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Instantiation in Partial Learning

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ABSTRACT

The adaptive learning systems are changing the learning process as we know it. One of the advantages they have over the traditional ways of learning is the attempt to adapt to the learner's capabilities in order to deliver the knowledge as optimizing as possible. Even in such sophisticated implementations there are differences in the treatment of the adaptive learning. During the past years spent in research of different aspects of the adaptive learning, we made a distinction of our latest development phase as an advanced adaptive learning, having more specific approach to the problem from the phase where the problem of adaptive learning is treated as a general case. Considering the conditions of advanced adaptive learning rather than basic adaptive learning, the process of learning is different and closely related to the human learner. In order to demonstrate this key improvement, we presented a general learner model through its learning mechanism and its behavior in the adaptive learning environment together with the instantiation process. In this paper we present a new way of learning with learning environment instances, constructed by choosing different ways to obtain the knowledge for a target unit.

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1. INTRODUCTION

Since our main focus has shifted from the BAL (Basic Adaptive Learning) which strictly defined the relations between our knowledge units – the concepts [4], towards more flexible knowledge organization within the learning environment, we succeeded in representing this kind of knowledge by introducing the BC (Blank Concept) [3], [6] so that the graph [5] structure of the ALE (Adaptive Learning Environment) is preserved. The next step in our analysis and experimenting with the components of the partial learning will be the instantiation of new LEs (Learning Environments) as a result of ALE's interaction with the learner through its LM (Learning Mechanism).

We defined the instantiation as a process of creating instances of ALE according to the learner's LM. Roughly explained, the purpose of these instances is to determine the best suitable LE for the appropriate learner. We represented ALE as graph of concepts and their relations, hence one instance of the ALE can be represented by one of its subgraphs. In the conditions of BAL, the result of the instantiation is the IALE (Instantiated-adapted learning environment) [1] and it is used as the best possible way for the learner to gain the planned knowledge.

Since the PL [2] does not allow knowledge to be represented as a pure graph, the instantiation in AAL (Advanced Adaptive Learning) needs to be redefined. The LM's representation also requires altering, caused by the fact that a learner can gain knowledge on more than one way. This means that the LM will have the same structure as the ALE - it will include blank concepts in order to distinguish the IC sets (the sets of input concepts).

The goal of the instantiation will remain the same – to create a new IALE from ALE that will be used to express the minimal set of concepts required for the learner to fill the gaps in its LM [1]. Considering this background theory, our goal was directed into simulating both LM and TS (test set) as a first step towards the interpreting of the instantiation. These activities require different methods than those used in the BAL or in other adaptive learning systems [7], [8], [9], [10], because the representation of the PL's components differ from their appropriate representations in the BAL. In these paper we will stick to the randomly simulated LMs in order to reflect the most general situations of partial learning.

2. RESEARCH METHOD

The main research approach will include the construction of the graph representation of the IALE in case of already present LM. Then we will test the instantiation in our learner model using different simulations of the LM.

3.1. IALE representation

In BAL, IALE has the same structure as ALE, often with less number of concepts and relations or, expressed in a different way, it simply represents a subgraph of ALE's graph. Considering that in the conditions of partial learning, ALE breaks the graph rules because of the blank concepts' [3] involvement, we expect the IALE to have the same structure as well. However this will not follow the purpose of IALE – to have a learning environment best suitable for the learner's LM.

Having in mind the goal of the instantiation, the representation of IALE will remain the same as in BAL, thus resulting in structure different than the ALE's. This means that the process of instantiation will suffer changes because the resulting learning environment as a pure graph must be derived from a learning environment which contains blank concepts along with the regular concepts.

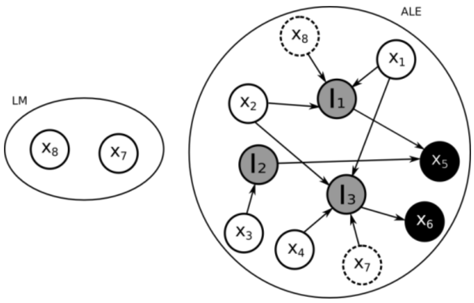

Figure 1. An example of learning mechanism and ALE in the process of partial learning

Because the blank concepts determine the IC sets [2] of the appropriate regular concept, they will not be included in the resulting IALE. Since there are no blank concepts in IALE anymore, then the existence of more than one IC set is not possible, which leads to the question – which IC set should be included in the IALE? The answer is simple – the one which leads to the most efficient learning of the contents overall (we determine the learning efficiency by the number of input concepts required to reach the learning targets) . For example, if we isolate one regular concept with its blank concept and IC sets, the answer is simple – the IC set with the smallest number of input concepts [1] will be included in the IALE and not the others. The ALE with all of its regular concepts, however, is a different story.

Often in an ALE you can find larger IC sets which include input concepts needed to help learn other concepts. Therefore there is a chance that the learning array [1] will get shorter if we choose these larger IC sets instead of smaller ones, thus making the learning process more efficient. This implies that the choosing of the right IC set to be included in the IALE is a complicated task even for a small ALE as it can be seen in Figure 1.

3.2. Instantiation

Figure 1 shows an ALE with only eight concepts, two of them (x_5 and x_6) terminal and another two (x_7 and x_8) already known by the learner – included in its learning mechanism. This state indicates that the resulting IALE will include the rest of the ALE's concepts required to make the learning of the terminal concepts possible. As the structure of the ALE shows, there are two possible ways of learning the concepts x_5 and x_6, therefore only two candidates for more suitable IALE can exist. The two candidates for IALE are shown on Figure 2.

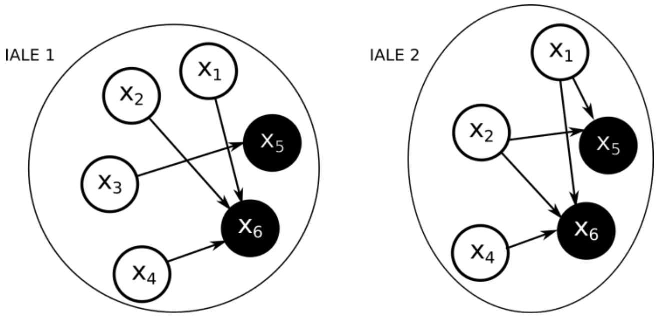

Figure 2. Two IALE candidates for the PL example on Figure 1

Although more efficient way to learn the concept x_5 is by using just one concept (x_3) instead of two (x_1 and x_2), in the case of IALE 2 choosing the larger IC set for the same concept results in a smaller number of concepts needed to be learned. The reason for this lays in the fact that both x_1 and x_2 concepts provide knowledge for the other terminal concept as well.

The example on Figure 1 shows a simple state of the learning mechanism consisting only of concepts which do not posses any IC sets at all. What happens when a learning mechanism contains concepts having several blank concepts passing knowledge from different IC sets? The answer can be different than the one given in conditions of BAL.

Let us analyze a PL process where at least one of the concepts included in the LM has more than one IC set. One such example is given on Figure 3.

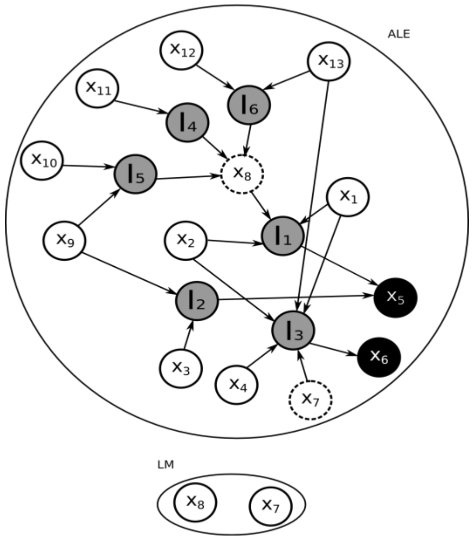

Figure 3. Learning mechanism containing a concept with more than one IC set in ALE

Using the method of unknown concepts [1] in order to instantiate new learning environments in BAL conditions, the resulting IALE will not include all of the concepts providing knowledge to the LM's concepts, in the case of Figure 3 - x_8. In the conditions of partial learning, if the learner is aware of the concept x_8, it does not imply that all of its input concepts (x_9, x_{10}, x_{11}, x_{12} and x_{13}) are also known. The reason for this is the distinguishing of the ways the concept is learned, unless we take for granted that the knowledge for x_8 can be passed by all of its blank concepts (I_4, I_5 and I_6). But in reality this is a very rare case and mistakes in judgment can be made which can alter the learning process negatively. For example, if we guess that by knowing x_8, the learner knows all of its input concepts, and the learner, in fact, knows the concept only from the knowledge provided by x_{11}, it will result in making a mistake when I_2 and I_3 have to pass knowledge to the terminal concepts because the input concepts x_9 and x_{13} will not be considered respectively.

In other words, the learner will have difficulty understanding the knowledge passed from the two blank concepts because it will not have knowledge about x_9 and x_{13}.

The initial step in instantiation in the partial learning consists of removing all input concepts of the concepts contained in the learning mechanism, which are not related to any other concept in ALE. This rule is applied recursively on their input concepts as well. Finally, the IC set containing the input concepts providing the lowest number of concepts for IALE, will be the first choice for the best resulting IALE. One such example is given on Figure 4 where the concepts x_{10}, x_{11} and x_{12} are not related to other concepts besides x_8 which is already included in the learning mechanism.

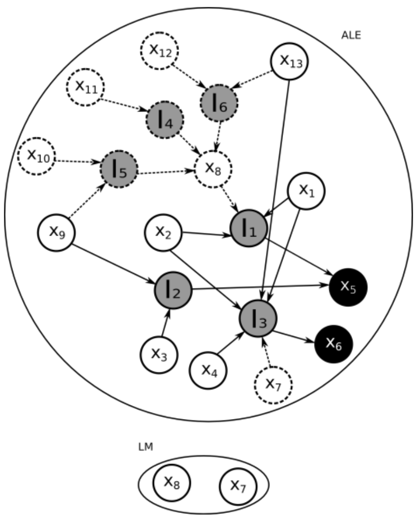

Figure 4. Initial step of instantiation for the example on Figure 3

In order to determine which IC set is known by the learner, every IC set must be checked until the first occurrence of its input concepts in the LM is found. This can be done with additional tests performed on the learner. It is enough to find only one such IC set to establish a connection in the learning process. This first instantiation strategy will be called, "the method of additional tests".

If it is impossible to determine the IC set already known by the learner, the following prediction is used – the IC set with the smallest number of input concepts providing knowledge to other blank concepts will be the best candidate. This is reasonable because the chosen IC set will make the least damage to the learning process. For the example on Figure 3, one such IC set is $\{x_{11}\}$, since x_{11} is not related to any other blank concept unlike the concepts x_9 and x_{13}. We call this instantiation strategy "the method of single IC set removal". The resulting IALEs are shown on Figure 5.

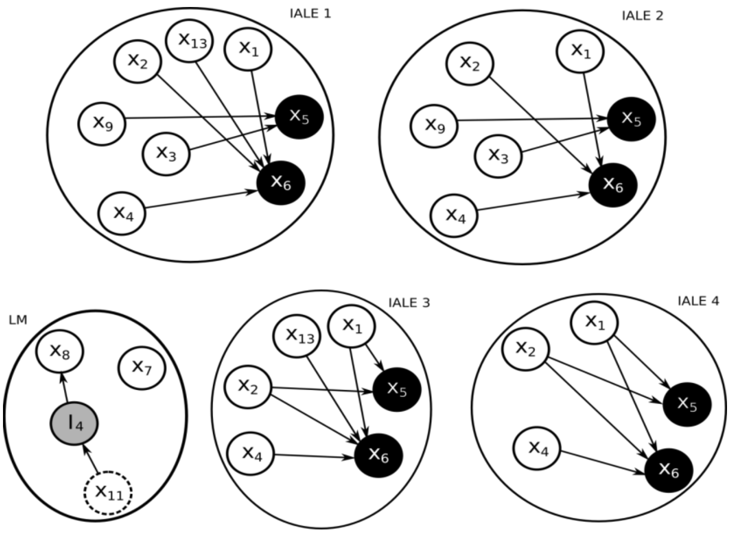

Figure 5. IALE candidates for the partial learning example on Figure 3, using the method of single IC set removal

Although, this method brings relative accuracy in determining a single IC set contained in the learning mechanism, it usually leaves more than one IC set to be considered in the instantiation process, in the case of the example on Figure 3, I_5 and I_6. Therefore an opposite approach can be done where instead of proposing an IC set to be included in the learning mechanism, it will be looked for another IC set to be included in an IALE, thus decreasing the number of resulting IALEs, which simplifies the instantiation process, overall. This one will be called “the prediction method“. Figure 6 demonstrates how the resulting IALEs will look by predicting that the best way to learn the concept x_8 is by using the IC set I_5.

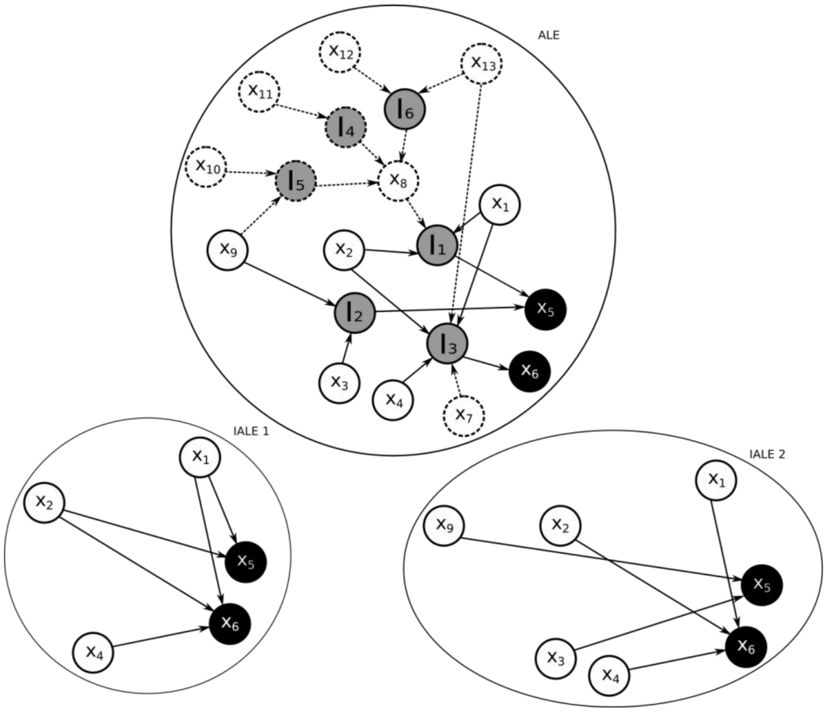

Figure 6. The result of the prediction method performed on the example on Figure 3

To sum up, the best way (although often costly) for creating an ALE's instance, which will offer the most efficient learning, is to remove all input concepts (direct or indirect) related to the learning mechanism's concepts, then construct every possible IALE using the remaining input concepts (if any) and finally choose the IALE with the smallest number of concepts. In some cases there is more than one such IALE.

3. RESULTS AND ANALYSIS

We already explained the representation of the LM as a relevant characteristic of the learner's model. For experimenting with the AAL process it is enough to simulate an LM according to the goal of the experiment. In addition we present the results which determine the effectiveness of the instantiation process.

3.1. Simulation of LM

The most simple LM simulation in BAL was the random simulation. In AAL it is also possible to make a random generation of LM from ALE. The difference is the structure of ALE where the blank concepts are also treated.

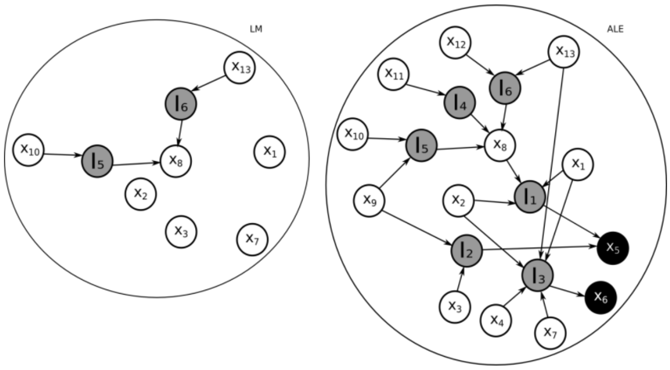

Figure 7. Random simulation of LM with 7 concepts

The procedure of random simulation of LM starts with choosing a number between 1 and |VALE|. Then a set of regular concepts is selected from the ALE, equal to the chosen number. Finally the BCs are added, but only those which gather the knowledge from the selected regular concepts. One such example is given on Figure 7, where 7 as a random number between 1 and 13 is chosen, and afterwards the concepts x_1, x_2, x_3, x_7, x_8, x_{10} and x_{13} are selected. According to the appropriate relations, only the BCs I5 and I6 are required for LM since the I4 does not have any concept to gather knowledge from and I_1 and I_3 do not have any concept to pass the gathered knowledge. The BC I_2 is not included because of the both reasons.

3.2. Analysis of the efficiency

In the analysis of the effectiveness of the instantiation process, we will proceed by assuming the ALE "is aware" of the LM's structure, for easier calculations. According to the assumption, the instantiation will always be successful no matter the chosen simulated LM. Our concern was the number of concepts omitted indirectly i.e. the concepts which are not found in both the LM and the IALEs after the instantantiation finishes. Therefore the efficiency will be calculated by percentage of the number of those concepts. The greater the number of omitted concepts, the more efficient is the learning provided by the IALE in terms of the number of concepts – the required knowledge to be offered to the appropriate learner.

The results of the testing of the instantiation in the same ALE with several simulated LMs are given on Table 1. Note that the performed tests were adjusted with relatively small number of concepts, but enough to describe in which situations the instantiation gives more effectiveness for the learning process.

Table 1. Instantiation efficiency for ALE containing 16 concepts

$\|V_{ALE}\|$	$\|V_{LM}\|$	$\|V_{IALE}\|$	Efficiency	Number of tests
16	6	7	0.19	19
16	5	9	0.13	16
16	1	15	0.00	16
16	5	11	0.00	16
16	4	12	0.00	18
16	5	7	0.25	16
16	2	13	0.06	16
16	7	5	0.25	16
16	4	4	0.50	19
16	0	16	0.00	16
16	3	6	0.44	16
Averages:	3.82	9.55	0.17	16.73

It can be noticed that the efficiency values are higher for smaller $|V_{IALE}|$ and $|V_{LM}|$, which is interpreting as the smaller the LM, the more the chances are to omit higher number of IALE's candidate concepts. Although the total efficiency percentage in Table 1 is low, it does not mean that our approach for creating IALEs is weak, instead it suggests that these values are relative to the chosen example of PL.

4. CONCLUSION

According to the given explanations about possible ways of constructing IALE from ALE, and considering the instantiation in the BAL conditions, it is clear that the instantiation process in PL is more difficult to achieve. There are two main reasons.

Firstly, there is high probability of more than one instance of IALE for the same LM. Furthermore, when it comes to choosing the best IALE, often there are more than one IALE with the smallest number of concepts. And there is no existing prediction method that will tell us which IALE is the best for the future learning of the same learner from some other ALE.

Secondly, the new established relations between the concepts involving BCs mean that there is more complex logic needed to resolve which concepts should be omitted in the final learning process. In BAL conditions this task was relatively easy – if a concept is already known by the learner, all of his ICs are assumed to be known, too. In PL, the task gets complicated because there are more than one way for a concept to be known by the learner, thus in order to omit its ICs, it must be clear which of the IC sets bring the knowledge to the same concept in the LM.

We have shown that although there are can exist more than one IALE candidate for a single ALE, there is at least one which is most suitable for a given learner, considering the fact that ALE is constructed with more than one way to obtain the knowledge for every included concept. Despite all of the difficulties, we managed to build a model of partial learning using oriented graphs [5] with blank nodes [6], so that the creation of the best learning environment for a certain learner in PL can be easier to compute.

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