Trust-aware Collaborative Denoising Auto-Encoder for Top-N Recommendation

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Abstract

Both feedback of ratings and trust relationships can be used to reveal users' tastes for improving recommendation performance, especially for cold users. However, both of them are facing data sparsity problem, which may severely degrade recommendation performance. In this paper, we propose to utilize the idea of Denoising Auto-Encoders (DAE) to tackle this problem. Specially, we propose a novel deep learning model, the *Trust-aware Collaborative Denoising Auto-Encoder* (TDAE), to learn compact and effective representations from both rating and trust data for top-N recommendation. In particular, we present a novel neutral network with a weighted hidden layer to balance the importance of these representations. Moreover, we propose a novel correlative regularization to bridge relations between user preferences in different perspectives. We also conduct comprehensive experiments on two public datasets to compare with several state-of-theart approaches. The results demonstrate that the proposed method significantly outperforms other comparisons for top-N recommendation task.

Keywords: Recommender Systems, Top-N Recommendation, Denoising Auto-Encoders, Deep Learning

1. Introduction

In recent years, recommender systems are widely used in most web applications to improve user experience. Although numerous recommendation algorithms have been proposed, there are still some well-known issues remaining open, such as data sparsity and cold start. Towards these problems, a lot of researchers propose to leverage additional information to help modeling users and items, such as contents [1, 2], tags [3, 4], social information [5, 6, 7, 8, 9, 10, 11] or multiple feedback of users [12, 13, 14].

With the development of social media, trust-aware recommendation algorithms attracts more and more attentions recently. Based on the phenomenon that users' tastes are often influenced by their friends [15, 16], there are numerous works been proposed to integrate trust information into recommender system [10, 8, 6, 5]. Their results demonstrate that the trust relationships are effective to help modeling user preference and improving recommendation performance.

Although existing works propose different ways to incorporate trust information into recommendation, there are still two critical issues with these trust-aware algorithms. First, most of them model the trust relationships with shallow model and ignore the high-order interactions among each users' friends; it is possible for a user to take all the opinions of his friends into account and then come out his own thinking rather than linearly combine all of them. Second, the trust relationships are also facing the sparse problem as well as ratings. This may limits the improvement of trust-aware algorithms and make it difficult to utilize deep model to learn high-order information from trust data.

Based on these motivations, we propose a novel deep model TDAE to tackle top-N recommendation task. In this model, we attempt to model user preferences in two perspectives: representations based on rating and trust data. Inspired of the idea of Auto-Encoder that reconstruct input data through a narrow neutral network, we build the TDAE model with a narrow shared layer which fuse user-specific preferences and user representations from rating and trust data. Moreover, to prevent from overfitting, we also consider the correlations between user-specific preference and these representations, and then improve the performance of recommendation.

In summary, the contributions in this paper is demonstrated as following:

- In this paper, we propose a novel deep learning model to learn user preferences from rating and trust data. Toward the big challenge of data sparse for this problem, the TDAE model is built by fusing two denoising autoencoders with a weighted layer, which is used to balance the importance of rating and trust data. This model can also easily be extended for other recommendation tasks with additional information.
- To keep away from overfitting, we further propose a correlative regularization to constraint the learning process. Since we model user preferences in two perspectives, we argue that they can be used to predict each other to a certain degree. This motivate us to propose the Correlative regularization to build relations between the layers in same level. This regularization can efficient improve the effectiveness and robust of TDAE model.

• We conduct comprehensive experiments with two datasets to compare our approach with state-of-the-art algorithms on Top-N recommendation task. There are several works show clearly that Top-N recommendation is more close to real application scenarios than rating prediction. So we adopt ranking-sensitive metrics to evaluate the TDAE model, i.e., MAP and NDCG. The results demonstrate that our model significant outperform other comparisons, and is further improved by incorporating correlative regularization.

2. Related Works

In this section, we discuss the related works in three branches of our TDAE model: (1) trust-aware recommendation algorithms; (2) recommendation with deep learning; (3) top-N recommendation algorithm.

2.1. Trust-aware Recommendation

Trust-aware recommendation algorithms have demonstrated great potential to improve recommendation quality in recent years [5, 6, 8, 10]. Specially, Jamali and Ester propose the SocialMF model by leveraging trust propagation mechanism to model user preference and integrating with matrix factorization for recommendation [5]. Ma *et al.* then propose a SoReg method by exactly modeling the influence and propagation mechanism between users [6]. Based on the observation that a user demonstrate different preference with roles of truster and trustee, Yang *et al.* proposed the TrustMF algorithm to further improve performance [8]. To handle the sparse problem of ratings and trust relationships, the TrustSVD model is proposed by taking both explicit and implicit feedback of user trust and ratings into account for rating prediction [10].

However, all these methods utilize trust data in shallow level and ignore the factor that trust relationships are very complex. To learn high-order information from these data, a big challenge is that trust relationships are very sparse and not sufficient to support deep model. Towards this problem, we propose a deep model to learn high-order representations by taking both feedback of ratings and trust relationships into account. First, we propose a TDAE by connecting two Auto-Encoders and user-specific preference with a weighted hidden layer to fuse these user preferences in two perspectives. Second, to relieve the data spare problem of rating and trust data, we propose a explicit correlative regularization to constraint the relations between these preferences for each user.

2.2. Deep Learning for Recommendation

In recent years, with the rapidly development of deep learning techniques in computer vision and neutral language processing domains, it raise a question that how to utilize deep learning techniques for recommender systems? This problem attracts more and more attentions recently and has become a hot topic in the field of recommender systems.

There are numerous works have been proposed to tackle this problem, and they can roughly be categorized into two classes: rating-based methods and auxiliary data based methods. Rating-based methods focus on utilizing deep learning model for recommendation solely based on ratings [17, 18, 19]. These methods leverage the denoising autoencoder (DAE) to learn compact representations of users or items from sparse rating data for recommendation. Their results demonstrate great improvement compare with previous linear models, such as matrix factorization. Auxiliary data based methods propose to learn compact representations from auxiliary data such as content, tag or images, and then combined with traditional matrix factorization method for recommendation [20, 21, 3, 22]. By leveraging these data with deep model, these methods can further push the performance of recommendation to a higher level.

However, all these above existing works focus on utilizing neural networks to learn representations from only one kind of information, such as ratings [17], contents [21], tags [3], or images [22]. In practice, there are numerous works been proposed to learn multiple features from different views [23, 24, 25, 26]. This motivate us to raise a question: how to utilize Auto-Encoder model to learn representations from two kinds of information for recommendation?

In this paper, we propose to utilize deep learning model to learn user preferences from both rating and trust data simultaneously. Compared with those aforementioned methods, the TDAE model are consist of two Auto-Encoders to model two kinds of data. They are tied together with a weighted hidden layer, which fuses user preferences of two perspectives. Moreover, inspired of the idea of multimodal deep learning [23], we further propose a novel correlative regularization to build relation between these user preferences for improving performance.

2.3. Top-N Recommendation Algorithm

Traditional recommendation algorithms most focus on predict the rating number that user may rate on a particular item [27, 12, 17], i.e., rating prediction task. However, in most scenarios, the goal of recommender systems are to predict a item list for each user to satisfy his/her taste. Therefore, a number of works have been

proposed to tackle the top-N recommendation problem, which is more suitable for real application [28, 29, 30, 11, 19].

For example, in [28], a ranking-oriented approach has been proposed to measure confidence for each user-item pair and improve the matrix factorization method for top-N recommendation. Specially, a Bayesian Personalized Ranking (BPR) [29] algorithm is proposed to direct learn the ranking relation based on implicit feedback for top-N recommendation. More recently, the Collaborative Denoising Auto-Encoders (CDAE) [19] is proposed to utilize the technique of Denoising Auto-Encoders (DAE) to further improve performance. In this paper, the authors propose to predict item list for each user based on user-specific vector and implicit feedback of users. Compared with precious works, this method demonstrates significantly improvement.

In this paper, inspired of the CDAE model, we propose an novel Auto-Encoder structure to learn user preferences based on rating and trust data. Compared with CDAE, we focus on the combination of these two kinds of information. Specially, we use a weighted layer and a correlative regularization to learn compact user representations and significantly improve the performance for top-N recommendation task.

3. TDAE: Trust-aware Collaborative Denoising Auto-Encoder

3.1. Problem Description

Assume there are a set of users $\mathcal{U}=\{1,...,n\}$ and a set of items $\mathcal{I}=\{1,...,m\}$, the task in this paper is to generate a list with N items for each user u to satisfy his/her taste. In our system, we have a user-item rating matrix $R\in\mathbb{R}^{n\times m}$ and a user-user trust matrix $T\in\mathbb{R}^{n\times n}$. There are only few entries in both of them are known and others are missing. For each user u, we denote \mathcal{O}^R_u to represent the item set that user u rated on and $\bar{\mathcal{O}}^R_u$ for the rest of unknown data set; We adopt \mathcal{O}^T_u indicates the user set that user u trusted on and $\bar{\mathcal{O}}^T_u$ for others.

3.2. Denoising Auto-Encoders

To handle the sparse problem, we utilize the idea of Denoising Auto-Encoders (DAE) model to build the TDAE model, which is described in next section. DAE model [31] is essentially an improved version of autoencoder [32]. It aims to prevent deep neutral networks from overfitting by reconstructing clean input data from its noising version through a narrow neutral network. In general, the output of the mid-layer represents the compact representations of the input data, and can be used for any other tasks.

With the inputs X and its corrupted version \tilde{X} , the DAE can be formulated by the following objective function:

$$L_{AE} = ||X - nn(\tilde{X})||_2^2 + \lambda \sum_{l} (||W_l||_2^2 + ||b_l||_2^2)$$
(1)

Where $nn(\cdot)$ is a symmetric neutral network with parameters W_l and b_l of layer $l \in \{1,...,L\}$; $||\cdot||_F^2$ denote Frobenius norm and λ is a hype-parameter to control the 12 regularization term.

3.3. The TDAE model

In recent years, Denoising Auto-Encoders model have been used to improve the performance of recommendation [18, 19, 22]. However, most existed works focus on utilizing Auto-Encoder model for only one kind of information, such as ratings, contents or tags. This motivate us to propose the TDAE model, which utilizes Denoising Auto-Encoder model to learn exactly user preferences from both of rating and trust data.

The graphical model of TDAE is demonstrated in figure 1. We can see that this network is started with a encoder layer, followed by a weighted layer and then ended with a decoder layer. Essentially, we tackle the problem that how to learn representations from two kind of sparse information through a weighted layer to balance contributions and a correlative regularization to exchange information.

In our approach, we utilize the idea of DAE model described in section 3.2 to build TDAE model. The basic idea of DAE is to reconstruct data from their corrupted version through a narrow network. The most commonly choices are Gaussian noise and drop-out noise. We employ the drop-out noise in our model, which is also used in [19] for top-N recommendation. For each entry x of inputs R and T, the corresponding corrupted version \tilde{x} is defined by:

$$P(\tilde{x} = 0) = q$$

$$P(\tilde{x} = \delta x) = 1 - q$$
(2)

Where q is the probability that randomly drop out a unit; δ is used to bias the corruptions, which set the clean inputs to $\delta = 1/(1-q)$ times their original values.

As shown in figure 1, we first map the rating and trust inputs into low-dimensional space with a encoder layer, which is given by:

$$Z_u^R = f(W^T \tilde{R}_u + b)$$

$$Z_u^T = f(V^T \tilde{T}_u + c)$$
(3)

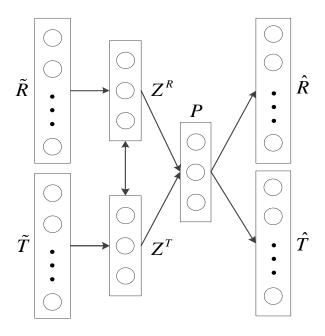


Figure 1: Graphical Model of TDAE

Where \tilde{R}_u and \tilde{T}_u denote the corrupted version of rating and trust data; Z_u^R and Z_u^T represent the latent user preferences of u that learn from rating and trust data, respectively; \tilde{R}_u and \tilde{T}_u denote the corrugated rating and trust data for user u; Parameters $W \in \mathbb{R}^{m \times k}, V \in \mathbb{R}^{n \times k}, b \in \mathbb{R}^{m \times 1}, c \in \mathbb{R}^{n \times 1}$ with dimension of k are training to learn user preferences; $f(\cdot)$ is a element-wise mapping function (e.g., identity function f(x) = x or sigmoid function $f(x) = 1/(1 + e^{-x})$), which we adopt sigmoid function in this paper.

Then we propose a weighted layer to integrate these two kinds of representations. A straightforward approach is to direct concatenate representations from rating and trust data for each user. However, the correlations between ratings and trust data are highly non-linear with different distribution [23]. It means that the information with higher variance may have stronger impact on the outputs, even if the other one may contains important information.

To balance the influences of these two kinds of data in TDAE, we develop a weighted hidden layer to fuse these representations. By this way, we can easily tune the contributions of these information for modeling user preference.

$$P_u = \alpha Z_u^R + (1 - \alpha) Z_u^T \tag{4}$$

Where P_u denotes the integrated user preference of user u; α is a hype-parameter

to balance the influences of Z_u^R and Z_u^T .

At last, the TDAE network is followed by two decoder layers to reconstruct original inputs from corrupted data. These two layers are formulated by:

$$\hat{R}_u = g(W'^T P_u + b')$$

$$\hat{T}_u = g(V'^T P_u + c')$$
(5)

Where \hat{R}_u and \hat{T}_u are the prediction value of rating and trust for each user; Parameters $W' \in \mathbb{R}^{m \times k}, V' \in \mathbb{R}^{n \times k}, b' \in \mathbb{R}^{m \times 1}, c' \in \mathbb{R}^{n \times 1}$ are training to reconstruct inputs; $g(\cdot)$ is also a element-wise mapping function, and we utilize sigmoid function in this paper.

To learn compact representations, we take both reconstruction errors of ratings and trust relationships into account, where existed works mostly ignore the trust relationship. Then we have the objective function of TDAE to minimize as following:

$$L_T = l(R, \hat{R}) + l(T, \hat{T}) + \frac{\lambda_T}{2} \Omega(W, W', V, V', b, b', c, c')$$
 (6)

Where $l(\cdot)$ denotes the loss function to compute reconstruction errors; $\Omega(\cdot)$ is a regularization term that make use of l2 norm and defined by:

$$\Omega(\cdot) = ||W||_F^2 + ||W'||_F^2 + ||V||_F^2 + ||V'||_F^2 + ||b||_F^2 + ||b'||_F^2 + ||c||_F^2 + ||c'||_F^2$$
(7)

Where λ_T is a hype-parameter to control the model complexity.

Specially, we utilize a element-wise cross entropy loss for $l(\cdot)$ in this paper, which demonstrated to be most suitable for top-N recommendation situation in [19]. Since $g(\cdot)$ is a sigmoid function, the cross entropy loss is equal to the logistic loss which is defined by:

$$l(y, \hat{y}) = -ylog(\hat{y}) - (1 - y)log(1 - \hat{y})$$
(8)

3.4. Correlations

There are a critical issue for trust-aware recommendation algorithms: both ratings and trust relationships are very sparse and facing severe overfitting problem; This may raise the risk for Auto-Encoder model to get trapped into local optimal. To improve the recommendation accuracy against sparse problem, we propose a novel correlative regularization term to build relations between the two kinds of information in TDAE.

Intuitively, since representations Z_u^R and Z_u^T represent user preferences for user u in different perspectives, there should exist implicit relation between these two representations. This motivate us to propose a novel regularization term to bridge a relationship between them to exchange information and thus enhance the robust for sparse problem.

Inspired by the idea of Auto-Encoder that reconstruct data from itself through a neural network, we argue that the correlative representations can be predicted by each other through a reconstruction function. Based on this idea, we propose a novel Correlative regularization term to build the relation between the rating and trust data, which is given by:

$$L_C = ||Z_u^R - \theta_0 Z_u^T||_F^2 + ||Z_u^T - \theta_1 Z_u^R||_F^2$$
(9)

Where parameters $\{\theta_1, \theta_2\}$ denote the parameters to reconstruct data from its corresponding layer, where we use a linear map function here. Note that any other neutral networks can also be used to build the relations.

Finally, we have the improved version of TDAE, which taking explicit corrections between hidden layers in TDAE into account to enhance robust. The objective function of TDAE model is rewritten by:

$$L_{T} = l(R, \hat{R}) + l(T, \hat{T}) + \beta(||Z_{u}^{R} - \theta_{0}Z_{u}^{T}||_{F}^{2} + ||Z_{u}^{T} - \theta_{1}Z_{u}^{R}||_{F}^{2}) + \frac{\lambda_{T}}{2}\Omega(W, W', V, V', b, b', c, c') + \frac{\lambda_{C}}{2}\mathcal{R}(\theta_{0}, \theta_{1})$$
(10)

Where β is used to control the importance of correlative regularization; $\mathcal{R}(\cdot) = ||\theta_0||_F^2 + ||\theta_1||_F^2$ is a regularization term to constraint the model complexity, which utilizes l2 norm in this paper; λ_C is hype-parameter to control this regularization term.

3.5. Complexity Analysis

We apply Stochastic Gradient Descent (SGD) algorithm to train the TDAE model and implement it with the open library TensorFlow¹. Since we contain two kinds of information, including rating and trust data, the input dimensionality of each user equals to the sum of item number m and user number n. Then the time complexity for each iteration over all users is O(nk(m+n)). This is not effective when the number of users and items are very large. Toward this problem, we

¹https://www.tensorflow.org/

use the learning strategy in [19] for our system. In consideration of that most entries in rating matrix R and trust matrix T are missing and labeled as zeros, we only sample a small subset S_u^R and S_u^T from zero entries set $\bar{\mathcal{O}}_u^R$ and $\bar{\mathcal{O}}_u^T$ for each user. Then we compute gradients for each user based on the collection of $S_u^R \cup S_u^T \cup \mathcal{O}_u^R \cup \mathcal{O}_u^T$. To prevent data imbalance problem, the sizes of sampled data S_u^R and S_u^T equal to \mathcal{O}_u^R and \mathcal{O}_u^T , respectively. In this way, the complexity of our model turns to be $O(k(|\mathcal{O}^R|+|\mathcal{O}^T|))$, which is much more practical than before and suitable for large datasets.

4. Experiments and Results

4.1. Datasets

To evaluate our approach with other state-of-the-arts algorithms, we utilize two real world datasets with both rating and trust data for comparison: Ciao and Epinions datasets. These datasets are independently crawled from two famous e-commerce website, Ciao.com and Epinions.com [33]. Users can rate items on these websites and build trust relation with other users to help making decision. The rating number is an integer range from 1 to 5. Small number indicate dislike while large for the opposite. The trust relationships are formulated in binary format, where 1 for trust and 0 for distrust. The statistics of these datasets are demonstrate in table 1.

To address the top-N recommendation task, we remove all ratings that less than 4 stars for all datasets and keep others with score of 1. This preprocessing method aims at recommender item list that users liked, and is widely used in existing works [19]. We then drop those users and items with less than 5 ratings [29].

We conduct a 5-fold cross-validation for training and testing. Specially, each dataset are split into 5 folds, and in each time 4 folds are used for training and the remaining one for testing. We conduct the experiments for 5 times to guarantee that each fold have been used for testing. The mean performance will be reported as the results of our experiments.

4.2. Evaluation Metrics

In recent years, top-N recommendation have been proved to be more close to real world scenario than rating prediction [34]. In this case, we present each user a item list with N items that have not be rated in training data to fit their potential tastes. Therefore, we adopt ranking-based metrics Mean Average Precision (MAP) and Normalized Discounted Cumulative Gain (NDCG) in our experiments

Table 1: Statistics of Epinions and Ciao					
Dataset	Epinions	Ciao			
Num of users	22,166	7,375			
Num of items	296,277	106,797			
Num of ratings	922,267	284,086			
Num of social links	300,548	111,781			
rating density	0.014%	0.036%			
social density	0.061%	0.205%			

Table 1: Statistics of Epinions and Ciao

to evaluate the top-N recommendation performance. These two metrics take ranking of the recommender item list into account, and are wildly adopted in existed literature [34].

Let I_u to denote the set of items that user u have rated in test data, and $\hat{I}_{N,u}$ to represent the N predicted items with highest value for user u. Then we have the definition of Precision:

$$Precision@N = |I_u \cap \hat{I}_{N,u}|/N \tag{11}$$

To more accrue evaluate the performance of precision at all positions of recommended items, Average precision gives higher weighs to the items that user adopted in test data. AP@N is defined as the weighted average of precisions with N recommender items:

$$AP@N = \frac{\sum_{k=1}^{N} Precision@k \times rel(k)}{min\{N, |I_u|\}}$$
(12)

Where Precision@k is the precision with k recommended items, and rel(k)=1 indicate the item at rank k is adopted. Finally, MAP@N is defined as the mean value of AP@N across all users.

For each user, Discounted Cumulative Gain (DCG@N) is defined as:

$$DCG@N = \sum_{k=1}^{N} \frac{2^{rel(k)} - 1}{\log_2(k+1)}$$
(13)

The Normalized Discounted Cumulative Gain (NDCG) is the normalized DCG over the ideal iDCG@N, and we denote the mean value of NDCG over all users as results in our experiments.

4.3. Comparisons and Parameter Settings

Since we focus on the top-N recommendation problem, it is unreasonable to compare with those for rating prediction task, such as SVD++ [12] or TrustSVD [10]. On this account, we select several state-of-the-art algorithms as comparisons to evaluate our approach:

- **Pop**. This is a commonly used basic algorithm which recommender items according to their popularity in training data.
- **BPR** [29]. This a simple and widely used ranking algorithm for recommendation. It is implemented by learning pairwise relation of rated and unrated items for each user rather than direct learning to predict ratings.
- **GBPR** [35]. This algorithm relax the individual and independence assumptions of BPR model. The authors propose an improved assumption by introducing rich interactions among users. The the size of user group in GBPR is fixed to 5 as suggested in coordinating reference
- **SBPR** [36]. This work improve the BPR model by considering social relation in the learning process, with the assumption that users tend to prefer items that rated by their friends.
- **SPF** [37]. This work proposes a Social Poisson Factorization (SPF) method to model rating and social data with Poisson distribution.
- **CDAE** [19]. The authors develop a deep learning recommendation model by leveraging *Stacked Denoising Autoencoder* (SDAE) technique. This work further injects user-special preference into hidden layer to improve performance.

We implement the TDAE model based on the TensorFlow library ², and utilize stochastic gradient descent (SGD) algorithm to minimized the loss function of equation 10. In all experiments, we tune the parameters by trail and error in our experiments or according to the suggestions in corresponding references, and report the best results for comparison.

Specially, we find that the noise variance make small impact on the results in our experiments. This phenomenon is the same as that in [19], and therefore the drop out possibility q is fixed to 0.2 in our experiments.

²https://www.tensorflow.org/

rable 2. Parameter settings of respective methods			
Methods	Optimal Parameters		
BPR	$\lambda_u = \lambda_v = 0.1$		
GBPR	$\lambda_u = \lambda_v = 0.01, \rho = 0.4$		
SBPR	$\lambda_u = \lambda_v = 0.01$		
SPF	$\mu_{\theta} = \mu_{\beta} = 0.1, \mu_{\tau} = 1$		
CDAE	$\lambda_u = \lambda_v = 0.001$		
TDAE	$\lambda_T = \lambda_C = 0.01, \alpha = 0.8, \beta = 0.01$		

Table 2: Parameter settings of respective methods

Table 3: Performance on Epinions and Ciao datasets

Datasets	Metrics	Pop	BPR	GBPR	SBPR	SPF	CDAE	TDAE	Improve
Ciao	MAP@10	0.0210	0.0198	0.0235	0.0204	0.0253	0.0277	0.0300	8.30%
k=5	NDCG@10	0.0369	0.0354	0.0413	0.0367	0.0452	0.0482	0.0515	6.85%
Ciao	MAP@10	0.0210	0.0221	0.0254	0.0207	0.0267	0.0291	0.0307	5.50%
k=10	NDCG@10	0.0369	0.0402	0.0450	0.0373	0.0461	0.0498	0.0526	5.62%
Epinions	MAP@10	0.0080	0.0101	0.0091	0.0075	0.0085	0.0106	0.0115	8.49%
k=5	NDCG@10	0.0153	0.0198	0.0176	0.0148	0.1721	0.0203	0.0220	8.37%
Epinions	MAP@10	0.0080	0.0103	0.0104	0.0077	0.0091	0.0121	0.0132	9.09%
k=10	NDCG@10	0.0153	0.0200	0.0204	0.0152	0.1795	0.0232	0.0248	6.90%

4.4. Experimental Results

4.4.1. Validations on all users

We now demonstrate the performance of TDAE model and compare it with other state-of-the-art algorithms mentioned in section 4.3. Table 3 shows the best results on metrics of MAP@10 and NDCG@10. Note that a larger value of these metrics indicates a better performance.

In table 3, we can see that the deep learning model CDAE significantly outperforms precious shallow model (BPR/GBPR/SBPR). It proves that deep learning technique have great potential to improve recommendation, and is worthy of

further development. In Particular, the TDAE and TDAE+ model significantly outperforms other model in metrics of MAP@10 and NDCG@10 for both Ciao and Epinions datasets. We also demonstrate the results with k=5 and k=10. The results shows that with dimensionality increase, the performance goes better, especially for Epinions data.

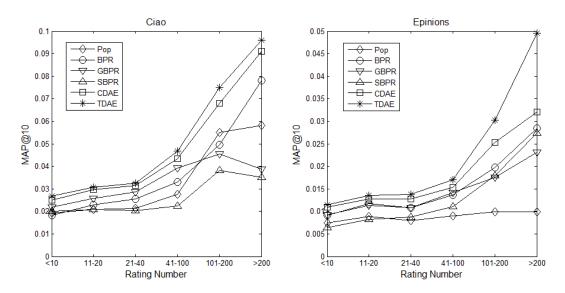


Figure 2: Validations on Cold Users

4.4.2. Validations on cold users

As mentioned in introduction section, rating and trust data are both very sparse and suffer the performance. In order to further evaluate the capabilities of these methods in views of Cold Users, we conduct validations on users with different rating number. In figure 2, we demonstrate the comparisons results in metric of MAP@10 with k=10. Since the metric NDCG@10 is in consistent with MAP@10, we omit the results in metric NDCG@10.

We can see that the TDAE model outperforms other comparisons for users with different rating numbers. This proves the effectiveness of the TDAE model for not only cold users but also dense users. Specially, we find that the improvement for TDAE is increasing along with the rating number grows. This maybe because the Auto-Encoder models are good at capturing nonlinear information for complex data. Moreover, the improvement of TDAE in Epinions is bigger than that in Ciao for users with rating number larger than 200. This maybe due

to the Epinions dataset contains more rating data than that in Ciao, and the Auto-Encoders can capture more information from these data.

4.4.3. Impact of parameter α on the results

We use parameter α to balance the influences of rating and trust data. Larger values of α indicates more impact of rating data for modeling user preferences. If we set $\alpha=1$, the TDAE only makes predictions based on user ratings and becomes close to the basic Auto-Encoder model. However, if we set $\alpha=0$, the TDAE only makes predictions based on user trust information and ignores user ratings.

In figure 3, we demonstrates the impact of α on the results in dataset Ciao and Epinions with k=10. In these figures, TDAE achieves its best results with $\alpha=0.6$ and $\alpha=0.8$ for datasets Ciao and Epinions, respectively. We can see that the best value of α for Ciao is smaller than that for Epinions, and both of them are larger than 0.5. This may indicates that users in Ciao are more likely to accept suggestions of their friends than those in Epinions. We can also say that rating data is more important than trust data for both datasets.

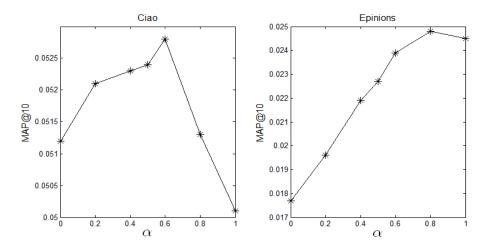


Figure 3: Impact of α on the results

4.4.4. The influence of correlative regularization

To evaluate the effectiveness of the proposed correlative regularization, we also conduct a serious of experiments to compare the TDAE model with and without this regularization. The comparison results is demonstrated in table 4 with metrics of MAP@10 and NDCG@10. Note that TDAE0 denotes a special

version of TDAE that set $\beta=0$ for the correlative regularization term. Specially, to evaluate the stability and robust, we also demonstrate the confidence intervals correspond to a 95% range for the 5-folds cross-validation.

The experiments results in table 4 demonstrate the TDAE model performs better than the TDAE0 in both datasets with k=5 and k=10. This implies that the proposed Correlative regularization can effectively improve the performance. Obviously, the confidence interval of TDAE is much smaller than that of TDAE0 model. This phenomenon proves that this regularization can make the algorithm more stable and robust. Moreover, we can see that the improvement in Epinions dataset is lager than that in Ciao dataset, which may indicate that the corrections between rating and trust data is more complex and difficult to learn in Epinions.

Datasets	Metrics	TDAE0	TDAE	Improve
Ciao	MAP@10	0.0292 ± 0.0026	0.0300 ± 0.0018	2.74%
k=5	NDCG@10	0.0507 ± 0.0040	0.0515 ± 0.0027	1.58%
Ciao	MAP@10	0.0300 ± 0.0051	0.0307 ± 0.0024	2.33%
k=10	NDCG@10	0.0519 ± 0.0055	0.0526 ± 0.0027	1.35%
Epinions	MAP@10	0.0110 ± 0.0015	0.0115 ± 0.0004	4.55%
k=5	NDCG@10	0.0210 ± 0.0024	0.0220 ± 0.0005	4.76%

 0.0127 ± 0.0015

 0.0240 ± 0.0025

 0.0132 ± 0.0008

 0.0248 ± 0.0012

3.94%

3.33%

Table 4: The Influence of Correlative Regularization

5. Conclusions

Epinions

k = 10

MAP@10

NDCG@10

In this paper, we propose a *Trust-aware Collaborative Denoising Autoencoder* (TDAE) for the top-N recommendation problem. TDAE learns high-order correlations from rating and trust data through two stacked denoising autoencoders which is united by a shared layer. Moreover, a robust Correlative regularization is proposed to build the relationship between hidden layers in TDAE. The results of several experiments demonstrate that TDAE significantly outperforms state-of-the-art algorithms. We also compare the performance of TDAE and TDAE+model to evaluate the effectiveness of correlative regularization and demonstrate

that it can not only improve the performance but also increase stability of TDAE. The TDAE is a flexible model and easily extended to learn compact representations from other kinds of information.

For future works, we intended to further develop the TDAE model for at least three directions but not limited. Firstly, since the rating and trust data are both very sparse, we intend to introduce information of items (such as images or videos) to improve recommendation performance and make use of the recent proposed methods [38, 39, 40, 41, 42]. Secondly, different from that in computer vision field, the data used in recommender systems are very spare and not suitable for most existing deep learning framework (e.g., Caffe, Theano, Torch or TensorFlow). This attract us to utilize multi-core CPU / many-core GPU power [43, 44, 45] for sparse inputs in the future works. Thirdly, the TDAE is a flexible model and can easily be extended to learn representations from other kinds of information. We intend to extend the proposed method for some other applications, such as CAD/CAM [46, 47, 48, 49, 50], social computing [51, 52, 53] and intelligent computing [54, 55, 56]

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