Modelling Learning Experiences in adaptive multi-agent learning environments

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***Abstract*—In next generation technology-enhanced learning environments, intelligent educational systems can benefit from tapping into multi-agent, adaptive, gamified learning experiences, which transform the traditional instructional paradigm from classroom-based learning to personalised learning in any setting, whether collective or individual. Such settings enable learning targeted to each individual's learning styles and needs, through the use of autonomous technological agents as actuators of the learning process. Learning components which will respond to the needs of such an educational framework should provide capabilities for adaptive, affective and interactive learning, automatic feedback and automatic assessment of the learners' behavioural state. A novel methodology is proposed to model such components, which focuses on the representation and management of learning objects (LOs) for any educational domain, any type of learner and learning style and any learning methodology, while fostering non-linearity in the educational process. This methodology is supported by a strategy for modelling and adapting re-usable learning objectives, coupled with an ontology that enables scalable and personalized decision-making over learning activities on autonomous devices, enabling dynamic modularisation of learning material during the learning process.**

I. Introduction

The emergence of new technologies has shifted the educational paradigm towards *Smart Learning Environments (SLEs)*. [1] defines intelligent learning environments as the learning setting, able to automatically adapt to the learning context, regarding the individual learner and the educational material at hand. SLEs can serve as means to move beyond traditional, linear education towards dynamic and personalized learning, while combining formal and non-formal education (general education, vocational training, lifelong training or specific skills learning) as well as the learners' own goals (informal education).

Adaptability and non-linearity in particular, are prominent directions in pedagogy today [2] and are more efficiently achieved in game-based learning [3], since educational games can be dynamically adjusted according to the learner's interaction and performance in the game, while goal-based learning, prominent in nonlinear pedagogy, can be instilled in the game's goals, while the gameplay structure of learning has been proven to engage learners to accomplish those goals [4].

SLEs in the ICT era take advantage of modern technologies and employ intelligent, technology-enabled, autonomous agents to draw towards the individual needs and learning skills of the learner in order to enhance the learning experience and render the learning process most effective. These agents can range from common desktops and laptops, to mobile devices and interactive whiteboards and to more advanced technological instruments such as specialized robots.

Consequently, a major factor that takes part in reflecting and eliciting learner needs in such an environment is the agents themselves. Their involvement is two-fold: (i) by adapting their own behaviour to accommodate the conveyance of the learning content and (ii) by capturing, through their sensors, the learners' affective behaviour when interacting with the content, in order to provide cues to the SLE for effectively personalising the learning experience. This is especially prominent in game-based learning environment, where the challenge level of the game and the way the agents actuate it can be adapted according to the learner's affective state and in-game performance.

Learning goals and the way they can be achieved through specific learning activities can be represented in the design of a learning experience in the form of learning objects. Learning objects (LOs) is a term coined in the e-Learning field and has evolved through the years, baring several definitions [5]. A rough definition specifies LOs as "any entity, digital or non-digital, which can be used, re-used or referenced during technology supported learning" [6].

The presented approach focuses on a novel framework for modelling LOs that represent, interrelate, manage and convey the learning objectives and learning activities in an adaptive, dynamic and modular way, rather than in traditional rigid and linear structures, in game-based learning and beyond. This framework has two distinct facets: a graph-based, modelling scheme for structuring re-usable learning objectives, described in Section III-A and a holistic, formal model under which learning activities and resources can be instantiated, in the form of an ontology, described in III-B. The latter is going to constitute the main focus of the presented work, along with its synergy to the graph-based learning objectives models. Validation and verification of the ontology is presented in

Section III-B2.

II. Related Work

A common practice concerning the representation and publication of the latter are learning object repositories (LORs), in which LOs reside in a structured schema, accompanied by metadata of designated formats, and in where educators and learners can store, search and retrieve them [7]. However, in most cases, LORs amass re-usable learning material, such as educational games or exercises and free-range metadata about them, with little to no content available concerning structured learning objectives and, most importantly, structured learning activities in relation to objectives.

Attempts to narrow down the definition of LOs have pinpointed three major axes [8] that characterize them: (i) accessibility, through the use of appropriate standards and meta-data, (ii) re-usability, which implies the need for LOs to be stand-alone and functional in different learning contexts and (iii) interoperability, implying independence of learning media and systems.

To this end, the aforementioned criteria for modelling LOs in technology-enhanced learning environments, and especially so in game-based learning, consist of (i) *re-usability* of LOs, (ii) *interoperability* (iii) *self-regulation*, (iv) long-term *personalisation* support, (v) *dynamic adaptation* support, (vi) *multi-agent* settings support (involving more agents than common mobile and desktop devices), (vii) ability to adjust to *cross-level* education, i.e. from primary education to vocational training, (viii) ability to adjust to multiple *cross-learner* requirements, i.e. applicable to standard learners as well to learners with learning disabilities, (ix) ability to support *multimodal* education, i.e. formal, informal, non-formal education and finally (x) ability to convey *nonlinear* learning processes.

A. Adaptive user-centric LOs

Overall, personalization and adaptation in learning environments usually concerns adaptation with regard to the learners' individual learning styles, their competencies and requirements and their affective response to smart agents. A major focus of adaptive learning systems involving LOs, pertains to e-Learning in particular and concerns the retrieval of suitable LOs for a user from a plethora of educational LOs available in online resources.

The Moodle_LS environment [9] employs a graph-based technique for educators to search and retrieve personalized LOs in LORs, based on metadata describing learners' personal attributes. The authors of [10] employ utility functions on learning context and fuzzy weighted multicriteria decision analysis to highlight the highest quality LOs out of a large set of e-Learning LOs. The work of [11] proposes a way to find the optimal path to travel across a hierarchical graph of nodes-lessons and edges-activities, based on the users' learning styles, via an ant-colony optimization algorithm. However, none of these approaches support adaptive, personalised or non-linear experiences, or self-sustained and reusable LOs.

Few learning environments proposed delve into the collaboration of learning agents or learners. The authors of [12] deal with collaborative robots, where "autonomous agents-robots pursue joint goals". Robots react with learners and accumulate information about the learners' affective behaviour towards a LO, while they exchange and combine this information to gain a clearer insight over the learner's styles.

[13] discusses the requirements and framework by which a personalized learning course can be constructed, tailored to learner's styles, while being aware of the course goals and relationships among LOs. Its constructors are the course requirements, the learner profile and the dependencies and semantic relations between LOs. It allows the educator to adjust the course and the learners to adapt their resources according to the type and amount of LOs needed for each learner to achieve a learning goal, however there is no implicit adaptation of the learning experience based on the LOs.

B. Knowledge-based approaches

A significant part of prior art focuses on employing ontological approaches to the representation and management of LOs, for over a decade, aiming to bring continuous and adaptive learning to the Web 3.0. Such approaches take advantage of the need for LOs' re-usability and self-sustainability and explicitly specify in ontological formalizations (i) educational content, (ii) teaching techniques and (iii) the structure of LOs for use in different systems [14]. They are oriented towards recommending aspects of the learning process to the users [15] according to their affective, cognitive and social history over educational content. These adaptive learning systems use ontological knowledge to personalize the learning experience according to each user's needs and learning styles [16] [17] [18] [19].

The Learning Activity Reference Model (LARM) [20] provided a generic reference model for representing learning activities and designing their procedural outline. It defined a learning activity as "an interaction between a learner or learners and an environment (optionally including content resources, tools and instruments, computer systems and services, 'real world' events and objects) that is carried out in response to a task with an intended learning outcome". In the LARM model, a taxonomy of learning activity characteristics was employed, which provided pre-defined denominations for different types of characteristics, spanning from general learning competences to definitions of learning contexts, roles of human mediators, to characteristics of learning styles and to listing electronic educational tools and resources.

While providing a solid starting point to structuring LOs and the learning experience, this taxonomy was not generic enough nor complete enough to model several aspects of multi-domain LOs and several conditions of SLEs, while it remained rigid to adapting to advances in educational technology, especially regarding the introduction of new educational agents with the evolution of ICT. The approach in [17] in particular addressed more recently the lack of a plausible methodology in literature to, not only personalise LOs according to learning style, but also connect this suitable content to the virtual learning environments, and subsequently to the virtual (technological) mediators, the users are educated through. They developed appropriate ontologies of learning materials, user learning styles, learning activities and contexts and interconnections between them.

The ontology of [4] proposes a model for learning objectives and learning activities modelling in game-based learning environments in particular, fostering re-usability and interoperability of modelled LOs, to support however a linear iteration of game-based learning materials, disregarding personalised and adaptive experiences over them.

However all aforementioned approaches fall short support of multi-agent, cross-learner and cross-level education and suffer from the static nature of predefined knowledge bases which does not allow for nonlinear learning experiences, apart from [16] which considers a nonlinear personalised selection of the learning objective for a user based on their static preferences and the preference of similar learners. On the other hand, the work does not supporting dynamic adaptation of this process based on the learner's reception of the objective.

III. Modelling framework

The approaches mentioned in the previous section induce an ambiguity in the definition of LOs. Most approaches, e.g. [17], imply that LOs consist mainly of the learning materials that convey the curriculum, i.e. the educational games in a game-based learning environment, and exclude learning objectives, the learning context and related activities (of the learning process actuator) from the definition. This restriction is not necessarily in line with the general definition of LOs by [6], which does not exclude any of these aspects being characterised as learning objects, as long as they conform with the characteristics of reference-able and re-usable educational contentsince they too consist of autonomous entities in technology-supported learning. In fact, the need to model all these aspects, according to the LO modelling criteria mentioned in the previous section, is imminent for enabling efficient learning experience design in multi-agent adaptive SLEs.

To this end, this section defines and details a novel framework for modelling LOs, in terms of both learning objectives as well as learning activities and material, that fulfills all the LO modelling attributes and fosters the capabilities of the digital era. The proposed modelling framework defines structures that represent re-usable, self-sustained, accessible and interoperable LOs that can take part in an end-to-end learning experience and supports highly personalised learning experiences in game-based learning and beyond.

Furthermore, it promotes dynamic adaptation and nonlinearity in learning by (i) enabling interaction of learners within a smart learning environment in a ubiquitous manner and (ii) incorporating and sharing different knowledge and experiences across actuating agents, thus providing a new, integrated, interoperable approach in learning. Such a holistic approach can serve a variety of educational domains, spanning from mainstream education and special needs education to vocational and industrial training.

A. Graph-based modelling of learning objectives

The main component that defines the learning content in a learning process is the learning objectives. One or more learning goals can be defined, denoting learners' skills or knowledge [21] over a comprehensive learning objective. In essence, *learning goals* consist of the particular competences the learners need to acquire in order to achieve a specific learning objective.

An innovative, optimal and nonlinear discretisation of the learning process, as well as a novel learning approach is opted through Smart Learning Atoms (SLAs). *Smart Learning Atoms (SLAs)* are atomic and complete pieces of learner knowledge and/or skills, which can be learned and assessed in a single, short-term learning session, i.e. in each iteration of the learning process. SLAs essentially comprise primordial learning goals, constituents of more advanced learning goals, that cannot be further reduced to more primitive notions. Therefore, such atomic learning goals can interoperate as constituents of more complex and objective-dependent learning goals, with their irreducible (atomic) nature rendering them re-usable in any given learning context and in many different learning objectives.

Although several pedagogical approaches aimed to define generic and specific structures under which to organise learning goals, such as Bloom's taxonomy [22], which classifies the process to achieve educational objectives in the cognitive, psychomotor and affective domains, or the mid-level skills classification taxonomy used in LARM, there is still no realistic way for educators to universally represent all possible types learning goals of different learning experiences (e.g. of different school course, training subjects, etc.), in different educational settings. Which means that the vastness of the learning objectives and specific learning goals in different domains and educational levels cannot be realistically represented under a single pre-defined schema, such as an ontology or a learning goal database. Even predefined linked data schemata for education [23] are hampered by the major deficits of all Linked Data: volume and inconsistency [24].

Consequently, the learning content can reliably be defined by the educator alone, given the learning objective at any given learning context. To this end, the proposed framework allows the educator to freely construct ***Learning Graphs (LGs)*** for each learning experience targeting a specific objective. These directed graphs represent the learning goals (atomic or complex) and relations between them. The learning goals comprise the nodes of the LG, with the SLAs consisting leaf nodes of the graph. Each relation between two nodes bears a significance weight which denotes the participation of the source node (SLAs or simpler learning goals) to the target node (composite learning goals). Obviously, SLAs as atomic entities cannot be related with each other, as no simpler notion can participate in an SLA, but rather only with their target learning goals.

By enabling educators to define learning goals and SLAs under interconnected Learning Graphs, the learning content and the learning process become tangible, exchangeable educational material that can be re-used by other educators. Accessibility to constructed SLAs and Learning Graphs is ensured through a cloud-based learning content editing mechanism, where publically available SLAs and LGs will be at the disposal of the users of the educational platform that will sustain the described models.

LGs can autonomously guide the procedure of materialising a learning process and ensure the fulfillment of an educator's teaching objective, thus are self-regulated. When a LG is created it is unpersonalised, i.e. it is the same for all learners that partake in a learning experience, thus LGs are self-sustainable.

However, personal instances of a core LG are assigned per learner during a given learning experience, in which SLAs will adapt (thus the term 'smart') to each learner in a different way based on their particular long-term needs and styles, as well as based on their affective response to the learning activities. This adaptation is represented by a competence weight, assigned to each SLA of the graph for this learner.

This competence weight will evolve in the short-term, during each iteration of the learning process, based on the learner's affective state (e.g. engagement, boredom, frustration). This affective state is tracked through the sensors of the technological agents conveying the learning materials and recognised by computer vision mechanisms (e.g. facial emotion recognition etc.) as well as through the learner's performance over the learning activities (e.g. the score in an educational game, the completion of certain tasks, etc.), while the learners are performing learning activities. The overall, long-term, state of the learner's competence, is computed based on the aggregated short-term statuses of the user, allowing to monitor the overall progress of the user over a graph's SLAs. The mechanisms used to capture the affective state and overall competence of the learners are out of scope for this paper.

The short-term fluctuation of SLA weights aims at dynamically adjusting the learning activity during the learning process, e.g. on-the-fly adaptation of a game's challenge level, in order to maintain the learner's engagement in the learning process. The long-term competence aims to determine the progress of the user in the particular learning experience and accordingly determine the most suitable learning materials for the user in order to maximise the efficiency of the learning process, i.e. converge faster to the completion of the learning objectives.

In turn, the learning goals of the LG are assigned with a weight derived collectively (*weighted average*) from the weights of the SLAs (and of learning goals where applicable) in each goal's neighbourhood, in accordance to the edge weights connecting the goal with its (source) neighbour. Formula 1 describes the learning goal weight computation for an LG $G = (V, E)$, where V are the LG nodes (SLAs and learning goals) and E the LG edges, $e \in E$, $u, v \in V$, $v \xrightarrow{e} u$, w_{e_i} is the educator-defined weight of e and w_{v_i} is the personalised weight of v for a given user .

$$\overline{u} = \frac{\sum_{i=1}^{n} w_{e_i} w_{v_i}}{\sum_{i=1}^{n} w_{e_i}} \tag{1}$$

Figure 1 illustrates two instances of an LG for two learners (portrayed as two different different sets of weights on the base LG).

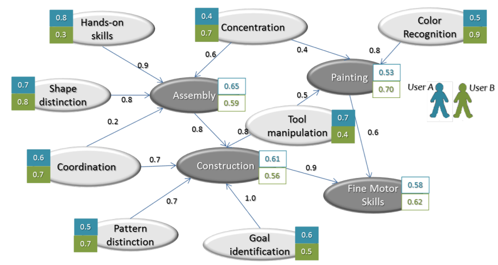

Fig. 1. An example of personalised LGs for two learners

This non-sequential graph structure allows for different goals to be pursued during different learning sessions, or even within the same session, based on the response of the learner to the learning process, as long as their overall achievement. Therefore, goals' fulfilment priority is adjusted on runtime, promoting goals with weaker achievement per learner. I.e., if a goal is achieved to a sufficient degree during a learning session while another goal remains significantly low, the personalisation and adaptation functionality will opt to move on to the goal in which the learner is now less competent on, while consequently selecting new SLAs to be taught/trained, thus altering the learning process. This allows detachment from the traditional linear educational paradigm and moving into an even more personalised learning process.

B. Knowledge-based modelling of learning activities

Learning activities and the resources that can actuate them are as vast as the learning objectives. However, the more abstract manifestations of types of resources (e.g. high-level types of learning activities, of learning contexts, of technological agents and of learning materials), especially so in game-based learning, where agents are the actuators of the learning process, can be finite. Thus, they can be represented under a structured, holistic schema, such as an ontology, which also models pre-defined relationships and logical restrictions between them.

A key objective for learning activities and the conditions that pertain to their materialization is for them to be reusable and extendable across learning contexts, but also across learning experience actuators (agents) and contexts that are not currently envisaged, e.g. emergence of new technologies that will bring forward a completely new type of agents. For this reason, the modelling framework defines *Learning actions (LAs)* as precise learning activities to be deployed in the real world, which each smart agent of a multi-agent SLE interprets in different ways, based on the learning materials available in different learning settings (e.g. classroom, factory, etc.). Learning actions stimulate and convey the learning process for one or more specific pieces of knowledge/skills (i.e. SLAs) to the learner.

Learning actions would be vast and diverse for each embodiment of a SLE, in different learning contexts (classrooms, factories etc.) and given the technological agents available to be used in these contexts. However, it is significant for their efficient use and re-use, and also with respect to efficient sharing of knowledge across agents, to have a standardised, uniform vocabulary to classify this information under. To this end, ontologies provide the needed expressivity and semantic basis to model this information (concepts), as well as the relationships among them, that affect the materialisation of learning actions.

In the design of the learning experience, specific Learning Actions are attached to each SLA of a Learning Graph. When the system promotes a specific learning goal for a personalised LG instance, so in extent promotes to improve the competences represented by the SLAs that comprise this goal, the Learning Actions attached to these SLAs are selected by a decision support support system, prioritised based on each specific SLA's weight.

1) Learning Actions Ontology: The re-usable, upper, **Learning Actions Ontology** (LAO)[1] is engineered, to serve as the uniform vocabulary under which all specific learning actions and conditions pertaining to their materialisation can be instantiated. It models a categorisation of generic to more specific types of Learning Actions, along with their semantic relationships with materialisation conditions, such as the learning materials that tangibly execute the learning action for any given type of learning context and agents that can support a given material.

This ontology will be used as the backbone for attaching agent-agnostic and context-independent learning actions to SLAs and for determining the agent-specific interpretation of these learning actions in different contexts.

The first version of the LAO has been developed under the HCOME human-centered engineering methodology [25], through a process of requirements gathering based on interviews and questionnaires among domain experts, including pedagogical, psychological and technical experts.

In order to build the first version, LAO engineers consulted with technical experts whose field of work focuses on collaboration among technological agents and computer vision. Based on their feedback, the sub-hierarchies concerning types of agents that can partake in a Learning Experience was filtered, and the need to model their sensorial capacity of agents arose, to enable knowledge sharing among different types agents, in the context of affect-based adaptation.

The most intricate part was gathering information from the pedagogical aspect. To this end, the LAO engineers conducted a survey involving pedagogical and psychological experts. Eight participants, covering all different learning contexts, from mainstream and special needs learning to vocational training, filled in an online questionnaire, based on examples of concepts and suggestions for the remaining concepts. Their responses have ultimately guided guide the creation of the first version of the LAO ontology.

[1]https://github.com/learningactionsontology/lao

This version will be used in large-scale forthcoming pilots for validating the educational platform that will utilise the described models and will be subject to validation and revision by on-site educators, based on interviews that will be conducted for the next development cycle.

Six top concepts comprise the Learning Actions Ontology: *Learning Action*, types of *Actuators* (a generalised term of technological agents), *Context* (comprised of the types of learners and the types of learning environments), *Learning Material* (types of different learning materials), *Learning Material Identifier* (categories of identifiers, e.g. RFIDs, QR-Codes, URLs etc.) and *Sensor*. These concepts, along with the relations among them, can serve as a holistic, uniform vocabulary, under which any specific learning action, material, available actuator and the context under which they are deployed, can be semantically connected in a structured way.

The *Learning_Action* top concept (Figure 2) is the central facet of the ontology. The top level LA hierarchy is what can be potentially attached to a LG's Smart Learning Atoms (SLAs). These actions need to be generic and materialisable through different agents. A minimal sub-hierarchy can be modelled, under which the general, agent-agnostic, learning actions can be broken down to more specific ones, which may (or may not) be bound to one or more actuator categories, thus enabling the possibility to model all possible interpretations of an action across all potential agents.

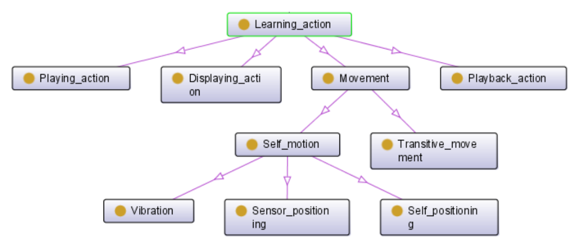

Fig. 2. Hierarchy of the *Learning_action* concept

Agent-specific actions might be non-exhaustive, but LAO aims to model a complete collection of the most abstract actions that can be performed by any type of smart agent, in order to enable creation of corresponding restrictions that will guide the interpretation of LAs per smart agent.

The *Actuator* top concept (Figure 3) contains a hierarchy of types of agents that can be used in a multi-agent SLE. The concepts in this hierarchy are generic enough so that any type of agent available today or envisioned to be used in the future can be instantiated. Different agents of the same type can also be instantiated within a learning experience, by mapping the agent's unique ID to the actuator type, e.g. two different smartphones can be instantiated by their device ID (or a combination of these) under the *"Smartphone"* concept (e.g. `<LG-H500f : Smartphone>`, `<GT-I9505: Smartphone>`).

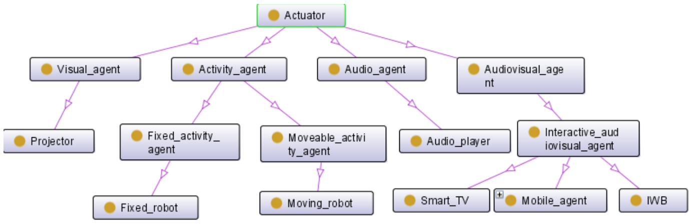

Fig. 3. Hierarchy of the *Actuator* concept

In the same manner, the *Sensor* top concept (Figure 4), can be used in order to attach specific sensorial capacities to particular Actuators, which will subsequently enable knowledge sharing among agents, and most importantly the introduction of new agents to the system, based on the agent's sensorial capacities. In this way, affect-based adaptation can continuously accommodate technological advances when a new, unforeseen, type of agent is injected to the system and affect recognition can be achieved with little to no re-training of the computer vision methodologies (mentioned in the previous section) based on common sensorial capacities the new agent shares with known agents.

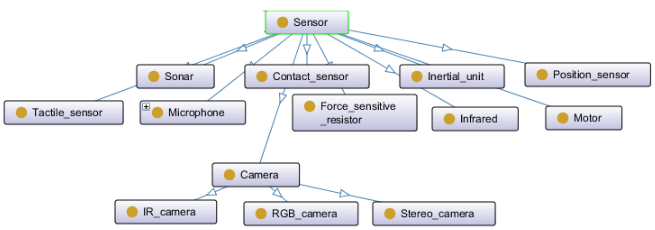

Fig. 4. Hierarchy of the *Sensor* concept

The *Context* top concept (Figure 5) contains the types of contexts that might affect the learning experience. They are broken down to two sub-facets: (a) the types of learners (in terms of learning/interaction capabilities or difficulties) and (b) the types of learning environments.

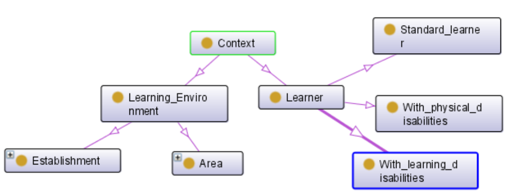

Fig. 5. Hierarchy of the *Context* concept

The former can be instantiated based on user information such as pre-defined medical and behavioural conditions, declared in an explicit learner profile and attached to a user dependent trust score, modelled as a data property (*hasTrustScore*) with *Actuator* and *Learner* as domains and a double data type as range. This property helps model the level of trust on affective state recognition for different types of users. For example, given the fact that the affective response of people with profound and multiple learning disabilities might differ substantially among different learners with different kinds or levels of disability, this trust score will help representing the degree as to which recognition of facial expressions can be reliable in a learner as opposed to another. An agent-based trust score might also be modelled in the case of actuators, where different precision might be expected given the type of smart agent involved in implicit recognition of learner behaviour (based on e.g. technical capabilities of the agent).

Lastly, LAO models types of learning materials (*Learning_material* top concept as seen in Figure 6) and types of identification means for the materials (*Learning_material_identifier* top concept, Figure 7). Learning materials (LMs) consist of specific digital and/or physical resources and artefacts that are involved in the materialisation of a learning action.

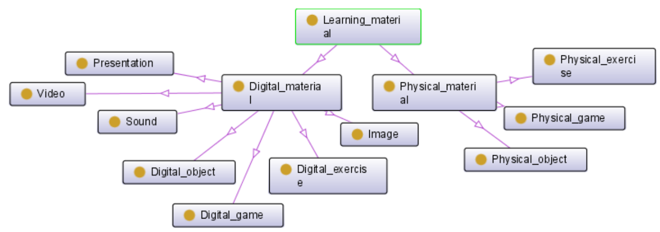

Fig. 6. Hierarchy of the *Learning_material* concept

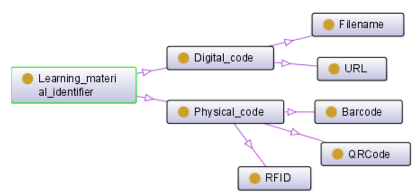

Fig. 7. Hierarchy of the *Learning_material_identifier* concept

In addition to the concept hierarchy, the Learning Actions Ontology models relations between concepts, through object properties (providing the means to create relations among concepts) and datatype properties (providing the means to create relations between a concept and a value (free-text, number etc.), such as the *hasTrustScore* data property). Object properties include relations such as *materialises*, with *Learning_Material* as domain and a *Learning_Action* as range, denoting that a Learning Material materialises a Learning Action, or *performableBy*, with *Learning_Material* as domain and *Actuator* as range, denoting that a Learning Material can be performed by an Actuator. It also models axioms modelling specific rules, applicable globally in the domain.

For example, axiom $((\exists \mathsf{materialises.Learning\_Action}) \sqcap (\exists \mathsf{performableBy.Actuator}) \sqsubseteq \mathsf{Learning\_Material})$ denotes that a specific Learning Material can be inferred (chosen by the decision support system) only if there exists in the current setting a Learning Action that it materialises and at the same time it is performable by an active agent. Axiom ($\mathsf{Learning\_Environment} \sqsubseteq \forall \mathsf{hasActuator.Actuator}$) restricts the individuals of object property *hasActuator* to both the Learning Environment (domain) and the Actuator (Range), i.e. stating that a particular environment is coupled with specific agents, and only those can be active for that environment.

The former axiom is useful for electing one or more learning materials (games) to be executed for the user for a particular promoted Learning Action, based on the particular agent that is active in the current time and setting. The latter is useful for limiting the former to agents that are available in a particular environment, if a learning experience is executed in different times at different environments for the same user (e.g. in the classroom with a robot or later at home on a tablet).

2) LAO validation and verification: Verification of LAO, i.e. ensuring that the ontology implements its definitions and requirements correctly [26], was based on its compliance on the questionnaires fulfilled and the requirements that the technical experts have posed. Furthermore, consistency checking of the ontology was performed via the LiFR reasoner [27], on an ABox[2] instantiating all concepts and relations of the ontology.

Validation of LAO, i.e. assuring that the ontology really models the world for which it was created [26], was performed through its use in eight simulated scenarios, defined by educators for the Learning Management System (LMS) that the ontology is going to be used in. These scenarios pertained to particular learning experiences, modelled based on the proposed framework. These learning experiences included particular Learning Graphs, with their SLAs attached to several Learning Actions and several materialisations involved for each Learning Action per different learning contexts.

Using the LiFR reasoner and the instances that were derived from these scenarios (of Learning Actions, Learning Environments and Actuators and their relations with particular Learning Materials) the ontology succeeded to accurately to fulfill the tasks that the world it represents requires, pertaining to the recommendation of the appropriate Learning Materials per a given context, prioritised based on the priority level of the Learning Actions, as those were extended through the competence weight of their attached SLAs.

For example, given a Learning Experience that may take place in a particular classroom of a school on a particular robot, in another classroom of the school on a particular Interactiive Whiteboard or at the learner's house on their particular smartphone, given the active setting (classroom #1, classroom #2 or home), the system was able to recommend the appropriate Learning Material for each setting, given the same list of Learning Actions, with a priority weight, corresponding to the priority of each Learning Action. A particular example can be seen below.

LAO axioms (subset)

$((\exists \mathsf{materialises.Learning\_Action}) \sqcap$
$(\exists \mathsf{performableBy.Actuator}) \sqsubseteq \mathsf{Learning\_Material})$
$(\mathsf{Learning\_Environment} \sqsubseteq \forall \mathsf{hasActuator.Actuator})$
$(\mathsf{Robot} \sqsubseteq \mathsf{Actuator})$
$(\mathsf{IWB} \sqsubseteq \mathsf{Actuator})$
$(\mathsf{Smartphone} \sqsubseteq \mathsf{Actuator})$
$(\mathsf{Classroom} \sqsubseteq \mathsf{Environment})$
$(\mathsf{Home} \sqsubseteq \mathsf{Environment})$

Learning Experience instances - apply for any setting for the given LG

$< \mathsf{naomark230} : \mathsf{Learning\_Material} >$
$< \mathsf{rfid134} : \mathsf{Learning\_Material} >$
$< \mathsf{turnover} : \mathsf{Learning\_Material} >$
$< \mathsf{shape_in_slot} : \mathsf{Learning\_Material} >$

$< \mathsf{athena} : \mathsf{Robot} >$
$< \mathsf{iwb\_2819fd} : \mathsf{IWB} >$
$< \mathsf{lg500f} : \mathsf{Smartphone} >$

$< \mathsf{naomark230}, \mathsf{athena} : \mathsf{performableBy} >$
$< \mathsf{rfid134}, \mathsf{athena} : \mathsf{performableBy} >$
$< \mathsf{turnover}, \mathsf{iwb_2819fd} : \mathsf{performableBy} >$
$< \mathsf{shape\_in\_slot}, \mathsf{lg500f} : \mathsf{performableBy} >$

$< \mathsf{naomark230}, \mathsf{matching\_shapes} : \mathsf{materialises} >$
$< \mathsf{rfid134}, \mathsf{find\_diff\_shapes} : \mathsf{materialises} >$
$< \mathsf{turnover}, \mathsf{matching\_shapes} : \mathsf{materialises} >$
$< \mathsf{shape\_in\_slot}, \mathsf{find\_diff\_shapes} : \mathsf{materialises} >$

Current setting instances - apply only in the current situation

Currently there are two learning actions, with two different priority weights

$< \mathsf{matching\_shapes} : \mathsf{Learning\_Action} \geqslant 0.7 >$
$< \mathsf{find\_diff\_shapes} : \mathsf{Learning\_Action} \geqslant 0.5 >$

Currently learner is in classroom1, that has only a Robot available

$< \mathsf{classroom1}, \mathsf{athena} : \mathsf{hasActuator} >$
$< \mathsf{classroom1} : \mathsf{Classroom} >$

The system responds with Learning Materials *naomark230* and *rfid134* that can be performed by the Robot *athena*, with respective priority weights 0.7 and 0.5 corresponding to the weights of the actions *matching_shapes* and *find_diff_shapes*. I.e., the system has eliminated materials *turnover* and *shape_in_slot*, since they cannot be materialised by a robot, the only active agent in the particular premise (*classroom1*) and has prioritised play-able materials according to the importance of the learning actions they materialise.

Similarly, the system responds accordingly when the classroom with the IWB is active or the home environment is enabled.

IV. Conclusion

This paper has presented a complete methodology to model reusable and interoperable Learning Objects (LOs) in learning experiences designed for adaptive, multi-agent Smart Learning

[2]Assertion Box, i.e. facts that instantiate entities of a TBox (an ontology)

Environments. This includes the representation of learning objectives and activities. The main modelling facets of this methodology are: (i) Learning Graphs, consisting of interrelations between primitive, self-sustained learning goals called Smart Learning Atoms and more complex learning goals for a particular learning objective, (ii) the Learning Actions Ontology, semantically representing learning actions that teach/train SLAs and given the materialisation conditions in a given learning environment.

Such a framework is as generic and as inclusive needed in order to model LOs and actuate efficient learning experiences for a wide range of learning domains and learner types, from elementary education to vocational instruction and from standard learners to learners with profound and multiple learning disabilities. Game-based environments particularly benefit from this approach, since it allows to fully harvest the adaptability and non-linearity of game-based pedagogy. The accessibility of the LO models is insured by (i) the publication of the LAO ontology and (ii) the adoption of cloud-based repositories for storing and retrieving LGs and SLAs, in accordance to privacy and ethical issues concerning the learners and LG creators (educators), as per the Learning Management System (LMS) that will deploy and employ the models.

Future work will capitalise on the proposed models by employing them to a LMS and validating them through three distinct phases of large-scale pilots in real-world scenarios and educational settings.

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