Customer Conversion

Princy lakov

TABLE OF CONTENTS

01

Data Insights

Understanding the data insights

02

Models Explored

Various models explored along with the metrics



Scripts and Web Application

Dive into the python scripts for data ingestion and web application created



Docker

Docker file for deployment

Data Insights

KEY NUMBERS

5,000

This is the total number of observations

29

Null Values

480

Accepted the personal loan

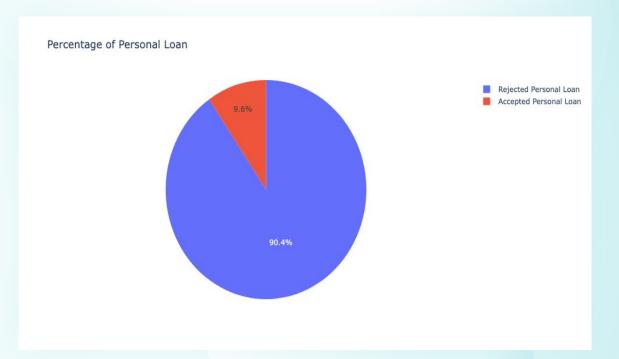
PERSONAL LOAN

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

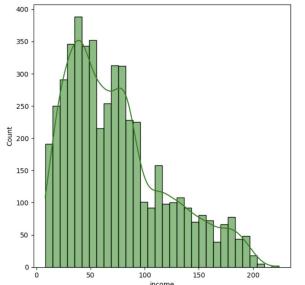


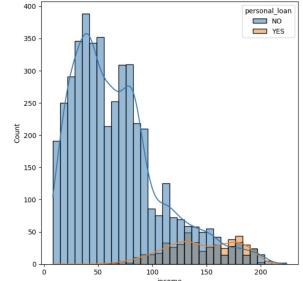
INCOME

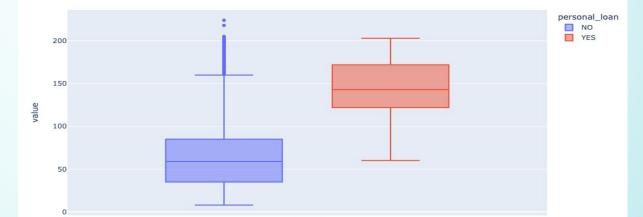
Data distribution is right skewed with people with majority earning less than 100k

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 have higher chance of accepting the loan





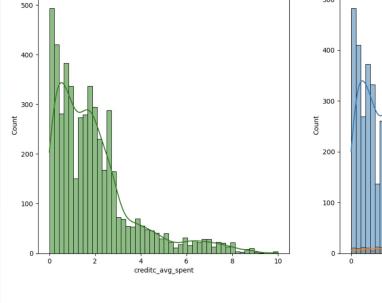


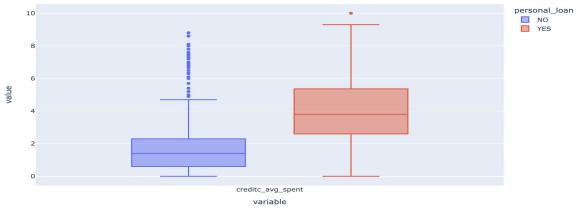
CREDIT CARD AVG SPENDING

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.





personal_loan

NO YES

creditc avg spent

DEPOSIT ACCOUNT

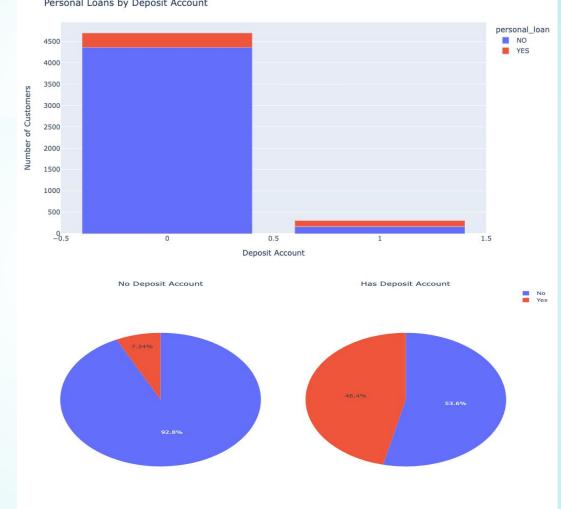
Though the number of people with deposit account is very low, we see a significant difference in loan acceptance rate

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

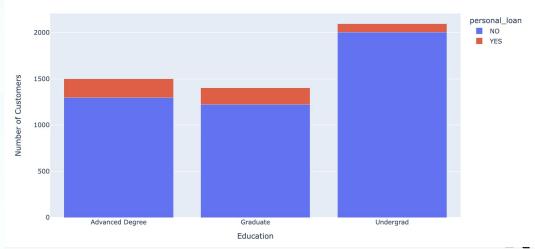
Accepted Personal loan offer

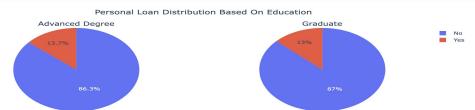
Clients with higher education tend to accept the personal loan more with 13.7 % for Advanced degree, 13% Graduate vs 4.44% acceptance for undergraduate

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

Personal Loans by Education Level





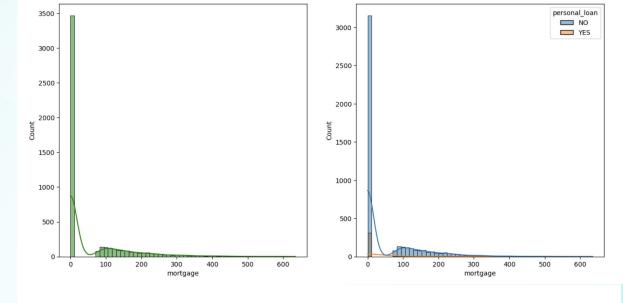


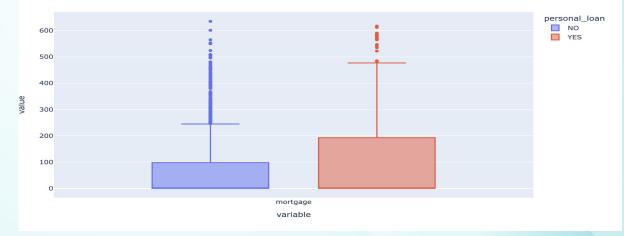
MORTGAGE

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

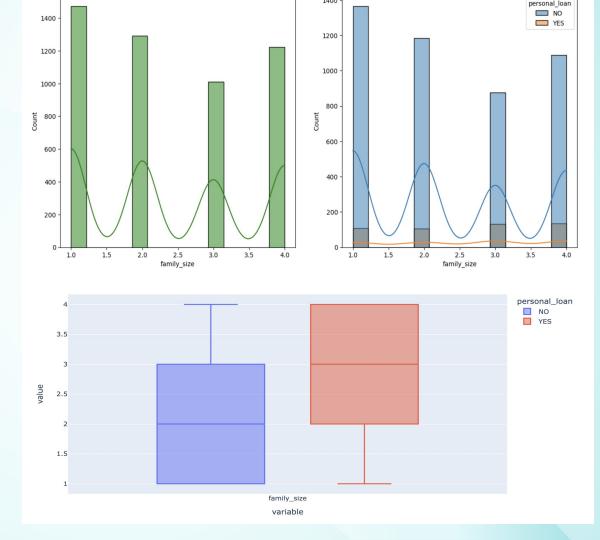




FAMILY SIZE

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

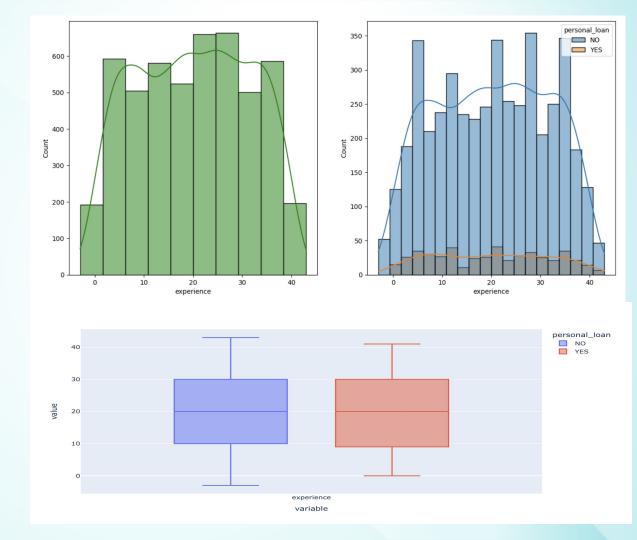
Clients with Family size ranging from 2-4 have higher chances of personal loan acceptance with median value 3 for personal loan acceptance



EXPERIENCE

Data distribution is normal

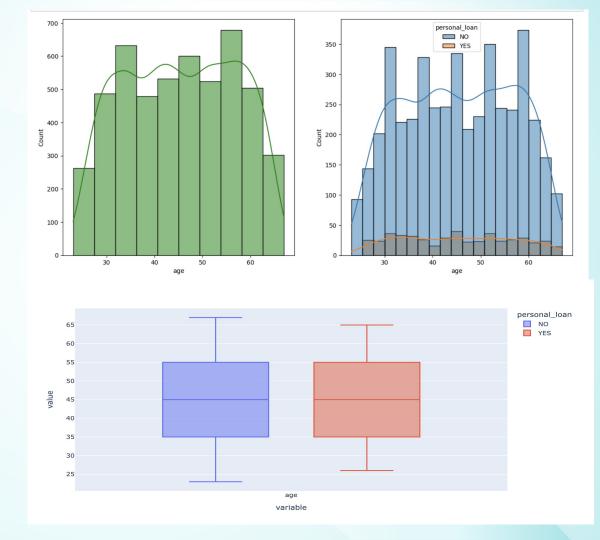
Box plot shows that there is hardly any difference in distribution for personal loan acceptance or rejection



AGE

Data distribution is normal

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





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

EDA

Click <u>here</u> for Github repository and <u>here</u>
Notebook for EDA

Dockerfile

Dockerfile created for seamless deployment of project



Feature Selection, Modelling

Click here for Notebook

End to end pipeline Scripts with web application

All the scripts are available in src folder of Github

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 1 0.90 macro avg 0.95 weighted avg 0.98	0 0.99 1 0.94 macro avg 0.96 weighted avg 0.98	0 0.99 1 0.92 macro avg 0.95 weighted avg 0.98	0.98
Gradient Boosting	0.969	0 0.99 1 0.95 macro avg 0.97 weighted avg 0.99	0 0.99 1 0.94 macro avg 0.97 weighted avg 0.99	0 0.99 1 0.94 macro avg 0.97 weighted avg 0.99	0.99
XGBClassifier	0.955	0 0.99 1 0.95 macro avg 0.97 weighted avg 0.99	0 0.99 1 0.92 macro avg 0.96 weighted avg 0.99	0 0.99 1 0.93 macro avg 0.96 weighted avg 0.99	0.99
KNeighborsClass ifier	0.932	0 0.97 1 0.89 macro avg 0.94 weighted avg 0.98	0 0.99 1 0.88 macro avg 0.93 weighted avg 0.98	0 0.99 1 0.88 macro avg 0.94 weighted avg 0.8	0.98

Scripts & Web Application

SCRIPTS

data_ingestion.py

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

model_trainer.py

Trains models on different hyperparameters and saves the best model

app.py

Runs web application built on flask for prediction

data_transformation.py

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

predict_pipeline.py

Performs prediction using saved model

Web Application



Customer Conversion Prediction

Choose the level of Education: Advanced Degree >
Has Deposit Account: YES V
How many members are there in the Family: 1
Has Investment Account: YES V
Annual Income (\$1000): 122
Credit Card Avg Spending per Month(\$1000): 2.6
Value of Home Mortgage if any (\$1000): 0
Predict

FINAL PREDICTION: Will take Personal Loan

DockerFile

DOCKERFILE

Created a dockerfile to enable smooth deployment on any platform

You can run the dockerfile using the following command from root of the projects:

- >>docker build -t customer_conversion.
- >>docker run -p 3000:3000 customer_conversion

THANK YOU!

Do you have any questions?

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

CREDITS: This presentation template was created by Slidesgo, including icons by Flaticon, and infographics & images by Freepik.