Bayesian Personalized Ranking with Multi-Channel User Feedback

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ABSTRACT

Pairwise learning-to-rank algorithms have been shown to allow recommender systems to leverage unary user feedback. We propose Multi-feedback Bayesian Personalized Ranking (MF-BPR), a pairwise method that exploits different types of feedback with an extended sampling method. The feedback types are drawn from different "channels", in which users interact with items (e.g., clicks, likes, listens, follows, and purchases). We build on the insight that different kinds of feedback, e.g., a click versus a like, reflect different levels of commitment or preference. Our approach differs from previous work in that it exploits multiple sources of feedback simultaneously during the training process. The novelty of MF-BPR is an extended sampling method that equates feedback sources with "levels" that reflect the expected contribution of the signal. We demonstrate the effectiveness of our approach with a series of experiments carried out on three datasets containing multiple types of feedback. Our experimental results demonstrate that with a right sampling method, MF-BPR outperforms BPR in terms of accuracy. We find that the advantage of MF-BPR lies in its ability to leverage level information when sampling negative items.

1. INTRODUCTION

In many domains, users provide unary feedback via a number of different 'channels'. For example, online marketplaces collect view, add-to-cart and buy signals, and music platforms log listen, favorite and add-to-playlist events. Bayesian Personalized Ranking [8], a pair-wise learning-to-rank method that learns the preferences of the users by sampling pairs, allows recommender systems to learn effectively from unary feedback. However, current instantiations of BPR fall short of taking full advantage of the entire range of different types of feedback that are available in certain domains.
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In this paper, we propose an approach called Multi-Feedback Bayesian Personalized Ranking (MF-BPR). The innovation of MF-BRP is a sampling method designed to simultaneously exploit unary feedback from multiple channels during training. New sampling methods have proven effective in improving BPR [7]. However, previous attempts to leverage different sources of unary feedback have focused on channels individually, e.g., [5].

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The key to our approach is to map different feedback channels to different 'levels' that reflect the contribution that each type of feedback can have in the training phase. BPR samples pairs such that the first item in the pair is preferred to the second item. The levels of MF-BPR help to automatically direct sampling to focus on the most informative pairs. The appeal of the approach is that it takes advantage of the available information consistently with the intuition that some user feedback signals are more reliable or meaningful than others.

The paper is organized as follows. In the next section, we cover relevant related work. Then, we present MF-BPR in detail, and introduce the three data sets on which we test it. Next, we report experimental results, which demonstrate the ability of MF-BPR to improve over BPR. Finally, we close with a discussion of the results, which sheds light on improvement delivered by judicious sampling of the 'negative' item of the item pair.

2. RELATED WORK

Since the BPR was introduced [8], many improvements have been proposed. MF-BPR belongs to that class of approaches that propose sampling refinements. The initial contribution in this direction was made by [3] who weights item sampling by popularity. Recently, [7] has proposed adaptive sampling, which over-samples informative pairs based on the current model. MF-BPR is similar to this approach in its focus on informative pairs, but its sampling is driven by feedback channels. In the remainder of this section, we cover a selection of the various techniques that have been proposed to exploit feedback from different sources, providing key examples of each, and noting the differences with MF-BPR.

Matrix factorization approaches have attempted to simultaneously factorize multiple matrices. The authors of [11] take into account different signals from social networks (comment, re-share, or create-post) with separate factorizations, which are used to make predictions that are subsequently combined. The work of [4] exploits multiple types of relations, and is directed at the cold start problem. In contrast, the 'multi' of MF-BPR refers to multiple types of feedback reflecting the same user-item relation.

Other approaches have leveraged the fact that ratings represent different levels of user feedback. A list-wise optimization criterion is proposed in [9], which allowed learning-to-rank to take advantage of graded feedback. Most closely related to our work is [5], which modified the BPR algorithm using graded implicit feedback derived from ratings and interaction counts, and also explores the contribution of temporal information. The outlook of the paper points out the promise of hybrid approaches. Our MF-BPR can be considered hybrid, since it simultaneously uses different sources of feedback. However, it differs from [5] in that it avoids hand-chosen weights, and, more significantly, uses multiple feedback channels simultaneously.

3. MULTI-FEEDBACK BPR

BPR-MF is based on the insight that user feedback collected via various channels reflects different strengths of user preference, and the sampling method of BPR can exploit these differences. In short, we allow BPR to learn from the fact that, e.g., a click represents a different level of commitment or preference than a 'like'.

For a given training set S consisting of user-item pairs (u, i), standard BPR creates tuples (u, i, j) by sampling an observed feedback pair (u, i) from S and a negative item j not observed with u. For each sampled tuple, the BPR algorithm updates the parameters with Stochastic Gradient Descent in such a way that i is ranked higher than j. MF-BPR maps different types of feedback onto *levels*, which allow us to constrain sampling to reflect the preference strengths that we associate with the feedback types. Figure 1 compares the standard BPR sampling method (A) with the extended sampling method used by MF-BPR (B), which imposes an order on the types of positive feedback, that makes finer-grained differences between feedback available during the learning phase.

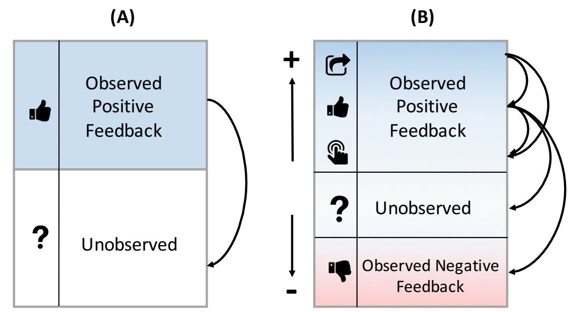

Figure 1: Sampling item pairs in BPR(A) and MF-BPR (B). The arrows show preferences. In MF-BPR any item at the higher level is preferred over all items in the lower levels. In the standard BPR, the only way of sampling item pairs is to sample from observed positive feedback and unobserved feedback.

We now express formally how MF-BPR takes advantage of feedback levels. Let $\mathbb{L} = (L_1, \ldots, L_p)$ represent a given ordered set of levels in a dataset such that a feedback in L_i is a stronger signal of interest compared to a feedback in L_{i+1}, that is $L_i \succ L_{i+1}$. For generality, the unobserved feedback is also considered to belong to a level L_{uo} such that for each positive feedback level L_i and negative feedback level L_j, $L_i \succ L_{uo}$ and $L_{uo} \succ L_j$. The set of training feedback in level L is denoted by S_L. We further define $\mathbb{L}^+$ and $\mathbb{L}^-$ as positive and negative feedback levels. In the standard BPR, $|\mathbb{L}| = 2$, $|\mathbb{L}^+| = 1$ and $|\mathbb{L}^-| = 0$ since there is only one level for positive and one level for unobserved feedback and there is no explicit negative feedback. We also define $I_{L,u}$ as the items in level L that user u interacted with and I_u as all items that u interacted with (in all levels). The set of all combinations of preferences in Multi-feedback BPR D_{MF} can be defined as:

$$D_{MF} = \{(u, i, j) | i \in I_{L,u} \wedge j \in I_{N,u} \wedge L \in \mathbb{L}^+ \wedge L \succ N\} \quad (1)$$

In the standard BPR the tuples (u, i, j) are sampled uniformly but in MF-BPR we introduce a non-uniform sampler that takes into account the level (importance) of the feedback channel. To use multiple levels, MF-BPR requires sampling L and N from $\mathbb{L}$, and then the tuples (u, i, j) can be sampled with respect to the given levels. The positive item is sampled by sampling an observed feedback from S using sampling distribution $p(u, i, L)$, which also samples the positive level L. The probability distribution $p(u, i, L)$ can be further expanded as $p(u, i, L) = p(u, i|L)p(L)$ such that $p(u, i|L)$ is a uniform distribution over S_L and $p(L)$ is the sampling distribution of level L. A trivial choice for $p(L)$ would be a uniform distribution over all levels. However, with a uniform distribution, levels with small cardinality will be oversampled, which can result in being a poor sampling. We propose a non-uniform distribution for $p(L)$ where the cardinality of feedback as well as the importance of a level is taken into account with a weight factor. The probability distribution $p(L)$ is defined by:

$$p(L) = \frac{w_L |S_L|}{\sum_{Q \in \mathbb{L}^+} w_Q |S_Q|} \quad (2)$$

where w_L is the weight of level L. With equal weights, positive items are sampled uniformly from all levels. This would be equivalent to the positive sampler of standard BPR. The weight values can be defined non-uniformly to reflect the importance of levels. The weight parameters can be influenced by the available context or other properties of the levels. In our experiments, we found that the inverse rank of positive levels are good candidates for weights (i.e., $w_1 = 1, w_2 = \frac{1}{2}, \ldots$). If the order of levels is not known a priori (for example whether a like should be considered more important that a share or vice versa), the optimal weights can be approximated by using a hyper-parameter search algorithm.

To sample negative item j, the level of the positive item should be given so that the sampler samples an item from one of the levels below it. Given the positive level L and a positive user-item pair (u, i), we denote $p(j, N|u, L)$ as the sampling distribution of and negative sample j and its corresponding level N. Similar to the positive sampler, the negative sampler can be expanded as $p(j, N|u, L) = p(j|u, L, N)p(N|u, L)$ where $p(j|u, L, N)$ is the negative item sampler and $p(N|u, L)$ is the conditional negative level sampler. We also propose a non-uniform negative item sampler, similar to (2), that takes into account the cardinality and the weights of the levels. The negative level sampler $p(N|u, L)$ is defined as:

$$p(N|u, L) = \begin{cases} \frac{(1-\beta) w_N |S_N|}{\sum_{Q \prec L} w_Q |S_Q|} & N \neq L_{uo} \\ \beta & N = L_{uo} \end{cases} \quad (3)$$

such that $0 \leq \beta \leq 1$ is a parameter that controls the ratio of unobserved feedback in the sampling. For the standard BPR $\beta = 1$, as all negative items are sampled from the unobserved feedback. The right value for β can be found experimentally. In our experiments, we found that with high values of β the model is more accurate. Our observation about the right value of β is discussed in more detail in Section 4.

Similar to the standard BPR, the negative sampler $p(j|u, L, N)$ can sample negative item uniformly from $I_{N,u}$ if $N \neq L_{uo}$ or from $I \backslash I_u$ if $N = L_{uo}$. We denote $p_{uni}(j|u, L, N)$ as the *uniform* negative item sampler which can be defined as:

$$p_{uni}(j|u, L, N) = \begin{cases} \frac{1}{|I_{N,u}|} & N \neq L_{uo} \wedge j \in I_{N,u} \\ \frac{1}{|I \backslash I_u|} & N = L_{uo} \wedge j \in I \backslash I_u \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

In addition, we also propose a *multi-level* item sampler with a non-uniform sampler when N is the unobserved level L_{uo}. We define the multi-level negative item sampler $p_{ml}(j|u, L, N)$ as:

$$p_{ml}(j|u, L, N) = \begin{cases} \frac{1}{|I_{N,u}|} & N \neq L_{uo} \wedge j \in I_{N,u} \\ p(j, u', L'|u) & N = L_{uo} \wedge j \in I \backslash I_u \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where $u' \neq u$ and $L' \in \mathbb{L}^+$. Here, if the given level L is an observed level, the negative item is sampled uniformly the same as the uniform-item sampler. However, if the the given level $N =$

```
procedure LEARN MF-BPR(S, β, W, 𝕃)
    initialize Θ
    repeat
        draw (u, i, L) from p(u, i, L)
        draw N from p(N|u, L)
        draw j from p(j|u, L, N)
        update Θ with BPR update rule [8]
    until convergence
    return Θ
end procedure
```

Figure 2: Learning MF-BPR with Stochastic Gradient Descent.

L_{uo}, the negative item is sampled non-uniformly with respect to $p(j, u', L'|u)$. Here the probability of sampling a negative item depends on its feedback from other users. Items that are more popular and have enjoyed user interactions from stronger levels, have a higher chance of being sampled. In other words, if $N = L_{uo}$ the sampler selects feedback by sampling a tuple (u', j, L') for which an interaction between u and j is not observed. Note that u' and L' for the tuple are subsequently discarded.

By sampling the tuple (u, i, j) the parameters of the model can be updated via Stochastic Gradient Descent (SGD) similarly to standard BPR. Note that here the parameters β, the weights of the levels W and the order of levels in $\mathbb{L}$ are given a priori. Figure 2 lists the learning algorithm of BPR with Multi-feedback sampler.

4. DATASET AND EXPERIMENTS

The MF-BPR is evaluated on three datasets and its performance is compared with different methods using 4-fold cross validation. The ground truth and relevant recommendations however, are different in the three datasets depending on the problem. The datasets, the splitting strategy and the feedback signals of the datasets are described bellow. Dataset statistics are presented in Table 1.

Kollekt.fm Kollekt.fm is an online music discovery platform. For Kollekt.fm the recommender task is to recommend playlists to users. Kollekt.fm is interested in increasing the number of followers for their playlists, so we predict follows. This dataset contains three different levels of feedback relevant to playlists: `follows`, which is considered the highest level of feedback. `listening` which refers to the ratio of the listening time to a playlist to the total time a user listened to any playlist. `favorites` is the ratio of the songs in a playlist which are favorited to the total number of songs in the playlist. For both listening and favorites we used only the occurrences with a value greater than a specific threshold. Due to space constraints, we report results setting both thresholds to 0.1.

XING XING[1] is a social network and a job discovery framework. This dataset is related to the job postings of in XING. This is the data used for the RecSys 2016 challenge. It contains four different levels of feedback: `click`, `bookmark`, `reply` and `remove`. To be compliant with XING's needs, we used 'click', 'bookmark' and 'reply' as positive feedback for both training and ground truth and 'remove' as negative. Adopting XING's own valuation of user feedback, we used reply as the highest level, then bookmark and click as the lowest level of positive feedback. In order to reduce data sparsity and the size of the dataset we filtered out all the users and jobs that have less than five instances of feedback.

MovieLens-1M For the sake of completeness, we also report the results for the MovieLens dataset [2], containing movie ratings on a 1-5 scale. We considered each discrete rating as a different level of feedback. For each user, we took the levels above the user's average rating as positive feedback, both for training and ground truth, and the ones below as negative. We consider a recommendation relevant if user has rated it above his average.

[1] http://xing.com/

[2] http://grouplens.org/datasets/movielens/

Table 1: The statistics of the datasets used in this work.

Dataset	#user	#item	#feedback	%density	#levels
Kollect	15972	34910	195k	0.0350	3
ML1M	6040	3706	1000k	4.4684	5
XING	11324	9857	569k	0.5097	4

The experiments are implemented with an open source toolkit developed by the authors and available online [6]. To measure performance we calculated Mean Reciprocal Rank (MRR), recall, precision, all at 10, as well as and mean average precision and nDCG. For calculating these metrics, we applied the approach known as *One-plus-random* [2, 1]. Here we report MRR@10. In the interest of space, we simply state that the other metrics were comparable.

The three datasets are evaluated with four different algorithms:

MF-BPR-UNI This is Multi-Feedback BPR with uniform item sampling. The positive item is sampled with the level-based sampler and the negative item is sampled according to (4).

MF-BPR-ML This is another variation of Multi-Feedback BPR with multi-level negative feedback sampler where negative feedback are sampled non-uniformly according to (5).

BPR This is the standard BPR [7] where all positive feedback are assumed to be equally strong.

BPR-Dynamic This is BPR with dynamic sampling method [7]. The items are re-scored after every few iterations and they are sampled proportional to their current score.

We also compared our results with random and popularity baseline. The popularity baseline exploits the positive feedback from all channels without differentiating levels. In all our experiments, we used 50 latent features and 100 iterations. For the SGD algorithm, learning-rate is set to 0.05 and the regularization parameter λ is set to 0.002 for all the four algorithms.

Figure 3 compares the performance of the two sampling models of MF-BPR with previous BPR methods. We report on the y-axis MRR@10 and on the x-axis the ratio of unobserved sampled items (i.e., parameter β), to see the influence of β on performance of MF-BPR. As we can see from the figure, increasing β improves the accuracy of the model. This observation implies that a combination of an observed and an unobserved item in a pair is a better candidate to train the model. This validates the 'missing not at random' hypothesis which is highlighted by [10]. That is, the missing (unobserved) items are most likely missed as negative items. Another implication is that the presence of feedback in lower levels indicates that all positive levels contribute in defining what is preferred by the user w.r.t to the unobserved feedback.

The performance improvement of MF-BPR-ML can be attributed to the fact that it selects unobserved feedback as negative samples using a non-uniform sampling strategy that is sensitive to the strength of the feedback given by other users. However an interesting observation is that the MF-BPR-ML method performs better than the standard BPR and MF-BPR-UNI in the XING and Kollect.fm datasets, while it performs worse in the Movielens dataset. This can be explained by the fact that MovieLens is rather a dense dataset and a uniform-item sampler can sample a good enough representative of items.

Another interesting result is that in the Kollekt.fm dataset the popularity-based method outperforms BPR. An explanation can be found in Figure 4 where the popularity-skewness of the three datasets

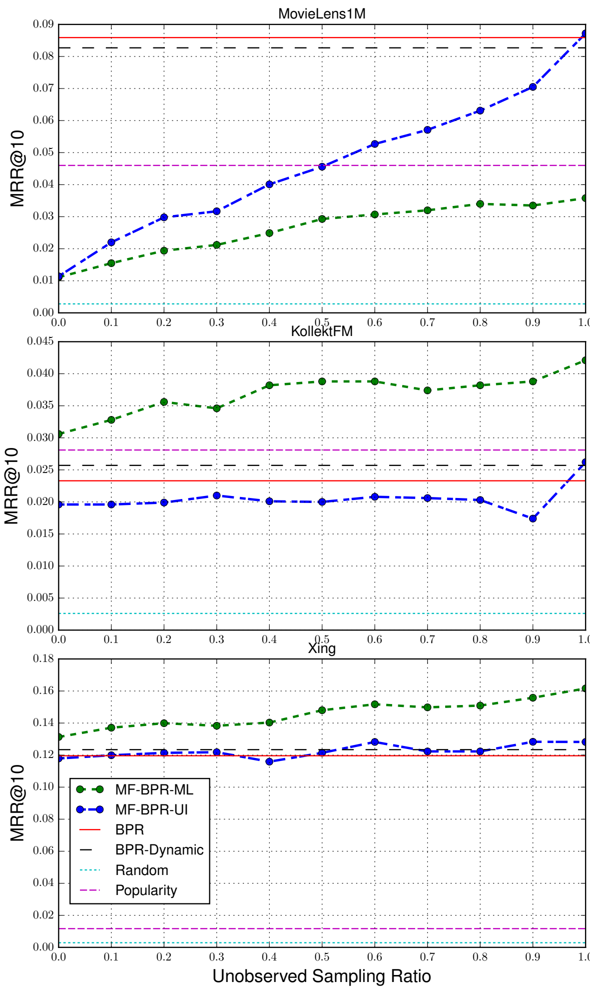

Figure 3: Comparison of results for our multi-level methods and the original and dynamic BPR algorithm. The horizontal axis represents the unobserved sampling ratio (β).

are plotted. The y axis represents the ratio of interactions for a given ratio of items on the x axis, sorted by decreasing popularity. Kollekt.fm is the most *popularity skewed* dataset, where 1% of the items accounts for 40% of the interactions. A consistent behavior of the popularity baseline can be found in the other datasets: the less the dataset is popularity skewed, i.e. the feedback is well distributed among the items, the worst are the popularity-based performances.

5. CONCLUSION

In this work we introduced MF-BPR, an extension to BPR that can be used when multiple types of feedback are available. MF-BPR extends the standard BPR sampling model by exploiting the difference in strength among user feedback 'channels'. From our experiments we can draw two insights. The first is that the data is 'not missing at random', but rather the missing data can be regarded as negative feedback. This supports the underlying assumptions in the BPR model and it is further validated by the fact that sampling negative items from the lower levels of observed feedback decrease the overall quality of the recommendation algorithm. Second, we showed that sampling the negative item with a level-based method has a substantial impact on the quality of recommendations. In future work, we will learn the optimal relative ordering of the levels automatically, and also explore the contribution of additional context information.

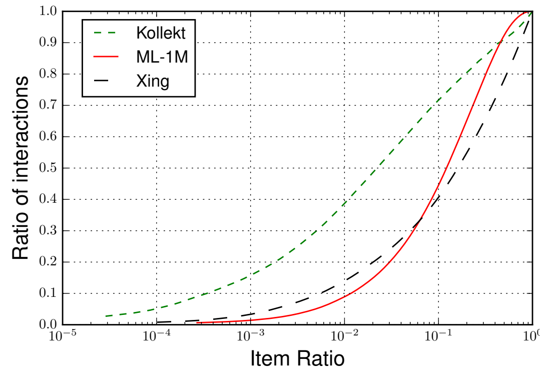

Figure 4: Popularity skewness of the datasets

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