Algorithms for Adaptive Learning: recommendation of learning paths, resource design and representation

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ABSTRACT

This document is a Research Proposal for a thesis in Artificial Intelligence applied to the field of *adaptive learning*, and more specifically to the problem of providing personalized recommendations of educational resources to learners.
As we will see later on, this is a challenging problem first because it is fundamentally multidisciplinary, second because it requires a large and complex modeling effort, and third because the data required to train and evaluate the models is not easily accessible.

1 INTRODUCTION

The field of Education is undergoing a major transformation. Since the 1970s, the advent of computers has led to the emergence of a new discipline, educational technology, which introduced a new form of learning based on human-computer interaction. This discipline which is at the intersection of several fields such as pedagogy, psychology, sociology, computer science and artificial intelligence aims at facilitating learning using technological processes and educational resources.

It has several advantages over the traditional learning methods where a teacher was playing the main role and controlling a classroom. The main advantages are availability (Thakkar and Joshi, 2015), reduced cost (Gilbert, 2015), a certain form of flexibility (students learn at their own convenience) (Dargham et al., 2012), etc.

The first attempts to set up E-learning systems were limited to providing users with a disorganized bag of learning materials, which could cause disorientation and cognitive overload, especially when users had a restricted learning experience (Nabizadeh et al., 2020). That is why in the 1970s E-learning systems started to propose directional sequences of learning materials, commonly referred to as "learning paths".

These learning paths were designed in a "one-size-fits-all" manner until the 1990s when the first pioneer intelligent and adaptive Web-based educational systems emerged. (Brusilovsky et al., 996a,b; De Bra, 1998; Nakabayashi, 1995; Okazaki et al., 1996)

Unlike "one-size-fits-all" approaches, adaptive systems make it possible to take into account singularity of each learner - knowledge background, progresses, preferences etc. - so as to adapt learning strategy accordingly.

Over the past decades these systems have evolved and developed at such a rapid rate that they were commonly accepted as an increasingly popular alternative to traditional face-to-face education (Basu et al., 2013).

In this document, we will first describe the research background as well as the state-of-the-art of learning paths recommendation approaches. Then we will discuss their limitations, in light of which we will suggest research directions for this thesis.

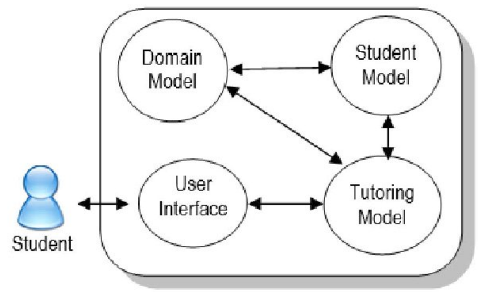


Figure 1: Main components of an Intelligent Tutoring System. Source: (Thai-Nghe and Schmidt-Thieme, 2015)

2 RESEARCH BACKGROUND

2.1 Adaptive Learning

Our research topic actually belongs to a larger research area: *adaptive learning*. Adaptive learning is often defined as the delivery of custom learning experiences that address the unique needs of an individual through just-in-time feedback, pathways and resources (rather than one-size-fits-all learning experience).
Adaptive learning systems - which are usually implemented through Intelligent Tutoring Systems (ITS) - have traditionally been divided into four distinct models (Nour et al., 1995) as shown in Figure 1:

- The Domain model
- The Student model
- The Instructional model
- The User Interface model

The Domain Model (or Expert Model)

The domain model contains a representation of the information to be taught. This can be as simple as the solutions for the question set but it can also include lessons and tutorials and, in more sophisticated systems, expert methodologies to illustrate approaches to the questions. It is ultimately used to produce detailed feedback, guide problem selection/generation, and as a basis for the student model (Martin, 2001).

The Student model (or Learner Model)

The student model represents and tracks information about an individual student's characteristics or state, such as the student's current knowledge, motivation, meta-cognition, and attitudes. Thus it provides input to the Instructional Model (Baker and Yacef, 2009; Thai-Nghe and Schmidt-Thieme, 2015).

The Instructional Model (or Tutoring Model or Pedagogical Model or Adaptation Model)

The Instructional Model takes the domain and student models as inputs and selects tutoring strategies, steps and actions to move the student to more optimal states. Concretely speaking, this module models the "teaching style" to be applied. For example, it may favor examples over the presentation of static text. It may make both low-level decisions, such as the level of difficulty of practice exercises, and high-level ones, such as when the student should move to the next topic of the curriculum (Martin, 2001; Sottilare et al., 2013).

The User interface Model

This module accepts input from the student through various input media (speech, typing, clicking) and displays output in different media (text, diagrams, animations, agents). An important question regarding this module is how the tasks (materials/learning objects) should be presented to the students in the most effective way (Martin, 2001; Sottilare et al., 2013; Thai-Nghe and Schmidt-Thieme, 2015).

In this study we will essentially focus on the first three modules, the last one being more related to educational sciences and UX design than to artificial intelligence.

2.2 Learning Paths Recommendation

In this part we will focus on a technical challenge often encountered in the design of Instructional Models, but that is also strongly related to the Student and the Domain models: learning path personalization.

A learning path is a sequence of educational contents designed to guide users in achieving their learning objectives. The main goal of learning path personalization is therefore to be able to generate and recommend sequences of contents that best fit users' constraints and objectives. Thus, it can be modeled as an optimization problem seeking to maximize a certain objective function (e.g. cumulative user score, final score, time spent studying etc.) by taking into account user and educational resources parameters.

As a consequence we can see that although this problem is directly related to the design of Instructional model, it cannot be considered independently of the other two, namely the Domain model and the Student model. That is why in this section we will first discuss the main principles of the Domain and Student models before moving to recommendation engines that generate learning paths.

2.2.1 Modeling the Domain

When it comes to recommending educational resources, the first question that arises is what type of resource it is.

(Duval and Hodgins, 2003) introduced a modular content hierarchy reported in Figure 2 in which educational contents are divided into 5 abstraction levels. In the literature on path personalization methods, the most frequently used level is probably the *learning object.*

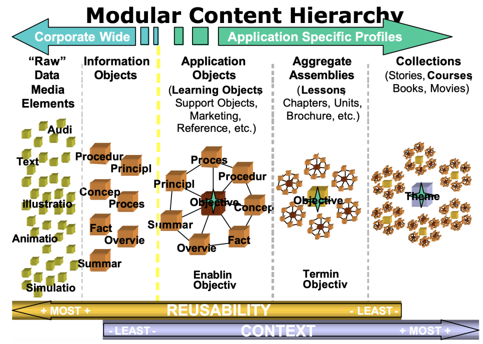


Figure 2: Modular content hierarchy by (Duval and Hodgins, 2003)

According to the Wisconsin Online Resource Center (WORC) learning objects are a new way of thinking about learning content, and this for several reasons:

- They are self-contained i.e. they can be taken independently
- They are reusable: a single learning object may be used in multiple contexts for multiple purposes
- They can be aggregated i.e. grouped into larger collections of content, including traditional course structures
- They are tagged with metadata: every learning object has descriptive information allowing it to be easily searched

A lot of information can be included in a learning object and its metadata, such as: general course descriptive data (e.g. *subject area, descriptive text, descriptive keywords*), instructional content (e.g. *text, web pages, images, sound, video*), terms glossary (e.g. *terms, definition, acronyms*), assessments, relationships to other courses (e.g. *prerequisite courses*), educational level (e.g. *grade level, age range, typical learning time, difficulty*).

There are two main classes of approaches to generate domain models: those based on manual generation and those based on automatic generation.

In the first ones, domain models are manually designed by one or more experts and defined as a graphs of concepts. Thus domain models are built as a hierarchy of concepts, with lower level concepts as prerequisites for upper level ones. The main flaw of these approaches is that the domain model becomes static throughout the learning process. (Aajli and Afdel, 2016)

The second ones are based on automatic building of domain models. To achieve this, they usually aim at assessing hierarchical relationships between the concepts identified in the corpora (often with fuzzy logic) so as to form concept maps ; then the contents are "projected" on these maps to produce documents hierarchies (Bai and Chen, 2008; Fotzo et al., 2005) which can take the form of course graphs (example in Figure 3).

Following the same idea, some methods use knowledge graphs as domain models to perform learning path recommendation (Ilkou and Signer, 2020), as shown in Figure 4.

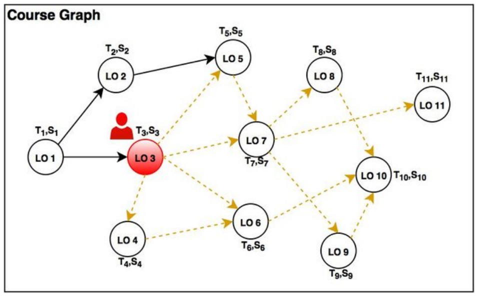


Figure 3: Course graph. Each LO has two attributes: time and score (T,S). The dash links show the potential paths for the learner who is located in LO 3. Source: (Nabizadeh et al., 2017)

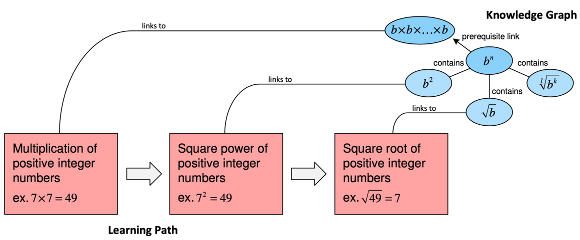


Figure 4: Proposed combination of a learning path and a knowledge graph. Source: (Ilkou and Signer, 2020)

2.2.2 *Modeling the Learner*

The Student Model is an important component of an ITS and provides the base for its personalization. During the interaction between a student and an ITS, the system observes student's actions and other behavioral properties to create a quantitative representation of this student's attributes (Sani et al., 2016).

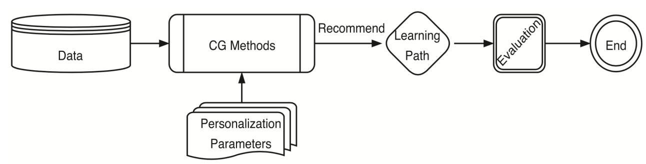
The latest research trends in Learner Modeling have been extensively described by (Abyaa et al., 2019) in their review over the last 5 years. They suggest that these approaches can be categorized according to the characteristics of the learner being modeled. Among the most common are knowledge, prior knowledge, skills, misconceptions, cognitive characteristics (working memory capacity, quickness, learning styles/preferences), social characteristics, motivation (learning goal, engagement, affect). Most works utilize combinations of these characteristics, which can be assessed using several modeling techniques:

- Clustering and classification techniques allow to assign the learner to a group that shares the same characteristics such as knowledge level or learning style (Chatti et al., 2014).
- Predictive Modeling approaches predict the learner's characteristics, such as personality traits or knowledge level. One of the most famous is Bayesian Knowledge Tracing which infers the learner's knowledge based on his previous performance (Corbett and Anderson, 2005) ; another interesting one is that of (Chaplot et al., 2016) which proposes a neural network that automatically defines the relationships between the different domain concepts.
- A third category covers Overlay Modeling where the learner's knowledge is mainly viewed as a subset of the domain knowledge (Sosnovsky and Brusilovsky, 2015).
- Another category covers Uncertainty Modeling approaches (such as fuzzy logic and Bayesian networks). These techniques are mainly used to approximate or estimate the learner's characteristics that are surrounded by uncertainties (Ferreira et al., 2016).
- The last category covers Ontology Based Learner Models. Ontologies are composed of the domain concepts and the relationships between these concepts. Their main goal is to structure the learner model and they are mostly used in combination with other techniques (Abyaa et al., 2019). Their main advantages are extensibility, reusability and the simplicity of their implementation. They can be used to model knowledge (Nonato et al., 2016), misconceptions (Hammad et al., 2017), interests (Ouf et al., 2016) etc.

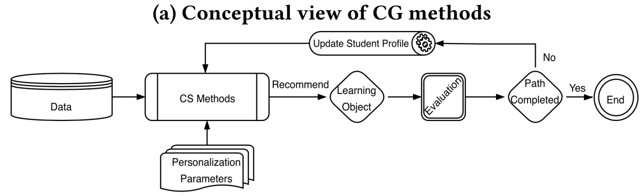
2.2.3 *Recommendation engines*

Now, given a set of learning resources and students - fully described by a series of parameters - and a learning objective expressed in a non-ambiguous quantitative form, it is possible to design a recommender engine that generates series of learning resources to help students best achieve their goals.

Such recommendation systems have already been proposed by a large number of works over the last decades and the state-of-the-art has been extensively described by (Nabizadeh et al., 2020). According to (Nabizadeh et al., 2017), these methods can roughly be classified into two main categories: Course Generation (CG) and Course Sequence (CS) methods. Conceptual views of these two approaches are presented in Figure 5.



(a) Conceptual view of CG methods



(b) Conceptual view of CS methods

Figure 5: Conceptual views of the two main approaches in learning path recommendation.
Source: (Nabizadeh et al., 2020)

Course Generation (CG)

In the Course Generation methods (CG), after determining a user's characteristics and requirements, the entire learning path is generated and recommended to him in a single shot.

A wide variety of techniques can be used, based on graph theory (Belacel et al., 2014), decision trees (Lin et al., 2013), Markov decision process (Durand et al., 2011), greedy algorithms (Basu et al., 2013), genetic algorithms (Bhaskar et al., 2010), LSTM neural networks (Zhou et al., 2018) etc.

The main limitation of these approaches is that they ignore user's performance and the changes that occur during the learning process. Therefore, users are at risk of wasting time by receiving a wrong path. (Nabizadeh et al., 2020)

Course Sequence (CS)

Unlike CG methods, Course Sequence approaches (CS) recommend a path LO by LO, as a user progresses in the learning path.

A number of methods have already been proposed, using Association Link Network (Yang et al., 2014), Evolutionary Algorithms (Govindarajan et al., 2016), Item Response Theory (Yarandi et al., 2013), Bayes theorem (Xu et al., 2012), Reinforcement learning (Cai et al., 2019) etc.

The main limitation of these methods is that they consider a fixed amount of time for all users to evaluate and update their profiles, which is not optimal since on the one hand too frequent updates are time-consuming and might be unnecessary, and on the other hand too rare updates might result in improper recommendations. Therefore the best strategy would consist in estimating a personalized time period to evaluate the user's knowledge and update his profile. (Nabizadeh et al., 2020)

2.3 Data in Adaptive Learning

The data that make it possible to design and use adaptive learning systems can be classified into four categories:

- Data on educational contents: these can be texts, tags, labels, metadata etc. that characterize educational resources and their contents
- Data on learners: these correspond to the data that make up the learner's profile. They may include information on his knowledge/academic background, his personal constraints (e.g. his time limitations), his learning goal etc.
- Data on teachers: these can be used to characterize course types and formats.
- Data on learning: these correspond to the logs, i.e. the traces left by users when using the platform (in particular their interactions with resources)

However, not all approaches use all these types of data. In particular, most learning paths recommendation systems do not use data on teachers.

Moreover one should note that it is perfectly possible to perform adaptive learning without having large volumes of data. For example, (Nabizadeh et al., 2017) conducted an *online evaluation* of their module with only 32 participants, which turned out to be sufficient to prove its effectiveness.

3 INDUSTRIAL CONTEXT

Onepoint - the partner company for this project - defines itself as an architect of major transformations of companies and public actors. It supports its clients from strategy to technological implementation in order to create new ways of working, new business models and new places.

Yet, digital transformation often requires cultural change, which involves extensive training phases.

In line with its policy of experimenting on itself the models it plans to deploy for its clients, Onepoint has developed a "learning company" approach and places all actions that promote the transmission of knowledge at the very heart of its mission.

That is why it founded the *Onepoint School*. This structure designs and offers continuous training courses with the support of more than 200 qualified trainers, who also work on client assignments. This enables a global pedagogical approach.

The *Onepoint School* has developed three main programs, which meet Onepoint's strategic needs as well as employees' need to be supported in their expertise, skills development and personal fulfilment:

- **Grow & Go:** this is a common base of training designed for Onepoint's 2,500 employees to provide them with the knowledge and skills required to meet the challenges of digital and human transformation. It is composed of 4 pillars: Cyberprotection, Data & AI, Design and Humanities.
- **Professionalizing programs:** these are certifying programs focused on innovation and adapted to current challenges.
- **The Academy:** it catalogs 150 training courses and continuously provides short sessions (up to 3 days) to improve the expertise and personal development of employees.

Also, Onepoint is currently working with top schools and universities to build co-certifying training courses.

Onepoint School aims to equip itself to be at the forefront of what is being done in terms of training. That is why it has been looking at adaptive learning as a technology that could be integrated into its training modules. Therefore this thesis is an opportunity for Onepoint to make a POC (proof of concept) by testing and validating the benefits of adaptive learning for the training of its employees and customers.

4 RESEARCH PROPOSAL

4.1 Approach

Our research proposal is based on the following observation: the different modules that compose Intelligent Tutoring Systems are usually designed separately. They are not really thought out in a global perspective focused on a single goal - recommending learning resources - but are rather considered independently of each other, in a way that the output of each module is interpretable to humans. For example, learner models usually attempt to predict characteristics that are commonly used to describe a student's profile, such as knowledge level, speed, background etc. In the same way, domain models generally allow to characterize educational resources by a set of parameters (difficulty, prerequisite relationships etc.) conceived by humans, for humans.

These "intermediate" predictions certainly allow a better interpretation of the overall framework [1] but are not necessarily best suited to a pure recommendation goal. These representations are indeed not very rich (only a few features) and therefore do not allow to exploit the full potential of modern recommendation engines.

[1] which certainly addresses major educational issues: see all the literature on Open Learner Models. According to (Kay, 1997), they can help students understand their learning progress and processes.

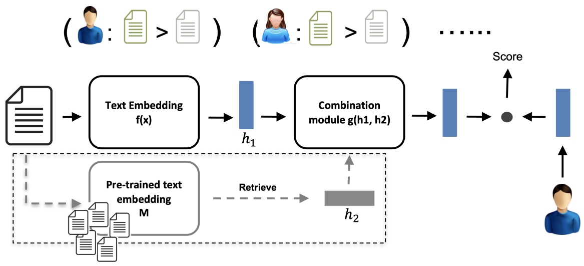


Figure 6: Texts and users embedding framework. Source: (Chen et al., 2017)

Replacing them for example by an embedding in a latent space may allow to come up with a much richer representation. It may also help to get around the problem of resource labelling, which is a very constraining issue in this research area.

Therefore the question we propose to address is the following: how to design a system capable of learning representations of both students and educational resources so as to perform learning path recommendation in an end-to-end fashion, with minimal human assistance?

To the best of our knowledge, no such approach has been proposed in the area of adaptive learning and intelligent tutoring systems. However, some researchers more oriented towards general recommendation engines have already proposed some methods to perform joint modeling of users and items in a recommendation perspective (Catherine and Cohen, 2017; Chen et al., 2017; Gan and Zhang, 2020; Zheng et al., 2017).

For example (Chen et al., 2017) designed an approach in which users and textual contents are embedded into a latent feature space, with the text embedding function being learned end-to-end by predicting users' interactions with items (see Figure 6). This model is actually combined with an unsupervised text embedding module to alleviate the "cold-start" problem, which is also mentioned by (Nabizadeh et al., 2020) as one of the major research challenges in the field of learning paths personalization.

The question that arises is then: how to apply this kind of approach to our highly constrained situation? Recommending educational resources is indeed more constraining than recommending films or ads because we need to pay particular attention to the prerequisite relationships between contents and must ensure the overall coherence of the learning paths. Consequently, we will also need to think of algorithmic approaches to structure and hierarchize educational contents in parallel with the embedding and/or recommendation phase(s).

All this suggests that we will work on a two-phase framework:

(1) An unsupervised learning phase to structure and embed educational resources (at this point no user feedback is available)
(2) An online learning phase to recommend educational resources to users while refining representations and parameters of the models thanks to users' feedback

Ideally, such a system should not exclude the possibility of adding educational resources progressively (i.e. not only at the beginning), which imposes particular constraints to the first phase.

Another issue we may want to address is the possibility to incorporate *a priori* knowledge into this framework. For example, assuming that we have a knowledge graph, or labels for each learning object, how can we allow the system (designed to build its own representations) to take advantage of this data?

Eventually, one might ask what parallels and divergences can be drawn between such an approach and the major learning theories (behaviorism, constructivism, cognitivism, connectivism etc.) and how far these theories can be used to refine this approach.

4.2 Timeline

(1) **Phase 1: 6 months**
  - Write a literature review on recommender systems coupled with text embedding processes
  - Write a literature review on domain modeling in e-learning
  - Get acquainted with the main (human) learning theories
  - Get acquainted with the main methods of texts corpus analysis
  - Start to build a dataset of educational contents suited for an experiment on learning paths recommendation
(2) **Phase 2: 6 months**
  - Write a literature review on learning paths recommendation methods
  - Design an unsupervised algorithm to embed, structure and hierarchize educational texts
  - Complete the conception of the dataset
(3) **Phase 3: 6 months**
  - Write a literature review on student modeling in e-learning
  - Design and implement an experiment to evaluate the performance of the embedding algorithm.
  - Design an algorithm that takes educational contents as inputs and recommends learning path for online users in an online-learning manner (recommender system)
(4) **Phase 4: 6 months**
  - Design and implement an experiment to evaluate the performance of the recommender system
  - Develop approaches that make it possible to integrate *a priori* knowledge into the system
(5) **Phase 5: 6 months**
  - Design and implement an experiment to evaluate the performance of the overall system (unsupervised + online learning algorithms) and to compare it with other state-of-the-art methods
  - Design and implement an experiment to quantify the impact of *a priori* knowledge on the system performance
(6) **Phase 6: 6 months**
  - Write the thesis.

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