eda_data_cleaning

December 18, 2025

1 Introduction

Predicting loan approval is an important problem in consumer facing finance. Bank lenders can receieve thousands to hundreds of thousands of applications from individuals with a wide variety of financial variables, leading to the necessity for automation of these loan approval processes. Approving loans which end up defaulting can increase financial risk, while being too conservative in lending loans can reduce business opportunity and leave valuable profits to waste. As a way to reduce these errors in the automated loan approval process, organizations rely on data driven methods and algorithms to get a better understanding of loan approval factors.

In this project, we will explore a synthetic loan approval dataset and identify key drivers behind approval decisions, allowing us to build a predictive machine learning model to accurately determine a loan applications approval status.

2 Adding Directory For Plots

[1]:
```
import os
os.makedirs("plots", exist_ok=True)
```

3 Data Description

The dataset contains information on thousands of past loan applications, each row repesenting an individual applicant, with a mix of variables that may be related to loan approval status.

This data contains 20 features (1 id, 1 target), a distribution of 55/45 in target status, and includes real world financial approval logic (DTI ratios, Filed Defaults, etc…)

This dataset provides a healthy combination of demographic, financial, and credit related information, making it suitable for understanding patterns in loan approvals. Before modeling, we will clean the dataset, address missing values, check for outliers, and explore some potential relationships between key features and loan outcomes.

4 Data Processing and Exploration

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
```

[3]:
```
df = pd.read_csv("data/Loan_approval_data_2025.csv")
df.head(5)
```

[3]:
```
  customer_id  age occupation_status  years_employed  annual_income  \
0  CUST100000   40          Employed            17.2          25579
1  CUST100001   33          Employed             7.3          43087
2  CUST100002   42           Student             1.1          20840
3  CUST100003   53           Student             0.5          29147
4  CUST100004   32          Employed            12.5          63657

   credit_score  credit_history_years  savings_assets  current_debt  \
0           692                   5.3             895         10820
1           627                   3.5             169         16550
2           689                   8.4              17          7852
3           692                   9.8            1480         11603
4           630                   7.2             209         12424

   defaults_on_file  delinquencies_last_2yrs  derogatory_marks   product_type  \
0                 0                        0                 0    Credit Card
1                 0                        1                 0  Personal Loan
2                 0                        0                 0    Credit Card
3                 0                        1                 0    Credit Card
4                 0                        0                 0  Personal Loan

          loan_intent  loan_amount  interest_rate  debt_to_income_ratio  \
0            Business          600          17.02                 0.423
1    Home Improvement        53300          14.10                 0.384
2  Debt Consolidation         2100          18.33                 0.377
3            Business         2900          18.74                 0.398
4           Education        99600          13.92                 0.195

   loan_to_income_ratio  payment_to_income_ratio  loan_status
0                 0.023                    0.008            1
1                 1.237                    0.412            0
2                 0.101                    0.034            1
3                 0.099                    0.033            1
4                 1.565                    0.522            1
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   customer_id             50000 non-null  object
 1   age                     50000 non-null  int64
 2   occupation_status       50000 non-null  object
 3   years_employed          50000 non-null  float64
 4   annual_income           50000 non-null  int64
 5   credit_score            50000 non-null  int64
 6   credit_history_years    50000 non-null  float64
 7   savings_assets          50000 non-null  int64
 8   current_debt            50000 non-null  int64
 9   defaults_on_file        50000 non-null  int64
 10  delinquencies_last_2yrs 50000 non-null  int64
 11  derogatory_marks        50000 non-null  int64
 12  product_type            50000 non-null  object
 13  loan_intent             50000 non-null  object
 14  loan_amount             50000 non-null  int64
 15  interest_rate           50000 non-null  float64
 16  debt_to_income_ratio    50000 non-null  float64
 17  loan_to_income_ratio    50000 non-null  float64
 18  payment_to_income_ratio 50000 non-null  float64
 19  loan_status             50000 non-null  int64
dtypes: float64(6), int64(10), object(4)
memory usage: 7.6+ MB
```

[5]:
```
df = df.drop('customer_id', axis=1)
```

4.1 Basic EDA

4.1.1 Target Variable Balance

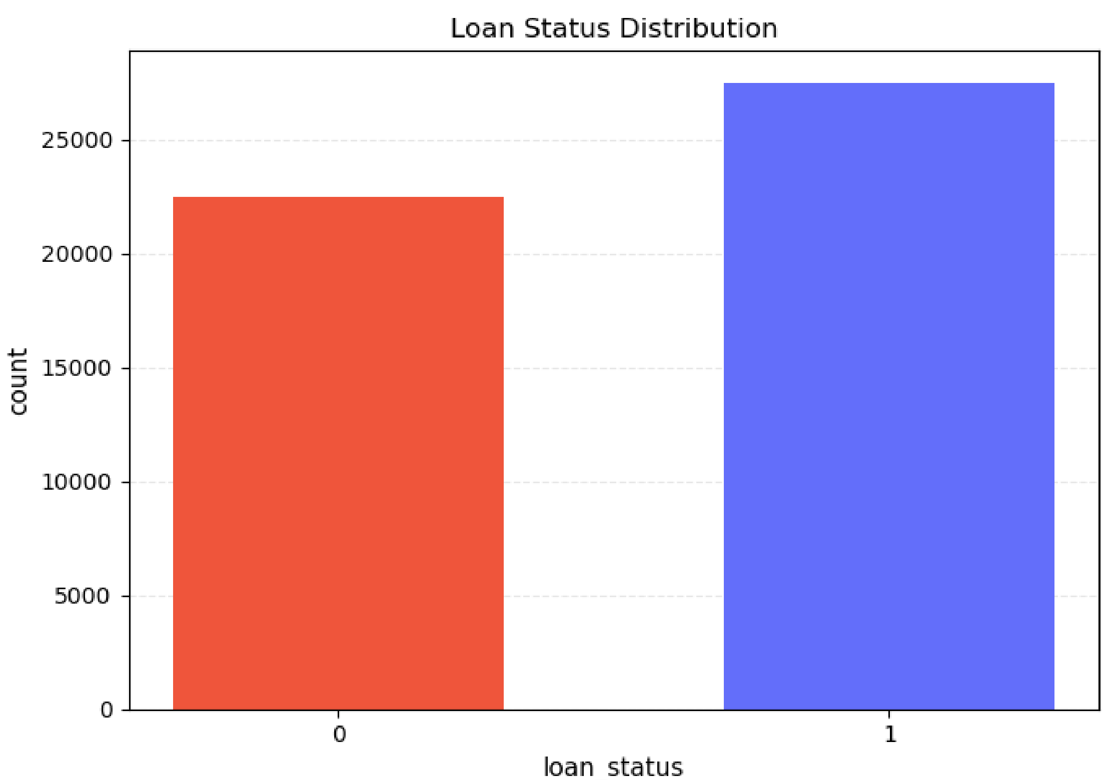
[6]:
```
df["loan_status"].value_counts().reset_index()
```

[6]:

	loan_status	count
0	1	27523
1	0	22477

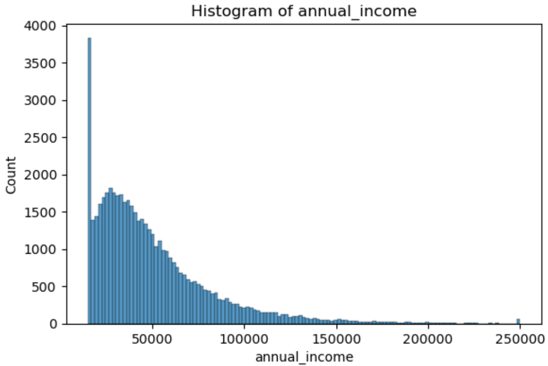
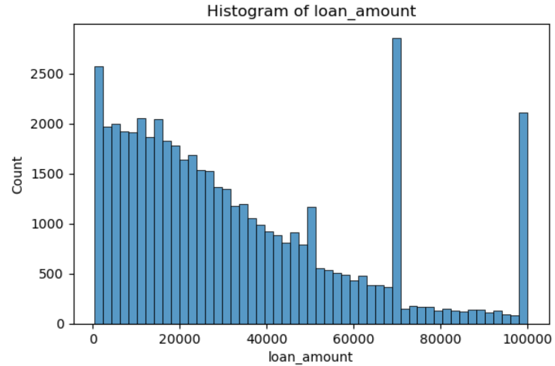
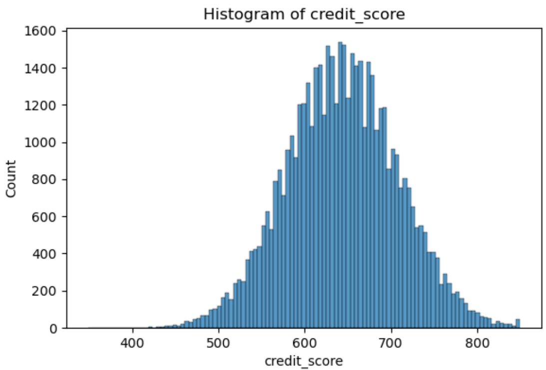
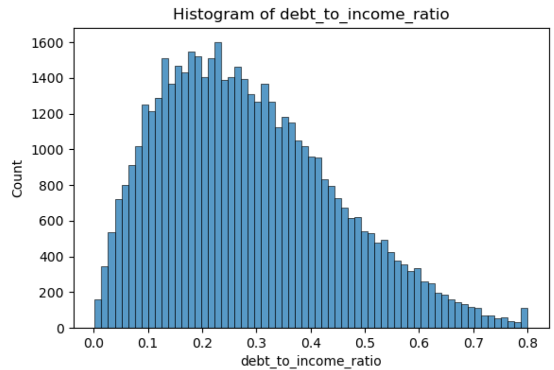
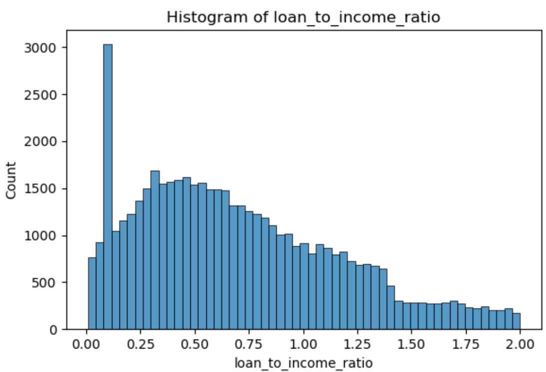
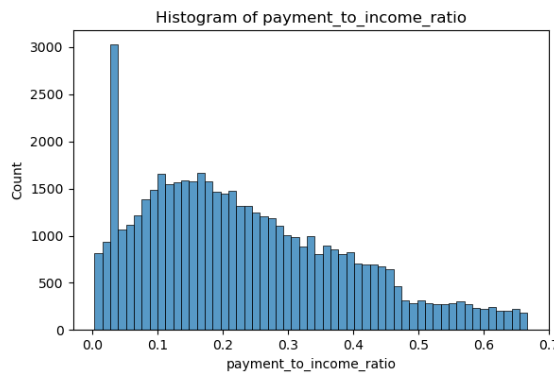
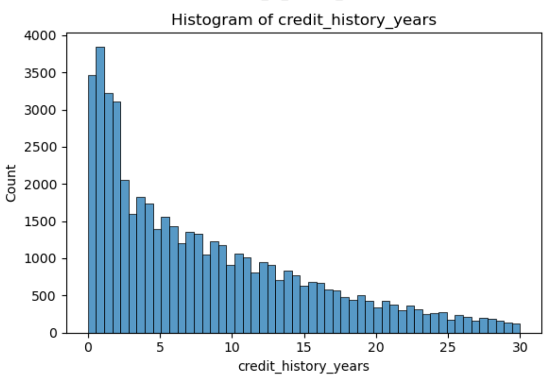
[7]:
```
# Get value counts
loan_counts = df["loan_status"].value_counts().sort_index()

# Create the figure
fig, ax = plt.subplots(figsize=(7, 5))

# Create bar plot
```

```
ax.bar(loan_counts.index, loan_counts.values,
       color=['#EF553B', '#636EFA'],  # Red and blue to match Plotly colors
       width=0.6)

# Customize
ax.set_xlabel('loan_status', fontsize=11)
ax.set_ylabel('count', fontsize=11)
ax.set_title('Loan Status Distribution', fontsize=12)
ax.set_xticks([0, 1])

# Optional: add gridlines for easier reading
ax.grid(axis='y', alpha=0.3, linestyle='--')
ax.set_axisbelow(True)

plt.tight_layout()
plt.savefig("plots/loan_status_distribution.png")
plt.show()
```



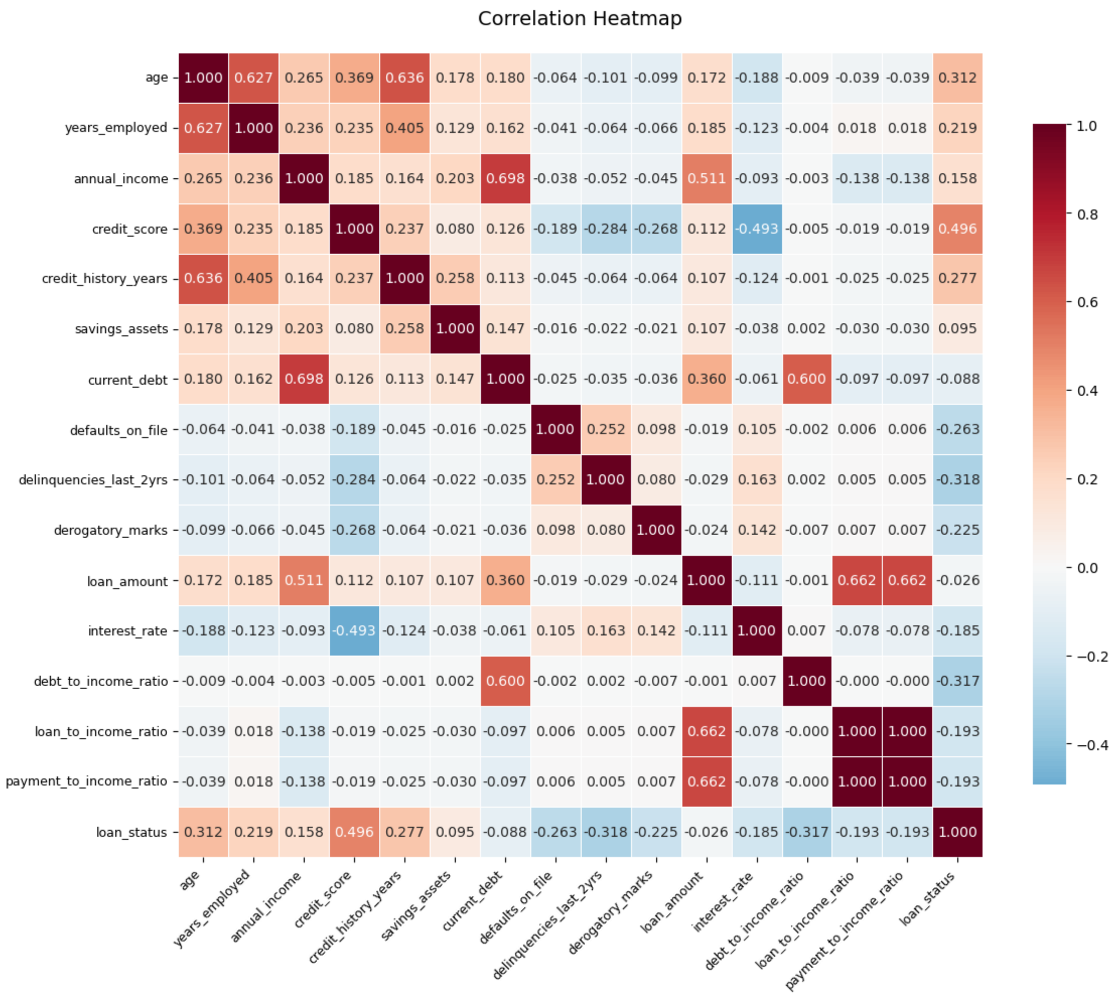
4.1.2 Univariate EDA for numerical columns

[8]:
```
num_col = ["annual_income", "loan_amount", "credit_score",
           "debt_to_income_ratio", "loan_to_income_ratio",
           "payment_to_income_ratio", "credit_history_years"]

n = len(num_col)
rows = (n + 1) // 2
plt.figure(figsize=(12, rows * 4))

for i, col in enumerate(num_col, 1):
    plt.subplot(rows, 2, i)
    sns.histplot(df[col])
    plt.title(f"Histogram of {col}")
    plt.savefig(f"plots/{col}_histogram.png")

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


Histogram of annual_income
Count
annual_income
0
500
1000
1500
2000
2500
3000
3500
4000
50000
100000
150000
200000
250000

Histogram of loan_amount
Count
loan_amount
0
500
1000
1500
2000
2500
0
20000
40000
60000
80000
100000

Histogram of credit_score
Count
credit_score
0
200
400
600
800
1000
1200
1400
1600
400
500
600
700
800

Histogram of debt_to_income_ratio
Count
debt_to_income_ratio
0
200
400
600
800
1000
1200
1400
1600
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

Histogram of loan_to_income_ratio
Count
loan_to_income_ratio
0
500
1000
1500
2000
2500
3000
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

Histogram of payment_to_income_ratio
Count
payment_to_income_ratio
0
500
1000
1500
2000
2500
3000
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

Histogram of credit_history_years
Count
credit_history_years
0
500
1000
1500
2000
2500
3000
3500
4000
0
5
10
15
20
25
30

4.1.3 Correlation Heatmap

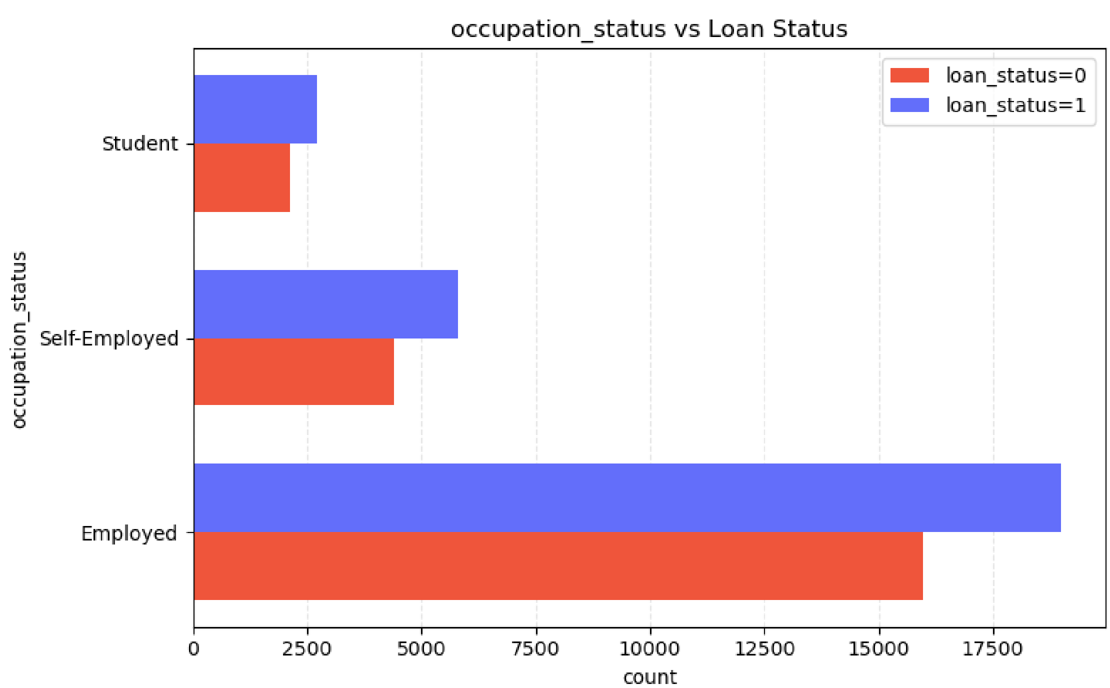
[9]:
```
numeric_df = df.select_dtypes(include="number")

corr = numeric_df.corr()

fig, ax = plt.subplots(figsize=(12, 10))

# Create heatmap
sns.heatmap(corr,
            annot=True,  # Show correlation values
            fmt='.3f',   # Format to 2 decimal places
            cmap='RdBu_r',  # Red-Blue reversed colormap
            center=0,    # Center colormap at 0
            square=True, # Make cells square
            linewidths=0.5,  # Add gridlines
            cbar_kws={"shrink": 0.8},
            ax=ax)

ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=9)
ax.set_yticklabels(ax.get_yticklabels(), rotation=0, fontsize=9)
ax.set_title('Correlation Heatmap', fontsize=14, pad=20)

plt.tight_layout()
plt.savefig("plots/correlation_heatmap.png", dpi=150, bbox_inches='tight')
plt.show()
```

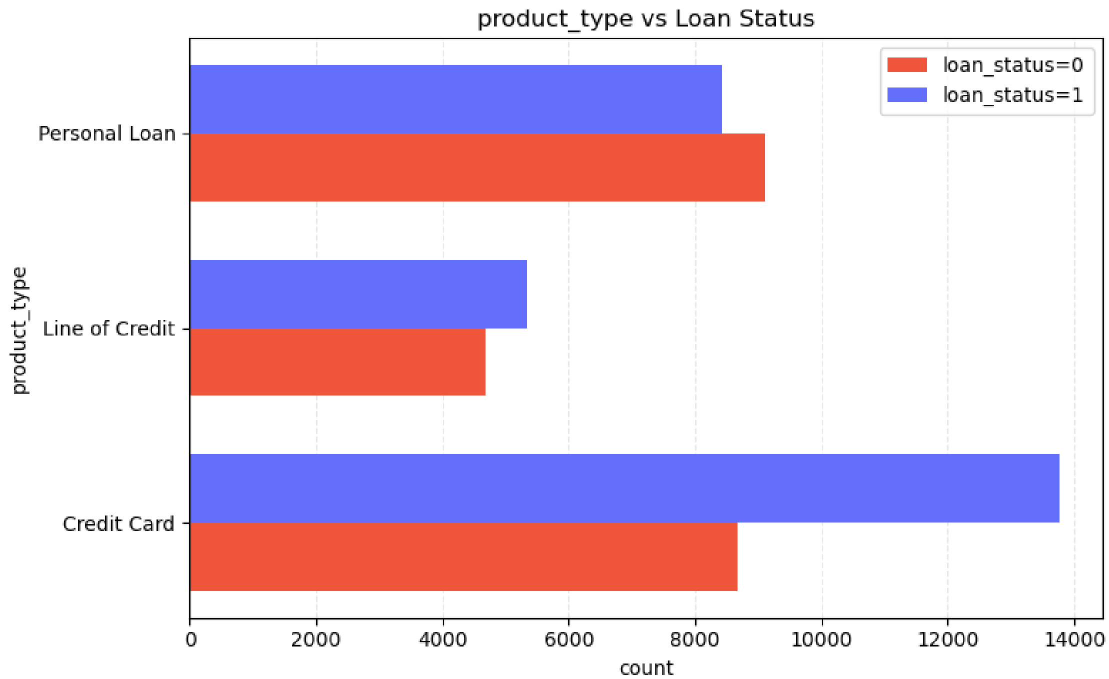


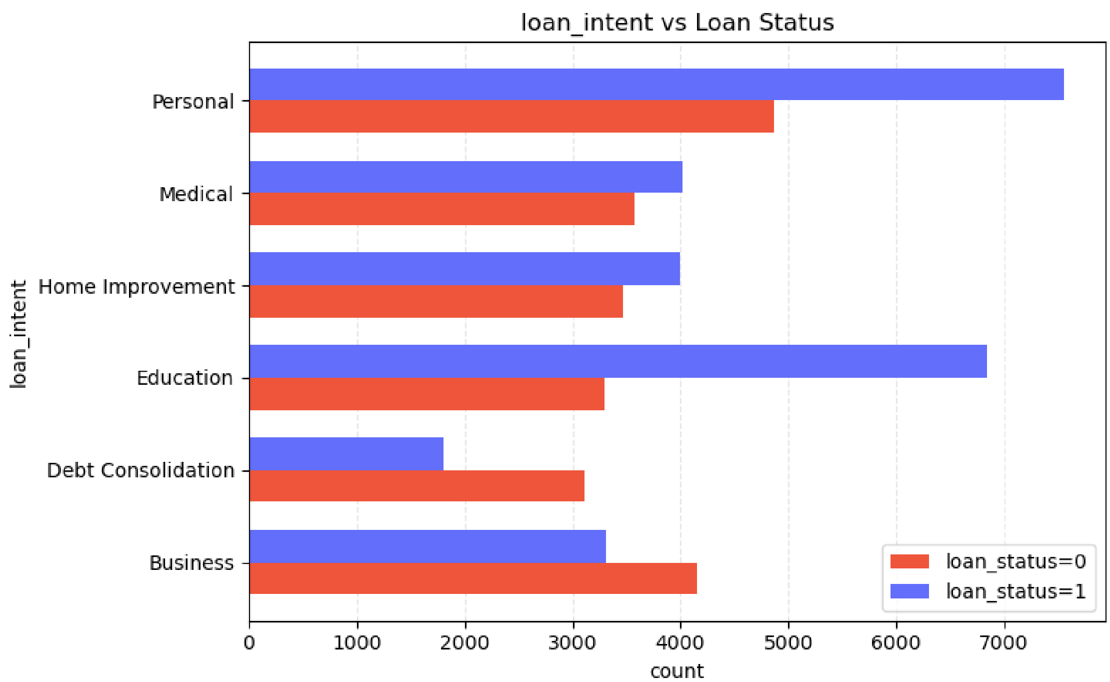
4.1.4 Bivariate Analysis

[10]:
```python
import matplotlib.pyplot as plt

categorical_cols = ['occupation_status', 'product_type', 'loan_intent']

for col in categorical_cols:
    # Get value counts for each loan status
    counts_0 = df[df['loan_status'] == 0][col].value_counts().sort_index()
    counts_1 = df[df['loan_status'] == 1][col].value_counts().sort_index()

    # Initializing figure to plot on
    fig, ax = plt.subplots(figsize=(8, 5))

    # Bar position configuration
    categories = sorted(df[col].unique())
```

```python
    x = range(len(categories))
    width = 0.35

    # Bars per group
    ax.barh([i - width/2 for i in x],
            [counts_0.get(cat, 0) for cat in categories],
            width, label='loan_status=0', color='#EF553B')
    ax.barh([i + width/2 for i in x],
            [counts_1.get(cat, 0) for cat in categories],
            width, label='loan_status=1', color='#636EFA')

    # Axis configuration
    ax.set_yticks(x)
    ax.set_yticklabels(categories)
    ax.set_xlabel('count')
    ax.set_ylabel(col)
    ax.set_title(f"{col} vs Loan Status")
    ax.legend()
    ax.grid(axis='x', alpha=0.3, linestyle='--')
    ax.set_axisbelow(True)

    plt.tight_layout()
    plt.savefig(f"plots/{col}_vs_loan_status.png", dpi=150, bbox_inches='tight')
    plt.show()
```

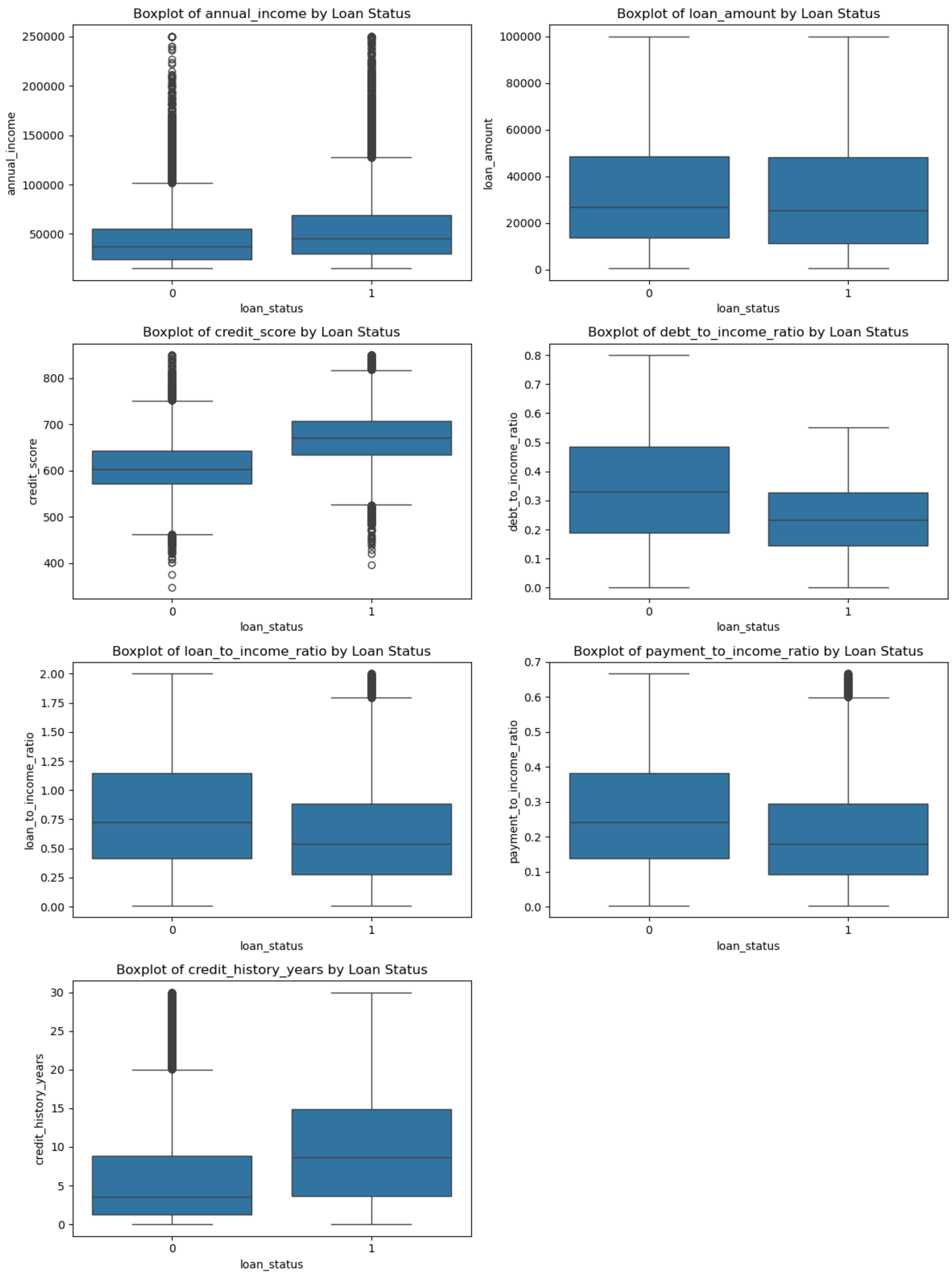






[11]:
```
n = len(num_col)
rows = (n + 1) // 2
```

```python
plt.figure(figsize=(12, rows * 4))

for i, col in enumerate(num_col, 1):
    plt.subplot(rows, 2, i)
    sns.boxplot(x=df['loan_status'], y=df[col])
    plt.title(f"Boxplot of {col} by Loan Status")
    plt.savefig(f"plots/{col}_boxplot.png")

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



[12]:
```
average_ratios = df.groupby("loan_status")[num_col].median().T
average_ratios
```

[12]:
```
loan_status                      0          1
annual_income            37127.000  45708.000
loan_amount              26900.000  25400.000
credit_score               603.000    671.000
debt_to_income_ratio         0.329      0.232
loan_to_income_ratio         0.726      0.539
payment_to_income_ratio      0.242      0.180
credit_history_years         3.600      8.600
```

4.2 Insight from EDA

Some details and insights that may be useful or interesting gathered from this exploratory data analysis.

- Most approved lendee's are on average older, longer employed, and higher credit score
- Most approved lendee's have lower debt
- Most approved lendee's have a better DTI, LTI, and PTI ratio (lower = better)
- Credit card loans on average have a higher rate of denial
- Credit history on average approved lendee's is 2x higher than those denied

Here we will convert our cleaned data into a csv for model training and evaluation:

[13]:
```
df.to_csv('data/cleaned_data.csv', index=False)
```