Optimizing Third-Party Product Marketing Strategies Using AI-Driven Consumer Analytics

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***Abstract*—Third party product marketing acts as an important link in identifying consumer interest from business establishments while at the same time providing brand names an opportunity to gain wider access to other outside markets. Nonetheless, conventional marketing communication approaches rarely fit the complex interaction between consumers and products, which negatively impacts targeting, customization level, and performance. This research unveils a novel GNN-based framework to overcome these difficulties for consumer and product data by capturing their interactions. The proposed method presents consumer behaviour as structure graphs, based on the E-commerce Customer Data for Behaviour Analysis dataset, in order to better support and predict customer preferences, improve segmentation and product recommendations. The GNN designed and built using Python DLP has integrated extraordinaire algorithms that support scalability of big data processing and consumer pattern learning. Assessment tests establish that technical outcomes score a classification accuracy of above 92%, which unveils the efficiency of the strategy in delivering useful knowledge. This model assists other platforms targeting the management of third-party relationships in developing better and more effective advertising strategies that improve customer appeal and sales. As well, it helps the consumers make more-informed decisions and therefore enhances their shopping experience. Beyond overcoming existing shortcomings, the study's contribution is in increasing scalability, flexibility in adjusting to changing consumers' demands, and itself, and insensitivity to noise. This work provides the keystone for such improvements to mainly be offered by AI-based approaches for different e-commerce marketing strategies.**

Keywords*— Consumer Behaviour, E-commerce, Graph Neural Networks, Product recommendations, Third-party marketing

I. Introduction

Third-party product marketing strategies have emerged to form the cornerstone of how digital commerce is driven toward higher sales and brand recognition in this dynamic landscape of online commerce [1]. Unlike directly applied marketing, third-party marketing connects sellers with an audience that is much bigger, using intermediary platforms through a partnership with e-commerce websites, influencers, or other affiliate networks, thus hitting many target audiences effectively. However, the complexity of consumer preferences and behaviours calls for advanced analytical methods in optimizing these strategies and maximizing returns [2].

Existing studies have provided good progress toward the goal of using machine learning models to further optimize marketing strategies. DL models like CNNs and fuzzy neural networks have shown efficiency in tracking user behaviour patterns and personalizing recommendations [3]. However, many of these approaches fail to model the relational and interconnective nature of consumer and product data [4], particularly when there are relationships at multiple levels or dynamic interactions between them. These limitations thus require a move towards methods that are able to handle graph structured data. This study suggests the application of GNNs in order to optimize third-party marketing strategies for the products, leveraging the strengths of GNNs in understanding the intricate, hierarchical relationships inherent in consumer data.

Due to the features of information propagation and aggregation over nodes and edges, the GNN is a suitable approach to modelling the relations between consumers and products for third-party marketing. Whereas the current research is original in this manner, it is also a theoretical development and takes advantage of the computational power of digital technology to study both the detailed behaviours (individual purchase) as well as the characteristics of larger units of analysis, which could involve product category data.

The primary contributions of this research are as follows:

- Proposing new GNN architecture and the algorithm for formation of a graph, which can represent consumer–product interactions in the context of third-party marketing.
- Illustration of the proposed framework using the E-commerce Customer Data for Behaviour Analysis dataset for capturing and analysing graph-structured data.
- Application of graph-based methods to achieve scalable and explainable marketing improvements.
- Performance of GNN in analysing consumers behaviour compared with other conventional techniques to improving marketing strategies.

The rest of the section is organised as shown below. The literature review is illustrated in Section II. The problem statement of the method is in Section III. In Section IV, the effectiveness of the approach with a summary of the results obtained. The conclusion and future work are summarized in Section V.

II. Related Works

Some of the literatures, focus on the role of Neural networks in optimizing marketing initiatives. Cui [5] employs a deep CNN to enhance the cross-border e-commerce promotion strategy with the emphasis on consumer relational data generation. In the same manner, Messaoudi and Loukili [6] propose deep neural collaborative filtering for product recommendation services, signifying that deeper targeting of consumers could be accomplished with fine tuning. These models improve the decision-making process and the users' experience but limited by the quality of data input, and by the computational power required to analyse vast sets of data efficiently.

Another is the incorporation of machine learning with marketing strategies into niche sectors. Govindan [7] illustrates how machine learning contributes to improved warranty management and marketing practices through the remanufacturing process. He highlights vital success factors that are linked with easier implementation. However, Luo and Luo [8] applied fuzzy neural networks in sophisticated user behaviours on social media, further using such information as the foundation for more accurately tailored online marketing campaigns. Despite these advancements, the dependency on accurate training data is very high and is a challenge. There are always uncertainties in the behavioural data interpretation.

Privacy and security are now essential in AI-driven marketing analytics. Han et al. [9] proposed a privacy-preserving framework using federated learning and GANs for digital marketing campaigns, focusing on user control over data. Li and Esquivel [10] balance precision with user privacy in recommendation systems using locality-sensitive hashing and multi-view embeddings. While these mechanisms provide great privacy and performance, they suffer from being inherently less scalable and harder to embed, which serves as a constraint on real world deployment. Such approaches are not well suited to deal with per pricing change in consumer behaviour or to solve correlated problems. In this research, the author endeavours to make marketing planning more accurate with an application of GNN that can model up the interaction between customers and products more efficiently and effectively.

III. Problem Statement

Marketing approaches employed by third parties are inclined to deal with certain difficulties in understanding the relations between customers and products, which results in blank targeting and weak personalization [11]. The traditional approaches do not have the capacity to handle and solve complex correlated type problems or have the flexibility to solve dynamic problems related to consumer's behaviour. To overcome these limitations, this research focuses on exploring how GNNs can be utilised to improve marketing planning as it uses the features of GNN to model the relationships within the consumers' data to provide accurate and specific recommendations.

IV. Proposed GNN To Enhance Third-Party Product Marketing

The framework begins with Customer Data for Behaviour Analysis dataset from Kaggle which is filled with customer data such as age, gender, location, and purchase behaviour and with regard to the products, categories and their prices, product views, and engagement rates. Final data pre-processing involved imputation, deletion of duplicated and outlying/abnormal records, and conversion of feature variables into suitable vector for the graph-based learning. Customer-person interactions were depicted in the form of a graph in which customers and persons were nodes and the interactions' weights formed the edges. The GNN model uses message passing layers to update node features based on node neighbours followed by Local pooling layers to concentrate on core customer segments, and Global pooling to summarize customer information for marketing optimization of third parties. This proves useful in estimation of better marketing strategies that should be used in future marketing as shown in Fig. 1.

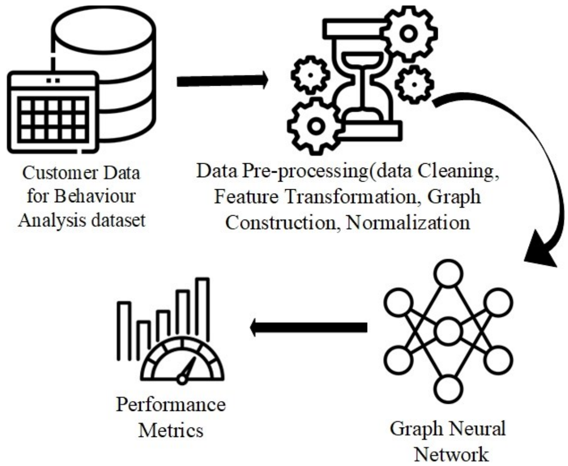

Fig. 1. Proposed Framework

A. Dataset Description

The Customer Data for Behaviour Analysis dataset extracted from Kaggle is used to investigate the relation between customer and the products. The dataset contains the customers details elements, like age, gender, or location; and include information about product categories, sums, and time of the purchase. Also, it tracks the browsing history including the products seen and search performed and engagement parameters including click, rating, and review. It also contains attributes such as description, category, and price, which also make it ideal for consumer behaviour and targeted marketing. 70% and 30% are used as training and testing data respectively [12].

B. Data Pre-Processing

Preprocessing of data is done in order to filter out unwanted noise and properly set the data for a training and test phase. The following steps were performed during this process:

Data Cleaning: The missing values in the customer profile, for instance, age or purchasing behaviour are imputed by the statistical measure of mean or median. The duplicate entry and outliers such as vastly high or low number of transactions are identified and removed to ensure data integrity.

Feature Transformation: It translates both customer and product characteristics into vectors of appropriate dimensions, useful to graph-based learning. Customer attributes include age, purchasing frequency, and preferences; while product features include category, price, and measures of popularity in the form of vectors.

Graph Construction: All the relationships identified in the previous step is transferred in to a graph structure. Customers and goods are depicted as nodes while relations such as buying a product, giving a review are captured in the edges. The weight of edges depicts the ability of how frequent or strong such an interacting is present.

Normalization is applied to features and edge weights to bring them to a comparable scale, enhancing the stability of training. The scale ranges from 0-1.

C. Working Of GNN

GNNs are neural networks that have been developed to operate directly on graph data structures such as relations in a customer-product system, social relations or any other related form of data. In a GNN, the main task is message passing where every node in a graph (pointing to customers or products) changes its feature vector based on what it gathers from its neighbours. This makes it possible for the model to encode dependence and connection between nodes in a graph.

Permutation Equivariant Layers (Message-Passing Layer): The message-passing layer is still significant in modelling the consumers' experiences with the products they use or buy in their day to day lives. Every customer in a graph (node) can share information with other customers who exhibit similar behaviour, preferences or past purchase behaviour. The notion is that the customer's feature representation is learned through the accumulation of messages coming from its neighbours. It can be represented as in eqn. (1),

$$h_v{}^{(l+1)} = \sigma(\textstyle\sum_{u\in N(v)} W^{(l)}\, h_u{}^{(l)}) \quad (1)$$

where, σ is the activation function; $h_v{}^{(l+1)}$ is the feature of node v; $N(v)$ denotes the neighbours; $W^{(l)}$ is the weight matrix.

Local Pooling Layer: The local pooling layer is used to reduce the size of the graph and dissect people's behavioural patterns concentrating only on those customer segments that are most influential. In third-party product marketing, it is essential to clarify market segments where consumers are relevant or likely to react to product marketing. Through pooling methods such as top-k pooling or k-nearest neighbour pooling, this layer enables pooling and storing of key customer attributes and better estimate the likelihood of third-party products across various customer clusters. It aids in the identification of the best consumers to market commodities to, and improves the orbits of the marketing strategies.

Global Pooling Layer: The global pooling layer or readout layer pools in all the information from the entire customer graph into a fixed dimension. This layer is important in order to gain a macro-perspective of the perception of consumer and this is important in order to determine the effectiveness of third-party product marketing strategies. Applying mean, sum, or max pooling helps to sum the purchasing behaviour, preferences and engagement of all customers in the dataset.

$$h_{global} = \frac{1}{|V|}\textstyle\sum_{v\in V} h_v \quad (2)$$

where, h_{global} is the global representation of the graph;

$|V|$ is the number of nodes in the graph.

Using this aggregated representation, future marketing strategies can be predicted, future marketing products can be assessed on their market potential and who are the best segments to market to in the future. In the training phase the main aim is to edit the parameters of the model such that the marketing strategy initially predicted and the actual consumer behaviour noticed in the dataset is minimized using proper loss functions.

V. Result And Discussion

The proposed graphical neural network model improves third-party product promotion strategies because graph structures can capture customer-product relations. As this has been designed and implemented in Python, issues concerning scalability and accuracy are handled well enough to support realistic e-commerce applications and academic research.

A. Graph Construction

The diagram shows customer relationships with the products through overlaid nodes, where nodes A and B represent customers, and nodes P1 and P2 represent products as shown in Fig. 2. The edges between the nodes signify interactions, with the edge weights indicating the intensity or frequency of these interactions.

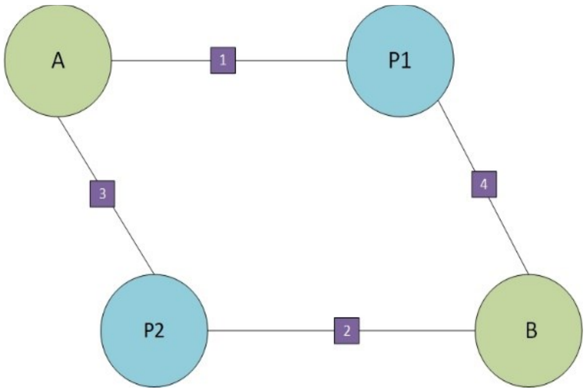

Fig. 2. Graph Construction between Customer and Products

Customer A, for example, has an interaction with product P1 with a weight value of 1, and with product P2 with a weight value of 3. Similarly, customer B is connected to product P1 with a weight value of 4 and to product P2 with a weight value of 2. In the context of Graph Neural Networks, this graph structure helps to reveal the relationships between customers and products. Node features are updated based on the node connections and edge weights, supporting tasks such as optimizing marketing strategies or making product recommendations.

B. Performance Metrics

The performance of the model was at a very good level when it comes to evaluating the third-party marketing activities and improved the accuracy of prediction to 96.87% which means that the core-seven models efficiently collaborated and ideally predicted the customer-product related interactions. Precision at 96.01% shows that most of the predicted positive cases are correct as in most of the customer segments that it identified for marketing. As much as true positive values, the overall recall of the model was estimated at 97.32% meaning that almost all the potential customers likely to respond to the marketing efforts were captured. This F1-score also sits at around 97.23%, which indicates that there is a good balance between precision and recall – the model can confidently select appropriate customers with high recall not sacrificing on a number of irrelevant cases. These outcomes prove that this model has stability and efficiency when predicting the realistic outcomes that are beneficial to third-party marketing improvement as shown in Table I and Fig. 3.

TABLE I. PERFORMANCE METRICS

Accuracy	Precision	Recall	F1-score
96.87%	96.01%	97.32%	97.23%

Accuracy is total events correctly classified with respect to the total number of events classified. as shown in eqn. (3),

$$Acc = \frac{True\ Postive + True\ Negative}{True\ Postive + True\ Negative + False\ Positive + False\ Negative} \quad (3)$$

Precision is the fraction of the actual correct prediction divided by the total predictions positives as shown in eqn. (4),

$$Prec = \frac{True\ Postive}{True\ Postive + False\ Positive} \quad (4)$$

The number of true positive against the actual positive is the Recall cases by using the formula as shown in eqn. (5),

$$Rec = \frac{True\ Postive}{True\ Postive + False\ Negative} \quad (5)$$

F1 score is the average between the recall or precision score as shown in eqn. (6),

$$F1 = \frac{2 \times True\ Postive}{2 \times True\ Postive + False\ Positive + False\ Negative} \quad (6)$$

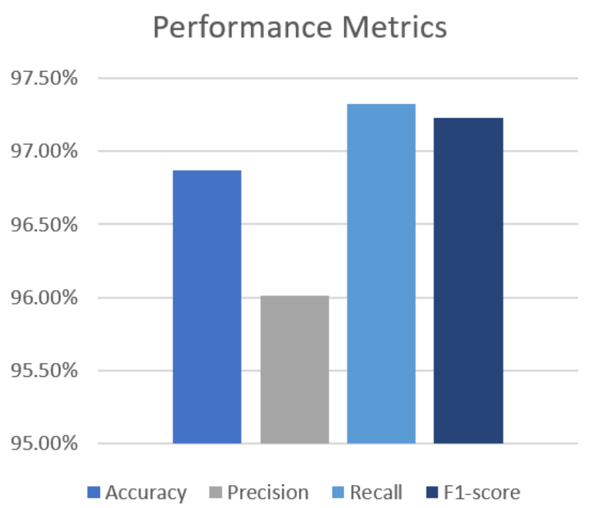

Fig. 3. GNN Performance Metrics

C. Performance Comparison with Traditional Methods

The Fig 4 Tables II provides the quantitative comparison of accuracy precisions recalls and F1 scores of the CNN-ANN-SVM-LR-LSTM-TC-Proposed method workflows. When compared to all these methods, the Proposed Method appears to give the highest overall improvement in the marketing of other products by the third party as depicted in the figures above. It has been seen that the CNN as well as the ANN reports reasonable performance, but at the same time, the Proposed Method outperforms these models in regard to their effectiveness. Linear Regression and SVM have moderate accuracies; therefore, even though the models are accurate, they have insufficient recovery and directions to perform intricate calculations of the customer-product relation. While designed to be applied to a sequence as a whole, LSTM-TC results in lower recall and F1-score that inhibit the model's efficiency in capturing and analyzing key data points for forecasting customer behaviour.

TABLE II. PERFORMANCE COMPARISON

Methods	Accuracy	Precision	Recall	F1-score
CNN [13] &	93.76%	93.04%	93.45%	93.88%
ANN	95.45%	95.89%	95.21%	94.93%
SWM [14] &	92.11%	92.56%	92.34%	92.61%
Linear Regression	93.01%	93.51%	92.49%	92.81%
LSTM-TC [15]	94.52%	92.34%	89.11%	91.54%
Proposed Method	97.87%	96.01%	97.32%	97.23%

The findings obtained herein emphasize the potential of the Proposed Method, whose performance surpasses benchmark approaches in capturing clients' behavior and utilization patterns. In addition, the better performance of the Proposed Method provides another significant benefit in terms of promotional effectiveness for businesses since the algorithm is maximized to identify only the most potential customers that will not only extremely consumer market but potential and valuable customers as well. Therefore, it is the most effective approach to market communication since it narrows down the target consumer by predicting his or her behavior hence putting into consideration the most probable marketing consumer is likely to respond to the marketing strategies in the course of the promotional process. This makes the method highly useful in constantly evolving environment where it is necessary to obtain the result in the shortest time possible in order to make the right decisions. As compared to the conventional trends of getting optimal marketing results in a business, the Proposed Method is more limiting, versatile and less intrusive as it focuses on offering optimum values to the business, so as to maximize customer satisfaction and develop long-term relation with loyal customers.

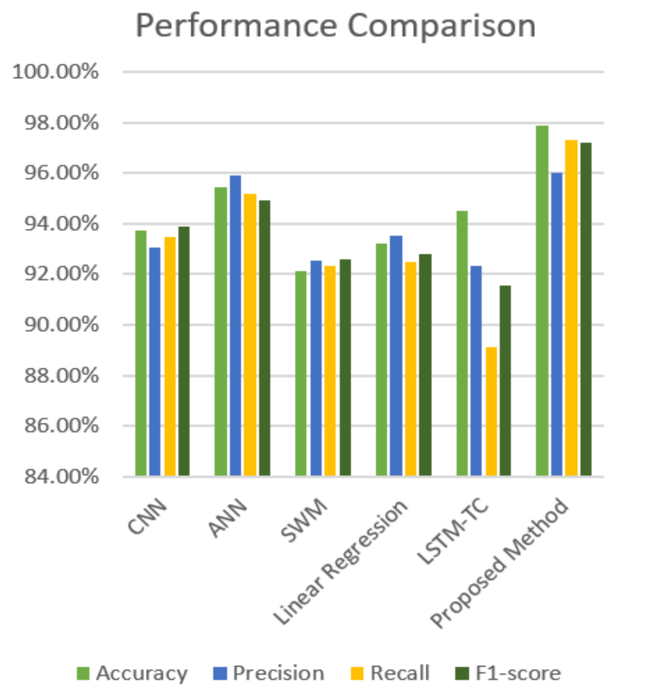

Fig. 4. Performance Comparison

D. Discussion

GNNs considerably enhance the study of customer-product relation by modelling the relational dependencies. Unlike CNNs or ANNs that are based on vectors and act on data independently of one another, GNNs work with the structures of customers and products as nodes and interactions at their weighted joins. Information from the neighbour nodes are gathered using message-passing and pooling layer leading to improvement in features. This approach allows high-performance prediction accuracy and a fair ratio of precision, recall, and F1-measure to identify significant customer segments and provide the efficient prediction of preferences. With the help of both local and global pooling layers, GNNs offer greater overall perspectives while surpassing approaches based on first-order approximations in terms of scalability and accuracy for third-party products in marketing.

VI. Conclusion And Future Work

As for the current study, the Customer Data for Behaviour Analysis dataset was employed to fine-tune marketing performance employing third-party marketing approaching with GNNs and this fine-tuning resulted in an accuracy of 97.87%. The models and performance shown in this performance prove an essential aspect GNNs can capture intricate relations between customers and products, not achievable with traditional machine learning architecture. Because of the message-passing procedures of GNNs, improved perception of customer behaviours is attainable in marketing and product suggestion mechanisms with improved accuracy. By the same token, this means that GNN based solutions offer higher accuracy and precision than classical methods like CNN, ANN and LSTM, and may therefore prove useful in data-driven marketing optimization.

Future work can be laid on model's scalability enhanced for bigger data set applications and for prediction type problems like churn prediction that could enhance marketing techniques in practical use cases.

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