Using learning analytics to measure 21st-century skills

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Abstract

The unprecedented opportunities to collect data about learning and contexts in which learning occurs has attracted great attention in education. The use of data analytics and machine learning methods have offered much potential to address many relevant questions in education. This talk will focus on the use of learning analytics to measure 21st-century skills in education and outline the types of data commonly used. It will also discuss approaches that are used for analysis and modelling of relevant learning processes and outline the ways in which learning analytics can be used to track learning progression and how the validity of the findings with data analytics is assured. Numerous empirical studies will be drawn upon to look at self-regulated learning, learning strategies, and problem solving in individual and group activities.

Introduction

The ability to collaborate, solve problems, seek information, critically and creatively think, and effectively self-regulate learning are just some of the examples of the skills now known as 21st-century skills (Griffin, McGaw, & Care, 2012). Their importance has been highlighted in policy and research frameworks and many employers have clear expectations about these skills, which are necessary for different jobs. To possess these skills also allows equitable participation in modern society and access to different public services. In response to these demands, education institutions on all levels have a range of programs that support the development of these skills.

With the growing attention of policymakers and employers, sophisticated approaches to the measurement of 21st-century skills have also been proposed (Wilson & Scalise, 2015). However, there has been much less advancement in measurement approaches that track the progress of 21st skill development 'in the wild'; that is, in authentic learning and working environments. For example, measurement of (complex and collaborative) problem-solving has been done by the Organisation for Economic and Co-operation and Development (OECD) through the Programme for International Student Assessment (PISA). However, PISA is undertaken in highly controlled conditions in which a) only predefined messages could be used for communication among human collaborators (Rosen & Foltz, 2014) and b) actual collaboration is assessed through joint work between humans and computer agents to control for possible issues associated with human–human collaboration (e.g. uncooperative or incompatible collaborator) (Rosen, 2014). Moreover, very little work has been completed in learning environments where pedagogical models can range from very structured approaches to collaborative learning to those where collaboration emerges due to the problems identified by individuals who seek help from their peers in their classes or from a broader social network.

Learning analytics offers promising approaches that can be leveraged to address measurement of 21st skills in authentic settings (Buckingham Shum & Deakin Crick, 2016). Learning analytics harnesses the potential of big data – collected as the digital footprint of learners' use of technology – to develop measurement techniques, by working at the intersection between machine learning, measurement science, and the learning sciences. Recent research has offered promising improvements in the measurement validity of learning analytics to provide reliable means for developmental assessment of 21st-century skills. This paper will outline a case study that demonstrate the use of learning analytics for developmental assessment of collaborative problem-solving as a 21st-century skill.

Case study: Measurement of collaborative problem solving

Collaborative problem-solving (CPS) offers several advantages over individual problem-solving approaches. In essence, working collaboratively on complex problems is now a fundamental part of contemporary life, work, and society (Griffin et al., 2012; National Research Council (US), 2011). For example, collaborative solutions are often more creative as they are built upon expertise, information, and knowledge from multiple (complementary) perspectives (Graesser et al., 2018). Yet, successful collaboration does not always happen and requires certain conditions to be met to enable for productive group work. CPS can be ineffective due to the influence of an uncooperative teammate or a counterproductive group composition (Yong, Sauer, & Mannix, 2014). At the same time, effective leadership can help overcome many challenges a group may face and ensure that all members can productively contribute to CPS outcomes (Graesser et al., 2018).

To support their development and assessment, several models of CPS skills have been proposed (Hesse, Care, Buder, Sassenberg, & Griffin, 2015; OECD, 2013). The CPS literature mainly defines CPS skills as a collection of two domains – cognitive and social (Griffin et al., 2012). The cognitive domain is typically related to the existing literature on problem-solving and self-regulated learning (Griffin et al., 2012) and includes skills for task regulation and knowledge building. The social domain is focused on the skills necessary for productive collaboration (OECD, 2013). For example, Hasse et al. (2015) posit that social skills of CPS include participation, perspective taking, and social regulation. CPS is also defined in the well-known model of communities of inquiry that identifies social and cognitive presence of learners (Garrison & Arbaugh, 2007). Rather than thinking of CPS as a collection of isolated social and cognitive skills, the literature on computer-supported collaborative learning suggests that being an effective collaborator means performing well in a role (Dillenbourg, Järvelä, & Fischer, 2009). A role is an ensemble of cognitive and social skills that assume interactions with the right people at the right times and in the right ways.

Learning analytics offers promising approaches that can enable the measurement of CPS in 'in the wild'. Measurement is performed into two phases: i) identification of traces of cognitive and social dimensions of CPS; and ii) measurement of CPS skill development by combining the identified traces over time. First, traces of both dimensions of CPS can be identified through automated analysis of transcripts of conversations learners may have. These conversations can be both online (social media, chats, or discussion boards) and face-to-face (transcribed recording or automatically recognized speech). Transcripts of such conversations can automatically be analysed with

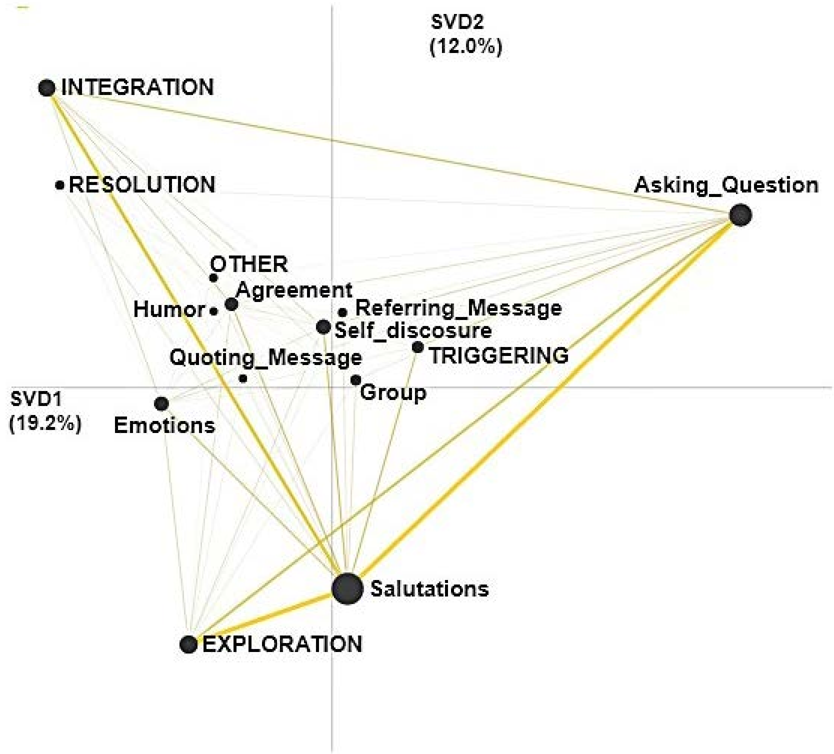

Figure 1 Epistemic network analysis of the association between cognitive and social presence in communities of inquiry: the epistemic network between phases of cognitive presence (capital letters) and indicators of social presence

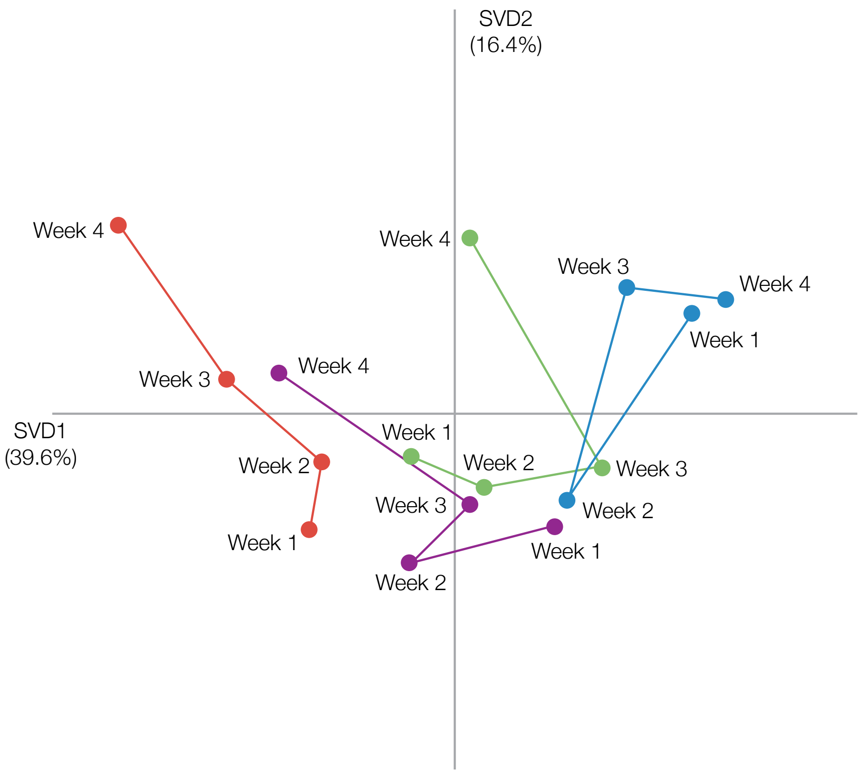

Figure 2 Epistemic network analysis of the association between cognitive and social presence in communities of inquiry: trajectory analysis of the students in the four conditions across four weeks of discussions – expert-control (red), expert-treatment (purple), practicing researcher-control (blue), and practicing researcher-treatment (green)

artificial intelligence-driven techniques to detect traces of cognitive and social dimensions of collaboration. For example, Kovanović et al. (2016) developed an automated classifier for automatic coding of discussion messages, with the coding scheme used to identify occurrences of different phases of cognitive presence in online discussions. The evaluation of Kovanović et al. (2016) demonstrated high levels of accuracy for messages in the English language. The high level of accuracy was further corroborated by Neto et al. (2018) for messages written in Portuguese.

Second, measurement of CPS skill development (i.e., progression) requires techniques that can ensemble the identified traces of cognitive and social dimensions and analyse the progress over time. Epistemic network analysis (ENA) can be applied to these tasks (Shaffer, Collier, & Ruis, 2016). ENA is based on the theory of epistemic frames (Shaffer, 2006), which posits that expertise in complex domains is not as a set of isolated processes, skills, and knowledge, but as a network of connections among knowledge, skills, values, and decision-making processes. Specifically, epistemic networks in ENA are built by looking at the co-occurrence of the codes in collaborative discourse.

To measure CPS and analyse track progression in CPS skill development, ENA was applied to combine phases of cognitive presence (i.e. triggering events, exploration, integration, resolution) and indicators of social presence (13 indicators categorised in general three categories – interactive, affective, and group cohesion) as proposed in the model of communities of inquiry (Rolim, Ferreira, Lins, & Gašević, 2019). The epistemic network in Figure 1 shows that the lower levels of cognitive presence (triggering event) were more connected with the indicators of the interactive category of social presence (e.g. asking questions or continuing a thread), while higher levels of cognitive presence (integration and resolution) were linked with the indicators of the affective category of social presence (e.g. use of humour or self-disclosure). The ENA also enabled unveiling of the difference in the links between social and cognitive presences of the students who were in different intervention groups (i.e. discussion scaffolded with external standards about the quality expectations versus only the expectation about the quantity of messages) and different roles assigned (experts and practicing researchers). The trajectory analysis diagram in Figure 2 indicates that the students who were only required to submit a set number of messages in the role of researcher did not make much progress in their cognitive inquiry across four weeks of discussions; that is, they did not move towards the left to reach integration and resolution phases of cognitive presence. For the other three groups, evidence of the progress was noted.

Conclusions

The case study introduced in this paper highlights some promising aspects of the use of learning analytics for measurement of 21st-century skills. Several points however need to be raised (Gašević, 2018). First, learning analytics at the stage of development offers promising measurement approaches that can be used for assessment for learning, rather than assessment of learning. Second, measurement approaches utilised in learning analytics need to be scrutinised against similar validity standards as commonly done in measurement science (Messick, 1995). Third, certain conditions needs to be built to assure the quality of data used by learning analytics, which directly impact the quality of the results produced in learning analytics. If learning tasks are inadequately designed and/or conditions in which data collection happens do not create conditions for learners to demonstrate skills measured, the value of learning analytics will be limited. Finally, future work is needed to establish validity, reliability and use frameworks for learning analytics when applied for measurement of 21st-century skills.

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