Exploring Patterns and Configurations in Networked Learning Texts

Caroline Haythornthwaite
University of British Columbia
c.haythorn@ubc.ca

Anatoliy Gruzd
Dalhousie University
gruzd@dal.ca

Abstract

Collaborative learning in contemporary online classes thrives on conversation and interaction among individual members of the class. Yet, many of these settings provide little feedback on interaction beyond summary lists of individual contribution. As more communication happens online for both place-based and distributed education, the more need there is to understand and provide information on online interactivity. This paper uses the data from class-wide bulletin boards of eight iterations of a distance learning class, taught by the same instructor, to explore ways of assessing interactivity. Using the relatively simple data of poster, posting sequence, and subject line text, activity and interactivity are examined with basic statistics and social network visualizations. Results provide details on posting behaviors across these classes which are offered as a baseline for comparison to other classes.

1 Introduction

Much of the discussion about the benefits and correct practice of e-learning, collaborative learning, computer-supported collaborative learning and networked learning revolves around communicating – creating the safe space in which discussion can take place, relying on peer-to-peer interaction, and moving from teacher-student, one-way communication to student-student, two-way communication. Promoting and supporting interaction is important for advancing intellectual understanding, as individuals try out their ideas on others, share experiences, and tie theory to practice and local conditions ([8,23,24,25,28]). It is also important for creating the social space in which trust, safety, sharing and collaboration are engendered ([4,17,36]), and where communities of inquiry can develop around group identity and practices ([3,11,37]). Finally, interactivity in computer-mediated environments has also been linked to mimicking interpersonal communication, social presence, user awareness, involvement, sense of fun, cognition, etc. (for a review, see [32]).

While much writing on pedagogy holds up conversation, collaboration, and interaction as essential components of how to teach online, and many networked learning environments depend on it, what do we really know about the interaction processes that actually take place online? How do we know that a class has the right amount of interactivity, or even a common rate? How do we know one class is interactive and another is not? Buried in the text records of online discussion is evidence of interactivity ([32,33]), social network dynamics ([6,15,18]), and conversation ([20,21]). Yet, these have been rarely been mined for learning. Even as sophisticated means of mining online data becomes prevalent, bringing in new methods of analysis (e.g., [14,34]), we are still left with basic questions about what to mine, what to mine for, and how to interpret results of such mining.

This paper examines the dynamics of interactivity among participants in eight online classes. This research examines what measures were obtainable on interactivity; and what these show for this set of classes. Although this paper will not answer the question of what a good interaction rate is, the aim is to offer a starting point for common interactivity measures and to see what that definition provides as a baseline from this set of eight classes.

This work began as a response to the presentation of streams of linear text in bulletin boards, chat, blogs, and twitter that keep invisible from participants the structures of who is talking to whom. While advances are being made in the kinds of interactivity included in online learning much less has been done in revealing that interactivity to students and instructors. It is hard to know who are the key actors, what stimulates a discussion and what halts it, and what is a normal interaction pattern. Moreover, while many online classes and discussions begin with a clean slate and build up the stream of text over a single semester, providing a chance for participants to develop a mental map of interaction patterns, other learning forums continue over years. Views of the text structures can help new users integrate into an ongoing discussion and community. Thus, this work came to the question of: How do we make the invisible structures in these streams of text both evident and useful to participants in online learning settings? In pursuing this, we also want to know how to make sense of conversational action and interaction, i.e., how to add meaningful interpretation to the depictions of social structures.
1.1 Defining Interaction Patterns

There are several interpretations of the term *interactivity*. Quiring describes three main interpretations: “interactivity as an attribute of technological systems, communication processes, and user perceptions” [30, p.901]. We focus on the communication process, the to-and-fro between participants as evident in conversational traces. Quiring reports five elements of communicative interaction: “exchange, dialogue, control, two-way communication and third-order dependency” [30, p.902]. Each of these draws attention to the flow of information from one person to another, with an added emphasis on bi-directional flow and the cumulative flow of repeated interaction (e.g.,[31,33]). The hope or expectation from these conversational turns, particularly as intended in collaborative learning, is that interaction will lead to the kind of dialogue that stimulates critical awareness, increased knowledge and understanding of subject matter and of others. While the current work does not address user perceptions, we concur with Smith [35] and Burbules [5], that “conversation like dialogue is, at heart, ‘a kind of social relation that engages its participants’ [5, p.19]. The act of engaging with another - whatever the subject matter - is significant in itself” [35]. Thus, the threading of conversational interaction, even without examination of content or user perceptions can provide a useful window into interactional practices and social engagement.

In online learning, there are at least two distinct ways to think about interactivity: content interactivity, and social interactivity [29]. We specifically focus on the latter. A lot of work has been done in defining and measuring interactivity on general websites on the Internet (e.g., [32]). However, little work has been done identifying and describing effective ways to measure and interpret interactivity that is unique to online learning environments.

1.2 Approaching Interactivity

Interactivity is made evident by an action between people, such as an utterance and a response, and can result in patterns that describe conversational genres and form the basis of communities ([1,2,27]). Such pairwise interactions also build into networks of information sharing, learning and debate that reflect how connected an entire class or group is around topics of discussion. A social network approach provides an analytical perspective that addresses the connections between individual actors in a network, and thus provides an ideal way to examine and visualize interaction patterns among network actors. Such connectivity can show where and what patterns of interaction facilitate information sharing on a wide or narrow scale, and how conversations are facilitated or dominated by individuals or groups of individuals. Social network approaches are being increasingly used to evaluate online learning settings and represents a growing area of interest for those researching and implementing collaborative learning systems and practices ([9,15,16,26]).

In applying a social network perspective, the first question to address is what criteria to choose as the indicator of connection among network members. With the emphasis here on interaction, the decision was made to use chains of postings on the same topic as indications of a tie between actors, using the subject line text to determine topic similarity (described below). These data provide basic statistics on rates and distribution of posting behavior, patterns of topic variability and thread length, and pairwise interaction. In keeping with theory on social networks, the strength of interpersonal ties is revealed in the frequency and variety of conversational ties revealed in the data. Strongly tied pairs are revealed in more frequent, immediate, and reciprocal interaction. In online educational settings, our premise is, in keeping with Burbules[5], that frequent, reciprocal conversation reveals engagement between pairs and with the subject matter, thereby fulfilling goals of engagement with the topic, and online educational goals of engagement through computer-mediated communication.

2 Method: Dataset

The dataset consists of online transcripts from the class-wide bulletin board communications from eight iterations of an online course, over a four year period (two classes each Fall semester from 2001 to 2004). While these data are from 2001-2004, the essential structure of online, threaded discussion is still highly common for asynchronous classes, and thus representative of what might be found in current online learning environments. Each class was taught by the same instructor, aided by three to four teaching assistants. The course was a required, introductory, graduate level class in library and information science. While some adjustment was made to course content over the four years, the course was not substantially revised in format or intention over these four years. The same, locally developed technology platform was used during the four years. The variety of media used included real-time audio for weekly, synchronous, two-hour class sessions. During these lecture times, students could ask questions and discuss via chat (both a public one for the class, break-out rooms for smaller group discussion, and whispering facilities for back-channel talk). The course relied on discussion via web-
based bulletin boards as a core part of the class. Readings were discussed there each week. Online students in this program also all come to campus over a weekend once per semester for one day sessions for each online class they were taking. Thus, students can be expected to have interacted in a face-to-face environment at least one day during the semester, with possibilities of other socializing during that period. A notice that the bulletin board and main chat texts would be used for research was posted to the class at the start of each semester, and that contributors would remain anonymous; participants were also able to ask that none of their text be directly quoted.

2.1 Data

The analyses below required only the following data from the postings to the bulletin board: the date and time of the post, the subject line text, and the unique identifier of the message poster. Only bulletin board texts posted to areas open to all students in the class were used. Private areas established for group use were not used. These data were compiled into Excel, with one sheet for each class. While class discussion had been separated into different bulletin boards, these were collapsed into one file for analysis, shifting the criterion from the organization of bulletin boards and threading created by the instructor to the threading resulting from all discussion. Although more in-depth examination may be made using the complete message texts, and is possible with this particular dataset, in many other settings permissions regarding access to data are restricted to just this set of data. Thus, what is presented here makes use of what may be a more generally accessible set of data than full text data.

A topic was taken to be the same if the text of a message subject line exactly matched the text as it appeared in the earlier message (ignoring the system added “re:” in the subject line). The amount of time elapsed between postings and whether there were intervening messages on other topics are ignored. Sorting by subject line, date and time, a set number was assigned to each message that was constant for all messages with the same subject line, and a sequence number from one to the number of messages in the set for each message within the set. The maximum set number provided the number of threads started in any class; the sequence number allowed ordering of the messages when evaluating ties between posters.

Ties between actors in the network were determined based on the position of the post within the chain of posts with the same subject line. A tie, referred to here as a post-response tie, is considered present between two actors when one actor’s post is the very next post on the same topic. The person who posts is then always the second person in the sequence – a respondent – while the alter is the person to whom they are responding (posters that start a thread are treated slightly differently, see below). These are directed ties, initiated by a respondent to a poster; the strength of the tie is taken as the number of times an individual was tied to another in such a post-response sequence.

Actors in the network were determined from the unique identifier (ID) associated with each person. Post-response tie data were assigned to each message as the user ID of the person who posted the message, and the ID of the person who posted the immediately preceding message on the same topic. Posters could be their own respondent. First posters were assigned themselves as the alter (i.e., the person responded to) since there was no one before them to whom they could have been responding. It was also common for individuals to post in sequence after themselves within a thread. It is likely that this represents an afterthought to the first post, although some individuals seem to have done this quite frequently (e.g., in class 2001A, there are 53 such instances). Analyses below distinguish between these self-responses and pairings between different people.

Limitations. While subject lines are a parsimonious way of looking at interaction, the simplification of the subject line text as the indicator of topic has limitations, notably that the content of a message may drift from the subject line of the message over the course of a thread of discussion. While short of a full-text analysis, subject line headings seemed a good compromise for access and efficiency. Another limitation is in the use of exact phrasing of the subject line text to indicate the continuation of a topic thread. This errs on the side of identifying more threads and less interactivity than might be the actual case. A visual inspection of the subject lines for class 2001A suggests 7 cases among the 373 threads where two threads were counted where one might have been more correct. These involved a truncation of a last word (e.g. ‘problem’ vs. ‘prob’), or the addition or deletion of end punctuation. It can be expected that a similar rate of error exists for the other classes. Finally, there is a caveat with this dataset that what is presented here is interactivity only on the class-wide bulletin boards. Although students are taking the course online, and reside at a distance from each other (and in most cases also at a distance from the university), this is not the only communication means for classes, nor for individuals. Thus, what is presented is only a slice of overall interaction among classmates.

3 Results: Patterns and Configurations

Since data on overall posting activity in online classes is not widely available, the first step was to
gather and analyze the posting and thread activity statistics about the classes based on the measures outlined above. These results presented next, address questions such as: What is the average number of posts per participant? How long do threads persist? And what is the rhythm of online interactions by week and semester? Later sections examine pairwise and class-wide interaction patterns, addressing questions related to interpersonal behavior and interaction networks.

3.1 Basic Statistics of Postings and Threads

**Postings.** Class sizes ranged from 31 to 54 students, with an additional 4 to 5 instructors (the lead faculty member plus 3 or 4 teaching assistants). Over the 15-week semester, participants posted 1205 to 2156 messages on the class-wide bulletin boards (Figure 1). With 2156 postings, class 2004B members ‘talked’ more publicly than most other classes, with Class 2002B not far behind with 1895 postings. Across the eight classes, participants posted an average of 21 to 57 messages over the 15-week semester. These postings are in addition to posting on private bulletin boards for group work where approximately an equal number of messages were posted.

**Figure 1. No. of Postings x Class**

Interestingly, the two classes with the largest number of students (2003A and 2003B) had the lowest average number of posts per participant. This may be because in larger classes there are more conversations occurring simultaneously making it difficult to follow all of the class conversations; students may then read more and post less. However, as will be seen below, the number of threads for these large classes is actually on the low side compared to other classes. This suggests that perhaps it is easier to hide in a large class and leave the responding to others. Although further research is needed to tease out these effects, the lower overall number of posts does suggest a different pattern of behavior in these larger classes.

**Threads.** While the average number of posts per participant is a simple and informative measure of students’ involvement in an online class, by itself this measure does not unequivocally indicate interactivity. Hypothetically, a class may have a high average number of posts per participant even though none of the students actually engaged in dialogue with others. To address this limitation, we can look at the number of threads as indicated by the subject line (how many different topics were discussed), and the number of posts in each thread (the popularity of each topic).

On average, threads appear to be short, 2-3 messages (Figure 2). However, the average obscures the way some threads begin but go nowhere, while other threads are quite long (19 to 36 messages). Thus, there is variation in response patterns, with some topics gaining greater engagement than others. What makes for a long thread versus a short one is an interesting question that requires in-depth analysis of full message content. Unfortunately, the subject line texts were insufficient to identify why a thread was long (e.g., one 24-messages thread in 2001A had only the subject line “HTML”; and the 36-message thread in 2002B had the subject line “Schemata/ Metaphor Failure”).

**Figure 2. No. of Threads x Class**

Patterns of Thread Length. Threads can garner no response, and hence be of length one, or they can gain one or more responses for lengths of two and higher. Figure 3 shows the distribution of thread lengths for the eight classes (from 0 to 10, and for length greater than 10). The patterns are fairly consistent across classes: 44-56% of threads consist of a single post, i.e., they garner no response; 15-20% gain one response; 8-12% gain two responses, etc. up to 1-6% of threads of length greater than 10. Although percentages are roughly the same, the actual number of what might be called ‘orphan posts’ is very high for class 2004B, which has the highest number of threads. This high orphan rate may signify issues with the thread identification, although the high number of threads does not appear to be an artifact of the thread derivation method to any greater extent than in other classes. It may, however, signify some different way of interacting in this class, e.g., using the subject line to signal a point rather than continuing with the subject line and making the point in the text.

**Figure 3. Distribution of Thread Lengths x Class**

Rhythms. Another aspect of interactivity that is of interest is how discussion activity unfolds over the whole time the participants are together, i.e., across the semester. Other studies of time online have shown
clear weekday/weekend patterns ([22]). What kinds of rhythms appear in online class discussion?

Given the likely importance of day of the week, to examine rhythms, the data were first aligned across classes according to the day of the week. This revealed the patterns shown in Figure 4. The time period shown in this figure was chosen deliberately to capture the peek of semester activity, spanning the middle of the semester (beginning of October to mid-November) before the U.S. Thanksgiving holiday period in November. This compilation shows that, in these classes as in other aspects of daily life, posting activity on the bulletin boards follows a weekly rhythm. Participants post more often on weekdays and less often on weekends. These results present a useful view of time allocation by students, a view that may be as useful to students as to instructors in coming to understand what and when to expect interaction online.

**Figure 4. Mid-Semester Weekly Posting Pattern**

If rhythms vary over the week, do they also vary across the semester? Figure 5 shows the posting behavior over the whole semester from the eight classes. This shows the rise of posting from the beginning of classes in late August to the decline at the end of the semester in December. As for the weekly rhythm, knowing about start up and finishing activity patterns can help both students and instructors in planning and expectations about online interaction.

**Figure 5. Semester Posting Pattern**

So far three basic measures have been examined: *posts* — including totals per class, and averages per participant; *threads* — the number per class, and the length; and *posting rhythms* by week and by semester. Results suggest that classes with more participants may suffer from reduced class-wide participation (i.e., lower posting rates per individual), perhaps because others can take over responding in such cases. While this does not mean the class is less successful, it does suggest students are less active in these classes. Long threads appear to be a good indication of a discussion that has gained engagement among participants. Overall these data suggest that a very simple check on interactivity might be found in looking at the combination of the average number of posts per participant and the proportion of long threads.

### 3.2 Patterns of Post and Response

One of the main limitations of the measures above is that they do not reveal whether students are engaging in conversations with many different class members, or whether they are talking to a small group of others. Wider engagement suggests a greater opportunity to be exposed to a diversity of opinions, information and life experiences, something potentially missing from in-group conversations. Next we look at how many students are involved in each thread and whether or not they talk to few or many classmates. The following section examines how many initial posts actually get replies, how often a particular person follows another’s post, how many of the post-response pairings involve the same pairs, and to what extent class members are attending and responding to the class as a whole.

**Post-Response Behavior.** Table 1 presents data on interactivity, but with a focus on responding patterns. The percent of starter posts (whether these are followed up on or not) ranges from 31 to 47% across the eight classes. Of these threads, about half are orphan posts which receive no follow-on, while about half receive at least one response. In general, response posting accounts for 50-65% of all posts across these classes. It is very tempting to say that this 50-65% response rate seems like a good indicator of collaborative, or at the least, interactive conversations, for example considering it in comparison to something much lower. However, with a lack of real comparators, and without confirmatory data from participants, it is beyond the data at hand to make a definitive statement about the ‘goodness’ of this rate. The emphasis here is on baseline numbers for comparison to other cases.

Interactivity can be further examined by using both the number of threads started but orphaned, and the number that develop into conversational thread practices. The response: orphan ratio, calculated as the proportion of starter posts receiving a response to the number orphaned (i.e., receiving no follow-on post), ranges from .8 to 1.3. A lower rate indicates a lower proportion of responding to others’ postings, and thus higher rates might be considered better than lower rates if looking for greater saturation in interactivity.

In evaluating this, we may start from the premise that some kind of response and responding behavior is necessary for individuals to keep posting. A class in which people post but get no response may soon fail to
gain critical mass for interaction, leading to a drop in further posting. Or, if the short thread habit persists, it may signal a class more attuned to broadcast practices than collaboration. We may see different class communication habits reflected in thread behaviors. Across these classes, 2001A and 2003B have the highest thread continuation ratios (1.3 and 1.1).

Response rates may also reflect the ability of individuals and the class as a whole to manage and follow the number of threads being started; e.g., 1022 threads were counted based on the subject line in class 2004B. This is a lot of material to follow, and, as noted, this class also has the highest number of orphan posts. Although this could be an artifact of the subject line method of determining threads, it is the same method used for other classes where thread numbers are much lower. Neither is 2004B a larger class, which might generate more threads.

Table 1. Statistics on Post and Response

<table>
<thead>
<tr>
<th></th>
<th>No. of posts</th>
<th>No. (%) of starting posts (same as No. of threads)</th>
<th>No. (%) of response posts (not to self)</th>
<th>No. of self-responses within the threads **</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001A</td>
<td>1205</td>
<td>373</td>
<td>31</td>
<td>786</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>65</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>46</td>
</tr>
<tr>
<td>2001B</td>
<td>1580</td>
<td>619</td>
<td>39</td>
<td>921</td>
</tr>
<tr>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>40</td>
</tr>
<tr>
<td>2002A</td>
<td>1469</td>
<td>603</td>
<td>41</td>
<td>820</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>56</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>46</td>
</tr>
<tr>
<td>2002B</td>
<td>1895</td>
<td>676</td>
<td>36</td>
<td>1144</td>
</tr>
<tr>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>75</td>
</tr>
<tr>
<td>2003A</td>
<td>1280</td>
<td>536</td>
<td>42</td>
<td>690</td>
</tr>
<tr>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>54</td>
</tr>
<tr>
<td>2003B</td>
<td>1242</td>
<td>408</td>
<td>41</td>
<td>775</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>59</td>
</tr>
<tr>
<td>2004A</td>
<td>1493</td>
<td>618</td>
<td>41</td>
<td>804</td>
</tr>
<tr>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>71</td>
</tr>
<tr>
<td>2004B</td>
<td>2156</td>
<td>1022</td>
<td>47</td>
<td>1076</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td>50</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>58</td>
</tr>
</tbody>
</table>

** Calculated: Column 1 – (Column 2 + Column 3). This column explains why 373 + 786 does not equal 1205. Higher ‘response: orphan ratios indicate greater response rate to initial posts.

To examine this a bit further, correlation coefficients were calculated for a number of comparisons. The number of participants in the class has a moderate, negative correlation with all the measures of posting behavior: total number of posts (r = -.31), number of starter posts (or threads) (-.36), and the number of response posts (-.20), as well as with the number of starting posts that do not (-.38) or do receive responses (-.34). This is interesting as it suggests that, in general, as classes grow in size there may be more free-riding, less contribution, and less attention to and interaction with others’ posts. Correlations are very high and positive among other posting behaviors. Number of posts is highly correlated with the number of starter posts (threads) (r = .94), number of response posts (.91), orphaned starter posts (.90), and starters posts gaining at least one response (.97).

In sum, this section presented a variety of correlating measures that are based on post-response behavior. For example, one of the very useful, easy to calculate and interpret measures in this section is a ratio of starter posts receiving a response to the number of orphaned posts. However, what these measures can not account for is whether or not interactions are class-wide or limited to small cliques of students. To address this limitation, the following set of measures look at pairwise behavior among students.

**Pairwise Behavior.** Table 2 presents data on pairwise behaviors. These data address the question of how many of the post-response pairings involve the same pairs. This shows to what extent activity is centered around a few pairs of discussants or whether posting and response is more generally distributed across the class. As noted above, there are some limitations to keep in mind when interpreting these data. First, that the data are directed, a response by B to A is treated separately from a response by A to B. Thus, the data underestimate two-person interactions by separating their interaction by posting order. Second, because ties are made only between immediately adjacent pairs of messages, this may miss interactions among cliques of three or more (A:B, B:C, C:A). Some of these limitations are addressed in the social network analyses below.

Table 2. Statistics on Pairwise Response

<table>
<thead>
<tr>
<th></th>
<th>No. responders posts (not to self)</th>
<th>No. unique post-response pairs (excluding self responders) *</th>
<th>Avg repeat pairing (Column 1/Column 2) Directed</th>
<th>Reciprocity (includes self-response) **</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001A</td>
<td>786</td>
<td>499</td>
<td>1.58</td>
<td>.39</td>
</tr>
<tr>
<td>2001B</td>
<td>921</td>
<td>601</td>
<td>1.53</td>
<td>.32</td>
</tr>
<tr>
<td>2002A</td>
<td>820</td>
<td>583</td>
<td>1.41</td>
<td>.32</td>
</tr>
<tr>
<td>2002B</td>
<td>1144</td>
<td>766</td>
<td>1.49</td>
<td>.34</td>
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<td>2003A</td>
<td>690</td>
<td>442</td>
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<td>.36</td>
</tr>
<tr>
<td>2003B</td>
<td>775</td>
<td>430</td>
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<td>.44</td>
</tr>
<tr>
<td>2004A</td>
<td>804</td>
<td>449</td>
<td>1.79</td>
<td>.41</td>
</tr>
<tr>
<td>2004B</td>
<td>1076</td>
<td>588</td>
<td>1.83</td>
<td>.44</td>
</tr>
</tbody>
</table>

* Determined by counting the number of times a particular set of actors are uniquely identified in a post-response pairing (B posts after A with the same subject line). Direction matters: B responds to A is treated as a separate pair from A responding to B.

** Indicates the proportion of postings of B after A that are matched by at least one posting by A after B. (Calculated using UCINET).
With these caveats in mind, we can see that, even with the restriction on direction of the tie, pairs are repeatedly responding to each other. Across all pairs in a class, there is an average repeat pairing (B responds to A) of 1.41 to 1.83 (Table 5). Also included in Table 2 is a measure of reciprocity, i.e., the extent to which, when B responds to A, a pairing of A responding to B is also found. These values are derived from the overall network data using the UCINET network analysis software. The results show reciprocity rates of from .32 to .44 (note again that this does not capture triadic interactions: A:B, B:C, C:A).

Ranking these two measures shows a high correspondence between the repeat pairing and the reciprocity measures. Although this is to be expected since they are capturing much the same effect, it useful to see that the non-network measure provides the same basic comparative information across the networks as the network measure. Overall the data show that while many pairs are in direct correspondence with each other at least once, there are differences across classes. Both sets of results reflect the repetitiveness with which individuals respond to the same person. Higher numbers indicate the conversations are happening between the same pairs; lower numbers suggest more wide-spread interaction. For example, out of the eight classes in the study, the class that has the most wide-spread interaction (and lowest pairwise interaction) is 2002A (average repeat pairing of 1.41, and reciprocity rate of .32) and the least wide-spread interaction is found for 2004B (average repeat pairing of 1.83, and reciprocity rate of .44).

Knowing values of these indices can help instructors determine if discussion is too focused within small cliques. This condition may appear in classes where some students already know each other prior to taking the class, since, as research by Cho et al ([6]) shows, students who have pre-existing connections to each other are less likely to form new connections in the class and instead gravitate toward their pre-existing connections. If this happens, it might be better for some learning outcomes to temporarily break up the (pre-)existing cliques and randomly assign students to new groups for some in-class activities (e.g., for exposure to new ideas). This way, the students will have a chance to make new connections with other students in the class (see also [16]).

In sum, this simple measure provides some insight into interactive behavior and can be used in combination with other data to consider the overall tenor of interactivity in a class.

**Distribution of Pairwise Responding Rates.** We can look more in depth at pairwise interaction using the frequency of post-response pairings across all threads during the semester, i.e., across all topics, rather than within any specific thread. This measure captures aspects of pairwise orientations rather than engagement in a particular discussion. Results show that the majority of pairings occur once or twice (56 to 73% of pairings occur only once; 17 to 24% twice; Figure 6). However, some pairs show higher rates of interaction, with three or more occasions on which they respond directly to the same person within a thread (6 to 11%).

**Figure 6. Strength of post-response pairing**
High rates of pairings suggest a set of dyadic relationships that are being demonstrated through class-wide bulletin board discussion. Although the majority of pairings do not repeat, and many repeat only once, proportions at higher rates begin to show where individuals are paying attention to the postings of others and carrying on conversations with those individuals. This is shown quite dramatically in network diagrams of interaction. As an example, Figure 7 shows the network for at least 1, 2, 3 and 4 post-response pairings for class 2002A. As can be seen the network for at least one tie appears quite dense, but the number of ties maintained at higher frequencies drops off quickly. What is left is a small set of interacting pairs – a clique – who are engaged with each other in much more intense dialogue than are others in the class. Such views reveal the hidden structure of online discussion, and may help instructors, students and/or newcomers understand and work with the dynamics of the ongoing discussion.

**Figure 7: Network configurations for 4 tie strengths (class 2002A)**

**Density of Pairwise Interaction.** The density of post-response ties shows how interconnected all members of the class are in terms of their responding to others’ posts. Table 3 gives the densities for each class. Density is calculated as the proportion of ties actually present to the number of possible pairs. For example, in 2002A there are 43 participants, making 1806 possible pairs. The actual number of ties found is
583, hence density is 583/1806=.32. This is the density shown in the first sociogram in Figure 7.

Density may be interpreted as the extent to which class members are attending to and responding to the class as a whole. Higher densities indicate more peer-to-peer interaction across the class; low densities indicate little generalized interaction. In the eight classes, densities for at least one post-response pairing range from lows of .13 and .14 in the 2003 year to highs of .28 to .42 for other years. The low densities are associated with a year when class sizes are their largest (56 and 58 participants), which may have some contributing effect to the low density. However, class 2002B had 50 students and yet still showed densities of .31, more in line with the other examples. Although the current data do not provide adequate explanations for the low densities in 2003, nor do these data reveal other kinds of interaction that might have been more dominant that year, as for other measures, a view of this kind of information may be useful for instructors in gauging how to place effort to increase peer-to-peer interaction for situations where collaborative learning is the goal.

Table 3. Network density (directed ties)

<table>
<thead>
<tr>
<th></th>
<th>Number of ties of strength ≥1</th>
<th>Density ≥1</th>
<th>Number of ties of strength ≥3</th>
<th>Density ≥3</th>
<th>Avg actor degree centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001A</td>
<td>499</td>
<td>.35</td>
<td>67</td>
<td>.05</td>
<td>3.3</td>
</tr>
<tr>
<td>2001B</td>
<td>601</td>
<td>.28</td>
<td>76</td>
<td>.04</td>
<td>2.0</td>
</tr>
<tr>
<td>2002A</td>
<td>583</td>
<td>.32</td>
<td>54</td>
<td>.03</td>
<td>1.4</td>
</tr>
<tr>
<td>2002B</td>
<td>766</td>
<td>.31</td>
<td>80</td>
<td>.03</td>
<td>1.4</td>
</tr>
<tr>
<td>2003A</td>
<td>442</td>
<td>.14</td>
<td>50</td>
<td>.02</td>
<td>1.3</td>
</tr>
<tr>
<td>2003B</td>
<td>430</td>
<td>.13</td>
<td>88</td>
<td>.03</td>
<td>3.3</td>
</tr>
<tr>
<td>2004A</td>
<td>449</td>
<td>.38</td>
<td>77</td>
<td>.06</td>
<td>1.7</td>
</tr>
<tr>
<td>2004B</td>
<td>588</td>
<td>.42</td>
<td>117</td>
<td>.08</td>
<td>3.6</td>
</tr>
</tbody>
</table>

Sociograms of the network connections give another view of the classes. Figure 8 shows the graphs of directed ties among the participants in four of the classes (only four are shown because of space considerations for this paper). The network diagrams reveal more differences in the structure of these ties than can be understood from a single density measure. In particular, it is possible to see a denser core of participants and a less dense periphery in the class from 2003, where the density is low. As for densities, this kind of feedback of network cohesion may be useful for participants in judging their place in the structure, as well as for instructors as a visual display of class-wide interaction patterns.

Although it is tempting to make judgments about these classes from these network patterns, at this stage, the only point to take from these sociograms is that they are different. Determining what configuration is best for a class or other kind of collaborative learning situation is going to depend on making the connection between these networks and different kinds of outcomes, e.g., in learning, collaboration or satisfaction. However, we do know from a wealth of social network studies, that density affects how information circulates a network, with denser networks creating more paths for exchanges ([19]). Even in these classes, we can see peripheral players who are less connected, particularly the isolates shown for class 2004A. Isolates in these diagrams are people who posted a starter post but received no response, nor were they the direct recipient of a post at any time during the semester. Isolated and hard to reach individuals are not likely to receive information in a timely manner, and are not integrated into the ongoing discussion.

Figure 8. Network configurations for 4 classes (2001A, 2002A, 2003A, 2004A)

Stronger Ties. Another aspect of in-class behavior can be revealed by looking at the densities and class configurations for pairs with higher interaction rates, i.e., those demonstrating stronger conversational ties, where tie strength is calculated as the number of times B responds to A. Networks formed by these strongly tied pairs reveal the way individual pairs are dominating conversations. As shown in Table 3, densities are very low at higher interaction rates. For pairs with at least 3 post-response pairings, densities range from .02 to .08 across the eight classes.

Some further information can be obtained about the strong tie connections. Looking at the actor degree centrality of these core discussants can show how much interaction is happening across the strong tie network. Actors with high degree centrality are connected to many others, and those with low degree are connected to few others. Again, previous work shows that those who are more connected are more likely to hear and receive information, and are more able to influence others. Comparing the average actor degree centrality across classes, it is possible to see whether core discussion networks in classes involve a small or large set of participants.

While the number of pairs involved in these stronger ties range from 50 to 117, neither higher
numbers, nor higher densities are necessarily associated (positively or negatively) with higher actor centrality (Table 3). For example, class 2002B and 2003B have about the same number of strong tie pairs, and about the same density, yet actor centrality for 2002B is 1.4, i.e., the average strong tie is maintained with about one to two others, and for 2003B is 3.3, i.e. maintained with about three to four others. Thus, a combination of numbers is needed to understand class dynamics: density for overall connectivity, actor degree centrality for engagement with others.

Network diagrams provide a compelling visualization of how these actors are connected, and the cliques and information pathways their relationships create. They also provide further information about these strong tie cliques and why some are in the one to two person range and others much higher at three to four people. With the aid of network diagrams outlining all of the strong ties within each class, it becomes very easy to figure out if a class is more or less interactive in comparison to other classes or for the same class but in different time periods. For instance, using network diagrams in Figure 9, we can easily tell which one of the two classes, 2002B or 2003B, had more engaging and interactive discussions.

One way to accomplish this is by determining the number of nodes that might be classified as central in the network, i.e., nodes with many connections to others. In class 2003B, seven people had at least four or more connections to other class participants. While in class 2002B, only two people had at least four or more connections. This suggests that class 2002B does not have class-wide discussions, but rather conversations are dominated by a very small number of students. A small clique that dominates discussions does not bode well for collaborative learning. Previous research on online forums has found that centrally dominant individuals are likely to be viewed negatively by other members of the discussion group ([10]). Their presence and behavior within the group may discourage others from actively taking part in class discussions and possibly stifle overall participation. Another problem associated with having only a few central network members is that the class becomes too dependent on these central individuals to carry on a discussion and engage others. If one or more of those central individuals misses or even drops the class, then the whole conversation is at risk of stalling.

Another way to use a network diagram is to look for disjoined islands (components), or an individual or group that is not connected to other group members. For example, in class 2003B, there is only one component, suggesting that there are no truly isolated individuals or groups in the network. In other words, conversation in this class could spread from one individual or a group to everybody else in the network. In class 2002B, there are a total of four components: one large component connecting most of the students in the class and three two-people components. The presence of these three smaller components suggests that those pairs tend only to reply to each others’ postings and are not very involved in the discussion with the rest of the class. If an instructor sees this kind of network configuration in their class, he or she should consider including some additional class activities that would help and encourage these smaller components to (re)join the wider class discussion; for example, by asking members of those smaller components to lead a class discussion on a particular topic.

Figure 9. Discussion networks for two classes (2002B, 2003B)

<table>
<thead>
<tr>
<th>2002B</th>
<th>2003B</th>
</tr>
</thead>
</table>

4 Conclusion

The purpose of this paper has been to explore different kinds of measures of interactivity in online classes to gain an understanding of the range of configurations that are found, to begin to have data for comparison across many, different classes and to use for examination of social and educational engagement. This paper examined data that are widely available, but not widely used for examining interactivity in online classes. The captured record of bulletin board discussion, posting sequence and subject line text combine to produce useful views of individual, subgroup and class-wide participation. The results presented here are, however, only half the story. Although we can count occurrences and present configurations, the other half of the research work is to tie these configurations to education and learning outcomes. The current presentation still leaves questions of which classes were considered by instructors or by students most successful, more collaborative, learned more, were more satisfied with outcomes, or best balanced work and cognitive load to these outcomes. Future work remains to gather and examine further the relationship between the statistics presented here and subjective experience of the class, with a view to finding the most useful statistics and presentations to provide to students, instructors, and others engaged in collaborative learning. Future work also adds text analysis of message headers and/or the
full content of the messages for more in-depth analysis of what composing topics that gain engagement. Other work also looks at using the content of the message to derive better views of the in-class social networks beyond the chaining used here. Work in this area [7, 12, 13] already reveals that text analyses of threaded discussion leads to better derivation of networks.

5 References