```
!pip install catboost
```

```
Collecting catboost
  Downloading catboost-1.2.8-cp312-cp312-
manylinux2014_x86_64.whl.metadata (1.2 kB)
Requirement already satisfied: graphviz in
/usr/local/lib/python3.12/dist-packages (from catboost) (0.21)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.12/dist-packages (from catboost) (3.10.0)
Requirement already satisfied: numpy<3.0,>=1.16.0 in
/usr/local/lib/python3.12/dist-packages (from catboost) (2.0.2)
Requirement already satisfied: pandas>=0.24 in
/usr/local/lib/python3.12/dist-packages (from catboost) (2.2.2)
Requirement already satisfied: scipy in
/usr/local/lib/python3.12/dist-packages (from catboost) (1.16.2)
Requirement already satisfied: plotly in
/usr/local/lib/python3.12/dist-packages (from catboost) (5.24.1)
Requirement already satisfied: six in /usr/local/lib/python3.12/dist-
packages (from catboost) (1.17.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.12/dist-packages (from pandas>=0.24->catboost)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.12/dist-packages (from pandas>=0.24->catboost)
(2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.12/dist-packages (from pandas>=0.24->catboost)
(2025.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib->catboost)
(1.3.3)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.12/dist-packages (from matplotlib->catboost)
(0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.12/dist-packages (from matplotlib->catboost)
(4.60.1)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib->catboost)
(1.4.9)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.12/dist-packages (from matplotlib->catboost)
(25.0)
Requirement already satisfied: pillow>=8 in
/usr/local/lib/python3.12/dist-packages (from matplotlib->catboost)
(11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib->catboost)
(3.2.5)
Requirement already satisfied: tenacity>=6.2.0 in
```

```
/usr/local/lib/python3.12/dist-packages (from plotly->catboost)
(8.5.0)
Downloading catboost-1.2.8-cp312-cp312-manylinux2014_x86_64.whl (99.2
MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 99.2/99.2 MB 8.2 MB/s eta
0:00:00
```

```
import pandas as pd
import numpy as np
import os
import kagglehub
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from catboost import CatBoostClassifier
from imblearn.over_sampling import SMOTE
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    roc_auc_score, classification_report, confusion_matrix,
    roc_curve, precision_recall_curve
)
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

# --- Step 1: Load Dataset ---
path = kagglehub.dataset_download("uciml/default-of-credit-card-
clients-dataset")
print("Dataset path:", path)
```

```
Using Colab cache for faster access to the 'default-of-credit-card-
clients-dataset' dataset.
Dataset path: /kaggle/input/default-of-credit-card-clients-dataset
```

```
# Find the file (xls or csv)
file = [f for f in os.listdir(path) if f.endswith('.xls') or
f.endswith('.xlsx') or f.endswith('.csv')][0]

if file.endswith(('.xls', '.xlsx')):
    df = pd.read_excel(os.path.join(path, file), header=1)
else:
    df = pd.read_csv(os.path.join(path, file))

print(df)
```

```
          ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2
PAY_3  \
0          1    20000.0    2          2         1   24      2      2
-1
1          2   120000.0    2          2         2   26     -1      2
0
2          3    90000.0    2          2         2   34      0      0
0
3          4    50000.0    2          2         1   37      0      0
0
4          5    50000.0    1          2         1   57     -1      0
-1
...      ...        ...  ...        ...       ...  ...    ...    ...
...
29995  29996   220000.0    1          3         1   39      0      0
0
29996  29997   150000.0    1          3         2   43     -1     -1
-1
29997  29998    30000.0    1          2         2   37      4      3
2
29998  29999    80000.0    1          3         1   41      1     -1
0
29999  30000    50000.0    1          2         1   46      0      0
0

       PAY_4  ...  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2
\
0         -1  ...        0.0        0.0        0.0       0.0     689.0

1          0  ...     3272.0     3455.0     3261.0       0.0    1000.0

2          0  ...    14331.0    14948.0    15549.0    1518.0    1500.0

3          0  ...    28314.0    28959.0    29547.0    2000.0    2019.0

4          0  ...    20940.0    19146.0    19131.0    2000.0   36681.0

...      ...  ...        ...        ...        ...       ...       ...

29995      0  ...    88004.0    31237.0    15980.0    8500.0   20000.0

29996     -1  ...     8979.0     5190.0        0.0    1837.0    3526.0

29997     -1  ...    20878.0    20582.0    19357.0       0.0       0.0

29998      0  ...    52774.0    11855.0    48944.0   85900.0    3409.0

29999      0  ...    36535.0    32428.0    15313.0    2078.0    1800.0


       PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6
```

```
default.payment.next.month
0            0.0       0.0       0.0       0.0
1
1         1000.0    1000.0       0.0    2000.0
1
2         1000.0    1000.0    1000.0    5000.0
0
3         1200.0    1100.0    1069.0    1000.0
0
4        10000.0    9000.0     689.0     679.0
0
...          ...       ...       ...       ...
...
29995     5003.0    3047.0    5000.0    1000.0
0
29996     8998.0     129.0       0.0       0.0
0
29997    22000.0    4200.0    2000.0    3100.0
1
29998     1178.0    1926.0   52964.0    1804.0
1
29999     1430.0    1000.0    1000.0    1000.0
1

[30000 rows x 25 columns]

# Clean columns names
df.columns = df.columns.str.strip().str.lower().str.replace(" ",
"_").str.replace(".", "_")

# Drop ID column if exists
if 'id' in df.columns:
    df.drop(columns=['id'], inplace=True)

print("Columns:", df.columns.tolist())

Columns: ['limit_bal', 'sex', 'education', 'marriage', 'age', 'pay_0',
'pay_2', 'pay_3', 'pay_4', 'pay_5', 'pay_6', 'bill_amt1', 'bill_amt2',
'bill_amt3', 'bill_amt4', 'bill_amt5', 'bill_amt6', 'pay_amt1',
'pay_amt2', 'pay_amt3', 'pay_amt4', 'pay_amt5', 'pay_amt6',
'default_payment_next_month']

# --- Step 2: Split features and target ---
target_col = 'default_payment_next_month'
X = df.drop(columns=[target_col])
y = df[target_col]

# --- Step 3: Preprocessing pipeline ---
num_cols = X.select_dtypes(include=[np.number]).columns.tolist()
```

```python
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer([
    ('num', num_pipeline, num_cols)
])

X_processed = preprocessor.fit_transform(X)

print(X)
print(y)
print(X_processed)
```

```
       limit_bal  sex  education  marriage  age  pay_0  pay_2  pay_3
pay_4  \
0        20000.0    2          2         1   24      2      2     -1
-1
1       120000.0    2          2         2   26     -1      2      0
0
2        90000.0    2          2         2   34      0      0      0
0
3        50000.0    2          2         1   37      0      0      0
0
4        50000.0    1          2         1   57     -1      0     -1
0
...          ...  ...        ...       ...  ...    ...    ...    ...
...
29995   220000.0    1          3         1   39      0      0      0
0
29996   150000.0    1          3         2   43     -1     -1     -1
-1
29997    30000.0    1          2         2   37      4      3      2
-1
29998    80000.0    1          3         1   41      1     -1      0
0
29999    50000.0    1          2         1   46      0      0      0
0

       pay_5  ...  bill_amt3  bill_amt4  bill_amt5  bill_amt6
pay_amt1  \
0         -2  ...      689.0        0.0        0.0        0.0
0.0
1          0  ...     2682.0     3272.0     3455.0     3261.0
0.0
2          0  ...    13559.0    14331.0    14948.0    15549.0
1518.0
3          0  ...    49291.0    28314.0    28959.0    29547.0
2000.0
```

```
4          0  ...    35835.0    20940.0    19146.0    19131.0
2000.0
...      ...  ...        ...        ...        ...        ...        ..
.
29995      0  ...   208365.0    88004.0    31237.0    15980.0
8500.0
29996      0  ...     3502.0     8979.0     5190.0        0.0
1837.0
29997      0  ...     2758.0    20878.0    20582.0    19357.0
0.0
29998      0  ...    76304.0    52774.0    11855.0    48944.0
85900.0
29999      0  ...    49764.0    36535.0    32428.0    15313.0
2078.0

       pay_amt2  pay_amt3  pay_amt4  pay_amt5  pay_amt6
0         689.0       0.0       0.0       0.0       0.0
1        1000.0    1000.0    1000.0       0.0    2000.0
2        1500.0    1000.0    1000.0    1000.0    5000.0
3        2019.0    1200.0    1100.0    1069.0    1000.0
4       36681.0   10000.0    9000.0     689.0     679.0
...         ...       ...       ...       ...       ...
29995   20000.0    5003.0    3047.0    5000.0    1000.0
29996    3526.0    8998.0     129.0       0.0       0.0
29997       0.0   22000.0    4200.0    2000.0    3100.0
29998    3409.0    1178.0    1926.0   52964.0    1804.0
29999    1800.0    1430.0    1000.0    1000.0    1000.0

[30000 rows x 23 columns]
0        1
1        1
2        0
3        0
4        0
        ..
29995    0
29996    0
29997    1
29998    1
29999    1
Name: default_payment_next_month, Length: 30000, dtype: int64
[[-1.13672015  0.81016074  0.18582826 ... -0.30806256 -0.31413612
  -0.29338206]
 [-0.3659805   0.81016074  0.18582826 ... -0.24422965 -0.31413612
  -0.18087821]
 [-0.59720239  0.81016074  0.18582826 ... -0.24422965 -0.24868274
  -0.01212243]
 ...
 [-1.05964618 -1.23432296  0.18582826 ... -0.03996431 -0.18322937
```

```
  -0.11900109]
 [-0.67427636 -1.23432296  1.45111372 ... -0.18512036  3.15253642
  -0.19190359]
 [-0.90549825 -1.23432296  0.18582826 ... -0.24422965 -0.24868274
  -0.23713013]]
```

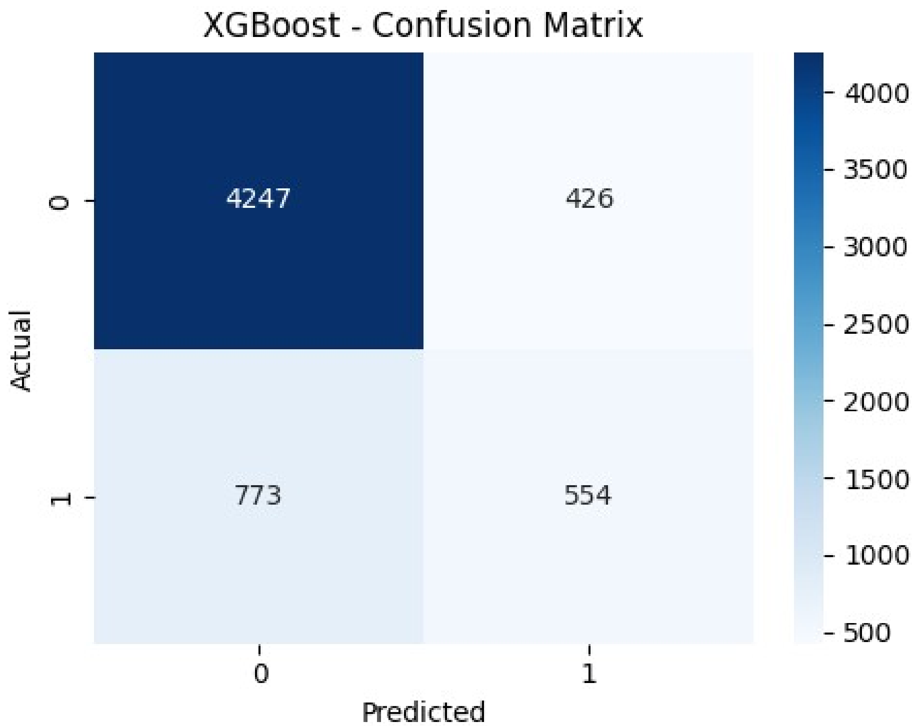
```
# --- Step 4: Train-test split ---
X_train, X_test, y_train, y_test = train_test_split(
    X_processed, y, test_size=0.2, random_state=42, stratify=y
)

# --- Step 5: Apply SMOTE to training data ---
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)

print(f"Before SMOTE: {np.bincount(y_train)}")
print(f"After SMOTE:  {np.bincount(y_train_resampled)}")
```

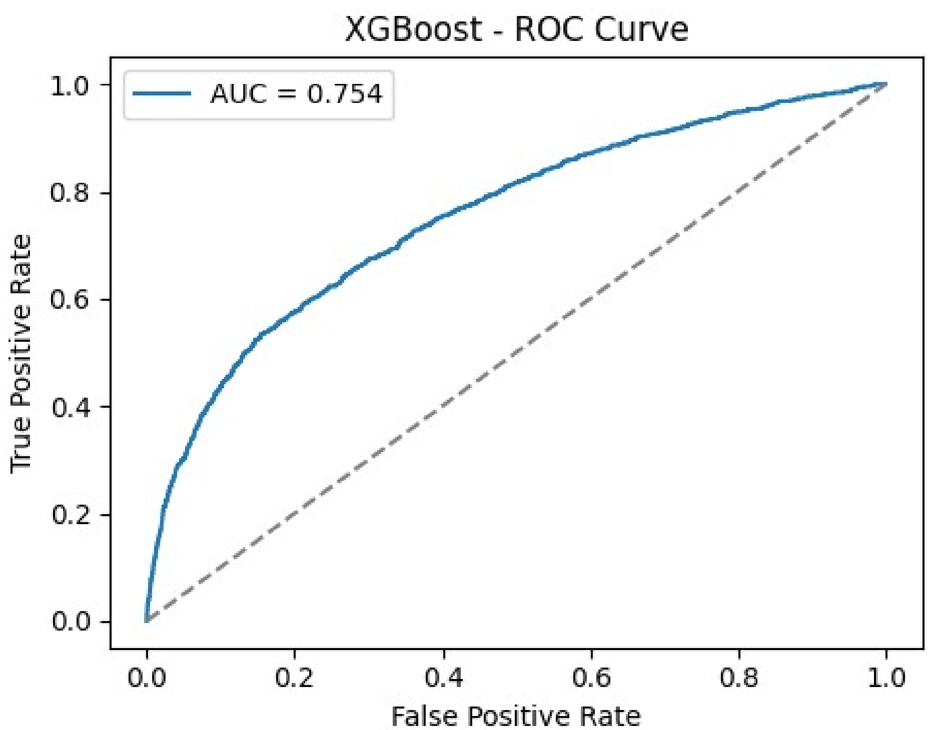
```
Before SMOTE: [18691  5309]
After SMOTE:  [18691 18691]
```

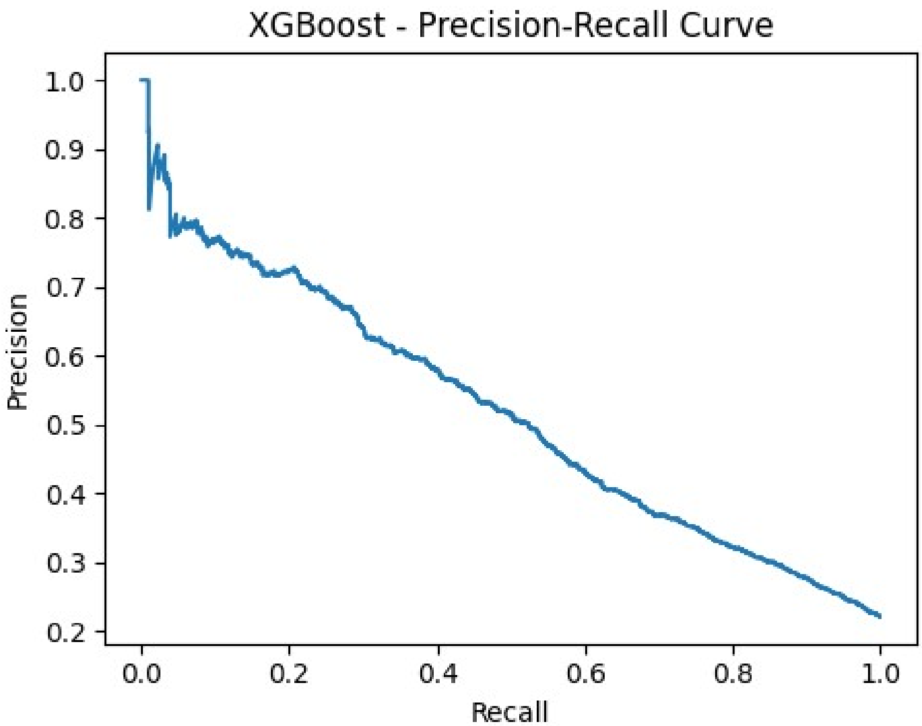
```
# --- Step 6: Define evaluation function ---
def evaluate_model(y_test, y_pred, y_proba, model_name):
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    auc = roc_auc_score(y_test, y_proba)

    print(f"\n{model_name} Performance:")
    print(f"Accuracy:  {acc:.4f}")
    print(f"Precision: {prec:.4f}")
    print(f"Recall:    {rec:.4f}")
    print(f"F1-score:  {f1:.4f}")
    print(f"AUC:       {auc:.4f}")
    print(classification_report(y_test, y_pred))

    # Confusion Matrix
    plt.figure(figsize=(5, 4))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d',
cmap='Blues')
    plt.title(f'{model_name} - Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.tight_layout()
    plt.show()

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_proba)
```

```python
    plt.figure(figsize=(5, 4))
    plt.plot(fpr, tpr, label=f'AUC = {auc:.3f}')
    plt.plot([0, 1], [0, 1], '--', color='gray')
    plt.title(f'{model_name} - ROC Curve')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.legend()
    plt.tight_layout()
    plt.show()

    # Precision-Recall Curve
    prec_curve, rec_curve, _ = precision_recall_curve(y_test, y_proba)
    plt.figure(figsize=(5, 4))
    plt.plot(rec_curve, prec_curve)
    plt.title(f'{model_name} - Precision-Recall Curve')
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.tight_layout()
    plt.show()

# --- Step 7: Train and evaluate XGBoost ---
xgb_model = XGBClassifier(use_label_encoder=False,
eval_metric='logloss', random_state=42)
xgb_model.fit(X_train_resampled, y_train_resampled)
xgb_pred = xgb_model.predict(X_test)
xgb_proba = xgb_model.predict_proba(X_test)[:, 1]
evaluate_model(y_test, xgb_pred, xgb_proba, "XGBoost")
```

```
XGBoost Performance:
Accuracy:  0.8002
Precision: 0.5653
Recall:    0.4175
F1-score:  0.4803
AUC:       0.7539
              precision    recall  f1-score   support

           0       0.85      0.91      0.88      4673
           1       0.57      0.42      0.48      1327

    accuracy                           0.80      6000
   macro avg       0.71      0.66      0.68      6000
weighted avg       0.78      0.80      0.79      6000
```


XGBoost - Confusion Matrix
4247
426
773
554
Actual
Predicted
0
1
4000
3500
3000
2500
2000
1500
1000
500

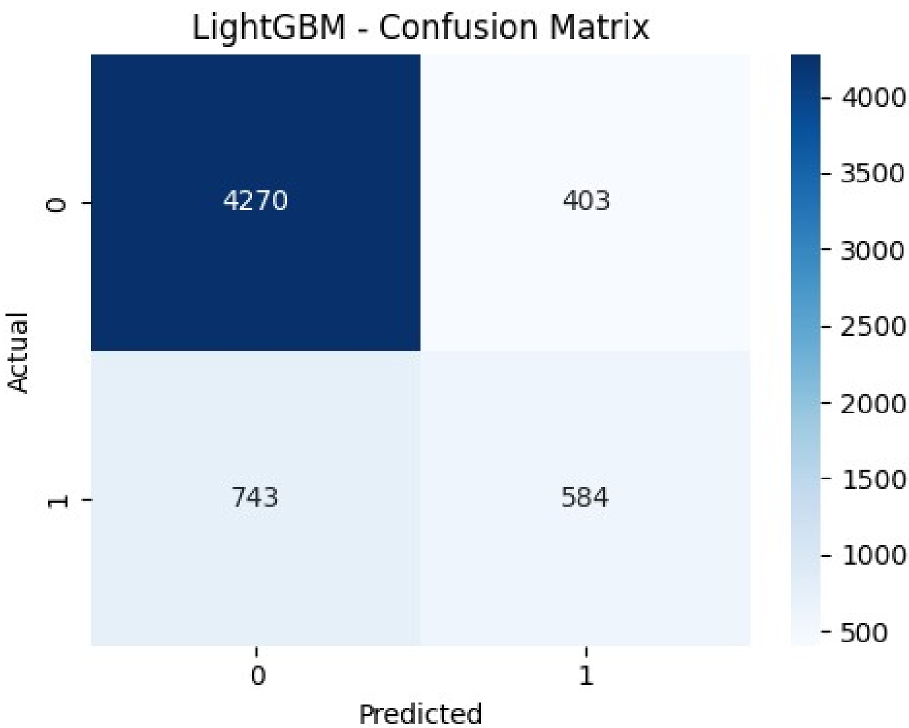

XGBoost - ROC Curve
AUC = 0.754
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

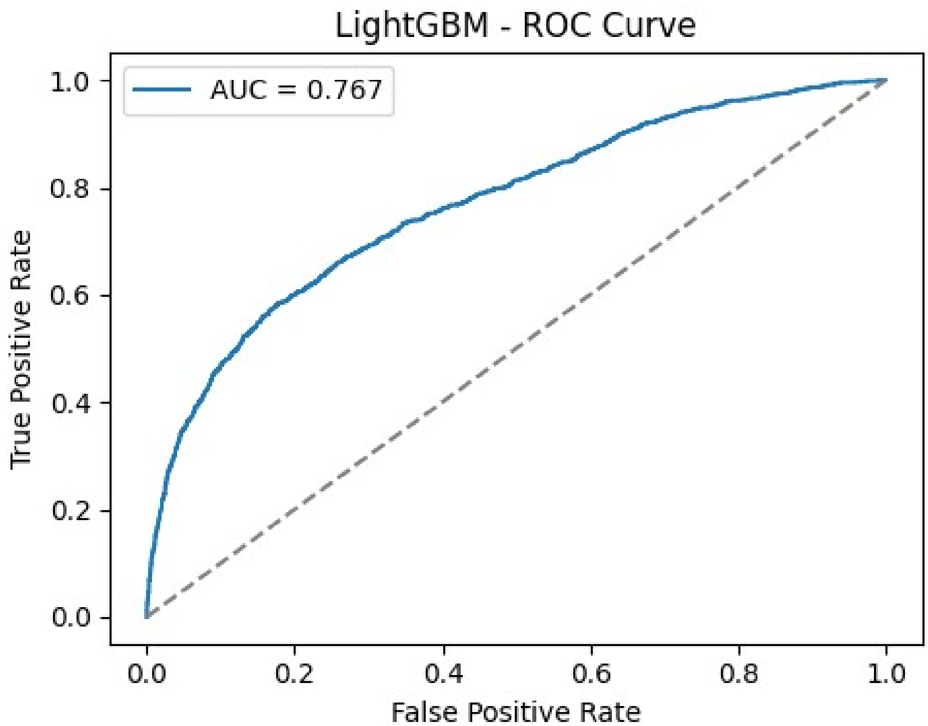


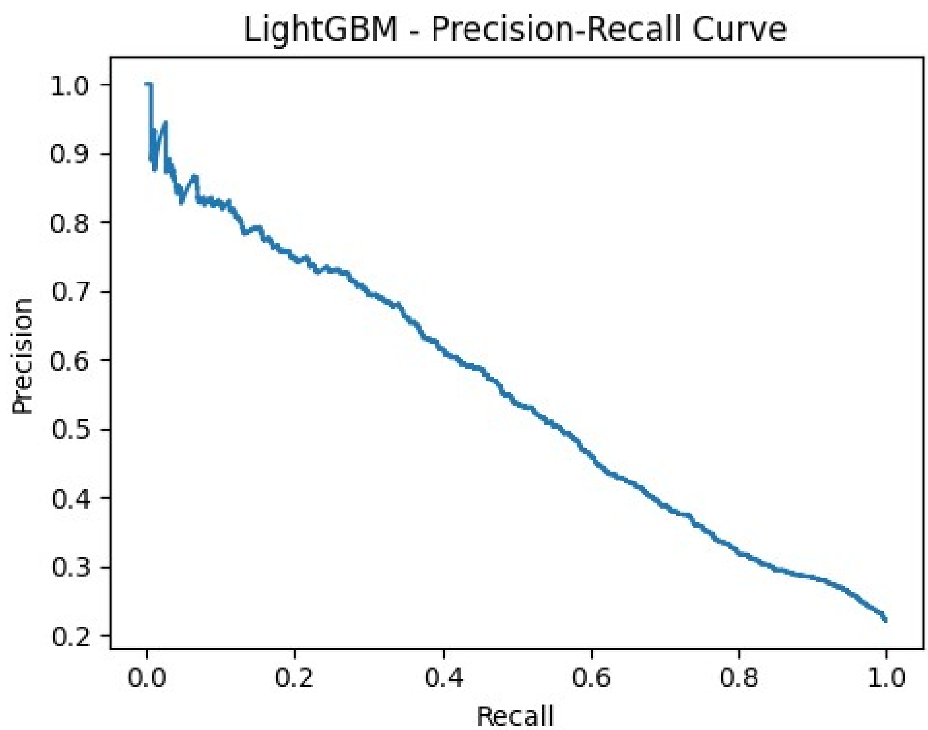

```python
# --- Step 8: Train and evaluate LightGBM ---
from lightgbm import LGBMClassifier

lgbm_model = LGBMClassifier(random_state=42)
lgbm_model.fit(X_train_resampled, y_train_resampled)
lgbm_pred = lgbm_model.predict(X_test)
lgbm_proba = lgbm_model.predict_proba(X_test)[:, 1]
evaluate_model(y_test, lgbm_pred, lgbm_proba, "LightGBM")
```

```
[LightGBM] [Info] Number of positive: 18691, number of negative: 18691
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead
of testing was 0.003322 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 5599
[LightGBM] [Info] Number of data points in the train set: 37382,
number of used features: 23
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500000 ->
initscore=0.000000

LightGBM Performance:
Accuracy:  0.8090
Precision: 0.5917
Recall:    0.4401
F1-score:  0.5048
AUC:       0.7674
              precision    recall  f1-score   support
```

```
           0       0.85      0.91      0.88      4673
           1       0.59      0.44      0.50      1327

    accuracy                           0.81      6000
   macro avg       0.72      0.68      0.69      6000
weighted avg       0.79      0.81      0.80      6000
```



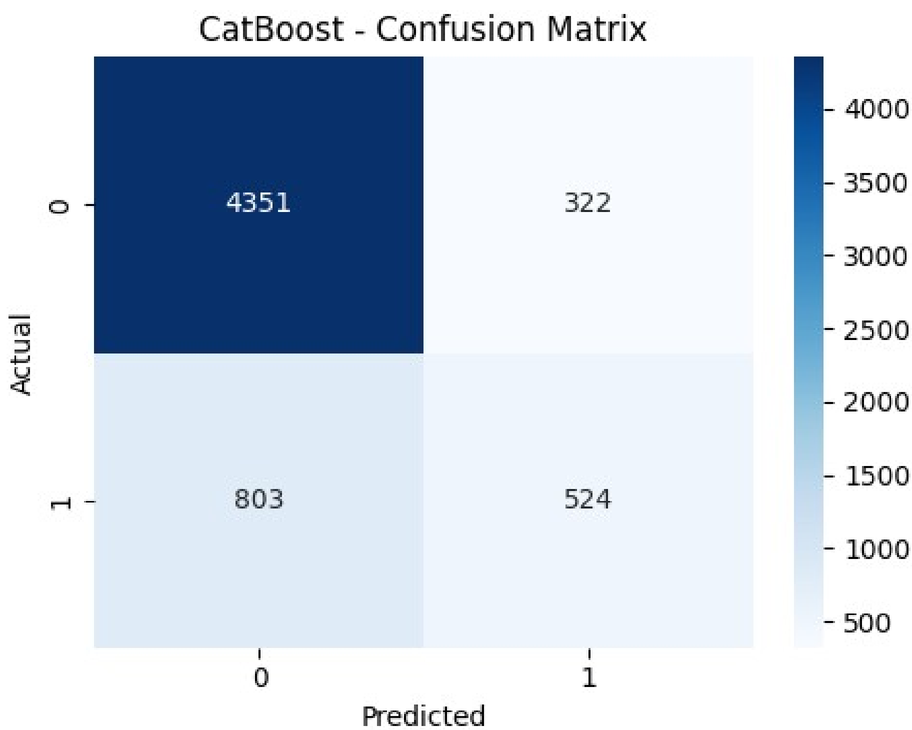


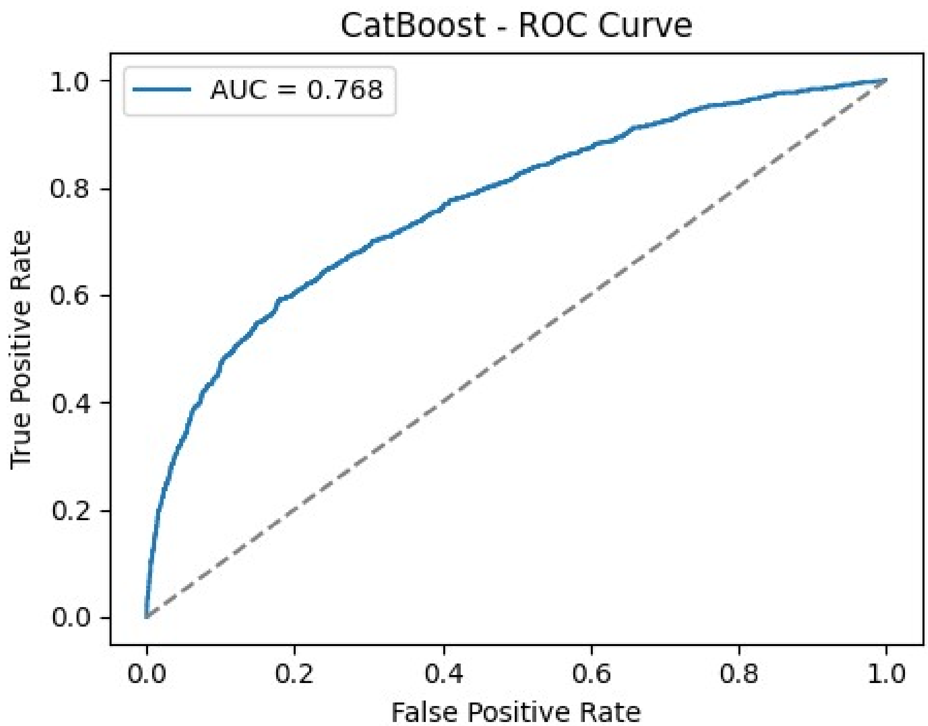


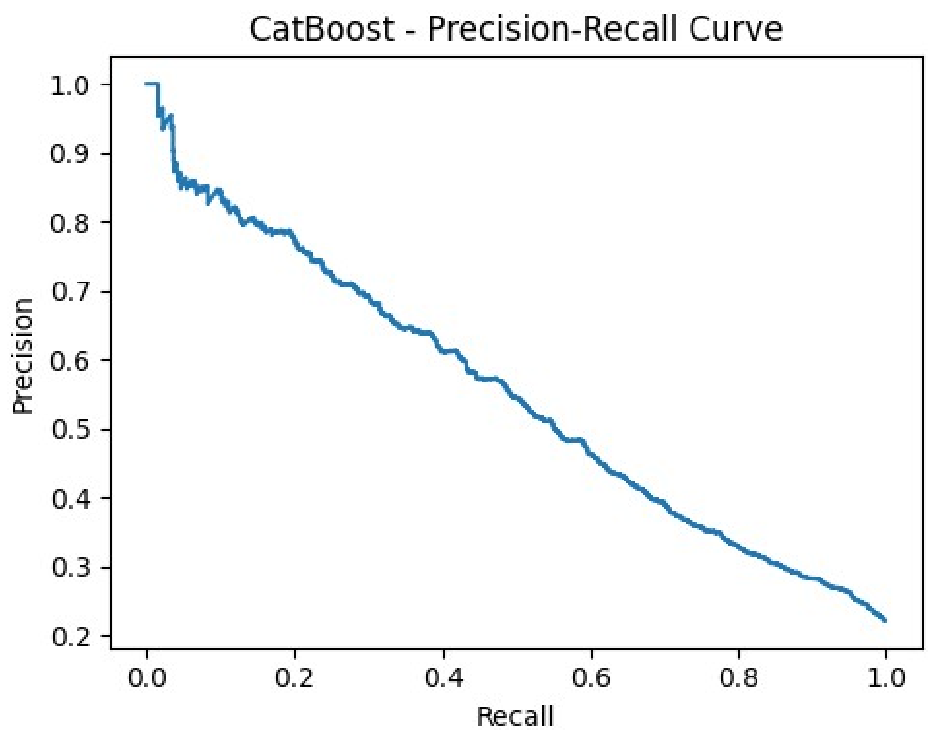

```
# --- Step 9: Train and evaluate CatBoost ---
from catboost import CatBoostClassifier

cat_model = CatBoostClassifier(verbose=0, random_state=42)
```

```
cat_model.fit(X_train_resampled, y_train_resampled)
cat_pred = cat_model.predict(X_test)
cat_proba = cat_model.predict_proba(X_test)[:, 1]
evaluate_model(y_test, cat_pred, cat_proba, "CatBoost")
```

```
CatBoost Performance:
Accuracy:  0.8125
Precision: 0.6194
Recall:    0.3949
F1-score:  0.4823
AUC:       0.7682
              precision    recall  f1-score   support

           0       0.84      0.93      0.89      4673
           1       0.62      0.39      0.48      1327

    accuracy                           0.81      6000
   macro avg       0.73      0.66      0.68      6000
weighted avg       0.79      0.81      0.80      6000
```

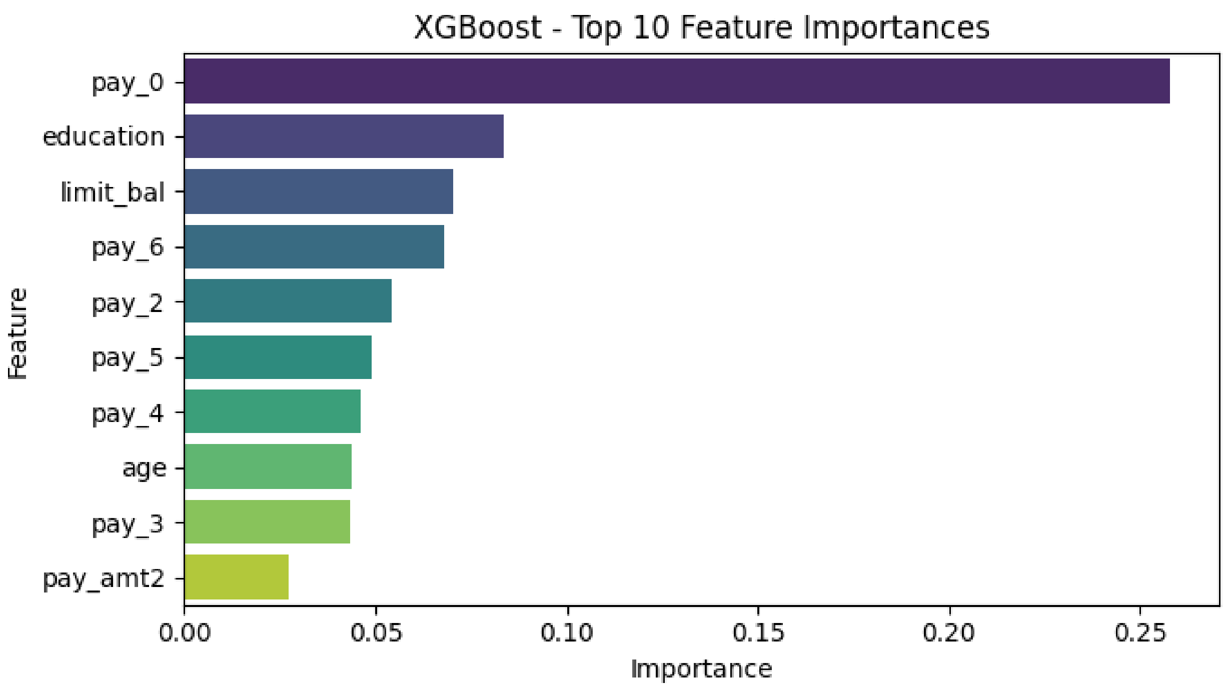


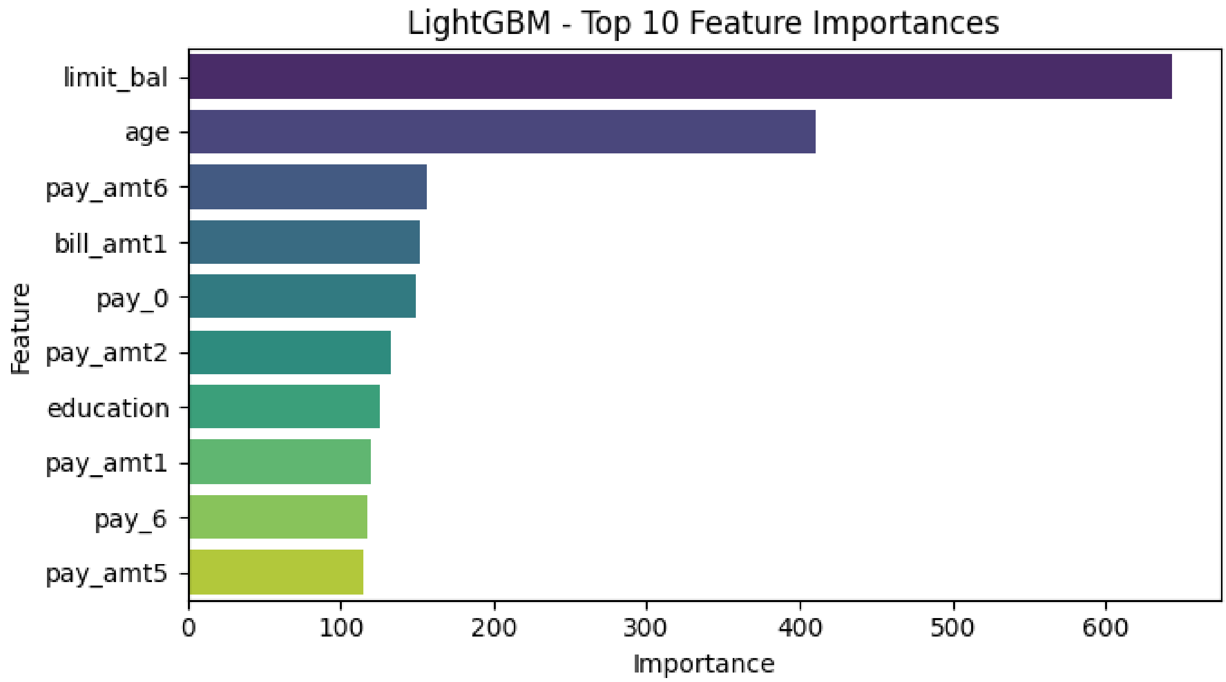


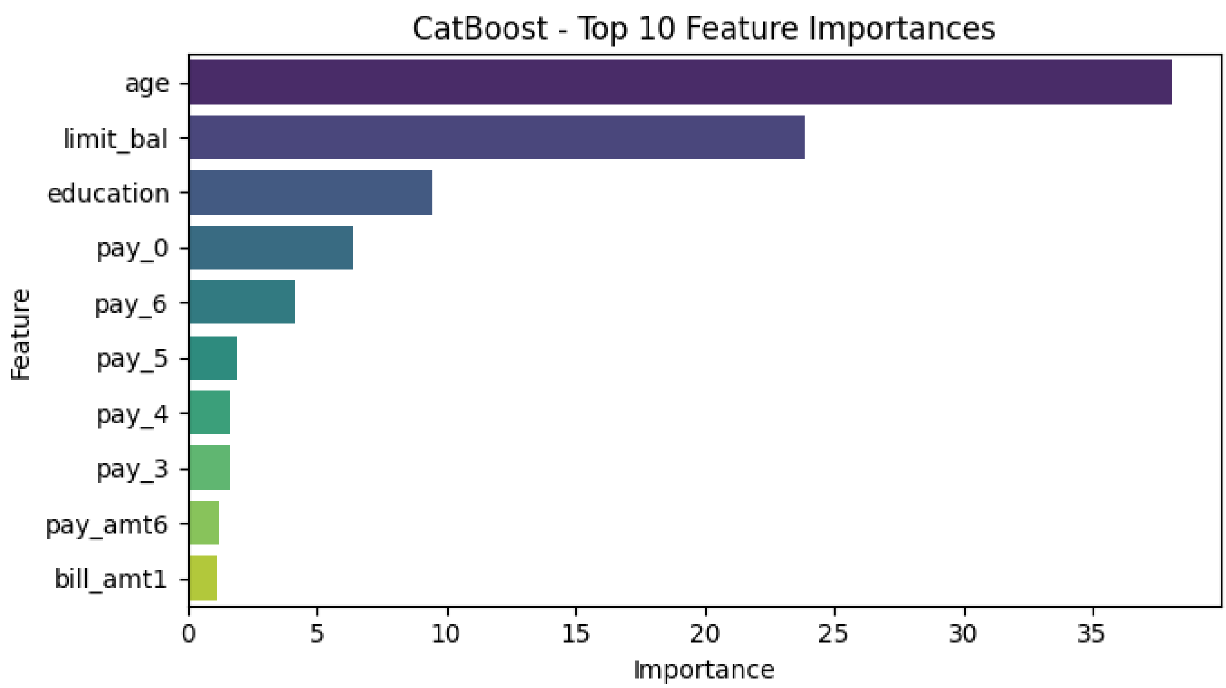



```
# --- Step 10: Feature importance plots ---
def plot_feature_importance(model, feature_names, model_name):
    importances = model.feature_importances_
    imp_df = pd.DataFrame({
```

```
        'Feature': feature_names,
        'Importance': importances
    }).sort_values('Importance', ascending=False).head(10)

    plt.figure(figsize=(7, 4))
    sns.barplot(x='Importance', y='Feature', data=imp_df,
palette='viridis')
    plt.title(f'{model_name} - Top 10 Feature Importances')
    plt.tight_layout()
    plt.show()

# Original feature names after preprocessing (num_cols)
plot_feature_importance(xgb_model, num_cols, "XGBoost")
plot_feature_importance(lgbm_model, num_cols, "LightGBM")
plot_feature_importance(cat_model, num_cols, "CatBoost")
```




LightGBM - Top 10 Feature Importances
limit_bal
age
pay_amt6
bill_amt1
pay_0
pay_amt2
education
pay_amt1
pay_6
pay_amt5
Feature
0
100
200
300
400
500
600
Importance


CatBoost - Top 10 Feature Importances
age
limit_bal
education
pay_0
pay_6
pay_5
pay_4
pay_3
pay_amt6
bill_amt1
Feature
0
5
10
15
20
25
30
35
Importance