Tracking learners' knowledge and skills development

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Abstract
This Ph.D. research proposal aims to investigate how exploiting educational data to track the learners' development of knowledge and skills, thus embedding this information in automated tools designed to enhance teaching and learning. The encoding of learners' knowledge and skills is a crucial issue which can be exploited in addressing several tasks, such as underachievement prediction and personalized learning. However, some challenges characterized how to design the encoding and include it in automated tools: dealing with several formats of data (among which also text, video, images, and audio recording), tackling the strong dependence of educational data from the context where they are collected, and consider ethical issues related to explainability and fairness. With this position paper, we introduce the research questions which lead the project, a brief state of the art about techniques used to tackle the students' knowledge and skills encoding, the methodology and the expected results. Specifically, we aim to investigate which data can be used to fulfill our main purpose, test our encoding solutions in two case studies (underachievement prediction and knowledge tracing), and assess the contribution of our encoding to tackle them. As for the methodology, we want to explore strategies of Informed Machine Learning, that is to say incorporating an external knowledge source in the machine learning pipeline, which can improve the explainability and fairness of the models and handle the influence of the external context on the educational data.

Keywords
knowledge tracing, skill development, educational computing, informed machine learning

1. Introduction

This position paper presents the research proposal for a Ph.D. in Educational Data Science discussed at a Doctoral Consortium, with a specific focus on the problem of how to track the development of students' knowledge and skills. The paper was presented a year and a half after the start of the Ph.D. and contains the conceptual and motivational framework, the expected development steps, and a summary presentation of the preliminary results of the work done so far.

The paper is organized as follows. In the next section, we describe the background for the research, focusing on some challenges, motivating the research questions for the proposal, and the rational for our methodological choices. The third section is dedicated to the methodology. We introduce Informed Machine Learning (IML) as a reference methodological approach and we outline some attention for its application to the educational context. Section 4 is for the introduction of two case studies which mainly serve to exemplify the application of an IML approach. For the first case study we also briefly discuss some preliminary results; the second case study is presented as future work. Finally, we conclude with a description of the expected results and some final remarks.

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2. Background

2.1. Datafication in the Educational field

In the last decade, the process of datafication in society has become increasingly pervasive, also affecting the educational field [1]. We assisted in a growing and varied interest in the application of artificial intelligence and data science techniques in this sector, with the rise of new research fields such as Learning Analytics (LA) and Educational Data Mining (EDM) [2]. Despite some differences, especially in the analysis techniques most commonly used by the two research communities, LA and EDM share the goal of extracting knowledge of interest for educational stakeholders –policy-makers, didactic coordinators, teachers, parents, and students– and using the extracted knowledge to improve the learning process in some way.

In this Ph.D. research proposal, in a broad perspective, we consider a key issue which is transversal to many educational situations: tracking the learners' development of knowledge and skills, thus embedding this information in automated tools designed to enhance teaching and learning. There are several tasks which can benefit from the encoding of students' knowledge and skills development, e.g. low achievement prediction models [3, 4] or automated feedback system for personalized learning [5]. As main objective, we aim to tackle the problem of how encoding the students' knowledge and skills development, identifying valuable data resources for its representation, and testing our solutions effectiveness in addressing the tasks listed above. There are three main starting considerations which motivate our proposal and lead to design our research questions.

2.2. Three challenges to address for automated tracking of knowledge and skills development

Firstly, the datafication process in the educational field is characterized by several types of data, namely product data, process data, and background data. Product data are related to what students produced, and how they show their learning. They can be collected while students are learning, e.g. personal notes during classes, production of diagrams, and concept maps, questions answering, resolutions, and formative and summative assessments. Process data deals with how students are learning a specific content or how they behave during their performance assessment. The possibility to gain process data increased in the last years due to a spread in the use of digital technology in education, e.g Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and computer-based tests (CBt), both at school and university. This was furtherly accelerated by the recent COVID-19 pandemic. These technologies allow to track individual students' learning processes and collect data such as their mouse clicks, scrolling behavior, or time spent on different tasks or content resources. Also face-to-face classes allow the collection of process data, although it is often challenging and more time-consuming. An example is the data collected through the Think-Aloud protocol [6]. As for background data, they usually contain student demographics (parents' education, family income, household registration), curriculum plans, teachers' quality and style, and student performance evaluation. The previous list shows the variety of formats for educational data referable to a single learning activity: numerical, categorical and boolean variables are enriched by other formats e.g. texts, images, videos, and voice recording. This leads to the problem of how multimodal data fusion can be conducted in learning analytics [7, 8]. We refer to this challenge as the *multimodal data challenge*

A second issue concerns how these data are collected, organized, and labeled [9]. On the one hand, the increasing availability of educational data promotes the application of data science and machine learning techniques, to exploit data potential in enhancing learning and teaching. On the other hand, we have to consider that educational data are often highly context-dependent. There are few standardized large-scale educational datasets, i.e. data are very heterogeneous for different class groups. Furthermore, data labeling is not a common practice in classroom settings, because it is not one of the main objectives of teachers or other stakeholders traditionally involved in training processes. Moreover, educational data are often indicators of a learning competence or behavior, whose evaluation depends to some extent also on the evaluator. Let us consider, for example, the evaluation of task on creative thinking skills: different evaluators can result in different evaluation labels. Therefore, we are affirming that the collection of data on students cannot ignore the context in which this occurs and can hardly be considered free from pedagogical, psychological, and cognitive science theories, consolidated over years of research and assumed more or less explicitly by teachers, by those who design the context of learning or by who carries out the data collection. The research on Intelligent Tutoring Systems or Adaptive Educational Systems already considers the domain model and the pedagogical model together with the learner model [10, 11]. However, in these systems, they are often separate components, while we are suggesting that the domain model and the pedagogical model directly influence the learner model. This assumption relies on the issue already stated in the literature of the theory-ladenness in data-intensive approaches [12]. We can name this as the *theory-ladennes challenge.*

As a consequence, it is not easy to have robust and fair datasets on which to apply automatic data mining techniques, pointing out the third issue on ethics. An unbalanced or unrepresentative dataset may disadvantage students not sufficiently represented by the sample. The model –here intended as an automated detector for a commonly seen outcome or measure in LA and EDM, such as dropout, underachievement, affects, learning strategies, and disengaged behaviors– may be prone to overfitting the profile of well-represented students, resulting inflexible to new cases or changes that may occur in the school population. According to Baker [13], this is not just a technical challenge but it is a challenge for inclusion. In fact, a lot of the populations that we want to focus on, including historically underserved and underrepresented populations, are the ones it is harder to collect data for. This can be seen as a generalizability challenge for the models developed in LA and EDM. We can refer to this last point as the *ethical challenge.*

2.3. Research Questions

To sum up, the datafication process, which affected the educational field, is an opportunity to promote data-informed decisions for revising the learning designs and avoiding behaviors that lead to poor learning. In particular, one of the central problems is how to use data for the design of a learner model, an essential component for data-informed pedagogies and educational actions. In the development of this model, there are some challenges to be taken into consideration: the multimodal data challenge, the theory-ladennes challenge, and the problems of inclusiveness, fairness, and generalizability, summarized in the ethical challenge. The considerations in the previous subsection lead us to formulate the following research questions.

Most studies in this area have a purely or highly data-driven approach, which does not consider how context and several pedagogical assumptions can affect and be integrated into the machine-learning pipeline. This leads us to formulate the following research questions.

> **RQ1** How different educational data can be used for a reliable representation of learners' development of knowledge and skills?
>
> **RQ2** Is there any prior knowledge which can be integrated into AI tools used for tracking learners' development of knowledge and skills to improve their performance or their explainability?

The first research question is motivated by both multimodal data and ethical challenges, and also wants to suggest the need to reflect on what information is actually collected and expressed in the data. The second question emphasizes the need to consider other sources of information. The term *prior knowledge* here is intended in the perspective of Informed Machine Learning, chosen as methodological paradigm, that we describe in the next section. In our discussion, we can assume the domain and the pedagogical models as integrative knowledge source to data.

3. Methodology: Informed Machine Learning

According to von Rueden et al. [14] Informed Machine Learning describes "learning from a hybrid information source that consists of data and prior knowledge". It is not a purely data-driven approach due to the integration of an external and independent knowledge source into the machine learning pipeline.

With the term *knowledge* they assumed a computer science perspective, defining it as "validated information about relations between entities in certain contexts". There are three types of knowledge, several possible representations, and different forms of integration, as shown in Table 1. When dealing with the approach of informed machine learning in the educational field, the main source of prior knowledge to consider is the expert knowledge, often informal and validated through a group of experienced specialists. Also world knowledge could be a source of information to take into account, referring to facts from everyday life that are known to almost everyone, subsuming also linguistics.

Some forms of knowledge integration in LA models already exist; it almost occurs with the search for synergy with learning design, oriented to data-informed learning and teaching practice that preserve the agency of students and teachers [15, 16], overcoming purely data-driven approach. This way can be seen as integrating prior knowledge into the final step of the machine learning pipeline when its output is validated or benchmarked against existing knowledge through human mediation. However, there are other forms of knowledge integration in the machine learning pipeline –Training Data, Hypothesis Set, and Learning Algorithm– that could be investigated to face the challenge of the reconstruction of students' learning trajectories and students' competence development. In this research proposal we want to address the problem of developing knowledge and skills by investigating which supplementary knowledge sources can be used, how they can be represented and where they can be integrated into the machine learning pipeline (training data, hypothesis set, learning algorithm, and final hypothesis). To do this we consider two case studies, i.e two situations in which the problem of tracking the development of knowledge or skills is relevant and which we propose to approach from the perspective of informed machine learning. The first case study concerns a predictive model of underachievement and represents a study already started for which there are some preliminary results. In this first case, we present an example of feature engineering strongly driven by an explicit integration of a theoretical framework. The second case study concerns the problem of knowledge tracing. It represents a work direction still to be developed which also requires an in-depth analysis of what already exists in the literature as attempts at hybrid approaches in which a theory-laden is present. Therefore, we propose to investigate the RQs through two case studies that allow to use of different data (in the first case it is a static dataset and in the second dynamic) for learner modeling and to test prior knowledge integration strategies.

Table 1
Informed Machine Learning taxonomy introduced by von Rueden et. al. [14]

Source Which source of knowledge is integrated?	Representation How is the knowledge represented?	Integration Where is the knowledge integrated in the ML pipeline?
Scientific knowledge	Algebraic equations	Training data
World knowledge	Differential equations	Hypothesis set
Expert knowledge	Simulation results	Learning algorithms
	Spatial invariances	Final Hypothesis
	Logic ruels	
	Knowledge graphs	
	Probabilistic relations	
	Human feedback	

4. Case studies

4.1. Low achievement prediction exploiting longitudinal large-scale assessment tests

4.1.1. Problem definition and State of the Art

Firstly, we examine data collected through national large-scale assessment tests. These tests are often used to support educational policy decisions [17] or in studies aiming to determine the relationship between socio-economic factors and school performances. Nevertheless, they are designed to measure students' knowledge and skills and often to track longitudinally the students' learning path [18]. These test design features enable the collection of data that can be useful for tracking the development of knowledge and skills and building predictive models for the risk of long-term *underachievement* or *dropout*. In [19], for example, the authors refer to data collected through the PISA international large-scale assessment tests to predict math proficiency.

Several machine learning techniques have been exploited to build predictive models for students' performance [4], including supervised learning, e.g., random forests, support vector machine and Bayesian network, unsupervised learning, e.g., k-means and hierarchical clustering, and recommender systems, e.g., collaborative filtering.

4.1.2. Specific objectives and outcomes

In [20] we present some preliminary results about maths low achievement prediction exploiting a very large italian dataset (more than 700000 students). Specifically, we exploit data collected through the INVALSI[1] large-scale assessment test to predict at grade 5 low achievement in math at the end of compulsory school at grade 10. We used three AI tools based on state-of-the-art machine learning models: random forest and two neural networks (categorical embedding neural network and feature tokenizer transformer). Finally, we presented a knowledge-based methods to encode students learning. Specifically, in the design of the learner model, we exploit features already present in the dataset regarding demographic information and the socio-cultural-economic context of the student, together with other features more related with the student's learning. This second set of features is obtained through engineering the boolean features that record the correctness of the student's responses to the individual items of the test. The new features are defined based on the framework used by INVALSI for classifying the items, in terms of areas, processes, and macro-processes. The rational for this choice is two-folds: firstly, this allows application to students from different cohorts who have taken different tests; secondly, they are directly related to students learning in terms of knowledge and skills, that are very important to design educational interventions to counteract the phenomenon of underachievement. The classification framework is shown in Table 2 This framework represents the source of integrative prior knowledge. Its representation is in the form of algebraic equations, with which we define the new features, i.e. for each student a correctness rate is computed for each area, process, or macro-process. The integration takes place into the train set.

Our results are summarized in table 3, which are promising. We aim to improve the research in three main directions. Firstly, we want to test the transferability to other disciplines such as Italian and English, which are tested by INVALSI, by using a similar representation or encoding for students learning. Secondly, we aim to improve the data quality by training and testing the model with students from different cohorts. This is possible by using at least four cohorts of students and may improve the transferability of the models to new cohorts. In fact, training the model on students' data from different school years could help in avoiding over-

[1]Italian National Institute for the Evaluation of the School System

Table 2
Maths INVALSI framework for question encoding.

Areas
(NU) Numbers (SF) Space and figures (DF) Data and forecasts (RF) Relations and functions
Process
(P1) Know and master the specific contents of mathematics (P2) Know and use algorithms and procedures (P3) Know different forms of representation and move from one to the other (P4) Solve problems using strategies in different fields (P5) Recognize the measurable nature of objects and phenomena in different contexts and measure quantities (P6) Progressively acquire typical forms of mathematical thought (P7) Use tools, models and representations in quantitative treatment information in the scientific, technological, economic and social fields (P8) Recognize shapes in space and use them for problem solving
Macro-process
(MP1) Formulating (MP2) Interpreting (MP3) Employing

fitting patterns to a specific test. Furthermore, we can try different student modeling approach, which is not driven by the Invalsi theoretical framework but which take into account other contextual information, e.g the items difficulty or the items embedding based on their texts. A last point of development concerns the interpretability which can be improved by comparing the feature importance analysis of the random forest model with the weights which define our neural networks.

To sum up, With this case study we want to investigate the potential of educational data collected through longitudinal large-scale assessment tests for the representation of the development of knowledge and skills, and look for other prior knowledge resources that can improve the performance of the model.

Table 3
Performance on test set

Models	Accuracy	Precision	Recall
Random Forest	0.77	0.62	0.67
CE neural network	0.76	0.76	0.76
FTT neural network	0.78	0.77	0.78

4.2. Knowledge tracing for personalized learning

4.2.1. Problem definition and State of the Art

As a second case study, let us consider an instructional unit provided through a learning management system (LMS). This is usual for MOOCs courses, it has also been the case for many students and teachers during COVID-19 pandemic [21] and potentially it may also be exploited in face-to-face classes, as a tool to organize teaching materials and manage different activities. As students work with the LMS they produce a wealth of data including product data (e.g. an explanation written in an electronic journal, or a video recorded through a mobile app) and process data (e.g. the number of edits made in the writing of this explanation, or log data). This data can be exploited for the well-known problem of *knowledge tracing* [22], which can be described as monitoring students' changing knowledge states during the learning process and accurately predicting their performance in future exercises. This information can be further applied to pursue *personalized learning* in order to maximize students' learning efficiency.

The most common machine learning techniques to handle knowledge tracing are Bayesian Network [22] and Dynamic Bayesian Network [23], to build probabilistic models. Another frequent approach is that of logistic models, such as learning factor analysis [24], performance factor analysis [25] and knowledge tracing machines [26]. In recent years, it has been explored also the use of deep neural networks [27], which outperform more traditional techniques, named Deep Knowledge Tracing (DKT).

4.2.2. Dataset and goals

For this case study we will consider data collected by the ALICE project (Learning Progression Analytics - Analyzing Learning for Individualized Competence development in mathematics and science Education), led by IPN Kiel, with the cooperation of DIPF Frankfurt and Ruhr-University Bochum. ALICE aims to exploit data from students' interactions with digital technologies in STEM –Science, Technology, Engineer, and Mathematics– classroom learning, both to predict the productivity of students' learning trajectories for their competence development and to identify underlying causes of unproductivity. The data is collected through the implementation of some instructional units in face-to-face classes using an LMS as a teaching aid. In this context, we want to investigate which useful prior knowledge related to ALICE educational context can be modeled and how. Furthermore, we aim to explore where they can be integrated in the ML pipeline to improve the learning trajectories analysis.

Our hypothesis is that the analysis of log data for the knowledge tracing can benefit from information on the face-to-face context, such as the choices of the teacher in the exposition of the unit contents and teaching times, relationships peer-to-peer, or the didactic model on which the unit itself is designed. We want to investigate the possibility of representing one or more of these sources of prior knowledge through a graph or a bayesian network, that can be used as input for a DKT network together with the log data collected on the student's interactions with the learning management system.

4.3. Remarks

In both cases, we refer to data collected about students' learning to build a *learner model.* However, we have to consider that the learning dynamics are strongly influenced by the *domain model* – understood as physical space, social-relational space, disciplinary space–, as well as by tutors/teachers and the *pedagogical model* they assumed. Domain model and pedagogical model may be considered as prior knowledge, here intended as a separate source with respect to data about students' learning behaviors or performances, which can be integrated into the machine learning pipeline, following the paradigm of Informed Machine Learning[14].

5. Expected results

On the one hand, the brief background presentation in the previous section demonstrates how crucial and transversal the proposed RQs are in the educational field. On the other, it highlights their complexity and the need to address them focusing on case studies, which may be very different from each other, although they share the need to identify suitable data to represent the learners' development of knowledge and skills. The comparative analysis of the results obtained in different case studies can bring out good practices or scalable solutions.

Therefore, in this research project, we aim to focus on different educational issues, referable to those presented in the previous section: underachievement and knowledge tracing. For each case study, we are going to identify or build a dataset useful for defining a learner model, intended as a representation of learners' development of knowledge and skills, thus contributing to RQ1. To handle RQ2, the proposed representations will be used to test several state-of-the-art solutions of machine learning, which can tackle the educational problem that motivates each case study. Furthermore, we aim to identify significant sources of prior knowledge (domain model and pedagogical model) and investigate how to integrate them into the machine learning tools. Hence we will evaluate their effectiveness, with respect to conventional machine learning solutions, by considering models' performances and their explainability, trying to come up with the main goal of RQ2.

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