The Definition of a Tunneling Strategy
between Adaptive Learning and Reputation-based Group Activities

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Abstract—We investigate the integration of LECOMPS, a web-based e-learning environment for the automated construction and adaptive delivery of learning paths, and SOCIALX, a web-based system for shared e-learning activities, which exploits a reputation system to provide feedback to its participants. Our overall goal is the integration of personalized and collaborative learning to support the Vygotskij’s educational theory of proximal development. Therefore we propose a two-way tunneling strategy: the LECOMPS student model is used to select the set of social activities (met in SOCIALX) according to the present individual learner state of knowledge; on the other hand, the solution of exercises, and the associated reputation derived in SOCIALX, is used to update the LECOMPS student model. In particular, we present a mapping between the student model and the definition of Vygotskij’s concepts of Autonomous Problem Solving and Proximal Development regions, with the aim to provide the learner with better guidance during the taking of the course.

Keywords: adaptive e-learning; reputation system; collaborative e-learning; ZPD; group modeling

I. INTRODUCTION

Our strategy aims to merge personalized learning paths and acquired learning reputation under the auspices of Vygotskij’s theory of proximal development [7], while further strengthening the sense of community in a class. We rely on the integration and exchange of data about students’ performances and achievements between two formerly developed web applications: LECOMPS, an environment for personalized e-learning, and SOCIALX, for collaborative and social learning activities. Personalized learning paths allow to better respond to learners’ needs and preferences, while reputation based techniques tend to increase the student's motivation. In our model, the learner’s activity in the socio-collaborative reputation system (SOCIALX), and the reputation itself, are used to enhance the individual student model (LECOMPS). In the other direction, the learner’s overall profile is used to enrich a course with individual, and/or group-based, social-learning activities.

A great deal of interest and research is presently dedicated to supporting automated construction, maintenance and delivery of adaptive e-learning courses. On the other hand, collaborative learning is winning in allowing the development of meta-cognitive abilities, e.g. critical thinking in learners, and to foster the acquisition of new knowledge. Moreover, it supports better retention and deepening of knowledge over time. In a collaborative environment the learners are prepared for team-based working activity, both by sharing their common experience and combining their skills [3]. This holds in formal learning, and also propagates along a lifelong perspective with the development of Communities of Practice (CoP) [9]. The integration of LECOMPS and SOCIALX is a first attempt towards the long term goal of fully developing an e-learning system including all required Co-like features. A reputation system is a natural component for building an LCoP, suitable in particular to motivating and transforming a class (or some classes) of learners into a real community. The reputation captures the contribution of each learner, and makes it apparent to the community (the group, the class and the course). The reputation is both a motivational tool and a way to evaluate and understand learner's psychological characteristics (learning and communication style) as well as preferences, relations with others, and ability to analyze/judge others' work (meta-cognitive achievements).

II. VYGOTSKIJ’S COOPERATIVE MODEL

One of the main achievements of Vygotskij’s research [7] is a model to demonstrate that cooperation provides the basis for the individual development. Even during childhood, targeted as well as casual interactions activate and spur the cognitive processes. The presence of people in the same environment, and the cooperation with peers, induces a reflection and an auto-regulation of one’s own behavior. Once such processes are interiorized, they become part of the child’s autonomous evolution. Social learning therefore precedes individual competencies and determines and prepares cognitive development. As a matter of fact, according to Vygotskij, the typical direction of learning is from outside to inside: the knowledge interiorization process mainly happens through the social “co-construction” (social learning), and then proceeds through a progressive transfer of the exterior social activity to the interior control. Once knowledge and processes are interiorized, the learner will be able to proceed in an autonomous and independent way. It follows that concrete growth can occur only in the Zone of Proximal Development (ZPD), which is characterized as [8] “the distance between the actual development level, as it is determined by the autonomous problem-solving, and the level of potential development, as determined by the problem-solving under an adult’s guidance or in collaboration with one’s own more capable peers”. In practice, when the learner has consolidated a region of Autonomous and independent Problem Solving (APS), it is
useless to further suggest exercises related to the same level of
difficulty. On the other hand, it is even more useless to
suggest exercises which are completely out of reach for the
learner (Unreachable Problem Solving – UPS). The right
zone of complexity is the one including exercises, that
the learner can solve according to own competence and/or with
a moderate support and/or in collaboration with companions
(Zone of Proximal Development – ZPD).

III. TWO WEB-APPLICATIONS FOR
PERSONALIZED SOCIAL LEARNING

LECOMPS [5] is a web-based e-learning environment,
supporting: 1) authoring of learning objects (Learning
Components – LCs); 2) enrolment of learners and
management of their individual Student Model (SM); 3)
automated adaptive construction of courses, personalized
over the topic learning goals (Target Knowledge – TK), and
the evolving SM. A whole set of LCs for each topic makes
the Learning Domain (LD) for the courses. A course C is
a sequence of LCs, to let the learner bridge the gap between
her initial state of knowledge and TK.

A learning component, lc, includes: 1) learning content
an XHTML-formatted resource, that can be given in
different, LS-wise, versions; 2) two sets of LOs: lc.RK
(required knowledge), and lc.AK (acquired knowledge, see
earlier); 3) questions, related to the LOs in AK, used in
questionnaires to assess knowledge acquisition; 4) effort,
informal measure of the LC content.

The knowledge associated to a learning component
(required to study its content, or acquired during its study) is
represented through the conceptual device of the Learning
Objective (LO), that is a predicate such as

\[ \text{LO}(\text{level}, \text{keyword}, \{\text{concepts}\}, \text{context}) \]

where level and keyword are cognitive characteristics
(see Bloom’s taxonomy) of the concepts (topics about which
the LO does express a skill), and context designates the
learning context of the concept(s).

Inference rules hold, such that the possession of certain
LOs (such as a set \( \{\text{lo}_i\}_{i=1}^n \)) can imply that some other LOs are
possessed too: \( \{\text{lo}_i\}_{i=1}^n \Rightarrow \{\text{lo}_j\}_{j=1}^m \). For instance, a skill at a
certain cognitive level implies the same skill at lower level:

\[ \text{LO}(3, \text{apply}, \text{cpt}, \text{ctx}) \Rightarrow \text{LO}(2, \text{describe}, \text{cpt}, \text{ctx}). \]

The set of all LOs associated to LCs in the LD is the
Knowledge Domain (KD) for the subject matter.

The student model SM denotes the state of knowledge
(CS – cognitive state) of the learner and her Learning Style
(LS) preferences, as a couple \(<\text{CS}, \text{LS}>\) where: 1) CS is a set of
pairs \( \{<\text{lo}_o, \text{cert(lo}_o)>\}; \) LOs presently “owned” by
the learner are listed and labelled by estimated certainty
(see later); 2) LS is a 4-tuple \( <d_1, v_1; \ d_2, v_2; \ d_3, v_3; \ d_4, v_4> \),
where \( v_i \) are in \([0,1]\), and \( d_i \) are values in the dimensions
of Felder-Silverman’s model [4] (active / reflexive, sensing /
intuitive, visual / verbal, sequential / global). The SM
evolves, allowing course adaptation. The possession /
acquisition of a LO in CS, and its certainty, are based on
learner’s answers to end-lesson tests (a lesson is a segment in
the sequence C). The system manages a set of parameters
(configurable by the teacher on each topic) to drive CS
updates during the course. When a \( \text{lo} \) is added to CS after a
test, it is assigned certainty \( c_{\text{lo}} \); then, after each further test,
\( \text{cert(lo)} \) is decreased/increased, by \( c_{\text{lo}}/c_{\text{OK}}, \) depending on
answers; should \( \text{cert(lo)} \) eventually be under/over thresholds
\( c_{\text{Promote}}, c_{\text{Denote}} \), though, it would be removed from CS or
permanently included in it (with no further tests).

SOCIALX [6] is a web-based system designed to support
collaborative and social aspects of learning. It supports the
practical/exercise experiences of a course, through the
management of socio-collaborative learning activities, in the
framework of a reputation system [3].

In particular, in SOCIALX the learners can contribute by:
1) providing solutions to available exercises; 2) reusing
others’ solutions; 3) evaluating others’ and one’s own work;
4) discussing exercises in dedicated micro-forums; 5)
participating to group-based projects, with a “social” bent.

The reputation in SOCIALX represents the following
learner’s characteristics and qualities: usefulness of learner’s
contribution, involvement, competence, judgment and self-
judgment, critical appraisal (the ability to select others’
contributions to be extended or corrected), and
group_reputation, (acquired during group work).

IV. MODEL OF INTEGRATION

A first step in the integration of the above systems is the
extended definition of SOCIALX exercises according to the
structure of an LC, by RK/AK/effort. This allows using
SOCIALX learning assets into LECOMPS pools and courses.
Since they have no questions embedded, we use a dedicated
assessment of their AK: the related reputation gained by the
learner in SOCIALX, states if its LOs can be included, with
according certainty, in the student model.

Since a course C can now contain both LCs and exercise-
LCs, it is essential to let the learner have a more personal
support to the navigation of the LCs, besides the default
sequencing, due to the presence of exercise-LCs, where
collaborative activities are met. To provide this support, a
classification of the course LCs (or, rather, of their Learning
Objectives) under the “zones” discussed in Sec. II is helpful.

In the following we assume that C=\{c_1, c_2, ..., c_n\} \subseteq LD
is the personalized course, in the learning domain, according
to learning goals TK. Denoting the knowledge acquired
through a LC c_i as c_i.AK, the overall knowledge provided by
C is C.AK = \bigcup_{c_i \in C} c_i.AK. We’ll call projection of
the knowledge domain over the course all the relevant LOs:

\[ \Pi^{\text{KD}, C} = C.RK \cup C.AK \]

(notice that C.RK and C.AK are not necessarily disjoint).

We define Autonomous Problem Solving region as the
set of all the LOs that are in CS with maximal certainty
APS = \{\text{lo} \in C / \text{cert(lo)} = c_{\text{Promote}} \}

For the zone of proximal knowledge, we have to define
which LOs of the KD (projected over C) are not “too far”
from the SM. Those LOs are the ZPD, that can be shown to
the learner, to help her in selecting next LCs to take in C. In
this use we: 1) a distance metrics: \( d(C, \text{lo}) \) measures how
far is a given LO, \( \text{lo} \), from the learner’s grasp (that is from
CS); 2) a “daring threshold” \( p() \) that states when a given LO
is “not too far” from CS (and so be in ZPD).
In order to acquire a given \( lo \in \prod_{KD}^{C} \), the learner is supposed to follow a path of LCs. Each LC, \( c \), needs an effort, \( c.effort \), and the distance between CS and \( lo \) is computed as the (minimal) sum of such efforts. So, be \( G(CS,lo) \) the minimal (wrt effort) subset of LCs in \( C \), to be studied in order to have CS be extended so to comprise \( lo \):

\[
G(CS,lo) = \{c_{ch1}, ..., c_{chK}\} \subseteq C
\]

\[
\sum_{c \in G(CS,lo)} c.RK \subseteq CS \cup \sum_{c \in G(CS,lo)} c.AK
\]

then it is

\[
d(CS, lo) = \sum c.effort
\]

(In Fig. 1, \( G(CS,lo)=\{\text{dark LCs}\} \) and \( d(CS, lo) = 9 \)).

The daring threshold expresses how far from the APS the learner could reach. We extend such definition by considering all the LOs in CS, weighted by their certainty. Then, the daring threshold for a given \( lo \) depends on the overall (average) certainty of the LOs in CS that are used to reach it (i.e. those in \( G(CS,lo) \)). We call support set in CS for \( lo \), the minimal subset of LOs required by \( G(CS,lo) \):

\[
Supp(CS,lo) = CS \cap (\cup_{c \in G(CS,lo)} c.RK)
\]

(In Fig. 1, \( Supp(CS,lo) \) is the highlighted subset of CS, with the three LOs, with their certainty). An average certainty \( (avgCert()) \) for a set of LOs can be defined straightforwardly.

Then, the daring threshold is to be defined as a function \( p() \), expecting the average certainty parameter and monotonically increasing with it. The zone of proximal development is then defined as the set of those LOs (excluding the APS) within the maximum distance \( p \) from CS, as determined by the average certainty of the support set:

\[
ZPD = \{lo \in \prod_{KD}^{C} \setminus APS / d(CS,lo) \leq p(avgCert(Supp(CS,lo))) \}
\]

The Pool of LCs and LOs defines an acyclic directed layered vertex-weighted AND-OR graph: LOs correspond to OR nodes (can be acquired by more than one LC) and the LCs correspond to AND nodes (they need their RK LOs). To compute the distance of an LO, \( lo \), from CS we compute the minimum subgraph rooted in \( lo \) with all leaves in CS. In Fig. 1, the distance of the rightmost LO (\( d=9 \)) is the sum of efforts (3, 4, 2) of the minimum set of LC (highlighted) needed to reach the LO. We consider only once the weight of any subgraph appearing on multiple paths.

V. CONCLUSIONS

Our long-term goal is a Learning Community of Practice with the teacher as organizer and supervisor. We support an adaptive design of the path of exercises, and the management of an extended student model, with feedbacks from the activities in a reputation system. We defined the Zone of Proximal Development, in terms of the Learning Objectives in each student model. ZPD is determined adaptively, according to the evolving student model; we have defined a cognitive distance between the state of knowledge of the learner and the learning objectives, and a dynamic maximum distance threshold, of the learning objectives in the ZPD, according to the certainty factors of the LO in SM. Cognitive

Figure 1: LO distances from the CS (boxes are LOs with their distance, circles are LCs with their effort, arrows show the “acquired” relation, the highlighted subset in CS is the support set of the rightmost highlighted LO

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