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Session centered Recommendation Utilizing Future Contexts in Social Media

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Abstract

Session centered recommender systems has emerged as an interesting and challenging topic amid researchers during the past few years. In order to make a prediction in the sequential data, prevailing approaches utilize either left to right design autoregressive or data augmentation methods. As these approaches are used to utilize the sequential information pertaining to user conduct, the information about the future context of an objective interaction is totally ignored while making prediction. As a matter of fact, we claim that during the course of training, the future data after the objective interaction are present and this supplies indispensable signal on preferences of users and if utilized can increase the quality of recommendation. It is a subtle task to incorporate future contexts into the process of training, as the rules of machine learning are not followed and can result in loss of data. Therefore, in order to solve this problem, we suggest a novel encoder decoder prototype termed as *space filling centered Recommender* (*SRec*), which is used to train the encoder and decoder utilizing space filling approach. Particularly, an incomplete sequence is taken into consideration by the encoder as input (few items are absent) and then decoder is used to predict these items which are absent initially based on the encoded interpretation. The general *SRec* prototype is instantiated by us employing *convolutional neural network* (*CNN*) by giving emphasis on both efficiency and accuracy. The empirical studies and investigation on two real world datasets are conducted by us including short, medium and long sequences, which exhibits that *SRec* performs better than traditional sequential recommendation approaches.

Key Words: Sequential Recommendation, Space-filling, seq2seq, Encoder and Decoder.
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1 Introduction

Session centered Recommendation systems (*SRS*) has emerged as an interesting and challenging topic in the field of recommendation, which is used to make a prediction about the next item by utilizing the past interactions within a user session. Although, deep neural networks [1]-[4] have undergone drastic advancements and are useful for modeling user short term sequences, but are not capable of catching sequential user behavior in long sequences [5]-[7].

Practically, long user session sequences broadly prevail in situations like news and short video recommendations. As an instance, TikTok users may see 110 short videos in 36 minutes, since every video runs on an average for 20 seconds.

In particular, two significant approaches exist to train the *recommender systems* (*RS*) utilizing sequential information: *autoregressive training* (*AT*) [7]-[8] and *data augmentation* (*DA*) [3], [4], [9]-[11].

Particularly, the data augmentation method like improved GRU4Rec [11] carries out preprocessing of data and produces novel training subsequences by utilizing the objective session, thereby, predicting the last product in the order by the recommender system.

The *autoregressive method* is used to depict the whole sequence in an end-to-end fashion, as compared to only last item. This approach leads to conventional left to right design framework termed as NextItNet [7].

The two approaches are based on the similar fact that while building the prediction function for an objective interaction, only historical user contexts are taken into consideration. If we observe the conventional sequential data prediction, it is a suitable option to predict an objective item based on the historical items [12] - [13]. But we claim that this may restrict the ability of the framework since the future contexts have not been taken into consideration.

Considering the *encoder decoder* (*ED*) framework, broadly employed in sequential data model [14] - [16], in language translation, while predicting the objective word in a sentence, the encoder considers words from two sides as the source. Because here the source and objective words pertain to diverse fields, loss of data does not occur. However, if the same *ED* framework is applied to user session modeling, it incurs data leakage.

To circumvent this problem, we suggest a novel *SRS* approach that takes into consideration the future data: Space-filling centered encoder decoder prototype for sequential recommendation (*SRec*). *SRec* renews the *ED* style by considering future contexts with no data loss i.e., the *ED* are collectively trained by space-filling approach [17], and is motivated by the construction of pre-trained framework [18].

Particularly, a part of products in a customer sequence are omitted by filling in the space characters (e.g., "_").

We have contributed the following:

(1) we have shed the light on depicting future data in session centered recommendation and developed a deep learning network prototype *SRec*,
(2) *SRec* is specified by us employing *CNN* with sparse kernels [7], combining the benefits of both autoregressive approach for sequence production and both sides contexts.

2 Groundworks

In this part, firstly the problem of session centered recommendations is defined by us. Afterwards, two conventional left to right design sequential recommendation approaches are summarized by us. In the end, earlier work of *SRS* is reviewed.

2.1 Top-N Session centered Recommendation

The interpretation of *Top-N* session centered recommendation in the research article has been done as in [3], [7], [11]. In *SRS*, the term session refers to group of items or objects i.e., songs, videos, etc. that occurred during an interval of time [10], [19]. For example, both a group of videos watched in an hour or a day and list of browsed web pages can be considered as a session.

Particularly, assume $\{a_1, a_2, ..., a_{s-1}, a_s\}$ as a customer sequence, where products are arranged in the consecutive fashion and $a_j \in \mathbb{R}^m$ $(1 \leq j \leq s)$ refers to directory of a searched product, m is the count of products in the sequence.

The objective of *SRS* is to instruct the framework for a session information, $a = \{a_1, ..., a_j\}$, it produces the distribution $\hat{b}$ for items occurring in the future, where $\hat{b} = \{\hat{b}_1, ..., \hat{b}_m\} \in \mathbb{R}^m$.

Remark 2.1 *SRS is capable of making larger than single recommendation by choosing the top-N items (e.g.,* $N = 15$*) in* $\hat{b}$ *termed as the Top-N SRS.*

2.2 Algorithms for Left-to-Right design

In this part, the sequential recommendation frameworks which consists of left-to-right designs are majorly reviewed by us, comprising of but not restricted to improved GRU4Rec [11], Caser [3], and NextItNet [7].

Data Augmentation. The researchers in [11] suggested a data augmentation approach to enhance the worth of recommendation of *SRS*, the concept which has been utilized in a large part of future research, like as in [3], [4], [10], [11].

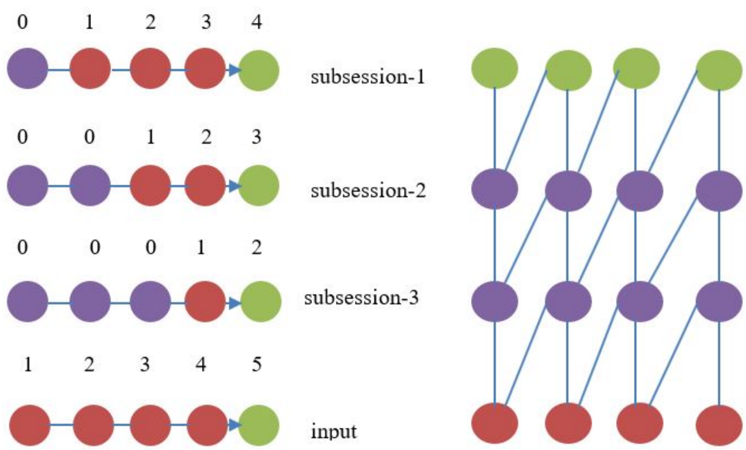
The conceptual clue behind *DA* in *SRS* is to consider entire prefaces in the customer session as sequences for training [1].

Particularly, consider a specified user session $\{a_1, a_2, ..., a_{s-1}, a_s\}$, the *DA* approach will produce a group of sequences

$$\{(a_2|a_1), (a_3|a_1, a_2), ..., (a_s|a_1, a_2, ..., a_{s-1})\}$$

as depicted in Figure 1 (a).

Utilizing this approach, the sequential framework is capable to know entire sequential dependence as compared to only the last item as and the sequence $\{a_1, a_2, ..., a_{s-1}\}$. Although, *DA* approach has been suitably utilized in several *SRS* algorithms, it may result in sharp increase in training times [7].



(a) Data Augmentation (DA) **(b) Autoregressive frameworks**

Figure 1: Two approaches to train *SRS* frameworks

Autoregressive (*AR*) Frameworks. The *AR* design learning approaches [7], [8] suggest to optimize all locations of the initial source sequence as compared to merely the concluding one.

Particularly, the framework gets into consideration $\{a_1, a_2, ..., a_{s-1}\}$ (or $a_{1:s-1}$) as the input and generate probabilities (e.g., `softmax`) over $a_{2:s}$ in a seq2seq (sequence-to-sequence) fashion.

In mathematical terms, the joint distribution of a user session $\{a_1, ..., a_{s-1}, a_s\}$ may be factorized as a multiplication of conditional distributions utilizing the chain rule as underneath:

$$p(a) = \prod_{j=1}^{s} p(a_j | a_1, ..., a_{s-1}; \theta), \tag{1}$$

where $p(a_j | a_1, ..., a_{j-1})$ refers to the probability of j-th item a_j based on its all $a_{1:j-1}$, θ as the parameters.

As stated earlier, these approaches, the *DA* and *AR* methods are used to get the customer session trained traversing left to right.

Remark 2.2 *Utilizing the future data can be considered as a means of DA which assists frameworks circumvent the sparseness issue in SRS.*

Inspired by the same, it is thought that it is significant to examine the effect to sequence recommendation frameworks by considering entire two directional sides.

2.3 Related Work

In the past many years, deep learning networks are being used in the arena of session centered *RS*. GRU4Rec [1] is considered as significant research which utilizes the *recurrent neural networks* (*RNN*) to predict the preference of the customer.

A variation of *RNN* called as improved *RNN* [11] exhibited good performance as compared to conventional *RNN* frameworks by incorporating *DA* approaches. The authors [20] suggested a ranking target functions to enhance the cross entropy and minimize loss. [2] suggested personalized *SRS*, whereas [21]- [22] showed utilizing contents and perspective characteristics to improve the accuracy in recommendation.

Some research work has been carried out centered on *CNN* and attention approaches. The significant goal is that there is a dependency on hidden state from all historical interactions in *RNN* centered sequential frameworks that is not capable of completely utilizing parallel processing capability of GPU [7].

As a matter of fact, the speed at which training and evaluation are carried out is somewhat restricted. As an alternative attention centered frameworks and *CNN* can be easily implemented in parallel because all the information pertaining to time periods in the customer sessions is recognized during the course of training.

The most significant *CNN* framework for *SRS* is Caser [3], that takes into consideration the matrix of product embedding as a picture and afterwards carries out two-dimensional convolution. In NextItNet [7], the researchers claimed that *CNN* operations of Caser had not been found appropriate for modeling large user sequences. As a consequence, the authors suggested employing stacked expanded *CNN* to enhance the responsive region of neurons existing in the higher layers.

Furthermore, the researchers argued that the data augmentation approaches broadly employed earlier research can be straightforwardly eliminated by constructing a seq2seq centered target function. They exhibited that the NextItNet employing autoregressive patterns is more influential contrasted to Caser and more effective compared to *RNN* frameworks for *Top-N* session centered recommendation job.

Motivated by Caser and NextItNet, many further researches [23]-[26] were carried out by enhancing the one-dimensional *CNN* or two-dimensional *CNN* for modeling the user item behavior. Furthermore, self-attention [8], [27], [28] frameworks also exhibited good outcomes in the field of *SRS*.

In the past few years, [5], [6] incorporated gated networks to enhance *SRS* by catching both long and short sequential designs. A related research in the same field is NARM [10], which suggested an attention centered encoder decoder approach for *SRS*.

3 Methodologies

3.1 Two-sides Data Augmentation

A well-defined method to bring the benefit of future contexts in is to inverse the customer series and get the recommendation trained by supplying it input and inversed output. This category of both sides *DA* method was utilized in many NLP functions [16].

The *RS* frameworks centered on these *AR* and *DA* approaches may be utilized with no change like employing NextItNet (NextItNet+) as underneath:

$$\begin{array}{llcl} \text{NextItNet+:} & \underset{\text{input}}{\{a_1, ..., a_{s-1}\}} & \longrightarrow & \underset{\text{output}}{\{a_2, ..., a_s\}} \\ & \underset{\text{input}}{\{a_s, ..., a_2\}} & \longrightarrow & \underset{\text{output}}{\{a_{s-1}, ..., a_1\}} \end{array} \tag{2}$$

3.2 Two-sides NextItNets

Identical to the NextItNet which is forward type, backward NetItNet executes throughout a customer sequence in inverse, estimating the earlier product based on futuristic data. The argument seems to be diverse compared to [7], when the guessed products and its futuristic information need to be concealed. In order to unite these sides in the target task, the combined log likelihood of these sides is maximized

$$p(a) = \prod_{j=1}^{s} p(a_j | a_1, ..., a_j; \theta_e, \vec{\theta}_{NextItNet}, \theta_s). \tag{3}$$

Remark 3.1 *The concept here is identical using the deep context word interpretation (ELMo) [29], the difference is that ELMo was formulated for word interpretation or for extraction of features, whereas we utilize the two sides NextItNet to answer the generating problem.*

3.3 Space-filling centered Encoder Decoder Model

In this part, firstly the general model and neural design of *SRec* is presented by us and afterwards, the association among *SRec* and other significant frameworks will be discussed.

seq2seq for SRS. The objective of seq2seq is to know a group of constraints θ to illustrate the conditional probability $P(c|a, \theta)$, and commonly utilizes the log likelihood as the target task [16], [30].

Remark 3.2 Utilizing the breakdown of the chain rule, the probability may be written as an autoregressive fashion as underneath:

$$p(c|a, \theta) = \prod_{j=2}^{s} P(c_j | c_{1:j-1}, a; \theta) = \prod_{j=2}^{s} P(a_j | a_{1:j-1}, a; \theta). \tag{4}$$

General model of pseq2pseq. It can be observed that it is not an easy task to construct a seq2seq framework utilizing Eq. (4) because the product which is estimated, e.g., a_j can be non-trivially observed from the encoder network by a.

To circumvent this problem, masked convolution functions are presented by us by incorporating the concept of space-filling [17] in the *ED* prototype.

The *ED* are depicted by utilizing the *CNN*; however, these networks can be swapped with attention [8] and recurrent networks [1].

The encoder interpretation can be compressed to a specific size vector [16] utilizing attention approach [14], [30].

4 Experimentations

The significant part of the research is to enhance the prevailing left-to-right design methods for *SRS* and *SRec* is evaluated using actual world datasets including short, medium and long session sequences and the empirical investigations are carried out by us to answer few research-oriented questions.

4.1 Empirical Setup

Datasets. The empirical investigation is conducted by us utilizing two real world datasets namely ML (short for MovieLens) and a short video dataset.

MovieLens. The dataset was built on 26th Sept., 2018 by MovieLens. Because this dataset comprises of cold items, a fundamental preprocessing is carried out to filter items which are observed less than 20 times, identical to [3].

The interaction sequence of the same user is generated by us in chronological fashion. The sequence is split into sub sequences after every p movies.

The sequences with length lesser than k are straightforwardly eliminated in our empirical investigations. In the investigation, we assign $p = 30$ with $k = 10$ and $p = 100$ with $k = 20$, which leads to 2 datasets, called as ML30 and ML100.

Table 1: Measurements of the datasets employed.

Datasets	No of sequences	No of actions	p	No of items
ML30	858160	25368155	30	18273
ML100	300624	25240741	100	18226
TW10	1048575	9986953	10	65997

TW10. This dataset is a short video dataset and built on October, 2018.

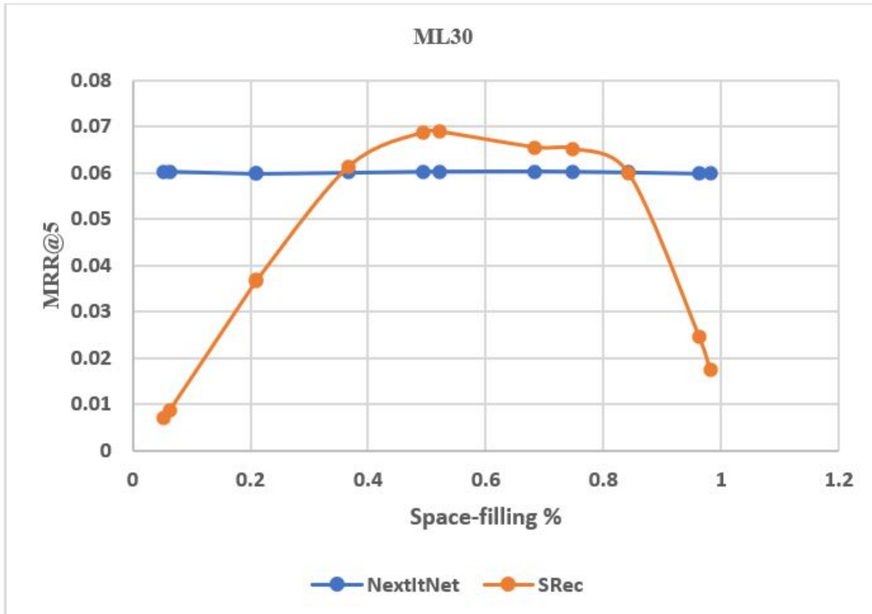
Table 1 depicts the different measurements of the 2 real world datasets employed for investigation in the research.

4.2 Assessment Guidelines

All user session sequences are split randomly by us into training (80%), validation (10%) and testing (10%) groups.

All the frameworks are evaluated by us utilizing three significant *Top-N* measures, called as HR@N (Hit ratio), MRR@N (Mean reciprocal rank) and NDCG@N (Normalized Discounted Cumulative Gain) [7], [31], [32].

For comparison purposes, N is set to 5 and 20. For every user session sequence in the testing groups, the accuracy of the last item is evaluated by us following [7], [8].



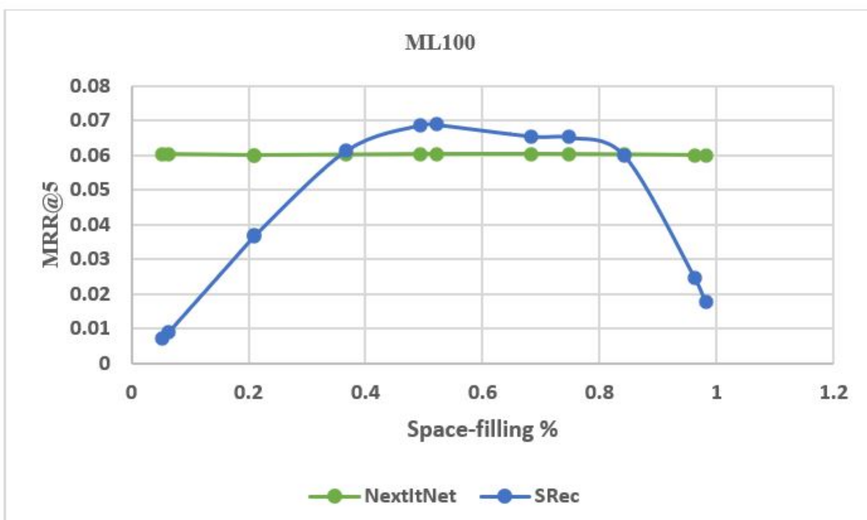


Figure 2: Performance behavior of *SRec* by adjusting the space filling percentage

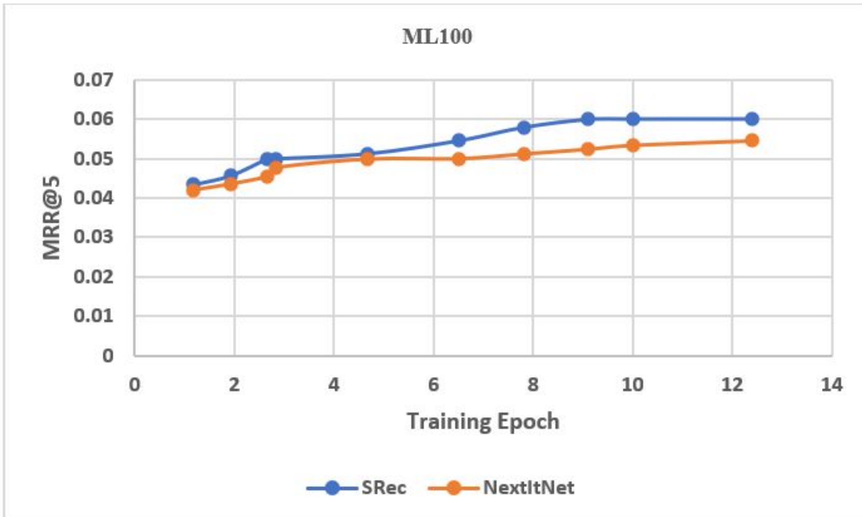


Figure 3: Pattern of convergence of NextItNet and *SRec*

4.3 Contrasted Approaches

The suggested augmentation approaches are contrasted with three significant *SRS* approaches, i.e., Caser [3], NextItNet [7] and GRU4Rec [1].

Table 2: Contrast of accuracy

Data	Frameworks	MRR@20	MRR@5	NDCG@20	NDCG@5	HR@20	HR@5
ML100							
	GRU4Rec	0.0630	0.0508	0.0972	0.0606	0.2210	0.0908
	Caser	0.0604	0.0490	0.0920	0.0582	0.2072	0.0862
	NextItNet	0.0685	0.0550	0.1058	0.0662	0.2410	0.1006
	SRec	0.0719	0.0587	0.1100	0.0701	0.2476	0.1056
ML30							
	GRU4Rec	0.0787	0.0651	0.1178	0.0775	0.2588	0.1155
	Caser	0.0738	0.0621	0.1082	0.0732	0.2322	0.1073
	NextItNet	0.0848	0.0703	0.1262	0.0836	0.2755	0.1241
	SRec	0.0888	0.0741	0.1314	0.0878	0.2849	0.1299

Table 2 depicts the accuracy for several frameworks.

Figure 2 and Figure 3 depicts the performance behavior and pattern of convergence respectively for the proposed *SRec* and conventional NextItNet approaches.

For the task of comparison, the usual pattern as in [5], [8], [33], [34] is followed by us by using value of 64 for embedding size. A sampled `softmax` [35] is carried out by us on TW10 and complete `softmax` on ML100 and ML30 for NextItNet and *SRec* in the whole research. All the frameworks utilize the Adam [36] optimizer.

5 Conclusion and Future Research Directions

However, in [37] user micro-behaviors and item knowledge has been incorporated and cross session information has been explored in [38] for *SRS*, in this research, we carry out examination on method of introducing futuristic data for the conventional left to right design approaches in the job of *SRS*.

The inspiration is that the designs of autoregressive centered *SRS* frameworks are not capable of modeling the historical and future information concurrently.

In order to remain with autoregressive approach and concurrently use two sides contexts, we suggested *SRec*, a new **pseq2pseq** *ED* deep learning network recommendation model with space-filling centered optimization concern.

The main advantage of *SRec* is its flexibility where the encoder and decoder can be jointly trained on the same user session sequence without loss of data.

By carrying out empirical investigations, we showed that *SRec* outperforms conventional frameworks.

As future research directions, we will be investigating further if the *SRec* is capable of enhancing the recommendation variety for *SRS*.

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