Linking Online Identities and Content in Connectivist MOOCs across Multiple Social Media Platforms

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The paper starts with a review of relevant literature about the multi-platform landscape of social media and learning, and discusses areas of interest that arise when people rely on multiple social media platforms to support learning and teaching (or what we call "social media multiplexity"). We also include some recent data obtained from a questionnaire about social media use by instructors in higher education [28]. Then we turn to the MOOC data issues, describing first pedagogical structures for multi-media use outlined for the two connectivist MOOCs examined, and then the array of data and identity resolution issues we faced when processing of data from these two MOOCs. The paper concludes with implications for future work in this area.

2. SOCIAL MEDIA AND LEARNING

Learning in new networked, mediated spaces is socially embedded. It is tied to the interests of the learner, the multiple, often overlapping, social spheres that the learner interacts with through various social media and communities, and the relationships and social contexts that are formed through such interactions. Learning through participation and social construction of understanding and meaning, along with the development of understanding how to be a member of a knowledge community, are core aspects of what has been termed Learning 2.0 [3]. Stemming from Learning 2.0 practices is a culture of freely creating and sharing content, along with opportunities for groups and crowds to share and participate in social learning activities, that is driving a change in who learns what, from whom, and via what means [19]. The roles that social media play in learning experiences are key to this development.

2.1 Formal and informal learning contexts

Higher education faculty are recognizing the value that social media can leverage in their curriculum, with over one third of teaching faculty in the US using some form of social media in their courses, and adoption rates of social media as high as 80% among university classrooms in the US [18]. A perusal of recent EDUCAUSE Studies of Undergraduate Students and Information Technology [6, 22] indicates that social media are both being formally integrated into institutional academic learning experiences, and are also being used informally by students to supplement their learning experiences. This allows students to reach wider social networks via social media while simultaneously "meeting the student population where it lives: i.e., online, in social networking sites and in the microforms of communication adopted in Twitter" and other popular online platforms [10].

Results from a recent survey by our research group provides further information on social media use by instructors [28]. In response to a questionnaire, the 333 respondents, showed a wide use of social media as presented in Figure 1. While 'consumption' of media is more prevalent than 'contribution', these early social media adopters are still active contributors. Moreover, they overwhelmingly find and use media from *outside* their institutional learning management system (Figure 2). Thus, even outside the MOOC environments, the greater use on non-institutional platforms increases the difficulty of determining the full extent of learners' media-based contributions.

Whether instructor-led or learner initiated, learners are using various forms of social media to bridge the gap between in-school and out-of-school learning. Use enables discovery of connections between traditional curricula, personal interests, and online communities [14], and connections to peers, communities, and resources across time and space [5]. Using resources in a self-directed manner enables the personalization of learning experiences, and the construction of personal learning environments [7, 17, 21].

Figure 1: Social media use by instructors (ordered by frequency of 'Contribute' response)

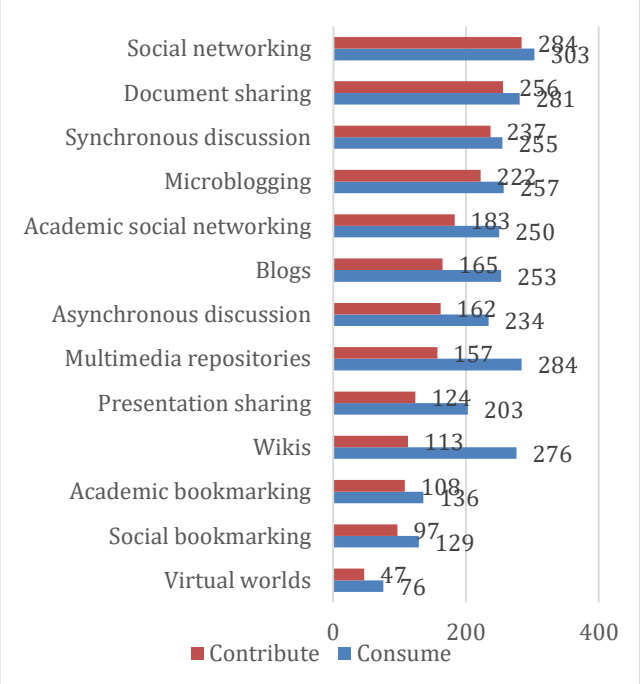
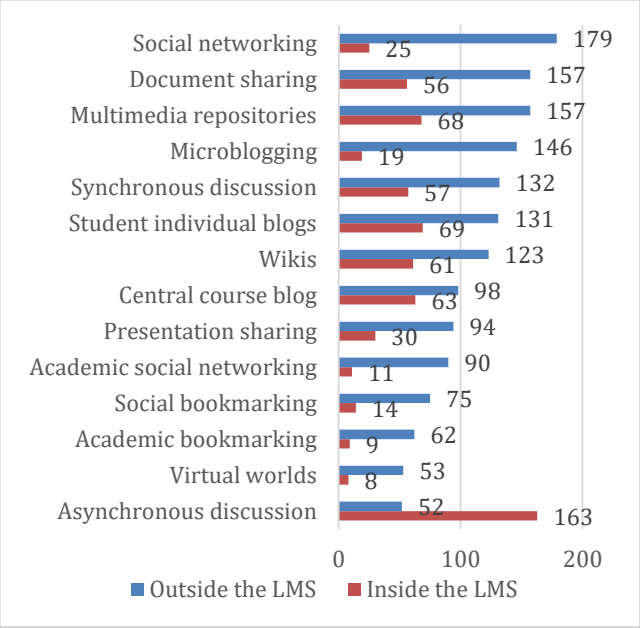


Figure 2: Use of social media inside and outside the LMS (ordered by frequency of 'Outside the LMS' response)



2.2 Social media multiplexity

Collaboration within one or more communities across a network supports the "social fabric" of learning [24]. Engagement in online communities benefits one's learning through the establishment of trust and confidence in a learning community, along with one's ability to create, re-use, and reimagine discourse and artifacts across communities in one's learning network [15].

For these reasons, participation in a number of platforms and communities allows learners to approach concepts and ideas from various perspectives and purposes, and exposes them to a variety of viewpoints to consider across a number of communities of learning. This connectivist approach to learning – where learners negotiate and construct meaning and knowledge across a network of learners, platforms, and information sources – emphasizes the interconnected nature of learning. Learners develop their sensemaking abilities by relating knowledge fragments across a variety of environments, within a large pool of collective knowledge [20].

Users associate different aspects of their lives, or even different facets of their identities, with particular social media platforms. For example, while LinkedIn and Facebook share many functional commonalities as social networking sites, users leverage them in very different ways and share very different types of information with their networks on either of these platforms. Xu et al. [25] conducted a large-scale user alignment study that mapped over 21 million users across 6 social media platforms (Twitter, Tumblr, Wordpress, Blogger, Instagram, and Facebook) in order to quantify the level of user engagement on different combinations of these platforms, and to identify the number of overlapping users. The results indicate that the majority of users use a combination of these platforms.

2.2.1 Challenges for users and researchers

From a user's perspective, managing information sharing across various platforms and personal preferences specific to each can be strenuous. Vu et al. [23] propose a system that aggregates the social data of an individual subscribed to multiple platforms, and identifies and filters relevant information to be shared on a particular platform with a particular subset or community of that users' platform-specific social network. For learners, particularly those engaged in connectivist MOOCs, the management of knowledge across several platforms and communities can be a difficult task with a great deal of cognitive overhead. To address this issue, knowledge management systems and web applications have been proposed and developed in order to aggregate information, resources, servicem r□nd " dnli qt] ss r]M" rca r ref

4) Feed Forward: The last step was to share their work with other people in the course or outside the course to spread the networked knowledge.

Course resources were provided using gRSShopper and online seminars delivered using Elluminate. The courses, however, were not restricted within a single platform or environment, and hence the content was distributed across the web. Participants were free to use a variety of technologies for sharing and participating in the course. To keep track of their learning and sharing content, participants were encouraged to create blogs using any blogging service, including blogger.com or wordpress.com, use del.icio.us, discuss on Google groups forums, tweet about items on Twitter, or use anything else such as Flickr, Second Life, Yahoo Groups, Facebook, or YouTube.

To be able to keep track of their content, participants were asked to use the #cck11 or #change11 tags in whatever content they created and shared. These tags were used to recognize content related to the courses using aggregators. The aggregated content was then displayed in an online "newsletter", which was created everyday to highlight some of the new content posted by learners.

To collect data, we scraped the archives of the daily newsletters for each course, and automatically extracted information on four types of data – Twitter messages, discussion threads, blog posts, and comments on blogs. The most popular platform (in both CCK11 and Change11) that generated the most number of posts was Twitter, followed by blogs (see Table 1).

Table 1: Number of posts on each platform

Platform	CCK11	Change11
Twitter posts (tweets)	1722	5665
Blog posts	812	2486
Blog comments	306	134
Discussion thread posts	68	87

In our research, we are interested in examining why and how online learners choose one platform over another or whether they use multiple platforms at the same time during the course of their class participation. We would also like to know whether and how each of the available platforms contributes to one's individual and collaborative learning. However, before we could answer these fundamental questions, first we need to retrieve and prepare our data to ensure their consistency and quality, as discussed below.

4. DATA CHALLENGES

Several research and technical challenges come up when collecting and processing data from cMOOCs, primarily because they do not use a single, centralized platform to support class interactions. This section discusses these challenges and offers some solutions to be used in our future work.

4.1 Data collection issues

We developed a custom script to collect (scrape) data from a publicly available archive of daily newsletters that included snippets of participants' blog posts (with the link to the original posts), comments left on each blog post, threaded discussions and Twitter messages. For these particular classes, class interaction data were archived and remained web accessible even after the end of the classes. However, for other classes where messages are not archived, the use of a real-time data collection tool might be required. Furthermore, since only Twitter messages that included class-specific hashtags (#CCK11 or #Change11) were recorded in the daily newsletters, we likely missed any direct replies among class participants that did not use these hashtags.

Since only snippets of blog posts were available in the daily newsletters, we attempted to "follow" links to the original blog posts to retrieve them as well. During this process, we encountered a number of technical issues. First, since blogs were hosted on different servers (independent from the class website), some URLs to blogs maintained by students have expired, leading to timeouts or "server not found" messages. Some domains have disappeared completely by the time of our data collection, while others are now password-protected. Some URLs launch modal dialogs (pop-ups) that need to be processed by the scraping tool accordingly to prevent the collection process from crashing. Some web pages launch scripts that may also crash the collection tool.

As part of this process, we also identified some issues related to the encoding of several webpages. The target HTML tags used for scraping the webpages need to be set for every host domain. This is less of a problem if a lot of the participants use the same domain (e.g. Wordpress or Blogspot), but more of a problem if they use self-hosted blogs on unique domain names. Some pages (particularly the instructor's pages) did not contain tags with class or ID attributes that make tag targeting easier. Finally, a few pages used non-standard tag formats, which required either filtering or using different parsing configurations that slowed down the data collection.

Other issues arose from the course material itself, since this can be presented and stored in a variety of formats. For example, some posts and webpages contained mostly images or video, with little or no explanatory text to scrape. Some course events were live seminars (presented on Elluminate) and did not include transcripts that can be scraped. This suggests that in order to fully capture all aspects of the class, one might want to consider using additional tools designed to retrieve and analyze multimedia content such as images and videos. In our case, since the majority of in-class interactions were text-based and due to the lack of effective tools to handle multimedia content automatically, we decided to focus only on the retrieval and analysis of text-based messages and exclude multimedia content.

The fact that participants were located around the world added another challenge to the pre-processing stage. More specifically, some of their posts were not in English and hence they required special consideration prior to the analysis stage. For example, one option would be to translate any non-English text automatically. For the purposes of our exploratory study, we decided to exclude non-English posts since they represented only a small portion of all posts.

Data collection also requires a significant amount of cleaning after extraction was complete. Some newsletter elements were redundant (e.g. point to the same blog entry) and had to be detected and removed. Discussion threads as stored in the course archive page only included replies to the original post, but unfortunately did not include the original post itself. This is further complicated by the fact that although all blog postings were RSS'd to the course page (by request of the course instructors), they were not archived, so we have to try to scrape the original blog pages themselves (i.e., if they are still available).

Finally, we noticed that some newsletter pages were missing from the archive. These are just some of the most common technical challenges that we encountered and that would need to be addressed by any similar data collection protocol.

4.2 Identity resolution

To analyze cross-platform data holistically, we need to be able to combine the data across all platforms. For this, we need an effective way to distinguish between the same participants across different platforms. The challenge is that participants may use different usernames for each platform, e.g., one for Twitter, one for blogs, etc. This kind of identity resolution has often been addressed using computational linguistics and machine learning techniques [11] and can be separated into two primary tasks: *coreference resolution* (resolving single identities across multiple platforms) and *alias resolution* (identifying two or more people with the same name or alias across platforms).

The quality of identity resolution approaches can be improved by also matching any metadata available about the users. Researchers often rely on users' profile information to find same users across different platforms [4]. However, in our case, cMOOCs participants could (and some did) remain entirely anonymous when participating in the class. As a result, in many instances, we simply did not have enough information to match users across platforms automatically. Therefore, to achieve the highest possible level of data, we have taken a manual brute-force approach of matching usernames across platforms. This also helped us identify challenges if trying to automate this process in the future.

During this process, every username from each platform was matched and cross-referenced with usernames from other platforms and any matching ones were grouped together. After exact matches, partial matches were also looked at – for example, jdoe and johndoe. Optional fields of First and Last names helped to determine if a slightly different username across two platforms may be the same too. For e.g., jdoe and johndoe are likely to be the same person if no other Doe's with first name starting with J are present in any of the platforms. This method is repeated for each platform until completed.

Through this process, we identified the unique users (aliases) who posted in each platform (see Table 2). We were also able to identify the users that posted in more than one platform (see Table 3). Although the number of users who posted across three or more platforms is small, a reasonable number of participants posted in at least two platforms. It should be noted that in Change11, out of the 103 users who did post in two platforms, the preferred media for posting or sharing for 93 of them were blogs and Twitter.

Table 2: Number of unique users who posted on each platform

Platform	CCK11	Change11
Twitter	145	794
Blog	105	278
Blog comments	56	27
Discussion thread posts	18	17

Table 3: Number of users who posted in more than 1 platform

No. of users posting in…	CCK11	Change11
4 platforms	2	3
3 platforms	10	5
2 platforms	32	103

Although this is a promising approach, it is time-consuming and may miss identifying single identities or erroneously group two separate identities as one. A faster, more reliable and real-time identity resolution method is required.

5. CONCLUSION AND FUTURE DIRECTIONS

The paper reported on the first stage of a larger project that strives to develop learning analytics methods to support assessment of collaborative learning in social media; specifically, when studying social media-based learning environments that rely on multiple platforms ("social media mutliplexity"). As the literature review section suggests, people are often engaged in learning processes (especially informal learning) on multiple social media platforms. In this context, our broad agenda is to determine whether and what types of learning occur on different social media platforms and how learners choose what platform to use and for what purposes. This current paper focused on the first stage of this research, which is to determine technical and logistical challenges (and possible solutions) associated with the collection of social media data and identity resolution across multiple platforms.

As a case study, we examined two cMOOC-type courses that relied on blogs, Twitter, and discussion forums to organize the class. We found that most of the technical challenges during the data collection process were access-related, and primarily due to the disappearance of old online resources and links. This was usually because we worked with so-called "legacy" data that remained publicly available once the classes were over. This suggests that one way to limit this type of issues is to implement live collection of class content and interactional data as it is being generated by online participants. If this is not feasible, we believe that our experience working with the archived social media data, as reported in this paper, will be a valuable starting point to those who are working on a similar project.

Since people may use different aliases on different social media platforms, another critical issue in this line of research is how to identify and "follow" the same individual across multiple platforms. Although the previous research has identified a number of automated approaches to address this issue, including techniques such as *coreference* and *alias resolution*, our manual analysis of users' accounts across multiple platforms for the two classes suggests that the class participants mostly relied on a single platform. Only a small percentage of users posted to multiple platforms during the class. Furthermore, since one of our primary goals is to assess collaborative learning, we are especially interested in analyzing interaction data among learners. But among the four different ways of interacting with others in the class (blog posts, blog comments, tweets and discussion threads), Twitter was the single, most popular platform for discussion. And even though blogs (specifically blog posts) were the second largest content generators after Twitter; our manual review of the blog posts revealed that they were primarily used to take notes and write reflection-type pieces, and they were not used to interact with one another. In sum, we started this project with the expectation that we would need to identify and resolve online identities across multiple platforms; but in reality, both classes primarily relied only on Twitter for user-to-user interaction. This is despite the fact that class participants were encouraged to use a wide range of social media platforms. Therefore, we conclude that for the two classes in question, the need for identity resolution is very low. We hypothesize that we might find a similar pattern in other cMOOC-type courses where only a few of the most active users rely on two or more social media platforms for class participation. Our future work will test this hypothesis on more datasets. If it holds, the main implication is that there might not be a need for resource-intensive identity resolution algorithms when studying social media multiplexity and that we might be able to

analyze each platform independently from other platforms, at least from the perspective of identifying overlapping communities of users across platforms.

The limitation of our data is that we cannot tell whether people are actually reading some of the content on platforms where they are not active. In our future research, we plan to conduct the content analysis of messages posted on different social media with the goal to identify the level of cross-referencing across platforms. For example, when a student promotes a blog post on Twitter or starts a discussion thread to discussion a resource mentioned by another class members in a blog post. Our next step is also to analyze emerging communication networks on each of the platforms to characterize and evaluate the types of connections and communities (or crowds) formed across participants and how they relate to the nature and type of the platform used. Finally, for few participants who did engage on multiple platforms, we would like to know whether their position in communication networks changes depending on the platform and why. Answers to these questions will help us determine the types of learning analytics techniques that might be useful in studying collaborative learning in such environments.

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