Likelihood of defaulting credit card payments

Data Analytics BootCamp
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Project proposal

We have two goals:

1. Creating a set of visualizations in Tableau of the default and non-default credit card clients and the relationship that defaulting has with demographic features and the payment history of each customer.
2. Creating a supervised machine learning model to predict whether a credit card holder will be on default or not depending on their demographic profile and payment history

Project breakdown

Data — Retrieved from Kaggle

ETL — Python, Pandas
Data loaded in iCloud MySQL DB

ML
- Random Forest with oversample / undersample
- XG Boost
- ADA Boost

Visualization — Tableau visualizations

Presentation — Summary In Google Presentations

Origin of the database

Source

Kaggle

Subject

Credit Card Clients

Geography

Taiwan

Numbers of observations

Almost 30,000 clients

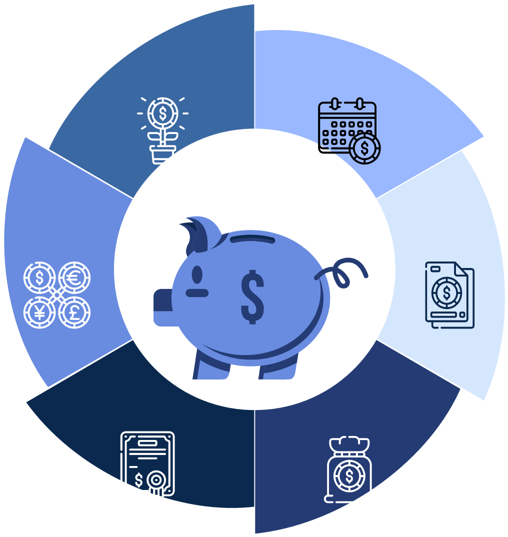
Number of variables

20 of explanatory variables

Target variable

Default (1) or Non-Default(0)

Variables



Credit Limit

Float

Gender

Categorical

Education

Categorical

Marital status

Categorical

Age

Categorical

Timeliness of past payments

Categorical

Amount of bill statement

Float

Amount of previous payment

Float

Default payment next month

Categorical

Data Cleanup, transform and preparation

Null Value Handling:
To ensure data integrity, null values are addressed by either removing or imputing missing values.

Standardization:
Numeric features are standardized by scaling them to have zero mean and unit variance. Dummy variables are excluded from this process.

Dummy Variable Creation:
Categorical variables are converted into binary variables, known as dummy variables, to effectively represent them in the dataset.

Principal Component Analysis (PCA):
PCA is used to reduce the dimensionality of the dataset by transforming the original variables into uncorrelated principal components. This helps identify the most important features while minimizing information loss.

Client clusterization (Unsupervised machines learning):
We clusterized the dataset before running the model to confirm if this clusterizations could increase the accuracy of our models.

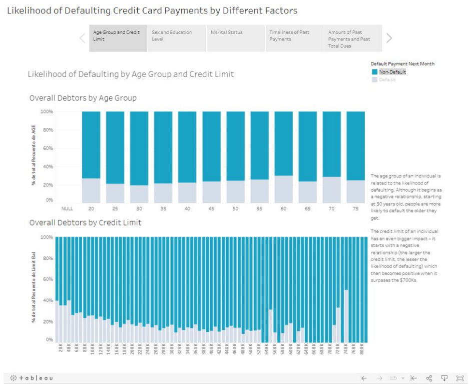
Train-Test Data Split with Stratification:
The data is split into training and testing sets, stratified based on the target values. This ensures a balanced distribution of target values in both sets, reducing bias in subsequent analyses and model training.

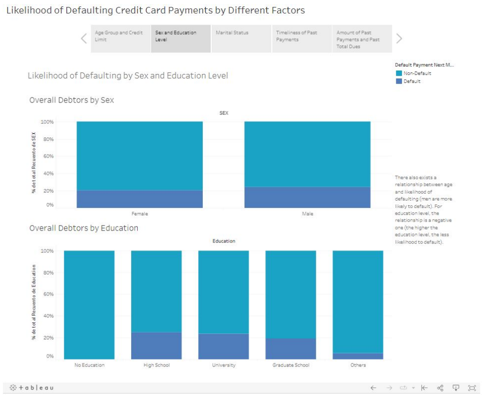
Tableau Story: Likelihood of defaulting credit card payments

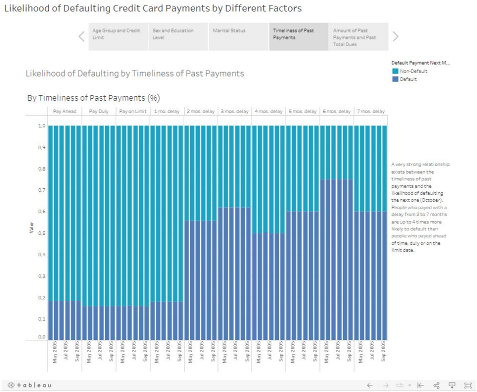
1. Dashboard 1: By age group and credit limit
2. Dashboard 2: By sex and education level
3. Dashboard 3: By marital status
4. Dashboard 4: By timeliness of past payments
5. Dashboard 5: By amount of past payments and past total dues

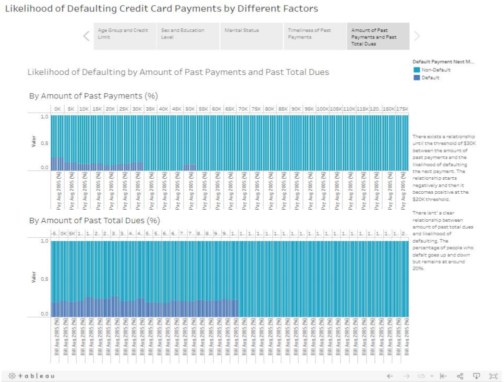
tableau

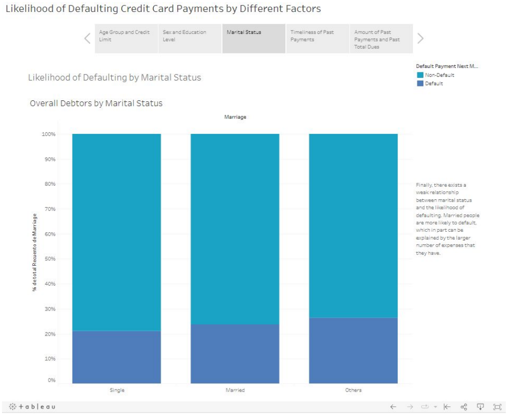
Tableau Story: Likelihood of defaulting credit card payments











Data Conclusions

Predicting credit card default is hard.

There are certain variables with a strong relationship, such as:

- Credit limit
- Timeliness of past payments

Some variables have a mild relationship, such as:

- Age group
- Sex
- Education level
- Amount of past payments

Some variables have a weak relationship or no relationship at all:

- Marital status
- Amount of past total dues

Despite of these challenges, we still managed to create a predictive model with acceptable accuracy.

Finding variables with more explanatory power might yield better results.

We applied 4 models to ensure the best performance

The accuracy of the models was compromised due to the exclusion of PCA and clusterization techniques, which were not incorporated into the analysis process.

Random forest with undersampler

Technique to address class imbalance by reducing the number of majority class instances.

XG Boost

Efficient gradient boosting algorithm that sequentially adds decision trees to improve prediction accuracy. It is known for its high performance and effectiveness in various machine learning tasks

Random forest with oversampler

Similar to the first model, this approach uses the Random Forest algorithm, but instead employs an oversampling technique to increase the number of minority class instances and balance the class distribution.

ADA Boost

Ensemble learning method that combines weak learners, such as decision trees, to create a strong learner. It iteratively adjusts the weights of misclassified instances to focus on difficult samples and improve overall model performance.

Model performance evaluation

The selection of the best model depends in the overall goal

Performance metric		Random Forest with under sampler	XG Boost	Random Forest with over sampler	Ada Boost
Accuracy Score		74%	77%	81%	76%
Precision	Non-default credits	88%	88%	85%	88%
	Default credits	44%	49%	61%	46%
Recall	Non-default credits	78%	82%	92%	80%
	Default credits	61%	60%	45%	61%

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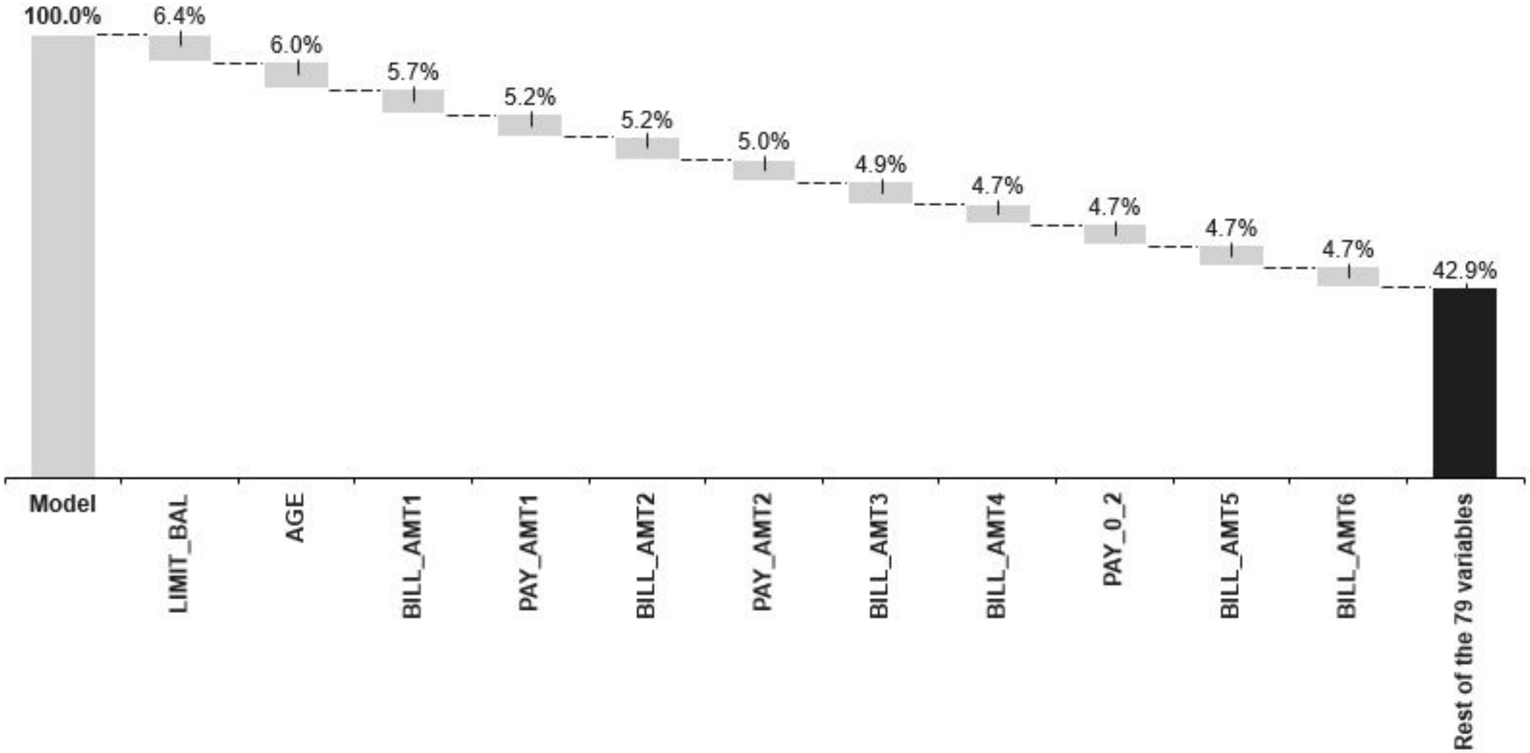
12 features represent 62% of the feature importance of the model



Overall Conclusions

1. Predicting the performance of credit cards yields to a good accuracy as long as you have good information on the past behaviour of the client, status and transactionality. Even though this is a hard task even for machine learning techniques.
2. Adding techniques and remediations methods (PCA and clustering) not necessarily implies an increase in accuracy.
3. Regardless of this, the dependency is concentrated if a few set of features of the credit car, such as limit balance approved , recent status and transactionality.
4. The selection of the best model depends on the main goal.
5. Finding variables with more explanatory power might yield better results.

References

Bansodesandeep. (2022). Credit Card Default Prediction. *Kaggle*. https://www.kaggle.com/code/bansodesandeep/credit-card-default-prediction/notebook