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Affirm’s Credit Scoring Model

Advanced credit scoring for buy now pay later approvals.

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INTRODUCTION

Problem statement:
How can Affirm use machine learning to predict whether a user will default on a BNPL loan?

Key Challenge:
How can we accurately predict if a customer will default on a loan?

Affirm uses:

- Affirm is a leading fintech company that offers Buy Now, Pay Later (BNPL) services.
- It uses real-time machine learning models to evaluate credit risk.
- These models combine financial, behavioral, and transactional data to make fast, informed lending decisions.
- Minimizing default risk is critical to profitability and user trust.

DATASET

We used a dataset Credit Score Classification

Reasons:

- Contains both traditional features (like FICO: income, debt, age, credit history)
- Includes alternative behavioral features (e.g., credit inquiries, payment patterns)
- Closely mirrors Affirm’s data strategy (alternative data + cash flow modeling)
- Flexible enough to support feature engineering, segmentation, and ML experiments

APPROACH

We tested six advanced machine learning models to predict loan defaults:

- Random Forest
- XGBoost
- LightGBM
- CatBoost
- Stacking using Random Forest + CatBoost
- Stacking using Random Forest + LightGBM + CatBoost

Each model was evaluated to identify the most effective for risk prediction.

STACKING

Accuracy

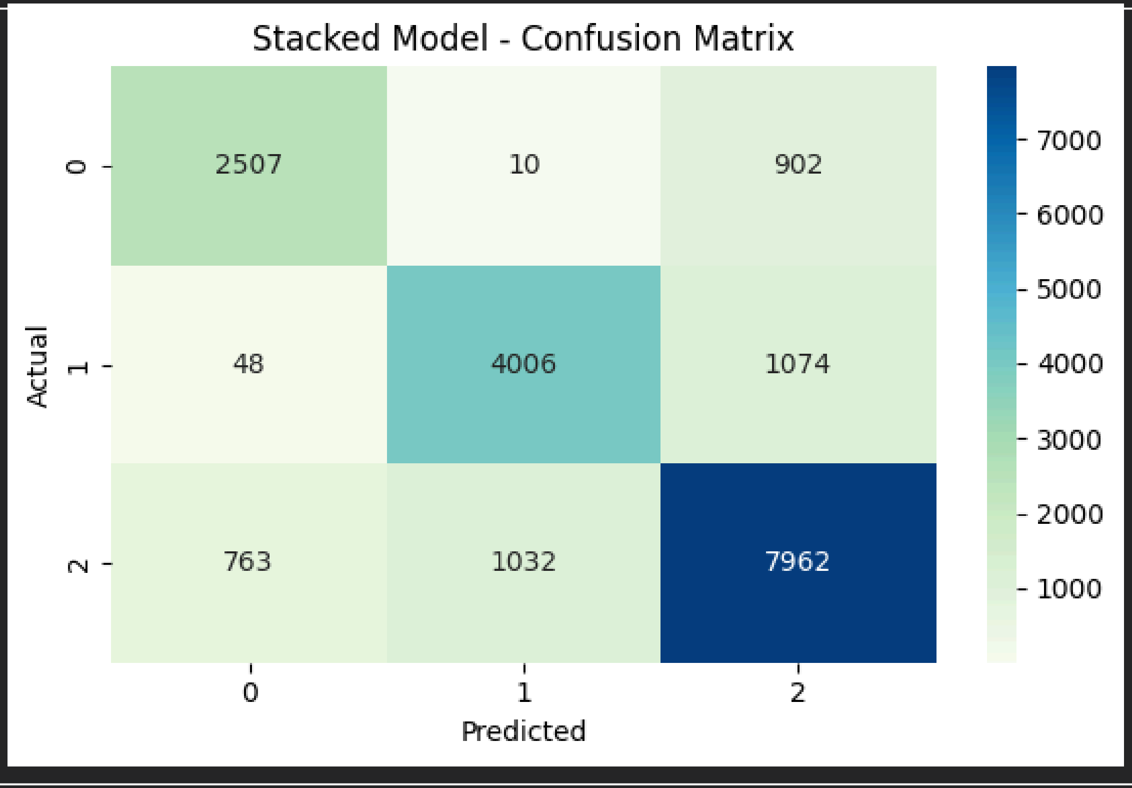
0.7908

F1-score (weighted)

0.7906

Auc-Roc

0.9151



Performance	The model performs exceptionally well in identifying high-risk borrowers, which is essential for Affirm. A high recall ensures that most defaulters are correctly identified reducing the chance of bad loans.
Limitations	The model shows some tendency to misclassify low-risk users as risky. While this reduces default exposure, it may lead to unnecessary rejections or lost business opportunities.

INSIGHTS

- Effectively identifies high-risk borrowers (Class 2) with 80% recall, helping Affirm prevent defaults and reduce credit loss.
- Achieves balanced performance on medium-risk users (Class 1), supporting Affirm's strategy of tiered or conditional loan offers.
- Shows conservative behavior on low-risk users (Class 0), some safe customers may be incorrectly indentified leading to lost lending opportunities.

INSIGHTS

- High overall AUC-ROC (91.5%) ensures strong class separability, critical for Affirm's automated risk decisioning.
- Outperforms other models proving that stacking enhances generalization, just like Affirm's production models.
- Aligns with Affirm's real-world approach of using ensemble models for scalable, accurate, and personalized BNPL credit decisions.

Thankyou