News Topic Recommendation using an extended Bayesian Personalized Ranking*

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Abstract. Bayesian Personalized Ranking (BPR) is a recommendation approach which learns to rank candidate items based on user's implicit feedback. In this study I use an extended version of BPR using consumption behavior of user on news articles to recommend them news topics. The extended version of BPR performs better compare to the original version based on two evaluation measures.

Keywords: News topic recommendation · Implicit feedback · Bayesian Personalized Ranking.

1 Introduction

Recommendation systems try to model user preferences based on their previous feedback. This feedback in many cases is implicit. For instance, when a user visits a web-page or clicks on a link or adds an item to her basket the feedback is implicit. Bayesian Personalized Ranking (BPR) [1] is a learning to rank recommendation framework which uses implicit feedback as input. In the original version, the user-item interaction matrix contains binary values (observed/ unobserved) and the general assumption is that user prefers observed items to unobserved items. BPR is trained based on bootstrap samples of user-specific relative preferences using Stochastic Gradient Descent (SGD).

Instead of using binary implicit feedback (observed/unobserved), some studies extend BPR by using different kinds of implicit feedback. Loni et al. [2] defined multi-channel implicit feedback and extended BPR to adapt the training process with these channels. For instance in a web-shop, a user may add an item to the basket (weak positive feedback), purchase an item (strong positive feedback), or even dislike the item (negative feedback). Lerche and Jannach [3] proposed a framework to draw bootstrap samples not only from observed and unobserved items but also from levels of observed items. Yu et al. [4] divided the implicit negative feedback into several levels and proposed a multiple pair-wise ranking using several items instead of individual pairwise ranking.

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2   Methodology

The approach of this study is similar to [3] in drawing bootstrap samples from observed items. The contribution is that we introduce consumption levels for user's reading behavior based on dwelling time, scroll-depth and timestamp, and use these levels to form pair-wise comparison between observed items.

3   Results

Table 1 shows the results of news topic recommendation with three methods: BPR, EBPR and CEBPR. BPR only uses the binary feedback, EBPR uses the number of user interactions with articles related to a specific topic, and CEBPR considers consumption behavior (dwelling time, scroll-depth and timestamp) in each interaction. CEBPR performs better in both AUC and nDCG metrics.

Table 1. Results of news topic recommendation

	AUC			nDCG@10		
#Iteration	BPR	EBPR	CEBPR	BPR	EBPR	CEBPR
10	**0.900**	**0.914**	0.913	0.236	0.256	0.373
20	0.876	0.865	**0.920**	**0.272**	**0.271**	**0.392**
50	0.833	0.838	0.920	0.238	0.256	0.385

4   Conclusion

In this study we propose an extended version of BPR which uses consumption levels to recommend news topics. The idea can be used in other domains such as playlist and video channel recommender systems.

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