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Adaptive game-based learning in multi-agent educational settings

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Abstract The traditional educational paradigm has been nowadays transformed to tech-aided personalised learning, tailored to individual learning styles and needs, applicable in any environment. Such an educational framework should provide capabilities for adaptive, affective and interactive learning, taking advantage of technological means to recognize the learners' performance, behaviour and progress over the learning process. A novel methodology is proposed to model an educational framework able to represent and optimally foster these needs, along with a methodology for non-linearly adapting networked learning objectives. In addition, the framework is supported with an ontology that enables personalised and contextualised decision-making over learning activities on autonomous devices, enabling their dynamic modularisation during the learning process.

Keywords Adaptative learning · multi-agent learning environments · learning activities ontology · graph-based learning experience · spectral analysis

1 Introduction

The emergence of new technologies has shifted the educational paradigm towards the full incorporation of technological solutions (Srisawasdi and Panjaburee, 2016) and has thus led to *Smart Learning Environments (SLEs)*. (Sampson and Karagiannidis, 2010) defines intelligent learning environments as the learning setting that is 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).

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Adaptability and non-linearity in particular, are prominent directions in pedagogy today (Chow, 2013) and are more efficiently achieved in game-based learning (Adcock and Van Eck, 2012), 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. In addition, a gameplay-based structure of the learning process has been proven to engage learners to accomplish learning goals (Raies and Khemaja, 2014).

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

Consequently, a major factor that takes part in eliciting and even predicting 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 environments, where the challenge level of the game and the way the agents materialise it can be adapted according to the learner's affective state and in-game performance.

The autonomy and learner-specific approach that such an environment offers allows for highly personalised, goal-driven learning approaches to be pursued in modern educational settings. Learning objectives 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 (Štuikys, 2015). A rough definition specifies LOs as "any entity, digital or non-digital, which can be used, re-used or referenced during technology supported learning" (Committee, 2000).

The presented approach focuses on a novel framework for modelling LOs that represent, manage and convey the learning objectives and learning activities in an adaptive, dynamic and modular way, beyond traditional rigid educational structures, in technological agent-assisted learning environments. This framework has two distinct facets: a graph-based modelling scheme for structuring re-usable learning objectives and the learner-specific adaptation mechanism behind it, described in Section 3.1 and a holistic, formal model in the form of an ontology, under which learning activities and the means to materialise them in the real world can be classified for each distinct educational setting, described in 3.2. Validation and verification of the ontology is presented in Section 3.2.2, along with an example of the learning process that incorporates the aforementioned modelling solutions. The synergy of the graph-based learning objective models with the ontology-based educational settings model, concludes in an innovative approach for self-regulated, non-linear learning, tailored to learners' needs.

2 Related Work

A common practice concerning the representation and publication of LOs are learning object repositories (LORs), i.e. a sort of shared digital libraries in which educators and learners can store, search and retrieve educational resources (Sampson and Zervas, 2013). LOs reside within such repositories, accompanied by metadata that facilitate sharing and search within the 'library', in a structured schema that usually follows specific representation standards. These digital LO libraries are usually part of a learning content management system (LCMS)(EduTech, 2016b), i.e. a platform that allows the storage, retrieval, management and use of LOs. A list of such repositories can be found in (EduTech, 2016a). However, in most cases, LORs only 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 (Polsani, 2006) that characterize them, namely (i) accessibility, (ii) reusability and (iii) interoperability. *Accessibility* involves the use of metadata to accompany LO resources, with this metadata abiding to appropriate standards and efficiently describing resources in a manner that makes them easily searchable and retrievable within repositories. *Re-usability* refers to the need for LOs to be functional in and transferable throughout different learning contexts, implying a requirement for stand-alone, context-independent LOs; such LOs, that may have been initially created for a specific purpose, may be picked up by educators and embedded in their own educational settings. Lastly, *interoperability* denotes that LOs should be system- and delivery medium-independent, implying the ability to function under different platforms and across different devices.

2.1 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 (Limongelli et al, 2012) 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 (Ke et al, 2013) 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 (Wang et al, 2008) 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.

(Yang and Wu, 2009) implements an ant colony optimization system to retrieve suitable LOs that combine users' learning attributes and LOs. The ant colony methodology has found more supporters recently in other adaptive learning domains, with (Kurilovas et al, 2014b) employing a dynamic swarm-based technique to recommend the best-suited learning path to a user, along a series of interconnected LOs, whose relations change over time, and according to users' learning attributes.

Few learning environments proposed delve into the collaboration of learning agents or learners. The authors of (Burbaite et al, 2013) 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.

(Garrido and Onaindia, 2013) 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.

2.2 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 (Brut et al, 2011). They are oriented towards recommending aspects of the learning process to the users (Han et al, 2010) 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 (Tsai et al, 2006) (Kurilovas et al, 2014a) (Casali et al, 2013) (Pukkhem, 2013).

More specifically, through the IEEE learning object metadata (LOM) (for Learning Object Metadata, 2009) common vocabulary, which focuses on modelling the metadata needed to index, search for and evaluate LOs, and it's comparison with a predefined ontology of specific courses on a subject, constructed manually before taking up a course, (Tsai et al, 2006) infers the learning objects a learner should study and fetches them automatically from their web location. LOM is also used in (Casali et al, 2013) and (Casali et al, 2013), with the former developing an automatic loader of LOs based on the ontology. The latter compares LOs annotated through LOM against a learner model ontology that models learning styles, in order to recommend LOs for specific users. The authors of (Kurilovas et al, 2014a) engineer ontological queries based on existing standards and vocabularies in order to provide more complex relations that will help personalise learning environments, construct learning methodologies and model activities based on individuals' learning styles.

Furthermore, the Learning Activity Reference Model (LARM) (Falconer et al, 2006) 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 (Kurilovas et al, 2014a) 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. The BROA model (Rodríguez et al, 2013) proposed an ontological-based system that can retrieve LOs from LORs based on their semantic definitions and seamlessly recommend them to multi-agent platforms, while tailored to learner profiles.

The ontology of (Raies and Khemaja, 2014) 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 (Tsai et al, 2006) 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.

2.3 Comparative study

A comparative study among the aforementioned learning object models provides significant insight on existing modelling strategies. The criteria used to compare LO models stem from the definition of LOs, as detailed in the beginning of this section, and from the specific needs of current technology-enabled learning environments. These include capabilities for learner-centric education support, multi-agent SLEs support and education that goes beyond traditional non-adaptable and non-modular structures.

To this end, after breaking down the three generic major axes of criteria for modelling LOs specifically for technology-enhanced learning environments, and oriented especially around game-based learning, the complete set of criteria boils down to: (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.

The study shows that there is a trade-off in the supported criteria of the LO models and usage methodologies between investigated prior art. While some approaches are heavily oriented on the learner-centric nature of the LOs for linear education (both in terms of instructional tools and of the educational scheme), others focus on the educational tools (multiple agents) and their interaction with the learners. Consequently, *re-usability* is a major common attribute of all examined approaches ((Kurilovas et al, 2014a), (Falconer et al, 2006), (Rodríguez et al, 2013), (Limongelli et al, 2012), (Burbaite et al, 2013), (Garrido and Onaindia, 2013), (Tsai et al, 2006)), with *personalisation* of some sort (usually according to pre-defined manual information from the teachers) being the second most prominent attribute ((Kurilovas et al, 2014a), (Falconer et al, 2006), (Burbaite et al, 2013), (Garrido and Onaindia, 2013), (Tsai et al, 2006)). *Interoperability* of LOs is also a major attribute ((Kurilovas et al, 2014a), (Falconer et al, 2006), (Rodríguez et al, 2013), (Limongelli et al, 2012)), while the rest of the target criteria are selectively present. *Self-regulation* of objects and learning processes is applicable for (Rodríguez et al, 2013) and (Limongelli et al, 2012), while *on-the-fly adaptation*, a most prominent requisite in game-based learning, is only available in (Burbaite et al, 2013) and (Tsai et al, 2006). Finally, only (Rodríguez et al, 2013) and (Burbaite et al, 2013) consider environments where *different technological agents* might facilitate the learning experience. (Kurilovas et al, 2014a), (Rodríguez et al, 2013), (Limongelli et al, 2012), and (Garrido and Onaindia, 2013) deal with more than one *educational levels*, with (Kurilovas et al, 2014a) and (Rodríguez et al, 2013) also considering *different types of learners*, with and without disabilities, as well as formal and non-formal education. Cross-learner LO modelling schemes is also supported by (Garrido and Onaindia, 2013). Lastly, *non-linearity* is vastly discarded by all approaches but for (Tsai et al, 2006).

The proposed modelling framework aims to foster for all the aforementioned criteria, which can especially enhance game-based learning, which inherently allows for dynamic modularisation and adaptation of the learning process, in contrast with static materials such as documents and presentations used in traditional educational practices.

3 Modelling framework

The approaches mentioned in the previous section induce an ambiguity in the definition of LOs. Most approaches, e.g. (Kurilovas et al, 2014a), 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 (Committee, 2000), 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 content, since 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 non-linearity 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.

3.1 Graph-based modelling of learning objectives

The main component that defines the content in a learning process is the learning objectives. One or more learning goals can be defined, denoting learners' skills or knowledge (Miller et al, 1996) 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 defined as 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 (Bloom et al, 1984), 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 (Dietze et al, 2013) are hampered by the major deficits of all Linked Data: volume and inconsistency (Jain et al, 2010).

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 publicly available SLAs and LGs will be at the disposal of the users of the educational platform (essentially a LCMS) 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. Figure 1 portrays a Learning Graph, describing skills pertaining to all learners of a particular (sub)domain, in this case some basic skills for learners of elementary skill level. SLAs in this illustration are represented as light-coloured vertices, while goals consist of the dark-coloured vertices.

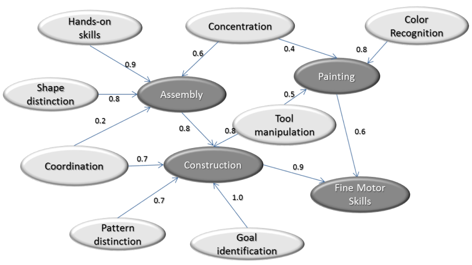

Fig. 1 An example of an unpersonalised LG

The capacities of the Learning Graph modelling scheme have few limits as to what can be represented, shared and re-used in terms of learning objectives. For instance, advanced vocational training goals can be modelled through a learning graph, as exemplified in Figure 2, or even very basic functional behaviours aimed for students with learning or physical disabilities can be represented, as exemplified in Figure 3. Respectively, one can observe that graphs can be as complex or simple as needed, since SLAs may not be shared between complex goals in a graph at all, as in Figure 2, but if needed, i.e. if a specific atomic goal may simultaneously contribute to training more than one complex learning goals, this can be reflected in the graph structure, along with each SLA's weight of contribution to each complex goal, as in Figure 3. In both cases one can observe that nested goals (goals contributing to other more complex goals) are also supported, while in any case, all LGs pertain to *connected graphs*, a prerequisite essential to the graph-based adaptation method described in Section 3.1.1.

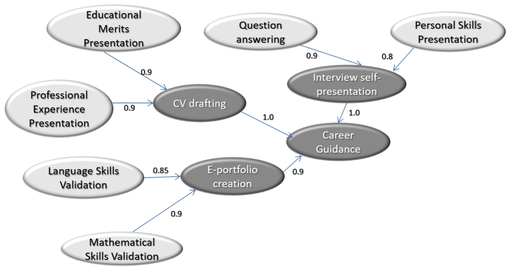

Fig. 2 An example of an unpersonalised LG for career guidance

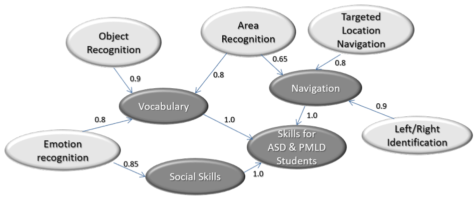

Fig. 3 An example of an unpersonalised LG for basic skill training in autistic and PMLD (Profound and Multiple Learning Disabilities) learners

Nonetheless, core unpersonalised LGs are instantiated independently per each learner during a given learning experience, with each instance's SLAs adapting (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 (Tsatsou et al, 2018). 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, by taking into account the smooth transition between graph states in each iteration of the learning process and in order to maintain the learner's engagement in the learning process (Kim et al, 2017). 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.

The latter is arguably achieved through the faster convergence towards the completion of the learning objectives, taking advantage of the information encoded in the graph structure, i.e. the contribution of the SLAs to the learning goal they partake to, as well as the uptake rate of the learner over the learning objectives, which can be evident through the past and current graph instance states. With the pursue of faster convergence, the aim is not to move up the competence levels faster *per se*, but rather to adjust competence levels or move across different goals in the graph in a manner that will boost the skill uptake rate of a learner, whether that pertains staying at the same competence level for a goal longer than foreseen for the peer-specific population, retreating to a lower competence level in order to allow the learner to be comfortable with the learning progress, moving faster to higher levels in order to keep an advanced learner stimulated by the learning process, or alternating between which skills to pursue next (including alteration pace), aiming to achieve more efficient skill uptake which will conceivably progress the overall learning objective fulfillment faster than in traditional educational settings. Further validation of the proposed methodology in a pedagogical environment will be pursued in the piloting phase of the learning management system that will incorporate the method.

Figure 4 illustrates two instances of the LG presented in Figure 1 for two learners (portrayed as two different sets of weights on the base LG).

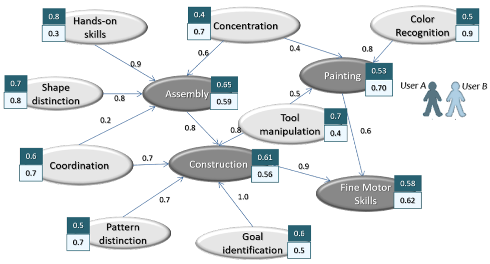

Fig. 4 An example of personalised LGs for two learners

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' fulfillment 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.

3.1.1 Adapting the graph-based learning experience model

Adaptation of the learning process relies on two axes: (a) the affect state of the learner while they are training in a specific atomic learning goal and (b) the learning graph structure and state of the personal graph instance in each iteration of the learning process. While the learner is training on one or more specific skills (SLAs) of the graph, monitoring their physical behaviour (e.g. facial expressions, body motion, etc.) or their scores and progression over the learning activities their performed provides an initial achievement score over the learner's skills (Tsatsou et al, 2018).

However, this is an initial indicator of the instantaneous response of the learner to the learning process, which is out of the scope of this paper, and may reflect only a temporal state. Correlating the effect of the affect sensing with the previous states of the graph and the contribution of each node to the node(s) they participate in, ensures smooth transition between graph states and consequently of competence uptake. This section will further analyse the method to achieve this in the proposed graph-based Learning Experience modelling scheme.

To this end, after an initial estimation of the learners' skill level's alteration from the affect state recognition, which brings the graph in state *(t)*, the graph-based adaptation process examines the state of the graph before this modification, i.e. at state *(t-1)* and the relationship between the nodes and edge weights and the spectrum of the graph's Laplacian, producing the graph-dependent modification of the graph at state *(t')*. Spectral analysis is the vehicle to achieve the optimal selection of node weights that will converge the graph faster to its optimal state. In this case, where competences, aka node weights, are normalized in the [0.0, 1.0] range, this optimal state is evidently the state here all graph node weights reach 1.0.

Given a directed connected graph $G = (V, E)$, V being the graph vertices, comprised of SLAs and learning goals and E the graph edges, each $v \in V$ carries a variating personal weight $w_v \in [0.0, 1.0]$, unique to the specific learner, which denotes the competence level of the learner in a specific SLA or learning goals. Each $e \in E$ carries a constant weight $w_e \in [0.0, 1.0]$, specific to the LG, standing for all personal instances of this LG, that is defined by the LG creator (educator) and denotes the contribution of a source vertex to a target vertex.

After one or more SLA weights have been updated through the affect sensing mechanisms, i.e. at *state (t)*, an intermediate/temporary LG state is created, reflecting these weights and the effect they have on related goals. The 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 $u, v \in V$,

$v \xrightarrow{e} u$.

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

After all graph node weights are updated as per Formula 1, a refactoring of the graph vertex weights takes place, based on the graph's spectral analysis at *state (t)*. This involves the computation of the graph's Laplacian matrix. A Laplacian matrix is used to find useful properties within a graph and in its simplest form deals with properties related to the degree and adjacency of nodes in the graph. Combinatorial Laplacians usually involve only edge weights, limiting again the analysis to the graph edges (e.g. connectivity identification, etc.). In this case, case, the interest lies in finding properties that can reflect traditional properties like adjacency and edge weights conjointly with the graph nodes' properties, i.e. their weight. To this end, the combinatorial Laplacian with vertex weights (Chung and Langlands, 1996) of the LG at state (t) is computed, to study the properties of our weighted, directed graph with node weights. This Laplacian matrix L is defined as $L = BTB^*$, where B is the incidence matrix, B^* is its transpose and T is the diagonal of the edge weights. Incidence in B is defined as per Formula 2.

$$B(u,v) = \begin{cases} \sqrt{w_u} & \text{if e = \{u,v\} and v enters u} \\ -\sqrt{w_u} & \text{if e = \{u,v\} and u enters v} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The Laplacian is then used to choose the vertex weight that will give faster completion, i.e. fastest convergence of the weights to the optimal state $w_v = 1.0$. This is an extension of the fast averaging optimization problem, which delved into choosing the edge weights that would give fast averaging (Boyd, 2006). The foundation of fast averaging lies in that a symmetric convex function of the positive Laplacian eigenvalues yields a convex function of the edge weights (Boyd, 2006). In the case of the combinatorial Laplacian with vertex weights, a case for which literature is scarce, we have identified that this extends to weighted graphs with fixed edge weights and varying vertex weights, i.e. that a symmetric convex function of the positive combinatorial Laplacian eigenvalues yields a convex function of the vertex weights.

Thus, the fast averaging optimization problem of (Boyd, 2006) was conveyed to the proposed problem space, where we define the optimal convergence rate α of the graph at *state (t)* the same way:

$$\text{minimize} \quad max_{i=2}^{n} \mid 1 - \lambda_i \mid \tag{3}$$

which is posed as the semidefinite problem

$$\begin{aligned} \text{minimize} \quad & \alpha \\ \text{subject to} \quad & -\alpha \leqslant max(1-\lambda_2, \lambda_n - 1) \leqslant \alpha \end{aligned} \tag{4}$$

where n are the total eigenvalues of the graph's Laplacian.

The optimal rate is then used to calculate the weights at *(t')*, applying the logic of the fast averaging solution of (Boyd, 2006), to the state-based fast completion that was identified for the proposed framework:

$$w_v(t') = w_v(t) - \alpha(w_v(t) - w_v(t-1)) \tag{5}$$

Figures 5, 6 and 7 portray some working examples of the vertex weights in each of the learning graph states, highlighting the smooth competence transition with respect to the learner's progression between states.

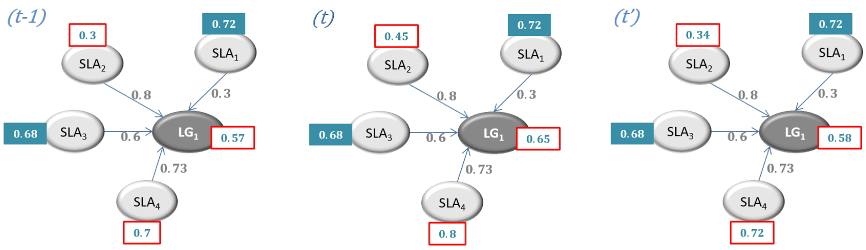

Fig. 5 Vertex weights rising from *(t-1)* to *(t)* and the final outcome at *t'*

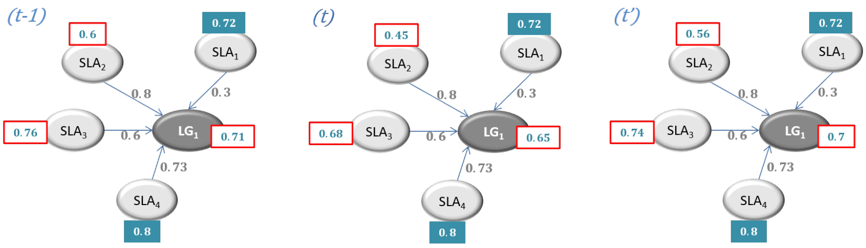

Fig. 6 Vertex weights dropping from *(t-1)* to *(t)* and the final outcome at *t'*

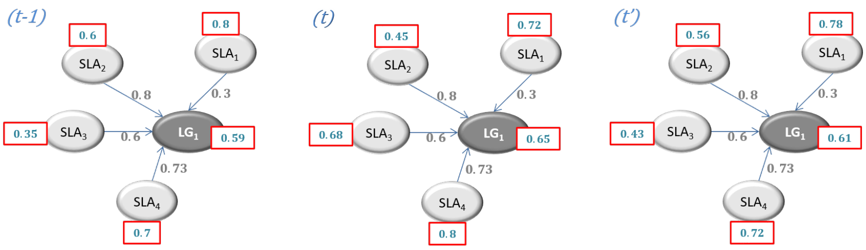

Fig. 7 Varying vertex weight levels from *(t-1)* to *(t)* and the final outcome at *t'*

3.2 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 materialisation is for them to be re-usable 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. Consequently, the models of the Learning Object Metadata ontology, used in several solutions presented in section 2.2 is not adequate to cover all these aspects. For this reason, the proposed 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, workplace, tutoring 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.

3.2.1 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 (Kotis and Vouros, 2006), through a process of requirements gathering based on interviews and questionnaires among domain experts, including pedagogical, psychological and technical experts.

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

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, 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 the creation of the first version of the LAO ontology. Additionally, a first round of validation and verification of the ontology was conducted *in simulacra* and *in situ*, as described in subsection 3.2.2, with its results guiding initial improvements of LAO, described in subsection 3.2.2, resulting to its second version.

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, QRCodes, 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 8) 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.

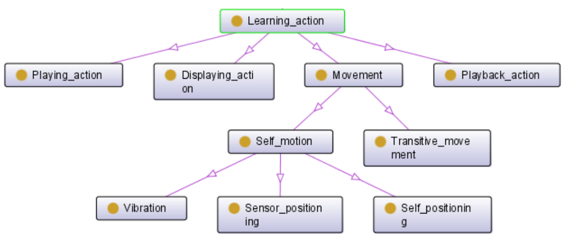

Fig. 8 Hierarchy of the *Learning_action* concept

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 9) 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>`).

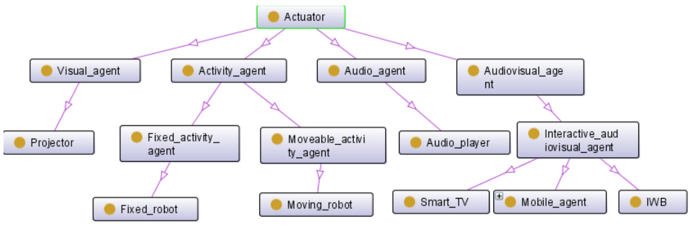

Fig. 9 Hierarchy of the *Actuator* concept

In the same manner, the *Sensor* top concept (Figure 10), 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.

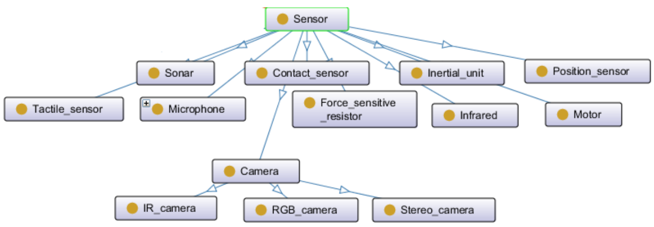

Fig. 10 Hierarchy of the *Sensor* concept

The *Context* top concept (Figure 11), which outlines the types of context that might affect the learning experience. These attributes may pertain to the learner type and personal characteristics, the situational context relevant to the learning environment as well as the technical context of the setup related to the learning materials.

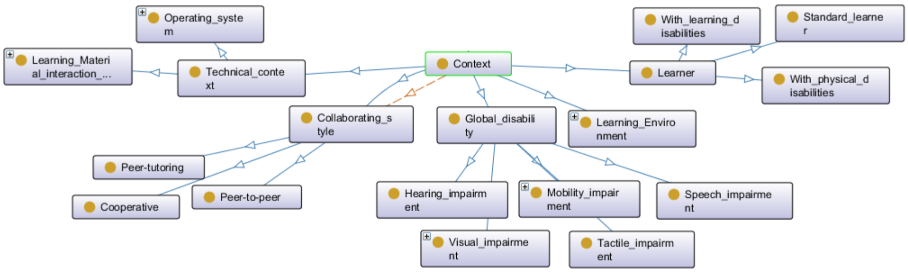

Fig. 11 Hierarchy of the *Context* concept

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).

Axioms 6, 7 and 8 represent examples of such restrictions, in the form of universal quantifications ($C \sqsubseteq \forall R.D$, where C, D are LAO classes and R is a LAO object property).

$$\texttt{Component\_positioning} \sqsubseteq \forall \texttt{hasActuator.Fixed\_activity\_agent} \tag{6}$$

$$\texttt{Self\_positioning} \sqsubseteq \forall \texttt{hasActuator.Moveable\_activity\_agent} \tag{7}$$

$$\texttt{Vibration} \sqsubseteq \forall \texttt{hasActuator.Mobile\_agent} \tag{8}$$

Lastly, LAO models types of learning materials (*Learning_material* top concept as seen in Figure 12) and types of identification means for the materials (*Learning_material_identifier* top concept, Figure 13). Learning materials (LMs) consist of specific digital and/or physical resources and artefacts that are involved in the materialisation of a learning action.

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

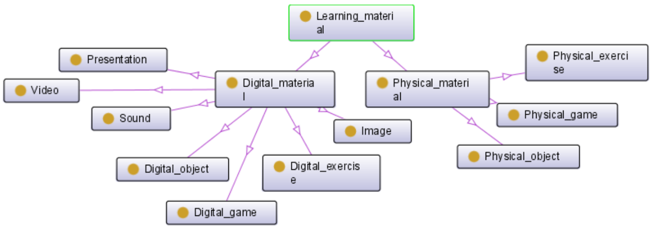

Fig. 12 Hierarchy of the *Learning_material* concept

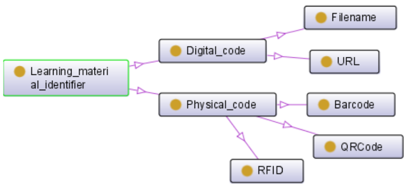

Fig. 13 Hierarchy of the *Learning_material_identifier* concept

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).

3.2.2 LAO validation and verification

Verification of LAO, i.e. ensuring that the ontology implements its definitions and requirements correctly (Staab and Studer, 2013), 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 (Tsatsou et al, 2014), on an ABox[2] instantiating all concepts and relations of the ontology.

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

Validation of LAO, i.e. assuring that the ontology really models the world for which it was created (Staab and Studer, 2013), was performed through its use in eight simulated scenarios, defined by educators for the Learning Content Management System (LCMS) 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. The scenarios were tested *in simulacra* by technical and pedagogical experts and *in situ* (in the actual premises where the large scale pilots will take place) by pedagogical experts and educators, keeping in mind the real scenarios and learners that will eventually take part in pilots.

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 Interactive 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 in Table 1.

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.

LAO improvements The validation process over the eight scenarios has lead to feedback from both technical and pedagogical experts as well as collaborating educators, pertaining to few modelling improvements concerning mostly previously unforeseen requirements. Addressing this feedback has eventually resulted to the second version of the ontology, as it is presented in 3.2.1.

To this end, the *Learning Action*, *Actuator*, *Learning Material* and *Learning Material Identifier* sub-hierarchies have undergone some minor modifications, pertaining to functional additions, removals and hierarchy re-factoring since the first version of the ontology.

The sub-hierarchy that has undergone the most substantial changes since the first version is the one pertaining to *Context*. While in the initial version, it was broken down to only two sub-facets, namely (a) *Learner*, denoting the high-level types of learners (in terms of learning/interaction capabilities or difficulties) and

Table 1 Example learning experience premises and setting

LAO axioms (subset)
Premises that apply globally in the domain
$((\exists \mathsf{materialises.Learning\_Action}) \sqcap$ $(\exists \mathsf{performableBy.Actuator}) \sqsubseteq \mathsf{Learning\_Material})$ $(\mathsf{Learning\_Environment} \sqsubseteq \forall \mathsf{hasActuator.Actuator})$ $(\mathsf{Robot} \sqsubseteq \mathsf{Actuator})$ $(\mathsf{IWB} \sqsubseteq \mathsf{Actuator})$ $(\mathsf{Smartphone} \sqsubseteq \mathsf{Actuator})$ $(\mathsf{Classroom} \sqsubseteq \mathsf{Environment})$ $(\mathsf{Home} \sqsubseteq \mathsf{Environment})$
Learning Experience instances
Facts that 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
Facts that apply only in the current situation
Two learning actions were elected, with two different priority weights
$< \mathsf{matching\_shapes} : \mathsf{Learning\_Action} \geqslant 0.7 >$ $< \mathsf{find\_diff\_shapes} : \mathsf{Learning\_Action} \geqslant 0.5 >$
*Learner is in classroom*1*, that has only a Robot available*
$< \mathsf{classroom1}, \mathsf{athena} : \mathsf{hasActuator} >$ $< \mathsf{classroom1} : \mathsf{Classroom} >$

(b) the types of *Learning Environment*s, subsequently educators, pedagogical and technical experts have identified several other facets that pertain to *Context*. To this end, it has been enriched with three new sub-facets, namely the *Collaboration Style*, the *Global Disabilities* and the *Technical Context*, as can be seen in Figure 11.

Collaborating Style has to do with the way a learner tends, more usually, to interact with another learner during a collaborative learning experience, where cooperative or mentoring activities may take place. The need for it has risen due to the addition of these kinds of experiences in the LCMS. The *Global disability* sub-facet has emerged as educators' requirement from the pre-piloting tests.

This parameter was identified as essential in order to appropriately assign facts applicable to the situational setting regarding learners with different common disabilities, like the inability to read, poor vision, poor hearing etc. These two new facets, along the *Learner* facet, which denotes high-level types of learners, consist the human-related aspect of *Context* and they can be seen in more detail in Figure 14.

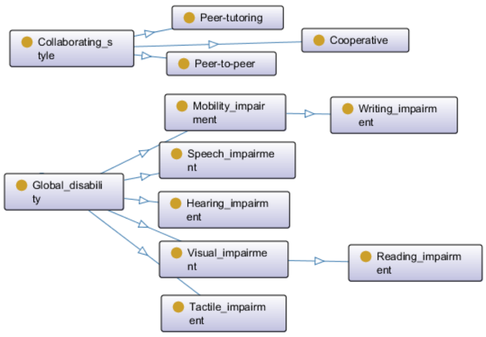

Fig. 14 Hierarchy of the *Collaborating_Style* and *Global_Disability* concepts

Similarly, during this testing phase, technical experts have identified the need for more specific parameters that define the technical set-up in each educational setting, leading to the addition of the *Technical Context* facet, which is discretized in two sub-facets, namely the *Learning Material Interaction Attributes* and the *Operating System*. The, self-explanatory, *Operating System* aims to serve in the decision-making process as means to discern from similar learning materials that however are performed in a different way in different operating systems, e.g. through an executable in Windows and through a shell script in Linux. The *Learning Material Interaction Attributes* refer to the means by which a learner can consume and interact with a learning material, e.g. through speech, touch, etc. Such attributes may be used to parameterise different learner-related settings based on their interaction preferences, but most prominently to be matched against a learner's *Global Disabilities*. This way, a learner that has a speech impairment will not be matched with a learning material that requires vocal interaction, rather another material that conveys the same learning action but though different interaction capacities will be elected instead. The *Technical Context* sub-facets can be seen in Figure 15.

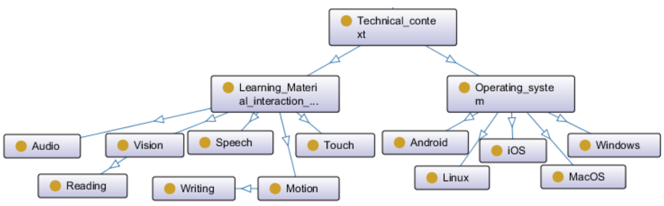

Fig. 15 Hierarchy of the *Technical_Context* concept

4 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 Environments, as well as the method to adapt them to individual learners' needs, styles and educational settings and capacities. 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 LCMS that will deploy and employ the models.

Future work will capitalise on the proposed models by validating them through large-scale pilots in real-world scenarios and educational settings.

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