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Emerging Technologies and Learning Innovation in the New Learning Ecosystem

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Abstract. This paper highlights a decade of research by the National Research Council in the area of Personal Learning Environments, including MOOCs and learning in networked environments. The value of data analytics, algorithms, and machine learning is explored in more depth, as well as challenges in using personal learning data to automate the learning process, the use of personal learning data in educational data mining (EDM), and important ethics and privacy issues around networked learning environments.

Keywords: Personal Learning Environments, data analytics, algorithms, machine learning, ethics and privacy.

1 Introduction

The National Research Council has been conducting research on emerging technologies and learning innovation since 2008, starting with Personal Learning Environments (PLEs), connectivist-type MOOCs (cMOOCs) and more recently, new learning ecosystems. A decade of research has identified important gaps, especially around the types of support mechanisms required by learners to be successful in these new open and accessible learning environments. Researchers at the NRC have contributed important findings which highlight some of the challenges in the research and analysis process, especially as significant amounts of both quantitative and qualitative data are involved. The NRC's contributions to the field span over a decade with the publication of important findings related to Big Data and Educational Data Mining (EDM), ethics and privacy issues in networked environments, and the use of personal learning data to feed into the research and development process.

2 New learning ecosystem landscape

The proliferation of Information and Communications Technologies in recent years has changed the educational landscape, creating a plethora of new opportunities for learning. New learning technologies are emerging outside formal education, and academics and technologists are experimenting with these in formal and informal settings. Personal Learning Environments (PLEs), including Massive Open Online Courses (MOOCs), are part of the new learning ecosystem landscape, offering a wide range of open and accessible learning opportunities to learners across the world. Novel technologies have prompted a new era of information abundance, far beyond the era of information scarcity and inaccessibility [1]. Social media now make it possible to communicate across networks on a global scale, outside the traditional classroom bound by brick walls. Communication on such a global scale would have been unimaginable not long ago. Data and data storage have evolved under the influence of emerging technologies. Instead of capturing data and storing it in a database, we now deal with large data-streams stored in the cloud, which might be represented and visualized using algorithms and machine learning. This presents

interesting opportunities to learn from data, revealing with it hidden insights but important challenges as well.

3 Opportunities and challenges around data

More than 70% of the Web is now user-generated and distributed via personal presence sites such as Facebook and YouTube in addition to micro blogging sites such as Twitter [2]. The exponential growth in the use of social media such as blogs and the ease of use of video-sharing sites has facilitate both the creation and sharing process for the common end-user. Another challenge, but also an opportunity, is that data and data storage have also evolved under the influence of emerging technologies. Data streams are increasingly stored in the cloud, rather than in databases and the data might be represented and visualized through the use of algorithms and machine learning. Software and algorithms are shaped by social, political and economic interests that might influence their value for education and learning [3].

A critical reflection is thus warranted, in light of the complexities around data analytics, including the ethics and values, ambiguities and tensions of culture and politics, even the context in which data is collected which for the most part is not accounted for [3]. Data analytics must move beyond simplistic premises which reduce complex problems into technical, knowable, and measurable parameters that can be solved through technical calculation. One of the problems already highlighted in the development of algorithms is the judgements made by researchers and developers that could introduce researcher biases in the tool, which clearly could affect the quality of the recommendation or search results [4].

4 Next generation learning environments

At the NRC, the design and development of next generation learning includes data-driven visualizations of trace data learners have left behind in their online learning activities and machine-learning techniques to personalize the learning experience. Other development efforts have focused on personal and context-aware information about the learner to help to counter issues of human bias in collecting and analyzing data, and interpreting results. New recommendation systems now rely on artificial intelligence and techniques which take into account user learning styles, preferences, prior experience and knowledge to better predict and anticipate the needs of learners, and act more efficiently in response to learner behaviors [5]. The application of various intelligent techniques from data mining and machine learning represents a more recent trend in attempting to study and model users' context-sensitive preferences.

The use of contextual information (e.g., user's current mood or location) is widely used by recommendation systems for mobile devices to search for and present the best resources to the users [6]. Social tags and resource metadata semantics (e.g., for deriving meaning from single words or text) are also used to enhance recommendation systems. Social networks like Facebook, Twitter, and LinkedIn are rich with detailed contextual information describing an individual's preferences and relationships. This contextual information can make recommendation more feasible and effective—extracting user social tags from external social networks while the collaborative tagging system is used as supplemental information [6].

5 Challenges and concerns around new learning ecosystems

Learning Analytics (LA) and Educational Data Mining (EDM) are emerging fields that make use of end-user data to enhance education and learning. Visualization techniques and algorithms are used to parse and filter information and data streams. LA and EDM also make visible and clarify aspects of learning or learning preferences, in order to support people in the management of their lifelong learning. For instance, the incorporation of intelligent and context-aware information about the user in the recommendation process allows for better prediction and for anticipating users' needs, and to improve system responsiveness and visualization of progress along the learning journey [5]. Prinsloo and Slade [7] argue that since the emergence of learning analytics in 2011, the field has not only matured, but also become more nuanced as fears and realities of ethical implications around data collection, analysis, and use of student data have come to the fore. Technological advances have also given rise to increasing concerns around pervasive surveillance, with a growing consensus that the future of higher education will be digital, distributed, and data-driven.

Our own research in LA and EDM has pointed out major challenges in using technology to analyze learning and using predictive analytics and visualizations to advance new learning ecosystems, as well as ethical concerns related to privacy and ownership of massive amounts of data [8-10]. The development of algorithms and other data-driven systems in education should include a critical reflection on the implications of what these systems are in fact replacing and whether the replacement is positive or negative. It is thus important to be informed about the power of learning analytics, the techniques and the kinds of findings that can be derived from the data, but also their limits. The literature underscores the need for further research around consent, potential conflicts between students' concerns, their right to opt-out from the collection and analysis of their data, and more clarity around the central question of "who benefits?" from the analytics [7]. Munoz, Smith, & Patil refer to a report by the Executive Office of the President of the US which highlights benefits, but also addresses concerns regarding the potential harm inherent in the use of big data [7]. The US report recognizes that if "these technologies [algorithmic systems] are not implemented with care, they can also perpetuate, exacerbate, or mask harmful discrimination" [7, p. 54]. Recommendations point to the need for investing in research to mitigate against algorithmic discrimination, including the development and use of robust and transparent algorithms, algorithmic auditing, improvements of data science "fluency", and the role of government and the private sector in setting codes of practices around data use [7].

New frameworks, code of practices, and conceptual mappings of the ethical implications of analytics (including big data analytics, learning analytics) provide guidelines for the collection, analysis, and use of personal data. New guidelines address the need to describe the scope and nature of the imposition; the quality of the data and the automation of the decisions relating to the collected data; the risk of negative unintended consequences; having the person whose data is collected agree (with an opt out option) to the collection and analysis; the nature and scope of the oversight (if any); and the security of the collected data [7]. These issues have been highlighted in research as well [10]. The literature also cites frameworks from the UK Government and Cabinet Office which require data scientists to clarify "tricky issues" as part of a "Privacy Impact Assessment", including reviewing the extent to which the benefits of the project outweigh the risks to privacy and negative unintended consequences; steps taken to minimize risks and ensure correct interpretation; and the extent to which the opinions of the person whose data is collected were considered [7]. The basis and scope of authority of the educational data scientists who are building data-driven systems is currently being called into question. The ethical implications and concerns over data ownership, data protection and privacy are multifaceted and require further consideration

and investigation. Williamson argues that learning analytics of the future will be based on and driven by algorithms and machine learning essentially, and we therefore have to consider how algorithms “reinforce, maintain, or even reshape visions of the social world, knowledge, and encounters with information [11 p. 4]. Regulatory frameworks, accountability, and transparency will be essential elements in frameworks that promote *ethical* learning analytic [7], [12], and [13]. The discussion of ethical implications around learning analytics adds an additional layer and a richer understanding of how analytics can be used to increase the effectiveness and appropriateness of teaching, learning, and student support strategies in economically viable and ethical ways. However, the practical implementations of that understanding remain largely incomplete, and thus fertile ground for sustained research.

New learning ecosystem must be designed to take these elements into considerations, as well as the place of communication and dialogue between participants in creating quality learning experiences, the importance of presence and engagement of knowledgeable others as being vital in extending the ideas, critical analysis, and thinking of participants in a learning setting [14], [15]. Research in the area of EDM also highlights the importance of affective dimensions in learning, in sentiment analysis [16], in creating affective knowledge [17], and keeping humans in the loop as desirable for the filtering and aggregation of information and Socratic questioning—which research has demonstrated is better through human mediation [15].

The complexity of introducing serendipity in the information aggregation process as an alternative to human mediation includes support for random or chance occurrences in information searches and discovery [18], the use of algorithm-based platforms to elevate levels of ‘serendipity’ in the information stream to enhance thinking and critical analysis levels [19], [20], as well as the use of collaborative Filtering (CF) methods in recommender systems in making connections between different types of data [21]. The use of AI and automation in learning platforms have been successful in simulating interactions with a critical knowledgeable human, interactions that are essential in creating quality learning experiences, but there are still important gaps to address.

6 Conclusion and discussion

This paper highlights important considerations for developing new learning ecosystems that rely on massive amounts of personal data to create quality learning experiences. Several issues have been raised around the content of data-driven systems, who influences this content, and the value they add to the educational process itself.

The affordances and effectiveness of new data driven learning environments come with important limits as well, including issues around automated systems; systems that do not consider the end-user (or learner) in the information discovery, capture, and analysis process and the ethics of moving from a learning environment characterized by human communication to an environment that includes technical elements over which the learner may have little or no control.

New frameworks, codes of practices, and conceptual mappings of the ethical implications around data analytics provide guidelines on the scope and authority of educational data scientists who are building data-driven systems, but practical implementations in new learning ecosystems are still incomplete. These gaps provide fertile ground for further research.

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