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Learning Pathway Recommendation based on a Pedagogical Ontology and its Implementation in Moodle

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Abstract. When learners may select among different alternatives, or are guided to do so by an adaptive learning environment (ALE), it is generally meaningful to discuss the concept of different learning pathways. Pedagogically, these learning pathways may either be defined macroscopically, e.g. in terms of desired learning outcomes or competencies, or microscopically in terms of a didactical model for individual knowledge objects. In this contribution we consider such learning pathways from a pedagogical point of view and then establish a mathematical model for their traversal by a learner and for the analysis of his behavior. This model is implemented in a novel ALE provided by the EU FP7 project INTUITEL, introduced in its Moodle version as concrete example.

1 Introduction

Technology Enhanced Learning (TEL) is one of the most rapidly expanding applications of computing machines to human needs. This development is driven from two sides: We are more and more accustomed to be connected to the internet at any position in space and time, and more and more the internet becomes the dominant storage and access medium to knowledge. While the verb "to google" has found its way into standard dictionaries and therefore signals the most abundant strategy for TEL, it is most likely not an efficient way to learn large amounts of complex knowledge. At the opposite end of the spectrum of TEL we find sophisticated Learning Management Systems (LMS) that contain didactically excellent courses, presented to the avid learner in a blockwise fashion on their digital access devices. In the "Google approach" as well as in most TEL courses, content blocks, or learning objects, are freely navigable by the learner. He may, at any point in time, choose to skip one of the blocks (henceforth called *knowledge objects*), and follow his own and highly individual *learning pathway* through the informational jungle.

This freedom of choice, while being the dominant characteristic of TEL considered from the learner side, may contradict the intention of the course design - where, for instance, the didactical designer had a sophisticated model of the most efficient learning process and wished the learner to progress in this "meaningful" and "orderly" fashion. Such a concept was already envisioned by the first intelligent tutoring system, the intrinsic or branched programming of Crowder [Cr77]. In this system, a repetition was enforced if a learner failed a test, generating an individualised learning pathway. The newly recommended learning pathway included additional content and explanations, but free choice of the next knowledge object was not allowed. Since then, decades of research into Adaptive Learning Environments (ALEs) have resulted in quite a few approaches towards a more learner-centric flexible tutoring system [Br96,PL04,KBP11]. The most advanced example was recently developed in the GRAPPLE project [Br13].

A very rough classification would put the "programmed" learning close to behavioristic concepts, whereas a purely user adaptive system may be seen as a cognitivistic learner model. However, the viewpoint of modern educational sciences is somewhat different from these learner-centric systems in the sense that a certain didactical concept should appear *explicitly* at the root of the teaching process - and that user adaptivity in learning must be seen before such a didactical background. The first one promoting such a concept was Meder [Me06], followed by a few protoypical and conceptual papers [Sw07,Ro07,CLM08], but no systematic implementation has been achieved so far. At most, after a typization the learner in such a pedagogically supported ALE was supposed to follow a fixed scheme [GKI10,PLH13,RA10].

In the EU project INTUITEL[8] we are attempting to overcome these problems, by joining user adaptivity with pedagogical knowledge and freedom of choice. In particular, when a learner is progressing through a complicated knowledge space, recommendations are issued in a dialog with the learner - but not enforced. Rather, we are watching over the progress of a learner, draw didactical conclusions from his behavior and then issue recommendations based on a pedagogical ontology. We thus keep the most prominent advantage of self-paced learning, the *freedom of choice*, and avoid user modeling as well as user typization in favour of an enhanced quality of learning, extending the cognitivistic learner model into the constructivistic regime.

[8] The research project INTUITEL leading to these results has received funding from the European Union's 7th Framework Programme (FP7/2007-2013) under grant agreement no. 318496, see http://www.intuitel.eu

2 Pedagogical ontology

We use as the basis of our new adaptive learning approach a meta vocabulary and metadata system based on the web-didactics concept of Meder [Me06]. It was generalized to describe learning content, learning pathways and learning activities as suitable for INTUITEL and as a next step implemented as ontology in OWL (Web Ontology Language) [Sw13a,Sw13b]. This *pedagogical ontology* (PO) is comprised of a three level hierarchy of learning object (LO) classes linked by containment relations:

1. The topmost class is the *knowledge domain* (KD), which represents the course level of learning. Attributes of each KD are a title and a description of the domain.
2. Each KD may contain two or more of instances of the second class, named *concept container* (CC). Each CC represents one instructionally framed concept within a KD, i.e. corresponds to the lesson level of learning. Every CC is linked to other learning objects by typed relations as well as structured by the logic of pedagogical models and the resulting didactical design of the KD. These relations are assembled in *Macro Level Pathways* or MLP. Examples for such MLP are "chronologically forward/backward" and "hierarchically forward/backward".
3. The third and lowest class of LO is the *knowledge object* (KO), each instance representing one atomic item of a certain knowledge. Each CC may contain two or more KOs, and each KO may be part of several CCs. For now let us assume that the knowledge objects correspond to a learning time of three to ten minutes. KOs are assembled according to a structure of pedagogical relevance which is derived from pedagogical knowledge models or from media type models and called a *Micro Learning Pathway* or μLP.

Note, that for any particular learner his actual sequence of knowledge objects is always a linear sequence of KOs - which may, or may not coincide with the μLP and MLP predefined by the ontology.

In our first application of INTUITEL we consider four different μLP: Good-Practice Multi Stage Learning, Simulation-Based Multi Stage Learning, Open Inquiry- Based Learning and Structured Inquiry-Based Learning.

The two different Multi-Stage Learning (MSL) pathways follow a behaviouristic and teacher-centered approach, involving a cognitive, an associative and an autonomous stage. The Simulation-Based MSL includes a simulation, whereas the Good-Practice MSL involves a good practice example. This is developed in a way that in the associative stage, the learner follows the example interactively by making personal notes.

The two different Inquiry Based Learning (IBL) pathways follow an active and constructivist approach of learning [Sc13], involving seven different steps. These steps are predefined in the Structured IBL pathway and the content must be available for the learner at glance. Conversely, the Open IBL pathway predefines only very little content and is therefore highly intensive for the tutor in giving individual feedback and support.

3 Machine based reasoning for tutorial guidance

The structure of the PO allows an implementation of each knowledge domain in an adjustable way in order to correspond to the different types of learning. While this concept provides a consistent structure, it also opens inconsistencies as playgrounds, which support the flexible structuring possibile in creating KDs [Sw13a]. Consequently this structure allows a flexible way of describing KDs, because a variable re-use of learning objects and the adjustment of multiple linking in between is given.

This flexibility is implemented as a layered set of additional ontologies, which on top of the abovementioned PO consists of

- A second ontological layer, the *cognitive map* (CM), for a particular domain of knowledge. Here, the pedagogical models and the didactical designs are implemented as concrete instances of the classes defined in the ontology
- A third ontological layer, the *cognitive content map* (CCM), which relates a particular learning content to the CM for this domain.
- A *learning model ontology* (LMO), which defines additional attributes for the dynamic enhancement of CMs and CCMs with didactic aspects.
- As the foremost learner-specific layer, a *learner state ontology* (LSO), which is automatically generated from data gathered about the learner, reflecting his current state and behavior and also including the cognitive deviations to some nearby knowledge objects on predefined μLP. The task to calculate these cognitive deviations is discussed in the next sections.

INTUITEL is, to our knowledge, the only existing approach using such a layered approach to model the learning process itself [Sw13b,He14]. As may be seen in the example section below, this has already led to some pedagogical insights. Let us note, that INTUITEL already exists as prototype for five different market relevant learning management systems (LMS): Moodle, ILIAS, Crayons, CLIX and eXact, and that also handbooks, technical descriptions and a software suite exists for the usage of the INTUITEL extensions to these LMS and are, to a large extent, openly available.

4 Cognitive space

A crucial aspect of our approach consists of determining the next recommendable KOs. In the following we describe a formalism and an algorithm suited for this purpose. We assume that a certain concept container C consists of a number N of knowledge objects K_i such that $C = \{K_i | i = 1 \dots N\}$. For each particular learner, each of these knowledge objects has a measure $k_i(K_i) \in [0, 1]$ which denotes the fraction *learned* about this knowledge object. Obviously, this requires further explanation, since *learned* is an experimental result that would have to be measured by somehow testing a learner in his learning environment. Several paradigms may be distinguished then:

– Case $\mathcal{S}$: In a simple learning environment, learning results are not tested on a step-by-step basis. A teacher, or a teaching system, at a given time only knows that a knowledge object has been acessed by a learner - and must assume that it has been learned then. The value of the corresponding k_i therefore is either 0 or 1.
– Case $\mathcal{N}$: In a normal learning environment, it is recorded what fraction of a knowledge object has been processed, and it is assumed that this fraction also has been learned.
– Case $\mathcal{A}$: In an advanced learning environment, the achieved knowledge is tested after each knowledge object processed by the learner. Therefore, the value of k_i is *measured* and not *assumed* .

At any given time t, the state of the learner, henceforth called his *cognitive position*, is an N-dimensional vector

$$P_t = \{k_i | i = 1, \ldots N\} \tag{1}$$

These vectors span a multi dimensional cognitive space (MCS) which is topologically equivalent to an N-dimensional hypercube.

In our picture, learning is a discretely measured process: In each of the learning environments described above (simple, normal or advanced), the position of the learner is determined with a certain granularity in time and value. We may then connect these discrete positions by straight lines, and obtain a piecewise linear curve called a *learning pathway* L:

$$\begin{aligned} L : \mathbb{R} &\mapsto [0,1]^N \\ t &\to P_t \end{aligned} \tag{2}$$

Obviously, this is a mathematical abstraction of the MLP and μLP introduced in the previous section.

Let us also assume without loss of generality that a learner starts at zero knowledge $P_i = (0, \ldots 0)$ and is supposed to learn each knowledge object in the concept container, equivalent to a final position $P_f = (1, \ldots 1)$. The learning pathway is a piecewise linear trajectory through the N-dimensional hypercube, leading from the corner P_i ideally to the corner P_f. In the context of the different types of learning environments defined above, this trajectory then has certain attributes:

– Case $\mathcal{S}$: In a simple learning environment, each cognitive position is a vertex of the hypercube, and this trajectory is a curve along the edges of the hypercube. It has N segments and vertices, and $N!$ different learning pathways exist for a concept container with N knowledge objects.
– Case $\mathcal{N}$: In a normal learning environment, two different sub-cases exist:
  - Case $\mathcal{N}1$: Each knowledge object is gradually processed to the very end by the learner, only then a new knowledge object is started. Every cognitive position which is obtained form the learning environment then is located at one of the edges of the hypercube.

- Case $\mathcal{N}2$: The learner jumps to a knowledge object different from the current one without having finished the present one. While staying piecewise linear, the learning pathway nevertheless becomes a much more complicated line, running possibly also through the interior of the hypercube. This also includes the possibility of leaving a certain knowledge object, processing another one and later coming back.

– Case $\mathcal{A}$: In an advanced learning environment, the cognitive position is determined by a measurement of the learner's progress. Again, by connecting subsequent positions with line segments, we obtain a piecewise linear curve which traverses the N-dimensional hypercube (and might also run through its interior).

5 Predefined micro learning pathways

Let us now consider a concept container with a number of M different μLP. Each of these conforms to two requirements:

– The knowledge objects are to be learned in a linear sequence, which is given as a *recommended sequence*

$$\mathcal{R}_j = (\alpha_{j1}, \alpha_{j2}, \dots \alpha_{jN}) \text{ where } \alpha_{jl} \in \{1 \dots N\}\, ;\ \alpha_{jl} \neq \alpha_{jm} \text{ if } l \neq m \qquad (3)$$

of integer numbers. Each integer number $i = \alpha_{jl}$ denotes the corresponding knowledge objects K_i. Each sequence therefore is a particular ordering of knowledge objects in the concept container C, where some of the KOs may be omitted.

– Each knowledge object K_i is either not yet processed or has been learned to 100%, e.g., the *desired* k_i is either 0 or 1, consequently may be represented by a single bit having positional value 2^{i-1}.

The number of possible learning pathways therefore may be assumed to be very much higher than the number of predefined ones. The predefined learning pathway $\mathcal{L}_j$, i.e. the sequence of cognitive positions corresponding to such recommended sequences therefore consists of a series of N-dimensional vectors denoting the subsequent edges of the hypercube to be visited by the learner, e.g.

$$(0, \dots 0), (0, \dots 0, 1, 0, \dots 0), (0, \dots 0, 1, 0, \dots 0, 1, 0, \dots 0) \dots$$

This may be read as sequence of N-bit binary numbers having zero, one, two, $\dots$ N bits set to "1" and $N, N-1, \dots, 1, 0$ bits set to "0". The first number in this set is always 0 (i.e., *nothing learned*), and the last one is always $2^N - 1$ (i.e., *everything learned*). Let us note, that in principle the requirement of starting at $P_i = 0$ and ending at $P_f = 2^N - 1$ may be dropped. One may envisage a concept container with different entry levels, or leading to different exit levels while still using partially the same learning content.

Formally the predefined μLP may be expressed as

$$\mathcal{L}_j = (0, 2^{\alpha_{j1}-1}, 2^{\alpha_{j1}-1} + 2^{\alpha_{j2}-1}, \dots 2^N - 1); \qquad (4)$$

and the m-th cognitive position of $\mathcal{L}_j$ is obtained as

$$\lambda_{jm} = \sum_{i=1}^{m} 2^{\alpha_{ji}-1} \ . \tag{5}$$

In the next step we will compare the *actual* learning pathway L, i.e. the sequence of P_t traversed by a learner with these predefined learning pathways $\mathcal{L}_j$. For tutorial guidance of the learner it must be decided if his cognitive position is close to one of the predefined learning pathways - and if yes, what the next knowledge object would be along this predefined learning pathway. In the first approximation we ignore the learner's history, i.e., we are only interested *where* he is in the cognitive space, and not *how* he came there.

We perform a mapping of a cognitive position to the edges of the MCS hypercube by introducing another N-dimensional vector

$$W = \{w_i | i = 1 \dots N\} \tag{6}$$

denoting the *relevance* or cognitive threshold of each knowledge object for the whole concept container. Discretization then is achieved by replacing

$$k_i \rightarrow \bar{k}_i = \theta(k_i - w_i) = \begin{cases} 1 \text{ if } k_i \geq w_i \\ 0 \text{ else} \end{cases} \tag{7}$$

with the well known θ distribution. In other words: If the fraction k_i learned about knowledge object K_i exceeds its relevance w_i, we tick it off as "done". Consequently each cognitive position P_t is mapped on a "discretized" position $\bar{P}_t$ which is a vertex of the hypercube and therefore represented by an N-bit binary number.

6 Cognitive deviation

It is easy to decide whether a certain discretized cognitive position is "on" a predefined learning pathway: One simply has to check, if the N-bit binary number $\bar{P}_t$ is part of the sequence of any of the predefined learning pathways - a simple binary XOR operation.

In relaxing this condition let us consider the case where among the $\mathcal{L}_j$ exists one that is close to the cognitive position in the sense that if the learner would learn only one more knowledge object, he would be "on" this predefined learning pathway. Consequently, one would have to check for each number in the sequence of a predefined learning pathway, if it has a single bit more set to "1" than are set in $\bar{P}_t$. The number of bits different in two binary numbers is called their *Hamming-Distance* H [Ha50], various algorithms exist for its efficient calculation.

We therefore look for a binary number λ_{jm} in each of the predefined $\mathcal{L}_j$ which has a $H = 1$ to $\bar{P}_t$ and fulfills $\lambda_{jm} > \bar{P}_t$. This approach may be generalized to two, three or more knowledge objects that need to be processed in order to reach one of the predefined learning pathways.

Of course, it could also happen that the learner has learned one object more than he was recommended to - in which case one could easily lead him along this predefined learning pathway, but skipping the one knowledge object he has already learned. This situation would correspond to finding a binary number in one of the predefined learning pathways which has a $H = 1$ to $\bar{P}_t$ and fulfills $\lambda_{jm} < \bar{P}_t$.

For ease of notation, we now introduce the cognitive deviation between the two cognitive positions:

$$\Delta(\lambda_{jm}, \bar{P}_t) = H(\lambda_{jm}, \bar{P}_t) * \text{sign}(\lambda_{jm} - \bar{P}_t) \ , \tag{8}$$

e.g., we extend the concept of Hamming distance with a sign.

A proper way to lead any learner from his current cognitive position $\bar{P}_t$ to one of the predefined learning pathways then would be

- If in any predefined learning pathway $\mathcal{L}_j$ exists a number $\lambda_{jm} = \bar{P}_t$, this LP will be used in further pedagogical guidance, no further search is carried out.
- If in any predefined learning pathway $\mathcal{L}_j$ exists a number λ_{jm} which has cognitive deviation $\Delta(\lambda_{jm}, \bar{P}_t) = 1$, the "missing" KO is recommended, no further search is carried out.
- If in any predefined learning pathway $\mathcal{L}_j$ exists a number λ_{jm} which has cognitive deviation $\Delta(\lambda_{jm}, \bar{P}_t) = -1$ this LP will be used in further pedagogical guidance, but the "surplus" KO will be skipped in recommendation, no further search is carried out.
- ... continued to larger and smaller values of the cognitive distance until a match is obtained

7 Ranked recommendation as extended semantics

If one would stick to the above algorithm as the only source of recommendation, the system would behave very similar to one of "programmed learning", a very simple type of ALE. Instead, by plugging this into the layered set of ontologies we are providing a system which allows *ranked* recommendation for the next knowledge object(s) to be processed. Such ranked recommendations are, on one hand, very well known to any Web user using a search engine - and on the other hand quite novel in semantic approaches (cf. [FAE10] for more references).

INTUITEL therefore constitutes a system that calculates a set of "next recommendable cognitive steps" in the multi-dimensional cognitive space according to the pedagogical and domain dependent knowledge contained in the CM and CCM. Such a recommendation of INTUITEL may be local, e.g. limited to micro deviations from a standard learning pathway. An example for a micro decision on the learning pathway is obtained when taking into account the learning environment of the learner, e.g., bandwidth, ambient noise etc. If INTUITEL decides that this would make more sense given these environmental factors, it recommends to read a text rather than to watch a video clip or to listen to an audio object.

A didactical recommendation may also be global, e.g. involving macro learning pathways. As an example we may consider learning about the concept "gravity" in physics: We may envisage one learning pathway to be chronological, leading from Newton via Einstein to modern Quantum Gravity; while another macro learning pathway could be based on purely geometrical considerations of curved spacetime. Both of these macro learning pathways would involve, to a large extent, the same knowledge objects - but in a completely different order.

This calculation is done by passing the dynamically constructed ontology to a standard reasoner to which the INTUITEL engine is coupled. Due to an open architecture with professional middleware, this reasoner is not only exchangeable, but one may also involve several reasoners in a distributed environment, guaranteeing the scalability and extensibility of the system.

8 Concrete implementation for General Didactics

The knowledge domain "General Didactics" is adapted in order to represent a five ECTS course of the University of Vienna with an audience exceeding around 200 students. No resources are available for individual human tutoring, consequently the usage of an adaptive eLearning system is the only reasonable way to provide the individual feedback for the single learner which is necessary in these learner-centered pathways. The course provides an overview of the history of the philosophy of didactics, and is represented in Moodle as a course. Covered are twelve philosophers and seven aspects: philosophy of education, learners, teachers, institutions, goals/content, media and methods. This results in a matrix of 12 x 7 = 84 concept containers. For each philosopher one Moodle structure called a *topic* was initialized and filled with the seven aspects for each philosopher.

Four MLP (chronologically forward/backward, and hierarchically forward /backward) are possible between the CC. In each CC, the KOs will either be offered in a seven-step Structured Inquiry Based Learning (IBL) μLP, or a three-step Good Practice Multi Stage Learning (MSL) μLP. Thus, ten KOs per CC are necessary.

While Moodle implements the concept of learning pathways, it does not permit to associate a particular CC to different pathways, as required by the PO. This has led to a re-design of the classical didactical design: The first steps of the abovementioned μLP were merged into a new didactical design called "Orientation Only". In our view this example demonstrates, that research on structural and semantic aspects of learning may lead to new insights also in didactics.

9 Concrete implementation for Network Design

The University of Valladolid has developed a CM for the KD "Network Design" as course object in Moodle. It provides an overview of the principles of computer networks design and then teaches design details of different types of networks that have already been viewed in previous courses. In this course, the different types of networks are usually studied sequentially - a didactical design called "Classical Learning Pathway" and following an MLP very similar to the chronologically forward/backward pathway. Another possibility is to classify different aspects of networking in a hierarchical way and then to analyse each aspect by type of network. This didactcal design, called "Alternative Hierarchical Learning Pathway" exhibits an MLP close to the "hierarchically forward/backward" scheme described before.

Specifically, four types of networks are covered in three different perspectives. The types of networks are: IP networks, WAN (Wide Area Networks), LAN (Local Area Networks) and SCS (Structured Cabling Systems), covered in the three perspectives: technology, topology and design. In contrast to the first example, not every combination of network type and perspective yields a meaningful CC. Moreover, some adjustments have been made to balance the nature and length of each topic by splitting some CCs in two or more parts. The implementation of the CCs was also realized with Moodle *topics*.

Several different modules of Moodle have been used for implementing the different KOs of this KD. They are classified by Moodle as either *resources* or *activities*. Resources are mainly non-interactive resources such as files (of different types), links to external resources videos and texts) and "books". Activities are mainly interactive resources such as assignments, choices, quizzes and forums.

"Network Design" is a very practical course, but with a wide theoretical foundation. Therefore, although both Good-Practice MLS and Simulation-Based MLS have been implemented, the first one is most common. Simulation-Based MLS has been implemented (besides Good-Practice MLS and Structured IBL) in CC "VLAN Planning" for demonstrating how to plan a good logical design with VLANs. Concerning the two IBL pathways, only the structured IBL pathway has been implemented in three CCs (the more practical ones). Structured Inquiry is teacher-centered, with students investigating questions presented by the teacher using methodology also prescribed by the teacher. Consequently, it is preferred over Open IBL because of the structural framework of the "Network Design" course and the competence level of its students. In this application each KO has been implemented as a Moodle module or Moodle item.

The attachment of a KO to MSL or IBL is neither obvious from its name nor from any meta datum, since students of this KD have a technical profile and are not familiar with these didactical concepts. We found it preferable to use INTUITEL for guiding students along the most suitable micro learning pathway without their awareness.

10 Conclusions and prospects

In this contribution wWe have introduced the learning pathway concept of INTUITEL. It resides at the core of INTUITEL's didactical reasoning process, which therefore

– is not *test driven*, e.g. does not try to figure out which knowledge is missing in the learner and then forces him towards the learning of the missing pieces;
– is not *curriculum driven*, e.g. does not model a user and then presents to him the seemingly appropriate knowledge object.

Rather, INTUITEL emphasizes the responsability of the learner to make a guided choice of learning content - and the guidance is carried out by a pedagogically competent non-intrusive teacher, even using natural language dialog components. Consequently *freedom of choice*, which is one of the most prominent motivations to use a computer in accessing learning resources, is maintained even though the system is adaptive.

The INTUITEL concept of multi-level ontologies is not new, but generally only used in the context of static ontologies. In contrast to such static systems, INTUITEL deals with time-varying data, where a single datum (say, the failing of a test) might receive a different interpretation at different learning stages. Not only does this prevent the learner from feeling controlled by a machine, it also still requires conscious decisions to be made. According to known phenomenological models, this should contribute to the meta-cognitive skills of the learner. Two of such models are quoted here:

1. According to the Actor Network Theory (ANT), INTUITEL may be seen as a directly observed *hybrid actor*. This hybrid actor obtains his skills partly from the human learner and partly from the supporting machine [La96]. INTUITEL allows to follow the machine decisions (which lead to certain recommendations) very easily and therefore allows to test ANT.
2. The reasoning system is a direct application of the Theory of Planned Behavior (TPB) to Human-Computer interaction [Aj91]. While precursors exist for a TPB analysis of this interaction [FS08], it has not been applied to TEL before.

This moves INTUITEL towards a completely new field of constructivistic learning that so far has been mapped only theoretically.

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