

Beyond Clickometry: Analytics for Constructivist Pedagogies

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This paper analyzes some current trends in Learning Management System's analytics. It points out that while the analysis of access log patterns – clickometry – is by far the most common form of analysis available in LMS systems its value is limited at best. Being a measure of behavior in its most basic sense clickometry is best suited for assessment of interactions in courses built around behaviorist pedagogy. More constructivist pedagogies require deeper analyses of the data, which is certainly available in most LMS systems but are usually left unanalyzed and unreported due to the complexity of the required methodologies. This paper shows that 85% of available data is not typically analyzed and presents a case study with proposed analyses.

Practitioners in the field of e-learning inevitably face the challenge of evaluating their students' progress within a course. The lack of face-to-face contact with the students in many ways puts the online instructor at a disadvantage compared to the traditional classroom-based instructor. This is particularly true when the instructor wishes to implement constructivist pedagogies in on-line learning environment. Learning Management Systems, both from commercial vendors as well as the open-source alternatives, have made some progress in recent years to support more collaborative learning methods however they fall short when it comes to providing tools for evaluating, analyzing and reporting on the pedagogical processes involved. What is typically available to the instructor in terms of feedback from the learning management system on student performance is usually limited to quantitative measures regarding student participation (e.g. log-in frequencies, time-on-task), test scores and survey results. Apart from multiple-choice exams

the online instructor is provided access to a summary of the students' clicks, *clickometry*¹, which is of little or no use for assessing the construction of knowledge in the course.

Faced with the choice between the often insurmountable task of *manual* assessment and adjusting the assessment strategy of the curriculum to conform to the tools available, the instructor is often forced to revert to more behaviorist approaches. This is a variation of insufficient *task-technology fit (TTF)* (McGill, Klobas, & Renzi, 2011) and in an extreme case the instructor's role reverts to that of the operator of a Teaching Machine in the Skinnerian (1958) sense of the word. Paradoxically the most up-to-date delivery mechanisms for learning tend to support the least avant-garde styles of pedagogy.

THE CASE OF MOODLE

In this section I shall give a brief review of the analytics tools available in Moodle (The Moodle Foundation, 2011), the leading open source alternative to commercial LMSs. Standard Moodle (version 1.9.8 used for these illustrations) has relatively few analytics tools available for the instructor. When entering the *activity reports* section there are four views that analyze the activity on a course and global level based on the input from the user (i.e. the instructor). Figures 1 through 4 show these views. The names of students, here and throughout the paper, were assigned randomly to protect students' privacy. The main difference between the *outline view* and the *complete report* consists of the inclusion of the actual posting of text in the case of discussion activity. In all other cases only the most recent *activity* date is reported and resources that have not been viewed by the student are marked *never seen*.

For even more detail the instructor or administrator can request a report on access logs which, as can be seen in Figure 3, reports date, time and place for all the clicks made by the student in a determined timeframe. Finally an overall graphic display of course activity (Figure 4) is available.

As meager as these analytic tools may seem, they can actually be quite useful to the instructor. They do provide him or her with a single (albeit scrolling) overview of what the student has read in the course, as well as a quick way of controlling that the required forum postings have been made. It is hard to see, however, that the "*logs*" report, whether displayed as a list of clicks (Figure 3) or as a graphical display (Figure 4) should have any practical value to the instructor.

1. I have coined the term *clickometry* to encompass analytics based on data generated by the participants' navigation in the LMS.

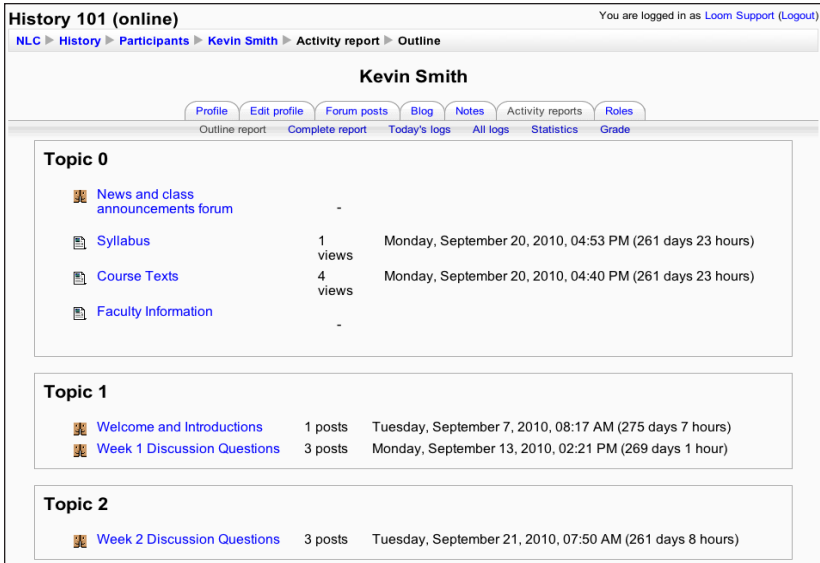


Figure 1. Moodle Outline report

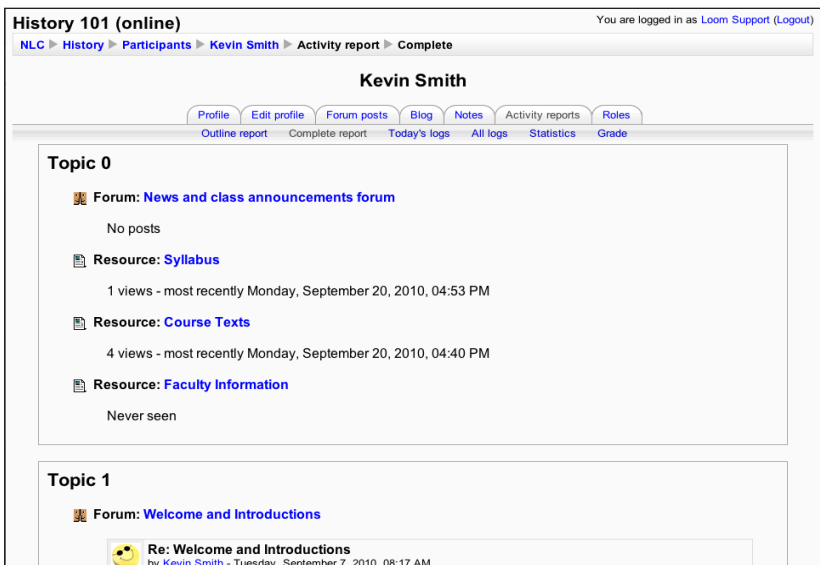


Figure 2. Moodle “Complete” report for single student.

History 101 (online) You are logged in as Loom Support (Logout)

NLC > History > Participants > Kevin Smith > Activity report > All logs

Kevin Smith

[Profile](#) [Edit profile](#) [Forum posts](#) [Blog](#) [Notes](#) [Activity reports](#) [Roles](#)

[Outline report](#) [Complete report](#) [Today's logs](#) [All logs](#) [Statistics](#) [Grade](#)

Displaying 118 records
Page: 1 2 (Next)

Time	IP Address	Full name	Action	Information
Wed September 22 2010, 11:27 AM	65.219.124.65	Kevin Smith	user view	John Borsos
Wed September 22 2010, 11:27 AM	65.219.124.65	Kevin Smith	forum view	Assignment for Week 3 (September 20, 2010)
Wed September 22 2010, 11:27 AM	65.219.124.65	Kevin Smith	forum view forum	News and class announcements forum
Wed September 22 2010, 11:27 AM	65.219.124.65	Kevin Smith	course view	History 101 (online)
Wed September 22 2010, 11:27 AM	65.219.124.65	Kevin Smith	user view	John Borsos
Wed September 22 2010, 11:27 AM	65.219.124.65	Kevin Smith	forum view	Assignment for Week 3 (September 20, 2010)
Wed September 22 2010, 11:26 AM	65.219.124.65	Kevin Smith	discussion	96
Wed September 22 2010, 11:26 AM	65.219.124.65	Kevin Smith	course recent	96
Wed September 22 2010, 11:26 AM	65.219.124.65	Kevin Smith	course view	History 101 (online)
Tue September 21 2010, 11:09 AM	65.219.124.65	Kevin Smith	forum view	Assignment for Week 3 (September 20, 2010)
Tue September 21 2010, 11:08 AM	65.219.124.65	Kevin Smith	discussion	Assignment for Week 3 (September 20, 2010)
Tue September 21 2010, 11:08 AM	65.219.124.65	Kevin Smith	forum view forum	News and class announcements forum
Tue September 21 2010, 11:08 AM	65.219.124.65	Kevin Smith	course view	History 101 (online)
Tue September 21 2010, 07:50 AM	65.219.124.65	Kevin Smith	forum view	Week 2 Discussion Questions
Tue September 21 2010, 07:50 AM	65.219.124.65	Kevin Smith	discussion	Week 2 Discussion Questions
Tue September 21 2010, 07:50 AM	65.219.124.65	Kevin Smith	forum add post	Re: Week 2 Discussion Questions

Figure 3. Moodle “Logs report” for single student.

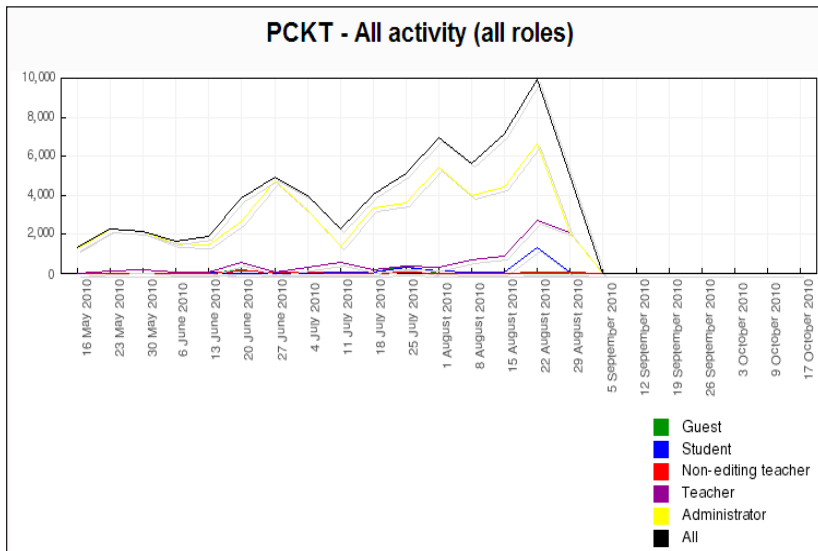


Figure 4. Moodle “Statistics” tab. From Moodle Security (Miletic, 2010, pp. 147), used with permission of the author.

In fairness to the Moodle-community I should point out that several add-on modules exist that provide a more sophisticated level of analysis. Space constraints prevent me from addressing these in any detail, so I will only make the observation that while most of these add-on modules constitute an improvement over what is available out of the box, they still focus on counting clicks on timelines, using more or less elegant data visualization techniques.

LOOKING BEYOND CLICKS

Research in the field of data-mining and text-mining (White, 2005) shows that only about 15% of all data stored is stored in a structured format allowing for easy analysis. The remaining 85% is unstructured data and often go un-analyzed. For comparison purposes I have analyzed the available data from two *Moodle* databases at my disposal. The data were divided into three categories:

1. Server-logs and quiz-type data: clickometric data.
2. Dynamic *unstructured* content such as discussion forums, blogs, chats and wikis.
3. Static content: essentially courseware, media assets, and external links.

It is not obvious if static content such as courseware, media assets and external links should be included as analyzable items – Courseware can sometimes be dynamic in the sense that it is updated by the instructor and/or institution during the course. Furthermore media assets may contain items that make measuring them difficult, for example: Should a video be included based on its length in time, size, download-time? Should a game be included based on its complexity? While these are both fascinating methodological questions, they are beyond the scope of this paper. For the purposes of this analysis I will disregard this data-type altogether, and simply compare the data in categories 1 and 2 above.

Throughout this paper open source technologies were used to access and analyze the data, specifically: MySQL Workbench (MySQL AB, 2011) and R, a Language and Environment for Statistical Computing (R Core Development Team, 2011).

A total of 54 courses were analyzed by accessing the back-up databases. The results are summarized in Table 1.

Table 1
Clicks vs. Words for 54 Courses

	Mean	Median
Clicks	9004	5773
Words	50,650	36,686
Total Data-points	59,654	45,459
Clicks/Total	.1509	.1299

As can be seen the pattern conforms to that of the universe of stored data. The amount of data analyzed by clickometry only constitutes about 15% (about 13% if the median is used instead of the arithmetic mean) of the available data in the system, close to 100% of the tools available to the instructor analyze and report on this part of the data.

Figure 5 plots the distribution of clickometric data-points vs. the data-points of the unstructured data. The very uniform distribution around the regression-line drawn (in blue) on the plot—the Pearson R calculated for the dataset was indeed .9167234—suggests that the ratio is stable regardless of the absolute volume of data. In other words we would expect to see the same ratio independently of the number of participants in or the length of the course. The p-value returned was highly significant, hardly a remarkable finding given the obvious necessity to generate clicks in order to get words into the system. I do not intend to explore the clicks-to-words (CTW) ratio in on-line courses, but rather to illustrate the likelihood that White's (2005) assertion is indeed valid for the realm of e-learning as well. The percentages reported are in line with what should be expected and suggest that we face similar methodological challenges.

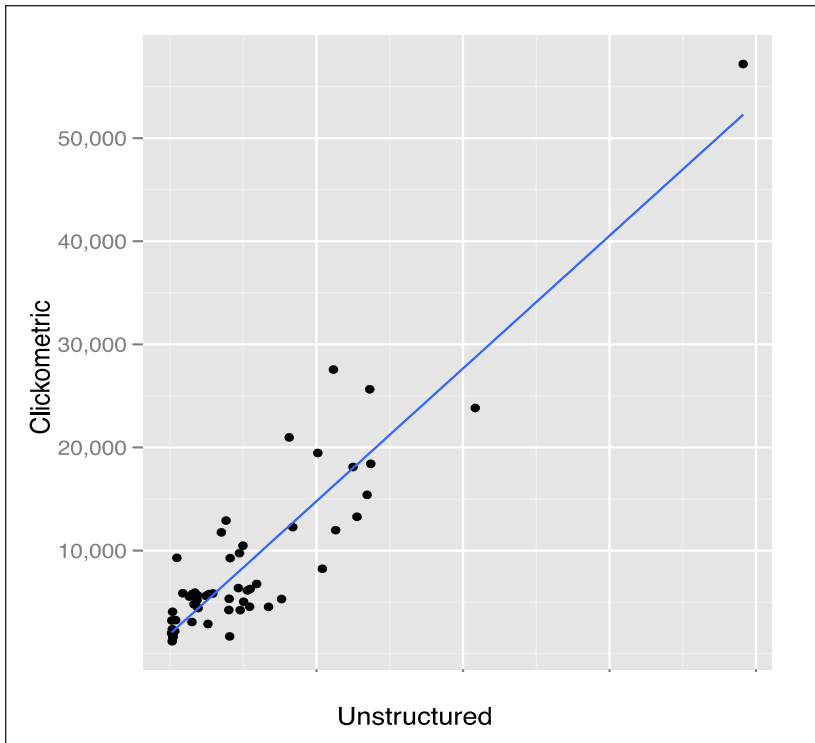


Figure 5. Clickometric vs. unstructured data-points. Scale on the x-axis is compressed by a factor of 10 compared to the y-axis.

ENHANCING CLICKOMETRY – A CASE STUDY

While it is clear from the previous section that clickometry only captures a fraction of the data available for analysis and that the resulting analyses are frequently lacking both in depth and breadth, this is not to say that clickometric analysis is useless in this realm, but rather that with a fuller analysis we can learn a lot more about what really goes on in an on-line course. As an example I will analyze discussion group data from a course, based purely on access log data, and then complement the analysis with layers of non-clickometric data, to show how these additions enhance our understanding of the underlying construct.

For the purposes of this case study I selected what might be considered an average course, clickometrically speaking. The CTW ratio was along the lines of what has been described; the course ran over a ten-week semester and had nine participants—I deliberately chose a course with relatively few participants so as not to over-clutter the examples to follow.

Social Network Analysis Based on Clickometry Alone

Based on the access logs, I extracted information about the discussion group interactions which had taken place during the course, but rather than collecting data about participation rates and posting frequency counts – the inveterate clickometrist’s approach – I analyzed which students responded to whose postings in the discussion groups. Simply put this analysis answers the question “who is talking to whom?”—while all postings are presumably meant for public display, the posters *choose* to post and choose whose threads to reply to and these choices shape the conversation. The resulting adjacency matrix is shown in table 2.

Table 2
Adjacency Matrix

	Ana	Brent	Carroll	Irving	Jacqueline	Kari	Kevin	Rebecca	Sammy
Ana	0	0	1	0	1	1	1	0	1
Brent	0	0	0	0	0	0	1	0	0
Carroll	1	0	0	1	0	1	1	1	1
Irving	0	0	1	0	1	0	0	0	0
Jacqueline	1	0	1	1	0	0	1	1	0
Kari	0	0	1	0	0	0	1	0	0
Kevin	1	1	1	1	1	1	0	1	1
Rebecca	0	0	0	0	0	0	1	0	1
Sammy	0	0	0	0	0	1	1	1	0

This table is a binary display meaning the 0 and 1 indicate presence or absence of interaction altogether. The analysis can be further enhanced by adding the number of interactions to each individual cell, I also replaced the zeros with empty space for easier interpretation. The resulting matrix is shown in Table 3.

Table 3
Adjacency Matrix with Number of Interactions in Each Cell.

	Ana	Brent	Carroll	Irving	Jacqueline	Kari	Kevin	Rebecca	Sammy
Ana			2		2	1	7		1
Brent							1		
Carroll	1			1		1	6	1	2
Irving			1		2				
Jacqueline	1		2	2			9	1	
Kari			2				4		
Kevin	10	2	10	3	12	10		10	9
Rebecca							8		1
Sammy						2	2	1	

Incidentally, in the case of this dataset the diagonals of the matrices are empty (or filled with zeros), meaning nobody responded to their own postings. I suppose it is generally good that course participants don't spend a lot of time talking to themselves, but I will leave it to the reader to speculate on the interpretation and implications of a lot of non-zero values along the diagonal.

While there is a sizeable amount of information stored in these displays, they are not easily interpreted, though a keen eye will already have singled out *Kevin* as the most talkative member of this group based on his high number of double-digit and high single digit entries on both his horizontal and vertical axes. I used the iGraph package (Csardi, 2011) available in the R framework, and chose the Kamada-Kawai (1989) algorithm for placing the vertices (nodes). The result is shown in Figure 6. In this social network diagram, or sociogram, each participant is represented by a circle carrying his or her name. An edge (or link) shows that the participant responded to a message by the other or vice-versa. In this diagram the direction of the communications (i.e. who is doing the post) is not signified.

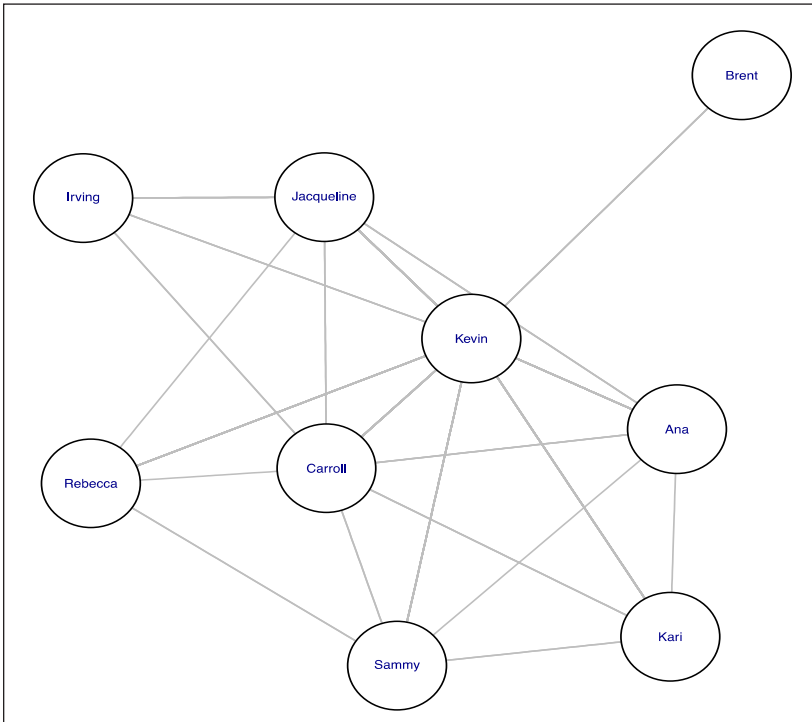


Figure 6. Sociogram

In Figure 7, I added an additional layer of information by stipulating that the width of the edges (links) should correspond to the number of interactions—the data contained in Table 3. Incoming and outgoing communication is split into two edges each bulging on the right relative to the direction of the communication – also indicated by arrows where possible.

From these displays it is relatively easy to see who the central actors in the course discussion are and who have taken a more peripheral role. We see that Kevin is the life of the party, with plenty of interactions with most of the other participants, while Brent is rather isolated and an outsider in this network. As can be seen, even a careful analysis of only clickometric data can help us understand the social structure of a course cohort. In the rest of this section I shall extend the analysis to include data extracted from actual interactions (in this case posts).

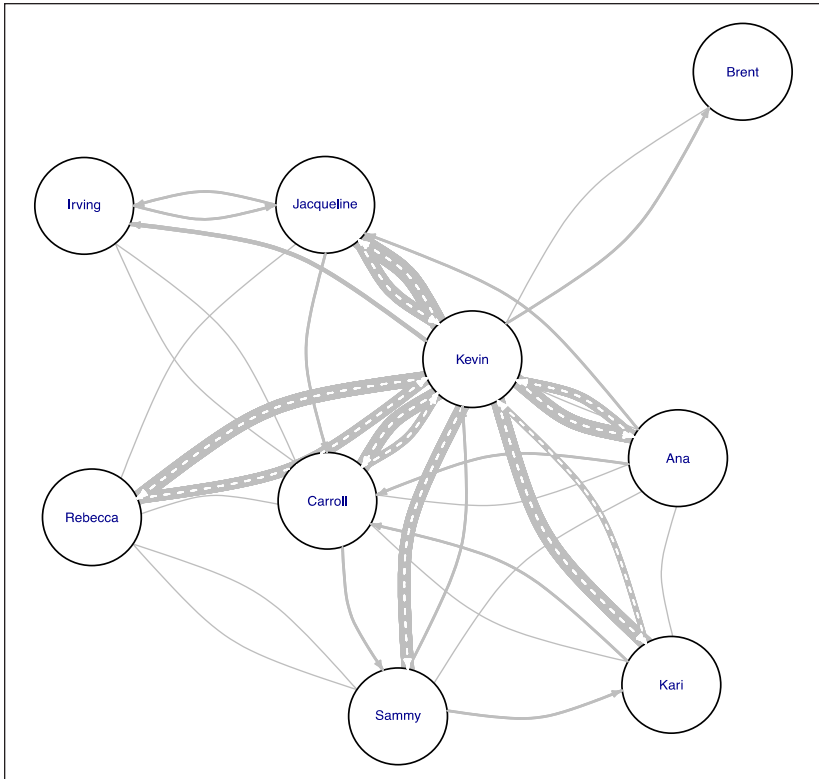


Figure 7. Sociogram with number of interactions signified by width of edges.

Adding Linguistic Data

Now, I shall add to the analysis developed in the previous paragraphs. I shall do this in three steps: first by incorporating a simple word-count for each post in the analysis and then, for a slightly more sophisticated entrée, I shall add a measure for vocabulary growth and contribution before finally calculating a measure suggested by Jeong (2003) based on Newman et al. (1995, 1996), assigning a *critical thinking coefficient* (CTC) to each interaction.

Adding Word Count

Word count is probably the simplest linguistic measure we can analyze in any text. Figure 8 shows the total number of words contributed to the discussion forum broken down by participant.

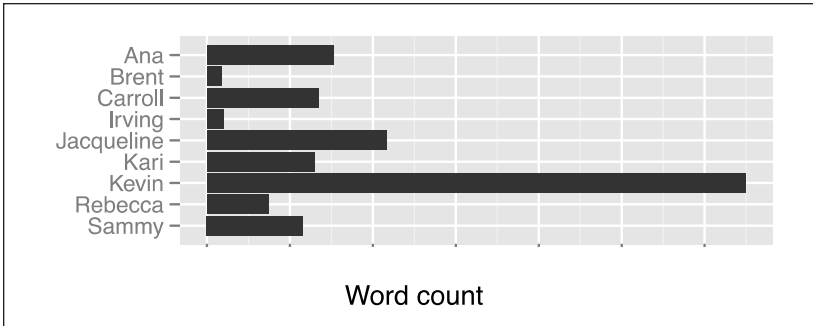


Figure 8. Raw word contributions by participant.

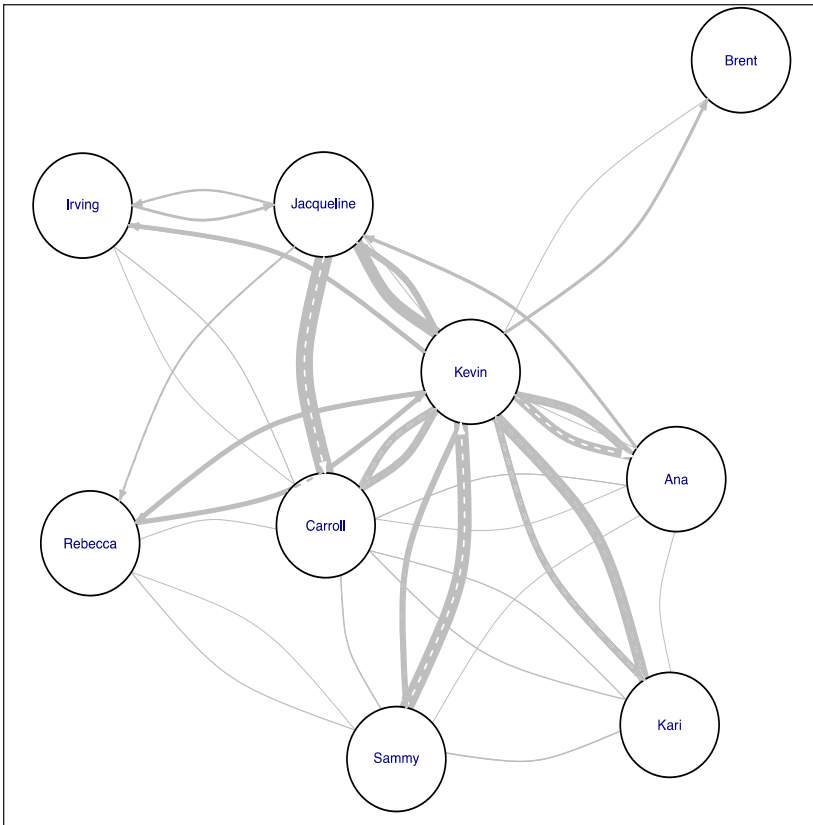


Figure 9. Sociogram with word count.

Figure 9 shows the information from Figure 8 distributed across the social network present. The width of the edges here correspond to number of words exchanged in these interactions, that is, we are displaying the information in Figure 8 in the context of the social network. It is easy to see that Kevin is the most productive member of this network, not only does he interact often, he also produces a lot of words, but we can see that the other weights have shifted some and are a little more evenly distributed among the central actors, especially Jacqueline and Sammy seem to make longer contributions when they do make them.

Vocabulary Growth

Vocabulary growth is a central topic in the field of quantitative linguistics. A distinction is made between a *type* (word forms) and *tokens* (individual occurrences of the types) in a text. The *type-token* ratio has been shown to be a helpful measure of lexical variety within a text, i.e., lexical density. *Vocabulary growth* is a related measure for how many “new” types are added in some dimension – typically time. For the purposes of analyzing discussion posts, the measure proves helpful for determining when and where new information enters the discussion, and where a posting is simply a regurgitation of previous points made, so it can work as a measure of the contribution of “new stuff” in the conversation. Figure 10 shows the raw vocabulary growth broken down by participant. Kevin is still in the lead by far, but we see Jacqueline catching up, with Ana and Carroll also making important contributions.

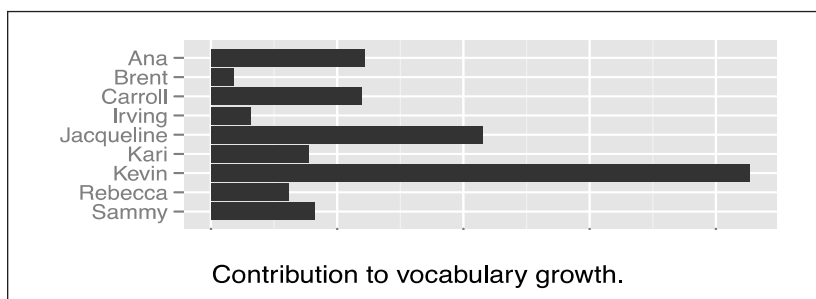


Figure 10. Contribution to vocabulary growth.

We can now distribute the vocabulary growth within a social network diagram by representing the growth in each participant’s posts by the thickness of the edges connecting the participants. This display technique will not only show us which individual participants make the most significant contributions, but also *where*, that is, *in which interactions* the most significant contribution for vocabulary growth happens.

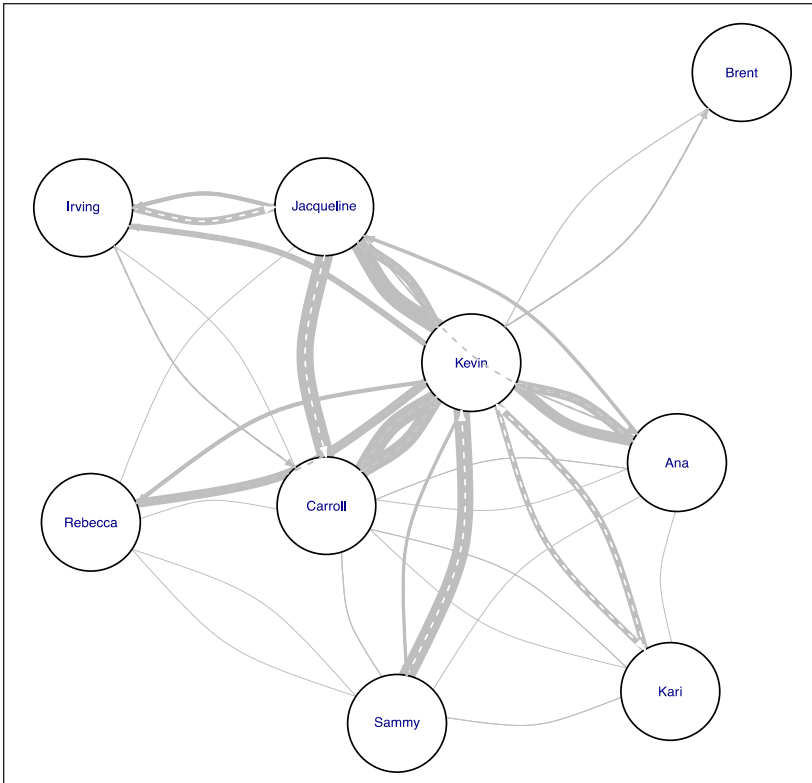


Figure 11. Sociogram with vocabulary growth

Semantic Analysis

Several methodologies have been proposed by researchers to approach the question of analyzing the actual content of discussion group postings. The methodology used in this section is loosely based on the *Newman protocol* (Newman et al., 1996; Newman et al., 1997). Briefly the methodology answers the question of “How much” critical thinking is occurring in each unit of analysis. It does so by assigning codes to each posting (in this case) and weighting and transforming these to a ratio or *coefficient*. For this purpose I implemented the methodology as a computer algorithm using open source *Natural Language Processing* packages (Feinerer, I., Hornik, K., & Hornik, M., 2011). The algorithm assigns a score to each posting based on the presence of vocabulary items as well as collocation indicators. While the algorithm is definitely a work in progress, and still quite rough around the edges, I asked a human subject to score each of the postings manually,

and found a coincidence of 62.45% (it might be claimed that the AI IQ is 62.45). It is well known that *NLP* algorithms have trouble analyzing certain rhetorical figures – the textbook example being sarcasm – and does, of course, not benefit from knowledge of context beyond the unit analyzed, leading to systematic under-prediction of the CTC. Yet the speed of analysis, 532ms for the computer as opposed to 2h30m for the human rater, probably outweighs these concerns for most practical purposes.

Figure 12 shows the CTC by participant.

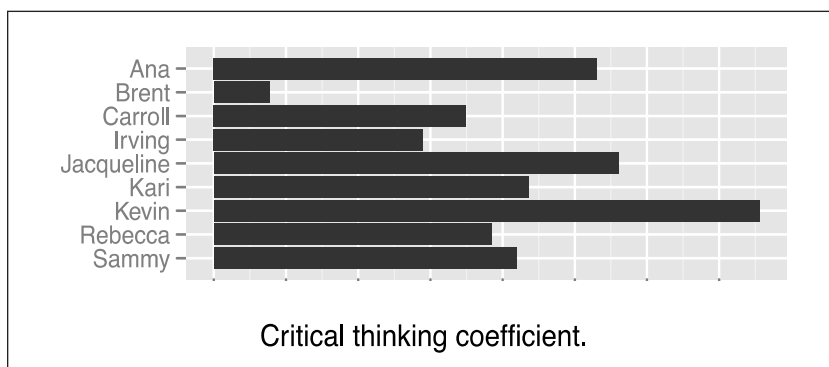


Figure 12. Critical thinking coefficient by participant.

Distributing the CTC measure across the social network present in the course results in the sociogram shown in Figure 13.

We see that Figure 13 resembles somewhat Figures 9 and 11. Kevin is still the central actor in this network; however, it can be seen that the CTC-measure is quite a bit higher in those posting originating *from* other participants *to* Kevin than vice-versa—the edges bulge to the right from the point of view of the *originator* of the post—that is, the participants in this forum think critically when they *respond to* Kevin, in fact more so than to any other participant in the network.

The avid reader will already have inferred that Kevin is not like *any other* participant in this discussion group. Technically speaking he has the same access and privileges as anyone else in the forum. In this case, however, he has been assigned the role of instructor and facilitator for the course. If the goal of facilitating the discussion forum is to foster critical thinking and reflection on the readings of the course – often a stated goal of constructivist teaching methodologies—then it is fair to say that Kevin is doing a good job with most of the students. Brent, however, should still be a cause for concern.

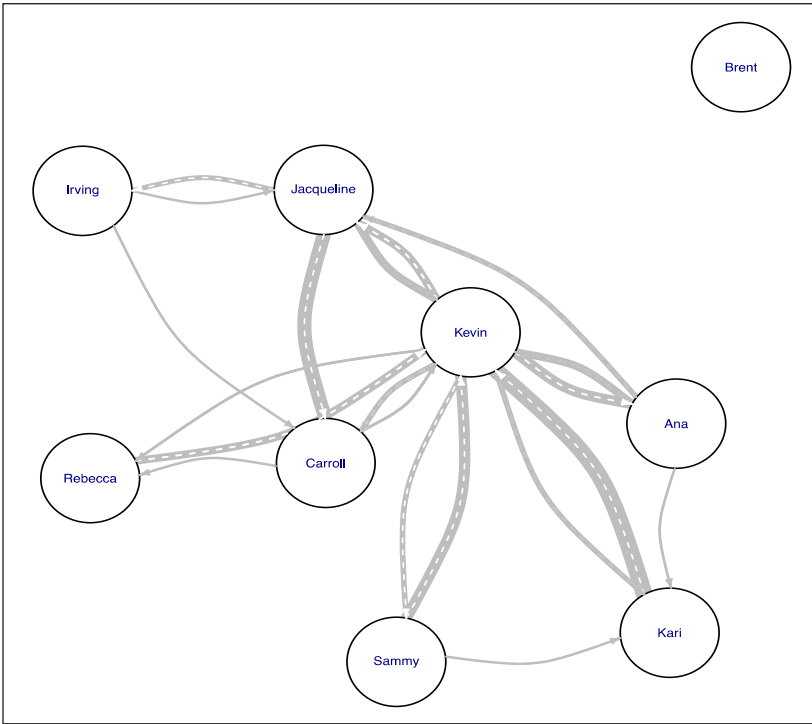


Figure 13. Sociogram with critical thinking coefficient.

We see that with the addition of a measure of critical thinking albeit crude and computer-extracted, we are able to elicit information not only on student performance but also on the instructor/facilitator's suitability for the undertaking he or she has been tasked with.

DISCUSSION

The analyses performed in the previous section are by no means intended to be exhaustive, but rather an example of what could and should be done in the realm on LMS analytics, and a suggestion for where this field needs to move. All the analyses are relatively straightforward, based on readily available open-source technologies, and computationally accessible, yet they allow us to explore dimensions of the data that clickometry alone cannot. When applied correctly these techniques allow us to identify the locus of the creation of knowledge in an on-line course, and measure each participant's contribution. Having access to this kind of information is likely to be

hugely advantageous to the on-line instructor as he or she teaches the course as well as an invaluable source of insight for post-mortem analyses of performance and activity for classroom and cohort management. If Brent and Irving are not inspired to contribute; if they do not connect, as it were, with Kevin, we may be dealing with a social or personality issue and maybe they should be assigned to a different section for “History 201.”

Clearly there is nothing *per se* wrong with clickometry; however, I will submit that the hegemonic status clickometry enjoys for analytic purposes in the realm of LMSs is counterproductive if our goal is to facilitate and evaluate the effectiveness of on-line learning. The explosion of social media starting in the second half of the last decade should have taught us that it is precisely the interactive, communicative and collaborative processes that need to be documented, analyzed and understood. Unfortunately the concentration of clickometric approaches to the problem of analytics for on-line learning environments leaves most if not all of the actual construction of knowledge in such spaces unreported and unanalyzed. Thus the status quo of LMS remains more suited to behaviorist approaches which have long fallen out of vogue on most levels of what we still like to refer to as education. E-learning has been and still is treated as education’s step-child, and the poor support for assessment of pedagogical processes does not help.

There are just too many dimensions – social, pedagogical and cognitive – which are not captured by counting clicks alone. As far back as 1992 (Henri) and as late as 2011 (Dyckhoff) researchers and practitioners alike have clamored for more qualitative methodologies to be applied to LMS data. While some interesting progress has been made in the field in the last half of the last decade the field is far from caught up with the advances in on-line pedagogy and the development of the e-learning industry in general.

The case can certainly be made that further knowledge of a student’s background, previous performance and general profile, data found outside the LMS, for example, in *Student Information Systems* (SIS) in the best of cases, will enhance our understanding of the on-line student and provide invaluable insights which should be included in any analytics model. Here too, however, we are likely to discover that most of the data is stored in the same unstructured fashion as the endogenous data and we will inevitably face similar methodological challenges.

I suspect the preference in focus, both among commercial vendors and the open source alternatives, is not based on any theoretical assumptions, but, rather, constitutes the path of least resistance for the industry. Clicks are easy to collect. Summarized and regurgitated in different layouts, they represent the simplest way of paying lip-service to the practitioners’ demand for information about what is going on in the classes they are teaching. Accrediting bodies too are fed a stream of clicks, and the intervals between

them as a *time-on-task* measure, and, absent any reasonable alternative, choose to accept this as proof of student progress and proper execution of the stated curriculum.

Usually limited to descriptive analysis, LMS analytics suffer miserably from lack of predictive power and useful forecasting models. This is due in part to the fact that only a minimal fraction of the data is being analyzed – the main argument of this paper – but also to a common misconception regarding the nature of e-learning analytics: the idea that we are dealing with a technology problem when in fact, the problem of LMS analytics still needs to be resolved conceptually on a research level.

FINAL THOUGHTS

In this paper I attempt to show that while sophisticated clickometry certainly has a place in the realm on LMS analytics, it needs to take its place alongside methodologies more suited to evaluating the pedagogical processes practitioners aspire to facilitate in their on-line courses. For instance I showed how the addition of relatively straightforward linguistic measures paired with social network analysis allowed us to approximate the locus of creation of knowledge in a course.

The mere volume of data available should be enough to persuade designers and developers of analytics tools to concentrate on non-clickometric data. Reasonable alternatives do exist, admittedly a lot more research is needed, and implementation may not be as straightforward as clickometry, but the burden should be on technology to be of service to the user, never the opposite. For LMS analytics to progress alongside on-line pedagogy researchers and developers need to think outside box and look beyond clickometry.

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