MP2: A Momentum Contrast Approach for Recommendation with Pointwise and Pairwise Learning

Menghan Wang
wangmengh@zju.edu.cn
eBay Inc.
Shanghai, China

Yuchen Guo
yuchguo@ebay.com
eBay Inc.
Shanghai, China

Zhenqi Zhao
kyriezhao@tencent.com
Tencent Inc.
Shanghai, China

Guangzheng Hu
Guangzheng@student.unimelb.edu.au
The University of Melbourne
Melbourne, Australia

Yuming Shen
yuming.shen@eng.ox.ac.uk
University of Oxford
London, United Kingdom

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ABSTRACT

Binary pointwise labels (aka implicit feedback) are heavily leveraged by deep learning based recommendation algorithms nowadays. In this paper we discuss the limited expressiveness of these labels may fail to accommodate varying degrees of user preference, and thus lead to conflicts during model training, which we call annotation bias. To solve this issue, we find the soft-labeling property of pairwise labels could be utilized to alleviate the bias of pointwise labels. To this end, we propose a momentum contrast framework (MP2) that combines pointwise and pairwise learning for recommendation. MP2 has a three-tower network structure: one user network and two item networks. The two item networks are used for computing pointwise and pairwise loss respectively. To alleviate the influence of the annotation bias, we perform a momentum update to ensure a consistent item representation. Extensive experiments on real-world datasets demonstrate the superiority of our method against state-of-the-art recommendation algorithms.

CCS CONCEPTS

• Information systems → Personalization; Learning to rank

KEYWORDS

Recommendation, Momentum update, Pointwise learning, Pairwise learning

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1 INTRODUCTION

Personalized recommendation is becoming a key component in web applications. It is often cast as a learning-to-rank (LTR) problem [4, 6, 11], where an ordered list of items are selected to meet users’ interest. Due to the superior ability to learn from big datasets, deep learning-based recommendation algorithms are becoming the mainstream solution for practitioners.

Since the implicit feedback (e.g., click or not click, purchase or not purchase) is abundant, binary labels are widely chosen in practice. However, user preferences are not stable and often influenced by context. For example, in Fig. 1 we can see that item B is annotated as 0 and 1 for the same user!

Figure 1: An example of one user’s two interaction records and the corresponding pointwise and pairwise labels. The pointwise labels of item B have an annotation bias problem.

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bias, which is widely ignored in binary pointwise labels. (In reality, zero labels are also collected from users’ impression logs, so the annotation bias is different from the well-studied exposure bias [14, 15].) One drawback of having annotation bias for the deep model is a high fluctuation of learned representations. For example, the two conflict labels of item $B$ will give opposite optimizing signals to its item representation.

On the other hand, pairwise labels are free of the annotation bias. As shown in Fig. 1, pairwise labels depict preference orders between items; it is a form of soft labeling and avoids annotating binary scores to items. Although pairwise learning is seldom studied in deep recommendations, traditional LTR studies have shown its effectiveness in learning users’ comparative preferences. We argue that pointwise and pairwise learning are complementary to each other, and we could combine them to address the annotation bias.

Particularly, in this paper, we propose a momentum contrast framework (MP2) with pointwise and pairwise learning for recommendation. MP2 consists of a three-tower network structure: one user network and two item networks. The two item networks are used for computing pointwise and pairwise loss, respectively. MP2 also take two strategies to alleviate the annotation bias: momentum update and weighting label with discrepancy. The momentum update is applied to ensure a consistent item representation for pointwise learning, and weighting label with discrepancy aims to tune the weights of pointwise labels automatically. Extensive experiments we show that MP2 achieves state-of-the-art performance compared with other competitive algorithms.

2 RELATED WORK

Deep Neural Networks in Recommendation. In recent years, deep neural networks (DNNs) have become successful in recommendations, some representative examples are PNN [12], Wide&Deep [4], DeepFM [6], and DLRM [11]. However, these methods fall into pointwise learning, leaving pairwise and listwise learning (beyond the scope of this work) almost blank in deep recommendations. There also exists researches [2, 5, 10, 16] combining pointwise and pairwise learning, most of which focuses on designing a mixed loss function. Instead in this paper, we focus on the backbone design.

Representation Learning with Momentum. Momentum-based methods [3, 7, 17] are intensively employed in the recent study in deep representation learning, of which the majority approaches require a set of slowly-progressing parameter counterparts, updated with a momentum as reference during training. This idea has been proven to be fully functioning and effective in the context of self-supervised feature learning and pre-training in computer vision. However, we clarify that our proposed model differs from the aforementioned methods in motivation. Existing methods basically resort to the momentum-based approaches as a memory-saving solution to construct contrastive samples for comparison [17], while we consider a slower evolving intensity with momentum on the item representations than the user ones throughout the training process for better performance.

3 MP2 FRAMEWORK

In this section we describe the proposed framework in details.

3.1 Three-Tower Design

From Fig. 2 we can see a three-tower architecture; it consists of a user network $\phi_u(\cdot, \theta_u)$, an item vanilla network $\phi_v(\cdot, \theta_v)$, and an item momentum network $\phi_m(\cdot, \theta_m)$, of which $\phi_u(\cdot, \theta_u)$ and $\phi_m(\cdot, \theta_m)$ have the same structure. Below the three towers are a feature embedding layer that deals with numerical and categorical features. The three towers use input feature embeddings to generate compact representations. Let $u$ be the user representation generated by $\phi_u(\cdot, \theta_u)$, $v$ be the item representation generated by $\phi_v(\cdot, \theta_v)$, and $v^m$ be the item representation generated by $\phi_m(\cdot, \theta_m)$. We then use these representations for pointwise and pairwise learning. For a data sample $(U_i, V_j, V_t, y_{ij}, y_{it}, j > u, t)$, we use $y_{ij} = u_v^m$ and $y_{it} = u_vv_t^m$ to predict pointwise labels, and use $\hat{y}_{pair} = u_vv_j - u_vv_t$ to predict pairwise labels.

Recalling that we aim to learn a consistent representation for items and this is the reason we design two item networks for representation learning. Intuitively, if the real-value of one item’s representation fluctuates a lot during the optimization, it indicates that the item representation fluctuates a lot and there may be an annotation bias in the corresponding labels.

We leverage the two item networks to model the fluctuation and then address the annotation bias, which consists of two phases: 1) Momentum update. Since pointwise labels suffer from an annotation bias, $v^m$ may highly fluctuate in traditional gradient-descent style optimizers. The item representation $v^m$ (pointwise learning) is optimized via momentum update rather than normal gradient back-propagation, which ensures a consistent, slowly-evolving update. 2) Weighting label with discrepancy. The fluctuation is measured via the discrepancy of two representations of a same item, which is further served as the confidence term of the pointwise label. A higher fluctuation indicates a lower weight of the corresponding pointwise label, which automatically lower the importance of untrustworthy pointwise labels.

Figure 2: Graphical architecture of MP2.
Algorithm 1: The Training Procedure of MP2

Input: A training dataset \( \mathcal{D} = \{(u_i, v_j, y_{ij}, y_{it}, j > u t)\} \)

Output: Network parameters \( \theta_u, \theta_v \) and \( \theta_m \).

repeat
  Randomly select a mini-batch from \( \mathcal{D} \)
  \( L_{total} \leftarrow \) Eq. 6
  Updating the vanilla and user network:
  \( \theta_u \leftarrow \theta_u - \Gamma (\nabla_{\theta_u} L_{total}) \)
  \( \theta_v \leftarrow \theta_v - \Gamma (\nabla_{\theta_v} L_{total}) \)
  Updating the momentum network:
  \( \theta_m \leftarrow \alpha \theta_m + (1 - \alpha) \theta_v \) according to Eq. 1
until convergence or reaching the maximum iteration;

3.2 Momentum Update

Different from the item vanilla network \( \phi_u(\cdot, \theta_u) \) that updates its weights \( \theta_u \) via gradient back-propagation, \( \phi_m(\cdot, \theta_m) \) updates \( \theta_u \) by averaging \( \theta_v \):\( \theta_m = \alpha \theta_m + (1 - \alpha) \theta_v \), \( \alpha \in (0, 1) \) is a momentum coefficient hyper-parameter, whose value controls the smoothness of \( \theta_m \). The momentum update in Eq. 1 makes \( \theta_m \) evolve more smoothly than \( \theta_v \). As a result, though some items may have 0 and 1 pointwise labels for a same user due to the annotation bias, the fluctuation of item representations can be made small. In contrast, in a classical recommendation model \( (y_{it} = u_i v_j) \) the \( v_j \) will receive opposite optimizing signals, which will influence the consistency of item representations.

The learning objective directly communicates \( \phi_u (\cdot, \theta_u) \) through \( \nabla_u L_{total} \) by back-propagation. For each step, the update of parameters \( \theta_u \) then is instantly reflected in the user representations in the next batch. On the other hand, the item representations do not strictly follow this procedure with \( \phi_u (\cdot, \theta_u) \). Instead, a momentum replicate \( \phi_m (\cdot, \theta_m) \) processes all items. Heuristically, this results in temporally consistent item encoding to compile our motivation.

3.3 Weighting Label with Discrepancy

After momentum update, we approximate the fluctuation with the discrepancy between two item representations \( \phi_u(\cdot, \theta_u) \) and \( \phi_m(\cdot, \theta_m) \). Formally, the discrepancy is defined as:

\[ \delta_j = \frac{1}{c} \sum_{d=1}^{c} (\delta^d_j), \delta_j = |v_j - v'_j|, \]

where \( \delta_j \) is the element-level discrepancy and \( | \cdot | \) is an element-wise absolute value operation. \( c \) is the vector length of \( \delta_j \), and \( \delta_j \) is a single value. We regard this whole discrepancy as the confidence term of the pointwise label. Intuitively, a large \( \delta_j \) indicates a high uncertainty so we use its reciprocal as the confidence term of pointwise label. Note that we have two items (i.e., \( j \) and \( t \)) in one data sample and they are related, we combine them for the labeling weight:

\[ w_{jt} = \frac{1}{\exp(\delta_j + \delta_t)}. \]

From Eq. 3, the similarity of two representation replica from the corresponding stochastic transformations \( \phi_u(\cdot, \theta_u) \) and \( \phi_m(\cdot, \theta_m) \) reflects the locality of the trained item representation space, which ideologically coheres with temporal ensembling [9] but with different approaches. [9] typically minimizes Eq. 2, while we consider re-weighting the loss functions to relate this discrepancy with the user representations.

3.3.1 Loss Calculation. As shown in Fig. 2, MP2 consists of two kinds of losses: pointwise loss and pairwise loss. For pointwise loss we use discrepancy term as the confidence to the data sample.

\[ L_{pointwise} = - \sum_{j=1}^{n} w_{jt} y_{jt} \log(p_j) + w_{jt} (1 - y_{jt}) \log(1 - p_j), \]

where \( p_j = \frac{1}{1 + \exp(-y_{jt})} \). Note that \( w_{jt} \) is the weight for both item \( j \) and item \( t \) in a data sample. As for pairwise loss, we use the multiplication of user representation and item representation from momentum network to compute the pairwise.

\[ L_{pairwise} = \sum_{u=1}^{m} \sum_{j=1}^{n} \sum_{t=1}^{n} I(j > u t) \log(1 + \exp(w_{u j} \times w_{u t})), \]

Finally the total loss function becomes a linear combination of Eq. 4 and Eq. 5. We also add L2-regularization terms to avoid overfitting:

\[ L_{total} = L_{pointwise} + \beta \times L_{pairwise} + \text{regularization}. \]

4 EXPERIMENTS

In this section, we conduct experiments to evaluate the effectiveness of MP2. We compare MP2 with competitive baselines, including pointwise and pairwise algorithms. Following that, we conduct additional experiments for investigating effectiveness of each component in MP2.

4.1 Datasets and Experimental Settings

In this section we introduce the used datasets and experimental settings, including baselines, offline metrics, and reproducibility.

4.1.1 Datasets. We selected four datasets for evaluating recommendation performance, two from MovieLens and two from Amazon. The datasets from MovieLens\(^1\) are ml-100k and ml-1m, separately. The other two datasets are Beauty and Office Products, which collect product reviews and metadata from Amazon\(^2\). The original ratings of the four datasets are explicit integer ratings range from 1 to 5. For pointwise labels, we use specific threshold 3 to binarize the rating scores as labels. For pairwise label, we select item pairs under the same user randomly, and then decide the labels based on relative scores of item pairs.

4.1.2 Baselines. We evaluate the performance of MP2 against the following baseline models. Baseline models are chosen from three fields: pointwise methods, pairwise methods, and pointwise + pairwise methods. 1) NeuMF [8]. This is a neural network based collaborative filtering method with binary cross-entropy loss. It consists of a two-tower structure. 2) BPR [13]. This is a pairwise ranking method optimizing the matrix factorization model with a pairwise ranking loss, which is a classical pairwise recommendation model.

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\(^1\)http://grouplens.org/datasets/movielens/

\(^2\)http://snap.stanford.edu/data/amazon/productGraph/categoryFiles/
Table 1: Comparisons of different models on four datasets.

| Models         | MovieLens-100K | MovieLens-1m |
|----------------|----------------|--------------|
|                | HitRate@5      | HitRate@20   | NDCG@5 | NDCG@20 | HitRate@5 | HitRate@20 | NDCG@5 | NDCG@20 |
| NeuMF          | 0.4799         | 0.8163       | 0.3311 | 0.4570 | 0.2182    | 0.5034     | 0.1961 | 0.3002  |
| BPR            | 0.4550         | 0.8182       | 0.3172 | 0.4526 | 0.4810    | 0.7194     | 0.4369 | 0.5241  |
| Ranknet-NN     | 0.5949         | 0.8822       | 0.4415 | 0.5493 | 0.4074    | 0.6939     | 0.3498 | 0.4627  |
| APPL           | 0.5877         | 0.8851       | 0.4590 | 0.5510 | 0.3381    | 0.6347     | 0.3447 | 0.4330  |
| T3             | 0.5927         | 0.8824       | 0.4531 | 0.5491 | 0.4832    | 0.7109     | 0.4391 | 0.5217  |
| MP2            | 0.5983         | 0.8947       | 0.4721 | 0.5604 | 0.4920    | 0.7270     | 0.4449 | 0.5314  |

| Models         | Office Products | Beauty       |
|----------------|-----------------|--------------|
|                | HitRate@5       | HitRate@20   | NDCG@5 | NDCG@20 | HitRate@5 | HitRate@20 | NDCG@5 | NDCG@20 |
| NeuMF          | 0.2347          | 0.9038       | 0.1336 | 0.2616 | 0.2229    | 0.8150     | 0.1145 | 0.2706  |
| BPR            | 0.2555          | 0.8629       | 0.1275 | 0.2605 | 0.2754    | 0.8613     | 0.1504 | 0.2858  |
| Ranknet-NN     | 0.3157          | 0.8824       | 0.1643 | 0.2889 | 0.2923    | 0.8449     | 0.1537 | 0.2829  |
| APPL           | 0.2780          | 0.8664       | 0.1429 | 0.2716 | 0.2311    | 0.8947     | 0.1192 | 0.2756  |
| T3             | 0.2811          | 0.9078       | 0.1440 | 0.2821 | 0.2657    | 0.8789     | 0.1436 | 0.2841  |
| MP2            | 0.3170          | 0.8850       | 0.1668 | 0.2917 | 0.3031    | 0.8894     | 0.1586 | 0.2915  |

3) Ranknet-NN [1]. This is a neural network model applying pairwise loss and a two-tower structure. 4) APPL [5] This model is a joint learning model that combines two pointwise losses and one pairwise loss. Its original version is based on matrix factorization, and we implemented a deep learning version that replaces matrix factorization with a two-tower neural network. 5) T3 (Three-Tower) This model is a truncated version of MP2, where we remove the momentum update and discrepancy term from MP2. So this model contains a three-tower structure with two pointwise labels and one pairwise label. Hyperparameter tuning is conducted by grid search, and each method is tested with the best hyperparameters for a fair comparison.

4.2 Performance Evaluation

We show the experimental results in Table 1, from which we can find that MP2 outperforms other baselines consistently on each dataset. This demonstrates the effectiveness of our proposed method. Further, we can get the following findings. 1) Models with joint loss (i.e., MP2, T3, and APPL) are generally better than models with pairwise loss (Ranknet-NN and BPR) or pointwise loss (NeuMF), showing that combining pointwise and pairwise learning is a promising approach for recommendation. 2) Pairwise models are empirically better than pointwise models. This is mainly because pairwise models capture relative relations of items and datasets are free of annotation bias. 3) Ranknet-NN (deep pairwise model) outperforms BPR (non-deep pairwise model) with a large margin on four datasets. Their loss function are the same and the difference is that Ranknet-(non-deep pairwise model) with a large margin on four datasets.

4.3 Effectiveness of Momentum Update

MP2 applies a momentum update strategy in the item momentum network in order to learn a consistent representation $\theta_m$. According to Eq. 1, the momentum coefficient hyper-parameter $\alpha \in [0, 1]$ controls the smoothness of $\theta_m$. To evaluate the effectiveness of the momentum coefficient $\alpha$, we perform a grid search by varying $\alpha \in [0, 0.1, 0.5, 0.9, 0.99, 0.999, 0.9999, 1]$ to find the optimal value. A larger $\alpha$ means a slower update of $\theta_m$. Note that $\alpha = 1$ indicates the item momentum network is equal to the item vanilla network at all times and there is no difference between $\theta_m$ and $\theta_t$. In other words, MP2 is deteriorated to a two-tower structure. Figure 3 shows the model performance of MP2 with different $\alpha$. We can find that the performance of MP2 is increasing monotonously when $\alpha$ increases, and reaches the peak when $\alpha = 0.999$, which shows a smoother momentum update will yield a better item representation and thus improve the recommendation performance. These results also validate our assumption of a consistent item representation.

Table 2: Performance (NDCG) of different labeling weights of MP2.

| Models         | MovieLens-100K | MP2uniform | MP2separate | MP2joint |
|----------------|----------------|------------|-------------|----------|
| NDCG@5         | 0.4683         | 0.4702     | 0.4740      |          |
| NDCG@20        | 0.5640         | 0.5617     | 0.5687      |          |
| Beauty         | MP2uniform     | MP2separate | MP2joint    |          |
| NDCG@5         | 0.1549         | 0.1519     | 0.1664      |          |
| NDCG@20        | 0.2871         | 0.2833     | 0.2897      |          |

4.4 Effectiveness of Discrepancy

To evaluate the effectiveness of the discrepancy term, we compare our proposed method (denoted as MP2joint in this subsection) against its two variants to: MP2uniform with uniform weights and MP2separate with separate weights for two pointwise labels in a data sample. Specifically, in a data sample $(U_t, V_j, V_t)$ the item $j$ is assigned a weight of $w_j = \frac{1}{\exp(\delta_j)}$, and the item $t$ has a weight.
In this paper, we study the annotation bias in recommendation, a widely existing but ignored problem caused by the limited expressiveness of binary pointwise labels. We propose MP2, a momentum contrast framework for recommendation that combines pointwise and pairwise learning to alleviate the annotation bias. The offline experiments showed the superiority of MP2 over other competitive methods. In the future, we plan to combine listwise loss and pairwise learning to alleviate the annotation bias. The offline experiments showed the superiority of MP2 over other competitive methods. In the future, we plan to combine listwise loss and pairwise learning to alleviate the annotation bias.

MP2 is the best among the three variants, showing the effectiveness of its weighting strategy. We also find that MP2 is worse than MP2 \textit{uniform}: uniform weights seem to be more competitive. One reason is that MP2 is the most complex model and is prone to overfitting. Meanwhile, MP2 is more like "pointwise" weighting while MP2 has a form of "pairwise" weighting. MP2 considers relations between two pointwise labels and thus is more robust to the annotation bias.

5 CONCLUSION

In this paper, we study the annotation bias in recommendation, a widely existing but ignored problem caused by the limited expressiveness of binary pointwise labels. We propose MP2, a momentum contrast framework for recommendation that combines pointwise and pairwise learning to alleviate the annotation bias. The offline experiments showed the superiority of MP2 over other competitive methods. In the future, we plan to combine listwise loss and pairwise loss in deep learning for recommendation.

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