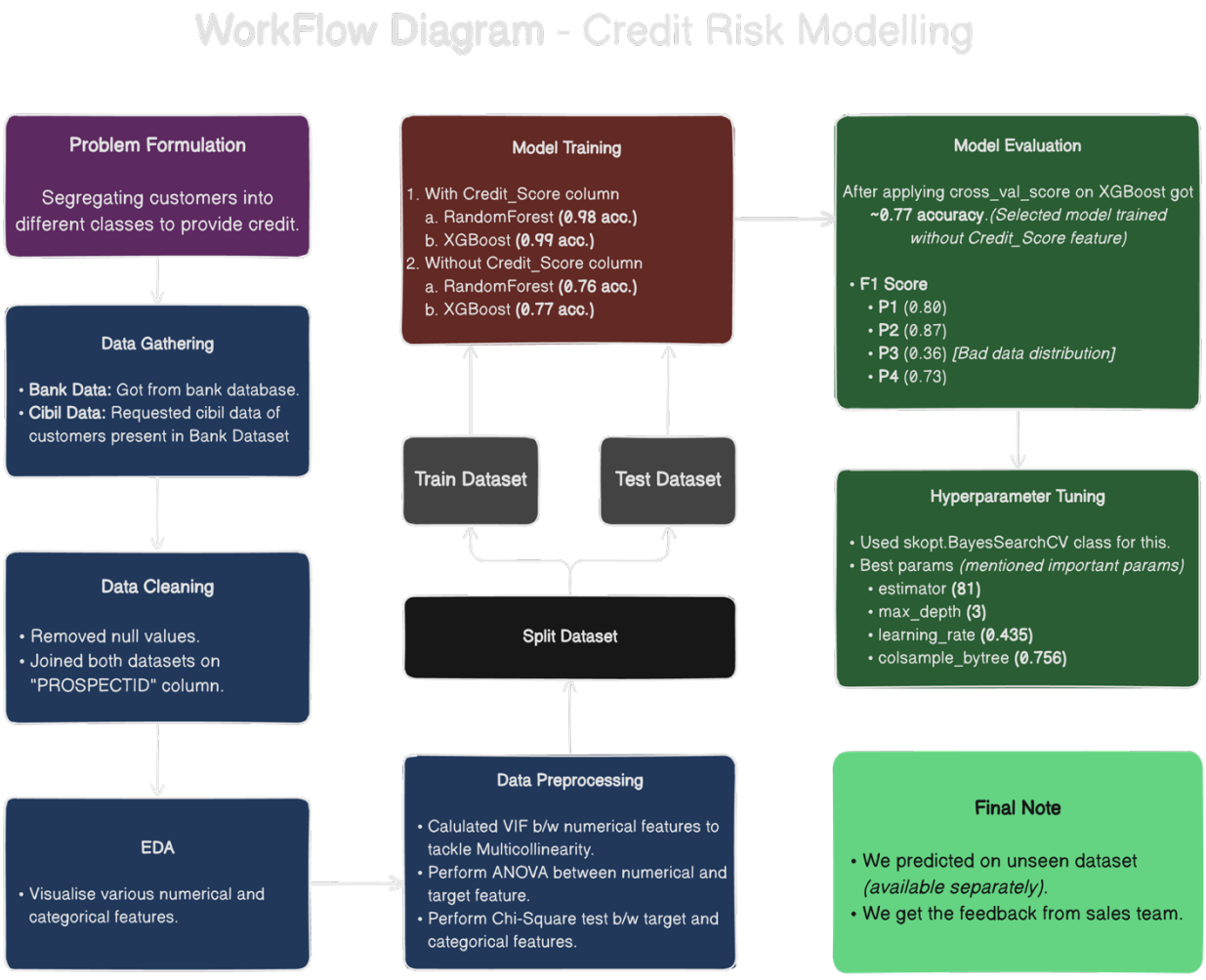
Credit Modelling Model

1. Problem Statement:-

Creating a machine learning model that can precisely segregate customers into class of giving credit based on past financial data and other pertinent borrower characteristics including income, credit score, and loan details is the aim. The likelihood that a borrower will fail on a loan should be estimated by the model, allowing it to determine the risk of lending to them. Such models can help financial institutions identify and measure their total risk exposure, set appropriate risk limits, and make informed investment decisions.

2. Solution Work Flow: -



3. Challenges Faced

One of the biggest challenges in credit risk modelling is the limited availability of relevant and reliable data. Credit risk models require historical data on loan performance, default rates, and economic indicators to accurately assess the likelihood of default. Challenges include data availability, data quality, complex modelling, and regulatory compliance. Example: One common challenge faced by financial institutions is obtaining accurate and reliable data for credit risk modelling purposes.

Detail Model Description:

1. There are two datsets. We need to solve the challenges that are faced by the bank during credit lending.
2. First dataset is (i) Internal bank dataset and second dataset is (ii) Cibil external dataset.
3. The target variable is Approved_Flag which contain 4 categories ['P2' 'P1' 'P3' 'P4'], segregating the customer into class of giving the credit. P1 being the category where the bank can easier give the credit to that customer whereas P4 being the category where it is not a good idea to give the credit to that customer, as it can increase the NPA accounts(Non-Performing assets) of the bank.
4. There are total 84 columns in two datasets. 26 columns in the first dataset and 62 columns in the second dataset.
5. PROSPECTID col is a common column in both the first and second datasets indicating unique customer ID.
6. To find association between numerical and numerical columns we will perform VIF test (Variance Inflation Factor). Reject columns whose p value is greater than a particular threshold.
6. For feature selection, we will perform chi2 square test and Anova test, since the target column is multi-class categorical column.
7. By checking the p_value of each column w.r.t target variable, we can decide if it's statistically significant or not.
8. Made two models. One without credit score and another with credit score.
9. It is observed that the accuracy of model without credit score feature has dramatically decreases.
10. Without credit score the accuracy is 77% and with credit score the accuracy is 99%.

Important Dataset Columns description:

Variable Name	Description
pct_tl_open_L6M	Percent accounts opened in last 6 months
pct_tl_closed_L6M	percent accounts closed in last 6 months
Tot_TL_closed_L12M	Total accounts closed in last 12 months
pct_tl_closed_L12M	percent accounts closed in last 12 months
Tot_Missed_Pmnt	Total missed Payments
CC_TL	Count of Credit card accounts
Home_TL	Count of Housing loan accounts
PL_TL	Count of Personal loan accounts
Secured_TL	Count of secured accounts
Unsecured_TL	Count of unsecured accounts
Other_TL	Count of other accounts
Age_Oldest_TL	Age of oldest opened account
Age_Newest_TL	Age of newest opened account

time_since_recent_payment	Time Since recent Payment made
max_recent_level_of_deliq	Maximum recent level of delinquency
num_deliq_6_12mts	Number of times delinquent between last 6 and last 12 months
num_times_60p_dpd	Number of times 60+ dpd
num_std_12mts	Number of standard Payments in last 12 months
num_sub	Number of sub standard payments - not making full payments
num_sub_6mts	Number of sub standard payments in last 6 months
num_sub_12mts	Number of sub standard payments in last 12 months
num_dbt	Number of doubtful payments
num_lss	Number of doubtful payments in last 12 months

recent_level_of_deliq	Number of loss accounts in last 12 months
CC_enq_L12m	Credit card enquiries in last 6 months
PL_enq_L12m	Personal Loan enquiries in last 6 months
time_since_recent_enq	Personal Loan enquiries in last 12 months
enq_L3m	Enquiries in last 6 months
last_prod_enq2	Lates product enquired for
first_prod_enq2	First product enquired for
MARITALSTATUS	Marital Status
EDUCATION	Education level
AGE	Age
GENDER	Sex
Time_With_Curr_Empr	Time with current Employer
CC_Flag	Credit card Flag
PL_Flag	Personal Loan Flag
pct_PL_enq_L6m_of_ever	Percent enquiries PL in last 6 months to last 6 months
pct_CC_enq_L6m_of_ever	Percent enquiries CC in last 6 months to last 6 months
HL_Flag	Housing Loan Flag
GL_Flag	Gold Loan Flag
Approved_Flag	Priority levels

Important Notes from both the dataset:

1. The shape of bank internal dataset of customer is (51336, 26).
2. The shape of cibil dataset is (51336, 62)
3. The common column in both datset is PROSPECTID which is unique ID for each customer.
4. The value "-99999" in both the datasets are null values.
5. We will remove all the null values if data lost is less than 20% of the total dataset.
6. Total trade lines is total no of accounts of a customer.

Unique Values from categorical columns:

MARITALSTATUS : ['Married' 'Single']

EDUCATION : ['12TH' 'GRADUATE' 'SSC' 'POST-GRADUATE' 'UNDER GRADUATE' 'OTHERS' 'PROFESSIONAL']

GENDER : ['M' 'F']

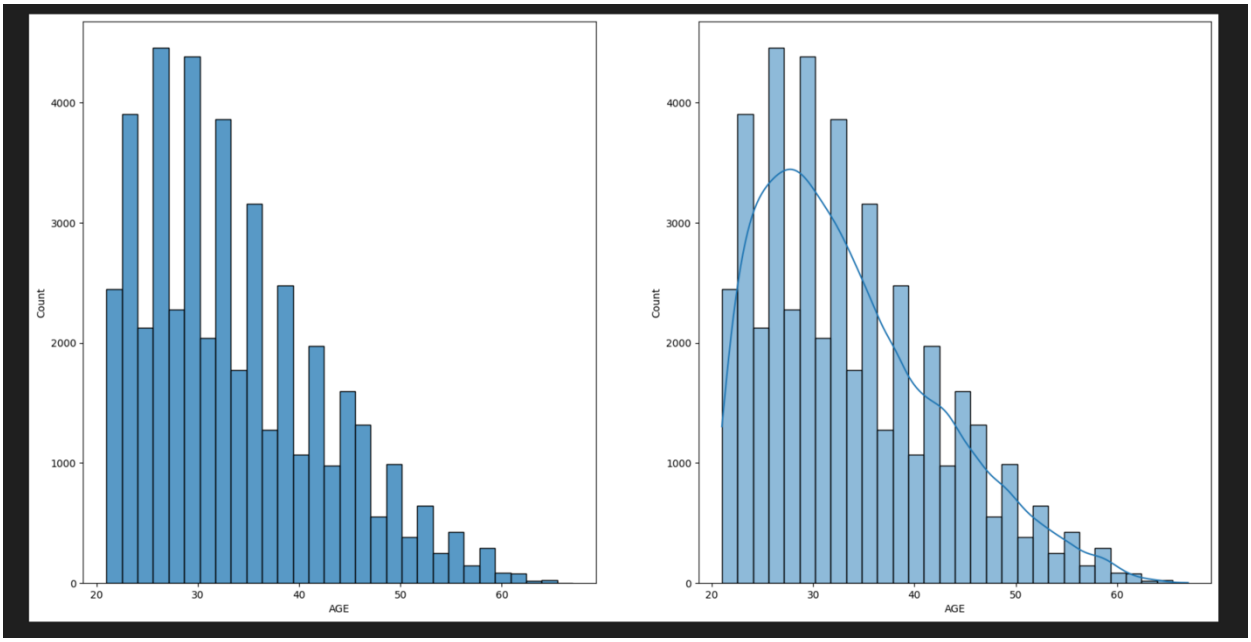
last_prod_enq2 : ['PL' 'ConsumerLoan' 'AL' 'CC' 'others' 'HL']

first_prod_enq2 : ['PL' 'ConsumerLoan' 'others' 'AL' 'HL' 'CC']

Target Column : Approved_Flag : ['P2' 'P1' 'P3' 'P4']

After performing all the statistics tests (i.e. chi square, VIF and Anova test), it is found that 43 columns are important out of 82 columns.

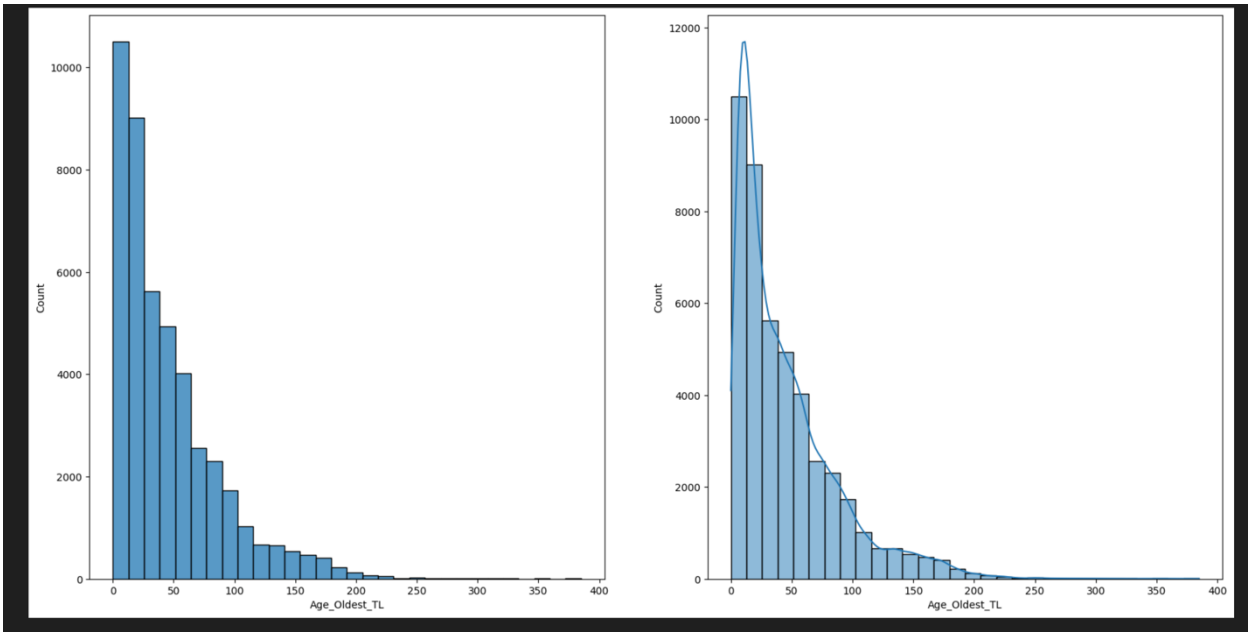
Data Visualization:



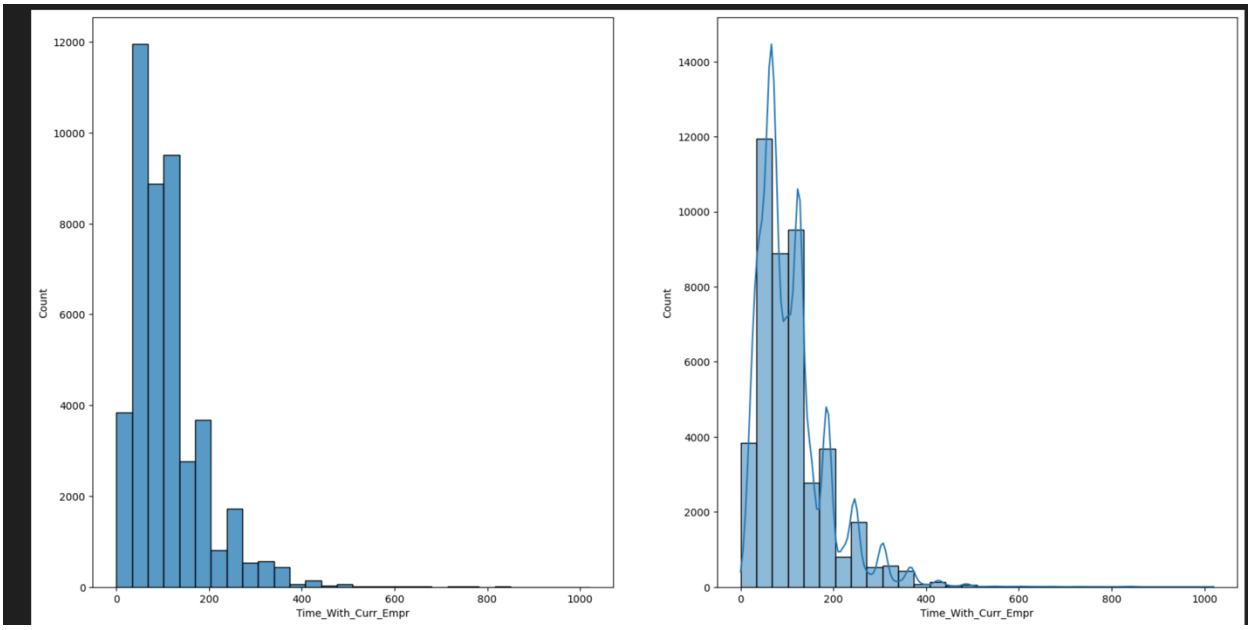
Age Distribution Graph

The bank is majorly targeting people between 20 to 40

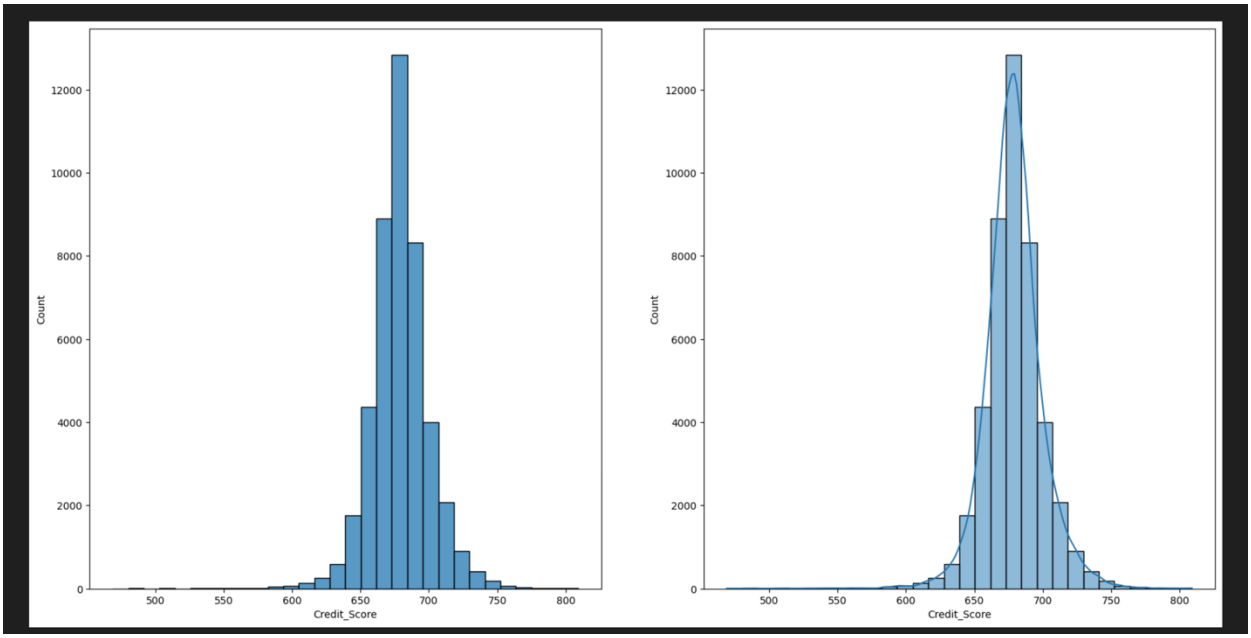
The data distribution of this dataset is majorly spread between the age group of 20 to 40.



Age of Oldest loan/Trade Line account (In Months)

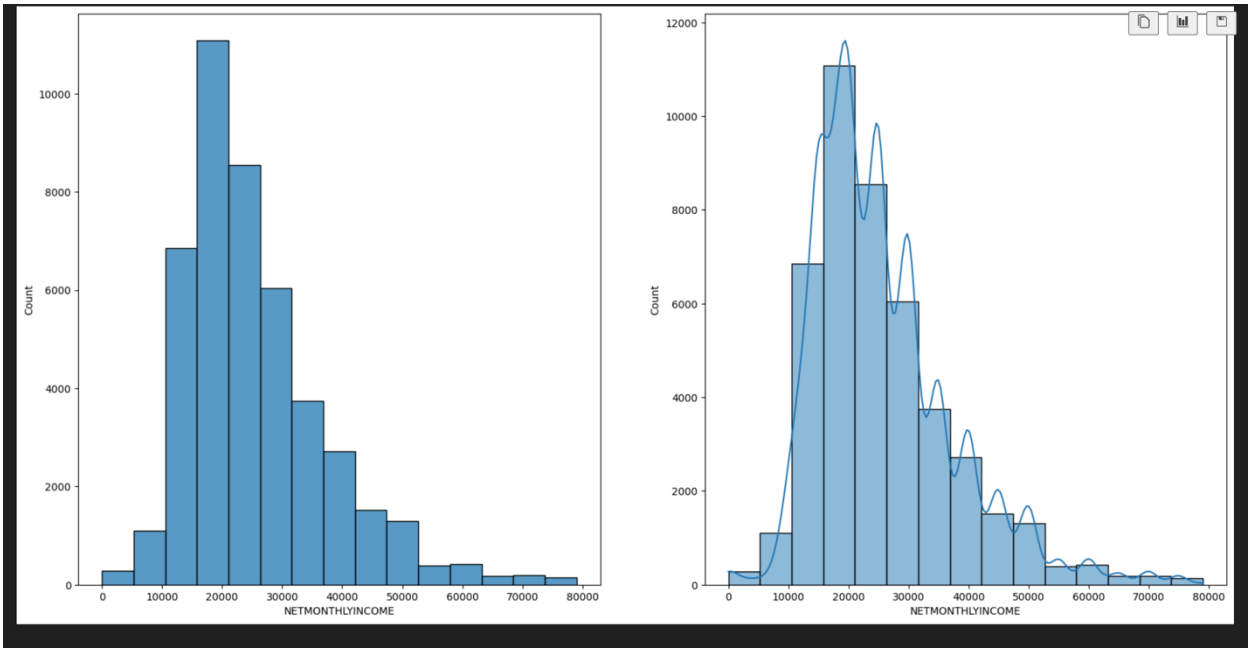


Time since recent enquiry (In Months)



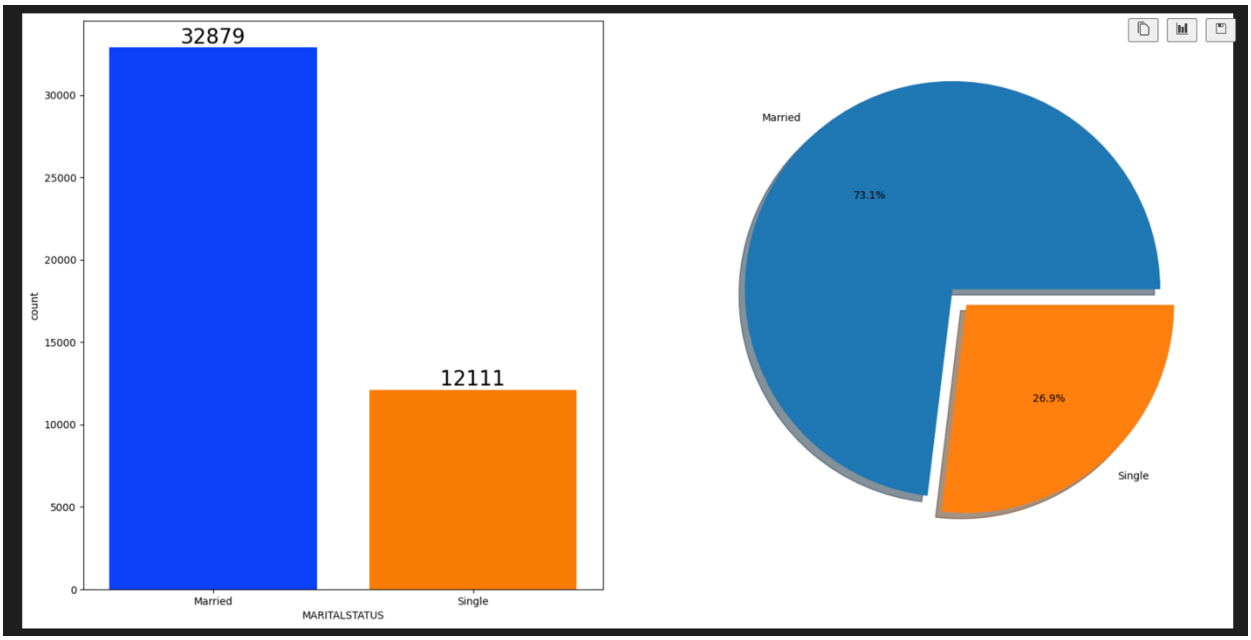
Credit Score Distribution

Most of the data distribution of credit score column is spread between 660 and 700 which fall under P2 category and that's why majorly category in target column is P2 category only.



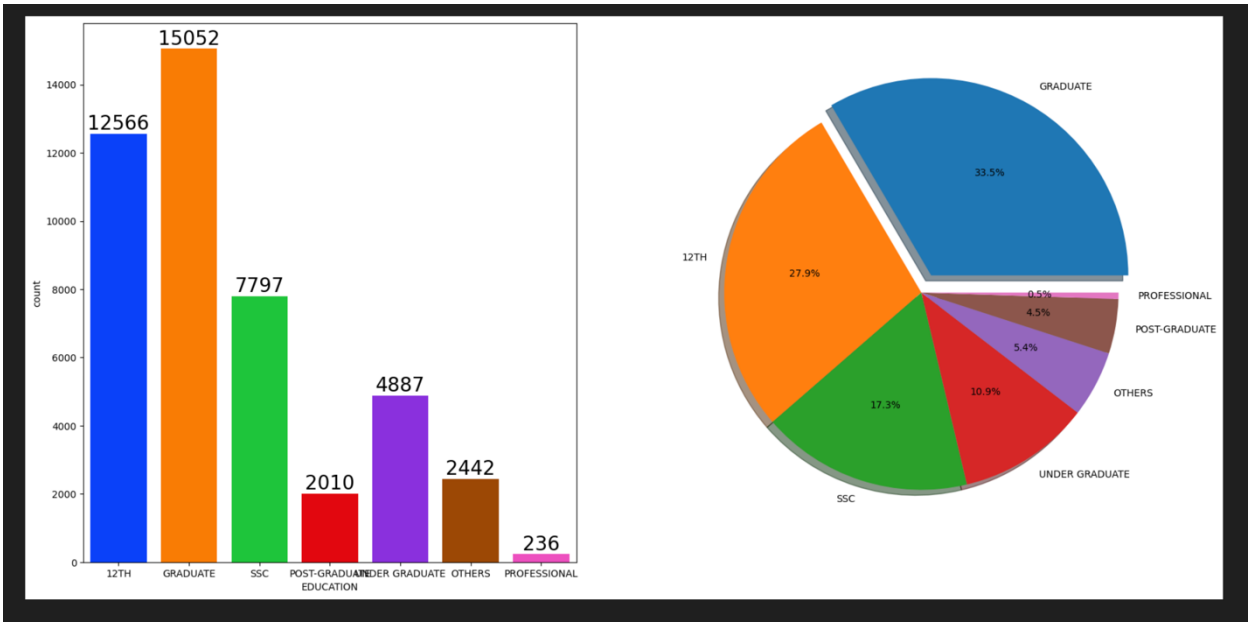
90 percentile Monthly Income Distribution

This column illusrate that the salary income majority of people falls between 20k to 35k. It can be observed that the bank is mainly targeting those people whose is under 50k per month



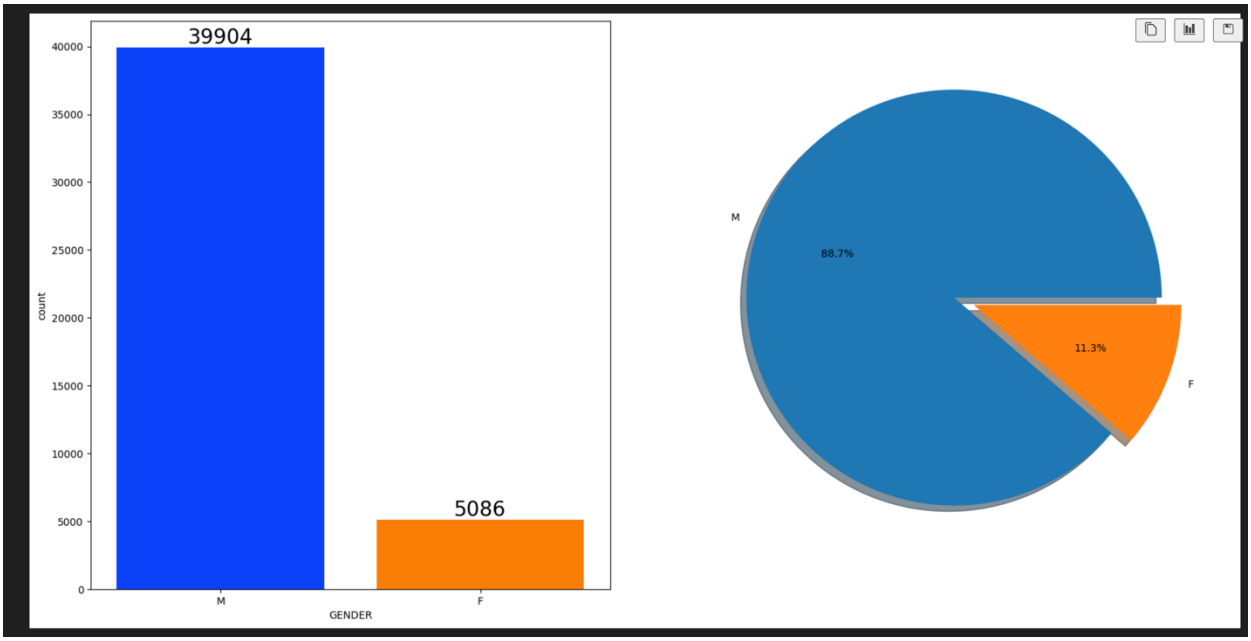
Marital Status Distribution Graph

This column indicates that 73.1% of people who are applying for the loan are married.



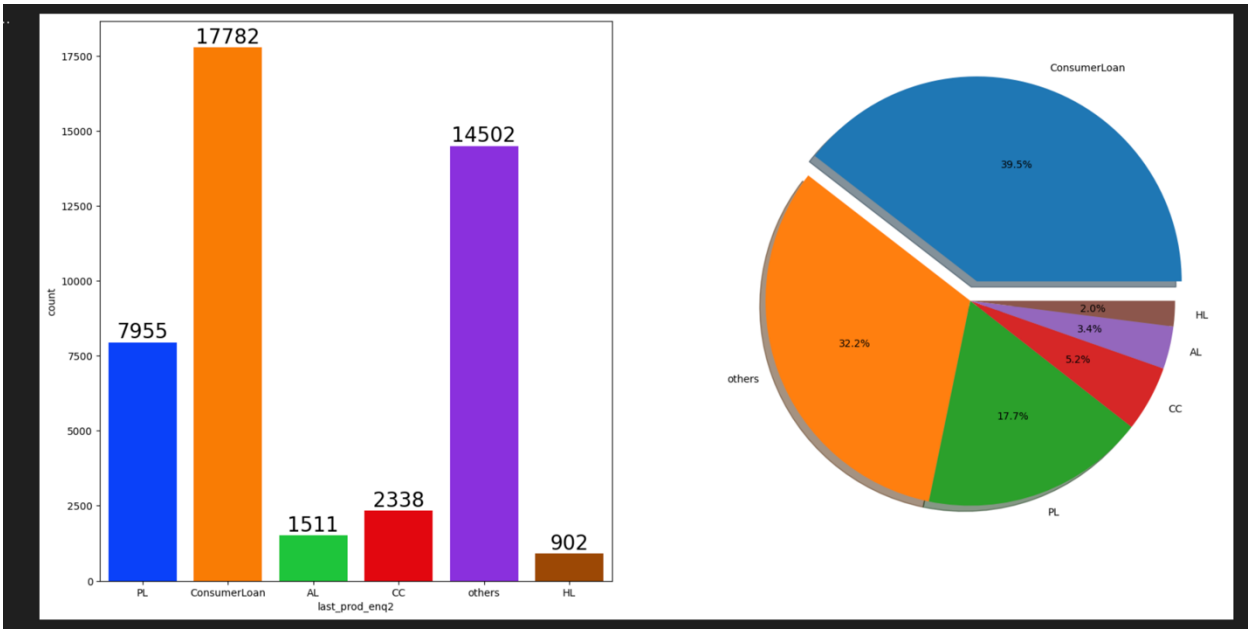
Education Distribution Graph

The Graduate and 12th pass population contribute significantly to the dataset



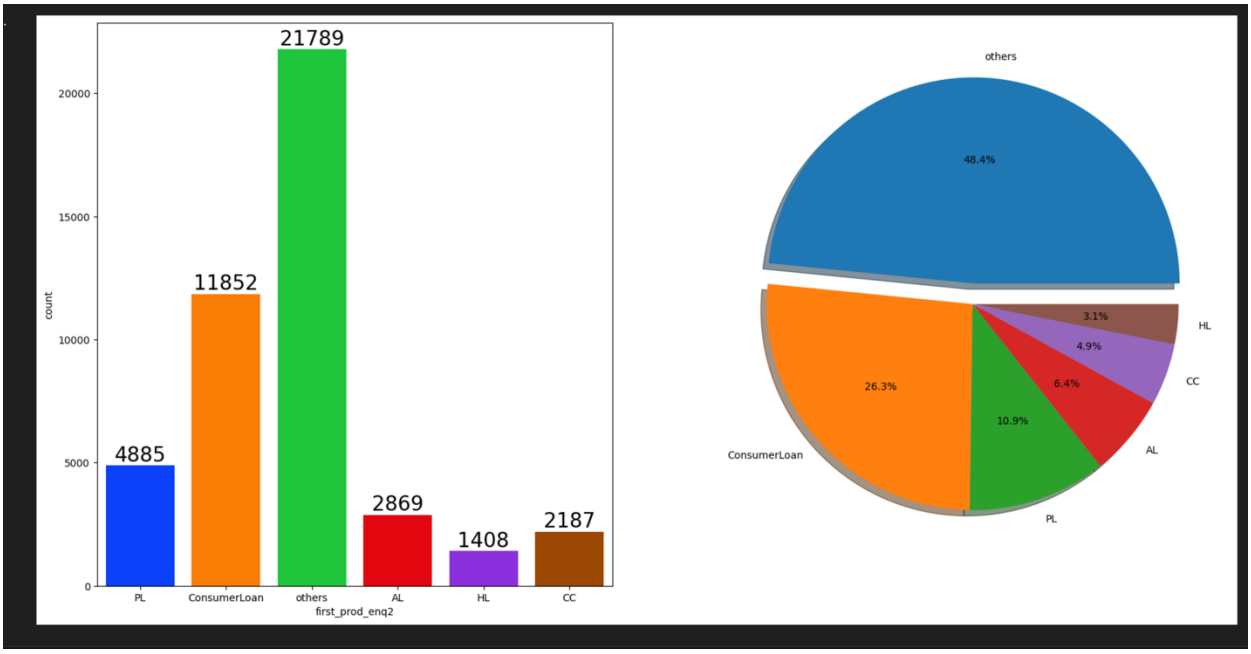
Gender Distribution Graph:

Gender wise, the dataset shows that 88.7% who are applying for loan are male or we can say that the bank is targeting male candidate more.

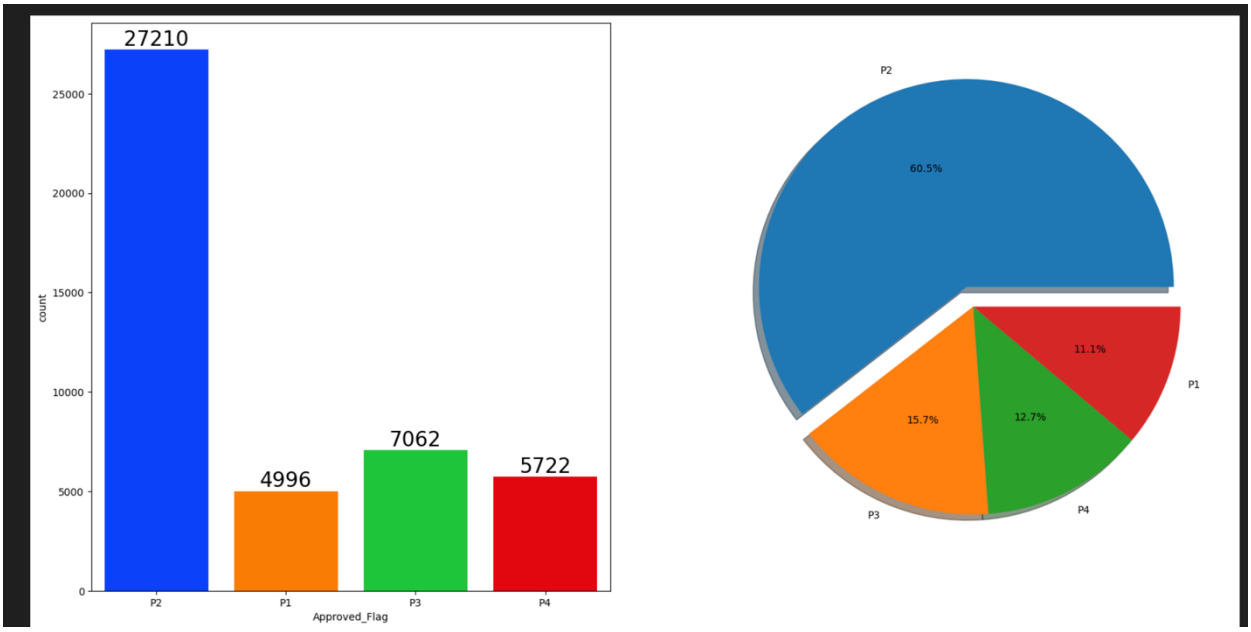


Last Product Enquiry Graph

Previous loans taken by the people in this dataset is other loan or consumer loans (such as furniture loan, fridge loan etc).



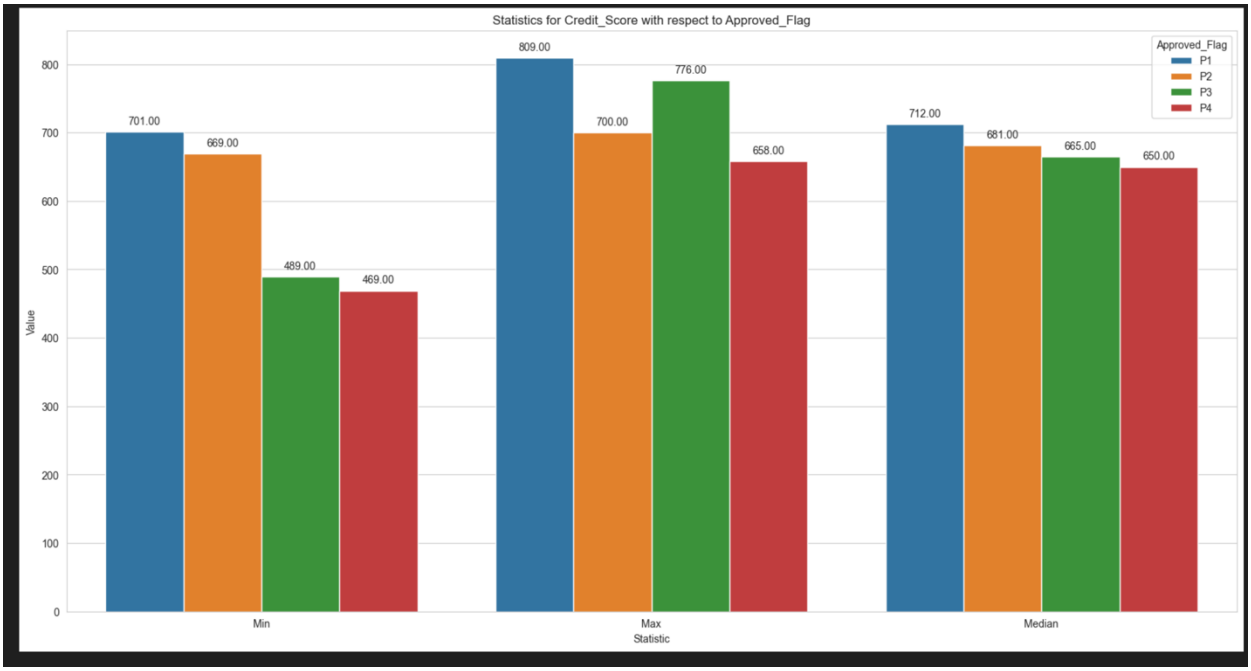
First Product Enquiry Graph



Distribution of Target Variable Categories

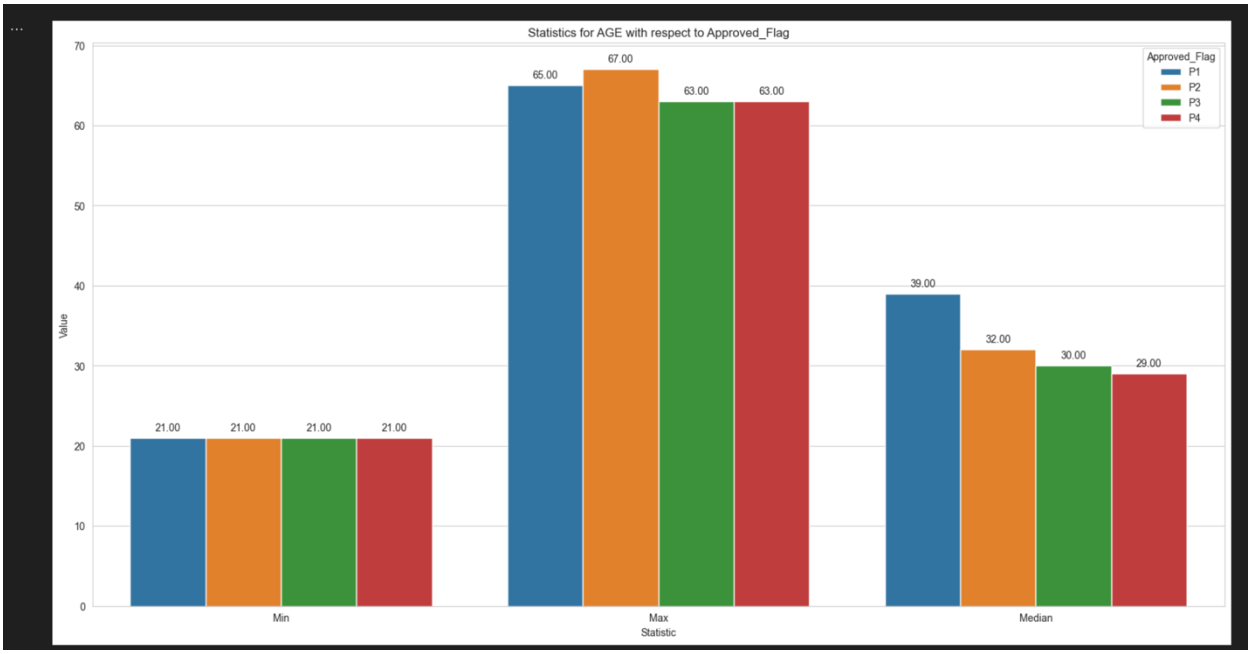
60% of the people in the dataset falls under P2 category for loan approval.

Relationship of Target variable w.r.t other features



Minimum, Maximum and median value of Credit Score for each category

The min and max credit score **is P3 category is 489 and 776** respectively. This range indicates that for P3 category creates **a big ambiguity** for the model to predict the output accurately. For P1 and P2 categories, it is easier for the model to predict as it range from **(701, 809)** and **(689 and 700)** respectively.



Minimum, Maximum and median value of Age for each category

Min age for all the category is **21**. Max age varies from **63 to 67**. It can be observed that for **P1 category the median age is higher** as compare to other categories and as the category decrease median age also decreses.

Observation of numerical and categorical cols w.r.t target variable i.e. (Approved_Flag)

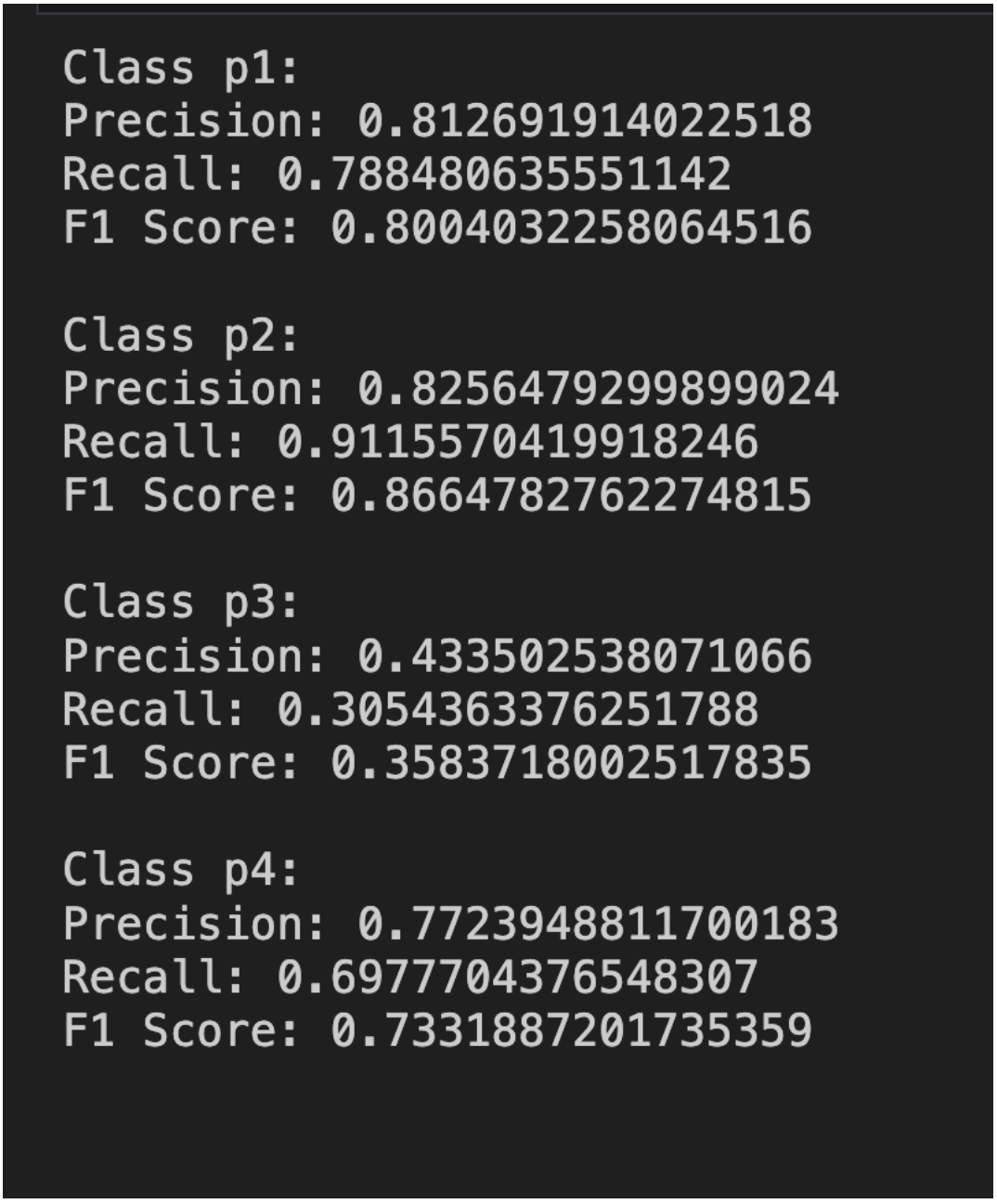
1. P1 category range is (701-809)
2. P2 category range is(669-700)
3. P3 category range is (489-776)
4. P3 category of target variable are the most ambiguous category. This can be observed by looking at the credit score min and max value for P3 category which range from 489 to 776, whereas in case of P2 it's ranges from 669 to 701.
5. Due to the most ambiguous category i.e. P3, during the predict also, the accuracy of the model is significantly decreases due to the most ambiguous category.
6. The median age who are getting P1 category loan are bit older than other categories. For eg. median age for P1 category is 40 whereas for P2 category it is 33 and for P3 category it is 31. Therefore it can be assumed that as the age increases, loan approval becomes easier.

Model Training:

We used ensemble techniques (bagging and boosting) to train the model. Mainly we used random forest and XGBoost classifier for classification. However, it is observed that XGboost classifier has better accuracy as compare to random forest classifier. With accuracy 99% XGboost is the best ML algorithm for the dataset with credit score feature is included. However, when credit score feature is excluded, there is a significant drop in the accuracy(76%). because the P3 category is most ambiguous category, the accuracy of the model is significantly decreases.

	precision	recall	f1-score	support
0	0.81	0.79	0.80	1007
1	0.83	0.91	0.87	5382
2	0.43	0.31	0.36	1398
3	0.77	0.70	0.73	1211
accuracy			0.77	8998
macro avg	0.71	0.68	0.69	8998
weighted avg	0.76	0.77	0.76	8998

Accuracy and F1_score for each category



F1_Score for each category

Hyperparameter Tuning:

Using BayesSearchCV, we got the best parameter for our XGBoost model. The parameters are:

1. objective = 'multi:softmax'
2. num_classes = 4
3. colsample_bytree = 0.9
4. learning_rate = 1.0
5. max_depth = 3
6. alpha = 10
7. n_estimators = 100

With these parameters, accuracy increases by 1% when the model is trained without credit score.