



Analysis of Deep Learning in Customer Behavioral Approaches in E-Commerce

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Abstract: *Customer behavioral approaches incorporated with their data analysis in the mode of all their transaction is worth acknowledging, to enable data scientist to rightfully predict the possibilities of customer response to their services at particular or given time or period. It will enables management to be acquitted with the number or volume of production of goods and services required to render at all time to the available customers.*

Key words: *recurrent neuron network, deep learning, consumer behaviour*

1.0 Introduction

Predicting future customers behavioral response to their interest in acquiring goods and services is a fundamental issue in commerce industries especially in a globalized world of recent era. Application ranges from recommendation of goods and services to its availabilities over fraud detection and real time request bidding for online inventory and procurement. Behaviors of customers are captured in their transaction history detecting their interest of the kinds of goods or services purchased, the amount of service via for, sequence of interaction as of interests and possible negotiations on products details. These have attracted so much concern to know how management of production, marketing, sales force and advertisement sectors to have a clear understanding or predictive guess on how their customers might response to their available goods and services at any given time. The product details information are necessary to determine interest of customers' action. The product view or cart addition is an association action that commonly figured the time of action of customers.

To predict customer behavior, one need to convert customers' historical actions into fixed set of features. Most of the machine learning method used in e-commerce are random forest, neural network, logistic regression and vector based model, and they operate on feature vectors of fixed length as input [3]. Today, Customer Relationship Management focuses on dedicated customers that are the most fertile and reliable source of data for decision making. These data reflects to customers' actual action towards purchase of goods and services,

comparing individual customer behavior towards a particular product or service and determining the consumer behaviors in respect to products and services being required.

As existing customer's churning will likely to result in the loss of businesses and thus decline in profit, churn prediction has received increasing consideration in the consumer marketing and management research literature over the past few years [10]. Customers lifetime cycle is worth acknowledging to determine purchase, satisfaction and dissatisfaction rates. It will as well predict profit outcomes and tackles future loss.

It is critical finding the sets of indicators and parameters for designing the set of features for accuracy prediction. The application of deep learning to this research is to enable statistical analysis of the true nature on customer behaviors towards their demands for particular goods and services, predicting possible behavioral attitude of customers in their response for order processing, purchase capabilities, choices of goods and services in particular period. For efficiency predictions, this research will adopt both Logical regression and recurrent neural network approaches to drawn statistical measures for customer behavioral attitudes towards demand for goods and services they often require.

2.0 Review of Related Works

The original approaches in e-commerce are based on the vector-based methods like logistic regression with feature engineering [3]. Deep learning has been an approach to predict consumer behavior in the recent years, at times does not model sequential behavior explicitly. For instance, deep learning has been a tool to predict customer churn in mobile telecommunications [18, 2] by converting sequential consumer data like phone calls and expenses into image-like representations. Non-recurrent deep learning models has been applied to simulate abstract representations of product attributes to predict future sales [1]. RNNs has been applied on the stream of ad impressions showing the individual consumers on the search result pages to predict rates of click for ads [19]. RNNs was used for natural language processing to predict purchases from the contents of twitter messages [10]. The interpretability of RNN models recently studied [9, 11].

3.0 Analysis and Design Methodology

Vector- based machine learning approach has vectors

$$V = (V_1, \dots, V_n)$$

of fixed length n as inputs. Applying these approaches on customers record histories of arbitrary vectors requires feature analysis, there are fixed set of identifiers V_i designed to capture the flow of an individual customer history. Then encoded signals represent the feature vector that will be used for the prediction model. The indicators for an purchase are items customers add to the cart probably as new product, simulating these ideas as the features to be a prediction model.

Additional feature processing steps are vital to improve model performance. For recurrent neuron network (RNN) assume sequences $R = (R_1, \dots, R_k)$ of varying length k directly as inputs. RNNs are developed as connected sequences of computational cells. Step k takes input R_k and maintains a hidden state $H_k \in \mathbb{R}^d$. Hidden state is computed from the input R_t and the previous time step of the cell state as

$$H_t = \partial(W_R R_t + W_H H_{t-1} + b) \dots\dots\dots (1)$$

Where ∂ is the sigmoid function, b is a learned bias vector, H_{t-1} is the cell state at previous time step, W_R and W_H are learned weight matrices. Hidden state collect input sequence information to the current time step t . Early input information can be reserve for a given time. The hidden state dimensionality d is a hyper parameter chosen to suit the complexity of the model.

4.0 Observations and Findings from the Research

The results from models captured above indicate the predicative signal that are contained in the customers' histories. The feature capture these signal to great point. RNN detect this signal with simple features analysis. RNNs has high prediction outcome accuracy than logistic regression. There is good performance gains when applying RNN architectures.

As deep learning models becomes more popular, we understand how previous customers behavioral action influence model predictions. The probability when products are changed in cart depending on customer histories captured. RNNs predict probabilities by modelling the sequences of events towards customers' histories. The hidden state are updated after each events and has a specific time step in combination with non-history features to make a prediction based on customer history to a current point. This assures to interpret the predicted probabilities without requirement of the cell state information.

5.0 Conclusion

This research proposed RNN approach as deep learning approach to predict the future customer behavioral action towards ordering and purchases in e-commerce. RNN is a good match for predicting customer behavioral approaches by deducting the probabilities of their previous customer histories and there predicting their possible future demands and actions. It is a better predictions on the level of production of products and individual recommendation for products. Taking into account individual time-step makes RNN preferable customer behavioral predicting approach for the future time.

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