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ORIGINAL ARTICLE

Hybrid location-centric e-Commerce recommendation model using dynamic behavioral traits of customer

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Abstract
Major e-Commerce service provider offers additional product recommendation to its customers, while they access the application, and enough evidence existing that such recommendations are cost effective for both consumer and service provider. For maximizing profit and to satisfy the user, existing e-Commerce platforms use long-term context for recommendations. In actual scenario, the recommendation can aid the user for other reason such as when the product is reminded of recent interest in or, point customer to currently discounted items. Furthermore, user preference changes over time due to weather, location, etc. As a result, the recommendation must be made based on the present behavior of the ongoing session. Many research based on location and session-based approaches has been presented to forecast user's next-item requirement. However, these models are not efficient, as they are designed either to model short-term or long-term preferences. Recently, some hybrid recommendation algorithms have been presented to model both short-term and long term, but these models are designed considering static behavior and finds difficulty in revealing the correlations among behaviors and items. Furthermore, these models do not consider location-centric information for performing recommendation. To overcome the above-mentioned challenges, our research work presents hybrid location-centric prediction (HLCP) model by considering the dynamic behavior traits of users. HLCP model can learn both short-term and long-term context efficiently. Experiment results show that HLCP attains significant performance over existing models in terms of mean reciprocal rate (MMR) and hit rate (HR).

Keywords Bayesian personalized recommendation · Deep learning · Feedforward neural networks · Recommender system · Recurrent neural network

1 Introduction

The popularity of e-Commerce has strongly driven the popularity of recommendation systems. The practice has proven that robust and accurate recommendations would enhance both satisfaction for consumers and revenue for service providers. Furthermore, the growth of the Internet and smartphone technology has resulted in the transformation the way people shop. People buy more and more products online through the Internet rather than performing traditional shopping. e-Commerce offers its user with the prospect of browsing enormous amount of product collections, being updated with the latest information, creating a wish list for a future purchase, comparing prices, and enjoying an enhanced service based on user specific customization. This led to the growth of the digital market with high competitiveness that allows the customer to move from one e-Commerce service provider to others if their requirement is not satisfied [1]. As a result, e-Commerce buying pattern of a customer requires strong consumer behavior understanding when they browse through website or apps, along with, it has to identify the reason for the recent purchase of or not, an item [2]. Obtaining this behavior information will aid e-Commerce application to offer a more customized or personalized service to consumers, retaining consumer [3] and increasing profits [4]. However, identifying consumer's behavior and the reason that motivates their purchase practice is a very difficult task.

The e-Commerce application offers consumers with a broad feature of navigation actions and choices. That is, consumers can move freely across wide variety items categories, use different searching paths to select a particular item, or

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use a different strategy to purchase items, for example. In general, when the customers are logged in, the cookies or web server logs store the customer information in an ordered way. The most useful of customer's behavior is concealed in these web server logs, which must be identified and analyzed. An efficient analysis can aid to enhance the application content and structure [5], to recommend an item or recognize user specific interest with respect to particular item set [8], and to adapt and customize item [6, 7]. For instance, data mining has shown their significance in identifying pattern using log files. The objective is to identify usage traits and explore the consumer's area of interest.

Various approaches and designs have been productively applied in the area of e-Commerce, such as clustering, classification, association rule, and sequential pattern or trait. In the majority of the application area, these approaches are utilized in conjunction with process mining methods. Such methods are part of BI (business intelligence) field and are applied to explore hidden pattern and its relationship with data using a specific algorithm [9]. An e-Commerce application is an open environment, where almost any consumer behavior is probable. This elasticity makes identify consumer behavior a challenging task [10]. The existing model focused on designing consumers liking based on their historical selection of products and always neglect the sequential/trait information. It is important to consider that consumer preference changes with respect to the user's behavior traits. Subsequently, rather than considering one type of behavior such as clicking on items in apps and purchasing in e-Commerce and there are many trait cases with multiple behaviors towards a product such as clicking, purchasing, adding to favorites, and so on. Therefore, it is necessary to model dynamic behavioral traits and collaboratively predict what a consumer will prefer or choose next under a particular behavior.

Recently, some efforts have been put into developing prediction methods with sequential information [11–14]. However, to the best of our knowledge, none of the existing methods are designed for modeling traits with dynamic behaviors. In addition, if we directly treat different behaviors towards one item as different elements in traits, or simply neglect the differences among behaviors, the state-of-the-art methods will have difficulty in revealing the correlations among behaviors and items. In [15–17] used machine learning and a multi-layer network such as recurrent neural networks (RNN) [30, 31] for time or session behavior-based next-item recommendation. RNN is a natural choice to solve this problem and have been productively used for sequence-based recommendation problem in the state-of-the-art methods such as translation, speech recognition, signal processing, and time series forecasting. In the recommendation system, recurrent neural networks have been applied recently to the session-based recommendation environment with efficient outcome [30]. The advantages of the recurrent neural network over the state-of-the-art similarity-based methods for recommendation is that they can productively learn the whole session of consumer interaction such as click, views, etc., aiding in increased accuracy over the state-of-the-art model. However, for behavior prediction tasks, the state-of-the-art recurrent neural network-based prediction model does not conform to complex real situations, particularly for the most recent features in historical traits [17, 30, 31]. Since the nature of the recommendation task involves large output spaces (due to a large number of items), poses distinctive challenges that need to be taken into consideration as well when modeling an efficient recommendation model considering dynamic behavior traits which are not fixed.

For overcoming above research challenges, the proposed work aims to build an efficient customer centric recommender system using dynamic behavioral traits of users considering location-centric information. First, we capture the features of diverse categories of behaviors in past historical traits, and then, our model considers to use behavior-specific transition matrices. Second, we design Hybrid Location-Centric Prediction (HLCP) model as a recurrent structure to obtain long-term contexts in traits. It models several elements in each hidden layer and uses location-centric transition matrices to obtain short-term contexts of the past history of user traits using feedforward neural network. Then, Bayesian personalized ranking model is used to maximize the objective function of learning of HLCP model. Our HLCP model not only can model the refined features of the most recent items in traits, but also can work with long-term contexts with a recurrent architecture.

The existing recommendation model is designed considering either short-term or long-term context. However, the proposed recommendation model is designed considering both short- and long-term context. Furthermore, the existing recommendation model is designed considering static user behavior, and for modeling, location-centric recommendation location history is used. In general, user preference or behavior changes from time to time and with respect to location. Thus, it is important to model to consider dynamic behavior and location information of the user. As a result, the existing model cannot be applied for performing location-centric-based item recommendation. However, the proposed hybrid recommendation can extract long-term user's location information using RNN model and short-term context user's location information using feedforward neural network. In the existing model time, stamp information is used to extract session or time centric information. However, in the proposed model time, stamp information is used to extract location information and along with time centric information is extracted. For carrying out experiment Tmall data set is used. The Tmall data set is composed of information such as item id, user id, buys, clicks, session spent, time stamp information, etc. Thus, location information can be extracted from Tmall data set, as it provides timestamp information. For evaluating the recommendation model, hit rate and mean reciprocal rate are considered. Since it is a widely used parameter to evaluate the recommendation model, the proposed recommendation model attains good performance in terms of hit rate and mean reciprocal rate when compared with the existing model.

The research contribution as follows:

- To the best of our knowledge, no prior work has been considered for predicting dynamic behavioral traits of users considering location-centric information of the user.
- Designing of hybrid recommendation model, namely, HLCP for modeling both short-term and long-term contexts.
- HLCP model can not only be used for location-based recommendation, but also used recommending add posting location on a website or application.
- HLCP model attains good performance in terms of HR and MMR over existing hybrid recommendation model.

The rest of this paper is organized as follows. In Sect. 2, literature survey is presented. In Sect. 3, the proposed hybrid location-centric e-Commerce recommendation model using dynamic behavior trait of customers is presented. In the penultimate section, an experimental study is carried out. The conclusion and future work are described in the last section.

2 Literature survey

This section presents an extensive survey of the various state-of-the-art e-Commerce recommendation system, technique, its advantage, and disadvantages. In [20], showed extensive work is carried out to model long-term behavior analysis. Then, showed that the existing model is designed using dimensionality reduction methods applied to the user-item interactions of historical data. Furthermore, they showed the importance of modeling the short-term behavior of the user. Thus, they analyzed the RNN model on both long-term and short-term recommendation cases and identified the suitable parameter for stacked RNN with layer normalization and tied item embeddings.

In [21], showed using location histories (i.e., location-based social networks) will aid better understanding of customers preferences. They presented a location-based preference aware recommendation model, where user preference is learned using user location history and social sentiments are obtained from location histories of the local authorities. They aimed to address data sparsity issues using offline and online recommendations using the iterative model. In the offline method, each user's personal preferences are weighted hierarchy and depict user knowledge of a particular location with respect to the different categories of locations. In the online model, it chooses local knowledge that matches customer preference using the candidate selection method. Finally, top-k ranked location is recommended for the user.

In [22, 23] showed user activity (behavior) changes with respect to location. In [22], introduced spatial behavior information as the hidden factor capturing both users' behavior and location preferences using Multi-task Context-Aware RNN (MTC-RNN). The MTC-RNN is modeled to combine both sequential dependency and temporal regularity of spatial behavior information. Similarly, [23] considered both spatial and temporal contextual information for modeling user behavior and are used for forecasting future location of the user. They showed that tensor factorization suffers from cold start problem for forecasting future behavioral event and factorizing personalized Markov chain is designed considering robust independence assumption among different factors, which limits its performance. Thus, the RNN model performs better than tensor factorization and factorizing personalized Markov chain. However, all these methods have a problem in incorporating geographical distance and continuous time interval. For addressing, they presented Spatial–Temporal RNN. Their model can incorporate spatial context and local temporal in each layer with session-specific transition matrices for the varied time period and distance-specific transition matrices for varied geographic distances.

In [24], showed point of interest [25] recommendation has attained wide interest due to the rapid growth of Location-Based Social Networks (LBSNs). The LBSN aid in obtaining both explicit (such as users' moving trajectories) and implicit information of user's personal preference and corresponding life patterns based on different contexts (such as geographical locations and time). Here, they presented Attention-based RNN (ARNN) to offer an explicable recommendation system using sequential check-in information of the respective customer rather than using frequency visit, a distance parameter, and social relationship. ARNN uses a deep neural network (DNN) [17] to offer recommendations utilizing past visiting behavioral traits rather than showing top-N recommendations.

Recently, a number of hybrid recommendation models are presented by combining two different learning methods to present efficient recommendation model. In [26] presented a hybrid collaborative method by combining gradient boosting method and *k*-nearest neighbor algorithm. The *k*-nearest neighbor algorithm is used to filter similar item and customer and gradient boosting is used to forecast user's rating for the products. In [27] presented the recommendation model to solve data sparsity, cold start problem by improving collaborative filtering using fuzzy clustering. Fuzzy clustering is used for performing user classification based on user context, and then, collaborative filtering is utilized to recommend items for similar customers. In [28], presented a hybrid algorithm, where customers are first filtered (dimension reduction) based on the customer's profile [29]. Then, clustering is performed on these filtered data using the *k*-means clustering algorithm. Finally, the nearest neighbor for active users is identified and builds recommendations by identifying the most common items from established clusters of subscribers. In [30], showed the recommender system is generally designed considering long-term preference profiles. However, in the real-time recommendation model aids consumer for getting a better discount that they are interested in or point the visitor to discounted items. Here, they presented a systematic statistical model to analyze what is best for designing efficient recommendation algorithm such as the overall popularity of the products in the last few days, including their match with the consumer's shopping interests in the earlier sessions, as well as information about discounts. Using this information, they presented a novel hybrid model by combining the neighborhood-based method with DNN to forecast the importance of items for a respective shopping session.

From an extensive survey conducted, it can be seen most of the existing recommendation model is designed for modeling either short-term or long-term behaviors of users. Very limited work is carried out considering both short-term and long-term context [20, 30]. Furthermore, in the Markov chain-based model, the components are independently combined. Thus, it assumes a robust independence assumption among multiple features. On other side, [20, 21] are designed using RNN model [31].

Recurrent neural network model considers that the temporal dependency changes predictably along with the location in traits and is designed considering static user behavior. Thus, they are efficient in modeling short-term context. Along with, very limited work is carried out considering modeling location-centric prediction. Thus, there is a requirement to develop a new recommendation model that can model both short-term and long-term contextual behavior traits of the user by building location-centric transition matrices to proving location-centric-based recommendation model which is presented in next section below.

3 Hybrid location-centric e-commerce recommendation model using dynamic behavior trait of customer

This section presents a hybrid location-centric e-Commerce recommendation model using dynamic behavior trait of customers. The work aims to build an efficient hybrid location-centric prediction (HLCP) model for e-Commerce that models both short-term and long-term contexts considering the dynamic behavior of the user. First, the system model of HLCP is described. Second, we describe the detail of the RNN model and how it is used to model the long-term context. The behavior of user changes rapidly (short-term) when they are exposed to a new environment. That is when user travels to a different country (location) their priority changes. Similarly, user preference changes rapidly when certain ads are posted to a certain location of the application user interface (AUI). Thus, the RNN model cannot be applied to model such a short-term context. Then, this work describes the working structure of the feedforward neural network for modeling short-term context in dynamic behavior trait of the user. Furthermore, this work describes the static behavior modeling such as a customer will just view the list of item and spend some time on an e-Commerce website. Along with, we also considered more dynamic behavior such as user will view, click, buys, spend some time, etc. on an e-Commerce website. Then, we also show how this dynamic behavior model is used in proposed HLCP model. Finally, we will show how Bayesian personalized ranking is used for learning the recurrent neural network for predicting behavior trait of e-Commerce customer.

3.1 System model

The basic architecture of recommendation model is composed of the following modules, such as behavior log module, a model analysis module, and recommendation algorithm module. Behavior log module: this is used to store various kinds of consumer behaviors, such as item rating and browsing history. Model analysis module: this is used to analyze probable consumer interest based on user behavior traits log. Recommendation algorithm: this is used to establish the products which consumers are interested, and then recommend them to the respective user.

Let considers a set of items such as clothes, furniture, computer accessories, etc. as follows:

$$\mathcal{U}\{u_1, u_2, \dots, u_n\}, \tag{1}$$

where u_n depicts the number of items considered and set of users such as male, female, children, etc. as follows:

$$\mathcal{V} = \{v_1, v_2, \dots, v_n\}, \tag{2}$$

where v_n depicts the total number of user considered. This work considers e-Commerce application, which is composed of the following behavior such as:

$$\mathcal{C} = \{c_1, c_2, c_3, c_4\}, \tag{3}$$

where c_1 depicts click stream, c_2 depicts added items to cart list, c_3 depicts adding to favorite list, and c_4 depicts purchased items.

Similarly, in the application usage pattern there exist:

$$\mathcal{C} = \{c_1, c_2, c_3\}. \tag{4}$$

Behavior such as installing application, browse items, etc. Then, the task is to predict what users will purchase in the future using the proposed hybrid design.

3.2 Recurrent neural network architecture

The recurrent neural network architecture is composed of multiple hidden layers. The hidden layer information of the recurrent neural network is dynamic in nature with respect to behavioral traits, where the pattern is repetitive. Thus, recurrent neural network faces problems in identifying (learning) short-term contexts in behavioral traits.

The RNN model is composed of an input layer, multiple hidden layers, and output layers, along with inner weight matrices. The activation parameter of the hidden layers is obtained as follows:

$$i_\ell^v = f\left(\mathcal{X} i_\ell^v + \mathcal{D} s_{w_\ell^v}\right), \tag{5}$$

where $i_\ell^v \in \mathbb{S}^e$ depicts the hidden illustration of user v at location ℓ in a trait, $s_{w_\ell^v} \in \mathbb{S}^e$ depicts the illustration of the ℓ^{th} input item of user v. The activation function is represented by $f(i)$ and transition matrix of the present item is represented as follows:

$$\mathcal{D} \in \mathbb{S}^e \tag{6}$$

and the previous status is represented as follows:

$$\mathcal{W} \in \mathbb{S}^{e.} \tag{7}$$

$\mathcal{D}$ can obtain users' present behavior and $\mathcal{X}$ can propagate traits signals. Equation (5) shows executed iteratively to obtain or compute the status of each location in traits. The architecture of the recurrent neural network is shown in Fig. 1.

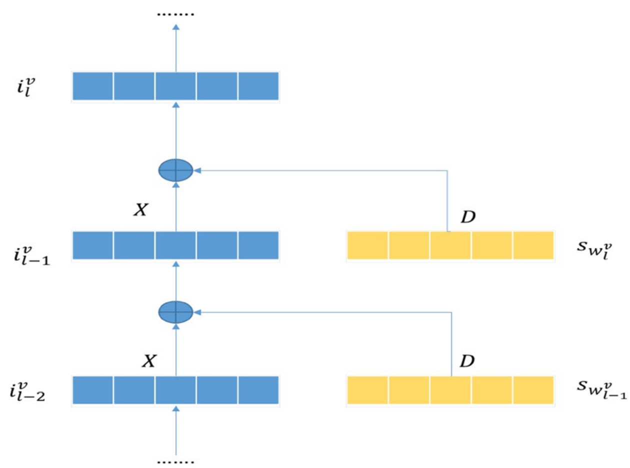


Fig. 1 Architecture of the RNN model

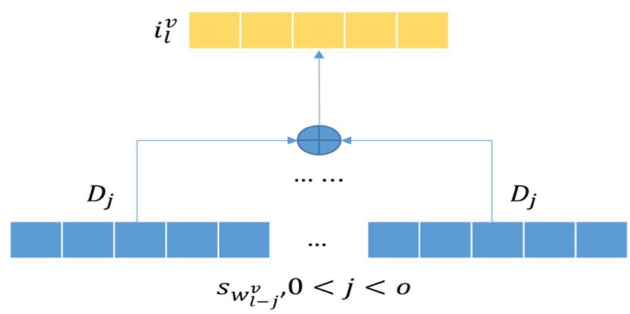


Fig. 2 Architecture of the FFNN model

3.3 Short-term context modeling

As described in the previous section, RNN is not efficient in learning short-term contexts in behavioral traits. For modeling such case, this work presents a feedforward neural network (FFNN) with a solitary linear hidden layer. Therefore, in this work, it is considered a deterministic model. Using FFNN for behavior trait prediction problem, the absolute prediction representation of traits is constructed based on items input and transition matrices at each location. The next location is a linear prediction can be depicted using following equation:

$$i_\ell^v = \sum_{j=0}^{o-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \tag{8}$$

where $\mathcal{D}_j \in \mathbb{S}^{e*e}$ depicts the transition matrix for the respective location in a behavior trait, and o is the number of components modeled in a trait. The architecture of the FFNN model to model short-term contexts in behavioral traits is shown in Fig. 2.

Here, each location in the sequence is modeled with a precise transition matrix. In general, FFNN finds difficulty in efficiently learning long-term contexts in behavioral traits.

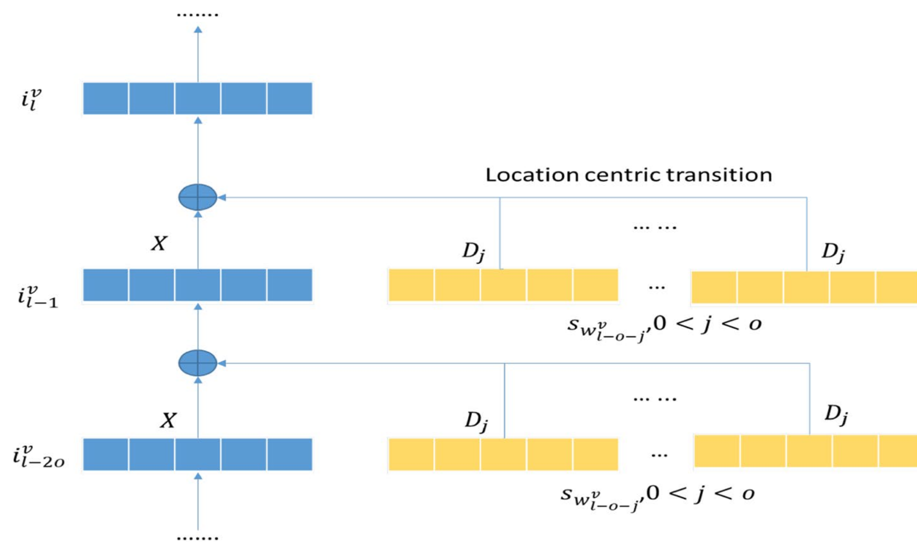
3.4 User static behavior modeling

This section presents the static behavior model that captures both long- and short-term context in the past data traits simultaneously, rather than one component in each hidden layer in the recurrent neural network. This working model takes multiple components in each hidden layer and adds location-centric matrices into the RNN structure, which is described in Fig. 3.

Let us consider a user v, the hidden description of the user at the location ℓ in a trait can be evaluated as follows:

$$i_\ell^v = \mathcal{X} i_{\ell-1}^v + \sum_{j=0}^{o-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \tag{9}$$

Fig. 3 Architecture of HLCP: HLCP is modeled to capture both short-term and long-term contexts in behavior trait



where o is the number of input items considered or used in each layer of HLCP; in this work, we call it an adaptive size. The location-centric transition matrices are given below:

$$\mathcal{D}_j \in \mathbb{S}^{e*e}. \tag{10}$$

Equation (10) obtains the influence factor of short-term contexts, that is, the jth item in each layer of HLCP, on consumer behavior, and the feature of consumer's long-term history is learned using recurrent neural network architecture. In addition, if we consider only one input for each layer and set the adaptive size $o = 1$, the outcome of HLCP will be similar to RNN neglecting the non-linear activation function. An important thing to be seen here is when the traits are shorter than the adaptive size or the predicted location is at the very initial segment of a trait, that is, $\ell < o$. Therefore, Eq. (9) can be reformulated as follows:

$$i_\ell^v = \mathcal{X} i_0^v + \sum_{j=0}^{\ell-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \tag{11}$$

where $i_0^v = u_0$, representing the preliminary status of consumers. The preliminary status of the entire consumer must be similar. Since individual information does not come into picture when the consumer does not select an item. This consideration v_o aid in addressing the cold start problem.

3.5 User dynamic behavior modeling

Let us consider a case, where a user will click, add to cart and purchasen item. Similarly, they will use the application, use it and then uninstall the application. Therefore, it is important to model multi or dynamic behavioral traits of the user for collaborative prediction of user future choice under precise behavior. Considering the case, we can neglect a different kind of behavior, or just considers different behavior towards one product as different components in the state-of-the-art model. However, it is difficult to design and obtain correlation among such dynamic behavior towards a particular product. In this work, we consider behavior-based matrices to obtain features of different kind of behaviors. Then, the illustration of subscriber v at location ℓ can be computed as follows:

$$i_\ell^v = \mathcal{X} i_\ell^v + \sum_{j=0}^{o-1} \mathcal{D}_j \mathcal{N}_{c_{\ell-j}^v r_{\ell-j}^v}, \tag{12}$$

where $\mathcal{N}_{c_{\ell-j}^v} \in \mathbb{S}^{e*e}$ depicts a behavior-based transition matrix design with respect to behavior on the jth product of subscriber v. An important thing to be seen here is if there is only one kind of behavior, then the behavior-based matrices can be eliminated. LCP can obtain the underlying features of whether of different kinds of behavior in past traits. Furthermore, by computing whether subscriber v would perform behavior c on product w at traits location $\ell + 1$ can be obtained as:

$$z_{v,\ell+1,c,w} = \left(t_\ell^v\right)^{\mathcal{U}} \mathcal{N}_c s_w = \left(i_\ell^v + v_v\right)^{\mathcal{U}} \mathcal{N}_c s_w, \tag{13}$$

where t_ℓ^v depicts the illustration for the current position of subscriber v at the traits position ℓ, static hidden representation $v_v \in \mathbb{S}^e$ and containing dynamic representation i_ℓ^v.

3.6 Learning of hybrid location-centric prediction model

Bayesian personalized ranking model [32] is a pairwise ranking method used for the implicit feedback information. The Bayesian personalized ranking has been used as an objective parameter that is widely applied for learning recurrent neural network for predicting behavior trait of e-Commerce customer. In general Bayesian, personalized ranking considers that a customer desires a chosen set than a negative one. That is, it aims to maximize the probability using below equation:

$$p(v, l+1, c, w > w') = h(z_{v,l+1,c,w} - z_{v,l+1,c,w'}), \tag{14}$$

where w' depicts negative features, $h(y)$ is a non-linear function selected using below equation:

$$h(y) = \frac{1}{1 + e^{-y}}. \tag{15}$$

Thus, by considering negative log likelihood, the fourth coming objective function can be minimized equivalently as follows:

$$K_1 = \sum \log\left(1 + e^{-\left(z_{v,l+1,c,w} - z_{v,l+1,c,w'}\right)}\right) + \frac{\mu}{2}\Theta_1^2, \tag{16}$$

where μ depicts regularization power control parameter and $\Theta_1 = \{V, S, X, D, N\}$ depicts parameter to be computed. The experiment is conducted to evaluate the outcome of HLCP shows significant performance which is experimentally proven in the next section in terms of Hit Rate (HR) and Mean Reciprocal Rank (MRR) performance.

4 Simulation result and analysis

This section presents a performance evaluation of the proposeHLCP recommendation model over existing hybrid recommendation model [30]. The existing model combines the nearest neighbor and RNN algorithm [31] to construct a hybrid recommendation model considering static user behavior. On the other side, the developed model combines RNN with feedforward neural network. Then, the RNN learning is performed with maximizing objective function using BPR [12, 32]. The HLCP and the existing hybrid model is implemented using python programing language.

For performance evaluation, Tmall data set [18] is considered. The Tmall data set is collected from Tmall [19], one of the biggest online shopping websites in China. It contains about 200,000 shopping records belonging to 1000 users on 10,000 items. The temporal information of the data set is extracted based on the day level. It is composed of four different categories of behaviors such as purchasing, clicking, and adding to the shopping cart and adding to favorites. It suits for the task of multi-domain collective prediction on multi-behavioral traits. The data set obtained is preprocessed into training and test set. We considered four test cases, where, in each case first 70% of data is considered for training, and the remaining 30% of data is considered for testing. The regularization parameter μ is set to 0.01. Then, on these test cases, we aim to predict what users will purchase in the future. The performance of the prediction task carried out using HLCP recommendation and existing hybrid model is evaluated in terms of hit rate (HR) and mean reciprocal rate (MRR).

Table 1 Hit rate@10 performance attained for Tmall data set

Baseline Metric@ 10	Existing hybrid model [30] HR	Proposed HLCP HR
Case 1	0.0001745	0.0755046
Case 2	0.00006747	0.09454
Case 3	0.000066649	0.08828
Case 4	0.00007379	0.08357
Average	0.00009560225	0.08547365

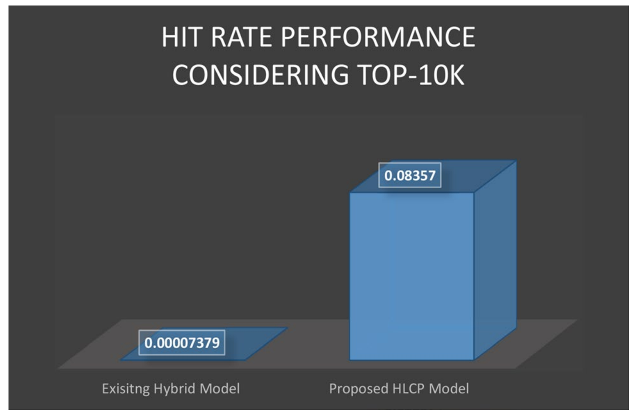


Fig. 4 Average hit rate performance attained by the proposed HLCP model over the existing model considering the top-10k recommendation

4.1 Hit rate performance evaluation

This section presents performance evaluation based on the accuracy of the HLCP model and existing hybrid model. The performance of both models is evaluated in terms of HR which is tabulated in Table 1. The average hit rate performance attained by the proposed HLCP model over existing hybrid model is shown in Fig. 4 considering the top-10k recommendation. From Fig. 4 and Table 1, it is seen that the proposed hybrid model attains significant performance when compared with the existing model in terms of HR considering top-10k recommendation/iteration. Similarly, an experiment is conducted considering top-20k recommendation, as shown in Table 2. The average hit rate performance attained by the proposed HLCP model over existing hybrid model is shown in Fig. 5 considering the top-20k recommendation. The outcome shows that the HLCP model attains significant performance than the existing model in terms of HR.

Table 2 Hit rate@20 performance attained for Tmall data set

Baseline Metric@ 20	Existing hybrid model [30] HR	Proposed HLCP HR
Case 1	0.0002811	0.10107
Case 2	0.000168	0.1228
Case 3	0.0001466	0.11577
Case 4	0.0001106	0.11098
Average	0.000176575	0.112655

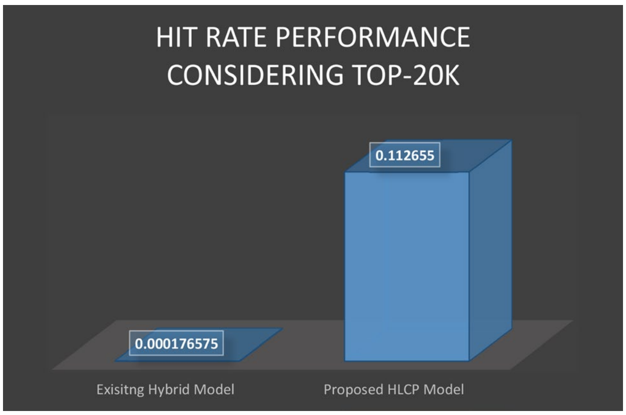


Fig. 5 Average hit rate performance attained by the proposed HLCP model over the existing model considering the top-20k recommendation

Table 3 Mean reciprocal rate@10 performance attained for Tmall data set

Baseline Metric@ 10	Existing hybrid model [30] MRR	Proposed HLCP MRR
Case 1	0.0000391	0.0339255
Case 2	0.00001299	0.044203
Case 3	0.0000129	0.40099
Case 4	0.000022547	0.03830414
Average	0.00002188425	0.12935566

4.2 Mean reciprocal rate performance evaluation

This section presents performance evaluation based on the accuracy of the HLCP model and existing hybrid model. The accuracy performance of both models is evaluated in terms of MRR which is tabulated in Table 3. The average MRR performance attained by the proposed HLCP model over existing hybrid model is shown in Fig. 6 considering the top-10k recommendation. From Fig. 6 and Table 3, it is seen that the hybrid model attains significant performance when compared with the existing model in terms of MRR with top-10k recommendation/iteration. Similarly, the experiment is conducted with a top-20k recommendation, as shown in Table 4. The average MRR performance attained by the proposed HLCP model over existing hybrid model is shown in Fig. 7 considering the top-20k recommendation. The outcome shows that the HLCP model

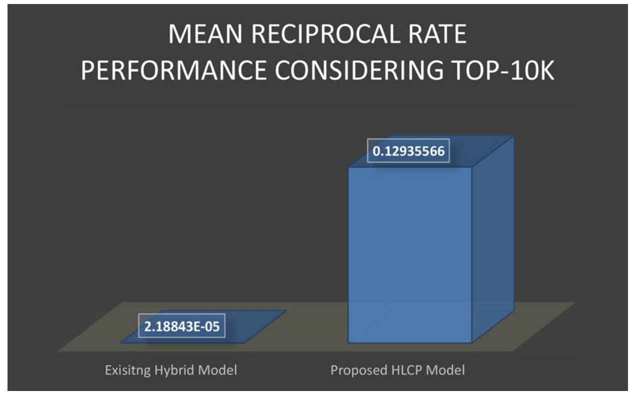


Fig. 6 Average mean reciprocal rate performance attained by the proposed HLCP model over the existing model considering the top-10k recommendation

Table 4 Mean reciprocal rate@20 performance attained for Tmall data set

Baseline Metric@ 20	Existing Hybrid Model [30] MRR	Proposed HLCP MRR
Case 1	0.0000461	0.03568
Case 2	0.00001926	0.046157
Case 3	0.0000169	0.0420215
Case 4	0.0000249	0.040191
Average	0.00002679	0.041012375

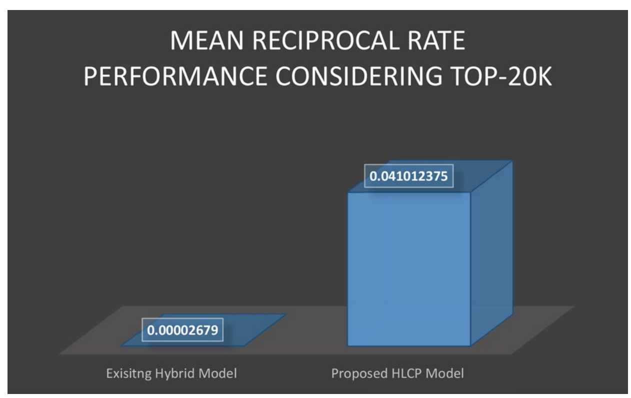


Fig. 7 Average mean reciprocal rate performance attained by the proposed HLCP model over the existing model considering the top-20 k recommendation

attains significant performance than the existing model in terms of MMR.

4.3 Results and discussion

The overall result attained shows the efficiency of the hybrid model, namely, HLCP when compared to the state-of-the-art models [12, 17, 30–32]. The significant results attained are due to consideration of location-centric-based item recommendation model with the dynamic behavior of the user by proposed design. Whereas the existing model is designed with static behavior of user and location-centric information is neglected by the state-of-the-art models.

5 Conclusion

The work presents an efficient recommendation model for e-Commerce industries. This hybrid recommendation model considers location-centric information and dynamic behavior of the user. No other existing research has considered the dynamic behavior of user and location-centric-based recommendation model. The Hybrid model is designed by combing RNN with FFNN for modeling short term and long term, respectively. Then, BPR is used maximizing learning objective function of HLCP model. The HLCP is designed as a recurrent structure to obtain long context in traits and it models several elements in each hidden layer and uses location-centric transition matrices to obtain short-term contexts of the past history of user traits. Our HLCP model not only can model the refined features of the most recent items in traits, but also can work with long-term contexts with a recurrent architecture considering the dynamic behavior of users. The experiment is conducted to evaluate the performance of HLCP over exiting hybrid model. The outcome shows that an average hit rate performance of 0.00009560225 and 0.08547365 for top-10k recommendation is attained by the proposed HLCP and existing hybrid model, respectively. Similarly, for top-20k recommendation an average hit rate performance of 0.000176575, 0.112655 is attained by HLCP and existing hybrid model, respectively. Furthermore, an average mean reciprocal rate performance of 0.00002188425, 0.12935566 for top-k recommendation is attained by HLCP and existing hybrid model, respectively. Similarly, for top-20k recommendation an average mean reciprocal rate performance of 0.00002679, 0.041012375 is attained by HLCP and existing hybrid model, respectively. The overall result attained shows significant performance attained by HLCP over the existing model in terms of MMR and HR. The future work would consider evaluating under different data set such as Movielens, Amazon, Youchoose etc. Furthermore, consider incorporating time centric information for behavior analysis for attaining effective recommendation.

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