Module 4: Classification

CREDIT CARD CHURN

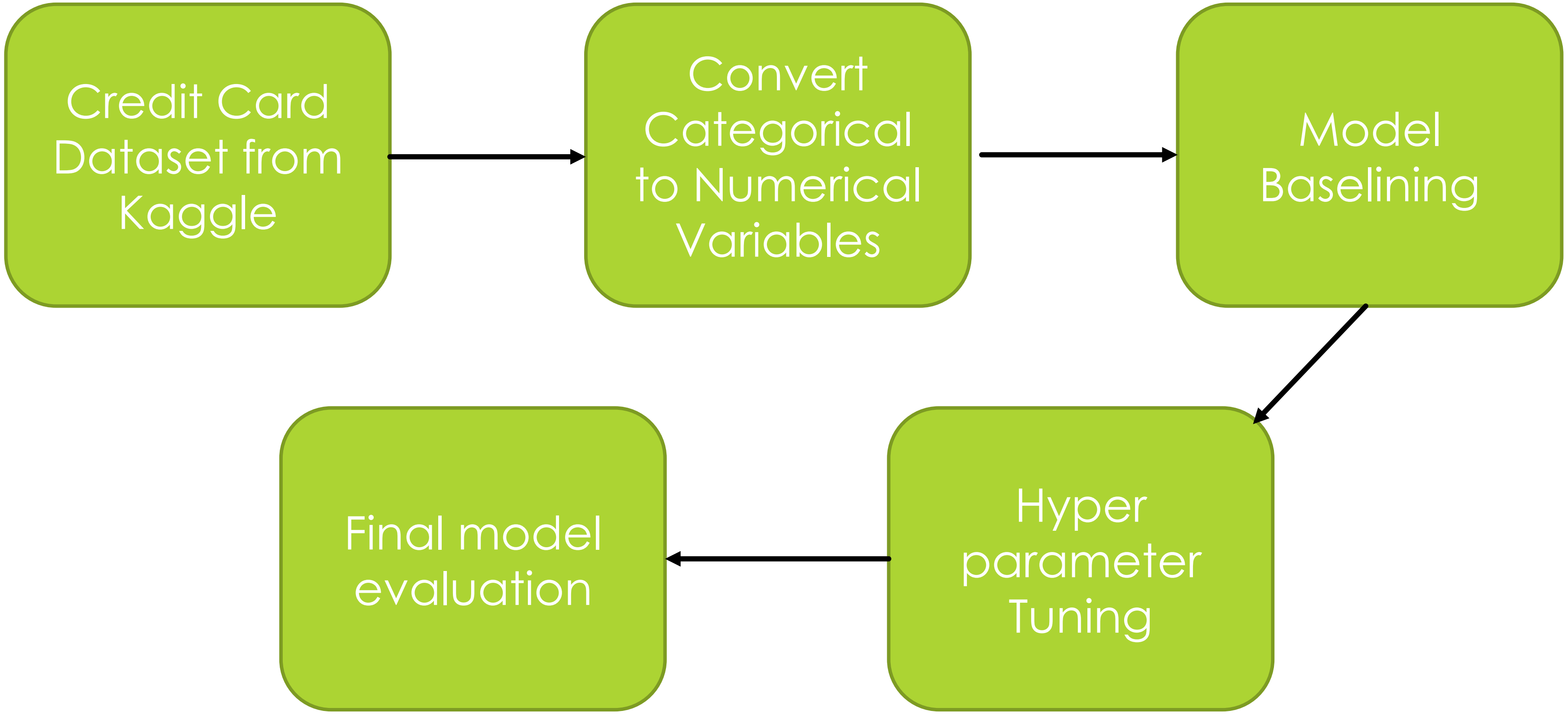
Objective

Credit card user churn is a big problem for credit card companies

In order to improve customer retainment, we must be able to predict what users are likely to “churn” or move on to other credit card companies

Let’s use Machine Learning!

Process



Credit Card Dataset from Kaggle
Convert Categorical to Numerical Variables
Model Baselining
Hyper parameter Tuning
Final model evaluation

Data

Demographic Info:
Gender,
Education,
Age,
Marital Status, etc.

Credit Card Behavior:
Total Transaction Amount,
Avg Utilization,
Avg change from Q4-Q1

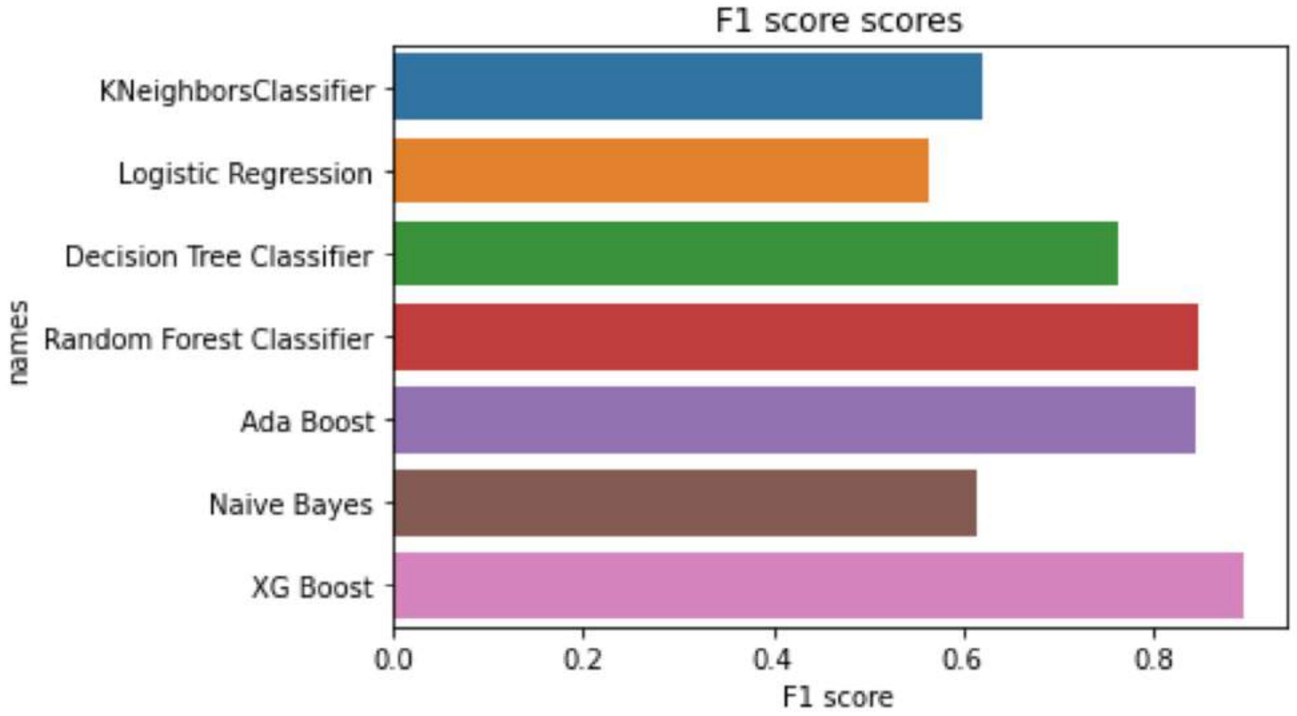
Financial Status:
Card Category,
Income Category,
Credit limit,
Relationship count, etc

21 Features

Churn Status
0 : No churn
1 : churn

Target

Baselining



- 7 models tried out for initial screening
- F1 score is the most relevant metric
- Naïve Bayes, Logistic Regression and Kneighbors are poor classifiers for this data
- **XG Boost is the best classifier**

Hyperparameter Tuning

Tuned across 4 key hyperparameters for XGBoost:

n_estimators: **50**, 100, 150, 200, 300

Learning_rate: 0.2, 0.25, 0.3, 0.45, **0.6**, 0.7

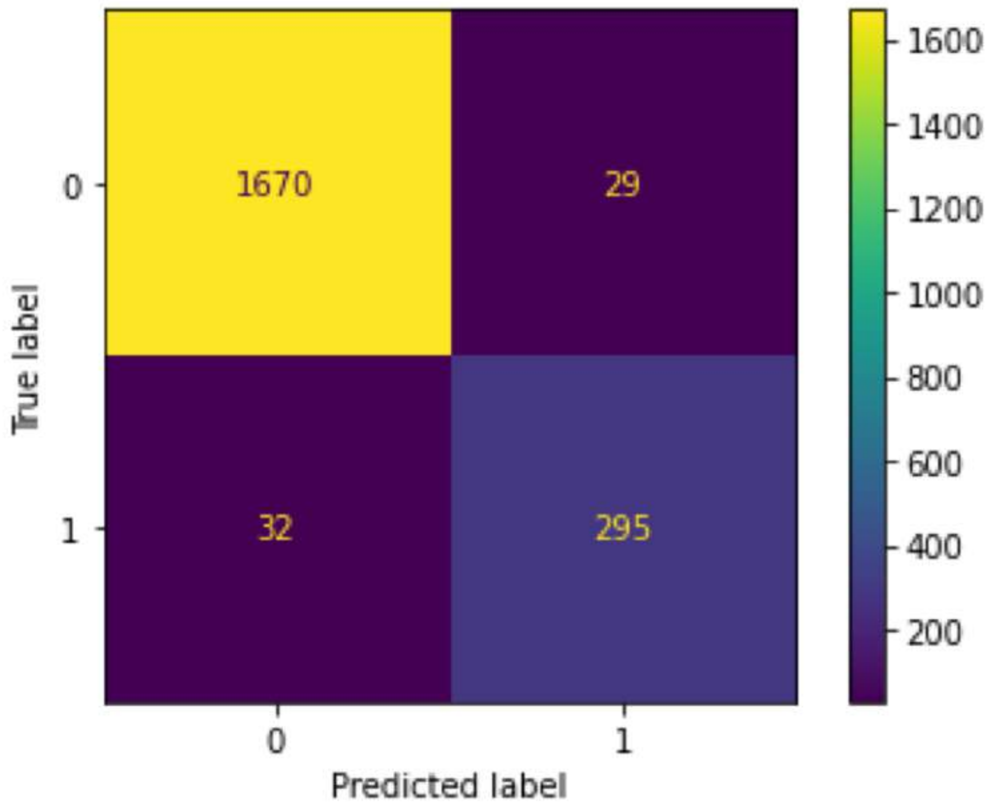
Reg_alpha: 0.0, 0.3, 0.5, **0.7**

Scale_pos_weight: 0.5, 0.7, 0.85, **1**

Screened 480 hyperparameter combinations

Final Optimized XGBoost Model

	Precision	Recall	F-1 Score
Before Optimization	91.40%	87.77%	**89.55%**
After Optimization	91.05%	90.21%	**90.63%**



The final tuned model is better in overall performance and is balanced

Conclusion

- **XGBoost** was the ideal model for our complex credit card churn problem
- After tuning hyperparameters, **our best model has a F-1 score of 90.63%,** exceeding the performance of our baseline model
- Using our model, we can target customers likely to churn, and give them targeted services and promotions