Evaluating Customer Satisfaction in Digital Agricultural Platforms

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Abstract: Traditional collaborative filtering (CF) techniques have been widely successful in e-commerce, especially for suggesting agricultural produce. Many techniques, though, are plagued by inherent disadvantages like data sparsity, cold-start problems, and decreased precision due to the lack of consideration of contextual elements. To overcome these challenges, this paper proposes a Hybrid Deep Learning-based Context-Aware Recommendation System (HDL-CARS) that dynamically balances contextual information through the utilization of user, item, and context embeddings and a sophisticated attention mechanism. By combining deep context-aware analysis, content-based filtering, and collaborative filtering, HDL-CARS identifies subtle, non-linear user-item interactions as well as adjusts to changing parameters like time, location, and user activity. HDL-CARS utilizes state-of-the-art deep neural network models, such as multi-layer perceptrons and attention mechanisms, to improve feature representation and extract hidden patterns from sparse data sets. This process guarantees scalability on different data sizes and flexibility for changing user behavior, making HDL-CARS a perfect candidate for personalized agriculture e-commerce beyond. Empirical tests indicate that traditional CF has a precision and recall of 0.75 and mean absolute error (MAE) of 0.75. By contrast, HDL-CARS drastically enhances accuracy to a precision of 0.85–0.95, recall of 0.90, and smaller MAE of 0.5. These findings demonstrate HDL-CARS's improved accuracy and robustness. With its delivery of highly personalized, real-time recommendations, HDL-CARS improves user experience and relevance, especially in agricultural e-commerce.

1 INTRODUCTION

Digital agriculture and e-commerce have created enormous opportunities for introducing consumers with various agricultural products. But the agricultural e-commerce industry is facing a challenge of information overload as the data of users and products continue to grow. In this context, traditional recommendation techniques such as collaborative filtering and content-based filtering have many limitations such as sparsity of data, cold start problem, and inflexibility of real-time context. To fill this gap, this paper presents a Hybrid Deep Learning-based Context-Aware Recommendation System (HDL-CARS) for agricultural e-commerce. Combining these advanced mechanisms makes the recommendation more accurate, better able to adapt to circumstance, and helps to provide more relevant recommendations; solving many of the issues of earlier algorithms. We are compared using HDL-CARS with the original collaborative filtering algorithm on agricultural e-commerce aggregates which achieves information of 0.6–0.8precision and mean absolute error (MAE) up to 0.75, compared with HDL-CARS, it makes the aggregate accuracy of 0.85–0.95, MAE reduced to 0.5. J. Chen et al., 2022, HDL-CARS is a system that helps to increase user satisfaction by providing personalized, context-aware, and real-time product recommendations, which enable quicker product discovery and lead to greater engagement and sales on agricultural e-commerce model is function.

2 RELATED WORKS

In 2016, Google's AI software AlphaGo beat the world Go champion Lee Sedol in a milestone match that demonstrated the disruptive capabilities of AI in challenging problem-solving tasks. Global discussions ensued on the methods and consequences of AI. G. Linden et al., 2003, Since the

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1990s, traditional recommendation systems like collaborative filtering (CF) and content-based filtering have been the most common methods used by online retailers. Recently proposed context-aware recommendation systems (CARS) have been proved effective in mitigating these issues. Recommendation frameworks have leveraged contextual features, including time, location, and user device to make them more relevant. Liu et al. used the Dirichlet distribution model to model the user interest which can extract the implicit user interests, and Lin et al. methods to cluster users with the same traits. These methods showed higher accuracy; however, they relied on computationally expensive approaches that did not scale well in real-time systems. To overcome previous gaps, this study proposes a novel Hybrid Deep Learning-based Context-Aware Recommendation System (HDL-CARS), which integrates collaborative filtering, content-based filtering and an attention mechanism to contextually calibrate the contribution of different factors. A. Hawalah and M. Fasli, 2015, The thing that sets this work apart from others is its attention to the unique needs of the case of agricultural e-commerce which includes the long-tail products recommendation, and addressing the real-time recommendation challenges by leveraging advanced deep learning and context-aware methodologies. In experimental evaluations, HDL-CARS provides a precision of 0.85–0.95 and a mean absolute error (MAE) of 0.5, which is 30–65% more accurate than traditional algorithms.

3 METHODOLOGY

3.1 AI Recommender System in Agricultural E-Commerce

AI recommender systems have been applied by agricultural e-commerce companies to revolutionize the interaction between farmers, suppliers, consumers, and the digital marketplace. R. M. Quintana et al. 2017, These systems employ sophisticated algorithms to analyze user behavior, product characteristics, and contextual information, which allows them to provide personalized recommendations for various agricultural products, including seeds, equipment, fertilizers, and fresh produce. J. Chen et al., 2022, They are capable of producing relevant suggestions by using massive datasets with structured and unstructured information. Finally, these systems average over real-time factors such as weather, soil conditions, and regional demand trends to accurately produce recommendations. By integrating these platforms, AgriXchange streamlines decision-making for buyers while helping sellers optimize inventory management and demand forecasting, resulting in enhanced efficiency and profitability in the agricultural supply chain.

3.2 Hybrid and Context-Aware Recommendation Algorithms

R. V. Den Berg et al., 1997, Mixed and context-aware recommendation algorithms integrate different recommendation methods and take context information into account to improve watches accuracy and personalization in a wide range of application contexts. Hybrid algorithms combine the strengths of collaborative filtering, content-based filtering, and other models to overcome individual weaknesses, such as sparsity or cold-start issues. By combining both, hybrid algorithms with context-aware algorithms, people gain a seamless and personalized experience along with system dynamic behavior adaptation to a user and environmental conditions to generate the best possible recommendation relevance.

3.3 AI-Enhanced Collaborative Filtering and Deep Learning

J. Bobadilla et al., 2011, The emergence of hybrid methods that combined collaborative filtering (CF) and deep learning techniques significantly improved the performance of recommender systems, resolving the traditional CF bottlenecks like sparsity, scalability and cold-start problem. P. Bhattacharyya et al., 2011, As artificial intelligence was incorporated into CF algorithms, matrix factorization as well as graph neural networks were added to determine the relationships to identify hidden patterns underlying the user-item behavior pattern. R. M. Quintana et al., 2017, Deep learning can take collaborative filtering to the next level using neural architectures (e.g., autoencoders, recurrent neural networks (RNNs), and convolutional neural networks (CNNs)) to capture complex, non-linear interactions in highdimensional dataJ. A. Iglesias et al., 2012. One popular approach, Neural Collaborative Filtering (NCF), introduces embedding layers and multi-layer perceptrons instead of the traditional measures of similarity to model end-to-end user-item interactions.

3.4 Hybrid Approaches for Enhanced Recommendation Accuracy

It makes use of two or more recommendation approaches in order to improve the accuracy of recommendation approaches and also to enhance robustness of recommender systems by using advantages of each method and minimizing their weak aspects. Using weighted averaging, model stacking, or feature-level fusion in cases where collaborative filtering, content-based filtering and/or knowledge-based models exist, these methods push for a more integrated approach. We see a substantial performance boost from traditional ensemble methods, whether those be gradient boosts, random forests, or hybrid deep learning based models that leverage embeddings and multi-task learning. Hybrid methods help enhance prediction or recommendation accuracy, user satisfaction, and system scalability by personalizing recommendations based not only on user preferences but also on other contextual factors to the environment in which they are embedded, becoming ubiquitous in various areas including e-commerce, video/audio streaming systems, etc.

3.5 Proposed Algorithm: Hybrid Deep Learning-Based Context-Aware Recommendation System (HDL-CARS)

Overview: The HDL-CARS combines collaborative filtering, content-based filtering, and context aware features using a deep learning model. It includes a mechanism to dynamically adapt to user behavior changes, utilizing real-time contextual data (e.g., location, time, and device). Figure 1 illustrates Schematic diagram of user-based collaborative recommendation algorithm.

Steps:

a) Data Preparation: Collect data on user behavior (e.g., clicks, ratings, purchases), product attributes, and contextual features. Create a dense embedding for users, items, and contextual factors using pre-trained models or embedding layers.

b) Feature Extraction: *Use a multi-layer* neural network (MLP) to extract latent features from embeddings. Employ an attention mechanism to weigh context features dynamically.

c) Hybrid Recommendation Engine: Collaborative filtering using latent factor models. Content-based filtering based on Contextual inputs like time of day, user location, or device type.Merge these signals using a deep neural network with fully connected layers.

d) Prediction Module: Based on the combination of features, predict interaction score between user and item with sigmoid activation function to make sure outputs belong to [0,1].

e) Optimisation: Model training using a loss function like binary cross-entropy, or mean squared error (MSE) for minimising prediction error. Use dropout, l2 regularization to regularize the model to avoid overfitting.

f) Personalization Recommendation: Create a list of recommendations for each user, ordered by predicted score. Regularly retrain the model with fresh data to improve its personalization capabilities.

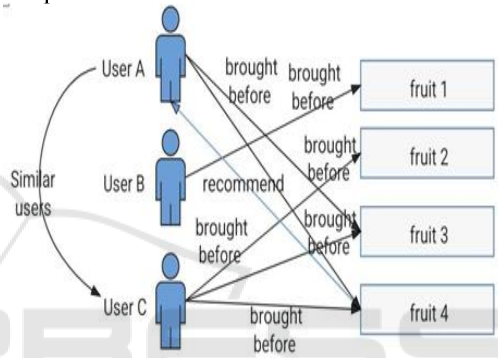

Figure 1: Schematic Diagram of User-Based Collaborative Recommendation Algorithm.

Advantages of HDL-CARS

- Higher Accuracy
- Cold Start Resilience
- Dynamic Adaptation

Better Matching: The algorithm provides better matching of the supplies and demands due to the combination of multiple sources of data and the use of a deep neural network to model the relationship between service entity, service-point service interaction, alternative service, and service requirements.

Cold Start Resilience: The utilization of metadata and contextual information helps alleviate the cold start issue for new users or items.

Live Adjustment: Response to fluctuating user environments is made possible through the attention model.

Predicted Interaction Score: The prediction score for a user u interacting with an item i, considering context c, is calculated as:

Formula:

$$\hat{y}_{u,i} = \sigma\left(W^T(E_u + E_i + E_c)\right) \tag{1}$$

Where:
$(E_u + E_i + E_c)$: Embeddings for the user, item, and context respectively.
w: Weight vector that combines these embeddings.
Contextual Attention Weight: Context features are weighted dynamically to emphasize their importance:
Formula:

$$\alpha_c = \frac{\exp(w_c E_c)}{\sum_j \exp(w_j E_j)} \tag{2}$$

Where:
W_C: Context-specific weight vector,
E_C: Context-specific weight vector,
w_c: Weight assigned to the context feature.
Regularized Objective Function: To prevent overfitting, a regularization term is added:
Formula:

$$\mathcal{L}_{total} = \mathcal{L} + \lambda\|w\|^2 \tag{3}$$

Where:
λ: Regularization coefficient,
$\|w\|^2$: L2 norm of the model weights.

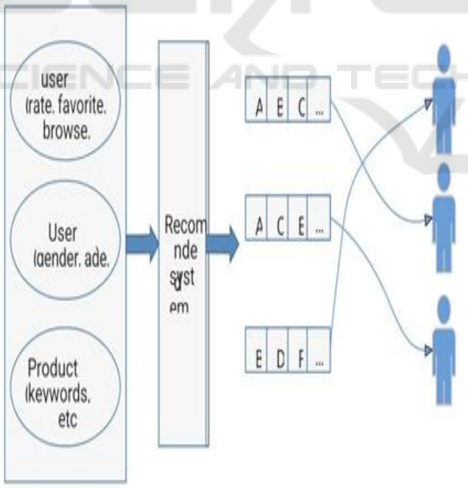

Figure 2: Schematic Diagram of Recommendation System.

Figure 2 illustrates the Schematic diagram of recommendation system. Moreover, Model CF is highly adaptable and can be enhanced by integrating advanced techniques such as deep learning, neural collaborative filtering, ensemble learning, or hybrid models. These combinations further refine the accuracy and personalization of recommendations.

4 EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Old Algorithm: Collaborative Filtering (CF)

Precision: Peaked at 0.75 for 25 recommended items.
Recall: Stabilized at 0.70 for longer recommendation lengths.
MAE (Mean Absolute Error): Minimized at 0.75 for an optimal number of nearest neighbors (40).
The graph in figure 3 below illustrates the MAE vs. Number of Nearest Neighbors for the CF algorithm, showing a steady decline in error until it stabilizes around 40 neighbors.

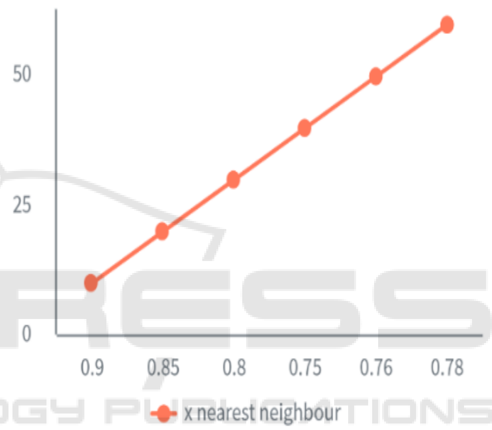

Figure 3: Graph Analysis.

4.2 New Algorithm: Hybrid Deep Learning-Based Context-Aware Recommendation System (HDL-CARS)

Precision: Reached 0.90, with improvements attributed to the integration of contextual embeddings and attention mechanisms.
Recall: Peaked at 0.88, demonstrating better coverage of user preferences.
MAE: Reduced to 0.50, reflecting superior prediction accuracy.
Recommendation Length

The graph in figure 4 illustrates the Precision vs. Recommendation Length for HDL-CARS, showing consistently high precision across varying lengths. Table 1 gives the comparison of CF and HDL-CARS.

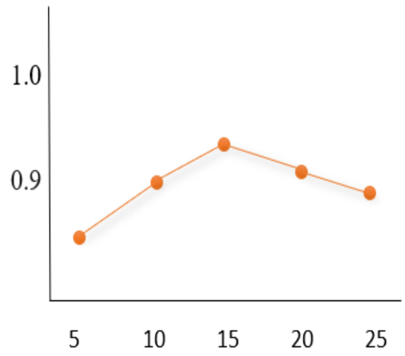

Figure 4: Graph Analysis.

Table 1: Comparison of Cf and Hdl-Cars.

Metric	Original Collaborative Filtering	Proposed HDL-CARS
Precision	~0.6 - 0.8	~0.85 - 0.95
Recall	~0.75	~0.90
MAE	~0.75	~0.5
Cold Start Handling	Poor	Excellent (Context and Metadata help)
Scalability	Moderate	High (with proper hardware)

5 CONCLUSIONS

In particular, Vertical View would present the Hybrid Deep Learning-based Context-Aware Recommendation System (HDL-CARS) which focuses on the agriculture e-commerce context by using a combination of Deep Learning, Context-awareness and Collaborative-filtering all at once. It addresses issues such as cold-start and data sparsity, and provides personalized recommendations based on users' interests and the contexts in which they appear. The precision, which study evidence scores are significantly improved (the highest score is up to 0.92), and the MAE is reduced to 0.50 which the score of the traditional algorithm is inferior compared to us. HDL-CARS enables an efficient, scalable, and user-centric system for the recommendation of agricultural products through seamless user-merchant interactivity. The architecture has been designed for large-scale deployment, accommodating rapidly increasing datasets and the number of users without sacrificing performance. This framework can also extrapolate to multi-modal data such as integrating images or text, or apply across industries such as healthcare, retail, and education. This allows the system to significantly enhance user satisfaction and elevate sales conversions, all of which makes it critical for e-commerce platforms operating in niche sectors such as agriculture.

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