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INTELLIGENT TUTOR USING PERIPHERAL ARTIFICIAL INTELLIGENCE: OPPORTUNITIES AND LIMITS

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Abstract

This article aims to present a model of Intelligent Tutoring System exploiting artificial intelligence to personalize the learning of the learner and to automate certain tasks of the teacher. All the resources consulted and the educational objectives achieved by the learner will be processed using the TinCan API and the limitation of the amount of sensitive data sent to the cloud will be ensured by the use of peripheral artificial intelligence. We start by defining the concepts of artificial intelligence and Intelligent Tutoring System, then we focus on the implementation of machine learning in such a system and the advantages that this technique brings. Finally, we describe the limits of such a technology and the possible solutions to it.

Keywords: *Learning, edge computing, peripheral artificial intelligence, pedagogical resources, semantic technologies.*

1. Introduction

For several years, the increase in the volume of data produced and progress in understanding the human brain have enabled engineers to create machines capable of simulating certain aspects of human intelligence. One of these aspects, the simulation of learning, has allowed the birth of machines capable of perceiving, learning and optimizing: this is machine learning, also called artificial intelligence. This technological evolution is perceived as a disruptive innovation that will upset our society, due to its possibility of interacting and helping humans in high-level tasks. However, the appearance of a powerful tool for processing information does not induce profound changes in learning practices: the practices of teachers and learners must evolve to use technology in an optimal with respect to the targeted objectives (Dai, Chai & Lin, 2020). Loeckx (2016) maintains that artificial intelligence can prove to be an effective tool for learning through its ability to personalize the learner's learning experience but also through the possibilities of automating tasks and summary of the results for the teacher. The increase in resources available online, the democratization of online learning and the development of this technology have allowed the development of tools allowing the construction of personalized learning environments: the Intelligent Tutoring System (ITS). These systems make it possible to personalize the learning on several axes such as the follow-up of the evolution of the learner and the achievement of his objectives, the adaptation of the educational resources proposed according to his style of learning or even the generation of personalized feedback in different formats. Some fear full automation of the teacher's role, but studies tend to say that human intervention cannot be completely replaced. On the other hand, IA and ITS will change the existing pedagogical relationship between knowledge, teacher and learner by adding an aspect of mediation between these entities, leading de facto to profound organizational changes in traditional teaching, both in terms of teaching and student practices: while teachers will see their roles and practices evolve, students will have to learn how to make optimal use of AI to enhance their learning outcomes (Seldon & Abidoye, 2018). However, it will be necessary to ensure that students are educated on the use of such a tool, because even if the mathematical concepts underlying AI begin to be integrated into school curricula, a poor understanding of this technology will inevitably lead to a decline effect on the effectiveness of the tool or even a negative effect on the quality of learning (Ijaz, Bogdanovych & Trescak, 2017). In addition, other problems must also be studied upstream such as learning biases or the management of sensitive data. In summary, this paper will focus on the representation of a field of knowledge and the modeling of a student, on the various opportunities linked to this technology but also on its limits and the means to overcome them.

The research questions we will try to answer are the following:

- What are the interests of artificial intelligence for the personalization of learning?
- How to overcome the intrinsic limits of this type of technology?

2. Methods

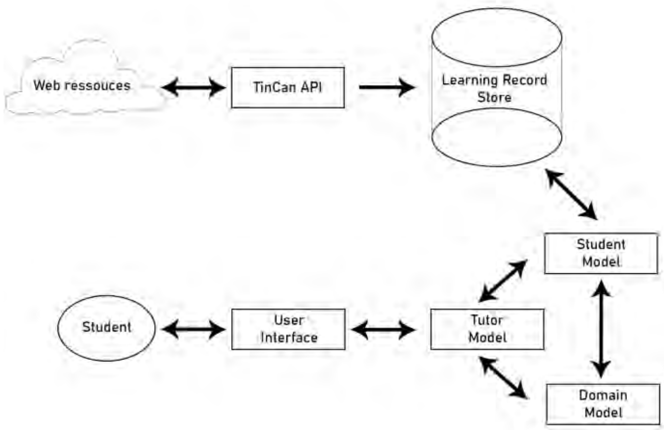
This article is a literature review aimed at analyzing the design and impact of an ITS on the learner and the teacher with a view to creating an intelligent semantic learning support system. Searches on ResearchGate, ScienceDirect, arXiv and Google were made using the keywords “artificial intelligence”, “education” and “intelligent tutoring system”. Other references were obtained by cross-referencing of the various selected articles. These articles include analytical or empirical studies of the topics researched.

3. Discussion

3.1. Architecture of an ITS

Even if ITS have different approach models, they all share a common architecture by having three main types of knowledge: knowledge related to the domain to be studied (stored in the domain model), knowledge about each learner in order to personalize the transmission of knowledge (stored in the student's model) and pedagogical knowledge allowing the tutor to make decisions on the resources to be offered and on the help to be provided to the learner (stored in the tutor's model). Thus, there are two main loops on the system, where one (outer loop) aims to determine the order of future tasks to be given to the learner according to the knowledge acquired and the other (inner loop) aims to follow the learning of the live student to bring him help in case of blockage (Vanlehn, 2006). This help can take different forms, depending on the type of model chosen during the design. This system can be enriched with a Learning Record Store (LRS), which allows the storage and manipulation of data of the learner's learning experiences on different types of web resources (fig.1).

Figure 1. Architecture of an ITS using a Learning Record Store.



3.1.1. Domain model. The knowledge model, also called the expert model or "knowledge expert", contains the concepts, facts and rules of the domain targeted by the learner. Generally produced from the knowledge of experts in the field, it offers the ITS a source of knowledge to present to the learner through different methods. In addition, it also serves as an assessment tool by comparing the learner's responses to their own domain knowledge model. If the answers differ from the model, then the latter must be able to produce multiple solution paths to lead the learner to the expected answer (Gharehchopogh & Khalifelu, 2011). Among the most common design approaches, we can cite the Cognitive Model which is based on the ACT-R theory of cognition and learning or even the Constraint Based Model, where domain knowledge is represented in the form of unbreakable rules (e.g. “If the relevance of the answer is true, then the answer must be correct”). The use of semantic technologies in the design of the knowledge model is important because they offer an ontological language operable by humans and machines by allowing to represent a domain and to symbolize the conceptualization of this domain (Héon, 2016). Composed of a list of Subject-Verb-Predicate statements, they allow the creation of data models representative of a set of concepts in addition to explaining the relationships between these concepts, which allows intelligent processing of these resources in addition to facilitating the inference capability of the system.

3.1.2. Student model. The student model represents their characteristics, knowledge and skills in order to provide the ITS with a source of information about it, allowing it to infer aspects of the learner's behavior. The system will then be able to compare the state of the learner's knowledge with that of the field to identify possible misconceptions and adapt the exercises to work on the weaknesses of student's skills. Two types of information must be processed in order to have a relevant model of the learner: their fixed characteristics (e.g. gender, mother tongue, level of study) and their dynamic characteristics (e.g. knowledge, emotional state, level of attention, problem-solving skills). This information allows the modeling of the learner's knowledge on a domain, which can take different forms (e.g. overlay, disturbance, stereotype, fuzzy modeling) each having their advantages and disadvantages (duChâteau, Mercier-Laurent, Bricault & Boulanger, 2020). The student model can be enriched by using a Learning Record Store (LRS), which makes it possible to precisely follow the progress of learners on various educational media by storing data on the learning experiences emitted by them. This technique makes it possible to capture the informal aspect of the flow of learning and to formalize this data in the form of xApi instructions adopting the form "User + Verb + Object" (e.g. "User read this article", "User played this game", "User participated in such activity"). In addition to allowing the storage of less formal learning data, LRS allow data analysis and exchange with other systems: this is valuable information for ITS because it provides additional data for monitoring student learning (Bealing, 2020).

3.1.3. Tutor model. The tutor model, also called the pedagogical module, is the engine of the system. He acts as a tutor in charge of choosing "what to teach, how and when", evaluating the learner's knowledge and adapting the content offered to his preferences, answering questions or even generating feedback in case of error or misunderstanding (Bourdeau & Grandbastien, 2010). These actions are based on the pedagogical content stored in the domain knowledge model in addition to the characteristics of the learner stored in the learner model, and are intended to encourage the learner to build even knowing her rather than following chain instructions. There are already semantic active learning systems (e.g. SASA) capable of enriching and personalizing the learner's experience, by exploiting a reasoner using the calculation of first-order predicates and ontologies modeling the entities participating in the process. learning (Szilagyi & Roxin (2012). The addition of artificial intelligence in such a semantic system allows the realization of a personal intelligent learning agent, which will aim to optimize the learning of each learner according to the model drawn up of this one and the knowledge to be transmitted through of the various educational resources available. The tutor making the link between the learner and the system, the use of Natural Language Processing (NLP) and various cognitive strategies improve the construction of the learner's knowledge while improving the quality of the student model (Rus, Niraula & al., 2015).

3.2. Opportunities and limitations of AI in an ITS

From a learner's point of view, AI acts as an intelligent tutor in a virtual environment to personalize the educational resources offered according to its learning style (Messika, 2019). All the data transmitted will be stored, analyzed, and processed to improve the representation of the learner's knowledge and skills. This precise representation improves the system's ability to infer the pedagogical content to be favored according to the profile of the learner and allows the personalization of his learning path through the choice of different pedagogical strategies according to each profile. The precise monitoring of the evolution of the learner's knowledge facilitates the production of feedback to be provided to him, through the synthesis of his progress and the achievement of the set educational objectives (Alkhatlan & Kalita, 2019). In addition, the use of artificial intelligence facilitates the processing of information by allowing the highlighting of the different ways in which learners interact with resources and the effect that these have on the quality of learning, data who then assist the teacher in making decisions about the usefulness and impact of the educational objects used. The ability to extract statistical regularity and synthesize the system also allows the teacher to have a summary of the evolution of each learner, both on the achievement of educational objectives and on the evolution of the style of teaching. learning or motivation (Franzoni & al., 2020). This analysis makes it possible to detect the difficulties specific to each learner but can also infer potential dropouts, reducing the digital divide linked to the use of a virtual system (Pitchforth, 2021). Finally, this technology offers the possibility of aggregating educational objects from a domain using semantic technologies and metadata. Properly described pedagogical resources make it possible to drastically increase the amount of relevant pedagogical resources available to the teacher because they are processable and categorizable by machines, which facilitates interoperability between different learning systems (Apoki, 2021). One of the standards that can be used is LOM (Learning Object Metadata), which is a description scheme for digital or non-digital educational resources using several categories (e.g. general, life cycle, rights, relationship, classification) to describe a resource. However, the use of AI in a tutoring system brings several constraints to consider. The first notable problem concerns learning biases during the training phase of the pedagogical model. This bias, coming from a biased data set, introduces a distortion in the training process which results in a systematic deviation of the model results. This bias can come from a confirmation bias, i.e. from cognitive biases of the designer, but can also be a statistical bias, i.e. from non-representative training data or statistical algorithms used inconsistent with the objective of the system (Mélot, Ris & Briganti, 2021). To limit them, it is necessary to define upstream the precise needs of the users, to control the coherence of the methods used according to the desired results and to surround yourself with experts of the subject to be treated to limit the impact of your own cognitive biases. Another problem is that of poor understanding of the technology, which can occur on the designer and user side. The main problem for the designer is the systemic problem of the black box: we know the input data, we observe an output result but it is complex to explain what is happening between the two. This problem sometimes makes it difficult to explain on what elements the model is based to produce the result, which de facto complicates the explanation of the feedback produced, the debugging of the system in the event of inconsistent output or the trust accorded to a system whose operation escapes human comprehension. There is currently no universal answer to this problem, easily explainable algorithms having lower performance than algorithms using multiple layers of learning (Vilani, 2018). Research continues to improve the transparency of these algorithms, even if this problem of algorithmic decisions may be more about the contestability of the results than the explainability (Abiteboul & Dowek, 2017). On the user side, the poor understanding of technology is rooted in the lack of education on this subject. Currently, at a low level of study, IT is only office automation. It is necessary to demystify this technology by learning the basic algorithms and techniques allowing the operation of artificial intelligence. The population must also be accustomed to using this tool to reduce user bias, better collect data and better understand the limits of this technology (O'Neil, 2016). Moreover, it may be more appropriate to speak of machine learning than artificial intelligence because intelligence is a fairly strong term and ultimately quite incorrect in view of the degree of intelligence that AI really demonstrates. Finally, one of the last important points is that of the processing of sensitive data. The Internet of Things makes it possible to use several different connected objects as learning media, which involves data transfers between devices. In addition, collecting as much information about the learner as possible is necessary in order to design a model of their knowledge and skills, which involves collecting all the data they emit in addition to pre-filled information (e.g. sex, age, level of education). All these data are essential to have an accurate and relevant model of the learner but are extremely sensitive. One of the solutions to avoid having them transit through the cloud is to use peripheral artificial intelligence, a method combining machine learning and cloud computing to process the data as close as possible to the source of transmission to avoid the transmission large amounts of data in clouds. Peripheral computing is a technique aimed at synchronizing on a server only relevant and pre-processed data (Ismael, 2018). This technique applied to artificial intelligence works in two stages: first a local learning where each device adjusts its learning model, followed by a global aggregation where the main server defines the weights of the new model and updates it. on the various connected objects. Data is not transferred between devices, only models are transferred (Li & al., 2019). Thus, time and bandwidth are saved, and the private aspect of the data is protected (Hosseinalipour & al., 2020). This technique also has its limits but remains a feasible and relevant solution for the processing of sensitive data.

4. Conclusion

Given the constant evolution of AI, it is important that students and teachers learn to master the technology to maximize its positive impact. Its possible contributions are not negligible: better personalization of learning, better generation of feedback, powerful tool for statistical inference and aggregation of relevant content. Like any technology, however, AI has limits such as learning biases, usage biases or securing the large amount of sensitive data retrieved. We must continue to work on these risks to avoid falling into a technological dictatorship where the tool becomes a constant monitoring instrument whose operation escapes the understanding of its users. It is certainly a powerful tool, but to be handled with care due to its various ethical and technological implications.

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