
Columns: [id, person_age, person_income, person_home_ownership,
person_emp_length, loan_intent, loan_grade, loan_amnt, loan_int_rate,
loan_percent_income, cb_person_default_on_file, cb_person_cred_hist_length,
loan_status]
Index: []
```

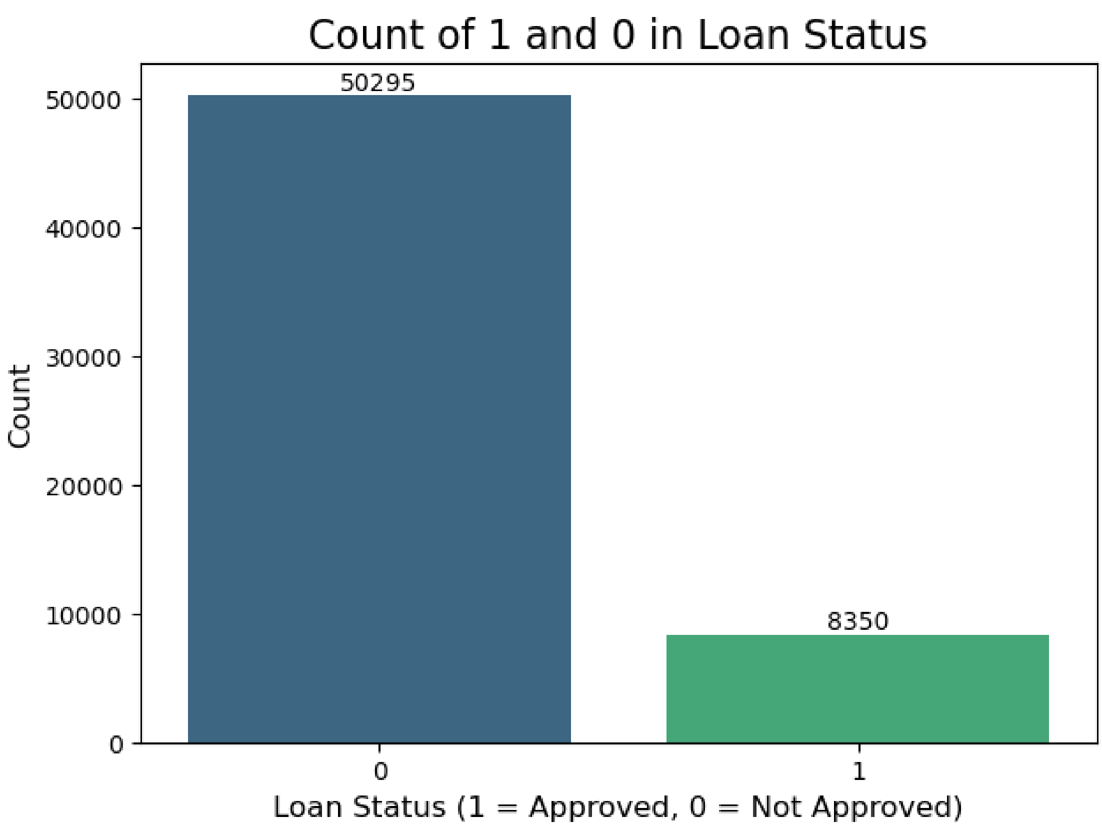
[12]:
```
duplicates_test = df_test.duplicated()
print(df_test[duplicates_test])
```

```
Empty DataFrame
Columns: [id, person_age, person_income, person_home_ownership,
person_emp_length, loan_intent, loan_grade, loan_amnt, loan_int_rate,
loan_percent_income, cb_person_default_on_file, cb_person_cred_hist_length]
Index: []
```

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

# Count the values in loan_status column (1s and 0s)
loan_status_counts = df_train['loan_status'].value_counts()

# Set figure size
plt.figure(figsize=(7, 5))

# Create a barplot using seaborn
sns.barplot(x=loan_status_counts.index,
            y=loan_status_counts.values,
            palette="viridis")
```

```python
# Add labels for each bar
for index, value in enumerate(loan_status_counts.values):
    plt.text(index, value, f'{value}', ha='center', va='bottom', fontsize=10)

# Titles and labels
plt.title('Count of 1 and 0 in Loan Status', fontsize=16)
plt.xlabel('Loan Status (1 = Approved, 0 = Not Approved)', fontsize=12)
plt.ylabel('Count', fontsize=12)

# Show the plot
plt.show()
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_10416\3937357170.py:11:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=loan_status_counts.index,
```

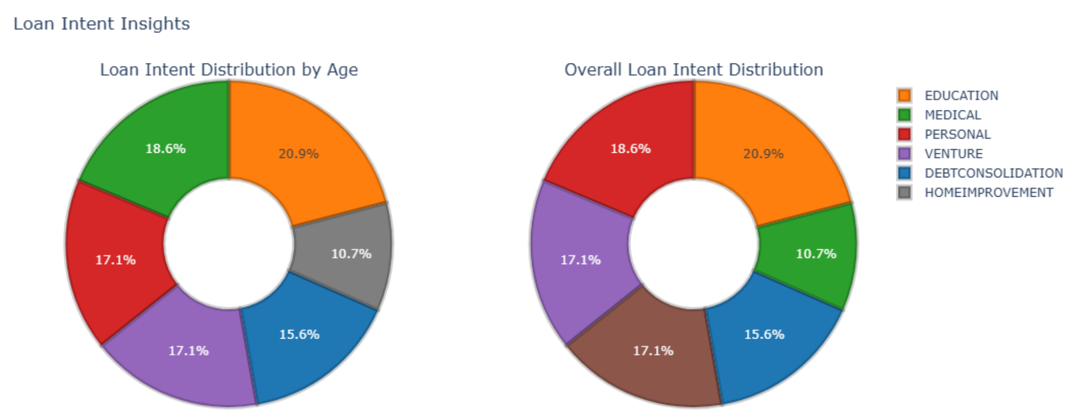


[23]:
```
# Import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.subplots as sp
import plotly.graph_objects as go
from plotly.subplots import make_subplots
# Importing essential libraries
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import roc_auc_score
from sklearn.preprocessing import LabelEncoder
import lightgbm as lgb
import xgboost as xgb
from catboost import CatBoostClassifier
from sklearn.ensemble import VotingClassifier
from IPython.display import display, HTML

from sklearn.metrics import roc_auc_score
from sklearn.model_selection import StratifiedKFold
import random

# Suppress warnings for clarity
import warnings
warnings.filterwarnings("ignore")
# Set Seaborn color palette for the notebook
sns.set_palette("deep")
sns.set_theme(style="whitegrid", palette="deep")
```

[25]:
```
# Preparing data for the donut chart (loan intent by age)
loan_intent_age_distribution = df_train.groupby(['person_age', 'loan_intent']).
 ↪size().reset_index(name='count')

# Create a combined string for hover data
loan_intent_age_distribution['hover_data'] = (
    loan_intent_age_distribution['person_age'].astype(str) +
    " - " + loan_intent_age_distribution['loan_intent']
)

# Preparing data for the second donut chart (overall loan intent distribution)
overall_loan_intent_distribution = df_train.groupby('loan_intent').size().
 ↪reset_index(name='count')

# Define a deep color palette
deep_colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd',␣
 ↪'#8c564b', '#e377c2', '#7f7f7f', '#bcbd22', '#17becf']
```

```
# Create the donut chart for loan intent by age
donut_chart_age = go.Pie(
    labels=loan_intent_age_distribution['loan_intent'],
    values=loan_intent_age_distribution['count'],
    name="Loan Intent by Age",
    hole=0.4,  # Set hole size for donut chart
    marker=dict(
        line=dict(
            color='rgba(0, 0, 0, 0.2)',  # Shadow color
            width=4  # Width of the shadow effect
        ),
        colors=deep_colors  # Use the deep color palette
    ),
    hovertemplate=(
        "<b>Details:</b> %{customdata}<br>"  # Display combined age and loan␣
 ↪intent
        "<b>Count:</b> %{value}<extra></extra>"  # Display count without extra␣
 ↪hover box
    ),
    customdata=loan_intent_age_distribution['hover_data'].values  # Use␣
 ↪combined data for custom hover
)

# Create the donut chart for overall loan intent distribution
donut_chart_overall = go.Pie(
    labels=overall_loan_intent_distribution['loan_intent'],
    values=overall_loan_intent_distribution['count'],
    name="Overall Loan Intent Distribution",
    hole=0.4,  # Set hole size for donut chart
    marker=dict(
        line=dict(
            color='rgba(0, 0, 0, 0.2)',  # Shadow color
            width=4  # Width of the shadow effect
        ),
        colors=deep_colors  # Use the same deep color palette
    ),
    hovertemplate=(
        "<b>Loan Intent:</b> %{label}<br>"   # Display loan intent
        "<b>Count:</b> %{value}<extra></extra>"  # Display count without extra␣
 ↪hover box
    )
)

# Create subplots
fig = make_subplots(rows=1, cols=2, specs=[[{'type': 'pie'}, {'type': 'pie'}]],
```

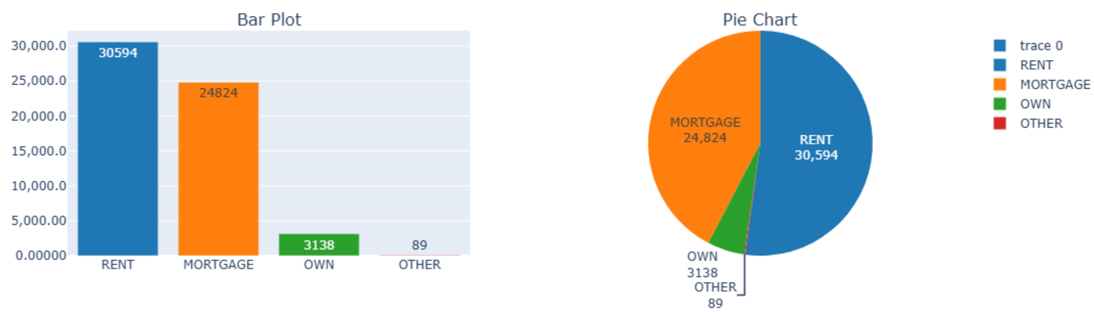
```
                    subplot_titles=("Loan Intent Distribution by Age", "Overall␣
↪Loan Intent Distribution"))

# Add donut charts to the figure
fig.add_trace(donut_chart_age, row=1, col=1)
fig.add_trace(donut_chart_overall, row=1, col=2)

# Step 6: Update layout to increase figure size and position the legend
fig.update_layout(
    height=500, width=900,  # Set figure size
    showlegend=True,
    legend=dict(
        x=1,  # Place the legend outside
        y=1,
        traceorder="normal",
        font=dict(size=12)
    ),
    title="Loan Intent Insights"
)

# Display the figure
fig.show()
```



[27]:
```
# Get counts of each category
home_ownership_counts = df_train['person_home_ownership'].value_counts().
↪reset_index()
home_ownership_counts.columns = ['person_home_ownership', 'count']

# Define a deep color palette
```

```python
deep_color_palette = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd', '#8c564b', '#e377c2']  # Add more colors if needed

# Create subplots with two columns, specifying the second column as a pie chart
fig = make_subplots(rows=1, cols=2,
                    specs=[[{"type": "bar"}, {"type": "pie"}]],
                    subplot_titles=('Bar Plot', 'Pie Chart'))

# Add the bar trace
fig.add_trace(go.Bar(
    x=home_ownership_counts['person_home_ownership'],
    y=home_ownership_counts['count'],
    text=home_ownership_counts['count'],
    textposition='auto',
    marker=dict(color=deep_color_palette[:len(home_ownership_counts)]),  # Use the deep color palette
    hovertemplate='Home Ownership: %{x}<br>Count: %{y}<extra></extra>'  # Display column names on hover
), row=1, col=1)  # Bar plot in the first subplot

# Add the pie chart
fig.add_trace(go.Pie(
    labels=home_ownership_counts['person_home_ownership'],
    values=home_ownership_counts['count'],
    marker=dict(colors=deep_color_palette[:len(home_ownership_counts)]),  # Use the deep color palette
    hoverinfo='label+percent+value',
    textinfo='label+value',
    hovertemplate='Home Ownership: %{label}<br>Count: %{value}<br>Percent: %{percent:.2%}<extra></extra>'  # Display column names and percent on hover
), row=1, col=2)  # Pie chart in the second subplot

# Update layout for better visualization
fig.update_layout(
    title='Home Ownership Distribution',
    height=400,
    width=800,
    yaxis=dict(
        tickformat=',g',  # Use thousands separator without abbreviating
        showspikes=False  # Disable spikes
    )
)

# Show the figure
fig.show()
```

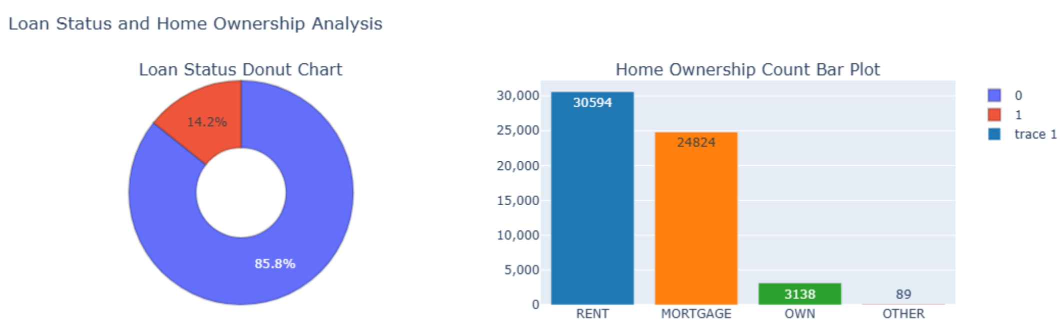
Home Ownership Distribution



[29]:

```
fig = make_subplots(
    rows=1, cols=2,
    specs=[[{'type': 'pie'}, {'type': 'bar'}]],
    subplot_titles=("Loan Status Donut Chart", "Home Ownership Count Bar Plot")
)

# Prepare data for the donut chart (loan_status)
loan_status_counts = df_train['loan_status'].value_counts().reset_index()
loan_status_counts.columns = ['loan_status', 'count']

# Prepare the donut chart
donut_chart = go.Pie(
    labels=loan_status_counts['loan_status'],
    values=loan_status_counts['count'],
    hole=0.4,  # Set hole size for donut chart
    marker=dict(line=dict(color='rgba(0, 0, 0, 0.2)', width=2))  # Add shadow␣
 ↪effect
)

# Add the donut chart to the figure
fig.add_trace(donut_chart, row=1, col=1)

# Prepare data for the bar plot (person_home_ownership)
home_ownership_counts = df_train['person_home_ownership'].value_counts().
 ↪reset_index()
home_ownership_counts.columns = ['person_home_ownership', 'count']

# Define a deep color palette
deep_color_palette = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd',␣
 ↪'#8c564b']  # More colors can be added if needed

# Add the bar trace
```

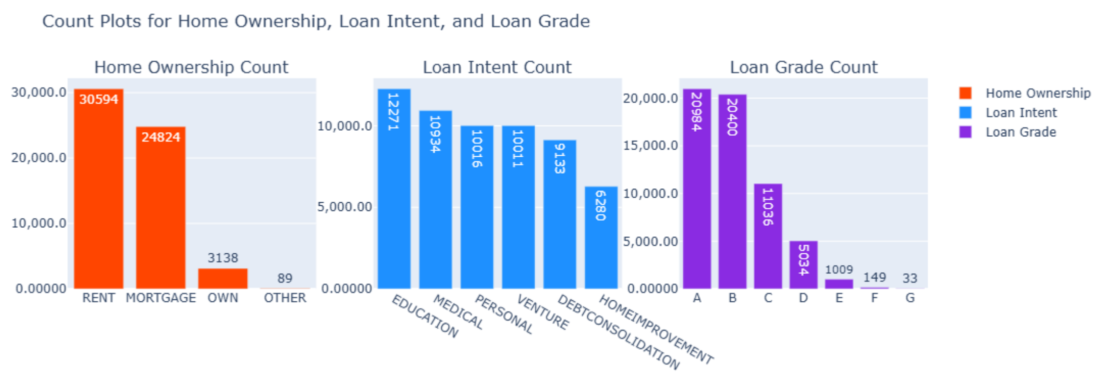
```
fig.add_trace(go.Bar(
    x=home_ownership_counts['person_home_ownership'],
    y=home_ownership_counts['count'],
    text=home_ownership_counts['count'],  # Display counts above bars
    textposition='auto',  # Automatically position the text
    marker=dict(color=deep_color_palette[:len(home_ownership_counts)])  # Use␣
↪colors from the deep palette
), row=1, col=2)

# Update layout for better visualization
fig.update_layout(
    title='Loan Status and Home Ownership Analysis',
    height=400,
    width=900,
    showlegend=True,
    yaxis_tickformat=',',  # Use a comma as a thousands separator
)

# Show the figure
fig.show()
```



[31]:
```
#  Create subplots
fig = make_subplots(
    rows=1, cols=3,
    specs=[[{'type': 'bar'}, {'type': 'bar'}, {'type': 'bar'}]],
    subplot_titles=("Home Ownership Count", "Loan Intent Count", "Loan Grade␣
↪Count")
)

# Prepare data for each column

# Count for person_home_ownership
```

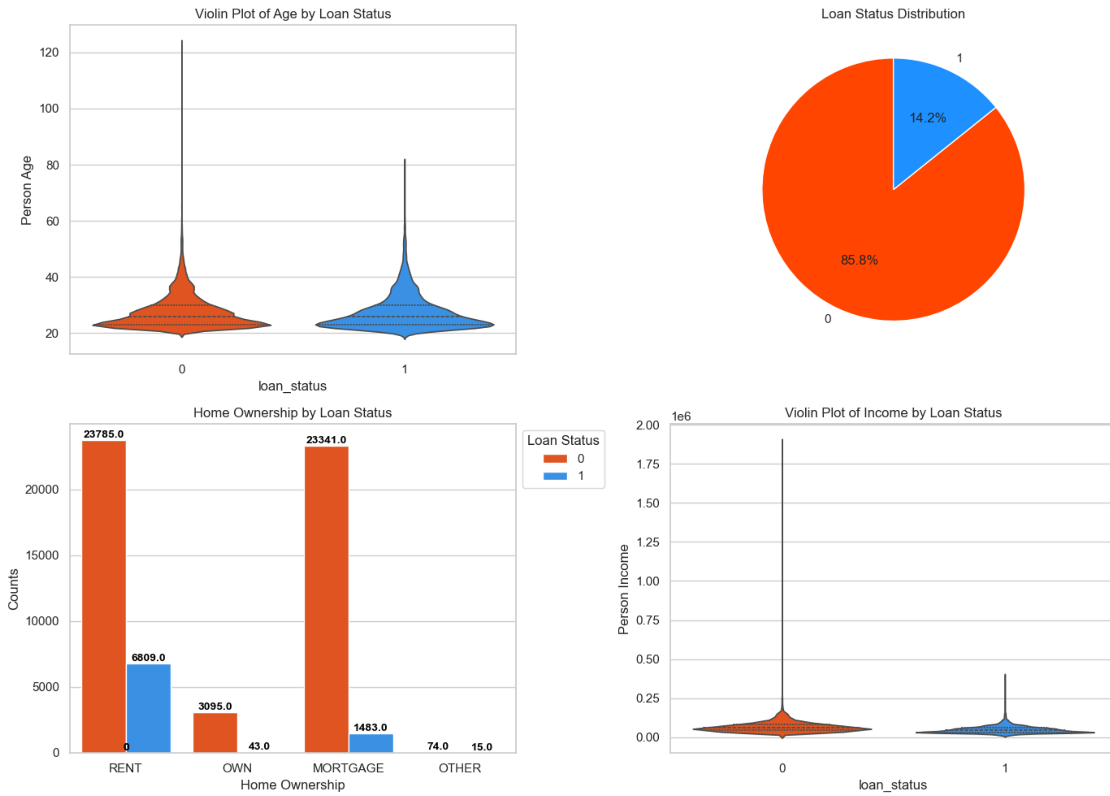
```
home_ownership_counts = df_train['person_home_ownership'].value_counts().
    ↪reset_index()
home_ownership_counts.columns = ['person_home_ownership', 'count']

# Define a deep color for home ownership
home_ownership_color = '#FF4500'  # OrangeRed

# Add the bar trace for home ownership
fig.add_trace(go.Bar(
    x=home_ownership_counts['person_home_ownership'],
    y=home_ownership_counts['count'],
    name='Home Ownership',  # Legend name
    marker=dict(color=home_ownership_color),
    text=home_ownership_counts['count'],  # Display counts above bars
    textposition='auto'  # Automatically position the text
), row=1, col=1)

# Count for loan_intent
loan_intent_counts = df_train['loan_intent'].value_counts().reset_index()
loan_intent_counts.columns = ['loan_intent', 'count']

# Define a deep color for loan intent
loan_intent_color = '#1E90FF'  # Dodger Blue

# Add the bar trace for loan intent
fig.add_trace(go.Bar(
    x=loan_intent_counts['loan_intent'],
    y=loan_intent_counts['count'],
    name='Loan Intent',  # Legend name
    marker=dict(color=loan_intent_color),
    text=loan_intent_counts['count'],  # Display counts above bars
    textposition='auto'  # Automatically position the text
), row=1, col=2)

# Count for loan_grade
loan_grade_counts = df_train['loan_grade'].value_counts().reset_index()
loan_grade_counts.columns = ['loan_grade', 'count']

# Define a deep color for loan grade
loan_grade_color = '#8A2BE2'  # BlueViolet

# Add the bar trace for loan grade
fig.add_trace(go.Bar(
    x=loan_grade_counts['loan_grade'],
    y=loan_grade_counts['count'],
    name='Loan Grade',  # Legend name
    marker=dict(color=loan_grade_color),
```

```
    text=loan_grade_counts['count'],  # Display counts above bars
    textposition='auto'  # Automatically position the text
), row=1, col=3)

# Update layout for better visualization
fig.update_layout(
    title='Count Plots for Home Ownership, Loan Intent, and Loan Grade',
    height=400,
    width=1200,
    showlegend=True,
)

# Update y-axis properties to display full numbers
for i in range(1, 4):
    fig.update_yaxes(
        tickformat=',g',  # Use thousands separator without abbreviating
        showspikes=False,  # Disable spikes on y-axis
        row=1, col=i  # Specify which subplot to update
    )

# Show the figure
fig.show()
```



[33]:
```
# Set the style for the plots
sns.set(style="whitegrid")

# Define a deeper color palette
colors = ['#FF4500', '#1E90FF', '#8A2BE2']  # Deep colors: OrangeRed, Dodger␣
↪Blue, BlueViolet

# Create a figure with subplots
fig, axs = plt.subplots(2, 2, figsize=(14, 10))
```

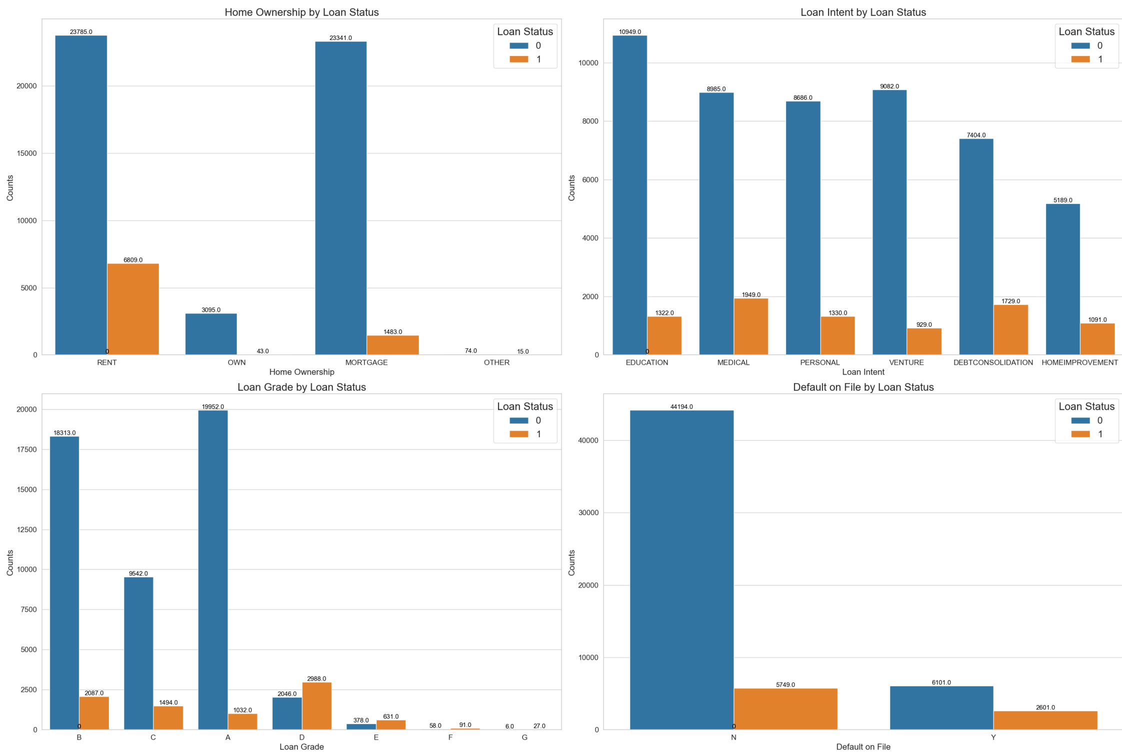
```
# Violin plot for person_age
sns.violinplot(x='loan_status', y='person_age', data=df_train, ax=axs[0, 0],␣
 ↪palette=colors[:2], inner="quartile")
axs[0, 0].set_title('Violin Plot of Age by Loan Status')
axs[0, 0].set_ylabel('Person Age')

# Pie chart for loan status
loan_counts = df_train['loan_status'].value_counts()
axs[0, 1].pie(loan_counts, labels=loan_counts.index, autopct='%1.1f%%',␣
 ↪startangle=90, colors=colors[:2])
axs[0, 1].set_title('Loan Status Distribution')

# Count plot for person_home_ownership by loan status
sns.countplot(x='person_home_ownership', hue='loan_status', data=df_train,␣
 ↪ax=axs[1, 0], palette=colors)
axs[1, 0].set_title('Home Ownership by Loan Status')
axs[1, 0].set_ylabel('Counts')
axs[1, 0].set_xlabel('Home Ownership')

# Add value annotations for count plot
for p in axs[1, 0].patches:
    axs[1, 0].annotate(f'{p.get_height()}',
                       (p.get_x() + p.get_width() / 2., p.get_height()),
                       ha='center', va='bottom',
                       color='black', size='small', weight='semibold')

# Violin plot for person_income
sns.violinplot(x='loan_status', y='person_income', data=df_train, ax=axs[1, 1],␣
 ↪palette=colors[:2], inner="quartile")
axs[1, 1].set_title('Violin Plot of Income by Loan Status')
axs[1, 1].set_ylabel('Person Income')

# Adjust legend positions
axs[1, 0].legend(title='Loan Status', labels=loan_counts.index.tolist(),␣
 ↪loc='upper left', bbox_to_anchor=(1, 1))

# Adjust layout
plt.tight_layout()
plt.show()
```



[35]:
```python
# Set the style for the plots
sns.set(style="whitegrid")

# Define a deeper color palette with rich tones
colors = ['#1F77B4', '#FF7F0E']  # Deep blue and deep orange

# Create a figure with subplots, increasing the figsize
fig, axs = plt.subplots(2, 2, figsize=(30, 20))  # Adjusted size for prominence

# Count plot for person_home_ownership by loan_status
sns.countplot(x='person_home_ownership', hue='loan_status', data=df_train, ax=axs[0, 0], palette=colors)
axs[0, 0].set_title('Home Ownership by Loan Status', fontsize=20)
axs[0, 0].set_ylabel('Counts', fontsize=16)
axs[0, 0].set_xlabel('Home Ownership', fontsize=16)
axs[0, 0].tick_params(labelsize=14)  # Adjust tick label size

# Add value annotations for person_home_ownership count plot
for p in axs[0, 0].patches:
    axs[0, 0].annotate(f'{p.get_height()}',
                       (p.get_x() + p.get_width() / 2., p.get_height()),
                       ha='center', va='bottom',
```

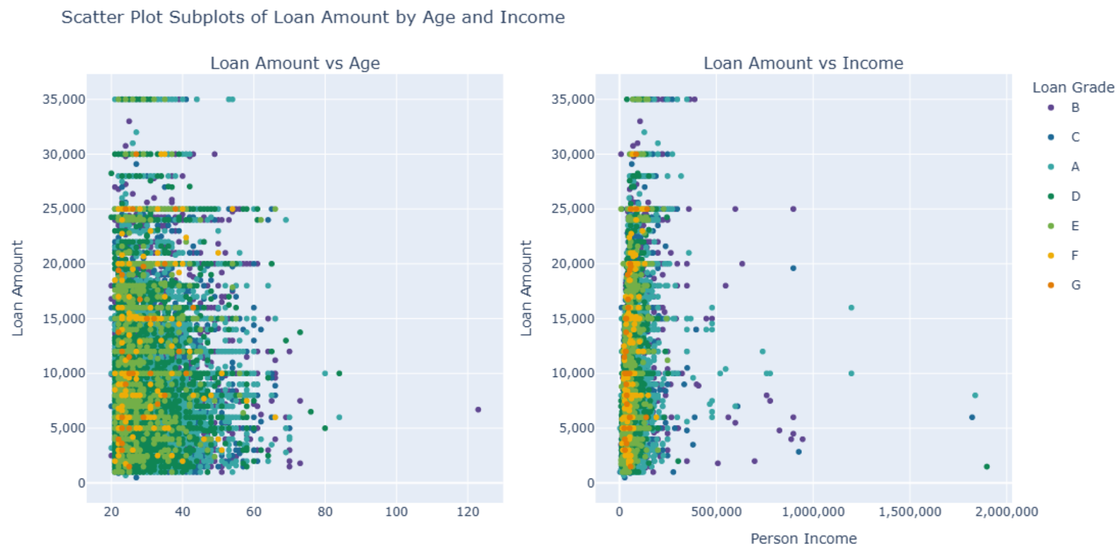
```
                        color='black', size='medium')

# Count plot for loan_intent by loan_status
sns.countplot(x='loan_intent', hue='loan_status', data=df_train, ax=axs[0, 1],␣
 ↪palette=colors)
axs[0, 1].set_title('Loan Intent by Loan Status', fontsize=20)
axs[0, 1].set_ylabel('Counts', fontsize=16)
axs[0, 1].set_xlabel('Loan Intent', fontsize=16)
axs[0, 1].tick_params(labelsize=14)  # Adjust tick label size

# Add value annotations for loan_intent count plot
for p in axs[0, 1].patches:
    axs[0, 1].annotate(f'{p.get_height()}',
                        (p.get_x() + p.get_width() / 2., p.get_height()),
                        ha='center', va='bottom',
                        color='black', size='medium')

# Count plot for loan_grade by loan_status
sns.countplot(x='loan_grade', hue='loan_status', data=df_train, ax=axs[1, 0],␣
 ↪palette=colors)
axs[1, 0].set_title('Loan Grade by Loan Status', fontsize=20)
axs[1, 0].set_ylabel('Counts', fontsize=16)
axs[1, 0].set_xlabel('Loan Grade', fontsize=16)
axs[1, 0].tick_params(labelsize=14)  # Adjust tick label size

# Add value annotations for loan_grade count plot
for p in axs[1, 0].patches:
    axs[1, 0].annotate(f'{p.get_height()}',
                        (p.get_x() + p.get_width() / 2., p.get_height()),
                        ha='center', va='bottom',
                        color='black', size='medium')

# Count plot for cb_person_default_on_file by loan_status
sns.countplot(x='cb_person_default_on_file', hue='loan_status', data=df_train,␣
 ↪ax=axs[1, 1], palette=colors)
axs[1, 1].set_title('Default on File by Loan Status', fontsize=20)
axs[1, 1].set_ylabel('Counts', fontsize=16)
axs[1, 1].set_xlabel('Default on File', fontsize=16)
axs[1, 1].tick_params(labelsize=14)  # Adjust tick label size

# Add value annotations for cb_person_default_on_file count plot
for p in axs[1, 1].patches:
    axs[1, 1].annotate(f'{p.get_height()}',
                        (p.get_x() + p.get_width() / 2., p.get_height()),
                        ha='center', va='bottom',
                        color='black', size='medium')
```

```python
# Adjust legends
for ax in axs.flat:
    ax.legend(title='Loan Status', fontsize=18, title_fontsize=20)

# Adjust layout
plt.tight_layout()
plt.show()
```



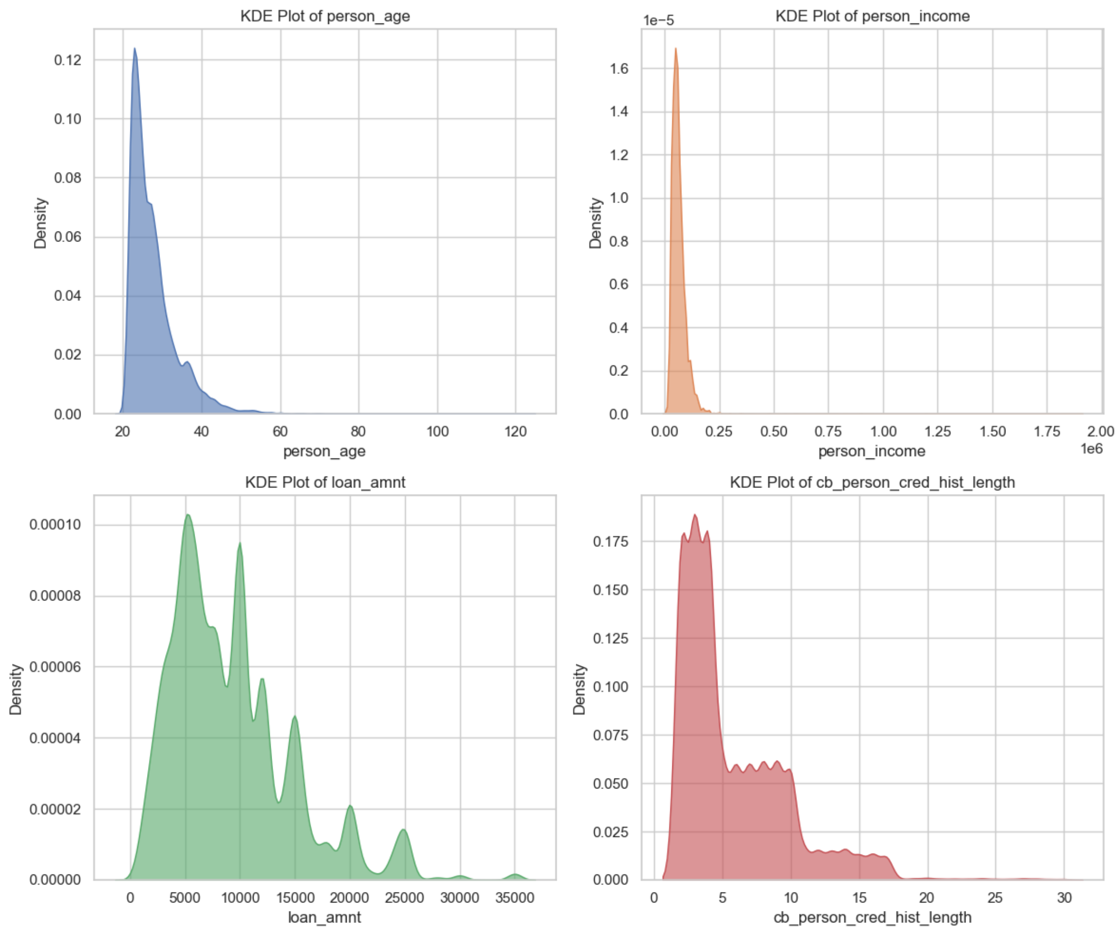
[37]:
```python
# Create scatter plots with Plotly Express
scatter_age = px.scatter(df_train, x='person_age', y='loan_amnt',␣
↪color='loan_grade',
                         title='Loan Amount vs Age Colored by Loan Grade',
                         labels={'person_age': 'Person Age', 'loan_amnt': 'Loan␣
↪Amount'},
                         color_discrete_sequence=px.colors.qualitative.Prism)

scatter_income = px.scatter(df_train, x='person_income', y='loan_amnt',␣
↪color='loan_grade',
                            title='Loan Amount vs Income Colored by Loan Grade',
                            labels={'person_income': 'Person Income',␣
↪'loan_amnt': 'Loan Amount'},
                            color_discrete_sequence=px.colors.qualitative.Prism)
```

```
# Set up a subplot with 1 row and 2 columns
fig = sp.make_subplots(rows=1, cols=2, subplot_titles=('Loan Amount vs Age',␣
↪'Loan Amount vs Income'))

# Add the scatter plots to the subplot figure
# For the first subplot, we keep the legend
for trace in scatter_age['data']:
    fig.add_trace(trace, row=1, col=1)

# For the second subplot, we hide the legend by setting `showlegend=False`
for trace in scatter_income['data']:
    trace.showlegend = False  # Disable legend for the second plot
    fig.add_trace(trace, row=1, col=2)

# Update layout for the overall figure
fig.update_layout(
    title_text="Scatter Plot Subplots of Loan Amount by Age and Income",
    showlegend=True,  # Display legend only once
    legend_title="Loan Grade",
    height=600, width=1200
)

# Ensure y-axis values show full numbers (e.g., 10000 instead of 10k)
fig.update_yaxes(tickformat=",", title_text="Loan Amount", row=1, col=1)  #␣
↪First subplot
fig.update_yaxes(tickformat=",", title_text="Loan Amount", row=1, col=2)  #␣
↪Second subplot

# Ensure x-axis values show full numbers for the second subplot (Loan Amount vs␣
↪Income)
fig.update_xaxes(tickformat=",", title_text="Person Income", row=1, col=2)  #␣
↪Second subplot

fig.show()
```



[39]:

```
# Define the columns for which you want to create KDE plots
columns = ['person_age', 'person_income', 'loan_amnt',␣
 ↪'cb_person_cred_hist_length']

# Set a deep color palette
deep_palette = sns.color_palette("deep", len(columns))

# Create a figure with subplots
plt.figure(figsize=(12, 10))

# Loop through the columns and create a KDE plot for each
for i, column in enumerate(columns):
    plt.subplot(2, 2, i + 1)  # Create a 2x2 grid of subplots
    sns.kdeplot(data=df_train[column], fill=True, color=deep_palette[i],␣
 ↪alpha=0.6)  # Create the KDE plot with a specific color
    plt.title(f'KDE Plot of {column}')  # Set the title for each subplot
    plt.xlabel(column)  # Label the x-axis
    plt.ylabel('Density')  # Label the y-axis

# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



[290]:
```python
# Create new features for df_train

# 1. Income to Loan Ratio
df_train['income_loan_ratio'] = df_train['person_income'] / df_train['loan_amnt']

# 2. Age-Employment Length Ratio
df_train['age_emp_length_ratio'] = df_train['person_emp_length'] / df_train['person_age']

# # 3. Loan to Employment Ratio
# df_train['loan_emp_ratio'] = df_train['loan_amnt'] / df_train['person_emp_length']

# 4. Loan Interest to Income Ratio
df_train['loan_int_income_ratio'] = df_train['loan_int_rate'] / df_train['person_income']
```

```
# 5. Credit History to Age Ratio
df_train['cred_hist_age_ratio'] = df_train['cb_person_cred_hist_length'] /␣
↪df_train['person_age']

# # 6. Loan Percent of Income per Year of Employment
# df_train['loan_percent_emp_year'] = df_train['loan_percent_income'] /␣
↪df_train['person_emp_length']

# 7. Default Risk Index
df_train['default_risk_index'] = (df_train['loan_amnt'] *␣
↪df_train['loan_int_rate']) / \
                                  (df_train['person_income'] *␣
↪df_train['cb_person_cred_hist_length'])

# 8. Employment Stability Indicator
df_train['emp_stability_indicator'] = df_train.apply(lambda row: 1 if␣
↪row['person_emp_length'] > (row['person_age'] * 0.6) else 0, axis=1)

# 9. Debt to Credit History Ratio
df_train['debt_cred_hist_ratio'] = df_train['loan_amnt'] /␣
↪df_train['cb_person_cred_hist_length']

# Now repeat the same for df_test
# Ensure the 'loan_amnt', 'person_income', etc. columns are present in df_test

# 1. Income to Loan Ratio
df_test['income_loan_ratio'] = df_test['person_income'] / df_test['loan_amnt']

# 2. Age-Employment Length Ratio
df_test['age_emp_length_ratio'] = df_test['person_emp_length'] /␣
↪df_test['person_age']

# # 3. Loan to Employment Ratio
# df_test['loan_emp_ratio'] = df_test['loan_amnt'] /␣
↪df_test['person_emp_length']

# 4. Loan Interest to Income Ratio
df_test['loan_int_income_ratio'] = df_test['loan_int_rate'] /␣
↪df_test['person_income']

# 5. Credit History to Age Ratio
df_test['cred_hist_age_ratio'] = df_test['cb_person_cred_hist_length'] /␣
↪df_test['person_age']

# # 6. Loan Percent of Income per Year of Employment
```

```
# df_test['loan_percent_emp_year'] = df_test['loan_percent_income'] /␣
↪df_test['person_emp_length']

# 7. Default Risk Index
df_test['default_risk_index'] = (df_test['loan_amnt'] *␣
↪df_test['loan_int_rate']) / \
                                  (df_test['person_income'] *␣
↪df_test['cb_person_cred_hist_length'])

# 8. Employment Stability Indicator
df_test['emp_stability_indicator'] = df_test.apply(lambda row: 1 if␣
↪row['person_emp_length'] > (row['person_age'] * 0.6) else 0, axis=1)

# 9. Debt to Credit History Ratio
df_test['debt_cred_hist_ratio'] = df_test['loan_amnt'] /␣
↪df_test['cb_person_cred_hist_length']

# Display the updated df_test dataframe with new features
df_test
```

[290]:

```
          id  person_age  person_income person_home_ownership  \
0      58645          23          69000                  RENT
1      58646          26          96000              MORTGAGE
2      58647          26          30000                  RENT
3      58648          33          50000                  RENT
4      58649          26         102000              MORTGAGE
…        …           …             …                     …
39093  97738          22          31200              MORTGAGE
39094  97739          22          48000              MORTGAGE
39095  97740          51          60000              MORTGAGE
39096  97741          22          36000              MORTGAGE
39097  97742          31          45000                  RENT

       person_emp_length        loan_intent loan_grade  loan_amnt  \
0                    3.0    HOMEIMPROVEMENT          F      25000
1                    6.0           PERSONAL          C      10000
2                    5.0            VENTURE          E       4000
3                    4.0  DEBTCONSOLIDATION          A       7000
4                    8.0    HOMEIMPROVEMENT          D      15000
…                    …                  …        …         …
39093                2.0  DEBTCONSOLIDATION          B       3000
39094                6.0          EDUCATION          A       7000
39095                0.0           PERSONAL          A      15000
39096                4.0           PERSONAL          D      14000
39097                6.0  DEBTCONSOLIDATION          B      19450

       loan_int_rate  loan_percent_income cb_person_default_on_file  \
```

0	15.76	0.36	N
1	12.68	0.10	Y
2	17.19	0.13	Y
3	8.90	0.14	N
4	16.32	0.15	Y
…	…	…	…
39093	10.37	0.10	N
39094	6.03	0.15	N
39095	7.51	0.25	N
39096	15.62	0.39	Y
39097	9.91	0.44	N

	cb_person_cred_hist_length	income_loan_ratio	age_emp_length_ratio	\
0	2	2.760000	0.130435	
1	4	9.600000	0.230769	
2	2	7.500000	0.192308	
3	7	7.142857	0.121212	
4	4	6.800000	0.307692	
…	…	…	…	
39093	4	10.400000	0.090909	
39094	3	6.857143	0.272727	
39095	25	4.000000	0.000000	
39096	4	2.571429	0.181818	
39097	9	2.313625	0.193548	

	loan_int_income_ratio	cred_hist_age_ratio	default_risk_index	\
0	0.000228	0.086957	2.855072	
1	0.000132	0.153846	0.330208	
2	0.000573	0.076923	1.146000	
3	0.000178	0.212121	0.178000	
4	0.000160	0.153846	0.600000	
…	…	…	…	
39093	0.000332	0.181818	0.249279	
39094	0.000126	0.136364	0.293125	
39095	0.000125	0.490196	0.075100	
39096	0.000434	0.181818	1.518611	
39097	0.000220	0.290323	0.475925	

	emp_stability_indicator	debt_cred_hist_ratio
0	0	12500.000000
1	0	2500.000000
2	0	2000.000000
3	0	1000.000000
4	0	3750.000000
…	…	…
39093	0	750.000000
39094	0	2333.333333

```
39095                        0          600.000000
39096                        0         3500.000000
39097                        0         2161.111111

[39098 rows x 19 columns]
```

[291]:

```
df_train.drop(columns=['id'], inplace=True)
df_test_ids = df_test['id']
df_test.drop(columns=['id'], inplace=True)
```

[292]:

```
# One-Hot Encoding
df_train = pd.get_dummies(df_train, columns=['person_home_ownership',␣
 ↪'loan_intent', 'loan_grade', 'cb_person_default_on_file'], drop_first=True)
df_test = pd.get_dummies(df_test, columns=['person_home_ownership',␣
 ↪'loan_intent', 'loan_grade', 'cb_person_default_on_file'], drop_first=True)
```

[293]:

```
df_train
```

[293]:

```
       person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
0              37          35000                0.0       6000          11.49
1              22          56000                6.0       4000          13.35
2              29          28800                8.0       6000           8.90
3              30          70000               14.0      12000          11.11
4              22          60000                2.0       6000           6.92
…             …            …                 …         …          …
58640          34         120000                5.0      25000          15.95
58641          28          28800                0.0      10000          12.73
58642          23          44000                7.0       6800          16.00
58643          22          30000                2.0       5000           8.90
58644          31          75000                2.0      15000          11.11

       loan_percent_income  cb_person_cred_hist_length  loan_status  \
0                     0.17                          14            0
1                     0.07                           2            0
2                     0.21                          10            0
3                     0.17                           5            0
4                     0.10                           3            0
…                    …                          …          …
58640                 0.21                          10            0
58641                 0.35                           8            1
58642                 0.15                           2            1
58643                 0.17                           3            0
58644                 0.20                           5            0

       income_loan_ratio  age_emp_length_ratio  …  loan_intent_MEDICAL  \
0               5.833333              0.000000  …                False
1              14.000000              0.272727  …                 True
```

```
2             4.800000            0.275862  …                False
3             5.833333            0.466667  …                False
4            10.000000            0.090909  …                 True
…                  …                   …   …            …
58640         4.800000            0.147059  …                False
58641         2.880000            0.000000  …                 True
58642         6.470588            0.304348  …                False
58643         6.000000            0.090909  …                False
58644         5.000000            0.064516  …                False

       loan_intent_PERSONAL  loan_intent_VENTURE  loan_grade_B  loan_grade_C  \
0                     False                False          True         False
1                     False                False         False          True
2                      True                False         False         False
3                     False                 True          True         False
4                     False                False         False         False
…                       …                    …           …            …
58640                 False                False         False         False
58641                 False                False         False          True
58642                 False                False         False         False
58643                 False                False         False         False
58644                 False                 True          True         False

       loan_grade_D  loan_grade_E  loan_grade_F  loan_grade_G  \
0             False         False         False         False
1             False         False         False         False
2             False         False         False         False
3             False         False         False         False
4             False         False         False         False
…             …           …            …            …
58640          True         False         False         False
58641         False         False         False         False
58642          True         False         False         False
58643         False         False         False         False
58644         False         False         False         False

       cb_person_default_on_file_Y
0                            False
1                            False
2                            False
3                            False
4                            False
…                            …
58640                         True
58641                        False
58642                        False
58643                        False
```

```
58644                         False

[58645 rows x 30 columns]
```

[294]:
```
df_train[df_train.select_dtypes(include='bool').columns] = df_train.
 ↪select_dtypes(include='bool').astype(int)
df_test[df_test.select_dtypes(include='bool').columns] = df_test.
 ↪select_dtypes(include='bool').astype(int)
```

[295]:
```
df_train
```

[295]:
```
       person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
0              37          35000                0.0       6000          11.49
1              22          56000                6.0       4000          13.35
2              29          28800                8.0       6000           8.90
3              30          70000               14.0      12000          11.11
4              22          60000                2.0       6000           6.92
…             …             …                  …         …             …
58640          34         120000                5.0      25000          15.95
58641          28          28800                0.0      10000          12.73
58642          23          44000                7.0       6800          16.00
58643          22          30000                2.0       5000           8.90
58644          31          75000                2.0      15000          11.11

       loan_percent_income  cb_person_cred_hist_length  loan_status  \
0                     0.17                          14            0
1                     0.07                           2            0
2                     0.21                          10            0
3                     0.17                           5            0
4                     0.10                           3            0
…                       …                          …          …
58640                 0.21                          10            0
58641                 0.35                           8            1
58642                 0.15                           2            1
58643                 0.17                           3            0
58644                 0.20                           5            0

       income_loan_ratio  age_emp_length_ratio  …  loan_intent_MEDICAL  \
0               5.833333              0.000000  …                    0
1              14.000000              0.272727  …                    1
2               4.800000              0.275862  …                    0
3               5.833333              0.466667  …                    0
4              10.000000              0.090909  …                    1
…                    …                  …  …                 …
58640           4.800000              0.147059  …                    0
58641           2.880000              0.000000  …                    1
58642           6.470588              0.304348  …                    0
```

```
58643          6.000000              0.090909  ...                0
58644          5.000000              0.064516  ...                0

       loan_intent_PERSONAL  loan_intent_VENTURE  loan_grade_B  loan_grade_C  \
0                         0                    0             1             0
1                         0                    0             0             1
2                         1                    0             0             0
3                         0                    1             1             0
4                         0                    0             0             0
...                     ...                  ...           ...           ...
58640                     0                    0             0             0
58641                     0                    0             0             1
58642                     0                    0             0             0
58643                     0                    0             0             0
58644                     0                    1             1             0

       loan_grade_D  loan_grade_E  loan_grade_F  loan_grade_G  \
0                 0             0             0             0
1                 0             0             0             0
2                 0             0             0             0
3                 0             0             0             0
4                 0             0             0             0
...             ...           ...           ...           ...
58640             1             0             0             0
58641             0             0             0             0
58642             1             0             0             0
58643             0             0             0             0
58644             0             0             0             0

       cb_person_default_on_file_Y
0                                0
1                                0
2                                0
3                                0
4                                0
...                            ...
58640                            1
58641                            0
58642                            0
58643                            0
58644                            0

[58645 rows x 30 columns]
```

[296]:
```python
numerical_cols_train = df_train.select_dtypes(include=['int64', 'float64']).
 ↪columns.tolist()
print("Numerical columns in df_train:")
```

```
print(numerical_cols_train)
```

```
Numerical columns in df_train:
['person_age', 'person_income', 'person_emp_length', 'loan_amnt',
'loan_int_rate', 'loan_percent_income', 'cb_person_cred_hist_length',
'loan_status', 'income_loan_ratio', 'age_emp_length_ratio',
'loan_int_income_ratio', 'cred_hist_age_ratio', 'default_risk_index',
'emp_stability_indicator', 'debt_cred_hist_ratio']
```

[297]:
```
# Check for NaN values in df_train and df_test
print("NaN values in df_train:")
print(df_train.isna().sum())

print("NaN values in df_test:")
print(df_test.isna().sum())

# Check for infinite values in df_train and df_test
print("Infinite values in df_train:")
print(np.isinf(df_train).sum())

print("Infinite values in df_test:")
print(np.isinf(df_test).sum())
```

```
NaN values in df_train:
person_age                     0
person_income                  0
person_emp_length              0
loan_amnt                      0
loan_int_rate                  0
loan_percent_income            0
cb_person_cred_hist_length     0
loan_status                    0
income_loan_ratio              0
age_emp_length_ratio           0
loan_int_income_ratio          0
cred_hist_age_ratio            0
default_risk_index             0
emp_stability_indicator        0
debt_cred_hist_ratio           0
person_home_ownership_OTHER    0
person_home_ownership_OWN      0
person_home_ownership_RENT     0
loan_intent_EDUCATION          0
loan_intent_HOMEIMPROVEMENT    0
loan_intent_MEDICAL            0
loan_intent_PERSONAL           0
loan_intent_VENTURE            0
loan_grade_B                   0
```

```
loan_grade_C                  0
loan_grade_D                  0
loan_grade_E                  0
loan_grade_F                  0
loan_grade_G                  0
cb_person_default_on_file_Y   0
dtype: int64
NaN values in df_test:
person_age                    0
person_income                 0
person_emp_length             0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
cb_person_cred_hist_length    0
income_loan_ratio             0
age_emp_length_ratio          0
loan_int_income_ratio         0
cred_hist_age_ratio           0
default_risk_index            0
emp_stability_indicator       0
debt_cred_hist_ratio          0
person_home_ownership_OTHER   0
person_home_ownership_OWN     0
person_home_ownership_RENT    0
loan_intent_EDUCATION         0
loan_intent_HOMEIMPROVEMENT   0
loan_intent_MEDICAL           0
loan_intent_PERSONAL          0
loan_intent_VENTURE           0
loan_grade_B                  0
loan_grade_C                  0
loan_grade_D                  0
loan_grade_E                  0
loan_grade_F                  0
loan_grade_G                  0
cb_person_default_on_file_Y   0
dtype: int64
Infinite values in df_train:
person_age                    0
person_income                 0
person_emp_length             0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
cb_person_cred_hist_length    0
loan_status                   0
income_loan_ratio             0
```

```
age_emp_length_ratio           0
loan_int_income_ratio          0
cred_hist_age_ratio            0
default_risk_index             0
emp_stability_indicator        0
debt_cred_hist_ratio           0
person_home_ownership_OTHER    0
person_home_ownership_OWN      0
person_home_ownership_RENT     0
loan_intent_EDUCATION          0
loan_intent_HOMEIMPROVEMENT    0
loan_intent_MEDICAL            0
loan_intent_PERSONAL           0
loan_intent_VENTURE            0
loan_grade_B                   0
loan_grade_C                   0
loan_grade_D                   0
loan_grade_E                   0
loan_grade_F                   0
loan_grade_G                   0
cb_person_default_on_file_Y    0
dtype: int64
Infinite values in df_test:
person_age                     0
person_income                  0
person_emp_length              0
loan_amnt                      0
loan_int_rate                  0
loan_percent_income            0
cb_person_cred_hist_length     0
income_loan_ratio              0
age_emp_length_ratio           0
loan_int_income_ratio          0
cred_hist_age_ratio            0
default_risk_index             0
emp_stability_indicator        0
debt_cred_hist_ratio           0
person_home_ownership_OTHER    0
person_home_ownership_OWN      0
person_home_ownership_RENT     0
loan_intent_EDUCATION          0
loan_intent_HOMEIMPROVEMENT    0
loan_intent_MEDICAL            0
loan_intent_PERSONAL           0
loan_intent_VENTURE            0
loan_grade_B                   0
loan_grade_C                   0
loan_grade_D                   0
```

```
loan_grade_E                  0
loan_grade_F                  0
loan_grade_G                  0
cb_person_default_on_file_Y   0
dtype: int64
```

[298]:
```python
# # Replace infinite values with NaN in both training and test data
# df_train.replace([np.inf, -np.inf], np.nan, inplace=True)
# df_test.replace([np.inf, -np.inf], np.nan, inplace=True)

# # Replace NaN values with the median value of each column
# # For df_train
# for column in df_train.columns:
#     if df_train[column].dtype != 'object':  # Only apply to numerical columns
#         median_value = df_train[column].median()
#         df_train[column].fillna(median_value, inplace=True)

# # For df_test
# for column in df_test.columns:
#     if df_test[column].dtype != 'object':  # Only apply to numerical columns
#         median_value = df_test[column].median()
#         df_test[column].fillna(median_value, inplace=True)

# # After this, you can proceed with your model training and prediction
```

[299]:
```python
# Train and Test Data Missing Values
print(df_train.isnull().sum())
print(df_test.isnull().sum())
```

```
person_age                    0
person_income                 0
person_emp_length             0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
cb_person_cred_hist_length    0
loan_status                   0
income_loan_ratio             0
age_emp_length_ratio          0
loan_int_income_ratio         0
cred_hist_age_ratio           0
default_risk_index            0
emp_stability_indicator       0
debt_cred_hist_ratio          0
person_home_ownership_OTHER   0
person_home_ownership_OWN     0
person_home_ownership_RENT    0
loan_intent_EDUCATION         0
```

```
loan_intent_HOMEIMPROVEMENT    0
loan_intent_MEDICAL            0
loan_intent_PERSONAL           0
loan_intent_VENTURE            0
loan_grade_B                   0
loan_grade_C                   0
loan_grade_D                   0
loan_grade_E                   0
loan_grade_F                   0
loan_grade_G                   0
cb_person_default_on_file_Y    0
dtype: int64
person_age                     0
person_income                  0
person_emp_length              0
loan_amnt                      0
loan_int_rate                  0
loan_percent_income            0
cb_person_cred_hist_length     0
income_loan_ratio              0
age_emp_length_ratio           0
loan_int_income_ratio          0
cred_hist_age_ratio            0
default_risk_index             0
emp_stability_indicator        0
debt_cred_hist_ratio           0
person_home_ownership_OTHER    0
person_home_ownership_OWN      0
person_home_ownership_RENT     0
loan_intent_EDUCATION          0
loan_intent_HOMEIMPROVEMENT    0
loan_intent_MEDICAL            0
loan_intent_PERSONAL           0
loan_intent_VENTURE            0
loan_grade_B                   0
loan_grade_C                   0
loan_grade_D                   0
loan_grade_E                   0
loan_grade_F                   0
loan_grade_G                   0
cb_person_default_on_file_Y    0
dtype: int64
```

[300]:

```
# Rescaling the relevant numerical features in both training and test sets
scaler = MinMaxScaler()
```

```
num_vars_train = ['person_age', 'person_income', 'person_emp_length',␣
 ↪'loan_amnt', 'loan_int_rate', 'loan_percent_income',␣
 ↪'cb_person_cred_hist_length', 'income_loan_ratio', 'age_emp_length_ratio',␣
 ↪'loan_int_income_ratio', 'cred_hist_age_ratio', 'default_risk_index',␣
 ↪'emp_stability_indicator', 'debt_cred_hist_ratio']
num_vars_test = ['person_age', 'person_income', 'person_emp_length',␣
 ↪'loan_amnt', 'loan_int_rate', 'loan_percent_income',␣
 ↪'cb_person_cred_hist_length', 'income_loan_ratio', 'age_emp_length_ratio',␣
 ↪'loan_int_income_ratio', 'cred_hist_age_ratio', 'default_risk_index',␣
 ↪'emp_stability_indicator', 'debt_cred_hist_ratio']
df_train[num_vars_train] = scaler.fit_transform(df_train[num_vars_train])
df_test[num_vars_test] = scaler.transform(df_test[num_vars_test])
from sklearn.preprocessing import StandardScaler

# # Initialize the scaler
# scaler = StandardScaler()

# # List of numerical columns for training and testing sets
# num_vars_train = ['person_age', 'person_income', 'person_emp_length',␣
 ↪'loan_amnt', 'loan_int_rate', 'loan_percent_income',␣
 ↪'cb_person_cred_hist_length', 'income_loan_ratio', 'age_emp_length_ratio',␣
 ↪'loan_int_income_ratio', 'cred_hist_age_ratio', 'default_risk_index',␣
 ↪'emp_stability_indicator', 'debt_cred_hist_ratio']
# num_vars_test = ['person_age', 'person_income', 'person_emp_length',␣
 ↪'loan_amnt', 'loan_int_rate', 'loan_percent_income',␣
 ↪'cb_person_cred_hist_length', 'income_loan_ratio', 'age_emp_length_ratio',␣
 ↪'loan_int_income_ratio', 'cred_hist_age_ratio', 'default_risk_index',␣
 ↪'emp_stability_indicator', 'debt_cred_hist_ratio']

# # Standardize the numerical columns in both training and test sets
# df_train[num_vars_train] = scaler.fit_transform(df_train[num_vars_train])
# df_test[num_vars_test] = scaler.transform(df_test[num_vars_test])

# # Display the first few rows to confirm the changes
# df_train.head()
```

[301]:
```
# Train and Test Data Missing Values
print(df_train.isnull().sum())
print(df_test.isnull().sum())
```

```
person_age                    0
person_income                 0
person_emp_length             0
loan_amnt                     0
loan_int_rate                 0
loan_percent_income           0
cb_person_cred_hist_length    0
```

```
loan_status                    0
income_loan_ratio              0
age_emp_length_ratio           0
loan_int_income_ratio          0
cred_hist_age_ratio            0
default_risk_index             0
emp_stability_indicator        0
debt_cred_hist_ratio           0
person_home_ownership_OTHER    0
person_home_ownership_OWN      0
person_home_ownership_RENT     0
loan_intent_EDUCATION          0
loan_intent_HOMEIMPROVEMENT    0
loan_intent_MEDICAL            0
loan_intent_PERSONAL           0
loan_intent_VENTURE            0
loan_grade_B                   0
loan_grade_C                   0
loan_grade_D                   0
loan_grade_E                   0
loan_grade_F                   0
loan_grade_G                   0
cb_person_default_on_file_Y    0
dtype: int64
person_age                     0
person_income                  0
person_emp_length              0
loan_amnt                      0
loan_int_rate                  0
loan_percent_income            0
cb_person_cred_hist_length     0
income_loan_ratio              0
age_emp_length_ratio           0
loan_int_income_ratio          0
cred_hist_age_ratio            0
default_risk_index             0
emp_stability_indicator        0
debt_cred_hist_ratio           0
person_home_ownership_OTHER    0
person_home_ownership_OWN      0
person_home_ownership_RENT     0
loan_intent_EDUCATION          0
loan_intent_HOMEIMPROVEMENT    0
loan_intent_MEDICAL            0
loan_intent_PERSONAL           0
loan_intent_VENTURE            0
loan_grade_B                   0
loan_grade_C                   0
```

```
loan_grade_D                 0
loan_grade_E                 0
loan_grade_F                 0
loan_grade_G                 0
cb_person_default_on_file_Y    0
dtype: int64
```

[302]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58645 entries, 0 to 58644
Data columns (total 30 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   person_age                   58645 non-null  float64
 1   person_income                58645 non-null  float64
 2   person_emp_length            58645 non-null  float64
 3   loan_amnt                    58645 non-null  float64
 4   loan_int_rate                58645 non-null  float64
 5   loan_percent_income          58645 non-null  float64
 6   cb_person_cred_hist_length   58645 non-null  float64
 7   loan_status                  58645 non-null  int64
 8   income_loan_ratio            58645 non-null  float64
 9   age_emp_length_ratio         58645 non-null  float64
 10  loan_int_income_ratio        58645 non-null  float64
 11  cred_hist_age_ratio          58645 non-null  float64
 12  default_risk_index           58645 non-null  float64
 13  emp_stability_indicator      58645 non-null  float64
 14  debt_cred_hist_ratio         58645 non-null  float64
 15  person_home_ownership_OTHER  58645 non-null  int32
 16  person_home_ownership_OWN    58645 non-null  int32
 17  person_home_ownership_RENT   58645 non-null  int32
 18  loan_intent_EDUCATION        58645 non-null  int32
 19  loan_intent_HOMEIMPROVEMENT  58645 non-null  int32
 20  loan_intent_MEDICAL          58645 non-null  int32
 21  loan_intent_PERSONAL         58645 non-null  int32
 22  loan_intent_VENTURE          58645 non-null  int32
 23  loan_grade_B                 58645 non-null  int32
 24  loan_grade_C                 58645 non-null  int32
 25  loan_grade_D                 58645 non-null  int32
 26  loan_grade_E                 58645 non-null  int32
 27  loan_grade_F                 58645 non-null  int32
 28  loan_grade_G                 58645 non-null  int32
 29  cb_person_default_on_file_Y  58645 non-null  int32
dtypes: float64(14), int32(15), int64(1)
memory usage: 10.1 MB
```

[303]:
```python
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39098 entries, 0 to 39097
Data columns (total 29 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   person_age                   39098 non-null  float64
 1   person_income                39098 non-null  float64
 2   person_emp_length            39098 non-null  float64
 3   loan_amnt                    39098 non-null  float64
 4   loan_int_rate                39098 non-null  float64
 5   loan_percent_income          39098 non-null  float64
 6   cb_person_cred_hist_length   39098 non-null  float64
 7   income_loan_ratio            39098 non-null  float64
 8   age_emp_length_ratio         39098 non-null  float64
 9   loan_int_income_ratio        39098 non-null  float64
 10  cred_hist_age_ratio          39098 non-null  float64
 11  default_risk_index           39098 non-null  float64
 12  emp_stability_indicator      39098 non-null  float64
 13  debt_cred_hist_ratio         39098 non-null  float64
 14  person_home_ownership_OTHER  39098 non-null  int32
 15  person_home_ownership_OWN    39098 non-null  int32
 16  person_home_ownership_RENT   39098 non-null  int32
 17  loan_intent_EDUCATION        39098 non-null  int32
 18  loan_intent_HOMEIMPROVEMENT  39098 non-null  int32
 19  loan_intent_MEDICAL          39098 non-null  int32
 20  loan_intent_PERSONAL         39098 non-null  int32
 21  loan_intent_VENTURE          39098 non-null  int32
 22  loan_grade_B                 39098 non-null  int32
 23  loan_grade_C                 39098 non-null  int32
 24  loan_grade_D                 39098 non-null  int32
 25  loan_grade_E                 39098 non-null  int32
 26  loan_grade_F                 39098 non-null  int32
 27  loan_grade_G                 39098 non-null  int32
 28  cb_person_default_on_file_Y  39098 non-null  int32
dtypes: float64(14), int32(15)
memory usage: 6.4 MB
```

[304]:
```python
# Prepare the training and validation data
X_train = df_train.drop('loan_status', axis=1)  # Features
y_train = df_train['loan_status']  # Target
```

[ ]:
```python

```

[305]:
```python
X_train, X_test, y_train, y_test = train_test_split(X_train, y_train,␣
↪test_size=0.2, random_state=42)
```

[306]:
```
# #Handle Imbalance using SMOTE for oversampling the minority class
# smote = SMOTE(random_state=42)
# X_resampled, y_resampled = smote.fit_resample(X_train, y_train)
```

[307]:
```
X_resampled
```

[307]:
```
       person_age  person_income  person_emp_length  loan_amnt  loan_int_rate  \
0        0.155340       0.024159           0.000000   0.194203       0.473596
1        0.067961       0.020572           0.024390   0.130435       0.350562
2        0.048544       0.034708           0.000000   0.217391       0.138202
3        0.184466       0.037346           0.016260   0.420290       0.062921
4        0.019417       0.021838           0.040650   0.101449       0.125843
…             …             …                  …        …             …
80411    0.044037       0.032021           0.018776   0.663220       0.241431
80412    0.031521       0.050436           0.035475   0.289970       0.548212
80413    0.116505       0.047708           0.069322   0.420290       0.628559
80414    0.097087       0.026870           0.008384   0.130989       0.492537
80415    0.114145       0.029215           0.014576   0.565217       0.311050

       loan_percent_income  cb_person_cred_hist_length  income_loan_ratio  \
0                 0.168675                    0.464286           0.005231
1                 0.144578                    0.250000           0.006570
2                 0.132530                    0.035714           0.006657
3                 0.240964                    0.321429           0.003696
4                 0.108434                    0.000000           0.008750
…                      …                           …                  …
80411             0.455104                    0.000000           0.001932
80412             0.128152                    0.013452           0.007475
80413             0.192771                    0.250000           0.004730
80414             0.108622                    0.142300           0.008425
80415             0.400086                    0.285714           0.002100

       age_emp_length_ratio  loan_int_income_ratio  …  loan_intent_MEDICAL  \
0                  0.000000               0.104558  …                    0
1                  0.018970               0.101838  …                    0
2                  0.000000               0.041502  …                    0
3                  0.008755               0.031773  …                    0
4                  0.038803               0.062752  …                    1
…                       …                    …  …                    …
80411              0.016348               0.056861  …                    0
80412              0.031041               0.058423  …                    0
80413              0.045493               0.065648  …                    0
80414              0.005869               0.097019  …                    0
80415              0.009514               0.068835  …                    0

       loan_intent_PERSONAL  loan_intent_VENTURE  loan_grade_B  loan_grade_C  \
0                         0                    0             0             1
```

```
1                        0                    0             0             1
2                        0                    0             0             0
3                        0                    0             0             0
4                        0                    0             0             0
…                      …                  …           …           …
80411                    0                    0             1             0
80412                    0                    0             0             0
80413                    0                    0             0             0
80414                    0                    0             0             1
80415                    0                    0             1             0

       loan_grade_D  loan_grade_E  loan_grade_F  loan_grade_G  \
0                 0             0             0             0
1                 0             0             0             0
2                 0             0             0             0
3                 0             0             0             0
4                 0             0             0             0
…               …           …           …           …
80411             0             0             0             0
80412             1             0             0             0
80413             1             0             0             0
80414             0             0             0             0
80415             0             0             0             0

       cb_person_default_on_file_Y
0                                1
1                                1
2                                0
3                                0
4                                0
…                              …
80411                            0
80412                            1
80413                            1
80414                            0
80415                            0

[80416 rows x 29 columns]
```

[308]:

```
# # Initialize the Random Forest model
# rf_model = RandomForestClassifier(random_state=42)

# # Train the model on the resampled data
# rf_model.fit(X_resampled, y_resampled)

# # Predict on the validation set
# y_pred = rf_model.predict(X_test)
```

```
# # Calculate the accuracy
# accuracy = accuracy_score(y_test, y_pred)
# print(f"Accuracy: {accuracy:.2f}")

# # Print the classification report for more detailed performance analysis
# print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.94
              precision    recall  f1-score   support

           0       0.96      0.97      0.97     10087
           1       0.81      0.75      0.78      1642

    accuracy                           0.94     11729
   macro avg       0.89      0.86      0.87     11729
weighted avg       0.94      0.94      0.94     11729
```

[309]:
```
# test_predictions = rf_model.predict(df_test)

# # Create a DataFrame with test IDs and predictions
# output = pd.DataFrame({
#     'id': df_test_ids,  # Use the test IDs from earlier
#     'loan_status': test_predictions  # Predictions from the model
# })

# # Export the results to an Excel file
# output.to_excel('loan_status_predictions.xlsx', index=False)
```

[310]:
```
from catboost import CatBoostClassifier
catboost_model = CatBoostClassifier(random_state=42, verbose=0)

# Train the model on the resampled data
catboost_model.fit(X_resampled, y_resampled)

# Predict on the validation set (X_test)
y_pred = catboost_model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"CatBoost Accuracy: {accuracy:.2f}")

# Print the classification report for detailed performance analysis
print(classification_report(y_test, y_pred))

# Optionally, you can save the model's predictions on the test dataset
```

```python
test_predictions = catboost_model.predict(df_test)

# Create a DataFrame with test IDs and predictions
output = pd.DataFrame({
    'id': df_test_ids,
    'loan_status': test_predictions
})

# Export the predictions to an Excel file
output.to_excel('catboost_loan_status_predictions.xlsx', index=False)
```

```
CatBoost Accuracy: 0.95
              precision    recall  f1-score   support

           0       0.96      0.99      0.97     10087
           1       0.90      0.74      0.81      1642

    accuracy                           0.95     11729
   macro avg       0.93      0.87      0.89     11729
weighted avg       0.95      0.95      0.95     11729
```

[311]:
```python
print(f"Length of df_test_ids: {len(df_test_ids)}")
print(f"Length of test_predictions: {len(test_predictions)}")
```

```
Length of df_test_ids: 39098
Length of test_predictions: 39098
```

[312]:
```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from sklearn.metrics import accuracy_score, classification_report


# Define the neural network model
model = Sequential()

# Input layer
model.add(Dense(128, activation='relu', input_shape=(X_resampled.shape[1],))) ␣
  ↪# Adjust input shape based on your feature set
model.add(Dropout(0.3))  # Dropout layer to prevent overfitting

# Hidden layers
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))

model.add(Dense(32, activation='relu'))
```

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model.add(Dropout(0.3))

# Output layer (1 neuron with sigmoid activation for binary classification)
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])

# Train the model
history = model.fit(X_resampled, y_resampled, epochs=50, batch_size=32,␣
↪validation_split=0.2)

# Predict on the test set
y_pred = (model.predict(X_test) > 0.5).astype("int32")

# Calculate the accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

# Print the classification report for more detailed performance analysis
print(classification_report(y_test, y_pred))
```

```
Epoch 1/50

C:\Users\Dell\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

2011/2011              5s 2ms/step -
accuracy: 0.8056 - loss: 0.4359 - val_accuracy: 0.7586 - val_loss: 0.4776
Epoch 2/50
2011/2011              3s 2ms/step -
accuracy: 0.8739 - loss: 0.3253 - val_accuracy: 0.7603 - val_loss: 0.4225
Epoch 3/50
2011/2011              3s 2ms/step -
accuracy: 0.8772 - loss: 0.3139 - val_accuracy: 0.7690 - val_loss: 0.4131
Epoch 4/50
2011/2011              3s 1ms/step -
accuracy: 0.8819 - loss: 0.3077 - val_accuracy: 0.7605 - val_loss: 0.4052
Epoch 5/50
2011/2011              3s 2ms/step -
accuracy: 0.8799 - loss: 0.3041 - val_accuracy: 0.7809 - val_loss: 0.3820
Epoch 6/50
2011/2011              3s 2ms/step -
accuracy: 0.8810 - loss: 0.3046 - val_accuracy: 0.7507 - val_loss: 0.4524
```

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Epoch 7/50
2011/2011            3s 2ms/step -
accuracy: 0.8808 - loss: 0.2988 - val_accuracy: 0.7636 - val_loss: 0.4272
Epoch 8/50
2011/2011            3s 2ms/step -
accuracy: 0.8812 - loss: 0.3005 - val_accuracy: 0.7518 - val_loss: 0.4329
Epoch 9/50
2011/2011            3s 2ms/step -
accuracy: 0.8811 - loss: 0.2947 - val_accuracy: 0.7476 - val_loss: 0.4335
Epoch 10/50
2011/2011            3s 2ms/step -
accuracy: 0.8835 - loss: 0.2918 - val_accuracy: 0.7294 - val_loss: 0.5167
Epoch 11/50
2011/2011            3s 2ms/step -
accuracy: 0.8817 - loss: 0.2969 - val_accuracy: 0.7592 - val_loss: 0.4305
Epoch 12/50
2011/2011            3s 2ms/step -
accuracy: 0.8848 - loss: 0.2883 - val_accuracy: 0.7711 - val_loss: 0.3941
Epoch 13/50
2011/2011            3s 2ms/step -
accuracy: 0.8847 - loss: 0.2874 - val_accuracy: 0.7643 - val_loss: 0.3893
Epoch 14/50
2011/2011            3s 2ms/step -
accuracy: 0.8883 - loss: 0.2836 - val_accuracy: 0.7583 - val_loss: 0.4092
Epoch 15/50
2011/2011            3s 2ms/step -
accuracy: 0.8854 - loss: 0.2889 - val_accuracy: 0.7429 - val_loss: 0.4473
Epoch 16/50
2011/2011            3s 2ms/step -
accuracy: 0.8848 - loss: 0.2852 - val_accuracy: 0.7507 - val_loss: 0.4334
Epoch 17/50
2011/2011            3s 2ms/step -
accuracy: 0.8854 - loss: 0.2849 - val_accuracy: 0.7562 - val_loss: 0.4379
Epoch 18/50
2011/2011            3s 2ms/step -
accuracy: 0.8850 - loss: 0.2868 - val_accuracy: 0.7598 - val_loss: 0.4415
Epoch 19/50
2011/2011            3s 1ms/step -
accuracy: 0.8846 - loss: 0.2863 - val_accuracy: 0.7423 - val_loss: 0.4679
Epoch 20/50
2011/2011            3s 2ms/step -
accuracy: 0.8856 - loss: 0.2838 - val_accuracy: 0.7551 - val_loss: 0.4316
Epoch 21/50
2011/2011            3s 2ms/step -
accuracy: 0.8870 - loss: 0.2827 - val_accuracy: 0.7683 - val_loss: 0.4111
Epoch 22/50
2011/2011            3s 2ms/step -
accuracy: 0.8877 - loss: 0.2805 - val_accuracy: 0.7542 - val_loss: 0.3992
```

```
Epoch 23/50
2011/2011             3s 1ms/step -
accuracy: 0.8874 - loss: 0.2806 - val_accuracy: 0.7769 - val_loss: 0.3755
Epoch 24/50
2011/2011             3s 1ms/step -
accuracy: 0.8856 - loss: 0.2819 - val_accuracy: 0.7580 - val_loss: 0.4143
Epoch 25/50
2011/2011             3s 2ms/step -
accuracy: 0.8873 - loss: 0.2801 - val_accuracy: 0.7638 - val_loss: 0.4015
Epoch 26/50
2011/2011             3s 1ms/step -
accuracy: 0.8891 - loss: 0.2773 - val_accuracy: 0.7622 - val_loss: 0.3833
Epoch 27/50
2011/2011             3s 2ms/step -
accuracy: 0.8889 - loss: 0.2755 - val_accuracy: 0.7609 - val_loss: 0.4049
Epoch 28/50
2011/2011             3s 2ms/step -
accuracy: 0.8883 - loss: 0.2743 - val_accuracy: 0.7672 - val_loss: 0.3996
Epoch 29/50
2011/2011             3s 2ms/step -
accuracy: 0.8870 - loss: 0.2785 - val_accuracy: 0.7609 - val_loss: 0.4252
Epoch 30/50
2011/2011             3s 2ms/step -
accuracy: 0.8884 - loss: 0.2750 - val_accuracy: 0.7680 - val_loss: 0.3960
Epoch 31/50
2011/2011             3s 2ms/step -
accuracy: 0.8884 - loss: 0.2780 - val_accuracy: 0.7538 - val_loss: 0.4167
Epoch 32/50
2011/2011             3s 2ms/step -
accuracy: 0.8889 - loss: 0.2732 - val_accuracy: 0.7612 - val_loss: 0.4162
Epoch 33/50
2011/2011             3s 2ms/step -
accuracy: 0.8888 - loss: 0.2749 - val_accuracy: 0.7713 - val_loss: 0.4198
Epoch 34/50
2011/2011             3s 2ms/step -
accuracy: 0.8904 - loss: 0.2734 - val_accuracy: 0.7701 - val_loss: 0.3713
Epoch 35/50
2011/2011             3s 2ms/step -
accuracy: 0.8874 - loss: 0.2772 - val_accuracy: 0.7680 - val_loss: 0.3810
Epoch 36/50
2011/2011             3s 2ms/step -
accuracy: 0.8901 - loss: 0.2705 - val_accuracy: 0.7663 - val_loss: 0.3911
Epoch 37/50
2011/2011             3s 2ms/step -
accuracy: 0.8900 - loss: 0.2692 - val_accuracy: 0.7604 - val_loss: 0.4015
Epoch 38/50
2011/2011             3s 2ms/step -
accuracy: 0.8879 - loss: 0.2769 - val_accuracy: 0.7471 - val_loss: 0.4369
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Epoch 39/50
2011/2011            3s 2ms/step -
accuracy: 0.8903 - loss: 0.2706 - val_accuracy: 0.7716 - val_loss: 0.3895
Epoch 40/50
2011/2011            3s 2ms/step -
accuracy: 0.8895 - loss: 0.2714 - val_accuracy: 0.7671 - val_loss: 0.4066
Epoch 41/50
2011/2011            3s 2ms/step -
accuracy: 0.8895 - loss: 0.2701 - val_accuracy: 0.7614 - val_loss: 0.4101
Epoch 42/50
2011/2011            3s 2ms/step -
accuracy: 0.8905 - loss: 0.2731 - val_accuracy: 0.7714 - val_loss: 0.3864
Epoch 43/50
2011/2011            3s 2ms/step -
accuracy: 0.8891 - loss: 0.2716 - val_accuracy: 0.7652 - val_loss: 0.4146
Epoch 44/50
2011/2011            3s 2ms/step -
accuracy: 0.8908 - loss: 0.2693 - val_accuracy: 0.7675 - val_loss: 0.4197
Epoch 45/50
2011/2011            3s 2ms/step -
accuracy: 0.8879 - loss: 0.2710 - val_accuracy: 0.7678 - val_loss: 0.3858
Epoch 46/50
2011/2011            3s 2ms/step -
accuracy: 0.8877 - loss: 0.2722 - val_accuracy: 0.7696 - val_loss: 0.3880
Epoch 47/50
2011/2011            3s 2ms/step -
accuracy: 0.8894 - loss: 0.2686 - val_accuracy: 0.7693 - val_loss: 0.3935
Epoch 48/50
2011/2011            3s 2ms/step -
accuracy: 0.8891 - loss: 0.2679 - val_accuracy: 0.7822 - val_loss: 0.3704
Epoch 49/50
2011/2011            3s 2ms/step -
accuracy: 0.8900 - loss: 0.2698 - val_accuracy: 0.7702 - val_loss: 0.3769
Epoch 50/50
2011/2011            3s 2ms/step -
accuracy: 0.8891 - loss: 0.2707 - val_accuracy: 0.7687 - val_loss: 0.4140
367/367            0s 1ms/step
Accuracy: 0.94
              precision    recall  f1-score   support

           0       0.96      0.97      0.96     10087
           1       0.78      0.75      0.77      1642

    accuracy                           0.94     11729
   macro avg       0.87      0.86      0.86     11729
weighted avg       0.93      0.94      0.94     11729
```

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```python
# Make predictions on the test set
test_predictions = model.predict(df_test)

# Flatten the predictions array if necessary
test_predictions = test_predictions.flatten()

# Create a DataFrame with test IDs and predictions
output = pd.DataFrame({
    'id': df_test_ids,
    'loan_status': test_predictions
})

# Export the predictions to an Excel file
output.to_excel('catboost_loan_status_predictions.xlsx', index=False)
```

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1222/1222              1s 779us/step
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[ ]:

```python

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