ytdtz6oz6

November 13, 2025

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
```

1 LendSmart Credit Risk Analysis

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2 Section 1

[ ]:
```
# Importar csv

df = pd.read_csv('credit_risk_data-1.csv')
df.head()
```

[ ]:
```
  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
```

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

```
<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
```

[ ]:
```
df.describe()
```

[ ]:
```
         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
```

[ ]:
```
# find nan values
df.isnull().sum()
```

[ ]:
```
application_id          0
application_date        0
```

```
loan_amount              0
annual_income            0
employment_years         0
job_stability_score      0
credit_score             0
credit_utilization       0
payment_history_score    0
open_credit_lines        0
debt_to_income_ratio     0
savings_ratio            0
asset_value              0
age                      0
education_level          0
marital_status           0
residential_stability    0
loan_status              0
dtype: int64
```

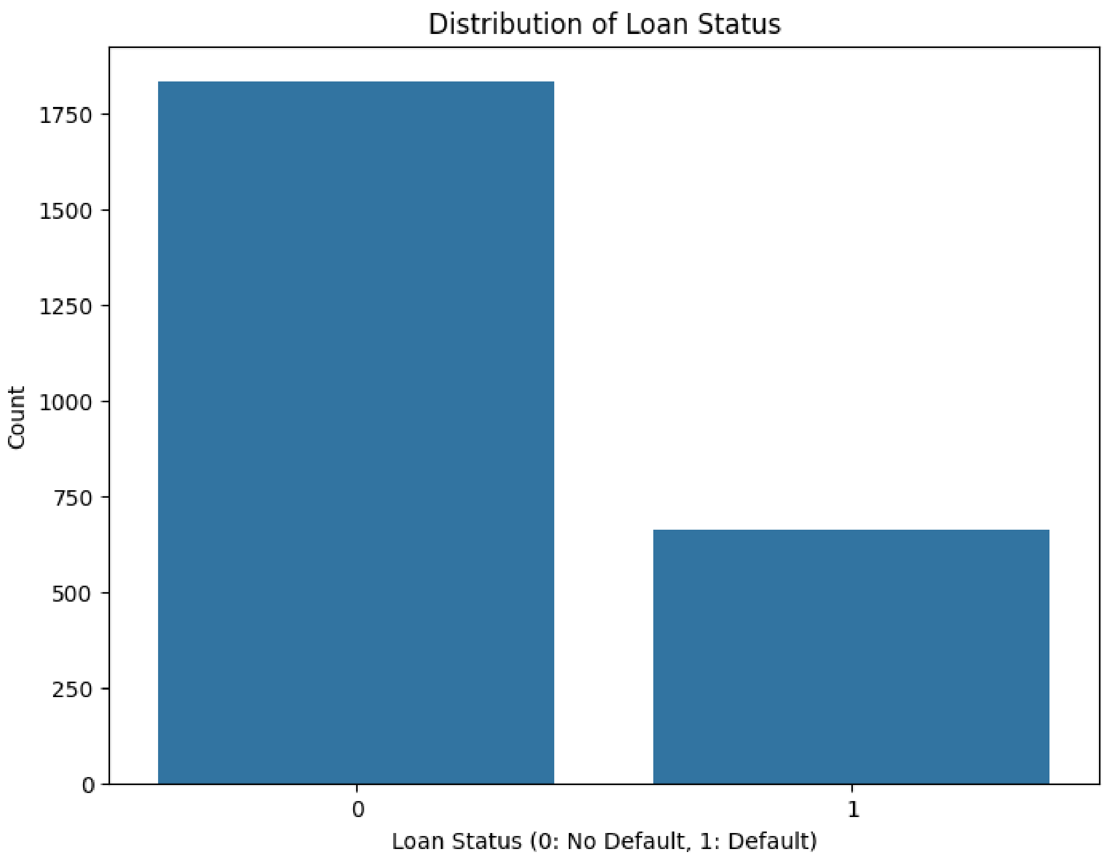
3 Section 2

[ ]:
```python
# Plot the distribution of loan_status and calculate the exact default rate.

loan_status = df['loan_status']

plt.figure(figsize=(8, 6))
# histogram
sns.countplot(x=loan_status)
plt.title('Distribution of Loan Status')
plt.xlabel('Loan Status (0: No Default, 1: Default)')
plt.ylabel('Count')
plt.show()


# Calculate the exact default rate.
total_loans = len(loan_status)
default_count = loan_status.value_counts()[1]
default_rate = (default_count / total_loans) * 100
print(f"Total Loans: {total_loans}")
print(f"Default Count: {default_count}")
print(f"Default Rate: {default_rate:.2f}%")
```




```
Total Loans: 2500
Default Count: 664
Default Rate: 26.56%
```

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

# Continuous variables to visualize
continuous_vars = [
    ␣
  ↪'credit_score','annual_income','debt_to_income_ratio','loan_amount','employment_years',
    'job_stability_score','credit_utilization','payment_history_score',
    'savings_ratio','asset_value','age','residential_stability'
]

# Set plot style
sns.set(style="whitegrid")

plt.figure(figsize=(15, 20))
```

```python
for i, var in enumerate(continuous_vars, 1):
    plt.subplot(6, 2, i)
    sns.boxplot(data=df, x='loan_status', y=var, palette='Set2')
    plt.title(f'{var} by Loan Status')
    plt.xlabel('Loan Status (0 = Non-Default, 1 = Default)')
    plt.ylabel(var)

plt.tight_layout()
plt.show()

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

```
/tmp/ipython-input-603495265.py:18: 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.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: 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
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  sns.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: FutureWarning:

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/tmp/ipython-input-603495265.py:18: FutureWarning:

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

```
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/tmp/ipython-input-603495265.py:18: 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.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: 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.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: 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.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: 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
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  sns.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: 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
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  sns.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: FutureWarning:

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  sns.boxplot(data=df, x='loan_status', y=var, palette='Set2')
/tmp/ipython-input-603495265.py:18: 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.
```
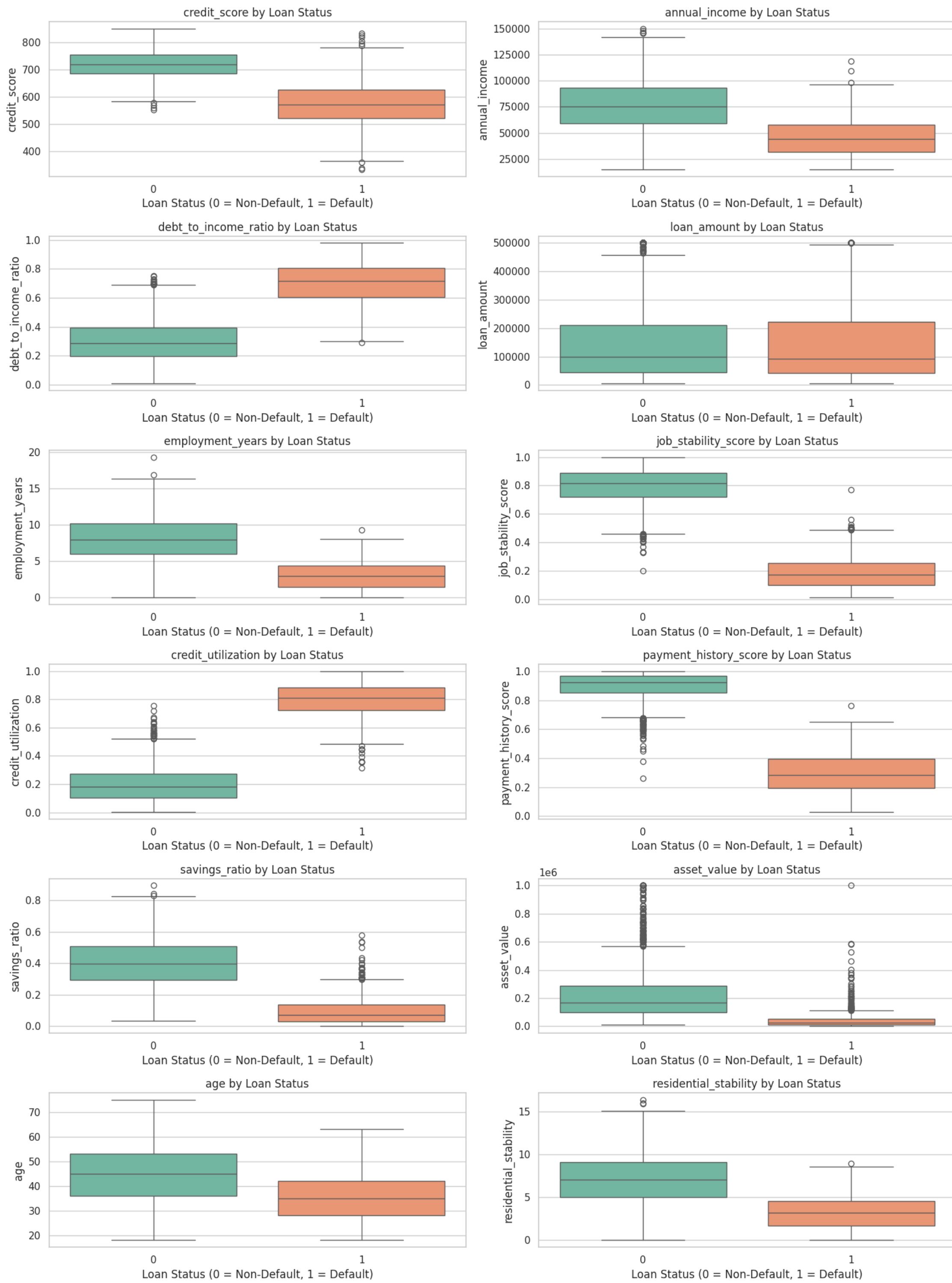
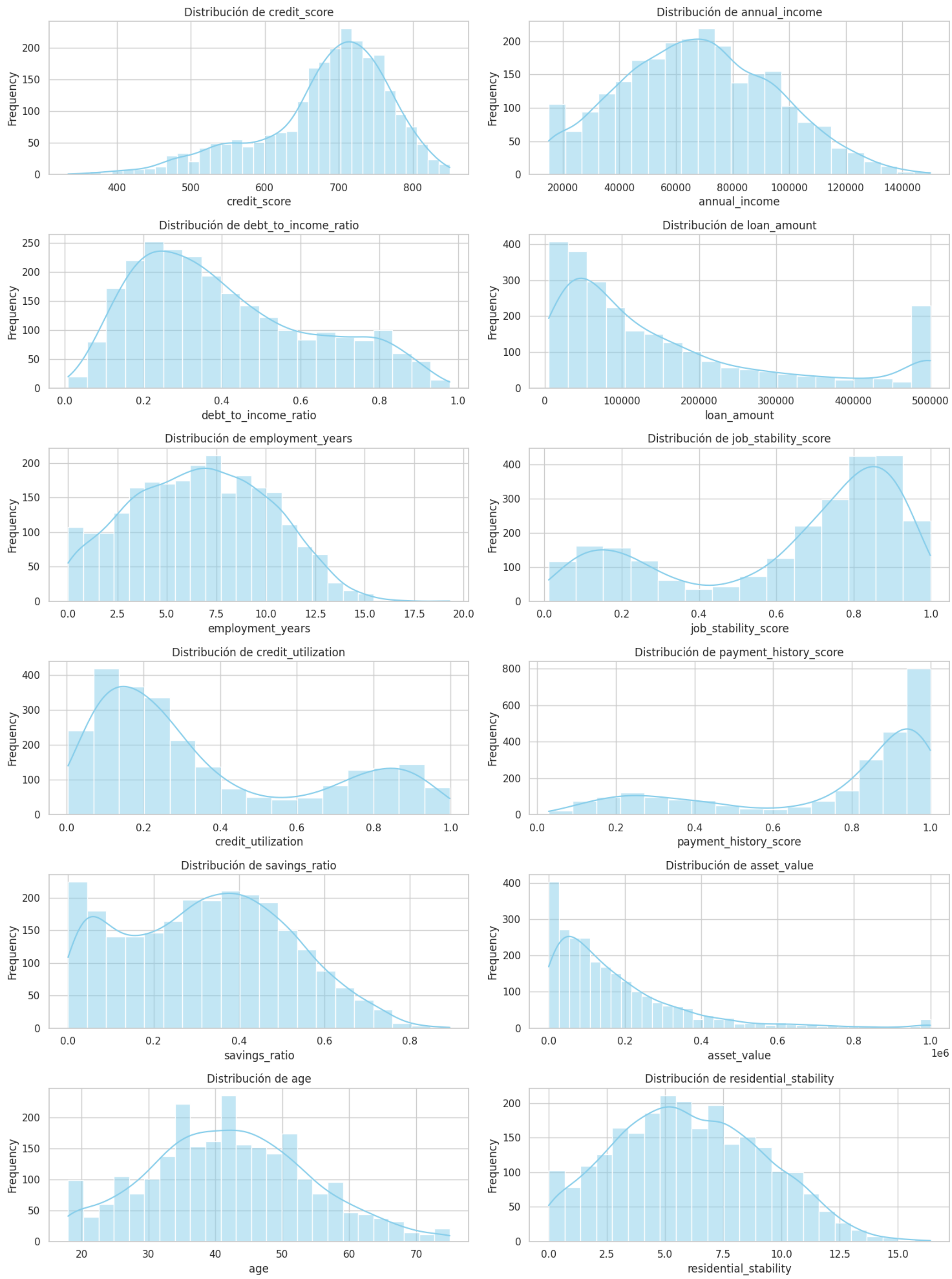

```
sns.boxplot(data=df, x='loan_status', y=var, palette='Set2')
```



<Figure size 640x480 with 0 Axes>

[ ]:
```
# Gráficar continous variables com histograms

plt.figure(figsize=(15, 20))
for i, var in enumerate(continuous_vars, 1):
    plt.subplot(6, 2, i)
    sns.histplot(data=df, x=var, kde=True, color='skyblue')
    plt
    plt.title(f'Distribución de {var}')
    plt.xlabel(var)
    plt.ylabel('Frequency')

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



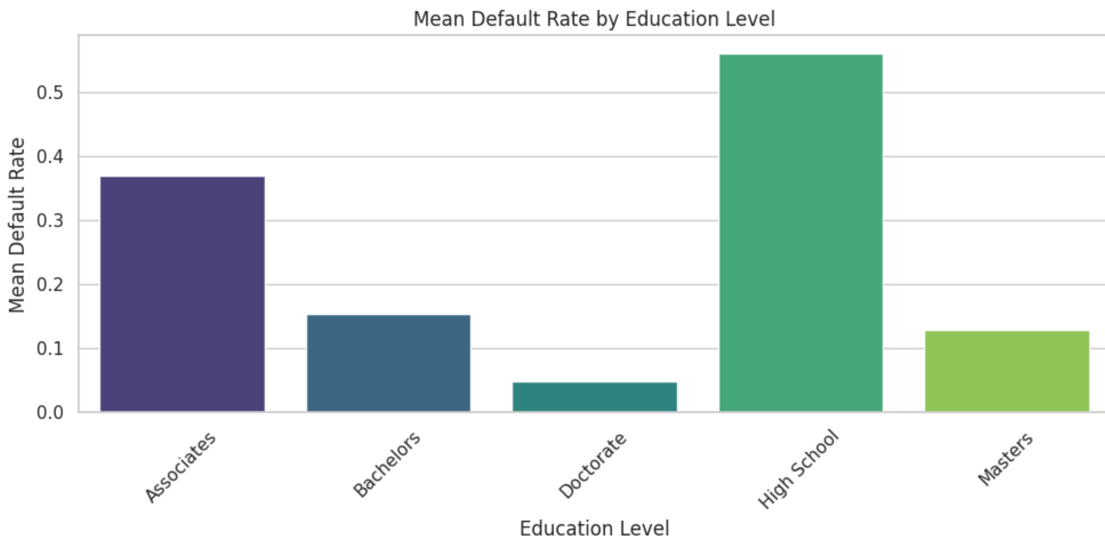

```
[ ]: df['education_level'].value_counts()
```

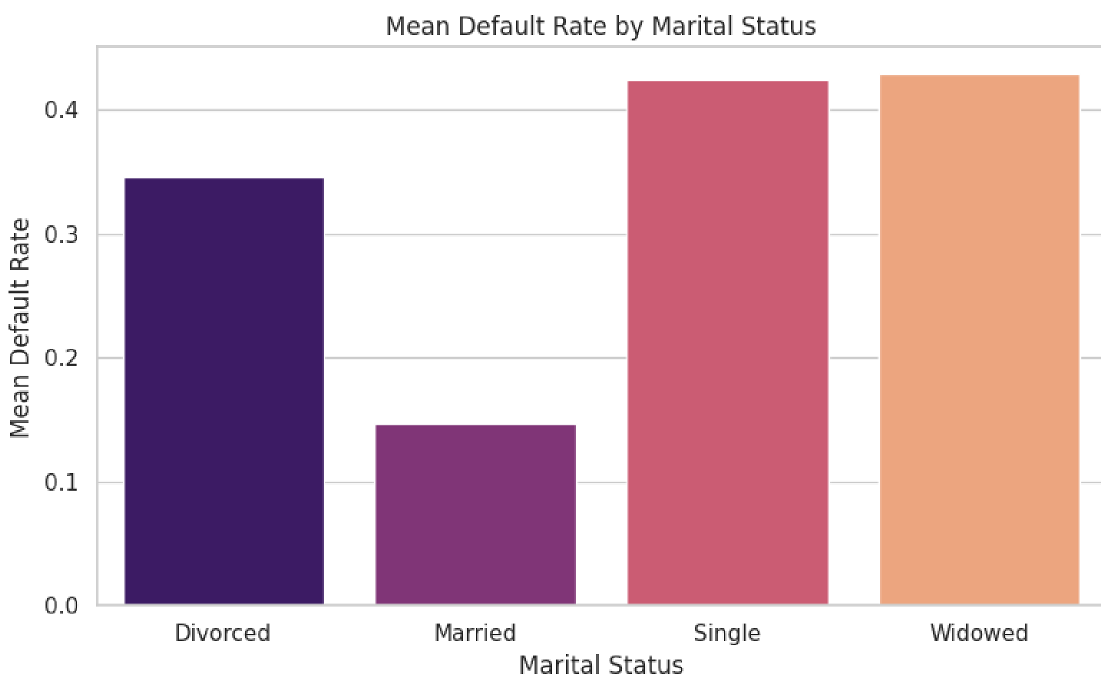
```python
# groupby educational level for mean default rate
df.groupby('education_level')['loan_status'].mean()
```

[ ]:
```
education_level
Associates     0.369128
Bachelors      0.154676
Doctorate      0.048913
High School    0.560811
Masters        0.128959
Name: loan_status, dtype: float64
```

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

default_rates_educ = (
    df.groupby('education_level')['loan_status']
      .mean()
      .reset_index()
      .rename(columns={'loan_status': 'default_rate'})
)

default_rates_marital = (
    df.groupby('marital_status')['loan_status']
      .mean()
      .reset_index()
      .rename(columns={'loan_status': 'default_rate'})
)



plt.figure(figsize=(10, 5))
sns.barplot(data=default_rates_educ, x='education_level', y='default_rate',␣
 ↪hue='education_level', legend=False, palette='viridis')
plt.title('Mean Default Rate by Education Level')
plt.xlabel('Education Level')
plt.ylabel('Mean Default Rate')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()


plt.figure(figsize=(8, 5))
sns.barplot(data=default_rates_marital, x='marital_status', y='default_rate',␣
 ↪hue='marital_status', legend=False, palette='magma')
plt.title('Mean Default Rate by Marital Status')
plt.xlabel('Marital Status')
plt.ylabel('Mean Default Rate')
```

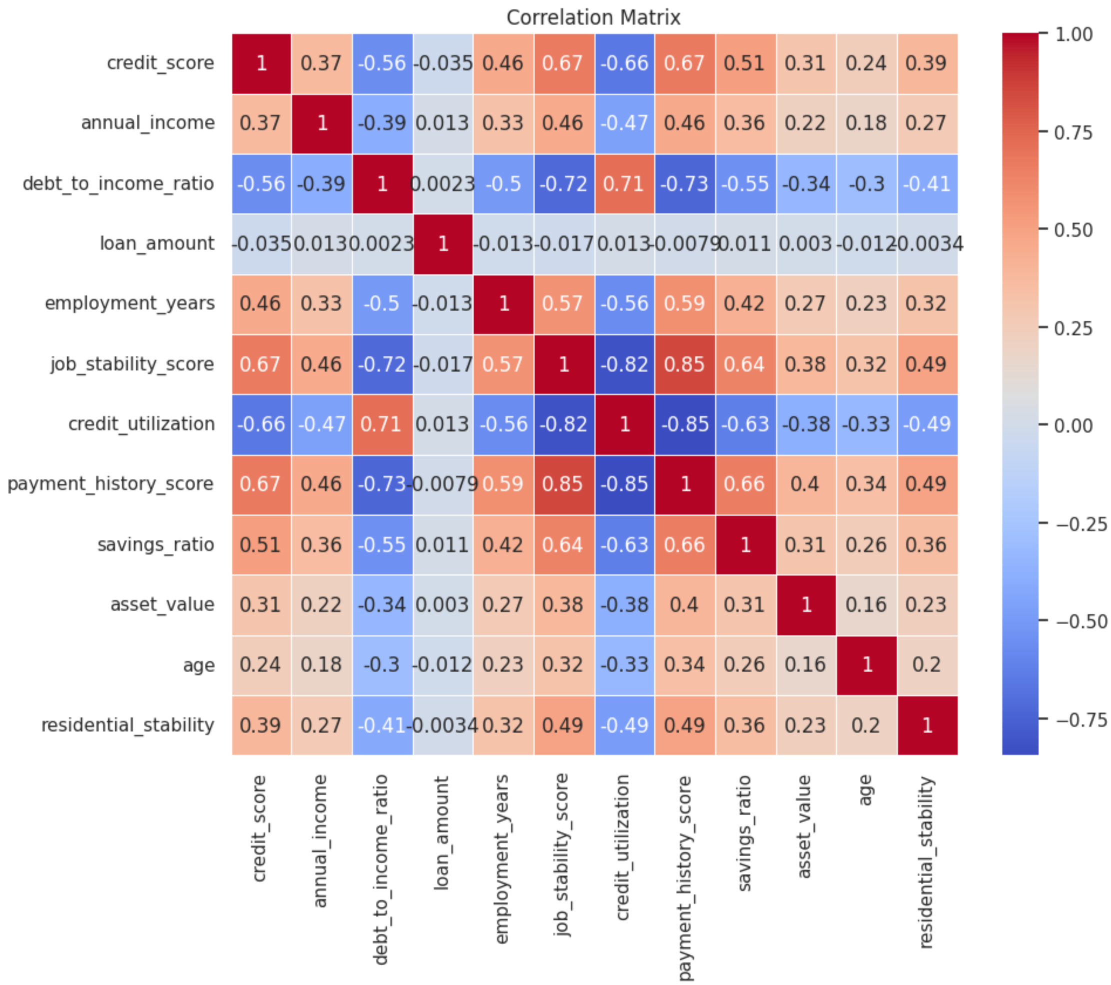
```
plt.tight_layout()
plt.show()
```





[ ]:
```
# Correltaion for continuous_vars

correlation_matrix = df[continuous_vars].corr()
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```



[ ]:
```
correlation_matrix.describe()
```

[ ]:

	credit_score	annual_income	debt_to_income_ratio	loan_amount	\
count	12.000000	12.000000	12.000000	12.000000	
mean	0.280763	0.233603	-0.232651	0.079472	
std	0.487464	0.389996	0.548401	0.290230	
min	-0.657600	-0.467363	-0.732091	-0.034981	
25%	0.171627	0.138400	-0.551312	-0.012127	
50%	0.379584	0.298325	-0.403739	-0.000569	
75%	0.550242	0.390495	-0.227114	0.011519	
max	1.000000	1.000000	1.000000	1.000000	

```
       employment_years  job_stability_score  credit_utilization  \
count         12.000000            12.000000           12.000000   
mean           0.258679             0.319335           -0.287300   
std            0.443269             0.568965            0.584199   
min           -0.563996            -0.817940           -0.845028   
25%            0.165648             0.237627           -0.634631   
50%            0.324901             0.475626           -0.476804   
75%            0.488187             0.643857           -0.243293   
max            1.000000             1.000000            1.000000   

       payment_history_score  savings_ratio  asset_value        age  \
count              12.000000      12.000000    12.000000  12.000000   
mean                0.323260       0.279506     0.214222   0.190159   
std                 0.578606       0.472911     0.358205   0.338189   
min                -0.845028      -0.626975    -0.380645  -0.328598   
25%                 0.251532       0.195030     0.121195   0.117523   
50%                 0.478424       0.358970     0.249944   0.213832   
75%                 0.663408       0.542854     0.329894   0.272843   
max                 1.000000       1.000000     1.000000   1.000000   

       residential_stability  
count              12.000000  
mean                0.237749  
std                 0.400431  
min                -0.486246  
25%                 0.150872  
50%                 0.293684  
75%                 0.416695  
max                 1.000000  
```

4 Variable con alta multiconilnealidad siendo 0.7

Credit utilization y job stability score - 0.82

job stability score y debt to income ratio - 0.72

Credit utilization y payment history score - 0.85

debt to income ratio y Credit utilization - 0.71

payment history score y job stability score - 0.85

debt to income ratio y payment history score - 0.73

Sin embargo para elegir las varibles se usara RFE para tomar las variables con baja multicolinealidad.

5 Section 3

[ ]:
```
df.education_level.unique()
```

[ ]:
```
array(['High School', 'Masters', 'Bachelors', 'Associates', 'Doctorate'],
      dtype=object)
```

[ ]:
```
df.marital_status.unique()
```

[ ]:
```
array(['Married', 'Divorced', 'Widowed', 'Single'], dtype=object)
```

[ ]:
```
educationMAP = {'High School':1, 'Masters':4, 'Bachelors':3, 'Associates':2,␣
↪'Doctorate':5}
df['education_level'] = df['education_level'].map(educationMAP)
```

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

```
<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   int64
 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(5), object(3)
memory usage: 351.7+ KB
```

[ ]:
```
df_encoded = pd.get_dummies(df, columns=['marital_status'],dtype = float)

df_encoded = df_encoded[['application_id', 'application_date', 'loan_amount',␣
↪'annual_income',
```

```
        'employment_years', 'job_stability_score', 'credit_score',
        'credit_utilization', 'payment_history_score', 'open_credit_lines',
        'debt_to_income_ratio', 'savings_ratio', 'asset_value', 'age',
        'education_level', 'residential_stability',
        'marital_status_Divorced', 'marital_status_Married',
        'marital_status_Single', 'marital_status_Widowed',"loan_status"]]
df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 21 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   int64
 15  residential_stability    2500 non-null   float64
 16  marital_status_Divorced  2500 non-null   float64
 17  marital_status_Married   2500 non-null   float64
 18  marital_status_Single    2500 non-null   float64
 19  marital_status_Widowed   2500 non-null   float64
 20  loan_status              2500 non-null   int64
dtypes: float64(14), int64(5), object(2)
memory usage: 410.3+ KB
```

[ ]:
```
X = df_encoded.iloc[:,3:20]

X.info()
y = df_encoded.iloc[:,-1]
y
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
```

```
 0   annual_income           2500 non-null   float64
 1   employment_years        2500 non-null   float64
 2   job_stability_score     2500 non-null   float64
 3   credit_score            2500 non-null   int64
 4   credit_utilization      2500 non-null   float64
 5   payment_history_score   2500 non-null   float64
 6   open_credit_lines       2500 non-null   int64
 7   debt_to_income_ratio    2500 non-null   float64
 8   savings_ratio           2500 non-null   float64
 9   asset_value             2500 non-null   float64
 10  age                     2500 non-null   int64
 11  education_level         2500 non-null   int64
 12  residential_stability   2500 non-null   float64
 13  marital_status_Divorced 2500 non-null   float64
 14  marital_status_Married  2500 non-null   float64
 15  marital_status_Single   2500 non-null   float64
 16  marital_status_Widowed  2500 non-null   float64
dtypes: float64(13), int64(4)
memory usage: 332.2 KB
```

[ ]:
```
0       0
1       0
2       0
3       0
4       0
       ..
2495    0
2496    1
2497    0
2498    1
2499    0
Name: loan_status, Length: 2500, dtype: int64
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,          # 20% para prueba
    random_state=42,        # Semilla para reproducibilidad
    stratify=y              # Opcional: mantiene proporciones de clases (útil en
 ↪clasificación)
)
```

[ ]:
```
X.columns
```

[ ]:
```
Index(['annual_income', 'employment_years', 'job_stability_score',
       'credit_score', 'credit_utilization', 'payment_history_score',
       'open_credit_lines', 'debt_to_income_ratio', 'savings_ratio',
       'asset_value', 'age', 'education_level', 'residential_stability',
```

```
       'marital_status_Divorced', 'marital_status_Married',
       'marital_status_Single', 'marital_status_Widowed'],
      dtype='object')
```

[ ]:
```
scaler = MinMaxScaler(feature_range=(0, 1))
columnas_a_escalar =['annual_income', 'employment_years',
        'credit_score',
        'open_credit_lines', 'debt_to_income_ratio',
       'savings_ratio', 'asset_value', 'age',␣
 ↪'education_level',"residential_stability"]




X_scaled_train = pd.DataFrame(
    scaler.fit_transform(X_train[columnas_a_escalar]),
    columns=columnas_a_escalar,
    index=X_train.index
)
```

[ ]:
```
X_train
```

[ ]:
```
      annual_income  employment_years  job_stability_score  credit_score  \
2082       62648.24               9.9                0.541           714
1319      113346.13               8.5                0.929           719
1569       57588.47              13.6                0.769           742
1257       83159.53              12.1                0.799           779
2096       64288.01               6.0                0.519           722
…              …                 …                    …            …
1165       45946.99               6.1                0.829           626
1334       86267.61               9.0                0.830           706
626        34526.29               4.5                0.181           545
1901       61908.46               5.0                0.818           643
1373       89359.66               6.5                0.824           695

      credit_utilization  payment_history_score  open_credit_lines  \
2082               0.171                  0.815                  3
1319               0.219                  0.938                  4
1569               0.244                  0.815                  1
1257               0.046                  0.732                  4
2096               0.148                  0.949                  2
…                    …                      …                 …
1165               0.085                  0.932                  5
1334               0.063                  0.994                  3
626                0.922                  0.261                  2
1901               0.222                  0.905                  4
1373               0.271                  0.941                  5
```

```
      debt_to_income_ratio  savings_ratio  asset_value  age  education_level  \
2082                 0.240          0.549    168748.10   39                2
1319                 0.303          0.516    272892.03   59                4
1569                 0.659          0.550     82093.48   41                3
1257                 0.646          0.402     74527.88   71                2
2096                 0.233          0.394    122808.69   52                5
…                    …              …            …    …              …
1165                 0.332          0.370    143994.83   26                1
1334                 0.462          0.392    218923.92   68                4
626                  0.786          0.246     25799.60   45                3
1901                 0.234          0.262     67014.03   52                4
1373                 0.222          0.550     97451.56   64                5

      residential_stability  marital_status_Divorced  marital_status_Married  \
2082                    3.1                      0.0                     1.0
1319                    5.5                      0.0                     1.0
1569                    3.8                      0.0                     1.0
1257                    5.8                      0.0                     0.0
2096                    7.2                      1.0                     0.0
…                     …                      …                     …
1165                    7.4                      1.0                     0.0
1334                    8.1                      0.0                     0.0
626                     2.9                      1.0                     0.0
1901                    7.7                      0.0                     1.0
1373                   10.0                      0.0                     0.0

      marital_status_Single  marital_status_Widowed
2082                    0.0                     0.0
1319                    0.0                     0.0
1569                    0.0                     0.0
1257                    0.0                     1.0
2096                    0.0                     0.0
…                     …                      …
1165                    0.0                     0.0
1334                    1.0                     0.0
626                     0.0                     0.0
1901                    0.0                     0.0
1373                    1.0                     0.0

[2000 rows x 17 columns]
```

[ ]:
```
X_scaled_train.columns = columnas_a_escalar
X_scaled_train
```

[ ]:
```
      annual_income  employment_years  credit_score  open_credit_lines  \
2082       0.353133          0.585799      0.736434           0.272727
1319       0.728868          0.502959      0.746124           0.363636
```

```
1569       0.315634          0.804734     0.790698           0.090909
1257       0.505147          0.715976     0.862403           0.363636
2096       0.365286          0.355030     0.751938           0.181818
…             …                 …           …                …
1165       0.229356          0.360947     0.565891           0.454545
1334       0.528182          0.532544     0.720930           0.272727
626        0.144714          0.266272     0.408915           0.181818
1901       0.347650          0.295858     0.598837           0.363636
1373       0.551098          0.384615     0.699612           0.454545

      debt_to_income_ratio  savings_ratio  asset_value       age  \
2082              0.229406       0.614782     0.168290  0.368421
1319              0.295099       0.577828     0.272491  0.719298
1569              0.666319       0.615901     0.081588  0.403509
1257              0.652763       0.450168     0.074018  0.929825
2096              0.222106       0.441209     0.122325  0.596491
…                    …             …           …         …
1165              0.325339       0.414334     0.143523  0.140351
1334              0.460897       0.438970     0.218494  0.877193
626               0.798749       0.275476     0.025263  0.473684
1901              0.223149       0.293393     0.066500  0.596491
1373              0.210636       0.615901     0.096954  0.807018

      education_level  residential_stability
2082             0.25               0.189024
1319             0.75               0.335366
1569             0.50               0.231707
1257             0.25               0.353659
2096             1.00               0.439024
…                 …                   …
1165             0.00               0.451220
1334             0.75               0.493902
626              0.50               0.176829
1901             0.75               0.469512
1373             1.00               0.609756

[2000 rows x 10 columns]
```

[ ]:
```
X_train = X_train.drop(columns = columnas_a_escalar)
X_train
```

[ ]:
```
      job_stability_score  credit_utilization  payment_history_score  \
2082                0.541               0.171                  0.815
1319                0.929               0.219                  0.938
1569                0.769               0.244                  0.815
1257                0.799               0.046                  0.732
2096                0.519               0.148                  0.949
```

```
…                   …                   …                     …
1165            0.829               0.085                 0.932
1334            0.830               0.063                 0.994
626             0.181               0.922                 0.261
1901            0.818               0.222                 0.905
1373            0.824               0.271                 0.941

      marital_status_Divorced  marital_status_Married  marital_status_Single  \
2082                      0.0                     1.0                    0.0
1319                      0.0                     1.0                    0.0
1569                      0.0                     1.0                    0.0
1257                      0.0                     0.0                    0.0
2096                      1.0                     0.0                    0.0
…                           …                       …                      …
1165                      1.0                     0.0                    0.0
1334                      0.0                     0.0                    1.0
626                       1.0                     0.0                    0.0
1901                      0.0                     1.0                    0.0
1373                      0.0                     0.0                    1.0

      marital_status_Widowed
2082                     0.0
1319                     0.0
1569                     0.0
1257                     1.0
2096                     0.0
…                          …
1165                     0.0
1334                     0.0
626                      0.0
1901                     0.0
1373                     0.0

[2000 rows x 7 columns]
```

[ ]:
```python
#X_scaled_train = X_scaled_train.reset_index(drop=True)
#X_train = X_train.reset_index(drop=True)

X_train = pd.concat([X_scaled_train, X_train], axis=1)
X_train
```

[ ]:
```
      annual_income  employment_years  credit_score  open_credit_lines  \
2082       0.353133          0.585799      0.736434           0.272727
1319       0.728868          0.502959      0.746124           0.363636
1569       0.315634          0.804734      0.790698           0.090909
1257       0.505147          0.715976      0.862403           0.363636
2096       0.365286          0.355030      0.751938           0.181818
```

```
…           …                …            …                …
1165        0.229356         0.360947     0.565891         0.454545
1334        0.528182         0.532544     0.720930         0.272727
626         0.144714         0.266272     0.408915         0.181818
1901        0.347650         0.295858     0.598837         0.363636
1373        0.551098         0.384615     0.699612         0.454545

      debt_to_income_ratio  savings_ratio  asset_value       age  \
2082              0.229406       0.614782     0.168290  0.368421
1319              0.295099       0.577828     0.272491  0.719298
1569              0.666319       0.615901     0.081588  0.403509
1257              0.652763       0.450168     0.074018  0.929825
2096              0.222106       0.441209     0.122325  0.596491
…                      …             …          …        …
1165              0.325339       0.414334     0.143523  0.140351
1334              0.460897       0.438970     0.218494  0.877193
626               0.798749       0.275476     0.025263  0.473684
1901              0.223149       0.293393     0.066500  0.596491
1373              0.210636       0.615901     0.096954  0.807018

      education_level  residential_stability  job_stability_score  \
2082             0.25               0.189024                0.541
1319             0.75               0.335366                0.929
1569             0.50               0.231707                0.769
1257             0.25               0.353659                0.799
2096             1.00               0.439024                0.519
…                 …                     …                   …
1165             0.00               0.451220                0.829
1334             0.75               0.493902                0.830
626              0.50               0.176829                0.181
1901             0.75               0.469512                0.818
1373             1.00               0.609756                0.824

      credit_utilization  payment_history_score  marital_status_Divorced  \
2082               0.171                  0.815                      0.0
1319               0.219                  0.938                      0.0
1569               0.244                  0.815                      0.0
1257               0.046                  0.732                      0.0
2096               0.148                  0.949                      1.0
…                   …                      …                      …
1165               0.085                  0.932                      1.0
1334               0.063                  0.994                      0.0
626                0.922                  0.261                      1.0
1901               0.222                  0.905                      0.0
1373               0.271                  0.941                      0.0

      marital_status_Married  marital_status_Single  marital_status_Widowed
```

```
2082                    1.0                   0.0                     0.0
1319                    1.0                   0.0                     0.0
1569                    1.0                   0.0                     0.0
1257                    0.0                   0.0                     1.0
2096                    0.0                   0.0                     0.0
…                     …                    …                     …
1165                    0.0                   0.0                     0.0
1334                    0.0                   1.0                     0.0
626                     0.0                   0.0                     0.0
1901                    1.0                   0.0                     0.0
1373                    0.0                   1.0                     0.0

[2000 rows x 17 columns]
```

6 Section 4

key statistical assumptions that differentiate LDA and QDA

Antes de aplicar los modelos, se debe determinar las diferencias estádisticas de LDA y QDA.

LDA es un modelo de clasificación que se basa en identificar grupos al considerar que todas las variables tienen una convarianza lineal. Esto quiere decir que se asume que todas las variables provienen de una distribución Gaussiana. Por otra parte, QDA asume que las covarianzas son cuadraticas.

Multivariate Normality: observando los histogramas hechos anteriormente, se puede observar como es que las varibles no tienen una distribución Gaussiana en su mayoría.

Homogeneity of Covariance Matrices: utilizando las gráficas anteriores se observa como es que no hay una homogeniedad en las matrices de covarianza, ya que la distribución de cada variable es diferente.

Por lo tanto, se plantea la siguiente hipótesis: Si las matrices de covarancia son diferentes, entonces, se espera que el modelo QDA tenga mejores resultados que LDA.

7 Section 5 - Linear Discriminant Analysis (LDA)

[ ]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
import pandas as pd
import numpy as np


# Fit LDA model
lda = LinearDiscriminantAnalysis()
lda.fit(X_train, y_train)

# Extract coeficientes
```

```
coefficients = pd.DataFrame({
    'Feature': X_train.columns,
    'Coefficient': lda.coef_[0],
    'Abs_Coefficient': np.abs(lda.coef_[0])
}).sort_values(by='Abs_Coefficient', ascending=False)

coefficients
```

[ ]:

	Feature	Coefficient	Abs_Coefficient
12	payment_history_score	-53.807819	53.807819
10	job_stability_score	-44.244810	44.244810
11	credit_utilization	40.412427	40.412427
2	credit_score	-22.301436	22.301436
4	debt_to_income_ratio	19.025892	19.025892
5	savings_ratio	-14.100416	14.100416
1	employment_years	-11.452017	11.452017
9	residential_stability	-8.690222	8.690222
0	annual_income	-7.820056	7.820056
6	asset_value	-6.702356	6.702356
3	open_credit_lines	-6.581518	6.581518
8	education_level	-3.315865	3.315865
7	age	-1.423588	1.423588
15	marital_status_Single	1.099684	1.099684
14	marital_status_Married	-0.910776	0.910776
16	marital_status_Widowed	0.702136	0.702136
13	marital_status_Divorced	-0.163043	0.163043

[ ]:

```
lda.classes_
```

[ ]:

```
array([0, 1])
```

[ ]:

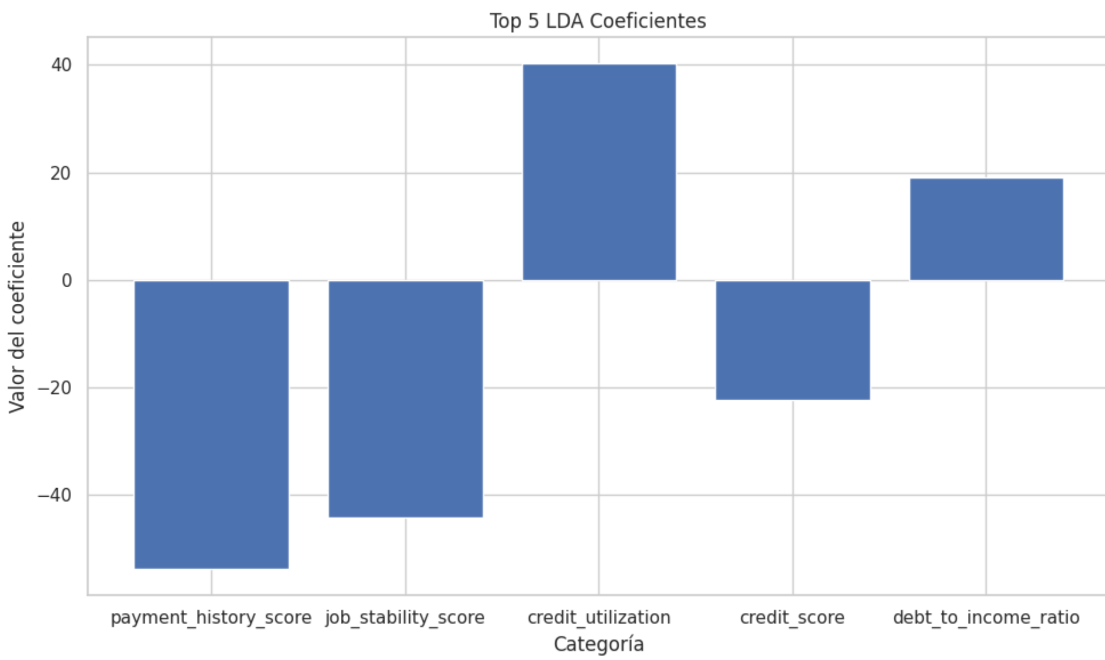
```
lda_scores = lda.transform(X_train)

lda_scores_df = pd.DataFrame(
    lda_scores,
    columns=[f"LD{i + 1}" for i in range(lda_scores.shape[1])],
)

lda_scores_df
```

[ ]:

	LD1
0	-1.471836
1	-4.005368
2	-1.634797
3	-2.193926
4	-2.033383
…	…

```
1995 -2.590404
1996 -3.692438
1997  8.446930
1998 -2.271978
1999 -3.304125

[2000 rows x 1 columns]
```

[ ]:
```python
# Show a simple bar chart of your top 3-5 LDA coefficients.
plt.figure(figsize=(10, 6))
plt.bar(coefficients['Feature'].head(5), coefficients['Coefficient'].head(5))
plt.xlabel('Categoría')
plt.ylabel('Valor del coeficiente')
plt.title('Top 5 LDA Coeficientes')
plt.tight_layout()
```



Observando los resultados anteriores, se puede identificar que las variables más importantes para predecir el riesgo deafult son:

- payment_history_score: -53.886626
- job_stability_score: -44.344218
- credit_utilization: 40.498805
- credit_score: -22.401797
- debt_to_income_ratio: 19.031001

Asismismo, se encontró que cuando el valor del coeficiente es positivo, es significa que cuando la variables incrementa, entonces el riesgo de ser default también. Por el contrario, si este es negativo, se tiene menos riesgo.

Por lo tanto, las variables que al crecer hacen que haya menos riesgo de tener un estado default, son payment_history_score, job_stability_score y credit_score. Por su parte, las variables que hacen que haya más riesgo son credit_utilization y debt_to_income_ratio.

Esto sugiere que al tener un mejor historial crediticio, tener un empleo estabile y un buen score crediticio, la persona tendrá menos riesgo a tener deudas de prestamos. Mientras que si hay un mal uso del credito, esto es si se gasta más de lo que se tiene en el crédito y si se tiene una alta deuda sobre lo que genera, entonces, es hay un riesgo más alto de ser default.

A continuación se realizara el modelo QDA para evaluar si la hipótesis de acepta o se rechaza.

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

[ ]:
```
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis

# Fit Quadratic Discriminant Analysis
qda = QuadraticDiscriminantAnalysis()
qda.fit(X_train, y_train)
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/discriminant_analysis.py:1024:
LinAlgWarning: The covariance matrix of class 0 is not full rank. Increasing the
value of parameter `reg_param` might help reducing the collinearity.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/sklearn/discriminant_analysis.py:1024:
LinAlgWarning: The covariance matrix of class 1 is not full rank. Increasing the
value of parameter `reg_param` might help reducing the collinearity.
  warnings.warn(
```

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

QDA no produce coeficientes lineales simples, por lo que no es posible realizar una interpetación en este caso.

A continuación se hara una comparación entre ambos modelos, para encontrar el mejor en este caso.

9 Section 7: Model Evaluation & Comparison

[ ]:
```
# Se debe de escalar X_test para que quede en las mismas dimensiones
X_train_fixed = X_train.copy()
X_train_fixed[columnas_a_escalar] = X_scaled_train



# Escalar columnas númericas
X_test_scaled_part = pd.DataFrame(
    scaler.transform(X_test[columnas_a_escalar]),
```

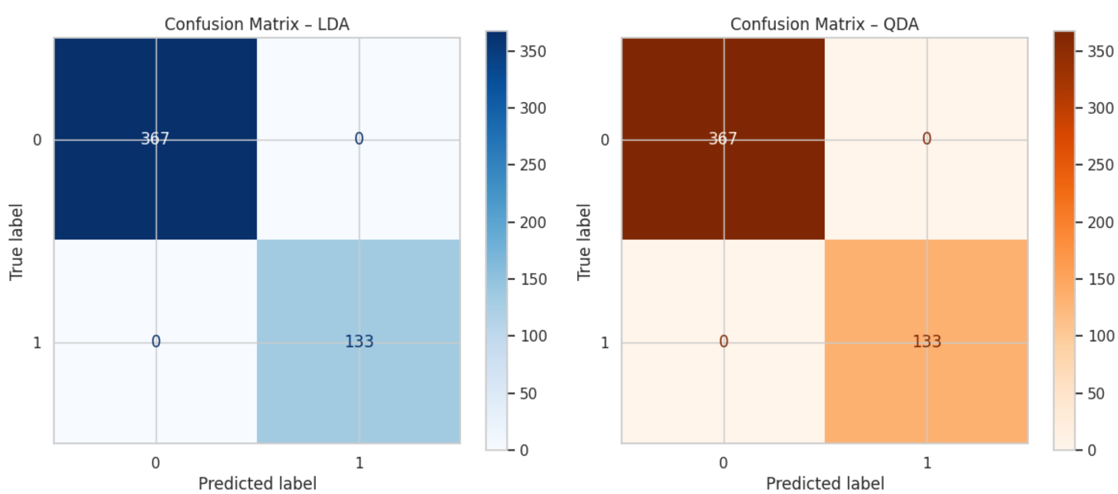
```
    columns=columnas_a_escalar,
    index=X_test.index
)

# Mantener el resto de las columnas igual
other_cols = [c for c in X_train_fixed.columns if c not in columnas_a_escalar]


# Juntar ambas partes, la escalada y el resto
X_test_pred = pd.concat([X_test_scaled_part, X_test[other_cols]], axis=1)

# Reordenar columnas como en X_train

feature_order = X_train_fixed.columns

X_test_pred = X_test_pred[feature_order]
```

[ ]:

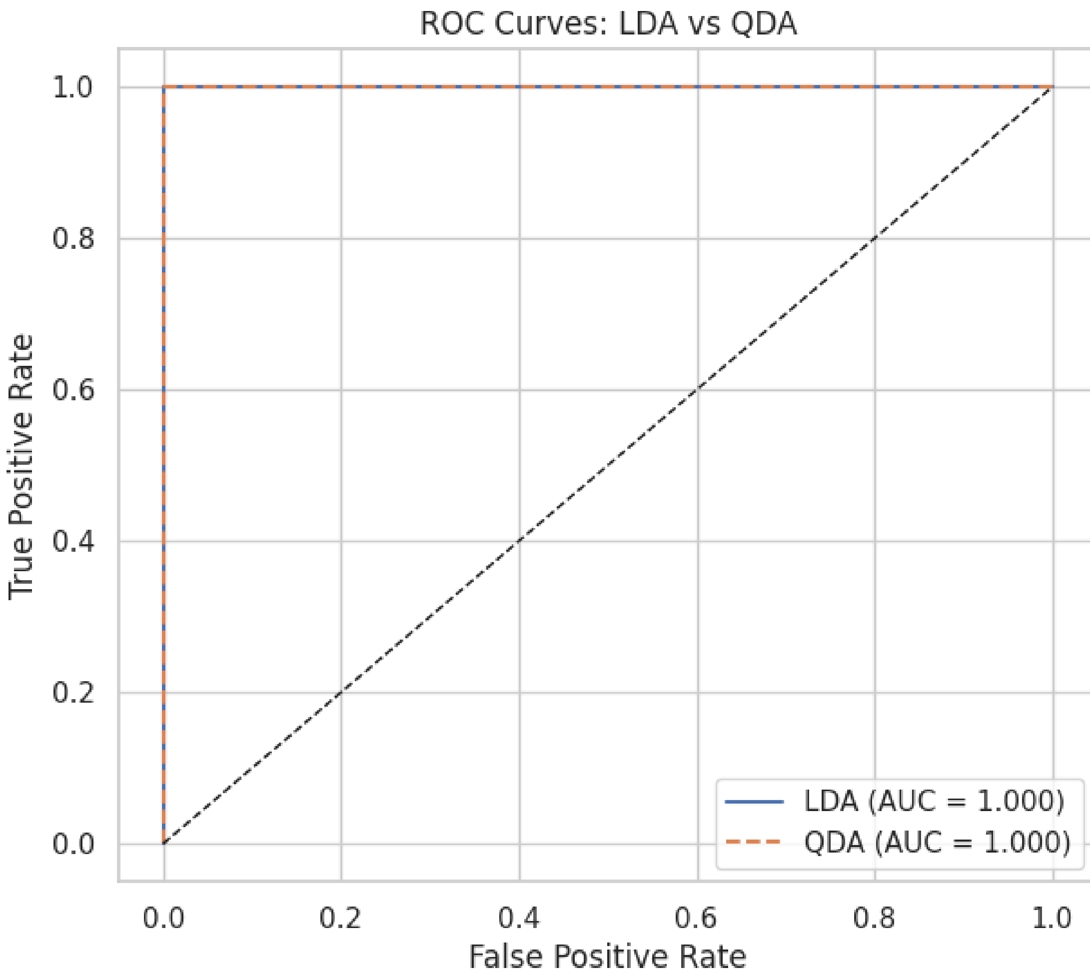
```
from sklearn.metrics import ConfusionMatrixDisplay, classification_report,␣
 ↪roc_curve, roc_auc_score
from sklearn.metrics import precision_score, recall_score, f1_score
import time


# Predicciones
start_lda = time.time()
y_pred_lda = lda.predict(X_test_pred)
end_lda = time.time()

start_qda = time.time()
y_pred_qda = qda.predict(X_test_pred)
end_qda = time.time()

# Tiempo de ejecución
lda_time = end_lda - start_lda
qda_time = end_qda - start_qda

print(f"Tiempo de predicción LDA: {lda_time:.6f} segundos")
print(f"Tiempo de predicción QDA: {qda_time:.6f} segundos")


# Generar matrices de correlación
fig, ax = plt.subplots(1, 2, figsize=(12, 5))
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_lda, ax=ax[0],␣
 ↪cmap="Blues")
ax[0].set_title("Confusion Matrix - LDA")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_qda, ax=ax[1],␣
 ↪cmap="Oranges")
```

```
ax[1].set_title("Confusion Matrix - QDA")
plt.tight_layout(); plt.show()


# Reporte de Clasificación
print("=== Classification Report: LDA ===")
print(classification_report(y_test, y_pred_lda))


print("\n=== Classification Report: QDA ===")
print(classification_report(y_test, y_pred_qda))

# Generate the RocCurveDisplay
y_prob_lda = lda.predict_proba(X_test_pred)[:, 1]
y_prob_qda = qda.predict_proba(X_test_pred)[:, 1]

fpr_lda, tpr_lda, _ = roc_curve(y_test, y_prob_lda)
fpr_qda, tpr_qda, _ = roc_curve(y_test, y_prob_qda)
auc_lda = roc_auc_score(y_test, y_prob_lda)
auc_qda = roc_auc_score(y_test, y_prob_qda)

plt.figure(figsize=(7, 6))
plt.plot(fpr_lda, tpr_lda, label=f"LDA (AUC = {auc_lda:.3f})")
plt.plot(fpr_qda, tpr_qda, label=f"QDA (AUC = {auc_qda:.3f})", linestyle="--")
plt.plot([0,1],[0,1],'k--', lw=1)
plt.xlabel("False Positive Rate"); plt.ylabel("True Positive Rate")
plt.title("ROC Curves: LDA vs QDA"); plt.legend(); plt.grid(True); plt.show()

print(f"AUC (LDA): {auc_lda:.3f}")
print(f"AUC (QDA): {auc_qda:.3f}")
```

```
Tiempo de predicción LDA: 0.002320 segundos
Tiempo de predicción QDA: 0.002247 segundos
```



```
=== 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
```




```
AUC (LDA): 1.000
AUC (QDA): 1.000
```

10 Section 8: Technical Conclusion & Model Selection

Observando, los resultados, se observa que ambos modelos logran clasificar el estatus de deuda al 100%, en todas las métricas. Asimismo, se midió el tiempo de ejecución de ambos modelos para observar cuál es más rápido. En este caso, se puede observar que el modelo que tarda menos es el de QDA, aunque la diferencia de tiempo es pequeña, por lo que no se puede concluir que el modelo es significativamente más rápido.

Por lo tanto, se rechaza la hipótesis, ya que a pesar de tener una matriz de covarianza diferente, el modelo LDA se comportó de la misma manera que el QDA. Por lo tanto, la elección de un modelo es indiferente; ambos resultados dan lo mismo. Sin embargo, en caso de que la empresa busque eficiencia, el mejor modelo es QDA, aunque el tiempo de diferencia es relativamente el mismo.

Es importante mencionar que en este caso lo que se quiere reducir el número de falsos negativos, ya que se busca evitar que los clientes con deudas, sean seleccionados como personas sin deudas. De igual manera, se busca reducir el número de falsos positivos, ya que esto haría que la empresa no seleccionara a clientes sin deuda. Lo que sería un resultado no deseado, ya que la empresa busca reducir la probabilidad de que las personas tengan una deuda default. Por lo tanto, la métrica que tiene más importancia en este caso es F1-score, ya que se busca tener un balance harmónico entre la precisión y sensibilidad.

Por ende, en este caso, es de mayor importancia observar el f1_score, aunque como se mencionó anteirormente, en este caso ambos modelos lograron un resultado del 100%.

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