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Modeling Users' Preferences and Social Links in Social Networking Services: A Joint-Evolving Perspective

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Abstract

Researchers have long converged that the evolution of a *S*ocial *N*etworking *S*ervice (SNS) platform is driven by the interplay between users' preferences (reflected in user-item consumption behavior) and the social network structure (reflected in user-user interaction behavior), with both kinds of users' behaviors change from time to time. However, traditional approaches either modeled these two kinds of behaviors in an isolated way or relied on a static assumption of a SNS. Thus, it is still unclear how do the roles of users' historical preferences and the dynamic social network structure affect the evolution of SNSs. Furthermore, can jointly modeling users' temporal behaviors in SNSs benefit both behavior prediction tasks? In this paper, we leverage the underlying social theories (i.e., social influence and the homophily effect) to investigate the interplay and evolution of SNSs. We propose a probabilistic approach to fuse these social theories for jointly modeling users' temporal behaviors in SNSs. Thus our proposed model has both the *explanatory* ability and *predictive* power. Experimental results on two real-world datasets demonstrate the effectiveness of our proposed model.

1 Introduction

Online SNSs, such as *Facebook*, *Twitter*, and location-based social networks, facilitate the building of social relations among people who share similar interests. Thus, people can stay connected with others and be informed of new consumption preferences of social friends.

Generally, a SNS platform is built upon two kinds of users' behaviors: *consuming items* (reflected in *user-item interaction* such as rating, buying and check-in) and *building social links* (reflected in *user-user interaction* such as the directed trust and the undirected friendship). One step further, discovering users' consumption preferences and suggesting new links are two core behavior prediction tasks for these systems: *C*ollaborative *F*iltering (CF), which discovers the like-minded users with similar consumption history, forms the basis of user preference discovery (Adomavicius and Tuzhilin 2005; Koren, Bell, and Volinsky 2009); *N*ode *P*roximity (NP) based models, which exploit the topological structure of social networks, play a central role in the social link suggestions (Liben-Nowell and Kleinberg 2007; Menon and Elkan 2011). In summary, these two directions utilized a particular kind of users' historical behavior to predict the same kind of behavior, and are usually well researched in parallel.

However, social scientists have long converged that these two kinds of users' behaviors are not isolated, instead, the interplay between them drives the evolution of SNSs. Two social theories explain this interplay: the *social influence* argues users' future preference behavior is affected by the social network around them, and the *homophily effect* states people tend to associate and bond with others that have similar preferences (Aral, Muchnik, and Sundararajan 2009). An example of such evolving of a SNS platform is shown in Figure 1. Thus, some research works have leveraged one type of users' behavior to help another behavior prediction task (Jamali and Ester 2010; Tang et al. 2013) or assumed a time-invariant user latent factor is shared among users' behaviors (Yang et al. 2011). Nevertheless, these works either modeled users' two kinds of behaviors in an isolated way or relied on a static assumption of a SNS. Thus, we still can not give an explanatory answer to the question – how do the roles users' two kinds of behaviors play in the evolution of SNSs? Furthermore, can jointly modeling users' temporal behaviors benefit both prediction tasks?

To answer these two questions, there are some technical challenges. First, both kinds of users' behaviors mix together to form the evolution of SNSs. Thus, it is hard to distinguish the contribution of each kind of users' behavior in the evolution process. Second, it is still unclear how to build connections among users' two kinds of behaviors over time and jointly model them. To tackle these challenges, in this paper, we propose an *E*volving *J*oint *P*rediction (*EJP*) approach to fuse the underlying social theories for explaining and jointly modeling users' two kinds of behaviors over time. Specifically, we associate users and items with latent representations, where the user latent factors are time-dependent and shared among these two kinds of behaviors. In the meantime, we clearly quantify the influence of current consumption preference and the social structure for the future users' behaviors with underlying social theories. Finally, we validate the effectiveness of our proposed model on both behavior prediction tasks by performing experiments on two real-world datasets. To the best of our knowledge, this is one of

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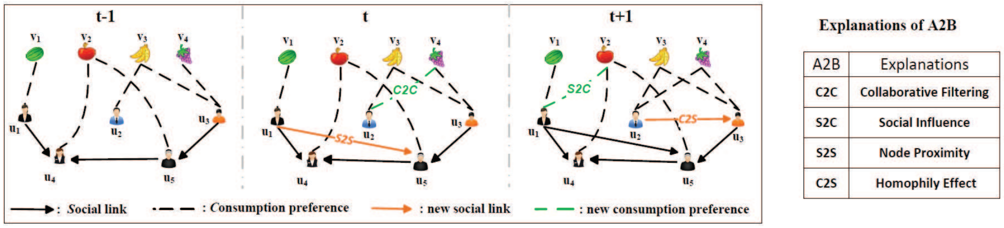


Figure 1: A showcase of the evolution of a SNS platform. At each time, users perform two kinds of behaviors: build a *S*ocial link or show her *C*onsumption preference. We use "A2B" at each newly added behavior to denote the current behavior of "A" leads to the future behavior "B". E.g., a "S2C" label is added from t to $t+1$ as $u1$ shows *C*onsumption preference to $v2$ possibly because her social neighbors ($u1$ has followed $u4$ and $u5$ before $t+1$) consumed item $v2$ before.

the few attempts that have both the explanatory ability and the predictive power for tracking the evolution of SNSs.

2 Related Work

We first summarize the traditional solutions for user preference discovery and social link prediction, then we introduce the efforts on modeling users' behaviors in SNSs.

Collaborative Filtering. Collaborative filtering (CF) is a technique to discover user consumption preference for personalized item suggestions (Adomavicius and Tuzhilin 2005). Among all CF techniques, latent factor based models have shown great success (Mnih and Salakhutdinov 2007; Koren, Bell, and Volinsky 2009; Zeng et al. 2015). With users' preferences change from time to time, some recent works took the temporal dynamics of users' interests into consideration (Liu et al. 2013; Rendle, Freudenthaler, and Schmidt-Thieme 2010; Xiong et al. 2010; Koren 2010). For instance, Xiong et al. introduced an additional latent dimension over time (Xiong et al. 2010) to model the overall trends of items for users' preference decision.

Link Prediction. Link prediction is the task of predicting the possible links in the near future given a snapshot of a social network. The literature can be classified into two categories: unsupervised (Liben-Nowell and Kleinberg 2007; Jeh and Widom 2002) and supervised (Menon and Elkan 2011). With the availability of evolving social network data, recent studies considered the temporal link prediction problem (Aggarwal and Subbian 2014). An intuitive yet effective approach is to collapse multiple time-sliced linked data into a single matrix with weighted averaging, then the static link prediction models could be applied (Acar, Dunlavy, and Kolda 2009; Gao, Denoyer, and Gallinari 2011). Others proposed tensor factorization or non-parametric time-series models to capture the temporal information in graph evolution (Dunlavy, Kolda, and Acar 2011; Sarkar, Chakrabarti, and Jordan 2012).

Modeling users' two kinds of behaviors in SNSs. The principles of the social influence and the homophily effect suggest that users' consumption preferences and the social linking behaviors are not isolated. Thus, the social-based recommendation system utilizes the social influence theory to help improve the performance of traditional CF (Jiang et al. 2014; Jamali and Ester 2010). Others proposed to exploit users' preference history, i.e., the homophily effect for link prediction (Tang et al. 2013). A recent work analyzed and modeled the temporal behaviors in a SNS using bidirectional effects (Jamali, Haffari, and Ester 2011). It differs from our problem formulation in that it focused on the global evolution of a SNS, thus can not be used for personalized recommendation. Yang et al. proposed to jointly model users' two kinds of behaviors in a unified framework, thus achieved better performance than modeling them separately. Our work advances their model in: (1) Their model assumed a static representation of SNSs while our work captures the temporal dynamics of the SNS evolution. (2) Our model has the explanatory power that explicitly quantifies the social network effect and users' historical preference for the evolution of SNSs.

3 The Proposed Model

In an online SNS platform, there are a set of users U ($|U| = N$) and items V ($|V| = M$). Users perform two kinds of behaviors over time: *consuming items* and *building social links* with others, which can be summarized into two tensors: a consumption tensor $C \in \mathbb{R}^{N\times M\times T}$ and a social link tensor $S \in \mathbb{R}^{N\times N\times T}$. If user a consumes item i at time window t, C^t_{ai} denotes the rating preference score. Otherwise it is 0 indicating the user does not show any preference during that time. Similarly, $S^t_{ab} = 1$ if user a connects a link to user b at time t, otherwise it equals 0. Without confusion, we use a, b, c to represent users and i, j, k to denote items. Then the problem can be defined as:

Definition 1 (PROBLEM DEFINITION) *Given the user consumption tensor C and the social tensor S, our goal is two-fold: (1) quantify the relative contribution of social influence and homophily effect of each user for the evolution of SNSs. (2) predict each user's consumption behavior and the social link behavior at time $T+1$.*

In this section, we propose a probabilistic latent approach to fuse the above two social theories. Specifically, for each user a at each time t, we associate her with a time-dependent latent consumption preference factor U^t_a . To model the social influence effect, U^t_a is influenced by her social neighbors' interests at previous time. To capture the homophily effect, each user's decision on whether to build a social link to another user is also influenced by the similarity between their latent interest factors. Thus the user latent factors are time-dependent and shared among these two kinds of users' behaviors. In the following, we first give an overview of our proposed framework, followed by the model learning.

Probabilistic Modeling

Evolutional Consumption Behavior Modeling For each user a and each item i, the predicted consumption preference between them at time t could be expressed as:

$$p(C|U,V) = \prod_{t=1}^{T}\prod_{a=1}^{N}\prod_{i=1}^{M}\mathcal{N}[(C_{ai}^{t}|\langle U_a^t, V_i\rangle, \sigma_C^2)]^{Y_{ai}^{t}}, \quad (1)$$

where $\mathcal{N}(\mu, \sigma^2)$ is a normal distribution with mean μ and variance σ^2. Y is an indicator tensor in which it equals 1 if user a rates item i at time t. $U_a^t \in \mathbb{R}^{D\times 1}$ is the latent preference of user a at time t in user latent tensor $U \in \mathbb{R}^{T\times N\times D}$ and $V_i \in \mathbb{R}^{D\times 1}$ is the item latent factor in item latent matrix $V \in \mathbb{R}^{M\times D}$. $\langle,\rangle$ denotes the inner product of two vectors. Given the limited observed preference data, a typical approach is to add priors to the latent variables. As other traditional CF models (Mnih and Salakhutdinov 2007), we add a zero-mean Gaussian prior on the item latent matrix:

$$p(V|\sigma_V^2) = \prod_{i=1}^{M}\mathcal{N}(V_i|0, \sigma_V^2\mathbf{I}), \quad (2)$$

Now our goal turns to how to model the evolution of users' latent interest tensor U. In fact, as shown in Figure 1, a user's current interest is mainly influenced by two underlying reasons: First, a user follows her previous preferences to make current consumption decisions. This effect uses the historical consumption behavior for future consumption prediction and is the base of traditional CF models. For example, a possible reason for $u2$ to consume $v4$ at time t in Figure 1 is that $u3$— a user that has similar consumption preference with her consumed $v4$ in the past. Second, in a social network, the social influence theory argues that people are affected by their social neighbors to make future decisions. E.g., $u1$ is influenced by her social friend $u4$, thus consumes $v2$ at time $t+1$. We explicitly model the two effects of each user's latent interests at time window $t = 2, 3, ...T$ as:

$$\begin{aligned} & p(U_a^t) = \mathcal{N}(U_a^t|\bar{U}_a^t, \sigma_U^2\mathbf{I}) \\ & \text{where} \quad \bar{U}_a^t = (1-\alpha_a)U_a^{(t-1)} + \alpha_a \textstyle\sum_{b\in N_a^{(t-1)}} F_{ab}^t U_b^{(t-1)} \\ & \textit{s.t.} \quad \forall a \in U, \quad 0 \le \alpha_a \le 1, \end{aligned} \quad (3)$$

where F_{ab}^t denotes the weight of b influences a at time t. N_a^t is the set the users that a has social links with till time t, i.e., $N_a^t = [b|S_{ab}^{t'} = 1, t' \le t]$. Here, we simply set this weight $F_{ab}^t = \frac{1}{|N_a^{(t-1)}|}$ as an average of all users that a connects. α_a is a non-negative parameter that balances these two influencing factors. As users may have their own decisions in balancing these two aspects, e.g., some people like to follow their own preferences and others are easily influenced by social neighbors' decisions, α_a is personalized and varies among people. The larger the α_a, the larger the social influence effect plays in this user's future consumption decision, the less likely this user follows her own previous preferences.

At the initial time $t = 1$, the social network has not been set up yet, thus each user's latent interests are only determined by her own consumption preferences without any social influence. We assume a zero-mean Gaussian distribution of users' latent factors at that time. Then we summarize the prior over user latent tensor as:

$$p(U|\sigma_U^2, \sigma_{U1}^2) = \prod_{a=1}^{U}\mathcal{N}(U_a^1|0, \sigma_{U1}^2\mathbf{I})\prod_{t=2}^{T}\mathcal{N}(U_a^t|\overline{U_a^t}, \sigma_U^2\mathbf{I}), \quad (4)$$

Evolutional Social Behavior Modeling Similar as the user consumption behavior, each user a's link behavior is also mainly influenced by two factors. First, user a connects to another user that is close to her based on the topological graph structure, which can be modeled by traditional link prediction measures. E.g., $u1$ bonds with $u5$ at time t in Figure1 can be mainly attributed to this reason. Second, user a finds another user that shows similar consumption preferences, then she is likely to associate with her in the near future to share consumption experience. This is termed as the homophily effect in social science and it is widely accepted in explaining the social network construction process (McPherson, Smith-Lovin, and Cook 2001). An illustration of this homophily effect is that $u2$ connects to $u5$ in Figure1.

As we represent users' consumption preferences with latent factors, the homophily effect between users could be measured by comparing their latent consumption preferences. Then the predicted link score $\hat{S}_{ab}^t$ between user a and b at time $t = 2, 3, ...T$ could be modeled as:

$$\hat{S}_{ab}^t = (1-\beta_a)h(a,b,t) + \beta_a\langle U_a^{(t-1)}, U_b^{(t-1)}\rangle, \textit{s.t.} 0 \le \beta_a \le 1,$$

where β_a is a coefficient that captures a user's unique characteristic in balancing these two factors. In this equation, $h(a, b, t)$ measures the node proximity between them in a social network and the second part measures the homophily effect. As the social network is dynamic and changes from time to time, it is reasonable to assume the node proximity between users also varies. Since the focus of our paper is not to devise more sophisticated models to measure node proximity between users, here, we simply adopt a classical *Adamic/Adar* metric (Liben-Nowell and Kleinberg 2007), and adapt it to a time varying version as:

$$h(a,b,t) = \frac{1}{\sum_{c\in N_a^{(t-1)}\cap N_b^{(t-1)}} log(|N_c^{(t-1)}|)}, \quad (5)$$

Though simple, this metric directly measures the weighted triangles between two potentially linked users and usually has very good link prediction performance (Liben-Nowell and Kleinberg 2007).

At $t = 1$, no historical user latent preference is available, it is reasonable to assume that the social structure is the only factor that determines the social relationships:

$$\hat{S}^1_{ab} = h(a, b, 1) = \frac{1}{\sum_{c \in N^1_a \cap N^1_b} log(|N^1_c|)}. \tag{6}$$

Given the predicted link score in Eq.(5), the likelihood of the predicted link value can also be modeled as:

$$p(S|U, \sigma_S) = \prod_{t=2}^{T} \prod_{a=1}^{N} \prod_{b=1}^{N} \mathcal{N}[(S^t_{ab}|\hat{S}^t_{ab}, \sigma^2_S)] \tag{7}$$

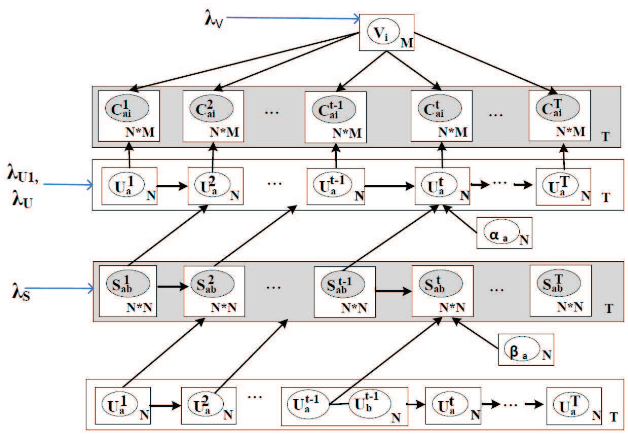


Figure 2: Graphical representation of the proposed model.

Model Learning and Prediction

We summarize the graphical representation of the proposed latent model in Figure 2, where the shaded and unshaded variables indicate the observed and latent variables. Given users' behavior tensors C and S, our goal is to learn the parameters $\Phi = [U, V, \alpha, \beta]$, where $\alpha = [\alpha_a]^N_{a=1}$ and $\beta = [\beta_a]^N_{a=1}$. Particularly, the posterior distribution over Φ is:

$$p(U, V, \alpha, \beta|C, S) \propto p(C|U, V, \alpha) \times p(S|U, \beta) \times p(U) \times p(V). \tag{8}$$

Maximizing the log posterior of the above equation is equivalent to minimizing the following objective:

$$\begin{aligned}
&\min_{\Phi} \mathcal{E}(\Phi) = \frac{1}{2} \sum_{t=1}^{T} \sum_{a=1}^{N} \sum_{i=1}^{M} Y^t_{ai} [\hat{C}^t_{ai} - C^t_{ai}]^2 \\
&+ \frac{1}{2} \sum_{t=1}^{T} \sum_{a=1}^{N} \sum_{i=1}^{M} \frac{\lambda_S}{2} \sum_{t=2}^{T} \sum_{a=1}^{N} \sum_{b=1}^{N} [\hat{S}^t_{ab} - S^t_{ab}]^2 + \frac{\lambda_V}{2} \sum_{i=1}^{M} ||V_i||^2_F \\
&+ \frac{\lambda_U}{2} \sum_{t=2}^{T} \sum_{a=1}^{N} ||\overline{U^t_a} - U^t_a||^2_F + \frac{\lambda_{U1}}{2} \sum_{a=1}^{N} ||U^1_a||^2_F \\
&\textit{s.t.} \quad \forall a \in U, \quad 0 \le \alpha_a \le 1, 0 \le \beta_a \le 1.
\end{aligned} \tag{9}$$

where $\lambda_S = \frac{\sigma^2_C}{\sigma^2_S}$, $\lambda_U = \frac{\sigma^2_C}{\sigma^2_U}$, $\lambda_{U1} = \frac{\sigma^2_C}{\sigma^2_{U1}}$ and $\lambda_V = \frac{\sigma^2_C}{\sigma^2_V}$. Among them, λ_S is a tradeoff coefficient between the consumption prediction loss and the social link prediction loss, and λ_U is a coefficient that measures how users' latent preference over time. λ_{U1}, and λ_V are regularization parameters for user latent matrix at time 1 and the item latent matrix.

The coupling between U,V and the balance parameters makes the objective function of Eq.(9) not convex, however, it is convex with regard to each parameter. Specifically, the derivative of each parameter is:

$$\begin{aligned}
\nabla_{U^t_a} &= \sum_{i=1}^{M} Y^t_{ai} (\hat{C}^t_{ai} - C^t_{ai}) V_j + \mathcal{I}[t = 1] \lambda_{U1} U^1_a \\
&+ \mathcal{I}[t \ge 2] \lambda_U (U^t_a - \overline{U^t_a}) + \lambda_U (1 - \alpha_a)(\overline{U^{(t+1)}_a} - U^{(t+1)}_a) \\
&+ \lambda_U \sum\nolimits_{a \in N^t_c} \alpha_c F^t_{ca} (\overline{U^{(t+1)}_c} - U^{(t+1)}_c) \\
&+ \mathcal{I}[t < T] \lambda_S \beta_a \sum_{b=1}^{N} (\hat{S}^{(t+1)}_{ab} - S^{(t+1)}_{ab}) U^t_b \\
&+ \mathcal{I}[t < T] \lambda_S \sum_{c=1}^{N} (\hat{S}^{(t+1)}_{ca} - S^{(t+1)}_{ca})(\beta_c U^t_c),
\end{aligned} \tag{10}$$

$$\nabla_{V_i} = \sum\nolimits_{t=1}^{T} Y^t_{ai} (\hat{C}^t_{ai} - C^t_{ai}) U^t_a + \lambda_V V_i, \tag{11}$$

$$\nabla_{\alpha_a} = \lambda_U \sum_{t=2}^{T} \sum_{i=1}^{N} \langle \overline{U^t_a} - U^t_a, \sum_{b \in N^{(t-1)}_a} F^t_{ab} U^{(t-1)}_b - U^{(t-1)}_a \rangle, \tag{12}$$

$$\nabla_{\beta_a} = \lambda_S \sum_{t=2}^{T} \sum_{b=1}^{M} (\hat{S}^t_{ab} - S^t_{ab}) \langle U^{(t-1)}_a, U^{(t-1)}_b \rangle - h(a, b, t), \tag{13}$$

where $\mathcal{I}[x]$ is an indicator function that equals 1 if x is true and 0 otherwise.

Since the objective function is convex with regard to each parameter, a local minimum can be achieved by updating each parameter iteratively. As there are no constraints on U and V, we can update them directly using *S*tochastic *G*radient *D*escent (SGD) method (Bottou 2010). With the bound constraints of α_a and β_a, a local minimum can be found by the *P*rojected *G*radient(PG) method (Lin 2007). Specifically, for each α_a ($0 \le \alpha_a \le 1$), the PG method update the current solution α^k_a in k-th iteration to α^{k+1}_a by the following rule:

$$\alpha^{k+1}_a = P[\alpha^k_a - \eta \nabla_{\alpha_a}], P(\alpha_a) = \begin{cases} \alpha_a & \text{if} \quad 0 \le \alpha_a \le 1, \\ 0 & \text{if} \quad \alpha_a < 0, \\ 1 & \text{if} \quad \alpha_a > 1 \end{cases} \tag{14}$$

After learning the related parameters, the two goals in the problem definition process can be answered: (1) the relative contribution of the social influence and the homophily effect can be directly obtained from parameters α and β. (2)The predicted behaviors of each user at $T + 1$ are:

$$U_a^{(T+1)} \approx (1-\alpha_a) * U_a^T + \alpha_a \sum\nolimits_{b \in N_a^T} F_{ab}^t U_b^T,$$
$$\hat{S}_{ab}^{(T+1)} \approx (1-\beta_a) h(a,b,T+1) + \beta_a \langle U_a^{(T+1)}, U_b^{(T+1)} \rangle,$$
$$\hat{C}_{ai}^{(T+1)} \approx \langle U_a^{(T+1)}, V_i \rangle. \tag{15}$$

We summarize the algorithm for our proposed model in Algorithm 1.

Algorithm 1: Parameter Learning of the Proposed Model

```
Initialize U, V, α and β ;
while not converged do
    for a = 1, 2, ...N do
        for t = 1, 2, ..., T do
            Fix V, α, β, update U_a^t using SGD;
        Fix U, V, update α_a and β_a using PG ;
    for i = 1, 2, ..., M do
        Fix U, α, β, update V_i using SGD;
Return U, V, α and β ;
```

Dealing with Data Imbalance. Note that in social link construction process, $S_{ab}^t = 0$ denotes a missing link between user a and b. If we consider all missing link records in the optimization function of Eq.(9), the problem turns to a highly imbalanced learning problem with much more labels of 0 than 1. Here, we borrow an effective undersampling technique. Particularly, for each newly added positive link, we randomly select m missing links as observed pseudo negative links with a weight of $\frac{1}{m}$ at each iteration of the learning process. Since the sampling process is random and each time the negative samples change, each missing link gives very weak negative signal (Jamali, Haffari, and Ester 2011; Menon and Elkan 2011).

Time Complexity. The main time complexity of the proposed algorithm lies in computing the latent representations of each user and the balance parameters. Suppose there are c non-empty consumption records in consumption tensor C and s social links in social tensor S ($c \ll M \times N, s \ll N \times N$), then the average consumption records and social connections of each user at each time are $t_c = \frac{c}{N \times T}$ and $t_s = \frac{s}{N \times T}$. In each iteration, the time complexity is $O(N \times T \times D \times (t_c + t_s + \frac{s}{N}) = O(D \times (c + T \times s))$ for U, $O(D \times c)$ for V, and $O(c+s)$ for the balance parameters. Thus the total complexity of parameter learning in each iteration is $O(D \times (c + T \times s))$, which is linear with the records and time windows.

4 Experiments

Data Description and Experimental Setup. The datasets we used are: the who-trust-whom online product sharing dataset *Epinions* (Richardson, Agrawal, and Domingos 2003) and the location based social networking dataset *Gowalla* (Scellato, Noulas, and Mascolo 2011). In both datasets, we treated each month as a time window. We filtered out users that have less than 2 consumption records and 2 social links. After that, each user's preference rating is normalized into 0 to 1. Table 1 shows the basic statistics of the two datasets after pruning. In data splitting process, we use the data till time T for model training, i.e., T=11 (T=3) in Epinion (Gowalla). Among them, we randomly extract 10% of the records as the validation dataset, which are used for parameter tuning. The newly added behaviors in T+1 are treated as the test data.

Table 1: The statistics of the two datasets.

Dataset	Epinions	Gowalla
Users	4,630	21,755
Items	26,991	71,139
Time	12	4
Training Consumptions	62,872	278,154
Training Links	75,099	251,296
Test Consumptions	2,811	52,448
Test Links	3,257	6,254
Consumption Density	0.050%	0.018%
Link Density	0.35%	0.053%

In the following, we report the resuts of our proposed model *E*volving *J*oint *P*rediction (*EJP*). The step size of EJP is empirically set to be 0.01. For each iteration, EJP costs about 50 seconds on Epinions and 200 seconds on Gowalla and it converges in less than 100 iterations on both datasets, so the training time is less than 6 hours. As we have already analyzed the time complexity of EJP (linear with the records and time windows), we focus on the effectiveness analysis due to page limit. We also devise two simplified models of EJP: *E*volving *C*onsumption *P*rediction (*ECP*) and *E*volving *L*ink *P*rediction (*ELP*). Specifically, ECP leverages the dynamic social network for consumption prediction (i.e.,$\lambda_S = 0$ in Eq.(9)) and ELP utilizes users' temporal consumption preferences for link prediction (i.e., we do not optimize the first term in Eq.(9)). There are several parameters in our model, we set the regularization parameters as $\lambda_{U1} = \lambda_V = 0.1$. λ_U is set to be 5 in Epinions and 1 in Gowalla, and λ_S is set to be 0.5 in Epinions and 5 in Gowalla.

User Consumption Preference Prediction. We compare the consumption prediction results with: *PMF* (Mnih and Salakhutdinov 2007), *TMF* (Xiong et al. 2010), SocialMF (Jamali and Ester 2010), and a joint learning model *FIP* (Yang et al. 2011). For better illustration, we summarize the details of these models in Table 2. We adopt the widely used *R*oot *M*ean *S*quared *E*rror (RMSE) measure for consumption prediction precision comparison (Mnih and Salakhutdinov 2007; Xiong et al. 2010). For fair comparison, all parameters in these baselines are tuned to have the best performance.

Figure 3 shows the consumption prediction results of various models with different latent dimension sizes D on both datasets. As can be seen from this figure, among all models, our proposed latent model EJP performs the best, followed by the related model ECP. Also, the SocialMF and TMF have better performance than PMF, indicating the effectiveness of incorporating the time and social network information. Last but not least, the performance improvement is significant for nearly all latent based models from $D = 5$

Table 2: Characteristics of the Baselines.

Model	Consumption	Social Link	Time	Consumption	Social	Evolution Explanation
PMF	√	×	×	√	×	×
SocialMF	√	√	×	√	×	×
TMF	√	×	√	√	×	×
AA	×	√	×	×	√	×
CMF	×	√	√	×	√	×
hTrust	√	√	×	×	√	×
FIP	√	√	×	√	√	×
ECP	√	√	√	√	×	√
ELP	√	√	√	×	√	√
EJP	√	√	√	√	√	√

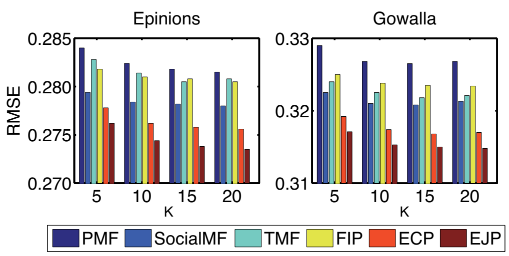


Figure 3: Consumption performance comparison. All results between baselines and EJP pass t-test at a confidence level of 0.01.

to 10, and changes slowly after the latent dimension further increases. Given this observation, we set $D = 10$ in the following experiments.

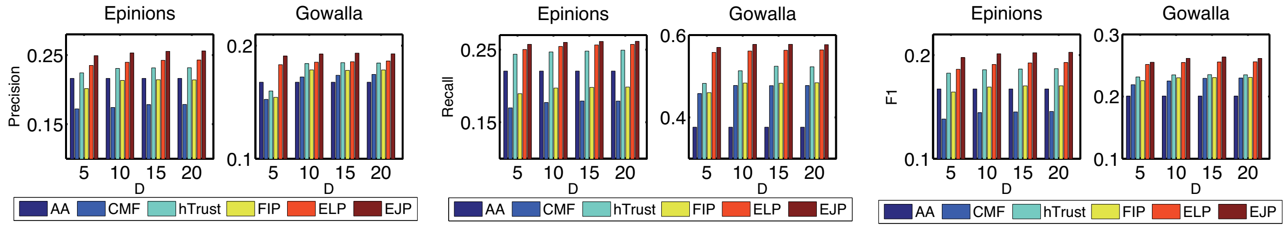
Social Link Prediction. We report link prediction results with: *AA* (Liben-Nowell and Kleinberg 2007), *CMF* (Dunlavy, Kolda, and Acar 2011), *hTrust* (Tang et al. 2013) and a joint model *FIP* (Yang et al. 2011). In link prediction task, our goal is usually to rank the potential linked users. As the user size is huge, it is impractical to take all users as candidates. Thus we adopt a similar approach that has been accepted by many works (Yang et al. 2011; Koren 2008): for each test user a, we randomly sample 100 negative linked users that are not connected to her till the test time window. Then we mix those positively linked users and the sampled users together to select the top potential linked users of each test user. This process is repeated 10 times and we report the average results. Particularly, we adopt three widely used top-*n* ranking metrics: *precision*, *recall*, and *F1* measure, where *n* denotes the size of the link prediction list (Tang et al. 2013; Yang et al. 2011). We set $n = 5$ as it is useless to recommend too many friends, also, most online social networks adopt a similar number of potential friends for recommendation.

Figure 4 shows the link prediction performance. We set $n = 5$ as it is useless to recommend too many friends. Among all models, EJP has significant better predictive power than all baselines and ELP ranks the second, followed by hTrust. This finding suggests it is effective to leverage the homophily effect reflected in users' consumption behavior for link prediction. The joint model improves over traditional baselines, nevertheless, it does not perform as well as our proposed model. We guess a possible reason is that FIP uses a shared same user latent factor to represent both users' consumption preferences and link structure, which may not well capture all the information of users' two kinds of behaviors. Note that besides $n = 5$, we have also measured the link prediction performance with other values of n (from $n = 1$ to $n = 20$) and we found the overall trend is the same. Therefore, due to page limit, we do not report the detailed results at other settings of n.

Visualization of the Balance Parameters. An important characteristic of our proposed model is that it has the explanatory power to distinguish each user a's *uniqueness* in balancing two vital social theories, i.e., the social influence (α_a) and the homophily effect (β_a). To visualize each user a's preference in balancing these two effects, we represent each user as a 2-dimensional data point (α_a, β_a) and randomly illustrate some users in Figure 5. As can be seen from this figure, different uses do have their own uniqueness in balancing these two social theories for decision making. For example, the upper right corner indicates users that are likely to be influenced by social neighbors and the homophily effect for decision making, while the bottom-left corner shows users that are not likely to be swayed by social neighbors and the homophily effect for future behaviors.

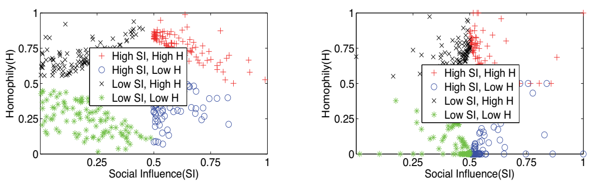
Parameter Setting. There are four parameters in our model: λ_{U1}, λ_V, λ_S and λ_U. These parameters are important but not difficult to tune. Among them, λ_{U1} and λ_V are the regularization parameters of users' latent factors at time 1 and the item latent factor. Since these two parameters have a similar form as the traditional PMF model (Mnih and Salakhutdinov 2007), we tune them on PMF and set them under the setting of the best performance on PMF. Thus we do not report the detailed setting of these two parameters. In the following, we report the setting of the remaining two parameters. Particularly, we choose the RMSE measure and F1 measure to evaluate the performance of these two tasks.

The setting of λ_S is shown in Figure 6. For each λ_S, we initialize EJP with the results from ECP ($\lambda_S = 0$ in ECP), and stop model learning when either prediction task performance begins to decrease. In this figure, as λ_S increases from 0.1 to larger values, the overall trend is that the consumption performance decreases while the link performance



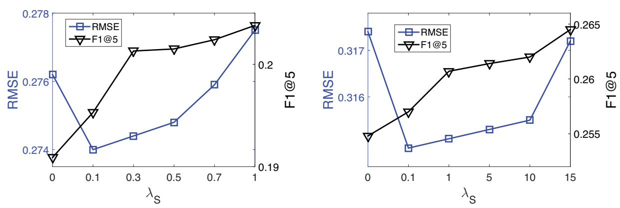
(a) Precision (b) Recall (c) F1

Figure 4: Link prediction comparison. All performance between the baselines and EJP pass the t-test at a confidence level of 0.01.



(a) Epinions (b) Gowalla

Figure 5: Visualization of the balance parameters for typical users.

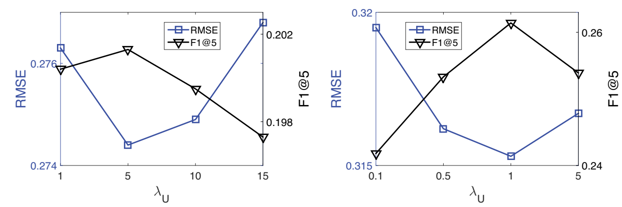


(a) Epinions (b) Gowalla

Figure 6: The impact of λ_S.

increases as we put more weight on the social network information. Please note that both behavior prediction performance increases as we set λ_S from 0 to a 0.1. We explained it before as there are mutual relationship between users' behaviors, thus jointly modeling them would have better results. Given the results, setting λ_S in a reasonable range would balance these two prediction tasks, e.g., λ_S in $[0.1, 0.7]$ in Epinions and $[1, 10]$ in Gowalla. A possible reason why λ_S has a much larger value in Gowalla than Epinions is that, we have much less new connected link records in Gowalla than Epinions, thus we should put more weights on the link prediction results of Gowalla data.

λ_U characterizes users' latent preference change over time, Figure 7 gives the performance with varying parameters of λ_U. We observe that the values of λ_U impacts both prediction results. As λ_U increases, the performance of both prediction results increase at first, but when λ_S surpasses 5 in Epinions and 1 in Gowalla, the performance of the prediction results of both tasks decrease. Given this observation, we set $\lambda_U = 5$ in Epinions and $\lambda_U = 1$ in Gowalla data.



(a) Epinions (b) Gowalla

Figure 7: The impact of λ_U.

5 Conclusions and Future Work

We provided a focused study on understanding users' temporal behaviors in SNS platforms. Particularly, by leveraging the social influence theory (homophily effect) for consumption prediction (link connection), we explicitly distinguished each kind of users' behavior for the evolution of SNSs. We established a joint latent model to address both prediction tasks in a unified framework. Experimental results validated that the users' preferences and the social network information are mutually helpful. In the future, we would like to follow this direction and explore how to build a more effective SNS platform based on our findings.

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