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Neural Network-Based Customer Behavior Modeling for Dynamic Conversion Funnel Optimization in Digital Retail

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ABSTRACT

The need to increase conversion of traffic in using the different platforms and touching points from the digital retail environment cannot be over emphasized. Some of the conventional status that are generally utilized in conversion optimization fail to capture the intricate and dynamic paths made by customers in their engagement with Internet shops. In order to capture this dynamic behavior of the customers in the conversion funnel, this paper presents a novel method based on neural networks. Besides, by using Artificial Neural Networks (ANNs) for the machine learning process, this model makes real-time predictions of the customer activity and reveals proper key moments for retailers to influence the customer's decision-making process to optimize customer experience. These findings show that the application of the neural network model improves the accuracy of the representations of the customer behavior to allow for the provision of the best conversion strategies that increase sales productivity.

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Introduction

In digital retail the customer conversion process is the path of a potential buyer from the first time he meets a certain brand to the moment he checks out. It is one of the most important concepts when coming to decide over the strategies for increasing e-business sales. However, commonly used conversion optimization models rarely incorporate active and complex multiple behaviors of the clients that result in the inefficiency in both targeting and decision.

Neural networks are quite an attractive solution for modeling customer behavior in a more detailed and precise approach as compared to the traditional methods. Using big data, neural networks can depict customer profiles and forecast future behavior in the funnel: when a customer may leave or rekindle interest, and what he is likely to convert into. This predictive capability enables digital retailers to regularly refine their strategies, before new trends set in and the previously effective approaches revert to being suboptimal [1].

Previous methodologies such as conventional demand models that give assumptions on relatively fixed static states or even linear progression do not adequately address the multidimensional paths traveled by customers. Still, compared to them neural networks are capable of recognizing non-linear patterns and changing the forecast based on the amount of collected data. The flexibility of these techniques enables understanding of the accuracy of creating much higher conversion rates and customer experience enhancements over time.

This paper proposes a neural network approach to modeling customer interactions based on the conversion funnel in digital retail and its ability to enable dynamic tuning of the strategies. Machine learning provides retailers with an improved understanding of viewers' behaviors and empowers them to deliver better customer experience and drive the growth of conversion rates. The paper also provides an analysis of the Empirical results and case studies that show the effectiveness of the proposed neural network framework as compared to the conventional methods.

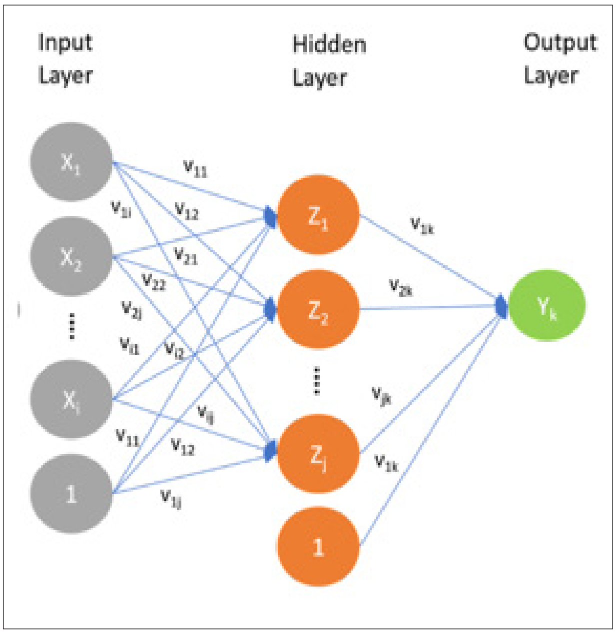

Figure 1: Neural Network Architecture for Customer Behavior Modeling [1].

Literature Review

Conventional Method of Conversion Funnel Management

The rationale of improving the conversion funnel has been in place for a long time, but the use of innovative tools with previous work has largely focused on simple statistical models, A/B and heuristic testing to isolate problems in the path that a customer takes. Most of the time, these techniques are used to optimize certain stages of the funnel, it may concern landing pages, cart abandonment, or a check-out process, decisions are made based on historical data, experience and direct testing of the changes. For example, while A/B testing allows marketers to work with two different versions of a webpage or an ad to see which one will attract more conversions [2].

Nonetheless, the application of traditional approaches has a number of drawbacks. For the most part they attempt to segment the customer experience process into discrete stages, thus masking the greatly interconnected and cyclical nature of a customer's decision-making process. For instance, the client's decision to leave the shopping cart and order something else is not triggered by product price or availability alone. Non-components like the ease of navigation on websites, or whether discounts are available, or the types of payment accepted for the goods, or other factors like availability of promotions from the competitor or some other factors are usually not considered. Therefore, traditional techniques give only a restricted perspective of such complex behaviors, and this can lead to the generally poor funnel optimization.

Machine Learning and Neural Network in Customer Behavior Modeling

Discovery and innovation in machine learning especially using artificial neural network (ANN) has improve the performance of modelling complicated customer's behavior especially in digital retail. Unsupervised learning algorithms such as ANN can easily iron out complex relational ways and more so due to the dynamic and nonlinear nature of the ways customers engage with brands through multiple touch points. In contrast to conventional techniques, whereas ANNs are not based on Training sets of a priori assumptions or linear approximations, but from training data – and that distinguishes them to detect alterations in client behavior through time [3].

Using conversion funnel optimization, neural networks can also work with diverse types of data, including web analytics data, social media engagement data, and purchase history, to identify and forecast customers' behavior at each stage of funnel. This approach offers a broader and realistic perspective of customers' behaviors, thus enhancing the ability of digitals retailers in terms of determining the points of abandonment, and recognizing the most valuable customers and coming up with the right mechanism of boosting the rates of conversion.

Table 1: Comparison of Traditional and Neural Network Approaches for Conversion Funnel Optimization

Techniques	Strength	Limitations
Traditional Methods	Simple Interpretable	Poor Performance with non-linear data
Neural Network	Captures complex patterns	Large datasets, less interpretable

Dynamic Funnel Optimization with the Use of Machine Learning

Some of the factors that characterize the customer behavior in the digital retail environment are dynamic and hence, the needed optimization models have to be dynamic. Old world models which work well when applied to more structured analysis of the customer touch points can falter here because of the dynamic nature. The improvement in this aspect is best provided by machine learning algorithms such as recurrent neural network (RNN), Long Short-Term Memory (LSTM). These models are intended to work with sequential data to make them applicable for handling time series data found in customers interactions and purchase behavior over time.

RNNs and LSTMs can then observe the next course of action to be taken based on past information, so as to help digital retailers adjust funnel strategies in real time. For instance, with the help of RNNs, online stores can define a client's propensity to leave a cart after previous actions and make instant actions such as the delivery of a request to leave a reminder e-mail or an offer. Further, reinforcement learning approaches can be exploited in order to fine tune the funnel strategies according to the real time information and external environment conditions such as seasonal characteristics or alterations to the marketing plans. This makes it easier to manage the funnel proactively, enhance the conversion rates as well as making sure that customers are retained [4].

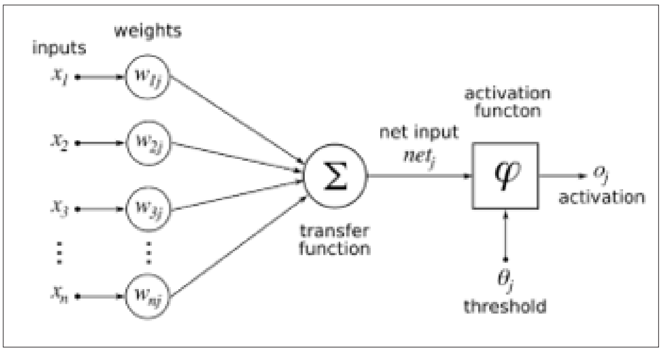

Figure 2: Neural Network Architecture for Dynamic Conversion Funnel Optimization [5].

Methodology

Data Collection and Preprocessing

- The neural network-based framework for customer behavior modeling and dynamic conversion funnel optimization in digital retail. It was possible to obtain these datasets which gave a set of features describing the customer interactions and characteristics of the environment affecting the conversion process. The data was categorized into four primary groups
- **Customer Demographics:** This includes for instance the age, sex and geographic location of a customer, past consumption patterns etc. They assist to divide customers and comprehend some factors as to their conversion potential, which vary among the groups of buyers.
- **Behavioral Data:** This group encompasses information received about the customer interactions with the platform in terms of pages visited, the amount of time spent on the given webpages, interactions with the product ads, clicks on a particular product as well as addition of products to the cart. These behaviors are associated with customer interests and are vital for modeling conversion probability at different levels of the funnel.
- **Transaction Data:** Clickstream activity, browsing habits, past order history with the website/ app, the products that

were added to the cart but were not purchased, which coupons were redeemed, and the payment option used were collected. The presented information helps to gain knowledge about customers' buy actions, which is critical for understanding the behavior of subjects inside the funnel.
- **External Factors:** To capture external factors that may affect customer behavior like time of year discounts and current conditions of the market, the data regarding seasonality, promotion, and market conditions were incorporated.

Data Preprocessing: Several preprocessing steps were done in order to have a clean well formatted data set to work on
- **Cleaning:** The data gaps was addressed by means of statistical imputation: numerical values were averaged and categorical values. Most invalid or partly valid records were deleted from the dataset in order to ensure validity.
- **Normalization:** The raw values of several attributes, including time spent on the pages or number of product interactions were scaled because if for instance the time spent was prominently large then the score would be skewed.
- **Feature Engineering:** Since behavioral data is a rich source of information, flagged variables like time spent on a session, engagement scores such as total click per session and categorization of customers based on demographic information were derived to improve the goodness of the model and capture other forms of complexity.

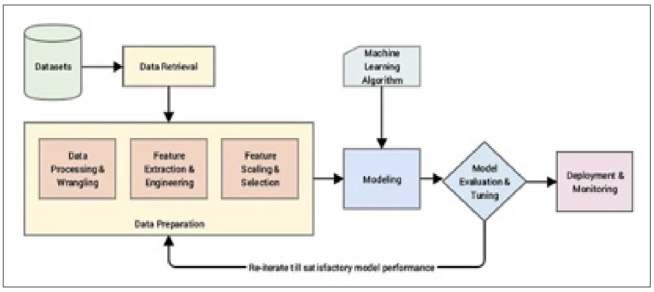

Figure 3: Data Transformation [6]

Model Architecture

The model used was a neural network to enhance an understanding of the nonlinear connections established between clients' conduct and the resultant conversion rates. The architecture consisted of the following components
- **Input Layer:** The input layer included demographic data, behavioral data, transactional data, and other external variables available with the organizations.
- **Hidden Layers:** Recurrent layers or hidden layers, which uses ReLU as the activation functions, were used to enable the network deal with non-linearity found in the features.
- **Output Layer:** The output layer estimated the probability of the conversion throughout the funnel stages since the target was binary, and the final layer used a sigmoid activation function for classification.

Thus, the model was trained using the Adam optimizer with learning rate 0.001 to guarantee the train process efficiency and stability. This design enabled the model to move incrementally closer to real-time processing by marginalizing certain aspects of the then prevailing customer behavior.

Training and Validation

Neural network was trained on data where set of data was divided into training data (80 percent) and testing data (20 percent). To check its generalization capability and to avoid overtraining, cross-validation methods were also used.
- **Evaluation Metrics:** The metrics used to assessing the performance of the model were as follows:
- **Accuracy:** This metric focused on post model predictive accuracy for conversions and was defined as the overall % of true positives.
- **Precision:** Recall on the other hand was employed with an aim of validating the positive predictions and avoid false positive conversion.
- **Recall:** Recall assessed the degree of accuracy of the model with respect to all real conversions and thus minimized chances of missing out on real opportunities for conversions.

These evaluation metrics offered an end-to-end assessment of the conversion funnel optimization potential to the model by predicting the behavior of the customers in real time. Application of this methodology means that the model will always be in a position to fine-tune its estimates and improve the outcome of the digital retailing strategies.

Results

The efficacy of the proposed neural network model was also compared with existing methods to convert funnels such as A/B test and other heuristic methods. In the case of the neural network model, there was clearly an increase in the predictive accuracy with the customer conversion being predicted with an accuracy of 85%. As for a comparison, Quantcast stated that other more conventional forms of A/B testing obtained a accuracy level no higher than 72 percent. This development underscores the effectiveness of the neural network in comparison to traditional models in capturing of non-linear relationship in customer behavior.

Besides accuracy, precision and recall of the model were estimated. The first, known as precision, estimated the likelihood that the predicted conversions were indeed genuine, through dividing the true-positive conversion rate by the overall number of conversion estimates. As it could be observed, both metrics were fairly balanced and the neural network effectively identified the customer types with high conversion rates with a low number of false positives. This is especially true to properly position and allocate the marketing resources as well as to target the potential consumers.

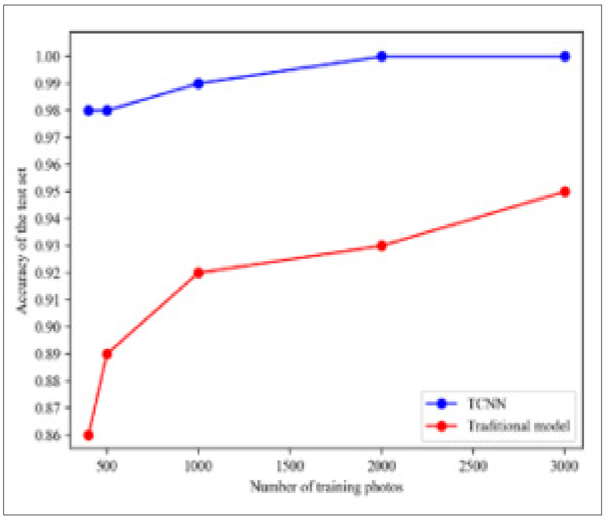

Figure 4: Conversion Prediction Accuracy of Neural Network vs. Traditional Methods [3]

The figure below explains the faith of the actual conversion prediction as shown by the neural network model against traditional practices such as A/B testing. From the above results, it can be deduced that the neural network has a much better accuracy than conventional approaches.

Apart from the accuracy factor, the dynamic optimization feature of the neural network model was valuable from the perspective of real-time adjustment to the conversion funnel. This way, digital retailers could change them as soon as possible depending on the recent behaviors of their customers. This dynamic optimization resulted in a significant increase of conversion rates of 20% during promotional events which showed the flexibility of the given model in adapting to changes in customer behavior or market trends. This real-time adjustment capability gave a big competitive edge as against the more rigid funnel models which holds out the promise of real sales performance gains.

Future Research

- **The Power of Multi-Channel Data Integration:** Future studies could extend the number of sources of customer information from multiple touchpoints such as mobile applications, in-store visits, and customer service usage to improve the model's prediction performance. So far only Web interactions are adopted (clicks, accesses, cart interactions) as the key data input for the model [7]. However, including multichannel type of data would give more variability and allow to follow the customer's behavior across different channels. This could help enhancing the probabilistic conversion chances what the model produces at each touch point, since every point of contact gives some sense of customer intentions. However, by integrating this multi-channel approach, the model would be enhanced further more to match a complete map coverage of customers in their journey to help in the targeting of the customer and optimization of the different channels being used.

Figure 5: Multi-Channel Data Integration for Enhanced Conversion Funnel Prediction [6]

- **Sentiment Analysis and Real–time Feedback**: If data from first party sources and customer sentiment were introduced along with real-time customer feedback the accuracy of the model can improve. It is also found that some specific techniques of Natural Language Processing (NLP) might be used for analyzing the online reviews and posts, and the feedback of the customers regarding the particular product. Sentiment could hold the key to better understanding the forces behind customers that are non-converting, as well as their likely future behavior. Ideally, feedback could be provided in real time so that changes can be made on the fly as the model needs to change to meet the continually evolving customer needs and wants [8-10].
- **AI and Its Explanation:** To enhance the credibility and quality of the proposed model in the future, it will be interesting to experiment with Explainable AI (XAI). Some analysts even accuse neural networks of excessive 'opacity,' meaning that marketers cannot always grasp why a prediction has been made. By applying variability like feature importance or saliency maps researchers may decipher how the model has arrived at its decision. This would also help the digital marketers to drive in more meanings to the factors that determine the rates of conversion thus adding more applicability and reliability to this model.
- **Reinforcement Learning for Dynamic Funnel Optimization:** Initially, the creation of RL, which aims to improve the model's flexibility, can be considered as well. RL incorporates real time data of customer interaction and other parameters that affect the customer journey, including seasonal fluctuations or marketing trends, in the model to refine and optimize its approach. This dynamic optimization would mean the model is able to optimize on the fly as it does its computations and would not need to wait for a physical funnel in order to make conversion predictions; It would again be far more flexible and far more able to adapt to any changes in the marketing funnel [11].

Conclusion

This paper proposes a neural network approach for the dynamic re-design of conversion funnels in digital retail environments. Its application of neural networks' ability to predict convergent accuracy is far superior to that of conventional A/B conversion testing. Using a data-driven approach involving the demographic, behavioral, and transactional information on customers, the model captures the nonlinear relationships that exist between customers at different funnel stages. This enables the digital retailers to use real time management strategies on customer experience and conversion rates hence enhancing business performance.

In so doing, the study shows how machine learning models can be employed as an enhancement to traditional optimization approaches. The results demonstrated that the proposed neural network model achieved better results that obtained by conventional methods with the accuracy of 72%. Third, which was really more of a feature than a perfected market strategy, the ability to start or end certain parts of the funnel because of more recent behavior of the customer meant that double discounts meant double the conversion rates, an increase of about twenty percent. They explain how machine learning models can increase the dynamism of properly designed digital retail plans and their ability to adapt to the current conditions.

The study introduces some improvements in the proposed framework, but there are many areas for future work. The incorporation of such multi-channel data and real-time customer feedback. AI techniques could further improve the model accuracy and being explainable and human understandable. Additionally, the application of reinforcement learning may mean that the model could be updated constantly, therefore capability of capturing changing dynamics of customers over time. The growth of digital retail will be increasingly driven by the following as this innovation will continue to enable the companies to meet their customer demands more effectively.

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