

# CREDIT CARD DEFAULT PREDICTION

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## Project Report

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## 1. Problem Statement / Objective

This project aims to predict whether a credit card customer will default in the upcoming month based on historical behavioral and demographic data. Accurately identifying potential defaulters is critical for risk management and financial planning in lending institutions like banks.

## 2. Dataset Description

- Source: Dataset loaded from Google Drive via Google Colab (provided in the problem statement by Finance Club, IITR)
- Rows: 25,247 records.
- Columns: 27 original features including demographics (age, sex, education, marriage), payment history, billing amounts, and the target variable ('next\_month\_default').

## 3. Data Cleaning & Preprocessing

- There are 126 null values in age column, otherwise no null values. Nulls in age column were replaced with median age.
- Checked the categorical variables, if there is any encoding other than expected. Marriage should have:
  - 1 for married
  - 2 for single
  - 3 for others.

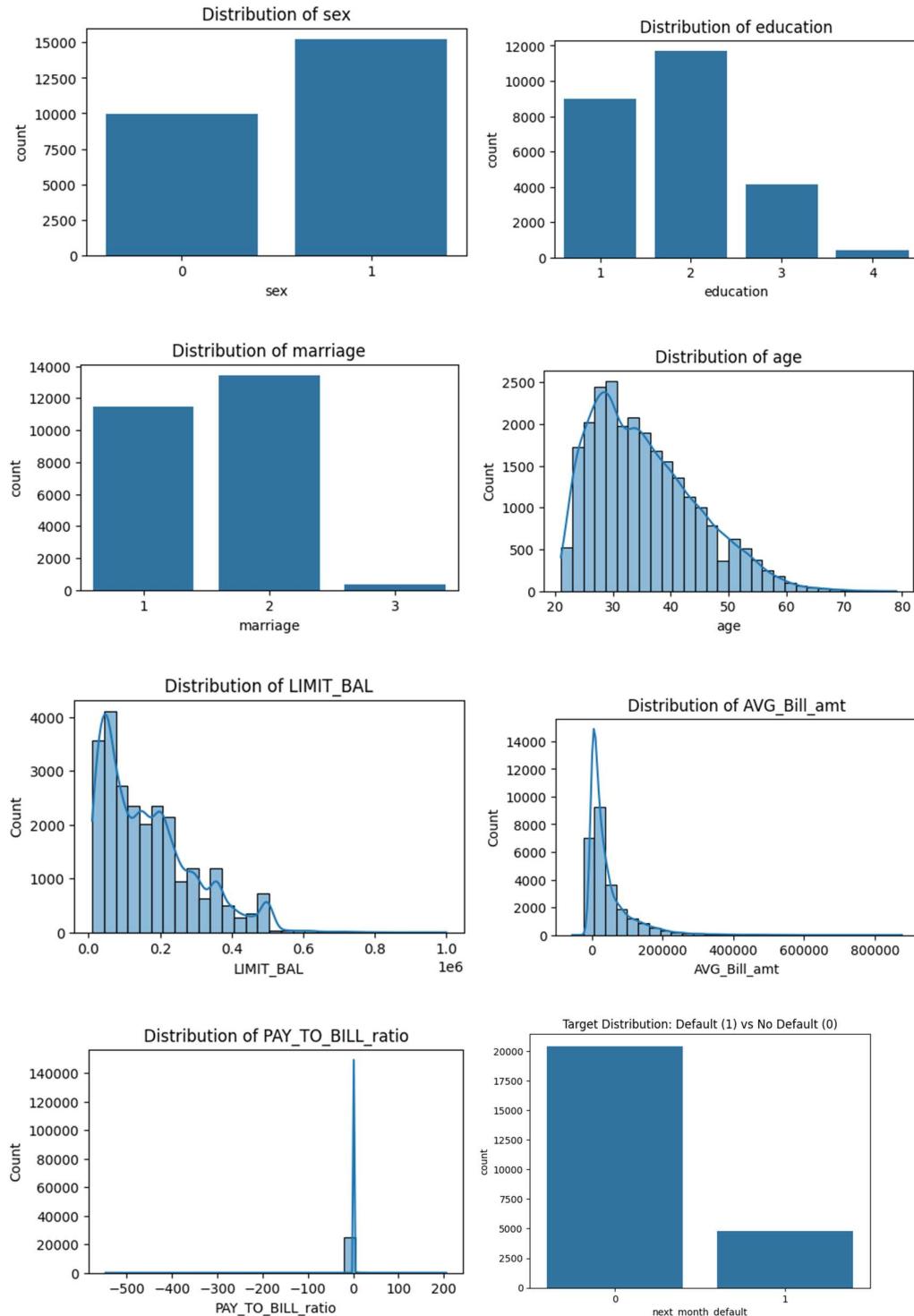
Similarly, education should have 1, 2, 3 and 4. But marriage contained 0's and education contained 0, 5 and 6.

- So, for marriage, mapped 0 to 3 (others), which is common in these cases. And, education values 0, 5, 6 are mapped to 4 (others).
- The columns AVG\_bill\_amt and PAY\_TO\_BILL\_ratio have errors. They are not calculated properly. No value in pay\_amt 's is negative but avg bill amounts are negative. Also this column has values which do not match with the average of bill amounts. That's why it is made again as avg\_bill\_amt with calculated averages and AVG\_BILL\_amt was dropped. Similarly, new pay to bill ratio was made according to new averages.

## 4. Exploratory Data Analysis (EDA)

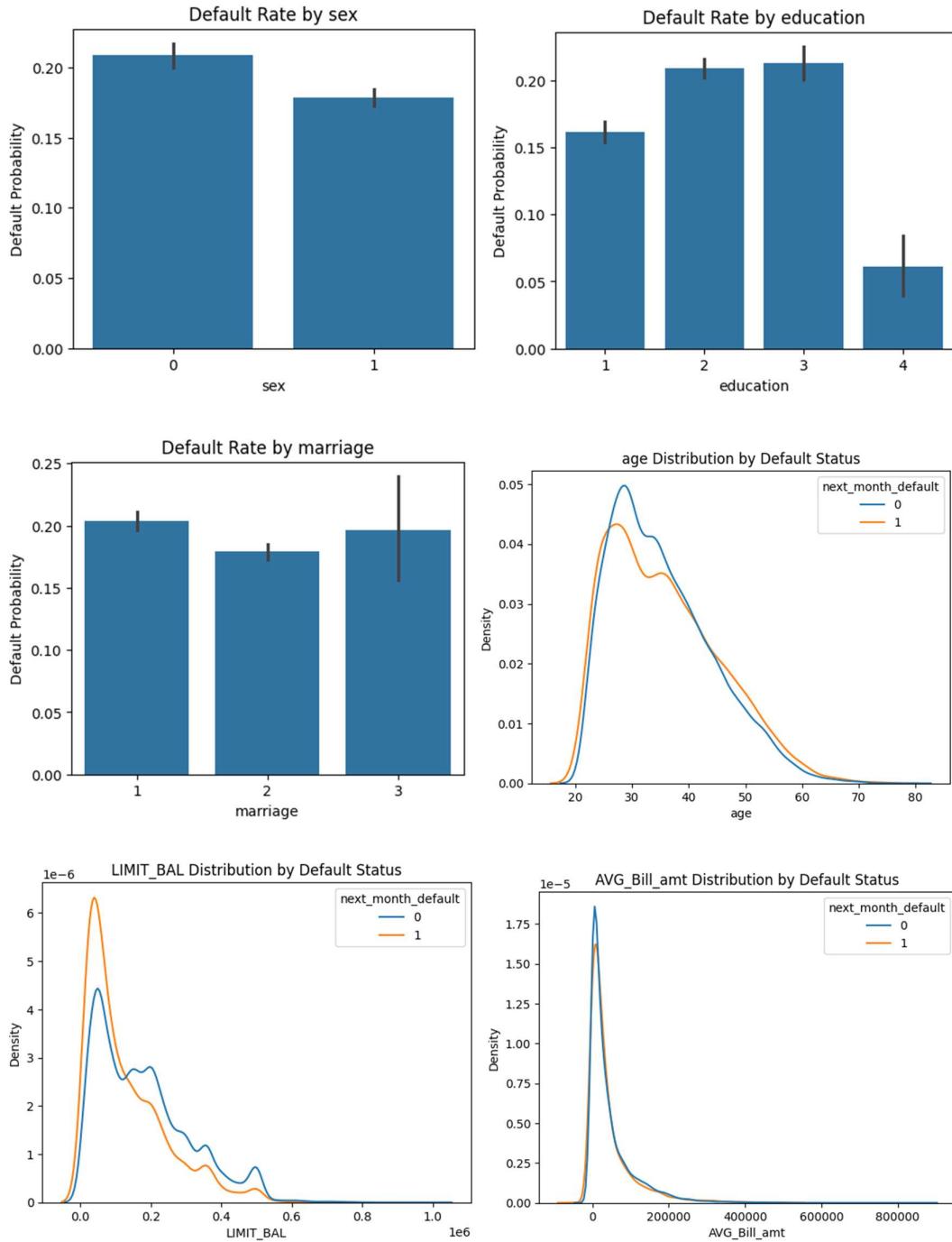
- Univariate and bivariate analyses were performed.
- Histograms and count plots for distributions.
- Heatmap revealed moderate correlation among payment history variables.

Univariate Analyses graphs and results:



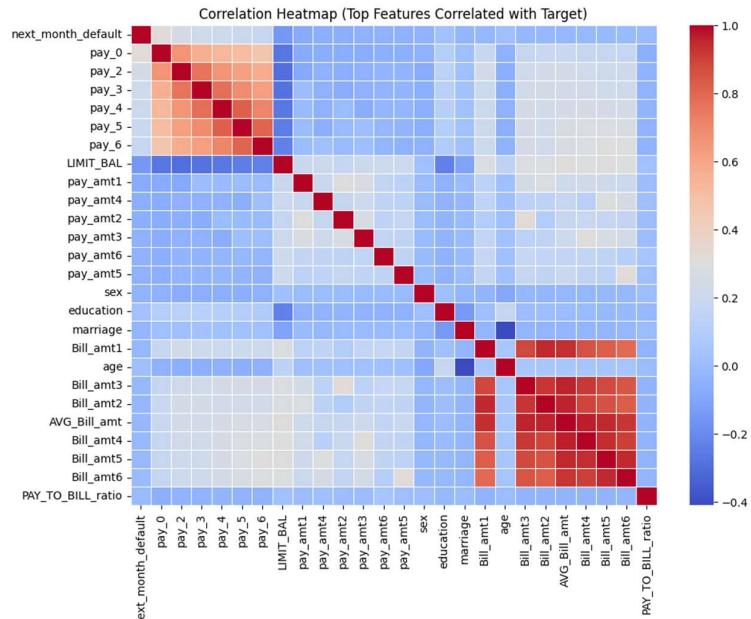
- It is clear from the graph that most of the people in the dataset are male, university level educated, single and have a mode age of 30.

## Bivariate Analyses graphs and Results:



Correlation of variables with target:  
`next_month_default` 1.000000

pay_0	0.312943
pay_2	0.252125
pay_3	0.226015
pay_4	0.207488
pay_5	0.196329
pay_6	0.180387
LIMIT_BAL	-0.146010
pay_amt1	-0.068882
pay_amt4	-0.053624
pay_amt2	-0.053623
pay_amt3	-0.050925
pay_amt6	-0.047116
pay_amt5	-0.046960
sex	-0.037537
education	0.032346
marriage	-0.029242
Bill_amt1	-0.021729
age	0.017703
Bill_amt3	-0.016706
Bill_amt2	-0.016079
AVG_Bill_amt	-0.014694
Bill_amt4	-0.012032
Bill_amt5	-0.008983
Bill_amt6	-0.005725
PAY_TO_BILL_ratio	-0.005528



- The correlation coefficients of all the features with the target variable are weak. None of the features gives a clear dependence for next month default.
- Also, other graphs for categorical and numerical variables don't show any significant trend. One thing is that females have more default rate. University and Graduate level have high defaults.

## 5. Feature Engineering

Created features related to:

### 1. Repayment behavior

- Max delay in any month: It is the maximum of the delays (pay\_0, pay\_2, etc.)
- n\_delinquent\_months : Count of delay months
- avg\_delay : average delay over delinquent months
- longest\_streak : Longest streak of consecutive overdue months

### 2. Consistency & discipline

- pay\_std : standard deviation of payment status > inconsistency
- n\_no\_usage : number of months with no usage (pay\_m == -2)
- prop\_delinquent : proportion of delinquent month

### 3. Utilization & affordability

- credit\_utilization : avg bill / limit
- pay\_to\_limit : pay to limit ratio = total payment / limit

## 6. Feature Encoding & Selection

Applied **one-hot encoding to categorical variables**. All engineered features retained after importance analysis.

## 7. Handling Imbalance

The dataset is imbalanced:

Next Month Default	Count
0	20440
1	4807

Next month default true values are very less (19%) compared to false values. This is handled using SMOTE (Synthetic Minority Oversampling Technique). SMOTE was applied on training data ( $X_{train}$ ,  $y_{train}$ ). SMOTE made the distribution of 0 and 1 equal in the training split.

Before SMOTE:

0	16352
1	3845

After SMOTE:

0	16352
1	16352

## 8. Model Building

Models used:

- Logistic Regression
- Decision Tree
- Adaboost
- Random Forest
- XGBoost
- LightGBM

Train-Test split of 80-20 was used. Then, Hyperparameter tuning was done for all the abovementioned models using GridSearchCV. The grid is in the project notebook.

- Scoring for tuning is done according to F2 score. That means we selected those hyperparameters which gave the most F2 Score.
- $$F2\ Score = (1 + 2^2) \frac{Precision \cdot Recall}{4Precision + Recall}$$
- F2 Score gives more importance to Recall. Recall is sensitive to False negative predictions. It is important in this project as a bank or any lending institution does not want to misclassify any Default customer. This comes in the risk management of the institutions. Recall is given importance due to the risk of leaving a default customer.

Following tabulates the best parameters:

Logistic Regression	<code>{'C': 0.01, 'penalty': 'l1'}</code>
Decision Tree	<code>{'criterion': 'gini', 'max_depth': None, 'min_samples_leaf': 1,}</code>

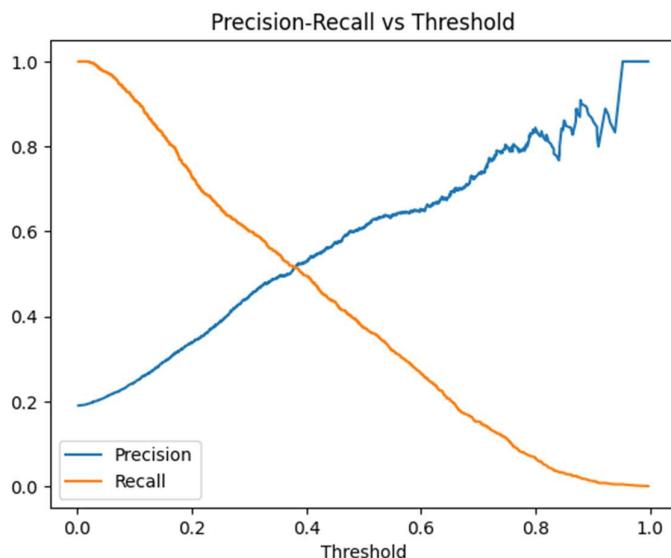
	'min_samples_split': 2}
<b>Random Forest</b>	{'max_depth': 20, 'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
<b>Adaboost</b>	{'learning_rate': 0.1, 'n_estimators': 100}
<b>XGBoost</b>	{'colsample_bytree': 1.0, 'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 200, 'subsample': 1.0}
<b>Light GBM</b>	{'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 200, 'num_leaves': 31, 'subsample': 0.8}

## 9. Model Evaluation

All models were evaluated on the basis of ScikitLearn's Classification report, train and test accuracy, ROC-AUC score and F2 score. Results are tabulated below:

Model	Train Accuracy	Test accuracy	ROC-AUC score	F2 score
<b>Logistic Regression</b>	0.8616	0.8269	0.7479	0.45829
<b>Decision Tree</b>	1.0	0.7487	0.6079	0.3744
<b>Adaboost</b>	0.80	0.7517	0.7299	0.5574
<b>Random Forest</b>	0.9954	0.8350	0.7788	0.4055
<b>XGBoost</b>	0.8547	0.8035	0.7548	0.4598
<b>LightGBM</b>	0.8806	0.8297	0.7740	0.4738

- It is clear that the ensembled models are performing better.
  - Decision Tree and Random Forest are overfitting, but still random forest has good results.
  - The accuracy and F2 score of all the models are low. It is not satisfactory. This is the consequence of the low correlation coefficients of all the features.
  - Threshold probability tuning of ensembled models is done to increase F2 score.
- Following graph illustrates the dependence of Precision and Recall on threshold.



- Since, F2 score depends more on recall, lower threshold is going to increase it. Also, lower threshold will decrease False negatives.

## 10. Model Comparison

- Random Forest  
Best F2-Score: 0.6094  
Accuracy at best threshold: 0.6279  
Threshold: 0.17
- XGBoost  
Best F2-Score: 0.6094  
Accuracy at best threshold: 0.6279  
Threshold: 0.17
- LightGBM  
Best F2-Score: 0.5994  
Accuracy at best threshold: 0.6133  
Threshold: 0.21

We will use Random Forest as final model for future predictions.

## 11. Application of Validation dataset

We used the trained random forest on provided validation dataset to do predictions. The predictions csv is also attached. The percentage of predicted defaults in validation csv were 19.56%.

## 12. Financial Analysis, Business Insights & Recommendations

### Business Insights

#### 1. Risk Assessment

- Payment delays (especially pay\_0) are strong predictors of default risk
- Customers with lower credit limits may be higher risk
- Younger customers (age 24-44) appear more frequently in the data

#### 2. Customer Segmentation

- Could segment customers by:
  - Credit limit ranges
  - Payment behavior patterns
  - Demographic groups
  - Default risk levels

#### 3. Financial Health Indicators

- Pay to bill ratio shows what portion of bill is being paid
- avg\_bill\_amt gives average spending patterns

### Recommendations

#### 1. Risk Management

1. **Early Warning System:** Monitor customers showing payment delays (especially  $\text{pay\_0} \geq 1$ )
2. **Credit Limit Adjustments:** Review limits for customers consistently showing high utilization
3. **Targeted Interventions:** Focus on higher-risk segments (younger, lower credit limits, payment delays)

#### 2. Customer Engagement

1. **Payment Reminders:** For customers showing first signs of delinquency

2. **Financial Education:** For younger customers and those with irregular payment patterns
3. **Customized Offers:** For reliable payers (increased limits, rewards)

### **3. Data-Driven Improvements**

1. **Feature Engineering:** Create more predictive features from existing data
    - o Payment delay trends over time
    - o Utilization ratios
    - o Spending volatility measures
  2. **Predictive Modelling:** Build default prediction models using this rich dataset
  3. **A/B Testing:** Test different intervention strategies on customer segments
- ### **4. Portfolio Management**
1. **Risk-Based Pricing:** Adjust interest rates based on customer risk profiles
  2. **Portfolio Diversification:** Balance high-risk and low-risk customers
  3. **Reserve Planning:** Better estimate potential defaults for financial planning

## **13. Conclusion**

Data was cleaned, features were engineered, models were tested. Results are promising but need further validation.

## **14. Appendices**

Code in Jupyter Notebook.

Libraries: pandas, numpy, matplotlib, seaborn, sklearn, xgboost, lightgbm.