Reciprocity in Student Online Discussions

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Abstract: Online discussion is a popular tool for information exchange in web-based education. Analyses of how students interact or their contribution styles can help us understand weaknesses or strengths of the participants. This paper presents a framework for capturing information trading behaviors in Q&A discussions using a 'reciprocity' model. We measure the reciprocity of a student based on (a) the degree of responses that he/she received from other students in discussing his/her questions and (b) the degree of contributions in discussing other students' problems. We use a linear regression to model the overall reciprocity rate over time, and correlate the regression coefficient of the reciprocity rate to the student course grade. We found that although the overall reciprocity rate is not statistically correlated to the grade, high performing students have larger reciprocity rates and help other students more actively. We expect that the reciprocity rates revealed from discussion participations can help instructors make online activities more balanced.

Introduction

Reciprocity, as a general concept for measuring the "trade" in social exchange, contains the common sense that giving and taking illuminate each other (Gouldner, 1960). As one of the essential and necessary attributes for the social community (Wellman, 1999), reciprocity indicates the members' behavior in the community (Herring, 2001) and maintains the stable social system by encouraging the mutual beneficial exchanges and preventing antisocial behavior (Alexander, 1987). Online learning networks, as an aspect of social life, also yield the resource exchanges (Swan and Shea, 2005). Specifically, online discussion platform is a classical application of learning networks, which supplies a platform for students to post problems they encounter during study as well as to assist other students. Reciprocity allows the online discussion works effectively by promoting students to 'give' under certain circumstances and they can also obtain help when they have problems. In previous work, reciprocity is treated as one of the "seven principles for good practice in undergraduate education" (Chickering, 1996). In addition, reciprocity belongs to one of the major motivating factors that promote individuals to contribute to online communities (Wang, 2003).

Although reciprocity requires giving and taking simultaneously, the degree of giving and taking for a group or an individual cannot be strictly identical. There is a common recognition that giving can generate more altruistic and stable reciprocity while taking yields more selfish reciprocity. Taking into account of characteristics of students, we classify them into three different groups: considerate, neutral and self-centered groups. Given the assumption that human behavior varies based on selfishness, we compare reciprocity rates among these three groups, which can provide insight on student knowledge sharing behavior (Soller, 2003). As the degree of reciprocity in learning is hard to measure, we propose a simple but effective way to define the rate between the degree of giving and the degree of taking using participation types without considering the inequality of each problem or question. We split the students into four different performance groups based on their final course grades. Such classification can facilitate an analysis of how does the reciprocity rate vary among different performance groups, allowing us to examine the relation between the grade and reciprocity.

Furthermore, we examine the change of the reciprocity rate over time within the semester. Such reciprocity trend, presenting changes in student participation styles, can assist the teacher in assessing students' contributions, comparing the performance of individuals or groups (Kapur, 2008), and detecting the cause for the change in participation styles.

Methodology

In this section, we first describe how we process discussion data. We then present a model of reciprocity in Q&A discussions. We show how the model captures the information trading behavior.

Data collection and processing

Our work takes place in an undergraduate course in Computer Science department at University of Southern California. Student grades and online discussion data have been collected from the same course taught by the same teacher in eight recent semesters, from 2006 to 2010 school year. The discussion data contain total 1,663 discussion threads and 7,164 messages. Among 370 active users, we chose 204 users who have at least two questions, so that we can capture the information trade trend over multiple questions. Given a thread, we classify which user the thread belongs to, based on the user id of the initial message in the thread. The first message in a thread usually presents a problem or a question that the user has (Feng et al., 2006). We can estimate how much help a user obtains by counting how many responses he/she gets from other users. On the other hand, we can also assess how much help the user provides to others by counting his/her replies to other users' questions.

Reciprocity rate in Q&A discussions

We examine asynchronous online Q&A forums where participants trade information by posting questions and sending answers to the questions. Reciprocity is a common activity in social life but the effectiveness of reciprocity in online education forums is not clearly observed (Edwards 2002; Halloran et al., 2002). One main reason is that relations between actors in online learning communities are not very rich especially when there is limited participation within a course. We use multiple (8) semesters' data from the same course to capture general behavioral patterns.

We define *reciprocity rate* (reciprocityR) as the ratio of giving and taking acts of a user. A user's message is classified as a giving act of the person when it responds to a question. A response to the user's question is counted as a taking act by the user. In computing the degrees of giving and taking ratio at a given time, we accumulate all the giving and taking acts until that time. More specifically, the reciprocity of user *i* at time *t* when he/she posts a question can be modeled as follows:

$$reciprocityR_i^t = \frac{\sum_t \sum_j giving_{i \to j}^t}{\sum_t \sum_k taking_{k \to i}^t}$$

where *t* is time at which user *i* posts a question. The overall reciprocity rate of the user within a semester can be computed by accumulating all the giving and taking acts in the semester. We used min-max normalization to rescale posting time ranges from the different semesters to the equal range between 0 and 1. For example, if user *i* posts *n* questions, we can calculate *n* reciprocity rates for the user, which shows how the rate change over time as the user posts more questions. Specifically, *k*-th reciprocity rate will be the rate between accumulated giving and taking acts until *k*-th question. Once we have the reciprocity at each time point for each user *i*, we can regress their reciprocity rates to capture the general trends on the time space as follows:

$$reciprocityR_i^t = \alpha_i + \beta_i t_i$$

where *t* is a value ranged between 0 and 1. In the fitted line, β_i is a slope called the regression coefficient. Such behavior trend information can be related to other variables such as student performance.

Results

Reciprocity by Behavior and Group

Figure 1 shows the distribution of each user's reciprocityR over time by his/her behavior style and performance group that he/she belongs. For performance-based grouping, we used normalized values of the course final grades since the raw grades across semesters cannot be directly comparable. We split students into four grade groups (high, high intermediate, low intermediate, and low grade group) using mean (0.82) and one standard deviation (0.08).

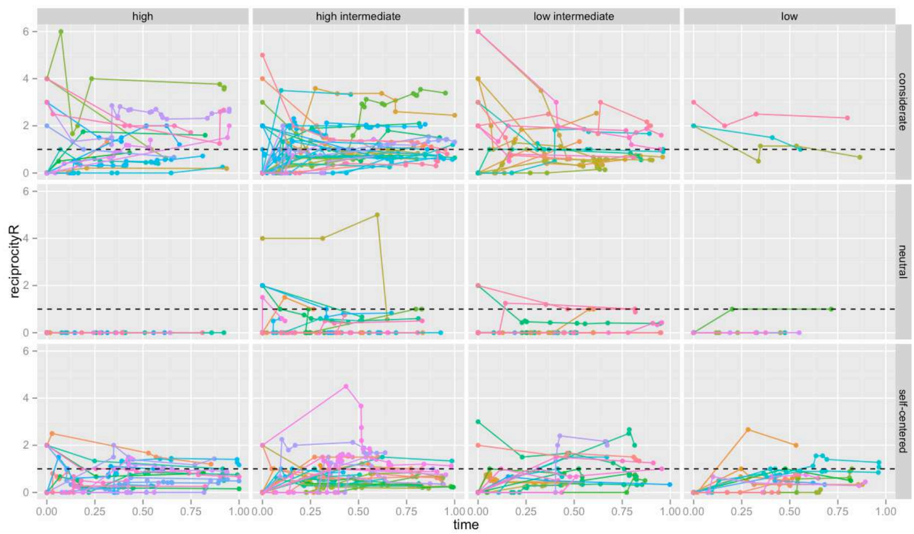

Figure 1. Reciprocity Trends by grade and behavior.

A user's responses can be split into two different types; responses in the discussions that he/she initiated and responses in other users' threads. The former represents discussion participations in answering his/her own question and the latter captures contributions to other people's problems. We use this to describe the user's behavior style. A *considerate* user sends more replies to discuss other people's problems than his/her own problems. A *self-centered* user posts more messages relevant to his/her own problems. Other users are considered *neutral*.

In Figure 1, each solid line represents reciprocityR of a user over time. A dotted line is called the "reciprocal line" since its reciprocityR is 1, i.e. the number of giving acts is equal to the number of taking acts. In the graphs in the top row (considerate group), we can observe that the reciprocitiRs of the high and the high-intermediate groups increase while those of the low-intermediate and low groups decrease over time. That is, higher performers tend to help other students. Although lower performers help other students sporadically, they stop helping before the final exam, which is located close to 1 in the timeline. In the middle second row (neural group), most lines are parallel to the reciprocity line but their reciprocitiyRs are close to zero. As shown in Table 1, those students asked fewer questions than other behavior groups and the average length of discussion threads is shorter than others. They seem to participate passively in the discussions resulting from the fact that; the number of message received from others (taking acts) is relatively smaller than the number of message sent to others (giving acts), as shown in Table 1.

Finally, in the graphs in the bottom row (self-centered group), reciprocityRs in all the performance groups increase because they present more giving acts for their own problems, which increases the numerator of raciprocityRs. Interestingly, the self-centered behavior group among the low performing students has the largest regression coefficient. They seem to concentrate on their own problems rather than others'.

Table 1: Summary of Reciprocity by Behavior and Grade

behavior	grade	N	Average						
			reg. coef	#questions	#giving for my problems	#giving for others' problems	#taking	#thread	#user
consi-derate	A	18	1.18	5.72	2.94	12.33	9.33	4.40	2.81
	B	34	1.11	6.76	3.12	11.32	10.53	3.37	2.59
	C	17	-0.74	5.82	2.18	8.47	12.88	3.24	2.58
	D	3	-1.14	3.00	0.00	5.00	5.00	2.47	2.22
neutral	A	9	0.00	2.89	0.00	0.00	3.56	2.56	2.37
	B	23	0.22	3.57	0.74	0.74	5.43	3.38	2.66
	C	16	0.04	3.44	0.56	0.56	5.00	2.75	2.41
	D	5	0.22	2.40	0.20	0.20	4.00	2.90	2.65
self-centered	A	20	0.76	7.85	5.00	1.15	9.60	3.89	2.55
	B	28	0.87	6.61	5.82	1.43	14.11	4.23	2.71
	C	18	0.82	5.00	3.39	1.11	7.56	3.66	2.46
	D	13	1.04	5.69	3.54	1.00	7.31	3.69	2.60

Note: reg.coef (regression coefficient)
A (high), B(high-intermediate), C(low-intermediate), and D(low)

Correlation Analysis between Reciprocity Trend and Grade

To investigate the relationship between reciprocity trends and grades, we generated a fitted line for each user with his/her reciprocityR values. We used a linear regress analysis as shown in Figure 2. Each slope, which is a regression coefficient ($\hat{\beta}_i$), represents reciprocityR trend for user *i*. As summarized in Table 1, high and high-intermediate performing group have the largest average regression coefficient. The low-intermediate and the low grade group have only negative average regression coefficients. In the graphs in the third row (self-centered group), the average regression coefficients are positive because the number of giving acts for own problems increase. Most of the high and low performing groups are either considerate or self-centered while high-intermediate and low-intermediate group members are equally distributed among different behavior groups.

Table 2: Correlation between Regression coefficient and Grade

	considerate users	neutral users	self-centered users	all users
regression coefficient	0.25^*	-0.01	-0.06	0.08
N	72	53	79	204

Note: $p^* < 0.05$

Table 2 summarizes the result of a correlation analysis between regression coefficients and course grades. As expected, overall, they are not statistically correlated to each other because regression rate changes of the neutral and self-centered behavior groups are similar regardless of their grade levels. However, only for the considerate behavior group, the regression coefficient is statistically and positively correlated to the course grades, $r(70) = 0.25$, $p<0.05$.

Conclusion and Future Work

We propose a simple but effective model that captures reciprocal behaviors in student online Q&A discussions. The model illustrates different information trading patterns among different grade groups. We utilize a "reciprocity line" to analyze the reciprocity trends of individual users. We found that although reciprocityR is not statistically correlated with the course grade, high performing students tend to present higher reciprocity rates.

The participation styles may be related to the nature of the problem (Kapur 2007), such as difficulty and well structuredness. Besides, the change of reciprocity may be associated with the emotion the student (Muukkonen 2007). We plan to explore use of reciprocity in explaining various aspects of student online learning behavior.

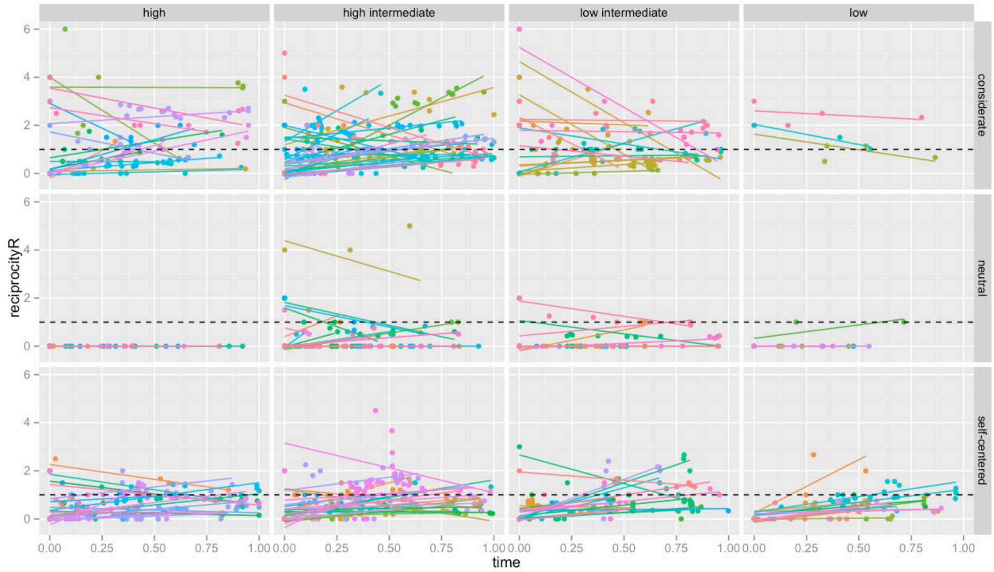

Figure 2. Regressing Reciprocity Trends by grade and behavior.

References

Alexander, R.D. (1987). The biology of moral systems. London: Aldine. American heritage dictionary. (1992). Boston: Houghton Mifflin.

Chickering, A. and Ehrmann, S. (1996). Implementing the Seven Principles: Technology as a Lever. AAHE bulletin. 49:3-6.

Feng, D., Shaw, E., Kim, J., and Hovy, E. (2006). An Intelligent Discussion-Bot for Answering Student Queries in Threaded Discussions, Proceedings of the International Conference on Intelligent User Interfaces.

Edwards, C. (2002). Discourses on Collaborative Networked Learning Networked Learning Conference, Sheffield, UK.

Gibbs, W., Simpson, L. D., & Bernas, R. S. (2008). An analysis of temporal norms in on- line discussions. International Journal of Instructional Media, 35(1), 63–75.

Gouldner, A.W. (1960). The norm of reciprocity: A preliminary statement. American Sociological Review, 25, 161–178.

Halloran, J., Rogers, Y. and Scaife, M. (2002). Taking the 'No' out of Lotus Notes: Activity Theory, Groupware, and Student Groupwork. In Stahl, G. (Ed.) Computer Support for Collaborative Learning: Foundations for a CSCL Community. Lawrence Erlbaum, Boulder, CO, pp 169-178.

Herring, S. C., Computer-Mediated Discourse. (2001). In Schiffrin, D., Tannen, D. and Hamilton, H.(Eds.) The Handbook of Discourse Analysis. Blackwell, Oxford, pp 612-634.

Jeong, A. (2005). A guide to analyzing message–response sequences and group interaction patterns in computer-mediated communication. Distance Education, 26(3), 367–383.

Manu K., John V., Charles K. (2008) Sensitivities to early exchange in synchronous computer-supported collaborative learning (CSCL) groups, Computers & Education, Volume 51, Issue 1, August 2008, Pages 54-66.

Manu K. , Charles K. Kinzer (2007) Examining the effect of problem type in a synchronous computer-supported collaborative learning (CSCL) environment, Educational Technology Research and Development, Volume 55.

Muukkonen, H. and Hakkarainen, K. and Kosonen, K. and Jalonen, S. and Heikkil A. (2007). Process-and context-sensitive research on academic knowledge practices: developing CASS-tools and methods. CSCL 2007.

Soller, A., and Lesgold, A. (2003) A computational approach to analyzing online knowledge sharing interaction. Proceedings of AI in Education 2003.

Swan, K. & Shea, P. (2005). The development of virtual learning communities. In S. R. Hiltz, & R. Goldman (Eds.), Asynchronous learning networks: The research frontier (pp. 239–260). New York: Hampton Press.

Suthers, D., Dwyer, N., Medina, R., & Vatrapu, R. (2010). A framework for conceptualiz- ing, representing, and analyzing distributed interaction. International Journal of Computer-Supported Collaborative Learning, 5(1), 5–42.

Wang, Y. and Fesenmarier, D. R. (2003). Understanding the Motivation of Contribution in Online Communities: An Empirical Investigation of an Online Travel Community. Electronic Markets. 13.

Wellman, B. and Gulia, M. (1999). Net Surfers Don't Ride Alone: Virtual Communities as Communities. In Kollock, P. and Smith, M.(Eds.) Communities and Cyberspace. Routledge, Net York, NY.

Wise, A. F., & Chiu, M. M. (2011). Analyzing temporal patterns of knowledge construc- tion in a role-based online discussion. International Journal of Computer-Supported Collaborative Learning, 6(3), 445–470.