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User Reputation computation Method Based on Implicit Ratings on Social Media

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Abstract

Social network services have recently changed from environments for simply building connections among users to open platforms for generating and sharing various forms of information. Existing user reputation computation methods are inadequate for determining the trust in users on social media where explicit ratings are rare, because they determine the trust in users based on user profile, explicit relations, and explicit ratings. To solve this limitation of previous research, we propose a user reputation computation method suitable for the social media environment by incorporating implicit as well as explicit ratings. Reliable user reputation is estimated by identifying malicious information raters, modifying explicit ratings, and applying them to user reputation scores. The proposed method incorporates implicit ratings into user reputation estimation by differentiating positive and negative implicit ratings. Moreover, the method generates user reputation scores for individual categories to determine a given user's expertise, and incorporates the number of users who participated in rating to determine a given user's influence. This allows reputation scores to be generated also for users who have received no explicit ratings, and, thereby, is more suitable for social media. In addition, based on the user reputation scores, malicious information providers can be identified.

Keywords: Social media, user reputation computation, social media activity analysis, trust

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1. Introduction

Social media services have made considerable advances lately as a communication hub, as users actively communicate with one another due to advances in internet technology and mobile devices. Internet technology provides users with fast access to social media services, and the quick and easy ways to generate and access information via mobile devices, while advances in mobile devices have allowed users access to social media at anytime and anywhere. As a means of generating, consuming, and sharing information, social media services are being developed actively, and the number of service users is growing rapidly [1, 2, 3, 4, 5]. While conventional media such as newspaper, magazine, TV, and radios, deliver information one way, social media services are two-way communication media, in which a user can be both an information provider and consumer [6, 7]. Social media has the characteristic of fast dissemination of information because users can generate, process, and share information directly, and the process is simple and convenient. Because of these characteristics, social media services are used by a great number of users [8, 9, 10, 11, 12, 13, 14].

Given the above, social media services offer users the advantage of acquiring a lot of information in a short period of time. However, because of the ease of information generation and anonymity, malicious information providers can easily generate inaccurate information and disseminate it fast. This has led to indiscriminant dissemination of unreliable information [15, 16]. Accordingly, a method to determine trust in the information shared on social media has become necessary. Moreover, an evaluation method that considers the trust in the information provider as well as in the information is necessary, because non-experts can provide invalid information. Most users want reliable information, and social media can more effectively provide this to users by determining the trust in the information.

Many studies on determination of trust in users on social media have been conducted. The methods proposed in previous studies, including the IRIS method [17], Multimedia Social Networks Trust Model (MSNTM) [18], and Trust-Relation Social Network (TRSN) [19] evaluate trust among users and establish trusted networks using only explicit aspects such as user profiles, relations among users, and explicit elements. However, users' explicit rating behaviors are relatively rare in the information consumption and sharing process on social media, and most users do not renew their profiles. Consequently, it is difficult to estimate reputation accurately on social media with existing user reputation computation methods.

Users engage in a large number of social activities including posting contents, writing comments, rating, reading, sharing, subscribing, bookmarking, and recommending in the information generation and consumption process on social media. Social network site also provide rich sources of naturalistic behavioral data [20, 21]. The social activities involved in the process of generating and exchanging information can be extracted as information consumers' implicit ratings. The existing methods such as those in [22, 23] estimate user reputation using only limited evaluative elements on social media, where a wide range of interactions take place. This poses challenge in determining user reputation or trust in the social media environment.

As generating and delivering information have become easier and faster due to advances in mobile devices and internet technology, the generation and dissemination of unreliable information by malicious users also became easier and faster. Consequently, it became important to identify users with malicious intent, and minimize or eliminate their influence to promote safe exchange of information. The methods proposed in previous studies [24, 25] determine user's malicious intent using only explicit evaluative elements or a limited number of behaviors.

To solve these limitations, we propose a user reputation computation method suitable for social media environments by extracting implicit ratings based on social media activities. Specifically, user reputation is estimated by considering both explicit and implicit ratings, and user activities are scored for estimation of implicit ratings. Explicit ratings are modified, by identifying malicious information raters and excluding their ratings, before incorporating them into reputation. In order to determine a user's expertise in individual specialty categories, reputation data is calculated by category. A user's final reputation score is generated by incorporating the user's influence based on the number of raters, and malicious information providers are identified based on the generated reputation score. Moreover, a user's specialty category is identified based on category-specific reputation scores. The proposed method addresses the problems associated with existing methods of estimating user reputation based only on user profiles, explicit relations, and explicit evaluative elements in order to increase suitability to the social media environment.

This study is organized as follows. Section 2 offers a literature review, and Section 3 describes the proposed user reputation computation method. Section 4 discusses the performance evaluation of the proposed method, and Section 5 provides conclusions.

2. Related Work

2.1 Explicit Reputation

Explicit elements refer to clearly expressed elements such as numeric ratings, user profiles, and explicit relations. Existing user reputation computation methods estimate trust in and reputation of users using explicit elements. Hamdi et al. proposed the IRIS method to estimate trust between directly connected users [17]. The method takes into account the type of relationship, similarity of interest, and explicit ratings. For instance, relations among users such as family, friends, coworkers, and neighbors are scored by type of relation. Family members are assigned the highest scores, and other relations are classified according to the intimacy level (more intimate relations are scored higher). Regarding scoring an interaction, 0 and 1 are assigned when a user is and is not satisfied, respectively, with an interaction with another user such as exchanging information. Regarding scoring similarity of interest, a higher score is assigned when the number of shared interests is higher. User trust is determined based on these three elements.

Zhang et al. proposed MSNTM to calculate the trust among users [18]. The method calculates trust between users by taking into account similarity of users' hobbies, evaluation score for information, and the trust score for information. Hobbies are one of the explicit elements that users include in their profiles. The evaluation score for information is the score assigned by the consumer after information exchange to the provided information. The trust score for information is the score assigned by the user who used the information and evaluated the trust in the information. All of the elements considered when calculating user's trust are explicit elements – the profiles users fill out when they register and the evaluation scores they assign explicitly. The trust between indirectly connected users is calculated based on direct trust. Therefore under MSNTM, calculation of direct trust is instrumental when calculating trust between users or in recommendation systems or sharing sites on social networks.

Louati et al. proposed TRSN to estimate trust between indirect users in the social network environment and establish trusted social networks [19]. The method calculates "social measure" when estimating the trust in users as a basis of building a trusted network. The social measure is evaluated by taking into account directly connected users and similarity of user profiles. Therefore, this method calculates trust on a social network by considering only explicit relations and user profiles.

2.2 Implicit Reputation

When a user shares another user's information or makes a decision based on the information on social media, information on the reputation of the user who provides the information is required for judging the trust in the user. On social media, a great number of interactions take place in the process of users generating and consuming information. Therefore, considering implicit evaluative elements when estimating user reputation and trust can address the problems of inaccuracy and underutilization of unique characteristics of the environment of social media associated with the user reputation computation methods based solely on explicit evaluative elements.

Han et al. proposed a method to estimate user reputation using user activities on YouTube [22]. As social networks are formed among video content, content provider, and consumer, user reputation is calculated using the PageRank algorithm developed by Google. The calculation of reputation involves application of three types of links generated on the content: the links based on subscription, sharing, and adding to the favorite list. In other words, user reputation is estimated based solely on those three social media activities. The data on a video content on YouTube includes ratings, addition to the favorite list, comments, user subscriptions, and related content inspired by the given content. Posting content and engaging in social media activity establish implicit relationships between content and user and between user and user.

Eirinaki et al. proposed a method to estimate trust in a user to suggest useful content and trustworthy users on social media [23]. The method estimates user reputation based on explicit and implicit links among users. User reputation is estimated by taking into account the estimated relationship between two users and time interval between their interactions.

2.3 Malicious User Identification

As generation and delivery of information become easier and faster due to advances in mobile devices and internet technology, a large amount of data has become available in a short period of time. Meanwhile, inaccurate and unreliable information are also easily generated by malicious users and disseminated fast. This has led to wide spread dissemination of unreliable information online. Accordingly, for safe exchange of information on social media, user reputation scores for judging the quality, expertise, and safety of information are required. Moreover, a method for identifying users with malicious intent and minimizing or eliminating the intent is necessary to establish trusted social networks.

Hosseinmardi et al. proposed the method to detect users who post malicious comments on social media [24]. The method classifies users into four types by extracting positive and negative words from users' comments to analyze user activity. The first type is the extremely negative user, who has posted at least three negative comments without posting any positive comments. The second type is the extremely positive user who has posted at least 10 positive comments. The third type is the user with both positive and negative attributes, who has posted at least three negative comments and at least four positive comments. The fourth type is the user who cannot be classified in any of the above categories.

Yan et al. proposed the distributed trust method for controlling unwanted contents and malicious content [25]. The method observes user activities using the distributed trust management system, and it detects and controls the malicious activity of distributing the content unwanted by other users.

2.4 Problems of Existing Methods

The previous studies based on explicit evaluative elements evaluate the trust in users and establish trusted networks based on user profiles, relations among users, and explicit ratings. Users' explicit evaluative actions are actually relatively rare compared to the amount of consumption of information generated on social media. Users rarely renew the status of explicit relationships and profiles on a regular basis, although they change over time. Consequently, existing user reputation methods are inadequate for accurately evaluating the trust in users who are currently active on social media. For this reason, a user reputation method is more suitable in the social media environment, where countless consumer activities take place, by taking into account implicit ratings in addition to explicit ratings.

Among the previous studies that employed implicit evaluative elements, Han et al. [22] calculated user reputation considering only three types of social media activities – subscribing, adding to the favorite list, and writing a comment. Moreover, the user reputation computation method proposed by Eirinaki et al. [23] was based only on writing contents and content uploads. These are examples of inadequate representation of social media activities to estimate user reputation, given that many more meaningful activities takes place on social media in addition to the these activities. Therefore, a method of estimating user reputation by incorporating a variety of activities observed on social media is required in order to accurately determine user reputation in the social media environment.

The method proposed by Hosseinmardi et al. [24] detects malicious users by extracting positive and negative words in user comments on social media and applying the criteria they developed. The method have shortcomings of considering only a few elements, the use of the criteria they developed themselves, and the lack of scoring system for the degree of maliciousness. The method proposed by Yan et al. [25] determined maliciousness of the information provider based on how information consumers handle the content to deduce whether the provider distributed the information unwanted by information consumers. While the method employed the implicit element on social media, it did not incorporate various social media activities that represent uniquely social media characteristics. Therefore, a method is required for identifying malicious users more suitable to social media through incorporation of characteristics of social media of highly active interactions among users.

3. Proposed User Reputation computation Method

3.1 System Architecture

Existing user reputation methods calculate user reputation values primarily using explicit elements only. Therefore, when explicit relations and explicit ratings are unavailable, it is difficult to determine trust in users. Since a variety of social media activities take place on social media, a user reputation method suitable for such an environment is required. Moreover, studies on detecting user malice also incorporate only explicit ratings or limited types of activities. The present study estimates trust by analyzing social media activities and deriving implicit ratings in order to address the limitations of explicit ratings. The study proposes a user reputation computation method more suitable for use in the social media environment than are the existing user reputation methods. Furthermore, the method provides more reliable user reputation information by modifying explicit rating values, and identifying malicious users based on implicit ratings in order to be more effective in malicious user identification.

Fig. 1 shows the overall process of the proposed method. In the content generation and consumption stage, content providers generate content and other users consume the content that the provider has created. In the consumption process, social activities take place and they are classified as implicit and explicit actions. In the social activity analysis stage, to estimate users' implicit ratings, the consumption activities that occur when users consume the content generated by information provider are classified into positive and negative actions, each of which is further classified into varying levels and scored accordingly. As an obvious part of reputation, explicit ratings are also incorporated into reputation along with implicit ratings; however, the values are modified based on the identification of malicious information raters. In the stage of determining the trust in the content, a comprehensive evaluation score is calculated by taking both implicit and explicit ratings; in the stage of determining the trust in a user, the user's expertise by specialty category is determined by generating the user's reputation score by specialty category, and incorporating the user's influence based on the number of raters for the user's content. Finally, in the user information saving stage, the information on the trust in user and the user's status regarding malicious information provision is saved.

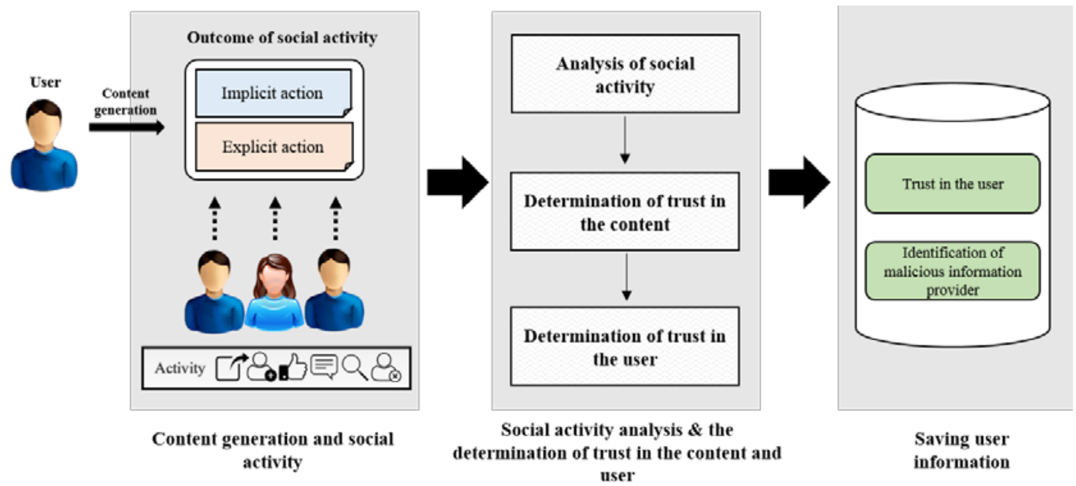

Fig. 1. Process of the proposed method.

3.2 Social Activity Analysis

To address the insufficiency of explicit elements on social media and calculate user reputation suitable for social media, the proposed method estimates implicit ratings through the analysis of social activities. In the social media environment, a user generates content, and other users consume and share the content in a variety of ways. Content consumers use the content based on the quality of the content, user's preference, and interest, and engage in various interactions with content provider. In the interaction process, which is shown in **Fig. 2**, various social activities take place.

The proposed method calculates the reputation of the user who provides the content based on other users' social activities in relation to the content. The users express their opinions with social activities including viewing and liking the content, adding it to their favorites lists, and sharing the content. In other words, users' social activities regarding contents can be regarded as the users' implicit rating activities. The explicit ratings are visible in numbers such as ratings. Although explicit ratings are meaningful elements in user reputation, most users rarely participate in rating in general, and ratings can be misused by malicious users. To address these problems, implicit evaluation scores need to be incorporated through the analysis of users' information consumption activities and social activities.

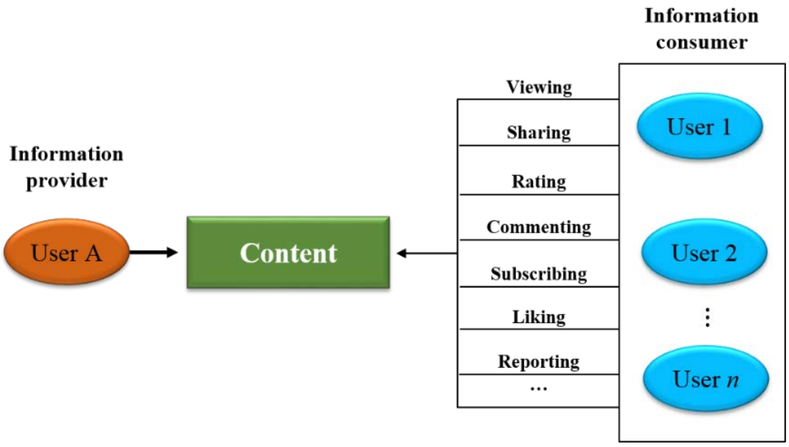

Fig. 2. Users' social activities on social media

The proposed method classifies and scores social activities in order to extract users' social activities on a content item into implicit ratings. Social activities are mainly classified into positive and negative actions. The positive actions take positive scores, while negative actions are assigned negative scores, and more negative actions on a content item result in a lower score thereon. Both the actions classified as positive and negative are further classified into multiple levels for scoring. The content is assigned a higher score when more proactive actions are taken about the content, as they are considered more meaningful actions.

The proposed method classifies the social activities into positive and negative implicit ratings in order to enable more effective user reputation computation. It assigns a score to each implicit social activity. We conducted a survey with social media users in order to assign a score to each social activity. To develop an objective scoring system for implicit ratings based on social activities, we employed a survey with 30 participants. The survey made a social media user give a score from 0 to 5 according that how much each social activity has an influence on reputation. Here, the score 5 means that the social activity is the most important and the score 0 means that it is the least. That is, the social activity with the higher score means that it has a significant influence on discriminating user reputation. **Table 1** shows the total sum of scores that users assign to each social activity. The results showed that among positive social activities, making a friend request and subscribing are the most proactive actions, while among negative social activities, reporting and blocking are the most proactive actions. As a result, we assigned the scores of social activities based on the survey result as shown in **Table 2**.

Table 1. Survey results on user proactivity on social activities

Classification	Activity	Score
Positive	Friend request/accepting	126
	Subscription	123
	Sharing	108
	Adding to favorites list	90
	Positive comment	87
	Tag	86
	'Like'	71
	View	64
Negative	Report	77
	Block	74
	Negative comment	53
	'Dislike'	39

Table 2 shows the implicit rating scores for social activities, which are used in evaluating the content of content providers. The scores in **Table 2** were assigned based on the results of the survey with 30 participants described above. Higher scores were assumed for more proactive actions taken by consumers of contents as mentioned, and the maximum score of 1.0 was assigned to the actions of continuing the relationship, and the next highest score of 0.75 was assigned to the action of distributing the content widely. The action of expressing one's opinion in a short comment or adding the content to one's favorites list received a mid-score of 0.5, since it was no more than a passive expression of opinion. The action of clicking "like" for the content was given a score of 0.25. Finally, viewing the content was considered the most passive action, and received the score of 0.1. Among negative actions, blocking and reporting were considered the most proactive negative actions and given –1.0, because they signified breaking a relationship with the user who created the content and reporting it as spam or illegal content. The next highest negative action, of negative comment, was given –0.5 because it expressed a negative opinion after watching the content. The action of clicking "dislike" was considered the most passive negative act and given –0.25 because it expressed the opinion of dislike by simply clicking once.

Table 2. Scores for social activities

<table>
<tr><th colspan="2">Classification</th><th>Activity</th><th>Example</th><th>Score</th></tr>
<tr><td rowspan="5">Positive</td><td rowspan="5">Active
↕
Passive</td><td>Act of seeking an ongoing relationship with information provider</td><td>Friend request/acceptance, subscription</td><td>1.0</td></tr>
<tr><td>Sharing</td><td>Sharing</td><td>0.75</td></tr>
<tr><td>Positive comment, adding to the list, linking with a short description</td><td>Positive comment, adding to the list, tag</td><td>0.5</td></tr>
<tr><td>Expressing opinion with a single click</td><td>Like</td><td>0.25</td></tr>
<tr><td>Viewing or other positive actions</td><td>Viewing</td><td>0.1</td></tr>
<tr><td rowspan="3">Negative</td><td rowspan="3">Active
↕
Passive</td><td>Act of breaking the ongoing relationship with information provider, reporting</td><td>Block, report</td><td>-1.0</td></tr>
<tr><td>Negative comment</td><td>Negative comment</td><td>-0.5</td></tr>
<tr><td>Expressing opinion with a single click</td><td>Dislike</td><td>-0.25</td></tr>
</table>

3.3 Determination of Trust in Content

The proposed method estimates the evaluation value for the content of individual users. The method estimates explicit and implicit ratings based on social activities in relation to the content, and conducts the trust evaluation of the content on that basis. The evaluation value of the content is calculated by considering implicit ratings based on social activities as well as explicit ratings in order to be more suitable for the social media environment. The information provider's reputation is calculated by analyzing explicit ratings and social activities in relation to the generated content. The content is evaluated based on the implicit rating items presented in **Table 2**, in addition to explicit ratings.

In the process of determining the trust in the content, social activities on the content are classified into implicit and explicit ratings, and each activity is scored; in the content evaluation stage, a comprehensive evaluation of the content is made based on the scores. **Fig. 3** shows the process of estimating the score of the content based on users' evaluative activities. Each content item is classified into a category, and users' consumption activities take place in a variety of ways. In **Fig. 3**, three users consumed Content 1; User 1 took actions of viewing, sharing, liking, and rating; User 2 took actions of reporting, disliking, and rating; and User 3 took actions of commenting, sharing, liking, and subscribing. The proposed method calculates trust in the content by scoring consumers' individual consumption activities on the content based on **Table 2**.

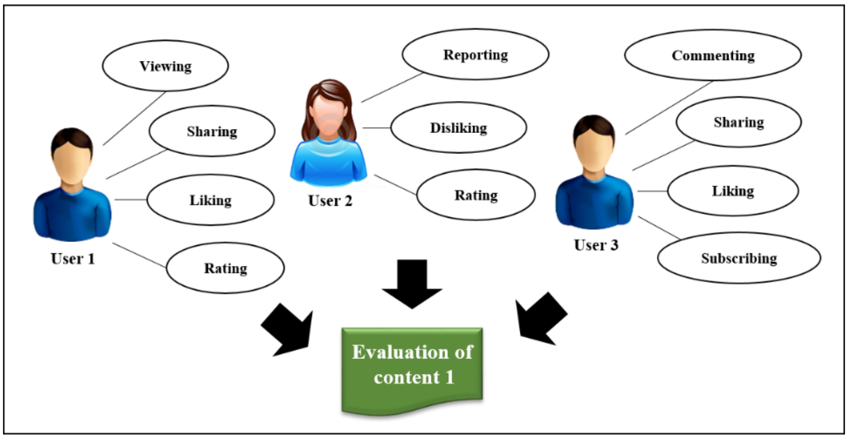

Fig. 3. Determination of trust in the content

Implicit evaluation scores of the content are calculated separately for positive and negative ratings. PI_i represents the positive implicit rating of the content ct_i. It is derived by summing the scores of m individual social activities for n information consumers for the content ct_i. Therefore, the Equation for PI_i, the positive implicit rating of the content ct_i, is shown in Equation (1). The negative implicit rating NI_i for the content ct_i is calculated by incorporating the scores of individual activities as in the positive implicit ratings PI_i. The negative implicit rating NI_i of the content ct_i is the sum of m social activities of n information consumers that a content received, and is expressed as Equation (2).

$$PI_i = \sum_{j=1}^{n} \sum_{k=1}^{m} PI_{jk} \tag{1}$$

$$NI_i = \sum_{j=1}^{n}\sum_{k=1}^{m} NI_{jk} \tag{2}$$

The implicit rating I_i of content ct_i is calculated based on the positive implicit rating and negative implicit rating computed by equations (1) and (2). Here, PI_i is the sum of positive social activities of content ct_i, NI_i is the sum of positive social activities of content ct_i, and n_i is the number of implicit ratings according to social activities. In order to alleviate the problem that the implicit rating values dramatically change by only a few rating values, the implicit rating of content ct_i is calculated by applying the average values of PI_i and NI_i to the log function. Therefore, the increase rate for the values below the mean is gradual, whereas the increase rate for the values above the mean is steep.

$$I_i = e^{\frac{PI_i + NI_i}{n_i}} - 1 \tag{3}$$

An explicit rating is the evaluation value in a clearly numeric nature, such as the rating that a user gives to a content. The explicit rating E_i for the content ct_i is the mean of n_e explicit evaluation scores that I_i received, and its range is [0, 1]. Therefore, the explicit rating for the content ct_i is expressed as Equation (4), where ER_j is an explicit rating score of user j.

$$E_i = \frac{1}{n_e}\sum_{j=1}^{n_e} ER_j \tag{4}$$

The proposed method derives the total evaluation value for the content by taking both implicit and explicit ratings into account. Once the explicit rating E_i, and the implicit rating I_i, for a content are obtained, they are incorporated to the total rating R_i for the content ct_i, which is expressed as Equation (5). The sum of the weights α and β in the Equation is 1. α is the weight for the explicit rating, and β is the weight for the implicit rating. The ratio of evaluative elements to incorporate can be modified by manipulating each weight of α and β. Social media services have different explicit and implicit rating methods each other. Social media services that ask explicit ratings to users can decide user reputation using them. Social media services that are not required to ask explicit ratings to users decide user reputation focusing on implicit ratings. Therefore, the weights of α and β should be assigned by considering such characteristics of a social media service.

$$R_i = \alpha E_i + \beta I_i \tag{5}$$

3.4 Determination of Trust in User

Since a user is rarely an expert in all specialty categories, it is important to consider users' specialty categories in order to determine the trust on social media. For instance, when a user has expertise in sports, it cannot be assumed that the user also has an expertise in cooking. Therefore, to enhance reputation information, users' reputation information needs to be specified for individual categories. The proposed method generates reputation information for determination of category-specific trust by grouping the contents generated by a user, and obtaining the evaluation value for the individual contents. **Fig. 4** shows the user reputation derived for individual categories. Calculation of user's category-specific reputation involves grouping the evaluated contents into categories, and summing them to obtain the user's reputation score for each category. **Fig. 4** shows the process of deriving the reputation for a user; the user's reputation for the category C_i, is calculated by adding up the scores of the contents.

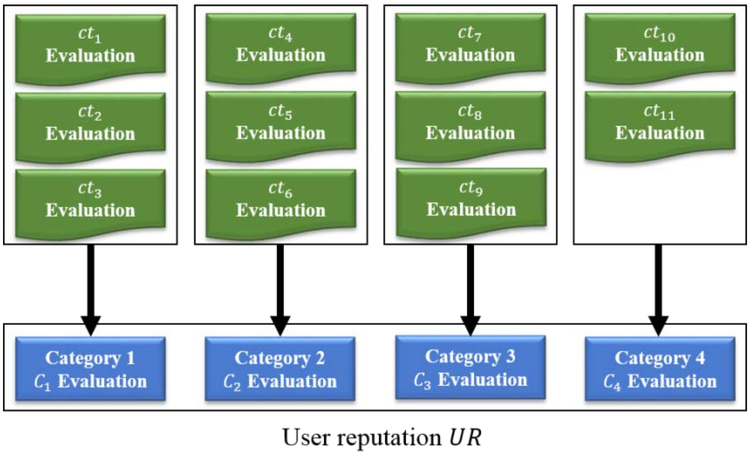

Fig. 4. Structure of user reputation in the proposed method

To obtain a user's category-specific rating UR_c, the reputations of the contents ct_i that belong to respective categories are each calculated. The user's category-specific reputations are obtained by averaging all the contents in respective categories. The number of contents in a category is denoted as n_c. To estimate the user's influence, the proportion of other users who evaluated the user among all users is considered, assuming that the user is more influential when the number of the evaluators of the content provider is larger. Once the influence is incorporated into reputation, the user's category-specific reputation information is saved. Equation (6) shows the user's total reputation score for a specific category, where n_r is the number of evaluators and n_u is the number of users.

$$UR_c = \frac{1}{n_c}\sum_{i=1}^{n_c} R_i \frac{n_r}{n_u} \tag{6}$$

3.5 Determination of Trust Considering Malicious Information Evaluator

In this paper, a malicious evaluator is a user who assigns evaluation values with a specific purpose. It is crucial to eliminate malicious evaluators, because their evaluations manipulate the trust in content and user and, consequently, reduce the trust in social media. Therefore, this study determines malicious intent of explicit ratings using standard deviation of ratings in order to determine malicious evaluators. Under the assumption that malicious users are relatively rare, the users who assign the evaluation values with greater deviations from the majority of ratings were defined as the evaluators with greater malicious intent.

Malicious evaluators were determined using maliciousness score (MS). MS is the maliciousness in explicit ratings, expressed as Equation (7), where t_{ne} denotes the total number of evaluations that the user u_i performed, $SD(ct_i, E)$ is the standard deviation (SD) of the evaluation values that u_i assigns to the content ct_i. $MS(u_i)$ denotes the mean SD of all explicit evaluations that the user u_i performed on contents. For instance, when User 1, User 2, and User 3 assigned 9, 8, and 2 points to the content, respectively, whose mean explicit rating is 9, User 3 is considered to have the highest MS among the three users.

$$MS(u_i) = \sum_{i=0}^{t_{ne}} \frac{SD(ct_i, E)}{t_{ne}} \tag{7}$$

The method is designed to increase the trust in explicit ratings by excluding the explicit ratings of the users who have $MS(u_i)$ above a specific threshold. The process of modifying explicit ratings using $MS(u_i)$ is shown in **Fig. 5**. u_i denotes a user, and E_{u_i} denotes the explicit rating that u_i assigns. When the value is above the threshold θ_{MS}, the user is determined to be a malicious information evaluator, and the explicit ratings of the users who have been rated by the malicious user are recalculated without the malicious evaluations. The threshold θ_{MS} is determined by the 9:1 rule in social media found by Web consultant Jakob Nielsen. That is, we assume that 10% of whole users carry out malicious ratings. Therefore, the proposed scheme set $MS(u_i)$ of top 10% users on the standard deviation of explicit ratings to the threshold θ_{MS} .

```
Malicious_information_evaluator_Filtering()
{
  if ( MS(u_i) ≥ θ_MS ) then {
    determine u_i as a malicious information evaluator;
    remove E_{u_i} from explicit evaluation values
    recalculate E_i ;
    return;
  }
}
```

Fig. 5. Explicit rating modification algorithm

3.6 Determination of Malicious Information Provider

This study proposes the method that determines malicious users using implicit and explicit ratings on social media. The method determines malicious users who adversely affect the trust on social media by separating malicious information providers and malicious raters. A malicious information provider is a user who provides other users with a poor level of information. The proposed method in this study identifies malicious information providers, and prevents them from providing poor-quality information, in order to increase the trust in information exchange on social media.

The proposed scheme determines a malicious information provider by the explicit rating scores, negative implicit rating scores, and user reliability scores of contents provided by a particular user. The conditions of the malicious information provider are expressed as

Equation (8). When n_{ct} is the number of contents created by a user, the explicit rating E of the user is equal to Equation (9). When E is small, the user is considered to provide unreliable contents. The negative implicit rating NI is equal to Equation (10). When NI is large, the user is considered to provide negative opinion. When n_{cc} is a number of content fields, the user reliability score UR is equal to Equation (11). When UR is small, the user is considered as an unreliable provider. A user is determined as a malicious information provider when meeting one of the following conditions: (1) the user's explicit rating E is below the lower limit θ_i; (2) the user's negative implicit rating NI is above the upper limit θ_j, or (3) the user's total reputation value is below the lower limit θ_k. The users who are classified as malicious information providers can be arranged to be disqualified from the right to provide information. The lower limits of the explicit rating and the total reputation value, and the upper limit of the negative implicit rating, can be set in variety of ways depending on the nature/purpose of applications. For instance, the user with the high explicit rating score may be disqualified from posting information if the user received many negative implicit ratings or the total rating score is not high enough to meet the minimum trust score; this allows building more trusted social media. The final trust score is generated by taking both user reputation information and the malicious information provider status.

$$E \le \theta_i \;||\; NI \ge \theta_j \;||\; UR \le \theta_k \tag{8}$$

$$E = \frac{1}{n_{ct}} \sum_{i=1}^{n_{ct}} E_i \tag{9}$$

$$NI = \frac{1}{n_{ct}} \sum_{i=1}^{n_{ct}} NI_i \tag{10}$$

$$UR = \frac{1}{n_{cc}} \sum_{c=1}^{n_{cc}} UR_c \tag{11}$$

By considering explicit, implicit, and total reputation scores in determining malicious information provider status, instead of the user's total reputation score as an indicator of the trust in user, the proposed method can establish a highly trusted social media environment, since the approach reduces inputs from only the users who provide poor-quality information, while retaining those from users who provide good-quality information.

4. Performance Evaluation

To demonstrate the superiority of the proposed method, this study conducted a comparative performance evaluation with the method proposed by Han et al. [22], using the same data. Most of the studies on user reputation computation in social media use user profiles, explicit ratings, and restricted implicit ratings. However, since most users do not provide explicit ratings when using social media, the existing methods cannot exactly discriminate the reputations of contents providers. In order to alleviate such a problem, the implicit ratings through user social activities as well as the explicit ratings should be used for user reputation computation. Han et al.'s method calculated user reputation by considering implicit social activities. The method [22] used the PageRank algorithm to calculate user reputation by incorporating social activities, including subscribing, sharing, and adding to the favorites list. The proposed method considers various social activities such as making friends, subscribing, sharing, comments, adding to the favorites list, view, block, report, like, and dislike. It also classifies the social activities into positive and negative implicit ratings in order to enable more effective user reputation computation. Therefore, we chose Han et al.'s method as the existing method for performance comparison with the proposed method in order to verify the validity of the implicit ratings.

The performance evaluation was conducted on a computer with Intel core i5-4440 3.10GHz processor, the Windows 7 operating system, and 4 GB memory using a Java language. As we already mentioned, social activities are mainly classified into positive and negative actions. Several social media services such as Twitter, Facebook, and YouTube have different social activities each other. In other words, there are no social media services that have all of the social activities in **Table 2**. Therefore, in order to conduct experiments using real data, we should use only social activities that we can get from a particular social media service. YouTube provides a variety of social activities among social media services. YouTube (http://www.youtube.com/) is a video content sharing site where a variety of interactions based on user generated contents (UGCs) take place. The experiment was conducted using the data on user interactions extracted from YouTube. Interactions of the set of data refer to user activities including liking, adding to a favorites list, sharing, subscribing, and disliking. In order to figure out the changes of user reputations, we need users with various social activities over the number of users in experiments. The experimental data used for performance evaluation was collected based on the types of interactions between actual users on YouTube at Arizona State University. The set of data for the experiment was collected from the videos in the entertainment category, and in order to fill in the lack of actual data, the number of negative comments and the explicit rating score were generated using an automatic random function, and added to actual data. In order to have us discriminate how much implicit ratings have influences on user reputation, we conduct performance evaluation with users who aggressively participate in implicit social activities. In order to figure out the changes of user reputations, we first chose users who did both one or more positive and one or more negative social activities out of 15,088 YouTube users. And then we selected 710 users with at least 7 or more positive and negative social activities among the chosen users. In order to conduct experiments using real data, we used the four positive activities and two negative activities from YouTube. We used 15,358 likes, 132,968 sharing, 442,823 subscriptions, and 243,834 adding to favorites list as positive social activities. We also used 8,880 negative comments and 17,648 dislikes as negative social activities. Each user did positive social activities such as 21 likes, 187 sharing, 623 subscriptions, 325 adding to favorite list and negative social activities such as 12 negative comments and 24 dislikes on average. We should set the values of α and β to discriminate the reliability of a content in Equation (5). YouTube used in the experiments has both explicit and implicit ratings. We conduct experiments by setting α and β to 0.5 to consider both explicit and implicit ratings. **Table 3** shows the property of the data used in the performance evaluation.

Table 3. Performance evaluation environment

Attribute	Value
User total	15,088
Collection period	June–October 2009 (5 months)
Reputation score	0–1
α , β	0.5

To evaluate the performance of the proposed method, three types of scores – the mean of explicit ratings only, the score that integrates implicit ratings into overall rating, and the score that integrated influence into the overall rating – for 20 users who scored the highest explicit ratings were compared in the experimental evaluation. **Table 4** shows the results of the performance comparison of user reputation calculations when implicit ratings and influence were taken into account. In the existing method, a user named ginaya was the most trusted user; however, once implicit ratings were considered, the trust in the user was lower than other users whose contents generated more activities on YouTube. Finally, when influence was taken into account, ginaya's trust score was quite low, at 0.027518, compared to other users who had more influence and whose contents generated more activities. The consideration of implicit ratings (i.e., consumption activities) demonstrated that a wide range of evaluative elements exist on social media in addition to explicit ratings, and led to the results being quite different from the results based on explicit ratings used in conventional methods.

Table 4. Top 20 users' reputation scores

rank	explicit		explicit+ implicit		explicit+ implicit + influence	
	user	value	user	value	user	value
1	ginaya	4.99	hopkinzz	0.602374	yatsubam	0.536708
2	hopkinzz	4.99	brianran*	0.562827	amigoeva	0.249649
3	animirc	4.98	howtofol*	0.559861	mook300	0.164641
4	celebrity*	4.98	animirc	0.559696	vfxviewt*	0.151608
5	mook300	4.98	ginaya	0.553273	mametar*	0.149914
6	mametar*	4.97	celebrity	0.548265	mrnebu	0.09761
7	yatsubam	4.97	mook300	0.548142	celebrity	0.072679
8	f1stofg0d	4.96	brokens*	0.547193	f1stofg0d	0.051562
9	howtofol*	4.96	mametar*	0.547055	dolekholl	0.051171
10	gongbird*	4.96	yatsubam	0.547013	hustla619	0.043285
11	vfxviewt*	4.96	f1stofg0d	0.546641	songbird*	0.042213
12	amigoeva	4.95	Songbird*	0.546617	brokens*	0.029774
13	brianran*	4.95	vfxviewt*	0.54609	jensyao	0.028759
14	dolekholl	4.95	mrnebu	0.545843	ginaya	0.027518
15	mrnebu	4.95	dolekholl	0.545534	theWarp*	0.01624
16	theWarp*	4.95	theWarp*	0.545423	gromek6	0.015752
17	brokens*	4.94	amigoeva	0.545203	hopkinzz	0.003125
18	gromek6	4.94	hustla619	0.544379	Animirc	0.002687
19	hustla619	4.94	gromek6	0.544348	brianran*	0.002659
20	jensyao	4.94	jensyao	0.544285	howtofol*	0.001589

In order to evaluate the quality of the proposed user reputation scheme, we surveyed 30 users how much they satisfy the ranking lists. To do this, we provided them with the real contents from 710 users and made them select the most reliable 20 users. The user reputation satisfaction is calculated by Equation (12). Here, SR_i is the user list that evaluator i selects as reliable users, CR is the list of top 20 users computed by "explicit", "explicit+implicit" and "explicit+implicit+influence", and n_u is the number of evaluation participants and is 30 in this experiment. **Fig. 6** shows the satisfaction of the reputation results of three types. As shown in **Fig. 6**, "explicit+implicit+influence" results in the highest satisfaction since it considers explicit ratings, implicit ratings, and influence. "explicit" results in the lowest satisfaction since it gives the high reputation to users with the negative implicit ratings by not considering the social activities of users. Although "explicit+implicit" considers both positive and negative ratings, it results in the lower satisfaction than "explicit+implicit+influence" since it does not consider the number of evaluators.

$$SF = \frac{\sum_{i=1}^{n_u} count(SR_i \cap CR)}{n_u} \tag{12}$$

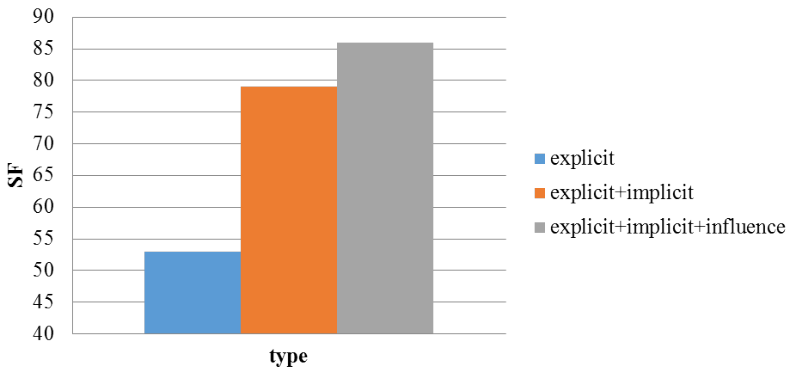

Fig. 6. Satisfaction of three types

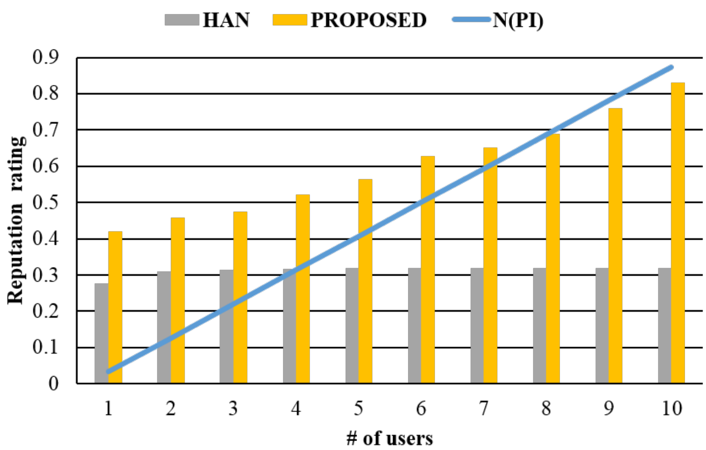

Fig. 7. Changes in reputation as a function of positive implicit activities

Fig. 7 shows the results of comparative performance evaluation with Han et al.'s method [22], which was designed to determine the performance of the proposed method in representing positive implicit ratings in reputation scores. The performances of the two methods were compared using randomly generated reputation data for 10 users, and varying the number of positive implicit ratings, while holding the number of negative implicit ratings constant. In the proposed method, users' reputation scores increased as the number of positive evaluative activities increased, representing positive implicit ratings well; however, in Han et al.'s method, users' reputation scores changed little as a function of the number of positive implicit evaluative activities. Han et al.'s method calculated user reputation by considering implicit social activities but considered only some of the social activities. In addition, they did not classify them into positive and negative activities. Therefore, even though a user's social activities change, the user reputation score is almost fixed to 0.3. However, in order to enable more effective user reputation computation the proposed method classifies the social activities into positive and negative implicit ratings, and considers additional social activities such as comments, like, dislike, and view. As a result, user 1 who has the least number of implicit ratings gets about relatively high reputation score by 51%, while user 10 who has the most number of implicit ratings gets about relatively high reputation score by 160% over Han's method. The proposed method also reflects positive implicit ratings very well for user reputation evaluation. As the number of the positive implicit ratings increases, the change of the user reputation score also increases. It is shown through performance evaluation that the proposed method improves the trust of user reputation by minimum 41%, maximum 160%, and average 91% over the existing method.

Fig. 8 shows the results of comparative evaluation between the proposed method and Han et al.'s method using randomly generated data by varying the number of negative evaluative elements, while holding the number of positive evaluative elements constant. The results show that, in the proposed method, user reputation scores decrease as the number of negative implicit ratings increases, whereas in the Han et al.'s method, reputation scores changed little as a function of the number of negative ratings. In common with experimental evaluations on positive social activities, even though a user's negative social activities change, the user reputation score is almost fixed to 0.3. However, the proposed method classifies the social activities into positive and negative implicit ratings, and considers additional social activities such as comments, like, dislike, and view. As a result, user 1 who has the least number of implicit ratings gets about relatively high reputation score by 116%, while user 10 who has the most number of implicit ratings gets about relatively high reputation score by 57% over Han's method. The proposed method also reflects negative implicit ratings very well for user reputation evaluation. As the number of the negative implicit ratings increases, the change of the user reputation score also increases. It is shown through performance evaluation that the proposed method improves the trust of user reputation by minimum 57%, maximum 116%, and average 78% over the existing method. This result shows that the proposed method represents the negative implicit activities in user reputation well.

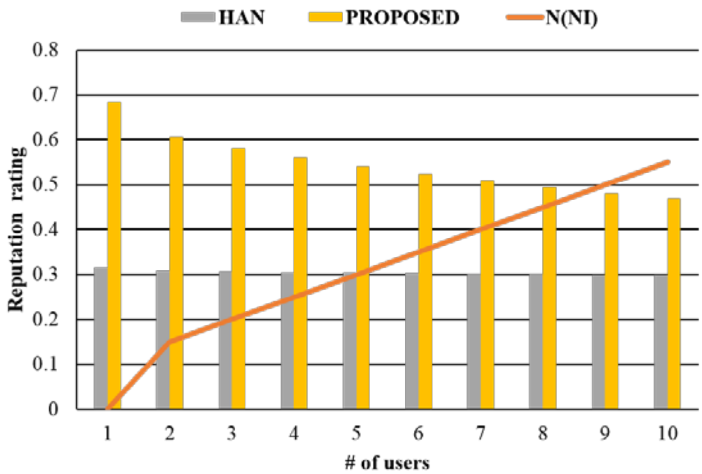

Fig. 8. Changes in reputation as a function of negative implicit activities

Fig. 9 shows the results of comparative evaluation of the two methods to determine how well they represent the changes in both evaluative values of positive and negative implicit activities, using randomly generated data. When the significant variation in implicit evaluative elements was introduced, Han et al.'s method showed little variation in user reputation. In contrast, in the proposed method, user reputation changed greatly, with great representation of evaluative elements in user reputation. Specifically, user reputation decreased significantly when the minimum value was assigned to the positive implicit rating, and a maximum value was assigned to the negative implicit rating, and vice versa. As already mentioned, Han et al.'s method considered only some of the social activities. In addition, they did not classify them into positive and negative activities. In common with experimental evaluations on each of the positive and negative social activities, even though both positive and negative social activities of a user change, the user reputation score is almost fixed to 0.3. However, the proposed method classifies the social activities into positive and negative implicit ratings, and considers additional social activities such as comments, like, dislike, and view. As a result, user 1 who has the least number of implicit ratings gets about relatively low reputation score by -21%, while user 10 who has the most number of implicit ratings get about relatively high reputation score by 115% over Han's method. The proposed method also reflects both positive and negative implicit ratings very well for user reputation evaluation. As the number of the implicit ratings increases, the change of the user reputation score also increases. It is shown through performance evaluation that the proposed method improves the trust of user reputation by minimum -21%, maximum 115%, and average 46% over the existing method. This result shows that the proposed method represents implicit evaluative elements well in user reputation.

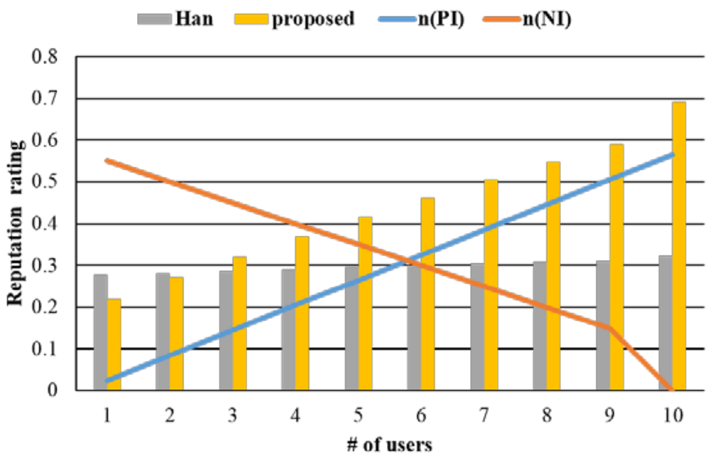

Fig. 9. Changes in reputation as a function of positive and negative implicit activities

Fig. 10 shows the results of the comparative performance evaluation of the proposed method and Han et al.'s method to determine the user reputation distribution for all notes, using the data from the performance evaluation environment of **Table 4**. The overall variation of the proposed method appeared large. The user reputation score depends on the implicit ratings of social activities as well as the explicit ratings of other users. That is, when explicit and implicit ratings are reflected well, user reputation distributions should vary. In general, variance and standard deviation are used as the evaluation metrics to show the diversity of user reputation [26]. When explicit and implicit ratings are reflected well, the variance and standard deviation of user reputation distributions are large. However, when explicit and implicit ratings are not reflected well, the variance and standard deviation of user reputation distributions are small. **Table 5** shows means, variances, and SDs. The results on Han et al.'s method show relatively small variance and SD. This suggests that implicit evaluative elements little influence reputation, despite a lot of social activities taking place on social media, which is likely to result from limited social activities being considered in Han et al.'s method. As already mentioned, Han et al.'s method considered only some of the social activities. In addition, they did not classify them into positive and negative activities. However, the proposed method classifies the social activities into positive and negative implicit ratings, and considers additional social activities such as comments, like, dislike, and view. As shown in previous experimental results, the proposed method reflects both positive and negative implicit ratings very well for user reputation evaluation. As the number of the implicit ratings increases, the change of the user reputation score also increases. As a result, the proposed method improved the variance and standard deviation of reputation ratings by about 94% and 75% over the existing method. This is likely to result from a wide range of social activities being considered in the method, and suggests that variety of social activities on social media was well represented in user reputation.

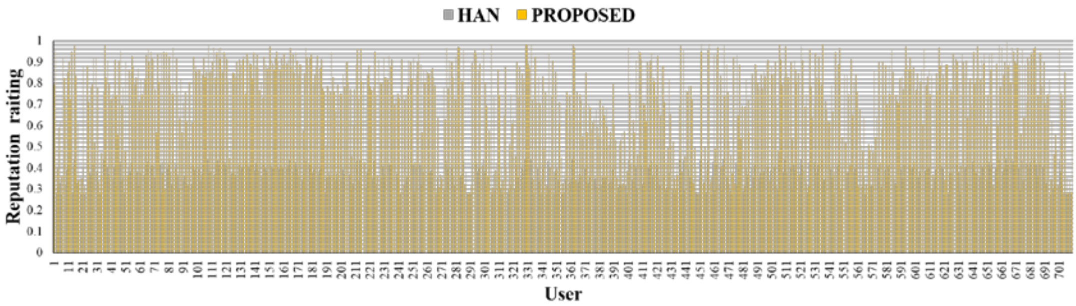

Fig. 10. Reputation distribution of all nodes

Table 5. Mean, Variance, and SD of all nodes

class	Han's method	proposed method
Average	0.36474	0.742506
Variance	0.002491	0.038523
Standard Deviation	0.04991	0.196274

Fig. 11 shows the results of comparative performance evaluation between the proposed method and Han et al.'s method to determine the variation in user reputation as a function of the number of implicit activities, conducted using the data from the performance evaluation environment of **Table 4**. The evaluation involved sorting users based on the number of implicit activities associated with them (from largest to smallest), and calculating the mean of user reputations for each unit of 100 users from the top. Han et al.'s method showed little variation across the units of sorted users. In contrast, the proposed method showed a relatively large variation in the units of the 1–400th users in terms of associated social activities. When the implicit activities were fewer, the variation of the proposed method was similar to that of Han et al.'s method; when higher levels of consumption activity was observed, the range of estimates for user reputation was wider since variety of implicit ratings were incorporated. The experiment demonstrates the excellent representation of implicit ratings in user reputation in the proposed method.

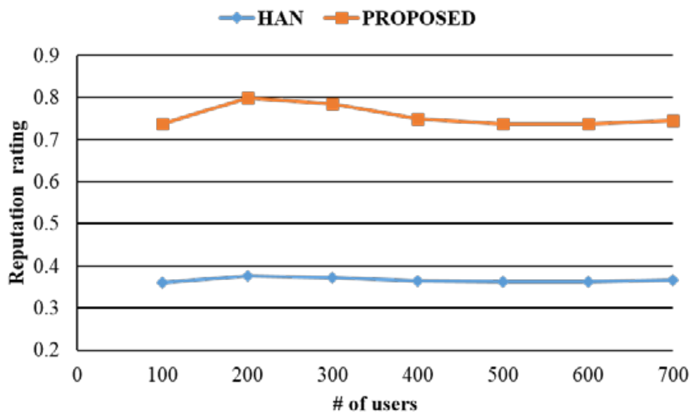

Fig. 11. Means of reputations by unit of users

Fig. 12 shows the results of the experiment to validate the scoring scheme for social activities shown in **Table 2**, using the data from the performance evaluation environment of **Table 4**. The experiment was conducted on the activities of liking, adding to the favorites list, sharing, and subscribing. The results are the means of the implicit evaluation scores for each activity type based on the scores of the top 30 users in each type. In the proposed method, dislike, adding to the favorite lists, sharing, and subscribing form 17%, 24%, 26%, and 34% of social activities, respectively. We can see through performance evaluation results that the scores of the social activities in **Table 2** are very reasonable. While implicit ratings varied as a result of assignment of weights, the difference between the means of adding to the favorites list and sharing activities were found to be small. The reason for the small difference was due to the high frequency of adding to the favorites list. In the experiment, a greater weight was assigned to sharing than to positive commenting, because positive comments were considered a rather passive expression, while sharing was considered proactive action. This is because the comment is restricted to the respective post, whereas sharing is the act of distribution to all users in relationships with the sharer. The weighting scheme was developed internally due to the absence of a dataset to use for objective validation of the weights.

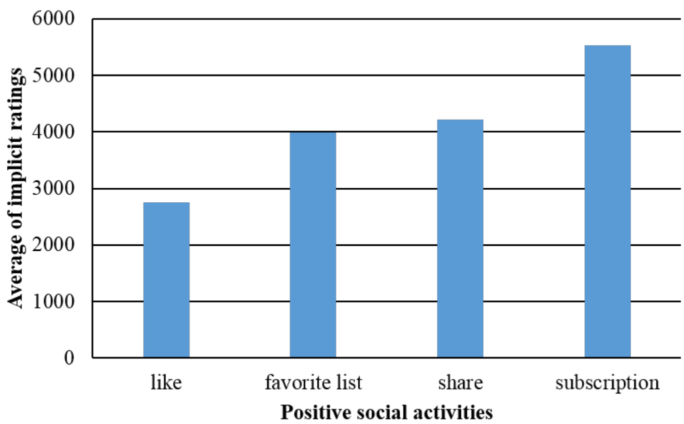

Fig. 12. Means of implicit ratings for top 30 users

Fig. 13 shows the results of comparative performance evaluation between the proposed method and the method proposed by Hosseinmardi et al. [24] regarding determination of malicious information evaluators, using the data from the performance evaluation environment of **Table 4**. Hosseinmardi et al.'s method distinguishes malicious information evaluators by using positive and negative words in users' comments on social media. It is not objective since it considers only restricted factors and does not score the malicious degrees. However, in the proposed method we assume that the number of malicious users is relatively much smaller than that of normal users. We consider a user who assigns the score significantly different from most ratings as a malicious information evaluator. That is, the proposed method improves the trust of explicit ratings by excluding the explicit ratings of users that are over a given threshold. In the experiment, the evaluation assessed the number of ratings required for a normal reputation score to be generated, when a user is evaluated in a social media environment where malicious information evaluators exist. In the evaluation, the number of malicious explicit ratings varied from 0 to 20. The results of the performance evaluation showed that in Hosseinmardi et al.'s method, the number of ratings required for normal reputation increased exponentially as the number of malicious explicit ratings increased. For instance, in the event of just 20 explicit malicious ratings, a total of 521 ratings are required to generate normal reputation. In contrast, in the proposed method, as few as 20 ratings could generate the normal reputation score. That is, it is possible to manage the higher trust of user reputation by providing the high level of information through the exclusion of malicious information evaluators.

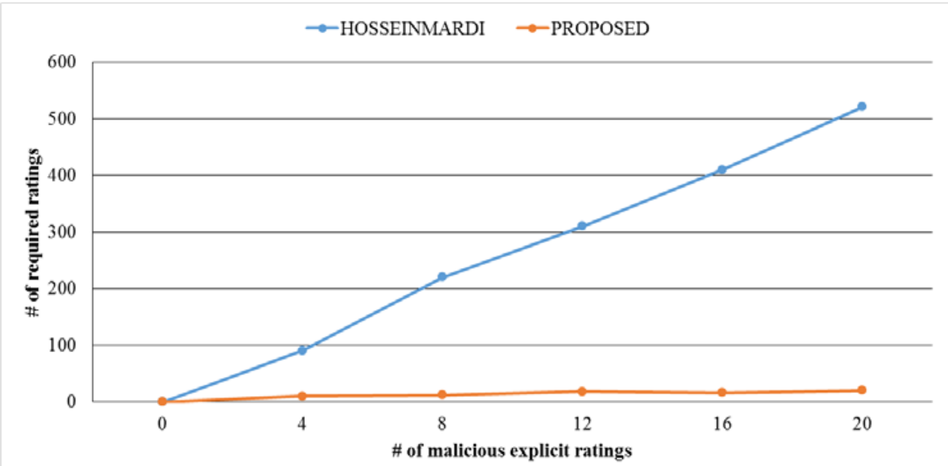

Fig. 13. Number of ratings required as a function of the number of malicious explicit ratings

Fig. 14 shows precision and recall of the identification of malicious explicit ratings. Hosseinmardi's scheme achieves lower precision and recall than the proposed scheme since it needs a large number of rating contents to discriminate malicious explicit evaluators. Especially, the recall of Hosseinmardi's scheme dramatically degrades since it does not discriminate users with the small number of ratings as malicious evaluators. As a result, the proposed scheme improves precision and recall by 12% and 100% over Hosseinmardi's scheme on average.

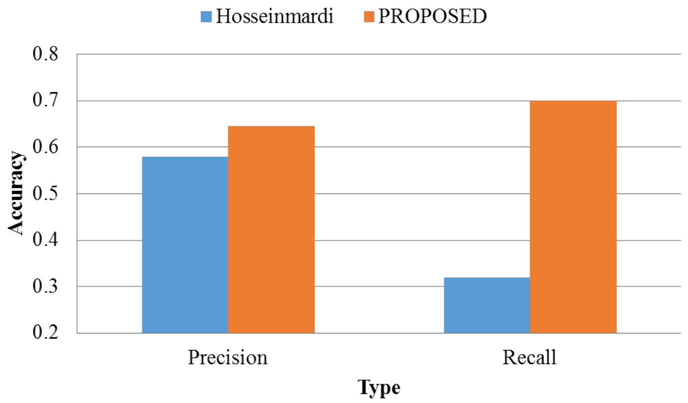

Fig. 14. Precision and recall of the identification of malicious explicit ratings

Fig. 15 shows the results of performance evaluation on determination of malicious information providers based on the data from the performance evaluation environment of **Table 4**. Malicious information providers were identified by setting the threshold for explicit ratings and user reputations at the mean of the bottom 10% of the respective element, and the threshold for malicious ratings at the mean of the upper 10%. The results of the evaluation showed that out of 719 users, 139 were identified as malicious information providers, and exclusion of the users increased overall trust in social media by about 28%.

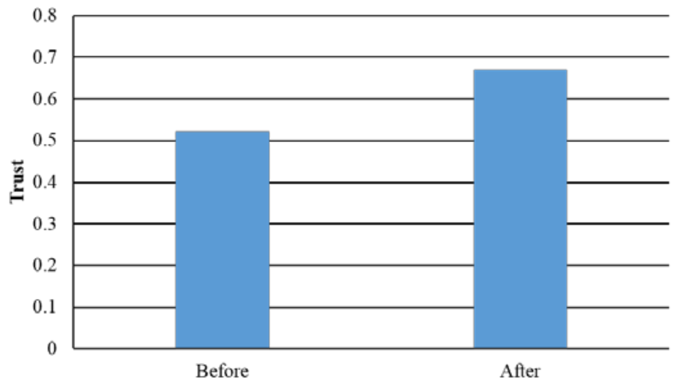

Fig. 15. Mean trust after identification of malicious information providers

5. Conclusion

As user activities in online social network services have grown due to advances in social media, a tremendous opportunity for communication has been created, including information exchange and opinion sharing among users. Users engage in countless interactions including posting, review, sharing, commenting, and bookmarking, as they generate, consume, and share information on social network services. The current social media have gone beyond the social network focusing on connection management, and create user networks based on a variety of social activities. Information providers and consumers make interactions and form mutually dependent relationships in addition to explicit relations in the process of generating and consuming information on such social media. The present study proposed a user reputation computation method that incorporates users' implicit ratings on social media, in which a lot of interactions between users and contents take place. The study also estimated implicit evaluation based on analysis of users' activities on social media and category-specific reputation based on explicit scores for contents in order to determine user expertise. Moreover, the method attempted to provide more reliable user reputation information by identifying malicious information raters and information providers, incorporating the explicit ratings modified based on the malicious intent information into reputation information, and providing users with information on malicious information providers. The results of performance evaluation of the method demonstrated that the proposed method was more suitable for social media environments in which a variety of social medial activities take place. This is because implicit ratings were better incorporated into user reputation, compared to existing methods of reputation determination, and generated more reliable reputation information than another method of determining malicious intent.

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