Adaptive Recommendation in Online Environments

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Abstract. Recommender systems form a class of Artificial Intelligence systems that aim to recommend relevant items to the users. Due to their utility, it has gained attention in several applications domains and is high demanded for research. In order to obtain successful models in the recommendation problem in non-prohibitive computational time, different heuristics, architectures and information filtering techniques are studied with different datasets. More recently, machine learning, especially through the use of deep learning, has driven growth and expanded the sequential recommender systems development. This research focuses on models for managing sequential recommendation supported by session-based recommendation. This paper presents the characterization in the specific theme and the state-of-the-art towards study object of the thesis: the adaptive recommendation to mitigate the information overload in online environments.

Keywords: Recommender systems · Information filtering · Sequential recommendation · Session-based recommendation · DNN recommendation

1 Introduction

The evolution of recommender systems (RS) as a field of scientific research has occurred since 1990 [1, 2] and it is studied as a feasible solution to the recommendation problem. Formally, the problem consists in the definition of a utility function to recommend one or more items with highest estimated ratings and ranked by one output score obtained for each item to the user [3]. Due to their utility, it has gained attention in several domains: e-commerce, e-business, e-learning, e-tourism, etc., attracting the interest of the companies, such as: Netflix, Amazon, Google, others.

Normally RS receives as input the users' data set $\boldsymbol{U} = \{\mathrm{u}_1, \ldots, \mathrm{u}_{|\boldsymbol{U}|}\}$, the items' data set $\boldsymbol{I} = \{\mathrm{i}_1, \ldots, \mathrm{i}_{|\boldsymbol{I}|}\}$, and the preference ratings available at the contextual moment $(\boldsymbol{U} \times \boldsymbol{I})$ that are obtained through explicit and implicit feedbacks. Preferences can be sparse (cold start problem), to undergo temporal changes or be estimated by means of the prediction

S. R. González et al. (Eds.): DCAI 2021, LNNS 332, pp. 185–189, 2022.
https://doi.org/10.1007/978-3-030-86887-1_17

mechanisms. Different approaches of the information filtering based on: collaboration, content, knowledge, demographics, context, or even hybrid [3–5], are usual to have as output one Top-N set containing relevant recommendations $R = \{rec_1, \ldots, rec_N\}$, where $N \in \mathbb{N} > 0$ and $R \subset I$. The performance of RS is evaluated through metrics that check whether the target user liked or interacted with a particular item among the recommended Top-N items [6, 7].

2 Related Works

Recent studies point towards exploration of the sequential recommendation (SRec) supported by session-based recommendation (SBRec) in online environments [4, 8, 9]. In addition to the features presented in Sect. 1, sequential recommender systems (SRS) require mechanisms of continuous adaptation, because they need to consider new and obsolete users, items and ratings in the recurring iterations over time intervals.

In theory, SRec considers the order of the events arising from the user behavior (historical sequential data of the preferences), which are modeled by recurrence for the predicting next Top-N items of interest to the same user [10]. With the monolithic session to record each system execution [11], personalization can use event data from the current session and stored previous sessions to provide SBRec in short-term and long-term sequential dynamics. In practice, SRec and SBRec are complementary.

SRS are characterized as special forms of the context-based RS in [12] due to the fact that the short-term dynamics involve the context of the user behavior. Characterization with a specific utility function is also found in [13], where SRS are classified into three distinct models: traditional sequence, latent representation, and deep neural network (DNN). Pioneered in [14] remarkable results in SBRec with the architecture recurrent neural network (RNN) are obtained. To capture the sequential dynamics, models have used Markov chains to model the probability of choosing one item from ordered list of the items already selected. A broad study is presented in [7] where methods such as sequential rule mining and session-based neighborhood are compared with more complex methods, such as those using DNN, resulting in better performance of the less complex methods in accuracy measurements. Some models with DNN present methods allowing to switch the calculation between more than one similarity and diversity metric in the information filtering [11]. According to the extensive review conducted in [5], DNN is growing in recent years in RS using reinforcement learning [15].

Self-Attention based Sequential Recommendation (SASRec) model proposed in [16] represents the state-of-the-art among SRS models in 2020 [9]. Unlike models based on Markov chains, RNN, or convolutional neural network (CNN), SASRec uses the economical multilayer perceptron (MLP) architecture with optimal computational performance, being able to model semantic and syntactic patterns between recurrent iterations over time intervals. At ACM RecSys 2020 was presented Adaptively Distilled Exemplar Replay (ADER) model [9] that specializes SASRec for building robust and scalable SBRec in online environments.

3 Keys Challenges

Accuracy and the ability to handle large data volumes are differentials of deep learning in real-world representations, however there are open questions regarding the computational performance of the DNN architectures in online environments [7], mainly to predict the user's short-term interest in a session. In [17] the lack of a unified systematic categorization is presented and a framework is proposed to reduce some theoretical and practical SRS confusions and inconsistencies. The vast majority of models are evaluated offline, although the online evaluation of the recommendation is also likely to be improved in the short-term and long-term sequential dynamics. Currently they are performed through A/B tests and point-of-interest (POI) with evaluation metrics based on the Longest Common Subsequence algorithm, for example. Personalization of the user experience in online environments [11] can be researched by explaining the recommendations to the users, seeking to increase their trust in the SRS. In addition, prediction can explore diversity or support the discovery of new, popular, and unexpected items.

4 Research Question and Proposal Work

By framing the study object within a dynamic scope, such as the Web environment, we intend to develop studies around the following research question (RQ):

RQ: Is it possible to build and validate a SRS model, by taking full advantage to historical data in each online update cycle, to efficiently and optimally provide realistic and scalable session-based recommendation in Web applications?

In carrying out this scientific investigation, the study has some concerns:

- By efficiency in sequential time intervals, it is necessary to achieve a feasible solution to the recommendation problem in a non-prohibitive runtime.
- To use historical data, it is necessary to observe contextual restrictions and current laws about what is allowed and possible to be reused.
- By online updating, it becomes necessary to consider both short-term and long-term sequential dynamics, prioritizing short interactions of user behavior.

However, the model produced through design science research will need to combine theory with practice by providing adaptive recommendation for Web applications. For the thesis work in the Web Science and Technology, we aim to research:

1. SRS models driven by DNN in Web applications (in progress). Specifically, perform experimentation with reinforcement and transfer learning or even another mechanism to obtain adaptive recommendation in real time;
2. Heterogeneous datasets with unstructured data, such as: textual, visual, audio and video resources. Specifically, perform experimentation on Web services using SRec and SBRec knowledge-based to improve recommendation quality;
3. Explainable recommendation in the short-term and long-term sequential dynamics in SRS. It is estimated to increase users trust in Web applications by allowing them to understand the factors behind the recommendation.

Besides some gaps and challenges presented to SRS research, others will certainly arise towards generating adaptive recommendation in online environments.

5 Final Remarks

SRS is gaining attention in research that addresses the relationship between the users' short-term and long-term interests, as well as the integration of the contextual information and their dynamic preferences in online environments. There are possibilities for scientific research in several aspects, such as: multiple online tracking, large heterogeneous and non-interconnected datasets, different mathematical methods in use, and the difficulty generalizing SRS for different domains. It is a research challenge for the thesis work to provide adaptive recommendation to mitigate information overload in online environments.

Acknowledgments. This research has been supported by the IFRS – Brazil.

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