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Studie: A Domain Ontology Based Solution for Knowledge Discovery in Learning and Assessment

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Abstract:

Continuous learning is a necessity in today's organizations. With the ongoing technization, technology enhanced solutions are now supporting learners, especially in situations of non-formal and blended learning. Furthermore, where workers are forced to constantly adapt to new roles and skill-sets, adaptive support solutions are mandatory. Yet adaptive and flexible solutions for learning in and across domains in the scope and need of organizations are still a rare breed. The flexible and adaptive STUDIO system for adaptive learning and self-assessment demonstrates how a well-defined use of domain knowledge helps to discover the knowledge of the learner. This article will introduce the STUDIO system and discuss based on STUDIO how user models, cognitive traits and adaptive systems can act as enablers for further flexible solutions.

Keywords: knowledge discovery, blended learning, domain ontology, assessment and pre-selection, de-linearized learning

I. INTRODUCTION

Since linear learning, where knowledge is directly transferred from teacher to students, no longer can satisfy the expectations of neither the new generations or the labour market, new approaches are needed. In this article a fundamentally new, flexible and different solution for technology enhanced learning and assessment will be considered and contrasted in the light of the current narratives for such systems, considering aspects of user modelling, learning traits and adaptive systems.

Single aspects of systems for technology enhanced learning are well explored for different applications of learning, recommendation, and assessment. The solution within this article models and uses knowledge as a network of knowledge, rather than accepting the still prevalent setting of knowledge as a set of isolated concepts, which are statically queued for learning. Furthermore, by using a network-based approach, extended adaptivity – in the dual context of the learner and the network-representation of knowledge to learn – becomes possible.

Networks are suitable to model the knowledge of people and can express how knowledge areas are related. They are applied in different knowledge focused application as in the context of human relationship management and as a general tool for knowledge modelling, assessment and pre-selection (Bizer et al., 2005; Vas, 2016). The importance of knowledge networks in learning is further emphasised by the approach of Connectivism (Siemens, 2005), where the interconnectivity of knowledge is seen as an enabler for learning. Taking connectivism one step further, individuals – as potential "external" storages of knowledge – can profit from collaborating in a connected world. Individuals can play different roles in a connected world – where identified roles can be used to optimize the building of relevant sets of knowledge, skills and attitude.

In this article we address a distinctive and well explored solution of technology enhanced assessment and learning, the STUDIO environment (Vas, 2016). The scope is to give a wholesome account of the STUDIO solution in the frame of adaptive systems. The system will be explained in the context of learning, exploring the knowledge of the user in an individual knowledge discovery process. Furthermore, the article will contrast the approach against the common technology enhanced learning narratives of user modelling, learning traits and adaptivity. Additionally, the article provides an outlook on how STUDIO can support the approach of **de-linearized learning,** that investigates the “role of IT in letting those involved in the learning process play all roles – students, teacher, researcher, practitioner - to fulfil expectations on the specific learning topic” (Abcouwer et al., 2016). This article is the basement for a data driven evaluation of the system, based on a study with more than 200 students in the field of Information Systems (Gkoumas et al., 2016).

Section II explores common aspects of approaches for technology enhanced learning and assessment, addressing how to model the learner (User Modelling), how to account for a different learning behaviour (Learning Traits) and how to adapt the system to the learner (Adaptive Systems). Section III introduces the STUDIO system in detail and contrasts the concept against Section II. Finally, Section IV describes how STUDIO can support playing different roles (students, teacher, researcher, practitioner) in the learning process.

II. TECHNOLOGY ENHANCED LEARNING – ASPECTS AND THEIR APPROACHES

Adaptive Hypermedia Systems (AHS) are a specialization of adaptive systems in education, implementing a specific user model for individual users to adapt hypermedia content as “linked content” to the user’s knowledge and goals (Brusilovsky, 1996). Henze and Nejdl split the concept of Adaptive Educational Hypermedia Systems (AEHS), based on the work of Brusilovsky, into four components: The Document Space, storing content but also meta-information and knowledge structures; the User Model, capturing information, knowledge and preferences about an individual user; the Observations, observing the interaction of the user with the system and the Adaptive Component, implementing rules for adapting the interaction of the system to the input of the complementary three components (Henze and Nejdl, 2004).

Fitting to this component model, this section will describe the user model, individual traits as an extension to a user model, and how they together shape what kind of observations can be made about users, which will highlight the concept of adaptivity in adaptive systems.

Approaches for modelling the user’s knowledge: User Modelling

In order to effectively support learners, teachers, researchers and practitioners of tomorrow, the applications they use to learn also have to adapt to their specific needs. To enable an adaptive behaviour, the system needs a conceptualisation of the user, captured as the user model (Chrysafiadi and Virvou, 2013). The user model provides the base for adapting the system to specific users by adjusting system behaviour and look, selection, rate and granularity of information presented. With a focus on the user as an individual of a designed model, Brusilovsky and Millán defines five features concerning “what to model”: “the user’s knowledge, interests, goals, background, and individual traits” (Brusilovsky and Millán, 2007).In contrast, this article will mainly focus on “user knowledge”, as captured by the ontology based domain model, and “individual traits”, to tackle and represent the observed learner’s behaviour.

A characteristic of a knowledge centred user model is that the user’s knowledge could change between two points in time. The knowledge could increase in terms of learning and decrease in terms of forgetting. As a consequence, the modelling of knowledge in an adaptive system comes with the additional need to recognise changes in the user’s knowledge and update the user model to reflect the detected knowledge changes.

A good solution for modelling the user’s knowledge are *structural models*. Structural models are based on the assumption that the domain knowledge is clustered into independent fragments which together compose the domain. Existing models can be differentiated by two considerations: what is the type of the represented knowledge – *procedural* or *declarative* – and what is the concept of comparison of the user's knowledge against an expert's level of knowledge in an area – addressed as "domain model", "expert model" or "ideal student model" (Brusilovsky and Millán, 2007).

An "ideal student model" can be directly modelled or derived from the interaction of a community by tracking the knowledge of other users in a similar domain, role or community. Especially in the latter case, the model can develop and improve over time, depending on the development of the community, or reinterpreted, based on other modelled and changing dimensions of the user model as roles and an updated background information.

A prominent example for *declarative* models is the overlay model, which represents the user's knowledge as a subset of an expert based *domain model*, while the estimation of the user's knowledge is composed of those knowledge elements in the domain model which are proven to be known by the user. An example for *procedural* models is *Learning Networks* (LN), created by Koper and Tattersall (Koper and Tattersall, 2004). Learning networks incorporate additionally to an expert-based learning network (a domain model), a graph of available learning events, called activity nodes. Users are mapped onto the learning network and create a learning track while moving from one learning event to another.

In a LN, the development of a user from one profile to another can be modelled and tracked e.g. the transition of one role to another (students, teacher, researcher, practitioner), can be tracked based on the sequence of events leading to a role change. In this regard, LNs are a powerful tool to share and recommend a learning track to other groups or individuals of learners. The caveat is that the emerging comprehensive networks are not well suited to consolidate a common knowledge domain to efficiently map the progress of the user onto the domain.

User's Individual Traits: Cognitive Styles and Learning Styles

User's individual traits are features which define the user as a specific individual in terms of behaviour and cognition. The individual traits are a collective name for a number of concepts and theories and gathers: personality traits, cognitive styles, cognitive factors and learning styles. As for the user's background, individual traits are considered as stable features which do not change or change only over an extended period of time. Individual traits are a valuable tool to adapt the interaction with the system to the specific needs of individuals or groups of users and can be used to differentiate users into groups with similar needs.

Within the literature, cognitive styles and learning styles are dominant in terms of researching individual traits. As cognitive styles and learning styles share a number of features, concepts, and considerations, they are considered to be interchangeable in some environments. Learning styles focus on human learning, while cognitive styles focus on the actual processing of information. In comparison to cognitive styles, learning styles are more actively applied and implemented in the field of adaptive systems, based on the assumption that certain learning styles have an impact on the process of learning.

Riding and Rayner define cognitive style as *"an individual's preferred habitual approach to organising and representing information"* (Riding and Rayner, 2013). Triantafillou, Pomportsis, Demetriadis and Georgiadou extend: "*Cognitive style is usually described as a personality dimension that influences attitudes, values and social interaction. It refers to the preferred way an individual processes information.*" (Triantafillou et al., 2004). Ausburn and Ausburn collect three specific aspects of cognitive styles (Ausburn and Ausburn, 1978), which can also characterize learning styles:

- *Stability: "[...] generality and stability over time and across tasks."* The majority of cognitive styles are behaving consistent across tasks for individuals.

- *Relationship to ability: "[...] minimal relationship with traditional measures of general ability."* Cognitive styles correlate to traditional measures as IQ tests but the correlation cannot account for all the variance in general ability.
- *Relationship to learning tasks: "[...] the most important characteristic of cognitive styles, at least to the field of educational technology and instructional design, is their relationship to a number of specific characteristics, abilities, and learning activities. "*

Learning styles are a well-used and well researched support for adaptive educational hypermedia but researchers also isolate limitations to the application of learning styles. One major critique is that across all present studies the general impact of learning styles on the learning performance is weak or missing at all (Coffield et al., 2004).

Robotham widens the discussion on learning styles and proposes to promote a more self-directed learner (Robotham, 1999): *Using existing inventories of learning styles, individuals are simply allocated to a narrow range of categories, containing a limited number of learning activities to which they are, in theory, best suited. [...] Higher education teaching should seek to move beyond the enhancement of performance [...] and consider the development of foundation skills, such as self-directed learning. An able self-directed learner may [...] choose to use a particular learning style that is relatively narrow in nature, but they are consciously taking that decision, in view of their perception of the needs of a particular situation.* While this critique shares the criticism of an unreflective use of learning styles it highlights a profit for adaptive systems: They can provide a conscious, self-directed choice of learning styles for content- and presentation-adaptation to the user. The choice may be supported by methodologies to detect learning styles but the choice has to be transparent to the user. In this regard a conscious selection of learning styles can complement the user model and can support the self-directed learner to fulfil the performed role within a learning platform.

Adapting the system to the learner

Burgos, Tattersall and Koper define adaptivity in the context of e-learning as *"the ability to modify eLearning lessons using different parameters and a set of pre-defined rules"*, while in contrast *"adaptability is the possibility for learners to personalize an eLearning lesson by themselves"* (Burgos et al., 2007).

They divide the phenomenon of adaptation into three types:

1. *Interface-based:* Which is also known as adaptive navigation. Elements and options or configurations are adapted in terms of properties as size, position and colour.
2. *Learning flow-based:* The learning process is adapted in terms of the sequence of learning contents. Learning is a dynamic and personalized learning path, customized to each user based on the known performance for each run of a course or system.
3. *Content-based:* The respective content of resources and activities changes based on the feedback and insights on learning.

Vandewaetere, Desmet, and Clarebout (Vandewaetere et al., 2011) extract a common ground on the development and structure of an adaptive system. In their approach, an adaptive instruction is considered as owning a tripartite nature that should be reflected in the system as separate functions. The first component captures the source of adaptive instruction (To what will it be adapted?). The second component summarizes the target of an adaptive instruction (What will be adapted?). The third component of the triple structure is the connection between the components as the pathway of adaptive instruction (How to translate the source into a target?). An overview of the concept and its building blocks is given in Figure 1.

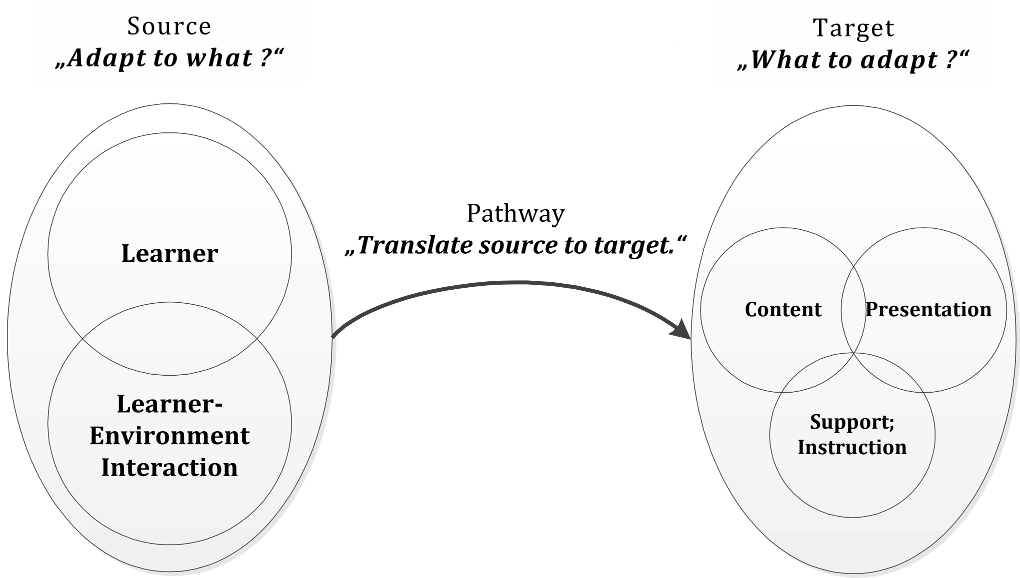

Figure 1: The Tripartite Structure of Adaptive Instruction (Vandewaetere et al., 2011).

III. THE STUDIO APPROACH TO TECHNOLOGY ENHANCED LEARNING

The knowledge within a domain can be represented in different technical and conceptual ways. Solutions can be differentiated into user model focused – modelling knowledge in the context of the user/learner – and into domain model focused – focusing on abstracting a world model to see knowledge as an extract of the real world. STUDIO makes use of the later concept and models the education as an interrelated knowledge structure, the domain ontology.

STUDIO follows a straightforward, yet powerful approach, shown in Figure 2:

1. Based on the domain ontology the learner receives questions for the domain in an adaptive self-assessment test. While the learner receives questions, his or her answers determine: what question from which knowledge area to receive next, and how long the assessment will last. In this adaptive process the system follows the network structure of the knowledge elements within the domain ontology and explores, based on the user interaction and the assessment-performance, the network of domain knowledge.

2. If the user fails considerably often, the assessment will stop and the learner will see a visualization of the domain in an interactive learning interface. Within the interface the domain visualization will colour-code the achieved assessment result with the main colours of 1) green, for correctly answered and accepted knowledge elements 2) red, for incorrectly answered elements, and 3) grey, for elements which are not explored yet. A 4th) colour is orange and highlights elements which were answered correctly but haven't had "enough" dependent knowledge elements answered correctly.

3. Based on the assessment results, the learner receives access to learning material for each assessed knowledge element. The learning material elaborates the background knowledge, needed to master each knowledge element and its questions. The access is granted for all knowledge elements which were part of the assessment. This way the learning is tailored to the learner, based on the assessment and the domain ontology.

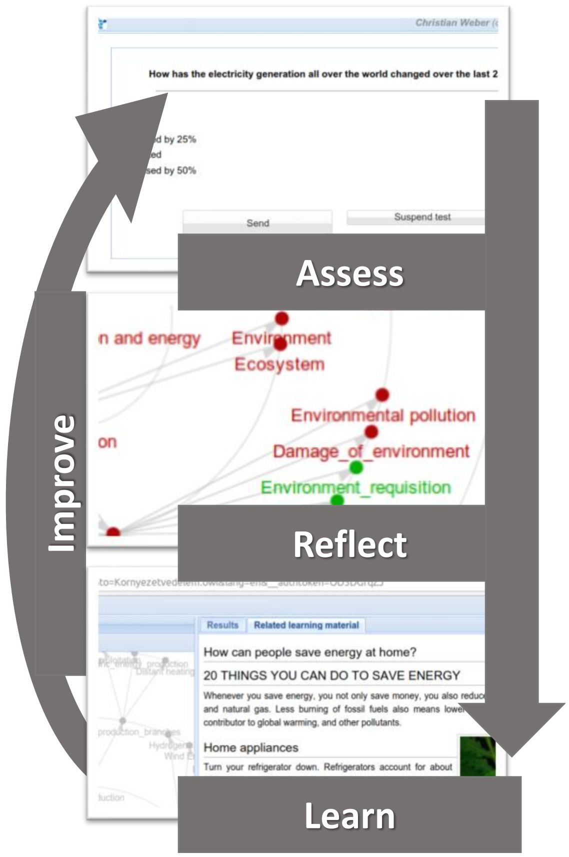

Figure 2: The STUDIO Adaption and Knowledge Discovery Cycle.

This process is designed to be accessed repeatedly by the learner to 1) frame the his/her knowledge, 2) then offer the right selection of learning material, and 3) continuously explore and unlock more material and “learn” the domain and its comprising knowledge elements. Through this cycle and its guided “learner domain ontology interaction” the system offers an adaptive tailoring of the domain’s complexity to the current understanding of the learner. The result is an adaptive assessment which “discovers” the learner’s knowledge.

A major strength of STUDIO is the domain ontology and the domain tailoring. Learners can use STUDIO to examine their knowledge in a process of self-assessment and self-learning. To set-up the learning environment, the tutor initiates the assessment domain by selecting those knowledge elements from the domain ontology which express the current domain of learning best. These selected elements are then – in an automated process – complemented by knowledge elements from the ontology. This process works based on the ontology structure and completes the desired sub-domain. The finished sub-domain is then used for assessment and learning within the system.

STUDIO is divided into three main components – the Domain Ontology, the Knowledge Repository, and the Knowledge Retrieval Engine. The Knowledge Retrieval Engine interprets the Domain Ontology, in terms of structure and semantic and adapts the adaptive self-assessment test with questions from the Knowledge Repository to the user and the Domain Ontology. Based on the outcomes of the self-assessment, the Knowledge Engine tailors learning material from the Knowledge Repository to the learning need of the user. The learning need is set into a context by the structure of the domain knowledge within the Domain Ontology. An overview of the architecture is given in Figure 3, while the components are described in detail in the following sections.

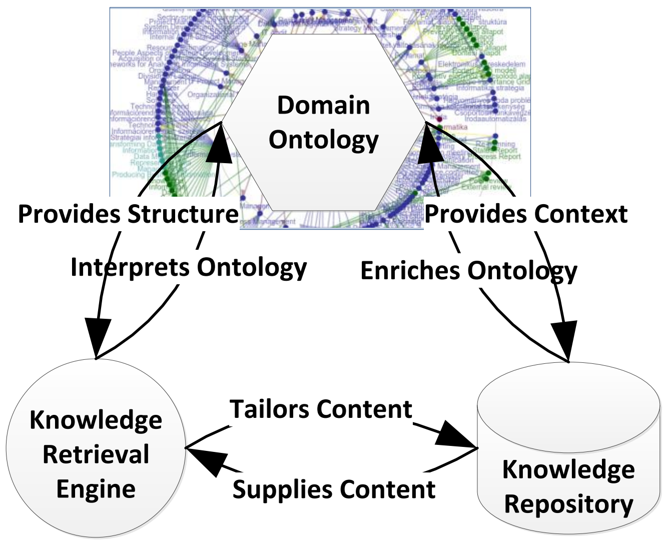

Figure 3: The Three Core Components of STUDIO and their Interaction.

The Domain Ontology

The base of STUDIO is to model the universe as a structure of interrelated knowledge elements from a learning perspective. The ontology structure divides the domain of interest into sub-domains and defines the knowledge items to know in each of these sub-areas. The model of the domain contains not only the knowledge elements but also the relations between them. Based on the relations, specific learning paths are built through which the sub-domains is mastered. These learning paths are used to tailor unique self-assessment tests for users. Using this structure assisted testing, users are not only able to find their missing knowledge, but also are able to explore the whole structure of the curricula in context – gaining insights on the relations of its parts. In this way, users are able to discover and understand the interrelations between the knowledge elements of the modelled domain.

The fundament of the STUDIO system is the domain ontology which is described in detail by Vas (Vas, 2007). In the field of knowledge management, the definition of ontology was given by Gruber, who defines it as an “explicit specification of a conceptualization” (Gruber, 1993). The ontology consists of a set of representational primitives (classes, properties and the relations among class members), which objects make it possible to build a model of a domain of knowledge (Gruber, 2009). The ontology therefore provides a conceptual framework with which the knowledge of a domain can be modelled. In the case of STUDIO, modelling is done with a focus on learning. Ontologies can model different aspects of the domain of interest and detail aspects relevant for the task of learning (Nodenot et al., 2004; Psyché et al., 2005), or describe the design, use and retrieval of learning materials (Bouzeghoub et al., 2003), or describe the learner within the learning environment (Chen and Mizoguchi, 2004).

Figure 4 shows an overview of the representational primitives of the STUDIO ontology. Due to the focus on learning, the fundamental class of the modelling toolkit of STUDIO is the *Knowledge Area*, which is detailed by additional, granular classes in order to support the precise modelling of the field of interest. The main structure of any domain is built upon Knowledge Areas, which can be recursively nested under each other in order to represent the hierarchy of the main concepts of the domain. In this way the hierarchical order of the knowledge elements is built using the *'Has sub-knowledge area'* inclusion relation. The other reason for having a hierarchical relation is to provide the potential for the knowledge engineer to break down a general knowledge area into more specific elements, which enhances the granularity of the model (Vas, 2007).

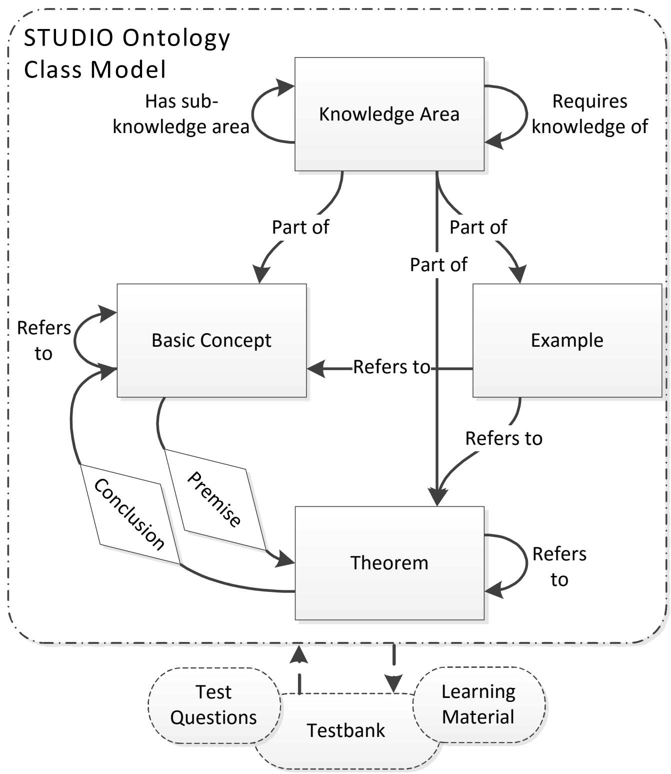

Figure 4: Model of the Educational Ontology (Weber and Vas, 2015).

Beside the hierarchical relationship, two knowledge areas can be in an ordered, non-hierarchical relationship as well, which can be modelled with the usage of the *'Requires knowledge of'* relation. The *'Requires knowledge of'* relation directly supports the testing. For example, the lack of knowledge concerning a Knowledge Area – which was required by another Knowledge Area – also points out the lack of knowledge concerning the second area (Vas, 2016). In this kind of relationship, the order of the pairs is important. If *'Knowledge Area$_{1}$'* requires the knowledge of *Knowledge Area$_{2}$* it does not mean that it is true by default from the opposite direction. The relation is not asymmetric though, but based on an explicit modelling. It is not prohibited to connect the two nodes with a *'Requires knowledge of'* relation from the inverse direction as well.

In order to support more accurate modelling and adaptive testing, the structure of Knowledge Areas is detailed in the STUDIO ontology with the classes *Basic Concept*, *Example,* and *Theorem*. "Theorems express in a condensed and structured way the fundamental insights within Knowledge Areas. They fuse and explain the Basic Concepts of the depicted knowledge and set them in relation to the environment of learning with Examples" (Weber and Vas, 2015). This way, any kind of object can be defined in connection with a Knowledge Area, to which questions can be added to enhance the adaptive testing ability of the system (Vas, 2007).

The Knowledge Repository

In the frame of knowledge-based systems (KBS) the system architecture is composed of an inference engine, implementing a core set of inference rules for the scope of reasoning; a knowledge base, storing rules and facts; and a user interface. In the scope of web-based and web-technology driven systems, e.g. in adaptive hypermedia systems (AHS), the knowledge base is seen as a knowledge repository (Leondes, 2010), storing only facts and descriptive content.

The two main goals of the STUDIO system are to give a framework with what the domain ontology can be built, and to enable self-assessment based on the formed structure. The repository contains questions and learning materials which are associated with knowledge elements of the ontology. There may be one or more questions associated with every ontology class instance.

In STUDIO multiple choice questions (MCQ) are used, with four possible answers, whereof always only one is correct. Beside test questions, the knowledge repository contains learning materials in the form of Wiki pages. A learning material comprises all the needed factual knowledge in connection with the associated ontology element. These hypermedia objects are providing support for not just textual content but for multimedia content as well. Through the integrated learning material, beside supporting self-assessment, STUDIO also provides the facility for self-improvement for the users.

The Knowledge Retrieval Engine

The flexibility of STUDIO rests on the use of the so called ***Concept Groups***, that contain only a certain, tailored part of the ontology. Concept Groups enable adaption to dynamic context in learning, including only those elements of the ontology that best fit to current learning needs. The knowledge retrieval engine can be considered as a specialized inference engine which implements testing algorithms. Testing algorithms use these tailored concept groups, based on the ontology, to determine in which order knowledge elements should be asked from the user. For our experiments two kinds of testing algorithms are developed, the drill-down and the concept-importance based algorithm.

STUDIO testing algorithms

The drill-down testing algorithm in STUDIO is based on the classical breadth-first graph traversing algorithm. From the data structure point of view, a Concept Group can be imagined as a directed, rooted tree, where the root represents the broadest knowledge element of the given domain and the branches point to the more specific areas. The aim of all algorithms is to find the “black spots” in the knowledge of the user, in other words, the aim is to discover the subset of the domain model which represents the user’s knowledge best. This subset discovery is a process of knowledge discovery and helps to understand the user – especially taking the perspective of different user roles and role interactions as student/research, tutor/student, etc., fitting to (Abcouwer et al., 2016).

In order to discover the knowledge of the user, the drill-down algorithm loops through the Concept Group (tailored domain model) and asks questions associated to the nodes (knowledge elements). First, it asks the questions connected to broader (or top level) knowledge elements, and if the answer is correct it continually goes downward the tree into the direction of the leafs, to the more specific knowledge areas. If the user is not familiar with a concept which represents a broader knowledge (giving an incorrect answer), the testing will be interrupted on the given “branch” and the concepts that require more specific knowledge underneath will not be asked. The more thoroughly the domain is known by the user, the more questions will be asked from him/her.

The test will come to an end when there are no other knowledge elements to evaluate in the Concept Group. In other words, all the concepts which can be asked based on the current level of the user’s knowledge are asked. The overall result is calculated in an aggregated manner. It is not enough if a question – which evaluates the knowledge of a concept – was answered correctly by the test taker. It is also necessary that a given proportion (by default 50%) of the underlying concepts (direct children of the node under examination) is answered correctly. For example, if the default proportion is set to 50%, a node which represents a broader knowledge element and which has four children will be accepted, if and only if the element itself was correctly answered and if, additionally, at least two of its children are correctly answered as well. The calculation is recursive, so the acceptance of the broadest knowledge element will mirror the acceptance of the more specific areas throughout the whole domain. This way a node can be in one of the three states of: accepted, passed, and not passed. Yet, a node which is passed can always only be accepted as well if it also passes the calculated acceptance criteria.

The STUDIO concept-importance based algorithm follows the idea that the question “What to learn first?” is not about simple directions but can be motivated by the consideration of “Can the structure of the sub-domain give an indication on what should be learned and tested first to explore the sub-domain best?”

In contrast to the drill-down algorithm, the concept-importance algorithm is a rating-based approach. It works on the same Concept Group structure as the drill-down algorithm. The rating of the single knowledge elements is based on three aspects: 1) the connectivity of knowledge elements, in other words the number of connections to other knowledge elements: 2) the position of the element within the concept group; and 3) the specific type of the relations connecting to the knowledge element. For every element of the Concept Group the algorithm derives each dimension and fuses them in a weighted approach to a measure. The algorithm will then make a selection, based on the measure of each node and will select first knowledge elements with a high measure (the concept-importance). So in other words, elements with a high number of connections, a position nearer to the leaves and relations with a high impact e.g. relations which indicate that the element is required by other elements are tested first.

The concept-importance algorithm explores the Concept Group freely, following and assessing the elements which are receiving a higher concept-importance. A passed knowledge element is accepted for the final evaluation if it is connected through a path of passed elements to the top-element.

IV. SUPPORTING DE-LINEARIZED LEARNING BY STUDIO

Currently STUDIO is not specifically focusing on supporting users in playing multiple roles (like students, teacher, practitioner or researcher). Yet, it offers the potential to adapt to a role perspective. By focusing on the supply of adapted and tailored knowledge, it can support different roles differently. In other words, a role approach of learning can be implemented based on the flexible and knowledge intense nature of the STUDIO approach. The potentials are here threefold (but not limited):

1. *Integrate roles into the user model:* User models are well elaborated and provide a variety of modelling perspectives. Roles could be explicitly modelled for STUDIO as part of the user background of the internal user model to reflect the current role. To account for role changes over time a Learning Network (LN) based approach can be used to trace the transition between roles over time, modelling significant events and transitions as change prequisites.

2. *Role-aware testing algorithms:* The STUDIO testing algorithms follow different concepts, but make use of the same flexible structure. The domain ontology and the Concept Group tailoring, in conjunction with the flexible Knowledge Retrieval Engine enable a variety of different test algorithms to support different strategies to learn for different roles to act. E.g. teachers can test specific blocks of the domain, practitioners receive stricter tests to be conform to organizational processes, student tests can vary stronger in length based on previous results, researchers can tweak the test parameters freely.

3. *Open selection of learning trait adaption:* Learning traits are a prominent source to decide on an adaption of the system interface and the user-interaction with provided content. By following a self-directed approach to learning the user can select the current adaption scheme actively, based on the current role he/she is acting. A student can select the (learning trait motivated) adaption he/she senses to most fit the current learning task; teachers can trial the different adaption scenarios to support and aid students in their selection; practitioners can profit from an active adaption to different learning traits to simulate scenarios which better fit the organizational environment; researchers may prepare tailored adaption scenarios for the interaction to explore the behaviour of users in other roles.

V. CONCLUSION

This article introduces the STUDIO approach. STUDIO offers a flexible and adaptive learning and self-assessment solution, using domain knowledge. In a unique process of self-assessment, reflection and learning – in the context of the domain knowledge –, the system discovers the user's knowledge and learning progress. Taking into account approaches of the well explored areas of user modelling, learning traits and adaptive systems, we show that STUDIO offers a valuable and different integration of the existing concepts. Yet there is a strong potential to take the current mix of theory and application one step further to a role-oriented mix by taking into account that users may act in systems in different roles.

Supporting different user roles can contribute to different perspectives on the system and require different ways of adaptivity. In this context of adaptivity, we the presented approach yields a considerable potential for a role-oriented vision. The system can contribute to a more de-linearized way of learning and a more conscious (take ownership of adaption) and informed (learn in context of a domain ontology) interaction of the users with their learning environment, providing a unique way to discover and extend the personal knowledge in a given learning domain.

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