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Module 4: Classification

Abstract

It is important for credit card companies to identify reasons for customer churn so they can understand the issue and take necessary steps to address customers who leave their company. In order to understand this behavior, many features are involved that could affect whether a user churns or not. Machine learning classification is ideally suited to address this problem.

Design

My original dataset consists of 10127 entries and 24 features. The features describe a customer ID, demographic information, and credit card behavior for each customer. Each customer also has a corresponding target that indicates whether that person is an Exisiting customer (not churned) or an Attrited customer (churned).

Categorical values were converted to numerical values, both by dummying as well as assigning graded numbers. These categorical values were mostly demographic features.

The target was transformed to a binary (0: not churned, 1: churned). Our dataset is inbalanced, so we had 83.93% of 0, and 16.07% of 1.

The final feature list can be shown as:

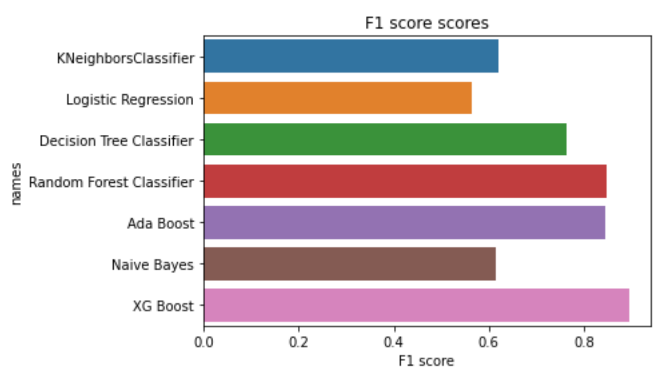
```
Customer_Age                int64
Gender                      int8
Dependent_count             int64
Education_Level             float64
Income_Category             float64
Card_Category               int64
Months_on_book              int64
Total_Relationship_Count    int64
Months_Inactive_12_mon      int64
Contacts_Count_12_mon       int64
Credit_Limit                float64
Total_Revolving_Bal         int64
Avg_Open_To_Buy             float64
Total_Amt_Chng_Q4_Q1        float64
Total_Trans_Amt             int64
Total_Trans_Ct              int64
Total_Ct_Chng_Q4_Q1         float64
Avg_Utilization_Ratio       float64
Marital_Status_Divorced     uint8
```

Marital_Status_Married uint8
Marital_Status_Single uint8

The data was split into Training and Test portions for the modelling portion. The Train and Test portions

Data and Results

The first step was baselining. In order to get an idea of what models were compatible with the data, we tried out 7 models. The results are the models are shown below:



Full Data can be seen as:

names	Jaccard Scores	Accuracy	Precision	Recall	F1 score
KNeighborsClassifier	45.10%	88.94%	69.43%	56.27%	62.16%
Logistic Regression	39.21%	88.60%	73.76%	45.57%	56.33%
Decision Tree Classifier	61.90%	90.92%	65.71%	91.44%	76.47%
Random Forest Classifier	73.49%	95.46%	92.73%	77.98%	84.72%
Ada Boost	73.00%	95.16%	88.04%	81.04%	84.39%
Naive Bayes	44.29%	88.45%	66.67%	56.88%	61.39%
XG Boost	81.07%	96.69%	91.40%	87.77%	89.55%

After baselining, we have identified XG Boost as the most promising model. From here, the goal is to improve the XGBoost model by optimizing the hyperparameters of the model. I briefly tested the impact of different hyperparameters on the model, and the ones that seemed to make the most impact were:

N_estimators: number of estimators
Learning_rate: step size shrinkage

Reg_alpha: regularization term
Scale_pos_weight: controls the balance of positive and negative weights.

We used a grid of values that netted 480 unique hyperparameter combinations that we created models for. After, this the top model was one where:

N_estimators = 50
Learning_rate = 0.6
Reg_alpha = 0.7
Scale_pos_weight = 1

When comparing this model with the model before optimization, we see a very large improvement in the Recall with a small sacrifice in Precision. Since we care about the balance of these two metrics as evaluated by the F-1 score, we are happy with these results.

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

Conclusion

- XGBoost was the most promising model when evaluated over F1 score from our list of 7 baselining models.
- By tuning our XGBoost model, we obtained a final F1 score of: **90.63%**

Next Steps

- Determine if the current churn rate is acceptable and if not, devise mitigation strategies targeted at customers with high probabilities of churning
- Continue to improve the current model with more granular hyperparameter optimizing, gathering different data from customers, and updating the model as more users are added to the database.
- Try further ensembling methods such as Stacking or Voting ensembling

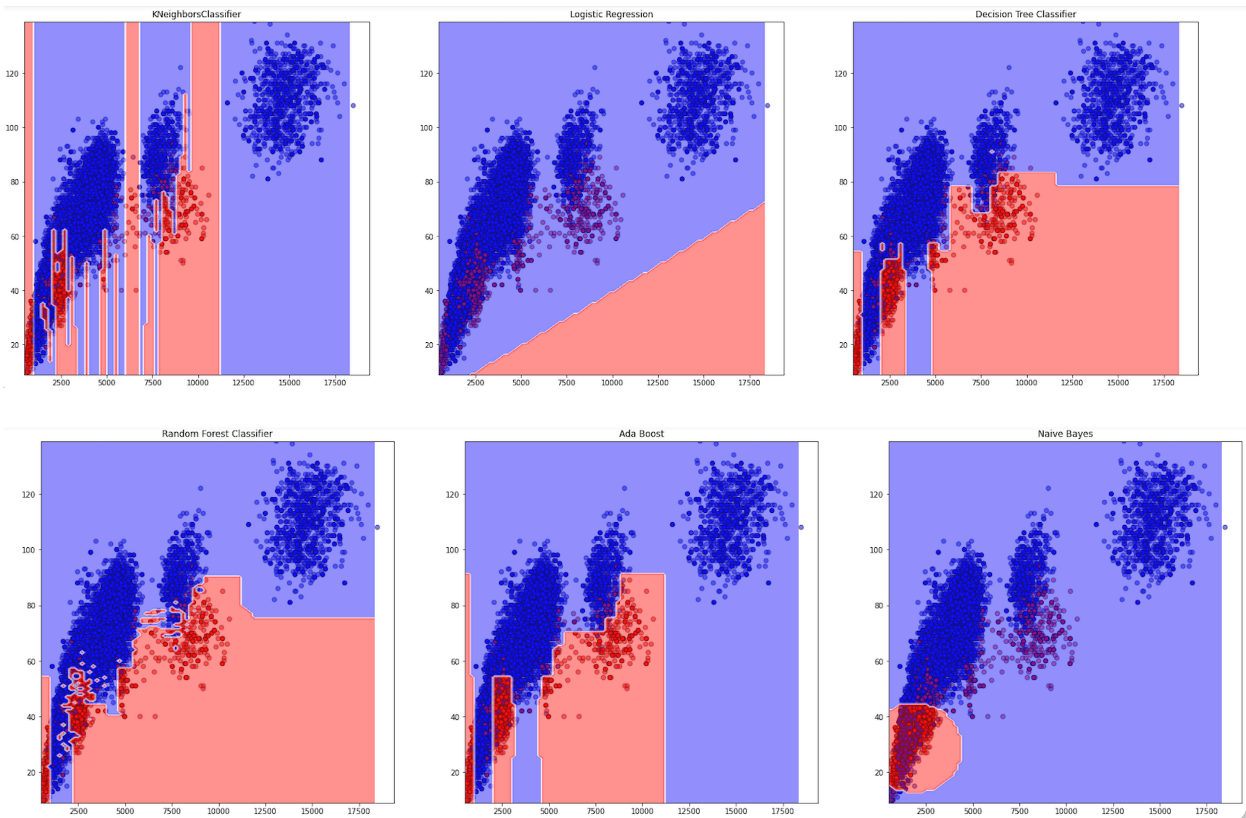
Tools

Pandas – Data preprocessing and feature engineering

Scikit-Learn – The larger majority of models and model utilities
XGBoost – XGBClassifier model
Matplotlib and Seaborn – Graphing and visualization

Extra:

I also worked on 2D decision trees to visualize how different models created decision boundaries with two selected features. The ensembling methods seem to be more precise towards fitting the data. However, it is clear that the higher dimensional models are more effective.



Communication

For additional information, please contact kenhua15@gmail.com. The project will also be posted on my github found here: https://github.com/kenhua15/Metis-Projects