

Self-referencing Agents for Inductive Non-Algorithmic e-Learning

IULIAN PAH *, ANDREI MOICEANU**, IOANA MOISIL***, BOLDUR E. BĂRBAT****

* Faculty of Sociology and Social Work, “Babeş-Bolyai” Univ. of Cluj-Napoca,
ROMANIA

** Faculty of Automation and Computers, “Politehnica” Univ. of Timișoara,
ROMANIA

*** Faculty of Engineering, “Lucian Blaga” Univ. of Sibiu, ROMANIA,

**** Faculty of Sciences, “Lucian Blaga” Univ. of Sibiu, ROMANIA,

If you hold a cat by the tail you learn
things you cannot learn any other way.
MARK TWAIN

Abstract: The paper presents an alternative approach to e-Learning, where “*Learning*” is action-oriented and highly personalised, while “*e-*” is carried out through a software entity acting as self-referencing coach and interacting with the user as interface agent. The focus is on aspects related to: a) domain theory (moving targets, refined strategies); b) trends in computer science (uncertain knowledge processing, obsolescence of algorithmic programming, and above all new ontologies); c) affordability (upholding a software engineering perspective, mainly an agent-oriented one). Specific objectives are: a) To defend the rationale for an unconventional outlook about e-Learning pertaining to all main system aspects. b) To draw a stepwise approach affordable within a limited academic research. c) To outline a generic architecture for successive experimental models and to present very roughly the current one. d) To employ this project as test field for a more comprehensive undertaking. (Details and implementation issues regarding mechanisms and models are described in other papers.) Preliminary estimations are encouraging as regards perspective, methods, and generic architecture.

Key-Words: Non-algorithmic Learning; Anthropocentric Interface; Induction; Self-Cloning Agent; Ontology.

1 Introduction. An Alternative Frame

The basic assumption is that the knowledge-based society – whatever shape it could get – entails new targets for e-Learning because: a) Humans must (interact in open, heterogeneous, dynamic and uncertain environments (OHDUE), quite different to the way they are familiar with. b) The challenges to cope with are major and involve other requirements. Indeed, seen as resources, time is even more expensive while information tends to be almost free. Unluckily, that works for *static* knowledge (information as *noun*), not for *dynamic* knowledge (information as *verb*) [10]. c) The information and communication technologies (ICTs) advanced dramatically offering possibilities, means, perspectives, and approaches unthinkable about forty years ago when e-Learning took off. d) Without an anthropocentric and transdisciplinary approach end-user acceptance will not be in line with the huge technological potential on hand.

The target is to present an alternative approach to e-Learning, where “*Learning*” is action-oriented and

highly personalised, while “*e-*” facets are carried out through software entities acting as self-referencing coaches and interacting as interface agents. The target is split into four specific objectives: a) To detail and defend the rationale for an unconventional outlook about e-Learning pertaining to all main system aspects: learner meta-profile, goals, methods, granularity, performance metrics, nature of agents involved, etc. b) To draw a stepwise approach according to this rationale and affordable within the scope of a limited academic research project. c) To outline a generic architecture for successive experimental models and to present very roughly the structure of the current one. d) To employ this project as the first test field for a more comprehensive undertaking regarding Gödelian self-reference in agent-oriented software. (The issue is treated in a related paper.)

Since the overall undertaking was first presented in [5] – mainly to illustrate the broad-band technology potential from an anthropocentric and transdisciplinary perspective –, here are reaffirmed only underlying ideas necessary to make this paper self-contained, while the focus is on aspects related

to: a) domain theory (moving targets for e-Learning, refined strategies); b) computer science (uncertain knowledge processing, obsolescence of algorithmic programming, and above all new ontologies); c) affordability (upholding a software engineering perspective, mainly an agent-oriented one).

The paper is organised as follows: Section 2, tries to clarify some concepts and describes the *rationale, explaining the title*. Section 3 outlines the *approach and related work*. Section 4 focuses on the *generic architecture* (primarily on e-Learning features, not on those suitable as benchmark for self-referential agent behaviour) and on the features implemented in the *current experimental model* (as well as the seeds of those of the next one). *Conclusions and future work*, ranked on time horizons, close the paper.

2 Rationale. Explaining the Title

For the sake of conciseness, the premises, criteria, context, motives, and connotations are not disjointed but grouped around the title key words. Also, since the paper target is e-Learning, these concepts are looked at in reverse order.

Learning. Here is considered the process per se – with or without “e-”. The essence of the paper stand is that human learning is best described by the information-processing approach in cognitive psychology, in line with the ideas promoted in [2]: “Most modern information-processing theories are “learning-by-doing” theories which imply that learning would occur best with a combination of abstract instruction and concrete illustrations of the lessons of this instruction. [...] combining abstract instruction with specific concrete examples [...] is better than either one alone”. Moreover, learning should be considered – in both humans and agents – as any other intellectual activity, i.e. as a process where most effectiveness is reached through a blend of symbolic (“left-hemisphere”-like) and subsymbolic (“right-hemisphere”-like) modi operandi. Hence, neither “apprenticeship learning”, nor “by rote learning”. However, the two extremes, albeit equally dangerous, are not similarly hard to fight: at least in Romania, nowadays, the average approach to learning is much closer to “by rote”. Thus, the balance has to be redressed, favouring right hemisphere tactic.

e-. Started as abbreviation for “*electronic*”, this prefix may be attached to anything that has moved from a traditional form to its IT alternative (e.g., e-mail, e-commerce, or e-government). Tough, here it gets also a metaphoric connotation (as for instance, in “eEurope” where it is not designating an “alternative” Europe): e-Learning should symbolise a differ-

ent kind of learning – not just conventional learning available through the Internet.

Non-Algorithmic. This is the core of the undertaking, and, hence, the cardinal issue of the rationale – in particular because in [5] it was (over)simplified by the phrase “less algorithmic learning”. Here, “non-algorithmic” suggests that: a) Conventional algorithms are not anymore *program backbone* (since in the era of “computing as interaction” in dynamic and uncertain environments [1] deterministic applications are vanishing – at least those affordable on usual configurations). b) Conventional algorithms are not anymore the main *programming instrument* (they are hidden in scripts or in procedures easily reached in a host of libraries). c) “Higher order thinking is nonalgorithmic” [17] (the path of action is not fully specified in advance). d) Not only “algorithmic reasoning”, but any algorithmic interaction of analogue beings within analogue environments is unnatural – in almost any meanings of the word. Even primeval animals move “algorithmically” (“if gap then get round, else go on) only a few steps, in very hostile environments. Moreover, reaction to stimuli cannot mean perpetual looking for the stimulus. e) The geometrically increasing computing power (due to Moore’s law) reduces radically most perceptible effects of the digital basis of information processing. On the other hand, “non-algorithmic” does *not* imply necessarily “sub-symbolic”, because: a) Symbolic processing is unavoidable in any learning process (fact rejected only by radical cognitive theories denying knowledge decomposition and de-contextualization [2]). b) Anthropocentric interfaces require symbolic human-computer communication. c) Massive (fine-grain) parallelism, implied by all widespread sub-symbolic processing paradigms, is hardly affordable with scarce resources [3]. d) Symbols are implied by “Piaget’s distinction between assimilation and accommodation as mechanisms of learning and development. Assimilation is a relatively passive incorporation of experience into a representation already available to the child” [2]. (From the related perspective of agent logics, the relationship between symbolic and sub-symbolic processing is discussed in [6].)

Inductive. Learning, as cognitive process, is inductive. The reasons why e-Learning should be too are based on affordability due to agent-technology potential: a) Even in the rather deductive and apodictic cognitive environment of college-level mathematics, inductive reasoning is vital: “The primary goal [...] is to define the skill threshold necessary [...]. We have discovered two salient themes in the literature concerning what this means precisely. The first is the knowledge [...]. The second theme con-

cerns the skills and abilities [...]. Abilities are attributes that affect the ability to perform a task, such as manual dexterity and inductive and deductive reasoning" [12]. b) Two of the main learning strategies are based on induction: "Among the processes that have been shown by recent research to have considerable power in speeding the learning process and encouraging the learner to achieve deeper levels of understanding are learning from examples and learning by doing. Computer tutors, using these and other methods, are beginning to show impressive effectiveness" [2]. c) Formal learning theory is "a normative framework for scientific reasoning and inductive inference" [18]. d) Moreover, inductive logic "is a system of reasoning that extends deductive logic to less-than-certain inferences" [13]. (Tough, at this research stage, it is not necessarily the best candidate for representing uncertain inferences). e) "There is almost universal consensus that only the active learner is a successful learner. Proponents of situated learning and constructivism have proposed a number of modes of instruction that are aimed at encouraging initiative from students and interaction among them" [2]. A chain of implications appears (simplified, see also below the rationale for self-reference): e-Learning → e-interaction → communication with interface agent → symbolic language → ontology → rules → inductive inference. f) The most subjective reason, that induction is, founded on the expectation that characteristics of our experience will persist in experience to come, and that is a basic trait of human nature and its advantage is that it can, with care and some luck, correct itself, as other methods do not.

Agents. No need anymore to justify their utility in any computer-aided intellectual tasks.

Self-referencing. In [5] were presented both content (scientific) and circumstantial (historical) reasons for endowing agents with some degree of self-awareness [9] and it was asserted that the starting point for trying to achieve self-awareness is Gödelian self-reference; thus "self-referencing" means here "first stage of self-awareness" (details in the related paper mentioned). At this stage the aim is to provide agents with a cognitive architecture as close as possible to that of the learner as "main actor" [15] (i.e., trainer and trainee should share a common ontology – at least for basic communication). The main reasons are revisited here: a) "Learning requires a change in the learner, which can only be brought about by what the learner does [...]. The activity of a teacher is relevant to the extent that it causes students to engage in activities they would not otherwise engage in" [2]. Hence, e-Learning should be maieutic. That implies intentionality, i.e., intensely

proactive interface agents. Moreover, their role is more complex than that of a *teacher*: they should be *coaches* (the connotation is that they should be "teleoreactive" and more skill oriented). b) To insert the concept of *learning* into a common ontology (humans *know* when *they* learned) and to exploit it, the agent must have minimal introspection ability. c) The same, for assessing learning. d) Teachers – and coaches even more – to be effective must be convincing, first of all credible; however, that means to deal with emotivity. (See also next sections. The influence of affective processing in education and training was reemphasised very recently in a dedicated workshop [8].) e) "Higher order thinking requires self-regulation; someone else is not giving directions" [17].

3 Approach and Related Work

Besides suiting the rationale detailed above, the stepwise approach must fulfil three conditions: a) to be workable within the scope of a university research undertaking; b) to ensure affordability for future end users with scarce resources (for instance, individual students); c) to be relevant for employing this project as test field for the architectonics of self-referencing agent-oriented software. However, to preserve research autonomy, model modularity and extendability, as well as to impair redundancy, the last restriction will not be taken into account explicitly, being dealt with in papers about Gödelian self-reference. As a result, agent features and mechanisms specific to the parent project (e.g., self-cloning) are not discussed here; thus, the approach outlined in [5] can be refined and updated, considering the rest of the system factors:

Learner. The basic difference lies in the dynamics of change, expressed through the speed of assessed performance improvement. Conventional approaches model the learner profile for time spans between weeks and decades. For instance, in a recent substantial work [11]: "Learners are assessed by several systems during their life-long learning. Those systems can maintain fragments of information about a learner derived from his learning performance and/or assessment in that particular system. Customization services would perform better if they would be able to exchange as many relevant fragments of information about the learner as possible". Of course, learner profiles exist but, for time spans between minutes and days, it is almost pointless to deal with, because the resource/usefulness ratio tends to become unacceptable. Hence, only a meta-profile describes (implicitly) the learner as: highly

motivated, very busy, pragmatic, goal-oriented, practised in using computers.

Learning. The Chinese proverb “Tell me and I’ll forget; show me and I may remember; involve me and I’ll understand” is usually seen, from an anthropocentric perspective, as comparing three *ways of learning*. Here it is revisited from an IT perspective: it reveals three *ages of e-Learning*. The first is totally obsolete but the second is still considered in e-Learning (a host of high-quality teachware is available [7]). Though, Moore’s law – mentioned above for one beneficial effect – has another most valuable consequence: “I may remember” is almost not anymore needed, since the computer remembers much better and faster (and WWW never forgets). Hence, the focus is on *understanding* (as *aim*) and on *involving* (as *means*), because, exaggerating a little, learners must not *know*, but *know how*. Hence, learning, seen as “acquiring knowledge”, is still vital but the emphasis moves from *static knowledge* towards *skill*. In addition to the features already mentioned, but closely related to them, knowledge (even static one) should be “coarse-grain”, fuzzy, revisable, and highly personalised. b) Taking into account the danger of learning (almost) “by rote” (see Section 2), the coach-trainee relationship will be approached – at least in the early stages – in Aristotelian manner (“what we have to learn to do, we learn by doing”); implying right hemisphere tactic, it should be assessed through a performance metrics suited to action-oriented “Simon-type machine learning” [16] [2] (i.e., the lesser duration of task completion).

Interaction. The approach follows as corollary of the above: a) uncertain knowledge processing is unavoidable (for representing uncertainty the most affordable tool seems to be Stanford Algebra); b) interaction between two basically reactive entities (coach and learner) must be mostly stimulus-driven (for instance, any monologue should be interruptible at any time and resumed in a coherent manner).

Related Work. Because related work regarding agent self-awareness was reviewed recently [5], here are added just some comments as regards this specific application domain. Albeit a broad consensus that learning is innately non-algorithmic [2] [10] [12] [17], the yet crushing predominance of algorithmic software impairs widespread approaches similar to that proposed here. Even inductive learning [13] [18] or emotional reactions [8] are often treated algorithmically. As a result, even recent e-Learning software is rather conventional (e.g., [11] [7]).

As regards the evolution of this undertaking, it is nothing to be added to the sources mentioned in [5].

4 Generic Architecture and Current Experimental Model

In line with the approach, the architecture is seen from two point of views: a) self-referencing agent architecture integrated in experimental models able to validate it – at least “in ovo” (dealt with in other papers); b) generic architecture to reach the objectives stated in Section 1, with an “externalised interface agent”, presented in Fig. 1 and outlined below (links to other papers are suggested by “[ref]”).

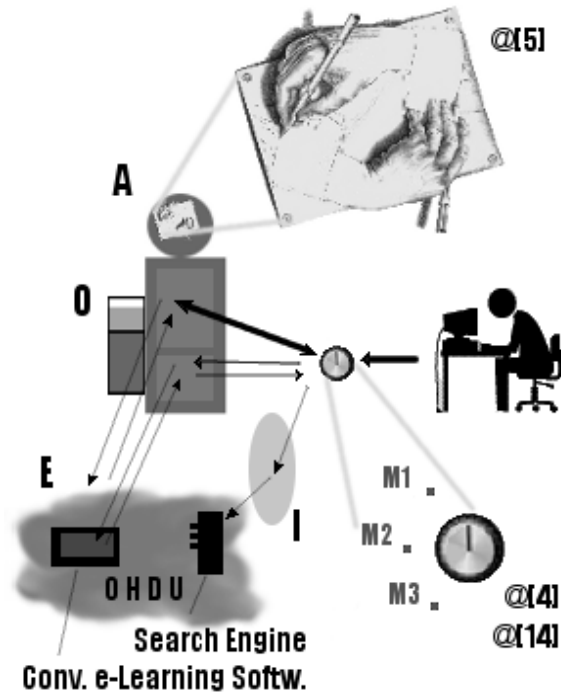


Fig. 1. Experimental Model.

E-Learning environment (E). The amoebic shape suggests its nature: open and heterogeneous (the resources involved are unlike and their availability is not warranted), dynamic (high pace of exogenous or endogenous changes) and uncertain (both information and processing rules are revisable, fuzzy, uncertain and basically non-deterministic – as every stimuli generator). On the other hand, micro-continuity and reusability require also some usual e-Learning software in the environment. Now it is modelled as a “very proactive search engine” (in the current experimental model it is oversimplified as a kind of “personalised Google with many messages”).

Dynamic Ontology (O). “Dynamic” suggests here “phenotypical expansion”: as the agent learns, it should fill out the ontology and, when assessing a significant improvement, it transfers the latest assimilated knowledge into its genotype by cloning itself. On the other hand, it is the weakest link of the

generic architecture, because filling out ontologies for real world problems is resource demanding (mainly, it takes much time; it is the only key application component still in the stage of suiting only toy problems). This drawback is somewhat balanced by some interesting features, as assigning semantic value to the iconic space (in the context of computer-aided semiosis in trans-cultural interfaces it is illustrated in another related paper). One more important difference: uncertainty is accepted from the very beginning, eliminating the unacceptable *closed world assumption* and replacing it by certainty factors assigned to both rules and facts.

Agent (A). It is separated from *its O* only because of modularisation, both architectural (ontologies are sub-domain specific and dynamic, while the rest of the agent can be the same and is static) and structural (because of affordability, some conventional software can be reused as agent component).

Interface (I). The unusual situation of having an interface beside the interface agent was justified by security reasons: the user is still in control even when the agent is (in part) out of function.

Security Work Modes (Mi). “Security” refers here rather to ethical aspects than to technological ones. There are three echelons of application functionality expressed through working modes: M1) Normally, the learning process is conceptualised in line with the modern IT paradigm “computing as interaction”, where the coach-trainee communication is intense in both directions (i.e., both parts are proactive). M2) If some agent action or behaviour seems deontologically suspicious, the application performs according to the older “client-server” paradigm, where the learner takes initiative while the agent is reduced to conventional e-Learning software. M3) In critical situations, the agent is totally cut short and the learner uses a conventional interface to interact with the environment or to access the ontology. Switching between modes is carried out with an “ethical potentiometer” (currently with five positions implemented first for virtual therapy [4] and later adapted for e-Learning [14]).

The current model describes a self-referencing, exception-driven agent, carried out as pseudo-avatar, able to: learn (mainly from environment stimuli, through inductive inferences); assess “Simon-learning” of humans and agents (by the task duration derivative); clone itself after learning to spawn a “smarter progeny” (transferring recently acquired knowledge into their genotype). Emphasis moves towards (parentheses embrace the “rather than ...”): interactive (bibliography), adaptive (e-tutorials), knowledge extraction (information retrieval), error-driven (grading test results), trends (detailed facts).

The model architecture reflects the principle of Occam’s razor in its procedural sense of “*lex parsimoniae*”: benefit from the incremental nature of self-awareness, by starting with few features and proceed stepwise. For instance, since the initial learning method is “learn by doing”, the first mental states avoid concepts as “self-awareness”, starting by simple analogies with computer states: active, hibernating, or turned off.

Detailed features of the mechanisms employed, implementation issues, test evaluations, and initial user comments will be presented in future papers about self-referential agents.

5 Conclusions and Future Work

For an undertaking that is unconventional in both *perspective* (“*What*”-questions: what learner, learning, or interaction?) and *methods* (“*How-to*”-questions: how to learn, become aware of learning, or assess it?), all conclusions must have attached a low certainty factor until real world applications are validated “in vivo”. Thus, the preliminary estimations below are just encouraging indicators about the outcome as regards both:

Perspective. An alternative approach is needed because: a) Moore’s law effects are striking: a search engine becomes a widespread e-tutor; b) learning occurs in OHDUE, where intense non-deterministic interaction decrease rapidly the role of algorithms; c) the emphasis moves from *static* towards *dynamic* knowledge.

Methods. Corollary of the new perspective: the non-algorithmic nature of the learning process should be much better reflected in e-Learning, through: a) increased role of dynamic entities (agents) instead of static ones (objects); b) uncertainty and revisable knowledge inserted in ontologies (no matter how simple); c) intense reactivity (stimulus-driven agents); d) suitable assessment method (based on a simple time derivative of task completion duration).

As regards the generic architecture, it proved to be affordable for toy problems and the current model was not difficult to implement (the only exception: filling out dynamic ontologies, even for toy problems is not only hard work but also very risky outside an authentic transdisciplinary effort).

Future Work. The targets are ranked on time spans. a) Short range: improving the ontology; adapting the ethical potentiometer; increasing substantially the number of exceptions. b) Middle range: testing the effectiveness of self-referencing agents (first allowing them to propose the moment of

self-cloning); integrating the model as selectable alternative in a conventional e-Learning system. c) Long range: investigating the chances that inductive learning could allow agents and humans to *learn from each other to learn*.

Acknowledgement. This work was supported by the Ministry of Education and Research through Contract No. 73-CEEX-II-03/31.07.2006.

References:

- [1] AgentLink III. *Agent based computing. Agent-Link Roadmap: Overview and Consultation Report*. University of Southampton, <http://www.agentlink.org/roadmap/al3rm.pdf>, 2005.
- [2] Anderson, J.R., L.M. Reder, H.A.Simon. *Applications and Misapplications of Cognitive Psychology to Mathematics Education*. Texas Educational Review, 2000.
- [3] Bărbat, B.E. *Agent-Oriented Intelligent Systems*. Romanian Academy Publishing House, Bucharest, 467 pages, 2002. (In Romanian.)
- [4] Bărbat, B.E., A. Moiceanu, H.G.B. Anghelescu. *Enabling Humans to Control the Ethical Behaviour of Their Virtual Peers*. Chapter in Enid Mante-Meijer, Leslie Haddon and Eugène Loos (Eds.). *The Social Dynamics of Information and Communication Technology*. (To be published by Ashgate, Aldershot, UK, 2007.)
- [5] Bărbat, B.E., A. Moiceanu, I. Agent. *The good, the bad and the unexpected: The user and the future of information and communication technologies*, Institute of the Information Society, Moscow (forthcoming, May 2007).
- [6] Bărbat, B.E., S.C. Negulescu. From Algorithms to (Sub-)Symbolic Inferences in Multi-Agent Systems. *International Journal of Computers, Communications & Control*, **1**, 3, 5-12, 2006. (Paper selected from the *Proc. of ICCCC 2006*.)
- [7] Bunschowski, M. et al. Harnessing Scalable and Future Proof Teachware for Existing Learning Management Systems by Providing a Service Based Middleware. *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2004*, 28-36, Chesapeake, VA, AACE, 2004.
- [8] Chalfoun, P., S. Chaffar, C. Frasson. Predicting the Emotional Reaction of the Learner with a Machine Learning Technique. *Workshop on Motivational and Affective Issues in ITS*. (G. Rebolledo-Mendez, E. Martinez-Miron, Eds). 8th International Conference on ITS, 13-20, 2006.
- [9] DARPA. *Workshop on Self-Aware Computer Systems 2004. Statements of Position*. <http://www.ihmc.us/users/phayes/DWSAS-statements.html#top>.
- [10] Dertouzos, M.L. *WHAT WILL BE: How the New World of Information Will Change Our Lives*. Harper Collins Publishers, New York, NY, 1997.
- [11] Dolog, P., M. Schäfer. A Framework for Browsing, Manipulating and Maintaining Interoperable Learner Profiles. In *User Modeling* (J.G. Carbonell, J. Siekmann, Eds.), Springer Berlin / Heidelberg, 2005.
- [12] Golfin, P. et al. *Strengthening Mathematics Skills at the Postsecondary Level: Literature Review and Analysis*. U.S. Department of Education. Office of Vocational and Adult Education. Division of Adult Education and Literacy, 2005.
- [13] Hawthorne, J. Inductive Logic. In *Stanford Encyclopedia of Philosophy* (E.N. Zalta, Ed.). <http://plato.stanford.edu/entries/logic-inductive/#1>, 2005.
- [14] Moiceanu, A., B.E. Bărbat. Ethical Behaviour of Self-Aware Agents. *The good, the bad and the unexpected: The user and the future of information and communication technologies*, Institute of the Information Society, Moscow (forthcoming, May 2007).
- [15] Moisil, I., I. Pah, B.E. Bărbat, E.M. Popa. Socio-cultural modelling of the student as the main actor of a virtual learning environment. *8th WSEAS Internat. Conf. on MATHEMATICAL METHODS AND COMPUTATIONAL TECHNIQUES IN ELECTRICAL ENGINEERING (MMACTEE '06)*, Bucharest, 2006.
- [16] Simon, H.A. Why should machines learn? In *Machine Learning. An Artificial Intelligence Approach* (Michalski, R.S. et al., Eds.), Springer-Verlag Berlin, 1984.
- [17] Resnick, L.B. *Education and Learning to Think*. National Academy Press, Washington, DC, 1987.
- [18] Schulte, O. Formal learning theory. In *Stanford Encyclopedia of Philosophy* (E.N. Zalta, Ed.). <http://plato.stanford.edu/entries/learning-formal>, 2002.