

Churn Prediction in Iran Banking Industry Case of a Private Iranian Bank

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Abstract

After the emergence of private banks in Iran, due to its attractiveness, this industry has witnessed a rapid growth such banks. The abundance of private banks led to a very high pressure competitive environment and gave dissatisfied customers a chance to easily switch banks. On the other hand, the most important advantage of the competitive environment among the banks is to have more resources at a low risk. Losing customers to another bank is equivalent to a decrease in a bank's resources. Since the acquisition of new customers, costs much more in comparison to maintaining the existing ones, the banks try hard to keep their customers. Thus, customers churn predictions via analyzing their financial behavior and finding possible methods for preventing customer defection is crucial. This research utilizes the hierarchical K-means clustering technique for detection of customers' churn and also applies Markov Chain model for calculating the probability of customer churning in the future. Using these techniques and financial data of an Iranian private bank, we build an example of this model that can predict the possibility of losing customers.

Introduction

Tough competition in the Iranian banking industry, especially among private banks, has forced them to pay more attention to customer relationship management. Because of the higher cost of customer acquisition compared to customer retention, banks try hard to preserve their customers. Customer churn prediction can help a bank to predict its customers' intention to stop using

bank's services. This can be done by using the customers' transaction data with the help of data mining techniques. Also, this prediction can help banks reduce the risk of deposit resource loss which is very important in banking business. Therefore, the main purpose of this study is to build a churn prediction model suitable for the Iranian banking industry.

Research Methodology

In this study a data set consisting of financial transactions of 385,912 customers of an Iranian private bank in a one-year period is used. For the purposes of churn detection, we first used a hierarchical K-means clustering on some churn-related parameters. Then, with the help of 11 experts we ranked the clusters by degree of churn. This ranking is done by comparing every two clusters from a churn perspective with the help of the experts. After that we group the clusters in 4 states of churn: Active, Steady, Churning and Churned. If a customer belongs to the Active state, it means that his/her behavior is just opposite of churning. When customers move to the next states from Steady to Churning and Churned, their behavior is more like churning. Then, we calculate the transition of customers between states through time. Finally, using a Markov chain technique we build a model that can predict the customers churn state change.

Findings

We calculate the three parameters of Recency, Frequency and Monetary for each customer. Based on these parameters the customers are clustered into ten clusters. The clusters are then grouped in four states of churn: Active, Steady, Churning, Churned. By determining the transitions of customers between these four states we build a Markov chain model. In order to determine the transitions, we use the states of customers in the first seven months of data compared to their states in the next five months.

Discussion

Most of the customers who belong to cluster number 18 and are in the Steady state of churn are not much active in the bank. The probabilities of state transitions indicate that 79 percent of customers who are in the Churned state will not change their state. This means that if a bank loses its customers, then there is very little opportunity to win them back. Therefore, the decision makers in the bank should try hard to prevent a customer, particularly one in Churning state, to go to the Churned state.

About 74 percent of customers in Active state will go to Steady state. If nothing happens, most of the customers who are active will be steady after sometime. The probability that a customer in Active state keeps his/her state is a little more than 12 percent. So the active customers are very unstable. However, the probability of a customer going from the Steady state to the Active state is around 39 percent. Hence, there is an opportunity for the banks to focus on customers in Steady state and give them incentives to persuade them to be more active.

The probability that a customer changes his/her state from Steady to Churning is around 20 percent. This means that in normal conditions 20 percent of customers that are in Steady state will go to Churning state. So it is very crucial for the banks to be more focused on customers in the Steady. In another words, the key state to focus on is the Steady state and if the banks give incentives to these customers they will not change their state to Churning.

The probability of getting a customer in the Churned state back to the Steady state is around one percent. So, it is very hard for a bank to win back a customer who has churned. The decision makers are well advised to have customer relationship plans to prevent customers from going to the Churned state. If this happens, however, there will be very little they can do to have them go back.

The model can help bank decision makers select some customers to pay more attention to. With the help of giving some incentives in the form of customer loyalty programs, banks can survive the loss of customers.

Key Words: Churn Prediction, Banking, Markov Model, Hierarchical K-Means, Data Mining