Social Learning Analytics: Five Approaches

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ABSTRACT

This paper proposes that *Social Learning Analytics* (SLA) can be usefully thought of as a subset of learning analytics approaches. SLA focuses on how learners build knowledge together in their cultural and social settings. In the context of online social learning, it takes into account both formal and informal educational environments, including networks and communities. The paper introduces the broad rationale for SLA by reviewing some of the key drivers that make social learning so important today. Five forms of SLA are identified, including those which are inherently social, and others which have social dimensions. The paper goes on to describe early work towards implementing these analytics on SocialLearn, an online learning space in use at the UK's Open University, and the challenges that this is raising. This work takes an iterative approach to analytics, encouraging learners to respond to and help to shape not only the analytics but also their associated recommendations.

Categories and Subject Descriptors

K.3.1 [**Computers and Education**]: Computer Uses in Education – *collaborative learning, distance learning.*

General Terms

Measurement, Design.

Keywords

social learning; learning analytics; discourse analytics; learning how to learn; transferable skills; 21st century skills; educational assessment; social learning analytics; SocialLearn

1. INTRODUCTION

The field of learning analytics has its roots in the appropriation of business intelligence concepts by educational institutions: the earlir terms 'academic analytics' [1] and 'action analytics' [2] refer respectively to the capture and report of data by educational administrators, and to the need for benchmarking to increase the effectiveness of educational institutions. Learning analytics shift the perspective from that of the institution gathering data about learners in order to inform organisational objectives, to that of providing new tools for the learner and teacher, drawing on experience from the learning sciences with the intention of understanding and optimizing not only learning but also the environments in which it takes place.

As part of this shift to learner-centred design, we propose that *Social Learning Analytics* (SLA) can be usefully thought of as a subset of learning analytics, which draws on the substantial body of work evidencing that new skills and ideas are not solely individual achievements, but are developed, carried forward, and passed on through interaction and collaboration. A socio-cultural strand of educational research demonstrates how language is itself one of the primary tools through which learners construct meaning, and its use is influenced by the aims, feelings and relationships of their users, all of which shift according to context [3] (as will be seen, discourse and context are two foci of the SLA we propose). Another strand of research emphasises that learning cannot be understood by focusing solely on the cognition, development or behaviour of individual learners; neither can it be understood without reference to its situated nature [4, 5].

As groups engage in joint activities, their success is related to a combination of individual knowledge and skills, environment, use of tools, and ability to work together. Understanding learning in these settings requires us to pay attention to group processes of knowledge construction – how sets of people learn together using tools in different settings. The focus must be not only on learners, but also on their tools and contexts.

Viewing learning analytics from a social perspective highlights types of analytic that can be employed to make sense of learner activity in a social setting. This does not require the development of a completely new set of tools; this paper cites numerous examples of related work in context. Instead, it groups a range of pre-existing and new tools and approaches to form the basis of a coherent set. In doing so, it identifies ways in which analytics may be developed and implemented in order to identify social behaviours and patterns that signify effective process in learning environments. The aim is to use analytics not only to identify these but also to render them both visible and actionable.

The paper is organized as follows. We introduce the broad rationale for focusing on social learning (§2), which is then developed specific to several forms of analytic which are inherently social (§3), or which have social dimensions (§4). We then describe progress towards the implementation of these analytics in a social learning space (§5), consider some of the challenges that we are encountering (§6), before concluding (§7).

2. WHY *SOCIAL* LEARNING ANALYTICS?

The focus on SLA reflects shifts in the broader cultural, technological and business landscapes, which together are reshaping the educational landscape platforms. We see these as a set of drivers for the growing importance of online social learning, and hence, for SLA.

2.1 Social media

No review of the forces shaping the educational landscape can ignore the digital revolution. Only very recently have we had the right infrastructural ingredients to provide almost ubiquitous internet access in wealthy countries and mobile access in many more. In addition, we now have user interfaces that have evolved through intensive use, digital familiarity from an early age, standards enabling interoperability and commerce across diverse platforms, and scalable computing architectures capable of servicing billions of real-time users, and mining that data. With the rise of very large social websites such as Facebook, YouTube and Twitter, plus the thousands of smaller versions and niche applications for specific tasks and communities, we have witnessed a revolution in the way that people think about online interaction and publishing. Such social media platforms facilitate the publishing, indexing and tracking of user-generated media, provide simple to learn collaboration spaces, and enable a new set of social 'gestures' that are becoming ubiquitous, and expected by the current generations: friending, following, messaging, microblogging, 'liking', rating, etc.

Potential implication: As ubiquitous access to social networks become a critical part of learners' online identity, and an expected part of learning platforms, social learning analytics should provide tools to provoke learning-centric reflection on how interpersonal relationships and interactions reflect learning, or can be more effectively used to advance learning.

2.2 Open/free content and data

There has been a huge shift in expectations about access to digital content. Learners expect increasingly to find reasonable quality information on the Web for free, to the point where they often feel aggrieved when confronted by a request for money, and will seek free avenues first. Within education, the Open Educational Resource (OER) movement has been a powerful vehicle for making institutions aware of the value of making quality learning material available, not only for free, but in formats that promote remixing, in an effort to reap the benefits seen in the open source software movement. This has by no means proven to be a simple matter, since educational staff, materials and institutions are different in important respects from open source programmers, source code and developer networks, but OER has made huge progress, and is gaining visibility at the highest levels of educational policy.

Free and open learning resources are mirrored by efforts within the open and linked data communities to make data open to machine processing as well as human interpretation. This requires both the shift in mindset by data owners (which OER has had to effect within education), as well as the laying of technological infrastructure to make it possible to publish data in useful formats.

Potential implication: A consequence of the information overload that now confronts learners is the need for more effective filtering and navigation, and it is here that social networks are playing an increasing role, as a means to maximize the increasingly scarce resource at a learner's disposal: focused attention. SLA should augment learners' capacities to build effective social learning networks.

2.3 Society increasingly values participation

Technology is always appropriated to serve what people believe to be their needs and values. Beyond what we can observe for ourselves informally, there is a significant body of research indicating that the period in which we find ourselves is moving towards a set of values mirrored in the affordances of social media. In 1997, the World Values Survey covered 43 societies, representing 70% of the world's population. Inglehart [6] argued that the shift to 'postmaterialism' (a finding from earlier surveys) was confirmed and he offered a new 'postmodernization' framework. He suggested that modernization helped society move from poverty to economic security, and that the success of this move led to a shift in what people want out of life. In postmodernity, as he used the term, people value autonomy and diversity over authority, hierarchy, and conformity. According to Inglehart, 'postmodern values bring declining confidence in religious, political, and even scientific authority; they also bring a growing mass desire for participation and self-expression.' We find these results interesting: on the one hand it is easy to recognise this shift in wealthy nations, but this shift seems also to be reflected even in the less developed regions surveyed, where poverty is still clearly a daily reality.

Another perspective on the shift in social value is the view that, since 1991, we have lived in the 'knowledge age' – a period in which knowledge, rather than labour, land or capital, has been a key wealth-generating resource [7]. This shift has occurred within a period when constant change in society has ben the norm, and it is therefore increasingly difficult to tell which specific knowledge and skills will be required in the future [8]. These changes have prompted an interest in 'knowledge-age skills' that will allow learners to become both confident and competent designers of their own learning goals [9]. Accounts of knowledge-age skills vary, but they can be broadly categorized as relating to learning, management, people, information, research/enquiry, citizenship, values/attributes and preparation for the world of work [10]. From one viewpoint they are important because employers are looking for 'problem-solvers, people who take responsibility and make decisions and are flexible, adaptable and willing to learn new skills' [11, p5]. More broadly, knowledge-age skills are related not just to an economic imperative but to a desire and a right to know, an extension of educational opportunities, and a 'responsibility to realize a cosmopolitan understanding of universal rights and acting on that understanding to effect a greater sense of community' [12, p111].

Potential implication: Research evidencing the growing desire in many societies for civic participation and self-expression provides another driver for social learning. Another is within education, with the perceived need to move away from a curriculum based on a central canon of information, towards learning that develops skills and competencies for coping with complexity and novel challenges. SLA should augment learners' capacities to assess themselves on 21st Century skills.

2.4 Innovation depends on social connection

The conditions for online social learning are also related to the pressing need for effective innovation in organisational life. In a succinct synthesis of the literature, Hagel, *et al.* [13] argue that social learning is the only way in which organisations can cope with the unprecedented turbulence they now face. They invoke the

concept of 'pull' as an umbrella term to signal some fundamental shifts in the ways in which we catalyse learning and innovation, and argue that the world is changing so rapidly that useful knowledge/understanding (in contrast to data or information) is rarely well codified, indexed or formalized, while socially transmitted knowledge is growing in importance as a source of timely, trustworthy insight. This leads them to highlight *quality of interpersonal relationships, tacit knowing, discourse and personal passion* as key capacities to foster, as we move in business from mere transactional relationships, to building and sustaining more meaningful relationships.

Potential implication: These business trends serve as another driver for social learning, and invite opportunities for SLA to augment personal and collective capacities by investigating how we can make visible representations of "quality of interpersonal relationships, tacit knowing, discourse and personal passion."

2.5 Summary

We have reviewed some of the 'tectonic forces' reshaping the learning landscape. These are 'signals' that many futures analysts and horizon scanning reports on learning technology have highlighted as significant. If taken together, these are shaping a radically new context for learning, then by extension, learning analytics must be reframed accordingly to place online social interaction and the social construction of knowledge at the heart of their models.

We now introduce five categories of analytic whose foci are driven by the implications of the drivers reviewed above. The first two categories are inherently social, while the other three can be 'socialized', ie. usefully applied in social settings:

- *social network analytics* — interpersonal relationships define social platforms
- *discourse analytics* —language is a primary tool for knowledge negotiation and construction
- *content analytics* — user-generated content is one of the defining characteristics of Web 2.0
- *disposition analytics* — intrinsic motivation to learn is a defining feature of online social media, and lies at the heart of engaged learning, and innovation
- *context analytics* — mobile computing is transforming access to both people and content.

We do not present these five categories as an exhaustive 'taxonomy', since this would normally be driven by, for instance, a specific pedagogical theory or technological framework, in order to motivate the category distinctions. We are not grounding our work in a single theory of social learning, nor do we think that a techno-centric taxonomy is helpful. The social learning platform and analytics we are developing is in response to the spectrum of drivers reviewed above, drawing on diverse pedagogical and technological underpinnings which will be introduced with each category.

3. INHERENTLY SOCIAL TYPES OF LEARNING ANALYTIC

3.1 Social learning network analytics

Networked learning uses ICT to promote connections between learners, tutors, communities and resources [14]. These networks consist of actors – both people and resources – and the relations between them. A tie describes the relationship between these actors and can be classified as strong or weak, depending on its frequency, quality or importance [15]. People make use of weak ties with people they trust when accessing new knowledge or engaging in informal learning, and go on to make increasing use of strong ties with trusted individuals as they deepen and embed their knowledge [16].

Social network analysis investigates ties, relations, roles and network formations, and a social learning network analysis is concerned with how these are developed and maintained to support learning [15]. Because of its focus on the development of relationships, and its view that technology forms part of this process, this type of analysis offers the possibility of identifying interventions that are likely to increase a network's potential to support the learning of its actors.

Social network analysis can be approached from the perspective of an individual or of the entire network. An egocentric approach may identify the people who support an individual's learning, the origin of conflicts in understanding, and some of the contextual factors that influence learning. On the other hand, a whole-network view provides insight into the interests and practices of a set of people, identifying elements that hold the network together [17]. It also has the potential to help with the identification of groupings within a network that can support learning, for example communities and affinity groups [18, 19].

As social network analysis is developed and refined in the context of social learning, it has the potential to be combined with other types of social learning analytic in order to define what counts as a learning tie and thus to identify interactions which promote the learning process. It also has the potential to be extended in order take more account of socio-material networks, identifying and, where appropriate, strengthening and developing indirect relationships between people which are characterised by the ways in which they interact with the same 'objects of knowledge' [20].

3.2 Social learning discourse analytics

The ties between learners in a network are typically established or strengthened by their use of dialogue. These interactions can be studied using the various forms of discourse analysis that offer ways of understanding the large amounts of text generated in online courses and conferences. For example, Schrire [21] used discourse analysis to understand the relationship between the interactive, cognitive and discourse dimensions of online interaction, examining initiation, response and follow-up (IRF) exchanges. More recently, Lapadat [22] has applied discourse analysis to asynchronous discussions between students and tutors, showing how groups of learners create and maintain community and coherence through the use of discursive devices.

Corpus linguistics, the study of language based on examples of real-life use, is a method of discourse analysis that relies heavily on electronic tools and computer processing power. This method employs software to facilitate quantitative investigation of vast corpora including millions of words of both speech and text [23].

Educational success and failure have been related to the quality of learners' educational dialogue [24]. Social learning discourse analytics can be employed to analyse, and potentially to influence, dialogue quality. The ways in which learners engage in dialogue indicate how they engage with the ideas of others, how they relate those ideas to their personal understanding and how they explain their own point of view. Mercer and his colleagues distinguished three social modes of thinking used by groups of learners in face-to-face environments: disputational, cumulative and exploratory talk [25-28]. Disputational dialogue is characterised by disagreement and individual decisions; in cumulative dialogue

speakers build on the contributions of others without critiquing or challenging them. Educators typically consider exploratory dialogue the most desirable because it involves speakers explaining their reasoning, challenging ideas, evaluating evidence and developing understanding together. Learning analytics researchers have built on this work to provide insight into textual discourse in online learning [29, 30], providing a bridge to the world of social learning analytics.

A related approach to social learning discourse analytics employs a structured deliberation/argument mapping platform to study what learners are paying attention to, what they focus on, which viewpoints they take up, how learning topics are distributed amongst participants, how learners are linked by semantic relationships such as *support* and *challenge*, and how learners react to different ideas and contributions [31]. This approach to overlaying discourse network models on social network models exemplifies what makes social *learning* analytics distinctive from generic social network analytics, which examine topology but take no account of the quality of stakeholder interactions.

4. *SOCIALIZED* LEARNING ANALYTICS

In this section, we consider three kinds of analytic, which although meaningful for an isolated learner who is making no use of interpersonal connections or social media platforms, take on significant new dimensions in the context of social learning.

4.1 Social learning content analytics

'Content analytics' is used here as a broad heading for the various automated methods used to examine, index and filter online media assets for learners. (Note that this not identical to content *analysis*, which is concerned with description of the latent and/or manifest elements of communication [32].) These analytics may be used to provide recommendations of resources tailored to the needs of an individual or a group of learners. This is a very fast-moving field, and the state of the art in textual and video information retrieval tools is displayed annually in competitions such as the Text Retrieval Conference [see 33 for a review].

One example is visual similarity search, which uses features of images in order to find material that is visually related, thus supporting navigation of educational materials in a variety of ways, including identifying the source of an image, finding items that offer different ways of understanding a concept, or finding other content in which a given image or movie frame is used [34].

This takes on a social learning aspect when it makes use of the tags, ratings and other data supplied by learners. An example is *iSpot*, a 'citizen science' social media site that helps learners to identify anything in the natural world [35]. When a photo is first uploaded to the site, it usually has little to connect it with other information. The addition of a possible identification by another user ties the image to other sets of data held externally. In the case of *iSpot*, this analysis is not solely based on the by-products of interaction; each user's reputation within the network is used to weight the data that they add. This suggests one way in which content analytics can be combined with social network analytics to support learning.

Other approaches to content analytics are more closely aligned with content analysis. These involve examination of the latent elements that can be identified within transcripts of exchanges between people learning together online. This method has been used to investigate a variety of issues related to online social learning, including collaborative learning, presence and online cooperation [36]. These latent elements of interpersonal

exchanges could also support sentiment analysis, revealing learners' emotions such as happiness and frustration.

It is also possible to draw on the manifest information about user activity and behaviour that is provided by tools such as *Google Analytics* and *userfly.com* as well as by the tools built into virtual learning environments (VLEs) such as *Moodle* and *Blackboard*. This is the approach taken by *LOCO-Analyst*, which uses content analysis to establish and investigate semantic relations between different learning resources and to provide feedback for content authors and teachers that can help them to improve their online courses [37].

4.2 Social learning disposition analytics

Learners who are prepared to learn and are open to new ideas have the potential to make good use of these resources and tools. A well established research programme has identified, theoretically, empirically and statistically, a seven-dimensional model of learning dispositions, termed 'learning power' [38]. These dispositions can be used to render visible the complex mixture of experience, motivation and intelligences that make up an individual's capacity for lifelong learning and influence responses to learning opportunities [39]. Learning dispositions are not 'learning styles', which have been critiqued on a variety of grounds, including lack of contextual awareness [40]. In contrast, an important characteristic of learning dispositions is that they have been validated as varying according to a range of variables [41]. As detailed in [41], a learning analytics platform and visual analytic has been developed to model and assess such dispositions and transferable skills. This visual analytic is used to reflect back to learners their self-perception on these dimensions, providing an explicit language for describing dispositions, catalysing changes in their engagement, activities and approach to learning.

From a social learning perspective, three elements of disposition analytics are particularly important. Firstly, they draw learners' attention to the importance of relationships and interdependence as one of the seven key learning dispositions. Secondly, they can be used to support learners as they reflect on their ways of perceiving, processing and reacting to learning interactions. Finally, they play a central role in an extended mentoring relationship. This type of relationship has an important role in online social learning, especially when learning is informal and not teacher-led. Mentors motivate, encourage, challenge and counsel learners, and can also provide opportunities to rehearse arguments and increase understanding [42, 43].

4.3 Social learning context analytics

All these types of social learning analytic can be applied in a wide variety of contexts, including formal settings such as universities, informal contexts in which learners choose both the process and the goal of their learning [44] and in the many situations in which learners are using mobile devices [45]. In some cases, many learners are simultaneously engaged in the same activity, and in other cases learning takes place in asynchronous environments, where the assumption is that is that learners will be participating at different times [30]. They may be learning alone, in a network, in an affinity group, in communities of inquiry, communities of interest or communities of practice [18, 46-48].

'Context analytics' are the analytic tools that expose, make use of or seek to understand these contexts. These analytics may be used alone, or may be employed as higher-level tools, pulling together data produced by other analytics. For example, if network analysis indicates that student Rebecca is on the edge of a community, and

dispositions analysis shows that she is currently working on her collaboration skills, then a context-focused recommendation might suggest that she could join a teamwork skills group and use analytics visualizations to monitor her position within the group. Several weeks later, she might be prompted to reflect on her collaboration skills and to rate the group. She might receive this prompt directly from the system, or the system could recommend her teacher, mentor or group leader to engage with her and to make the recommendation.

5. DESIGN & IMPLEMENTATION

Having identified different types of social learning analytic, the challenge is to employ these to analyse learners' behaviour and to offer visualizations and recommendations that can be shown to spark and support learning. This section focuses on progress towards the implementation of these analytics in a social learning space developed by The Open University, a UK-based university with a strong emphasis on open and distance learning.

SocialLearn is a social media space tuned for learning. It has been designed to support online social learning by helping users to clarify their intention, to ground their learning and to engage in learning conversations [49]. The system's architecture includes a Recommendation Engine, a pipeline designed to process data and output it in a form for analysis by SocialLearn recommendation web services.

The second element of SocialLearn's architecture is the Identity Server that supplies, with the learner's informed consent, data to the Recommendation Engine. These data include learners' profiles and activities within SocialLearn, selected elements of their activity at The Open University, and selected elements of their activity and interactions on social media sites such as LinkedIn, Twitter and sites employing OpenID. The SocialLearn Analytics and Delivery Channels depend on the Identity Server to maintain a unified user profile.

The final element of SocialLearn's architecture is the SL Delivery Channel, which includes sites for both input and output. Data are collected, with the learner's informed consent, from use of the SocialLearn website, from use of the SocialLearn 'backpack' (browser toolbar) while elsewhere on the web, from use of SocialLearn applications embedded on external sites and, where applicable, from calls on the SocialLearn application programming interface (API). At the same time, data that has been analysed by the Recommendation Engine may be presented to learners in the form of recommendations or visualizations available on the SocialLearn website, via the SocialLearn backpack, within embedded applications or by ways of calls on the API. Reactions to these visualizations and recommendations, together with options for feedback by learners, make this an iterative process because these responses are fed back via the SL Delivery Channel and influence subsequent output.

The architecture is designed to be flexible, so that new algorithms can be added at any time, and analytics can be trialed, developed, combined or set aside without disruption.

Sections 4.1-4.6 describe progress towards the implementation of different types of social learning analytic, including work carried out at The Open University and elsewhere that supports the development of social learning analytics, recommendations and visualizations. Work on some types of social learning analytic is still at the stage of planning how work carried out elsewhere might be adapted. In other cases, mock-ups and wireframes are in place or pilot studies are underway.

5.1 Implementing social learning network analytics

In the case of social learning network analytics, the SocialLearn team is considering the possibilities offered by SNAPP (Social Networks Adapting Pedagogical Practice), a freely available network visualization tool that analyses forum contributions and presents them as a network diagram. Its architects identify uses for such diagrams from the point of view of teachers, including:

- identifying disconnected students
- identifying key information brokers within a class
- indicating the extent to which a learning community is developing within a class [50]

In the case of SocialLearn, the intention is to deploy social learning network analytics to exploit data in the Identity Server, in order to support both individual and group recommendations. For example, individuals might see:

- One of your key search terms is 'learning analytics'. This has been mentioned five times in the 'Future Developments' thread. View thread?
- John Smith has been identified as a key information broker in your network, View John's most recent posts?
- Ten people you have replied to list 'social learning' as a key search term. Add this to your key search terms?

In learning groups that are not formally led by a teacher, members may share responsibility for welcoming newcomers, engaging all members and encouraging meaningful participation. Social learning network feedback for a group or moderator will seek to use what is known about effective group structure and dynamics and feed this back for reflection [51]. For example:

- Research shows that effective learning groups tend to be structured like this <network diagram> whereas your group currently looks like this <group diagram>.

5.2 Implementing social learning discourse analytics

In order to support meaningful participation, SocialLearn is developing two sets of discourse analytics – the first based on the work of Neil Mercer and his colleagues around exploratory dialogue [27], and the second building on development of Contested Collective Intelligence and Concept Mapping to scaffold structured deliberation and argument mapping [52].

Key characteristics of exploratory dialogue include challenge, evaluation, reasoning and extension. Initial research suggests that these are signaled in forum interaction by key words and phrases [29]. For example: 'alternative', 'but if' and 'I don't believe' suggest challenge; 'good point', 'important' and 'how much' suggest evaluation; 'next step', 'it's like' and 'relates to' suggest extension, and 'does that mean', 'my understanding' and 'take your point' suggest reasoning. Figure 1 shows how a visualization of these elements of dialogue could be presented to learners, together with recommendations.

The coloured shapes in Figure 1 indicate comparative levels of use of different types of dialogue. In this case, indicators of reasoning, evaluation and extension appeared several times within the learner's discussion and are represented by green squares. Only one challenge was detected, and this lower level is represented by a yellow circle. The final sentence, 'Positive challenges…' suggests ways of increasing indicators of exploratory dialogue.
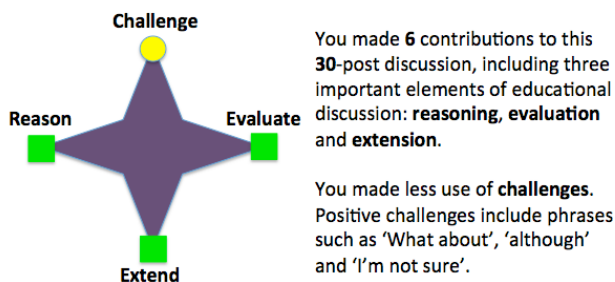
Figure 1: Visualization of learner's use of indicators of exploratory dialogue

This example focuses on a single learner. A group version of the visualization could be used to represent the dialogue of a group or a thread, with the aim of achieving a more widespread shift in the quality of the learning dialogue.

Explicit semantic networks provide a computational system with a more meaningful understanding of the relationships between ideas than natural language. Following the established methodological value of Concept Mapping [53], the mapping of issues, ideas and arguments extends this to make explicit the presence of more than one perspective and the lines of reasoning associated with each.

In a comprehensive review of computer-supported argumentation [54], Scheuer et al concluded that studies have demonstrated 'more relevant claims and arguments… disagreeing and rebutting other positions more frequently… and engaging in argumentation of a higher formal quality.' However, appropriate tools need to be part of an effective learning design:

> "The overall pedagogical setup, including sequencing of activities, distributions of roles, instruction on how to use diagramming tools, usage of additional external communication tools, and collaboration design, has an influence on learning outcomes" [54]

On this basis, *Cohere* is being developed to interoperate with SocialLearn. As preliminary results show [31], this holds the promise of giving the platform access to proxy indicators of participants' attitudes towards the topic under discussion, and of the roles they play within the group (e.g. forging meaningful links between peers' contributions, or a tendency to challenge others). This provides the representational basis to automate recommendations that encourage new approaches to a given subject, either by providing links to resources that challenge or extend learners' point of view, or by providing links to other groups talking about the same subject or resources but in different ways.

5.3 Implementing social learning content analytics

When viewing online resources, SocialLearn's *'Backpack'* – a toolbar of apps and resources – can be used on any Internet site. The Backpack currently includes the basic components of social learning content analytics. Clicking on the Backpack's light bulb icon provides the option of viewing the keywords, hotlinks or images connected with the open web page (as in the large box on the right of Figure 2). This information about images can be combined with visual similarity search to identify and recommend other resources that make use of these images, for instance:

Figure 2: The SocialLearn *Backpack* open at the foot of a BBC News page, showing a list of images on the page

- This image appears to be *The Mona Lisa*, and is used twice in this Renaissance 101 lecture webcast [view]

- This image appears to be Steve Jobs, and is used in the following blogs by academics in Design faculties [view]

As SocialLearn develops, it will be possible to refine these recommendations, based on the number of users following or recommending links or on the relevance of key words on a site to the key words associated with individual learners or groups of learners. In the case of learners who are developing the learning dispositions of *resilience* and *critical curiosity* (the desire and capacity to be taken out of one's comfort zone, and to dig beneath the surface), these analytics could recommend online resources that both stretch a learner to a new level and which are rated as rewarding investigative skills.

5.4 Implementing social learning disposition analytics

Theoretical and empirical evidence in the learning sciences substantiates the view that deep engagement in learning is a function of a complex combination of learners' identities, dispositions, values, attitudes and skills. When these are fragile, learners struggle to achieve their potential in conventional assessments, and critically, are not prepared for the novelty and complexity of the challenges they will meet in the workplace, and the many other spheres of life which require personal qualities such as resilience, critical thinking and collaboration skills. As detailed in an accompanying LAK paper [41], learning dispositions can be modelled as a multi-dimensional construct called Learning Power, currently assessed by learner self-report via a web questionnaire called ELLI (Effective Lifelong Learning Inventory), whose data warehouse platform supports a range of analytics. ELLI has been extensively validated, and is now being piloted within The Open University [55]. ELLI generates a spider diagram visual analytic which is used to support self-reflection and change. Figure 3 suggests how these meta-cognitive processes could be supported within SocialLearn.
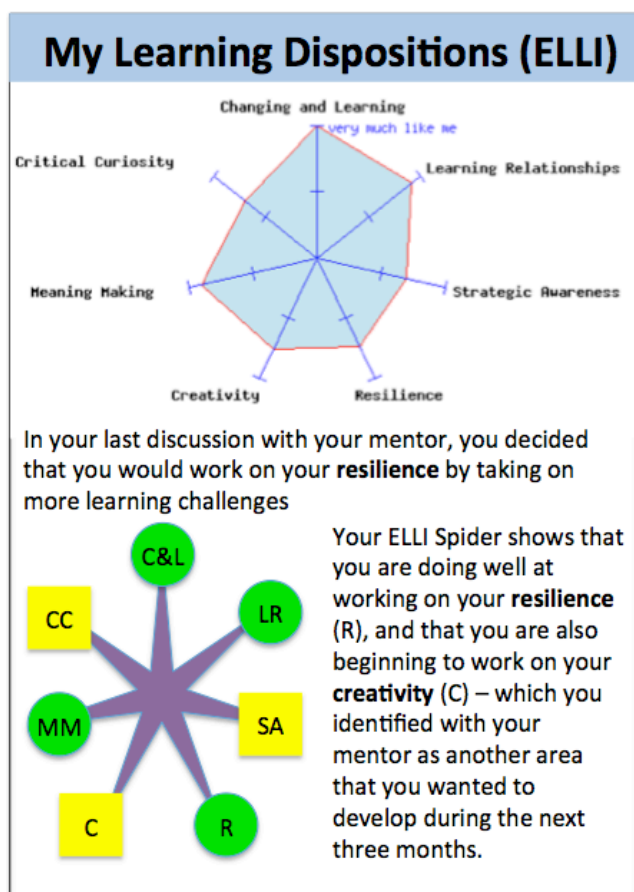
Figure 3: ELLI Profile (top) visualizing results of most recent self-report questionnaire. ELLI Spider and summary (bottom) highlighting recent work on dispositions

The ELLI profile generated by completing the self-report questionnaire appears at the top of Figure 3. In this case, the learner saw herself as fairly strong on changing and learning, learning relationships and meaning making, but her resilience was low at that point. The central text indicates that, within a mentored discussion, she agreed that she would work on this area. Working to develop resilience involves accepting that learning can be hard for everyone, taking on a challenge and persisting even when the outcome and the way ahead are uncertain. The ELLI Spider at the foot of Figure 3 visualizes her progress since the mentored discussion. Red triangles would indicate no activity on a dimension, yellow squares signal some activity and green circles indicate the learner has been very active in an area. The ELLI Spider is fed by self-report data (for example, within a learning blog [56]) and by data about activity and interactions that is processed within the Recommendation Engine and provided via the Identity Server and the Delivery Channel.

We are now operationalising the dimensions against candidate activity traces that could signify them. For example, indicators of growing resilience that could be fed back to the learner, rendering the Recommendation Engine's rationale transparent:

- You seem to be making progress in building your learning resilience. Last time you declared yourself Stuck on a path you did not return to it. This time you returned to Step 3 on Photosynthesis 101 after a week and, after requesting help, solved the problem.

5.5 Implementing social learning context analytics

Within SocialLearn, dispositions analysis and subsequent activity are among the data items that feed into the Identity Server and Delivery Channel, Together, the server and channel provide data about a learner's current context, including goals, activities, group membership and learning roles. A future SocialLearn app will make use of this data, adding geolocation to the mix – to produce recommendations tailored to the learner.

Figure 4 shows a mock-up of the SocialLearn app, currently under development, which will recommend and provide access to learning materials in response to search terms. The app will allow resources to be rated and recommended to individuals or to groups. If users choose to make their location data available, this can be used to influence recommendations, For example, if Simon is working on 'Climate Change' the app might suggest a podcast on coastal defences when he visits a seaside resort, and could provide a map showing a local site where Simon would be able to view the effects of erosion.
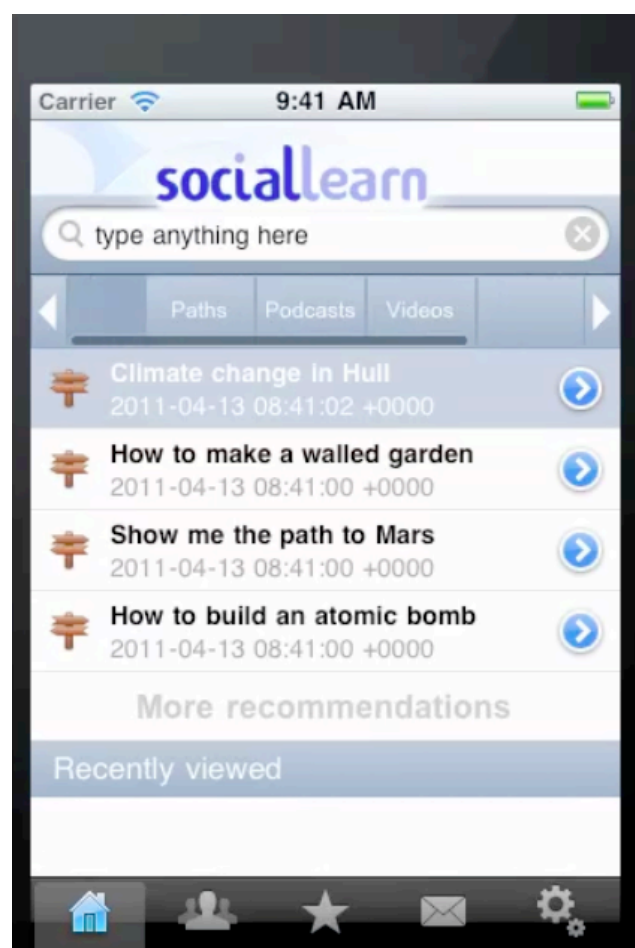

Figure 4: Mock-up produced by designer of SocialLearn app making use of social learning context analytics

5.6 Different dashboard views

Because SocialLearn is designed to work in a wide variety of contexts, users are likely to move between roles while using it. At some points they will be learners, at others mentors or teachers and at others group leaders or administrators. In many cases this will involve tailoring recommendations and visualizations to take

into account these different roles. The intention is to provide different dashboard views of analytics.

Figure 5 (below) shows what an individual learner's dashboard could look like – providing 'Kris Mann' with an overview of different analytics and recommendations. If Kris were mentoring someone, he would also have agreed access to elements of their dashboard and could rate the system-generated recommendations and add his own. As a teacher, he would need an overview of his pupils' analytics and recommendations, with clear visualizations and teacher recommendations helping him to find his way through these. In the role of group leader or administrator he would need an overall view of group activity and dialogue, without needing a breakdown of individual learners' activities. The challenge is to provide sufficient dashboard options to meet users' needs without overburdening them with possibilities.

6. CHALLENGES AND POSSIBILITIES

All the social learning analytics described here are currently under development. An initial and ongoing challenge is to gain learners' informed consent to their data being used to support these analytics. Data harvesting on websites generally goes unnoticed, it is often only by looking at the list of cookies stored on our computer that we realise how much information about our activity is being gathered, analysed, bought and sold. In the context of education, analytics are likely to include sensitive information about identity, status, background and achievements. Ethical use therefore involves making users aware of the data that is being collected, how it is being used and who has access to it. This is difficult to do clearly and concisely, giving users sufficient privacy options without overwhelming them.

At this early stage, a second challenge is to experiment with and refine these analytics, while continuing to provide a supportive experience for learners. In the case of social learning discourse analytics, for example, the correlation of words and phrases with elements of exploratory dialogue needs to be investigated in more detail. In the case of social learning dispositions analytics, we need to be clear which levels of activity should prompt colour changes in the visualization, signaling a move from low to high levels of activity. Each area of social learning analytics requires further research in order to optimise support for learners.

A final challenge is to ensure that these analytics, recommendations and visualizations spark and support learning. There is a danger that learners could be overwhelmed and discouraged by the amount of information presented to them, confused by being presented with too many visualizations, or misled by system-generated analytics. The SocialLearn research programme therefore works in the case of each analytic from a theory of how learning can be triggered or improved. It then develops an appropriate analytic and monitors what happens when it is implemented, looking not only for the predicted positive changes, but also for any significant changes. At this stage, the challenge is to improve on or refine the analytic and how it is presented to learners.

7. CONCLUSION

Social learning analytics make use of data generated by learners' online activity in order to identify behaviours and patterns within the learning environment that signify effective process. The intention is to make these visible to learners, to learning groups and to teachers, together with recommendations that spark and support learning. In order to do this, these analytics make use of data generated when learners are socially engaged. This engagement includes both direct interaction – particularly dialogue – and indirect interaction, when learners leave behind ratings, recommendations or other activity traces that can
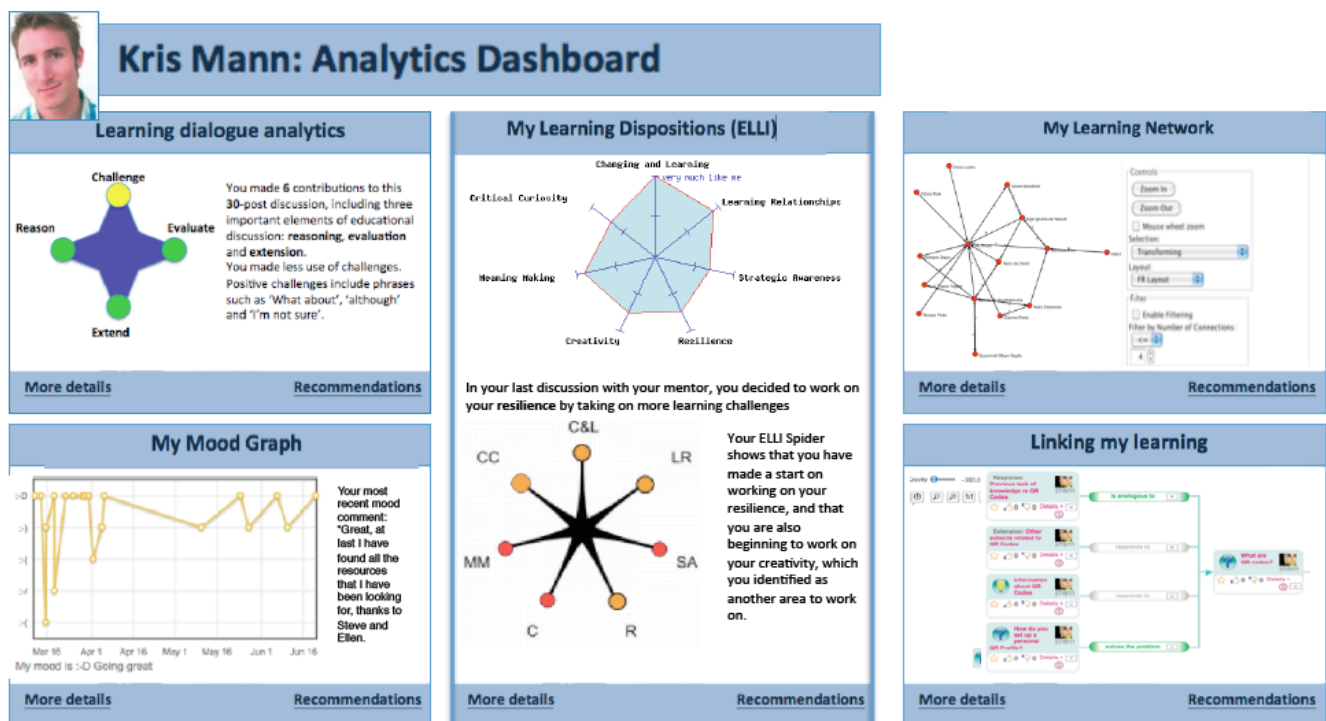

Figure 5: Mock-up of SocialLearn dashboard for an individual learner

influence the actions of others. Another important source of data consists of users' responses to these analytics and their associated visualizations and recommendations.

At present, we are focusing on the five broad categories of social learning analytic described in this paper: network analytics, discourse analytics, content analytics, dispositions analytics and context analytics. The Open University is currently developing these within SocialLearn, which provides a technical architecture enabling different analytics and recommenders to be deployed. Their initial deployment in 2011-12 is part of a research programme at the university, focused on the effective use of social learning analytics through evaluation of both their use and their effects. In addition, the research programme is beginning to address some of the important challenges relating to the ethical use of data to support learning.

8. ACKNOWLEDGMENTS

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