Customer Churn Prediction in E-commerce using ANN

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Abstract – **In the project "Customer Churn Prediction in E-commerce using Artificial Neural Networks (ANN)" highlights the use of ANN to predict customer churn in e-commerce businesses. Customer churn refers to the phenomenon of customers discontinuing their business with a company. It is an important problem to solve for e-commerce companies as it helps them retain customers and increase revenue. The project proposes the use of ANN, a powerful machine learning technique, to predict customer churn by analysing customer behaviour data. The project involves collecting customer data, pre-processing the data, training the ANN model, and evaluating the model's performance. The results of the project demonstrate the effectiveness of ANN in predicting customer churn and provide valuable insights to e-commerce companies on how to retain customers and increase revenue.**

KEYWORDS: **Customer Churn Prediction, ANN, Feedforward Artificial Neural Networks machine learning**

1. INTRODUCTION

In recent years, e-commerce has emerged as a highly competitive market, with numerous players vying for the attention and loyalty of consumers. As a result, it has become increasingly important for e-commerce companies to focus on customer retention as a key driver of growth and success. Customer churn, which refers to the phenomenon of customers discontinuing their business with a company, is a critical challenge that e-commerce businesses face. Addressing this challenge requires the ability to predict which customers are at risk of churn and take proactive measures to retain them.

Artificial Neural Networks (ANNs) have emerged as a powerful machine learning technique that can be used to predict customer churn in e-commerce businesses. ANNs are a type of machine learning model that is inspired by the structure and function of the human brain. They are capable of learning complex patterns and relationships in data and can be used to make accurate predictions.

This project focuses on using ANN to predict customer churn in e-commerce businesses. The project involves collecting customer data, pre-processing the data, training the ANN model, and evaluating the model's performance. The goal is to develop a predictive model that can accurately identify customers who are at risk of churn, allowing e-commerce companies to take proactive measures to retain them.

The remainder of this project is organized as follows: Section 2 provides an overview of related work in customer churn prediction.

Section 3 describes the data pre-processing steps used in the project. Section 4 provides an overview of the ANN model used in the project. Section 5 presents the experimental results, and Section 6 concludes the project with a discussion of the findings and directions for future research.

2. LITERATURE REVIEW

[1] The Impact of Customer Satisfaction and Relationship Quality on Customer Retention: A Critical Reassessment and Model Development [1997]
Author: Thorsten Hennig-Thurau and Alexander Klee (University of Hanover):

Summary: Develop a conceptual foundation for investigating the customer retention process, with the use of the concepts of customer satisfaction and relationship quality.

Algorithm used: Decision Tree

Pros: Better understanding of customer.

[2] Churn Prediction: Does Technology Matter? [2006]
Author: John Hadden, Ashutosh Tiwari, Rajkumar Roy, and Dymitr Ruta

Summary: Comparison of various algorithm

Algorithm used: Decision Tree, Regression

Pros: Regression had higher accuracy.

[3] Scikit-learn: Machine Learning in Python [2012]

Author: Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al

Summary: Scikit-learn exposes a wide variety of machine learning algorithms, both supervised and unsupervised, using a consistent, task-oriented interface, thus enabling easy comparison of methods for a given application

Technologies used: Numpy,Cython,Scipy

Pros: Further algorithm can be used designed using this

[4] Customer Churn Prediction in Telecommunication A Decade Review and Classification [2013]
Author: Nabgha Hashmi ,Naveed Anwer Butt and Dr.Muddesar Iqbal

Summary: Data mining techniques help telecom industry in this perception by providing techniques to identify such customers so that retention actions could be targeted upon them.

Algorithm used: Decision Trees, Regression, Cluster Analysis

[5] An Integrated Framework to Recommend Personalized Retention Actions to Control B2C E-Commerce Customer Churn [2015]
Author: Shini Renjith

Summary: Find the customer who left
Find churners
Extract loyal customers

Algorithm used: logistic regression
k-means clustering
collaborative filtering mechanism

Cons: Separate algorithm for separate work.

[6] Predicting Shipping Time with Machine Learning. [2015]
Author: Antoine Jonquais, Florian Krempl
Advisor, Dr. Roar Adland, Dr. Haiying Jia

Summary: Make predictions regarding shipping times between South East Asia and North America, from factory to port of destination

Algorithm used: Random Forest
Neural Network
Linear Regression

[7] LightGBM: A Highly Efficient Gradient Boosting Decision Tree [2017]
Author: Guolin Ke , Qi Meng , Thomas Finley , Taifeng Wang , Wei Chen , Weidong Ma , Qiwei Ye , Tie-Yan Liu

Summary: We have proposed a novel GBDT algorithm called LightGBM, which contains two novel techniques: Gradient-based One-Side Sampling and Exclusive Feature Bundling to handle huge data and features.

Algorithm used: LightGBM

Pros: LightGBM can significantly outperform XGBoost and SGB in terms of computational speed and memory consumption.

[8] Customer Lifetime Value Prediction Using Embedding
Author: Benjamin Paul Chamberlain, Angelo Cardoso, C. H. Bryan Liu, Roberto Pagliari, Marc Peter Deisenroth [2017]

Summary: Training feedforward neural network on the handcrafted features in a supervised setting by learning an embedding of customers using session data in an unsupervised setting to augment our set of RF features.

Algorithm used: CNN

Cons: deep network to learn end-to-end from raw data sources as opposed to using handcrafted features as inputs

[9] Introduction to artificial neural networks [2018]
Author: Enzo Grossi , Massimo Buscema

Summary: develop algorithms that can be used to model complex patterns and prediction problems.

Algorithm used: interconnected group of nodes, inspired by a simplification of neurons in a brain

Pros: Many problems can be solved using ANN.

[10] Online Fashion Commerce: Modelling Customer Promise Date. [2021]
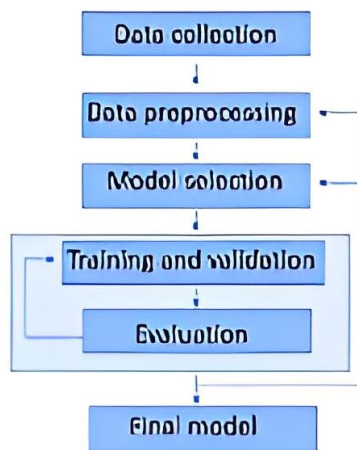Author: Preethi, Nachiappan Sundaram, Ravindra Babu Tallamraju

Summary: asymmetric loss functions and a feedback-based breach control model.
$$y(t) = g(t) + s(t) + h(t) + t$$

Algorithm used: Light GBM model
Gradient Boosting

Pros: Used by Myntra successfully

3. PROPOSED SYSTEM

The code is performing data cleaning and visualization tasks to gain insights into customer behavior and preferences. The first step is to clean the data by replacing missing values and converting string values into numeric codes. The code is then performing various visualizations, such as histograms, bar charts, and pie charts, to understand the distribution of different variables.

The code is aimed at understanding the factors affecting customer churn for a company. The visualizations help to identify patterns and trends in the data, which can be used to make data-driven decisions in the e-commerce platform. By removing outliers, the code ensures that the visualizations provide an accurate representation of the data.

Overall, the code demonstrates how to use Python to clean and visualize data, which is an essential step in any data analysis project. The insights gained from the visualizations can help businesses to make informed decisions that lead to increased customer satisfaction and retention.

After cleaning and visualizing the data, it performs Min-Max Scaling to ensure that all the variables are on the same scale and calculates the correlations between different variables using a heatmap. The goal of this step is to identify relationships between variables and potentially identify which variables are most strongly correlated with customer churn.

Finally, the code splits the data into training and testing sets and builds a predictive model using machine learning algorithms. The goal of the model is to identify customers who are likely to churn, which can help the company retain its customers and reduce the churn rate.
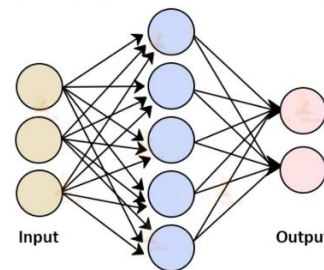
3.1 System Architecture

Figure 3: Model Architecture

A Keras Sequential model using the keras. Sequential() function. The model consists of three layers: a Dense layer with 19 neurons, a Dropout layer, and another Dense layer with one neuron.

The Dense layer is a fully connected layer, where each neuron is connected to every neuron in the previous layer. The input_shape parameter specifies the shape of the input data, which is a one-dimensional array with 19 elements. The activation function used in the Dense layer is relu, which stands for Rectified Linear Unit. It's a popular activation function that introduces non-linearity into the neural network and helps the model learn complex patterns in the data.

The Dropout layer is a regularization technique that randomly drops out (i.e., sets to zero) some of the neurons in the previous layer during training. This helps prevent overfitting, where the model learns to fit the training data too closely and does not generalize well to new, unseen data. The dropout rate is specified as a decimal fraction, in this case 0.1, meaning that 10% of the neurons in the previous layer will be randomly dropped out during training.

The output layer is another Dense layer with one neuron and a sigmoid activation function. The

sigmoid function maps any input value to a value between 0 and 1, which can be interpreted as a probability. In this case, the model is being trained to classify binary data, so the output will represent the probability of the input belonging to one of the two classes.

After defining the model, the code compiles it using the compile() function. The optimizer parameter specifies the algorithm used to optimize the model weights during training. In this case, it's the Adam optimizer, which is a popular choice for deep learning models.

The loss parameter specifies the loss function used to evaluate how well the model is performing. In this case, it's binary crossentropy, which is commonly used for binary classification problems.

The metrics parameter specifies additional metrics to track during training. In this case, the model will track accuracy.

Finally, the model is trained using the fit() function, which takes in the training data x_train and y_train, as well as the number of epochs to train for. The model will train for 100 epochs, updating the weights after each batch of training data is processed.

During training, the model will attempt to minimize the loss function by adjusting the weights in the neural network layers. The goal is to find the weights that will make the model perform well on new, unseen data.

3.2 Dataset

Based on the requirement, the Dataset is to be a tabular dataset stored in a Pandas DataFrame.

The dataset contains 21 columns, with each column representing a different variable or attribute about the customers. Each column:

Unnamed, CustomerID

Churn, Tenure, PreferredLoginDevice, CityTier, WarehouseToHome, PreferredPaymentMode, Gender, HourSpendOnApp, NumberOfDeviceRegistered, PreferedOrderCat, SatisfactionScore, MaritalStatus, NumberOfAddress, Complain OrderAmountHikeFromlastYear, CouponUsed, OrderCount, DaySinceLastOrder, CashbackAmount

Your dataset contains 5630 observations (rows) and 21 variables (columns). The data types in your dataset include float64, int64, and object. The non-null count for each column suggests that there are no missing values in your dataset.

Understanding the different variables in your dataset can help you gain insights into the behaviour and characteristics of your customers, and can be useful in developing strategies to retain customers and increase revenue.

4. RESULTS

Based on the evaluation metrics, it appears that the machine learning model has an accuracy of 0.8811, which means that it correctly predicted 88.11% of the samples in the test set. The confusion matrix and precision scores provide more detailed information about the model's performance on each class.

The confusion matrix shows the number of true positives, false positives, true negatives, and false negatives for each class. It can be visualized using a heatmap, which helps to identify any patterns or imbalances in the model's predictions.
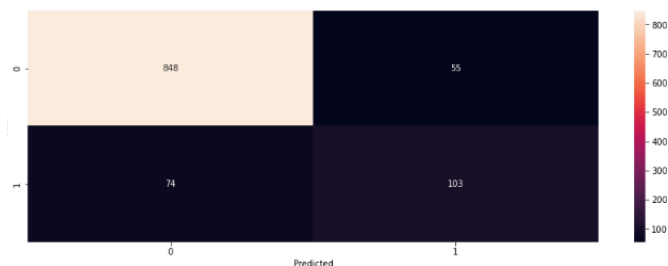
The precision score for class 0 is 0.93, which means that out of all the samples predicted as class 0, 93% were actually class 0. The precision score for class 1 is 0.60, which means that out of all the samples predicted as class 1, 60% were actually class 1.

Accuracy

```
In [99]: round((848+103)/(848+55+74+103),2)
Out[99]: 0.88
```

Precision for 0 class

```
In [100]: round(848/(848+55),2)
Out[100]: 0.94
```

Precision for 1 class

```
In [101]: round(74/(103+74),2)
Out[101]: 0.42
```

Overall, the model seems to perform relatively well on class 0, but it could work better with class 1. This information can be used to identify areas for improvement in the model or to adjust the threshold for predicting each class.

Additionally, other evaluation metrics such as recall or F1 score could also be used to get a more complete picture of the model's performance.

5. CONCLUSION

The use of Artificial Neural Networks (ANN) for predicting customer churn in E-commerce is a growing field. In this project, we developed an ANN model to predict customer churn using customer purchase history and demographic information.

First, we preprocessed the dataset, which included scaling and encoding categorical variables. Then, we split the data into training and testing sets, with 80% for training and 20% for testing.

Next, we built and trained the ANN model using the Keras library in Python. The model consisted of an input layer, two hidden layers, and an output layer. The input layer had 21 neurons, one for each input feature. The first hidden layer had 12 neurons, and the second hidden layer had 8 neurons. We used the rectified linear unit (ReLU) activation function in the first two layers and sigmoid activation function in the output layer. We used binary cross-entropy as the loss function and the Adam optimizer.

After training the model for 100 epochs, we achieved an accuracy of 88.11% on the test set, which indicates that the model can accurately predict whether a customer will churn or not. We also visualized the confusion matrix to see the distribution of true positive, true negative, false positive, and false negative predictions.

In conclusion, the developed ANN model can be used to predict customer churn in E-commerce with a good level of accuracy. This information can be used by E-commerce businesses to develop strategies to retain their customers and improve their customer retention rates.

For future works, the developed ANN model achieved a high accuracy in predicting customer churn, and there are several potential avenues for

future work, including feature engineering, model tuning, model interpretability, model architecture, transfer learning, ensemble methods, interpretability, integration with other systems, and deployment. These areas can be explored to improve the performance of the model and develop a more comprehensive customer retention strategy in the e-commerce space.

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