

Dynamic Reputation Rating Mechanism for Social Content Curation Services

Jinhyung Cho^{1*}, Hwansoo Kang¹ and Seawoo Kim²

¹School of Computer Engineering, Dongyang Mirae University, Seoul 152 – 714, South Korea;
cjh@dongyang.ac.kr, hskang@dongyang.ac.kr

²Department of Digital Media, Soongyei Women's College, Seoul 100 – 751, South Korea;
nt21jjang@naver.com

Abstract

Recently various social curation mechanisms have been developed to organize and suggest digital contents around one or more particular themes or topics for online users on Social Network Services (SNS). Collaborative filtering method can be used to improve efficiency of automated social curation systems, and so we have already applied this method to enhance credibility of curators in previous research, but these approaches have problem in extracting user preferences for users who have not evaluated many contents. In this study, we use dynamic curator groups which are automatically formed to recommend and organize domain specific contents. The group members have dynamic reputation value depending on their evaluation performance. Social curations over online digital contents are very effective to find relevant information in a specific domain. In addition, we show simulation results to evaluate the reliability enhancement of the proposed dynamic curator model for automated curation services of social content.

Keywords: Collaborative Filtering, Dynamic Curators, Expertise, Reputation Rating, Social Content, Social Curation

1. Introduction

Social curation is collaborative sharing process of online content organized around one or more particular themes or topics^{1,2}. The development of automated social curating mechanism has emerged as an important issue in Social Network Service (SNS) related area. An example of curation services is to recommend new products or content of interest to SNS users, using other users' explicit evaluation or implicit preferences^{3,4}. Recently various social curation mechanisms have been developed to organize and suggest digital contents around one or more particular themes or topics for online users on SNS⁵⁻⁹. Collaborative filtering method can be used to improve efficiency of automated social curation systems, and so we have already applied this method to enhance credibility of curators in previous research, but these approaches have difficulty in deriving user preferences for users who have not evaluated many content. In this study, we adopt a modified collaborative filtering method to evaluate digital

content in SNS community by a representative board of human agents; we call it a curator group. We suggest dynamic curator groups among general users should be automatically created to estimate domain-specific content for post ranking and also the group members have dynamic authority weights (reputation value) depending on their evaluation performance. This method is quite effective in curating social content that many users have not evaluated. A voting board of curators with expertise on a domain category is operated to rate the content. Our curation mechanism using dynamic model of curator group may be extended to challenge other reputation system designs.

2. Related Works

2.1 Automated Curating Mechanisms

Automated curating mechanisms can be broadly categorized into explicit rating based and implicit rating

* Author for correspondence

based mechanisms^{2,3}. Explicit curating mechanisms use feedback information such as user reputation evaluated by other users^{3,4}. As an alternative method, the implicit curating mechanisms are a promising solution to overcome insufficient and untruthful feedback problem of explicit curating mechanisms^{5,10-13}. The implicit curating mechanisms describes a user's preference with respect to each content by mining the usage data collected in the SNS site. Most automated curation systems require the user to judge many items in order to obtain the user preferences. In general, many SNS users are interested in other users' opinion or ratings about content that belong to a certain domain, before they become used to searching for content of interest⁵. However, curation systems still have the problem in providing relevant curating information before they receive a large number of user ratings.

2.2 Social Curation and Collaborative Filtering

Recently, the social curation mechanism is becoming more and more important for building trust of the SNS market. The website Pinterest is one of the representative social curation services, combining the social features sharing, liking, following and commenting, with the curating capabilities of bookmarking, tagging, and recommending⁴. In comparison with social curating mechanisms, collaborative filtering tends to be limited to reducing the noise in a channel and filtering out less relevant content rather than organizing it in a meaningful way. Meanwhile, Collaborative filtering can be used to improve efficiency of social curation systems^{5,7}, and we apply this method to computing expertise of curators. The overall ratings for content curation can be predicted by adopting the modified mechanism of traditional collaborative filtering methods.

3. Proposed Mechanism

The overall process of our proposed curating mechanism is divided into the "curator group formation process" and the "content reputation rating process" Figure 1. The curator group formation process is composed of two steps. In the first step, each expertise weighting of each user is measured implicitly from the user's explicit social features as bookmarking, tagging, and recommending for SNS content. In the second step, we form a dynamic group comprising the most credible curators on the basis of the user expertise. We select as the qualified curators

who had the top N expertiseweight value. The content reputation rating process is a collaborative filtering process to predict general community users' evaluation ratings of each content item. Through the curator group formation, content reputation ratings will be generated by the weighted average ratings of the group. In this paper, a "community user" means the group of entire users within a specific SNS community and a "curator group" means the group of most credible users that are selected on the basis of their expertise. It is a subset of a community user group.

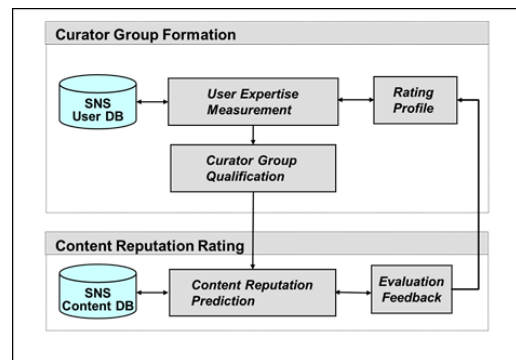


Figure 1. The proposed curation mechanism.

3.1 User Expertise Measurement

We define the expertise factor as the degree of a user's competency to provide an accurate prediction and exhibit a high activity in the item domain, on the basis of the previous research^{6,7}. Based on the definition, the expertise is measured by considering activity and prediction competency at a domain level. The expertise of a user u for domain d , $\omega_E(u, d)$ is defined as following equation. If a user's ratings are exactly same as the others, $|R_{u,j} - R_{a,j}|$ in the equation is equal to 0 and the expertise of the user is 1 without considering an activity weighting.

$$\omega_E(u, d) = \beta(u, d) \left(1 - \frac{\sum_{j \in D(i)} \sum_{a \in U(j)} |R_{u,j} - R_{a,j}|}{N_{D(i)}} \right)$$

where,

$U(j)$: the users in the community who gave rating for item j

$D(i)$: an item set that have ratings in the category of target item i

$N_{D(i)}$: the cardinality of $D(i)$

$\beta(u, d)$: the activity weighting

The activity weighting, $\beta(u, d)$ is defined as $1 - 1/n$ (n: the number of ratings within the domain d) in order

to obtain a higher value of expertise with more rating activities for more items within a particular domain.

3.2 Dynamic Curator Group Qualification

In order to predict the overall ratings for content, we form a dynamic group comprising the most credible curators on the basis of the user expertise. We select as the qualified curators who had the top N expertiseweight value; we term them “the dynamic curator group.”

3.3 Content Reputation Prediction

This dynamic curator group approach can present the curated content list by the estimated score using the modified collaborative filtering mechanism. This estimated score is called “content item rating.” The average rating $R(i)$, which is weighted by user expertise, of the curator group is calculated by the following equation and is used to generate content item rating. This average is called “expertise-weighted average” of the curator group and is used to predict the social network users’ curated list.

$$R(i) = \frac{\sum_{u=1}^n \omega_E(u, d) \times R_{u,i}}{\sum_{u=1}^n \omega_E(u, d)}$$

ω_E : the expertise weighting of the user u

$R_{u,i}$: the rating for item i given by the user u

4. Performance Evaluation

We simulated the dynamic process of SNS content rating and creation of curator group depending on their expertise in a specific SNS community. The prediction performance of curator groups was experimentally evaluated. The purpose of the simulation test is to confirm that the dynamic curator groups reflect general SNS user’s opinions or ratings and has the potential to predict value of content that have not been evaluated yet. In the simulation, we have experimentally evaluated the performance of the proposed curating mechanism based on Expertise Weighting [called EW model] by comparing with the other benchmark curating mechanisms, which are Non-Weighted model [NW model] and Similarity Weighting based collaborative filtering model [SW model].

For the performance evaluation, this study adopted the predictive accuracy widely used in researches related

to the collaborative filtering method¹⁴. The Mean Absolute Error (MAE) measure was used to compare the predictive accuracy of each mechanism. Here, MAE is the absolute difference between general SNS users’ rating for an item and the predicted rating of the curator group for the same item. This study has evaluated the feasibility and advantages of the proposed curation mechanism with an actual rating data collected from a SNS community site. This site provides the content evaluation showing the reviews and ratings that range from 1 to 5 from numerous users for the e-Learning content as the “User Ratings.” We gathered the ratings for the content which have more than 50 ratings from the individual users who have more than 10 ratings. For the evaluation, we separated this data set into two parts—a calibration set comprising the ratings for 200 items and a validation set comprising the ratings for the remaining 100 items. In other words, we calculated the expertise of the users in the calibration set, and we verified the performance of the benchmark systems in the validation set.

The experimental results provide evidence that the curating mechanism using collaborative filtering method is generally better than the non-weighted curating mechanisms as Table 1. In addition, it was proven that the proposed expertise weighted dynamic curator group mechanism could improve the performance of the curation systems to a greater extent than could the conventional similarity weighted collaborative filtering method by experiments.

Table 1. Comparison of curation accuracy

Benchmark Curating Mechanisms	Curator group size [number of curators]						MAE Avg.
	50	100	150	200	250	300	
[EW Model]	0.454	0.402	0.369	0.301	0.289	0.266	0.346
[NW Model]	0.602	0.565	0.486	0.446	0.424	0.398	0.487
[SW Model]	0.462	0.412	0.379	0.331	0.310	0.287	0.364

5. Conclusion and Future Work

In this paper we have shown dynamic curator groups for social content curation through human interactions. Curators committee is automatically formed among general SNS users. Each curator has its own authority

to evaluate content. Currently we are applying this idea to design a reputation rating system for e-learning content and shopping products. In many applications, users are interested in seeing the top ranked content or products. The social curation system with dynamic expert groups will be a feasible solution to curate SNS content in the field that conventional automated curation systems cannot cover.

Future work in this area should be along the following directions. First, the measure of expertise should be improved by employing practical data such as users' implicit or explicit profile data. Second, the curator group formation method should incorporate more refined approach. In addition, the performance of our proposed mechanism should be experimentally evaluated by using implicit SNS usage data.

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7. References

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