Analyzing Learner's Participation in a WordPress-based Personal Teaching Environment

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Abstract:

Just as there has been a growing interest on personal learning environments as useful learning tools, interest should be also paid to "personal teaching environments", light open source content management systems (CMS), such as WordPress or Drupal, that, configured in an appropriate way, allow a teacher to set up quickly and easily an open environment for a virtual classroom. In this paper we describe a reputation scheme that can be used to rank resources in a blog (posts, comments and even other users) according to the interaction they generate. Most blogs allow users the possibility of browsing recent posts, but finding older posts (and other blog contents) can be a difficult task. Using the proposed reputation scheme, users would be able to find the most interesting resources, thus breaking the imposed timeline of a blog-based light CMS. Our experiments show that the number of comments and votes is not enough for determining the importance of a post (or a comment). On the other hand, the structure of the graph (i.e. the number and depth of the branches representing discussions around a post) is a more interesting indicator of post relevance. In order to do so, we have manually labeled each post according to its importance and we have tested several measures trying to determine the "optimal" one, which is based on graph path lengths. Then we have tried to compute a weighted metric combining some of these measures using principal component analysis. Our results show that we can automatically detect the most relevant posts and comments. Once implemented as a WordPress plug-in, we expect this reputation scheme to help learners to better follow and engage into blog-based open courses.

Keywords: reputation scheme, voting, open LMS, personal teaching environment, social network analysis

Introduction

The emergence of the Internet –and most especially since its full disclosure in 1995– has undoubtedly transformed how education, in general, and distance education, in particular is understood. However, the "fifth generation distance education" as described by Taylor (2001) is suffering yet another profound (r)evolution as the Internet has folded on itself with the appearance and pervasive use of web 2.0 applications and services, including social networking sites.

Fair enough, technology is now yielding before a renaissance of more pedagogy-centered approaches to ride the wave of the Information Revolution. On the one hand, it is now possible to adopt and use different technologies according to different learning theories and their corresponding pedagogic models (Baumgartner, 2004; Baugmartner, 2005); it is now also possible to challenge the model based on the virtualization of all the institutions of a “bricks-and-mortar” world (the classroom, the handbook, the syllabus, etc.) as we face more open and distributed learning experiences, and thus shift from the “old” LMS to other architectures based on e-portfolios and PLEs (Wilson et al., 2007; Atwell, 2007); and, thus, it becomes necessary to absolutely evaluate the pedagogic evolution of distance education in order to plan a future based on solid ground (Anderson & Dron, 2010).

Defined as “a set of conscious strategies to use technological tools to gain access to the knowledge contained in objects and people and, through that, achieve specific learning goals” (Peña-López, 2013a), personal learning environments are the litmus test of the impact of Information and Communication Technologies in Education. And their importance relies not on a heavy usage of “new” technologies, but on how they disrupt and challenge most educational institutions by disclosing opening up new learning spaces (Kalz, 2005).

A review of Vygotsky (Vygotsky, 1978; Kozulin, 1986; Wertsch, 1985) can be very helpful in determining how the concept of the “more knowledgeable other” has been radically transformed in recent years. Who is “more knowledgeable”? Who determines who is that “more knowledgeable” one? Can learning objects be “more knowledgeable others”? Are “more knowledgeable others” always the same (a static concept) or can they change along time, or even shift in and out depending on the context? In fact, this “more knowledgeable other”, sometimes a teacher, is not even a static actor herself: if we acknowledge that teaching requires learning, that knowledge transmission requires research, we find out that (now in our case) the teacher switches too between being a learner and a teacher depending on the context, on the nature of the community (of learning, of practice) that she is part of, depending on the role that others confer to her (Peña-López, 2013b).

Under this point of view, personal learning environments, in plural, can be seen as a mesh of single and individual learning strategies facilitated by technology and learning objects that overlap one with other ones, being one’s output the input of the nearer one and so on.

These learning webs (Brown, 2010), or, indeed, learning webs of webs are the quintessential spirit of the do-it-yourself ethos put into practice in the learning scenario. What was then driven by institutions can be now led by individuals, even *inside* institutions, that is, even by teachers themselves as individuals. PLEs, put in the hands of educators, are both a powerful tool for them to learn as a valuable device to set up their own communities of learning we time ago used to call “classrooms”, or “teaching groups”, though now their architecture is flexible, liquid, extremely customizable and personalizable (for both the educator and the learners) and, most important, open to the people that belong to the community of learning by lie outside of the core of it.

Blogging has been an educational tool for more than a decade now (for a discussion, see Downes, 2004). That article refers mainly to conventional uses of blogging, but for a long time educators have seen the possibilities of blogging tools as lightweight LMSs: Tomberg and Laanpere (2008), for example, analyse the use of WordPress for assessment purposes. The growing power of a system such as WordPress, combined with an almost limitless number of available multi-purpose plug-ins make it possible to mix and match a series of off-the-shelf components in order to compose a lightweight LMS with moderate time and money investment.

In this scenario, learning management systems build upon blog-like light CMS are very easy to set up and promote dynamic engagement, but they do not provide good 'out of the box' mechanisms for finding and sharing useful resources within the system. This problem becomes intractable if the learning experience spans across time and the number of newcomers and returning users is continuously increasing. An example of this complexity is the Digital Storytelling course (DS106) given at University of Mary Washington, which was created and offered under a completely open framework (Groom et al., 2012). On the other hand, and as stated by Thoms (2011), most blog posts never receive comments, mainly because most blog visitors have no time for developing a valuable comment. Nevertheless, such visitors would participate if they were provided with an easy feedback system, such as a voting or ranking scheme. These systems are simple mechanisms to bring forth the desired feedback, encouraging other visitors to participate, as in a game (McGonigal, 2011). Therefore, promoting and analyzing this interaction among peers is very important to improve both course participation and learning.

This paper is structured as follows. Next section describes how WordPress was used to support an open course about "Open Data". The following section describes the data generated during this course, including learner-generated interaction data. Then, in the following section we describe the reputation scheme we propose to summarize the relative importance of each blog post and comment. Finally, the main conclusions and possible extensions of this work are highlighted in the last section.

Building a course using WordPress

The course described and analyzed in this paper was created as an open educational experience, exploring the possibilities of moving away from a very tight scenario such as the one defined by the Universitat Oberta de Catalunya (UOC). The LMS used at UOC (namely the Virtual Campus) is a complete virtual learning environment supporting a fully pure online university. The Virtual Campus began as a system to centralize all academic management tasks (enrolment, personal records, etc.) and quickly evolved into a full virtual learning environment to virtually provide any kind of teaching-learning activity. In its fifth version, it underwent a major reconceptualization that enabled the connection of most digital tools (blogs, virtual classrooms, quizzes, etc.) in order to use them for teaching purposes. Although UOC's Virtual Campus is fully capable of handling different kinds of educational experiences, we decided to explore the use of light-weight CMS to carry out short courses in a more open and flexible environment, without (or with minimum) institutional support. One of these courses is about “Open Data”, which is described as follows.

An introductory course on “Open Data”

Open (and, especially) big data has been one of the recent hypes that has drawn many attention from both mass media and public in general, since the concept started to be known (Doctorow, 2008). Gartner added “Big Data” to its famous hype cycle of emerging technologies in 2011, reaching almost the peak of inflated expectations in 2013. Actually, Gartner even developed a hype cycle for all the concepts related to “Big Data”, as it comprises a lot of technologies and methodologies that are already in use (Henschen, 2013). On the other hand, Catalunya Dades[1] is a collective of professionals interested in open and big data, which aim to promote and disseminate the philosophy behind the open movement in Catalonia, Spain. Following the same principles used by UNESCO to determine how to promote open educational resources (D’Antoni, 2008), several activities related to raising awareness, community building and capacitation are developed every year, especially under the umbrella of the Big Data Week[2], an international distributed event gathering people with common interests about Big Data. Among these activities, an open course about the basic concepts of open data was designed, as it was the perfect excuse for pursuing the three goals mentioned above. The course was designed taking into account the following facts:

- It should be based on open educational resources and open software. All the resources generated during the course should be also published under an open license.
- The course is also open in the sense that anybody can join at any moment, as in an open conversation. There is a registration procedure but it is only used for improving our understanding of the potential audience and for planning purposes (i.e. what if ten thousand students enroll into the course?).
- It should be an introductory course, trying to reach a wide audience (with very different backgrounds), providing learners with basic knowledge about open data.
- It is very important to get people with common interests together in a single space, where they can share resources and answer other peers’ questions.
- There will not be a traditional teacher in front of a traditional audience, although the teacher will establish the course pace. Several experts (one each week) will also act as facilitators, guiding the debate. Nevertheless, participants are encouraged to ask questions and answer other participants’ questions, without waiting for teacher intervention. Actually, teachers and experts become learners, too.
- Finally, several optional activities are proposed (e.g. trying to reproduce some experiments described in a video lesson), giving the participants the final decision of doing it or not, and sharing their results if available.

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[1] http://catalunyadades.cat/
[2] http://bigdataweek.com/

Course planning was very simple. Every week, three or four blog posts were created, usually with two or three days between consecutive posts. Only the teacher was allowed to post, while learners were encouraged to comment (either a post or another comment) and rate both posts and comments. Each post was a combination of basic knowledge about a topic (i.e. the definition of Big Data), some activities (readings, videos, tools, …) and a discussion about an imaginary scenario where such concepts and tools were supposed to be put into practice. Each post is just a starting point from which course participants engage in a rich discussion, trying the dialogue described in Downes (2004).

LMS limitations

Groom and Lamb (2014) present five arguments against the conventional LMS:

- The use of the LMS considers learning as a technology problem, leading to formulaic and rigid instruction.
- Most LMS implementations still lack elementary capacities to publish to and interact with the wider web and the public.
- LMS do nothing to equip students with practical web skills: students do not engage the wider web in a spirit of critical inquiry.
- Enterprise LMSs are expensive and the commitment required to maintain them represents an immense set of challenges.
- The complexity and rigidity of LMSs lead to poor online experiences.

They propose a concrete set of recommendations:

- Do everything possible to minimize reliance on an enterprise LMS.
- Explore ways to support activity and content development in environments that foster collaboration and also interoperability with a wide range of tools.
- Before directing activity to a complex, locked-down system, ask: "Do we really need to do it this way? Is there a simpler, cheaper, open alternative that will do the job?"

They also state that MOOCs generally “lack the basic Web 2.0 premises of aggregation, openness, tagging, portability, reuse, multichannel distribution, syndication, and user-as-contributor. In most of the available MOOCs (and LMSs), students and faculty have no real control over their work, no sense of creating a distributed network in which they can utilize their own, existing online identities as part of any one course or even a campus community”.

While part of Groom and Lamb’s arguments concern specifically enterprise LMSs such as Blackboard, some of them apply to LMSs in general, including open source tools such as Moodle. The features that LMSs incorporate make them powerful tools, but they also make them complex and relatively hard to learn and customize.

That can make other alternatives attractive to set up a personal teaching environment, especially in some circumstances:

- If courses are sporadic and thus make the learning curve for an LMS harder to justify;
- if typical LMS teaching functionalities, such as assessment tools, are not going to be employed, because, for example, we are dealing with a MOOC-like environment and do not intend to provide certification at the end of the course;
- if significant student re-enrolment is not anticipated, thus negating the need for student management functionalities.

In those cases, the use of a light Content Management System (CMS) such as Drupal or, even simpler, WordPress, can be a better option, providing a more open and easier to learn, manage and customize tool. It must be noted that while the learning curve will typically be easier, it will not completely flatten it: considerable thought and some technological expertise are still needed to set up a working, efficient teaching environment.

In line with Groom and Lamb's recommendations, if we are to move to a non-conventional way of teaching, light CMSs provide a good alternative to LMSs for personal teaching environments.

Promoting user participation through voting

While WordPress, as we have seen, is a good option to set up a personal teaching environment, out of the box it lacks some functionalities that are important for an online course. Most such functionalities can be added through existing plug-ins (the are more than 30,000 plug-ins in the WordPress official repository), though some will need the development of specific tools.

It has been shown that promoting easy and meaningful interaction among students and between students and instructors has a positive effect on participation, engagement and learning in the classroom (Bouhnik & Marcus, 2006). It is indeed our intention, to analyse that interaction in order to feed our reputations scheme (Josang et al., 2007). In order to provide that functionality we combine an existing WordPress plug-in with some custom development. The plug-in has been made available to the community[3] following the WordPress guidelines and open source spirit.

The *GD Star Rating* plug-in allows users to vote any post or comment that any user has left on the course website and records and displays the corresponding results for every item. Complementing such plug-in, another WordPress plug-in was developed in order to mine information accumulated by the *GD Star Rating* plug-in and by regular user interactions on the site (that is, posting and commenting activity). This plug-in provides a .csv file that contains, for every user interaction, the following data: the time and date for the interaction, available user information (if the used was logged in, the credentials; if the user was not logged in but provided

[3] https://github.com/ccasadom/MAVSEL-post-comment-vote-analyzer

a name, that name; finally, nothing for anonymous votes), the type of interaction (post, comment to a post, comment to a comment or a vote for a post or a comment) and the interaction data, as follows:

- for posts, it returns the post identifier;
- for comments, it returns either the post identifier if the user was commenting on a post or the comment identifier if the user was commenting on some other comment;
- for votes, it returns the post or comment identifier and the numerical vote value.

These data will allow for the intended interaction analysis which follows.

Available data

The first edition of the course was scheduled between January the 7th and February the 24th, 2013, comprising a total of seven weeks, where the first week (week 0) was just warming up. During these weeks, a total of 1732 different users generated 6455 sessions, visiting a total of 27787 pages (4.31 pages / session). It is worth to mention that average session was 5’16’’ and that 76.9% of visitors were returning visitors. Figure 1 shows the number of sessions per day during the seven weeks it lasted. Notice that this course reproduces also the typical behaviour of MOOC users, that is, the number of active users decreases every week, especially after the first one (Yang & Leskovec, 2011).

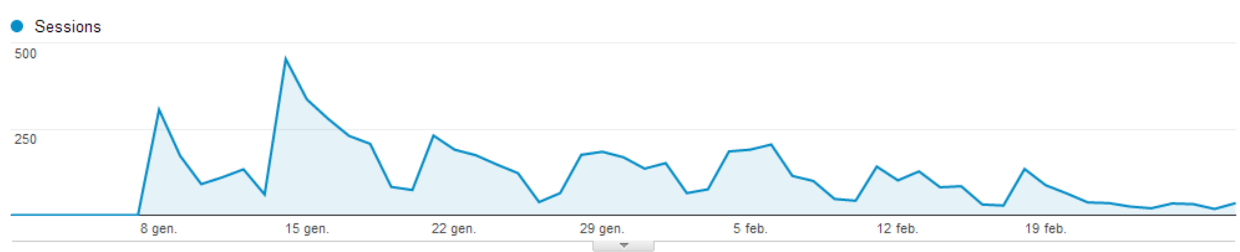

Figure 1. Number of sessions by day.

Regarding interaction, 24 posts were created by the teacher during the course. These posts generated a total of 506 comments and 278 votes. Even though the voting mechanism was very simple and user-friendly, most of the users never used it, following the well-known pattern described by Nielsen (2006), where 90% of the users are lurkers, 9% do what they are asked to do and only 1% goes beyond.

Data analysis

Using a more formal approach, all these data can be arranged in tuples according to the following structure:

(U, T, A, R, X)

where U represents a user who, in moment T, performs an action A on the resource R obtaining X as the result of her action. As only teachers are allowed to create blog posts, in this paper we will only define two different possible actions, namely “comment” and “vote”, as follows:

(U, T, “comment”, post/comment id, comment id)

and

(U, T, “vote”, post/comment id, vote)

where id represents the internal code used to identify a blog post, comment or vote. Actually, as the action can be applied to different types of resources and we want to analyze them separately, we have a pair of action-resource type for each possible combination. If these tuples are sorted by T, then they represent all the interaction following a timeline. In fact, the plug-in developed for extracting data from the GD Star Rating plug-in creates a .csv file according to this structure, thus simplifying further analysis.

Table 1 shows a typical fragment of the .csv file for a given post (ID=#230). User U1 creates the post and almost two hours and a half later, an anonymous user votes the post giving it 10 points. One hour later, U2 makes a comment on that post, and five hours later U3 does the same, creating a second comment. Twenty minutes later, another anonymous user votes the second comment, giving it 5 points.

User	Date / Time	Action	Resource	Result
U1	2013-01-21 08:24:23	POST	---	#230
---	2013-01-21 10:46:23	VOTE-POST	#230	10
U2	2013-01-21 11:42:47	COMMENT-POST	#230	#260
U3	2013-01-21 16:35:16	COMMENT-POST	#230	#266
---	2013-01-21 16:54:43	VOTE-COMMENT	#266	5

Table 1. Typical fragment of a sequence of actions around a new post.

Notice that we indistinctly use Result for both pointing to an element (i.e. post ID) or for providing the result of an action (i.e. voting with 10 points). There is no ambiguity as semantic is provided by Action. In fact, we could think of Result as a link to the resulting object, but in the case of voting, it is easier to store just the result of the action rather than a link to it. Using this representation we can reproduce the interaction around each post or comment and proceed with the analysis of all interaction data.

Analyzing user interaction

By default, most of the WordPress themes show the last five posts and the last five comments as part of the blog landing page. This information might be useful for a blog understood as a place where only recent activity is important, but this is not the case of our course, where interesting resources (posts or comments) may have been generated several days ago. Blogs provide a mechanism for browsing through posts, usually by means of “previous” and “next” buttons, thus reinforcing the linearity imposed by time. Therefore, reaching a specific post can be difficult unless the exact timestamp of such post is known. We propose to define a measure for “post interestingness” that takes into account all the interaction generated around a post: number of visits, number of comments and number of votes. This concept can also be extended to “comment interestingness”, taking into account that a comment can be seen as a sub-post generating its own interaction. We will explore different measures derived from the fact that each post generates a graph containing said post, comments (and comments to comments), votes (and votes to comments).

Analyzing post relevance

Table 2 shows 8 interesting posts and presents their basic characteristics, including its number of votes (*PV*) and average score (*PA*), the number of comments (*C*) and the number of votes (*CV*) and average score (*CA*) for each comment. In the first approach, one usually only considers the number of votes and their average score, since intuitively the posts with higher number of votes and score will be the most important ones.

Nevertheless, considering the number of votes or their average score is not enough to catch the relevance of each post. For instance, post #159 is the welcome message, where students introduce themselves. It has more than a hundred comments and 15 votes with an average score of 4.133 (out of 5). It might looks like an interesting post, but clearly this message is not interesting in order to follow the course and understand the subject.

ID	*Description*	*PV*	*PA*	*C*	*CV*	*CA*
#159	Welcome	0	0	102	15	4.133
#169	Basics	0	0	83	10	2.800
#189	Summary 1	21	9.333	0	0	0
#194	Open Data	1	1	47	42	4.048
#230	Legal aspects	2	10	33	14	3.429
#260	Tech. aspects	3	9	22	18	4.611
#272	Access types	2	9	24	14	4.571
#379	Good practices	3	8.667	11	6	4.167

Table 2. Basic characteristics of 8 posts. For each post we present its ID, a description, publication date, post's votes number (*PV*), post's average score (*PA*), number of comments related to this post (*C*), comment votes number (*CV*) and comment average score (*CA*).

Figure 2 shows the underlying graph of this post. As we can see, there are several comments (blue squares) related to the original post (yellow square), but few comments about other comments (light-blue squares) which means that there is no discussion chains in this post.

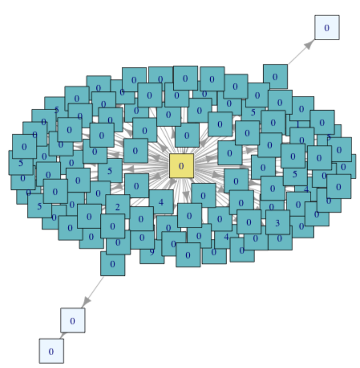

Figure 2. Post #159 ("Welcome"), where the yellow square represents the post, the blue ones the comments and the light-blue are comments about comments.

Therefore, we are interested in capturing and quantifying the discussion related to one specific post. Intuitively, a discussion creates a chain of comments, usually with some branches. For instance, Figure 3(a) shows post #230 "*Legal aspects*", which generates quite controversy and an interesting discussion among students. The underlying graph presents some comment's chains with branches, indicating different threads of discussion about the main topic. A similar behaviour can be seen on Figure 3(b), where post #379 "*Good practices*" shows a similar but smaller structure.

Figure 3(a) (leftmost) and 3(b) (rightmost). Posts #230 and #379.

We propose to consider several graph theory based measures (Borgatti & Everett, 2006) for capturing the post relevance, instead of considering only the number and the score of the votes. Nevertheless, as our graphs are, in fact, trees, we will use graph measures adapted to such tree structure. We have modelled them as directed graphs where an arc *e=(i,j)* is a path from node *i* to node *j* meaning that node *j* is subordinated to node *i*, which is the sequence used when someone reads the post and the comments.

The measures are the following ones:

- the number of nodes (*n*);
- the number of edges (*m*); notice that trees satisfy *m=n-1* so we will use only n;
- diameter (*D*), which is defined as the largest minimum distance between any two vertices in the network; in the case of trees, diameter is the length of the deepest branch;
- average distance (*AD*) is the average of the distances between each pair of nodes in the graph;
- betweenness centrality (BC) of a node is defined by the number of shortest paths going through this node (Freeman, 1978); we use the maximum value trying to capture the maximum discussion part of the post;
- closeness centrality (CC) measures how many steps are required to access every other node from a given one; we use the outgoing paths to quantify the subgraph generated from a specific node;
- and lastly, the out-degree (*out-deg*) of a node is the number of its successors; note that we do not consider the in-degree since every node has only one predecessor.

We analyse two methods to assign a score to the posts: in the first one, we will manually design score functions based on our intuition and observations, while in the second one we will use a machine learning approach to calculate the score function.

In both cases, we will need to categorize our posts according to their relevance in order to compare our results to some “expected” results. Thus, we manually assigned a value to each post representing its interestingness. These values allow us to compare the results using different methods and also to compute the error of each method. Although these values can be subjective, it is necessary to assess and quantify the post’s relevance to evaluate the results, as we are exploring different possibilities for the reputation scheme. We can consider them as a baseline for our results, just for validation purposes. Our scoring function works as follows: 0.5 points are given to interesting topics (according to teacher’s opinion) and another 0.5 points are given to posts which have generated a rich discussion. So, a score value between 0 and 1 is given to every post.

First approach: intuitively score function

Using these measures we want to capture the discussions associated to a post and compute the relevance of each one. The first approach, as we have commented before, is the most simple and intuitive function: we compute the relevance of each post using only the number of votes and its average score. This method is called Score #1. Figure 4(a) presents its relevance score on the vertical axis (values are normalized) and all posts on the horizontal axis. The grey dashed line represents the baseline values assigned to posts and the red solid one represents the values computed using the Score #1 metric. As we can see, this metric estimates quite well the value of some posts, but it fails in many other cases (for instance, on posts 11th, 22nd and 23rd).

Therefore, looking at the number and average score of votes allows us to approximate the relevance of a post, but it is not enough to pick out the most significant ones. Thus, other metrics must be taken into account in order to improve the score function. We propose to use one graph theory based measure in conjunction with the number and the average score both on the post and on the comments, since we want to include user opinion in our recommendation system.

After analyzing all measures described above, we empirically have realized that measures related to path lengths in the graph (actually, the tree) are the best ones to capture post’s relevance. We will discuss three more score functions: diameter (Score #2), average distance (Score #3) and the betweenness centrality (Score #4). Results for these measures are also depicted in Figure 4. The results of diameter and average distance are very similar, due to the fact that they evaluate a similar characteristic in the trees. On the contrary, the first eigenvalue of the adjacency matrix does catch the post’s relevance, as Figure 4(d) shows.

We utilize the mean squared error (MSE) as a measure to quantify the error introduced by each measure to our baseline values. It is computed using the following equation:

$$MSE(x,y) = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2$$

The first approach gets an MSE of 0.223, while the second and third ones fall to 0.097 and 0.099, showing a better fit. Lastly, the fourth one does not achieve good results, presenting an MSE of 0.244, even worse than the first one.

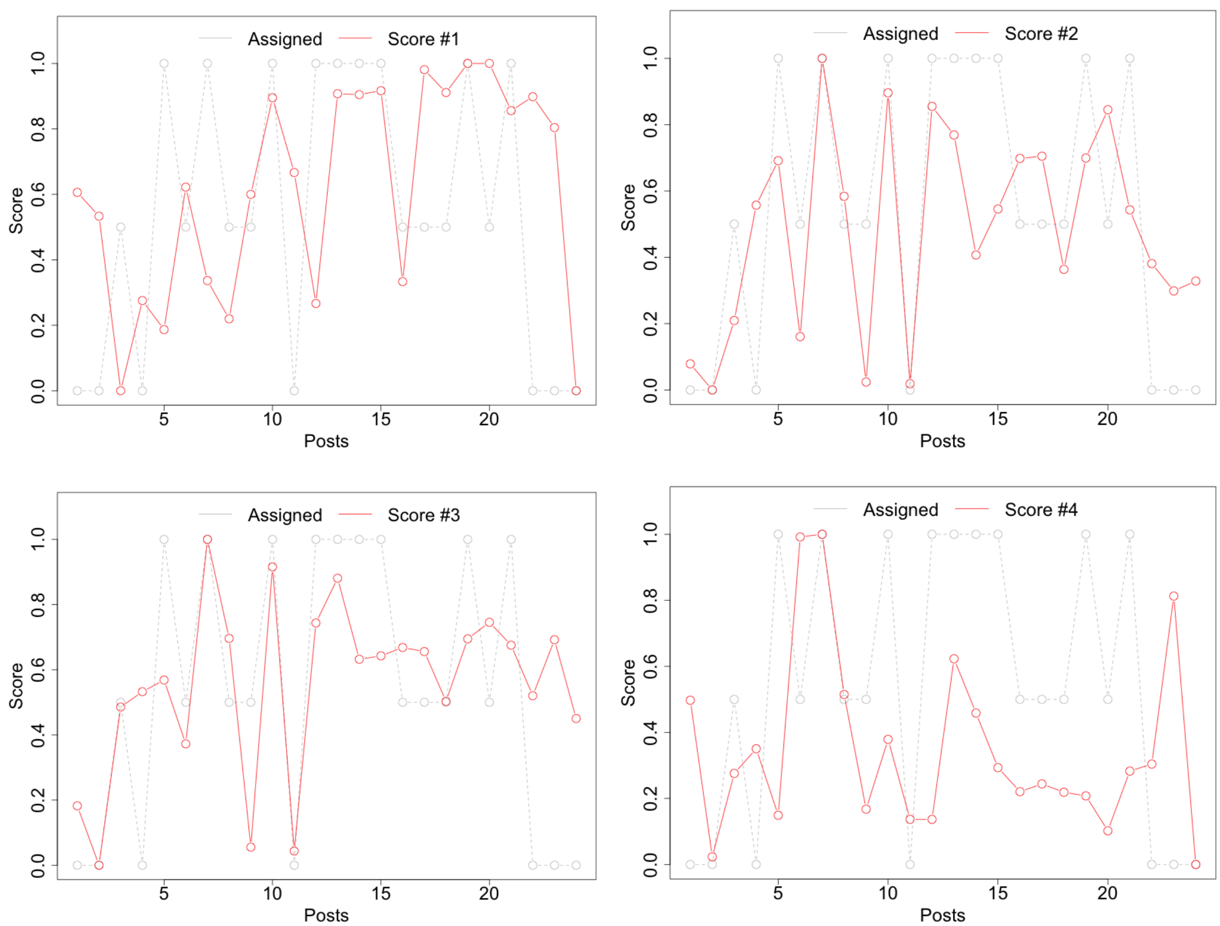

Figure 4(a) (upper leftmost), 4(b) (upper rightmost), 4(c) (lower leftmost) and 4(d) (lower rightmost). Assigned and computed score for the basic metric (a), diameter (b), average distance (c) and the first eigenvalue of the adjacency matrix (d).

Clearly, measures related to distances between nodes and path lengths are useful to capture the interest of a post, in terms of discussion and participation. We will try to combine these measures to improve the proposed reputation scheme.

Second approach: PCA-based score function

Here we want to address the same problem, but using machine learning approaches to compute the best combination of metrics. We will use a supervised learning method to compute the best combination of metrics in order to assign a score value to each post and choose the most important ones. Our approach is divided into two main steps: firstly, we analyse the correlation between our set of measures in order to reduce the space of metrics and do not consider too similar metrics, and secondly, we try to find the best combination of metrics using principal component analysis (PCA).

As we have commented before, we use seven graph-theoretic metrics (n, m, D, AD, BC, CC, out-deg), three measures related to posts (number of votes, total score and average score) and four measures related to comments (number of votes, total score, average score and the total score divided by the number of comments). Therefore, we have to deal with 14 metrics and measures, and it can be quite interesting to analyse which ones present the same information, i.e, which ones are equivalent. To perform this analysis, we use Pearson correlation, which gives a value in range [0,1] indicating the linear correlation or dependence between two variables.

After a basic correlation analysis, we can state the following conclusions:

- As we commented before, there exists an absolute correlation (+1) between the number of nodes (*n*) and edges (*m*), due to the fact that *n=m-1* in out graphs.
- The correlation between average distance (*AD*) and diameter (*D*) is very strong, achieving a value of 0.935. Additionally, the comment average score also gets a moderate/strong correlation close to 0.8 to both measures.
- Closeness centrality (*CC*) and out-degree (*out-deg*) present similar information, since their correlation value is 0.994.
- The total score and the number of votes for a specific post show a strong correlation value of 0.998. Intuitively, the greater the number of votes, the larger the score. Usually, users vote only for good posts, giving them a medium or high score (a post with a lot of low-score votes is very unusual).
- Finally, the total score and the number of votes for a specific comment also present very strong correlation (0.988). The total score divided by the number of comments gets a moderate correlation value of 0.713.

Thus, we only consider the following set of eight metrics and measures: number of nodes, average distance, betweenness and closeness centrality, number of votes and average score of a post and number of votes and average score of a comment. The second step of this approach consists on developing a score function to quantify the relevance of each post. To achieve our goal, we propose to use the principal component analysis (PCA) to choose which are the best attributes to use and the formula to merge them to get a unique real score value for each post.

After reducing the set of metrics and measures to eight, we can use the sets of size 2, …, 8 to choose the most relevant metrics and compute the score for each post. Obviously, we benefit from removing some metrics and reducing the set, since the total number of combinations is drastically reduced. Formally, the number of possible combinations (NoC) is defined by the following equation:

$$Number\ of\ combinations\ =\ \sum_{i=2}^{t} C_{t,i}$$

where t is the number of considered metrics. NoC is, in fact, 2^t - t -1, which rapidly grows with t.

The PCA algorithm provides the tool to transform input metrics in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible). Thus, we set the number of components to be extracted from the PCA algorithm to 1. The combination of metrics generated by PCA are used as the score function, trying to identify the most important posts. As in the previous experiments, we utilize the mean squared error (MSE) as a measure to quantify the error introduced by each PCA-based score and our baseline values.

The best metric set found by our PCA-based approach is the following one: average distance, number of votes (CV) and average score (CA) of a comment. The formula to compute the resulting score is:

$$PCA\_based\ score\ =\ 0.911 \times AD + 0.690 \times CV + 0.907 \times CA$$

Results for this measure is depicted in Figure 5. Firstly, we can see the assigned and computed values for our PCA-based score function in Figure 5(a). The mean squared error (MSE) for this experiment is 0.094, achieving the best results. Finally, Figure 5(b) presents the rank of the posts based on their score value. The leftmost column (blue color) are the posts assigned to “low” importance, and they all get score values below 0.5, while the “medium” important posts (central column, green color) get score values between 0 and 0.85. And the posts identified as an “important” ones are shown in the rightmost column (red color). Their score values are the highest ones.

Notice that we are not really able to separate the three post “scores” but we are able to separate posts with 0 score (neither interesting nor with rich discussion) from those with 1 score (both interesting and with rich discussion).

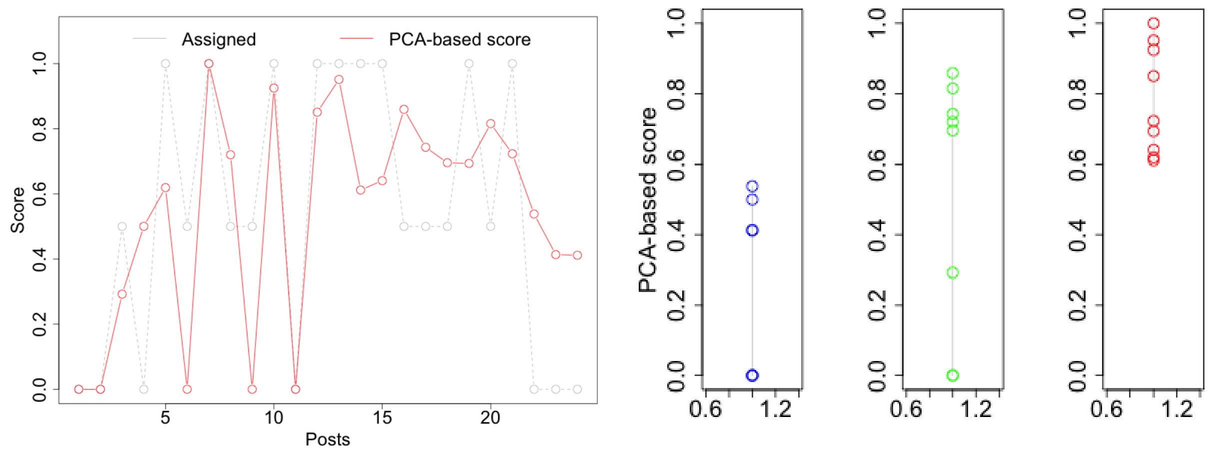

Figure 5(a) (leftmost), 5(b) (rightmost). Assigned and computed score for the PCA-based metric (a) and the posts ranking based on their score (b).

Once we have a measure for post relevance, we are able to rank posts (and comments) using WordPress capabilities, such as post metadata and hooks, for instance. Every time a user makes a comment or votes a post, a WordPress hook can capture such action and recompute interestingness for such post, storing it in an extra field (as post metadata). As posts are "isolated" and compete with each other, we do not need to propagate this new computed interestingness score, so this process can be executed very fast. This value, stored as post metadata, will be used for sorting posts so they are shown according to their interestingness rather than to their timestamp. Notice that a comment to a post is, in fact, a subtree of the original tree defined by such post, so we can apply the same metrics to compute its relevance.

Limitations

Using the proposed scheme, it is possible to determine post and comment relevance. Nevertheless, there are several problems that should be addressed before implementing this proposal in a practical solution through a WordPress plug-in.

First, we need to include a temporal window, as post interestingness decays, in general over time. This window should be a typical smoothing function that rapidly reduces post interestingness for posts older than *d* days or, alternatively, that have not had activity in more than *d* days, using a sigmoid function, for instance (using last activity instead of creation date allows for older posts, e.g. from other editions of a course, to regain relevance). Even though a post can be very interesting during a few days, it cannot draw attention continuously for several weeks. Through this parameter *d*, the teacher should be able to play with the concept of interestingness balancing post importance and recentness. In fact, posts with no interaction will never appear on the top of the most interesting posts, so recent posts need some initial boost in order to appear in the top of the list, at least during a few days or until the next one is posted.

Second, we are ranking posts according to the interaction they generate, but we are not penalizing the lack of interaction, that is, posts that receive a lot of visits but not comments or votes. This would be also interesting to measure the ratio of blog active users, that is, those users that perform an action on a post beyond just reading it.

Third, and related to the previous fact, an interesting question is: “how do course participants reach a post?”. Currently now, every time a new blog post is created, a tweet is also published, containing post title, its link and a hashtag identifying the course and edition (for searching purposes). This strategy has shown to be more useful than using RSS, which is considered to be dead by many. Currently now, there is only one tweet for each post, but it would be possible to tweet again depending on the attention drawn by each post. Obviously, this could be combined with other channels such as RSS (for those blog subscribers still using it) and even e-mail.

Fourth, and last but not least, this reputation scheme could be also extended to rank users. Nevertheless, this would introduce some additional complexity as several new premises should be taken into account. First, users could use different identities to make comments (i.e. different mail accounts). Second, the ranking system does not require users to log in, so users can vote their own comments. Both facts could be addressed by using cookies, for instance. On the other hand, if both users and their posts and comments are ranked, a combined reputation scheme could be designed, propagating reputation from users to their actions and recomputing users’ reputation according to other users’ actions, following a recursive approach. This would improve the ranking system, but it could also penalize the whole reputation scheme if every single action implies recomputing all posts, comments and user ranks.

Conclusions

From the point of view of the teacher, light CMSs such as WordPress are excellent tools to quickly and easily set up ‘personal teaching environments’ in the cases where traditional LMSs are not necessary and their sophistication is a hindrance rather than an asset. Those CMSs are general purpose and thus lack some of the functionalities one would expect from an LMS, but they offer easy frameworks for the creation of plug ins providing those missing functionalities (and vibrant communities that have already created thousands of plug ins). We have added one plug-in to allow basic analysis of interaction in a course.

The flexibility and versatility of open tools such as WordPress imply, to education and learning, much more than a simple tool brought into the classroom. As we have shown, the power of a blogging experience (quite different to “using a blog”) in education lies on how challenging and transformative it is in relationship with long-established educational institutions. Horizontality, interaction and quick feedback, openness, multimedia and permeability of inbound and outbound content and resources, etc. are just features from a technological point of view. But from a pedagogical point of view, if correctly leveraged, they represent actual changes in concepts such as the handbook as *the* resource, the classroom as *the* space (and *the* time!) or the teacher as *the* more knowledgeable other.

We have tested several measures related to graph size and structure. Some of these measures can be discarded taking into account that graphs are, in fact, trees, so some of these measures are completely correlated. Furthermore, we have seen that the number of votes and total score are also highly correlated (as most users rank posts and comments very high). Therefore, we could simplify the voting scheme substituting the 5 or 10 level star system by a “+1” or “I like it” scheme. The proposed measure combines average distance between nodes (i.e. both the quantity and length of discussions generated by a post), the number of votes received by the post comments and their average score. This metric separates posts that generate high levels of interaction but very different in nature, such as the welcome post (very popular but not very interesting from teacher’s perspective) and a post containing an interesting discussion about legal aspects related to open data, for instance.

Future research in this topic involves the development of tree-based specific measures that better capture the nature of the interaction around a post. Extending this reputation scheme to users (without propagation between content and users) will be also very interesting, in order to discover potential “experts”, for instance. Currently now we are gathering data from the second edition of the same course, which will be used to validate the measures and results obtained in this paper. We are also in the process of developing the WordPress plug-in that will allow us to rank posts and comments according to their interestingness. We expect to deploy such plug-in for the next edition (third) of the course that will start in 2015. Finally, we would like to analyze how blog users interact with content (posts and comments) once the reputation scheme is active, in order to determine whether it is a useful tool for content browsing or not.

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