Recommendation for Repeat Consumption from User Implicit Feedback (Extended Abstract)

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I. Introduction

Most of the previous work on recommender systems focuses on discovering *novel* items that meet users' personalized interest. But there is barely any study about recommending repeat items that consumed by the target user before. In fact, people's consumption behaviors are a mixture of repeat and novelty-seeking behaviors [1]. Since people forget about things as time elapses, it is possible that users may prefer the previously consumed items but cannot remember them at certain times. Therefore, **R**ecommendation for **R**epeat **C**onsumption (RRC) has some real utility and should be studied in depth. Some efforts have been done in related work [1]. However, they only consider item popularity and recency effect, and fail to take full advantage of behavioral features.

In this paper, we attempt to address the RRC problem (illustrated in Fig 1) by proposing a **T**ime-**S**ensitive **P**ersonalized **P**airwise **R**anking (abbr. **TS-PPR**) model based on the behavioral features extracted from user implicit feedback in the consumption history. **TS-PPR** factorizes the temporal user-item interactions via learning the mappings from the behavioral features in observable space to the preference features in latent space, and combines users static and dynamic preferences together in recommendation. An empirical study on real-world data sets shows encouraging results.

II. The Proposed Model

A. Problem Description

Suppose that each user $u \in \mathcal{U}$ is observed with a consumption sequence $\mathbf{S}_u = \{x_1^u, ..., x_t^u, ...\}$ where x_t^u is the consumption behavior of user u at time step t. A consumption behavior is a user's positive action on a certain consumable item, e.g. buy product, visit location, watch news article and listen to music track. The elements in $\mathbf{S}_u$ are sorted in a time ascending order. Let $\mathbf{W}_{ut}$ be a subsequence of $\mathbf{S}_u$ ending on the consumption behavior x_t^u, i.e. $\mathbf{W}_{ut} = \{x_{t-|\mathbf{W}_{ut}|+1}^u, ..., x_t^u\} \subseteq \mathbf{S}_u$. $\mathbf{W}_{ut}$ is called a time window w.r.t. user u and time t. In this paper, we use $\mathbf{W}$ to denote a general time window. Then, we can define the RRC problem as: Given the time window $\mathbf{W}_{ut}$, if the next incoming unknown consumption behavior x_{t+1}^u is predicted (e.g. using method in [2]) very likely to be a repetition from $\mathbf{W}_{ut}$, the RRC problem is to recommend items $v \in \mathbf{W}_{ut}$ to u at time $t+1$, which satisfy u's personalized preference.

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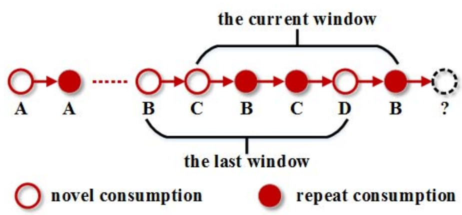

Fig. 1. An illustration of the RRC problem. People's consumption behaviors are represented by circles along timeline. Empty circles are novel consumption behaviors, while solid circles are repeat consumption behaviors defined over a time window (e.g. capacity is 5). Characters under circles represent different items. The RRC problem is to recommend items from the current time window if the next incoming circle is predicted to be solid.

B. The *TS-PPR* Model

The **TS-PPR** model is designed based on the Bayesian Personalized Ranking framework [3] by incorporating time-sensitive user behavioral features. Let $\mathbf{f}_{uvt}$ denote the behavioral feature vector representing the interaction between user u and item v by time point t. We define the preference function:

$$r_{uvt} = \mathbf{u}^\top \mathbf{v} + \mathbf{u}^\top \mathbf{A}_u \mathbf{f}_{uvt} = \mathbf{u}^\top (\mathbf{v} + \mathbf{A}_u \mathbf{f}_{uvt}), \quad (1)$$

where $\mathbf{u}$ and $\mathbf{v}$ are the latent features of user u and item v, respectively, and $\mathbf{A}_u$ is the personalized feature space transformation matrix of u. Therefore, we focus on learning a time-sensitive personalized pairwise ranking function $p(v_i >_{ut} v_j) = \frac{1}{1+e^{-r_{uvt}}}$. We formulate our objective function with regularizations as:

$$\mathcal{J} = \sum_{(u,v_i,v_j,t)\in\mathcal{D}} -\ln p(v_i >_{ut} v_j) + \frac{\lambda}{2}\sum_u \|\mathbf{A}_u\|_F^2 + \frac{\gamma}{2}(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2),$$

where $\mathcal{D}$ contains quadruples (u, v_i, v_j, t) representing that u reconsumes v_i rather than v_j at time step t.

Unlike $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{A}_u$, time-sensitive feature $\mathbf{f}$ is directly extracted from user-item interactions in the current window. In this work, we consider four behavioral features as follows:

Item Quality. For a given item v, we compute its normalized item quality $\bar{q_v}$ as: $q_v = \ln(1+n_v)$, $\bar{q_v} = \frac{q_v - q_{min}}{q_{max} - q_{min}}$, where n_v is the frequency of item v in the training set. q_{min} and q_{max} are the minimum and the maximum q_v ($\forall v \in \mathcal{V}$) observed in the training set, respectively.

Item Reconsumption Ratio. The item reconsumption ratio for v is defined as $r_v = \frac{\sum_u \sum_t \mathbb{I}_{x_{t+1}^u \in \mathbf{W}_{ut} \wedge x_{t+1}^u = v}}{\sum_u \sum_t \mathbb{I}_{x_{t+1}^u = v}}$, where $\mathbb{I}$ is an indicator function. The numerator and the denominator are the number of observations on item v as a repeat consumption

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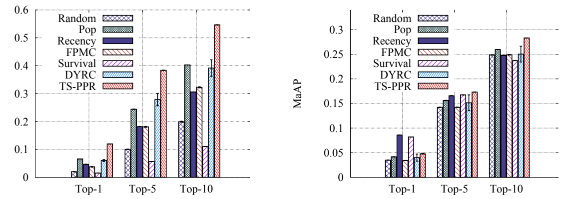

(a) Gowalla (b) Lastfm

Fig. 2. Macro average precision performance of all the methods.

and the number of total observations on it, respectively. It measures the probability of item v to be reconsumed based on the observations in the training set. Please note that the length of time window $\mathbf{W}_{ut}$ is fixed regardless of time t.

Recency Feature. In [4], it is found that the hyperbolic function performs better compared with the other alternatives to measure the decay of people's interest. Thus, the hyperbolic definition of recency feature is $c_{vt} = \frac{1}{t - l_{ut}(v)}$, where $l_{ut}(v)$ is u's last consumption time on item v before time t. Apparently, c_{vt} is a time-decaying feature.

Dynamic Familiarity. Inspired by the previous work [2], a user may choose to reconsume the items which (s)he is familiar with. The dynamic familiarity of user u on item v in the proposed method is defined as $m_{vt} = \frac{|\{x | x \in \mathbf{W}_{ut} \wedge x = v\}|}{|\mathbf{W}_{ut}|}$. The numerator is the number of consumption on item v in $\mathbf{W}_{ut}$, while the denominator is the length of the time window. This feature measures the fraction of consumption on item v in time window $\mathbf{W}_{ut}$. A larger value of m_{vt} indicates u's higher dynamic familiarity with v.

Thus, in this paper, the feature vector $\mathbf{f}$ is interpreted as $\mathbf{f} = \{\bar{q_v}, r_v, c_{vt}, m_{vt}\}^\top$. Obviously, these features have already been normalized into the range $[0, 1]$.

To this end, the optimization problem can be solved by using the stochastic gradient descent method. The gradient w.r.t. a training quadruple (u, v_i, v_j, t) is:

$$\begin{aligned} &\frac{\partial}{\partial \theta}\left(\ln p(v_i >_{ut} v_j) - \frac{\eta_\theta}{2}\theta^2\right) \\ &= (1 - p(v_i >_{ut} v_j))\frac{\partial}{\partial \theta}(r_{uv_it} - r_{uv_jt}) - \eta_\theta \theta, \end{aligned} \tag{2}$$

where $\eta_\theta \in \{\gamma, \lambda\}$, $\theta \in \{\mathbf{A}_u, \mathbf{U}, \mathbf{V}\}$. The training quadruples can be obtained by: (1) moving a sliding window on one user's consumption history step by step from the start; (2) if at time t, the next consumption on item v_i is repeat w.r.t. time window, then sample a negative item $v_j \neq v_i$ and add (u, v_i, v_j, t) to training set. The testing set is similarly constructed.

III. Experiments

We conducted the experiments on two publicly-available data sets: **Gowalla** (location check-ins) [5] and **Lastfm** (music listening) [6]. We use each user's 70% consumption sequence for training while the rest 30% for testing. The evaluation metric is the average precision to recommend the real reconsumed item given the current time window for all users.

The baselines include: the random recommendation **Random**, the popularity-based **Pop**, the recency-based **Recency**, **FPMC** [7], **Survival** [8] and **DYRC** [1].

Fig. 2 illustrates the macro average precision of all the baselines and **TS-PPR** on the two real-world data sets. Obviously, **TS-PPR** outperforms all the baselines on both data sets under most evaluation settings — Top-1, Top-5 and Top-10 recommendations, except for the results of Top-1 recommendation on the Lastfm data set. Thus, we can say that **TS-PPR** is effective for the RRC problem in most cases, except that the accuracy performance of the proposed method on the Top-1 recommendation task may fluctuate due to the high volatility in recommending only one item each time. Meanwhile, it can be seen that the incorporation of time-sensitive behavioral features is very useful to improve the accuracy performance in the RRC problem. Since only four generic domain-independent behavioral features are extracted in the experiments, we believe that there is still much room to improve the results by incorporating more elaborate off-the-shelf domain-specific features.

TABLE I. Evaluation combining **STREC** and **TS-PPR**.

Data Set	**STREC**	**TS-PPR** (on **STREC** correct classification)		
		MaAP@1	MaAP@5	MaAP@10
Gowalla	0.6912	0.1343	0.4487	0.6314
Lastfm	0.8070	0.0862	0.2819	0.4336

Furthermore, we combine **STREC** [2] and **TS-PPR** together as a holistic algorithm for repeat consumption behavior prediction. More specifically, we perform personalized recommendations with **TS-PPR** on real repeat consumption correctly identified by **STREC**. The experimental results are shown in Table I. The accuracy of **STREC** to predict whether or not a user will perform a repeat consumption is about 0.7 and 0.8 on the two data sets, respectively. Meanwhile, the recommendation accuracy of **TS-PPR** conditional on the repeat consumption correctly classified by **STREC** is also very promising (e.g. 0.6314 MaAP@10 on Gowalla). By timing the numbers under **STREC** and **TS-PPR**, we will get the accuracy of jointly addressing both the **RRC** and the **STREC** problems at the same time.

Acknowledgment

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References

[1] A. Anderson, R. Kumar, A. Tomkins, and S. Vassilvitskii, "The dynamics of repeat consumption," in *WWW*, 2014, pp. 419–430.

[2] J. Chen, C. Wang, and J. Wang, "Will you "reconsume" the near past? fast prediction on short-term reconsumption behaviors," in *AAAI Conference on Artificial Intelligence*, 2015, pp. 23–29.

[3] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "BPR: Bayesian personalized ranking from implicit feedback," in *UAI*, 2009, pp. 452–461.

[4] J. Chen, C. Wang, and J. Wang, "A personalized interest-forgetting markov model for recommendations," in *AAAI Conference on Artificial Intelligence*, 2015, pp. 16–22.

[5] E. Cho, S. A. Myers, and J. Leskovec, "Friendship and mobility: User movement in location-based social networks," in *SIGKDD*, 2011, pp. 1082–1090.

[6] O. Celma, *Music Recommendation and Discovery in the Long Tail*. Springer, 2010, ch. 3.

[7] S. Rendle, C. Freudenthaler, and L. Schmidt-Thieme, "Factorizing personalized markov chains for next-basket recommendation," in *WWW*, 2010, pp. 811–820.

[8] K. Kapoor, M. Sun, J. Srivastava, and T. Ye, "A hazard based approach to user return time prediction," in *SIGKDD*, 2014, pp. 1719–1728.