Your Click Knows It: Predicting User Purchase through Improved User-Item Pairwise Relationship

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ABSTRACT
Understanding users’ behavior and predicting their future purchase are critical for e-commerce companies to boost their revenue. While explicit user feedback such as ratings plays the most significant role in eliciting users’ preferences, such feedback is scarce, which prompts the need for leveraging more abundant implicit user feedback such as purchase record. Consequently, recent studies focused on leveraging users’ past purchase record to predict their purchase. However, their performance is not satisfactory due to 1) the lack of purchase history of users, and 2) more importantly the ill-posed assumption of non-purchased items equally being considered as negative feedback. In this paper, we define new pairwise relationships among items aiming at overcoming the limitations of existing works, and propose a novel method called P3S that stands for modeling pairwise relationships among three disjoint item sets, which leverages users’ click record in conjunction with their purchase record. Precisely, we partition the items into three disjoint sets based on users’ purchase and click record, define new pairwise relationships among them with respect to users, and reflect these relationships into our pairwise learning-to-rank method. Experiments on two real-world datasets demonstrate that our proposed method outperforms the state-of-the-art baselines in the task of predicting users’ future purchase in e-commerce.

KEYWORDS
Purchase prediction, E-commerce, Learning to rank

1 INTRODUCTION
Due to ever increasing growth of online shopping market these days [2], competitions among e-commerce companies to attract more users has become intense. To this end, it is crucial to understand and characterize users’ online shopping behaviors, and eventually to provide them personalized item recommendations. Notably, it has been reported that Amazon.com generates about 35% of their revenue through their recommendation engine [9], which implies that modeling and predicting users’ future purchase are paramount for a successful e-commerce.

In order to accurately predict users’ future purchase, their past purchase record along with their explicit feedbacks are desired. In particular, explicit feedbacks such as ratings and review texts, in which users’ preferences are explicitly expressed are the most valuable type of user feedback. However, a vast majority of users do not frequently purchase items, and even if they do, they rarely provide explicit feedback on purchased items. Furthermore, requesting for feedback would only impose burden on users, which may lead to their withdrawal. Thereby, e-commerce companies should rely on the limited amount of implicit user feedback, i.e., past purchase record, when building their systems.

Many existing studies focused on leveraging implicit user feedback to model users’ preferences. Hu et al. [3] introduced the concept of confidence where non-purchased items are given a lower confidence than purchased items. Rendle et al. [11] proposed a pairwise learning-to-rank method called Bayesian Personalized Ranking (BPR) in which each user is assumed to prefer purchased items over every non-purchased item. However, since existing works consider non-purchased items as negative feedback (i.e. All Missing as Negative (AMAN) assumption [10]), the effect of non-purchased items is overemphasized. Moreover, existing works still suffer from data sparsity problem as users’ purchase record is often scarce.

To overcome the aforementioned limitations, we leverage users’ past click record overlooked by previous works, in conjunction with users’ purchase record. Click record is another type of implicit user feedback that contains implicit preference of users. To be precise, while not being selected for purchase after all, clicked items still reveal users’ broad interests, because a purchased item is selected among numerous clicked items. Therefore, we expect that click record helps to relieve the AMAN assumption when combined with purchase record. Furthermore, since in practice the amount of click record usually greatly exceeds the amount of purchase record, we expect that users’ click record alleviates the data sparsity problem.

In this paper, we define new pairwise relationships among items aiming at overcoming the limitations of existing works, and propose a novel method called P3S that stands for modeling pairwise relationships among three disjoint item sets, which leverages users’ click record in conjunction with their purchase record. Precisely, based on users’ purchase and click record, we split the items into three disjoint sets, i.e., 1) purchased items, 2) clicked-but-not-purchased
2 RELATED WORK

In this section, we briefly review studies that are directly related to ours, i.e., recommender systems using implicit feedback dataset and methods for modeling user behaviors.

Recommender Systems with Implicit Feedback. Thanks to its abundance compared with explicit feedback, research to build recommender systems based on implicit user feedback has gained much attention. Implicit user feedback includes clicks on a news website [10], music listening history [12], check-in behaviors [6] and TV channel tune events [16], to name a few. In particular, Hu et al. [3] and Pan et al. [10] proposed a weighted regularized matrix factorization for item recommendation using implicit feedback where a confidence matrix is introduced to differentiate the influence of observed (purchased) items and unobserved (non-purchased) items:

\[
L = \sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} c_{ui}(r_{ui} - a_u^T \beta_i)^2 + \lambda_0||\Theta||_F^2
\]

where \( r_{ij} = 1 \) if user \( u \) observed (purchased) item \( i \), and 0 otherwise. \( \Theta \) is the set of parameters to be learned. \( a_u \in \mathbb{R}^K \) and \( \beta_i \in \mathbb{R}^K \) represent the latent models of user \( u \) and item \( i \), respectively, where \( K \) is the latent dimensionality. \( \mathcal{U} \) and \( \mathcal{I} \) are sets of users and items, respectively. Here, \( c_{ui} \) measures the confidence of \( r_{ui} \) being equal to 1, which is determined in advance. Moreover, Rendle et al. [11] proposed a Bayesian Personalized Ranking (BPR) framework that directly optimizes the pairwise ranking between observed (purchased) items and unobserved (non-purchased) items. The objective function is to maximize the following:

\[
L = \sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{I} \setminus \mathcal{P}_u} \ln(\sigma(\hat{x}_{ui} - \hat{x}_{uj})) - \lambda_0||\Theta||_F^2
\]

where \( \mathcal{P}_u \) is the set of items purchased by user \( u \) and the predicted preference of user \( u \) on item \( i \) is modeled by \( \hat{x}_{ui} = a_u^T \beta_i + y_i \) where \( y_i \) denotes the item bias term. \( \sigma(\cdot) \) is the sigmoid function.

However, the above methods assume all the unobserved (non-purchased) feedback as negative (AMAN), while the non-purchased items should not be equally considered as negative. Our method is distinguished from theirs in that we incorporate another type of implicit user feedback, i.e., click record, and define new pairwise relationships among items with respect to users to relieve the AMAN assumption.

Modeling User Behavior. With the advent of e-commerce, much work has been devoted to understanding behavior of online users [1, 8], and specifically predicting purchase behaviors [5, 7]. As the former line of work, Lo et al. [8] studied user activity and purchasing behaviors that vary over time, especially focusing on user purchasing intent. Most recently, Cheng et al. [1] extended [8] by generalizing their analysis on characterizing the relationship between a user’s intent and his behavior. Our goal is different in that rather than predicting users’ various intents from their online behaviors, we focus on predicting users’ future purchase.

Meanwhile, as the latter line of work, given implicit user feedback including their demographics, click record and purchase record, Liu et al. [7] proposed an ensemble method to predict which customers would return to the same merchant within six months period. They formulated the problem as a classification task and trained various classification methods. While using both purchase record and click record, our task is different in that we aim to predict items that users will purchase in the future rather than to predict repeat buyers. Moreover, Li et al. [5] proposed a matrix factorization based method that predicts the conversion response of users in display advertising, the goal of which inherently differs from our task. To the best of our knowledge, our work is the first attempt to predict users’ future purchase by jointly modeling both users’ click and purchase record.

3 PROBLEM STATEMENT

We first introduce notations used throughout this paper. Let \( \mathcal{U} = \{u_1, u_2, \ldots, u_n\} \) be the set of users and \( \mathcal{I} = \{i_1, i_2, \ldots, i_m\} \) be the set of items, where \( n \) and \( m \) are the number of users and items, respectively. The purchase record of users in \( \mathcal{U} \) on items \( \mathcal{I} \) are represented by the purchase matrix \( P = [p_{ui}]_{n \times m} \), where \( p_{ui} = 1 \) if user \( u \) purchased item \( i \), and 0 otherwise. The case of the click matrix \( B \) is similar and omitted for brevity. Note that \( \mathcal{P}_u \) and \( b_u \) denote set of items purchased and clicked by user \( u \), respectively.

Given the aforementioned notations, purchase matrix and click matrix, our problem is defined as:

**Problem Definition**

**Given:** The purchase matrix \( P \) and click matrix \( B \)

**Goal:** For each user \( u \in \mathcal{U} \), predict items \( i \in \mathcal{I} \setminus \mathcal{P}_u \) that are likely to be purchased in the future.

4 METHOD

In this section, we first explain our model assumptions regarding different types of implicit user feedback, i.e., purchase and click record. Next, we describe how these two records are jointly combined to relieve the AMAN assumption, and eventually to enhance the accuracy of predicting users’ future purchase.

4.1 Relieving the AMAN Assumption

Recall the AMAN assumption taken by previous pairwise methods [4, 11]. For each user \( u \) and his purchased item set \( \mathcal{P}_u \), the following assumption holds:

\[
\forall i > j, \forall i \in \mathcal{P}_u \land \forall j \in \mathcal{I} \setminus \mathcal{P}_u \quad (3)
\]

which implies that a user \( u \) prefers purchased items \( i \) to non-purchased items \( j \). However, under such assumption, non-purchased items are equally considered as negative feedback, while some of them attract the user more than others. To overcome this limitation, we incorporate users’ click record, which is another type of implicit user feedback. Although the user preference reflected therein is not as strong as in purchase record, we expect that click record helps to relieve the AMAN assumption when combined with purchase record.
To this end, based on users’ purchase and click record, we split the items into three disjoint sets, i.e., 1) purchased items, 2) clicked-but-not-purchased items, and 3) non-clicked items, and propose three different assumptions considering pairwise relationships among them with respect to users. Note that we assume $p_u \in I$, i.e., all purchased items are selected from clicked items.

**Assumption 1.** We assume that a user prefers purchased items to non-clicked items.

$$i > u \iff \forall i \in p_u \wedge \forall j \in I \setminus b_u$$  \hspace{1cm} (4)

Instead of regarding non-purchased items as users’ negative feedback as in Eqn 3, here we assume non-clicked items as their negative feedback. This narrows down the candidates for the negative feedback, which is expected to alleviate the AMAN assumption.

**Assumption 2.** We assume that a user prefers purchased items to clicked-but-not-purchased items, and clicked-but-not-purchased items to non-clicked items.

$$i > u \iff \forall i \in p_u \wedge \forall j \in b_u \setminus p_u \wedge \forall k \in I \setminus b_u$$  \hspace{1cm} (5)

We draw on Assumption 1 by adding another set of items, i.e., clicked-but-not-purchased items ($b_u \setminus p_u$). Eqn 5 agrees with our expectation that 1) a user $u$ generally decides to purchase items ($p_u$) among many other candidates ($b_u \setminus p_u$) according to his preference, and thus 2) the user $u$ prefers clicked items to items that are neither purchased nor clicked ($I \setminus b_u$).

**Assumption 3.** We assume that a user prefers purchased items to clicked-but-not-purchased items, and non-clicked items to clicked-but-not-purchased items.

$$i > u \iff \forall i \in p_u \wedge \forall j \in b_u \setminus p_u \wedge \forall k \in I \setminus b_u$$  \hspace{1cm} (6)

Eqn 6 implies that a user $u$ dislikes items that are only clicked ($b_u \setminus p_u$) more than those that are not clicked at all ($I \setminus b_u$). This assumption also holds in the sense that while being aware of clicked-only items, the user still chose not to purchase them, which implies that the user dislikes them.

### 4.2 The Proposed Model: P3S

Inspired by BPR model [11], we describe how our assumptions are materialized to formulate an optimization objective whose goal is to eventually predict users’ future purchase. Note that due to the space limitation, here we discuss only Assumption 2, while we empirically compare the methods based on all three assumptions in Section 5.

Given parameters $\Theta$ to be learned, the likelihood function to maximize is represented as:

$$L(\Theta) = \prod_{u \in U} \left( \prod_{i \in p_u} \prod_{j \in b_u \setminus p_u} \prod_{k \in I \setminus b_u} \Pr[i > u \land j \wedge k]>0 \right)$$  \hspace{1cm} (7)

where $\Pr[i > u \land j \wedge k]$ denotes the probability that user $u$ prefers item $i$ to item $j$. The probability function $Pr[\cdot]$ is approximated by a sigmoid function of the form $\sigma(x) = \frac{1}{1 + e^{-x}}$ as in [11]:

$$\Pr[i > u \land j] = \sigma(x_{ui} - x_{uj})$$  \hspace{1cm} (8)

$$x_{ui} = a_u^T \beta_i + y_{u}$$  \hspace{1cm} (9)

where $a_u \in \mathbb{R}^K$ and $\beta_i \in \mathbb{R}^K$ represent the $K$-dimensional latent factors for user $u$ and item $i$, respectively, and $y_{u}$ denotes the item bias term for item $i$.

In order to maximize the likelihood function defined in Eqn 7, we take the logarithm of $L(\cdot)$, and adopt $l_2$-norm regularization term $\text{reg}(\Theta)$ for model parameters $\Theta = \{a_u, \beta_i, \beta_k, y_{u}, y_{j}, y_{k}\}$ and learn them by stochastic gradient ascent to obtain a local maximum solution. Given the learning rate $\eta$, each parameter is updated as follows:

$$\Theta \leftarrow \Theta + \eta \times \frac{\partial L(\Theta)}{\partial \Theta}$$  \hspace{1cm} (10)

### 5 EXPERIMENTS

#### 5.1 Experimental Settings

**Dataset.** We evaluate our proposed method on two real-world datasets (NAVER Shopping$^1$ and RecSys2015$^2$) each of which contains both purchase record and click record of the same set of users. NAVER is a web portal that provides a platform for online shopping. We collect users’ click and purchase record for six months (Oct. 2016 ~ Mar. 2017), and remove users with less than 8 purchases and 40 clicks. RecSys2015 dataset consists of sessions of clicks and purchases sequences extracted from an e-commerce website. Here, we assume each session as a user. We remove users with less than 8 purchases and 10 clicks. For both datasets, 1) we split the sequence of chronologically ordered purchase record in half for each user, and use the first half as training data and the second half as test data, and 2) we use the click record of the user upto the timestamp of the last purchase in the training data. Table 1 shows the detailed statistics of the datasets.

**Evaluation Setting.** Predicting users’ future purchase among clicked items is rather a trivial task, and obviously the performance is expected to be significantly improved by incorporating users’ click record as in our method, because items are purchased from clicked items. Indeed, our method greatly outperformed the competitors under such setting, which we omitted due to the space limitation. Therefore, to make the problem more challenging and practical, we evaluate our method on how well it predicts users’ future purchase.

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$^1$http://shopping.naver.com

$^2$http://2015.recsyschallenge.com/challenge.html

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| Dataset   | Type   | #Users | #Items | #Feedback | Density |
|-----------|--------|--------|--------|-----------|---------|
| RecSys2015| Purchase| 9,184  | 7,649  | 90,597    | 0.128%  |
| NAVER     | Shopping| 20,108 | 89,500 | 129,279   | 0.007%  |
Table 2: Performance Comparisons

|                      | RecSys2015 | NAVER Shopping |
|----------------------|------------|----------------|
|                      | MostPop    | WMF | BPR | P3S-1 | P3S-2 | P3S-3 | MostPop    | WMF | BPR | P3S-1 | P3S-2 | P3S-3 |
| Prec@5               | 0.0028     | 0.0126 | 0.0354 | 0.0379 | **0.0430** | 0.0000 | 0.000008 | 0.00018 | 0.00035 | 0.00018 | 0.00051 | 8.1 × 10⁻² |
| Recall@5             | 0.0022     | 0.0232 | 0.0932 | 0.0911 | **0.1227** | 0.0000 | 0.000033 | 0.00888 | 0.00159 | 0.00074 | 0.00229 | 0.00040 |
| MAP                  | 0.0075     | 0.0229 | 0.0720 | 0.0802 | **0.0896** | 0.0000 | 0.00064 | 0.00075 | 0.00122 | 0.00078 | 0.00188 | 0.00027 |
| MRR                  | 0.0107     | 0.0412 | 0.0998 | 0.1011 | **0.1131** | 0.0000 | 0.00073 | 0.00089 | 0.00131 | 0.00092 | 0.00221 | 0.00029 |
| NDCG                 | 0.1354     | 0.1536 | 0.2109 | 0.2161 | **0.2406** | 0.1065 | 0.07830 | 0.07514 | 0.07764 | 0.07791 | 0.08320 | 0.07355 |
| AUC                  | 0.7469     | 0.7561 | 0.8514 | 0.8582 | **0.8794** | 0.5360 | 0.59146 | 0.50970 | 0.58026 | 0.58537 | 0.67808 | 0.50447 |

Evaluation Metrics. Although methods based on BPR including our proposed method are originally designed to optimize the AUC [11], we evaluate our method using six different ranking metrics (Precision@5, Recall@5, MAP (Mean Average Precision), MRR (Mean Reciprocal Rank), NDCG (Normalized Discounted Cumulative Gain) and AUC (Area under the ROC curve)) to demonstrate the superiority of our method in general ranking metrics.

Parameters. For all baselines, we tune hyperparameters by performing grid search with $K \in \{10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, 200\}$, $\eta \in \{0.01, 0.05, 0.1\}$ and $\lambda \in \{0.01, 0.05, 0.1\}$ where $\lambda$ is the strength of the model regularization. Note that the results are average over 5 runs with different random seed for initialization. Standard deviations are omitted due to the space limitation. For each method, we choose the parameter with the best AUC value.

5.2 Performance Analysis

Table 2 summarizes the evaluation results of all methods in terms of multiple ranking metrics on two real-world datasets. We observe that our proposed method outperforms the competitors. The major observations are: 1) The personalized recommendation methods generally outperform the method that recommends the most frequently purchased items. (MostPop) 2) Incorporating pairwise constraints among items generally improves the performance compared with conventional regression based method (WMF), 3) P3S-2, which is based on the Assumption 2, consistently shows the best overall performance in all the metrics in both datasets. This implies that non-purchased items should not be equally considered as negative feedback, and that new pairwise relationships among them with respect to users should be considered. Precisely, by assuming that a user prefers purchased items to clicked-but-not-purchased items, and clicked-but-not-purchased items to non-clicked items, we successfully relieve the AMAN assumption of Eqn 3. 4) The performance of P3S-1, which is based on the Assumption 1, does not significantly differ from that of BPR. This implies that clicked-but-not-purchased items play a vital role in relieving the AMAN assumption, and 5) P3S-3, which is based on Assumption 3, fails to achieve high performance that is even worse than BPR. This again demonstrates that clicked-but-not-purchased items contain more positive feedback of users than those that are not clicked at all.

6 CONCLUSION

In this paper, we presented a pairwise learning-to-rank method aiming at predicting users’ future purchase in e-commerce. Precisely, in order to alleviate the AMAN assumption and the data sparsity problem of users’ purchase record, 1) we partitioned the items into three disjoint sets based on users’ purchase and click record, 2) defined new pairwise relationships among them with respect to users, and 3) reflected these relationships into our pairwise learning-to-rank method. The experimental results on two real-world datasets demonstrate the superiority of our method compared with the state-of-the-art baselines. Our method is useful for any e-commerce companies that collect users’ purchase and click record. In the future, we plan to investigate the contextual information in which a user’s click or purchase occurs, and model the temporal dynamics of users’ evolving interest.

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among non-clicked items. In other words, for each user we consider only the items neither clicked nor purchased by the user in the past as the candidates for prediction.

Comparison Methods.

- MostPop: A method that provides globally the most frequently purchased items as prediction for every user.
- WMF [3]: A regression-based weighted matrix factorization algorithm with implicit feedback data as in Eqn 1.
- BPR [11]: A pairwise learning-to-rank method based on Eqn 3 combined with matrix factorization as in Eqn 2.
- P3S-1: Our proposed method based on Eqn 4.
- P3S-2: Our proposed method based on Eqn 5.
- P3S-3: Our proposed method based on Eqn 6.

Parameters. For all baselines, we tune hyperparameters by performing grid search with $K \in \{10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, 200\}$, $\eta \in \{0.01, 0.05, 0.1\}$ and $\lambda \in \{0.01, 0.05, 0.1\}$ where $\lambda$ is the strength of the model regularization. Note that the results are average over 5 runs with different random seed for initialization. Standard deviations are omitted due to the space limitation. For each method, we choose the parameter with the best AUC value.
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