# Credit Card Approval Prediction

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## Ways Bank Make Money

- Interest income
- Capital markets income
- Fee-based income

#### Interest Income



### **Problem**



By assuming 1 person creditor lending Rp 1.000.000 with interest 5%.

Interest: 5% Profit: Rp 50.000

## **Target & Goals**



## **Data Pre-Processing & Analysis**

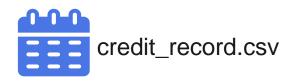


**438.557** Rows 18 Columns

Duplicate data : 12 Rows

Missing Values

134203 Rows on Occupation type



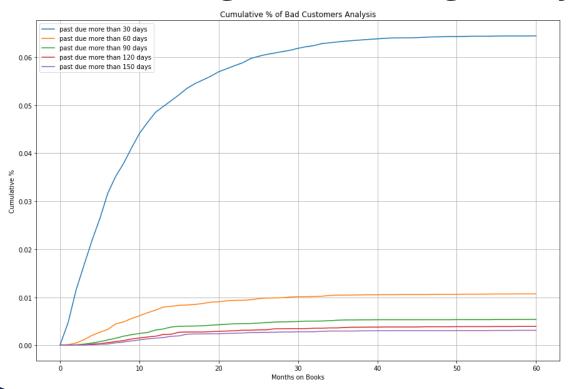
1.048.574 Rows 3 Columns

Duplicate data : 0 Rows

Missing Values : 0 Rows

## **Data Pre-Processing & Analysis**

#### **Determine Target with Vintage analysis**



User 30 Days past due looks higher than other user, it happens more often.

We can't just say user who 30 past days are Bad User

User 60 Past due or more will be categorized as Bad User



## Feature Engineering

#### New feature column



#### Age

Define Age of user,
Transformed from
`days\_birth` column divided
by 365 days

\$13.392.000



#### Months\_in\_books

Define How many Months user join Credit service, Pivoted from `Credit.csv`



#### **Status (Target)**

Define whatever user are Bad User or Good user,

Score =< 60 past due =Bad score Score < 30past due = Good Score

Good Score > Bad Score = Good User Good Score < Bad Score = Bad User

## Feature Engineering

#### **Encoding**



Convert the negative value to 0 and the positive value to 1



More than 2

Convert the Column with One Hot Encoding Technique

#### **Imbalance**

Extremely Imbalance Data between Good & Bad User

**Over Sampling** with Smooth

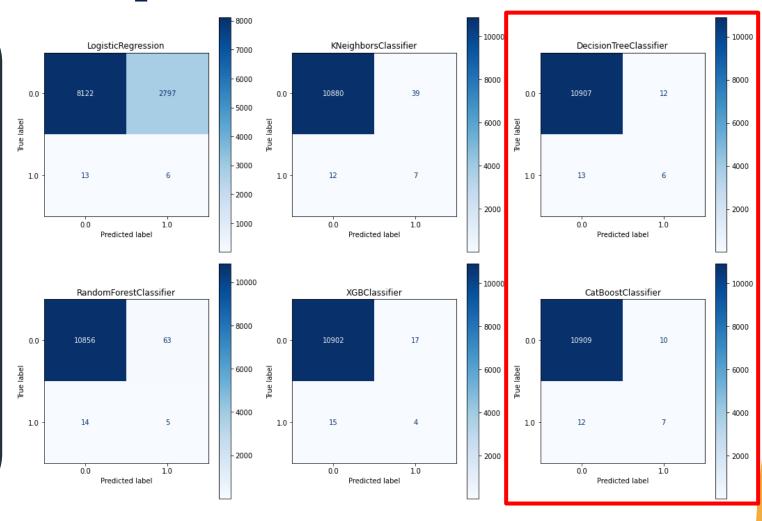
#### **Scaling**

Non-Categorical / Numeric don't have normal distribution **Standard Scaler** 

## **Model Comparison - Classifier**

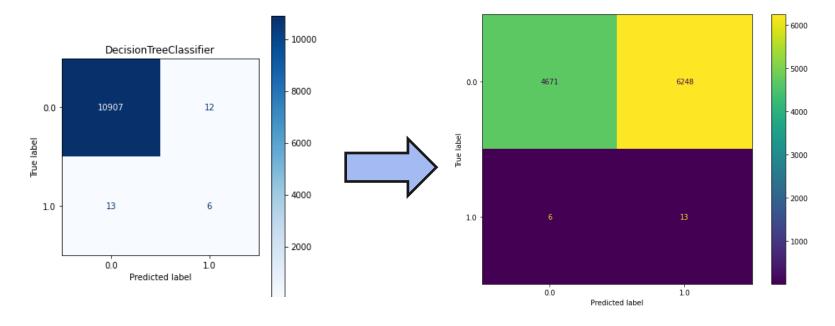
Choose model with highest **recall** with tolerable **accuracy**, we want false negative **smallest** as possible

**Decision Tree** & **Cat Boost** have good
performance



## Hyperparameter tuning

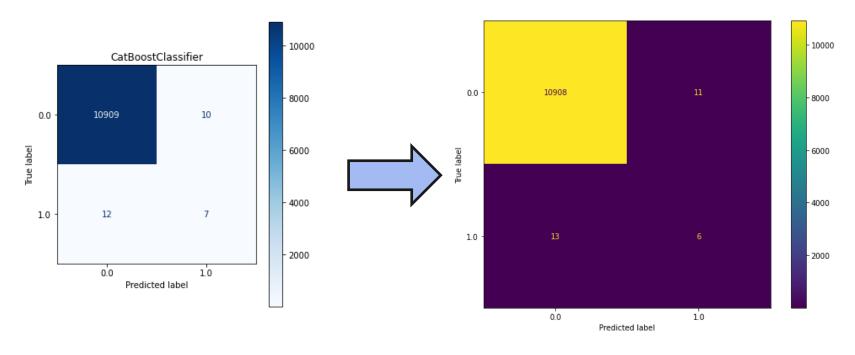
#### **Decision Tree**



Although the recall score increases, the false negative in the model is huge. More than half of the test data was incorrectly predicted, making the model unreliable.

## Hyperparameter tuning

#### **Cat Boost Classifier**

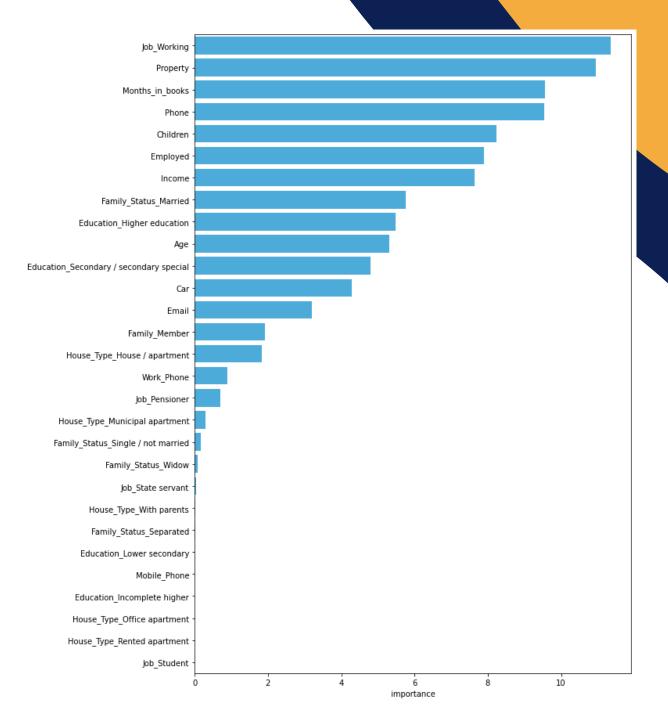


The new parameter found using grid search hyperparameter tuning has a worse score than the default parameter. Therefore, we keep the last parameter as our model.

## How Model Interpret the Data

Job\_Working, Property, Months\_in\_books are features with the most contributions





## Model's accomplishments

Model successfully reduce loss from Defaulters

Rp 1.250.000 26%

**Assumption**: Before using model all defaulter approval credit are approved, returned 75% value, 5% interest and Rp 1.000.000 loan money each person

#### **Before**

- Defaulters : 19
- Prevented : 0
- Loss : Rp 4.750.000

#### **After (with Model)**

- Defaulters : 19
- Prevented : 7
- Wrong predict : 10
- Loss : Rp 3.500.000

## Conclusion

- The Cat Boost model successfully reduce loss from defaulters, with 26,3% percentage there are more room for improvement
- Job with working attributes are the most important feature. By analysis, it is
  found that good user able to pay their dept from working as worker with their
  stable income than other job.
- The Extreme Imbalance of data set make it hard to create model, example if model predict all value as good user model still have 99% accuracy but cannot predict even a single Bad User
- For Profit purpose User predicted as Bad User by the model still have a chance actually a Good User, we must still consider user economics value with their property or other valuable value for loss recovery in credit risk management.
- Failure in Hyper Parameter tuning because there is a chance wrong with chosen parameter, more trial with new parameter value for finding best parameter.



## Thanks!

Do you have any questions?

