“Remember to hand out medals”: Value and peer rating in an online open study group

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Abstract

Rating systems are popular in recommender systems and ecommerce websites, but recently there have been some implementations in online educational settings as well. This paper presents an exploratory qualitative study of the role(s) a peer rating system plays in value creation within a large, teacherless online open study group where the participants connect to and help each other in their process of learning Python, a programming language. In this study group, the participants ask questions and receive answers from their peers. The participants are strongly encouraged to acknowledge good answers from their peers by rewarding them with medals. Using a combination of preexisting and inductive codes, qualitative content analysis was used to examine instances of the value provided by good answers, which were rated as “best responses” and awarded medals. The analysis focused on 108 closed questions asked by a homogeneous sample of participants whose title indicated the status of beginners. Closed questions are threads including a top-level question about a topic, followed by one or more answers and/or other questions. Turning attention on the materiality of the rating system, this study attempts to bring into focus how this device contributes to value creation. The analysis suggests that the peer rating system makes visible what the participants find immediately valuable. By making good responses recognizable, the rating system makes more visible what the participants can gain from each other and what they can achieve by helping each other. The medals awarded to participants giving good responses act as “tokens of appreciation” and partake of a mechanism aimed at supporting motivation, engagement, and commitment to participation in the study group. The rating system contributes to a rank measured in capacity to be committed to the study group, help others and solve problems.

Keywords

Assessment, expertise, online learning networks, open education, peer rating, rating systems, sociomateriality

Rating systems have become important mechanisms in many forums, blogs and social media. While these devices are especially popular in recommender systems, such as TripAdvisor, and ecommerce websites, such as eBay and Amazon, more recently there have been some implementations in online educational settings as well (Thoms, Garrett, & Ryan, 2010). Given that the phenomenon is still in its infancy, little research appears to exist regarding the use of rating systems in online education. This paper presents an exploratory qualitative study of the role(s) a peer rating system plays in value creation within a large, teacherless online open study group, where participants ask questions and receive answers from their peers. Peer rating is defined here as assessment obtained by having study group participants rate answers from their peers. Value creation is defined as the value for learning enabled by networking and engagement of participants (Wenger, Trayner, & de Laat, 2011). Following Wenger, Tryner and de Laat, networks or communities can create value when they are used for social learning activities such as sharing information, tips and documents, learning from each other’s experience, helping each other with challenges, creating knowledge together, and stimulating change.
Specifically, the empirical focus of this study is on the sociomaterial agency of the rating system. Putting materiality in the foreground allows bringing into focus what values are inscribed in the rating system and understanding the influence this system can exert.

Background and Theoretical Perspective

According to Rheingold (2002), online rating system (which he calls online reputation systems) are “computer-based technologies that make it possible to manipulate in new and powerful ways an old and essential human trait” (p. xix). Rating systems are quick and easy methods for users to leave an opinion or evaluation and about an object, person, place or thing, and read opinions and evaluation left by other participants (Yahoo! Developer Network, n.d.). Common rating systems are designed in the forms of 5-star systems, like/dislike systems, and thumbs-up/thumbs-down systems. Recommender systems, such as TripAdvisor, and ecommerce websites, such as eBay and Amazon, have used successfully the contributions of millions of customers, enhanced by rating systems that monitors the quality of the content and transactions exchanged through these sites. Rheingold (2002) pointed out that the market value of these businesses increases as more people use them, and the aggregate value of the opinions provided by customers gives a measure of the trust necessary for transactions to succeed in the cyberspace.

With respect to education, some writers, such as Schmidt (2009), in the field of peer-based learning advocate the use of online rating systems to continuously evaluate the contributions of participants in communities of peers. According to Schmidt, this form of assessment can help address what he perceived to be two main challenges in education. First, the inadequacy of standardized tests to evaluate the kind of skills that are considered relevant in the digital economy, such as the ability to analyze complex information and collaborate with others. Second, the lack of scalability of common models for assessment, which require an individual expert to review the work of students and seem inadequate to scale to very large numbers of students. Further to this, Anderson and Dron (2011) argued that “a faceless intelligence that is partly made of human actions, partly of a machine’s” (p. 91) might support the next generation of distance education pedagogy. Although they did not refer explicitly to online rating systems, their argument is relevant. They asserted that crowd-based elements, for example hash tags and profile fields, can influence participants’ social interaction in forms of communication taking place, for example, in blogs or microblogs (e.g., Twitter) in which most of the time a post addresses an unknown set of people, in the hope that they will be interested in what the post says. Crowd-based elements can guide and help participants to find posts and reply to them. Anderson and Dron concluded that, although it was unclear how best to exploit these crowd-based elements in learning, it seems at least possible that technologies that make effective use of such elements will enable the next generation of distance education pedagogy.

While there is an established tradition of studying the role of online peer feedback in fostering positive learning experiences and enhancing learning outcomes (see the table summarizing previous research in Melville, 2014), empirical studies of the use of online rating systems in educational settings are scarce, given the novelty of the phenomenon. Mixed results emerge from the few studies apparently available. For example, Thoms, Garrett, and Ryan (2010) conducted a quasi-experimental design study to examine the effects of a blog rating system on course learning, social interaction and course motivation in five online university graduate courses during two semesters. They found that compared to non-raters, raters perceived higher levels of social interaction but not higher levels of perceived learning. Across the whole population of raters, only 49% agreed that that the rating system was useful, indicating the importance of reciprocity for participants, who are less likely to take part in the course when they perceive other members to be inactive. Further to this, Melville (2014) conducted a pilot study of the use of a crowdsourcing platform in an MBA elective, which enabled students and outside experts to assess the quality of assignments using voting and commenting. His findings suggest that viewing and commenting on other assignments increase engagement and may enhance learning, but voting and the use of badges and points were not perceived as especially beneficial.

This paper attempts to examine the sociomaterial agency of an online rating system and its influence in an open study group. Following Leonardi (2012), sociomaterial agency is meant as the ways in which the entanglement of social phenomena (e.g., values, norms, discourses) and material phenomena (e.g., technologies) acts. Putting materiality at the center of the analysis allows giving attention to the devices that come to shape rating and influence the activity rating refers to. Such is the importance of materiality that, as Pollock (2012) suggested, there can be no rating without the *devices of rating*. He argued that it is only through working with these devices that ranking organizations can produce and communicate ratings. This view emphasizes the *material and distributed character of rating,* which means that this action is not performed by individuals alone, but through the enrollment of a variety of material artifacts. Similarly, in this study, it is argued that examining the devices of rating offers the possibility to understand how production and communication of rating occurs. To study this phenomenon, the analysis focuses on the ways in which a rating system is involved in creating value in a large, teacherless, peer-based, online open study group, MIT 6.189 A Gentle Introduction to Python run by Openstudy.com. Specifically, the analysis focuses on peer rating as a form of recognition based on offering medals to participants giving good responses to their peers’ questions.

The Peer Rating System

The online peer rating system featured in this study is used in MIT 6.189 A Gentle Introduction to Python, an online open study group born from the collaboration between OpenStudy (www.openstudy.com) and MIT OpenCourseWare (OCW) (http://ocw.mit.edu/index.htm). The aim of this study group is to allow learners to connect to and help each other in their process of learning Python, a programming language, while using course materials made available by MIT OCW. The study group is run by OpenStudy, which describe themselves on their web site as a "social learning network where students ask questions, give help, and connect with other students studying the same things". The study group is structured around questions and answers from the participants. OpenStudy is a peer-based environment, without professional teachers tutoring and assessing learners. The responsibility to run the study group is distributed across participants. Participants are expected to engage and contribute by helping their peers. They can ask questions, report problems and difficulties, share coding, and link to external materials. At the time of this writing, the study group counted 1437 members and 382 asked questions.

When OpenStudy was developed, the designers envisioned a platform supporting "open social learning", and decided to draw from the features of social media and games. They imagined a Facebook-like platform where the goal is to study together and not to trade pictures and jokes, as well as a World of Warcraft where students earn points by helping each other. According to their vision, the behavior to be motivated to support social interactions and engagement is to be good and helpful. Participants need to develop soft skills including teamwork, problem solving and engagement, and they are rewarded for demonstrating mastery of these skills. In fact, these skills are mapped onto an individual scorecard, called SmartScore (Figure 1), which is visualized next to the participant's name. As described in the OpenStudy's blog, "much is embedded in the three core categories: a willingness to help others; an ability to collaborate, communicate, and build relationships among the team; the willingness to contribute to finding solutions; and dedication to a task or group". Based on their level of development, participants earn different titles ranging from Hatchling (a title indicating the status of beginner) to Rookie and Lifesaver, among the others.

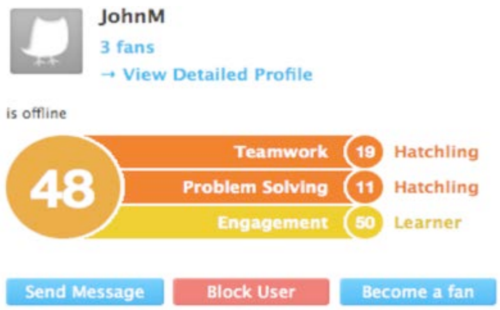

Figure 1. Example of SmartScore

To motivate helpful behavior, the designers developed a rating system to assess the development of these soft skills. One main component of this system is peer rating as form of recognition based on offering medals to participants giving good responses to their peers' questions (Figure 2). Peer rating is based on a simple mechanism: an asker asks a question and an answerer answers it. An asker can give the medal, or someone else in the study group can give the medal, but the answerer cannot give him/herself a medal. Crediting answerers with "best responses" by offering medals is a code of conduct in OpenStudy, thus study group participants are strongly encouraged – although not obliged – to acknowledge good answers from their peers.

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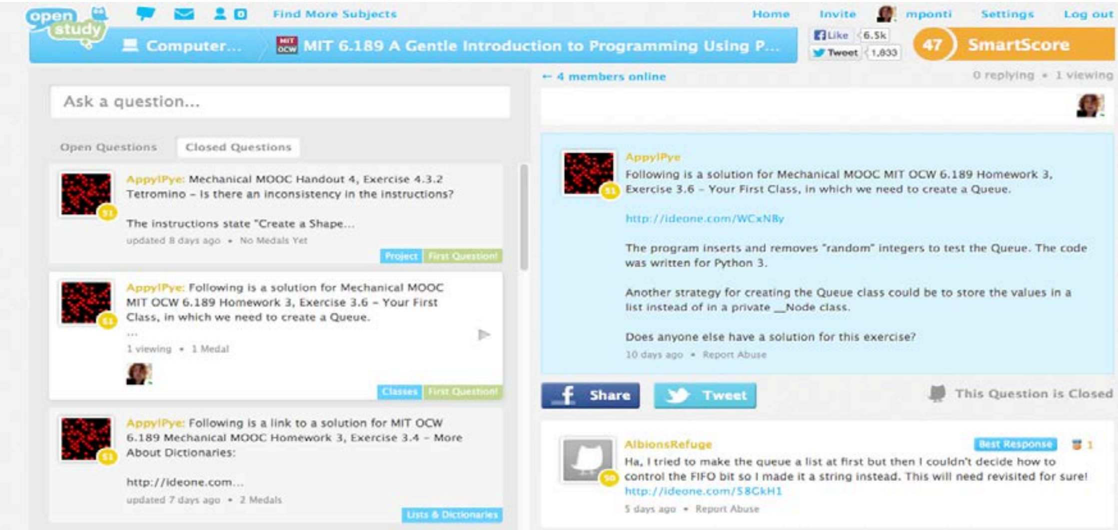

Figure 2. Example of Question with Response Awarded a Medal

Method

Data Collection and Sampling

This study is based primarily on the questions and answers posted in MIT 6.189 A Gentle Introduction to Python from the start of this study group, approximately October 2012, until the beginning of September 2013. This study group is named after the massive open online course (MOOC) with the same title (http://mechanicalmooc.org/), but it is available as a standalone study group as well. In every OpenStudy group, two sections are visible: open questions and closed questions. When a question is closed by the asker, it moves to the "closed questions" section. In the “open questions” section, questions can be unanswered, waiting for someone giving answers, therefore I included in the research data only the closed questions. Closed questions are threads including a top-level question about a topic, followed by one or more answers and/or other questions. They can be as short as including one question and one answer, or as long as including 30 posts. Closed questions can be closed without being answered, but generally they are answered by at least one participant, and often by several participants. Therefore, it is possible to see if helpers with “good answers” were credited with “best responses” and awarded medals. At the time of conducting this study, there were 260 closed questions, out of a total of 397 questions.

In order to make the analysis manageable I sampled the participants who asked closed questions. Sampling can be problematic when conducting online research (Fricker, 2008). Similarly, I had to address some issues. Membership is based on interest in the study group topic and little information is required when registering to the study group. Registration typically involves asking for the individual's name, school and a little description, but only few participants provide this information about themselves in their profile, and even this information may be questionable, because there is no guarantee that participants provide accurate demographic or personal information. This issue makes it difficult to generate a sample frame, but it is somewhat less of a concern because this study is nonprobabilistic. Therefore, I chose a nonprobabilistic homogeneous sample (Patton, 2002). The sample was homogeneous only in the sense that participants met the selection criterion of being Hatchling. Therefore, I only included people whose overall title was Hatchling, as I came across them rather than selecting them through random procedure. Other than sharing that title, the participants included in the sample come from a vast range of backgrounds and ages, although with a substantial gender difference, in that there is a prevalence of men.

Sampling participants who asked closed questions occurred in two stages. Since this study is part of a larger analysis of newcomers’ participation in the study group, after examination of the entire corpus of closed questions, the focus was on Hatchling participants. The sample included only those who were Hatchling at least in two skills, and whose questions received at least one response rated as “best response” and thus awarded medals. From the sample were excluded closed questions unrelated to Python and those followed by answers with no medals. Finally, 108 closed questions were included in the homogenous sample. Sampled questions were saved as image files and archived for further analysis. As a secondary source of data, I collected data from

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openly available documents such as blog entries written by the OpenStudy's team members, and videos where one of the social platform's cofounders described the design and development of the platform.

Data Analysis

Qualitative content analysis (CA) was used to examine the content of the answers rated as "best responses" and awarded medals. Since the interest was on the value provided by these good answers, I chose to examine indicators of such value, which were manifest in the content of the answers, rather than indicators of rating skills displayed by participants. Rourke, Anderson, Garrison, and Archer (2003) defined manifest the content that is at the surface of communication and is therefore easily observable. The value provided by good answers is not seen as an attribute intrinsic to these answers, but as a relational property that depends on peer evaluation and recognition thorough medals award.

A mix of preexisting and inductive codes were used to analyze instances of value provided by good answers. Preexisting codes were brought in from two schemes. The first scheme was developed by Mason (1991, p. 168) and includes seven broad categories to analyze interactions in an online forum. The categories include use of personal experience related to a course theme, reference to appropriate materials outside a course and tutors acting as facilitator, among the others. The second scheme was developed by Anderson, Rourke, Garrison, and Archer (2001, p. 8) and includes six categories to analyze facilitation discourse. The categories include drawing in participants and prompting discussion, setting climate for learning, and encouraging or reinforcing student contributions, among the others. These two schemes were chosen because previous observations of the whole corpus of closed questions provided a sense of what was interesting there. Based on those observations, the two schemes provided a set of broad categories that did not constrain openness to new concepts suggested by the data. In coding the data, the message was chosen as a unit of analysis, being less time consuming and facilitating unit reliability (Rourke, Anderson, Garrison, & Archer, 2003). Answers rated as "best responses" were coded as exhibiting one or more indicators of each of the categories used in the analysis. The same content was coded on two different occasions to determine intracoder reliability (Johnson & Christensen, 2012). The scientific software HyperResearch was used to mark segments of the text with the codes that were claimed represent indicators of the value provided by good answers.

Results

Table 1 shows the codes, percent of coded best answers, and representative answers for the 20 categories resulting from the content analysis.

Codes	**Percent/ Frequency**	**Examples**
Giving help for fixing coding errors or solving exercises	26% (112)	*"I can't give you the deep theory, but if you try this, you'll see what's going on: x ="012345"…"*
Setting climate for learning	9% (38)	*"Welcome to OpenStudy!!! If you ever need help with a question, just post it in the correct section and I'm sure you'll get help very soon…"*
Drawing on one's own experience	8% (34)	*"I tried to make the queue a lust at first but then I couldn't decide how to control the FIFO bit so I made it a string instead…"*
Giving examples of code	8% (35)	*"[x**3 for x in range (1,11)]"*
Giving help about the functioning of the MOOC	7% (30)	*"At this early stage, peer review is maybe not so important unless you are a complete programming beginner. Later, with more complicated assignments, peer review is a good way to get new ideas…"*
Acknowledging and reinforcing peer contribution	6% (27)	*"Thanks! I wasn't aware you could use the "for x in list" structure inside a list bracket, but that's pretty nice…"*
Drawing in peers and prompting interaction	6% (24)	*"In the first example, can you determine the number, when multiplied by itself (or squared) gives you 16?"*
Giving help for fixing technical concerns	6% (25)	*"We've noticed Codecademy can be a little flaky sometimes. Try a different browser or come back later and try…"*
Linking or referring to relevant material outside the MOOC	5% (20)	*"According to this is possible* [*http://stackoverflow.com/questions/4583367/how-to-run-*](http://stackoverflow.com/questions/4583367/how-to-run-)

Codes	Percent/ Frequency	Examples
		multiple-python-version-on-windows and there is similar article if you are using linux…"
Referring to participants by name	4% (19)	*"Great to see you all online. Want to stress that @e.mccormick said above. The resources are persistently available…"*
Communication serving purely social function	3% (13)	*"You're welcome"*
Linking or referring to material in the MOOC	3% (13)	*"The sequence for the course is available here http://mechanicalmooc.wordpress.com/sequence/…"*
Using the study group effectively	3% (12)	*"For medals, click on the Best Response button. To become someone's fan, hover over their screenname and there's a "Become a Fan" button…"*
Linking to examples of code in online compilers	2% (7)	*"I'm not very excited about my solution to that problem, but here it is: http://ideone.com/yioELL"*
Presenting content related to Python	2% (10)	*"…Python is modelled after the Fortran line; there is a clear distinction between expressions and statements…"*
Assessment of the efficacy of the process	1% (3)	*"…I also think the MOOC definitely should have included more lectures for these exercises – it's a big leap from week 6 to week 7 without the lecture I think"*
Giving general information	1% (4)	*"This is Python study group"*
Complimenting and expressing appreciation	0% (2)	*"Yeah Buddy! I'm so excited guise."*
Referring to others' posts	0% (2)	*"Check other messages. There was a thread sharing their nims code. At least 3 people did submit working examples…"*
Self-disclosure	0% (2)	*"… I'm just a lowly electrician who is studying to be an electrical engineer and also like computers."*

Table 1. Codes and representative answers

Discussion

This study indicates that the peer rating system makes visible what the participants find immediately valuable (Wenger, Trayner, & de Laat, 2011). Unsurprisingly, the results show that the most useful answers were those helping to fix coding errors and solve exercises. The next category of useful answers included statements promoting and maintaining a positive atmosphere in the study group, where the importance of encouragement, kindness, and courtesy among participants is a code of conduct. The next two largest categories of valuable answers included responses where participants applied their own experience to learning Python and gave examples of code, by linking to external documents or copying and pasting code in the study group. These results correspond partially to previous research on a web-based reciprocal peer review system by Cho and Schunn (2007), who has shown that learners benefit from receiving feedback from others with similar experiences, especially when the review process is scaffolded, anonymous, and reciprocal. In this study group, however, the review process is not anonymous (although the majority of the study group members provides fictitious names and scarce personal information) and does not imply reciprocity.

By making good responses recognizable, the rating system makes more visible what the participants can gain from each other and what they can achieve by helping each other. Rating a response as 'best response' may act as natural scaffold to help participants learn what makes a good response. The analysis of how rating occurs shows that individual participants evaluate by themselves whether a response is valuable to them. In this non-formal educational setting, there is no teacher or facilitator performing this assessment on behalf of participants. Indeed, learners asking questions - or other lurking learners - decide on their own and award medals accordingly. Since the reward is given to what the participants find immediately valuable, it could be suggested that it reinforces instrumental learning (Greeno, Collins, & Resnick 1996), where the effect of instruction in the study group depends on being able to reinforce desired responses, which must occur in order for the reward to be provided. We can question whether the absence of legitimate knowledge and legitimate attributes (e.g., being a teacher or an accredited expert) also supports instrumental learning, as, without a teacher, a good response is what provides a quick solution, with no apparent obligation to develop deep thinking. While in formal education legitimation is primarily based on possessing both legitimate knowledge and legitimate attributes (e.g., being a teacher or an accredited expert), in this study group, legitimation is restricted neither to specialist knowledge nor by knower attributes. In the study group, knowledge can come from a plurality of sources, because the networked environment allows participants to connect with one another and share information either generated by themselves or drawn from other sources. This situation of information abundance is likely to make models of traditional gatekeepers oversight untenable, due to the large amount of information to be filtered and evaluated. This shift in information provision suggests circumstances under which sources that are not considered experts in a traditional sense – as they lack special training and credentials – can be in the position to provide valuable information. Indeed, good responses given by the participants who consider themselves beginner programmers have been awarded medals as those provided by the participants with more experience in programming. This evidence can be related to the peer-based learning approach adopted by the designers of the system, which privilege participation and engagement of all the members of the group over prior accreditation. Furthermore, along with awarding medals, other two elements are likely to influence the extension of the modes of legitimation: the increased access to information and knowledge resources and the empowerment of all the study group members, regardless of their attributes. In this study group, every participant can access a plethora of external resources on Python, and it is claimed that everyone can provide valuable knowledge in the form of suggestions, experience and coding, provided that they comply with the code of conduct of OpenStudy.com. Privileging participation over prior accreditation as a basis for recognizing expertise and knowledge is a way to address the familiar problem of social scale in large social networks and communities (David, 2007). As David suggested, rating systems such as that used in the examined study group can be seen as serving as a proxy for expertise that is not intended as a final level of achievement but as a continuous process, which is developed and maintained through a "feedback loop between participation and community recognition" (David, 2007, p. 183).

Unlike formal education where the accredited expert controls the definition of what counts as good work, and "assessment confirms that the tutor is in the position of holding specialist and superior knowledge" (Jones, 1999), it can be suggested that in this study group the peer rating system allocates a form of recognition that extends the modes of legitimation of skill development. The number of medals received by the participants contributes to their SmartScore (Figure 1), and it is used, in combination with other analytics (e.g., number of fans and testimonials) to report on skills and competencies demonstrated in the study group, in a manner that the rating system designers think more effective than grades and credits gained through high-stake assessment. This view resonates with the belief that focusing on high stake testing in credentialing is detrimental to education because it stresses the validity of tests of abstracted and isolated skills over continuing and formative assessment for learning, which is harder to fit into formal examination contexts (Knight, Buckingham, Shum, & Littleton, 2013). By defining achievements in terms of developing and demonstrating skills such as teamwork, problem solving and engagement (Figure 1) and not only transmitting subject knowledge, I would argue that the system aims to change the "legitimation code" which refers to what makes someone different and worth of distinction (Maton, 2000). The peer rating system enables the participants to see what individual peers think about a response. The medals awarded to good responses act as "tokens of appreciation" and partake of a mechanism aimed at supporting motivation, engagement, and commitment to participation in the study group. It can be suggested that this system contributes to build confidence in what counts as good responses in an environment where there is no credentialed teacher or expert acting as the arbiter of their validity.

Conclusion

In summary, the results of this study suggest that the peer rating system influences value creation. As suggested above, awarding medals is used to make clear what the participants find immediately valuable. Being awarded many medals can be used to make clear who is more likely to be considered helpful and knowledgeable in the study group. As a community architecture, the study group relies on this system to award medals to good responses. The system contributes to a rank within the Openstudy.com community measured in terms of capacity to be committed to the study group, help others and solve problems. Although not faceless, this peer rating system is partly made of human actions and partly of a machine's. Similarly to liking in social media, medals are a form of non-text feedback that can encompass several social practices. While this paper focuses on the content of the answers rated as "best responses" and awarded medals, further study must be done to integrate this data in the context of personal stories where participants account for their experiences of interactions signalled as valuable, but also for those activities and interactions whose value is not recognized by the existing rating system.

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