# DATA SCIENCE INTERNSHIP

**PROJECT ON**

# Predicting the Likelihood of Loan Repayment for a Microfinance Institution

**Presented By**

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## Introduction:

MFI stands for microfinance institution, and it refers to a comprehensive package of financial services provided to the underprivileged, particularly those living in rural areas. MFIs have made MFS provision a standard practice in recent years because it is less time-consuming and expensive. However, implementing the MFS is not easy at all. Our client is a telecom business that interacts with the MFI to provide microcredit on mobile users' balances.

## Problem Statement:

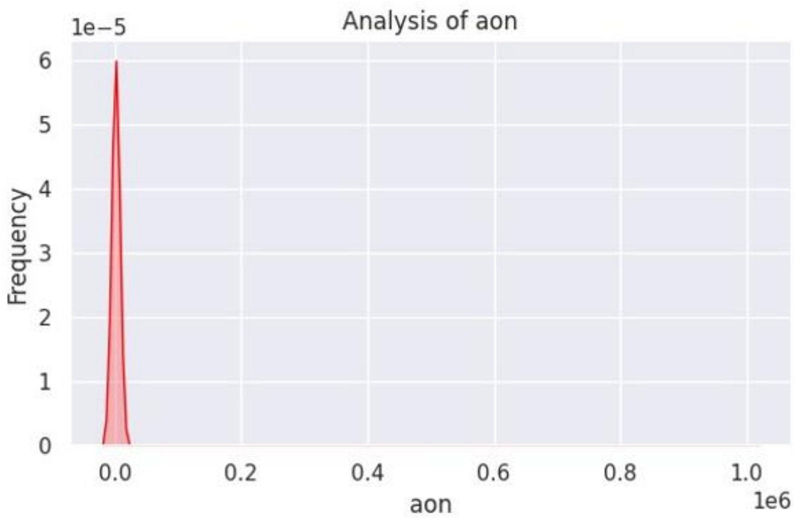
The purpose is to anticipate if clients are likely to repay their loan within 5 days. This is represented by the labels '1' for repayment and '0' for default.

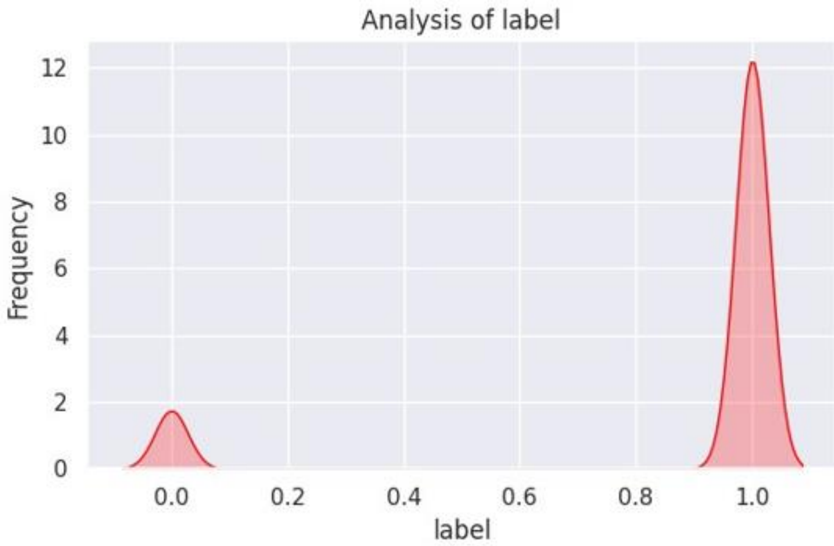
# Data Preparation and Cleaning:

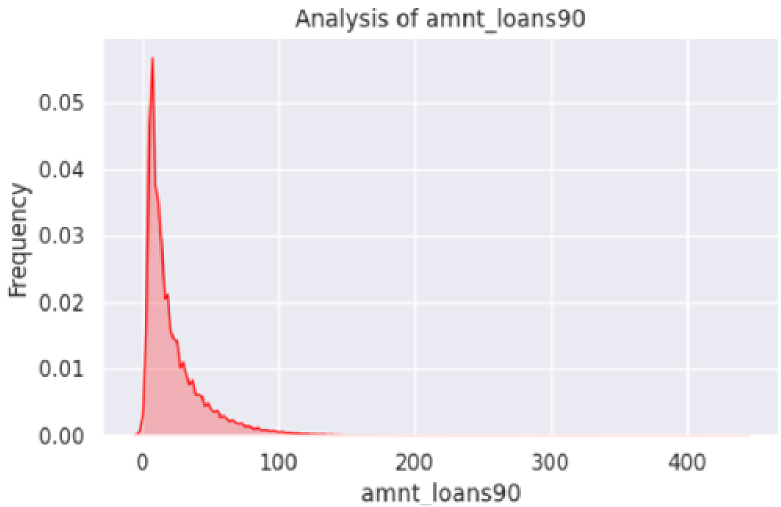
- Collect historical loan transaction data, including features such as **'Unnamed: 0', 'label','msisdn', 'aon', 'daily_decr30', 'daily_decr90','rental30','rental90', 'last_rech_date_ma', 'last_rech_date_da', and 'last_rech_amt_ma'. 'cnt_ma_rech30', 'fr_ma_rech30', 'sumamnt_ma_rech30', 'medianamnt_ma_rech30', 'medianmarechprebal30', 'cnt_ma_rech90', 'fr_ma_rech90', 'sumamnt_ma_rech90', 'medianamnt_ma_rech90', 'medianmarechprebal90', 'cnt_da_rech30' 'fr_da_rech30', 'cnt_da_rech90', 'fr_da_rech90', 'cnt_loans30','amnt_loans30', 'maxamnt_loans30', 'medianamnt_loans30', 'cnt_loans90', 'amnt_loans90', 'maxamnt_loans90', 'medianamnt_loans90', 'payback30','payback90', 'pcircle', 'pdate'**.
- This dataset contains no NULL values.
- We remove the functionality "Unnamed:0".
- We remove the feature "pcircle" as it only has one unique value.

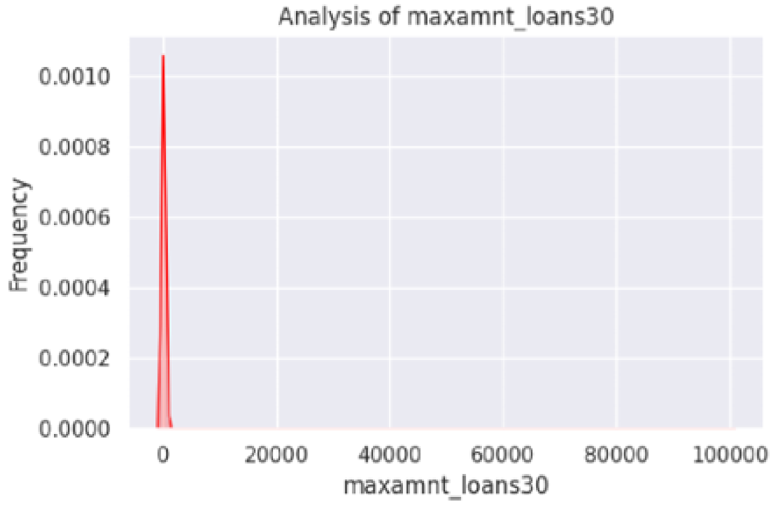
# Exploratory Data Analysis:

- We visualize the univariate analysis on numerical features. Some of the Visualization are given below.

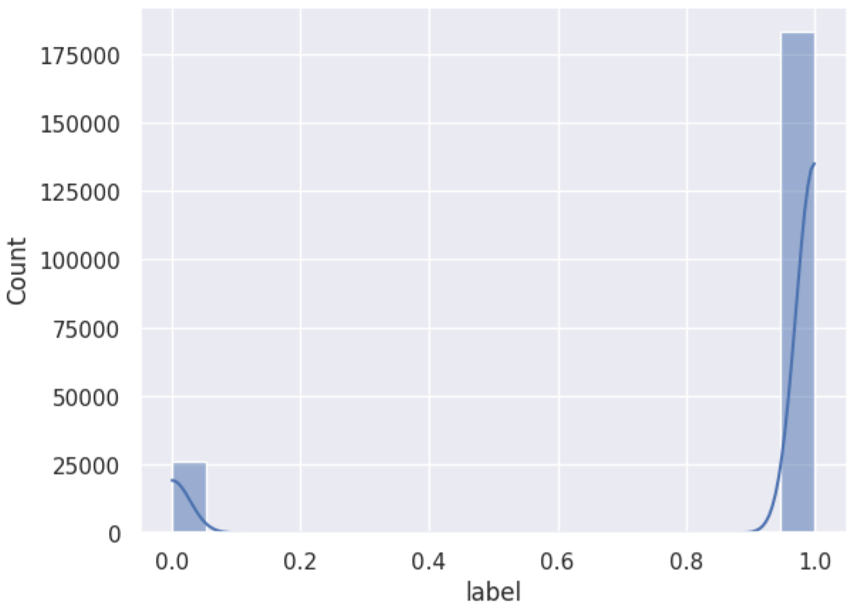





- Then we visualize the distribution of target feature.




## Feature Engineering:

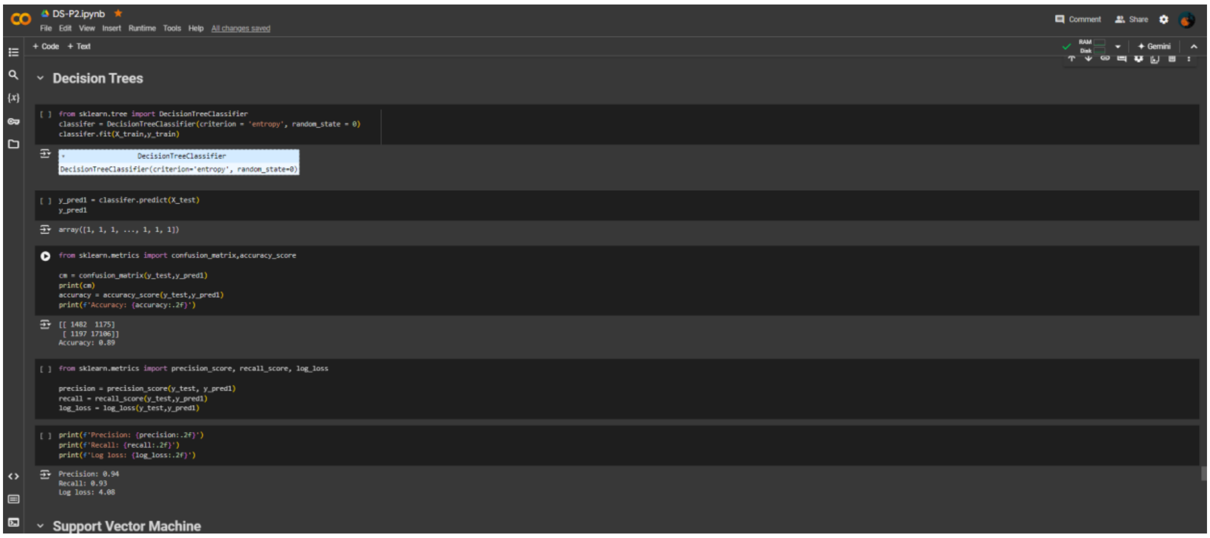
- We separated the temporal variable "pdate" into three new features: "Day", "Month", and "Year". & remove the "pdate" features. Convert the new features to an integer type.
- Here, the features are tied to one another. Let's discover the average of each connected feature and transform it into a single unique feature. rental30 and rental90, payback30 and payback90, cnt_ma_rech30 and cnt_ma_rech90, fr_ma_rech30 and fr_ma_rech90, sumamnt_ma_rech30 and sumamnt_ma_rech90, medianamnt_ma_rech30 and medianamnt_ma_rech90, medianmarechprebal30 and medianmarechprebal90, cnt_da_rech30 and cnt_da_rech90, fr_da_rech30 and fr
- Remove the above features.
- We encode labels for category features.
- We scale all features using Standard Scalar.
- Separate the dataset into two parts: X (all features except the target feature "label") and Y (the target feature "label").

## Model Selection and Training:

- Separate X and Y into training and testing sets.
- In this classification task, we employ Logistic Regression, Decision Trees, Support Vector Machines, and Neural Networks: Multilayer Perceptron with GridSearchCV.

| | **Accuracy** | **Precision** | **Recall** | **Log Loss** |
|---|---|---|---|---|
| **Logistic Regression** | 0.87 | 0.87 | 1 | 4.57 |
| **Decision Trees** | 0.89 | 0.94 | 0.93 | 4.08 |
| **SVM** | 0.87 | 0.87 | 1 | 4.57 |
| **MLP with GridSearchCV** | 0.89 | 0.91 | 0.97 | 3.87 |

## Output Screenshots:


## Model Evaluation:

| | Accuracy | Precision | Recall | Log Loss |
|---|---|---|---|---|
| Logistic Regression | 0.87 | 0.87 | 1 | 4.57 |
| Decision Trees | 0.89 | 0.94 | 0.93 | 4.08 |
| SVM | 0.87 | 0.87 | 1 | 4.57 |
| MLP with GridSearchCV | 0.89 | 0.91 | 0.97 | 3.87 |

## Hyyperparameter Tuning:

- We use GridSearchCV to tune hyperparameters in MLP Neural Network.
- We set the 'batch size' to [16, 32] and the 'learning rate' to [0.001, 0.01].

## Feature importance Analysis:

- After feature engineering, use all 21 features with "from sklearn.linear_model import LogisticRegression" and "from sklearn.feature_selection import SelectFromModel".
- Logistic regression yields coefficients for each feature's impact on the target variable (property price in this case).
- Positive coefficients imply a positive impact on price, whereas negative coefficients indicate a negative influence.
- Regularisation options for logistic regression include L1 and L2.
- Regularisation reduces overfitting and enhances feature selection.

## Business Implication:

- Surprise Housing uses a predictive model to estimate property prices.
- Make investment decisions by identifying undervalued properties.
- Prioritise features, such as schools and location, to reduce risk.
- Adjust approach based on market timing and coefficient changes.
- Determine competitive prices for selling or renting.
- Assess risks associated with features.
- Marketing tip: Highlight appealing qualities in postings.

## Conclusion and Future Steps:

- Surprise Housing can utilise the prediction model to make informed investment decisions, find undervalued homes, and optimise pricing tactics.

- The model's insights increase marketing efforts and risk assessment.

## Limitations Encountered:

- Data Quality: The presence of mistakes or missing values in a dataset has an impact on model performance.

## Market Trends

- Improve accuracy with advanced models such as Random Forest and Gradient Boosting.
- Enhance important features, such as neighbourhood mood and property history.
- Incorporate local insights, such as impending developments and zoning changes.
- Adjust dynamic coefficients to reflect market trends over time.
- Use user feedback to continuously enhance the model.

**The code with output for the above Project is given below**

DS-P2.ipynb