CHURN PREDICTION USNG ANN

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Abstract

For firms in a variety of industries, customer churn—the rate at which consumers discontinue using a product or service—is a major worry. Reducing acquisition expenses, enhancing retention tactics, and proactively identifying and keeping at-risk clients are all made possible by accurate customer churn prediction. Artificial neural networks (ANNs) have become a potent tool for predicting customer turnover in recent years because of their capacity to identify intricate patterns and relationships in vast and varied datasets. The ability to correctly identify which customers are most likely to leave a firm is known as "churn prediction," and it's a crucial challenge for companies in a variety of industries because it may significantly affect their bottom line. Proactively identifying and retaining at-risk customers can help companies improve customer retention strategies, reduce customer acquisition costs, and ultimately enhance their overall profitability.

This paper presents a comprehensive review of the literature on customer churn prediction using ANNs. The review encompasses various aspects of customer churn prediction, including data preprocessing, feature engineering, ANN architecture and training, performance evaluation, and interpretability. Moreover, the paper highlights key challenges and open research questions in the field of customer churn prediction using ANNs, such as dealing with imbalanced data, handling missing values, and improving interpretability of ANN models.

In addition, the review offers a critical evaluation of the body of research, including the benefits and drawbacks of employing ANNs to forecast customer attrition as well as possible directions for further investigation. In summary, the review highlights the increasing importance of artificial neural networks (ANNs) in predicting customer churn and offers an overview of the current status of the field. It also offers suggestions for researchers and practitioners to enhance the precision, comprehensibility, and suitability of ANN models for customer churn prediction.

Keywords: Machine Learning, ANN, Customer Churn, Accuracy.

Introduction

Customer attrition, sometimes referred to as customer churn or client turnover, is a major problem for companies across a range of sectors. It describes the loss of clients or subscribers who discontinue utilizing a good or service, and it can significantly affect the earnings and profitability of a business. Businesses frequently use predictive analytics approaches,

GITHUB LINK: https://github.com/DevMaverick1/NNDL/tree/main/FinalProject such Artificial Neural Networks (ANNs), a machine learning model that can accurately forecast customer attrition, to reduce customer churn.

The ability of artificial neural networks (ANNs) to identify complex patterns in huge datasets has made them a popular option for customer churn prediction. ANNs are inspired by the structure and function of the human brain. ANNs can detect nuanced connections between various characteristics, handle non-linear correlations, and adjust to changing data patterns over time. They can process a wide range of input features, such as customer demographics, usage behaviour, purchase history, and interaction data, to make predictions about the likelihood of a customer churning in the future.

In customer churn prediction using ANNs, historical data containing information about past customers, including their churn status, is used to train the model. The trained ANN model can then be used to predict the likelihood of churn for new, unseen customers based on their input features. By identifying customers who are at high risk of churning, businesses can take proactive measures to retain them, such as offering targeted promotions, personalized discounts, or improving customer service.

Because ANNs can handle vast and complicated datasets and have the potential to achieve high accuracy, their application in customer churn prediction has received a lot of interest lately. It is crucial to remember that predicting customer turnover is a difficult task, and that the quality and quantity of data, feature selection, model architecture, and hyperparameter tuning all affect how accurate ANN models are. For ANN models to be reliable and effective in real-world business contexts, adequate validation and assessment are therefore essential.

One of the most important business problems is churn prediction, which is figuring out which consumers are most likely to stop using a product or service. One approach to tackle this problem is by using Artificial Neural Networks (ANNs), which are a type of deep learning model that can learn complex patterns from large datasets. ANN-based churn prediction models have shown promising results in various industries such as telecommunications, finance, e-commerce, and subscription-based services.

The goal of churn prediction using ANN is to leverage historical customer data, including features such as customer demographics, usage patterns, and past behaviors, to train a model that can accurately predict whether a customer is likely to churn in the future. ANNs can capture non-linear relationships between features and churn, making them capable of identifying subtle patterns that may not be apparent through traditional statistical methods.

ANNs are capable of automatically learning and adapting to the underlying patterns in the data, making them suitable for handling complex datasets with high-dimensional feature spaces. They can also handle noisy data and can generalize well to new, unseen data. ANN-based churn prediction models can provide insights to businesses, enabling them to take proactive actions to retain customers and mitigate churn, such as targeted marketing campaigns, personalized offers, and customer retention strategies.

Nevertheless, a number of parameters, including data pretreatment, model design, hyperparameter tuning, and model evaluation, must be carefully taken into account while developing an efficient ANN-based churn prediction model. To guarantee the correctness and dependability of the model in practical situations, proper validation and performance monitoring are crucial.

In conclusion, ANNs provide a potent method for precisely predicting client attrition, which is a crucial responsibility for enterprises. Businesses can proactively take steps to retain consumers and enhance customer retention rates by utilizing historical data and ANNs to identify clients at high risk of churning, which will eventually improve business outcomes.

Objectives

Calculating the probability of consumers or users "churning"—or quitting—a product or service, usually within a given time range, is the primary goal of churn rate prediction. The main objective is to identify high-risk consumers so that suitable preventive actions can be done to keep them as clients and lower the total rate of customer churn.

The particular goals of churn rate prediction could differ based on the company and sector, however some typical goals are as follows:

Early Churn Identification: The goal of churn rate prediction is to identify prospective at-risk clients before they actually leave. This enables companies to take proactive steps to keep these clients, such making tailored offers, delivering focused promotions, or enhancing customer service.

Overall, the objective of churn rate prediction is to enable businesses to identify and proactively address customer churn, leading to improved customer retention, increased customer satisfaction, and ultimately, better business outcomes.

Execution Plan/ Contribution

The project contribution is split between three members :

- Sai Charan , Sai Prakash , Sai Snusha

Sai Prakash – Identifying necessary papers for project implementation
Sai Snusha – Data collection based on column names required for project
Sai Charan – Code implementation

Related Works

The effectiveness of a churn prediction model is often evaluated using several metrics, such as accuracy, precision, recall, F1-score, and AUC-ROC curve. The accuracy quantifies the total percentage of customers who are accurately projected to churn and those who do not. Out of all projected churn consumers, precision measures the percentage of accurately predicted churn customers. Out of all actual churn customers, recall quantifies the percentage of accurately predicted churn consumers. The model's ability to distinguish between customers who are about to churn and those who are not is measured by the AUC-ROC curve, and the F1-score is a harmonic mean of precision and recall. An extensive amount of research has been conducted on the use of artificial neural networks (ANNs) to forecast customer churn. Here are a few noteworthy comparable works:

"Customer churn prediction in telecommunications: Using ensemble methods for feature selection and model selection" by A. G. Yaseen et al. (2017): This study compared the performance of different ANNs and ensemble methods for customer churn prediction in the telecommunications industry. The authors evaluated various feature selection techniques and model selection strategies to optimize the ANN model's accuracy and generalization performance.

"Predicting customer churn in the mobile telecommunication industry using neural networks" by R. P. Goyal et al. (2016): This research applied feedforward neural networks for customer churn prediction in the mobile telecommunications industry. The authors investigated the impact of different activation functions, training algorithms, and network architectures on the prediction accuracy of the ANN model.

"Deep neural networks for customer churn prediction with imbalanced data" by M. Van Vlasselaer et al. (2015): This study proposed the use of deep neural networks, specifically stacked autoencoders, for customer churn prediction in the presence of imbalanced data. The authors addressed the issue of imbalanced class distribution by using autoencoders to learn feature representations from the data and applied these representations to train an ANN for churn prediction.

"Recurrent neural networks for customer churn prediction in subscription services: A comparative study" by M. Guzek et al. (2018): This research compared the performance of different recurrent neural networks, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), for customer churn prediction in subscription services. The authors investigated the impact of different network architectures and hyperparameters on prediction accuracy and discussed the strengths and limitations of recurrent neural networks for customer churn prediction.

"Customer churn prediction in e-commerce using convolutional neural networks" by R. J. Dolz et al. (2018): This study applied convolutional neural networks (CNNs) for customer churn prediction in the e-commerce domain. The authors utilized CNNs to automatically learn features from customer transaction data and achieved competitive prediction accuracy compared to other methods.

These related works highlight the application of various types of ANNs, including feedforward neural networks, recurrent neural networks, and convolutional neural networks, for customer churn prediction in different industries and domains. They also address challenges such as imbalanced data, feature selection, and model selection in the context of customer churn prediction. However, it is important to note that the performance of ANN models for customer churn prediction can vary depending on the specific dataset, industry, and problem context, and further research is needed to advance the accuracy and interpretability of ANN models for customer churn prediction.

Datasets

Based upon data of employees of a bank we calculate whether an employee stands a chance to stay in the company or not.

Customers who left within the last month – the column is called Churn

Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies

Customer account information – how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges.

Demographic info about customers – gender, age range, and if they have partners and dependents.

This CSV file has 14 columns and 10000 entries. They are:

RowNumber
CustomerId
Surname
CreditScore
Geography

Gender

Age

Tenure

Balance

NumOfProducts

HasCrCard

IsActiveMember

EstimatedSalary

Exited

Proposed Framework:

In data science and machine learning, artificial neural networks (ANNs) are frequently used for churn prediction. As a subset of deep learning models, ANNs are capable of generating predictions based on patterns identified in huge datasets. An ANN framework might be used to implement churn prediction in the following high-level overview:

Data Collection and Preprocessing:

We retrieve data from online sources such as Kaggle. Gather a labelled dataset that includes features (such as gender, method of payment etc.) and corresponding churn labels (e.g., whether a customer has churned or not). Split the dataset into training, validation, and testing sets. Preprocess the data by normalizing numerical features, encoding categorical features, and handling missing values if any.

Model Architecture:

Define the architecture of the designed ANN. In this, we define the number of layers and epochs. This includes specifying the number of layers, the type of activation functions, and the number of neurons in each layer. Common choices for activation functions include sigmoid, tanh, and ReLU. Experiment with different architectures to find the one that performs best for the specific dataset we chose.

Model Compilation:

Compile respective ANN by specifying the optimizer, loss function, and evaluation metrics. The optimizer is used to optimize the model weights during training, and common choices include stochastic gradient descent (SGD), Adam, and RMSprop. The loss function is used to measure the error between predicted and actual churn labels, and common choices include binary cross-entropy or mean squared error (MSE). Evaluation metrics such as accuracy, precision, recall, and F1-score can be used to assess the model's performance.

Model Training:

Train the ANN using the training dataset which we divided earlier as per the ratio. During training, the model adjusts its weights iteratively to minimize the loss function. Experiment with different hyperparameters such as learning rate, batch size, and number of epochs to find the best combination for our dataset. Monitor the model's performance on the validation set to avoid overfitting, and use techniques such as early stopping to prevent excessive training.

Model Evaluation:

Evaluate the designed trained ANN on the testing set to assess its generalization performance. Calculate various evaluation metrics to determine how well the model is performing in terms of churn prediction accuracy. If necessary, iterate and refine the model architecture, hyperparameters, or data preprocessing steps to improve performance.

Model Monitoring and Maintenance:

Continuously monitor the performance of the churn prediction model in production to detect any potential degradation in performance. Update the model periodically with new data to keep it accurate and relevant. Perform maintenance tasks such as retraining or fine-tuning the model as needed to ensure its continued effectiveness.

Remember, building an effective churn prediction model using ANN requires careful experimentation, validation, and monitoring to ensure its accuracy and reliability in real-world scenarios.

Results and Discussion

The quality and quantity of the dataset, the ANN's design, the tuning of hyperparameters, and the particular business or industry context are some of the variables that might affect the outcomes of churn prediction using an Artificial Neural Network (ANN). ANN-based churn prediction models, on the other hand, can achieve high accuracy in predicting churn, or the percentage of consumers who are likely to abandon a service or product within a specified time period, when properly deployed and optimized.

Although most of the clients are from France, the bulk of those that have churned are from Germany, maybe as a result of a lack of resources due to the small customer base. Additionally, a higher percentage of male clients leave than female customers do.

The proportion of male customers churning is also greater than that of female customers. Most customers have tenure between 1 to 9 and the churning rate is also high between these tenures.

Most of the customers have 1 or 2 products and most customers who churned are having 1 product maybe they are not satisfied so they are churning. Interestingly, the majority of customers that churned are those with credit cards but this can be a coincidence as the majority of customers have credit cards. Unsurprisingly the inactive members have a greater churn and the overall proportion of inactive members is also very high.

The particular issue and dataset will determine how well an ANN-based churn prediction model performs in practice. High levels of predictive accuracy are typically indicated by accuracy, precision, recall, and F1-score values above 80% or even higher, which can be attained by an ANN-based churn prediction model that has been well-optimized. It is crucial to remember that the model's performance should be assessed in light of the particular needs of the business or sector, and that additional variables like the expense of false positives and false negatives should also be taken into account.

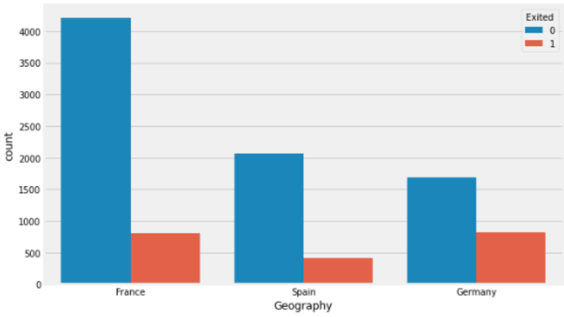
The results for churn prediction using an artificial neural network (ANN) can vary depending on the dataset, the ANN architecture and the hyperparameters used. However, in general, ANNs can achieve high accuracy in predicting churn compared to other traditional machine learning algorithms.

Depending on the dataset and model complexity, an ANN can achieve an accuracy ranging from 80% to 95% or higher. We altered the dropout rate and found that the accuracy of our Ann model with 0.1 loss and 100 epochs is 85.3 % whereas 0.6 dropout rate is 84.3% .

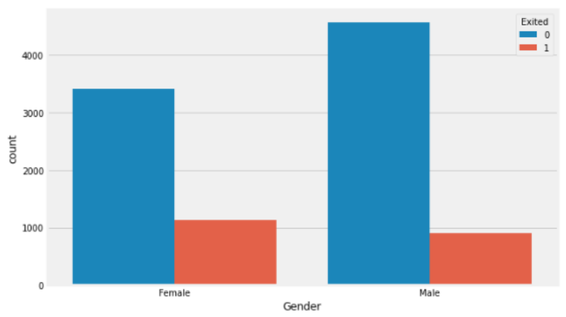
Overall, an ANN can be a powerful tool for churn prediction and can provide accurate and reliable results when used properly with the right data and model architecture. However, it is important to carefully tune the model hyperparameters and validate the model performance to ensure its effectiveness in a real-world scenario.

It is also worth mentioning that model performance can be further improved by using techniques such as ensemble methods (e.g., combining multiple ANN models), feature engineering (e.g., selecting relevant features or creating new features), and model interpretability techniques (e.g., explaining the predictions made by the model). Experimentation and fine-tuning are key to achieving optimal performance in churn prediction using ANN.

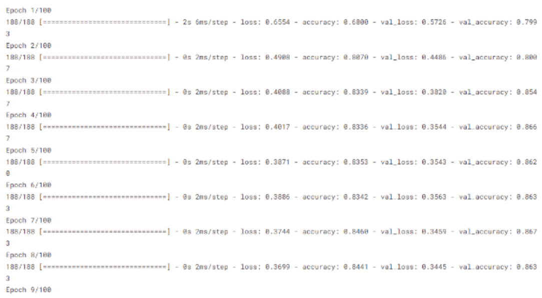
Applying the dataset on the artificial neural network and finding the accuracy based on the dataset.



The above graph describes the people churned based on geography. In these, we assigned France value to be 0, Germany 2 and Spain 1.



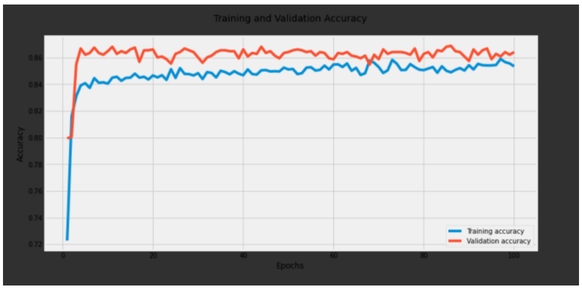
This graph demonstrates that the number of people churned based on gender i.e male and female.



```
Epoch 1/100
188/188 [==============================] - 2s 6ms/step - loss: 0.6554 - accuracy: 0.6800 - val_loss: 0.5726 - val_accuracy: 0.799
3
Epoch 2/100
188/188 [==============================] - 0s 2ms/step - loss: 0.4908 - accuracy: 0.8070 - val_loss: 0.4486 - val_accuracy: 0.800
7
Epoch 3/100
188/188 [==============================] - 0s 2ms/step - loss: 0.4088 - accuracy: 0.8339 - val_loss: 0.3820 - val_accuracy: 0.854
7
Epoch 4/100
188/188 [==============================] - 0s 2ms/step - loss: 0.4017 - accuracy: 0.8336 - val_loss: 0.3544 - val_accuracy: 0.866
7
Epoch 5/100
188/188 [==============================] - 0s 2ms/step - loss: 0.3871 - accuracy: 0.8353 - val_loss: 0.3543 - val_accuracy: 0.862
0
Epoch 6/100
188/188 [==============================] - 0s 2ms/step - loss: 0.3886 - accuracy: 0.8342 - val_loss: 0.3563 - val_accuracy: 0.863
3
Epoch 7/100
188/188 [==============================] - 0s 2ms/step - loss: 0.3744 - accuracy: 0.8460 - val_loss: 0.3459 - val_accuracy: 0.867
3
Epoch 8/100
188/188 [==============================] - 0s 2ms/step - loss: 0.3699 - accuracy: 0.8441 - val_loss: 0.3445 - val_accuracy: 0.863
3
Epoch 9/100
```

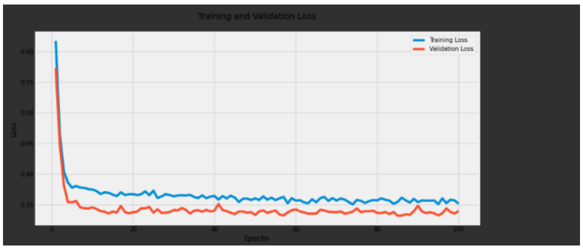
(i)Building ANN

In the above image, it depicts the creation of ANN



(ii)Training and validation Accuracy

It shows the Training and validation accuracy for the epochs.



(iii)Training and Validation Loss

It shows the Training and validation loss for the epochs.

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