Advancing Sustainable Marketing through Empowering Recommendation: A Deep Learning Approach

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***Abstract*- In the contemporary era, online shopping has become the preferred mode of retail for consumers. Addressing users' demands for personalized products while simultaneously promoting sustainable marketing practices is of paramount importance for major e-commerce platforms. This paper explores the integration of deep learning techniques into recommendation systems, focusing on the Inception structural neural network (NCF-i), to enhance prediction accuracy and operational efficiency. We also introduce sustainable marketing concepts into the context of personalized recommendations. To achieve this, we design a pairwise self-encoder that improves the content-aware recommendation algorithm for sustainable and personalized products, leveraging the gate attention mechanism. Experimental results demonstrate that our proposed recommendation system not only outperforms current mainstream models in terms of prediction accuracy and stability but also fosters sustainable marketing practices, showcasing its effectiveness and broad applicability**

Keywords-deep learning; personalised recommendation; e-commerce platforms; sustainable marketing; neural networks.

I. INTRODUCTION

The rapid expansion of the Internet in recent years has led to an unprecedented proliferation of online information, presenting users with the formidable challenge of sifting through vast digital landscapes to access the specific information they seek. In response to the diverse and evolving needs of consumers, e-commerce providers have responded by curating extensive catalogs of products. However, the key to fostering user satisfaction and cultivating lasting brand loyalty lies in the art of seamlessly connecting consumers with products that not only align with their preferences but also resonate with their values, including sustainability concerns.

China stands as a prominent leader in the global e-commerce landscape, consistently experiencing exponential growth [1]. In this dynamic digital ecosystem, users increasingly seek not just products that fulfill their immediate needs but also those that align with their sustainability aspirations. Simultaneously, merchants endeavor to strategically position their offerings before a receptive audience, one that values environmentally responsible and socially conscious product recommendations [11].

While existing personalized recommendation systems have demonstrated commendable efficacy in improving user experiences, they are not without their limitations. Recent years have witnessed the meteoric rise of deep learning, which has ushered in a transformative era in the realms of internet big data and artificial intelligence. This burgeoning field has given rise to a parallel surge in research aimed at harnessing deep learning techniques to enhance recommendation systems. Of particular interest is the exploration of recommendation systems rooted in user behavior data, as well as the integration of sustainable marketing concepts into these systems [2, 11].

In light of these developments, this paper embarks on a comprehensive exploration of deep learning-based product recommendation algorithms. By incorporating the principles of sustainable marketing into the heart of our investigation, we aim to not only achieve significant research milestones but also pave the way for e-commerce platforms to thrive in an era where sustainability-conscious consumers are seeking products that align with their values.

II. ANALYSIS OF E-COMMERCE RECOMMENDATION SYSTEM PRINCIPLES

The e-commerce recommendation system is divided into three main parts, as shown in Figure 1.

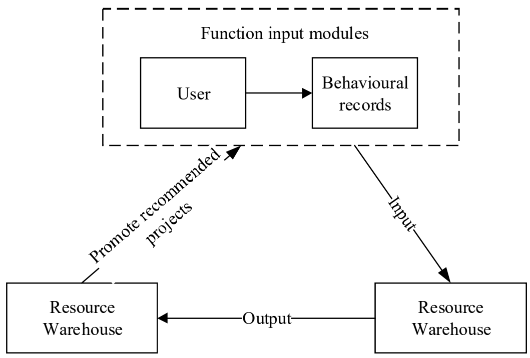

Figure 1. E-commerce recommendation system architecture

Input function module: It is mainly used to store and input the user's behaviour during the purchase process of products, mainly including implicit browsing behaviour and explicit browsing behaviour. Implicit browsing behaviour refers to the behaviour of users visiting the e-commerce system without their knowledge, including clicking, viewing, adding shopping cart, etc. Explicit browsing behaviour is mainly the interests left by the user in the recommendation system, such as the interests selected when registering on the website, etc.

Recommendation technology module: This module mainly selects the most suitable algorithm according to the input data and the recommendation object, and calculates the most suitable recommended products for the target user [3].

Output function module: according to the different output objects, the recommendation system can be roughly divided into two kinds, one is to use web mining technology to recommend web pages of interest to users, the recommendation object of this recommendation system is mainly in the form of web pages; the other is to use big data mining technology, the online shopping consumer as the recommendation subject, the recommended goods as the recommendation object, while in the form of a list for its. The other is to use big data mining technology to take online shoppers as the recommendation subject, and take recommended products as the recommendation object, while displaying and recommending them in the form of a list [4].

The four most commonly used metrics for evaluating recommendation systems are recommendation accuracy, user satisfaction, recommendation coverage and recommendation diversity.

III. COMMONLY USED RECOMMENDATION ALGORITHMS

The commonly used recommendation algorithms are divided into the following three categories.

A. *Research on content-based recommendation algorithms*

Content-based recommendation algorithms make recommendations for users by intuitively predicting their preferences using features of the user and the item itself. The central idea of content-based recommendation is to measure the similarity between an item that the user has not interacted with and an item that the user has interacted with in terms of attributes, features and other dimensions, using the similarity to perform the task of predicting the user's interests and recommending a list of items that may be of interest to the user [5]. There is a wide range of information that can be used in the recommendation scenario, such as the product's attributes, tags, and the user's clicks, favorites, and likes on the product. Content-based recommendation methods are also highly interpretable, an advantage that makes them widely used in recommendation tasks, as illustrated in Figure 2. There are three main steps in the content-based recommendation algorithm, which are item representation, content learning and recommendation generation.

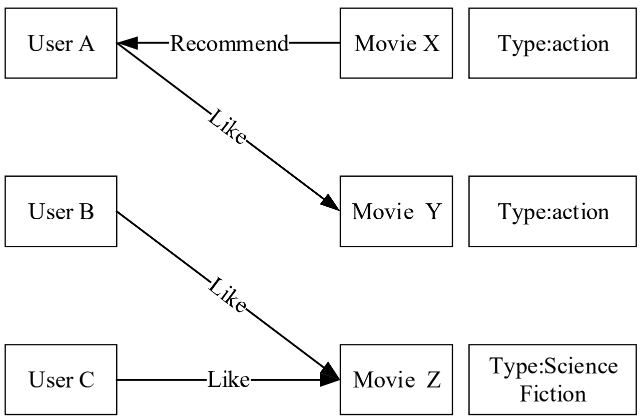

Figure 2. Example of a content-based recommendation algorithm

B. *Research on collaborative filtering recommendation algorithms*

The collaborative filtering recommendation algorithm is the most widely used recommendation algorithm in industry. It can take advantage of the large amount of historical user-item interaction data and generate candidate recommendation items. The core idea of collaborative filtering is that people are grouped together by categories [6]. It assumes that if a user has similar preferences for an item, it means that the user has similar preferences for such items, which also explains the importance of the user's historical interaction with the product. In the fine-grained division, collaborative filtering recommendations can be further divided into model-based collaborative filtering and neighbourhood-based collaborative filtering.

Neighbourhood-based collaborative filtering uses users and goods to generate predictions. Each user has a group of people with similar interests, called neighbours, and the system can generate predictions for that user by using neighbours. This is the key to neighbourhood-based collaborative filtering.

C. *Research on hybrid recommendation algorithms*

Content-based recommendations and collaborative filtering recommendations each have their own limitations and drawbacks in industrial applications, and there is no one-size-fits-all algorithm.

Hybrid recommendation algorithms take advantage of the strengths of each technique compared to the first two. Commonly used hybrid recommendation methods are weighted, switched, crossover, feature combination and meta-hierarchical. Weighted is the output of a weighted combination of different recommendation methods; switched is the output of different recommendation methods depending on the actual context; crossover is the output of multiple recommendations using different recommendation methods at the same time; feature combination is the output of one method using the input of another recommendation method; and meta-hierarchical is the model generated by using another recommendation method on the input of one recommendation method [7].

IV. INCEPTION STRUCTURE-BASED COLLABORATIVE NEURAL NETWORK FILTERING METHOD

This paper proposes a collaborative filtering method (NCF-i model) based on the NCF with Inception structure. The method first analyses the product review information based on the convolutional neural network of Inception structure and extracts its multivariate feature model, then adds the multivariate feature model to the NCF neural network collaborative filtering model and obtains the non-linear correlation between users, products and product reviews through multi-layer fully connected layers, and finally predicts and recommends products based on this non-linear relationship. The final product prediction and recommendation is based on this non-linear relationship.

A. *Deep learning based recommendation systems*

In this paper, the NCF-i model with product reviews is built on the basis of the NCF model, which contains the user's preferences for the product in the text of the product reviews. Figure 3 shows the Schematic diagram of the NCF-i model.

Word embedding is the process of mapping words to a fixed dimension to obtain a low-dimensional, data-dense word vector model. Thus, text can be processed by word embedding into a two-dimensional matrix whose dimension size is the product of the sentence length and the word embedding dimension.

In applying word embeddings, we can use either pre-trained word vectors such as word2vec or randomly generated dimensions that obey a normal distribution as word vectors. Also, words with similar semantics mapped into word vectors by pre-training have a closer distance.

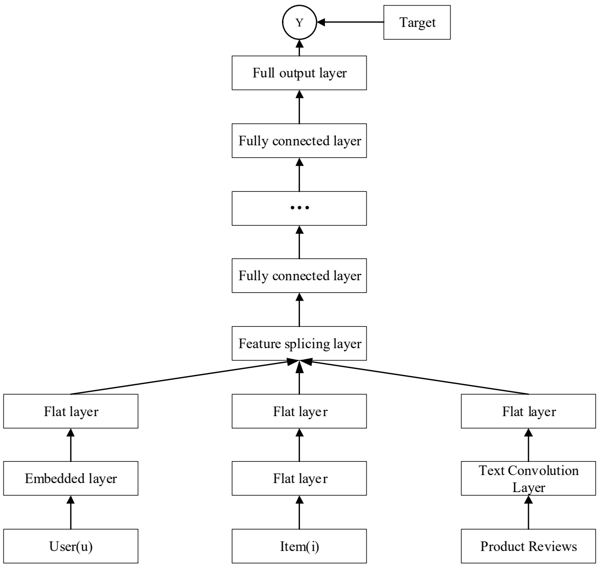

Figure 3. Schematic diagram of the NCF-i model

After combining the word embedding model, a convolutional neural network is applied for text processing of product reviews. The most critical operations in a convolutional neural network are convolution and pooling. The convolution operation is the process where convolutional kernels are sequentially slid through the input layer, inner product with the corresponding matrix of the input layer and finally map the result to the output layer [8]. Convolutional neural networks effectively reduce the number of parameters that need to be trained due to the shared parameters of the convolutional kernel. The depth of the convolution kernel is equal to the depth of the input layer, and the depth of the output layer is equal to the number of convolution kernels.

When text is analysed using a convolutional neural network, as each word is represented by an entire row of data in the word embedding layer, the width of the convolutional kernel is equal to the dimensionality of the word embedding, otherwise the full information of each word cannot be extracted [9]. This is shown in Figure 4.

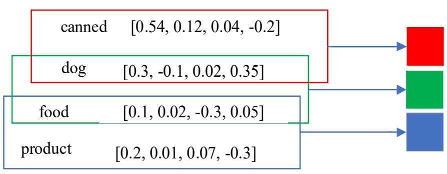

Figure 4. Illustration of the convolution process for text vectors using a convolutional neural network

In Figure 4 we use a convolutional kernel with a width of 2 and a step size of 1, which is mapped into a one-dimensional vector after the convolution operation. In addition, since long text is truncated and short text is padded with placeholders when text pre-processing is performed, there is no need to 0-populate the input matrix when using the convolutional neural network.

The dimension of the text vector obtained after convolution with the convolution kernel is: Text vector dimension = sentence length - convolution kernel size + 1.

In this paper, we use a convolutional neural network with an Inception structure in order to fully extract the features of the product text, using multiple filters of different sizes to convolve and pool the input layers, and then stitching the resulting mappings in the depth dimension. This parallel convolution and pooling operation allows the extraction of different features of the convolutional layers. The Inception structure of a simple convolutional neural network is shown in Figure 5.

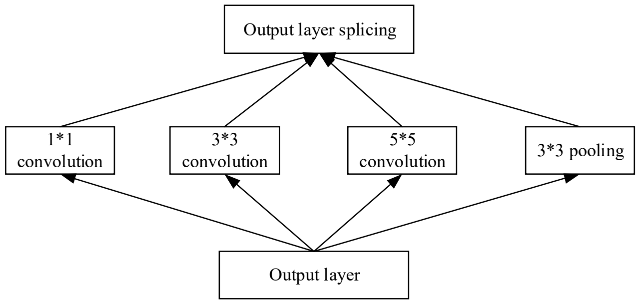

Figure 5. Schematic representation of the Inception structure of a convolutional neural network

In Figure 5, the input layer is convolved using a 1*1 convolutional kernel, a 3*3 convolutional kernel and a 5*5 convolutional kernel, and the input layer is pooled using a 3*3 spatial window, and the output layer is stitched together in the depth dimension as the final extracted features. Tests have shown that the convolutional neural network using the Inception structure is more computationally efficient in extracting features and achieves better results.

B. *Simulation experiments and analysis*

In order to verify the effectiveness of the NCF model with product reviews, the NCF-i model is compared with a general NCF model, a traditional recommendation algorithm FM model and a collaborative filtering model with product reviews, using precision as a measure of the model's effectiveness [10]. The accuracy is defined as the proportion of the total data that the machine learning model predicts to be equal to the actual user rating of the product, and is defined as

$$acc = \frac{1}{m}\sum_{i=1}^{m} I(f(x_i) = y_i) \tag{1}$$

where I(*) is the indicator function, and I takes 1 when * is true and 0 when * is false.

In this paper, the models were trained and tested using Amazon's food review dataset and Amazon's infant product dataset. Firstly, the Amazon food review dataset was cleaned and 40,000 items were selected, and three models were trained and tested with this dataset: the NCF model, the NCF-i model and the FM model, and the loss rate of the NCF-i model on the test set is shown in Figure 6. The loss rate was found to drop significantly in the first 20 training rounds, after which the loss rate levelled off.

In order to better compare the accuracy of the three models, the accuracy of the different models on the test set is observed by means of a line graph, which is shown in Figure 7. It can be observed that the NCF-i model works better than the FM model and better than the NCF model.

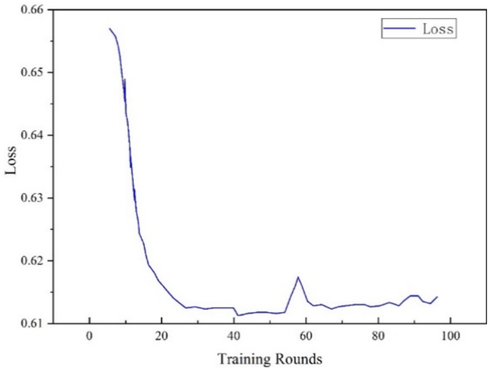

Figure 6. NCF-i model loss plot on Amazon food review dataset

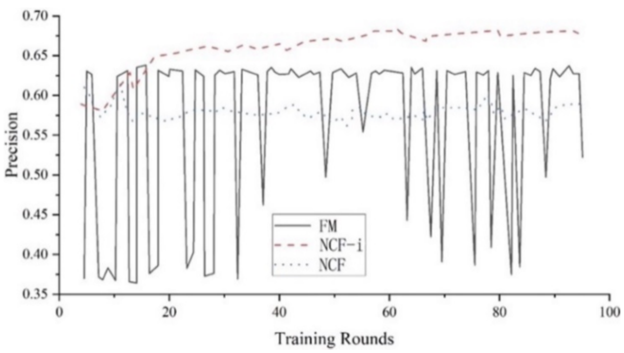

Figure 7. Test accuracy graphs for NCF model, FM model and NCF-i model

V. Conclusion

In conclusion, our study introduces the NCF-i model, which marries the power of deep learning with the goal of advancing sustainable marketing in e-commerce platforms. By incorporating sustainable product recommendations into the recommendation system, we address both user needs and societal concerns. Our experimental results confirm the superiority of the NCF-i model in terms of accuracy and stability while promoting sustainable marketing practices.

This innovative approach not only enhances the shopping experience for users but also aligns with the principles of sustainable marketing, emphasizing the importance of eco-friendly and socially responsible product recommendations. As consumers increasingly prioritize sustainability, our NCF-i model paves the way for e-commerce platforms to thrive in a socially conscious market while providing personalized recommendations that meet the unique needs of each user. It represents a significant step toward a more sustainable and user-centric future for online retail.

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