Credit Card Default Prediction

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Problem Statement

- **This project is aimed at predicting the case of customers default payments in Taiwan. From the perspective of risk management, the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification -credible or not credible clients.**
- **Before approving the credit card, It is important to predict if a customer will be a defaulter or not, so that we can filter out customers who have high chances of being a defaulter and thus reduce the loss for the company.**

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Data Summary

This data employed a binary variable, default payment (Yes = 1, No = 0), as the response variable. This study reviewed the literature and used the following 23 variables as explanatory variables:

- X1: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.
- X2: Gender (1 = male; 2 = female).
- X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).
- X4: Marital status (1 = married; 2 = single; 3 = others).
- X5: Age (year).
- X6 - X11: History of past payment. We tracked the past monthly payment records (from April to September, 2005) as follows: X6 =the repayment status in September, 2005; X7 =the repayment status in August, 2005; . . .;X11 =the repayment status in April, 2005. The measurement scale for the repayment status is: -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.
- X12-X17: Amount of bill statement (NT dollar). X12 = amount of bill statement in September, 2005; X13 = amount of bill statement in August, 2005; . . .; X17 = amount of bill statement in April, 2005.
- X18-X23: Amount of previous payment (NT dollar). X18 = amount paid in September, 2005; X19 = amount paid in August, 2005; . . .;X23 = amount paid in April, 2005.

Feature Engineering

- Categorical Variables
  - Labelling the Genders as Male and Female
  - Labelling the Education column into Graduate, University, High School and Others
  - Labeling the Marital Status column into Married, Single and Others
  - Binning the Age column with a bin size of 5 years each

- Repayment Status columns
  - Labelling the values -2,-1 and 0 , 0, to consider the labels as payment made on time.

Outlier treatment

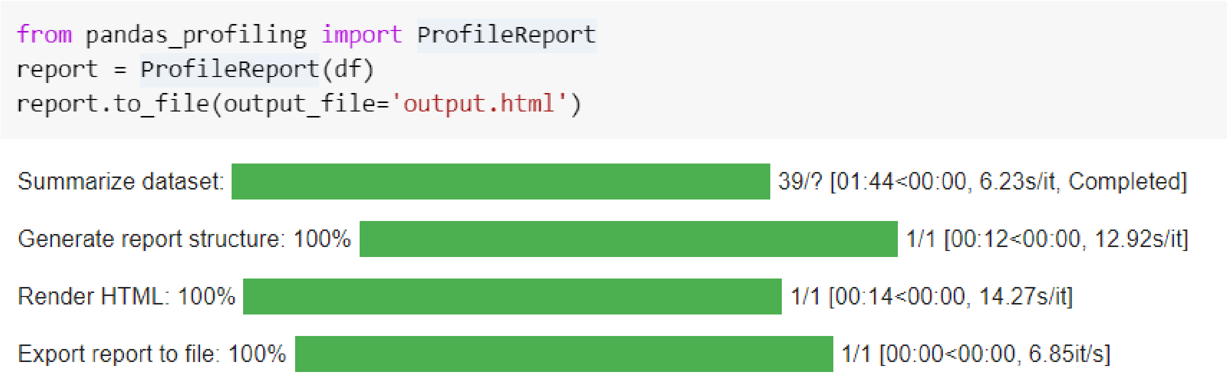
As the available dataset is small, using IQR method for outlier removal was not feasible hence we have used Manual method to select the values, beyond which the records are deleted.

- Limit Balance: After Visualizing the outliers, the values more than 703000 were removed.
- Bills Columns: There are 6 columns (April - September), each column was Visualized individually using box plot and were grouped into 11 bins each, and different values for upper and lower limits were chosen manually (September: 504218 & -2000, August: 522039, July: 505046 & -5000, June: 467719 & -5000, May: 494494 & -5000, April: 510935 & -5000) and the records exceeding these values were removed.
- Payments Columns: There are 6 columns (April - September), each column was Visualized individually using box plot and were grouped into 11 bins each, and different values were chosen manually (September: 238241, August: 220994, July: 161644, June: 169363, May: 155101, April: 192242) and the records exceeding these values were removed.

Profile Formatting

Pandas profiling is an open source Python module which was used for quick EDA to extract useful information.

The following code snippet was used and html file was obtained.



```python
from pandas_profiling import ProfileReport
report = ProfileReport(df)
report.to_file(output_file='output.html')
```

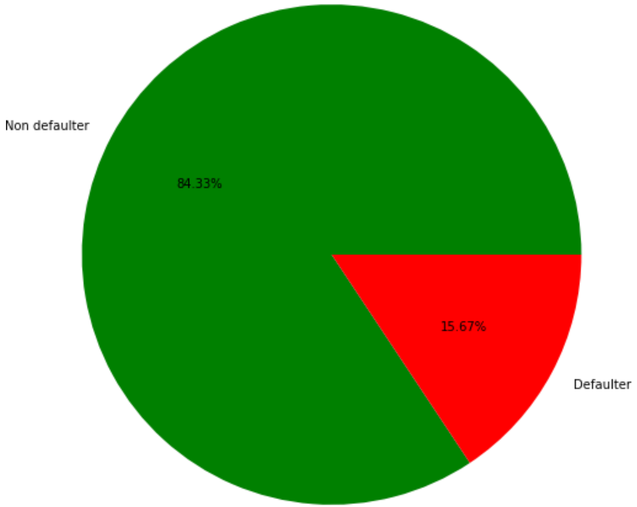
```
Summarize dataset:                      39/? [01:44<00:00, 6.23s/it, Completed]
Generate report structure: 100%         1/1 [00:12<00:00, 12.92s/it]
Render HTML: 100%                       1/1 [00:14<00:00, 14.27s/it]
Export report to file: 100%             1/1 [00:00<00:00, 6.85it/s]
```

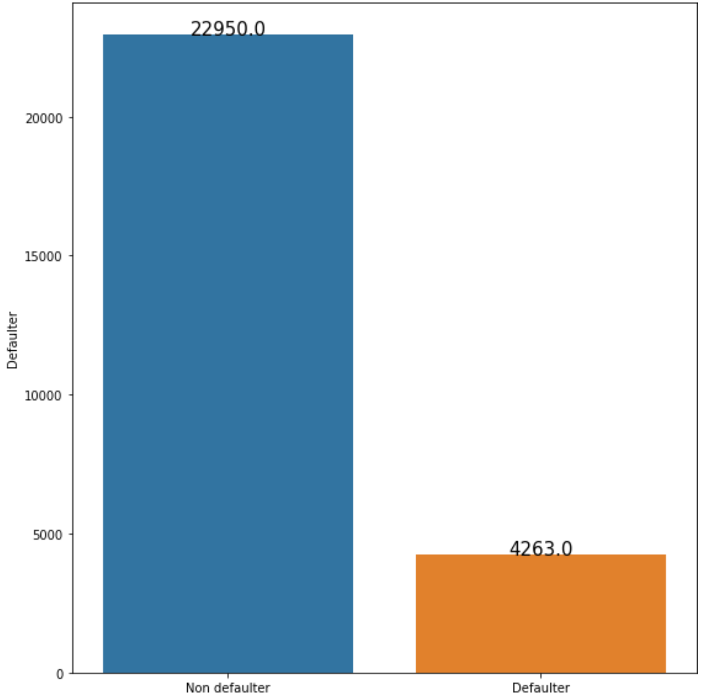
Further in depth EDA was performed as per our need which is show in our next slides.

Exploratory Data Analysis

Dependant Variable

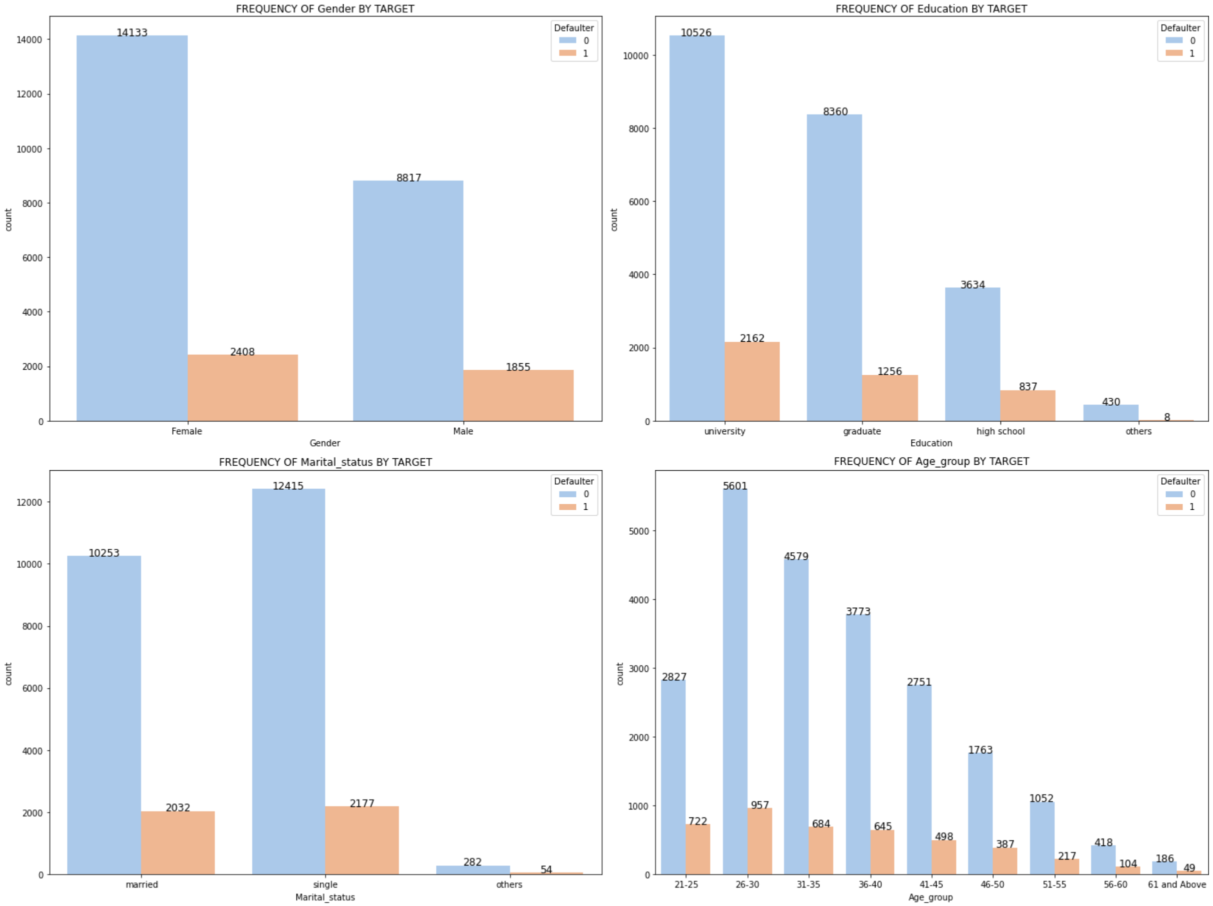
Defaulter vs non defaulter





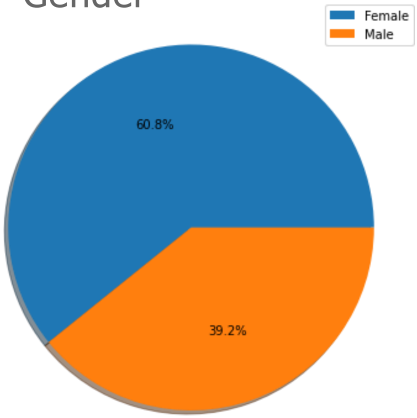
We observe that 15.67 % of the customers are Defaulters and rest are non defaulters, thus we can say that data is imbalanced

Categorical variables

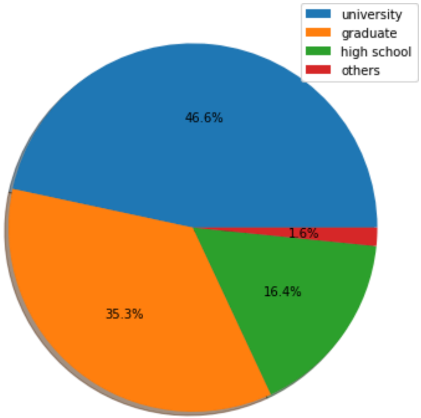


- This is the visualized comparison of Defaulters and non defaulters with respect to categorical features.
- We observe that the ratio of defaulters and non defaulters are following same trend on all the categorical features.

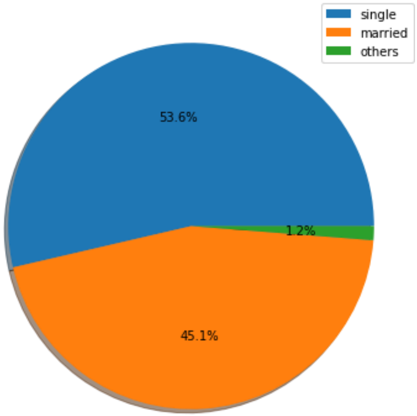
Gender



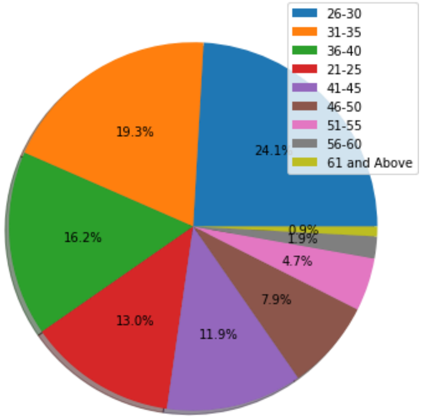
Education



Marital Status

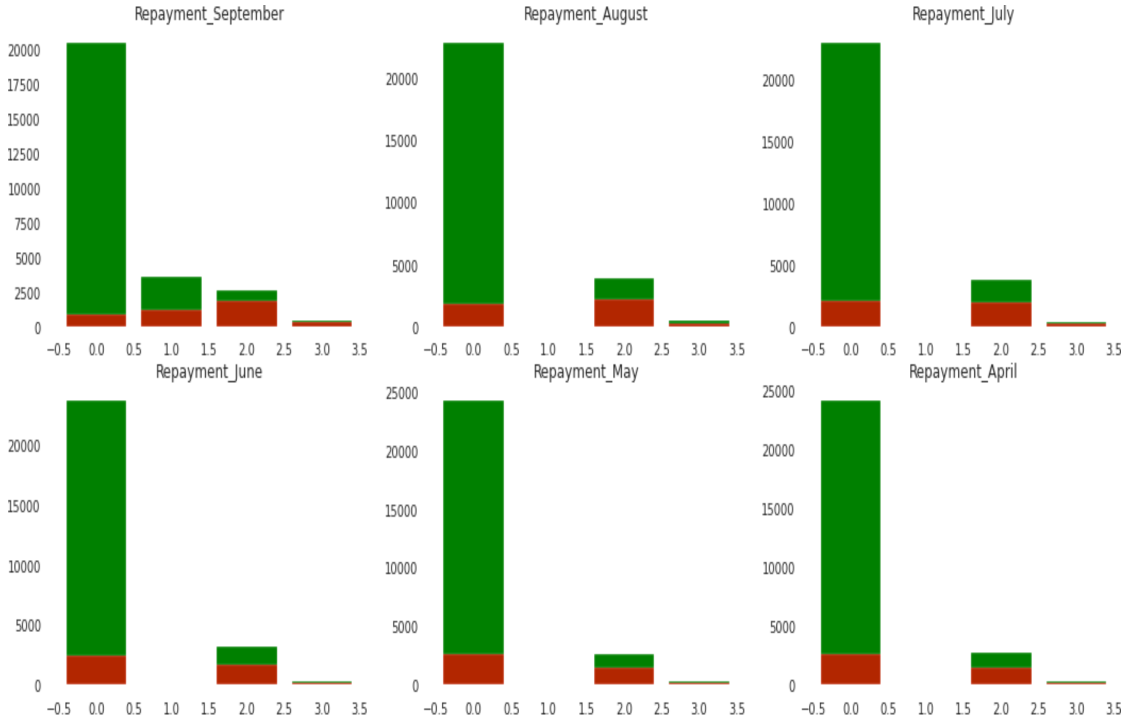


Age



- We can observe that over 60% of the customers are females and rest 39.2% are males.
- In Education column, 46.6% of the customers are from university, 35.3% are graduates, 16.4% are from high school and rest 1.6% belongs to others.
- We can observe 53.6% of the customers are single and 45.1% are married, the remaining 1.2% belongs to others.
- We can observe that as the age increases, the number of customers decreases and vice-versa.

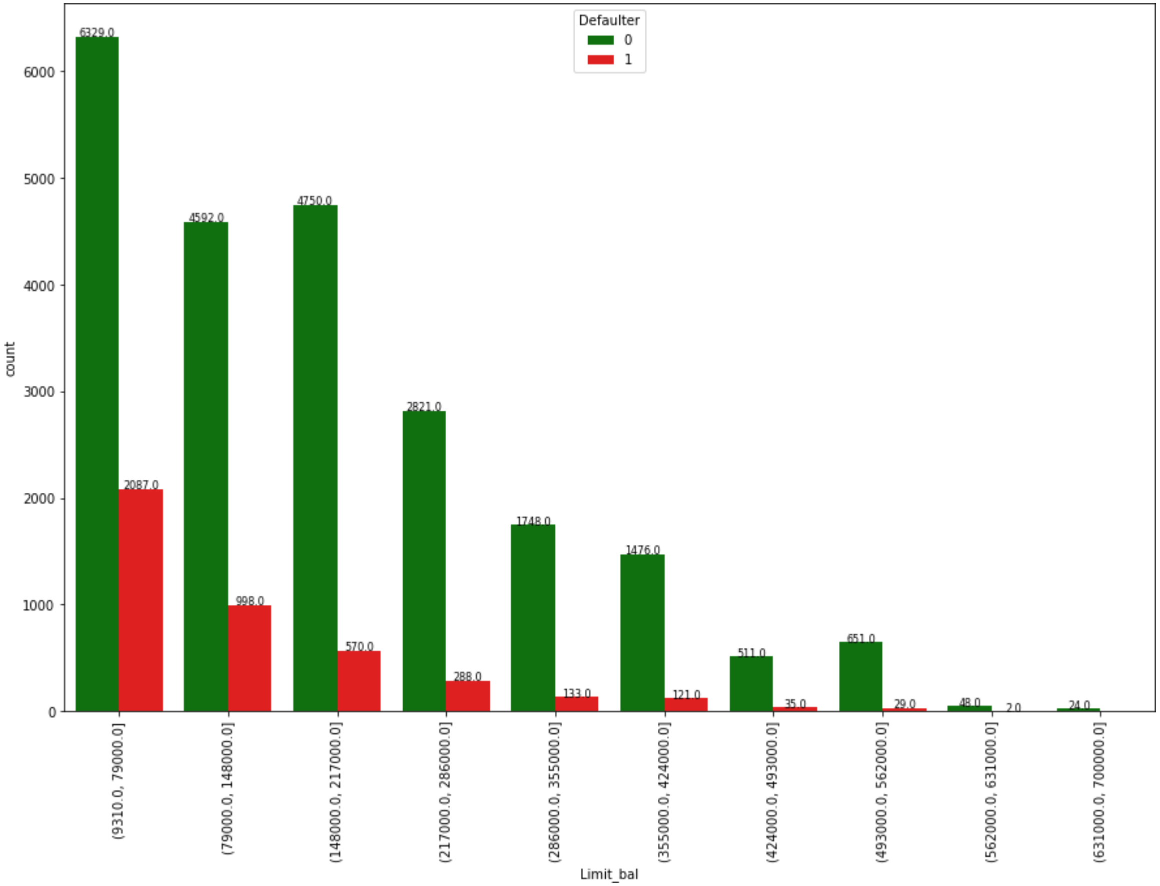
Numerical Variables - Repayments column



- We can observe that majority of customers made repayment on time.
- We can also observe that in case of delay in repayment, it is usually 2 months of delay.

0: Repayment on time
1: One month delay
2: Two months delay
3: Three months delay

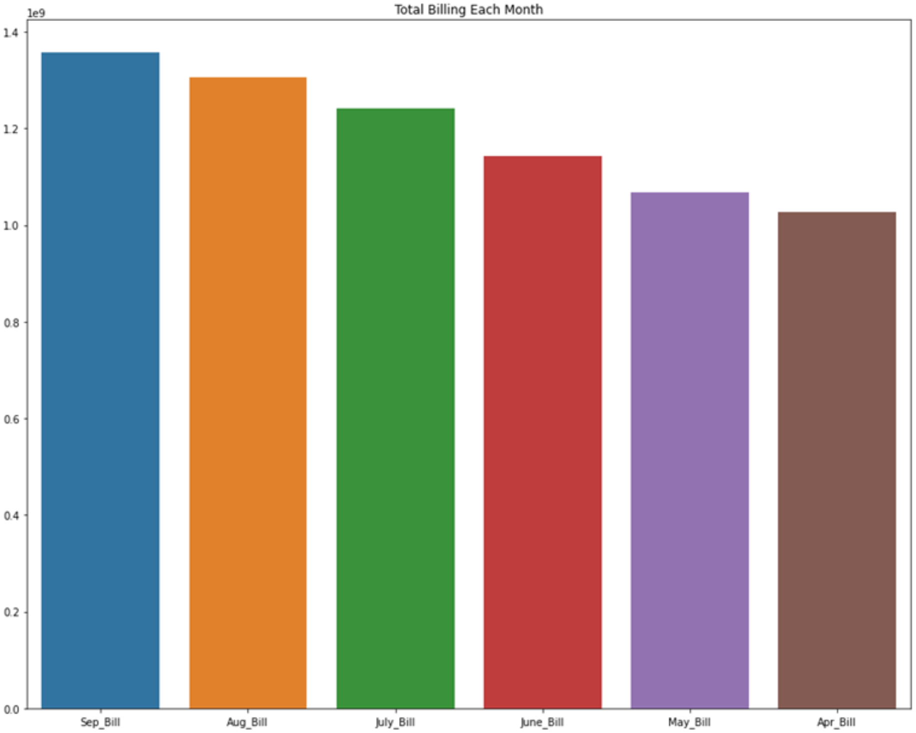
Numerical Variables - Limit Balance

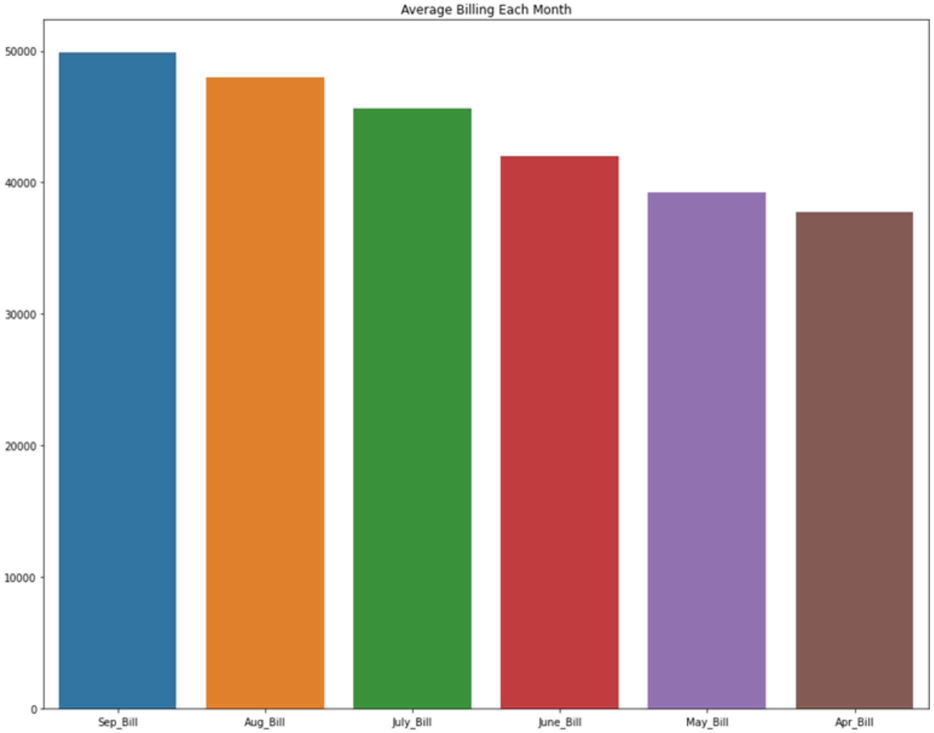


Most of the customers have a limit balance of less than NT$424,000.

We observed that the limit balance does not have a high impact on the customer being a defaulter.

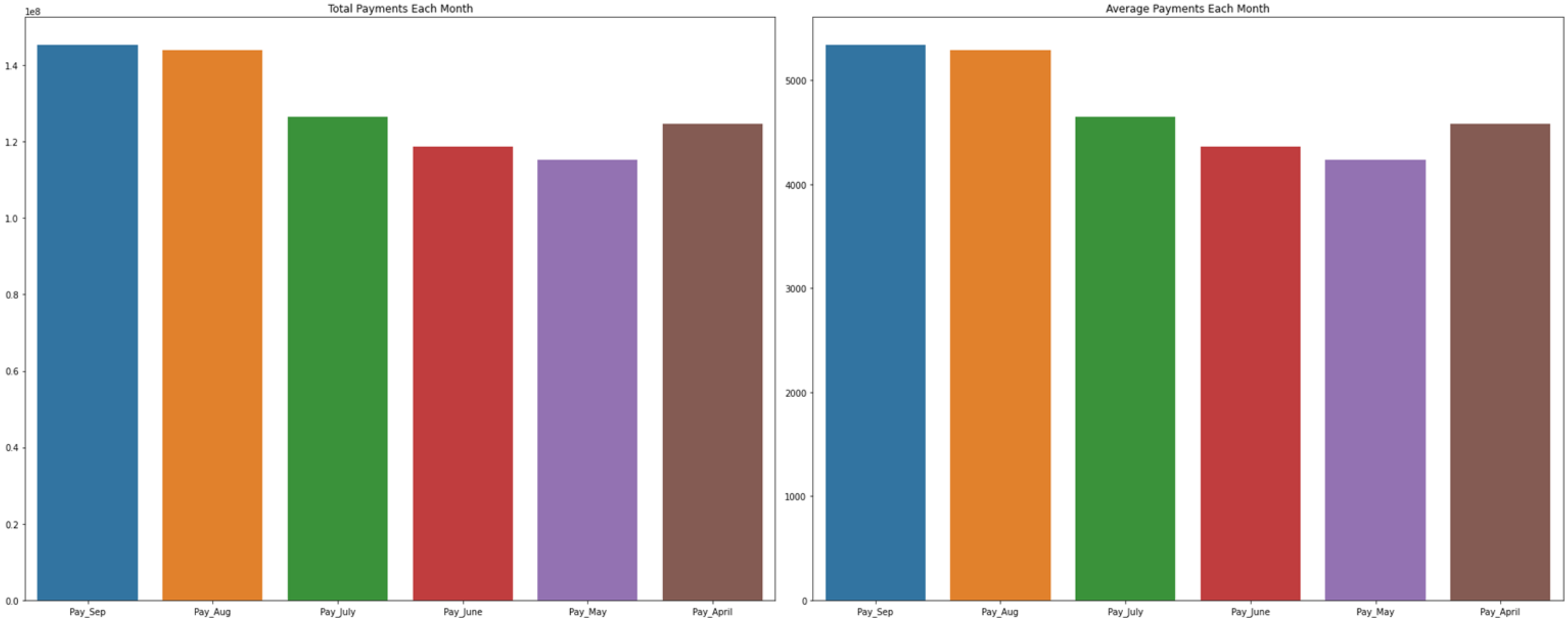
Numerical Variables - Monthly Bills


Total Billing Each Month


Average Billing Each Month

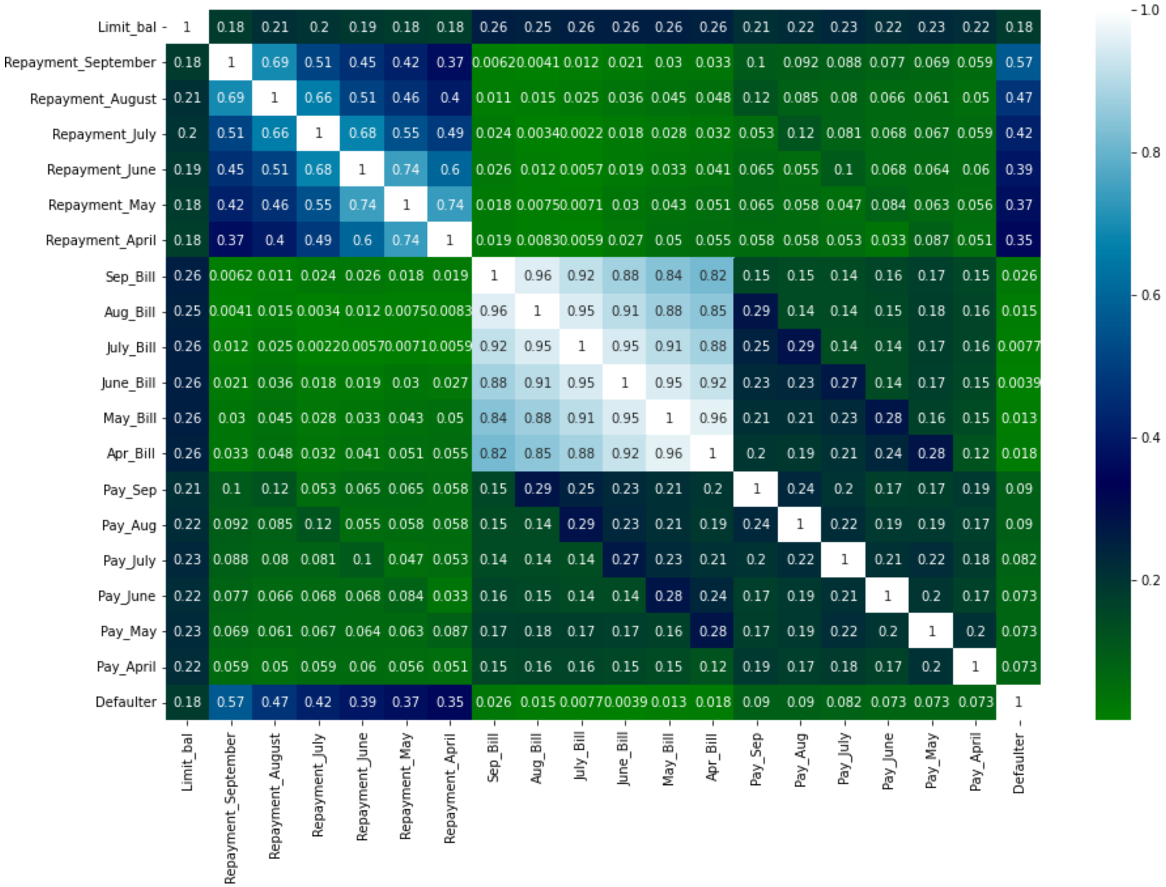
It is observed that the both total biling of the month and the average billing has an increasing trend over each month, (The graph is showing decreasing order of months).

Numerical Variables - Monthly Payments



Overall payments were slightly higher in the month of April and we can see a dip in the month of May and from there we can see an increase in payments every month. **(The graph is show in reverse order of months).**

Correlation Graph



It is observed that repayment columns and limit balance have higher correlation with the dependant variable.

Insights from EDA

- 22 % of the customers are Defaulters and rest are non-defaulters, we observed data is imbalanced
- This is the visualized comparison of Defaulters and non-defaulters with respect to categorical features. and we observe that the ratio of defaulters and non-defaulters are following same trend on all the categorical features
- In the given data, we observed that there are more female customers with 60.4% than male customers with 39.6%, however men have slightly higher chance of being a defaulter than women.
- There are higher nos of customers from university level, and next highest is from graduate level and 3rd comes the high school level and a small portion of customers from others. The customers from high school level have the highest of 25% chance of being a defaulter and other categories have the least chance of 7.1% of being a defaulter.
- The customers are mostly single or married, and we can notice that married customers have a slightly higher chance of 23.1% being a defaulter compared to singles having 20.9% chance of being a defaulter.
- The probability of customer being Defaulter is directly proportional to delay in repayment and When Customers have payed duly then the count of defaulter is low.
- There is increasing trend in the average billing of the month, it was lowest in the month of April and highest in the month of September

Optimization

Before moving into performance metrics, let’s discuss optimization. What metric exactly are we optimizing? In this case, we are optimizing recall.

Ideally, we do not want to allow any defaults to fall through the cracks, so our optimal model will minimize False Negatives (So Recall Score is as high as possible).

Defining Function

By defining the function, we are creating a template to show the reports.

Two Functions to show the following reports. One with cross validation and hyperparameter tuning, and other without it.

- Training score
- Metrics scores on Train and Test Set
  - Accuracy Score
  - Precision Score
  - Recall Score
  - F1 Score
  - ROC Score
- Classification Report
- Confusion Matrix
- ROC AUC Curve

Three more functions were created for model Explainability.

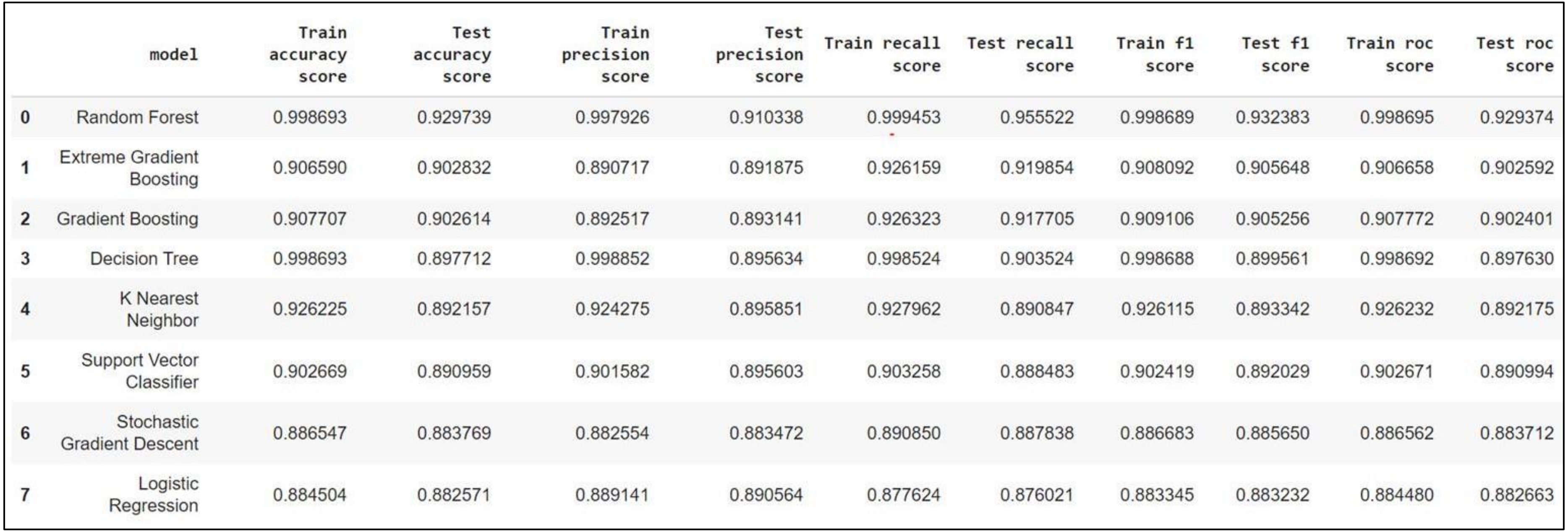
- Lime
- ELI5
- Shap

Modelling

The following algorithms were built and hyperparameter tuning and cross validation was performed.

1. **Logistic Regression**
2. **Stochastic Gradient Descent**
3. **Support Vector Classifier**
4. **K Nearest Neighbor**
5. **Decision Tree**
6. **Random Forest**
7. **AdaBoostClassifier**
8. **Gradient Boosting**
9. **Extreme Gradient Boosting**
10. **Stacking**

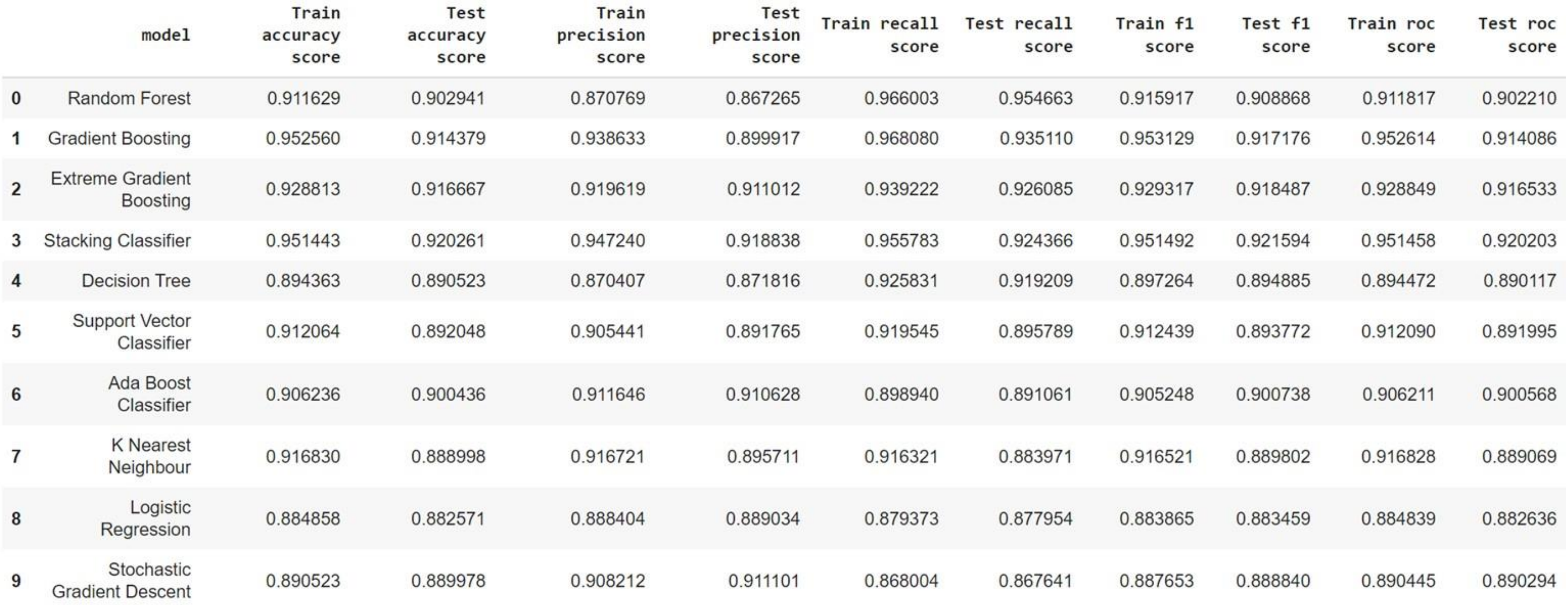
Final Results before Hyperparameter Tuning And Cross Validation



	model	Train accuracy score	Test accuracy score	Train precision score	Test precision score	Train recall score	Test recall score	Train f1 score	Test f1 score	Train roc score	Test roc score
0	Random Forest	0.998693	0.929739	0.997926	0.910338	0.999453	0.955522	0.998689	0.932383	0.998695	0.929374
1	Extreme Gradient Boosting	0.906590	0.902832	0.890717	0.891875	0.926159	0.919854	0.908092	0.905648	0.906658	0.902592
2	Gradient Boosting	0.907707	0.902614	0.892517	0.893141	0.926323	0.917705	0.909106	0.905256	0.907772	0.902401
3	Decision Tree	0.998693	0.897712	0.998852	0.895634	0.998524	0.903524	0.998688	0.899561	0.998692	0.897630
4	K Nearest Neighbor	0.926225	0.892157	0.924275	0.895851	0.927962	0.890847	0.926115	0.893342	0.926232	0.892175
5	Support Vector Classifier	0.902669	0.890959	0.901582	0.895603	0.903258	0.888483	0.902419	0.892029	0.902671	0.890994
6	Stochastic Gradient Descent	0.886547	0.883769	0.882554	0.883472	0.890850	0.887838	0.886683	0.885650	0.886562	0.883712
7	Logistic Regression	0.884504	0.882571	0.889141	0.890564	0.877624	0.876021	0.883345	0.883232	0.884480	0.882663

Random Forest Classifier has given the best performance, but we can observe that the model is overfitted. Over all, XGBC and Gradient Boosting also performs the better with train recall of 0.92 and test recall of 0.91

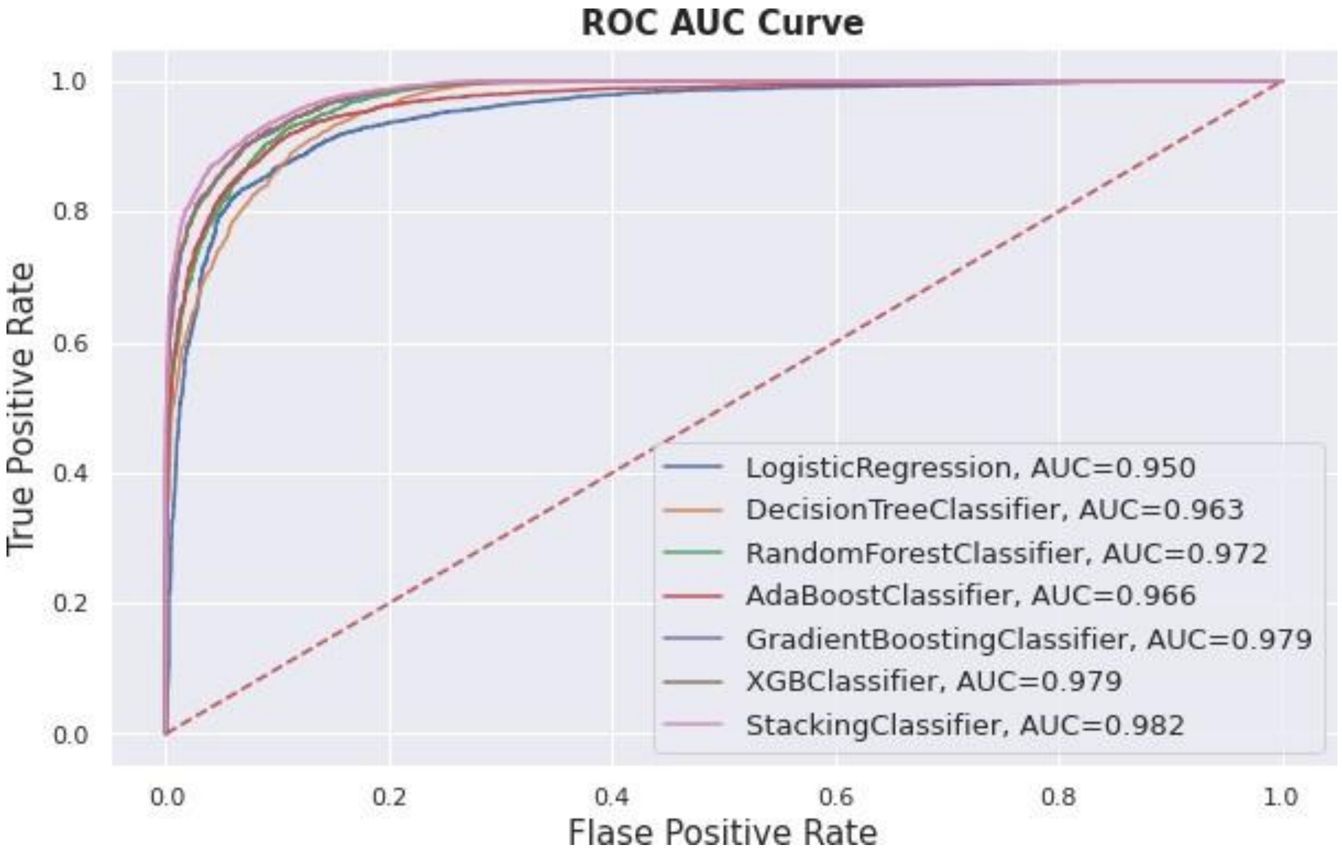
Final Results after Hyperparameter Tuning And Cross Validation



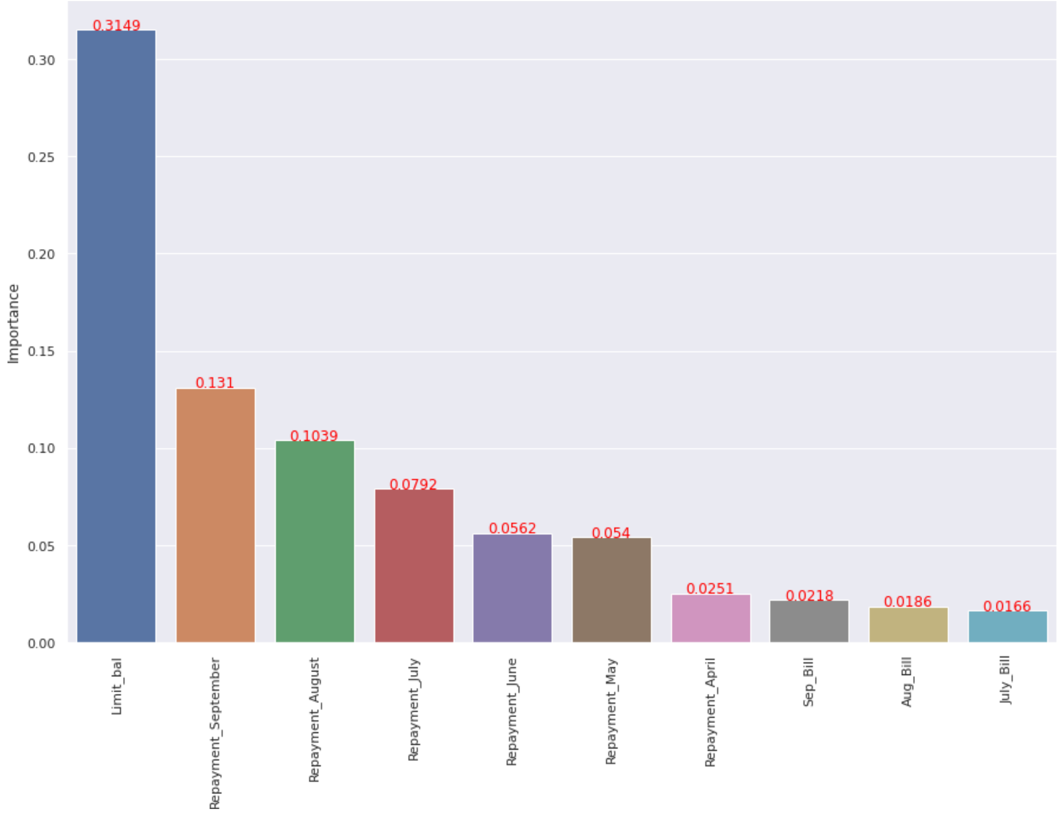
	model	Train accuracy score	Test accuracy score	Train precision score	Test precision score	Train recall score	Test recall score	Train f1 score	Test f1 score	Train roc score	Test roc score
0	Random Forest	0.911629	0.902941	0.870769	0.867265	0.966003	0.954663	0.915917	0.908868	0.911817	0.902210
1	Gradient Boosting	0.952560	0.914379	0.938633	0.899917	0.968080	0.935110	0.953129	0.917176	0.952614	0.914086
2	Extreme Gradient Boosting	0.928813	0.916667	0.919619	0.911012	0.939222	0.926085	0.929317	0.918487	0.928849	0.916533
3	Stacking Classifier	0.951443	0.920261	0.947240	0.918838	0.955783	0.924366	0.951492	0.921594	0.951458	0.920203
4	Decision Tree	0.894363	0.890523	0.870407	0.871816	0.925831	0.919209	0.897264	0.894885	0.894472	0.890117
5	Support Vector Classifier	0.912064	0.892048	0.905441	0.891765	0.919545	0.895789	0.912439	0.893772	0.912090	0.891995
6	Ada Boost Classifier	0.906236	0.900436	0.911646	0.910628	0.898940	0.891061	0.905248	0.900738	0.906211	0.900568
7	K Nearest Neighbour	0.916830	0.888998	0.916721	0.895711	0.916321	0.883971	0.916521	0.889802	0.916828	0.889069
8	Logistic Regression	0.884858	0.882571	0.888404	0.889034	0.879373	0.877954	0.883865	0.883459	0.884839	0.882636
9	Stochastic Gradient Descent	0.890523	0.889978	0.908212	0.911101	0.868004	0.867641	0.887653	0.888840	0.890445	0.890294

After performing hyper parameter tuning and cross validation, there is an improvement in the performance. The Random Forest classifier has the best recall score of 0.95 on test set followed by Gradient Boosting and XGBoost model having a recall score of 0.93 and 0.92 on test set.

ROC AUC Curve

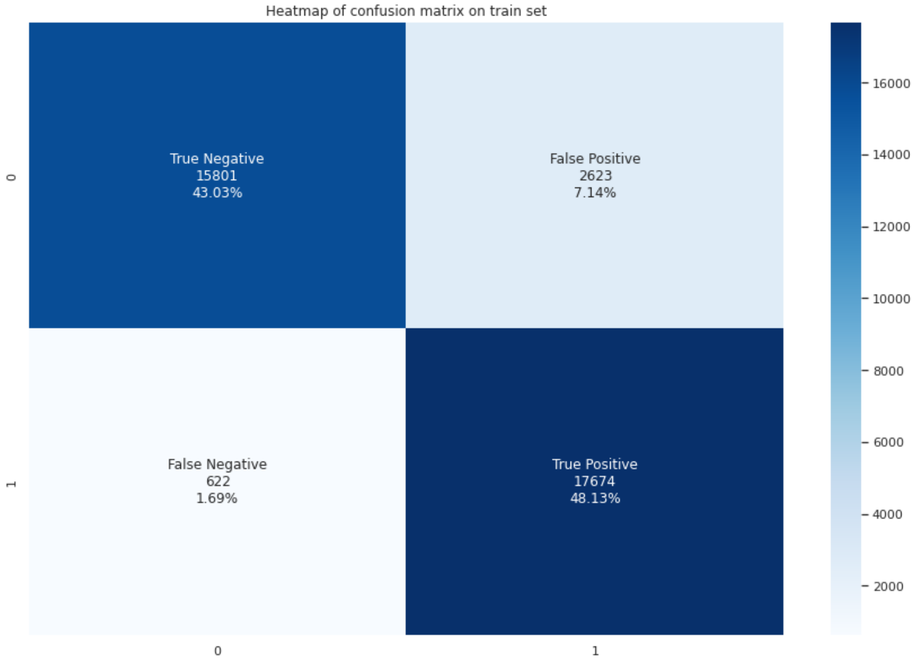


Model Explainability - Random Forest

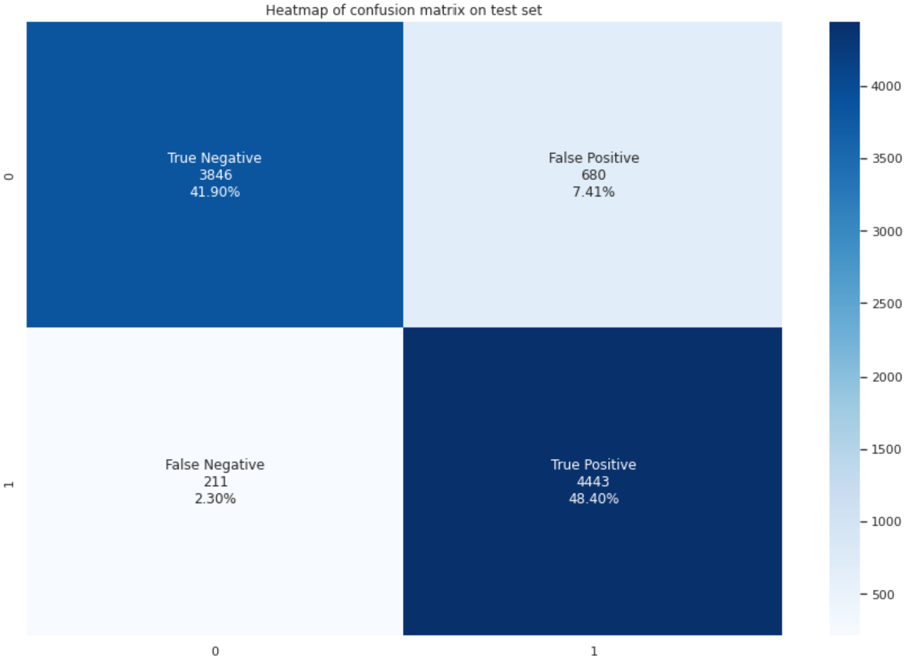


Top 10 Important features are shown in the figure along with their relative importance. Limit Balance has the highest significance on the final prediction.

Confusion Matrix - Random Forest



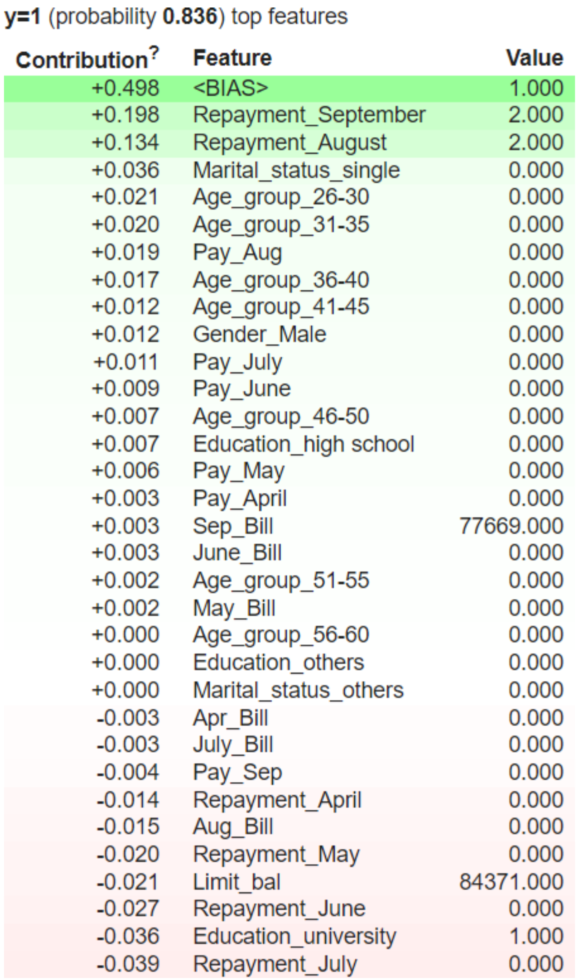
Heatmap of confusion matrix on train set



Heatmap of confusion matrix on test set

As per the use case, we need the false negative as low as possible. Train set has a false negative of 7.14% and test set has 7.41%.

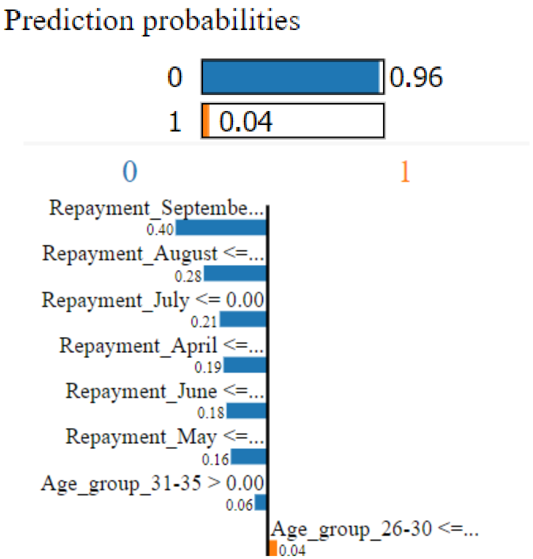
ELI5 AND Lime

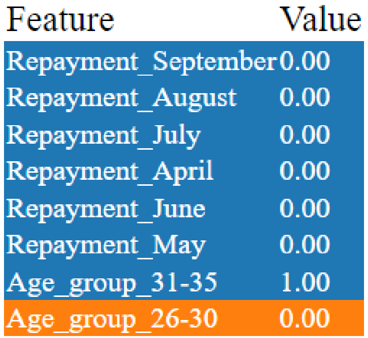


y=1 (probability **0.836**) top features

Contribution?	Feature	Value
+0.498	<BIAS>	1.000
+0.198	Repayment_September	2.000
+0.134	Repayment_August	2.000
+0.036	Marital_status_single	0.000
+0.021	Age_group_26-30	0.000
+0.020	Age_group_31-35	0.000
+0.019	Pay_Aug	0.000
+0.017	Age_group_36-40	0.000
+0.012	Age_group_41-45	0.000
+0.012	Gender_Male	0.000
+0.011	Pay_July	0.000
+0.009	Pay_June	0.000
+0.007	Age_group_46-50	0.000
+0.007	Education_high school	0.000
+0.006	Pay_May	0.000
+0.003	Pay_April	0.000
+0.003	Sep_Bill	77669.000
+0.003	June_Bill	0.000
+0.002	Age_group_51-55	0.000
+0.002	May_Bill	0.000
+0.000	Age_group_56-60	0.000
+0.000	Education_others	0.000
+0.000	Marital_status_others	0.000
-0.003	Apr_Bill	0.000
-0.003	July_Bill	0.000
-0.004	Pay_Sep	0.000
-0.014	Repayment_April	0.000
-0.015	Aug_Bill	0.000
-0.020	Repayment_May	0.000
-0.021	Limit_bal	84371.000
-0.027	Repayment_June	0.000
-0.036	Education_university	1.000
-0.039	Repayment_July	0.000

ELI5





Feature	Value
Repayment_September	0.00
Repayment_August	0.00
Repayment_July	0.00
Repayment_April	0.00
Repayment_June	0.00
Repayment_May	0.00
Age_group_31-35	1.00
Age_group_26-30	0.00

Lime

ELI5 and Lime was coded to check the model explainability and the above tables were obtained for **first row in our dataset.** We can observe that, for our selected point Repayment September has the most significant effect on the final Prediction. The process can be checked on any data point on the dataset for similar tables.

Challenges

- The data had a imbalanced data set with the dependant variable having two classifications of 77.79% and 22.21% respectively.
- We noticed that, in payments and bills columns there were outliers and outlier treatment was necessary. Using IQR and Percentile method, many values were removed which is not acceptable considering the size of the original data. Hence manually the values were selected for each column and the rows having values beyond that was removed.
- As multiple models were run along with cross validation and hyperparameter tuning, the computational time was quite high. Gradient boost, XGBoost and stacking had the highest computational time.

Challenges

- It can also be said ,our model may perform even better if we incorporate a few more variables for which data is not available. For example, credit score, income, etc, this will help in training the data better than what we have now.
- Having said that considering only past six months data for predicting defaults in the immediate future is not the best way to solve the problem.

Conclusions

- Random Forest Classifier performs the best with a recall of 0.95 on the test set.
- Followed by RFC we observed that Gradient Boosting and XGBoost performed the best with test recall score of 0.93 and 0.92 respectively.
- We could overcome the overfitting of multi models by using hyperparameter tuning and cross validation, which is evident by comparing the scores before and after.
- Model explainability was performed on the Random Forest Classifier using Lime and ELI5, Repayments columns (especially the latest months) has the most significant impact on whether a customer is a Defaulter or Not.

THANK YOU