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Learnability as an Indicator for Planning and Control of Learning Systems

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Abstract. *The paper discusses a generalized approach to determining the indicator "learnability" for an individual student or a cluster of students in intelligent learning systems. Learnability is treated as a complex indicator that takes into account the impact of all key elements in the overall learning process. Learnability is a reliable indicator in planning and managing the learning process in all its aspects, taking into account its current state and forecasts for short and long time horizons.*

1. Introduction

"Learnability" is an important property, especially important in planning the procedure for reaching a solution to the problem both in various machine learning systems (prediction, classification, modelling) and in educational systems, where the most important thing is to achieve the set educational purpose. Unfortunately, in the field of machine learning (ML) there is still no agreement on a uniform formulation of this concept, similar to the approach in the theory of automatic control, where the concepts of "controllability", "observability" and "reachability" are defined unambiguously by the characteristics of the system in question. Most often in machine learning "learning" is understood as the property of an algorithm to predict certain qualities or attributes characteristic of a given set of data, extracting previously unknown patterns (structures, images, models) through iterative learning. The results obtained within the statistical theory of education have the greatest completeness in ML [1, 2]. In a system of great complexity, it turns out that the standard statement for finding with high probability a classifier with a small error with limited time and available data is not applicable. In some recent work [3], this problem is overcome by adding additional "privileged information" to each element of the training data. The obtained theoretical and practical results can be very important in the direct learning work in teaching students complex concepts, where the source of "privileged information" is a well-prepared teacher.

The concept of "learnability" in machine learning systems is associated with strictly defined mathematical structures [1, 2, 3]. They do not have a clear correspondence with the relevant concepts in the numerous theories of traditional learning, which is different in structure and meaning from machine learning. Therefore, definitively and conceptually the concept of "learnability" in traditional education systems should be developed independently.

In contrast to the "learnability" of machine learning (ML) systems, for which – as shown above – the task is objectified and formalized after the choice of an alternative, in systems where people are trained, additional degrees of freedom of the concept of "learnability" appear. They arise from the non-algorithmic nature of man – his/hers personal characteristics, cognitive skills, reactive behavior, environmental influences, social impact. Therefore, the concept of "learnability" in human-dominated learning systems (including a teacher and a pupil/student) does not have an unambiguous definition. Despite the fact that the training system can be considered as a complex closed feedback management system [4, 5], the concepts established in the theory of automatic control such as "manageability", "observability" and above all "reachability" cannot apply. The reason is that these properties are uniquely defined explicitly only for linear stationary control systems. The human-teacher/human-learner system ($H_1 - H_2$) is non-stationary, nonlinear and indeterminate. Therefore, the term "learnability" has a different semantic orientation in the specific considerations. First of all, there is no conceptual clarification of the concept. It is most often perceived as "an opportunity for the learner to acquire the target knowledge". In a number of publications [6, 7, 8] learnability is accepted as "an opportunity for easy and efficient perception of knowledge". In particular cases of learning, this imposes morphological requirements or requirements on the volume, pronunciation, spelling, semantics of learning a second language ($L2$); specific requirements for the human-machine interface and the way of software design. In many cases, learnability in this sense has the meaning of a conceptual approach, rather than a wording. In Collins's famous Oxford Dictionary, "learning" is defined in an extensible tautology as "learning opportunity." In some cases, learnability is associated with the possibility of career realization (learnability and employability) [11, 12, 13].

In the present research, a stricter approach has been adopted, taking into account the real structures and features of the overall learning process.

2. Basic Assumptions Introduction

1. It is assumed, as stated above, that the purpose of learning is several types of knowledge:

a) Targeted knowledge $K^0 = K_g^0 + I^0 + S^0$, where

K_g^0 are facts and procedural knowledge,

I^0 is useful information,

S^0 are the corresponding K_g^0 and I^0 skills and habits;

b) With cognitive K_g^0 and epistemic E_p^0 knowledge and skills:

– Understanding,

– Innovation,

– Generalization,

– Judgment;

c) Special knowledge and skills G:

– Search for knowledge in knowledge bases (KB), databases (DB), Internet,

– Communication skills,

– Teamwork skills,

– Leadership skills (if included in the course objectives).

Thus, if the indicator "relative degree of knowledge acquisition" is introduced, the term "partial learnability" can be defined for each of the cutting groups of knowledge.

2. It is assumed that the degree of acquired knowledge of each type can be assessed in terms of:

– Volume of perceived knowledge V,

– Durability of knowledge R,

– Depth of knowledge J.

3. It is assumed that the learnability depends on the individual characteristics of the learner P, including:

– Preliminary basic knowledge of the forthcoming target area for training,

– Ability to understand the curriculum in this area,

– Memory quality,

– Skills for reasoning with logical inference,

– Practical habits and skills.

4. It is assumed that the learnability of the subject depends on the quality of the overall learning process A including [4, 5, 9, 10]:

a) Structural elements A_S determining the given learning trajectory Q^0:

– Strategy,

– Pedagogical decisions,

– Management impacts aimed at the learning process,

– Methods for assessment of the acquired knowledge.

b) Procedures that improve the learning process A_P, realizing the set learning trajectory Q^0:

– Modeling,

– Optimization,

– Adaptation.

c) System for regulating the emotional state of the learner A_E, stabilizing the set learning trajectory Q^0 [9, 10], including:

– Complex system for detecting and recognizing the emotional state of the learner (by face, voice, gestures),

– Mathematical model of the emotional state of the learner,

– Module managing the emotional state,

– Module detecting the mutual influence of learning and emotional state.

d) A system providing freely available learning resources A_R :

– Data mining system,

– Content analysis system,

– Question/answer system,

– Intelligent recommender system,

– Laboratories with remote access,

– Virtual laboratories.

5. It is assumed that the learnability depends on the pedagogical qualification B_p and the emotional intelligence B_e of the teacher *B*, which in the course of the learning process and especially in the usual cases of periodicity may change.

6. It is assumed that the set amount of knowledge and skills *V* with certified quality *W* must be realized within a certain time frame T^0.

Figure 1 shows a block diagram of the overall learning process, where the following generalized designations are accepted: *L* – learning, *Em* – emotion, *u*, *d* – control and disturbing effects, *ESR* – Emotion Self Regulation, *Ep* – epistemic state, *Ass* – assessment information, *K* – knowledge state, *C* – cognitive state.

3. Learnability

Learnability *L* is determined by the following factors:

(1) $L = (D, W, A, B, P, T)$.

Reachability *D* is presented as:

(2) $D = D\left(K, C, E_p, G \right)$.

Quality of knowledge acquisition *W*:

(3) $W = W\left(V, R, J \right)$.

Quality of the training system *A*:

(4) $A\left(k \right) = A\left(A_S, A_P, A_E, A_R \right)$.

Teacher's characteristic *B*:

(5) $B = \left(B_P, B_E \right)$.

The individual attributes of the learner *P*. Training time *T*.

Thus, given the requirements for the learning process

(6) $$D^0 = D\left(K^0, C^0, E_p^0, G^0 \right), \quad W^0 = W\left(V^0, R^0, J^0 \right), \quad T^0$$

and with fixed data for the training system

(7) $$P\left(k \right) = P^0, \quad A\left(k \right) = A^0, \quad B\left(k \right) = B^0,$$

the quality "learnability" *L* (1) is realized if and only if

(8) $$D\left(T_f \right) \geq D^0, \quad W\left(T_f \right) \geq W^0, \quad T_f \leq T^0.$$

In a cyclical learning process, the quality of "learning" can be systematically improved because:

a) Some of the parameters *P* of the learner – understanding, judgment, practical skills, preparation, use of learning resources, communication skills – are likely to develop in a positive direction;

b) The quality of the learning process *A* will iteratively improve in the intelligent learning system (ILS) related to the procedures (optimization, adaptation, machine learning);

c) The opportunities for freely available learning resources are systematically improved in ILS;

d) The quality of the human-teacher system (*H*) and in particular the hybrid teacher-system plus the auxiliary computing system ($H + M$) will improve from one learning cycle to another.

The quality of "learnability" should be defined as follows:

a) Before the beginning of a cycle according to the goals for planning and schedule – time resources T_f, the content of the main structural elements A_S, learning resources A_R;

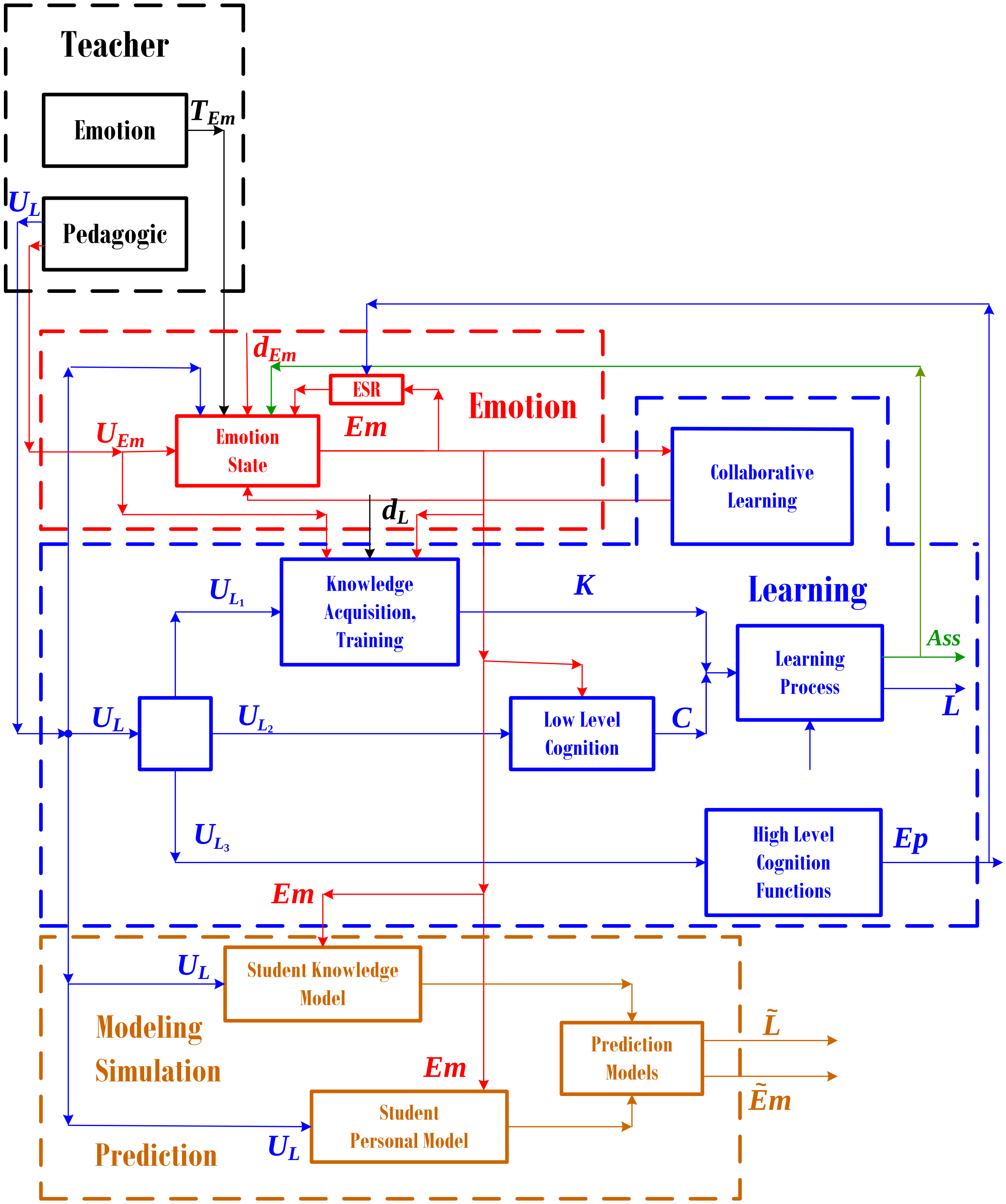

Figure 1.

b) In the course of the training, in order to assess the dynamic indicator “learnability” in the rest of the learning process in order to improve its effectiveness (e.g. $T_f < T^0$).

Defining the quality “learnability” is feasible in the following cases:

a) in traditional (non-machine) training only on the basis of the expert knowledge and historical experience of the teacher. The estimates obtained will be very subjective and inaccurate. They will lack a constructive focus for improving the attributes in complexes *P*, *A* and *B*;

b) in ILS the quality “learnability” *L* is determined on the basis of a multimodel approach to the learning process [4, 5, 9, 10]. This approach can be implemented in two ways:

– Average. According to archival data from previous cycles of education and from preliminary input data for the given cycle (survey, interview, dialogue) the average statistical components of the parametric vector P of the qualities of the "average" student in the trained group are determined. The data for the components of factors A and B are taken from the previous cycle as:

$$\begin{aligned} &P(k) = P(k-1), \\ (9)\quad &A(k) = A(k-1), \\ &B(k) = B(k-1). \end{aligned}$$

The obtained model-based estimates for $D(T_f)$, $W(T_f)$ and T_f are average.

– Group. The composition of the student body is divided into three groups – best, average and weaker. Based on the a priori and input information, three sets of mathematical models are created, which determine the expected quality "learnability" for each of the groups. A special object of attention is the group of weaker students, for whom the average requirements for $D(T_f)$ and $W(T_f)$ at a given time of research $T_f = T^0$ may be unattainable. Therefore, lower but acceptable certification requirements should be set for this group of learners:

$$(10)\quad \begin{aligned} &D_l^0(T_f) < D^0(T_f), \\ &W_l^0(T_f) < W^0(T_f). \end{aligned}$$

which will represent new but realistically achievable goals for this group of learners.

– Individualized. In the presence of an intelligent training system (ITS) at the beginning of the classes for a given course it will be possible to determine the perspective for "individual trainability" of each trainee, which will be directed to the respective group of certification requirements. Thus, the training for each student will be consistent with its initial capabilities, reflected in the complex $P(0)$, his/hers development in the course of training $P(k)$ and his/hers ability to cover for the terminal time T_f a higher specification category. For many courses commissioned by industry, this is essential for its future staff development. Thus, the often discussed issue of the relationship "learnability" – "personal feasibility" [11, 12, 13] receives a real approach to implementation.

4. Conclusion

Learning in the systems of traditional learning systems $(H_1 - H_2)$ and $((H_1 + M) - H_2)$ differs significantly from machine learning due to the presence of different levels of cognitive procedures – understanding, memorization, generalization, as well as specific features of the person – the subject of learning H_2: forgetting, fatigue, mental states (distraction, negative emotions, lack of motivation). This imposes a different concept of the concept of "learnability" in this type of systems as opposed to those of machine learning.

Since in both traditional and ILS the acquisition and accumulation of new knowledge is essential, there are separate types of knowledge that must be taken into account when formulating the general concept of "learnability" as well as to define partial indicators for learnability in each component.

The factors that determine the assessment of the indicator "learnability" are identified.

A method for assessing learnability in traditional learning systems with a dominant human-teacher (H_1) role has been proposed.

It is shown that the indicator "learnability" can play an important constructive role in different stages of traditional learning:

– At the planning stage: synthesis of training documentation and training resources,

– At the individual stages (cycles) of the learning process,

– In the processes of defining strategy and decision-making for pedagogical actions,

– In the processes of optimization and adaptation of various structural elements in the learning process (mathematical models, methods for testing and evaluation, learning resources, dialogue system).

The concept and the "learnability" indicator are important for intelligent systems of the type $((H_1 + M) - H_2)$ in the following directions:

– Formation of individualized training of clusters of students,

– Individual help and motivation of certain students.

The indicator "learnability" is essential in the teaching processes of teachers themselves on the basis of the accumulation of new pedagogical knowledge and skills, the acquisition of human-machine interface with their subordinate machines $(H_1 - M)$, the new approaches in interactive cooperation with students in individualizing learning.

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