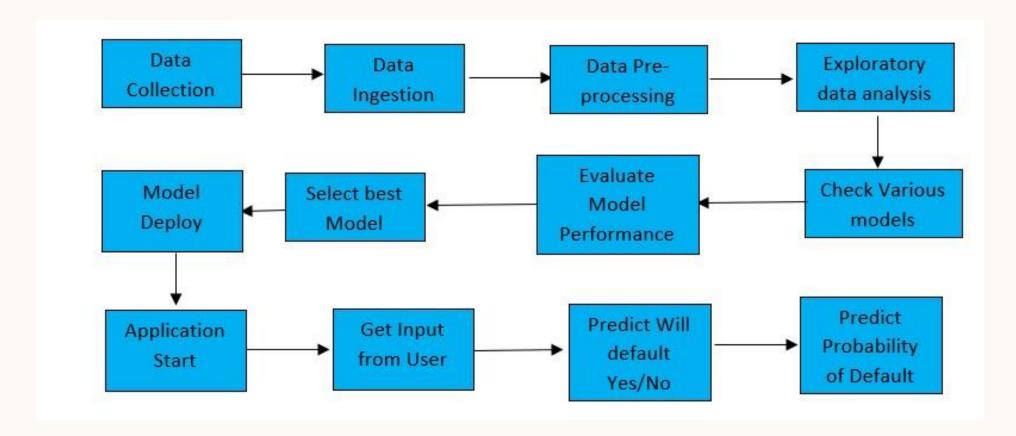
CREDIT CARD DEFAULT PREDICTION

Utkarsh Gaikwad

INTRODUCTION

- Financial threats are displaying a trend about the credit risk of commercial banks as the incredible improvement in the financial industry has arisen.
- In this way, one of the biggest threats faced by commercial banks is the risk prediction of credit clients.
- The goal is to predict the probability of credit default based on credit card owner's characteristics and payment history.

ARCHITECTURE



DATASET

- This dataset contains information on default payments, demographic factors, credit data, history of payment, and bill statements of credit card clients in Taiwan from April 2005 to September 2005.
- DATA SET LINK-
- https://www.kaggle.com/datasets/uciml/defaultof-credit-card-clients-dataset

Variable Name	Measurement Unit	Description			
LIMIT_BAL	NT Dollar	Amount of given credit			
SEX	Integer	Gender (1=male, 2=female)			
EDUCATION	Integer	1=graduate school, 2=university, 3=high			
		school, 4=others, 5=unknown, 6=unknown			
MARRIAGE	Integer	Marital status (1=married, 2=single,			
		3=others)			
AGE	Years	Age of the person in years			
PAY_0-6	Integer	Repayment status for various months			
BILL_AMT1-6	NT Dollar	Amount of billed statements for various			
		months			
PAY_AMT1-6	NT Dollar	Amount of Previous payments done			
default.payment.next.month	Binary	Will Customer default? Yes/No			

DATA PRE-PROCESSING

- Drop the column which is statistically not Important, here I dropped the ID column
- Convert variables: SEX, EDUCATION, MARRIAGE into object as they are categorical variables
- Separate Categorical and Continuous variable.
- For Continuous variables Scale the model with StandardScaler or MinMaxScaler if necessary for model. Scaling is not necessary for tree-based models.
- Perform One-Hot Encoding on Categorical variables
- > Join Continuous and One Hot Encoded Variables
- Data Pre-processing is done.

MODEL BUILDING

- ➤ I have built various classification models like Decision Tree, Random Forest, XGBoost, K-Nearest-Neighbours, MLP(Multi Layer Perceptron).
- > Base model of each above model was created
- Hyperparameter tuning for each model was done using 4-Fold GridSearchCV
- Model with best accuracy score and which required less training time was selected
- Classification report of Models was also checked

MODEL EVALUATION

- Metrics used for Evaluation are: Accuracy Score and Classification Report
- A Classification report is used to measure the quality of predictions from a classification algorithm.
- How many predictions are True and how many are False
- More specifically, True Positives, False Positives, True negatives, and False Negatives are used to predict the metrics of a classification report.

BEST MODEL - XGBOOST

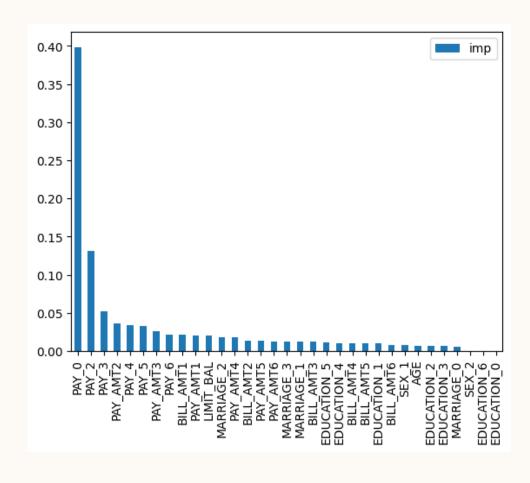
Training Accuracy	0.8236
Testing Accuracy	0.8230

Parameters	Value
n_estimators	500
Learning_rate	0.01
max_depth	4

Classification Report of Testing Data

	precision	recall	f1-score	support	
0	0.84	0.96	0.89	4654	
1	0.71	0.36	0.48	1346	
accuracy			0.82	6000	
macro avg	0.77	0.66	0.69	6000	
weighted avg	0.81	0.82	0.80	6000	

FEATURE IMPORTANCE



DEPLOYMENT

- Saved the XGBoost Classifier Pickle file.
- Used Dash library to create Front-end
- Used @app.callbacks decorator for User Interaction
- Created a Procfile for deployment using Gunicorn
- Committed All project to GitHub Repository
- Deployed the Web-Application to Heroku
- Web-App URL: https://creditcarddefaultutkarshg.herokuapp.com/
- Project Demo URL: https://youtu.be/ltktrNRSWEU

Credit Card Default Prediction - Utkarsh Gaikwad								
GitHub Repository for this project								
Limit Balance : [LIMIT_BAL								
Sex:								
Select								
Education:								
Select								•
Marrtial Status :								
Select								•
Age : AGE								
PAY_0:								
-2 -1 PAY_2:	0	1	2	3	4	5	6	7 8
4 4	0	1	2	3	4	5	6	7 8
PAY_3:								
2 1	0	1	2	3	4	5	6	7 8
PAY_4:	0	1	2	3	4	5	6	7 8
PAY_5:	•		2	,	•	,	•	,
4 -1	0	1	2	3	4	5	6	7 8
PAY_6:								
-2 -1	0	1	2	3	4	5	6	7 8
BILL_AMT1 : BILL_AMT1								
BILL_AMT2 : BILL_AMT2								
BILL_AMT3 : BILL_AMT3								
BILL_AMT4 : BILL_AMT4								
BILL_AMT5 : BILL_AMT5								
BILL_AMT6: BILL_AMT6								
PAY_AMT1 : PAY_AMT1								
PAY_AMT2 : [PW_AMT2								
PAY, AMTS : [BW, AMTS								
PAY_ANT4: [PW_ANT4								
PAY_ANTS: [Pay_ANTS								
PAY_ANT6: [PAY_ANT6								
Predict								
Output								