Default of Credit Card Clients

Course: MIS 451 - Machine Learning for Business
Lecturers: Mr. Dang Thai Doan & Ms. Huynh Gia Linh
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Presented by: Group 4 Pieces

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Introduction

Dataset: UCI Default of Credit Card Clients (30,000 records, 23 features)

Business Problem:
Credit card default prediction is crucial for risk management in the banking sector

Identifying **high-risk clients in advance** allows financial institutions to **take early preventive actions**

Objective: Build and evaluate classification models to predict whether a customer will default on their next credit card payment

Data Collection

Dataset Source:

- UCI Machine Learning Repository
- Dataset: Default of Credit Card Clients in Taiwan
- 30,000 records, 23 features

Feature Types:

- Demographics: Gender, age, education, marital status
- Financial Info: Credit limit, bill amounts, payments
- Repayment History: Monthly payment status (April–September 2005)

Target Variable:

- default.payment.next.month → 1 = default, 0 = no default

Data Collection

Variable	Description
LIMIT_BAL	Credit limit (maximum amount the client can borrow)
SEX	Gender (1 = Male, 2 = Female)
EDUCATION	Education level (1 = Graduate, 2 = University, etc.)
MARRIAGE	Marital status (1 = Married, 2 = Single, etc.)
AGE	Client's age in years
PAY_0 to PAY_6	Repayment status for past 7 months (-1 = paid early, 0 = on time, >0 = delay in months)
BILL_AMT1 to BILL_AMT6	Bill statement amount for each month
PAY_AMT1 to PAY_AMT6	Amount actually paid for each month
default.payment.next.month	Target variable: 1 = default, 0 = no default

Exploratory Data Analysis (EDA)

EDA Steps:

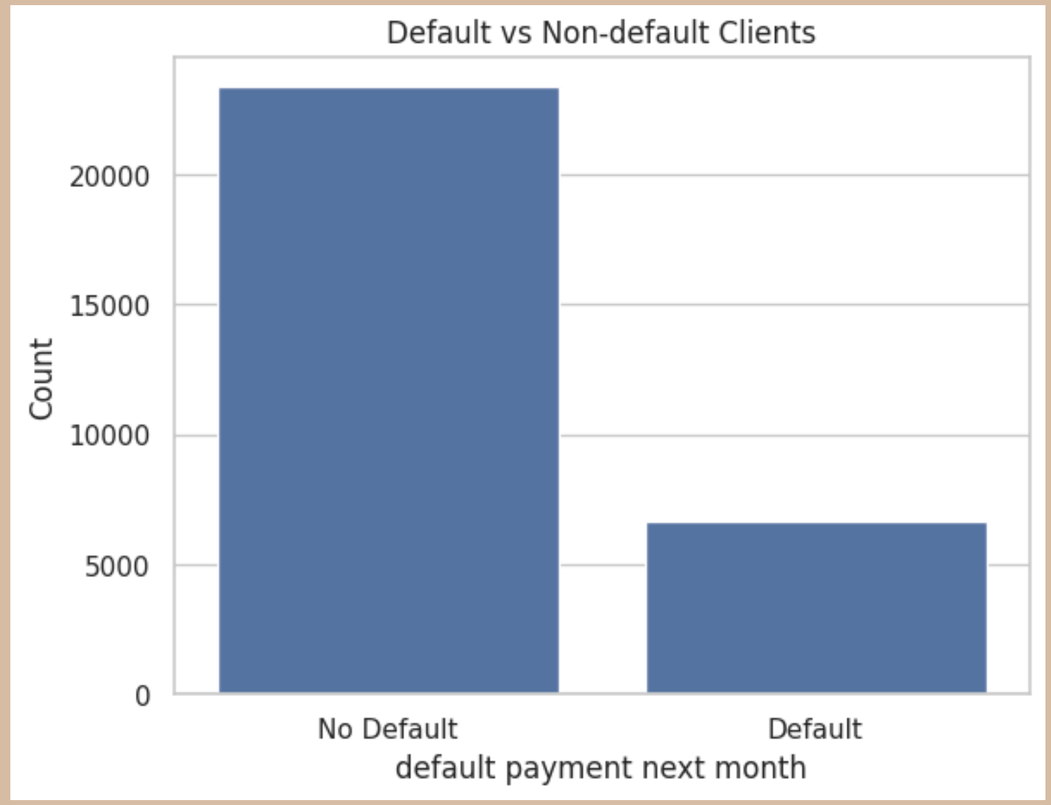
- Checked missing values → None found
- Class distribution: ~23% default, ~77% non-default → imbalanced
- Visualized gender, education, and marriage status
- Heatmap of correlations:
  - Strongest predictors: PAY_0 (0.32), PAY_2, PAY_3
  - Demographics had weak correlation

Key Insight:

Late recent payments are strong indicators of default.

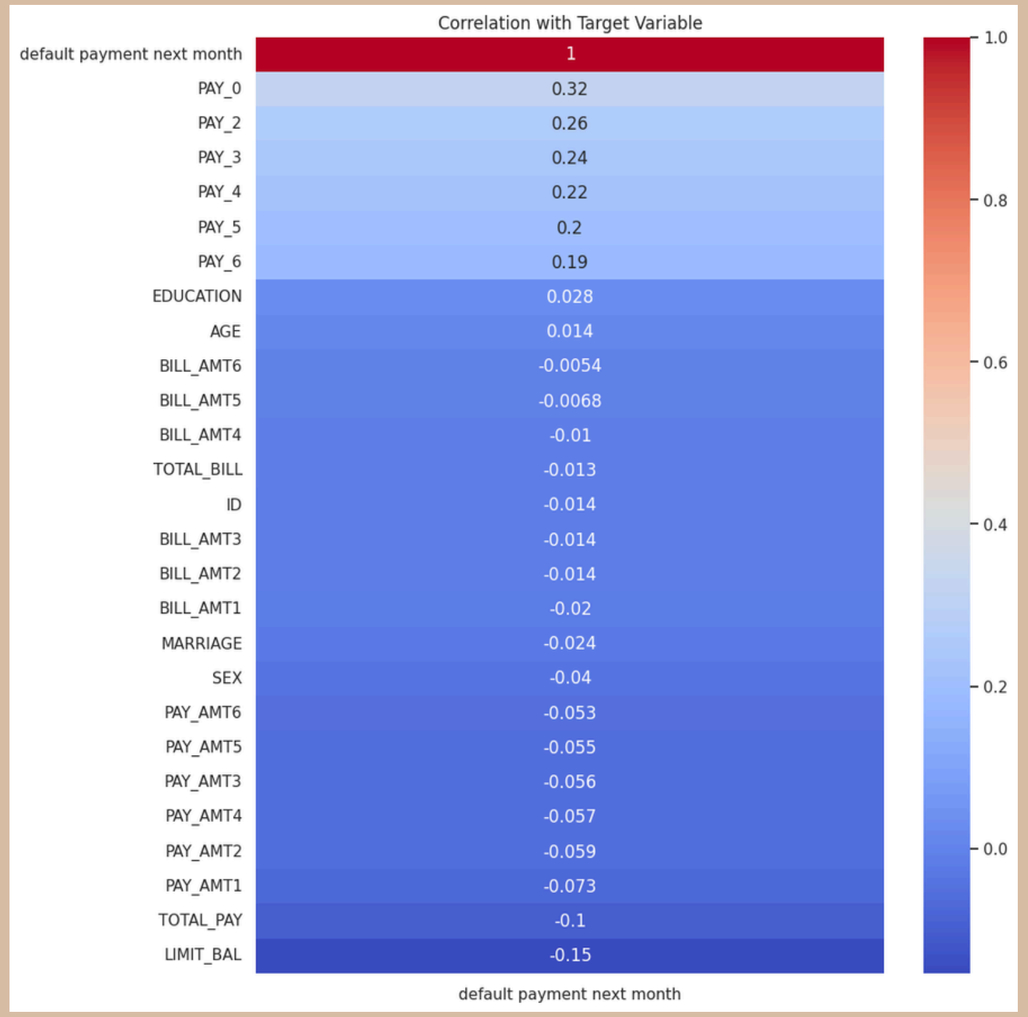
Exploratory Data Analysis (EDA)

Significant class imbalance, avoid biasd learning



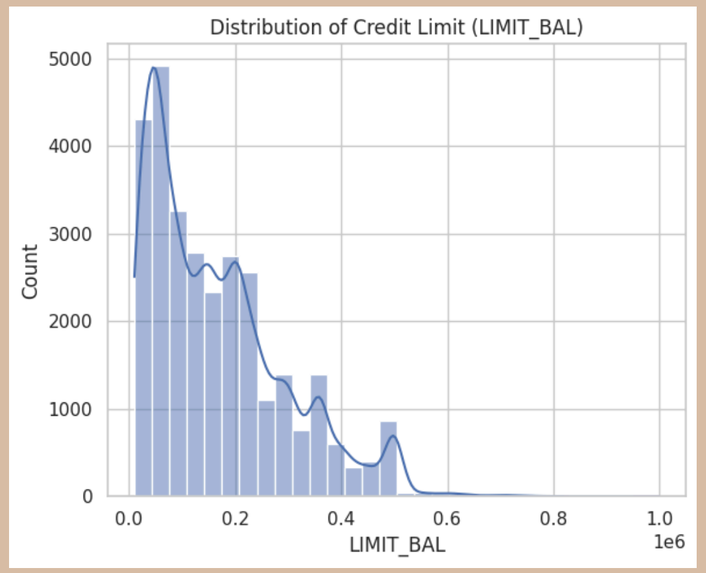
Exploratory Data Analysis (EDA)

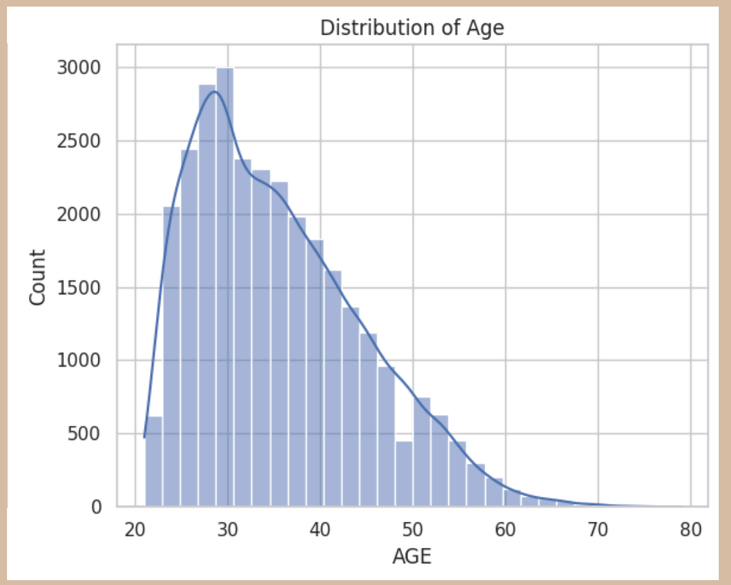
Late payments predict default, higher credit limits lower risk, data needs cleaning



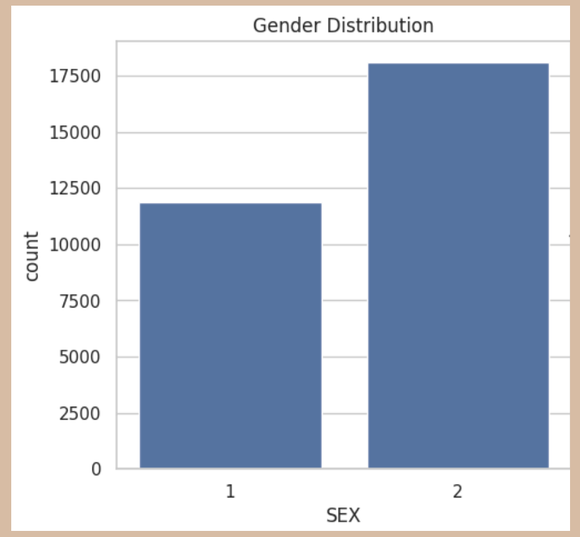
Exploratory Data Analysis (EDA)

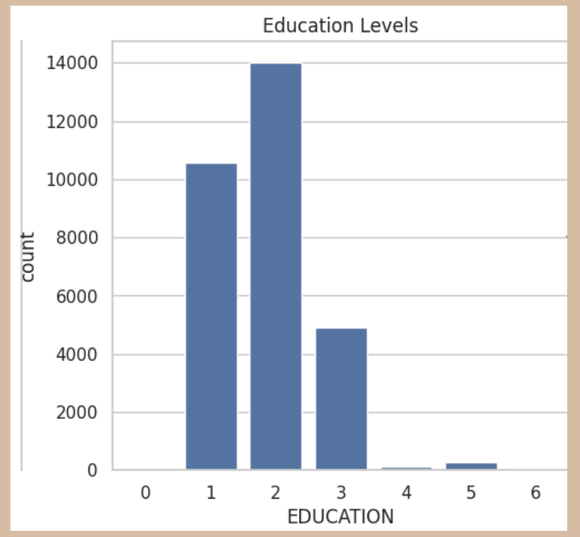
- Mostly credit limit, 200,000 NT$, long tail on the right
- 25-40 years old, fewer older customers, left-skewed

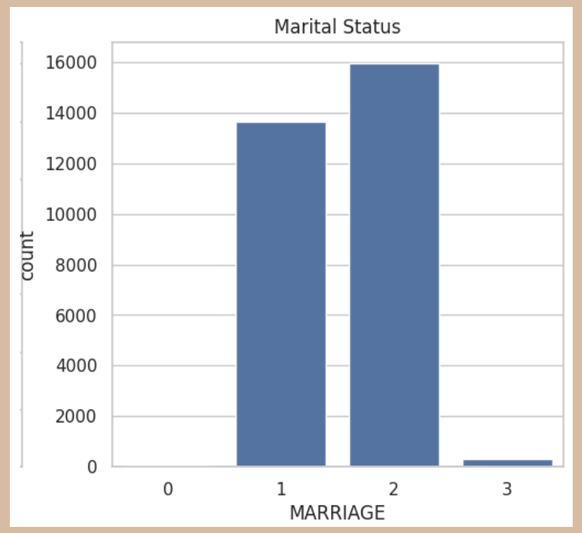




EDA







- 60% female (code 2), 40% male (code 1)
- College/graduate degree (code 1, 2), rae values (0, 4, 5, 6), group as ‘Others’
- Married/single (code 1, 2), unusual values (0, 3), group as ‘Others’

Data Cleaning & Transformation

Cleaning Steps:

- Grouped invalid values in education & marriage → ‘Others’
- No missing data, no duplicates
- Transformation:
- One-hot encoding for categorical variables

Feature engineering:

- TOTAL_BILL_AMT: Sum of 6 months’ bills
- TOTAL_PAY_AMT: Sum of 6 months’ payments
- Feature selection using ANOVA F-test
- Standardized all features using StandardScaler
- Applied SMOTE to balance class in training set

Data Cleaning & Transformation

```
[ ]  # Combine rare/unexpected values
     data_bank['EDUCATION'] = data_bank['EDUCATION'].replace({0: 4, 5: 4, 6: 4})
     data_bank['MARRIAGE'] = data_bank['MARRIAGE'].replace({0: 3})
```

```
[ ]  # One-Hot Encode Categorical Variables
     data_encoded = pd.get_dummies(data_bank, columns=['SEX', 'EDUCATION', 'MARRIAGE'], drop_first=True)
```

```
[ ]  # Total amount billed and paid across 6 months
     data_encoded['TOTAL_PAY'] = data_encoded[[f'PAY_AMT{i}' for i in range(1, 7)]].sum(axis=1)
     data_encoded['TOTAL_BILL'] = data_encoded[[f'BILL_AMT{i}' for i in range(1, 7)]].sum(axis=1)
```

```
[ ]  from sklearn.feature_selection import SelectKBest, f_classif
```

```
[ ]  # 4. Apply SMOTE to the TRAINING data only (to balance classes)
     smote = SMOTE(random_state=42)
     X_train_resampled, y_train_resampled = smote.fit_resample(X_train_scaled, y_train)
```

Model Development

Model Evaluation - Metrics

Metrics Used:

- Accuracy: Overall correctness
- F1-score: Focused on default class
- ROC-AUC: How well model separates default vs non-default (The higher the AUC, the better the model is at classification)

Model Development

Model Evaluation - Results

Model	Accuracy	F1 (Default)	ROC-AUC
Logistic Regression	64%	44	7.089
Random Forest	78%	50	7.356
SVM	77%	52	7.469
MLP Neural Network	**80%**	**52**	**7.572**

Best model: MLP Neural Network

Interpretation & Business Insights

Top Predictive Features:

- PAY_0, PAY_2, PAY_3 → late payments = higher risk
- LIMIT_BAL and TOTAL_PAY_AMT → higher values = lower risk

Insights:

- Payment history is more predictive than demographic data.
- Financial institutions can use these models to:
- Detect risky clients early
- Adjust credit policies or offer support
- Improve customer retention and reduce loss

Team Member Roles & Responsibilities

Member	Responsibilities
Bùi Gia Tuệ	Designed presentation slides and implemented model code in Google Colab
Nguyễn Thanh Giang	Focused on model development and selection, including testing different classifiers
Trần Tiến Thảo Hiếu Ngân	Conducted final review and enhancement of all project steps, including improvement suggestions
Bùi Thị Thanh Thảo	Provided feedback and edits for the slides; served as the primary presenter

From: Team 4 Pieces

To: Class

Thank you very much!