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Cognitive Computing and Education and Learning

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ABSTRACT

Its enormous potential in learning spurs Cognitive Computing. The overreaching purpose here is to devise computational frameworks to help us learn better by exploiting the learning process and activities. The research challenge recognized the broad spectrum of human learning, the complex and not fully understood human learning process, and various learning factors, such as pedagogy, technology, and social elements. From the theoretical point of view, Cognitive Computing could replace existing calculators in many applications. This paper focuses on applying data mining and learning analytics, clustering student modeling, and predicting student performance when involved in the education field with possible approaches.

KEYWORDS: *Cognitive Computing, Learning Process, Education*

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INTRODUCTION

Cognitive computing is the new wave of Artificial Intelligence (AI), relying on traditional techniques based on expert systems and exploiting statistics and mathematical models. It uses computerized models to simulate the human thought process in complex situations where the answers may be ambiguous and uncertain (Bernard, 2016). Cognitive computing systems can be regarded as "more human" artificial intelligence (Mauro C, Paolo M. Lidia S., 2016). The overreaching goal here is to devise computational frameworks to help us learn better by exploiting the learning process and activities. There are two essential aspects of it- the mechanisms or insights about how we know and the external manifestations of our learning activities (Lake et al., 2015). The goals of cognitive computing use self-learning algorithms that use data mining, pattern recognition, and natural language processing can mimic how the human brain works. In education, cognitive computing refers to reasoning, language processing, machine learning, and human capabilities that help everyday computing solve problems and analyze data. By learning patterns and behaviors and becoming more intelligent, a computer system challenges complex decision-making processes. It can identify three main areas in which cognitive computing will cover a significant role: advancements in computation capabilities, human-computer interactions and communications, and the evolution of the Internet of Things (IoT) (Mauro C, Paolo M. Lidia S., 2016).

Cognitive computing successfully deals with complex tasks such as natural language processing and classification, data mining, and knowledge management; hence cognitive systems can perform sophisticated duties. It is a relationships extraction from unstructured corpus, speech-to-text, and text to speech conversions, pattern recognition, computer vision, and machine learning which involve research areas based on human-like reasoning techniques. Cognitive computing systems owe their ability to a large amount of data analysis and process to feed the machine learning algorithms. For example, popular technology Artificial Intelligence is employed in search engines;it provides in a seamless manner entity extraction, clustering, and classification and pulls back only information that is relevant to the users, based both on personal data and on the application of patterns. (Pazzani & Billsus, 2007).

Cognitive computing fosters new ways of interaction between humans and computers. Since cognitive computing simulates human reasoning processes by translating them into suited templates, it can help machines learn and teach humans new concepts and behaviors. Such intelligent systems could be used in training and customization or other activities requiring data analytics to improve processes and products (Earley, 2015).It generates big data in education and learning through activities, presenting enormous potential and a great challenge. Big data are typically characterized by five V's-volume (data are large scale), variety (data come in many different forms), velocity (data have some elements of uncertainty), and value (extracting actionable intelligence). The first four V" are visible in education and learning application settings. For example, a learning Management system (LMS) like Moodle (2016) or any Massive Open line Course (MOOC) generates a considerable volume of data. Moreover, the data come in various forms, such as student answers to quantitative questions and essay-type questions, which are very difficult. The cognitive computing community has embarrassed the emergence of Big Data, thereby shaping up several subfields relevant to education and learning. From the e-learning point of view, it reported some experiences that witnessed how cognitive computing can be an accelerator for students' achievements and valuable support for the teachers. In particular:

1. Integrating cognitive computing services in software applications can enormously enhance students' performance in computer science classes.
2. Studying cognitive computing behavior can lead to significant results in AI-related studies.
3. Using a cognitive computing layer for digital interactions with students enhances their performance and eases the teachers' jobs in managing classes and learning materials.

Educational Data Mining

The increasing use of technology in educational systems has presented a large amount of data. EDM provides a significant amount of essential data (Mostow. J & Beck. J, 2006) and offers a clearer picture of learners and their learning process. Advances have inspired EDM in data mining and machine learning. The overreaching goal is to help teachers, students, and other stakeholders achieve their respective objectives by utilizing Big Data in education. The International Educational Datamining Society (2016) has defined the field as "concerned with developing techniques for discovering the unique and increasingly large-scale data that come educational settings, and using those methods to understand students better, and the settings they learn in."

1. Educational Data Mining allows consumers to extract information from student data. This information can be used in different ways, such as validating and evaluating an educational system, improving the quality of teaching and learning practices, and laying the groundwork for a more effective learning process (Romero. C, Ventura S., & Bra De. P., 2004). Baker (2009) suggested four key areas of EDM application: improving student models, improving domain models, studying the pedagogical support provided by learning software and conducting scientific research on learning and learners. Five approaches are available: prediction, clustering, relationship mining, the distillation of data for human judgment, and discovery with models.
2. EDM tasks mention four different areas of applications that deal with the assessment of (a) students learning performance, (b) course adaptation and learning recommendations to customize students learning based on individual students' behaviors, (c) developing a method to evaluate materials in online courses, (d) approaches that use response from students and teachers in e-learning courses, and it detects the models for uncovering student learning behaviors (Castro, 2007).

Learning Analytics

Learning analytics represents data about learners to develop a learning environment where a new model makes a difference through which teachers can understand education. The first International Conference on Learning Analytics and Knowledge (LAK) was held in 2011. At that time, the LA community identified the LA field as Learning Analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts to understand and optimize learning and the environments in which it occurs" (Long and Siemens, 2011).

Learning analytics is the application of these Big Data techniques to improve learning. Learning analytics is currently a fixture in educational horizon-scanning reports (Johnson et al., 2011; Johnson, Adams, and Cummins, 2012; Sharples et al., 2012) and a raft of other publications aimed at practitioners and aspiring practitioners from organizations concerned with technology in education, such as Educause, JISC and SURF. For instance, Blackboard, Desire2Learn, Instructure, and Tribal have all released tools, and there is also an activity in the Moodle community.

The high-profile providers of Massively Open Online Courses (MOOCs)- Coursera, Udacity, and edX- use analytics tools to inform their practice.

A key concern in learning analytics is using the insights gathered from the data to make interventions to improve learning and generate "actionable intelligence" (Campbell, DeBlois, and Oblinger, 2007), which informs appropriate interventions. Compared to Educational data mining, learning analytics embodies a broader umbrella of learning settings, tools, techniques, human and social factors, and applications. Educational data mining is focused on automation and is frequently concerned with unearthing hidden patterns from data, whereas Learning analytics is more holistic and human-centric (Siemnes and Baker, 2012). In contrast, learning analytics is inherently an area of analytics, and therefore various analytics instruments, such as discourse analysis and social network analysis, are more important in learning analytics and educational data mining.

Clustering and Student Modeling

Clustering is used to operate data into different groups on certain standard features. Unlike the classification method, in clustering, the data labels are unknown. The clustering method gives the user a broad view of what is happening in that dataset. Clustering is sometimes an unsupervised classification because class labels are unknown (Fayyad, 1996). The number of groups can be predefined in the clustering methods. Clustering is a common technique where EDM for aggregating student data to examine student behavior. An evolutionary clustering technique for sequential student data (Klingeler et al., 2016). Compared to previous works, their approach improves clustering stability for noisy data.

Student modeling is the structure of a qualitative representation that accounts for student behavior in a system's knowledge background. These three – the student model, the student behavior, and the background knowledge- are the essential elements of student modeling. Student behavior refers to a student's observable response to a particular stimulus in each domain that, together with the inspiration, serves as the primary input to a student modeling system (Raymund Sison & Masamichi Shimura, 2008). Moreover, another central problem in EDM is student modeling. When using data from Duolingo (2016), Streeter (2015) has used probabilistic mixture models to capture the learning curves of language learners. An individual learning curve represents error percentages over time. Streeter's work generalizes knowledge tracing and offers an elegant probabilistic model for modeling learning curves. The model parameters have been learned using the well-known expectation-maximization algorithm. Based on the large-scale Duolingo dataset, the mixture model outperforms many previous approaches, including popular cognitive models like the Additive Factor Model (AFM) (Cen et al., 2006).

Predicting Student Performance

Prediction of students' performance has become an urgent desire in most educational entities and institutes. That is essential to help at-risk students and assure their retention, provide excellent learning resources and experiences, and improve university ranking and reputation. Furthermore, it has been a famous line of research in EDM based on various factors. Student performance has been measured in specific disciplines or topics, such as algebra (Stapel et al., 2016) and programming in Java (Tomkins et al., 2016).

Student records analysis for startups to medium-sized institutes or schools, like the British University in Dubai, which has small student records, has never been explored in the educational or learning analytics domain. (Ingrassia & Morlini, 2005; Pasini, 2015). Additionally, most researchers aimed to classify or predict; researchers spent many efforts extracting the essential indicators that could be more useful in constructing reasonably accurate predictive models. They will either use features ranking algorithms or look at the selected features while training the dataset on different machine learning algorithms. (Comendador, Rabago, & Tanguiling, 2016; Mueen, Zafar, & Manzoor, 2016).

Many students received coaching while taking MOOC, and coaching students performed better than the independent students in the MOOC (Tomkins et al., 2016). Another study shows that the context of MOOCs predicts student dropout and proposes an intervention study (Whitehill et al., 2015). Student dropout is a widespread phenomenon in MOOCs (Onah et al., 2014; Riverd, 2013). The post-course survey is ineffective in detecting the reasons for the dropout since the response rates for such surveys are usually very low. The techniques for detecting student dropout and prose an intervention strategy in the form of early surveys to retain students. They used the HarvardX MOOC educational program to evaluate the effectiveness of their approach to knowing more about dropouts.

Conclusion

Technology is valuable day by day. The increase in education generates a large amount of data every day, which has become an aim for many academics worldwide; educational mining is proliferating. And it has the advantage of containing new algorithms and techniques developed in different data mining areas and machine learning. The interaction between academia and industry is a remarkable feature of cognitive computing, especially in its applications in education and learning. For example, companies like IBM embrace cognitive computing to harness the power of Big Data in multiple application areas, including education (Davis, 2016). Learning analytics is the inspiration of teachers and students to understand the wealth of data related to their learning in the educational platform. Engaging in the process is a way of taking concern of the economic framing that can be supplemented with respect for knowledge. The focus on the data alone is not sufficient: to achieve institutional transformation, learning analytics data need to be presented and contextualized in various ways that can drive organizational growth (Macfadyen and Dawson, 2012). Soon, cognitive computing technology and related applications will be possible in a complex ecosystem where the valuable data available within the education system, including institutions and municipalities, can be exchanged between applications and organizations seamlessly and transparently, which will help students learn more in future.

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