CREDIT CARD DEFAULT PREDICTION

High Level Design (HLD)

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Contents

Abstract

In the current society, banks often face the risk of credit card defaults, which can result in significant financial losses and penalties. When a customer defaults on their credit card payments, the bank loses the potential interest income and may have to write off the debt as a loss. Additionally, the bank may incur legal and administrative expenses associated with debt collection. To mitigate these risks, banks can develop machine learning techniques to predict customer defaults based on demographic and behavioral data, such as age, gender, payment history, and transaction patterns. By leveraging these predictive models, banks can take proactive measures to prevent defaults and minimize their financial losses.

1. Introduction

1.1 Why this high Level Design Document?

The purpose of this High level Design (HLD) Document is to add necessary detail to the current project description to represent a suitable model for coding. This document is also intended to help detect contradictions prior to coding and can be used as a reference manual for how the modules at the high level.

1.2 Scope

The HLD document presents the structure of the system, such as the database architecture, application architecture (layers), application flow (Navigation) and technology architecture. The HLD uses non-technical to mildly technical terms which should be understandable to the administrators of the system.

1.3 Definitions

Term	Description
Credit Card Default	credit card holder fails to pay the required amount on their credit card by the due date
IDE	Integrated development Environment
AWS	Amazon Web Services

2. Project Introduction

2.1 Problem Statement

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 faces 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.

2.2 Dataset Description

ID: ID of each client

LIMIT_BAL: Amount of given credit in NT dollars (includes individual and family/supplementary = credit)

SEX: Gender (1=male, 2=female)

EDUCATION: (1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)
MARRIAGE: Marital status (1=married, 2=single, 3=others)

AGE: Age in years

PAY_0,1,2,3,4,5,6: Repayment status in September,August, July, June, May, April , 2005 (-1=pay duly, 1=payment delay for one month, 2=payment delay for two months, … 8=payment delay for eight months, 9=payment delay for nine months and above)

BILL_AMT1: Amount of bill statement in September, 2005 (NT dollar)

BILL_AMT2: Amount of bill statement in August, 2005 (NT dollar)

BILL_AMT3: Amount of bill statement in July, 2005 (NT dollar)

BILL_AMT4: Amount of bill statement in June, 2005 (NT dollar)

BILL_AMT5: Amount of bill statement in May, 2005 (NT dollar)

BILL_AMT6: Amount of bill statement in April, 2005 (NT dollar)

PAY_AMT1: Amount of previous payment in September, 2005 (NT dollar)

PAY_AMT2: Amount of previous payment in August, 2005 (NT dollar)

PAY_AMT3: Amount of previous payment in July, 2005 (NT dollar)

PAY_AMT4: Amount of previous payment in June, 2005 (NT dollar)

PAY_AMT5: Amount of previous payment in May, 2005 (NT dollar)

PAY_AMT6: Amount of previous payment in April, 2005 (NT dollar)

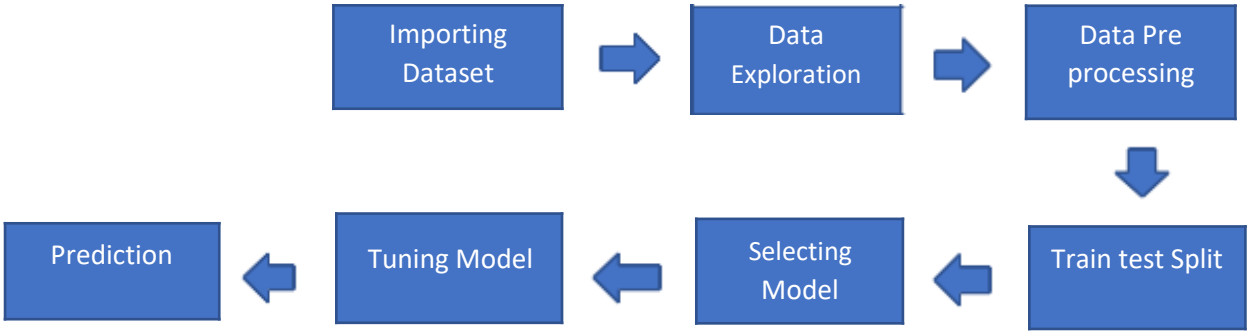
default.payment.next.month: Default payment (1=yes, 0=no)

3. Tools Used

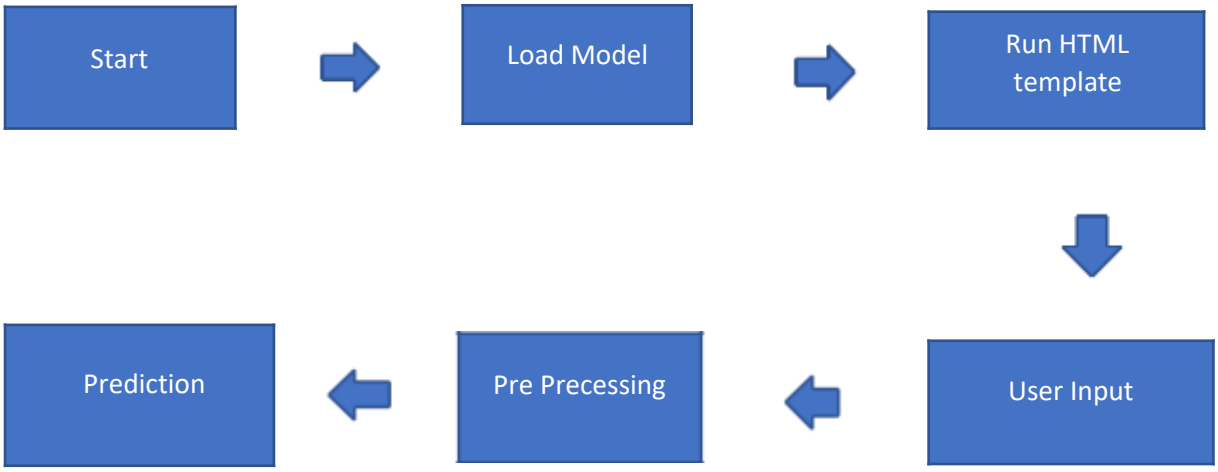
Python programming language and frameworks such as NumPy, Pandas, Scikit-learn, Imbalanced-Learn, Matplotlib, Seaborn, AWS are used to build the whole model.

4. Design Details

4.1. Process Flow



4.2. Deployment Process



4.3. Event Log

The system should log every event that user will know what process is running internally. The system identifies at what step logging required. It should be able to log each and every system flow. Developer can choose logging method.

4.4. Error Handling

Should errors be encountered, an explanation will be displayed as to what went wrong? An error will be defined as anything that falls outside the normal and intended usage.

5. Conclusion

Credit Card Default Prediction model will determine whether the issued person default in the next month based on his demographic details and past payment behaviour. So, that card issuer can issue the credit, card based on his default status. To mitigate these risks, banks can develop machine learning techniques to predict customer defaults based on demographic and behavioural data, such as age, gender, payment history, and transaction patterns. By leveraging these predictive models, banks can take proactive measures to prevent defaults and minimize their financial losses.