A Matrix Factorization Model for Hellinger-based Trust Management in Social Internet of Things

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Abstract—The Social Internet of Things (SIoT), integration of Internet of Things and Social networks paradigms, has been introduced to build a network of smart nodes which are capable of establishing social links. In order to deal with misbehavioral service provider nodes, service requestor nodes must evaluate their trustworthiness levels. In this paper, we propose a novel trust management service provider nodes, service requestor nodes must evaluate their trustworthiness levels. In this paper, we propose a novel trust management system through a real-world SIoT application. Our results demonstrate that the proposed mechanism is resilient to different types of network attacks and it can accurately find the proper service provider with high trustworthiness.

Index Terms—Social Internet of Things, Trust Management, Bipartite Graphs, Matrix Factorization, Hellinger Distance.

I. INTRODUCTION

The Internet of Things (IoT) can be seen as a variety of heterogeneous technologies and a large number of things (aka objects) that tend to interact with each other through unique addressing schemes, reaching a common goal such as managing transportation in a smart city [1], [2]. The number of IoT objects is growing unprecedently [3], [4]. In order to build a network of objects (a set of smart nodes with the ability of establishing social links for information sharing), combination of IoT and social networking paradigm, Social Internet of Things (SIoT), has been introduced [5]. Based on [6], one can observe a generational leap from objects with a certain level of smartness to objects with a concrete social awareness which are able to use environmental consciousness to take an appropriate action. Without considering this potential, the evolution and progress of the SIoT, containing trillions of objects, cannot be achieved. In SIoT, objects act as autonomous agents. Alongside their individuality, they can request and provide information and services to each other. The advantages of this convergence are as follows [7]:

1) A Social IoT guarantees both the network navigability, which refers to effective discovery of objects and services, and the network scalability just like the human social networks.
2) Levels of trustworthiness could be established by leveraging the degree of interaction among autonomous things which are friends.
3) The previously designed models to study social networks could be extended to re-use in Social IoT.

A. Problem Statement

The concept of trust is a longstanding research topic in computer science, and its meaning varies in how it is represented in different communities [8]. Since trust is a complicated concept, no categorical consensus on definition of trust can be found in the scientific literature. Furthermore, one of the most significant problems is that there is no unified metric or evaluation methodology [9], [10]. In this paper, our trust definition is inspired by the trust notion given in [11], as:

Definition 1. After a service requestor send-out a task for execution, the initiator of the task loses its control on the task, then the service provider is able to perform its probable malicious animus. Thus, in order to receive the desired service, a service requestor must evaluate the service providers competence, and decide whether to delegate its task to the service provider. The evaluation process of a service provider’s competence by a service requestor is called trust.

For convenience, we define trustor and trustee, as follows:

Definition 2. Trustor is a service requestor node in SIoT which has a task to delegate, and evaluates the outcome of the service providers returned response.

Definition 3. Trustee is a service provider node in SIoT that is capable of providing some type of services as the trustor asks, and is beyond the trustors direct control.

The nature of trust is context-dependent, i.e., a trustor trusts a trustee in a specific context, but as the context alters, the trustor may decide not to trust that trusted [12]. The context is related to the characteristics of the service. Depending on which service is requested, it is possible to emphasize the necessity of the service characteristics [13]. The trustor expects proper result from the trustee. The expectation is positive if the trustee returns the desired result. The trustor may not produce a favorable result. Thus, the trustor is subject to the potential loss and failure imposed by the trustee. After getting a response, the trustor measures and rates the trustworthiness of the trustee based on the characteristic of the received service, and keep its experience to use in future decisions.

From the definition of trust between SIoT objects, a malicious node (object) may break the basic functionality of the network by destroying the reputation of good behavior nodes, or increasing the trustworthiness of malicious ones. In this paper, we focus on the five popular attacks by which a node can violate the existing

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trust or break functionality of the devices in the network, as follows:

1) **Whitewashing Attack (WWA)**: A malicious node which has unfavorable (bad) reputation leaves and rejoins the network to avoid the retributions it may encounter due to its poor trustworthiness value. This attack usually happens when the attacker (malicious node) can easily change its identity.

2) **Self-Promoting Attack (SPA)**: A malicious node pretends to be a beneficial trustee by recommending itself as a trustworthy (good) object, but represents bad behavior.

3) **Bad-Mouthing Attack (BMA)**: A malicious node annihilates the reputation of a well-behaved node by faking bad experiences about it, and thereby intercepts its services.

4) **Ballot Stuffing Attack** or **Good-Mouthing Attack (GMA)**: A malicious node falsely promotes a misbehavior node (as a well-behaved node) to boost its chance of being selected as a trustee.

5) **Opportunistic Service Attack (OSA)**: A malicious node behaves like a non-malicious node in its early appearance to gain high reputation opportunistically. Then, as soon as gaining enough reputation, the node begins its malicious behaviors like SPA, BMA, and GMA attacks.

Trust management is a mechanism to predict the most reliable trustee for a certain trustor. Trust management lets SIoT objects to overcome the risk of exposing to malicious nodes and the perceptions of uncertainty. Trust management systems can improve the trust among the objects in an IoT system. These systems encourage nodes to have honest collaboration, while reducing the effect of malicious nodes and their anomalous functionality. A practical and effective trust management mechanism must fulfill the following requirements:

- **Resistance to attack**: Trust management mechanism should provide resiliency against related attacks.

- **Overcoming resource constraints**: In IoT, objects are often very constrained in terms of memory, power supply, and processing power; thus, strong security measures like heavy cryptography are not applicable.

- **Locality**: A trust management method must not depend too much on a remote central node, that restricts the scalability and induces harmful effects. For instance, a pitfall of centralized trust management can cause the failure of the whole system.

- **Robustness against data sparsity**: Trust management systems should not suffer from the data sparsity problem and the cold start problem, which is an inability of the system to predict trust values properly due to lack of enough data for recently joined users.

Until now, we have described the concept of trust and the requirements for a trust management system in SIoT. Next, we explain the motivation and importance of trust management in SIoT.

**B. Motivation**

Over time, it is anticipated that IoT is going to be extensively practical from smart homes to business applications, however, security (in particular trust) remains a major challenge in such networks. For instance, imagine a smart door which could be opened or locked remotely via the Internet. This smart door can collect the most sensitive and personal information of our lives. In such automated communications, the personal information usually processed by an external service provider (trustee) which is beyond the reach of the user. Trust is a fundamental issue since several devices with various behaviors characterize the SIoT environment.

Hilton described a distributed denial-of-service (DDoS) attack conducted against domain name service provider Dyn, leading to service outages of major sites like Github, Twitter, Netflix, Paypal on October 21, 2016. In a DDoS attack, the perpetrator botnet seeks to make a network resource unavailable to its legitimate users by flooding the targeted machine or resource with superfluous requests. What is notable about this attack is the fact that the attack was not carried out with spoofed source addresses, but rather a direct attack from numerous of IP addresses belonging to constrained IoT devices including printers, coffee makers, washing machines, refrigerators, etc.

Consequently, the motivation for proposing an efficient trust management method for SIoT is obvious; there are misbehavior devices (objects) owned by misbehavior users that aim to attack others with the goal of gaining more profit, while causing others’ services cut off. These misbehavior nodes entail restriction and denial of a class of services. Since the provision of trust in this environment is integrated with provision of service, each trustor have to decide whether to use the trustee’s service based on the level of trust between them or not. So, trust is one of the most critical issues in SIoT which must be addressed before the prevalence of the network.

To the best of our knowledge, there is no sufficient work on trust management in SIoT, and most of the previous works could not achieve an efficient trust management model. This paper aims to present a novel trust management mechanism with the capability of trust prediction in SIoT. Later, we will show that our method is accurate yet resilient to different attacks and satisfies the aforementioned requirements.

**II. Related Work**

To the best of our knowledge, there is limited relevant work on trust management in SIoT, particularly considering misbehavior users who attack the well-behavior nodes through their possessed SIoT devices. In this section, we discuss previous related works.

Chen et al. developed an adaptive trust management protocol for SIoT systems and tried to reduce the probability of being attacked by dynamically changing the configuration of devices. However, their model is user-based which means the network nodes have social relation through their owners’ social network, hence, the social relation between SIoT objects are constrained to the social relation between the owners. The other weakness of this model is that the authors divided SIoT devices into two inflexible types (i.e., devices and owners), such that trustees should be selected from the pre-defined devices and trustors are only selected from the owners.

Nizamkari followed the same idea as Chen et al. The truster uses its own experience and its friends’ experiences for evaluating the trustworthiness of a trustee. However, the most important difference between them is that, in the former, if the truster’s friends do not have appropriate requested experiences, truster inquires its friends of friends. The influence of friends of friends recommendation could be obtained from nodes similarity or the network structure. Nevertheless, there are two inabilities to tackle the prediction issues. First, their proposed recommender cannot predict the rating for an object which has not been rated yet. Second, the author did not propose any solution for the situation when searching nodes for finding friends of friends (experience) terminates in identical results.

Kantarci et al. studied a cloud-centric IoT, which is called crowd computing. In their framework, mobile sensors are used...
as IoT devices that reside in the cloud. In this scenario, users can utilize other users’ phone sensors by installing a specific application and joining its associated social network. Then, a user issues a task and a crowd management authority candidates some of the social network users for assigning the task. After that, one of the candidates is selected based on its reputation in the social network for performing the task. The most significant weakness of this framework is the need for a central node to manage the issues, store users’ reputation, and process a large amount of data per issue. Today, accepting a central node for processing and managing all the tasks is not practical because of the scalability issues, as the number of IoT devices is tremendously growing.

Mendoza and Kleinschmidt used the experiences of trustor’s neighbors and the quality of trustee’s services to evaluate the trust between trustors and trustees. However, each trustor must store a table of other nodes and their experiences. This trust management model can detect malicious behaviors, but storing such a large table is non-practical for lightweight IoT objects.

Chen et al. proposed a trust management model based on fuzzy reputation to evaluate trust in IoT systems. However, their trust management model considers only wireless sensors which is a specific IoT environment, and they take into account only QoS trust metrics such as energy consumption and packet delivery ratio. Moreover, they did not take into consideration the social relationship between the objects.

Sharma et al. proposed a novel solution for the maintenance of trust and preservation of privacy rules in SloT in the form of a lightweight query mechanism with the help of fission computing. For the implementation of the proposed solution, mini-edge servers are used as crowdsources. Although the authors asserted that the trust would be provided without sanctioning adversaries, claimed that users may expose selfish behavior in relaying data for others due to limited resources or social objectives. Furthermore, demanding for 5G infrastructure and a center to administer the queries are other weaknesses of their mechanism.

Yu et al. suggested blockchain for data management to provide end-to-end trust and remove the trusted third-party in decentralized IoT systems. However, there is a trade-off between scalability and privacy in their proposed mechanism. Hence, it could not afford both parameters, simultaneously. Moreover, the authors ignored the fundamental constraints of the IoT objects.

Premarathne proposed a model to compute trust among pairs of nodes in SloT networks. The trust between nodes is indicated by link probability which is computed based on objects’ social relationships or their attributes. However, the overhead of storing such attributes and related data is not negligible. Furthermore, this model needs an authorized central node to configure appropriate attributes and multiply the affinity values of node attributes.

Due to the problem of fully distributed and centralized trust management systems, Kim proposed an authentication and authorization infrastructure for IoT to be locally centralized and globally distributed. His solution is scalable and utilizes edge devices. However, it ignores dynamism and sociality of the network devices.

Xiao et al. proposed a trust model for SloT that uses two parameters, Guarantor and Reputation. Their model enables to detect and isolate malicious nodes by penalizing malicious activities. However, their model needs a central server to store, update, and manage the reputations of the objects and respond to reputation queries. Another drawback of their model is that they did not consider the resource constraints of SloT objects.

Chen et al. proposed a scalable and adaptive trust management protocol in SOA-based SloT systems which is distributed and utilizes users’ feedbacks using similarity rating of friendship, social contact, and community of interest relationships. Their protocol takes some SloT constraints into account such as limited storage and computing capacity of devices by storing trust information only for a limited set of nodes and demanding less process to update trust. However, considering only a limited set of nodes is not a scalable solution fundamentally.

According to our literature review, there are very few previous works on SloT trust management which test their proposed solutions against the aforementioned attacks in section 1-B. In this paper, we propose a novel trust management mechanism in SloT and analyze it in the presence of malicious nodes.

III. Proposed Method

In this section, we (1) introduce a bipartite graph model for social Internet of Things (Section III-A); (2) build a social network among trustors using Hellinger distance (Section III-B); (3) introduce a new social trust model for trustors based on the constructed social network (Section III-C); (4) utilize a matrix factorization mechanism to recommend a model which trustors can employ in order to find the most trustworthy trustee (Section III-D); (5) discuss in Section III-E how the proposed model fulfills the required obligations mentioned in section I-A.

A. Bipartite SloT Model

Based on the applications of SloT objects, a well-known architecture for SloT would be service-oriented. Each device in the system can play the role of trustor, trustee, or both.

Hence, we believe that bipartite graphs are suitable models for representing social Internet of Things. Without loss of generality, one can assume that there is a limited number of service types which could be performed among SloT objects. For each service type, we can consider a bipartite network with two sets of nodes, trustors and trustees. Considering a specific bipartite network, trustor \( u \) in \( U \) has a directed link (edge) to trustee \( v \) in \( V \), if trustor \( u \) has used at least one of the services provided by trustee \( v \); otherwise, there is no edge between them. Each edge in the bipartite network has a weight in interval \([0,1]\), which represents the trust experience of \( u \) by using a service from \( v \). Figure 1 illustrates a bipartite graph corresponding to an IoT system.

The trust experience consists of weighted sum of parameters like accuracy of response, return time of response, etc. These parameters vary based on the trustor and the requested service type.

Let \( G = (U, V, E) \) be a bipartite graph with two sets of nodes, trustors \( U = \{ u_1, u_2, \ldots, u_n \} \) and trustees \( V = \{ v_1, v_2, \ldots, v_m \} \), and \( E = \{ (u_i, v_j), \ldots, (u_n, v_m) \} \) represents the weighted edges from trustors to trustees. Bi-adjacency matrix \( B \) of graph is a matrix of size \( n \times m \) wherein \( b_{i,j} \neq 0 \) if and only if \( (u_i, v_j) \in E \), and \( b_{i,j} = 0 \) otherwise. Row \( i \) in the bi-adjacency matrix is a vector corresponding to trustor \( u_i \) and represents the experience rates of this trustor to any trustees.

B. Social Network of Trustees

In this section, we want to extract implicit social relations between trustors from the aforementioned bipartite graph, based on the trustors scores and their past experiences. The extracted social relations can indicate behavioral trust similarity among trustors in the network. Since the similarity measures are in some
sense the inverse of the distance metrics \[23\]–\[31\], we generate a social network of trustors using a distance metric.

**Hellinger distance** (aka Bhattacharyya distance) is a type of f-divergence metrics which was introduced by Ernst Hellinger \[32\]. We chose Hellinger distance as a distance metric for three reasons: (1) as trust concept is inherently a non-deterministic problem, we need a statistical metric to measure distances between the nodes; (2) Hellinger distance satisfies the triangle inequality, so, differences between trustors will be properly demonstrated; (3) it holds symmetry and positive definite properties which are essential for a well-defined distance metric \[30\].

To measure the similarity between each pair of trustors, we apply Hellinger distance to the degree distribution of their neighbors. Let \[L_u = \{l_k|k \in d\}\] be the probability distribution over all neighbors of trustor node \(u\), where \(k\) is the number of neighbors of \(u\) with degree of exactly \(k\), and \(d\) is the greatest degree of trustees in the network. Now, the Hellinger distance between two trustors \(u_i\) and \(u_j\) can be defined as:

\[
\text{Hell}(u_i, u_j) = \frac{1}{2\sqrt{2}} \left\| L_{u_i} - L_{u_j} \right\|_1
\]

(1)

Now, we have an \(n \times n\) distance matrix, where \(n\) is the number of trustors in the bipartite network. By considering an appropriate threshold, a social relation between any pair of trustors, based on how close nodes are to each other, could be formed. As a result, a new social network of trustors is created. The network can be displayed by adjacency matrix \(A_{n \times n}\) as:

\[
A_{i,j} = \begin{cases} 
1, & \text{Hell}(u_i, u_j) < \text{threshold} \\
0, & \text{otherwise}
\end{cases}
\]

C. Social Trust Model

In this section, we aim to develop a trust model which expresses how similar the trustors are, based on their trust patterns. For this purpose, past experiences of trustors, the social network from the previous section, and various similarity and centrality measures are employed.

1) **Similarity**

Similarity between network nodes (trustors) is one of the most essential factors that adheres to their trust patterns \[33\]–\[37\]. Different similarity metrics are mentioned here, and we use them in order to extract trust patterns among users of the network.

**Bayesian Similarity.** Cosine similarity (COS) and Pearson correlation coefficient (PCC) are widely used to determine the degree of similarity between nodes in a network. However, they suffer from substantial shortcomings, such as: (1) These metrics have flat-value, opposite-value, single-value, and cross-value problems as illustrated in \[31\]; (2) COS and PCC could be misleading because they are known as similarity measures that disregard rating vector length but only consider rating direction \[38\], as mentioned in \[39\]. According to these issues, we chose Bayesian similarity (BS) metric which is based on the Dirichlet distribution \[34\]. Even though this similarity is a rating-based measure, it does not suffer from the data sparsity problem or many other problems that pointed out in \[40\]. BS does not consider mutually rated trustees, instead utilizes the preferences of trustors by considering both direction (rating distances) and length (ratings amount) of rating/experience vectors. Rating distance between two nodes \(u_i\) and \(u_j\) is modeled by the Dirichlet distribution and can be calculated as \(d_{u_i, u_j} = |r_{u_i} - r_{u_j}|\), then the similarity between trustors \(u_i\) and \(u_j\) could be:

\[
BS(u_i, u_j) = \max(BS_i'_{u_i, u_j} - BS_i''_{u_i, u_j} - \delta, 0)
\]

(2)

In this relation \(BS_i'_{u_i, u_j} = 1 - d_{u_i, u_j}/d_{\text{max}}\) is called overall similarity where \(d_{\text{max}}\) is the maximum possible rating distance. Bayesian similarity is computed by removing the chance correlation \(BS_i''_{u_i, u_j}\) and user bias \(\delta\) from the overall similarity. In addition, the similarity originated from data sparsity problem would be resolved by subtracting the chance correlation \[30\].

**Hellinger Similarity.** For Hellinger similarity, we use the Hellinger distance discussed in Equation (1). This measure is analogously a rating-based measure but tolerates the problems mentioned earlier.

**Connection Similarity.** The connection similarity takes the advantage of connections in the proposed social network of trustors to derive similarity between trustors (nodes). From the perspective of this similarity measure, the mutual connections between nodes are considerable. The list of connections for each node can be easily obtained with the adjacency matrix of the network. Let \(F(u_i)\) be the list of friends for trustor \(u_i\). For each node pair, the connection similarity is proportional to the number of their mutual friends, as \[41\]–\[42\]:

\[
\text{conn}(u_i, u_j) = \frac{F(u_i) \cap F(u_j)}{F(u_i)}
\]

(3)

2) **Centrality**

Another criterion in social networks which has a significant impact on nodes’ trustworthiness is centrality \[43\]–\[45\]. In social networks, a node with high centrality is more likely to be followed in comparison to the other nodes \[46\]–\[50\]. Hence, the following centrality measures are considered to be used in order to discover trustor’s behavior.

**Degree Centrality.** Degree centrality is the simplest and easiest centrality measure to compute. It (basically) indicates the importance of nodes in a social network \[51\]–\[55\]. It is defined as the number of edges (links) incident upon a node. Degree centrality \(deg_u\) of a trustor \(u_i\) can be formalized as:

\[
deg(u_i) = \sum_{j \neq j \neq i} A_{i,j}
\]

(4)
where $A_{i,j}$ is an element of the adjacency matrix of trustors network which indicates the connection between trustors $u_i$ and $u_j$.

**Betweenness-Local Clustering Centrality (BLC).** Since we need a centrality measure to evaluate nodes’ influence on its neighborhood, we employ betweenness-local clustering (BLC) centrality as described in [53]. Even though the betweenness centrality [53] partially describes the importance of nodes, as it is a global evaluation parameter, it cannot present the relative influence of nodes in a local environment precisely, especially in large-scale complex networks [54]. With the combination of betweenness centrality and local clustering coefficient [54], the importance of node $u_i$ would be attained more accurate [54], as:

$$BLC(u_i) = \frac{BC_{u_i}}{CC_{u_i}}$$

(5)

where $BC_{u_i}$ is betweenness centrality of node $u_i$ and $CC_{u_i}$ denotes its local clustering coefficient.

3) **Trust Pattern Similarity**

In order to achieve trust pattern similarity of trustors, we utilize the combination of similarity and centrality to create a new measure to evaluate how much trustors $u_i$ and $u_j$ have similar behavior in trusting the trustees [41], [43], [63]:

$$\Gamma(u_i, u_j) = \frac{\sum_{u_k \mid A_{u_i, u_k} = 1} Sim(u_i, u_k) + (1 - \beta) \sum_{u_k \mid A_{u_i, u_k} = 1} Cen(u_k)}{\sum_{u_k \mid A_{u_i, u_k} = 1} Sim(u_i, u_k)}$$

(6)

where parameter $\beta$ indicates the amount of contribution of similarity and centrality. Indeed, $\Gamma(u_i, u_j)$ constructs a similarity matrix based on trustors trust pattern in the proposed method.

**D. Prediction Mechanism using Matrix Factorization**

Matrix factorization has become a powerful technique in bipartite network analysis [58], [60], and is a practical technique to engage with trust relations [63]–[65]. It can be used in dimensionality reduction, latent features extraction, and mitigating the sparsity property of data. A matrix factorization technique has different models, including Singular Value Decomposition (SVD) [66], Principal Component Analysis (PCA) [67], Probabilistic Matrix Factorization (PMF) [68], and Non-negative Matrix Factorization (NMF) [60].

There are three important factors when a trustor wants to select a particular trustee to dispatch its task: (1) features of the trustor, (2) features of the trustee, and (3) the previous (trust) experiences between them. It is a tough work to extract, maintain, and keep the node features up to date. Besides, most of the times, there are few experiences available, particularly when the node is a newcomer to the network. Therefore, we chose a SVD model [41], [43], [64] to extract latent features and mitigate the data sparsity issue. To the best of our knowledge, this is the first trust management mechanism that employs a matrix factorization model.

In order to learn two $L$-dimensional latent feature representations of trustors $S$ and trustees $R$ matrices, the bi-adjacency matrix $B$ is factorized. Thus, each column of $S \in \mathbb{R}^{L \times n}$ and $R \in \mathbb{R}^{L \times m}$ respectively performs as a $L$-dimensional trustor and trustee latent feature vector. Due to the fact that trustors only have experience about a limited number of trustees, the bi-adjacency matrix $B$ is highly sparse. Here, the low-rank matrix factorization approach seeks to approximate the bi-adjacency matrix $B$ by multiplying the two $L$-dimensional factors $S$ and $R$.

$$B = S \times R$$

(7)

The SVD method usually utilizes the following cost function to reconstruct and predict the missing values of bi-adjacency matrix $B$:

$$\mathcal{L}(S, R, B) = \frac{1}{2} \| B - S^T R \|_F^2$$

(8)

where $\| \cdot \|_F$ implies the Frobenius norm. As mentioned earlier, $B$ is mostly sparse, so we only should factorize the existing values. Thus, the above cost function can be reduced to:

$$\mathcal{L}(S, R, B) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{m} I_{ij} (B_{ij} - S_i^T R_j)^2$$

(9)

Here, $I_{ij}$ is an indicator function that takes value 1 if $B_{ij}$ exists and 0 otherwise.

Users in social networks mostly trust their friends [70], consequently, we assume that objects in IoT trust their social network friends as which specified in Section III-B. Therefore, depending on how much a trustor object is similar to its friends based on the trusting behavior function $\Gamma$, reconstruction of matrix $B$ relies on both trustor’s features and its friends’ features. So, we can redefine the cost function as:

$$\mathcal{L}(S, R, B) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{m} I_{ij} \left( B_{ij} - g(\alpha S_i^T R_j + (1 - \alpha) \sum_{k \in F(i)} \Gamma_{ik} S_k^T R_j) \right)^2$$

(10)

where $\alpha$ balances between the two mentioned factors, and $\Gamma$ function is calculated according to Equation [6]. $k \in F(i)$ shows the social network friends (neighbors) of trustor $u_i$. The argument that passed to $g(\cdot)$ is employed to predict missing values of $B$, which may exceed the valid range $(0,1]$, hence, it is mapped through a nonlinear logistic function $g(x) = 1/(1 + \exp(-x))$ to rebound to the valid range.

One can also add a regularization term to the cost function to avoid the over-fitting issue. Finally, the sum-of-squared-errors cost function with quadratic regularization terms could be defined as:

$$\mathcal{L}(S, R, B) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{m} I_{ij} \left( B_{ij} - g(\alpha S_i^T R_j + (1 - \alpha) \sum_{k \in F(i)} \Gamma_{ik} S_k^T R_j) \right)^2$$

$$+ \frac{\lambda_S}{2} \| S \|_F^2 + \frac{\lambda_R}{2} \| R \|_F^2$$

(11)

where hyper-parameters $\lambda_S, \lambda_R > 0$ are $S$ and $R$ latent variance ratios. As, finding the global optimum is often difficult, Stochastic Gradient Descent (SGD) could be applied several times to get the best local minimum [64]. Also, this cost function has an attractive probabilistic interpretation with Gaussian observation noise (for more detail, see [68]).

Now, a trustor node $u_i$, by having the bi-adjacency matrix $B$, can acquire the two latent feature matrices $S$ and $R$; then, it can utilize the following equation in order to reproduce $B$, as:

$$\hat{B} = g(S^T R)$$

(12)

where $g$ is the non-linear logistic function.

Afterward, the trustor $u_i$ can extract the $i^{th}$ row of $\hat{B}$ and sort it to obtain a vector of trustees ordered by their trustworthiness value. Consequently, a trustor can select the most trustworthy trustee to dispatch its task. In this way, a trustor can predict which service provider (trustee) is most reliable and best suited for it.

**E. How our Method Addresses the Requirements?**

In this section, we demonstrate how the proposed trust management mechanism meets the requirements discussed in
Section I-A We use the locally centralized, globally distributed architecture to show how a trustor can predict the most trustworthy trustee for its requested service in a scalable and distributed manner. As depicted in figure 2 we assume each SloT object is a member of a physical group which has a central node. For example, considering a smart home as a group, it contains not only lightweight objects such as smart light and smart thermostat but also non-lightweight objects like smart TV and Google Home assistant. Thus, these groups at least have one non-lightweight node which could be selected as the central node of its group. Also, since each group is owned by just one individual or organization, all the SloT objects in a group have the same behavior as their owner does. So, it is not necessary for all trustor nodes to perform matrix factorization themselves. Instead, whenever nodes in a group need to select an external service provider, the group leader (central node of the group) collects prior experiences from the other nodes of the group and also from other groups to perform the matrix factorization. Then, the central node gives each node its related row from the reconstructed bi-adjacency matrix $B$. In this way, each group is locally centralized, but the whole system is globally distributed, and the lightweight SloT devices do not have to factorize any matrices which is a heavy computational task or save any data more than their own experiences.

As mentioned earlier, the mechanism of matrix factorization intrinsically alleviates the data sparsity. We assume that each node in SloT has an identification number (like MAC address), so its trust information could be saved along with its identifier. Consequently, if a node decides to leave and/or rejoin the network, its trust data will not be lost. Thus, our trust management protocol deals with nodes which perform whitewashing attack. Furthermore, it is obvious that selecting an appropriate threshold for Hellinger distance will lead to construction of a suitable network between trustors. This social network specifies the friends of each node in such a way that bad behavior nodes retire from the network, and none of the mentioned attacks (in section I-A) could affect our prediction protocol. We will discuss about the malicious nodes performing these attack in details in the next section.

IV. Experimental Evaluation

In this section, we evaluate the performance of the proposed trust management system in three different scenarios. First, we investigate the quality of the matrix factorization mechanism. Then, we follow the evaluation procedure outlined in [28], to assess the performance of our trust management model. Finally, we apply our trust management mechanism to a real-world SloT application in order to exhibit the utility of our protocol.

A. Accuracy of the Matrix Factorization Mechanism

To test the accuracy and quality of the matrix factorization model, we have performed several experiments on the Epinions dataset. We also compare the proposed method with the best existing trust prediction methods.

1) Dataset

Epinions.com is a well-known review website that was established in 1999. Users can review products and assign them integer ratings from 1 to 5. Users also express their Web of Trust, i.e., each user maintains two lists of its trusted and blocked users [71]. This part of the dataset is not used in our model because this information is within privacy limits and is not always in hand. Instead, we employ our Hellinger-based social network, constructed only from the rating matrix. This dataset consists of 922,267 ratings given by 22,166 users to 296,277 items, which leads to an extremely sparse rating matrix with density percentage of 0.014. Figures 3 and 4 show the dataset item-rating and user-rating distributions, respectively. The item-rating distribution reveals that most of the items did not have the chance to be seen by numerous users. Also, the user-rating distribution unveils the fact that there are a few users who rate too small or vast amount of items. On average, each user rates 41,607 times in her era. Figure 5 illustrates the users’ behavior in conjunction with rating values. It implicitly shows that users mostly give high rates to items.

2) Settings & Metrics

We used predictive accuracy and classification accuracy measures for evaluating the proposed matrix factorization method.

www.cse.msu.edu/ tangjili/trust.html
Accuracy of a prediction system measures the closeness of the methods predicted ratings to the true (actual) user ratings [72].

**Mean Absolute Error (MAE)** is the standard metric for computing predictive accuracy [73]. It measures the average absolute deviation between the users true rating and the method’s predicted rating, as defined in:

\[
\text{MAE} = \frac{\sum_{i,j} |B_{i,j}^{\text{pre}} - B_{i,j}^{\text{act}}|}{N} \quad (13)
\]

Where \(N\) is the number of nonzero elements in the rating matrix \(B^{\text{act}}\).

**Root Mean Squared Error (RMSE)** is another popular predictive accuracy metric. It is the square root of the average of squared differences between true and predicted ratings, and is defined as:

\[
\text{RMSE} = \sqrt{\frac{\sum_{i,j} (B_{i,j}^{\text{pre}} - B_{i,j}^{\text{act}})^2}{N}} \quad (14)
\]

Where \(N\) is the number of nonzero elements in matrix \(B^{\text{act}}\).

Although both MAE and RMSE express average prediction error, RMSE can be more relevant in cases that large errors are intolerable. Whereas the errors are squared before they are averaged, the RMSE gives higher weights to higher errors [74]. From the Equations (13) and (14), we can observe that the smaller the value of MAE or RMSE is, the higher the model performance (in terms of accuracy) will be. For comparing with other methods, we use RMSE, Coverage, Precision, and F-measure.

**Coverage** is the percentage of ratings which the method has been able to generate predictions. Systems with higher coverage are more advantageous, since there are more decisions they are able to help with [73, 75]. Coverage can be defined as:

\[
\text{Coverage} = \frac{\# \text{ ratings that system can make prediction}}{\# \text{ available ratings (items) to predict}} \quad (15)
\]

**Precision**, within this context, is associated with the normalized form of RMSE and obtained as follows [76].

\[
\text{Precision} = 1 - \frac{\text{RMSE}}{\text{RMSE}_{\text{max}}} \quad (16)
\]

where \(\text{RMSE}_{\text{max}}\) is the maximum possible value for the RMSE error.

**F-measure** is a harmonic mean of precision and coverage to consider both metrics into a single evaluation metric. It is defined as [76]:

\[
F\text{-measure} = \frac{2 \times \text{Precision} \times \text{Coverage}}{\text{Precision} + \text{Coverage}} \quad (17)
\]

The best desired setting for our algorithm can be achieved when we set the size of latent features \(L\) to 4 and the parameters \(\alpha\) in Equation (10) and \(\beta\) in Equation (9) to 0.4 and 1, respectively. We also use 75 percent of the Epinions data as the training set and the rest of the instances for testing. The reason for picking such values for the aforementioned parameters will be discussed later in the subsequent sections. The hyper-parameters \(\lambda_3\) and \(\lambda_R\), in Equation (11), are set to 0.001 as proposed by [64], and the maximum number of iterations for the stochastic gradient descent phase was usually around 60.
a specific trustee relies on a linear function of both trustor’s features and its friends’ features using a weighting factor $\alpha$. The lower the $\alpha$ is, the more impact of trustor’s friends will be on trust prediction. According to Equation (6), the aforementioned impact introduced as the linear combination of centrality of the friends and similarity between them with the weighting factor $\beta$. In Figures 6a and 6b, we analyze how the changes of $\beta$ can affect the prediction accuracy in terms of MAE measure. Also, we introduce binary trust model and assess its MAE. Since both the actual and the predicted rating could be between 1 and 5, the maximum possible MAE is 4.

The binary trust model is a model that the similarity and centrality of nodes do not affect the trust pattern similarity between nodes, and just the friendship between nodes in the social network is considered. That means, for the binary trust model, $\Gamma$ is equal to 1 in Equation (10). The magenta and light-green straight dashdot lines in Figure 6 show the MAEs of binary trust models using Hellinger-based users network and Epinions dataset users network, respectively. As depicted in Figure 6, MAE of our Hellinger-based binary trust is less than the MAE of Epinions dataset binary trust model. This observation specifies that the social network extracted based on our proposed Hellinger distance provides valuable information about trustors connections and their trust behavior. Moreover, our prediction mechanism based on trust pattern similarity, regardless of which centrality and similarity measures it uses, outperforms both binary trust models. In both figures, which contain all the different combinations of similarities and centralities, it is shown that by increasing the $\beta$ value, consequently by decreasing the impact of user centralities, the accuracy of prediction protocol strictly increases. It illustrates that considering nodes’ centrality does not help the prediction mechanism. Furthermore, separation of Figure 6a from Figure 6b gives a better sight of similarity measures differences, irrespective of centrality measures. Comparison of similarity measures in combination with both degree and BLC centrality measures shows that the connection similarity has the worst MAE by increasing $\beta$, and Hellinger similarity has the least MAE with both centrality measures.

Figure 7 restates the efficiency of the proposed prediction method for different values of $\beta$, separated by similarity measure. This figure demonstrates that BLC centrality, which is a local measure, is more suitable to show trust pattern similarity than degree centrality; because in higher centrality values (i.e. lower $\beta$), degree-based MAE is higher than BLC-based MAE.

According to Figure 2 and Equation 5, our prediction protocol with $\beta = 1$ has the lowest error compared to the binary trust model and centrality based prediction ($\beta = 0$), without the impact of similarity. It affirms that incorporating nodes’ similarities significantly enhance the effectiveness of the prediction mechanism.

In Figure 8, we got very similar behavior for our prediction mechanism in terms of RMSE measure, as analogous to MAE figures. This indicates that the results are consistent.

In order to analyze how much node’s friends might affect the prediction protocol, one can leverage the idea of the Elbow method, which is designed to help finding the best number of clusters in Clustering Analysis, to find the best value of $a$ in Equation 10. In Figure 6b, we can see that until $a = 0.4$, the gradients of both lines are high, but from there on, adding to $a$ does not help the precision much more. Hence, $a = 0.4$ is selected as the best setting.

As depicted in Figure 10, increasing latent features size improves the accuracy of our prediction, however it imposes extra overhead because of larger latent feature matrices. According to the application of prediction protocol, one can select the appropriate latent feature size by trades off between more accuracy and light-weight process. Since it seems that the testing error reaches its expected (true) error value at $L = 4$, which is not too large to cause intolerable overhead, we use this value ($L = 4$) to learn $l$-dimemional (trustors and trustees) latent feature matrices.

Figure 11 shows that using more training data generally improves the precision of the prediction, which is somehow obvious. In general, there is not an approved ratio (percentage) for division of training versus testing sets. Less testing data results in non-generalized model (i.e. high variance). On the other hand, less training data causes that training loss no longer bears relation to test loss (high bias) and brings overfitting problem. However, this problem becomes less severe when the size of training data increases. Therefore, between 90:10, 80:20, and 75:25 splits, we chose 75:25 split, since our dataset is large.
In order to show the effectiveness of our prediction method in comparison with the best existing methods, we evaluate the methods in terms of RMSE, coverage, precision, and F-measure. To the extent of our knowledge, there is not any other IoT/SloT trust management model, which utilizes matrix factorization related mechanism. Therefore, we compared our method with relevant social network methods. The best existing methods in the literature for comparison are (1) Item-based [77], (2) SoRec [78], (3) TrustWalker [79], (4) Similarity-based [41], (5) Centrality-based [42], and (6) SocialTieTrust [42].

As it is depicted in Figure 13, our method clearly provides very low RMSE, since the other methods have very higher RMSE. SocialTieTrust, the second-best method in terms of RMSE, has 0.31 more RMSE than our method. As Koren states in [79], even small improvement in RMSE could have significant enhancements. Since for all competing methods, $RMSE_{max}$ is equal to 4, and according to the combination of RMSE and $RMSE_{max}$, our method is selected as the best candidate in terms of precision. SocialTieTrust and TrustWalker are the second and third best methods, respectively, with slight differences (in terms of precision). Our method advantageous is achieved by considering Hellinger-based social network of trustors as well as using inversion of Hellinger distance as the similarity measure. Moreover, our proposed method's coverage is 100%, that is the best coverage a prediction mechanism can provide. Other methods, except for TrustWalker and Item-based, provides 100% coverage too. Eventually, our proposed method outperforms all the other competing methods in terms of F-measure. These aforementioned results appear to be the ideal ones among all the previously obtained results. Therefore, we may conclude that the implicit social information from Hellinger distance can be incorporated into matrix factorization to perform predictions effectively.

B. Trust Protocol Performance

As we mentioned in Section 11 there are few trust management methods which we can compare our method with. Hence, we follow the same simulation evaluation strategy as in [23] which is one of the most noteworthy works in the SloT trust management literature. Our goal is to investigate the performance of our trust management mechanism using the best setting as analysed in the previous subsection and the two best centrality-similarity measurement pairs, BLC-Bayesian and BLC-Hellinger, as shown in Figure 8, in a hostile SloT environment.

1) Settings & Metrics

We conducted several experiments through 150 hours simulation to validate the convergence, accuracy, and attack resiliency properties. For determining the interaction-contact time, the simulation interaction pattern follows a bounded power-law distribution ranging between [10 mins, 2 days] with the slope equals to 1.4 which leads to about 4 hours interaction-contact time. It is worth noting that this setting is close to real traces generated in [80].

We consider a SloT environment with maliciousness factor $\lambda \in [10\%, 50\%]$ which will be selected randomly in each simulation execution. The maliciousness factor $\lambda$ indicates the percentage of malicious nodes relative to all nodes. A malicious
node can perform any kind of attacks, addressed in section I-A.
Our SIoT simulation environment consists of 70 trustees and 100
trustors to which form 14 and 20 physical groups, respectively.
Although SIoT nodes can leave or join the SIoT network anytime,
the number of things remains fixed throughout the simulation.

During the simulation, the trustor groups form a social net-
work of trustees as explained in Section III-B then perform the
matrix factorization mechanism and predict missing values of
the bi-adjacency matrix L as detailed in Section III-D every 24
hours. We believe that performing matrix factorization once a
day (i.e. every 24 hours) is not computationally a heavy task, also
the trust management system does not need to perform it more
frequently. Each SIoT node has an objective (ground) trustworth-
iness value in the interval [1, 5] which specified randomly with
respect to the level of its malicious behavior at the beginning of
the simulation. For example, malicious nodes receive objective
trustworthiness values closer to minimum of the interval (i.e.
1), and non-malicious nodes acquire objective trustworthiness
values near maximum of the interval (i.e. 5). The trustworthiness
value of SIoT nodes remains unchanged during the simulation
except for malicious nodes which perform opportunistic service
attack. Still, we permit the SIoT nodes to change their behavior
(trustworthiness value) ±0.3 of one unit randomly in order to
simulate the behavior tolerance of actual SIoT devices. As
mentioned earlier in Section I-A trustees measure and rate
the trustworthiness of trustees based on the past service usage
experiences. This rating scales between 1 and 5 and would be
maintained to benefit the future decisions. Our proposed trust
management mechanism set the initial trustworthiness of all
SIoT nodes to middle of its range (i.e. 3).

2) Evaluation Results
This subsection first investigates the effect of β, similarity/central-
ity contribution parameter, on trustworthiness evaluation
operation. Then, changes to the similarity method will
be studied, and hostility changes will be examined finally. In
this experiment, we analyses the performance of our selected
mechanisms through trust evaluation results of trustor nodes
toward three trustee nodes randomly picked from a 30% hostile
SIoT environment. The first trustee node is a non-malicious
node which its objective trustworthiness is equal to 4.5 (out of
[1, 5]). The second and third trustees are malicious nodes. The
former malicious node does not perform opportunistic service
attack, and it’s trustworthiness value remains fixed on 1.5. But,

\[ L = 4, \alpha = 0.4, \text{and } \beta = 1 \]
the latter performs opportunistic service attack and its objective trustworthiness value decreases from 4.5 to 2.5 in the middle of the simulation.

Figure 14 shows trustworthiness evaluation toward a non-malicious node. The colorless area around lines exhibits the empirical confidence intervals with 90% confidence. The trustworthiness value of trustors toward this trustee node starts at 3 and approximates to 4.5, which is the benign trustee’s trustworthiness value. Predictably, BLC-Bayesian setting converges with more confidence and faster with $\beta = 0.5$, also, BLC-Hellinger performs better with $\beta = 1$ as expected from Figures 8 and 9. Furthermore, we observe that as trustworthiness converges, it fluctuates around the objective trustworthiness with more confidence.

Figure 15 demonstrates trustworthiness evaluation toward a random malicious node which does not perform opportunistic service attack. As it should, the trustworthiness value decreases to approach the objective value. Again, we can observe that BLC-Bayesian setting performs better with $\beta = 0.5$ and also, BLC-Hellinger with $\beta = 1$. However, the difference between the two similarity settings, Bayesian and Hellinger, is not so significant. The other phenomenon that attracts our attention is that the mechanism underestimates the trustworthiness value just after it reaches the objective trustworthiness. The reason for this phenomenon is that trustors do not trust and use malicious trustees just after the trustworthiness values decrease, so no further usage experience affects the trustworthiness value, but matrix factorization mechanism still reduces the trustworthiness value due to trustors’ past experiences. Figure 15b shows 20 hours of low confidence since $\alpha = 55$ for BLC-Bayesian setting. This case
Fig. 16: Effect of $\beta$ and centrality-similarity measures on our trust management trustworthiness evaluation of a randomly picked malicious trustee (performing opportunistic service attack)

Fig. 17: Effect of centrality-similarity and $\beta$ measures on our trust management trustworthiness evaluation of a randomly picked benign trustee

Fig. 18: Effect of centrality-similarity and $\beta$ measures on our trust management trustworthiness evaluation of a randomly picked malicious trustee (not performing opportunistic service attack)

Fig. 19: Effect of centrality-similarity and $\beta$ measures on our trust management trustworthiness evaluation of a randomly picked malicious trustee (performing opportunistic service attack)
Fig. 20: Effect of malicious factor $\lambda$ on our trust management (trustworthiness evaluation) efficiency using our best setting (BLC as centrality, Hellinger as similarity, $L = 4$, $\alpha = 0.4$, and $\beta = 1$)

Next, we investigate the effect of malicious factor $\lambda$ on our mechanism efficiency. For sensitivity analysis, we change the SIoT environment hostility from low hostile ($\lambda = 10\%$) to a very hostile environment ($\lambda = 50\%$). Figures 20a to 20c demonstrate the trustworthiness value of trustors toward randomly picked trustees as mentioned before through our best trust management mechanism setting which utilizes Hellinger as the similarity and no effect of centrality ($\beta = 1$).

Figure 20a is trustworthiness evaluation toward a benign trustee. We can see that all three lines approach to the (trustee’s) objective trustworthiness value. However, we observe that the green line falls down excessively at $t = 75$, because of lots of malicious nodes which perform opportunistic service attack and change their behavior that time, but then it keeps on converging to the objective trustworthiness value, as we expected. An interesting observation in Figure 20a is that for $\lambda = 10\%$, our proposed trust management overestimated the trustworthiness value of a trustee, however, it does not estimates the value, greater than trustworthiness value of more trusted nodes. As mentioned in [81], trust overshoot destroys the stability of the trust management system. Indeed, the trust management system preserves the order of trustees in terms of their trustworthiness values (among the network nodes).

Moreover, Figure 20b indicates that our trustworthiness evaluation mechanism converges toward a trustee’s objective trustworthiness accurate, yet quick. We can see that our mechanism confidence and convergence rate are higher in a less hostile environment. But, as the malicious factor increases, the protocol is still acceptable. These results demonstrate our mechanism’s high resiliency toward various attacks even in a highly hostile SIoT environment.

C. SIoT Application Performance

This section evaluates the effectiveness of our proposed trust management mechanism through a real-world SIoT application [92, 93]. We aim to run such a scenario on top of our protocol in order to validate its robustness against the cold start problem. We compare the performance of our system with a random system in which trustors select their service providers among all available trustees randomly.

1) Settings & Metrics

We consider a smart city in which people benefit from smart health-care systems. In addition, individuals may have health-care applications installed on their mobile phones. Providing air pollution information for individuals who suffer from respiratory (breathing) diseases is one of the applications of this health-care system. We consider Alice, who is a respiratory patient, and wants to go jogging. Alice’s doctor advises her not to get into polluted areas. So she let her smartphone connect to sensor devices in an area she is about to step into and alert her if any air pollution detected. She knows that there are many malicious and imperfect SIoT sensors which provide wrong or inaccurate data. Besides, her smartphone as a trustor is entirely strange in the environment that she runs in, so it needs to decide which of those new trustees are reliable. This situation causes the cold start problem for the trustor (Alice’s smartphone). We assume that the whole SIoT system utilizes our trust management mechanism with the best setting described in the last section. We want to analyze how her smartphone behaves in this situation.

2) Evaluation Results

Figure 21 compares our mechanism against a random method which picks trustees randomly and without considering the trustees’ trustworthiness value. We classify trustees by their
the convergence, accuracy, and attack resiliency properties of different settings of our mechanism in a hostile SIoT environment. Our simulation results demonstrated that our proposed mechanism accurately converges to the trustee’s ground trustworthiness value and resists the malicious nodes (performing different types of attacks). We have further shown the utility of our proposed trust management mechanism through a real-world SIoT application. The simulation showed that our proposed mechanism is successful in helping trustors in order to find trustworthy trustees. Also, it certainly outperforms the random model and mitigates the cold start problems.

As future work, we plan to model the SIoT with hypergraphs, because we have found that by representing some social relations with naive edges (in traditional graphs), we may lose some information [84]–[87]. From the experience of this paper, we believe that finding more meaningful and deeper social relations between SIoT nodes helps us to understand their trust pattern similarities better.

V. CONCLUSION

In this paper, we proposed a novel trust management mechanism in SIoT. We employed Hellingler distance to build a social network of trustors. The social relations in the network shows behavioral trust similarity among network nodes. The trustworthiness value of trustees predicted using both trustor’s experience and its friends’ feedbacks (analogous to recommendations). In order to utilize the feedbacks, we designed a social trust model, using centrality and similarity measures. To the best of our knowledge, it is the first paper using matrix factorization technique to predict trustworthiness values of trustees in SIoT. Our proposed mechanism is globally distributed and considers the data sparsity problems and resource-constraint of IoT devices. We demonstrated the effectiveness of our prediction mechanism by evaluating its accuracy using different settings. We found that the best accuracy occurs when we use inversion of Hellingler distance as the similarity measure in our proposed social trust model, without considering the impact of centrality. Then we compared our prediction mechanism with the best existing methods in the social network literature and the results showed the superiority of our proposed method in terms of RMSE, coverage, precision, and F-measure. To investigate the applicability of our trust management mechanism, we evaluated the number of times that each system selects each group. Figure 21 shows the number of times that each group has been used by Alice’s smartphone did not discover it until the last minutes of the simulation. One can conclude that our mechanism successfully helps trustors to detect and exploit most trustworthy trustees, and definitely outperforms the random model even for newcomer nodes (i.e., cold start situations).

Fig. 21: Performance comparison of our proposed trust management, using its best setting, versus a random system in a real-world SIoT application scenario. Y-axis shows ground trustworthiness values that represent trustee groups, and X-axis shows the number of times that each system selects each group. The numbers on bars show the order of selecting each group.

| # Utilization | Our Mechanism | Random System |
|---------------|---------------|---------------|
| 0             | 8             | 15            |
| 1             | 1             | 8             |
| 2             | 1             | 2             |
| 3             | 1             | 1             |
| 4             | 1             | 1             |
| 5             | 1             | 1             |
| 6             | 1             | 1             |
| 7             | 1             | 1             |
| 8             | 1             | 1             |
| 9             | 1             | 1             |

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