Churn Prediction for Gym Members Using Artificial Neural Networks Assisted with The Psychological Concept of Habit Formation in The Fitness Industry

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Abstract

Because of the growth of the health and fitness awareness, the gym industry is booming. Consequently, the competition between gym businesses is becoming increasingly fierce. So, it is vital for gyms to develop membership retention strategies to keep their customers from switching to a competitor. An important step in such strategies is to proactively detect members who are vulnerable to ending their memberships (Churning) to make efforts into retaining them. Utilizing technology for predicting churn can be advantageous for fitness clubs that aim to stay at the top of the business. Hence, the purpose of this paper is to develop a model that predicts gym membership churn by employing multi-layer perceptron (MLP) artificial neural networks (ANN) using backpropagation with an emphasis on feature selection. Two methods were used to base feature selection on: literature review and filtering method. The results found that implementing the psychological concept of habit formation served as a link for introducing an effective ANN model into the fitness retention strategies, as the model achieved high prediction performance metrics, namely, accuracy, sensitivity, and specificity, 92.1%, 89.1% and 93.8% respectively.

Keywords
Churn prediction, Artificial Neural Network, fitness clubs, habit formation, feature selection

1. Introduction and Literature Review

By definition, a customer who decides to leave a service provider for another one is called churn (Hassan and Mizra 2018). In subscription-based businesses, it costs five times more to attract a new customer, than to keep an existing one (Jackson 1988). Also, a 5% increase in retention can lead to 25% increase in profit (Reichheld 2001). Keeping customers from switching to another service provider becomes especially crucial when the competition in a field is intense; "a customer lost is a customer gained by a competitor" (Kon 2004). In addition to competition, retention rates in the fitness industry are generally low, sometimes dropping to 60% (Watts 2012). This further necessitates the need for fitness clubs to apply gym membership retention strategies to keep their customers from switching.

Most literature found on gym membership retention is focused on members' behavior, such as frequency of attendance, interaction with gym staff and engagement on social media platforms. It was found that people tend to overestimate their ability to commit to attending the gym, which results in them subscribing to packages that are not ideal to their own frequency of attendance. For example, members who have a monthly gym subscription may find it more beneficial to pay per visit (DellaVigna 2006). One proposed explanation for this behavior is that people tend to overestimate their ability to form new routines. Habit formation is a phenomenon that is closely studied in the fitness industry, and it is believed that if a member can commit to routinely going to the gym, then they are more likely to be retained in the long run (Oliveira 2018). Furthermore, behavior repetition is influenced by positive outcomes, such as satisfaction or financial incentives (Oliveira 2018, Royer et al. 2015). Client commitment can, also, be affected by one's inner motivations, such as finding joy or intrinsic value in going to the gym (Watts 2012). In addition, retention

is affected by social dynamics between gym goers and the staff whether it is face to face or on social media (García-Fernández et al. 2017, Watts 2012). It is, also, argued that perceived service quality, perceived value for money, brand and usage has an impact of the longevity of a customer's membership (Watts 2012). Keeping these facts in mind, gyms can tailor strategies and membership programs that can boost retention rates.

Customer retention in the fitness industry has been closely studied in terms of psychological perspectives, but these studies seldom incorporate machine learning algorithms (ML) as an assisting tool to predict gym membership churn, even though such tools can be of great help for both gyms and fitness related research. Churn prediction using artificial intelligence has been widely used across industries, and it is most popularly utilized in the telecom and banking sectors. Random forest and decision trees are two of the commonly used algorithms in those sectors (Prasad and Madhavi 2012, Ahmad et al. 2019). ML is also used in streaming services; Martins (2017) used recurrent artificial neural networks to predict churn. Furthermore, Viljanen (2018) utilized playtime to build survival analysis model to describe mobile game usage. Combining two different ML algorithms to derive a more robust model is a practice found in several studies; Lee et al. (2012) combined KNN and time series to predict churn in telecom, and Hassan and Mizra (2018) used Bayesian neural networks for prediction in the banking sector.

For predictive modeling in gyms two papers were found, one study, made use of the rich data that a university's fitness center collects from students' ID cards to construct three predictive models (namely, random forest, ARIMA and seasonal naive model) (Du et al. 2019). The purpose of those predictive models was to assist students on choosing the best time to visit the gym. Another study by Semrl and Matei (2017) employed "off-the-shelf" ML platforms, such as AzureML and BigML to evaluate if such platforms can be used by non-professionals to improve gym retention rates. Several machine learning algorithms were applied in that paper including neural networks.

The aim of this study is to build an artificial neural network (ANN) multilayer perceptron (MLP) using backpropagation, to predict gym membership churn. We based our feature selection on two methods: literature review and filtering method. To our knowledge, this paper is the first to include a thorough feature selection process to develop an efficient ANN model in predicting membership churn in fitness clubs.

2. Methodology

2.1 Data

In this paper, we use a proprietary dataset from a relatively new Saudi female gym chain. The dataset, of 809 records, contains details on subscriptions and visiting behavior of clients whose memberships were either expired or active. Memberships are manually renewed. So, if a customer does not renew after a month of expiry, they are considered churn, if, however, they resubscribe they are regarded as non-churn. Furthermore, upon renewal a member needs to choose one of three packages (Called: Active, Active+, Athlete) and specify a period until expiry of the package. The three packages differ in details of the services provided (Such as the maximum number of classes to attend in a week, number of consultations to have…etc.).

The time horizon of the extracted data is a year, from November 2019 to November 2020, and amid the COVID-19 pandemic, the gym closed its doors in March of 2020 and reopened in July 2020. During this period, all memberships were frozen and online classes were provided, most of them were for free. When the gym reopened, clients were given the option to reactivate their memberships. Thus, clients that did not unfreeze their memberships were dropped, for they cannot be considered churn nor non-churn. Lastly, the business manages customers' attendance and usage of the gym's facilities by relying on a reservation procedure, clients need to make reservations for any available service before attending the gym. This is done by using a mobile application, and upon arrival, they are signed in by the reception and by the trainer on online classes.

2.2 Feature Selection

Feature selection for predictive modeling has been studied thoroughly in literature (García et al. 2017). Customer relation management data, CRM, are generally used as features especially when studying abandonment in telecommunication and banking sectors (Ahmad et al. 2019, Hassan and Mizar 2018). Amount of time spent on a service is a feature that is included in prediction for businesses that rely on customer length of usage, such as mobile games, (Viljanen 2018) and phone calls (Sharma and Panigrahi 2011). For gym membership retention, the studies

found used timestamps of gym goers' ID cards. Along with that, Du et al. (2019) took student details such as college level and semester into account, and Semrl and Matei (2017) included CRM information such as age, contract, and payment history. Our feature selection process consists of two parts: review in the sports and psychology literature and filter method.

The gym chain, from which the data was taken, stores a variety of information about their staff, classes, clients, inventory…etc., this means that there is a large pool of features to select from. As a result, we based our data extraction on reviewed literature. Thus, from the earlier literature review, we extracted data that reflects habit formation, as it is an important factor in predicting retention (Oliveira 2018).

Table 1 illustrates the extracted features, their description and type. The dataset holds for each customer: total number of visits, number of absences, number of cancellation and number of months since a client joined, namely, "Total_Visits", "No_Shows", "Cancelled" and "Member_Since", respectively. Furthermore, we extracted membership information, such as type of membership, membership period until renewal, "Membership_Package" and "Membership_Period", respectively. A sample of the records before filtration is shown in Table 2.

Table 1. Extracted features

Feature	Description	Type
Total_Visits	Total number of times a member made and attended a reservation	Quantitative, discrete (Integer)
No_Shows	Total number of times a member made a reservation then did not show up	Quantitative, discrete (Integer)
Cancelled	Total Number of times a member made and cancelled a reservation	Quantitative, discrete (Integer)
Member_Since	Number of months since the member joined the gym	Quantitative, discrete (Integer)
Membership_Package	The type of package a member chooses when signing, which are three types: Active, Active+, Athlete	Qualitative, nominal (Text)
Membership_Period	Sign up period which is either 3 or 6 months	Qualitative, ordinal (Integer)
Status	Either 1 for churn or 0 for non-churn	Qualitative, ordinal (Binary)

Table 2. Sample of Records

Client ID	Total_Visits	No_Shows	Cancelled	Membership_Period	Member_Since	Membership_Package	Status
1	47	0	1	3	6	Athlete	0
2	58	5	0	6	9	Active+	1
3	23	2	2	6	12	Active	0

After extraction, we applied filter method to select the highest influential predictors. The features are all quantitative or ordinal except for "Membership_Package". Consequently, we used Spearman correlation to find associations among the quantitative features (With "Membership_Period" included since it is ordinal), then we calculated the association between those features and the target. If there exists strong association between certain features, we only take the highest correlated feature with the target as a representative and drop the rest. In addition, we used Cramer's V to find association between the nominal feature, namely "Membership_Package", and the target. Lastly, features that are *very weakly* correlated with the target were, also, dropped to achieve the highest performance metrics.

2.3 Proposed Model

Artificial neural network, ANN, is an algorithm that mimics learning process of the biological neural network in the human brain. ANN's are widely used in modern technologies, such as self-driving cars, image recognition and speech recognition.

ANN's possess a simplistic structure, they mainly consist of input layer, hidden layers, and output layer. Each layer contains nodes (also called neurons); the selected features are the nodes of the input layer, and the target is the node of the output layer. The hidden layer is where most of the learning happens in which the features go through a series of linear combinations and nonlinear transformations (called activation functions). The key to the model's learning is the weights of the linear combinations; an ANN is said to converge when the ideal weights are found in such a way that the model achieves acceptable to excellent performance metrics.

There are many types of artificial neural networks, and in our case, we utilize fully connected multilayer perceptron (MLP) with backpropagation (BP). Fully connected means that every weight in ANN is accounted for, and BP is a method used to find ideal weights by minimizing the model's loss function through updating weights in a reverse manner. Learning rate is a constant that determines the magnitude of change applied on weights while updating them, it is considered the most important element in finding the ideal weights (Géron 2019 and Goodfellow et al 2016).

While constructing a neural network, several training parameters need to be specified, such as the number of hidden layers, number of nodes each hidden layer consists of, learning rate, activation function, loss function and optimizer. Unfortunately, there is no general formula to use when specifying most training parameters (Géron 2019). Additionally, the literature on our given problem is limited. Thus, we tackled this issue by relying on two approaches; on what is generally practiced in the ANN field and on systematic experimentation.

Since there are many training parameters to fine-tune and experiment with, we made some of them fixed throughout the experimentation process to simplify, namely, the activation function, loss function and the optimizer. We set the activation function as ReLU, figure 1, since it is generally considered a good function to start with when building an ANN model (Géron 2019). Also, we used binary cross entropy as our loss function because our target is dichotomous (Chollet 2017). Lastly, our dataset is relatively small, 809 records, so we used Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimizer as it performs better for small datasets (Pedregosa 2011).

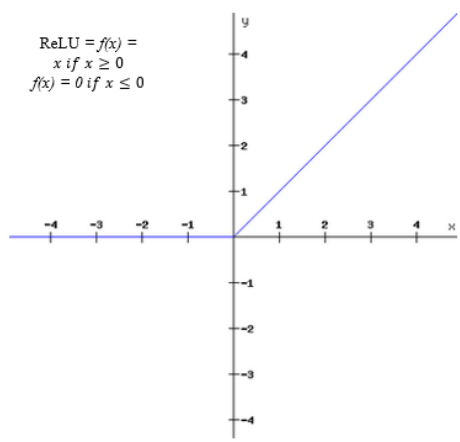

Figure 1. ReLU function

We extensively experimented with the hidden layers, their nodes, and the learning rate. For hidden layers, a single layer is usually enough "An MLP with just one hidden layer can theoretically model even the most complex functions,

provided enough neurons" (Géron 2019). However, to make sure this is the case for our problem, we began with a single hidden layer, and gradually increased the number until no difference in performance is exhibited. Once this happened, we decreased the number of the hidden layers to the best performing number of layers. For hidden nodes, we began with a very large number of nodes to achieve satisfactory results, then gradually decreased the number of neurons keeping in mind that the decrease does not negatively affect the performance metrics. We experimented with learning rate by using a small learning rate then increasing it gradually.

The filtering and model building procedures were done using Python 3.8.3 and Jupyter Notebook 6.0.3.

2.4 Model Performance Measures

To measure the validity of our model, we used 5-fold cross validation, and for each fold, the model's performance is measured using three metrics: accuracy, sensitivity, and specificity shown in equations (1), (2) and (3), respectively. Then the mean was taken for each metric. Accuracy is the overall rate of correct classifications, and even though it is the most used metric, it does not always convey the true performance of a model (Géron 2019). This is especially the case in binary classification problems. Therefore, we used the two other metrics to make sure that the model can differentiate between potential churn and non-churn memberships. This can further the reliability and validity of our model. Sensitivity is the rate of churns that are correctly classified, while specificity is the rate of correctly classified non-churn.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Number\ of\ all\ Predictions} \tag{1}$$

$$Sensitivity = \frac{Number\ of\ correct\ churn\ predictions}{Total\ number\ of\ churn} \tag{2}$$

$$Specificity = \frac{Number\ of\ correct\ nonchurn\ predictions}{Total\ number\ of\ nonchurn} \tag{3}$$

3. Results

In the filter step, we first explored correlations among features, then we moved to associations between features and target. In figure 2, the three features: "Paid Visits", 'Cancelled" and "No_Shows" were found to be strongly correlated, so one of them needs to be selected as a representative. For "Member_Since" and "Membership_Period", they were found to be weakly correlated with the other quantitative features and between each other. Furthermore, by examining correlations between features and target in figure 3, we see that "Total Visits" is the highest associated, -0.4196 followed by "Member_Since", "No_Shows", "Membership_Period", "Cancelled" and "Membership_Package. Hence, we selected "Paid Visits" as a representative feature for the group of strongly correlated features and dropped both "No_Shows", and "Cancelled". Furthermore, "Membership_Package" is dropped due to its *very* weak correlation with "Status", 0.1518. On the other hand, "Membership_Period" and "Member_Since" are weakly associated with "Status", 0.2684 and -0.3557, respectively, but were kept because they may possess information that would lead to better performance.

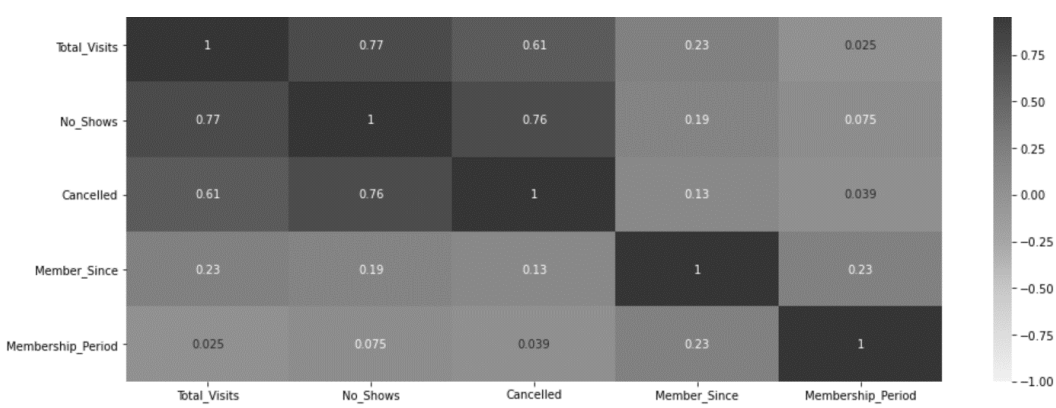

Figure 2. Correlations among features

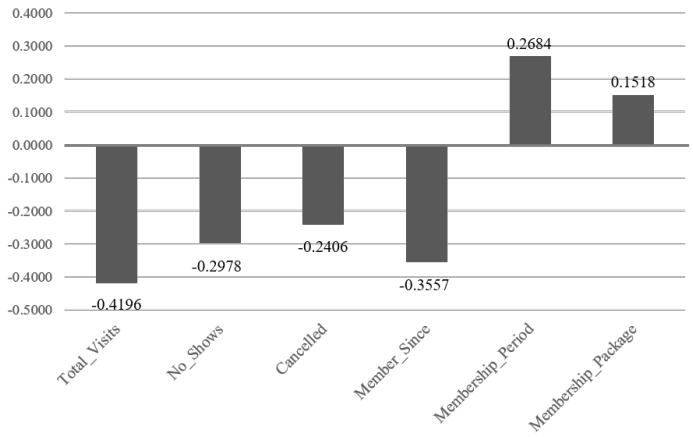

Figure 3. Correlations between features and status

To optimize the network's training parameters, we applied ANN multiple times and experimented with different number of hidden layers and neurons and learning rates until we reached to satisfactory metrics. The metrics were achieved by using a single hidden layer with 150 nodes. A visualization of the final model is shown in figure 4. The best learning rate found was 0.01, which had the greatest effect on the model. The prediction performance is found to be: 92.1%, 89.1% and 93.8% for accuracy, sensitivity, and specificity, respectively.

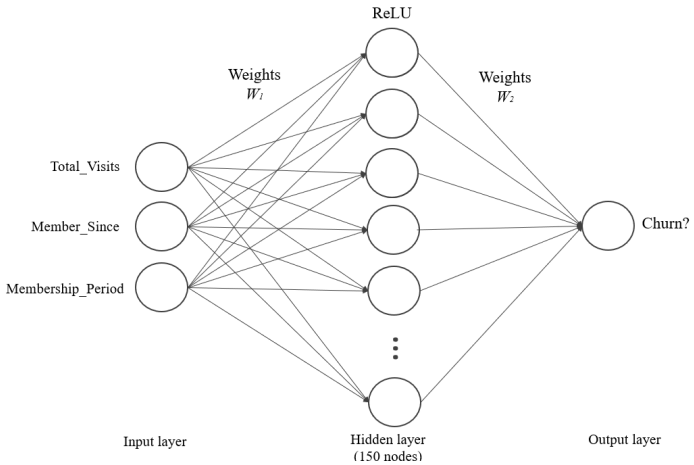

Figure 4. Visualization of the final model

4. Discussion

In the filtering method we found that there is a negative correlation between attendance and the tendency for members to churn. This agrees with the study that states that habit formation of going to the gym is vital for membership retention in the long run (Oliveira 2018), even with the global pandemic affecting the gym's business conduct. Furthermore, the model correctly predicted 92.1%, of the records, 89.1% of the churn records were correctly classified, and the model identified 93.8% of non-churn. These results are satisfactory, especially given the small dataset used. In addition, the accuracy of our model exceeded the accuracy of the best performing model in the study conduct by Semrl and Matei (2017), 74.6%. Furthermore, during the experimentation phase, the learning rate proved to be the most effective parameter in increasing the performance of our ANN model, and this agrees with literature in the ANN field.

5. Conclusion

This study proposes a tool for predicting churn in the fitness industry - artificial neural networks, which can be of benefit in constructing effective retention strategies. Features were extracted and selected by first relying on existing literature then by using filtering method. The type of ANN used was fully connected multilayer perceptron with backpropagation. Results report that by applying the psychological concept of habit formation then filtering redundant features, the model was able to attain good prediction performance with all metrics above 85%.

For future work, several directions can be taken in the cross section of machine learning and fitness industry. Some ideas include combining different algorithms to increase performance metrics or utilizing other available data to unveil different patterns in gyms to increase efficiency and revenue while decreasing churn.

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May Aldosary received undergraduate degree in mathematics from King Saud University, Saudi Arabia, and currently working towards graduate degree in engineering and systems management at Alfaisal University, Saudi Arabia. Main areas of interest are artificial intelligence, machine learning and deep learning.