# **Predicting Churning Customers**

Data 1030 Midterm Report — Yingfei Hong
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### 1. Introduction

A manager at the bank is disturbed by more and more customers leaving their credit card services. The problem I am trying to solve is to predict the "churned customers" for the bank managers based on the given data so they can proactively go to the customer to provide them better services and turn customers' decisions in the opposite direction. Predicting churn is very important especially when clear customer feedback is absent. Retaining existing customers and thereby increasing their lifetime value is something everyone acknowledges as being important, however, there is little the bank managers can do about customer churn if they don't see it coming in the first place. This is where predicting churn has its value. Early and accurate churn prediction empowers CRM and customer experience teams to be creative and proactive in their engagement with the customer. In fact, by simply reaching out to the customer early enough, 11% of the churn can be avoided [1].

This dataset comes from LEAPS <sup>[2]</sup> and contains 21 columns and 10127 data points with 'Attrition\_Flag' as its target variable in which "Attrited customer" means that this customer is the churned customer we are looking for.

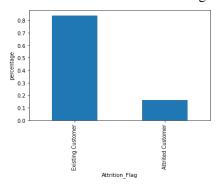


Figure 1 The distribution of 'Attrition Flag'

It is an imbalanced dataset since the proportion of the 'Attrited customer' is about 16.07%. Besides, through the distribution of the target variable, this task is certainly a typical classification problem.

The rest 20 features are described in the following table which contains their feature name, type, and meaning.

| Variable                 | Type      | Description  |
|--------------------------|-----------|--|
| Clientnum                | Num       | Client number. Unique identifier for the                           |
|                          |           | customer holding the account                                       |
| Attrition_Flag           | char      | Internal event (customer activity) variable -                      |
|                          |           | flag to indicate if the customer is an existing                    |
| Customer_Age             | Num       | customer or has attrited  Demographic variable - Customer's Age in |
|                          |           | Years  |
| Gender                   | Char      | Demographic variable - M=Male, F=Female                            |
| Dependent_count          | Num       | Demographic variable - Number of                                   |
|                          |           | dependents   |
| Education_Level          | Char      | Demographic variable - Educational                                 |
|                          |           | Qualification of the account holder (example:                      |
|                          |           | high school, college graduate, etc.)                               |
| Marital_Status           | Char      | Demographic variable - Married, Single,<br>Unknown                 |
| Income_Category          | Char      | Demographic variable - Annual Income                               |
|                          |           | Category of the account holder (< \$40K,                           |
|                          |           | \$40K - 60K, \$60K - \$80K, \$80K-\$120K,                          |
|                          |           | > \$120K, Unknown)   |
| Card_Category            | Char      | Product Variable - Type of Card (Blue,<br>Silver, Gold, Platinum)  |
| Months on book           | Num       | Months on book (Time of Relationship)                              |
| Total Relationship Count | Num       | Total no. of products held by the customer                         |
| Months Inactive 12 mon   | 1 1 44111 | No. of months inactive in the last 12 months                       |
|                          | Num       | No. of Contacts in the last 12 months                              |
| Contacts_Count_12_mon    |           |  |
| Credit_Limit             | Num       | Credit Limit on the Credit Card                                    |
| Total_Revolving_Bal      | Num       | Total Revolving Balance on the Credit Card                         |
| Avg_Open_To_Buy          | Num       | Open to Buy Credit Line (Average of last 12 months)                |
| Total_Amt_Chng_Q4_Q1     | Num       | Change in Transaction Amount (Q4 over Q1)                          |
| Total_Trans_Amt          | Num       | Total Transaction Amount (Last 12 months)                          |
| Total_Trans_Ct           | Num       | Total Transaction Count (Last 12 months)                           |
| Total_Ct_Chng_Q4_Q1      | Num       | Change in Transaction Count (Q4 over Q1)                           |
| Avg_Utilization_Ratio    | Num       | Average Card Utilization Ratio                                     |

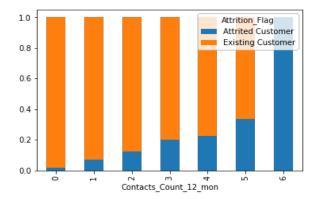
**Table 1** Description for each feature

For this data, there are two main tasks, one is to improve the performance of predicting churned customers while the other is to find the most influential factors that make the customers "churn". However, finding the factors that matter most is a common strategy when enhancing the model performance so I rather treat them as a same task. Several projects have already been done to solve this problem and achieve good results.

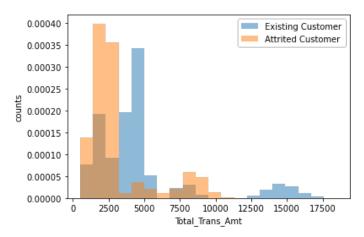
Thomas<sup>[3]</sup> used SMOTE which is an approach to address imbalanced datasets by oversampling the minority class and found great improvement when processing the data generated by this strategy. The result showed that compared to the raw data, this new data could improve the F1 score from average 0.6 to average 0.9. Andi<sup>[4]</sup> looked into the details about the raw data and found some interesting relationships between the features and the target variable. The EDA showed that the likelihood of the customers' leaving is related to the money they spend annually, the months of inactivity in their bank account and their credit limit. Joseph<sup>[5]</sup> used Random Forest and LightGBM to predict with 97% recall and 95% accuracy and plotted the importance of these features which showed that the transaction feature ranked top in both models, so we need to look these features thoroughly when doing exploratory data analysis.

### 2. EDA

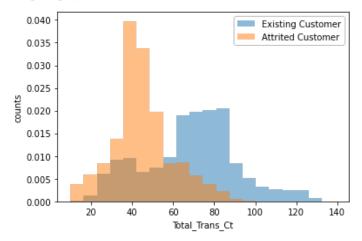
I've plotted the relationship between every feature and the target variable and found some relations that are worth notice.



**Figure 2** This graph displays how the number of contacts is distributed across two different customers. It seems that churning customers have had more contacts in the last 12 months with the bank managers.



**Figure 3** This graph shows that the total transaction amount of attrited customers is smaller than that of existing customers which explains why this feature ranks top in both models of Joseph's projects.



**Figure 4** This graph has a similar pattern as figure 3 which shows that total transaction count is also a important feature when we try to classify attrited customer from the existing customer.

## 3. Data Proprocessing

This dataset is not IID since all features are not identically distributed. It does not have a group structure, nor does it have time-series data. But it is imbalanced, so it is better to use stratify method when splitting. The train size is set as 0.6 and the validation size as well as the test size both as 0.2 because it is how people normally split their data when they have lots of data points.

I treated discrete numerical features (dis\_fea) as ordinal features and put them directly into the model since they are already in numerical form. Categorical features (cat fea) need

to be treated with OneHotEncoder because it is not sensible if we put gender and marital status in order. For ordinal features(ord\_fea), OrdinalEncoder is the best fit because there is ordinal information contained in educational level, income category, and card category. For continuous numerical feature(con\_fea), I chose StandardScaler. Since in these columns, 'Customer\_Age', 'Monts\_on\_book', and 'Total\_Trans\_Ct' are nearly normally distributed though some are skewed while other features have long tails which are not suitable to use MinMaxScaler.

In this case, the target variable also needs to be preprocessed by LabelEncoder to make it machinecomprehensible since it is a binary classification problem and the type of the values in the target variable is 'string'.

There are some missing values in some demographic variables like educational level, income category, and marital status and we can treat them as one special category since they are all categorical features.

#### 4. Reference

- [1] Why customers leave & Danks do? Tiger Analytics. (2020, September 16). Retrieved October 12, 2021, from <a href="https://www.tigeranalytics.com/blog/addressing-customer-churn-in-banking/">https://www.tigeranalytics.com/blog/addressing-customer-churn-in-banking/</a>.
- [2] Predict Customer Attrition Using Naïve Bayes Classification. ATH Leaps. Retrieved October 12, 2021, from https://leapsapp.analyttica.com/cases/11.
- [3] Konstantin, T. (2021, May 1). Bank churn data exploration and churn prediction. Kaggle. Retrieved October 12, 2021, from <a href="https://www.kaggle.com/thomaskonstantin/bank-churn-data-exploration-and-churn-prediction">https://www.kaggle.com/thomaskonstantin/bank-churn-data-exploration-and-churn-prediction</a>.
- [4] IDW, A. (2021, January 31). Customer churn EDA, 95% ACC and 85% recall. Kaggle. Retrieved October 12, 2021, from <a href="https://www.kaggle.com/paotografi/customer-churn-eda-95-acc-and-85-recall">https://www.kaggle.com/paotografi/customer-churn-eda-95-acc-and-85-recall</a>.
- [5] Chan, J. (2021, January 13). Bank Churners Classifier (Recall: 97% accuracy: 95%). Kaggle. Retrieved October 12, 2021, from <a href="https://www.kaggle.com/josephchan524/bankchurnersclassifi">https://www.kaggle.com/josephchan524/bankchurnersclassifi</a>

er-recall-97-accuracy-95.

### 5. Github repository

https://github.com/YingfeiHong01/Data1030-FinalProject