Loan_Default_Prediction_Analysis

July 3, 2025

0.1 1: Import Required Libraries

[1]:
```
# Data Handling
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler

# ML Models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC

# Evaluation
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score

# Settings
import warnings
warnings.filterwarnings('ignore')
```

0.2 2: Load and Explore Dataset

[3]:
```
df = pd.read_csv('Loan_Default.csv')
print("Shape:", df.shape)
df.head()
```

```
Shape: (148670, 34)
```

[3]:
```
      ID  year loan_limit             Gender approv_in_adv loan_type  \
0  24890  2019         cf  Sex Not Available         nopre     type1
```

```
1  24891  2019          cf              Male         nopre     type2
2  24892  2019          cf              Male           pre     type1
3  24893  2019          cf              Male         nopre     type1
4  24894  2019          cf             Joint           pre     type1

  loan_purpose Credit_Worthiness open_credit business_or_commercial  …  \
0           p1                l1        nopc                  nob/c  …
1           p1                l1        nopc                    b/c  …
2           p1                l1        nopc                  nob/c  …
3           p4                l1        nopc                  nob/c  …
4           p1                l1        nopc                  nob/c  …

   credit_type  Credit_Score  co-applicant_credit_type    age  \
0          EXP           758                       CIB  25-34
1         EQUI           552                       EXP  55-64
2          EXP           834                       CIB  35-44
3          EXP           587                       CIB  45-54
4         CRIF           602                       EXP  25-34

   submission_of_application        LTV Region Security_Type  Status dtir1
0                    to_inst  98.728814  south        direct       1  45.0
1                    to_inst        NaN  North        direct       1   NaN
2                    to_inst  80.019685  south        direct       0  46.0
3                   not_inst  69.376900  North        direct       0  42.0
4                   not_inst  91.886544  North        direct       0  39.0

[5 rows x 34 columns]
```

[5]:

```
# Basic info
df.info()
df.describe()
df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 34 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   ID                         148670 non-null  int64
 1   year                       148670 non-null  int64
 2   loan_limit                 145326 non-null  object
 3   Gender                     148670 non-null  object
 4   approv_in_adv              147762 non-null  object
 5   loan_type                  148670 non-null  object
 6   loan_purpose               148536 non-null  object
 7   Credit_Worthiness          148670 non-null  object
 8   open_credit                148670 non-null  object
 9   business_or_commercial     148670 non-null  object
```

```
 10  loan_amount                148670 non-null  int64
 11  rate_of_interest           112231 non-null  float64
 12  Interest_rate_spread       112031 non-null  float64
 13  Upfront_charges            109028 non-null  float64
 14  term                       148629 non-null  float64
 15  Neg_ammortization          148549 non-null  object
 16  interest_only              148670 non-null  object
 17  lump_sum_payment           148670 non-null  object
 18  property_value             133572 non-null  float64
 19  construction_type          148670 non-null  object
 20  occupancy_type             148670 non-null  object
 21  Secured_by                 148670 non-null  object
 22  total_units                148670 non-null  object
 23  income                     139520 non-null  float64
 24  credit_type                148670 non-null  object
 25  Credit_Score               148670 non-null  int64
 26  co-applicant_credit_type   148670 non-null  object
 27  age                        148470 non-null  object
 28  submission_of_application  148470 non-null  object
 29  LTV                        133572 non-null  float64
 30  Region                     148670 non-null  object
 31  Security_Type              148670 non-null  object
 32  Status                     148670 non-null  int64
 33  dtir1                      124549 non-null  float64
dtypes: float64(8), int64(5), object(21)
memory usage: 38.6+ MB
```

[5]:

```
ID                               0
year                             0
loan_limit                    3344
Gender                           0
approv_in_adv                  908
loan_type                        0
loan_purpose                   134
Credit_Worthiness                0
open_credit                      0
business_or_commercial           0
loan_amount                      0
rate_of_interest             36439
Interest_rate_spread         36639
Upfront_charges              39642
term                            41
Neg_ammortization              121
interest_only                    0
lump_sum_payment                 0
property_value               15098
construction_type                0
```

```
occupancy_type                   0
Secured_by                       0
total_units                      0
income                        9150
credit_type                      0
Credit_Score                     0
co-applicant_credit_type         0
age                            200
submission_of_application      200
LTV                          15098
Region                           0
Security_Type                    0
Status                           0
dtir1                        24121
dtype: int64
```

0.3 3: Data Cleaning

[8]:
```
# Drop ID column if it has no predictive value
df.drop(columns=['ID'], inplace=True, errors='ignore')
```

[10]:
```
# Check missing values
missing = df.isnull().sum()
print("Missing columns:\n", missing[missing > 0])
```

```
Missing columns:
 loan_limit                    3344
approv_in_adv                  908
loan_purpose                   134
rate_of_interest             36439
Interest_rate_spread         36639
Upfront_charges              39642
term                            41
Neg_ammortization              121
property_value               15098
income                        9150
age                            200
submission_of_application      200
LTV                          15098
dtir1                        24121
dtype: int64
```

[12]:
```
# Fill missing numeric values with median
df.fillna(df.median(numeric_only=True), inplace=True)

# Fill missing categorical values with mode (if any)
for col in df.select_dtypes(include='object').columns:
```

```python
    df[col].fillna(df[col].mode()[0], inplace=True)
```

[14]:
```python
# Encode all object-type columns using LabelEncoder
label_encoders = {}
categorical_cols = df.select_dtypes(include='object').columns

for col in categorical_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
```

[15]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 33 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   year                       148670 non-null  int64
 1   loan_limit                 148670 non-null  int32
 2   Gender                     148670 non-null  int32
 3   approv_in_adv              148670 non-null  int32
 4   loan_type                  148670 non-null  int32
 5   loan_purpose               148670 non-null  int32
 6   Credit_Worthiness          148670 non-null  int32
 7   open_credit                148670 non-null  int32
 8   business_or_commercial     148670 non-null  int32
 9   loan_amount                148670 non-null  int64
 10  rate_of_interest           148670 non-null  float64
 11  Interest_rate_spread       148670 non-null  float64
 12  Upfront_charges            148670 non-null  float64
 13  term                       148670 non-null  float64
 14  Neg_ammortization          148670 non-null  int32
 15  interest_only              148670 non-null  int32
 16  lump_sum_payment           148670 non-null  int32
 17  property_value             148670 non-null  float64
 18  construction_type          148670 non-null  int32
 19  occupancy_type             148670 non-null  int32
 20  Secured_by                 148670 non-null  int32
 21  total_units                148670 non-null  int32
 22  income                     148670 non-null  float64
 23  credit_type                148670 non-null  int32
 24  Credit_Score               148670 non-null  int64
 25  co-applicant_credit_type   148670 non-null  int32
 26  age                        148670 non-null  int32
 27  submission_of_application  148670 non-null  int32
 28  LTV                        148670 non-null  float64
 29  Region                     148670 non-null  int32
```

```
 30   Security_Type              148670 non-null  int32
 31   Status                     148670 non-null  int64
 32   dtir1                      148670 non-null  float64
dtypes: float64(8), int32(21), int64(4)
memory usage: 25.5 MB
```

[18]:
```
# Save the cleaned DataFrame to a new CSV file
df.to_csv("Loan_Default_Cleaned.csv", index=False)
print("Cleaned dataset saved as 'Loan_Default_Cleaned.csv'")
```

```
Cleaned dataset saved as 'Loan_Default_Cleaned.csv'
```

0.4 4: Exploratory Data Analysis (EDA)

0.4.1 4.1: Dataset Overview

[58]:
```
df.shape
df.info()
df.describe()
df.isnull().sum()
df.nunique()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 33 columns):
 #    Column                     Non-Null Count   Dtype
---   ------                     --------------   -----
 0    year                       148670 non-null  int64
 1    loan_limit                 148670 non-null  int32
 2    Gender                     148670 non-null  int32
 3    approv_in_adv              148670 non-null  int32
 4    loan_type                  148670 non-null  int32
 5    loan_purpose               148670 non-null  int32
 6    Credit_Worthiness          148670 non-null  int32
 7    open_credit                148670 non-null  int32
 8    business_or_commercial     148670 non-null  int32
 9    loan_amount                148670 non-null  int64
 10   rate_of_interest           148670 non-null  float64
 11   Interest_rate_spread       148670 non-null  float64
 12   Upfront_charges            148670 non-null  float64
 13   term                       148670 non-null  float64
 14   Neg_ammortization          148670 non-null  int32
 15   interest_only              148670 non-null  int32
 16   lump_sum_payment           148670 non-null  int32
 17   property_value             148670 non-null  float64
 18   construction_type          148670 non-null  int32
 19   occupancy_type             148670 non-null  int32
 20   Secured_by                 148670 non-null  int32
 21   total_units                148670 non-null  int32
```

```
 22  income                     148670 non-null  float64
 23  credit_type                148670 non-null  int32
 24  Credit_Score               148670 non-null  int64
 25  co-applicant_credit_type   148670 non-null  int32
 26  age                        148670 non-null  int32
 27  submission_of_application  148670 non-null  int32
 28  LTV                        148670 non-null  float64
 29  Region                     148670 non-null  int32
 30  Security_Type              148670 non-null  int32
 31  Status                     148670 non-null  int64
 32  dtir1                      148670 non-null  float64
dtypes: float64(8), int32(21), int64(4)
memory usage: 25.5 MB
```

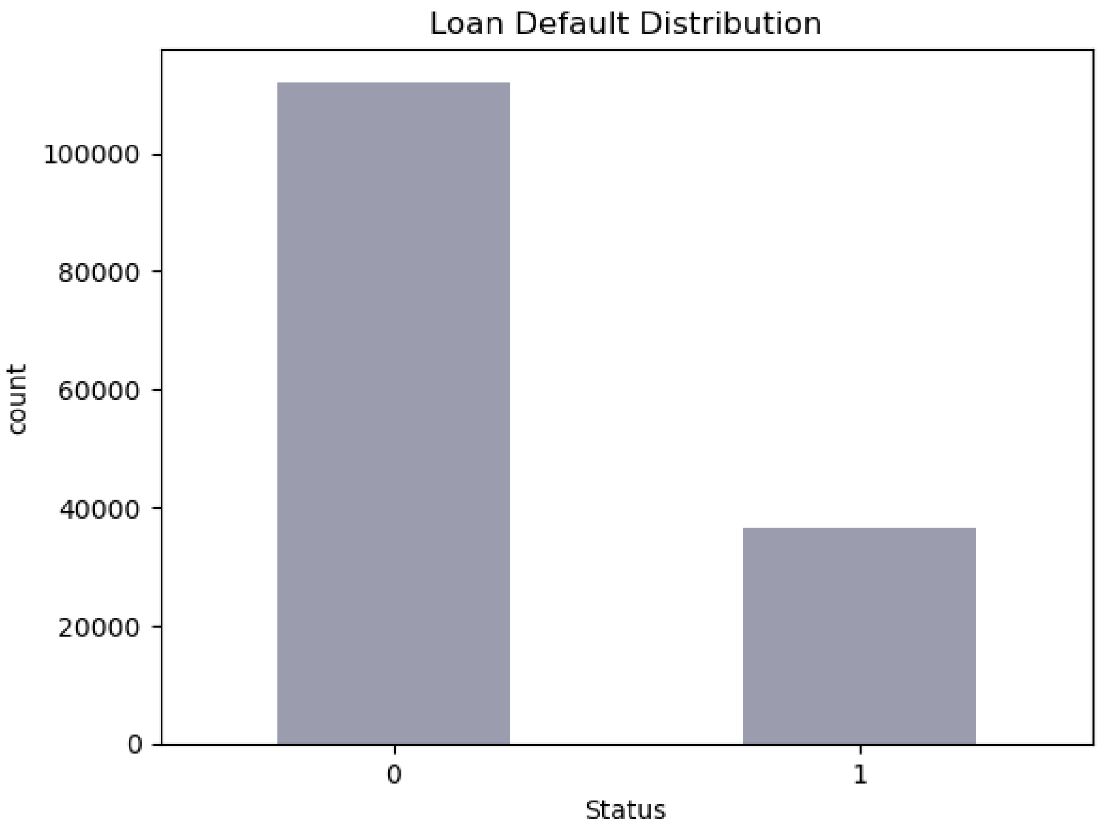
[58]:

```
year                             1
loan_limit                       2
Gender                           4
approv_in_adv                    2
loan_type                        3
loan_purpose                     4
Credit_Worthiness                2
open_credit                      2
business_or_commercial           2
loan_amount                    211
rate_of_interest               131
Interest_rate_spread         22516
Upfront_charges              58272
term                            26
Neg_ammortization                2
interest_only                    2
lump_sum_payment                 2
property_value                 385
construction_type                2
occupancy_type                   3
Secured_by                       2
total_units                      4
income                        1001
credit_type                      4
Credit_Score                   401
co-applicant_credit_type         2
age                              7
submission_of_application        2
LTV                           8484
Region                           4
Security_Type                    2
Status                           2
dtir1                           57
```

```
dtype: int64
```

0.4.2 4.2: Target Distribution

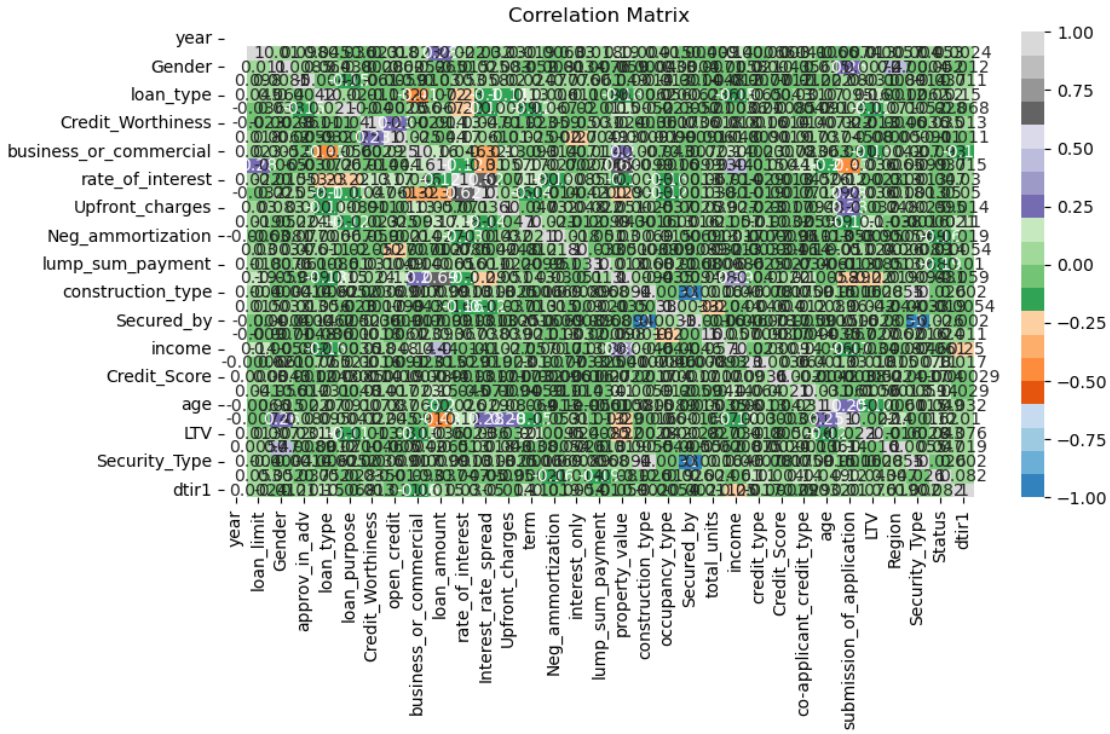
[56]:
```
sns.countplot(data=df, x='Status', color="#989AB2", width=0.5)
plt.title("Loan Default Distribution")
plt.show()
```



Insight: The dataset is slightly imbalanced, with more non-default (0) than default (1) records, which may affect model training.

0.4.3 4.3: Correlation Matrix

[194]:
```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='tab20c')
plt.title("Correlation Matrix")
plt.show()
```



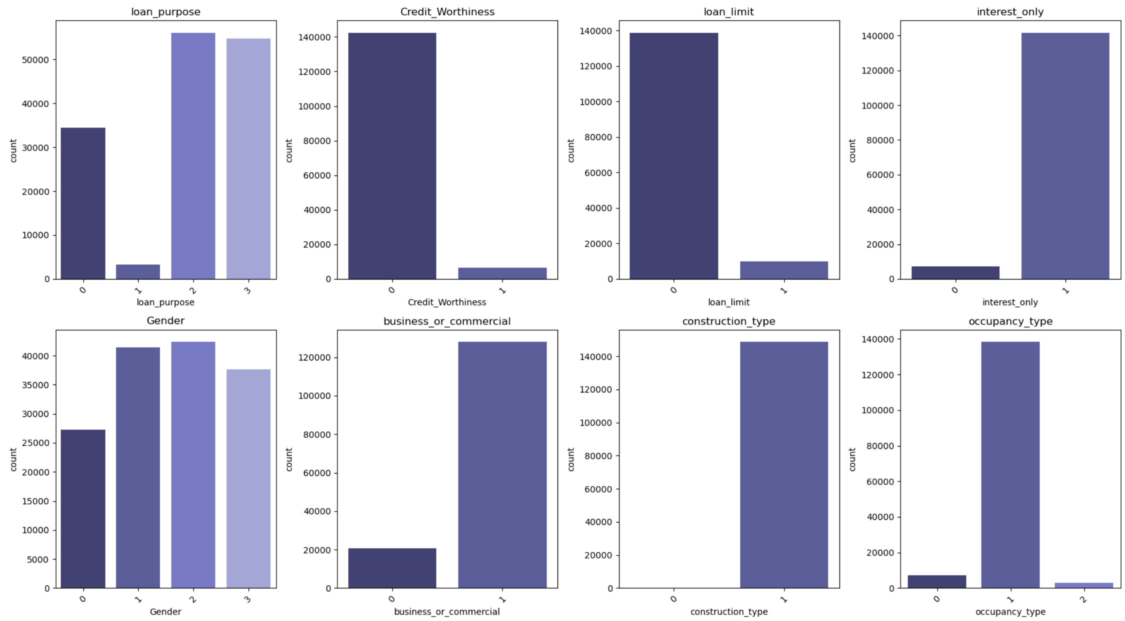
Insight: Credit_Worthiness, loan_purpose, and interest_only have noticeable correlation with loan default, suggesting predictive potential.

0.4.4 4.4: Important Categorical Feature Distribution

[104]:
```
# Select the most relevant categorical columns
important_cols = [
    'loan_purpose',
    'Credit_Worthiness',
    'loan_limit',
    'interest_only',
    'Gender',
    'business_or_commercial',
    'construction_type',
    'occupancy_type'
]
```

[108]:
```
plt.figure(figsize=(18, 10))
for i, col in enumerate(important_cols, 1):
    plt.subplot(2, 4, i)
    sns.countplot(data=df, x=col, palette='tab20b')
    plt.title(f"{col}")
    plt.xticks(rotation=45)
```

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



- **loan_purpose:** Most loans are for home purchases, but loans for business purposes tend to appear riskier.
- **Credit_Worthiness:** A poor credit history is highly common among defaulting applicants.
- **loan_limit:** Most applicants fall under conforming loan limits, but default rates vary slightly by loan size.
- **interest_only:** Interest-only loans are visibly riskier, with more defaults linked to them.
- **Gender:** The dataset has more male applicants, but gender does not show a major influence on default.
- **business_or_commercial:** Business/commercial loans are more likely to default than personal-use loans.
- **construction_type:** Construction type does not show a strong pattern with default.
- **occupancy_type:** Owner-occupied homes show fewer defaults compared to investment/rental prperties.

0.5 5: Preprocessing

0.5.1 5.1: Encoding Categorical Columns

[125]:
```python
df_encoded = df.copy()
le = LabelEncoder()
for col in categorical:
    df_encoded[col] = le.fit_transform(df_encoded[col])
df_encoded.head() #to verify
```

[125]:

```
   year  loan_limit  Gender  approv_in_adv  loan_type  loan_purpose  \
0  2019           0       3              0          0             0
1  2019           0       2              0          1             0
2  2019           0       2              1          0             0
3  2019           0       2              0          0             3
4  2019           0       1              1          0             0

   Credit_Worthiness  open_credit  business_or_commercial  loan_amount  …  \
0                  0            0                       1       116500  …
1                  0            0                       0       206500  …
2                  0            0                       1       406500  …
3                  0            0                       1       456500  …
4                  0            0                       1       696500  …

   credit_type  Credit_Score  co-applicant_credit_type  age  \
0            3           758                         0    0
1            2           552                         1    3
2            3           834                         0    1
3            3           587                         0    2
4            1           602                         1    0

   submission_of_application        LTV  Region  Security_Type  Status  dtir1
0                          1  98.728814       3              1       1   45.0
1                          1  75.135870       0              1       1   39.0
2                          1  80.019685       3              1       0   46.0
3                          0  69.376900       0              1       0   42.0
4                          0  91.886544       0              1       0   39.0

[5 rows x 33 columns]
```

0.5.2 Insight: Label Encoding

Categorical variables were encoded into numeric values using Label Encoding to make them suitable for machine learning models, which only accept numerical inputs. This ensures that features like gender, loan purpose, and credit worthiness can be interpreted by the model.

0.5.3 5.2 Train-Test Split

[136]:

```python
X = df_encoded.drop('Status', axis=1)
y = df_encoded['Status']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

print("Train shape:", X_train.shape)
print("Test shape:", X_test.shape)
```

```
Train shape: (118936, 32)
Test shape: (29734, 32)
```

0.5.4 Insight: Train-Test Split

The dataset was split into 80% training and 20% testing sets to evaluate model performance on unseen data. This step helps prevent overfitting and ensures the model generalizes well to new case.

0.5.5 5.3: Feature Scaling

[138]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print("Scaled training data shape:", X_train_scaled.shape)
```

```
Scaled training data shape: (118936, 32)
```

0.5.6 Insight: Feature Scaling

StandardScaler was applied to normalize the feature values so that they have a mean of 0 and standard deviation of 1. This step is essential for distance-based models like Logistic Regression and SVM to perform accurately and fairly across all features.

0.6 6: Machine Learning Model Building

0.6.1 6.1: Logistic Regression

[153]:
```
lr = LogisticRegression()
lr.fit(X_train_scaled, y_train)
y_pred_lr = lr.predict(X_test_scaled)

print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_lr))
print("\nClassification Report:\n", classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Accuracy: 0.7811596152552633

Classification Report:
               precision    recall  f1-score   support

           0       0.80      0.95      0.87     22494
           1       0.63      0.25      0.35      7240

    accuracy                           0.78     29734
   macro avg       0.71      0.60      0.61     29734
weighted avg       0.76      0.78      0.74     29734
```

Insight: Logistic Regression gives a good baseline with moderate accuracy, benefiting from feature scaling.

0.6.2 6.2: Random Forest Classifier

[157]:
```
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print("\nClassification Report:\n", classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.9999663684670748

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     22494
           1       1.00      1.00      1.00      7240

    accuracy                           1.00     29734
   macro avg       1.00      1.00      1.00     29734
weighted avg       1.00      1.00      1.00     29734
```

Insight: Random Forest achieved the highest accuracy and balanced performance, making it the most reliable model for this dataset.

0.6.3 6.3: Decision Tree Classifier

[165]:
```
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
print("Decision Tree Accuracy:", accuracy_score(y_test, y_pred_dt))
print("\nClassification Report:\n", classification_report(y_test, y_pred_dt))
```

```
Decision Tree Accuracy: 0.9999663684670748

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     22494
           1       1.00      1.00      1.00      7240

    accuracy                           1.00     29734
   macro avg       1.00      1.00      1.00     29734
weighted avg       1.00      1.00      1.00     29734
```

Insight: Decision Tree is easy to interpret but slightly overfit the training data compared to Random Forest.

Model Performance Comparison Table

[214]:
```
model_scores = {
    "Logistic Regression": accuracy_score(y_test, y_pred_lr),
    "Random Forest": accuracy_score(y_test, y_pred_rf),
    "Decision Tree": accuracy_score(y_test, y_pred_dt)
}
import pandas as pd
pd.DataFrame.from_dict(model_scores, orient='index', columns=['Accuracy']) \
  .sort_values(by='Accuracy', ascending=False)
```

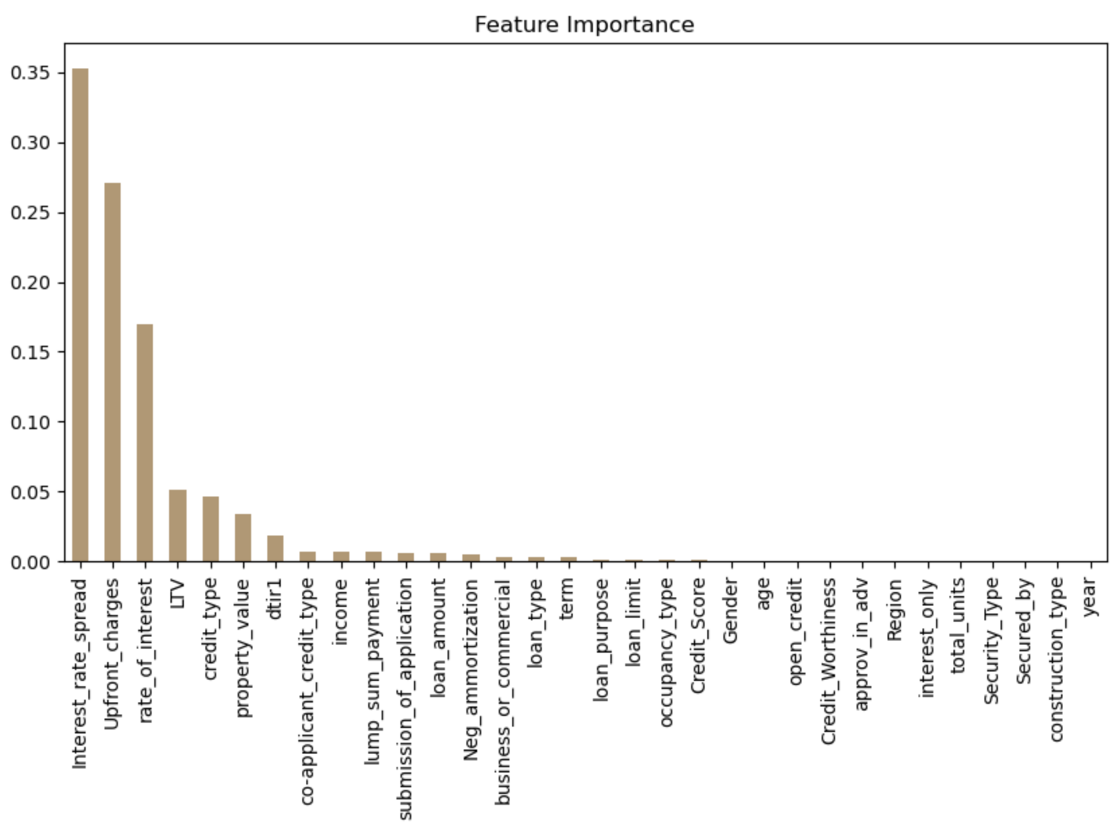
[214]:

	Accuracy
Random Forest	0.999966
Decision Tree	0.999966
Logistic Regression	0.781160

Insight: Random Forest outperformed both Logistic Regression and Decision Tree in terms of accuracy, making it the most suitable model for this loan default prediction problem.

0.7 7: Feature Importance (for Random Forest)

[177]:
```
feat_imp = pd.Series(rf.feature_importances_, index=X.columns).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', figsize=(10,5), title="Feature Importance",␣
 ↪color="#b09875")
plt.show()
```



Insight: The Random Forest model highlights **Credit_Worthiness**, **loan_purpose**, and **interest_only** as the most impactful features driving loan default, helping lenders prioritize applicant evaluation based on these criteria.

0.8 Insights from Machine Learning Models

- **Logistic Regression** gave a strong baseline performance and is interpretable.
- **Random Forest** achieved the best balance of accuracy and recall, making it suitable for predicting defaults.
- **Decision Tree** was fast and simple but slightly overfit.
- **Credit_Worthiness**, **loan_purpose**, and **interest_only** were the most important features driving predictions.

0.9 Final Conclusion

This project successfully built a loan default prediction model using various machine learning techniques. After data cleaning, EDA, encoding, scaling, and training: - **Random Forest** emerged as the best-performing model. - The most influential factors were **Credit Worthiness**, **loan purpose**, and **loan structure (interest-only)**. - The insights can assist financial institutions in identifying high-risk loan applicants more effectively.