TT-SVD: an Efficient Sparse Decision Making Model with Two-way Trust Recommendation in the AI Enabled IoT Systems

Guangquan Xu, Yuyang Zhao, Litao Jiao, Meiqi Feng, Zhong Ji, Emmanouil Panaousis, Si Chen, Xi Zheng

***Abstract*—The convergence of AI and IoT enables data to be quickly explored and turned into vital decisions, and however, there are still some challenging issues to be further addressed. For example, lacking of enough data in AI-based decision making (so-called Sparse Decision Making, SDM) will decrease the efficiency dramatically, or even disable the intelligent IoT networks. Taking the intelligent IoT networks as the network infrastructure, the recommendation systems have been facing such SDM problems. A naive solution is to introduce trust information. However, trust information may also face the difficulty of sparse trust evidence (a.k.a sparse trust problem). In our work, an accurate sparse decision-making model with two-way trust recommendation in the AI-enabled IoT systems is proposed, named *TT-SVD*. Our model incorporates both trust information and rating information more thoroughly, which can efficiently alleviate the above-mentioned sparse trust problem and therefore be able to solve the cold start and data sparsity problems. Specifically, we first consider the two-fold trust influences from both trustees and trusters, which can be represented by a factor named trust propensity. To this end, We propose a dual model, including a truster model (*TrusterSVD*) and a trustee model (*TrusteeSVD*) based on an existing rating-only recommendation model called SVD++, which are integrated by the weighted average and yield the final model, *TT-SVD*. The experimental results show that our model outperforms the state-of-the-art including *SVD* and *TrustSVD* in both the "all users" and "cold start users" cases, and the accuracy improvement can reach a maximum of 29%. Complexity analysis shows that our model is equally suitable for the case of large sparse datasets. In a summary, our model can effectively solve the sparse decision problem by introducing the two-way trust recommendation, and hence improve the efficiency of the intelligent recommendation systems.**

***Index Terms*—AI-enabled IoT systems, collaborative filtering, two-way trust recommendation, intelligent recommendation system, sparse decision making.**

I. Introduction

AS an essential component of AI-enabled IoT systems, intelligent recommendation systems have been gradually playing a significant role in facilitating people's daily life to date. For example, numerous shopping and movie APPs may recommend some items to us in terms of our interests. Many shopping guide robots are used in supermarkets or shopping malls to provide guidance for customers. These helpful, personalized recommendation require the support of IoT devices. There will be a total of 30 billion connected things by 2020 according to the research from **IDC [1].** The unprecedented data explosion provides immense opportunities for valuable information mining. Most recommendation systems, unfortunately, have some intrinsic problems in tackling such issues of cold start and data sparsity, which may bring remarkably negative influence in accuracy, efficiency, and security of the recommendation. Cold start is a common problem led by the lack of behavior data of new users across the system. The data sparsity will lead to insufficient samples when training the model, and the inadequate samples will further affect the AI-based decision making in the IoT systems. In this paper, we named such a dilemma as "Sparse Decision Making," SDM for short. However, with the widespread usage of social network applications, trust information, as auxiliary information, has been adopted in the intelligent recommendation system to enhance the recommendation performance.

The recommendation tasks of the existing intelligent recommendation systems can be divided into two types: one is the top-n item recommendation [2] and another is rating prediction [3]–[5]. These two types of tasks have been combined with trust information in some related research work [2], [6]; however, trust information is sometimes sparser than rating information [7], [8]. In practice, we need to further explore potential trust relationships.

In the intelligent IoT systems, we notice that the dataset is huge in size, but very sparse and contains a lot of useless data, which will significantly increase the difficulty in sparse decision making and mining useful sparse information. For example, the vehicle's route recommendation and aggregate signature authentication in InVANETs will provide users with rich experiences [9]. But the behavior data [10] and trust information also increase explosively. Machine learning (ML) technology can effectively process and analyze data. However, these ML models are susceptible to noises and outliers, which will affect the robustness of the models. One popular solution would be to introduce auxiliary information into the model to enrich the training and test data, which can improve the efficiency at decision making and the accuracy of the model prediction. However, even though the trust information as auxiliary data can effectively enhance the recommendation performance and solve the two problems mentioned above: cold start [11] and sparse decision making, trust information itself is often more sparse.

G. Xu is with Qingdao Huanghai University and Tianjin University.
Y. Zhao and Meiqi Feng are with Tianjin University.
L. Jiao is with Qingdao Huanghai University.
Z. Ji is with Tianjin University.
E. Panaousis is with the University of Greenwich.
S. Chen is with West Chester University of Pennsylvania.
X. Zheng is with the Macquarie University.
Yuyang Zhao and Zhong Ji are the corresponding authors.

As mentioned previously, trust information may be sparser than rating information, both of which have been the critical elements in the design of recommendation systems. As common sense, two people who trust each other have a strong positive correlation, and two people with similar hobbies will be more likely to become friends and trust each other. Excessive attention to either kind of information can lead to a weak recommendation. One possible way to solve these problems is to build a universal trust-based model by considering both trust and rating information simultaneously [12]. These studies inspire us to consider both the influence of truster and the influence of trustee in the trust-based model.

Our work, distinct from SVD++ [4], combines the explicit influence and implicit influence proposed by the SVD++ model, and then further investigate the impact of the trust interaction strategy between users, and propose a dual model called two-way trust recommendation. In this paper, we propose a novel sparse decision-making model based on a two-way trust recommendation. Our model alleviates the problem of not enough data in AI-based decision making by introducing trust information, which is of great help to IoT systems. The existing researches show that, when users are rating the items, they will follow not only personal preferences but also the opinions of the media and friends. In other words, users are more susceptible to existing ratings and trusted people. In the trust networks, a user may play two roles, namely truster and trustee:

Situation 1. As a truster, the user can be affected by the ratings of the person which the user trusts [13].

Situation 2. As a trustee, the user's ratings of the items will have an impact on the ratings of others who trust the user.

Most trust-based recommendation systems only consider Situation 1. We incorporate the two-way trust into our model. We decompose the trust networks based on the directionality of trust, mapping user space into two low-dimensional spaces: truster space and trustee space. In the trust antecedent framework [14], the trustee has three essential qualities, namely ability, benevolence, and integrity. The key to the ability of trustees to gain the trust of others lies in these three qualities. Moreover, the trust propensity as a personal characteristic determines the degree to which users trust others. In addition, the user space and item space will be combined with both the trustee space and the truster space to build a dual model, namely *TrusterSVD* and *TrusteeSVD*. Finally, the results from these two models are combined to yield the final recommendation decision making.

Compared to the existing generic trust-based recommendation systems, our model is tailored for the AI-based IoT system. The main contributions, as well as the advantages of our work, are as follows.

1) We find a challenge called sparse decision making in the AI-based IoT systems. The root cause of the issue is the large but sparse datasets in nature, which will lead to inaccurate decision making in the AI-based IoT systems. And we solve it by introducing trust information: we consider not only the influence of truster but also the influence of trustees. By examining the two-way trust, we can effectively alleviate the sparse trust problem and improve the performance of recommendation systems in the AI-enabled IoT systems.

2) We incorporate trust propensity with the model of trustee and limit the impact of trusters on users by considering the influence from the trustee is not direct but feedback.

3) We consider that trust is dynamic. The final ratings are affected by the influence of the trustee model and the truster model.

4) We decompose the trust networks according to the directionality of trust and extend the SVD++ with the influence of trustees.

II. Related Work

In this section, we will review two kinds of intelligent recommendation methods: classical and social recommendation systems.

A. Classical Recommendation Systems

Classical recommendation systems are divided into two main categories, including content-based recommendation systems and collaborative filtering (CF) recommendation systems. The CF-based approaches look for other users who have similar interests to a particular user. The CF-based approaches can be further divided into memory-based approaches and model-based approaches in terms of whether or not using machine learning. According to the user dimension and item dimension, memory-based CF approaches consist of user-based CF approaches and item-based CF approaches. Item-based CF approaches calculate the similarity between items and recommend similar items to specific items that users liked before. Similar to the above method, user-based CF approaches use functions to calculate the similarity between different users. Model-based approaches adopt machine learning to train recommendation models based on the past ratings of users, then make recommendations based on input data. Matrix decomposition as a method of model-based recommendation systems has shown great potential. Ruslan et al. [3] proposed a Probabilistic Matrix Factorization (PMF) method to further optimize the traditional matrix factorization method by introducing a probabilistic model. Koren et al. [4] built a model called SVD++ based on SVD, which integrates the implicit behavior of users with the items. Both of them have achieved a wonderful performance, and however, they are also suffering from the same problems: cold start and data sparsity.

B. Social Recommendation Systems

Social recommendation systems can alleviate the above two problems. The trust information is combined with the traditional recommendation systems. For example, Guo et al. [15] combined trust information with SVD++, and proposed a state-of-the-art model called TrustSVD, considering both the explicit influence and implicit influence. Guo et al. [2] extended the FISM model [2] with the trust networks and proposed a model called FST, which yields a rank score from the viewpoint of both users and items. Yang et al. [13] established the model from the perspective of the trustee and truster and proposed the TrustMF model. At the same time,

they improved the PMF model and combined it with trust information. But trust information may be sparser, which will surely influence the performance of the social recommendation systems. Many publications adopted an appropriate trust inference mechanism [16]. Gao et al. [17] proposed a solution to the trust propagation in the trust networks, which advanced a nonlinear semiring framework called STAR that combined trust propagation and trust aggregation. Gohari et al. [18] proposed a novel model called Confidence-Based Recommendation (CBR), which combined the trust information and the other information.

In summary, the existing social recommendation models cannot solve the sparse trust problem perfectly, most of which just yield the ratings from the viewpoint from the truster. To this end, in this paper we propose the *TrusterSVD* model and the *TrusteeSVD* model. The experimental results show that, compared to classical recommendation systems and social recommendation systems, our approach performs better in coping with the cold start and other problems, and hence alleviates the sparse decision-making problem.

III. TT-SVD: A Sparse Decision Making Model in Intelligent Recommendation Systems

Our sparse decision-making model can solve the traditional cold start problem by introducing our designed two-way trust method in the intelligent recommendation systems. First, we will describe the trust networks and rating matrix and then introduce a dual model of *TT-SVD*, which consists of the *TrusterSVD* model and the *TrusteeSVD* model.

A. Problem Description

The recommendation task of our model is to predict the unknown ratings on items that a user has not experienced ever before. The model adopts three real-world datasets, namely FilmTrust [2], Epinion [15], and CiaoDVD [4]. The datasets are represented by matrices and contain rating information and trust information concurrently. The rating information is represented by a rating matrix consisting of users and items, assuming that m users and n items are included in the matrix R, and the matrix is $m \times n$ in size. The rating matrix R is expressed as $[r_{u,i}]_{m\times n}$. Let $[r_{u,i}]_{m\times n}$ denote that a user u has a rating of item i as $r_{u,i}$ and the rating range from 1 to 5. We state that the higher the number is, the higher the preference we have. Two low-rank matrices can be obtained by performing singular value decomposition on the rating matrix, namely user matrix $P \in \mathbb{R}^{d\times m}$ and item matrix $Q \in \mathbb{R}^{d\times n}$. The rating matrix R is the multiplication of these two matrices $P^\top Q$. Let p_u denotes the latent feature vector of user u and q_i represents the latent feature vector of item i. The inner product of two specific vectors represents the predicted rating. Accordingly, the unknown rating $\hat{r}_{u,i}$ can be predicted by ${q_j}^\top p_u$. We need to make the predicted rating as close as possible to the real rating, so we adopt the method of minimizing the loss function to solve the problem.

Besides, the trust networks N can be represented by a graph. It is assumed that there are m nodes in the networks, each node denotes a user in the networks, and trust relationship between different users is represented by an edge. In this way, the networks can be represented by a trust adjacency matrix T, and we use $[t_{u,v}]_{m\times m}$ to denote the trust adjacency matrix T. Let $(u, v, t_{u,v})$ denote that the trust degree from user u to user v is $t_{u,v}$. Since the trust information and the rating information are from the same group of users. In order to consider the relationships between the two matrices, we decide to share the same user-feature space between the truster in the trust information and the users of the rating matrix. Given that the trust matrix is asymmetric, we decompose the trust matrix to obtain the truster-feature matrix $P^{d\times m}$ and trustee-feature matrix $W^{d\times m}$. We can get the approximate trust matrix T by multiplying the two low-rank user matrices $P^\top W$. Let p_u and w_v denote the latent feature vector of truster p and trustee w, respectively. The unknown trust value $\hat{t}_{u,v}$ can be predicted by the inner product ${w_v}^\top p_u$. Similar to the rating matrix, we also need to learn the matrices P and W by minimizing the loss function, so that we can reduce the error between the real value and the predicted value.

Trust propensity is an important factor that determines whether users will easily believe in others. As mentioned above, users will refer to the ratings of trusted people. Truster with low trust propensity value will not trust others easily, as the number of people trusted by the user decreases, user and the referred objects will become more similar since fewer objects are available for reference. There are two ways for us to model trust propensity [19], and these two approaches are modeled based on global user kindness and the number of users who trust, respectively. In the case of little difference in performance between the two methods, in order to reduce the time complexity, we choose the second method: $\psi(x; \alpha, \mu)$. We use a logistic regression function to denote the trust propensity $\frac{1}{1+e^{-\alpha(x-\mu)}}$, where x the number of people the user trusts. We can control the slope and midpoint of the function curve by adjusting α and μ. We set $\alpha = 0.1$ and $\mu = 5$ to be inline with [14]. We control the influence of trusters by trust propensity because trust relationships are asymmetric, and trusters have a sparse effect on users, but they cannot be ignored.

In order to adopt both trust and rating information, our work is based on the SVD++ model, which was proposed by Koren [4]. The SVD++ model not only adopted singular value decomposition to predict rating (explicit influence) but also considered the impact of those rated items on predictions (implicit influence). But the SVD++ does not use the trust information, which leads to the normal performance of the SVD++. Therefore, we, in this paper, propose a novel trust-based model based on the SVD++.

To adopt trust information more reasonably and practically, we consider that trust is directional in social networks, and users not only trust others but also be trusted by others. Most models only consider the user as a truster, and he/she is influenced by the rating information of the people they trust. However, we here additionally consider the user as both a truster and a trustee. Two models are built on the basis of SVD++.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2020.3006066, IEEE Internet of Things Journal

B. Two-way Trust Recommendation

In our daily life, users can make comments and ratings on movies or purchased items, and other users express trust values for different users based on existing opinions, therefore creating trust networks. Under the influence of trust information, the opinions of the user may be influenced by others but also affect others. Below we propose a dual model, including the truster model and a trustee model.

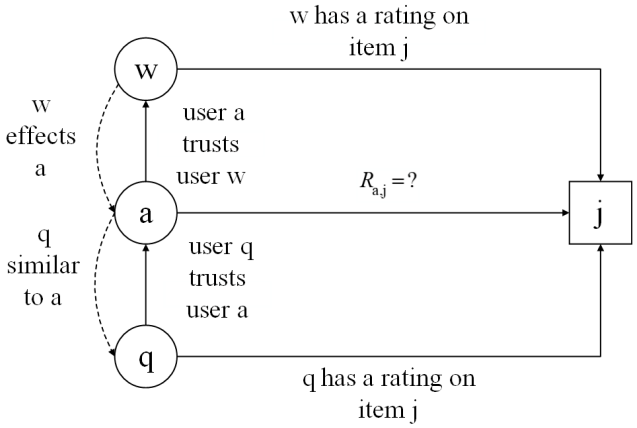

Fig. 1: The two-way influence of trust relationship on $R_{a,j}$

We illustrate an example in Fig. 1, trustee q, trustee a, and item j form a trustee model. Since the a, q users in the rating matrix, and the a, q users in the trust matrix are the same. In this model, we choose the truster-specific feature matrix Q as the latent space commonly shared by the trust matrix and rating matrix, thereby bridging a relationship between the trust matrix and the rating matrix. The trustee model in Fig. 1 shows how user q affects the rating of user a on item j, and user a is trusted by user q. Since user q trusts user a, user q will refer to the past rating records of user a and will be affected by user a when evaluating item j. But the more people q trust, the more rating records he will refer to, and the impact of a on q will be smaller and smaller, thus reducing the similarity between a and q. If the q trusts fewer people, the similarity between q and a is helpful for predicting $R_{a,j}$.

As shown in Fig. 1, the truster model consists of truster a, trustee w, and item j. Distinct from the trustee model, the rating of user a on item j is affected by a group of people trusted by a.

C. TrusteeSVD Model

Based on SVD++, we consider two-way trust and propose the *TrusteeSVD* model. We perform a gradient descent method on the loss function of the *TrusteeSVD* model in order to obtain local minimization. Finally, the final user-specific vector of trustee ${w_u}^e$ and item-specific vector ${q_j}^e$ are obtained through learning. We explain the process of rating prediction as follows.

1) We decompose the SVD++ model according to the two-way trust and build the *TrusteeSVD* model

$$\hat{r}_{u,j} = b_u + b_j + u + {q_j}^\top \left(\begin{array}{l} w_u + |I_u|^{-\frac{1}{2}} \sum\limits_{i \in I_u} y_i + \\ |E_u|^{-\frac{1}{2}} \sum\limits_{v \in E_u} (1 - \psi(x;\alpha,\mu)) * p_v \end{array} \right) \quad (1)$$

where we use b_u, b_j to denote the user and item bias, respectively. User u, v represents the trustee and truster. μ is the global average rating; I_u is a set of items that have been rated by user u, E_u represents a group of users who trust user u. The inner product ${q_j}^\top y_i$ indicates how rated items influenced the rating on item j of user u. p_v represents the user-specific feature vector of the truster v, and p_v denotes the influence of users who trust user u on the rating of unrated items. Recall that trust information plays an essential role in improving the performance of recommendation. Therefore, we not only retain the explicit influence and the implicit influence (rated items) on the basis of SVD++ but also consider the impact of the truster.

2) We can learn the user-specify and item-specify vector and both the user bias and item bias by minimizing the loss function of the *TrusteeSVD* model.

$$\begin{aligned} L = & \tfrac{1}{2} \sum_u \sum_{j \in I_u} (\hat{r}_{u,j} - r_{u,j})^2 + \tfrac{\lambda_t}{2} \sum_u \sum_{v \in E_u} (\hat{t}_{v,u} - t_{v,u})^2 \\ & + \tfrac{\lambda}{2} \sum_u |I_u|^{-\frac{1}{2}} b_u^2 + \tfrac{\lambda}{2} \sum_j |U_j|^{-\frac{1}{2}} b_j^2 \\ & + \sum_u (\tfrac{\lambda}{2} |I_u|^{-\frac{1}{2}} + \tfrac{\lambda_e}{2} |E_u|^{-\frac{1}{2}}) \|w_u\|_F^2 + \tfrac{\lambda}{2} \sum_j |U_j|^{-\frac{1}{2}} \|q_j\|_F^2 \\ & + \tfrac{\lambda}{2} \sum_i |U_i|^{-\frac{1}{2}} \|y_i\|_F^2 + \tfrac{\lambda}{2} |E_v^+|^{-\frac{1}{2}} \|p_v\|_F^2 \end{aligned} \quad (2)$$

To avoid over-fitting and reduce the complexity of the model, we use the same regularization parameters λ. Although assigning different regularization parameters to each variable can contribute to finer control of the model. Here $\|\|_F$ represents the Frobenius norm. Furthermore, the user-specify feature vector obtained from the trust matrix decomposition and the user-specify feature vector obtained from the rating matrix decomposition share a common feature space. In the same model, both of the information can be utilized. Thus, the loss function contains both trust information and rating information. In work [15], they realize that users who are more active in social networks and items that are more popular with users should accept less penalty, and the inactive users and less well-known projects may be more penalized. This is so because they are more likely to over-fitting. Above all, the final loss function of the Trustee model is shown above. We use U_i and U_j to denote a group of users who rated the item i and item j, respectively; λ_e is a parameter which controls the degree of trust regularization; and E_v^+ represents a set of users who trust user in the social networks.

3) Local minimization of the loss function can be obtained by performing the method of gradient descent on b_u, b_j, q_j, w_u, y_i and p_v. Finally, we can get the user-specify feature vector and item-specify feature vector after learning, and put the trained vector into the *TrusteeSVD* model for calculation, so that the predicted value can be obtained.

D. TrusterSVD Model

Based on SVD++, we consider two-way trust and propose the *TrusterSVD* model.

$$\begin{aligned}\hat{r}_{u,j} &= b_u \\ &+ b_j + u + \\ &q_j^\top \left(\begin{array}{l} p_u + |I_u|^{-\frac{1}{2}} \sum\limits_{i \in I_u} y_i \\ \\ +|T_u|^{-\frac{1}{2}} \sum\limits_{v \in T_u} \psi(x;\alpha,\mu) * w_v \end{array} \right)\end{aligned} \tag{3}$$

For unknown items, users often would like to refer to the opinions of people they trust. But the social networks are filled with many fake accounts. Thus, we incorporate user reliability into the model, and we incorporate T_v^+ into the loss function

$$\begin{aligned}L &= \tfrac{1}{2} \sum_u \sum_{j \in I_u} \left(\hat{r}_{u,j} - r_{u,j}\right)^2 + \tfrac{\lambda_t}{2} \sum_u \sum_{v \in T_u} \left(\hat{t}_{u,v} - t_{u,v}\right)^2 \\ &+ \tfrac{\lambda}{2} \sum_u |I_u|^{-\frac{1}{2}} b_u^2 + \tfrac{\lambda}{2} \sum_j |U_j|^{-\frac{1}{2}} b_j^2 \\ &+ \sum_u \left(\tfrac{\lambda}{2} |I_u|^{-\frac{1}{2}} + \tfrac{\lambda_t}{2} |T_u|^{-\frac{1}{2}}\right) \|p_u\|_F^2 + \tfrac{\lambda}{2} \sum_j |U_j|^{-\frac{1}{2}} \|q_j\|_F^2 \\ &+ \tfrac{\lambda}{2} \sum_i |U_i|^{-\frac{1}{2}} \|y_i\|_F^2 + \tfrac{\lambda}{2} |T_v^+|^{-\frac{1}{2}} \|w_v\|_F^2\end{aligned} \tag{4}$$

where T_v^+ represents a group of users who trust user v. We do so because active users are often more trustworthy. We can learn user-specify feature vector w_v, p_u and item-specify feature vector q_j by minimizing the loss function of the *TrusterSVD* model.

E. TT-SVD Model

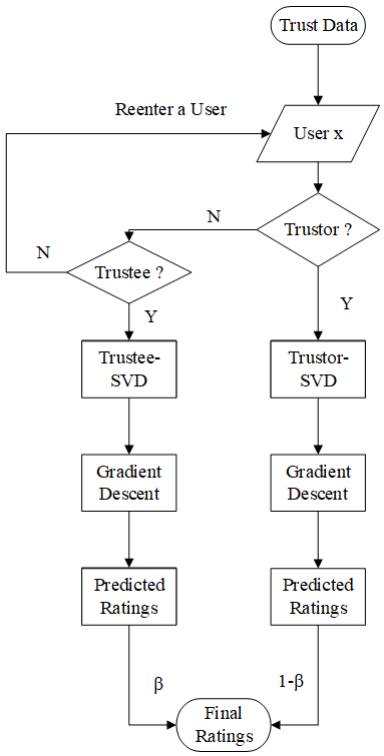

Fig. 2: The process of ratings prediction

Consider that trust is dynamic: users will influence the trust relationship between each other during the rating process. That is to say, the rating of a user on items will refer to the opinions of the people he/she trusts, and will also influence the choices of his/her trusters. Through the rating interaction between users, the propagation and feedback of trust can have an impact on trust relationships in social networks. Thus, we need to combine the two models above to get the final dual recommendation model called the *TT-SVD* model.

$$\begin{aligned}\hat{r}_{u,j} &= \beta \left(TrusteeSVD\right) \\ &+ (1-\beta) \left(TrusterSVD\right)\end{aligned} \tag{5}$$

After independent training of the *TrusterSVD* and *TrusteeSVD* model, we unify the influence of the two models by weight β. Following this strategy, we acquire the final predicted rating $\hat{r}_{u,j}$. The main process is shown in Fig. 2.

F. Complexity Analysis

The learning time of the model includes two aspects. The first is to calculate the loss function $O\left(td\left|\mathrm{I}\right| + td\left|\mathrm{T}\right|\right)$, where d is the dimensionality of the feature vector, t represents the number of iterations and we user $O\left(td\left|\mathrm{I}\right| + td\left|\mathrm{T}\right|\right)$ denote to the number of the ratings and trust relationships. The second is to compute its gradients of L against feature vectors: $b_u, b_j, q_j, w_u, y_i, p_v$. After derivation, the total time complexity is still $O\left(td\left|\mathrm{I}\right| + td\left|\mathrm{T}\right|\right)$, which means that the learning time of the model is linear with the number of observed entries in both trust information and rating information. With the rapid development of the Internet of Things, how to process data and mine useful data has become a difficult problem. The method of applying deep learning to recommendation systems has also been questioned recently. Still, the complexity analysis results show that our model has the ability to deal with the large-scale dataset. The problems of sparse decision making and cold start can be alleviated. Besides, the user behavior data is very private data, and therefore we need to protect data security through security measures [20], [21]. Wireless sensor networks [22]–[24] are an important part of the IoT systems,and the development of wireless sensor networks has greatly increased the type and amount of data collected, so efficiency issues must be considered in IoT systems to reduce computing costs [25].

IV. Experients

In this section, we design our experiments on three datasets to verify our work has a better performance compared to the other related methods.

TABLE I: Datasets used in our work

Aspect	[2]	[15]	[4]
Users	1508	3000	3000
Items	2071	9000	9000
Ratings	35,497	38751	25931
Trust relationship	1853	4700	5642

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2020.3006066, IEEE Internet of Things Journal

TABLE II: Experimental results in "all user" view

Datasets	Metrics	[3]	[8]	[4]	[13]	[26]	[27]	[28]	TT-SVD
FilmTrust	MAE	0.664	0.594*	0.640	0.627	0.651	0.654	0.668	0.586
	(improve)	11.75%	1.35%	8.4%	6.54%	9.98%	10.40%	12.28%	
	RMSE	0.873	0.753*	0.869	0.809	0.875	0.872	0.879	0.741
	(improve)	15.12%	1.59%	14.73%	8.41%	15.31%	15.02%	15.70%	
CiaoDVD	MAE	0.961	0.851*	0.862	0.855	0.886	0.924	0.868	0.820
	(improve)	14.67%	3.64%	4.87%	4.09%	7.45%	11.26%	5.53%	
	RMSE	1.235	1.072*	1.148	1.079	1.154	1.209	1.151	1.045
	(improve)	15.38%	2.25%	8.97%	3.15%	9.45%	13.56%	9.21%	
Epinions	MAE	1.129	0.884*	0.892	0.892	1.008	1.001	0.993	0.883
	(improve)	21.79%	0.11%	1.01%	1.01%	12.40%	11.79%	11.08%	
	RMSE	1.588	1.174*	1.174	1.197	1.325	1.289	1.321	1.171
	(improve)	26.26%	0.26%	0.26%	2.17%	11.62%	9.15%	11.36%	
Average	MAE	0.918	0.776*	0.798	0.791	0.848	0.860	0.843	0.763
	(improve)	16.88%	1.72%	4.39%	3.58%	10.06%	11.24%	9.49%	
	RMSE	1.232	1.000*	1.064	1.028	1.118	1.123	1.117	0.986
	(improve)	19.99%	1.37%	7.33%	4.15%	11.84%	12.26%	11.76%	

TABLE III: Experimental results in "cold start user" view

Datasets	Mertrics	[3]	[8]	[4]	[13]	[26]	[27]	[28]	TT-SVD
FilmTrust	MAE	0.780	0.664*	0.669	0.687	0.671	0.754	0.728	0.650
	(improve)	16.67%	2.11%	2.84%	5.39%	3.13%	13.79%	10.71%	
	RMSE	0.985	0.868*	0.869	0.880	0.895	0.920	0.901	0.855
	(improve)	13.20%	1.50%	1.61%	2.84%	4.47%	7.07%	5.11%	
CiaoDVD	MAE	1.141	0.850*	0.882	0.905	0.936	0.974	0.941	0.835
	(improve)	26.82%	1.76%	5.33%	7.73%	10.79%	14.27%	11.26%	
	RMSE	1.295	1.095*	1.348	1.149	1.254	1.279	1.241	1.080
	(improve)	16.60%	1.37%	19.88%	6.01%	13.88%	15.56%	12.97%	
Epinions	MAE	1.279	0.897*	0.901	0.962	1.028	1.011	0.997	0.897
	(improve)	29.87%	0.44%	0.33%	6.76%	12.74%	11.28%	10.03%	
	RMSE	1.648	1.204*	1.206	1.307	1.335	1.309	1.306	1.201
	(improve)	27.12%	0.41%	1.15%	8.11%	10.04%	8.25%	8.04%	
Average	MAE	1.067	0.805*	0.817	0.851	0.878	0.913	0.889	0.794
	(improve)	25.56%	1.37%	2.82%	6.73%	9.60%	13.03%	10.65%	
	RMSE	1.309	1.056*	1.144	1.112	1.161	1.169	1.149	1.045
	(improve)	20.16%	1.07%	8.62%	6.00%	9.99%	10.60%	9.05%	

A. Datasets

Three real-world datasets are used in our designed experiments, namely Epinions, FilmTrust, and CiaoDVD. These datasets contain trust information and rating information. The rating data in the CiaoDVD and Epinions is an integer range from 1 to 5, while the rating data in FilmTrust are from 0.5 to 4. Due to the excessive amount of data in the datasets, we randomly select subsets from these three datasets for experiments in order to prevent memory overflow. Table 1 shows the information in three datasets.

B. Evaluation Metrics

In the experiments, our model solves two major problems with the recommendation system - cold start and the accuracy of prediction is not high; thus, we conducted two sets of experiments. First, the experiment of "all user" view means that the experimental data is all users and ratings. Secondly, the experiment of "cold start user" view represents that the experimental data is the part of the users and the ratings. When the user evaluates the less than 5 items, the user is defined as a cold start user. We choose a method called five-fold cross-validation approach and two mainstream metrics are adopted by us, including root mean square error (RMSE) and mean absolute error (MAE).

C. Recommendation Methods Comparison

1) Comparison Model: We choose two types of approaches, classical recommendation systems, and social recommendation systems, to compare our design with others. The classical recommendation systems predict ratings based on rating information, while the social recommendation systems predict ratings based on both trust information and rating information. There are seven models in total in the literature, which are classical recommendation systems: PMF [3] and SVD++ [4]. Social recommendation systems: RSTE [26], SoRec [27], SocialMF [28], TrustMF [13].

In addition to the classical algorithms mentioned above, Hu et al. [8] proposed a novel trust-based semi-supervised learning recommendation algorithm: SSL-SVD in 2019. We also compared this latest work with our model. SSL-SVD decomposed trust into four fine-grained factors, predicted unknown trust values through semi-supervised learning. Finally, Hu combined SVD model with trust information. Different from the above method, Hu analyzed trust as the emotional factor.Rather than simply processing the trust data.

2) Parameter Settings: We can adjust the parameters in the experiments and get the best parameters for each model according to the suggestions of the previous works. We set the dimensions of the user-specify and the item-specify feature

vector as 10. The parameter settings are as follows.or PMF: we set λ=0.001. SVD++: the settings of parameter recommendation in [4]; for RSTE: we set α=1.0, λ=0.001 and λ_t=1; for SocialMF: we set λ. =0.001 and λ_t=1; for TrustMF: we set λ=0.001 and λ_t=1; for SoRec: we set different parameters for different datasets, λ=0.1,1.0,0.01 for FilmTrust, Epinions, and Ciao respectively; SSL-SVD: the settings of parameter recommendation in [8].

3) Results And Analysis: The results of above two experiments are listed in Table 2 and Table 3. The best performing model except for our method is marked by signal "*." Table 2 shows the recommendation performance for "all users," and Table 3 shows the recommendation performance for "cold start users." From the experimental results in the two tables, our dual model achieves better performance than other methods, both from the cold-start user perspective and from the all user perspective. The experimental results show that our method can effectively solve the problem of sparse decision making and cold start, and improve the accuracy of prediction compared with other recommendation models. And the two-way trust scheme can also effectively solve the problem of sparse trust. As shown in Table 2, in the "all user" view, the prediction accuracy of the traditional recommendation model represented by PMF is inferior to the prediction accuracy of trust-based recommendation models such as SoRec, RSTE, and SocialMF. But, the SVD++ model performs better than the three trust-based models above. Hu [8] incorporates the trust information into the SVD++ model and finally creates the SSL-SVD model. In Table 2, SSL-SVD performs better than SVD across all three datasets, and the performance of our method in FilmTrust, CiaoDVD, Epinions is the best compared to the rest. Thus, we state that trust information is a necessary need for recommendation. As shown in Table 3, the second experiment is conducted in the "cold start users" view. As there is not sufficient rating information and trust information, the prediction accuracy of all models has declined. SSL-SVD performs best in FilmTrust, Epinions, CiaoDVD. But the gap between the performance of the SSL-SVD model and others in Epionions is not significant. Because the trust and rating information in the Epinions is sparser than other datasets. The performance of our method is comparable to SSL-SVD in Epinions, but ours performs better in FilmTrust and CiaoDVD because of sufficient information. Most trust-based models only consider that users are affected by people they trust, so that the trust data is also sparse, and the recommendation performance is not good. Here we propose a dual model by considering the two-way trust. Effectively utilize trust relationships and improve the recommendation performance.

V. Conclusion And Future Work

To solve the problems of cold start and sparse decision making in the AI-based IoT recommendation systems, and improve the performance of the existing recommendation methods, we proposed a novel sparse decision making model called *TT-SVD*, which incorporates both trust and rating information. Considering that individuals will affect the trust of each other in common sense, the opinions of users may be affected by both trusters and trustees. We decomposed the trust networks into *TrusterSVD* and *TrusteeSVD* according to the direction attribute of trust after improving the SVD++ model. Finally, we unified the influence of the two models by the weighted average and got a hybrid model called *TT-SVD*. Experiments show that our method improves the recommendation efficiency and accuracy compared to the other intelligent recommendation systems. Thus, IoT devices will provide users with more accurate decisions and favorite items, which will enhance the interaction between users and devices. There is great application prospect in driving assistance, smart home and shopping guidance. Our proposed *TT-SVD* solves the problem of sparse decision making in the AI-based IoT systems. Our method not only improves the accuracy of prediction but also has the ability to deal with large datasets with the characteristics of robustness and high efficiency. For future work, we plan to use dynamic trust data as a test dataset and consider the trust propagation. With the development of the IoT systems, there will be a huge leap in data collecting, processing, and propagating. Utilizing trust information to make sparse decision making will become a standard operation in the AI-based IoT systems, which can be solved by our further research on the *TT-SVD*.

Acknowledgment

This work is partially sponsored by the State Key Development Program of China (No. 2018YFB0804402, 2019YFB2101700), National Science Foundation of China (U1736115).

References

[1] P. Roberts, "Idc: 30 billion autonomous devices by 2020." https://securityledger.com/2013/10/idc-30-billion-autonomous-devices-by-2020/. Accessed October 7, 2013.

[2] G. Guo, J. Zhang, F. Zhu, and X. Wang, "Factored similarity models with social trust for top-n item recommendation," *Knowledge-Based Systems*, vol. 122, no. APR.15, pp. 17–25, 2017.

[3] R. Salakhutdinov and A. Mnih, "Probabilistic matrix factorization," *Neural Information Processing Systems(NIPS08)*, pp. 1257–1264, 01 2008.

[4] Y. Koren, "Factorization meets the neighborhood: A multifaceted collaborative filtering model," in *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '08, (New York, NY, USA), p. 426–434, Association for Computing Machinery, 2008.

[5] G. Zhou, G. Xu, J. Hao, S. Chen, J. Xu, and X. Zheng, "Generalized centered 2-d principal component analysis," *IEEE transactions on cybernetics*, vol. PP, 08 2019.

[6] J. O'Donovan and B. Smyth, "Trust in recommender systems," in *Proceedings of the 10th International Conference on Intelligent User Interfaces*, IUI '05, (New York, NY, USA), p. 167–174, Association for Computing Machinery, 2005.

[7] M. Liu, G. Xu, J. Zhang, R. Shankaran, X. Zheng, and Z. Zhang, *Roundtable Gossip Algorithm: A Novel Sparse Trust Mining Method for Large-Scale Recommendation Systems*, pp. 495–510. 18th International Conference, ICA3PP 2018, Guangzhou, China, November 15-17, 2018, Proceedings, Part IV, 11 2018.

[8] Z. Hu, G. Xu, X. Zheng, J. Liu, Z. Li, Q. Sheng, W. Lian, and H. Xian, "Ssl-svd: Semi-supervised learning–based sparse trust recommendation," *ACM Transactions on Internet Technology (TOIT)*, vol. 20, pp. 1–20, 01 2020.

[9] G. Xu, W. Zhou, A. K. Sangaiah, Y. Zhang, X. Zheng, Q. Tang, N. Xiong, K. Liang, and X. Zhou, "A security-enhanced certificateless aggregate signature authentication protocol for invanets," *IEEE Network*, vol. 34, pp. 22–29, 03 2020.

[10] W. Yao, J. He, G. Huang, and Y. Zhang, "Modeling dual role preferences for trust-aware recommendation," in *Proceedings of the 37th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '14, (New York, NY, USA), p. 975–978, Association for Computing Machinery, 2014.

[11] J. Wei, J. He, K. Chen, Y. Zhou, and Z. Tang, "Collaborative filtering and deep learning based recommendation system for cold start items," *Expert Systems with Applications*, vol. 69, 10 2016.

[12] D. Rafailidis and F. Crestani, "Learning to rank with trust and distrust in recommender systems," in *Proceedings of the Eleventh ACM Conference on Recommender Systems*, RecSys '17, (New York, NY, USA), p. 5–13, Association for Computing Machinery, 2017.

[13] B. Yang, Y. Lei, D. Liu, and J. Liu, "Social collaborative filtering by trust," in *Proceedings of the Twenty-Third International Joint Conference on Artificial Intelligence*, IJCAI '13, p. 2747–2753, AAAI Press, 2013.

[14] V.-A. Nguyen, E.-P. Lim, J. Jiang, and A. Sun, "To trust or not to trust? predicting online trusts using trust antecedent framework," in *Proceedings of the 2009 Ninth IEEE International Conference on Data Mining*, ICDM '09, (USA), p. 896–901, IEEE Computer Society, 2009.

[15] G. Guo, J. Zhang, and N. Yorke-Smith, "Trustsvd: Collaborative filtering with both the explicit and implicit influence of user trust and of item ratings," *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence*, pp. 123–129, 01 2015.

[16] T. Duricic, E. Lacic, D. Kowald, and E. Lex, "Trust-based collaborative filtering: Tackling the cold start problem using regular equivalence," in *Proceedings of the 12th ACM Conference on Recommender Systems*, RecSys '18, (New York, NY, USA), p. 446–450, Association for Computing Machinery, 2018.

[17] P. Gao, H. Miao, J. S. Baras, and J. Golbeck, "Star: Semiring trust inference for trust-aware social recommenders," in *Proceedings of the 10th ACM Conference on Recommender Systems*, RecSys '16, (New York, NY, USA), p. 301–308, Association for Computing Machinery, 2016.

[18] F. Gohari, F. Shams Aliee, and H. Haghighi, "A new confidence-based recommendation approach: Combining trust and certainty," *Information Sciences*, vol. 422, pp. 21–50, 09 2017.

[19] G. Guo, J. Zhang, D. Thalmann, and N. Yorke-Smith, "Etaf: An extended trust antecedents framework for trust prediction," in *Proceedings of the 2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, ASONAM '14, p. 540–547, IEEE Press, 2014.

[20] G. Xu, W. Wang, L. Jiao, L. Xiaotong, K. Liang, X. Zheng, W. Lian, H. Xian, and H. Gao, "Soprotector: Safeguard privacy for native so files in evolving mobile iot applications," *IEEE Internet of Things Journal*, vol. PP, pp. 1–1, 09 2019.

[21] G. Xu, B. Guo, C. Su, X. Zheng, K. Liang, D. Wong, and H. Wang, "Am i eclipsed? a smart detector of eclipse attacks for ethereum," *Computers and Security*, vol. 88, p. 101604, 09 2019.

[22] L. Li, G. Xu, L. Jiao, L. Xiaotong, H. Wang, H. Jing, H. Xian, W. Lian, and h. gao, "A secure random key distribution scheme against node replication attacks in industrial wireless sensor systems," *IEEE Transactions on Industrial Informatics*, vol. PP, pp. 1–1, 07 2019.

[23] X. Li, G. Xu, X. Zheng, K. Liang, E. Panaousis, T. Li, W. Wang, and C. Shen, "Using sparse representation to detect anomalies in complex wsns," *ACM Transactions on Intelligent Systems and Technology*, vol. 10, pp. 1–18, 10 2019.

[24] Y. Li, S. Xia, m. Zheng, B. Cao, and Q. Liu, "Lyapunov optimization based trade-off policy for mobile cloud offloading in heterogeneous wireless networks," *IEEE Transactions on Cloud Computing*, vol. PP, pp. 1–1, 08 2019.

[25] G. Xu, Y. Zhang, L. Jiao, E. Panaousis, K. Liang, H. Wang, and L. Xiaotong, "Dt-cp: A double-ttps based contract-signing protocol with lower computational cost," *IEEE Access*, vol. PP, pp. 1–1, 11 2019.

[26] H. Ma, I. King, and M. R. Lyu, "Learning to recommend with social trust ensemble," in *Proceedings of the 32nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '09, (New York, NY, USA), p. 203–210, Association for Computing Machinery, 2009.

[27] H. Ma, H. Yang, M. R. Lyu, and I. King, "Sorec: Social recommendation using probabilistic matrix factorization," in *Proceedings of the 17th ACM Conference on Information and Knowledge Management*, CIKM '08, (New York, NY, USA), p. 931–940, Association for Computing Machinery, 2008.

[28] M. Jamali and M. Ester, "A matrix factorization technique with trust propagation for recommendation in social networks," in *Proceedings of the Fourth ACM Conference on Recommender Systems*, RecSys '10, (New York, NY, USA), p. 135–142, Association for Computing Machinery, 2010.

Guangquan Xu [M'18] (losin@tju.edu.cn) is a Ph.D. and full professor at the Tianjin Key Laboratory of Advanced Networksing (TANK), College of Intelligence and Computing, Tianjin University, China. He received his Ph.D. degree from Tianjin University in March 2008. He is a member of the CCF and IEEE. His research interests include cyber security and trust management.

Yuyang Zhao (zyytju1214@163.com) is a master's student at the Department of Intelligence and Computing, Tianjin University, China. he received her B.S. degree from the School of Computer Science and Technology, Hebei University of Technology in 2018. his current research interests include privacy-preservation and trust model.

Litao Jiao (jiaolitao_11@163.com) received his MBA degree in 2016 from Shandong University of Science and Technology. He is now an associate professor in Qingdao Huanghai University, China. He has been awarded the prize of Provincial Educational Achievement in year 2018, participated in 5 major provincial and municipal research projects, and posted more than 10 papers. His research interests include HR management and information security.

Meiqi Feng (fengmeiqi@tju.edu.cn) is studying for a master's degree in Intelligence and Computing, Tianjin University, China. She graduated from Tianjin University with a bachelor's degree in computer science and technology in 2019. Her main research direction is cyberspace security. She is interested in web security and the combination of artificial intelligence and security.

Zhong Ji [M' 13] (jizhong@tju.edu.cn) is an Associate Professor with the School of Electrical and Information Engineering, Tianjin University. He received the Ph.D. degree from Tianjin University in 2008. He is a member of the CCF and IEEE. His research interests include multimedia understanding, zero/few shot leanring, cross-modal analysis, and video summarization.

Emmanouil Panaousis (e.panaousis@greenwich.ac.uk) is an Associate Professor at the University of Greenwich.His main research interests are within cybersecurity and privacy engineering.He received the B.Sc. degree in Informatics and Telecommunications from the University of Athens,Greece, in 2006, and the M.Sc. degree in Computer science from the Athens University of Economics and Business, Greece, in 2008, and the Ph.D. degree in Mobile Communications Security from Kingston University London, U.K., in 2012. He has previously heldpositions at Univ. of Surrey, Univ. of Brighton, Imperial College and Queen Mary.

Si Chen (GS'12–M'17) received the Ph.D. degree in computer science and engineering from the University at Buffalo–SUNY, Buffalo, NY, USA, in 2016.He is an Assistant Professor with the Computer Science Department, West Chester University, West Chester, PA, USA. His research is supported by Microsoft. His current research interests include security and privacy in mobile sensing and cyber-physical systems.Dr. Chen was a recipient of the Best Student Paper Award of IEEE ICDCS 2017. He is a member of the ACM.

Xi Zheng [M'16] (james.zheng@mq.edu.au) is in Software Engineering from UT Austin, Master in Computer and Information Science from UNSW, Bachelor in Computer Information System from FuDan; now he is an assistant professor/lecturer in Software Engineering at Macquarie University.