

Kaggle Playground

Problem Statement / Real World Implementations

```
In [1]: !pip install optuna-integration[xgboost]
```

```
Collecting optuna-integration[xgboost]
  Downloading optuna_integration-4.5.0-py3-none-any.whl.metadata (12 kB)

Requirement already satisfied: optuna in /usr/local/lib/python3.11/dist-packages (from optuna-integration[xgboost]) (4.5.0)

Requirement already satisfied: xgboost in /usr/local/lib/python3.11/dist-packages (from optuna-integration[xgboost]) (2.0.3)

Requirement already satisfied: alembic>=1.5.0 in /usr/local/lib/python3.11/dist-packages (from optuna->optuna-integration[xgboost]) (1.16.5)

Requirement already satisfied: colorlog in /usr/local/lib/python3.11/dist-packages (from optuna->optuna-integration[xgboost]) (6.9.0)

Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from optuna->optuna-integration[xgboost]) (1.26.4)

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Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost->optuna-integration[xgboost]) (1.15.3)

Requirement already satisfied: Mako in /usr/local/lib/python3.11/dist-packages (from alembic>=1.5.0->optuna->optuna-integration[xgboost]) (1.3.10)

Requirement already satisfied: typing-extensions>=4.12 in /usr/local/lib/python3.11/dist-packages (from alembic>=1.5.0->optuna->optuna-integration[xgboost]) (4.15.0)

Requirement already satisfied: greenlet>=1 in /usr/local/lib/python3.11/dist-packages (from sqlalchemy>=1.4.2->optuna->optuna-integration[xgboost]) (3.2.3)

Requirement already satisfied: mkl_fft in /usr/local/lib/python3.11/dist-packages (from numpy->optuna->optuna-integration[xgboost]) (1.3.8)

Requirement already satisfied: mkl_random in /usr/local/lib/python3.11/dist-packages (from numpy->optuna->optuna-integration[xgboost]) (1.2.4)

Requirement already satisfied: mkl_umat in /usr/local/lib/python3.11/dist-packages (from numpy->optuna->optuna-integration[xgboost]) (0.1.1)

Requirement already satisfied: mkl in /usr/local/lib/python3.11/dist-packages (from r->optuna->optuna-integration[xgboost]) (2025.2.0)

Requirement already satisfied: tbb4py in /usr/local/lib/python3.11/dist-packages (from numpy->optuna->optuna-integration[xgboost]) (2022.2.0)

Requirement already satisfied: mkl-service in /usr/local/lib/python3.11/dist-packages (from numpy->optuna->optuna-integration[xgboost]) (2.4.1)
```

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Requirement already satisfied: MarkupSafe>=0.9.2 in /usr/local/lib/python3.11/dist-packages (from Mako->alembic>=1.5.0->optuna->optuna-integration[xgboost]) (3.0.2)

Requirement already satisfied: intel-openmp<2026,>=2024 in /usr/local/lib/python3.11/dist-packages (from mkl->numpy->optuna->optuna-integration[xgboost]) (2024.2.0)

Requirement already satisfied: tbb==2022.* in /usr/local/lib/python3.11/dist-packages (from mkl->numpy->optuna->optuna-integration[xgboost]) (2022.2.0)

Requirement already satisfied: tcmlib==1.* in /usr/local/lib/python3.11/dist-packages (from tbb==2022.*->mkl->numpy->optuna->optuna-integration[xgboost]) (1.4.0)

Requirement already satisfied: intel-cmplr-lib-rt in /usr/local/lib/python3.11/dist-packages (from mkl_umath->numpy->optuna->optuna-integration[xgboost]) (2024.2.0)

Requirement already satisfied: intel-cmplr-lib-ur==2024.2.0 in /usr/local/lib/python3.11/dist-packages (from intel-openmp<2026,>=2024->mkl->numpy->optuna->optuna-integration[xgboost]) (2024.2.0)
```

Downloading optuna_integration-4.5.0-py3-none-any.whl (99 kB)

· 99.1/99.1 kB 3.2 MB/s eta 0:00:00

Installing collected packages: optuna-integration

Successfully installed optuna-integration-4.5.0

```
In [2]: # --- 1. Importing Libraries ---
import numpy as np
import pandas as pd
import warnings
import optuna
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import display

from sklearn.model_selection import KFold, train_test_split, StratifiedKFold
from sklearn.preprocessing import OrdinalEncoder, StandardScaler, RobustScaler,
from sklearn.metrics import roc_auc_score, mean_squared_error, mean_absolute_err

from xgboost import XGBRegressor
from catboost import CatBoostRegressor
# (LightGBM imports have been removed)

# Notebook settings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
optuna.logging.set_verbosity(optuna.logging.WARNING)

N_TRIALS_XGB = 50
N_TRIALS_CATBOOST = 30
N_SPLITS_OOF_CHECK = 5
N_SPLITS_TUNE = 5
GLOBAL_RANDOM_STATE = 42

print("Version 10: AUC-Driven 2-Model (XGB + CAT) CV-Tuned Blend")
print(f"--- 1. Loading Data ---")
```

```

# Define file paths
TRAIN_PATH = "/kaggle/input/playground-series-s5e11/train.csv"
TEST_PATH = "/kaggle/input/playground-series-s5e11/test.csv"

# Load the datasets
train_df = pd.read_csv(TRAIN_PATH)
test_df = pd.read_csv(TEST_PATH)

print(f"Train shape: {train_df.shape}, Test shape: {test_df.shape}")

# --- 2. Preprocessing & Feature Engineering (V4 DNA + V10 Experimental) ---
print("--- 2. Defining Preprocessing & Feature Engineering Pipelines ---")

def create_financial_features_v4(df):
    """ V4 Champion DNA Features """
    df_feat = df.copy()
    df_feat['loan_to_income_ratio'] = df_feat['loan_amount'] / (df_feat['annual_
    df_feat['interest_x_loan'] = df_feat['interest_rate'] * df_feat['loan_amount']
    df_feat['available_income'] = df_feat['annual_income'] * (1 - df_feat['debt_'
    df_feat['loan_to_available_income'] = df_feat['loan_amount'] / (df_feat['ava'
    df_feat.replace([np.inf, -np.inf], np.nan, inplace=True)
    return df_feat

def add_experimental_features(df):
    """ V10 Experimental Features (Point 1) """
    df_feat = df.copy()
    df_feat['interest_to_income_ratio'] = df_feat['interest_rate'] / (df_feat['a'
    df_feat['credit_score_x_interest'] = df_feat['credit_score'] * df_feat['inte'
    df_feat['credit_score_to_loan'] = df_feat['credit_score'] / (df_feat['loan_a'
    df_feat.replace([np.inf, -np.inf], np.nan, inplace=True)
    return df_feat

# FIX: Create map from TRAIN data ONLY to prevent Leakage
all_grades = train_df['grade_subgrade'].unique()
grades_sorted = sorted([g for g in all_grades if pd.notna(g)])
ALL_GRADES_MAP = {grade: i for i, grade in enumerate(grades_sorted)}

def apply_logical_encoding(df, all_grades_map):
    """ Applies logical ordinal mapping as per V4 DNA """
    df_encoded = df.copy()
    education_map = {'Other': 0, 'High School': 1, "Bachelor's": 2, "Master's": 3}
    df_encoded['education_level'] = df_encoded['education_level'].map(education_
    df_encoded['grade_subgrade'] = df_encoded['grade_subgrade'].map(all_grades_m
    return df_encoded

def preprocess(df, use_experimental_features=False, train_cols=None, encoder=None):
    """ Full preprocessing pipeline """
    df_proc = df.drop('id', axis=1, errors='ignore')

    # 1. V4 Features
    df_proc = create_financial_features_v4(df_proc)

    # 2. Experimental Features
    if use_experimental_features:
        df_proc = add_experimental_features(df_proc)

    # 3. Logical Encoding
    df_proc = apply_logical_encoding(df_proc, ALL_GRADES_MAP)

    # 4. Other Categorical Features

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categorical_cols = list(df_proc.select_dtypes(include='object').columns)

if encoder is None:
    df_proc[categorical_cols] = df_proc[categorical_cols].fillna('Missing')
    encoder = OrdinalEncoder(handle_unknown='use_encoded_value', unknown_val='Missing')
    df_proc[categorical_cols] = encoder.fit_transform(df_proc[categorical_cols])
else:
    df_proc[categorical_cols] = df_proc[categorical_cols].fillna('Missing')
    df_proc[categorical_cols] = encoder.transform(df_proc[categorical_cols])

# 5. Handle NaNs with sentinel value -1 (V4 DNA)
df_proc = df_proc.fillna(-1)

# 6. Align columns
if train_cols is not None:
    missing_cols = set(train_cols) - set(df_proc.columns)
    for c in missing_cols:
        df_proc[c] = -1
    df_proc = df_proc[train_cols]

return df_proc, encoder

# --- 3. Feature & Scaler Selection (Point 1 & 2) ---
print("--- 3. Testing Feature Sets and Scalers (Points 1 & 2) ---")

# Prepare data for testing
y_full = train_df['loan_paid_back']

# Base V4 features
train_proc_v4, cat_encoder_v4 = preprocess(train_df.drop('loan_paid_back', axis=1))
X_train_v4, X_val_v4, y_train_v4, y_val_v4 = train_test_split(train_proc_v4, y_full, test_size=0.2, random_state=42)

# Experimental features
train_proc_exp, cat_encoder_exp = preprocess(train_df.drop('loan_paid_back', axis=1))
X_train_exp, X_val_exp, y_train_exp, y_val_exp = train_test_split(train_proc_exp, y_full, test_size=0.2, random_state=42)

# Scalers to test (Point 2)
scalers = {
    "Standard": StandardScaler(),
    "Robust": RobustScaler(),
    "Quantile": QuantileTransformer(output_distribution='normal', random_state=42)
}

results = []
# --- FIX: Use XGBRegressor for the quick test ---
xgb_test_params = {'tree_method': 'gpu_hist', 'predictor': 'gpu_predictor', 'gpu_id': 0, 'n_estimators': 100, 'max_depth': 5, 'learning_rate': 0.1, 'scale_pos_weight': 1, 'gamma': 0, 'min_child_weight': 1, 'subsample': 1, 'colsample_bytree': 1, 'reg_alpha': 0, 'reg_lambda': 1, 'missing': -1}

# Test V4 Features
print("Testing V4 Features with different scalers...")
for name, scaler_obj in scalers.items():
    model = XGBRegressor(**xgb_test_params) # Use XGB for the test
    X_tr_s = scaler_obj.fit_transform(X_train_v4)
    X_val_s = scaler_obj.transform(X_val_v4)
    model.fit(X_tr_s, y_train_v4)
    preds = model.predict(X_val_s)
    auc = roc_auc_score(y_val_v4, preds)
    results.append({"features": "V4_Baseline", "scaler": name, "auc": auc})

# Test Experimental Features (Point 1)
print("Testing V10 Experimental Features with different scalers...")

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for name, scaler_obj in scalers.items():
    model = XGBRegressor(**xgb_test_params) # Use XGB for the test
    X_tr_s = scaler_obj.fit_transform(X_train_exp)
    X_val_s = scaler_obj.transform(X_val_exp)
    model.fit(X_tr_s, y_train_exp)
    preds = model.predict(X_val_s)
    auc = roc_auc_score(y_val_exp, preds)
    results.append({"features": "V10_Experimental", "scaler": name, "auc": auc})

results_df = pd.DataFrame(results).sort_values(by="auc", ascending=False)
print("\n--- Scaler and Feature Validation Results ---")
print(results_df)

# Select best config
best_config = results_df.iloc[0]
best_feature_set_name = best_config['features']
BEST_SCALER_CLASS = scalers[best_config['scaler']].__class__ # Get the class, no
USE_EXPERIMENTAL_FEATURES = (best_feature_set_name == "V10_Experimental")

# (Point 1 Check)
baseline_auc = results_df[results_df['features'] == 'V4_Baseline']['auc'].max()
exp_auc = results_df[results_df['features'] == 'V10_Experimental']['auc'].max()
auc_gain = exp_auc - baseline_auc

if (USE_EXPERIMENTAL_FEATURES and auc_gain > 0.002):
    print(f"\nDecision (Point 1): V10 Experimental features kept (AUC Gain: {auc
else:
    if USE_EXPERIMENTAL_FEATURES:
        print(f"\nDecision (Point 1): V10 features gain ({auc_gain:+.6f}) < 0.0
    else:
        print(f"\nDecision (Point 1): V4 features performed best. Sticking with
USE_EXPERIMENTAL_FEATURES = False
# Re-select the best scaler *just* for V4 features
best_config_v4 = results_df[results_df['features'] == 'V4_Baseline'].iloc[0]
BEST_SCALER_CLASS = scalers[best_config_v4['scaler']].__class__

print(f"Selected Features: {'V10_Experimental' if USE_EXPERIMENTAL_FEATURES else
print(f"Selected Scaler (Point 2): {BEST_SCALER_CLASS.__name__}")

# --- 4. OOF Sanity Check ---
print(f"\n--- 4. OOF Sanity Check ({N_SPLITS_OOF_CHECK}-Folds) ---")
train_proc_final, cat_encoder_final = preprocess(train_df.drop('loan_paid_back',
                                                               use_experimental_features=USE_E
y_full = train_df['loan_paid_back']
FINAL_TRAIN_COLS = train_proc_final.columns

kf = KFold(n_splits=N_SPLITS_OOF_CHECK, shuffle=True, random_state=GLOBAL_RANDOM
oof_preds = np.zeros(len(train_proc_final))

# --- FIX: Use XGBRegressor for the sanity check ---
xgb_test_params = {'tree_method': 'gpu_hist', 'predictor': 'gpu_predictor', 'gpu
model_oof = XGBRegressor(**xgb_test_params)
# --- End Fix ---

for fold, (train_idx, val_idx) in enumerate(kf.split(train_proc_final, y_full)):
    print(f"Running OOF Fold {fold+1}/{N_SPLITS_OOF_CHECK}...")
    X_tr, X_v = train_proc_final.iloc[train_idx], train_proc_final.iloc[val_idx]
    y_tr, y_v = y_full.iloc[train_idx], y_full.iloc[val_idx]

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scaler_oof = BEST_SCALER_CLASS()
X_tr_s = scaler_oof.fit_transform(X_tr)
X_v_s = scaler_oof.transform(X_v)

model_oof.fit(X_tr_s, y_tr)
oof_preds[val_idx] = model_oof.predict(X_v_s)

oof_auc = roc_auc_score(y_full, oof_preds)
print(f"\nSanity Check OOF AUC: {oof_auc:.6f}")

# --- 5. Unified AUC Tuning Function (CV-Based) ---
print(f"\n--- 5. AUC-Driven Optuna Tuning (with {N_SPLITS_TUNE}-Fold CV) ---")

X_train_final = train_proc_final
y_train_final = y_full

def train_auc_model(model_type="xgb", n_trials=30):
    """
    Unified Optuna-AUC pipeline function
    Uses K-Fold CV for robust tuning.
    """

    def objective(trial):
        # --- Create parameters ---
        if model_type == "xgb":
            param = {
                'tree_method': 'gpu_hist', 'predictor': 'gpu_predictor', 'gpu_id':
                'lambda': trial.suggest_loguniform('lambda', 1e-3, 10.0),
                'alpha': trial.suggest_loguniform('alpha', 1e-3, 10.0),
                'colsample_bytree': trial.suggest_categorical('colsample_bytree',
                'subsample': trial.suggest_categorical('subsample', [0.6, 0.7, 0.8]),
                'learning_rate': trial.suggest_float('learning_rate', 0.01, 0.05),
                'n_estimators': trial.suggest_int('n_estimators', 400, 1500),
                'max_depth': trial.suggest_int('max_depth', 4, 10),
                'min_child_weight': trial.suggest_int('min_child_weight', 1, 300),
                'random_state': GLOBAL_RANDOM_STATE, 'verbose': 0
            }

        elif model_type == "catboost":
            param = {
                'task_type': 'GPU', 'iterations': trial.suggest_int('iterations',
                'learning_rate': trial.suggest_float('learning_rate', 0.01, 0.05),
                'depth': trial.suggest_int('depth', 4, 10),
                'l2_leaf_reg': trial.suggest_loguniform('l2_leaf_reg', 1.0, 10.0),
                'random_strength': trial.suggest_loguniform('random_strength', 1.0,
                'bagging_temperature': trial.suggest_loguniform('bagging_temperature',
                'eval_metric': 'AUC', 'od_type': 'Iter', 'od_wait': 50,
                'random_seed': GLOBAL_RANDOM_STATE, 'verbose': 0
            }

        # --- Run 5-Fold Cross-Validation ---
        kf = KFold(n_splits=N_SPLITS_TUNE, shuffle=True, random_state=GLOBAL_RANDOM_STATE)
        fold_auc_scores = []

        for fold, (train_idx, val_idx) in enumerate(kf.split(X_train_final, y_train_final)):
            X_tr, X_v = X_train_final.iloc[train_idx], X_train_final.iloc[val_idx]
            y_tr, y_v = y_train_final.iloc[train_idx], y_train_final.iloc[val_idx]

            scaler_cv = BEST_SCALER_CLASS()

```

```

X_tr_s = scaler_cv.fit_transform(X_tr)
X_v_s = scaler_cv.transform(X_v)

if model_type == "xgb":
    model = XGBRegressor(**param)
    model.fit(X_tr_s, y_tr,
              eval_set=[(X_v_s, y_v)],
              eval_metric='auc',
              callbacks=[optuna.integration.XGBoostPruningCallback(t
early_stopping_rounds=100,
verbose=0)

elif model_type == "catboost":
    model = CatBoostRegressor(**param)
    model.fit(X_tr_s, y_tr,
              eval_set=[(X_v_s, y_v)],
              early_stopping_rounds=100,
              verbose=0)

preds = model.predict(X_v_s)
auc = roc_auc_score(y_v, preds)
fold_auc_scores.append(auc)

trial.report(auc, fold)
if trial.should_prune():
    raise optuna.exceptions.TrialPruned()

return np.mean(fold_auc_scores)

# --- Run the study ---
pruner = optuna.pruners.MedianPruner(n_warmup_steps=2)
study = optuna.create_study(direction='maximize', pruner=pruner)
study.optimize(objective, n_trials=n_trials, timeout=7200)

print(f"Best {model_type.upper()} CV AUC: {study.best_value:.6f}")
return study.best_params, study.best_value

# --- Run tuners (LGBM removed) ---
print(f"Tuning XGB for CV AUC ({N_TRIALS_XGB} trials)...")
params_xgb, val_auc_xgb = train_auc_model("xgb", n_trials=N_TRIALS_XGB)

print(f"Tuning CatBoost for CV AUC ({N_TRIALS_CATBOOST} trials)...")
params_cat, val_auc_catboost = train_auc_model("catboost", n_trials=N_TRIALS_CAT

# --- 6. AUC-Weighted Ensemble & Submission ---
print("\n--- 6. Final Training, Blending, and Submission ---")

print("Calculating AUC-based blend weights...")
total_auc = val_auc_xgb + val_auc_catboost
weight_xgb = val_auc_xgb / total_auc
weight_catboost = val_auc_catboost / total_auc

print(f"XGB Weight: {weight_xgb:.4f} (CV AUC: {val_auc_xgb:.6f})")
print(f"CAT Weight: {weight_catboost:.4f} (CV AUC: {val_auc_catboost:.6f})")

# Retrain models on 100% of the *best* feature set
print("Retraining models on 100% data...")
scaler_final = BEST_SCALER_CLASS()
X_full_final_s = scaler_final.fit_transform(train_proc_final)

```

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y_full = train_df['loan_paid_back']

# Initialize and train final models
xgb_final = XGBRegressor(**params_xgb, tree_method='gpu_hist', predictor='gpu_pr
xgb_final.fit(X_full_final_s, y_full)

if 'iterations' not in params_cat:
    params_cat['iterations'] = 1000
catboost_final = CatBoostRegressor(**params_cat, task_type='GPU', eval_metric='A
catboost_final.fit(X_full_final_s, y_full)

# Prepare test data
print("Preprocessing test data...")
test_proc, _ = preprocess(test_df,
                           use_experimental_features=USE_EXPERIMENTAL_FEATURES,
                           train_cols=FINAL_TRAIN_COLS,
                           encoder=cat_encoder_final)
X_test_scaled = scaler_final.transform(test_proc)

# Predict
print("Generating predictions from both models...")
preds_xgb = xgb_final.predict(X_test_scaled)
preds_catboost = catboost_final.predict(X_test_scaled)

# Blend
blended_preds = (weight_xgb * preds_xgb) + \
                 (weight_catboost * preds_catboost)

# Clip predictions to prevent AUC penalties
clipped_preds = np.clip(blended_preds, 0.001, 0.999)

# Create submission file
print("Creating submission.csv...")
submission = pd.DataFrame({'id': test_df['id'], 'loan_paid_back': clipped_preds})
submission.to_csv('submission_v10.csv', index=False)

print("❖ Version 10 Complete. Submission file generated.")
display(submission.head())

# Display prediction distribution
print("\nFinal Prediction Distribution:")
sns.histplot(clipped_preds, bins=50, kde=True)
plt.title("Version 10 Final Blended Prediction Distribution")
plt.xlabel("Predicted loan_paid_back")
plt.show()

```

```
Version 10: AUC-Driven 2-Model (XGB + CAT) CV-Tuned Blend
--- 1. Loading Data ---
Train shape: (593994, 13), Test shape: (254569, 12)
--- 2. Defining Preprocessing & Feature Engineering Pipelines ---
--- 3. Testing Feature Sets and Scalers (Points 1 & 2) ---
Testing V4 Features with different scalers...
Testing V10 Experimental Features with different scalers...

--- Scaler and Feature Validation Results ---
      features      scaler        auc
2       V4_Baseline  Quantile  0.918066
5   V10_Experimental  Quantile  0.918045
1       V4_Baseline    Robust  0.917813
0       V4_Baseline   Standard  0.917812
3   V10_Experimental   Standard  0.917790
4   V10_Experimental     Robust  0.917606

Decision (Point 1): V4 features performed best. Sticking with V4 features.
Selected Features: V4_Baseline
Selected Scaler (Point 2): QuantileTransformer

--- 4. OOF Sanity Check (5-Folds) ---
Running OOF Fold 1/5...
Running OOF Fold 2/5...
Running OOF Fold 3/5...
Running OOF Fold 4/5...
Running OOF Fold 5/5...

Sanity Check OOF AUC: 0.918671

--- 5. AUC-Driven Optuna Tuning (with 5-Fold CV) ---
Tuning XGB for CV AUC (50 trials)...
Best XGB CV AUC: 0.919579
Tuning CatBoost for CV AUC (30 trials)...
```


Default metric period is 5 because AUC is/are not implemented for GPU
AUC is not implemented on GPU. Will use CPU for metric computation, this could significantly affect learning time

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Default metric period is 5 because AUC is/are not implemented for GPU
AUC is not implemented on GPU. Will use CPU for metric computation, this could significantly affect learning time

Best CATBOOST CV AUC: 0.918577

--- 6. Final Training, Blending, and Submission ---
Calculating AUC-based blend weights...
XGB Weight: 0.5003 (CV AUC: 0.919579)
CAT Weight: 0.4997 (CV AUC: 0.918577)
Retraining models on 100% data...

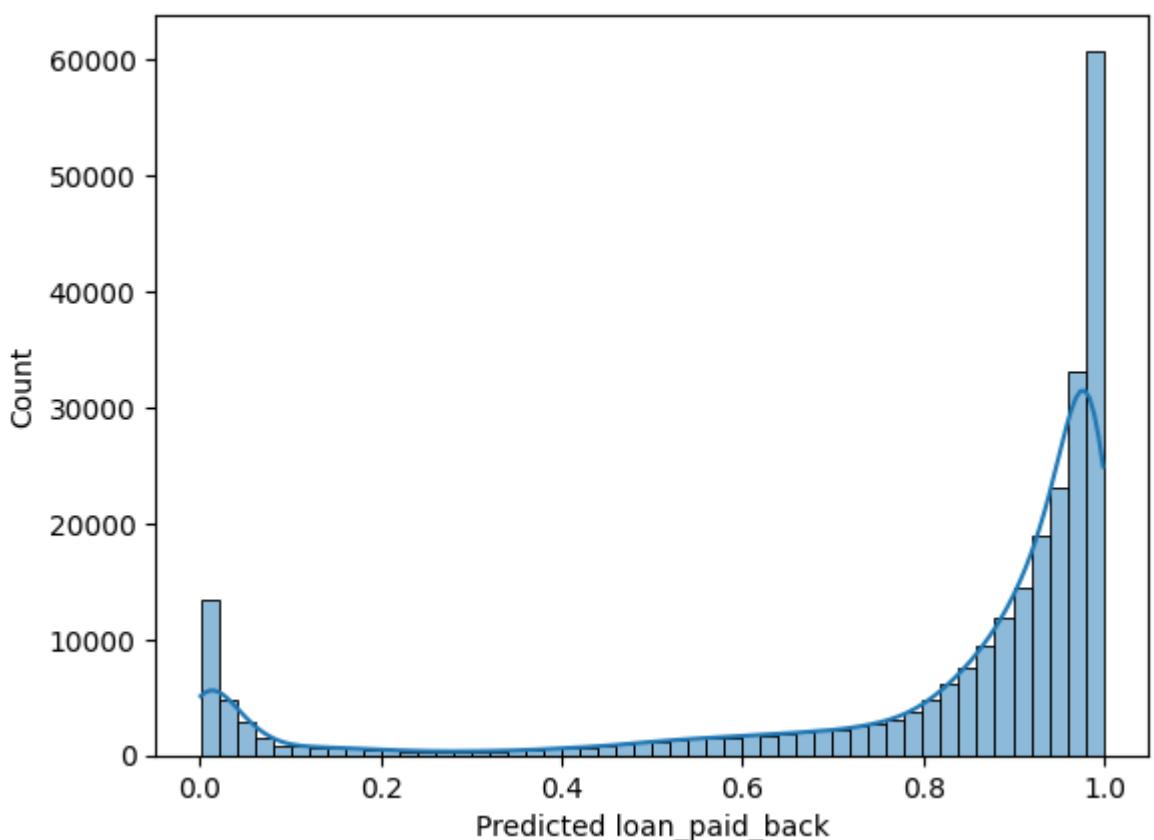
Default metric period is 5 because AUC is/are not implemented for GPU
AUC is not implemented on GPU. Will use CPU for metric computation, this could significantly affect learning time

Preprocessing test data...
Generating predictions from both models...
Creating submission.csv...
✓ Version 10 Complete. Submission file generated.

id	loan_paid_back
0	593994 0.938722
1	593995 0.972072
2	593996 0.382090
3	593997 0.928766
4	593998 0.967541

Final Prediction Distribution:

Version 10 Final Blended Prediction Distribution



In []: