EXPLORE: Explainable Item-Tag Co-recommendation

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Abstract

Tag-based recommendation has become increasingly important in recent years owing to the popularization of social tagging systems. Related studies on this subject can be categorized into item recommendation and tag recommendation ~~on the basis of~~ the objective of the recommendation. In both categories, most existing recommendation approaches focus on improving ~~the~~ prediction accuracy~~.~~ ~~However~~, they ignore ~~the fact that~~ the explanations ~~for the~~ of recommendations also greatly affect the decision-making of users. In social tagging systems, tags not only behave as ~~the~~ auxiliary information of items but also show the implicit preferences of users. Therefore, they can be used ~~for both improving the~~ prediction accuracy and ~~providing~~ explanations to ~~the~~ recommended items. Items and tags have interrelation and mutual effects. By focusing only on either item recommendation or tag recommendation, users may miss some information and can only achieve marginal gains. Fusing the two types of recommendations ~~would~~ improve the performance of both approaches. On the basis of the above ideas, in this study, we propose an EXPLainable item-tag CO-REcommendation (EXPLORE) framework that jointly recommends items and the corresponding tags. Different from conventional recommendations that utilize a single source of content, EXPLORE takes advantage of ~~user's~~ interests, item contents, and item tags. The experiments conducted on three real-world ~~data sets~~ demon-

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strate that EXPLORE outperforms the state-of-the-art methods. Importantly, the recommended tags ~~could~~ provide explanations to the recommended items, thus making the recommendation results explainable.

Keywords: Collaborative filtering, Recommender system, Topic model, Co-recommendation.

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1. Introduction

Recommender systems have been studied and deployed in various domains. They become indispensable because they help ~~to deal with the~~ information overload ~~problem~~ and provide customized recommendations based on users' preferences. Collaborative filtering (CF) is one of the most successful approaches to recommendations [30, 14]. The core idea of CF is that users with similar tastes share similar rating distributions toward the same items. Popular methods combine CF with auxiliary information to make recommendations.

Recently, social tagging systems (e.g., Delicious, CiteULike, and Flickr) have become prevalent and accumulated abundant tags. These tags contain rich information and provide effective ways for users to organize, manage, share, and search various kinds of items [7]. Researchers have exploited tags to improve recommendations ~~in~~ various methods. We can categorize the existing studies into two groups: (1) tag-based item recommendation~~,~~ and (2) tag recommendation. Tag-based item recommendations use tags as auxiliary information to improve ~~the~~ recommendation accuracy. Some researchers used tags to calculate the similarity of users [40] or items [41], and applied these similarities into the CF procedure. Other researchers mined the semantic meanings of tags to model users' interests and ~~item's~~ features [7, 33, 39]. These studies ~~confirmed~~ the abundance and semantic meanings of tags ~~could~~ help improve the performance of recommender systems. Tag recommendation refers to the automated process of suggesting useful and informative tags to an emerging object ~~on the basis of~~ historical information [29]. Researchers explored ~~tags' co-occurrences~~

[28], the interactions between items and tags [36, 21, 20, 10], and the semantic meanings of tags [11, 18] to recommend tags. For both item recommendation and tag recommendation, CF-based techniques have been well studied and have shown promising results.

However, most existing studies ~~only focus~~ on improving the accuracy of ~~item or tag recommendations.~~ In reality, a social tagging system requires both types of recommendations. When viewing the recommendations from a unified perspective, we can utilize ~~more~~ coherent features and mine the relations between ~~two~~ recommendations. We can consider not only the accuracy but also other factors that influence recommendation (e.g., recommendation novelty, explanation, metric design). Aside from accuracy, in this study, we mainly consider two issues that have been overlooked in single recommendation scenarios.

One issue is that recommendations lack explainability, which reveals why users might like the items that a recommender system has recommended thus helping users make appropriate decisions. For example, as depicted in Fig. 1, we recommend two papers about CF to users. The tags serve as the explanations to the papers. Two users with different interests look through the recommended list to decide which paper to read. Alice is new to recommender system and wants to learn about ~~what CF is~~. She finds the first paper *"Item-based Collaborative Filtering Recommendation Algorithms"* is explained with *"Classic"* and *"Beginner"* tags and thus ~~she~~ decides to read this paper. Bob is an engineer in distributed systems and has some knowledge about CF. He wants to implement CF in a distributed style and he chooses the second paper *"Fast Item-based Collaborative Filtering"* when he sees the explanations are *"Parallel," "Clustering,"* and *"Hashing"*. Both Alice and Bob make the right decisions with the tags serving as the explanations to the recommended papers. By contrast, one may not choose the right paper without any explanations because the titles of two papers are too similar and users, especially those who lack preliminary knowledge, may take time to tell the difference between them. Thus, the explanations play an important role in the decision making of users. Compared ~~to~~ other forms of explanations (e.g., keywords of items [5], similar users' choices [4], and items'

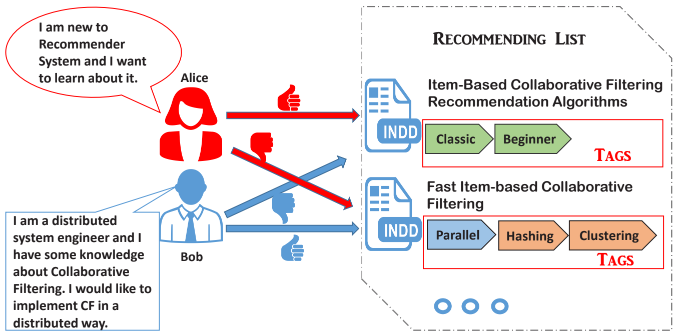


Figure 1: An example of recommending papers with explainability. The tags serve as explanations. Two people ~~are deciding~~ which paper to read ~~based on~~ the paper titles and paper explanations.

features [32]), tags contain both factual and subjective information that are more friendly and acceptable to users. However, tags are ~~human~~ annotated and unevenly distributed~~, not every item has sufficient tags~~ for explanation.

The other issue is the metric design for tag recommendation. A proper metric is vital to evaluate the effectiveness of a recommender system. Existing works use all the items to compute the evaluation metrics for tag ~~recommendation~~ (e.g., precision~~,~~ recall), assuming that users will look through each item with the same probability and ~~treating~~ items equally in the evaluation procedure. In real scenarios, items have different levels of exposures to users. Some popular items are frequently searched or recommended, and the accuracy of theses items' recommended tags is important for a social tagging system to improve user experience. Other unpopular items draw less ~~attentions~~ from users and the recommended tags of these items have less influence on user experience. Ignoring this issue may lead to biased evaluations. An ideal item subset ~~could~~ be based on item popularity or item exposure to users, which ~~is~~ difficult to compute. A reasonable alternative is needed.

We ~~come up with~~ the idea of item-tag co-recommendation to address the two main issues identified in single-recommendation scenarios. ~~It means~~ the recommender system ~~recommends~~ an item and the corresponding tags to users simultaneously. For the *explainability issue*, we use r~~ecommend tags so every~~

item ~~has the recommended tags as explanations~~. In this ~~way~~, the problem of unevenly distributed tags is alleviated, and the item-tag co-recommendation system can ~~provide better~~ explanations. For the *metric issue*, we design a ~~more~~ meaningful metric when the recommended items and recommended tags are available at the same time. The recommended items can be viewed as ~~the exposures to users~~. We test the tag recommendation performance by only using users' recommended items instead of the whole set of items. ~~It is~~ a novel metric that provides a new perspective for observing the effectiveness of a recommender system. We further realize this idea by proposing a novel model that combines the training phases of item recommendation and tag recommendation, thus enabling the simultaneous recommendation of items and their corresponding tags.

Item-tag co-recommendation also has two additional ~~advantages: One~~, the training phases are unified under the same framework, which means that item-tag co-recommendation can model ~~the~~ interrelation and mutual effects by simultaneously updating the common factors used in item recommendation and tag recommendation. ~~As~~ all the parameters are tuned together, we can also explore the tradeoff between item recommendation and tag ~~recommendation; Two, more~~ different aspects of auxiliary information can be exploited to improve ~~the~~ performance. The existing item recommendation or tag recommendation methods often utilize ~~the~~ content from a single source (e.g., user profiles, product descriptions, reviews, or tags) to capture latent factors ~~exploiting~~ only one aspect of items or users. In our item-tag co-recommendation, multiple aspects of content information are involved and we can utilize all of them rather than one ~~of them~~ to capture the latent factors of items. Here, we leverage the implicit feedback of users and the descriptions and tags of items to capture the items ~~more~~ comprehensively. This method also helps alleviate the sparsity problem, which means that the recorded data ~~is~~ extremely sparse compared ~~to~~ the user-product matrix.

In this ~~paper~~, we ~~proposed~~ a novel unified framework named "EXPLainable item-tag CO-REcommendation" (EXPLORE) to item and tag recommendations for providing explanations to recommendation results, ~~and~~ thus boosting the prediction performance ~~on both on~~ items and tags. The main contributions are listed as follows:

- We ~~proposed~~ a novel co-recommendation framework that jointly recommends items and corresponding tags simultaneously. To the best of our knowledge, this ~~it is the first work~~ to use content CF-based techniques ~~to perform~~ co-recommendation.

- The recommended tags serve as explanations to the recommended items, making the recommendation more convincing and interpretable. We also introduce a new metric to evaluate ~~the~~ tag recommendation.

- We capture the latent factors of an item by considering user's implicit feedback, item's content, and the tags people annotated to. Contrary to most existing studies that utilize a single source of content, we take advantage of the multiple aspects of content to capture items ~~more~~ comprehensively.

- Experiments on real-world datasets show that EXPLORE achieves higher performance in both item and tag recommendations than the state-of-the-art methods. The Co-recommendation proves to be a mutual promotion.

The remainder of this paper is organized as follows. In Section 2, we introduce the related work including item recommendation, tag recommendation, topic-based CF techniques, and recommendation explainability. In Section 3 we describe the details of our EXPLORE framework. In Section 4, we present the experiments and discussions~~, and In~~ Section 5, we discuss the conclusions and future works.

2. Related Work

In this section, we review three groups of work related to this study, including (1) CF-based recommendation, (2) recommendation ~~explanability,~~ and (3) collaborative topic regression (CTR).

2.1. CF-based Recommendation

CF-based ~~Recommendations~~ have proven their effectiveness ~~and~~ have become a trend in the recommendation area. In this ~~paper~~, we focus on the hybrid approaches integrated with auxiliary information in the setting of social tagging systems. We briefly introduce the state-of-the-art hybrid models for item recommendation and tag recommendation ~~separately~~.

Item recommendation. Researchers have exploited various auxiliary information to alleviate the ~~cold start problem~~ and improve the prediction performance of item recommendation. Trust-based approaches [1, 15] incorporate trust relationships between users to mine the similarity among users rather than the rating similarity calculated in pure CF approaches. ~~Social-network-based~~ approaches [25, 8] ~~studied~~ the influence of users' social circle and capture ~~the~~ similarity by groups. Content-based approaches enhance user and item representations by incorporating additional user or item information such as user profiles, item descriptions, customer reviews [24, 35, 13]. The prevalent approach is to extract topic information from content and apply them to CF techniques ~~in proper ways~~, ~~which we will discuss~~ later. In social tagging systems, tags are used as auxiliary information to improve item recommendation. Zhou et al. [41] proposed a unified probabilistic matrix factorization that connects user-item matrix, user-tag matrix, and item-tag matrix. ~~The~~ factorization does not utilize the content information and the complexity is linear with respect to the number of observations in the three sparse matrices. Tso-Sutter et al. [33] extended the user-item matrix by including user tags as items and item tags as users~~,~~ (i.e., the fusion of users and items). The fusion-based prediction was ~~carried out through a combination of~~ standard user- and item-based ~~CF~~. Zhen et al. [40] proposed a framework named ~~tag informed~~ collaborative filtering (TagiCoFi) to seamlessly integrate tagging information into the CF procedure. TagiCoFi employs the user similarities defined ~~based on~~ the tagging information to regularize the MF procedure. Chen et al. [7] used tags as a bridge to capture the implicit semantic correlation between users and items in social tagging systems. The difference between EXPLORE and the~~se~~ content CF-based methods is that EXPLORE exploits multiple aspects of content to capture item's latent factors. Recently, some researchers [37, 19, 9] utilized deep learning techniques to learn the item features from ~~text and~~ showed promising performances.

Tag recommendation. Several works have used CF to recommend tags but ~~have~~ differed in accounting similarities between users, resources, and tags. Some researchers explored the co-occurrence of tags [28], k best ~~neighbours~~ of the item's tags [22], TF-IDF [38], and Latent Dirichlet Allocation [18] to calculate the similarities. Recent hybrid methods [29, 21, 26, 36] have shown promising ~~performance~~. Rendle and Schmidt-Thieme [26] presented a factorization model ~~that learned with an adaption of~~ the Bayesian personalized ranking criterion. ~~It works by modeling~~ the pairwise interactions ~~between~~ users, items and tags. Wang et al. [36] introduced a hierarchical Bayesian model combing CTR and social regularization to recommend tags to items. The model integrates the item-tag matrix, item content information, and social networks between items. Song et al. [29] proposed a document-centered model for tag recommendation~~.~~ ~~It~~ works by ~~finding~~ the most representative documents within the data collections and ~~advocates~~ a sparse multi-class Gaussian process classifier for efficient document classification. Documents are first classified into topic clusters and then the most relevant tags ~~of~~ are selected as recommended tags.

2.2. Recommendation Explainability

Recommendation explainability can help users make more accurate decisions, improve user acceptance of recommendations, and enhance trustfulness in the recommender system [34]. The common solution to explanation is to find an explainable intermediary entity ~~bridging~~ users and recommended items. An intermediary entity is needed because the direct relationship between user and item is always unknown or implicit. User-based intermediary entity uses the choices of similar users to explain the recommendation [12, 4]. Feature-based intermediary entity uses predefined categories (e.g., genre, director, cast) and keywords of items (e.g., books, articles, websites) [32, 5, 23]. However, this entity is limited because some types of items, such as music or pictures, may not have available textual content. In recent years, tags have been exploited to provide explanations for recommendations [34]. As a source of user-generated content, tags ~~are~~ more relevant to items and more friendly and preferred by users.

2.3. Collaborative Topic Regression

CTR [35] is the most related work to our ~~paper and~~ is the preliminary work of our model. CTR is proposed to recommend documents to users ~~by~~ seamlessly ~~integrating~~ feedback matrix and item (document) content information into the same model. CTR provides an interpretable latent structure for users and items and can form recommendations about both existing and newly published articles. CTR assumes there are K topics $\beta = \beta_{1:k}$. The generative process of CTR is as follows:

1. For each user i, draw a user latent vector $u_i \sim \mathcal{N}(0,\lambda_u^{-1} I_K)$.
2. For each item j:
   (a) Choose $\theta_j \sim \text{Dirichlet}(\alpha)$.
   (b) Draw the topic proportion $\epsilon_j \sim \mathcal{N}(0,\lambda_v^{-1} I_K)$ and set the item latent vector as $v_j = \epsilon_j + \theta_j$.
   (c) For each word w_{jn}:
      (a) Draw the topic assignment $z_{jn} \sim \text{Mult}(\theta)$.
      (b) Draw the word $w_{jn} \sim \text{Mult}(\beta_{z_{jn}})$.
3. For each user-item pair (i,j), draw the rating:
   $r_{ij} \sim \mathcal{N}(u_i^T\ v_j,\ c_{ij}^{-1})$.

CTR introduces an item latent offset ϵ_j between the topic proportion u_j in LDA and the item latent vector v_j in CF. The offset can be explained by the gap between what the article is about (represented by u_j) and what the users think of it (represented by v_j). CTR achieves a high prediction performance and shows a promising direction of exploiting text information in recommendation. ~~It~~ has been widely used as a baseline in recent recommendation studies, and many recommendation models are extensions of this work.

3. EXPLORE: An Explainable Item-Tag Co-recommendation Framework

We now focus on describing the details of our proposed framework ~~–~~ EXPLORE. We first formulate the problem of item-tag co-recommendation ~~and then~~ introduce the model formulation of EXPLORE by explicating ~~both~~ the parameter estimation algorithm and prediction method. Some important notations are explained in Table 1.

3.1. Problem Definition

Assume we have a set of users $U = \{u_i\}_{i=1}^{I}$, a set of items $V = \{v_j\}_{j=1}^{J}$, a set of tags $T = \{t_r\}_{r=1}^{R}$, and two rating matrices R^I and R^T. $R^I \in \mathbb{R}^{U \times I}$ is a user-item rating matrix where the element $r_{I_{ij}}$ refers to the rating that user i gives to item j, $R^T \in \mathbb{R}^{I \times R}$ is an item-tag rating matrix where the element $r_{T_{jr}}$ refers to the tag r that is given to item j. $r_{I_{ij}} > 0$ means user i is interested in item j~~,~~ and $r_{I_{ij}} = 0$ means an unknown rating because user i may either dislike or not know item j.

For item recommendation, we aim to predict the unknown rating $r_{I_{ij}}$ from a user i to an item j. For tag recommendation, we aim to predict the unknown rating $r_{T_{jr}}$ from an item j to a tag r. After calculating all the unknown ratings, we choose the tags with top ratings ~~to recommend~~. For the item-tag co-recommendation in our EXPLORE method, we aim to recommend ~~a~~ user i a list of items with top ratings. For each of the recommended items, we likewise recommend a list of tags with top ratings. Then, items and tags are recommended simultaneously, and the tags serve as the explanations to the items. The training procedures are unified. The key point of EXPLORE is ~~combining~~ item recommendation and tag recommendation in the training procedures to achieve improved performance.

3.2. Model Formulation

The basic idea of combining item and tag recommendations is to set the item latent factor V as a shared component. In item recommendation we predict a

Table 1: Notation

Symbol	**Description**
U, V, T	latent factors for users, items, tags
C	a rating confidence matrix
$r_{I_{ij}}$	the rating that user u_i gives to v_j
$r_{T_{jr}}$	the tag t_r that is given to item I_j
K	the number of latent dimensions/topics
α_u, α_v	Dirichlet parameters
θ_i	user interest proportions of u_i
θ_j	item topic proportions of v_j
$\lambda_u, \lambda_v, \lambda_t$	regularization parameters for U, V, T
λ_{uv}	the contribution of implicit preference
λ_{vt}	the contribution of tag information to item
w_{in_u}	n^{th} word of interests of user u_i
w_{jn_v}	n^{th} word of content of item v_j
z_{in_u}	topic for the n^{th} word of interests of user u_i
z_{jn_v}	topic for the n^{th} word of interests of user v_j
$\beta_{z_{in_u}}, \beta_{z_{jn_v}}$	word probability of w_{in_u} and w_{jn_v}, respectively

rating user i gives to item j by $r_{I_{ij}} = u_i^T v_j$~~, and in~~ tag recommendation we predict a rating of a tag r with ~~a~~ item j by $r_{T_{jr}} = v_j^T t_r$. In the unified model, we use one latent factor v_j to represent an item for both recommendations. This is a simple combination of two CF models that only utilize rating information.

Furthermore, we incorporate text information into the ~~collaborative filtering~~ models. We run LDA [6] on the text information of the item's content and the user's interests, and ~~get~~ topic proportion θ_i for item and topic proportion θ_j for users ~~separately~~. The topic proportions are fixed vectors and are well fitted to latent factor models. In this ~~paper,~~ we apply the same strategy in CTR [35]; that is, we initialize latent factors with topic proportions and add an offset variable to balance the effectiveness between text information and rating information. To utilize additional aspects of auxiliary information, we introduce two arrows to connect U and T to V. $U \to V$ indicates that we utilize the interests of users who rated the item to capture the item's latent factors. These interests are the implicit feedbacks of users ~~which~~ reveal the implicit characteristics of items that attract a certain group of users. $T \to V$ indicates the utilization of tags to capture the item's latent factors. These tags are explicit feedbacks of users showing their experiences and the supplementary description of items. Note that θ_j shows natural characteristics of items. The underlying intuition is that all three aspects of the auxiliary information ~~could~~ contribute to ~~constructing~~ a more comprehensive latent factor of items.

To better describe our proposed framework, we show the graphical representation of EXPLORE in Fig. 2. The red dashed rectangle is the item recommendation part, the blue dashed rectangle is the tag recommendation part, and the purple dashed rectangles are the LDA part. The following is the generative process of EXPLORE~~:~~

1. For each user u_i,
   (a) Draw the user interest proportions $\theta_i \sim \text{Dirichlet}(\alpha_u)$;
   (b) Draw the user latent offset $\epsilon_i \sim \mathcal{N}(0, \lambda_u^{-1} I_K)$ and set the user latent vector as $u_i = \epsilon_i + \theta_i$~~;~~
   (c) For each word w_{in_u} in the interests of user u_i,
      i. Draw the topic assignment $z_{in_u} \sim \text{Mult}(\theta_i)$~~;~~
      ii. Draw the word $w_{in_u} \sim \text{Mult}(\beta_{z_{in_u}})$~~;~~
2. Draw the tag latent vector for each tag t_r, $t_r \sim \mathcal{N}(0, \lambda_t^{-1} I_K)$~~;~~
3. For each item v_j,
   (a) Draw the item topic proportions $\theta_j \sim \text{Dirichlet}(\alpha_v)$;

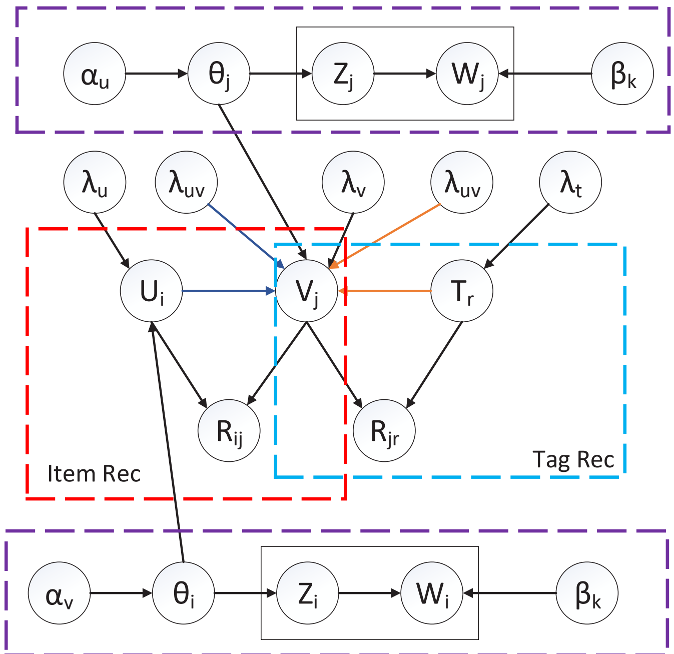


Figure 2: Graphical representation of EXPLORE. The red dashed rectangle is the item recommendation part, the blue dashed rectangle is the tag recommendation part, and the purple dashed rectangles are the LDA part.

(b) Draw the item latent vector as

$$lv_j \sim \mathcal{N}(\theta_j, \lambda_v^{-1} I_K) \times \prod_i I_{ij}^R \mathcal{N}(u_i, \lambda_{uv}^{-1} I_K) \times \prod_r I_{jr}^R \mathcal{N}(t_r, \lambda_{vt}^{-1} I_K);$$

(c) For each word w_{jn_v} in the content of item v_j,

i. Draw the topic assignment $z_{jn_v} \sim \mathrm{Mult}(\theta_j)$;

ii. Draw the word $w_{jn_v} \sim \mathrm{Mult}(\beta_{z_{jn_v}})$;

4. For each user-item pair (i, j), draw the item rating:

$$r_{I_{ij}} \sim \mathcal{N}(u_i^T v_j, c_{I_{ij}}^{-1}); \tag{1}$$

5. For each item-tag pair (j, k), draw the tag rating:

$$r_{T_{jr}} \sim \mathcal{N}(v_j^T t_r, c_{T_{jr}}^{-1}). \tag{2}$$

In the above generative process, $\mathcal{N}(x|\mu, \sigma^2)$ is a Gaussian distribution with a mean μ and a variance σ^2, and I_K is an identity matrix with K rows and K columns. I_{ij}^R is an indicator function, the value of which equals 1 if user u_i rated item v_j, and 0 otherwise. I_{jr}^R is an indicator function, the value of which equals 1 if tag t_r is attached to item v_j, and 0 otherwise. C is a rating confidence matrix with element $c_{i,j}$ denoting the rating confidence, which is similarly defined in [35].

The parameter λ_u balances the contribution of user semantic information provided ~~by~~ user's interests and the rating information to the model performance. Similarly, the parameter λ_v balances the contribution of item content to the item latent factors V_j. The parameter λ_{uv} balances the contribution of implicit preference of users to latent factors of items on model performance~~, and the~~ parameter λ_{vt} balances the contribution of tag information to latent factors of items.

3.3. Parameter Estimation

Given parameters λ_u, λ_v, λ_t, λ_{uv}, λ_{vt}, β_u, and β_v, our goal is to compute the maximum a posterior (MAP) estimation of U_j, V_j, T_j, θ_i, and θ_j. The full posterior of U, V, T, θ_u, and θ_v is

$$\begin{aligned}
&p(U, V, T, \theta_u, \theta_v | R_I, R_T, C, \lambda_u, \lambda_v, \lambda_t, \lambda_{uv}, \lambda_{vt}, \beta_u, \beta_v, \alpha) \\
&\quad \propto p(R_I|U, V, T, C) \times p(R_T|U, V, T, C) \\
&\quad \times p(U|\theta_u, \lambda_u) \times p(V|U, T, \theta_v, \lambda_{uv}, \lambda_v, \lambda_{vt}) \\
&\quad \times p(T|\lambda_t) \times p(\theta_u|\beta_u, \alpha) \times p(\theta_v|\beta_v, \alpha)
\end{aligned} \tag{3}$$

However, computing the posterior directly is ~~intractable~~. Maximizing the posterior is equivalent to maximizing the complete log likelihood of U, V, T, θ_u, θ_v, R_I, and R_T given λ_u, λ_v, λ_t, λ_{uv}, λ_{vt}, β_u, and β_v.

$$
\begin{aligned}
\mathcal{L} = -\frac{\lambda_u}{2}\sum_i (u_i-\theta_i)^T(u_i-\theta_i) \\
-\frac{\lambda_v}{2}\sum_j (v_j-\theta_j)^T(v_j-\theta_j) - \frac{\lambda_t}{2}\sum_r t_r^T t_r \\
+\sum_i \sum_{n_u} log(\sum_k \theta_{ik}\beta_{k,w_{in_u}}) \\
+\sum_j \sum_{n_v} log(\sum_k \theta_{jk}\beta_{k,w_{jn_v}}) \\
-\frac{\lambda_{uv}}{2} I_{ij}^R \sum_i (u_i-v_j)^T(u_i-v_j) \\
-\frac{\lambda_{vt}}{2} I_{rj}^T \sum_i (t_r-v_j)^T(t_r-v_j) \\
-\sum_{ij}\frac{c_{ij}^I}{2}(r_{ij}^I-u_iv_j)^2 - \sum_{rj}\frac{c_{ij}^T}{2}(r_{rj}^T-t_rv_j)^2
\end{aligned}
\tag{4}
$$

We omit a constant and set the Dirichlet priors $\alpha_u = \alpha_u = 1$~~. Because~~ the posteriori is not convex and finding its global optima ~~directly~~ is difficult. Inspired by the parameter estimation procedure in CTR, we optimize the function by using the coordinate ascent algorithm, which iteratively optimizes the ~~collaborative filtering~~ variables u_i, v_j, and t_k and the topic proportion θ_i, θ_j. For u_i, v_j, t_k, given the current estimate of θ_i, θ_j, we take the gradient of $\mathcal{L}$ in Equation

(4) with respect to u_i, v_j, and t_k and set it to zero, which leads to:

$$
\begin{aligned}
u_i \leftarrow (VC_i^I V^T + \lambda_u I_k + \lambda_{uv} \sum_j I_{ij}^R I_k)^{-1} \\
(VC_i^I R_i^I + \lambda_u \theta_i + \lambda_{uv} \sum_j I_{ij}^R v_j) \\
t_r \leftarrow (VC_r^t V^T + \lambda_t I_k + \lambda_{vt} \sum_j I_{rj}^R I_k)^{-1} \\
(VC_r^t R_r^t + \lambda_u \theta_i + \lambda_{uv} \sum_j I_{ij}^R v_j) \\
v_j \leftarrow (UC_j^I U^T + TC_j^t T^T + \lambda_v I_k + \lambda_{uv} \sum_i I_{ij}^R I_k \\
+ \lambda_{vt} \sum_r I_{rj}^t I_k)^{-1} \\
(UC_j^I R_j^I + UC_j^t R_j^t + \lambda_v \theta_j + \lambda_{uv} \sum_i I_{ij}^R v_j \\
+ \lambda_{vt} \sum_r I_{rj}^t T_r),
\end{aligned}
\tag{5}
$$

where C_i^I is a diagonal matrix with $c_{I_{ij}}, j = 1, ..., J$ as its diagonal elements, and $R_i^I = (r_{ij}^I)_{j=1}^J$ for user u_i. ~~The~~ C_r^t is a diagonal matrix with $c_{T_{rj}}, j = 1, ..., J$ as its diagonal elements, and $R_r^t = (r_{rj}^T)_{j=1}^J$ for tag t_r. For item j, $C_j^I, C_j^t, R_j^I, R_j^t$ are similarly defined.

Given U, V, and T, we ~~now~~ update the topic proportions θ_i and θ_j. For θ_i, we first define $q(z_{jn} = k) = \phi_{jnk}$, ~~then~~ separate the users that contain θ_i and apply Jensen's inequality.

$$
\begin{aligned}
\mathcal{L}(\theta_i) \quad & \geq -\tfrac{\lambda_u}{2}(u_i - \theta_i)^T (u_i - \theta_i) \\
& + \textstyle\sum_{n_u} \sum_k \Phi_{in_u k} (log\theta_{ik}\beta_{k,w_{in_u}} - log\Phi_{in_u k}) \\
& = \mathcal{L}(\theta_i, \phi_i).
\end{aligned}
\tag{6}
$$

Here, $\Phi_i = \Phi_{in_u K_{n_u=1,k=1}}^{N_u \times K}$. $\mathcal{L}(\theta_i, \phi_i)$ is the tight lower bound of $\mathcal{L}(\theta_i)$ and we use projection gradient [3] to optimize θ_i. θ_j is updated in a similar ~~way~~. The optimal ϕ_{ink} and ϕ_{jnk} are

$$\Phi_{in_uk} \propto log\theta_{ik}\beta_{k,w_{in_u}},$$
$$\Phi_{jn_vk} \propto log\theta_{jk}\beta_{k,w_{jn_v}}. \tag{7}$$

As for the parameter β, we update with the same M-step for topics in LDA.

$$Ll\beta_{kw} \propto \sum_j \sum_n \phi_{jnk} 1[w_{jn} = w]\cancel{.} \tag{8}$$

3.4. Rating Prediction

After the parameters U, V, T, θ_u, θ_v,β_u, and β_v are learned, our framework can be used for item recommendation and tag recommendation, both of which include in-matrix and out-matrix predictions.

Similar to [35], for in-matrix predictions, we use the following equations:

$$r^*_{I_{ij}} \approx (u^*_i)^T v^*_j, \tag{9}$$

$$r^*_{T_{jr}} \approx (v^*_j)^T t^*_r. \tag{10}$$

For out-matrix predictions, we use following equations:

$$r^*_{I_{ij}} \approx (u^*_i)^T \theta^*_j, \tag{11}$$

$$r^*_{T_{ij}} \approx (\theta^*_j)^T t^*_r. \tag{12}$$

3.5. Discussion

In this section, ~~we will discuss~~ several ~~detailed~~ issues for our proposed approach.

In Fig. 2, the model shows that the latent variable V is involved with latent variables U and T~~,~~ and item topic distributions θ_j, which indicates that ~~we utilize~~ the implicit feedback of users and the tags and contents of the item to capture item's latent factors. One ~~benefit~~ of this approach is ~~that~~ we can balance the weights of users' implicit feedbacks and tags with two confidence parameters

λ_{uv} and λ_{vt}. If we combine all three aspects of sources to generate the item's latent factors, some problems will arise when the quantities of different sources are uneven. The source with a small quantity will be overwhelmed by the source with a large quantity. ~~So~~, the final latent factors will be ~~mainly~~ influenced by the source with the largest quantity. Our approach ensures three aspects of the auxiliary information will be used to capture latent factors with settable proportions regardless of the quantity distribution of three sources.

Another ~~detail lies in~~ the parameter estimation phrase. In ~~every~~ loop of ~~parameters~~ update, ~~the~~ v_j is affected by ~~the~~ U and T. (Note that they are not multiplied by λ_{uv} and λ_{vt} and are different from what was described in the ~~last~~ paragraph.) ~~While~~ in a single item recommendation or tag recommendation, ~~the~~ v_j is only affected by U or T. In our framework, the training phases are unified, which indicates that it can model the interrelation and mutual effects between item recommendations and tag recommendations by simultaneously updating the common factors v_j with U and T. In addition, the parameters are tuned together. We can explore the tradeoff between item recommendations and tag recommendations.

4. Experiments

We conducted comprehensive experiments on three datasets and compared EXPLORE with several baseline algorithms to show the superiority of our framework. The questions we ~~aim~~ to answer ~~are:~~

1. How does EXPLORE outperform the baseline methods~~,~~ in terms of item recommendation and tag recommendation?
2. How is the prediction performance affected by the parameters? What roles do the two confidence parameters λ_{uv} and λ_{vt} play in recommendation?
3. To what extent do the recommended tags provide explanations to the recommended items?

4.1. Datasets

Given that our proposed framework exploits user interests (implicit feedbacks), item content, and tag information for recommendations, we select real well-known datasets that meet these conditions. We use three real-world datasets, two from *CiteULike*[1]~~, and the third~~ from *BibSonomy*[2]. These datasets contain user-item ratings, item-tag ratings, item content, and user interests. The content information of items includes titles and abstracts of articles and we process them with the same procedure in [35]. We remove the stop-words and choose the top 8000 distinct words according to the *tf-idf* values. User interests are the collection of ~~keywords of the articles a user likes, and they are preprocessed in a similar way.~~ To reduce data noise and alleviate the data sparsity problem, we use p-cores [16] to remove infrequent tags, which means the tags we used in experiments occur at least p times. ~~Below is the~~ description of the datasets, some statistical data are shown in Table 2, and the distributions of these entities are shown in Figs. 3-5.

CiteULike is a website that allows researchers to create their own reference libraries for the ~~articles they are interested in~~ and share them with other researchers. This has opened the door to applying recommendation methods [17] as a third way to help researchers find papers that fit their needs. We used two real datasets from CiteULike named *citeulike-a* and *citeulike-t*. The dataset *citeulike-a* is originally from [35], and the corresponding tag information is collected by [36]. ~~And~~ the dataset *citeulike-t* is collected by [36]. ~~Note that the~~ two datasets do not contain any keywords of articles, which we believe are more concise to capture users' interests. We crawled the keywords of these articles from Baidu Xueshu[3] (a web search engine that indexes the full text or metadata of scholarly literature) and used them as the context of interest topics. For the p-cores, we set $p = 5$ for ~~both~~ dataset *citeulike-a* and dataset *citeulike-t*.

[1] http://www.citeulike.org/
[2] http://www.bibsonomy.org/
[3] http://xueshu.baidu.com/

Table 2: ~~Datasets details~~

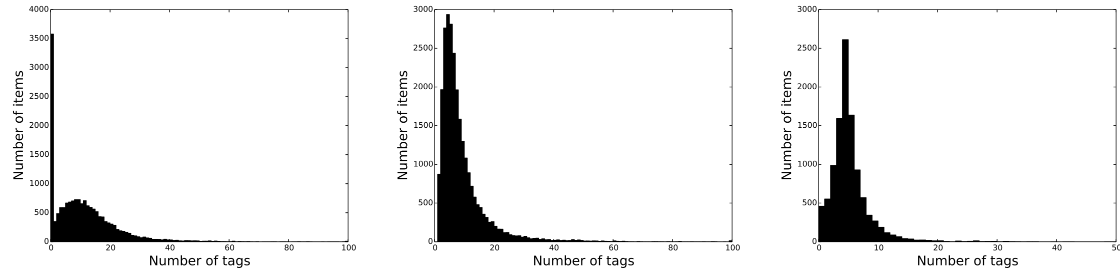
	Citeulike-a	Citeulike-t	Bibsonomy
#users	5551	7947	1047
#items	16980	25975	10662
#tags	7386	8311	4617
#user interests	4951	9871	5910
#rating density	0.217%	0.065%	1.057%
#tagging density	0.145%	0.092%	0.128%
avg #items per user	36.93	16.97	112.66
avg #tags per item	24.60	27.12	4.82
avg #interests	132.01	48.00	43.71

BibSonomy is a social resource sharing ~~systems~~ on which users can categorize and archive bookmarks and literature references [2]. The data we used were gathered and made available online by the system administrators[4]. Unlike CiteUlike ~~which~~ focuses on academic papers, BibSonomy supports ~~literature such as books and publications more~~. Similar to data preparation of Citeulike, we extracted the literature references and crawled corresponding abstracts and keywords from Baidu Xueshu. For the p-cores, we set $p = 3$~~, as~~ the tag sparsity problem of dataset *BibSonomy* is more severe than ~~that~~ of dataset *citeulike-a* and dataset *citeulike-t*, as ~~is~~ shown in Fig. 3.

4.2. Evaluation Metrics

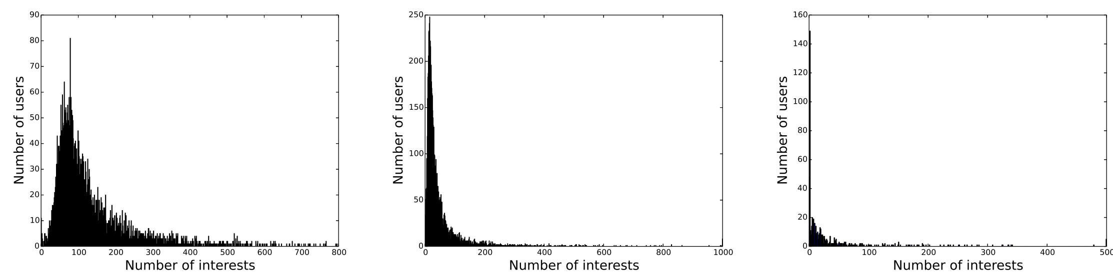
In this work we adopt accuracy-based metrics and co-recommendation metrics to evaluate our model. Accuracy-based metrics (i.e., recall and precision)

[4]Knowledge and Data Engineering Group, University of Kassel: Benchmark Folksonomy Data from BibSonomy, version of June 30~~th~~, 2007.



(a) Citeulike-a (b) Citeulike-t (c) Bibsonomy

Figure 3: Item count distribution on number of tags. (a) distribution on *CiteULike-a*, (b) distribution on *CiteULike-t*, (c) distribution on *BibSonomy*.



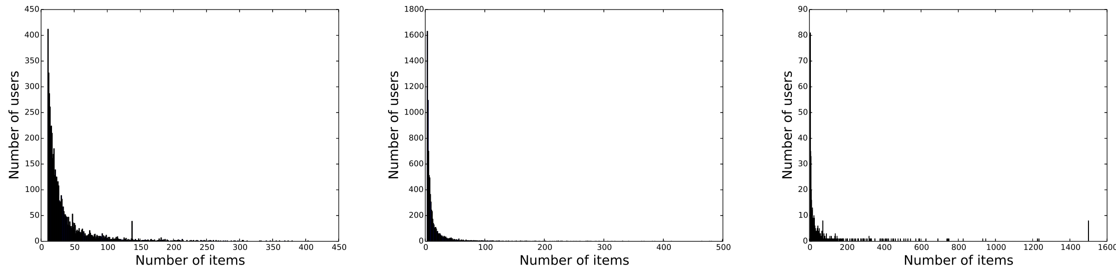
(a) Citeulike-a (b) Citeulike-t (c) Bibsonomy

Figure 4: User count distribution on number of interests. (a) distribution on *CiteULike-a*, (b) distribution on *CiteULike-t*, (c) distribution on *BibSonomy*.

are widely used in the recommendation area. We ~~design~~ a novel metric to test the performance of co-recommendation compared ~~to~~ recommending separate items and tags.

- **Accuracy-based metrics**: Recall is the proportion of relevant recommended items from the number of relevant items. It only considers the positively rated items within the top M recommended items. For each user, the definition of $recall_{item}@M$ is

$$recall_{item}@M = \frac{\mid T_{h-item} \cap T_{r-item}^{M} \mid}{\mid T_{h-item} \mid}, \tag{13}$$



(a) Citeulike-a (b) Citeulike-t (c) Bibsonomy

Figure 5: User count distribution on number of rated items. (a) distribution on *CiteULike-a*, (b) distribution on *CiteULike-t*, (c) distribution on *BibSonomy*.

where T_{h-item} is set of items the user likes, and T^M_{r-item} is the set of top M items recommended to the user. Similarly, the recall of an item is defined as~~:~~

$$recall_{tag}@M = \frac{\mid T_{h-tag} \cap T^M_{r-tag} \mid}{\mid T_{h-tag} \mid}, \tag{14}$$

where T_{h-tag} is the set of the tags that users gave to the item, T^M_{r-tag} is the set of top M tags recommended to the item. Precision is not a proper evaluation here because zero ratings may indicate that a user does not like the items or does not know the items. The precision metric also ~~suffers~~ the same problem for tag recommendation. For both metrics, the higher the values, the better the recommendation performances.

- **Co-recommendation metrics**: We proposed rec-item tag recall ~~for evaluation of~~ co-recommendation. The rec-item tag recall measures the tag recall of the recommended items~~,~~ rather than all of the items. ~~Under~~ this setting, ~~for each user,~~ the rec-item tag recall $recall_{rec-i-t}@M$ is defined as follows:

$$recall_{rec-i-t}@M = \frac{\sum_i recall_{tag}(i)@M}{\mid T^M_{r-item} \mid}, i \in T^M_{r-item} \tag{15}$$

where $recall_{tag}(i)@M$ is the tag recall of item i defined in equation (14), and T^M_{r-item} is the set of top M items recommended to the user. For

$recall_{rec-i-t}@M$, the higher the value, the better the recommendation performances. The intuition of this new metric is reasonable~~. In~~ a real recommendation scenario, users are ~~recommended~~ with a top-N list of items~~ and~~ they are likely to have more exposures to these items. Thus the performance of tag recommendations on these top ranked items is vital to ~~the~~ recommendation explainability. Compared ~~to~~ traditional metrics for tag recommendation, our new metric considers the rank orders of items ~~and~~ is a practical evaluation method ~~to the~~ co-recommendation.

4.3. Baselines

To evaluate the performance of our proposed EXPLORE framework, we compare it with a variety of baseline algorithms. The baseline algorithms are chosen according to the following criteria: (i) state-of-the-art algorithms for item prediction~~,~~ (ii) state-of-the-art algorithms for tag prediction. In detail, we consider the following algorithms as baselines~~:~~

- **PMF**: PMF [27] is a Bayesian generative model that draws user latent feature matrix and item latent feature matrix separately. It is a widely used matrix factorization model for recommendation. The information PMF used is simply the records of ratings~~. It~~ factorizes the training matrix into two low-rank matrices U and V~~,~~ and recovers the original matrix by UV^T. Here we use PMF model for both item recommendation and tag recommendation.

- **CTR**: CTR [35] combines traditional CF with topic modeling for item recommendation. It utilizes reviews information as items' content for topic modeling~~, and~~ is a widely used baseline model for recent recommender systems that utilize ~~collaborative filtering~~ and content information.

- **CTR+**: This is an improved CTR model, in which the tags ~~as well as~~ reviews are used to form the content of items.

- **TRCF**: This model [7] uses tags as a bridge to capture the implicit semantic correlation between users and items. It incorporates shared semantic information into matrix factorization and is one of the state-of-the-art models ~~which~~ utilize topic models for recommendation.

- **CDL**: This model [37] jointly performs deep representation learning for the content information and ~~collaborative filtering~~ for the ratings. It utilizes generalized stacked ~~Denoising Auto-encoders~~ to learn the features.

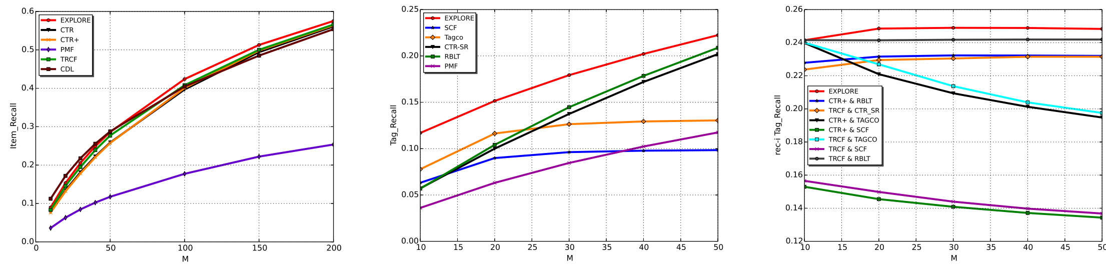
- **TAGCO**: This is a ~~co-occurrence based~~ tag recommendation model [28]. ~~This model~~ normalizes the co-occurrence counts with the overall frequency of the tags to measure the quality of the relationship between two tags, then it recommends tags to items based on the scores of tags' qualities.

- **SCF**: This is a similarity-based tag recommendation model [22]. It finds k best ~~neighbours~~ of the item's tags and recommends new tags according to its ~~neighbours'~~ tags.

- **CTR-SR**: This is a tag recommendation model based on CTR with social regularization [36]. CTR-SR incorporates the item-tag matrix, item content, and social networks ~~between~~ items. In this ~~paper,~~ we do not consider social factors, and we fix the social matrix as a constant matrix.

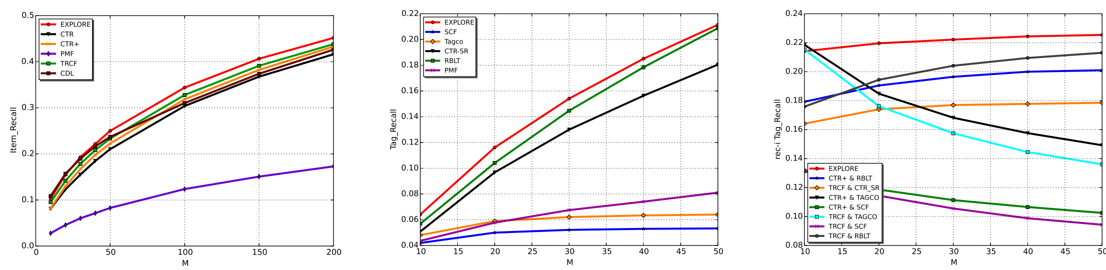
- **RBLT**: Rating-Boosted Latent Topics [31] ~~boosts~~ raw content with the sentiment orientations of users for topic learning. It ~~is~~ originally proposed to boost review content ~~by~~ rating (e.g., 1-5) times for item recommendation. In this ~~paper~~, we use ~~it~~ for tag recommendation. We use item content and tags for topic learning and the tags are boosted by occurrence times.

Here, we compare the performance of item prediction with the baselines for item recommendation and the performance of tag prediction with the baselines for tag recommendation. For the co-recommendation metric, we take a Cartesian product of the experimental results of item recommendation baselines and tag recommendation baselines and compare them ~~to~~ the performance of our model.



(a) $recall_{item}@M$ (b) $recall_{tag}@M$ (c) $recall_{rec-i-t}@M$

Figure 6: Experimental results on *CiteULike-a* datasets. (a) ~~shows the~~ recall of item recommendation $recall_{item}@M$, (b) ~~shows the~~ recall of tag recommendation $recall_{tag}@M$, (c) ~~shows the~~ rec-item tag recall $recall_{rec-i-t}@M$

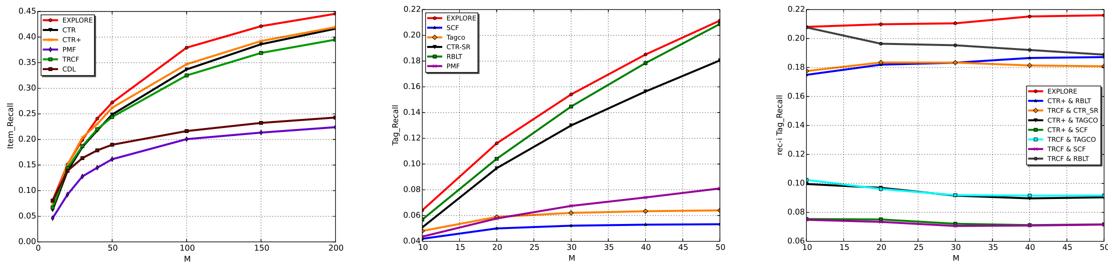


(a) $recall_{item}@M$ (b) $recall_{tag}@M$ (c) $recall_{rec-i-t}@M$

Figure 7: Experimental results on *CiteULike-t* datasets. (a) ~~shows the~~ recall of item recommendation $recall_{item}@M$, (b) ~~shows the~~ recall of tag recommendation $recall_{tag}@M$, (c) ~~shows the~~ rec-item tag recall $recall_{rec-i-t}@M$

4.4. Performance

We evaluate our proposed method on three datasets and compare EXPLORE with the aforementioned baseline algorithms. The results are plotted in Figs. 6-8. We use grid search to observe the optimal parameters. For EXPLORE, we set $\lambda_u = 1.0$, $\lambda_v = 10.0$, $\lambda_t = 1.0$, $\lambda_{uv} = 0.1$, $\lambda_{vt} = 1.0$, $K = 200$, $a = 1$, $b = 0.01$, $a_t = 1$, and $b_t = 0.01$. For CTR and CTR+, we set $\lambda_u = 1.0$, $\lambda_v = 100.0$, $K = 200$, $a = 1$, and $b = 0.01$. For TRCF, we set $\lambda_u = 1.0$, $\lambda_v = 10.0$, $\lambda_{uv} = 0.01$, $K = 200$, $a = 1$, and $b = 0.01$. For RBLT, we set



(a) $recall_{item}@M$ (b) $recall_{tag}@M$ (c) $recall_{rec-i-t}@M$

Figure 8: Experimental results on *BibSonomy* datasets. (a) ~~shows the~~ recall of item recommendation $recall_{item}@M$, (b) ~~shows the~~ recall of tag recommendation $recall_{tag}@M$, (c) ~~shows the~~ rec-item tag recall $recall_{rec-i-t}@M$

$\lambda_u = 1.0$, $\lambda_v = 1.0$, $K = 200$. For CDL, we follow the same setting in [37].

4.4.1. Performance on item recommendation

For item recall, we set $M = 10$, 20, 30, 40, 50, 100, 150, and 200 ~~respectively~~. From part (a) of Figs. 6-8, we can ~~deliver~~ the following findings: (1) PMF always achieves the worst performance because it only uses rating information during the MF procedure, ignoring the rich information ~~in item~~ content. The sparsity in the usern–item matrix also accounts for the poor performance of PMF. (2) CTR outperforms PMF in all the cases because PMF does not utilize items' content. PMF only uses rating information during the matrix factorization procedure, whereas CTR utilizes rating information and content information. (3) CTR and CTR+ perform similarly on CiteUlike-a and BibSonomy, while CTR+ performs ~~a little~~ better than CTR on *CiteUlike-t*. The consequences are influenced by tag quality and quantity ~~in~~ the datasets. The statistics ~~shown~~ in Table 2 indicate the items in dataset *CiteUlike-t* have more tags annotated ~~with~~ them than those in other two datasets, which accounts for the ~~different~~ performance of CTR+ among the datasets. (4) TRCF outperforms CTR+ and CTR on three datasets ~~as~~ it utilizes shared semantic information between users and items. However, because it uses the same content ~~to~~ model user and item, only one aspect of information is used. (5) CDL ~~has a high performance~~ when $M < 30$, but its performance deteriorates compared ~~to~~ other models when M ~~gets~~ large~~. There are mainly~~ two reasons. ~~The first is that~~ deep learning does not perform well when the dataset is small, this shortcoming ~~is~~ more apparent in dataset *BibSonomy*. ~~The second reason is that~~ CDL only ~~utilized~~ item content to learn the features of items, whereas in our model, we not only capture the item but also the user with item content, user interests, and tags. (6) Our method EXPLORE outperforms all the baseline algorithms ~~mainly~~ because it utilizes multiple aspects of information. Compared ~~to~~ TRCF and CTR+, ~~we can conclude that it is better to~~ treat multi-aspects of content ~~in a separate way~~ rather than ~~putting them together~~.

4.4.2. Performance on tag recommendation

For tag recall, we set $M =$ 10, 20, 30, 40, and 50 ~~respectively.~~ Similar to item recall, from part (b) of Figs. 6-8, we can ~~deliver~~ the following findings: (1) PMF, SCF, and TAGCO achieve ~~lower~~ tag recall performances in all the three datasets ~~mainly~~ because they only utilized rating information between items and tags. Meanwhile, the tag recalls of SCF and TAGCO increase slowly when M increases, especially ~~in~~ dataset *BibSonomy*. SCF is a ~~k-neighborhood based~~ algorithm and TAGCO is a co-occurrence-based algorithm. Although they are ~~count-based~~, the numbers of neighbors and co-occurrences are limited, which ~~accounts~~ for the poor performance of SCF and TAGCO. (2) CTR-SR outperforms PMF, SCF, and TAGCO in most cases ~~as~~ CTR-SR utilizes item content. RBLT consistently outperforms CTR-SR in all three datasets, especially when M ~~gets~~ large~~. The reason lies in that tags are~~ utilized in topic models that show more semantic relevances in tag recommendation. (3) EXPLORE is significantly better than other methods in most cases. If we look further at the tagging density listed ~~on~~ Table 2 and the fluctuations of all the models' performances ~~on~~ three datasets, PMF, SCF, and TAGCO are ~~more~~ sensitive to the tag sparsity problem. They perform the worst in dataset *CiteUlike-t* ~~that suffers~~ the severest sparsity problem. CTR-SR and RBLT perform better than the ~~former~~ three models. EXPLORE performs stably on all three datasets, ~~which~~ is better than all the baseline models owing to the utilization of multi-aspects of content and ~~the~~ integration with item recommendation.

4.4.3. Performance on co-recommendation metric

For rec-i tag recall, we also set M= 10, 20, 30, 40, and 50 ~~respectively~~. For baseline algorithms, we take ~~a~~ Cartesian product of item recommendation algorithms and tag recommendation algorithms to form a set of new baselines ~~to compare this metric~~. For example, *"TRCF & TAGCO"* means we use the results of both TRCF and TAGCO to calculate $recall_{rec-i-t}$. ~~As~~ there are 30 combinations of item recommendation algorithms and tag recommendation algorithms, some baselines with poor performances are omitted in the figures because of clarity problems. From part (c) of Figs. 6-8 we can see that~~:~~ (1) our method EXPLORE consistently outperforms all the baselines in three datasets. EXPLORE performs better when M increases, whereas some other baselines (e.g., *"CTR+ & TAGCO"* and *"TRCF & SCF"*) perform ~~poorer~~ when M increases. EXPLORE is ~~more~~ robust and stable. (2) Among the baselines, we can find *"CTR+ & RBLT," "TRCF & RBLT,"* and *"TRCF & CTR-SR"* ~~achieve~~ better performances than other baselines, ~~showing~~ the superiority of CTR-SR and RBLT. Similarly, we find SCF and TAGCO perform poorly in the $recall_{rec-i-t}$ metric. The reasons are similar to the analysis in Section 4.4.2~~:~~ CTR-SR and RBLT utilize content information~~;~~ SCF and TAGCO are count-based algorithms, and the datasets have limited numbers. (3) Compared ~~to~~ $recall_{tag}$, ~~we can see that~~ the differences between algorithms ~~are~~ more apparent in the co-recommendation metric $recall_{rec-i-t}$, indicating its effectiveness as a metric to evaluate tag recommendation performance. ~~Meanwhile, a~~ higher $recall_{rec-i-t}$ indicates that the recommended tags provide more specific explanations to recommended items, and users will be more likely to accept these items.

From the ~~above analysis we can see that~~ EXPLORE ~~shows superiority~~ in both item recommendation and tag recommendation, and outperforms baseline

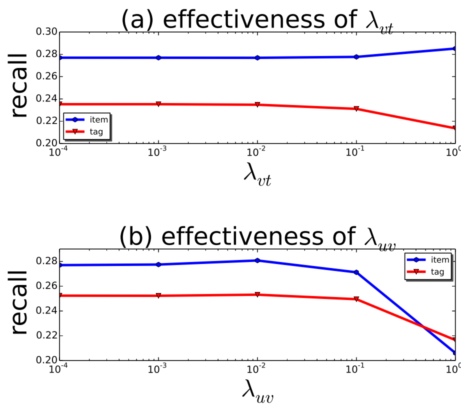


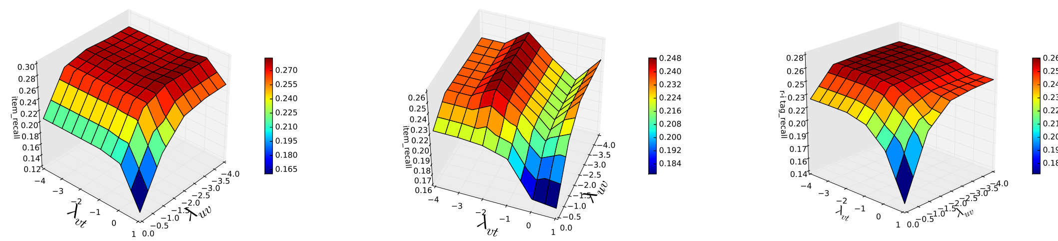
Figure 9: ~~The marginal~~ effects of λ_{uv} and λ_{vt} on *CiteULike-a*

combinations ~~in~~ the co-recommendation metric.

4.5. Parameter Effect Analysis

To examine the sensitivity of EXPLORE to parameters λ_{uv} and λ_{vt}, we set $\lambda_u = 1.0$, $\lambda_v = 10.0$, $\lambda_t = 1.0$, $K = 200$, $a = 1$, $b = 0.01$, $a_t = 1$, and $b_t = 0.01$. We fix $\lambda_{uv} = 0$, $M = 50$ and vary λ_{vt} to ~~see~~ the item recall and tag recall~~, then~~ we fix ~~fix~~ $\lambda_{vt} = 0$ and vary λ_{uv} to ~~see~~ the item recall and tag recall. Fig. 9 shows the results ~~on~~ *CiteULike-a*. ~~From~~ Fig. 9 (a) ~~we can see that~~ item recall and tag recall ~~stay~~ stable when λ_{vt} varies 0.001 to 0.01. As λ_{vt} increases from 0.01 to 1, the item recall increases while the tag recall decreases. Fig. 9 (b) shows the item recall and tag recall first ~~increase~~ with λ_{uv} and then ~~decrease~~ after $\lambda_{uv} = 0.01$.

To further explore the joint effect of λ_{uv} and λ_{vt}, we conduct a grid search on these two parameters. The results on *CiteULike-a* are shown ~~on~~ Fig. 10. Fig. 10 (a) shows the $recall_{item}$@50 on *CiteULike-a*~~. We can see that~~ the item recall achieves the best performance when $\lambda_{uv} = 0.01$ and $\lambda_{vt} = 1$. When λ_{uv} ~~achieves~~ larger than 0.1 and λ_{vt} ~~gets larger than~~ 1, the item recall ~~falls~~ dramatically. Fig. 10 (b) shows the $recall_{tag}$@50 on *CiteULike-a*~~. We can see that~~ the tag recall ~~gets~~ the best performance when $\lambda_{uv} = 0.01$ and $\lambda_{vt} = 0.01$.



(a) $recall_{item}@M$ (b) $recall_{tag}@M$ (c) $recall_{rec-i-t}@M$

Figure 10: Experimental results on *CiteULike-t* datasets. (a) ~~shows the~~ recall of item recommendation $recall_{item}@M$. (b) ~~shows the~~ recall of tag recommendation $recall_{tag}@M$. (c) ~~shows the~~ rec-item tag recall $recall_{rec-i-t}@M$

The tag recall increases when λ_{vt} increases from 0.0001 to 0.01 and from 1 to 10, and decreases when λ_{vt} increases from 0.01 to 1. The performance of tag recall ~~stays~~ stable when λ_{uv} ~~stays~~ between 0.0001 and 1 and ~~falls~~ dramatically after λ_{uv} ~~increases over~~ 0.1. Fig. 10 (c) shows the $recall_{rec-i-t}@50$ on *CiteULike-a*. The performance of $recall_{rec-i-t}@50$ ~~stays~~ stable when $\lambda_{uv} < 0.1$ and $\lambda_{vt} < 0.1$, which is ~~a~~ tradeoff between item recall and tag recall.

4.6. Interpretability

Besides ~~the~~ superior recommendation performance, our proposed framework can also ~~provide a very good~~ interpretation compared ~~to~~ baseline models in two aspects: user modeling and tag ~~explanability.~~ With the learned latent factors of users, items, and tags, EXPLORE can present more inner relations ~~among them~~. We can present a user's preference with learned topics and recommended tags. ~~Two~~ examples in Tables 3 and 4 (see ~~the~~ appendix) show users with their top 3 topics and their top 10 preferred articles predicted by EXPLORE and CTR~~, the~~ EXPLORE ~~also~~ provides the top 10 recommended tags for each corresponding articles. As shown in Table 3, User I is a biologist with a research interest on RNA, specifically RNA sequencing (RNA-Seq). This information is shown by the first two words in the first topic of EXPLORE and the ninth and tenth words of the topic ~~of~~ CTR. The precision of the top 10 articles for EXPLORE and CTR are ~~80 percent and 30 percent respectively~~ for User *I*. Similarly, User *II* ~~in Table 4~~ is interested in social networks. The precisions of EXPLORE and CTR are ~~90 percent and 40 percent respectively.~~

If we ~~look further into~~ the training set and the recommended tags, we can find more about user's interest and the correlation between ~~his~~ interest and the articles ~~he~~ rated. User *I* is a biologist interested in mRNA and isoform, he focuses on RNA sequencing and ~~heads for the~~ next generation sequencing. The tags *"isoform," "mrna-seq," "isoform," "next-generation-sequenzing," "altsplice"* prove~~d~~ this inference. From the recommendation result of EXPLORE, ~~almost~~ all of the top 10 articles are closely related to the specific interest of User *I*~~, while~~ the recommended articles by CTR are from a ~~larger~~ domain related ~~to~~ *"gene activity"* and ~~*"RNA-Seq",*~~ thus leading to ~~a~~ low precision. Similarly, User *II* is ~~more likely to be~~ a software designer focused on network learning, the top 10 articles recommended by EXPLORE contain social network theories and software design. From the attached recommended tags, ~~we can see that~~ the user ~~focuses~~ on *"personal-learning-ENV," "c-sap,"* and *"e-learn"*. Meanwhile, all the recommended articles of CTR are about social network except for one, namely, *"Social software: E-learning beyond learning management* ~~*systems",*~~ which is about software design.

The tags recommended by EXPLORE can ~~also~~ provide explanations and help users in the decision making ~~for the~~ recommended articles. ~~Think about~~ the case when User *I* sees the articles recommended to him by EXPLORE. He looks through the titles with tags and decide if he should read ~~it~~ in detail later. For example the article *"Mapping and quantifying mammalian transcriptomes by RNA-Seq"* with its recommended tags *"4countseq," "mrna-seq," "aziz," "hesis-pmi," "altsplice," "doctoral-thesis," "mapping-rnaseq," "solid," "isoform,"* and *"aligner."* User *I* finds the title is in his research domain and the tags meet his specific interests, which will help him ~~make~~ the decision to read this article. ~~While this case comes to~~ CTR, User *I* only finds the title of the article~~;~~ he ~~would not~~ know if this article meets his specific interest on *"mRNA-Seq"* rather than *“RNA-Seq”* because the title fails to convey ~~enough~~ information. ~~It~~ will take some time f~~or him~~ to decide whether to read this article~~ or not~~.

5. Conclusion and Future Work

In this ~~paper~~, we developed a novel hierarchical framework named EXPLORE that jointly ~~recommends~~ items and corresponding tags ~~synchronously~~ for explanations. We explored multi-aspects of content information to capture the item ~~more~~ comprehensively ~~with~~ the user’s implicit feedback and the item’s contents and tags. ~~Comprehensive~~ experimental results ~~on~~ the three real-world datasets show that ~~our method~~ EXPLORE ~~outperforms~~ both item recommendation methods and tag recommendation methods in prediction accuracy. EXPLORE also shows superiority in co-recommendation metrics ~~against the combination of~~ item and tag recommendation methods. ~~We conclude that the~~ item-tag co-recommendation in EXPLORE has mutual promotion, and EXPLORE can ~~better~~ alleviate the ~~cold start problem~~ of recommender systems and provide explanations ~~of~~ recommendation results ~~to~~ users.

In the future, we intend to extend our work ~~in~~ two main directions. ~~One~~ direction is to design new methods to balance the performance of item recommendation and tag recommendation. The other direction is to ~~add more~~ constraints and auxiliary information~~ into consideration~~, such as time, user-item subgroups, and social connections.