LendSmart_Analysis

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1 LendSmart Credit Risk Analysis

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Section 1: Project Setup & Data Loading

- Import all necessary libraries

[2]:
```python
import pandas as pd
import numpy as np
import sklearn as sk
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import RocCurveDisplay, roc_auc_score
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.preprocessing import StandardScaler
from sklearn.discriminant_analysis import␣
↪LinearDiscriminantAnalysis,QuadraticDiscriminantAnalysis
```

- Load the credit_risk_data.csv file.

[3]:
```python
df=pd.read_csv("../datos/credit_risk_data-1.csv")
df.head()
```

[3]:
```
  application_id application_date  loan_amount  annual_income  \
0       APP_2328       2022-01-01    132221.82       60451.82
1        APP_558       2022-01-01    134906.42      114634.08
2       APP_2477       2022-01-01     30285.19       82772.53
3        APP_741       2022-01-01     32516.09       94023.36
4        APP_145       2022-01-02     77900.99       53515.02

   employment_years  job_stability_score  credit_score  credit_utilization  \
0               6.6                0.898           679               0.106
```

```
1             10.3                0.808          718                 0.030
2             12.1                0.964          768                 0.174
3              9.1                0.690          670                 0.141
4              7.2                0.679          651                 0.097

   payment_history_score  open_credit_lines  debt_to_income_ratio  \
0                  0.876                  1                 0.451
1                  0.719                  4                 0.090
2                  0.775                  6                 0.201
3                  0.993                  3                 0.322
4                  0.946                  2                 0.222

   savings_ratio  asset_value  age education_level marital_status  \
0          0.500    352569.55   41     High School        Married
1          0.235    224364.21   46         Masters       Divorced
2          0.172    514765.55   44     High School        Widowed
3          0.368    182541.72   26       Bachelors         Single
4          0.324    223691.29   50      Associates         Single

   residential_stability  loan_status
0                    3.5            0
1                   11.4            0
2                    8.6            0
3                    3.9            0
4                    9.6            0
```

- Perform an initial inspection: .head(), .info(), .describe().

[ ]:
```
display(df.head())
display(df.describe())
display(df.info())
```

```
  application_id application_date  loan_amount  annual_income  \
0       APP_2328       2022-01-01    132221.82       60451.82
1        APP_558       2022-01-01    134906.42      114634.08
2       APP_2477       2022-01-01     30285.19       82772.53
3        APP_741       2022-01-01     32516.09       94023.36
4        APP_145       2022-01-02     77900.99       53515.02

   employment_years  job_stability_score  credit_score  credit_utilization  \
0               6.6                0.898           679               0.106
1              10.3                0.808           718               0.030
2              12.1                0.964           768               0.174
3               9.1                0.690           670               0.141
4               7.2                0.679           651               0.097

   payment_history_score  open_credit_lines  debt_to_income_ratio  \
0                  0.876                  1                 0.451
```

```
1                 0.719                  4                 0.090
2                 0.775                  6                 0.201
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4                 0.946                  2                 0.222

   savings_ratio  asset_value  age education_level marital_status  \
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1          0.235    224364.21   46         Masters       Divorced
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4          0.324    223691.29   50     Associates          Single

   residential_stability  loan_status
0                    3.5            0
1                   11.4            0
2                    8.6            0
3                    3.9            0
4                    9.6            0
         loan_amount  annual_income  employment_years  job_stability_score  \
count    2500.000000    2500.000000       2500.000000          2500.000000
mean   155716.305344   67707.807596          6.675640             0.634643
std    149605.357952   27302.931731          3.488021             0.293276
min      5000.000000   15000.000000          0.000000             0.011000
25%     42984.517500   47475.317500          4.000000             0.375500
50%     97054.315000   66963.475000          6.700000             0.752000
75%    213214.992500   87347.642500          9.300000             0.866000
max    500000.000000  149929.960000         19.300000             0.999000

       credit_score  credit_utilization  payment_history_score  \
count   2500.000000         2500.000000            2500.000000
mean     681.728400            0.358176               0.740733
std       88.683309            0.289995               0.285966
min      334.000000            0.004000               0.029000
25%      642.750000            0.131000               0.517500
50%      700.000000            0.246000               0.880500
75%      743.000000            0.592250               0.956000
max      850.000000            0.998000               1.000000

       open_credit_lines  debt_to_income_ratio  savings_ratio     asset_value  \
count        2500.000000           2500.000000    2500.000000     2500.000000
mean            3.451600              0.408094       0.320784   175666.741236
std             2.083793              0.224736       0.192079   182652.568930
min             0.000000              0.009000       0.000000      550.630000
25%             2.000000              0.228000       0.161000    49513.082500
50%             3.000000              0.359000       0.327000   121018.750000
75%             5.000000              0.565000       0.464000   235513.902500
max            11.000000              0.979000       0.893000  1000000.000000
```

```
              age  residential_stability  loan_status
count  2500.000000            2500.000000  2500.000000
mean     42.045600               6.023200     0.265600
std      12.092395               3.205397     0.441741
min      18.000000               0.000000     0.000000
25%      34.000000               3.600000     0.000000
50%      42.000000               5.900000     0.000000
75%      50.000000               8.400000     1.000000
max      75.000000              16.400000     1.000000
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   application_id         2500 non-null   object
 1   application_date       2500 non-null   object
 2   loan_amount            2500 non-null   float64
 3   annual_income          2500 non-null   float64
 4   employment_years       2500 non-null   float64
 5   job_stability_score    2500 non-null   float64
 6   credit_score           2500 non-null   int64
 7   credit_utilization     2500 non-null   float64
 8   payment_history_score  2500 non-null   float64
 9   open_credit_lines      2500 non-null   int64
 10  debt_to_income_ratio   2500 non-null   float64
 11  savings_ratio          2500 non-null   float64
 12  asset_value            2500 non-null   float64
 13  age                    2500 non-null   int64
 14  education_level        2500 non-null   object
 15  marital_status         2500 non-null   object
 16  residential_stability  2500 non-null   float64
 17  loan_status            2500 non-null   int64
dtypes: float64(10), int64(4), object(4)
memory usage: 351.7+ KB
```

```
None
```

- Write a brief summary of your initial findings

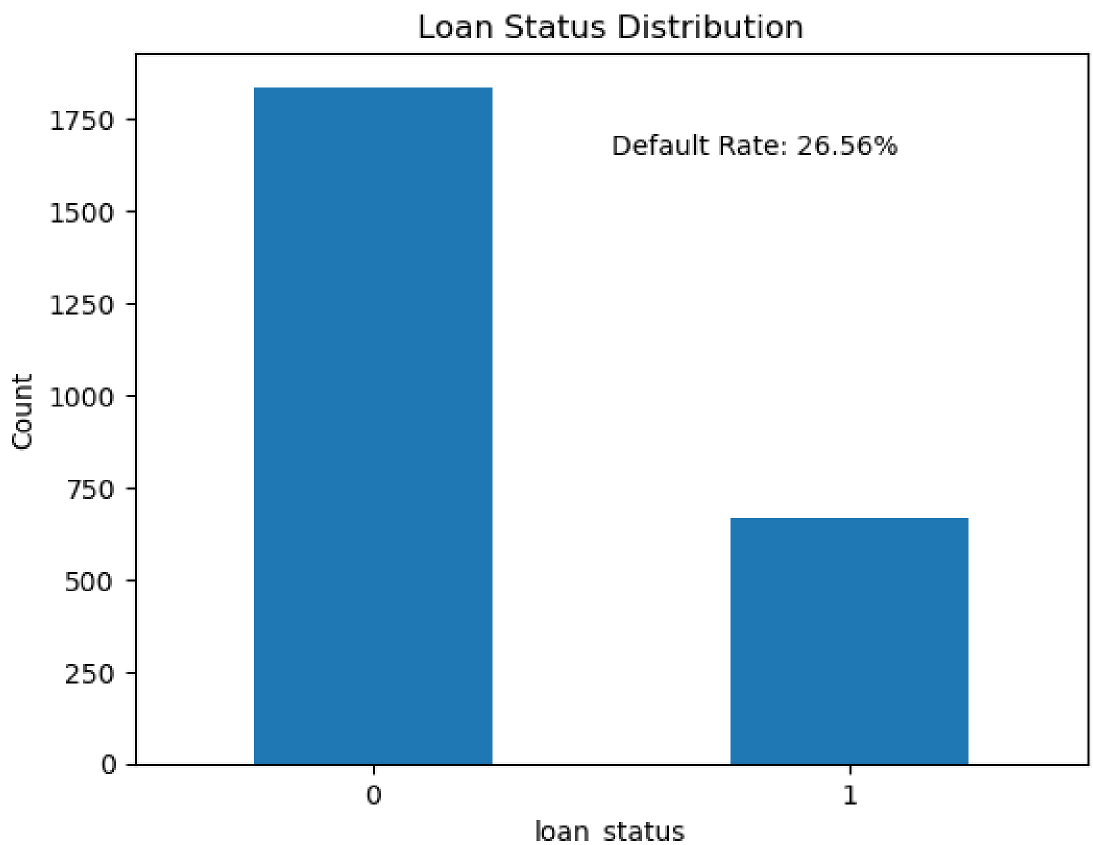
The dataset contains 2,500 loan application records from 2022 to 2024, all without null values. The variables cover financial, demographic, and credit aspects of the applicant. The target variable (loan_status) indicates whether the loan was repaid or defaulted on, with a default rate of 26.56%.

The data shows that loan applicants have highly varied financial profiles. For example, the loan amount requested ranges from $5,000 to $500,000, with an average of approximately $155,000. Annual income also varies considerably, from $15,000 to nearly $150,000. Most customers have a credit score of 682, but there are also individuals with very low scores. Indicators such as credit utilization, job stability score, and payment history score reflect that many customers have good credit history, although there are extreme values that could indicate risk. Furthermore, the debt-to-income ratio shows that some applicants have a high debt burden relative to their income. Variables such as savings ratio, asset value, and age also show significant differences between individuals. All of this indicates that LendSmart needs an analysis model capable of accurately distinguishing between reliable and unreliable customers.

Section 2: Exploratory Data Analysis (EDA)

- **Target Variable**: Plot the distribution of loan_status and calculate the exact default rate.

[5]:
```
default_rate=(len(df[df["loan_status"]==1])/len(df))*100
plt.figure()
df["loan_status"].value_counts().plot(kind="bar")
plt.title("Loan Status Distribution")
plt.xticks(rotation=0)
plt.ylabel("Count")
plt.annotate(f'Default Rate: {default_rate:.2f}%', xy=(0.5,␣
↪max(df["loan_status"].value_counts())*0.9)),
plt.show()
```



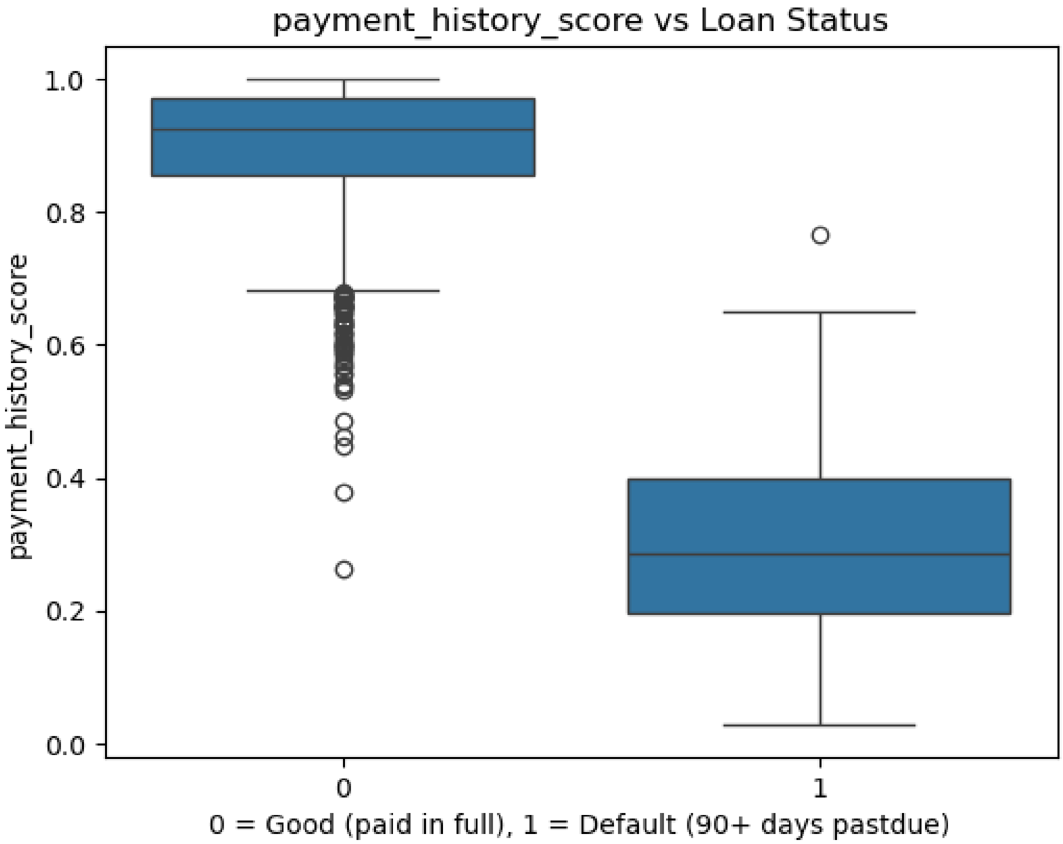
- **Continuous Variables**: For key predictors (credit_score, annual_income, debt_to_income_ratio, etc.), create plots (e.g., box plots or histograms) that **com-**

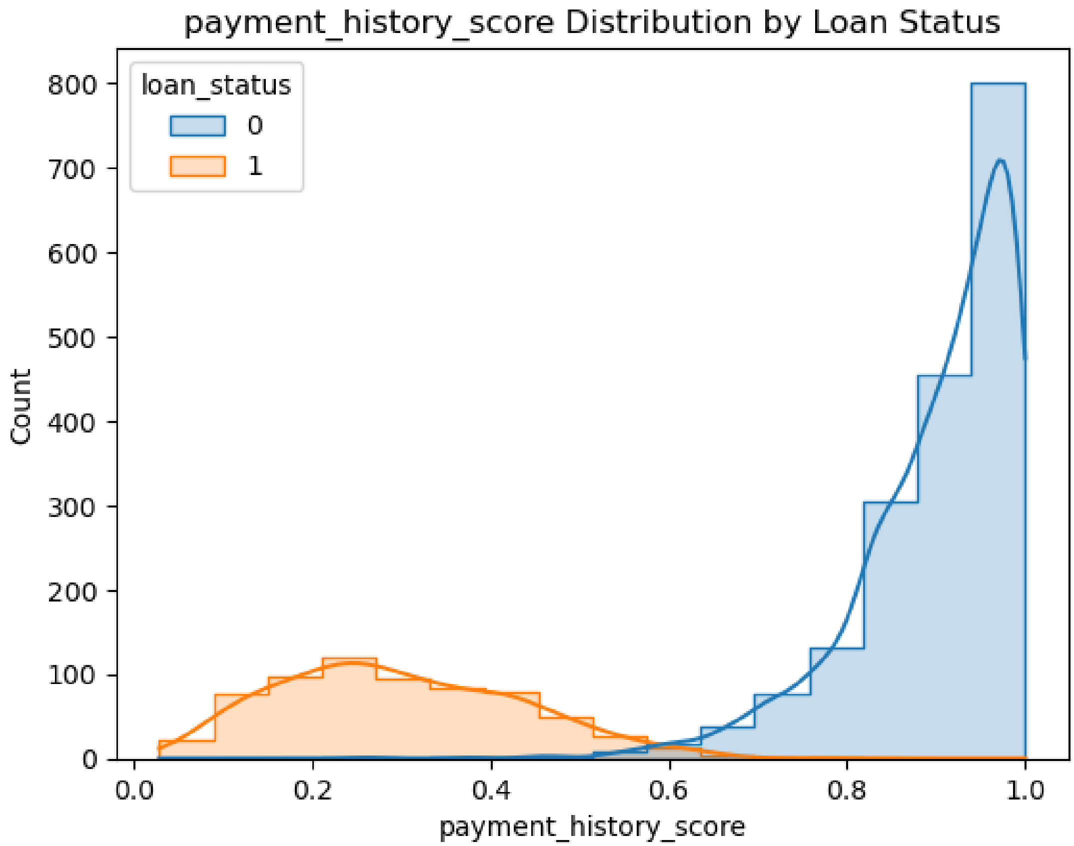
pare the distribution for defaulters (1) vs. non-defaulters (0).

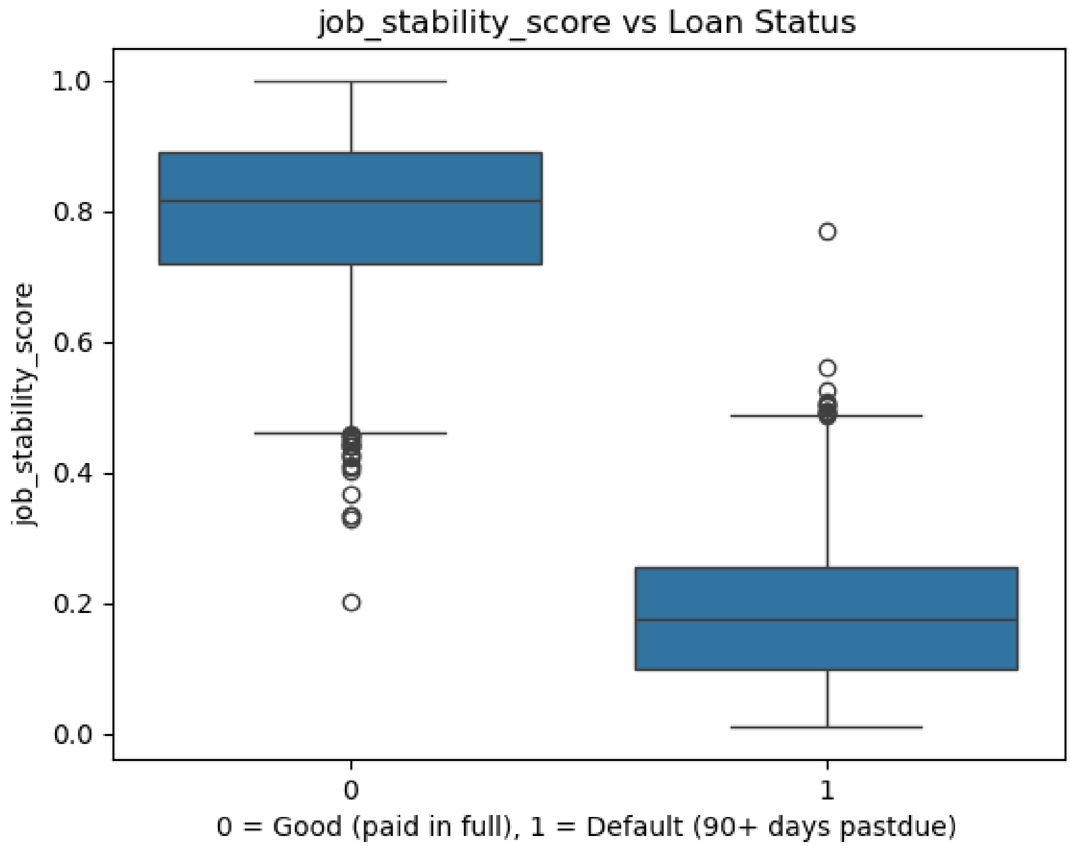
[84]:
```
numeric_features=["loan_amount", "annual_income",␣
↪"employment_years","credit_score", "payment_history_score",␣
↪"debt_to_income_ratio", "job_stability_score", "credit_utilization",␣
↪"open_credit_lines","asset_value","age","residential_stability","savings_ratio"]
df[numeric_features + ["loan_status"]].corr()["loan_status"].abs().
↪sort_values(ascending=False)
```

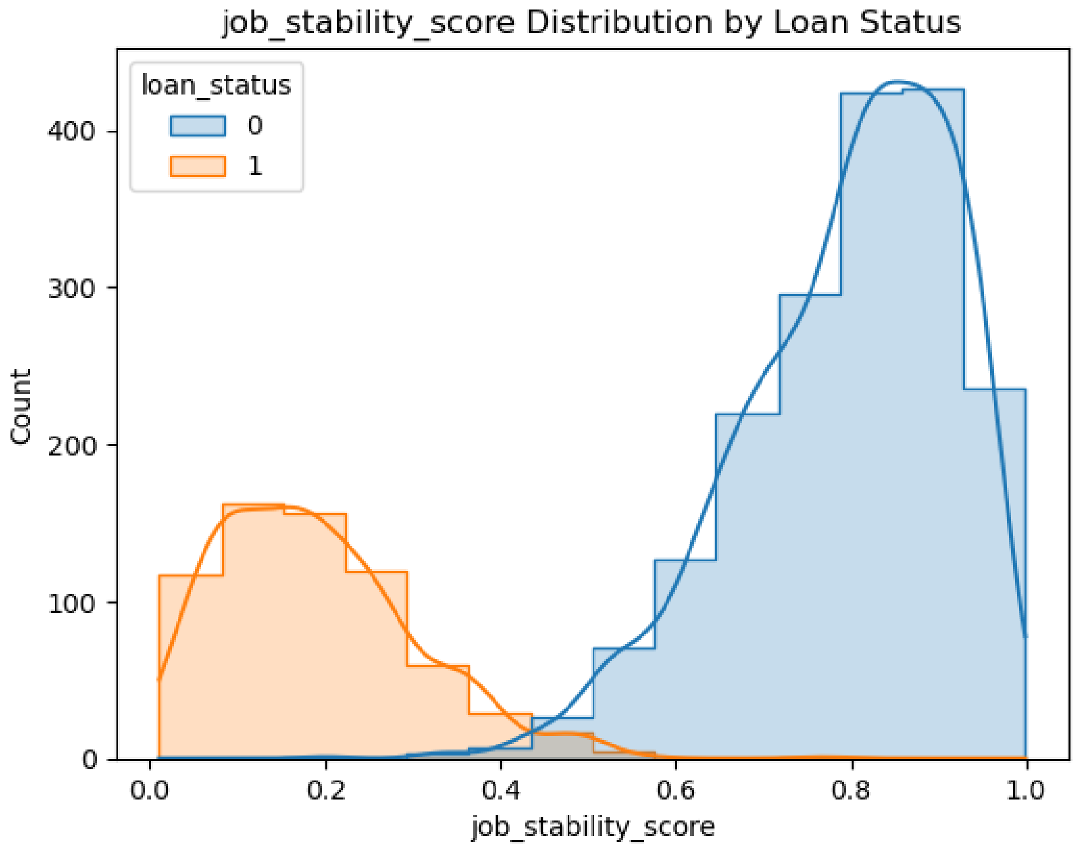
[84]:
```
loan_status              1.000000
payment_history_score    0.931093
job_stability_score      0.912006
credit_utilization       0.906134
debt_to_income_ratio     0.785210
credit_score             0.728160
savings_ratio            0.697444
employment_years         0.628269
residential_stability    0.531898
annual_income            0.508140
asset_value              0.430579
open_credit_lines        0.429446
age                      0.355555
loan_amount              0.003192
Name: loan_status, dtype: float64
```

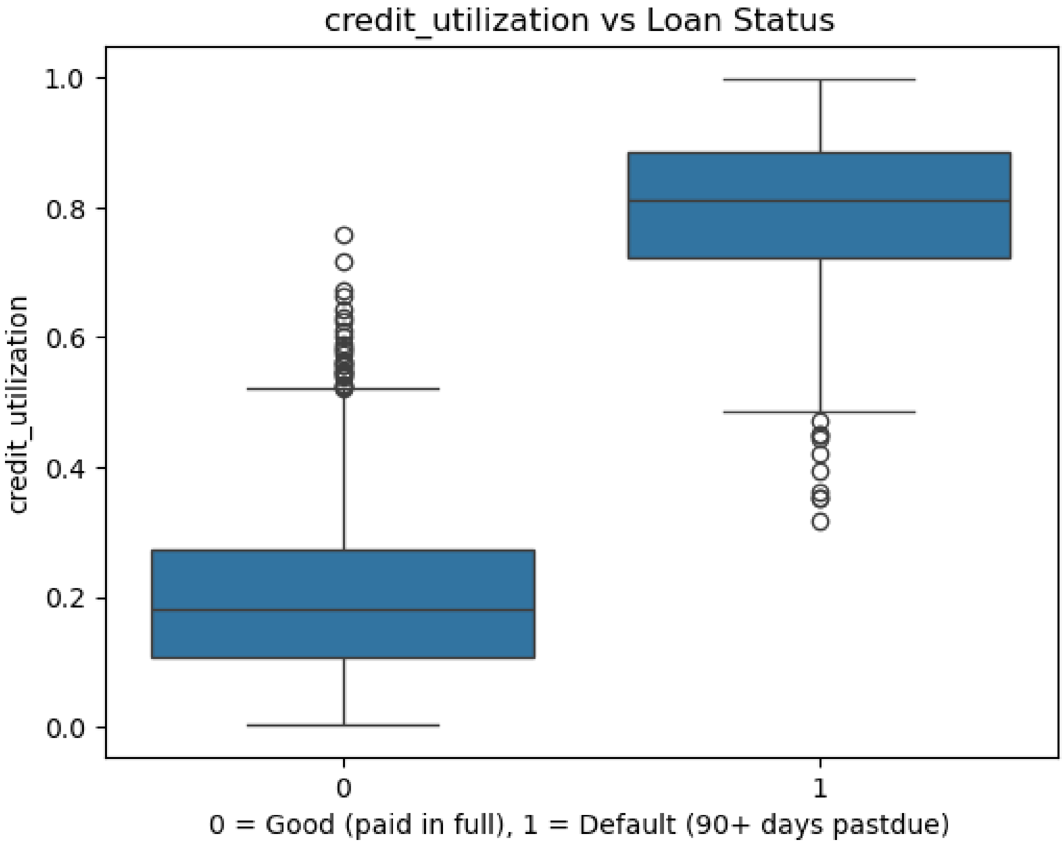
[86]:
```
key_predicors=["payment_history_score", "job_stability_score",␣
↪"credit_utilization", "debt_to_income_ratio", "credit_score"] # Top 5␣
↪predictors based on correlation with loan_status
for predictor in key_predicors:
    # Boxplots
    plt.figure()
    sns.boxplot(x="loan_status", y=predictor, data=df)
    plt.title(f"{predictor} vs Loan Status")
    plt.xlabel("0 = Good (paid in full), 1 = Default (90+ days pastdue)")
    plt.ylabel(predictor)
    plt.show()
    # Histograms
    plt.figure()
    sns.histplot(data=df, x=predictor, hue="loan_status", kde=True,␣
↪element="step", stat="count")
    plt.title(f"{predictor} Distribution by Loan Status")
    plt.xlabel(predictor)
    plt.ylabel("Count")
    plt.show()
```

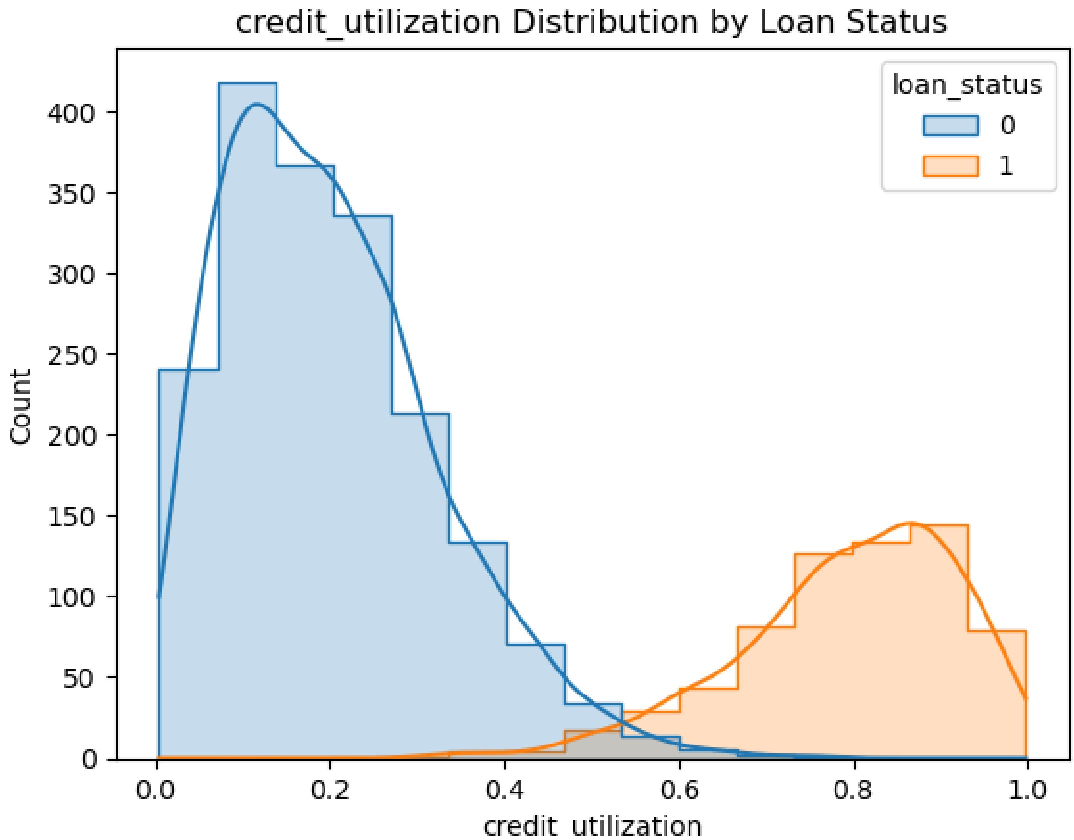

payment_history_score vs Loan Status
payment_history_score
1.0
0.8
0.6
0.4
0.2
0.0
0
1
0 = Good (paid in full), 1 = Default (90+ days pastdue)

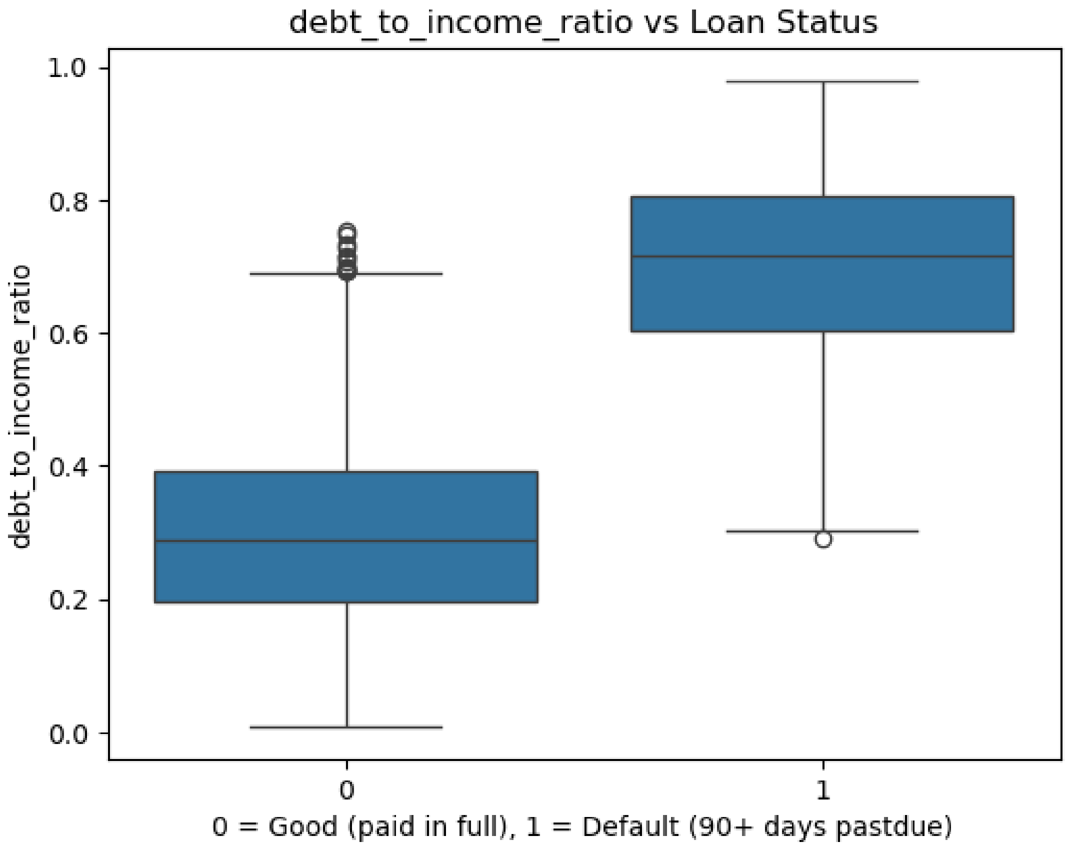

payment_history_score Distribution by Loan Status
loan_status
0
1
Count
800
700
600
500
400
300
200
100
0
0.0
0.2
0.4
0.6
0.8
1.0
payment_history_score

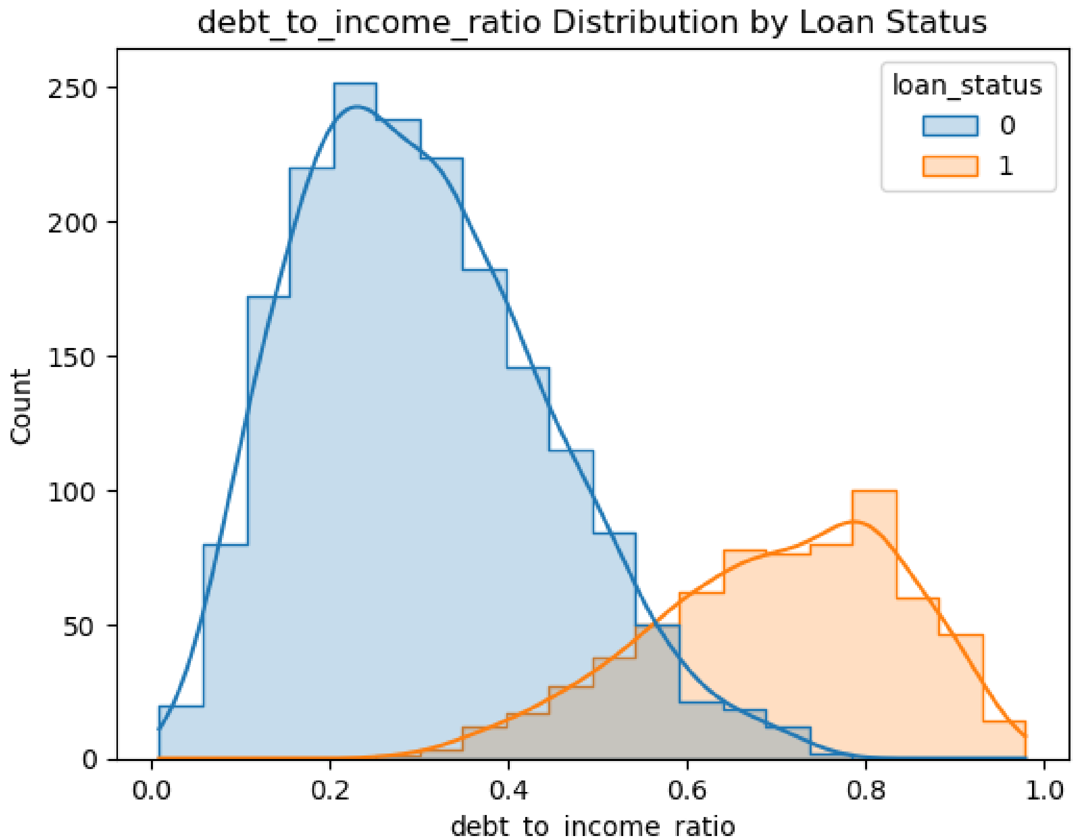

job_stability_score vs Loan Status
1.0
0.8
0.6
0.4
0.2
0.0
job_stability_score
0
1
0 = Good (paid in full), 1 = Default (90+ days pastdue)

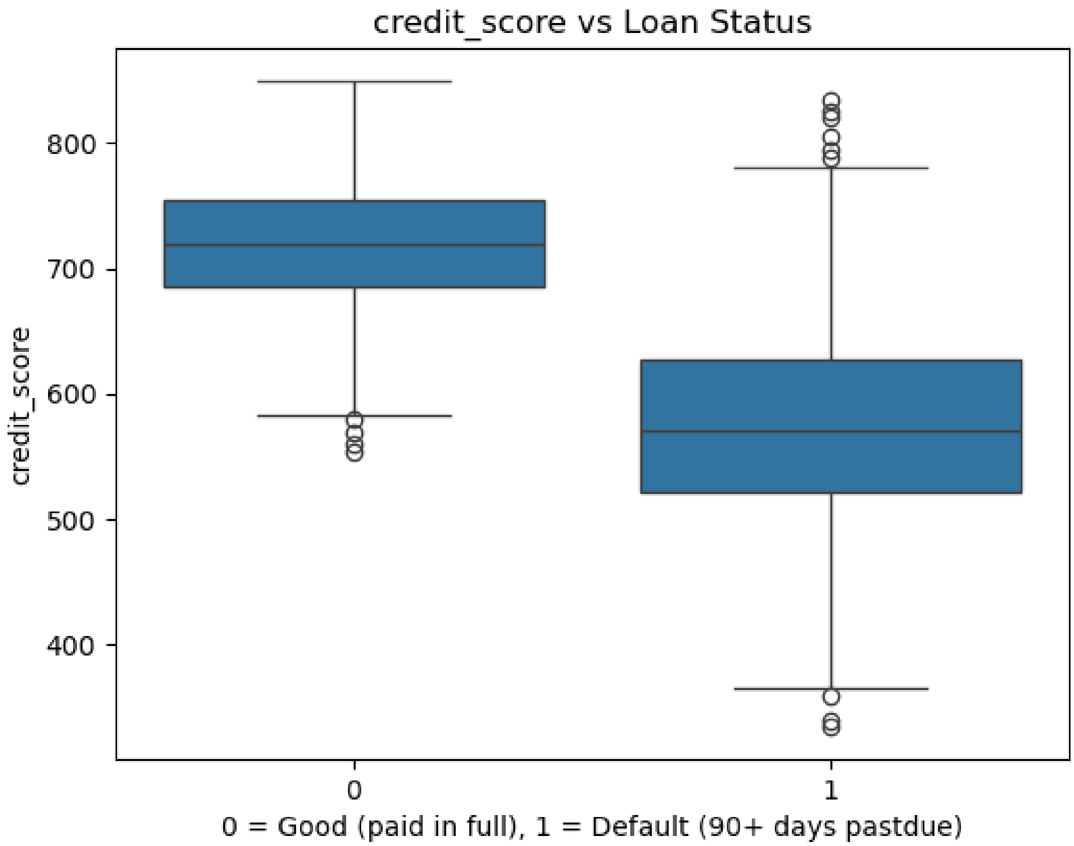

job_stability_score Distribution by Loan Status
loan_status
0
1
Count
400
300
200
100
0
0.0
0.2
0.4
0.6
0.8
1.0
job_stability_score

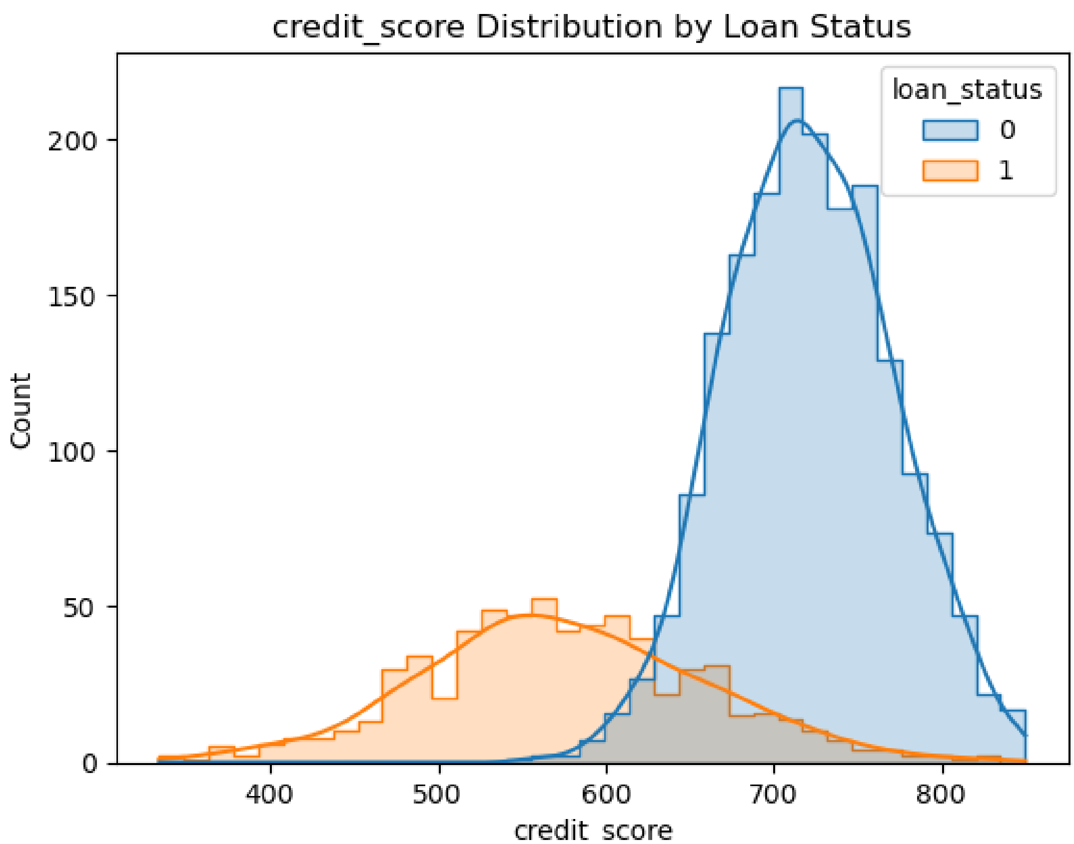

credit_utilization vs Loan Status
1.0
0.8
0.6
0.4
0.2
0.0
credit_utilization
0
1
0 = Good (paid in full), 1 = Default (90+ days pastdue)


credit_utilization Distribution by Loan Status
loan_status
0
1
Count
400
350
300
250
200
150
100
50
0
0.0
0.2
0.4
0.6
0.8
1.0
credit_utilization


debt_to_income_ratio vs Loan Status
debt_to_income_ratio
1.0
0.8
0.6
0.4
0.2
0.0
0
1
0 = Good (paid in full), 1 = Default (90+ days pastdue)


debt_to_income_ratio Distribution by Loan Status
loan_status
0
1
Count
250
200
150
100
50
0
0.0
0.2
0.4
0.6
0.8
1.0
debt_to_income_ratio


credit_score vs Loan Status
credit_score
800
700
600
500
400
0
1
0 = Good (paid in full), 1 = Default (90+ days pastdue)

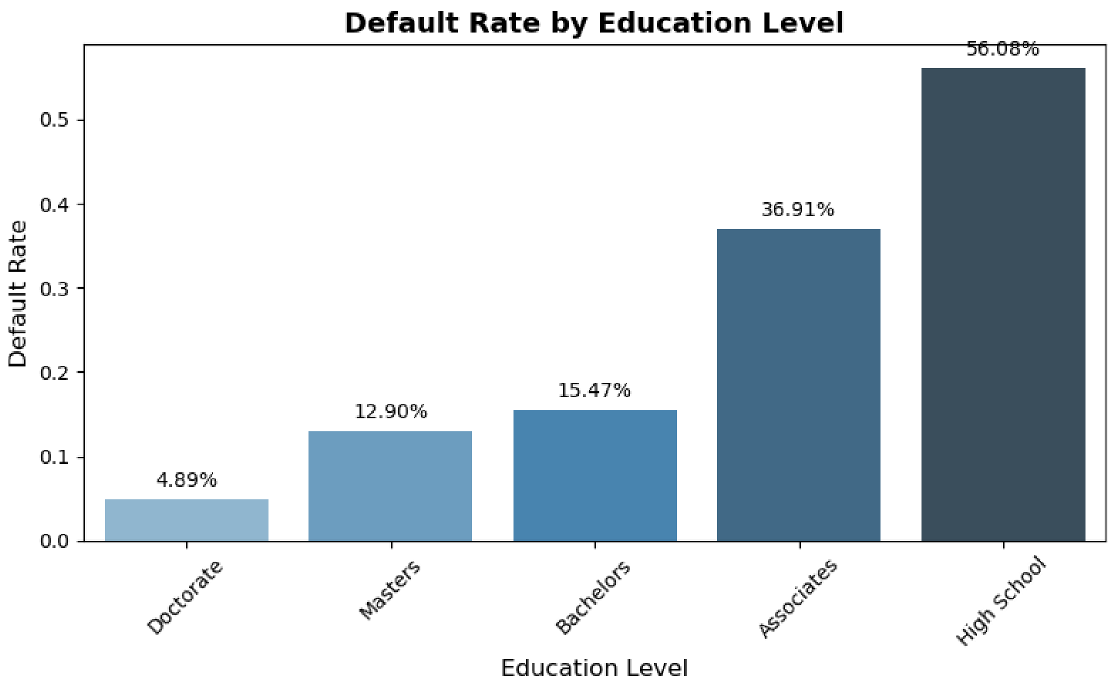


- **Categorical Variables**: Create bar plots showing the mean default rate for each category in education_level and marital_status.

[87]:
```
edu_default = df.groupby('education_level')['loan_status'].mean().sort_values()
plt.figure(figsize=(8, 5))
ax = sns.barplot(x=edu_default.index, y=edu_default.values, palette='Blues_d')

plt.title('Default Rate by Education Level', fontsize=14, weight='bold')
plt.xlabel('Education Level', fontsize=12)
plt.ylabel('Default Rate', fontsize=12)
plt.xticks(rotation=45)

for i, rate in enumerate(edu_default.values):
    plt.text(i, rate + 0.01, f'{rate:.2%}', ha='center', va='bottom',␣
↪fontsize=10)
plt.tight_layout()
plt.show()
```

```
C:\Users\Asus\AppData\Local\Temp\ipykernel_13240\3893837441.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
```

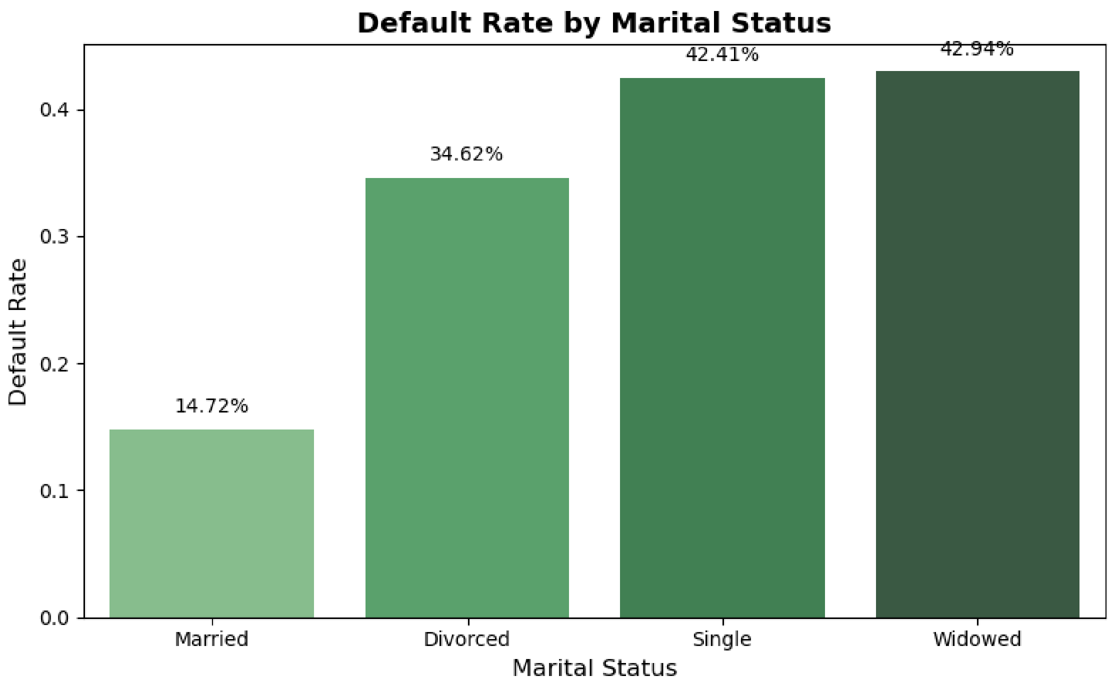
```
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.barplot(x=edu_default.index, y=edu_default.values, palette='Blues_d')
```



[ ]:
```
marital_default = df.groupby('marital_status')['loan_status'].mean().
  ↪sort_values()

plt.figure(figsize=(8, 5))
ax = sns.barplot(x=marital_default.index, y=marital_default.values,␣
  ↪palette='Greens_d')

plt.title('Default Rate by Marital Status', fontsize=14, weight='bold')
plt.xlabel('Marital Status', fontsize=12)
plt.ylabel('Default Rate', fontsize=12)

for i, rate in enumerate(marital_default.values):
    plt.text(i, rate + 0.01, f'{rate:.2%}', ha='center', va='bottom',␣
  ↪fontsize=10)

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

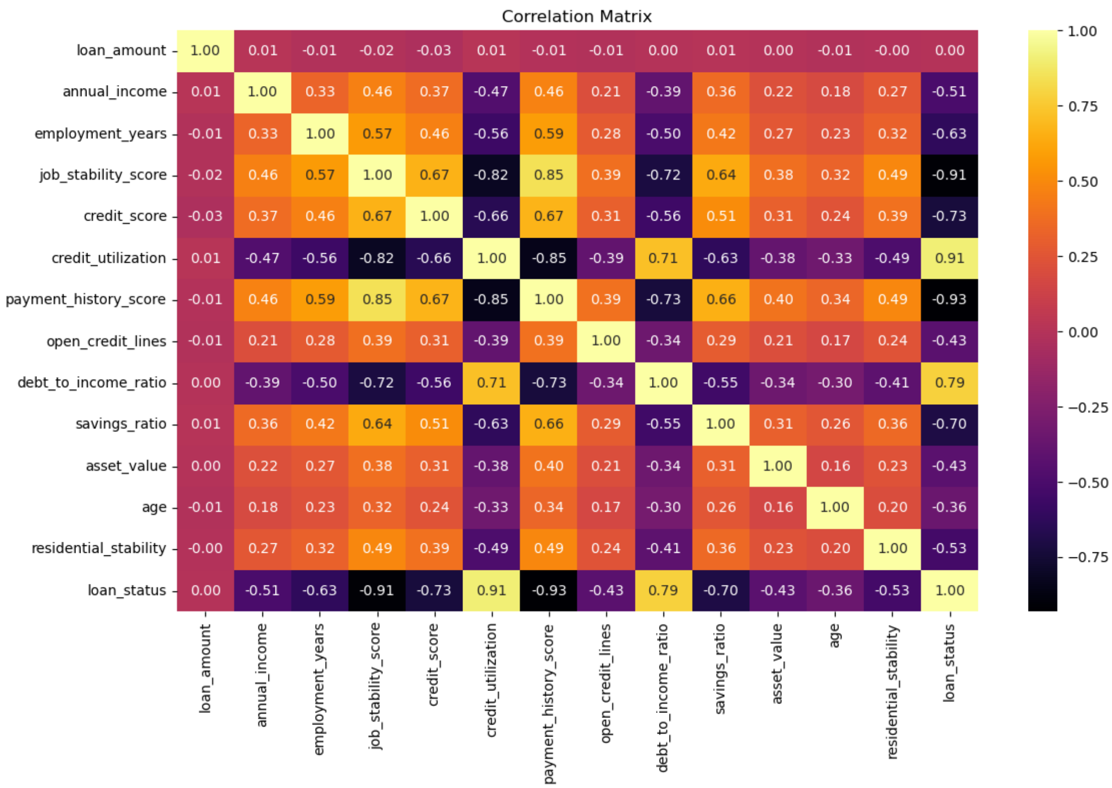
```
C:\Users\Asus\AppData\Local\Temp\ipykernel_13240\585239893.py:4: FutureWarning:
```

```
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.

  ax = sns.barplot(x=marital_default.index, y=marital_default.values,
palette='Greens_d')
```



- **Correlations**: Generate a correlation matrix heatmap for all numeric predictors.

[ ]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(numeric_only=True), annot=True, fmt=".2f", cmap='inferno')
plt.title('Correlation Matrix')
plt.tight_layout()
plt.show()
```



Section 3: Data Preprocessing

- **Handle Categorical Data**: Convert education_level and marital_status into numerical dummy variables (pd.get_dummies()).

[90]:
```
dummies_edu = pd.get_dummies(df["education_level"], prefix="edu",␣
↪drop_first=True)
dummies_mar = pd.get_dummies(df["marital_status"], prefix="marital",␣
↪drop_first=True)

dummies_edu
```

[90]:

	edu_Bachelors	edu_Doctorate	edu_High School	edu_Masters
0	False	False	True	False
1	False	False	False	True
2	False	False	True	False
3	True	False	False	False
4	False	False	False	False
…	…	…	…	…
2495	True	False	False	False
2496	False	False	False	False
2497	False	False	False	True
2498	False	False	True	False

```
2499          True         False            False         False

[2500 rows x 4 columns]
```

- **Define Predictors (X) and Target (y)**: Create X (features) and y (target) variables. Be sure to drop non-predictive columns like application_id.

[91]:
```python
x_features=["credit_score", "payment_history_score", "debt_to_income_ratio", "job_stability_score", "credit_utilization"]
X = pd.concat([df[x_features], dummies_edu, dummies_mar], axis=1)

y_target=df["loan_status"]
```

- **Train-Test Split**: Split the data into X_train, X_test, y_train, y_test. Use test_size=0.2 and a random_state=42 for reproducibility.

[92]:
```python
x_train, x_test, y_train, y_test=train_test_split(X, y_target, test_size=0.2, random_state=42, stratify=y_target)
```

- **Standardization**: Initialize a StandardScaler. **Fit** it only on X_train, then **transform** both X_train and X_test. This is critical for interpreting LDA coefficients.

[ ]:
```python
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)
```

Section 4: Statistical Assumption Testing

- **Key Statistical Assumptions Differentiating LDA and QDA**

  Both Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) assume that the predictors within each class follow a multivariate normal distribution. The main difference lies in how they treat the covariance matrices of these distributions.

  - Multivariate Normality:

    This assumption means that the predictors for each class should be approximately normally distributed. Based on the EDA plots, most variables (credit_score, credit_utilization, debt_to_income_ratio, job_stability_score) show roughly bell-shaped distributions, though some exhibit moderate skewness (payment_history_score being the most skewed). While not perfectly normal, the data are reasonably smooth and unimodal within each loan status group, suggesting that the multivariate normality assumption is reasonably met for applying discriminant analysis.

  - Homogeneity of Covariance Matrices:

    LDA assumes that all classes share a single covariance matrix, producing linear decision boundaries, while QDA allows each class to have its own covariance matrix, resulting in quadratic boundaries. If the class scatterplots or spreads differ noticeably—as suggested by some variation in variable ranges between “Default” and “Paid in Full” loans—this indicates unequal covariance structures.

- **Hypothesis:** If the covariance matrices are unequal, we expect QDA to outperform LDA, as QDA can better model differing class variances and correlations, though at the cost of greater model complexity.

Section 5: Model 1 - Linear Discriminant Analysis (LDA)

- Initialize LinearDiscriminantAnalysis and fit it on your standardized X_train and y_train.

[95]:
```
LDA=LinearDiscriminantAnalysis()
LDA.fit(x_train_scaled, y_train.values.ravel())
```

[95]:
```
LinearDiscriminantAnalysis()
```

- Interpret Coefficients: Extract the lda.coef_. Place them in a DataFrame with their feature names. Sort by absolute value.

[96]:
```
coef=LDA.coef_[0]
feature_names=x_train.columns

df_coef=pd.DataFrame({"Feature":feature_names, "Coefficient":coef})
df_coef["Abs_Coefficient"]=df_coef["Coefficient"].abs()
df_coef.sort_values(by="Abs_Coefficient", ascending=False, inplace=True)
df_coef
```

[96]:

	Feature	Coefficient	Abs_Coefficient
1	payment_history_score	-15.543899	15.543899
3	job_stability_score	-13.070033	13.070033
4	credit_utilization	11.643710	11.643710
2	debt_to_income_ratio	4.506771	4.506771
0	credit_score	-3.937238	3.937238
7	edu_High School	1.133565	1.133565
10	marital_Single	0.515575	0.515575
9	marital_Married	-0.492058	0.492058
6	edu_Doctorate	-0.417348	0.417348
5	edu_Bachelors	-0.181114	0.181114
8	edu_Masters	-0.174104	0.174104
11	marital_Widowed	0.051486	0.051486

- Write a clear interpretation: Which 3-5 variables are the most important drivers of default risk? What does the sign (+/-) tell you?

The top predictors of loan default risk, based on the absolute value of LDA coefficients, are:

- Payment History Score (−15.54): A poor payment history greatly increases default risk. Customers who have missed prior payments or shown inconsistent repayment patterns are significantly more likely to default again.
- Job Stability Score (−13.07): Applicants with unstable employment—frequent job changes or short tenure—tend to face higher financial uncertainty, which increases the likelihood of falling behind on loan payments.

- Credit Utilization (+11.64): High credit utilization indicates that the borrower is already heavily relying on credit. This pressure raises the probability of default, as the borrower has limited capacity to absorb additional debt.
- Debt-to-Income Ratio (+4.51): This is one of the strongest predictors. Applicants whose debt obligations take up a large share of their income are much more likely to struggle with repayment and default.
- Credit Score (−3.94): Lower credit scores strongly correlate with higher default risk. Credit Score remains a reliable indicator of financial discipline and borrower reliability.

Section 6: Model 2 - Quadratic Discriminant Analysis (QDA)

- Initialize QuadraticDiscriminantAnalysis and fit it on your standardized X_train and y_train

[97]:
```
QDA = QuadraticDiscriminantAnalysis()
QDA.fit(x_train_scaled, y_train)
```

[97]:
```
QuadraticDiscriminantAnalysis()
```

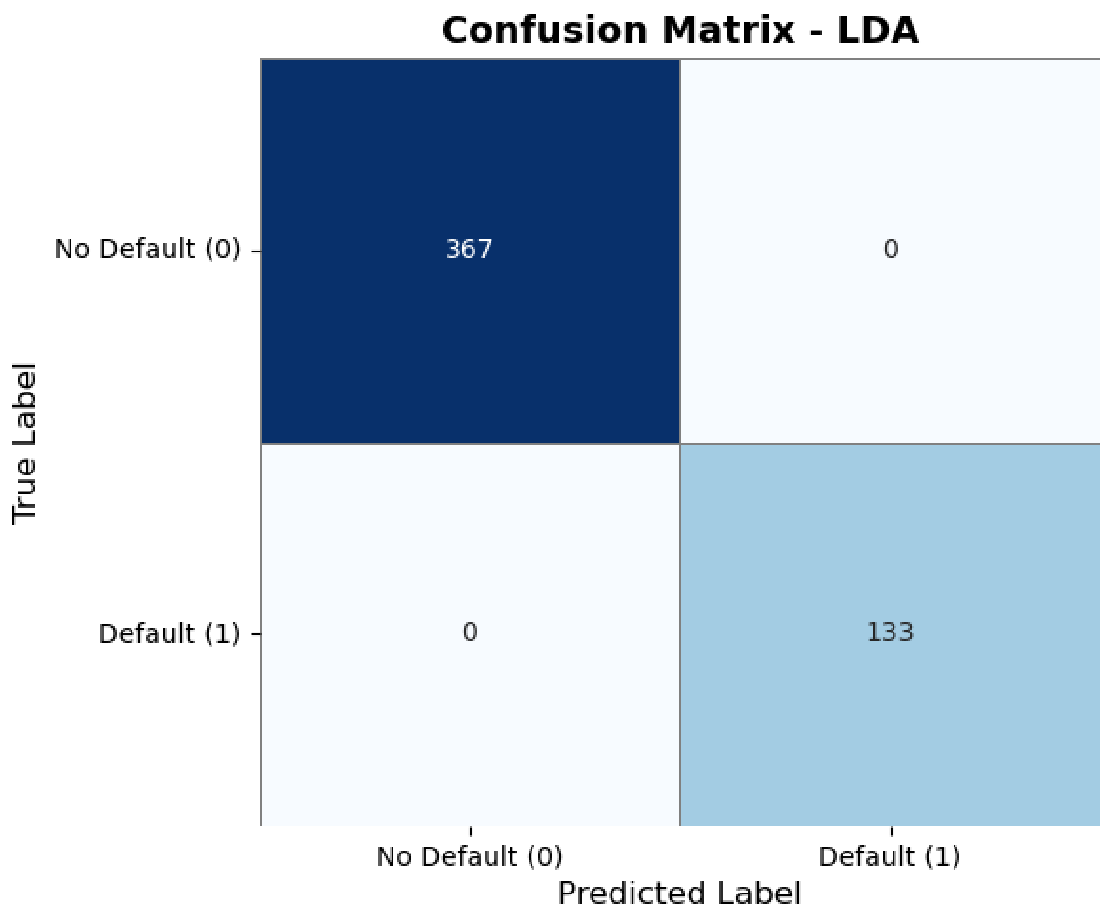
Section 7: Model Evaluation & Comparison

- Generate predictions (.predict()) for both models on the X_test data.

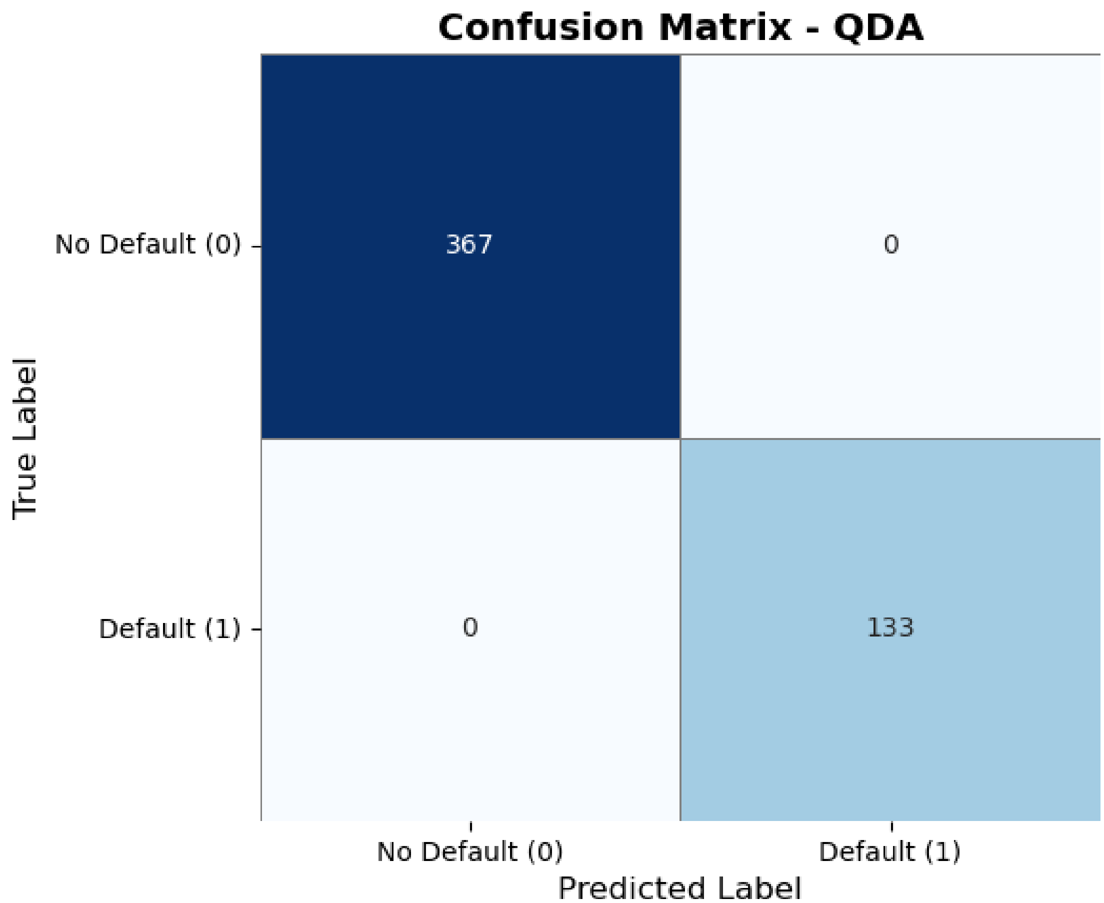
[98]:
```
y_pred_lda = LDA.predict(x_test_scaled)
y_pred_qda = QDA.predict(x_test_scaled)
```

- Confusion Matrices: For both models, generate and plot a ConfusionMatrixDisplay.

[99]:
```
def plot_confusion_matrix(y_true, y_pred, model_name):
    cm = confusion_matrix(y_true, y_pred)
    labels = ["No Default (0)", "Default (1)"]

    plt.figure(figsize=(6, 5))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
                xticklabels=labels, yticklabels=labels, linewidths=0.5,␣
 ↪linecolor='gray')

    plt.title(f"Confusion Matrix - {model_name}", fontsize=14, weight='bold')
    plt.xlabel("Predicted Label", fontsize=12)
    plt.ylabel("True Label", fontsize=12)
    plt.xticks(rotation=0)
    plt.yticks(rotation=0)
    plt.tight_layout()
    plt.show()
plot_confusion_matrix(y_test, y_pred_lda, "LDA")
plot_confusion_matrix(y_test, y_pred_qda, "QDA")
```



Confusion Matrix - LDA
No Default (0)
Default (1)
367
0
0
133
True Label
No Default (0)
Default (1)
Predicted Label



- Classification Reports: For both models, print the classification_report.

[100]:
```python
print("Classification Report - LDA")
print(classification_report(y_test, y_pred_lda))

print("Classification Report - QDA")
print(classification_report(y_test, y_pred_qda))
```

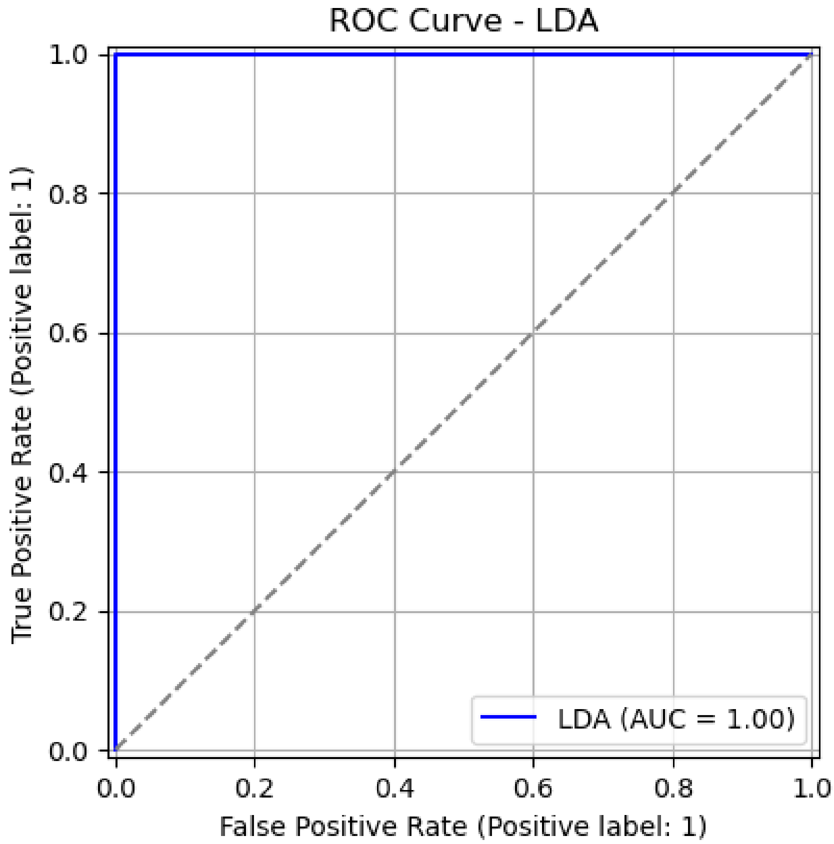
```
Classification Report - LDA
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       367
           1       1.00      1.00      1.00       133

    accuracy                           1.00       500
   macro avg       1.00      1.00      1.00       500
weighted avg       1.00      1.00      1.00       500

Classification Report - QDA
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       367
           1       1.00      1.00      1.00       133

    accuracy                           1.00       500
   macro avg       1.00      1.00      1.00       500
weighted avg       1.00      1.00      1.00       500
```

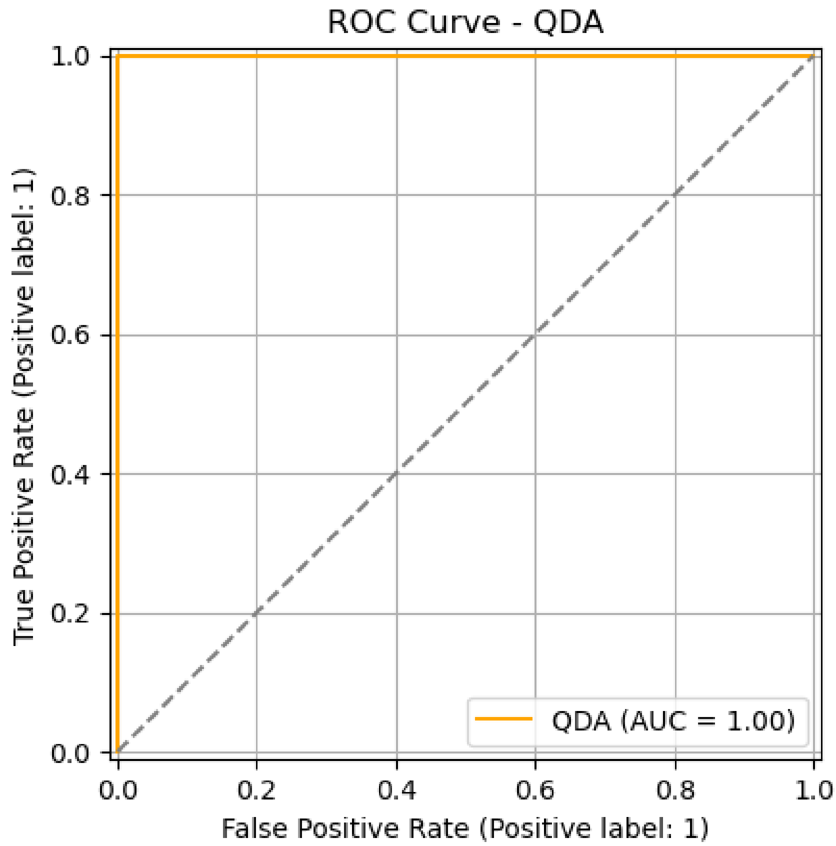
- ROC Curves: Generate the RocCurveDisplay for both models and plot them on the same axis for a direct visual comparison. Report the AUC (Area Under the Curve) score for both.

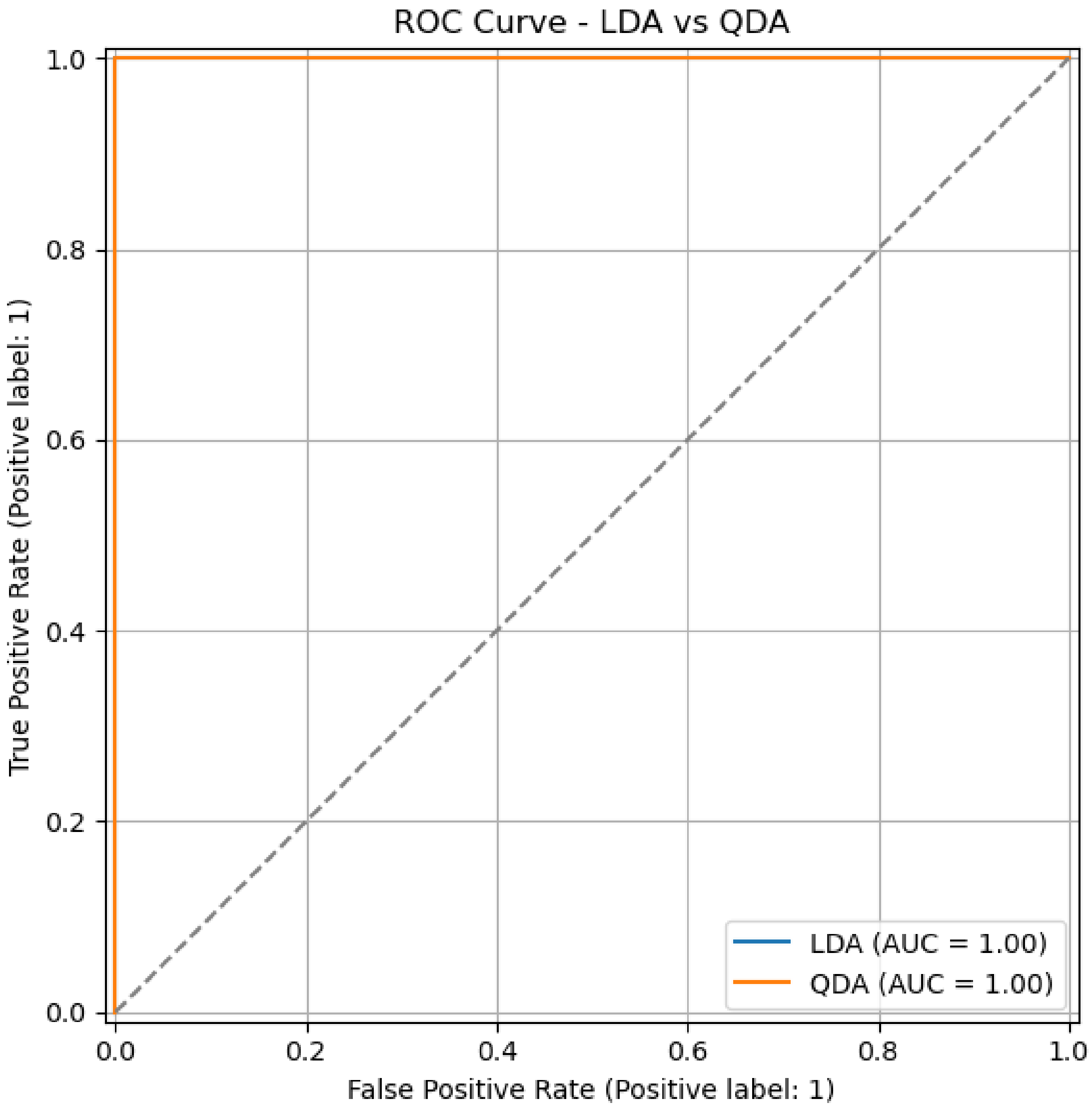
[80]:
```python
y_proba_lda = LDA.predict_proba(x_test_scaled)[:, 1]
y_proba_qda = QDA.predict_proba(x_test_scaled)[:, 1]

plt.figure(figsize=(8, 6))
RocCurveDisplay.from_predictions(y_test, y_proba_lda, name="LDA", color="blue")
plt.plot([0, 1], [0, 1], '--', color='gray')
plt.title("ROC Curve - LDA")
plt.grid(True)
plt.show()

plt.figure(figsize=(8, 6))
RocCurveDisplay.from_predictions(y_test, y_proba_qda, name="QDA",␣
 ↪color="orange")
plt.plot([0, 1], [0, 1], '--', color='gray')
plt.title("ROC Curve - QDA")
plt.grid(True)
plt.show()

# Combined plot
fig, ax = plt.subplots(figsize=(8, 6))

RocCurveDisplay.from_predictions(y_test, y_proba_lda, name="LDA", ax=ax)
RocCurveDisplay.from_predictions(y_test, y_proba_qda, name="QDA", ax=ax)

ax.plot([0, 1], [0, 1], linestyle='--', color='gray')
ax.set_title("ROC Curve - LDA vs QDA")
ax.grid(True)

plt.tight_layout()
plt.show()
auc_lda = roc_auc_score(y_test, y_proba_lda)
auc_qda = roc_auc_score(y_test, y_proba_qda)

print(f"AUC Score - LDA: {auc_lda:.4f}")
print(f"AUC Score - QDA: {auc_qda:.4f}")
```

<Figure size 800x600 with 0 Axes>



<Figure size 800x600 with 0 Axes>


ROC Curve - QDA
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
QDA (AUC = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)




```
AUC Score - LDA: 1.0000
AUC Score - QDA: 1.0000
```

Section 8: Technical Conclusion & Model Selection

Based on the evaluation results in Section 7, both the LDA and QDA models achieve perfect classification performance on this test set, as shown by the ROC curves for both models reaching the top-left corner of the chart and yielding an AUC of 1.0. This means that each model correctly identified every single default and non-default case, with no false positives and no false negatives. In other words, the predicted probabilities for defaulters were always higher than those for non-defaulters, showing complete separability between the two groups. Although this kind of perfect performance is extremely rare in real-world lending environments, it is statistically possible when the underlying predictors are highly informative and the dataset exhibits a strong, clean distinction between risk profiles. The overlap of the two curves indicates that LDA and QDA produced the same correct classifications despite using different types of decision boundaries, reinforcing the strength of the financial indicators used. For the business, this result implies that the model can accurately distinguish between high-risk and low-risk borrowers in this sample, providing a powerful tool for reducing default losses with minimal risk of unnecessarily rejecting good customers, while noting that further validation on real-world data is recommended to confirm this level of performance.

LDA works because it assumes that both classes share the same covariance structure, which creates a clean linear boundary between defaulters and non-defaulters. This makes it stable, easy to interpret, and highly reliable when the predictors are well-separated. QDA works because it allows each class to have its own covariance matrix, giving it the flexibility to model more complex, curved decision boundaries. When the data is highly structured and the class distributions differ significantly, QDA can capture these patterns and achieve perfect separation.

In this case, either model works equally well, but LDA may be preferred for its simplicity and interpretability, especially since the results were the same. This means that LDA got the same results as QDA, but with simpler assumptions.