Session-based Personalized Recommender System for Online Shopping

B. R. Sreenivasa, C. R. Nirmala, and M. V. Manoj Kumar

1 Introduction

The development of web and smartphone innovations have brought about changing how individuals shop. Individuals purchase increasingly more items online through the web or mobile application instead of performing traditional-style shopping. Recommendation systems [1] help customers in taking care of data over-burden by suggesting new things (i.e. products) that suit the client's needs (i.e. favourites) and requirements. Recommendation systems gather data on the client's inclinations for the products in a respective area such as an online shopping environment and movie and afterwards endeavour to forecast what different products the customer is probably going to discover significant (i.e. useful). Data related to customers' inclinations might be procured in an explicit manner through likes/dislikes, a rating, etc. and on. Similarly, the data can be procured in an implicit manner by verifiably observing the customer's activities. The well-known RS methods are content-based, collaborative or by combining multiple methods in designing hybrid methodologies. Collaborative filtering (CF) methodologies [2, 3] depend on the collaborative information of historical information of subscribers as well as of product for carrying out forecasting operation. The content-based methodologies endeavour to forecast products using content features likeness/similarities. The hybrid forecasting method [4,

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5] generally combines multiple methodologies discussed above for building efficient forecasting designs.

The state-of-the-art forecasting method concentrated on modelling customers' preferences and choices of likeness under users' historical behaviour on particular items and in general and consistently disregards the sequence behaviour data. Consider that shopper inclination/choice changes considering different customers' behaviour sequence. In this way, as opposed to considering one sort of behaviour, for example adding to cart, click stream and buying, there exist different behavioural sequences corresponding to products qualities cases with various conduct towards an item. Thus, it is preliminary to incorporate multiple behaviour sequences and forecast collaboratively what a user will purchase, select or prefer in future considering the certain behavioural context. In recent times, a few endeavours have been placed into creating forecast techniques using customer behaviour sequence data [6, 7]. Nonetheless, none of the current techniques is intended for learning sequence information considering a multi-behaviour sequence by our knowledge. Furthermore, if we straightforwardly treat various behaviours towards a product as different components in sequence, or just disregard the variance among behaviour sets, existing forecasting strategies will pose issues in establishing a correlation concerning behaviour sets and product sets. In [8, 9], utilized artificial intelligence (AI) and recurrent neural network (RNN) for session-based product forecasting. RNN has been widely used in the most existing method as a natural choice for addressing the issue of learning behaviour sequences efficiently. The model is applied to various sequence-based forecasting issues in time series forecasting, signal processing (SP), pattern recognition, etc. in a productive manner. In RS, RNN is widely used for modelling a session-based forecasting environment with good results.

This work focuses on building efficient session-based RS for the e-commerce environment [10]. His work endeavours to establish if a set of products looked into by the customer during an ongoing session is probably going to end with a buy. For meeting real-world challenges and circumstances, the above-discussed problems are challenging because the forecasting model needs to learn inter-product dependencies and its relationship. Recent work modelled based on session-based RS [5, 11] and [12] centre around forecasting future top-k products list of the session, as opposed to foreseeing the utilization purpose/goal. This paper accepts that forecasting the purpose of the customers early in the session may aid the number of strategies improving the session result. For example if the model can predict the session purpose (i.e. if the RS model predicts the user leaves the ongoing session without purchase), then the system might provide a certain discount for changing the mood or intent of the customer. Along with this, this paper addresses the cold-start issues for purchasing purpose forecasting in the current ongoing session where customers' purchase history is not available for new entrant products in the e-commerce environment. This circumstance generally occurs in an e-commerce environment when new products are added frequently. However, these issues have not yet been overcome by existing methodologies. For overcoming research challenges, this work presents a time-centric predication model for online shopping environment using a hybrid learning technique. Research contribution as follows:

- This work presented a time-centric prediction model combining both short and long-term behaviour sequences.
- TCP model attains good performance considering hit rate (HR) and mean reciprocal rate (MRR) concerning state-of-the-art RS methods.

The manuscript is articulated as follows. In Sect. 2, some baseline methods are described. In Sect. 3, the proposed time-centric recommendation model for online shopping portal is presented. In Sect. 4, the experiment is conducted using online shopping portal data and the performance of TCP, and the existing recommendation model is evaluated. The conclusion and future work are described in the last section.

2 Literature Baseline Methods

Many research work has been carried out in literature to overcome the shortcomings of traditional recommender system by considering user preferences based on the characteristics of items to provide more accurate recommendations [13], and it is been used in many product-based RS [14], tourisms RS [15], restaurant RS problems [16] and many others. In [17], the author described how the RNN model is used to predict the user next buying pattern based on the previous history log files. To minimize the costs and to increase the prediction accuracy, all older states are combined into single window and keeps only latest states. Quadrana et al. [18] presented a hierarchical recurrent neural network for session-based RS, and it mainly focuses on user indentities. Methods based on recurrent neural networks concentrate on session-oriented proposal issues. Out of these techniques, gru4rec is a significant method used for effectively planning for session-based recommendation scenarios [11, 12]. Then, gru4rec constructs gated recurrent units with the help of RNN [19, 20] to predict the likelihood of possible events (e.g. click streams) at the start of every session. The solitary item determines the contribution of the method, which is based on vector in one-hot encoded form and yield. It gives a positioning circulation. Typical GRU layer screens a state that encodes existing items in the same session. While predicting with the help of GRU, the items of a session must be fed of into the system. As far as activation functions, tanh functions to work best for GRU and the ranking layer. Use of RNNs for prediction issues is a characteristic decision. Decision of the loss function and utilization of session parallel mini-batches to accelerate the training phase are key components of the approach.

3 Time-Centric Recommendation Model for Online Shopping Portal Environment

This section presents a time-centric prediction/recommendation (TCP) model for online shopping portal using session-centric behaviour information of customers. For obtaining a relationship between user current session and past behaviour for recommending items, it is important for modelling both short and long-term behaviour contexts (i.e. time-centric HLCP model [21]). As discussed in [21], the RNN model is efficient in modelling the long-term behaviour of the customer. Thus, this work uses RNN for modelling long-term dynamic behaviour. The architecture of the RNN model is shown in Fig. 1. Similarly, in [21] showed that FFNN is efficient in modelling short-term behaviour context of the customer when compared with RNN. Thus, this work uses FFNN for modelling short-term sequence. The architecture of FFNN is shown in Fig. 2.

For capturing the dynamic behaviour of the customer, this paper uses behaviour-based matrices for obtaining feature sets of various sorts of behaviour sets. Then, the illustration of subscriber v at ℓ is estimated using the following equation

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

where $\mathcal{N}_{c_{\ell-j}^v} \in \mathbb{S}^{e*e}$ depicts a behaviour-based transition matrix design concerning behaviour on the jth product of subscriber v.

The cold-start problem can be addressed by considering $i_0^v = v_0$. Further, the existing sequence-based model generally neglects continuous session variance (SV)

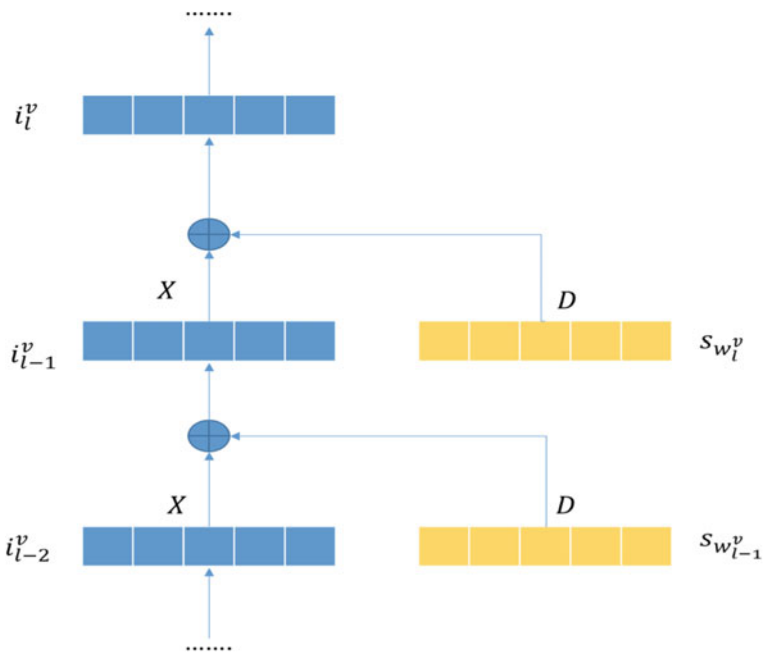


Fig. 1 Architecture of RNN model

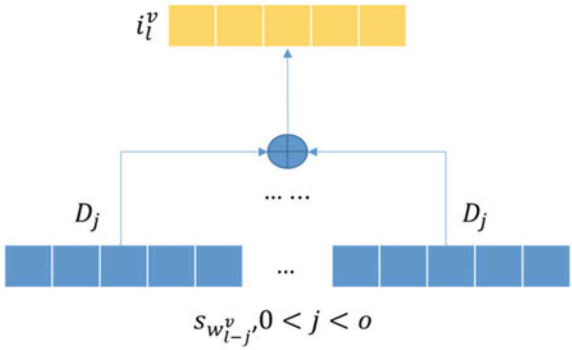


Fig. 2 Architecture of the FFNN model

among input feature sets. The session variance feature is very useful in forecasting as short-term session window variances generally have higher effects on future buying than using long-term session variances. Besides, as the behaviour of purchasing certain items are periodic. Thus, the impact of session variances results in more dynamic in such conditions. Considering these conditions, this work improves the HLCP model [21] by incorporating session variances knowledge and model time-centric prediction model.

Using [21], user preference can be learned better considering customer location. However, it is still important to consider incorporating time/session variance data into HLCP. Thus, this work presents an efficient time-centric prediction (TCP) model by substituting location-centric (LC) transition matrices (TM) with session-centric TM's. The TCP model is shown in Fig. 3. From Fig. 3 , for a given customer v, the location l is computed as follows

$$i_l^v = Xi_{l-o}^v + \sum_{j=0}^{o-1} U_{u_l^v - u_{l-1}^v} s_{w_{l-j}^v}, \tag{2}$$

where u_l^v depicts the present time, u_{l-1}^v depicts the time of every product of each layer of TCP, and $U_{u_l^v - u_{l-1}^v}$ depicts the time-centric TM of time variance $u_{l-1}^v - u_l^v$ among time u_{l-1}^v and u_l^v. The time-centric TM aids in capturing session-specific effects behaviour on the most recent activity log. Further, Eq. (2) is rewritten similarly with the HLCP model as follows

$$i_l^v = Xi_0^v + \sum_{j=0}^{l-1} U_{u_l^v - u_{l-1}^v} s_{w_{l-j}^v}, \tag{3}$$

where $i_l^v = v_0$ is depicting the preliminary condition of customers. From modelling dynamic behavioural traits, behavioural-centric TM's is used in the TCP model as follows

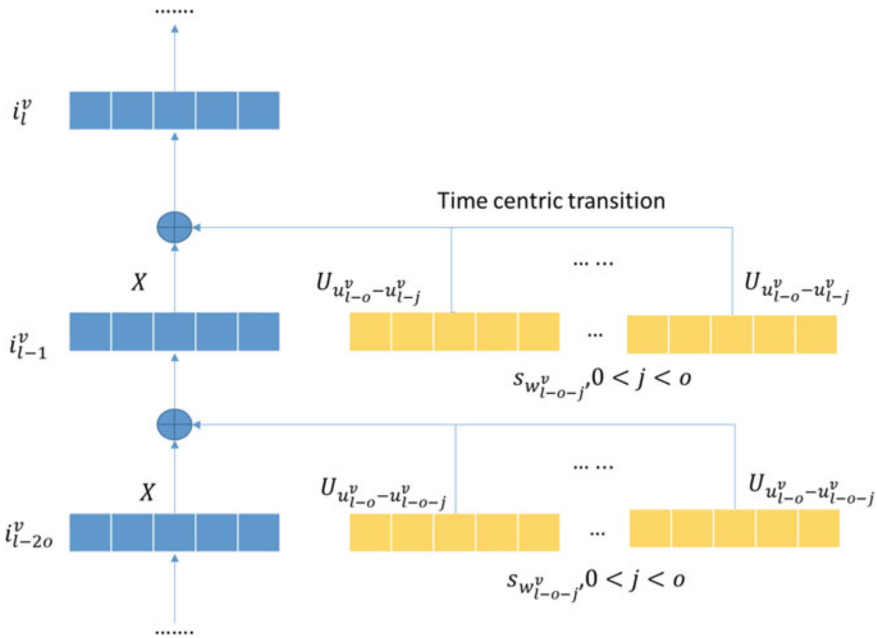


Fig. 3 Architecture of TCP that combines both short and long-term session behaviour sequences

$$i_l^v = Xi_{l-o}^v + \sum_{j=0}^{l-1} U_{u_l^v - u_{l-1}^v} N_{c_{l-m}^v} s_{w_{l-j}^v}. \tag{4}$$

Then, carry out forecasting operation whether a customer v will carry out certain behaviour c on particular product w at sequential location $l + 1$ is estimated similarly to HLCP using following equation

$$z_{v,l+1,c,w} = \left(t_l^v\right)^U N_c s_w = \left(i_l^v + v_v\right)^U N_c s_w. \tag{5}$$

The experiment is conducted using an online shopping portal dataset for both proposed TCP and existing recommendation models. The TCP model attains significant recommendation accuracy performance when compared with the existing recommendation model which is experimentally shown below.

4 Experiment Results and Discussions

This section discusses the results of the proposed algorithm and comparison in reference to evaluation benchmark, performance metrics and accuracy based on various standard datasets.

Table 1 Characteristics of the e-commerce datasets

Dataset RSC15	TMALL
Actions	13.42 M
Sessions	1.77
Items	425,348
Timespan in days	91
Action per session	7.56
Unique items per session	5.56
Action per day	149,096
Session per day	19,719

Evaluation Protocol and Performance Measures

The general computational error and in session-based recommendation issues are to produce a list of ranked items that in some structure "matches" a given session starting. What speaks to a decent match relies upon the particular application situation. It could be a set of alternative shopping things in an online business situation or a continuation of a given music listening meeting. The experiment is conducted on the Tmall dataset [11]. This dataset was distributed with regards to the Tmall competition and contains user-interaction logs of the tmall.com site for one year. For Tmall, each split comprises of 30 days of training and 1 day of test information. It is one of china's greatest Internet business web-based interface. Then, the preliminary job of the RS model is to forecast what the customer will buy in the current ongoing session using time-centric prediction and existing recommendation model. The performance of TCP and existing recommendation (ER) methodologies are evaluated using HR and MRR metrics. The characteristics of the data set used for the implementation of the proposed work is shown in Table 1. The Hit Rate and Mean Reciprocal Rank performance for different cases using Tmall dataset is shown in Table 2. Table 3 represents the comparison of of proposed and the existing work. Figures 4 and 5 represents the Mean Reciprocal rank and Hit Rate of the proposed work for Top 20 and 10 recommendations respectively with different iterations.

(a) *Hit rate/Accuracy outcome achieved by TCP and ER methodologies:*

Table 2 Hit rate (HR) and mean reciprocal rank (MRR) for a list length of 10 and 20 obtained for the e-commerce TMALL datasets considering different cases

Case	Metrics	Metrics MRR@20	Metrics HR@20	Metrics MRR@10	Metrics HR@10
Case1	Proposed HTCP	0.2976	0.5307	0.1969	0.4589
Case2		0.2983	0.5319	0.1977	0.4568
Case3		0.2989	0.5341	0.1984	0.4562
Case4		0.2986	0.5353	0.1982	0.4569
Average		**0.2984**	**0.5347**	**0.1978**	**0.4571**

Table 3 Result comparison with proposed work and existing work in terms of HR and MRR

Metrics	Metrics MRR@20	Metrics HR@20	Metrics MRR@10	Metrics HR@10
Proposed HTCP	0.2984	0.5347	0.1978	0.4571
Existing gru4rec (ER)	0.1852	0.4038	0.0986	0.2119

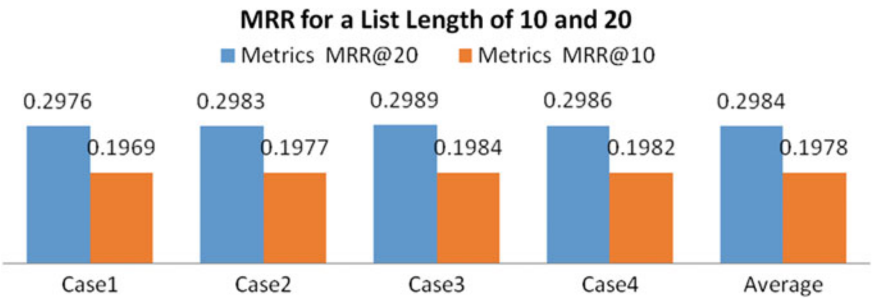


Fig. 4 Mean reciprocal rank for the list length of 20 and 10 with different cases for Tmall dataset

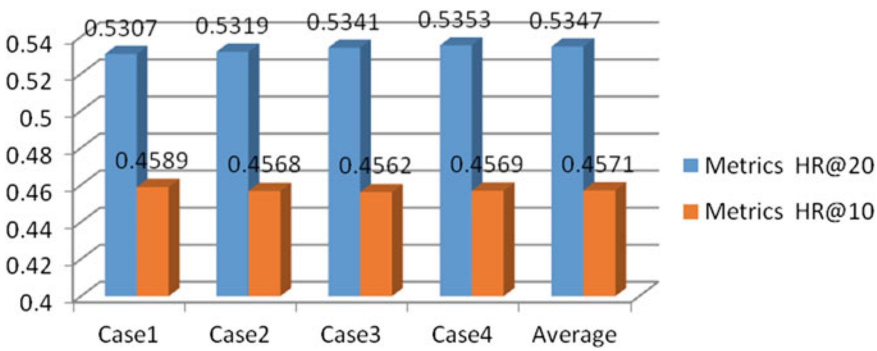


Fig. 5 Hit rate for the list length of 20 and 10 with different cases for Tmall dataset

The accuracy outcome (i.e. HR) of TCP and existing recommendation methodologies is evaluated in this section. The accuracy outcome is evaluated considering top-10 k recommendation as shown in Fig. 6. The TCP achieves an HR outcome of 0.4571, and ER (i.e. existing system (ES)) method achieves an HR outcome of 0.2119. From the result attained, it shows the TCP method achieves much superior HR outcome when compared with ER methodologies considering the top-10 k recommendation. Further, the accuracy outcome is evaluated considering top-20 k recommendation as shown in Fig. 7. The TCP achieves an HR outcome of 0.5347, and the ER method achieves an HR outcome of 0.4038. From the result attained, it shows the TCP method achieves much superior HR outcome when compared with ER methodologies considering the

Fig. 6 Hit rate performance considering the top-10 k recommendation

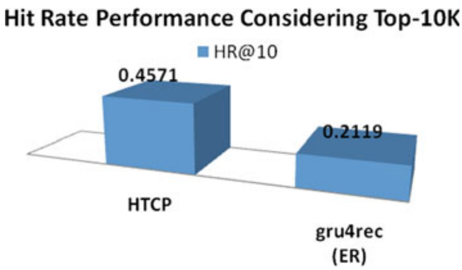
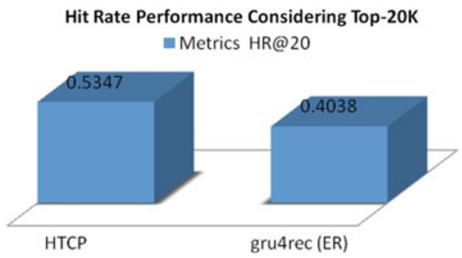


Fig. 7 Hit rate performance considering the top-20 k recommendation

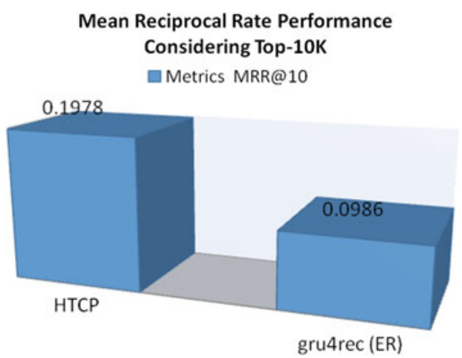


top-20 k recommendation. The overall result attained considering the top-10 k recommendation and top-20 k recommendation shows TCP achieves much superior HR outcomes.

(b) *Mean reciprocal rate/Accuracy outcome achieved by TCP and ER methodologies:*

The accuracy outcome (i.e. MRR) of TCP and existing recommendation methodologies is evaluated in this section. The accuracy outcome is evaluated considering top-10 k recommendation as shown in Fig. 8. The TCP achieves an MRR outcome of 0.1978, and the ER method achieves an MRR outcome of 0.0986. From the result attained, it shows the TCP method achieves much superior MRR outcome when compared with ER methodologies considering the top-10 k recommendation.

Fig. 8 Mean reciprocal rate performance considering the top-10 k recommendation



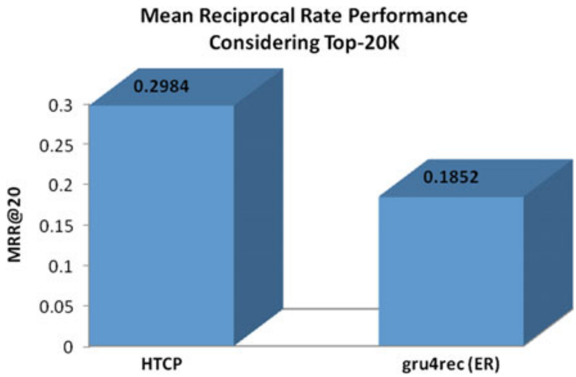


Fig. 9 Mean reciprocal rate performance considering the top-20 k recommendation

Further, the accuracy outcome is evaluated considering top-20 k recommendation as shown in Fig. 9. The TCP achieves an MRR outcome of 0.2984, and the ER method achieves an MRR outcome of 0.1852. From the result attained, it shows the TCP method achieves much superior MRR outcome when compared with ER methodologies considering the top-20 k recommendation. The overall result attained considering the top-10 k recommendation and top-20 k recommendation shows TCP achieves many superior MRR outcomes. TCP achieving better HR and MRR will aid in improving better profitability for the e-commerce environment.

5 Conclusion

Having the option to predict the users short-term interest for an online session is an exceptionally applicable issue practically speaking, which has brought expanded intrigue additionally up in the academic field as of late. Despite the fact that various diverse algorithmic methodologies were proposed throughout the years, no standard benchmark datasets and baseline algorithm exist today. In this work, we have looked at some of the recent and computationally complex calculations for session-based product recommendation. The experiment investigations on various diverse datasets show in many cases one of the simpler methods is able to outperform even the most recent methods based on recurrent neural networks in terms of the prediction accuracy. The work showed the effectiveness of using hybrid forecasting combining RNN and FFNN for forecasting user's choices in the current session. It is seen by combing RNN and FFNN, the hybrid model is efficient enough to minimize the cold-start and data sparseness problems in time-centric recommendation system. The experiment is carried out for evaluating the outcome achieved by the proposed TCP concerning existing recommendation methodologies. The overall result attained describes that HR outcome of 0.4571 and 0.2119 achieved by TCP and ER methodologies, respectively. Then, the HR outcome of 0.5347 and 0.4038 is achieved by TCP and ER methodologies for a list length of 10 and 20, respectively. Along with, MRR outcome of 0.1978 and 0.0986 and 0.2984 and 0.1852 is achieved by TCP and ER methodologies for a list length of 10 and 20, respectively. Result attained in this work shows that the proposed TCP model is very efficient when compared with ER methodologies considering HR and MMR evaluation metrics. Thus, will aid in improving better productivity (i.e. better sales resulting in good profit) of the e-commerce environment. Further work will study performance evaluation considering varied datasets and also consider refining mathematically the TCP model.

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