



CAPSTONE PROJECT

PYTHON AND POWER BI



INTRODUCTION

- ❑ This project is about **Loan Eligibility Prediction**
- ❑ A loan eligibility prediction system needs a dataset containing information about past loan applicants and whether they were approved or denied.
- ❑ A historical data is used to train the machine learning model to predict whether new loan applicants are likely to be approved or denied based on their characteristics.

DESCRIPTION OF COLUMN HEADERS

- **loan_amount**: The amount of loan requested.
- **loan_term**: The duration of the loan in months.
- **cibil_score**: The credit score of the user.
- **residential_assets_value**: Value of residential assets owned by the user.
- **commercial_assets_value**: Value of commercial assets owned by the user.
- **luxury_assets_value**: Value of luxury assets owned by the user.
- **bank_asset_value**: Value of assets in the bank account of the user.
- **loan_status**: The status of the loan (1 for eligible, 0 for ineligible).



Introduction to the Problem

- In the financial industry, particularly in the domain of lending, the issue of loan default poses a significant challenge. Loan default occurs when a borrower fails to repay a loan as per the agreed terms and conditions. This problem has far-reaching implications, affecting not only financial institutions but also borrowers and the overall economy.
- By achieving these objectives, the project aims to provide lending institutions with a powerful tool for mitigating the risk of loan default and promoting responsible lending practices in the financial industry.



Goals and Objectives:*

- The primary goal of the project is to build a robust machine learning model for predicting loan default, thereby assisting lending institutions in risk assessment and decision-making processes.
- By achieving these objectives, the project aims to provide lending institutions with a powerful tool for mitigating the risk of loan default and promoting responsible lending practices in the financial industry.

DASHBOARD WITH OF LOAN ELIGIBILITY

9.11M

Sum of loan_id

2.56M

Sum of cibil_score

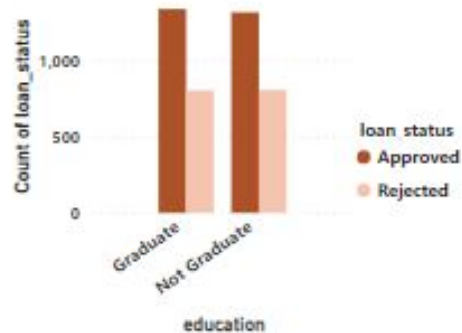
\$21.25bn

Sum of bank_asset_value

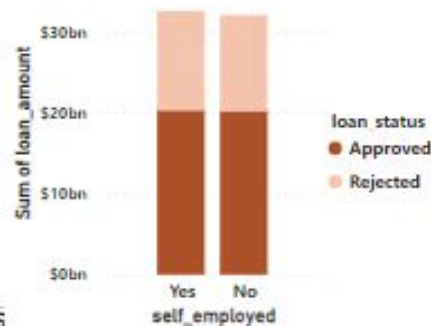
\$21.6bn

Sum of income_annum

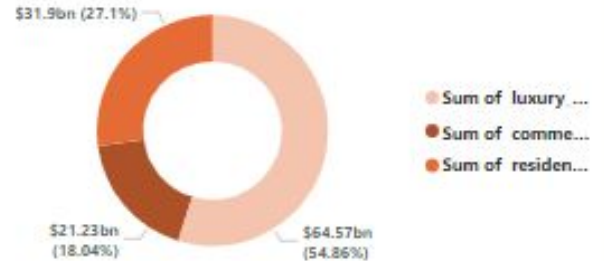
Count of loan_status by education and loan_status



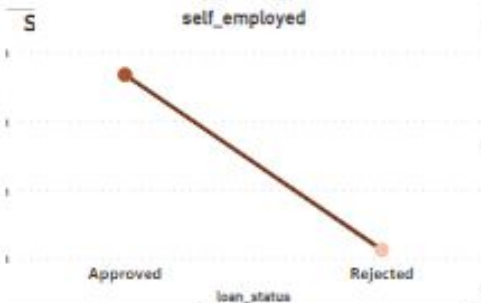
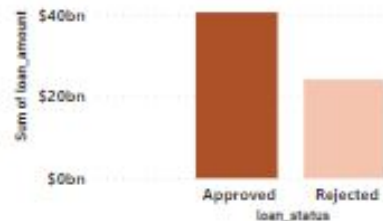
Sum of loan_amount by self_employed and loan_status



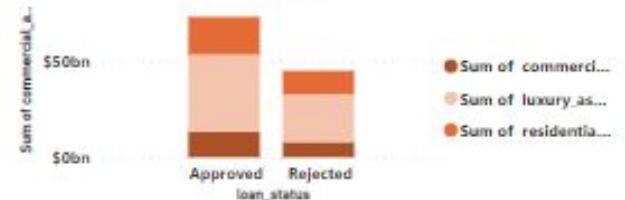
Sum of luxury_assets_value, Sum of commercial_assets_value and Sum of residential_assets_value



Sum of loan_amount by loan_status



Sum of commercial_assets_value, Sum of luxury_assets_value and Sum of residential_assets_value by loan_status





INSIGHT

- ❑ From the dashboards, there isn't a significant difference between the loan status of both graduate and non graduate.
- ❑ The sum of approved loans(\$40,496,700,000) was higher than that of rejected loans(24,108,000,000).
- ❑ Individuals with higher luxury-assets-values had the highest approved loans followed by commercial-asests-values then the lowest was the residential -asset-value.



RECOMMENDATIONS

- ❖ Job security
- ❖ Collateral verification
- ❖ Granting loans to business owner

