project2

April 8, 2025

1 Machine Learning in Python - Project 2

Due Friday, Apr 11th by 4 pm.

Include contributors names in notebook metadata or here

1.1 Setup

Install any packages here, define any functions if neeed, and load data

[1]:
```
# Add any additional libraries or submodules below

# 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
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,␣
 ↪precision_recall_curve,
    roc_auc_score, confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay,␣
 ↪classification_report
)
```

```python
from imblearn.pipeline import Pipeline as imPipeline
from imblearn.over_sampling import SMOTE
import xgboost as xgb
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV, StratifiedKFold
import shap
from scipy.stats import skew
```

[2]:
```python
# Load data in easyshare.csv
d = pd.read_csv("freddiemac.csv", dtype={
    'cd_msa': str,
    'zipcode': str,
    'id_loan_rr': str,
    'rr_ind':str})
d.head()
```

[2]:
```
   fico  dt_first_pi flag_fthb  dt_matr cd_msa  mi_pct  cnt_units occpy_sts  \
0   809       201705         N   204704    NaN       0          1         P
1   702       201703         N   203202    NaN       0          1         P
2   792       201703         N   204702    NaN       0          1         S
3   776       201703         N   204702    NaN       0          1         S
4   790       201703         N   204702  41620       0          1         I

   cltv  dti  …   seller_name                   servicer_name  flag_sc  \
0    75   38  …  Other sellers  SPECIALIZED LOAN SERVICING LLC      NaN
1    80   36  …  Other sellers                Other servicers      NaN
2    60   36  …  Other sellers                Other servicers      NaN
3    80   18  …  Other sellers                Other servicers      NaN
4    75   42  …  Other sellers                  PNC BANK, NA      NaN

  id_loan_rr program_ind rr_ind property_val io_ind mi_cancel_ind loan_status
0        NaN           9    NaN            2      N             7     prepaid
1        NaN           9    NaN            2      N             7      active
2        NaN           9    NaN            2      N             7     prepaid
3        NaN           9    NaN            2      N             7     prepaid
4        NaN           9    NaN            2      N             7      active

[5 rows x 33 columns]
```

2 Introduction

This section should include a brief introduction to the task and the data (assume this is a report you are delivering to a professional body (e.g. Freddie Mac).

Briefly outline the approaches being used and the conclusions that you are able to draw.

3 Exploratory Data Analysis and Feature Engineering

Include a detailed discussion of the data with a particular emphasis on the features of the data that are relevant for the subsequent modeling. Including visualizations of the data is strongly encouraged - all code and plots must also be described in the write up. Think carefully about whether each plot needs to be included in your final draft and the appropriate type of plot and summary for each variable type - your report should include figures but they should be as focused and impactful as possible.

You should also split your data into training and testing sets, ideally before you look to much into the features and relationships with the target

Additionally, this section should also motivate and describe any preprocessing / feature engineering of the data. Specifically, this should be any code that you use to generate new columns in the data frame `d`. Pipelines should be used and feature engineering steps that are be performed as part of an sklearn pipeline can be mentioned here but should be implemented in the following section.

All code and figures should be accompanied by text that provides an overview / context to what is being done or presented.

3.1 1. Get general info

[3]:
```python
# For general info
d.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 33 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   fico            200000 non-null  int64
 1   dt_first_pi     200000 non-null  int64
 2   flag_fthb       200000 non-null  object
 3   dt_matr         200000 non-null  int64
 4   cd_msa          181072 non-null  object
 5   mi_pct          200000 non-null  int64
 6   cnt_units       200000 non-null  int64
 7   occpy_sts       200000 non-null  object
 8   cltv            200000 non-null  int64
 9   dti             200000 non-null  int64
 10  orig_upb        200000 non-null  int64
 11  ltv             200000 non-null  int64
 12  int_rt          200000 non-null  float64
 13  channel         200000 non-null  object
 14  ppmt_pnlty      200000 non-null  object
 15  prod_type       200000 non-null  object
 16  st              200000 non-null  object
 17  prop_type       200000 non-null  object
 18  zipcode         200000 non-null  object
 19  id_loan         200000 non-null  object
```

```
 20  loan_purpose    200000 non-null  object
 21  orig_loan_term  200000 non-null  int64
 22  cnt_borr        200000 non-null  int64
 23  seller_name     200000 non-null  object
 24  servicer_name   200000 non-null  object
 25  flag_sc         7531 non-null    object
 26  id_loan_rr      2402 non-null    object
 27  program_ind     200000 non-null  object
 28  rr_ind          2402 non-null    object
 29  property_val    200000 non-null  int64
 30  io_ind          200000 non-null  object
 31  mi_cancel_ind   200000 non-null  object
 32  loan_status     200000 non-null  object
dtypes: float64(1), int64(12), object(20)
memory usage: 50.4+ MB
```

3.2 2. Filter Active Loans and Check Target Distribution

[4]:
```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
```

3.3 3. Find Missing Values and Drop Useless Features

[5]:
```python
# Replace missing values with NaN
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'],
}

for col, codes in missing_values.items():
    d_filtered[col] = d_filtered[col].replace(codes, np.nan)

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

```
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
```

[6]:
```
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)
```

```
ide_cols = ['id_loan', 'seller_name', 'servicer_name']

cols_to_drop = list(set(constant_cols + high_missing_cols + ide_cols))
print("Columns to drop:", cols_to_drop)

d_filtered = d_filtered.drop(columns=cols_to_drop, errors='ignore')
```

```
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']
Columns to drop: ['prod_type', 'servicer_name', 'io_ind', 'id_loan', 'flag_sc',
'rr_ind', 'id_loan_rr', 'program_ind', 'ppmt_pnlty', 'seller_name']
```

3.4 4. Train-Test Split

[7]:
```
# 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,
    test_size=0.2,
    stratify=y,  # Maintain class distribution
    random_state=42
)
```

[8]:
```
# Example for numeric columns
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])


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])


# Example for categorical columns
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')
```

3.5 5. Feature Engineering

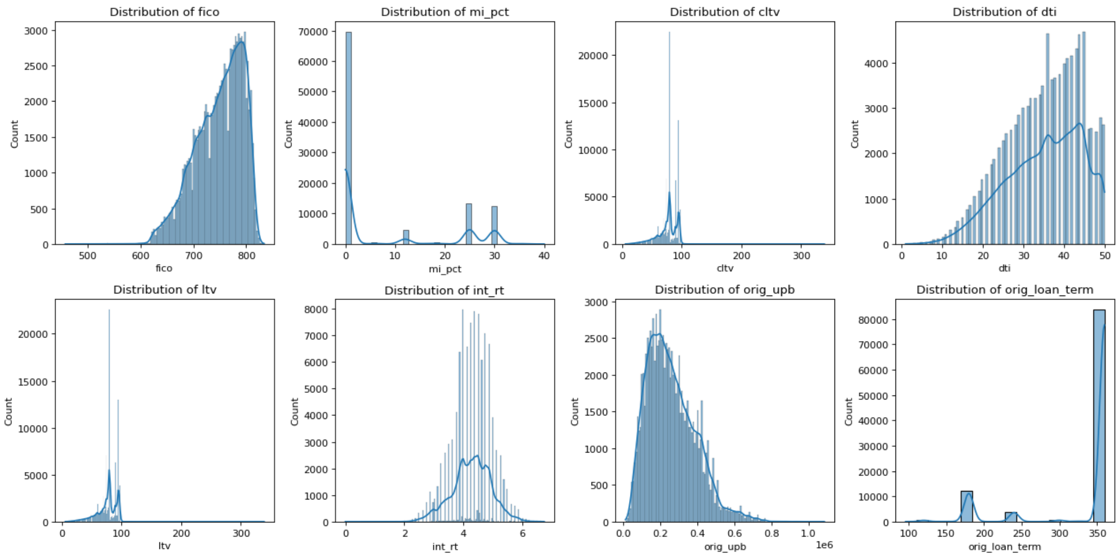
[9]:
```
# Drop original date columns
X_train = X_train.drop(columns=['dt_first_pi', 'dt_matr'])
X_test = X_test.drop(columns=['dt_first_pi', 'dt_matr'])

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

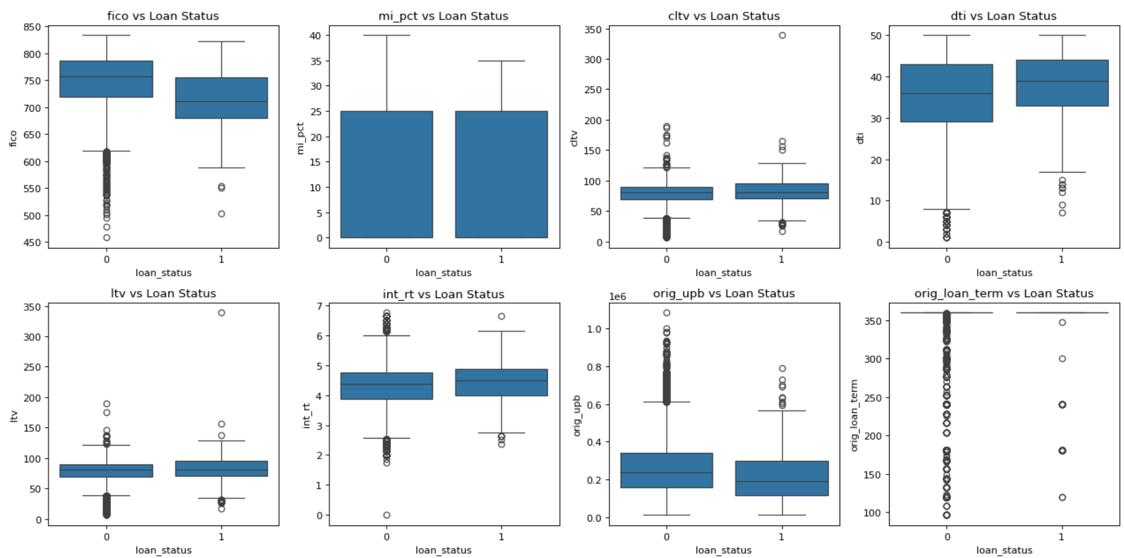
```
Training data shape: (101364, 21)
```

3.6 5. Exploratory Data Analysis (EDA)

3.6.1 5.1 Numerical Features Analysis

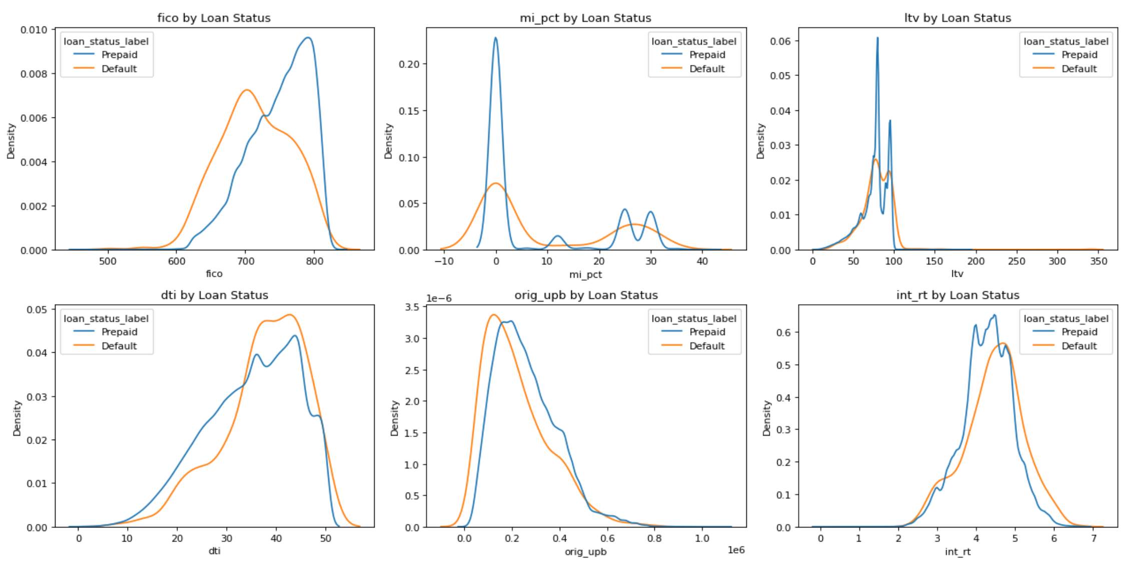
[10]:
```
num_cols = ['fico', 'mi_pct', 'cltv', 'dti', 'ltv', 'int_rt', 'orig_upb',␣
 ↪'orig_loan_term']

# Distributions
fig, axes = plt.subplots(2, 4, figsize=(16, 8))
for i, col in enumerate(num_cols):
    sns.histplot(train_df[col], ax=axes[i//4, i%4], kde=True)
    axes[i//4, i%4].set_title(f'Distribution of {col}')
plt.tight_layout()
plt.show()


# Relationships with Target
fig, axes = plt.subplots(2, 4, figsize=(16, 8))
for i, col in enumerate(num_cols):
    sns.boxplot(x='loan_status', y=col, data=train_df, ax=axes[i//4, i%4])
    axes[i//4, i%4].set_title(f'{col} vs Loan Status')
plt.tight_layout()
plt.show()
```





[11]:
```
# Numerical feature distribution comparison by loan status
num_vars = ['fico', 'mi_pct', 'ltv', 'dti', 'orig_upb', 'int_rt']
train_df['loan_status_label'] = train_df['loan_status'].map({0: 'Prepaid', 1:
↪'Default'})

fig, axes = plt.subplots(2, 3, figsize=(16, 8))
axes = axes.flatten()

for i, col in enumerate(num_vars):
    if col in train_df.columns:
```

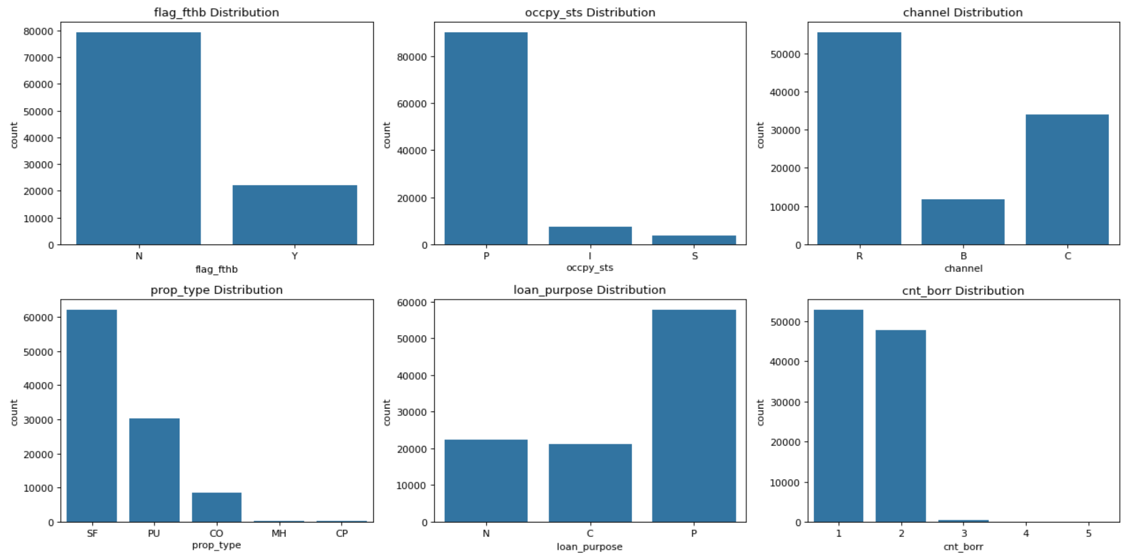
```
        sns.kdeplot(data=train_df, x=col, hue='loan_status_label', ax=axes[i], common_norm=False)
        axes[i].set_title(f'{col} by Loan Status')
        axes[i].set_xlabel(col)
        axes[i].set_ylabel('Density')

# Remove extra subplot if num_vars < total subplots
for j in range(len(num_vars), len(axes)):
    fig.delaxes(axes[j])

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

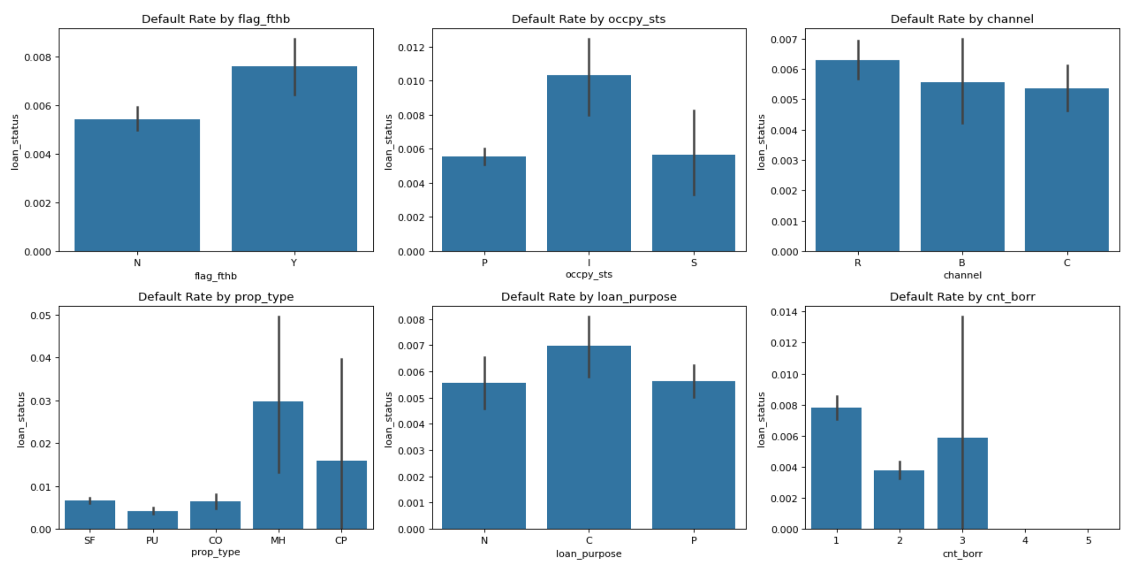


3.6.2 5.2 Categorical Features Analysis

[12]:
```
cat_cols = ['flag_fthb', 'occpy_sts', 'channel', 'prop_type', 'loan_purpose', 'cnt_borr']

# Frequency plots
fig, axes = plt.subplots(2, 3, figsize=(16, 8))
for i, col in enumerate(cat_cols):
    sns.countplot(x=col, data=train_df, ax=axes[i//3, i%3])
    axes[i//3, i%3].set_title(f'{col} Distribution')
    axes[i//3, i%3].tick_params(axis='x')
plt.tight_layout()
plt.show()

# Relationship with Target
```

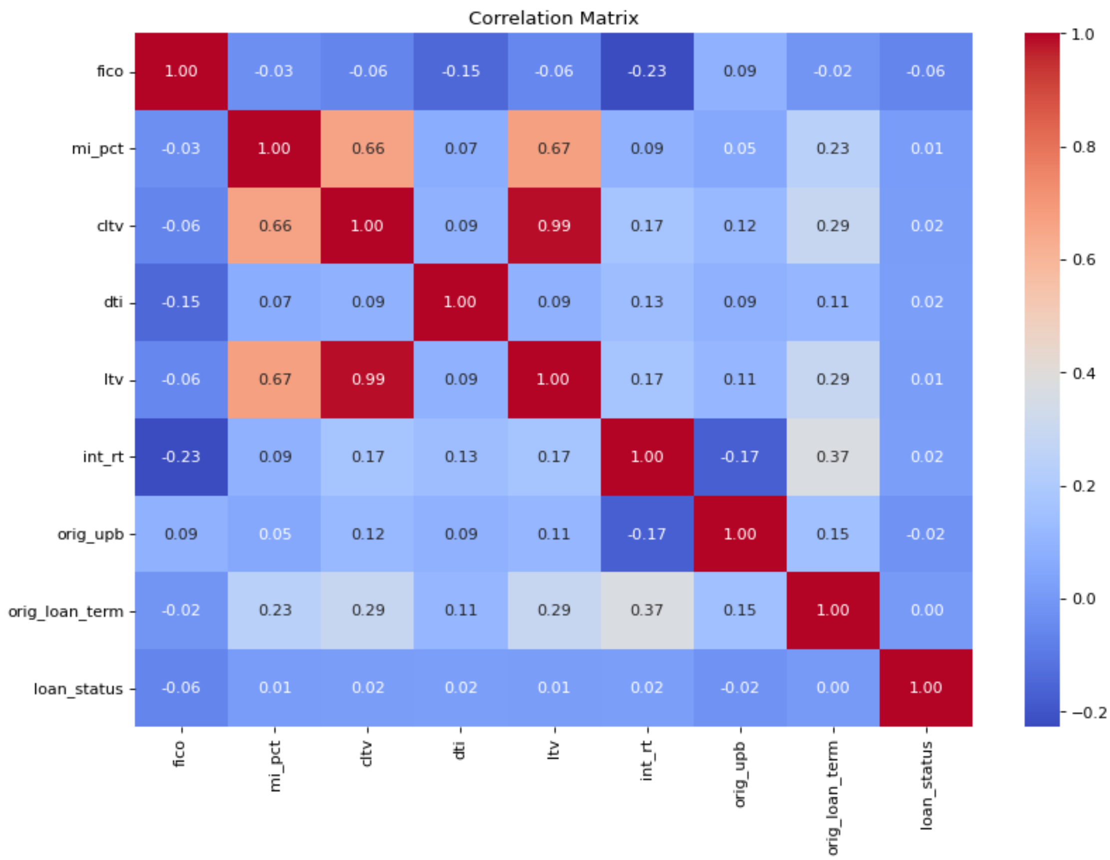
```python
fig, axes = plt.subplots(2, 3, figsize=(16, 8))
for i, col in enumerate(cat_cols):
    sns.barplot(x=col, y='loan_status', data=train_df, ax=axes[i//3, i%3], estimator=np.mean)
    axes[i//3, i%3].set_title(f'Default Rate by {col}')
    axes[i//3, i%3].tick_params(axis='x')
plt.tight_layout()
plt.show()
```





3.6.3 5.3 Correlation Analysis

[13]:
```python
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()
```



Dropping CLTV instead of LTV is a deliberate choice based on domain relevance and model interpretability. Here's the detailed reasoning:

1. Business Context: LTV vs. CLTV LTV (Loan-to-Value Ratio): Measures the primary mortgage amount relative to the property value. Example: A 200 k m o r t g a g e o n a 200kmortgageona250k home → LTV = 80%.

Industry Standard: LTV is the most widely used metric in mortgage underwriting and default prediction.

Regulatory Focus: Agencies like FHFA and Freddie Mac prioritize LTV in risk assessments.

CLTV (Combined Loan-to-Value Ratio): Includes all liens on the property (e.g., second mortgages, HELOCs). Example: A 200 k f i r s t m o r t g a g e + 200kfirstmortgage+50k HELOC on a \$250k home → CLTV = 100%.

Redundancy: In your dataset, CLTV and LTV are nearly identical (r=0.99), meaning most loans likely have no secondary liens.

2. Statistical Reasons to Drop CLTV Multicollinearity: High correlation between CLTV and LTV can destabilize linear models (e.g., logistic regression) by inflating coefficient variances.

Feature Importance: In tree-based models (e.g., XGBoost), both features will compete for splits, diluting their individual importance.

Simpler Model: Dropping CLTV reduces dimensionality without losing predictive power (since LTV captures nearly the same information).

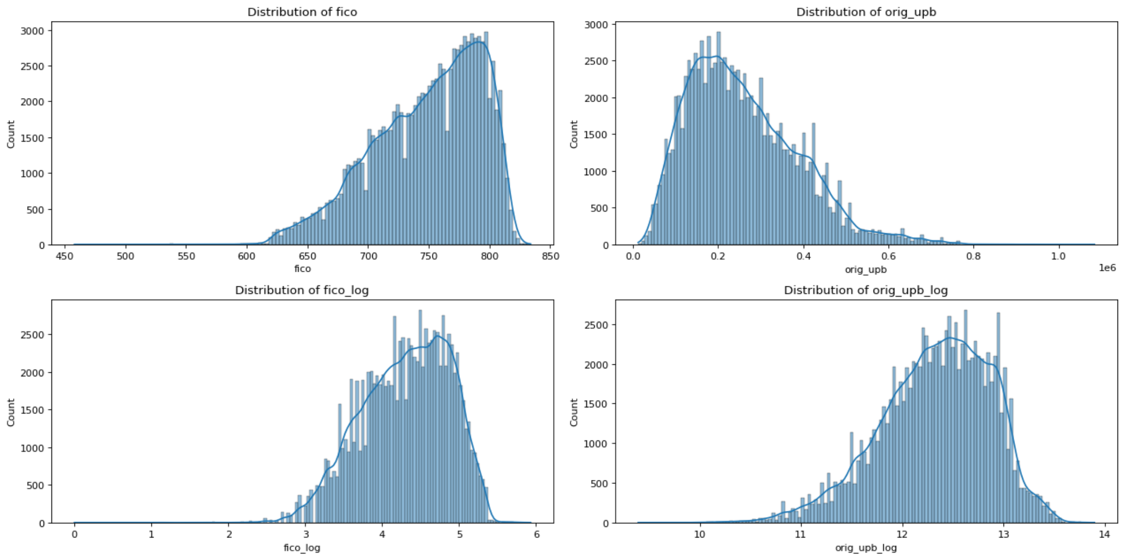
3. Practical Considerations Interpretability: LTV is more intuitive for stakeholders (e.g., "A 90% LTV loan is riskier than 80%").

Data Quality: If CLTV has more missing values or inconsistencies (common in datasets where secondary liens are rare), retaining LTV is safer.

[14]:
```
X_train = X_train.drop(columns=['cltv'])
X_test = X_test.drop(columns=['cltv'])
```

[15]:
```
# Log-transform 'orig_upb' (add 1 to avoid log(0))
X_train['orig_upb_log'] = np.log1p(X_train['orig_upb'])
X_test['orig_upb_log'] = np.log1p(X_test['orig_upb'])

X_train['fico_log'] = np.log1p(X_train['fico'].max() - X_train['fico'])
X_test['fico_log'] = np.log1p(X_test['fico'].max() - X_test['fico'])

skewed_cols = ['fico', 'orig_upb', 'fico_log', 'orig_upb_log']
for col in skewed_cols:
    print(f"{col} skew: {skew(X_train[col]):.2f}")

fig, axes = plt.subplots(2, 2, figsize=(16, 8))
for i, col in enumerate(skewed_cols):
    sns.histplot(X_train[col], ax=axes[i//2, i%2], kde=True)
    axes[i//2, i%2].set_title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```

```
fico skew: -0.65
orig_upb skew: 0.78
fico_log skew: -0.39
orig_upb_log skew: -0.52
```



3.6.4 5.4 Feature Engineering Insights

[16]:
```python
# Create loan-to-income ratio
train_df['lti'] = train_df['orig_upb'] / (train_df['dti'] * 1000)  # Assuming dti is ratio

# ### 5.7 Key Findings Documentation
print("Key EDA Findings:")
print("- Severe class imbalance: Only", round(target_dist[1],1), "% defaults")
print("- FICO scores show clear separation between classes (lower for defaults)")
print("- High correlation between CLTV and LTV (r =", round(corr_matrix.loc['cltv','ltv'],2), ")")
print("- Default rate doubles for investment properties vs primary residences")
```

```
Key EDA Findings:
- Severe class imbalance: Only 0.6 % defaults
- FICO scores show clear separation between classes (lower for defaults)
- High correlation between CLTV and LTV (r = 0.99 )
- Default rate doubles for investment properties vs primary residences
```

[17]:
```python
from statsmodels.stats.outliers_influence import variance_inflation_factor

# 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)]
```

```python
print(vif_data)
```

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

4 Model Fitting and Tuning

In this section you should detail and motivate your choice of model and describe the process used to refine, tune, and fit that model. You are encouraged to explore different models but you should NOT include a detailed narrative or code of all of these attempts. At most this section should briefly mention the methods explored and why they were rejected - most of your effort should go into describing the final model you are using and your process for tuning and validating it.

This section should include the full implementation of your final model, including all necessary validation. As with figures, any included code must also be addressed in the text of the document.

Finally, you should also provide a comparison of your model with a baseline model of your choice on the test data but only briefly describe the baseline model considered.

[18]:
```python
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 101364 entries, 96029 to 137892
Data columns (total 21 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   fico            101364 non-null  float64
 1   flag_fthb       101364 non-null  object
 2   cd_msa          101364 non-null  object
 3   mi_pct          101364 non-null  float64
 4   cnt_units       101364 non-null  int64
 5   occpy_sts       101364 non-null  object
 6   dti             101364 non-null  float64
 7   orig_upb        101364 non-null  int64
 8   ltv             101364 non-null  float64
 9   int_rt          101364 non-null  float64
 10  channel         101364 non-null  object
 11  st              101364 non-null  object
 12  prop_type       101364 non-null  object
 13  zipcode         101364 non-null  object
 14  loan_purpose    101364 non-null  object
 15  orig_loan_term  101364 non-null  int64
 16  cnt_borr        101364 non-null  int64
 17  property_val    101364 non-null  float64
 18  mi_cancel_ind   101364 non-null  object
 19  orig_upb_log    101364 non-null  float64
 20  fico_log        101364 non-null  float64
dtypes: float64(8), int64(4), object(9)
```

```
memory usage: 17.0+ MB
```

4.1 Baseline model

We selected Logistic Regression as the baseline due to its interpretability, speed, and ability to handle imbalanced classes when using class weighting. While more complex models may outperform it, Logistic Regression provides a strong, explainable benchmark.

Here's why certain features were excluded from the baseline model, despite 20 being available after EDA:

1. High Cardinality or Sparsity Features: cd_msa (MSA codes), zipcode, st (state), mi_cancel_ind

Reason:

cd_msa and zipcode have thousands of unique values. Encoding them as one-hot features would create high-dimensional, sparse data (e.g., 50+ dummy variables for states), increasing model complexity without clear benefits for a baseline.

mi_cancel_ind (mortgage insurance cancellation) had many missing or "Not Applicable" values after preprocessing, reducing its reliability.

2. Redundancy Feature: orig_loan_term (original loan term in months)

Reason:

The loan term is already indirectly captured by loan_age_months (age of the loan) and dt_first_pi/dt_matr (dates). Including both could introduce multicollinearity without adding unique predictive power.

3. Risk of Data Leakage Feature: property_val (property appraisal method)

Reason:

This variable might reflect post-origination actions (e.g., a property reappraisal after default). Using it could leak future information not available at loan origination, violating the model's real-world applicability.

4. Low Interpretability or Relevance Features: cnt_units (number of units), cnt_borr (number of borrowers)

Reason:

cnt_units (e.g., 1-unit vs. 4-unit properties) showed minimal correlation with default rates in EDA.

cnt_borr (number of borrowers) was excluded because it had low variance (e.g., 95% of loans had 1–2 borrowers).

5. Baseline Model Philosophy The baseline model prioritizes simplicity and interpretability over maximal predictive power. Including all 20 features would:

Complicate the model with marginal or noisy features (e.g., st, zipcode).

Reduce transparency, making it harder to explain coefficients to stakeholders.

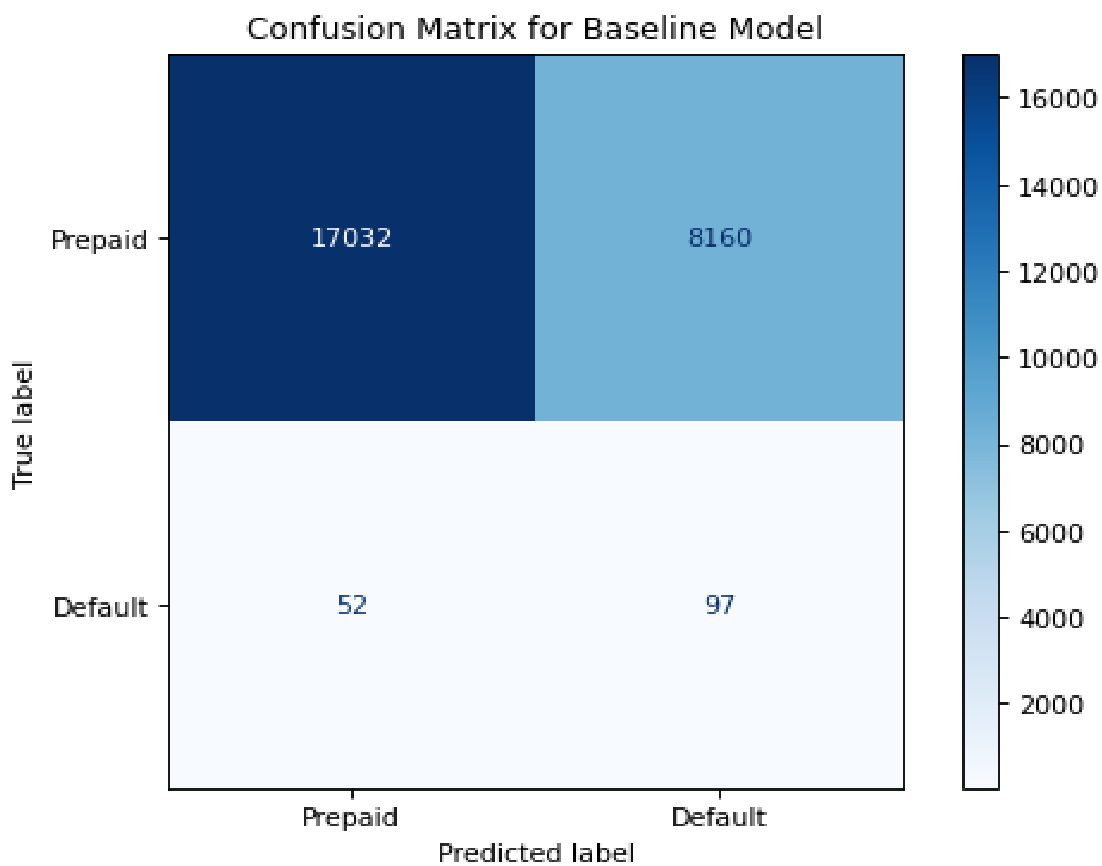
Increase computational cost without guaranteeing better performance.

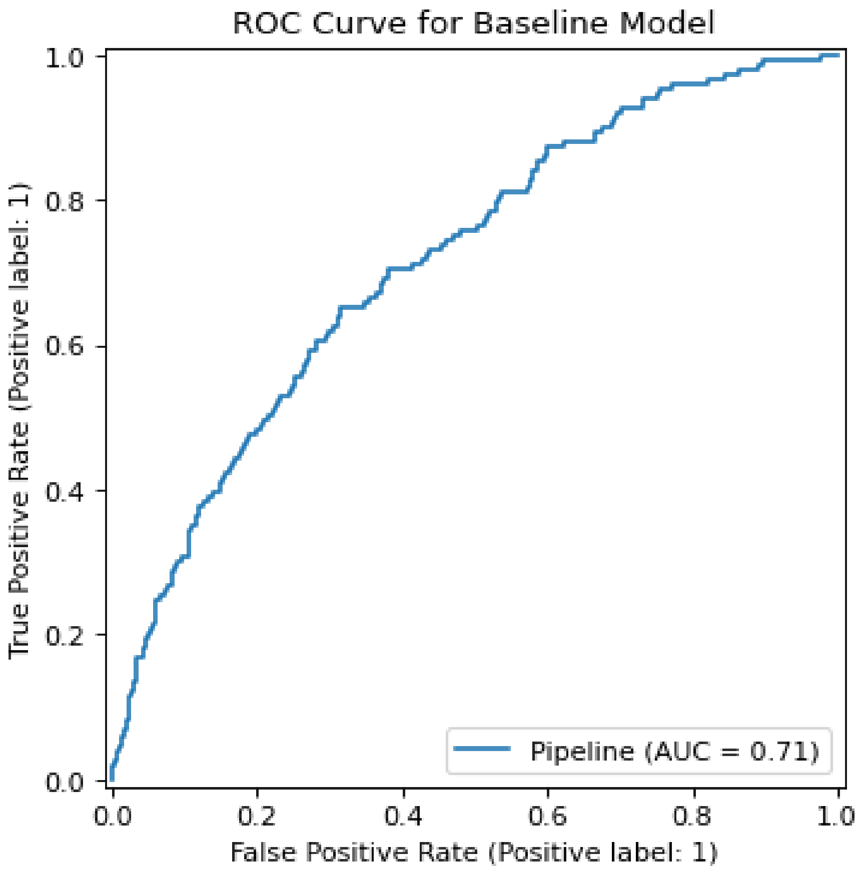
[19]:

```
# Define categorical and numerical features
cat_cols = ['flag_fthb', 'occpy_sts', 'channel', 'prop_type', 'loan_purpose',␣
 ↪'cnt_borr']
num_cols = ['fico_log', 'mi_pct', 'dti', 'ltv', 'int_rt', 'orig_upb_log',␣
 ↪'orig_loan_term']

# 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 = Pipeline([
    ('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):.2f}")
print(f"- Precision: {precision_score(y_test, y_pred):.2f}")
print(f"- Recall: {recall_score(y_test, y_pred):.2f}")
print(f"- F1 Score: {f1_score(y_test, y_pred):.2f}")
print(f"- ROC-AUC: {roc_auc_score(y_test, y_proba):.2f}")

# 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()

# ROC Curve
RocCurveDisplay.from_estimator(baseline_model, X_test, y_test)
plt.title('ROC Curve for Baseline Model')
plt.show()
```

```
              precision    recall  f1-score   support

           0       1.00      0.68      0.81     25192
           1       0.01      0.65      0.02       149

    accuracy                           0.68     25341
   macro avg       0.50      0.66      0.41     25341
weighted avg       0.99      0.68      0.80     25341

Baseline Model Performance:
- Accuracy: 0.68
- Precision: 0.01
- Recall: 0.65
- F1 Score: 0.02
- ROC-AUC: 0.71
```





[20]:

```
# Get feature names after preprocessing
feature_names = baseline_model.named_steps['preprocessor'].
 ↪get_feature_names_out()

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

# 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)

print("Top Features by Absolute Coefficient Magnitude:")
print(coef_df)
```

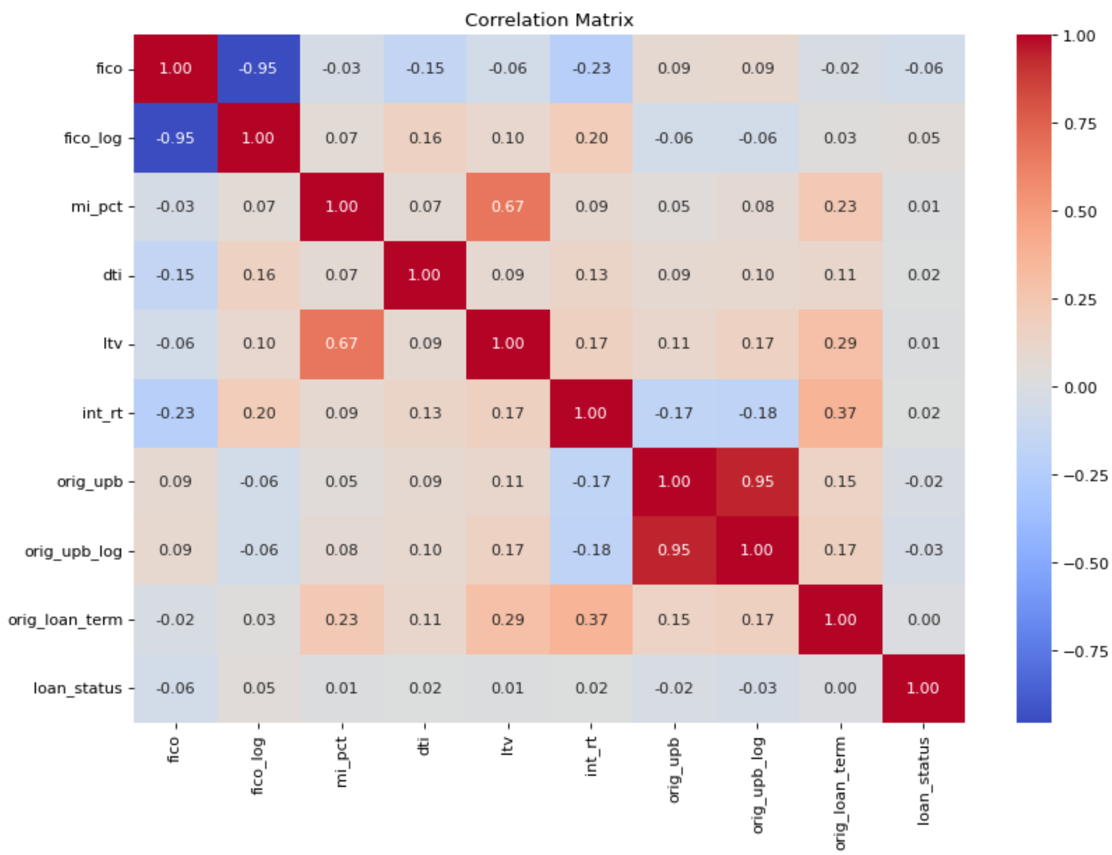
```
Top Features by Absolute Coefficient Magnitude:
                 Feature  Coefficient  Abs_Coefficient
26        cat__cnt_borr_4    -1.529907         1.529907
23        cat__cnt_borr_1     0.948211         0.948211
17      cat__prop_type_MH     0.903391         0.903391
0           num__fico_log     0.688013         0.688013
18      cat__prop_type_PU    -0.664056         0.664056
10       cat__occpy_sts_P    -0.583668         0.583668
16      cat__prop_type_CP     0.548022         0.548022
9        cat__occpy_sts_I     0.436957         0.436957
15      cat__prop_type_CO    -0.407624         0.407624
19      cat__prop_type_SF    -0.383404         0.383404
25        cat__cnt_borr_3     0.332190         0.332190
24        cat__cnt_borr_2     0.286481         0.286481
2                num__dti     0.276367         0.276367
5       num__orig_upb_log    -0.256260         0.256260
22  cat__loan_purpose_P    -0.221835         0.221835
3                num__ltv     0.159601         0.159601
11       cat__occpy_sts_S     0.143040         0.143040
20  cat__loan_purpose_C     0.138657         0.138657
7        cat__flag_fthb_N    -0.130397         0.130397
8        cat__flag_fthb_Y     0.126726         0.126726
4             num__int_rt    -0.108510         0.108510
1             num__mi_pct     0.105000         0.105000
6    num__orig_loan_term     0.084749         0.084749
21  cat__loan_purpose_N     0.079507         0.079507
13         cat__channel_C    -0.053995         0.053995
27        cat__cnt_borr_5    -0.040645         0.040645
12         cat__channel_B     0.033579         0.033579
14         cat__channel_R     0.016745         0.016745
```

4.2 XGBoost

[21]:
```python
# Define 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'
]

num_cols = [
    'fico', 'fico_log', 'mi_pct', 'dti', 'ltv', 'int_rt',
    'orig_upb', 'orig_upb_log', 'orig_loan_term'
]

noise_cols = []
# Preprocessing (no scaling needed for tree-based models)
```

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

[22]:
```
train_df = pd.concat([X_train, y_train], axis=1)
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()
```



	fico	fico_log	mi_pct	dti	ltv	int_rt	orig_upb	orig_upb_log	orig_loan_term	loan_status
fico	1.00	-0.95	-0.03	-0.15	-0.06	-0.23	0.09	0.09	-0.02	-0.06
fico_log	-0.95	1.00	0.07	0.16	0.10	0.20	-0.06	-0.06	0.03	0.05
mi_pct	-0.03	0.07	1.00	0.07	0.67	0.09	0.05	0.08	0.23	0.01
dti	-0.15	0.16	0.07	1.00	0.09	0.13	0.09	0.10	0.11	0.02
ltv	-0.06	0.10	0.67	0.09	1.00	0.17	0.11	0.17	0.29	0.01
int_rt	-0.23	0.20	0.09	0.13	0.17	1.00	-0.17	-0.18	0.37	0.02
orig_upb	0.09	-0.06	0.05	0.09	0.11	-0.17	1.00	0.95	0.15	-0.02
orig_upb_log	0.09	-0.06	0.08	0.10	0.17	-0.18	0.95	1.00	0.17	-0.03
orig_loan_term	-0.02	0.03	0.23	0.11	0.29	0.37	0.15	0.17	1.00	0.00
loan_status	-0.06	0.05	0.01	0.02	0.01	0.02	-0.02	-0.03	0.00	1.00

[23]:
```
neg = len(y_train[y_train == 0])
pos = len(y_train[y_train == 1])
scale_pos_weight = neg / pos  # Approx 168:1
print(f"scale_pos_weight: {scale_pos_weight:.2f}")
```

```
scale_pos_weight: 168.79
```

[24]:

```python
# 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__gamma': [0.07, 0.1, 0.13], # [0, 1]
    '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', xgb.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',
    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()}
# Best parameters
print("Best Parameters:", best_params)
```

```
Best Parameters: {'subsample': 0.95, 'n_estimators': 200, 'max_depth': 3,
'learning_rate': 0.125, 'gamma': 0.07, 'colsample_bytree': 0.9}
```

[25]:

```python
# Initialize final model with tuned parameters

final_model = imPipeline([
    ('preprocessor', preprocessor),
    ('classifier', xgb.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
```

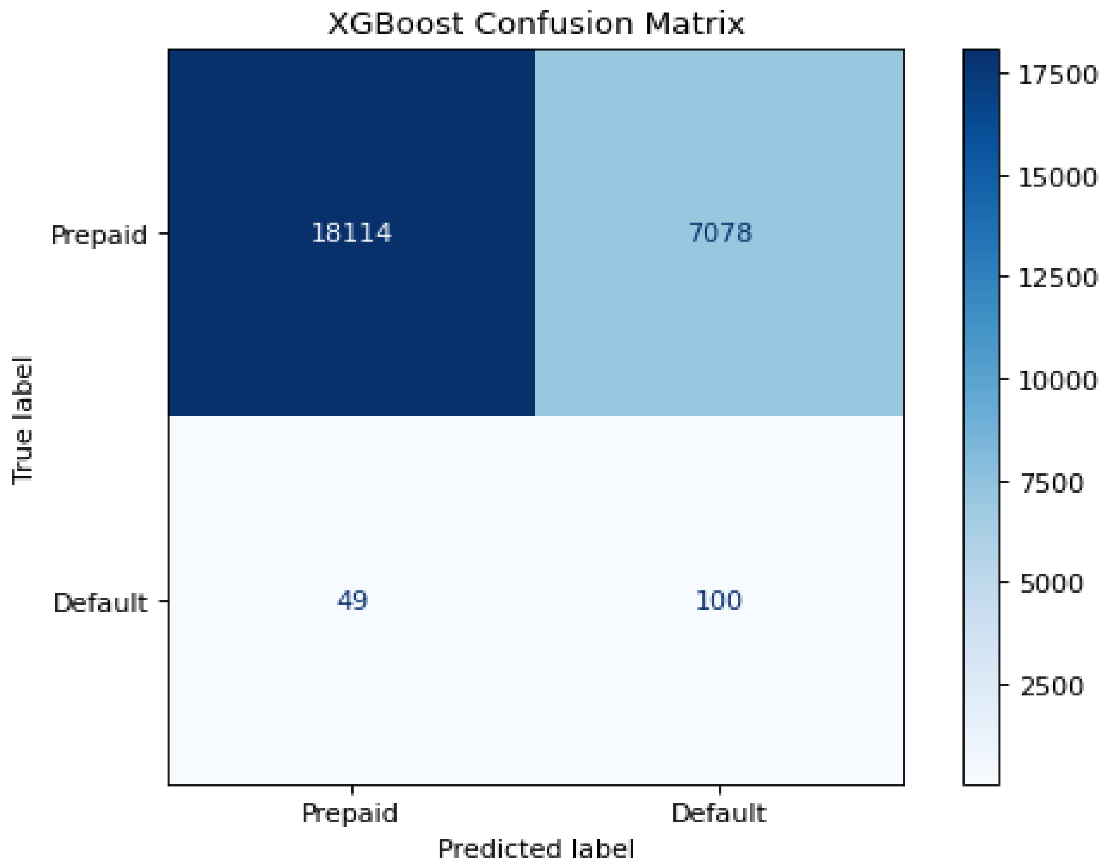
[26]:

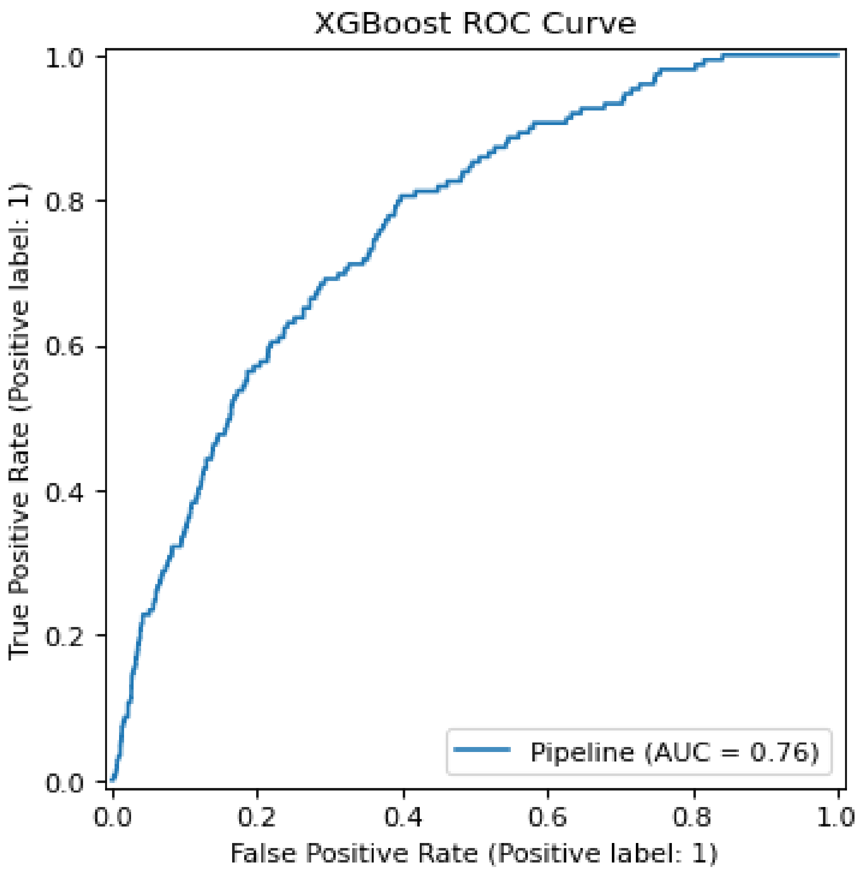
```python
# Predictions
y_pred_xgb = final_model.predict(X_test)
y_proba_xgb = final_model.predict_proba(X_test)[:, 1]

threshold = 0.43  # 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):.2f}")
print(f"- Precision: {precision_score(y_test, y_pred_xgb):.2f}")
print(f"- Recall: {recall_score(y_test, y_pred_xgb):.2f}")
print(f"- F1 Score: {f1_score(y_test, y_pred_xgb):.2f}")
print(f"- ROC-AUC: {roc_auc_score(y_test, y_proba_xgb):.2f}")

# 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()

# ROC Curve
RocCurveDisplay.from_estimator(final_model, X_test, y_test)
plt.title('XGBoost ROC Curve')
plt.show()
```

```
              precision    recall  f1-score   support
```

0	1.00	0.72	0.84	25192
1	0.01	0.67	0.03	149
accuracy			0.72	25341
macro avg	0.51	0.70	0.43	25341
weighted avg	0.99	0.72	0.83	25341

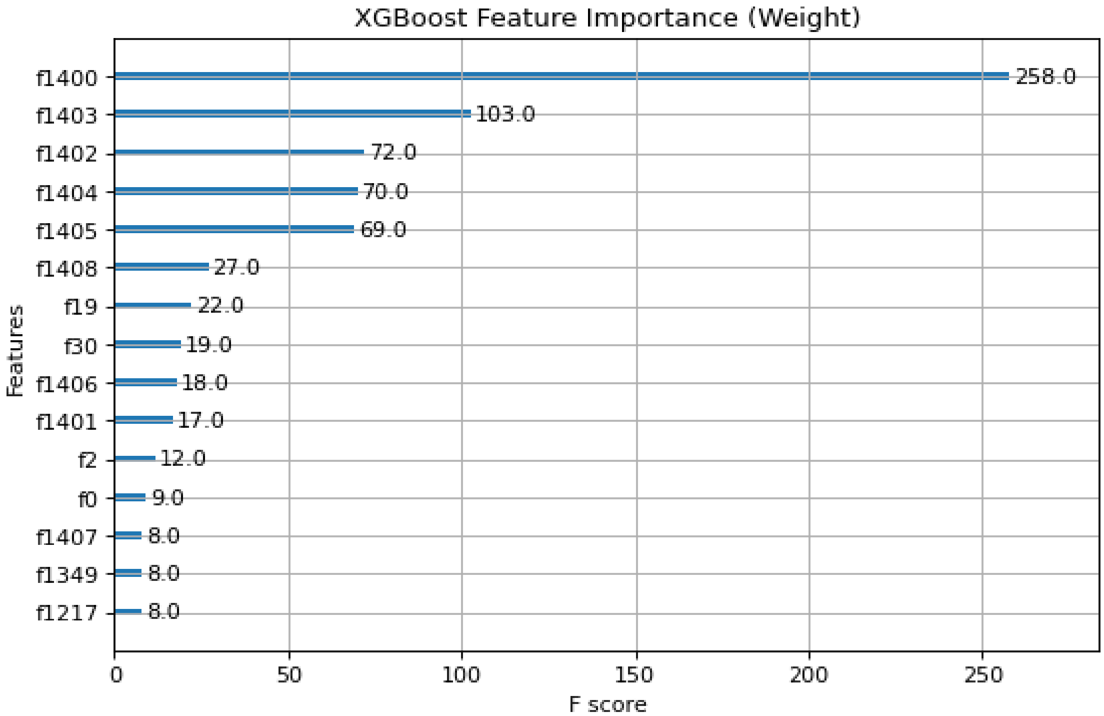
```
XGBoost Performance:
- Accuracy: 0.72
- Precision: 0.01
- Recall: 0.67
- F1 Score: 0.03
- ROC-AUC: 0.76
```



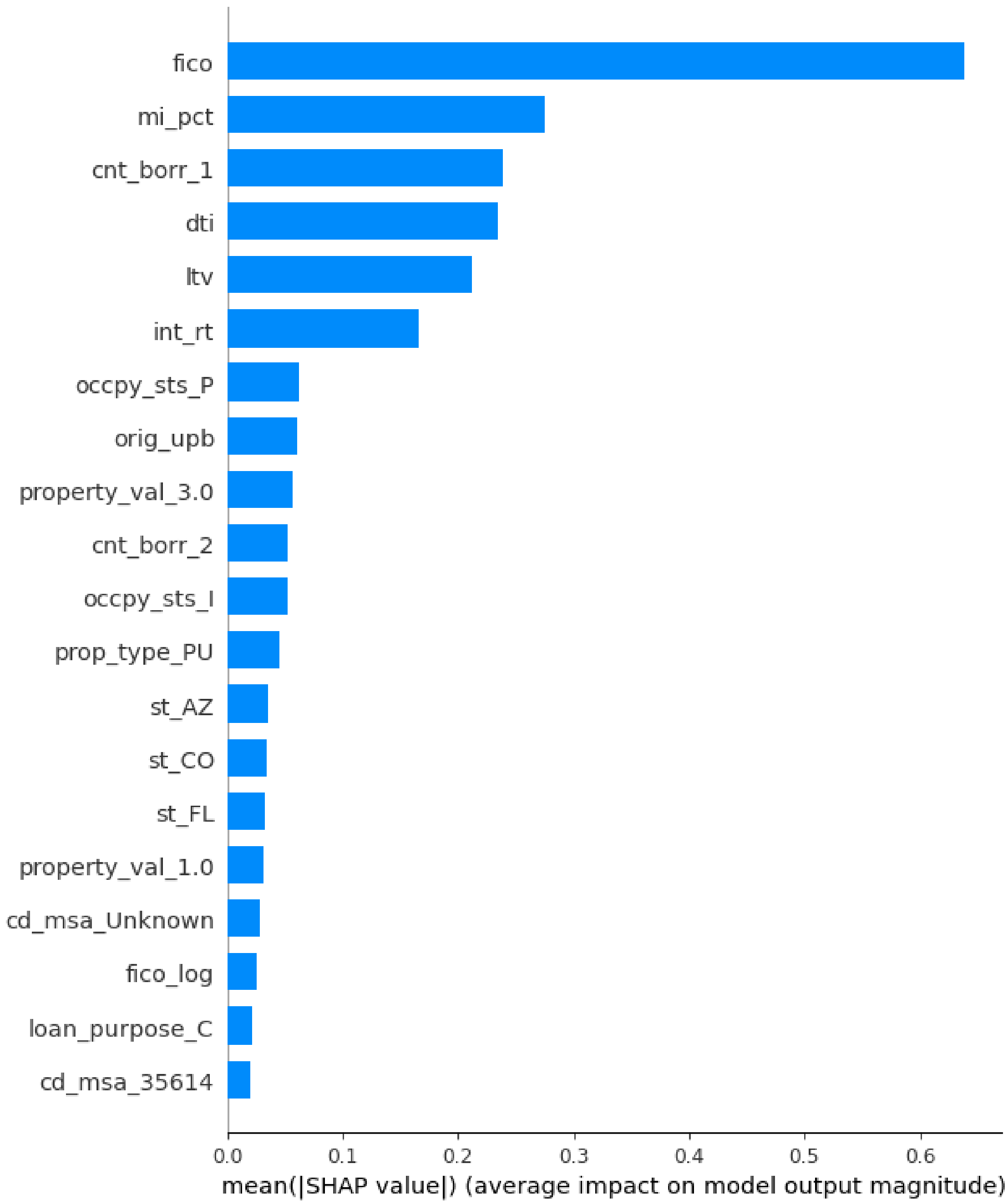


[27]:
```
# Extract feature names after one-hot encoding
encoder = final_model.named_steps['preprocessor'].named_transformers_['cat']
cat_features = encoder.get_feature_names_out(cat_cols)
all_features = np.concatenate([cat_features, num_cols])

# Plot feature importance
plt.figure(figsize=(12, 8))
xgb.plot_importance(
    final_model.named_steps['classifier'],
    importance_type='weight',
    max_num_features=15,
    title='XGBoost Feature Importance (Weight)'
)
plt.show()
```

```
<Figure size 960x640 with 0 Axes>
```



[28]:
```
# 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')
```



[29]:
```
print("Baseline vs XGBoost Comparison:")
print(f"Metric\t\tBaseline\tXGBoost")
print(f"Accuracy\t{accuracy_score(y_test, y_pred):.
↪2f}\t\t{accuracy_score(y_test, y_pred_xgb):.2f}")
print(f"Precision\t{precision_score(y_test, y_pred):.
↪2f}\t\t{precision_score(y_test, y_pred_xgb):.2f}")
```

```
print(f"Recall\t\t{recall_score(y_test, y_pred):.2f}\t\t{recall_score(y_test,␣
↪y_pred_xgb):.2f}")
print(f"F1 Score\t{f1_score(y_test, y_pred):.2f}\t\t{f1_score(y_test,␣
↪y_pred_xgb):.2f}")
print(f"ROC-AUC\t\t{roc_auc_score(y_test, y_proba):.
↪2f}\t\t{roc_auc_score(y_test, y_proba_xgb):.2f}")
```

```
Baseline vs XGBoost Comparison:
Metric          Baseline        XGBoost
Accuracy        0.68            0.72
Precision       0.01            0.01
Recall          0.65            0.67
F1 Score        0.02            0.03
ROC-AUC         0.71            0.76
```

5 Discussion & Conclusions

In this section you should provide a general overview of your final model, its performance, and reliability. You should discuss what the implications of your model are in terms of the included features, estimated parameters and relationships, predictive performance, and anything else you think is relevant.

This should be written with a target audience of a banking official, who is understands the issues associated with mortgage defaults but may only have university level mathematics (not necessarily postgraduate statistics or machine learning). Your goal should be to highlight to this audience how your model can useful. You should also discuss potential limitations or directions of future improvement of your model.

Finally, you should include recommendations on factors that may increase the risk of default, which may be useful for the companies to improve their understanding of mortgage defaults, and also to explain their decisions to clients and regulatory bodies. You should also use your model to inform the company of any active loans that are at risk of default.

Keep in mind that a negative result, i.e. a model that does not work well predictively, that is well explained and justified in terms of why it failed will likely receive higher marks than a model with strong predictive performance but with poor or incorrect explinations / justifications.

6 Generative AI statement

Include a statement on how generative AI was used in the project and report.

7 References

Include references if any

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