# Customer Conversion

Princy Iakov

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01

# Data Insights

# KEY NUMBERS

**5,000**

This is the total number of observations

**29**

Null Values

**480**

Accepted the personal loan

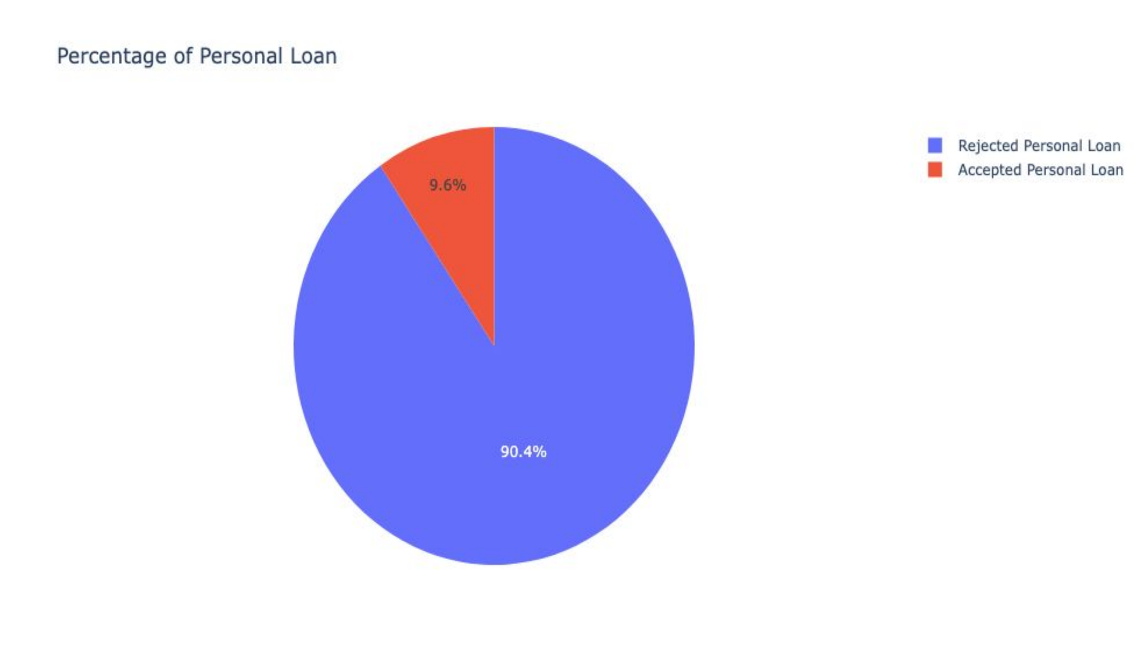
# PERSONAL LOAN

- **Accepted Personal loan offer**

  9.6% i.e 480 people accepted the personal loan

- **Rejected Personal loan offer**

  90.4% i.e 4520 people rejected the personal loan

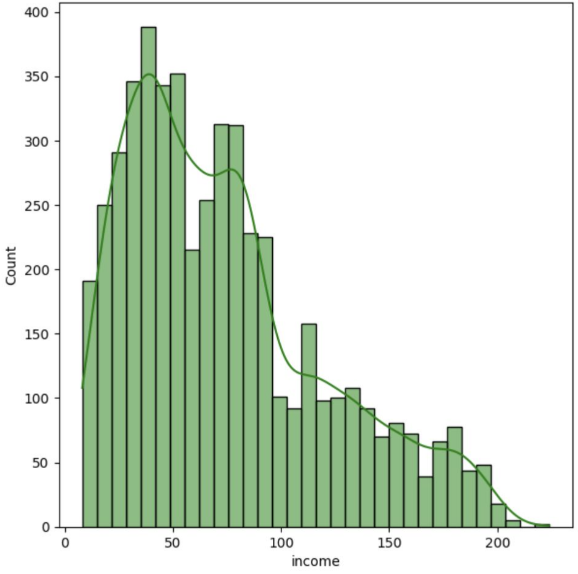


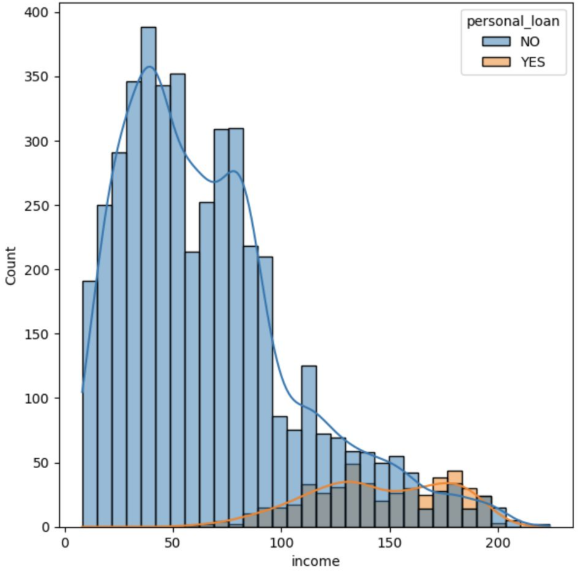
# INCOME

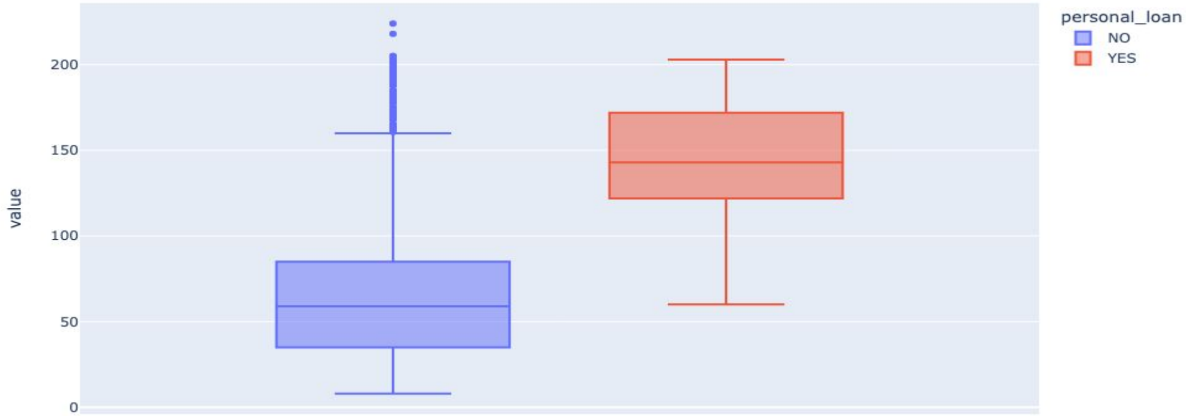
Data distribution is right skewed with people with majority earning less than 100k

We see a distinct difference between people accepting and rejecting personal loans in the box plot with median value 143k for personal loan acceptance

People with income ranging between 122k to 172k tend to have higher chance of accepting the loan



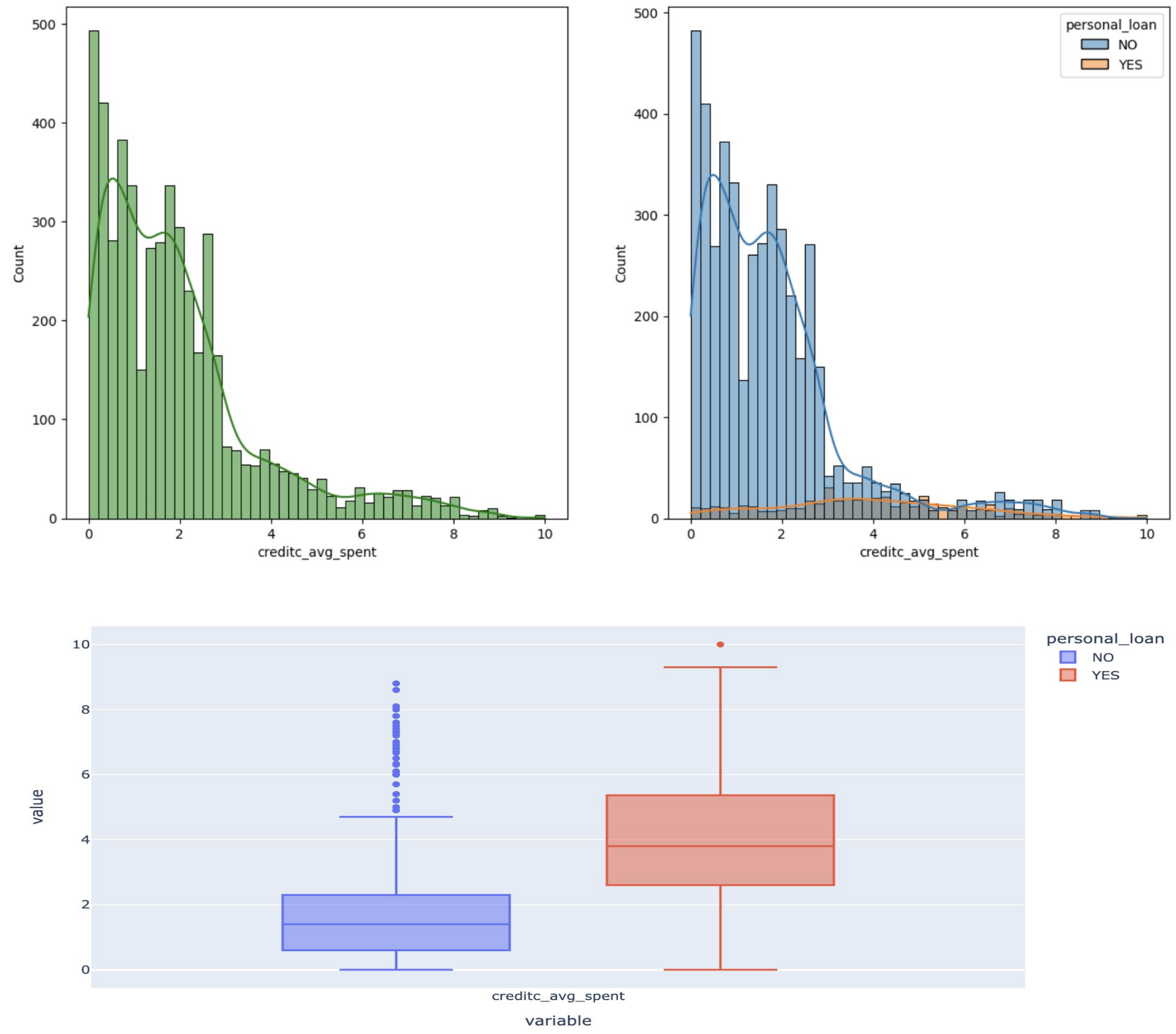



# CREDIT CARD AVG SPENDING

Data distribution is right skewed.  Majority spending less than 3k per month

We see a difference between people accepting and rejecting personal loans in the box plot with median value 3.8k for personal loan acceptance

People with average spending ranging between 2.6k to 5.4k have higher chance of accepting the loan.



# DEPOSIT ACCOUNT

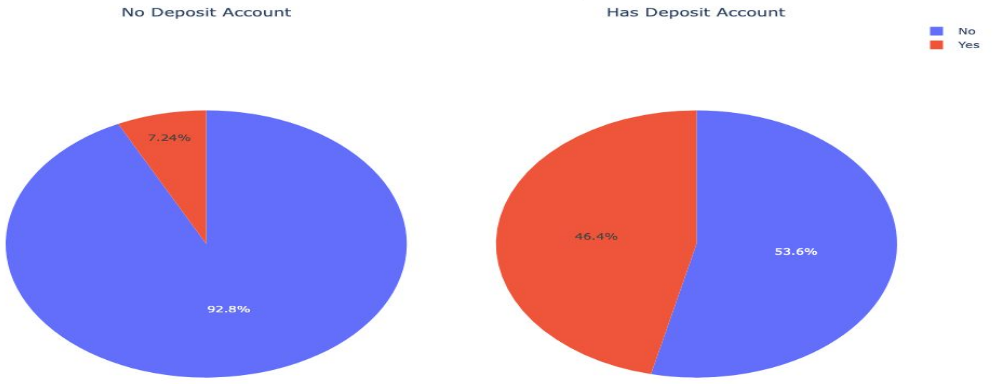
Though the number of people with deposit account is very low, we see a significant difference in loan acceptance rate

## Accepted Personal loan offer

46% of people having deposit account accepted personal loan compared to 7.24 % without an account

## Rejected Personal loan offer

Only 53% of people having deposit account rejected personal loan compared to 92.8% without an account

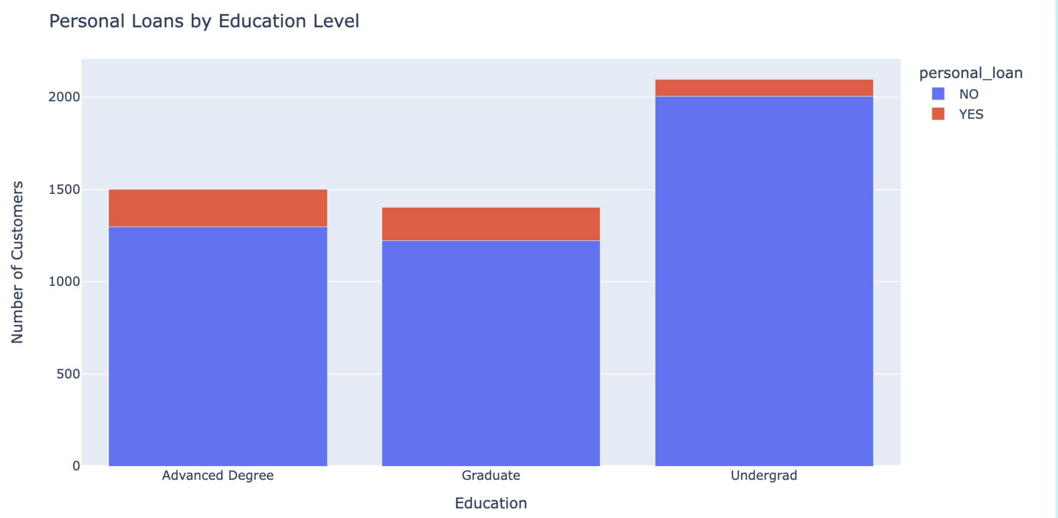
# EDUCATION

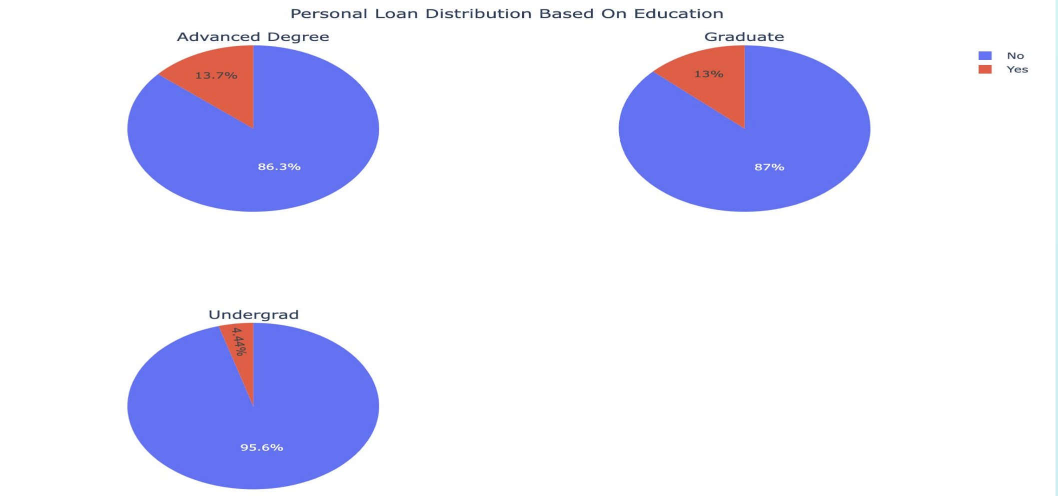
## Accepted Personal loan offer

Clients with higher education tend to accept the personal loan more with 13.7 %  for Advanced degree, 13% Graduate vs 4.44% acceptance for undergraduate

## Rejected Personal loan offer

Clients with less education tend to reject the personal loan more with 95.6% rejection for Undergraduate vs 87 %  for Graduate, 86.3% Advanced degree



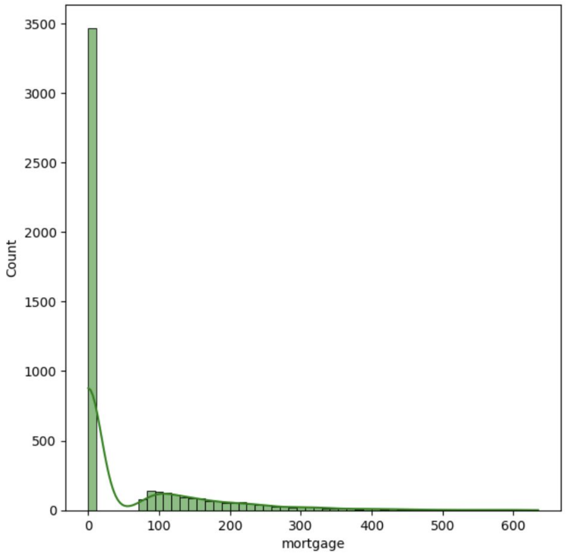



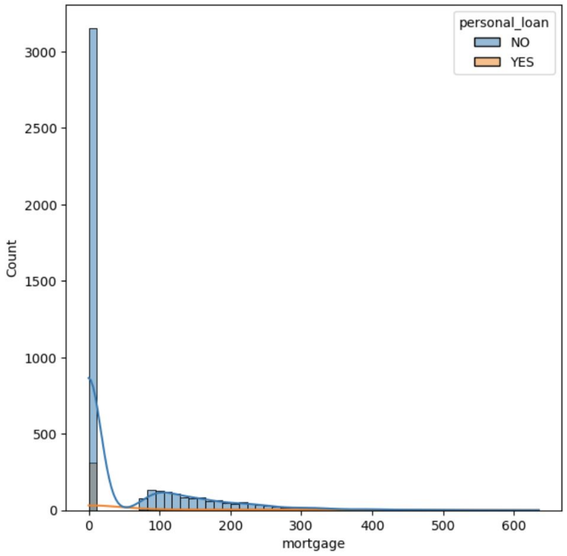
# MORTGAGE

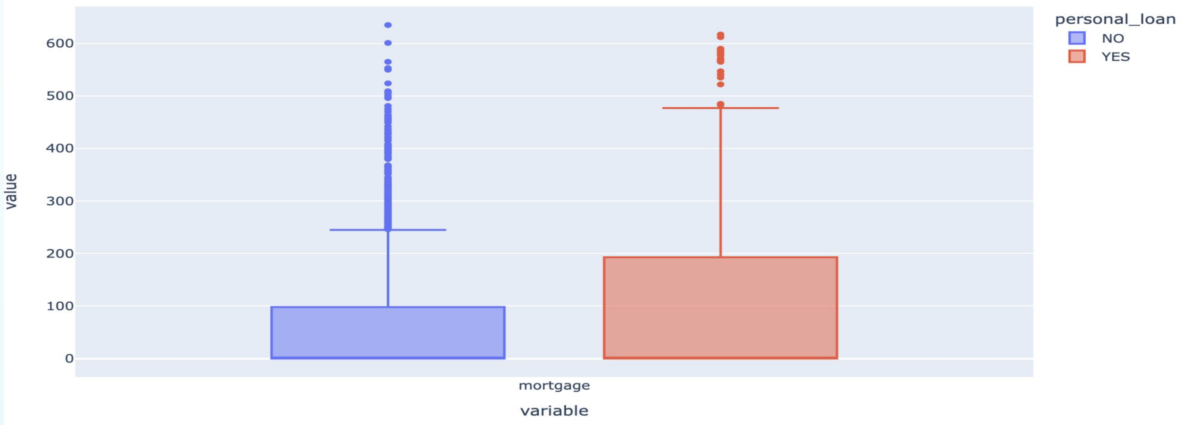
Data distribution is right skewed with people with Maximum people having no mortgage

We see a mild difference between people accepting and rejecting personal loans in the box plot with median value 0

50% of people accepting loan have mortgage ranging from 0 to 193k



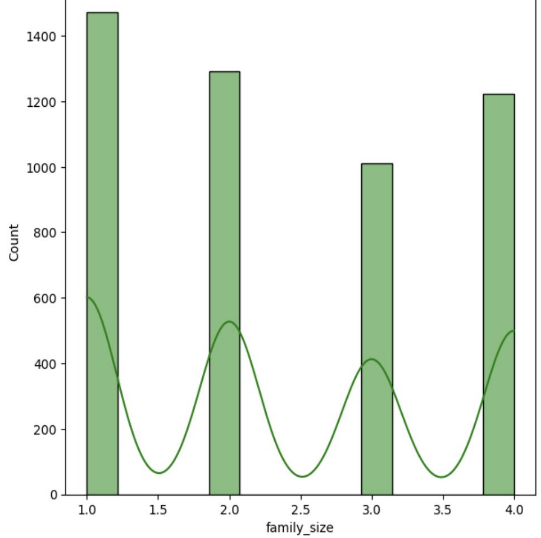



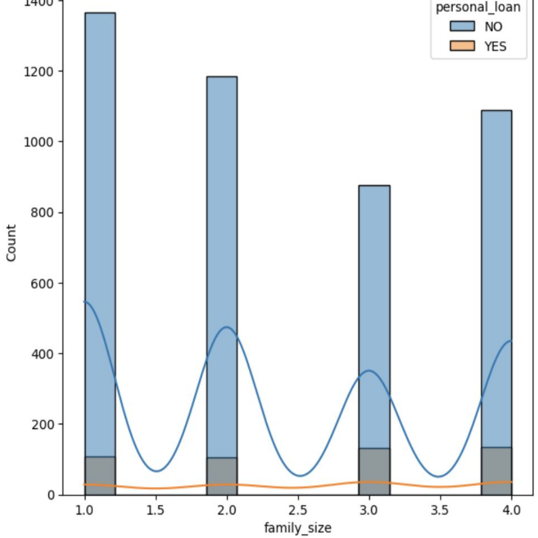



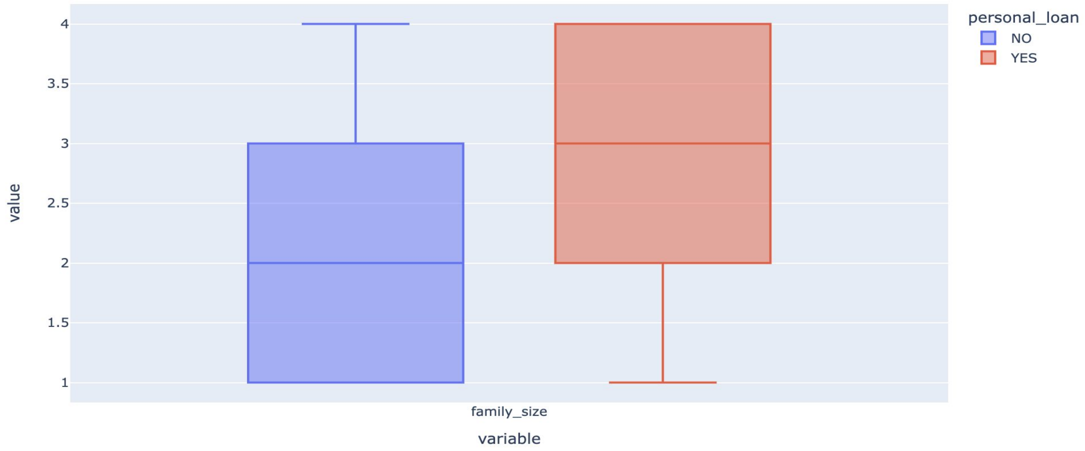
# FAMILY SIZE

Box plot shows that there is a mild  difference in distribution for personal loan acceptance or rejection

Clients with Family size ranging from 2-4 have higher chances of personal loan acceptance with median value 3 for personal loan acceptance

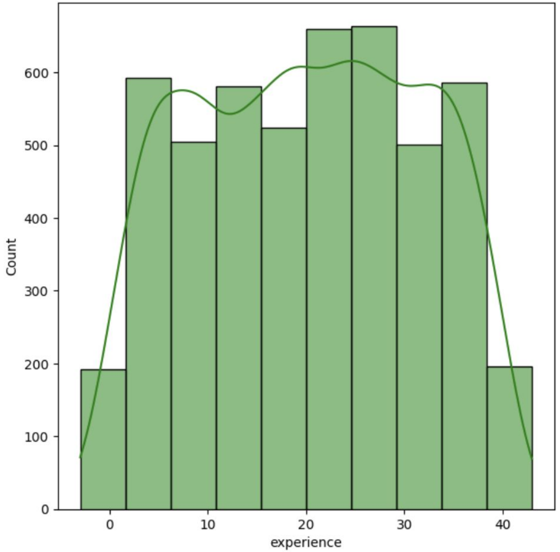


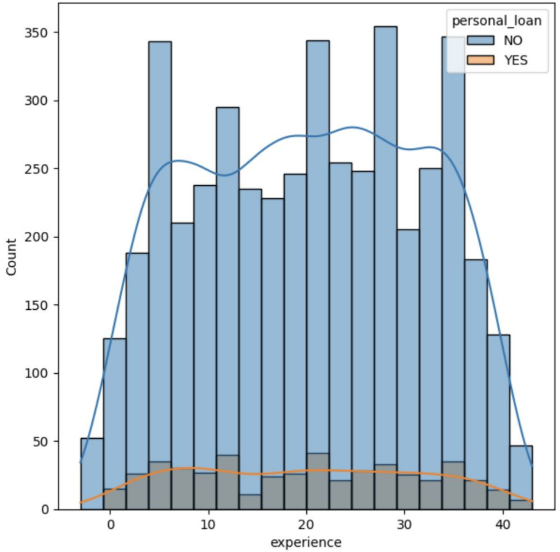



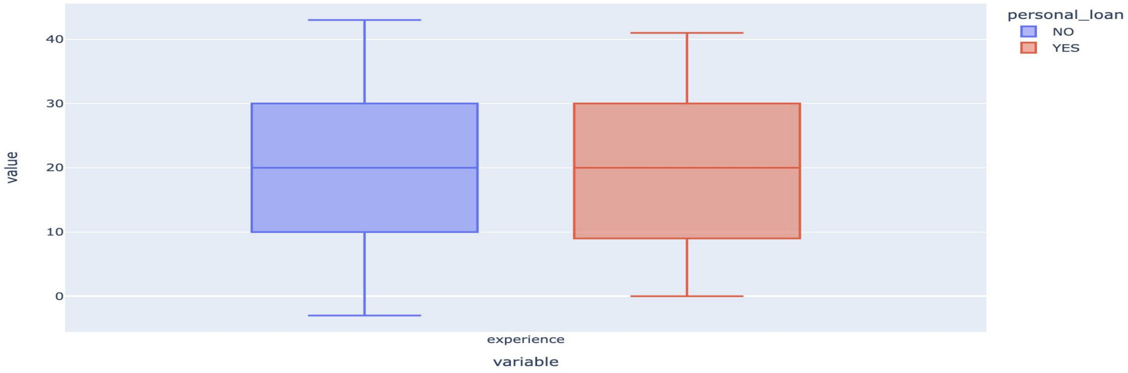



# EXPERIENCE

Box plot shows that there is hardly any  difference in distribution for personal loan acceptance or rejection

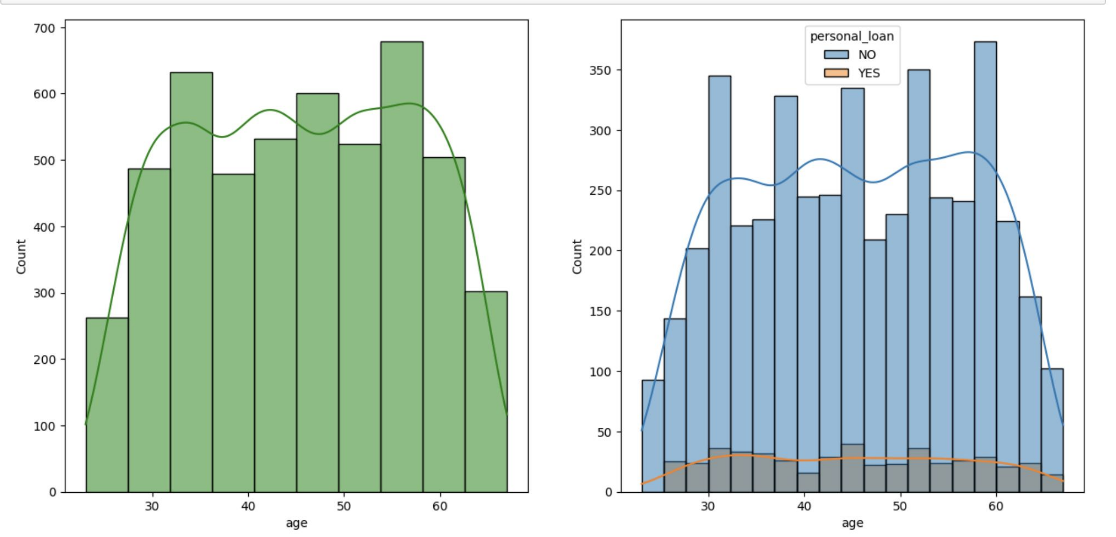


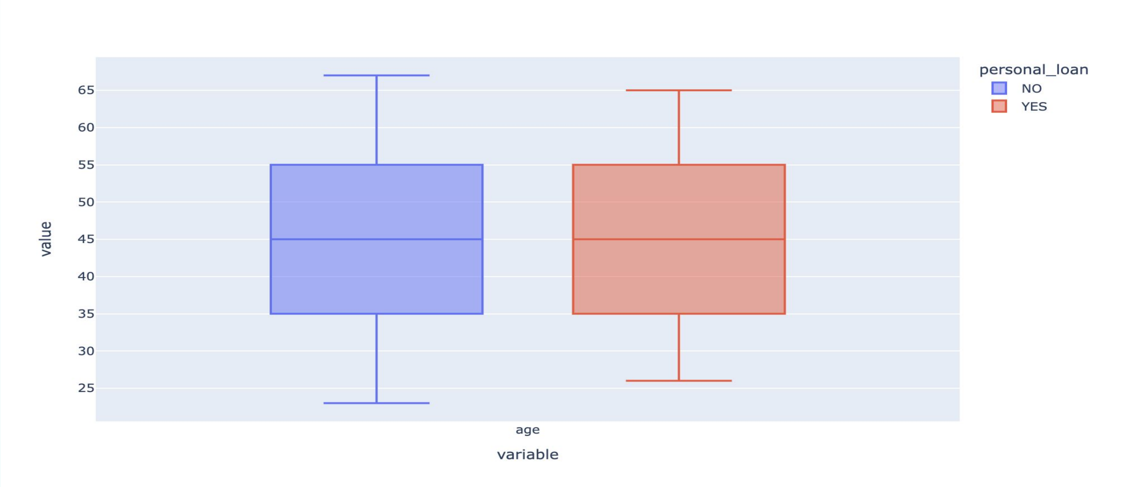



# AGE

Box plot shows that there is hardly difference in distribution for personal loan acceptance or rejection



# Primary Target Audience

01

## Income

Income ranging between 122k to 172k

02

## Average Credit Card Spending

Credit card average spending ranging between 2.6k to 5.4k

03

## Deposit Account

People with deposit account

# PROCESS

## 01

### EDA

Click here for Github repository and here Notebook for EDA

## 02

### Feature Selection, Modelling

Click here for Notebook

## 03

### End to end pipeline Scripts with web application

You can navigate through the scripts by clicking here

## 04

### Dockerfile

Dockerfile created for seamless deployment of project

02

# Models Explored

# MODELS & THEIR METRICS

I explored the following models with and without SMOTE oversampling . Models trained on SMOTE oversampled data performed better.

| MODEL NAME | ROC AUC SCORE | PRECISION | RECALL | F1 SCORE | ACCURACY |
|---|---|---|---|---|---|
| Random Forest | 0.963 | 0 0.99<br>1 0.90<br>macro avg 0.95<br>weighted avg 0.98 | 0 0.99<br>1 0.94<br>macro avg 0.96<br>weighted avg 0.98 | 0 0.99<br>1 0.92<br>macro avg 0.95<br>weighted avg 0.98 | 0.98 |
| Gradient Boosting | 0.969 | 0 0.99<br>1 0.95<br>macro avg 0.97<br>weighted avg 0.99 | 0 0.99<br>1 0.94<br>macro avg 0.97<br>weighted avg 0.99 | 0 0.99<br>1 0.94<br>macro avg 0.97<br>weighted avg 0.99 | 0.99 |
| XGBClassifier | 0.955 | 0 0.99<br>1 0.95<br>macro avg 0.97<br>weighted avg 0.99 | 0 0.99<br>1 0.92<br>macro avg 0.96<br>weighted avg 0.99 | 0 0.99<br>1 0.93<br>macro avg 0.96<br>weighted avg 0.99 | 0.99 |
| KNeighborsClassifier | 0.932 | 0 0.97<br>1 0.89<br>macro avg 0.94<br>weighted avg 0.98 | 0 0.99<br>1 0.88<br>macro avg 0.93<br>weighted avg 0.98 | 0 0.99<br>1 0.88<br>macro avg 0.94<br>weighted avg 0.8 | 0.98 |

03

# Scripts & Web Application

# SCRIPTS

**data_ingestion.py**

Script for reading data from source and ingesting data splits and model creation

**data_transformation.py**

Transform data using sklearn pipeline. Handle missing data, apply Scalar transformation

**model_trainer.py**

Trains models on different hyperparameters and saves the best model

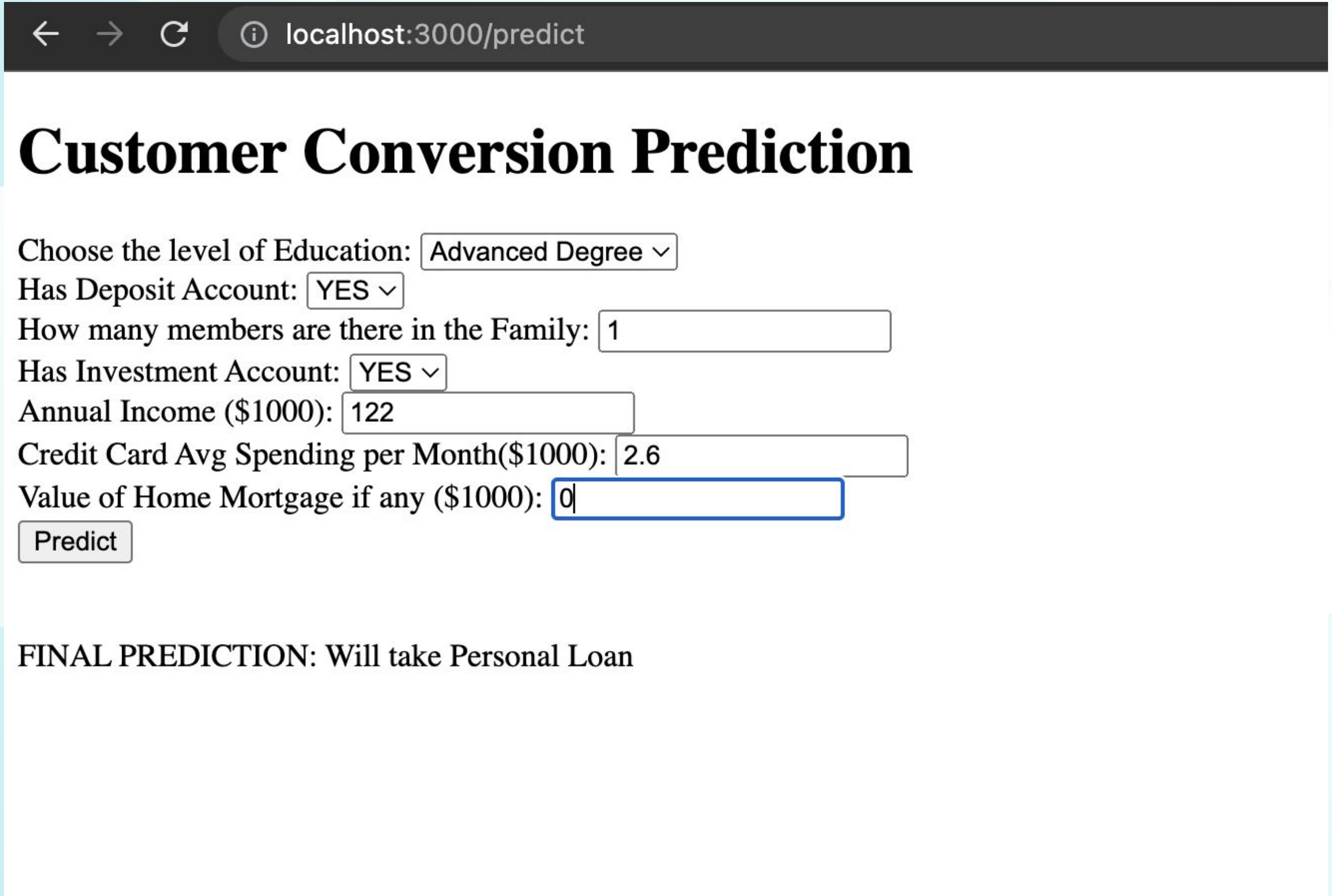
**predict_pipeline.py**

Performs prediction using saved model

**app.py**

Runs web application built on flask for prediction

# Web Application



04

# DockerFile

# DOCKERFILE

Created a dockerfile to enable smooth deployment on any platform

Click here to see the commands to  run the docker file

# THANK YOU!

## Do you have any questions?

princy.iakov@gmail.com
+65 81099121
https://github.com/princyiakov