Capstone Project – 3

Supervised Machine Learning
-Classification

Credit Card Default Prediction

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Will Be Discussing On:

1. Problem Statement
2. Introduction
3. Data Cleaning
4. Exploratory Data Analysis
5. Handling Class Imbalance
6. Transforming Data
7. Splitting Data
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10. Comparison of Model
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1. Problem Statement:

•Predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients.

• Predicting whether a customer will default on his/her credit card.

2. Introduction:

- **ID:** Unique ID of each client
- **LIMIT_BAL:** Amount of the given credit (NT dollar).
- **Gender:** Gender of customer. (1 = male; 2 = female)
- **Education:** Education qualification of customers.

  (1 = graduate school; 2 = university; 3 = high school; 4 = others)
- **Marital Status:** Marital status of customer. (1 = married; 2 = single; 3 = others)
- **Age:** Age of customer in years.

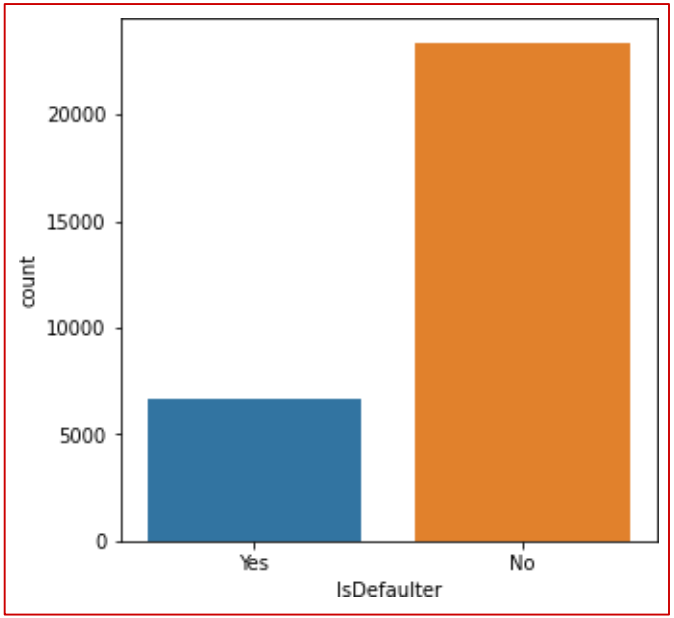
- **History of Past Payment: (PAY)** Repayment status in September, August, July, June, May and April 2005.
- **Amount of Bill Statement: (BILL_AMT)** Amount of bill statement in September, August, July, June, May and April 2005.
- **Amount of Previous Payment:(PAY_AMT)** Amount of previous payment in September, August, July, June, May and April 2005.

3. Data Cleaning

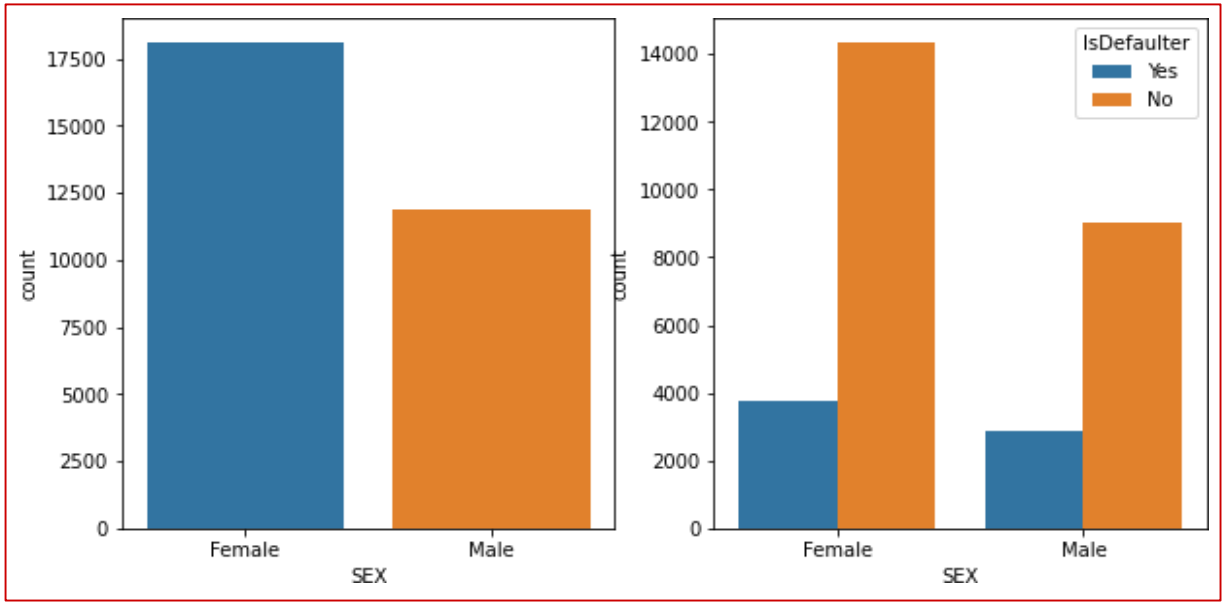
- Null Values Treatment
- Duplicate Values Treatment

4. Exploratory Data Analysis (EDA)

- Both the classes are not in proportion.
- Which means that dataset imbalanced.
- Data balancing is required.

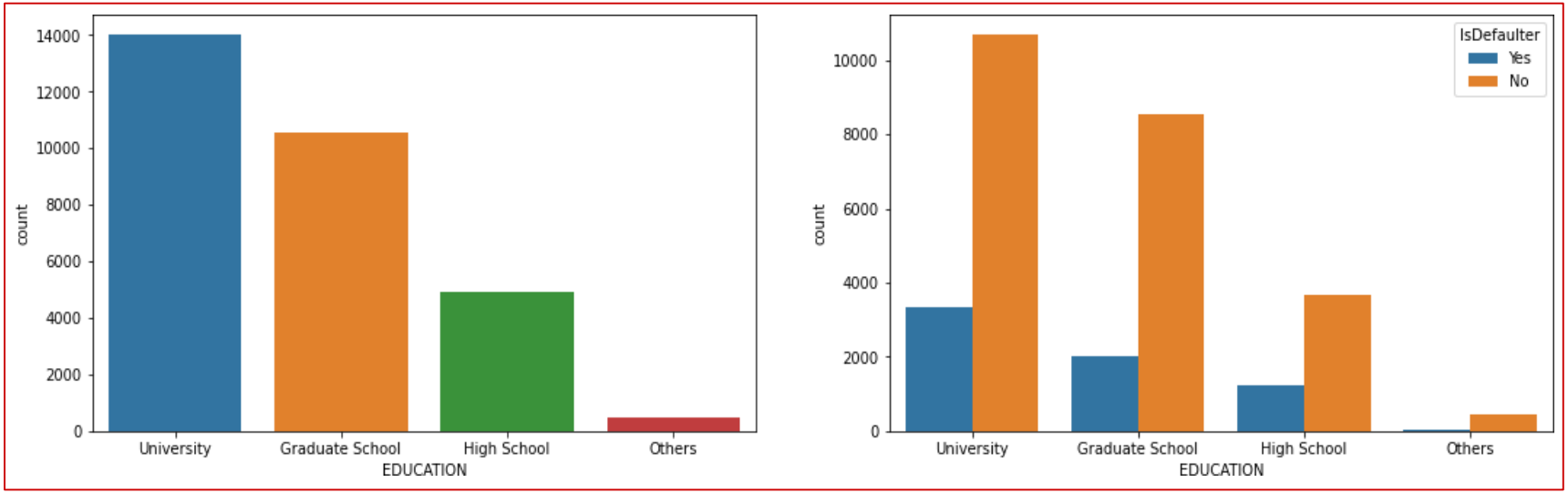


EDA (Continued)



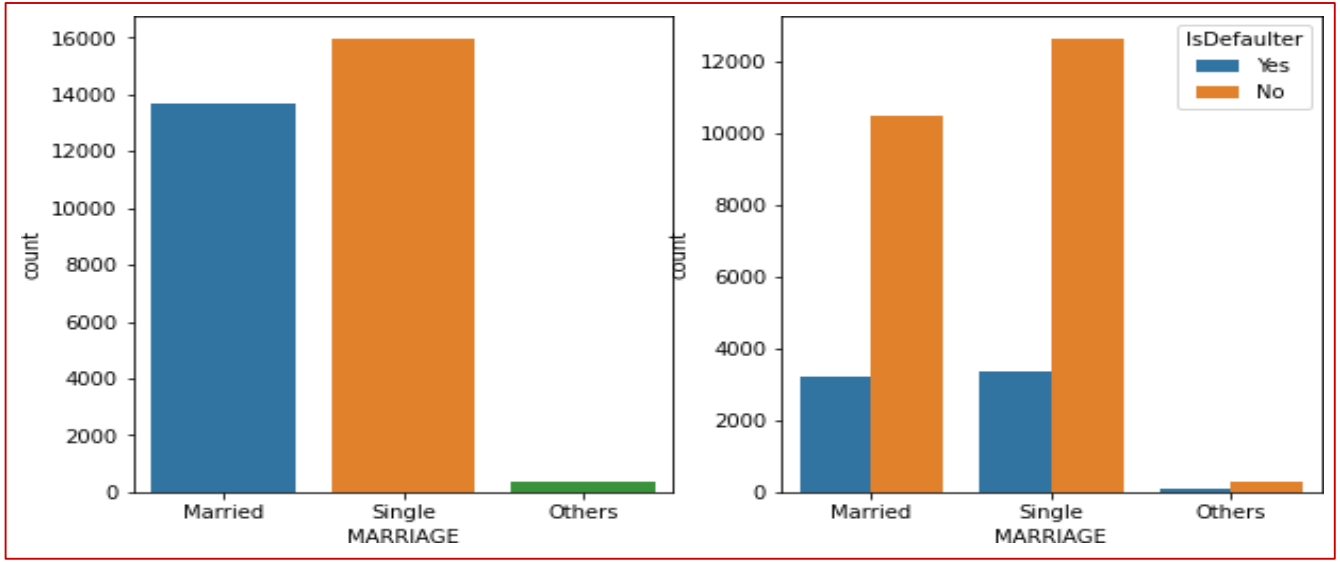
- Female credit card holders are larger than male credit cards holders.
- As the number female credit card holder is larger than male, their credit card defaults are also higher than male.

EDA (Continued)



- University and graduate school has maximum credit card holder.
- As the number university and graduate school credit card holder is higher their credit card default are also higher.

EDA (Continued)

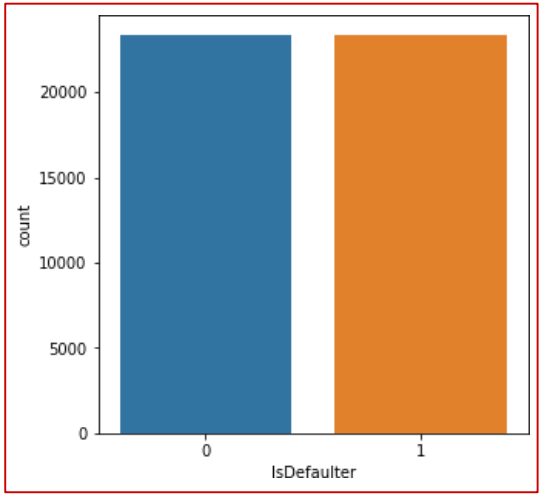


- Number of credit card holder is maximum in singles.
- But credit card defaults are almost same in case of single and married people.

5. Handling Class Imbalance

- Both the classes are not in proportion.
- SMOTE (Synthetic Minority Oversampling Technique) is the technique to make data class balanced.
- SMOTE works by selecting examples that are close in the feature space, drawing a line between the examples in the feature space and drawing a new sample at a point along that line.

- After applying SMOTE.



- Data class is balanced now.

6. Transformation of Data

- To scale data into a uniform format that would allow us to utilize the data in a better way.
- For performing fitting and applying different algorithms to it.
- The basic goal was to enforce a level of consistency or uniformity to dataset.

7. Splitting Data

- Data splits into training dataset and testing dataset.
- Training dataset is for making algorithm learn and train model.
- Test dataset is for testing the performance of train model.
- Here 80% of data taken as training dataset & remaining 20% of dataset used for testing purpose.

8. Fitting Different Model

- Following classifier used for prediction credit card default:

- • Logistic Regression
- • Decision Tree Classifier
- • Random Forest Classifier
- • Support Vector Machine
- • Gradient Boosting
- • XG Boosting

9. Cross Validation & Hyperparameter Tunning

AI

•It is a resampling procedure used to evaluate machine learning models on a limited data sample.

•Basically, Cross Validation is a technique using which Model is evaluated on the dataset on which it is not trained that is it can be a test data or can be another set as per availability or feasibility.

• Tuning the hyperparameters of respective algorithms is necessary for getting better accuracy and to avoid overfitting.

8.1 Logistic Regression

- Logistic regression is a machine learning algorithm for classification problem.
- In this algorithm, the probabilities describing the possible outcomes of a single trial are modelled using a logistic function.
- It is most useful for understanding the influence of several independent variables on a single outcome variable.

LOGISTIC REGRESSION						
	Accuracy		Precision	Recall	F1	AUC
	Train	Test				
Baseline Model	0.828	0.831	0.795	0.857	0.825	0.833
Tunned Model	0.827	0.832	0.799	0.855	0.826	0.833

8.2 Decision Tree Classifier

• Given a data of attributes together with its classes, a decision tree produces a sequence of rules that can be used to classify the data.

•Decision Tree is simple to understand and visualize, requires little data preparation, and can handle both numerical and categorical data.

Decision Tree Classifier						
	Accuracy		Precision	Recall	F1	AUC
	Train	Test				
Baseline Model	1	0.791	0.810	0.781	0.795	0.792
Tunned Model	0.837	0.824	0.779	0.857	0.816	0.827

8.3 Random Forest Classifier

•Random forest classifier is a meta-estimator that fits a number of decision trees on various sub-samples of datasets and uses average to improve the predictive accuracy of the model and controls over-fitting.

•The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement.

Random Forest Classifier						
	Accuracy		Precision	Recall	F1	AUC
	Train	Test				
Baseline Model	1	0.863	0.821	0.897	0.857	0.866
Tunned Model	0.844	0.833	0.794	0.860	0.826	0.835

8.4 Support Vector Machine

•Support vector machine is a representation of the training data as points in space separated into categories by a clear gap that is as wide as possible.

•New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

Support Vector Machine						
	Accuracy		Precision	Recall	F1	AUC
	Train	Test				
Baseline Model	0.848	0.840	0.765	0.900	0.827	0.848
Tunned Model	0.846	0.841	0.768	0.900	0.829	0.849

8.5 Gradient Boosting

•It is a technique of producing an additive predictive model by combining various weak predictors, typically Decision Trees.

•Due to this sequential connection, boosting algorithms are usually slow to learn, but also highly accurate.

•The final model aggregates the result of each step and thus a strong learner is achieved.

Gradient Boosting						
	Accuracy		Precision	Recall	F1	AUC
	Train	Test				
Baseline Model	0.847	0.843	0.801	0.875	0.836	0.846
Tunned Model	0.951	0.866	0.824	0.899	0.860	0.868

8.6 XG Boosting

•XG Boost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework.

•It is a perfect combination of software and hardware optimization techniques to yield superior results using less computing resources in the shortest amount of time.

XG Boosting						
	Accuracy		Precision	Recall	F1	AUC
	Train	Test				
Baseline Model	0.847	0.843	0.799	0.877	0.836	0.846
Tunned Model	0.995	0.871	0.831	0.904	0.866	0.874

10. Comparison of Model

	Classifier	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score	AUC
11	Optimal XG Boosting	0.995	0.871	0.831	0.904	0.866	0.874
2	Random Forest	0.999	0.867	0.832	0.895	0.862	0.869
10	Optimal Gradient Boosting	0.951	0.866	0.824	0.899	0.860	0.868
3	SVM	0.846	0.841	0.768	0.900	0.829	0.849
9	Optimal SVM	0.846	0.841	0.768	0.900	0.829	0.849
4	Gradient Boosting	0.845	0.845	0.801	0.878	0.838	0.848
5	XG Boosting	0.847	0.844	0.801	0.877	0.837	0.847
8	Optimal Random Forest	0.844	0.833	0.794	0.860	0.826	0.835
0	Logistic Regression	0.827	0.832	0.796	0.857	0.826	0.834
6	Optimal Logistic Regression	0.826	0.832	0.797	0.857	0.826	0.834
7	Optimal Decision Tree	0.841	0.825	0.779	0.858	0.817	0.828
1	Decision Tree	1.000	0.802	0.814	0.795	0.804	0.802

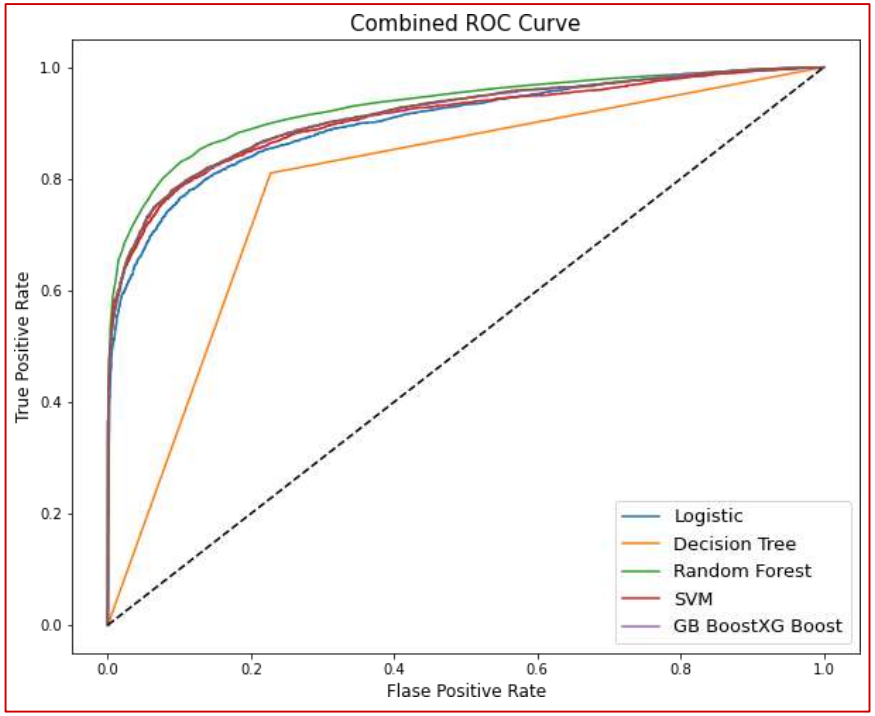
- XG Boost shows highest test accuracy score of 87% and AUC is 0.874.

11. Combined ROC Curve

•An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds.

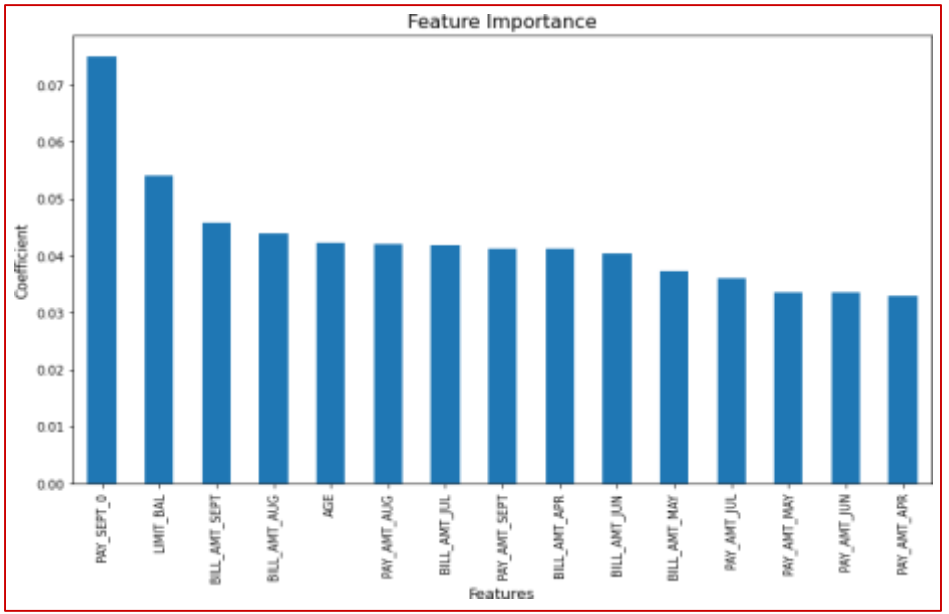
•An ROC curve plots TPR vs. FPR at different classification thresholds.

• Lowering the classification threshold classifies more items as positive, thus increasing both False Positives and True Positives.



12. Feature Importance

- Feature selection is the process of reducing the number of input variables when developing a predictive model.
- It is desirable to reduce the number of input variables to both reduce the computational cost of modeling and, in some cases, to improve the performance of the model.



13. Conclusion

1. From all baseline model, Random Forest classifier shows highest test accuracy and F1 score and AUC.

2.Baseline model of Random Forest and decision tree shows huge difference in train and test accuracy which shows overfitting.

3.After cross validation and hyperparameter tunning, XG Boost shows highest test accuracy score of 87% and AUC is 0.874.

4.Cross validation and hyperparameter tunning certainly reduces chances of overfitting and also increases performance of model.