project2

April 11, 2025

1 Machine Learning in Python - Project 2

Due Friday, Apr 11th by 4 pm.

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1.1 Setup

[1]:
```
# Data libraries
import pandas as pd
import numpy as np
# Plotting libraries
import matplotlib.pyplot as plt
import seaborn as sns
# Plotting defaults
plt.rcParams['figure.figsize'] = (8,5)
plt.rcParams['figure.dpi'] = 80
# sklearn modules
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
↪StratifiedKFold
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder, StandardScaler,␣
↪PowerTransformer
from sklearn.compose import ColumnTransformer
from sklearn.metrics import (
    classification_report, accuracy_score, precision_score, recall_score,␣
↪f1_score,
    roc_auc_score, confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay,␣
↪PrecisionRecallDisplay
)
# Imbalanced-learn modules
from imblearn.pipeline import Pipeline as ImPipeline
from imblearn.over_sampling import SMOTE
# XGBoost
from xgboost import XGBClassifier
# SHAP
import shap
```

```
# Skewness
from scipy.stats import skew, probplot
# Statsmodels for VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

```
[2]: # Load data in freddiemac.csv with specific dtype handling for categorical and␣
     ↪coded columns
     d = pd.read_csv("freddiemac.csv", dtype={
         'cd_msa': str, 'cnt_units': str, 'cnt_borr': str, 'zipcode': str,␣
     ↪'id_loan_rr': str, 'rr_ind':str, 'property_val': str
     })
```

2 Introduction

Mortgage default prediction plays a critical role in credit risk assessment and portfolio management, particularly for large institutions such as Freddie Mac. Early identification of high-risk loans allows lenders to take proactive measures, reduce potential losses, and comply with regulatory requirements. This project develops a machine learning model to predict the likelihood of loan default using historical data from Freddie Mac's Single-Family Loan-Level Dataset (2017–2020).

The dataset includes over 120,000 completed loans, with features covering borrower demographics, credit indicators (e.g., FICO score, DTI, LTV), loan structure, property characteristics, and loan outcomes (prepaid or defaulted). To prepare the data for modeling, we conduct preprocessing steps including missing value imputation, categorical encoding, numerical transformation to correct skewness, and interaction feature engineering to capture combined risk signals.

We begin with exploratory data analysis (EDA) to understand the distribution of key variables and the relationships between borrower characteristics and default risk. Logistic regression is used as a baseline model, followed by XGBoost as the final model due to its strong performance with imbalanced, tabular data. Hyperparameter tuning is performed using randomized search with cross-validation, and model explainability is addressed using SHAP values.

Results show that FICO score is the most influential predictor, while other important features include DTI, borrower count, and interaction terms such as LTV $\times$ DTI. The final XGBoost model achieved a recall of 69.8%, ROC-AUC of 0.7656, and significantly improved performance over the baseline. These findings demonstrate that machine learning, when properly calibrated and interpreted, can provide an effective and transparent tool for identifying loans at risk of default and informing risk management decisions.

3 Exploratory Data Analysis and Feature Engineering

This section explores the structure and quality of the dataset to prepare it for predictive modeling. We begin by filtering and inspecting the target variable, handling missing data, and removing irrelevant or redundant columns.

The dataset is then split into training and testing sets to avoid data leakage. Exploratory analysis is performed on numerical and categorical variables to identify trends and potential predictors of loan default. Finally, we apply appropriate transformations and create new features to improve model performance.

3.1 Filter Active Loans and Check Target Distribution

To ensure our modeling task only focuses on completed loan outcomes, we first filter out active loans. We then examine the distribution of the target variable (loan_status) to understand class imbalance and motivate later adjustments in modeling strategy.

[3]:
```python
# Filter out active loans (only keep 'default' and 'prepaid')
d_filtered = d[d['loan_status'].isin(['default', 'prepaid'])].copy()
d_filtered['loan_status'] = d_filtered['loan_status'].map({'default': 1,␣
↪'prepaid': 0})
print("Data shape after filtering active loans:", d_filtered.shape)

# Check target distribution
target_dist = d_filtered['loan_status'].value_counts(normalize=True) * 100
print("\nTarget Distribution (%):")
print(target_dist)
```

```
Data shape after filtering active loans: (126705, 33)

Target Distribution (%):
loan_status
0    99.411231
1     0.588769
Name: proportion, dtype: float64
```

We first filter out active loans and retain only those labeled as "prepaid" and "default". These are encoded as 0 and 1 respectively for binary classification.

After filtering, we are left with 126,705 loan records. However, only 0.59% of them are defaults, confirming a highly imbalanced target distribution. This imbalance poses challenges for classification and will be explicitly addressed in later stages of the pipeline.

3.2 Find Missing Values and Drop Features

Here, we identifiy columns with excessive missingness or low informational value.

[4]:
```python
# Define not available values as missing values
missing_values = {'fico': [9999], 'flag_fthb': ['9'], 'mi_pct': [999],␣
↪'cnt_units': ['99'], 'occpy_sts': ['9'],
                  'cltv': [999], 'dti': [999], 'ltv': [999], 'channel': ['9'],␣
↪'prop_type': ['99'], 'loan_purpose': ['9'],
                  'program_ind': ['9'], 'property_val': ['9'], 'mi_cancel_ind':␣
↪['7', '9'], 'flag_sc': ['N'], 'rr_ind': ['N']
}
# Replace missing values with NaN
for col, codes in missing_values.items():
```

```
    d_filtered[col] = d_filtered[col].replace(codes, np.nan)

# Check for missing values
missing_values = d_filtered.isna().sum().sort_values(ascending=False)
missing_percent = (missing_values / len(d_filtered)) * 100
missing_df = pd.DataFrame({'Missing Count': missing_values, 'Percentage (%)':␣
 ↪missing_percent})[missing_values > 0]
print("Missing Values in Training Data:")
print(missing_df)
```

```
Missing Values in Training Data:
               Missing Count  Percentage (%)
id_loan_rr            125406       98.974784
rr_ind                125406       98.974784
flag_sc               121241       95.687621
program_ind           116496       91.942702
mi_cancel_ind          87026       68.683951
cd_msa                 11294        8.913618
dti                     1304        1.029162
property_val              94        0.074188
fico                      24        0.018942
ltv                        1        0.000789
mi_pct                     1        0.000789
cltv                       1        0.000789
```

Many features contain placeholder values indicating missingness (e.g., '9', '999', 'N'). These are first replaced with standard NaN. We then examine the proportion of missing data per column. Features such as id_loan_rr, rr_ind, and flag_sc have over 90% missing values, making them unsuitable for modeling.

Next step we will remove features that are mostly missing, constant across all rows, or irrelevant for prediction (e.g., IDs and redundant date fields).

[5]:
```
print("Columns to drop:")
# Check for columns with >90% missing values
missing_pct = d_filtered.isna().mean()
high_missing_cols = missing_pct[missing_pct > 0.9].index.tolist()
print("Columns with >90% missing values:", high_missing_cols)

# Check for columns with all same non-NaN values
constant_cols = []
for col in d_filtered.columns:
    if d_filtered[col].nunique(dropna=True) == 1:
        constant_cols.append(col)
print("Columns with constant values:", constant_cols)

# Drop identifier columns
ide_cols = ['id_loan', 'seller_name', 'servicer_name']
```

```
print("Identifier columns:", ide_cols)

# Drop date columns redundant with 'orig_loan_term' (loan term is derived from␣
↪first payment and maturity dates)
date_cols = ['dt_first_pi', 'dt_matr']
print("Date columns:", date_cols)

# Drop columns with constant values, >90% missing values, and identifier columns
cols_to_drop = list(set(constant_cols + high_missing_cols + ide_cols +␣
↪date_cols))
d_filtered = d_filtered.drop(columns=cols_to_drop, errors='ignore')
```

```
Columns to drop:
Columns with >90% missing values: ['flag_sc', 'id_loan_rr', 'program_ind',
'rr_ind']
Columns with constant values: ['ppmt_pnlty', 'prod_type', 'flag_sc', 'rr_ind',
'io_ind']
Identifier columns: ['id_loan', 'seller_name', 'servicer_name']
Date columns: ['dt_first_pi', 'dt_matr']
```

Several features are removed to enhance model efficiency and reduce the risk of overfitting. Columns with a high missing rate (over 90%) are excluded, as they tend to introduce noise and offer limited modeling value. Features with constant values are also dropped due to their lack of variability and predictive power. In addition, identifiers such as loan IDs and seller or servicer names are not generalizable and are therefore excluded. Finally, date-related features such as dt_first_pi and dt_matr are removed because the loan term is already captured by the variable orig_loan_term, making the original dates redundant.

3.3 Train-Test Split

Before any detailed exploration, we split the dataset into training and testing sets. This avoids data leakage and ensures a fair evaluation of model performance on unseen data.

[6]:
```
# Split data before EDA to avoid data leakage
X = d_filtered.drop('loan_status', axis=1)
y = d_filtered['loan_status']

# Stratified split to maintain class balance
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    shuffle= True,
    test_size=0.2,
    stratify=y,  # Maintain class distribution
    random_state=42
)
```

We use the train_test_split function to divide the dataset into 80% training and 20% testing data. By setting stratify=y, we ensure that the distribution of the minority class is preserved in both subsets, thereby maintaining the overall imbalance in the test set.

3.4 Missing Value Imputation

To ensure model compatibility and avoid training errors due to missing values, we applied imputation strategies tailored to the data type and distribution of each variable.

[7]:
```
# Numerical columns: Median imputation
num_cols = ['fico', 'mi_pct', 'cltv', 'dti', 'ltv']
num_imputer = SimpleImputer(strategy='median')
X_train[num_cols] = num_imputer.fit_transform(X_train[num_cols])
X_test[num_cols] = num_imputer.transform(X_test[num_cols])

# Ordinal categorical: Most frequent category
ord_cols = ['property_val']
ord_imputer = SimpleImputer(strategy='most_frequent')
X_train[ord_cols] = ord_imputer.fit_transform(X_train[ord_cols])
X_test[ord_cols] = ord_imputer.transform(X_test[ord_cols])

# Nominal categorical: Fill with 'Unknown'
cat_cols = ['cd_msa', 'mi_cancel_ind']
X_train[cat_cols] = X_train[cat_cols].fillna('Unknown')
X_test[cat_cols] = X_test[cat_cols].fillna('Unknown')
```

For numerical columns, we used the median rather than the mean, as the median is more robust to skewed distributions and outliers. For the ordinal categorical variable property_val, we imputed using the most frequent category to preserve its rank order while minimizing distortion from rare categories. Finally, for nominal categorical features like cd_msa and mi_cancel_ind, which do not have an inherent order, we filled missing values with the placeholder "Unknown", maintaining their categorical structure while allowing the model to treat them as a distinct group during encoding. This structured approach ensures that we preserve key information while keeping the dataset clean and model-ready.

3.5 Exploratory Data Analysis (EDA)

In this section, we explore patterns and relationships in the training data to better understand the factors associated with loan defaults. We begin by merging features and target labels for visualization, then examine both numerical and categorical variables, as well as potential correlations, to guide later modeling decisions.

Before performing EDA, we combined the training features and labels into a single DataFrame (train_df) for easier analysis, allowing for the inspection of feature distributions, class imbalance, and relationships between features and the target variable (loan_status).

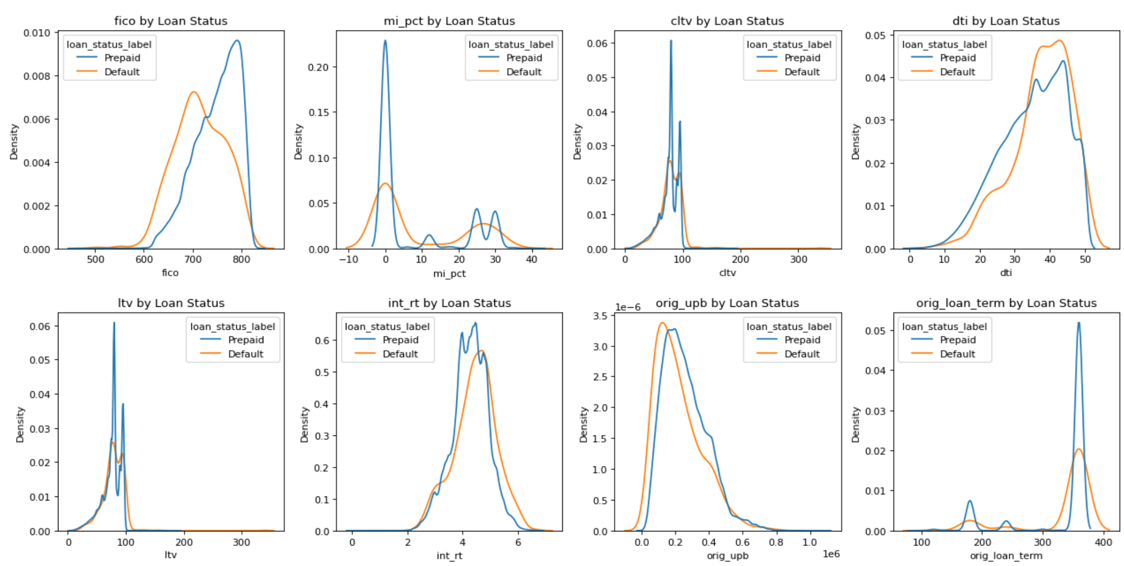
[8]:
```
# Combine training data for EDA
train_df = pd.concat([X_train, y_train], axis=1)
print("\nTraining data shape:", train_df.shape)
```

```
Training data shape: (101364, 21)
```

3.5.1 Numerical Features Analysis

In this section, we visualize and compare the distributions of key numerical features across prepaid and defaulted loans. This helps us identify which features may be informative for classification. We also assess skewness to determine whether transformations are needed to improve model performance.

[9]:
```python
num_cols = ['fico', 'mi_pct', 'cltv', 'dti', 'ltv', 'int_rt', 'orig_upb',␣
↪'orig_loan_term'] # Numerical columns
n = 2 # Number of rows for subplots
m = len(num_cols) // n + len(num_cols) % n # Number of columns for subplots

# Numerical feature distribution comparison by loan status
train_df['loan_status_label'] = train_df['loan_status'].map({0: 'Prepaid', 1:␣
↪'Default'})

fig, axes = plt.subplots(n, m, figsize=(16, 8))
axes = axes.flatten()

for i, col in enumerate(num_cols):
    if col in train_df.columns:
        sns.kdeplot(data=train_df, x=col, hue='loan_status_label', ax=axes[i],␣
↪common_norm=False)
        axes[i].set_title(f'{col} by Loan Status')
        axes[i].set_xlabel(col)
        axes[i].set_ylabel('Density')

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

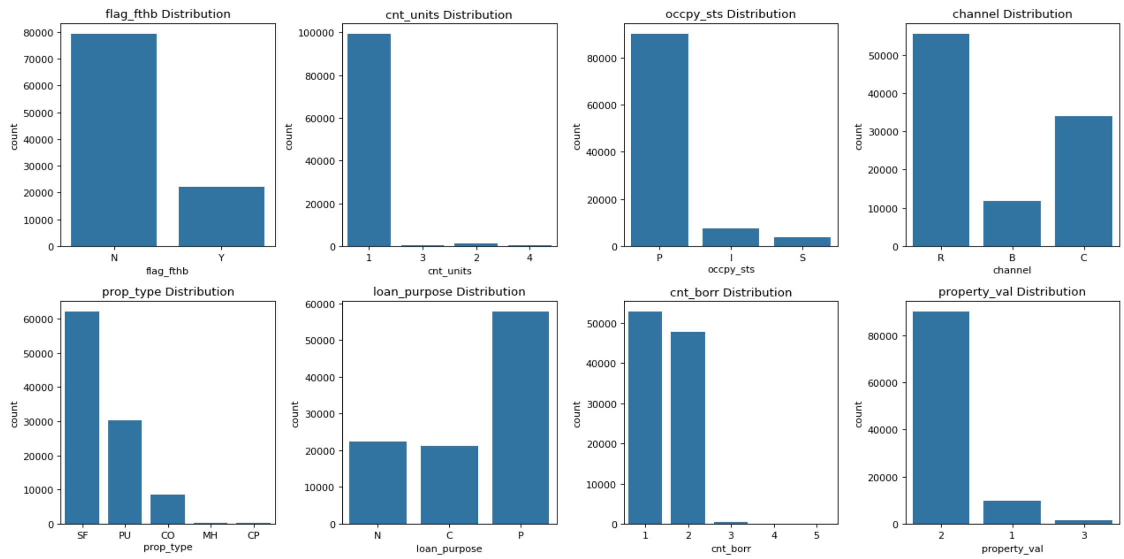


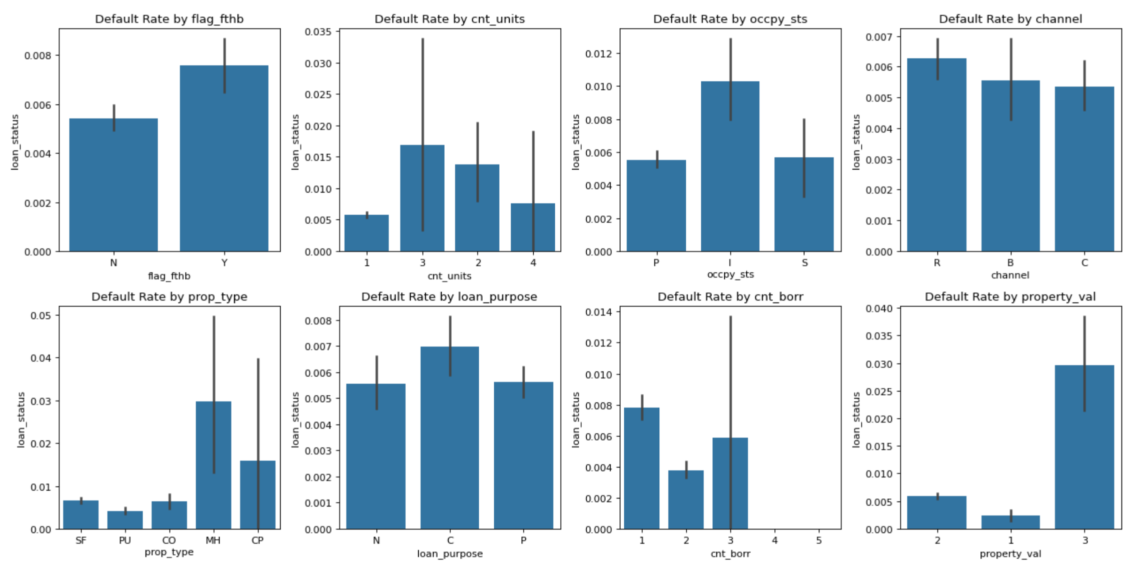
This figure illustrates the distribution of key numerical features for loans that were prepaid versus those that defaulted. Several features display meaningful differences between the two groups. For instance, FICO scores around 700 are more associated with defaults, while scores closer to 800 are more common among prepaid loans, suggesting that credit score is a strong predictor of loan outcome. From a distributional perspective, FICO and DTI are left-skewed, while orig_upb is heavily right-skewed, highlighting the need for appropriate feature transformations before modeling.

3.5.2 Categorical Features Analysis

We explore the distribution and default rates of categorical features to identify high-risk groups. By combining count plots with class-wise default rates, we gain insights into which categories are most relevant for distinguishing between prepaid and default loans.

[10]:
```python
cat_cols = ['flag_fthb', 'cnt_units', 'occpy_sts', 'channel', 'prop_type',␣
↪'loan_purpose', 'cnt_borr', 'property_val'] # Categorical columns
n = 2 # Number of rows for subplots
m = len(cat_cols) // n + len(cat_cols) % n # Number of columns for subplots
# Frequency plots
fig, axes = plt.subplots(n, m, figsize=(16, 8))
for i, col in enumerate(cat_cols):
    sns.countplot(x=col, data=train_df, ax=axes[i//m, i%m])
    axes[i//m, i%m].set_title(f'{col} Distribution')
    axes[i//m, i%m].tick_params(axis='x')
plt.tight_layout()
plt.show()

# Relationship with Target
fig, axes = plt.subplots(n, m, figsize=(16, 8))
for i, col in enumerate(cat_cols):
    sns.barplot(x=col, y='loan_status', data=train_df, ax=axes[i//m, i%m],␣
↪estimator=np.mean)
    axes[i//m, i%m].set_title(f'Default Rate by {col}')
    axes[i//m, i%m].tick_params(axis='x')
plt.tight_layout()
plt.show()
```



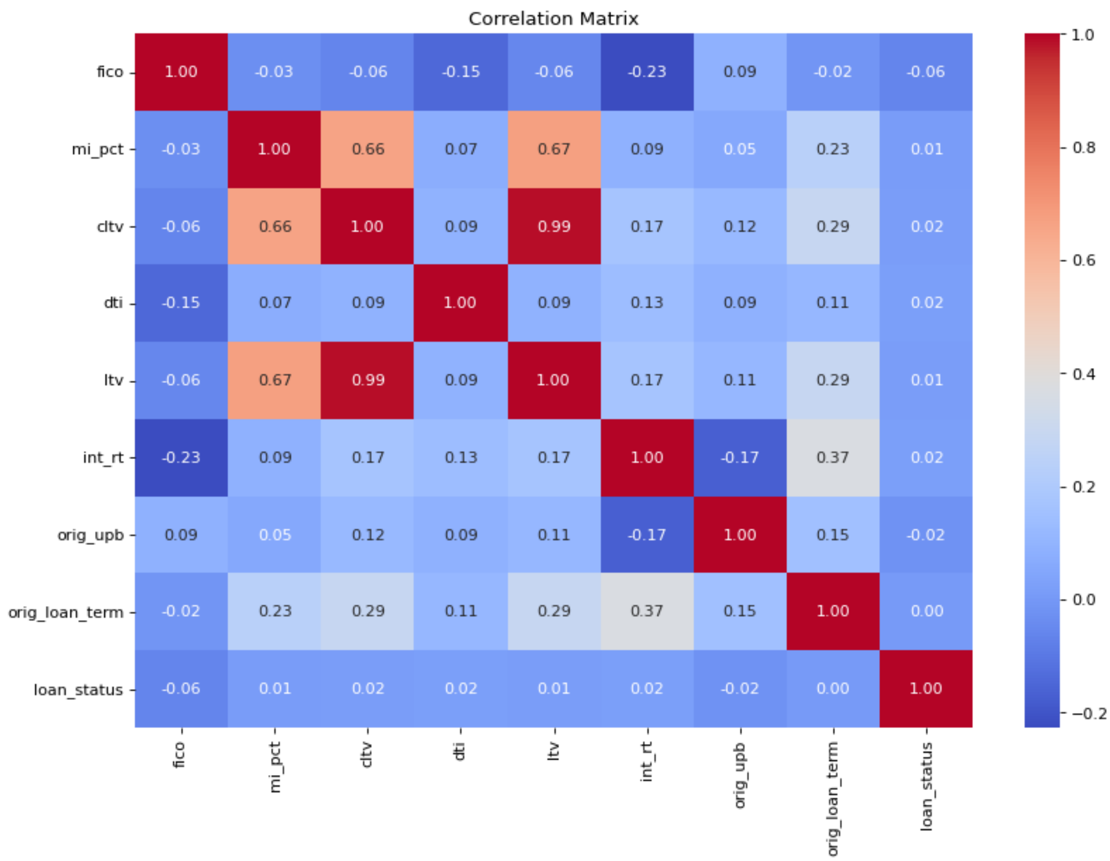


The plots above show the distribution and default rates for key categorical features. While many variables are heavily skewed — for instance, most loans are for single-family homes and primary residences with a single borrower — we can still spot useful patterns. Certain categories stand out with higher default rates, such as investment properties (occpy_sts = I) and manufactured homes (prop_type = MH). These patterns suggest that even though the distributions are imbalanced, some categorical features may carry strong signals for predicting default.

3.5.3 Correlation Analysis

To check for multicollinearity and understand linear relationships between numerical variables, we compute and visualize a correlation matrix.

[11]:
```
corr_matrix = train_df[num_cols + ['loan_status']].corr()
plt.figure(figsize=(12,8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



This matrix shows how numerical features relate to each other. One key thing that stands out is the extremely high correlation between ltv and cltv—around 0.99—which suggests they carry nearly identical information. Keeping both could introduce multicollinearity, especially in linear models, and add unnecessary complexity. We chose to drop cltv and keep ltv, as LTV is more interpretable, widely used in industry.

[12]:
```
X_train = X_train.drop(columns=['cltv'])
X_test = X_test.drop(columns=['cltv'])
```

We also observed a moderately strong correlation (0.67) between ltv and mi_pct. While this isn't high enough to trigger concern by itself, we checked their VIF values to make sure they don't cause multicollinearity issues.

[13]:
```python
# Compute VIF for features
vif_data = pd.DataFrame()
vif_data["feature"] = X_train[["mi_pct", "ltv"]].columns
vif_data["VIF"] = [variance_inflation_factor(X_train[["mi_pct", "ltv"]].values, i) for i in range(2)]
print(vif_data)
```

```
  feature      VIF
0  mi_pct  1.73093
1     ltv  1.73093
```

The VIF (Variance Inflation Factor) values for numerical features are all below 5, indicating that multicollinearity is not a concern. VIF quantifies how much the variance of a regression coefficient is inflated due to linear correlation with other predictors. A VIF above 5 usually suggests problematic collinearity. In our case, both ltv and mi_pct have VIFs around 1.73, showing that they are not excessively correlated with other variables, so we decide to retain both features in the final model.

3.5.4 EDA Findings

Our EDA revealed several important patterns that shaped our feature engineering strategy. Defaulted loans, though representing less than 1% of the data, tend to cluster around lower FICO scores, and higher values for DTI, LTV, and interest rate—indicating these financial ratios are closely tied to risk.

In the categorical features, we found that certain infrequent categories—such as investment-purpose loans and manufactured homes—are associated with significantly higher default rates. This suggests that even low-frequency categories can carry strong predictive signals and should be handled carefully.

We also discovered a near-perfect correlation between ltv and cltv (r 0.99), which raised concerns about multicollinearity. To avoid redundancy and keep the model interpretable, we decided to drop cltv and retain ltv, as it is more commonly used in industry practice.

These insights directly influenced our upcoming steps—especially in how we transform skewed features, construct interaction terms, and streamline the variable set for modeling.

3.6 Feature Engineering

This section focuses on transforming and enriching the feature set to better capture relationships that influence default risk. Based on our EDA findings, we apply skewness correction and construct interaction features that reflect domain knowledge and underlying borrower behavior.

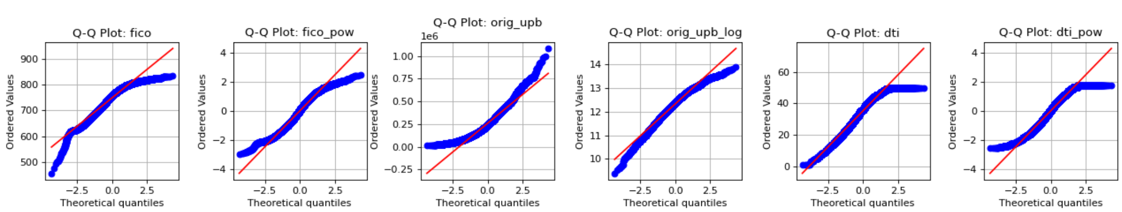
3.6.1 Transformations and Skewness Checking

To improve model performance and meet assumptions of certain algorithms, we examine the distribution of numerical features and apply transformations where needed. Left-skewed variables (e.g., fico, dti) are normalized using power transforms, while right-skewed ones (e.g., orig_upb) are log-transformed. QQ plots and skewness values are used to evaluate the effectiveness of these transformations.

[14]:

```python
# Apply log transformation on orig_upb to reduce right skewness
X_train['orig_upb_log'] = np.log1p(X_train['orig_upb'])
X_test['orig_upb_log'] = np.log1p(X_test['orig_upb'])

# Apply Yeo-Johnson transformation on fico to reduce left skewness
pt = PowerTransformer(method='yeo-johnson')
X_train['fico_pow'] = pt.fit_transform(X_train[['fico']])
X_test['fico_pow'] = pt.transform(X_test[['fico']])

# Apply Yeo-Johnson transformation on dti to reduce left skewness
X_train['dti_pow'] = pt.fit_transform(X_train[['dti']])
X_test['dti_pow'] = pt.transform(X_test[['dti']])

# Check skewness of transformed columns
skewed_cols = ['fico', 'fico_pow', 'orig_upb', 'orig_upb_log', 'dti', 'dti_pow']
for col in skewed_cols:
    print(f"{col} skew: {skew(X_train[col]):.2f}")

# Plot Q-Q plots for skewed columns
n = 1
m = len(skewed_cols)//n + len(skewed_cols)%n
fig, axes = plt.subplots(n, m, figsize=(16, n*(16//m+1)))
axes = axes.ravel()  # Flatten axes for easy iteration
for i, col in enumerate(skewed_cols):
    probplot(X_train[col], plot=axes[i]) # Q-Q plot
    axes[i].set_title(f'Q-Q Plot: {col}')
    axes[i].grid(True)
plt.tight_layout()
plt.show()
```

```
fico skew: -0.65
fico_pow skew: -0.12
orig_upb skew: 0.78
orig_upb_log skew: -0.52
dti skew: -0.48
dti_pow skew: -0.16
```



To address the skewness observed during EDA, we applied transformations to selected numerical features to make their distributions more symmetric and closer to normality, which often helps models learn more effectively. Specifically, we used the Yeo-Johnson transformation for fico and dti, which were left-skewed, and a log transformation for orig_upb, which was heavily right-skewed.

The Yeo-Johnson transform is a flexible power transformation that can handle both positive and negative values. It helps stabilize variance and normalize distributions, making it suitable for variables like fico and dti that include a wide but bounded range. The log transformation is a common choice for right-skewed variables like orig_upb, as it compresses large values and brings the distribution closer to symmetric.

The Q-Q plots above compare the distributions before and after transformation. When the blue dots follow the red diagonal, it indicates the variable is approximately normally distributed. After transformation, skewness values improved significantly—for example, fico changed from –0.65 to –0.12, and orig_upb from 0.78 to –0.52. The transformation of dti had a more modest effect visually, but we observed a slight boost in baseline model performance, which supported keeping the transformed version for consistency across features.

3.6.2 Interaction Features

To enhance the model's ability to capture nonlinear patterns and interactions that may influence default risk, we engineered three interaction features based on both domain knowledge and exploratory analysis.

[15]:
```
# Create categorical interaction: occupancy status + property type
# Captures combined effects (e.g., investment properties in condos)
X_train['occpy_prop'] =  X_train['occpy_sts'] + '_' + X_train['prop_type']
X_test['occpy_prop'] =  X_test['occpy_sts'] + '_' + X_test['prop_type']

# Create categorical interaction: loan purpose + number of borrowers
# Identifies purpose-specific borrower patterns (e.g., refinance with multiple
 ↪borrowers)
X_train['purpose_borr'] = X_train['loan_purpose'] + '_' + X_train['cnt_borr']
X_test['purpose_borr'] = X_test['loan_purpose'] + '_' + X_test['cnt_borr']

# Create numerical interaction: LTV * DTI
# Captures synergistic risk from high leverage and high debt burden
X_train['ltv_dti'] = X_train['ltv'] * X_train['dti']
X_test['ltv_dti'] = X_test['ltv'] * X_test['dti']
```

First, we combined occupancy status and property type into a single categorical feature (occpy_prop), as certain combinations—like investment properties in condos—might carry distinct risk profiles compared to primary residences in single-family homes.

Second, we merged loan purpose and number of borrowers into purpose_borr, since scenarios like refinancing with multiple borrowers may indicate different risk behaviors.

Lastly, we created a numerical interaction feature ltv_dti by multiplying loan-to-value (LTV) and debt-to-income (DTI) ratios to capture the compounded financial risk from both high leverage and high monthly obligations.

These three features consistently improved model performance and were therefore retained in the final dataset. With our final feature set complete—including original variables, transformed inputs, and engineered interactions—we now move on to the model fitting stage, where we evaluate various classification algorithms to identify the most effective approach for predicting loan default.

4 Model Fitting and Tuning

In this section, we fit and evaluate two models for predicting loan default: a baseline logistic regression model and an XGBoost classifier. We also experimented with other models, including Random Forest and a simple neural network, but they did not perform as well in terms of recall and overall stability, so they were not selected. Both final models were trained using the processed feature set and evaluated on the same test data. Given the severe class imbalance, we applied class weighting and threshold adjustment where appropriate. Model performance was assessed using precision, recall, F1 score, and ROC-AUC.

4.1 Baseline model

We implemented a logistic regression model to serve as a transparent and interpretable baseline. Logistic regression is a linear classification algorithm that estimates the probability of a binary outcome by applying the sigmoid function to a weighted sum of input features:

$$\mathbb{P}(y = 1 \mid \mathbf{x}) = \frac{1}{1 + \exp\left(-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)\right)}$$

This formulation ensures predicted probabilities lie between 0 and 1 and allows each coefficient β to be interpreted as the feature's influence on the likelihood of default. While relatively simple, logistic regression provides a strong foundation for model comparison and helps clarify how individual features contribute to predictions.

To address the severe class imbalance in our dataset, we used class_weight='balanced' to assign greater importance to the minority class (defaults) during training. Additionally, all preprocessing steps—including standard scaling for numerical variables and one-hot encoding for categorical features—were implemented within a pipeline to ensure consistency and prevent data leakage.

4.1.1 Model Pipeline and evaluation

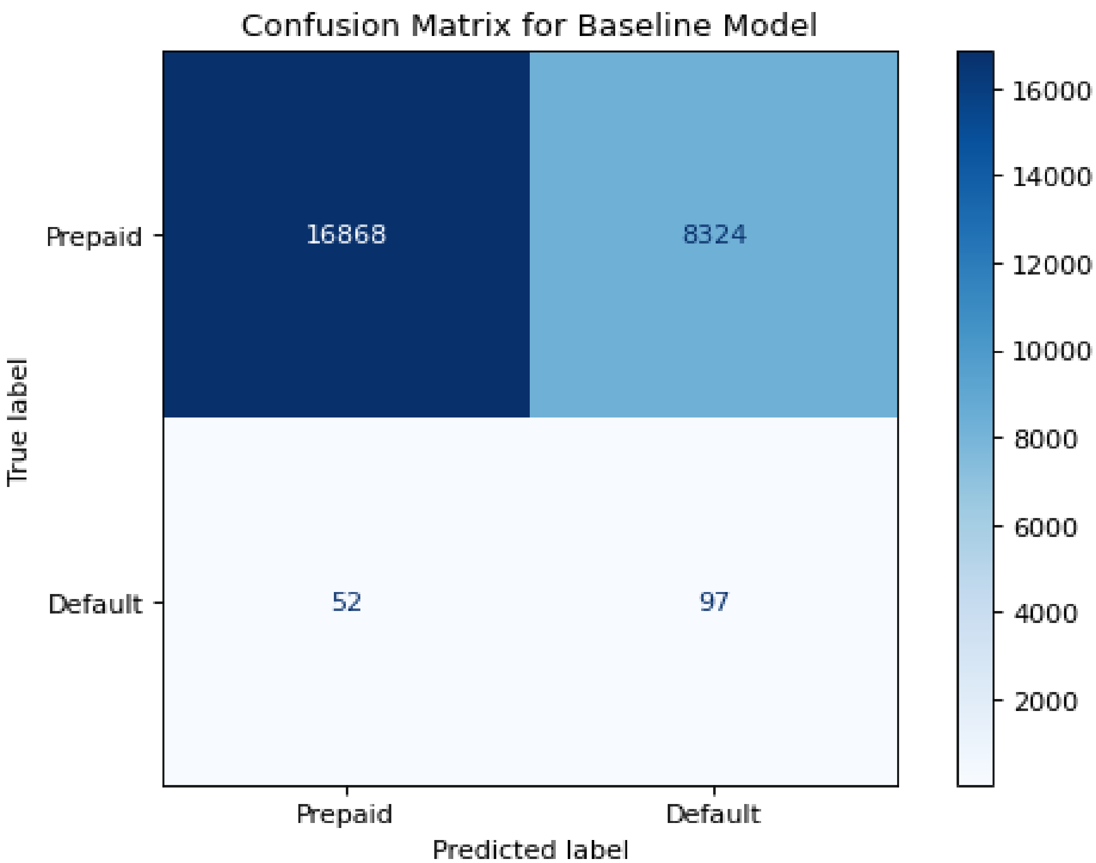
To evaluate our baseline logistic regression model, we trained it on the preprocessed data pipeline and assessed its performance on the test set. We calculated five key metrics—accuracy, precision, recall, F1 score, and ROC-AUC—and visualized the results using a confusion matrix. This helps us understand the model's ability to detect defaults under severe class imbalance.

[16]:
```
# Define categorical and numerical features
cat_cols = ['flag_fthb', 'occpy_sts', 'channel', 'loan_purpose', 'cnt_borr',␣
↪'occpy_prop', 'prop_type']
num_cols = ['fico_pow', 'mi_pct', 'ltv', 'dti_pow', 'int_rt', 'orig_upb_log',␣
↪'orig_loan_term', 'ltv_dti']

# Create a preprocessing pipeline
preprocessor = ColumnTransformer(
    transformers=[
```

```
        ('num', StandardScaler(), num_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), cat_cols)
    ]
)

# Combine preprocessing and model into a pipeline
baseline_model = ImPipeline([
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(
        class_weight='balanced',  # Adjusts weights for imbalance
        max_iter=1000,
        random_state=42
    ))
])

# Train the model
baseline_model.fit(X_train, y_train)

# Predict on test data
y_pred = baseline_model.predict(X_test)
y_proba = baseline_model.predict_proba(X_test)[:, 1]  # Probabilities for␣
 ↪default

print(classification_report(y_test, y_pred))
# Evaluate performance
print("Baseline Model Performance:")
print(f"- Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"- Precision: {precision_score(y_test, y_pred):.4f}")
print(f"- Recall: {recall_score(y_test, y_pred):.4f}")
print(f"- F1 Score: {f1_score(y_test, y_pred):.4f}")
print(f"- ROC-AUC: {roc_auc_score(y_test, y_proba):.4f}")

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Prepaid',␣
 ↪'Default'])
disp.plot(cmap='Blues')
plt.title('Confusion Matrix for Baseline Model')
plt.show()
```

```
              precision    recall  f1-score   support

           0       1.00      0.67      0.80     25192
           1       0.01      0.65      0.02       149

    accuracy                           0.67     25341
   macro avg       0.50      0.66      0.41     25341
```

```
weighted avg       0.99      0.67      0.80     25341

Baseline Model Performance:
- Accuracy: 0.6695
- Precision: 0.0115
- Recall: 0.6510
- F1 Score: 0.0226
- ROC-AUC: 0.7176
```



This baseline logistic regression model is evaluated using five key metrics:
1. Accuracy (66.95%) measures the overall proportion of correct predictions. About 67 out of every 100 loans were correctly classified, but this is mostly driven by the dominant class (prepaid), so it doesn't reflect performance on defaults.
2. Precision (1.15%) is the percentage of predicted defaults that are actually correct. This means that for every 100 loans flagged as defaults, only about 1 is truly a default—indicating many false positives.
3. Recall (65.1%) measures how many actual defaults the model successfully identified. For every 100 defaulted loans, the model correctly flags about 65—showing decent sensitivity.
4. F1 Score (0.0226) combines precision and recall. Its low value reflects the imbalance: the model can catch defaults, but it also mislabels many prepaid loans.

5. ROC-AUC (0.7176) evaluates how well the model separates default and prepaid cases overall. A score above 0.7 suggests moderate discriminative ability.

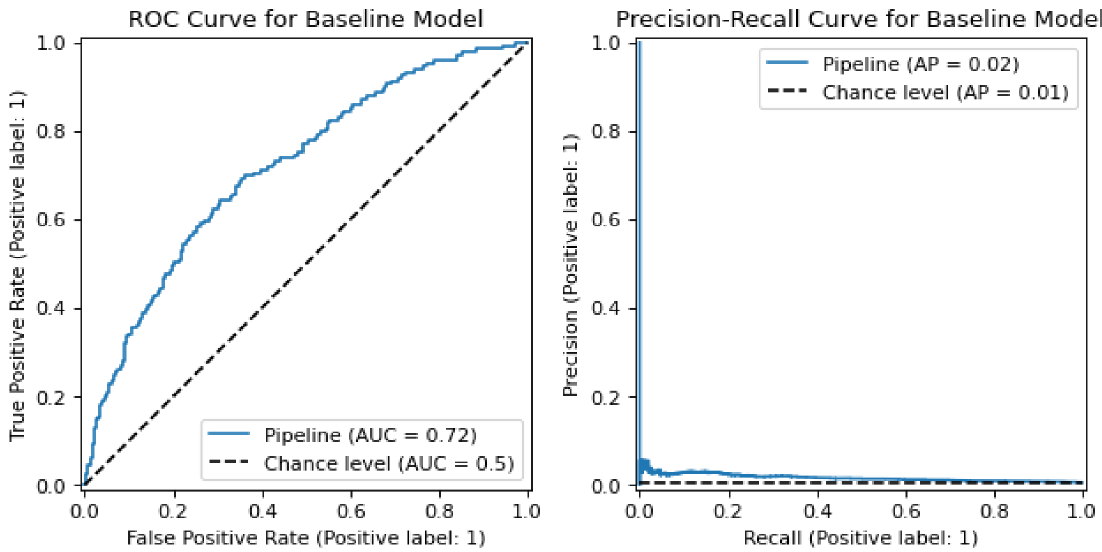
To handle the class imbalance, we tried over-sampling, under-sampling, and class weighting. All gave similar results, so we chose class_weight='balanced' for simplicity and integration into the pipeline.

The confusion matrix supports this interpretation: the model correctly identifies 97 out of 149 defaults, but also incorrectly classifies over 8,300 prepaid loans as defaults. This highlights the model's strength in recall but weakness in precision, suggesting it needs further refinement for real-world use.

4.1.2 Performance Visualization: ROC and PR Curves

To further assess the model's predictive quality, we plotted the ROC curve and Precision-Recall curve. These visualizations provide a clearer picture of how well the model balances true positive rates and precision across different thresholds, especially useful under class imbalance.

[17]:
```
fig, axes = plt.subplots(1, 2)

# ROC Curve
RocCurveDisplay.from_estimator(baseline_model, X_test, y_test, ax=axes[0],␣
↪plot_chance_level=True)
axes[0].set_title('ROC Curve for Baseline Model')

# Precision-Recall Curve
PrecisionRecallDisplay.from_estimator(baseline_model, X_test, y_test,␣
↪ax=axes[1], plot_chance_level=True)
axes[1].set_title('Precision-Recall Curve for Baseline Model')
axes[1].legend(loc='upper right')

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



These two plots provide a deeper understanding of how the baseline logistic regression model performs under class imbalance.

The left plot is the ROC (Receiver Operating Characteristic) curve, which shows the trade-off between the true positive rate (recall) and the false positive rate. The diagonal dashed line represents random guessing (AUC = 0.5). Our model achieves an AUC of 0.72, indicating a moderate ability to distinguish between default and prepaid loans—it performs meaningfully better than chance.

The right plot is the Precision-Recall (PR) curve, which is more informative when evaluating models on imbalanced datasets. It focuses on the performance for the minority class—in our case, defaults. The average precision (AP) is only 0.02, which means that even though the model can recall many defaults, most predicted defaults are incorrect (false positives). This highlights the model's struggle with precision, despite acceptable recall.

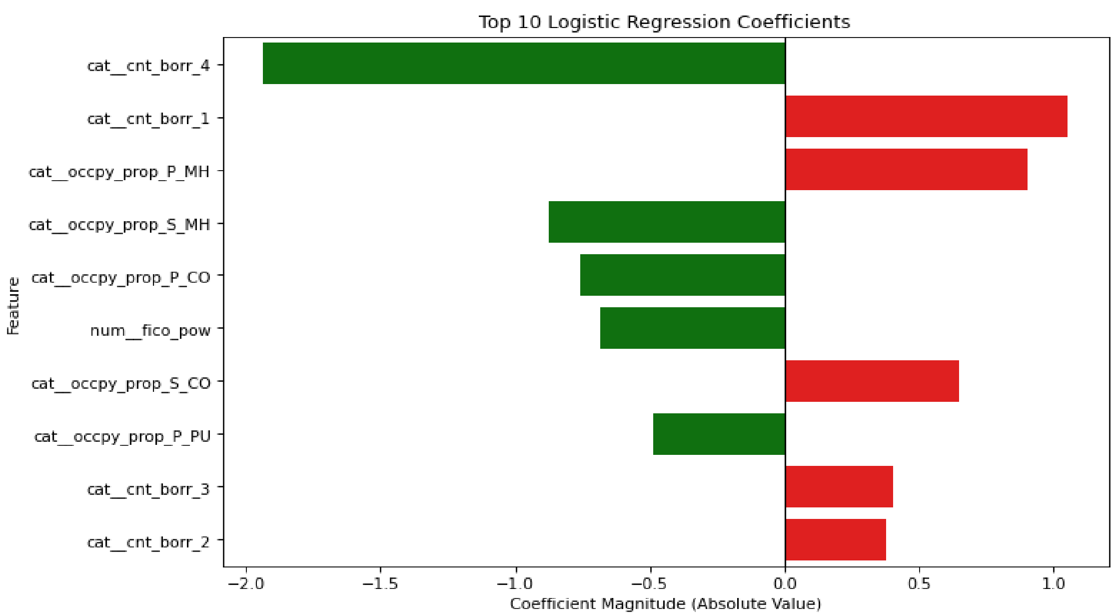
Together, these plots confirm that while the model has some predictive power, especially in recall, its precision remains a major limitation due to the severe class imbalance.

4.1.3 Feature Coefficients Overview

We extracted and visualized the top 10 most influential coefficients from the logistic regression model. This gives insight into which features most strongly increase or decrease the likelihood of a loan default, helping us interpret the model's decisions.

[18]:
```
# Get feature names from the preprocessor
feature_names = baseline_model.named_steps['preprocessor'].
  ↪get_feature_names_out()

# Extract coefficients from logistic regression
coefficients = baseline_model.named_steps['classifier'].coef_[0]
```

```python
# Create a DataFrame for interpretation
coef_df = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': coefficients,
    'Abs_Coefficient': np.abs(coefficients)
}).sort_values(by='Abs_Coefficient', ascending=False)

plt.figure(figsize=(10,6))
sns.barplot(
    x='Coefficient',
    y='Feature',
    hue='Feature',
    data=coef_df.head(10),
    palette=['Red' if x > 0 else 'Green' for x in coef_df.
 ↪head(10)['Coefficient']]
    )
plt.axvline(0, color='black', linestyle='-', linewidth=1)
plt.title('Top 10 Logistic Regression Coefficients')
plt.xlabel('Coefficient Magnitude (Absolute Value)')
plt.show()
```



This plot shows the top 10 most influential features in our logistic regression model, ranked by the absolute value of their coefficients. Features on the right (red bars) have positive coefficients, meaning they are associated with a higher likelihood of default. For example, loans with only one borrower (cat___cnt_borr_1) or manufactured homes used as primary residences (cat___occpy_prop_P_MH) appear linked with increased risk.

On the left (green bars) are features with negative coefficients, which contribute to lowering the model's predicted probability of default. Notably, loans with four borrowers (cat___cnt_borr_4) show the strongest protective signal, and higher credit scores (fico_pow) also align with better repayment performance—patterns consistent with earlier EDA findings.

While coefficient magnitude offers a useful sense of relative importance within the model, it is influenced by how features are processed. Nonetheless, this visualization helps validate that the model captures reasonable patterns and that key engineered features, such as borrower count and combined occupancy/property types, carry meaningful predictive value.

4.2 XGBoost

We implemented an XGBoost model to improve upon the baseline and better capture complex patterns in the data. XGBoost (Extreme Gradient Boosting) is an ensemble learning method that builds a sequence of decision trees, where each new tree focuses on correcting the errors made by previous ones. It optimizes a regularized objective function that balances model fit and complexity, making it robust to overfitting:

$$\text{Obj} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum k = 1^K \Omega(f_k)$$

where l is the loss function (e.g., logistic loss for binary classification), and Ω is a regularization term applied to each tree f_k.

XGBoost is particularly well-suited for tabular data and handles imbalanced classification tasks effectively through the scale_pos_weight parameter. In our pipeline, we incorporated hyperparameter tuning via cross-validation to optimize performance. The final model was trained on the same preprocessed features as the baseline, using all encoded categorical and scaled numerical variables, ensuring fair comparison.

4.2.1 Model Setup

We initialize the XGBoost classifier and define preprocessing steps using a pipeline. This ensures consistent scaling, encoding, and data flow, and makes integration with model evaluation and tuning more efficient.

[19]:
```
# Define full categorical and numerical features
cat_cols = ['flag_fthb', 'occpy_sts', 'channel', 'prop_type', 'loan_purpose',␣
 ↪'mi_cancel_ind', 'cnt_borr',
            'cnt_units', 'property_val', 'cd_msa', 'zipcode', 'st',␣
 ↪'occpy_prop', 'purpose_borr'
]

num_cols = ['fico', 'fico_pow', 'mi_pct', 'dti', 'dti_pow', 'ltv', 'int_rt',
    'orig_upb', 'orig_upb_log', 'orig_loan_term', 'ltv_dti'
]

# Preprocessing
preprocessor = ColumnTransformer(
    transformers=[
```

```
        ('cat', OneHotEncoder(handle_unknown='ignore'), cat_cols)
    ],
    remainder='passthrough',  # Pass numerical features unchanged
)

# Calculate scale_pos_weight for XGBoost
neg = len(y_train[y_train == 0])
pos = len(y_train[y_train == 1])
scale_pos_weight = neg / pos
print(f"scale_pos_weight: {scale_pos_weight:.2f}")
```

```
scale_pos_weight: 168.79
```

For the XGBoost model, we included all available features—both original and engineered—without dropping high-cardinality or interaction terms. Tree-based models like XGBoost are generally robust to feature redundancy and can naturally capture non-linear interactions, making them well-suited to learning patterns even from raw, less-processed inputs. While we considered using target encoding for high-cardinality categorical features (e.g., zipcode, cd_msa), one-hot encoding consistently performed better in our validation results, likely due to reduced target leakage and more stable splits.

To handle class imbalance, we calculated scale_pos_weight as the ratio of negative to positive samples in the training set, resulting in a value of 168.79. This parameter plays a critical role in helping XGBoost correctly account for the rare default cases during training by assigning greater importance to the minority class without changing the underlying data distribution.

4.2.2 Hyperparameter Search

We perform randomized search with stratified cross-validation to efficiently explore XGBoost's hyperparameters. SMOTE is included in the pipeline to improve recall under class imbalance.

[ ]:
```
# Define parameter grid
param_grid = {
    'classifier__subsample': [0.95, 1.0], # [0.5, 1.0]
    'classifier__n_estimators': [175, 200, 225, 250], # [50, 2000]
    'classifier__max_depth': [2, 3, 4],  # [1, 20]
    'classifier__learning_rate': [0.075, 0.1, 0.125, 0.15], # [0.01, 0.3]
    'classifier__colsample_bytree': [0.9, 0.95, 1.0] # [0.5, 1.0]
    }

# Create pipeline
xgb_model = ImPipeline([
    ('preprocessor', preprocessor),
    ('smote', SMOTE(sampling_strategy=0.3, random_state=42)),  # Optional: add␣
 ↪SMOTE for oversampling
    ('classifier', XGBClassifier(
        objective='binary:logistic',
        scale_pos_weight=scale_pos_weight,  # Adjust for class imbalance
        random_state=42,
```

```
        eval_metric='auc'
    ))
])

# RandomizedSearchCV with stratified K-fold
cv = StratifiedKFold(n_splits=3, shuffle=True, random_state=42)
search = RandomizedSearchCV(
    xgb_model,
    param_grid,
    n_iter=20,
    scoring='roc_auc', # Aim for AUC
    cv=cv,
    n_jobs=-1
)

# Fit model
search.fit(X_train, y_train)
# Get best parameters without the pipeline prefix
best_params = {k.replace('classifier__', ''): v for k, v in search.best_params_.
 ↪items()}
print("Best Parameters:", best_params)
```

```
Best Parameters: {'subsample': 0.95, 'n_estimators': 200, 'max_depth': 2,
'learning_rate': 0.15, 'colsample_bytree': 1.0}
```

We used RandomizedSearchCV to tune the XGBoost hyperparameters, aiming to maximize ROC-AUC through stratified 3-fold cross-validation. Compared to grid search, this method is more efficient when exploring a large hyperparameter space, especially when many combinations yield similar results.

To further address class imbalance, we added SMOTE (Synthetic Minority Over-sampling Technique) as a preprocessing step during tuning. SMOTE is commonly used in imbalanced classification tasks; it works by generating synthetic examples of the minority class through linear interpolation between existing instances. This helps improve the model's ability to learn decision boundaries and often leads to more stable recall during cross-validation.

While scale_pos_weight already offered some correction for imbalance, combining it with SMOTE provided better recall and reduced variability. After tuning, we manually selected the best-performing parameter configuration for final training. We did not include gamma in tuning, as preliminary testing showed it had minimal impact on performance for this dataset.

4.2.3 Model Training

After identifying the best configuration, we retrain the final XGBoost model on the full training data. This step ensures the model is optimized using all available training samples.

[21]:
```
# Initialize final model with tuned parameters
final_model = ImPipeline([
    ('preprocessor', preprocessor),
```

```
    ('classifier', XGBClassifier(
        **best_params,
        objective='binary:logistic',
        scale_pos_weight=scale_pos_weight,
        random_state=42
    ))
])

# Train
final_model.fit(X_train, y_train)
print("Final Model Trained")
```

```
Final Model Trained
```

We used RandomizedSearchCV to tune the XGBoost hyperparameters, aiming to maximize ROC-AUC through stratified 3-fold cross-validation. Compared to grid search, this method is more efficient when exploring a large hyperparameter space, especially when many combinations yield similar results.

To further address class imbalance, we added SMOTE (Synthetic Minority Over-sampling Technique) as a preprocessing step during tuning. SMOTE is commonly used in imbalanced classification tasks; it works by generating synthetic examples of the minority class through linear interpolation between existing instances. This helps improve the model's ability to learn decision boundaries and often leads to more stable recall during cross-validation.

While scale_pos_weight already offered some correction for imbalance, combining it with SMOTE provided better recall and reduced variability. After tuning, we manually selected the best-performing parameter configuration for final training. We did not include gamma in tuning, as preliminary testing showed it had minimal impact on performance for this dataset.

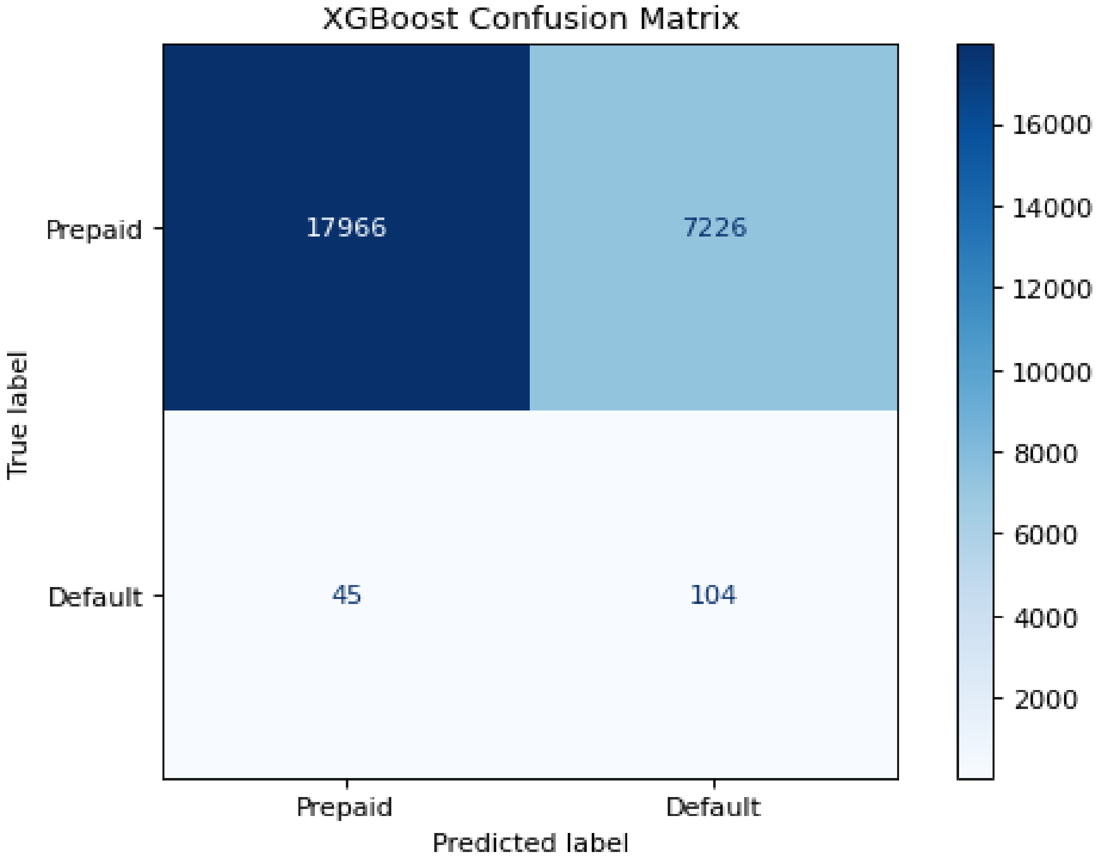
4.2.4 Model Prediction

We evaluate the trained model on the test set by generating predictions and predicted probabilities. This allows us to compute performance metrics and assess generalization.

[22]:
```
# Predictions
y_pred_xgb = final_model.predict(X_test)
y_proba_xgb = final_model.predict_proba(X_test)[:, 1]

threshold = 0.45  # Adjust based on PR curve analysis
y_pred_xgb = (y_proba_xgb >= threshold).astype(int)
print(classification_report(y_test, y_pred_xgb))
# Performance metrics
print("XGBoost Performance:")
print(f"- Accuracy: {accuracy_score(y_test, y_pred_xgb):.4f}")
print(f"- Precision: {precision_score(y_test, y_pred_xgb):.4f}")
print(f"- Recall: {recall_score(y_test, y_pred_xgb):.4f}")
print(f"- F1 Score: {f1_score(y_test, y_pred_xgb):.4f}")
print(f"- ROC-AUC: {roc_auc_score(y_test, y_proba_xgb):.4f}")
```

```python
# Confusion Matrix
cm_xgb = confusion_matrix(y_test, y_pred_xgb)
disp_xgb = ConfusionMatrixDisplay(confusion_matrix=cm_xgb,␣
↪display_labels=['Prepaid', 'Default'])
disp_xgb.plot(cmap='Blues')
plt.title('XGBoost Confusion Matrix')
plt.show()
```

```
              precision    recall  f1-score   support

           0       1.00      0.71      0.83     25192
           1       0.01      0.70      0.03       149

    accuracy                           0.71     25341
   macro avg       0.51      0.71      0.43     25341
weighted avg       0.99      0.71      0.83     25341

XGBoost Performance:
- Accuracy: 0.7131
- Precision: 0.0142
- Recall: 0.6980
- F1 Score: 0.0278
- ROC-AUC: 0.7656
```



This output summarizes the performance of our final XGBoost model on the test set, using a classification threshold of 0.45. Instead of the default 0.5, we selected this lower threshold based on the precision-recall curve, aiming to increase recall for the minority class (defaults), which is the primary focus of our task.

The model achieved a recall of 69.8% on defaults, successfully identifying most default cases—an improvement over the baseline. Precision remains low at 1.42%, which is expected given the class imbalance, but the trade-off results in fewer missed defaults. The F1 score also shows a slight gain, reflecting a better balance between precision and recall.

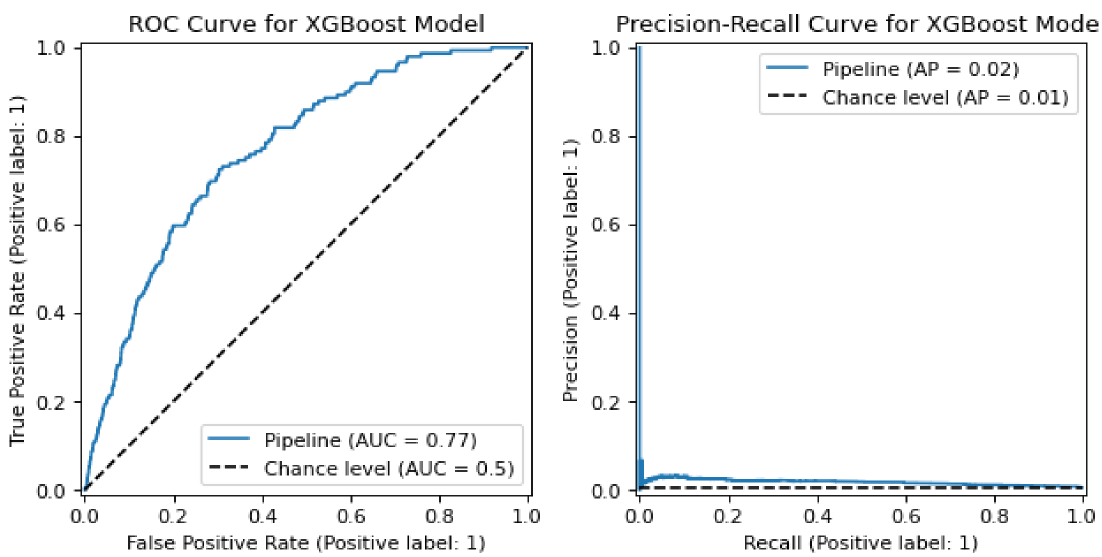
The confusion matrix further illustrates this: 104 out of 149 defaults were correctly identified, while 45 were missed. Around 7,200 prepaid loans were incorrectly flagged as defaults. Although this results in a relatively high number of false positives, it is acceptable in a setting where catching defaults is more important than avoiding false alarms.

Overall, the model's accuracy improved to 71.3%, and the ROC-AUC increased to 0.7656, indicating stronger overall separation between classes. The use of a tuned threshold contributed meaningfully to these improvements.

4.2.5 ROC and PR Curves

To visualize performance, we plot the ROC and Precision-Recall curves. These plots help assess how well the model distinguishes defaults from non-defaults in an imbalanced setting.

[23]:
```
fig, axes = plt.subplots(1, 2)

# ROC Curve
RocCurveDisplay.from_estimator(final_model, X_test, y_test, ax=axes[0],␣
 ↪plot_chance_level=True)
axes[0].set_title('ROC Curve for XGBoost Model')

# Precision-Recall Curve
PrecisionRecallDisplay.from_estimator(final_model, X_test, y_test, ax=axes[1],␣
 ↪plot_chance_level=True)
axes[1].set_title('Precision-Recall Curve for XGBoost Model')
axes[1].legend(loc='upper right')

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



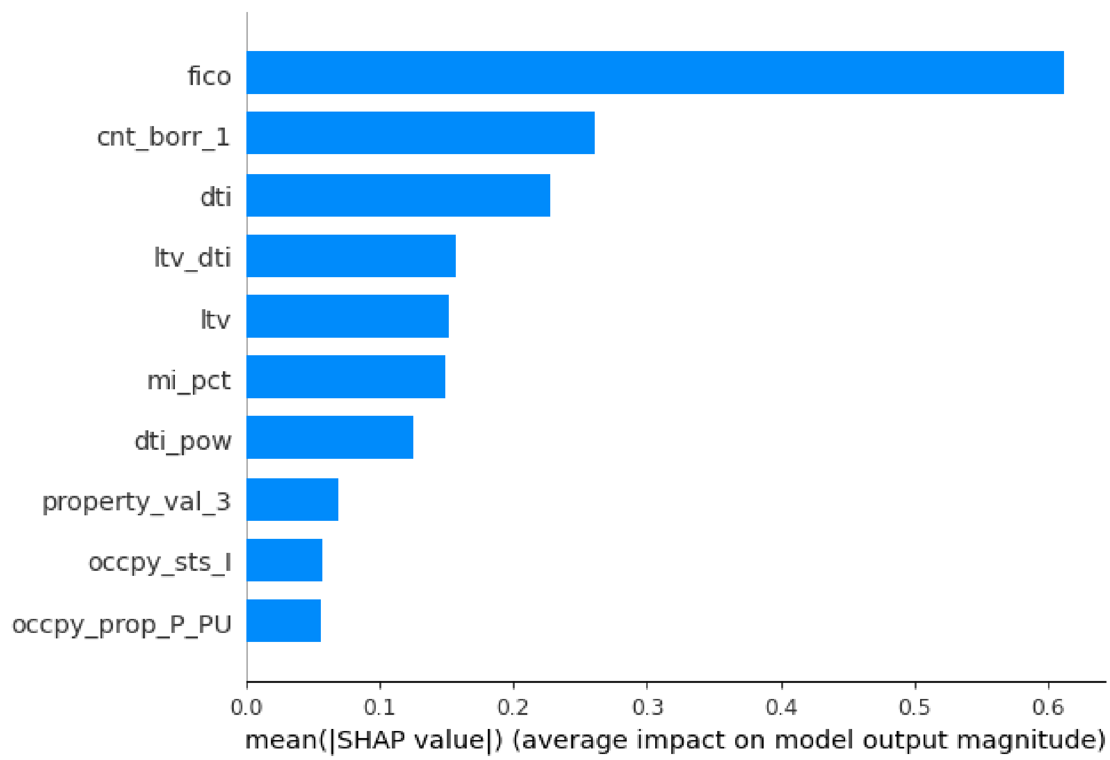
The ROC and Precision-Recall curves above summarize the XGBoost model's performance. With an ROC-AUC of 0.77, the model shows strong overall separability. The PR curve indicates that while precision is still low, the model performs consistently better than chance.

Compared to the baseline, XGBoost improves slightly in ROC-AUC while maintaining similar precision-recall trade-offs.

4.2.6 SHAP Interpretation

We apply SHAP to interpret the model's predictions and quantify each feature's contribution. This helps ensure the model's decisions align with domain knowledge and are explainable to stakeholders.

[24]:
```python
# Extract feature names after one-hot encoding
encoder = final_model.named_steps['preprocessor'].named_transformers_['cat']
cat_features = encoder.get_feature_names_out(cat_cols)
all_features = np.concatenate([cat_features, num_cols])

# Get preprocessed data
X_processed = final_model.named_steps['preprocessor'].transform(X_train)

# SHAP summary plot
explainer = shap.TreeExplainer(final_model.named_steps['classifier'])
shap_values = explainer.shap_values(X_processed)
shap.summary_plot(shap_values, X_processed, feature_names=all_features,␣
↪plot_type='bar', max_display=10)
```



This SHAP summary plot highlights the most influential features driving the XGBoost model's predictions. SHAP (SHapley Additive exPlanations) is a model explanation method based on co-operative game theory. It assigns each feature a value that reflects its contribution to the prediction, ensuring that the sum of SHAP values matches the model output for each instance.

SHAP is widely used due to its consistency, local accuracy, and strong theoretical foundation. For tree-based models like XGBoost, SHAP offers fast and exact computation, making it both practical and interpretable.

In our results, fico stands out as the most impactful feature, with a much larger effect than others. Additional key drivers include cnt_borr_1, dti, and ltv_dti—all of which align with financial expectations, providing further confidence in the model's reasoning.

4.2.7 Baseline Comparison

We compare XGBoost with the logistic regression baseline across multiple metrics. This highlights whether the added complexity of XGBoost translates to meaningful performance gains.

[25]:
```
print("Baseline vs XGBoost Comparison:")
print(f"Metric\t\tBaseline\tXGBoost")
print(f"Accuracy\t{accuracy_score(y_test, y_pred):.
↪4f}\t\t{accuracy_score(y_test, y_pred_xgb):.4f}")
print(f"Precision\t{precision_score(y_test, y_pred):.
↪4f}\t\t{precision_score(y_test, y_pred_xgb):.4f}")
print(f"Recall\t\t{recall_score(y_test, y_pred):.4f}\t\t{recall_score(y_test,␣
↪y_pred_xgb):.4f}")
print(f"F1 Score\t{f1_score(y_test, y_pred):.4f}\t\t{f1_score(y_test,␣
↪y_pred_xgb):.4f}")
print(f"ROC-AUC\t\t{roc_auc_score(y_test, y_proba):.
↪4f}\t\t{roc_auc_score(y_test, y_proba_xgb):.4f}")
```

```
Baseline vs XGBoost Comparison:
Metric          Baseline        XGBoost
Accuracy        0.6695          0.7131
Precision       0.0115          0.0142
Recall          0.6510          0.6980
F1 Score        0.0226          0.0278
ROC-AUC         0.7176          0.7656
```

This final comparison highlights XGBoost's consistent improvement over the baseline logistic regression model across all metrics. While the absolute gains are not dramatic, they are meaningful—XGBoost achieved higher accuracy (71.3% vs. 66.97%), recall (69.8% vs. 65.1%), and F1 score (0.0278 vs. 0.0227). Its ROC-AUC also increased from 0.7166 to 0.7656, indicating stronger overall ability to separate defaults from non-defaults.

Although precision remains low—expected in such an imbalanced classification task—the model strikes a better balance between identifying defaults and avoiding too many false positives. These consistent gains across the board support the choice of XGBoost as our final model.

5 Discussion & Conclusions

Our final model, based on XGBoost, demonstrates solid performance in predicting mortgage default risk, outperforming the baseline logistic regression in all key metrics. On the Freddie Mac test set, it achieved 71.3% accuracy, 69.8% recall, and a ROC-AUC of 0.7656, indicating reliable separation between defaulted and non-defaulted loans. In comparison, the baseline model yielded 65.1% recall and an AUC of 0.7176. The overall improvement across metrics confirms the robustness and adaptability of the XGBoost approach for this task.

Feature importance analysis, supported by SHAP values, highlights fico as the most influential predictor—lower credit scores sharply increase the probability of default. Other key features include cnt_borr_1 (single borrower), dti, and the engineered ltv_dti ratio. These patterns match financial expectations and confirm the model is learning interpretable and meaningful relationships.

One limitation is the model's low precision (1.4%)largely due to the highly imbalanced nature of the dataset. This means that for every 100 loans predicted as "default", only about one is actually a default. While this seems high in false alarms, it's a deliberate tradeoff: the model prioritizes high recall to capture as many actual defaults as possible—crucial in early-stage risk screening where missing a default may be more costly than investigating a false positive.

From a business standpoint, this model can be used as an early warning system: predicted defaults should not be treated as final decisions, but as signals for enhanced scrutiny. Lenders could integrate this into their credit risk workflow—e.g., by flagging risky loans for manual review, applying stricter underwriting policies, or conducting additional borrower verification.

In summary, our XGBoost model provides a transparent and data-driven foundation for mortgage risk management. It balances predictive power with interpretability and offers actionable insights into borrower risk, helping financial institutions better allocate resources, improve loss mitigation strategies, and comply with regulatory expectations.

6 Generative AI statement

In this project, we used generative AI solely as a tool to assist with debugging code. All data and analysis results were processed and evaluated by us. The AI helped us refine our code and address errors, ensuring the technical aspects of the project were accurate and functional. The final outcomes and interpretations are entirely our own, and we have adhered to responsible use of AI as outlined in the guidelines.

7 References

[1] mlp_week06_key.ipynb

[2] mlp_week11_key.ipynb

[ ]:
```
# Run the following to render to PDF
!jupyter nbconvert --to pdf project2.ipynb
```