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Badges of Friendship: Social Influence and Badge Acquisition on Stack Overflow

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Abstract

Badges can provide a number of advantages to networked, self-directed learners, including making visible social networks of support and direction. If badges do allow for this, we would expect to see badge acquisition to be predicted by the presence of a particular badge among a learner's social connections. In examining the badges and "tags" used on the question-and-answer site Stack Overflow. We find that the more general badges are closely related to tenure on the site, while the numerous "tag" badges provide for more socially-determined differentiation.

1. Introduction

The emergence of connected learning environments [1] has influenced the degree to which we consider social connections--always important to the process of learning [2]--to be especially vital to the process of creating personal learning networks and environments. Because there is often a relative lack of social signaling in such environments, badges can be used to make social context more visible, and improve the structures for supporting learning.

The question-and-answer site Stack Overflow provides a widely used space for individualized exploration, with a relatively long history of issuing various badges to its users. It provides a good environment for understanding the conditions under which badges might shape learners choices and behaviors.

This study adapts a social learning analytics (SLA) perspective to study the network effects on badge selection on the site. SLA focuses on the learner's networked participation: who they talk to, how often they interact, group project membership, and shared discussion content [3]. SLA is particularly useful to understand informal online learning experiences such as forums, blogs, discussion boards, and Q&A communities, qualitatively differentiating the evaluative criteria from traditional assessment and performance [4, 5]. Considering that such a learning environment requires networked collaboration and participatory social interactions among the members, this paper attempts to investigate whether an individual user's badge earning is motivated by the exposure to others' achievements.

We conclude that the influence friends on badge selection is weak, but has an effect, particularly for topically-constrained badges (referred to as "tags") on this site. We further find that there appear to be different roles for the two different kinds of badges on Stack Overflow, with general badges being more related to tenure in the community, and "tags" providing a clearer way of finding paths through related topical areas. While these represent fairly modest findings, they suggest further work on the nature of badge use and wayfinding is needed.

2. Learning badges

Badges serve several functions in online communities, including goal setting, group affiliation, experience, authority, and identity [6, 7]. The initial use of badges online is often traced back to gaming, and their application elsewhere sometimes referred to as part of a process of "gamification" of the environment [8]. Most implementations of badges, including their use on Stack Overflow, intend for users to earn badges by interacting with a site or system in particular ways. They are used primarily to motivate certain behaviors.

But for badges to be motivational, they must represent something more meaningful than points in a game. A significant part of this meaning is as a representation of social prestige. A website indicating someone is an "expert" matters only if the process of awarding that moniker is valued. More recently, badges have found prominent use as learning objects,

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intended to help frame new forms of credentialing, assessment, motivation, and collaboration. Much of the empirical investigation of learning badges remains nascent, and little of it has addressed the social and structural effects of badges.

The rise in the popularity of participatory contexts online has led to new opportunities for distributed, connected learning. Such communities are often heavily participatory, breaking down traditional institutional roles of teachers and learners, and drawing more heavily on peers for instruction and assessment [9, 10]. In peer learning communities, there are often those who have "gone before" along a certain path--what the Japanese refer to as *sempai* [11, 12]. These are contrasted with the *kohai*: those who are new to a particular learning community and intend to learn from their peers; those who are engaged in what Lave & Wenger [13] refer to as "legitimate peripheral participation." In physical environments, these roles are often marked in ways that are both formal and more subtle: ranging from titles and offices to proxemics and forms of address. In lower-context online settings it can be more difficult to identify the more and less experienced members of the community. Given the importance of participation to peer learning environments [14], being able to mark pathways toward expertise is vital.

3. Network threshold model

Social networks scholars are often interested in the diffusion of behaviors, opinions, and attitudes via social networks, a system of relationships that provide members with friendship, support, information, or communication [15]. Diffusion processes and social networks are intertwined given that networks are the venues through which an individual observes and receives information, opinions, attitudes, and behaviors from their social environment. Young [16] differentiates three types of network diffusion models: social learning, contagion, and social influence. First, in social learning process, individuals assess the worthiness of the innovation before adopting it, based on the observation of the outcomes among prior adopters. Social learning assumes a rational decision-making process, which usually accompanies a cost-benefit analysis. Second, the contagion process refers to a rather unintentional cognitive process when an individual comes in contact with others who have already adopted. The pattern is like an epidemic transmission. Social contagion literature, therefore, highlights the conditions that increase "social infectiousness," for example tie strengths and structural equivalence with a prior adopter [17, 18]. Lastly, social influence refers the process in which people adopt when enough number of others in the group have adopted. Young [16] defines social influence process as the "spread by a conformity motive" (p. 1900). Therefore, the social influence diffusion literature is interested in understanding threshold behaviors [19] or how to reach critical mass of the population [20].

Recent studies bring these contagion models to online sociality. Both contagion and social influence highlight the "exposure" to prior adopters as important antecedent to shaping opinions and behaviors [16]. For example, social media marketing researchers find that social cues in Facebook, defined as the exposure to networked peers' adoption behaviors, play an important role in consumer response to online ads, even when controlling for homophily such as common interests and geographical proximity [21]. Social influence from the visibility of peer practices is reported to drive five times more referrals to the advertised websites than search engines do [22]. Another recent large-scale study also found that political attitudes and voting behaviors are influenced by exposure to the attitudes and behaviors presented by Facebook friends [23].

The effects of social networks on new badge adoptions in massive online learning communities, if any, are likely to follow social influence process rather than social learning given that the direct, tangible costs (i.e. money) are not incurred through participation, thus the rational decision-making in selecting a particular badge over others is less important. We also assume that social influence explains the process better than the contagion logic, because high social contagion conditions seem to be absent in such communities: Most of virtual contacts are better defined as weak tied relationships than strong ties, and each member's structural positions in an informal and non-hierarchical community setting are likely to be not as much important as in formal organizations. On the other hand, public presentation of online badges make clear which badges are popular among a given user's friends.

One well-known approach to understanding the effect of social influence on network diffusion is to look at the magnitude of direct connections to adopters within a user's personalized social environment. Valente's [24] threshold model of diffusion in social networks, in particular, postulates that an individual adopts a new behavior, opinion, attitude, or innovation based on the proportion of people in their personal network who have already adopted it. The threshold of the proportion of adopters in an ego-network is defined as "personal network exposure" (p. 43). A person with a low threshold requires fewer social contacts engaging in the behavior in order to adopt the behavior themselves while a person with a high threshold may wait for a majority of the social network in order to adopt a change. Thresholds are best measured by direct network links since this variance in adoption threshold is partly due to perception of the new behavior. In earning badges, users might perceive a certain badge as being more authoritative, important, and prestigious than other badges based on the adoption patterns by those with whom they communicate.

Social network approaches undergird much of the work in learning analytics, providing means to improve learning outcomes [25]. Learning analytics draws on large-scale, often unobtrusive, collecting of data about the behavior of students, instructors, and employees, for the purposes of understanding and improving virtual learning environments such as Blackboard and Moodle [26], and other learning environments.

Personal Learning Environments (PLE) provide researchers with a virtual “map” of learners’ tools, resources, and Personal Learning Network (PLN) that have been compiled and personalized by the learner [27]. Elliott [28] suggests that an important step in starting or expanding your PLN is to become active in other forms of social media, such as blogging, wikis, or mailing lists. It is essential to comment in these forums in order to become active. While this approach does risk criticism, it also enables information to be exchanged and social influence to occur. Stack Overflow represents just one site in which learners may engage, most certainly as part of a larger collection of resources and communities. But it also provides an open window through which we can observe self-directed learning.

The risk of semi- or un-structured PLEs is that learners are left without clear paths toward success. Ironically, one of the earliest hopes of the web is that it might provide just such pathways through a sea of information, highlighting ways of linking together and making sense the unstructured collection [29]. Wayfinding is the process of navigating an environment, analyzing the surroundings and making decisions on how best to end up at the desired location [30]. Research comparing wayfinding in the physical world with that of the virtual world suggests that the mechanisms are similar, relying on social and psychological cues as well as physical. One of the ways in which badges may help individual learners in networked environments is by acting as social signposts toward interesting areas of investigation.

4. Stack Overflow

Stack Overflow is a question and answer site for computer programmers. Joel Spolsky and Jeff Atwood, both programmers, created the site in 2008 out of the need for a non-monetized community resource to answer the questions of "coders and computer geeks" [31]. In less than a year, the site evolved into a multi-sited community platform that has become a significant resource for many coders, and has taken on the role of online documentation for many open source projects. The popularity of Stack Overflow inspired spin-offs to support community demands in other topical areas, collectively referred to as the Stack Exchange. Stack Exchange hosts a large network of question and answer sites (104 and growing), on diverse topics from software programming to cooking to photography and gaming. Stack Exchange sites do not try to place boundaries on who accesses the site, participates in forums, or contributes--only the quality and quantity of questions, answers, and intention matters.

As Joel Spolsky noted in a 2009 Google Tech Talk: “In order to get people to do the things we want them to do on the site, we have the concept of badges” [32]. Badges can be earned by accumulating points from others and performing particular tasks on Stack Overflow, and building reputation in the process. Bosu et al. [33] created a model of rapid reputation building based on four parameters: topic, competition, time of day, and speed (2013). This suggests the possibility a new user could gain status quickly on Stack Overflow and eventually move to a trust position in the Stack Exchange community. However, this empirical reduction of the reputation algorithm does not take into account the effect general badges and tags have on users’ perception of trustworthy users.

There are several ways to contribute to Stack Overflow and a range of badges that represent these contributions. All of the badges that users earn are displayed on their publicly available profiles. Earned badges do not affect the site’s functionality or give the user any enhanced rights; they are symbols of achievement.

The (currently 75) “general” badges represent achievements of merit and contributions of time, and are joined by a couple thousand “tag” badges that mark subject matter expertise. “Tag” badges are awarded to users that achieve a specific number of positive votes, known as upvotes, for questions with a particular tag. A tag like “ruby-on-rails,” for example, must appear on a minimum of 100 questions to be considered for a badge. Similar to the merit-based general badges, the tags may be awarded at bronze, silver, and gold levels, according to the total number of upvotes. Research indicates badges are an essential component in reputation building and influencing learning and cultural uptake in Stack Overflow [7, 33, 34].

Despite being created as a method of motivating participation, badges meet a range of needs in any environment. Stack Overflow's badges, for example, have been considered an exemplar in providing an indication of expertise that carries weight not just on the site itself, but in the larger field [35]. Our interest in badging on Stack Overflow is related to questions of social influence and wayfinding. The mechanism by which badges might be used to find new learning challenges and accomplish them is, no doubt, a complex one. To understand whether this is indeed occurring on Stack Overflow, we first need to obtain empirical evidence that such contagion exists: do those who see badges displayed among the commenters in their milieux then seek to obtain those badges? The first step in understanding badging as a process is to ascertain whether this basic mechanism is present in badged environments like Stack Overflow.

5. Method

We are interested in whether the appearance of either general badges or tags could be attributed to the influence of a user's community. To better understand this, we collected a sample of earned badges and tags and sought to relate these to the same badges found among the user's affiliates on the site.

5.1. Data

Extracting the necessary badge assignment information was a simple matter of parsing the information from Stack Overflow's public data dump. The site does not, however, allow for public or private indication of association or "friendship." Indeed, the developers are clear about their desire to steer clear from social elements, indicating that "Stack Overflow is not a social networking site. There's no private messaging. There's no 'friends' list. The entire focus is on the knowledge shared." [36]

Therefore, it was necessary to infer social connections through a measure that was publicly available: co-posting behavior. There is some history of attempting to operationalize social connections, particularly in online environments [37, 38], but social relationships are remarkably difficult to reliably measure, even when explicit [39]. In this case, we have little observable interaction with which to infer social exposure to others on the site. We inferred a social tie between any two users who commented on the same post on the site. Co-posting interactions are analogous to co-citation or co-authorship networks that reflect the structure of attention [40] or the structure of collaboration [41]. Co-posting networks can similarly suggest the shared interest or expertise in a same topic. If, in the process of commenting and answering, users repeatedly are exposed to the profiles (and potentially, badges) of their co-posters, we might expect this would lead to pursuit of the same badges. While not an ideal way to measure an authentic sense of friendship or strong ties, it provides some approximation of shared conversational and attention space.

Because of the scale of the data, we collected separately for the general badges and the tags. For general badges, we limited our collection to February of 2013. We checked each of the new badges awarded in February against the portfolio of badges held by the recipient's social ties in January. In addition, we assigned a random badge that the recipient did not hold (a "pseudobadge") and checked this against their network of associates in the previous month. In this way, we were able to determine whether the *actual* selection of a badge was significantly more likely that the selection of another badge taken at random. We also calculated the density of badges held by associates of the new recipient, the Personal Network Exposure (PNE), for both the actual earned badge and non-earned pseudobadges.

Considering personal differences in badging practices, we controlled intra-individual differences by looking at "within-individual" differences by comparing earned and pseudobadges by the same user. The combination of user *i* and badge *j* was considered to be a case in our dataset. Given that a user can earn multiple badges, a single user comprises multiple cases. From these, badges that appear to be duplicated in the data dump and those issued to users that had no ties to other users (in the previous month) were removed. Many of the general badges were earned by users new to Stack Overflow, with far fewer of the tags being awarded to new users. After this process, the collection of general badges data included 325,792 cases based on 75 unique badges and 151,292 unique users.

We followed a similar methodology for tags, though because they were both more numerous and sparse than the general badges, we extended our frame to the first five months of 2013. We also ignored levels of badges (i.e., treated "gold" and "silver" as identical). Even with this larger collection period, the total number of tags collected was much smaller: 16,909 cases based on 1,940 unique tags and 5,616 unique users.

5.2. Paired t-test

First, we tested for significant difference in PNE between the earned and pseudobadges. Each case that combines user i and earned badge j (C_{ij}) was paired up with a counterpart case that combines the same user i and a randomly selected unearned pseudobadge q (C_{iq}).

Table 1. Paired-T Test between earned and unearned Badges.

Badge Type		# of Pairs	Paired Differences			
			M	*SD*	*t*	*df*
General Badges	Adopter ***	151542	57.365	198.129	105.212	15141
	PNE ***	151542	0.106	0.365	400.896	15141
Tags	Adopters ***	8293	53.548	80.399	64.976	8292
	PNE ***	8293	0.376	0.883	10.893	8292

Note: p < .001

Table 2. Parameter estimates of the effects of badge differences, number of adopters, and PNE on a user's badge adoption (100,173 users and 75 badges)

			Hypothesis Test			C.I.	
Parameter	*β*	*SE*	*Wald χ2*	*df*	E(β)	Lower	Upper
(Intercept)	2.019	0.040	2557.089	1	7.531	6.964	8.144
Badges ***			48463.429	74			
#Adopter ***	0.002	0.000	134.469	1	1.002	1.001	1.002
PNE ***	0.120	0.029	17.384	1	1.128	1.066	1.193

Badges: The reported values of "Badges" is the model effect; Parameter estimates that compares each badges to a reference badge are not reported in this table due to space limit. *** *p* < .001

On average, general badges showed a larger number of adopters and higher rate of PNE for both earned (76.81 adopters, 0.607 PNE) and unearned badges (23.26 adopters, 0.231 PNE) than tags. For earned tags, each tag included on average of 58.18 adopters with 0.127 PNE. Unearned pseudotags, in particular, included less than one adopter on average (0.81) and showed very low PNE (0.021). The paired t-tests showed that the mean differences of the number of adopters and PNE between C_{ij} and C_{iq} were significantly different for both general badges and tags (table 1). However, the correlation tests showed that while C_{ij} and C_{iq} were moderately correlated for general badges (adopters r = 0.536, $p < .001$; PNE r = 0.129, $p < .001$), there are no correlations for tags (adopters r = 0.009, *n.s.*; PNE r = - 0.007, *n.s.*). In other words, the true difference between the pairs seems to be among taggers rather than general badgers.

While paired t-tests show the differences in prior adopters and PNE between earned and pseudobadges, the results are limited for two reasons. First, every user-badge combination was assumed to be a unique case. For example if a user *i* earned Badge A and B, and did not earn Badge C and D, one pair could be matched between user *i*'s A and user *i* s C. Then, another pair between user *i*'s B and user *i*'s D could be matched and independently treated from the A-C pair. Although this pair design puts user's intra-individual differences into consideration, neglecting the non-independence between cases could overestimate the result. Second, the paired t-tests do not predict the effects of social influence on each user's adoption of a new badge: The mean difference between the earned badges and unearned badge could be produced not from a different level of social influence a user receives from others but simply from the easiness or popularity of a particular badge. In other words, a badge-contingent effect should be controlled to properly estimate the relationship between social influence and a badge adoption.

5.3. Generalized estimating equation

To assess the limitations mentioned above, we applied a generalized estimating equation model. GEE allows us to fit a repeated measure logistic regression to the data. The repeated measure means that a single subject is observed multiple times across different time points or different treatments. Our dataset is considered to be a repeated design in that each user's badge-earning behavior (either earned or not) is recorded across different badges. GEE then estimates the badge effects along with the effects of the number of adopters and PNE.

We were only able to perform a GEE analysis with the general badge data. Multi-level modeling, including GEE, requires a large number of observations with a moderate number of a higher-order level (i.e. badges in our study). While general badge data included a reasonable size of badges (N =75), the tags data collection had too many badges (N = 1,940) to result in a workable computed estimate.

Table 2 shows the badge differences account for the biggest effects on a user's badge adoption, combined Wald $\chi 2(74) = 48463.429$, $p < .001$. Considering the variety of badge availability that a user can achieve, ranging from very popular and easily obtained badges like "Popular Question" (11.6% cases in the data) to relatively rare badges like "Pundit" (0.8% cases in the data), this large effect is not very surprising.

The results show that the number of adopters and PNE are also significant predictors, albeit showing much smaller effects. Specifically, users who have more adopter friends were more likely to adopt a badge with the log odds β = 0.002, Wald $\chi 2(1) = 134.469$, $p < .001$. The exponent of log odds E(β) was 1.002, indicating that the likelihood of getting a new badge increases 1.002 times with every single adopter friend added. PNE also was significant with the log odds β = .120, Wald $\chi 2(1) = 17.384$, $p < .001$. The exponent of log odds E(β) was 1.128, indicating that the likelihood of getting a new badge increases 1.128 times by every one unit increase in PNE.

6. Friendless badging and tag teams

Given the two types of badges available on Stack Overflow, the natural assumption was that the general badges--which have social positional labels, like "Editor," "Teacher," or "Organizer"--would be the most influenced by peers. Indeed, our initial impulse was to ignore the tags. In fact, it appears that the general badges may have a greater community function, while the tags represent learning pathways, interests, and opportunities more directly.

Although they do represent different groupings or pathways, the general badges as a rule are designed as a ladder, providing early opportunities for badges for new members on the site, and increasingly more difficult ("gold") badges for those who rise to prominence on the site. The badges are relating directly

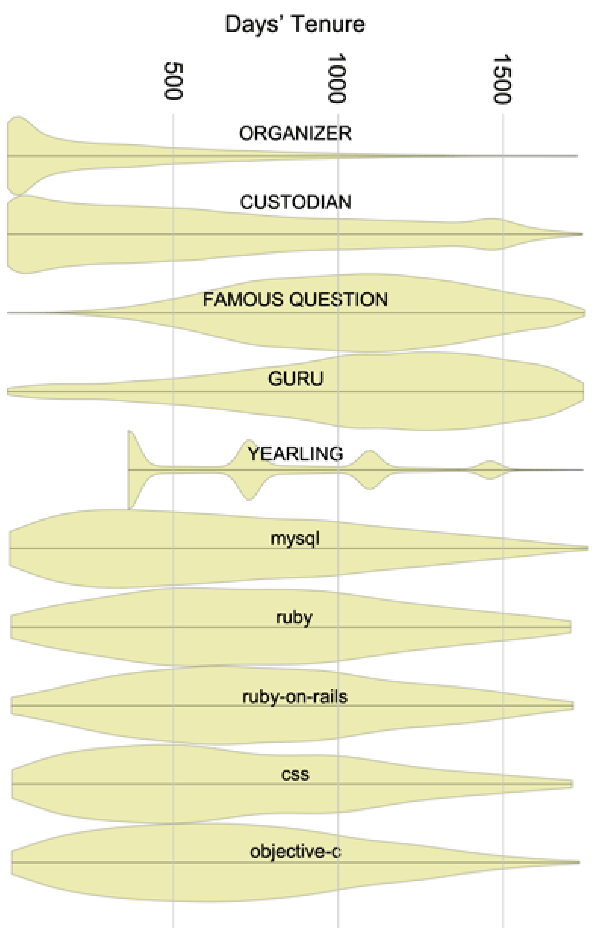

Figure 1. Violin plot of distribution of tenure on site (in days) of badge earners for selected general badges and tags.

to Stack Overflow--it is less obvious that they represent knowledge that is useful outside of the site.

But rather than the subject matter represented by the general badges, it is probably their structural relationship to the site that makes them less likely to be influenced by social factors. In fact, while tags may be earned at just about any time in a user's tenure, general badges tend to require actions that place a user at some point in their lifecycle on the site. By examining the average tenure of users when they receive a badge, we get some idea of this. Figure 1 provides five general badges and five tags that give some indication of these differences.

The "Yearling" badge, because of its particularly temporal requirements, is probably an anomaly, but many of the general tags tend to be more likely to be awarded at an early or late point in the user's tenure. The tags, however, seem to be awarded at almost any time after the user has established herself on the site. If we included metrics of participation as well (e.g., number of questions asked or answered), this would likely produce an even more pronounced difference between the two.

Table 3. PNE for largest volume tags during 2013 and comparison with non-earned (pseudo) PNE.

Tag	PNE Earner	PNE Pseudo
mysql	0.101	0.040
ruby	0.114	0.007
sql	0.121	0.035
ruby-on-rails	0.140	0.004
c	0.198	0.018
css	0.111	0.023
objective-c	0.178	0.004
html	0.116	0.024
iphone	0.210	0.008
ios	0.149	0.004
c++	0.301	0.087
python	0.206	0.041
jquery	0.161	0.047
php	0.197	0.064
android	0.192	0.026
javascript	0.182	0.033
c#	0.291	0.037
java	0.236	0.105

Table 3 shows some of the more popular tags and the degree to which the Personal Network Exposure appears to influence users to adopt them. Perhaps because of the much wider variety of tags, users must pick and choose which are worth pursuing, and they are likely to be influenced by those they affiliate with on the site in that decision. Of course, that relationship is not clearly causal: it is likely that user questions and answers already coalesce around similar topics, and the process of badge earning recapitulates and makes visible homophily that already exists [42, 43]. There are ways the two may be teased out more directly, but here we have been interested only in whether the badges have a social component. Whether via social influence or a confounding source of homophily, earning tags is more deeply entangled with the social fabric of the site, and with the process of learning.

A community can, of course, benefit from both types of indicators. As suggested above, badges can be used to make clear who is more likely to represent expertise within the community. Many badge systems are designed to leverage this sort of "breadcrumb" approach of establishing a ladder of badges, and with it the illusion of self-determination. But perhaps this examination suggests that real community--based on peer-influence--is better fostered by badges that aren't universally desired, and that can be earned without chains of prerequisites.

There can be little doubt that this initial foray into social influence barely scratches the surface of the relationship of badges to personal wayfinding in PLNs and the ways in which badges can be used to navigate learning. But hopefully it begins to build a framework for further investigation, and particularly explicating the mechanisms of badge recognition, orientation, and acquisition that apply to the individual learner within a larger, structuring environment.

7. Conclusion

Stack Overflow has become a target of some attention precisely because it represents an interesting and successful model. Indeed, the growth of several dozen other topical areas on Stack Exchange, and adoption of the model in other contexts, attests to the usefulness of the structure. This success includes a badge system that is not only widely used, but includes valued badges that are sometimes shared beyond the immediate community and appear on developers' resumes and profiles. But it would be a mistake to assume that the reputation or badge system from Stack Overflow could be taken wholesale and applied to a dissimilar online environment.

Stack Overflow nonetheless provides an instructive case. The scale of use of badges on the site provides an excellent test bed for discovering how badges are used and could be improved. What has been presented here suggests that social influence and personal network exposure to badges represent an important avenue for exploration.

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