Customer Churn Prediction Using Artificial Neural Network: An Analytical CRM Application

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Abstract

Customer need is the most important factor in the formation of each market and business. It engages companies in order to meet their need by developing new products and services. Although it can make an appropriate attraction for company customers, a company needs to have a good understanding of their customer dynamic behavior. Based on this understanding, they can provide appropriate planning for customer's retention. In banks, customers are key components of the banking business. All of their strategies and plans are organized to attract new customers, retain current customers, and ultimately enhance customer satisfaction. Meanwhile, customer churn is one of the most important problems for this business. It deprives a bank of various earnings and fee incomes. And more importantly, customer deposit is the main source of the incomes earned by a bank in the Islamic banking system. It may lead to the withdrawal part of a bank's deposits. By considering the loss of these two sources of incomes, along with the possibility of increasing the reputational risk, can lead a bank to the brink of bankruptcy. The present study provides a model of customer churn prediction for retail customers of a commercial bank in Iran. By applying advanced data analysis techniques on transaction and operation data of the bank customers, appropriate classification of customers is presented in terms of the churn rate. Thus, by executing suitable strategies for each category, it can be developed to reduce the amount of customer churn. In this research, a private bank in Iran has been used to predict the customer's bank data. The results show that the jobs associated with food services including restaurants and fast food retailers, as well as the technical services, have the highest churn rate in the bank. After them, the sports centers, as well as the household, are in the next ranks of churn from the bank services. In contrast to counseling centers, kindergartens, and governmental organizations, respectively, were the lowest risky corporate customers of the bank. Also, in retail customers, clients aged 30-40 years had the largest churn in the bank's services.

Keywords
Customer Churn, Prediction, Classification, Customer Retention, Neural Network

1. Introduction

Customer retention is one of the major aspects of customer relationship management (CRM) and, it is considered as the core of CRM. Customer churn is one of the concepts associated with customer retention, which pays attention to the customers opting out from continuing to work with a company. Customer churn is an important issue for all organizations because today the cost of attracting new customers is much higher than the cost of maintaining existing customers.

On the other hand, in recent years, marketing strategies have shifted from production orientation to customer orientation, and many organizations have focused on customer relationship management.

Losing an existing customer leads to lower revenue and the cost of attracting new customers. Customer retention is a valuable strategy that ensures long-term profitability and organizational success. Successful customer care reduces the need to search for new customers that are potentially risky. By doing so, companies can focus more closely on the needs of their current customers by establishing an appropriate relation (Dawes and Swailes, 1999; Engel et al., 1995).

Due to the high cost of attracting new customers and the significant benefits of retaining current customers, a churn modeling that facilitates customer rejection and churn are essential for the success, profitability, and survival of organizations in today's highly competitive environment. If the insight from the behavior analysis of customer churn is properly used, then the customer retention rate can be increased. Also, more profit can be gained by making the appropriate action (Van den Poel and Lariviere, 2004).

A modern banking business consists of five essential pillars; capital management, risk management, liquidity management, asset management, and customer management (Bastan et al., 2016a). Optimum business management actually means that by applying the five principles above, the business will be directed to maximize gain for a bank (Bastan et al., 2016b). In retail banking, customers are the base of business, so customer management process in this business line is extremely important in terms of the spread, volume, variety, and distribution of customers. Selection and formation of a customer portfolio, customer retention and development are the main processes of retail banking business management. Also, the right information about the risk of customer withdrawal and their churn, are very important criteria in designing and developing a retail customers portfolio for a bank (Bastan et al., 2017).

In fact, when designing a customer's optimal portfolio, in addition to considering the profitability of each class of customers, the probable rate of their churn should also be considered. The churn rate can affect to design and implementation of customer retention programs. Also, it is necessary to estimate the lifetime of each customer. The lifetime of a customer in a bank is a period beginning to work with the bank until the date of the last transaction of a customer with the bank, in terms of the day (Tabandeh and Bastan, 2014). It can also identify and analyze jobs and other customer demographics with high and low exit risk and provide a deep insight into the customer churn.

2. Literature and Background

Customer churn is an expression used to express the loss of a customer for various reasons. More specifically, churn management is the concept of identifying those customers who are intending to move their custom to a competing service provider (Hadden et al., 2007).

Churning customers can be divided into two main groups, voluntary and non-voluntary churners. Non-voluntary churners are the easiest to identify, as these are the customers who have had their service withdrawn by the company. There are several reasons why a company could revoke a customer’s service, including abuse of service and nonpayment of service.

Voluntary churn is more difficult to determine because this type of churn occurs when a customer makes a conscious decision to terminate his/her service with the provider. Voluntary churn can be sub-divided into two main categories, incidental churn and deliberate churn (Hadden et al., 2007).

Incidental churn happens when changes in circumstances prevent the customer from further requiring the provided service. Examples of incidental churn include changes in the customer’s

financial circumstances so that the customer can no longer afford the service or a move to a different geographical location where the company's service is unavailable. Incidental churn usually only explains a small percentage of a company's voluntary churn.

Deliberate churn is the problem that most churn management solutions try to battle. This type of churn occurs when a customer decides to move his/her custom to a competing company. Reasons that could lead to a customer's deliberate churn include technology-based reasons when a customer discovers that a competitor is offering the latest products, while their existing supplier cannot provide them. Economic reasons include finding the product at a better price from a competing company. Examples of other reasons for deliberate churn include quality factors such as poor coverage, or possibly bad experiences with call centers, etc. (Kim and Yoon, 2004).

In the present research, the meaning of churn is the deliberate churn of customers due to dissatisfaction with the services provided by a bank. Customer churn management consists of three steps; 1) identifying churner customers, 2) determining the reasons, and 3) designing decision-making policies to reduce the churn rate (Bharti, 2017). Customer churn is recognized as one of the factors that result in a loss of profitability for a company or organization, and a variety of financial and social losses. This concept is very useful in service-based companies such as banks, insurance, and so on.

Research on customer churn can be divided into two groups. The first group has predicted the churn rate and the other is focused on identifying the factors that affect it. The first category of research has been designed to predict the churn rate based on customer behavioral records.

Datta et al. (2000) in his research, in order to predict the churn rate in the communications industry, provided a churn rate forecast, by using a decision tree method on transaction data, customers' consumption records. A major part of the churn researches is the effort to increase the accuracy of prediction patterns. To identifying churners, Coussement andVan den Poel (2008) tried to increase the accuracy of the model by adding customers' call centers to the traditional system of predictive churn rates. Glady et al. (2009) used the concept of the value of the customer life cycle as a parameter involved in the churn rate prediction. In this approach, the devaluation of the customer is considered as a churn criterion.

Part of the researches has focused on the development of prediction techniques. Verbeke et al. (2011) used a combination of inference techniques to identify churners, and compared its performance with other common data mining techniques. De Bock andVan den Poel (2011) used a combination of classification methods to predict customer churn. They also compared the effectiveness of this new method with common methods.

In the second researches category, which focused on the identification of factors affecting churn problem, fewer researches have been done than the first category. To analyze the effect of different factors on customer churn, Shin andKim (2008) used sampling and statistical analysis. Kim andYoon (2004) investigated the factors affecting churn in the communication industry. They evaluate the effect of service quality and demographic feature on churn, by using a statistical test. To identify the causes of customer churn in the banking industry and E-Banking services, Chiang et al. (2003) used associative rules and analysis on customer transactions to discover the most important patterns of churn. Hadden et al. (2007) believe that the identification of churner customers will provide a context for studying the reasons for customers churn that are affected by different factors. They provided a five-stage framework for customer churn management, including 1) Identification of the best data, 2) Data semantics, 3) Feature selection, 4) development of a predictive model and 5) Validation of results.

Some studies also have been done by applying optimization and soft computing methods to solve churn related problems. Pendharkar (2009) used an improved neural network model using a genetic algorithm (GA) to predict a customer's churn in a communications company. The fitness function in the genetic algorithm is based on maximizing the accuracy of the model and minimizing entropy. Based on the results, they founded GA models have a better performance than neural network models. B. Huang et al. (2010) proposed a multi-objective feature selection method to predict churn of services based on the NSGA-II optimization approach.
Idris et al. (2012) used particle swarm optimization (PSO) algorithm to treat unbalanced data and minimum of redundancy and maximum connection for the reduction of the feature and from the rotating forest to predict churn. Y. Huang andKechadi (2013) used a hybrid model based on the learning system, in order to obtain a more accurate result. This model integrates supervised and unsupervised approaches to predict customer behavior. Peng et al. (2013) used the combination of the re-sampling method with the support vector machine (SVM) to solve the unbalanced data problem in predicting customer churn in the telecommunications company.

3. Methodology

To provide a suitable model for predicting and analyzing bank customers' churn, by using machine learning tools and deep learning techniques, a methodology is designed as below.

1. **Preprocessing phase:** Due to this fact that the bank customers information comes from different sources, and in different formats, a preprocessing phase should be performed before the data is analyzed. This phase includes these steps.

   1.1. Data Preparation: Considering that the process of an indicator in the analysis of data should be considered, the data for each index should be extracted as a process. This process has been active inactive customers since the last month of activity to the last few months ago. Given that, in addition to the active customer, the reactive customers also are seen in the data, so the last month's activity has to be calculated for reactive customers for several months. Therefore, it is necessary to calculate the last month's activity data for the past few months for reactive clients, which is a time-consuming process that complicates this step.

   1.2. Delete missing data: Due to a large amount of data, the probability of missing data is high. Therefore, some of these missing data which there is not the possibility of estimating or fitting them with other values should be removed from the final table. As an example, it may not have been registered a job for a customer, since the customer's job estimation is not possible, this customer will be removed from the final table.

   1.3. Performing calculations related to the age of the customer: In the Bank’s database, the customer’s age is not calculated and ready. Therefore, the current date should be subtracted of the customer's production history recorded in the system to obtain the customer's age. Given the high volume of the records, this stage also adds to the complexity of this stage.

1.4. Calculation of customer's lifetime: In addition to the customer's age, the customer's lifetime should also be calculated. This indicator does not exist in the database, and the date of the last month of customer activity has to be subtracted from the date of creation of the customer to the customer's lifetime. In calculating customer's age lifetime, extracting results is not a straightforward deduction of two numbers, since the format of the data storage is a day, month, and year. these numbers should be carefully, and with considering leap years should be deducted, Therefore, a function is used to run the calculation.

2. Designing a prediction model: At this stage, a model to solve the problem should be investigated in the techniques available in data sciences. The issue of the present research is considered as a categorization issue, and we seek to categorize bank customers in terms of withdrawal privileges.

3. Using software: Python software will be used to test and implement the prediction and classification model. Python software is an appropriate tool for the implementation of artificial intelligence techniques, and its powerful libraries can be used.

4. Verification: Confusion matrix is a common method used in data science to verify a classification model.

5. Validation: In order to validate the model, according to the type of present study, which supported by a bank for its implementation, the result is presented to the bank's business analysis unit, and if the results are not confirmed by this unit, the process is repeatedly re-engineered, until the achievement results of the approval of the business unit of the bank will be continued.

4. Neural Network Model

Intelligent approaches have appealed to researchers as an invaluable tool for addressing various prediction and optimization problems (e.g., see Akbarpour et al., 2014; Babajani et al., 2019; Hassan Gharoun et al., 2018; Habibifar et al., 2019; Mahdi Hamid et al., 2019; Hamid et al., 2018; Mahdi Hamid et al., 2019; Hejazi et al., 2013; Mokhtari et al., 2012; Nasiri and Hamid, 2019; Salmasnia et al., 2012). Among intelligent approaches, artificial neural networks (ANNs) are suitable instruments to solve complicated decision-making, optimization, forecast, process control, and many other problems (Hasan Gharoun et al., 2018; Yazdanparast et al., 2018). ANNs delineate the nonlinear relationship among inputs via the training process of the network. ANNs outperform many statistical and computational approaches inasmuch as they can map better inputs of the model to outputs without involving any complicated, formulation and do not demand detailed knowledge concerning the relationship between inputs and outputs. There is an extensive literature about ANNs, mostly in the empirical field, which investigates ANN's superiority or comparability to ordinary methods in terms of estimating different functions.

An ANN comprises the two essential processes of training and testing. Training of the network refers to the learning process required to accurately characterize the relationship between inputs and outputs. In the testing phase of an already trained network, if the network manages to identify the input pattern, the outputs will be produced. Conversely, in case the

output of the trained network features an unacceptable error. This training procedure is sustained until a certain limit is reached.

Using an efficient learning algorithm, an optimized network structure, and suitable training data could enhance the performance of the network and lower its complexity. Choosing the right complexity (i.e., regularization parameters) of the model in question is a significant challenge of ANNs (Choy et al., 2003). Additionally, the number of neurons in the hidden layer(s) of the network is commonly determined based on certain experiments.

The most conventional ANN model is the Multilayer Perceptron (MLP). It has one or several layers between the input layer and the output layer. Hence, this category of ANNs may deploy a host of techniques to offer a model for input-output relationships and produce greater outputs that might do a single layer neural network. We employed MLP model to predict customer churn for retail customers of a commercial bank in Iran.

5. Results

5.1. Selection of indicators used to churn diagnosis

According to the previous and similar studies in the banking industry as well as the Iranian banking business context, indicators were extracted as follows.

1. Job
2. Age
3. Sex
4. lifetime (day)
5. The province of occupation
6. Debtor turnover of the last month of activity
7. The debtor's turnover of one, two, three, four, five and six months before the last month of activity
8. creditor turnover last month activity
9. Creditor turnover of one, two, three, four, five and six months before the last month of activity
10. The average balance of the last month of customer deposit activity
11. The average balance of one, two, three, four, five and six months before the last month of activity
12. Interest paid to customer deposits in the last month of customer activity
13. Interest paid to customer deposits in one, two, three, four, five and six months before the last month of activity.

5.2. Description of selected indicators

Demographic factors: including age, occupation, gender, and the province of the area of activity, and because of the significant difference between customer behavior in terms of the difference in these indices. Obviously, businesses have different revenues and different income levels which means different behavior in falling or not, or the level of customer activity with the bank. In addition to occupation, the province of the area of activity also influences the level of customer activity. As an example, a physician in rural areas has higher earnings than a similar physician in Tehran, which is the capital of Iran. Gender is also another very effective factor in banking behavioral differences. Housewives have a different level of activity than employee man. Given that the technique used in this learning study is monitored, there is, for each

observation, an output that indicates the exit or non-exit of the customer, so the system can better identify the similar cases by learning from the exit process.

Debtor Turnover: This index shows the status of the output of resources to the customer's account.
The six-month trend of this variable is significant and meaningful since it is possible to monitor the flow of money from the customer's account to churn.

Creator Turnover: This index, along with its six-month trend, actually shows the status of the input of resources to the customer's account. Therefore, considering that the learning technique used is supervised, monitoring the state of entry of money in previous cases can be effective in determining the way out.

Average: Two debtor and creditor turnover indicators cannot show customer behavior well. The average of the account, which is the difference between the debtor and the creditor, is a suitable indicator. its trend over a period of six-months can also be effective in detecting churn.

Paid interest to the customer: Change in the interest rate on deposits that can be affected by any agent, such as the central bank's laws, is the other used indicators. Reducing the interest rate of deposit can be a cause of churn for customers who are sensitive to it. Thus, the six-month trend of this indicator, along with the tags of each observation, can help the system to classify better.

5.3. Software used and analysis process

In this research, Python and EViews are used. Python is used for designing the engine of data analysis and also an implementation of the neural network. EViews is used to feature selection and also examining the impact of each feature. In Python, the artificial neural network delivers each customer's churn score as output. To feature selection, each feature is introduced one by one into the neural network. The output of the network will be a continuous number, second, it imports into a linear regression. The use of linear regression is simply to examine the effect of each feature on the output. High interpretability of the linear model is the main reason for using a linear model.
Although the artificial neural network has high power in solving nonlinear problems, as well as this power, it has more difficult interpretability. To interpret the model, we apply regression on the results of the output of the network on signal inputs.
In the customer classification structure, customers due to the degree of churn were ranked in five classes: very high, high, medium, low and very low. A very high class means that the falling rate of this group of customers is very high. Thus, as much as we move from the very high class to the very low class, the churn score decreases as the probability of churn does as its following.

5.4. Validation of the model

The analytical and forecasting result is delivered to the bank’s business unit. Then, in order to validate the outputs of the model, using a random sampling method, several bank customers were selected, and with a precise assessment of their situation, the accuracy and reliability of the model were assured.

6. Discussion

Given that the output of the designed model is a list of customers who are the candidates for being churner, we can present some more analysis. One of these analyses is to figure out what is the jobs of those customers with the most probability to be churner? And what are the jobs of the customers with the lowest churn score? Understanding these occupations and businesses is used to portfolio selection and also the development of new services for target customers.

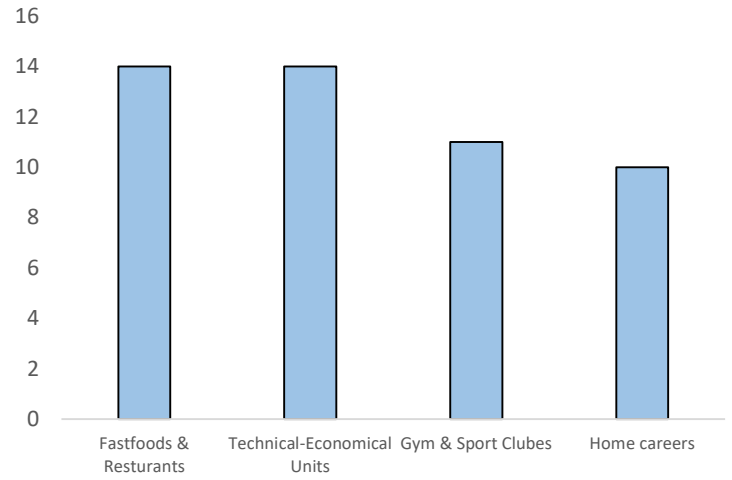

Figure 1- Banks' low-risk customers by jobs

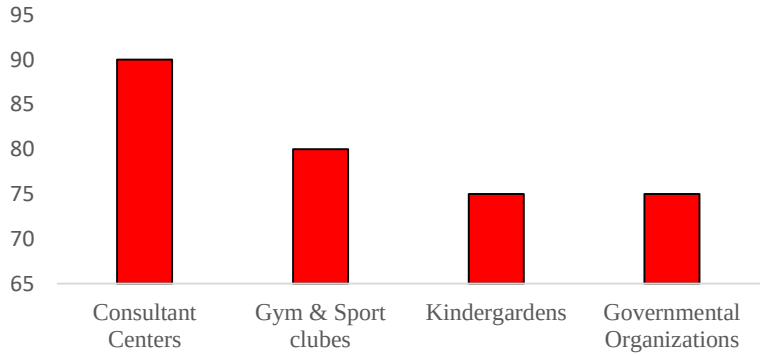

Figure 2-Bank's High-risk customers by jobs

One of the achieved results of the additional analysis is the statistical distribution of the age of high-risk customers whose histogram is figure 2.

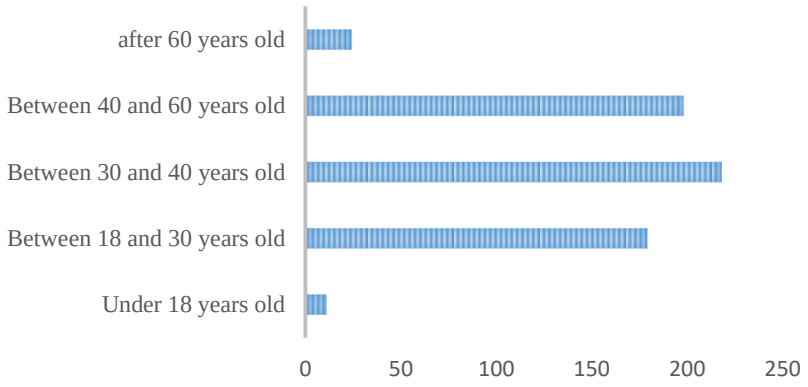

Figure 6 - Distribution of the age of the high-risk customers of the bank in terms of churn

7. Conclusion

Many organizations and companies are suffering from this fact that their customers constantly change their service provider, and join the services of rival organizations. In business related to the retail customers, due to a large number of customers, also the high speed of data generation, there is no possibility of achieving business intelligence without the use of machine learning mechanisms. Therefore, it is very important to find a suitable prediction model for customer churn using machine learning methods for a bank's business analysis unit. The present study aimed to investigate the customers churn from the retail banking services of a private bank in Iran. It provides a customer's classification according to the degree of churn risk.

By estimating the degree of customer churn, along with analyzing them with different indicators, a deeper understanding of the behavior of bank customers was obtained. The results show that demographic characteristics affect customer churn. Also, changes in various occupations and jobs are a significant effect on customer churn. Jobs related to food services including restaurants and fast foods, as well as the technical-economical services industries, have the highest degree of churn in bank customers. After them, the sports industry, as well as the home carriers, are in the next ranks turning churner from the bank services. In contrast, consultant centers, kindergartens, and government organizations, respectively, were the lowest risky customers of the bank from the perspective of the churn rate. Also, customers aged between 30 and 40 years had the largest amount of churn in the banking services of the surveyed bank.

Considering the proposed model and the possibility of producing various analytical reports, the following solution can be recommended to the bank's managers.

Avoid Customers churn: By knowing customers who have high churn score, Bank can prevent these customers from turning to churner class. Introducing the bank's services to them is one of the suggested solutions. As described in the previous section, the lack of good awareness of the last and new services of the bank is one of the main attributes of this customer. Notification is the first solution.

The list of customers who have the most churn score is extracted and informed to the bank's call center and CRM unit. CRM unit introduces bank services to the customers and keeps relationships with them.

Creating customers' portfolio: creating a customer portfolio based on customer's job is necessary. Knowing the list of customers who have the highest churn rates can identify high-risk and low-risk businesses and recognize the low-risk business portfolio and consider it in design. To reduce the risk of bank concentration, it is necessary to form a customer basket and using the analyzes obtained from this research is a suitable decision support system for the formation of customers' portfolios.

Customers Development: Considering that most of these customers are not loyal to the bank, they can be chosen as a high priority group for loyalty management. In fact, this part of the customers can be selected as the target market and implement customer development plans for them.

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