

Risk Clients Scorecard Model

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Home Credit Indonesia PBI FINAL TASK:



Project Journey (PACE Framework)



PLAN

Including study case Background, Goals, and Objective for this project



ANALYZE

Build a dataframe and conduct Exploratory Data Analysis/EDA process



CONSTRUCT

Building Predictive and Machine Learning with their model performance evaluation



EXECUTE

Choose the best model and conduct recommendation

PACE Workflow: Plan Stage

Project Background

Home Credit saat ini sedang menggunakan berbagai macam metode statistik dan Machine Learning untuk membuat prediksi skor kredit. Sekarang, kami meminta anda untuk membuka potensi maksimal dari data kami. Dengan melakukannya, kita dapat memastikan pelanggan yang mampu melakukan pelunasan tidak ditolak ketika melakukan pengajuan pinjaman, dan pinjaman datap diberikan dengan principal, maturity, dan repayment calendar yang akan memotivasi pelanggan untuk sukses.



Goals

The goal of this project is to create a Scorecard Model that can predict which clients are likely to be late in paying far beyond their due date (payment difficulties).

Objectives

- Conducting EDA as Data Cleaning dan Data Processing process
- Build Predictive Models and Machine Learning
- Evaluate and Compare which models that perform better
- Implement best model to predict test data
- Give recommendation to reduce potential clients with risky behavior.



PACE Workflow: Plan Stage

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PACE: Plan

Step 1. Initial EDA of the Dataset

The main dataset in this training stage is application_train.csv. This dataset has 307511 rows and 122 columns.

| [3]: | SK_ID_CURR | TARGET | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | AMT_INCOME_TOTAL | AMT_CREDIT | AMT |
|--------|------------|--------|--------------------|-------------|--------------|-----------------|--------------|------------------|------------|-----|
| 307506 | 456251 | 0 | Cash loans | M | N | N | 0 | 157500.0 | 254700.0 | |
| 307507 | 456252 | 0 | Cash loans | F | N | Y | 0 | 72000.0 | 269550.0 | |
| 307508 | 456253 | 0 | Cash loans | F | N | Y | 0 | 153000.0 | 677664.0 | |
| 307509 | 456254 | 1 | Cash loans | F | N | Y | 0 | 171000.0 | 370107.0 | |
| 307510 | 456255 | 0 | Cash loans | F | N | N | 0 | 157500.0 | 675000.0 | |

This train dataset is a mix of categorical and numerical value. The 'TARGET' column which is as a differentiator between train and test dataset can be our main parameter for this study case. 'TARGET' variable contains:

- 1 - client with payment difficulties (he/she had late payment more than X days on at least one of the first Y installments of the loan in our sample)
- 0 - all other cases



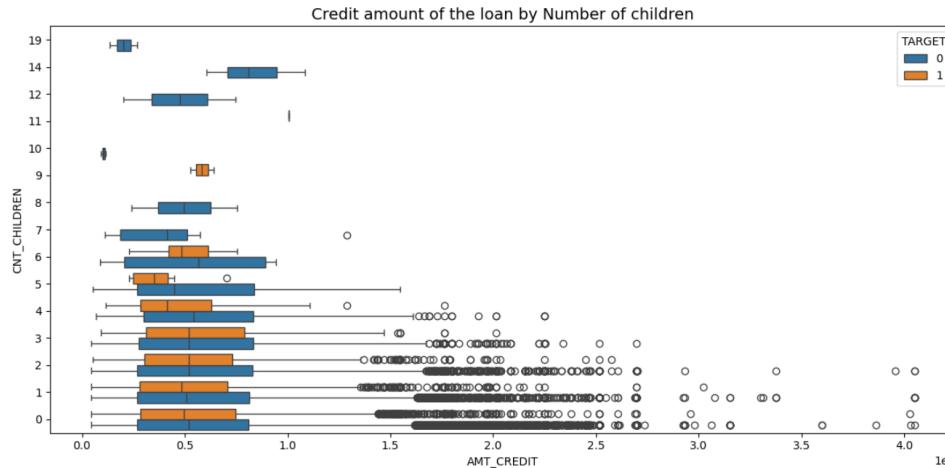
PACE Workflow: Analyze Stage

2

PACE: Analyze

Step 2. EDA Stage and Initial Analyze

This step will include: Data Cleaning and Data Processing (missing data, redundant data, outlier checking), as well as Initial Analysis with visualization. Several insights can be gained from this initial analysis stage.



Insight:

- Clients with 'TARGET' status fall into two general categories: Clients with more children (>6) tend to have less difficulty paying and clients with fewer children (especially those aged 0 - 2) often apply for large loans and are also late in paying.
- The histogram shows that there are relatively few clients with 'Payment Difficulties' along with the increasing of their number of children. It's possible that they're the higher-paid employees or always aware to apply for loans.



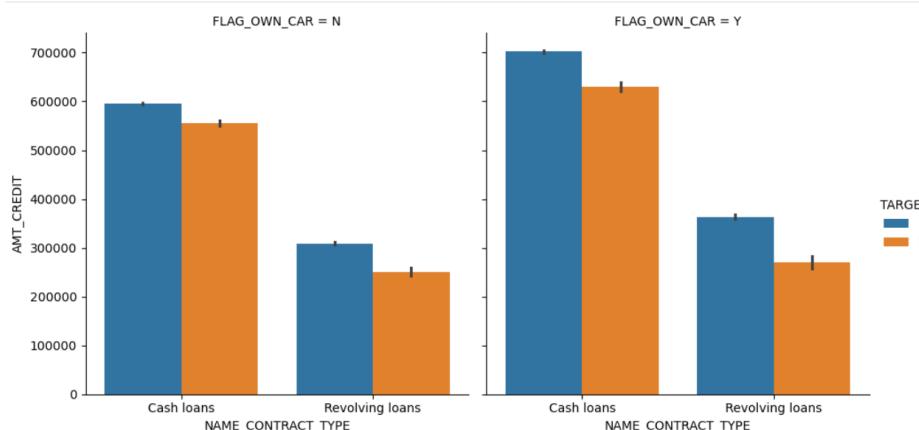
PACE Workflow: Analyze Stage

2

PACE: Analyze

Step 2. EDA Stage and Initial Analyze

Relations of variable AMT_CREDIT (Credit amount of the loan), Contract Type, & Car Ownership (Split by TARGET).



Insight:

- Clients with higher loan amounts tend to pay better across both car ownership groups (FLAG_own_car = Y & N). Suggests larger loans are issued to more creditworthy applicants (Stronger financial profile = lower risk of delinquency)
- Car ownership correlates with higher loan amounts but also a higher risk of late payments. Car ownership should be considered as a factor in determining clients' creditworthiness.
- Borrowers with greater financial capacity, evidenced by car ownership and higher credit limits, show lower payment difficulties. Cash loans carry higher exposure but appear to be given more carefully to stable clients.



PACE Workflow: Construct Stage

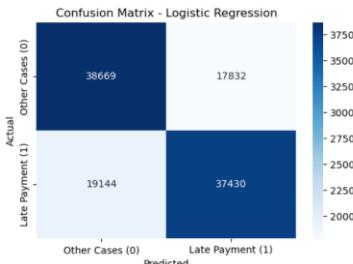
3

PACE: Construct

Step 3. Model Building and Performance Evaluation

Since the variables I wanted to predict (Clients with 'Late Payments' and 'Other Cases') were categorical, I tested several Classification algorithms (supervised learning). The Machine Learning algorithms I build are: Logistic Regression, Naïve Bayes, Random Forest, and XGBoost, and then determined which model performed best.

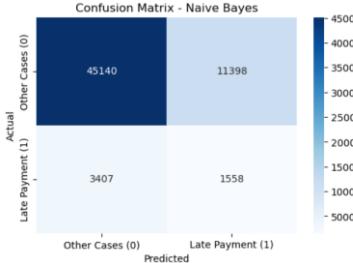
1. Logistic Regression (With Resampling Method)



3. Random Forest



2. Naïve Bayes (With Oversampling Method)



4. XGBoost



PACE Workflow: Execute Stage

4

PACE: Execute

Step 4. Evaluation and Determine which Best Model

| Models | Training Accuracy Score | Testing Accuracy Score | Error | ROC AUC |
|------------------------|-------------------------|------------------------|-------|---------|
| 2 Random Forest | 100.00 | 91.93 | -8.07 | 0.7297 |
| 3 XGBoost | 71.57 | 70.46 | -1.11 | 0.7493 |
| 0 Logistic Regression | 67.16 | 67.30 | 0.14 | 0.7324 |
| 1 Gaussian Naive Bayes | 60.00 | 60.28 | 0.28 | 0.6514 |

Evaluation Summary

- **Random Forest** : Very high overfitting (Train score 100% & 91.9% Testing score), and error -8.07
- **XGBoost** : Has stable accuracy and best ROC AUC score
- **Logistic Regression** : Balanced but lower performance
- **Naive Bayes** : Weakest overall

Based on the machine learning model performance comparison table, **XGBoost** was found to be the best model with high score in AUC score 0.74 and least error with -1.11. Although Random Forest get the highest accuracy, this model has very high overfitting (Train score 100% & 91.9% Testing score), with error -8.07 highest rather than XGBoost has stable accuracy and Best ROC AUC. However, both models perform well and have been shown to work well with imbalanced data without using resampling.



PACE Workflow: Execute Stage

4

PACE: Execute

Step 4. Test best model (XGBoost) with 'Test' dataset & Recommendation

Summary of Payment Difficulties Status
Total Records: 48,744
Late Payment (1): 14,791 (30.34%)
Other Cases (0): 33,953 (69.66%)



Recommendation

A 30% late-payment rate is high/nearly one-third of customers struggle to pay on time. The recommendation to Reduce Late Payment Customers (TARGET = 1) as follows:

- 1. Improve Credit Scoring and Approval Policies.** Use ML models (XGBoost, Random Forest) to act as a pre-screening tool.
 - Predict high-risk clients before approving credit
 - Set lower credit limits for risky applicants
 - Require additional verification (e.g. proof of income)
 - Higher interest for customers flagged as late-payment risk
- 2. More Flexible Repayment Schedules.** People with irregular income often pay late, then I suggests:
 - Offer smaller, weekly payment options
 - Give customers payment date choices aligned to salary cycles
- 3. Early-Warning & Intervention Strategy.**
 - Early SMS/email/push reminders before due date
 - Suggested minimum payment reminders
 - Chatbot financial help line



Thank You!

Project

Home Credit : **Predict Potential Risk Clients**
[GitHub Project](#)

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Project Based
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