User- and Community-Adaptive Rewards Mechanism for Sustainable Online Community

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Abstract. Abundance of user contributions does not necessarily indicate sustainability of an online community. On the contrary, excessive contributions in the systems may result in "information overload" and user withdrawal. We propose an adaptive rewards mechanism aiming to restrict the quantity of the contributions, elicit contributions with higher quality and simultaneously inhibit inferior ones. The mechanism adapts to the users preferences with respect to types of contributions and to the current needs of the community depending on the time and the number of existing contributions.

1 Introduction

The proliferation of online communities (OCs) may lead designers and researchers to the conclusion that the development of custom-made communities for particular purpose is straightforward. Unfortunately, this is not the case. Although software providing basic community infrastructure is readily available, it is not enough to ensure that the community will "take off" and become self-sustainable. A critical mass of user participation is necessary. Besides, the quality of the resources shared by users is crucial to the sustainability of the community.

Developed at the MADMUC lab at University of Saskatchewan, Comtella is a small-scale OC for sharing academic papers and class-related web-articles among students. The initial problem encountered was the scarcity of the user participation and contributions since most users tended to free-ride instead of sharing new resources. To address the problem, we introduced a set of hierarchical memberships into the system to stimulate users to contribute [2, 3]. While the strategy was effective in increasing participation in terms of *quantity* of contributions, it led to a deteriorating *quality* of contributions, catalyzed "information overload" [7] in the system, and resulted in disappointment and withdrawal of some users.

Therefore, to make OCs more self-sustaining and long-lasting, a new mechanism is needed to measure and monitor the quality of user contributions, elicit the ones of high quality and restrict the overall number of contributions.

2 Related Works

It is not easy to measure the value of contribution impartially and accurately since quality measures are usually subjective. Centralized moderation is feasible only for

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small and narrowly focused communities, where members have very similar evaluation criteria. Therefore, decentralized mechanisms for quality measurement are necessary. There are two kinds of such mechanisms – implicit and explicit – depending on how evaluation is elicited from users. An example of implicit social quality evaluation mechanism is the impact factor which counts how many times a paper has been cited by other researchers. In a similar way, one can measure the quality of a posting in an OC by counting the times it was viewed (clicked). However, this method is based on the assumption that people who view a resource hold a positive attitude to its quality, which is not always the case.

Another way of evaluating the quality of resources or comments is through explicit user ratings, as in the peer-reviewing process in academia or in OCs like Slashdot. Since the final ratings of resources are computed based on ratings from many users, they are more unbiased. However, a study of the Slashdot rating mechanism showed that some deserving comments may receive insufficient attention and end up with an unfair score, especially those that were contributed late in the discussion [5]. Therefore the timeliness of making a contribution is important and a motivational mechanism should encourage early contributions. The Slashdot study showed also that comments starting their life at a low initial rating have a lower chance to be viewed and rated and are therefore more likely to end up with unfair score. In Slashdot, the initial rating depends on the "karma" of the user who made the comment. The user's "karma" is a measure of reputation computed from the quality of the user's previous contributions. In this way, good comments made by new users or the users who haven't contributed highly rated comments so far tend not to receive a deserving attention and to collect sufficient ratings to raise the "karma" level of their contributor. This causes a feedback loop resulting in the Matthew effect [6].

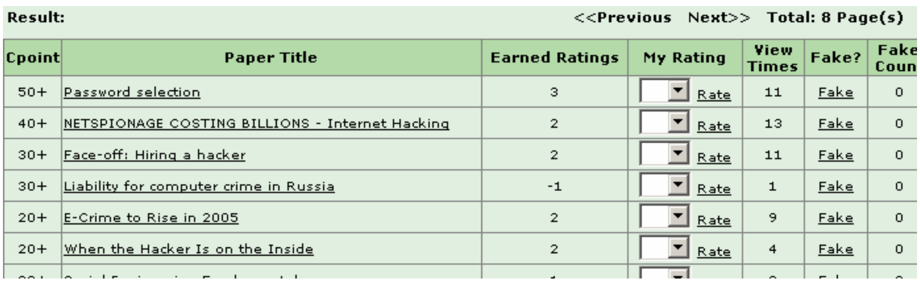
An important problem in systems that rely on ratings is ensuring that there are enough ratings. The evaluation of an approach to motivate users to rate movies in MovieLens through sending them email-invitations showed that users seemed to be influenced more by personalized messages emphasizing the uniqueness of their contributions and by those that state a clear goal (e.g. number of movies the user should rate) [1]. It is interesting that personalization seems important and that setting specific goals are more persuasive than general appeals. However, this approach is questionable as a long-term solution since the effect of receiving email invitations will likely wear off.

3 Rewarding Users for Rating Papers

The Comtella rating mechanism is inspired from the Slashdot moderation system. In order to have a broader source of ratings, all the users can rate others' contributions by awarding them points (either +1 or -1). However, the users with higher membership levels receive more points to give out, which means they are more influential in the community. To ensure that contributions have equal chance initially to be read and rated, the initial rating for every new contribution is zero regardless of its providers' membership level or the quality of her previous contributions. In the end, the final rating for the contribution is the sum of all the ratings it has obtained.

The summative rating for each contribution is displayed in the list of search results, which can be sorted by the user and viewed as a “top 10” list of articles for any topic.

According to the reciprocation theory from social psychology [4], it is logical to motivate users to rate papers by rewarding them for this kind of actions. As an incentive for users to rate contributions, a virtual currency is introduced, called “*c-points*”. A certain number of *c-points* are awarded to a user for rating papers, depending on her reputation of giving high-quality ratings. The earned *c-points* can be used to increase the initial visibility of the users’ postings in the search result list. Most users desire that their new contributions appear in salient positions, e.g. in the first place or among the top 10, because in those positions they will have a better chance to be read and rated. The Comtella search facility displays all the contributions matching a query in a sorted list according to the number of *c-point* allocated by the contributor (Fig 1). Unlike the mechanism in Slashdot, it allows the user flexibility to invest *c-point* in a particular posting. Rating papers leads to immediate reward, which we believe will be a powerful incentive for the users.


Result: <<Previous Next>> Total: 8 Page(s)

Cpoint	Paper Title	Earned Ratings	My Rating	View Times	Fake?	Fake Coun
50+	Password selection	3	Rate	11	Fake	0
40+	NETSPIONAGE COSTING BILLIONS - Internet Hacking	2	Rate	13	Fake	0
30+	Face-off: Hiring a hacker	2	Rate	11	Fake	0
30+	Liability for computer crime in Russia	-1	Rate	1	Fake	0
20+	E-Crime to Rise in 2005	2	Rate	9	Fake	0
20+	When the Hacker Is on the Inside	2	Rate	4	Fake	0

Fig. 1. A segment of a search result list

4 Community Model, Individual Model and Adaptive Rewards

In our previous motivation mechanism [3], the comprehensive evaluation of a user’s participation was based on the times of the user engaged in cooperative activities (e.g. sharing, rating, etc.) and the weights introduced to denote the importance of each kind of the activities. The users were classified into several levels of membership depending on the evaluation of their participation. The adaptive reward mechanism is introduced as an extension of our pervious work. The basic idea is to substitute the constant weights for the cooperative activities with varying weights adaptable to the users’ individual status and the current needs of the community.

Fig.2 presents an overview of the mechanism. Community model is used to describe the current phase of the whole community. It includes the expected sum of user contributions for current topic (Q_c) and the community reward factor (F_c). For each week, a new discussion topic is introduced and Q_c is set by a community administrator for the new topic depending on the feature of the topic, users’ spare time and energy, etc. F_c reflects the extent to which new contributions are useful for the whole community. It has its maximum value when a new topic discussion begins and decreases gradually with the time. After the middle of the discussion period, it decreases faster (Fig.3).

Each user has an individual model that contains the average quality of his/her previous contributions and ratings (C_I and R_I) and the data describing him/her current status. The expected number of contributions of each user (Q_I) is a fraction of Q_c. The users with higher C_I will get a larger Q_I. The individual reward factor (F_I) defines the extent to which the user's contributions are being rewarded. F_I has its maximum value as long as the number of the user's contributions is less than or equal to his/her Q_I. When the number exceeds the expectation, F_I drops to its one fourth suddenly and keeps decreasing with the increment of the users' contributions (Fig.4).

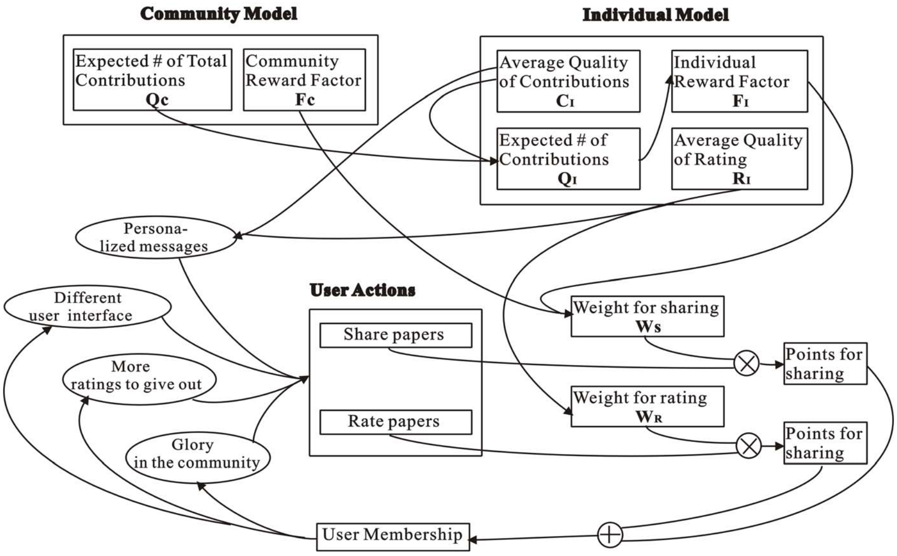


Fig. 2. An overview of adaptive motivational mechanism

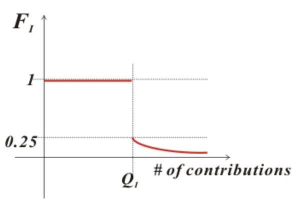


Fig. 3. The change of the community reward factor (F_c)

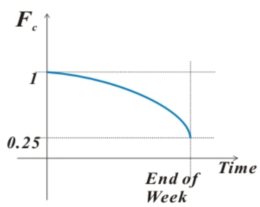


Fig. 4. The change of the individual reward factor (F_I)

The adaptive weight for sharing resources (W_S) inherits the features of both reward factors, F_c and F_I. In this way, the user who shares many papers but does not pay enough regard to their quality gets a low C_I and a small Q_I and therefore, little reward for his/her subsequent contributions. Thus the personalized message to the user would be to contribute less in next period but improve the quality. On the other hand, if the user tends to share good resources in a small number, she obtains a high C_I and a large Q_I. Therefore, potentially she is able to earn more rewards by sharing resources. Therefore W_S is able to restrict the quantity of user contributions, inhibit low-quality ones, and stimulate users to share resources early in the discussion period, which fully exposes them to the quality control rating system.

The adaptive weight for giving ratings is proportional to the users' average quality of previous ratings (R_I). The users who have gained a good reputation in making ratings get higher weight for their subsequent ratings, which stimulates them to rate more papers. However, those with poor R_I will not get much reward for rating contributions. They have to improve the quality of their ratings to win their reputation back and this would be the suggestion of the personalized message.

5 Conclusions

While designing incentives into the software to ensure sustainable OCs has been recognized as one of the most challenging and important problems facing researchers in this area, to our best knowledge there are only few works directly addressing the problem. We propose a dynamic, adaptive mechanism for rewarding contributions in an OC which takes into account the current needs of the community (e.g. more new papers, versus more ratings, depending on the time since the topic is introduced and the current level of contributions) and the user's personal style of contributing (e.g. less but higher-quality contributions versus fewer but more mediocre ones). The hypothesis is that such a mechanism will stimulate users to contribute when and what is most useful for the community at the moment, thus achieving a level of activity that makes the community sustainable and avoids the "information overload" in OCs. Our study to test the effectiveness of the proposed mechanism is currently underway in a fourth year undergraduate class with 32 students.

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