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Social Recommendation in Dynamic Networks

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Synonyms

Collaborative filtering; Matrix factorization; Social network analysis; Social recommender system

Glossary

Recommender System A system that provides recommendations for users

Collaborative Filtering A type of recommendation technique

Social Relations Various social relationships between users, like social trust relationships

Matrix Factorization Factorizing the user-item matrix into user latent matrix and item latent matrix

Definition

The research of social recommendation aims at modeling recommender systems more accurately and realistically. The characteristic of social recommendation that is different from the tradition recommender system is the availability of social network, i.e., relational information among the users. Social recommendation focuses on how to utilize user social information to effectively and efficiently compute recommendation results.

Introduction

As the exponential growth of information generated on the World Wide Web, the *Information Filtering* techniques like *recommender systems* have become more and more important and popular. Recommender systems form a specific type of information filtering technique that attempts to suggest information items (movies, books, music, news, Web pages, images, etc.) that are likely to interest the users. Typically, recommender systems are based on *collaborative filtering*, which is a technique that automatically predicts the interest of an active user by collecting rating information from other similar users or items. The underlying assumption of collaborative filtering is that the active user will prefer those items which other similar users prefer (Ma et al. 2007). Based on this simple but effective intuition, collaborative filtering has been widely employed in some large, well-known commercial systems, including product recommendation at Amazon and movie recommendation at Netflix.

Due to the potential commercial values and the great research challenges, recommendation techniques have drawn much attention in data mining, information retrieval, and machine learning communities. Recommendation algorithms suggesting personalized recommendations greatly increase the likelihood of customers making their purchases online.

Traditional recommender systems assume that users are independent and identically distributed. This assumption ignores the social relationships among the users. But the fact is, offline, social recommendation is an everyday occurrence. For example, when you ask a trusted friend for a recommendation of a movie to watch or a good restaurant to dine, you are essentially soliciting a verbal social recommendation. In (2001), Sinha and Swearingen have demonstrated that, given a choice between recommendations from trusted friends and those from recommender systems, in terms of quality and usefulness, trusted friends' recommendations are preferred, even though the recommendations given by the recommender systems have a high novelty factor. Trusted friends are seen as more qualified to make good and useful recommendations compared to traditional recommender systems (Bedi et al. 2007). From this point of view, the traditional recommender systems that ignore the social network structure of the users may no longer be suitable.

Thanks to the popularity of the Web 2.0 applications, recommender systems are now associated with various kinds of social information. This kind of information contains abundant additional information about users, hence providing a huge opportunity to improve the recommendation quality. For example, in users' social trust network, users tend to share their similar interests with the friends they trust. In reality, we always turn to friends we trust for movie, music, or book recommendations, and our tastes and characters can be easily affected by the company we keep. Hence, how to incorporate social information into the recommendation algorithms becomes a trend in the research of recommender systems.

Historical Background

As mentioned in Huang et al. (2004), one of the most commonly used and successfully deployed recommendation approaches is collaborative filtering. In the field of collaborative filtering, two types of methods are widely studied: neighborhood-based approaches and model-based approaches.

Neighborhood-based methods mainly focus on finding the similar users (Breese et al. 1998; Jin et al. 2004) or items (Deshpande and Karypis 2004; Linden et al. 2003; Sarwar et al. 2001) for recommendations. User-based approaches predict the ratings of active users based on the ratings of similar users found, while item-based approaches predict the ratings of active users based on the computed information of items similar to those chosen by the active user. User-based and item-based approaches often use Pearson Correlation Coefficient (PCC) algorithm (Resnick et al. 1994) and Vector Space Similarity (VSS) algorithm (Breese et al. 1998) as the similarity computation methods. PCC method can generally achieve higher performance than VSS approach, since the former considers the differences of user rating style.

In contrast to the neighborhood-based approaches, the model-based approaches to collaborative filtering use the observed user-item ratings to train a compact model that explains the given data, so that ratings could be predicted via the model instead of directly manipulating the original rating database as the neighborhood-based approaches do (Liu and Yang 2008). Algorithms in this category include the clustering model (Kohrs and Merialdo 1999), the aspect models (Hofmann 2003, 2004; Si and Jin 2003), the latent factor model (Canny 2002), the Bayesian hierarchical model (Zhang and Koren 2007), and the ranking model (Liu and Yang 2008). Kohrs and Merialdo (1999) presented an algorithm for collaborative filtering based on hierarchical clustering, which tried to balance both robustness and accuracy of predictions, especially when few data were available. Hofmann (2003) proposed an algorithm based on a generalization of probabilistic latent semantic analysis to continuous-valued response variables.

Recently, due to the efficiency in dealing with large datasets, several low-dimensional matrix approximation methods (Rennie and Srebro 2005; Salakhutdinov and Mnih 2008a, b; Srebro and Jaakkola 2003) have been proposed for collaborative filtering. These methods all focus on fitting the user-item rating matrix using low-rank approximations and employ the matrix to make further predictions. The Low-rank matrix factorization methods are very efficient in training since they assume that in the user-item rating matrix, only a small number of factors influence preferences and that a user's preference vector is determined by how each factor applies to that user. Low-rank matrix approximations based on minimizing the sum-squared errors can be easily solved using Singular Value Decomposition (SVD), and a simple and efficient Expectation Maximization (EM) algorithm for solving weighted low-rank approximation is proposed in Srebro and Jaakkola (2003). In (2004), Srebro et al. proposed a matrix factorization method to constrain the norms of U and V instead of their dimensionality. Salakhutdinov and Mnih presented a probabilistic linear model with Gaussian observation noise in (2008b). In Salakhutdinov and Mnih (2008a), the Gaussian-Wishart priors are placed on the user and item hyperparameters.

Traditional recommender systems have been well studied and developed both in academia and in industry, but they are all based on the assumption that users are independent and identically distributed, and ignore the relationships among users. Based on this intuition, many researchers have recently started to analyze trust-based recommender systems (Bedi et al. 2007; Massa and Avesani 2004, 2007; O'Donovan and Smyth 2005).

Bedi et al. in (2007) proposed a trust-based recommender system for the Semantic Web; this system runs on a server with the knowledge distributed over the network in the form of ontologies and employs the Web of trust to generate the recommendations. In Massa and Avesani (2004), a trust-aware method for recommender system is proposed. In this work, the collaborative filtering process is informed by the reputation of users, which is computed by propagating trust. Trust values are computed in addition to similarity measures between users. The experiments on a large real dataset show that this work increases the coverage (number of ratings that are predictable) while not reducing the accuracy (the error of predictions). In O'Donovan and Smyth (2005), two trust-aware methods are proposed to improve standard collaborative filtering methods. The experimental analysis shows that these trust information can help increase recommendation accuracy.

Previously proposed trust-aware methods are all neighborhood-based methods which employ only heuristic algorithms to generate recommendations. There are several problems with this approach, however. The relationship between the trust network and the user-item matrix has not been studied systematically. Moreover, these methods are not scalable to very large datasets since they may need to calculate the pairwise user similarities and pairwise user trust scores.

Social Recommendation Using Matrix Factorization

Matrix Factorization

In this subsection, we review one popular matrix factorization method that is widely studied in the literature.

Considering an $m \times n$ matrix R describing m users' ratings on n items, a low-rank matrix factorization approach seeks to approximate the frequency matrix R by a multiplication of d-rank factors $R \approx U^T V$, where $U \in \mathbb{R}^{d\times m}$ and $V \in \mathbb{R}^{d\times n}$ with $d \ll \min(m,n)$. The matrix R in the real world is usually very sparse since most of the users only visited a few Web sites.

Traditionally, the Singular Value Decomposition (SVD) method is employed to estimate a matrix R by minimizing

$$\min_{U,V} \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(r_{ij} - \mathbf{u}_i^T \mathbf{v}_j)^2, \qquad (1)$$

where $\mathbf{u}_i$ and $\mathbf{v}_j$ are column vectors with d values and I_{ij} is the indicator function that is equal to 1 if user i rated item j and equal to 0 otherwise.

In order to avoid overfitting, two regularization terms are added into (1). Hence we have the following Regularized SVD equation:

$$\min_{U,V} \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(r_{ij} - \mathbf{u}_i^T \mathbf{v}_j)^2 + \frac{\lambda_1}{2}||U||_F^2 + \frac{\lambda_2}{2}||V||_F^2, \qquad (2)$$

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where $\lambda_1, \lambda_2 > 0$. The optimization problem in (2) minimizes the sum-of-squared-errors objective function with quadratic regularization terms. Gradient-based approaches can be applied to find a local minimum. It also contains a nice probabilistic interpretation with Gaussian observation noise, which is detailed in Salakhutdinov and Mnih (2008b). In Salakhutdinov and Mnih (2008b), the conditional distribution over the observed data is defined as

$$p(R|U, V, \sigma_R^2) = \prod_{i=1}^{m} \prod_{j=1}^{n} \times \left[\mathcal{N}\left(r_{ij} | \mathbf{u}_i^T \mathbf{v}_j, \sigma_R^2\right)\right]^{I_{ij}}, \quad (3)$$

where $\mathcal{N}(x|\mu, \sigma^2)$ is the probability density function of the Gaussian distribution with mean μ and variance σ^2. The zero-mean spherical Gaussian priors are also placed on user and item feature vectors:

$$p(U|\sigma_U^2) = \prod_{i=1}^{m} \mathcal{N}(\mathbf{u}_i | 0, \sigma_U^2 \mathbf{I}),$$
$$p(V|\sigma_V^2) = \prod_{j=1}^{n} \mathcal{N}(\mathbf{v}_j | 0, \sigma_V^2 \mathbf{I}). \quad (4)$$

Through a Bayesian inference, we can easily obtain the objective function in (2).

By adopting a simple stochastic gradient descent technique, for each observed rating r_{ij}, we have the following efficient updating rules to learn latent variables $\mathbf{u}_i, \mathbf{v}_j$:

$$\mathbf{u}_i \leftarrow \mathbf{u}_i + \gamma_1(\Delta_{ij}\mathbf{v}_j - \lambda_1 \mathbf{u}_i),$$
$$\mathbf{v}_j \leftarrow \mathbf{v}_j + \gamma_2(\Delta_{ij}\mathbf{u}_i - \lambda_2 \mathbf{v}_j), \quad (5)$$

where $\Delta_{ij} = r_{ij} - \mathbf{u}_i^T \mathbf{v}_j$, and γ_1, γ_2 are the learning rates.

The Regularized SVD algorithm introduced in this section is both effective and efficient in solving the collaborative filtering problem, and it is perhaps one of the most popular methods in collaborative filtering.

Social Trust Ensemble

However, the above algorithm does not consider any information from users' social network. In order to better model the recommendation problem, in Ma et al. (2009), Ma et al. proposed a matrix factorization-based Social Trust Ensemble (STE) method upon the following intuitions:

- Users have their own tastes.
- Users can also be easily influenced by the trusted friends they have.
- A user's final rating is composed of the combination of this user's own taste and this user's friends' tastes.

Based on the above interpretations, the objective function can be formulated as

$$L = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}\left(r_{ij} - \left(\alpha \mathbf{u}_i^T \mathbf{v}_j + (1-\alpha)\sum_{k \in \mathcal{T}(i)} w_{ik}\mathbf{u}_k^T \mathbf{v}_j\right)\right)^2 + \frac{\lambda_1}{2}\|U\|_F^2 + \frac{\lambda_2}{2}\|V\|_F^2, \quad (6)$$

where α is a parameter to balance the impact of user's own taste and user's friends' tastes, $\mathcal{T}(i)$ represents a list of user i's trusted friends, and w_{ik} is a normalized weight that equals to $1/|\mathcal{T}(i)|$.

We can see that in this approach, a user's latent factor is smoothly integrated with this user's trusted friends' tastes. This equation also coincides with the real-world observation that we always ask our friends for movies, books, or music recommendations.

For each observed rating r_{ij}, the stochastic gradient decent learning rules for this method are

$$\mathbf{u}_i \leftarrow \mathbf{u}_i + \gamma_1\Big(\Delta_{ij}\Big(\alpha + (1-\alpha)\sum_{p\in\mathcal{B}(i)} w_{pi}\Big)\mathbf{v}_j - \lambda_1\mathbf{u}_i\Big),$$
$$\mathbf{v}_j \leftarrow \mathbf{v}_j + \gamma_2\Big(\Delta_{ij}\Big(\alpha\mathbf{u}_i + (1-\alpha)\sum_{k\in\mathcal{T}(i)} w_{ik}\mathbf{u}_k\Big) - \lambda_2\mathbf{v}_j\Big), \tag{7}$$

where

$$\Delta_{ij} = r_{ij} - \Big(\alpha\mathbf{u}_i^T\mathbf{v}_j + (1-\alpha)\sum_{k\in\mathcal{T}(i)} w_{ik}\mathbf{u}_k^T\mathbf{v}_j\Big), \tag{8}$$

and $\mathcal{B}(i)$ is the set that includes all the users who trust user i.

Social Regularization

The STE method mentioned above is originally designed for trust-aware recommender systems. In trust-aware recommender systems, we can always assume that users have similar tastes with other users they trust. Unlike trust relationships among users, the tastes among social friend relationships are more diverse. User k is a friend of user i does not necessarily indicate that user k has similar taste with user i. Hence, in order to model the social recommendation problems more accurately, another more general social recommendation approach, Social Regularization (SR), is proposed in Ma et al. (2011).

The objective function of this approach is formulated as

$$L = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(r_{ij} - \mathbf{u}_i^T\mathbf{v}_j)^2 + \frac{\alpha}{2}\sum_{i=1}^{m}\sum_{f\in\mathcal{F}^+(i)} s_{if}\|\mathbf{u}_i - \mathbf{u}_f\|_F^2 + \frac{\lambda_1}{2}\|U\|_F^2 + \frac{\lambda_2}{2}\|V\|_F^2, \tag{9}$$

where s_{if} indicates the similarity between user i and user f and $\mathcal{F}^+(i)$ represents user i's outlink friends.

In this method, the social network information is employed in designing the social regularization term to constrain the matrix factorization objective function. The social regularization term also indirectly models the propagation of tastes. More specifically, if user i has a friend f and user f has a friend user g, this regularization term actually indirectly minimizes the distance between latent vectors $\mathbf{u}_i$ and $\mathbf{u}_g$. The propagation of tastes will reach a harmonic status once the learning is converged.

Similarly, for each observed rating r_{ij}, we have the following stochastic gradient descent updating rules to learn the latent parameters:

$$\mathbf{u}_i \leftarrow \mathbf{u}_i + \gamma_1\Big(\Delta_{ij}\mathbf{v}_j - \alpha\sum_{f\in\mathcal{F}^+(i)} s_{if}(\mathbf{u}_i - \mathbf{u}_f) - \alpha\sum_{g\in\mathcal{F}^-(i)} s_{ig}(\mathbf{u}_i - \mathbf{u}_g) - \lambda_1\mathbf{u}_i\Big),$$
$$\mathbf{v}_j \leftarrow \mathbf{v}_j + \gamma_2(\Delta_{ij}\mathbf{u}_i - \lambda_2\mathbf{v}_j), \tag{10}$$

where $\Delta_{ij} = r_{ij} - \mathbf{u}_i^T\mathbf{v}_j$, and $\mathcal{F}^-(i)$ represents user i's inlink friends.

The experiments conducted in Ma et al. (2009, 2011) suggest that social recommendation algorithms outperform traditional recommendation algorithms, especially when the user-item matrix is sparse. This indicates that using social information is a promising direction in the research of recommender systems.

Future Directions

The methods mentioned above can be solved efficiently by using simple gradient descent or stochastic gradient descent algorithms. However, for statistical machine learning's point of view, the methods themselves are not full Bayesian methods. Hence, learning those methods can easily have the overfitting problem. How to apply full Bayesian method on these models hence becomes worth of studying.

We already demonstrate how to recommend by incorporating users' social trust and friend information. Actually, sometimes there are more data sources available on Web 2.0 sites, such as tags issued by users to items and temporal information. These sources are also valuable information to improve recommender systems.

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Cross-References

- ▶ Human Behavior and Social Networks
- ▶ Inferring Social Ties
- ▶ Matrix Decomposition
- ▶ Probabilistic Graphical Models
- ▶ Recommender Systems Using Social Network Analysis: Challenges and Future Trends
- ▶ Social Recommender System

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Social Recommender System

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▶ Social Recommendation in Dynamic Networks

Social Reconnaissance

▶ Reconnaissance and Social Engineering Risks as Effects of Social Networking

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